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AI/ML in Finance: Applications, Cases and Research

2nd Machine Learning & AI in Quantitative Finance Conference

Marcelo Labre

15 November 2018

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Applications

Is AI a hype? Is AI useful at all in finance?

Report: AI Is More Hype Than Reality

Venture Capitalist: A.I. Hype Still “Has a Ways to Go Up”

Have We Reached The Peak Of AI's Hype?

What Happens if AI Doesn’t Live Up to the Hype?

AI is already doing this!

https://towardsdatascience.com/self-learning-ai-agents-part-ii-deep-q-learning-b5ac60c3f47

And this!

It Was a Big Year for A.I.

By CHRISTINA BONNINGTON DEC 28, 2017

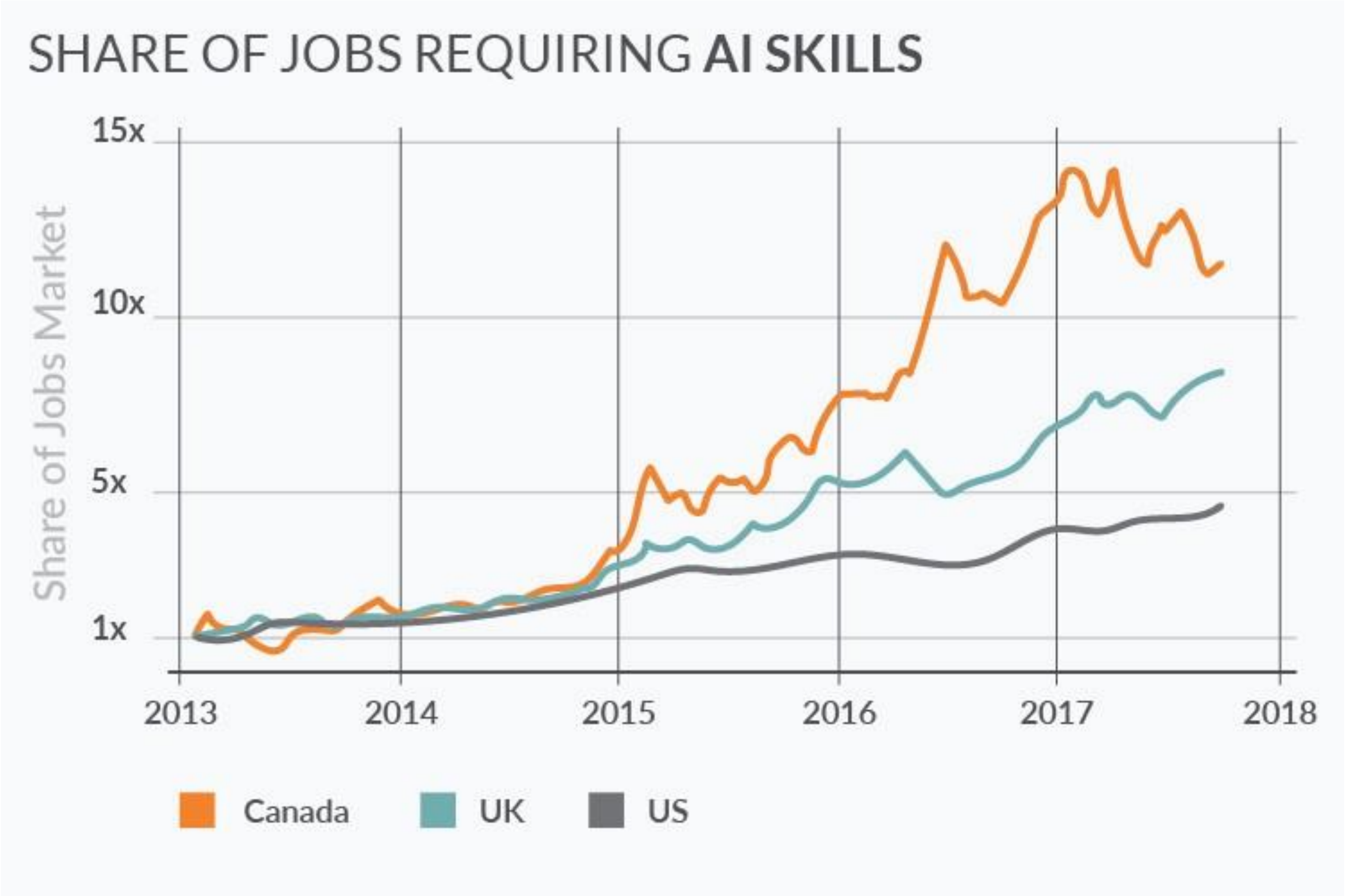
https://slate.com/technology/2017/12/year-in-artificial-intelligence-most-impressive-ai-and-machine-learning-accomplishments.html

- A.I. Spotted An Eight-Planet Solar System
- Beat The World Champion Go Player
- Bested Poker Pros at No-Limit Texas Hold'Em
- Taught Itself To Program

