Robo [(Financial) Advisory]

RegTech, Artificial Intelligence and the art of computing sound Investment Decisions

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Robo [(Financial) Advisory] - Agenda

Why? What? How?

Artificial Intelligence

Robo Advisory & RPA

Robo Financial Advisory & RegTech Issues

Robo Investment Advisory for Long-Term Strategic Investment Decisions

Conclusions and future outlook

Why?

EU Horizon 2020 Project FinTech
A FINancial supervision and TECHnology compliance training programme.

SupTech Part II: Modeling market risk arising from Artificial Intelligence applications in financial robo advisory.

EU Project Use Case Coding Sessions today in the afternoon. This part:

- Scientific partner: WU Vienna University of Economics and Business.
- Business partner: algorithmic.finance - Bespoke Asset Management Solutions.

What?

Research Question

Why did most (if not all) Robo Investment Advisors fail or at least not live up to their expectations?

As of summer 2019 many financial institutions already closed down their Robo Advisory business which was set up in the last few years - most recently in May 2019 Investec after having lost more than USD 32 million. CFO Interview (FT):

- Robo Advisors are a poor fit with the rest of the business because of the kind of customers that tend to use them, and
- it is difficult to sell investment products to people with no money.

What?

We need to understand (A) the investment product and (B) the individual to be advised automatically (long-term risk perception, target expectation, ...).

Hypotheses
H1: Most Robo Advisors are monolithic pieces of code written by a single person or a small group of persons without a structured and generalized scientific process.

H2: Portfolio optimization is a research field where everyone who does it thinks (s)he is an utmost smart person - and this smartness is questionable.

H3: Computational psychology is rarely applied properly nor linked to portfolios.

How?

Implementing the well-known and utmost successful Software Engineering concept:

Simplify and Do it!

This concept can be accomplished following a path along these steps:

1. Deconstruction of existing models (those in use and related ones).
2. Simplification, Generalization, Componentization.
3. Dynamic reconstruction of specific (decision) processes using certain (probably small but utmost intelligent) components.

Adapted from: Unfreeze - Change - Refreeze [K. Lewin, Change Management].

Artificial Intelligence
A Short Summary

Artificial Intelligence

Quite likely the third AI Winter is already here.

AI scope is far too broad - everyone thinks of something different!

- Pamela McCorduck, 2004: AI began with an ancient wish to forge the gods.
- Python Gurus, since 2015: AI means training and deployment of Machine Learning models based on Artificial Neural Networks with at least two intermediate layers which are most likely non-standard (i.e. not standard multi-layer perceptrons) but rather CNNs, LSTMs, GANs along with other auxiliary layers (e.g. Dropout). Focus on complexity and weirdness.
- Symbolic AI? GOFAI ("Good Old-Fashioned Artificial Intelligence").

Artificial Intelligence and Data Science / Decisions?

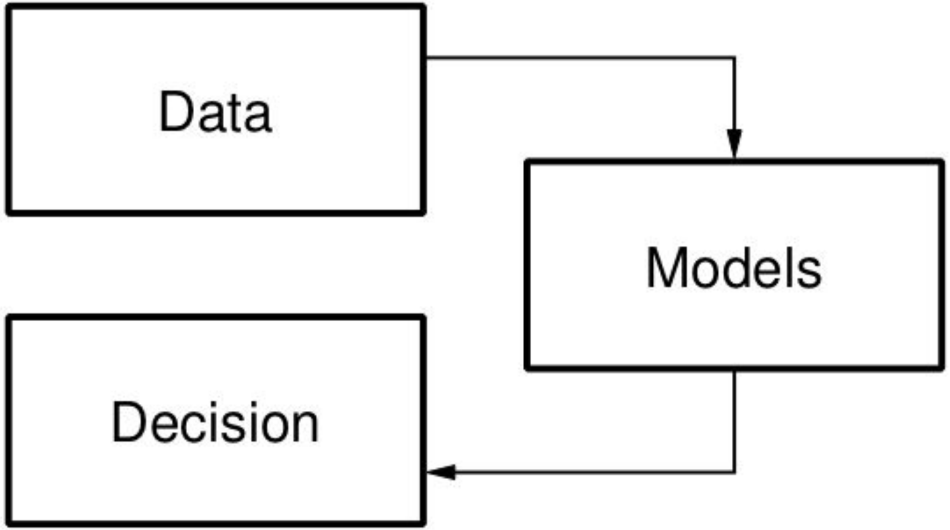
Data Science / Artificial Intelligence (the current hype, 2015-2018, still ongoing)

- Discovering patterns in, asserting meaning to, extracting messages from data.
- Data Science is turning numbers into stories.
- Use data stories to take responsible management decisions. (?)

