Creation of a customer experience measure – an application of MARS

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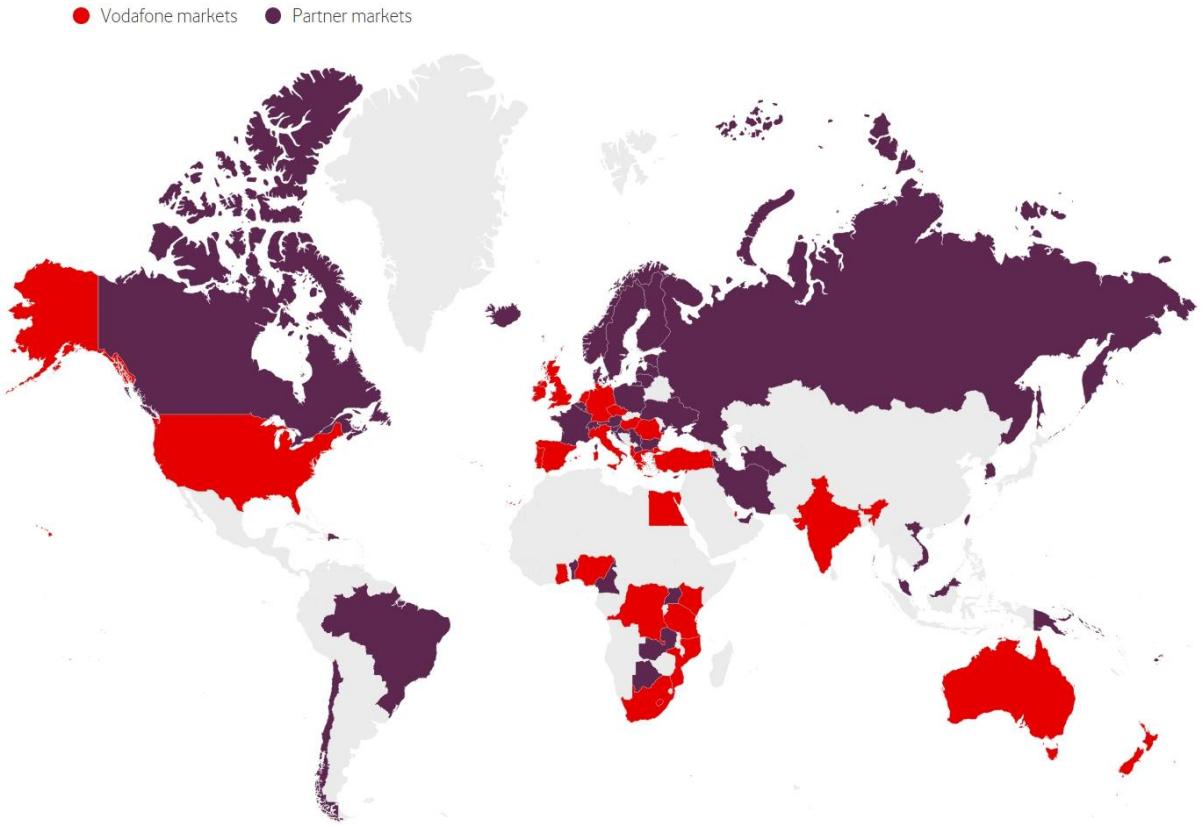
Vodafone in the world



- Mobile voice/data
- Fixed line voice / broadband / TV
- IoT services
- Cloud & Hosting
- Carrier services
- M-Pesa payment services
- ...

The Experience Outcome Measurement (EOM) project: overview

Situation

- Area: Vodafone Group Enterprise (**VGE**)
- **Many thousand** incidents or requests per year
- We are much interested in the **customer experience** with regard to the resolution process
- tNPS surveys are useful feedbacks, but are just very **rarely available**

? How to assess our performance in the absence of a direct tNPS response? ?

May need explanation...

- What is an NPS score?

