# A cat is a cat and a Euro is a Euro, not (?)[1]

## An assessment of AI/ML methods applied to Asset Allocation

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[1] Quote: 'a Euro is a Euro' by Willem F. Duisenberg, ECB Press Conference, 4th February 1999.

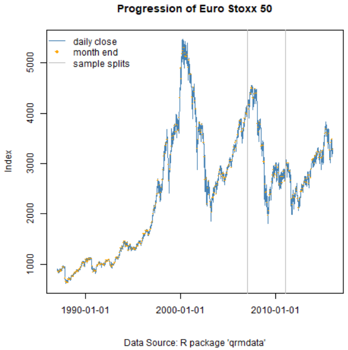
# Introduction

- First wave of ML-/AI methods applied to problems in finance dates back to the 1990s and was inspired by applications in the field of engineering (quality control), *e.g.*, Karlruher Ökonometrie Workshops, see Bol, Nakhaeizadeh, and Vollmer 1994; Bol, Nakhaeizadeh, and Vollmer 1996; Bol, Nakhaeizadeh, and Vollmer 2000.
- Second wave (attempt) of applying ML-/AI-method to problems in finance since the mid 2010s and was motivated by successful applications in image/video classification, NLP, *etc.*
- What has changed in the interim?
  1. Computational capacity.
  2. Count of data records/observations.
  3. Access to 'ready-made' software implementations, *e.g.* Chollet and Allaire 2018.
- Will this second wave last and form a new paradigm?[2]

[2] Kuhn 1970.

# The Challenge
## Euro Stoxx 50 Index

- Binary classification:
  Predict sign of subsequent monthly returns (aka as *label*).
- Use trailing daily observations for defining explanatory variables (aka as *features*).
- Sample Split:
  1. Training:
     31.01.1987 – 31.12.2006.
  2. Validating:
     31.01.2007 – 31.12.2010.
  3. Testing:
     31.01.2011 – 31.12.2015.



# The Challenge

## The Peer Models/Methods

1. Linear Discriminant Analysis: Fisher 1936
2. k-Nearest Neighbours: Hart 1968
3. Support Vector Machines: Vapnik and Lerner 1963; Vapnik and Chervonenkis 1974; Vapnik 1995; Vapnik, Golowich, and Smola 1997
4. Classification Trees: Breiman et al. 1984
5. Random Forest: Kleinberg 1990; Kleinberg 1996; Kleinberg 2000; Ho n.d.; Ho 1998; Breiman 2001
6. (Extreme) Gradient Boosting: Friedman 2001; Friedman 2002
7. Feed-Forward Neural Networks: Chollet and Allaire 2018; Goodfellow 2016; Prado 2018; Rosenblatt 1958; Russell 2010

# The Features

## Alternative Momentum Measures

1. Sign of (significant) slope coefficient in local trend regression; set of indicator values $\{-1, 0, 1\}$.
2. Two-part trend (last five and ten trading days in a month) based on simple moving averages; set of indicator values $\{-1, 0, 1\}$.
3. Relative strength index (RSI) with hurdles 30 and 70; set of indicator values $\{-1, 0, 1\}$.
4. Trend Detection Index (TDI) derived from last ten trading days in a month; set of indicator values $\{-1, 0, 1\}$.

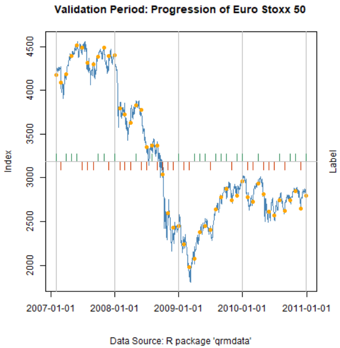
# The Features

## Alternative Risk Measures

1. Standard deviations of intra-month daily returns (last ten trading days vs. all observations);
   set of indicator values $\{-1, 1\}$.
2. Realized volatility of intra-month daily returns (last ten trading days vs. all observations);
   set of indicator values $\{-1, 1\}$.
3. Sharpe ratio (last ten trading days vs. all observations);
   set of indicator values $\{-1, 1\}$.
4. Sign of skewness of intra-month daily returns;
   set of indicator values $\{-1, 1\}$.
5. Sign of excess kurtosis of intra-month daily returns;
   set of indicator values $\{-1, 1\}$.

