Cambridge Judge Business School

ARTIFICIAL INTELLIGENCE IN ASSET MANAGEMENT

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- AI Risks and Challenges: What can go wrong?
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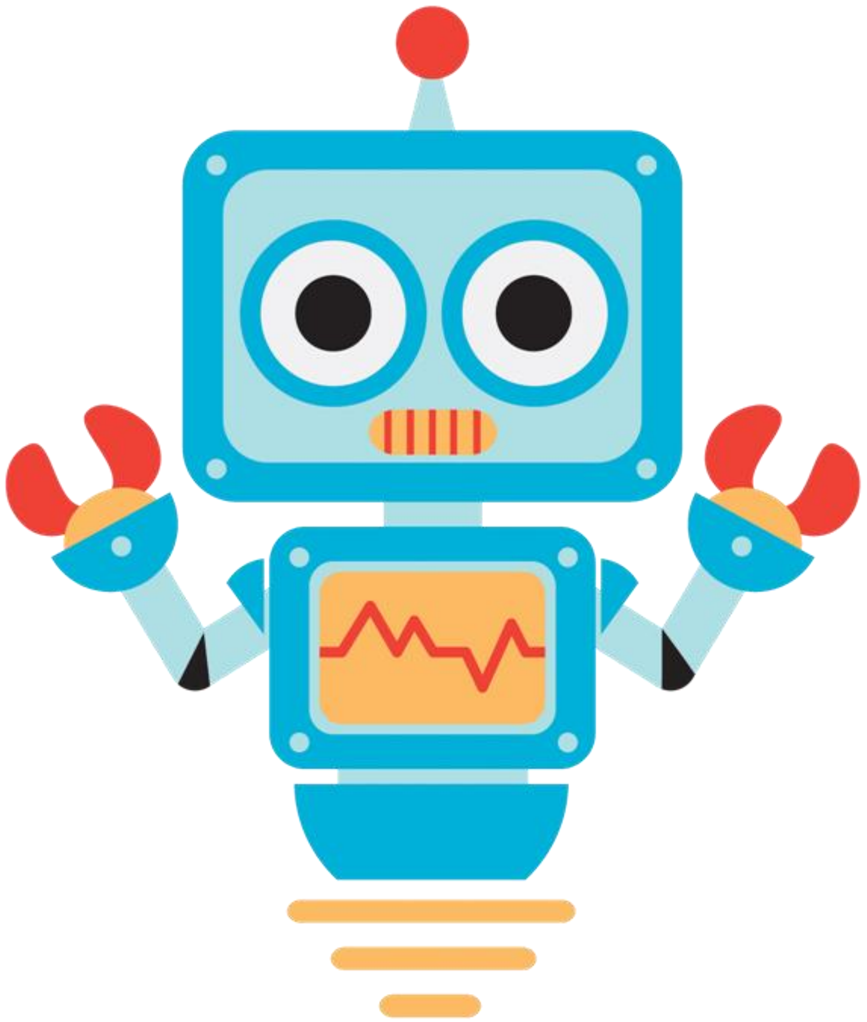
What is Artificial Intelligence?

- The goal of Artificial Intelligence (AI): Thinking/acting humanly/rationally (Russell and Norvig, 2009)
- Machine Learning (ML) is a subset of Artificial Intelligence.
- In ML, algorithmic and statistical modeling ‘learns’ and identifies patterns in data.
- **Greater computer processing speed and volumes and breadths of data has made ML popular.**

