Chaos, overfitting and equilibrium:

To what extent can machine learning beat the financial market?

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Summary

Abstract

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III **Data:** We collected daily data between April 1st, 2020 and November 19th, 2021 for the 30 firms that compose the Dow Jones Industrial Average (DJIA).

Abstract

Main Results

- Our results indicated that while the out-of-sample accuracy converged to 50%, 14.27% of the hyperparameter combinations yielded gains above the buy-and-hold strategy; on the other hand, no clear patterns about the best-performing hyperparameter combinations emerged, as the behavior of the out-of-sample performance was much more chaotic than its in-sample counterpart.

Summary

The Bias-Variance Dilemma

- One critical aspect of empirical applications of machine learning models is to maximize their generalization ability, by finding the ideal balance between in-sample fitness and complexity – often known as the bias-variance dilemma. The essence of generalization is to learn patterns from a sample of data and make inferences for out-of-sample data, and a good model should be complex enough to be able to learn the relevant patterns, but also simple enough to not incorporate the effect of noisy and irrelevant information on the final predictions.

The Bias-Variance Dilemma

- This result can be observed in Hoeffding's inequality [Hoeffding, 1963]:

$$\mathbb{P}(|E_{in}(h) - E_{out}(h)| > \varepsilon) \leq 2 \cdot \mathbb{M} \cdot e^{-2 \cdot \varepsilon^2 \cdot n} \tag{1}$$

where $E_{in}(h)$ and $E_{out}(h)$ are, respectively, the in-sample error and the out-of-sample error associated with a predicting model h; ε is user-specified margin, n is the sample size and $\mathbb{M}$ is a measure of the model's complexity, thus representing the overall variance level of the model and, consequently, the potential sensitivity of the out-of-sample predictions to small variations in the observed data.

The Bias-Variance Dilemma

- Expression **1** can be rearranged as:

$$\begin{aligned}\underbrace{E_{out}(h)}_{\text{out-of-sample generalization error}} &\leq E_{in}(h) + \sqrt{\frac{1}{2\cdot n} log\left(\frac{2\cdot \mathbb{M}}{\delta}\right)} \\ &\leq \underbrace{E_{in}(h)}_{\text{in-sample error}} + \underbrace{\Omega}_{\text{model complexity}} \qquad (2)\end{aligned}$$

where $\delta = 2 \cdot \mathbb{M} \cdot e^{-2\cdot\varepsilon^2\cdot n}$ is a constant and Ω represents the penalization for the complexity of the model. The bias-variance dilemma is concisely stated in expression **2**, showing that the generalization error E_{out} assumes higher values with both a high in-sample bias or a high out-of-sample variance (complexity).

Technical Analysis Indicators

Independent variable	References
Simple Moving Average	[Chiang et al., 2016, Gorenc Novak and Velušček, 2016, Kumar et al., 2016] [Chen and Hao, 2017, Gunduz et al., 2017, Li and Tam, 2017] [Shynkevich et al., 2017, Weng et al., 2017, Alhashel et al., 2018] [Henrique et al., 2018, Merello et al., 2019, Sezer and Ozbayoglu, 2018]
Exponential Moving Average	[Gorenc Novak and Velušček, 2016, Kumar et al., 2016, Chen et al., 2017] [Chen and Hao, 2017, Gunduz et al., 2017, Li and Tam, 2017] [Shynkevich et al., 2017, Weng et al., 2017, Alhashel et al., 2018] [Nakano et al., 2018, Sezer and Ozbayoglu, 2018]
Moving Average Convergence-Divergence	[Chiang et al., 2016, Kumar et al., 2016, Chen and Hao, 2017] [Gunduz et al., 2017, Li and Tam, 2017, Alhashel et al., 2018] [Nakano et al., 2018, Sezer and Ozbayoglu, 2018]
Momentum	[Chiang et al., 2016, Gorenc Novak and Velušček, 2016, Kumar et al., 2016] [Gunduz et al., 2017, Weng et al., 2017, Merello et al., 2019]
Accumulation/Distribution Oscillator	[Patel et al., 2015a, Patel et al., 2015b, Alhashel et al., 2018] [Henrique et al., 2018]
Rate of Change	[Gorenc Novak and Velušček, 2016, Kumar et al., 2016, Gunduz et al., 2017] [Li and Tam, 2017, Shynkevich et al., 2017, Weng et al., 2017] [Alhashel et al., 2018]
On Balance Volume	[Creamer, 2012, de Oliveira et al., 2013, Chen and Hao, 2017] [Nakano et al., 2018, Sezer and Ozbayoglu, 2018]
Relative Strength Index	[Gorenc Novak and Velušček, 2016, Chen and Hao, 2017, Gunduz et al., 2017] [Weng et al., 2017, Shynkevich et al., 2017, Li and Tam, 2017] [Alhashel et al., 2018, Henrique et al., 2018, Nakano et al., 2018] [Sezer and Ozbayoglu, 2018]

