IASD M2 at Paris Dauphine

# Deep Reinforcement Learning

## 10: Applying Deep RL in practice with Kaggle

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# Regime changes are ubiquitous


Very challenging for backward looking portfolio methods

# Standard portfolio theory

**Markowitz and beyond optimizes a risk criteria based on past data**

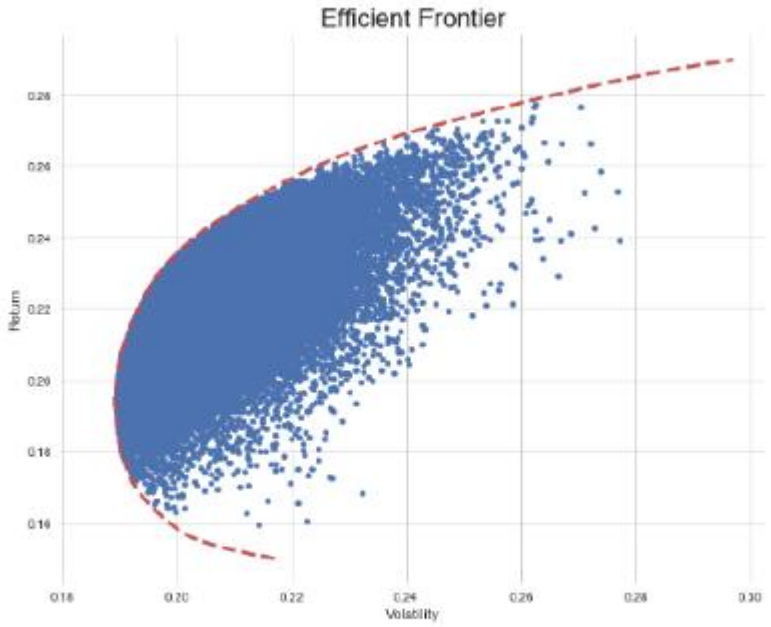



Figure 1: Markowitz efficient frontier for the GAFA: returns taken from 2017 to end of 2019

denote by $w = (w_1, ..., w_l)$ the allocation weights

$\mu = (\mu_1, ..., \mu_l)^T$ be the expected returns

$\Sigma$ the matrix of variance covariances

$r_{min}$ be the minimum expected return

$$\underset{w}{\text{Minimize}} \quad w^T \Sigma w \tag{1}$$

$$\text{subject to} \quad \mu^T w \geq r_{min}, \sum_{i=1...l} w_i = 1, 1 \geq w \geq 0$$

