VPBank
Ngân Hàng Việt Nam Thịnh Vượng

# Defining optimal approaches in building revenue scoring models for credit cards: a case study

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# Introduction - imperatives

**Tense competition.** In Vietnam, banks compete in providing credit cards to retail customers with many loyalty programs, f.e. discounts with partners, decreased interest rate, charge backs.

**Dominating role.** VPBank is one of the fastest - growing credit card issuer in South East Asia with 2+ million of active credit cards. Sound revenue/profitability strategy is a must to balance targets of market share growth vs P&L.

**Revenue/Profitability modelling.** Revenue scoring model for credit card has been initiated to assess profitability of credit card holders and then realize their profitability to real revenue by relevant policies to individual customers.

**Theory & empirical studies.** We have explored several theoretical studies about profitability modeling for credit cards. However, **we could not find practical studies that guide on this topic and provide clear insights of the usage of the models**. Consulting with the leading data science companies was unsatisfactory and showed **luck of consistency** in the approaches.

**Benefits**. This presentation might save several weeks of your time by providing practical insights on:

- ✓ Analysis of different modeling approaches of profitability/revenue.
- ✓ The case study of VP Bank with the example of real revenue models, experiments with their modelling and practical outcome.

# Profit scoring model – common approaches

| No | Approach | Target | Shortcomings |
|---|---|---|---|
| 1 | Matrix scoring | Derive profitability from parameters of the existing scorecards such as (a) response, (b) retention/attrition, and (c) credit risk. | Not focused on profit/revenue and therefore accuracy might be lower compared to other approaches. |
| 2 | Linear regression applied to application variables | The model is built on categorical variable from application form. | Censored data issue is not satisfactorily addressed. |
| 3 | Markov chain and its variation | Model can be used for different purposes like limit optimization, reward maximization, cut-off identification for credit risk model based on profit, etc. | Homogeneity of inputs and applicability on a portfolio level should be addressed. |
| 4 | Survival model | Use of second purchase survival analysis could improve the predictive accuracy of profit of non-default credit card and second purchase.<br>Aside of profit estimation models can be used for other tasks such as predicting defaults, attritions or transactions. | Estimation of profit is done without considering attrition rates which is important factor. |
| 5 | Logistic regression applied to available behavioral information | The model is built for existing credit card portfolio and potentially can be used together with risk model to define appropriate strategy for portfolio management. | Necessity to identify important independent variables.<br>No empirical results are disclosed. |

# Profit/Revenue measurements

Common profit/revenue measurements can be summarized as follows:

1. Absolute values:
   - ✓ present value of total net revenue of card from disbursement date till the end of performance period or till the time of default;
   - ✓ net revenue minus non performing loans.

2. Relative values:
   - ➢ the relative profit measured as the customer lifetime revenue divided by the outstanding debt;
   - ➢ the internal rate of return for each account;
   - ➢ lender's effective interest rate;
   - ➢ expected maximum profit.

3. Customers' lifetime revenue which can be quantified as the net present value of discounted cash flow generated by customers.

# VPBank case study – revenue vs profitability

**Objective**: it was decided to predict **revenue** per credit card contract **instead of** predicting **profitability** due to the following limitations:

- unavailable detailed operational costs at a single client level;
- unavailable full expenses on credit card rewards;
- frequently changed customer acquisition and reward strategies supplemented by 40% growth of customer base year-on-year.

**Modeling approaches:** after analyzing (i) data availability, (ii) predictive power of models and (iii) ease of production deployment it was decided to apply:

✓ **Status approach (SA).** Markov chain based approach (Approach 3) with focus on credit card statuses. This approach was described by Dr. Denys Osipenko* however it was limited to (a) interest, (b) revenue from POS and (c) ATM transactions. We **added more easily available revenue sources** into the model, f.e. (d) revenue from abroad transaction, (e) penalties and (f) conversion fees.

✓ **Income source approach (ISA).** Logistic Regression approach (Approach 5) that applies weighted logistic regression to model revenue of the credit card.

**Advantage:**

✓ Used grouping based on WOE to show the business meaning of covariates.

✓ All types of revenue are identified and modeled, except for annual fee.

* Dr. Osipenko D. (2017) An investigation into methods of predicting income from credit card holders using panel data, *PhD thesis, The University of Edinburgh*.

# Income source and Status types matrix

6 income sources

4 operational status types

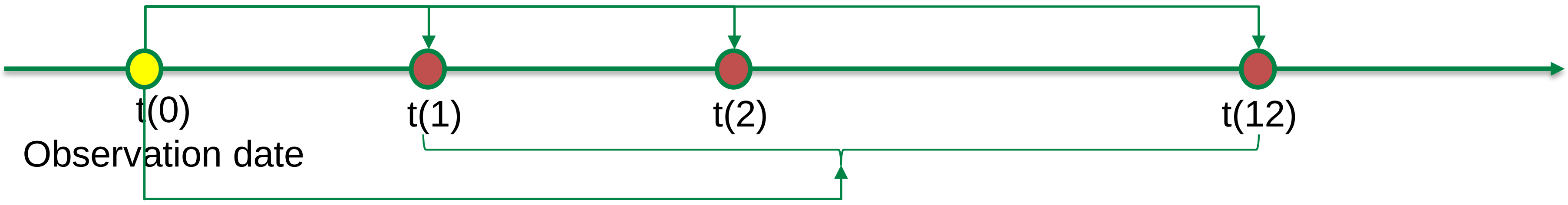
| | | ATM Income | Transaction Income | | Interest | Penalty | Installment |
|---|---|---|---|---|---|---|---|
| Inactive | Inactive | No | No | No | No | No | No |
| Current | *Transactor* | *Fee ATM* | *Exchange fee* | *Interchange* | *Interest* | No | *Fee* |
| | *Revolver* | *Fee ATM* | *Exchange fee* | *Interchange* | *Interest* | No | *Fee* |
| Overdue | Overdue | Fee ATM | Exchange fee | Interchange | Interest | Overdue Penalty | Fee |
| Default | Default | No | No | No | No | No | No |

**Some researches** classify **5 operational status types of credit cards holders**: Inactive, Transactor, Revolver, Overdue and Default. Models are built for each type to predict monthly revenue.

