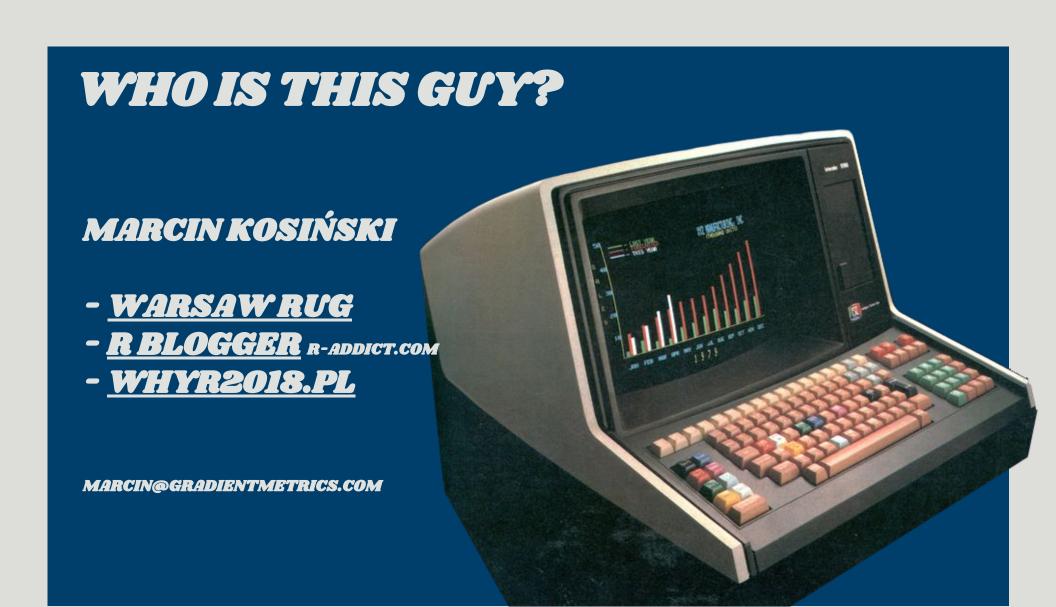


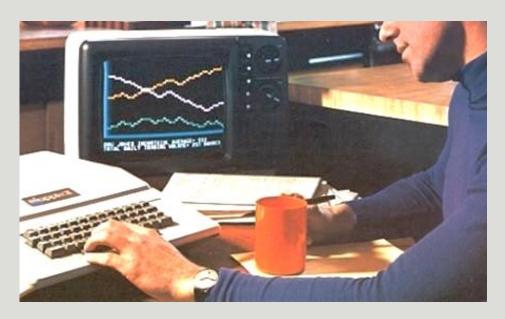
# **MULTI-STATE CHURN ANALYSIS**

WITH A SUBSCRIPTION PRODUCT

**GRADIENT** 



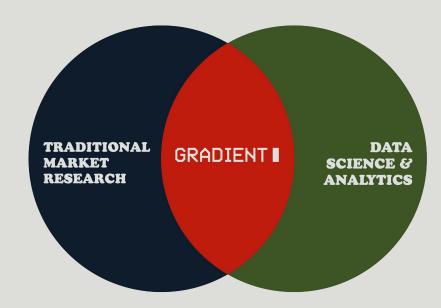
# Nice to meet you!



#### WE'RE GRADIENT:

A crew of quantitative marketers and technologists that gather hard data and build robust statistical models to guide organizations through their most difficult decisions.

We're confirmed data geeks, but word on the street is that we're easy to work with and pretty fun, too.



**GRADIENTMETRICS.COM** 

# SURVIVAL ANALYSIS

**DEFINITION & EXAMPLES** 

# LET'S START TALKING

A branch of statistics for analyzing the **expected duration of time until** one or more **events** happen.

#### Examples

- 1. A death of the patient.
- 2. A deactivation of the service.
- 3. An accident on the road.
- 4. The device failure.
- 5. An employee leaving the company.
- 6. A customer cancelling subscription.