59 impressive things artificial intelligence can do today

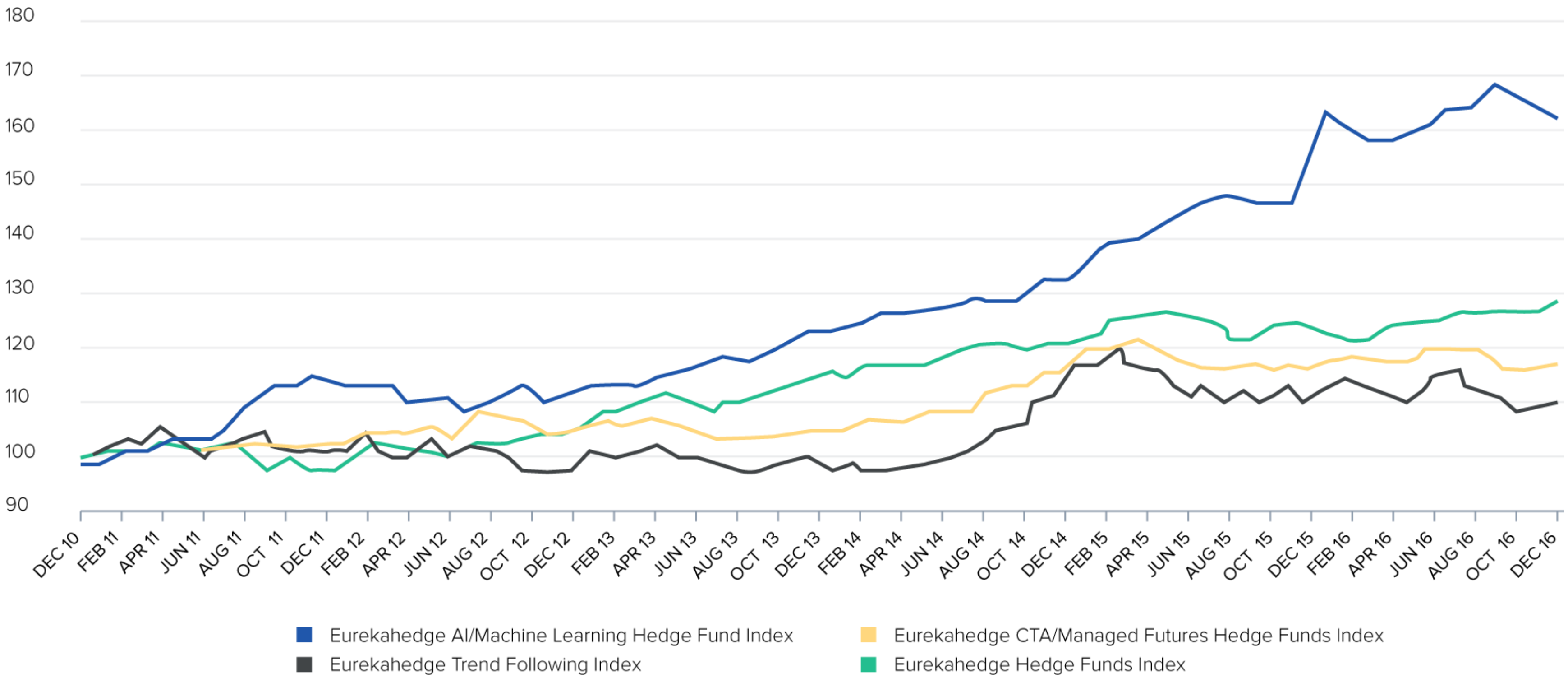
https://www.businessinsider.com/artificial-intelligence-ai-most-impressive-achievements-2017-3

AI Skills Demand



Performance of AI/ML Funds

Chart 2: AI/Machine Learning Hedge Funds Index vs. Quants and Traditional Hedge Funds



Source: Eurekahedge

Well Known Applications in Finance

- Portfolio Management
  - Robo-advisor, calibration of investment portfolios to goals and risk tolerance
- Algorithmic Trading
  - Hedge fund strategies, High Frequency Trading (HFT)
- Financial Crimes
  - AML
- Underwriting
  - Loans, insurance

Less Known Applications in Finance

- Automation
  - Chat bots, management of accounts, digital assistants
- Cyber Security
  - One of the biggest items in the agenda of financial institutions
- Sentiment Analysis
  - Predicting trends and market reversals
- Sales
  - Recommendation of financial products to customers
- Risk Management
  - Various applications from hedging books to risk measurement

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Use Cases

Overview

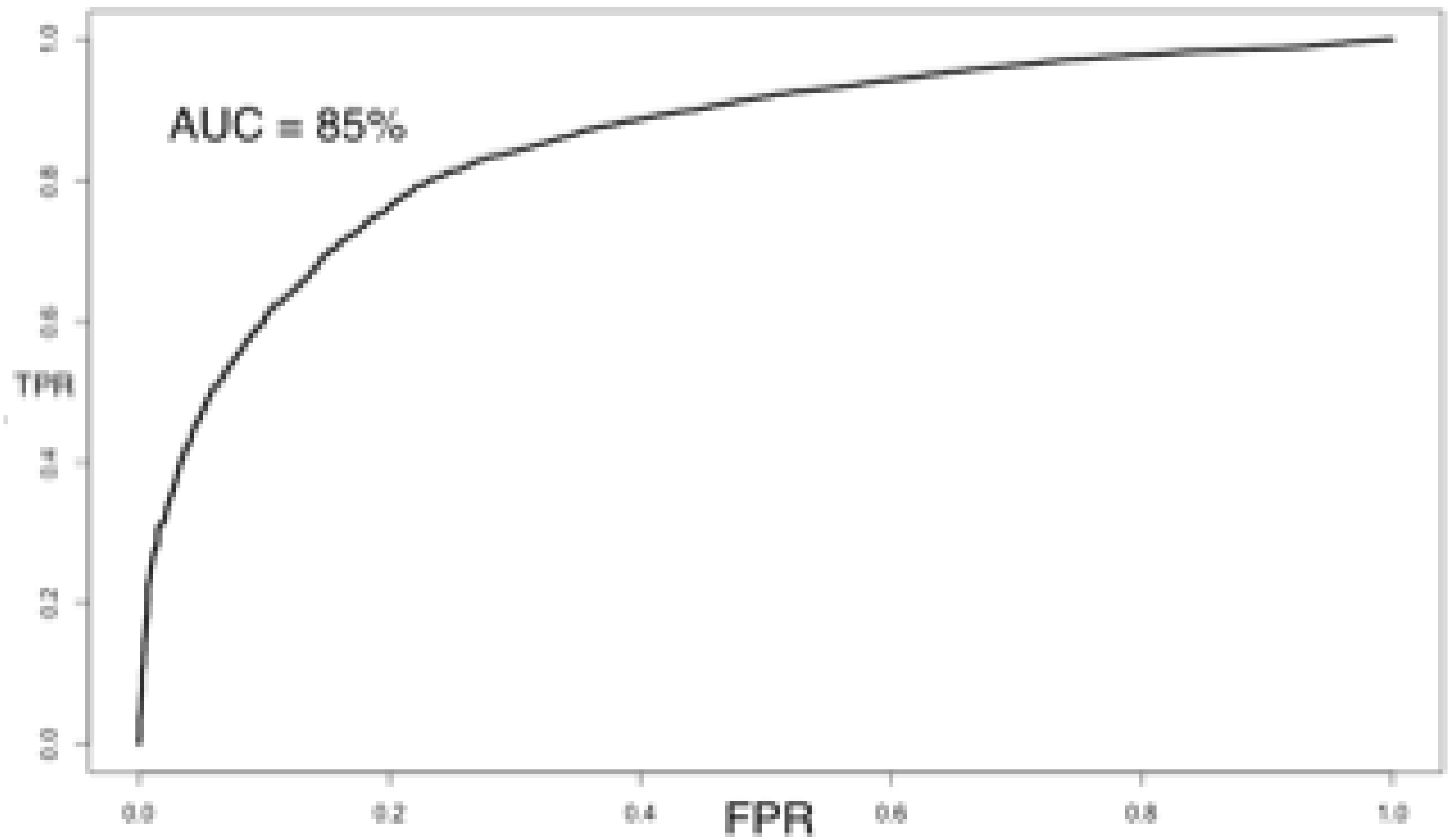
- Case 1: Equity Macro Hedging
- Case 2: Term Deposits Rolling
- Case 3: Implied Ratings
- Case 4: Corporate Credit Loss Distribution Cohorting
- Case 5: AML Alerts

