Rumor detecting

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M.Sc. Internet Technologies and Information Sytems

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Abstract

In this thesis, we propose a approach of detection of rumors in Twitter.

Twitter is a microblogging service that which is already used by millions users. Users can publish and exchange information with short tweets whenever and wherever. This advantage makes Twitter an ideal media for spreading breaking news and false rumors.

So automatic detecting rumors on social media has become a trending topic. But early researches mostly focused on rumors during one or several events like earthquake or terrorist attack [35] [45][43]. But in our work, we study on the general rumors.

And most previous work for rumor detection modeled on static features like the content of tweets or propagation features, but they ignored that those features can change during the information's propagation over time.

We build up a system with random forest and the Dynamic Series-Time Structure (DSTS) [29] using the temporal features and their varieties over time. And we test the Spike Model [23], SIS Model and SEIZ Model [16] as temporal features in our model. To improve the time series model's performance at early stage of the event, we develop a single tweet's credibility scoring model with zhou's CNN+LSTM model [52] which can predict a single tweet whether is rumor related or not with 81.20% accuracy. Finally our time series rumor detecting model gets 90% accuracy within 48 hours.

As far as we know, we are the first research about the performances of features changing over time like the sentiment features are useless after 25 hours.

Zusammenfassung

In dieser Arbeit, schlagen wir einen Ansatz der Erkennung von Gerüchten in Twitter.

Twitter ist ein Microblogging-Dienst, der bereits von Millionen Benutzern verwendet wird. Benutzer können Informationen irgendwo und irgendwann mit kurzen Tweets veröffentlichen und austauschen. Dies macht Twitter zu einem idealen Medium für die Verbreitung von aktuellen Nachrichten und falschen Gerüchten.

So automatische Erkennung von Gerüchten auf Social Media hat sich zu einem Trend Thema. Aber frühe Forschungen konzentrierten sich hauptsächlich auf Gerüchte während eines oder mehrerer Notfällen wie Erdbeben oder terroristische Angriffe zitieren oh2010exploration [45] [43]. Aber in unserer Arbeit studieren wir über die allgemeinen Gerüchte.

Wir erstellen ein System mit Ramdom-Forest und die Dynamische Serien-Zeit-Struktur (DSTS) [29] mit den zeitlichen Merkmalen und deren Sorten im Laufe der Zeit. Und wir testen das Spike Modell [23], das SIS Modell und das SEIZ Modell cite jin2013epidemiological als zeitliche Merkmale in unserem Modell. Um die Leistungsfähigkeit des Zeitreihenmodells im frÃijhen Stadium des Ereignisses zu verbessern, entwickeln wir ein Modell für die Glaubwürdigkeit einzelnes Tweets von Zhou mit Zhou’s CNN + LSTM-Modell [52], das einen einzelnen Tweet vorhersagen kann, ob es sich um ein Gerücht oder nicht um eine Genauigkeit von 81,20% handelt. Schließlich haben wir die Genauigkeit der Zeitreihe Gerücht Erkennung Modell erhalten 90% Genauigkeit innerhalb von 48 Stunden.

Soweit wir wissen, sind wir die erste Forschung über die Leistungsfähigkeit von Merkmalen im Laufe der Zeit wie die Sentiment Features sind nutzlos nach 25 Stunden.

Acknowledgment

Acknowledgment

First I want to thank my parents. Without their support I can't finish my master study in a foreign country.

I am very grateful to my mentor M.Sc. Tu Nguyen who gave me lots of help and inspiration in master thesis.

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The last but not least I want to thank my girlfriend for accompanying me thought all the hard and good time.

Without you all my masters would not have been a success.

Contents

1 Introduction

Twitter is a mircoblogging service which is used by millions users. Users can publish and exchange information with short tweets within 140 characters. It is cheap and can be accessed though several types clients like website, email or mobile phone. Those advantages make Titter agile and simple to use. A study by the Pew Research Center shows that the people in USA under age of 30 consider Internet becomes the major resource of news and in all ages crowds Internet became the second important media [20].

But these advantages make Twitter become one of the most importance resources of breaking news, at the same time it becomes into a ideal media for spreading unverified information. On Twitter everyone can be a journalist and publish news or rumors without any substantiation which must be done by traditional journalists before news' publishing.

Rumor could be defined as a statement whose truth value is unverified or deliberately false [38]. And they could be harmful to the government, market and society. One case is some hacked accounts spread a rumor about Obama had been injured in white house. The S&P crashed and wiped off 130 Billion dollars of stock value [31].

So a method of detecting rumors on Twitter can be very useful and it will better it can detect rumors so soon as possible before it widely spreads. The structure is shown in figure 1.1. First 1) we crawled the data from Twitter interface, 2) we use beautiful soup and spark technologies to extract feature from the tweets, 3) we extract time series features and fit to the dynamic series-time structure 4) we use the text of tweets as feature to train the single tweet's credibility scoring model neural network and merge the its output to the time series features, 5) training the our time series model with DSTS.

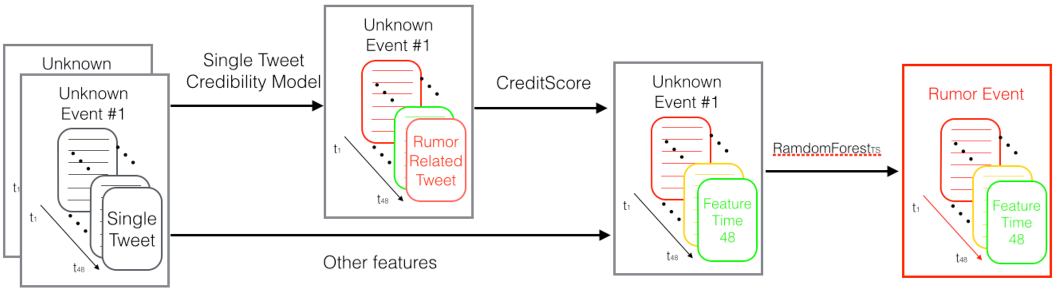


Figure 1.1: pipeline of the rumor detecting system

1.0.1 Contributions

In this thesis, we make the following contributions:

- We are the first research which clearly defines the time period of rumor events. Other works either use natural time period like June of 2012 or didn't explain their definition. We develop the method of definition of rumor's time period in section 2.3.2.
- We develop a model of classification of single tweet with high credibility or low credibility. We call it single tweet's creditability scoring model. Considering it could be set up online for the early rumor events detection in the further and it should response as quick as possible. So we use only the features which can be extracted from one tweet in the Twitter's interface. We test 2 models. One is random decision forest with handcrafted features. Because the features are limited, it gets only 64% accuracy. Second model what we tested is based on zhou's[52] work, it is a hybrid CNN and LSTM model for text classification. The result of this model we called it credit score with 81% accuracy.
- We develop a time series model for detecting rumor events. We used Dynamic Series-Time Structure (DSTS)[27] to capture the changes of features over time. And we tested 3 time series model as feature: modified Spike Model [23], SIS model and SEIZ model[16]. We add the results of credit scoring model as a feature into time series model to improve the performance in the early stage. And we approved that credit score is one of the best feature in the rumor detection task. In 48 hours after the event's spreading we got 90% accuracy to detect the rumor events.
- We study how the performances of features change over time during the spreading of rumors. For example the performance of features of external URLs gets

better after 24 hours and the features of sentiments are useless after 25 hours. And within 25 hours which is average time for human editors detecting rumors we get 87% accuracy.

1.0.2 Thesis Outline

The rest of this these is organized as follows: In Chapter 2 we explain some terminology of Twitter and some techniques which we use for extracting feature and modeling. in Chapter 3, we introduce our single tweet credibility model. We show the performance of models with handcrafted features are worse than the neutral network model. In4, we mainly introduce the time series model and its time series features. We compare the time series model and static model and we discuss the performance of features changing over time. Finally, in Chapter 5 we add some concluding remarks and describe future work.

2 Background and Related Work

2.1 Twitter

Twitter is a microblogging service. Now there are more than 140 million active users[1]. User can publish short messages within 140 characters aka tweets.

2.1.1 Retweet

A retweet is re-posting of a tweet by other users. One way of retweet is using RT at the beginning of the tweet which is retweeted. The other way is using "retweet button" which is officially launched by Twitter after 2015. The difference between these two retweet is tweets are retweeted by "retweet button" can't be searched by Twitter's searching interface, but manually retweets with RT keyword can. So in our work retweet means the tweets are retweeted manually. The number of how many times of this tweet has been retweeted is showed behind it.

2.1.2 Mentions

Mentions are in form like "@username" which are added in the text of tweet. The users are mentioned will receive the notification of this tweet on their homepage.

2.1.3 Hashtags

Mentions are in form like "#topic". It means this tweet belongs to some topics.

2.1.4 Favorite

Favorites means how many users like this tweet. It is showed on the interface of Twitter

[1] https://blog.Twitter.com/2012/Twitter-turns-six

2.1.5 Verified User

Verified User means this account of public interest is authentic by Twitter. It is showed by a blue icon behind the name of the poster.

2.1.6 Followers

The followers of a user are accounts who receive this user's posting. The total number of followers can been seen in the profile of poster.

2.1.7 Following

The following are other accounts who follow this user. The total number of following can been seen in the profile of poster.

2.1.8 Twitter API

Twitter API is provided by Twitter[2] for developer. But the search API only return a sampling of recent Tweets published in the past 7 days[3]. We need the full stories of the events, so we crawled the data directly from the searching interface[4].

2.2 Credibility of Tweets

Titter has been used for reporting breaking news when emergency events happen like disaster [21]. But the people are likely to trust the news which post on traditional news website more than the news with same headline but posted on twitter[15]. And Thomson's work shows that different crowds of people trust tweets basing on different kinds of sources [46].

2.3 Definition of Rumor

The definition of rumor in our work is unverified information spreading on Twitter over time. It is a set of tweets including the the sources, spreaders, retweets, doubting tweets and the denying tweet.

[2] https://dev.twitter.com/overview/api
[3] https://dev.twitter.com/rest/public/search
[4] https://twitter.com/search-home

2.3.1 Rumor Event

If a rumor didn't widely spread and it could be harmless. So we more focused on the rumors which are widely spread and contain one or more bursty pikes during propagation. We call it "rumor event".

2.3.2 Time Period of an Event

The beginning of a rumor event is hard to define. As far as I know there is related work which give us a approach to define the beginning of one rumor event. One reason is a rumor may be created serval years ago and kept exiting in Twitter, but it didn't attract the people's attention. However it can be triggered by other events and suddenly quickly spread as a bursty event.

For example, a rumor[5] claimed that Robert Byrd was member of KKK. This rumor has been circulating in Internet for a while, as shown in figure 2.1 that almost every day there are several tweets talking about this rumor. But this rumor was triggered by a picture about Robert Byrd kissing Hillary Clinton in 2016 and twitter users suddenly notice this rumor and this rumor was bursty spread. So what we are really interested in is the hours around the bursty pike.

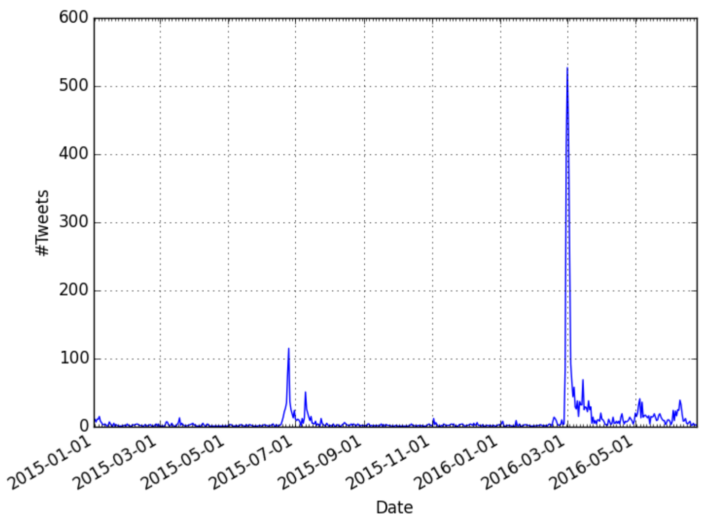


Figure 2.1: large scale tweet volume of event Robert Byrd

We defined the hour which has the most tweet's volume as t_{max} and we want to detect the rumor event as soon as possible before its burst, so we define the time of the first tweet before t_{max} within 48 hours as the beginning of this rumor event,

[5] http://www.snopes.com/robert-byrd-kkk-photo/

marked as t_0. And the end time of events we defined as $t_{end} = t_0 + 48$. We show the tweet volume in figure 2.2 of the above rumor events after defined 48 hours time period.

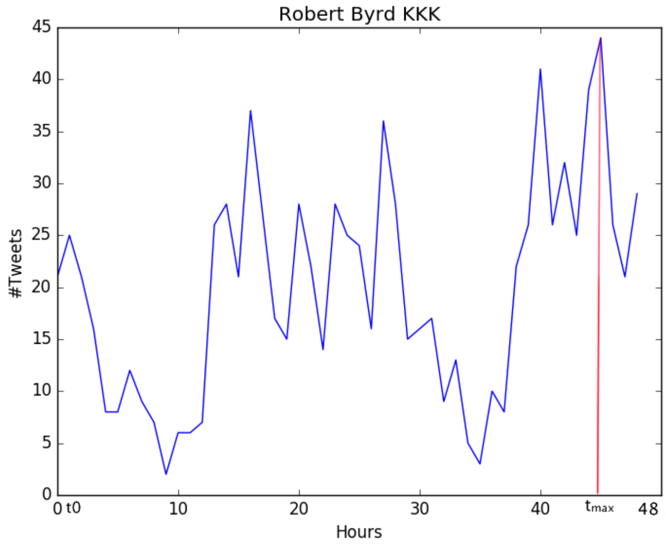


Figure 2.2: tweet volume of the rumor event of Robert Byrd after selected time period

2.4 Machine Learning

2.4.1 Machine learning Overview

Machine learning covers vast numbers of algorithms and has been successful applied in different field. The challenges of ML are finding the best model which is suitable for this task, fitting the parameters and selecting the features.

Normally we split the ML methods into Supervised learning, Unsupervised learning and Reinforcement learning[40].

The supervised learning is the most popular method of ML. It needs a set of inputs and a set of desired outputs. And the algorithm will learn to produce the correct output based on the new input.

The unsupervised learning needs a set of inputs but no outputs. The algorithm will generate the outputs like clusters or patterns. The unsupervised learning task can be used for example when people can't label the outputs.

2.4.2 Decision Tree

Classification is a supervised data mining technique. Our work can be considered as a classification task. Decision tree is a model we use for base line in the after work. A decision tree uses a tree model of decisions and their possible consequences as shown in figure 2.3. DT is an non-parametric supervised learning method used for classification and regression. Because the trees structure is very simple to visualize, so the result of DT is easy to understand. But Decision trees are unstable [7]. DT is the basic unit of random forest.

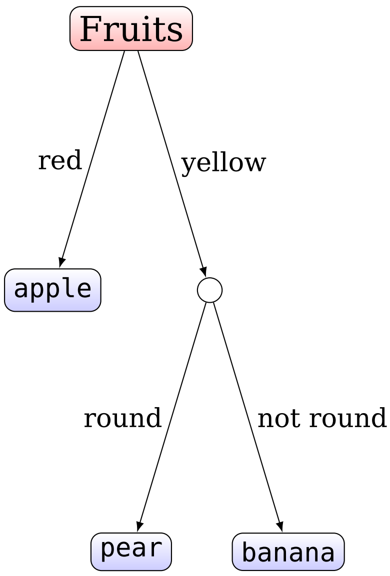


Figure 2.3: Decision tree

2.4.3 Random Forest (RF)

Another we use for testing is random forest.

RF is an algorithm of supervised learning which developed by Leo Breiman [8]. It's built by a set of classification trees [9]. Each tree is trained by a small bootstrap sample of training set and while prediction each tree votes one single candidate. RF generates the result of prediction By taking the majority vote.

For example we got task to classify pears and apples. We have the features are whether the fruit round, whether the fruit has seeds, whether the fruit red and whether the fruit is juicy. We build up a 3 trees random forest as the graph 2.4. Tree 1 randomly takes the subset of the features red and seeds and votes to apple. Tree 2 randomly takes the subset of the features red and seeds and votes to pear. Tree 3 randomly takes the subset of the features round and red and votes to apple. The most vote is apple, so the output of RF is apple.

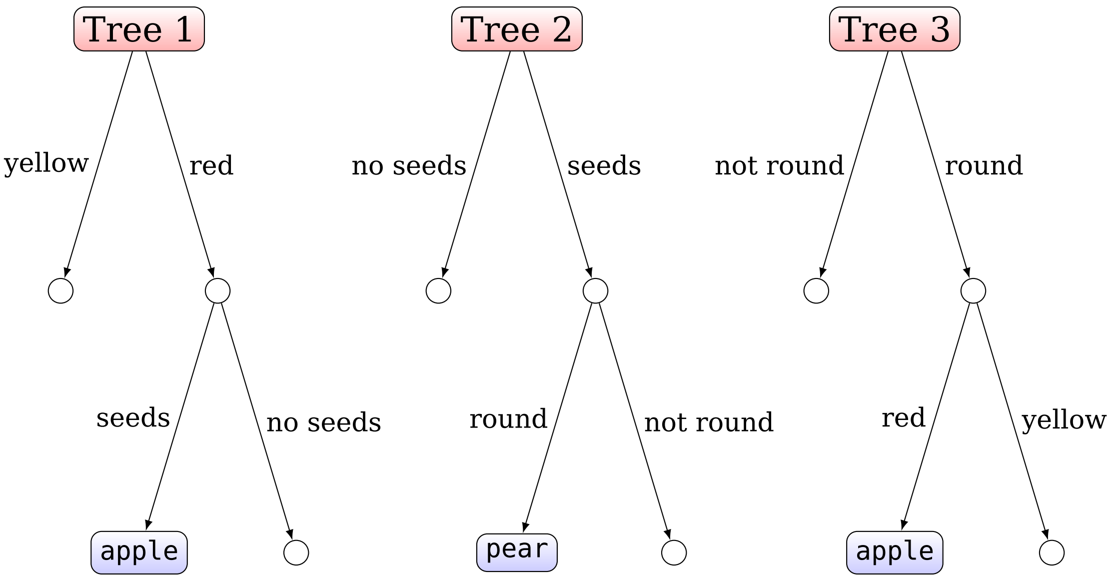


Figure 2.4: An example of random forest with 3 trees

Because RF uses a random subset of features instead of the best features in every node, so it can avoid the overfitting problem [8].

