## Phd Program in Transportation

## Transport Demand Modeling

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## Session 1

Hazard-Based Duration Models
Nonparametric, Semiparametric and Parametric models

## Outline of the Module on Hazard-Based Duration Models

Our objectives for this session:

- Background information: statistical analysis of road safety data
- Characteristics of duration data
- Nonparametric models
- Semiparametric models
- Fully Parametric models
- Build your first Kaplan-Meier estimate (using R)
- Build your first Cox proportional-hazards model (using R)


## How big is the road safety problem?

- Have you ever been injured in a crash?
- Have any of your family members or friends been injured or killed in a crash?
Do you know someone who has been injured or killed in a crash?


Key facts about road safety

Source: http://www.who.int/roadsafety

## Perspectives on road safety



Motorists' complaints
Experts' judgement

## Objective safety



## Expected or actual

 crash frequency and severity
## How safe is this road?



## How do we evaluate alternatives?



## Good news

## －There is a lot of information on substantive safety

Sinalização Vertical
Sinalização de Nós de Ligação
Sinalização de Rotundas
Sinalização de Cruzamentos e Entroncamentos
Sinalização de Orientação－Sistema Informativo
Instrução Técnica sobre a utilização da Sinalizaçao de Mensagem Variável
Sinalização Vertical－Características
Princípios da Sinalização do Trânsito e Regimes de Circulação
Sinalização Vertical－Critérios de Utilização
Sinalização Vertical－Critérios de Colocação
Destinos Principais e Pólos Não Classificados
Pavimentação
Construção e Reabilitação de Pavimentos－Agregados
Construção e Reabilitação de Pavimentos－Indicadores de Estado de Conservação dos Pavimentos
Construção e Reabilitação de Pavimentos－Reciclagem de Pavimentos
Cirectivas para a concepção de pavimentos－Critérios de dimensionamento
Construção e Reabilitação de Pavimentos－Ligantes Betuminosos
Manuais
Recomendações para definição e sinalização de limites de velocidade máxima
Área Adjacente à Faixa de Rodagem－Manual sobre Aspectos de Segurança
Sistemas de Retenção Rodoviários－Manual de Aplicação
Inspeções de Segurança Rodoviária－Manual de Aplicação

FEUP

Marcação Rodoviária
Marcas Rodoviárias－Características Dimensionais，Critérios de Utilização e Colocação

Sistemas de Retenção Rodoviários－Manual de Aplicação
Inspecções de Segurança Rodoviária－Manual de Aplicação

Guias de Procedimentos

| 完 | Apresentação dos Projectos das Condições de Execução das Obras | Metodologia a seguir por Concessionárias em processos PCEO－Projectos das Condições de Execução das Obras，para intervenções com duração superior a 72 horas，previstos na Lei n．${ }^{0}$ 24／2007，de 18 de Julho e no seu D．R．n．${ }^{\circ}$ 12／2008，de 9 de Junho． |
| :---: | :---: | :---: |
| 园 | Auditorias de Segurança Rodoviária aos Projectos de Infra－estruturas Rodoviárias | Orientações técnicas sobre a realização de Auditorias de Segurança Rodoviária a projectos de infra－ estruturas，definir o seu âmbito de aplicação e a forma como devem ser promovidas pelas entidades gestoras das vias． |
| 园 | Colocação de Sinalização Turístico－Cultural／Património em Auto－Estradas | Metodologia a seguir para instalação，na rede rodoviária nacional，de sinalização turístico－cultural． |
| Notas Técnicas |  |  |
| 园 | Levantamento das Características dos Agregados produzidos em Portugal |  |
| 完 | Ensaios Comparação Interlaboratorial Avaliação Sensibilidade à Água Misturas Betuminosas Compactadas |  |
| 园 | InIR Apoia Instituto Sueco de Investigação das Estradas em Estudo sobre Acalmia de Tráfego |  |
| 园 | Inquérito a utentes de estradas europeias－ 2006 |  |
| 园 | Guia para as administraçoes rodoviárias intervenientes no processo de normalização |  |
| 园 | Abordagem Integrada à Segurança de Túneis Rodoviários |  |
| 园 | Integração dos Indicadores de Desempenho |  |

－Apresentação dos Projectos das Metodologia a seguir por Concessionárias em processos PCEO－Projectos das Condições de Execusção Obras
Auditorias de Segurança Rodoviária aos Projectos de
Colocação de Sinalização Turístico－Cultural／Património

Notas Técnicas
http：／／www．imt－ip．pt／sites／IMTT／Portugues／InfraestruturasRodoviarias／InovacaoNormalizacao／Paginas／DivulgacaoTecnica．aspx

## Bad news

- Many study results are problematic
> Poor study design \& analysis
> Highly variable results
> Limited reproduction of results
> Most sources are regarding normative safety


## System approach

- Understand the system as a whole.
> Understand interactions between different components.
> Consider not only underlying factors, but also role of different agencies and actors in prevention efforts.



