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Intelligent Monitoring of Incidents in Complex Systems

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Declaration

I declare that this document is an original work of my own authorship and that it fulfils all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa

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Abstract

Business companies started using computers since the middle of the last century. Nowadays, most companies, even if not technology related, depend on the correct operation of complex computational systems. Such systems generate data from several running services, microservices, and tasks that can reveal a lot about the systems' behavior. Events or observations that deviate from the normal system behavior are considered anomalous and may indicate near-future critical incidents, such as technical bugs and glitches, system malfunctions or hardware problems.

However, the amount of data that can be extracted from running machines, cannot be analyzed manually due to its dimension and complexity nor can it be done by setting simple metric thresholds. Throughout the thesis, an intelligent monitoring system will be studied and implemented in order to predict recurring incidents. The eagerly sought-after perfect system is unfortunately unattainable. Incidents occur, which is somewhat accepted in the Information Technology (IT) industry. In contrast, what is not accepted, is a repetition of a similar incident that already took place in the past. The goal of this thesis is to study and develop a monitoring system that predicts repeated or recurrent incidents. Making use of service metric datasets, provided by real world organizations. Data is fed in real time to the intelligent monitoring system, which will attempt to learn from past incidents and generate reliable future predictions. Service engineers will then use these predictions to perform preventive maintenance, rapidly adapting and acting upon changing conditions to avoid service failures.

Keywords

Artificial Intelligence Artificial Intelligence (AI); Artificial Intelligence for IT Operations (AIOps);

Development and Operations (DevOps); Event Detection; Incident Fingerprint; Incident Prediction; Information Technology (IT) Monitoring; Machine Learning; Monitoring IT Operations; Pattern Recognition; Preventive Maintenance; Site Reliability Engineering;

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Acronyms

AD	Anomaly Detection
AI	Artificial Intelligence
AIOps	Artificial Intelligence for IT Operations
APM	Application Performance Monitoring
CCTA	Central Computer and Telecommunications Agency
DevOps	Development and Operations
ETL	Extract, Transform and Load
IT	Information Technology
ITIL	Information Technology Infrastructure Library
KPI	Key Performance Indicator
LOF	Local Outlier Factor
IF	Isolation Forest
LU	Luminol Univariate
LS	Level Shift
VS	Volatility Shift
HM	Hand Made
SFBP	Seasonal Facebook Prophet
ML	Machine Learning
MTTA	Mean Time To Acknowledge
MTTR	Mean Time To Repair
SaaS	Software as a Service
SLIs	System Level Indicators

SLOs	System Level Objectives
SRE	Site Reliability Engineering
CSV	Comma-separated values
NLP	Natural Language Processing

1

Introduction

1.1 Background and Motivation

Due to ever changing business and market requirements, digital transformation has taken over all sorts of companies. Businesses, even if not technology related, now rely on computers to either sell their products/services or internal tools that employees use. As businesses scale and demand increases, companies start adopting complex infrastructures, moving from legacy on-premises to a hybrid mix between on-prem and cloud, or moving completely to a full cloud solution.

In the late 1980s, Central Computer and Telecommunications Agency (CCTA) created Information Technology Infrastructure Library (ITIL) [4], a standardized way of managing IT operations as a service.

When incidents happen the business is impacted, whether it is directly because users cannot checkout on an e-commerce website or indirectly, such as workers not being able to perform tasks in their internal tools because the company databases are down. Reliability plays an important role in delivering the best experience to the end user, monitoring applications and services' health is crucial when users rely on them in real time. The goal is to prevent incidents by solving minor issues before they impact the business' revenue or customers' satisfaction.

Service running machines generate metadata that can reveal a lot about the systems' behavior. With such a large volume and complexity of data, typical manual monitoring simply isn't effective. Trying to set up simple metric threshold alarm rules generates too many false positives due to the dynamic nature of these infrastructures. A high number of false positives leads to alert fatigue, which desensitizes Information Technology (IT) teams and can have disastrous consequences. A study conducted by McCafee regarding alert fatigue in IT security professionals revealed "Of the 2,542 anomalous *events*, only 23.2 are actual threats, a ratio of nearly

110:1 that reveals the potential scale of false positive alerts." [5]. In fig. 1.1 we can analyze that 31.9% of the sample data ignored alerts due to alert fatigue and as a consequence, they receive more *events* than one can manage and investigate. The survey and study regards to IT security incidents, but this can be equally applied to IT service incidents.

Figure 1.1: A survey conducted by the Cloud Security Alliance on how false alerts compromised data security.

Gathering all metrics in one place and using Artificial Intelligence (AI) to learn the normal behavior of a service would be the desired approach to monitoring complex dynamic infrastructures. As shown in section 2.3, current tools in the market focus mostly on the direct connection between metric univariate or multivariate anomaly detection to incidents. These approaches work for some use cases, however, there are two major problems. Most of the time incidents have already happened and damage has been done. Currently available approaches do not solve the recurring incident problem, which terrifies companies. An incident in a specific service is one thing, nevertheless, a repeated incident in the upcoming days or weeks damages services' reputation. Ideally, IT service engineers would be alerted in real time when an incident is predicted based on evidence found in metric behavior. This way, they can act quickly to minimize damage or even avoid the potential incident.

1.2 Objective of this Thesis

The goal behind this study is to create an intelligent monitoring system using a machine learning pipeline, capable of monitoring a variety of different complex system infrastructures. This system learns from past incidents and proactively alerts the service engineers to a predicted future incident. With enough time, damage can be minimized. This intelligent monitoring vision is based on three main principles - real time, model-agnostic and low configuration.

The three principles were chosen according to today's picture of Development and Operations (DevOps) and Site Reliability Engineering (SRE) teams [6] [7] [8]. One can understand the benefits of getting notified before a problem happens, service engineers have time to react and hopefully avoid a potential incident (problem or failure of one or more services). Due to the ever-changing nature of IT systems and complex architectures present in most organizations these days, the importance of an agnostic approach becomes obvious, an operator fires up a new component in the service architecture, for instance, a server, and the intelligent monitoring system automatically starts keeping track of that component's metadata. The goal is to eliminate recurring incidents that organizations suffer from, e.g. fig. 1.2. The success of this study relies on the hypothesis that a monitoring system can be built to determine causality between detected metadata events and real world incidents, thus exposing and storing incident fingerprints that can afterward be detected in real time and alerted upon, insuring incidents of the same type don't happen ever again.

SERVICE	CHECK	OCCURRENCES	MTBF (HRS)	LAST EVENT
Call Center	Increased Delays in call center	1221	0.58	5e77f8eb0543094ed81031aa
Cancellation service	500 errors	1175	0.57	5d259ab289e8d93a3ab1a4e1
Booking	Drop in Booking in last hour	708	0.99	5bf5863e70085a25eec26866
Web API	Increase load	648	1.07	5d404cc55b72155fb20c0968
Manufacturing	Unexpected errors in step 5	422	1.63	5cf24d50141e4527d9aee7ae
Booking	Business Transaction error rate is much higher t...	420	1.65	5d42546faf25055cee03b66e

Figure 1.2: Examples of correlated Events by BigPanda [1].

1.3 Accomplishments

In the end, the results achieved prove that there are incidents that can be predicted using the approach of the study's hypothesis. Incidents predicted have shown there is time between the incident prediction moment and the incident occurring. Prediction interval time averaged between 3 minutes and 38 seconds up to 7 minutes and 8 seconds, depending on the trial run. This means, the service engineer responsible for maintaining service reliability has more than enough time to act, Mean Time To Acknowledge (MTTA) is zero, hence minimizing Mean Time To Repair (MTTR), which can be translated directly into reducing or avoiding downtime altogether. Although recall values are low for 100% precision trials, a way to improve recall while maintaining precision was found. It is suggested as future work. It involves the combination of different input module parameters for the best trials in a single trial. A more detailed explanation of this suggestion can be found in chapter 5.

1.4 Organization of the Document

This thesis is organized as follows. Chapter 2 summarizes the current state of the art of incident prediction in AI operations. Available tools/platforms and research papers are discussed. During this chapter, a gap in the literature is identified which this study intends to fill.

Chapter 3 sintetizes the collection and pre-processing of data needed for this study. Followed by a detailed explanation of how the events and fingerprints are extracted, as well as the process of predicting future incidents.

Chapter 4, includes an explanation of the methodology behind the performance analysis and the analysis itself.

To sum up all findings and provide some future suggestions on how to further improve the system, chapter 5.

In the end of the document, appendix A, beholds all the trial results, correspondent to the chapter 4. The appendix B holds the glossary, as some expressions or terms used may not immediately be obvious to the reader in the context of IT operations.

2

Literature and state-of-the-art review

2.1 Current state of AIOps Incident Prediction

Artificial Intelligence for IT Operations (AIOps) is a term created by Gartner [9] and it's about using AI and Machine Learning (ML) techniques to empower software and service engineers to build, maintain and operate services. The use of these techniques improves engineering productivity, reduces human operational costs and helps to ensure high reliability of services which directly translates to customer satisfaction. [10]

"AIOps combines big data and machine learning to automate IT operations processes" [9].

AIOps tools are a combination of three different service insights - Event Correlation, Anomaly Detection and Causality Determination - the following shall be explained along with the current state-of-the-art and experience using the current tools in the market.

2.1.1 Event Correlation

A process of discovering the relationship between different events that are related to each other. The ability to relate events from service metrics and logs has a lot of advantages, for instance, it enables service engineers to quickly aggregate services that are having problems simultaneously, thus reducing the time to understand what is happening and the time to repair. Even though there are tools in the market that take advantage of this to create dashboards and collaborative spaces to help solve incidents, the damage is already done and the user felt the impact. The incident happened and only then, in a reactive manner, the event correlation was useful, and the problem with this approach is that most likely service engineers are not even going to fix the root cause of the problem, they will limit themselves to rebooting the service back on waiting for it to happen again. In this thesis, the use of event correlation will be explored to proactively predict and prevent the re-occurrence of a problem. Thus, hopefully

giving a chance to service engineers to prevent the end user from being affected, whether it is by fixing the root cause problem or minimizing downtime since they expect the incident.

2.1.2 Anomaly/Event Detection

Anomaly Detection (AD) is an important step in time series data analysis that consists in identifying outliers in a group of data points. Outliers can indicate service system failures, change in end-user behavior or malicious attacks. An intelligent monitoring system should automatically detect outliers, select the most relevant ones and present them in an intuitive interface, enabling service engineers to analyze, troubleshoot and prioritize reliability work accordingly.

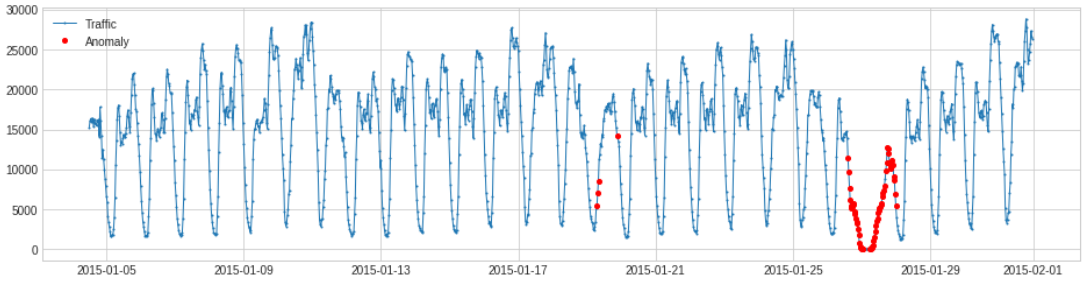

Figure 2.1: Example of detected anomalies of seasonal traffic pattern

AD is particularly useful in a scaling infrastructure since the number of services and machines rises. It becomes impossible for human operators to manage monitoring by themselves. Input data is time series data that increases over time, meaning huge amounts of unlabeled data with an unknown pattern, trend or seasonality. To perform AD, an Unsupervised solution is required. Multivariate AD is a plus, as every timestamp aggregates a large amount of features.

There are three types of time series data outliers:

Global outliers Datapoints that present themselves clearly outside of a normal range of values. A manual approach would include setting static thresholds, an interquartile range (IQR), level shifting and others, see fig. 2.2.

Contextual outliers Datapoints that deviate from the normal context of the dataset. These outliers cannot be detected using global outliers approaches as values range according to

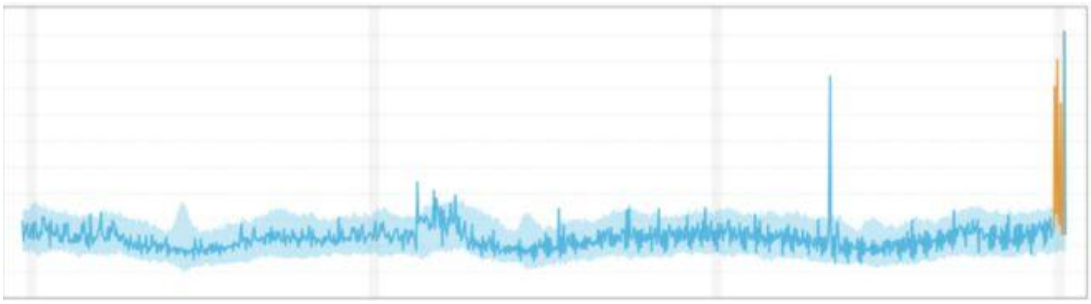

Figure 2.2: Global outlier example by Anodot [2].

context. A trend or seasonality approach is needed. Graphical examples of this can be found in fig. 2.1 and fig. 2.5.

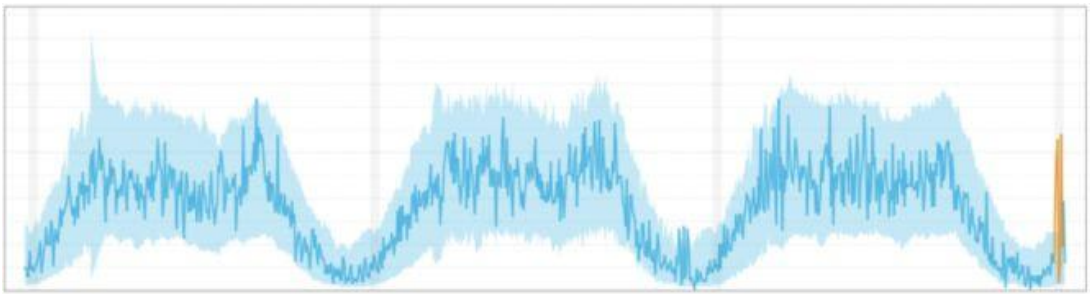

Figure 2.3: Contextual outlier example by Anodot [2].

Collective outliers Collective outliers can be found when datapoints of two or more metrics within a dataset represent anomalous behavior. Watching one metric at a time one could not realize anomalous behavior was happening, because contextually or globally it would not stand out, observe fig. 2.4, the metric on top deviates in the end. Even though it presents a low value, it cannot be perceived as anomalous without the correlation to the metric on the bottom. Only by studying the bigger picture, it could become clear the time window is anomalous.

The goal is to find outliers worth alerting the service engineers. One of the problems with AD in current tools is the excess of notifications creating a symptom called alert fatigue. ”Our engineers were tired of getting useless alerts so they turned most of them off”, said a CTO of a company in an interview led by Tiago Marques, regarding monitoring practices. A different

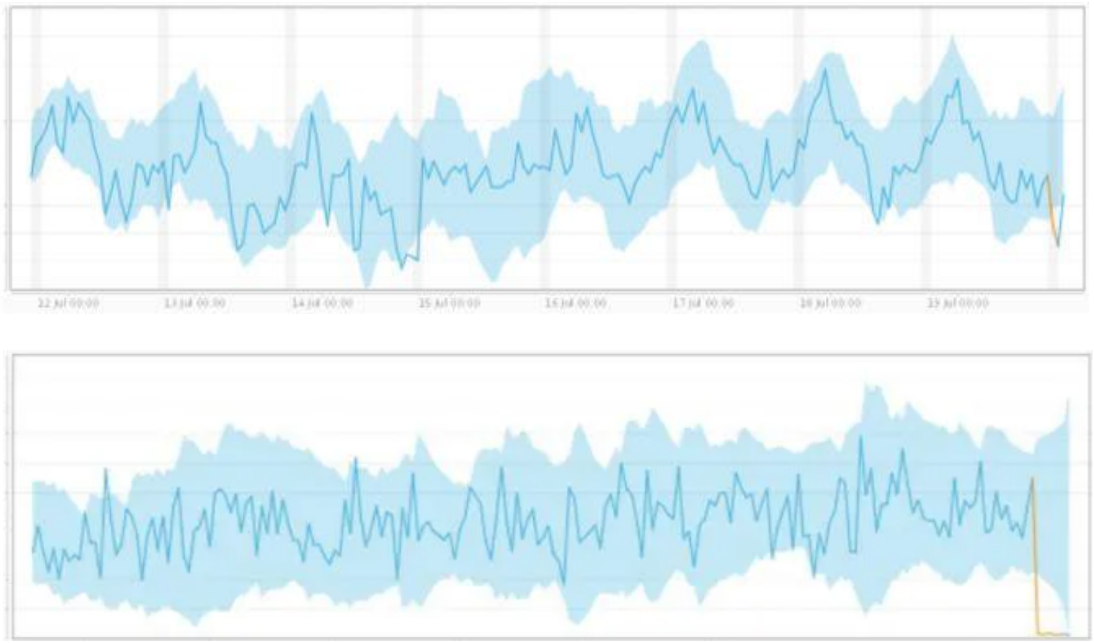

Figure 2.4: Collective outlier example by Anodot [2].

metric behavior doesn't automatically mean something is wrong and should be alerted on, so storing these outliers to understand patterns is one area of focus of this thesis.

In order to extract the metric behaviors several anomaly/outlier detection algorithms were studied, the selected ones were Local Outlier Factor (LOF) [11] [12], Isolation Forest (IF) [13], Level Shift (LS) [14], Volatility Shift (VS) [14], Luminol Univariate (LU) [15], Seasonal Facebook Prophet (SFBP) [16]. Further introduction and explanation regarding these algorithms can be found in section 3.6.1.

2.1.3 Causality Determination

"The idea that every event is necessitated by antecedent events and conditions together with the laws of nature" [17]. Causality determinism associated with AIOps is the path to understanding the temporal sequence of events that led to the incident (see fig. 2.5), establishing a fingerprint that caused the issue. Acknowledging that, engineers can now perform reliability work to ensure it doesn't happen again. It is important to note that the temporal sequence is relevant to establishing the incident fingerprint as distributed systems rely on different com-

ponents that compose the service architecture. These components work with each other to provide the end goal of the service, so one can understand the direct connection between one component failing and another failing moments after and so on, presenting a ”Domino effect” of failing components.

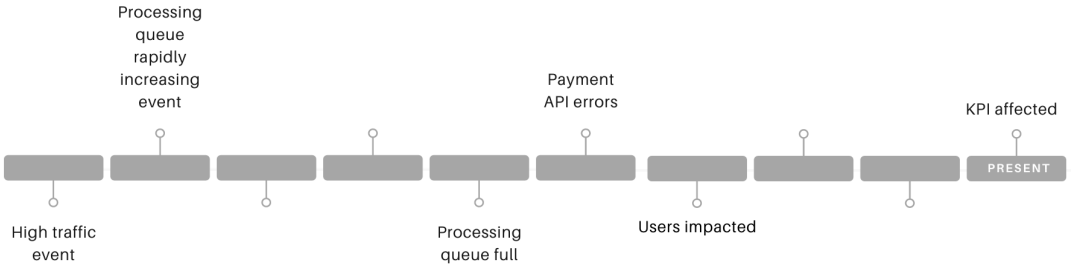

Figure 2.5: Example of how a series of events unfolded into a real world incident that impacted end users and ultimately a Key Performance Indicator (KPI)

Understanding the cause-effect pair, an intelligent monitoring system would be able to predict another incident that has the same fingerprint (sequence of events), simply by analyzing its components' metrics in real time and matching it to the known fingerprint.

2.2 Fuzzy Fingerprints Identification Method

In this assignment, it is proposed to use a modified version of the Fuzzy Fingerprints classification method explained in [18].

The fuzzy fingerprint concept, introduced by Kóczy [19], presupposes the ”qualitative meaning of an object is represented by the quantities of the VVFS (Vector Valued Fuzzy Sets).” [18]. It is assumed that an object contains a signature. This signature can be recognized in a form of the number of observations of contextual events. Contextual events can take shape of any data type, however, they need to be carefully chosen according to context. Levering the repetition of these events, a signature can be constructed. For instance, in a book context, events can be the words used by the author. The author's signature could be detected by analyzing the frequency of a specific subset of words in a book and posteriorly, comparing them to the author's known fingerprint.

In work [20], the goal is to help a user find specific content. To do that, event detection in excerpts of text is performed with the intent to classify it into a specific category. The way the fuzzy fingerprint is implemented here is by counting the occurrences of words in the training dataset, ACE 2005 Multilingual Corpus [21], and building fuzzy fingerprints for the categories. To classify a text excerpt, the fingerprints database is used to find the correct category or no category at all, this is performed by attempting to match fingerprints to the events detected in the test sentence. The documents/text used is generally in a bag of words form. This form is a list of words included in the document and their respective number of occurrences. Word order and syntax are ignored. Words correspond to the features and the number of occurrences is the feature space [20].

In [22], text categorization is attempted using Natural Language Processing (NLP), finding the adequate topic for each document. In this case, the documents are tweets, from the social network Twitter. The categorization steps are:

”

1. Decide the categories that will be used to classify the instances;
2. Provide a training set for each of the categories;
3. Decide on the features that represent each of the instances;
4. Choose the algorithm to be used for the categorization;

” [22].

This fuzzy logic approach has been widely used in the text and documents domain, by Prof. Dr. João Paulo Carvalho [23]. Now, a modified approach for the IT area of incident prediction. This study involves creating and matching fingerprints directly from the extracted events that are outputted by the algorithms. The categorization steps for the IT use case would be:

1. Extract events using outlier/anomaly detection algorithms.
2. Provide training set (events) for each category (incidents).
3. Fine tune features, correspondent to events extracted

4. Fine tune fingerprint extraction and prediction parameters

Another important aspect of the modification needed for this application is the fingerprint composition. As it is not just event type and count. The metric from which the event was extracted plays a relevant role in the prediction process, hence it needs to be included in the fingerprint. This means the features are the combination of event types with metric names. This will be further discussed in section 3.7.

2.3 Existing Solutions

2.3.1 New Relic

New Relic is one of the first Software as a Service (SaaS) monitoring solution that focuses on application and infrastructure observability [24]. It uses agents installed on the running machines and collects metrics. A service engineer can set up alarms, for instance, static threshold rules to be alerted on. Obviously, this required high amounts of user intervention and expertise and definitely does not solve the recurrent incident problem. New Relic does not offer any alert or incident prediction functionality.

2.3.2 Dynatrace

Dynatrace, just like New Relic, is a SaaS monitoring solution with a focus on application and infrastructure observability, however this time with more emphasis on Cloud environments [25]. Dynatrace offers a prediction-based anomaly detection tool, which leverages statistical data from metrics collected by agents installed on machines to predict what a timeseries will look like in the next thirty minutes [26]. While this may seem interesting and definitely useful for predicting simple linear metrics, volatile metrics such as CPU consumption don't work so great [27]. This functionality focuses not on incident prediction, but on metric values prediction. This then allows Dynatrace to spot some inconsistencies and fire up an alarm for an ongoing problem. They have no incident learning feature as their approach is different, hence they do not tackle the recurring incident problem.

2.3.3 InsightFinder

InsightFinder is a platform that provides incident root cause analysis, prediction and prevention of incidents in production environments [28]. This online tool/platform ingests metrics from running services and performs anomaly detection on them. It then uses those anomalies datapoints to, using a patented algorithm, predict a future incident. Nevertheless, it seems to be focused only in application business direct metrics, for instance, a simple payment API. These metrics need to be specified by a service engineer, requiring loads of manual work labeling metrics, otherwise, the system will fire up alarms and incident predictions on volatile metrics, for instance, CPU, just like Dynatrace example in section 2.3.2. These volatile metrics cannot be used directly for incident prediction. Even though they have incident prediction capabilities based directly on metric analysis they require a lot of human intervention. They also do not let the public test out their functionalities, as they only show a demonstration of how the high-level platform works. After analysis, they do not seem to solve recurrent incidents.

2.3.4 IBM Tivoli/Cloud Monitoring

IBM Tivoli/Cloud Monitoring is a product that monitors the performance and availability of distributed systems [29]. IBM Tivoli is very popular and it has been used since 1989 [30]. This tool has changed from systems management to service management to accompany the times of change in the last decades. Now with the cloud expansion, IBM Tivoli has evolved to IBM Cloud. This platform includes IBM Cloud Monitoring, which is the responsible tool that uses agents to capture system metrics, just like other tools described above, alerts are once again manual. IBM Cloud Monitoring requires extensive setup by service engineers and does not have both metric or incident predictive capabilities.

2.3.5 Datadog

Datadog is an Application Performance Monitoring (APM) and observability SaaS platform. Once again, this platform also uses agents installed on the service-running machines to fetch metrics. The only predictive monitoring available is metrics forecast [31]. Machine learning

algorithms continuously follow metrics evolution and predict, just like Dynatrace, section 2.3.2, future metric values. Once again, incident prediction is done directly by metric anomaly detection using static rules set up by the service engineers, which leads to alert fatigue. In most other cases an alert is set off and the incident has already happened. The tool does not have a solution to the recurring incident problem.

After analyzing existing solutions available in the market, one can realize there is no direct solution for the recurrent incident problem. Existing solutions focus on alerting or predicting the first time an incident happens. This is a good thing, but since the incident has already happened, the system has been impacted. The hypothesis of this study is based on accepting that, although an incident, of some type, can happen once it will be predicted and prevented in future occurrences. Other tools also connect metric abnormal behavior directly with incidents, using simple metric predictions and alerting when these seem out of normal values. This normally leads to a high amount of false alerts, leading to alert fatigue. Unfortunately, there is no algorithm, tool or platform to test this study hypothesis as it is a problem that no one has yet been able to tackle, at least according to what is publicly available online.

3
Implementation

In this chapter, new entities are introduced and defined. Throughout the study, entities such as *event*s and *fingerprint*s are mentioned extensively. Therefore, context and definition are provided. These are abstract concepts are crucial to understanding how the system works. The monitoring system's architecture is explained, as well as all the implementation steps *Event Extraction*, *Fingerprint Extraction* and *Incident Prediction*. In the *Fingerprint Extraction* section, there are assumptions and hypotheses regarding the construction of the fingerprints. These will be tested and analyzed in the *Incident Prediction* section. Finally, the computational challenges one can expect are described and a solution to them is provided.

3.1 Events

An ***event*** is an arbitrary behavior that is directly or indirectly related to what the underlying machine is running. It is spotted by an algorithm. These are not necessarily abnormal behavior, they can correspond to normal metric behavior as well. An *event* is composed of a timestamp, type, metric and machine. A behavior is not a discrete point in time, it is metric movement during a time window. Nevertheless, its time it defined as the initial timestamp value at which the detected movements started. it is an integer in "Unix epoch" format, which is the number of seconds that have elapsed since January 1, 1970 (midnight UTC/GMT). The event type is an acronym of the algorithm's name that extracted the event. For instance, if an event is extracted using the *Level Shift* algorithm its type will be *LS*. In the case of volatility, the *event* caught by the algorithm *Volatility Shift* 3.6.1 is stored with the field type being *VS*. The metric and machine identification fields are strings that indicate the metric used for the event extraction and from which machine it came from, respectively. These provide relevant information, that will be used in the modules that will process *events*.

The structure of the object *event* can be defined as follows:

```
{
    'Timestamp': epoch seconds (integer),
    'EventType': algorithm acronym (string),
    'MetricId': metric identification (string),
    'MachineId': machine identification (string),
}
```

The monitoring system uses metrics as raw material to produce events. These are, from then on, the base element. They are used to build, compare against and spot fingerprints. A detailed explanation of how *events* are extracted can be found in section 3.6.

3.2 Fingerprint

A ***fingerprint*** is a trace of *events* that have been proven to precede an incident. Even though it differs substantially, the idea was born from the Fuzzy Fingerprints classification method [19]. It is defined by the *event* types and their frequency count for each metric.

In human anatomy, a fingerprint is "an impression made by the papillary ridges on the ends of the fingers and thumbs" [32]. When this impression is found somewhere it is evidence of the correspondent individual's presence. This happens because fingerprint characteristics are specific for each individual. Once extracted they can be used, in a direct way, to indicate someone's presence. The hypothesis of this study consists in extracting incident impressions/fingerprints so that, just like in human anatomy, the system can indicate the presence of an incident. A particularity of the approach is that, instead of past presence, it is future presence. This is because it is believed the impressions are left in the machine metrics moments before it happens.

A fingerprint can be seen as an object, in which its keys are metric names. Each metric comprises another object in which the keys are event types and values are the number of

occurrences. It can be defined and visualized in a ”dictionary style”, its structure is as follows:

```
{
    'MetricId' (string):
      {
          'EventType' (string): count (integer),
          ...
      },
    ...
}
```

The purpose of this abstract fingerprint concept is to store the events and their counts in a single object in an organized way. This fingerprint is then stored in the fingerprint database. It can later be fetched and compared its events against real time happening ones.

