# Valuatum Platform

Efficient tools for Credit Risk Analysis

Slide numbers:

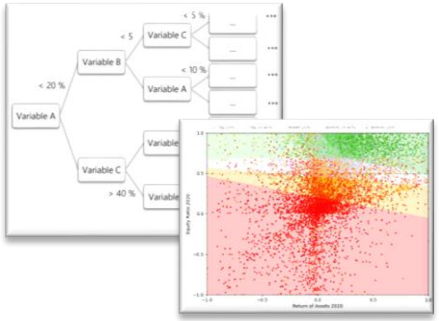
# Valuatum platform overview

- Automatic bankruptcy risk forecasts and credit risk reports
- Access to historical financial statements, provided by external data providers, integrated in the system.
- Our service can be mass-customized quite effortlessly
- Standardized data enables comparisons
- Visual and verbal explanations for the given credit rating
- Our system can support multiple languages e.g. Finnish, English, Swedish and German

Customizable platform offering company-specific information based on customer's needs


View how any company is compared to its peers

Bankruptcy and default risk measures are calculated with the help of machine learning



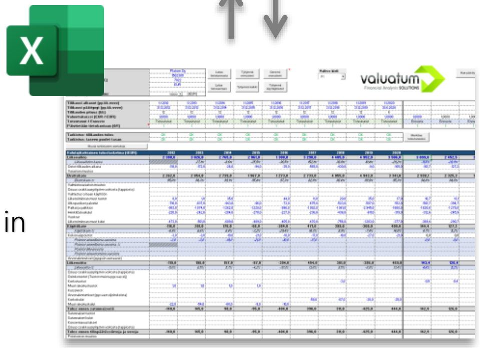
Generate an automated credit risk report based on the company's financial information

REST API integration

Valuatum database

External data providers

creditsafe schufa BÜRGEL Creditreform asiakastieto dun & bradstreet



The system can be used both in Excel and via a web-interface.

# Benefits of our product

- Our AI-based credit risk rating product offers **three** benefits for users:
    1. Accuracy
    2. Efficiency
    3. Enhanced customer experience
- Our credit risk model gives **more accurate** credit ratings and recognizes bankrupt companies 50-60 % better than traditional models commonly used by loan institutes. See more on next three slides.
- Our platform **increases efficiency** by utilizing AI and machine learning models. Our credit ratings are calculated with machine learning model and with AI all items in financial statements are adjusted automatically. Generative AI is also used for giving automatic explanations for credit risk rating decisions. Furthermore, with AI it is possible to read financial statements of companies to get numbers easily and quickly to our system. All these reduce manual work.
- Loan institutions using our platform can **provide superior customer experience**, as the credit applicants can get an answer in a matter of seconds. Alongside the initial credit decision, customers get insights about the possible credit amount or why they are not granted with loan and what should they do to improve their possibilities to get an approved application. Credit applicants can also be given an access to download both credit risk and valuation reports immediately when applying for a loan.

# Model performance comparison with steps (1/3)

## 1) Initial situation

Our comparison starts with the financial data from all approx. 200 000 Finnish companies

**200 000 Finnish companies**

## 2) Risk calculation

We first calculate the bankruptcy risks of all 200 000 companies using both our AI model and a logistic regression model.

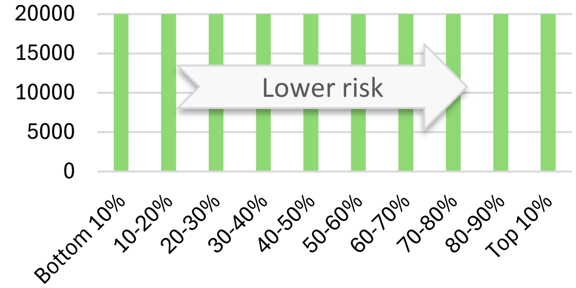
Valuatum AI model

Log. Reg. Risk model

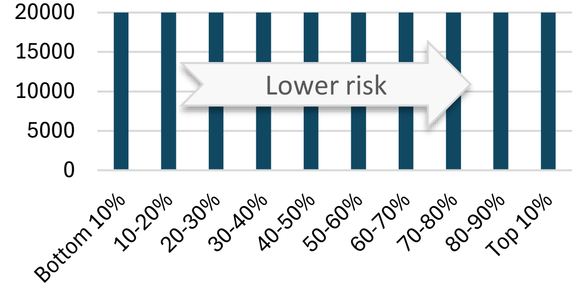
## 3) Company distribution

We distribute the companies into ten equally weighted groups (10% of companies in each group) ranging from 'Bottom 10%' to 'Top 10%' based on their assessed risk.

Companies by Valuatum’s credit rating deciles



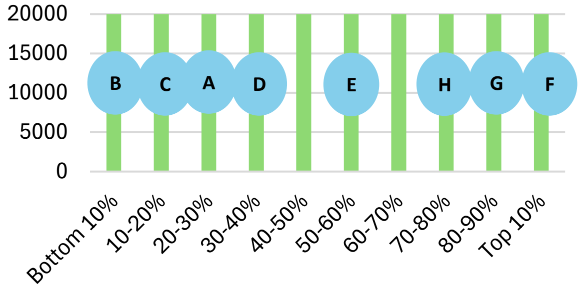

Companies by log.reg.’s credit rating deciles



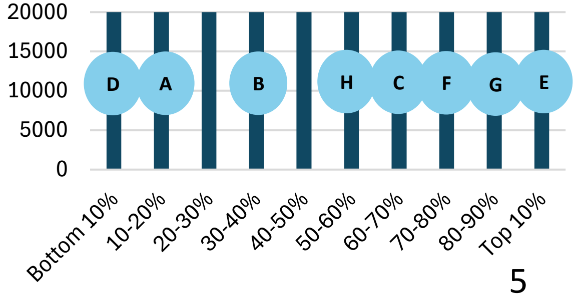

## 4) Different distributions

While every group includes 10% of companies, note that the models might categorize the companies in different deciles, which we can not see from the graph. We have demonstrated this with eight exemplary companies.

Companies by Valuatum’s credit rating deciles




Companies by log.reg.’s credit rating deciles



# Model performance comparison with steps (2/3)

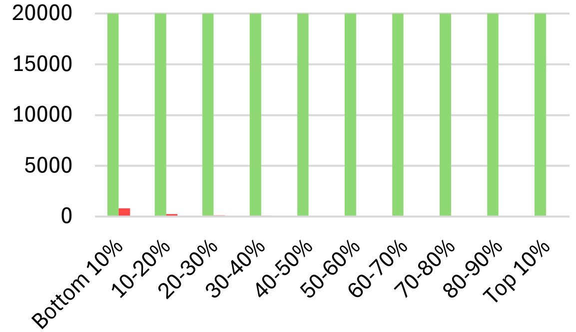
## 5) Bankrupties in 2023

To compare the accuracies of the model predictions, we separated all companies that went bankrupt in 2023

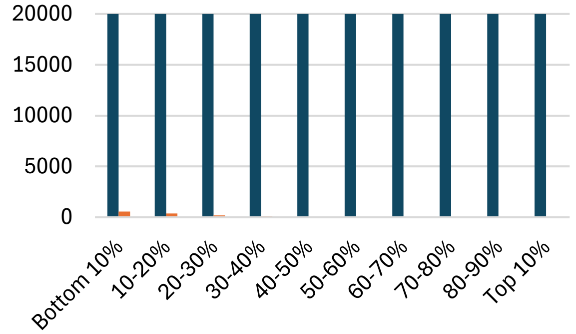

## 6) Bankruptcies in the distribution

We then checked how they were categorized by the models based on the 2021 financial data

Companies by Valuatum's credit rating deciles



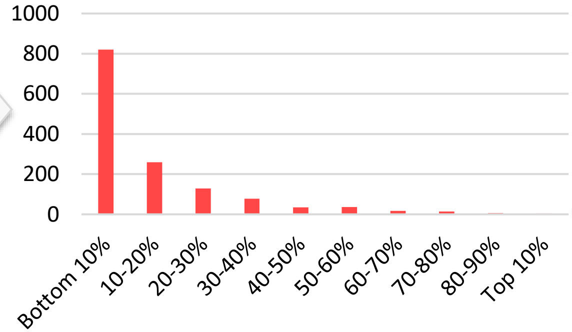

Companies by log.reg.'s credit rating deciles



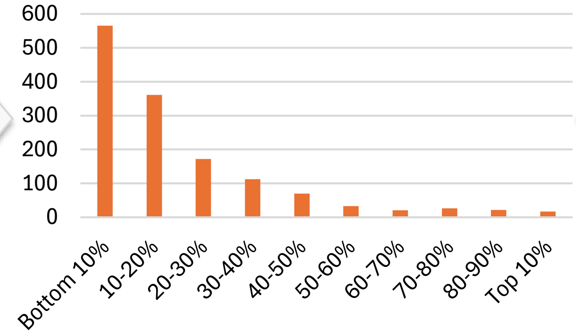

## 7) Bankruptcies by risk deciles

To get a better sense of the differences, we removed all non-bankrupt companies from the comparison.

Bankruptcies by Valuatum's credit rating deciles



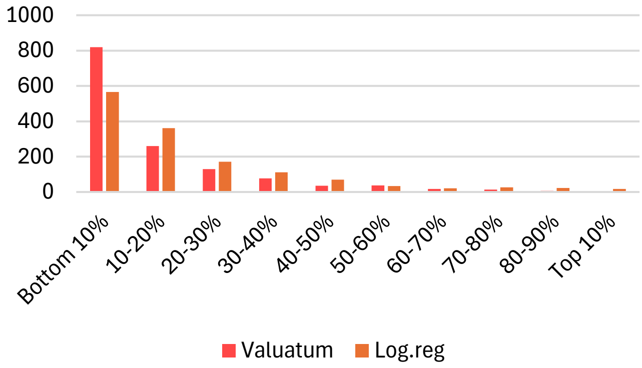

Bankruptcies by log.reg.'s credit rating deciles




## 8) Bankruptcy comparison

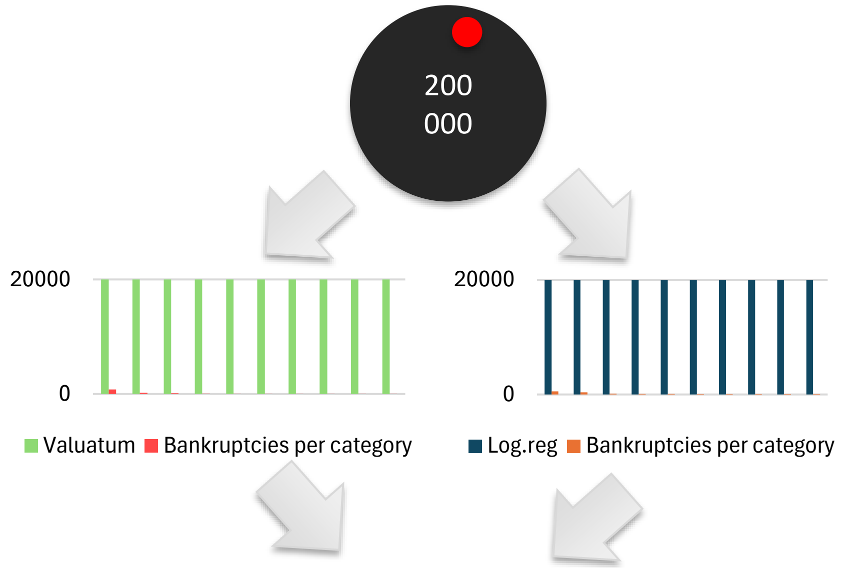
Finally, we combined them into a single graph. As expected, more companies went bankrupt in the higher risk percentiles, while fewer companies in the lower risk percentiles faced bankruptcy. We also notice differences between our AI-based model and the logistic regression model. In the next slide, we'll show how this can be translated into potential savings for the lender.

