Lecture 9: Sequence-to-Sequence Models

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Deep Learning Course, Winter 2022-2023

Today's Roadmap

Lecture 8 focused on sequence tagging and sequence generation. Today we focus on sequence-to-sequence models.

- Machine translation
- Sequence vector representation
- Encoder-decoder architecture
- Sequence matrix representation
- Attention mechanism
- Encoder-decoder with attention

Sequence-to-Sequence

Sequence-to-sequence models map a source sequence (of arbitrary length) into a target sequence (also of arbitrary length)

This differs from sequence tagging, where the two sequences are of the same length

Example: Machine Translation

Goal: translate a **source sentence** x in one language into a **target sentence** y in another language.

Example (Portuguese to English):

x: *"A ilha de Utopia tem 200 milhas de diâmetro na parte central."*

$$\downarrow$$

y: *"The island of Utopia is two hundred miles across in the middle part."*

Outline

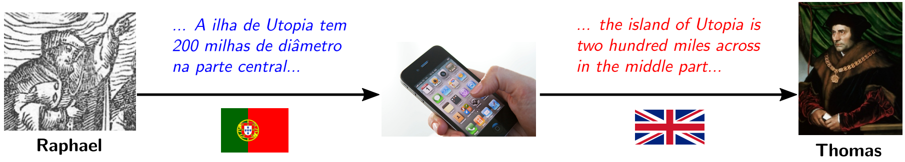
1950s: Early Machine Translation

(Source: `https://youtu.be/K-HfpsHPmvw`)

- MT research began in early 1950s
- Mostly Russian-English (motivated by the Cold War!)
- Systems were mostly rule-based, using a bilingual dictionary

Noisy Channel Model (Shannon and Weaver, 1949)

"When I look at an article in Russian, I say: 'This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode.' "


... A ilha de Utopia tem
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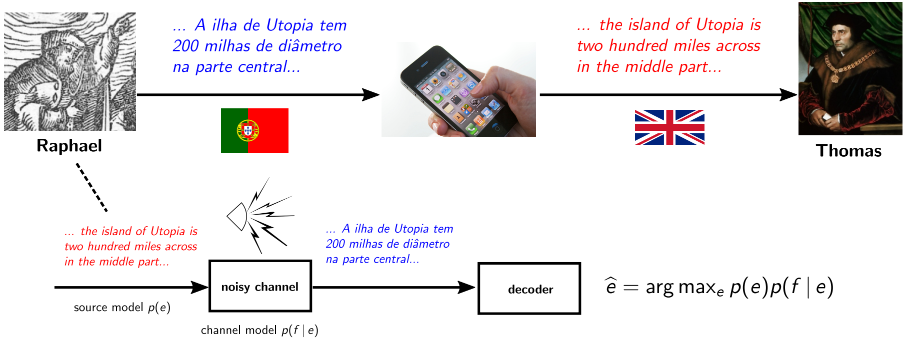
Raphael
Thomas



A very simple model: builds a generative story that works "backwards" (flips source and target, via Bayes law)

Yet, the dominant paradigm in MT for several decades (until 2014)

In 2014: neural machine translation (later)

1990s-2010s: Statistical Machine Translation

Goal: find the "best" (most probable) English sentence y, given the Russian sentence x

$$\widehat{y} = \arg\max_{y} \mathbb{P}(y \mid x)$$

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- **Translation model:** models how words/phrases are translated (learnt from **parallel** data)
- **Language model:** models how to generate fluent English (learn from **monolingual** data)

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- Need large amounts of monolingual data
  (easy to get for most languages).

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- We covered language models in previous lectures:
  - Markov models (maybe with *smoothing*)
  - Neural language models
  - ...

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- Pick your favorite!

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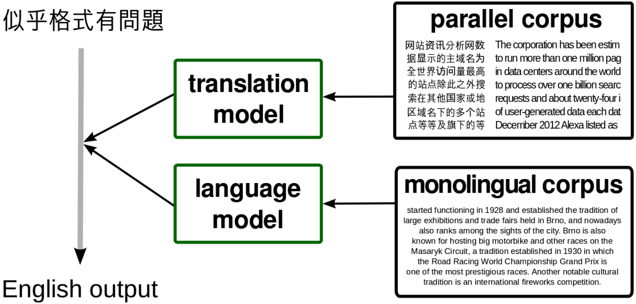
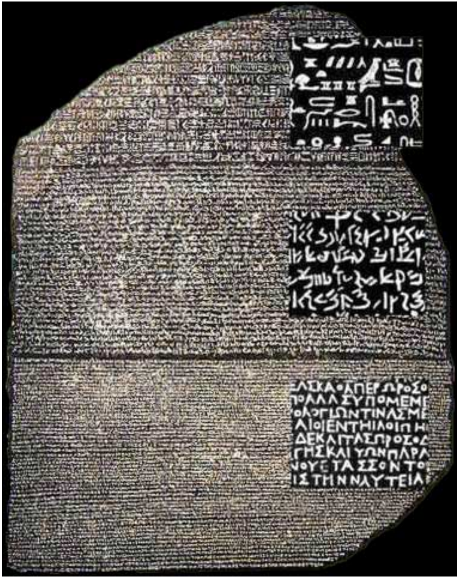


