

# Feature selection and deep neural networks for stock price direction forecasting using technical analysis indicators

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# Outline

- 1 Motivation
- 2 Theoretical Background
- 3 Method
- 4 Empirical analysis
- 5 Conclusions and remarks



# Stock price forecasting

**Efficient-market hypothesis** (weak form): The present prices reflect all information of past prices (random walk)

- Thus, based on this assumption, indicators based on past prices and trading volumes have no consistent predictive power for future stock price variations

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**Efficient-market hypothesis** (weak form): The present prices reflect all information of past prices (random walk)

- Thus, based on this assumption, indicators based on past prices and trading volumes have no consistent predictive power for future stock price variations
- Still, a lot of people (still) try! (Kara et al. (2011); Chen et al. (2014); Laboissiere et al. (2015); Patel et al. (2015); Chen et al. (2017); Zhong and Enke (2017), among (many) others)

# Stock price forecasting and machine learning

In particular, machine learning methods (mainly Artificial Neural Networks and Support Vector Machines) are one of the more researched topics in the recent financial forecasting literature (Henrique et al., 2019).

- Many papers focused on both direction and price prediction, as well as using both individual stocks and market indexes as target assets.

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In particular, machine learning methods (mainly Artificial Neural Networks and Support Vector Machines) are one of the more researched topics in the recent financial forecasting literature (Henrique et al., 2019).

- Many papers focused on both direction and price prediction, as well as using both individual stocks and market indexes as target assets.
- Specifically using technical analysis indicators as input variables: Kara et al. (2011), Chen et al. (2014), Patel et al. (2015), Gorenc Novak and Velušček (2016), Chiang et al. (2016), Chen et al. (2017), among others.



# Main contributions

- 1 Compendium of technical analysis indicators considered in recent scientific articles on stock prices prediction and market professionals
- 2 Evaluate the relative importance of each mapped technical analysis indicator
- 3 Test the empirical performance of deep neural networks for stock price direction prediction and the profitability from the yielded strategies

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# The “Factor Zoo”

There is a “zoo” of candidate factors for asset pricing models (Cochrane, 2011)

- Harvey et al. (2016) listed 316 factors used by the literature to model the cross-section of expected financial returns



# Another “Factor Zoo”

There is another “factor zoo” composed by technical analysis indicators used as independent variables in machine learning models for forecasting the value/direction of financial stock prices/market indexes

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- 51 technical analysis indicators were used as predictors in papers published in high impact journals between 1999 and 2018
- Another 74 indicators are used by the “trader side” – specialized websites that offer financial services and technical analysis softwares

# Feature selection in finance

## Garbage in, garbage out! (bias-variance dilemma)

- Harvey et al. (2016) listed 316 factors, most of which did not bring significant improvements on the models' performance
- Kozak et al. (2017) tested 130 factors and their interactions up to degree-3 polynomials, finding that a small number of principal components are able to capture almost all of the out-of-sample explanatory power

# Feature selection in finance

- Hwang and Rubesam (2018) searched the best model from a set of 83 factors, finding out that only 5 to 6 showed actual significance on explaining the assets returns. Additionally, the study showed that the only factor that was consistently selected throughout the periods was the excess market return
- The market systematic risk represents a principal component in financial covariance matrices with far more explained variance than the remaining ones, while the vast majority of eigenvalues are statistically “noise” (Laloux et al., 1999; Sensoy et al., 2013)



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# Logistic regression and neural networks

- Logistic regression:  $y = \psi(Xw + b), \psi(x) = \frac{1}{1+e^{-x}}$
- Artificial neural network (ANN):  
$$Y = \psi_\ell(\dots\psi_2(\psi_1(XW_1 + b_1)W_2 + b_2)\dots W_\ell + b_\ell)w$$

An ANN with one hidden layer is an universal approximator of the space of continuous functions (Universal approximation theorem)

- However, the insertion of additional hidden layers allows to create a **hierarchical representation** of the knowledge



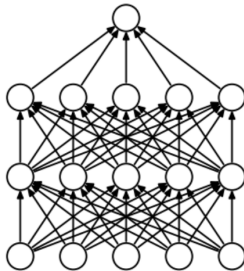


# Dropout

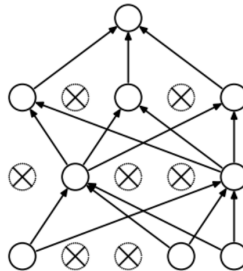
Dropout (Srivastava et al., 2014) is a regularization method to avoid overfitting in the ANN training process.

- In each iteration, instead of computing every possible parameter throughout the network in the backpropagation, each neuron is deactivated with a probability  $p$ .
  - Exploitation vs exploration (bias-variance dilemma)
- Applications of dropout for financial applications are still scarce (Nazário et al., 2017; Henrique et al., 2019)

# Dropout



(a) Standard Neural Net



(b) After applying dropout.

