Valuatum Platform

Efficient tools for Credit Risk Analysis

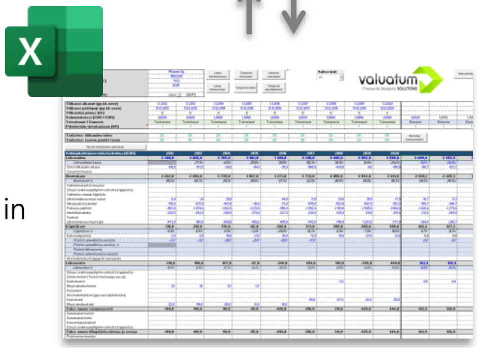
Slides:

Valuatum platform overview

- Automatic bankruptcy forecasts and reports
- Access to historical financial statements, provided by external data providers, integrated in the system.
- Standardized data enables comparisons and sophisticated bankruptcy estimations
- Visual and verbal explanations for the given bankruptcy estimations
- Our system can support multiple languages: Finnish, English, Swedish and German

External data providers

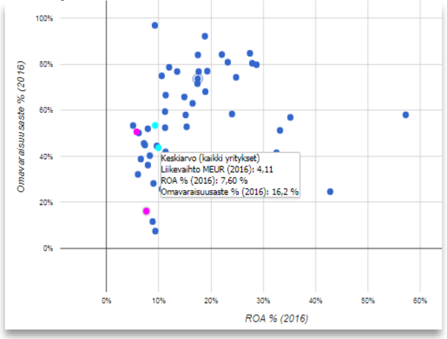
Valuatum database



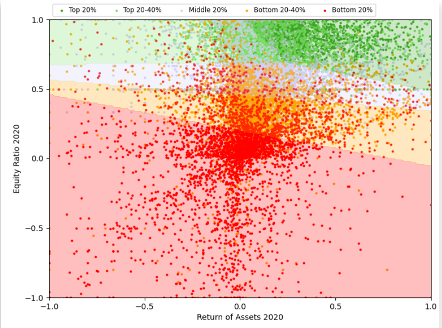
The system can be used both in Excel and via a web-interface.

Overview of the company with the option for integrated financial statements

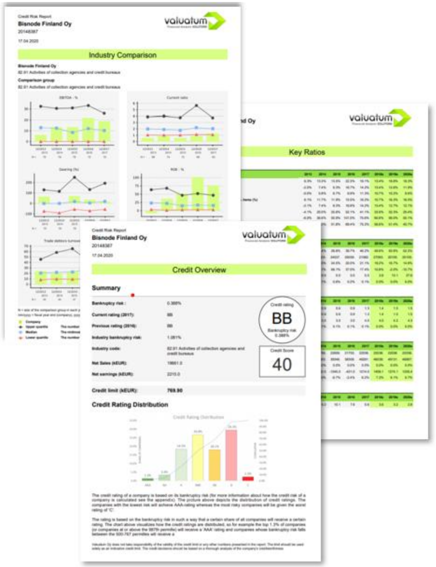
Compare how the company of interest is situated to its peers or any group of companies



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



Create an automated report based on the company's financial information

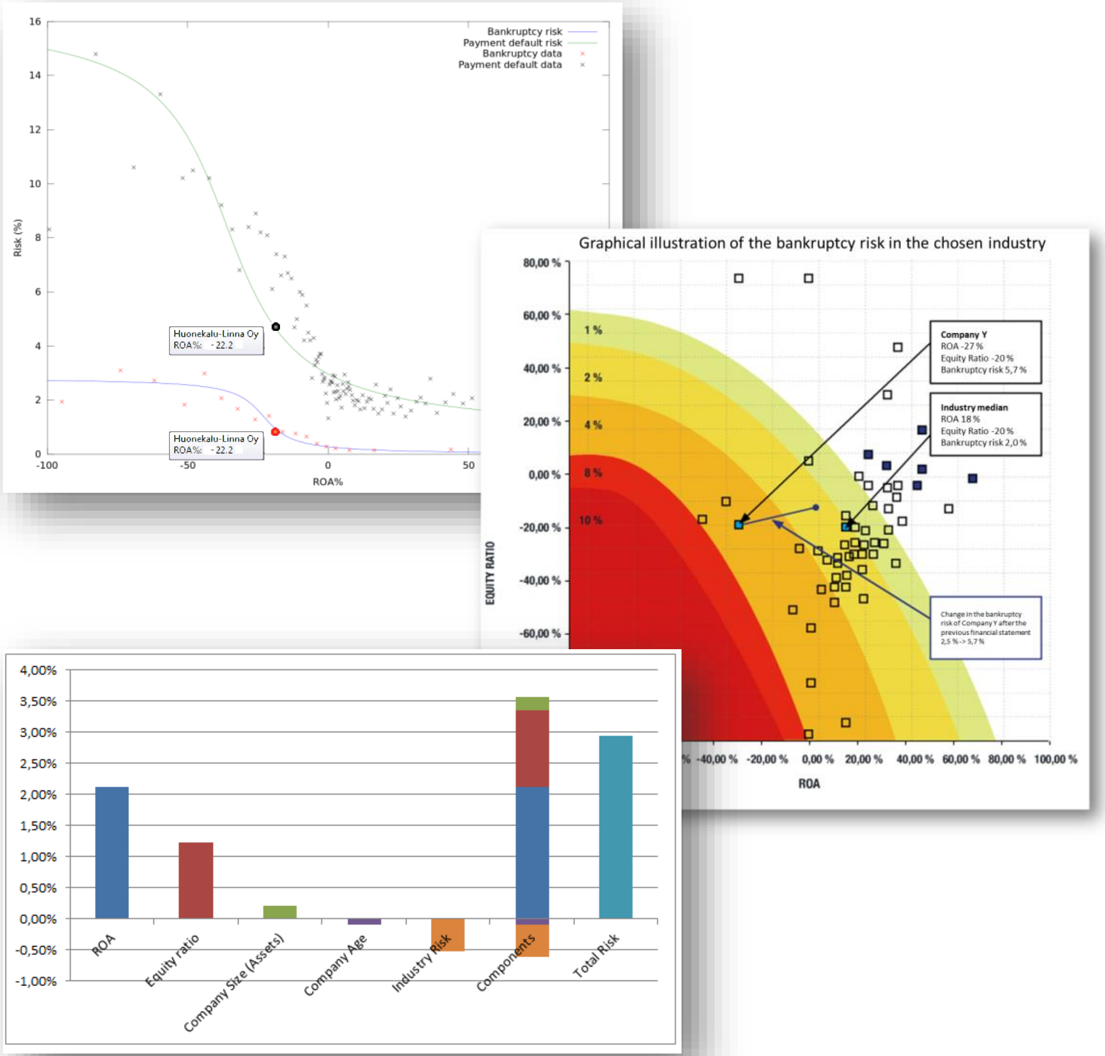


History of credit and default risk assessment

- Credit and bankruptcy risk predictions have usually been based on simple linear 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
  - Gives a polynomial function 1/(1 + e^(-X)) that tells the probability of default, where 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) + …



Logistic regression problems

- Each variable has a constant weight, i.e., it has the same importance for every firm
  - Some variables might be less important in credit risk assessment for some company A than for company B
  - Hard to segment data so that varying weights could also be allowed in logistic regression
    - Possible to make IF-statements which can segment data into different groups
    - For example:
      ROA-% > 10 % ➔ "-0.224 * ROA_percent"
      10 % > ROA-% > 0 % ➔ "-0.162 * ROA_percent"
      ROA-% < 0 % ➔ "-0.024 * ROA_percent"
    - Very hard to find the correct thresholds and makes the formula very complex very quickly

