Boosting Credit Risk Models

Lessons learnt from more than two decades of research and consulting

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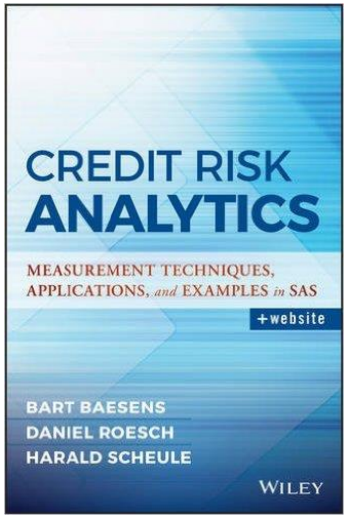
- Studied at KU Leuven (Belgium)
  - Business Engineer in Management Informatics, 1998
  - Ph.D. in Applied Economic Sciences, 2003
- Ph.D. title: Developing Intelligent Systems for Credit Scoring Using Machine Learning Techniques
- Lecturer at School of Management at University of Southampton (UK)
- Research: big data & analytics, credit risk, fraud analytics
- www.bluecourses.com
- www.bartbaesens.com

Books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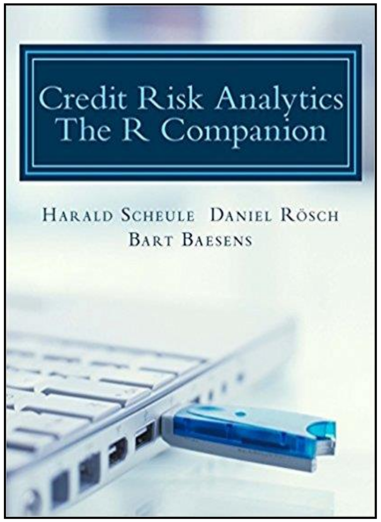
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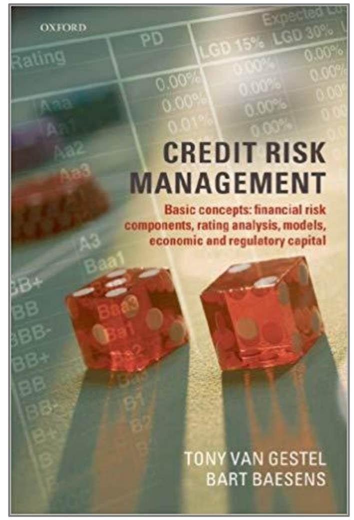
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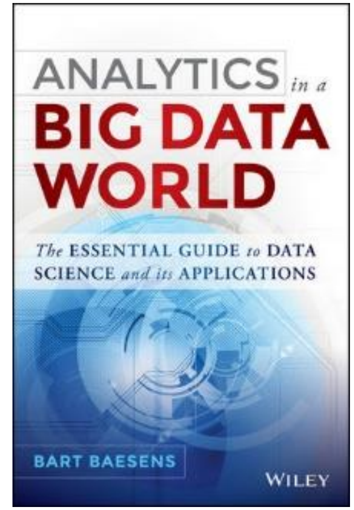
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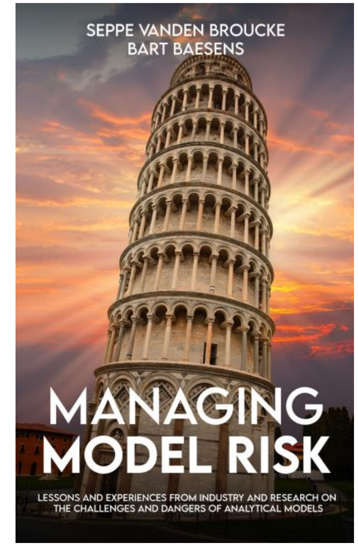
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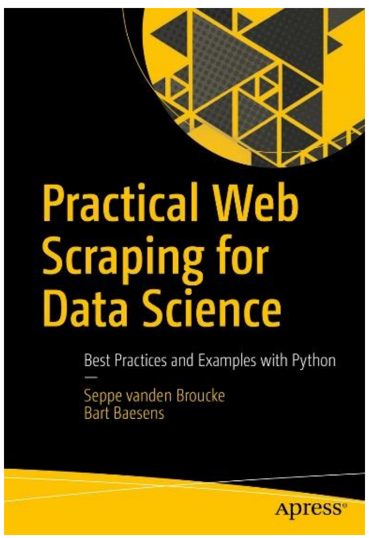
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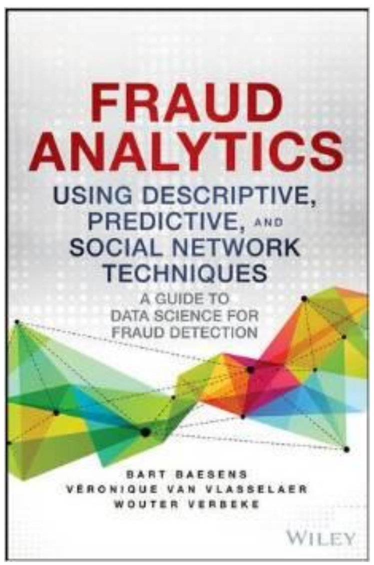
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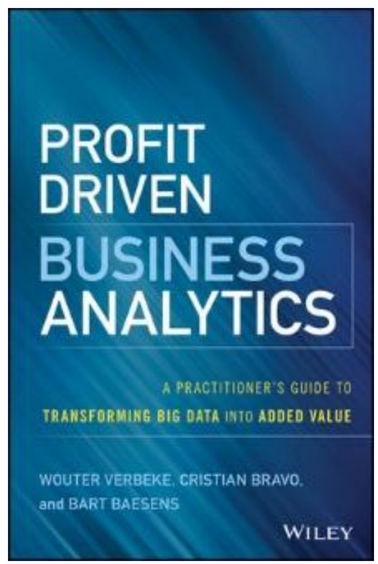
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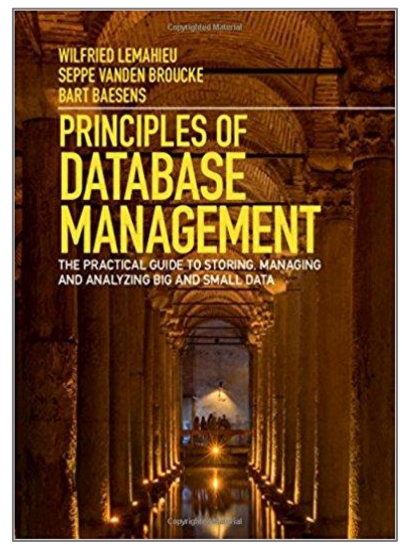
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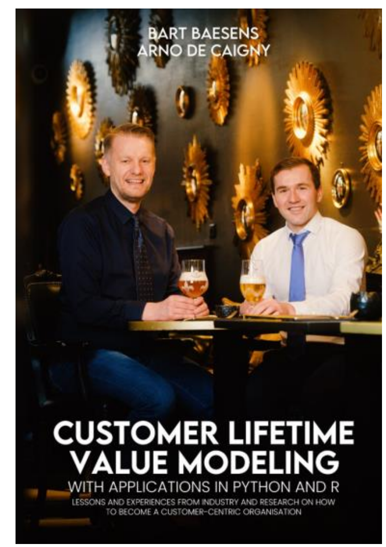
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Basic Credit Risk Modeling for Basel/IFRS 9 using