Case 1: Equity Macro Hedging

- **Background**
  - Need for effective macro hedging of equities portfolios
- **Typical Approaches**
  - Non-predictive mean-variance optimization (Markowitz), theoretical
  - Questionable subject matter expertise
- **Solution**
  - Machine learning predictive model for predicting equities performance on a certain horizon

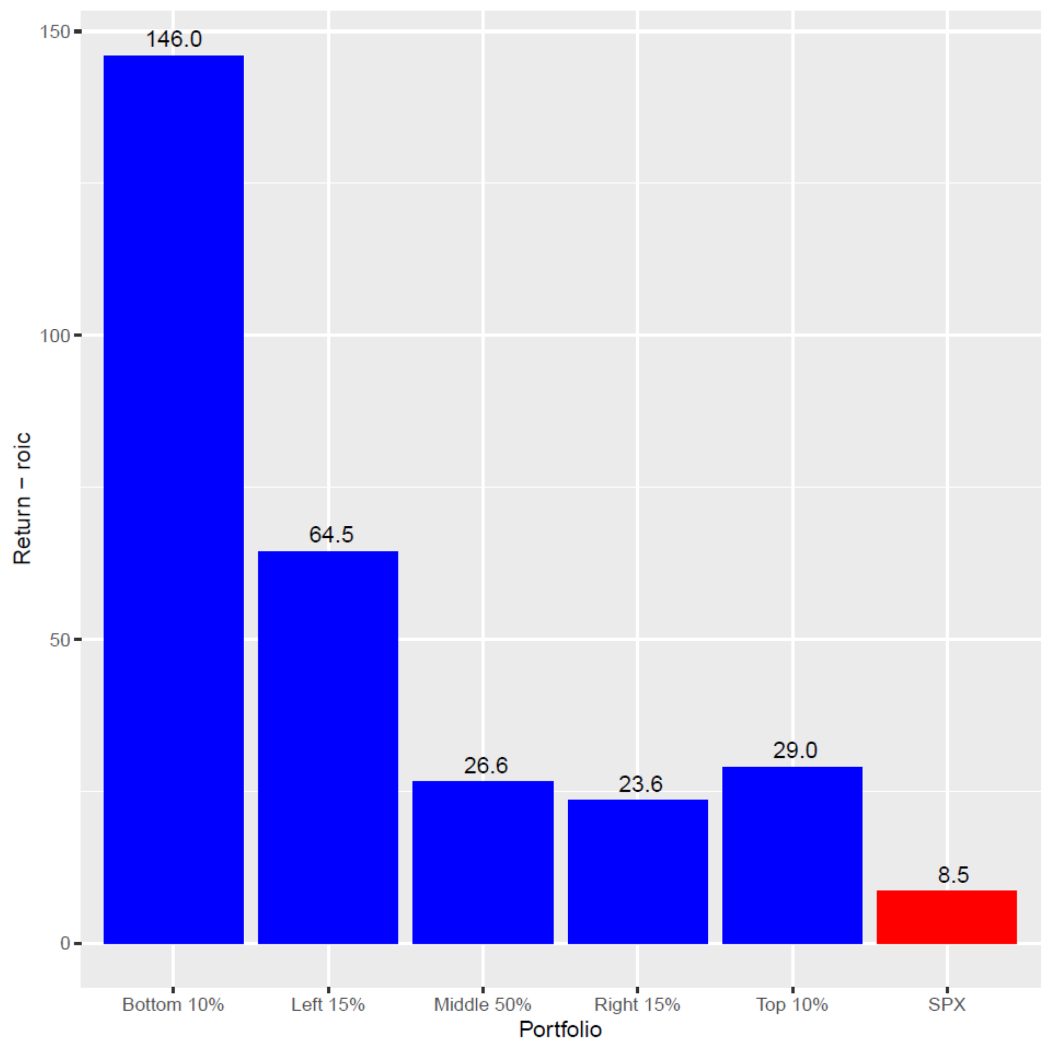
Case 1: Equity Macro Hedging

- Random forest model performance (ROC/AUC)



Source: Research conducted at NUS

Case 1: Equity Macro Hedging



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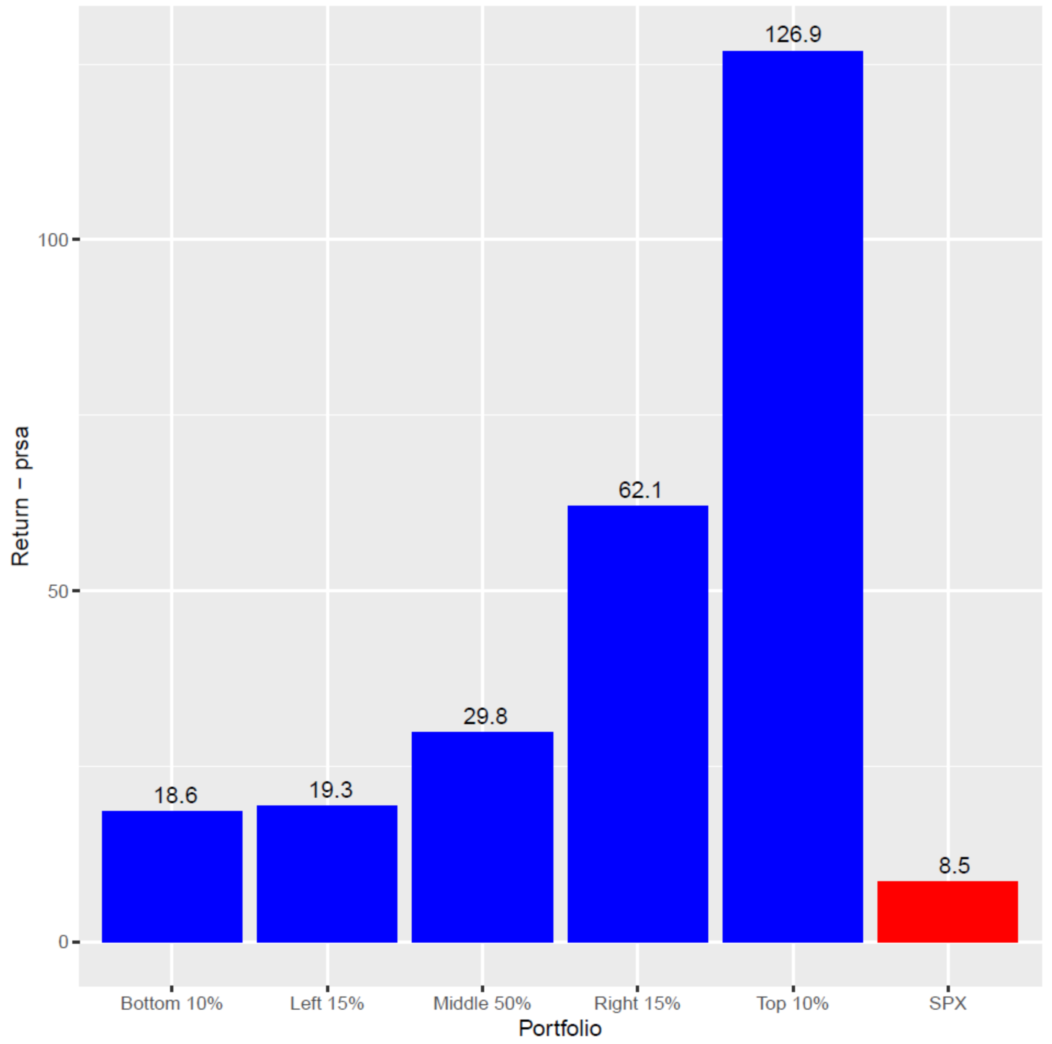