**Transactor creates interest income** when customer withdraw money at ATM or convert any credit card transaction to loan which have the same revenue category with Revolver. Therefore for model development purposes, it was decided to merge **Transactor & Revolver into one group (Current status)**.

# Difference in Revenue Periods

**SA**: predicts revenue for a single month (end of the month), and total revenue will be a sum of months over a one year period (12 months) to evaluate model performance.




**ISA**: predict total revenue in one year after the observation date.

| | Status Approach | Income Source Approach |
|---|---|---|
| Target definition | Target for each sub model is **monthly revenue** because status is identified based on the statement information. | Target is **total revenue in one year**. |
| Regression methodology | **Panel data** is proposed to include time factor into the models. | Weighted logistic models is proposed to predict **continuous target**. |

# Panel data methodology

| Obs. ID | Predicted Variables | | | Target variables | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Var 1 | … | Var n | T=1 | | | | … | T=12 | | | |
| | | | | Status | ATM | … | Retail | … | Status | ATM | … | Retail |
| 1 | M | … | 30 | Novd | 100$ | … | 200$ | … | Novd | 0$ | … | 150$ |
| 2 | F | … | 25 | Ovd | 50$ | … | 10$ | … | Novd | 60$ | … | 15$ |
| 3 | M | … | 35 | Inac | 0$ | … | 0$ | … | Ovd | 10$ | … | 20$ |
| … | … | … | … | … | … | … | … | … | … | … | … | … |

| Obs. ID | Predicted Variables | | | Target variables | | | | |
|---|---|---|---|---|---|---|---|---|
| | Var 1 | … | Var n | Status | ATM | … | Retail | T |
| 1 | M | … | 30 | Novd | 100$ | … | 200$ | 1 |
| … | … | … | … | … | … | … | … | … |
| 1 | M | … | 30 | Novd | 0$ | … | 150$ | 12 |
| 2 | F | … | 25 | Ovd | 50$ | … | 10$ | 1 |
| … | … | … | … | … | … | … | … | … |
| 2 | F | … | 25 | Novd | 60$ | … | 15$ | 12 |
| 3 | M | … | 35 | Inac | 0$ | … | 0$ | 1 |
| … | … | … | … | … | … | … | … | … |
| 3 | M | … | 35 | Ovd | 10$ | … | 20$ | 12 |
| … | … | … | … | … | … | … | … | |

The estimated formula:

$$f(target_T) = \alpha + \sum_{1}^{m} \beta_i \times g(Var_i) + \gamma_i \times f_i(t)$$

Where:

- $f(target_T), T = \overline{1{,}12}$ are transformed target at period T.
- $\alpha, \beta, \gamma$ are regression coefficients (slopes).
- $g(Var_i)$ are transformed value of predicted variables.
- $f_i(t)$ are random-effect functions based on T.

# Regression methodology with panel data

**Logistic model with time varying effects:**

We assume that time varying effects is heterogeneity in the entire duration and we denotes the random variables as cubic spline basis functions for more flexibility of time varying effects:

$$u_t = \sum_{j=1}^{m} \alpha_j S_{jt} + \varepsilon$$

The important assumption is that time varying effects are not correlated with any prediction variables in the model.

Approaching from logistic with time varying effects method, P(Y=1) is represent as:

$$ln\left(\frac{P(Y_{it} = 1)}{P(Y_{it} = 0)}\right) = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ikt} + \sum_{l=1}^{L} \alpha_l S_{lt} + \varepsilon$$

or

$$P(Y = 1) = \frac{e^{\beta_0 + \sum_{k=1}^{K} \beta_k X_k + \sum_{l=1}^{L} \alpha_l T_l}}{1 + e^{\beta_0 + \sum_{k=1}^{K} \beta_k X_k + \sum_{l=1}^{L} \alpha_l T_l}}$$

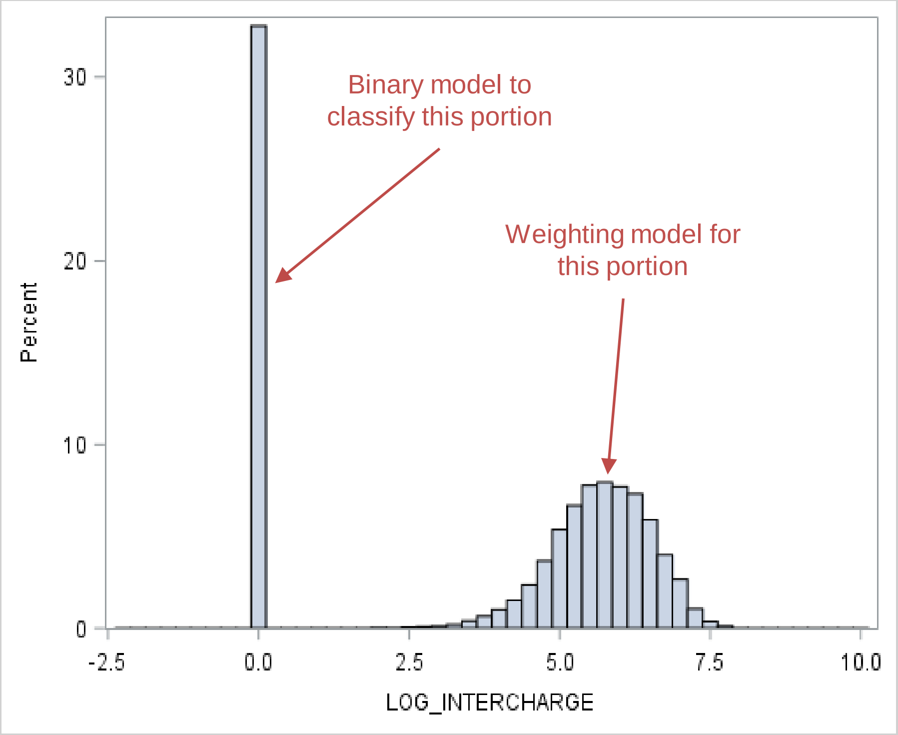
Where

- $X_k(k = \overline{1, K})$ are prediction variables.
- $T_l(l = \overline{1, L})$ are time varying effects variables.