Decision Science / Data Based Management (out of fashion, before 2015)

- Management decisions based on quantitative data.
- Mathematical and statistical models to compute decisions.
- Operations Research / Management Science.

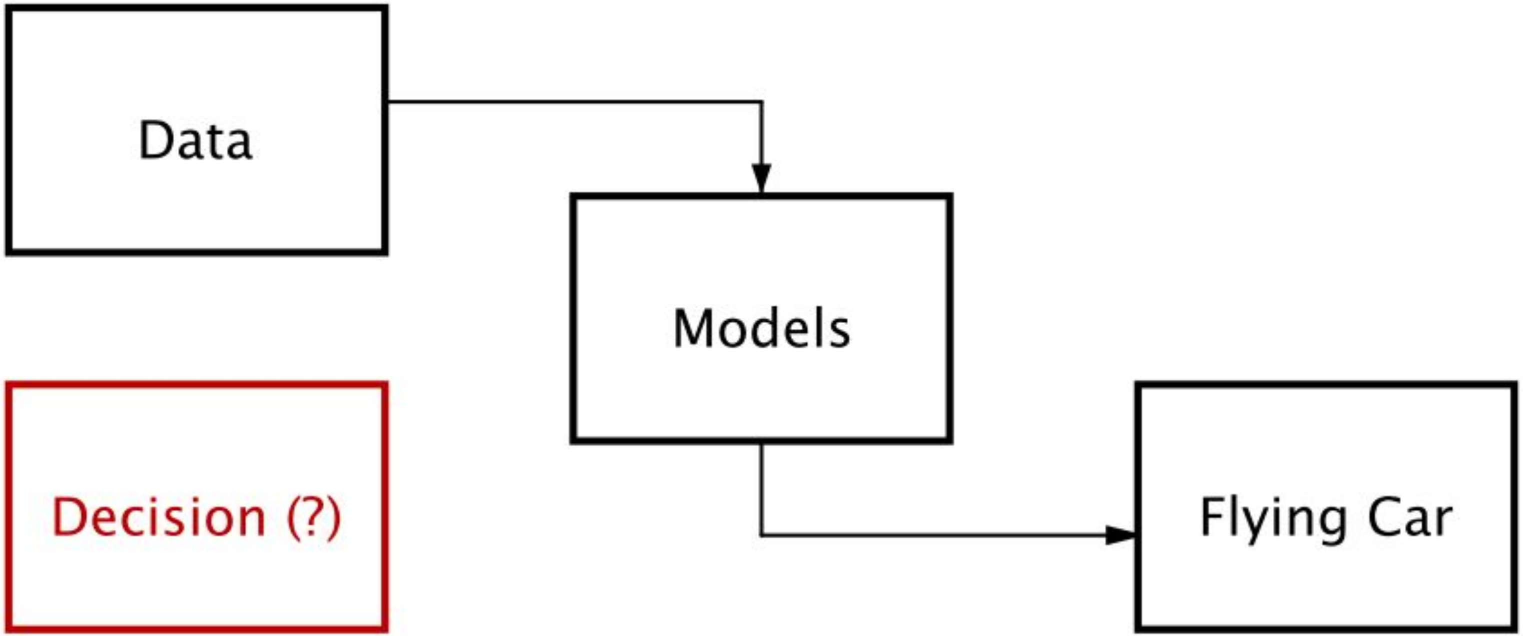
Decision Science / Data Science



Decision Science Process:

1. Model the specific decision quantitatively.
2. Find an appropriate (Optimization) Model.
3. Simulate future-proof Scenario Data.
4. Compute and Integrate.

Decision Science / **Data Science**



Decision Science / **Data Science**

The “contemporary” hype-based Data Science / AI process:

1. Find the most complex and fancy model available: Deep Learning CNNs, GANs.
2. Hire lots and lots of “smart” Data Scientists to implement these models.
3. Figure out that there is not enough nor appropriate data available to fit such models, i.e. there are problems with IT/DB people or even “just” with the GDPR.
4. Still though: desperately try to compute solutions using those too complex models using non-appropriate data.
5. Figure out that the solution has nothing to do with what you actually need.
6. Hire even more Data Scientists to convert the result into something useful or to use even more complex models to make sense of the computed nonsense.

(At least) Two Shades of Artificial Intelligence

Is there a one-fits-all Artificial Intelligence approach?

- Third AI Winter: Artificial Intelligence (AI) promises to change everything.
- Data Science and (Statistical) AI is mainly a (re-)discovery of Machine Learning methods which were around for at least 20-30 years: plain pattern matching.

There are actually two contradictory types of AI problems - different mindsets:

- Robotics, Industry 4.0 and Internet of Things (IoT), … pattern matching!
- Erratic structures like humans (customers, clients, employees, …), financial markets and meteorological data, … pattern matching?