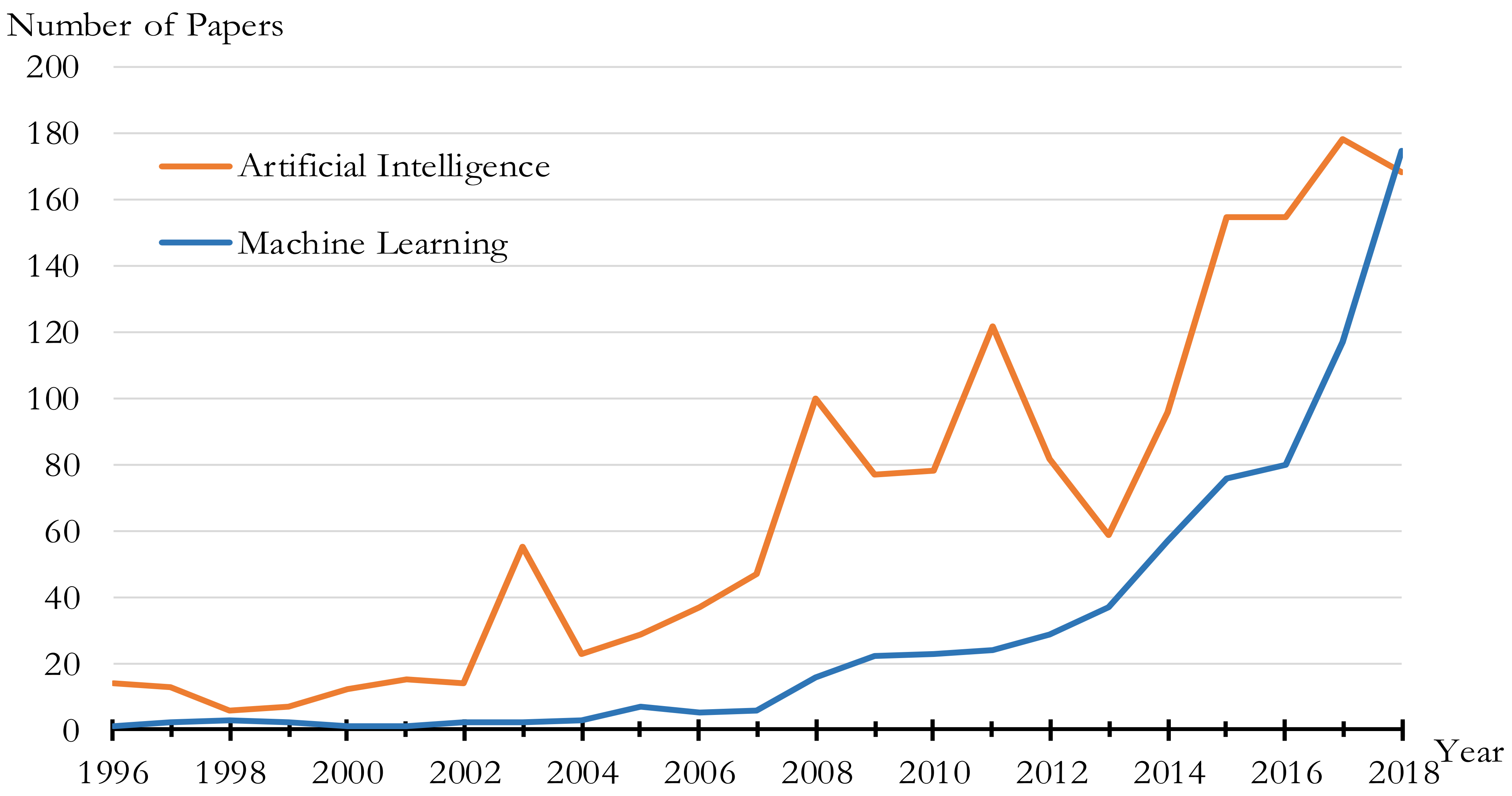


Key AI/ML Techniques Used in Finance

Technique	Method	Typical Application in Finance
Artificial Neural Networks	- Learning algorithm that links input and output variables using a networks of interconnected nodes (neurons)	- Forecasting
Cluster Analysis	- Clusters data into large groups based on similarity of features	- Asset Classification - Forecasting
Decision Trees	- Decision tree learns patterns based on training set of data; classifies units based on features	- Classification - Forecasting
Evolutionary (Genetic) Algorithms	- Searches through large, complex, non-linear sets of solutions, identifying preferred solutions	- Parameter optimization - Portfolio optimization
LASSO Regressions	- Regression model with a penalty term to select best independent variables	- Forecasting
Natural Language Processing	- Range of techniques used to process natural language (e.g., text, audio)	- Automatic analysis of corporate annual reports and news articles
Support Vector Machines	- Learning algorithm that links input and output variables using mapping into higher-dimensional space	- Forecasting