- Increasing the number of explanatory variables can lead to more noisy estimates and make the predictions more unstable

- Possible outliers can have a big influence on the final regression formula

Machine learning solutions

- Allows for automatic segmentation with varying weights
  - Tree-based machine learning models split up the company data into hundreds or thousands of segmented end groups
  - Each small end group has their own set of weights for the variables

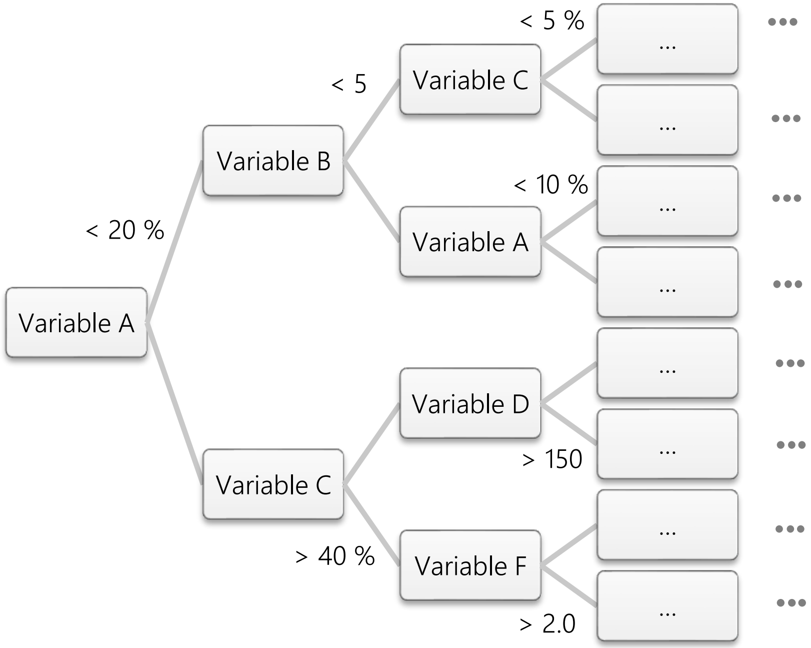
- The number of explanatory variables does not affect machine learning models as much
  - While each variable is considered in the estimation, it is possible that some variables are not even used in the final credit risk assessment reducing the number of final explanatory variables
  - Can automatically eliminate the least important variables from the evaluation

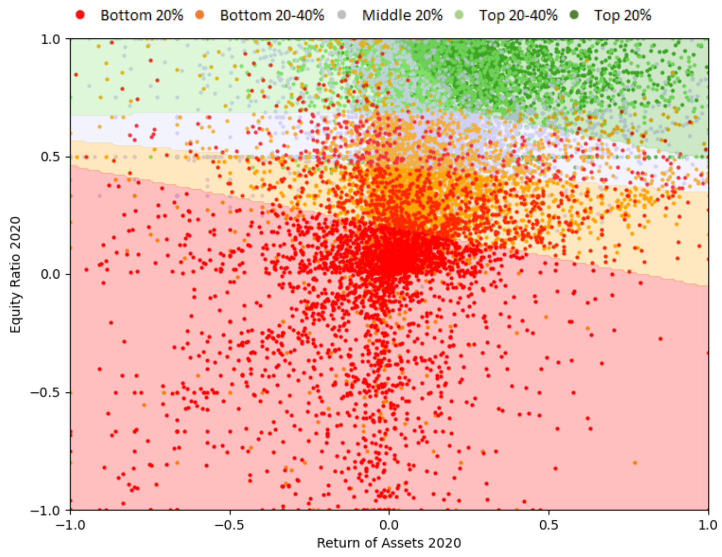
- Possible outliers do not influence the model as much
  - Outliers are usually segmented into their own end group

Many academic studies have also shown that AI-based methods outperform regression-based methods

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

-> can be utilized in automatic text generation

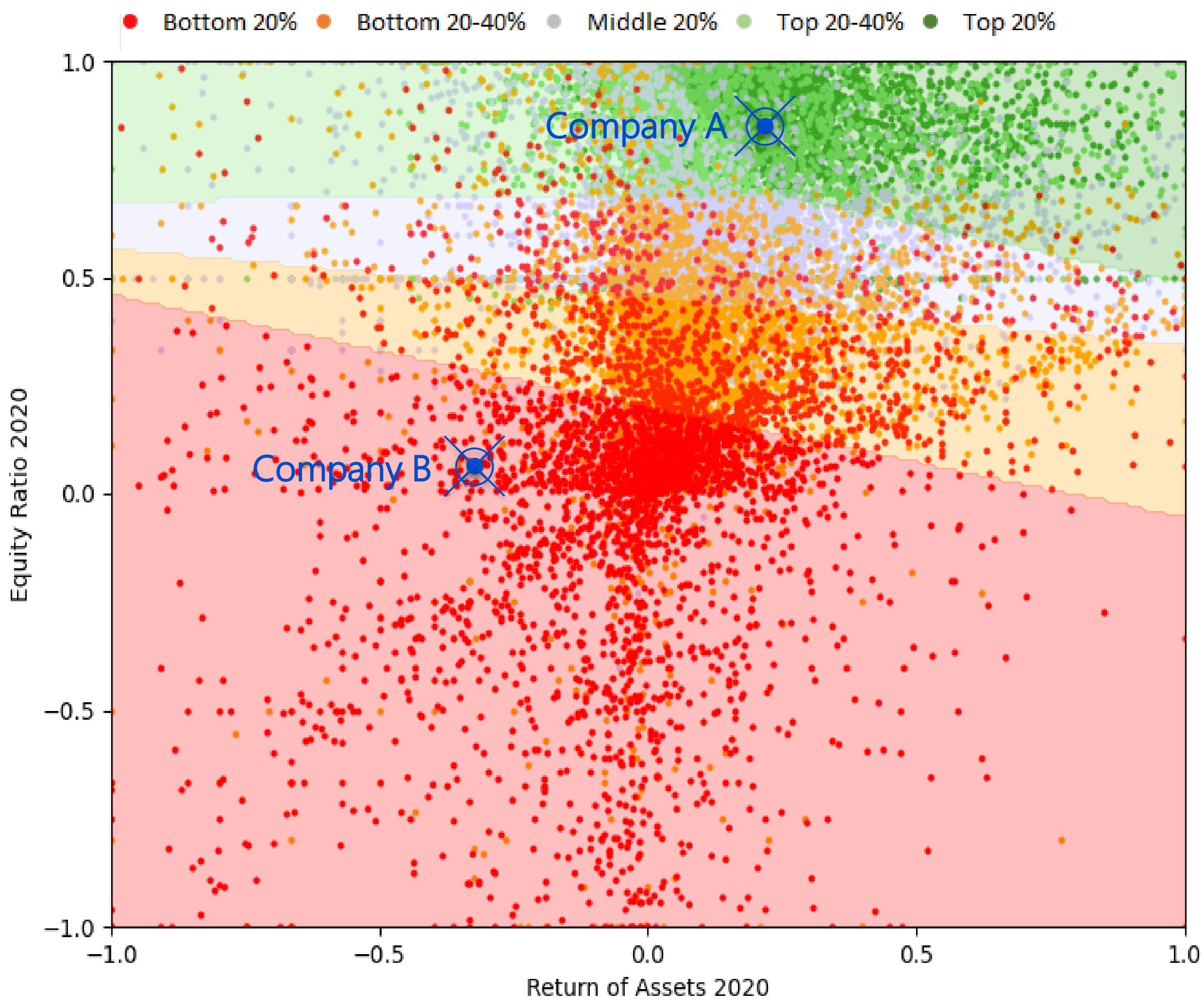
Machine Learning: Advantages

- The advantage of machine learning models is their ability to make use of dynamic weights for different variables.
  - Whereas a simple regression model is a polynomial equation, a machine learning model consists of a large amount of decision trees, from which the correct choice of a decision tree branch is made according to the situation.
- Machine learning algorithms support the use of a considerably larger number of variables.
  - The current model used by Valuatum consists of some 30 explanatory variables.

