Forecasting Corporate Distress in the Asian and Pacific Region

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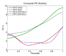
Motivation

Credit risk modelling in the perspective of statistics:

"... the large majority in statistical profession" are using statistical packages "filled with a lot of crank-it-out procedures and very few up-to-date methods."

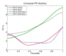
Prof. Leo Breiman, one of the inventors of Classification and Regression Trees (CART)



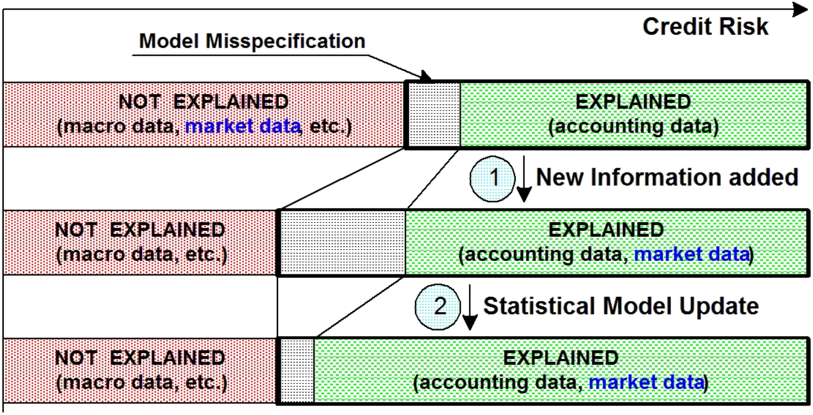
Motivation. Data

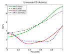
- Mostly only accounting data are used
- Biased data, (self-)selection problem e.g. the companies that submit accounts are those which expect to be rated positively
- Aggregation of incompatible data, e.g. across countries or industries
- Relationship between companies, e.g. companies can belong to the same holding

Modelling results are only as good as the data



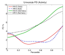
Credit Risk Modelling





Credit Risk: Towards a Better Understanding

1. Use market data and different types of financial distress. Country-specific and industry-specific modelling
2. Selection of a model with "better" statistical properties: **Support Vector Machines** (SVM)



Definition of Distress

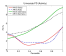
Most common credit events identifying distressed firms:

- restructuring
- liquidation
- being sued by creditors
- failing in coupon and principle payments

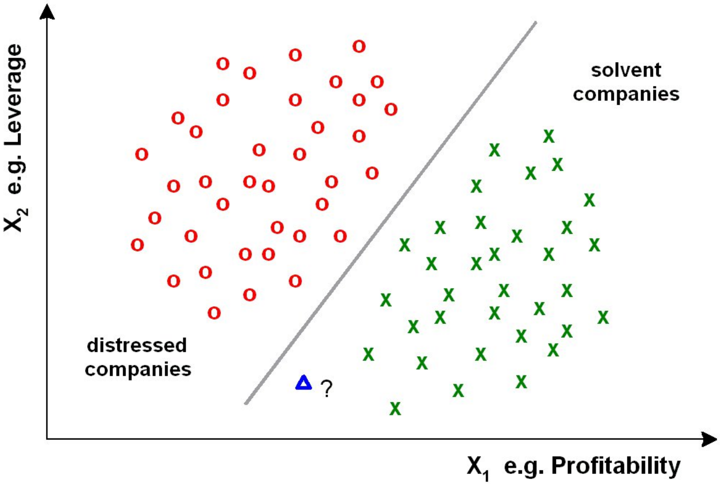
Credit event codes 100–120 and 300–333, RMI database

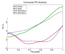
Time to default $\leq$ 2 years (similar results for other horizons)

PD: 2 year cumulative PD



Company Classification Problem



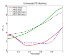


Company Classification Problem

Learning is carried out on the **training set**: $\{(x_i, y_i)\}_{i=1}^{n}$ with the distribution $P(x_i, y_i)$.

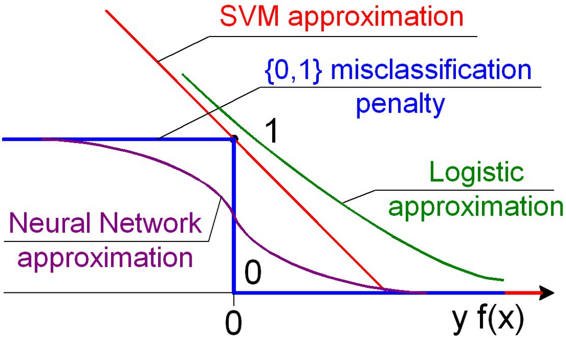
- $x_i \in \mathbb{X}^d$ is the vector of characteristics describing company i e.g. financial ratios;
- $y_i \in \{1; -1\}$ or $\{1; 0\}$ is the class of the i-th company. $y_i = 1$ for distressed, $y_i = -1$ for solvent firms