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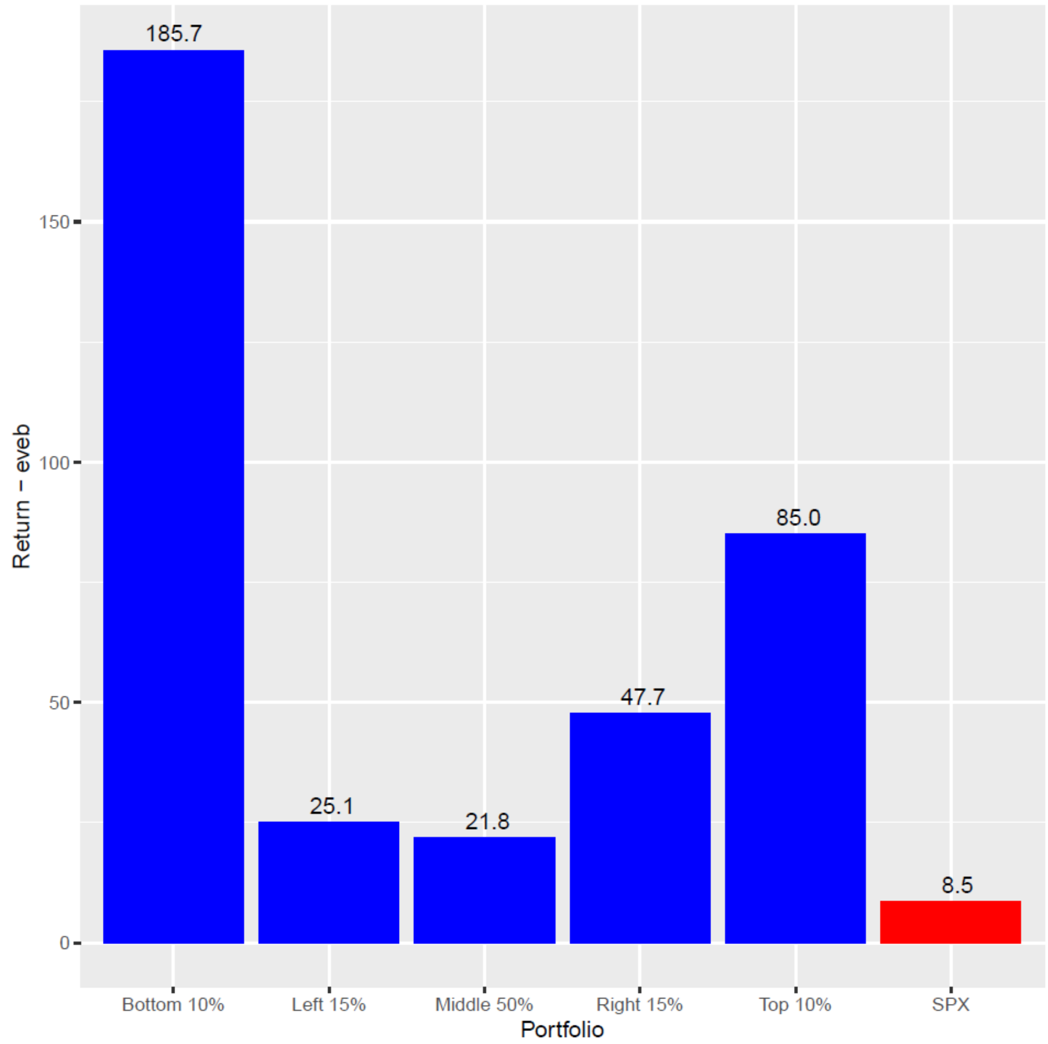
Case 1: Equity Macro Hedging



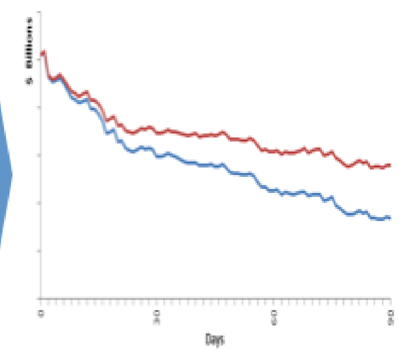
Source: Research conducted at NUS

Case 2: Term Deposits Rolling

- **Background**
  - Prediction of renewal (roll) of term deposit accounts
  - Implications for assets-liabilities management as well as potential regulatory capital impact
- **Typical Approach**
  - Historical Simulation
- **Solution**
  - Decision tree model for predicting and interpreting term deposit renewals