Another benefit of RF is that it can return the **features' importance**. RF is built up by a subset of training data. If there are N trees, RF will take N times bootstrap sampling. So some features we didn't select to use for training the model. The data we didn't selected we call it out-of-bag (OOB) data. In the above example the feature whether the fruit is juicy didn't join the construction the Trees, so it is a OOB data. These data can be use for validating the model and the output is OBB error $E_{oob}(G) = \frac{1}{N}\sum_{n=1}^{N} err(y_n, G_n^{-}(X_n))$ with X_n are features only in OOB. At last we get the importance of feature by permuting one feature to random numbers. $importance(i) = E_{oob}(G) - E_{oob}^{p}(G)$; where $E_{oob}^{p}(G)$ is the OBB error after permuting a feature. The more performance drop down, that means the more important this feature is. We use this method to measure the performance of features and evolute the models later. One more important benefit of RF is it can easily visualize, so it can convince people not only by the test accuracy but also by the giving us a good explanation, for example rumor containing more negative sentiment or the poster of real news more likely living in large city.

2.5 Neural Network

Figure 2.5 is a simple model of forwarding neural network which is a computing systems that processes information by their dynamic state response to external inputs [39]. In the figure 2.5 the round nodes are called neurons. Each neuron has a active function like sigmod or tanh 2.6 Neurons are connected each others with weight. The process of training the model is actually the process learning the weights of the connections of the network. With the back-propagation algorithm we 1) compute the loss from the network output and 2) update the weights by passing the error backwards through the network [39].

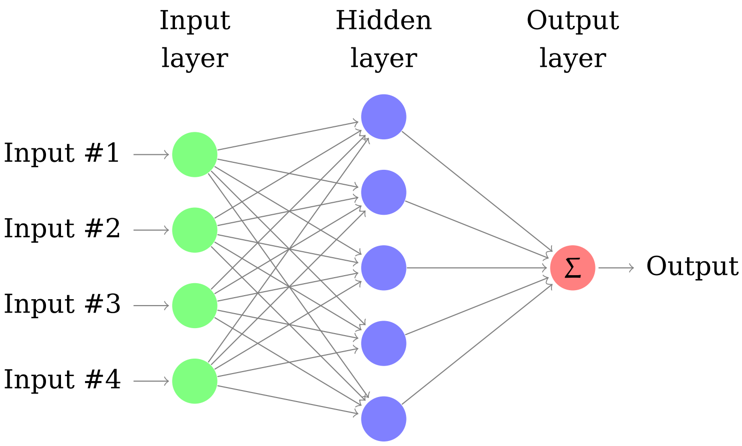


Figure 2.5: An example of 1 layer neural network

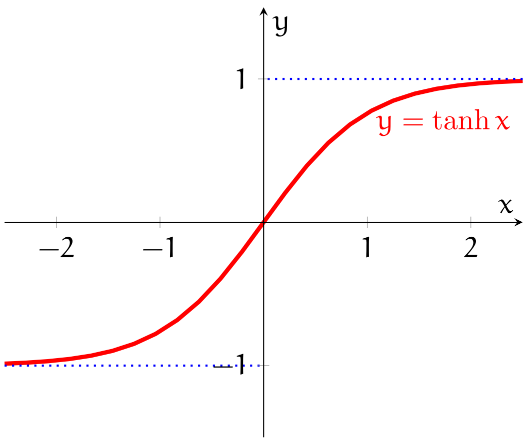


Figure 2.6: tanh function

2.5.1 Convolutional Neural Network

CNN is a kind of neural network which contains a convolutional layers. First CNN is developed by LeCun et al. [25] for computer vision to resolve the problem of imagines' shift or rotation. With the convolutional layer CNN make that is possible to learn from the local features. Figure 2.7 is an example p of CNN in application of text classification. The word "wait" and its following word "for" are mapped together into different classes though different convolutional filters. That makes convolutional neural network does not learn from the single word form sentence but from the word and its context. That makes sense because one word can in different context have different meaning. For example "Apple Tree" and "Apple Company", the same apple but contains different meaning. Pooling layer often follows after the convolutional layers in CNN models whose mainly task is to down-sample from the output of convolutional layers.

We use it for for single tweet's creditability score model in the later section 3.4.2

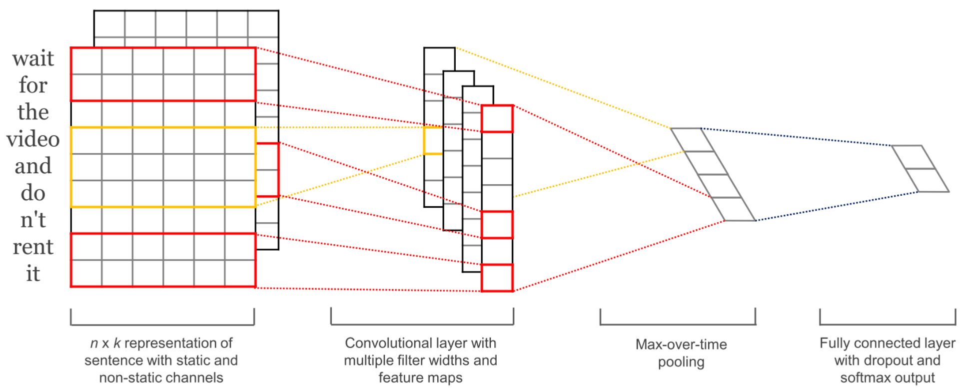


Figure 2.7: CNN for Text Classification (source from[18])

2.5.2 Recurrent Neural Network

A Recurrent neural network (RNN) is one of of class of neural network. The different between RNN and other neural network is there are feedback connections between the hidden layers showing as figure 2.8, that makes the input from the past also can influence the network. The activation status of the hidden layer neurons presents as an internal state which can be considered as a kind of memory. That makes recurrent neural network has the ability to process the sequence input. Human understand the words of a sentence often need the help of the previous words, but the feed forwarding neural network will ignore the previous inputs.

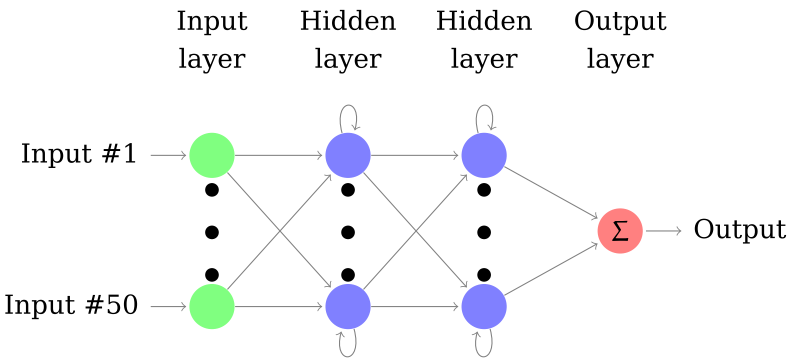


Figure 2.8: 2 layer Recurrent neural network

There are several types of applications of RNN. First one is multi-input and single-output 2.9, application in for example text classification. Second is single-input and multi-output 2.10, application in for example input an imagine and generate a sentence for description. Third is multi-input and multi-output 2.11, application in for example the translation system.

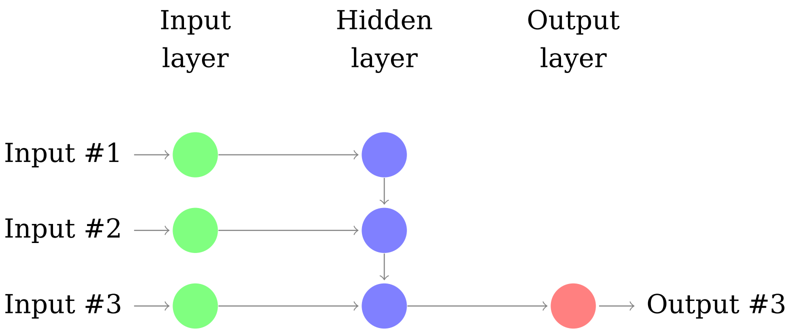


Figure 2.9: multi-input single-output Recurrent neural network

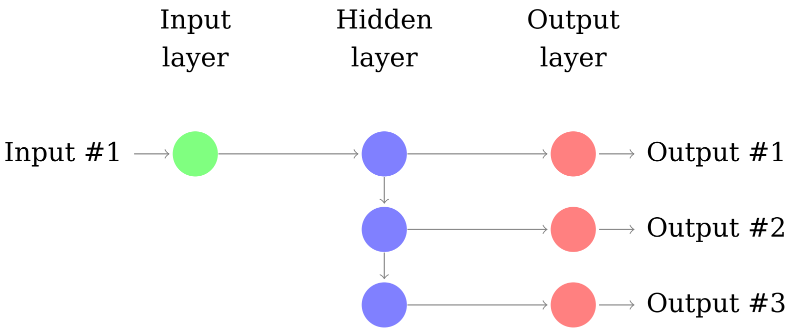


Figure 2.10: single-input multi-output Recurrent neural network

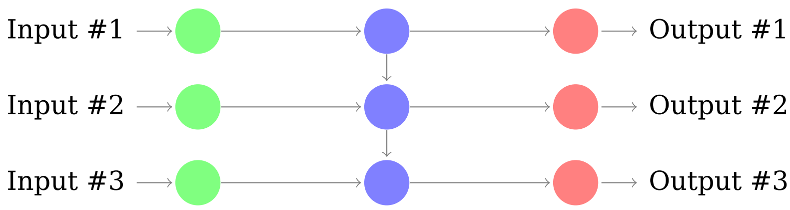
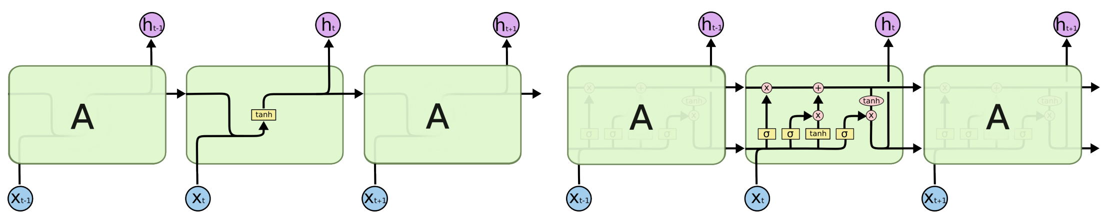


Figure 2.11: multi-input multi-output Recurrent neural network

2.5.3 Long Short-Term Memory

But recurrent neural networks are difficult to train for a long sequence input, because there are two problems **"gradient explode"** and **"gradient vanish"** [37]. Gradient vanish means that the gradient of the earlier inputs goes exponentially fast towards zero. That make recurrent neural networks can't learn the long-term dependencies in sequences. Gradient explode means the gradients become exponentially large while training.

People can change the active function like ReLU to avoid the vanishing gradient problem, but more popular solution is using Long Short-Term Memory which is first invented by Hochreiter and Schmidhuber [14]. An LSTM memory cell contains self-connected memory cell with its a memory cell, an input gate, an output gate and a forget gate units. LSTM uses a series gate units to control the cell receiving data flow, extracting data flow or forgetting the current state at each time step.



(a) Simple RNN model

(b) LSTM RNN model

Figure 2.12: Two models of RNNs (a) Normal model of RNN with tanh Unit (b) RNN with LSTM Cells (source [36])

2.5.4 GRU Cell

GRU Cell is a special case of LSTM which is invited by Cho, et al [11]. The forget and input gates are merged into a update gate. The cell state and hidden state are combined as one state. These changes make the structure of GRU simpler than LSTM.

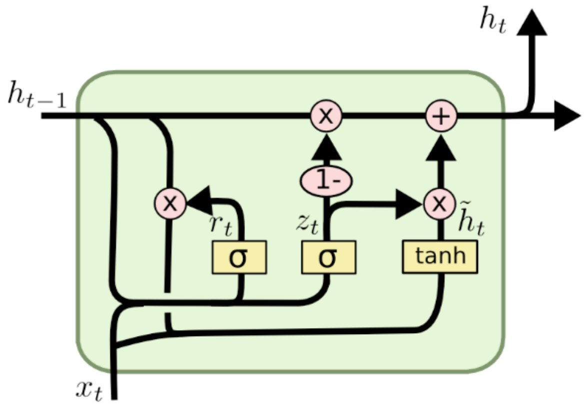
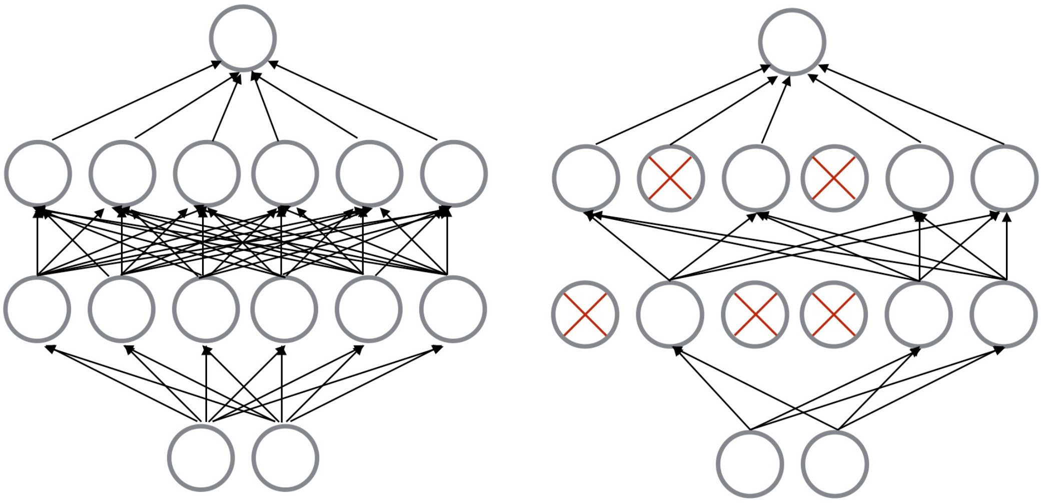


Figure 2.13: GRU Cell (source [36])

2.5.5 Dropout

To avoid the overfitting we used dropout methode[42]. The main idea of dropout is to dropout some units in hidden layer in neural network while training. When training the model some of the units are removed temporarily with probability p as figure 2.14. But while testing the dropout units still join the test. The aim of dropout is to avoid one best state keeping existing, by disabling some units time to time of the network dropout makes the model to be trained in different form every time. Dropout causes to the convergence speed slower than without it, the model needs more epochs to find the local best solution. But the benefit is it can avoid the overfitting [42].



(a) standard NN model (b) NN with dropout

Figure 2.14: Dropout Neural Net Model. (a) a standard neural network (b) after deploying dropout

2.6 K Fold Cross Validation

To limit the overfitting and improve the robustness of the model we often use cross validation technology. K fold cross validation is that the dataset was shuffled and split into k subsets. We train the model with some of subsets and others are used for testing.

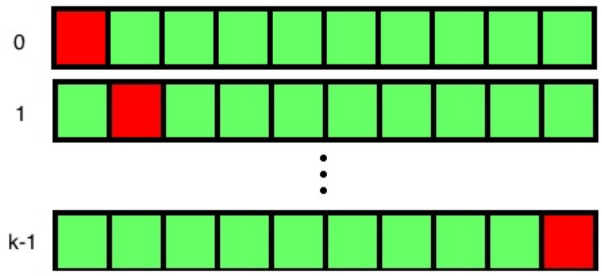


Figure 2.15: K Fold Cross Validation (green rectangle is the training set, red rectangle is the testing set)

In our work we split the data not equally, we consider an event as a unit. We use 10 times cross validation, so we split 260 event into 10 subsets. And we test all models with the same shuffled sequence, aka same training sets and test sets.

2.7 Levenberg-Marquardt Method

The Levenberg-Marquardt algorithm (LMA), Aka. damped least-squares (DLS) method, is used to solve non-linear least squares problems which usually happen in least squares curve fitting.

The algorithm was first published in 1944 by Kenneth Levenberg[26].

In our work we use it to fit SpikeM model, SIS and SEIZ models.

2.8 Tensorflow

TensorFlow[6] is an open source software library for numerical computation using data flow graphs which is used in the single tweet credibility scoring model. It is developed by google. But it still hard for beginner to use and debug. So we use a high-level neural networks library Keras[7] which can run on top of TensorFlow. It is much simpler to configure or to implement.

2.9 Related Work

People research on Twitter for a long time and there are a lots directions to study this complex social network like event detection [19] of Kimmey and David, spam detection [1] [48] or sentiment detection[4]. Those works are similar to our task rumor detection but there are still many differences. In Javier and Yamir's work[6] they use the struct of real world blogs network to identify the influential spreaders of rumor events.

People first studied on rumors in psychology area for years [2] [44]. They summarized the type of rumors or the sentiment with rumors. They are quite help for rumor analyzing in Twitter.

But since Twitter becomes an important platform for people sharing and exchanging information including rumors, the detection of misinformation on twitter turns to be a trending researching topic.

Researcher first began from studying rumor spreading during several special events like natural disasters[35] [45][33] or terrorist attacks [43]. In the work of Tanaka et al. [45], they analyzed the how the psychological factors influence the information transmission via tweets. But these results are not general enough to other types of rumors. Our data includes sports, politic, entertainment, also natural disasters and other kinds of rumors.

Carlos Castillo et al. researched the information credibility on Twitter[10][12]. They hired people to label the tweets as trustful, mostly untrustworthy and untrustworthy. And they trained a SVMRank model to rank the credibility of Tweets. But

[6] http://tensorflow.org

[7] https://keras.io/

his work is based on people's opinion (trustful or not) to a tweet not the credibility of tweet itself. In other words, a false rumor tweet can be trusted by human, but some comments of true news seems not trustful. But it still a good start of researching this problem. Lots of other works are based on Castillo's work [50] [27] and used different set of features, for example yang [50] added the location of poster and the client type of user (web client or mobile phone) as two important features.

And there are some simulation studies about the propagation of rumor in twitter. The work of Eunsoo et al. [41] builds a simulation system with random sources. And they use the propagation graph to detect the sources. Rudra et al.'work [47] use the SIS model to discuss the strategies of preventing rumors' spreading on social networks. They are great works but the simulation environment can not compare with the complex of real network.

There are recent researches based on the propagation structure of rumor on Sina Weibo for example work of Liu et al.[49]. They use the unique feature of Sina Weibo to study the propagation pattern of rumors and achieved good results. But unfortunately Twitter doesn't give us such detail of propagation process like Weibo, so these works can help us. And Liu's work [49] focused on one type of rumor "the false photos" on social network not the general type of rumors.

Xiaomo et al. claimed their system is the first real time rumor debunking system on Twitter [27]. But their work are similar with above other previous works, they use the static features of rumors and ignored the feature's changing over time during the event spreading on the social network, but one feature called "crowd wisdom" is an new idea and we use it in our work.

Other researchers used propagation models like SpikeM [23] Kwon et al. and SEIZ models [16] Jin et al. to capture the tweet's volume changing over time, but they didn't use other features into time series model. And these features can't show the effect in the early stage of rumor spreading. We can provide it in the later section 4.5.2. Bao et al. used SPNR model which is an extended SIS model as a strategy to control rumors [3].