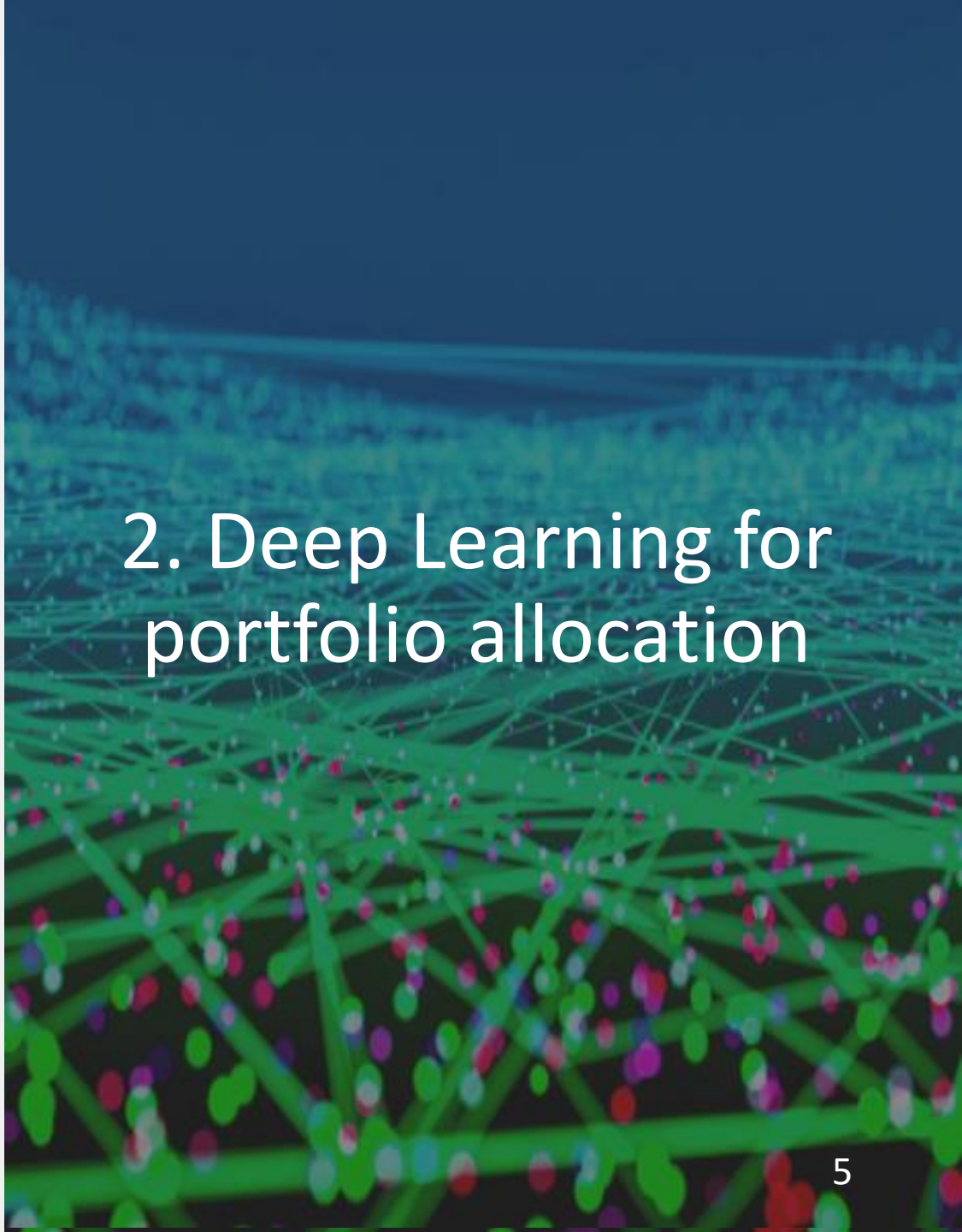
# Why standard portfolio methods fail?

- **Standard portfolio methods rely:**
  - **on simplified settings (easy solving for convex optimization),**
  - **on few parameters (returns, volatility, correlation).**

- **By construction, these methods:**
  - **uses past data that are non stationary,**
  - **do not connect market data and context to allocation,**
  - **do not aim at capturing regime change.**

Standard methods do not perform so well in out of sample data. The question is: can we do better?

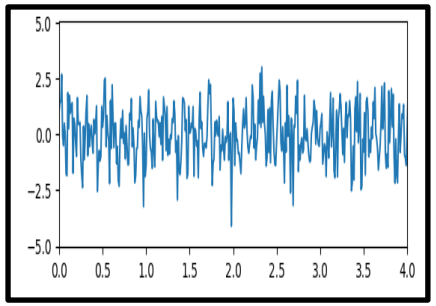
A modern approach to Markowitz portfolios

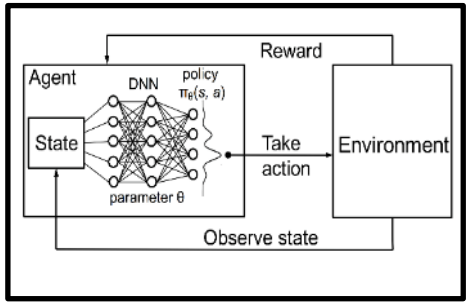


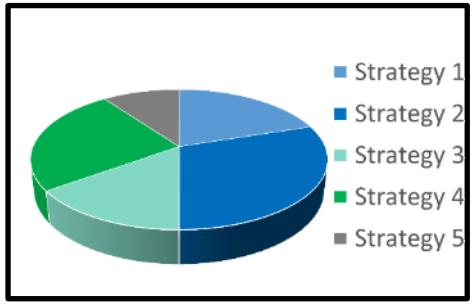
## 2. Deep Learning for portfolio allocation