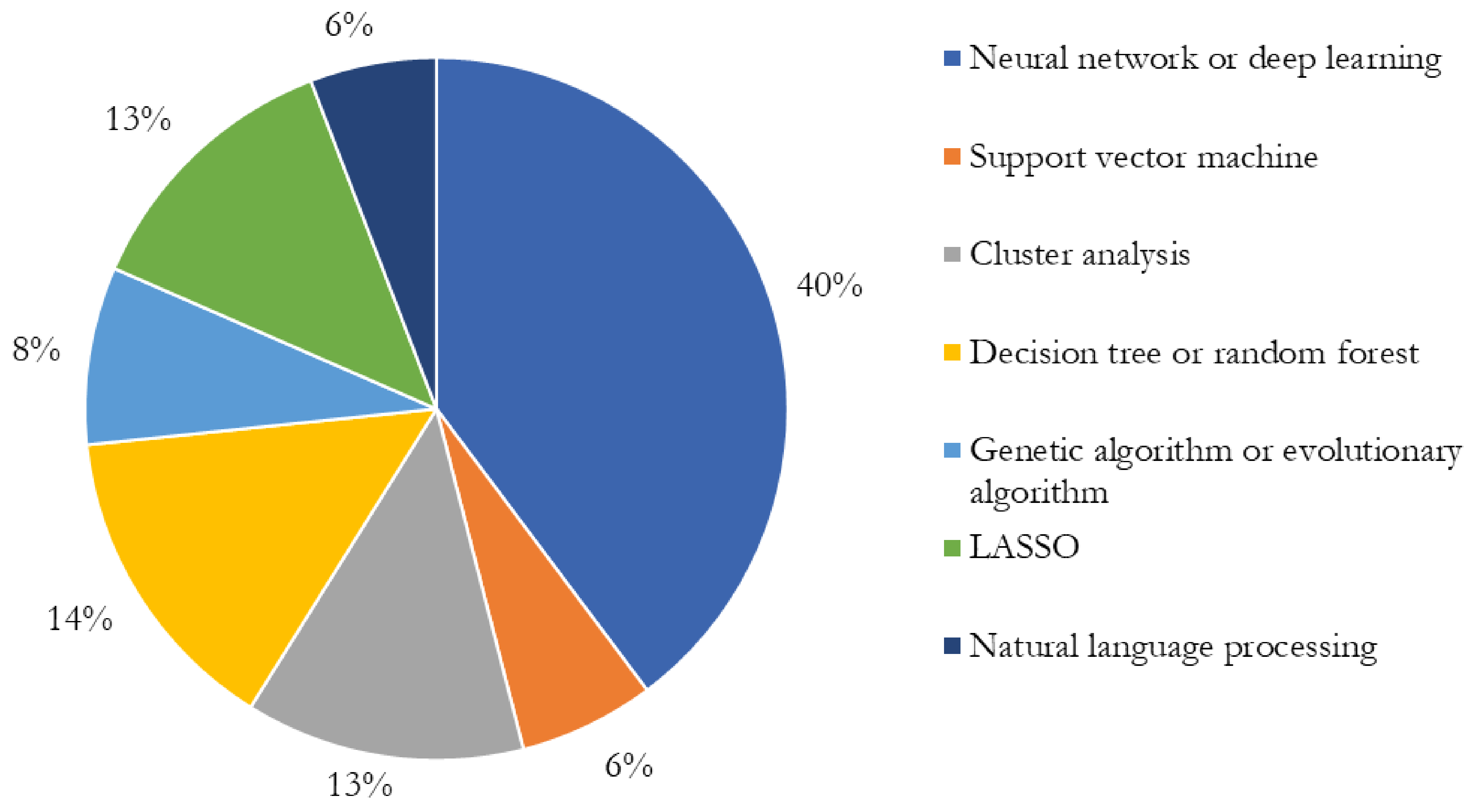
Trends in Artificial Intelligence

Number of Published Finance Papers With AI or ML Keywords (Scopus, 1996-2018)



Trends in Artificial Intelligence

Number of Finance Working Papers by AI or ML Keywords (SSRN FEN, 1996-2020)



Artificial Intelligence (AI)'s Growing Role in Asset Management

Portfolio Management

Using AI, portfolios can:

- Incorporate novel investment strategies
- Have more complex constraints
- Be based on more accurate risk and return estimates

Trading

AI is used to:

- Devise novel trading signals
- Execute trades with lower transaction costs.

