Machine learning for empirical asset pricing and risk premia forecasting

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Contents

1 Introduction

Relative to traditional empirical methods in asset pricing, machine learning accommodates a far more expansive list of potential predictor variables, as well as richer specifications of functional form. Machine learning methods can be successfully applied to the two canonical problems of empirical asset pricing: predicting returns in the cross section and time series.

The literature has accumulated a staggering list of predictors that various researchers have argued possess forecasting power for returns. The number of stock-level predictive characteristics reported in the literature numbers in the hundreds and macroeconomic predictors of the aggregate market number in the dozens. Additionally, predictors are often close cousins and highly correlated. Traditional prediction methods break down when the predictor count approaches the observation count or predictors are highly correlated. With an emphasis on variable selection and dimension reduction techniques, machine learning is well suited for such challenging prediction problems by reducing degrees of freedom and condensing redundant variation among predictors.

Moreover, there is ambiguity regarding functional forms through which the high-dimensional predictor set enter into risk premia. Should they enter linearly? If nonlinearities are needed, which form should they take? Must we consider interactions among predictors? Such questions rapidly proliferate the set of potential model specifications.

Three aspects of machine learning make it well suited for problems of ambiguous functional form. The first is its diversity. As a suite of dissimilar methods it casts a wide net in its specification search. Second, with methods ranging from generalized linear models to regression trees and neural networks, machine learning is explicitly designed to approximate complex nonlinear associations. Third, parameter penalization and conservative model selection criteria complement the breadth of functional forms spanned by these methods in order to avoid overfit biases and false discovery.

Moreover, macroeconomic signals seem to substantially improve out-of-sample performance, especially when non-linear features are incorporated via machine learning.

2 Literature Review

Main references:

Rapach et al. (2019), Weigand (2019), Kozak et al. (2019),Freyberger et al. (2018), Feng et al. (2018a), Messmer (2017), Liew and Mayster (2017), Gu et al. (2019b), Popescu (2019), Kolanovic and Krishnamachari (2017), Messmer and Audrino (2017), Feng et al. (2018b) and Feng et al. (2019a), Bianchi et al. (2019), Chen et al. (2019)

Other relevant references include:

Simonian et al. (2019), Brogaard and Zareei (2018), Li et al. (2020), Feng et al. (2019b), Bryzgalova et al. (2019a) and Bryzgalova et al. (2019b), Choi et al. (2019), Harvey and Liu (2019), Kozak et al. (2019), Gu et al. (2019a)

3 Forecasting approaches

3.1 To be added

4 Metrics for assessing forecast performance

There are many measures available in the forecasting literature for evaluating the performances of forecasting method, as described in Makridakis et al. (2019), Makridakis et al. (2018), and Hyndman and Athanasopoulos (2019). A comprehensive list of metrics is presented in Botchkarev (2019) and Gasthaus et al. (2019). Other references on such metrics include Ryll and Seidens (2019), Petropoulos et al. (2018), and Siliverstovs (2017), de Kok (2017), Fan et al. (2017), and Hsiao and Wan (2014), Cheng et al. (2019), Chiu et al. (2019), Granziera and Sekhposyan (2019), Gibbs (2017), Hyndman and Koehler (2006), Jin et al. (2015), Kim and Durmaz (2012), and Samuels and Sekkel (2017).

4.1 Performance measures for point forecasts for M4 competition

For M4 competition it was decided to use the average, referred to as the overall weighted average (OWA), of two of the most popular accuracy measures:

- symmetric mean absolute percentage error sMAPE

$$sMAPE \triangleq \frac{2}{h} \sum_{t=n+1}^{n+h} \frac{\left|Y_t - \widehat{Y}_t\right|}{|Y_t| + \left|\widehat{Y}_t\right|} * 100\,()$$

- mean absolute scaled error M

$$sMAPE \triangleq \frac{1}{h} \frac{\sum_{t=n+1}^{n+h} \left|Y_t - \widehat{Y}_t\right|}{\frac{1}{n-m} \sum_{t=m+1}^{n} |Y_t - Y_{t-m}|}$$

where Y_t is the value of the time series at point t, $\widehat{Y}_t$ the estimated forecast, h the forecasting horizon, n the number of the data points available in-sample, and m the time interval between successive observations considered for each data frequency, i.e., 12 for monthly, four for quarterly, 24 for hourly and one for yearly, weekly and daily data.

The first measure uses percentage errors that are scale independent, intuitive to understand and part of an everyday vocabular. The second measure aims to correct some potential problems of the first and to provide an alternative with better mathematical properties Franses (2016). For instance, the proposed MASE has a defined mean and a finite variance, is scale-independent and can be computed for a single forecast horizon, being less than one if it arises from a better forecast than the average one-step Naive S forecast (Forecasts are equal to the last known observation of the same period) computed in-sample, and vice-versa

The OWA of sMAPE and MASE was computed by first dividing their total value by the corresponding value of Naive 2 (random walk model, seasonally adjusted, if needed) to obtain the relative sMAPE and the relative MASE, respectively, and then computing their simple arithmetic mean.

