The Impact of Corporate Crisis on Firm Equity Value: An Event-driven Approach

Ziqian Song

Dissertation submitted to the Faculty of the

Virginia Polytechnic Institute and State University

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Computer Science and Application

Edward A. Fox, Chair

Weiguo (Patrick) Fan, Co-Chair

Tanushree Mitra

Andrea L. Kavanaugh

Kang Zhao

July 31, 2020

Blacksburg, Virginia

Keywords: Corporate Crisis Events, Stock Prediction, Social Media, Deep Learning, News Propagation, Stock Indicator

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(ABSTRACT)

Corporate crisis events such as cyber attacks, executive scandals, facility accidents, fraud, and product recalls can damage customer trust and firm reputation severely, which may lead to tremendous loss in sales and firm equity value. My research aims to integrate information available on the market to assist firms in tackling crisis events, and to provide insight for better decision making. We first study the impact of crisis events on firm performance. We build a hybrid deep learning model that utilizes information from financial news, social media, and historical stock prices to predict firm stock performance during firm crisis events. We develop new methodologies that can extract, select, and represent useful features from textual data. Our hybrid deep learning model achieves 68.8% prediction accuracy for firm stock movements. Furthermore, we explore the underlying mechanisms behind how stakeholders adopt and propagate event information on social media, as well as how this would impact firm stock movements during such events. We adopt an extended epidemiology model, SEIZ, to simulate the information propagation on social media during a crisis. The SEIZ model classifies people into four states (susceptible, exposed, infected, and skeptical). By modeling the propagation of firm-initiated information and user-initiated information on Twitter, we simulate the dynamic process of Twitter stakeholders transforming from one state to another. Based on the modeling results, we quantitatively measure how stakeholders adopt firm crisis information on Twitter over time. We then empirically evaluate the impact of different information adoption processes on firm stock performance.

We observe that investors often react very positively when a higher portion of stakeholders adopt the firm-initiated information on Twitter, and negatively when a higher portion of stakeholders adopt user-initiated information. Additionally, we try to identify features that can indicate the firm stock movement during corporate events. We adopt Layer-wised Relevance Propagation (LRP) to extract language features that can be the predictive variables for stock surge and stock plunge. Based on our trained hybrid deep learning model, we generate relevance scores for language features in news titles and tweets, which can indicate the amount of contributions these features made to the final predictions of stock surge and plunge.

The Impact of Corporate Crisis on Firm Equity Value: An Event-driven Approach

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(GENERAL AUDIENCE ABSTRACT)

Corporate crisis events such as cyber attacks, executive scandals, facility accidents, fraud, and product recalls can damage customer trust and firm reputation severely, which may lead to tremendous loss in sales and firm equity value. My research aims to integrate information available on the market to assist firms in tackling crisis events and providing insight for better decision making. We first study the impact of crisis events on firm performance. We investigate five types of crisis events for S&P 500 companies, with 14,982 related news titles and 4.3 million relevant tweets. We build an event-driven hybrid deep learning model that utilizes information from financial news, social media, and historical stock prices to predict firm stock performance during firm crisis events. Furthermore, we explore how stakeholders adopt and propagate event information on social media, as well as how this would impact firm stock movements during the events. Social media has become an increasingly important channel for corporate crisis management. However, little is known on how crisis information propagates on social media. We observe that investors often react very positively when a higher portion of stakeholders adopt the firm-initiated information on Twitter, and negatively when a higher portion of stakeholders adopt user-initiated information. In addition, we find that the language used in the crisis news and social media discussions can have surprising predictive power on the firm stock. Thus, we develop a methodology to identify the importance of text features associated with firm performance during crisis events, such as predictive words or phrases.

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Chapter 1

Introduction

1.1 Motivation

The stock market often reacts quickly to the release of corporate crisis events and relevant information [1, 2, 3]. For example, the announcement of firm events such as cyber attacks, product recalls, facility accidents, and so on may cause a significant impact on firm stock performance since it may directly affect public perception of firm reputation, and further lead to impact on product sales or firm earning potentials, etc. In December 2013, Target confirmed that it experienced a massive data breach that affected 40 million consumers. The financial loss associated with the breach event exceeded \$100 million. A more recent corporate crisis incident was the Facebook data scandal in March 2018. The estimated cost of the event was around \$35 billion after the reveal of the breach [4]. For a significant crisis event, the media announcement of the event can bring significant negative returns to the firm. However, corporate crises are not all the same, and we may see different impacts on firms for similar types of events. Hence, there is a need to differentiate them and find what drives different effects of the crisis events. For instance, during crisis events, some firms strategically leverage various media sources to either disclose more information (e.g., remedy action, plans, more details about the incidents, etc.) or communicate with investors/customers directly to guide conversations. These behaviors may potentially assuage the anger and frustrations of investors, and help restore the firms' reputation and image, preventing the crisis event from causing further damage. These are all reflected in different sources of online information. As incidents of corporate crisis become more frequent, determining how to effectively utilize event-related information to evaluate the impact of varying crises is crucial for researchers and practitioners.

1.2 Research Questions

My research employs an event-driven approach to investigate the impact of crisis event-related information, including the impact of event-related news and social media posts, and the diffusion of event-related information on social media. In addition, we try to identify the predictive features for stock movement during firm crisis events. The primary research question for this study is how firm crisis events impact firm stock returns. Our primary research question can be decomposed into the following sub-questions:

- *Can we effectively predict stock performance during crisis events using available information?*
- *How do stakeholders perceive the crisis information sent by a firm as opposed to by other stakeholders, over time? Will different information diffusion patterns influence firm stock movement during the event?*
- *Which words or phrases are more relevant to the predictions of firm stock movements (surge or plunge) during corporate events?*

1.3 Research Hypotheses

Firm crisis events and associated information may trigger a change in the firm's stock price immediately. In recent years, financial news that reflects different types of firm/market event information has become the primary data source for stock prediction. Researchers develop a variety of methods to generate text representations of financial news and adopt machine learning algorithms to make predictions of stock movements. However, the stock prediction using financial news mostly focuses on investigating the impact of each news item, and ignores the cumulative effect of different news stories associated with the same event. As firm crisis events occur more frequently, an event-driven methodology is crucial in evaluating the impact of crisis events.

Besides, the popularity of social media has provided a new information dissemination channel and fundamentally changed the way investors acquire information. As a new information source for investors, social media is powerful in the prediction of major financial indexes and firm stock performance [3, 5]. While previous studies have mainly focused on one information source, or use simple text representations, it is necessary to develop more complex feature representations that can extract the critical contents from different information sources. Thus, we propose our first hypothesis that:

H1: Our event-driven hybrid deep learning model can effectively integrate event-related information from different sources and make better predictions on firm stock movements during firm crisis events.

Researchers provide empirical evidence that social media has a significant predictive relationship with firm equity value [5]. However, the previous studies often focused on volume-based measures from readily available social media data (e.g., message volume, emotion, etc.) [3, 5, 6]. During crisis events, firms initiate and then propagate clarifications, remedy actions, or apologies, to stakeholders in real-time. They do so to investors via posting on corporate accounts. Stakeholders' perception toward the firm-initiated information varies, depending on multiple factors such as the quality of the information, the credibility of the source, etc. When stakeholders consider the information released by firms as high quality, credible, and useful, many of them may adopt and spread the information on social media. Thus, the information tends to be propagated to a wider audience quickly, which may potentially increase stakeholders' perception of the firms during crisis events, and further influence stock performance. Therefore, we investigate the propagation of firm-initiated crisis information. We also measure stakeholders' adoption of firm-initiated news on Twitter to see whether it can enhance or moderate stakeholders' reaction to corporate crises.

Similarly, user-initiated information is part of the messages that shape post-crisis firm reputations. Social media has empowered stakeholders to vent their emotions and express complaints about firms. During a corporate crisis, investors often react very negatively when the information related to the event is spread widely by non-corporate users on social media [3]. Such can lead to a severe social media crisis if not properly managed. Therefore, we propose the following hypothesis:

H2: Stakeholders' adoption of event-related tweets in the information propagation process is associated with the stock price reaction after a firm's crisis incident.
H2a: Stakeholders' increasing adoption of firm-initiated tweets in the information propagation process has a positive impact on stock price reaction after a firm's crisis incident.
H2b: Stakeholders' increasing adoption of user-initiated tweets in the information propagation process harms stock price reaction after a firm's crisis incident.

As demonstrated previously, language used in firm news and social media has shown predictive power for stock movements [7, 8, 9]. Firm news and social media discussions may convey critical information such as firm actions and investor perception of firm performance.

Researchers have used the negative words contained in the news articles to measure the impact of news on stock price and suggest that the linguistic information was incorporated in firm stock price [10]. Yet, there are many more language features to be investigated. Thus, we hypothesize that:

H3: The language features in news or social media have predictive power on firm stock movements during corporate events.

1.4 Research Framework

We design a hybrid deep learning model and develop new textual representation methodologies for news and social media data. Our hybrid model can make more accurate predictions for firm stock performance. Furthermore, we model the diffusion of event-related information on social media and evaluate the impact of information diffusion on firm stock performance during the crisis events. Finally, we propose methodologies to identify features that may be able to signal future stock movement during a firm event. Our research demonstrates how firm crisis events would impact the stock performance, and what causes the impact, using available information.

We work with three sets of data: financial news, social media, and historical stock prices. We extract events from financial news, then retrieve event-related news reports, tweets, and historical stock data in the event window. Subsequently, we use the data for those events, in three studies, that are summarized below, and then elaborated upon in the following three chapters.

After we have the event-related information, as summarized in the first subsection below, we build a hybrid deep learning model to predict firm stock performance during the event.

We extract features, and generate a vector representation with these features, from news and social media. After that, we feed the generated vector representation along with the historical stock prices to a hybrid deep learning model, and generate the stock predictions for firm crisis events. In the second subsection, we discuss the diffusion of information. The main content of this subsection was presented in the 2019 Conference on Information Systems and Technology [11].

We use Twitter to study the spread of event-related information. We look into two types of information based on the information resources, firm-initiated information and user-initiated information. We model the diffusion process of the two types of information and generate two indicators, which measure people's information adoption behavior for firm-initiated information and user-initiated information. We empirically evaluate the impact of the two indicators on stock performance. In the third subsection, we will identify features from event-related information that can be signals for stock movement during firm events. As described in a previous publication, we extract text features from firm disclosures to identify firm actions toward crisis events and the impact on firm stock return [12]. In this subsection, we try to interpret our deep learning model to generate more predictive features from news and social media for firm stock prediction during firm events.

1.4.1 A Hybrid Deep Learning Model for Stock Prediction during Corporate Crisis Events

As shown in the research framework (see Figure 1.1), our model integrates multiple data sources to make predictions of firm stock performance during crisis events. We developed new methodologies that can extract, select, and represent useful features from textual data. For news data, we generated meaningful text representations for news titles and defined

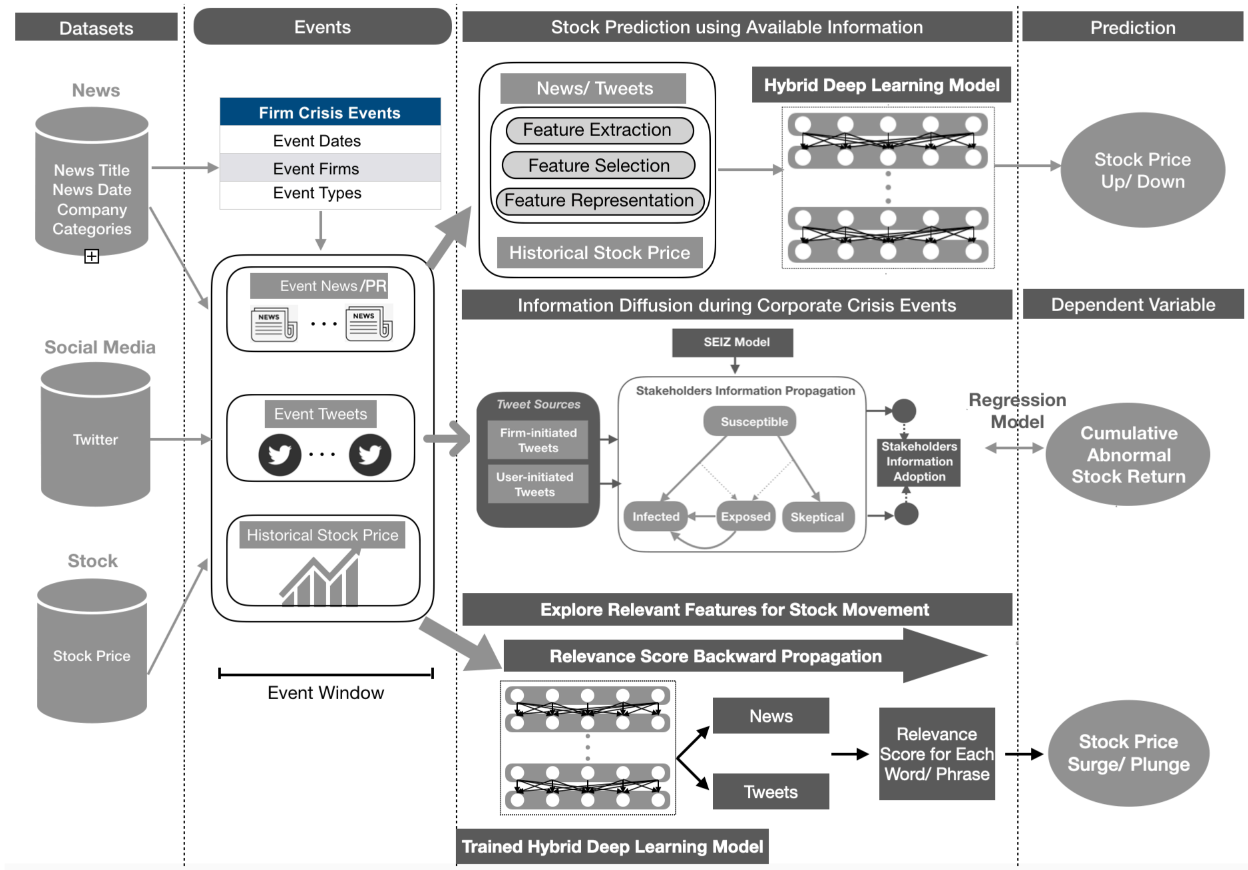


Figure 1.1: Proposed Research Framework

event "Actor", "Action", and "Object" from the news titles by applying Open Information Extraction (Open IE). We then developed methodologies that can better represent the dominant news features and make predictions using these features. Our model also incorporated social media data, which is much larger than the news titles collection. Once a significant crisis event happened, different types of information or emotions were generated and spread on social media. To capture the different types of social media discussions, for each event, we cluster all social media posts and use cluster centroids to characterize the classes of social media posts. In addition to textual data, for each event, we feed the historical stock prices in the event time window to an LSTM (Long-Short Term Memory) network to make predictions. Finally, we integrate all the predictions into a hybrid deep learning model to make the final prediction, which reaches 68.8% accuracy.

1.4.2 Measuring the Impact of Corporate Crisis News Propagation via Twitter

We model the crisis information propagation process using real social media data from Twitter. Drawing from the information propagation process, we quantify stakeholders' information adoption behavior for both firm-initiated and user-initiated information on Twitter during major firm crises. Besides, we propose these two measurements as indicators for firms' stock reactions during crisis events. We empirically test the association between the stakeholders' information adoption behavior and firm stock performance. Our results suggest that a higher portion of stakeholders adopting the firm-initiated information on Twitter is beneficial for firm stocks during crisis events. In contrast, a higher proportion of stakeholders adopting user-initiated information on Twitter can have a significant negative impact on firm stocks.

1.4.3 Exploring Predictive Features from Text-based Information for Stock Movement during Corporate Events

The language used in the financial news and social media discussions can have surprising predictive power on the firm's stock. In the third section, we identify the features associated with firm performance during corporate events, such as predictive words or phrases. We propose the application of the Layer-wise Relevance Propagation (LRP) algorithm [13] to interpret the hybrid deep learning architecture. In this process, we calculate the relevance score of features from financial news and social media, which indicate the amount of contribution the features made to the final predictions of stock movements.

Chapter 2

A Hybrid Deep Learning Model for Stock Prediction during Corporate Crisis Events

2.1 Introduction

Corporate crisis events are becoming increasingly common, and firms are believed to incur substantial financial cost. However, the impact of different crisis events on stock prices may not be the same, even when the event is similar. For example, the announcements of the Target 2013 data breach and Home Depot 2014 data breach had obviously different impacts on the impacted firms' stock price change during the event. Target announced a data breach incident on December 18, 2013, that over 40 million credit and debit card accounts might have been impacted. Then the massive news reports related to the event reached the public. Evidence showed that Target had known the information between November 27, 2013, and December 15, 2013, before the information was officially released to the public. After this information was released, a vast number of news media started to blame Target for delayed responses. Besides, the dissatisfied stakeholders spread their negative emotions in social media, and many of them canceled their Target credit cards. The stock price of Target plummeted initially but bounced back after Target announced that it had security breach insurance and was going to buy Fireeye's security services. In this breach event, Target showed a series of poor management decisions about the event, which was also reflected in the massive amount of news reports, social media posts, and its stock prices during the event.

Home Depot, instead, was considered a success in handling its security breach [14]. Home Depot was hacked in September 2014, with 56 million cards compromised. The CEO of Home Depot acted immediately and sent an announcement to the public with a guarantee that Home Depot would take full responsibility if any unauthorized transaction occurred with Home Depot cardholders. The announcement also mentioned other remedial actions such as providing free credit monitoring services and quickly increasing the call center capacity for customer inquiries. A variety of major news media reported the information to the public, and the announcement also dominated the discussions on social media. As a result, Home Depot's stock price did not drop much, and recovered quickly within a few days of the event.

The investigation of the above events inspired our research. When firm crisis events are released to the public, they generate a large amount of news reports, which can have a significant predictive power for firm performance during the event [15, 16, 17, 18]. As social media become increasingly adopted, a large number of users discuss and express their opinions during firm crisis events. Social media also have shown a significant predictive relationship with firm equity value [5, 19, 20, 21].

After we recognize the correlations between the stock price and crisis-related event information, how to effectively utilize techniques to extract useful event information to support decision making has become a critical task. In this chapter, we propose an event-driven stock prediction model, which considers the joint impact on the stock market of all available event-related information for a specific event.