Portfolio Risk Management

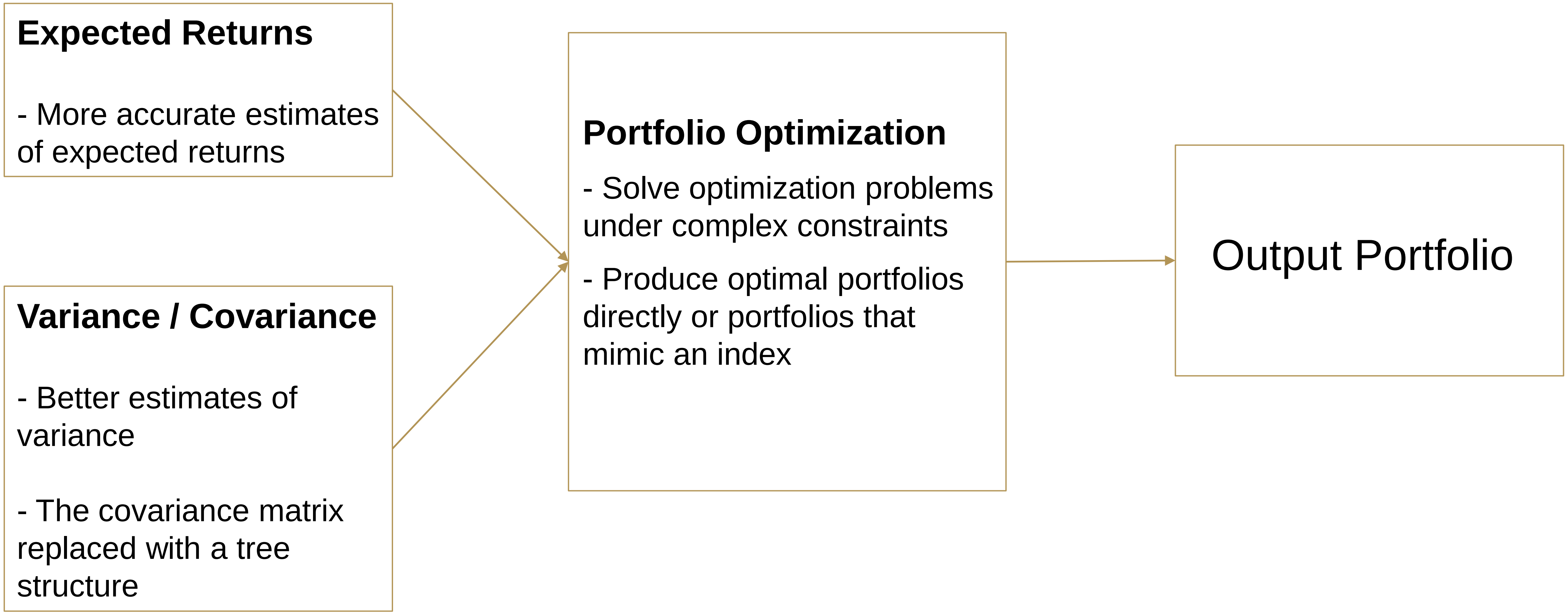
AI is used to generate insights from new data sources for:

- Improved risk modeling
- Validating and back-testing

AI in Portfolio Construction

Portfolio parameters:

Optimization:



Predicting Returns: What Works Best?

- **Artificial neural networks**:
  - Predict returns better (Gu et al., 2020)
  - Popular for predicting returns of stocks (Vui et al., 2013; Abe and Nakayama, 2018) and other asset classes such as bonds (Bianchi et al., 2020)
  - Produce profitable trading signals even in long-only portfolio: 0.78% abnormal returns per month for value-weighted portfolio (Avramov et al., 2020)

- **Support vector machines** can be better than **artificial neural networks** at predicting the first two moments of asset returns (Arrieta-ibarra and Lobato, 2015; Chen et al., 2006; Huang et al., 2005).

- A popular implementation consists of using the **average prediction (“ensemble”** approach), which produces better predictions than (Borghi and De Rossi, forthcoming).

Variance-Covariance Modelling

- AI can be used for estimating variance-covariance matrices amid its restrictive structure in the Markowitz framework.

- Hierarchical cluster analysis:
  - Replaces the covariance structure of asset returns with a tree structure (De Prado, 2016)
  - Uses all the information contained in the covariance matrix but requires fewer estimates
  - Minimum variance portfolio under this approach has a **31.3% higher Sharpe ratio** than that under the classical Markowitz framework

Portfolio Optimization

- Issues with the mean-variance framework (Michaud and Michaud, 2008):
  - Weights are sensitive to expected return estimates.
  - The variance-covariance matrix requires large time series.
  - Equally-weighted portfolio has a higher out-of-sample Sharpe ratio (DeMiguel et al., 2007).

  - Cannot accommodate more advanced constraints

- Synthetic replication: replicating an index by holding a fraction of the constituents while minimizing the tracking error

