Capstone Report

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NOTE: This draft is based on our work so far. Some contents are complete (e.g., introduction), but details such as variable selection & result analysis might be subject to change in the later half of the semester.

1. Introduction

1.1 Background and Motivation

Financial markets are inherently complex and dynamic environments where anomalies are not just aberrations but can signal significant economic events such as market crashes, fraud, or sudden changes in investor behavior. Traditional methods of detecting these anomalies often fall short due to the sheer volume and variety of data, the nuanced nature of market behavior, and the need for real-time analysis. As a result, there is a substantial interest in developing more advanced, automated methods to detect these occurrences promptly and accurately (Poutré, Chételat, & Morales, 2024).

Among the various machine learning techniques available, autoencoders have emerged as particularly powerful tools for this purpose. Autoencoders are a form of neural network used to learn efficient codings of unlabeled data (Bourlard & Kamp, 1988). The network is trained to use input data to reconstruct the output, minimizing the difference between the input and the output, which teaches the model to capture the most important features present in the data. The efficacy of autoencoders in anomaly detection stems from their ability to reconstruct normal behavior; anomalies are identified by a significant increase in the reconstruction error, indicating that the model encounters data that deviate from the norm (Sakurada & Yairi, 2014).

1.2 Objectives of the Study

This report focuses on the application of an LSTM-based autoencoder—a specialized type of recurrent neural network suited for sequence data like stock prices—to enhance anomaly detection in financial time-series. LSTMs are well-regarded for their ability to capture temporal dependencies and long-term relationships in time-series data, which are critical in accurately modeling stock market data (Hochreiter & Schmidhuber, 1997). By learning to reconstruct such data and highlighting instances with high reconstruction errors, the model can effectively pinpoint anomalous events that could indicate critical market movements. This capability is tested using historical data from the S&P 500 and Russell 3000, providing a broad and varied dataset for robust model training and evaluation.

The findings from this project indicate that the autoencoder effectively identifies anomalies within the stock market data, with a high sensitivity to unusual patterns. These deviations are quantitatively assessed using the MAE, which provides a clear measure of how significantly an instance differs from the norm. This distinction between normal fluctuations and genuine anomalies was quantified using MAE, where the model demonstrated both high accuracy and reliability. These results suggest that autoencoders, with their ability to use reconstruction errors as a diagnostic tool, could serve as a valuable tool for financial analysts, aiding in the proactive monitoring and analysis of market conditions.

1.3 Structure of the Report

The paper is structured as follows: the Literature Review section explores the evolution and various models of anomaly detection with a focus on financial applications; the Methodology section details our data collection and preprocessing practices along with our model and variable selection rationale; in the Results section, we present the model's performance and the challenges encountered; and finally, the Conclusion and Future Work section summarizes our findings and outlines potential avenues for further research.

2. Literature Review

2.1 Overview of Anomaly Detection

Anomaly detection is essential for identifying irregular patterns in dynamic fields like finance, where unexpected behavior may indicate fraud, market manipulation, or system vulnerabilities. With growing data complexity, selecting effective detection methods tailored to specific data characteristics is increasingly important. This part explores various approaches to anomaly detection, emphasizing the strengths and limitations of different techniques across financial data applications.

Anomalies can usually be divided into three types: abnormal time points, time intervals and time series when we are dealing with time series data (Li and Jung, 2023). Li and Jung (2023) also reviewed the state-of-the-art deep learning models in anomaly detection, they point out that LSTM and autoencoders are most used in time points and time intervals anomaly detection, and for time series, PCA is popular because an abnormal time series exhibits significantly different patterns and can be detected in a low dimensional features space. Meanwhile, time interval abnormality is more important because it typically represents an event (Li and Jung, 2023).