J Ma et al. used Recurrent Neural Networks for rumor detection [28], they input the tweet of rumor event into RNN time sequentially. Without any other handcrafted features, they got almost 90% accuracy. As the same disadvantage of all kinds of Neural Networks models, the process of model's training and testing is black box to us, so we can't know the reason why we got this result. In our case we can't get the evidences to convince people why the detected event is more likely to be a rumor or rather than a breaking news.

Another work from J Ma et al. used a time series model called Dynamic Series-Time Structure [29] to capture the variation of features. But they only used the features of social content and they didn't further explain how the performances of features change over time or how do they improve the performance of the model in first few hours after the events beginning. We use their Series-Time Structure with our extended data and we will show how do these features change during time.

3

Single Tweet's Creditability Scoring Model

3.1 Introduce

At the beginning of an event, the tweet volume is limited and there is no propagation pattern yet, so as human verifying rumors we can only focus on the information from each single tweet. So a single tweet classification model can help us detect the rumors on the early stage.

3.2 Related Work

Most of the pervious researches are focusing on event level rumors and claims that the task of classification for individual tweet is not reliable [27] [29] [51], because a single tweet is to short to contains enough features. But Carlos Castillo designed a single tweet's creditability rank system Tweetcred [12]. So we think it is still enable to build up a single tweet creditability model.

Recently deep learning is new technology which is used in various areas. And we were inspired by the J Ma's work [24] that we may use neural network without handcrafted features to build up the single tweet's creditability model which in later experiments outputs a better performance. Zhou invented a C-LSTM model [52] for short text classification. The architecture of the model is shown in figure 3.3. Front hidden layer is a CNN which can split the text to different features and the pooling layer group the same type of feature together then the last hidden layer is a LSTM layer. They test the model with comments on IBMb website. According to his paper C-LSTM achieved the best result for a 2-classification task with 87.8% accuracy. We adapt their work in our rumor detecting task.

3.3 Features

We use a collection of features major from Castillo's Tweetcred system[12] totally 27 features in table 3.1. These features can be extracted directly from Twitter interface without third part website.

3.3.1 Text Features

The Text features capture the content of the text of the tweets. There are 16 Text features. **Sentiment Features** are included in text features. We used the python natural language Toolkit (nlTK) [1] to analyze the tweets' sentiment and extract the features: the NumPositiveWords, NumNegativeWords and Polarityscores. Polarity scores is a float for sentiment strength of one tweet[2] $Polarity\_scores = \frac{1}{N}\sum_0^n Polarity(token_n)$.

3.3.2 User Features

We selected total 5 features of the poster. These features are extracted directly from the twitter interface as in figure 3.1. ReputationScore is defined as the ratio between #Friends over # Followers. $ReputationScore = \frac{\#Friends}{\#Friends+\#Followers}$.

3.3.3 Twitter Features

Twitter Features are the features of twitter's special functions. It includes Hashtag, Mention, Number of URLs, Number of retweets and whether this tweet is retweet (contains RT as keywords or "*QuoteTweet-innerContainer u-cf js-permalink js-media-container*" as the CSS class of the tweet in html).

3.4 Classification Models

We developed two kinds of classification model traditional classifier with handcraft features and neural network without handcraft features.

3.4.1 Single Tweet's Creditability Model with handcrafted features

We follow Castillo's [12] idea to implement a single tweet's creditability model with above handcrafted features in section 3.3 and we select the most popular classification models: decision trees, decision forest and SVM.

[1] http://www.nltk.org/
[2] http://www.nltk.org/api/nltk.sentiment.html

Figure 3.1: Sample of Users' Information on Twitter Interface

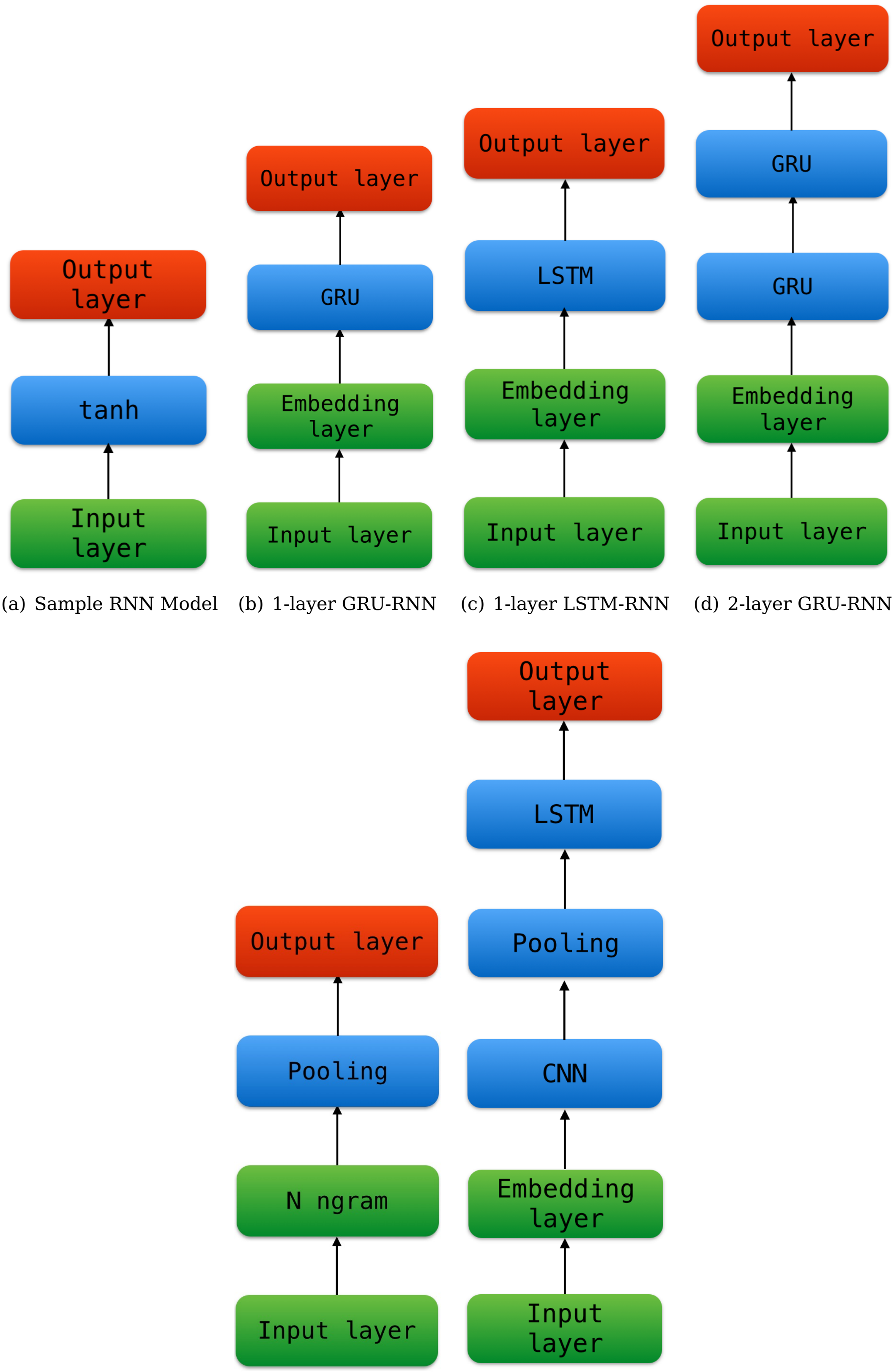
3.4.2 Single Tweet's Creditability Model without handcrafted features

Inspired by the Lai and J Ma's works [24] [28] we test neural networks as the classifier which does not need to extract features from the data. Based on the previous work we tested it with 6 models: Basic tanh-RNN 3.2(a) as baseline, 1-layer GRU-RNN 3.2(b) ,1-layer LSTM 3.2(c), 2-layer GRU-RNN 3.2(d), FastText 3.2(e) and CNN+LSTM 3.2(f) model as figure 3.2(d) model. Basic tanh-RNN, 1-layer GRU-RNN, 1-layer LSTM-RNN and 2-layer GRU-RNN models are based on the work of J Ma's works [28]. FastText comes from joulin's work [17] which is a fast text classification model no need of GPU acceleration. The hybrid model of CNN and LSTM (C-LSTM) is zhou idea [52] which has the best performance in out experiments. Zhou tested their C-LSTM for sentiment classification with the dataset of comments of movies in IMDb which are similar short text as tweets and got best accuracy 86%. And we adapt their model into our work.

3.4.3 Experiment setting

We implement these 3 model with scikit-learn library[3]. We shuffled the 260 events and split them into 10 subset, we uses them for 10 times cross-validation. We show

[3] scikit-learn.org/



(a) Sample RNN Model (b) 1-layer GRU-RNN (c) 1-layer LSTM-RNN (d) 2-layer GRU-RNN

(e) FastText (f) Hybrid CNN + LSTM (C-LSTM)

Figure 3.2: neural network model for single tweet classification 1

Category	**Feature**	**Description**
Twitter Features	Hashtag	Whether the tweet contains #hashtag
	Mention	Whether the tweet mentions others @user
	NumUrls	# url in the tweet
	Retweets	How many times this tweet has been retweeted
	IsRetweet	Whether this tweet is retweeted from others
Text Features	LengthOfTweet	The length of tweet
	NumOfChar	# of individual characters
	Capital	Fraction of characters in Uppercase
	Smile	Whether this tweet contains :->, :-), ;->, ;-)
	Sad	Whether this tweet contains :-<, :-(, ;->, ;-(
	NumPositiveWords	# of positive words
	NumNegativeWords	# of negative words
	PolarityScores	polarity scores of the Tweet
	Via	Whether this tweet contains via
	Stock	Whether this tweet contains $
	Question	Whether this tweet contains ?
	Exclamation	Whether this tweet contains !
	QuestionExclamation	Whether this tweet contains multi Question or Exclamation mark
	I	Whether this tweet contains first pronoun like I, my, mine, we, our
	You	Whether this tweet contains second pronoun like U, you, your, yours
	HeShe	Whether this tweet contains third pronoun like he, she, they, his, etc.
User Features	UserFollowers	# of followers
	UserFriends	# of friends
	UserTweets	# of tweets which are posted by this user
	UserDescription	Whether this user has description
	UserVerified	Whether this user is a verified user
	UserReputationScore	Ratio between #Friends over (# Followers + #Friends)

Table 3.1: Features for Single Tweet's Creditability Scoring Model

the parameters after optimization for each model them in table 3.2.

Model	**Parameters**	**Value**
Random Forest	Number of Trees	200
SVM	kernel	radial basis function
	penalty parameter of the error term	2.0
	gamma	$\frac{1}{27}$
Decision Trees	criterion	gini

Table 3.2: Parameters of Classification models

We implement the neural network with tensor-flow and python library Keras [4].

Embedding Layer

The first layer is embedding layer which is set up the same to all models.The embedding size is 50. The output of the embedding layer is the vectors presenting the

[4] https://keras.io/

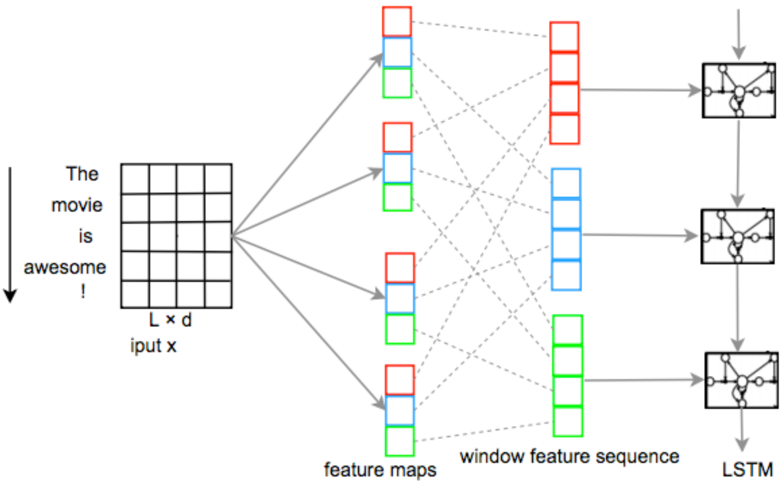


Figure 3.3: The architecture of C-LSTM Interface (source: [52])

words.

Limit Overfitting

To avoid overfitting we use 10-fold cross validation and dropout technology.

3.5 Tested Results

We show the results in the table 3.3. The best accuracy result is C-LSTM model. In table 3.5 and 3.6 we show some samples of correct labeling and in correct labeling.

The non-neural network model with the highest accuracy is RF, but it reaches only 64.87% and the other two models are even worse, so it is clear to see with manually handcrafted features, one single tweet is difficulty to be classified.

3.6 Disscution

We rank the features using the features importance which we mentioned in section 2.4.3, showing in table 3.4. The best feature is polarity scores of sentiment. It means that there is a big bias between the rumors tweets and the tweets real events. It was mentioned by previous work [2] where he gathered a large rumors collection during WW2 which are printed in the Boston Heralds Rumor Clinic. He summarized rumors as several types: pipe-dream, fear and aggression. The most researches believe that rumors mostly contain negative sentiment and polarity [44][22]. In our

Model	Accuracy
CNN+RNN	**0.8119**
2-layer GRU	0.7891
GRU	0.7644
LSTM	0.7493
Basic RNN with tanh	0.7291
FastText	0.6602
Random Forest	**0.6487**
SVM	0.5802
Decision Trees	0.5774

Table 3.3: Prediction Accuracy of Different Single Tweet's Creditability Scoring Models

study average polarity score of news event is -0.066 and average polarity score of rumors is -0.1393, it means that rumors contain more negative sentiment.

And we usually think the verified users may have less possibility to be involved in the rumors' spreading, but the result shows that the verified users may be not really trustful like we thought. And "IsReweet" feature is neither a good feature which means the probability of people retweeting the rumors or true events are similar.

In table 3.6 and 3.5 we show some example of neural network's misclassification and correctly classification. The misclassification of news are likely some common users' comments like "Who the hell is Mo Yan? Obviously a genious.........or a total bore.". We can compare them with true news tweets like "Congratulations! Mo Yan of this year Nobel Prize!", these misclassification tweets maybe contain doubt, banter or even rumor related. And on the other hand, the misclassification tweets of rumors, some of them are reports of news website or they may have a news-likely style like 'Texas Town Quarantined After Family Of Five Test Positive For The Ebola Virus http://fb.me/3Bbw1uFLS'.

But the sometime the action of neural network is hard to explain, because we don't know how it exactly works inside. For example "Dolphins 'deserve human rights' http://zite.to/zEfVKi" is labeled as rumors but similar tweet "Dolphins 'deserve human rights' http://bbc.in/yFU3og" is labeled to news.

Feature	**Feature Importance**
PolarityScores	0.1460686474
Capital	0.09638447209
LengthOfTweet	0.09283739724
UserTweets	0.08750049577
UserFriends	0.08065591431
UserReputationScore	0.08002109553
UserFollowers	0.07938657292
NumOfChar	0.07659755102
Stock	0.04920394972
NumNegativeWords	0.03068379335
Exclamation	0.02304551015
NumUrls	0.02124370609
NumPositiveWords	0.01976939973
Hashtag	0.01851408745
Mention	0.01596532677
Question	0.01486070376
Retweets	0.01349486577
I	0.0109471116
You	0.00998103276
HeShe	0.00774915859
UserDescription	0.007402174886
Via	0.005545157727
QuestionExclamation	0.005422123705
IsRetweet	0.003240079497
UserVerified	0.003081752983
Smile	0.0003979192278
Sad	0

Table 3.4: Features Importance

Catalogue	Tweet
News	Who the hell is Mo Yan? Obviously a genious.........or a total bore.
	we'll know in a few minutes...EU to win 2012 Nobel Peace Prize: Norwegian broadcaster http://reut.rs/WXXzLU via @reuters
	Wait, are these the Bizarro-world Nobels?
	Little girl in California swims with huge 8 year old pet python http://bit.ly/2a3y7R7 via @BmaxNG
	Head of Fifa partner 'flees arrest': Ray Whelan, head of Fifa partner Match Hospitality, has fled to escape ar... http://bbc.in/1mkvNYZ
	Ahhh really, Dolphins deserve the same rights as humans? What's next, a race option for "porpoise" on legal documents? http://bbc.in/ArhIeb
Rumors	#Cancer Cell Phone Use at Night Does Not Cause Eye Cancer âĂŞ http://snopes.comÂă http://goo.gl/i6qNQA
	BBC News: Afghan refugee involved in #Wurzburg attack 'had IS flag in room' http://www.bbc.co.uk/news/world-europe-36832909ÂăâĂę #ISIS #Merkel #Germany #EU
	Texas Town Quarantined After Family Of Five Test Positive For The Ebola Virus http://fb.me/3Bbw1uFLS
	Yeahhhhh to stop making music period ! RT ShallowShan_: Bill gates really offered young thug 9 million to stop rapping ?
	Redbox is Hiring Kiosk Ambassadors! http://fb.me/1c5WGQIy2
	Samsung Pays Apple $1 Billion Sending 30 Trucks Full of 5 Cents Coins: http://en.paperblog.com/samsung-pays-apple-1-billion-sending-30-trucks-full-of-5-cents-coins-294795/ ... Comments: http://news.ycombinator.com/item?id=4447550

Table 3.5: Example of False Classification by Single Tweet Model

Catalogue	**Tweet**
News	Congratulations! Mo Yan of this year Nobel Prize!
	The Writer, the State and the Nobel - New York Times (blog): New York Times (blog)The Writer, the State and the ... http://bit.ly/Wa542QÂă
	The incompetent, collapsing EU wins the Nobel Peace Prize? Perhaps next year they could give it to Lance for uniting the world, against him
	Just saw a video of a girl swimming with a Burmese Python on Facebook and i'm just sitting here like WTF?!? O.O
	FIFA Partner, Wanted in World Cup Ticket Scam, Is On the Run: SAO PAULO, Brazil – FIFA partner Ray Whelan gav... http://on.mash.to/1njwnGx
	Dolphins 'deserve human rights' http://bbc.in/yFU3og
Rumors	Osama Bin Laden is Still Alive - Edward Snowden http://www.middleeastrising.com/breaking-osama-bin-laden-is-still-alive/ ...
	Samsung pays Apple $1 billion sending 30 trucks full with 5 cents coin! Crazy! #dirtybutgenius
	AMC Announces 'Breaking Bad' To Return For 6th Season; You Won't Believe This Plot Twist http://fb.me/6OYRIMdKx
	For Bill Gates to offer Young Thug $9mill to stop doing music
	Redbox Kiosk Ambassadors #booths http://dragplus.com/post/id/34363441 ...
	Gabourey Sidibe on Joining American Horror Story: Coven: I Hope I Don't Die! http://owl.li/2wzo2t

Table 3.6: Example of Correct Classification by Single Tweet Model

4

Time Seriers Rumor Detection Model

As we showed in figures 4.1 and 4.2, The fraction of tweets containing url with top 5000 domain and the fraction of poster living in large city which are both constantly changing. In order to capture these changes of the each features we use Dynamic Series-Time Structure (DSTS) which was presented in Ma's work [29]. In the an Event E_i there is a set of tweets tw_{ij} and we split them into different time intervals according to the creation time so that we can analyze the features in time series. We test the different classifiers with this model, we compare it with static features and in the end we rank all features and show their performance over time.