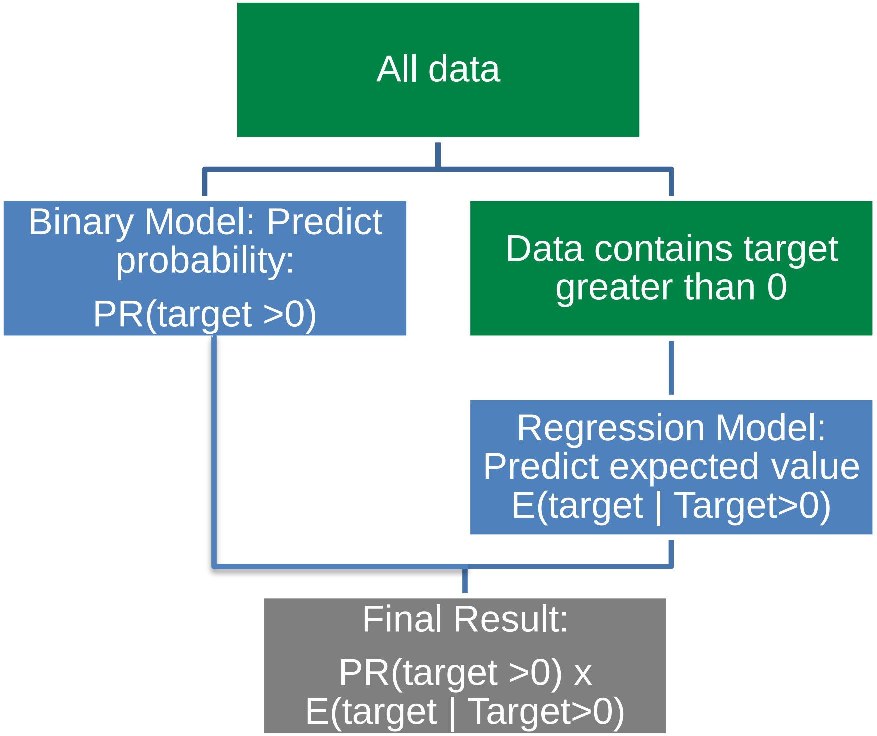
# Two stages methodology

Two-stage model is often used when the distribution of target variable is not normal. The model uses different techniques for each portion of target variable.

Chart below shows an example of not-normal distribution of target variable.




Two stage model contains 2 sub-models:

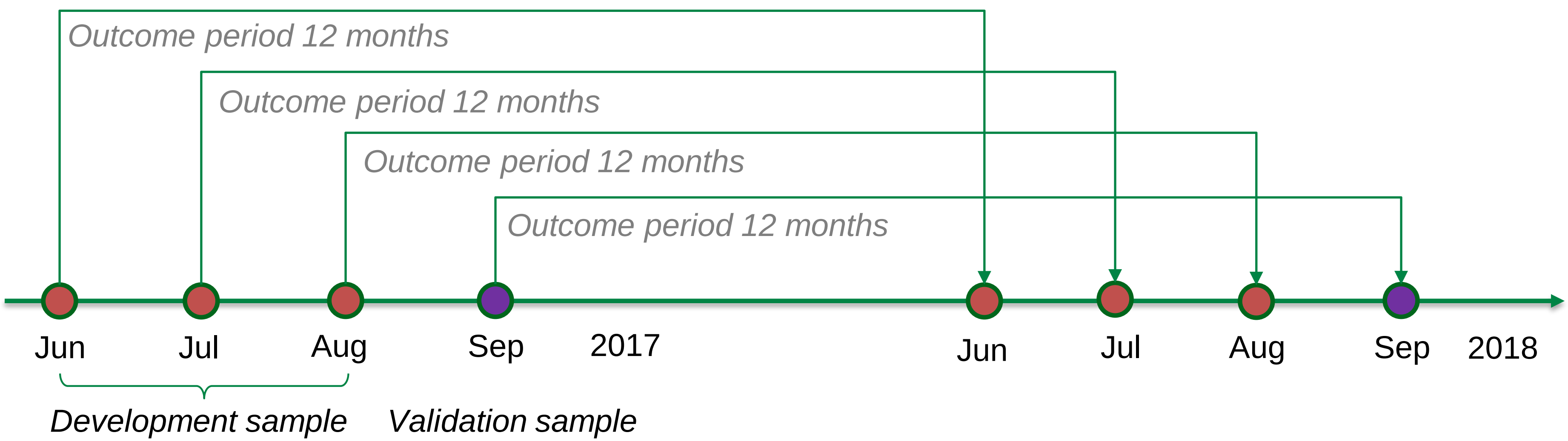


# Development sample

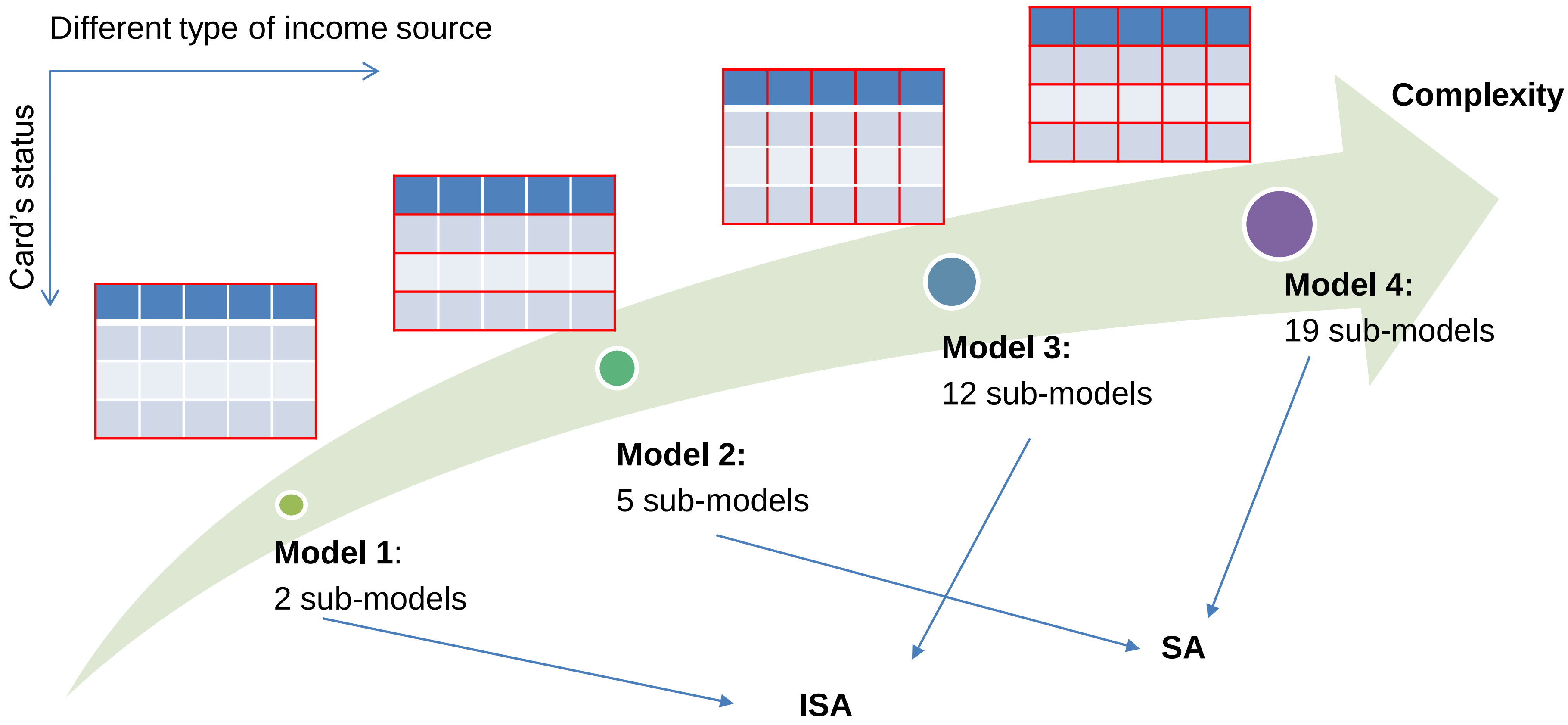
- ✓ A sample of all credit card accounts with the following criteria was taken for the development:
  1) Delinquency of clients is less than or up to 30 days (DPD 30); such definition makes sense as it is similar to existing behavioral collection risk models and allows to leverage them.
  2) Credit card disbursement time is 6 months or more.

- ✓ Accounts with observation date on the last day of June, July and August 2017 were combined into the **development sample**.

- ✓ **Outcome period** is 12 months after the observation date.



# 4 models and 38 sub-models developed




This study tests 4 models developed by 2 mentioned approaches and analyzes the optimal approach for the available data. The model name denoted the increasing complexity:

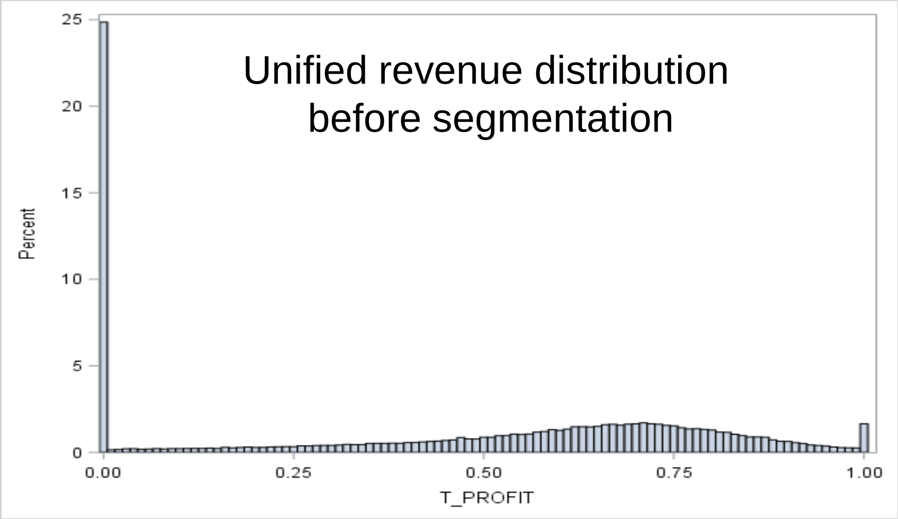
1. Model 1 and Model 3 with 14 sub-models were developed within Approach 5, i.e. weighted logistic regression to model the total revenue with and without segmentation on income sources.
2. Model 2 and Model 4 with 24 sub-models were developed within Approach 3, i.e. panel data regression based on credit card status with and without segmentation of income sources.

