Financial data structures

or why machine learning in finance is nothing like Kaggle competitions / research papers / industrial best practices

Alex Honchar | UCU Data Science Summer School 2020

About speaker

Entrepreneur

creating and selling AI solutions worldwide as Chief AI Officer and Co-founder at Neurons Lab

Practitioner

7 years building data-driven products, top-10% at the hardest data science contest Numerai

Educator

Medium with >1M views, scientific articles >150 citations, taught at UNIVR, UCU, KPI

About you…?

let’s get to knowing each other

What we are not going to discuss

- Technical analysis with patterns, golden rations, fractals and similar things. Leave it for amateurs :)
- Fundamental analysis with reading reports, book-to-price rations, assets and liabilities analysis
- Complex financial mathematics, advanced probability and stochastic processes theory (although I highly recommend to follow-up after this course exactly with stochastic calculus)
- Deep learning for price prediction and getting rich ;)

Day 1

Safe path to save money for your retirement days

- Algorithmic investments: roles and goals
- Financial data structures: from retail to alternative data
- Criteria of success in algorithmic investment
- Classical approaches to algorithmic investment [PRACTICE]
- “Learning”-like approaches to algorithmic investment [PRACTICE]

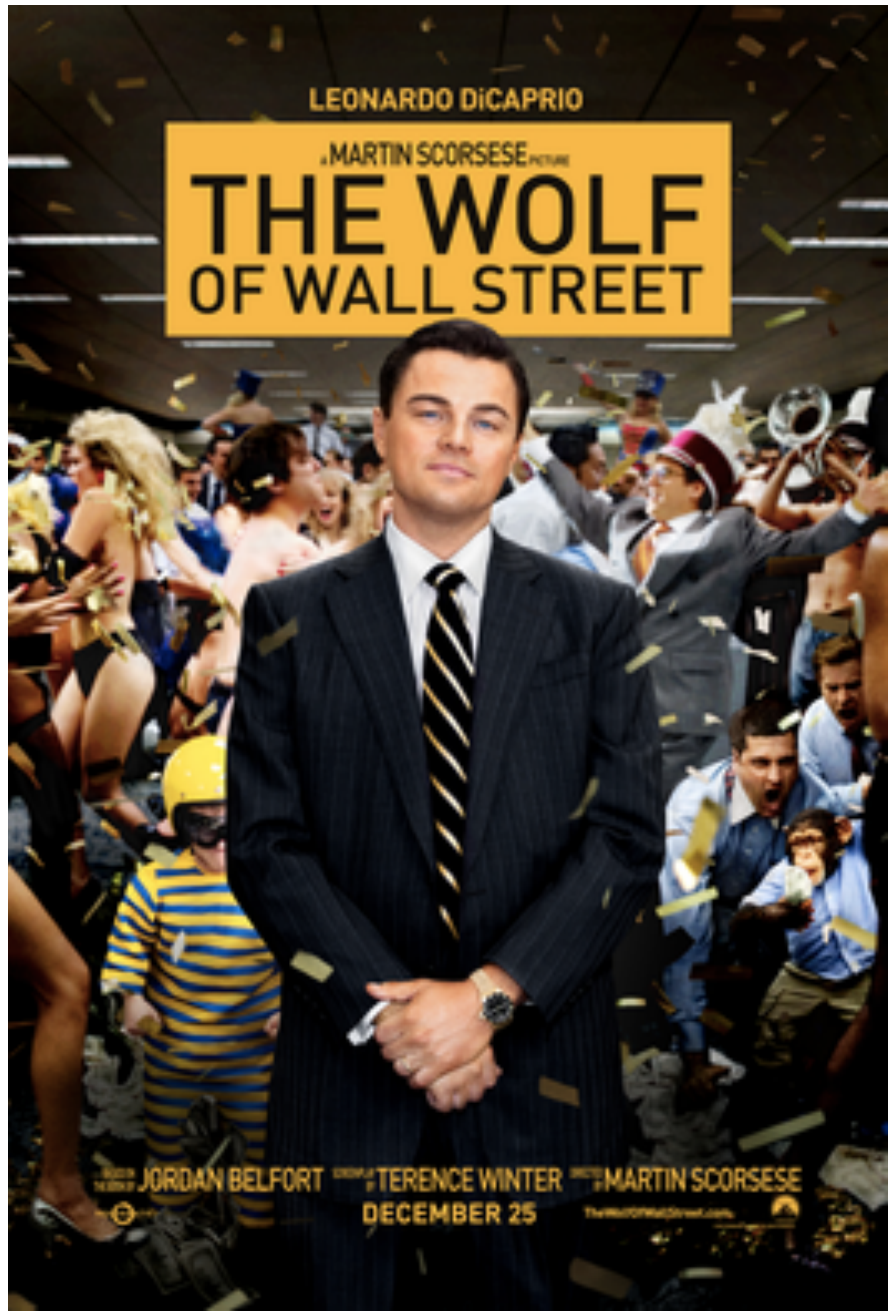
Day 2

Hazardous path of speculations and wild guesses with ML

- Active investment management: what is that alpha?
- Why financial machine learning is different from regular one?
- Predicting asset prices in Python in a Kaggle way [PRACTICE]
- Fixing inputs and outputs with respect to financial logic
- Predicting asset prices in Python as you never did before [PRACTICE]
- Why theoretical physicists success in this job and what to do next?