However, event-driven stock prediction is challenging, partially because firm crisis event information, as well as event-related information we can extract from the news, is limited. In addition, different parties may describe the same event in different ways, and it is a challenging task to gather and curate information for a particular event. Besides, how to integrate different data sources into the prediction model effectively, and model their joint effect, also is tricky, especially when the data has different structures and characteristics [22]. Previous work mainly uses features from one data source, such as using sets of words, noun phrases, and named entities, to extract features from news articles [16, 17, 23]. Some researchers have developed strategies to concatenate the features from multiple sources into one compound feature. Nevertheless, these features do not capture the characteristics of different types of data, which limits their potential utility.

In this chapter, we present a novel hybrid deep learning framework that can effectively predict event stock price movements by fusing various sources of information. We extensively collect event-related information, including event-specific news titles, event-related social media posts, and stock time-series data. Furthermore, we use different methodologies to extract features from news media, social media, and the historical stock data.

The rest of this chapter is organized as follows. In the next section, we introduce the related literature of our study, followed by a description of our datasets. We then describe our model framework, including how we process information from different sources with our hybrid deep learning model. We then show the effectiveness of the proposed approach. Finally, we conclude the chapter and describe planned future work.

2.2 Related Work

Stock market prediction has been a complex issue. It has attracted much attention from both researchers and practitioners [24]. In Figure 2.1 and Figure 2.3, we summarize the previous representative works that utilize text mining, machine learning, and deep learning for stock predictions. Traditionally, the most common stock prediction methodology is technical analysis, in which predictions are made based on historical stock prices. Neural networks have been proposed by researchers to model the predictive relationships [25, 26, 27]. However, in many cases and contexts, these models have limitations on their predictive power because they rely solely on past stock movements [28].

Firm fundamentals were also considered to have an association with future earnings and abnormal stock returns. Researchers investigate firm fundamental data from different sources and make predictions based on information from fundamentals [29, 30, 31, 32]. Nevertheless, fundamental data is usually unstructured, and it is challenging to extract useful content from fundamental data and then make efficient use of it.

More recently, the study of financial news became popular due to the dramatic increase of available online information. Financial news can reflect market expectations and a firm's stock performance. When using financial news for stock prediction models, researchers usually apply natural language processing to extract features from textual content. However, existing literature typically relies on simple textual representation with bag-of-words, named entity recognition, term frequency-inverse document frequency (TF-IDF), and sentiment score [10, 16, 23, 33, 34]. Besides, they mostly use machine learning predictive models such as Naïve Bayes, regressions, support vector machines, and decision trees [16, 23, 35, 36, 37]. Compared with traditional machine learning with simple features, researchers have achieved better prediction results using deep learning [34, 38].

Table 2.1: Stock Prediction Literature using Firm Fundamentals or Historial Stock Prices as Data Sources

Data Sources	Methodologies	Authors	Predictions	Data Details
Fundamental analysis	Word List	Loughran and McDonald (2011)		10-K
	Bag-of-words, Tone, Dictionary	Li (2010)	Index, Earning, Stock Return	Corporate Filings
	Naïve Bayes, K-NN, ANN, SVM	Groth and Muntermann (2011)	Abnormal Risk	Corporate Disclosures
	Neural Networks	Hulme and Xu (2001)	Australian Stock Exchange (ASX)	Fundamental Indexes
Technical analysis	Neural Networks	T. Kimoto et al. (1990)	Tokyo Exchange Index	Stock Price
	Neural Networks	Yu and Huarng (2010)	Stock Index Taiwan	
	Stochastic Time Effective Neural Network Model	Liao and Wang (2010)	Global Stock Indices	

Table 2.2: Stock Prediction Literature using News as Data Source

Data Sources	Methodologies	Authors	Predictions
News media	SVM-light (good/bad news)	Mittermayer (2004)	Stock price trends
	Bag-of-words for Negative Words	Tetlock (2008)	S&P 500 Firms, Stock Return
	SVM with Standard Linear Kernel	Soni, Eck, and Kaymak (2007)	11 Oil and Gas Company
	SVM- Bag-of-words, Name Entities, Noun Phrases	Schumaker and Chen (2009)	Stock Return
	Regression	Jin et al. (2013)	Exchange Rate
	Bag-of-words, SVM	Luss and Aspremont (2015)	Individual Stock
	Stepwise Multivariate Regression Model	Chatrath et al. (2014)	Exchange Rate
	Event-embeddings	Ding et al. (2015)	S&P 500 Index, Individual Stock
	Bag-of-words, RNN, LSTM	Kraus and Feuerriegel (2017)	Abnormal Returns
	Deep Learning and Knowledge Graph Embedding	Yang et al. (2018)	1 stock

The increase of user engagement in social media effectively strengthens the influence of social media in stock prediction. Social media users may spread information and emotion on social media, which can potentially lead to an impact on firm stock price [39, 40]. Some researchers focus on predicting the financial performance of the firms using social media data. For example, Bollen and Mao [40] captured the public sentiment from tweets to forecast stock market movements. Luo *et al.* reported that social media was a leading indicator of firm equity value based on the investigation of the software and hardware industries [5]. Yang and Counts provided evidence that social media attributes were more relevant to stock performance than conventional media attributes [41]. However, studies have been focused on numerical data like sentiment score and the volume of posts [40, 42, 43, 44, 45]; the textual contents of social media were barely studied.

Besides, some researchers have taken advantage of inputs from multiple sources, for example, using social media text/sentiment combined with textual features from financial news or using technical indicators combined with textual features [17, 19, 46, 47]. A more recent approach uses Graph CNN, which helps generate company relationships that may facilitate the prediction [48].

Different from previous research, our study develops more comprehensive feature representations and a hybrid model that integrates news, social media, and historical stock data (Table 2.3). We focus on event-driven predictions and measure the cumulative impact of all related information on firm stock during an event, which was barely mentioned in the previous literature.

Table 2.3: Stock Prediction Literature using Social Media or Comprehensive Data Sources

Data Sources	Methodologies	Authors	Predictions	Data Details
Social media	Self-organizing Fuzzy Neural Network (SOFNN) - Mood	Bollen et al. (2015), Bollen and Huina (2011)	DJIA	Social Media Data
	Sentiment SVM Linear Kernel	Nguyen, Shirai, and Velcin (2015)	18 stocks	
	Sentiment - Multiple Classification Algorithms	Das and Chen (2007)	Stock Index, Volumes and Volatility	
	Decision Tree - Sentiment	Vu et al. (2012)	DJIA	
Comprehensive	POS-tagging, SVM	Zhai, Hsu, and Halgamuge (2007)	1 stock	News and Technical Indicators
	Sparse Matrix Factorization (SMF)	Sun et al. (2016)	S&P 500 Index	Social Media and Stock Price
	Advanced Sentiment Analysis Technique	Yu, Duan, and Cao (2013)	Stock Return and Risk	Blog, Forum and News
	SVM, Chi²-based feature selection	Hagenau et al. (2013)	Stock Return	Corporate Announcement and Financial News
	Graph Convolution Neural Network	Yingmei Chen (2018)	20 Stocks	Historical Stock/ Company Relation Graph
	Word2vec, RCNN	Vargas, De Lima, and Evsukoff (2017)	S&P 500 Index	Financial News and Technical Inidcators
Event Information	***A Hybrid Deep Learning Model Comprehensive Feature Representation***	***Our Approach***	***Event Stock***	***News, Social Media and Stock Price***

2.3 Data

Our initial data collection contains financial news titles for S&P 500 companies between January 2010 and March 2019, from Ravenpack[1]. Each news title in our collection has a predefined event category label. We choose five types of firm news for the event category: 1) cyber attack; 2) fraud; 3) facility accident; 4) executive scandal; and 5) product defect. These are operational crises that may have a significant impact on firm performance. We assume a firm would only have one crisis event of the same type in 30 days. Based on that assumption, we define the start of an event as the date that the firm news showed up the first

[1]http://www.ravenpack.com/

time and the end of an event as 30 days after. Our total number of events extracted from the news is 1619, with 14,982 related news titles and 4.3 million relevant tweets. Since we also evaluate the role of social media in stock predictions, we exclude events that do not have Twitter discussions during the event time. We generated an event-related keywords list for the five types of events. For each event, we query tweets based on the event-related keywords, with company name or the company's Twitter screen name within the event window. After removing the events for which we can not get any Twitter posts, we have 1319 events for our prediction model. Finally, for each firm event, we define four event windows for prediction: 3-day, 7-day, 15-day, and 30-day. We then test our model accuracy for these different event windows.

2.4 Approach

In this chapter, we propose a framework to predict the influence on stock price from particular firm events. We try to integrate the knowledge from the news, social media, and historical stock prices to predict the change of stock price at the event level.

Next we introduce the model in our framework. Figure 2.1 shows how we represent news titles in our model. For each event day, for one news title, we generate a vector representation by the following procedure:

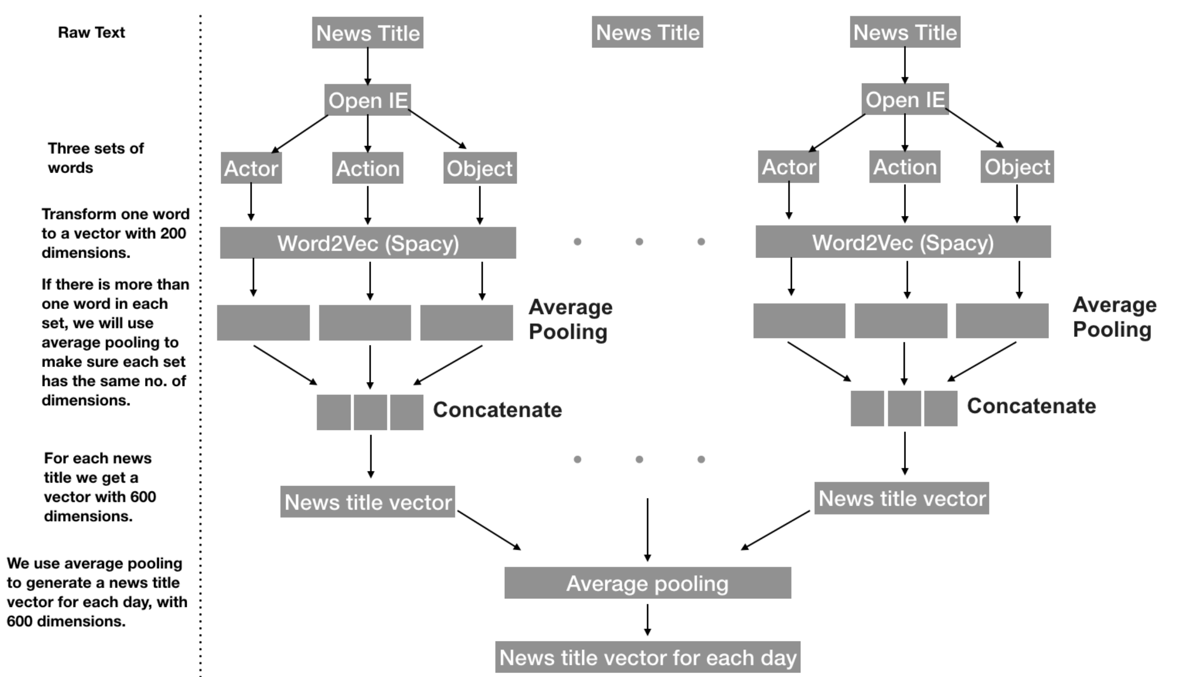


Figure 2.1: News Titles Representations for Each Day

We use Open IE (Open Information Extraction) to generate three sets of words ("Actor", "Action", and "Object") from the news titles. With Open IE, we can extract the event's structure from the news titles and eliminate the information that may not be important in our further analysis. It helps us to extract more useful knowledge from the news titles. Then, we use word2vec to embed the three sets of words to generate the words' vectors. If there is more than one word in each set, we use average pooling to ensure the vector in each set has the same size. We concatenate the vector from each set to generate the new title vector N_{ijk} with 600 dimensions, for further analysis. For N_{ijk}, i indicates the i^{th} event, j indicates the j^{th} day, and k indicates the k^{th} news item. Typically, in one day, there are several news titles about the same event. In our model, we try to generate the most representative vector for each day's news titles. To do so, we average all news vectors in one day to obtain the one-day news vector representation:

$$ND_{ij} = \frac{\sum_{k=1}^{K_{ij}} N_{ijk}}{K_{ij}}. \tag{2.1}$$

Here K_{ij} is the number of news items for the i^{th} event and j^{th} day. With average pooling, the model generates vectors with the same dimension for each day of a specific event, even when the number of news titles is different, which is important for our further analysis. In this study, we predict the changes of stock price based on the news titles within the event window. According to previous research, the CNN method may improve the accuracy of the prediction [49, 50]. As shown in Figure 2.2, we use the convolution layer and max pooling to generate the comprehensive news vector NC_i^{30} with size 600 for all news titles in the event window for the i^{th} event.

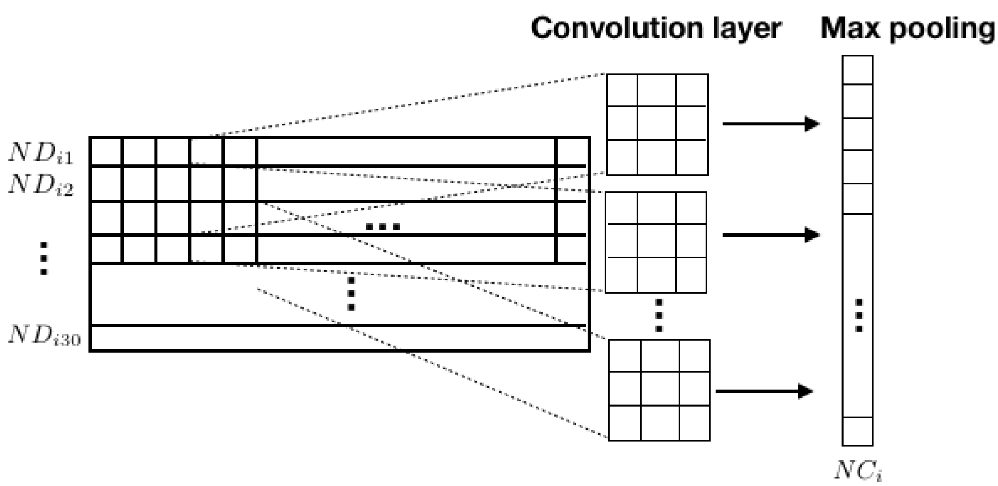


Figure 2.2: Convolution Layer and Max Pooling for 30 Days News

For tweet processing, we know that for major events, there would be a large number of tweets discussing the event. The discussions can be about many different types of opinions or emotions. So we need to use a different methodology to process tweets. Figure 2.3 is the schematic for tweet processing.

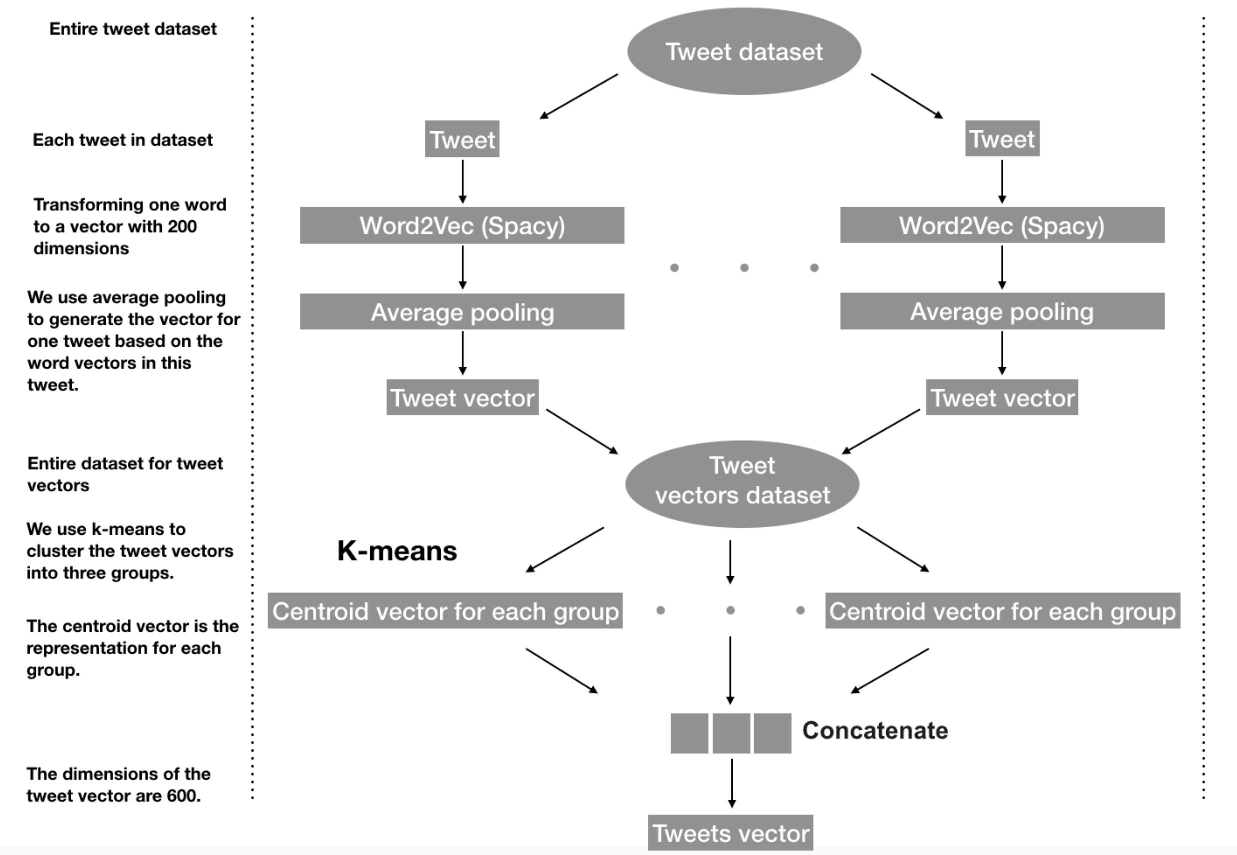


Figure 2.3: Tweets Representations for the Entire Event Window

For each tweet in the entire event window, we use word2vec to transform a word in the tweet to a vector with 200 dimensions. We use average pooling to generate the vector for one tweet. Tweets, as compared to news titles, mostly reflect the emotions or attitudes from Twitter users, and there are no clear representative tweets for most of the events. To obtain the knowledge from tweets, for each event, we cluster the collection of tweets into groups and analyze the tweets from different groups separately. The centroid vector is the representative for each group. There is no clear way to determine the number of groups for each event. In our work, we use three because, for each event, there are usually three kinds of emotion expressed in tweets —— positive, negative, and neutral. Then, we concatenate the centroid vector from each group as our tweet vector T_i^l with 600 dimensions, where l indicates the tweet vectors are generated over l days.