The AI Model Complexity Paradox

Sometimes one has to accept that there is no universal structure hidden in data available for a specific decision task or business process.

Still, many people blindly (want to) believe in “Dumb AI” (including Deep Learning) and create ever more complex models, which require a complex guesswork of input parameters (“smartly” named Hyperparameter Optimization).

Dumb AI models are entirely non-understandable - and almost grotesquely there are AI gurus developing extremely complex methods to make the un-understandable understandable, i.e. absurdity to the power of absurdity.

Robo Advisory

Robo Advisors vs. RPA

Robotic process automation (or RPA) is an emerging form of business process automation technology based on the notion of metaphorical software robots or artificial intelligence (AI) workers.

Robo Advisors are a class of financial advisors that provide financial advice or investment management online with moderate to minimal human intervention. Digital financial advice is based on mathematical rules or algorithms. These algorithms are executed by (online) software - no human advisor required. The software utilizes its algorithms to automatically allocate, manage and optimize clients' assets.

Robo Advisors vs. RPA - RegTech Issues

Robo Advisors were only used to compute Investment Advice at the inception. Nowadays, RPA and Robo Advisory is sometimes mixed up, i.e.

Robo HR Secretary - teaching software robots to read to automate a part of some recruiting process - Intelligent Process Automation. [Incube Blog]

Chat-bot based Advice: Especially for rather standard insurance contracts!

FMA report on Digitalization: most content on Robo Advisory is Insurance-based.

Robo Financial Advisors - How does AI blend in

There are two main streams of Robo Financial Advisors regarding AI:

- Chatbot-based: standardized insurance products.
- Survey-based or using Interactive Charts: long-term investment management.

AI especially predominant in the Chatbot Advisors (NLP, Deep Text Learning. ...)

Applicability of Chatbots depends on the complexity of the advised products:

- Homeowner's insurance policy: almost no personality information required.
- Car insurance: personality information regarding risky driving style.
- Long-Term Investment (Pension) Plan: comprehensive personality required.

Robo Investment Advisor - Components

Two important sub-modules need to be configured and combined:

- Financial Personality Engines - FiPeE (pronounce like Phoebe).
- Investment Portfolio Kernels - PoKer.

The combination aims at achieving a sound Portfolio-Personality Matching, which should be the core focus of any Robo Investment Advisor.

Focus on Investment Portfolio Kernels in this talk.

However: Financial Personality Engines are definitely more important - as well as the link of FiPeEs to PoKer performances.

Financial Personality Engines - FiPeE

Only a few demographic details required - pseudonymous sufficient (age brackets).

It is important to understand the personality and quantify the psyche of our client:

- Big Five/OCEAN Personality: 5 features on a scale from 1-5.
- Spotify API Artists: a set of 20-50 favorite artists.
- Political Compass 2 features on a scale from -10 to 10.
- Quantitative Risk Assessment (various surveys available).

One may learn a lot from Facebook and especially Cambridge Analytica.

Split into Micro features (e.g. OCEAN) and Macro features (Political Compass).

Investment Portfolio Kernels

Portfolio Kernel (PoKer)

Statistics

Kernel (statistics) - a weighting function used in kernel density estimation to estimate the probability density function of a random variable.

In Non-parametric Statistics, a kernel is a weighting function used in non-parametric estimation techniques.

Portfolio Optimization

Kernel (portfolio) - a function returning relative weights of the assets under consideration, i.e. a weighting function given our available investment budget.

PoKer Models: Gap between Industry and Academia

	Industry	Academia
Data & Preparation	Complex	Simple (e.g. Yahoo! Finance)
Portfolio Models	Simple	Complex
Trading Engine / Backtest	Complex	Simple

Portfolio Kernels – The Basics

We consider a finite set of (liquid) financial assets *n*.

With this one parameter *n*, various PoKers can already be computed, e.g.

- Most simple PoKer: One-over-N - `poker.basic.1overN`
- Another simple one: Drawing uniform pseudo-random numbers and do a budget normalization - optionally with some “lucky number” seed. Simulates the monkey dart-throwing asset management technique [B. Malkiel, 1973].

For our numerical studies we consider (A) all stocks from the S&P 100 as well as (B) a manually selected set of 52 ETFs by S. Boyd, Stanford. Benchmark: S&P 500.