## Major risk factors

- Factors influencing exposure to risk
$>$ economic factors
> demographic factors
> land-use planning practices
$>$ traffic mix
$>$ road function versus design and layout
$\square$ Risk factors influencing crash involvement
> speed
> alcohol or drugs
> fatigue
$>$ gender
$>$ vehicle defects
> age
> vulnerable road users


## Major risk factors

- Risk factors influencing crash severity
> speed
> seat-belts, child restraints
> helmets
> Non-crash protective roadside objects
> insufficient vehicle crash protection
> alcohol and other drugs
- Risk factors influencing post-crash outcome of injuries
$>$ delay in detecting crash
> delay in transport to a health facility
> fire resulting from collision
> leakage of hazardous materials
> alcohol and other drugs
> rescue, extraction, evacuation
> poor trauma care and rehabilitation


## Measuring objective safety

- Why Analyze?
> Identify crash-prone locations
> Hoping that data analysis will suggest effective countermeasures
$>$ Evaluate the effectiveness of an implemented countermeasure
> ...
- Traditional Analysis Approaches:
> Models of crash frequency over some specified time and space
$>$ Models of crash-injury severity (which is conditional the crash having occurred)
> Some modeling approaches have combined the two (frequency and severity)


## Crash Data Modeling

- Crash Frequency Models
> Study crash frequency over some specified time and space
$>$ Various count-data and other methods have been used
> Explanatory variables:
- Traffic conditions
- Roadway conditions
- Weather conditions
- Crash Severity Models
>Study injury severities of specific crashes
> Various discrete-outcome and other methods have been used
> Explanatory variables:
- Traffic Conditions, Roadway conditions, Weather conditions
- Specific crash data: Vehicle information, Occupant information, Crash specific characteristics


## Data

- Traditional Crash Data
> Available mostly from police and possibly other reports
> Provide basic data on the characteristics of the crash
- Road conditions
- Estimates of injury severity
- Occupant characteristics (age, gender)
- Vehicle characteristics
- Crash description, primary cause, etc.
- Emerging Data Sources
> Data from driving simulators
$>$ Data from naturalistic driving
> Data from automated vehicles
> Data from other sources


## Emerging data sources

- Naturalistic Driving Data
> Extensively instrumented conventionally operated vehicles
- Simulator Data
> Massive amounts of data collected from driving simulators
- Automated Vehicle Data
> Including automated vehicle performance and response of drivers of conventional vehicles
- Others


## Methodological Barriers

- Unobserved Heterogeneity
> Many factors influencing the frequency and severity of crashes are simply not observed
- Endogeneity
> Factors correlated with frequency and severity of crashes
- Temporal Correlation
>Crashes in occurring near the same or similar times will share correlation due to unobserved factors associated with time (precise weather conditions, similar sun angle, etc.)
- Spatial Correlation
> Crashes in close spatial proximity will share correlation due to unobserved factors associated with space (unobserved visual distractions, sight obstructions, etc.)
- Omitted Variables
> Many crash frequency models use few explanatory variables (some only use traffic)


## Duration Models

- In many instances, one encounters the need to study the elapsed time until the occurrence of an event or the duration of an event. Data such as these are referred to as duration data, and are encountered often in the field of transportation research.
> Examples include the time until a vehicle accident occurs, the time between vehicle purchases, the time devoted to an activity (shopping, recreational, etc.), the time until the adoption of new transportation technologies, or the distance traveled until a vehicle stops.
- To study duration data, hazard-based models are applied to study the conditional probability of a time duration ending at some time $t$, given that the duration has continued until time $t$.
> Hazard-based duration models can account for the possibility that the likelihood of a driver becoming involved in an accident may change over time.


## Duration Models

- Cumulative distribution function $F(t)$ :

$$
F(t)=P(T<t)
$$

> where $P$ denotes probability, $T$ is a random time variable, and $t$ is some specified time.

- The density function corresponding to this distribution function (the first derivative of the cumulative distribution with respect to time) is:

$$
f(t)=\frac{d F(t)}{d t}
$$

## Duration Models

- And the hazard function is:

$$
h(t)=\frac{f(t)}{1-F(t)}
$$

> where $h(t)$ is the conditional probability that an event will occur between time $t$ and $t+d t$, given that the event has not occurred up to time $t$.

$$
h(t)=\lim _{\delta \rightarrow 0} \frac{\operatorname{pr}(t<T<t+\delta \mid T>t)}{\delta}
$$

- The cumulative hazard $H(t)$ is the integrated hazard function, and provides the cumulative rate at which events are ending up to or before time t .

$$
H(t)=\int_{0}^{t} h(t) d t
$$

## Duration Models

- The survivor function (the probability that a duration is greater than or equal to some specified time $t$ ) is:

$$
S(t)=P(T \geq t)
$$

- If one of these functions is known any of the others are readily obtained.

$$
\begin{aligned}
& S(t)=1-F(t)=1-\int_{0}^{t} f(t) d t=E X P[-H(t)] \\
& f(t)=\frac{d}{d t} F(t)=h(t) E X P[-H(t)]=-\frac{d}{d t} S(t) \\
& H(t)=\int_{0}^{t} h(t) d t=-L N[S(t)] \\
& h(t)=\frac{f(t)}{S(t)}=\frac{f(t)}{1-F(t)}=\frac{d}{d t} H(t)
\end{aligned}
$$