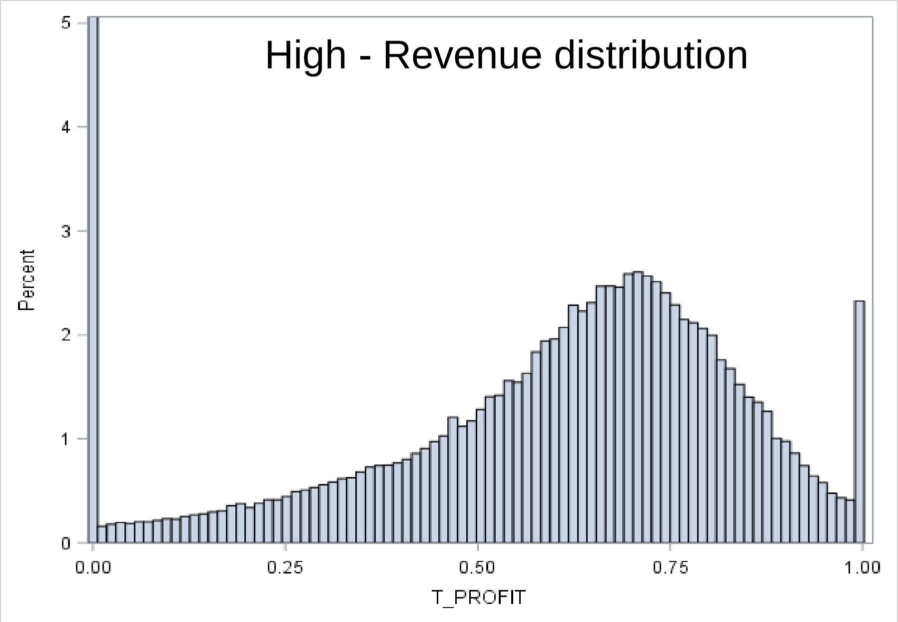
# Model 1: based on gross revenue amount

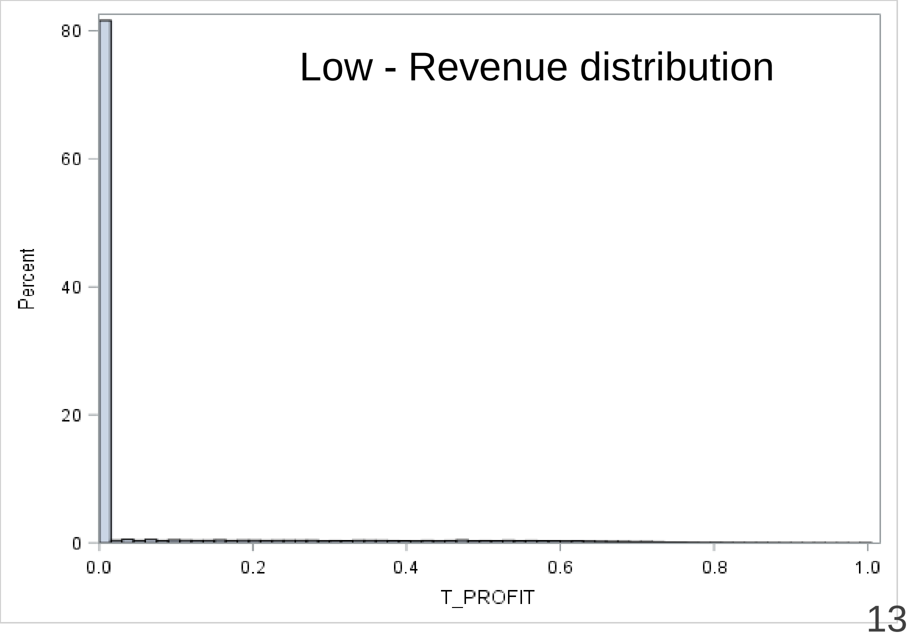
Total revenue is estimated for the next 1 year using segmentation based on gross revenue.

- Distribution of revenue was concentrated at zero and we separated sample into two groups: high and low revenue.
- Using decision tree, the criteria “average of credit card balance in last month before observation date” was chosen for segmentation (see on the right chart).