# SURVIVAL ANALYSIS

QUESTIONS IT (MIGHT) ANSWER

### LET'S START ASKING

What's the probability an event will (not) occur after a specific period of time?

Which characteristics indicate a reduced or increased risk of occurrence of an event?

What periods of time are most (or least) exposed to the risk of an event?



# SURVIVAL ANALYSIS

CHALLENGES IT FACES

### DEPENDING ON THE SCENARIO

#### Data

- 1. Censoring.
- 2. Interval data.
- 3. Observations may not be independent.
- 4. Time varying features.

#### **Events**

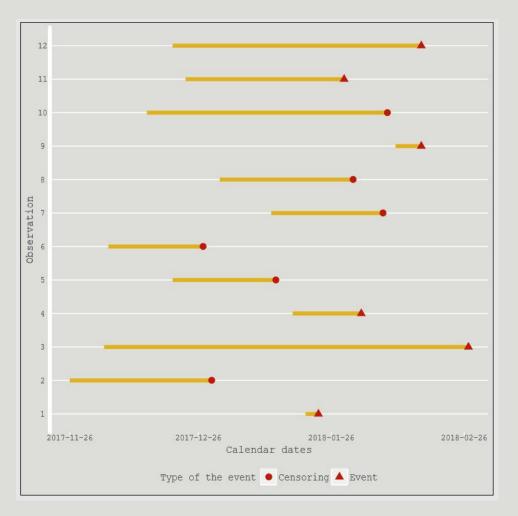
- 1. Recurring events one event might occur multiple times.
- 2. Competing risks one of multiple events might occur.
- 3. A multi-state (cyclic/acyclic) nature of the process.



#### HOW YOU OBSERVE EVENTS

### DATA STRUCTURE

#### SIMPLE CASE



#### **HEAD OF THE DATA**

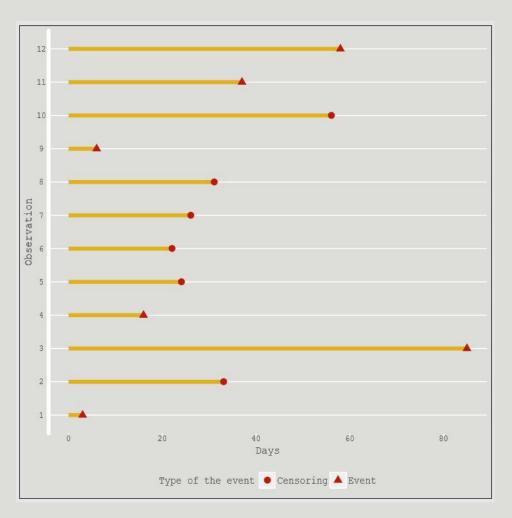
| ID | Start Date | End Date   | Status    |
|----|------------|------------|-----------|
| 1  | 2018-01-28 | 2018-02-22 | Censoring |
| 2  | 2017-12-16 | 2018-01-08 | Event     |
| 3  | 2017-12-09 | 2018-01-06 | Censoring |
| 4  | 2018-01-16 | 2018-02-23 | Censoring |
| 5  | 2017-12-16 | 2018-02-11 | Event     |
| 6  | 2018-02-18 | 2018-03-01 | Event     |

Data **do not** correspond to the plot.

#### HOW YOU HANDLE THEM

# DATA STRUCTURE

#### SIMPLE CASE



#### **HEAD OF THE DATA**

| Status    | Time |    | ID |
|-----------|------|----|----|
| Event     | days | 3  | 1  |
| Censoring | days | 33 | 2  |
| Event     | days | 85 | 3  |
| Event     | days | 16 | 4  |
| Censoring | days | 24 | 5  |
| Censoring | days | 22 | 6  |
|           |      |    |    |

Data **do** correspond to the plot.