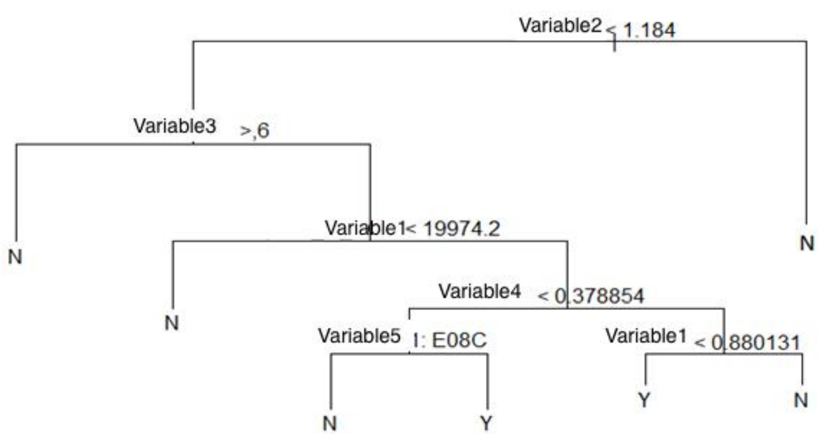
Day	Balance	Change	Scenarios
90	56.60	-0.20	56.00
89	55.50	-1.10	55.10
88	57.10	1.60	57.80
5	58.50	0.50	56.70
4	57.40	-1.10	55.10
3	56.70	-0.70	55.50
2	56.00	-0.70	55.50
1	55.30	-0.70	55.50
0	56.20	0.90	57.10

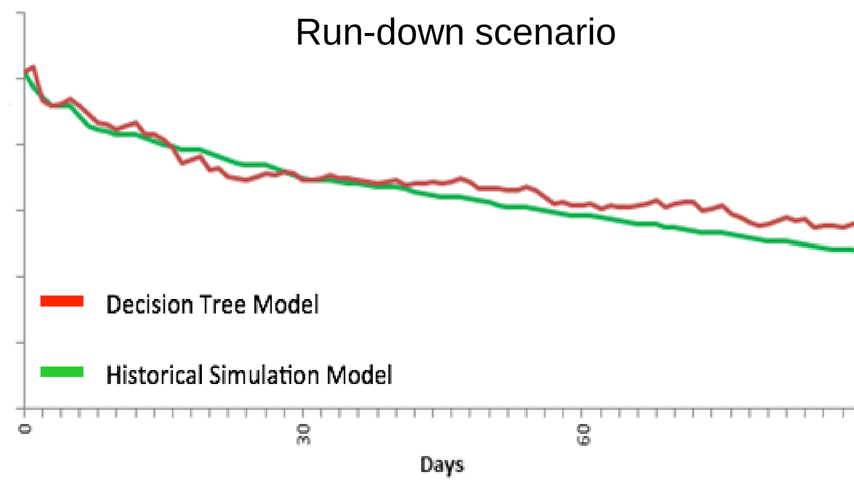
Scenarios	
1	57.80
2	57.10
3	56.70
4	56.00
5	55.50
6	55.50
88	55.50
89	55.10
90	55.10



Case 2: Term Deposits Rolling

- Highly interpretable model, 75% out of sample accuracy
- Attributes: interest paid on balance, outstanding balance, account term, number of times account has previously rolled, client segment, etc





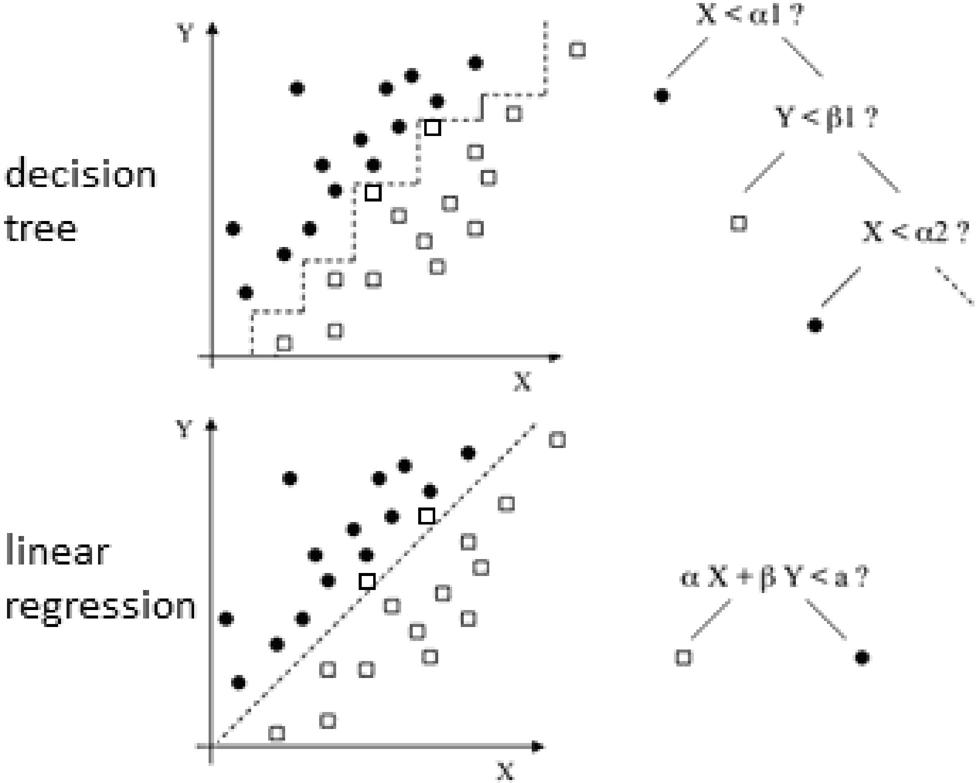
Source: Research conducted at NUS

Case 3: Implied Ratings

- **Background**
  - Rating proxy of corporate credit not rated by rating agencies (Moody’s, Standard & Poors’, Fitch)
- **Typical Approaches**
  - Conservative, arbitrary rating (e.g., B to all no-rated issuers)
  - Proxy by average of region/sector
  - Tedious and costly replication of rating agencies methodologies
- **Solution**
  - AI/ML predictive model for replicating the rating behavior or rating agencies