Number of companies gone bankrupt by credit rating deciles in 2023

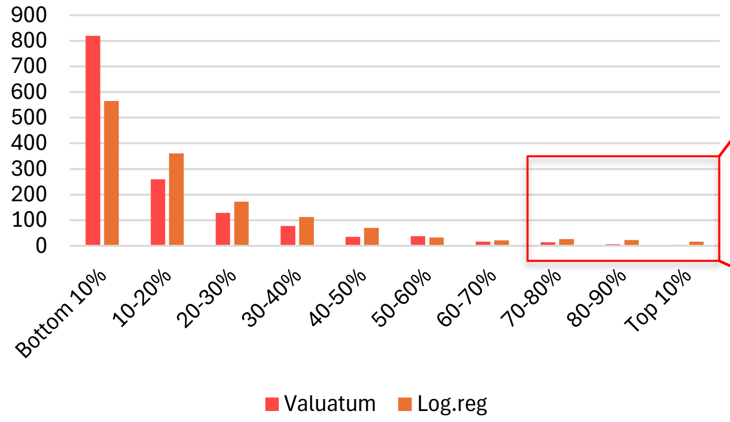


# Model performance comparison with steps (3/3)

## The route so far:

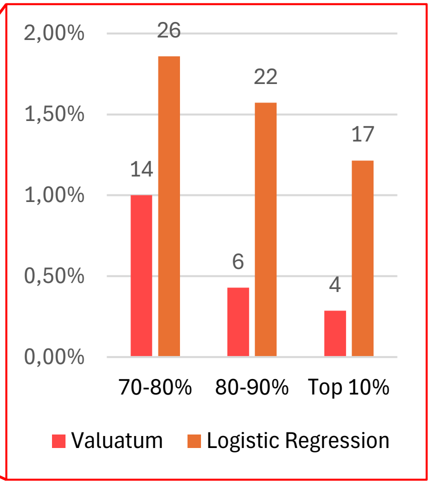



Number of companies gone bankrupt by credit rating deciles in 2023




## The 'Top 30%' comparison

Since lenders usually lend to the most creditworthy companies, the large difference in predictive accuracy in the top companies directly affects potential financial losses. Below, we have zoomed in on the predictive differences of the 'Top 30%' companies.




## Let's talk about this comparison in terms of potential savings

Assume, that a lender has issued 10 billion euros of credit to the most creditworthy 30% of companies using their logistic regression model. They recorded a credit loss of 25 million euros or 0.25% of issued credit when 65 companies that they granted loans to went bankrupt.

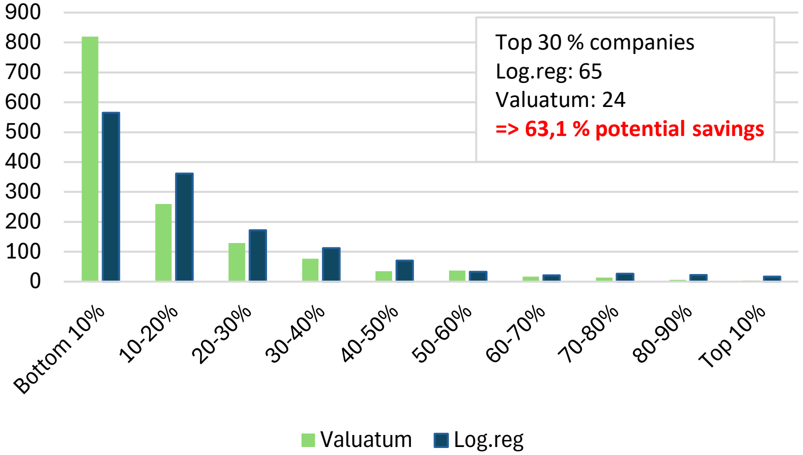
By using our AI model and the same threshold, only 24 companies that later went bankrupt would've received a loan.

**Using our AI model would have saved the lender 63.1 % of the losses or 15.8 million euros.**

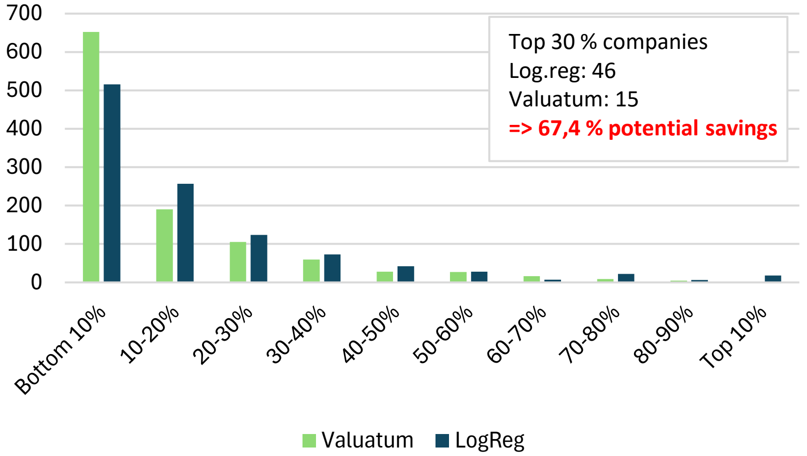
| Loan grant threshold | Bankrupt companies (Valuatum) | Bankrupt companies (Log.reg.) | Savings % |
|---|---|---|---|
| Top 30% | 24 | 65 | 63.1 % |
| Top 20% | 10 | 39 | 74.4 % |
| Top 10% | 4 | 17 | 76.5 % |

# Valuatum's AI-based model and logistic regression model comparison between 2018-2023

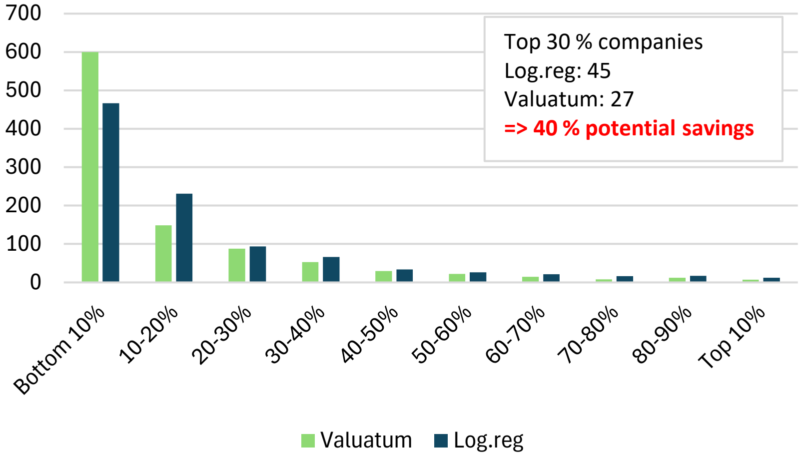
## Number of companies gone bankrupt by credit rating deciles in 2023



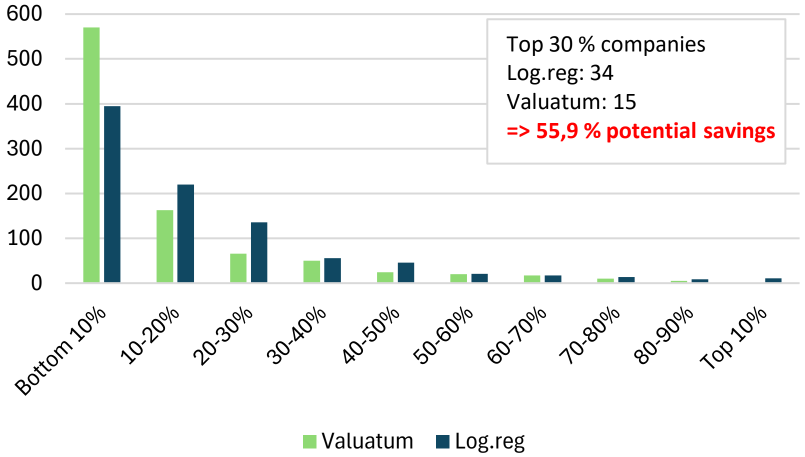

## Number of companies gone bankrupt by credit rating deciles in 2022



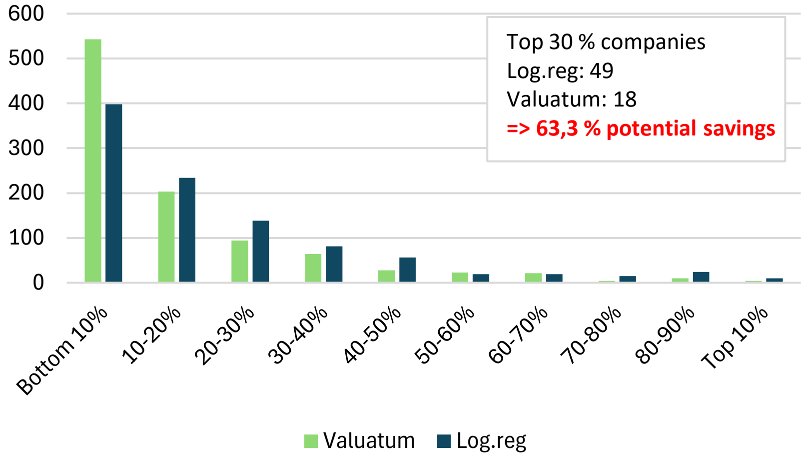

## Number of companies gone bankrupt by credit rating deciles in 2021



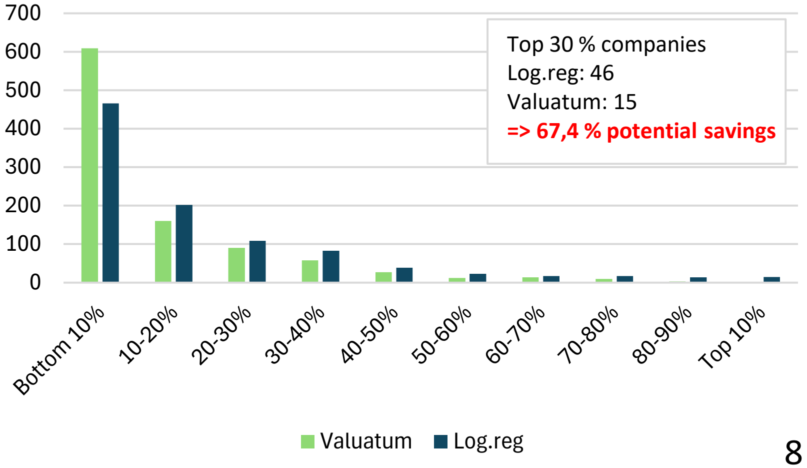

## Number of companies gone bankrupt by credit rating deciles in 2020




## Number of companies gone bankrupt by credit rating deciles in 2019




## Number of companies gone bankrupt by credit rating deciles in 2018



# Why our model is superior?

There are two key reasons for our model performance:

## 1) Dynamic variable weights

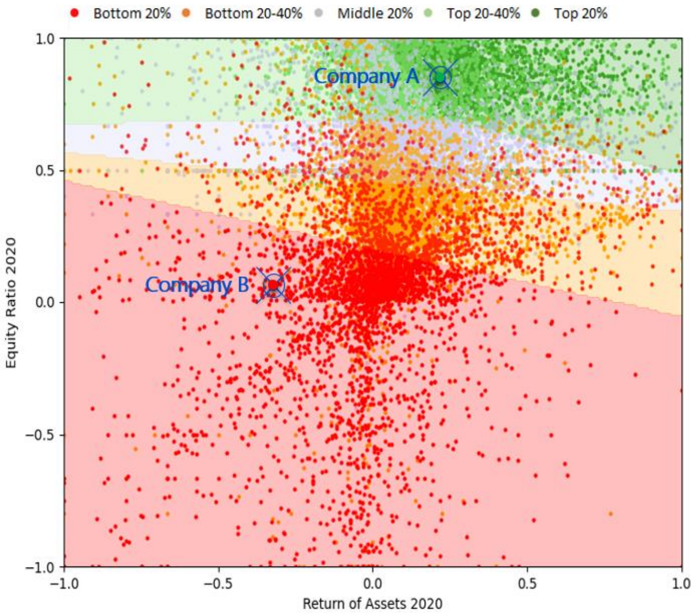
Machine learning models can produce company-specific risk estimates by dynamically adjusting the importance of different variables. This flexibility allows the model to accurately assess credit risk by considering each company's specific strengths and weaknesses.

In contrast, traditional regression models assign the same importance (i.e., weight) to variables for every company they assess. For instance, a typical regression formula might look like this: *X = -0.112 * Equity ratio + -0.162 * ROA + -0.054 * Quick ratio +* ... *+ 0.124*. This 'one-size-fits-all' approach often fails to capture the variation in individual companies. See example below.

**Example:** Company A has a very good solvency and profitability. Company B on the other hand has very poor solvency and it is unprofitable. When assessing their credit risk, these companies should have different weights for the explanatory variables like liquidity.

Here, Company A doesn't need to have good liquidity since it is able to fund itself through its operations or by loaning money. On the contrary, Company B is losing money and can't raise loans. The most important feature it has is its liquidity.

It can be clearly seen that varying weights are necessary for succesful credit risk assessment. Logistic regression has constant weights and thus it is unable to account for these firm-specific characteristics. Machine learning algorithms on the other hand can recognize that the significance of liquidity becomes larger with unprofitable companies and will adjust its credit ratings accordingly.