Roles and Goals

Bobby Axelrod,
“Billions”, HBO



Jordan Belfort,
“Wolf of Wall Street”

Warren Buffet,
Berkshire Hathaway

Ray Dalio,
Bridgewater

Jobs Types

http://isomorphisms.sdf.org/maxdama.pdf

	Front Office	Back Office
Buy Side	**Asset management** at a big bank. **Hedge fund** (strategies constrained to prospectus) **Prop trading** (fastest moving) *Matlab, Java, Functional Languages.* 70-100k+large bonus	**Data scraping and maintenance, Execution, Server administration** *Bash, SQL, SVN, Linux, C++.* 90-100k+small bonus
Sell Side	**Sales & Trading** at a big bank (taking & executing orders, creating derivatives by client reques, execution algos) *Excel.* 70-80k+medium bonus	**Technology**, **Operations**, or **Risk Management** at a big bank (hard to transition to front office) *C++, internal language, hacky code.* 90-100k+small bonus

Applied directions

Banking	Asset Management	Trading
Retail operations	Representation learning	Price forecasting
P2P operations	Portfolio optimization	Optimal execution
Lending, credit scoring	Risk management	Optimal strategy development

Algorithmic investments dream team

From the idea to the execution

- Analysts
- Data curators
- Feature analysts
- Strategists
- Backtesters
- Deployment team
- Portfolio managers

10 ML applications in Finance

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3257415

Finance after COVID-19

https://ssrn.com/abstract=3562025

Financial data structures

Inputs

What we are basing our ideas on?

- Banking data: clients information, transactions…
- Fundamental data: assets, liabilities, sales, earnings…
- Market data: price, volume, dividends, open interest…
- Analytics data: recommendations, credit rankings, news sentiment…
- Alternative data: CCTV, satellite images, Amazon, Twitter…

Outputs

Problems we’re trying to solve

Regression:

- earnings prediction
- credit loss forecasting
- price forecasting

Classification:

- rating prediction
- default modeling
- credit card fraud
- anti-money laundering

Clustering:

- customer segmentation
- stock segmentation

Representation learning:

- factor modeling
- denoising
- regime change detection

What do we optimize for?

focusing on trading / investment management

What we optimize for in normal ML?

- **“Accuracy”-like surrogate on OOS data**
  accuracy of prediction? “understanding the market?” do I really want to be exactly accurate in random conditions?

- **Mathematical loss function on OOS data**
  logloss? MSE? of what? for what? how do I measure something in the future?

- **Business metrics**
  returns on investment? some risk? maximal potential loss? diversification?

One step back to the process

Portfolio selection for the retirement

- **Select desired universe of financial instruments**
  it should grow
  it should be diversified
  it should be “calm”, predictable

- **Select desired factor exposure**
  they should explain the market now and in the future

- **Select preferred allocation scheme**
  “not bet everything on one horse”

- **Select final investment goal and metric**
  “maximize returns but minimize risks”

- **“Optimize” to have that all in the real future, not just in the Jupyter Notebook**

Growth and security

We want to grow profits but feel safe same time

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Returns

$$\sigma^2 = w^T \sum w$$

Variance

Explainability by the factors

We want to predict growth based on something useful

$$R_i = R_f + \beta_i * (R_m - R_f)$$

Capital Asset Pricing Model

$$r = R_f + \beta_3(K_m - R_f) + b_s \cdot SMB + b_v \cdot HML + \alpha$$

Fama-French Model

Allocation schemes and diversification

Don’t but all eggs in a single basket

- Cap-based
- Equal allocation
- Risk diversification

Final metrics

How do we value a constructed portfolio?

$$SharpeRatio = \frac{E[Returns] - RiskFreeRate}{\sqrt{V[Returns]}} * \sqrt{n}$$

Normally, some form of risk-adjusted returns. What will be the risk?