Rosetta Stone



- (Re-)discovered in 1799 near Alexandria
- Parallel corpora: ancient Egyptian, demotic Egyptian, ancient Greek

Europarl

- Proceedings from the European parliament sessions, translated into all EU official languages
- Around 1M parallel sentences for some language pairs
- Other corpora: Hansard, MultiUN, News Commentary, Wikipedia, OpenSubtitles, Paracrawl, ...

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where $\boldsymbol{a}$ are word alignments, i.e., word-level correspondences between sentence x and sentence y

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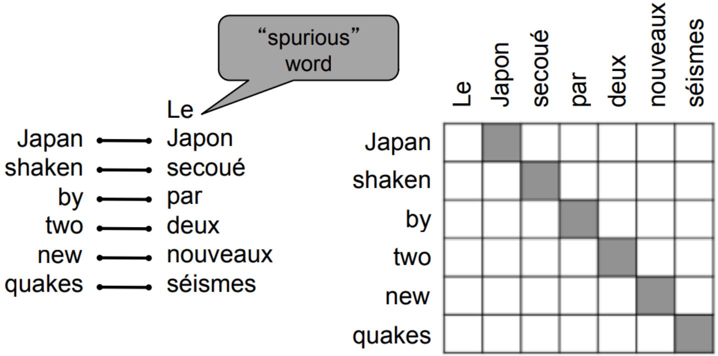
- Word alignments are generally a latent/missing variable at training time, and need to be marginalized over at test time,

$$\mathbb{P}(x \mid y) = \sum_{\boldsymbol{a}} \mathbb{P}(x, \boldsymbol{a} \mid y),$$

Word Alignments

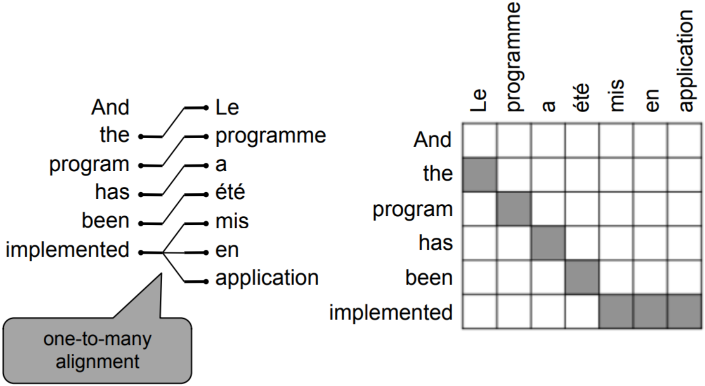
Example for English-French:



Some words may be unaligned (no counterpart in the other language)!

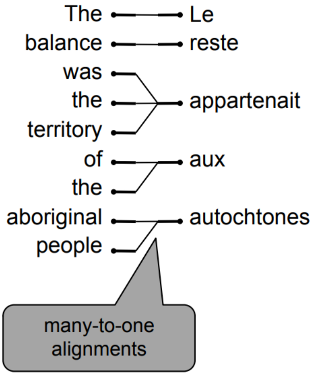
Word Alignments

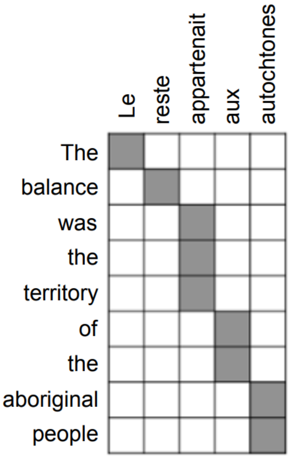
Alignment can be one-to-many (word fertility):



Word Alignments

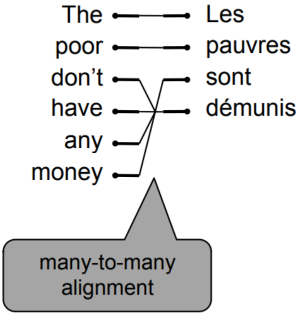
Alignment can be many-to-one:

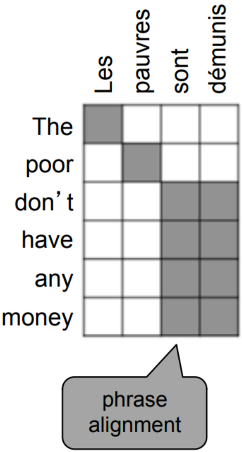




Word Alignments

Alignment can be many-to-many (phrase-level): phrase-based MT:





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- Learn $\mathbb{P}(x, \boldsymbol{a} \mid y)$ as a combination of several factors:
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  - Probability of particular words aligning (co-occurrence, relative position, etc.)
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- This has lead to IBM models 1, 2, 3, 4, ...