**The total number of sub-models: 2**



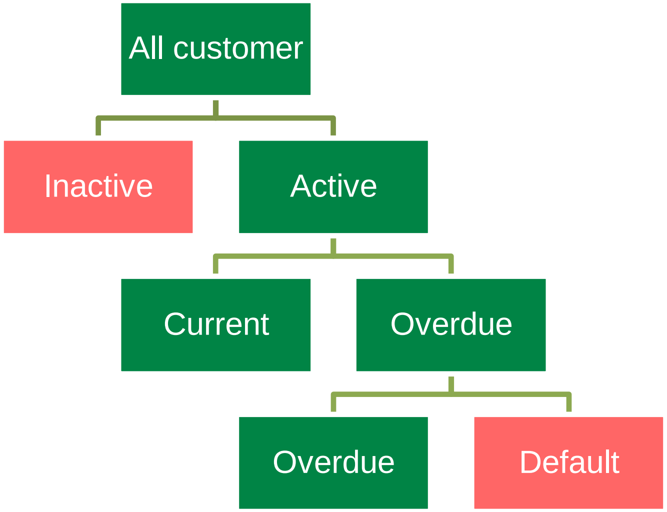



# Model 2: based on credit card status

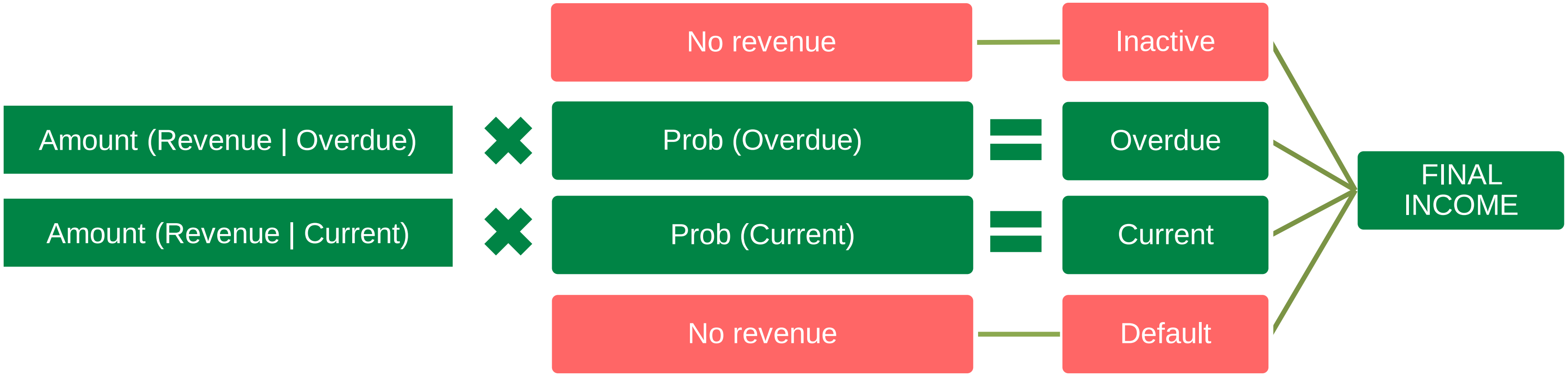
**Total revenue is modeled for each type of status.** There are two types of revenue and two types of no revenue.

Two stages - modeling is used:

- Multinomial sub-models to predict probability of customer that belongs to each of these status: Inactive, No Overdue, Overdue, Default.
- Weighting models to predict total revenue given one of the statuses above.



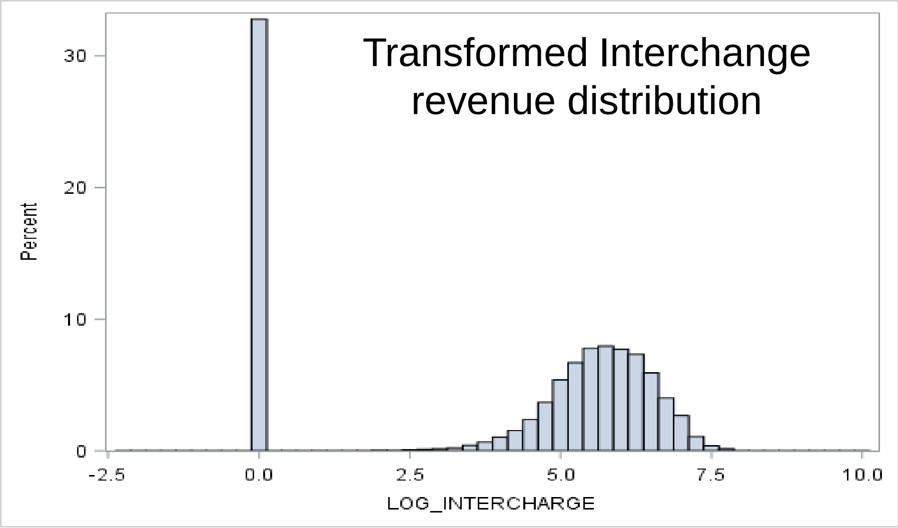

**The total number of sub-models: 5**



# Model 3: based on income sources

**Total revenue is estimated through 6 components** (see below). Each component is predicted by two-stages model due to bimodal distribution of revenue:

- Binary sub-model to predict probability of customer having type A of revenue: prob (A), where A is one of the 6 types of revenues.
- Weighted sub-model to predict amount of revenue type A given that customers have such type of revenue: Amount (A).




**The total number of sub-models: 12**

| | | | | |
|---|---|---|---|---|
| Prob (ATM withdrawal) | × | Amount(ATM) | = | Fee ATM |
| Prob (Retail) | × | Amount(Retail) | = | Retail Income |
| Prob (Interest) | × | Amount(Interest) | = | Interest Income |
| Prob (Abroad) | × | Amount (Abroad) | = | Fee abroad |
| Prob (Installment) | × | Amount (Installment) | = | Fee installment |
| Prob (Overdue fee) | × | Amount (Overdue fee) | = | Fee Overdue |

FINAL INCOME

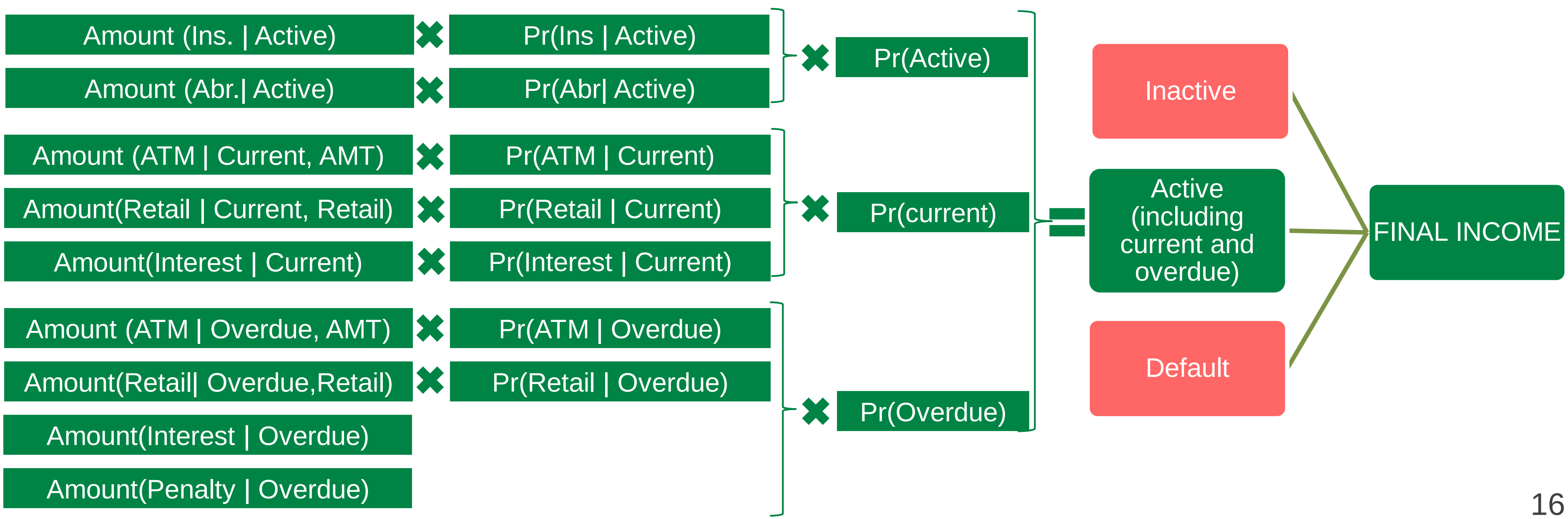
# Model 4: based on credit card status and income sources