In this course, students learn how to develop credit risk models in the context of the Basel and IFRS 9 guidelines

Advanced Credit Risk Modeling for Basel/IFRS 9

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Machine Learning Essentials

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Overview

- Credit Risk Model Architecture
- Credit Risk Model Requirements
- Boosting Credit Risk Models
  – Alternative Data Sources
  – Feature Engineering
  – Deep Learning
  – Profit Driven Modeling
- Model Risk

Credit Risk Model Architecture

Level 2

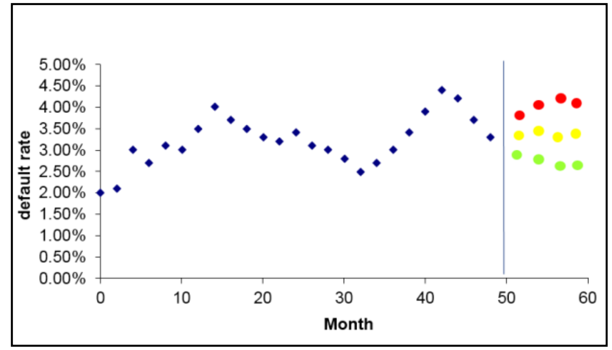
Risk ratings definition
PD calibration

Level 1

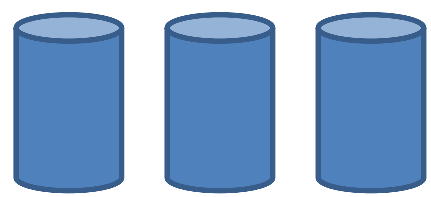
Model
Scorecard
Logistic Regression

Level 0

Internal Data
External Data
Expert Judgment



Characteristic Name	Attribute	Scorecard Points
AGE 1	Up to 26	100
AGE 2	26 - 35	120
AGE 3	35 - 37	185
AGE 4	37+	225
KNOWN CUSTOMER	NO	90
KNOWN CUSTOMER	YES	180
SALARY 1	Up to 500	120
SALARY 2	501-1000	140
SALARY 3	1001-1500	160
SALARY 4	1501-2000	200
SALARY 5	2000+	240



Baesens et al, *Credit Risk Analytics*, Wiley, 2016.