In the comprehensive study by Schmidl et al. (2022), a diverse evaluation of anomaly detection algorithms is conducted, focusing on time series data across various fields, including finance. The authors implement 71 different algorithms from distinct families—such as deep learning, outlier detection, statistical, and data mining approaches—to analyze their performance on 976 datasets. Each algorithm's strengths, weaknesses, and suitability for specific types of anomalies are assessed, providing insights into effectiveness, efficiency, and robustness. The study emphasizes the variability in anomaly detection requirements across domains, highlighting that no single approach is universally best. This work serves as a valuable resource for selecting algorithms tailored to different time series characteristics and anomaly detection goals. (Schmidl, 2022)

Shi et al. (2019) explored anomaly detection in the Bitcoin market through price return analysis across five major platforms: OKCoin, BTC-e, Coinbase, bitFlyer, and Bitfinex. By examining the statistical properties of price returns, the study uncovers irregularities, particularly on the bitFlyer platform, where metrics such as kurtosis and power-law exponent diverge significantly from the others. This anomaly is potentially linked to price manipulation or money laundering, as evidenced by simultaneous irregular bid and ask prices on bitFlyer. These findings suggest that price return analysis can be an effective method for detecting unusual activity in cryptocurrency markets, highlighting regulatory challenges due to the decentralized nature of Bitcoin trading platforms. (Shi, 2019)

2.2 Example of Applicable Models

Deep learning models have shown significant potential in anomaly detection and predictive analysis across various domains. By combining approaches such as LSTM-Autoencoders and wavelet transforms with stacked autoencoders, these models can capture complex patterns and irregularities in time series data. Their ability to handle non-stationary data, extract high-level features, and detect deviations makes them particularly suitable for applications like network security and financial market predictions. This part explores the structure and effectiveness of these models in diverse contexts, emphasizing their adaptability and high accuracy in complex, real-time environments.

In the study by Kim et al. (2023), a novel anomaly detection method using multiple LSTM-Autoencoder models is applied to in-vehicle networks, particularly for CAN (Controller Area Network) protocol vulnerabilities. Given that CAN lacks encryption and authentication, it's susceptible to attacks like spoofing and denial of service (DoS). This method addresses these issues by analyzing key features such as transmission intervals and payload value changes. Each LSTM-Autoencoder model captures distinct characteristics of normal network behavior, enabling the detection system to recognize deviations that signify potential intrusions. Experiments show a high detection rate (99%) on real vehicle network traffic, confirming the approach's precision and low computational requirements, suitable for real-time monitoring within in-vehicle systems. (Kim, 2023)

According to Bao et al. (2017), a novel deep learning framework integrates wavelet transforms, stacked autoencoders (SAEs), and long-short term memory (LSTM) networks for stock price prediction. The framework operates in three stages: wavelet transforms first denoise the time series data, then stacked autoencoders extract high-level features, and finally, LSTM networks forecast stock prices based on these features. Tested across six stock indices—including CSI 300 and S&P 500—the model demonstrates superior predictive accuracy and profitability compared to other approaches, such as LSTM-only or recurrent neural networks (RNN). This method addresses the complex, non-stationary nature of financial data, enhancing both trend prediction and trading strategy performance. (Bao, 2017)

2.3 Application in Finance

Machine learning models have been widely used in the field of financial and time series anomaly detection. Primarily, hybrid and unsupervised models such as autoencoders, LSTMs, and SVMs are frequently employed due to their adaptability in modeling complex patterns in high-dimensional and temporal data.

Shon and Moon (2007) introduced a new SVM approach applied in anomaly detection without the need for the label, and at the same time, maintained the low false alarm capability, named Enhanced SVM. In this paper, Shon and Moon applied three techniques: Self-Organized Feature Map (SOFM), Passive TCP/IP Fingerprinting (PTF), and Genetic Algorithm (GA) to fulfill the goal. Golmohammadi and Zaiane (2015) proposed a prediction-based contextual anomaly detection tailored for fraud and manipulation in stock markets. The model proposed in this paper outperforms the traditional KNN and Random Walk models, but still flags false positives which need a double check.

There is a link between long-short anomaly portfolio returns and the time-series predictability of the aggregate market excess return (Dong et al., 2022). Dong et al. showed the link by using high-dimensional shrinkage methods, and it also showed significant predictive power for market returns. The findings suggest anomaly returns capture asymmetric arbitrage limits, affecting overall market pricing. Techniques such as forecast combination and machine learning enhance anomaly-based return prediction.