We demonstrate our model using 30-day as the event window. With the information from news titles and Twitter during 30 days of the event, we have the vector NC_i^{30} for the news and the vector T_i^{30} for tweets. We concatenate NC_i^{30} and T_i^{30} as a new vector NS_i^{30}. We employ 10 fully-connected layers with 0.5 dropout and the softmax layer to get the probability of stock price change for the 31^{st} day, which is denoted as Pn_i^{31}.

For the historical stock price P_{ij}, we employ the long short-term memory (LSTM) method to predict the stock price after the event. For P_{ij}, i indicates the i^{th} event and j indicates the j^{th} day. The schematic of LSTM is shown in Figure 2.4:

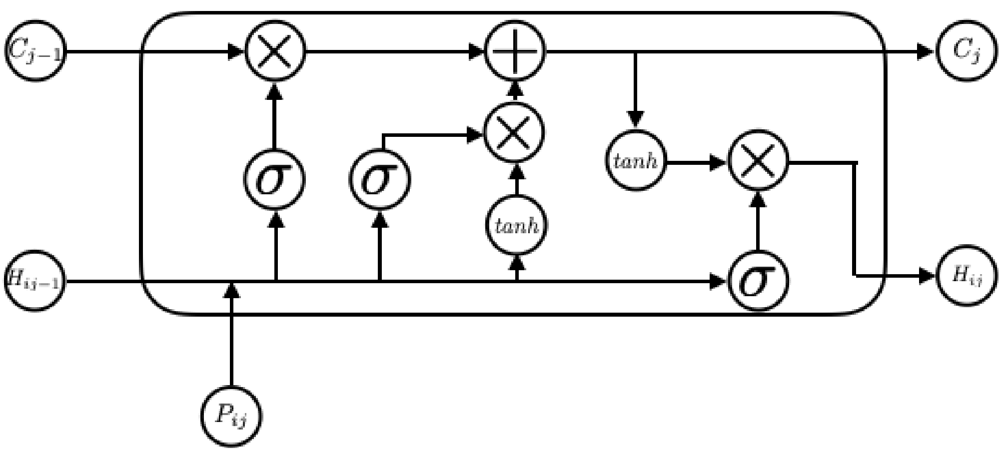


Figure 2.4: The Schematic of LSTM

In Figure 2.4, σ indicates the sigmoid activation function which is:

$$\sigma(x) = \frac{e^x}{1 + e^x}$$

In Figure 2.4, $\times$ indicates the element-wise multiplication, $+$ represents the element-wise summation, and $tanh$ indicates the hyperbolic tangent activation function which is:

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}.$$

Here C_j indicates the state of the LSTM model at the j^{th} day and H_{ij} represents the output of the LSTM model at the j^{th} day for the i^{th} event. The formal equations for LSTM are:

$$\begin{aligned}
f_j &= \sigma(W_f \cdot [H_{ij-1}, P_{ij}] + b_f) \\
i_j &= \sigma(W_i \cdot [H_{ij-1}, P_{ij}] + b_i) \\
\tilde{C}_j &= \tanh(W_c \cdot [H_{ij-1}, P_{ij}] + b_c) \\
C_j &= f_t \times C_{j-1} + i_j \times \tilde{C}_j \\
o_j &= \sigma(W_o \cdot [H_{ij-1}, P_{ij}] + b_o) \\
H_{ij} &= o_j \times \tanh(C_j).
\end{aligned} \tag{2.2}$$

In Equation 2.2, f_j indicates the information we intend to forget from the last state C_{j-1}, while i_j indicates the new information we want to store based on the last state C_{j-1}. We use the softmax layer to transform the output vector H_{ij} to the probability of stock price change Ps_i.

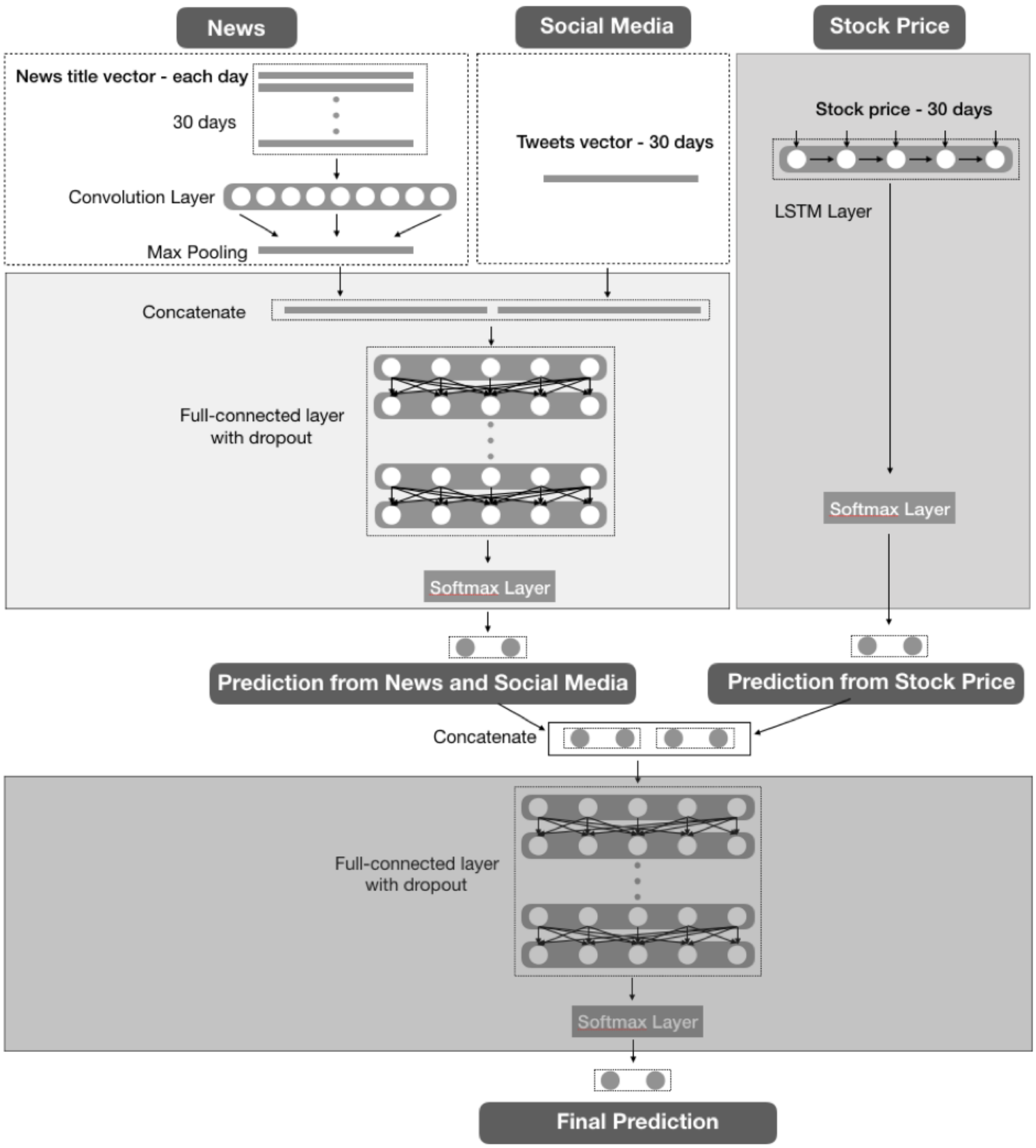


Figure 2.5: Tweets Representations for the Entire Event Window

With the knowledge from news titles, tweets, and historical stock prices, we propose the hybrid model to merge these three pieces of information to predict the sign of the stock price change. In our work, we evaluate the 3-day model, 7-day model, 15-day model, and 30-day model. Using the 30-day model as an example, for the news and tweets, we generate the probability of the change of the stock price Pn_i^{31}. We also generate the probability of the stock price change Ps_i^{31} from the historical stock prices. We concatenate Pn_i^{31} and Ps_i^{31} as a new vector. We then employ another 5 fully-connected layers with 0.5 dropout and the softmax layer to get the probability of the change of the stock price. The entire model is shown in Figure 2.5.

2.5 Evaluation Results

As necessary, we first implement the most commonly used machine learning approaches for stock prediction, and apply them to the news title dataset for model evaluation. We use bag-of-words and TF-IDF as the feature selection methods and evaluate their prediction accuracy [16, 23]. We generate text tokens using unigrams, bigrams, n-grams with 2 to 4 words, and n-grams with 3 to 4 words, since they are the common token sequence lengths that researchers use. We try three frequently used classification algorithms, including LinearSVC, Naïve Bayes, and RandomForest, and present the best results in Figure 2.6 [23, 35]. Figure 2.6 shows the prediction results of the two feature extraction methods when selecting different tokens. In general, for bag-of-words, larger token size suggests higher prediction accuracy. Besides, we calculate the average prediction accuracy for easy comparison. Table 2.4 shows that the performance for the two feature processing methods are almost the same.

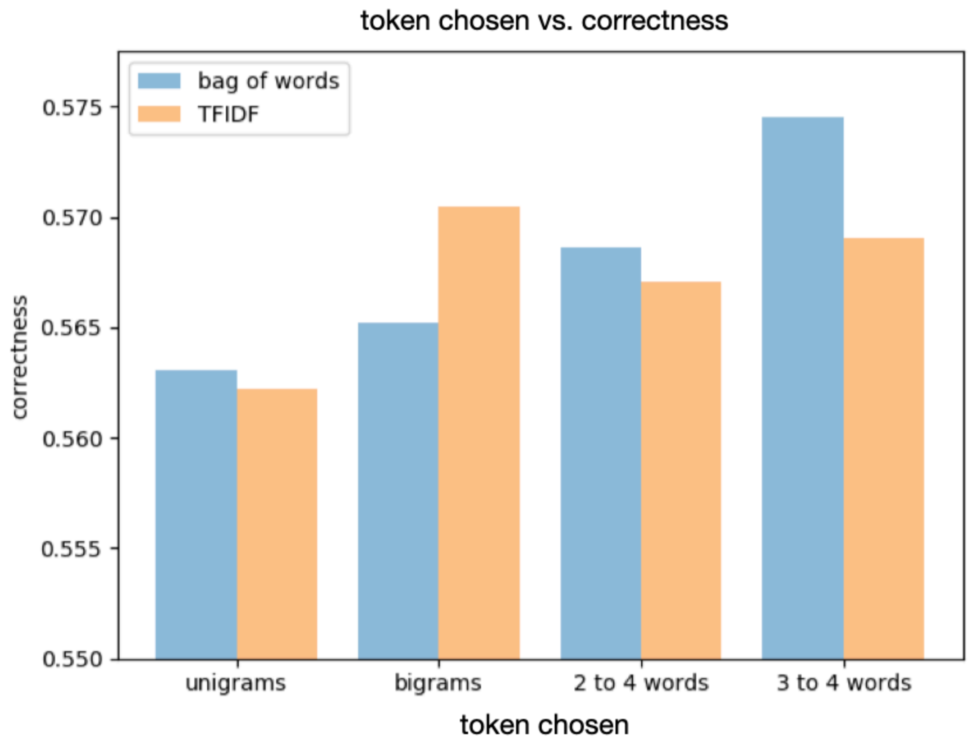


Figure 2.6: Features vs. Prediction Results

Table 2.4: Feature Extraction and Average Accuracy

Feature Extraction	Average Accuracy for all Event Windows
Bag-of-words	0.5679
Tfidf	0.5672

Figure 2.7 shows the best prediction results for LinearSVC, Naïve Bayes, and RandomForest in different event windows after conducting experiments across all feature extraction methods. In Figure 2.7, the x-axis presents the results for 3-day, 7-day, 21-day, and 30-day event windows for prediction. All dots are lined up only for the four event windows. The y-axis indicates the prediction correctness. Table 2.5 shows the average prediction accuracy for

all the event windows. Overall, bag-of-words with RandomForest classification has shown slightly higher correctness with an accuracy of 0.57.

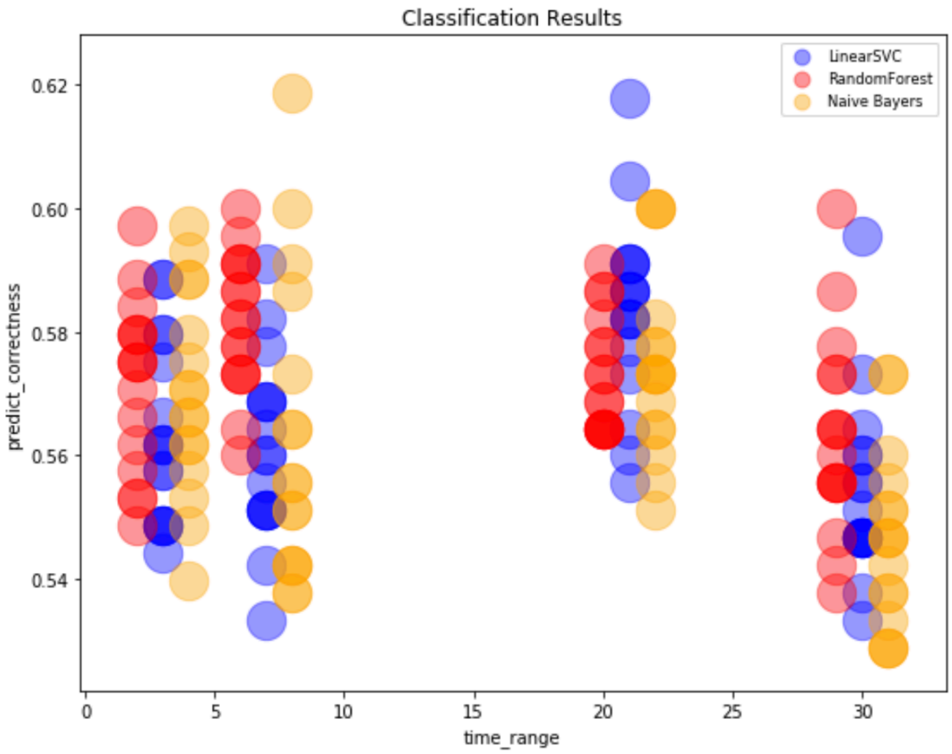


Figure 2.7: Prediction Results for Different Classification Methods

Table 2.5: Classification Algorithms and Average Accuracy

Classifier	Average Accuracy for all Event Windows
LinearSVC	0.5669
NB	0.5646
RandomForest	0.5712

In addition, we implement multiple deep learning models for stock prediction using information from news titles, social media, and historical stock prices. Following Ding *et al.* and

Xie *et al.* [7, 38], we use prediction accuracy (Acc) and Matthews Correlation Coefficient (MCC) to evaluate the stock prediction results.

Table 2.6 and Table 2.7 show that the model performance is not good when we use LSTM to generate predictions from historical stock prices within a short event window. For the basic models, using our feature selection methodologies for textual features from social media or news media generates better results. From Table 2.6, Table 2.7, Table 2.8, and Table 2.9, we observe that for prediction using news titles, OpenIE + CNN performs better than CNN for all four event windows. Similarly, for prediction using social media, K-means + Average Pooling has better performance than Average Pooling. Furthermore, compared with the basic models, the combination of news and social media further improves the prediction performance. Comparing to the traditional machine learning and feature extraction methods, our hybrid model outperforms all other algorithms, and the model yields favorable results when predicting based on 7-day and 21-day event windows.

Table 2.6: Deep Learning Model Prediction Accuracy using Different Information for 3-day Event Window

<table>
<tr><th>Category</th><th>Data Source</th><th>Model</th><th>Accuracy</th><th>MCC</th></tr>
<tr><td rowspan="5">Basic</td><td>Stock Price</td><td>LSTM</td><td>0.5559</td><td>0.1105</td></tr>
<tr><td rowspan="2">News Title</td><td>CNN</td><td>0.5435</td><td>0.0784</td></tr>
<tr><td>OpenIE + CNN</td><td>0.5721</td><td>0.1446</td></tr>
<tr><td rowspan="2">Social Media</td><td>Average Pooling</td><td>0.5128</td><td>0.0231</td></tr>
<tr><td>K-means + Average Pooling</td><td>0.5730</td><td>0.1497</td></tr>
<tr><td rowspan="2">Hybrid Model</td><td>News Title
Social Media</td><td>OpenIE + CNN
K-means + Average Pooling</td><td>0.5999</td><td>0.2021</td></tr>
<tr><td>Stock Price
News Title
Social Media</td><td>LSTM
OpenIE + CNN
K-means + Average Pooling</td><td>0.6180</td><td>0.2381</td></tr>
</table>

Table 2.7: Deep Learning Model Prediction Accuracy using Different Information for 7-day Event Window

Category	**Data Source**	**Model**	**Accuracy**	**MCC**
Basic	Stock Price	LSTM	0.5328	0.0664
	News Title	CNN	0.5314	0.0625
		OpenIE + CNN	0.5882	0.1738
	Social Media	Average Pooling	0.5269	0.0507
		K-means + Average Pooling	0.6008	0.2118
Hybrid Model	News Title Social Media	OpenIE + CNN K-means + Average Pooling	0.6134	0.2358
	Stock Price News Title Social Media	LSTM OpenIE + CNN K-means + Average Pooling	0.6859	0.3812

Table 2.8: Deep Learning Model Prediction Accuracy using Different Information for 21-day Event Window

Category	Data Source	Model	Accuracy	MCC
Basic	Stock Price	LSTM	0.5788	0.1570
	News Title	CNN	0.5229	0.0427
		OpenIE + CNN	0.5558	0.1094
	Social Media	Average Pooling	0.5326	0.0571
		K-means + Average Pooling	0.5784	0.1590
Hybrid Model	News Title Social Media	OpenIE + CNN K-means + Average Pooling	0.5872	0.1778
	Stock Price News Title Social Media	LSTM OpenIE + CNN K-means + Average Pooling	0.6884	0.3782

Table 2.9: Deep Learning Model Prediction Accuracy using Different Information for 30-day Event Window

<table>
<tr><th>Category</th><th>Data Source</th><th>Model</th><th>Accuracy</th><th>MCC</th></tr>
<tr><td rowspan="5">Basic</td><td>Stock Price</td><td>LSTM</td><td>0.6124</td><td>0.2247</td></tr>
<tr><td rowspan="2">News Title</td><td>CNN</td><td>0.5325</td><td>0.0647</td></tr>
<tr><td>OpenIE + CNN</td><td>0.5983</td><td>0.1972</td></tr>
<tr><td rowspan="2">Social Media</td><td>Average Pooling</td><td>0.5246</td><td>0.0489</td></tr>
<tr><td>K-means + Average Pooling</td><td>0.5678</td><td>0.1358</td></tr>
<tr><td rowspan="2">Hybrid Model</td><td>News Title
Social Media</td><td>OpenIE + CNN
K-means + Average Pooling</td><td>0.6201</td><td>0.2414</td></tr>
<tr><td>Stock Price
News Title
Social Media</td><td>LSTM
OpenIE + CNN
K-means + Average Pooling</td><td>0.6473</td><td>0.2946</td></tr>
</table>

2.6 Conclusion and Future Directions

In our study, we propose an event-driven stock prediction methodology which focuses on studying the impact of corporate events on firm stock performance. We design a hybrid deep learning model that integrates features extracted from various data sources including news, social media, and the historical stock data. We use different methodologies to obtain features from different sources and demonstrate improvement in prediction accuracy over previously reported approaches. The future work to extend our study includes:

(1) For the news data, the most difficult problem for us is how to extract the effective information from extremely high dimensional data. In the future, we may try other deep learning methods to gain more accurate information from news data like LSTM or the

attention model.

