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Using A.I. in asset management

Challenges and opportunities

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March 2019

See important disclosures at the end of this presentation.

| Introduction

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Qplum
Chief Investment Officer + Chief Data Scientist

- 14+ years experience in ML based trading
- Founder and CEO of a global High Frequency Trading firm (2010 to 2015)
- Youngest partner at Tower Research Capital. Established one of the most profitable trading groups at Tower Research Capital.
- M.S in CS from University of Pennsylvania.
- B.Tech in CS from the prestigious I.I.T. Kanpur.

References: Previous talk at GTC 2017, Podcast, Opalesque, SSRN, Amazon

Outline

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- Business overview of the asset management landscape
  - Who is using ML and why
- Machine Learning methods used
  - Which ML methods are used and where
- Software Engineering aspects
  - SWE aspects specific to finance
  - Importance of looking at data science as a bridge between SW and BD
  - Need for continuous deployment

Business reasons for A.I. adoption

Who is trying to use A.I. and why?

Business overview

1. Fast - High frequency trading - dynamic
2. Mutual funds - stock selection using multiple types of variables
3. Multi-manager firms - performance attribution
4. Large institutional investors - Tactical asset allocation
5. RIAs : Understanding the customer better

Business overview

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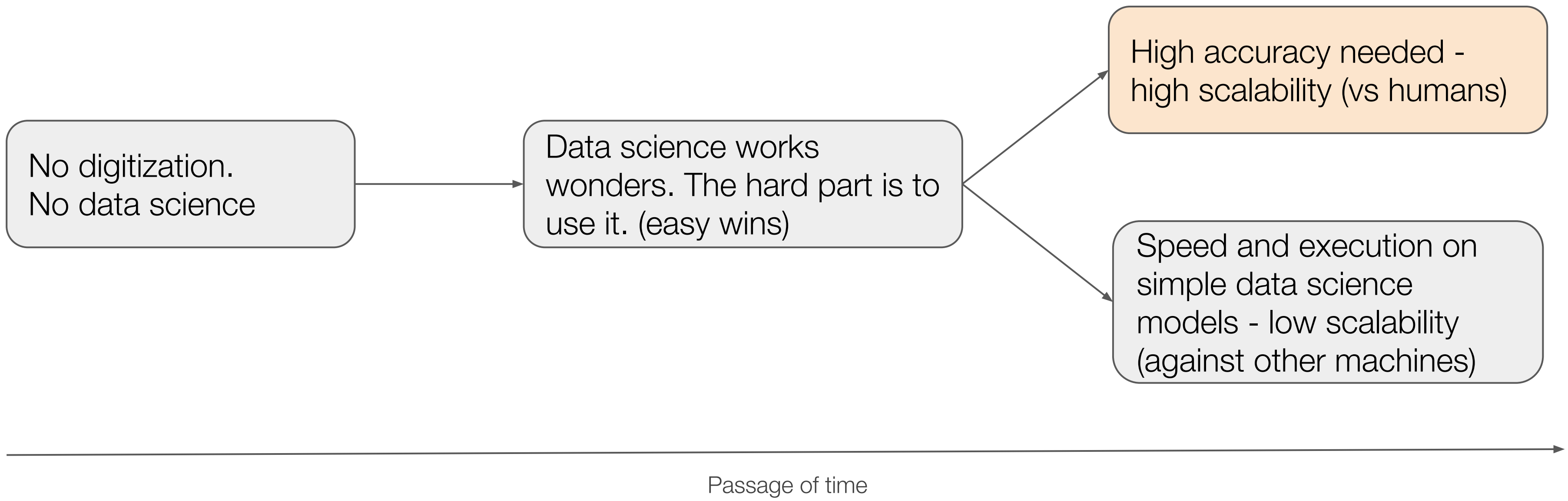

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Fast - High frequency trading

- About 800 GB of new data per data.
- However, very little new information in the data.
- Very hard to figure out the right objective function, or what to learn.
- Data is created by machines and hence it is very dynamic. A market could totally change in a span of a few weeks.

References:

1. Machine learning infrastructure : key to High Frequency Trading (Qplum)
2. Use of ML in high frequency trading (Qplum)
3. Eric Schmidt heralds Machine Learning to Combat High Frequency Trading: SALT 2017
4. A step by step tutorial on the evolving use of ML in HFT (video)
5. A primer on high frequency trading and the importance of algorithmic and ML innovation in it (Investopedia)
6. High frequency trading as a service (Qplum)

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Mutual funds - security selection

- Very little alpha left in few variables like “value” and “quality”.
- To justify fees firms have to show that they are taking all factors into account, and not just a few.
- Data driven commentaries and outlooks are given prominence over prescient “gut feelings”.

References:

1. Guide to machine learning jobs (JP Morgan)

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Multi-manager firms

- Attribution of performance, alpha and beta and uniqueness of managers, or trading strategies.
- Deciding risk allocation among strategy styles
- Deciding capital allocation and incentives for managers.

