

### Problem definition and Primary goal

### **Business problem**

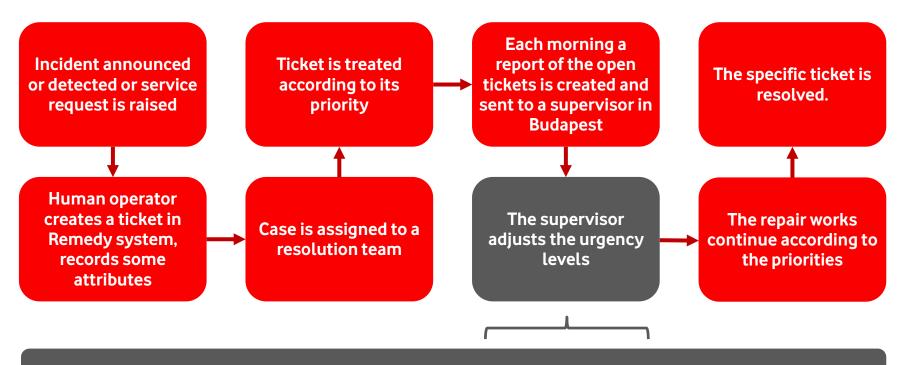
- A small but still important % of the telecommunication service related incident cases and service request cases take too much time to solve
- (at a specific Vodafone entity),
- and those cases violate some service level agreements (SLAs).
- The violations have reputational and financial impacts.
- The percentage of the problematic cases should be reduced.

### **Primary goal**

Create a solution that helps the work
 distribution managers in their everyday
 work by pointing out the cases
 threatened by violating the SLAs, as
 soon as possible after the ticket has
 been created.



# The lifecycle of an incident ticket - simplified



Analytical help was required here, for the assessment of the tickets opened last day

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# The goals in more details

Learn statistical differences between tickets breaching and meeting the SLAs

Implement the model in a real process

Recognise the problematic tickets in time and prevent SLA breaches

Increase customer satisfaction
Support the process efficiency

Train a statistical model that is able to separate SLA violating and observing tickets

#### Scope:

- VGE customers
- Incidents and Service Requests
- High Medium Low priority tickets (Critical excluded)
- SLA breaches and extreme TTR
- 201505 201607 data used for learning, 201608-201609 for final testing, from the VGE Remedy ticketing system

#### Reduce the number of SLA violations

- Save problematic tickets from reaching the SLA thresholds by listening to early warnings
- Put special effort in those flagged for extra riskiness

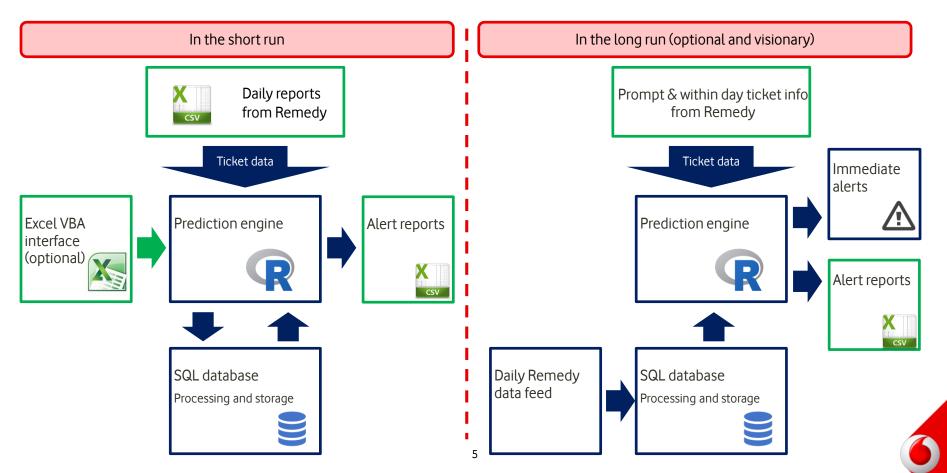
# Deploy a solution in the daily case prioritisation process

• Integrate the model into the daily data streams to raise alerts

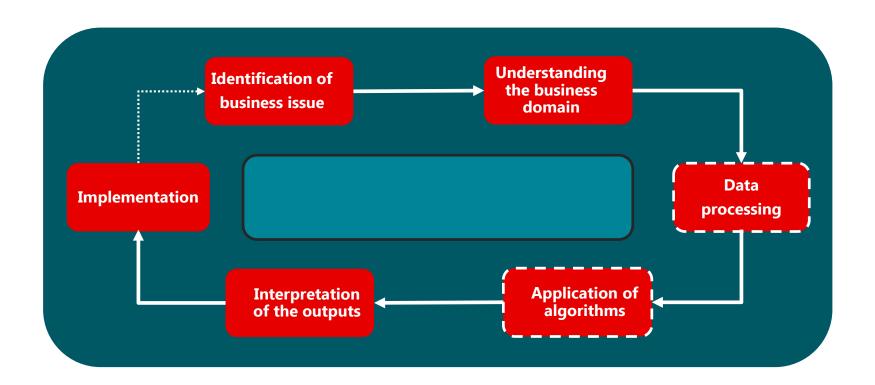
#### Realise increased satisfaction

- Measure the effects of the model
- Integrate closer into Remedy

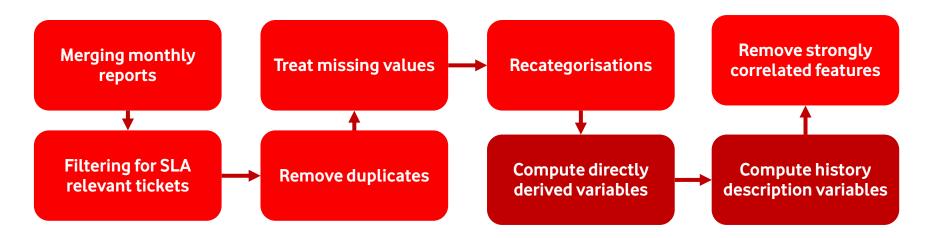
# The system from a distance



### From now on we shall concentrate on training the prediction engine



# Data preparation for modelling



### Explanatory data candidates in the raw data

- Customer
- Ticket type
- Timestamps
- (Assigned group)

- SLA relevant time
- (Text summary)
- Trouble category (3 levels)
- Affected product

- Channel of announcement
- Priority
- If external vendor was involved

# Training the engine = learn from the past what is worth learning

A statistical discovery method learns the complex interactions between the variables.