**Model 4 is de facto a mixture of ISA and SA: total revenue is estimated for each type of status + by income sources**:

1. Multinomial sub-models to predict probability of customer that belongs to each status N: Inactive, No Overdue, Overdue, Default.
2. Binary sub-model to predict customers' having revenue type A: Pr(A) given the status N.
3. Weighting sub-models to predict amount of revenue A given that customers have such type of revenue and belong to status N.

*Note: Due to the small amount of cards with abroad & installment revenue (a) separate sub-models have been built for them and (b) no need for statuses No Overdue / Overdue.*

**The total number of sub-models: 19**



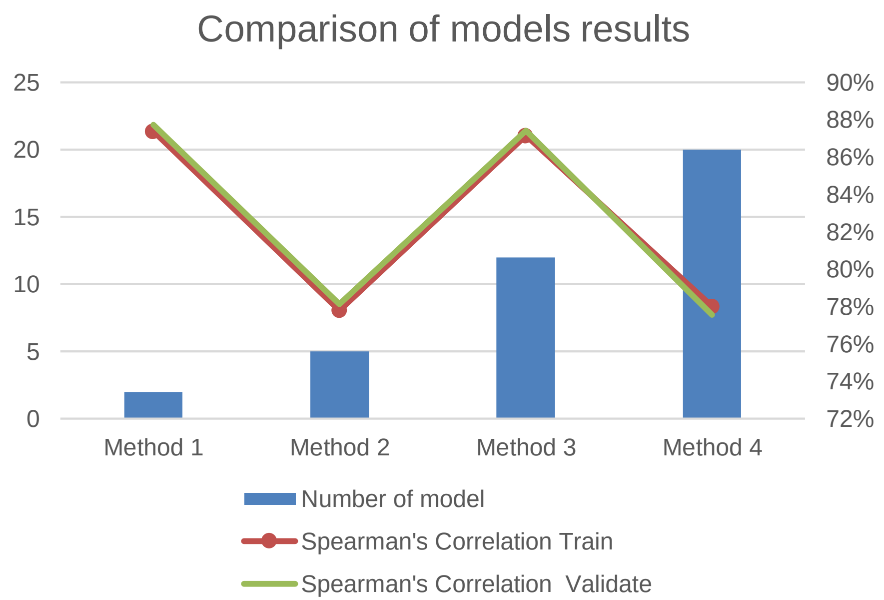
# Performance assessment of the models

Below is the comparison of predictive power of 4 models. The assessment coefficient is Spearman's Correlation.

| Methodology | Number of model | Approach | Spearman's Correlation | |
|---|---|---|---|---|
| | | | Dev. sample | Val. sample |
| Model 1 | 2 | ISA | 87% | 88% |
| Model 2 | 5 | SA | 78% | 78% |
| Model 3 | 12 | ISA | 87% | 87% |
| Model 4 | 19 | SA + ISA | 78% | 78% |

The result shows that Income Source Approaches gives better results than the Status Approaches.

In each approach, simple model is better than complex ones; Model 1 has the best performance out of all models.



# Comparison of models

## By Income Source

- Simple model show stronger performance.
- Easy in data collection.
- Revenue score need to be crossed with a risk score to define appropriate strategy for customer.

### Model 1

- Simple model show strongest performance.
- Sensitive to any policy changes, for example: promotion on cash out, new source of revenue, etc.
- Total revenue is predicted, but not granular re individual revenue type.

### Model 3

- Each component can be easily updated when credit policies change.
- Any new type of revenue can be added into model.
- Extensive workload is required (12 sub-models) and result does not outperform Model 1.

## By Status

- The result includes risk factors. Model can be used directly without crossing with risk score.
- Individual revenue component can be predicted from each income source per specific period.
- Models are not robust/unstable over the time.
- Complex data collection.

### Model 2

- Simple model shows stronger performance than Model 4.
- Total revenue is predicted but not granular re individual revenue type.

### Model 4

- Individual revenue component can be predicted from each income source per specific period.
- High complexity with 19 sub-models and result does not significantly outperform other models.

# Model 1 - Source of information

| Data source | Description | 207 Variables | Predictive power |
|---|---|---|---|
| **General information** | 4 variables of credit card and 4 demographic information of customers. | 8 | Most variable has low predictive power, only one variable is used in low revenue model. |
| **Credit card transaction data** | All data about transaction: number, amount, time, category and derived variables. | 73 | Predictive power fluctuate from medium to high. Each sub-model has some variables belonging to this group. |
| **Credit card delinquency** | All information about delinquencies of credit card contracts, for example number of times reach certain DPD state, maximum DPD in (i) months before observation date, etc. | 31 | Most variables are quite weak, both models have no variable in this group. |
| **Current account and deposit information** | All information about current account of customers for example number of deposit, term of deposit, amount of transaction (in and out), etc. | 23 | Variables are weak, and only one variable is in low revenue model. |
| **Credit card revenue information** | All information about historical revenue of credit card contract: fee, interest, interchange, revenue, etc. | 44 | Those variables are the strongest and some variables used in both models. |
| **Credit card balance information** | All historical data about balance of credit card contract: average balance, maximum balance, balance divided by revenue, etc. | 28 | This group has high predictive power as credit card revenue group, some of them used in both model. |