*The image above represents a random sample of Finnish companies arranged by their profitability (x-axis) and solvency (y-axis). The color of each dot indicates the creditworthiness of the company, with red representing companies with highest credit risk, and dark green representing companies with lowest risk.*

## 2) Number of model variables

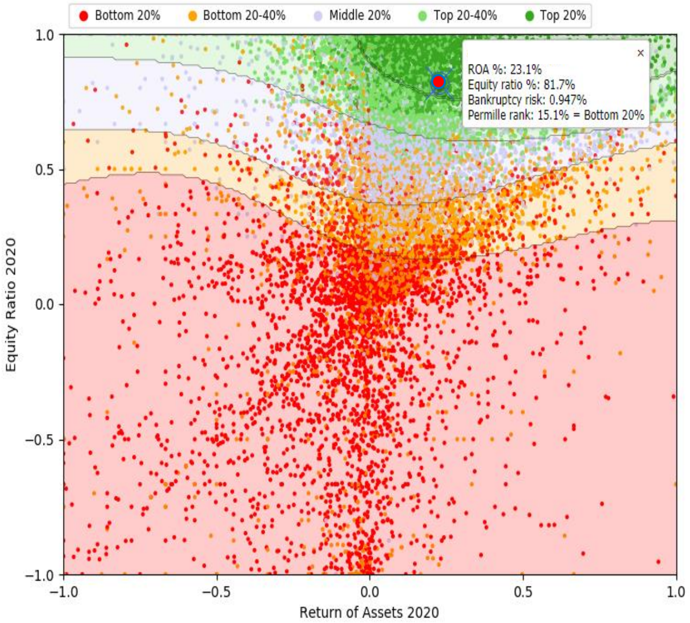
Machine learning models support the use of a **considerably larger number of variables than traditional models** without losing predictability. For example, our AI model includes around 30 explanatory variables, in order to capture all necessary variables that can affect a company's credit risk.

In contrast, traditional regression models struggle when faced with a large number of variables. Increasing the number of variables often leads to unstable predictions and overfitting. To avoid this, traditional models typically rely on just a few key variables, but this approach can result in removing important factors. See example below.

**Example:** Company has an excellent profitability and a high equity ratio, along with other key variables like liquidity. A traditional logistic regression model, which only considers these main variables, would likely assess that the company is highly creditworthy.

However, a machine learning model can evaluate a broader range of variables. It might notice that the company's sales receivables per net sales have been rising significantly in the last couple of years. This could indicate that a part of the receivables may not be collected, posing a risk to the company's figures.

If this is the case, the actual profitability and solvency of the company can be significantly lower than it would seem at a first glance. Our AI model can automatically take this into account in its assessment. Traditional models need a credit risk expert to manually adjust the profitability and solvency figures to account for possible non-receivable items beforehand.



# Model comparison

| Key ratios | Jujo Thermal (mEUR) | Idan.fi (kEUR) |
|---|---|---|
| Net sales | 112 | 1 046 |
| Balance sheet (total) | 56 | 583 |
| Short-term receivables | 24.8 | 541 |
| Cash & cash equivalents | 1.2 | 36 |
| ROA % | -2.8 % | 83.4 % |
| Equity ratio | 52.5 % | 43.6 % |
| Quick ratio | 1.0 | 1.7 |
| | | |
| Log. reg. bankruptcy risk | B (0.67 %) | A (0. 44 %) |
| Log. Reg. percentile | 51 % | 57% |
| Valuatum bankruptcy risk | C (3.59 %) | C (1.93 %) |
| Valuatum percentile | 9 % | 4 % |

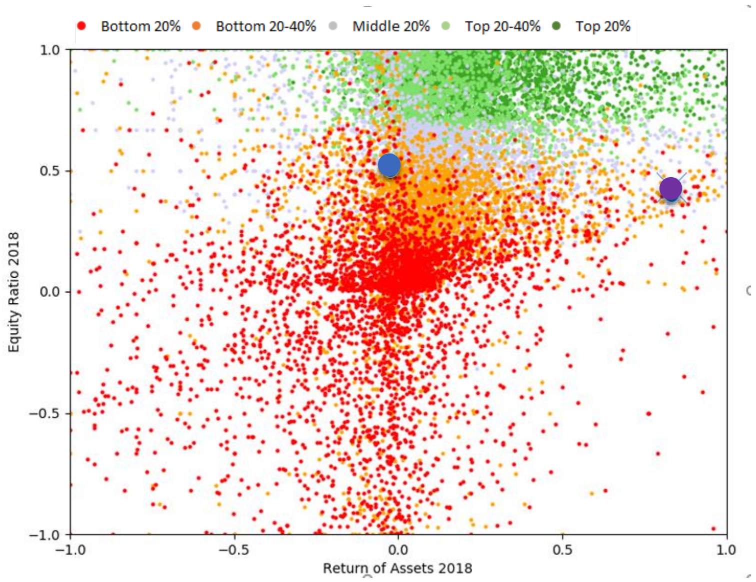
## Explanation of the model comparison example:

In these two cases, the calculated bankruptcy risks differ a lot between our model and the logistic regression model. Let's investigate the details.

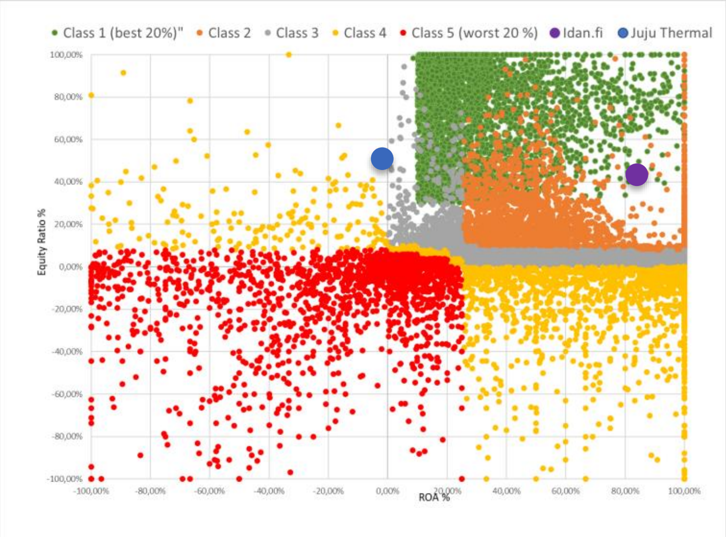
The financial situation of Idan.fi seems to be excellent based on ROA and equity ratio. Jujo is making a loss, but it still has a good equity ratio. However, if we take a closer look at the assets, logistic regression model misses something that the machine learning model notices immediately. A large amount of the balance sheet total (583kEUR & 56mEUR) consist of short-term receivables (541kEUR & 24.8mEUR). Moreover, the companies have very little cash on their balance sheet. The companies' own equity is quickly gone if some part of these receivables are not valid.

Our model acknowledges and includes above in the calculation of the bankruptcy risk as an increase in short-term receivables does often tell of some financial struggles. Models based on logistic regression do not notice this as an important warning signal since the weights for each variable are constant. This is where the logistic regression model fails. It doesn't factor in the short-term assets when calculating bankruptcy risk – even when it should.

Valuatum model

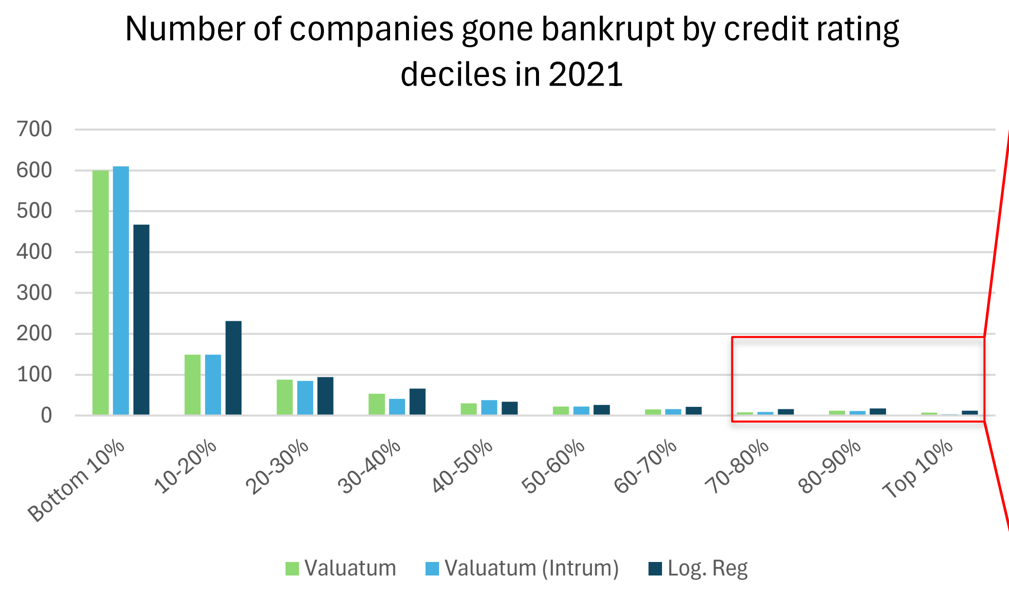


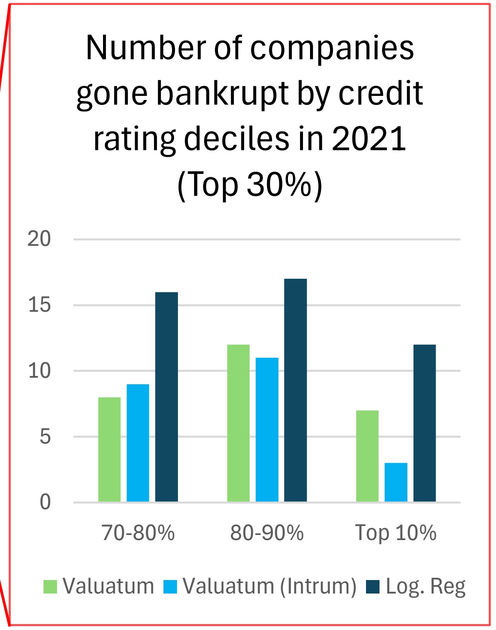

Logistic regression - based model

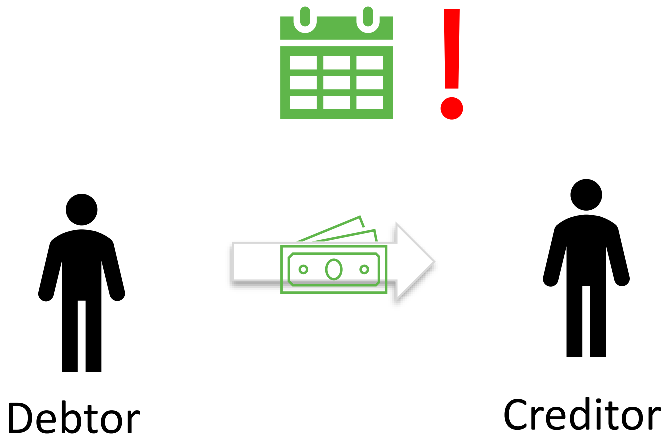


# Payment behavior data

- Information on how the company pays their bills (related to the due date)
  - Integrated into our machine learning model
  - Data provided by collection agencies etc.
- Possible shifts for worse (more payments overdue) usually indicates a weaker financial status -> higher credit risk
- The inclusion of payment data has improved the performance of our credit risk model in our tests according to statistical metrics**
  - ROC – AUC: 0.9066 -> 0.9110
  - PR – AUC: 0.1765 -> 0.1823
- The payment behavior data can further increase the accuracy of Valuatum's model, as the graph below shows. However, the difference between regular model and model including payment behavior data is not that significant.



