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

COMP 451 Final Project: Final Report

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Introduction Inigo

thesis statement

Litterature Review Adrien

We are not the first to attempt to compare ML models performance on their prediction of market crashes using SP500 historical data. Multiple approaches have been tried and tested. Time series analysis has used ARIMA and RNN based models, with the more recent addition of Transformers boosting and improving their performance [1]–[3]. Reviews of these models have been done before, but the comparison of these three models on short-term prediction using very recent market data is lacking in litterature.

One article compared Linear Regression and Autoregressive Moving Average (ARIMA) to predict the volatility and trend of SP500. [4]. Key-findings show that ARIMA struggled on short term predictions, particularly during the 1930s and 2020 volatile markets.

Market Crashes do not hold a single definition. While historical data tags specific periods as depressions and bubbles, there are no specific metrics that are universally defined [5], [6].

RNNs are cool

Time series in the stock market are non-stationary. Their statistical properties thus change over time. ARIMA models can be adapted to capture the behavior of non-stationary time-series [7]. A mehodology formalized by Box et Al. in 2015 to apply the ARIMA model with a moving average component [8]. This makes ARIMA suitable for predicting non-stationary time series, such as financial markets, as demonstrated by M. K. Ho et al. in their paper [7]. The ARIMA model is defined mathematically as [8]:

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

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.

The use of ACF (autocorrelation function) and PACF (partial ACF) will help us decide the hyperparameters p, d, q for building our model [9], and performing Grid-Search on the specific hyperparameters will help us pin point the exact best accuracy we can get. Transformers are cool

Drastic market crashes are rare [cite]. Models can achieve extremely high accuracy by simply predicting no market crash for every datapoint. Other methods are thus needed to evaluate the models. Others in litterature have used many methods, such as evaluating true positives and true negatives [cite]. Other have used mean absolute error (MAE) to assess prediction accuracy [9]. Finally, some have used runtime and resource usage for practical feasibility to assess their performance [10].

Methodology Adrien for market crash and Experiment choice Everyone for their assigned model

Definitions used in our project

RNN Implementation

ARIMA Implementation

Transformers Implementation

Experiments

1. Adrien - 30 days sliding window, 14 days shift days
2. Oscar - 14 days sliding window, 7 days shift days
3. Inigo - 7 days sliding window, 3 days shift days

Empirical Evaluation Oscar

Discussion Everyone discusses their experiment

Conclusion Everyone does the conclusion for their own experiments

Future Directions Inigo

Self-Assessment Oscar

Contributions Everyone writes their own contribution

1. Adrien - For the report, my main contributions were for writing the Litterature Review and parts of the Methodology, Discussion and Conclusion. I've also contributed to the code by implementing the RNN model, consolidating the three models in a notebook and helping design the experiments.
2. Ping-Chieh
3. Inigo

Appendix

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