Credit Risk Model Requirements

- Statistical performance
  - Lessmann S., Baesens B., Seow H.V., Thomas L.C., Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research, *European Journal of Operational Research*, 2015.
- Profitability
  - Verbraken T., Bravo C., Weber R., Baesens B., Development and application of consumer credit scoring models using profit-based classification measures, *European Journal of Operational Research*, 2014.
- Interpretability
- Operational efficiency
- Privacy and Ethics
- **Ecological footprint**

Boosting Credit Risk Models

- Alternative Data Sources
- Feature Engineering
- Deep Learning
- Profit Driven Modeling

Alternative Data Sources

- Call Detail Record (CDR) Data
- Google Street View
- Google Trends
- Social Media Data
- API/Web Scraping
- Open data
- Note: privacy/ethics always respected!

Alternative Data Sources: CDR Data

- Óskarsdóttir M., Bravo C., Sarraute C., Vanthienen J., Baesens B., The Value of Big Data for Credit Scoring: Enhancing Financial Inclusion using Mobile Phone Data and Social Network Analytics, *Applied Soft Computing*, 2019.
- Use Call Detail Record (CDR) data for credit scoring
- People tend to call those in their economic circle
- Inspect default influence for credit scoring
- Featurize CDR data and combine with other data

Alternative Data Sources: CDR Data

- Combining CDR with traditional data in credit scoring significantly increases AUC
- In terms of profitability, best model built with only calling behavior features
- Calling behavior features predictive both in terms of statistical and economic performance
- Closing thoughts
  - financial inclusion in developed countries: people joining financial market for first time
  - financial inclusion in developing countries: no historical financial data
  - privacy: check local privacy regulations and ethical guidelines

Alternative Data Sources: Google Street View

- Gebru et al., Using deep learning and Google Street View to estimate the demographic makeup of neighborhoods across the United States, *PNAS*, 2017 (https://www.pnas.org/content/114/50/13108)
- Portray demographic and economic makeup of neighborhoods using Google Street View
- Socioeconomic attributes such as income, race, education, and voting patterns can be inferred from cars detected in Google Street View images using deep learning
- More foreign cars in neighbourhood, implies higher average income
  - German and Japanese cars (Lexus in particular) found in areas with high median household income
  - American cars made (Buicks, Oldsmobiles and Dodges) associated more with lower median incomes
- Add deep learning features to credit scoring models
- Privacy (e.g., GDPR)