A fingerprint example may look something like the following:

```
{
    'File read bytes per second': {'HM': 15},
    'Free disk space on 1': {'LS': 10},
    'Incoming network traffic on 1': {'HM': 22, 'IF': 9},
    'Outgoing network traffic on 1': {'LS': 24, 'IF': 14, 'HM': 9}
}
```

In the above fingerprint example, there are four metrics with a total of 103 *events*. These events precede an incident. They are an indication that a future incident might happen. These four metrics and their event count, build the fingerprint leading to an incident. It is structured by each metric and its event count for each event type. For instance, in metric *Outgoing network traffic on 1*, there were found a total of 47 *events* from three *event* types, 24 LS, 14 IF and 9 HM *events*. In a timeline, one would see the 103 events first and moments after an incident.

A detailed explanation of how these fingerprints and their events are extracted can be found in section 3.7 and section 3.6, respectively.

3.3 Architecture

In order to study this new predictive maintenance approach it is indispensable to acquire quality data. The material can be divided into two parts - metrics and incident/alert logs. Server machine metrics characterize the behavior of the machines the server(s) runs on, therefore characterizing the server. Incident/alert logs report meaningful occurrences that translate directly into service problems.

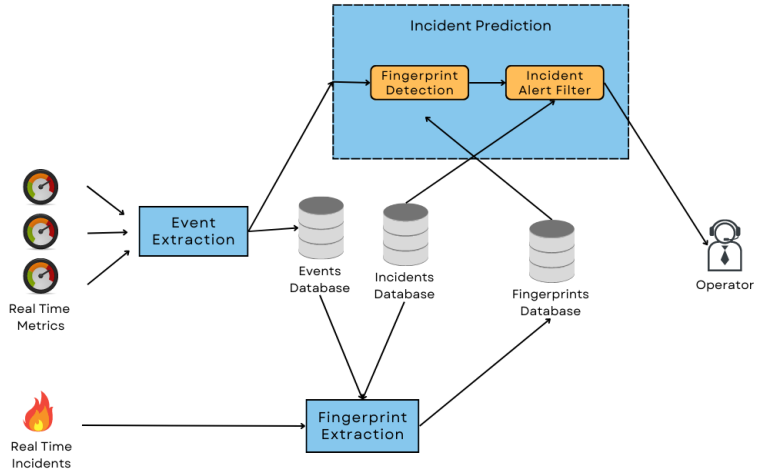

Figure 3.1: Monitoring system architecture overview

In fig. 3.1 an overall overview of the thesis monitoring system modular architecture is presented. It is an Extract, Transform and Load (ETL) system pipeline approach, in which two non-synchronized branches transform data and are interconnected by a shared storage platform used to keep track of *events, incidents and fingerprints*. The top branch starts with the ingestion of real time metrics sourced from machines in which monitor services are running. Metrics start their journey at the *Event Extraction* module, where transformation extracts *events*

from the ”sea” of metrics, they are then stored in their respective database. At the lower branch, incidents that happen or are stored in a database are consumed by the *Fingerprint Extraction* module as well as *events* from the respective database. This module is responsible for exporting and saving a fingerprint, composed of prior *event* occurrences, that were found out to correspond to the cause of incidents in a cause-effect manner. These fingerprints are stored in a fingerprint database accessible to the top real-time branch of the system architecture. The *Incident Prediction* module is placed in series with the *Event Extraction* module. Freshly extracted *events* from metrics are loaded into the module, which can be subdivided into two serially connected sub-modules. The *Fingerprint Detection* sub-module is responsible for ingesting *events* and using a comparison engine to match *events* with the fingerprints from the database. When a match is detected it is fed to the *Incident Alert Filter*, responsible for deciding whether to alert or not the operator.

In the following sections, one can find a detailed explanation of the different steps of the implementation process and how decisions were taken with the study's success in mind. Metric ingesting, choice of algorithms and module development details are elaborated, as well as some examples based on real data to accompany the monitoring system's breakdown.

3.4 Gathering data

In the interest of this study, real world data was mandatory, as sandbox environments would not represent real world stochastic *events* that directly influence legitimate incidents or outages. Finding good data is difficult, as it is required to find a company that has servers with recurring incidents and is willing to supply service metadata for analysis. Luckily, a company was kind enough to make available data on 2 different services that are known to have recurring outages. This data was extracted using Zabbix agents [3] installed on the server machines. These agents collect a variety of Network, CPU, Memory, Disk metrics, log texts, as well as others.

It was established that the definition for quality metrics during the study relied on three characteristics - continuous, high frequency and long time window dataset. The intent was to conduct the work in a manner that is very close to a real time, around the clock, predictive

system. Therefore, the use cases were of services running 24 hours per day, 7 days a week, except when there were outages. One interesting fact, discovered throughout metric extraction, was the difficulty in extracting continuous metrics. Storage limitations of monitoring systems, such as Zabbix, do not enable saving high frequency metrics for more than 30 days. This led to manual sequential extraction, which resulted in time windows where no data was found. The implemented solution was to use different continuous time windows as different datasets for the same service, making sure that blank time windows would not contaminate the *event* extraction process and be considered as relevant *events*. They were not used in the study in order to not influence it negatively. Each datapoint indicates a value of a specific type for a specific service. The higher the frequency of these datapoints, the higher the resolution of the metric which translates to a more complete information regarding the behavior of a service. Using critical thinking, a frequency value of around 1 minute would be ideal. Nevertheless, the frequency of the firstly used data was 1h, meaning small time framed fluctuations were lost. Our hypothesis was that slow happening events would still be captured. Another preferred requirement is not necessarily the quantity of data, but the continuous longevity of the dataset. A dataset with a continuous metric datapoints with a time window superior to 2 months would fulfill the longevity prerequisite.

A dataset was made available regarding Service 1 and Service 2. Both services run on Machine 1, which is interesting and considerably more challenging than a single service running on a singular machine. When a machine has two services running, metrics are a sum of two different behaviors. Contrary to a single service machine, the *events* extracted cannot be directly correlated to the service, since there are two of them. The agnostic approach of the monitoring system is designed to withstand these situations, so as an assumption, this should not pose a problem. Yet it is something that will be discussed in the next sections 3.6 and 3.7. This dataset even though not fully continuous, has metric continuity for more than 3 months and around 30 second frequency, satisfying 3 of the conditions for quality metrics.

Alongside metrics, logs retain critical information on the machine's behavior and give an inside view of the machine's perception of what is happening in a string format. These logs include text information with significant words like *Warning*, *Error*, *Critical* and *Restart*. It can be

easily understood how using NLP, these logs can help identify critical occurrences/incidents. Logs also include other interesting information that otherwise one could not find in metrics. During section 3.5 a detailed explanation of how the logs are processed is given, section 3.6 covers the extraction of *events* utilizing the metrics constructed.

3.5 Pre-Processing data

The available dataset was in the structure of a Comma-separated values (CSV) file format. Examples of these can be found in fig. 3.2 and fig. 3.3. For high frequency metrics, a timestamp and the real time values were presented. Low frequency metrics contained epoch time and three values for each point in time - minimum, maximum and average. Since three datapoints are available for every metric at each point in time, a strain arises when feeding this data to a continuous real time pipeline [33]. Even though the conduct of this study is made offline with backlog data, the goal of the real time system is always in mind. One could argue only maximum values should be contemplated, but that process thinking would not work for all metrics. *CPU* maximum values of close to 100% can show a problematic event, but *Free Memory* maximum values close to 100% do not show a questionable event. The taken approach was to discard - maximum, minimum, average - metrics, and use the real time measured values found in logs.

```
1442433600, 1.1515, 4.7638, 1.6590
1442437200, 1.1954, 6.0262, 1.7935
1442440800, 1.1645, 3.6879, 1.6691
1442444400, 1.2387, 8.2503, 1.8720
1442448000, 1.2098, 3.8170, 1.6385
1442451600, 1.1731, 3.6855, 1.6113
1442455200, 1.1994, 4.4026, 1.7530
1442458800, 1.2533, 3.9492, 1.7350
1442462400, 1.2583, 4.8963, 1.8110
1442466000, 1.3397, 5.2099, 1.9025
1442469600, 1.2608, 3.8329, 1.7697
1442473200, 1.3657, 4.1472, 1.8400
```

Figure 3.2: Raw metrics extracted from Zabbix [3]

In order to fulfill the characteristics for quality metrics mentioned in section 3.4, the removal of noncontinuous data values throughout the time window is necessary. Upon confirmation, it was detected missing data in certain time windows. During the data cleaning stage, the missing values were deleted and the whole dataset was then subdivided into sub-datasets which still verified the three conditions for quality metrics. It is believed that deleted data did not impact

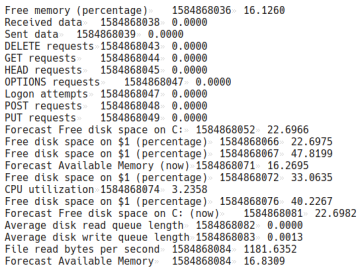

Figure 3.3: Raw logs extracted from Zabbix [3]

Timestamp (sec)	Metric 1	Metric 2	...
1442412000	1.455	45.321	...
1442415600	23.111	56.256	...
1442419200	4.123	48.937	...
...	...	...	...

Table 3.1: Example of organized pre-processed metrics ready for the next phase of *event* extraction in section 3.6.

the study since it corresponded to less than 1% of the total dataset. In the data transformation stage, it was chosen not to perform metric normalization. The initial training set may not include the total range of values for all feature metrics. Normalization would be of most importance if multivariate algorithms were applied since the higher range metric will intrinsically influence the outcomes because of its dimension, but that is not the case in this study. The metrics were formatted into a simple data structure with timestamps and respective values. An example can be found in table 3.1.

The pre-processing of logs involves more work than pre-processing metrics, as logs will be used to build a metric dataset. Observing the extracted logs we can see some interesting information that is not detailed in the provided metrics, in this case, by Zabbix [3]. So one can create a metric from the logs. The Zabbix agents log forecasts for certain metrics, one example is *Forecast Available Memory* or *Forecast Free disk space*. If this forecast is a very low value, it means the machine is close to running out of memory or disk space, which then leads to an incident. This low value forecast log represents an *event* that could be created at this stage. Nevertheless, this would require user input to create these *events*. Hence, *events* will not be created directly from logs, but a metric will be built from them to further perform *event* extraction

in the *event* extraction stage referred in section 3.6. The important information to be collected is: the machine id, the service which it may impact, the timestamp and finally the metric reading value. All this information regarding the *event* is explained and detailed in section 3.6.

This monitoring proposition relies on the analysis of machine symptoms to predict service problems. Metrics are ingested and predictions regarding machines and their running services are made. One can intuitively understand that monitoring must be isolated between machines. In order to do this, during this phase, all metrics were labeled with the corresponding machine and service. This is an important step because even though a monitoring system can be ingesting metrics from one or more machines and its services, the pipeline must be prepared to internally isolate machines during the metric processing phases and not mix insights and fingerprint information between services running on different machines. Machine isolation is implicit in the next sections.

In the next sections, the subdivided datasets will be used as training and testing datasets. Typical ML training testing split is applied. The total dataset available includes information from March 21, 2020 to April 20, 2020 and then April 9, 2022 to June 8, 2022. Even though part of the dataset is from 2020, 2 years of difference, the *events* from that year were also used, as the services running in the machine remained the same. This is because the hypothesis of the study is a continuous learning mechanism, that extracts and stores incident fingerprints over time. There should be no problem using past fingerprints as the training set. In the worst case scenario, some fingerprints are detected from past incidents that do not happen in the test dataset, this presents no problem whatsoever. The training/test dataset was split into two parts training (2/3) and one part testing (1/3). Event extraction, explained in section 3.6, will be performed on the whole dataset. Fingerprint extraction, detailed in section 3.7, will be applied to the training dataset. Finally, incident prediction, described in section 3.9, is only executed to the testing set.

3.6 Event Extraction

At this stage, the goal is to transform the pre-processed metrics and logs into useful insights regarding machines' behavior. These insights are called *events*.

In order to achieve a list of *events*, the pre-processed metrics will serve as input to a set of univariate anomaly detection algorithms enumerated in chapter 2. A brief introduction, expected outputs and findings throughout the extraction process will be described further in this section.

The intention is to extract timestamp values that correspond to a certain metric behavior. It is relevant to acknowledge that these *events* do not necessarily and directly indicate abnormal or critical behavior. They represent an arbitrary behavior that is directly or indirectly related to what the underlying machine is running. To extract these behavior *events* each metric must go through the following selection of algorithms.

The more meaningful the *events* we extract, the better the data we have to later build real fingerprints that result in incidents. The following algorithms must be analyzed to understand which hyperparameters to select. These will directly influence the extracted *events*. One can already question how can this be done in a general way that would work for all machines and their running services? The selection of these hyperparameters is not trivial. Even less trivial for a generalized approach. Nevertheless, a fully agnostic approach, as future work, is discussed in chapter 5. The hyperparameters of the algorithms were tuned with consideration to the dataset metric.

3.6.1 Selection of Algorithms

3.6.1.1 Local Outlier Factor (LOF)

LOF is used with the intent to extract anomalies by computing the local density deviation of each datapoint with respect to its neighbors [34]. Both LOF and IF perform outlier detection using the distance between datapoints, although with a rather different approach. Extracted *events* will benefit from this diversity. *Events* from different algorithms have characteristic properties that will enrich the quality of a fingerprint in section 3.7.

Now, let us focus on LOF. There are two hyperparameters needed to fulfill before applying the algorithm to the datasets, *n_neighbors* and *contamination* [12]. The algorithm goes through the neighbor datapoints and compares the distance to the pivoting datapoint. The higher the number of comparisons, the heavier the processing becomes in each datapoint, hence the longer it takes to run. The process for figuring out the parameters relied on metric frequency and the experimental process of testing for different outcomes.

Before diving into the selection of hyperparameters let us quickly analyze an example. In fig. 3.4 one can indicate the spikes as outliers, but one would be wrong as the goal is to point out unusual metric movement. The spikes are normal movements and should not be marked as anomalies. During analysis is easy to fall into the trap of considering drops or spikes as representatives of anomalous behavior. This is specially not true when it happens regularly or seasonally. These types of anomalies are covered in the next algorithms.

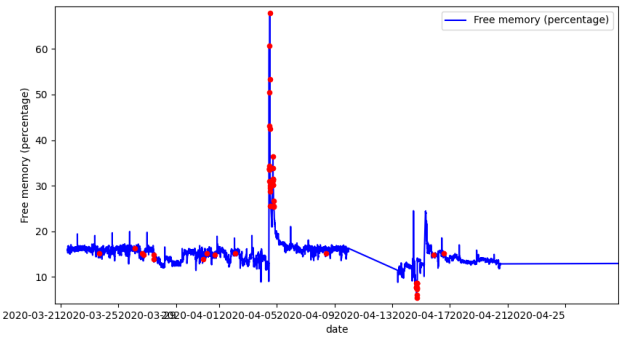

Figure 3.4: Local Outlier Factor (LOF) chart with marked outliers (red dots). The metric represented (in blue) is *"Free Memory (percentage)"*.

In [11] it is proposed some quick instructions on how to select the neighborhood size. The number of neighbors should be at least the minimum number of cluster elements, in this case, because it is a timeseries, the time variable is not taken into account, so it is a 1 dimensional problem using only the metric values. To come up with the minimum number of cluster elements, one must analyze the number of occurrences of each metric. Considering a 1 minute frequency, a number between 4 and 15 would be considered appropriate. These values were chosen because they correspond to the time frame of what a noticeable event can last. This

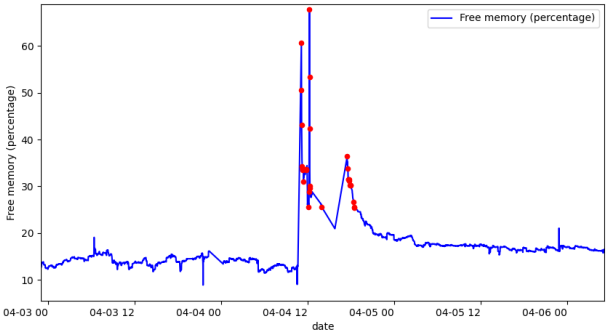

Figure 3.5: Figure 3.4 zoomed view of a clear anomaly.

is so that the other datapoints have a chance to be local outliers relative to the cluster datapoints (that represent normal values in this use case). The original paper [11] also indicates the upper limit of the neighborhood size, the number of maximum anomalous datapoints that can be found near each other. Let us look at a clear example of an anomaly in fig. 3.5, which is a zoomed version of fig. 3.4. During this anomalous time window we can find 26 datapoints.

Continuing analysis on fig. 3.4, the *n_neighbors* parameter was chosen to be 20. With a metric resolution of 1 minute, comparing the values of the 20 neighbors surrounding the pivoting datapoint, would provide a time window long enough to spot a considerable Manhattan distance difference. If a small amount of neighbors is chosen the algorithm becomes fast, which is good, but very reactive to sudden metric changes. For this use case it would not be advantageous to get those outliers. This is strictly because sudden metric movements in small time windows are normal behavior in most IT service machine metrics. Take for instance, CPU measurements with 1 minute frequency, it can hop between 10% and 30% between datapoints. It does not represent anomalous behavior. If a substantial amount of neighbors is inputted, the algorithm will lose performance as more computational power is needed and will become insensitive to metric changes. This happens because it considers a high spectrum of metric values across time, therefore if that value has ”appeared” before then that value is fine. This logic does not work in our use case because if there was already one anomaly with that value then next time it will not be considered.

Finally, choosing 20 neighbors also is in accordance with the proposed instructions for choosing hyperparameters in [11]. As seen above, 20 is between 15 and 26, the minimum number of cluster elements and the number of maximum anomalous datapoints that can be found near each other, respectively.

Anomalies are rare, a very small percentage of datapoints are anomalous datapoints. When choosing *contamination* this has to be taken into account. Therefore very small numbers were used and changing between order of magnitude made a tremendous difference in the number of outliers detected. After testing, the final value selected was 0.002. When using this value, for several different metrics, the charts with marked anomalies presented what seemed an acceptable anomaly per normal datapoint ratio and good anomaly placement.

As described above, the tuning of LOF hyperparameters was completed with experimentation of the algorithm with the metrics of the training dataset, corresponding to 2/3 of the total available dataset. Nevertheless, these can be generalized to other IT services running in other machines if the metric frequency is the same, it can be considered agnostic, but that is subject to future work. This is covered in more detail at the end of section 3.6.1. Another interesting way of setting up hyperparameters is by using heuristic functions to determine the parameters [35]. But this comes with many challenges. One consists in knowing the number of anomalies in a dataset in order to choose *contamination*. This can be proven difficult as there are several aspects of this approach that makes it not trivial to identify anomalies. In the context of this approach, the anomalies extracted from the algorithms are marked as *events*, but *events* are not anomalies, they can be just a behavior and not necessarily an anomaly. Hence the difficulty of manually selecting the anomalies for a heuristic approach. Even an SRE operator would not be able to tell the anomalies in a timeseries metric that would make sense in the final scheme of the prediction. Another difficulty of this approach is the performance impact, as computational complexity rises. It becomes very challenging to use this automatic heuristic tuning. This idea was therefore discarded and proposed for future work.

3.6.1.2 Isolation Forest (IF)

IF performs an ensemble of decision trees, it randomly splits the data space and identifies anomalies when the trees are shallow. The trees are built using the distance between datapoints. In order to extract relevant outlier datapoints we need to capture datapoints that are far from the normal values the machine operates. The contamination hyperparameter must be selected with a value that is high enough to capture the outliers, but low enough not to select many normal datapoints. The first analysis is performed using a histogram with the scores [13], calculated using eq. (3.1). Variable *h(x)* corresponds to the average search height from the isolation trees built for feature *x*. Variable *c(n)* is the average search depth to find a general node in the built isolation trees. The total count of leaf nodes, residing at the ends of the three, is the *n*. Carefully inspecting fig. 3.6 most datapoints are comprised in that 0.45 score. These correspond to regular datapoints. It can also be found two very shallow bars that to someone inattentive would go unnoticed, they represent the outliers. Datapoints regarding those two bars are 1088 of 80412 total datapoints. Leading to a contamination value of around 0.01. This value would for sure be enough to get those outliers, nonetheless, after trials, the detection algorithm continued very sensitive. Selecting 1088 datapoints as anomalous. It was then proposed to reduce the order of magnitude, opting to use 0.001. After testing, a contamination value of 0.001 proved to be a reasonable start to collect some significant events.

$$s(x, n) = 2^{-\frac{E(h(x))}{c(n)}} \tag{3.1}$$

A good example of an *event* detected is in a metric called "Average disk read queue length". Queues are very commonly used in services to perform asynchronous work, many depend on them to store information that will soon be processed and stored or given back to the user. As one could see, they represent an important metric when predicting outages, since a high rise in the queue length can be a symptom of the consumer processing the queue slowly or performing no processing work at all. In a specific case of this metric, an interesting *event* was caught where the queue jumped from very low values close to 0 to a value more than 100, see fig. 3.7. This may not represent a problem as the queue may get consumed, but it

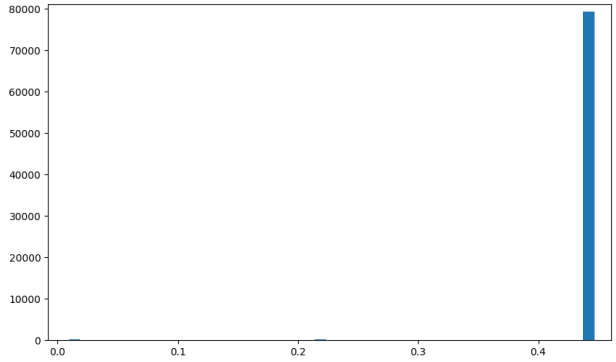

Figure 3.6: Isolation Forest (IF) histogram of calculated scores from *"Average disk read queue length"* metric.

certainly indicates suspicious behavior. These are exactly the types of *events* we intend to extract. Again, these *events* are not necessarily anomalies, but changes in behavior. We store these *events*, even if not real issues because, in the next section 3.7, they will be filtered and only kept if connected to real problems.

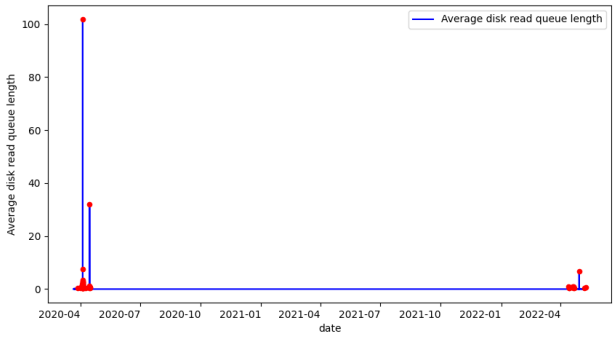

Figure 3.7: Isolation Forest (IF) extracted *events* from *"Average disk read queue length"* metric.

3.6.1.3 Level Shift (LS)

In an attempt to identify other types of pertinent *events*, LS was applied to all metrics in the dataset.

LS detects shifts of values by keeping a record of the median values of two sliding time windows one after the other. One of the advantages of this algorithm is that it is not sensitive to global outliers or noisy datapoints. The ambition of using this algorithm is to diagnose sudden movements in metrics that are known to be stable, in time-window defined groups or steps, along the timeline. These groups present a very low standard deviation value. They behave like plateaus, for example in fig. 3.8. The average values of the consecutive groups can vary a lot, as the step can be considerable or minor. Nevertheless, the goal is to identify the moment in time between groups. The change can indicate behavior that will be used in the following stages of the monitoring system. We can use an example in fig. 3.8, red dots indicate quick metric shifts alongside the *y* axis.

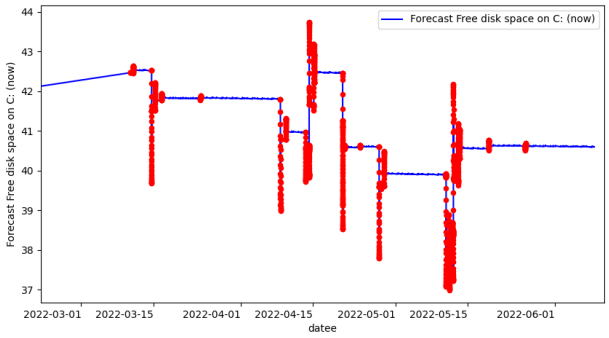

Figure 3.8: Level Shift (LS) extracted *events* from *"Forecast Free disk space on C"* metric. It shows a clear plateau metric type. In red the detection of steps is presented.

3.6.1.4 Volatility Shift (VS)

VS detects shifts of values by keeping a record of the standard deviation values of two sliding time windows one after the other. This detector is used in parallel to the LS. While LS tracks level movements with median values, VS tracks volatility movements using standard deviation values. The same metric "Forecast Free disk space on C", that was used in fig. 3.8 for LS*event*extraction, is now used for VS. Observing fig. 3.9, the algorithm is much more sensitive to metric movement and seems to mark anomalies even when metric seems to behave

quite steadily. Algorithm parameters were tweaked to increase the sliding time window size to 60 datapoints and a new run was performed, it is shown in fig. 3.10, this time VS seems to perform much better. Interestingly, comparing the extracted *events* from algorithms LS and VS, fig. 3.8 and fig. 3.10, respectively. One can see similar results are extracted, so why use both algorithms? In fact, results are similar, but that does not pose a problem, as when later a fingerprint is extracted different*event*types lead to a more consistent fingerprint. Hence the use of two algorithms that use different approaches and create similar results.

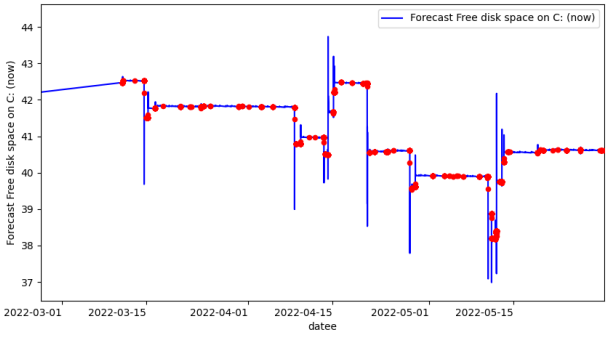

Figure 3.9: Volatility Shift (VS) extracted *events* from *"Forecast Free disk space on C"* metric. The default algorithm detects volatility even when the metric looks steady on the y axis.

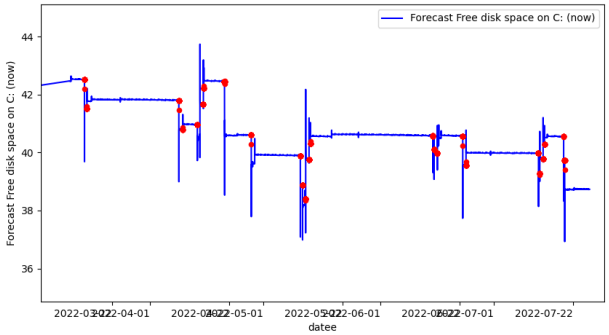

Figure 3.10: Volatility Shift (VS) extracted *events* from *"Forecast Free disk space on C"* metric. Algorithm parameters were tweaked to increase the sliding time window size.

3.6.1.5 Luminol Univariate (LU)

LU [15] is an open-source Python library with an anomaly/outlier detection algorithm for time series data. It was created by LinkedIn [36] to identify anomalies in real user monitoring of their applications. LU ingests time series data and calculates anomaly scores for each data point. A high score means a high probability of it corresponding to an anomaly in comparison with the other data points. Just like most other algorithms above, LU is statistical based [37], and cannot be used directly to determine real world anomalies, hence the importance of the next steps of building a reliable fingerprint, section 3.7. In fig. 3.11, metric "Forecast Available Memory (now)" shows clearly anomalous upwards spikes as well as downwards, red dots are the outlier detection performed by LU. If this metric would have been analyzed by a human and manual outlier detection was performed, the anomalous datapoints would match with the ones extracted by the LU algorithm. Of course this may not be the case for all metrics, hence the reason why these *events* are not being used directly to predict incidents.

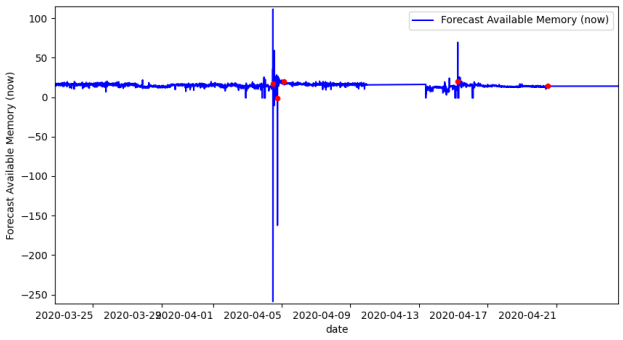

Figure 3.11: Luminol Univariate (LU) extracted *events* from *"Forecast Available Memory"* metric.