## Duration Models



Illustration of hazard $(h(t))$, density $(f(t))$, ${ }^{t}$ cumulative distribution $(F(t))$, and survivor functions $(S(t))$.
Source: Washington et al. (2011)


Illustration of four alternate hazard functions.
Source: Washington et al. (2011)

## Duration Models

- In addition to duration dependence, hazard-based duration models account for the effect of covariates on probabilities.
> Proportional hazards models
> Accelerated lifetime models
- The proportional-hazards approach assumes that the covariates, which are factors that affect the probability that an event will occur, act multiplicatively on some underlying hazard function.

$$
h(t \mid \mathbf{X})=h_{\mathrm{o}}(t) E X P(\boldsymbol{\beta} \mathbf{X})
$$

$>$ where $h_{0}(t)$ denotes the underlying (or baseline) hazard function, $\mathbf{X}$ is the covariate vector and $\beta$ is a vector of estimable parameters
$>h(t)$ is separable into $h_{0}(t)$ and the effects of $X s$
$>h_{0}(t)$ depends on $t$ but not on individual characteristics
> Absolute differences in $\mathrm{X} \rightarrow$ proportional differences in $h(t) \sim$ scaling of $h_{0}(t)$

Duration Models


Illustration of the proportional-hazards model.
Source: Washington et al. (2011)

## Duration Models

- The accelerated lifetime method assumes that the covariates rescale (accelerate) time directly in a baseline survivor function. This accelerated lifetime method again assumes covariates influence the process with the function $\operatorname{EXP}(\beta X)$. The accelerated lifetime model is written as

$$
S(t \mid \mathbf{X})=S_{0}[t E X P(\boldsymbol{\beta} \mathbf{X})]
$$

- which leads to the conditional hazard function

$$
h(t \mid \mathbf{X})=h_{\mathrm{o}}[t E X P(\boldsymbol{\beta} \mathbf{X})] E X P(\boldsymbol{\beta} \mathbf{X})
$$

> where $h_{0}(t)$ denotes the underlying (or baseline) hazard function, $t$ is the time, $\mathbf{X}$ is the covariate vector and $\beta$ is a vector of estimable parameters

## Characteristics of Duration Data

- Duration data are often left or right censored.

Left and right censored


[^0]
## Characteristics of Duration Data

- Hazard-based models can readily account for right-censored data.
- Left-censored data creates a far more difficult problem because of the additional complexity added to the likelihood function.
- Another challenge may arise when a number of observations end their durations at the same time. This is referred to as the problem of tied data. Tied data can arise when data collection is not precise enough to identify exact duration-ending times. When duration exits are grouped at specific times, the likelihood function for proportional and accelerated lifetime models becomes increasingly complex.


## Nonparametric Models

- The Kaplan-Meier method (based on individual survival times) is the most widely applied nonparametric method in survival analysis
- The basic method for calculating survival probabilities using the KaplanMeier method begins by specifying the probability of surviving $r$ years (without event $A$ occurring) as the conditional probability of surviving $r$ years given survival for $r-1$ years times the probability of surviving $r-1$ years (or months, days, minutes, etc.). In notation, the probability of surviving $k$ or more years is given by

$$
\hat{S}(k)=\left(p_{k} \mid p_{k-1}\right) \ldots\left(p_{4} \mid p_{2}\right)\left(p_{3} \mid p_{2}\right)\left(p_{2} \mid p_{1}\right)\left(p_{1}\right)
$$

> where $\left(p_{k} \mid p_{k-1}\right)$ is the proportion of observed subjects surviving to period $k$, given survival to period $k-1$, and so on.

## Nonparametric Models

- The Kaplan-Meier method provides useful estimates of survival probabilities and a graphical presentation of the survival distribution.
It is the most widely applied nonparametric method in survival analysis.
- A few observations:
$>$ If the largest (survival) observation is right-censored, the Kaplan-Meier estimate is undefined beyond this observation.
> If the largest observation is not right censored, then the Kaplan-Meier estimate at that time equals zero.
> The median survival time cannot be estimated if more than $50 \%$ of the observations are censored and the largest observation is censored.
> The Kaplan-Meier method assumes that censoring is independent of survival times. If this is false, the Kaplan-Meier method is inappropriate.