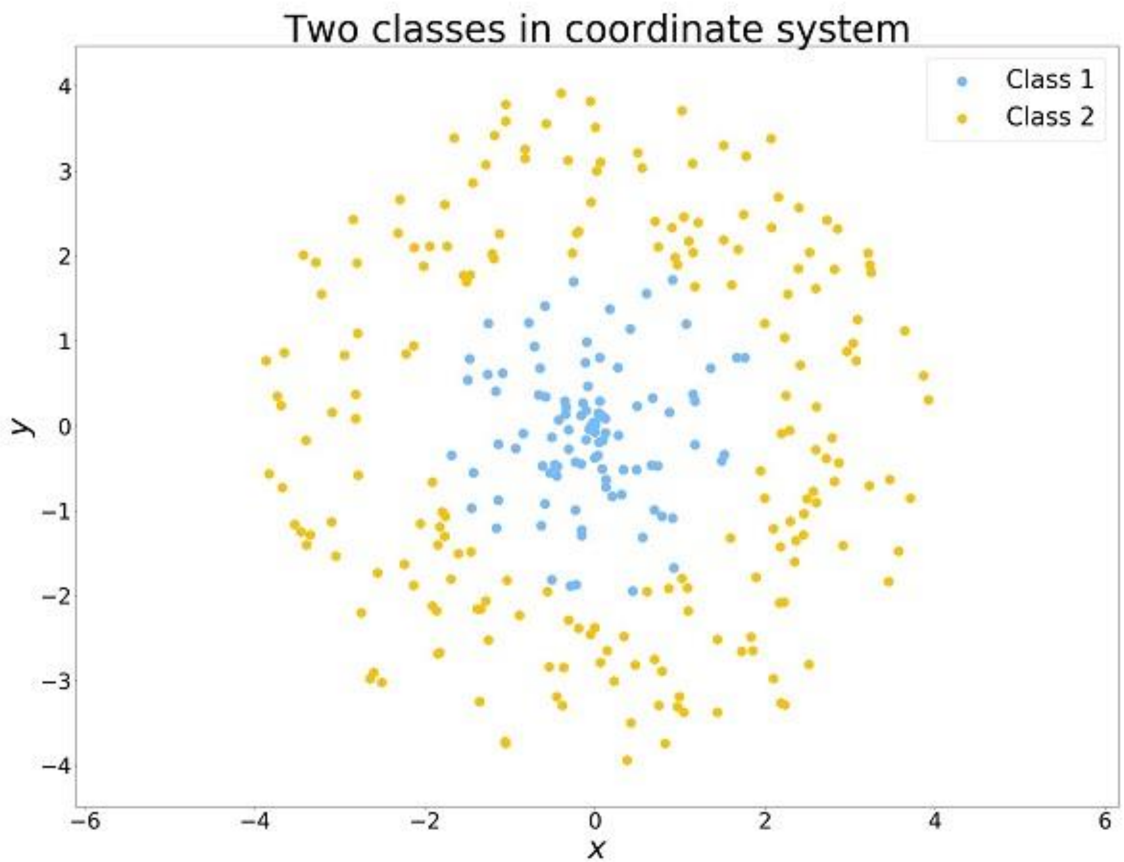
Alternative Data Sources: Google Trends

- Provides search data and popular search terms across time, geography, etc.
- Can be used for nowcasting where aim is to forecast present or near future
- Allows to spot trends more quickly than traditional channels
- E.g., forecasting unemployment based upon Google searches with key terms jobs, unemployment (benefits), social security, etc.
- Useful for
  - PD/LGD/EAD calibration (e.g., PIT calibration in IFRS 9 setting)
  - anticipating economic downturns
  - stress testing

Feature Engineering

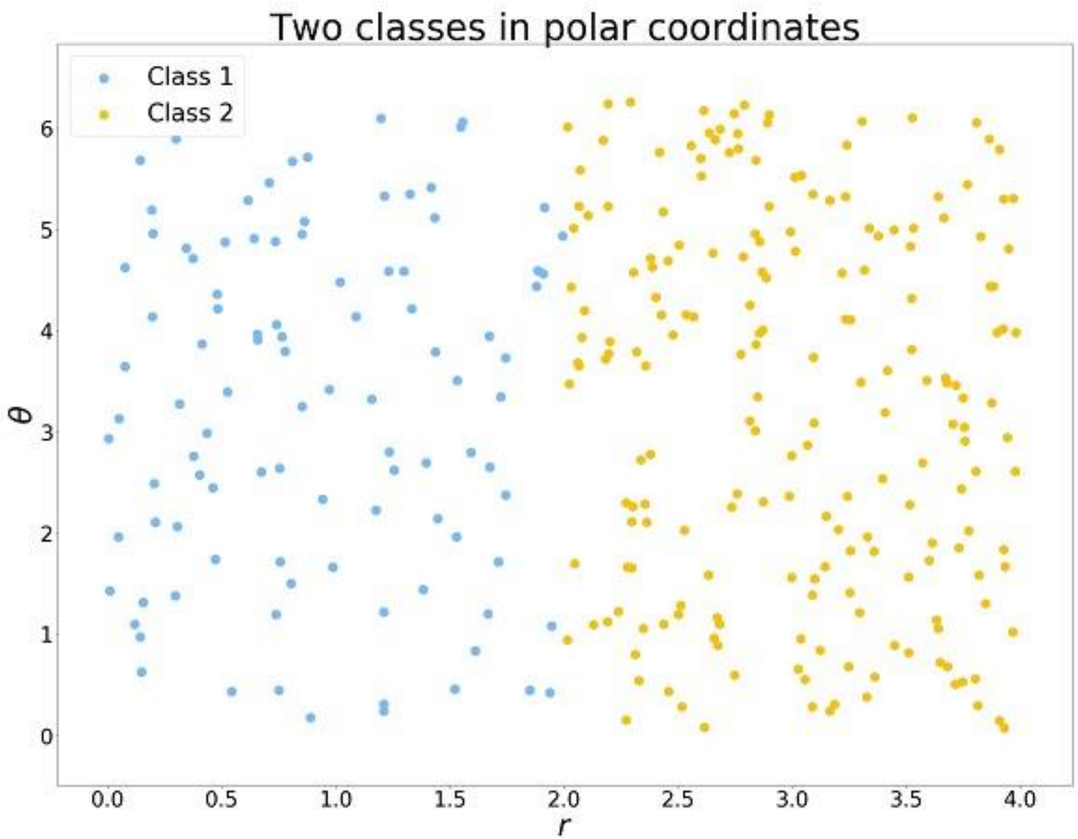
- Transforming data set variables into features to help credit risk modes achieve better performance in terms of
  - predictive power
  - interpretability
- Simple example
  - date of birth ➔ age
- Manual feature engineering versus automated feature engineering
- Best way to improve performance of credit risk models is by designing smart features!