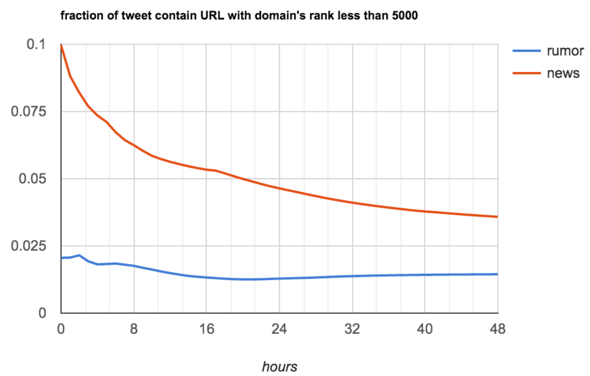


Figure 4.1: The fraction of tweets containing url with top 5000 domain

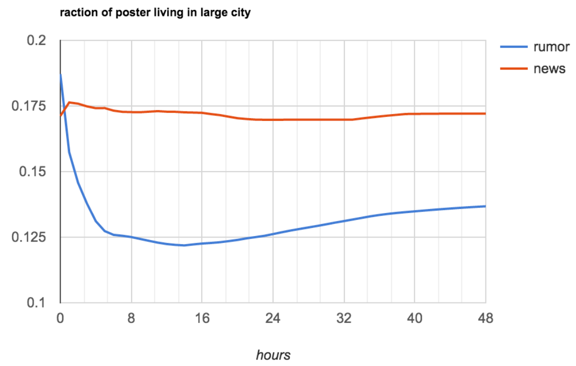


Figure 4.2: The fraction of poster living in large city

4.1 Dynamic Series-Time Structure (DSTS)

4.1.1 Time Stamps Generation

For an event E_i we define $timeFirst_i$ as the start time of the event, $timeFirst_i$ as the time of last tweet of the event. We split the each tweet tw_{ij} into N time intervals according to the creation time. The length of each time interval we define as follow:

$$Interval(E_i) = \frac{\lceil(timeLast_i - timeFirst_i)\rceil}{N} \tag{4.1}$$

And the index of time interval $TS(t_{ij})$ where a tweet tw_{ij} which is created in time t_{ij} should fall into, we define as follow :

$$TS(t_{ij}) = \frac{\lfloor(t_{ij} - timeFirst_i)\rfloor}{Interval(E_i)} \tag{4.2}$$

In our work $Interval(E_i)$ as we defined in section 2.3.2 is one hour and N is constant 48 hours for each event.

4.1.2 Dynamic Series-Time Structure (DSTS)

Now we have all the time intervals of an event E_i and we can generate a vector V(E_i) of features in each time interval. And in order to capture the changes of feature over time we should no only model the features in individual time intervals but also we should model their difference between two time intervals. So the model of DSTS is represented as:

$$V(E_i) = (\mathbf{F}^D_{i,0}, \mathbf{F}^D_{i,1}, ..., \mathbf{F}^D_{i,N}, \mathbf{S}^D_{i,1}, ..., \mathbf{S}^D_{i,N}) \tag{4.3}$$

where the $\mathbf{F}^D_{i,t}$ is the feature vector in time interval t of event E_i. $\mathbf{S}^D_{i,t}$ is the difference between $\mathbf{F}^D_{i,t}$ and $\mathbf{F}^D_{i,t+1}$. $V(E_i)$ is the time series feature vector of the event E_i.

$$\mathbf{F}^D_{i,t} = (\widetilde{f}_{i,t,1}, \widetilde{f}_{i,t,2}, ..., \widetilde{f}_{i,t,D}) \tag{4.4}$$

$$\mathbf{S}^D_{i,t} = \frac{\mathbf{F}^D_{i,t+1} - \mathbf{F}^D_{i,t}}{Interval(E_i)} \tag{4.5}$$

We use Z-score to normalize feature values which is implemented by sklearn.

$$\widetilde{f}_{i,t,k} = \frac{f_{i,t+1,k} - \overline{f}_{i,k}}{\sigma(f_{i,k})} \tag{4.6}$$

where $f_{i,t,k}$ is the k-th feature in time interval t of the event E_i in time interval t. $\overline{f}_{i,k}$ is the mean of the feature k of the event E_i and $sigma(f_{i,k})$ is the standard deviation of the feature k over all time intervals. We skip this step when we use random forest and Decision Trees because they do not need feature normalization.

4.2 Features

We use a collection of features based on previous works [10][12] [50][27][28][33][29][49][16]. They are totally 50 features shown in table 4.4. These features are not only extracted from Twitter interface but also other external websites like bluecoat.com which are mentioned in section 4.4.

4.2.1 Text Features

Text features is normal feature set of tweets' content. It contains 16 features as shown in table 4.4. The difference of the text features in single tweet model and in time series model is in time series model we use the percent of tweets which contain some attributes or average number of some attributes.

NumOfChar is the average number of individual characters of tweets, it is case sensitivity. The average number of characters of rumor is 34 and news is 36.

4.2.2 Twitter Features

Twitter features is the features of Twitter's functions like Hashtag and mention. And we add 3 features of the URLs of the tweets. The first one is the WOT Score which is crawled from the website wot.com [1]. WOT is short for Web of Trust and it scores the domains' credibility and safety. It offers API for developer. The second one is catalog of domain which I crawled from the bluecoat.com [2]. I group them

[1] https://www.mywot.com/en/api
[2] http://sitereview.bluecoat.com/

into 2 parts news website or not. The last one is the rank of the domain which I crawled from alexa.com[3]. I also split them into 2 group rank less than 5000 or not. In our experiment those 3 feature about URL is better than others original Twitter functions like hashtag or mention.

4.2.3 User Features

User's features is similar with others works. We add one feature which can only get from the website interface is how many photos has the user posted (UserNumPhoto). It is in the BestSet of features. And one other user feature is if the user lives in a large city. We got the list of large city in the report of demographia[4]. It is also a good feature contained in the Bestset.

4.2.4 Epidemiological Modeling Features

Jin's work is as far as we know the first people using epidemiological model to analyze rumors' prorogation on twitter [16]. They fits the volume of the rumors and news events into two models SIS (Susceptible, Infected, Susceptible) and SEIZ (susceptible, exposed, infected, skeptic).

SIS is one of the most popular epidemiological model. To adapt to the scenario of Twitter, we define a user who posts a tweet of relevant event as **(I)** infected, a user who didn't we define as **(S)** susceptible. But unlikely as a normal epidemiological scenario infected nodes can be cured and return to be susceptible, the user once posts a tweet of the certain events, he will be classified into the infected component forever. He can't be return susceptible class. At time t the total number of population is $\Delta N(t) = I(t) + S(t)$ where $I(t)$ is the size of infected population and $S(t)$ is the size of susceptible population. As shown in Figure 4.3, SIS model works as follow:

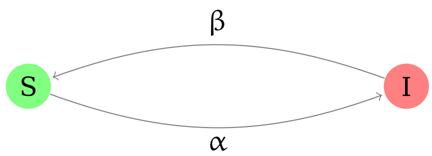


Figure 4.3: SIS Model

- A user who posts tweets about the certain event is regarded as infected.
- A susceptible user has not tweeted about the certain event

[3] http://www.alexa.com/siteinfo/bbc.com
[4] http://www.demographia.com/db-worldua.pdf

- A susceptible user may see the a tweet about the certain event from a infected users and he immediately retweets or posts a tweet about this events, and in that he turns himself to infected.
- Susceptible user will remain susceptible until he contacts (via tweet) with infected person.

we show SIS model mathematical as follow:

$$\frac{d[S]}{dt} = -\beta SI + \alpha I \tag{4.7}$$

$$\frac{d[I]}{dt} = \beta SI - \alpha I \tag{4.8}$$

SIS model assumes that a susceptible user once exposed to a infected user turns to infected immediately. That is one reason of this model why it didn't fit to Twitter. If fact when twitter users see a tweet they have their normal senesce to judgment the truth of the information and they can decide wether further spreading the tweet or ignoring them.

Another popular model is SIR which contains one more term than the SIS. The definitions of **(S)** and **(I)** are the same of SIS but the term **(R)** stands for recover. Once a susceptible user is recover, he will be removed from the susceptible component and he can't be infected again. But we can't get a reasonable explanation of the term R if we model the an event spreading on Twitter.

Because of the Shortcomings of above two model, they test another model called SEIZ which reference from [5] . To adapt to Twitter context, the compartments of

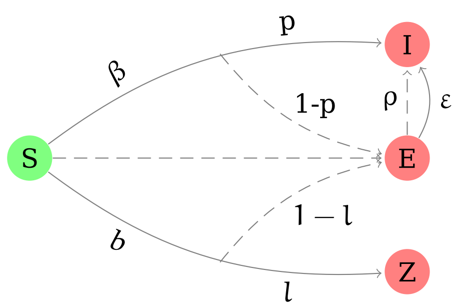


Figure 4.4: SEIZ Model

the SEIZ model can be mapped like this: **(S)** Susceptible is a user who has not been exposed to the event aka he didn't see any tweets about the certain event yet, **(I)** infected means a user has posted tweets about the certain events, **(Z)** skeptic is a user who has been exposed to the certain event but he decides to ignore it and **(E)** exposed is a user who been exposed to the certain event but he will post the tweets after some delay.

We show the model in figure 4.4. And the SEIZ works as follow:

- People recruit from **(S)** Susceptible compartment to Skeptics with rate b. But with probability l some of them directly deny the events and turn to **(Z)** skeptic compartments. Others with probability 1-l probability turn to **(E)** exposed compartment.
- People recruit from **(S)** Susceptible compartment to Infected with rate β. But with probability p some of them directly believe the events and repost it and turn them to be **(Z)** skeptic compartments. Others with probability 1-p probability turn to **(E)** exposed compartment.
- People from **(E)** exposed compartment have ρ probability contacting again with the Infected and turn them to **(I)** infected compartment. And others have ε probability turn into **(I)** infected compartment by themselves for example external shock.

And we show the model mathematical like: we show SEIZ model mathematical as follow:

$$\frac{d[S]}{dt} = -\beta S \frac{I}{N} - bS\frac{Z}{N} \tag{4.9}$$

$$\frac{d[E]}{dt} = (1-p)\beta S\frac{I}{N} + (1-l)bS\frac{I}{N} - \rho S\frac{Z}{N} - \varepsilon E \tag{4.10}$$

$$\frac{d[I]}{dt} = p\beta S\frac{I}{N} + \rho S\frac{Z}{N} + \varepsilon E \tag{4.11}$$

$$\frac{d[Z]}{dt} = lbS\frac{Z}{N} \tag{4.12}$$

The author presents an index of SEIZ called R_{SI} as equation 4.13. It contains all rate values of SEIZ and related to the flux ratio of the **(E)** exposed compartment, the ratio of entering **(E)** to leaving **(E)**. If R_{SI} is bigger than 1 means the influx of exposed compartment is bigger than the efflux. This index may be a good candidate of feature to analyze rumor spreading on Twitter.

$$R_{SI} = \frac{(1-p)\beta + (1-l)b}{\rho + \varepsilon} \tag{4.13}$$

We use Levenberg-Marquard algorithm which we present in section 2.7 to learn the parameters of the SIS and SPEI. The fitting data is the tweet volume of the 260 events (130 rumors and 130 news). In time each interval from t_0 to t_n, we fit the sequenced tweet volume from the beginning time the t_0 to the current time interval t_n of an event to SIS and SEIZ model and learn. From SIS we get two feature β_n, α_n

Symbol	Definition
β	S-I contact rate
b	S-Z contact rate
ρ	E-I contact rate
ε	Incubation rate
$1/\varepsilon$	Average Incubation Time
bl	Effective rate of S -> Z
$\beta\rho$	Effective rate of S -> I
b(1-l)	Effective rate of S -> E via contact with Z
$\beta(1-p)$	Effective rate of S -> E via contact with I
l	S->Z Probability given contact with skeptics
1-l	S->E Probability given contact with skeptics
p	S->I Probability given contact with adopters
1-p	S->E Probability given contact with adopters

Table 4.1: Parameters of SEIZ

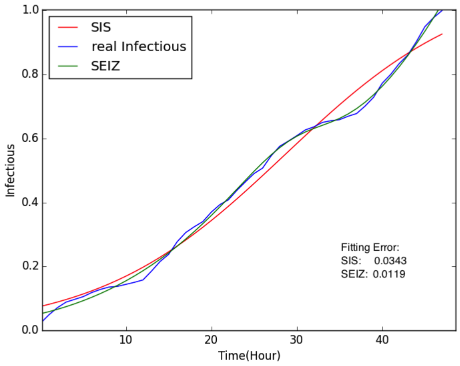
and from SEIZ we get 7 features $\beta_n, b_n, l_n, p_n, \varepsilon_n, \rho_n, RSI_n$. We add them into our DSTS.

$FittingFunction_{SIS}(TweetVolume_0, ..., TweetVolume_n)$->$\beta_n, \alpha_n$

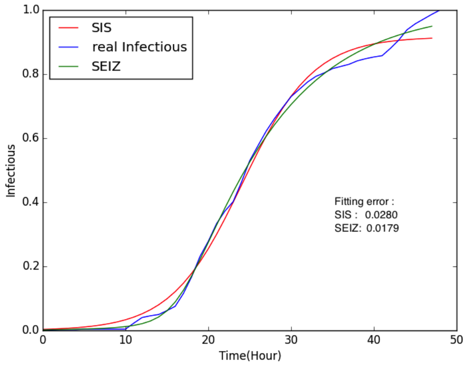
$FittingFunction_{SEIZ}(TweetVolume_0, ..., TweetVolume_n)$->$\beta_n, b_n, l_n, p_n, \varepsilon_n, \rho_n, RSI_n$

We show 4 examples as following two rumors in figure 4.6(a) 4.6(b) and two news in figure 4.6(c) 4.6(d). It is obvious that SEIZ is more appropriate than SIS to model in our Twitter application, because the fitting error of SPEI is less than SIS.

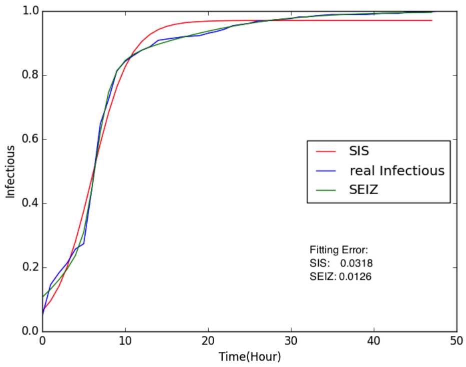
But fitting the models needs enough input data. We don't have enough data to learn the parameters at the first few hours. We show the performance of fitting these two model with only the first 10 hours tweet volume in figure 4.6. As we can see excepting the first one, the fitting result of other three is not good enough.



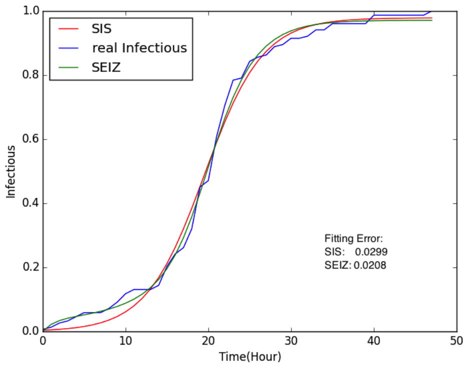
(a) SIS and SEIZ model for rumor 1



(b) SIS and SEIZ model for rumor 2

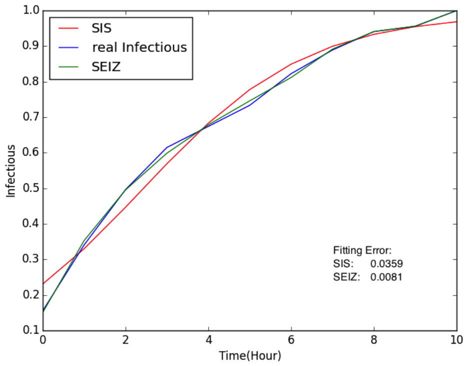


(c) SIS and SEIZ model for news 1

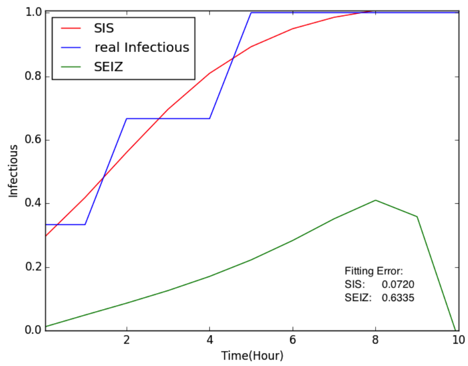


(d) SIS and SEIZ model for news 2

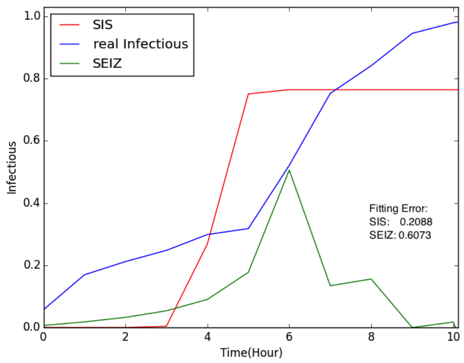
Figure 4.5: Fitting results of SIS and SEIZ model of (a) Rumor: Robert Byrd was a member of KKK (b) Rumor: CNN altered a photograph of a shooter making him look white (c) News: Doctor announces Michael Schumacher is making process (d) News: Two U.S. sailors are arrested over an alleged rape of a Japanese woman on Okinawa



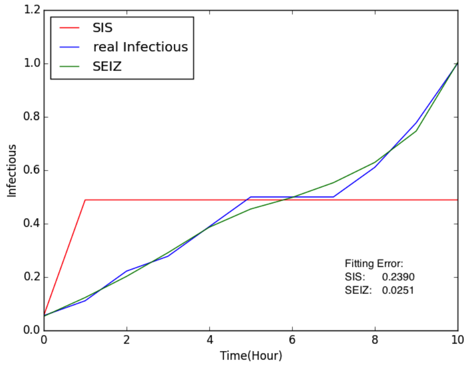
(a) SIS and SEIZ model for rumor 1 with 10 hours data



(b) SIS and SEIZ model for rumor 2 with 10 hours data



(c) SIS and SEIZ model for news 1 with 10 hours data



(d) SIS and SEIZ model for news 2 with 10 hours data

Figure 4.6: Fitting results of SIS and SEIZ model with only first 10 hours tweet volume data (same 4 stories as above)

4.2.5 SpikeM model Features

Kwon showed us another approach [23] for finding the differences between the rumors' propagation pattern and the news events' propagation pattern on twitter. He adjusted the SpikeM Model and also used the parameters as features.