Objective: find a decision rule $f(x) : \mathbb{X}^d \mapsto \{1; -1\}$ determining the class y of any comany x, s.t. the model can **generalise** well. $\hat{y} = \mathrm{sign}\{f(x)\}$

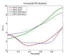


Support Vector Machine (SVM)

From all **convex** classification models, which provide the **stability of the rating**, SVM has the tightest approximation of the $\{0,1\}$ misclassification loss:

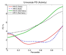


$yf(x)$ – scoring error; $f(x)$ – score



Outline

1. Motivation ✓
2. Predictors of Distress (Asia and Germany)
3. Distress Forecasting (Logit and Support Vector Machines)
4. Massively parallel computing: FPGAs and GPUs



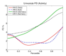
Data Description

Data provided by the Risk Management Institute of the National University of Singapore (RMI NUS)

12 countries; 1986–2010

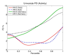
311,000 observations; 7,450 cases of distress

S - sales; TA - total assets; NI - net income; OI - operating income; OK - own capital; CL - current liabilities; TD - total debt; STD - short term debt; QA - quick assets; CA - current assets; WC - working capital; INV - inventories; AR - accounts receivable; AP - accounts payable; CS - cost of sales; INT - interest payments; D - debt; CASH - cash and equivalents



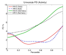
Data Distribution Across Countries

Country	Distressed firms	Solvent firms
Australia	6 (4.03 %)	143
China	4182 (7.22 %)	53739
Hong Kong	19 (0.34 %)	5505
India	148 (0.51 %)	28775
Indonesia	70 (1.12 %)	6186
Japan	258 (0.36 %)	71380
Malaysia	1100 (3.12 %)	34173
Philippines	267 (4.16 %)	6154
Singapore	77 (1.08 %)	7050
South Korea	232 (0.46 %)	50153
Taiwan	604 (2.47 %)	23809
Thailand	486 (2.77 %)	17028



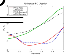
Summary Statistics (1)

	Distressed firms			Solvent firms		
Variable	$q_{0.05}$	Med	$q_{0.95}$	$q_{0.05}$	Med	$q_{0.95}$
			Leverage			
OK/TA	-1.25	0.34	0.63	0.12	0.53	0.88
CL/TA	0.18	0.54	2.02	0.08	0.32	0.73
TD/TA	0.15	0.44	1.06	0.00	0.21	0.60
			Activity			
TA/S	2.53	9.79	107.11	1.75	4.77	25.78
INV/S	0.09	0.90	9.48	0.01	0.48	2.54
AR/S	0.19	1.00	6.54	0.08	0.72	2.18
AP/CS	0.08	0.65	4.97	0.04	0.42	1.38



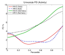
Summary Statistics (2)

	Distressed firms			Solvent firms		
Variable	$q_{0.05}$	Med	$q_{0.95}$	$q_{0.05}$	Med	$q_{0.95}$
			Liquidity			
STD/D	0.17	0.89	1.00	0.08	0.71	1.00
CASH/TA	0.00	0.05	0.30	0.00	0.08	0.38
CASH/CL	0.00	0.08	0.71	0.01	0.26	2.63
QA/CL	0.10	0.64	1.91	0.27	1.09	5.47
CA/CL	0.15	0.90	2.40	0.44	1.49	6.51
WC/TA	-1.67	-0.04	0.37	-0.29	0.16	0.58
CL/TL	0.33	0.88	1.00	0.32	0.79	1.00
			Size			
log(TA)	4.70	7.31	11.49	4.89	9.16	13.46
log(S)	1.39	4.70	9.39	2.18	6.93	11.80



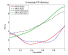
Summary Statistics (3)

	Distressed firms			Solvent firms		
Variable	$q_{0.05}$	Med	$q_{0.95}$	$q_{0.05}$	Med	$q_{0.95}$
			Profitability			
NI/TA	-0.15	0.00	0.03	-0.06	0.01	0.05
NI/S	-4.18	-0.03	0.26	-0.69	0.03	0.28
OI/TA	-0.09	0.00	0.03	-0.04	0.01	0.05
OI/S	-1.81	0.01	0.29	-0.44	0.05	0.29
EBIT/TA	-0.09	0.00	0.03	-0.04	0.01	0.05
EBIT/S	-2.12	0.00	0.30	-0.43	0.05	0.29