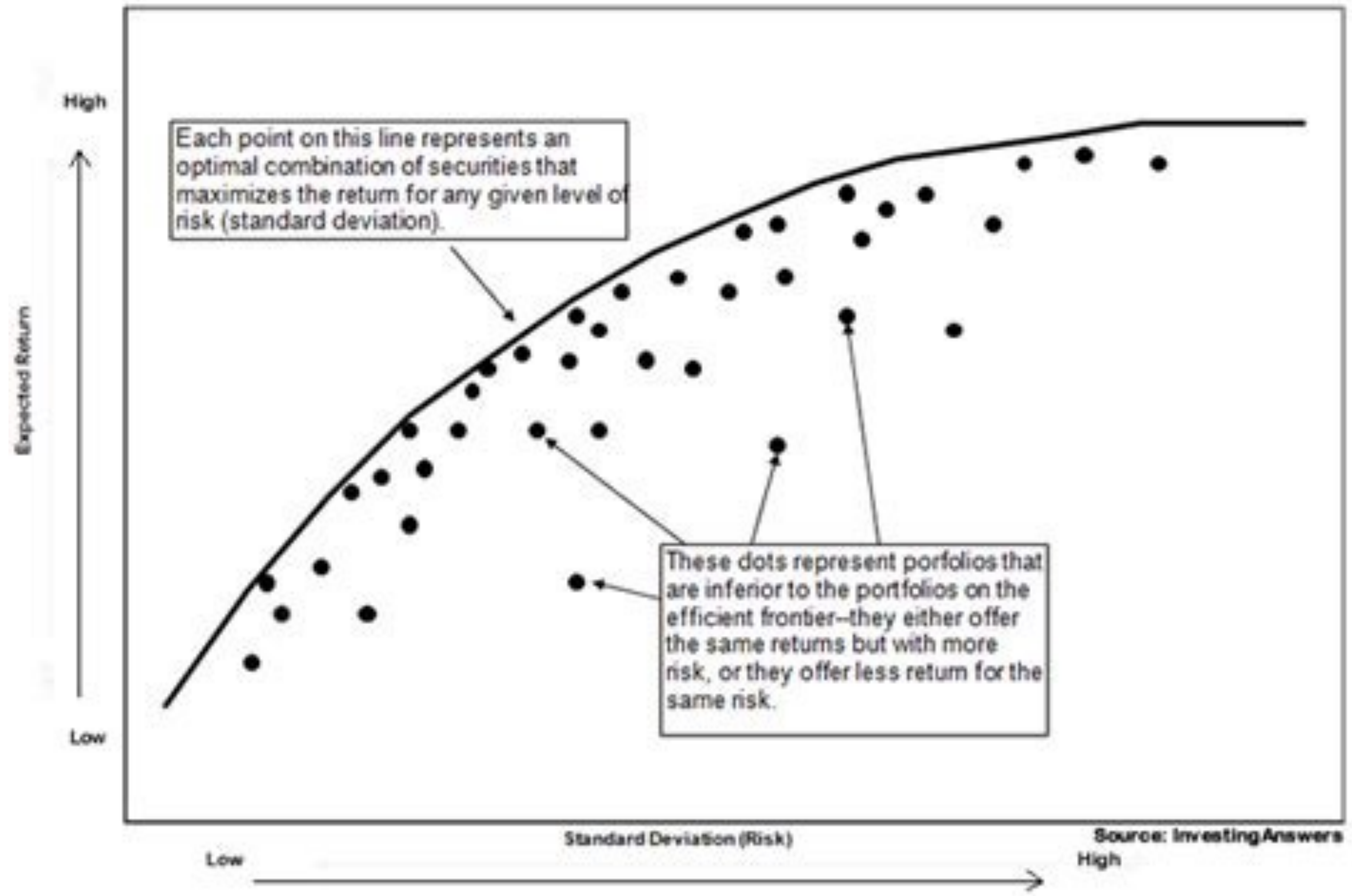
Classical approaches

directly optimizing for the metrics based on the data

Markowitz portfolio

The only free lunch in Finance

- De-correlated assets combined together in a portfolio get lower volatility



Markowitz portfolio

Mathematical optimization formulation

$$
\begin{aligned}
\max_{\mathbf{x}} \quad & f(\mathbf{x}) \\
\text{s.t.} \quad & g(\mathbf{x}) \leq 0 \\
& h(\mathbf{x}) = 0
\end{aligned}
$$

$$\Rightarrow$$

$$
\begin{aligned}
\min_{\mathbf{w}} \quad & w^T \sum w \\
\text{s.t.} \quad & \sum_{i=1}^{n} w_i = 1 \\
& \mu^T w = \mu_t
\end{aligned}
$$

Maximal Sharpe Portfolio

Mathematical optimization formulation

$$
\begin{aligned}
\underset{\mathbf{w}}{\text{maximise}} \quad & \frac{\mu^T w - R_f}{(w^T \sum w)^{1/2}} \\
\text{s.t.} \quad & \sum_{j=1}^{n} w_j = 1 \\
& w_j \geq 0, j = 1, \ldots, N
\end{aligned}
$$

$$
\begin{aligned}
\underset{\mathbf{w}}{\text{minimise}} \quad & y^T \sum y \\
\text{s.t.} \quad & (\mu^T w - R_f)^T y = 1 \\
& \sum_{j=1}^{N} y_j = \kappa, \\
& \kappa \geq 0, \\
& w_j = \frac{y_j}{\kappa}, j = 1, \ldots, N
\end{aligned}
$$

Naive diversification

Don’t put all eggs in a single basket

- How to measure number of baskets?
- It’s not just the numbers of assets in the portfolio. Why? Because you can have several concentrated bets on small amount of assets and almost nothing on all the others
- Effective number of constituents (ENC) measures it and can be optimized directly

$$\mathrm{ENC}_\alpha(\boldsymbol{w}) = \|\boldsymbol{w}\|_\alpha^{\frac{\alpha}{1-\alpha}} = \left(\sum_{k=1}^{N} w_k^\alpha\right)^{\frac{1}{1-\alpha}}$$

alpha >= 2

Risk-Parity Optimization

Baskets of risks, not dollars

- Imagine a portfolio with 50% allocated in risky asset with 30% volatility and not-risky bond with 10% volatility (both not correlated)
- ENC = 2, but are these two baskets actually equal from the risk point of view?
- Instead of stacking and normalizing for weights for the asset, we can do the same for the volatility per asset

$$q_k = \frac{w_k \left[\boldsymbol{\Sigma w}\right]_k}{\boldsymbol{w}'\boldsymbol{\Sigma w}}, \text{ where } \sum_{k=1}^{N} q_k = 1$$

$$\mathrm{ENCB}_\alpha(\boldsymbol{w}) = \|\boldsymbol{q}\|_\alpha^{\frac{\alpha}{1-\alpha}} = \left(\sum_{k=1}^{N} q_k^\alpha\right)^{\frac{1}{1-\alpha}}$$

Other options

Same optimization process :)

$$w^{MV} = \arg\min w^T \cdot \Sigma \cdot w$$

min variance

$$w^{MD} = \arg\max \frac{w \times \sigma}{\sqrt{w^T \cdot \Sigma \cdot w}}$$

max diversification

$$w^{MDec} = \arg\min w^T \cdot A \cdot w$$

max de-correlation

$$\textstyle\sum_i^N w = 1$$

Ensuring that it wasn't just an overfit

Alternative useful metrics to track

- Information ratio - how much (if we do at all) we perform better than a benchmark

