Project Report: Public Rumor Determination

Dasong Li 515030910607
ldsgy123@sjtu.edu.cn

IEEE Pilot Class, SEIEE
Shanghai Jiao Tong University

Abstract

In this project, we explore the rumor detection and determination. At first, I collect data from weibo.com. Three famous classification methods are implemented to classify the unfriendly users. It is believed that these users are inclined to become the source of rumors. Once can we detect this unfriendly users, the rumor will be successfully suppressed.

1 Introduction

A rumor (American English) or rumour (British English; see spelling differences) is "a tall tale of explanations of events circulating from person to person and pertaining to an object, event, or issue in public concern."

Rumors are also often discussed with regard to "misinformation" and "disinformation" (the former often seen as simply false and the latter seen as deliberately false, though usually from a government source given to the media or a foreign government). Rumors thus have often been viewed as particular forms of other communication concepts.

Rumor has always played a major role in politics, with negative rumors about an opponent typically more effective than positive rumors about one's own side. The Internet's recent appearance as a new media technology has shown ever new possibilities for the fast diffusion of rumor, as the debunking sites such as snopes.com, urbanlegend.com, and factcheck.org demonstrate. Nor had previous research taken into consideration the particular form or style of deliberately chosen rumors for political purposes in particular circumstances. In the early part of the 21st century, some legal scholars have attended to political uses of rumor, though their conceptualization of it remains social psychological and their solutions to it as public problem are from a legal scholarly perspective, largely having to do with libel and privacy laws and the damage to personal reputations.

Working within political communication studies, in 2006, Jayson Harsin introduced the concept of the "rumor bomb" as a response to the widespread empirical phenomenon of rumoresque communication in contemporary relations between media and politics, especially within the complex convergence of multiple forms of media, from cell phones and internet, to radio, TV, and print. Harsin starts with the widespread definition of rumor as a claim whose truthfulness is in doubt and which often has no clear source even if its ideological or partisan origins and intents are clear. He then treats it as a particular rhetorical strategy in current contexts of media and politics in many societies. For Harsin a "rumor bomb" extends the definition of rumor into a political communication concept with the following features:

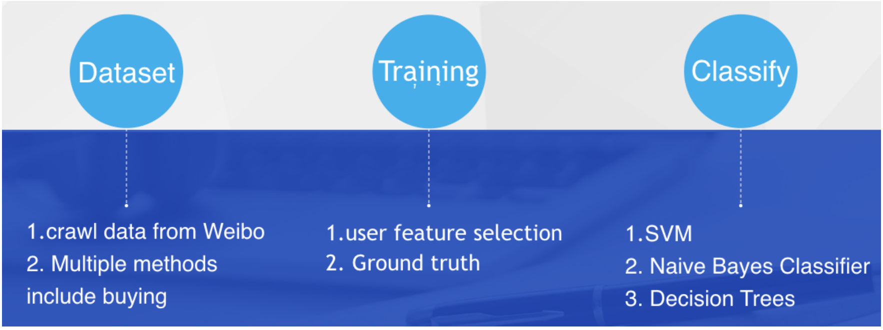

Figure 1: Flow Chart. Three steps of My project.

1. A crisis of verification. A crisis of verification is perhaps the most salient and politically dangerous aspect of rumor. Berenson (1952) defines rumor as a kind of persuasive message involving a proposition that lacks 'secure standards of evidence' (Pendleton 1998).
2. A context of public uncertainty or anxiety about a political group, figure, or cause, which the rumor bomb overcomes or transfers onto an opponent.
3. A clearly partisan even if an anonymous source (e.g."an unnamed advisor to the president"), which seeks to profit politically from the rumor bomb's diffusion.
4. A rapid diffusion via highly developed electronically mediated societies where news travels fast.

2 Related Work

2.1 Early Study

In the 1947 study, Psychology of Rumor, Gordon Allport and Leo Postman[2] concluded that, "as rumor travels it grows shorter, more concise, more easily grasped and told."[6] This conclusion was based on a test of message diffusion between persons, which found that about 70% of details in a message were lost in the first 5-6 mouth-to-mouth transmissions.[6]

In the experiment, a test subject was shown an illustration and given time to look it over. They were then asked to describe the scene from memory to a second test subject. This second test subject was then asked to describe the scene to a third, and so forth and so on. Each person's reproduction was recorded. This process was repeated with different illustrations with very different settings and contents.

Allport and Postman[2] used three terms to describe the movement of rumor. They are: leveling, sharpening, and assimilation. Leveling refers to the loss of detail during the transmission process; sharpening to the selection of certain details of which to transmit; and assimilation to a distortion in the transmission of information as a result of subconscious motivations.