Srivastava et al. (2014)

# Outline

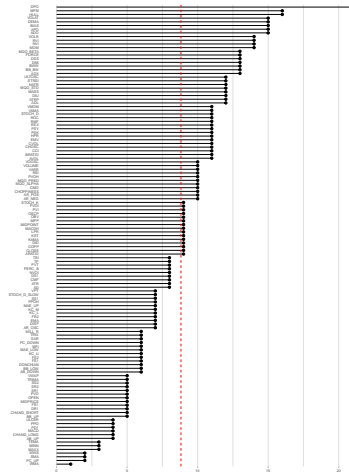
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# Empirical analysis

- **Data:** Stock prices of firms from 7 markets: United States, United Kingdom, France, Germany, China, Japan and Brazil
- **Feature selection methods:**
  - Sequential Forward Floating Selection: Sequential wrapper method
  - Tournament screening: Heuristic wrapper method
  - LASSO: Embedded method
  - Feature selection was performed for a subset and ANNs were fitted on another
- **Performance evaluation:** Accuracy/Precision/Recall/F1 Score

# Selected indicators – Literature + Market





# Prediction results

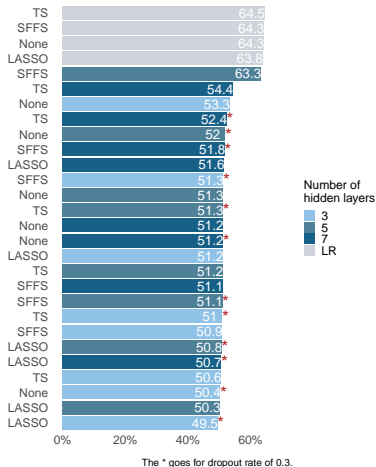
- 40 out of 336 combinations of hyperparameters yielded one class predictions (“only up” or “only down”)
- The emergence of a “strange attractor” (65%) was observed in some combination of hyperparameters for all markets

# Out-of-sample prediction results for the S&P 100 Index

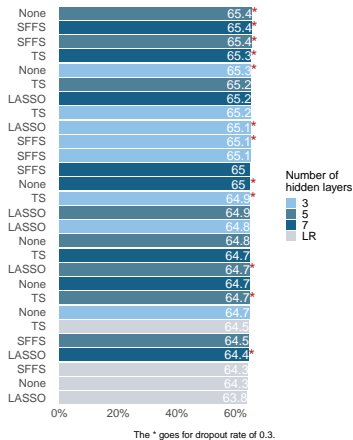
Technical Analysis indicators	Feature selection method	Hidden layers	Dropout	Accuracy	Precision	Recall	F-Score
Literature	LASSO	3	0	0.5128	0.5265	0.6990	0.6006
			0.3	0.5200	0.5268	0.8248	0.6430
		5	0	0.5109	0.5258	0.6783	0.5924
			0.3	0.5181	0.5267	0.7931	0.6330
		7	0	0.5121	0.5253	0.7161	0.6060
			0.3	0.4947	0.5256	0.3669	0.4321
Literature + market	LASSO	3	0	0.6477	0.6577	0.6834	0.6703
			0.3	0.6542	0.6667	0.6804	0.6735
		5	0	0.6497	0.6510	0.7148	0.6814
			0.3	0.6539	0.6588	0.7043	0.6808
		7	0	0.6481	0.6667	0.6567	0.6617
			0.3	0.6513	0.6794	0.6335	0.6557



# Prediction results for the S&P 100 Index (Literature)



# Prediction results for the S&P 100 Index (Literature + Market)



# Prediction results

Out-of-sample accuracy grouped by target assets and variable sets:

Assets	Literature		Literature + Market	
	Acc. $\leq 55\%$	Acc. $\geq 60\%$	Acc. $\leq 55\%$	Acc. $\geq 60\%$
United States (S&P 100 Index)	23	5	0	28
United Kingdom (FTSE 100 Index)	28	0	7	21
France (CAC 40 Index)	24	4	3	25
Germany (DAX-30 Index)	28	0	5	23
Japan (Top 50 assets from NIKKEI 225 Index)	24	4	2	26
China (Top 50 assets from SSE 180 Index)	24	4	0	28
Brazil (Bovespa Index)	24	4	0	28

# Market efficiency and chaos

- Is the second attractor a reflex of a “follow-up” behavior of the market?
  - Momentum strategies tend to yield a small average return consistently over time (Jegadeesh and Titman, 1993; Swinkels, 2005; Barroso and Santa-Clara, 2015)
- Is there a “regime-switch” at a systematic level?

# Profitability of the strategies

- The profitability of the machine learning strategies oscillated between the value of the Buy-and-Hold strategy – some small gains and some big losses
  - Momentum strategies tend to have a high turnover (measure of transaction cost) and yield a large loss in events of crisis or market retraction

# Profitability and transaction costs for the S&P 100 Index

Technical Analysis indicators	Feature selection method	Hidden layers	Dropout	Strategy profitability	Number of transactions	$TC_0$	$TC_{BH}$
Literature	LASSO	3	0	-26.4434	195	-0.1963	-0.3705
			0.3	-130.7093	1	-130.7092	-160.3766
		5	0	79.8481	89	0.8421	0.5438
			0.3	77.9161	93	0.7701	0.4981
		7	0	-111.1510	89	-1.4438	-1.7723
			0.3	-20.1832	71	-0.1628	-0.9002
Literature + market	LASSO	3	0	61.9372	219	0.2759	0.1193
			0.3	-53.5714	91	-0.6422	-1.0093
		5	0	79.2360	94	0.8422	0.5369
			0.3	65.0487	85	0.8121	0.4136
		7	0	-43.1031	132	-0.3601	-0.5558
			0.3	-31.4264	66	-0.6612	-1.0125
Buy-and-Hold strategy profitability over the out-of-sample period: 31.04701							

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# Main conclusions

- The extended “factor zoo” yielded better prediction performance across the markets
- The indicators were not uniformly selected by the feature selection methods
- Out-of-sample accuracy converged to two “attractors”: 50% and 65%
- Overall profitability did not outperform the Buy-and-Hold strategy



# Recommendations for future studies

- Test for other markets and machine learning models
- Test for other settings of hyperparameters (activation functions, dropout, etc.)
- Test for rolling windows/dynamic models
- Check the temporal consistency of the “second attractor”

# Thank you!

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