# Model 1 – Predicative Variables

Will be disclosed during the presentation

# Model 1.1 High revenue –analysis of characteristics

Will be disclosed during the presentation

# Model 1.2 Low revenue –analysis of characteristics

Will be disclosed during the presentation

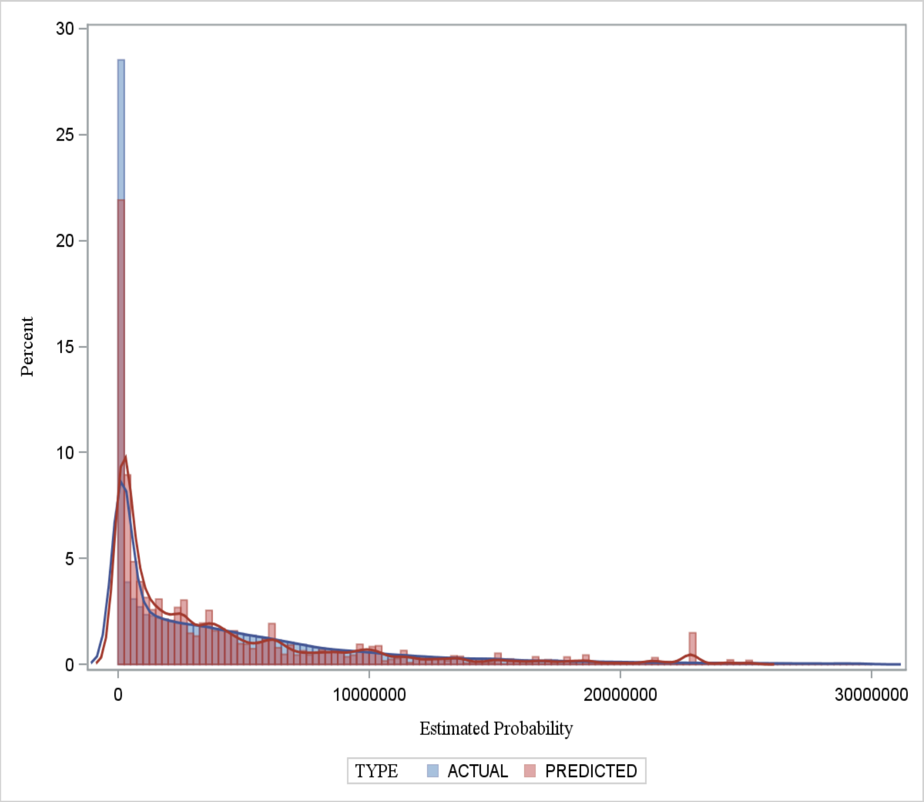
# Model 1 - Performance

| CROSS MATRIX (%) | PREDICTED | | |
|---|---|---|---|
| ACTUAL | 0 - 0.6 | 0.6 - 4 | > 4 |
| 0 - 0.6 | 83.22 | 15.39 | 1.39 |
| 0.6 - 4 | 16.06 | 71.65 | 12.28 |
| > 4 | 2.58 | 23.41 | 74.01 |

| Sample | R-Square | Correlation | |
|---|---|---|---|
| | | Pearson | Spearman |
| Development | 67.6% | 86.3% | 87.5% |

Model 1 is strong due to the following facts

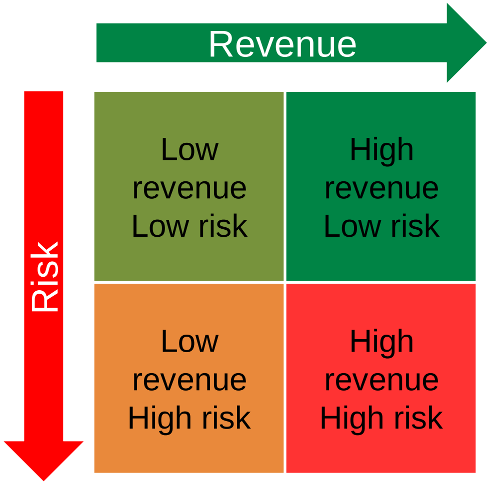
- Cross matrix shows high accuracy of model.
- High R-Square, Pearson's and Spearman's correlations.
- Distribution of actual revenue and predicted revenue are close to each other.



# Summary - VPBank case study

**Summary:**

- Model 1 is the best model in term of performance and simplicity.
- In VPBank, we combine Model 1 with Risk behavioral model to classify customers into 4 groups as showed beside to define the appropriate strategy for each group of customers.
- Detail score of each model with strategies are showed in the table below.




<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="5">Revenue Score</td></tr>
<tr><td>0-299</td><td>300-499</td><td>500-599</td><td>600-799</td><td>800+</td></tr>
<tr><td rowspan="5">Risk Score</td><td>0-189</td><td colspan="5">Convert balance to installment loan</td></tr>
<tr><td>190-209</td><td colspan="2">Decrease Limit</td><td colspan="2"></td><td></td></tr>
<tr><td>210-229</td><td>No promotions</td><td colspan="2">Keep limit unchanged</td><td colspan="2">Increase limit</td></tr>
<tr><td>230-249</td><td colspan="2">Stimulate utilization</td><td colspan="2">Second tier of promotion budget</td><td>Increase Limit</td></tr>
<tr><td>250+</td><td></td><td></td><td colspan="3">Free annual fee and top for promotions</td></tr>
</table>

- In 2018 application of the Revenue model in combination with the credit risk behavioral model resulted in annualized revenue increase of ~USD 2 million (figure of 2018).

# Conclusion

**Summary:**

1. Income Source Approach outperforms Status Approach.
2. When adding status the predictive power reduces.
3. For the first timers in revenue/profitability estimation we recommend to use simple models as they have better result than more complex models within the same approach.

**Further research**:

1. Develop model to predict profit when data of real profit are available, f.e. acquisition cost and rewards data.
2. Define the appropriate strategy for customers based on their response the proposed loyalty programs.

# Q&A ☺

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