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# Credit Scoring and Credit Control XIV

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# Behavioral Scoring Evolution: From Monthly Aggregates to Single Transactions

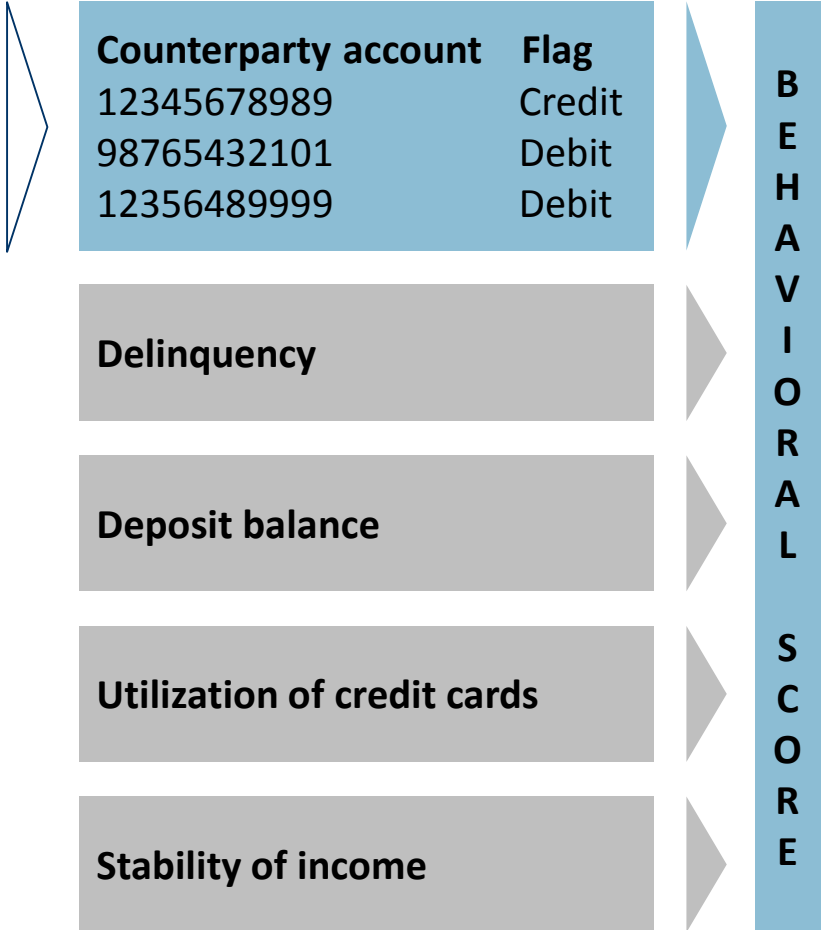
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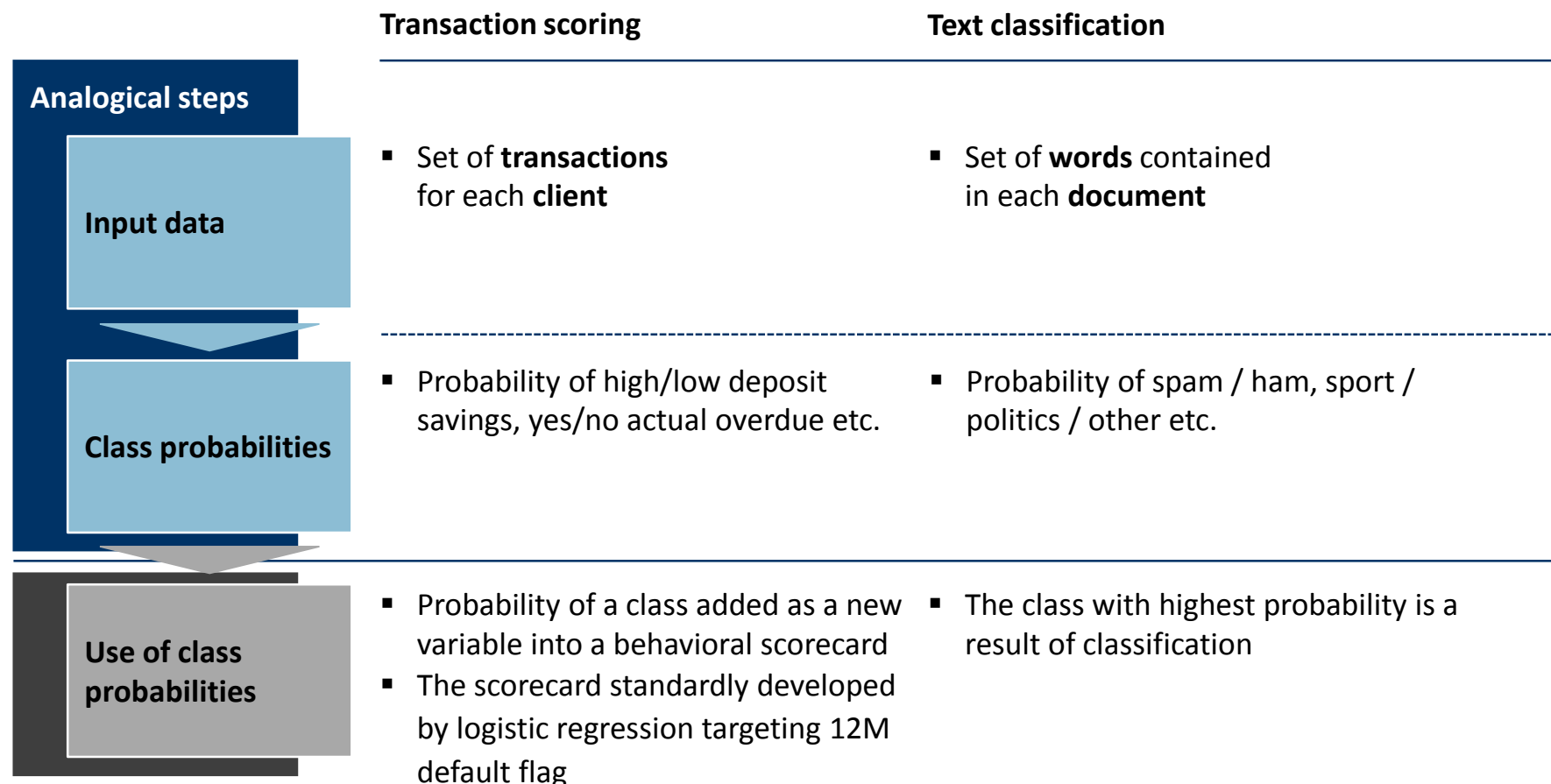
Erste Group Bank  
April 2015