(2) For the Twitter data, currently, for every event we set the number of clusters to three, when we divide our data. We can try other methods to optimize the number of clusters in the future.

(3) We currently use the historical stock prices as the indicator for historical market movement. The problem with this is that we may miss some information from the entire market. In the future, we may use the abnormal stock return as our index for the event-based analysis, which can include the fluctuation of the whole market.

Chapter 3

Measuring the Impact of Corporate Crisis News Propagation via Twitter

3.1 Introduction

The main content of Chapter 3 has been presented in the 2019 Conference on Information Systems and Technology [11].

Corporate crises such as cyber attacks, executive scandals, facility accidents, fraud, product recalls, etc. can damage customer trust and firm reputation severely, which may lead to tremendous loss in sales and firm equity value. For example, Facebook suffered a data scandal in March 2018 when over 50 million Facebook user accounts were accessed without authorization by a political consulting firm, Cambridge Analytica. The estimated cost of the incident was around $35 billion after the breach was revealed [4]. The company's stock fell as much as 5% in one single day following the announcement [4]. Such crises are disastrous for firms, and it is crucial for firms to come up with appropriate communication strategies in a timely manner for crisis mitigation [51]. In recent years, the rise of social media has transformed the way firms communicate with their stakeholders. As stakeholders increasingly seek and adopt information from social media to assist with their decision making, firms now face both opportunities and challenges for managing crisis information communication on social media [52].

Researchers also have shown growing interest in the role of social media for corporate management, especially during a firm crisis. Many studies demonstrate the double-edged sword effect of social media for corporate crisis management. Specifically, there are two streams of research. First, social media helps firms with better crisis communication and management through directing firm-initiated contents to the public [51, 53, 54, 55, 56]. Second, anxious stakeholders' negative publicity may spread widely through the propagation of social media posts, thereby exacerbating the negative perception of the firm [57, 58, 59]. Furthermore, researchers look into the impact of social media on firm stock performance during firm product crises and demonstrate that increasing posts by corporate accounts potentially moderate the adverse price reaction brought by product crises, whereas increasing posts by stakeholders worsen the negative price reaction [3]. However, previous research often uses static data (e.g., message volume, emotion score, etc.) to measure the information on social media [3, 6]. The underlying mechanisms behind how stakeholders adopt and propagate different information on social media, as well as how these behaviors would impact firm stock performance during firm crises, are not well understood.

For example, how do stakeholders perceive the crisis information sent by a firm as opposed to other stakeholders over time? Do stakeholders adopt or question the information? We believe stakeholders' adoption and dissemination of social media information play important roles in influencing firm stock performance during firm crises. Yet, little is known on how to model these behaviors. This inspires us to go beyond the existing studies to investigate the crisis information propagation on social media. When exposed to information on social networks, stakeholders usually go through a process of evaluating the credibility of the information and make their decision of whether to share the information subsequently [60]. To further understand this process, we propose to adopt an extended epidemiological model, the SEIZ model, to simulate the crisis information propagation on social media [61]. We differentiate two types of social media crisis information based on the source of the information: firm-initiated information and user-initiated information. By modelling the propagation of firm-initiated information and user-initiated information on social media, we derive measures to quantify stakeholders' information adoption behaviors for both information sources. We then empirically show that these information adoption behaviors indeed have strong impacts on firm equity value.

The SEIZ model defines four categories which reflect the state of an individual during information propagation. The four categories denote susceptible (S), exposed (E), infected (I), and skeptical (Z) individuals. Individuals are transformed from one state to another with an estimated transaction rate and probability. The SEIZ model introduces an exposed state (E), when individuals are exposed to the crisis information on Twitter but have not yet adopted the information (infected(I)). Such a state provides us with additional information for mapping stakeholder's information adoption behavior during the information propagation. When seeking information on Twitter, most users will experience a process of evaluating the quality, usefulness, and credibility of a message [62]. However, the process is hard to measure in the real world. We propose a new application of the SEIZ model to understand such a process. By modelling the propagation of firm-initiated information and user-initiated information on Twitter, we demonstrate the dynamic process of stakeholders transiting from one state to another for both information sources. Our results suggest that the SEIZ model is effective in simulating the crisis information propagation on social media. Therefore, we are capable of conducting an in-depth analysis, measuring stakeholder's information adoption in this process.

In our study, we use Twitter data to measure information propagation during corporate crises since Twitter is often the primary social media channel adopted by firms [63]. We especially focus on five types of incidents (cyber attack, fraud, facility accident, executive scandal, and product defect) since they often cause severe reputation damage to firms. This offers a compelling setting to study the impact of information propagation during crisis events. By conducting an empirical analysis of 652 crisis events for S&P 500 companies, we demonstrate the impact of the different information propagation patterns on firm stock performance during crises.

The remainder of the chapter is structured as follows. We provide the background and related literature of our study in the next section. We then introduce the SEIZ model and how we adopt the SEIZ model for modeling the information propagation on Twitter. We show the results of model fitting and quantify a stakeholder's information adoption process. Following a description of the research design and sample selection, we show the empirical results and evaluate the impact of Twitter crisis information propagation on firm stock performance during crises. Finally, we discuss the implications of our findings and provide insights for firm crisis management.

3.2 Background and Literature Review

3.2.1 Social Media, Crisis Communication, and Firm Stock Performance

The emergence of social media has transformed a firm's information environment following corporate crisis events. Research shows that information related to corporate crises on social media can be valuable proxies for researchers and financial professionals to gain insights on firm performance following crises [58, 59, 64]. On the one hand, social media offer firms an efficient way to communicate to a large number of stakeholders with critical event information [65]. Firms can initiate and propagate information such as clarifications, remedy actions, or apologies to stakeholders, in real-time without going through information intermediaries [66]. Such information on social media makes corporate disclosure more timely and useful for stakeholders, which can help firms to minimize the damage to corporate reputation and customer trust [67, 68]. A previous study explores the volumes of firm social media posts during product crises and finds that increasing volumes of firm social media posts are beneficial for firm performance [3]. Researchers further investigate the content of social media posts and show how a firm's social media crisis communication strategy may mitigate the negative impact from a crisis event [54, 56].

One the other hand, information related to firm crises on social media comes not only from the event firms, but also from non-corporate social media users [69, 70]. The content produced by these users also has a strong predictive power on firm stock return or product sales [3, 64, 71, 72]. For example, during a major crisis event, the announcement of the event can bring a significant negative impact to the affected firm and the impact can be magnified through stakeholders' propagation of social media posts [57].

3.2.2 The Application of Epidemiological Models in Modelling Information Propagation

Understanding the propagation of crisis information on social media is essential to corporate management. However, quantifying various stages of the information propagation is not an easy task. Previous researchers have demonstrated that epidemic models have the capability to aid interpretation of information propagation. In earlier research, researchers extracted the general characteristics of idea propagation and estimated the process of adoption. They showed that the SEIZ model could be adapted to simulate the adoption process with reasonable errors [61]. Abdullah *et al.* [73] first proposed the approach of using epidemic models to understand the news spreading on Twitter. Following the above research, Jin *et al.* [74] applied two epidemiological models to simulate the information spreading on Twitter and concluded that the SEIZ model, is more accurate in capturing the information diffusion of news and rumor.

Inspired by previous studies, we apply the SEIZ model to model the crisis news propagation process. By simulating the dynamic process of information propagation on Twitter, we propose a novel approach that can not only be used to analyze news propagation, but also come up with indicators that could quantitatively measure the stakeholders' information adoption on Twitter during firm crises.

3.3 The SEIZ Model

In our research, we adopt the SEIZ model to simulate how news propagates on Twitter. The SEIZ model has been considered an applicable and robust model for information propagation [74]. The SEIZ model is an epidemiological model that was originally used mathematically to model disease spreading in a human network. The SEIZ model assumes the process of news propagation on social media can be comparable to the infectious disease transmission between individuals. In the context of Twitter information propagation, stakeholders can be divided into four categories. Susceptible (S) represents those stakeholders who have not known about the corporate crisis information on Twitter; Infected (I) denotes the stakeholders who tweeted about the corporate crisis; Exposed (E) includes stakeholders who have acknowledged the crisis information but have not determined whether to tweet about it; and Skeptics (Z) contains stakeholders who have acknowledged the crisis information but choose not to tweet about it.

The framework of the SEIZ model is shown in Figure 3.1. We describe the information

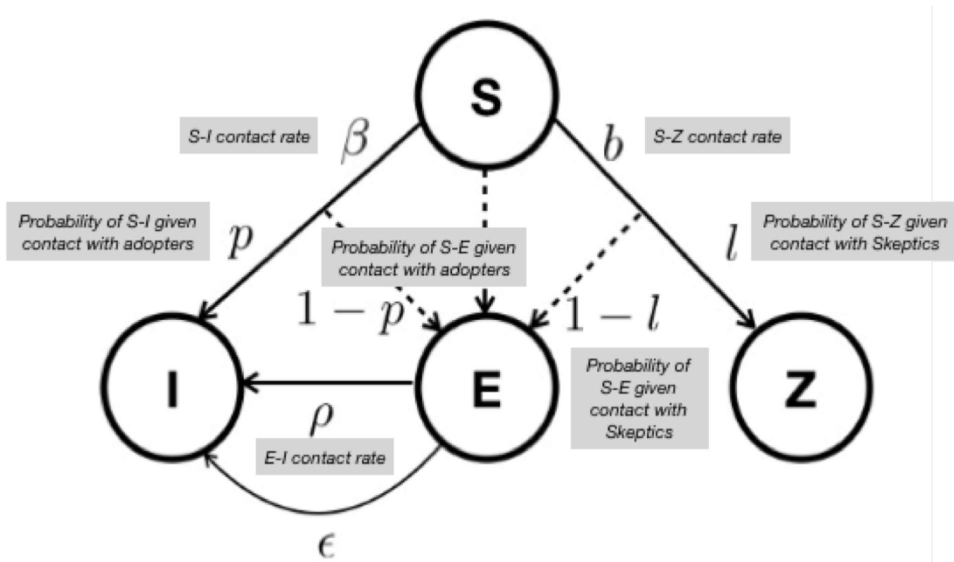


Figure 3.1: SEIZ Model Framework

propagation process as follows.

- Stakeholders in susceptible state adopt the crisis information and transit to infected (I) state immediately when they hear it, with probability p. Otherwise, if stakeholders can not decide whether to adopt the information, they transit to the exposed (E) state with probability $(1 - p)$.

- Stakeholders exposed to the crisis information can adopt the information and change themselves to infected state based on two mechanisms: (1) Stakeholders in the Exposed (E) state have further contact with stakeholders who already adopted the information (with contact rate ρ). (2) Stakeholders in the exposed (E) state adopt the information purely caused by self adoption (with rate ϵ) without additional contact with stakeholders who already adopted the information.

- Stakeholders who are skeptical of the crisis information when they hear it will remain in skeptics (S) state with probability l. Otherwise, they are converted to exposed (E) state with probability $(1 - l)$.

The above process can be formally defined using the set of ordinary differential equations in Equation (3.1). At any given period t, N denotes the total population concerned about a crisis event, S denotes the number of stakeholders in susceptible state, I denotes the number of stakeholders in infected state, and Z denotes the skeptical population size. More detailed parameter definitions for the SEIZ model can be found in Table 3.1 [61, 74].

Table 3.1: Parameter Definitions for the SEIZ Model

Parameter	Definition
S	Susceptible stakeholders from social media who are seeking information related to a corporate crisis event
E	Stakeholders from social media who are exposed to the information related to a corporate crisis event, but have not yet determined whether they should adopt the information
I	Stakeholders from social media who adopted information related to a corporate crisis event and posted a related tweet
Z	Stakeholders from social media who remain skeptical about the information related to a corporate crisis event
β	$S - I$ contact rate
b	$S - Z$ contact rate
	$E - I$ contact rate
ϵ	Incubation rate for information related to a corporate crisis event
βp	Effective rate of $S- > I$
$b(1 - l)$	Effective rate of $S- > E$ given contact with skeptics
$\beta(1-p)$	Effective rate of $S- > E$ given contact with adopters
l	Probability from $S- > Z$ given contact with skeptics
$1 - l$	Probability from $S- > E$ given contact with skeptics
p	Probability from $S- > I$ given contact with adopters
$1 - p$	Probability from $S- > E$ given contact with adopters

$$
\begin{cases}
\frac{dS}{dt} = -\beta S\frac{I}{N} - bS\frac{Z}{N} \\
\frac{dE}{dt} = (1-p)\beta S\frac{I}{N} + (1-l)bS\frac{Z}{N} - \rho E\frac{I}{N} - \epsilon E \\
\frac{dI}{dt} = p\beta S\frac{I}{N} + \rho E\frac{I}{N} + \epsilon E \\
\frac{dZ}{dt} = lbS\frac{Z}{N}
\end{cases}
\tag{3.1}
$$

3.4 Research Design and Sample Collection

3.4.1 Data

We use the same initial data collection and event definition from Chapter 2. We collect the following five types of major firm crisis events from Ravenpack: (1) cyber attack; (2) fraud; (3) facility accident; (4) executive scandal; and (5) product defect. We obtain data on the news coverage of S&P 500 companies during the period from January 2010 to March 2019. Since we focus on the social media information diffusion for both firm-initiated information and user-initiated information, we exclude firms that do not have a social media account and events that do not have Twitter discussions during the event time. Our final data set contains 1259 events for analysis.

3.4.2 Measurement of Social Media Crisis Information Propagation

Before we start to collect data from Twitter, we first define the event window as 10 days before the event date and 30 days after the event date. We then define a set of event-related keywords associated with the five types of firm crises to retrieve as many relevant tweets as possible. Firm-initiated information contains tweets that match the keywords, from the timeline of a firm account during the event period. In order to study the propagation of such firm-initiated information, we also include re-tweets by collecting any tweets containing RT @ with a firm's Twitter handle and event-related keywords. User-initiated information contains all the tweets that match the event window and event keywords, but were not sent by or re-tweeted from the event firm. The detailed summary of the data is shown in Table 3.2.

Table 3.2: Summary of Crisis Events and Collected Data Listed by Firm Industry

Industry	Count of RP Events	Count of RP News	Count of Firm-initiated Tweets	Count of User-initiated Tweets
Consumer Discretionary	335	3,027	17,270	482,336
Consumer Staples	131	1,039	22,550	36,037
Energy	72	615	1,080	10,129
Financials	230	1,978	7,620	392,749
Health Care	147	1,357	1,140	23,101
Industrials	130	1,293	50,190	78,100
Information Technology	447	4,625	14,900	3,145,129
Materials	37	284	550	1,834
Telecommunications Services	37	358	3,680	20,840
Utilities	53	406	1,990	1,477

* RP stands for RavenPack; Firm-initiated tweets include all the re-tweets for firm tweets; User-initiated tweets include all the original user tweets and re-tweets.

Table 3.3: Summary of Crisis Events and Collected Data Listed by Event Type

Type of Event	Count of RP Events	Count of RP News	Count of Firm-initiated Tweets	Count of User-initiated Tweets
cyber attack	360	3,653	7,460	3,123,813
executive scandal	176	2,082	26,960	230,262
facility accident	252	1,679	30,650	256,030
fraud	251	2,213	9,310	125,336
product fault/ recall	580	5,355	46,590	456,291

* RP stands for RavenPack; Firm-initiated tweets include all the re-tweets for firm tweets; User-initiated tweets include all the original user tweets and re-tweets.

SEIZ Fitting results

Following the previous literature [74], we fit the collected events to the proposed SEIZ model with a nonlinear least square estimation. We optimize the set of parameters by identifying values that can minimize |I(t)-tweets(t)|. We adopt a forward Euler function that was developed by Jin *et al.* [74] to solve the ODE system. We calculate the relative error in 2-norm (Equation 3.2) to select models with good fit. We keep the events that have good fitting results; the final data for further analysis is reduced to 652 events.

To demonstrate the fitted results, we selected 6 crisis events listed in Table 3.4. The "Event Type" column shows the type of an event. The "F/S" column indicates whether the model fitness is generated from firm-initiated information or user-initiated information.

$$\frac{||I(t) - tweets(t)||_2}{||tweets(t)||_2} \tag{3.2}$$

Figure 3.2 shows the corresponding best fitted results of the SEIZ model for events listed in Table 3.4. In Figure 3.2, the x axis shows the time duration of the event tweets. Following [74], we use 6 hours as our time interval. The y axis shows the volume of event tweets. A dotted line shows the number of tweets for the specific event over time using real data, and a straight line shows the simulation of tweet volumes over time.