Goals

1. Find some case level measure which can fill the information gap (mobile/fixed)
2. Create efficency segments for the cases
3. Deliver an EOM measure for any sets of cases
4. Create a joint mobile + fixed score for the customer level

Approach overview

0

In the beginning we have:

- A few tickets with tNPS
- Many tickets w/o tNPS
- Some additional event data for all the tickets

1

A proxy function for the NPS score is created

- Using the tickets with known NPS
- Using the other event data
- The goal is just to have a well correlated proxy: higher NPS - higher proxy

2

The proxy function is spread for all tickets

- Can be done as we have the event info for all tickets

3

Finding segments

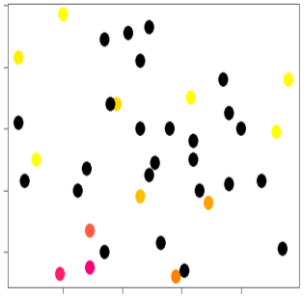
Locating groups of similar tickets so that:

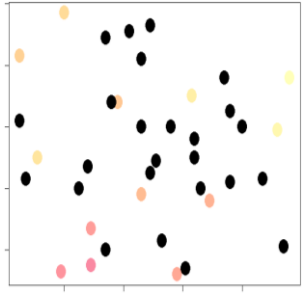
- Within group the variability of the proxy is small
- Between groups the variability of the proxy is large

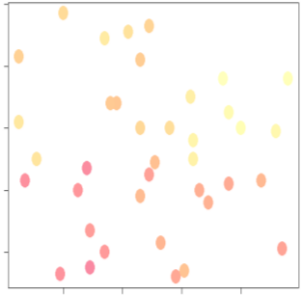
4

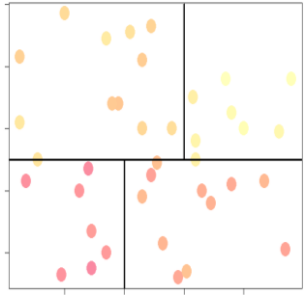
Defining the final EOM scores

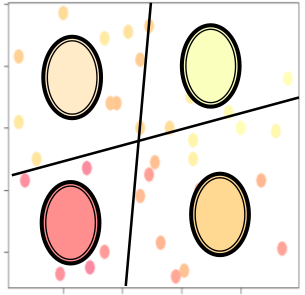
- Some sort of aggregation for ticket sets
- Gives a measure of the relative impact on the customer experience











Data

Base stats

	Mobile	Fixed
Absolute number of explicit response	Very low	
% of response	<2%	<0.5%
Explanatory variables	Target resolution time Actual resolution time Priority level	
	4 integer efficiency measures	6 integer efficiency measures

Preprocessing

Impute missing time data

- Average value by product & priority
- Multilevel process

Outlier management

- Long tails
- Textbook method was not satisfactory
- Strict capping

A MARS model– what does it look like?

MARS = Multivariate Adaptive Regression Splines

A MARS model has the form

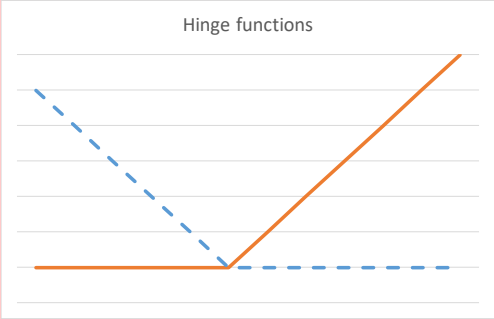
$$f(x) = \sum_{i=1}^{k} c_i B_i(x)$$

where

$$c_i \in R$$

and $B_i(x)$ takes one of the next three forms:

1. constant 1
2. a hinge function
   $\max(0, const - x)\ or\ \max(0, x - const)$
3. a product of two or more hinge functions



An example:

$$f(x, y) = 3 + 4 \times \max(0,3 - x) - 2 \times \max(0,1 - x) \times \max(0, y - 2)$$