Summary Statistics (4)

	Distressed firms			Solvent firms		
Variable	$q_{0.05}$	Med	$q_{0.95}$	$q_{0.05}$	Med	$q_{0.95}$
Cost Structure						
INT/D	0.01	0.04	3.02	0.00	0.02	0.57
EBIT/INT	-22.50	-0.38	12.90	-28.00	4.18	322.00
Dynamics						
S_Growth	-78.25	-7.82	117.90	-51.28	5.12	100.80
NI_Growth	-6.71	0.48	19.97	-4.77	0.19	5.31



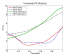
Comparison of the Predictors of Distress

Comparison between similar financial ratios, RMI and Deutsche Bundesbank (Germany) data

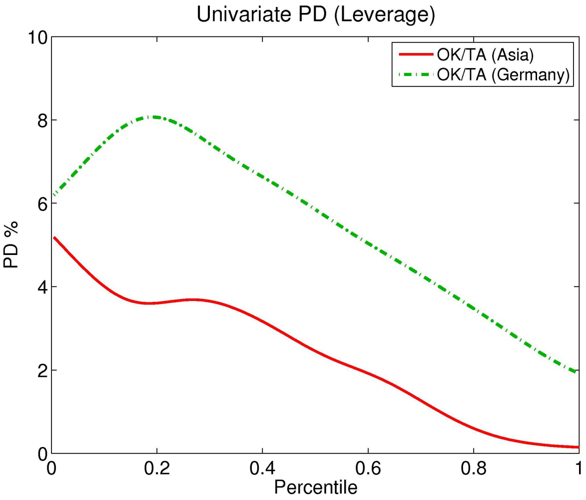
Bundesbank data: 500,000 observations, from them 8,000 instances of default, 1987–2005

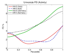
Horizon: 3 years cumulative

Nadaraya-Watson estimator with a Gaussian kernel ($\sigma = 0.08$)