Case 3: Implied Ratings

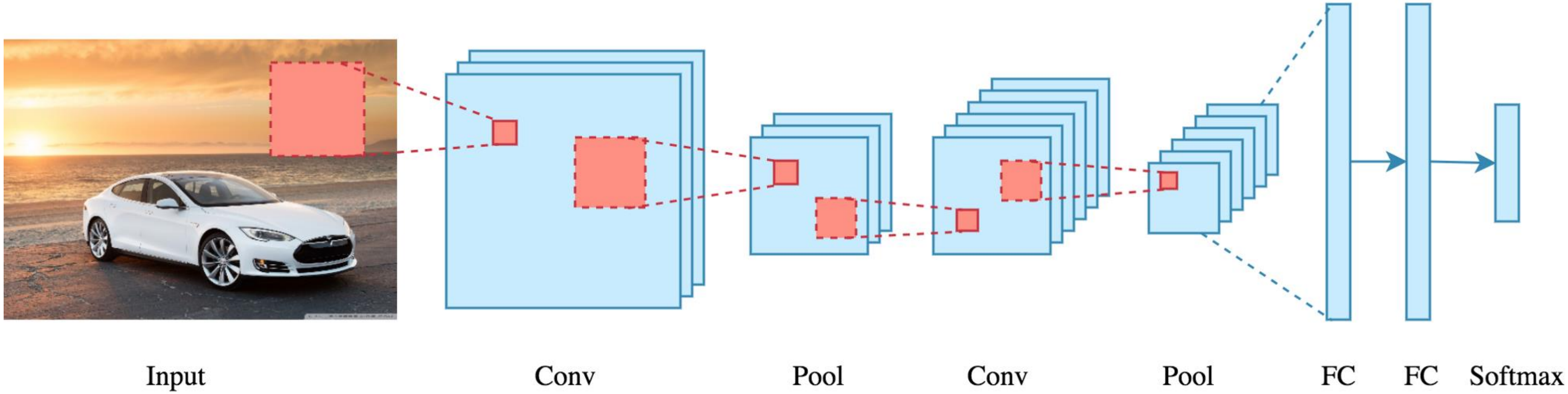
- Random forest model
- Training performance (1,100 issuers)
  - 72% average 12-month accuracy on exact rating
  - 97% average 12-month accuracy on +/- 1 notch rating
- Backtesting performance
  - 87% accuracy on exact rating
  - 98% accuracy on +/- 1 notch rating