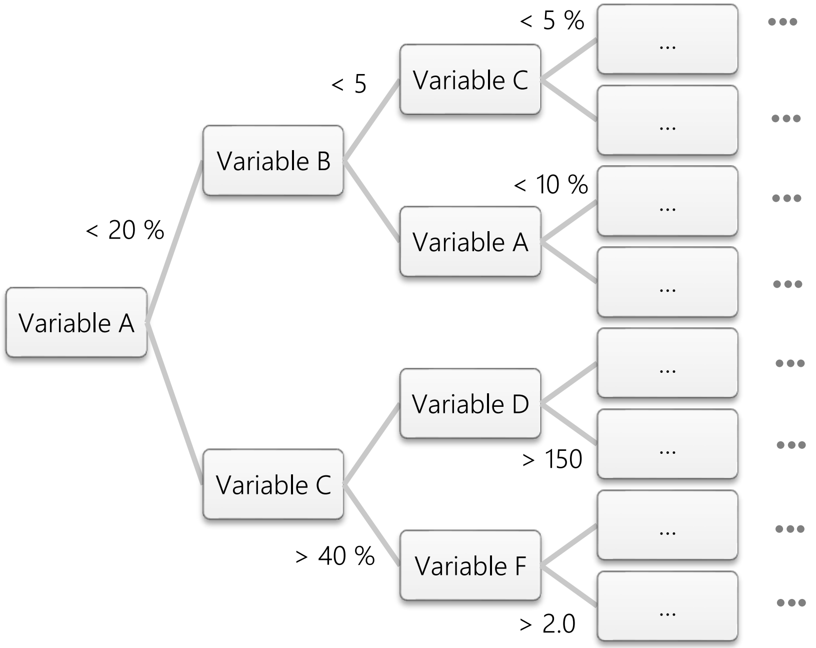



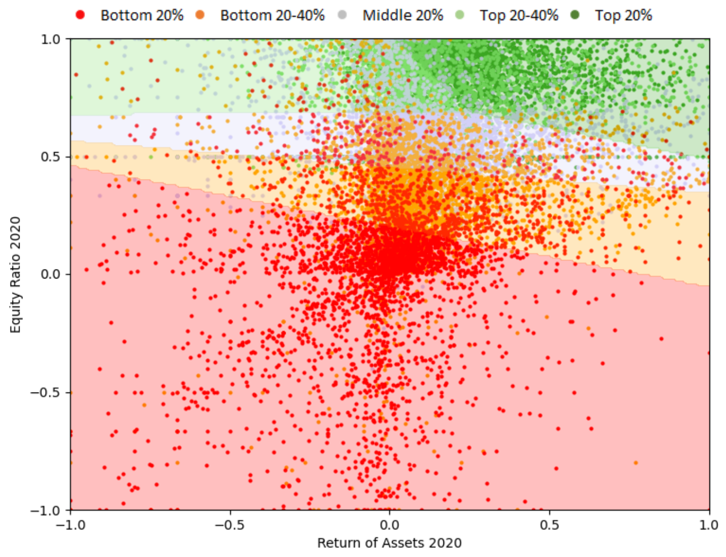




** More information on these metrics and how to interpret them can be found from the following links: ROC-AUC curves & PR-AUC curves

# XGBoost (eXtreme Gradient Boosting)

- We have utilized machine learning methods in the development of our bankruptcy risk model
  - Data with hundreds of thousands of data points from different companies is provided to the machine learning algorithm.
- The best results have been achieved with an algorithm called XGBoost
  - Well-suited for classification problems such as bankruptcy risk
  - Better and faster performance than other methods
- Our XGBoost model generates a decision tree with tens of thousands of nodes, each describing a unique combination of key figures and empirically assigning a characteristic probability of default




*Groups of companies are very intertwined. Contours added to help visualize areas where most of the observations for each company group lie*

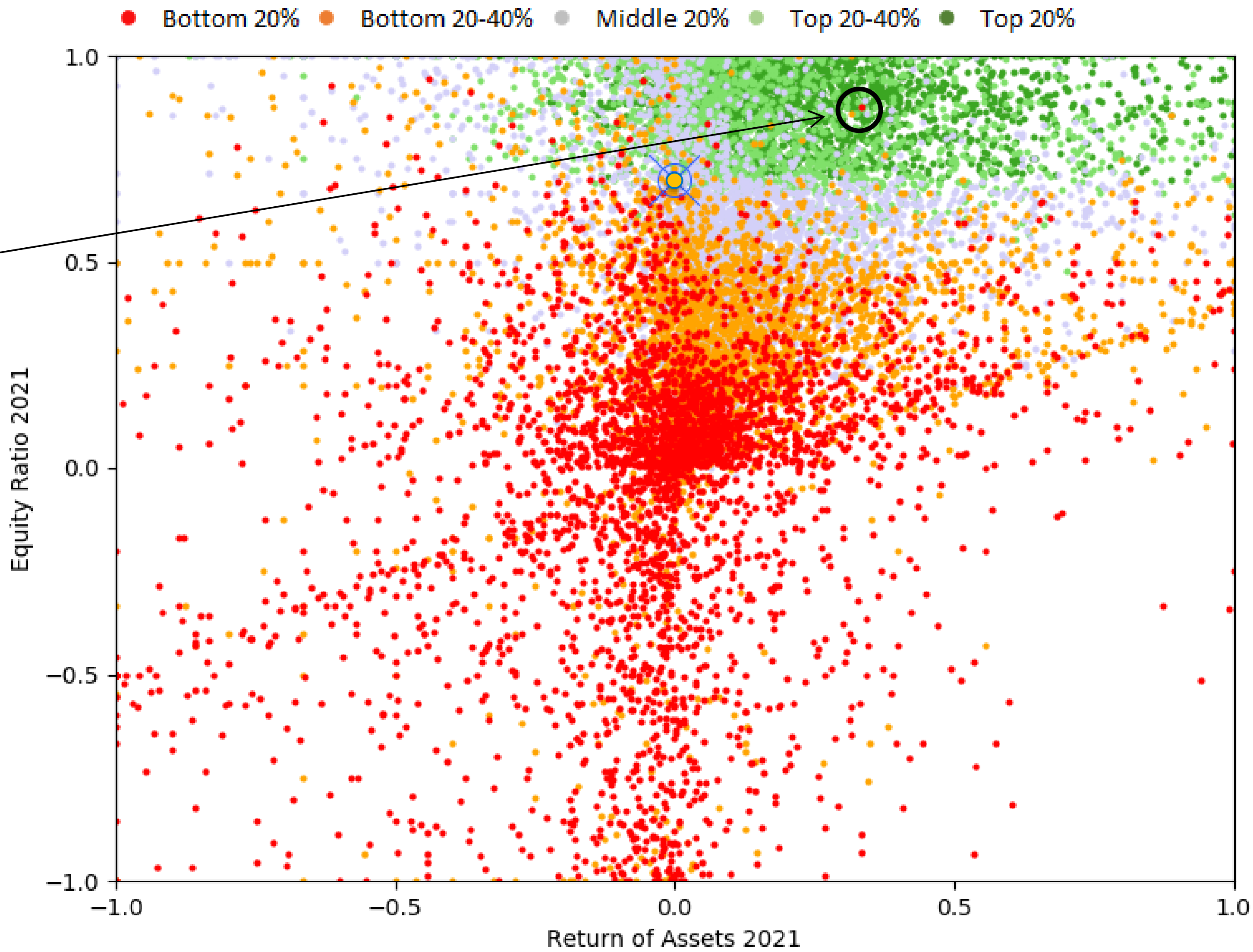
*-> visualizations can be utilized in automatic text generation (see slides 9 & 10)*

# Credit risk visualization

- Visualization graphs can be used to find outliers in the data, e.g., high credit risk companies with ROA & Equity ratio similar to low credit risk companies
  - A "bad apple" -> high bankruptcy risk despite of being surrounded by top companies

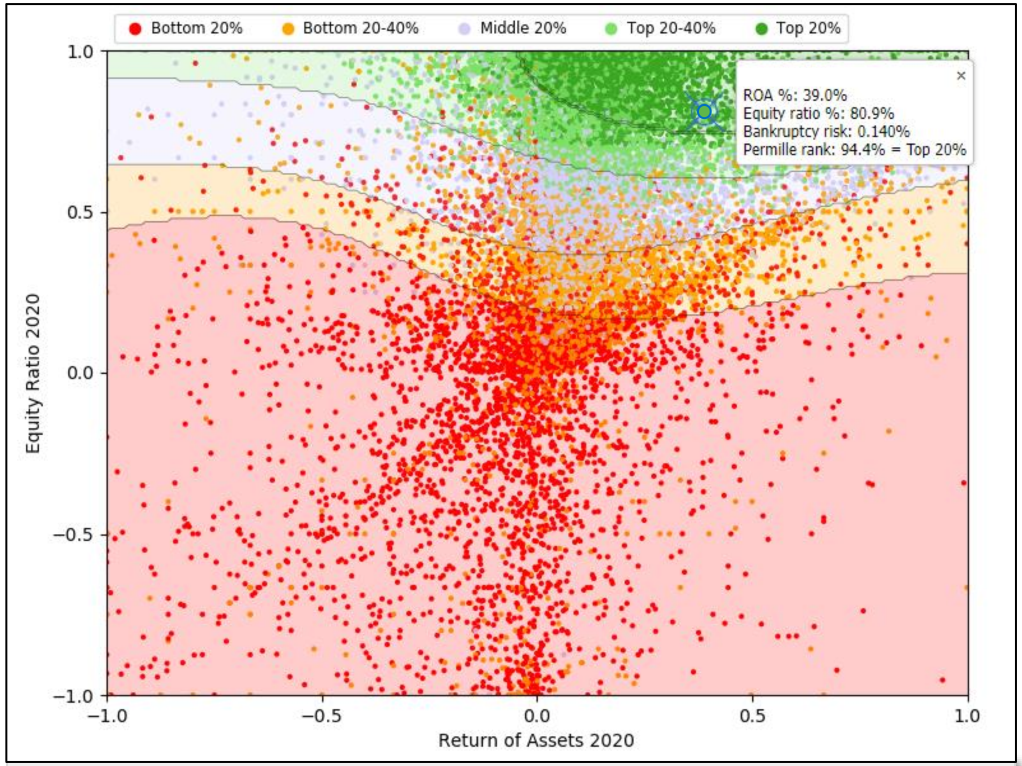
- Allows for examination of these "bad apples" are located with the top 20-40%, when they belong in bottom 20%?
  - Most common reason for this is a weak balance sheet, e.g., high level of receivables in the balance sheet or low cash reserves
  - In our report, the reasons can be generated with automatic text (see next slides)

Example of an outlier/anomaly



# Example: visualization & automatic text (1/2)

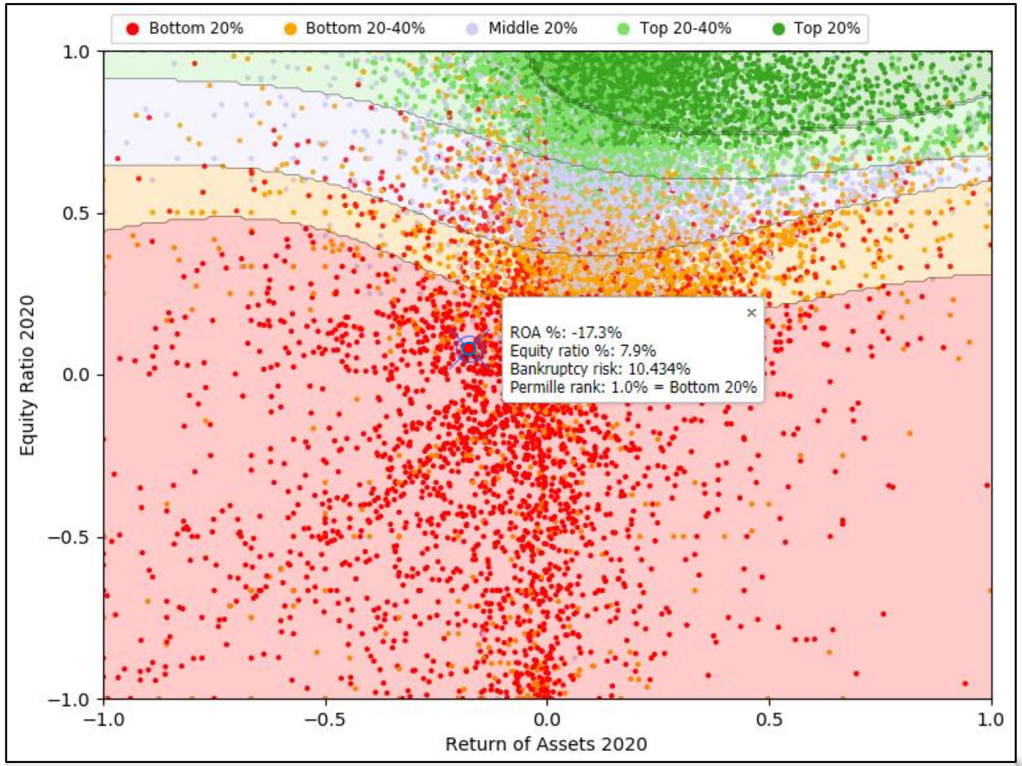
A) Good company in good area




Automatically generated description:

The company has been excellent in terms of profitability and solvency. For example, in 2020, the ROA-% of Company X was 39.0 % and the equity ratio was at 80.9 %. The net sales in 2020 were 1,020 kEUR which represents a growth of 11.5 % from the year before. Based on these factors and many others, our credit risk model has assessed that the company has a very low bankruptcy risk of 0.14 %, which corresponds to a credit rating of AA (excellent).