Feature Engineering



See https://www.kdnuggets.com/2018/12/feature-engineering-explained.html

Feature Engineering



See https://www.kdnuggets.com/2018/12/feature-engineering-explained.html

Feature Engineering

- Trend features
- Ratio features
- Transformations
  - Logarithmic transformation
  - Power transformation
  - Box-Cox transformation
  - Yeo-Johnson transformation
  - Principal Component Analysis
  - Percentile coding
  - Thermometer coding

Trend Features

- Trends summarize historical evolution
- Absolute trends: $\frac{F_t - F_{t-x}}{x}$
- Relative trends: $\frac{F_t - F_{t-x}}{F_{t-x}}$
- Useful for size variables (e.g., asset size, loan amounts) and ratios
- Beware with denominators equal to 0!
- Can put higher weight on recent values
- Extension: time series analysis!
- Van Gestel T., Baesens B., Martens D., Predictive Analytics Techniques and Applications in Credit Risk Modelling, OUP, forthcoming, 2023.

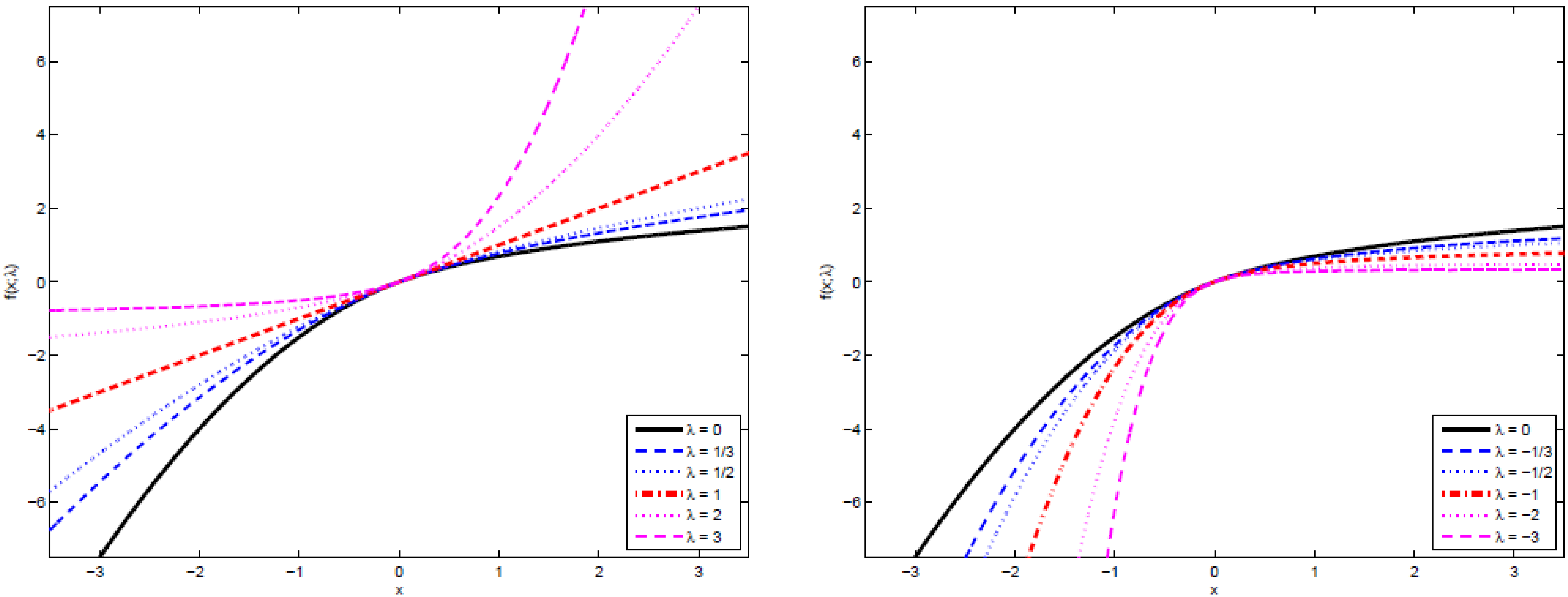
Yeo Johnson Transformation

- Yeo Johnson (Yeo and Johnson, 2000)

