Agenda

► Introduction 10 min
► What is credit risk 25 min
► Model development and validation 35 min
► Tools 10 min
► Questions 10 min
What is credit risk?
Credit risk agenda

- Risk management function reshaping roadmap
- Credit risk strategy and linkage to business strategy
- Risk appetite framework and statements
- Credit risk processes and segregation of duties
- Model governance framework (model request, design implementation, validation)
- Stress testing framework

Diagnostics on the effectiveness & efficiency of the collections process
Development of a collections strategy, strategic and tactical (cost-benefit) analysis of available outsourcing options
Design of a collections framework
Support with collections technology requirements analysis, selection and implementation of an appropriate solution

Application process

- Application scoring
  - Business model request specification
  - Application scorecard design and validation
  - Design and review of the application processes
  - Support with application workflow technology

- Rating models
  - Model design / validation / internal audit reviews
  - Regulatory compliance
  - PD estimation
  - Model usage for business purposes

- Provisioning
  - Design of impairment methodology in line with IFRS
  - Effective interest rate and recognitions of fees and commissions
  - Back-testing analyses
  - Proprietary IT tools

- LGD models
  - LGD estimates design and validation
  - LGD (scoring) models design and validation
  - LGD data warehouse specification
  - Collateral valuation scenarios

Performing portfolio

Non-performing portfolio

Governance
Components of credit risk

- **Probability of Default:** The likelihood the borrower will default on its obligation either over the life of the obligation or over some specified horizon.

- **Loss Given Default:** Loss that lender would incur in the event of borrower default. It is the exposure that cannot be recovered through bankruptcy proceedings or some other form of settlement. Usually expressed as a percentage of exposure at default.

- **Exposure at Default:** The exposure that the borrower would have at default. Takes into account both on-balance sheet (capital) and off-balance sheet (unused lines, derivatives or repo transactions) exposures.

\[
\text{Expected Loss (EL) = PD \times LGD \times EAD}
\]
IRB approach
Risk weight in detail

Capital > Capital requirement = Capital ratio * RWA

\[
RW = 12.5 \times 1.06 \times \left[ LGD \times N \left( \frac{N^{-1}(PD) + \sqrt{R} \times N^{-1}(0.999)}{\sqrt{1 - R}} \right) - PD \times LGD \right]
\]

- **Conservatism factor**
- **Value at Risk (VaR)**
- **Expected loss (EL)**
- **Unexpected loss (UL) = VaR - EL**

Fudge factor - Introduced to get STA and RWA to the same basis.

The RW formula (without 12.5 multiplication) gives us exactly what we need, i.e. the money (when multiplied by EAD) that bank needs to hold as the capital requirement.

However, because the overall capital adequacy is calculated as 8% or RWA, we need to multiply it by 12.5 to cancel the 8%.

Remember that the constant is still 12.5, even when the requirement is more or less than 8%.

Note that Capital charges for Market risk and operational risk are multiplied for the same reason.
Risk weight as function of PD (retail segment)

- Secured LGD 30%
- Unsecured LGD 50%
Risk weight
Retail - Unsecured loans

Risk weight as function of PD
Unsecured loans

Probability of default

Risk weight

LGD 40%
LGD 50%
LGD 60%
Models

The purpose of the **scorecard/rating/PD model** is to determine the creditworthiness of the clients (either new or existing) and to assign expected probability of default (PD) value. Typically like this:

- Scorecard (using client's characteristics) is used to determine the score
- The score range is split into several rating grades
- Each rating grade is assigned expected PD value

The purpose of the **LGD model** is to determine the loss the bank will incur in case that the account defaults. Typically like this:

- Clients are categorized into homogeneous segments (e.g. by LTV)
- Each segment is assigned LGD value

The purpose of the **CCF model** is to determine the part of the off-balance exposure that will be drawn by client before the default
Scoring/rating and PD models

Introduction

► Scoring/Rating
  ► Order of the clients
  ► Good clients are the clients with high creditworthiness
  ► Expressed in rating grades (A-, 4+)