# Deep Learning Portfolios

1.Data analysis → 2. Model free DRL → 3. Portfolio allocation



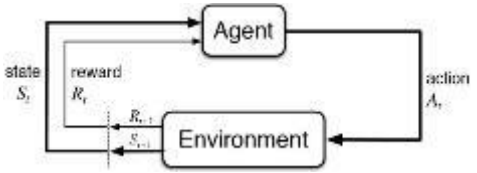

- Enriching the data set
  - Portfolio data : prices series of assets
  - Contextual data : volatility, sentiment, risk aversion, economic variables..

- Usually, data is fed directly into a DL algorithm, and allocation is decided, based on some reward function. Lots of choices :
  - Auto encoders
  - RNN
  - Convolution network…

# Dynamic allocation based on Deep Reinforcement Learning

## Reinforcement Learning (RL)

RL consists in **finding the optimal action** (the portfolio allocation) **according to state** (financial information) **given a reward** (the best net portfolio final performance).




$$A_t^* = \pi(S_t)$$ ?

RL **learns** and **finds the optimal portfolio allocation** in an interactive environment **by trial and error** using feedback from actions and rewards.

## Deep RL (DRL)

DRL uses deep learning in RL to find the function that maps states to optimal action.

$$A_t^* = \pi(S_t)$$

Deep networks can represent complex functions thanks to non-linear activation and multiple layers (universal approximation).

DRL has been **successfully applied in challenging problems** (games such as Go (Google), Poker (Facebook), or autonomous driving) to find solutions that perform better than human.

# The mathematical problem

We have a portfolio whose daily NAV is $(P_t)$. Portfolio is composed of $n$ assets whose daily returns are $R_t = \left[r_t^0, ..., r_t^n\right]$. Transaction assumed proportional to portfolio size and denoted by $b$

- **States** $S_t$: strategies past returns + volatility + correlation + additional contextual variables (other markets, macro, options, etc..)
- **Action** Reallocation at the end of each day $W_t(S_t) = (w_t^0, ..., w_t^n)$
- **Reward** Sharpe ratio at the end of the training period $SR(T) = \frac{Return(P)}{Volatility(P)}$

Find best function: $\pi : S_t \mapsto W_t$ to maximize $SR(T)$. We parametrize the deep function by $\pi(\theta)$

# The DRL portfolio manager

We hire a smart portfolio manager- Mr. Deep Reinforcement Learning. **Mr. DRL** will observe multiple variables and give us daily advice on **the portfolio weights**

**Algorithm 1** Portfolio allocation using Deep Reinforcement Learning (DRL)

**Input:** $S_t$, state space including
past performance, volatility and other multiple financial data
**Output:** Daily portfolio allocation decisions $\pi : S_t \mapsto W_t$

Initialize policy function $\pi_0$
**while** Not converged **do**
    Initialize $P_0 = \$1,000,000$
    **for** t=0,...,T **do**
        Portfolio manager DRL observes $S_t$ and outputs $W_t = \pi_\theta(S_t)$
        Calculate next day portfolio value
$$P_{t+1} = P_t : \times \left(1 + W_t^T R_T - \mu^T |W_t - W_{t-1}|\right)$$
    Compute Training Sharpe ratio $SR(T) = \frac{(P_T/P_0 - 1)^{250/T}}{Std(P_t/P_{t-1} - 1) \times 250}$
    Update policy weight $\theta_\pi$

# Link with previous portfolio methods

## Similarities

It has a reward that takes into account both risk and returns.
It is an optimization.
It includes Markowitz and Black Litterman. Why?