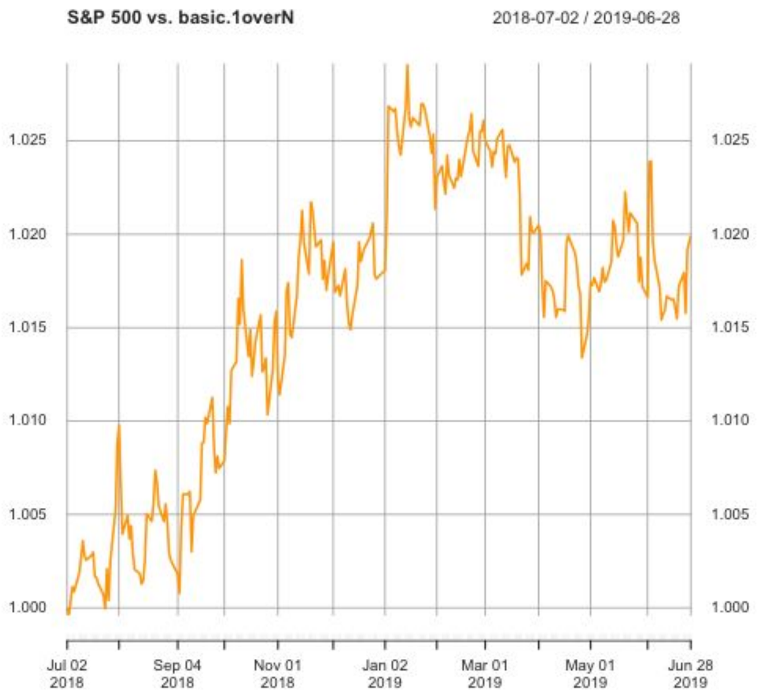
Portfolio Kernels - Monkey Darts

`poker.basic.monkeydarts` - drawing uniform pseudo-random numbers and do a budget normalization - optionally with some "lucky number" seed. Simulates the monkey dart-throwing asset management technique [B. Malkiel, 1973].

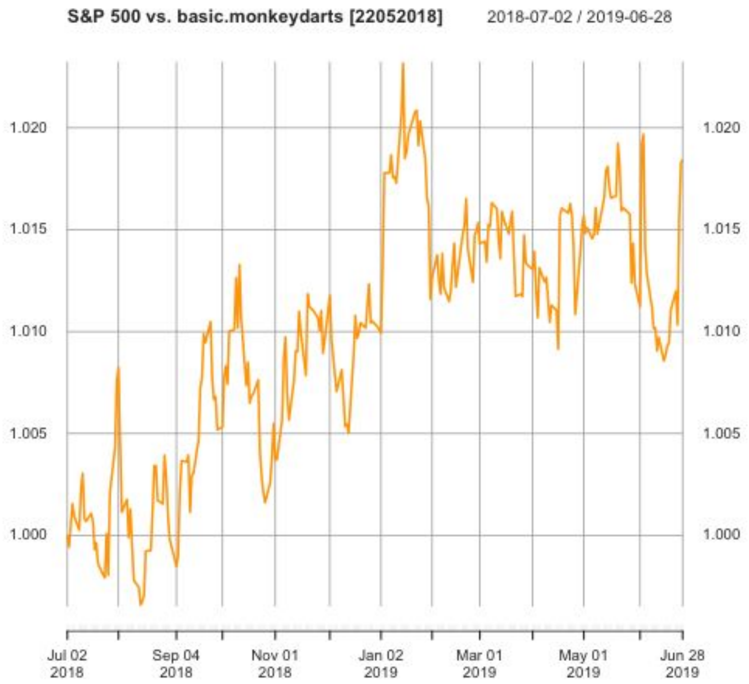
Even in this completely simple PoKer - additional parameters are useful:

- Random Seed.
- Uniform cutoff (between 0 and 1): all weights below the cutoff are set to 0 (before normalization).
- Amount of assets to select (n or %, min/max): how many assets should be minimally/maximally (randomly) selected - all other weights are set to 0.

A first Performance Check



A first Performance Check



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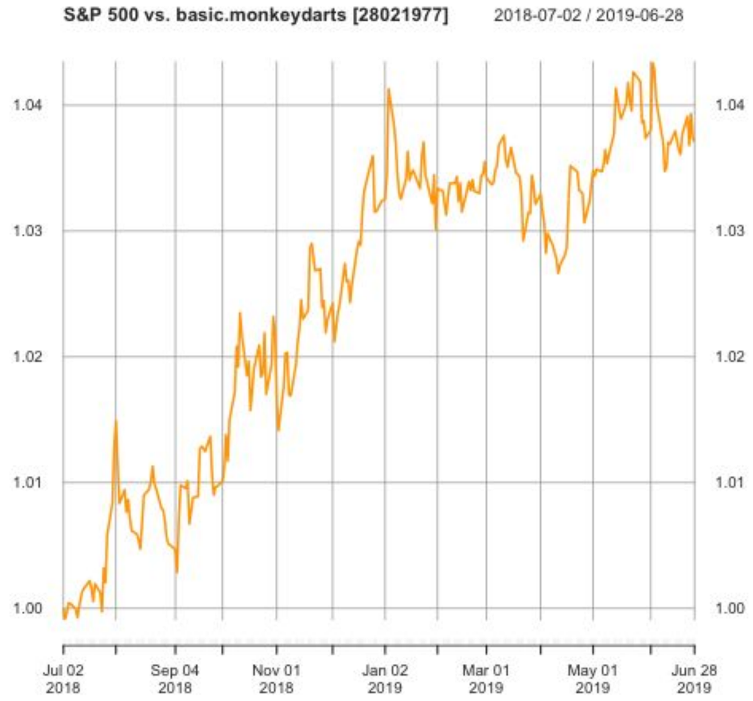


Investment Portfolio Kernels - Model Families

Most people only stick to one certain group of PoKer model families, i.e.