► Probability of default (PD)
  ► Measure of creditworthiness
  ► Probability that the client will not be able to pay the debt
  ► Assigned to each rating grade (0.03, 3%)

► Areas of applications
  ► Approval process, loan regular reviews
  ► Risk management - impairment losses, capital adequacy
Scoring/rating and PD models

Types

► Retail
  ► Application rating
    ► New clients
    ► Demographic data, loan characteristics, data from registers

► Behavioral rating
  ► Clients with history (6M)
  ► Data about transactions behavior

► Corporate
  ► Financial rating
    ► Financial statements data
  ► Qualitative rating - questionnaires
  ► Behavioral rating
PD models

Methods

► Target variable - probability of default
  ► “Default”: Yes (1) / No (0)

► Default definition is regulatory requirement
  ► 90 DPD
  ► Any other reason indicating higher probability of inability to pay the commitments (insolvency proceeding, bankruptcy, restructuring,..)

► How to model 0-1 variable? -> Logistic regression

\[
Y = \alpha + \sum \beta_i X_i
\]

\[
\downarrow
\]

\[
Y = \frac{1}{1 + e^{-(\alpha + \sum \beta_i X_i)}}
\]
PD models
Scorecards

Example:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant (α)</td>
<td>2.0</td>
</tr>
<tr>
<td>Age &lt; 25</td>
<td>0</td>
</tr>
<tr>
<td>Age 25-50</td>
<td>0.5</td>
</tr>
<tr>
<td>Age &gt; 50</td>
<td>-0.2</td>
</tr>
<tr>
<td>Education - Elementary</td>
<td>0</td>
</tr>
<tr>
<td>Education - High school</td>
<td>0.25</td>
</tr>
<tr>
<td>Education - University</td>
<td>0.8</td>
</tr>
<tr>
<td>Sex - Male</td>
<td>0</td>
</tr>
<tr>
<td>Sex - Female</td>
<td>0.4</td>
</tr>
<tr>
<td>Income &lt; AUD 100 000</td>
<td>0</td>
</tr>
<tr>
<td>Income &gt; AUD 100 000</td>
<td>0.9</td>
</tr>
<tr>
<td>Region = Prague, Brno</td>
<td>0</td>
</tr>
<tr>
<td>Region = Plzen</td>
<td>-0.4</td>
</tr>
<tr>
<td>Region = Rest</td>
<td>-1.0</td>
</tr>
</tbody>
</table>

* Higher score is better

$Score = \alpha + \sum \beta_i \cdot X_i$

- Each relevant characteristic has several possible values with different assigned score
- Continues characteristics are typically transformed to several intervals
- Clients from Prague and Brno will always have better score than the exactly same clients (regarding the other factors) from other regions
- Output: order of the clients
**PD models**

**Calibration**

► **Calibration at rating level**

<table>
<thead>
<tr>
<th>Rating grade</th>
<th>Expected default rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>A+</td>
<td>1.5 %</td>
</tr>
<tr>
<td>A</td>
<td>2.5 %</td>
</tr>
<tr>
<td>A-</td>
<td>3.5 %</td>
</tr>
<tr>
<td>B+</td>
<td>4.5 %</td>
</tr>
<tr>
<td>B</td>
<td>6.0 %</td>
</tr>
<tr>
<td>B-</td>
<td>8.5 %</td>
</tr>
<tr>
<td>C</td>
<td>15.0 %</td>
</tr>
<tr>
<td>D</td>
<td>100 %</td>
</tr>
</tbody>
</table>

► **Calibration at portfolio level**

- \[ PD = PD_i \cdot CT / \text{avgPD} \], where CT is average default rate at portfolio
Parameters
LGD and EAD

► LGD:
  ► Single LGD for performing portfolio and LGD curve for non-performing portfolio should be built
  ► Must not be downturn
  ► Should be forward looking:
    ► Uses forecasted values of any collateral and best estimate of haircuts
    ► Current and future modelled value of the house collateral (HPI evolution)
    ► Costs of repossession and sale

► EAD:
  ► EAD estimates for off-balance sheet exposures
  ► EAD model for prediction of exposure run till maturity of the loan
LGD models
Introduction

➢ The probability of default is not the only information about risk related to the client:

<table>
<thead>
<tr>
<th>Client A</th>
<th>Client B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Higher PD</td>
<td>Lower PD</td>
</tr>
<tr>
<td>Consumer loan 1M</td>
<td>Mortgage loan 1M</td>
</tr>
<tr>
<td>Unsecured</td>
<td>Real estate collateral 2M</td>
</tr>
</tbody>
</table>

Whom would you give the loan?