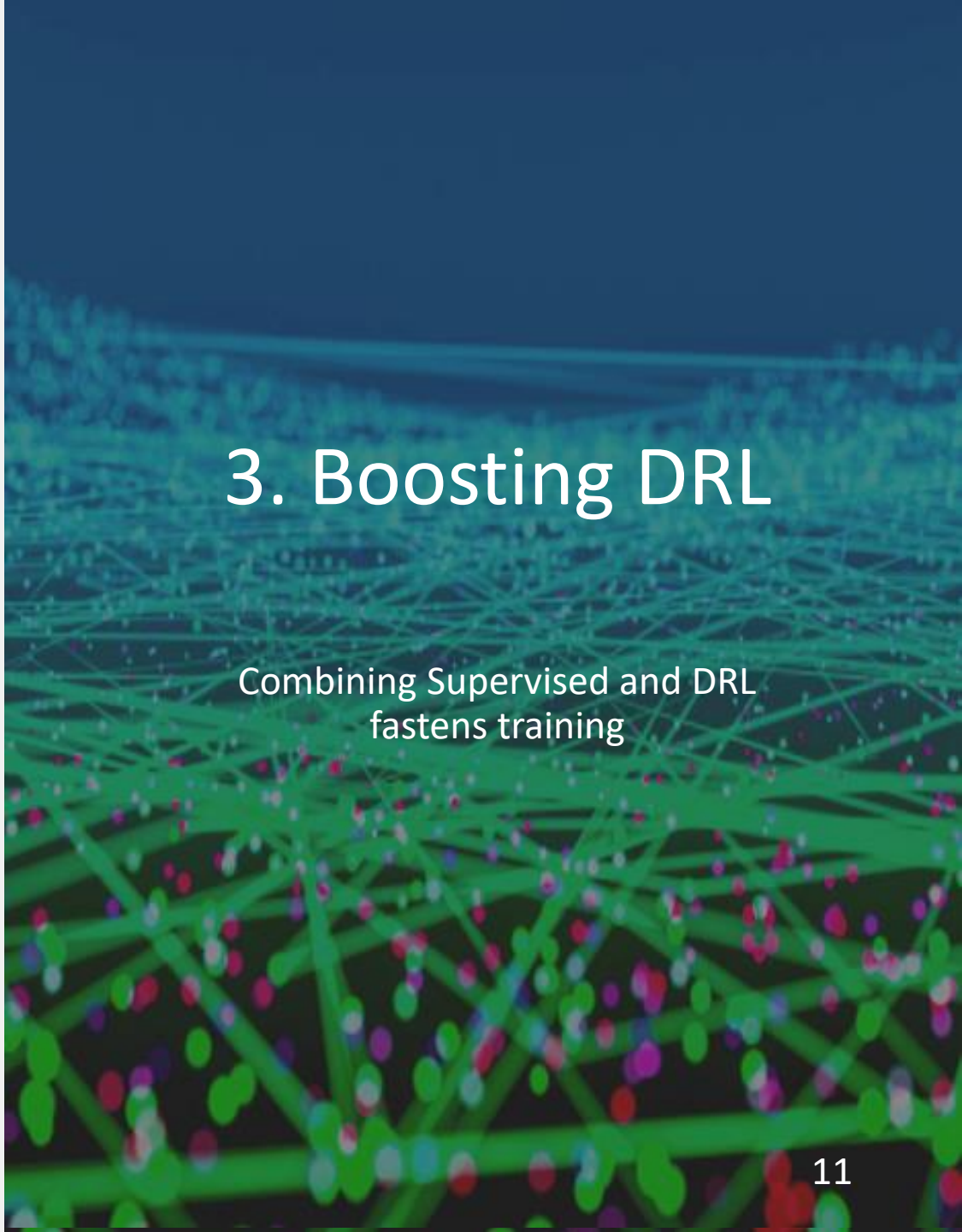
Simply by taking very simple states like returns and variance.

## Differences

Conceptually, we try to find a function rather just parameters.
Optimization is strongly non convex.
By design, it connects allocation to multiple financial data.