Ahmed et al. (2016) provides a comprehensive survey of anomaly detection techniques in the financial sector, focusing on clustering-based approaches due to the limited availability of labeled data. The survey categorizes anomaly detection methods and emphasizes unsupervised clustering techniques—like k-means, DBSCAN, and hierarchical clustering—as effective tools for identifying outliers, which often indicate fraud or irregular activities. Key assumptions in these methods include the grouping of normal data in dense clusters, with anomalies emerging as distant or isolated points. Additionally, Ahmed et al. discuss the challenge of data scarcity in financial applications, noting the reliance on synthetic data to simulate real-world scenarios. This survey offers a foundational view of clustering methods for anomaly detection, which is particularly relevant for analyzing stock price irregularities. (Ahmed, 2016, 11)

Zhang (2022) proposes an advanced approach for detecting anomalies in financial data by combining decision tree and random forest algorithms, which excel at handling complex financial datasets. The study highlights the decision tree's classification abilities, particularly in segmenting data based on hierarchical priorities that align with regulatory needs, such as those set by the China Securities Regulatory Commission. To address noise tolerance and refine anomaly identification, Zhang introduces an "abnormal point scale" to quantify the degree of abnormality in data samples based on their similarity to typical patterns. The random forest model, an ensemble of multiple decision trees, leverages tree diversity and a voting mechanism to deliver robust, consensus-driven classifications, minimizing overfitting. Experiments reveal that random forest outperforms distance-based methods like the Mahalanobis distance, enhancing both accuracy and computational efficiency. The model is especially effective for large, complex datasets, reducing computational time by avoiding matrix inversions required in other techniques. Zhang’s research underscores the potential of random forest models for scalable, high-precision anomaly detection in financial data, positioning it as a valuable tool for real-time and high-volume monitoring in financial institutions. (Zhang, 2022)

In the paper by Bakumenko and Elragal (2022), machine learning methods are applied to detect anomalies in financial data, particularly focusing on general ledger entries. They explore both supervised and unsupervised machine learning techniques, including deep learning methods like autoencoders and algorithms like isolation forests, to improve the efficiency and accuracy of anomaly detection. By using models trained on both real and synthetic datasets, they address common challenges in financial auditing, such as the inefficiency of manual inspection and the risk of missing fraudulent transactions in large data volumes. The study finds that unsupervised models, such as the isolation forest and autoencoder, are highly effective for identifying patterns and anomalies without labeled data, offering robust tools for auditors to prioritize high-risk entries and enhance sampling precision. This research underscores the potential of advanced ML models to revolutionize anomaly detection in auditing by automating the detection of irregularities in complex financial datasets (Bakumenko, 2022).

Gu, Kelly, and Xiu (2021) introduced a nonlinear asset pricing model using autoencoders, their model improved autoencoder neural networks by incorporating information from covariates along with returns. Nguyen et al. (2021) implemented a LSTM Autoencoder network-based method combined with a one-class support vector machine algorithm for detecting anomalies in sales. The model effectively captures dependencies in multivariate data, outperforming traditional approaches and supporting decision-making in inventory and demand forecasting (Nguyen et al., 2021).

Autoencoder is further widely used in time series anomaly detection. There is a two-step methodology combining K-means clustering and an autoencoder to categorize time series data, achieving 87.5% clustering accuracy (Tavakoli et al., 2020). The first stage is to apply a technique to create labels, transforming the problem from an unsupervised learning to supervised learning. The second stage is based on an autoencoder-based deep learning model, to build both known and hidden non-linear features of time series data (Tavakoli et al., 2020). Wong et al. (2022) proposes an AER (Auto-encoder with Regression) for time series anomaly detection. The model integrates an auto-encoder and LSTM regression model to predict and reconstruct time series, detecting anomalies through a combined prediction-reconstruction error approach. By using datasets like those from NASA and Yahoo, AER showed improved accuracy (23.5% over ARIMA) and efficiency across univariate anomaly detection datasets (Wong et al., 2022).

Azevedo and Hoegner (2023) applied over 30 machine learning techniques across over 250 models on a dataset with more than 500 million firm-month observations, finding that non-linear models such as Gradient Boosting Machine (GBM), Distributed Random Forest (DRF), and neural networks reveal complex market inefficient and outperform linear models in anomaly-driven returns.