SpikeM first was introduced by Yasuko Matsubara [30] which cab describe the pattern of information diffusion. We present it as follow:

$$\Delta B(n+1) = p(n+1) \cdot (U(n) \cdot \sum_{t=n_b}^{n} (\Delta B(t) + S(t)) \cdot f(n+1-t) + \varepsilon) \tag{4.14}$$

$$p(n) = 1 - \frac{1}{2} P_a(\sin(\frac{2\pi}{P_p}(n + P_s))) + 1) \tag{4.15}$$

$$U(n+1) = U(n) - \Delta B(n+1) \tag{4.16}$$

where

$$f(\tau) = \beta \cdot \tau^{-1.5} \tag{4.17}$$

and initial conditions:

$$\Delta B(0) = 0, U(0) = N \tag{4.18}$$

In addition, adding an external shock $S(n)$, a spike generated at beginning time n_b. Mathematically, it is defined as follows:

$$S(n) = \begin{cases} 0 & (n \neq n_b) \\ S_b & (n = n_b) \end{cases} \tag{4.19}$$

As the definition:

$$B(n) + U(n) = N \tag{4.20}$$

The term of $\sum_{t=n_b}^{n} (\Delta B(t) + S(t))$ is the total number of informed users at time n, so $\Delta B(n+1) = p(n+1) \cdot (U(n) \cdot \sum_{t=n_b}^{n} (\Delta B(t) + S(t)) \cdot f(n+1-t) + \varepsilon)$ means that at time n+1 an infected node n randomly select a node m of all nodes and if the node m is susceptible the probability of m turning to infected is β, so it is a standard SI model. SpikeM extends the SI model from

- a power-law decay term $f(\tau) = \beta \cdot \tau^{-1.5}$ in equation 4.24. So the earlier infected nodes has less strength of infection in a power-law decay pattern.
- a periodic interaction function in equation 4.22. It stands for that people have a periodic interaction patterns, like people go to sleep at night so they post much more tweets in the day. Parameters P_p, P_a, and P_s are the period, strength, and shift of the periodic interaction function.
- ε is the background noise term.

Symbol	Definition
N	total population of available bloggers
n_d	duration of sequence
n	time-tick ($n=0, \ldots, n_d$)
$U(n)$	count of **u**n-informed bloggers
$B(n)$	count of informed **b**loggers
$\Delta B(n)$	count of informed **b**loggers at time n
$f(n)$	in**f**ectiveness of a blog-post, at age n
β	strength of infection
$\beta \cdot N$	"first-burst" size of infection
$S(n)$	volume of external **s**hock at time n
n_b	starting time of **b**reaking news
S_b	strength of external shock at birth (time n_b)
ε	background noise
P_a	strength of periodicity
P_p	period of periodicity
P_s	phase shift of periodicity

Table 4.2: Parameters of SpikeM

But the SpikeM can't fit to the events with multi-pike like the figure 2.2. So the author think the term external shock $S(n)$ in equation 4.25 should not occur once but more. So they extend the SpikeM model by adding a periodic interaction function the term external shock $S(n)$.

$$\Delta B(n+1) = p(n+1) \cdot (U(n) \cdot \sum_{t=n_b}^{n} (\Delta B(t) + \bar{S}(t)) \cdot f(n+1-t) + \varepsilon) \tag{4.21}$$

$$p(n) = 1 - \frac{1}{2} P_a (\sin(\frac{2\pi}{P_p}(n + P_s))) + 1) \tag{4.22}$$

$$U(n+1) = U(n) - \Delta B(n+1) \tag{4.23}$$

$$f(\tau) = \beta \cdot \tau^{-1.5} \tag{4.24}$$

The external shock $S(n)$ is added a a periodic interaction function

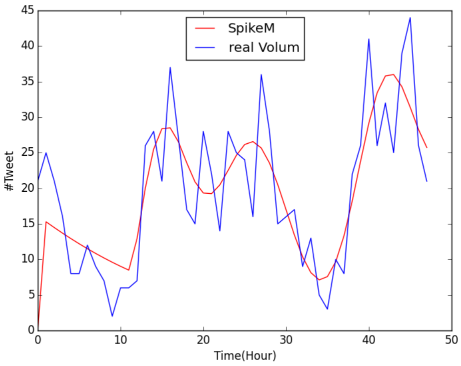
$$\bar{S}(t) = S(t) + q(t) \tag{4.25}$$

$$q(t) = q_a(\sin(\frac{2\pi}{q_p}(t + q_s))) + 1) \tag{4.26}$$

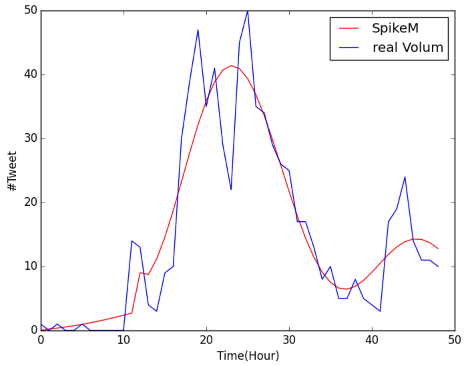
Symbol	**Definition**
q_a	strength of periodicity of the external shock
q_p	period of periodicity of the external shock
q_s	phase shift of periodicity of the external shock

Table 4.3: New Parameters of extended SpikeM

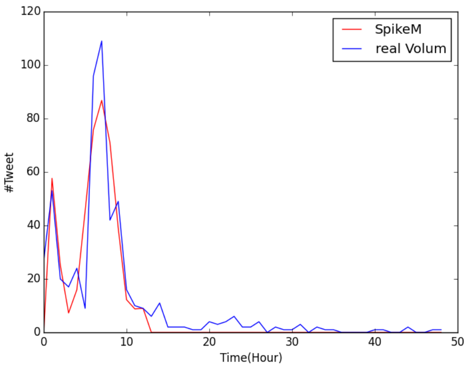
As the same approach of fitting SIS model, we learn the parameters of SpikeM model with Levenberg-Marquard algorithm. We fit the sequenced tweet volume from the beginning time the t_0 to the current time interval t_n of an event to the model and use the output parameters as the features adding into DSTS. We use the p_a, p_p, p_s and q_a, q_p, q_s as feature. We show 4 examples of the SpikeM fitting result in figure 4.7. But same problem as fitting SIS or SEIZ, if we test only within 10 hours data the result seems much worse than the result with full 48 hours showing in figure 4.8.



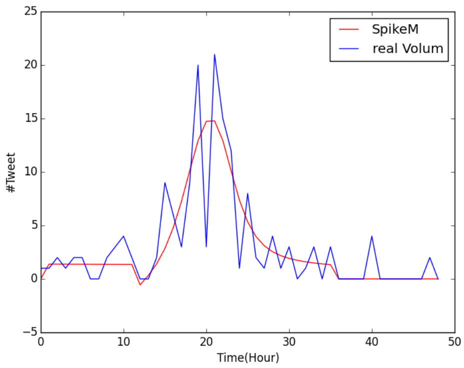
(a) SIS and SEIZ model for rumor 1



(b) SIS and SEIZ model for rumor 2

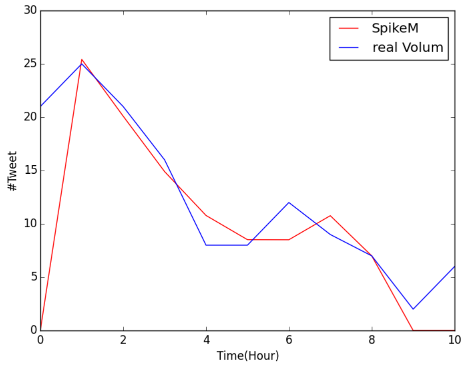


(c) SIS and SEIZ model for news 1

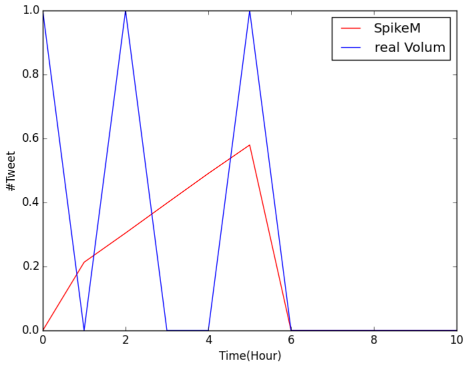


(d) SIS and SEIZ model for news 2

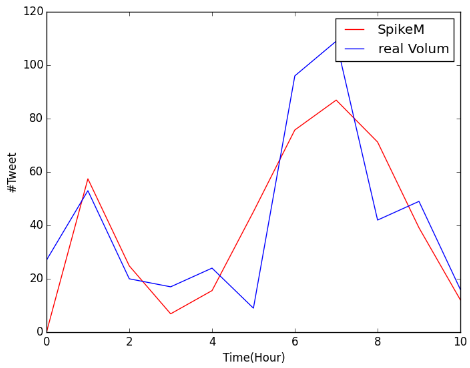
Figure 4.7: Fitting results of SpikeM model of (a) Rumor: Robert Byrd was a member of KKK (b) Rumor: CNN altered a photograph of a shooter making him look white (c) News: Doctor announces Michael Schumacher is making process (d) News: Two U.S. sailors are arrested over an alleged rape of a Japanese woman on Okinawa



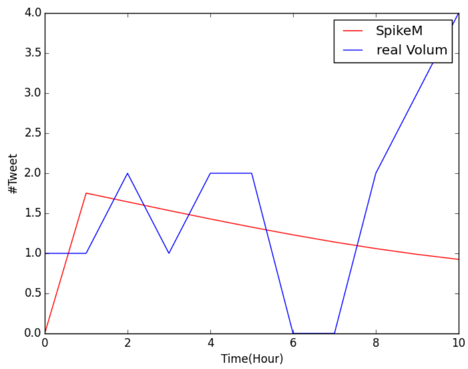
(a) SIS and SEIZ model for rumor 1 with 10 hours data



(b) SIS and SEIZ model for rumor 2 with 10 hours data



(c) SIS and SEIZ model for news 1 with 10 hours data



(d) SIS and SEIZ model for news 2 with 10 hours data

Figure 4.8: Fitting results of SpikeM model with first 10 hours data (same stories as above)

4.2.6 Crowd Wisdom Features

The idea come from Liu's work [27] but not same. The core idea is using the public's common sense to detecting the rumors. If there are more people denying or doubting the truth of an event, this event are more likely to be a rumor. In the Liu's work he uses a extensive list of positive, negative and negation keywords and a set of rules like "negative words without negation words means the poster denies the event". And he uses the ratio number of positive poster (supporter) to the negative poster (deny the events).

Our work is simpler than than his work. We have only a set of negative words, we call it "debunking words" like hoax, rumor, not true, etc. In our test, it is a good feature, but it needs 17 hours to "warm up". It is logical because crowds can debunk rumors but they need time to wait the professionals' advices or to unify the attitude the event.

4.2.7 CreditScore Features

This feature is new feature. We our trained single tweet's creditability model the predict the tweets of the events. If the output is rumor we label it 1 otherwise 0 and we calculate the average score of the events in certain hour. We call this feature creditsScore. We will show it late, this is the best of our dataset, it improves the performance of time series model especially in the first 12 hours. When the event begin bursting in the early stage, people can only rely on the information from the single tweet itself. Because there is no clear propagation structure (pattern) or the wise men or journalists deny the event yet. Our neural network model "sees and check" the text of a single tweet and "give us the advise" when we have no other features in the first few hours since the beginning of the events.

The result shows this feature is the best feature.

Category	**Feature**	**Description**
Twitter Features	Hashtag	% of the tweets containing #hashtag [10][27][38][12][27]
	Mention	% of the tweets mentioning others @user [10][27][38][12][27]
	NumUrls	# of url in the tweet [10][38][12][50][27]
	Retweets	average times of tweets have been retweeted [27]
	IsRetweet	% of tweets are retweeted from others [10][12]
	ContainNEWS	% of tweets containing URL and its domain's catalogue is News [27]
	WotScore	average WOT score of domain in URL [12]
	URLRank5000	% of tweets contains URL whose domain's rank less than 5000 [10]
	ContainNewsURL	% of tweets contains URL whose domain is News Website
Text Features	LengthofTweet	average length of tweets [10][12]
	NumOfChar	average number of individual characters of tweets [10][12]
	Capital	average fraction of characters in Uppercase of tweets [10]
	Smile	% of tweets containing :->, :-), ;->, ;-) [10][12]
	Sad	% of tweets containing :-<, :-(, ;->, ;-([10][12]
	NumPositiveWords	average number of positive words [10][12][50][27]
	NumNegativeWords	average number of negative words [10][12][50][27]
	PolarityScores	average polarity scores of the Tweets [10][50][27]
	Via	% of tweets containing via [12]
	Stock	% of tweets containing $ [10][12]
	Question	% of tweets containing ? [10][27]
	Exclamation	% of tweets containing ! [10][27]
	QuestionExclamation	% of tweets containing multi Question or Exclamation mark [10][27]
	I	% of tweets containing first pronoun like I, my, mine, we, our [10][12][27]
	You	% of tweets containing second pronoun like U, you, your, yours [10]
	HeShe	% of tweets containing third pronoun like he, she, they, his, etc. [10]
User Features	UserNumFollowers	average number of followers [10][12][27]
	UserNumFriends	average number of friends [10][12][27]
	UserNumTweets	average number of users posted tweets [10][12][50][27]
	UserNumPhotos	average number of users posted photos [50]
	UserIsInLargeCity	% of users living in large city [50][27]
	UserJoinDate	average days since users joining Twitter [10][50][27]
	UserDescription	% of user having description [10][50][27]
	UserVerified	% of user being a verified user[50][27]
	UserReputationScore	average ratio of #Friends over (#Followers + #Friends) [27]
Epidemiological Features	β_{SIS}	Parameter β of Model SIS [16]
	α_{SIS}	Parameter α of Model SIS [16]
	β_{SEIZ}	Parameter β of Model SEIZ [16]
	b_{SEIZ}	Parameter b of Model SEIZ[16]
	l_{SEIZ}	Parameter l of Model SEIZ [16]
	p_{SEIZ}	Parameter p of Model SEIZ [16]
	ε_{SEIZ}	Parameter ε of Model SEIZ [16]
	ρ_{SEIZ}	Parameter ρ of Model SEIZ [16]
	R_{SI}	Parameter R_{SI} of Model SEIZ [16]
SpikeM Model Features	P_s	Parameter P_s of Model Spike [23]
	P_a	Parameter P_a of Model SpikeM [23]
	P_p	Parameter P_p of Model SpikeM [23]
	Q_s	Parameter Q_s of Model SpikeM [23]
	Q_a	Parameter Q_a of Model SpikeM [23]
	Q_p	Parameter Q_p of Model SpikeM [23]
Crowd Wisdom Features	CrowdWisdom	% of tweets containing "Debunking Words" [27] [51]
Credit Score Features	CreditScore	average CreditScore

Table 4.4: Features of Time Series Rumor Detection Model

4.3 Classification Models

Same reason as the single tweet's Creditability we test the time series model also with 3 popular models Decision Trees, SVM, Random Forest and one more model the multilayer perceptron (MLP). We show the optimized parameters in the table 4.5. After 10-fold cross validation with same shuffled sequence testing above models, the result is shown the figure 4.7.

Model	Parameters	Value
$RandomForest_{ts}$	Number of Trees	350
SVM_{DSTS}[29]	kernel penalty parameter of the error term gamma	radial basis function 3.0 $\frac{1}{50}$
Decision Trees	criterion	gini
MLP	alpha activation function hidden layer sizes weight optimization	0.0001 ReLU 2 layer(50 nodes each layer) adam

Table 4.5: Parameters of Classification models

4.4 Experiment Setting

We collected rumor stories from a rumor tracking website **snopes.com** and **urban-legends.about.com**. We crawled 4300 stories from the website and we manually constructed 130 queries of them. The approach of constructing queries is mainly following the work[12]. The regular expression of a query is:

$(Object\&Subject\&Description(Description1||Description2||...))$

for example a story is about Obama removing a flag in pearl harbor. Object is Obama, subject is flag and its synonym like flags, flagpole. Description is remove and its synonym removes, removed, removal, removing, "token down" or a url about this rumor "Departed.co". In this case there is a proper noun "pearl harbor" is also useful. Finally we transfer the regex to Twitter's query: Obama (flag OR flags OR flagpole) (remove OR removes OR removed OR removal OR removing OR "token down" OR "Departed.co") pearl harbor.

Pervious work [27] used the news which are reported on snopes.com. But after we test them, we think these news event contain too less tweets. So we use the dataset from the work of Mcminn et al.[32]. These events are manually checked that they really happened. We pick the top 90 events contains most tweet volume and we add other 40 famous news events like Munich shooting.

The detail of tweet volume is shown in table 4.6.

After we crawled and parsed the whole timeline of an event. We detect the 48 hours time period of the burst in the way we mentioned in section 2.3.2. We crawled the homepage of poster of the tweets within the event time period total 133,396 users. We also extracted 11,038 domains which are contained in the tweets in the 48 hours time period and we crawled these domains' catalogs in bluecoat.com [5], their ranks in alexa.com[6] and WOT score in wot.com [7].

As we told in the section 2.1.8, the Twitter limits its API with the return result only in recent 7 days. So we have to crawl the data from the web interface. We use Beautiful Soup as the html parsing library to parse the Twitter timeline pages and the users' homepage [8]. Beautiful Soup is a Python library for pulling data out of HTML and XML files. For increasing the speed of parsing html and extracting features from raw data, we use Spark[9] technology, because it can simply manage multithread and its mapReduce in memory technology makes the process much faster.

[5] http://sitereview.bluecoat.com/sitereview.jsp#/?search=bbc.com

[6] http://www.alexa.com/siteinfo/bbc.com

[7] https://www.mywot.com/en/api

[8] https://www.crummy.com/software/BeautifulSoup/bs4/doc/

[9] http://spark.apache.org/

Type	Min Tweet Volume	Max Tweet Volume	Total Tweet Number	Average Tweet Number
News	18	17414	172616	1327.82
Rumors	44	26010	91268	702.06

Table 4.6: Tweet Volume of News and Rumors

Model	Accuracy in hours			
	6	12	24	48
$\mathrm{RandomForest}_{ts}$	**0.8615**	**0.8615**	**0.8692**	**0.9076**
MLP_{DSTS}	0.7423	0.7423	0.7692	0.8192
SVM_{DSTS}[29]	0.7423	0.7884	0.7769	0.7538
DT_{DSTS}[29]	0.7807	0.8115	0.75	0.7385

Table 4.7: Prediction Accuracy of Different Single Tweet's Creditability Scoring Models

4.5 Experiment Result

The $\mathrm{RandomForest}_{ts}$ is the best model for our task, so we use RF as the test model for the further features' Evolution.