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 asset it has is its liquidity.

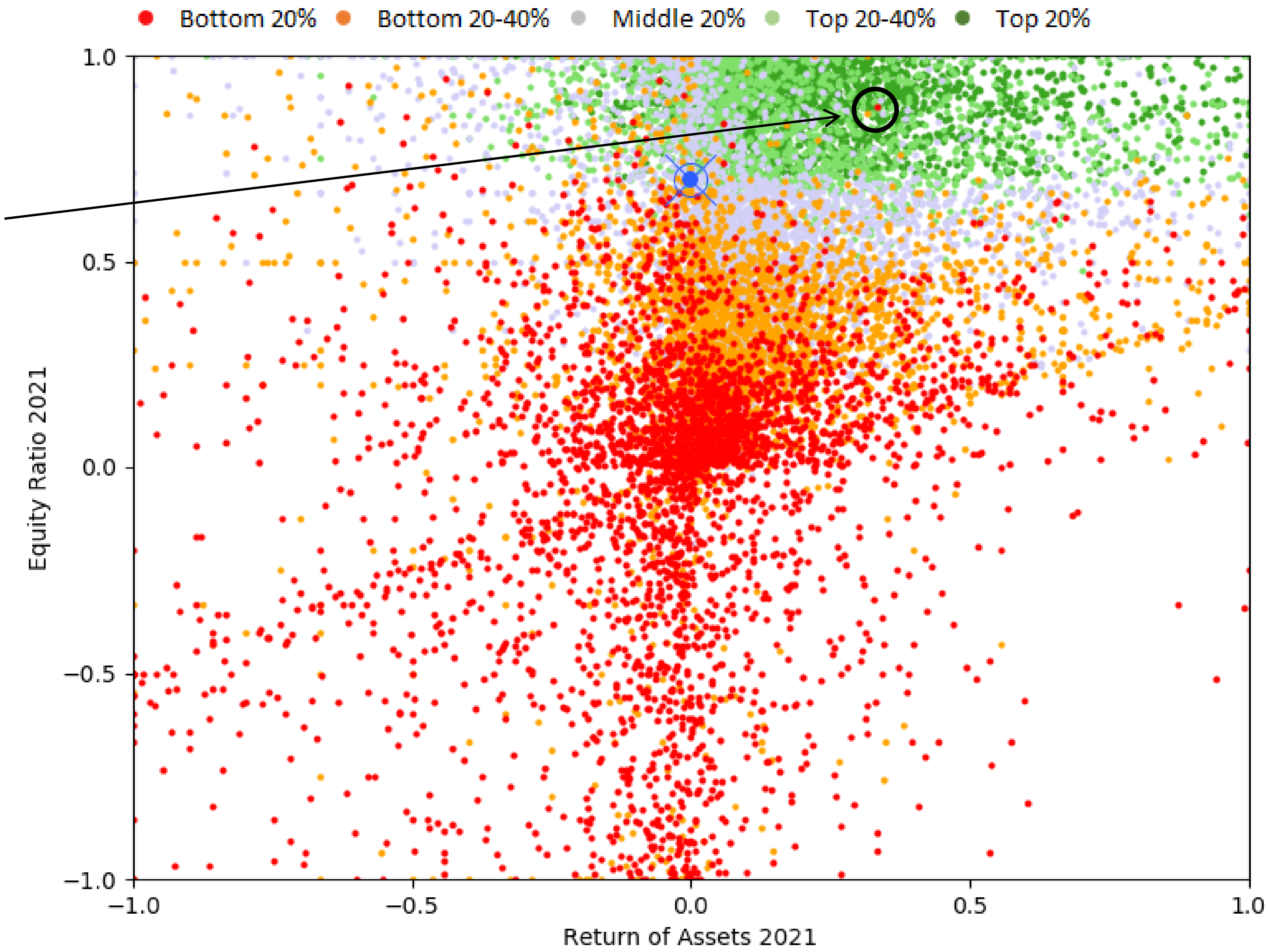
It can be clearly seen that varying weights are necessary for succesful credit risk assessment. Logistic regression has constant weights and thus it is unable to account for these firm-specific characteristics. Machine learning algorithm on the other can recognize that the significance of liquidity becomes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



Credit risk visualization

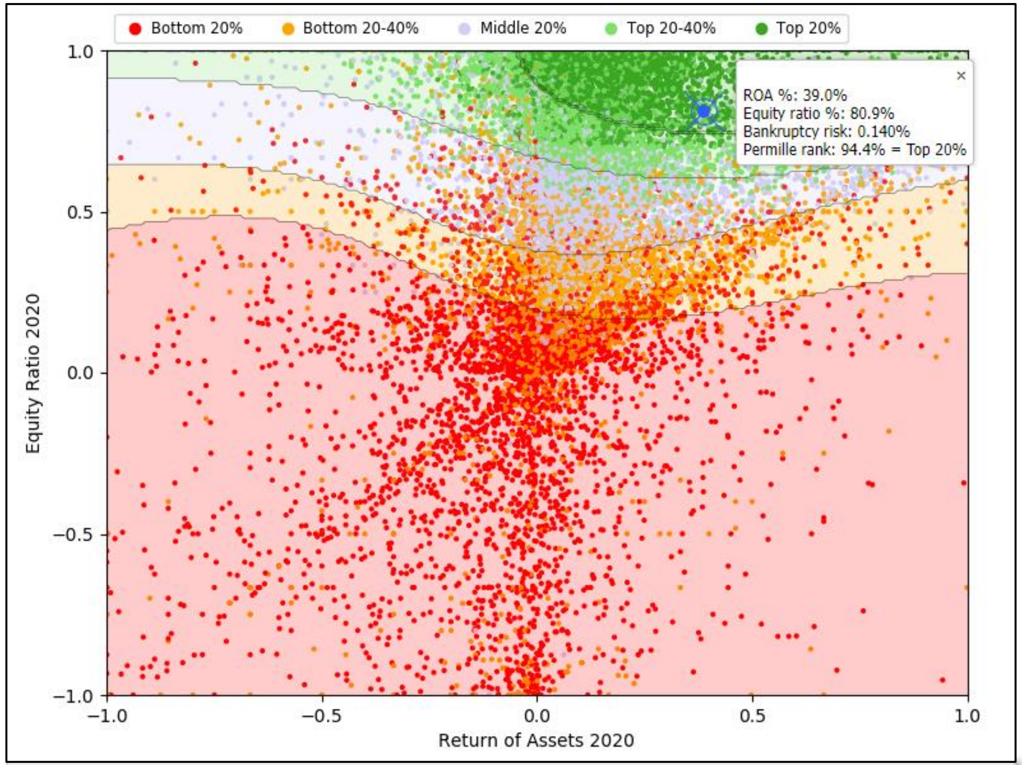
Example of an outlier/anomaly

- Company with ROA & Equity ratio similar to top companies
- A "bad apple", high bankruptcy risk despite of being surrounded by top companies
- Why are they located with 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
  - Explanations for individual observations are given (see next slides).