SEIZ Compartments over Time

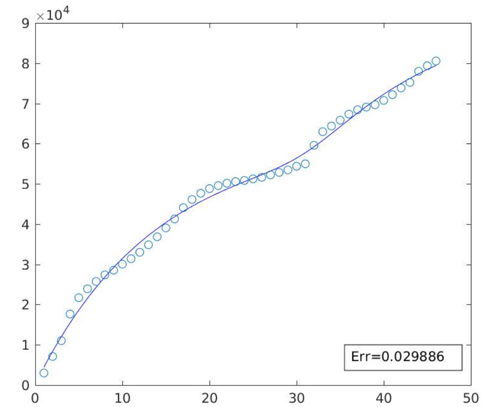
The fitted models provide us with the contact rates and transition probabilities, which help us observe the transitions of user state from different compartments of the SEIZ model. In Figure 3.3, we show the dynamic changes of the four compartments for the sample events

Table 3.4: Selected Sample Events

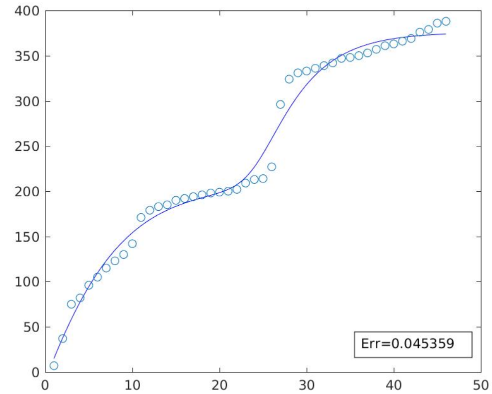
Date	**Firm**	**Select News Titles in RavenPack**	**Event Type**	**N**	F/U
2018-03-21	Facebook	FACT CHECK: Did Cambridge Analytica 'Hack' Facebook?	Cyber Attack	80559	U
2010-03-05	Nvidia	Nvidia recalls 3D card drivers due to overheating risk	Product Recall	388	F
2011-06-02	Chevron	Chevron UK refinery - fire, Explosion, fire at Chevron UK refiner	Facility Accident	2358	U
2012-06-18	JPMorgan	Jpmorgan Sued for Securities Fraud,JPMorgan Sued for Securities Fraud	Fraud	163	F
2015-01-09	Amazon	Fire contained at Amazon data center,3-alarm fire contained at Amazon data center construction site in Loudoun County	Facility Accident	12111	U
2018-11-01	Goldman Sachs	Goldman banker, was arrested in Malaysia",Justice Department to Charge Former Goldman Bankers in Malaysia 1MDB Scandal	Executive Scandal	1879	U

F: Firm-initiated information U: User-initiated information

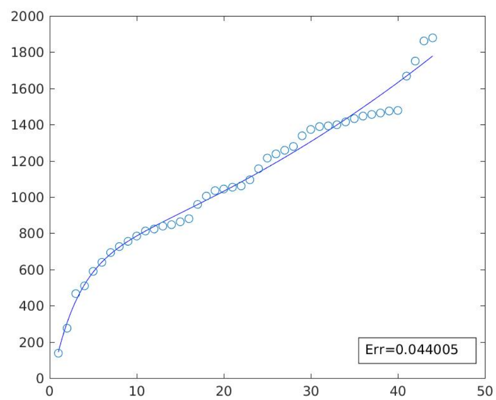
based on the fitted models. We define a fixed time window to evaluate the information propagation for each event.



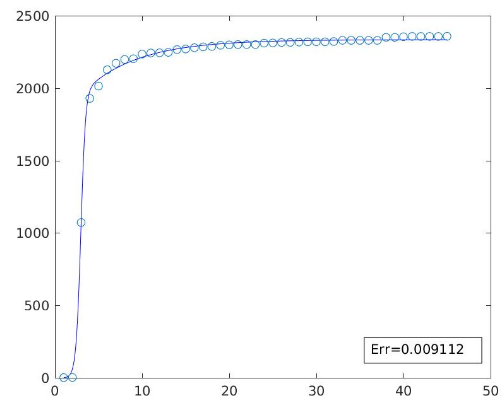
(a) Facebook Cyber Attack



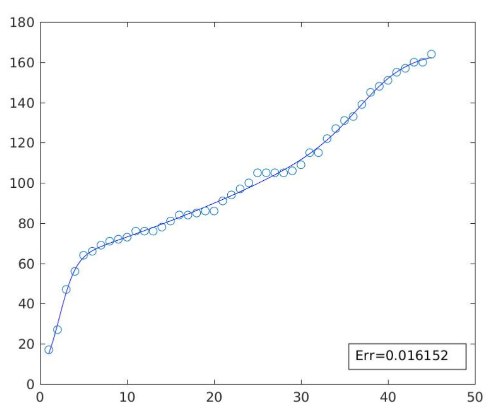
(b) Nvidia Recall



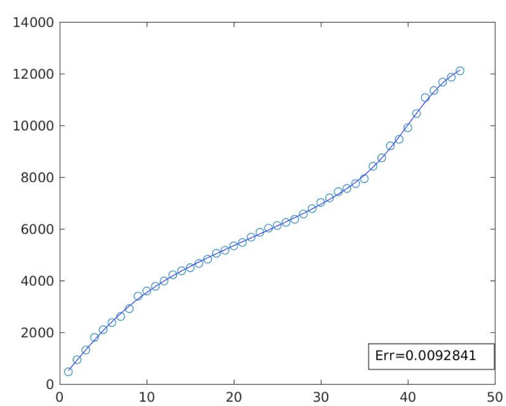
(c) Goldman Sach Scandal



(d) Chevron Facility Accident



(e) JPMorgan Fraud

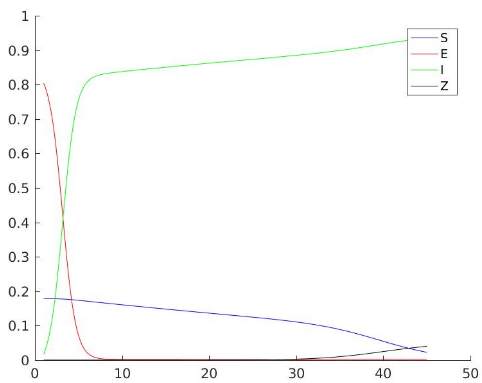


(f) Amazon Facility Accident

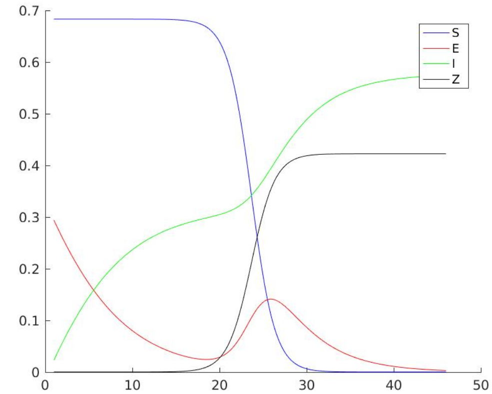
Figure 3.2: Best Fit Modelling for Tweet Volume (y axis) over Time (x axis)

The time window is between -1 and +21 days of the event date. We choose this time window because it matches the schedule of event rising and diminishing for the majority of events in our collection. Though in the data collection process, the time window is between -10 and +30 days, the analysis shows that Twitter data is very sparse for the event windows for -10 to -2 days and +22 to +30 days. In Figure 3.3, the x axis indicates the event window and the y axis indicates the proportion of stakeholders in each category.

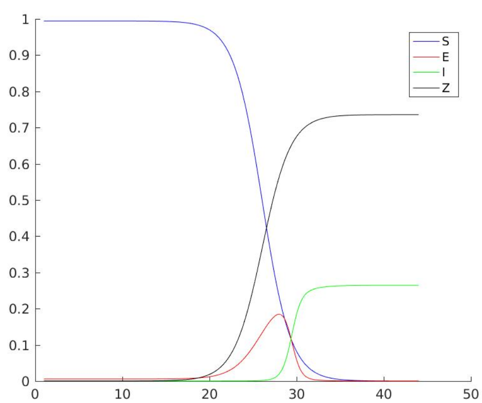
For example, Figure 3.3a demonstrates the propagation of user-initiated tweets for the Facebook cyber attack. We can see from the figure that the E(t) occurs directly with increase in I(t), which indicates that a greater portion of stakeholders exposed to the user-initiated tweets start to adopt the information and send tweets. We can rarely see the Z(t) because there are almost no stakeholders skeptical to the information in the whole process.



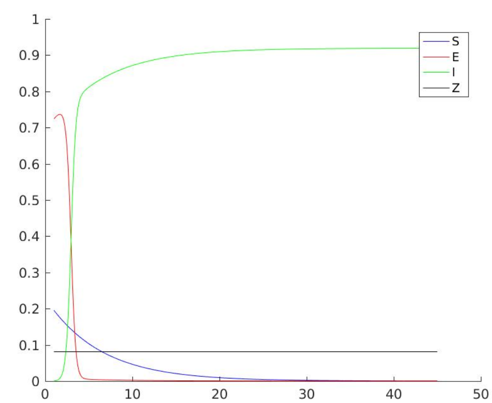
(a) Facebook Cyber Attack



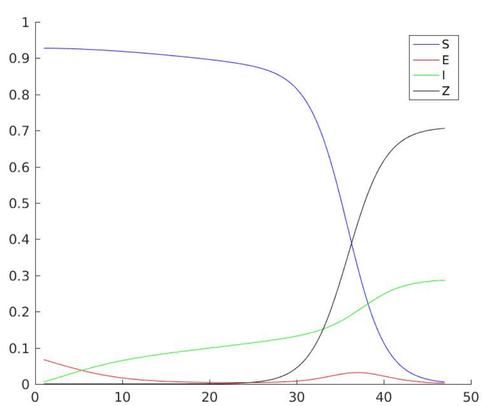
(b) Nvidia Recall



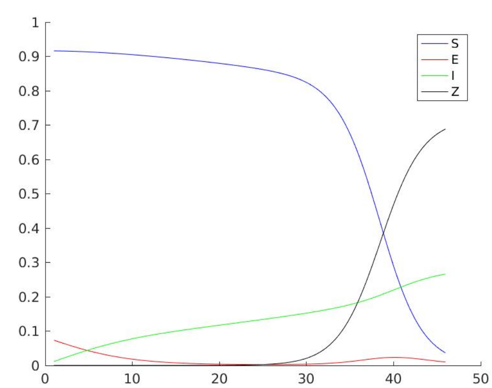
(c) Goldman Sach Scandal



(d) Chevron Facility Accident



(e) JPMorgan Fraud



(f) Amazon Facility Accident

Figure 3.3: The Proportion of Tweets (y axis) in SEIZ Compartment over Time (x axis)

Figure 3.3e shows a fairly different pattern for the propagation of firm-initiated information related to the JPMorgan Fraud event. Most stakeholders remain ‘Susceptible’ in the process, suggesting that they have not heard about any firm-initiated information. Near the end of the event, the majority of stakeholders gradually change to ‘Skeptical’ state. Thus, most stakeholders do not know the information at the beginning and become skeptical about the information at the end.

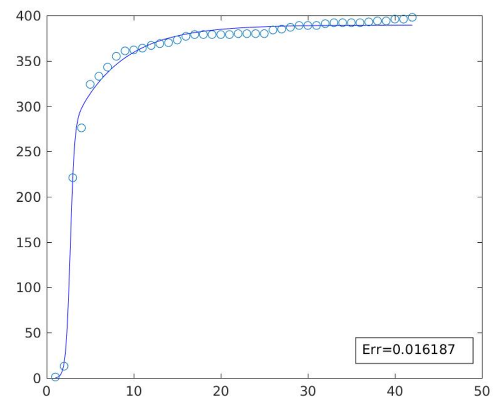
In addition, we observe that the ratio of stakeholders adopting the information slightly increases over time. From Figure 3.3, we can also find that not all stakeholders are in the susceptible compartment initially. We can infer that some of the stakeholders may have already gotten information from other external sources.

Case studies: The Home Depot and Target Corporations

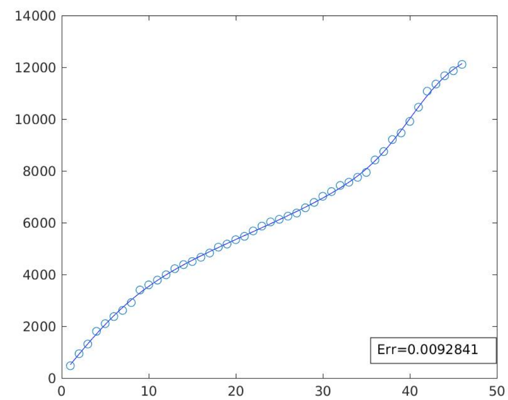
Apart from the six sample events, we conduct two case studies for Target and Home Depot data breach events. We compare the different diffusion patterns of the events, and explore the impact of diffusion patterns on firm stock performance during the events.

In Chapter 2, we discussed and compared the two firms’ managerial decisions on handing their data breach events. During the breach event, though Target sent multiple updates related to the event on its website as well as the Twitter account, the stock price still plummeted. In contrast, Home Depot’s stock price did not drop much and recovered quickly within a few days of the event. Thus, Home Depot was considered a success in handling its security breach.

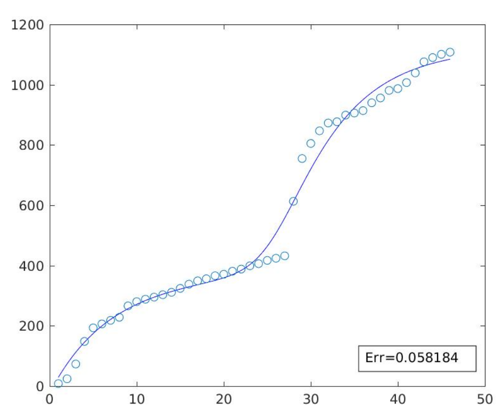
We investigate how Twitter users propagate information from the official Twitter account (firm-initiated information) of Target and Home Depot, as well as information from other Twitter users (user-initiated information). Figure 3.4 shows our SEIZ model fitting results for tweets related to both events.



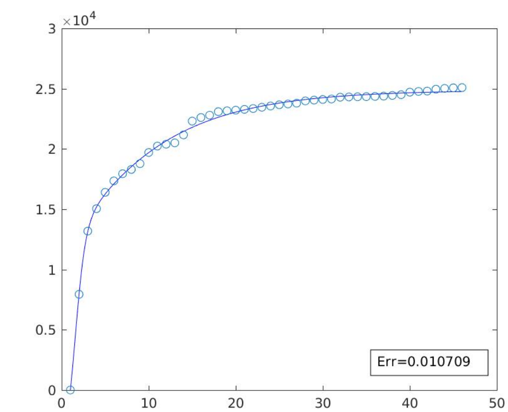
(a) Firm-initiated Tweets for Home Depot Data Breach



(b) User-initiated Tweets for Home Depot Data Breach



(c) Firm-initiated Tweets for Target Data Breach

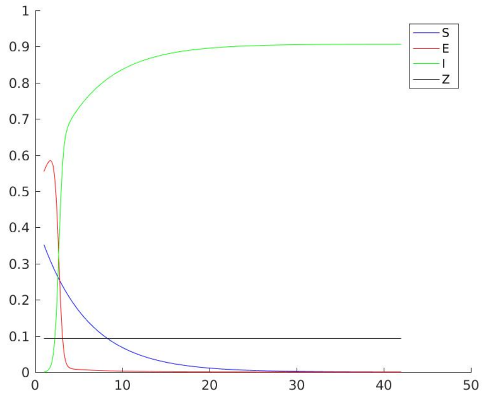


(d) User-initiated Tweets for Target Data Breach

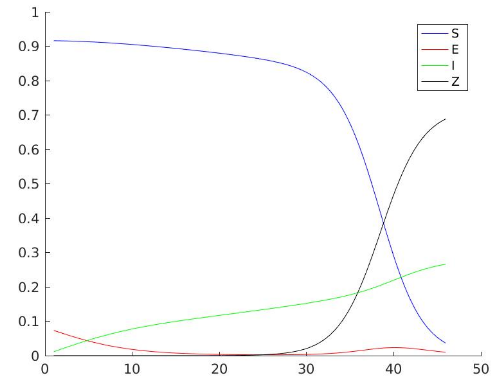
Figure 3.4: Best Fit Modelling for Tweet Volume (y axis) over Time (x axis) for Home Depot and Target Data Breaches

From the fitted model, we can observe the dynamic changes of the four compartments for the both events. As mentioned in Chapter 2, during the event, Target showed a series of poor management decisions about the event. We believe the decisions can also impact how people diffuse the event related information on social media. In Figure 3.5c, for information sent by Target, the majority of stakeholders stay in S(t) over time, then transform from S(t) to Z(t). In Figure 3.5d, for information sent by other Twitter users, stakeholders transform to I(t) from the very beginning of the event and stay in I(t) over time. The patterns in Figure 3.5c and Figure 3.5d indicate that people tend to be skeptical of the information sent by the Target's official Twitter account and instead adopt information sent by other Twitter users, which may be harmful for Target's stock price.

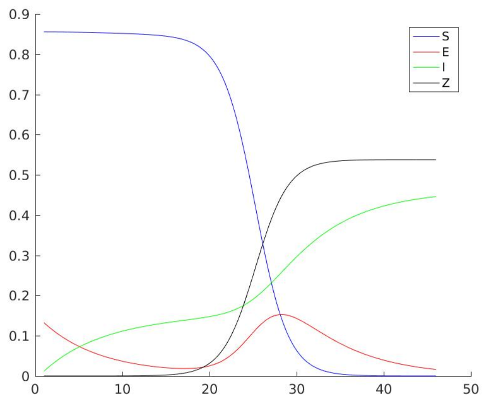
Figure 3.5a and Figure 3.5b show the SEIZ compartments over time for the Home Depot Data Breach. In Figure 3.5a, I(t) increases directly with a decrease in E(t) when Home Depot posts information on their official account, indicating that stakeholders adopt information initiated by Home Depot immediately when exposed to the information. Figure 3.5b shows a larger proportion of stakeholders are in S(t) for a long period of time, then the majority of them transform to Z(t), indicating that stakeholders were not aware of the information sent by other Twitter users in the beginning and skeptical of the information near the end of the event. We think this pattern associates with the fact that Home Depot has efficient communication with stakeholders for the event, and Twitter users tend to trust and propagate information initiated by Home Depot, which further led to a better performance than Target on the stock market.