# TOOLS SURVIVAL CURVES

### KAPLAN-MEIER ESTIMATES

$$\hat{S}(t) = \prod_{t_i \le t} \frac{n_i - d_i}{n_i}$$

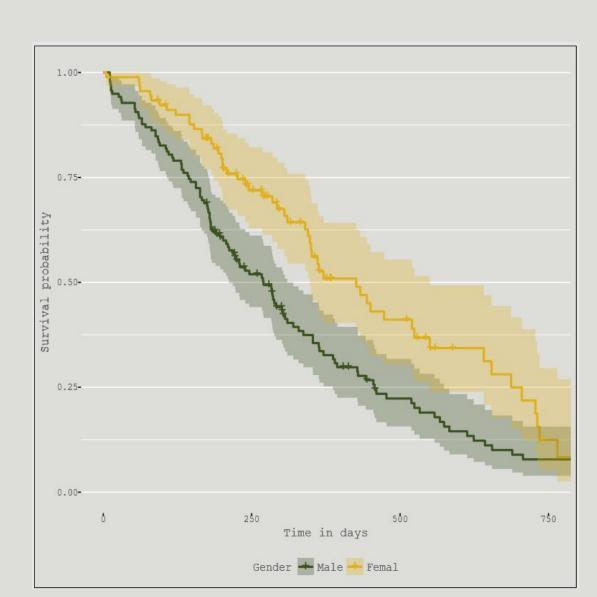
#### where

t<sub>i</sub> - time of i-th event

 $n_i$  - number of observations in a risk set at time  $t_i$ 

 $d_i$  - number of events at  $t_i$ 

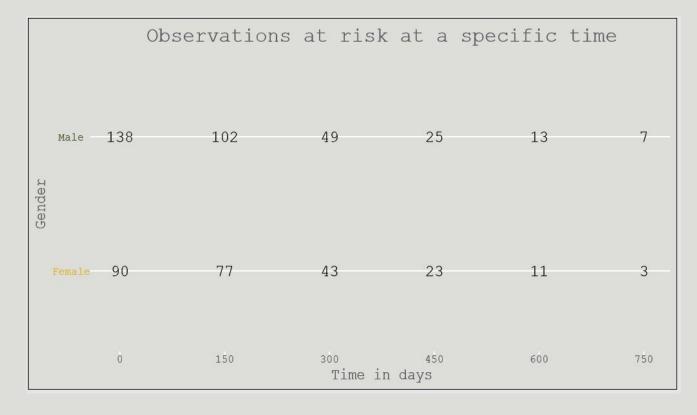
**Log-rank** test seeks for statistically significant differences between curves.

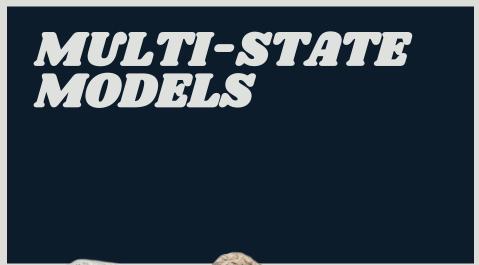


# TOOLS RISK SET (TABLE)

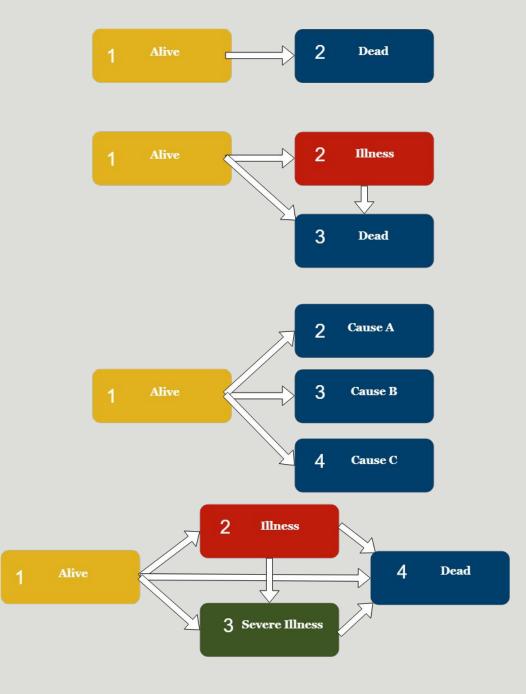
# SURVIVORS AT A TIME

Useful when considering whether results at a specific time point are significant due to the sample size.