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- To search the best translation, we need to solve

$$\widehat{y} = \arg\max_{y} \sum_{\boldsymbol{a}} \mathbb{P}(x, \boldsymbol{a} \mid y)\, \mathbb{P}(y),$$

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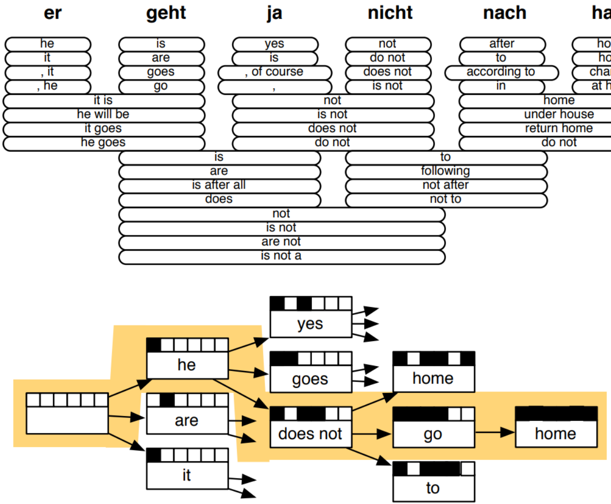
- Enumerating all possible hypothesis and alignments is intractable.

- Typical approach: heuristic search to gradually build the translation, discarding hypotheses that are too low probability.

Searching for the Best Translation



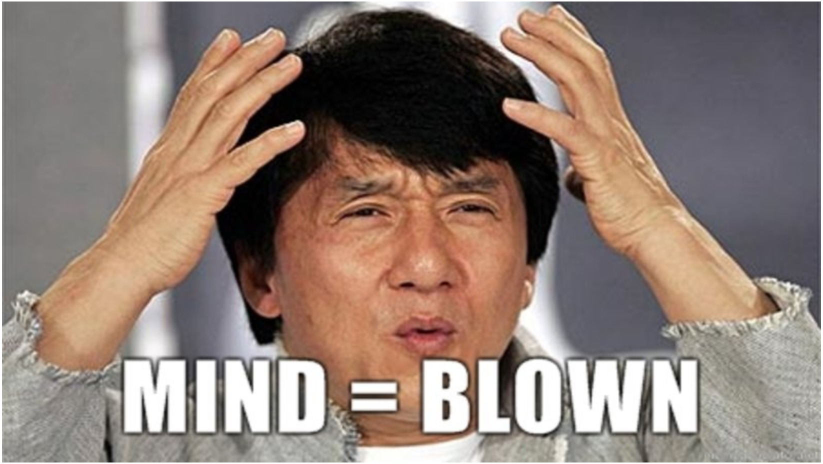
(Slide credit: `https://web.stanford.edu/class/cs224n/lectures/lecture10.pdf`)

Summarizing: Statistical Machine Translation

We only glimpsed the tip of the iceberg: SMT is (was?) a huge research field.

- The best systems are extremely complex;
- Usually a big pipeline, with many separately-designed subcomponents (translation and language model are only two examples);
- Lots of feature engineering;
- System design is very language-dependent;
- Requires compiling and maintaining resources (e.g., phrase tables);
- Models are storage/memory hungry;
- Lots of human effort to maintain.

2014: Neural Machine Translation



Outline

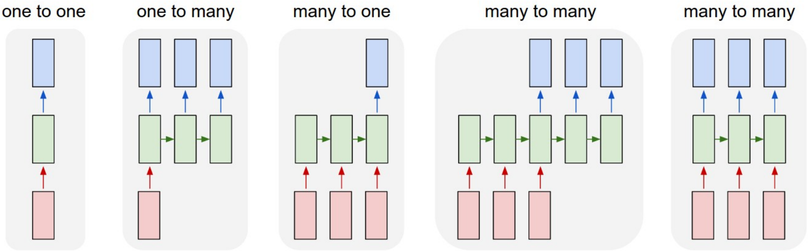
What is Neural Machine Translation (NMT)?

- NMT = MT with a single neural network
- End-to-end training with parallel data (no more complex pipelines!)
- The underlying architecture is an encoder-decoder (also called a **sequence-to-sequence model**)
- In fact, NMT is also statistical; however, historically, "statistical MT" refers to non-neural models, and NMT to NN-based models.