➢ Loss Given Default (LGD)

➢ The loss amount expected in the case that the client comes to default.

\[ LGD = 1 - RR \]

\[ RR_i = \frac{\sum_{j=1}^{i} PV(CF_{ij})}{EAD_i} \]

➢ RR is a recovery rate = recoveries after default related to exposure at default
LGD models
Structure

► Types of recover
  ► Repayments from clients
  ► Realization of collaterals
  ► Costs - direct/indirect

► Recovery horizon: The last day when a recovery is expected

► Haircut (h): Adjustment for collaterals real value
  \[ CF = Coll \cdot h \]

► Interest rate used for discounting
  ► Choice is up to bank for Basel purposes (market rate is usually used)
  ► Original effective interest rate (EIR) is used for IAS 39/IFRS purposes

► Cases
  ► Closed: Recoveries finished till the end of development time window
  ► Open: Future recoveries remain unknown, must be estimated
  ► Typically, open cases from minimal lasting time threshold included (24M)
LGD models
Distribution

- "U-shape"
- It does not make sense to use average LGD = 45% for these clients
- Real LGD is lower than 10% for the best 1/3 of the clients and higher than 90% for the worst 1/4 of the clients
LGD models
Methods - decision trees

- **Loss class** -> a class of exposures with a similar level of loss given default
- **Regression trees** -> explanatory variables
- Thresholds for split
- Additionally pruned or trimmed to abandon spurious dependencies without economical interpretation and over-fitting
Recovery rate can be calculated for different time $t$ -> **Recovery curve**

**Regression by time $t$** can be used to “smooth” the curve

- E.g. for all cases or by individual cohorts (for individual segments)

Graphical analysis allows better expert view about recovery horizon setting, segmentation, etc.
LGD models

Residual LGD curve

Residual recovery rate: \( \frac{80-30}{70} = 71.4\% \)

Residual LGD: \( 100\% - 71.4\% = 28.6\% \)
Model development

- Historical data storage setting
- Data preparation and quality assessment
- Data transformations
- Univariate analysis of individual data characteristics
- Choice of method
- Model versions development
- Battery of tests
- Expert assessment of interpretation and data form
- Calibration
- Documentation of model and development results
- Management approval
- Implementation
- Data storage, reporting
Model validation

- Validation of the model should cover both qualitative (process) and quantitative (model performance) aspects of the model.

- Typical model validation should cover the following areas:

  - Qualitative validation:
    - Model governance, model lifecycle, model documentation
    - Model implementation, change management
    - Model usage, monitoring, reporting
  
  - Quantitative validation:
    - Data
    - Internal structure of model
    - Model stability, performance, calibration
Model validation
Stability - Population stability index (PSI)

The aim of the stability analysis is to assess whether there is significant shift in the underlying data since development:

- Shift in rating distribution
- Shift in distribution of each model variable

Not crucial aspect of the model but instability might make the model assumptions incorrect.