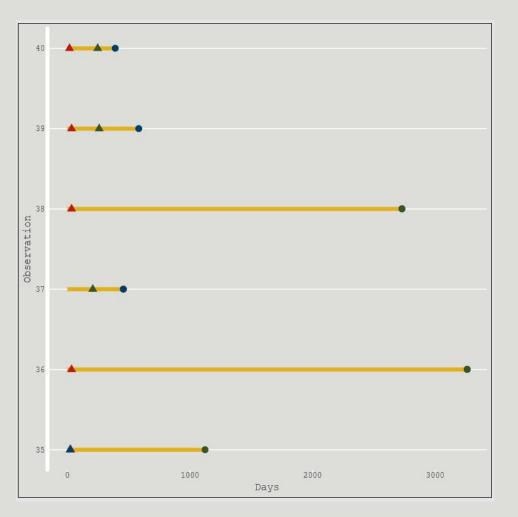






### DATA STRUCTURE

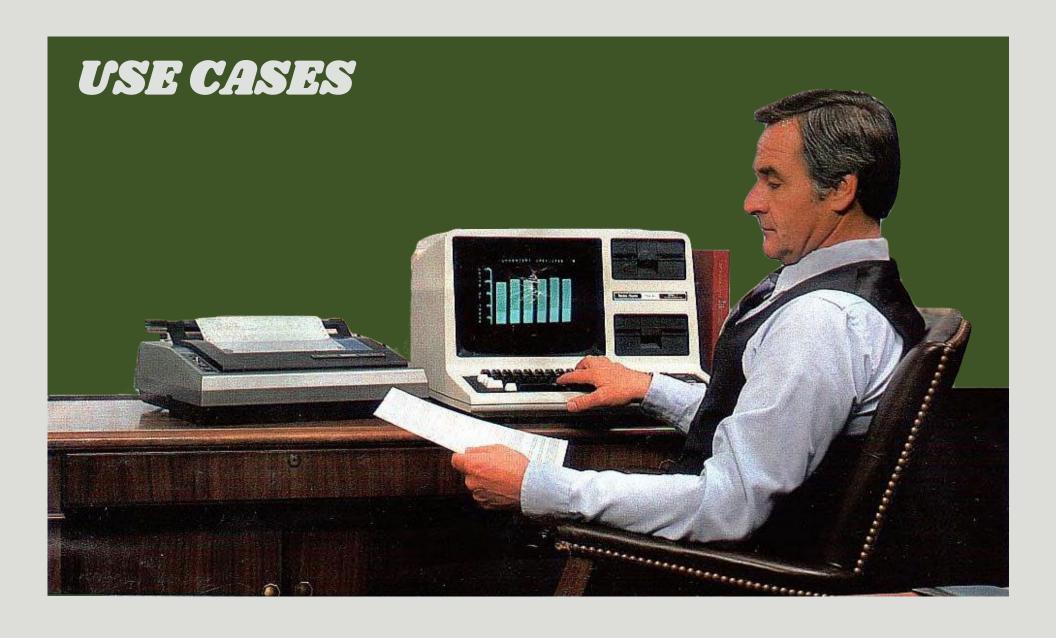
#### **MULTI-STATE CASE**



#### **HEAD OF THE DATA**

| ID | Time 1 | Event 1 | L | Time 2 | Event 2 | 1 | Time 3 | Event | 3 |
|----|--------|---------|---|--------|---------|---|--------|-------|---|
| 1  | 22     |         | L | 995    | 0       | ) | 995    |       | 0 |
| 2  | 29     |         | L | 12     | 1       |   | 422    |       | 1 |
| 3  | 1264   | (       | ) | 27     | 1       |   | 1264   |       | 0 |
| 4  | 50     |         | L | 42     | 1       |   | 84     |       | 1 |
| 5  | 22     |         | L | 1133   | 0       | ) | 114    |       | 1 |
| 6  | 33     | 1       | L | 27     | 1       |   | 1427   |       | 0 |

Demonstrational data.