Example: visualization & automatic text (1/2)

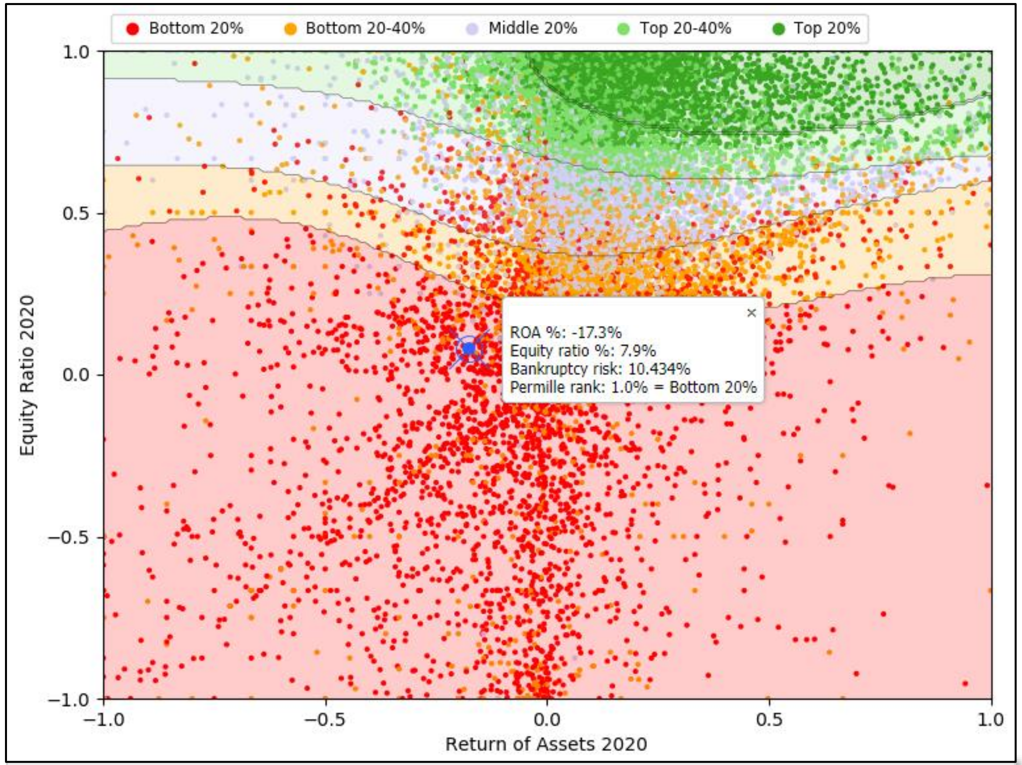
A) Good company in good area



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



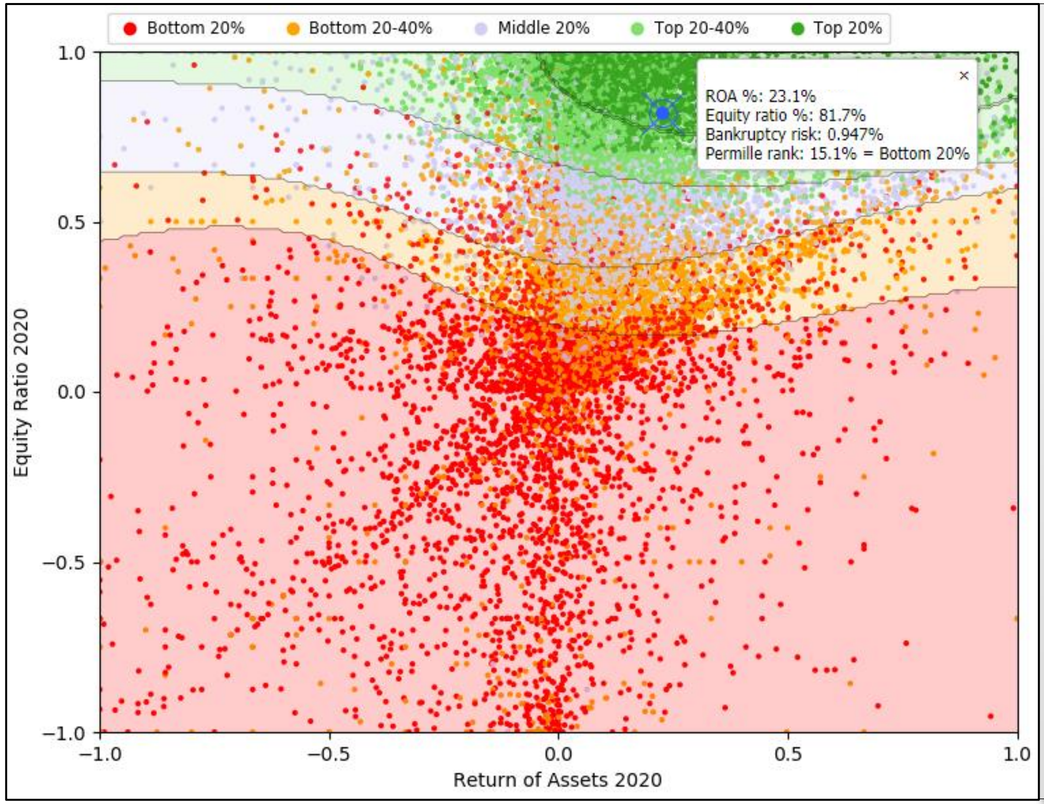
Automatically generated description:

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).

ML model identifies a "bad apple", 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

Results:

- Our model outperforms the others in study. This is in line with academic research that have concluded that ML methods are more effective than others.
  - For example, in ROC – AUC metric our model (0.9066 or 0.9110) beats Altman's Z-score (0.894) with a clear margin.
- A total of approximately 170 000 Finnish companies and 30 input variables were used in the development of the models
- One half of the data was used for training the models, while the other half formed the testing set
- The results are presented below and compared to the results obtained by Altman et al. (2014)*
  - A study based on approximately 2.6 million companies from more than 30 countries using financial data from 2007-2010
- The maximum value for both ROC-AUC and PR-AUC is 1.0. However, the values are not directly comparable. **
  - 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
  - PR-AUC is more difficult to interpret, and there is no general guideline for what can be considered good

	Our model	**Our model w/ payment behavior data**	**Random forest**	**Artificial neural network**	**Ensemble method**	**Altman et al. (2014)**
ROC – AUC**	0.9066	0.9110	0.904	0.880	0.902	0.894
PR – AUC**	0.1765	0.1823	0.189	0.146	0.192	-