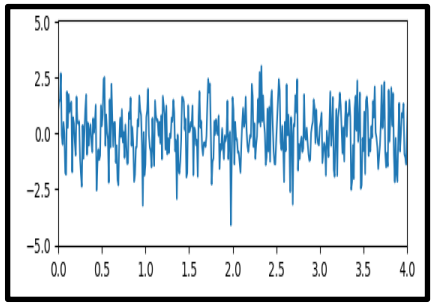
Stability and sensitivity to noisy data is an issue

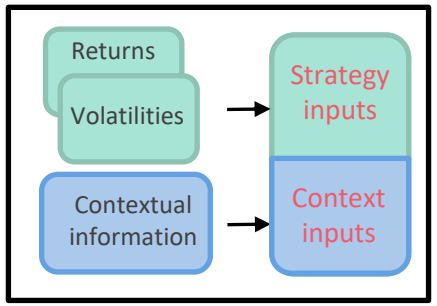
Using supervised predictions is closer to human decision and accelerate training

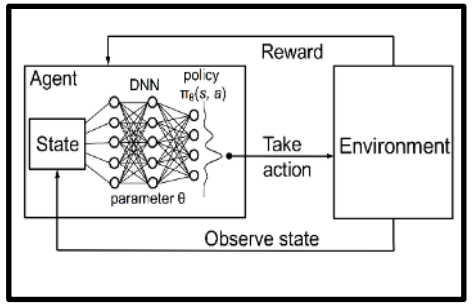


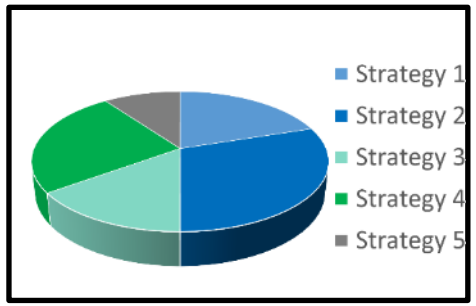
# Methodology with boosting DRL

1.Data analysis → **2. State augmentation** → **3. Regime prediction** → 4. Model free RL → 5. Portfolio allocation