4.5.1 $\mathrm{RandomForest}_{ts}$ VS Static Features

First we compare our time series model and the normal static feature model. We show the result is in table 4.8 the full 48 hours details in Appendix table .2 and in figure 4.9. As we can see from the result that the accuracy of time Series in most of time is better than the static model. But after 24 hours the advantage of the time series is very limited. The reason may be after 24 hours the static model already has enough data to ignore the offset of features at the different time points. But the time series model still has the benefit of detecting rumors at the beginning of spreading.

Hour	$\mathrm{RandomForest}_{ts}$	Static model	Difference
1	0.82	0.78	0.03
6	0.86	0.8	0.06
12	0.87	0.83	0.04
18	0.88	0.83	0.05
24	0.87	0.85	0.01
30	0.88	0.85	0.03
36	0.87	0.86	0.01
42	0.88	0.88	0
48	0.89	0.87	0.02

Table 4.8: Accuracy: Time Series VS Static Features

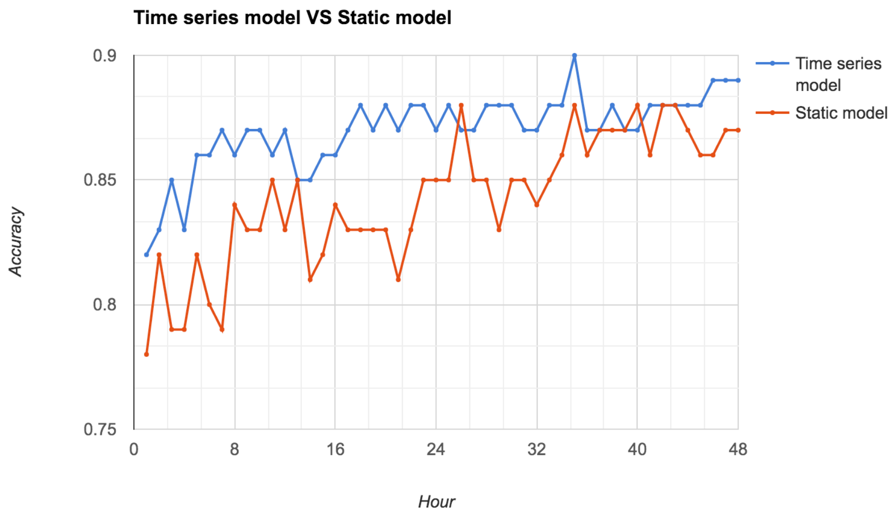


Figure 4.9: Accuracy: Time Series VS Static Features

4.5.2 Feature Analyzing Over Time

We rank the features' importance using the method we introduced in section 2.4.3, the full result is shown in appendix table .1. First we split the features in 7 catalogues as in table 4.4: Tweet_Feature, User_Feature,Text_Feature, Credit Score, SpikeM Features, Epidemiological Features, CrowdWisdom and the BestSet. The BestSet is a combination of the 28 top best average rank of 48 hours features, they are shown in table 4.9. The results over 48 hours are in figure 4.10 .

As we can see in figure 4.10 the best result on average over 48 hours in the *BestSet* with top 28 features. Second is the *All features*. Except those two the best group feature is *Text feature*. One reason is the text feature set has the largest group of feature with totally 16 features. But if look into each feature in text feature group we can see the best and the worst features are all in this set. *User feature* and *Twitter feature* are stable over time around 82%. The performances of 3 different models (SIS, SEIZ and SpikeM) describing the propagation pattern of rumors and news are not so well especially within 24 hours. *Crowd Wisdom* and *Credit Score* both contain only one feature but they already have impressive result comparing with the *User feature* and *Twitter feature*.

4.5.3 BestSet Features

We pick the 28 top best average rank of 48 hours features, see table 4.9 and group them as the BestSet Feature. Adding one more feature and removing one will both cause the accuracy dropping down. So we think it is the best combination of features for rumor detection.

Best Feature set	
CreditScore	ContainNEWS
NumOfChar	UserTweetsPerDays
QuestionExclamation	UserReputationScore
WotScore	Question
UserJoin_date	Mention
LengthOfTweet	DebunkingWords
UserFollowers	Exclamation
UserVerified	Hashtag
Capital	You
UserNumPhoto	numUrls
UserFriends	NumPositiveWords
Via	P_a
UserIsInLargeCity	PolarityScores
UserDescription	R_{SI}

Table 4.9: Best Features

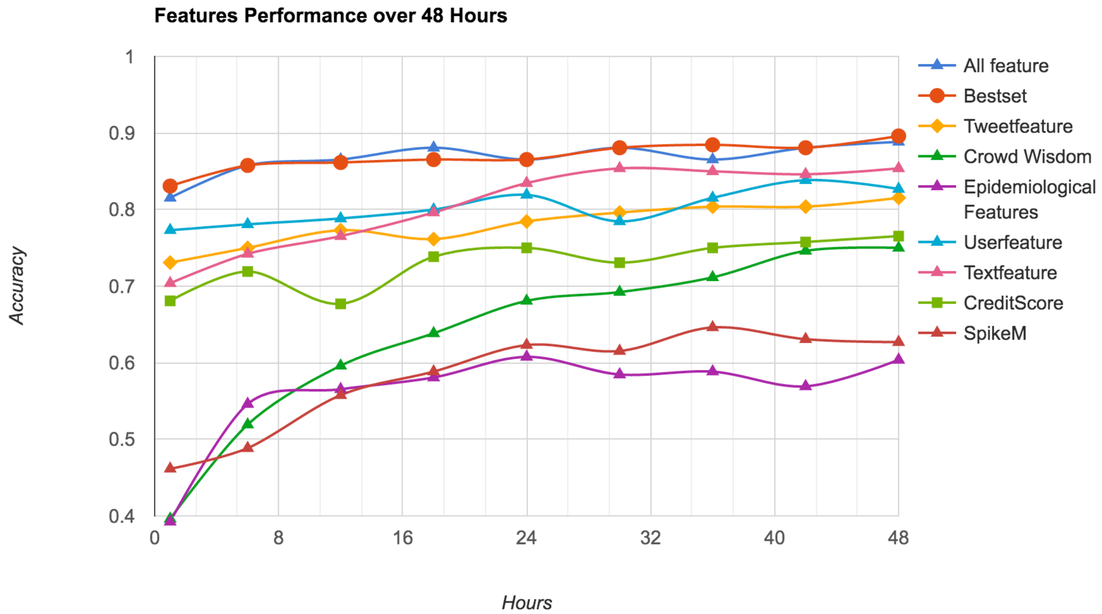


Figure 4.10: Accuracy: Time series VS static Features

4.5.4 Text Features

Text feature set contains 16 features. The ranks of feature as shown in table 4.10. The best one is *NumOfChar* which is the average number of different characters in tweets. It is quite hard to explain why it is like that.

PolarityScores is the best feature when we tested the single tweets model, but its rank in time series model is not so good. It is true that rumor contains more negative sentiment, but in an event (rumor or news) people can show their different views about this event [33] [43] like discussing or denying, so the *PolarityScores*'s performance becomes worse and worse over time. *Text feature* overall is the the best feature set.

Features	**Ranks**									
Hours	1	6	12	18	24	30	36	42	48	AVG
NumOfChar	3	3	4	3	3	8	7	6	4	4.29
QuestionExclamation	25	16	2	1	1	1	3	7	5	4.79
Question	15	11	13	7	5	4	8	5	8	8.29
LengthOfTweet	6	6	9	6	14	16	13	16	13	11.96
PolarityScores	12	15	23	28	33	33	34	31	32	28
Stock	34	44	47	47	47	47	47	47	48	46.15
Smile	35	45	45	48	48	48	48	48	48	47.06
Sad	36	46	46	49	49	49	49	49	49	47.9

Table 4.10: Rank of Part of Text Feature

4.5.5 Twitter Features

Twitter feature is stable over time from the beginning to the end.

The 3 best of *Tweet Features* are all the features about the contained ULR in tweet: *ContainNEWS*, *UrlRankIn5000*, *WotScore* showing in table 4.11. It it quite logical that the news will have higher probability reported by news websites or higher ranked website. And it is clear to see the that their performance significantly improve after 24 hours.

But the other original twitter functions like the retweets or mention do not contribute much.

4.5.6 User Features

The performance of user features is similar with the twitter, they are both quite stable from the first hour to the last hour. But one difference is in the first few user feature is the best feature set except all feature set.

As in table 4.12 shown, the best feature of user feature is UserTweetsPerDays. And it is the best feature overall in the first 4 hours, but it drops down over time. Others user features like Reputation Score and Join date have also better performance at the first fews hours.

Features	**Ranks**									
Hours	1	6	12	18	24	30	36	42	48	AVG
ContainNEWS	8	4	5	4	4	2	2	2	2	3.48
UrlRankIn5000	14	13	7	11	7	3	1	4	6	5.96
WotScore	4	10	6	10	10	6	9	8	7	7.63
Mention	13	5	10	14	13	10	12	12	10	10.98
Hashtag	20	20	15	18	16	13	15	17	17	17.46
Retweets	21	21	27	38	42	35	31	37	34	33.25

Table 4.11: Rank of Part of Twitter Feature

That means the sources (the poster in the first few hours) of news and rumors are quite different with each other, but more and more users join in the discussion, so the bias of two groups of user is less and less. After 6 hours we distinguish the rumors basing on the content of the tweet(text features) already better basing on the feature of the poster.

Features	**Ranks**									
Hours	1	6	12	18	24	30	36	42	48	AVG
UserTweetsPerDays	0	1	1	2	2	9	5	10	14	4.63
UserReputationScore	1	2	3	5	6	5	6	3	3	5.06
UserJoin_date	5	8	8	8	12	14	16	11	9	10.58
UserVerified	24	17	12	16	17	12	11	14	19	16.25

Table 4.12: Rank of Part of User Feature

4.5.7 SpikeM Features and Epidemiological Features

The two feature sets of these two models seem not so well. Only one feature P_a from the SpikeM is added in the BestSet features. As the problem of these two models which we have already figured out in section 4.2.4 is Both of these models need enough data to fit the parameters. Only after 24 hours these two models' features can reach 60% accuracy. In other words before 24 hour these is no clear propagation pattern of these events. In the work of Kwon [23], the durations of dataset which he uses are more than (wenxian). In the work of Jin[16], he uses () to fit the SEIZ models. Their data's durations are far larger than ours 48 hours.

P_a parameter from SpikeM is the only one feature in the top 26 feature set. It stands for the strength of periodicity. Kwon add 3 more parameters to explain the periodicity of the external shock. They are not so functional because of short time period.

Features					**Ranks**					
Hours	1	6	12	18	24	30	36	42	48	AVG
P_a	29	28	34	30	33	24	23	21	23	25.75
R_{SI}	47	24	30	23	36	39	38	24	30	29.56
β_{SIS}	49	30	33	28	31	36	28	33	25	30.15
Q_a	44	47	47	21	38	40	44	41	33	38.04

Table 4.13: Rank of Part of SpikeM Features and Epidemiological Features

4.5.8 Credit Score

Credit Score is the pre-trained Single Tweet Credibility Scoring model's output in section 3.4.2. As shown in table 4.15, excepting the first 4 hours Credit Score is the best feature overall. In figure 4.11 we show the result of model without Credit Score feature and model with full features set. Before the first 24 hours the model without credit score has worse performance than the full feature set, so the credit score feature contributes much for the early stage of rumor detecting.

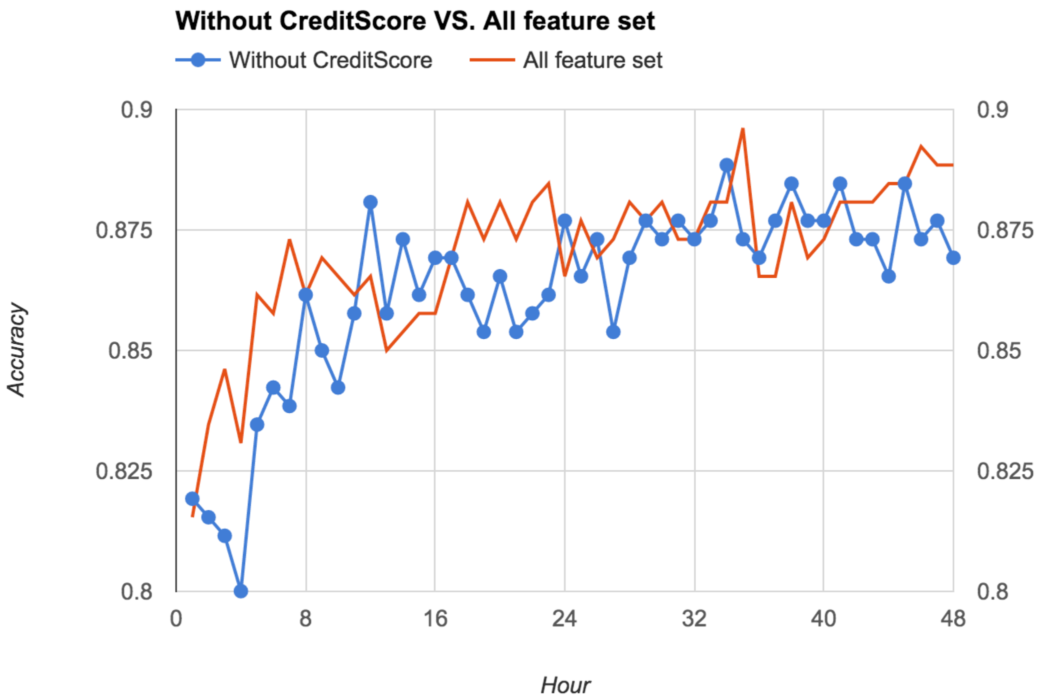


Figure 4.11: Accuracy: Time series VS static Features

Hour	**Rank**
1	2
2	1
3	1
4	1
5	0
..	0
48	0

Table 4.14: Ranks of CreditScore

4.5.9 Crowd Wisdom

Crowd Wisdom is also a good feature which can get 75.8% accuracy as a single feature. But its performance is very poor (less than 70%) in the first 32 hours. The crowds need time to unify their views to the event after absorbing all kind of information. That is also one reason we need this automatic detecting system.

4.5.10 Machine vs Human

Our system is meaningless if the system detecting the rumors after the human recognize them. In this section we will compare our system with the human rumor debunking website snopes.com and urbanlegend.com.

Snopes.com has their own Twitter account [10]. They will post tweets via this account about rumors which they collected and verified. We consider the creation time of the first tweet which contains the keyword "snopes" OR "urbanlegend" in the tweets or URL of "snopes.com" is the time stamp of human confirming rumors.

But some of the rumors have a long duration, the website may report it several months ago or later the biggest burst peak. For example in figure 4.12 it is a rumor about the rapper Tupac Shakur, who is thought to have been killed in 1996, is alive and comes out of hiding. This topic bursted in 2012, 2015 and 2016 several times and the tweet volume of 2012 is the highest so our t_{max} is defined in 2012. But "snopes.com" reported this rumor in the september 2015[11]. So we think that they don't refer to the same rumor affair.

So we set up a threshold 72 hours. We only consider the first tweet containing snopes keyword or snopes URL within 72 hours before or after the beginning time of the events which is defined in section 2.3.2. We show two examples here. First one in figure 4.13 is a rumor about okra Curing diabetes[12] which we detected the

[10] https://twitter.com/snopes
[11] http://www.snopes.com/media/notnews/tupac.asp
[12] http://www.snopes.com/medical/homecure/okra.asp

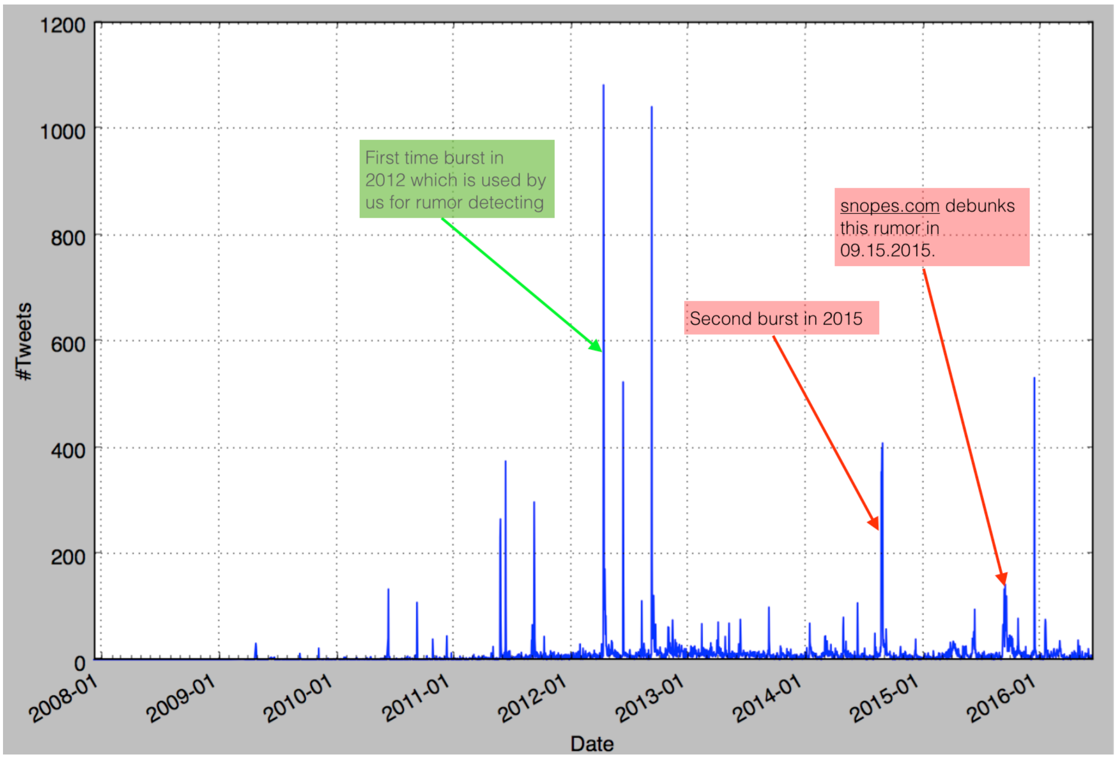


Figure 4.12: Tweet Volume Of Rumor about Tupac Shakur

beginning time is 01.31.2014 04:00. So we scan the first tweet about snopes and we find it in 01.28.2014 21:00 which is 55 hours earlier than the beginning time. Snopes didn't explain their source of this rumor, maybe they detect the story not from Twitter. Other example is in figure 4.14 is that human detect rumor 71 hour after the event beginning. The result is shown in table. On average the editors of "snopes.com" need 25.49 hours to verify the rumors and post it. Our system already achieves 87% accuracy in 25 hours.