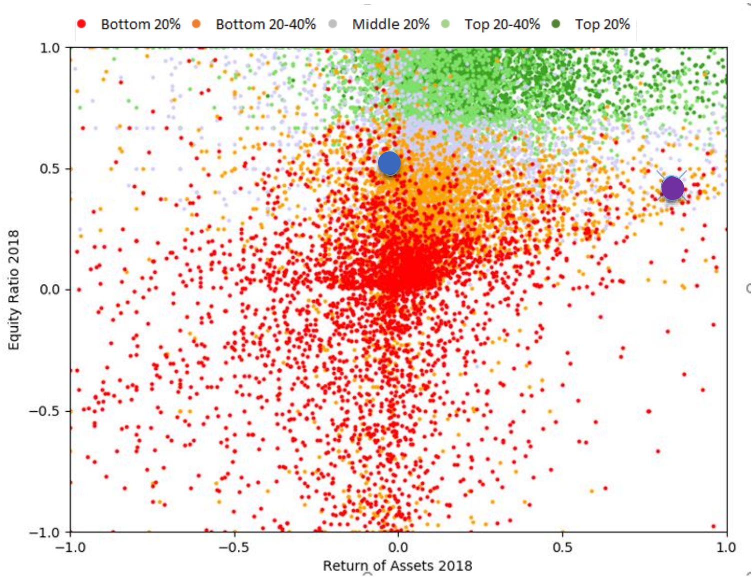
* Altman et. al. (2014), "Distressed Firm and Bankruptcy prediction in an international context: a review and empirical analysis of Altman's Z-Score Model", Available [online]: https://pdfs.semanticscholar.org/257c/b4227101b4da636e90b323736c68c0653a4f.pdf

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

Model comparison

Key ratios	Idan.fi (kEUR)	Jujo Thermal (mEUR)
Net sales	1 046	112
Balance sheet (total)	583	56
Short-term receivables	541	24.8
Cash & cash equivalents	36	1.2
ROA %	83.4 %	-2.8 %
Equity ratio	43.6 %	52.5 %
Quick ratio	1.7	1.0
Log. reg. bankruptcy risk	A (0.74 %)	A (0.37 %)
Valuatum bankruptcy risk	B&C (1.93 %)	B&C (3.59 %)

Valuatum model



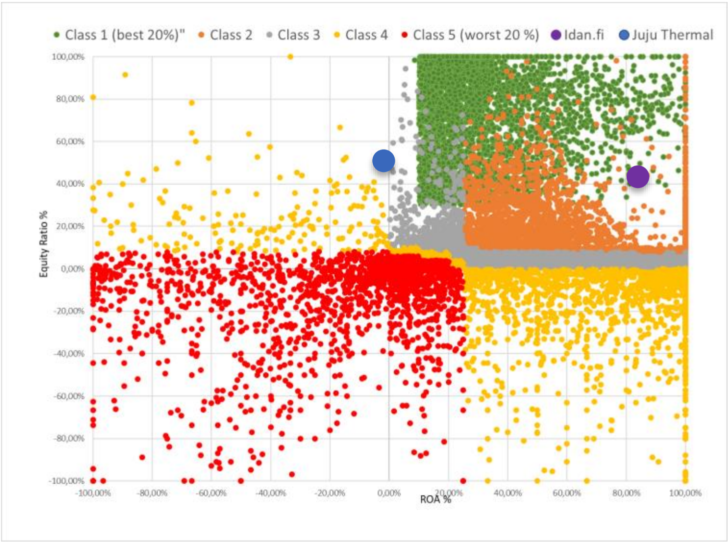
Explanation of the model comparison example:

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, and while Jujo is making a loss it also has a good equity ratio. However, if we take a closer look at the assets, it will give away what 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 this 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. It is very possible that most companies' short-term assets do not really contribute to their bankruptcy probabilities and therefore it has little effect overall, even when it should have a bigger effect.

Logistic regression - based model



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 firms available in our database (data from the years 2017-2018)
  - Firms 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
  - 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 %	

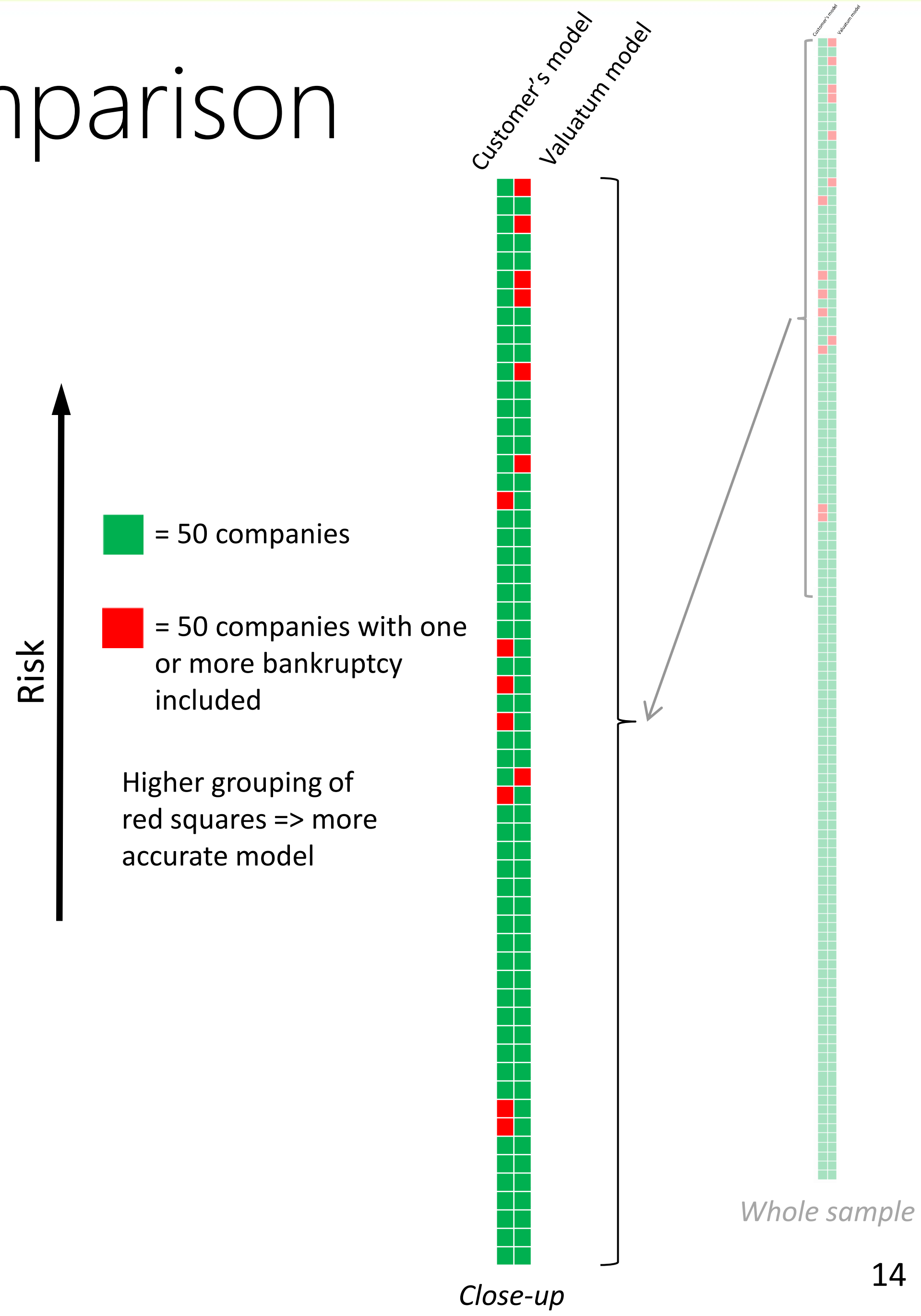
Model accuracy comparison

On the right is a comparison that we made for 6000 companies who applied for a loan from our customer

- **Our model has given a higher risk score for each company that has gone bankrupt than our customer's own model.**

