

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.

Zhou et al. demonstrated that transformers handle long-term dependencies well with the "Informer model," which efficiently handles long sequences and improves trend forecasting accuracy using a "self-attention" mechanism [5]. Moreover, Lim et al. were even able to outperform traditional methods (like ARIMA) by combining the Transformer architecture with recurrent layers [6].

Zhen Zeng studied the applicability of Transformers combined with RNNs in trend detection specifically for financial time series in his paper [7]. He concluded that combining these two architectures significantly improved forecasting accuracy for intraday stock price movements of the SP500.

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 [8], [9].

Time series in the stock market often exhibit complex trends and non-linear patterns. Long Short-Term Memory (LSTM) Recurrent Neural Networks (RNN) are designed to learn long-term trends in sequential data, making them very good at modeling and forecasting financial market time series [10], [11].

LSTM networks address the vanishing gradient problem encountered in standard RNNs on this type of data by introducing specialized LSTM cells. These cells incorporate gates to control flow, allowing LSTMs to forget and remember information over long sequences [10].

The LSTM cell can be defined as follows [10]:

$$\begin{aligned}i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i), \\f_t &= \sigma(W_f x_t + U_f h_{t-1} + b_f), \\o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o), \\\tilde{c}_t &= \tanh(W_c x_t + U_c h_{t-1} + b_c), \\c_t &= f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t, \\h_t &= o_t \cdot \tanh(c_t),\end{aligned}$$

where:

- x_t is the input at time t , representing market data (e.g., stock price, volume),
- h_{t-1} is the hidden state (output) of the previous time step,
- i_t, f_t, o_t are the input gate, forget gate, and output gate
- \tilde{c}_t is the candidate memory cell state,
- c_t is the cell state at time t , capturing long-term dependencies,
- W and U are the weight matrices and b is the bias vector,
- σ is the sigmoid activation function

The *forget* gate, f_t , determines how much of the previous cell c_{t-1} is retained. The *input* gate i_t updates the cell with new information. The *output* gate o_t controls the hidden state, which is the LSTM output at time t [10].

Time series in the stock market are non-stationary, which means that their statistical properties (Avg, median) change over time. ARIMA models can be adapted to capture the behavior of non-stationary time-series [12]. A methodology formalized by Box et Al. in 2015 to apply the ARIMA model with a moving average component [13]. 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 [12]. The ARIMA model is defined mathematically as [13]:

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

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 [14], and performing Grid-Search on the specific hyperparameters will help us pin point the exact best accuracy we can get.

Transformers are based on self-attention mechanisms. They are able to weigh the importance of input elements by computing *attention scores*. While transformers were originally developed for natural language processing tasks, they have become popular for time-series forecasting due to their ability to handle long-range dependencies [15].

This makes transformers an ideal choice for predicting trends in volatile time series, as they can capture complex temporal patterns by assigning varying importance to different time steps.

Their adaptable mathematical design makes them a powerful tool for predicting any kind of time series. Financial markets are no exception. Hence, the literature suggests that the self-attention mechanism of Transformers makes them a pertinent choice for financial trend forecasting.

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 literature have used many methods, such as evaluating true positives and true negatives [cite]. Other have used mean absolute error (MAE) to assess prediction accuracy [14]. Finally, some have used runtime and resource usage for practical feasibility to assess their performance [6].

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

Definitions used in our project

RNN Implementation

RNN

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 Literature 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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