- Maximal drawdown and corresponding periods

- Factor exposure: how much we "overfit" to some feature (factor models + ML feature importance)

$$InformationRatio = \frac{E[Returns - Benchmark]}{\sqrt{V[Returns - Benchmark]}} * \sqrt{n}$$

Ensuring that it wasn’t just an overfit

Corrections for distributions and trials

- Probabilistic Sharpe: adjusted estimate of SR, by removing the inflationary effect caused by short series with skewed and/or fat-tailed returns.

$$PSR[SR^*] = Z[\frac{(SR - SR^*)\sqrt{T-1}}{\sqrt{1 - \gamma_3 * SR + \frac{\gamma_4 - 1}{4} * SR^2}}]$$

- Deflated Sharpe: a PSR where the rejection threshold is adjusted to reflect the multiplicity of trials.

$$SR^* = \sqrt{V[\{SR_n\}]}((1-\gamma) * Z^{-1}[1 - \frac{1}{N} + \gamma * Z^{-1}[1 - \frac{1}{N} * e^{-1}]$$

- Minimum track record: “How long should a track record be in order to have statistical confidence that its Sharpe ratio is above a given threshold?”

$$MinTRL = 1 + [1 - \gamma_3 * SR + \frac{\gamma_4 - 1}{4} * SR^2] * (\frac{Z_\alpha}{SR - SR^*})^2$$