- In the comparison, our customer's results are on the left column and our results are on the right column
  - The companies are sorted according to their bankruptcy risk, so that the companies with highest risk are on the top
  - Explanations of the squares:
    - Each square equals 50 companies
    - A red square means that at least one company in the group has gone bankrupt
  - <u>-> the higher the red squares = more accurate model</u>

- The risk scored have been determined 2018. The companies have gone bankrupt either 2018 or 2019



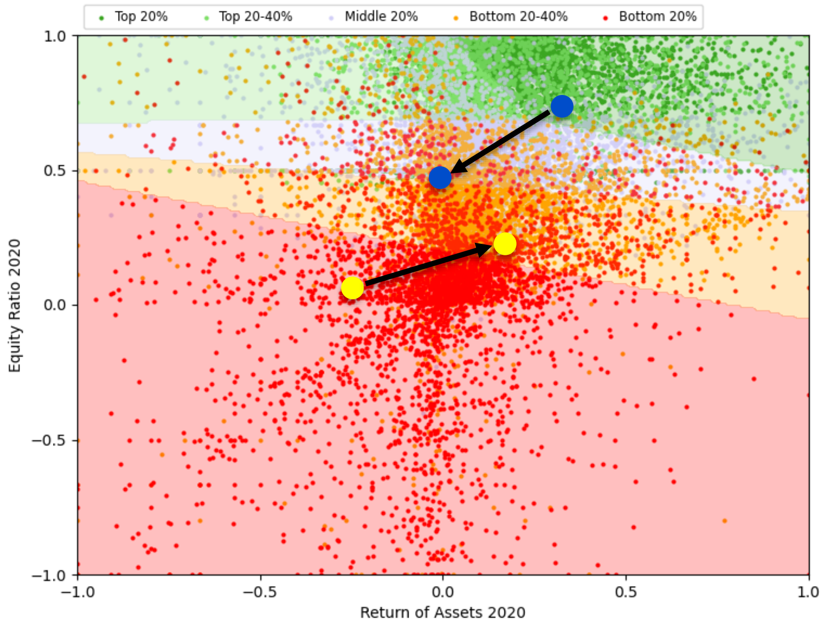
Payment behavior data

- 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

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

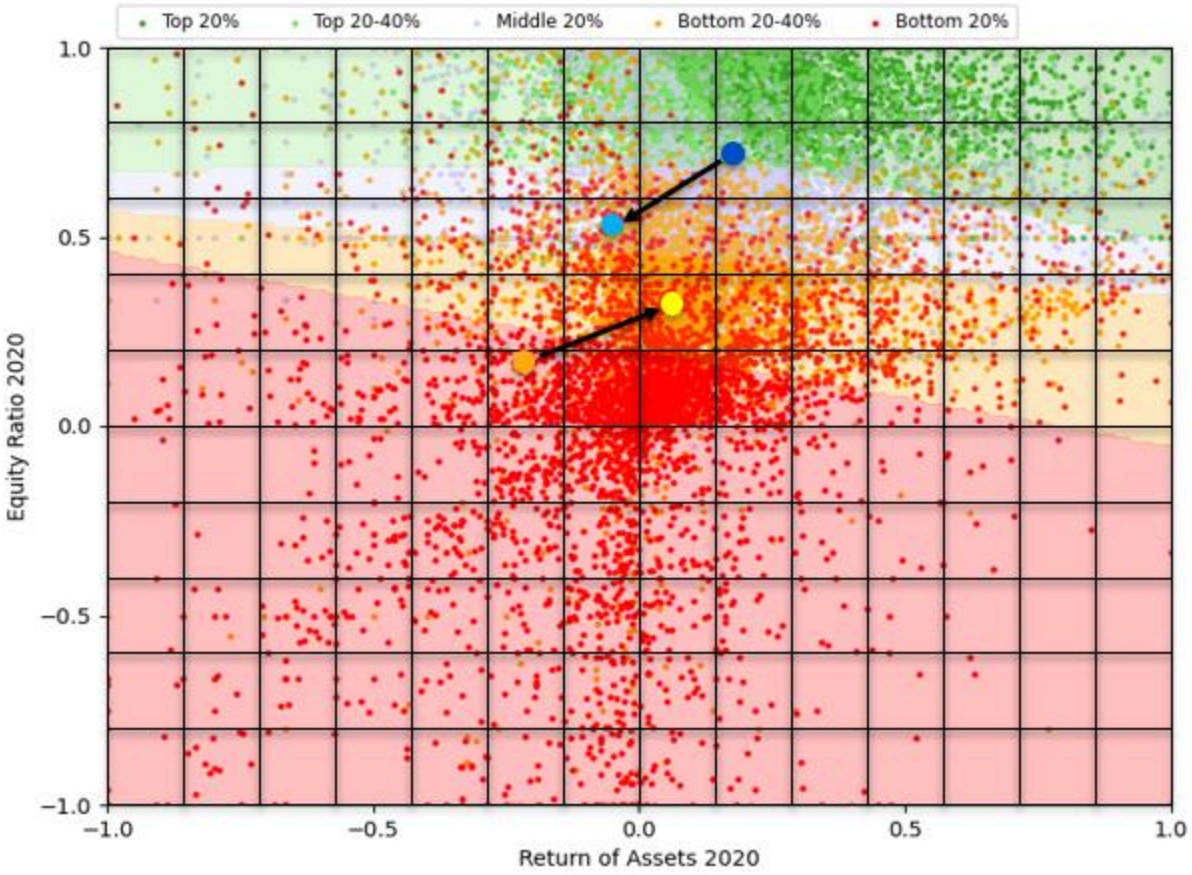


Effects of PSD2 implementation:

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

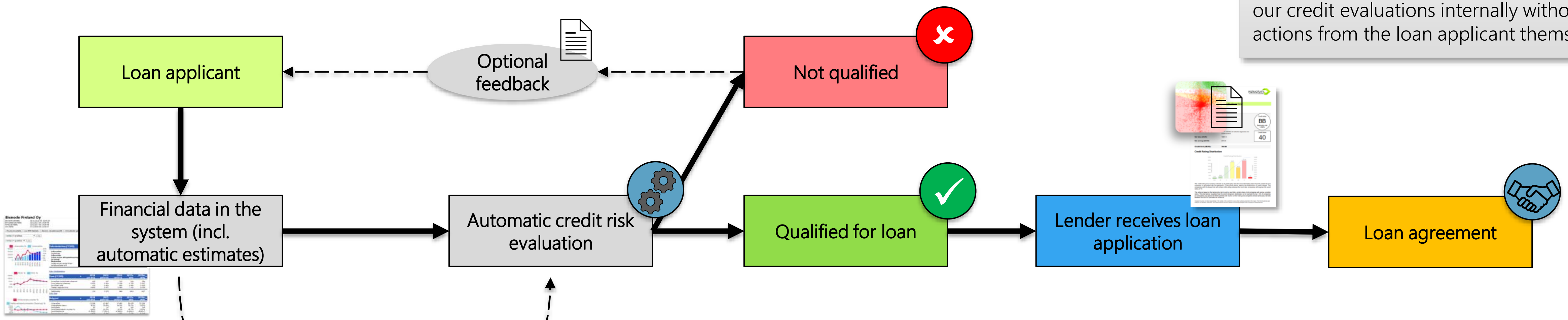


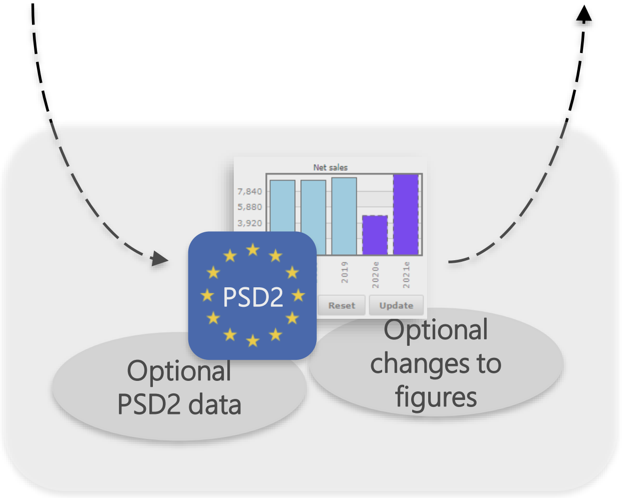
Based on PSD2 data, the company in dark blue has worse explanatory variables (ROA and equity ratio) than its place on the graph suggests and it should be located where the light blue dot is. To adjust its credit risk, we calculate the median credit risks of the areas around dark blue and light blue. 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:

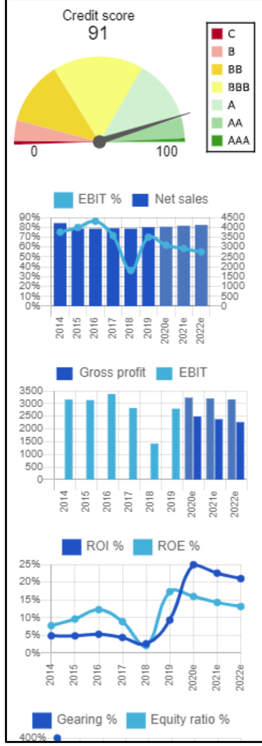
One possible solution on how our system could be integrated into our customers' processes:

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



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**

Income statement (kDKK)	2015 2015/12	2016 2016/12	2017 2017/12	2018 2018/12	2019 2019/12
Net sales	**3,931**	**3,926**	**3,946**	**3,930**	**4,000**
Gross profit	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
EBITDA	3,053	3,503	2,823	1,421	2,797
EBIT	**3,134**	**3,378**	**2,823**	**1,421**	**2,797**
Pre-tax profit (PTP)	**1,488.8**	**2,116.6**	**1,764.3**	**411.7**	**2,301.6**
Net earnings	**1,488.8**	**2,116.6**	**1,764.3**	**411.7**	**2,301.6**
Pre-tax profit without non-rec. items	1,489	2,117	1,764	412	2,302

See the entire income statement

Balance sheet (kDKK)	2015 2015/12	2016 2016/12	2017 2017/12	2018 2018/12	2019 2019/12
Tangible assets total	45,969	45,758	45,092	10,940	7,843
Shareholders equity total	16,436	18,158	21,609	17,093	9,532
Interest bearing liabilities	39,556	52,955	35,213	33,475	0.0
Balance sheet total (assets)	56,311	71,421	58,284	53,270	10,116
Net Debt	38,334	51,754	32,132	31,336	-2,259

See the entire balance sheet

Volume	2015 2015/12	2016 2016/12	2017 2017/12	2018 2018/12	2019 2019/12
Net sales	3,931	3,926	3,946	3,930	4,000
Net sales growth	-6.6%	-0.1%	0.5%	-0.4%	1.8%
Gross profit	0.0	0.0	0.0	0.0	0.0
Gross profit growth	0.0%	0.0%	0.0%	0.0%	0.0%
Employee growth%	0.0%	0.0%	0.0%	0.0%	0.0%
Employee expenses	-276.2	-178.2	-356.5	-334.7	-222.9
Balance sheet total (assets)	56,311	71,421	58,284	53,270	10,116
Balance sheet change%	-0.0%	26.8%	-18.4%	-8.6%	-81.0%
Added value	3,410.2	3,556.4	3,179.6	1,755.4	3,019.6
Added value %	86.7%	90.6%	80.6%	44.7%	75.5%
Investments	-9,858	-211	-666	-34,153	-3,096
Net sales trend	-1.0	-2.0	1.0	-1.0	1.0
EBIT trend	4.0	5.0	5.0	5.0	5.0

Financial statements

Income statement (kDKK)	2019 2019/12	2020e N/A	2021e N/A	2022e N/A	2023e N/A
Fiscal year (months)	12	0	0	0	0
Net sales	**4,000**	**4,027**	**4,077**	**4,116**	**4,195**
Change in finished goods inventory	0.1	0.1	0.1	0.2	0.2
Manufacturing for enterprise's own use	0.0	0.0	0.0	0.0	0.0
Other operating income	0.0	0.0	0.0	0.0	0.0
External services	0.0	0.0	0.0	0.0	0.0
Administrative expenses	-222.9	-285.1	-314.0	-342.6	-375.4
Gross profit	**0.0**	**3,231**	**3,200**	**3,159**	**3,147**
Net Income from Associates	0.0	0.0	0.0	0.0	0.0
Wages and salaries	0.0	0.0	0.0	0.0	0.0
Other operating expenses	-580.4	-742.2	-817.5	-892.0	-977.3
Reduction in value of non-current assets	0.0	0.0	0.0	0.0	0.0
EBIT	**2,796.7**	**2,488.4**	**2,382.1**	**2,266.5**	**2,169.2**
Other financial income	0.0	0.0	0.0	0.0	0.0
Other financial expenses	-495.1	-495.1	-495.1	-495.1	-495.1
Pre tax profit less extra ordinaries	**2,301.6**	**1,993.4**	**1,887.0**	**1,771.4**	**1,674.1**
Pre-tax profit (PTP)	**2,301.6**	**1,993.4**	**1,887.0**	**1,771.4**	**1,674.1**
Income taxes	0.0	-398.7	-377.4	-354.3	-334.8
Net earnings	**2,301.6**	**1,594.7**	**1,509.6**	**1,417.1**	**1,339.3**

Assets (kDKK)	2019 2019/12	2020e N/A	2021e N/A	2022e N/A	2023e N/A
Intangible assets total	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Buildings	7,843.2	9,056.7	9,168.3	9,256.1	9,434.9
Tangible assets total	**7,843.2**	**9,056.7**	**9,168.3**	**9,256.1**	**9,434.9**
Other receivables	0.0	0.0	0.0	0.0	0.0
Investments total	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Other stocks	0.0	0.0	0.0	0.0	0.0
Current assets total	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Long term receivables total	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Current trade debtors	0.0	0.0	0.0	0.0	0.0
Current other receivables	12.6	12.7	12.8	13.0	13.2
Prepayments and accrued income	1.4	1.4	1.5	1.5	1.5
Short term receivables total	**14.0**	**14.1**	**14.3**	**14.4**	**14.7**
Cash equivalents total	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Cash and bank deposits	2,258.8	2,274.2	2,302.2	2,324.3	2,369.2
Cash (generated)	0.0	472.7	583.3	696.0	704.3
Balance sheet total (assets)	**10,116.0**	**11,817.7**	**12,068.2**	**12,290.7**	**12,523.0**