## Nonparametric Models



## Semiparametric Models

- Semiparametric models do not assume a distribution of duration times (like Weibull or exponential), although they do have a parametric assumption on the functional form of the covariates' influence on the hazard function (usually $E X P(\beta X)$ ).
- The Cox proportional-hazards model is semiparametric because $\operatorname{EXP}(\beta X)$ is used as the functional form of the covariate influence.
- Produces estimated hazard ratios (sometimes called rate ratios or risk ratios)
- Regression coefficients are on a log scale
$>$ Exponentiate to get hazard ratio


## Semiparametric Models

- Cox proportional-hazards model

$$
h_{i}(t)=h_{0}(t) \exp \left(\beta_{1} x_{i 1}+\beta_{2} x_{i 2}+\ldots \ldots .+\beta_{n} x_{i n}\right)
$$

> $h_{i}(t)$ is the hazard function for individual $i$
$>h_{0}(t)$ is the baseline hazard function and can take any form
$>X_{\mathrm{i} 1}, X_{\mathrm{i} 2} \ldots X_{\mathrm{in}}$ are the covariates
$>\beta_{11}, \beta_{\mathrm{i} 2} \ldots \beta_{\mathrm{in}}$ are the regression coefficients estimated from the data
> PH assumption needed
> Estimate $\beta$ s without estimating $\mathrm{h}_{0}(\mathrm{t}) \rightarrow$ semi parametric model

## Semiparametric Models

- Cox proportional-hazards model
$>$ If we divide both sides of the equation on the previous slide by $h_{0}(t)$ and take logarithms, we obtain:

$$
\ln \left(\frac{h_{i}(t)}{h_{0}(t)}\right)=\beta_{1} x_{i 1}+\beta_{2} x_{i 2}+\ldots \ldots .+\beta_{n} x_{i n}
$$

$>$ We call $h_{\mathrm{i}}(t) / h_{0}(t)$ the hazard ratio
$>$ The coefficients $\beta_{\mathrm{i} 1}, \beta_{\mathrm{i} 2} \ldots \beta_{\text {in }}$ are estimated by Cox regression, and can be interpreted in a similar manner to that of multiple logistic regression
$>\exp \left(\beta_{\mathrm{i}}\right)$ is the instantaneous relative risk of an event

## Semiparametric Models

- This model is readily estimated using standard maximum likelihood methods.
> If only one observation completes its duration at each time (no tied data), and no observations are censored, the partial log-likelihood is

$$
L L=\sum_{i=1}^{\mathrm{I}}\left[\boldsymbol{\beta} \mathbf{X}_{i}-\sum_{j \in R_{i}} \operatorname{EXP}\left(\boldsymbol{\beta} \mathbf{X}_{j}\right)\right]
$$

> If no observations are censored and tied data are present with more than one observation exiting at time $t$, the partial log-likelihood is the sum of individual likelihoods of the $n$ observations that exit at time t

$$
L L=\sum_{i=1}^{\mathrm{I}}\left[\boldsymbol{\beta} \sum_{j \in \epsilon_{\mathrm{i}}} \mathbf{X}_{j}-n i \sum_{j \in R_{i}} \operatorname{EXP}\left(\boldsymbol{\beta} \mathbf{X}_{j}\right)\right]
$$

## Semiparametric Models

- Cox regression assumptions
> Assumption of proportional hazards
> No censoring patterns
> True starting time
> Plus assumptions for all modelling
- Sufficient sample size, proper model specification, independent observations, exogenous covariates, no high multicollinearity, random sampling, and so on.


## Fully Parametric Models

- With fully parametric models, a variety of distributional alternatives for the hazard function have been used with regularity in the literature. These include gamma, exponential, Weibull, log-logistic, and Gompertz distributions, among others.
- The choice of any one of these alternatives is justified on theoretical grounds or statistical evaluation.
- The choice of a specific distribution has important implications relating not only to the shape of the underlying hazard, but also to the efficiency and potential biasedness of the estimated parameters.


## Fully Parametric Models

| Name | Hazard Function $h(t)$ |
| :--- | :--- |
| Compound exponential | $h(t)=\frac{P}{t+\left(P / \lambda_{0}\right)}$ |
| Exponential | $h(t)=\lambda$ |
| Exponential with gamma heterogeneity | $h(t)=\frac{\lambda}{1+\theta \lambda t}$ |
| Gompertz | $h(t)=(P) E X P^{\lambda t}$ |
| Gompertz-Makeham | $h(t)=\lambda_{0}+\lambda_{1} E X P^{\lambda_{2} t}$ |
| Log-logistic | $h(t)=\frac{(\lambda P)(\lambda t)^{P-1}}{1+(\lambda t)^{P}}$ |
| Weibull | $h(t)=(\lambda P)(\lambda t)^{P-1}$ |
| Weibull with gamma heterogeneity | $h(t)=\frac{(\lambda P)(\lambda t)^{P-1}}{1+\theta(\lambda t)^{P}}$ |

Some Commonly used Hazard Functions for Parametric Duration Models Source: Washington et al. (2011)

## Fully Parametric Models

- Exponential distribution
$>$ With parameter $\lambda>0$, the exponential density function is

$$
f(t)=\lambda E X P(-\lambda t)
$$

> with hazard,

$$
h(t)=\lambda
$$

> The equation above implies that this distribution's hazard is constant, (as illustrated by $h_{4}(\mathrm{t})$ ).
$>$ This means that the probability of a duration ending is independent of time and there is no duration dependence.