$$x \rightarrow f(x;\lambda) = \begin{cases} ((1+x)^{\lambda}-1)/\lambda & for\ \lambda \neq 0, x \geq 0 \\ \log(x+1) & for\ \lambda = 0, x \geq 0 \\ -\dfrac{(1-x)^{2-\lambda}-1}{2-\lambda} & for\ \lambda \neq 2, x < 0 \\ -\log(-x+1) & for\ \lambda = 2, x < 0 \end{cases}$$

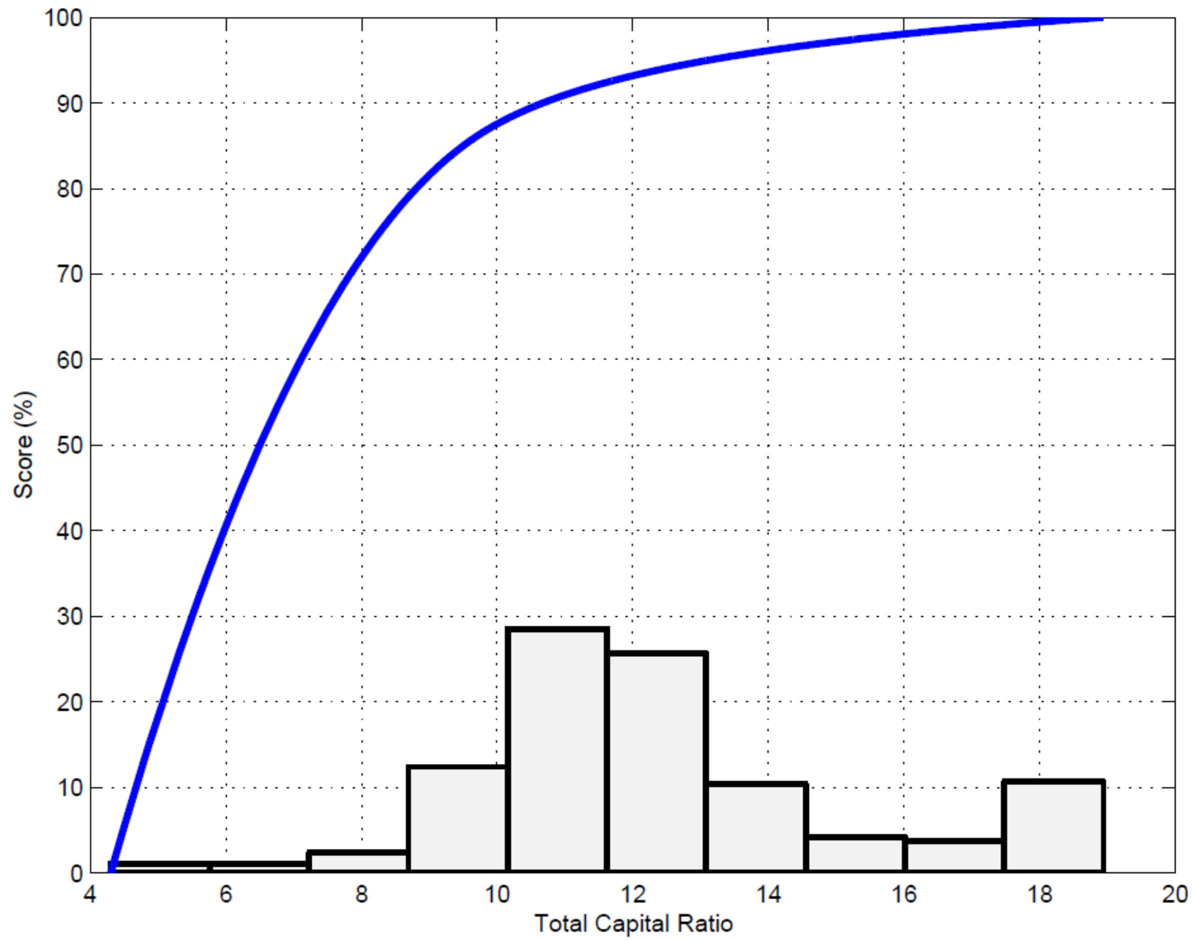
- Set λ by
  - experimentation
  - visual inspection
  - performance optimization (AUC, profit)

Yeo Johnson Transformation



Van Gestel T., Baesens B., Martens D., *Predictive Analytics: Techniques and Applications in Credit Risk Modelling*, Oxford University Press, 2020.