4.2 Performance measures for prediction intervals for M4 competition

The M4 Competition adopted a 95% prediction interval (PI) for estimating the uncertainty around the point forecasts. The performances of the generated PIs were evaluated using the Mean Scaled Interval Score (MSIS) described in Makridakis et al. (2019)

5 Practical Info

5.1 Software

The recommended software packages:

- R version 3.6.2 or 3.6.3
- Python latest version (currently 3.8.2) or Python 3.7.6 or Anaconda Python 3 latest version (currently 2020.02 for Python 3.7)
- RStudio Desktop Open Source latest version (currently 1.2.5042)
- PyCharm Community Edition latest version (currently 2020.1)
- LyX latest version (currently 2.3.4.4)
- JabRef latest version (currently 5.0)
- TexLive latest version (currently 2020)
- R packages (to be discussed)
- Python packages (to be discussed)
- source control repository (such as Git)

5.2 Datasets

The following datasets are suggested

Table 1: Daily data sets

Name	Description	Name	Description
BCOMTR	Bloomberg Commodity Index Total Return	RU20VATR	iShares Russell 2000 Value ETF
HFRIFWI	HFRI Fund Weighted Composite Index	RUMCINTR	iShares Russell Mid-Cap ETF
LBUSTRUU	Bloomberg Barclays US Aggregate Bond Index	RUMRINTR	iShares Micro-Cap ETF
LG30TRUU	Bloomberg Barclays Global High Yield Total Return Index Value Unhedge	RUTPINTR	iShares Russell Top 200 ETF
LMBITR	Bloomberg Barclays Municipal Bond Index Total Return Index Value Unhedged USD	S5COND	S&P 500 Consumer Discretionary Index
NDDUE15X	Amundi MSCI Europe Ex UK Ucits ETF Dr	S5CONS	S&P 500 Consumer Staples Index
NDDUJN	MSCI Japan Index	S5ENRS	S&P 500 Energy Index
NDDUNA	iShares MSCI North America UCITS ETF	S5FINL	S&P 500 Financials Sector GICS Level 1 Index
NDDUPXJ	MSCI Pacific ex Japan UCITS ETF	S5HLTH	S&P 500 Health Care Index
NDDUUK	iShares MSCI UK ETF	S5INDU	S&P 500 Industrials Index
NDDUWXUS	MSCI World ex USA total net return	S5INFT	S&P 500 Information Technology Index
NDUEEGF	SPDR MSCI Emerging Markets UCITS ETF	S5MATR	S&P 500 Materials Index
RU10GRTR	iShares Russell 1000 Growth ETF	S5RLST	S&P 500 Real Estate Index
RU10VATR	iShares Russell 1000 Value ETF	S5TELS	S&P 500 Communication Services Index
RU20GRTR	iShares Russell 2000 Growth ETF	S5UTIL	S&P 500 Utilities Index
RU20INTR	Russell 2000 Total Return	SPXT	Proshares S&P 500 EX Technology ETF

Table 2: Monthly data sets

Name	Description	Name	Description
IBXXSHY1	iShares 0-5 Year High Yield Corporate Bond ETF	M2USEV	MSCI USA Enhanced Value Index
IDCT20RT	ICE U.S. Treasury 20+ Year Bond Total Return Index	M2USRWGT	MSCI USA Risk Weighted Index
LBUSTRUU	Bloomberg Barclays US Agg Total Return Value Unhedged USD	M2USSNQ	MSCI USA Sector Neutral Quality Index
LC07TRUU	Bloomberg Barclays U.S. Universal Total Return Index Value Unhedged	MID	S&P 400 Mid Cap Index index
LD01TRUU	Bloomberg Barclays 1-3 Yr Credit Total Return Index Value Unhedged US	MXEA	MSCI EAFE Index
LT01TRUU	Bloomberg Barclays US Treasury 1-3 Year Index	MXEF	MSCI Emerging Markets Index
LUICTRUU	Bloomberg Barclays U.S. Intermediate Credit Total Return Index	MXUSMVOL	MSCI USA Minimum Volatility Index
LULCTRUU	Bloomberg Barclays U.S. Long Credit Index	MXWD	MSCI All Countries World Index
M1CXBRU	iShares Core MSCI International Developed Markets ETF	MXWOUIM	MSCI All Countries World Index
M1USMVOL	MSCI USA Minimum Volatility (USD) Index	NDDUUS	MSCI Daily Total Return Net USA USD Index
M2US000$	iShares Edge MSCI USA Momentum Factor ETF	SPX	S&P 500 Index

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Appendix A: First Appendix

Just a placeholder for now