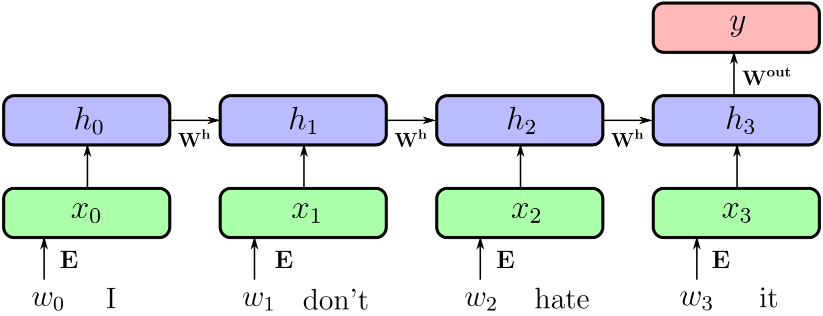
Outline

Recap: Recurrent Neural Networks

Lecture 9 covered RNNs and showed they can have several uses...

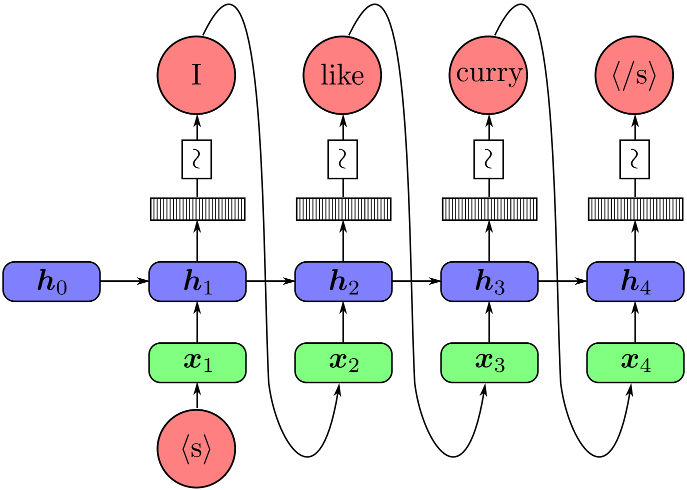


Recap: RNNs for Pooled Classification



(Slide credit: Ollion & Grisel)

Recap: Auto-Regressive RNNs for Sequence Generation



Sequence-to-Sequence Learning (Cho et al., 2014; Sutskever et al., 2014)

- Can we put the two things together?

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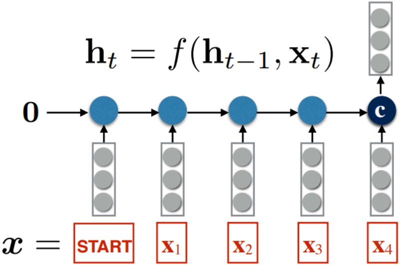
- Can we put the two things together?

- Yes!

  1. Encoder RNN encodes source sentence, generating a vector state
  2. Decoder RNN generates target sentence conditioned on vector state.

Encode a Sequence as a Vector



(Slide credit: Chris Dyer)

What is a vector representation of a sequence $\boldsymbol{x}$?

$$\boldsymbol{c} = \text{RNN}(\boldsymbol{x})$$

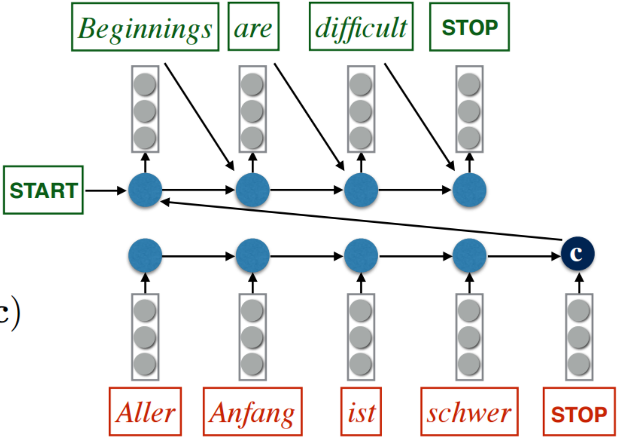
What is the probability of a sequence $\boldsymbol{y} \mid \boldsymbol{x}$?

$$\boldsymbol{y} \mid \boldsymbol{x} \sim \text{RNNLM}(\boldsymbol{c})$$

Encoder-Decoder Architecture

$$\mathbf{c} = \mathrm{RNN}(\boldsymbol{x})$$

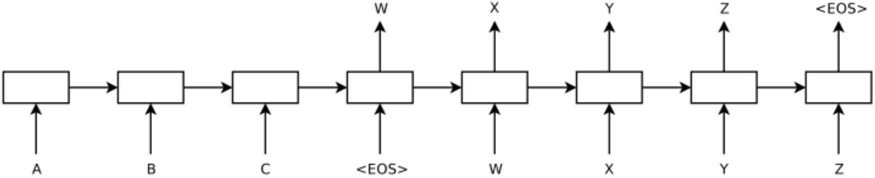
$$\boldsymbol{y} \mid \mathbf{c} \sim \mathrm{RNNLM}(\mathbf{c})$$



(Slide credit: Chris Dyer)

Encoder-Decoder Architecture

Another way of depicting it (from Sutskever et al. (2014)):



Some Problems

- If the source sentence is long, the encoder may forget the initial words and the translation will be degraded
  - Cheap solution: reverse the source sentence.

