Empirical Review of Models used for Predicting Financial Market Crashes Using Market Data

Project: Literature Review

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Background and Introduction

The idea of predicting stock market crashes using machine learning is not new. Multiple papers have approached stock market crash prediction using Machine Learning techniques. Traditionally, time series analysis has relied on models like Recurrent Neural Networks (RNNs) and ARIMA. More recently, the introduction of Transformer-based architectures has expanded the range of tools available for this approach [1], [2].These models have been retroactively used with success in Market Crash prediction [3].

Reviews and comparisons of these models, such as this project aims to do, have been made such as [3], but a comprehensive empirical review of Time-Series Analysis models on equal footing is lacking in literature. This project aims to address this lack, by providing an empirical comparison of the three aforementionned commonly used models in Time-Series Analysis to predict Market Crashes. [1] [2] We shall use data freely available on the Yahoo finance database, and tag historically factual Market Crashes by hand, as there are only few. We shall use the crashes as listed in this National Bureau of Economic Research's report. [4]

ARIMA on predicting market crash Oscar

Time series in stock market are mostly non-stationary. Except for differences in the local level or in trend, all parts of the series behave in a similar way [Box et al. 2015]. Box et al suggested a model called Autoregressive Integrated Moving Average (ARIMA) model which combines an autoregressive model and a moving average model. This model can be used in non-stationary time series to make predictions [M K Ho et al 2021 J. Phys.: Conf. Ser. 1988 012041]. The ARIMA model ARIMA(p, d, q) has general form [Box et al. 2015]:

$$\varphi(B)z_t = \phi(B)\nabla^d z_t = \theta_0 + \theta(B)a_t$$

where

1. $\phi(B)$ is the autoregressive part with p degrees,

2. $\theta(B)$ is the moving average part with q degrees,

3. ∇ is the integrated (degree of differencing) part with d degrees,

4. and θ_0 is the constant term.

Using ACF (autocorrelation function) and PACF (partial ACF) can help us decide the hyperparameters p, d, q for building our model [Hyndman et al. 2018].

Reccurent Neural Networks Adrien

Recurrent Neural Networks are a class of neural network architectures designed to detect patterns in sequential data, such as handwriting, genomes, text, or numerical time series. In time-series, they are used to make sequential predictions based on sequential inputs. [5] In our context, they usually take the form of Long Term Short Memory (LSTM) cells [6], which we will use in our project, to mitigate the vanishing gradient problem. They do so by having cells with three gates: An input, output and a forget gate combined with a feedback loop to enhance long-term accuracy. These gates help control how the information flows through the network. [6] They have been used in multiple projects accounting to market Crashes, such as this project led by Tolo et al. [7] It is not well established when RNNs and Arimas outperform one another [6], this project will take a step into clearing up the most appropriate in the context of Market Crashes prediction.

Transformers Inigo

Transformers are neural network architectures based on self-attention mechanisms. In other words, they are able to weigh the importance of input elements by computing attention scores between all positions. While transformers were originally developed for natural language processing tasks like machine translation **vaswani2017attention**, they have become popular for time-series forecasting due to their ability to handle long-range dependencies.

Transformers can capture complex temporal patterns by assigning varying importance to different time steps, which is particularly useful in volatile financial markets. In fact, Zhou et al. demonstrated this with the Informer model, which efficiently handles long sequences and improves forecasting accuracy using self-attention **zhou2021informer**. Moreover, Lim et al. were able to outperform traditional methods by combining the Transformer architecture with recurrent layers **lim2021temporal**.

Hence, the literature suggests that Transformers are a pertinent choice for identifying complex patterns in financial time series, as they can model dependencies across multiple time scales and potentially improving the precision of crash predictions compared to traditional methods like ARIMA and standard RNNs.

Criterias and Analysis Oscar?

A market crash is typically defined as a rapid decline of 20% or more from a recent peak over a short period[8][9]. This threshold distinguishes a crash from a correction, which is generally a decline of 10% to less than 20%. The "recent peak" refers to the highest market level before the downturn, and the "short period" often spans days to weeks, though exact durations can vary.

References

[1] S. Ahmed, I. E. Nielsen, A. Tripathi, S. Siddiqui, R. P. Ramachandran, and G. Rasool, "Transformers in time-series analysis: A tutorial," *Circuits Syst. Signal Process.*, vol. 42, no. 12, pp. 7433–7466, 2023, ISSN: 0278-081X. DOI: 10.1007/s00034-023-02454-8. [Online]. Available: https://doi.org/10.1007/s00034-023-02454-8.

[2] K. E. ArunKumar, D. V. Kalaga, C. Mohan Sai Kumar, M. Kawaji, and T. M. Brenza, "Comparative analysis of gated recurrent units (gru), long short-term memory (lstm) cells, autoregressive integrated moving average (arima), seasonal autoregressive integrated moving average (sarima) for forecasting covid-19 trends," *Alexandria Engineering Journal*, vol. 61, no. 10, pp. 7585–7603, 2022, ISSN: 1110-0168. DOI: https://doi.org/10.1016/j.aej.2022.01.011. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1110016822000138.

[3] P. Okpeke, P. O. Paul, and T. V. Iyelolu, "Predicting stock market crashes with machine learning: A review and methodological proposal," *Open Access Research Journal of Science and Technology*, 2024.

[4] F. S. Mishkin and E. N. White, "U.s. stock market crashes and their aftermath: Implications for monetary policy," National Bureau of Economic Research, Working Paper 8992, Jun. 2002. DOI: 10.3386/w8992. [Online]. Available: http://www.nber.org/papers/w8992.

[5] R. M. Schmidt, "Recurrent neural networks (rnns): A gentle introduction and overview," *CoRR*, vol. abs/1912.05911, 2019. [Online]. Available: http://arxiv.org/abs/1912.05911.

[6] H. Hewamalage, C. Bergmeir, and K. Bandara, "Recurrent neural networks for time series forecasting: Current status and future directions," *International Journal of Forecasting*, vol. 37, no. 1, pp. 388–427, 2021, ISSN: 0169-2070. DOI: https://doi.org/10.1016/j.ijforecast.2020.06.008. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0169207020300996.

[7] E. Tölö, "Predicting systemic financial crises with recurrent neural networks," *Journal of Financial Stability*, vol. 49, p. 100 746, 2020, ISSN: 1572-3089. DOI: https://doi.org/10.1016/j.jfs.2020.100746. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1572308920300243.

[8] M. Fonville, "Understanding stock market corrections and crashes (2024)," 2024. [Online]. Available: https://www.covenantwealthadvisors.com/post/understanding-stock-market-corrections-and-crashes?utm_source=chatgpt.com.

[9] J. Chen, "Guide to stock market crash," 2022. [Online]. Available: https://www.investopedia.com/terms/s/stock-market-crash.asp.