B) Bad company in bad area



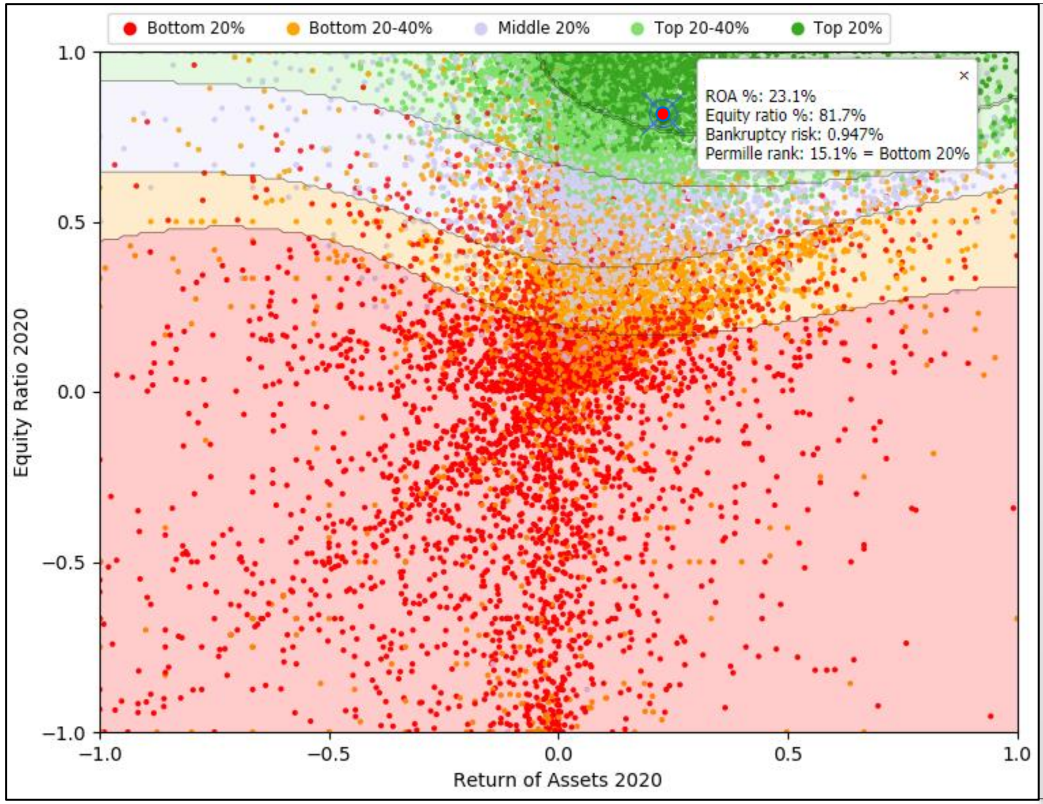

Automatically generated description:

The company has been very weak in terms of profitability and solvency. For example, in 2020, the ROA-% of Company X was -17.3 % and the equity ratio was 7.9 %. The net sales for 2020 were 2,275 kEUR which represents a decline of -13.9 % from the year before. Based on these factors and many others, our credit risk model has assessed that the company has a very high bankruptcy risk of 10.434 %, which corresponds to a credit rating of B&C (very poor).

*Both cases are straightforward: bankruptcy risk estimate correlates with placement in the chart (ROA, Equity ratio)*
*However, sometimes the cases might not be as simple, and they might need further explanation (see next slide)*

# Example: visualization & automatic text (2/2)

C) Bad company in good area




*Automatically generated enhanced description:*

The company has very high profitability and solvency. For example, in 2020, the ROA-% of Company X was 23.1 % and the equity ratio was at 81.7 %. The net sales in 2020 were 845 kEUR which represents a growth of 13.1% from the year before. While the company has excellent figures in these aspects, the credit risk model has rated the company much lower than other companies with similar profitability and solidity. The higher credit risk is a result of the following weaknesses identified by the model:

1. *Increasing current loans receivable: From 2016 to 2020, current loans receivable grew from €22k to €186k, indicating that the company is lending out more money, which could result in bad debt if borrowers default.*

2. *Low cash and cash equivalents: The company has consistently low cash balances, with only €5k in cash at the end of 2020, which may make it difficult to cover short-term obligations or unexpected expenses.*

3. *High non-interest-bearing liabilities: In 2020, non-interest-bearing liabilities reached €68k, putting pressure on the company's liquidity and potentially increasing bankruptcy risk if they are unable to pay off these liabilities.*

Generated by ChatGPT

Based on the above-mentioned factors, our credit risk model has assessed that the company has a high bankruptcy risk of 0.947 %, which corresponds to a credit rating of BAA (poor).

*When our XGBoost model identifies a bad apple – a company with high bankruptcy risk in a green zone - automatically generated description is supplemented with key reasons for high bankruptcy risk (can be generated with our own system or with ChatGPT via an API)*

# Performance evaluation

- All recent academic research that we have found has shown that machine learning (ML) models tend to outperform traditional regression-based methods in bankruptcy risk estimation *

- We have also conducted a study to compare our model to multiple benchmark models
  - Studied models include XGBoost, random forest model, artificial neural networks, an ensemble method and logistic regression
  - Results are also compared to the results obtained by Altman et al. (2014) **
  - A total of approximately 170 000 Finnish companies and 30 input variables were used in the training of the models
    - Half of data was used for the training set and half for the testing set

- Our XGBoost model outperforms all benchmark methods in our study.
  - For example, in ROC – AUC metric our model (0.9066 or 0.9110) beats the logistic regression model (0.895) and Altman's Z-score (0.894) with a clear margin

- The maximum value for ROC-AUC is 1.0. ***
  - ROC-AUC of 0.8 can be considered good, while values exceeding 0.9 are excellent. A random model has a ROC-AUC of 0.5.

| | **Our XGBoost model** | **Our model w/ payment behavior data** | **Random forest (RF)** | **Artificial neural network (ANN)** | **Ensemble method (RF & ANN)** | **Logistic regression** | **Altman et al. (2014)** |
|---|---|---|---|---|---|---|---|
| ROC – AUC** | 0.9066 | 0.9110 | 0.904 | 0.880 | 0.902 | 0.895 | 0.894 |

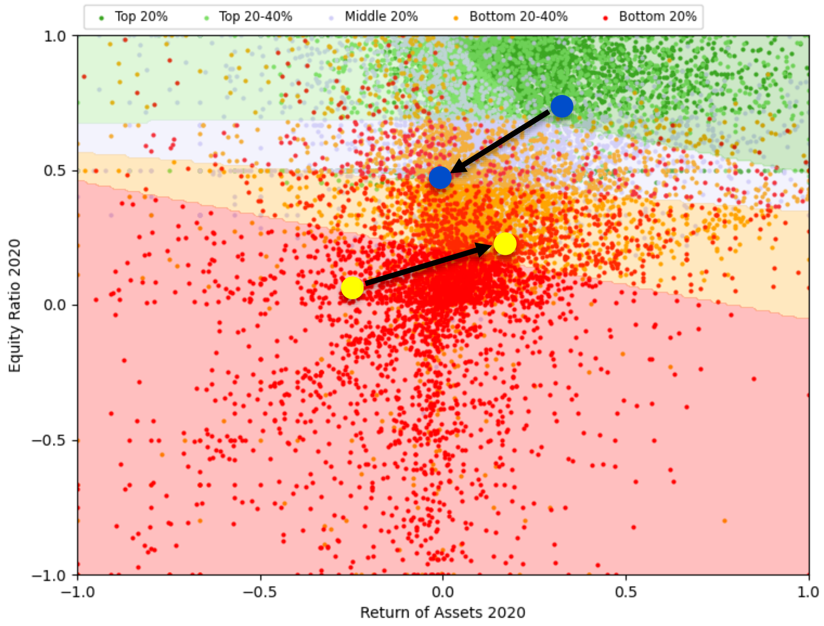
* See, e.g., Ciampi, Francesco & Gordini, Niccolò (2013) ”Small Enterprise Default Prediction Modeling through Artificial Neural Networks: An Empirical Analysis of Italian Small Enterprises” & López Iturriaga, Félix J. & Sanz, Iván Pastor (2015) “Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks”

** Altman et. al. (2014), ”Distressed Firm and Bankruptcy prediction in an international context: a review and empirical analysis of Altman's Z-Score Model”, Available [online]: https://pdfs.semanticscholar.org/257c/b4227101b4da636e90b323736c68c0653a4f.pdf

*** More information on the metric and how to interpret it can be found from the following link: ROC-AUC curves

# PSD2 data

- PSD2 is a directive to regulate payment services and the transparency of payment information by requiring banks to open payment infrastructure to third parties
- Implemented separately into the credit risk decision
- Can allow access to the account transaction information of a specific company from the past 12 months
  - The company in question must approve of their data being used
- Our machine learning based bankruptcy risk is adjusted by estimating new key figures with the PSD2 data and by comparing median risk of companies with similar figures

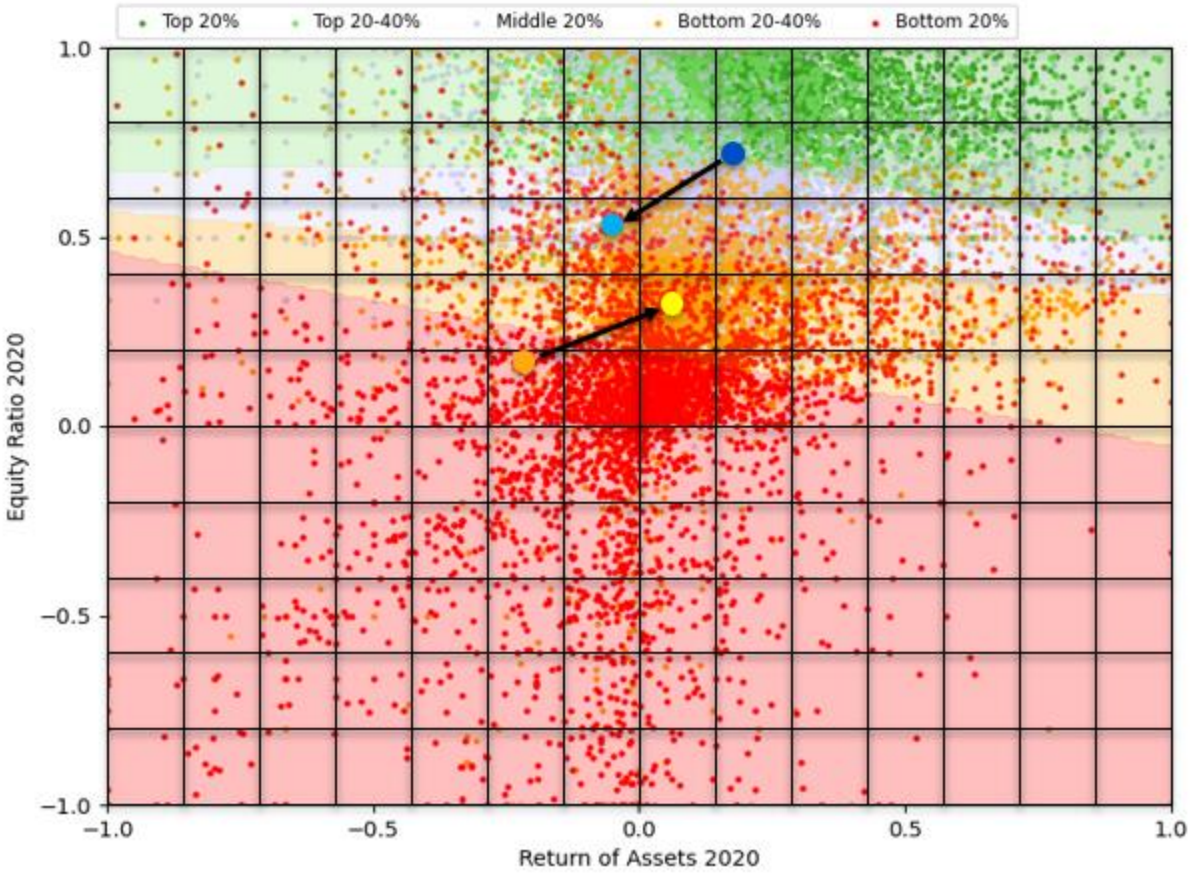



Effects of PSD2 implementation:

Blue company (class Top 20%):
PSD2 data shows declining net sales and significantly negative cash flows and therefore the credit risk is adjusted from "Top 20%" to class "Bottom 20-40%".

Yellow company (class Bottom 20%):
PSD2 data shows notable improvement in net sales and significantly positive cash flows and therefore the credit risk is adjusted from "Bottom 20%" to class "Bottom 20-40%".