Yeo Johnson Transformation



VAN GESTEL T., BAESENS B., ET AL.,Linear and nonlinear credit scoring by combining logistic regression and support vector machines, *Journal of Credit Risk*, 2005.

Deep Learning

- Gunnarsson B.J., vanden Broucke S., Baesens B. et al., Deep learning For Credit Scoring: Do or Don’t, *European Journal of Operational Research*, 2021.
- Motivation
  - performance of classification algorithms for credit scoring extensively researched
  - deep learning little attention within credit scoring community
  - deep learning algorithms compared to performance of 2 ensemble methods (random forests, XGBoost) and 2 conventional methods (logistic regression, decision trees)

Deep Learning

Data set	Cases	Covariates	Prior default rate	Nx2 cross-validation
AC	690	14	.445	10
GC	1,000	20	.300	10
Th02	1,225	14	.264	10
Bene1	3,123	28	.667	10
HMEQ	5,960	12	.199	5
Bene2	7,190	27	.300	5
UK	30,000	15	.040	5
TC	30,000	23	.221	5
Bene3	38,649	11	.002	5
GMC	150,000	10	.067	5

Deep Learning

- 2 ensemble methods considered overall best performing classifiers
  - XGBoost is best performing classifier on all performance measures considered except one where random forests is best
- Deep networks do not outperform shallower networks with 1 hidden layer
- Deep learning algorithms not appropriate for credit scoring and 2 ensemble methods considered should be preferred

Neural Networks in Credit Risk

- Not as final credit risk model because of black box property
- Benchmarking
- Detecting non-linear or interaction effects
- Use features/score from deep learning neural network as input to logistic regression model
- Combine neural network with linear/logistic regression in two stage model
- Start from property address, retrieve Google Street\Satellite view image, estimate value using deep learning (e.g. convolutional neural network) and relate to default (PD) or loss (LGD) risk
- Privacy + Ethics!

Profit Driven Modeling

- Verbraken T., Bravo C., Weber R., Baesens B., Development and application of consumer credit scoring models using profit-based classification measures, *European Journal of Operational Research*, 2014.
- Key ideas
  - profit-based classification performance measure for credit scoring (as opposed to AUC, Brier score, etc.)
  - enables selection of most profitable credit scoring model and provides optimal cutoff point
  - results indicate that this outperforms traditional approaches in terms of accuracy and monetary value

Profit Driven Modeling

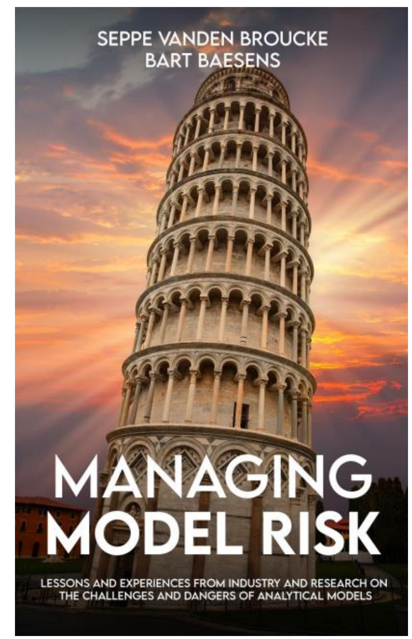
- EMP package
  - https://cran.r-project.org/web/packages/EMP/index.html
- ProfLogit
  - use EMP to estimate coefficients of logistic regression model
  - Stripling E., vanden Broucke S., Antonio K., Baesens B., Snoeck M., Profit Maximizing Logistic Model for Customer Churn Prediction Using Genetic Algorithms, *Swarm and Evolutionary Computation*, Volume 40, pp. 116-130, 2018.
- ProfTree
  - use EMP to estimate decision tree
  - Höppner S., Stripling E., Baesens B., vanden Broucke S., Verdonck T., Profit Driven Decision Trees for Churn Prediction, *European Journal of Operational Research*, forthcoming, 2019.