References:

1. Optimal Tactical Allocation – Using Netflix style Recommender Systems for manager selection

Large institutional investors
e.g. pension funds, endowment funds, insurance firms

- Regime detection
- Generative scenario analysis
- Understanding risks of current portfolio - risk analytics
- Demystification of performance of managers and risk allocation
- Manager selection

References:

1. Deep learning for tactical asset allocation - Gaurav, Ankit (Qplum), Brandon (OPTrust)
2. A study on the use of Artificial Intelligence on the investment management practices of Japan's GPIF by GPIF and Sony
3. CIO of Japan praises A.I. technology
4. World’s biggest pension funds sees A.I. replacing asset managers
5. GPIF to use A.I. for manager selection

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Financial Advisors

- Understanding the client better (classification, objective estimation)
- Providing more applicable solutions (strategy classification)
- A.I. in tax optimization

References:
1. How RIAs are using A.I. to scale their practices (Investopedia)
2. Tax optimization needs multi objective multi variable prediction, hence A.I. - Anshul (Qplum, IB)

Which M.L. methods are used in asset mgmt?

Cataloging the methods used in different parts of asset management

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Machine Learning needs to answer why - decision trees and generative modeling

- Not enough to output a portfolio likely to do well. We need to demystify it. We need to explain why is the model predicting this portfolio now.

- Generative modeling - make data that trumps up my strategy

- Unsupervised learning for dynamic factorization (both for risk and more stable alphas)

References:

1. Using Boosting to demystify complicated multi-parameter models like Neural Networks (video)
2. Making A.I. driven investment strategies more transparent
3. Static factors don't work (SSRN, Research Affiliates)
4. Generated (hypothetical) data is key to improving accuracy of machine learning strategies

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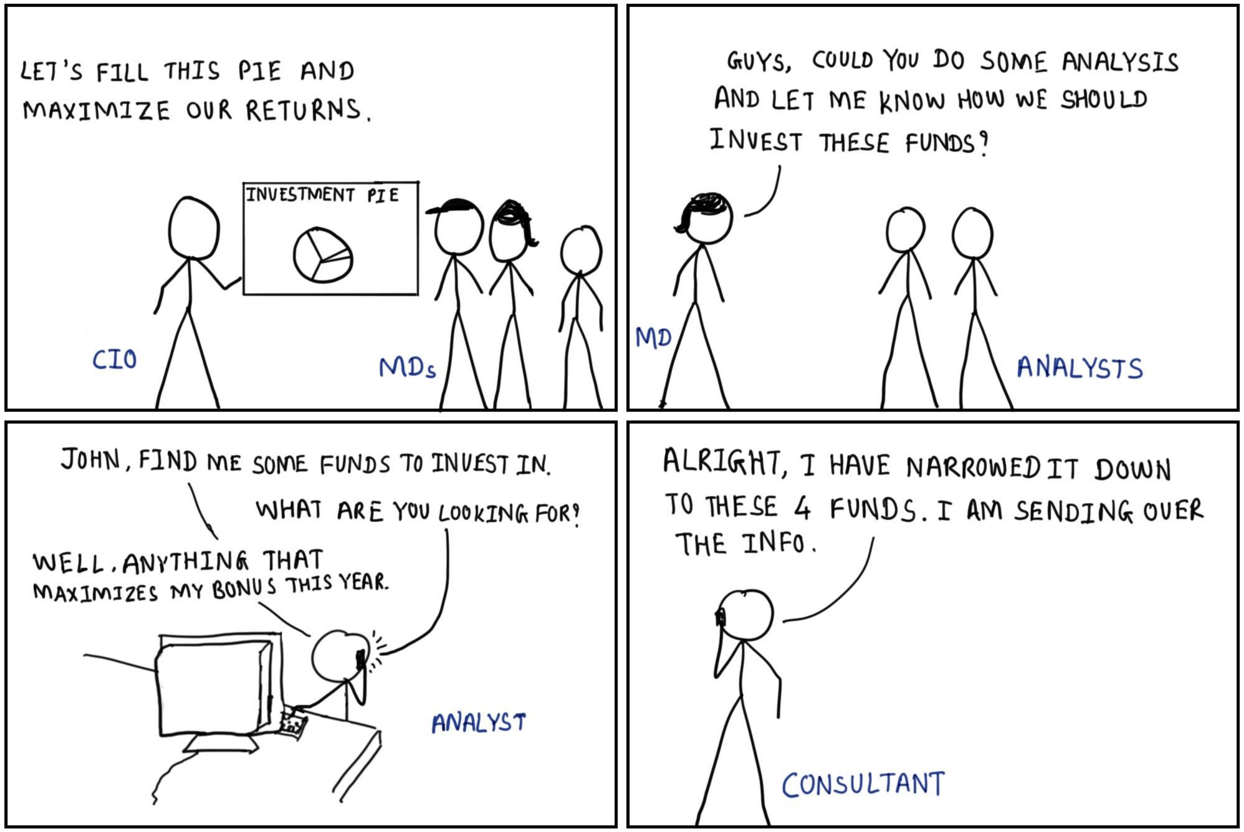
Strategy/manager selection used to like a hierarchical basket filling