3.6.1.6 Seasonal Facebook Prophet (SFBP)

A particularity of the Prophet algorithm is the ability to point out not only global outliers but also contextual outliers. Global outliers present themselves as datapoints that appear far from the rest of the metric values, generally, a spike is an accurate example of a global outlier. Patterns

or seasonality behavior changes are considered contextual outliers. Datapoints can be within the maximum and minimum range of the normal values and still be considered anomalies. An isolated significant difference in the normal pattern behavior is what is to be considered a contextual outlier, these can vary depending on sampling, aggregation method and time scale of metrics. The way Seasonal Prophet accomplishes it is by taking into account daily, weekly and yearly seasonality. Let us take for instance an example of fig. 3.12, where one can get some insights of trends found in this metric. Analyzing it we can disregard yearly seasonality due to the dataset available only consisting of 2 months of data. Weekly trending is quite high on Saturday compared to the other days of the week, which indicates a consistent Saturday value for this specific metric. This means, if an outlier is detected here, it certainly will be higher. Daily seasonality is interesting, as higher trends appear to be from 9 am to 2 pm. Speculating, one could find a correlation with the working hours. Prophet calculates what they

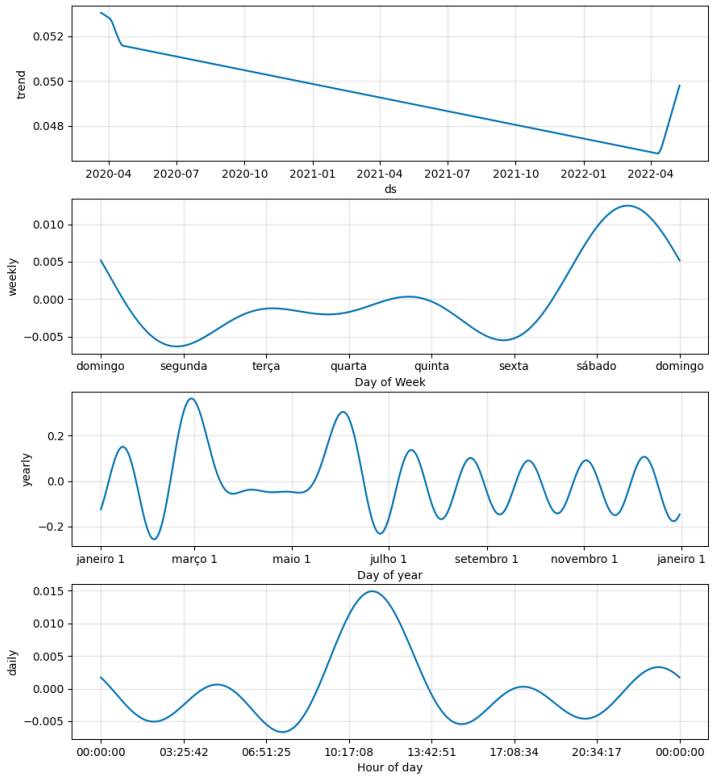

Figure 3.12: Seasonal Facebook Prophet (SFBP) trend components of *"Average disk read queue length"* metric.

call *trend and seasonality components* fig. 3.12. These charts represent the influence of the hour, day and week on the datapoints values. These can be used to spot contextual outliers, which otherwise would be left unnoticed.

Changepoint_range is the confidence level of the output. When prophet predicts the value, target predicted value, a score for the confidence level, based on historic data, is also calculated. By default prophet suggests 0.8. The algorithm, uses a train dataset to learn and predicts the future values for a specific datapoint with an upper and lower limit, *yhat_upper* and *yhat_lower*, respectively. Outlier datapoints are selected if they exceed predicted upper or lower bound limits.

3.6.2 Final Event List Picture and Static Rules Applied

The approach used for *event* extraction generates a high number of *events*. This abundance will cause noise to the fingerprint detection stage section 3.7. This is due to *events* in the moments prior to an incident occurring being compared against other *events* in the same scenario. If the algorithms at this stage section 3.6.1, are very sensible, it will result in a swarm of datapoints around the relevant *events* inside the time window prior to the incident, disrupting the capture of clean, high resolution fingerprints. This can be called the *"Event selection paradox"*. Too many *events* and there are too many outliers for a fingerprint extraction or detection. Too few *events* and no fingerprints are detected. In order to solve this, the sensitivity of the algorithms must be lowered to the point where only relevant *events* are extracted. This is obviously not a trivial task, however, one can manually analyze and use critical thinking to check if detected *events* represent meaningful ones. It could be said that a drastic reduction in *events* would sabotage the monitoring system. Naturally, the absence of *events* will incapacitate the system of predicting incidents. Quality over quantity is desirable, better quality *events* will provide a more accurate fingerprint. Another separate attempt to get meaningful *events* was performed using static rules. These static rules were put in place specifically for each metric available. Even though this is dataset specific, it was implemented. The reasoning behind this is most companies have already defined static rules for their metrics. The monitoring system can leverage them and extract events. These rules are set up by manually analyzing metrics one by

one and defining their normal behavior limits. Some of the applied rules are stated in table 3.2. These static rules involved metrics above, below or equal to certain values. Another reason to use static rules is to, in the final results, study how these perform compared to the other unsupervised anomaly detection algorithms. This is a merge of the legacy static rules (already defined by most companies) with the unsupervised agnostic algorithms. The events extracted are labeled with Hand Made (HM) event type. Metric *"CPU utilization"* is a simple use case that can be studied here. In the industry, machine usage types vary significantly depending on what their attributed function. For instance, certain machines' job function is to process extensive amounts of data. These machines will most certainly be overloaded, hence, for example, constantly running on maximum CPU. Even though it may behold a negative connotation, that is their normal behavior. On the other hand, machines contrary to this type, are not supposed to run overloaded. When overloading occurs, it may represent abnormal behavior. In these cases, an operator would appreciate being notified of this occurrence. A traditional threshold approach rule is set, above 90% an *event* is created. Another example is *"Free memory (percentage)"* metric. A low free memory value implies a problem or an indication of one. Hence a rule for below 10% value was set. Certain metrics can have more than one rule. Having two thresholds in different directions, above or below. An evolution of this static rule based approach for *event* extraction was the selection of specific algorithms for specific metrics. For instance, *"Outgoing network traffic"* metric in this case represents a seasonal behavior and does not cross the value *50000000*. Therefore a static rule of *events* if above 50000000 was put in place, as well as seasonal anomaly detection by Seasonal Prophet algorithm.

3.7 Fingerprint Extraction

In this section, it is detailed the fingerprint extraction module. It analyzes previously extracted *events* and detects fingerprints that lead to incidents.

After the *event* extraction phase, referred in section 3.6, an inventory of *events* is now available. These *events* represent outlier datapoints captured by the AD algorithms in section 3.6.1. It is important to note that a detected outlier datapoint or datapoints are only really anomalies

Metric	**Operator rule**	**Value**
Forecast Available Memory (now)	$<$	0
Free disk space on 1 (percentage)	$<$	10
CPU utilization	$>$	90
Average disk read queue length	$>$	60
Average disk write queue length	$>$	60
File read bytes per second	$>$	2
Forecast Available Memory	$<$	0
Processor load	$>$	2
Free memory (percentage)	$<$	10
Logon attempts	$>$	25
Incoming network traffic on 1	$>$	1000000
Number of threads	$<$	2000
Number of processes	$<$	65
Number of processes	$>$	87.5
...	...	...

Table 3.2: Static rules are set for each metric. These are examples of rules that were set by analyzing the metric behavior and range of normal values.

in the context of the metric. In other words, it is only considered a real world anomaly if it presents a problem in the context of the use case. For example, two metric behaviors: network traffic drastic increase and server memory increase to 100%. Both use case *events* could hopefully be detected using the AD algorithms in section 3.6.1. A network traffic increase is not a problem, yet it may convey the impression of anomalous behavior just by analyzing the metric itself. Nevertheless, in context, it does not represent a threat to the service or business, being quite the opposite, considered by the business side, something positive. In the second behavior example, quite the opposite occurs. A server memory abruptly maxes out. When an operator notices this behavior, he quickly understands this may pose a real world problem. Servers cannot function properly without memory left. This affects the service, thus affecting end users that rely on it.

The list of *events* is full of these true positives and false positive anomalous *events*. Nevertheless, they represent actual *events* that might contribute to a service incident. With that in consideration, the work during this study phase consists in finding or developing an algorithm that can successfully, efficiently and rapidly expose the *event* pattern, in a ”sea” of *events*, that

leads to a labeled incident. Labeled incidents are provided by the user or extracted from a monitoring tool. In the context of this experimentation, the labeled used incidents are derived from the Zabbix agent logs and captured directly from the monitored machine. These logs contain information about the services state, as well as the state of the underlying machine. Note that not all these incidents correspond to outages and failures that were felt by the service end-users. Some refer to ”Lack of free space” or ”Error/Critical *events*” that are obviously distressing, yet may or may not compromise the usability of the service. Nevertheless, all critical logs were labeled as incidents for the purpose of this study, since they are as close as was available to real incident labeling. In another scenario, labeled incidents may derive strictly from human input or a specific monitoring pinging service, such as, for example, UptimeRobot [38] .

The chosen approach is based on the fuzzy fingerprints classification method to ingest *events* and output incident fingerprints. The frequency of *events* in a sliding time window is used to classify incidents.

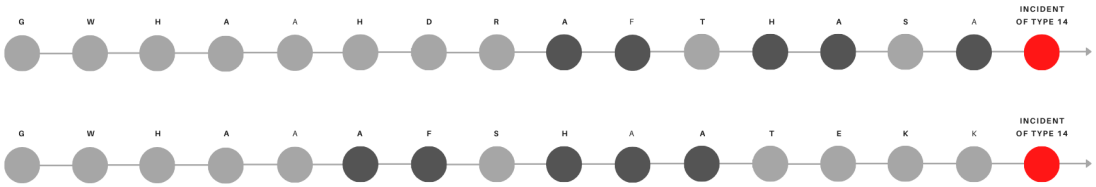

Figure 3.13: Two example timelines of *events* that resulted in the same incident type. The color of the dots is related to the frequency of events. Darker dots mean more events of that type.

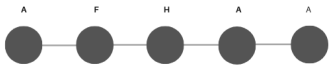

Figure 3.14: *Event* pattern detected in figure fig. 3.13.

The approach used is based on the fuzzy fingerprints classification method. In order to understand how it is applied to the use case, a simplified explanation is presented. Observe the two temporal time windows of distinct points in time represented in fig. 3.13. Both of them resulted in the same specific incident type. In fig. 3.14 it is represented the *event* pattern that resulted in the incident, one can observe the darker circles in fig. 3.13 to understand the pattern of fig. 3.14 is also there. In order to capture the fingerprint, the frequency of occurrence for

each *event* type is calculated and compared against a database of other incident fingerprints. Naturally, one may ask, what are the criteria for fingerprint detection and storage?

The fingerprint extraction module required setting certain parameters. They were defined as follows:

- FINGERPRINT_INTERVAL_MINS - Δ - Time in minutes prior to an incident that *events* should be accounted for when building an incident fingerprint. This defines the time window of a fingerprint. If, for instance, a 30 minute time window were to be selected, during the learning process when an incident happens, all *events* in the last half hour are held responsible.

- FINGERPRINT_SIMILARITY_MARGIN - α - Margin of acceptance between a fingerprint and a potential fingerprint. When a new fingerprint is encountered it is compared to other already defined fingerprints. This margin is the accepted similarity difference *event* type. A direct example is a potential fingerprint that contains 3 *events* of type IF and an already defined fingerprint containing 4 *events* IF, (the difference is 1 event). If this parameter is set to one or more, then this potential fingerprint will be acknowledged and that fingerprint count is incremented. It is only acknowledged if it meets the requirement for all *event* types of the fingerprint. The fingerprint count is used in order to decide which fingerprints will later be used. This is explained in more detail below in MINIMUM_FINGERPRINTS_FOR_STORAGE.

- MINIMUM_FINGERPRINTS_FOR_STORAGE - β - Minimum number of fingerprints counted for use in incident prediction phase. This parameter regulates which fingerprints should be used in the later stages based on how many similar fingerprints were found. The reasoning behind this is that a fingerprint that only happened once is more likely to be a false-positive compared to the ones that took place numerous times. Fingerprints that present a count value lower than this parameter will not be used in the incident prediction stages.

- N_OF_TYPES_PER_FINGERPRINT - γ - Minimum number of *event* types in a fingerprint. This parameter serves to increase*event*type diversity in fingerprints. A fingerprint that is

constituted by more than one *event* type is, in principle, more trustworthy. The reasoning behind this statement is that *events* from different types can be directly translated into distinctive metric behaviors. The hypothesis behind this study, is that in the prior moments of an incident odd metric behavior can be detected using different anomaly/outlier time series detection algorithms. Hence the relevance in enforcing a fingerprint to behold more than one *event* type, since it will represent more than one odd behavior, which increases incident fingerprint confidence.

When developing and implementing the algorithm, initial parameters were required to be set. They influence directly the time window size and sensitivity of the fingerprint detection module. These variables include the fingerprint interval, number of types per fingerprint to be accepted, similarity margin and minimum fingerprints for storage described above. These variables were trialed with a span of values considered adequate to the use case. A comparison table alternating these is shown in section 3.9. Let us now dive into the reasoning of how these important parameter values were chosen for trialing.

The time between the first *event* and the incident happening is the time window interval the system should use when analyzing *events*. It is not the same in every incident. Hence the difficulty in choosing the value to set it up. The smaller the value the shorter the fingerprint. Many *events* leading to the incident probably happen very close to it. It is at this time the machine metrics fluctuate the most. Nevertheless, this study focuses on the prediction of incidents, and there is no gain in predicting an incident thirty or twenty seconds prior to happening. The advantage rises when the prediction is greater than one minute prior to happening. This way service operators still have time to act and hopefully fix the issue or just minimize service downtime. For the study, it was agreed that at the largest interval would be thirty minutes long. Therefore a span of values between one and thirty minutes was inputted.

Minimum number of fingerprints, β, is one of the chosen parameters of the monitoring system, this number is chosen accordingly, and throughout this study, this variable includes an array of values. Choosing a minimum number of fingerprints equal to one, turns the system fingerprint extraction and storage sensibility up, as all incident fingerprints detected will be stored and used in further incident detection. Note that, in reality, no matter the value of this

variable, the system will always store all fingerprints detected. What happens is the system decides whether to use that fingerprint for incident detection or not. The reason behind this is so that, the next time an incident happens, the found fingerprint can be compared against the previous one. If they are a match, the fingerprint counter increases and if higher than the minimum number of fingerprints variable, it is used by the prediction system. Selecting a higher value, for instance, ten fingerprints, will increase the aptitude to detect recurring incidents. The reasoning behind this is that by increasing β, the system will filter out the fingerprints that are not recurrent, which is more in line with the overall goal of the study.

During the decision on which a set of *events* corresponds to a fingerprint, a question was posed, regarding the diversification of metrics in a fingerprint. Extracting fingerprints composed of *events* regarding only one metric seems to contaminate the fingerprints database with false ones caught due to the high occurrence of *events*. Now, the question was, how many metrics does a fingerprint need to be composed of, in order for it to be considered a quality fingerprint? Well, it was decided as minimum criteria for a fingerprint extraction that it was composed of at least *events* from two distinct metrics. The thought process was, using one metric is a problem as we saw before, and choosing a higher value would restrict the extraction too much, hence two metrics diversification should solve the problem and improve the fingerprint extraction module.

A fingerprint is determined by the *events* occurring in a determined Δ. These *events* are relative to a system metric that runs the monitored service. While extracting fingerprints and classifying them as real, criteria needed to be set. Two fingerprints are similar if, and only if, abide by the next rules:

- *Events* of the same metrics can be found in both fingerprints. When comparing a new fingerprint to an already defined fingerprint, the metrics from the *events* found in that time window Δ, must also be present in this new fingerprint.
- Number of *event* types per fingerprint detected is the minimum number of *event* types per metric present for it to be considered a fingerprint.

Since *event* types are defined by the algorithm that was used to catch the event. In principle, a diversified sample of *event* types enriches the fingerprint information. A fingerprint

happening several times, that beholds more than one type of *events* can be considered more reliable because it not only contains at least two types of diversified information (event types) but also presents that diversification in distinct time windows that resulted in an incident. In consequence, it was chosen to set up at least two *event* types for it to be considered a fingerprint. This will likely ensure higher precision. A nuance arises, noise *events* in fingerprints cause similar incidents to behold different fingerprints. This can be mitigated by accounting for an error/similarity margin. Notice this error margin is mandatory for all *event* types for all metrics in each fingerprint, if one does not satisfy this condition then that fingerprint matching is discarded. This margin should correspond to how many outliers are present in each fingerprint. Unfortunately, calculating this is a nontrivial problem. Therefore, just like the minimum number of fingerprints, this will also include an array of different values, looping these parameters will create different results for further analysis in the next chapter 4.

3.8 Incident Prediction

This is the last component of the monitoring system. It is the one that intends to deliver value, in the form of correct incident predictions, to the service engineers responsible for the reliability of the service. It is responsible for the decision of alerting preemptively, giving time to the service engineers to act while there is still time before a major incident occurs again. It is the last layer between the monitoring system and the operator, and beholds a responsibility sense, maintaining a trusting relationship between man and machine. This module must fulfill the operator alerting needs, especially when intervention is needed. Minimizing false alerts is essential, as the McCafee [5] study in section 1.1 showcases.

It is of utmost importance to filter predicted incidents before handing them to the operator, as well as present important metric charts in order to speed up the investigation process.

This last *Incident Prediction* component is composed by two sub-components, *Fingerprint Detection* and *Incident Alert Filter*.

Let us start with the *Fingerprint Detection* module. There are two inputs, the real time *events* that are detected by the *Event Extraction* module and access to the fingerprints database. It

is responsible for ingesting the real time *events*, assessing the occurrences of each type in a certain time interval, time window Δ, before the current moment, and finally matching the fingerprint found with the ones in the database accounting a certain degree of error, α. The time interval is characterized as a time window that is calculated as delineated in section 3.8. This time interval, as well as the fingerprint similarity margin, are defined as parameters to the monitoring system. These variables were trialed with a span of values that were thought to fit the use case. These trials can be found in chapter 4 and appendix A.

$$\textit{Fingerprint Detection Interval (t0)} = [t0 - \Delta; t0] \tag{3.2}$$

$$|nOfOccurs(DetectedFgprt[type]) - nOfOccurrences(DBFgprt[i][type])| < ErrorMargin$$

$$\forall type \text{ in available types, } \forall i \text{ in fingerprints available in the fingerprint database} \tag{3.3}$$

ErrorMargin = defined margin for error

Δ = interval of time defined for a fingerprint to be detected
t0 = current time

A real world example of a fingerprint extracted from the dataset, that was proven to result in incidents can be seen below. It is composed of extracted *events* from five different metrics. *Event* types include LS and SFBP.

```
{
    'Free disk space on 1': {'LS': 8},
    'Forecast Free disk space in C: (now)': {'LS': 2},
    'Forecast Available Memory (now)': {'LS': 2, 'SFBP': 2},
    'Processor load (1 min average)': {'LS': 2},
    'CPU utilization': {'SFBP': 1}
}
```

A plot of these occurrences can be seen in fig. 3.15. This plot shows the time window of the fingerprint, in this case, 5 minutes, plus an extra 3 minutes after the incident happened. The system predicted 10 incidents in a short time window. The plot is the same for the 10 incidents, identical to fig. 3.15. The incidents that happened were of the following types: *"Error/Criticalevent on host service-1.site.com Application log"* and *"Machine-1 is having problems on service-1.site.com"*, these incident logs indicate critical problems that may cause damage to the end user. Predicting them, using the found fingerprint, would hopefully give time to the service engineers to perform preventive maintenance. The monitoring system was able to extract these *event* occurrences in these metrics and link them to real incidents using the fingerprint extraction process. Afterward, using the extracted fingerprint above, an incident was predicted based on the fingerprint found while examining the extracted metric *events* in real time.

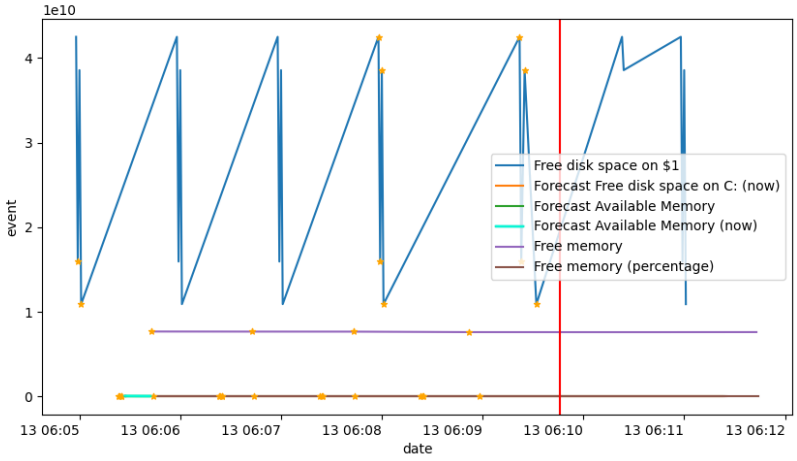

Figure 3.15: Metrics and *events* plot before an incident at 06:07:55. Metrics are represented according to the legend. The incident is marked with a vertical red line across the plot. Extracted *events* are plotted in yellow on top of the corresponding metric.

The implementation of the *Fingerprint Detection* module was done offline, not in real time. The reason behind this was to enable running the module several times with different initial parameters, as well as ingesting data from the datasets. Nevertheless, the module was designed to work with online almost real time metric ingestion in addition to full dataset ingestion.

The *Incident Alert Filter* module is another step in the incident detection group responsible for determining when the service engineer should be alerted. It receives the timestamp and information regarding incident fingerprint detection from the *Fingerprint Detection* module and using its built-in memory determines if an alert has already been released. If in the last $\Delta/2$ minutes (half of the fingerprint interval defined time) a prediction is made with the same fingerprint found, then it is discarded. The goal is to alert once, provide relevant metrics and let the operators handle the situation. Although alerts from the same service are not set off repeatedly, alerts from other services are set off normally and the operator is prompted immediately. Nevertheless, if different services run on the same machine if one fails, the other one is also likely to do so.

3.9 Computational Challenges

During implementation, the dataset was fed to the system multiple times. Due to its size, each runtime was taking hours to process. This is verified to be evident due to its $O(n^2)$ complexity. In order to study different hyperparameters, the detection module was run dozens of times. This posed a problem as it would take a long time to run the algorithms. To solve the problem multiprocessing was applied. The computer used is equipped with a 6-core processor capable of handling 12 threads simultaneously. To take advantage of this feature the algorithm splits the dataset into 12 equal parts and 12 parallel jobs were deployed. Leveraging 12 available threads the jobs ran simultaneously. Complexity dropped to $O((n/12) * (n/12)) = O(n^2/144)$. This means an improvement in runtime by 144x compared to the original complexity $O(n^2)$. The only disadvantage of this performance approach is that some data in the hedges of the split dataset is not processed as intended and can lead to data loss. Notwithstanding, the loss is minimal, calculated to be less than 0.1%. It is more than enough to fulfill the study purpose. When running the system in real time, there would be no need to split data, since the data amounts are of a smaller scale.

4

Results Analysis

During this chapter, result analysis methodology is explained, followed by result analysis. Short table excerpts with results are presented in this chapter, however, full table data results can be found in appendix A.

4.1 Ensemble Algorithm Performance Methodology

In the context of understanding and evaluating the detection performance of the incident predictor, appropriate scores must be chosen. Upon making a prediction, an individual generally provides information regarding its trustworthiness. Whether it comes in the form of *"I am confident that..."* or *"I am 50% sure that..."* it represents a qualification of the decision taken. In the context of ML, it is commonly referred, along the lines of *"Score of confidence"*. A number which is part of the information most ML algorithms provide after the forecasting. The most commonly used metrics for evaluation purposes are accuracy, recall and precision [39].

The following definitions are rather important in the context of evaluating the detection performance. [40]

- True-Positives - The number of predicted incidents that are real. Incidents that were predicted correctly, as in, actually happened;
- False-Positives - The number of predicted incidents that are not real. Incidents that were wrongly predicted, as in, never happened and prediction did not match reality;
- True-Negatives - Incidents that did not exist and were also not predicted. The algorithm acted correctly, it predicted no incident and in fact, none occurred.
- False-Negatives - Number of incidents that happened but were not predicted. The system acted poorly, as it did not predict incidents that turned out to be real.

Accuracy represents the ”proportion of correct answers among the whole dataset” [39]. Using this metric as a performance indicator in this use case is not advised for several reasons. The *accuracy* metric is proposed to be used when false-positives and false-negatives are not of significant importance [39]. In eq. (4.1), one can see the false-positives influence in the denominator and false-negatives in the numerator when calculating this indicator. In a monitoring system a false negative corresponds to an incident that was not predicted, even though this may lead to the untrustworthiness of the system, it is not critical in the sense that it is expected that the *accuracy* is not 100%, leading to a margin of error that is accepted by the service engineer in charge. Continuing with this logic one could discard the importance of false negatives, the concern arises with the false positives as they correspond to predicted incidents that do not correspond with reality. Wrongly predicted incidents influence directly the life of the service engineers, one of the goals of this monitoring system is to reduce alert fatigue, which happens when there is an unreasonable number of alerts. Therefore, the sum of false positives is pertinent. The true-negatives count is one input of the indicator *accuracy*, and it is the major reason why the indicator must be discarded. Time is not discrete, it is a continuous variable which translates into an infinite amount of true-negatives in the prediction task. [41] There is an unlimited amount of non detected incidents that are true, hence not applicable. The eq. (4.2) shows what happens to the *accuracy* formula when used into a continuous time space. It results in 100% *accuracy* no matter the data input, which proves useless.

$$\textit{Accuracy} = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{4.1}$$

$$\lim_{T_n \to +\infty} \textit{Accuracy} = \lim_{T_n \to +\infty} \frac{T_p + T_n}{T_p + T_n + F_p + F_n} = 1 \tag{4.2}$$

”*Precision* is a measure for efficiency” [41]. The true positive rate is of the most importance. This indicator can be seen as a measure of quality, favoring a careful approach to deciding on when to, in this use case, alert the operator. In eq. (4.3) the denominator contemplates the total count of predicted incidents, while the numerator the only the correct predictions, hence *precision*.

$$\textit{Precision} = \frac{T_p}{T_p + F_p} \tag{4.3}$$

Recall is another indicator of the system's performance. It can be interpreted as the effectiveness of predicting the incidents. In other words, the higher the *recall* the higher the number of true-positives over all real incidents, see eq. (4.4). This indicator is especially useful when testing the event extraction algorithms' hyperparameters and system hyperparameters in general. It is important for one to note that precision is favored over recall. If one would aim to recall 100%, disregarding precision, it would promote a "machine gun" approach. The system would spam predictions in order to hit all points in time that correspond to real incidents, resulting in a huge number of false-positives. An increase in false-positives is reflected in a decrease of *precision* by eq. (4.3). Preferably, one would desire the best recall with little to no sacrifice of precision.

$$\textit{Recall} = \frac{T_p}{T_p + F_n} \tag{4.4}$$

Precision measures frugality and *recall* prodigality, both are used to tune the underlying system parameters. Efforts to increase *recall* may lead to poor *precision*, and attempts to boost *precision* may decrease recall drastically up to the extent of the system being of no use to the operators. A problem emerges, how can one tune the system with respect to two performance indicators? An aggregated indicator, *F1 Score*, helps to harmonize. This indicator reflects both perspectives. In eq. (4.5), the denominator includes the sum, *precision* plus *recall*, while the numerator doubles the multiplication of the percentage. This reflects both previous indicators with the same weight in a single new percentage value. This *F1 Score* is a simplification of the *Fβ Measure*, with $\beta = 1$. Depending on the prioritization of precision or recall, the *Fβ Measure* helps to aggregate scores into a single result, the formula can be found in eq. (4.6). *F0.5-Measure*($\beta = 0.5$) has more weight on precision, and less weight on recall. *F2-Measure* ($\beta = 2$) for less weight on precision, and more weight on recall.

$$\textit{F1 Score} = \frac{2 * \textit{Precision} * \textit{Recall}}{\textit{Precision} + \textit{Recall}} \tag{4.5}$$

$$F\,\beta\ Measure = \frac{(1+\beta^2) * Precision * Recall}{\beta^2 * Precision + Recall} \tag{4.6}$$

To sum up, the decision was to use **precision**, **recall**, **f1 score**, **f0.5 measure** and **f2 measure** as the monitoring system performance indicators, while tuning the parameters and event extractor underlying hyperparameters.

4.2 Ensemble Algorithm Performance

The monitoring system developed during this study was tested using different combinations of parameters Δ, α, β, γ and $algos$. These parameters are described and detailed in section 3.7. The intention is to find the best combination of parameters that maximizes precision and recall, hence fβmeasures.

The study hypothesis is that, by extracting events from the metrics and correlating them to incidents that have already happened, next time, when there is evidence of new events like the previously spotted ones, a recurring incident is caught before it happens. Before analyzing results and comparing test trials it is relevant to acknowledge the main goal, stop recurring incidents. In order to achieve desired results the important indicators to consider are high precision and a low number of false-positives. Naturally, high recall is also desired. The rationale is that precision proves it is capable of predicting real incidents and the low number of false-positives ensures that alert fatigue is reduced.