2.2 Social cognition

In 2004, Prashant Bordia and Nicholas DiFonzo[1] published their Problem Solving in Social Interactions on the Internet: Rumor As Social Cognition and found that rumor transmission

```
headers = {
    'Host':'162.105.71.185:8080',
    'User-Agent' : 'Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36
        (KHTML, like Gecko) Chrome/54.0.2840.99 Safari/537.36',
    'Connection' : 'keep-alive',
}

def getUserInfo(userList,userInfoPath):

    fInfo=open(userInfoPath,"a")
    i = 1
    for uid in userList:
        #gain userAttributes from API
        # userInfoUrl = "http://162.105.71.185:8080/weibova/moapi/statuses/
            search?fuid=%s&filter_ori=4" % uid
        userInfoUrl = "http://162.105.71.185:8080/weibova/moapi/apiv2/users/
            show?uid=%s"%uid
        html_sample = str(tool.exceptRequest(userInfoUrl, headers).read())

        if "exception" in html_sample:
            print "用户不存在"
            continue
        dicInfoi = json.loads(html_sample)

        #write to file
        fInfo.write(json.dumps(dicInfoi) + "\n")
        fInfo.flush()
        print i, dicInfoi["id"], "Finished!"
        i += 1
        # time.sleep(5)
        # if i % 18 == 0:
        #     time.sleep(100)
```

```
#采用10折交叉验证法
cv=10
listX, listY, idList, nameList=getXYIdName(keyList,userInfoPath)
# 朴素贝叶斯
print "\n============== NB Report =============="
clf =  MultinomialNB()
predictProcess(cv,clf, listX, listY, idList, nameList)
# drawROCWith2Keylist(clf,userInfoPath)
# C4.5决策树
print "\n============== C4.5 Report =============="
clf = tree.DecisionTreeClassifier(criterion='entropy')
predictProcess(cv,clf, listX, listY, idList, nameList)
# drawROCWith2Keylist(clf,userInfoPath)
#打印信息增益
# print "============== Rank by information gain =============="
# informationGain=clf.feature_importances_
# #key及其信息增益的字典
# featureRank={}
# i=0
# for ki in keyList:
#     featureRank[ki]=informationGain[i]
#     i+=1
# #按信息增益升序排列
# rowsByInfoGain = sorted(featureRank.items(),key=lambda d:d[1],reverse=True)
# #输出
# for fi in rowsByInfoGain:
#    print fi
# SVM
print "\n============== SVM Report =============="
clf = svm.SVC(probability=True,kernel='rbf')
predictProcess(cv,clf, listX, listY, idList, nameList)
```

Figure 2: Some code. From left to right: crawl code and classifier code.

is probably reflective of a "collective explanation process". This conclusion was based on an analysis of archived message board discussions in which the statements were coded and analyzed. It was found that 29% (the majority) of statements within these discussions could be coded as "sensemaking" statements.

There are four components of managing rumors that both of you need to understand for the sake of your relationship's success. The first, anxiety (situational and personality), is when people who either have a more anxious personality, or people who are in an anxiety-lifting situation are more likely to create rumors in order to relieve some of their insecurities. The second component of managing rumors is ambiguity. Ambiguity is when someone is not sure about what is going on, so they end up assuming the worst. The third component is information importance. Information is key, and if that information is not juicy or if it does not interest people, there won't be rumors, but information can often be false. Information can also be ambiguous. The last component of managing rumors is credibility. Rumors are often spread by sources that are not credible. A rumor itself is not credible unless it is proven to be true. That is why people say to never trust the tabloids.

2.3 Code Presentation

3 Method

From my mind, it is very possible that public rumor is manipulated by some people. The key to determine the public rumor is that we need to distinguish these people from the public. I select Weibo as the dream land for rumor detection and determination. Since Weibo is the very place from which almost every information comes. As we all know, there are many unfriendly users there to spread useless or rumor. In this project, I want to detect the spkecital users from all the users. Only when we find the rumor sources, the rumor could be determinate and suppressed. We propose a novel method to detect the unfriendly users. It is believed that our method could make contributions to a complete system in which we can evaluate the probability that the users are rumor beginners or spreaders. We note that this evaluation is not constant but variational according to their activities.

3.1 Background

Rumor is an important form of social communications, and spread of rumors plays a significant role in a variety of human affairs. There are two rumor models that are widely used, i.e. DK model and MK model. Particularly, we can view rumor spread as a stochastic process in social networks. This project is not focusing on the rumor spread, so the details of DK model and MK model will not be mentioned.