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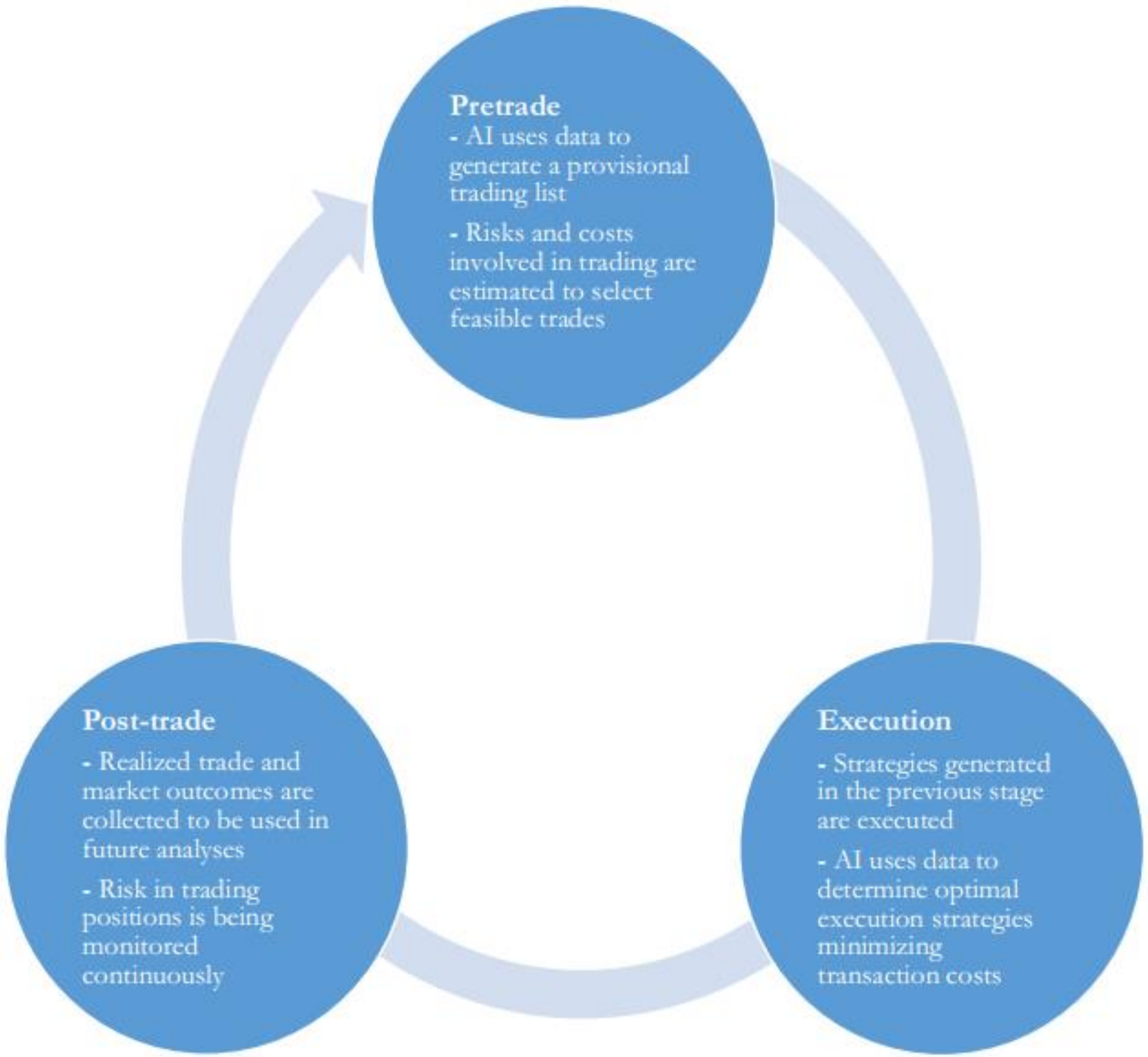
  - Weights are sensitive to expected return estimates.
  - The variance-covariance matrix requires large time series.
  - Equally-weighted portfolio has a higher out-of-sample Sharpe ratio (DeMiguel et al., 2007).
    - ➢ AI can produce more accurate return estimates and covariance estimates with fewer observations
  - Cannot accommodate more advanced constraints
    - ➢ Evolutionary algorithms and neural networks can accommodate complex constraints (Branke et al., 2009)
- Synthetic replication: replicating an index by holding a fraction of the constituents while minimizing the tracking error
  - ➢ Artificial neural networks capture non-linear relationships so can be very useful (Heaton et al., 2017)

Trading

- AI is an essential part of **algorithmic trading** (Nuti et al., 2011).
- Algorithmic trading strategies are often based on technical analysis.
- Technical indicators dominate fundamental ones in generating profitable trading signals using AI (Borghi and De Rossi, forthcoming).
- AI techniques such as artificial neural networks can now be implemented in close to real time (Leshik and Cralle, 2011).
- Modern technical analysis incorporates information from fund flows, investor trades, and textual data from news articles or online sources.