To put anomalies research into practice, profitability is also quite important. By aggregating anomalies into a global mispricing model through machine learning models, it can generate a sustained return in large-cap stocks even after transaction costs (Tobek and Hronec, 2021). When taking region into consideration, Tobek and Hronec (2021) further illustrated that out-of-sample performance in the U.S. is not improved by the inclusion of international evidence in the training sample for the mispricing strategy, while Most of the predictability of the expected stock returns in all the regions can be captured solely with the U.S. training sample.

These past papers and research underline the importance of multi-technique integration and data-driven insights, marking a progressive shift in anomaly detection and financial modeling towards machine learning-enhanced frameworks. These methodologies showcase increased robustness and predictive accuracy, advancing understanding of anomalies and financial markets. In our research, we will focus on a combination of Autoencoder and LSTM to detect anomalies.

3. Methodology

3.1 Data Collection & Preprocessing

The dataset for this project was collected from two of the major and most used U.S. stock indices, S&P 500 and Russell 3000. The first step of this project is to retrieve the historical daily data of all stocks in these two indices and key features such as the date, open, high, low, close, adjusted close price, and volume of the stock on each trading day. The adjusted_close feature adjusts for corporate actions such as stock splits and dividends, making it a more accurate representation of the stock's market value. The volume feature reflects the level of trading activity, offering insight into market behavior and investor sentiment. This project chooses to focus on the adjusted_price feature and the volume feature.

Data preprocessing included several steps. First, the dataset was cleaned by removing missing stocks and converting all data points to float32 for computational efficiency. The dataset was then split into training and test sets, with training data covering the period up to December 31, 2020, and test data spanning from January 1, 2021, onward. To normalize the data, the StandardScaler was applied to both adjusted_close and volume, ensuring that all input features were on the same scale. A logarithmic return was also calculated by calculating the logarithm of the ratio of the adjusted close price at each time point and the previous time point for each stock to account for relative price changes over time. These preprocessing steps were critical for ensuring the stability and accuracy of the model.

3.2 Model Selection

This project uses an LSTM Autoencoder model as the primary tool for anomaly detection in stock price movements. The LSTM Autoencoder was selected due to its capacity for processing sequential data, making it highly suitable for time-series analysis. Unlike traditional feedforward neural networks, Long Short-Term Memory networks are capable of retaining and learning from data dependencies over long sequences, which is essential for analyzing trends and patterns in stock prices over time.

The autoencoder architecture consists of two main components: the encoder and the decoder. In this LSTM Autoencoder, the encoder takes in the stock data, including features like log_return, which is calculated in the data preprocessing stage, and volume over a window of consecutive days and compresses it into a lower-dimensional latent representation. This latent representation serves as a compressed version of the original sequence, capturing the essential patterns. The decoder then takes this latent representation and attempts to reconstruct the original sequence.

The input data for the model includes a sequence of stock data organized into sliding windows. Each window represents a 7-day period, chosen as the model's "window size," and contains two essential features: log return and volume. The log return feature represents the relative daily price change for a stock, calculated as the natural logarithm of the ratio between consecutive adjusted close prices in the data preprocessing stage. This feature provides the model with a way to observe relative price changes, allowing it to focus on percentage shifts rather than absolute price values, which is particularly useful for spotting unusual price fluctuations. The second feature, volume, measures the number of shares traded each day. Volume is a critical indicator of market sentiment and is reasonable to assume potential abnormal trading activity when there exists a sharp increase or decrease. Together, these two features, log return and volume, form the input for each 7-day window, allowing the model to capture both price dynamics and trading intensity.

3.3 Variable Selection

For this project, the input variables were log return and volume, which were selected based on their significance in stock market analysis. Log return measures the relative change in adjusted stock price in two consecutive days, providing a normalized representation of price movements. This is particularly useful for comparing price changes across different stocks. Volume represents the total number of shares traded on each trading day, which offers significant insight into market activity and liquidity. By focusing on these two key variables, the model was able to capture both price trends and trading behavior, which are crucial for detecting anomalies, which is the goal of this project.