Standard measure is Population Stability Index (PSI)

$$ PSI = \sum_{i=1}^{n} \left( p_{i0} - p_{i1} \right) \log \left( \frac{p_{i0}}{p_{i1}} \right) $$

<table>
<thead>
<tr>
<th>PSI</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 0.1</td>
<td>Stable</td>
</tr>
<tr>
<td>0.1 – 0.25</td>
<td>Warning</td>
</tr>
<tr>
<td>&gt; 0.25</td>
<td>Not stable</td>
</tr>
</tbody>
</table>
Model validation
Stability - Transition matrices

► PSI provides us with aggregate view of stability
► Transition matrix provides us with client/loan level dynamics
► Unless there is significant change on client’s quality scorecard/rating model should be stable (i.e. assigning similar rating in consecutive periods)

Transition matrices evaluation criteria (indicative)¹

<table>
<thead>
<tr>
<th>Condition</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Each eligible* rating grade has at least 75% of transitions on the main diagonal</td>
<td>Strong</td>
</tr>
<tr>
<td>Each eligible* rating grade has at least 60% of transitions on the main diagonal AND Each eligible rating grade has at least 80% of transitions in +/-1 transitions range</td>
<td>Acceptable</td>
</tr>
<tr>
<td>At least one eligible* rating grade has less than 60% of transitions on the main diagonal</td>
<td>Unsatisfactory</td>
</tr>
</tbody>
</table>

¹ More complex assessment of transition matrix is described in the Model validation methodology, chapter 4.1.5 Complex stability test
* Rating grade has to contain at least 100 observations to be eligible
Model validation
Concentration - Herfindahl – Hirschman Index (HHI)

► The aim of the analysis of concentration is to assess whether there is undue concentration in the underlying data
► Concentration on rating level
► Concentration on variable level
► Not crucial aspect of the model but it can indicate model deficiency
► Standard measure is Herfindahl-Hirschman Index (HHI)

\[ HHI = \sum_{i=1}^{n} \left( \frac{N_i}{N} \right)^2 \]

<table>
<thead>
<tr>
<th>HHI</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 0.1</td>
<td>Not concentrated</td>
</tr>
<tr>
<td>0.1 – 0.25</td>
<td>Warning</td>
</tr>
<tr>
<td>&gt; 0.25</td>
<td>Too concentrated</td>
</tr>
</tbody>
</table>
The crucial aspect of a rating model is its ability to distinguish between groups of “bad” (defaulted) and “good” (non-defaulted) clients.

Weak discriminatory power should always lead to re-development.

Standardized measures

- **Gini**
- **AUC (Gini = 2 * AUC - 1)**
- **Kolmogorov-Smirnov**

<table>
<thead>
<tr>
<th>Gini</th>
<th>AUC</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;= 0.5</td>
<td>&gt;= 0.75</td>
<td>Strong</td>
</tr>
<tr>
<td>0.3 - 0.5</td>
<td>0.65 - 0.75</td>
<td>Acceptable</td>
</tr>
<tr>
<td>&lt; 0.3</td>
<td>&lt; 0.65</td>
<td>Weak</td>
</tr>
</tbody>
</table>
Model validation
 Discriminatory power – Gini/AUC

- Coefficient Gini = 2*AUC-1

- Sensitivity = true positive observations
- Specificity = true negative observations

- If Gini < 0%, it’s better to throw a dice at client approval process.

Gini from 0% (No predictive) to 100% (Ideal)
Model validation
Discriminatory power - ROC

► While Gini is important measure of discriminatory power, it is important to analyze the ROC curve itself
► Analysis of the shape of the curve can point out specific deficiencies not observable from the Gini index
► Both of the ROC curves shown on the right have the same Gini value but each point to deficiency in different part of the rating scale
  ► Yellow line indicates that the model has high share of good clients who are assigned the lowest score
  ► Black line indicates (in particular its “flat” segment in the middle) that there is a part of the score band, with very limited number of bad clients
Model validation

Discriminatory power - Information value

- Gini/AUC measure can be used for variables as well
- However, Information Value (IV) measure is more widely used

\[ IV_v = \sum_{i=1}^{n} \left\{ \left( \frac{G_i}{G} - \frac{B_i}{B} \right) \times \ln \left( \frac{G_i}{B_i} \times \frac{B}{G} \right) \right\} \]

- where
  - \( G \) is the total number of good observations
  - \( G_i \) is the number of good observations in given category
  - \( B \) is the total number of bad observations
  - \( B_i \) is the number of bad observations in given category