# IEVENT / COX PROPORTIONAL HAZARDS

#### COX METHODOLOGY OVERVIEW

# 1. Proportional hazards assumptions.

- 2. Functional form of continuous variables.
- 3. Independent observations.
- 4. Independent censoring from the mechanism that rules of event's times.
- 5. Non informative censoring
   does not give an
  information on parameters of
  the time distribution of
  events because it does not
  depend on them

#### NOTE

One can use accelerated failure time (AFT) models.

#### **EXAMPLE COEFFICIENTS**

| variable | coef  | exp(coef) |
|----------|-------|-----------|
| age      | 0.15  | 1.16      |
| ecog.ps  | 0.10  | 1.11      |
| rx       | -0.81 | 0.44      |

#### coxph(Surv(futime, fustat) # age + ecog.ps + rx, data=ovarian)

#### DIAGNOSTIC PLOTS

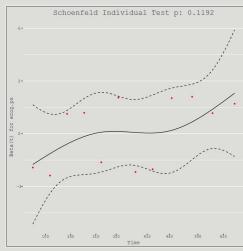
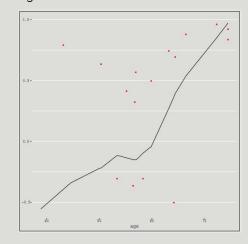


Fig. 1: Shoenfeld residuals.



#### OVARIAN DATA

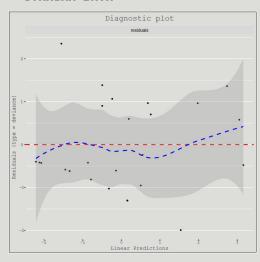


Fig. 2: Deviance residuals.

#### FUNCTIONS (survminer)

- 1. ggcoxzph
- 2. ggcoxdiagnostics
- 3. ggcoxfunctional

Fig. 3: Martingale residuals.

# NEVENTS (ACYCLIC) MULTI-STATE MODEL

TRANSITION MATRIX

1 2 3 4 5

to

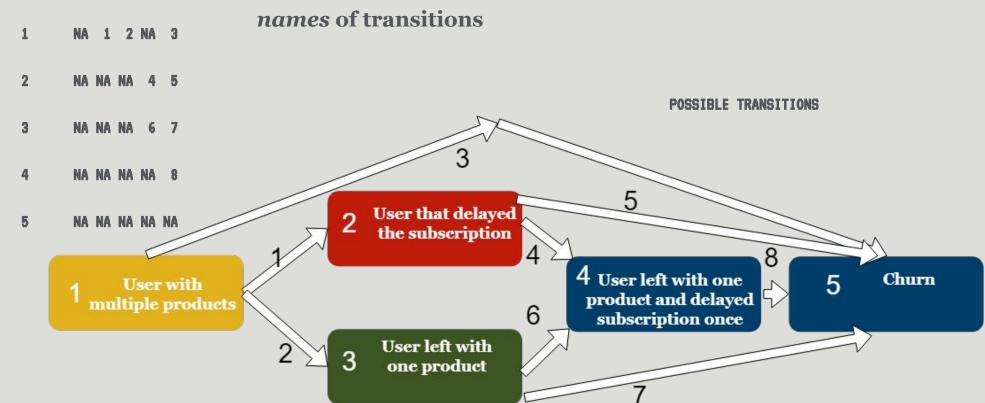
from

NA = transition not possible

numbers in cells

=

The most complicated part is the proper data coding for the model's input.