# PSD2-based adjustment in practice

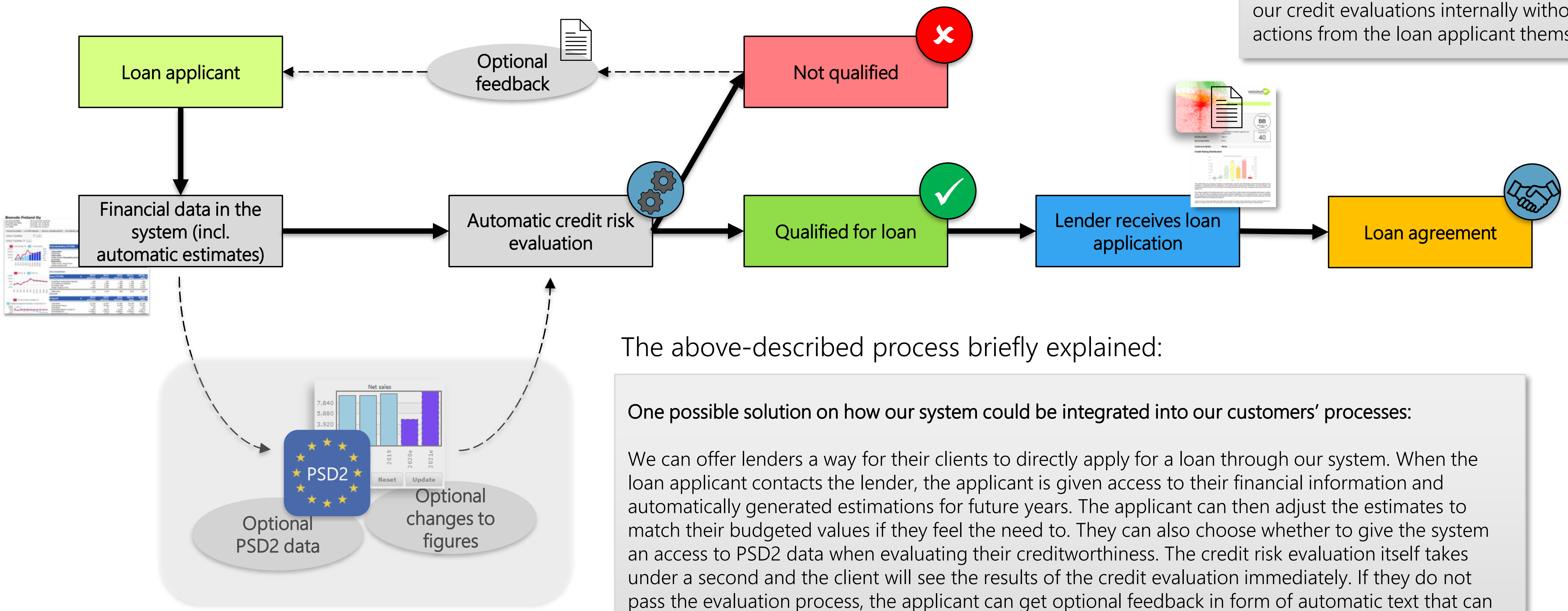



Based on PSD2 data, the company in dark blue has worse explanatory variables (ROA and equity ratio) than its place on the graph suggests and it should be located where the light blue dot is. To adjust its credit risk, we calculate the median credit risks of the areas around dark blue and light blue. If, for example, the median risk in dark blue area is 0.2 % and the median of light blue area is 0.5 %, the credit risk of the dark blue company is adjusted by increasing its credit risk by the difference of the two medians, i.e., 0.3 %.

Similarly, the orange company has better characteristics than its current placement dictates and based on PSD2, it should be located where the yellow dot is. Thus, its credit risk is reduced by the difference of risk medians in the areas where orange and yellow are.

# Loan process example with Valuatum system

NB! We are able to customize this process in multiple ways and it is also possible to use our credit evaluations internally without any actions from the loan applicant themselves.




The above-described process briefly explained:

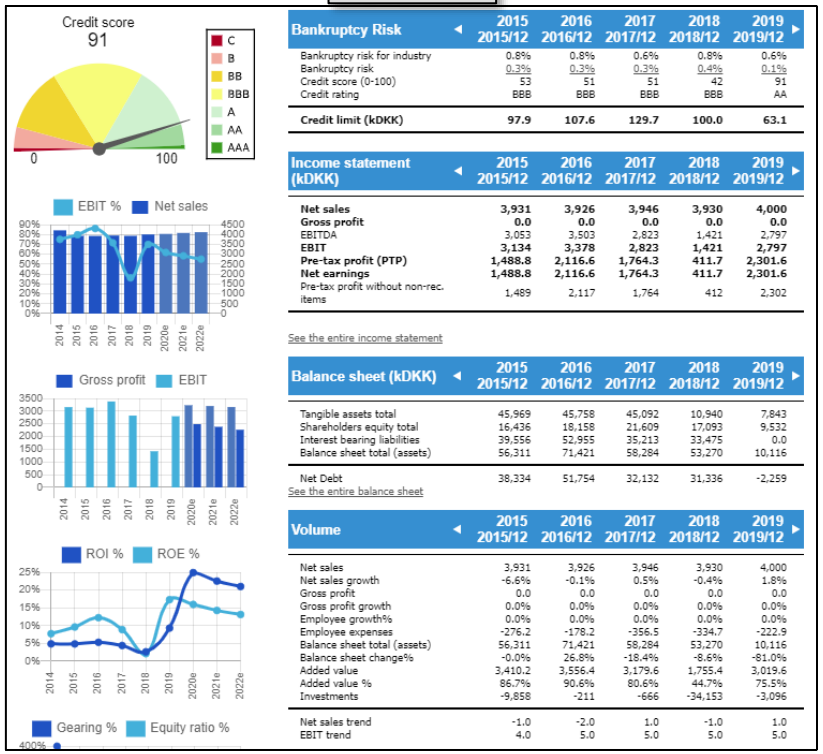
**One possible solution on how our system could be integrated into our customers' processes:**

We can offer lenders a way for their clients to directly apply for a loan through our system. When the loan applicant contacts the lender, the applicant is given access to their financial information and automatically generated estimations for future years. The applicant can then adjust the estimates to match their budgeted values if they feel the need to. They can also choose whether to give the system an access to PSD2 data when evaluating their creditworthiness. The credit risk evaluation itself takes under a second and the client will see the results of the credit evaluation immediately. If they do not pass the evaluation process, the applicant can get optional feedback in form of automatic text that can tell why they did not qualify. Naturally, the lender also instantly receives the loan application in the form of an automatically generated report that displays the financial state of the company with text and visualizations. After this the lender can continue the evaluation on their own as they see best.

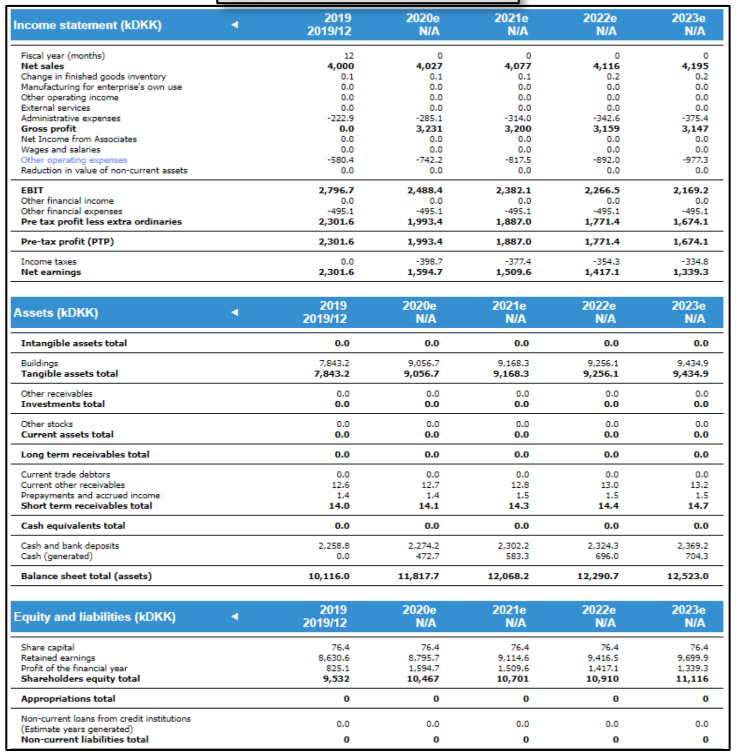
# Company Views

- Company Views is our web interface that gives a comprehensive outlook into the financial position of a company
- Layout of Company Views can be modified to fit customer needs
  - Select pages that you want (e.g., Financial statements, Cash flow statements, Valuation)
  - Choose which figures and graphs you want to display
- System is developed for financial statement analysis:
  - System can generate estimates automatically or user can make own estimates
  - User can create multiple scenarios for the company
  - User can also adjust historical figures
- Formulas for calculations can easily be checked by clicking the variable

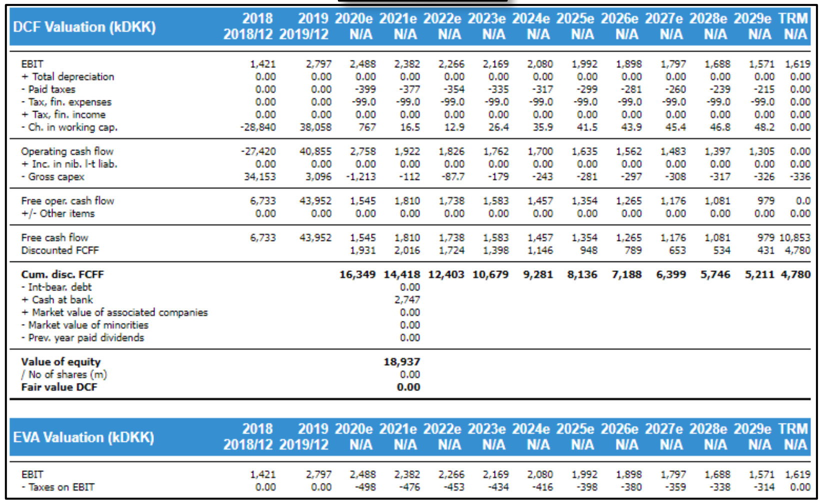
Overview



Financial statements

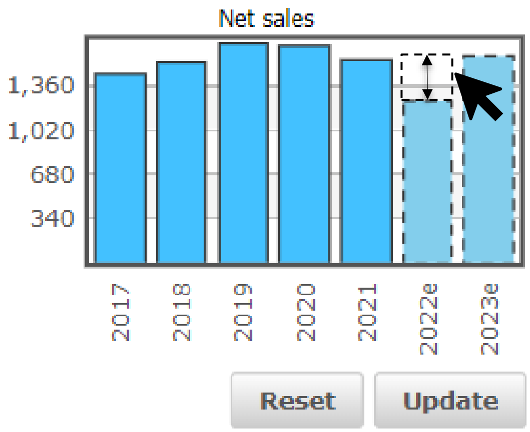


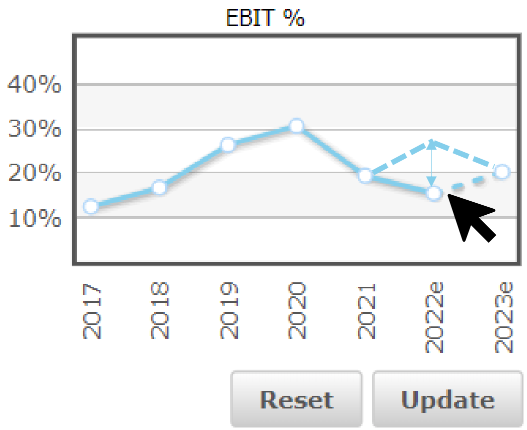
Valuation



# Company Views: Estimates and Adjustments

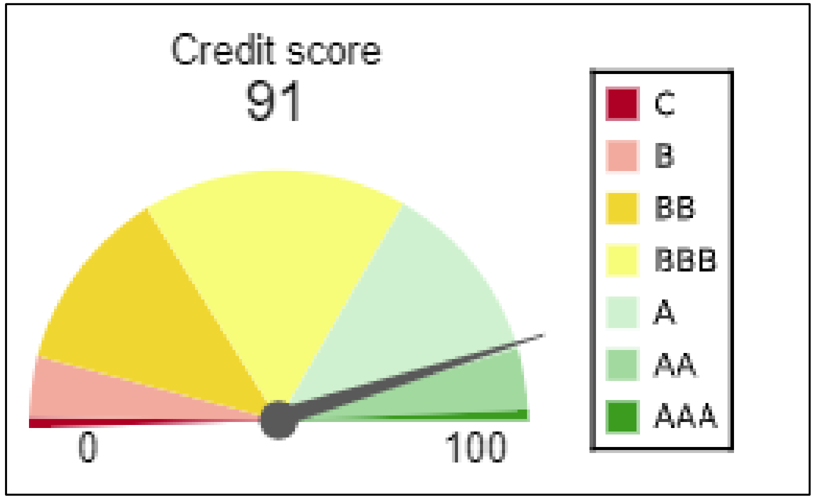
| Income statement (EURm) | 2017 N/A | 2018 2018/12 | 2019 2019/12 | 2020e N/A |
|---|---|---|---|---|
| Fiscal year (months) | 0 | 12 | 12 | 0 |
| **Net sales** | 9,116 | 9,071 | 9,382 | 9,518 |
| *Net sales growth* | 7.5% | -0.5% | 3.4% | 1.4% |
| Other operating income | 0.0 | 22.0 | 22.8 | 23.1 |
| *Other operating income / Net sales* | 0.0% | 0.2% | 0.2% | 0.2% |
| Purchases during the financial year | 0.0 | -3,614.4 | -3,739.7 | -3,799.1 |
| *Purchases during fiscal year / Net sales* | 0.0% | -39.8% | -39.9% | -39.9% |
| Wages and salaries | 0.0 | -2,818.4 | -2,916.1 | -2,962.4 |
| *Wages and salaries / Net sales* | 0.0% | -31.1% | -31.1% | -31.1% |
| Other operating expenses | -7,755.6 | -1,498.6 | -1,550.5 | -1,575.2 |