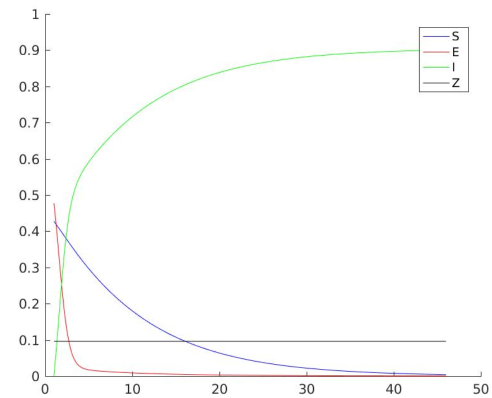
(a) Firm-initiated Tweets for Home Depot Data Breach



(b) User-initiated Tweets for Home Depot Data Breach



(c) Firm-initiated Tweets for Target Data Breach



(d) User-initiated Tweets for Target Data Breach

Figure 3.5: The Proportion of Tweets (y axis) in SEIZ Compartment over Time (x axis) for Home Depot and Target Data Breaches

Generating Indicators for Information Adoption

With the parameters provided by the fitted SEIZ model, we obtain more knowledge on the dynamic process of stakeholders exposing, adopting, and becoming skeptical of firm-initiated information and user-initiated information. We propose an information adoption indicator of both firm-initiated news propagation and user-initiated news propagation by using the key parameters of the SEIZ model.

We compute a ratio by considering the sum of effective transition entering the Exposed state to the sum of effective transition exiting the E state and converting to I. We denote this ratio as R_{SEI}_Firm and R_{SEI}_User indicating R_{SEI} for firm-initiated information and user-initiated information, respectively.

$$R_{SEI} = \frac{\rho + \epsilon}{(1-p)\beta + (1-l)b} \tag{3.3}$$

This measure utilizes all of the parameters of the SEIZ fit. Here a R_{SEI}_Firm value greater than 1 implies that the number of stakeholders entering the infected state is greater than the number of stakeholders exiting exposed state (to infected), suggesting that a larger portion of stakeholders who were exposed to the information adopted the information over time. Similarly, a value less than 1 indicates that stakeholders entered the infected state more slowly than they exited, which suggests a small portion of stakeholders adopting the information in the propagation process. Similar to R_{SEI}_Firm, R_{SEI}_User measures a stakeholder's information adoption for user-initiated information. A larger R_{SEI}_User value indicates a greater ratio of stakeholders exposed to the information have adopted the information over time and vice versa.

3.5 Empirical Models and Results

In this section, we try to analyze the relationship between firm abnormal stock return and stakeholder's information adoption behavior on Twitter. In the previous section, we measure R_{SEI}_Firm and R_{SEI}_User that indicate stakeholder's adoption behavior for firm-initiated tweets and user-initiated tweets. In order to investigate the impact of the two variables on firm equity value during firm crisis events, we employ the event study methodology [75, 76, 77]. We use the fixed event window (-1, +21) which we defined when modelling the information propagation on Twitter.

3.5.1 Measures for Firm Equity Value

We measure the firm stock performance following the event by calculating the cumulative abnormal return (CAR) based on the 652 corporate crisis events. We estimate CAR using the four-factor model [78], which indicates a linear relationship between the stock return and four factors over a given period (Equation 3.4).

$$R_{it} = \alpha_i + R_{ft} + \beta_{i1}[R_{mt} - R_{ft}] + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}UMD_t + \varepsilon_{it} \tag{3.4}$$

Here R_{it} represents the return of firm stock i at time t, α_i is the intercept of model, R_{ft} represents the risk-free rate on day t, R_{mt} is defined as the return of the market portfolio on day t, SMB_t is defined as the small minus big size portfolio return on day t, HML_t is defined as the high minus low book-to-market portfolio return on day t, and UMD_t is defined as the past one-year winners minus losers stock portfolio return on day t. Abnormal returns describes the variation between the actual return and an estimated expected return when there is no event. We set an event estimation window from day –200 until day -11 of the event [79, 80]. We then estimate the parameters of the four-factor model. The abnormal return AR_{it} for firm i on day t is calculated as follows.

$$AR_{it} = R_{it} - (\hat{\alpha}_i + R_{ft} + \hat{\beta}_{i1}[R_{mt} - R_{ft}] + \hat{\beta}_{i2}SMB_t + \hat{\beta}_{i3}HML_t + \hat{\beta}_{i4}UMD_t + \varepsilon_{it}) \tag{3.5}$$

Thus, the cumulative abnormal return (CAR) can be calculated using

$$CAR[t_1, t_2] = \sum_{t=t1}^{t2} \bar{A}_t \tag{3.6}$$

3.5.2 Control Variables

We include control variables from five perspectives: (1) control for information from traditional media; (2) control for other firm actions (press release); (3) control for firm characteristics; (4) control for social media volumes; and (5) control for historical events.

To evaluate the influence of social media information propagation on market reaction, we control for the effect from traditional media announcements. We obtain the volume $News\_Volume$, as well as the composite sentiment score $News\_Sentiment$ of news reports related to the crisis events from RavenPack. Furthermore, since stock market reaction to a crisis event may vary across firms, we control for firm heterogeneity through firm size and firm type. $Firm\_Size$ measures the total assets of a firm. In addition, we control for firm activities during a crisis event. We collect firms' press releases and define $Firm\_PR$ as the number of a firm's press releases related to a crisis event. $Firm\_Tweets$ and $User\_Tweets$ indicate the volumes of a firm's social media posts and user's social media posts. $Historical\_News$ measures the number of event-related traditional media articles during an event window.

3.5.3 Regression Models

This chapter tries to examine the impact of stakeholder's information adoption pattern for firm-initiated information and user-initiated information on Twitter on firm performance. For each of the 652 events, we first calculate the cost of the crisis events using cumulative abnormal returns (CAR) within the window of day -1 to day 21. We use CAR as the dependent variable in our analysis. Next, we conduct a regression analysis to investigate the possible factors that could impact stock reactions.

We investigate the effect of firm-initiated news propagation on stock reaction during firm crisis events. We also evaluate the impact of firm/user-initiated Twitter message propagation using Equation (3.7) and present the result in Table 3.5.

$$
\begin{aligned}
CAR[t_1, t_2] = \beta_0 + \beta_1 R_{SEI}\_Firm + \beta_2 R_{SEI}\_User + Firm\_Tweets + Other\_Tweets \\
+ News\_Volume + News\_Sentiment \\
+ Firm\_PR + \beta Controls + \varepsilon
\end{aligned}
\tag{3.7}
$$

Table 3.5: The Effect of Tweet Propagation on Stock Return Surrounding Firm Crisis Events

Variables	Model 1	Model 2	Model 3
R_{SEI}_Firm			0.0016
			(0.0007)**
R_{SEI}_User			-0.0013
			(0.0007)*
$Firm\_Tweets$		0.0025	0.0026
		(0.0015)*	(0.0015)*
$User\_Tweets$		-0.0038	-0.0038
		(0.0011)**	(0.0011)***
$News\_Volume$	0.0004	-0.0002	-0.0004
	(0.0044)	(0.0043)	(0.0043)

News_Sentiment	-0.0370	-0.0383	-0.0384
	(0.0185)**	(0.0184)**	(0.0185)**
Firm_PR	-0.0147	-0.0150	-0.0167
	(0.0109)	(0.0109)	(0.0109)
Firm_Size	0.0037	0.0051	0.0049
	(0.0020)*	(0.0020)**	(0.0020)**
Historical_News	-0.0000	-0.0000	-0.0007
	(0.0000)	(0.0000)	(0.0007)
Financials	-0.0101	-0.0089	-0.0078
	(0.0046)**	(0.0046)*	(0.0046)*
Consumer	0.0048	0.0059	0.0056
	(0.0034)	(0.0034)*	(0.0034)
IT	-0.0000	0.0017	0.0018
	(0.0038)	(0.0039)	(0.0039)
Industrials	0.0018	0.0019	0.0018
	(0.0049)	(0.0048)	(0.0048)
$AdjR^2$	0.11	0.16	0.18
N	652	652	652

* p<0.10, ** $p < 0.05$, *** $p < 0.01$ Standard errors in parentheses

Model 1 presents a basic model, which captures the impacts of traditional media disclosure on CAR. Model 2 investigates the volumes of social media posts for both firm tweets and user tweets. The result indicates that increasing volumes of firm posts related to the crisis event would benefit the firm in terms of stock return. In addition, increasing volumes of user posts are harmful for firm stock performance. This result is consistent with the findings from the prior literature [3].

In Model 3, we further explore the impact of information propagation during the crisis events on the stock reaction. The significant positive coefficient for R_{SEI}_Firm in Model 3 indicates that when the majority of stakeholders exposed to the firm-initiated information choose to adopt the information, the firm is likely to have a positive stock reaction. In contrast, the coefficient for R_{SEI}_User is negative, suggesting that when the majority of stakeholders exposed to the user-initiated information choose to adopt the information, firms tend to have greater loss of market value.

3.6 Conclusions and Future Directions

While social media has become an increasingly important channel for crisis communication, there is limited research exploring the diffusion pattern and whether it would influence firm performance in the crisis management context. Our research provides a template and methodology for us and others to follow and extend. In particular, we use the SEIZ model to describe the information propagation process. By utilizing the parameters generated by the SEIZ model, we quantitatively measure the information adoption process on social media.

Our investigation indicates that firms can take managerial control in order to minimize the damage caused by crisis events. The previous literature shows that the content and volume of firm social media posts can impact stakeholders' perception of firms' image and stock performance [3, 54]. Our model goes beyond purely looking at the information itself, but also includes the observation of the dynamic process of stakeholders' propagation of information. We generate new indicators that can measure a stakeholder's information adoption process. Our results show that a larger portion of stakeholders' adoption of firm-initiated information on social media can lead to a positive impact on firm stock performance, while a larger portion of stakeholders adopting user-initiated information may magnify the negative impact caused by the crisis events. To encourage stakeholders to adopt firm-initiated information as opposed to user-initiated information, firm managers should put more effort into expanding information disclosure and increasing the quality and credibility of information.

The future work for this study will focus on comparing the diffusion patterns of different events and trying to cluster events that share common characteristics related to diffusion patterns. We hope to identify specific patterns that have a significant impact on firm stock performance.

Chapter 4

Exploring Predictive Features from Text-based Information for Stock Movement during Corporate Events

4.1 Introduction

In Chapter 2, we demonstrate that the texts used in financial news and social media are capable of indicating firm stock movements during crisis events. The hybrid deep learning model we proposed has achieved satisfactory prediction results. In this chapter, we target the research problem of how to interpret the hybrid deep learning stock prediction model for researchers and practitioners interested in stock prediction. In particular, we aim to detect text-based predictive features for stock movements from multiple sources of information. We investigate research questions, including what features can be efficiently extracted from the hybrid deep learning model and how they relate to the prediction results.

However, understanding the mechanism behind how deep learning models work can be quite challenging. First, a deep learning model is often regarded as a black-box model, and it is difficult to trace a prediction back to which features are important. Second, in the hybrid deep learning stock prediction model, we add word embeddings and additional data processing, such as OpenIE and clustering, to map text collections onto the feature space, which makes it harder to interpret.

We propose the application of the layer-wise relevance propagation (LRP) algorithm [13] to explain the hybrid deep learning architecture for stock price prediction. Although a deep learning model is traditionally considered a black-box, the layer-wise relevance propagation method allows us to explain the mechanism of the model. Previous researchers applied LRP in the interpretation of image classification and achieved good performance [13, 81]. They decomposed the neural network, layer by layer, and assigned scores for each neural unit. These scores were computed for inputs and could explain the amount of contribution of a pixel or region to the final prediction of an image class. In our study, we apply LRP to the hybrid deep learning stock prediction model to compute the contribution of the input text features. We demonstrate that LRP is capable of extracting the text features (i.e., keywords and phrases) that are relevant to the prediction results. Notably, we are able to generate predictive features from financial news and social media separately.

The next section describes the literature related to methods in interpreting deep learning models for Image Processing and Natural Language Processing (NLP) that have inspired this work. We then describe the data collection, followed by a step by step introduction of our model design. Finally, the corresponding analytical results, evaluations, and conclusions are presented.

4.2 Literature Review

We aim to interpret our hybrid deep learning model proposed in the second chapter to find the features that drive stock surge or plunge predication. In the literature, there is a surge in the topic of deep neural network interpretation. Setiono and Liu [82] introduced the method to discretize the neural networks and fit them to a decision tree, to understand the neural networks. Dimopoulos *et al.* [83] introduced sensitivity analysis to quantify the influence of the change of the input, on the output. Erhan *et al.* [84] developed the activation maximization method and a sampling-based method to increase the interpretability of convolutional neural networks. Zeiler *et al.* [85, 86, 87] proposed deconvolutional networks to extract the most important features related to the predictions of the convolutional layers. Further, Simonyan *et al.* [88] developed the idea of the deconvolutional networks applied to the non-convolutional neural network based on the first-order Taylor expansion, which is considered as the gradient-based method [89, 90].

More recently, Bach *et al.* [13] proposed the layer-wise relevance propagation method to compute the relevance score for each neuron. Based on their method, the contribution of each neuron can be quantitatively evaluated. Furthermore, the relevance score is conserved during the propagation. Their method can be used in different neural network structures, including convolutional neural networks and recursive neural networks [91].

Arras *et al.* [92] made a comparison between layer-wise relevance propagation and the sensitivity analysis method, which is a gradient-based method. In their work, the layer-wise relevance propagation performs better than the sensitivity analysis method in natural language processing.

Researchers also attempt to improve the explainability of neural networks for the stock prediction model. Shi *et al.* [49] implemented the layer-wise relevance propagation method for a stock price prediction model based on the financial news, and built a visualization application to assist investors with their trading decisions. However, the study focused on generating prediction and interpretation for every single firm.

Our model builds on a hybrid deep learning architecture that integrates news, social media, and historical stock data. We measure the cumulative impact of all related information on the firm stock during a corporate event. We apply the layer-wise relevance propagation method to find the relevance score for each input feature from financial news and social media. In this way, we are able to generate predictive features from stock surge predictions and stock plunge predictions for a large collection of corporate events. Specifically, we would know which words and phrases in the financial news and social media make the most contribution to the stock predictions.

4.3 Data

We expand our study to broader categories of corporate events that we collected, including 49 main categories and 335 subcategories of corporate events with 4.6 million related news titles for S&P 500 companies. We summarize the collection of corporate events and the collection size in Figure 4.1.

Group	Size	Group	Size
earnings	516 M	crime	1020 K
products-services	169 M	war-conflict	712 K
analyst-ratings	160 M	transportation	708 K
equity-actions	154 M	domestic-product	648 K
acquisitions-mergers	128 M	indexes	552 K
technical-analysis	123 M	government	512 K
insider-trading	117 M	exploration	468 K
stock-prices	110 M	bankruptcy	376 K
revenues	108 M	balance payments	208 K
labor-issues	81 M	civil-unrest	184 K
price-targets	55 M	interest-rates	76 K
credit-ratings	48 M	consumption	60 K
order-imbalances	44 M	taxes	52 K
legal	43 M	employment	44 K
dividends	38 M	foreign-exchange	44 K
investor-relations	34 M	public-opinion	32 K
partnerships	33 M	housing	32 K
assets	28 M	health	20 K
marketing	26 M	pollution	16 K
credit	7.7 M	inventory	12 K
regulatory	4.9 M	economic-union	12 K
stock-picks	2.9 M	commodity-prices	12 K
security	2.1 M	public-finance	12 K
corporate-responsible	2.1 M	production	8.0 K
industrial-accidents	1.4 M		

Figure 4.1: Categories of Corporate Events

For each event, we first calculate the cumulative abnormal return (CAR). We estimate CAR using the four-factor model [78], as mentioned in Chapter 3, which indicates a linear relationship between the stock return and four factors over a given period. It is hard to predict the exact value of what the stock change will be. Therefore, we classify the direction of stock movements during firm events into: up, down, and no change. In addition, we only focus on the "relatively large" changes in stock movements and ignore the small fluctuations.

Following the previous research [1], we define "relatively large" using a threshold of 0.05, and we define a CAR value that stays between 0.025 and -0.025 to be stable. We ignore the events that fall into the intermediate area, as shown in Figure 4.2. Accordingly, the events are classified into three stock movement categories: Surge, Stable, and Plunge. In Figure 4.3 and Figure 4.4, column 1 shows the main categories of corporate events, while column 2 shows the sub-categories of corporate events. The following columns show the number of corporate events that fall into the stock Surge, Stable, and Plunge categories. The color bars in Figure 4.3 and Figure 4.4 show the average CAR value of the listed corporate events.