# NEVENTS (ACYCLIC) MULTI-STATE MODEL

#### SOME COEFFICIENTS

| year=2013-2017 | year=2008-2012 | gender=female | discount=yes | age=20-40 | age=>40 | transition |
|----------------|----------------|---------------|--------------|-----------|---------|------------|
| 0.94           | 0.80           | -0.72         | -0.26        | -0.77     | -1.15   | 1          |
| 0.31           | 0.39           | -0.58         | -0.15        | -0.72     | -1.34   | 2          |
| -0.11          | 0.02           | -0.53         | 0.08         | -0.04     | -0.43   | 3          |
| 0.23           | 0.13           | -0.22         | -0.09        | -0.66     | -0.86   | 4          |
| -0.63          | -0.54          | -0.24         | 0.14         | -0.64     | 0.14    | 5          |
| 1.33           | 0.88           | -0.35         | 0.24         | -1.23     | -1.65   | 6          |
| 0.09           | -0.35          | -0.57         | 0.39         | -0.57     | -0.82   | 7          |

#### Reference level for

- age below 20
- year 2002-2007

# NEVENTS (ACYCLIC) MULTI-STATE MODEL

#### PREDICTIONS OF THE STATE

Depending on the customer features, the predictions of being in a state after particular time are different.

Credits for modeling:

cran.r-project.org/package= mstate

#### Customer A

· Discount: Yes

· Gender: Female

Joined: 2013-2017

• Age: Younger than 20

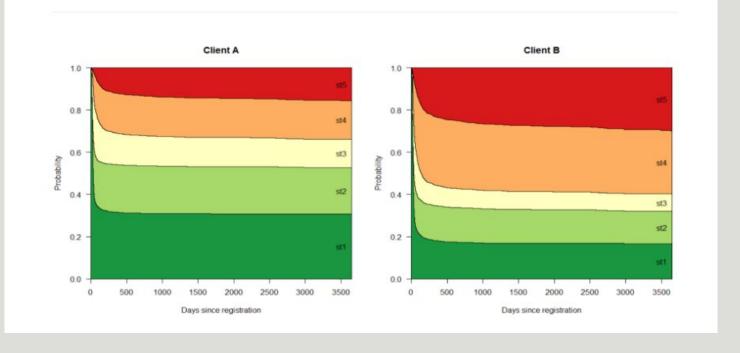
#### Customer B

· Discount: No

Gender: Male

Joined: 2002-2007

Age: 20-40



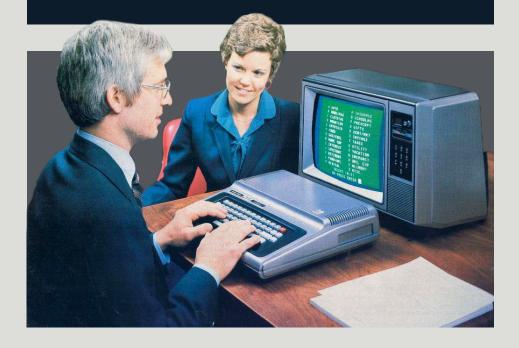


Model assumptions should be considered for every possible transition.

Time varying variables can be taken into the account when handling subscription based data.

Playing with cyclic models requires domain knowledge in (sub) Markov Chain field.

# PLOTS BASED ON SURVMINER



Credits:
cran.r-project.org/package=survminer
github.com/kassambara/survminer
www.ggplot2-exts.org/gallery/
stdha.com/english/rpkgs/survminer

### DID YOU LIKE THE TALK? JOIN US AT WHY R? 2018 CONFERENCE.



WROCŁAW, 2-5 JULY 2018

HTTP://WHYR2018.PL/



Presentation and codes

github.com/g6t/mchurn

THANK YOU FOR THE ATTENTION