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  - Cheap solution: reverse the source sentence.

- The decoder does greedy search—this leads to error propagation
  - Solution: beam search.

Beam Search

Ideally we want to find the target sentence y that maximizes

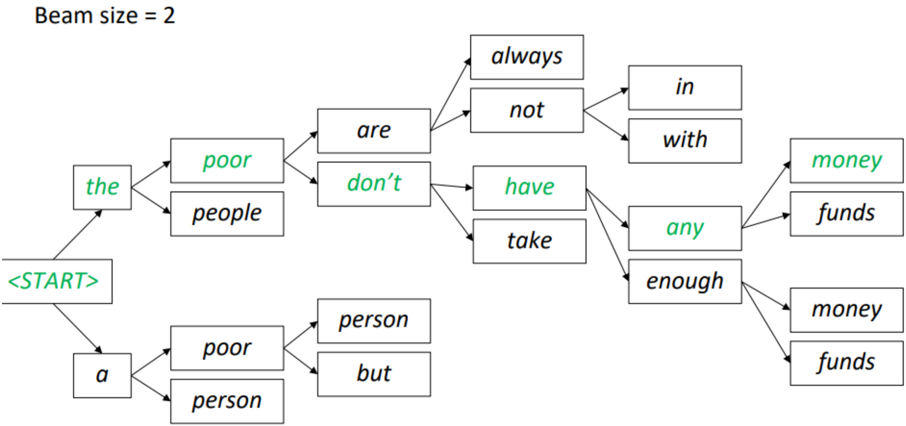
$$\hat{y} = \arg\max_{y} \mathbb{P}(y \mid x) = \arg\max_{y_1,\ldots,y_L} \mathbb{P}(y \mid x) = \prod_{i=1}^{L} \mathbb{P}(y_i \mid y_{1:i-1}, x)$$

Enumerating all y is intractable!

Beam Search:

- Approximate search strategy
- At each decoder step, keep track of the k most probable partial translations; discard the rest
- k is the beam size
- For $k = 1$, we have greedy search.

Beam Search



(Slide credits: Chris Manning)

Beam Search

- A little better than strictly greedy search, but still greedy
- Linear runtime as a function of beam size k: speed/accuracy trade-off
- In practice: beam sizes $\sim$ 4–12

Some Additional Tricks

From Sutskever et al. (2014):

- Deep LSTMs
- Reversing the source sentence

Method	test BLEU score (ntst14)
Bahdanau et al. [2]	28.45
Baseline System [29]	33.30
Single forward LSTM, beam size 12	26.17
Single reversed LSTM, beam size 12	30.59
Ensemble of 5 reversed LSTMs, beam size 1	33.00
Ensemble of 2 reversed LSTMs, beam size 12	33.27
Ensemble of 5 reversed LSTMs, beam size 2	34.50
Ensemble of 5 reversed LSTMs, beam size 12	**34.81**

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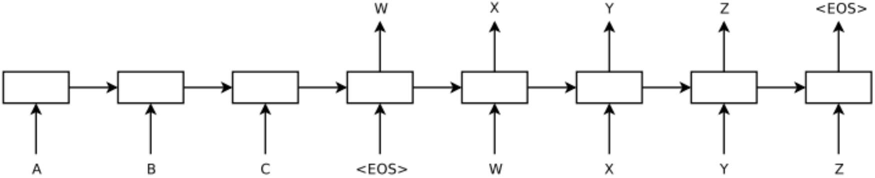
At run time:

- Beam search;
- Ensembling: combine N independently trained models and obtaining a "consensus" (always helps!).

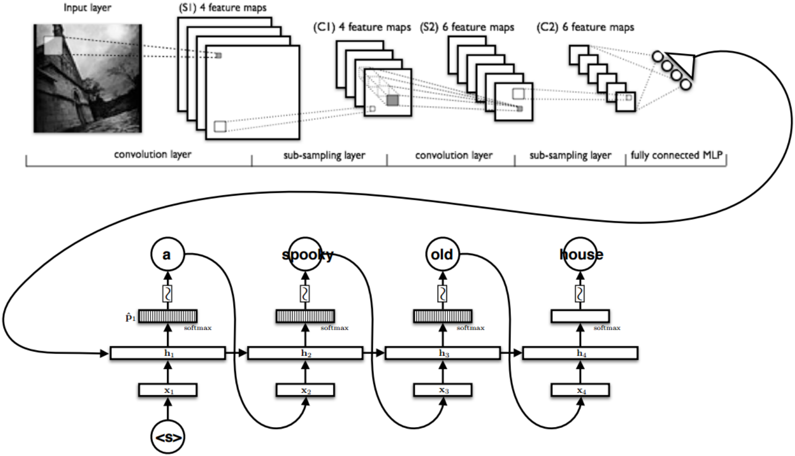
End-to-End Neural Machine Translation

- Previous statistical machine translation models were complicated pipelines (word alignments $\rightarrow$ phrase table extraction $\rightarrow$ language model $\rightarrow$ decoding a phrase lattice);
- Alternative: end-to-end NMT uses a simple encoder-decoder;
- Doesn't quite work yet, but gets close to top performance