# Model Training
## Outline

- Each specified model is trained on the training set, and evaluated by its predictive accuracy on the validation set.
- An extending recursive training/shrinking validation set by 12 months is utilized.
- The model specification of a ML-method with the highest hit rate is used for the test set.



# Model Training

## Linear Discriminant Analysis

| LDA models | Validation Periods | | | | |
|---|---|---|---|---|---|
| | 48 Months | 36 Months | 24 Months | 12 Months | Average |
| Method = moment, DF = NA | 54.2 | 55.6 | 45.8 | 41.7 | 49.3 |
| Method = mle, DF = NA | 54.2 | 55.6 | 45.8 | 41.7 | 49.3 |
| Method = t, DF = 5 | 56.2 | 52.8 | 45.8 | 50.0 | 51.2 |
| Method = t, DF = 10 | 56.2 | 52.8 | 45.8 | 50.0 | 51.2 |
| Method = t, DF = 15 | 56.2 | 52.8 | 45.8 | 50.0 | 51.2 |
| Method = t, DF = 20 | 54.2 | 52.8 | 45.8 | 50.0 | 50.7 |

Table: Predicitve Accuracy of LDA on Validation Set.

# Model Training

## k-Nearest Neighbours

| KNN models | Validation Periods | | | | |
|---|---|---|---|---|---|
| | 48 Months | 36 Months | 24 Months | 12 Months | Average |
| k = 1 | 52.1 | 61.1 | 54.2 | 25.0 | 48.1 |
| k = 2 | 60.4 | 61.1 | 54.2 | 33.3 | 52.3 |
| k = 3 | 60.4 | 61.1 | 50.0 | 33.3 | 51.2 |
| k = 4 | 52.1 | 52.8 | 50.0 | 25.0 | 45.0 |
| k = 5 | 56.2 | 61.1 | 54.2 | 25.0 | 49.1 |
| k = 6 | 56.2 | 55.6 | 58.3 | 41.7 | 53.0 |
| k = 7 | 54.2 | 52.8 | 50.0 | 41.7 | 49.7 |
| k = 8 | 45.8 | 52.8 | 50.0 | 41.7 | 47.6 |
| k = 9 | 45.8 | 47.2 | 41.7 | 41.7 | 44.1 |
| k = 10 | 45.8 | 52.8 | 45.8 | 41.7 | 46.5 |

Table: Predicitve Accuracy of KNN on Validation Set.

# Model Training

## Support Vector Machine

| SVM models | Validation Periods | | | | |
|---|---|---|---|---|---|
| | 48 Months | 36 Months | 24 Months | 12 Months | Average |
| Kernel = linear, cost = 1 | 47.9 | 44.4 | 54.2 | 41.7 | 47.0 |
| Kernel = linear, cost = 10 | 47.9 | 44.4 | 54.2 | 41.7 | 47.0 |
| Kernel = linear, cost = 100 | 47.9 | 44.4 | 54.2 | 41.7 | 47.0 |
| Kernel = radial, cost = 1 | 47.9 | 44.4 | 41.7 | 33.3 | 41.8 |
| Kernel = radial, cost = 10 | 54.2 | 52.8 | 50.0 | 33.3 | 47.6 |
| Kernel = radial, cost = 100 | 52.1 | 58.3 | 54.2 | 33.3 | 49.5 |
| Kernel = polynomial, cost = 1 | 52.1 | 55.6 | 45.8 | 33.3 | 46.7 |
| Kernel = polynomial, cost = 10 | 54.2 | 55.6 | 37.5 | 33.3 | 45.1 |
| Kernel = polynomial, cost = 100 | 54.2 | 52.8 | 37.5 | 33.3 | 44.4 |
| Kernel = sigmoid, cost = 1 | 47.9 | 47.2 | 58.3 | 50.0 | 50.9 |
| Kernel = sigmoid, cost = 10 | 33.3 | 25.0 | 66.7 | 66.7 | 47.9 |
| Kernel = sigmoid, cost = 100 | 33.3 | 30.6 | 29.2 | 58.3 | 37.8 |

Table: Predicitve Accuracy of SVM on Validation Set.