	Hours
Latest Time of Human Detection	71
Earliest Time of Human Detection	-55
Average	25.49

Table 4.15: Time of Human Confirming Rumors

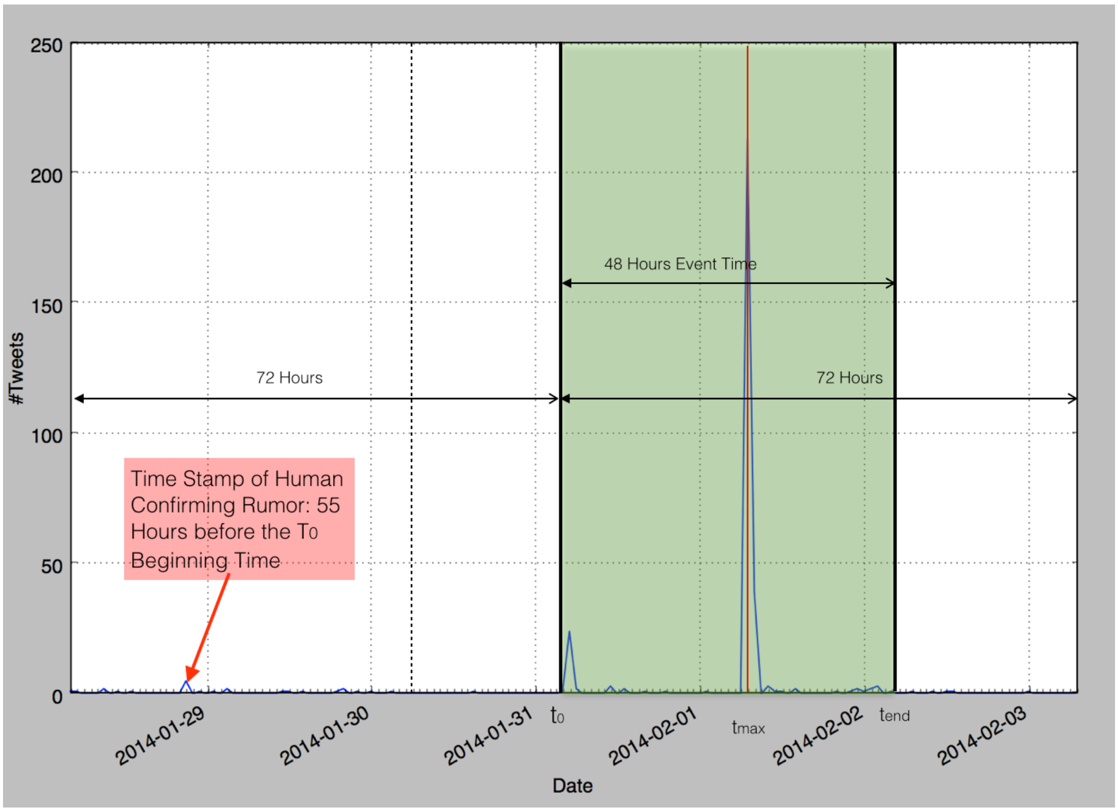


Figure 4.13: The Earliest Time Stamp Of Human Confirming Rumor

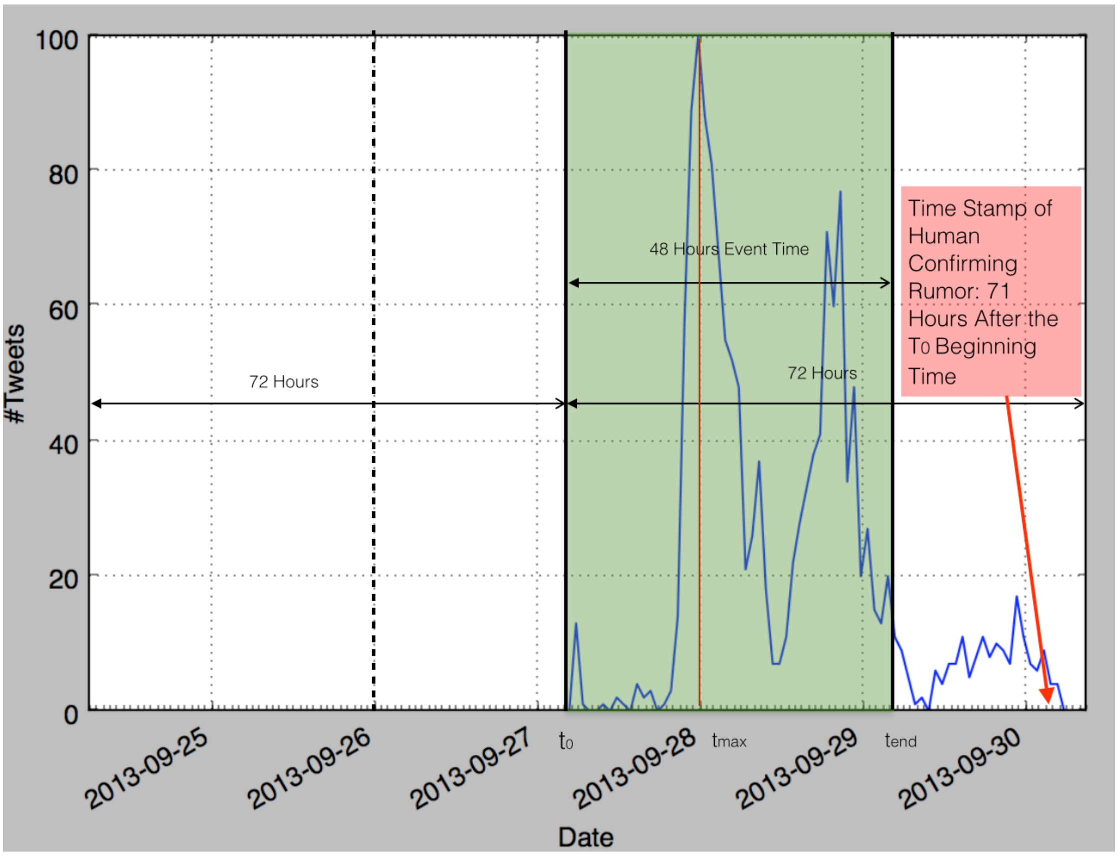


Figure 4.14: The Lastest Time Stamp Of Human Confirming Rumor

4.6 Discussion

4.6.1 Why sentiment doesn't work so well in time series model

PolarityScores is the best feature of single tweet model. But it dose not work well in time series. Generally the performance of *PolarityScores* drops down over time. In table 4.16 we reference the result from Thomas Heverin's work [13]. He analyzed the tweets which responded to the 2009 Violent Crisis. The number of tweets containing original information and emotion are less and less over time. In the other hand more and more people start to share their different opinions even technology problems after 24 hours. That may make difference of sentiment features between rumors and news less and less in first 12 hours and after 24 hours it becomes useless.

Time Period	Information	Opinion	Technology	Emotion	Action	Other
0-12hours	90.0%	6.8%	1.1%	5.6%	1.1%	0.0%
12-24 hours	86.6%	13.0%	3.1%	4.5%	1.3%	0.7%
24-36 hours	73.9%	18.3%	7.0%	2.7%	0.5%	3.7%
26-48 hours	74.6%	21.3%	1.0%	3.8%	0.5%	2.8%

Table 4.16: . Percentage of tweet type (non-exclusive) per 12 hour time period (source: [13])

4.6.2 performance of external URLs features

In our experiment we have 3 features about the external URLs *ContainNEWS*, *UrlRankIn5000* and *WotScore*. It is clear to see in table 4.11 that after 24 hours the performances of these features are better than before 24 hours.

In Alexander's work [34], he also shows similar phenomenon that credibility of the information from twitter is higher than external website in the first 24 hours 4.15.

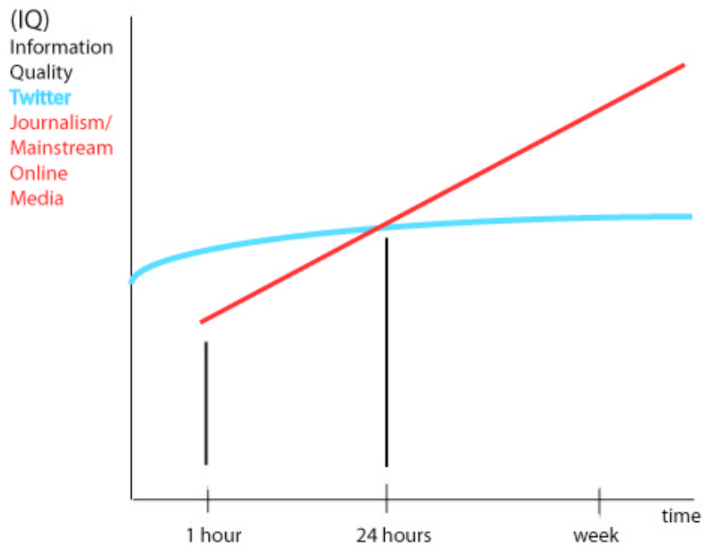


Figure 4.15: Information Quality over time (source: [34])

That may be the reason why the features of external links need 24 hours to performance better.

4.7 Case Study: Munich Shooting

At 17:52 CEST a shooter opened fire in the vicinity of the Olympia shopping mall in Munich. 10 people, including the shooter, were killed and 36 others were injured[13].

At 18:22 first tweet was posted. It might contain some delay here, because our query is constructed in English and maybe the very first tweets are in german language. The tweet is "Sadly, i think there's something terrible happening in #Munich #Munchen . Another Active Shooter in a mall. #SMH". 3 minutes later at 18:25 the second tweet was posted: "Terrorist attack in Munich????". Both of them are labeled by the single credit model as news related.

At 18:27 the traditional media (BBC) posted their first tweet. "'Shots fired' in Munich shopping centre - http://www.bbc.co.uk/news/world-europe-36870800a02026 @TraceyRemix gun crime in Germany just doubled".

The first misclassification tweet is at 18:31. It was a tweet with shock sentiment and swear words. "there's now a shooter in a Munich shopping centre.. What the fuck is going on in the world. Gone mad"

We show the credit score of Munich attack event in figure 4.16. It is clear to see

[13] https://en.wikipedia.org/wiki/2016_Munich_shooting

that the credit score of Munich Shooting is below the average of news.

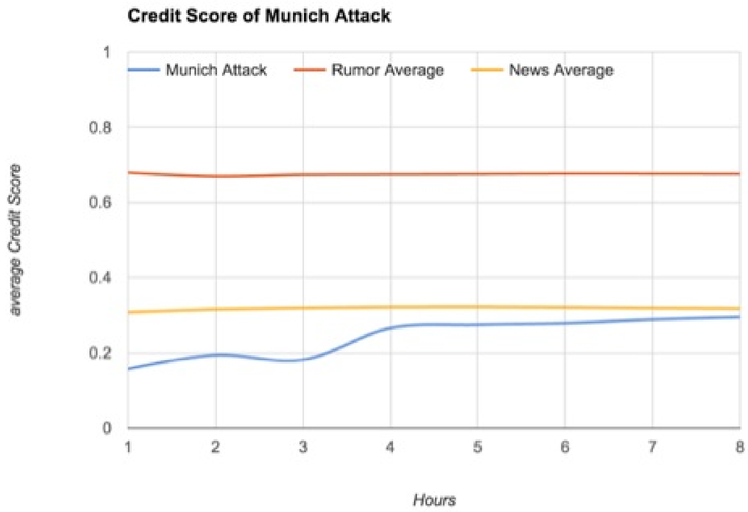


Figure 4.16: Credit Score of Munich Shooting

And there are several kinds of misclassification in table 4.17: unrelated to the events, strong emotional and rumor related. We searched the tweet in English, so most of user are in America not in Germany which can talk about some extend topic like gun law. These comments are labeled as rumors by our system. And some tweets contain strong personal emotion even swear words. These tweets have higher probability being labeled as rumor. The third type is rumor. Some rumors were spreading with the news events. For example some tweets claimed Sam Hyde was the shooter and posted a photo in which there is a man with gun. Or some claimed the shooter was member of ISIS. They are also detected by our system. But generally the average credit score is more like a news event.

The second best feature is ContainNews which is the percent of the URLs of tweet containing News Website domain. We are showing the ContainNews of Munich attack in figure 4.17. We can see the curve of ContainNews of Munich shooting event is close to the curse of ContainNews average News events.

Our

Catalogue	Examples of Tweets
Event Unreleted	Looks like the EU’s gun ban has continued to do its job. What a success. #Munich https://twitter.com/RT_com/status/756525863093538817
	The strict gun laws in Munich kept guns out of innocent hands, didn’t stop the terrorists, in fact made their job easier. @realDonaldTrump
	@KummersTim @ShepNewsTeam Shep Smith is colluding with Hillary’s camp also what he tried during Munich attack was disgusting #TrumpPence16
Strong Emotional	Munich Another day another attack. when is this shit gonna end. It is becoming the norm now. Saddening .
	there’s now a shooter in a Munich shopping centre.. What the fuck is going on in the world. Gone mad
Rumors	ISIS On Munich Terror Attack: Everything Hurting Infidels Makes Us Happy http://www.weaselzippers.us/285113-isis-on-munich-terror-attack-everything-hurting-infidels-makes-us-happy/ via @WeaselZippers
	Obama released photo of shooter #Munich pic.twitter.com/GzJkyNpYDP
	Nice attack 7 days ago, Wurzburg axe attack Monday, Alps knife attack on Wednesday & Munich shootings ongoing. All are Jihad, get used to it
	New info: Munich shooter has been consuming high amounts of a chemical substance called Ḧ2O!̈ #banH2O #banChemistry
	@M7madSmiry @TheBpDShow hearing reports that the shooter is a white supremacist... Has that been confirmed? #Munich
	Witness In Munich Shooting Says: The Shooter Cried Out Allahu Akbar As He Slaughtered Children http://shoebat.com/2016/07/22/witness-in-munich-shooting-says-the-shooter-cried-out-allahu-akbar-as-he-slaughtered-children/ via @walidshoebat
others	@ThatTimWalker seems you were wrong re the Munich attack.

Table 4.17: Example of Misclassification by Single Tweet Model on Munich Shotting

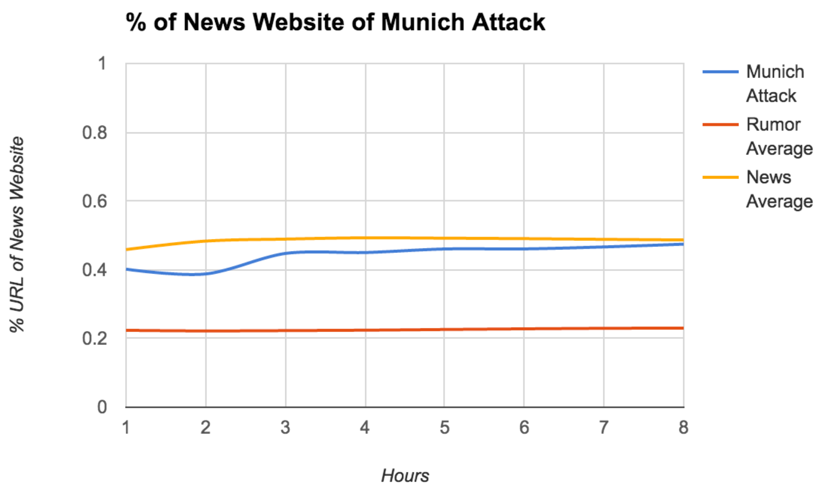


Figure 4.17: % of Tweet Containing News Websites of Munich Shooting

5 Outlook

5.1 Conclusion

With the developing of social media. Twitter becomes an important platform for exchanging information. But the problem of the low credibility of tweet bothers all the users of Twitter. Without the complex process of verification like traditional media, Twitter users can easily publish breaking news or their opines, but they also can produce many rumors. Our work is using the temporal features to detecting rumor on Twitter. But at the first few hours after the beginning of the events, the tweet volume is limited and there is no propagation features yet, so we can only focus on the information of each single tweets. So we develop a single tweet credibility scoring model. We follow the Zhou's idea using neural network for short text classification task which get 81% accuracy. We use the output of single tweet credibility scoring model as a new feature CreditScore which is the best feature in our experiment and it can improve the performance of our time series model $\mathsf{RF}_{\mathsf{ts}}$.

And we analyze the performance of each features over 48 hours. The CreditScore is the feature and ContainNews is the second. Sentiment features are useless after 25 hours. And the crowd wisdom starts effect only after 24 hours. And there is no obvious difference of the verified users' behavior in a rumor event or a news event. Famous people is not guarantee of truth. Features of propagation models no matter SpikeM, SIS or SEIZ are not good enough. Because we limited the time period of events within 48 hours, the propagation pattern is still not so obvious. Comparing the previous work their time period of an event is more than one month. But our model has better timeliness.

5.2 Future Work

In the future work we can do following works:

- Because of limitation of time, we crawled only 260 events in twitter. We can extend it in the future.
- The tweets are labeled as a whole event for single tweet credibility scoring model. But in the news event there are rumors or low credibility tweets, on other hand in rumor there are also denying tweet or high credibility tweets. We can manually label every single tweet.
- The time period in our experiment is constant 48 hours and the interval time is 1 hour. In the future work we can make the time period variable length according to the events' duration.
- Because of limitation of time and ability, I test only several parameters' combination of neural network.