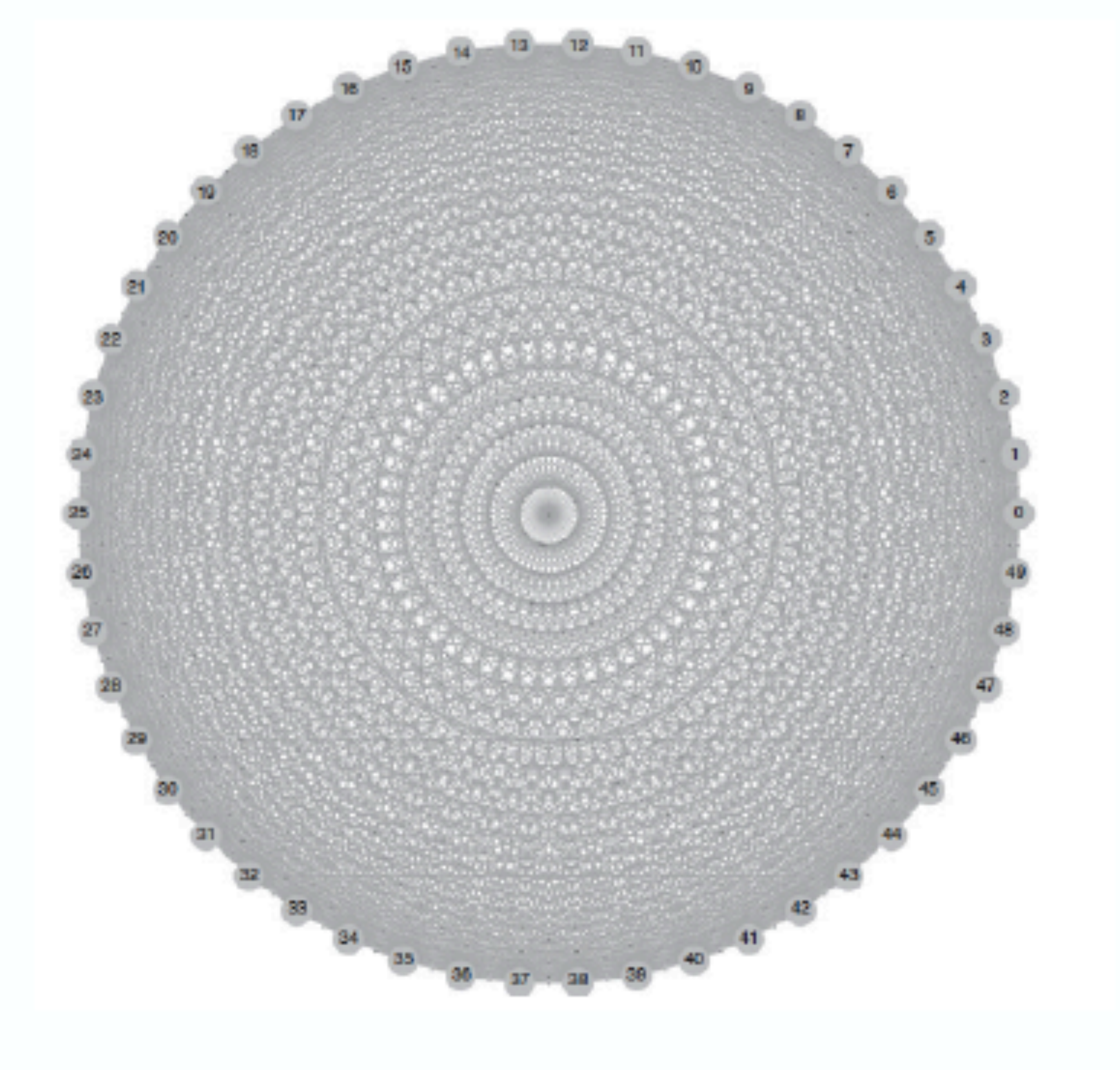
Let’s put it together into a strategy

ML-based approaches

curse of dimensionality and overfitting

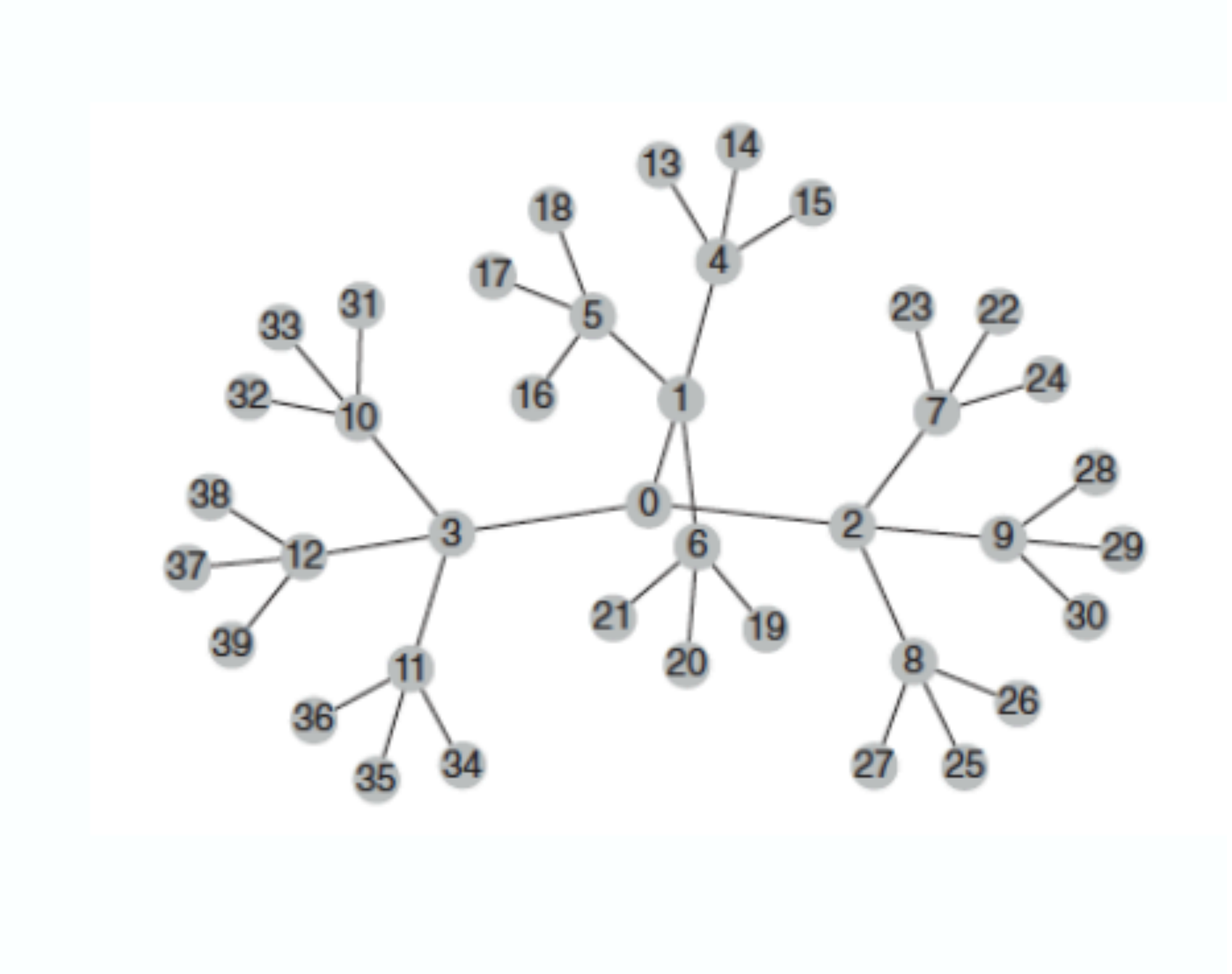
Optimization problems

Dimensionality curse



complete graph
of assets

N(N-1)/2 correlations



hierarchical tree
of assets

- increase sample period of frequency
- decrease number of parameters
- impose a structure

Other problems of Markowitz and Co

- Small deviations in the forecasted returns will cause very different portfolios
- Quadratic programming methods require the inversion of a positive definite covariance matrix (all eigenvalues must be positive)
- Markowitz's curse: The more correlated the investments, the greater the need for diversification, and yet the more likely we will receive unstable solutions. The benefits of diversification often are more than offset by estimation errors.
- Anyway need to rebalance, because correlations change all the time

Constant correlation model

Reducing dimensionality of the model

- We can impose a model of the same correlation between the assets
- N(N-1)/2 parameters -> 1 parameter
- But meanwhile, we are introducing a model specification risk!