- Finance/Optimization (Markowitz, ERC, Shrinkage/BL, …)
- Finance/Factor Models.
- Operations Research (CVaR/ES optimization, Omega measure, ...)
- Technical Trading (MA Crossovers, RSI 80/20, Alpha Compiler, ...)
- Data Mining (Recommender Engines, …)
- Machine Learning (Supervised (Predictive) Models: Up/Down, …)
- AI & Deep Learning (CNNs, LSTMs, GANs, …)

Robo Advisor tools most likely only implement one model: optimal FiPeE matching?

Investment Portfolio Kernels - Parametrization

Some people tend to underestimate the amount of parameters required per method of each model family.

- Even in simple models there are already a plenty of parameters to estimate.
- MSc Quantitative Finance Masters Theses: often experienced.
- Not even considered yet: rebalancing/transaction structure!

Two instances of model families - both ends of the parameter complexity spectrum:

- Finance/Factor Models: the Ticker-Letter Factor.
- AI & Deep Learning: CNN-based graphical pair investment structure predictor.

Finance/Factor Models

Sometimes unbelievable what Factors people come up with, e.g.

Factor Ticker-Letter: invest into all ticker symbol starting with a certain letter (e.g. the letter A) and generate an equally weighted portfolio out of these stocks.

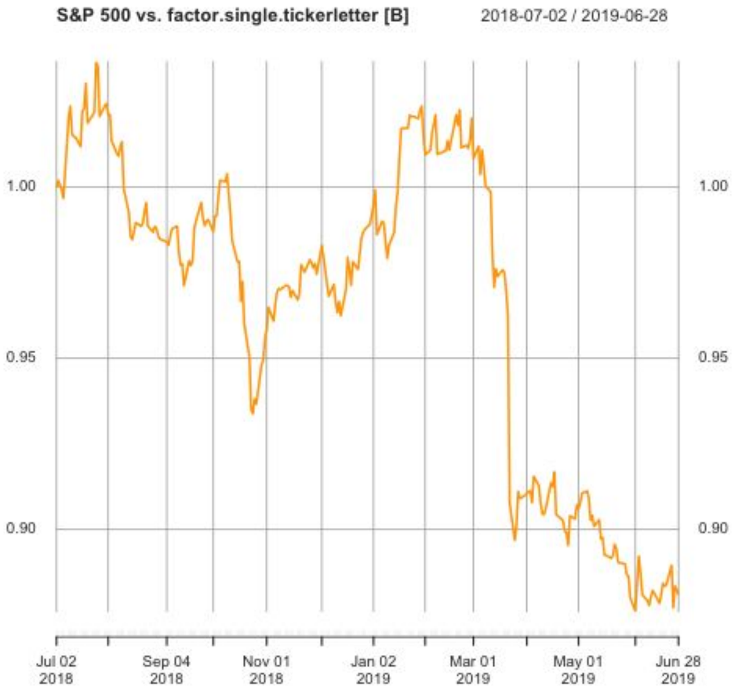
Extension: Replace equal weighting with (inverse) length of company name.

Parameters required:

- Ticker Letter (A-Z)
- Weighting (equal weight/length/inverse length, optional: factor, cap)