- Limitations
  - Does not work if there are no bad (or no good) observations at all or even in one category
  - It’s zero if the Good/Bad ratio is the same for each category of variable

<table>
<thead>
<tr>
<th>Information value</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;= 0.25</td>
<td>Strong</td>
</tr>
<tr>
<td>[0.10,0.25)</td>
<td>Acceptable</td>
</tr>
<tr>
<td>[0,0.10)</td>
<td>Unsatisfactory</td>
</tr>
</tbody>
</table>
Model validation
Discriminatory power - Kolmogorov-Smirnov (KS) test (1/2)

- Non-parametric test for the equality of two continuously valued distributions
- Testing the equivalence of two distributions
  - distribution of score of good clients
  - distribution of score of bad clients
  - This statistic is defined as the maximum difference between the cumulative percentage of goods and the cumulative percentage of the bads:

\[ KS = \max |F_0 - F_1| \]

- Evaluation criteria

\[ KS_{\text{max}} = c(\alpha) \sqrt{\frac{n_1+n_0}{n_1n_0}} \]

<table>
<thead>
<tr>
<th>(c(\alpha))</th>
<th>0.1</th>
<th>0.05</th>
<th>0.01</th>
<th>0.001</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.22</td>
<td>1.36</td>
<td>1.63</td>
<td>1.95</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Kolmogorov-Smirnov test evaluation criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition</td>
</tr>
<tr>
<td>KS &gt; KS_{\text{max}}</td>
</tr>
<tr>
<td>KS &lt; KS_{\text{max}}</td>
</tr>
</tbody>
</table>
Model validation

Discriminatory power - Kolmogorov-Smirnov (KS) test (2/2)

Kolmogorov-Smirnov test - Example
Model validation
Calibration

- The main aim of the analysis of the calibration of the model is to assess whether the observed default rate is in line with expected PD values.
- Calibration is the second most important aspect of the model.
- Incorrect calibration of the model leads to incorrect level of capital requirement and requires recalibration of the model.
- Various statistical tests are used:
  - Hosmer Lemeshow Chi-square test
  - Binomial test

<table>
<thead>
<tr>
<th>Rating class</th>
<th>Expected PD</th>
<th>Observed default rate (#1)</th>
<th>Observed default rate (#2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>0.13%</td>
<td>0.15%</td>
<td>0.11%</td>
</tr>
<tr>
<td>4</td>
<td>0.20%</td>
<td>0.22%</td>
<td>0.22%</td>
</tr>
<tr>
<td>5</td>
<td>0.32%</td>
<td>0.37%</td>
<td>0.35%</td>
</tr>
<tr>
<td>6</td>
<td>0.49%</td>
<td>0.52%</td>
<td>0.45%</td>
</tr>
<tr>
<td>7</td>
<td>0.68%</td>
<td>0.70%</td>
<td>0.66%</td>
</tr>
<tr>
<td>8</td>
<td>0.89%</td>
<td>0.82%</td>
<td>0.82%</td>
</tr>
<tr>
<td>9</td>
<td>1.20%</td>
<td>1.12%</td>
<td>0.93%</td>
</tr>
<tr>
<td>10</td>
<td>1.82%</td>
<td>1.87%</td>
<td>1.40%</td>
</tr>
<tr>
<td>11</td>
<td>2.59%</td>
<td>2.17%</td>
<td>2.08%</td>
</tr>
<tr>
<td>12</td>
<td>3.44%</td>
<td>3.22%</td>
<td>2.74%</td>
</tr>
<tr>
<td>13</td>
<td>4.40%</td>
<td>4.61%</td>
<td>3.71%</td>
</tr>
<tr>
<td>14</td>
<td>5.44%</td>
<td>4.51%</td>
<td>4.48%</td>
</tr>
<tr>
<td>15</td>
<td>6.77%</td>
<td>6.27%</td>
<td>7.52%</td>
</tr>
<tr>
<td>16</td>
<td>8.86%</td>
<td>8.47%</td>
<td>6.16%</td>
</tr>
<tr>
<td>17</td>
<td>11.81%</td>
<td>8.26%</td>
<td>5.98%</td>
</tr>
<tr>
<td>18</td>
<td>17.81%</td>
<td>12.68%</td>
<td>3.77%</td>
</tr>
</tbody>
</table>