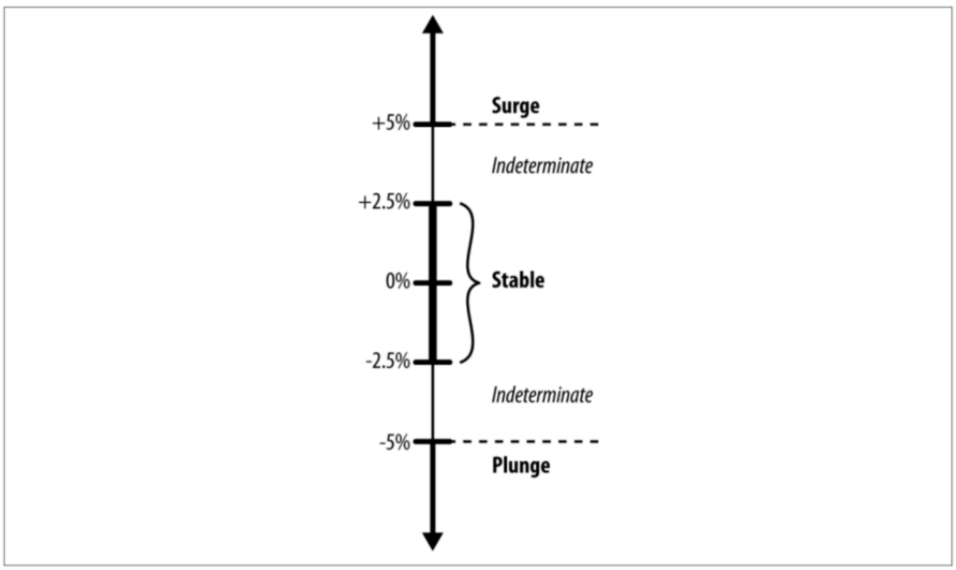


Figure 4.2: Definition of Changes in Stock Price [1]

Main Categories	Sub-categories filename	Surge	Plunge	Stable	
acquisitions-mergers	acquisition-bid.csv	287	264	1,026	0.00328
	acquisition-regulation.csv	55	56	252	0.00171
	acquisition.csv	771	750	2,679	0.00203
	merger-regulation.csv	25	20	140	-0.00350
	merger.csv	132	155	689	0.00739
	unit-acquisition.csv	493	487	1,887	0.00014
analyst-ratings	analyst-ratings-change.csv	1,646	1,574	8,596	0.00009
	analyst-ratings-set.csv	945	812	4,889	0.00053
assets	asset.csv	188	209	746	0.00048
	commodity-assets.csv	16	10	57	-0.00117
	company-for-sale.csv	37	45	151	0.00935
	facility.csv	559	589	2,386	-0.00015
	headquarters-change.csv	27	25	59	-0.00062
	patent.csv	197	180	588	0.00235
corporate-responsibility	donation.csv	122	107	557	-0.00106
credit-ratings	credit-rating-change.csv	473	458	2,751	0.00011
	credit-rating-outlook.csv	108	114	577	-0.00120
	credit-rating-watch.csv	60	62	367	0.00753
crime	robbery.csv	42	44	79	-0.00272
	shooting.csv	33	26	127	-0.00069
domestic-product	gross-domestic-product-guidance.csv	17	21	101	-0.00002
earnings	earnings-estimate.csv	1,062	1,055	2,067	0.00015
	earnings-expectations.csv	1,174	1,070	5,836	0.00031
	ebit-expectations.csv	1,625	1,656	4,190	0.00062
	ebit-guidance-expectations.csv	209	212	316	0.00214
	ebita-expectations.csv	65	63	192	-0.00336
	ebitda-expectations.csv	1,661	1,660	3,626	0.00060
	interest-income.csv	33	31	209	0.00043
	operating-earnings.csv	251	265	976	-0.00333
	pretax-earnings-expectations.csv	1,905	1,939	3,766	0.00046
	pretax-earnings.csv	1,807	1,838	3,698	0.00066
industrial-accidents	facility-accident.csv	21	16	99	-0.00259
legal	discrimination.csv	22	16	116	-0.00132
	fraud.csv	17	13	97	-0.00826
	legal-issues.csv	261	245	1,931	-0.00042
	patent-infringement.csv	49	48	280	-0.00419
	sanctions.csv	121	95	720	0.00092
	settlement.csv	144	150	972	0.00137
	verdict.csv	161	131	692	-0.00011
marketing	campaign-ad.csv	74	84	629	0.00142
	conference.csv	604	555	2,612	0.00122
	press-conference.csv	21	18	29	0.00111

Avg. CAR

-0.00826 0.00935

Figure 4.3: Summary of Corporate Events Classified as Surge, Plunge, and Stable (Part 1)

Main Categories	Sub-categories filename	Surge	Plunge	Stable	
order-imbalances	buy-moc.csv	497	580	3,101	-0.00325
	buy-moo.csv	71	75	427	-0.00344
	sell-moc.csv	466	504	3,010	0.00194
	sell-moo.csv	146	126	401	0.00715
partnerships	joint-venture.csv	45	50	306	0.00454
	partnership.csv	892	876	3,294	-0.00094
products-services	award.csv	450	464	931	0.00017
	business-combination.csv	58	57	73	0.01225
	business-contract.csv	1,515	1,473	2,836	0.00052
	clinical-trials.csv	141	157	289	-0.00016
	competition.csv	36	47	107	0.00057
	demand.csv	114	102	178	0.00381
	market-entry.csv	230	225	477	-0.00010
	market-exit.csv	79	77	81	0.00564
	orphan-drug-designation.csv	18	13	7	0.00048
	product-development.csv	255	260	735	0.00116
	product-discontinued.csv	162	175	305	-0.00228
	product-enhancement.csv	396	396	1,574	0.00041
	product-fault.csv	16	11	43	0.00678
	product-outage.csv	95	94	141	-0.00192
	product-pricing.csv	220	215	471	-0.00116
	product-promotion.csv	39	33	90	-0.00229
	product-recall.csv	109	109	265	0.00021
	product-release.csv	1,215	1,255	2,493	0.00115
	product-resumed.csv	46	50	102	-0.00057
	product-review.csv	126	126	224	0.00323
	product-support.csv	31	36	52	-0.00154
	regulatory-product-application.csv	27	31	53	-0.00525
	regulatory-product-approval.csv	187	192	426	0.00062
	regulatory-product-review.csv	36	29	31	0.00049
	supply.csv	118	122	274	-0.00117
regulatory	exchange-compliance.csv	25	16	14	-0.00403
	exchange-noncompliance.csv	16	23	36	0.00147
	regulatory-investigation.csv	233	238	370	-0.00138
revenues	operating-margin-guidance.csv	27	29	132	-0.00769
	operating-margin.csv	53	52	572	-0.00056
	revenue-guidance.csv	473	531	4,076	0.00106
	revenue-volume.csv	95	91	653	-0.00058
	revenue.csv	966	1,024	6,974	0.00067
	same-store-sales-guidance.csv	47	46	352	0.00249
	same-store-sales.csv	99	75	686	0.00076
security	cyber-attacks.csv	52	50	230	-0.00062
stock-picks	stock-pick.csv	214	208	1,518	0.00537

Avg. CAR
-0.00769 0.01225

Figure 4.4: Summary of Corporate Events Classified as Surge, Plunge, and Stable (Part 2)

In the following sections, we look into the stock surge and plunge events to explore different predictive features from financial news and social media discussions. To avoid certain corporate events dominating the results and simplifying our processing, we randomly pick 100 events for each event type listed in column 2 if the number of stock surge or plunge events is greater than 100. By applying the hybrid deep learning stock prediction model proposed in Chapter 2 to the new data collection, we obtain a 63.78% prediction accuracy. We then extract only the correct predictions from the stock surge and plunge predictions for our model interpretation.

4.4 Model Interpretation

Our model interpretation is based on the idea of back propagation. In Figure 4.5, the top section is a trained deep learning model. x_I represents the input data, x_i^n indicates the value of the ith neuron in the nth layer, x_j^{n+1} indicates the value of the jth neuron in the $n+1$th layer, and x_o is the output data. Since it is a trained model, we can calculate x^{n+1} based on x^n. Sigma is the activation function and w is the weight matrix.

The layer-wise relevance propagation algorithm can calculate the relevance score of x_I at the input layer, which indicates the amount of contribution to x_O at the output layer. With the backward propagation, as shown in the lower section of Figure 4.5, the relevance score at the input layer can be calculated from the relevance score at the output layer. In Figure 4.5, R_i^n is the relevance score of the ith neuron in the nth layer. With the knowledge of the value of neuron x and weight matrix w, we can get the relevance score at the nth layer from the $n+1$th layer. To continue this processing, we can get the relevance score at the input layer R_I.

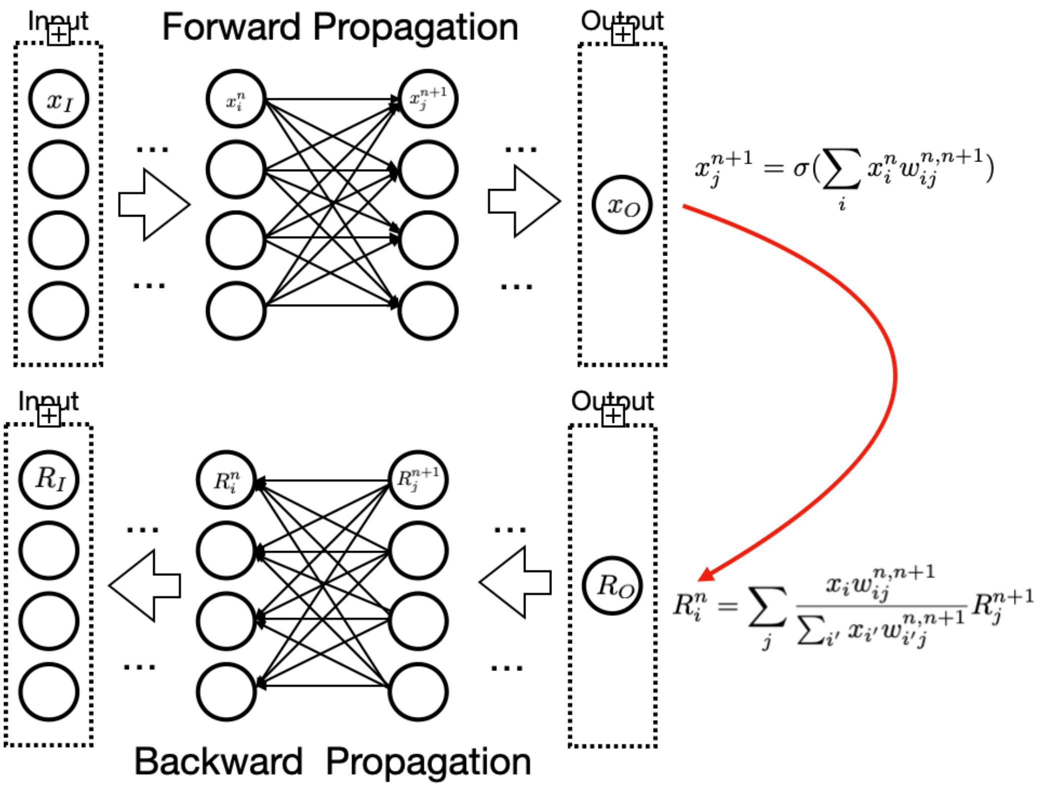


Figure 4.5: Backward Propagation

Since our stock prediction model is a hybrid deep learning model, we will introduce the layer-wise relevance propagation in several steps. Considering LRP as a backward propagation method, we will introduce it from the final prediction of our hybrid deep learning model, as shown in Figure 4.6. Assuming we predict that the stock price will increase at the end, and it is a successful prediction, we will assign the initial relevance score at the red neuron in the bottom and ignore the grey neuron. In Figure 4.6, the darker neuron represents a larger relevance score. The relevance score propagates backward, as shown by the arrows. We will then distribute the relevance score to the text-based predictions from news and social media as well as predictions from historical stock prices. We divide the relevance score into two groups in the backward propagation process since we concatenate the predictions from news and social media as well as predictions from historical stock price during the forward propagation. We will only calculate the relevance score related to the text-based predictions and ignore the predictions from the historical stock prices. Figure 4.7 further demonstrates how we calculate the relevance score for the text-based prediction.

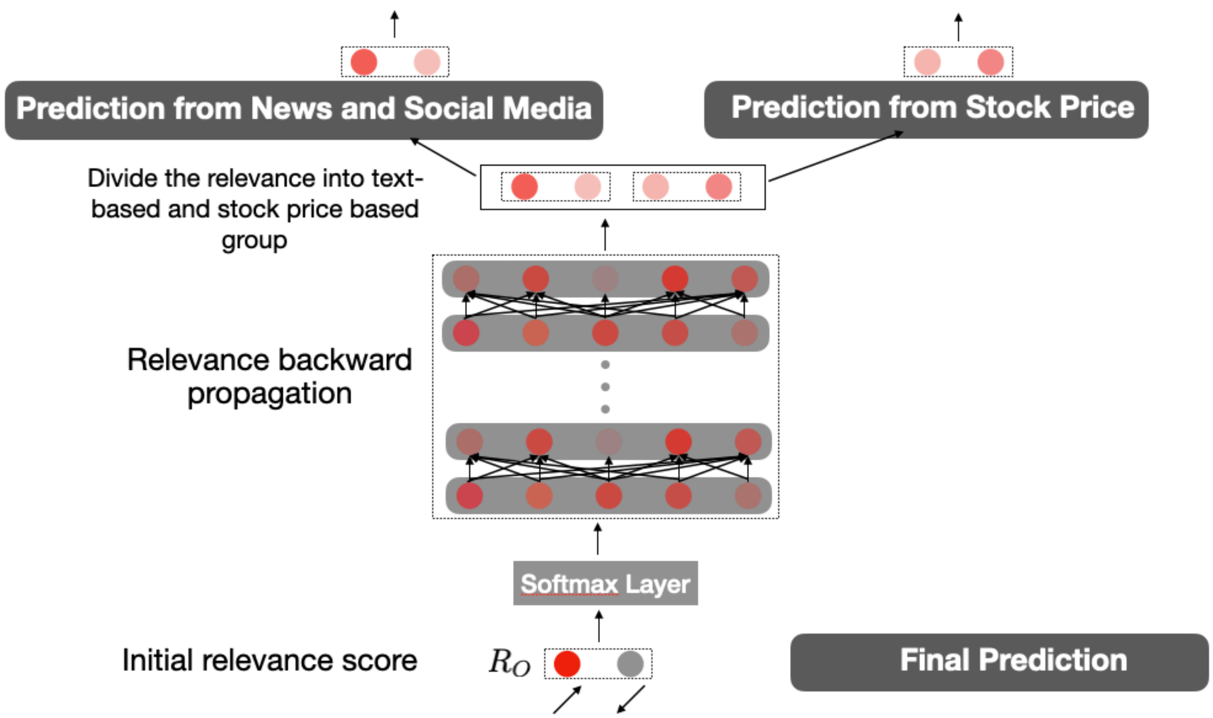


Figure 4.6: Generating the Relevance Score for News and Social Media

Figure 4.7 shows the backward propagation for the relevance score of news and social media. Since we concatenate the news vector and social media vector, we can divide the relevance score vector into the news portion and social media portion.

In the news portion, we use the convolutional neural network (CNN) to extract the most important information from the news in the forward propagation process. The left section shows how the relevance score backward propagation works in a CNN. For the CNN method, we use the max-pooling to get the most significant feature representation in the panel (dashed line box). In Figure 4.7, values represent the representative features during the forward propagation process; the darker red color indicates a larger relevance score, and the black indicates zero relevance score during the backward propagation process. The arrows represent the direction of the backward propagation.

In Figure 4.7, the three values on the black dashed line show the representative features from the corresponding dashed line box in the forward propagation process. The red color on the values in the dashed line box indicates which element is assigned the relevance score after the backward propagation. For example, in the left dashed line box, the largest value is 0.81. After the max pooling, we will only keep the element with the value 0.81 in the forward propagation. During the relevance score backward propagation, we will use the "winner-takes-all" strategy, so the element with the largest value in the panel will take all the relevance scores. Thus, the element with the value 0.81 at the left dashed line box will take all the relevance scores. The other elements in the dashed line box will get 0 relevance scores.

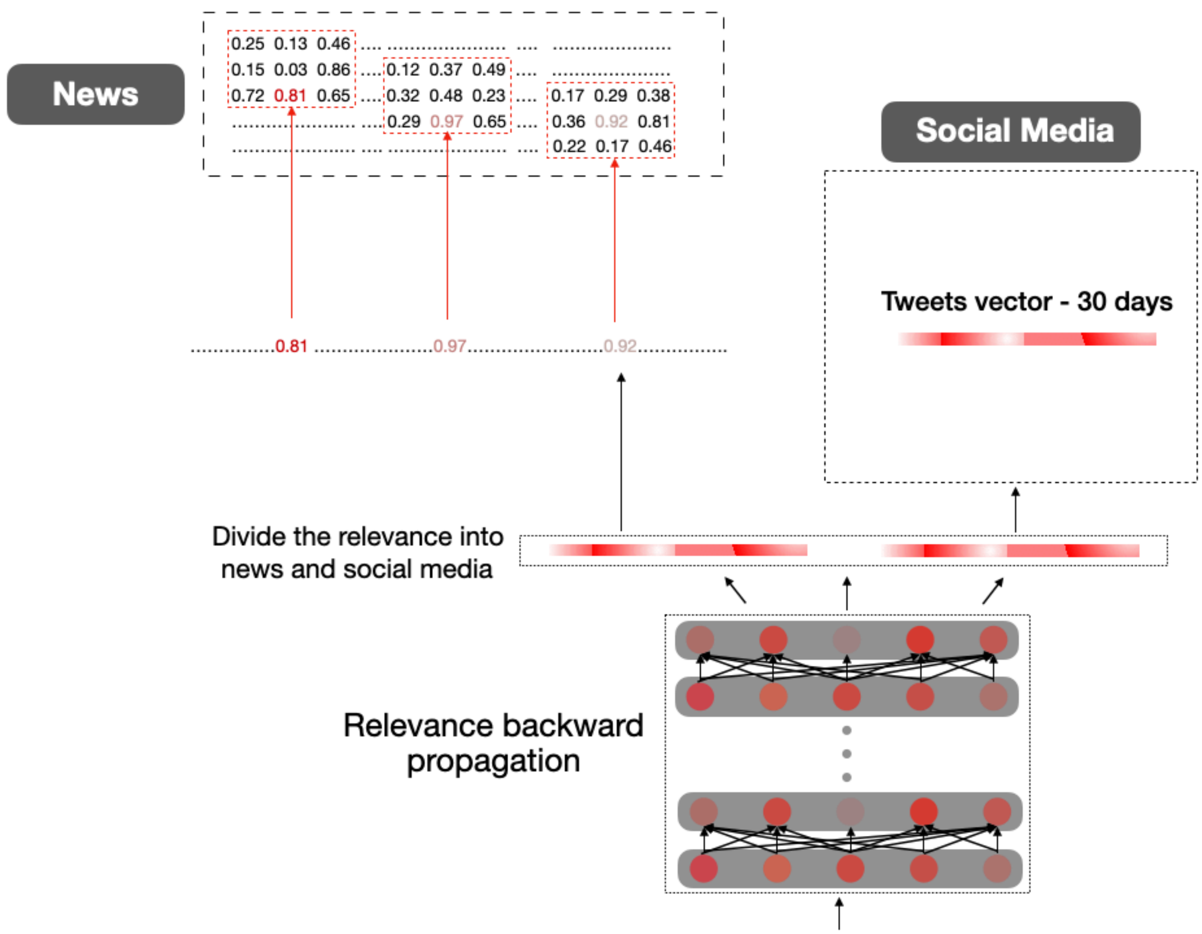


Figure 4.7: Generating the Relevance Score for News

Figure 4.8 shows the details of how we distribute the relevance score for news using a 30-day event window as an example. In the bottom section of Figure 4.8, each line indicates the average vector for all the news in one day. We distribute the sum of the relevance scores in one line to the corresponding one-day news collection equally. In the upper section, each line in the one-day news collection represents one news title. Since it is concatenated from the "Actor", "Action", and "Object" vector, we divide the relevance score to "Actor", "Action", and "Object". Finally, we have the relevance score for each part of the news title.