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Appendix

time	CreditScore	ContainNEWS	NumChar	UserTweetsPerDays	QuestionExclamation	UserReputationScore	UrlRankIn5000	WotScore	Question	UserJoin_date	Mention	LengthOfTweet	DebunkingWords	UserFollowers	Exclamation	UserVerified	Hashtag	Capital	You	UserNumPhoto	numUrls	UserFriends	NumPositiveWords	Via	P_a	UserIsInLargeCity	PolarityScores	UserDescription	R_{SI}	β_{SIS}	ε_{SEIZ}	NumNegativeWords	P_s	b_{SEIZ}	β_{SEIZ}	Retweets	p_{SEIZ}	α_{SIS}	Q_s	P_p	ρ_{SEIZ}	I	Qp	l_{SEIZ}	Q_a	HeShe	IsRetweet	Stock	Smile	Sad
1	2	8	3	**0**	25	1	14	4	15	5	13	6	33	7	27	24	20	10	28	9	22	11	18	30	29	19	12	23	45	42	39	17	31	43	46	21	40	41	47	44	49	16	38	37	48	26	32	34	35	36
2	1	5	2	**0**	18	3	11	4	12	7	15	6	43	8	36	22	21	14	40	9	30	10	23	34	25	24	13	38	31	28	41	16	29	27	20	19	39	32	48	26	35	17	47	33	49	37	42	44	45	46
3	1	4	2	**0**	17	5	12	3	10	8	11	6	44	9	38	24	23	15	41	7	30	13	20	32	25	22	14	39	21	26	27	18	36	37	35	19	29	33	48	28	40	16	47	31	49	34	42	43	45	46
4	1	5	3	**0**	16	2	13	4	14	7	11	9	43	6	39	34	21	12	30	8	37	10	23	32	26	25	15	41	28	33	31	17	19	22	27	24	38	40	48	18	29	20	47	35	49	36	42	44	45	46
5	**0**	4	3	1	16	2	13	10	11	8	5	6	42	7	38	17	20	14	33	9	36	12	22	28	35	30	15	41	31	24	23	18	32	25	34	21	29	19	48	37	40	27	47	26	49	39	43	44	45	46
6	**0**	4	2	1	14	3	11	9	8	10	7	6	41	5	35	29	22	15	34	12	40	16	17	21	28	25	18	42	24	30	13	19	36	20	27	26	23	37	48	33	31	32	47	39	49	38	43	44	45	46
7	**0**	6	2	1	7	3	11	12	10	8	4	5	23	9	22	28	21	15	39	13	37	14	20	19	27	26	18	42	24	38	17	16	34	35	25	31	29	41	48	30	33	32	47	40	49	36	43	44	45	46
8	**0**	4	2	1	5	3	7	9	8	10	13	6	24	11	18	15	21	14	41	12	34	19	20	31	28	17	22	40	23	29	27	16	25	35	33	26	32	37	48	30	36	38	47	39	49	42	43	44	45	46
9	**0**	8	2	1	4	3	7	5	10	6	13	9	25	11	15	14	23	12	32	16	28	19	22	24	26	33	20	37	31	30	18	17	41	35	29	21	27	36	48	39	34	38	47	40	49	42	43	44	45	46
10	**0**	8	3	1	2	4	5	10	11	6	12	7	18	9	17	19	20	13	32	14	26	24	23	27	29	36	16	39	41	30	21	15	35	28	34	31	22	25	48	38	37	33	47	40	49	43	42	44	45	46
11	**0**	5	4	1	2	3	7	6	13	8	10	9	19	11	17	12	15	14	24	16	18	20	25	31	33	32	23	40	26	29	36	21	37	39	22	27	38	30	48	35	42	28	47	34	49	41	43	44	45	46
12	**0**	6	3	1	2	4	7	5	13	8	9	11	18	12	16	15	17	10	21	20	23	14	28	27	34	25	19	41	30	33	36	31	40	26	37	24	32	22	48	35	29	39	47	38	49	42	43	44	45	46
13	**0**	7	3	1	2	4	9	5	12	6	8	11	15	13	22	14	17	10	35	18	20	16	31	27	36	24	23	43	40	30	26	34	37	28	32	21	29	19	42	33	25	38	39	41	44	45	46	47	48	49
14	**0**	6	3	1	2	4	5	9	12	7	8	11	15	13	17	14	22	10	26	19	18	16	27	36	34	29	21	39	24	23	25	33	41	28	32	20	40	42	31	35	30	44	38	37	43	46	45	47	48	49
15	**0**	5	4	1	2	3	6	13	8	7	11	10	12	16	9	15	27	14	20	26	19	18	22	25	32	34	30	40	24	37	17	21	38	33	41	28	35	44	29	39	23	43	36	42	31	46	45	47	48	49
16	**0**	4	3	2	1	5	7	10	11	9	12	6	13	17	8	15	21	14	20	22	23	24	43	36	18	30	29	39	33	37	16	28	41	26	38	32	31	34	35	44	19	42	40	27	25	45	46	48	47	49
17	**0**	4	3	2	1	5	11	10	7	8	14	6	12	17	9	16	18	13	15	21	20	19	44	26	35	43	28	31	22	32	36	34	37	39	40	38	30	23	25	41	27	33	24	29	42	45	46	47	48	49
18	**0**	5	3	2	1	4	9	8	7	10	12	11	14	16	6	15	17	13	18	24	20	19	40	26	30	32	29	35	23	28	25	31	41	27	38	37	33	36	34	43	39	44	22	42	21	45	46	47	48	49
19	**0**	4	3	2	1	7	8	9	6	11	12	10	13	15	5	18	17	14	16	24	19	20	36	26	22	38	29	43	28	33	35	30	23	32	25	41	27	39	34	40	37	42	21	31	44	45	46	47	48	49
20	**0**	3	4	2	1	7	5	6	8	13	12	11	10	16	9	17	18	15	14	21	20	23	35	33	28	30	41	29	22	27	39	36	37	43	32	31	25	24	38	40	42	46	19	26	34	45	44	48	47	49
21	**0**	4	3	2	1	7	6	8	10	14	12	13	5	17	9	18	15	16	11	27	20	19	30	35	24	33	29	28	25	22	44	37	26	31	36	38	40	21	39	32	42	43	23	41	34	46	45	47	48	49
22	**0**	4	3	2	1	7	6	8	11	14	12	13	5	18	9	17	15	16	10	20	21	22	26	33	24	36	30	28	35	25	38	27	23	37	41	43	31	19	40	42	29	39	34	44	32	46	45	47	48	49
23	**0**	4	3	2	1	6	7	10	5	12	13	14	9	15	8	17	16	18	11	19	24	23	34	35	25	43	33	32	27	38	29	39	21	41	28	42	37	40	22	30	36	46	20	26	31	44	45	47	48	49
24	**0**	3	5	2	1	6	4	14	7	13	10	11	9	17	8	16	15	19	12	20	18	26	25	24	33	32	30	22	36	31	35	37	23	39	41	40	42	38	21	27	34	45	29	43	28	44	46	47	48	49
25	**0**	3	4	2	1	10	7	9	5	13	11	14	6	17	8	19	18	15	12	22	16	30	23	20	37	26	29	24	21	32	31	40	41	28	39	42	36	35	27	38	43	44	25	34	33	45	46	47	48	49
26	**0**	4	6	2	1	8	3	9	7	12	14	13	5	18	11	16	15	17	10	22	20	24	19	32	23	28	36	21	26	37	31	34	27	33	43	44	29	35	25	39	41	38	40	42	30	46	45	47	48	49
27	**0**	3	8	4	1	7	2	9	6	15	12	13	5	17	14	16	11	18	10	22	21	29	19	25	23	24	33	20	26	30	36	31	34	42	27	44	38	40	28	32	41	37	45	39	35	43	46	47	48	49
28	**0**	1	7	9	2	8	3	6	4	14	10	15	5	17	13	16	11	21	12	23	19	27	20	26	35	24	29	18	32	30	22	38	25	28	41	42	44	31	36	37	43	40	34	39	33	46	45	47	48	49
29	**0**	2	8	9	1	5	3	6	4	14	10	16	7	17	15	12	13	22	11	23	21	24	19	25	18	32	33	20	31	34	27	36	28	44	39	35	41	38	26	29	42	40	37	43	30	46	45	47	48	49
30	**0**	3	8	7	1	9	2	5	4	14	10	16	6	17	13	15	12	20	11	22	21	31	18	23	24	25	29	19	39	26	27	32	36	38	33	34	43	37	35	28	44	30	42	41	40	45	46	47	48	49
31	**0**	3	9	4	2	7	1	5	6	16	10	15	8	20	13	14	12	21	11	22	18	24	23	29	17	34	28	19	25	26	30	37	31	36	35	32	44	39	27	46	43	38	41	40	33	45	42	47	48	49
32	**0**	2	6	4	3	7	1	9	5	16	10	15	8	17	12	14	13	21	11	22	18	24	23	30	19	26	33	20	28	25	32	42	31	38	34	27	36	44	40	41	43	39	35	29	37	45	46	47	48	49
33	**0**	2	4	7	3	8	1	6	11	13	10	15	5	17	12	9	14	19	16	22	20	30	21	24	25	26	42	18	29	23	36	37	33	35	32	27	43	31	28	40	34	39	41	38	46	44	45	47	48	49
34	**0**	1	5	3	4	6	2	8	12	16	9	15	7	13	11	10	17	23	14	24	20	27	21	25	19	28	36	18	37	26	32	33	22	39	34	31	45	29	38	40	35	42	43	41	30	44	46	47	48	49
35	**0**	2	7	5	3	6	1	9	8	16	12	13	4	10	14	11	15	24	17	21	19	38	20	22	27	23	34	18	32	30	37	33	28	25	26	31	40	45	29	42	36	35	44	43	39	41	46	47	48	49
36	**0**	2	6	7	5	4	1	8	9	14	12	15	3	13	10	11	18	25	16	24	19	30	21	20	23	22	32	17	38	28	31	37	27	39	26	36	42	45	33	29	40	35	34	43	44	46	41	47	48	49
37	**0**	1	6	9	3	5	2	7	8	12	11	14	4	16	10	13	18	27	15	23	17	26	21	24	20	22	32	19	39	25	28	34	30	43	29	41	45	33	38	31	35	40	36	44	37	46	42	47	49	48
38	**0**	1	6	8	4	7	3	5	9	10	14	16	2	15	12	11	18	26	13	22	23	30	24	19	21	20	35	17	29	31	38	44	28	25	32	37	46	36	33	27	34	40	41	45	39	42	43	48	47	49
39	**0**	1	5	10	4	7	3	6	9	13	14	16	2	8	12	11	17	27	15	23	24	32	21	20	22	19	39	18	25	26	33	37	28	29	36	41	34	35	38	30	31	45	40	46	42	43	44	47	48	49
40	**0**	1	7	13	4	6	3	8	5	11	12	17	2	9	14	10	16	27	18	26	24	28	23	20	22	19	33	15	45	31	38	40	25	36	39	32	34	41	21	30	35	46	37	43	29	42	44	47	49	48
41	**0**	2	6	10	7	3	4	8	5	11	12	16	1	9	15	14	17	29	13	21	23	26	25	18	22	19	31	20	32	35	40	42	27	33	28	37	44	46	24	30	41	39	36	34	38	45	43	47	48	49
42	**0**	1	4	11	8	3	6	7	5	9	10	16	2	12	14	13	19	27	15	20	25	29	23	18	21	17	35	22	24	33	40	45	26	30	32	43	36	31	39	37	38	42	34	46	41	44	28	47	49	48
43	**0**	2	3	11	7	4	6	8	5	9	10	15	1	16	12	14	17	28	13	21	23	30	24	18	22	19	32	26	25	31	35	45	36	27	20	44	37	42	29	43	41	38	33	34	39	46	40	47	48	49
44	**0**	2	4	10	5	6	7	8	3	9	11	15	1	14	12	16	18	26	13	23	22	27	24	20	19	17	31	21	25	29	37	40	36	32	30	44	38	43	35	39	28	46	41	33	34	45	42	47	49	48
45	**0**	2	3	10	6	4	7	8	5	9	11	16	1	14	12	15	19	28	13	22	20	30	24	18	23	17	31	21	26	33	41	36	42	25	29	39	27	46	35	43	45	40	34	37	32	44	38	47	49	48
46	**0**	2	5	11	4	3	6	7	8	9	12	17	1	16	10	18	15	25	13	23	21	35	26	14	24	19	29	20	30	32	40	44	33	22	34	38	27	46	28	42	43	45	39	41	31	37	36	48	49	47
47	**0**	2	4	13	3	6	5	7	8	9	11	15	1	19	10	18	16	25	12	22	20	37	24	17	21	14	33	23	29	27	41	36	32	26	30	45	38	44	28	43	42	35	34	40	31	46	39	48	47	49
48	**0**	2	4	14	5	3	6	7	8	9	10	13	1	18	11	19	17	24	12	22	20	35	27	15	23	16	32	21	30	25	43	40	38	29	26	34	28	42	31	45	36	37	39	46	33	41	44	48	47	49
AVG	0.10	3.48	4.29	4.63	4.79	5.06	5.96	7.63	8.29	10.58	10.98	11.96	12.35	13.63	15.15	16.25	17.46	18.65	19.15	19.65	22.85	23.54	24.73	25.42	25.75	26.13	28.00	28.06	29.52	30.00	31.67	31.69	31.81	32.46	32.65	33.35	35.27	35.54	35.75	35.83	36.50	37.31	37.60	37.96	38.58	42.81	43.08	46.15	47.06	47.90

Hour	Time series model	Static model	Difference
1	0.82	0.78	0.03
2	0.83	0.82	0.01
3	0.85	0.79	0.05
4	0.83	0.79	0.04
5	0.86	0.82	0.04
6	0.86	0.8	0.06
7	0.87	0.79	0.08
8	0.86	0.84	0.03
9	0.87	0.83	0.04
10	0.87	0.83	0.04
11	0.86	0.85	0.01
12	0.87	0.83	0.04
13	0.85	0.85	0
14	0.85	0.81	0.04
15	0.86	0.82	0.03
16	0.86	0.84	0.02
17	0.87	0.83	0.04
18	0.88	0.83	0.05
19	0.87	0.83	0.05
20	0.88	0.83	0.05
21	0.87	0.81	0.06
22	0.88	0.83	0.05
23	0.88	0.85	0.04
24	0.87	0.85	0.01
25	0.88	0.85	0.02
26	0.87	0.88	-0.01
27	0.87	0.85	0.02
28	0.88	0.85	0.04
29	0.88	0.83	0.04
30	0.88	0.85	0.03
31	0.87	0.85	0.02
32	0.87	0.84	0.03
33	0.88	0.85	0.03
34	0.88	0.86	0.02
35	0.9	0.88	0.02
36	0.87	0.86	0
37	0.87	0.87	0
38	0.88	0.87	0.02
39	0.87	0.87	0
40	0.87	0.88	0
41	0.88	0.86	0.02
42	0.88	0.88	0
43	0.88	0.88	0
44	0.88	0.87	0.01
45	0.88	0.86	0.02
46	0.89	0.86	0.03
47	0.89	0.87	0.02
48	0.89	0.87	0.02

Table .2: Time seriers VS static Features in detail

time	All Feature	BestSet	Tweet Feature	Crowd Wisdom	SIR	User Feature	Text Feature	CreditScore	SpikeM
1	0.815	**0.831**	0.731	0.396	0.392	0.773	0.704	0.681	0.462
2	0.835	**0.838**	0.727	0.396	0.562	0.762	0.685	0.712	0.515
3	0.846	**0.850**	0.769	0.423	0.565	0.758	0.708	0.708	0.492
4	0.831	**0.854**	0.762	0.477	0.538	0.765	0.738	0.712	0.550
5	**0.862**	0.854	0.758	0.508	0.554	0.781	0.746	0.692	0.500
6	**0.858**	**0.858**	0.750	0.519	0.546	0.781	0.742	0.719	0.488
7	**0.873**	0.854	0.754	0.573	0.554	0.769	0.754	0.700	0.554
8	0.862	0.862	0.773	0.573	0.542	0.754	0.758	0.692	0.542
9	**0.869**	0.858	0.754	0.573	0.565	0.785	0.754	0.700	0.588
10	0.865	**0.881**	0.758	0.588	0.565	0.788	0.746	0.708	0.573
11	0.862	0.869	0.769	0.585	0.538	0.781	0.735	0.708	0.542
12	**0.865**	0.862	0.773	0.596	0.565	0.788	0.765	0.677	0.558
13	0.850	**0.873**	0.754	0.588	0.554	0.796	0.785	0.692	0.550
14	0.854	**0.865**	0.777	0.600	0.573	0.800	0.762	0.708	0.542
15	0.858	**0.865**	0.777	0.619	0.546	0.804	0.777	0.731	0.550
16	0.858	**0.862**	0.773	0.627	0.565	0.792	0.788	0.754	0.565
17	**0.869**	0.858	0.777	0.635	0.538	0.792	0.788	0.735	0.577
18	**0.881**	0.865	0.762	0.638	0.581	0.800	0.796	0.738	0.588
19	**0.873**	0.862	0.773	0.646	0.585	0.808	0.819	0.742	0.608
20	**0.881**	0.862	0.773	0.662	0.604	0.812	0.815	0.746	0.596
21	**0.873**	**0.873**	0.785	0.669	0.592	0.808	0.838	0.742	0.600
22	**0.881**	0.873	0.788	0.685	0.600	0.819	0.827	0.746	0.588
23	**0.885**	0.865	0.785	0.677	0.592	0.815	0.838	0.731	0.608
24	**0.865**	0.865	0.785	0.681	0.608	0.819	0.835	0.750	0.623
25	**0.877**	**0.877**	0.769	0.692	0.600	0.819	0.842	0.746	0.623
26	0.869	**0.881**	0.785	0.696	0.581	0.800	0.846	0.735	0.600
27	0.873	**0.888**	0.788	0.696	0.612	0.804	0.854	0.735	0.600
28	**0.881**	0.881	0.788	0.692	0.596	0.796	0.846	0.735	0.612
29	**0.877**	**0.877**	0.781	0.688	0.596	0.792	0.854	0.727	0.608
30	**0.881**	**0.881**	0.796	0.692	0.585	0.785	0.854	0.731	0.615
31	0.873	**0.888**	0.800	0.692	0.604	0.785	0.850	0.735	0.588
32	0.873	**0.892**	0.808	0.696	0.588	0.792	0.850	0.746	0.631
33	0.881	**0.892**	0.808	0.700	0.581	0.812	0.846	0.762	0.642
34	0.881	**0.896**	0.804	0.704	0.558	0.808	0.854	0.735	0.658
35	**0.896**	0.881	0.815	0.712	0.585	0.804	0.854	0.731	0.658
36	0.865	**0.885**	0.804	0.712	0.588	0.815	0.850	0.750	0.646
37	0.865	**0.885**	0.796	0.715	0.577	0.812	0.862	0.727	0.646
38	**0.881**	0.873	0.804	0.738	0.577	0.808	0.846	0.754	0.646
39	0.869	**0.888**	0.800	0.731	0.573	0.827	0.850	0.742	0.635
40	0.873	**0.885**	0.808	0.735	0.588	0.819	0.854	0.758	0.646
41	0.881	**0.892**	0.804	0.738	0.577	0.812	0.854	0.758	0.631
42	**0.881**	**0.881**	0.804	0.746	0.569	0.838	0.846	0.758	0.631
43	0.881	**0.888**	0.812	0.750	0.600	0.838	0.854	0.742	0.627
44	0.885	**0.896**	0.815	0.754	0.577	0.835	0.858	0.746	0.600
45	0.885	**0.900**	0.804	0.754	0.577	0.835	0.858	0.738	0.646
46	**0.892**	0.888	0.804	0.754	0.612	0.835	0.854	0.731	0.662
47	0.888	**0.904**	0.819	0.754	0.596	0.827	0.858	0.750	0.619
48	0.888	**0.896**	0.815	0.750	0.604	0.827	0.854	0.765	0.627

Table .3: Accuracy of Different Feature Sets over 48 Hours

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