References:

1. Using a matrix factorization approach to categorizing managers and strategies and asset classes (OReilly)

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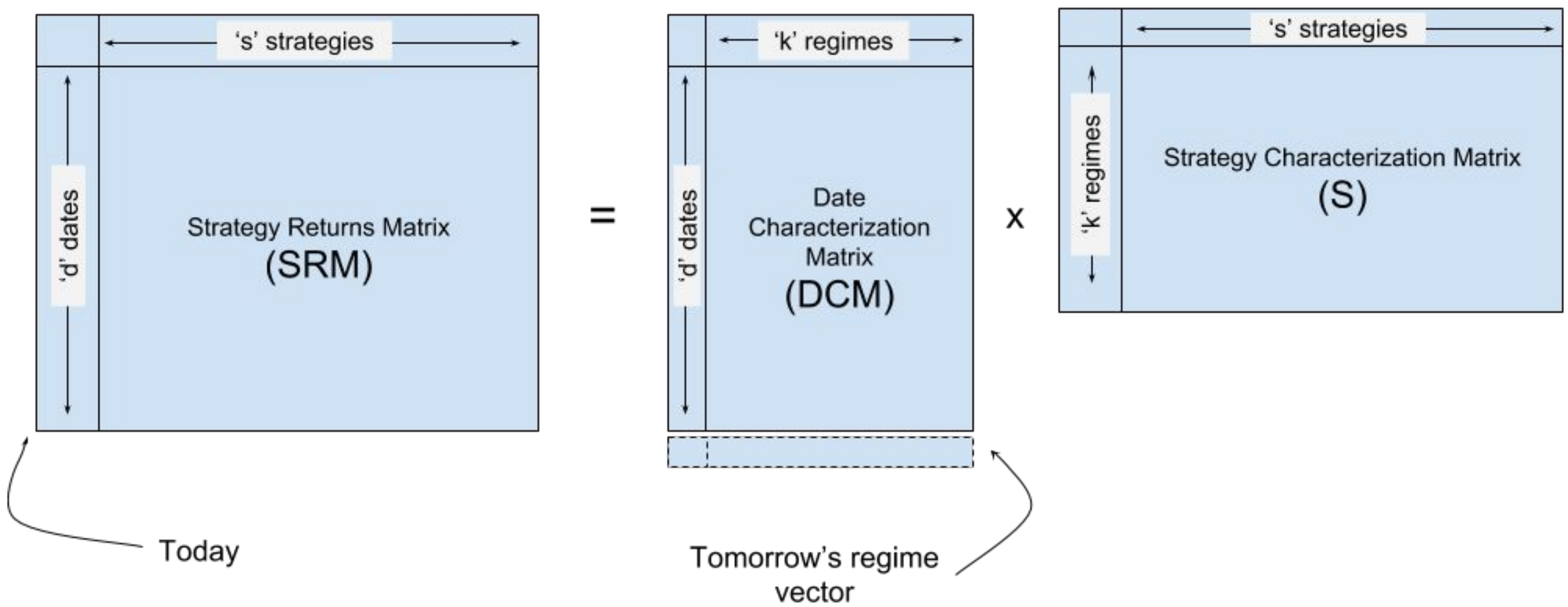
Recommender systems approach to manager selection



References:

1. [Using a matrix factorization approach to categorizing managers and strategies and asset classes (OReilly)]

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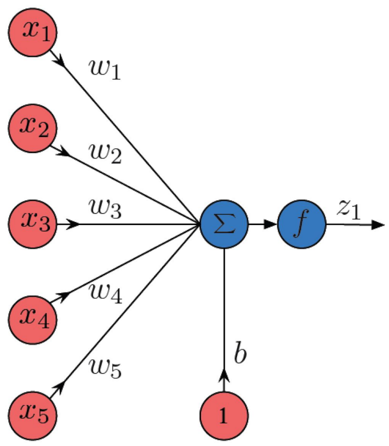
Trades with short holding periods / High frequency trading:

- Linear regression of sophisticated indicators.
- Ensemble methods approach to strategy construction
- Reinforcement learning approach to detecting non-standard behavior in markets or specific stocks
- Walk-forward measurement of strategy performance