Source: Research conducted at NUS

Case 3: Implied Ratings

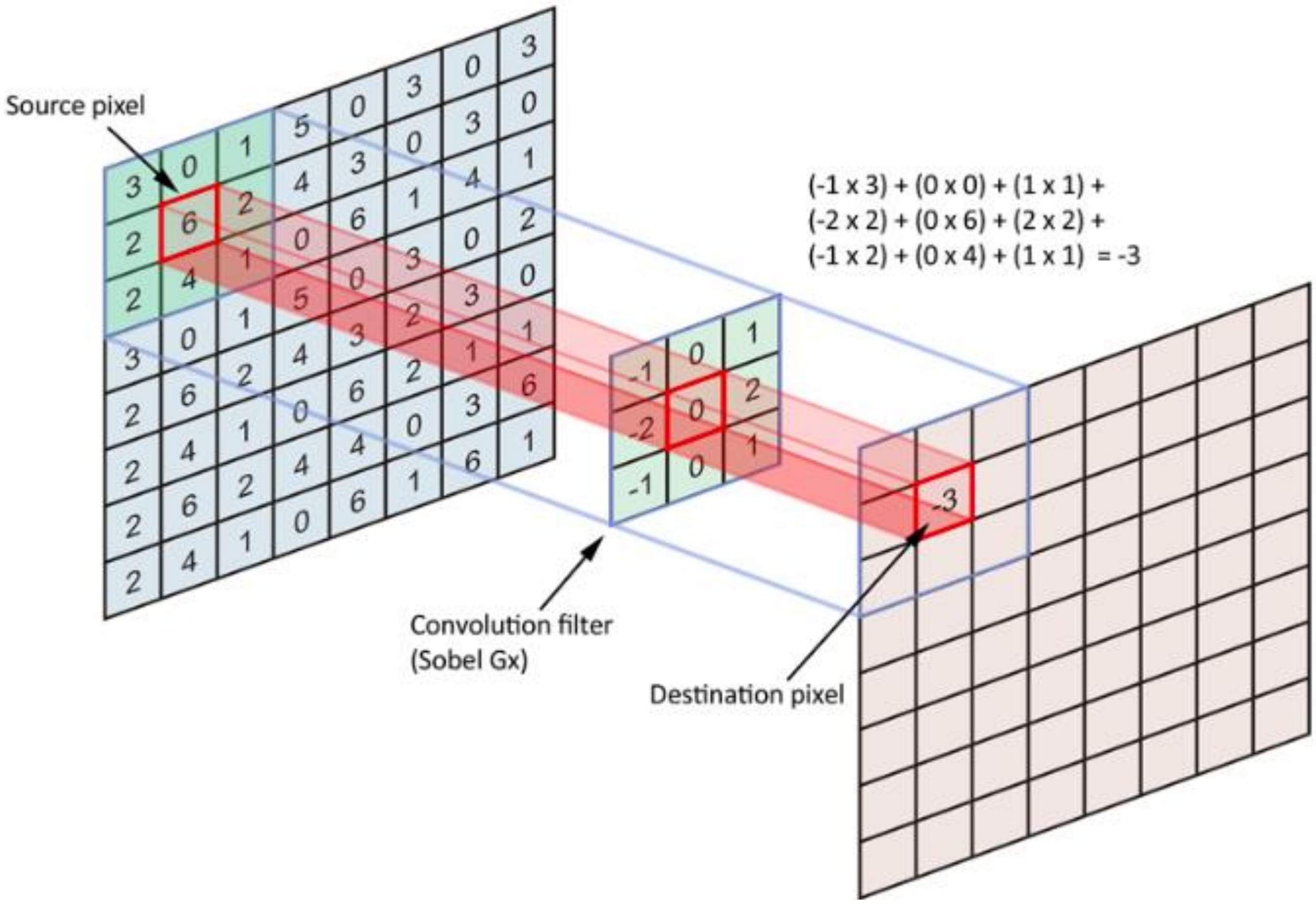
- Convolutional Neural Networks



https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

Case 3: Implied Ratings

- Convolutional Neural Networks - convolution



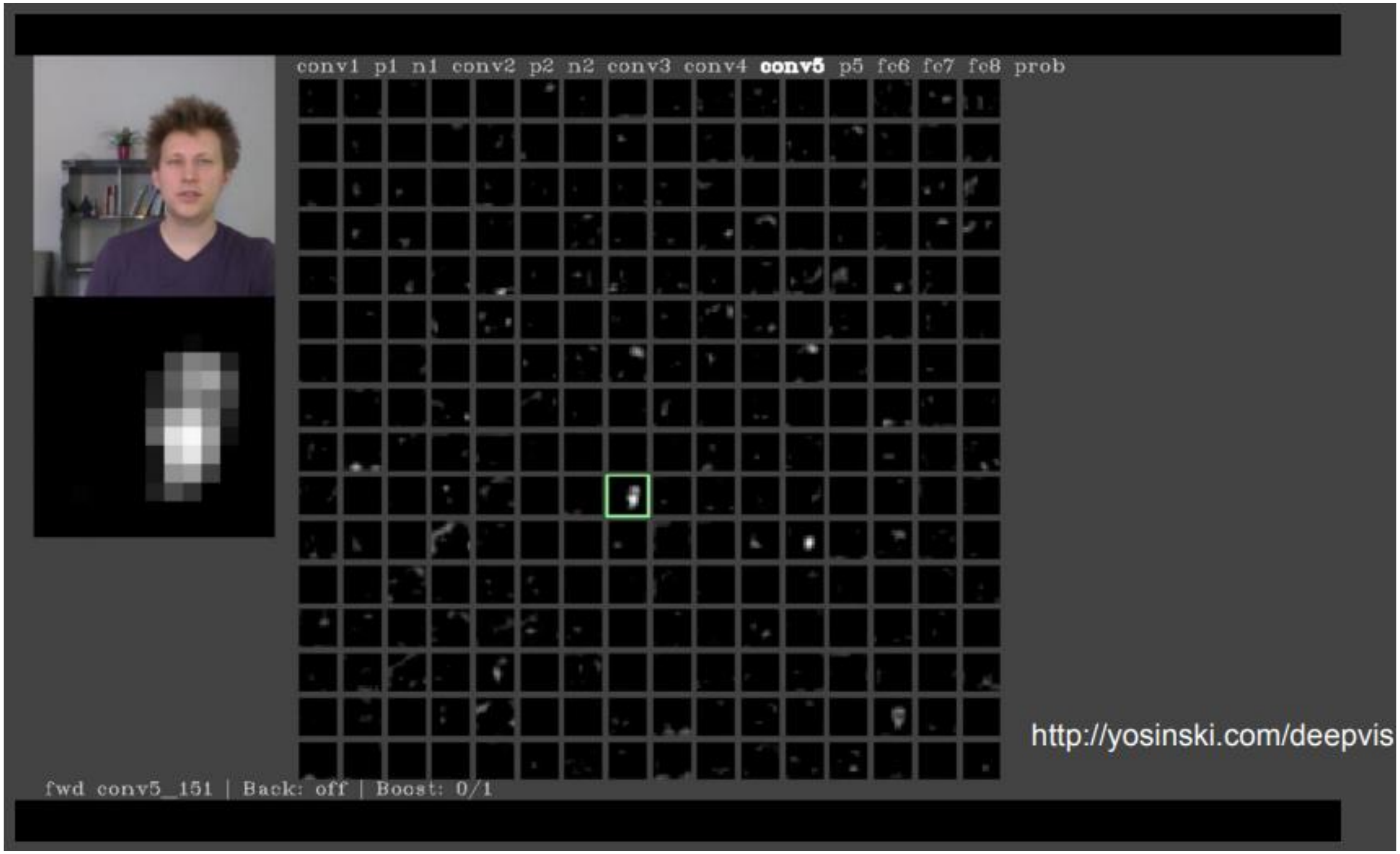
Case 3: Implied Ratings

- Convolutional Neural Networks – filters

https://www.youtube.com/watch?v=AgkfIQ4IGaM

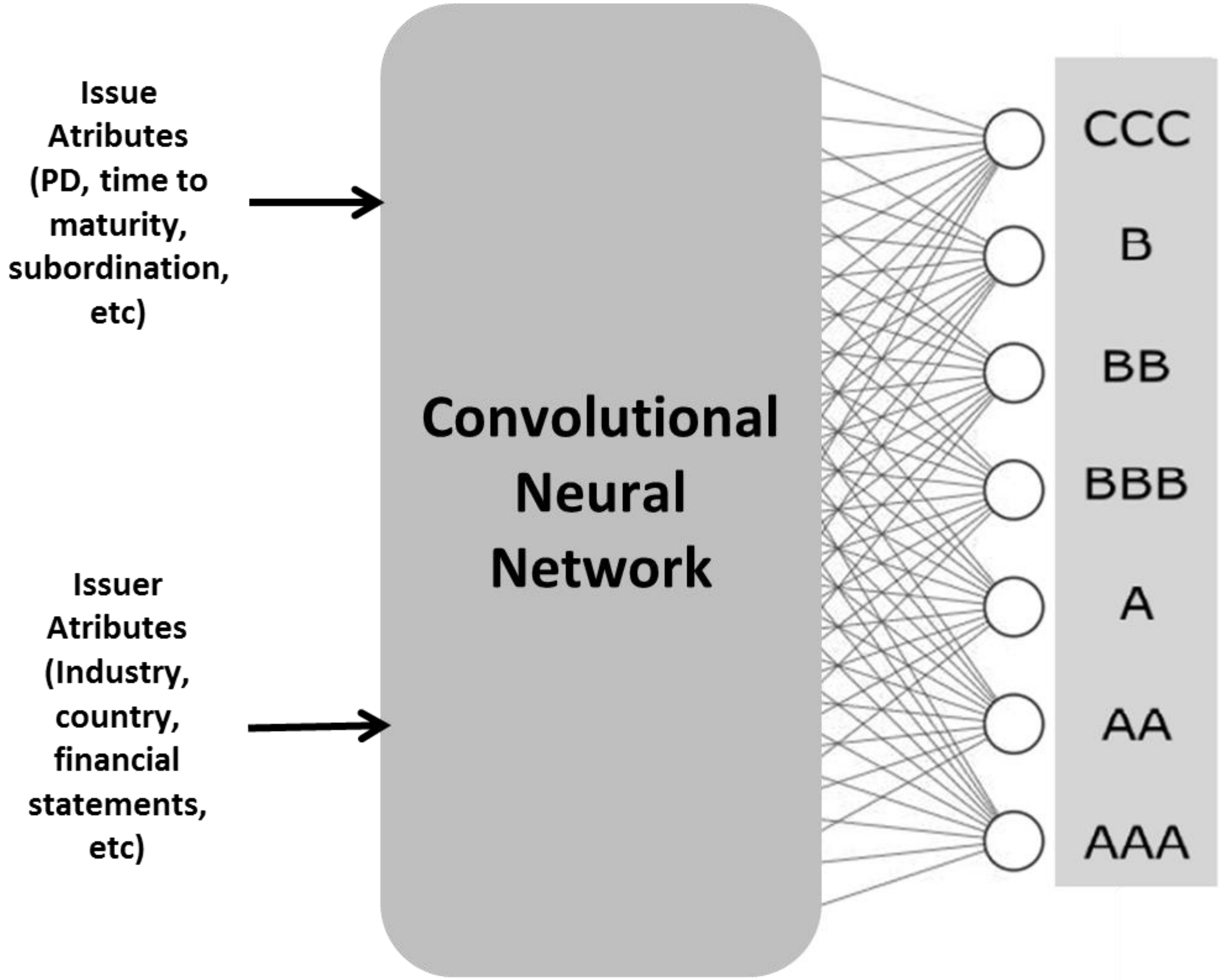
Case 3: Implied Ratings

- Convolutional Neural Networks – filters



Case 3: Implied Ratings

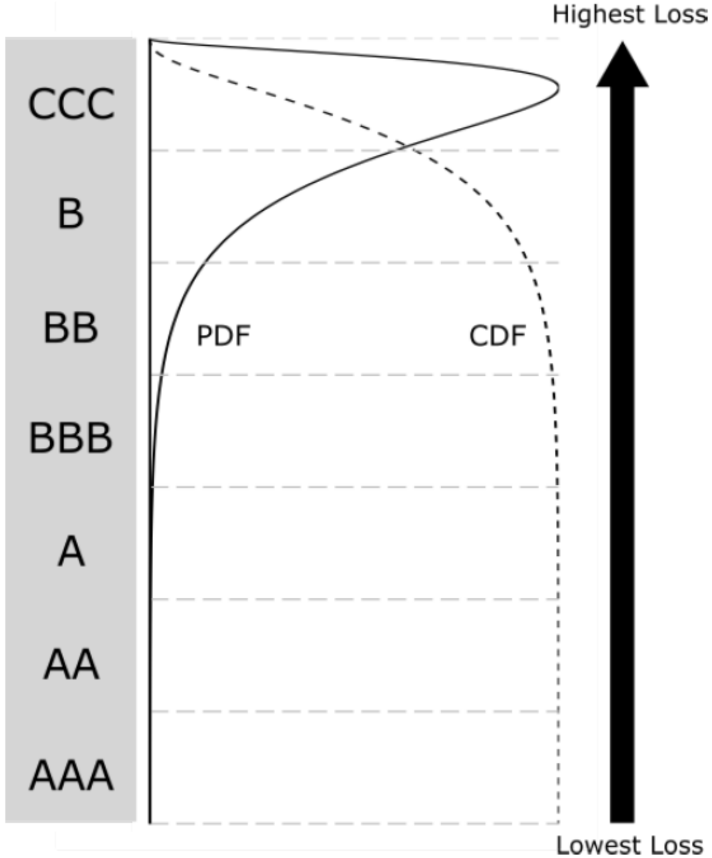
- Deep learning model



Case 4: Corporate Credit Loss Distribution Cohorting

- **Background**
  - Corporate credit cohorts must be established for capital models, issuer/issue risk proxying, generic credit curves, etc
- **Typical Approach**
  - Arbitrary proxying of cohorts (rating, industry, region, etc) given insufficient cohort data (e.g., BB)
- **Solution**
  - Assumption-free entropy optimization model with parameters learned and cost function minimized through deep learning tools (TensorFlow)