Equity and liabilities (kDKK)	2019 2019/12	2020e N/A	2021e N/A	2022e N/A	2023e N/A
Share capital	76.4	76.4	76.4	76.4	76.4
Retained earnings	8,630.6	8,795.7	9,114.6	9,416.5	9,699.9
Profit of the financial year	825.1	1,594.7	1,509.6	1,417.1	1,339.3
Shareholders equity total	**9,532**	**10,467**	**10,701**	**10,910**	**11,116**
Appropriations total	**0**	**0**	**0**	**0**	**0**
Non-current loans from credit institutions (Estimate years generated)	0.0	0.0	0.0	0.0	0.0
Non-current liabilities total	**0**	**0**	**0**	**0**	**0**

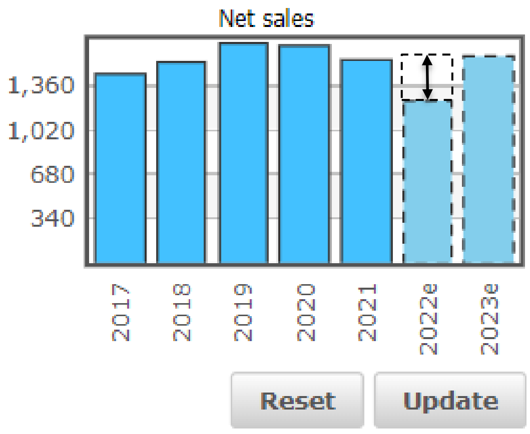
Valuation

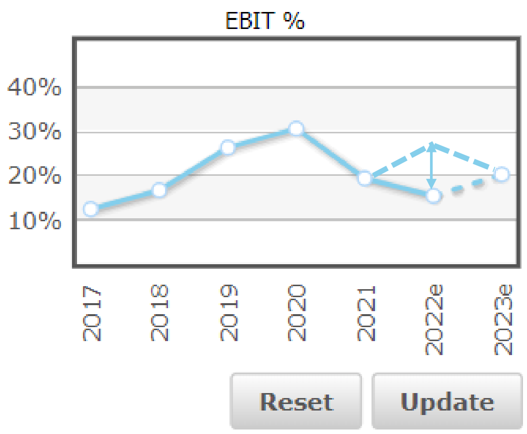
DCF Valuation (kDKK)	2018 2018/12	2019 2019/12	2020e N/A	2021e N/A	2022e N/A	2023e N/A	2024e N/A	2025e N/A	2026e N/A	2027e N/A	2028e N/A	2029e N/A	TRM N/A
EBIT	1,421	2,797	2,488	2,382	2,266	2,169	2,080	1,992	1,898	1,797	1,688	1,571	1,619
+ Total depreciation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
- Paid taxes	0.00	0.00	-399	-377	-354	-335	-317	-299	-281	-260	-239	-215	0.00
- Tax, fin. expenses	0.00	0.00	-99.0	-99.0	-99.0	-99.0	-99.0	-99.0	-99.0	-99.0	-99.0	-99.0	0.00
+ Tax, fin. income	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
- Ch. in working cap.	-28,840	38,058	767	16.5	12.9	26.4	35.9	41.5	43.9	45.4	46.8	48.2	0.00
Operating cash flow	-27,420	40,855	2,758	1,922	1,826	1,762	1,700	1,635	1,562	1,483	1,397	1,305	0.00
+ Inc. in nib. l-t liab.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
- Gross capex	34,153	3,096	-1,213	-112	-87.7	-179	-243	-281	-297	-308	-317	-326	-336
Free oper. cash flow	6,733	43,952	1,545	1,810	1,738	1,583	1,457	1,354	1,265	1,176	1,081	979	0.0
+/- Other items	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Free cash flow	6,733	43,952	1,545	1,810	1,738	1,583	1,457	1,354	1,265	1,176	1,081	979	10,853
Discounted FCFF			1,931	2,016	1,724	1,398	1,146	948	789	653	534	431	4,780
Cum. disc. FCFF			**16,349**	**14,418**	**12,403**	**10,679**	**9,281**	**8,136**	**7,188**	**6,399**	**5,746**	**5,211**	**4,780**
- Int-bear. debt				0.00									
+ Cash at bank				2,747									
+ Market value of associated companies				0.00									
- Market value of minorities				0.00									
- Prev. year paid dividends				0.00									
Value of equity				**18,937**									
/ No of shares (m)				0.00									
Fair value DCF				**0.00**									

EVA Valuation (kDKK)	2018 2018/12	2019 2019/12	2020e N/A	2021e N/A	2022e N/A	2023e N/A	2024e N/A	2025e N/A	2026e N/A	2027e N/A	2028e N/A	2029e N/A	TRM N/A
EBIT	1,421	2,797	2,488	2,382	2,266	2,169	2,080	1,992	1,898	1,797	1,688	1,571	1,619
- Taxes on EBIT	0.00	0.00	-498	-476	-453	-434	-416	-398	-380	-359	-338	-314	0.00

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
- 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

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

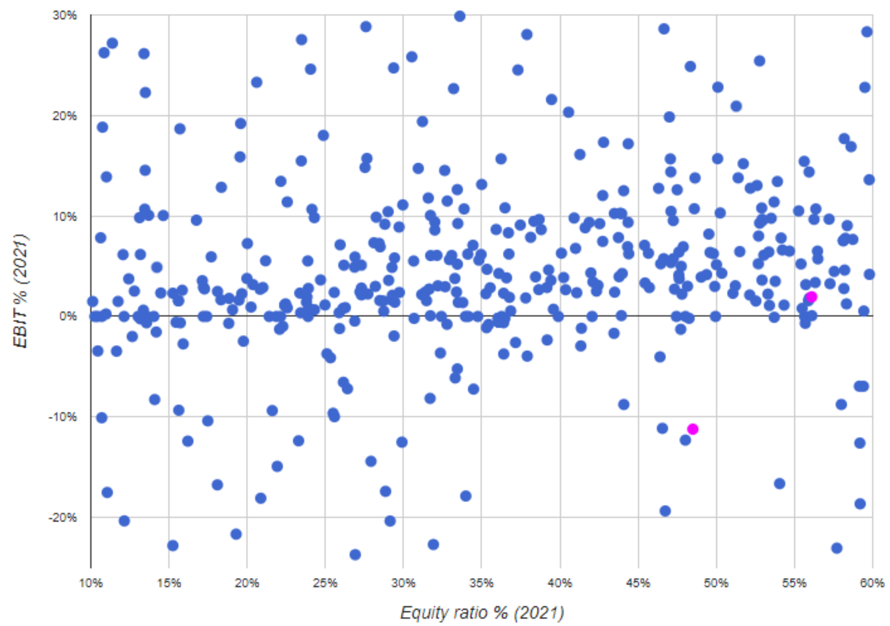
Results: 13656 | 100

	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 -> financials can be then uploaded through XBRL

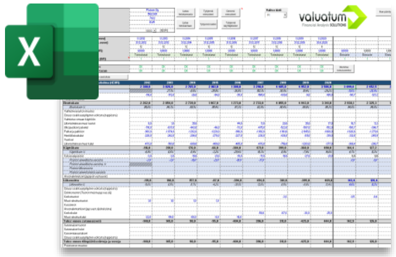
Annual report 2022
XHTML

1. Analyst downloads a financial report into our database

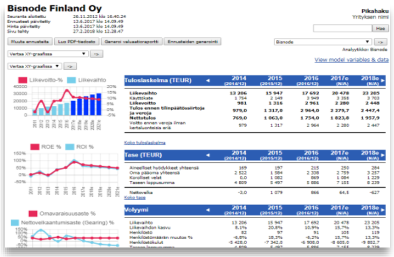
Valuatum database

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/

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