Overview of the warm-up project

- Best writing award: LIU Changxi, SUN Yifei, WANG Liangshu, YU Yang
- Best technique award: LI Aoran, MA Yijia, WENG Langting, ZHOU Tianying
- Best overall award: CHEN Hongxi, DING Guobin, QIAO Guan, XUE Wenjing
- Congratulations! You can gain some bonus for your grades!
- By the way, the grade of the warm-up project does not count a lot for the final score; you still have the opportunity to earn a bonus during the following projects!
- Besides, please submit your project reports / review / rebuttal in time, otherwise, you may lose some point.

Introduction to "Empirical Asset Pricing via Machine Learning"

By

Shihao Gu University of Chicago

Bryan Kelly
Yale University, AQR Capital Management, and NBER

Dacheng Xiu
University of Chicago Booth School of Business

Background

- ➤ Risk premium is difficult to measure: market efficiency forces return variation to be dominated by unforecastable news that obscures risk premiums.
- Machine learning accommodates a far more expansive list of potential predictor variables, which enables gains that can be achieved in prediction and identifies the most informative predictor variables.

This paper uses machine learning methods to predict asset's excess return->regression problem

- Linear models: OLS, elastic net
- Dimension reduction: PLS, PCR
- Generalized linear model
- Tree models: Gradient boosted regression tree, random forest
- Neural networks

Experiment preparation

Data and feature

Monthly total individual equity returns for all firms listed in NYSE, AMEX, NASDAQ. ~30,000 stocks over 60 years from March 1957 to December 2016.

Characteristics including:

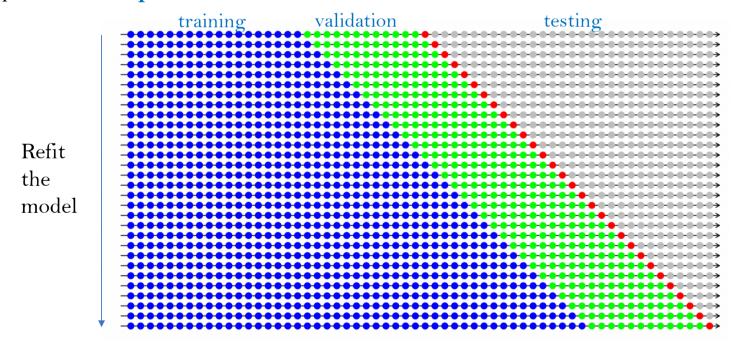
- 94 firm characteristics
- 8 macroeconomic predictors
- 74 industry dummies

More details are described in Sec. 2.1

Experiment preparation

Divide the 60 years of data into 18 years of training sample (1957-1974), 12 years of validation sample (1975-1986), and the remaining 30 years for out-of-sample testing (1987-2016).

Adopt a recursive performance evaluation scheme.



More details are described in Sec. 2.1

Objective function => Tune the model's parameter on the training set

Model's Label, Mean Squared Error (MSE) loss prediction i.e., real return $\mathcal{L}(\theta) = \frac{1}{NT} \sum_{i=1,\dots,N: \text{ stock index}} \sum_{t=1,\dots,T: \text{ month index}} i = 1,\dots,N: \text{ stock index}$ $t = 1,\dots,T: \text{ month index}$ Basic formula:

Evaluation function =>Evaluate the models' performance on the testing set

 \triangleright Out-of-sample R^2

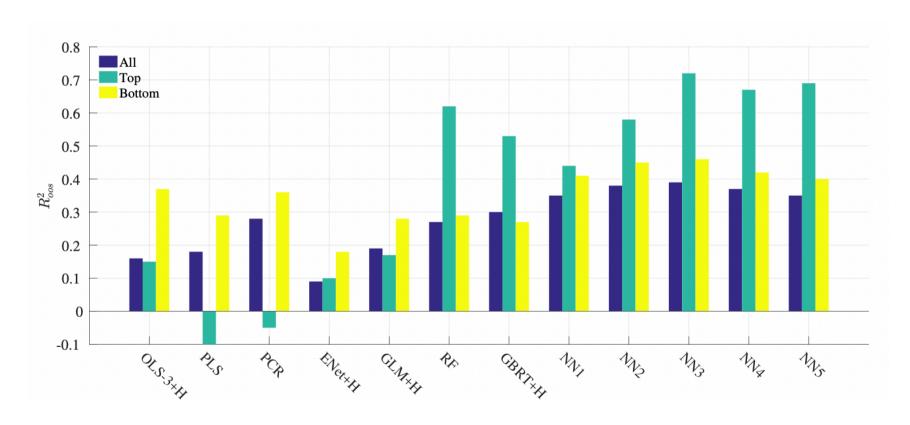
Basic formula:

Label, Model's i.e., real return prediction
$$R_{\text{oos}}^{2} = 1 - \frac{\sum_{(i,t) \in \mathcal{T}_{3}} (r_{i,t+1} - \widehat{r_{i,t+1}})^{2}}{\sum_{(i,t) \in \mathcal{T}_{3}} r_{i,t+1}^{2}}$$
Testing set

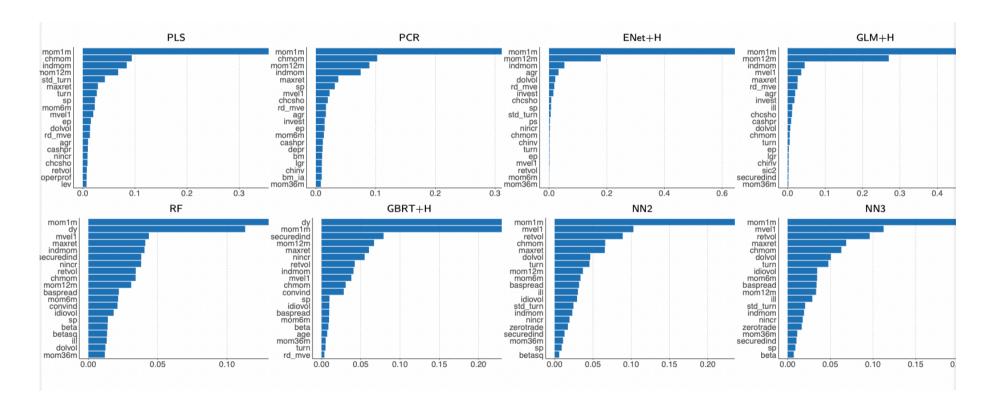
Model's

Some results:

• Individual Stock Returns Prediction



Characteristic Importance



Requirements for replication

- Data Preparation (Adopt the recursive performance evaluation scheme)
- Model selection
 - > Replicate at least 6 models (Hints of parameter chosen are presented in the paper).
- Results analysis
 - ➤ Variable importance
 - ➤ Model performance comparison and analysis
- ☐ You do not need to replicate the results of section 2.4: Portfolio forecast.
- Supplementary material can be helpful to you.