- Adjustments to historical figures and estimates can be made on the web interface
- Adjustments can be made in two different ways:
  1. Changing the values in tables
  2. Dragging the bars or lines in charts (see the picture on the left!)
- After adjustments, the financial statements and key ratios are updated accordingly
- Estimates can be input either as absolute or relative values (e.g., net sales or net sales growth-%)
- Adjustments and estimates can also be easily edited in the Excel model

# Bankruptcy Risk




| Bankruptcy Risk | 2015 2015/12 | 2016 2016/12 | 2017 2017/12 | 2018 2018/12 | 2019 2019/12 |
|---|---|---|---|---|---|
| Bankruptcy risk for industry | 0.8% | 0.8% | 0.6% | 0.8% | 0.6% |
| Bankruptcy risk | 0.3% | 0.3% | 0.3% | 0.4% | 0.1% |
| Credit score (0-100) | 53 | 51 | 51 | 42 | 91 |
| Credit rating | BBB | BBB | BBB | BBB | AA |
| Credit limit (kDKK) | 97.9 | 107.6 | 129.7 | 100.0 | 63.1 |

# Comparisons: Lists and Scatters

- The user can either make comparisons in a scatter or list form.
- The comparison group can be narrowed to any industry or list of user's choice.

**Columns and criteria** (Show/hide)

| Variable | Minimum | Maximum | Significant digits |
|---|---|---|---|
| Equity ratio % (2021) | 50 | 100 | 3 |
| EBIT % (2021) | 10 | 50 | 3 |
| ROA % (2021) | 20 | 50 | 3 |

Add new criteria | Apply filters | Save current criteria

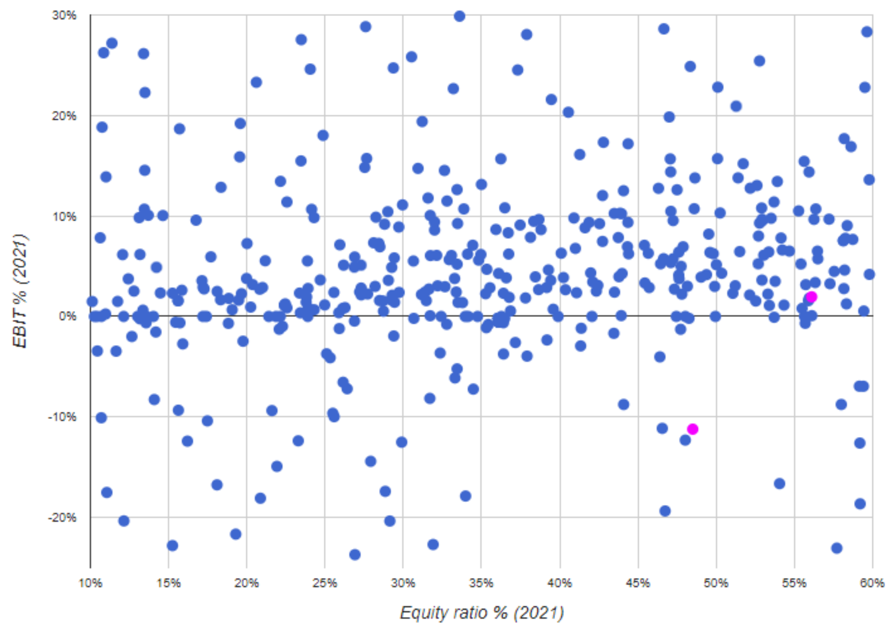
Results: 13656 | 100

| | Company | Equity ratio % (2021) | EBIT % (2021) | ROA % (2021) |
|---|---|---|---|---|
| 1 | Oy PaStra Ab | 50.0 % | 10.0 % | 20.0 % |
| 2 | Oy Transientti Radio Ab | 50.0 % | 11.1 % | 20.0 % |
| 3 | Pekosa Oy | 50.0 % | 15.2 % | 20.0 % |
| 4 | KRK Huoltopalvelut Oy | 50.0 % | 23.1 % | 20.0 % |
| 5 | RantaOksa Oy | 52.3 % | 10.8 % | 20.0 % |
| 6 | MindMaker Oy | 53.3 % | 11.8 % | 20.0 % |
| 7 | Tretekno Oy | 56.5 % | 19.3 % | 20.0 % |

**Columns and criteria** (Show/hide)

| Variable | Minimum | Maximum | X-axis | Y-axis | Significant digits |
|---|---|---|---|---|---|
| Equity ratio % (2021) | 10 | 60 | ● | ○ | 3 |
| EBIT % (2021) | -30 | 30 | ○ | ● | 3 |
| Balance sheet total (assets) EURm (2021) | 10 | 12 | ○ | ○ | 3 |

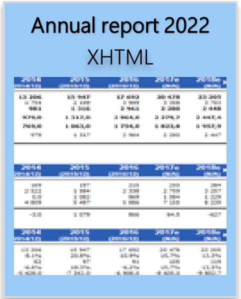
Add new criteria | Apply filters | Save current criteria



# Automatic financial reports with XBRL

- XBRL is a standardized format that enables efficient exchange of financial information through digital means
- Possible to upload XHTML-type financial reports into our system which then automatically completes the financial statements for analysts
- Useful if data can't be automatically found from an external data provider. This can happen with e.g. foreign companies.

  -> financials can then be uploaded through XBRL

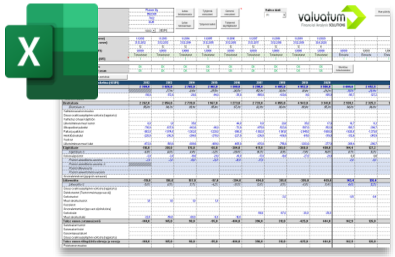



1. Analyst downloads a financial report into our database

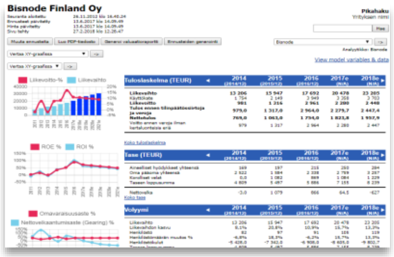
Valuatum database

2. Our system parses the XHTML file and fills in the financial information automatically

Valuatum Excel model



Valuatum system



3. Analyst can now focus on what matters the most – the complete data is already available!

# More information about our services

Overview of our credit risk services:
https://www.valuatum.com/credit-risk/

Our bankruptcy risk model (includes a technical white paper):
https://www.valuatum.com/credit-risk/bankruptcy-risk/

Our other methods for risk estimation:
https://www.valuatum.com/credit-risk/bankruptcy-risk/machine-learning-in-risk-estimation/

Example of how our system can be used in practice for credit risk assessment:
https://www.valuatum.com/credit-risk/credit-risk-in-practice/

# Contact information

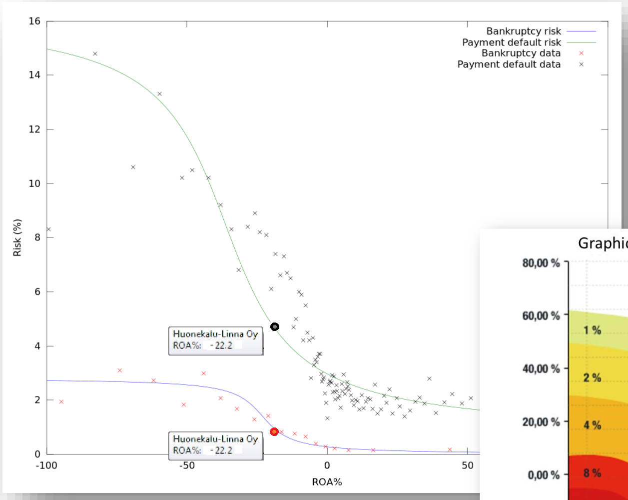
Customer support
contact@valuatum.com
+358 45 123 0308

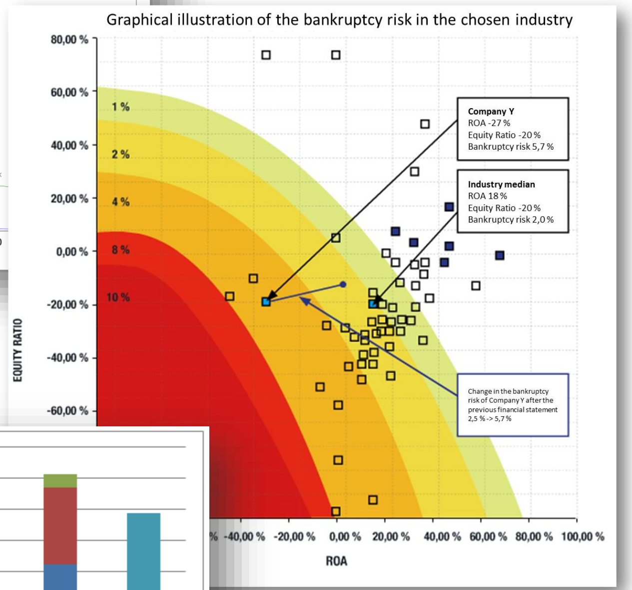
# Additional Information

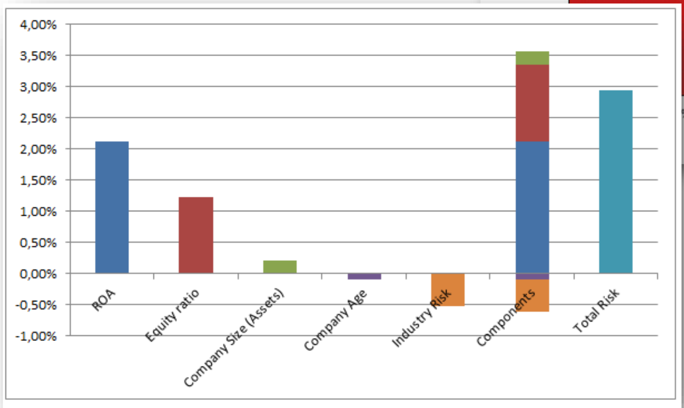
# History of credit and default risk assessment

- Credit and bankruptcy risk predictions have usually been based on simple linear statistical models that use a few financial ratios such as ROA, Debt to Equity and Quick ratio
  - The Altman Z-score is a famous method that uses five explanatory variables to calculate the probability of bankruptcy
  - One of the most well-known methods is the logistic regression