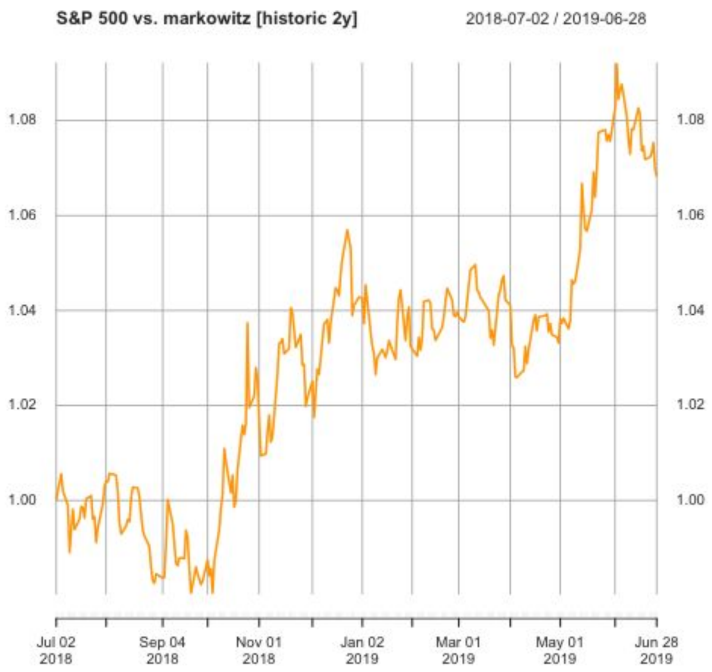
Finance/Factor Models - Performance

Finance/Factor Models - Performance

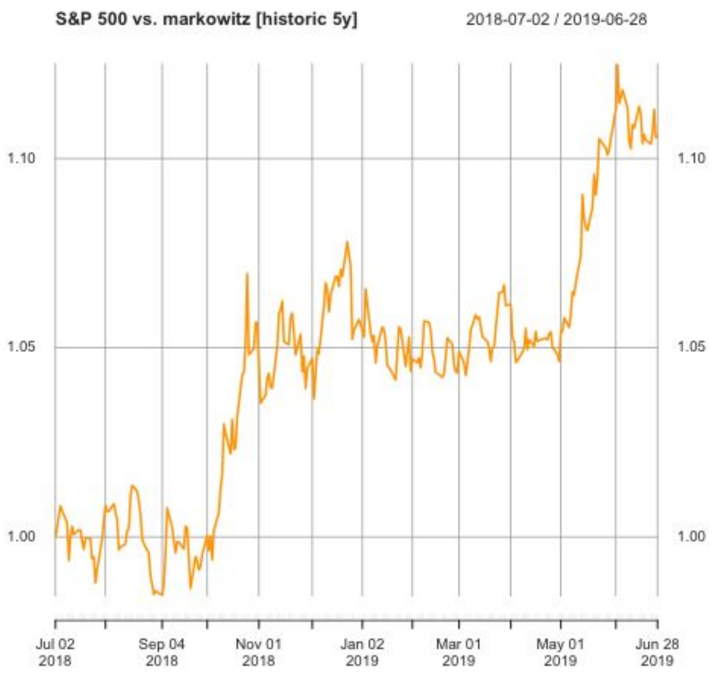


Finance/Factor Models - Performance

Good Old Markowitz?



Good Old Markowitz?



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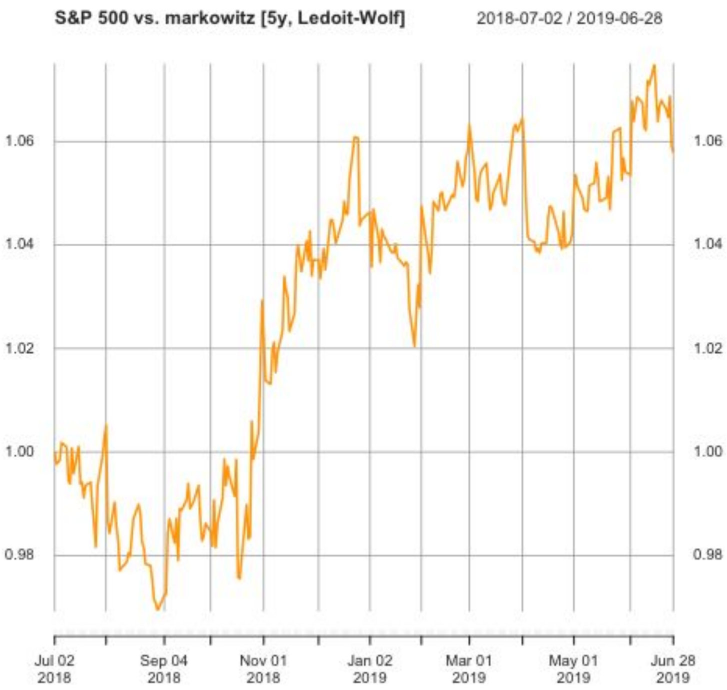


AI & Deep Learning

CNN-based graphical pair investment structure predictor.

- Image-based pair movement analysis - not to confuse with pairs trading.
- Estimated over a set of rather homogeneous assets, e.g. S&P 100.

Two class or five class Deep Learning estimation and prediction model:

- Two class: only whether Asset 1 goes up or down.
- Five class: Asset 1 up, Asset 2 up; 1+, 2-; 1-,2+; 1-,2-; o.