## Fully Parametric Models

- Weibull distribution
$>$ With parameters $\lambda>0$ and $\mathrm{P}>0$, the Weibull density function is

$$
f(t)=\lambda P(\lambda t)^{P-1} E X P\left[-(\lambda t)^{P}\right]
$$

$>$ with hazard,

$$
h(t)=(\lambda P)(\lambda t)^{P-1}
$$

> As indicated in the equation above, if the Weibull parameter $P$ is greater than one, the hazard is monotone increasing in duration (see $h_{3}(t)$;
$>$ If $P$ is less than one, it is monotone decreasing in duration (see $h_{1}(t)$ )
$>$ If $P$ equals one, the hazard is constant in duration and reduces to the exponential distribution's hazard with $h(t)=\lambda\left(\right.$ see $\left.h_{4}(t)\right)$.

## Fully Parametric Models

- Log-logistic distribution
$>$ With parameters $\lambda>0$ and $\mathrm{P}>0$, the log-logistic density function is

$$
f(t)=\lambda P(\lambda t)^{P-1}\left[1+(\lambda t)^{P}\right]^{-2}
$$

$>$ with hazard,

$$
h(t)=\frac{(\lambda P)(\lambda t)^{P-1}}{1+(\lambda t)^{P}}
$$

$>$ Equation above indicates that if $P<1$, then the hazard is monotone decreasing in duration (see $h_{1}(t)$ )
$>$ If $P=1$, then the hazard is monotone decreasing in duration from parameter $\lambda ;$
$>$ If $P>1$, then the hazard increases in duration from zero to an inflection point, $t=(P-1)^{1 / P} / \lambda$, and decreases toward zero thereafter (see $\left.h_{2}(t)\right)$.

## Example: Roadside safety analysis

- Roque, C. and Jalayer, M. 2018. Improving roadside design policies for safety enhancement using hazard-based duration modeling, Accident Analysis \& Prevention, Volume 120, 2018, Pages 165-173.
> The distance traveled by an errant vehicle in a ROR crash was modeled .
> Two Cox mixed-effects regression models were developed.
> Results confirmed the contribution of roadside obstacles to the distance travelled.
> Results suggest that clear-zone distances proposed in guidelines should be evaluated.
> This study can facilitate the appropriate planning and design of forgiving roadsides.


## Example: Roadside safety analysis

| Type of crash | Variable | Description | Mean (Std. Dev.) | Minimum | Maximum |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Overturns | Distance traveled (ft) |  | 60.008 (79.062) | 0 | 999 |
|  | Roadway Variables |  |  |  |  |
|  | Speed limit (mph) | Speed limit at the location of the crash (mph) | 52.598 (8.149) | 20 | 70 |
| Fixed-object crashes | Distance traveled (ft) |  | 63.366 (98.021) | 0 | 1421 |
|  | Roadway Variables |  |  |  |  |
|  | Speed limit (mph) | Speed limit at the location of the crash (mph) | 53.631 (9.048) | 20 | 70 |
|  | AADT (vpd) | Average Annual Daily Traffic | 15333.880 (27383.540) | 50 | 183000 |
|  | Shoulder Width (ft) | Paved shoulder width (Right) | 6.496 (3.562) | 0 | 22 |

Descriptive statistics of the continuous variables.
Source: Roque and Jalayer (2018)