3.2 Detect Unfriendly Users

Based on the model mentioned above, we can propose an assumption that the rumor could be suppressed if we could find the source of rumor. This project focuses on the rumor detection and determination. We suppose that there are many users who tend to spread the rumors. These users are called unfriendly users. We use several ways to detect these unfriendly users.

3.3 Problem Definition

We define the set of users as $U = \{u_1, u_2, ..., u_n\}$ and the class of users as $A = \{a_1, a_2, a_3\}$. The core target of this project is to learn a function $f : U \to A$. The features of one single user are represented by $X = (x_1, x_2, x_3, ..., x_{10})$. The meaning of these 10 features will be interpreted in the following.

3.4 Classifiers

In this project, we tried several classifiers: Naive Bayes classifier, SVM, decision tree.Naive Bayes classifier is the very classifier based on naive bayes assumption. SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

A decision tree is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm that only contains conditional control statements. Decision trees are commonly used in operations research, specifically in decision analysis, to help identify a strategy most likely to reach a goal, but are also a popular tool in machine learning.

4 Experiment

4.1 Dataset

Collecting data and find features are really a tough problem. I used the following two ways to locate the target users:

1. Let some unfriendly users to attention myself. Some data could be found in internet. I bought some data as well.

2. Find users in the explicitly hot topics.

After locate the users(UID), I use beautifulSoap to crawl the data from weibo.com. One open source API is also used there. At last, I successfully get about 1000 normal users and 1000 unfriendly users.

4.2 Feature Selection

id	feature	id	feature
1	weibo V	6	attentioned
2	user name	7	visible weibo
3	personal statement	8	original weibo
4	logo	9	attention
5	number of weibo	10	collection

The features X of users are collected from weibo data. These features are listed in the above table.

4.3 Code Presentation

The code of classifier and crawling data is shown in figure2. As for classifiers, I adopt the open source code – scikit-learn as the tools.

4.4 Results

id	feature	information
1	weibo V	0.000435688
2	user name	0.000731187
3	personal statement	0.027192084
4	logo	0.003511677
5	number of weibo	0.012699345
6	attentioned	0.182043367
7	visible weibo	0.098595146
8	original weibo	0.025670454
9	attention	0.007327128
10	collection	0.011369416

This table illustrate the information how the features affect the classification, which is obtained from training. In test dataset(about 100), we achieve about pretty great accuracy.

5 Conclusion

In this project, I explore the rumor detection and determination. At first, by training, we could find users who tends to spread fake news. Then when users are collectedly detected, rumors will be determined. There are so many benefits to help social media to detect and determine the rumors. I wish one day this system will be used in practice to detect and suppress rumors.

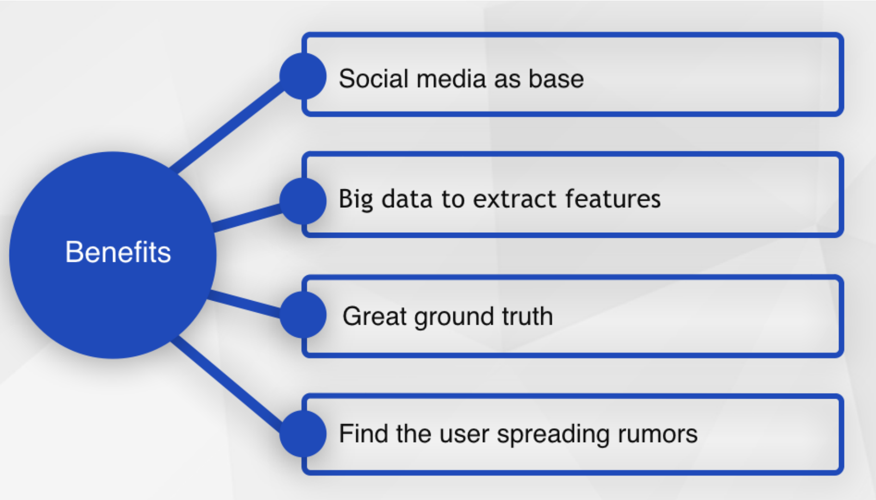

Figure 3: Benefits

References

[1] Prashant Bordia and Nicholas Difonzo. Problem solving in social interactions on the internet: Rumor as social cognition. *Social Psychology Quarterly*, 67(1):33–49, 2004.

[2] David Krech. The psychology of rumor. *Jornal of Daonal Yhology*, (2):171–173, 1948.