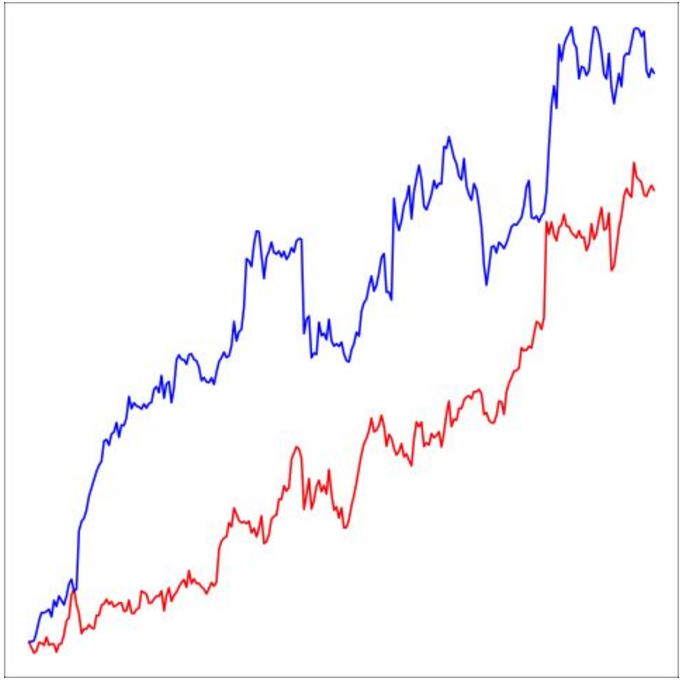
CNN-based graphical pair investment predictor

Main ingredient: Image/Label input generator. A set of heterogeneous parameters for a first version of the image generator:

- Length of historical time series.
- Plain Time Series (yes/no) - normalized.
- Moving Averages (Type P/E/S, Length).
- Other technical indicators in graphs below the main series
  - e.g. those between 0 and 1 (RSI, ...)
  - barcharts.

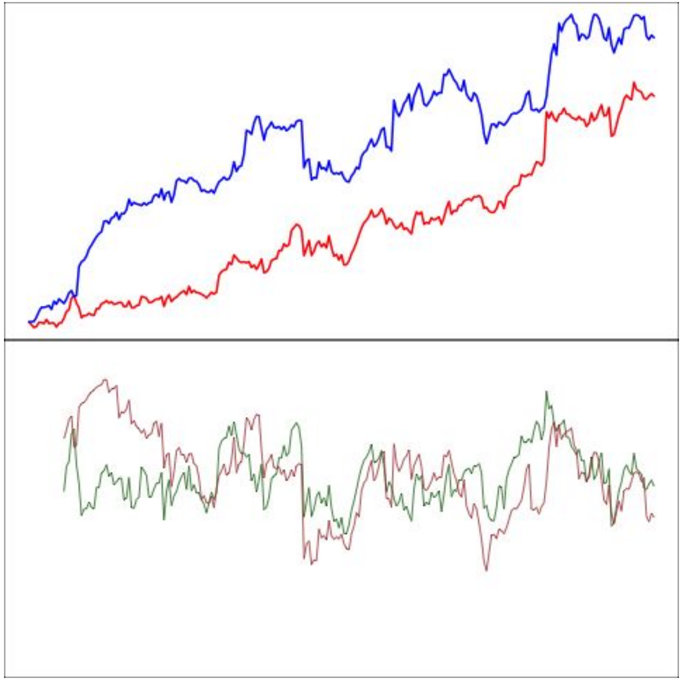
Every series or indicator uses a distinct color to allow the Deep Learner to learn concepts.

Main ingredient: Image/Label input generator



Thousands of images - per asset combination and day generated.

Main ingredient: Image/Label input generator



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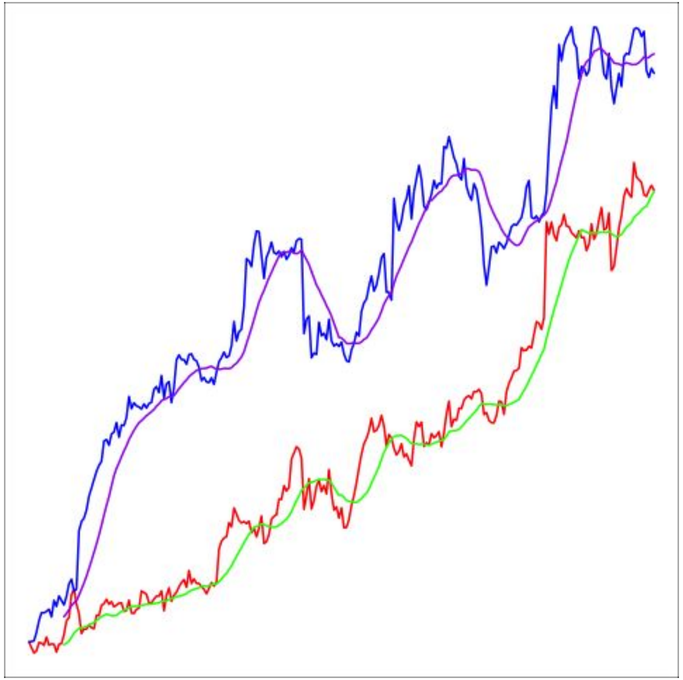