Pros	Cons
• Flexible, nonlinear • Simple interpretation • Good for continuous and categorical data • Somewhat protected against outliers • Automatic variable selection • Fast to build • Fast to predict	• Parameter reliability assessment needs cross-validation • Boosted trees might give better fit • Might have problems in case of missing values

MARS - Fitting the model

Starting from an intercept-only model → Adding basis functions in pairs → The forward building stops when the improvement in the error is small or maximum allowed complexity is reached → Backward pruning → Optimal model in the sense of error-complexity balance

- The added B_i pairs are almost identical, except containing the two mirrored side of a hinge function
- The pair reducing most the sum of squares residual error is selected
- Each new basis function consists of
  - a term already in the model
  - multiplied by a new hinge function
- The search is not fully brute force as a smart least squares update technique can be applied

- The backward steps reduce the overfit by deleting terms contributing least to the efficiency
- GCV (Generalized cross validation) measure is used for submodel comparison

$$GCV = \frac{RSS}{N \cdot \left(1 - \frac{EffectiveNumberOfParameters}{N}\right)^2}$$

where the effective number of the parameters is a function of the complexity

MARS in EOM – Why?

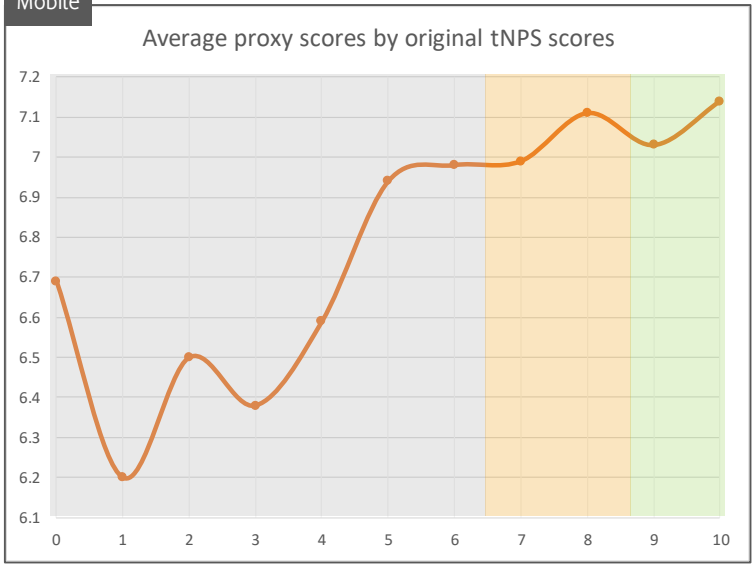
- Other tried mainstream / less mainstream regression methods were unable to produce any acceptable solution
- Reliable tool delivering results in the given very short timeframe – quick modeling cycles, few parameters
- The success of MARS may be given some psychological explanation if one thinks of the structure of the basis functions
- Built-in protection against heavy overfit (which had a high risk due to the low case numbers)

MARS – how well did it work?

The earth R package has been used for model building. Tests were done using 7-fold cross validation with 30 repetitions.

```
proxy_model_mars ← earth( formula , data=current_train_sample , degree=3 )
```