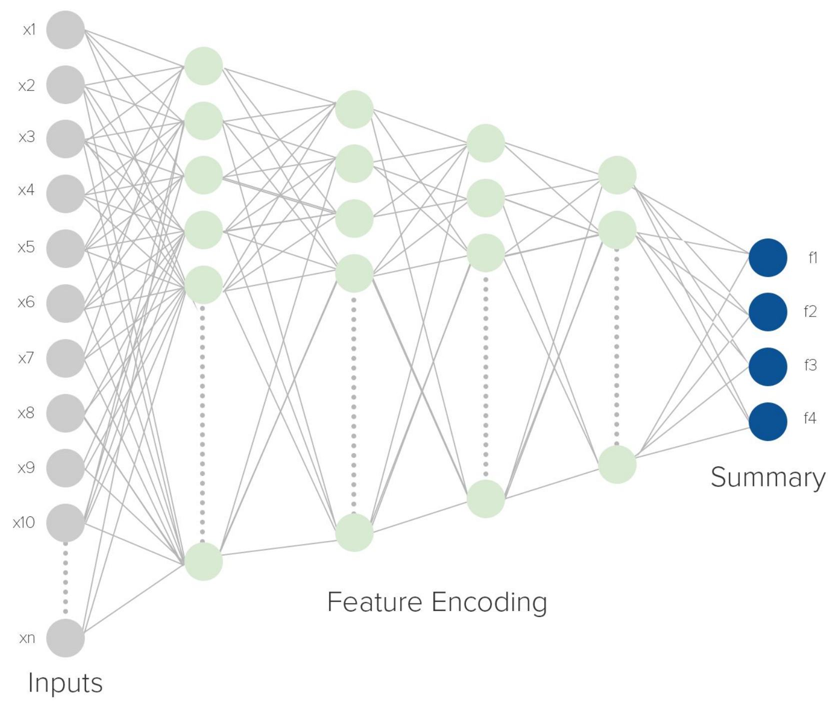


References:
1. Machine learning infrastructure : key to High Frequency Trading (Qplum)
2. What is walk-forward backtesting? Why non-walk-forward results should be discounted in strategy construction
3. Use of ML in high frequency trading (Qplum)
4. Reinforcement learning approach to market microstructure learning - Kearns et. al
5. Eric Schmidt heralds Machine Learning to Combat High Frequency Trading: SALT 2017
6. A step by step tutorial on the evolving use of ML in HFT (video)

Institutional investment

| AI can map complex relationships in financial markets

Automated Feature Extraction



- Regime detection
- Data-driven strategies
- Expected returns model
- Portfolio characteristics

Input Layer

Neural networks separate strong indicators from weak indicators in an adaptive manner

Output Layer

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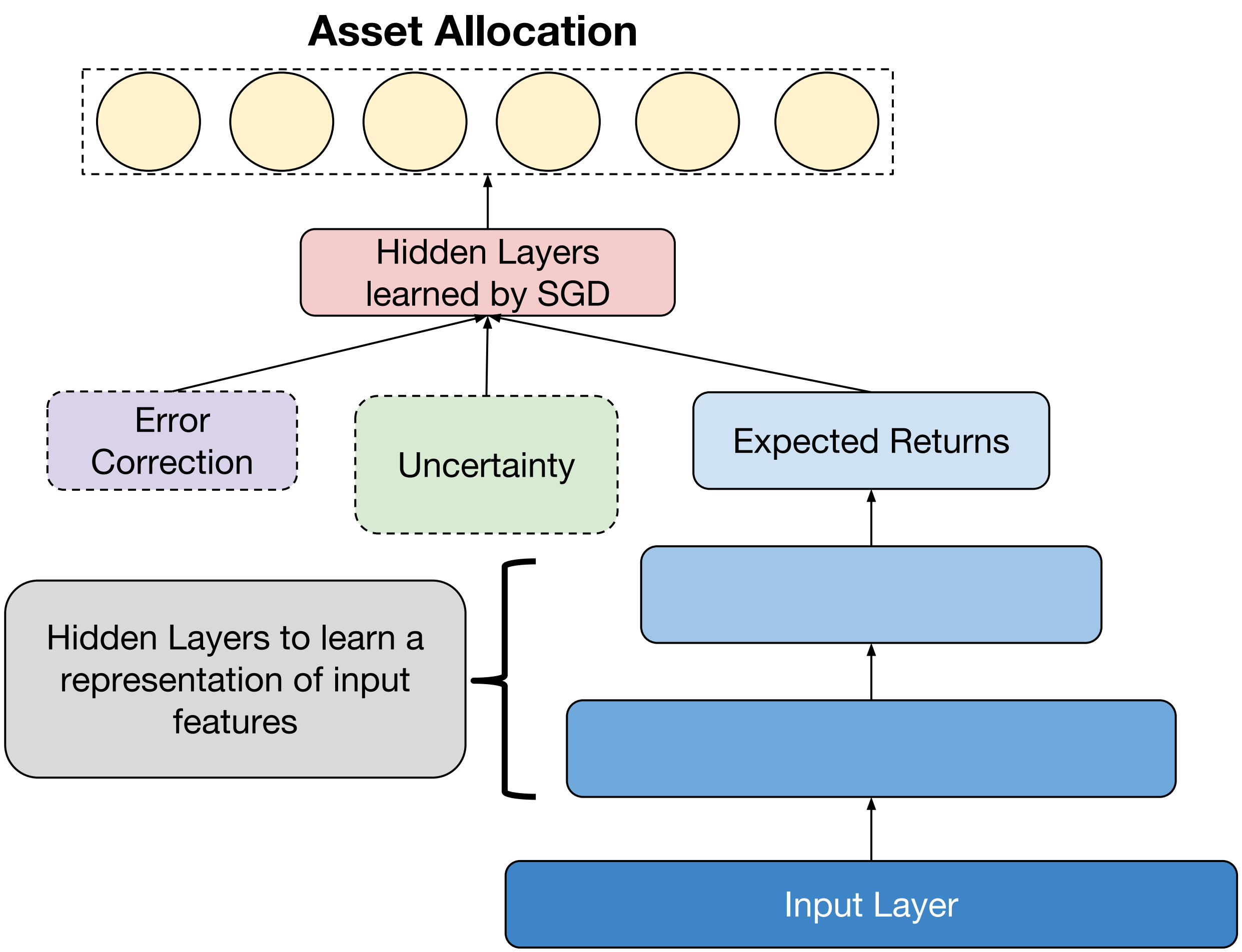
| Deep Learning for Tactical Asset Allocation