# Model Training

## Classification Tree

| CTR models | Validation Periods | | | | |
|---|---|---|---|---|---|
| | 48 Months | 36 Months | 24 Months | 12 Months | Average |
| SplitCrit = information, minsize = 2 | 43.8 | 47.2 | 45.8 | 33.3 | 42.5 |
| SplitCrit = information, minsize = 4 | 43.8 | 47.2 | 41.7 | 33.3 | 41.5 |
| SplitCrit = information, minsize = 6 | 45.8 | 47.2 | 41.7 | 33.3 | 42.0 |
| SplitCrit = information, minsize = 8 | 45.8 | 47.2 | 45.8 | 41.7 | 45.1 |
| SplitCrit = information, minsize = 10 | 45.8 | 44.4 | 41.7 | 33.3 | 41.3 |
| SplitCrit = gini, minsize = 2 | 45.8 | 47.2 | 45.8 | 33.3 | 43.1 |
| SplitCrit = gini, minsize = 4 | 43.8 | 47.2 | 41.7 | 33.3 | 41.5 |
| SplitCrit = gini, minsize = 6 | 45.8 | 47.2 | 41.7 | 33.3 | 42.0 |
| SplitCrit = gini, minsize = 8 | 45.8 | 47.2 | 45.8 | 41.7 | 45.1 |
| SplitCrit = gini, minsize = 10 | 45.8 | 44.4 | 41.7 | 33.3 | 41.3 |

Table: Predicitve Accuracy of CTR on Validation Set.

# Model Training

## Random Forest

| RFM models | Validation Periods | | | | |
|---|---|---|---|---|---|
| | 48 Months | 36 Months | 24 Months | 12 Months | Average |
| Node size = 1, mtry = 2 | 52.1 | 52.8 | 45.8 | 33.3 | 46.0 |
| Node size = 1, mtry = 3 | 45.8 | 50.0 | 45.8 | 33.3 | 43.8 |
| Node size = 1, mtry = 4 | 45.8 | 50.0 | 45.8 | 33.3 | 43.8 |
| Node size = 1, mtry = 5 | 43.8 | 47.2 | 45.8 | 33.3 | 42.5 |
| Node size = 1, mtry = 6 | 45.8 | 47.2 | 41.7 | 33.3 | 42.0 |
| Node size = 1, mtry = 7 | 43.8 | 47.2 | 45.8 | 33.3 | 42.5 |
| Node size = 10, mtry = 2 | 54.2 | 58.3 | 45.8 | 33.3 | 47.9 |
| Node size = 10, mtry = 3 | 50.0 | 58.3 | 45.8 | 33.3 | 46.9 |
| Node size = 10, mtry = 4 | 52.1 | 58.3 | 45.8 | 33.3 | 47.4 |
| Node size = 10, mtry = 5 | 52.1 | 52.8 | 45.8 | 33.3 | 46.0 |
| Node size = 10, mtry = 6 | 50.0 | 52.8 | 45.8 | 33.3 | 45.5 |
| Node size = 10, mtry = 7 | 50.0 | 55.6 | 45.8 | 33.3 | 46.2 |
| Node size = 20, mtry = 2 | 58.3 | 52.8 | 37.5 | 33.3 | 45.5 |
| Node size = 20, mtry = 3 | 56.2 | 50.0 | 41.7 | 33.3 | 45.3 |
| Node size = 20, mtry = 4 | 58.3 | 52.8 | 41.7 | 33.3 | 46.5 |
| Node size = 20, mtry = 5 | 56.2 | 52.8 | 41.7 | 33.3 | 46.0 |
| Node size = 20, mtry = 6 | 56.2 | 52.8 | 41.7 | 33.3 | 46.0 |
| Node size = 20, mtry = 7 | 56.2 | 55.6 | 41.7 | 33.3 | 46.7 |

Table: Predicitve Accuracy of RFM on Validation Set.