A pertinent question came across. How does one define a correctly predicted incident? In other words, what are the criteria for a true-positive? It is ideally a prediction that was made and turned out to be, in fact, correct. This definition is yet not translatable to a programming language. A prediction is made at a single point in time, it is remotely impossible to predict the exact timestamp of the real incident due to the infinite characteristic of time. To solve this it was defined, arbitrarily, a positive error margin of half of the fingerprint interval, $\Delta/2$. For instance, when a 15 minute fingerprint is found, the incident is considered a TP if it happens in the next 7 min and 30 seconds. The time between prediction and incident can be then used to perform preventive maintenance by the service engineers.

In appendix A the full results can be found. They include a total of 3 tables, each table corresponds to $\gamma = 1$, $\gamma = 2$ and $\gamma = 3$.

Before diving into the analysis of the results one might notice that, in some trials there seems to be an unprecedented number of predicted incidents (column **pred**) compared to real incidents (column **inc**), whilst being low on precision and/or recall. Let us understand the reason why it happens and why that is not an error. This only happens because the *Incident Alert Filter* module is turned off, this was turned off so we can first analyze the *Fingerprint Detection* module predictions without the filtering module. The way the system works, in terms of predicting incidents, is by detecting a known incident fingerprint in a certain time window size, Δ, right before the moment of analysis t, i.e. $timewindow = \lceil t - \Delta, t \rceil$. Let us say, at time t, a matching fingerprint is detected, hence an incident is predicted to occur in the following moments, i.e. $t + i$, $i \in \lceil 1, 2, 3, ..., \Delta/2 \rceil$. The incident is marked at time t. In the next moment, $t+1$, the same known incident fingerprint is detected again in the $timewindow = \lceil t-\Delta+1, t+1 \rceil$, regarding the same incident detected in t. In other words, the system has detected the same fingerprint in those two time windows, one after the other, and consequently has predicted incidents in timestamps t and $t + 1$. This repetition of detecting the same fingerprint regarding the same incident happens regularly and can repeat indefinitely, obviously limited by metric frequency and error margin, for $t+2$, $t+3$, $t+4$, ... This results in a real incident, having most of the time, more than one accepted correct prediction. Thereupon the discrepancy in number of predicted incidents regarding real incidents. The following table 4.1, table 4.3 and table 4.5 show excerpts with a selection of best precision, recall and f measurements. The table 4.7, shows an excerpt of the best results with the *Incident Alert Filter* module turned on.

The difference between table A.1, table A.3 and table A.5 with $\gamma = 1$, $\gamma = 2$ and $\gamma = 3$, respectively, is the number of distinct event types used for the test runs. The intention was to analyze the monitoring system's performance under different conditions in order to pinpoint which parameters work best for our dataset's use case and how this could work out in an arbitrary use case. At our disposal we have algorithms HM, LU, IF, LS, LOF, SFBP and VS extracting events of types HM, LU, IF, LS, LOF, SFBP and VS, respectively. The first trial testing involved locking the system's events, so that, it can only use events of a specific type at

the time, $\gamma = 1$.

Table 4.1: Trial results for a fixed number of event types, γ, to 1 (event types are also referred to as algorithms, since one event type means an event detected by an algorithm, two event types mean events that were captured by two distinct algorithms of the algorithm list in section 3.6.1). Table columns include: precision percentage, recall percentage, f1 score percentage, f2 measure percentage, f0.5 measure percentage, number of real incidents, number of predicted incidents by the system, number of true-positive incidents predicted by the system, number of false-positive incidents predicted by the system, Δ algorithm parameter referring to the interval in minutes considered for a fingerprint, α algorithm parameter referring to the fingerprint similarity margin, β algorithm parameter regarding the minimum number of fingerprints, γ the number of event types used, algos refers to the algorithms used for event extraction. This is an excerpt of table A.1 that can be found in appendix A.

Δ	α	β	γ	algo	precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP
5	15	2	1	IF	82.18	2.87	5.55	3.56	12.6	2506	752	618	134
5	999	2	1	IF	82.18	2.87	5.55	3.56	12.6	2506	752	618	134
20	5	10	1	IF	80.82	2.87	5.55	3.56	12.58	2506	709	573	136
30	999	2	1	VS	54.55	61.05	57.62	59.63	55.74	2506	39244	21407	17837
30	15	2	1	VS	54.52	60.73	57.46	59.38	55.66	2506	38931	21224	17707
30	999	10	1	VS	54.68	57.62	56.11	57.01	55.24	2506	37682	20604	17078
30	15	10	1	VS	54.79	57.22	55.98	56.72	55.26	2506	37268	20419	16849
5	5	10	1	LU	60	1.8	3.49	2.23	8.02	2506	85	51	34
5	15	10	1	LU	60	1.8	3.49	2.23	8.02	2506	85	51	34
5	999	10	1	LU	60	1.8	3.49	2.23	8.02	2506	85	51	34
30	999	2	1	HM	59.16	51.6	55.12	52.95	57.47	2506	38428	22733	15695
30	999	2	1	LS	55.11	21.75	31.19	24.74	42.17	2506	12152	6697	5455
30	999	2	1	SFBP	52.75	13.81	21.89	16.2	33.72	2506	3623	1911	1712
30	15	2	1	LOF	51.68	10.42	17.34	12.39	28.83	2506	1219	630	589

In table 4.1 an excerpt of table table A.1 is displayed. Examining long table A.1, precision ranges from 0 to 82.18%, while recall ranges from 0 to 61.05%. The goal is to create a monitoring system for recurring incidents, therefore precision is of greater importance when compared to recall. The system is not expected to predict all happening incidents. It is expected to predict the recurring ones and do it with high confidence values, translated to performance analysis nomenclature, precision. Interestingly, varying Δ, α, β parameters do not show major differences in precision, however, we can see a heavy influence in recall. Sorting the table for the

highest f1 score we can see VS algorithm dominating, as it seems to have the best balance between precision (ranging from 50% to 55%) and recall (ranging from 45% to 61%). Once examining the number of incorrect predictions, FP, one can understand the alert fatigue consequences. Hence the choice not to consider those trials as most appropriate for a production environment. Sorting the table by event type algorithm we can analyze the real influence of Δ, α, β. VS seems to maintain the results no matter the parameters. Parameter Δ does not impact the monitoring system's performance. This is a sign that the fingerprint in the moments before the incidents are proving a constant event count during different time-window intervals. As it seems, α also does not influence final values. This demonstrates a high similarity of event counts, if the event count numbers across the same type fingerprint are exactly the same, then varying α will not influence results. Finally, β, which represents the minimum number of fingerprints for storage also does not influence precision, only recall values. An explanation for this may be related to the number of fingerprints of the same type found. Arbitrary $\beta = 2$, $\beta = 10$ and $\beta = 60$ values were trialed, these may not influence precision due to the normal frequency of recurring incident fingerprints being higher. In fact after analysis, frequency counts ranged from 1 to 192. High frequency incident fingerprints are in fact the recurrent incident that we intent to predict, therefore we limit the minimum of fingerprints to a reasonable value.

Let us investigate other event types. Higher Δ seems to be correlated with higher precision, as a 30 minute time window for the fingerprint is capable of gathering more information, this indicates a 5 or 10 minute fingerprint may not be enough. No matter the event type, parameter α has no influence on results. α trials values 5, 10 and 999. The higher value, 999, is intended to represent infinite similarity, this is the case in which the fingerprint comparison is carried out using only the metrics that itself is composed of, not limited by event type count. Minimum fingerprint count, β, has a huge impact, as a higher β inhibits the system's predictions. This is interesting, especially because, after analysis, fingerprint counts range from 0 to 192, yet β, limiting fingerprints to the ones that have occurred at least 60 times prejudices the system. This is at least counter-intuitive, as one would expect the most repeated fingerprint would happen more times. This is probably a misconception, the reason this happens is most likely related to the high saturation of events leading to false fingerprints that just happened to be present

before incidents and were wrongfully labeled as fingerprints that precede incidents. Reducing this value increases precision in most algorithms.

One event type conditions, $\gamma = 1$, seem to prove there is hope in correct incident predictions. Nevertheless, values range far from acceptable. Having 54.55% precision and 61.05% recall is not bad but it still translates to an alarmingly number of false-positives, 17837. Service engineers can lose confidence in a system that exports too many false-positives, hence the importance of alert fatigue throughout this study.

Table 4.3: Trial results for a fixed number of event types, $\gamma = 2$ (event types are also referred to as algorithms since one event type means an event detected by an algorithm, two event types mean events that were captured by two distinct algorithms of the algorithm list in section 3.6.1). Table columns include: precision percentage, recall percentage, f1 score percentage, f2 measure percentage, f0.5 measure percentage, number of real incidents, number of predicted incidents by the system, number of true-positive incidents predicted by the system, number of false-positive incidents predicted by the system, Δ algorithm parameter referring to the interval in minutes considered for a fingerprint, α algorithm parameter referring to the fingerprint similarity margin, β algorithm parameter regarding the minimum number of fingerprints, γ the number of event types used, algos refers to the algorithms used for event extraction. This is an excerpt of table A.3 that can be found in appendix A.

Δ	α	β	γ	algo	precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP
5	5	2	2	LS;SFBP	100	0.4	0.79	0.5	1.96	2506	57	57	0
15	5	2	2	LU;VS	100	0.08	0.16	0.1	0.4	2506	22	22	0
5	5	2	2	LU;IF	100	0.08	0.16	0.1	0.4	2506	19	19	0
5	15	2	2	LU;IF	100	0.08	0.16	0.1	0.4	2506	21	21	0
5	999	2	2	LU;IF	100	0.08	0.16	0.1	0.4	2506	21	21	0
20	5	2	2	VS;SFBP	100	0.04	0.08	0.05	0.2	2506	2	2	0
5	5	2	2	LU;LS	100	0.04	0.08	0.05	0.2	2506	2	2	0
15	5	2	2	LS;SFBP	100	0.04	0.08	0.05	0.2	2506	7	7	0
20	5	2	2	LS;SFBP	100	0.04	0.08	0.05	0.2	2506	12	12	0
30	5	10	2	HM;LS	100	0.04	0.08	0.05	0.2	2506	6	6	0
30	5	60	2	HM;LS	100	0.04	0.08	0.05	0.2	2506	6	6	0
30	999	2	2	HM;VS	55.17	27.29	36.52	30.36	45.81	2506	24432	13478	10954
30	999	2	2	HM;IF	60.68	15.92	25.22	18.68	38.84	2506	9728	5903	3825
30	15	10	2	HM;VS	54.37	16.16	24.92	18.8	36.91	2506	13306	7234	6072
30	999	2	2	HM;LOF	59.88	15.4	24.5	18.09	37.96	2506	11556	6920	4636
30	999	10	2	HM;IF	60.74	15.28	24.42	17.97	38.08	2506	9447	5738	3709
30	999	2	2	LS;VS	54.55	12.33	20.11	14.59	32.38	2506	10893	5942	4951

Δ	α	β	γ	algo	precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP
30	999	2	2	HM;SFBP	60.51	12.13	20.21	14.44	33.66	2506	10935	6617	4318
30	999	2	2	IF;VS	55.93	10.18	17.22	12.17	29.45	2506	7257	4059	3198

Results in table A.3 are surprising. Precision is higher, even reaching 100%. This could be expected, as two event types lead to a higher diversity in fingerprint classification. Recall dropped to really low values, averaging around 2%, this is explained by the similarity of incidents, and now with this two-event type approach, $\gamma = 2$, incidents that used to be fitted in the same fingerprint now show distinct ones. One of these might not even reach β minimum count values, hence not being predicted. It would be expected that by increasing δ, precision would rise and recall would get lower, nevertheless, that did not happen. The reasoning behind this might have to do with low fingerprint count, which is a result of the criteria for fingerprint similarly explained in section 3.7.

It is interesting how the number of predicted incidents lowered drastically, proving a more prudent decision by the system. Combination of algorithms LU:VS, LU:IF and LS:SFBP show high precision results with almost no wrong predictions. LS combined with SFBP seems to have the best precision results, keeping in mind alert fatigue. Now, with two event types the influence of α is more noticeable, increase upwards of 100% on the number of predicted incidents is shown. Algorithms LS and SFBP, show a clear increase in prediction numbers while maintaining precision values. This phenomenon can be attributed to the similarity margin increase, the higher the error margin the higher the predicted incidents count. Since precision is maintained, opting for a lower error margin guarantees fewer predictions, reducing alert noise. Another interesting comparison worth noticing is that now, β values influence the predicted incident count. This may be due to, in comparison with one event type, incident fingerprints having more ”resolution”, hence higher number of distinct fingerprints are found. This means, on average, there are fewer occurrences of distinct fingerprints, as they were split into new ones. In conclusion, there are more fingerprints leading to a reorganization of occurrences between them, which were before concentrated in more ”general” fingerprints. The problem with these

general fingerprints is that they are contaminated by nonuseful events. This causes the fingerprint extraction module to mix what should be distinct fingerprints into a single one, resulting in predictions with a very high absolute number of false-positives. HM and VS combined are able to reach 27.29% recall with 55.17% precision, nonetheless 10954 false positives were found. Maybe with the *Incident Alert Filter* module turned on these number will improve.

Let us compare statistics for the trial with algorithms LS:SFBP, $\Delta = 5$, $\alpha = 5$, $\beta = 2$. In the trial with 57 predicted incidents, there was an average prediction interval time of 3 minutes and 38 seconds, meaning on average the service engineers would have a heads-up of the upcoming incident 3 minutes and 38 seconds before it happens. The median was around 3 minutes and 48 seconds, with values ranging from 2 seconds up to 7 minutes and 30 seconds.

Table 4.5: Trial results for a fixed number of event types, $\gamma = 3$ (event types are also referred to as algorithms since one event type means an event detected by an algorithm, two event types mean events that were captured by two distinct algorithms of the algorithm list in section 3.6.1). Table columns include: precision percentage, recall percentage, f1 score percentage, f2 measure percentage, f0.5 measure percentage, number of real incidents, number of predicted incidents by the system, number of true-positive incidents predicted by the system, number of false-positive incidents predicted by the system, Δ algorithm parameter referring to the interval in minutes considered for a fingerprint, α algorithm parameter referring to the fingerprint similarity margin, β algorithm parameter regarding the minimum number of fingerprints, γ the number of event types used, algos refers to the algorithms used for event extraction. This is an excerpt of table A.5 that can be found in appendix A.

Δ	α	β	γ	algo	precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP
5	15	2	3	HM;LU;LS	100	0.08	0.16	0.1	0.4	2506	22	22	0
30	5	10	3	HM;IF;LS	100	0.08	0.16	0.1	0.4	2506	6	6	0
20	5	2	3	LU;IF;LS	100	0.08	0.16	0.1	0.4	2506	8	8	0
30	5	2	3	LU;IF;LS	100	0.08	0.16	0.1	0.4	2506	7	7	0
15	5	2	3	LU;IF;VS	100	0.08	0.16	0.1	0.4	2506	25	25	0
30	5	2	3	LU;LS;VS	100	0.04	0.08	0.05	0.2	2506	3	3	0
15	5	2	3	IF;LS;SFBP	100	0.04	0.08	0.05	0.2	2506	7	7	0
20	5	2	3	IF;LS;SFBP	100	0.04	0.08	0.05	0.2	2506	13	13	0
5	15	2	3	HM;LU;IF	82.58	0.2	0.4	0.25	0.99	2506	132	109	23
5	999	2	3	HM;LU;LS	78.39	0.16	0.32	0.2	0.79	2506	199	156	43
30	5	2	3	HM;IF;LS	78	0.08	0.16	0.1	0.4	2506	50	39	11
30	999	2	3	IF;LS;VS	55.99	8.26	14.4	9.96	25.97	2506	8658	4848	3810
30	999	2	3	HM;IF;LS	57.21	5.27	9.65	6.44	19.25	2506	6064	3469	2595

Δ	α	β	γ	algo	precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP
30	999	2	3	HM;LS;VS	56.4	4.71	8.69	5.77	17.65	2506	6298	3552	2746

Let us analyze results with, $\gamma = 3$, which indicates the need for three event types to define a fingerprint. The logical thinking behind it is: more event type diversification more features to extract and further identify a fingerprint. In table 4.5, the most interesting results can be found for $\gamma = 3$, once again, the full table can be found in appendix A. This time there are 8 trials with 100% precision, nevertheless, recall is very low. Just like $\gamma = 2$, it is proven it is possible to precisely predict future incidents based on learning past behavior. Let us further analyze the algorithms used and how parameters influence the results.

Two parameters might catch one's attention, α and β. Isolating the 100% precision trials it is noticeable $\alpha = 5$ in most trials. Following $\alpha = 15$ in less precise trials. The lower the error similarity margin, the more precise the system gets. Next up, β trials perform in a rather interesting way. The higher the β the more selective the system should be, in the sense, it only uses that fingerprint for prediction if it happens β number of times. The logic is, if a fingerprint only happens once, then it is probably not worth predicting an incident based on that fingerprint data. Nonetheless, trial results prove precision works the opposite way. A minimum of 2 fingerprints achieve the best results, with exception of only one trial, in which $\beta = 10$. Why do low β values get the best results? This can be explained by the number of fingerprint occurrences being very low. Using three algorithms to extract three event types makes it very difficult or unlikely to catch the same fingerprint multiple times. After analysis fingerprint counts for these parameters ranges between 1 and 15, which adds up to this reasoning. Also, it is important not to forget that there is also a metric limitation in the fingerprint, as it is needed at least two metrics for a fingerprint to be recognized, as explained in section 3.7, hence the reason why the fingerprint count is so low. Predominant algorithms which achieved the best precision results are the combination of IF:LU:VS with 25 predictions and also the trial composed by HM:LS:LU with 22 total predictions. Let us compare the statistics of these two trials. In the trial with 25 predicted incidents, there was an average prediction interval time of 4 minutes and 46 seconds,

warning the service engineers almost 5 minutes before it happens. The median was around 5 minutes and 38 seconds, with values ranging from 2 seconds up to 7 minutes and 30 seconds. The trial with 22 predictions averaged 7 minutes and 8 seconds of prediction interval time, a median of 7 minutes and 7 seconds, with values ranging from 6 minutes and 48 seconds to 7 minutes and 30 seconds. Even though this trial predicted three incidents less it performs best in terms of average and median prediction interval time values, but also in the worst case scenario the service engineer would have 6 minutes and 48 seconds to perform preventive maintenance. That is more than enough for the service engineer to be prepared to act, Mean Time To Acknowledge (MTTA) is zero, hence minimizing Mean Time To Repair (MTTR), which can be translated directly into downtime [42].

Running trials for different parameters shows the best performance of precision and correctness results with $\gamma = 2$, which presented double the number of correct predictions. Nevertheless, one should not discard $\gamma = 3$ trial runs. They showed almost double the interval prediction time, this increases the chances of the incident not occurring since service engineers have more time to perform preventive maintenance work once they get alerted. Why should the monitoring system be restricted by the use of just one parameter combination? This will be further discussed in chapter 5.

Table 4.7: Selected trial results with *Incident Alert Filter* module turned on. Table columns include: precision percentage, recall percentage, f1 score percentage, f2 measure percentage, f0.5 measure percentage, number of real incidents, number of predicted incidents by the system, number of true-positive incidents predicted by the system, number of false-positive incidents predicted by the system, Δ algorithm parameter referring to the interval in minutes considered for a fingerprint, α algorithm parameter referring to the fingerprint similarity margin, β algorithm parameter regarding the minimum number of fingerprints, γ the number of event types used, algos refers to the algorithms used for event extraction.

Δ	α	β	γ	algo	precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP
30	15	2	1	VS	97.35	53.71	69.23	59	83.74	2506	2412	2348	64
30	15	10	1	VS	97.71	49.52	65.73	54.94	81.79	2506	2229	2178	51
30	999	2	1	VS	97.19	41.98	58.63	47.36	76.95	2506	1175	1142	33
30	999	10	1	VS	97.39	38.71	55.4	44.01	74.73	2506	1033	1006	27
20	15	2	1	VS	74.57	37.35	49.77	41.49	62.18	2506	1758	1311	447
20	15	10	1	VS	75.02	33.96	46.75	38.13	60.41	2506	1481	1111	370
20	999	2	1	VS	72.98	32	44.49	36.05	58.1	2506	1262	921	341
20	999	10	1	VS	73.71	29.13	41.76	33.14	56.44	2506	1103	813	290
15	15	2	1	VS	55.68	27.97	37.24	31.06	46.47	2506	1575	877	698
15	999	2	1	VS	55.06	25.74	35.08	28.81	44.84	2506	1264	696	568
30	5	2	1	LS	93.08	21.31	34.68	25.19	55.62	2506	1373	1278	95
15	15	10	1	VS	56.22	24.74	34.36	27.86	44.82	2506	1350	759	591
15	999	10	1	VS	55.68	22.91	32.46	25.96	43.29	2506	1092	608	484
30	15	2	1	LS	92.84	19.55	32.3	23.22	53.06	2506	991	920	71
30	15	10	1	LS	92.67	18.6	30.98	22.13	51.58	2506	914	847	67
20	5	2	1	LS	70.37	18.2	28.92	21.36	44.72	2506	1512	1064	448
30	999	2	2	HM;VS	96.37	15	25.97	18.05	46.23	2506	413	398	15
30	15	2	2	HM;VS	96.79	14.45	25.14	17.41	45.23	2506	561	543	18
20	15	2	2	HM;VS	77.46	12.73	21.87	15.28	38.4	2506	692	536	156
30	15	10	2	HM;VS	98.25	11.73	20.96	14.24	39.7	2506	458	450	8
15	5	2	2	HM;VS	53.29	12.17	19.82	14.39	31.8	2506	974	519	455
20	999	2	2	HM;VS	75.06	10.89	19.03	13.14	34.46	2506	393	295	98
30	999	10	2	HM;VS	96.39	10.14	18.34	12.35	35.67	2506	277	267	10
30	15	2	2	IF;VS	96.02	8.82	16.15	10.78	32.25	2506	352	338	14
30	15	2	2	LS;VS	94.35	8.34	15.33	10.2	30.81	2506	336	317	19

In table 4.7, the *Incident Alert Filter* module was turned on. Comparing these results with ones in previous tables 4.1, 4.3 and 4.5 it is noticeable the reduction in incident predictions. Repeated predictions accounted for the precision discrepancy between the previous trials and theses ones. The consecutive repetition of predictions spammed the timeline with true-positives and false-positives around the real incident. This spam of predictions may also be responsible for the drop in recall in table 4.7, since spam predictions would accidentally match other real incidents. Comparing trial $\Delta = 30$, $\alpha = 15$, $\beta = 2$, $\gamma = 1$, $algo = VS$ of table 4.1 against

the same trial specification parameters in table 4.7 there is a precision increase and a slight recall decrease. It was also noted that the number of predictions lowered drastically, from 17707 to 2412, which is really close to the number of real incidents. In this trial, there was an average prediction interval time of 7 minutes and 11 seconds. The service engineer is warned 7 minutes and 11 seconds before it happens. The median was around 7 minutes and 5 seconds, with values ranging from 1 seconds up to 12 minutes. In trial $\Delta = 20$, $\alpha = 15$, $\beta = 2$, $\gamma = 1$, $algo = VS$, there was an average prediction interval time of 4 minutes and 28 seconds. The median was around 4 minutes and 43 seconds, with values ranging from 1 seconds up to 10 minutes.

Table 4.7 does not contain $\gamma = 3$ results since recall values were less than 0.1%. During planning and implementation, there was the hypothesis of achieving better results if $\gamma > 1$. Albeit results with the *Incident Alert Filter* module turned off presented higher precision values as hypothesized, when turning it on, $\gamma = 1$ showed to have better precision. Also the recall was consistently higher in $\gamma = 1$ results.

5
Conclusions

This final section beholds the conclusions of this research and study, as well as future work suggestions that would further improve the monitoring system if implemented and deployed in a production environment.

The goal of this study is to create an intelligent monitoring system, capable of predicting recurrent incidents in order to take preventive measures. Using an ensemble of outlier detection algorithms combined with the modified approach of the fingerprints identification method, conclusions were achieved and shall be discussed in the next paragraphs. This study was performed in partnership with a company - Identity. Datasets used throughout the research correspond to a real IT server running in production, therefore it can be considered a real-world scenario.

At the beginning of the study, one hour frequency metrics were available, it quickly became clear higher frequency was necessary. A low-frequency metric implies events happening in the machine are comprised into one hour buckets, which makes impossible the prediction feature of the intended system. The bigger the bucket the highest the odds of *events* falling into it. Nonetheless, more *events* are not necessarily beneficial, since there are other occurrences that are not incident related. These are considered contamination *events*. High contamination in the bucket and the prediction will not only be less precise, but also present lower recall values. Naturally, the idea of the study with these conditions was readily discarded. Also at the beginning of the study, it was found that the metric datapoints of the dataset showed inconsistent frequencies due to the extraction tool limitations. Therefore, throughout the study, there were no set frequencies defined, notwithstanding, as reference values, a 30 second to 1 minute minimum metric frequency should present similar performance results.

During outlier detection algorithms implementation, hyperparameter choice is of the highest importance. Metrics and corresponding algorithms were carefully analyzed and parameters

were chosen accordingly to the use case. Nevertheless, the conclusion was arbitrary values seem to show equal performance results to specific use case scenario parameters. However, for future work, one cannot discard a heuristic approach for an agnostic solution. Implementations such as [35], may impact the event extraction process, hence having relevant impact in later fingerprint detection and prediction stages.

The incident prediction module uses the almost real time extracted events from the event extraction module and matches those with already acknowledged fingerprints. This is performed in a direct comparison way. As a further improvement, a fingerprint weighted decision is suggested. It may outperform these study results. It is accomplished by giving more relevance to certain event types, as in ones are more relevant than others. The way to implement this would be in the fingerprint extraction module. The module would perform the fingerprint extraction in a rather different and more complex way. Incident fingerprint is the collection of events occurring, in an arbitrary Δ, before an incident happens. These event collections of incidents of the same type would be compared against each other. The goal would be to discard outlier events, events that appear just rarely and establish a weighted distribution for each event type. This weighted distribution would be linear to the event type occurrences, to do so, for instance applying the division by the greatest common divisor. This way, in the incident prediction module, proportional fingerprints can now be found. It is also relevant to point out, the usefulness of discarding outlier events, specially in a machine running more than one service. Having several services running on the same machine sharing components introduces metric noise, as the metrics represent the sum or aggregation of both service processes running at the same type. Critical machine problems shouldn't be affected by this as extracted events from metrics should reveal these anyway, however service problem detection is negatively influenced. To combat this, using SRE might be the solution. This is further explained in the last paragraph of this chapter.

The performance results showed in chapter 4 prove there can be a correlation between metric behavior and service incidents. It is difficult to point out the best results, since they may vary depending on the type of services being monitored and how the service engineers prefer to be alerted. If one decides to prioritize precision over recall, then the f0.5 measure is the

best indicator. If favoring recall over precision then the f2 measure is the indicator to look at. This is a subjective case since it depends on the problem being tackled. Nevertheless, in my opinion, precision should, in most cases, be favored over recall, hence f0.5 measure is more appropriate. The reasoning behind this comes from false-positives leading to alert fatigue, therefore, the need to minimize them.

The hypothesis of the study is coherent with the results and there are useful insights that can be discussed and concluded. The number of event types for fingerprint extraction can be one, but the metrics composing it needs to be at least two. Also fingerprint interval proved to work best with a 30 minute time window. In the performance results of this study, individual fingerprint types were tested in each run. It would be interesting to see if the results could be improved, as future work, with predictions made using fingerprints extracted from the best trials $\gamma = 1$, $\gamma = 2$ and $\gamma = 3$ runs. The reasoning behind this composition is to have dynamic fingerprint extraction module, that updates itself according to performance results, in an completely unsupervised manner. A scheduled update would recalculate performance results for different parameters and classify those runs according the results of each run. Then accordingly decide whether or not to use those trial runs parameters for real world alerting. This is specially important in systems that change over time. This schedule should include important dates such as major update deployments and scalability changes. Preset parameters include arbitrarily chosen values, the same way proceeded in this study. In the end of chapter 4, a question rose up. Why should the monitoring system be restricted to the use of just one parameter combination? In fact, it doesn't need to be limited to just one. Recalculating performance results and choosing several parameter combinations to be applied in the monitoring system would increase the overall performance. The way this works is by combining the best results. Each parameter combination will have a specific aptitude to catch its types of incidents, hopefully resulting in an overall higher precision and recall values.

Even though the goal is an unsupervised monitoring approach, incidents may occasionally be incorrectly predicted, false-positives. To deal with this, a simple supervised module could be implemented with a training feature. A false-positive incident is predicted, the service engineer acknowledged no incident happened in the following moments. The suggestion would be to add

the possibility to manually activate a function to delete or reevaluate that fingerprint, whether it is deleted completely off the fingerprint database, or adjust α value, corresponding to the error margin allowed for a fingerprint to be matched with one another.