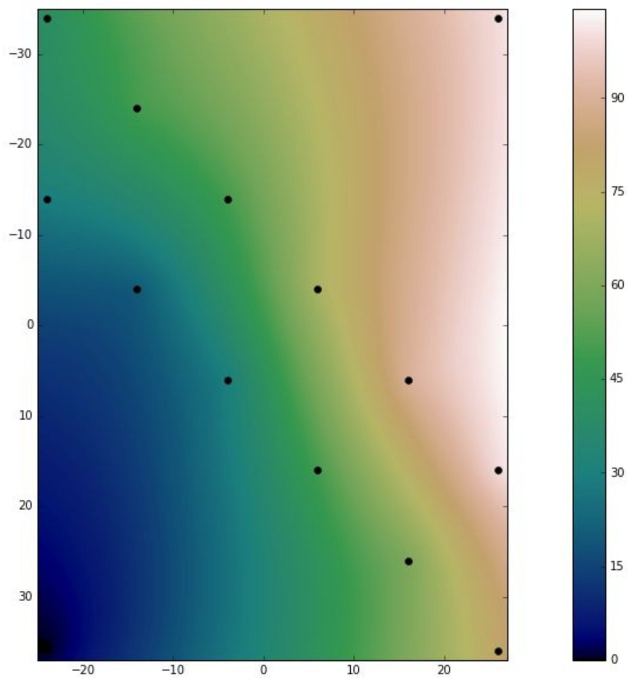


References:

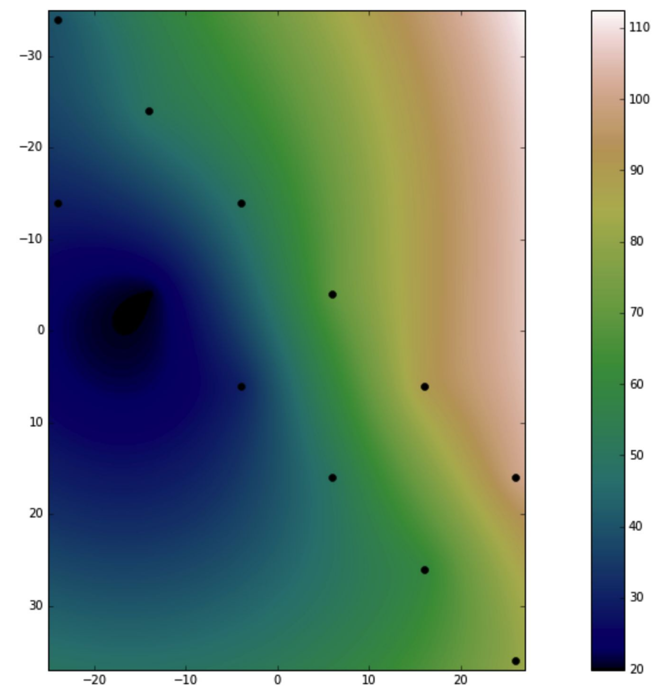
1. Deep learning for tactical asset allocation - Gaurav, Ankit (Qplum), Brandon (OPTrust)
2. Empirical Asset Pricing via Machine Learning - Gu (UChicago), Kelly (AQR), Xiu (UChicago)

Using A.I. in better client profiling:

- higher client retention if PM understands the scenario response surface of the client.