$$\sigma_{ij} = \begin{cases} \sigma_{ii} = \sigma_i^2 & \text{when } i = j \\ \sigma_{ij} = \rho\sigma_i\sigma_j & \text{when } i \neq j \end{cases}$$

a parameter ***rho*** in covariance matrix stays the same for all ***i,j***

Robust Risk Estimation

i.e. regularization of the model

- Sample risk suffers from “overfitting” and curse of dimensionality
- Model risk comes from mainly from misspecification
- A tradeoff between sample views and model views: shrinkage, the sample covariance matrix is ‘shrunk’ towards the structured estimator

$$\hat{\Sigma}_{Shrink} = \hat{\delta}^* F + (1 - \hat{\delta}^*) S$$

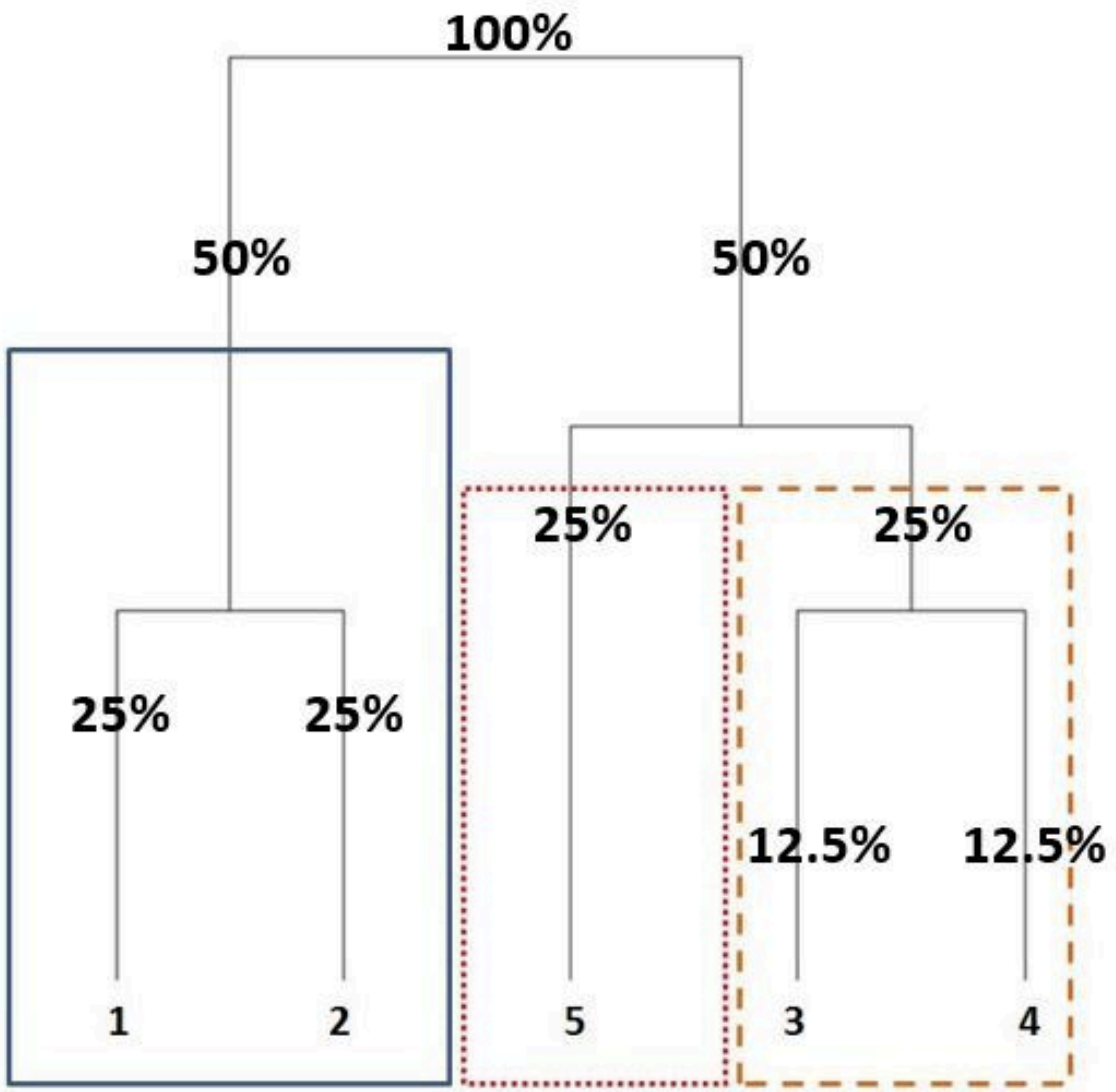
S - sample cov, **F** - model

Hierarchical Risk Parity

Imposing structure in the model

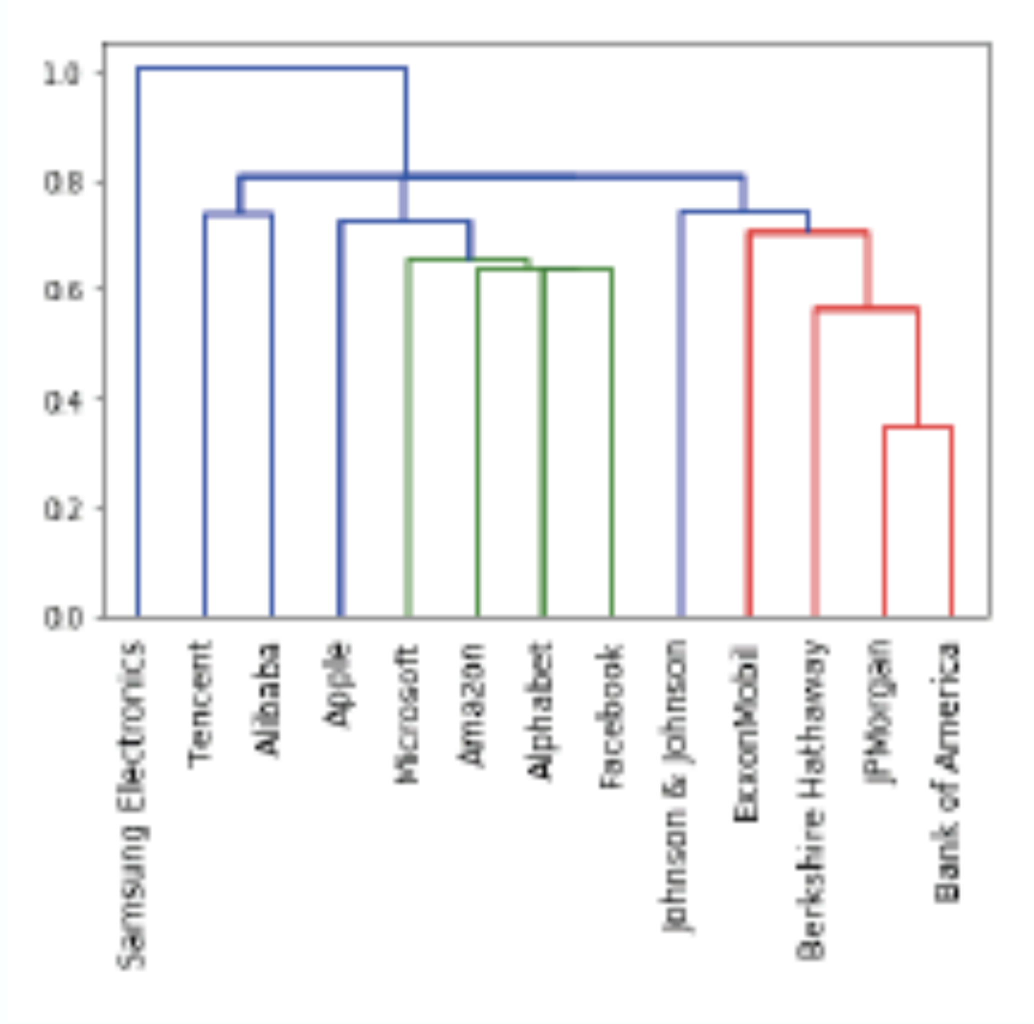
- Hierarchical clustering
- Selecting the optimal number of clusters
- Capital is allocated across clusters
- Capital is allocated within clusters

- In the Equal Weighting portfolio, all the clusters are weighted equally in terms of risk to construct our optimal portfolio. The following image shows how asset allocation works with a small example