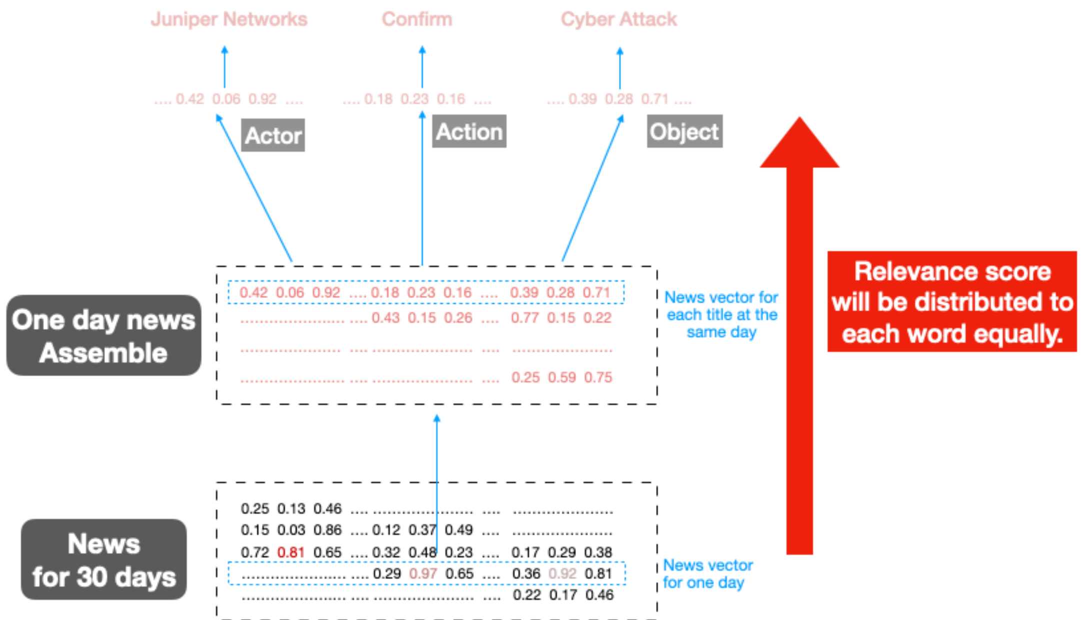


Figure 4.8: Distributing the Relevance Score for News Features

Figure 4.9 shows how the relevance score is distributed to each word of tweets. Since the tweets vector is concatenated from three clusters, we divide the relevance score into three clusters, as shown in Figure 4.9. In each cluster, the relevance score is distributed to each tweet vector based on its distance to the centroid vector. Then we distribute the relevance scores to all the words in these tweets equally. Finally, we get the relevance score for each word in the tweets.

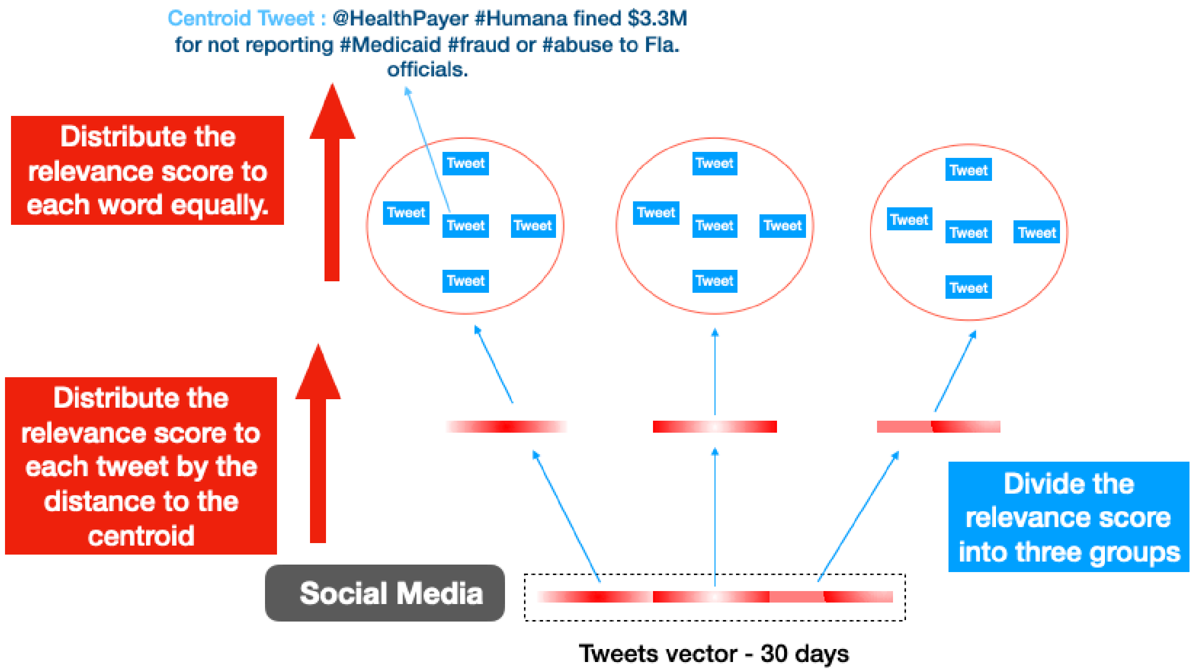


Figure 4.9: Generating the Relevance Score for Social Media

4.5 Exploring Predictive Features with Relevance Scores

As demonstrated in Section 4.4, we assign each input feature a relevance score, which indicates how relevant the input feature is for explaining the prediction. In our hybrid deep learning model, we make predictions on stock surge and plunge; therefore, we show the top relevant words or phrases for the two predictions. In addition, we apply different methodologies to extract representative features from financial news and social media. With LRP, we can generate the relevance scores for features of the two types of data separately.

Table 4.1 shows the top relevant words or phrases from financial news data for stock surge predictions. Since we extract three types of features from news titles – "Actor", "Action", and "Object" – to represent news titles in the hybrid deep learning model, we distribute the relevance score to the words or phrases in the news titles that fall into "Action", "Actor", and “Object”. Since “Actor” mainly contains specific company names, we only show features from “Action” and “Object”, which we believe may be more useful for stock prediction. We also remove the ones that relate to specific corporate events. Similarly, Table 4.1 shows the top relevant words or phrases from financial news data for stock plunge predictions.

Table 4.1: Top Relevant Words or Phrases from News for Stock Surge Predictions

News Surge			
Action	**Relevance Score**	**Object**	**Relevance Score**
reach	0.00592%	settlement	0.01425%
raise	0.07050%	services	0.25300%
support	0.07117%	sales Increase	0.00158%
acquire	0.05292%	award	0.02367%
upgrade	0.02467%	sales growth	0.00458%
promote	0.00142%	target	0.02708%
unveil	0.00608%	agreement	0.01675%
get	0.28383%	new product	0.00092%
receive	0.02058%	income adjusted	0.07558%
donate	0.00367%	revenue growth	0.00433%

Table 4.2: Top Relevant Words or Phrases from News for Stock Plunge Predictions

News Plunge

Action	Relevance Score	Object	Relevance Score
be affected	0.94892%	new issue	0.00013%
claim	0.00358%	profit drop	0.00019%
impact	0.00375%	falling	0.00024%
deny	0.00275%	disapointment	0.00028%
resign	0.02350%	decline	0.00099%
to pay	0.00692%	early termination	0.00014%
shut	0.00292%	miss estimates	0.00107%
cost	0.01825%	misconduct	0.00003%
dismiss	0.00200%	lawsuit	0.00083%
lower to	0.02050%	shut down	0.00317%

Table 4.3 shows the relevant keywords from social media for both stock surge and plunge predictions. In our hybrid deep learning model, we distribute the relevance score to every single word; hence we only show the list of keywords.

Table 4.3: Top Predictive Words Generated from Social Media Stock Surge and Plunge Predictions

Social Media Surge		Social Media Plunge	
Keywords	**Relevance Score**	**Keywords**	**Relevance Score**
disclosure	0.00059%	falling	0.00143%
investment	0.00705%	suspension	0.02530%
provide	0.00712%	fallback	0.00016%
growth	0.00529%	mislead	0.00237%
plan	0.00247%	battle	0.00046%
service	0.00014%	dispute	0.00271%
take	0.00061%	throw	0.00168%
drive	0.02838%	refuse	0.00009%
make	0.00206%	legal	0.00756%
get	0.00037%	panic	0.00043%

4.5.1 Evaluation

To evaluate the LRP model, we perform a sequence of "word deletions" and track the impact of the deletions on the prediction performance. We carry out four deletion methods: delete words by order of relevance score generated by LRP, delete words by order of the word frequency, delete words by word frequency for words in the Loughran & McDonald Word List [93], and delete words randomly. Figure 4.10 summarizes our results. We find the performance of our model from the word deleting based on the order of relevance score falling much faster than others, suggesting that features with larger relevance scores contribute more to the prediction decision.

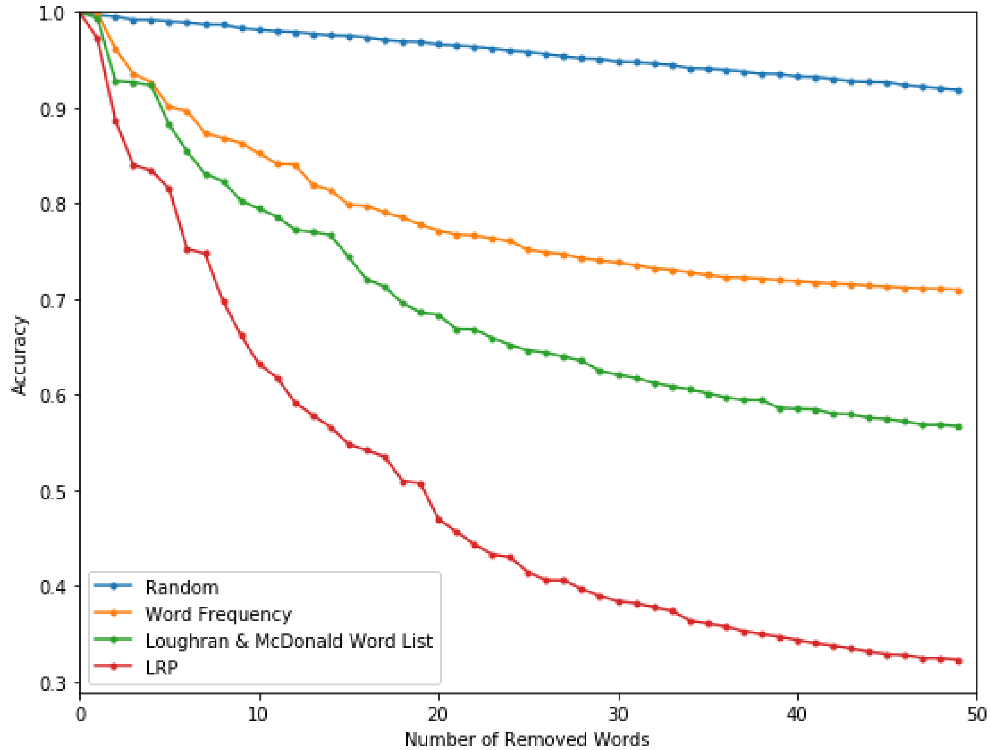


Figure 4.10: Compare Accuracy Changes

4.6 Conclusions and Future Directions

In this chapter, we extract the predictive features from financial news and social media that can indicate firm stock movements. In particular, we identify text features such as predictive words or phrases based on the hybrid model we proposed in Chapter 2. In addition, we evaluate how relevant these features are to firm stock surge and plunge predictions. We believe our study can help investors or financial analysts to identify signals of firm stock movements during corporate events. The potential directions for future work include:

- Currently, when we process the text-based data, we don't consider the sequence of the text. In the future, we can use the sequence to sequence method, such as encoder-decoder, to capture more information from the text-based data.

- Our model can also generate predictive features of stock movements for specific types of events or specific companies. In the future, we plan to build a visualization system that can help investors or financial analysts to highlight important information from the financial news and social media related to stock movements.

Chapter 5

Contributions and Future Work

5.1 Contributions

This research studies how corporate events impact firms' stock returns. We conduct an event-driven study and collect event-related information for stock predictions during crisis events. We then look into how event-related information was propagated on social media and whether the information propagation can impact firm stock performance. Finally, we extract predictive language features from event-related news and social media. The main contribution of our research can be summarized as follows:

For stock prediction during corporate events, we build a hybrid deep learning model that integrates the prediction from multiple sources of information, including financial news, social media postings, and historical stock prices. We identify the associated information in the event window and consider the cumulative impact of information on a firm's stock return during a specific event. Besides, we explore various methods when we extract feature vectors for news and social media. Instead of a simple combination of the features, we propose different feature extraction, selection, and representation methodologies for each data source. We use OpenIE to capture key features from news titles [38] and process the large sparse text data on social media using clustering. We evaluate our model accuracy for different event windows. Our model results show that the best result we can achieve is 68.8% accuracy in a 21-day event window. Compared with the state-of-the-art algorithms, our model has better performance. We demonstrate that the event-driven hybrid deep learning model can effectively integrate event-related information from different sources and make better predictions on firm stock movements during firm crisis events. Thus, hypothesis 1 is supported.

For measuring the diffusion of event-related information on social media during a firm crisis, we are among the first to adopt the SEIZ model to estimate the information propagation process using real social media data from Twitter. Drawing from the information propagation process, we quantify stakeholders' information adoption behavior for both firm-initiated and user-initiated information on Twitter during major firm crises. In addition, we propose these two measurements as indicators for firms' stock reactions during crisis events, which has not been discussed in the previous literature. We empirically test the association between the stakeholder's information adoption behavior and firm stock performance. Our results suggest that a higher portion of stakeholders adopting the firm-initiated information on Twitter is beneficial for firm stocks during crises. In contrast, a higher portion of stakeholders adopting user-initiated information on Twitter can have a significant negative impact on firm stocks. Thus, hypothesis 2 is supported.

For investigating the predictive language features for firm stock movements, we apply the layer-wise relevance propagation algorithm, which can highlight the features that lead to the predictions of a stock price surge or plunge with the hybrid deep learning model. We interpret the hybrid deep learning stock prediction model that utilized information from multiple sources. We develop strategies to distribute feature relevance scores to the textual features from financial news and social media data separately since we apply different methodologies to generate feature representations for the two data sources in our hybrid deep learning model. In the hybrid deep learning model, we define "Action", "Actor", and "Object" to extract useful knowledge from financial news titles. We generate predictive words and phrases from financial news features that fall into the "Action", "Actor", and "Object" categories. In addition, we generate the predictive words from different clusters of social media posts. We show that the language features in the news or social media have predictive power on firm stock movements during corporate events. Thus, hypothesis 3 is supported.

5.2 Publications

Several papers have been published during my Ph.D. program. There are two papers related to the research in Chapter 3 and Chapter 4. The main content of Chapter 3 was published in the first paper. The second paper extracts textual features from news and social media data for data breach events related to the study conducted in Chapter 4. Chapter 4 uses advanced methods and extracts language features by interpreting deep learning models.

1. **Ziqian Song**, Wenqi Shen, Weiguo (Patrick) Fan, Edward A. Fox. Measuring the Impact of Corporate Crisis News Propagation via Twitter, *Informs 11th Conference on Information Systems and Technology (CIST 2019)* [11].

2. **Ziqian Song**, G Alan Wang, Weiguo (Patrick) Fan. Firm Actions Toward Data Breach Incidents and Firm Equity Value: An Empirical Study, *in Proceedings of the 50th Hawaii International Conference on System Science (HICSS), 2017* [12].

Other publications related to social media analysis or user-generated content are listed below.

1. Andrea L. Kavanaugh, **Ziqian Song**, Liuqing Li, Edward A. Fox. Communication Behavior in an Emerging Democracy, *in Proceedings of the 20th Annual International Conference on Digital Government Research. Dubai, United Arab Emirates, ACM, 2019* [94].

2. **Ziqian Song**, Qianzhou Du, G. Alan Wang, Weiguo (Patrick) Fan. Predicting Success on Kickstarter based on Experienced Backer Preference, *in Proceedings of the 12th China Summer Workshop on Information Management (CSWIM 2018)* [95].

3. Andrea L. Kavanaugh, **Ziqian Song**. Engaging a community through social media-based topics and interactions. *First Monday, 23(4), 2018. ISSN 13960466* [96].

4. Liuqing li, **Ziqian Song**, Xuan Zhang, Edward A. Fox. A Hybrid Model for Role-related User Classification on Twitter, *arXiv preprint arXiv:1811.10202, 2018* [97].

5. Andrea L. Kavanaugh, **Ziqian Song**. Reflecting Community Events and Social Interactions through Archived Social Media, *in Proceedings of the 18th International Conference on Digital Government Research, New York, USA, ACM, 2017* [98].

5.3 Future Work

In the future, we will continue to work on the three major topics of my dissertation research. For event-driven stock prediction, we will explore other deep learning methods to gain more accurate information representation from news data (e.g., LSTM or the attention model) and techniques to optimize the number of clusters (e.g., the "Elbow" Method, Gap Statistic). Besides, we will use other dependent variables to measure the impact of crisis events on firm performance (e.g., abnormal stock return, credibility score).

For measuring event information diffusion, we will work on cluster events that share the common characteristics for the diffusion patterns and identify specific patterns that may have a significant impact on firm stock performance. We will identify social media influential users and measure the effect of influential users on stock returns.

For extracting predictive language features, we will use the sequence to sequence method, such as encoder-decoder, to capture more information from the text-based data. Based on our results, we will build a visualization system that can help investors or financial analysts to highlight important information from financial news and social media.

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