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

Project: Literature Review

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Background and Introduction

We are not the first to approach this subject. Multiple papers have approached prediction of stock market crashes using Machine Learning. In a time series analysis approach, models used have traditionally included RNNs and Arima, and more recently Transformers [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 that are based on "self-attention mechanisms" (allowing the model to weigh the importance of different elements in the input by computing attention scores between all positions) to model dependencies in sequential data. while Transformers were originally developped for natural language processing tasks like machine translation [Vaswani et al., "Attention is All You Need"], 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 fluctuative/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 [Zhou et al., "Informer: Beyond Efficient Transformer for Long Sequence Time-Series Forecasting"]. Moreover, Lim et al. were even able to outperform traditional methods by combining Transformer architecture with recurrent layers [Lim et al., "Temporal Fusion Transformers for Interpretable Multi-horizon Time Series Forecasting"].

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

Criterias and Analysis Oscar?

- Summarize criterias and metrics in literature for comparing models.
  - Justify the selection of those comparison methods based on sources

References

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