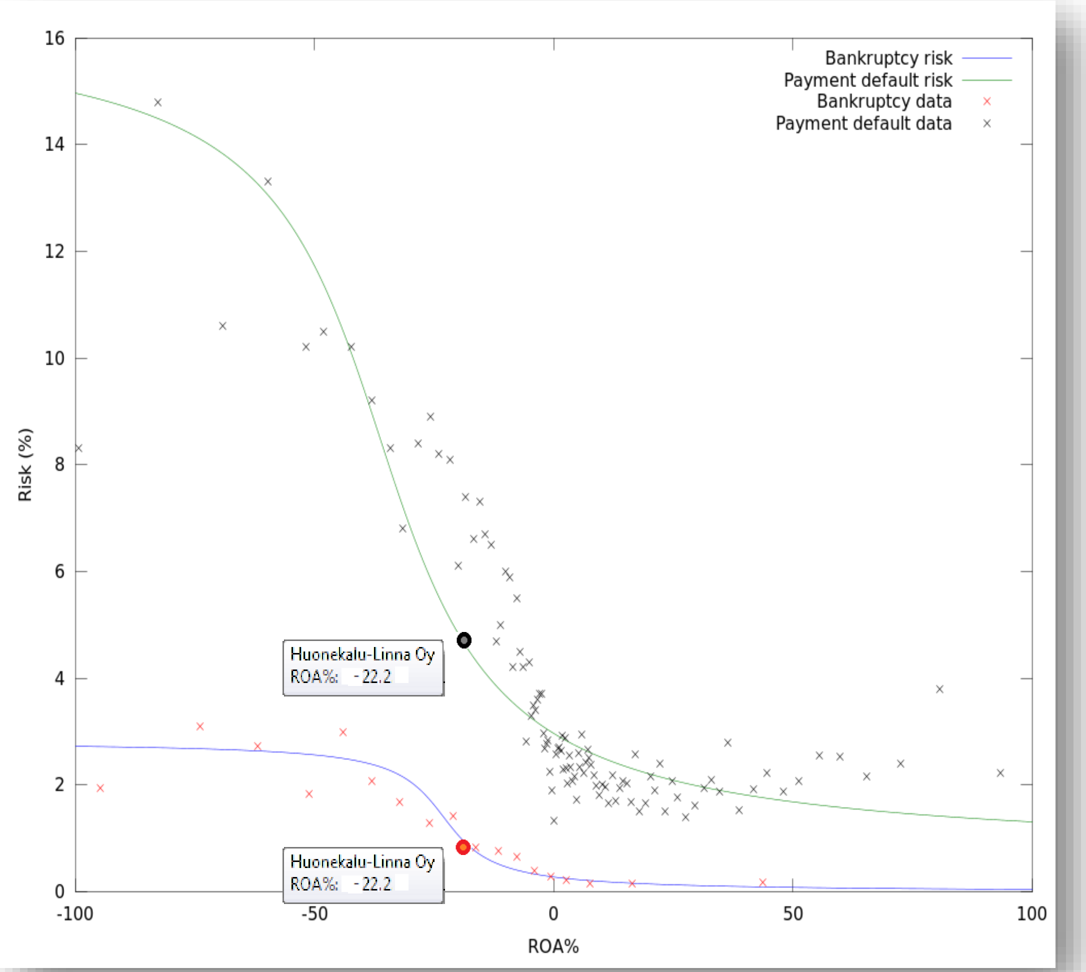
- Logistic regression-based models remain one of the most widely used methods for bankruptcy risk prediction even today
  - Based on regression of defaults and several key figures
  - Often used because of its simplicity and efficiency
    - The decision of the model is also easy to interpret as the model coefficients provide the relative importance of the variables
  - Outputs a function 1/(1 + e^(-X)) that tells the probability of default, where X is a polynomial function. For example,
  - *X = -0.112 * Equity ratio + -0.081 * ROA + -0.054 * Quick ratio + …*
    *+ 0.124 * IF(Industry A, 1, 0) + 0.056 * IF(Industry B, 1, 0) + … + -0.321 * IF(StDev(ROI) < 0.05, 1, 0) + 0.167 * IF(StDev(ROI) > 0.20, 1, 0) + … + IF(Net sales < 3 mEUR, (1 - (Net sales / 3)), 0) + IF(Net sales > 30 mEUR, log(Net sales) / log(30) - 1, 0) + …*



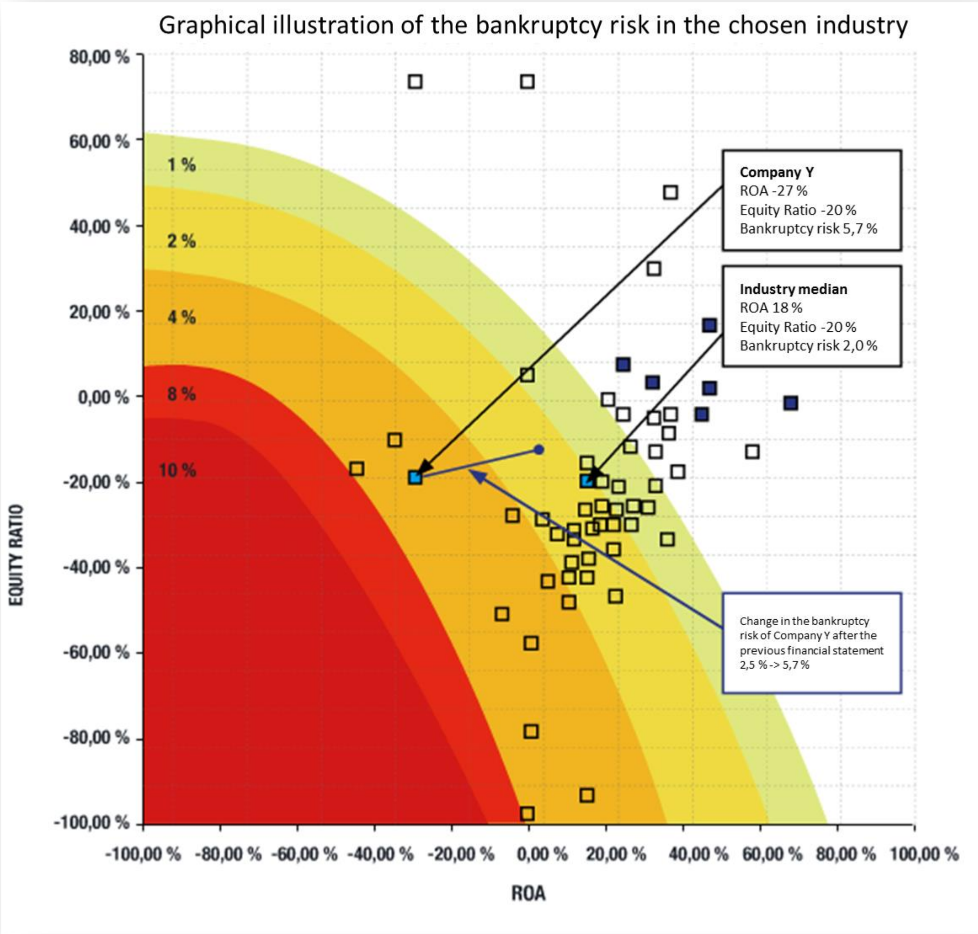



# Credit and Default Risk: Single Variable



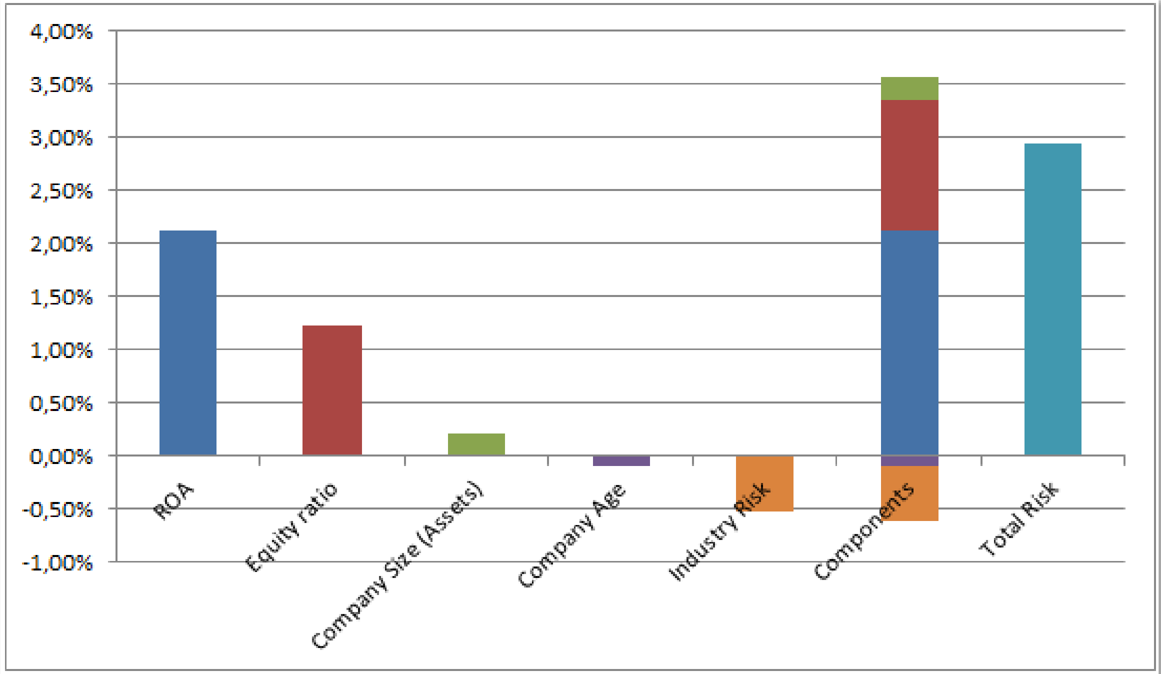

- What is the probability that a company will not be able to serve its debt e.g. in the next two years?
- The probablities are defined by observing the relationship between defaults and financial, e.g. profitability, variables with statistical methods.
- The graph illustrates the relationship of Return on Assets to defaults and financial distress within some 200 000 Finnish companies so that each dot represents approximately 4000 entities.

# Credit and Default Risk: Two Variables




- Forecasting with one variable only gives a quite simple one-dimensional view.
- With a model using two variables, graphical representation is still possible and illustrates the possibility that another variable can compensate the high risk that a single variable could imply.
- The graph also shows how the default risk of a company has been developing during the years.

# Credit and Bankruptcy Risk: Multivariable




In the diagram, bankruptcy risk is forecasted with five variables.

The variables are sorted from biggest contributor to risk to least contributing variable.

- Even though single and two variable models can offer a lot, the best prediction and illustration of financial distress is given by multivariable models, which take multiple aspects, e.g. profitability, profitability development, solvency, balance sheet quality, the age and size of a company, industry risk level etc., into account.
- Under our R&D at Valuatum we have empirically learned that examples of good predictive variables include but not limit to worsening profitability, stable profitability, increase in bad assets and rapid relative growth of accounts payable
- The component representation represents, which factors contribute to the default risk the most in the case of given company.

# Accuracy of our XGBoost model

- Table on the right demonstrates how firms that have gone bankrupt were positioned according to the risk estimate made by ValuBooster model
  - Comparisons were done for companies available in our database (data from the years 2017-2018)
  - Companies have been sorted according to our bankruptcy risk scores and then divided into 10 equally large groups (Group 10 comprises of companies that have the highest 10 % of bankruptcy risk scores)

- In general, the results show that the higher the bankruptcy estimate given by the model was, the more bankruptcies happened

**Not convinced?**

- The same comparison can be done for any group of firms

- It is also possible to compare how the firms are ranked according to our metrics and yours
  - o Provide us with the data (hundreds or thousands of previously rated potential clients) and we will generate, e.g., the probability of bankruptcy within the next two years based on the financial information available at the time of the original rating

| 2017 | | | |
|---|---|---|---|
| Group number (sampled according to bankruptcy risk) | # of bankruptcies in the group | % of whole sample that have gone bankrupt | Highest bankruptcy risk in the group |
| 1 | 6 | < 0.01 % | 0.0015 |
| 2 | 11 | 0.01 % | 0.0016 |
| 3 | 19 | 0.01 % | 0.0018 |
| 4 | 30 | 0.02 % | 0.0023 |
| 5 | 26 | 0.01 % | 0.0030 |
| 6 | 43 | 0.02 % | 0.0039 |
| 7 | 71 | 0.04 % | 0.0052 |
| 8 | 126 | 0.07 % | 0.0081 |
| 9 | 253 | 0.14 % | 0.0162 |
| 10 | 1054 | 0.57 % | 0.6667 |
| Total | 1640 | 0.89 % | |

| 2018 | | | |
|---|---|---|---|
| Group number (sampled according to bankruptcy risk) | # of bankruptcies in the group | % of whole sample that have gone bankrupt | Highest bankruptcy risk in the group |
| 1 | 2 | < 0.01 % | 0.0015 |
| 2 | 2 | < 0.01 % | 0.0016 |
| 3 | 13 | 0.01 % | 0.0018 |
| 4 | 13 | 0.01 % | 0.0023 |
| 5 | 7 | 0.00 % | 0.0029 |
| 6 | 12 | 0.01 % | 0.0038 |
| 7 | 23 | 0.01 % | 0.0051 |
| 8 | 43 | 0.02 % | 0.0080 |
| 9 | 93 | 0.05 % | 0.0165 |
| 10 | 563 | 0.29 % | 0.6858 |
| Total | 771 | 0.39 % | |