# Model Training

## Extreme Gradient Boosting

| XGB models | Validation Periods | | | | |
|---|---|---|---|---|---|
| | 48 Months | 36 Months | 24 Months | 12 Months | Average |
| Depths = 2, eta = 0.25 | 50.0 | 47.2 | 45.8 | 50.0 | 48.3 |
| Depths = 2, eta = 0.5 | 50.0 | 47.2 | 45.8 | 50.0 | 48.3 |
| Depths = 2, eta = 0.75 | 50.0 | 47.2 | 45.8 | 33.3 | 44.1 |
| Depths = 2, eta = 1 | 50.0 | 44.4 | 45.8 | 33.3 | 43.4 |
| Depths = 3, eta = 0.25 | 50.0 | 47.2 | 41.7 | 33.3 | 43.1 |
| Depths = 3, eta = 0.5 | 50.0 | 47.2 | 50.0 | 33.3 | 45.1 |
| Depths = 3, eta = 0.75 | 47.9 | 44.4 | 45.8 | 33.3 | 42.9 |
| Depths = 3, eta = 1 | 47.9 | 44.4 | 41.7 | 41.7 | 43.9 |
| Depths = 4, eta = 0.25 | 43.8 | 44.4 | 45.8 | 41.7 | 43.9 |
| Depths = 4, eta = 0.5 | 47.9 | 44.4 | 41.7 | 41.7 | 43.9 |
| Depths = 4, eta = 0.75 | 52.1 | 47.2 | 41.7 | 58.3 | 49.8 |
| Depths = 4, eta = 1 | 45.8 | 52.8 | 50.0 | 50.0 | 49.7 |
| Depths = 5, eta = 0.25 | 43.8 | 50.0 | 41.7 | 41.7 | 44.3 |
| Depths = 5, eta = 0.5 | 43.8 | 47.2 | 45.8 | 41.7 | 44.6 |
| Depths = 5, eta = 0.75 | 56.2 | 47.2 | 41.7 | 50.0 | 48.8 |
| Depths = 5, eta = 1 | 43.8 | 50.0 | 45.8 | 41.7 | 45.3 |

Table: Predicitve Accuracy of XGB on Validation Set.

# Model Training

## Neural Network

| RFM models | Validation Periods | | | | |
|---|---|---|---|---|---|
| | 48 Months | 36 Months | 24 Months | 12 Months | Average |
| 1st hidden = 2, 2nd hidden = 0 | 52.1 | 55.6 | 41.7 | 50.0 | 49.8 |
| 1st hidden = 3, 2nd hidden = 0 | 39.6 | 44.4 | 50.0 | 58.3 | 48.1 |
| 1st hidden = 4, 2nd hidden = 0 | 58.3 | 36.1 | 33.3 | 50.0 | 44.4 |
| 1st hidden = 5, 2nd hidden = 0 | 52.1 | 52.8 | 58.3 | 41.7 | 51.2 |
| 1st hidden = 2, 2nd hidden = 1 | 45.8 | 44.4 | 54.2 | 75.0 | 54.9 |
| 1st hidden = 3, 2nd hidden = 1 | 50.0 | 44.4 | 54.2 | 41.7 | 47.6 |
| 1st hidden = 4, 2nd hidden = 1 | 62.5 | 44.4 | 41.7 | 58.3 | 51.7 |
| 1st hidden = 5, 2nd hidden = 1 | 56.2 | 55.6 | 50.0 | 58.3 | 55.0 |
| 1st hidden = 2, 2nd hidden = 2 | 54.2 | 47.2 | 41.7 | 50.0 | 48.3 |
| 1st hidden = 3, 2nd hidden = 2 | 43.8 | 58.3 | 50.0 | 41.7 | 48.4 |
| 1st hidden = 4, 2nd hidden = 2 | 47.9 | 44.4 | 45.8 | 58.3 | 49.1 |
| 1st hidden = 5, 2nd hidden = 2 | 43.8 | 41.7 | 54.2 | 50.0 | 47.4 |

Table: Predicitve Accuracy of FNN on Validation Set.