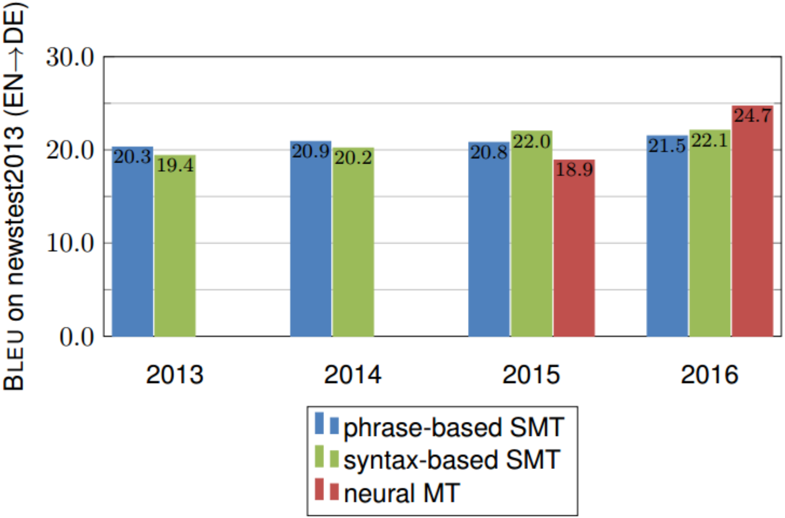
Caption Generation

Works for image inputs too!



(Slide credit: Chris Dyer)

Progress in Machine Translation



Slide credit: Rico Sennrich

NMT: A Success Story

- Neural MT went from a fringe research activity in 2014 to the leading standard method in 2016
  - 2014: First seq2seq paper published
  - 2016: Google Translate switches from SMT to NMT
- This is amazing!
- SMT systems, built by hundreds of engineers over many years, outperformed by NMT trained by a handful of engineers in a few months.

So Is Machine Translation Solved?

No!

Many difficulties and open research fronts remain:

- Out-of-vocabulary words
- Domain mismatch between train and test data
- Low-resource language pairs
- Specific domains (medical, scientific, legal, ...)
- Maintaining context over longer text (coming next!)

Limitations

A possible conceptual problem:

- Sentences have unbounded lengths
- Vectors have finite capacity

"You can't cram the meaning of a whole %&$# sentence into a single $&# vector!" (Ray Mooney)

A possible practical problem:

- Distance between "translations" and their sources are large—can LSTMs help?

Outline

1. Statistical Machine Translation

2. Neural Machine Translation

    Encoder-Decoder Architecture

    Encoder-Decoder with Attention

3. Conclusions

Encode Sentences as Matrices, Not Vectors

Problem with the fixed-size vector model:

- Sentences are of different sizes but vectors are of the same size
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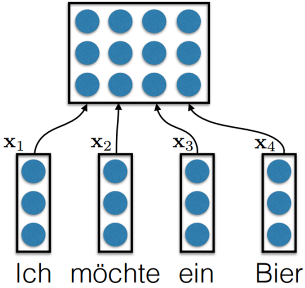
Solution: use matrices instead!

- Fixed number of rows, but number of columns depends on the number of words
- Then, before generating each word in the decoder, use an attention mechanism to condition on the relevant source words only

How to Encode a Sentence as a Matrix?

First shot: define the sentence words' vectors as the columns



(Image credit: Chris Dyer)

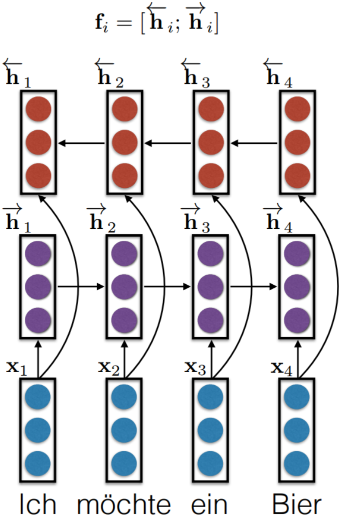
- Not very effective: word vectors carry no context information

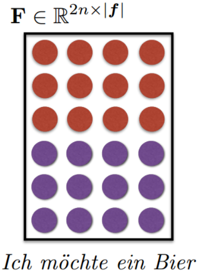
How to Encode a Sentence as a Matrix?

