WUTIS

MACHINE LEARNING PORTFOLIO ALLOCATION

Systematic Trading

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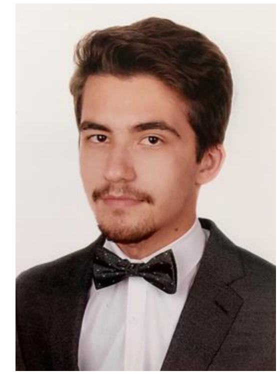

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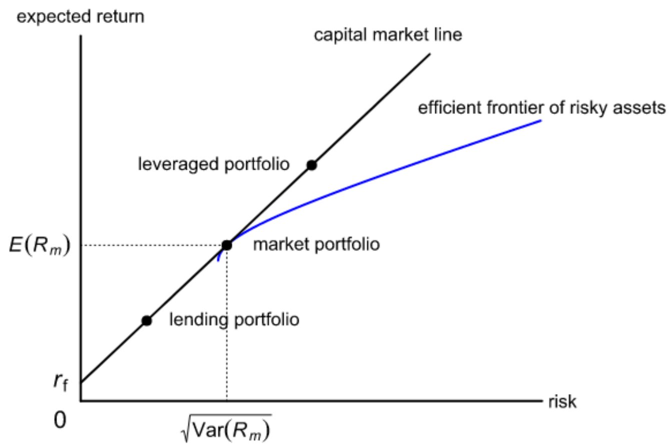
Problem

… and how we try to solve it

In a world where the **Capital Asset Model** holds true...

- Investors will only put their money into the market portfolio and the risk free asset
- But how should one allocate their money?
  - risk averse investors will invest (all) their money in the risk free asset
  - risk loving ones will buy as much of the market portfolio as possible
  - maybe even borrow at the risk free rate
- How to account for an individual risk sentiment?



What is the perfect weight?

- Master equation:

$$w_t^* = \frac{E[r_t - r_t^f]}{\gamma \cdot var[r_t|\mathcal{F}_{t-1}]}.$$

- How did we get here?
  - Pinelis, M., & Ruppert, D. (2020). Machine Learning Portfolio Allocation

Aim and data

AIM

Find economically & statistically significant gains by using ML to dynamically allocate b/w the market index and the risk-free asset

- Modelling market price of risk as a function of lagged dividend yields and volatilities;
- Forecasting direction of next month's excess return and constructing dynamic volatility (risk) estimator that is optimized with a ML model.

DATA

- Monthly data from Kenneth French's website on the market return (Mkt) and risk-free asset return (Rf);
- Daily returns are retrieved to compute the realized volatility;
- Data on the payout yield from Michael Robert's website.

Base Model and Linear Model

W U T I S

Base:

- Expanding window estimate of the reward (arithmetic mean)
- The volatility t is computed as the realized volatility for the past month

Linear:

- Linear regression estimation of monthly excess returns,
- f as a function of the lagged payout yields x and risk-free rates rf.
- Volatility is lagged as in the Base Model.

$$f_t = \alpha + \sum_{i=1}^{9} \beta_i x_{t-i} + \sum_{j=10}^{14} \beta_j r^f_{t-j+9} + \epsilon_t$$

- Residuals are serially correlated,
- therefore modelled as an ARIMAX process where zt is the noise

$$\epsilon_t = \phi_1 \epsilon_{t-1} + \cdots + \phi_p \epsilon_{t-p} + \theta_1 z_{t-1} + \cdots + \theta_q z_{t-q} + z_t,$$

RandomForestRegressor: Risk premia forecasting

- Using a Machine Learning technique called Random Forests we calculate the expectation of excess returns

  (the reward part of the master equation): $$w_t^* = \frac{E[r_t - r_t^f]}{\gamma \cdot var[r_t|\mathcal{F}_{t-1}]}.$$

- Random Forests are an ensemble machine learning algorithm that works by creating a "forest" of random trees/decision trees

- The random forest works by taking the majority vote of all decision trees

- This is achieved using a Random Forest Regressor which takes in the risk free rate and net annualized payout yields at time t-1 and calculates an estimate for the expected return;

- In order to beat the market we expect an accuracy rate of 55% which will be enough to provide a substantial alpha.

RandomForestClassifier: Volatility window forecasting

Risk-reward timing involves adjusting portfolio allocation according to beliefs about future asset returns, and future volatilities. Therefore we resort to:

- Employing a separate Random Forest model to predict the optimal parameters of a volatility estimator: specifically, estimating the volatility reference window as a function of lagged volatilities.
- In order to beat random guessing the lookback length, N, which contains 4 possible values we expect an accuracy of our Random Forest model of 40% (instead of 25%).
- Using the lookback length N we can calculate a variable volatility for time t which will either maximize volatility (when we want to avoid losses) or minimize volatility (when we are confident that we will make money).

Thank you!