# Model Training

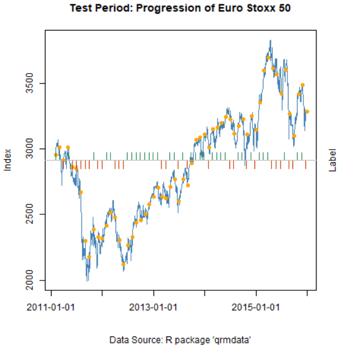
## Assessment

- Classification accuracy of models roughly equivalent with coin-tossings.
- No clear improvement of correct predictions with increasing training data set.
- Results depend on models' specifications and are sensitive to those hyperparameters.
- Methods delivered in general poor results, whence evaluated on last twelve month of validation period ('sideway market environment'). In these market phases directional guidance is required the most, but ML-models did not excel (whip-saw effect).
- Lack of structural stability in data generating process might be an explaination for the rather sobering result of ML during the validation period.

# Model Testing

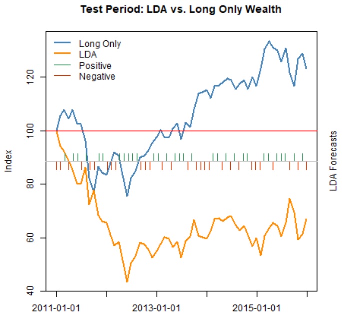
## Outline

- Utilize 'optimal' model specifications determined from validation stage in test period.
- Re-estimate models based on training and validation data.
- Compute one-step ahead predictions.
- Evaluate wealth progressions by entering at the beginning of each month a position with exposure equivalent to one hundred monetary units and close position at month's end.



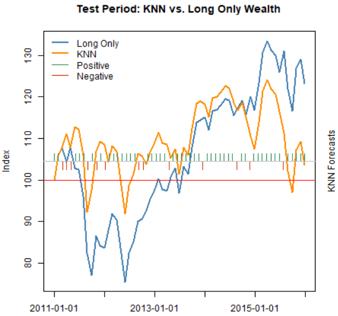
# Model Testing

## Linear Discriminant Analysis




| Performance | LDA | LongOnly |
|---|---|---|
| Return (annualized) | −7.67 | 4.26 |
| Risk (annualized) | 26.04 | 16.74 |
| Sharpe Ratio | −0.29 | 0.25 |
| Maximum Drawdown | 56.49 | 30.04 |
| Average Drawdown | 56.49 | 9.07 |
| Hit Rate (percentage) | 45.00 | |
| False Positive (percentage) | 48.39 | |
| False Negative (percentage) | 62.07 | |

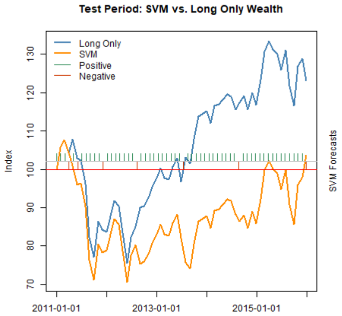
# Model Testing
## k-Nearest Neighbours




| Performance | KNN | LongOnly |
|---|---|---|
| Return (annualized) | 0.69 | 4.26 |
| Risk (annualized) | 15.88 | 16.74 |
| Sharpe Ratio | 0.04 | 0.25 |
| Maximum Drawdown | 21.82 | 30.04 |
| Average Drawdown | 11.81 | 9.07 |
| Hit Rate (percentage) | 48.33 | |
| False Positive (percentage) | 46.81 | |
| False Negative (percentage) | 69.23 | |

# Model Testing

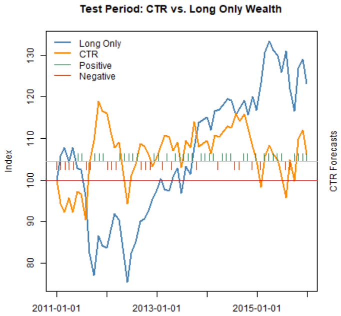
## Support Vector Machine




| Performance | SVM | LongOnly |
|---|---|---|
| Return (annualized) | 0.74 | 4.26 |
| Risk (annualized) | 19.54 | 16.74 |
| Sharpe Ratio | 0.04 | 0.25 |
| Maximum Drawdown | 34.43 | 30.04 |
| Average Drawdown | 34.43 | 9.07 |
| Hit Rate (percentage) | 55.00 | |
| False Positive (percentage) | 43.40 | |
| False Negative (percentage) | 57.14 | |