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A model, e. g. a set of generally valid rules

" IF

V1 equals A AND

V2 falls between B and C AND

V4 falls between D and E THEN the probability of the SLA breach is P"

Many **variable candidates were calculated** and proposed for the learner:

#### Ticket-level attributes, like

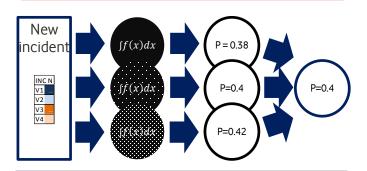
Priority, product, day of week, source, problem categorisation

#### Recent history attributes, like

- Number of high priority tickets opened during the last 30 days
- Percentage of missed SLAs for similar tickets during the last 90 days
- Average TTR for similar tickets opened during the last 90 days

Not all candidates turn up in the final model

### Model application

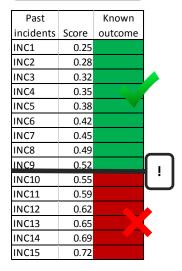


- For sake of stability a number of slightly different models is built using random sampling methods
- The random forest prediction is the average of the individual predictions
- If you apply the random forest model on a given ticket, **the result is a score between 0 and 1**, proportional to the risk of violating the SLA.

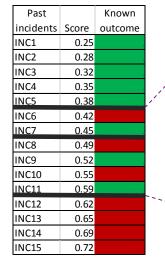
## But I need a definite prediction!

### Finally you have to turn your score into a yes/no prediction

# You hope to see something like this



# But reality will always look like this:



There is a trade-off between problem recall and overall accuracy

Optimal cutoff? 100 % of problems detected! But accuracy is low.

Optimal? Perhaps...

Optimal cutoff? Only bad cases are flagged! But many remain undetected. Cutoff setting aspects:

- High recall: find a large portion of the SLA breaches
- High accuracy: do not misclassify too many cases
- Low false positive rate: do not raise unnecessary alerts

Final recall =

The portion of the avoidable SLA breaches

Measuring the model performance on data not used for training the model gives a realistic measure of the expectable model performance in the real environment, on new cases

### Different models for different uses

Model for repeated scoring Lifetime scoring model

Can be used to re-score older tickets with a daily frequency and considers the age of the ticket as well.

TTR 48h

SLA breach

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TTR 72h

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Limited usefulness as meaningful only in a short period of the lifetime

Models for scoring at ticket creation

Digestdata model

Prompt model

Scores the new tickets using information available till last midnight – including the new ticket itself

SLA breach

Recall: 40%

Accuracy: 97%

TTR 48h

Recall: 56%

Accuracy: 79%

TTR 72h

Recall: 44%

Accuracy: 81%

Most realistic to be implemented in the short run.

Scores the new tickets using information up to the moment the new ticket is created - about the other tickets as well.

TTR 48h

Accuracy: 79%

Accuracy: 97%

Recall: 40-45%

SLA breach

TTR 72h

Recall: 56-70%

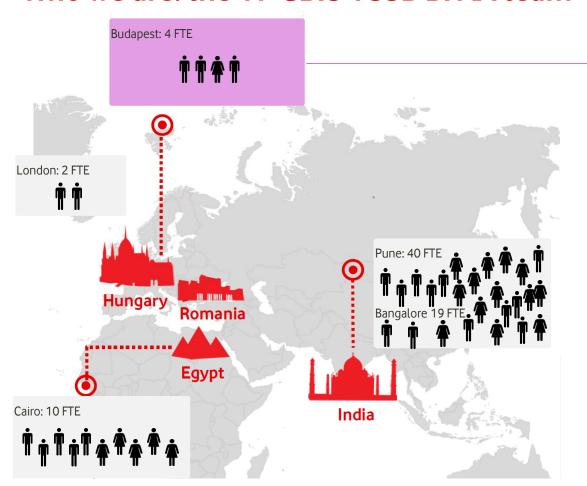
Recall: 44-50%

Accuracy: 81%

Much depends on the data feeding technological possibilities.

40 % of the SLA breaches can be avoided by utilising predictions from the simplest digest data model

### Who we are: the VF GBIS VSSB BI AA team



### Working already with

- Supply Chain Management
- Global HR Services
- VSSB local HR
- Enterprise Sales
- Enterprise Operations
- Finance

On local and global projects

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# Ticket analysis status and next steps

#### **Status**

- VGE ticket SLA breach model was put into productive use early October 2016
- HR Services SLA breach model for Germany to be deployed by end of October
- Development of further HR SLA models has been started
- Development of productive model for UK Enterprise and Vodafone Carrier Services is in progress.

### **Next steps**

- Monitoring model performance
- Increasing user ergonomics
- Experiencing with the forecasting methodologies
- Process mining / Process analysis using detailed ticket status changes data
- Closer integration into ticketing system
- Possible rollout of incident SLA breach prediction models to
  - VSS India incident resolution teams
  - All markets served by VSSB HR Services
  - All markets served by VSS India HR Services