# Goal of transaction scoring is to include information about counterparties of individual payments to the behavioral scorecard

- Information about counterparties of client's individual money transfers shall be accounted for in her behavioral score
- For example, clients paying in casinos are expected to default more likely on their loans
- Approach of a manually-maintained list of casinos (and other presumably risky counterparties) shall be avoided due to operational risk and maintenance costs



# The problem of scoring clients according to their account transactions is analogical to the problem of text classification



NOTE: Class in the transaction scoring is NOT equivalent to a target from the logistic regression (risk of overfitting, late accommodation to new transaction types)

# Multinomial Naïve Bayes is a simple model widely used in text classification

## Assumption

- Assumption of multinomially-distributed transaction counts  $\mathbf{x}$  for a given client in class  $c_k$ :

$$p(\mathbf{x}|c_k) = \frac{(\sum_j x_j)!}{\prod_j x_j!} \prod_{j=1}^d p^{x_j}(t_j|c_k)$$

- $t_j$  denotes occurrence of transaction  $j$
- Transactions of a particular client are assumed to be drawn from a “*bag of words*” containing all transactions of all clients from class  $c_k$

## Result used in transaction scoring

- Probability of each class  $c_k$  conditional on the client’s transaction counts  $\mathbf{x}$ :

$$p(c_k|\mathbf{x}) \propto p(c_k) \prod_{j=1}^d \frac{p^{x_j}(c_k|t_j)}{p^{x_j}(c_k)}$$

- $p(c_k | t_j)$  and  $p(c_k)$  estimated from the “*bag*”, containing pairs  $[c_k, t_j]$  for each transaction of each client
- The reason is consistency with the usual estimation of input  $p(t_j | c_k)$  from the “*bag of words*” instead of our input  $p(c_k | t_j)$

# Naïve Bayes estimate of probability the client is actually overdue is a powerful scorecard variable

## Formula of scorecard variable

- Assume binary class,  $c_1$  = the client is overdue,  $c_1$  otherwise
- Estimate of  $p(c_1 | \mathbf{x})$  will be a scorecard variable:

$$p(c_1 | \mathbf{x}) = \frac{1}{1 + \frac{1-p}{p} \cdot \exp(-L)},$$

where

$$L = \sum_{j=1}^d x_j \ln \frac{p_j}{1-p_j}$$

$$p = p(c_1),$$

$$p_j = p(c_1 | t_j).$$

## Practical findings

- $L$  is monotonous transformation of  $p(c_1 | \mathbf{x})$ , i.e. can be used in the scorecard instead
- Significant improvement of a scorecard even besides the client's known overdue days:  $p(c_1 | \mathbf{x})$  interpreted as equilibrium value of overdue flag
- 20 pseudo-observations – clients with overdue flag equal to  $p$  – added to the sample for calculation of  $p_j$  to account for potential low number of observations
- A simplified Term-Frequency transformation improves performance

# Naïve Bayes estimate of mean log deposit balance has also good predictive power in the scorecard

## Formula of scorecard variable

- Assume numeric class  $C'$  with its mean having an economic interpretation, e.g. log deposit balance (for clients with balance  $> 1$ )
- $C'$  will be approximated by normal distribution and normalized to  $C \sim N(0,1)$ .
- Estimate of mean  $m = E[C|\mathbf{x}]$  will be a scorecard variable:

$$m = \frac{\sum_{j=1}^d x_j \mu_j}{\sigma^2 + (1 - \sigma^2) \sum_{j=1}^d x_j}$$

where  $\mu_j = E[c_k | t_j]$  is estimated from the data and  $0 \leq \sigma \leq 1$  is a parameter.

## Practical findings

- Significant improvement of a scorecard even besides the client's known deposit balance
- 20 pseudo-observations – clients with normalized log deposit balance equal to 0 – added to the sample for calculation of  $\mu_j$  to account for potential low number of observations
- Simplified Term-Frequency transformation improves performance
- Choices of  $0 \leq \sigma \leq 0.5$  show highest univariate Somers' D

# The suggested transaction scoring has been successfully implemented in a bank

## Behavioral scorecard

- Implemented in CEE bank with **high market share** – precise assessment of more transaction types
- **Somers' D of behavioral score** improved from **81%** to **86%** with significant impact on loan approval
- The transaction variables in the form of deviation from the mean: **political decisions** affecting, e.g., overall level of deposit balances **do not shift all scores** in the same direction

## Technical implementation

- Implemented in **SQL DWH** – competitive advantage in the times Big Data platforms were not in place among the competitors
- IT requirement in the form of fully-functional **prototype** – fast implementation, low costs

# There are lots of opportunities for further improvement...

- A simplified Term-Frequency transformation showed to be useful. Full TF and other transformations, performing well in text classification, can be investigated.
- More sophisticated text classification algorithms implemented in Big Data platforms can be used.
- Analogy with text classification can be established for different problems.
- Other ways forward can be investigated 😊





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