## Example: Roadside safety analysis

| Type of crash | Variable | Description | Percentage | Frequency |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Overturns | Seasonal Variables |  |  |  |  |
|  | Clear weather | $1=$ if the crash occurred with clear weather conditions $/ 0=$ otherwise | 70.2\% / 29.8\% | 1411 / 598 |  |
|  | Daylight | $1=$ if the crash occurred during daylight / 0 $=$ otherwise | 63.3\% / 36.7\% | 1271 / 738 |  |
|  | Wet | $1=$ if the road surface was wet when the crash occurred $/ 0=$ otherwise | 13.5\% / 86.5\% | 272/1737 |  |
|  | Vehicle Information |  |  |  | INSTITUTO |
|  | Airbag deploy | $1=$ if the vehicle's airbag was deployed when the crash occurred $/ 0=$ otherwise | 56.9\% / 43.1\% | 1143 / 866 | SUPERIOR TECNICO |
|  | Driver Characteristics |  |  |  |  |
|  | Normal condition | $\begin{aligned} & 1=\text { if the physical condition of the driver when the crash occurred was apparently normal / } 0 \\ & =\text { otherwise } \end{aligned}$ | 81.6\% / 18.4\% | 1640 / 369 |  |
|  | Driver PDO | $1=$ if no injury for the driver $/ 0=$ otherwise | 39.9\% / 60.1\% | $801 / 1208$ |  |
|  | Male | $1=$ if male driver $/ 0=$ otherwise | 73.4\% / 26.6\% | $1474 \text { / } 535$ |  |
| Fixed-object crashes | Seasonal Variables |  |  |  |  |
|  | Clear weather <br> Roadway Variables | $1=$ if the crash occurred with clear weather conditions $/ 0=$ otherwise | 57.6\% / 42.4\% | 10049 / 7408 | FEUP |
|  | Rural | $1=$ if the crash occurred in a rural road $/ 0=$ otherwise | 90.3\% / 9.7\% | 15763 / 1694 |  |
|  | Crash Variables |  |  |  |  |
|  | Tree | $1=$ if first harmful event is collision with tree $/ 0=$ otherwise | 0.8\% / 99.2\% | 148 / 17309 |  |
|  | Non-breakaway pole | $1=$ if first harmful event is collision with luminaire pole non-breakaway / 0 $=$ otherwise | 0.2\% / 99.8\% | 31/17426 |  |
|  | Breakaway pole | 1 = if first harmful event is collision with luminaire pole breakaway / 0 = otherwise | 0.1\% / 99.9\% | 10/17447 |  |
|  | Sign non-breakaway | $1=$ if first harmful event is collision with sign non-breakaway / 0 = otherwise | 1.2\% / 98.8\% | 212/17245 |  |
|  | Guardrail | $1=$ if first harmful event is collision with guardrail face on shoulder / 0 = otherwise | 0.7\% / 99.3\% | 122 / 17335 |  |
|  | Bridge rail | $1=$ if first harmful event is collision with bridge rail face $/ 0=$ otherwise | 0.3\% / 99.7\% | $57 / 17400$ |  |
|  | Curb/Median | $1=$ if first harmful event is collision with traffic island curb or median $/ 0=$ otherwise | 0.3\% / 99.7\% | $55 / 17402$ |  |
|  | Ditch | $1=$ if first harmful event is collision with ditch $/ 0=$ otherwise | 1.0\% / 99.0\% | 167 / 17290 |  |
|  | Front of the vehicle | $1=$ if the point of contact of the vehicle was its central front/ $0=$ otherwise | 10.3\% / 89.7\% | 1801 / 15656 |  |
|  | Driver Characteristics |  |  |  |  |
|  | Normal condition | $\begin{aligned} & 1=\text { if the physical condition of the driver when the crash occurred was apparently normal / } 0 \\ & =\text { otherwise } \end{aligned}$ | 77.7\% / $22.3 \%$ | 13563 / 3894 |  |
|  | Driver PDO | 1 = if no injury for the driver / 0 = otherwise | 64.1\% / 35.9\% | 11188 / 6269 |  |
|  | Ejection | $1=$ if occupant not ejected in the crash $/ 0=$ otherwise | 97.6\% / 2.4\% | 17041 / 416 |  |
|  | Male | $1=$ if male driver $/ 0=$ if female driver | 61.1\% / 38.9\% | 10673 / 6784 |  |
|  | Descriptive statistics of the categorical variables. |  |  |  |  |
|  |  | Source: Roque and Jalayer (2018) |  |  |  |
| din Transpo | tation / Trans | port Demand Modelling |  |  | 44 |

## Example: Roadside safety analysis




Kaplan-Meier estimate of the distance traveled for overturns and fixed-object crashes. Source: Roque and Jalayer (2018)

## Example: Roadside safety analysis

- In the Cox proportional-hazards model, the hazard ratio (HR) is a measure of the relative importance of the explanatory variables concerning hazard, while controlling for distance.
$\square$ The HR is often used to interpret results predicted by the Cox proportional-hazards model and can be obtained by the exponentiation of each regression coefficient.
- Specifically, the HR indicates the time rate of stopping at any distance during the study period, compared to that of the reference category.
> If $\mathrm{HR}=1$, then the explanatory variable in the model does not affect and does not change the baseline hazard, $\mathrm{h}_{0}(\bar{\delta})$.
$>$ If $\mathrm{HR}<1$, then the time rate of stopping is decreased throughout the study period.
$>$ If $\mathrm{HR}>1$, the time rate of stopping is increased throughout the referred period


## Example: Roadside safety analysis

| Variable | Overturns |  |  | Fixed-object crashes |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Coefficient estimate | p-value | Hazard ratio | Coefficient estimate | p-value | Hazard ratio |
| Clear weather | -0.148 | 0.031 | 0.862 | -0.165 | $<0.001$ | 0.848 |
| Daylight | 0.195 | $<0.001$ | 1.215 | - | - | - |
| Wet | 0.146 | 0.110 | 1.157 | - | - | - |
| Rural | - | - | - | -0.252 | $<0.001$ | 0.777 |
| Two-way | - | - | - | 0.179 | < 0.001 | 1.196 |
| Speed limit | -0.013 | $<0.001$ | 0.987 | -0.017 | < 0.001 | 0.983 |
| AADT(/10000) | - | - | - | 0.029 | $<0.001$ | 1.029 |
| Shoulder width | - | - | - | -0.015 | $<0.001$ | 0.985 |
| Tree | - | - | - | 0.698 | < 0.001 | 2.009 |
| Non-breakaway pole | - | - | - | 0.927 | 0.001 | 2.527 |
| Breakaway pole | - | - | - | -1.589 | 0.001 | 0.204 |
| Sign non-breakaway | - | - | - | 0.427 | < 0.001 | 1.532 |
| Guardrail | - | - | - | 0.437 | $<0.001$ | 1.548 |
| Bridge rail | - | - | - | 0.450 | 0.010 | 1.568 |
| Curb/median | - | - | - | -0.530 | 0.003 | 0.588 |
| Ditch | - | - | - | 0.361 | 0.001 | 1.414 |
| Front of the vehicle | - | - | - | 0.291 | $<0.001$ | 1.338 |
| Airbag deploy | 0.104 | 0.058 | 1.110 | 0.146 | < 0.001 | 1.158 |
| Normal condition | 0.226 | 0.001 | 1.254 | 0.387 | $<0.001$ | 1.472 |
| Driver PDO | 0.510 | < 0.001 | 1.666 | 0.272 | $<0.001$ | 1.312 |
| Ejection | - | - | - | 0.201 | 0.002 | 1.222 |
| Male | -0.087 | 0.150 | 0.917 | -0.117 | $<0.001$ | 0.890 |
| Variance of log-normal random effects | 0.215 | < 0.001 |  | 0.482 | $<0.001$ |  |
| Likelihood ratio test statistics | 177.4 |  |  | 1656.9 |  |  |
| Sample size | 2009 |  |  | 17545 |  |  |