Algorithmic Trading with AI



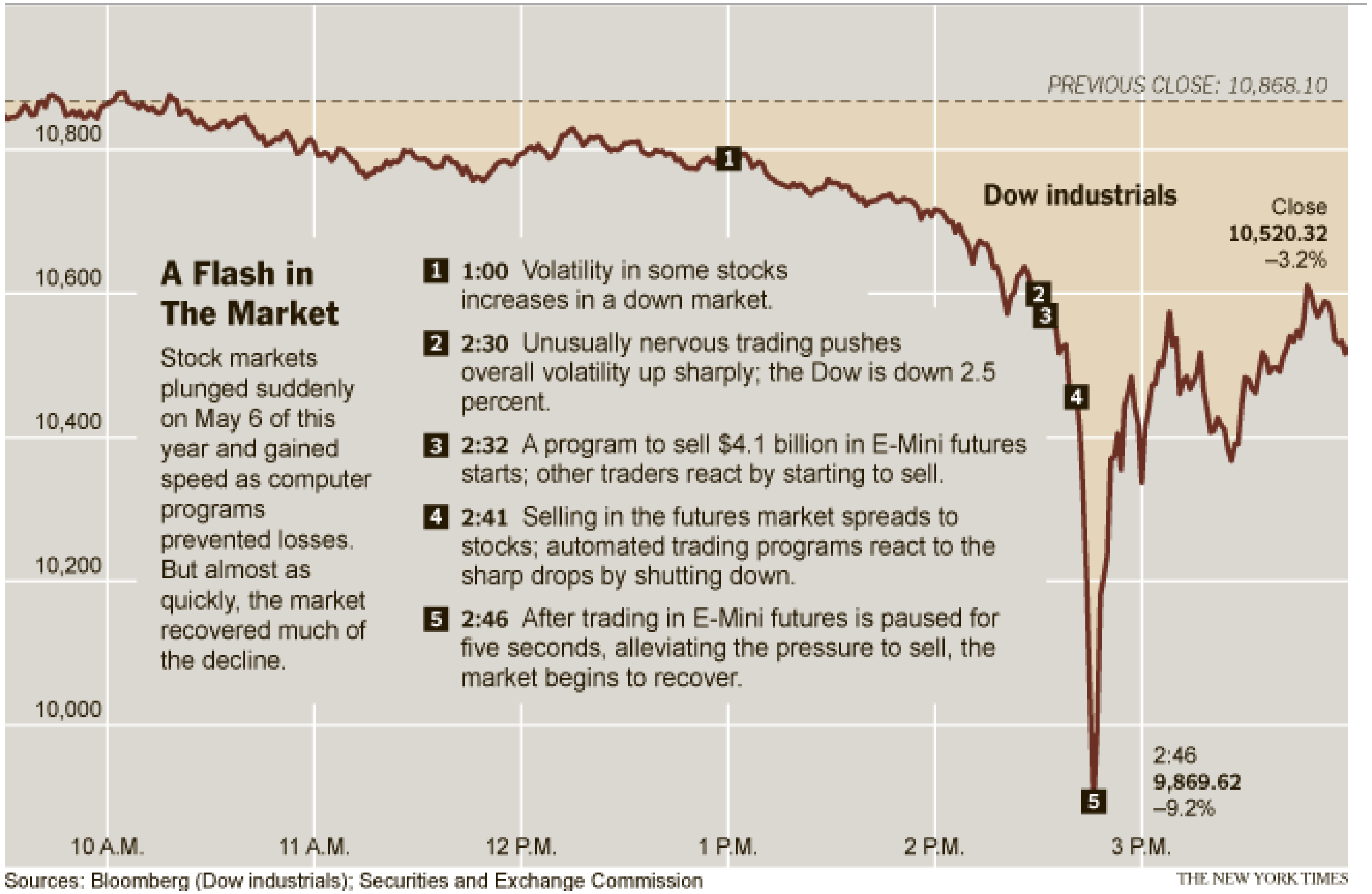
Transaction Cost Analysis and Trade Execution

- Market impact costs absorb **two-thirds** of trading gains made by systematic funds (The Financial Stability Board, 2017).
  - Non-parametric AI models predict market impact (Booth et al., 2015).
  - Parametric AI models determine the drivers of market impact (Zheng et al., 2013).
  - Clustering or Bayesian networks estimate the market impact in assets that lack sufficient data (Briere et al., 2019).

- Reinforcement learning techniques can be used to minimize transaction costs while completing the transaction in a specified period of time (e.g., Kearns and Nevmyvaka, 2013; Hendricks and Wilcox, 2014).