Other strategies:

- Convolutional NNs (Kalchbrenner et al., 2014) capture context;
- **Typical choice:** bidirectional LSTMs (Bahdanau et al., 2015);
- Later: transformer networks (Vaswani et al., 2017).

Bidirectional LSTM Encoder





(Slide credit: Chris Dyer)

Generation from Matrices

- We now have a matrix $\boldsymbol{F}$ representing the input.
- How to generate from it?
- **Answer:** use attention! (Bahdanau et al., 2015)
- Attention is the neural counterpart of word alignments.

Generation from Matrices with Attention

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- The input columns weighting at each time-step ($\boldsymbol{a}_t$) is called the attention distribution.

Attention Mechanism (Bahdanau et al., 2015)

Let $\boldsymbol{s}_1, \boldsymbol{s}_2, \ldots$ be the states produced by the decoder RNN

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When predicting the t-th target word:

1. Compute "similarity" with each of the source words:

$$z_{t,i} = \boldsymbol{v}^T \boldsymbol{g}(\boldsymbol{W}\boldsymbol{h}_i + \boldsymbol{U}\boldsymbol{s}_{t-1} + \boldsymbol{b}), \quad \text{for } i = 1, ..., L$$

   where $\boldsymbol{h}_i$ is the i-th column of $\boldsymbol{F}$ (representation of the i-th source word) and $\boldsymbol{v}$, $\boldsymbol{W}$, $\boldsymbol{U}$, $\boldsymbol{b}$ are model parameters

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3. Use attention to compute input conditioning state $\boldsymbol{c}_t = \boldsymbol{F}\boldsymbol{a}_t$

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Let $\boldsymbol{s}_1, \boldsymbol{s}_2, \ldots$ be the states produced by the decoder RNN

When predicting the t-th target word:

1. Compute "similarity" with each of the source words:

$$z_{t,i} = \boldsymbol{v}^T \boldsymbol{g}(\boldsymbol{W}\boldsymbol{h}_i + \boldsymbol{U}\boldsymbol{s}_{t-1} + \boldsymbol{b}), \quad \text{for } i = 1, ..., L$$

   where $\boldsymbol{h}_i$ is the i-th column of $\boldsymbol{F}$ (representation of the i-th source word) and $\boldsymbol{v}$, $\boldsymbol{W}$, $\boldsymbol{U}$, $\boldsymbol{b}$ are model parameters

2. From $\boldsymbol{z}_t = (z_{t,1}, \ldots, z_{t,L})$ compute attention $\boldsymbol{a}_t = \text{softmax}(\boldsymbol{z}_t)$
3. Use attention to compute input conditioning state $\boldsymbol{c}_t = \boldsymbol{F}\boldsymbol{a}_t$
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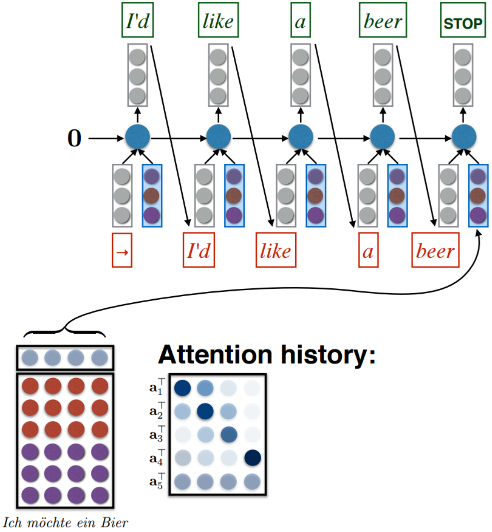
5. Predict $y_t \sim p(y_t \mid \boldsymbol{s}_t)$

Encoder-Decoder with Attention



(Slide credit: Chris Dyer)

Putting It All Together

obtain input matrix $\boldsymbol{F}$ with a bidirectional LSTM
$t = 0$, $y_0 = \text{START}$ (the start symbol)
$\boldsymbol{s}_0 = \boldsymbol{w}$ (learned initial state)
repeat
  $t = t + 1$
  $\boldsymbol{z}_t = \boldsymbol{v}^T \boldsymbol{g}(\boldsymbol{W}\boldsymbol{F} + \boldsymbol{U}\boldsymbol{s}_{t-1} + \boldsymbol{b})$
  compute attention $\boldsymbol{a}_t = \text{softmax}(\boldsymbol{z}_t)$
  compute input conditioning state $\boldsymbol{c}_t = \boldsymbol{F}\boldsymbol{a}_t$
  $\boldsymbol{s}_t = \text{RNN}(\boldsymbol{s}_{t-1}, [\boldsymbol{E}(y_{t-1}), \boldsymbol{c}_t])$
  $y_t \sim \text{softmax}(\boldsymbol{P}\boldsymbol{s}_t + \boldsymbol{b})$
until $y_t \neq \text{STOP}$

Notice that each y_t is conditioned (depends on) $y_{t-1}, \ldots, y_1$ and $\boldsymbol{x}$.