Cox mixed-effects model estimation results of distance traveled by an errant vehicle. Source: Roque and Jalayer (2018)
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## Example: Roadside safety analysis

- The hazard ratio is the ratio of the hazard for a unit change in the covariate
$>H R=1.157$ for wet road surface vs. other conditions (overturns model)
$>$ This indicates that there is a $16 \%$ increase in the risk associated with stopping after adjusting for the other explanatory variables in the model, resulting in a decrease in the expected distance traveled.
- Hazard ratio assumed constant over time
> At any time point, the stopping hazard for wet road surface is 1.157 times the hazard for other road surface conditions


## Exercise 1: work-to-home departure delay

- A survey of 204 Seattle-area commuters was conducted to examine the duration of time that commuters delay their work-to-home trips in an effort to avoid peak period traffic congestion. Of the 204 commuters surveyed, 96 indicated that they sometimes delayed their work-to-home trip to avoid traffic congestion. These commuters provided their average time delay-thus each commuter has a completed delay duration so that neither left nor right censoring is present in the data.
> Plot the Kaplan-Meier estimate of the duration of time that commuters delay their work-to-home trips
> Determine the significant factors that affect the duration of commuters' delay using a Cox model.
> Examine the work-to-home departure delay using exponential, Weibull, and log-logistic proportional-hazards models.


## Exercise 1: work-to-home departure delay

| Variable No. | Variable Description |
| :---: | :---: |
| 1 | Minutes delayed to avoid congestion |
| 2 | Primary activity performed while delaying: 1 if perform additional work, 2 if engage in nonwork activities, or 3 if do both |
| 3 | Number of times delayed in the past week to avoid congestion |
| 4 | Mode of transportation used on work-to-home commute: 1 if by single occupancy vehicle, 2 if by carpool, 3 if by vanpool, 4 if by bus, 5 if by other |
| 5 | Primary route to work in Seattle area: 1 if Interstate 90, 2 if Interstate 5, 3 if State Route 520, 4 if Interstate 405, 5 if other |
| 6 | In the respondent's opinion, is the home-to-work trip traffic congested: 1 if yes, 0 if no |
| 7 | Commuter age in years: 1 if under 25, 2 if 26-30, 3 if 31-35, 4 if 36-40, 5 if 41-45, 6 if 46-50, 7 if over 50 |
| 8 | Respondent's gender 1 if female, 0 if male |
| 9 | Number of cars in household |
| 10 | Number of children in household |
| 11 | Annual household income (US dollars per year): 1 if less than 20,000, 2 if 20,000-29,999, 3 if $30,000-39,999,4$ if 40,000-49,999, 5 if 50,000-59,999, 6 if over 60,000 |
| 12 | Respondent has flexible work hours? 1 if yes, 0 if no |
| 13 | Distance from work to home (in kilometers) |
| 14 | Respondent faces level of service D or worse on work-to-home commute? <br> 1 if yes, 0 if no |
| 15 | Ratio of actual travel time at time of expected departure to free-flow (noncongested) travel time |
| 16 | Population of work zone |
| 17 | Retail employment in work zone |
| 18 | Service employment in work zone |
| 19 | Size of work zone (in hectares) |

$$
\text { occupancy vehicle, } 2 \text { if by carpool, } 3 \text { if by vanpool, } 4 \text { if by bus, } 5 \text { if by other }
$$

Primary route to work in Seattle area:1 if Interstate 90, 2 if Interstate 5 ,

In the respondent's opinion, is the home-to-work trip traffic congested: 1 if yes, 0 if no
Commuter age in years: 1 if under 25, 2 if 26-30, 3 if $31-35,4$ if 36-40,
Respondent's gender 1 if female, 0 if male
Number of cars in household
Number of children in household
(US dollars per year). 1 if less than 20,000, 6 if over 60,000
Respondent has flexible work hours? 1 if yes, 0 if no
Distance from work to home (in kilometers)