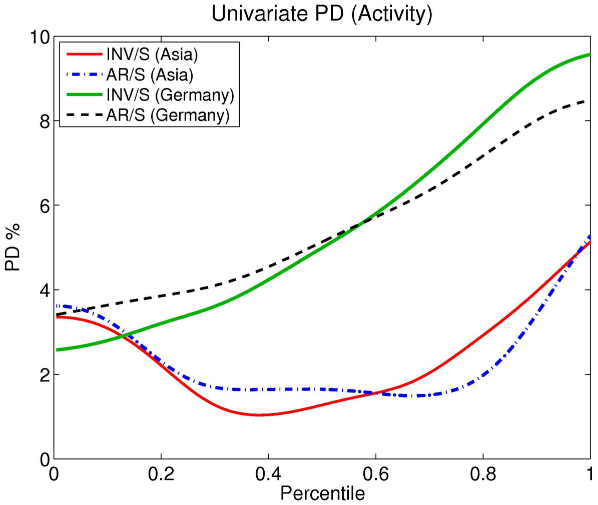


Univariate PD. Leverage

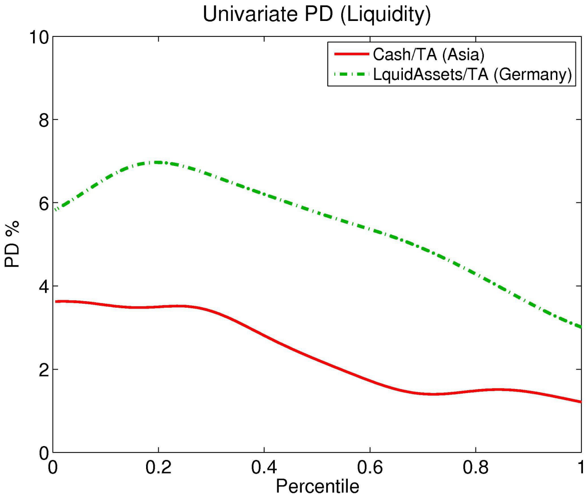


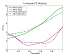


Univariate PD. Activity

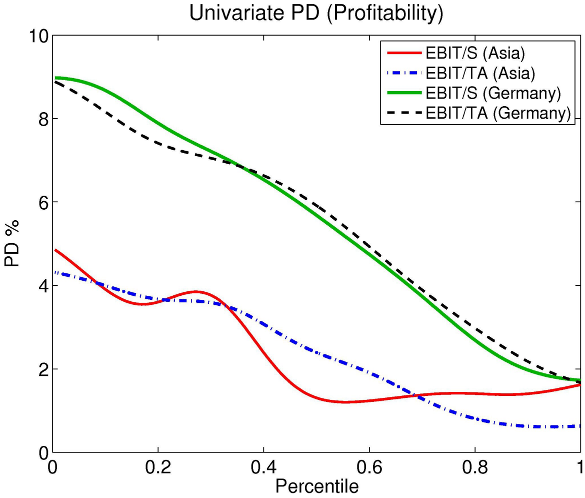


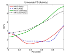
Univariate PD. Liquidity



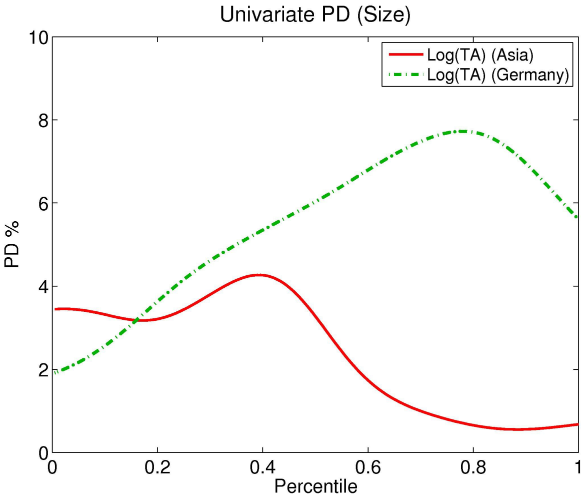


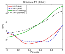
Univariate PD. Profitability





Univariate PD. Size

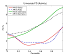




Selection of the Indicators of Distress (1)

Forward variable selection with a bootstrap procedure:

1. Select **non-overlapping** subsamples as training and testing sets (500 solvent and 500 distressed companies in each)
2. Calibrate the model (Logit or SVM) on the training set and estimate the Accuracy Ratio (AR) on the testing set
3. Repeat steps 1 and 2 100 times and estimate the distribution of AR
4. Select a model based on the highest median AR: robustness



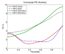
Selection of the Indicators of Distress (2)

	Logit				SVM ($R = 2.5$, $C = 1$)			
Step	Var	MAR	p_{max}	p	Var	MAR	p_{max}	p
1	TD/TA	57.5	0	–	TD/TA	57.5	0	–
2	log(S)	69.0	0	0	log(S)	69.7	0	0
3	CL/TA	71.1	0	0	CL/TA	71.7	3	5
4	log(TA)	**73.2**	–	**0**	TA/S	**73.5**	–	**3**
5	WC/TA	73.3	–	19	RV	73.4	–	75

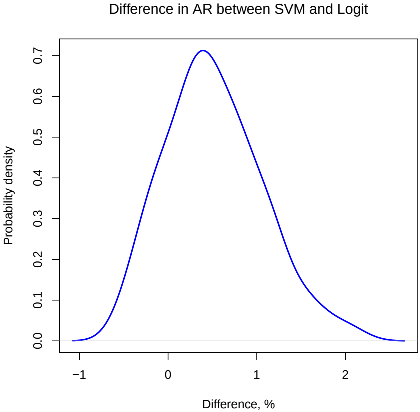
MAR – median accuracy ratio

p – significance level of including an additional variable

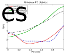
p_{max} – significance in comparison with the four variable model



Comparison of the SVM and Logit



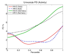
Distribution of the differences of AR between SVM and Logit estimated on 100 bootstrapped subsamples for four variables



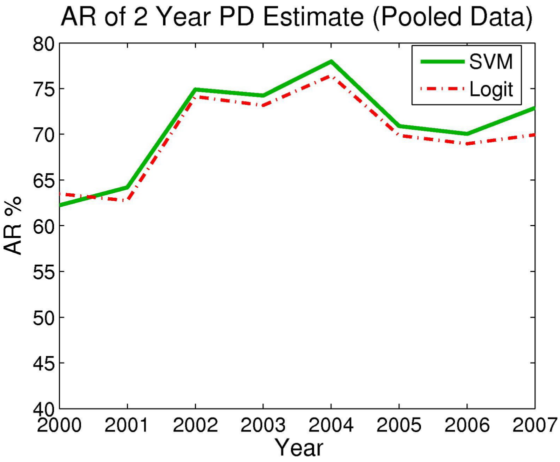
Forecasting

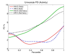
- Calibrate the model (Logit or SVM) on the data from year T
- Estimate AR for the data from year $T + 2$