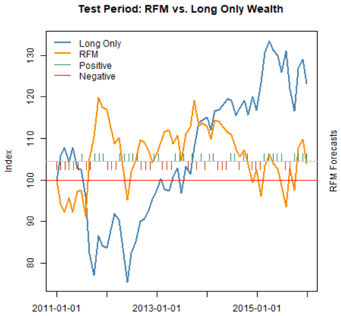
# Model Testing

## Classification Tree




| Performance | CTR | LongOnly |
|---|---|---|
| Return (annualized) | 1.20 | 4.26 |
| Risk (annualized) | 16.49 | 16.74 |
| Sharpe Ratio | 0.07 | 0.25 |
| Maximum Drawdown | 20.85 | 30.04 |
| Average Drawdown | 15.22 | 9.07 |
| Hit Rate (percentage) | 45.00 | |
| False Positive (percentage) | 48.65 | |
| False Negative (percentage) | 65.22 | |

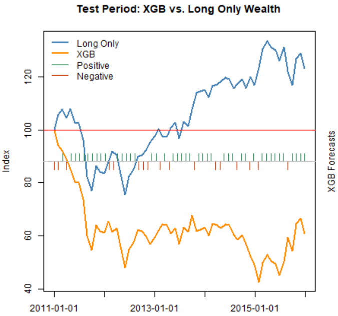
# Model Testing
## Random Forest




| Performance | RFM | LongOnly |
|---|---|---|
| Return (annualized) | 0.78 | 4.26 |
| Risk (annualized) | 16.52 | 16.74 |
| Sharpe Ratio | 0.05 | 0.25 |
| Maximum Drawdown | 22.06 | 30.04 |
| Average Drawdown | 15.36 | 9.07 |
| Hit Rate (percentage) | 45.00 | |
| False Positive (percentage) | 48.39 | |
| False Negative (percentage) | 62.07 | |

# Model Testing

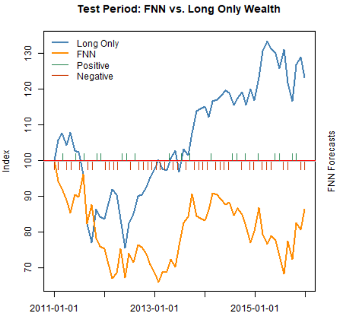
## Extreme Gradient Boosting




| Performance | XGB | LongOnly |
|---|---|---|
| Return (annualized) | −9.45 | 4.26 |
| Risk (annualized) | 28.53 | 16.74 |
| Sharpe Ratio | −0.33 | 0.25 |
| Maximum Drawdown | 57.39 | 30.04 |
| Average Drawdown | 57.39 | 9.07 |
| Hit Rate (percentage) | 38.33 | |
| False Positive (percentage) | 53.49 | |
| False Negative (percentage) | 82.35 | |

# Model Testing

## Neural Network




| Performance | FNN | LongOnly |
|---|---|---|
| Return (annualized) | −2.90 | 4.26 |
| Risk (annualized) | 21.02 | 16.74 |
| Sharpe Ratio | −0.14 | 0.25 |
| Maximum Drawdown | 33.97 | 30.04 |
| Average Drawdown | 33.97 | 9.07 |
| Hit Rate (percentage) | 40.00 | |
| False Positive (percentage) | 55.00 | |
| False Negative (percentage) | 62.50 | |

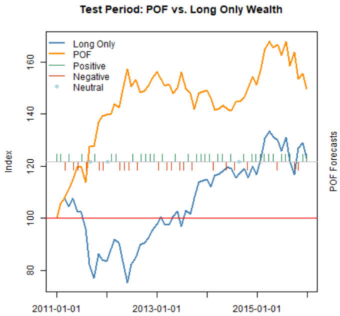
# Model Testing

## Neural Network: Comments

- Activation by rectified linear unit; full batch optimization (rmsprop); no dropout in layers.
- Results depend on chosen optimization engine.
- Results can be not reproducible, even if `keras::use_session_with_seed()` is used (in particular, for settings like mini-batch, stochstic gradient decent, random dropout in layers and non-fixed validation data).
- The peril of data augmentation, *e.g.* by adding Gaussian noise: Beforehand, models should better generalize in testing period, but how much jitter to add? If to small, then no big generalization gains are made, if to high, the labels in the training/validation set might not be any longer in sync with randomly created records.