1 if yes, 0 if no
Ratio of actual travel time at time of expected departure to free-flow
Population of wone
Retail employment in work zone

Size of work zone (in hectares)

## Source: Washington et al. (2011)

## Exercise 1: work-to-home departure delay

- Install and load packages
install.packages("survival")
install.packages("coxme")
install.packages("survminer")
library(survival)
library(coxme)
library(survminer)
- Read and attach data
data.delay <-
read.table(file="C:|\Users\|Carlos||OneDrivel|Cursos\|Exercise.txt",head er=T)
attach(data.delay)
head(data.delay,5)


## Exercise 1: work-to-home departure delay

- Renaming variables
data.delay["minutes"] <- NA
data.delay\$minutes <- data.delay\$X1
data.delay["number_of_times"] <- NA
data.delay\$number_of_times <- data.delay\$X3
$\square$ Sort the data by time
data.delay <- data.delay[order(data.delay\$minutes),]
print(data.delay)
- Create graph
with(data.delay, plot(minutes, type="h"))


## Exercise 1: work-to-home departure delay

- Create the life table survival object for data.delay \# The functions survfit() and Surv() create a life table survival object. data.delay2 <-subset(data.delay, minutes>0) data.delay.survfit = survfit(Surv(minutes) $\sim 1$, data= data.delay2) summary(data.delay.survfit)
- Plot the Kaplan-Meier curve
plot(data.delay.survfit, xlab = "Time (minutes)", ylab="Survival probability", conf.int=TRUE)
ggsurvplot(data.delay.survfit, xlab = "Time (minutes)", xlim = range(0:250) , conf.int = TRUE, color = "red", ggtheme = theme_minimal())


## Exercise 1: work-to-home departure delay

- Cox Proportional Hazard Model Estimates of the Duration of Commuter Work-To-Home Delay to Avoid Congestion result.cox <- coxph(Surv(minutes) ~ gender + rate_of_travel + distance + population, data= data.delay2)
summary(result.cox)


## Exercise 1: work-to-home departure delay

$\square$ Testing proportional Hazards assumption
> Include an interaction between the covariate and a function of time (or distance). Log time often used but could be any function. If significant then assumption violated
> Test the proportional hazards assumption on the basis of partial residuals. Type of residual known as Schoenfeld residuals
test.ph <- cox.zph(result.cox)
$>$ For each covariate, the function cox.zph() correlates the corresponding set of scaled Schoenfeld residuals with time, to test for independence between residuals and time. Additionally, it performs a global test for the model as a whole.
plot(test.ph)
ggcoxzph(test.ph)
$>$ In principle, the Schoenfeld residuals are independent of time. A plot that shows a non-random pattern against time is evidence of violation of the PH assumption.

## Exercise 1: work-to-home departure delay

$\square$ Plot the baseline survival function ggsurvplot(survfit(result.cox), color = "\#2E9FDF", ggtheme = theme_minimal())
$\square$ Plot cumulative hazard function ggsurvplot(survfit(result.cox), conf.int = TRUE, palette = c("\#FF9E29", "\#86AA00"), risk.table = TRUE, risk.table.col = "strata", fun = "event")

- Log-likelihood
\#nitial log-likelihood
result.cox \$loglik[1]
\#Final log-likelihood
result.cox \$loglik[2]
- McFadden Pseudo-R2

Pseudo.R2 <- (1- (result.cox \$loglik[2]/ result.cox \$loglik[1]))

## Exercise 1: work-to-home departure delay

- Parametric Model Estimates of the Duration of Commuter Work-ToHome Delay to Avoid Congestion
\# The argument dist has several options to describe the parametric model used ("weibull", "exponential", "gaussian", "logistic", "lognormal", or "loglogistic")
result.expon <- survreg(Surv(minutes)~ gender + rate_of_travel + distance + population, data= data.delay2, dist="exponential") result.weib <- survreg(Surv(minutes)~ gender + rate_of_travel + distance + population, data= data.delay2, dist="weibull")
result.loglog <- survreg(Surv(minutes) ~ gender + rate_of_travel + distance + population, data= data.delay2, dist="loglogistic")


## Exercise 2

- What else can we do with this dataset?

| Variable No. | Variable Description |
| :---: | :---: |
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| 3 | Number of times delayed in the past week to avoid congestion |
| 4 | Mode of transportation used on work-to-home commute: 1 if by single occupancy vehicle, 2 if by carpool, 3 if by vanpool, 4 if by bus, 5 if by other |
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| 6 | In the respondent's opinion, is the home-to-work trip traffic congested: 1 if yes, 0 if no |
| 7 | Commuter age in years: 1 if under 25, 2 if 26-30, 3 if $31-35,4$ if $36-40$, 5 if 41-45, 6 if 46-50, 7 if over 50 |
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| 16 | Population of work zone |
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| 18 | Service employment in work zone |
| 19 | Size of work zone (in hectares) |

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[^0]:    Phd in Transportation / Transport Demand Modelling