Model Risk

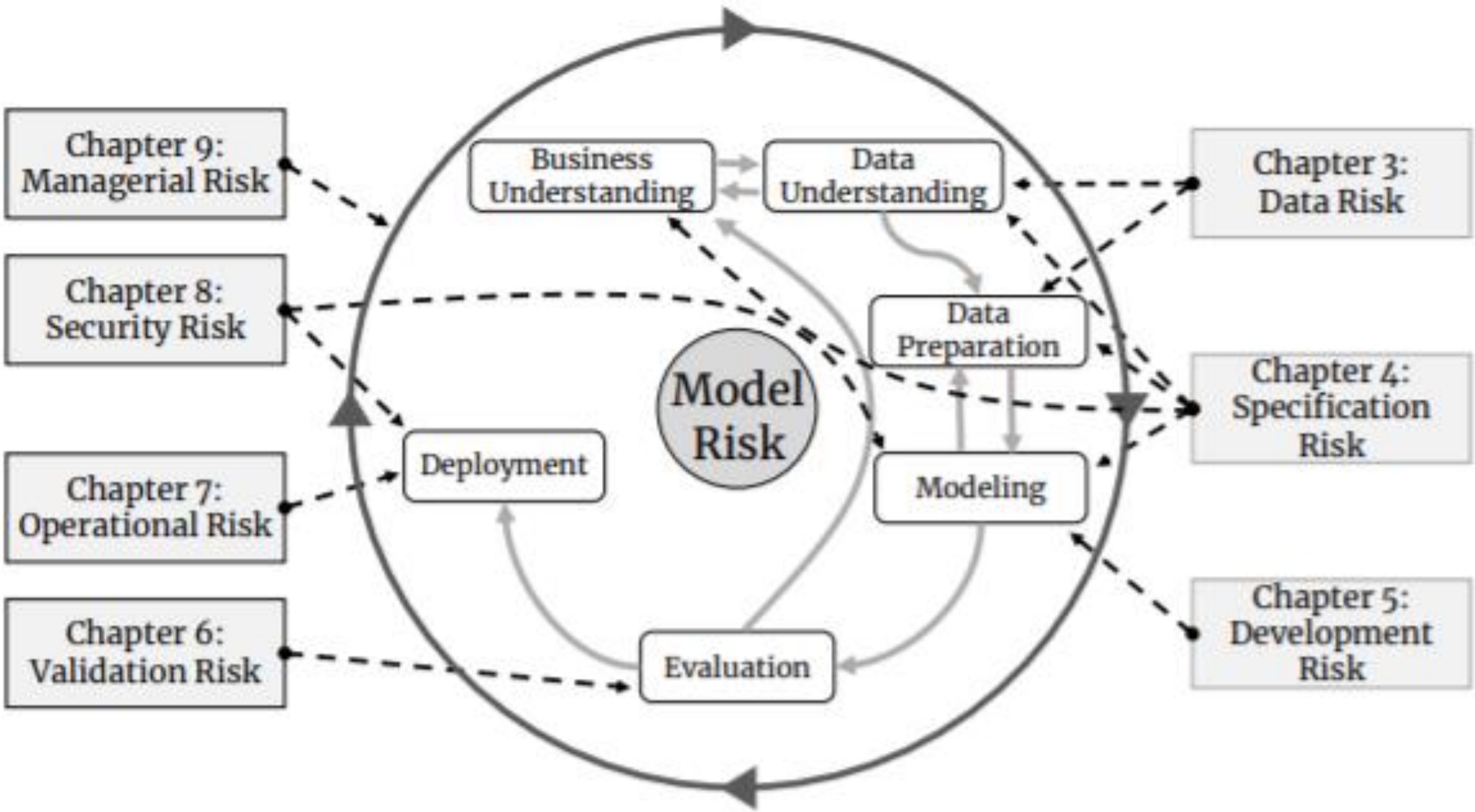
- FICO (2021)
  - 65% of companies cannot explain how specific AI model decisions or predictions are made
  - 73% have struggled to get executive support for prioritizing AI ethics
  - Only 20% actively monitor their models in production
  - 30% of organizations report an increase in adversarial and other attacks against their model

Model Risk

- *"Model risk is the risk of expected or unexpected loss resulting from the inadequate development or usage of analytical models across all business units and activities of the company."*



Model Risk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Chapter 8: Security Risk
Chapter 7: Operational Risk
Chapter 6: Validation Risk
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Data Understanding
Data Preparation
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Deployment
Modeling
Evaluation
Chapter 3: Data Risk
Chapter 4: Specification Risk
Chapter 5: Development Risk

Conclusions

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