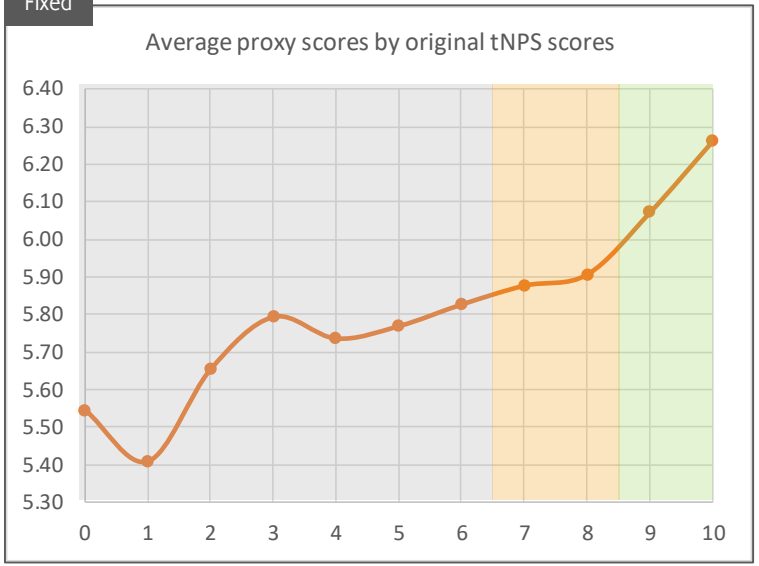
Mobile



tNPS – proxy pearson correlations:

On ticket level:	0.26
On NPS score level:	0.86

Fixed



tNPS – proxy pearson correlations:

On ticket level:	------
On NPS score level:	0.93

The segmentation – with regression trees

The requirements against the segmentation

1. Allow all the EOM input variables as explanatory variables, but
2. Be homogenous with regard to the proxy score

were conveniently fulfiled by the regression tree methodology.

Observations about the variables:

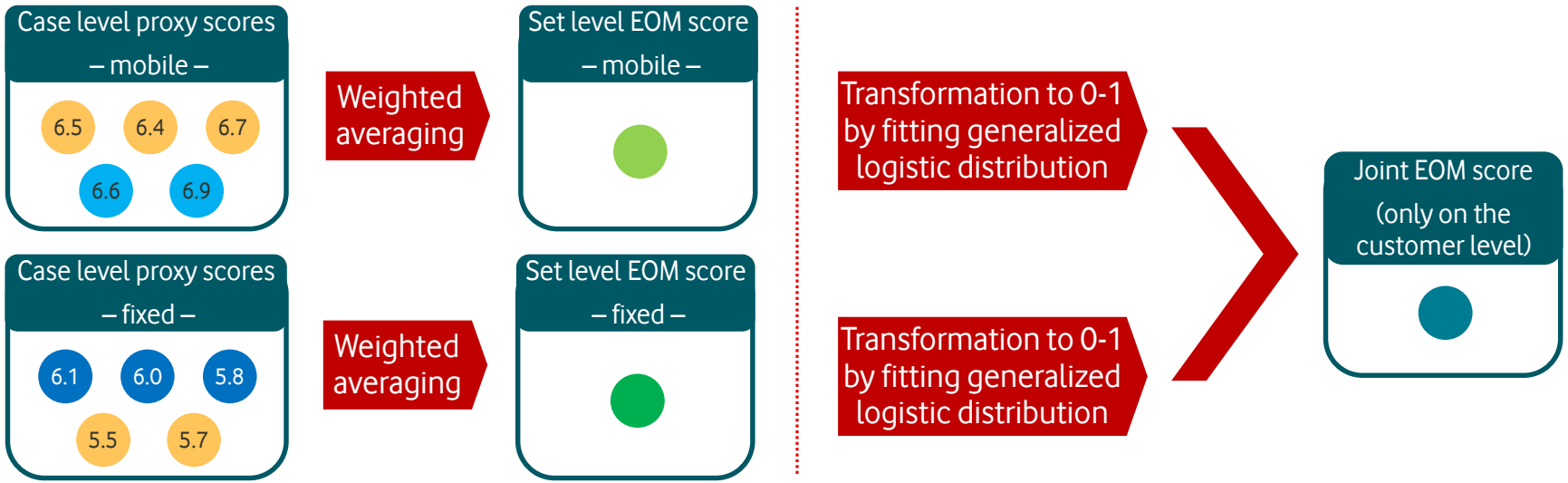
1. Not all variables turned up in the trees
2. Not necessarily the same as those in the proxy

```
expl_variables = c( ....);
formul <- reformulate( response=target_variable, termlabels=expl_variables );
fixed_eom_regrtree <- rpart(formul, data=all_ticket_data, method="anova");
```

By manual merging 5 final mobile and 6 final fixed segments were created.