Absolute risk aversion



Relative risk aversion

References: [Investment objective != maximize returns]

Software / Hardware engineering aspects

- What’s specific to finance?
- Data science = data insights.
- Continuous deployment

| Engineering aspects

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Specific to finance

- Losses hurt a lot: In applying ML to trading and portfolio management cost of a mistake is much higher than thousands of correct trades.
- Data walls: Quality data is expensive and high information data is virtually unavailable. No collaboration.
- Preference to build everything in house

References:

1. Sourcing data can be challenging for new firms. These are some great free sources.
2. Datasets to use and avoid in quantitative portfolio management

| Engineering aspects

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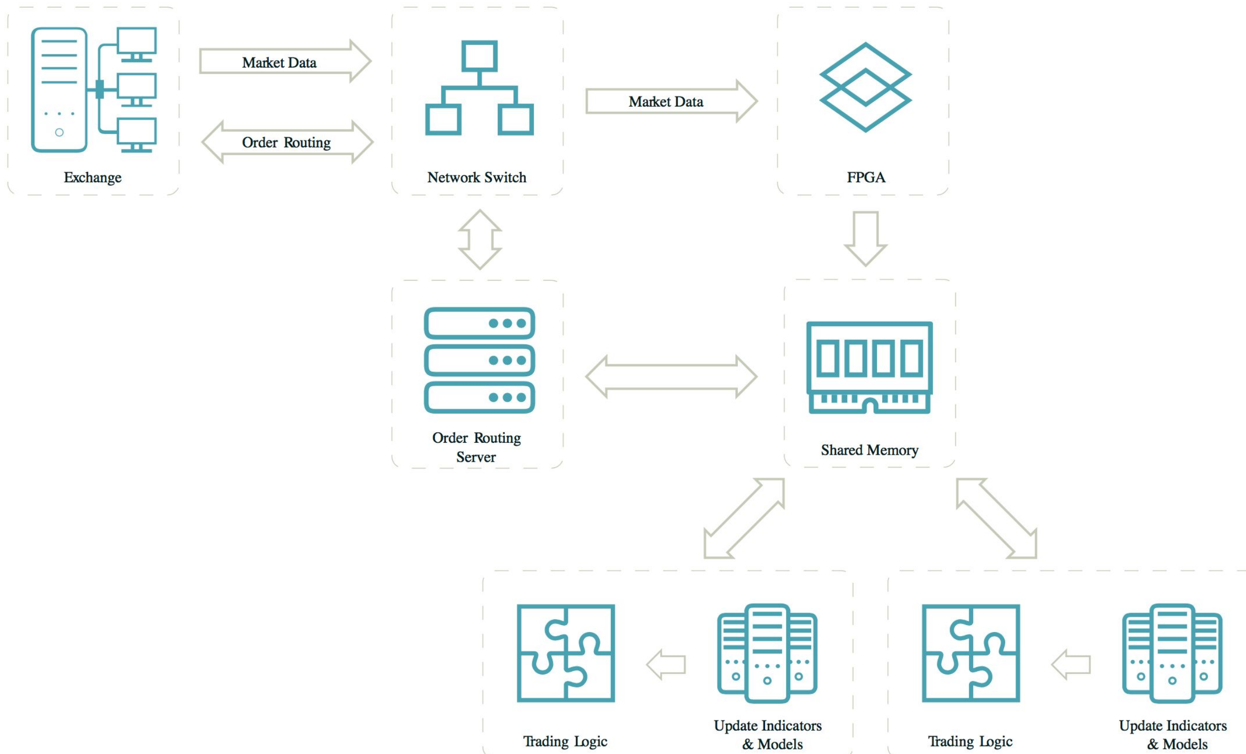

As parts of the ML system become more standard, the focus changes to speed. Most of the ML in production HFT systems are now written on Network card and FPGA cards.

Software ML code is only used to set hyper parameters or for higher level choices.

References:

1. FPGA leading to speed being an edge in delivering machine learning

| Engineering aspects

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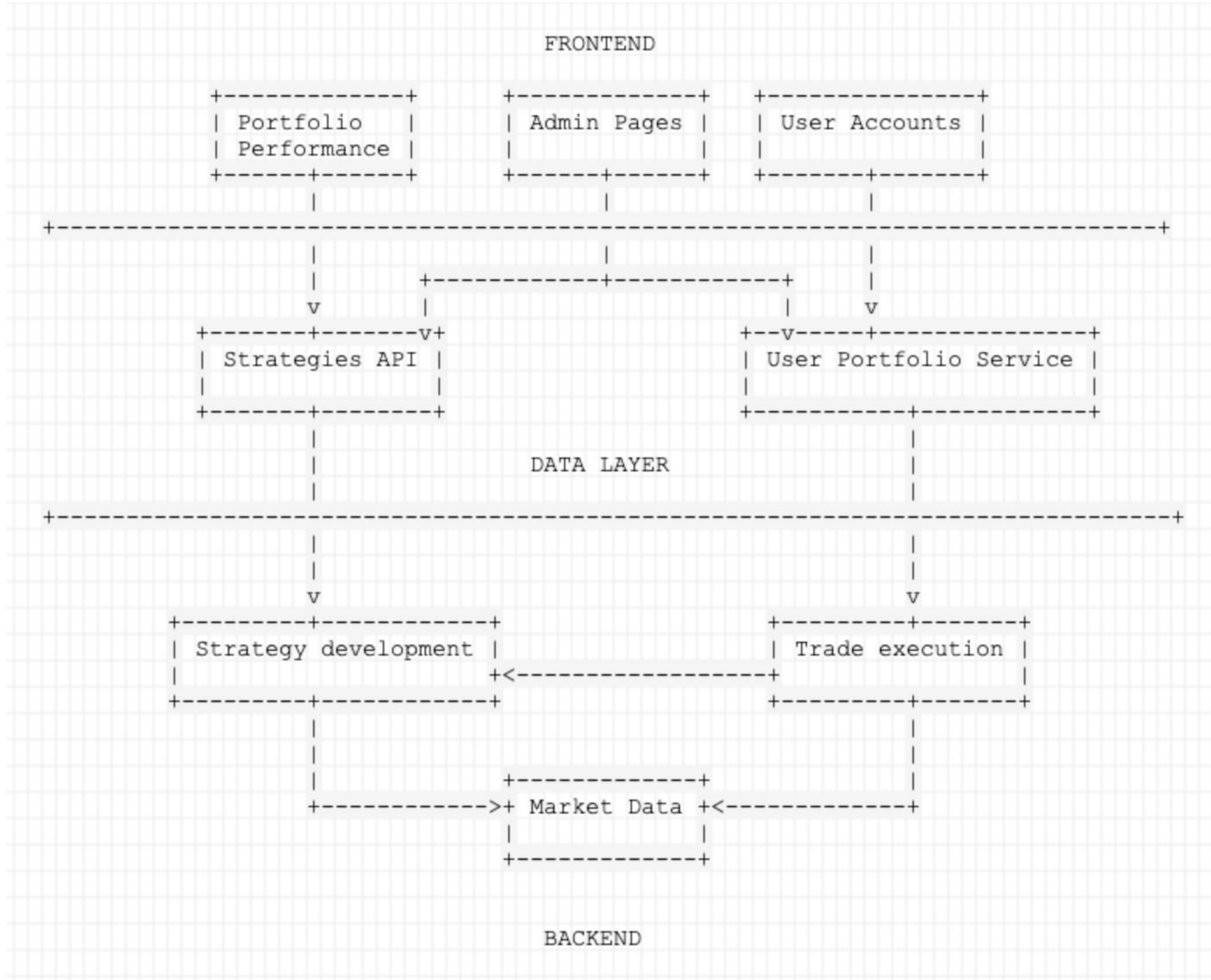

Separate the pipeline into separate APIs and services for robustness and for different teams to work in an agile fashion.

References:

1. [Complete architecture for systematic investing - including transactional, data and research systems (Qplum)]

| Engineering aspects

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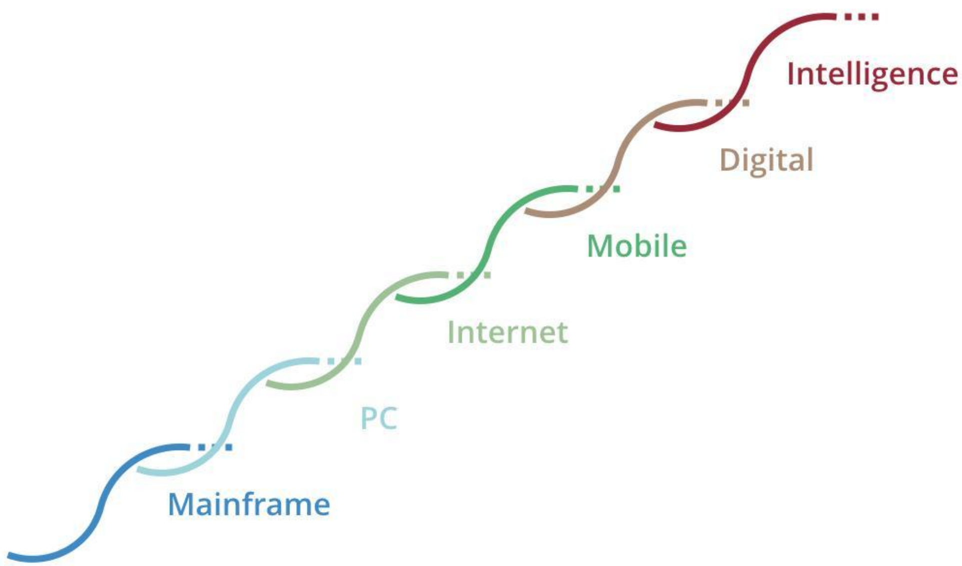

Source: [Thoughtworks Intelligent empowerment]

Data Insights = Product Development using Data Science

While *Mobile* and *Digital* were about distribution and getting closer to the client,
Intelligence (ML systems development) is about delivering more precisely what the clients want.

Hence many industries, like trading and portfolio management have data-science teams working closely with product development teams.

This is particularly true in asset management where clients are inundated with products and they need solutions for their unique situations.