Technical Analysis Indicators

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Stochastic K%	[Kumar et al., 2016, Gunduz et al., 2017, Shynkevich et al., 2017] [Alhashel et al., 2018, Nakano et al., 2018]
William's R%	[Kumar et al., 2016, Gunduz et al., 2017, Li and Tam, 2017] [Shynkevich et al., 2017, Alhashel et al., 2018, Sezer and Ozbayoglu, 2018]

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$$\begin{aligned} \text{Minimize :} \quad & \frac{1}{2}\boldsymbol{w^T w} + C\boldsymbol{\xi^T 1} \\ \text{Subject to :} \quad & \boldsymbol{D}(\boldsymbol{\Phi w} - b\boldsymbol{1}) \geq \boldsymbol{1} - \boldsymbol{\xi} \\ & b \in \mathbb{R}, \boldsymbol{w} \in \mathbb{R}^q, \boldsymbol{\xi} \geq 0 \end{aligned} \tag{3}$$

where $C \in \mathbb{R}^+$ is a user-defined hyperparameter that represents the penalization for misclassified observations, ξ is a vector of slack variables, $\boldsymbol{D}$ is the diagonal square matrix of the class labels for each observation, Φ is the matrix of non-linear mappings applied to each pair of observations $\boldsymbol{x_i}$ and $\boldsymbol{x_j}, i, j = 1, 2, 3 \ldots, n$, and n is the sample size.

Methods and Empirical Analysis

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$$f(\boldsymbol{x_i}) = sgn\left(\sum_{j=1}^{n} \kappa(\boldsymbol{x_i}, \boldsymbol{x_j}) y_j \lambda_j - b\right) \tag{4}$$

where $sgn(.)$ is the sign function, $\kappa(\boldsymbol{x_i}, \boldsymbol{x_j}) = \varphi(\boldsymbol{x_i}) \cdot \varphi(\boldsymbol{x_j}) \in \mathbb{R}, i, j = 1, 2, 3 \ldots, n$ is the Kernel function that generalizes the inner product of the mappings φ for each pair of observations, $y_i \in \{-1, +1\}$ is the label of the i-th observation, λ_i is the i-th Lagrange multiplier of problem **4**, and $b \in \mathbb{R}$ is the bias term (intercept) of the decision function.

Methods and Empirical Analysis

- The data was split into two sequential and mutually exclusive subsets: the training set being composed by observations between April 1st, 2020 and July 30th, 2021, while the observations between August 1st, 2021 and November 19th, 2021 composed the test set. The dependent variable was the price direction movement between periods t and $t+1$, and the set of independent variables was composed by 10 technical analysis indicators commonly utilized in the recent literature of machine learning models applied to financial forecasting.

- For each model, we applied 10-fold cross-validation for the respective training set and applied the respective decision functions to the observations from the test set.

Methods and Empirical Analysis

- The grid of hyperparameters that we used is displayed in table **1** below:

Hyperparameter	Grid-search interval
C	$[e^{10^0}, e^{10^{0.25}} \ldots, e^{10^{9.75}}, e^{10^{10}}]$
σ	$[0, 0.25, \ldots, 9.75, 10]$

Table: Hyperparameters intervals used for the models' training

Summary

Results

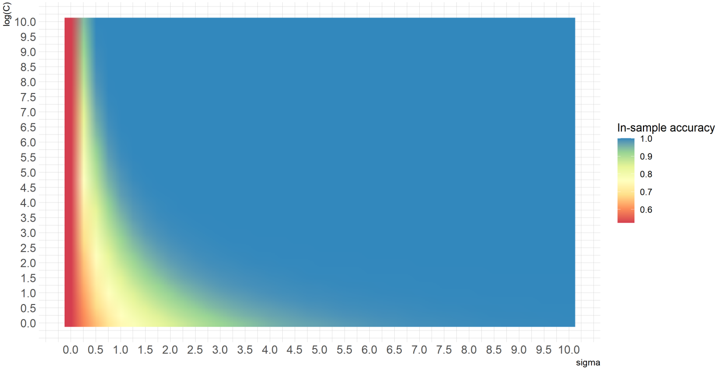
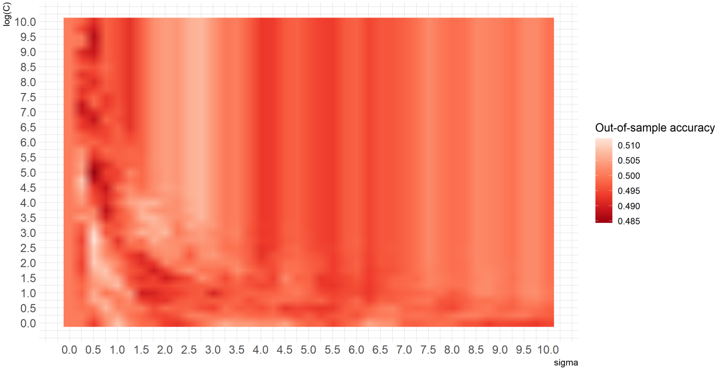