In the incident prediction module, an interesting phenomenon was discovered. The prediction of incidents is based on the events occurrences in an arbitrary Δ time window. Δ is a fixed value during a prediction run. So, what happens when positively and negatively shifting the time window interval $\Delta = [t_i - \Delta - T; t_i - T]$ by a set of small values T? These shifted time windows correspond to the time iterations with T values being the size of the metric period. For example, T can be one, two, three minutes and so forth. The result is the same fingerprint can be found several times in different neighbor time windows. In other words, a single incident is predicted several times. A mechanism must be put in place to deal with this ”spray” of incident predictions. The *Incident Alert Filter* module must filter out incident repetition, in order not to spam the service engineer responsible.

The idea of running a real time monitoring system using heavy algorithms, like IF and SFBP, may concern one about computational processing challenges. What is needed to run this setup? Well, it scales linearly, horizontally, with the number of machines being monitored, since they are independent in regards to metrics. IF algorithm uses heavy processing, but as shown in chapter 4, it is not one of the best performing algorithms, so most likely it will not be used in the real case scenario. Nevertheless, SFBP presented good results, and it requires heavy processing if a significant amount of metrics need to be processed. The first time the monitoring system is turned on there are two options: train with past data immediately or start with the real data and predict only when it finds good precision values. The first option will require additional processing power, but once it has overcome that first processing batch, it will be much faster. The first processing batch with 3 months of data took 5 hours in an Intel i7-9750H, it is an hexa-core with 12 threads available, with base frequency of 2.60 GHz and 12MB of cache [43]. It is running with 16GB of RAM, but that is not the limiting factor, the CPU is. In normal running conditions with event types already selected, only certain algorithms will be used, therefore even a dual-core with 4 threads available is more than enough to monitor 2 or 3 servers. For instance, if the deployment of the monitoring is in a dynamic cloud environment,

then during scheduled update or first batch processing, a high-performance CPU could be selected to shorten the processing time. However, this would increase running costs. The monitoring system leverages multi-threading to parallelize tasks. More specifically in the event extraction module. Algorithms IF, LOF and SFBP leverage multi-threading. During the study a 3 month batch of data needed to be processed, therefore multi-threading was also implemented in the fingerprint extraction and incident prediction module, splitting the time window of events and distributing it to the available 12 threads. This resulted in an improvement in runtime performance of almost 144x.

An incident database is a reliable and vital source of information for the deployment of a monitoring system like this. It may not always be available, therefore an input source must be provided, as future work a solution to this challenge is suggested leveraging one of the latest topics in the industry, SRE. SRE (Site Reliability Engineering) is a set of principles and practices first introduced in 2003, by Ben Sloss, a Service Reliability Engineer at Google. It ”incorporates aspects of software engineering and applies them to infrastructure and operations problems” [44]. The suggestion is to implement SRE principles, more specifically the definition of System Level Indicators (SLIs) and their respective System Level Objectives (SLOs). The way this would be implemented is by defining availability, latency, performance, and capacity metrics. SLIs are in the form defined in eq. (5.1). In the formula, *Good Events* are for example number of successful HTTP requests or number of calls that completed successfully in less than 100 ms. *Bad Events* are the opposite, more information can be found in the SRE Google book [6]. These metrics are operational metrics, instead of infrastructure metrics. They paint the picture on the customer/end-user level. A combination of the monitoring system studied in this thesis with the input of SLIs defined by the service engineer, would result in a trustworthy source of information regarding incidents/problems that impact the business. This approach would correlate the infrastructure layer with the business and operational layers. Using the infrastructure metrics to predict business and operational incidents. Providing the root cause analysis of how it all happened. This is especially relevant to the service engineers that could use this information. They would not only get up to speed on the incident resolution process much faster but also understand the cause and further perform reliability work, in order to make

sure it does not happen again.

$$SLI = \frac{GoodEvents}{GoodEvents + BadEvents} \tag{5.1}$$

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A

Prediction Results Tables

This appendix beholds the trial results for a fixed number of event types (event types are also referred to as algorithms since one event type means an event detected by an algorithm, two event types mean events that were captured by two distinct algorithms of the algorithm list in section 3.6.1), $\gamma = 1$, $\gamma = 2$, $\gamma = 3$ in three separate tables, table A.1, table A.3, table A.5, respectively. Table columns include: precision percentage, recall percentage, f1 score percentage, f2 measure percentage, f0.5 measure percentage, number of real incidents, number of predicted incidents by the system, number of true-positive incidents predicted by the system, number of false-positive incidents predicted by the system, Δ algorithm parameter referring to the interval in minutes considered for a fingerprint, α algorithm parameter referring to the fingerprint similarity margin, β algorithm parameter regarding the minimum number of fingerprints, γ the number of event types used, algos refers to the algorithms used for event extraction.

Table A.1: Trial results for a fixed number of algorithms to 1. Varying $\alpha, \beta, \gamma, \delta$

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
82.18	2.87	5.55	3.56	12.6	2506	752	618	134	5	15	2	1	IF
82.18	2.87	5.55	3.56	12.6	2506	752	618	134	5	999	2	1	IF
80.82	2.87	5.55	3.56	12.58	2506	709	573	136	20	5	10	1	IF
80.76	2.83	5.47	3.51	12.42	2506	707	571	136	15	5	10	1	IF
80.69	2.83	5.47	3.51	12.42	2506	694	560	134	5	5	2	1	IF
80.5	3.27	6.29	4.05	14.07	2506	928	747	181	20	999	10	1	IF
80.45	3.27	6.29	4.05	14.07	2506	926	745	181	20	15	10	1	IF
79.46	3.23	6.21	4	13.9	2506	881	700	181	15	15	10	1	IF
79.46	3.23	6.21	4	13.9	2506	881	700	181	15	999	10	1	IF
78.87	3.63	6.94	4.49	15.33	2506	1013	799	214	30	15	10	1	IF
78.87	3.63	6.94	4.49	15.33	2506	1013	799	214	30	999	10	1	IF
75.54	2.51	4.87	3.12	11.09	2506	556	420	136	30	5	10	1	IF
70.55	2.79	5.37	3.46	12.06	2506	309	218	91	15	5	10	1	SFBP
70.53	4.31	8.12	5.31	17.32	2506	1347	950	397	20	999	2	1	IF
70.48	4.23	7.98	5.21	17.06	2506	1345	948	397	20	15	2	1	IF
70.42	4.23	7.98	5.21	17.05	2506	1342	945	397	20	5	2	1	IF
70.27	4.23	7.98	5.21	17.04	2506	1315	924	391	15	999	2	1	IF
69.88	4.15	7.83	5.11	16.77	2506	1298	907	391	15	5	2	1	IF
69.88	4.15	7.83	5.11	16.77	2506	1298	907	391	15	15	2	1	IF
69.56	4.63	8.68	5.69	18.28	2506	1452	1010	442	30	999	2	1	IF
69.5	4.51	8.47	5.55	17.9	2506	1449	1007	442	30	15	2	1	IF
68.06	4.47	8.39	5.5	17.7	2506	1362	927	435	30	5	2	1	IF
67.42	3.03	5.8	3.75	12.85	2506	356	240	116	20	5	10	1	SFBP
64.56	4.19	7.87	5.15	16.63	2506	474	306	168	30	5	10	1	SFBP
63.42	11.41	19.34	13.65	33.18	2506	5632	3572	2060	5	15	10	1	HM
63.42	11.41	19.34	13.65	33.18	2506	5632	3572	2060	5	15	60	1	HM
63.42	11.41	19.34	13.65	33.18	2506	5632	3572	2060	5	999	10	1	HM
63.42	11.41	19.34	13.65	33.18	2506	5632	3572	2060	5	999	60	1	HM
63.25	11.41	19.34	13.65	33.14	2506	5494	3475	2019	5	5	10	1	HM
61.88	11.41	19.27	13.64	32.84	2506	5257	3253	2004	5	5	60	1	HM
60.45	39.39	47.7	42.34	54.61	2506	33421	20203	13218	5	5	2	1	HM
60.45	39.39	47.7	42.34	54.61	2506	33484	20241	13243	5	15	2	1	HM
60.45	39.39	47.7	42.34	54.61	2506	33484	20241	13243	5	999	2	1	HM
60	1.8	3.49	2.23	8.02	2506	85	51	34	5	5	10	1	LU
60	1.8	3.49	2.23	8.02	2506	85	51	34	5	15	10	1	LU

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
60	1.8	3.49	2.23	8.02	2506	85	51	34	5	999	10	1	LU
59.8	46.33	52.21	48.51	56.51	2506	36495	21824	14671	20	15	10	1	HM
59.78	46.37	52.23	48.55	56.51	2506	36607	21885	14722	20	999	10	1	HM
59.76	46.53	52.32	48.68	56.55	2506	36648	21902	14746	20	15	2	1	HM
59.76	46.53	52.32	48.68	56.55	2506	36667	21913	14754	20	999	2	1	HM
59.73	3.27	6.2	4.03	13.42	2506	1418	847	571	5	5	60	1	LS
59.7	45.25	51.48	47.55	56.11	2506	35585	21243	14342	15	15	10	1	HM
59.66	45.29	51.49	47.58	56.1	2506	35658	21272	14386	15	999	10	1	HM
59.65	45.41	51.57	47.69	56.13	2506	35709	21301	14408	15	15	2	1	HM
59.65	45.41	51.57	47.69	56.13	2506	35715	21304	14411	15	999	2	1	HM
59.64	45.41	51.56	47.69	56.12	2506	35538	21194	14344	15	5	2	1	HM
59.27	1.36	2.65	1.69	6.21	2506	410	243	167	30	5	60	1	LS
59.16	51.6	55.12	52.95	57.47	2506	38428	22733	15695	30	999	2	1	HM
59.16	51.44	55.03	52.82	57.44	2506	38358	22694	15664	30	999	10	1	HM
59.07	9.5	16.36	11.41	28.9	2506	1378	814	564	30	5	2	1	SFBP
59.03	19.59	29.42	22.61	42.09	2506	9218	5441	3777	15	5	60	1	HM
58.94	19.75	29.59	22.78	42.2	2506	10073	5937	4136	15	15	60	1	HM
58.91	21.95	31.98	25.1	44.07	2506	12267	7226	5041	20	999	60	1	HM
58.91	19.79	29.63	22.82	42.22	2506	10192	6004	4188	15	999	60	1	HM
58.85	20.35	30.24	23.41	42.7	2506	10692	6292	4400	15	5	10	1	HM
58.79	21.87	31.88	25.01	43.95	2506	12065	7093	4972	20	15	60	1	HM
58.37	21.63	31.56	24.74	43.57	2506	11044	6446	4598	20	5	60	1	HM
58.26	21.63	31.55	24.74	43.52	2506	11064	6446	4618	20	5	10	1	HM
58.26	0.56	1.11	0.7	2.69	2506	218	127	91	20	15	60	1	LOF
58.26	0.56	1.11	0.7	2.69	2506	218	127	91	20	999	60	1	LOF
58.25	28.77	38.52	32.01	48.35	2506	16011	9327	6684	30	999	60	1	HM
58.18	21.99	31.91	25.11	43.77	2506	11261	6552	4709	20	5	2	1	HM
58.16	29.05	38.75	32.28	48.45	2506	16058	9340	6718	30	15	10	1	HM
58.1	28.61	38.34	31.84	48.17	2506	15679	9110	6569	30	15	60	1	HM
57.99	29.25	38.89	32.47	48.47	2506	16288	9446	6842	30	15	2	1	HM
57.14	1.84	3.56	2.28	8.13	2506	91	52	39	5	5	2	1	LU
57.14	1.84	3.56	2.28	8.13	2506	91	52	39	5	15	2	1	LU
57.14	1.84	3.56	2.28	8.13	2506	91	52	39	5	999	2	1	LU
57.09	11.61	19.3	13.81	32.01	2506	6369	3636	2733	5	999	10	1	LS
57.07	11.61	19.3	13.81	32.01	2506	6366	3633	2733	5	15	10	1	LS
56.91	26.74	36.38	29.91	46.43	2506	13092	7451	5641	30	5	2	1	HM
56.81	12.33	20.26	14.62	33	2506	6436	3656	2780	5	5	2	1	LS
56.77	10.85	18.22	12.95	30.75	2506	4969	2821	2148	5	5	10	1	LS
56.69	12.41	20.36	14.71	33.08	2506	6782	3845	2937	5	15	2	1	LS
56.69	12.41	20.36	14.71	33.08	2506	6782	3845	2937	5	999	2	1	LS
56.43	3.31	6.26	4.08	13.41	2506	1648	930	718	5	15	60	1	LS
56.43	3.31	6.26	4.08	13.41	2506	1648	930	718	5	999	60	1	LS
56.19	2.04	3.93	2.52	8.89	2506	105	59	46	20	5	10	1	LU
56.19	2.04	3.93	2.52	8.89	2506	105	59	46	20	15	10	1	LU
56.19	2.04	3.93	2.52	8.89	2506	105	59	46	20	999	10	1	LU
56.07	2.08	4	2.57	9.04	2506	107	60	47	30	5	10	1	LU
56.07	2.08	4	2.57	9.04	2506	107	60	47	30	15	10	1	LU
56.07	2.08	4	2.57	9.04	2506	107	60	47	30	999	10	1	LU
55.96	3.03	5.75	3.74	12.46	2506	445	249	196	15	5	10	1	LOF
55.91	27.93	37.25	31.04	46.58	2506	21872	12229	9643	5	15	60	1	VS
55.91	27.93	37.25	31.04	46.58	2506	21872	12229	9643	5	999	60	1	VS
55.87	2.15	4.15	2.67	9.33	2506	383	214	169	5	5	10	1	LOF
55.87	2.15	4.15	2.67	9.33	2506	383	214	169	5	15	10	1	LOF
55.87	2.15	4.15	2.67	9.33	2506	383	214	169	5	999	10	1	LOF
55.67	37.75	44.99	40.35	50.85	2506	26238	14608	11630	15	999	60	1	VS
55.67	37.75	44.99	40.35	50.84	2506	26236	14606	11630	15	15	60	1	VS
55.64	13.85	22.17	16.29	34.69	2506	7878	4383	3495	20	15	60	1	LS
55.56	1.92	3.7	2.37	8.42	2506	99	55	44	15	5	10	1	LU
55.56	1.92	3.7	2.37	8.42	2506	99	55	44	15	15	10	1	LU
55.56	1.92	3.7	2.37	8.42	2506	99	55	44	15	999	10	1	LU
55.54	40.94	47.13	43.21	51.84	2506	28211	15667	12544	20	999	60	1	VS
55.53	40.94	47.13	43.21	51.84	2506	28209	15665	12544	20	15	60	1	VS
55.5	14.13	22.52	16.6	35	2506	6768	3756	3012	20	5	10	1	LS
55.42	13.97	22.31	16.42	34.78	2506	8138	4510	3628	20	999	60	1	LS
55.36	0.64	1.26	0.8	3.05	2506	233	129	104	30	15	60	1	LOF
55.36	0.64	1.26	0.8	3.05	2506	233	129	104	30	999	60	1	LOF
55.32	45.37	49.86	47.06	53	2506	30289	16757	13532	30	15	60	1	VS
55.32	3.11	5.89	3.84	12.7	2506	479	265	214	15	15	10	1	LOF
55.32	3.11	5.89	3.84	12.7	2506	479	265	214	15	999	10	1	LOF
55.3	1.92	3.7	2.37	8.41	2506	839	464	375	20	5	60	1	LS
55.24	45.97	50.18	47.57	53.1	2506	31116	17190	13926	30	999	60	1	VS
55.21	44.49	49.27	46.29	52.67	2506	28986	16002	12984	15	5	10	1	VS
55.2	24.14	33.59	27.2	43.91	2506	12175	6721	5454	30	5	60	1	VS
55.16	16.4	25.28	19.08	37.46	2506	9383	5176	4207	30	999	60	1	LS
55.15	39.43	45.98	41.81	51.08	2506	28538	15739	12799	5	5	10	1	VS
55.11	21.75	31.19	24.74	42.17	2506	12152	6697	5455	30	999	2	1	LS
55.07	21.67	31.1	24.66	42.09	2506	12140	6686	5454	30	999	10	1	LS
55.07	18.75	27.98	21.6	39.7	2506	10755	5923	4832	20	999	2	1	LS
55.05	14.76	23.28	17.3	35.61	2506	7817	4303	3514	30	15	60	1	LS
55.02	45.25	49.66	46.92	52.74	2506	26177	14403	11774	30	5	10	1	VS
54.99	39.55	46.01	41.9	51.01	2506	28682	15772	12910	5	15	10	1	VS
54.99	39.55	46.01	41.9	51.01	2506	28682	15772	12910	5	999	10	1	VS
54.98	18.75	27.97	21.6	39.66	2506	10650	5855	4795	20	15	2	1	LS
54.95	18.68	27.88	21.52	39.58	2506	10722	5892	4830	20	999	10	1	LS
54.89	5.35	9.74	6.53	19.24	2506	1146	629	517	30	15	10	1	SFBP
54.82	45.01	49.43	46.68	52.53	2506	27490	15069	12421	20	5	10	1	VS
54.81	18.44	27.59	21.26	39.3	2506	10482	5745	4737	20	15	10	1	LS
54.79	57.22	55.98	56.72	55.26	2506	37268	20419	16849	30	15	10	1	VS
54.79	51.8	53.25	52.37	54.16	2506	32500	17807	14693	20	5	2	1	VS
54.78	54.91	54.84	54.88	54.81	2506	33915	18579	15336	30	5	2	1	VS
54.76	49.64	52.07	50.59	53.65	2506	33840	18530	15310	15	15	10	1	VS
54.73	51.12	52.86	51.8	53.97	2506	34210	18723	15487	15	5	2	1	VS
54.73	20.95	30.3	23.9	41.38	2506	11247	6155	5092	30	15	2	1	LS
54.72	49.76	52.12	50.68	53.65	2506	34003	18608	15395	15	999	10	1	VS
54.71	24.7	34.04	27.74	44.02	2506	12270	6713	5557	15	5	60	1	VS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
54.69	2.83	5.39	3.5	11.73	2506	554	303	251	5	5	2	1	LOF
54.68	57.62	56.11	57.01	55.24	2506	37682	20604	17078	30	999	10	1	VS
54.63	42.58	47.86	44.54	51.71	2506	30840	16849	13991	5	5	2	1	VS
54.62	20.11	29.4	23.02	40.66	2506	10702	5845	4857	30	15	10	1	LS
54.61	53.23	53.91	53.5	54.33	2506	35319	19288	16031	20	15	10	1	VS
54.6	25.14	34.43	28.18	44.23	2506	12824	7002	5822	20	5	60	1	VS
54.57	53.35	53.95	53.59	54.32	2506	35613	19434	16179	20	999	10	1	VS
54.56	42.78	47.95	44.71	51.71	2506	31396	17129	14267	5	999	2	1	VS
54.56	42.74	47.93	44.67	51.7	2506	31232	17039	14193	5	15	2	1	VS
54.55	61.05	57.62	59.63	55.74	2506	39244	21407	17837	30	999	2	1	VS
54.52	60.73	57.46	59.38	55.66	2506	38931	21224	17707	30	15	2	1	VS
54.46	2.11	4.07	2.62	9.15	2506	112	61	51	20	5	2	1	LU
54.46	2.11	4.07	2.62	9.15	2506	112	61	51	20	15	2	1	LU
54.46	2.11	4.07	2.62	9.15	2506	112	61	51	20	999	2	1	LU
54.44	17.32	26.28	20.05	38.1	2506	7947	4326	3621	30	5	2	1	LS
54.41	52.63	53.51	52.98	54.04	2506	35760	19456	16304	15	15	2	1	VS
54.4	52.67	53.52	53.01	54.05	2506	35818	19486	16332	15	999	2	1	VS
54.39	56.03	55.2	55.69	54.71	2506	37162	20212	16950	20	15	2	1	VS
54.38	56.11	55.23	55.75	54.72	2506	37283	20275	17008	20	999	2	1	VS
54.36	17.84	26.86	20.61	38.56	2506	9309	5060	4249	20	5	2	1	LS
54.24	2.83	5.39	3.5	11.72	2506	590	320	270	5	15	2	1	LOF
54.24	2.83	5.39	3.5	11.72	2506	590	320	270	5	999	2	1	LOF
54.2	11.65	19.18	13.82	31.32	2506	4882	2646	2236	30	5	10	1	LS
54.14	11.41	18.85	13.55	30.96	2506	3188	1726	1462	15	15	2	1	SFBP
53.99	14.57	22.94	17.06	35.03	2506	7200	3887	3313	15	5	10	1	LS
53.77	2	3.85	2.47	8.69	2506	106	57	49	15	5	2	1	LU
53.77	2	3.85	2.47	8.69	2506	106	57	49	15	15	2	1	LU
53.77	2	3.85	2.47	8.69	2506	106	57	49	15	999	2	1	LU
53.71	10.97	18.22	13.05	30.19	2506	2672	1435	1237	20	15	2	1	SFBP
53.57	12.09	19.73	14.31	31.77	2506	3420	1832	1588	20	999	2	1	SFBP
53.52	8.9	15.26	10.68	26.72	2506	1887	1010	877	15	5	2	1	SFBP
53.5	25.74	34.76	28.72	44.01	2506	16124	8626	7498	5	5	60	1	VS
53.49	11.49	18.92	13.63	30.9	2506	3313	1772	1541	15	999	2	1	SFBP
53.45	16.88	25.66	19.56	37.29	2506	9859	5270	4589	15	999	2	1	LS
53.42	2.43	4.66	3.01	10.29	2506	951	508	443	15	5	60	1	LS
53.36	3.39	6.38	4.17	13.52	2506	521	278	243	20	5	10	1	LOF
53.24	3.39	6.38	4.17	13.52	2506	524	279	245	20	15	10	1	LOF
53.24	3.39	6.38	4.17	13.52	2506	524	279	245	20	999	10	1	LOF
53.14	16.88	25.62	19.55	37.17	2506	9794	5205	4589	15	15	2	1	LS
53.08	16.84	25.57	19.5	37.11	2506	9771	5186	4585	15	999	10	1	LS
52.99	16.8	25.51	19.46	37.03	2506	9717	5149	4568	15	15	10	1	LS
52.99	2.15	4.14	2.67	9.27	2506	117	62	55	30	5	2	1	LU
52.99	2.15	4.14	2.67	9.27	2506	117	62	55	30	15	2	1	LU
52.99	2.15	4.14	2.67	9.27	2506	117	62	55	30	999	2	1	LU
52.96	12.37	20.06	14.61	31.98	2506	7300	3866	3434	15	15	60	1	LS
52.91	16.64	25.32	19.28	36.85	2506	9138	4835	4303	15	5	2	1	LS
52.88	12.37	20.05	14.61	31.95	2506	7315	3868	3447	15	999	60	1	LS
52.75	13.81	21.89	16.2	33.72	2506	3623	1911	1712	30	999	2	1	SFBP
52.52	11.69	19.13	13.84	30.92	2506	2445	1284	1161	30	15	2	1	SFBP
52.38	4.35	8.03	5.33	16.33	2506	609	319	290	30	5	10	1	LOF
52.29	4.35	8.03	5.33	16.32	2506	612	320	292	30	15	10	1	LOF
52.29	4.35	8.03	5.33	16.32	2506	612	320	292	30	999	10	1	LOF
52.14	6.82	12.07	8.26	22.39	2506	911	475	436	15	15	2	1	LOF
52.14	6.82	12.07	8.26	22.39	2506	911	475	436	15	999	2	1	LOF
52.1	6.74	11.94	8.17	22.22	2506	881	459	422	15	5	2	1	LOF
51.69	8.1	14.01	9.74	24.9	2506	1008	521	487	20	15	2	1	LOF
51.69	8.1	14.01	9.74	24.9	2506	1008	521	487	20	999	2	1	LOF
51.68	10.42	17.34	12.39	28.83	2506	1219	630	589	30	15	2	1	LOF
51.68	10.42	17.34	12.39	28.83	2506	1219	630	589	30	999	2	1	LOF
51.68	8.66	14.83	10.39	25.92	2506	1726	892	834	20	5	2	1	SFBP
51.64	7.94	13.77	9.56	24.58	2506	976	504	472	20	5	2	1	LOF
51.6	10.26	17.11	12.21	28.57	2506	1188	613	575	30	5	2	1	LOF
51.5	4.83	8.83	5.9	17.56	2506	1765	909	856	20	999	10	1	SFBP
51.47	4.83	8.83	5.9	17.56	2506	1764	908	856	20	15	10	1	SFBP
51.3	4.35	8.02	5.32	16.24	2506	1575	808	767	15	15	10	1	SFBP
51.3	4.35	8.02	5.32	16.24	2506	1575	808	767	15	999	10	1	SFBP
50.54	6.15	10.96	7.45	20.67	2506	2038	1030	1008	30	999	10	1	SFBP
48.81	3.63	6.76	4.46	13.99	2506	1426	696	730	5	15	2	1	SFBP
48.81	3.63	6.76	4.46	13.99	2506	1426	696	730	5	999	2	1	SFBP
48.76	3.63	6.76	4.46	13.99	2506	1415	690	725	5	5	2	1	SFBP
38.08	0.76	1.49	0.94	3.51	2506	772	294	478	5	5	10	1	SFBP
38.08	0.76	1.49	0.94	3.51	2506	772	294	478	5	15	10	1	SFBP
38.08	0.76	1.49	0.94	3.51	2506	772	294	478	5	999	10	1	SFBP
32.43	0.04	0.08	0.05	0.2	2506	74	24	50	30	5	10	1	HM
32.43	0.04	0.08	0.05	0.2	2506	74	24	50	30	5	60	1	HM
0	0	0	0	0	2506	0	0	0	5	5	60	1	SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	1	SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	1	SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	1	SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	1	SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	1	SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	1	SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	1	SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	1	SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	1	SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	1	SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	1	SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	1	LU
0	0	0	0	0	2506	0	0	0	5	15	60	1	LU
0	0	0	0	0	2506	0	0	0	5	999	60	1	LU
0	0	0	0	0	2506	0	0	0	15	5	60	1	LU
0	0	0	0	0	2506	0	0	0	15	15	60	1	LU
0	0	0	0	0	2506	0	0	0	15	999	60	1	LU
0	0	0	0	0	2506	0	0	0	20	5	60	1	LU
0	0	0	0	0	2506	0	0	0	20	15	60	1	LU

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	20	999	60	1	LU
0	0	0	0	0	2506	0	0	0	30	5	60	1	LU
0	0	0	0	0	2506	0	0	0	30	15	60	1	LU
0	0	0	0	0	2506	0	0	0	30	999	60	1	LU
0	0	0	0	0	2506	0	0	0	5	5	60	1	LOF
0	0	0	0	0	2506	0	0	0	5	15	60	1	LOF
0	0	0	0	0	2506	0	0	0	5	999	60	1	LOF
0	0	0	0	0	2506	0	0	0	15	5	60	1	LOF
0	0	0	0	0	2506	0	0	0	15	15	60	1	LOF
0	0	0	0	0	2506	0	0	0	15	999	60	1	LOF
0	0	0	0	0	2506	0	0	0	20	5	60	1	LOF
0	0	0	0	0	2506	0	0	0	30	5	60	1	LOF
0	0	0	0	0	2506	0	0	0	5	5	10	1	IF
0	0	0	0	0	2506	0	0	0	5	5	60	1	IF
0	0	0	0	0	2506	0	0	0	5	15	10	1	IF
0	0	0	0	0	2506	0	0	0	5	15	60	1	IF
0	0	0	0	0	2506	0	0	0	5	999	10	1	IF
0	0	0	0	0	2506	0	0	0	5	999	60	1	IF
0	0	0	0	0	2506	0	0	0	15	5	60	1	IF
0	0	0	0	0	2506	0	0	0	15	15	60	1	IF
0	0	0	0	0	2506	0	0	0	15	999	60	1	IF
0	0	0	0	0	2506	0	0	0	20	5	60	1	IF
0	0	0	0	0	2506	0	0	0	20	15	60	1	IF
0	0	0	0	0	2506	0	0	0	20	999	60	1	IF
0	0	0	0	0	2506	0	0	0	30	5	60	1	IF
0	0	0	0	0	2506	0	0	0	30	15	60	1	IF
0	0	0	0	0	2506	0	0	0	30	999	60	1	IF

Table A.3: Trial results for a fixed number of algorithms to 2. Varying $\alpha, \beta, \gamma, \delta$