Trade Execution - Challenges

- Challenges of AI approaches:
  - Can be complex, especially for large portfolios
  - Systematic execution strategies can cascade into a systemic event such as the Flash Crash of 2010 (Kirilenko et al., 2017)

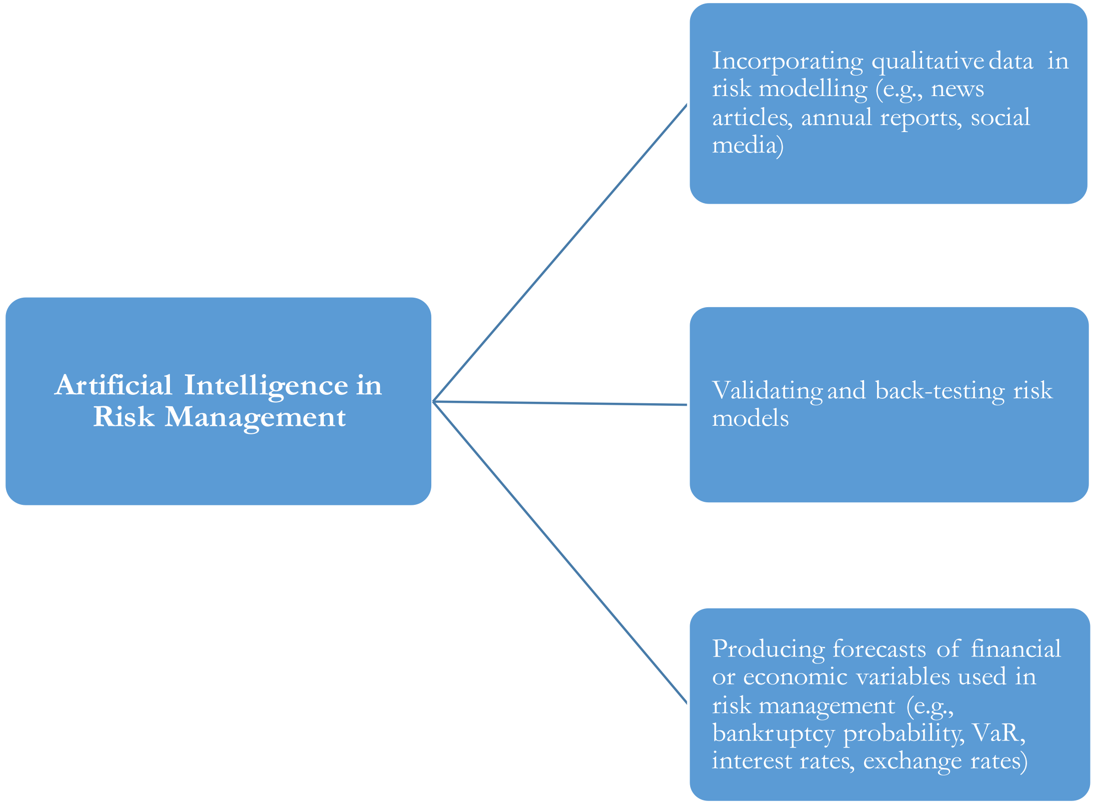


Portfolio Risk Management

- **Market risk** and **credit risk** estimation are the main applications of AI in portfolio risk management.

- **Market risk**: The likelihood of loss due to aggregate market fluctuation.

- **Credit risk**: The risk of a counterparty not fulfilling its contractual obligations, which results in a loss of value.



How Can AI Help Model Market Risk?