Case 4: Corporate Credit Loss Distribution Cohorting



$$S_j \sum_{n=1}^{N} \Big[(t_n - t_{n-1}) B_n (1-\alpha)\left(q_n + q_{n-1}\right) \Big] - (1-R) \sum_{n=1}^{m \cdot N} B_n \left(q_{n-1} - q_n\right) = 0$$

$$\mathscr{L} = \log \Big[\sum_{k=1}^{n} \exp\Big(- \sum_{j=1}^{n} \lambda_j (u_j \mathbb{1}_{kj} - u_{j-1} \mathbb{1}_{k(j-1)}) \Big) \Big] - \sum_{j}^{n} \lambda_j (u_j - u_{j-1})(1 - s_j)$$

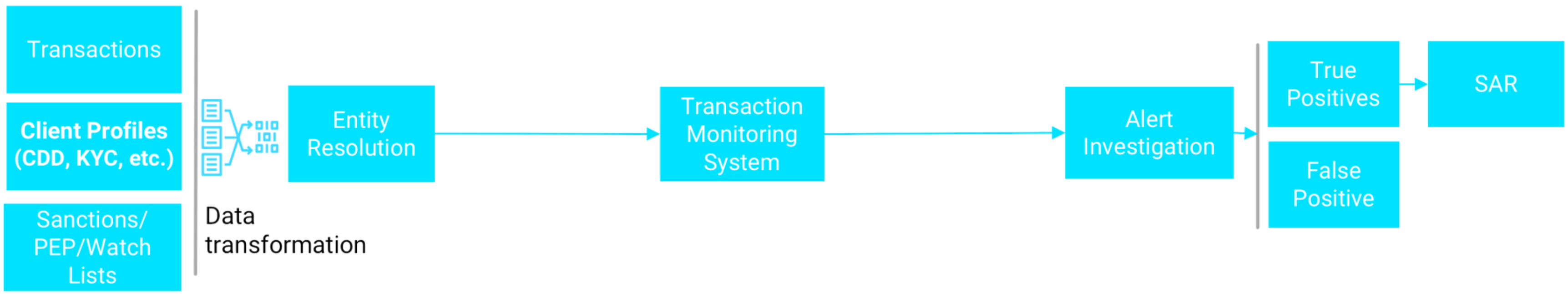
"Construction of Appropriate Generic Credit Curves," Labre M., Le Nézet B., 2015

Case 5: AML Alerts

- **Background**
  - Alerts generated and evaluated for decision of whether to file AML case
- **Typical Approach**
  - Hard-coded scenarios generating high number of false positives
- **Solution**
  - Deep neural networks for predicting case escalation and reducing false positives

Case 5: AML Alerts

- **AML Flow**



https://www.ayasdi.com/blog/aml/longer-lever-aml-intelligent-alerts-typologies-segmentation/

- **Convolutional neural networks again?**
  - Applying of fully connected networks has been reported in the industry
  - CNNs appear to be conceptually suitable

Research