The data was structured into windows of 7 days, with each window providing the input for the LSTM Autoencoder model. This windowing approach allowed the model to capture short-term trends in the stock prices and volumes, which are often crucial features that potentially implies market anomalies, which is the goal of this project. The decision to limit the variables to these two features also ensured that the model remained interpretable while focusing on the most relevant aspects of the data.

3.4 Implementation Details (Algorithms, Tools, etc.)

This project was implemented using Python, with several powerful libraries supporting data preprocessing, model construction, and visualization. The data preparation process relied heavily on Pandas and NumPy, which were used to manage, clean, and structure the stock market data into the necessary 7-day window sequences. These libraries also facilitated feature engineering, such as calculating the log_return and scaling the data. StandardScaler from Scikit-Learn was applied to normalize both the log_return and volume features, ensuring that they were on the same scale and limiting outliers. Normalization is essential for neural networks because it prevents features with larger magnitudes, such as volume, from overshadowing those with smaller ranges, like log_return.

4. Results & Analyses

4.1 Model Evaluation - Revisiting Reconstruction Error

To detect anomalies in stock returns, we first establish a threshold for reconstruction error, using the mean absolute error (MAE) as the core metric. During the training phase, the model is exposed to historical stock data and learns to recreate the return patterns. By minimizing reconstruction error, the autoencoder attempts to build a reliable representation of stock return dynamics.

To ensure that the model generalizes well and can be applied to the testing set, it is critical to assess the training and validation loss. As seen in the training history plot below, under the 30-epoch configuration, both the training and validation losses converge to an identical and relatively small value of approximately 0.07. This convergence indicates that the model has not overfitted the training data and exhibits good generalizability. In other words, the model is equally capable of reconstructing patterns in both training and unseen validation data, suggesting that the error metrics derived from the training set can be reasonably extended to the testing phase.

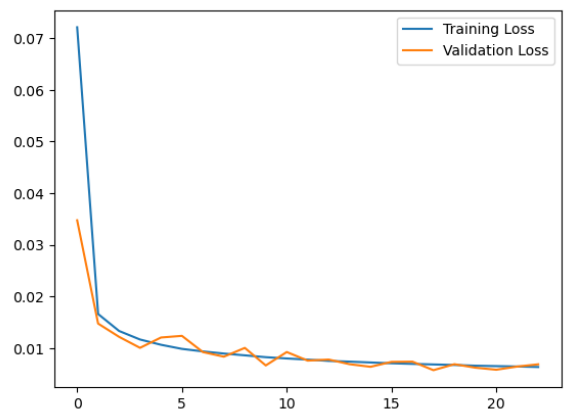

Figure 1. Training Loss and Validation Loss

Had the validation loss been significantly higher than the training loss, this would signal overfitting, and it would imply that the model struggles to generalize beyond the training data. In such a scenario, using the largest training loss as a threshold for detecting anomalies would be problematic, as the maximum error observed in training would likely be too small relative to the errors in the validation or testing sets. This discrepancy would lead to many false negatives, where significant anomalies in the test data could go undetected because the threshold would be set too low.

Now that it is established that the training set can be used as a reliable basis for designing an evaluation metric, the next challenge is determining the most appropriate way to set the threshold. To filter out the outliers, we choose to take the 90th percentile of the training loss distribution as our THRESHOLD.