Chi square test result
Binomial test result
Model validation
Calibration - Hosmer-Lemeshow Chi-square test

- Hosmer-Lemeshow Chi-square test

\[ \chi^2 = \sum_{k=1}^{K} \frac{(O_k - N_k ePD_k)^2}{N_k ePD_k (1 - ePD_k)} \]

- K - number of rating grades
- \( O_k \) - number of defaults in rating \( k \)
- \( N_k \) - number of accounts in rating \( k \)
- \( ePD_k \) - expected PD for rating \( k \)

- Advantage
  - Standardized test
  - Easy to perform with limited number of information

- Main disadvantage
  - Result only on the portfolio level
  - It will trigger red even when overestimation (PD > DR) is present (i.e. the model is conservative), which is not such a big issue in Basel world

<table>
<thead>
<tr>
<th>Hosmer-Lemeshow test evaluation criteria</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition</td>
<td>Performance</td>
</tr>
<tr>
<td>Calculated chi-square statistic is less than the critical value</td>
<td>Strong</td>
</tr>
<tr>
<td>Calculated chi-square statistic is more than the critical value</td>
<td>Unsatisfactory</td>
</tr>
</tbody>
</table>
In case that scorecard/rating model is used for application purposes, often override is allowed by credit officer (i.e. he can shift the rating by several notches)

In such cases, it is important that analysis of this process is done

In case that significant share of cases is overridden, it indicates that the model might not be reflecting some important aspects of client’s behaviour

Individual analysis of the significant overrides should be performed as well

<table>
<thead>
<tr>
<th>Override analysis evaluation criteria (indicative)</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Override rate &lt; 10%</td>
<td>Strong</td>
</tr>
<tr>
<td>10% &lt; Override rate &lt; 25%</td>
<td>Warning</td>
</tr>
<tr>
<td>Override rate &gt; 25%</td>
<td>Unsatisfactory</td>
</tr>
</tbody>
</table>
Model validation
LGD model

► Validation of LGD models is very specific to the model structure, which can vary significantly from bank to bank
► However, typical structure of the LGD model looks like this:

\[ \text{LGD} = \text{PC} \times \text{LGC} + (1-\text{PC}) \times \text{LGWO} \]

► where
  ► PC - Probability of cure
  ► LGC - Loss given cure - typically around 1-2%
  ► LGWO - Loss given write-off - based on recoveries and written-off amount

► Within the validation, assessment/validation of each element is done employing various suitable tests
► In case that scorecard is involved in any of the elements, standard tests that are used for scorecards are used
Model validation
LGD model - test examples

- Segmentation - assessing whether segments have different LGD values
- Calibration - testing Average observed LGD vs. Average expected LGD
- Outliers - analysis using Box-plots
- Population stability - using Population Stability Index
- Discriminatory power (if scorecard used for segmentation) - Gini/AUC
- Concentration - Herfindahl-Hirschman Index
- Qualitative assessment of model development process
- Independent recalculation
Model validation
LGD model – analysis example

- Analysis whether data used to determine the outcome is based on time period with sufficient number of closed cases

Distribution of defaulted accounts by outcome

- Closed no loss
- Cured
- Default
- Write-off
Model validation
Overall assessment

► Final step in validation of any model is to conclude on its overall assessment

► This process might be numeric/quantitative. For each assessment/analysis (e.g. PSI, HHI, Gini, Binomial, ...) we must determine the following:
  ► weight of each assessment/analysis
  ► score of each assessment/analysis
  ► Final score of the model is weighed sum of the partial scores

► However, selection of weights and scores might be difficult to justify
► Expert assessment is then needed

► For scorecards/rating models, indicative priority/weight of the areas is as follows:
  ► Discriminatory power ~ 50%
  ► Calibration ~ 40%
  ► Stability and concentration ~ 10%
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