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
100	0.4	0.79	0.5	1.96	2506	57	57	0	5	5	2	2	LS;SFBP
100	0.08	0.16	0.1	0.4	2506	22	22	0	15	5	2	2	LU;VS
100	0.08	0.16	0.1	0.4	2506	19	19	0	5	5	2	2	LU;IF
100	0.08	0.16	0.1	0.4	2506	21	21	0	5	15	2	2	LU;IF
100	0.08	0.16	0.1	0.4	2506	21	21	0	5	999	2	2	LU;IF
100	0.04	0.08	0.05	0.2	2506	2	2	0	20	5	2	2	VS;SFBP
100	0.04	0.08	0.05	0.2	2506	2	2	0	5	5	2	2	LU;LS
100	0.04	0.08	0.05	0.2	2506	7	7	0	15	5	2	2	LS;SFBP
100	0.04	0.08	0.05	0.2	2506	12	12	0	20	5	2	2	LS;SFBP
100	0.04	0.08	0.05	0.2	2506	6	6	0	30	5	10	2	HM;LS
100	0.04	0.08	0.05	0.2	2506	6	6	0	30	5	60	2	HM;LS
90.16	0.28	0.56	0.35	1.38	2506	61	55	6	15	999	2	2	LU;IF
90.16	0.28	0.56	0.35	1.38	2506	61	55	6	20	999	2	2	LU;IF
88.68	0.28	0.56	0.35	1.38	2506	53	47	6	15	15	2	2	LU;IF
88.68	0.28	0.56	0.35	1.38	2506	53	47	6	20	15	2	2	LU;IF
87.5	0.28	0.56	0.35	1.38	2506	48	42	6	15	5	2	2	LU;IF
87.5	0.28	0.56	0.35	1.38	2506	48	42	6	20	5	2	2	LU;IF
87.23	0.4	0.79	0.5	1.96	2506	94	82	12	5	15	2	2	LS;SFBP
86.32	0.4	0.79	0.5	1.96	2506	95	82	13	5	999	2	2	LS;SFBP
85.19	0.32	0.64	0.4	1.57	2506	81	69	12	30	15	2	2	LU;IF
85.19	0.32	0.64	0.4	1.57	2506	81	69	12	30	999	2	2	LU;IF
81.82	1.24	2.44	1.54	5.83	2506	154	126	28	15	5	2	2	LOF;SFBP
81.82	0.04	0.08	0.05	0.2	2506	33	27	6	30	5	60	2	HM;IF
81.03	2.39	4.65	2.97	10.71	2506	933	756	177	5	999	2	2	IF;VS
80.33	0.32	0.64	0.4	1.57	2506	61	49	12	30	5	2	2	LU;IF
79.5	1.4	2.75	1.74	6.52	2506	161	128	33	20	5	2	2	LOF;SFBP
78.82	1.76	3.44	2.18	8.06	2506	170	134	36	30	5	2	2	LOF;SFBP
78.05	0.16	0.32	0.2	0.79	2506	41	32	9	30	999	2	2	LU;SFBP
77.55	0.08	0.16	0.1	0.4	2506	49	38	11	20	5	2	2	HM;SFBP
77.55	0.08	0.16	0.1	0.4	2506	49	38	11	30	5	2	2	HM;SFBP
76.92	0.04	0.08	0.05	0.2	2506	26	20	6	20	15	2	2	LU;SFBP
76.92	0.04	0.08	0.05	0.2	2506	26	20	6	20	999	2	2	LU;SFBP
74.97	4.71	8.86	5.79	18.82	2506	2525	1893	632	5	15	60	2	HM;IF
74.51	0.24	0.48	0.3	1.18	2506	153	114	39	5	15	2	2	HM;LU
74.29	4.71	8.86	5.79	18.78	2506	2653	1971	682	5	15	10	2	HM;IF
74.29	4.71	8.86	5.79	18.78	2506	2653	1971	682	5	999	10	2	HM;IF
74.29	4.71	8.86	5.79	18.78	2506	2653	1971	682	5	999	60	2	HM;IF
73	4.71	8.85	5.79	18.71	2506	2248	1641	607	5	5	10	2	HM;IF
72.88	6.58	12.08	8.05	24.18	2506	3636	2650	986	5	5	2	2	HM;IF
72.73	0.04	0.08	0.05	0.2	2506	11	8	3	30	5	2	2	LU;VS
72.61	6.58	12.07	8.05	24.16	2506	3764	2733	1031	5	15	2	2	HM;IF
72.61	6.58	12.07	8.05	24.16	2506	3764	2733	1031	5	999	2	2	HM;IF
72.29	2.79	5.38	3.46	12.1	2506	1050	759	291	5	5	10	2	IF;LS
72.15	4.67	8.77	5.74	18.54	2506	2122	1531	591	5	5	60	2	HM;IF
71.67	0.8	1.58	0.99	3.82	2506	240	172	68	5	15	2	2	IF;SFBP
71.67	0.8	1.58	0.99	3.82	2506	240	172	68	5	999	2	2	IF;SFBP
71.43	0.24	0.48	0.3	1.18	2506	189	135	54	5	999	2	2	HM;LU
70.85	0.24	0.48	0.3	1.18	2506	223	158	65	15	999	10	2	HM;LU
70.56	0.8	1.58	0.99	3.82	2506	231	163	68	5	5	2	2	IF;SFBP
70.15	0.24	0.48	0.3	1.18	2506	268	188	80	20	999	10	2	HM;LU
69.98	3.39	6.47	4.19	14.21	2506	1759	1231	528	5	5	2	2	IF;LS
69.05	0.24	0.48	0.3	1.18	2506	210	145	65	15	15	10	2	HM;LU
68.97	0.08	0.16	0.1	0.4	2506	58	40	18	20	15	10	2	HM;LU
68.97	0.08	0.16	0.1	0.4	2506	58	40	18	30	15	10	2	HM;LU
68.92	0.28	0.56	0.35	1.37	2506	148	102	46	30	5	2	2	HM;LS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
68.54	3.03	5.81	3.75	12.88	2506	2114	1449	665	5	15	10	2	IF;LS
68.54	3.03	5.81	3.75	12.88	2506	2114	1449	665	5	999	10	2	IF;LS
68.5	3.55	6.75	4.38	14.71	2506	2267	1553	714	5	15	2	2	IF;LS
68.06	0.44	0.87	0.55	2.14	2506	382	260	122	5	15	10	2	LOF;LS
68.06	0.44	0.87	0.55	2.14	2506	382	260	122	5	999	10	2	LOF;LS
67.57	0.36	0.71	0.45	1.76	2506	185	125	60	5	5	10	2	LOF;LS
67.55	3.59	6.82	4.43	14.81	2506	2373	1603	770	5	999	2	2	IF;LS
66.03	0.76	1.5	0.95	3.62	2506	468	309	159	30	999	2	2	LS;SFBP
65.9	0.72	1.42	0.9	3.44	2506	437	288	149	15	15	2	2	HM;LU
65.63	2.19	4.25	2.72	9.68	2506	739	485	254	20	5	2	2	IF;SFBP
65.26	8.18	14.54	9.91	27.24	2506	3425	2235	1190	15	5	60	2	HM;IF
65.17	0.56	1.11	0.7	2.7	2506	379	247	132	30	15	2	2	HM;LU
65.14	2.27	4.4	2.82	9.98	2506	832	542	290	20	999	2	2	IF;SFBP
64.89	9.18	16.08	11.08	29.31	2506	5221	3388	1833	20	15	60	2	HM;IF
64.87	9.26	16.2	11.17	29.47	2506	5496	3565	1931	20	999	60	2	HM;IF
64.85	0.36	0.71	0.45	1.76	2506	367	238	129	30	999	10	2	HM;LU
64.7	8.7	15.34	10.52	28.28	2506	3671	2375	1296	20	5	10	2	HM;IF
64.62	9.46	16.5	11.4	29.83	2506	7196	4650	2546	5	5	2	2	HM;SFBP
64.62	9.46	16.5	11.4	29.83	2506	7196	4650	2546	5	15	2	2	HM;SFBP
64.62	9.46	16.5	11.4	29.83	2506	7196	4650	2546	5	999	2	2	HM;SFBP
64.62	9.14	16.01	11.03	29.18	2506	4127	2667	1460	20	5	2	2	HM;IF
64.3	2.19	4.24	2.72	9.66	2506	790	508	282	20	15	2	2	IF;SFBP
64.25	0.8	1.58	0.99	3.8	2506	593	381	212	15	999	2	2	HM;LU
64.25	0.36	0.71	0.45	1.76	2506	179	115	64	20	5	2	2	HM;LU
64.08	8.38	14.82	10.14	27.51	2506	4441	2846	1595	15	15	60	2	HM;IF
64.01	11.93	20.11	14.25	34.18	2506	7185	4599	2586	20	15	10	2	HM;IF
63.8	11.93	20.1	14.25	34.13	2506	7328	4675	2653	20	999	10	2	HM;IF
63.73	8.42	14.87	10.19	27.54	2506	4638	2956	1682	15	999	60	2	HM;IF
63.69	12.45	20.83	14.84	34.93	2506	7474	4760	2714	20	15	2	2	HM;IF
63.63	10.65	18.25	12.78	31.9	2506	5953	3788	2165	15	5	10	2	HM;IF
63.59	3.87	7.3	4.77	15.56	2506	2917	1855	1062	5	15	2	2	LS;VS
63.58	11.13	18.95	13.33	32.74	2506	6394	4065	2329	15	15	2	2	HM;IF
63.54	3.87	7.3	4.77	15.56	2506	2929	1861	1068	5	999	2	2	LS;VS
63.53	5.55	10.2	6.79	20.56	2506	2416	1535	881	15	5	2	2	IF;VS
63.51	12.45	20.82	14.84	34.89	2506	7562	4803	2759	20	999	2	2	HM;IF
63.4	4.99	9.25	6.11	18.97	2506	2377	1507	870	20	5	2	2	IF;VS
63.38	0.24	0.48	0.3	1.18	2506	71	45	26	5	5	2	2	HM;LU
63.35	11.09	18.88	13.29	32.62	2506	6200	3928	2272	15	5	2	2	HM;IF
63.32	10.69	18.3	12.83	31.91	2506	6104	3865	2239	15	15	10	2	HM;IF
63.18	10.69	18.29	12.83	31.88	2506	6231	3937	2294	15	999	10	2	HM;IF
63.13	11.13	18.93	13.33	32.64	2506	6439	4065	2374	15	999	2	2	HM;IF
63.03	2.27	4.39	2.82	9.94	2506	733	462	271	15	5	2	2	IF;SFBP
62.61	2.75	5.27	3.4	11.71	2506	872	546	326	30	5	2	2	IF;SFBP
62.59	1.04	2.04	1.29	4.86	2506	719	450	269	20	999	2	2	HM;LU
62.41	0.96	1.89	1.19	4.51	2506	548	342	206	20	15	2	2	HM;LU
62.37	5.67	10.39	6.93	20.78	2506	2825	1762	1063	30	5	2	2	IF;VS
62.31	0.72	1.42	0.9	3.43	2506	390	243	147	15	5	2	2	HM;LU
62.11	3.19	6.07	3.94	13.24	2506	966	600	366	30	15	2	2	IF;SFBP
61.87	5.15	9.5	6.3	19.31	2506	4907	3036	1871	5	999	2	2	HM;LS
61.84	5.15	9.5	6.3	19.31	2506	4903	3032	1871	5	15	2	2	HM;LS
61.79	0.84	1.65	1.04	3.97	2506	390	241	149	5	5	2	2	IF;VS
61.64	3.27	6.21	4.04	13.5	2506	1048	646	402	30	999	2	2	IF;SFBP
61.5	11.17	18.91	13.36	32.35	2506	10065	6190	3875	20	15	2	2	HM;SFBP
61.5	11.17	18.91	13.36	32.35	2506	10065	6190	3875	20	999	2	2	HM;SFBP
61.06	0.8	1.58	0.99	3.79	2506	624	381	243	5	5	2	2	LOF;LS
60.98	12.01	20.07	14.31	33.59	2506	7115	4339	2776	30	999	60	2	HM;IF
60.94	2.43	4.68	3.01	10.49	2506	384	234	150	30	15	2	2	LOF;SFBP
60.94	1.52	2.96	1.88	6.9	2506	1024	624	400	30	999	2	2	HM;LU
60.86	0.84	1.65	1.04	3.97	2506	396	241	155	5	15	2	2	IF;VS
60.74	15.28	24.42	17.97	38.08	2506	9447	5738	3709	30	999	10	2	HM;IF
60.69	12.01	20.05	14.31	33.52	2506	8504	5161	3343	20	999	2	2	HM;LOF
60.68	15.92	25.22	18.68	38.84	2506	9728	5903	3825	30	999	2	2	HM;IF
60.61	10.81	18.35	12.94	31.55	2506	9523	5772	3751	15	15	2	2	HM;SFBP
60.61	10.81	18.35	12.94	31.55	2506	9523	5772	3751	15	999	2	2	HM;SFBP
60.58	2.31	4.46	2.87	10.04	2506	822	498	324	15	15	2	2	IF;SFBP
60.51	12.13	20.21	14.44	33.66	2506	10935	6617	4318	30	999	2	2	HM;SFBP
60.51	5.83	10.63	7.11	21.03	2506	4533	2743	1790	20	15	2	2	IF;LS
60.46	5.71	10.43	6.97	20.71	2506	4390	2654	1736	20	999	10	2	IF;LS
60.46	5.71	10.43	6.97	20.71	2506	4390	2654	1736	20	999	60	2	IF;LS
60.45	5.99	10.89	7.3	21.44	2506	4930	2980	1950	20	999	2	2	IF;LS
60.45	2.35	4.53	2.91	10.19	2506	837	506	331	15	999	2	2	IF;SFBP
60.44	0.4	0.79	0.5	1.94	2506	182	110	72	20	5	2	2	LU;LS
60.43	0.88	1.73	1.09	4.15	2506	786	475	311	5	15	2	2	LOF;LS
60.43	0.88	1.73	1.09	4.15	2506	786	475	311	5	999	2	2	LOF;LS
60.35	12.21	20.31	14.53	33.74	2506	6787	4096	2691	30	15	2	2	HM;IF
60.32	5.71	10.43	6.97	20.7	2506	4373	2638	1735	20	15	60	2	IF;LS
60.31	5.71	10.43	6.97	20.7	2506	4374	2638	1736	20	15	10	2	IF;LS
60.25	11.93	19.92	14.21	33.29	2506	6702	4038	2664	30	15	10	2	HM;IF
60.25	10.49	17.88	12.57	30.93	2506	6838	4120	2718	15	999	2	2	HM;LOF
59.98	10.49	17.86	12.57	30.87	2506	5183	3109	2074	15	15	2	2	HM;LOF
59.9	0.44	0.87	0.55	2.13	2506	202	121	81	30	5	2	2	HM;LU
59.88	15.4	24.5	18.09	37.96	2506	11556	6920	4636	30	999	2	2	HM;LOF
59.85	0.32	0.64	0.4	1.56	2506	132	79	53	15	5	2	2	LU;LS
59.71	3.83	7.2	4.71	15.24	2506	2869	1713	1156	20	999	10	2	IF;VS
59.66	4.83	8.93	5.92	18.24	2506	3768	2248	1520	5	5	2	2	HM;LS
59.65	5.67	10.35	6.92	20.53	2506	3854	2299	1555	20	5	2	2	IF;LS
59.62	8.3	14.57	10.03	26.66	2506	5287	3152	2135	20	999	2	2	IF;VS
59.52	5.15	9.48	6.3	19.12	2506	2705	1610	1095	20	5	60	2	IF;LS
59.27	2.35	4.53	2.91	10.16	2506	1316	780	536	30	999	10	2	HM;LOF
59.23	5.63	10.28	6.87	20.39	2506	3750	2221	1529	20	5	10	2	IF;LS
59.08	1.2	2.35	1.49	5.54	2506	865	511	354	30	999	2	2	LU;LS
59.06	9.86	16.89	11.83	29.55	2506	4135	2442	1693	30	5	2	2	HM;IF
59.04	0.72	1.42	0.9	3.42	2506	481	284	197	20	15	2	2	LU;LS
59.02	1.36	2.65	1.69	6.21	2506	1003	592	411	20	999	10	2	LOF;LS
58.99	3.23	6.13	3.99	13.26	2506	1858	1096	762	30	15	60	2	HM;LS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
58.81	8.46	14.79	10.21	26.85	2506	9537	5609	3928	20	999	2	2	HM;LS
58.76	7.54	13.37	9.13	24.92	2506	4653	2734	1919	20	15	2	2	IF;VS
58.75	0.08	0.16	0.1	0.4	2506	80	47	33	30	5	10	2	HM;IF
58.63	4.07	7.61	5	15.93	2506	3638	2133	1505	15	5	2	2	HM;SFBP
58.57	4.99	9.19	6.11	18.6	2506	2252	1319	933	30	5	60	2	IF;LS
58.55	8.46	14.78	10.21	26.81	2506	9403	5505	3898	20	15	2	2	HM;LS
58.33	3.51	6.62	4.32	14.15	2506	2275	1327	948	15	999	10	2	IF;VS
58.28	5.31	9.73	6.49	19.45	2506	4087	2382	1705	15	15	2	2	IF;LS
58.2	8.26	14.47	9.97	26.34	2506	9115	5305	3810	20	999	10	2	HM;LS
58.16	8.26	14.47	9.97	26.34	2506	9023	5248	3775	20	15	10	2	HM;LS
58.01	0.84	1.65	1.04	3.96	2506	662	384	278	20	999	2	2	LU;LS
57.98	1.36	2.65	1.69	6.2	2506	978	567	411	20	15	10	2	LOF;LS
57.88	10.34	17.54	12.37	30.15	2506	11544	6682	4862	30	999	2	2	HM;LS
57.88	7.34	13.03	8.9	24.35	2506	5776	3343	2433	30	999	2	2	IF;LS
57.83	4.87	8.98	5.96	18.21	2506	5397	3121	2276	20	15	60	2	HM;LS
57.69	6.94	12.39	8.43	23.43	2506	5100	2942	2158	30	999	10	2	IF;LS
57.69	6.94	12.39	8.43	23.43	2506	5100	2942	2158	30	999	60	2	IF;LS
57.68	4.87	8.98	5.96	18.2	2506	5465	3152	2313	20	999	60	2	HM;LS
57.62	7.1	12.65	8.61	23.79	2506	5043	2906	2137	30	15	2	2	IF;LS
57.59	5.47	9.99	6.68	19.81	2506	6385	3677	2708	30	999	60	2	HM;LS
57.56	0.92	1.81	1.14	4.31	2506	443	255	188	30	15	2	2	LU;LS
57.55	3.39	6.41	4.18	13.72	2506	3065	1764	1301	5	5	10	2	HM;LS
57.55	3.39	6.41	4.18	13.72	2506	3065	1764	1301	5	5	60	2	HM;LS
57.55	3.39	6.41	4.18	13.72	2506	3065	1764	1301	5	15	10	2	HM;LS
57.55	3.39	6.41	4.18	13.72	2506	3065	1764	1301	5	15	60	2	HM;LS
57.55	3.39	6.41	4.18	13.72	2506	3065	1764	1301	5	999	10	2	HM;LS
57.55	3.39	6.41	4.18	13.72	2506	3065	1764	1301	5	999	60	2	HM;LS
57.53	6.54	11.75	7.95	22.49	2506	4561	2624	1937	30	15	60	2	IF;LS
57.45	7.5	13.27	9.08	24.64	2506	8407	4830	3577	15	999	2	2	HM;LS
57.41	10.02	17.06	12	29.5	2506	11110	6378	4732	30	999	10	2	HM;LS
57.28	5.47	9.98	6.67	19.78	2506	4345	2489	1856	15	999	2	2	IF;LS
57.25	2.15	4.15	2.67	9.36	2506	662	379	283	15	15	2	2	LOF;SFBP
57.25	2.15	4.15	2.67	9.36	2506	662	379	283	15	999	2	2	LOF;SFBP
57.24	6.78	12.13	8.24	23.01	2506	4773	2732	2041	30	15	10	2	IF;LS
57.15	6.7	12	8.14	22.81	2506	6506	3718	2788	30	15	2	2	HM;LS
57	4.83	8.9	5.91	18.03	2506	4823	2749	2074	30	15	10	2	HM;LS
56.98	7.42	13.13	8.99	24.4	2506	6586	3753	2833	20	999	10	2	LS;VS
56.94	5.67	10.31	6.91	20.26	2506	2840	1617	1223	20	5	10	2	HM;VS
56.89	4.95	9.1	6.05	18.35	2506	3811	2168	1643	15	15	10	2	IF;LS
56.89	4.95	9.1	6.05	18.35	2506	3811	2168	1643	15	15	60	2	IF;LS
56.89	4.95	9.1	6.05	18.35	2506	3811	2168	1643	15	999	10	2	IF;LS
56.89	4.95	9.1	6.05	18.35	2506	3811	2168	1643	15	999	60	2	IF;LS
56.84	7.26	12.88	8.8	24.03	2506	4384	2492	1892	15	999	2	2	IF;VS
56.83	7.5	13.25	9.08	24.55	2506	8217	4670	3547	15	15	2	2	HM;LS
56.73	5.35	9.77	6.53	19.42	2506	3261	1850	1411	30	5	2	2	LS;VS
56.47	9.18	15.79	11.02	27.81	2506	8114	4582	3532	20	999	2	2	LS;VS
56.47	0.48	0.95	0.6	2.32	2506	278	157	121	15	15	2	2	LS;SFBP
56.47	0.48	0.95	0.6	2.32	2506	278	157	121	15	999	2	2	LS;SFBP
56.41	0.16	0.32	0.2	0.79	2506	78	44	34	15	5	10	2	IF;VS
56.39	5.07	9.3	6.2	18.64	2506	3472	1958	1514	15	5	2	2	IF;LS
56.33	4.35	8.08	5.33	16.62	2506	2393	1348	1045	30	5	10	2	LS;VS
56.28	6.82	12.17	8.28	22.98	2506	6546	3684	2862	15	5	10	2	HM;LS
56.23	6.07	10.95	7.38	21.19	2506	3354	1886	1468	30	5	10	2	IF;LS
56.19	7.18	12.74	8.7	23.76	2506	7836	4403	3433	15	5	2	2	HM;LS
56.15	6.78	12.1	8.23	22.87	2506	5658	3177	2481	20	15	10	2	LS;VS
56.15	4.35	8.07	5.33	16.6	2506	4611	2589	2022	15	5	60	2	HM;LS
56.09	6.38	11.46	7.76	21.94	2506	3644	2044	1600	30	5	2	2	IF;LS
56.08	4.59	8.48	5.62	17.29	2506	2468	1384	1084	20	5	10	2	LS;VS
56.06	0.32	0.63	0.4	1.56	2506	198	111	87	5	15	2	2	IF;LOF
56.06	0.32	0.63	0.4	1.56	2506	198	111	87	5	999	2	2	IF;LOF
56.01	5.35	9.76	6.53	19.35	2506	3985	2232	1753	30	999	10	2	IF;VS
55.98	7.22	12.79	8.75	23.82	2506	7879	4411	3468	15	15	10	2	HM;LS
55.98	7.22	12.79	8.75	23.82	2506	7879	4411	3468	15	999	10	2	HM;LS
55.94	0.56	1.11	0.7	2.69	2506	320	179	141	20	999	2	2	LS;SFBP
55.93	10.18	17.22	12.17	29.45	2506	7257	4059	3198	30	999	2	2	IF;VS
55.93	4.35	8.07	5.33	16.59	2506	4836	2705	2131	15	15	60	2	HM;LS
55.93	4.35	8.07	5.33	16.59	2506	4836	2705	2131	15	999	60	2	HM;LS
55.72	6.78	12.09	8.23	22.81	2506	3997	2227	1770	15	15	2	2	IF;VS
55.69	1.56	3.03	1.93	7	2506	808	450	358	20	999	10	2	HM;LOF
55.68	0.2	0.4	0.25	0.98	2506	88	49	39	20	15	2	2	LU;VS
55.65	1.04	2.04	1.29	4.83	2506	832	463	369	15	15	10	2	LOF;LS
55.65	1.04	2.04	1.29	4.83	2506	832	463	369	15	999	10	2	LOF;LS
55.61	6.19	11.13	7.52	21.4	2506	3809	2118	1691	20	5	2	2	LS;VS
55.52	1.68	3.25	2.08	7.48	2506	607	337	270	20	5	2	2	LOF;VS
55.44	2.59	4.96	3.2	10.92	2506	790	438	352	20	999	2	2	LOF;SFBP
55.42	1.08	2.11	1.34	5	2506	480	266	214	30	15	2	2	IF;LOF
55.4	0.44	0.87	0.55	2.13	2506	139	77	62	30	15	2	2	LS;SFBP
55.28	1.88	3.63	2.32	8.26	2506	1391	769	622	20	15	2	2	LOF;LS
55.23	2.04	3.93	2.52	8.87	2506	1653	913	740	20	999	2	2	LOF;LS
55.21	0.72	1.42	0.89	3.41	2506	518	286	232	20	999	2	2	VS;SFBP
55.2	6.58	11.77	7.99	22.29	2506	3163	1746	1417	20	5	2	2	HM;VS
55.17	27.29	36.52	30.36	45.81	2506	24432	13478	10954	30	999	2	2	HM;VS
55.15	8.86	15.27	10.65	26.97	2506	5967	3291	2676	30	15	2	2	IF;VS
55.1	17.04	26.03	19.77	38.09	2506	14261	7858	6403	15	5	2	2	HM;VS
55	0.08	0.16	0.1	0.4	2506	20	11	9	20	5	2	2	LU;VS
54.98	8.38	14.54	10.09	26.03	2506	6972	3833	3139	20	15	2	2	LS;VS
54.98	3.67	6.88	4.51	14.49	2506	2281	1254	1027	15	5	10	2	LS;VS
54.94	4.51	8.33	5.52	16.97	2506	2472	1358	1114	15	5	60	2	IF;LS
54.88	21.47	30.86	24.45	41.85	2506	18753	10292	8461	20	999	2	2	HM;VS
54.56	18.16	27.25	20.95	38.94	2506	15856	8651	7205	15	999	2	2	HM;VS
54.55	20.27	29.56	23.19	40.76	2506	18848	10281	8567	30	999	10	2	HM;VS
54.55	12.33	20.11	14.59	32.38	2506	10893	5942	4951	30	999	2	2	LS;VS
54.55	0.08	0.16	0.1	0.4	2506	11	6	5	30	5	2	2	LU;SFBP
54.55	0.08	0.16	0.1	0.4	2506	11	6	5	30	15	2	2	LU;SFBP
54.53	13.21	21.27	15.57	33.54	2506	11640	6347	5293	15	999	10	2	HM;VS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
54.49	17.8	26.83	20.57	38.58	2506	15635	8520	7115	15	15	2	2	HM;VS
54.49	17.68	26.7	20.44	38.47	2506	14400	7847	6553	30	15	2	2	HM;VS
54.49	0.44	0.87	0.55	2.13	2506	301	164	137	30	15	10	2	IF;VS
54.45	21.07	30.38	24.01	41.35	2506	18333	9983	8350	20	15	2	2	HM;VS
54.45	13.21	21.26	15.57	33.52	2506	11527	6277	5250	15	15	10	2	HM;VS
54.41	1.64	3.18	2.03	7.3	2506	1270	691	579	30	999	10	2	LOF;LS
54.4	4.75	8.73	5.81	17.6	2506	3224	1754	1470	15	5	10	2	IF;LS
54.37	16.16	24.92	18.8	36.91	2506	13306	7234	6072	30	15	10	2	HM;VS
54.25	7.86	13.73	9.48	24.88	2506	6324	3431	2893	30	15	10	2	LS;VS
54.22	3.11	5.89	3.84	12.66	2506	1623	880	743	20	15	2	2	HM;LOF
54.21	0.48	0.95	0.6	2.31	2506	214	116	98	20	5	10	2	LOF;LS
54.21	0.4	0.79	0.5	1.94	2506	190	103	87	5	5	2	2	HM;LOF
54.21	0.4	0.79	0.5	1.94	2506	190	103	87	5	15	2	2	HM;LOF
54.21	0.4	0.79	0.5	1.94	2506	190	103	87	5	999	2	2	HM;LOF
54.09	2.31	4.44	2.86	9.88	2506	1028	556	472	15	5	2	2	HM;LOF
54.09	0.84	1.65	1.04	3.95	2506	379	205	174	30	15	2	2	VS;SFBP
53.97	9.54	16.21	11.42	27.94	2506	8631	4658	3973	30	999	10	2	LS;VS
53.92	1.4	2.72	1.73	6.33	2506	868	468	400	30	999	2	2	VS;SFBP
53.9	0.84	1.65	1.04	3.94	2506	436	235	201	20	15	2	2	IF;LOF
53.9	0.84	1.65	1.04	3.94	2506	436	235	201	20	999	2	2	IF;LOF
53.79	15.68	24.28	18.27	36.2	2506	14009	7535	6474	20	999	10	2	HM;VS
53.78	1.48	2.87	1.83	6.65	2506	675	363	312	20	15	10	2	HM;LOF
53.68	0.44	0.87	0.55	2.13	2506	136	73	63	30	5	2	2	LU;LS
53.66	15.68	24.27	18.27	36.15	2506	13866	7441	6425	20	15	10	2	HM;VS
53.47	9.3	15.84	11.14	27.42	2506	8597	4597	4000	15	5	10	2	HM;VS
53.47	1.08	2.11	1.34	4.99	2506	505	270	235	30	999	2	2	IF;LOF
53.38	1.92	3.7	2.37	8.38	2506	399	213	186	20	15	2	2	LOF;SFBP
53.37	7.74	13.52	9.34	24.5	2506	6816	3638	3178	15	999	2	2	LS;VS
53.34	3.39	6.38	4.17	13.52	2506	973	519	454	30	999	2	2	LOF;SFBP
53.3	0.6	1.18	0.75	2.86	2506	394	210	184	15	999	2	2	VS;SFBP
53.29	1.16	2.27	1.44	5.32	2506	593	316	277	15	999	10	2	HM;LOF
53.27	0.72	1.42	0.89	3.41	2506	413	220	193	15	15	2	2	IF;LOF
53.27	0.72	1.42	0.89	3.41	2506	413	220	193	15	999	2	2	IF;LOF
53.2	0.96	1.88	1.19	4.47	2506	453	241	212	30	5	2	2	IF;LOF
53.18	1	1.96	1.24	4.64	2506	393	209	184	15	5	10	2	HM;LOF
53.07	9.7	16.4	11.59	28.01	2506	7937	4212	3725	30	15	2	2	LS;VS
52.95	5.15	9.38	6.28	18.53	2506	3921	2076	1845	15	5	2	2	LS;VS
52.92	1.44	2.8	1.78	6.48	2506	907	480	427	20	5	2	2	LOF;LS
52.81	0.28	0.56	0.35	1.37	2506	231	122	109	30	15	2	2	HM;SFBP
52.44	2.04	3.92	2.52	8.81	2506	1432	751	681	30	15	2	2	LOF;LS
52.41	1.16	2.26	1.44	5.32	2506	790	414	376	15	5	2	2	LOF;LS
52.38	6.23	11.13	7.56	21.1	2506	5563	2914	2649	15	999	10	2	LS;VS
52.37	1.56	3.02	1.93	6.95	2506	1289	675	614	15	999	2	2	LOF;LS
52.3	5.39	9.77	6.56	19.08	2506	4797	2509	2288	15	15	10	2	LS;VS
52.22	0.68	1.34	0.85	3.22	2506	360	188	172	15	5	2	2	IF;LOF
52.13	2.55	4.87	3.15	10.68	2506	2112	1101	1011	30	999	2	2	LOF;LS
51.94	6.98	12.31	8.45	22.71	2506	6068	3152	2916	15	15	2	2	LS;VS
51.89	0.76	1.49	0.94	3.58	2506	530	275	255	15	999	2	2	LU;LS
51.87	1.8	3.47	2.23	7.89	2506	563	292	271	30	5	2	2	LOF;VS
51.84	0.36	0.71	0.45	1.75	2506	245	127	118	20	15	10	2	IF;VS
51.73	9.5	16.05	11.35	27.38	2506	8405	4348	4057	5	999	2	2	HM;VS
51.71	9.46	15.99	11.3	27.31	2506	8402	4345	4057	5	15	2	2	HM;VS
51.61	0.8	1.57	0.99	3.76	2506	372	192	180	20	5	2	2	IF;LOF
51.47	0.32	0.63	0.4	1.56	2506	204	105	99	15	15	10	2	IF;VS
51.37	1.12	2.19	1.39	5.14	2506	475	244	231	15	15	10	2	HM;LOF
51.32	7.7	13.39	9.28	24.06	2506	6769	3474	3295	5	15	10	2	HM;VS
51.32	7.7	13.39	9.28	24.06	2506	6769	3474	3295	5	999	10	2	HM;VS
51.29	0.2	0.4	0.25	0.98	2506	232	119	113	30	15	60	2	HM;IF
51.01	1.36	2.64	1.68	6.13	2506	939	479	460	30	15	10	2	LOF;LS
50.98	9.46	15.95	11.3	27.14	2506	8203	4182	4021	5	5	2	2	HM;VS
50.85	7.62	13.26	9.18	23.82	2506	6655	3384	3271	5	5	10	2	HM;VS
50.55	1.48	2.87	1.83	6.61	2506	1185	599	586	15	15	2	2	LOF;LS
50.26	6.03	10.76	7.31	20.36	2506	2939	1477	1462	30	15	2	2	LOF;VS
50.18	0.44	0.87	0.55	2.12	2506	281	141	140	15	15	2	2	VS;SFBP
50	0.2	0.4	0.25	0.98	2506	88	44	44	15	15	2	2	LU;VS
50	0.04	0.08	0.05	0.2	2506	48	24	24	5	5	2	2	LOF;SFBP
50	0.04	0.08	0.05	0.2	2506	48	24	24	5	15	2	2	LOF;SFBP
50	0.04	0.08	0.05	0.2	2506	48	24	24	5	999	2	2	LOF;SFBP
49.91	6.94	12.19	8.39	22.3	2506	3745	1869	1876	30	999	2	2	LOF;VS
49.89	0.72	1.42	0.89	3.4	2506	457	228	229	15	15	2	2	LU;LS
49.59	4.51	8.27	5.51	16.53	2506	2341	1161	1180	20	999	2	2	LOF;VS
49.27	0.52	1.03	0.65	2.49	2506	341	168	173	20	15	2	2	VS;SFBP
49.19	4.19	7.72	5.13	15.63	2506	2173	1069	1104	20	15	2	2	LOF;VS
49.15	0.12	0.24	0.15	0.59	2506	59	29	30	30	5	10	2	IF;VS
49.06	0.28	0.56	0.35	1.37	2506	106	52	54	30	15	2	2	LU;VS
48.9	1.28	2.49	1.59	5.78	2506	454	222	232	5	5	2	2	LS;VS
48.53	0.2	0.4	0.25	0.98	2506	68	33	35	20	5	10	2	IF;VS
48.21	2.35	4.49	2.91	9.85	2506	1616	779	837	20	5	2	2	HM;LS
47.77	0.32	0.63	0.4	1.55	2506	157	75	82	5	5	2	2	IF;LOF
47.76	0.44	0.87	0.55	2.12	2506	268	128	140	20	15	2	2	LS;SFBP
47.46	0.2	0.4	0.25	0.98	2506	118	56	62	20	999	2	2	LU;VS
46.32	2.08	3.97	2.57	8.8	2506	1291	598	693	20	5	10	2	HM;LS
46.02	3.19	5.97	3.92	12.49	2506	1645	757	888	15	15	2	2	LOF;VS
45.94	3.23	6.04	3.97	12.61	2506	1698	780	918	15	999	2	2	LOF;VS
45.81	0.52	1.03	0.65	2.48	2506	227	104	123	15	5	10	2	LOF;LS
43.86	0.16	0.32	0.2	0.79	2506	57	25	32	30	5	2	2	HM;VS
43.45	0.76	1.49	0.94	3.54	2506	359	156	203	5	5	2	2	LOF;VS
43.45	0.76	1.49	0.94	3.54	2506	359	156	203	5	15	2	2	LOF;VS
43.45	0.76	1.49	0.94	3.54	2506	359	156	203	5	999	2	2	LOF;VS
43	1.04	2.03	1.29	4.73	2506	607	261	346	30	5	2	2	LOF;LS
42.59	0.2	0.4	0.25	0.98	2506	108	46	62	15	999	2	2	LU;VS
41.11	1.52	2.92	1.88	6.61	2506	849	349	500	15	5	2	2	LOF;VS
40.91	0.04	0.08	0.05	0.2	2506	66	27	39	20	5	60	2	HM;IF
36.67	1.16	2.24	1.44	5.14	2506	450	165	285	20	5	60	2	HM;LS
36.36	0.08	0.16	0.1	0.4	2506	33	12	21	30	5	10	2	HM;VS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
35.26	0.32	0.63	0.4	1.54	2506	190	67	123	30	999	2	2	LU;VS
33.05	0.12	0.24	0.15	0.59	2506	118	39	79	30	15	2	2	HM;LOF
25.61	0.08	0.16	0.1	0.39	2506	82	21	61	5	15	2	2	LU;LS
25.61	0.08	0.16	0.1	0.39	2506	82	21	61	5	999	2	2	LU;LS
25	0.24	0.47	0.3	1.15	2506	152	38	114	30	5	10	2	LOF;LS
22.47	0.08	0.16	0.1	0.39	2506	89	20	69	30	15	10	2	HM;LOF
21.74	0.08	0.16	0.1	0.39	2506	92	20	72	20	5	2	2	HM;LOF
11.63	0.04	0.08	0.05	0.2	2506	43	5	38	20	5	10	2	HM;LOF
0	0	0	0	0	2506	0	0	0	5	5	2	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	2	VS;SFBP
0	0	0	0	0	2506	2	0	2	15	5	2	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	2	VS;SFBP
0	0	0	0	0	2506	2	0	2	30	5	2	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	2	VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	2	2	LU;VS
0	0	0	0	0	2506	0	0	0	5	5	10	2	LU;VS
0	0	0	0	0	2506	0	0	0	5	5	60	2	LU;VS
0	0	0	0	0	2506	0	0	0	5	15	2	2	LU;VS
0	0	0	0	0	2506	0	0	0	5	15	10	2	LU;VS
0	0	0	0	0	2506	0	0	0	5	15	60	2	LU;VS
0	0	0	0	0	2506	0	0	0	5	999	2	2	LU;VS
0	0	0	0	0	2506	0	0	0	5	999	10	2	LU;VS
0	0	0	0	0	2506	0	0	0	5	999	60	2	LU;VS
0	0	0	0	0	2506	0	0	0	15	5	10	2	LU;VS
0	0	0	0	0	2506	0	0	0	15	5	60	2	LU;VS
0	0	0	0	0	2506	0	0	0	15	15	10	2	LU;VS
0	0	0	0	0	2506	0	0	0	15	15	60	2	LU;VS
0	0	0	0	0	2506	0	0	0	15	999	10	2	LU;VS
0	0	0	0	0	2506	0	0	0	15	999	60	2	LU;VS
0	0	0	0	0	2506	0	0	0	20	5	10	2	LU;VS
0	0	0	0	0	2506	0	0	0	20	5	60	2	LU;VS
0	0	0	0	0	2506	0	0	0	20	15	10	2	LU;VS
0	0	0	0	0	2506	0	0	0	20	15	60	2	LU;VS
0	0	0	0	0	2506	0	0	0	20	999	10	2	LU;VS
0	0	0	0	0	2506	0	0	0	20	999	60	2	LU;VS
0	0	0	0	0	2506	0	0	0	30	5	10	2	LU;VS
0	0	0	0	0	2506	0	0	0	30	5	60	2	LU;VS
0	0	0	0	0	2506	0	0	0	30	15	10	2	LU;VS
0	0	0	0	0	2506	0	0	0	30	15	60	2	LU;VS
0	0	0	0	0	2506	0	0	0	30	999	10	2	LU;VS
0	0	0	0	0	2506	0	0	0	30	999	60	2	LU;VS
0	0	0	0	0	2506	0	0	0	5	5	2	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	2	LU;SFBP
0	0	0	0	0	2506	1	0	1	15	5	2	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	2	LU;SFBP
0	0	0	0	0	2506	5	0	5	15	15	2	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	2	LU;SFBP
0	0	0	0	0	2506	5	0	5	15	999	2	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	2	LU;SFBP
0	0	0	0	0	2506	2	0	2	20	5	2	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	2	LU;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	2	LU;SFBP