The SVM is always used with a Gaussian kernel and the same complexity parameters ($R = 2.5$, $C = 1$). The higher R and the lower C is, the higher is complexity

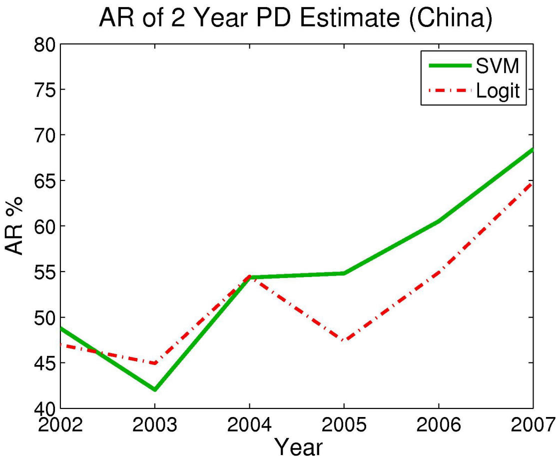


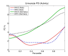
Forecasting. Pooled Data



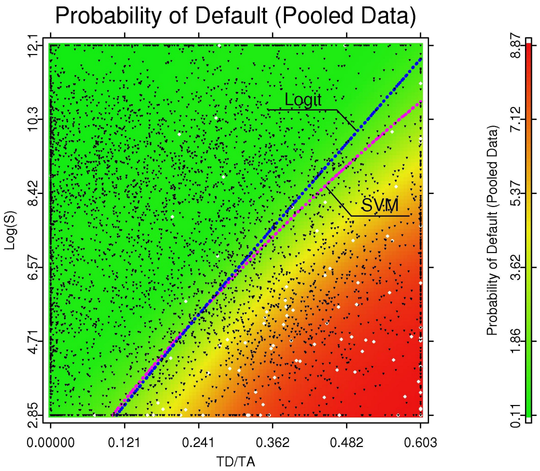


Forecasting. China

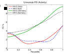




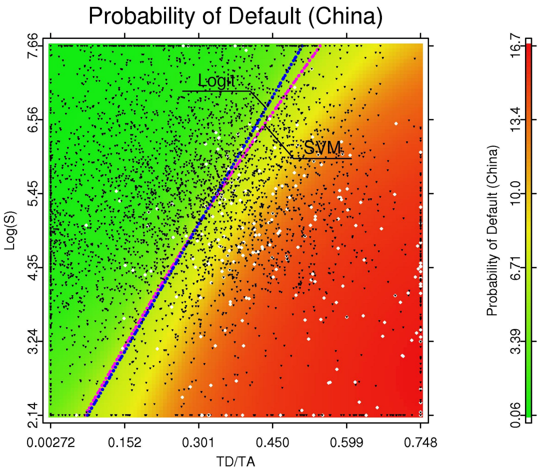
Graphical Interpretation. Pooled Data



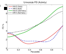
Black points – solvent firms; white point – distressed firms.
Isoquants correspond to the average PD=2.01%



Graphical Interpretation. China



Black points – solvent firms; white point – distressed firms.
Isoquants correspond to the average PD=6.01%



Hardware Acceleration. Reprogrammable Microchips (FPGA)

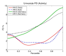
FPGA – field-programmable gate array

Conventional Programming:

- ▷ Does not change the hardware which is universal and unchanged for any programme.

Hardware Programming:

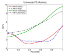
- ▷ Uses hardware description language (HDL) to design and “burn” a customised microchip.



Reprogrammable Microchips (FPGA)

A processor programmed on an FPGA can be 10–400 times faster than a conventional analogue.

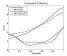
It is possible to programme multiple but simple processors on one FPGA. Then an FPGA can function as a multiprocessor for parallel computations.



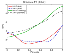
Parallel Computing with GPU

GPU – Graphical Processing Unit

- Massively parallel (Nvidia GeForce-8: 12288 threads)
- Typical acceleration: 10x–200x
- Supported by MATLAB
- Programmable with C (CUDA)



Thank You!



References

Lacerda, A. I. and R. A. Moro (2008). "*Analysis of the Predictors of Default for Portuguese Firms*", working paper 22, Banco de Portugal

Härdle, W. K., R. A. Moro and D. Schäfer (2009). "*Estimating Probabilities of Default with Support Vector Machines*", submitted

Moro, R. A., W. K. Härdle, S. Aliakbari and L. Hoffmann (2011). "*Forecasting Corporate Distress in the Asian and Pacific Region*", Brunel E&F discussion paper