# Model Testing

## 'Alternative facts: these classy features are all great!' Majority voting of features[3]




| Performance | POF | LongOnly |
|---|---|---|
| Return (annualized) | 8.43 | 4.26 |
| Risk (annualized) | 11.58 | 16.74 |
| Sharpe Ratio | 0.73 | 0.25 |
| Maximum Drawdown | 10.72 | 30.04 |
| Average Drawdown | 6.04 | 9.07 |
| Hit Rate (percentage) | 64.91 | |
| False Positive (percentage) | 32.35 | |
| False Negative (percentage) | 39.13 | |

[3] Bates and Granger 1969.

# Model Testing

## Performance Summary

| Performance | LDA | KNN | SVM | CTR | RFM | XGB | FNN | POF | LongOnly |
|---|---|---|---|---|---|---|---|---|---|
| Return (annualized) | −7.67 | 0.69 | 0.74 | 1.20 | 0.78 | −9.45 | −2.90 | 8.43 | 4.26 |
| Risk (annualized) | 26.04 | 15.88 | 19.54 | 16.49 | 16.52 | 28.53 | 21.02 | 11.58 | 16.74 |
| Sharpe Ratio | −0.29 | 0.04 | 0.04 | 0.07 | 0.05 | −0.33 | −0.14 | 0.73 | 0.25 |
| Maximum Drawdown | 56.49 | 21.82 | 34.43 | 20.85 | 22.06 | 57.39 | 33.97 | 10.72 | 30.04 |
| Average Drawdown | 56.49 | 11.81 | 34.43 | 15.22 | 15.36 | 57.39 | 33.97 | 6.04 | 9.07 |
| Hit Rate (percentage) | 45.00 | 48.33 | 55.00 | 45.00 | 45.00 | 38.33 | 40.00 | 64.91 | |
| False Positive (percentage) | 48.39 | 46.81 | 43.40 | 48.65 | 48.39 | 53.49 | 55.00 | 32.35 | |
| False Negative (percentage) | 62.07 | 69.23 | 57.14 | 65.22 | 62.07 | 82.35 | 62.50 | 39.13 | |

# Model Testing

## Lifting the Veil of Secrecy

- Signs and magnitudes of Kendall correlations between predicators and label give hindsight to differing relations.
- Pooled forecasts by majority votes yield a more robust outcome compared 'trained' ML-/AI models.

| Variable | All | Train | Valid | Test |
|---|---|---|---|---|
| EuroStoxx | 1.00 | 1.00 | 1.00 | 1.00 |
| Kurtosis | 0.02 | 0.04 | −0.07 | 0.00 |
| RSI | −0.11 | −0.10 | −0.06 | −0.23 |
| RvRisk | 0.00 | −0.05 | −0.04 | 0.23 |
| SdRisk | −0.01 | −0.05 | −0.13 | 0.23 |
| SharpeRatio | −0.01 | −0.01 | −0.08 | 0.07 |
| Skewness | 0.00 | 0.01 | −0.09 | 0.03 |
| SlopeCoef | 0.08 | 0.09 | 0.07 | 0.03 |
| TrendDetection | 0.07 | 0.07 | −0.04 | 0.18 |
| TwoPart | −0.02 | 0.02 | −0.15 | −0.07 |

# Summary & Conclusion

- ML-/AI methods have been applied to a binary classification problem.
- All tested methods showed inferior results compared to either a long-only and/or pooled majority forecasts of the predictors.
- Potential reason for this empirical finding is a lack of structural stability across training, validation and testing periods.
- In this sense: ‘a euro is not a euro’.
- So, ‘Will this second wave last . . . ?’: Probably not in the field of empirical social science, but in fairly stable and structured domains *e.g.* in which ‘a cat is still a cat’.

# References: Literature I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