The final EOM scores

EOM score = the aggregation of the scores to any group of cases. In special: to customer, product or resolution team.



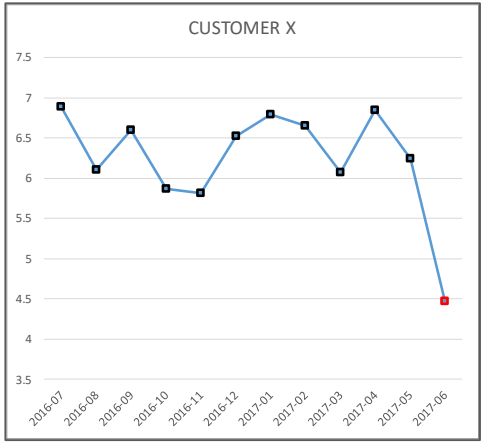
The generalized logistic distribution is a multiparameter version of the simple logistic distribution. Quite efficient in approximating cumulative distribution functions. As such, can be used for normalisation, which has been vital for EOM because of the different score ranges.

$$L(x) = \frac{1}{\left(1 + Qe^{-B(x-M)}\right)^{1/\nu}}$$

Anomaly detection in the EOM time series
To find critical cases and lessons to learn from

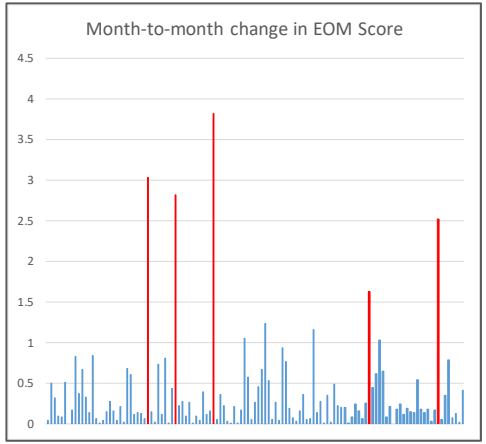
Individual prompt outliers

The time series proceeds unexpectedly compared to its own previous behavior



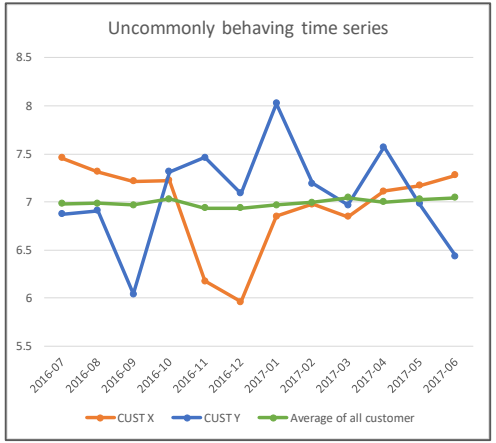
Relative prompt outliers

The time series proceeds unexpectedly compared to the other series



Shape outliers

The time series evolves very unusually along a longer time period



Any 1-dimensional outlier detection method can be applied. Our choice: Grubbs-test, testing for the presence of any outliers.

$$G > \frac{N-1}{\sqrt{N}} \sqrt{\frac{t^2_{\frac{\alpha}{2N},\, N-2}}{N-2+t^2_{\frac{\alpha}{2N},\, N-2}}},$$

Any multidimensional method can be used. For example Mahalanobis distance calculation.

The outcomes and the future

- Analytical components ready: proxy function, segments, EOM score, joint EOM score, anomaly detection
- Initial implementation as CSV + Alteryx + R. Productive implementation as Oracle + Talend + R
- Serving as benchmark model for environment tests: AWS / Azure / Enterprise Big Data
- Becomes a monthly report by December 2017, inducing retention and process improvement actions

Questions?