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	5	5	10	2	LU;LS
0	0	0	0	0	2506	0	0	0	5	5	60	2	LU;LS
0	0	0	0	0	2506	0	0	0	5	15	10	2	LU;LS
0	0	0	0	0	2506	0	0	0	5	15	60	2	LU;LS
0	0	0	0	0	2506	0	0	0	5	999	10	2	LU;LS
0	0	0	0	0	2506	0	0	0	5	999	60	2	LU;LS
0	0	0	0	0	2506	0	0	0	15	5	10	2	LU;LS
0	0	0	0	0	2506	0	0	0	15	5	60	2	LU;LS
0	0	0	0	0	2506	0	0	0	15	15	10	2	LU;LS
0	0	0	0	0	2506	0	0	0	15	15	60	2	LU;LS
0	0	0	0	0	2506	0	0	0	15	999	10	2	LU;LS
0	0	0	0	0	2506	0	0	0	15	999	60	2	LU;LS
0	0	0	0	0	2506	0	0	0	20	5	10	2	LU;LS
0	0	0	0	0	2506	0	0	0	20	5	60	2	LU;LS
0	0	0	0	0	2506	0	0	0	20	15	10	2	LU;LS
0	0	0	0	0	2506	0	0	0	20	15	60	2	LU;LS
0	0	0	0	0	2506	0	0	0	20	999	10	2	LU;LS
0	0	0	0	0	2506	0	0	0	20	999	60	2	LU;LS
0	0	0	0	0	2506	0	0	0	30	5	10	2	LU;LS
0	0	0	0	0	2506	0	0	0	30	5	60	2	LU;LS
0	0	0	0	0	2506	0	0	0	30	15	10	2	LU;LS
0	0	0	0	0	2506	0	0	0	30	15	60	2	LU;LS
0	0	0	0	0	2506	0	0	0	30	999	10	2	LU;LS
0	0	0	0	0	2506	0	0	0	30	999	60	2	LU;LS
0	0	0	0	0	2506	0	0	0	5	5	2	2	LU;LOF
0	0	0	0	0	2506	0	0	0	5	5	10	2	LU;LOF
0	0	0	0	0	2506	0	0	0	5	5	60	2	LU;LOF
0	0	0	0	0	2506	0	0	0	5	15	2	2	LU;LOF
0	0	0	0	0	2506	0	0	0	5	15	10	2	LU;LOF
0	0	0	0	0	2506	0	0	0	5	15	60	2	LU;LOF
0	0	0	0	0	2506	0	0	0	5	999	2	2	LU;LOF
0	0	0	0	0	2506	0	0	0	5	999	10	2	LU;LOF
0	0	0	0	0	2506	0	0	0	5	999	60	2	LU;LOF
0	0	0	0	0	2506	0	0	0	15	5	2	2	LU;LOF
0	0	0	0	0	2506	0	0	0	15	5	10	2	LU;LOF
0	0	0	0	0	2506	0	0	0	15	5	60	2	LU;LOF
0	0	0	0	0	2506	0	0	0	15	15	2	2	LU;LOF
0	0	0	0	0	2506	0	0	0	15	15	10	2	LU;LOF
0	0	0	0	0	2506	0	0	0	15	15	60	2	LU;LOF
0	0	0	0	0	2506	0	0	0	15	999	2	2	LU;LOF
0	0	0	0	0	2506	0	0	0	15	999	10	2	LU;LOF
0	0	0	0	0	2506	0	0	0	15	999	60	2	LU;LOF
0	0	0	0	0	2506	0	0	0	20	5	2	2	LU;LOF
0	0	0	0	0	2506	0	0	0	20	5	10	2	LU;LOF
0	0	0	0	0	2506	0	0	0	20	5	60	2	LU;LOF
0	0	0	0	0	2506	0	0	0	20	15	2	2	LU;LOF
0	0	0	0	0	2506	0	0	0	20	15	10	2	LU;LOF
0	0	0	0	0	2506	0	0	0	20	15	60	2	LU;LOF
0	0	0	0	0	2506	0	0	0	20	999	2	2	LU;LOF
0	0	0	0	0	2506	0	0	0	20	999	10	2	LU;LOF
0	0	0	0	0	2506	0	0	0	20	999	60	2	LU;LOF
0	0	0	0	0	2506	0	0	0	30	5	2	2	LU;LOF
0	0	0	0	0	2506	0	0	0	30	5	10	2	LU;LOF
0	0	0	0	0	2506	0	0	0	30	5	60	2	LU;LOF
0	0	0	0	0	2506	0	0	0	30	15	2	2	LU;LOF
0	0	0	0	0	2506	0	0	0	30	15	10	2	LU;LOF
0	0	0	0	0	2506	0	0	0	30	15	60	2	LU;LOF
0	0	0	0	0	2506	0	0	0	30	999	2	2	LU;LOF
0	0	0	0	0	2506	0	0	0	30	999	10	2	LU;LOF
0	0	0	0	0	2506	0	0	0	30	999	60	2	LU;LOF
0	0	0	0	0	2506	0	0	0	5	5	10	2	LU;IF
0	0	0	0	0	2506	0	0	0	5	5	60	2	LU;IF
0	0	0	0	0	2506	0	0	0	5	15	10	2	LU;IF
0	0	0	0	0	2506	0	0	0	5	15	60	2	LU;IF
0	0	0	0	0	2506	0	0	0	5	999	10	2	LU;IF
0	0	0	0	0	2506	0	0	0	5	999	60	2	LU;IF
0	0	0	0	0	2506	0	0	0	15	5	10	2	LU;IF
0	0	0	0	0	2506	0	0	0	15	5	60	2	LU;IF
0	0	0	0	0	2506	0	0	0	15	15	10	2	LU;IF
0	0	0	0	0	2506	0	0	0	15	15	60	2	LU;IF
0	0	0	0	0	2506	0	0	0	15	999	10	2	LU;IF
0	0	0	0	0	2506	0	0	0	15	999	60	2	LU;IF
0	0	0	0	0	2506	0	0	0	20	5	10	2	LU;IF
0	0	0	0	0	2506	0	0	0	20	5	60	2	LU;IF
0	0	0	0	0	2506	0	0	0	20	15	10	2	LU;IF
0	0	0	0	0	2506	0	0	0	20	15	60	2	LU;IF
0	0	0	0	0	2506	0	0	0	20	999	10	2	LU;IF
0	0	0	0	0	2506	0	0	0	20	999	60	2	LU;IF
0	0	0	0	0	2506	0	0	0	30	5	10	2	LU;IF
0	0	0	0	0	2506	0	0	0	30	5	60	2	LU;IF
0	0	0	0	0	2506	0	0	0	30	15	10	2	LU;IF
0	0	0	0	0	2506	0	0	0	30	15	60	2	LU;IF
0	0	0	0	0	2506	0	0	0	30	999	10	2	LU;IF
0	0	0	0	0	2506	0	0	0	30	999	60	2	LU;IF
0	0	0	0	0	2506	0	0	0	5	5	10	2	LS;VS
0	0	0	0	0	2506	0	0	0	5	5	60	2	LS;VS
0	0	0	0	0	2506	0	0	0	5	15	10	2	LS;VS
0	0	0	0	0	2506	0	0	0	5	15	60	2	LS;VS
0	0	0	0	0	2506	0	0	0	5	999	10	2	LS;VS
0	0	0	0	0	2506	0	0	0	5	999	60	2	LS;VS
0	0	0	0	0	2506	0	0	0	15	5	60	2	LS;VS
0	0	0	0	0	2506	0	0	0	15	15	60	2	LS;VS
0	0	0	0	0	2506	0	0	0	15	999	60	2	LS;VS
0	0	0	0	0	2506	0	0	0	20	5	60	2	LS;VS
0	0	0	0	0	2506	0	0	0	20	15	60	2	LS;VS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	20	999	60	2	LS;VS
0	0	0	0	0	2506	0	0	0	30	5	60	2	LS;VS
0	0	0	0	0	2506	0	0	0	30	15	60	2	LS;VS
0	0	0	0	0	2506	0	0	0	30	999	60	2	LS;VS
0	0	0	0	0	2506	0	0	0	5	5	10	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	2	LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	2	LOF;VS
0	0	0	0	0	2506	0	0	0	5	5	60	2	LOF;VS
0	0	0	0	0	2506	0	0	0	5	15	10	2	LOF;VS
0	0	0	0	0	2506	0	0	0	5	15	60	2	LOF;VS
0	0	0	0	0	2506	0	0	0	5	999	10	2	LOF;VS
0	0	0	0	0	2506	0	0	0	5	999	60	2	LOF;VS
0	0	0	0	0	2506	0	0	0	15	5	10	2	LOF;VS
0	0	0	0	0	2506	0	0	0	15	5	60	2	LOF;VS
0	0	0	0	0	2506	0	0	0	15	15	10	2	LOF;VS
0	0	0	0	0	2506	0	0	0	15	15	60	2	LOF;VS
0	0	0	0	0	2506	0	0	0	15	999	10	2	LOF;VS
0	0	0	0	0	2506	0	0	0	15	999	60	2	LOF;VS
0	0	0	0	0	2506	0	0	0	20	5	10	2	LOF;VS
0	0	0	0	0	2506	0	0	0	20	5	60	2	LOF;VS
0	0	0	0	0	2506	0	0	0	20	15	10	2	LOF;VS
0	0	0	0	0	2506	0	0	0	20	15	60	2	LOF;VS
0	0	0	0	0	2506	0	0	0	20	999	10	2	LOF;VS
0	0	0	0	0	2506	0	0	0	20	999	60	2	LOF;VS
0	0	0	0	0	2506	0	0	0	30	5	10	2	LOF;VS
0	0	0	0	0	2506	0	0	0	30	5	60	2	LOF;VS
0	0	0	0	0	2506	0	0	0	30	15	10	2	LOF;VS
0	0	0	0	0	2506	0	0	0	30	15	60	2	LOF;VS
0	0	0	0	0	2506	0	0	0	30	999	10	2	LOF;VS
0	0	0	0	0	2506	0	0	0	30	999	60	2	LOF;VS
0	0	0	0	0	2506	0	0	0	5	5	10	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	2	LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	2	LOF;LS
0	0	0	0	0	2506	0	0	0	5	15	60	2	LOF;LS
0	0	0	0	0	2506	0	0	0	5	999	60	2	LOF;LS
0	0	0	0	0	2506	0	0	0	15	5	60	2	LOF;LS
0	0	0	0	0	2506	0	0	0	15	15	60	2	LOF;LS
0	0	0	0	0	2506	0	0	0	15	999	60	2	LOF;LS
0	0	0	0	0	2506	0	0	0	20	5	60	2	LOF;LS
0	0	0	0	0	2506	0	0	0	20	15	60	2	LOF;LS
0	0	0	0	0	2506	0	0	0	20	999	60	2	LOF;LS
0	0	0	0	0	2506	0	0	0	30	5	60	2	LOF;LS
0	0	0	0	0	2506	0	0	0	30	15	60	2	LOF;LS
0	0	0	0	0	2506	0	0	0	30	999	60	2	LOF;LS
0	0	0	0	0	2506	0	0	0	5	5	10	2	IF;VS
0	0	0	0	0	2506	0	0	0	5	5	60	2	IF;VS
0	0	0	0	0	2506	0	0	0	5	15	10	2	IF;VS
0	0	0	0	0	2506	0	0	0	5	15	60	2	IF;VS
0	0	0	0	0	2506	0	0	0	5	999	10	2	IF;VS
0	0	0	0	0	2506	0	0	0	5	999	60	2	IF;VS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	15	5	60	2	IF;VS
0	0	0	0	0	2506	0	0	0	15	15	60	2	IF;VS
0	0	0	0	0	2506	0	0	0	15	999	60	2	IF;VS
0	0	0	0	0	2506	0	0	0	20	5	60	2	IF;VS
0	0	0	0	0	2506	0	0	0	20	15	60	2	IF;VS
0	0	0	0	0	2506	0	0	0	20	999	60	2	IF;VS
0	0	0	0	0	2506	0	0	0	30	5	60	2	IF;VS
0	0	0	0	0	2506	0	0	0	30	15	60	2	IF;VS
0	0	0	0	0	2506	0	0	0	30	999	60	2	IF;VS
0	0	0	0	0	2506	0	0	0	5	5	10	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	2	IF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	2	IF;LS
0	0	0	0	0	2506	0	0	0	5	15	60	2	IF;LS
0	0	0	0	0	2506	0	0	0	5	999	60	2	IF;LS
0	0	0	0	0	2506	0	0	0	5	5	10	2	IF;LOF
0	0	0	0	0	2506	0	0	0	5	5	60	2	IF;LOF
0	0	0	0	0	2506	0	0	0	5	15	10	2	IF;LOF
0	0	0	0	0	2506	0	0	0	5	15	60	2	IF;LOF
0	0	0	0	0	2506	0	0	0	5	999	10	2	IF;LOF
0	0	0	0	0	2506	0	0	0	5	999	60	2	IF;LOF
0	0	0	0	0	2506	0	0	0	15	5	10	2	IF;LOF
0	0	0	0	0	2506	0	0	0	15	5	60	2	IF;LOF
0	0	0	0	0	2506	0	0	0	15	15	10	2	IF;LOF
0	0	0	0	0	2506	0	0	0	15	15	60	2	IF;LOF
0	0	0	0	0	2506	0	0	0	15	999	10	2	IF;LOF
0	0	0	0	0	2506	0	0	0	15	999	60	2	IF;LOF
0	0	0	0	0	2506	0	0	0	20	5	10	2	IF;LOF
0	0	0	0	0	2506	0	0	0	20	5	60	2	IF;LOF
0	0	0	0	0	2506	0	0	0	20	15	10	2	IF;LOF
0	0	0	0	0	2506	0	0	0	20	15	60	2	IF;LOF
0	0	0	0	0	2506	0	0	0	20	999	10	2	IF;LOF
0	0	0	0	0	2506	0	0	0	20	999	60	2	IF;LOF
0	0	0	0	0	2506	0	0	0	30	5	10	2	IF;LOF
0	0	0	0	0	2506	0	0	0	30	5	60	2	IF;LOF
0	0	0	0	0	2506	0	0	0	30	15	10	2	IF;LOF
0	0	0	0	0	2506	0	0	0	30	15	60	2	IF;LOF
0	0	0	0	0	2506	0	0	0	30	999	10	2	IF;LOF
0	0	0	0	0	2506	0	0	0	30	999	60	2	IF;LOF
0	0	0	0	0	2506	0	0	0	5	5	60	2	HM;VS
0	0	0	0	0	2506	0	0	0	5	15	60	2	HM;VS
0	0	0	0	0	2506	0	0	0	5	999	60	2	HM;VS
0	0	0	0	0	2506	0	0	0	15	5	60	2	HM;VS
0	0	0	0	0	2506	0	0	0	15	15	60	2	HM;VS
0	0	0	0	0	2506	0	0	0	15	999	60	2	HM;VS
0	0	0	0	0	2506	0	0	0	20	5	60	2	HM;VS
0	0	0	0	0	2506	0	0	0	20	15	60	2	HM;VS
0	0	0	0	0	2506	0	0	0	20	999	60	2	HM;VS
0	0	0	0	0	2506	0	0	0	30	5	60	2	HM;VS
0	0	0	0	0	2506	0	0	0	30	15	60	2	HM;VS
0	0	0	0	0	2506	0	0	0	30	999	60	2	HM;VS
0	0	0	0	0	2506	0	0	0	5	5	10	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	2	HM;SFBP

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	30	999	60	2	HM;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	2	HM;LU
0	0	0	0	0	2506	0	0	0	5	5	60	2	HM;LU
0	0	0	0	0	2506	0	0	0	5	15	10	2	HM;LU
0	0	0	0	0	2506	0	0	0	5	15	60	2	HM;LU
0	0	0	0	0	2506	0	0	0	5	999	10	2	HM;LU
0	0	0	0	0	2506	0	0	0	5	999	60	2	HM;LU
0	0	0	0	0	2506	0	0	0	15	5	10	2	HM;LU
0	0	0	0	0	2506	0	0	0	15	5	60	2	HM;LU
0	0	0	0	0	2506	0	0	0	15	15	60	2	HM;LU
0	0	0	0	0	2506	0	0	0	15	999	60	2	HM;LU
0	0	0	0	0	2506	0	0	0	20	5	10	2	HM;LU
0	0	0	0	0	2506	0	0	0	20	5	60	2	HM;LU
0	0	0	0	0	2506	0	0	0	20	15	60	2	HM;LU
0	0	0	0	0	2506	0	0	0	20	999	60	2	HM;LU
0	0	0	0	0	2506	0	0	0	30	5	10	2	HM;LU
0	0	0	0	0	2506	0	0	0	30	5	60	2	HM;LU
0	0	0	0	0	2506	0	0	0	30	15	60	2	HM;LU
0	0	0	0	0	2506	0	0	0	30	999	60	2	HM;LU
0	0	0	0	0	2506	0	0	0	5	5	10	2	HM;LOF
0	0	0	0	0	2506	0	0	0	5	5	60	2	HM;LOF
0	0	0	0	0	2506	0	0	0	5	15	10	2	HM;LOF
0	0	0	0	0	2506	0	0	0	5	15	60	2	HM;LOF
0	0	0	0	0	2506	0	0	0	5	999	10	2	HM;LOF
0	0	0	0	0	2506	0	0	0	5	999	60	2	HM;LOF
0	0	0	0	0	2506	0	0	0	15	5	60	2	HM;LOF
0	0	0	0	0	2506	0	0	0	15	15	60	2	HM;LOF
0	0	0	0	0	2506	0	0	0	15	999	60	2	HM;LOF
0	0	0	0	0	2506	0	0	0	20	5	60	2	HM;LOF
0	0	0	0	0	2506	0	0	0	20	15	60	2	HM;LOF
0	0	0	0	0	2506	0	0	0	20	999	60	2	HM;LOF
0	0	0	0	0	2506	0	0	0	30	5	2	2	HM;LOF
0	0	0	0	0	2506	0	0	0	30	5	10	2	HM;LOF
0	0	0	0	0	2506	0	0	0	30	5	60	2	HM;LOF
0	0	0	0	0	2506	0	0	0	30	15	60	2	HM;LOF
0	0	0	0	0	2506	0	0	0	30	999	60	2	HM;LOF

Table A.5: Trial results for a fixed number of algorithms to 3. Varying $\alpha, \beta, \gamma, \delta$