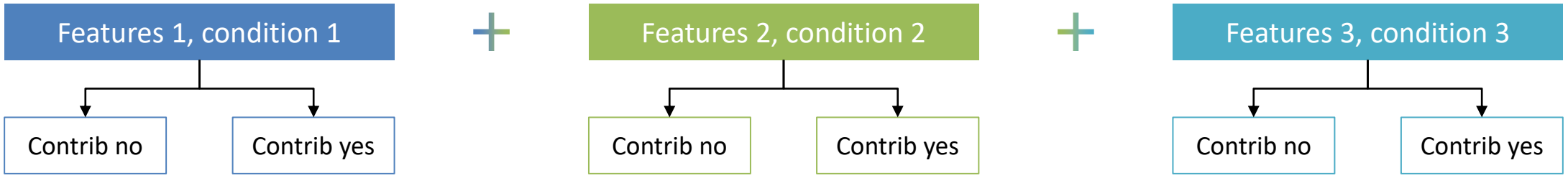



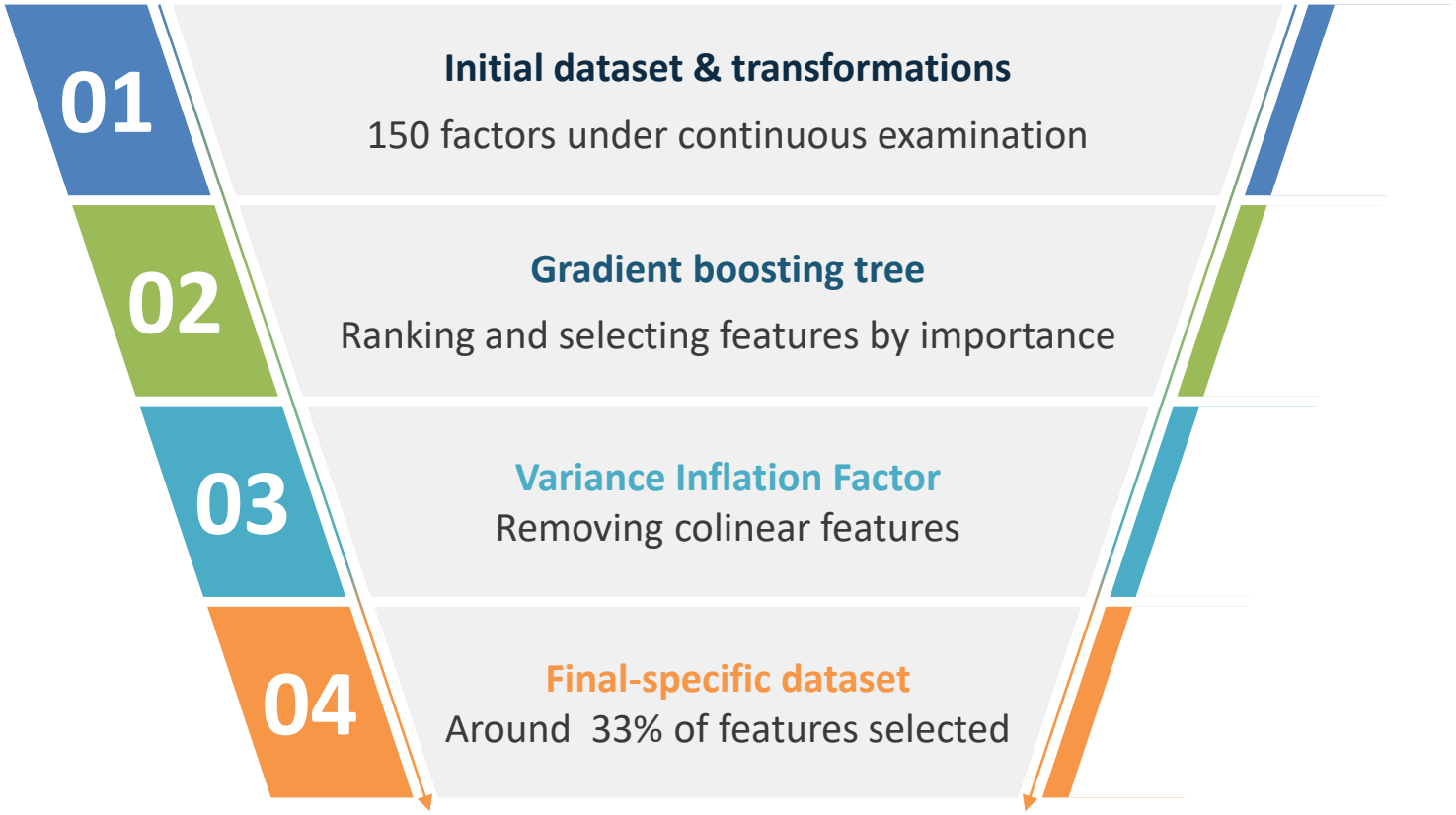

- Data is prepared to create list of features, that are used to predict regimes
- We identify two regimes:
  - Bull regime: quantile 65% over 2 months
  - Bear regime: quantile 15% over 2 months
- The regimes are predicted independently with two distinct models

# Regime prediction

Estimating the likelihood of market regimes is a data classification problem.
We use Gradient-Boosting-Tree models (e.g. XGBoost, LightGBM) over other approaches (e.g. deep learning) since they dominate many ML competitions for classification problems and Kaggle competitions



# Robust filtering of features




But interpretability and transparency of the model is still an issue

# Interpretability with Shapley values

- Researchers at Microsoft Research have proposed an approach to interpret model predictions using the Shapley values.
- The Shapley value is a concept based on game theory and is based on the work from Lloyd Shapley, who won the Nobel Prize in Economics for it in 2012.
- Back in the 1950s, Lloyd Shapley tried to fairly allocate the total gain to players in a cooperation game. The concept of fairness in this instance was defined by three main axioms:
  - efficiency : the sum of the gains attributed to each players should be equal to the total gains,
  - symmetry : if one player can replace another one then they should get the same reward,
  - linearity - a player that has a bigger impact than all other players in all games should receive a bigger reward.

# Kaggle challenge