References:

1. How data science is key to new product development, and hence software is not permanently unstable
2. Clients want solutions not new products from Asset Management firms

| Software Engineering in a data science world

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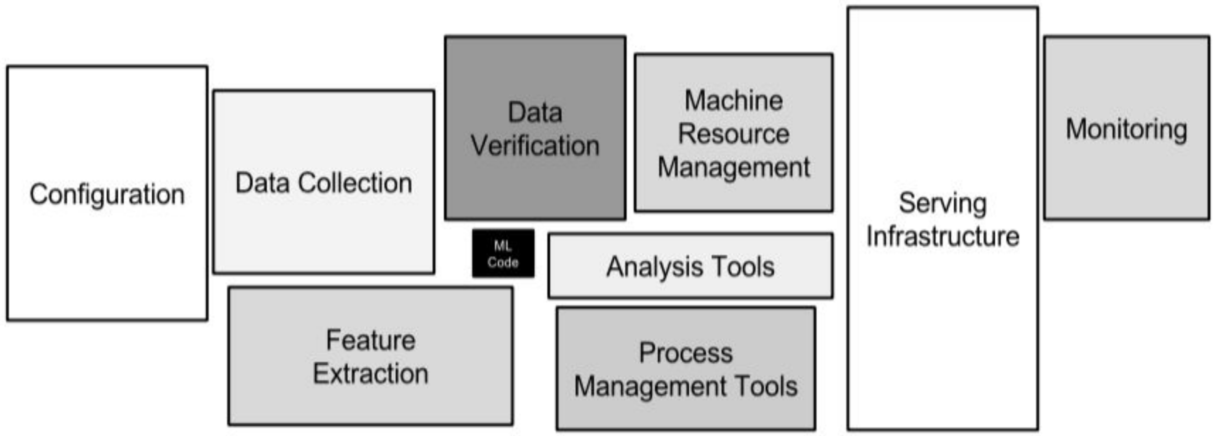


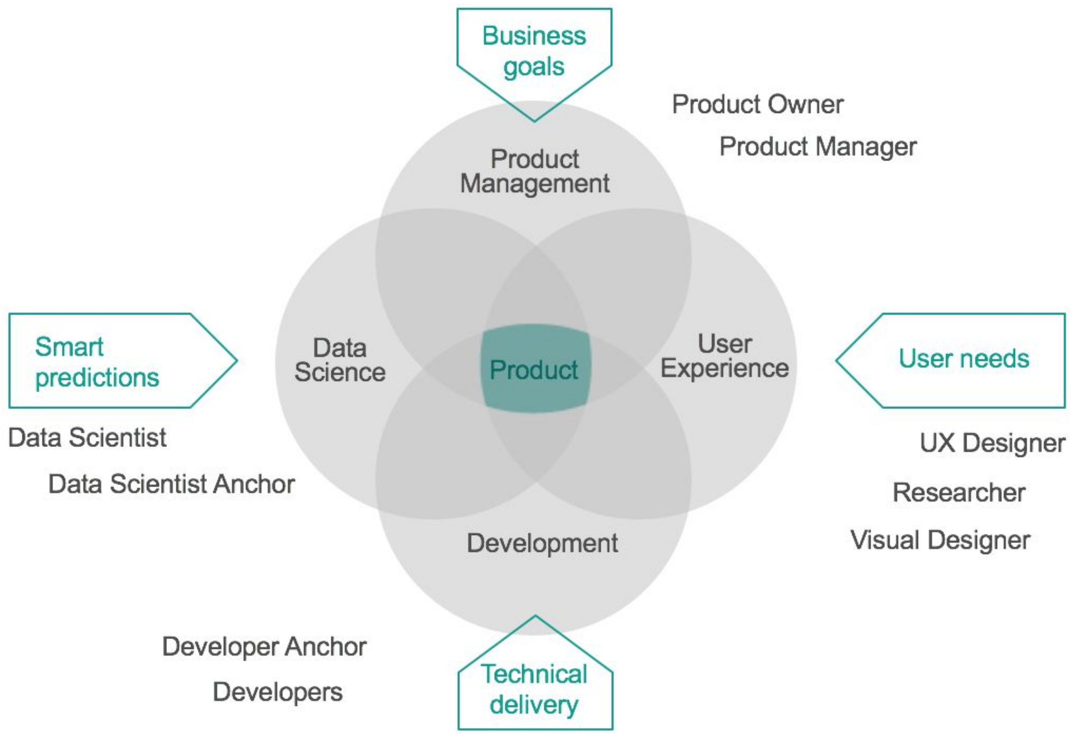
Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

Source: NIPS (see ref blow)

References:

1. [Hidden technical debt in machine learning systems (NIPS, Google)]

| Software Engineering in a data science world



Source: Pivotal (see ref blow)

References:
1. [Continuous integration for data-science (Pivotal)]

Thank you

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Presentations: https://slides.com/gchak

Publications: Hosted by SSRN, Hosted by Qplum

Acknowledgements: Mansi Singhal, Dr. Michael Steele