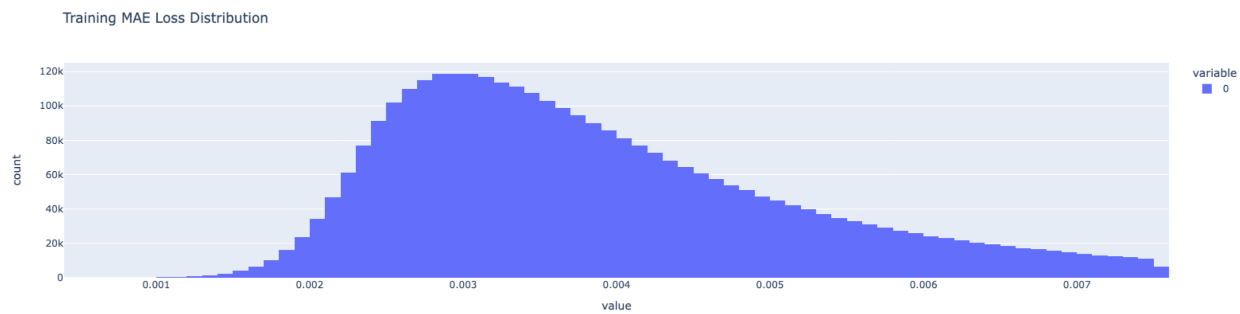

Figure 2. Training MAE Loss Distribution

The graph above shows the distribution of training MAE losses, highlighting a thin right tail, which underscores the importance of removing the top outliers that would have otherwise skewed the threshold calculation.

For anomaly detection, we feed the model with testing data, which consists of all stock returns beyond January 1, 2021, for the selected stocks. For each stock, the model calculates the MAE for every window of size WIN_SIZE (7 days in our case). If the MAE for any given window exceeds the 80th percentile threshold derived from the training data, that period is flagged as anomalous. This approach allows us to systematically identify periods of returns where the model's predictions significantly deviate from actual returns. For instance, this plot illustrates the MAE loss for Apple (AAPL) in the test set. The threshold effectively filters out only extreme values in the MAE loss, which demonstrates our threshold metric, derived from the training data, conveys useful information in determining anomalies in the test set.

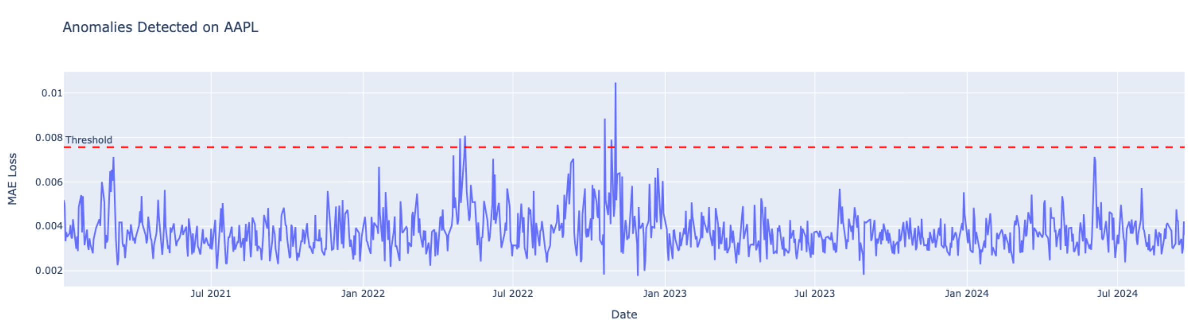

Figure 3. Anomalies Detected on AAPL

4.2 Limitations of Using MAE for Anomaly Detection

While the use of MAE as a threshold is a sensible and necessary choice for training and evaluating the model, it presents some challenges when defining anomalies, especially in the context of financial markets. Stock market anomalies are inherently subjective and difficult to quantify, and a simple statistical threshold like the MAE, while useful for model calibration, may not fully capture the complexity behind what constitutes an "anomaly."

A high MAE within a given period means that the absolute difference between the actual returns and the model's predicted returns exceeds our predefined threshold. However, this raises the question: Why does this particular threshold indicate an anomaly? In financial terms, a deviation might result from, amongst a myriad of other causes, normal market fluctuations that swing just above the level our model deems normal, rather than an actuarial anomaly.

Thus, while the MAE offers a quantifiable way to measure the model's accuracy in predicting stock returns, it lacks interpretive power for users attempting to distinguish between regular market noise and truly abnormal behavior. In essence, the concept of an "anomaly" in stock returns is subjective and depends on additional context, which MAE alone does not provide. Therefore, although MAE serves as a useful tool in training, more sophisticated methods are necessary to better define and interpret anomalies in the results.

4.3 Contextualizing Anomalies Using Real-World Events

One of the primary methods for giving meaning to the flagged anomalies is to associate them to the broader framework of real-world events. This approach seeks to provide an interpretive layer to the anomalies by examining whether the periods flagged by the model correspond to notable market events, such as earnings releases, central bank policy announcements, geopolitical tensions, or macroeconomic data releases.