Figure: Heatmap of the models' in-sample accuracy

Results



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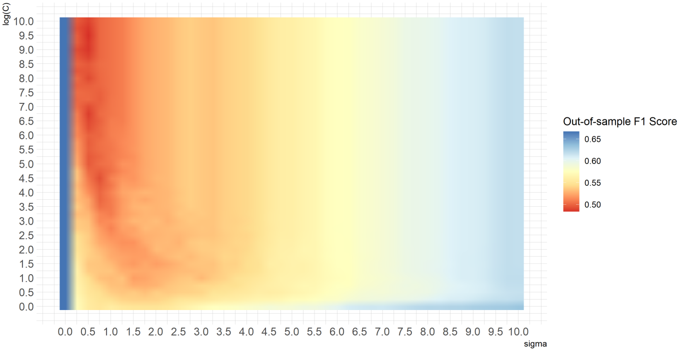


Figure: Heatmap of the model's out-of-sample F1 Score

Results

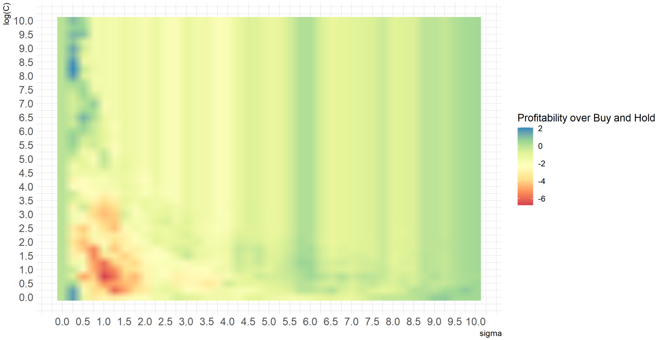
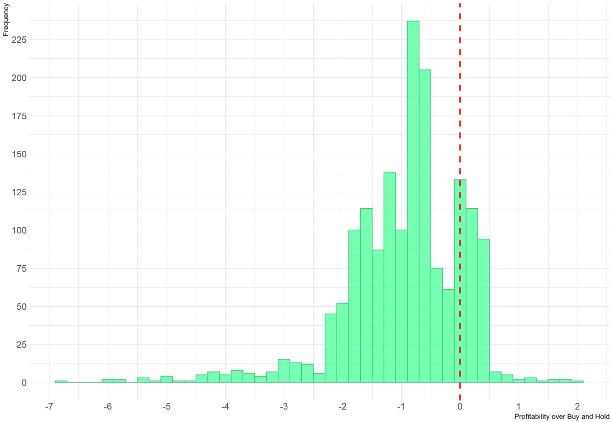


Figure: Heatmap of the model's out-of-sample profitability over the buy-and-hold strategy

Results


Frequency
225
200
175
150
125
100
75
50
25
0
-7
-6
-5
-4
-3
-2
-1
0
1
2
Profitability over Buy and Hold

Results

Metric	Strategy profitability	TC_0	TC_{BH}
Maximum	5.9422	1.9437	0.0765
Third quartile	3.6302	0.1262	−0.0094
Median	3.0899	0.1004	−0.0275
First quartile	2.3960	0.0690	−0.0435
Minimum	−2.8630	−0.0875	−0.2062
Mean	2.9321	0.1439	−0.0288
Standard deviation	0.9976	0.2879	0.0299
Skewness	−1.3164	5.9481	−1.1628
Kurtosis	6.8896	37.2863	6.9468
Buy-and-hold strategy mean profitability over the out-of-sample period: 3.38			

Table: Descriptive statistics of the models' profitability and maximum transaction costs

Summary

Final Remarks

- The results indicated that most models had a high in-sample accuracy but only around 50% when applied to out-of-sample data.

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- The findings of this research provide an assessment of empirical challenges of machine learning applications to quantitative finance, while also adding to the literature of financial theory by exploring the connections between well-established concepts in finance and novel evidence brought by data science methods.
- As topics for further research, we suggest improvements and additional cases to the combination of hyperparameters. For instance, the only predictive model that we used was the SVM with Gaussian Kernel, there is a range of Kernels that can be used in this same methodology that may lead to different results. In addition to combinations of other predictive methodologies such as ensemble-based models that can improve the predictive capacity of our strategies.

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