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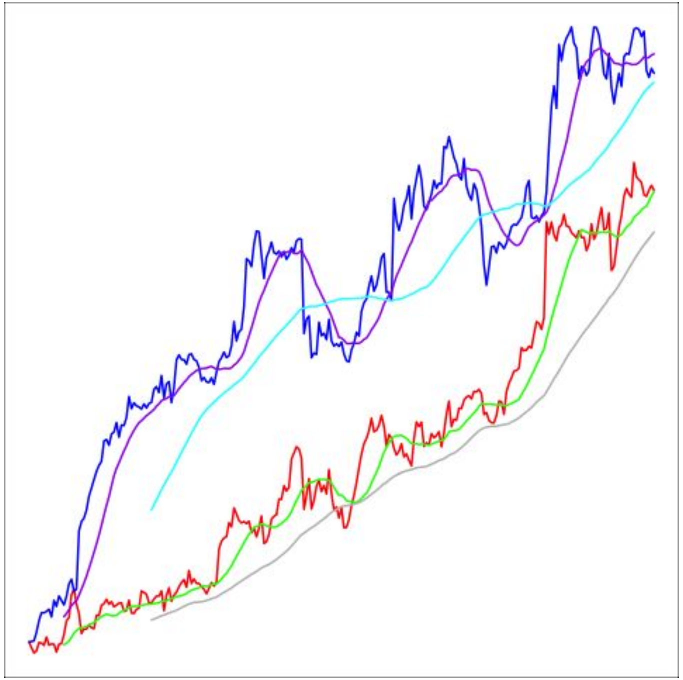

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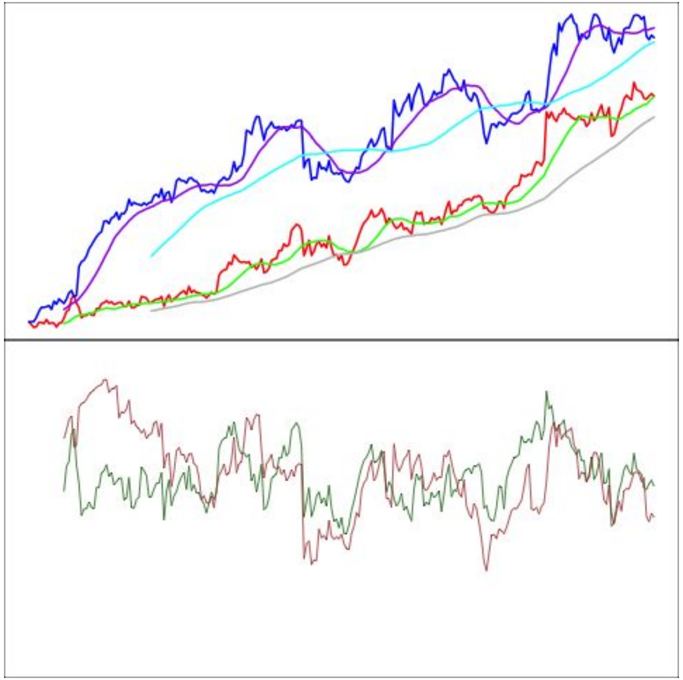

Thousands of images - per asset combination and day generated.

The parameter inferno (AI people love it)

So many parameters before even getting to the Deep Learning process:

- Also included in the meta learning process: Which assets to choose out of the S&P 500 to optimize for a certain pair. Preprocessing using Genetic Algorithms.
- Furthermore important to choose the correct measure to define optimality (Sharpe Ratio, IR, Weighted Mean/ES (current version), Mean/VaR, ...).
- Short-term out-sample-testing: Not relying on the best in-sample model but rather on the best model testing out-of-sample within the last two trading weeks.
- Add a ML learner for understanding optimal in-sample selection and out-of-sample performance.

Intermediate Conclusions

Data- and model-based quantitative portfolio optimization methods are by nature grossly unstable and always perform almost erratic once applied on real markets.

A method which minimizes Variance or maximizes the Sharpe Ratio by model definition might (almost surely) not do so in almost any realistic setting.

Restricting a Robo Advisor to just one portfolio computation family (because your guru likes it) might never satisfy customers in the long run.

Build a flexible, adaptive system based on a set of different model families, also to reduce the Market risk associated not just for the clients but also the providers.

Upcoming Meetings & Contact

Upcoming Meetings

- February 26th, 2020, WU Vienna, Austria: EU H2020 RegTech Meeting
- September 19-20, 2019, WU Vienna, Austria: Second International Conference on Data Science in Finance: http://dsf.academy/conference/

Contact

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