Contextualizing the anomalies also involves analyzing how these events impact different stocks or sectors. Certain events may only affect stocks with specific traits (e.g., oil price shocks affecting energy companies), while broader macroeconomic shifts might impact a wider range of stocks. This can help distinguish between trait-specific anomalies and broader market-wide anomalies, offering additional layers of interpretation. For example, as highlighted in (Kim & Ha, 2010), small-cap, low-price and low book-to-market value stocks in the Korean stock market were shown to be significantly influenced by investor sentiment, even after accounting for market anomaly factors and price effects.

NOTE: We’re still researching the best way to incorporate real world events into our analysis, but so far haven’t found much luck with finding suitable data sources to automate this task. Currently our plan is to pick some stocks & research their anomalies manually (hence the section below), but this may be subject to change.

4.4 Demonstration: Contextualizing Anomalies from S&P 500 Constituents

While this approach is undoubtedly powerful and widely applicable, the lack of access to a comprehensive news feed data stream in our study poses a limitation on automating the contextualization of anomalies. Despite this, it remains possible to assess the efficacy of our method by manually correlating the flagged anomalies with significant market events or shifts.

In this demonstration, we select several representative stocks from the S&P 500 dataset. For each selected stock, we conduct manual online research to align periods flagged as anomalous by our autoencoder model with key events, such as earnings announcements, market-wide shocks, or sector-specific developments. This case-by-case analysis provides a deeper understanding of how real-world events and investor reactions manifest in stock price anomalies detected by the model.
(<u>work in progress, to be populated later</u>)

5. Conclusion & Future Work

This study demonstrates the effectiveness of using an LSTM-based autoencoder for anomaly detection in financial time-series data, specifically targeting U.S. stock indices like the S&P 500 and Russell 3000. By focusing on key features such as log returns and trading volume, the LSTM autoencoder successfully identifies periods with unusual market behavior, as indicated by elevated reconstruction errors. The use of a 90th percentile threshold for reconstruction error was chosen to balance sensitivity and specificity in identifying anomalies, ensuring that extreme deviations from normal behavior are highlighted without being overwhelmed by minor fluctuations. This choice is based on prior studies that suggest using high-percentile thresholds for anomaly detection in time-series data to filter out normal variability while capturing significant outliers (Chandola, Banerjee, & Kumar, 2009). This anomaly detection method provides a promising approach for automating the monitoring of market conditions and detecting unusual behaviors that could signify important economic shifts.

The results further highlight the utility of MAE as a metric for assessing the reconstruction performance of the autoencoder. However, the limitations of relying solely on statistical thresholds to define anomalies were also apparent, given the subjective nature of financial anomalies and the challenges in interpreting the economic significance behind these deviations. The manual contextualization of anomalies with real-world events underscored the importance of connecting statistical signals with underlying market dynamics to better understand and validate detected anomalies.

While the current approach has shown promising results, several avenues for improvement and further research are identified. One major direction for future work is to automate the contextualization of anomalies by incorporating real-world events, such as earnings announcements, macroeconomic reports, and geopolitical developments, into the model. This could be achieved by integrating financial news feeds or utilizing natural language processing (NLP) techniques to analyze news headlines and correlate them with detected anomalies (Lamon et al., 2017). The incorporation of such data would add an interpretative layer, enhancing the model's ability to distinguish between market noise and true anomalies.

Another potential enhancement is to expand the model by incorporating additional features, such as technical indicators, investor sentiment data, and macroeconomic variables, which could improve the robustness of anomaly detection. Moreover, experimenting with other deep learning architectures, such as Transformer-based models, could provide deeper insights into long-term dependencies in financial time-series data (Vaswani et al., 2017). Evaluating different threshold-setting techniques, including adaptive thresholds based on dynamic market conditions, could also lead to better accuracy in distinguishing genuine anomalies from regular market movements.

Lastly, applying this methodology across different financial markets, such as cryptocurrencies or foreign exchange, could assess the generalizability and adaptability of the proposed model. Extending the research to other asset classes would provide valuable insights into the model's versatility and highlight areas where improvements are needed to adapt to different market structures and dynamics.

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