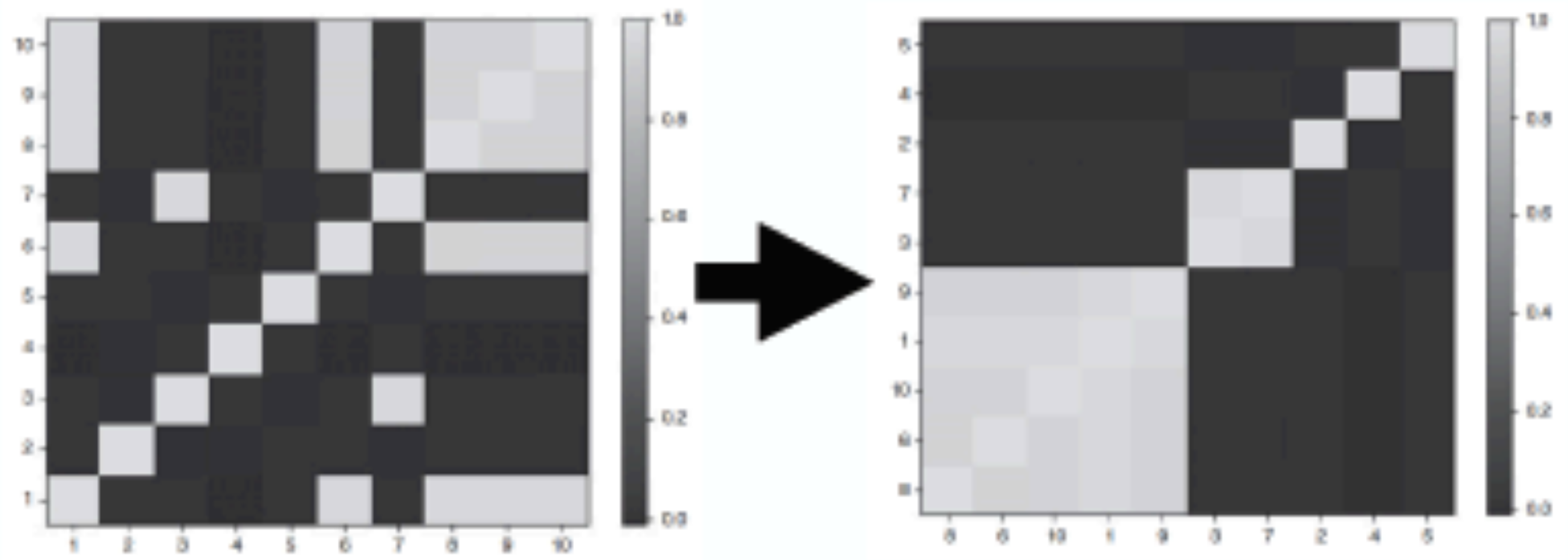


Hierarchical Risk Parity

Imposing structure in the model



Perform tree clustering of the covariance matrix



Regroup covariance matrix based on the clusters and quasi-diagonalize it

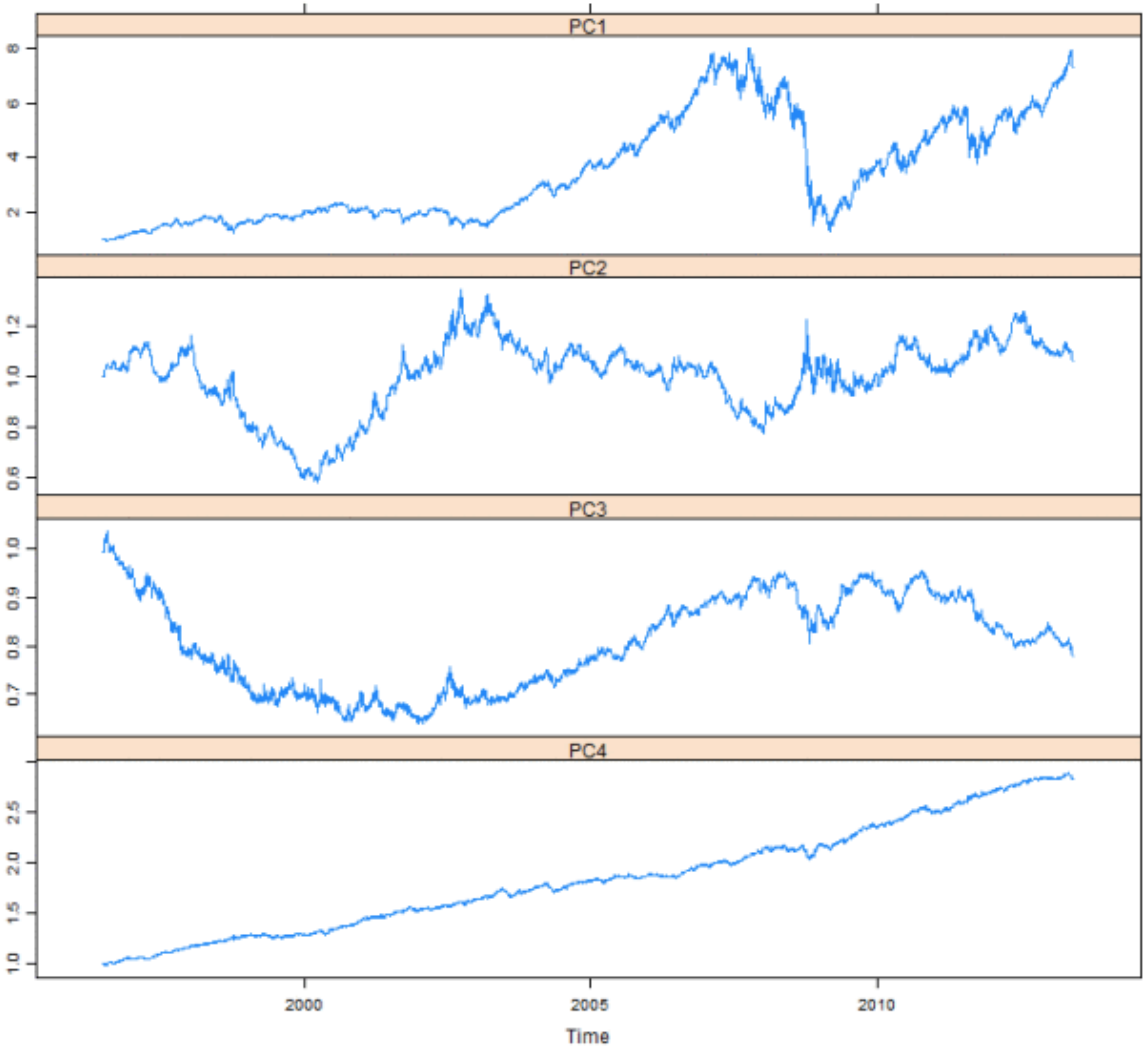
RECURSIVE ALLOCATION

Recursively apply weights to the assets

PCA and Autoencoders

Imposing structure in the model

- Your portfolio is a linear combination of the assets
- CW, EW, GMV portfolios are good benchmarks, “proxies” to the market
- How to select such proxy based on the the explanation of the variance of the market?
- Or based on the explanation of the predictability of the market?



Let’s do the horse racing

Why we did it?

Sometimes it's even worse than equal allocation…

- As we discussed above, everything starts with selection of the trading universe and strong underlying factors
- Yes, we really want to be active and predict things before other participants of the market figure that out, so we get advantage and extra-profit
- But first, we want to build a baseline of our market, a fundament that will be stable long-term by itself. That's why everything today was about some sort of "unsupervised" learning of the market structure
- We will allocate X% of our assets there to cover our liabilities and to be secure, and put the rest (1-X)% to the performance-seeking part, which we are going to discuss tomorrow

Future improvements

For the portfolio optimization

- Using expected returns: teaching models to forecast prices, merging together with baselines using Black-Litterman portfolios
- Working on the risks: correlation is the most primitive measure of similarity of the assets. How about non-linear measures? Statistical measures?
- Rethinking the whole setup. We don't construct portfolio only once and hold it forever. Time-to-time we refresh information about the market and update the weights. It already looks a bit more like optimal control / reinforcement learning, rather a single function optimization

Day 2

Hazardous path of speculations and wild guesses with ML

- Active investment management: what is that alpha?
- Why financial machine learning is different from regular one?
- Predicting asset prices in Python in a Kaggle way [PRACTICE]
- Fixing inputs and outputs with respect to financial logic
- Predicting asset prices in Python as you never did before [PRACTICE]
- Why theoretical physicists success in this job and what to do next?