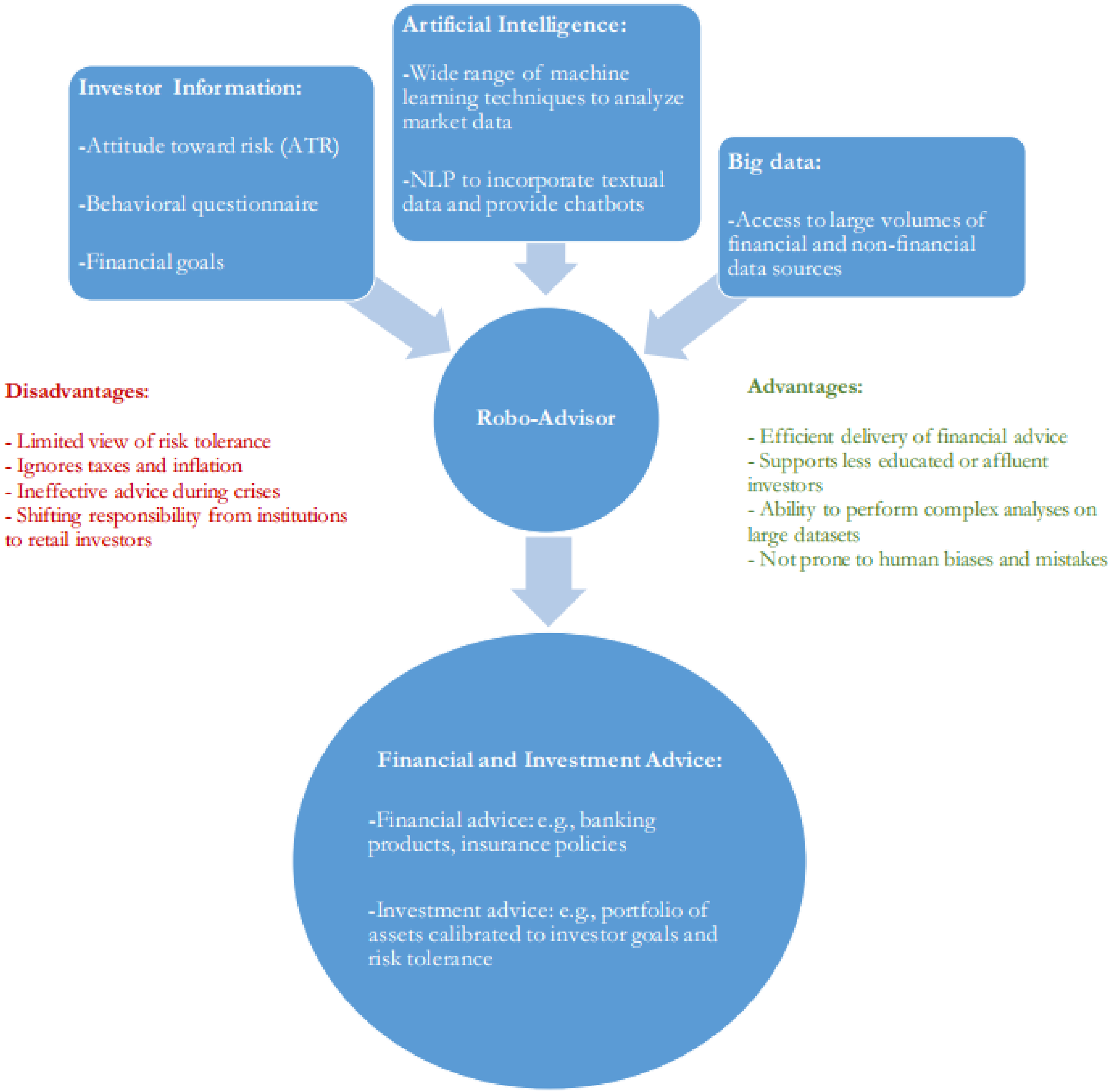
Market risk:

- Using textual information improve predictions of market crashes (Manela and Moreira, 2017), interest rates (Hong and Han, 2002), and other major macroeconomic outcomes (Cong et al., 2019)
- Validating and back-test risk models (The Financial Stability Board, 2017)
- Estimate economic variables including **macroeconomic indicators**, **interest rates**, **exchange rates**, **market volatility**, **currency crises**, **banking crises, recessions**

Credit risk:

- Artificial neural networks and support vector machines perform well at estimating bankruptcy risk and loss given default.
- A wide range of other AI approaches can be used for credit risk modelling (Kumar and Ravi, 2007; Pena et al., 2011).

Robo-Advising using AI



AI Risks and Challenges: What Can Go Wrong?

AI Risks and Challenges: What Can Go Wrong?

AI models are opaque and complex:

- It is hard to predict how AI models would respond to “black swan” events.
- AI models can introduce the risk of cascading market crashes.
- AI can make wrong decisions based on incorrect inferences capturing spurious patterns.
- Fund performance would be difficult to explain to investors.

AI Risks and Challenges: What Can Go Wrong?

- AI models rely heavily on data quality:
  - Poor data quality can easily trigger what is famously known as “garbage in, garbage out”.
  - AI models require large amounts of data during the learning phase, often more than available.
  - The short time series of financial data might miss certain extreme events (Patel and Lincoln, 2019).
- Other issues:
  - Cybersecurity risk (Board of Governors of the Federal Reserve System, 2011)
  - Costs of investing in the software, hardware, human resources, and data

Conclusion

AI has vast applications and many strengths in asset management!

However,

- AI in finance is still far from replacing humans completely.
- AI’s greatest strength can also be its greatest weakness: AI always generates a result even when there should not be one!
- We don’t understand the new sources of AI risk just yet.

Thank you for your attention!

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