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
100	0.08	0.16	0.1	0.4	2506	22	22	0	5	15	2	3	HM;LU;LS
100	0.08	0.16	0.1	0.4	2506	6	6	0	30	5	10	3	HM;IF;LS
100	0.08	0.16	0.1	0.4	2506	8	8	0	20	5	2	3	LU;IF;LS
100	0.08	0.16	0.1	0.4	2506	7	7	0	30	5	2	3	LU;IF;LS
100	0.08	0.16	0.1	0.4	2506	25	25	0	15	5	2	3	LU;IF;VS
100	0.04	0.08	0.05	0.2	2506	3	3	0	30	5	2	3	LU;LS;VS
100	0.04	0.08	0.05	0.2	2506	7	7	0	15	5	2	3	IF;LS;SFBP
100	0.04	0.08	0.05	0.2	2506	13	13	0	20	5	2	3	IF;LS;SFBP
82.58	0.2	0.4	0.25	0.99	2506	132	109	23	5	15	2	3	HM;LU;IF
78.39	0.16	0.32	0.2	0.79	2506	199	156	43	5	999	2	3	HM;LU;LS
78	0.08	0.16	0.1	0.4	2506	50	39	11	30	5	2	3	HM;IF;LS
77.86	1.44	2.82	1.79	6.69	2506	569	443	126	5	5	2	3	HM;IF;LS
77.78	0.04	0.08	0.05	0.2	2506	27	21	6	20	5	2	3	HM;LU;LS
75	0.2	0.4	0.25	0.99	2506	180	135	45	5	999	2	3	HM;LU;IF
73.24	0.2	0.4	0.25	0.99	2506	71	52	19	30	15	2	3	LU;IF;LS
72.73	0.04	0.08	0.05	0.2	2506	11	8	3	30	5	2	3	LU;IF;VS
72.07	1.04	2.05	1.29	4.91	2506	752	542	210	20	999	2	3	IF;VS;SFBP
71.93	0.16	0.32	0.2	0.79	2506	57	41	16	5	5	2	3	HM;LU;IF
71.6	0.12	0.24	0.15	0.59	2506	81	58	23	20	15	2	3	LU;IF;LS
71.43	0.04	0.08	0.05	0.2	2506	7	5	2	5	5	2	3	HM;LU;LOF
71.43	0.04	0.08	0.05	0.2	2506	7	5	2	5	15	2	3	HM;LU;LOF
71.43	0.04	0.08	0.05	0.2	2506	7	5	2	5	999	2	3	HM;LU;LOF
70.97	0.16	0.32	0.2	0.79	2506	124	88	36	20	999	2	3	HM;IF;SFBP
70.87	3.03	5.82	3.75	12.95	2506	2348	1664	684	5	15	2	3	IF;LS;VS
70.76	0.84	1.66	1.04	4	2506	407	288	119	15	15	2	3	IF;VS;SFBP
69.9	3.03	5.81	3.75	12.92	2506	2389	1670	719	5	999	2	3	IF;LS;VS
68.75	0.16	0.32	0.2	0.79	2506	80	55	25	15	15	2	3	LU;IF;VS
68.26	0.32	0.64	0.4	1.57	2506	356	243	113	15	15	2	3	HM;LU;LS
67.94	0.2	0.4	0.25	0.99	2506	131	89	42	30	999	2	3	LU;IF;SFBP
67.82	0.4	0.79	0.5	1.95	2506	404	274	130	20	999	2	3	HM;LU;VS
67.45	0.28	0.56	0.35	1.37	2506	298	201	97	15	15	2	3	HM;LU;VS
67.31	1.8	3.5	2.23	8.11	2506	1909	1285	624	5	15	2	3	HM;IF;LS
66.27	1.84	3.57	2.28	8.26	2506	2022	1340	682	5	999	2	3	HM;IF;LS
66.08	0.4	0.79	0.5	1.95	2506	339	224	115	15	999	2	3	HM;LU;VS
65.96	0.96	1.89	1.19	4.53	2506	614	405	209	15	999	2	3	IF;VS;SFBP
65.57	0.12	0.24	0.15	0.59	2506	61	40	21	20	5	2	3	HM;IF;LS
65.41	0.72	1.42	0.9	3.44	2506	344	225	119	15	15	2	3	HM;LU;IF
65.38	0.08	0.16	0.1	0.4	2506	26	17	9	20	15	2	3	HM;LU;LOF
65.38	0.08	0.16	0.1	0.4	2506	26	17	9	20	999	2	3	HM;LU;LOF
64.81	0.12	0.24	0.15	0.59	2506	108	70	38	5	15	2	3	HM;LOF;LS
64.81	0.12	0.24	0.15	0.59	2506	108	70	38	5	999	2	3	HM;LOF;LS
64.71	0.16	0.32	0.2	0.79	2506	68	44	24	15	15	2	3	HM;IF;SFBP
64.63	0.32	0.64	0.4	1.57	2506	376	243	133	20	15	2	3	HM;LU;LS
64.17	0.92	1.81	1.14	4.34	2506	734	471	263	20	999	2	3	HM;LU;IF
64.1	0.4	0.79	0.5	1.95	2506	312	200	112	20	15	2	3	HM;LU;VS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
63.63	0.44	0.87	0.55	2.14	2506	811	516	295	20	999	2	3	HM;LU;LS
63.32	2.43	4.69	3.01	10.55	2506	2072	1312	760	15	5	2	3	HM;IF;VS
63.19	0.68	1.34	0.85	3.25	2506	326	206	120	20	15	2	3	HM;LU;IF
62.96	0.08	0.16	0.1	0.4	2506	27	17	10	30	15	2	3	LU;IF;SFBP
62.88	0.8	1.58	0.99	3.8	2506	625	393	232	15	999	2	3	HM;LU;IF
62.88	0.64	1.26	0.8	3.07	2506	994	625	369	30	999	2	3	HM;LU;LS
62.85	0.6	1.19	0.75	2.88	2506	533	335	198	30	999	2	3	HM;LU;VS
62.5	0.08	0.16	0.1	0.4	2506	24	15	9	20	5	2	3	LU;IF;VS
62.32	0.12	0.24	0.15	0.59	2506	69	43	26	20	15	2	3	LU;IF;VS
61.7	0.16	0.32	0.2	0.79	2506	94	58	36	15	999	2	3	HM;IF;SFBP
61.5	0.24	0.48	0.3	1.18	2506	187	115	72	30	15	2	3	HM;LU;LS
61.19	0.88	1.73	1.09	4.15	2506	286	175	111	20	15	2	3	IF;VS;SFBP
61.12	0.28	0.56	0.35	1.37	2506	409	250	159	30	999	2	3	LU;IF;LS
60.87	0.24	0.48	0.3	1.18	2506	184	112	72	30	999	2	3	HM;IF;SFBP
60.09	3.67	6.92	4.52	14.75	2506	3683	2213	1470	20	999	2	3	HM;IF;VS
60.04	6.7	12.06	8.15	23.17	2506	6770	4065	2705	20	999	2	3	IF;LS;VS
59.96	1.24	2.42	1.54	5.71	2506	979	587	392	30	999	2	3	HM;LU;IF
59.94	0.2	0.4	0.25	0.98	2506	352	211	141	20	999	2	3	LU;IF;LS
59.9	6.03	10.95	7.35	21.48	2506	5372	3218	2154	20	15	10	3	IF;LS;VS
59.56	6.26	11.34	7.63	22.05	2506	5588	3328	2260	20	15	2	3	IF;LS;VS
59.47	4.87	9	5.96	18.34	2506	3074	1828	1246	20	5	2	3	IF;LS;VS
59.32	4.99	9.2	6.11	18.66	2506	4906	2910	1996	30	999	2	3	HM;IF;VS
59.22	0.2	0.4	0.25	0.98	2506	206	122	84	20	999	2	3	LU;LS;VS
59.21	6.66	11.98	8.1	22.98	2506	6588	3901	2687	20	999	10	3	IF;LS;VS
59.09	1.6	3.11	1.98	7.2	2506	1369	809	560	30	999	2	3	IF;VS;SFBP
59.06	4.67	8.65	5.72	17.74	2506	2711	1601	1110	20	5	10	3	IF;LS;VS
59.01	3.83	7.19	4.71	15.21	2506	4667	2754	1913	20	999	2	3	HM;IF;LS
58.99	3.63	6.84	4.47	14.57	2506	4128	2435	1693	20	15	2	3	HM;IF;LS
58.97	1.96	3.79	2.42	8.63	2506	1182	697	485	15	5	10	3	HM;IF;LS
58.75	3.35	6.34	4.13	13.65	2506	3287	1931	1356	20	15	2	3	HM;IF;VS
58.7	4.35	8.1	5.34	16.78	2506	2574	1511	1063	30	5	10	3	IF;LS;VS
58.67	0.04	0.08	0.05	0.2	2506	75	44	31	15	15	2	3	IF;LS;SFBP
58.67	0.04	0.08	0.05	0.2	2506	75	44	31	15	999	2	3	IF;LS;SFBP
58.45	2.75	5.26	3.4	11.58	2506	2799	1636	1163	15	15	2	3	HM;IF;VS
58.33	0.12	0.24	0.15	0.59	2506	12	7	5	20	5	10	3	HM;IF;LS
58.3	3.15	5.98	3.89	12.96	2506	3024	1763	1261	15	999	2	3	HM;IF;VS
58.27	4.67	8.64	5.72	17.68	2506	2964	1727	1237	30	5	2	3	IF;LS;VS
58.22	3.95	7.4	4.86	15.54	2506	2815	1639	1176	15	5	2	3	IF;LS;VS
58.22	3.47	6.55	4.28	14.02	2506	3909	2276	1633	20	999	10	3	HM;IF;LS
58.1	3.83	7.19	4.71	15.16	2506	2468	1434	1034	15	5	10	3	IF;LS;VS
57.9	3.43	6.48	4.23	13.87	2506	3646	2111	1535	20	15	10	3	HM;IF;LS
57.55	0.16	0.32	0.2	0.79	2506	106	61	45	20	999	2	3	LU;IF;VS
57.21	5.27	9.65	6.44	19.25	2506	6064	3469	2595	30	999	2	3	HM;IF;LS
57.17	0.44	0.87	0.55	2.13	2506	642	367	275	15	999	2	3	HM;LU;LS
57.07	5.59	10.18	6.82	20.07	2506	4957	2829	2128	15	15	2	3	IF;LS;VS
56.93	3.47	6.54	4.27	13.95	2506	4788	2726	2062	20	999	2	3	HM;LS;VS
56.83	3.15	5.97	3.89	12.9	2506	3519	2000	1519	15	15	2	3	HM;IF;LS
56.82	2.95	5.61	3.64	12.22	2506	3502	1990	1512	20	15	2	3	HM;LS;VS
56.67	6.03	10.89	7.34	21.14	2506	5848	3314	2534	15	999	2	3	IF;LS;VS
56.53	4.79	8.83	5.86	17.88	2506	4546	2570	1976	15	15	10	3	IF;LS;VS
56.52	0.16	0.32	0.2	0.79	2506	69	39	30	30	15	2	3	HM;LOF;LS
56.5	4.71	8.69	5.77	17.66	2506	5106	2885	2221	30	999	10	3	HM;IF;LS
56.42	0.28	0.56	0.35	1.37	2506	179	101	78	30	999	2	3	LU;IF;VS
56.4	4.71	8.69	5.77	17.65	2506	6298	3552	2746	30	999	2	3	HM;LS;VS
56.39	0.8	1.57	0.99	3.78	2506	931	525	406	30	999	2	3	HM;LOF;LS
56.32	0.2	0.4	0.25	0.98	2506	174	98	76	15	999	2	3	LU;LS;VS
56.25	6.5	11.66	7.9	22.24	2506	5858	3295	2563	30	15	10	3	IF;LS;VS
56.17	0.48	0.95	0.6	2.32	2506	486	273	213	20	15	2	3	HM;LOF;LS
56.16	0.44	0.87	0.55	2.13	2506	146	82	64	30	999	2	3	IF;LS;SFBP
56.09	7.1	12.61	8.61	23.57	2506	6309	3539	2770	30	15	2	3	IF;LS;VS
56	0.16	0.32	0.2	0.79	2506	100	56	44	15	999	2	3	LU;IF;VS
55.99	8.26	14.4	9.96	25.97	2506	8658	4848	3810	30	999	2	3	IF;LS;VS
55.98	1.4	2.73	1.73	6.35	2506	895	501	394	15	5	2	3	HM;LS;VS
55.59	0.48	0.95	0.6	2.31	2506	599	333	266	20	999	2	3	HM;LOF;LS
55.56	0.08	0.16	0.1	0.4	2506	36	20	16	30	999	2	3	HM;LU;LOF
55.51	2.87	5.46	3.55	11.9	2506	3174	1762	1412	15	15	10	3	HM;IF;LS
55.49	0.72	1.42	0.89	3.41	2506	474	263	211	30	999	2	3	HM;IF;LOF
55.4	8.18	14.26	9.86	25.71	2506	8491	4704	3787	30	999	10	3	IF;LS;VS
55.26	0.08	0.16	0.1	0.4	2506	38	21	17	30	5	2	3	HM;LU;LS
55.22	2.83	5.39	3.5	11.75	2506	2872	1586	1286	15	5	2	3	HM;IF;LS
55.1	3.35	6.32	4.13	13.48	2506	3864	2129	1735	15	999	2	3	HM;IF;LS
55	0.04	0.08	0.05	0.2	2506	80	44	36	20	15	2	3	IF;LS;SFBP
55	0.04	0.08	0.05	0.2	2506	80	44	36	20	999	2	3	IF;LS;SFBP
54.98	2.91	5.53	3.59	12.02	2506	3236	1779	1457	15	999	10	3	HM;IF;LS
54.86	5.67	10.27	6.9	20.05	2506	5518	3027	2491	15	999	10	3	IF;LS;VS
54.75	0.44	0.87	0.55	2.13	2506	263	144	119	15	15	2	3	HM;IF;LOF
54.75	0.44	0.87	0.55	2.13	2506	263	144	119	15	999	2	3	HM;IF;LOF
54.58	2.95	5.6	3.64	12.14	2506	4005	2186	1819	15	999	2	3	HM;LS;VS
54.55	0.08	0.16	0.1	0.4	2506	22	12	10	30	5	2	3	LU;IF;SFBP
54.45	0.4	0.79	0.5	1.94	2506	191	104	87	5	5	2	3	HM;IF;LOF
54.45	0.4	0.79	0.5	1.94	2506	191	104	87	5	15	2	3	HM;IF;LOF
54.45	0.4	0.79	0.5	1.94	2506	191	104	87	5	999	2	3	HM;IF;LOF
54.26	2.39	4.59	2.96	10.18	2506	3343	1814	1529	15	15	2	3	HM;LS;VS
53.96	0.4	0.79	0.5	1.94	2506	202	109	93	15	5	2	3	HM;IF;LOF
53.59	0.56	1.11	0.7	2.68	2506	334	179	155	20	15	2	3	HM;IF;LOF
53.59	0.56	1.11	0.7	2.68	2506	334	179	155	20	999	2	3	HM;IF;LOF
52.33	0.2	0.4	0.25	0.98	2506	86	45	41	30	15	2	3	LU;IF;VS
52.28	0.32	0.63	0.4	1.56	2506	285	149	136	30	999	2	3	LU;LS;VS
51.24	0.04	0.08	0.05	0.2	2506	121	62	59	20	15	2	3	IF;LOF;VS
48.44	0.04	0.08	0.05	0.2	2506	128	62	66	15	999	2	3	IF;LOF;VS
47.67	0.88	1.72	1.09	4.09	2506	516	246	270	30	15	2	3	IF;VS;SFBP
47.06	0.04	0.08	0.05	0.2	2506	17	8	9	15	5	2	3	HM;LU;LOF
47.06	0.04	0.08	0.05	0.2	2506	17	8	9	15	15	2	3	HM;LU;LOF
47.06	0.04	0.08	0.05	0.2	2506	17	8	9	15	999	2	3	HM;LU;LOF
47.04	0.2	0.4	0.25	0.98	2506	253	119	134	30	999	2	3	IF;LOF;VS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
47.01	0.12	0.24	0.15	0.59	2506	117	55	62	30	15	10	3	HM;IF;LS
46.79	0.16	0.32	0.2	0.79	2506	109	51	58	30	15	2	3	IF;LS;SFBP
46.15	0.08	0.16	0.1	0.4	2506	13	6	7	5	5	2	3	HM;LOF;LS
45.99	0.36	0.71	0.45	1.74	2506	137	63	74	15	5	2	3	HM;LU;IF
45	0.16	0.32	0.2	0.79	2506	240	108	132	30	15	2	3	IF;LOF;VS
43.16	0.32	0.63	0.4	1.55	2506	424	183	241	15	15	2	3	HM;LOF;LS
43.16	0.32	0.63	0.4	1.55	2506	424	183	241	15	999	2	3	HM;LOF;LS
42.97	0.12	0.24	0.15	0.59	2506	128	55	73	30	15	2	3	HM;IF;LS
42.17	0.04	0.08	0.05	0.2	2506	83	35	48	5	999	2	3	LU;IF;LS
41.72	0.08	0.16	0.1	0.4	2506	151	63	88	20	999	2	3	IF;LOF;VS
38.2	0.04	0.08	0.05	0.2	2506	89	34	55	15	15	2	3	IF;LOF;VS
36.36	0.12	0.24	0.15	0.59	2506	110	40	70	15	5	2	3	HM;LOF;LS
33.33	0.12	0.24	0.15	0.59	2506	210	70	140	15	999	2	3	LU;IF;LS
31.33	0.8	1.56	0.99	3.62	2506	150	47	103	5	5	2	3	IF;LS;VS
31.31	0.16	0.32	0.2	0.78	2506	99	31	68	15	15	2	3	LU;LS;VS
20	0.08	0.16	0.1	0.39	2506	20	4	16	30	15	2	3	LU;LS;VS
16.67	0.08	0.16	0.1	0.39	2506	36	6	30	5	999	2	3	HM;IF;VS
16.67	0.04	0.08	0.05	0.2	2506	30	5	25	15	15	2	3	LU;IF;LS
14.08	0.08	0.16	0.1	0.39	2506	71	10	61	20	15	2	3	LU;LS;VS
5.88	0.04	0.08	0.05	0.19	2506	17	1	16	30	15	2	3	HM;LS;VS
5.88	0.04	0.08	0.05	0.19	2506	17	1	16	20	5	2	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	20	5	2	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	30	15	2	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;LU;IF
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	20	5	2	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	30	15	2	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;LU;LOF
0	0	0	0	0	2506	0	0	0	5	5	2	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	15	5	2	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;LU;LS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;LU;LS
0	0	0	0	0	2506	0	0	0	5	5	2	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	5	15	2	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	5	999	2	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	15	5	2	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	20	5	2	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	30	15	2	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;LU;VS
0	0	0	0	0	2506	0	0	0	5	5	2	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	15	15	2	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	15	999	2	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	20	999	2	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	30	15	2	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	30	999	2	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;LU;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	20	5	2	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;IF;LOF

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	2	0	2	30	15	2	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;IF;LOF
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;IF;LS
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;IF;LS
0	0	0	0	0	2506	20	0	20	5	5	2	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;IF;VS
0	0	0	0	0	2506	30	0	30	5	15	2	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;IF;VS
0	0	0	0	0	2506	9	0	9	20	5	2	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;IF;VS
0	0	0	0	0	2506	9	0	9	30	15	2	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;IF;VS
0	0	0	0	0	2506	0	0	0	5	5	2	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	2	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;LOF;LS
0	0	0	0	0	2506	3	0	3	20	5	2	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;LOF;LS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;LOF;LS
0	0	0	0	0	2506	0	0	0	5	5	2	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	5	15	2	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	5	999	2	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	15	5	2	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	15	15	2	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	15	999	2	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	20	5	2	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	20	15	2	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	20	999	2	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	30	15	2	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	30	999	2	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;LOF;VS
0	0	0	0	0	2506	0	0	0	5	5	2	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	2	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	2	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	2	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	2	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	2	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	2	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	5	15	2	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	5	999	2	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;LS;VS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;LS;VS
0	0	0	0	0	2506	7	0	7	20	5	2	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;LS;VS
0	0	0	0	0	2506	0	0	0	5	5	2	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	2	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	2	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	2	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	2	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	2	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	2	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	2	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	2	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	2	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	2	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	2	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	HM;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	2	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	5	5	10	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	5	5	60	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	5	15	2	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	5	15	10	3	LU;IF;LOF

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	5	15	60	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	5	999	2	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	5	999	10	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	5	999	60	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	15	5	2	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	15	5	10	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	15	5	60	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	15	15	2	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	15	15	10	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	15	15	60	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	15	999	2	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	15	999	10	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	15	999	60	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	20	5	2	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	20	5	10	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	20	5	60	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	20	15	2	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	20	15	10	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	20	15	60	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	20	999	2	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	20	999	10	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	20	999	60	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	30	5	2	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	30	5	10	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	30	5	60	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	30	15	2	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	30	15	10	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	30	15	60	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	30	999	2	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	30	999	10	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	30	999	60	3	LU;IF;LOF
0	0	0	0	0	2506	0	0	0	5	5	2	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	5	5	10	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	5	5	60	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	5	15	2	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	5	15	10	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	5	15	60	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	5	999	10	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	5	999	60	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	15	5	2	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	15	5	10	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	15	5	60	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	15	15	10	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	15	15	60	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	15	999	10	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	15	999	60	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	20	5	10	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	20	5	60	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	20	15	10	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	20	15	60	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	20	999	10	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	20	999	60	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	30	5	10	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	30	5	60	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	30	15	10	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	30	15	60	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	30	999	10	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	30	999	60	3	LU;IF;LS
0	0	0	0	0	2506	0	0	0	5	5	2	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	5	5	10	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	5	5	60	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	5	15	2	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	5	15	10	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	5	15	60	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	5	999	2	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	5	999	10	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	5	999	60	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	15	5	10	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	15	5	60	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	15	15	10	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	15	15	60	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	15	999	10	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	15	999	60	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	20	5	10	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	20	5	60	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	20	15	10	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	20	15	60	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	20	999	10	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	20	999	60	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	30	5	10	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	30	5	60	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	30	15	10	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	30	15	60	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	30	999	10	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	30	999	60	3	LU;IF;VS
0	0	0	0	0	2506	0	0	0	5	5	2	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	LU;IF;SFBP

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	15	5	10	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	2	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	2	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	2	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	LU;IF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	2	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	5	5	10	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	5	5	60	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	5	15	2	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	5	15	10	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	5	15	60	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	5	999	2	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	5	999	10	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	5	999	60	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	15	5	2	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	15	5	10	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	15	5	60	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	15	15	2	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	15	15	10	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	15	15	60	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	15	999	2	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	15	999	10	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	15	999	60	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	20	5	2	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	20	5	10	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	20	5	60	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	20	15	2	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	20	15	10	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	20	15	60	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	20	999	2	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	20	999	10	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	20	999	60	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	30	5	2	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	30	5	10	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	30	5	60	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	30	15	2	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	30	15	10	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	30	15	60	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	30	999	2	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	30	999	10	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	30	999	60	3	LU;LOF;LS
0	0	0	0	0	2506	0	0	0	5	5	2	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	5	5	10	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	5	5	60	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	5	15	2	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	5	15	10	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	5	15	60	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	5	999	2	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	5	999	10	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	5	999	60	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	15	5	2	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	15	5	10	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	15	5	60	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	15	15	2	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	15	15	10	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	15	15	60	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	15	999	2	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	15	999	10	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	15	999	60	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	20	5	2	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	20	5	10	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	20	5	60	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	20	15	2	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	20	15	10	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	20	15	60	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	20	999	2	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	20	999	10	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	20	999	60	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	30	5	2	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	30	5	10	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	30	5	60	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	30	15	2	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	30	15	10	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	30	15	60	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	30	999	2	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	30	999	10	3	LU;LOF;VS
0	0	0	0	0	2506	0	0	0	30	999	60	3	LU;LOF;VS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	5	5	2	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	2	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	2	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	2	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	2	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	2	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	LU;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	2	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	5	5	10	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	5	5	60	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	5	15	2	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	5	15	10	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	5	15	60	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	5	999	2	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	5	999	10	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	5	999	60	3	LU;LS;VS
0	0	0	0	0	2506	9	0	9	15	5	2	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	15	5	10	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	15	5	60	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	15	15	10	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	15	15	60	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	15	999	10	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	15	999	60	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	20	5	10	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	20	5	60	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	20	15	10	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	20	15	60	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	20	999	10	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	20	999	60	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	30	5	10	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	30	5	60	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	30	15	10	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	30	15	60	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	30	999	10	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	30	999	60	3	LU;LS;VS
0	0	0	0	0	2506	0	0	0	5	5	2	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	2	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	2	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	2	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	2	3	LU;LS;SFBP

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	30	15	10	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	2	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	LU;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	2	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	2	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	2	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	2	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	2	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	2	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	LU;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	2	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	5	5	10	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	5	5	60	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	5	15	2	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	5	15	10	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	5	15	60	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	5	999	2	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	5	999	10	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	5	999	60	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	15	5	2	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	15	5	10	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	15	5	60	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	15	15	2	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	15	15	10	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	15	15	60	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	15	999	2	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	15	999	10	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	15	999	60	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	20	5	2	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	20	5	10	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	20	5	60	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	20	15	2	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	20	15	10	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	20	15	60	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	20	999	2	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	20	999	10	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	20	999	60	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	30	5	2	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	30	5	10	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	30	5	60	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	30	15	2	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	30	15	10	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	30	15	60	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	30	999	2	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	30	999	10	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	30	999	60	3	IF;LOF;LS
0	0	0	0	0	2506	0	0	0	5	5	2	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	5	5	10	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	5	5	60	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	5	15	2	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	5	15	10	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	5	15	60	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	5	999	2	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	5	999	10	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	5	999	60	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	15	5	2	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	15	5	10	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	15	5	60	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	15	15	10	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	15	15	60	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	15	999	10	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	15	999	60	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	20	5	2	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	20	5	10	3	IF;LOF;VS

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	20	5	60	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	20	15	10	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	20	15	60	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	20	999	10	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	20	999	60	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	30	5	2	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	30	5	10	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	30	5	60	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	30	15	10	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	30	15	60	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	30	999	10	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	30	999	60	3	IF;LOF;VS
0	0	0	0	0	2506	0	0	0	5	5	2	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	2	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	2	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	2	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	2	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	2	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	IF;LOF;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	5	5	60	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	5	15	10	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	5	15	60	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	5	999	10	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	5	999	60	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	15	5	60	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	15	15	60	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	15	999	60	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	20	5	60	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	20	15	60	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	20	999	60	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	30	5	60	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	30	15	60	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	30	999	60	3	IF;LS;VS
0	0	0	0	0	2506	0	0	0	5	5	2	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	IF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	2	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	IF;VS;SFBP

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	5	15	10	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	IF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	2	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	5	5	10	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	5	5	60	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	5	15	2	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	5	15	10	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	5	15	60	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	5	999	2	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	5	999	10	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	5	999	60	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	15	5	2	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	15	5	10	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	15	5	60	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	15	15	2	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	15	15	10	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	15	15	60	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	15	999	2	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	15	999	10	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	15	999	60	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	20	5	2	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	20	5	10	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	20	5	60	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	20	15	2	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	20	15	10	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	20	15	60	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	20	999	2	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	20	999	10	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	20	999	60	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	30	5	2	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	30	5	10	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	30	5	60	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	30	15	2	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	30	15	10	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	30	15	60	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	30	999	2	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	30	999	10	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	30	999	60	3	LOF;LS;VS
0	0	0	0	0	2506	0	0	0	5	5	2	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	2	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	2	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	2	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	2	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	LOF;LS;SFBP

precision (%)	recall (%)	f1score (%)	f2m (%)	f0.5m (%)	inc	pred	TP	FP	Δ	α	β	γ	algo
0	0	0	0	0	2506	0	0	0	30	999	2	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	LOF;LS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	2	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	2	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	2	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	2	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	2	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	2	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	LOF;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	2	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	10	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	5	60	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	2	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	10	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	15	60	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	2	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	10	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	5	999	60	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	2	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	10	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	5	60	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	2	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	10	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	15	60	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	2	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	10	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	15	999	60	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	2	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	10	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	5	60	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	2	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	10	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	15	60	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	2	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	10	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	20	999	60	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	2	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	10	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	5	60	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	2	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	10	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	15	60	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	2	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	10	3	LS;VS;SFBP
0	0	0	0	0	2506	0	0	0	30	999	60	3	LS;VS;SFBP

B

Glossary

Events - A behavior of metrics spotted by some algorithm. These are not necessarily abnormal behavior, they can correspond to normal metric behavior as well. An event is defined as a timestamp value at which this behavior started.

Event Types - Algorithms used for event extraction. An event of type *A*, is an event that was extracted using the algorithm *A*.

Incidents - Unexpected event that disrupts business and operational processes or/and reduces the quality of services offered to the end user.

Service Engineer - Engineer responsible for the reliability of the running services. Examines systems and services and makes updating, modifying or replacing decisions. These can be directly translated to Site Reliability Engineers, DevOps or Monitoring Engineers.

Fingerprint - A technological trace of events in a defined time window. Ex: Incident fingerprint is a set of events and their types, that are proven to lead to an IT incident.

Metric - List of datapoints. Each datapoint holds at least a timestamp and a value.

Prediction interval time - Elapsed time between the moment an incident is predicted by the system and its occurrence. Can also be seen as the time the service engineer has got to perform preventive maintenance until the incident occurs. $interval = t_{incident} - t_{incPrediction}$