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- Some following work adds some "structural" biases (Luong et al., 2015; Cohn et al., 2016)
- Other works constrains the amount of attention each word can receive (based on its fertility): Malaviya et al. (2018).

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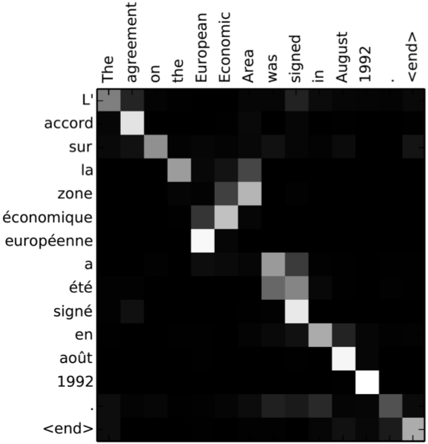
- This is good because we never explicitly trained a word aligner; the network learns it by itself!

Attention Map



Dzmitry Bahdanau, KyungHuyn Cho, and Yoshua Bengio. ***Neural Machine Translation by Jointly Learning to Translate and Align****. ICLR'15.*

Example: Machine Translation

Some positive examples where NMT has impressive performance:

Source	When asked about this, an official of the American administration replied: "The United States is not conducting electronic surveillance aimed at offices of the World Bank and IMF in Washington."	
PBMT	Interrogé à ce sujet, un responsable de l'administration américaine a répondu : "Les Etats-Unis n'est pas effectuer une surveillance électronique destiné aux bureaux de la Banque mondiale et du FMI à Washington".	3.0
GNMT	Interrogé à ce sujet, un fonctionnaire de l'administration américaine a répondu: "Les États-Unis n'effectuent pas de surveillance électronique à l'intention des bureaux de la Banque mondiale et du FMI à Washington".	6.0
Human	Interrogé sur le sujet, un responsable de l'administration américaine a répondu: "les Etats-Unis ne mènent pas de surveillance électronique visant les sièges de la Banque mondiale et du FMI à Washington".	6.0
Source	Martin told CNN that he asked Daley whether his then-boss knew about the potential shuffle.	
PBMT	Martin a déclaré à CNN qu'il a demandé Daley si son patron de l'époque connaissaient le potentiel remaniement ministériel.	2.0
GNMT	Martin a dit à CNN qu'il avait demandé à Daley si son patron d'alors était au courant du remaniement potentiel.	6.0
Human	Martin a dit sur CNN qu'il avait demandé à Daley si son patron d'alors était au courant du remaniement éventuel.	5.0

(From Wu et al. (2016))

Example: Machine Translation

... But also some negative examples:

- Dropping source words (lack of attention)
- Repeated source words (too much attention)

Source:	1922 in Wien geboren, studierte Mang während und nach dem Zweiten Weltkrieg Architektur an der Technischen Hochschule in Wien bei Friedrich Lehmann.
Human:	Born in Vienna in 1922, Meng studied architecture at the Technical University in Vienna under Friedrich Lehmann *during and after the second World War.*
NMT:	*Born in Vienna in 1922, Mang studied architecture at the Technical College in Vienna with Friedrich Lehmann.
Source:	Es ist schon komisch, wie dies immer wieder zu dieser Jahreszeit auftaucht.
Human:	It's funny how this always comes up at *this time* of year.
NMT:	*It's funny how **this time** to come back to **this time** of year.

Example: Caption Generation

Attention over images:

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.

A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

(Slide credit to Yoshua Bengio)

A More Extreme Example...

(Slide credit to Dhruv Batra)

Attention and Memories

Attention is used in several problems, sometimes under different names:

- image caption generation (Xu et al., 2015)
- speech recognition (Chorowski et al., 2015)
- memory networks for reading comprehension (Sukhbaatar et al., 2015; Hermann et al., 2015)
- neural Turing machines and other "differentiable computers" (Graves et al., 2014; Grefenstette et al., 2015)

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Other Attentions

- Can we have more interpretable attention? Closer to hard alignments?
- Can we upper bound how much attention a word receives? This may prevent a common problem in neural MT, repetitions
- Sparse attention via sparsemax (Martins and Astudillo, 2016)
- Constrained attention with constrained softmax/sparsemax (Malaviya et al., 2018)

Outline

Conclusions

- Machine translation is a key problem in AI since the 1950s
- Neural machine translation with sequence-to-sequence models was a breakthrough
- Representing a full sentence with a single vector is a bottleneck
- Attention mechanisms allow focusing on different parts of the input and solve the bottleneck problem
- Other applications beyond MT: speech recognition, image captioning, etc.

Thank you!

Questions?

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