# SOCIAL SPAM DETECTION VIA CONVEX NON NEGATIVE MATRIX FACTORIZATION

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### ABSTRACT

With the increasing popularity of social network platforms such as Twitter and Sina Weibo, a lot of malicious users, also known as social spammers, disseminate illegal information to normal users. Several approaches are proposed to detect spammers by training a classifier with optimization methods and mainly using content and social following information. Due to the development of spammers' strategies and the courtesy of some legitimate users, social following information becomes vulnerable to fake by spammers. Meanwhile, the possible social activities and behaviors vary significantly among different users, which leads to a large yet sparse feature space to be modeled by existing approaches. To address issues, in this paper, we propose a new approach named CNMFSD for spammer detection in social networks, which exploits both content information and users interaction relationships in an innovative manner. We have empirically validated the proposed method on a real-world Twitter dataset, and experimental results show that the proposed CNMFSD method improves the detection performance significantly compared with baselines.

#### **Introduction:**

Social networks, such as Twitter, Facebook, and Sina Weibo, are increasingly used to disseminatez and share information easily and quickly. However, it is a double-edged sword since the success of social networks also attracts more social spammers. They try to seize our privacy, send us unwanted information, publish malicious content and links, and promote commodity information, which thoroughly impacts social stability and organizational management models. According to a study by Nexgate, the number of social spammers grows so fast that one in two hundred social messages is spam. Meanwhile, to increase their influence and be undetected, spammers collude with each other to construct the criminal communities. Thus, social spammer detection is a challenging task for researchers. Successful social spammer detection presents its significance to improve the quality of user experience, and positively impact the overall value of the social systems going forward. In the past decade, researchers have tried different techniques to detect spammers, such as link analysis and content analysis. The methods of content-based detection of spammers mainly focus on analyzing and extracting users' features and then directly applying existing classification approaches such as support vector machines (SVM) to detect spammers. Recently, more advanced deep learning-based approaches have been proposed to detect social spammers only based on content. However, with the development of spamming strategies, these methods could not accurately detect spammers with new strategies, only relying on the extracted features. Another category of methods is proposed to detect spammers via social network analysis. These methods assume that spammers cannot establish an arbitrarily large number of social trust relations with legitimate users. The users, who have relatively low social influence or social status in social networks, will be determined as spammers. Unfortunately, only depending on network information, these methods are hard to distinguish between legitimate users and spammers. In this paper, we study the problem of social spammer detection with social interaction and content information. In essence, we investigate: how to model the social interaction information and content information properly; and how to seamlessly utilize both social interaction and content information for the problem we are studying. Our solutions to these two challenges result in a novel spammer detection framework name Convex-NMF based Supervised Spammer Detection with Social Interaction (CNMFSD). Based on statistical analysis, we observe that spammers and legitimate users have different characteristic distributions.

### LITERATURE SURVEY

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# **Existing System:**

Many different methods have been proposed to combat social spammers firstly surveyed potential solutions and challenges in social spammer detection. They elaborated a classification of spammer detection techniques, including fake content, URL-based spam detection, detecting spam in trending topics, and fake user identification. In this paper, we only focus on the binary classification task, i.e., spammer or legitimate user identification. Many approaches employed machine learning methods to train a classifier to detect spammers. Some of them are jointly modeled user activities' information and the social following information to learn a classifier. Also, they proposed a hybrid technique that utilizes user-based, content-based, and graph-based characteristics for spammer profiles detection. They presented a policy for the detection of spammers on Twitter and used the popular techniques, i.e., Naive Bayes, clustering, and decision tree. An important line of research in spam detection relies on analyzing the tweet content, where suspicious use of hashtags or URLs is traced. The main objective is to study the semantics of short texts or messages in contrast with a set of Wikipedia text pages that are modeled and used as an aggregation of entities. Other directions adopted in detecting Twitter spammers focus on discovering traits or patterns that best describe the spammer's behavioral profile. In such works, the main contribution is to determine deceptive double characters for user profiles, which is done by analyzing nonverbal behavior variables as a function of time, such as follows and retweets.

### **Disadvantages of Existing System:**

□ The system is not implemented Convex-NMF based Supervised Spammer Detection with Social Interaction (CNMFSD).

□ The system is not implemented any ml classifier for test and train the datasets.

### **Proposed System:**

□ The system proposes a three-stage optimization model that conducts feature extraction and classifier learning simultaneously. First, we use Convex Non-negative Matrix Factorization (CNMF) and Non-negative Matrix Factorization (NMF) to induce latent feature from content information, then train an SVM classifier and finally, refine latent features using social interaction information as the input representations of the classifier. Through iteratively learning among content information, social interaction regularization, and classification model, the proposed method can train an accurate classifier.

 $\Box$  The system proposes a novel method to induce latent features and a novel social interaction regularization term. Using CNMF, we get the latent content matrix of spammers and legitimate users, respectively, and then obtain the user feature latent matrix by NMF according to the latent content matrix. The latent feature refine process is guided by the social interaction relationship matrix and the label information.

□ The proposed system evaluates our method on a large-scale real-world social network data set from Twitter, one of the largest social networks in the world. The experimental results show that the proposed framework can identify more spammers compared with baseline approaches. We conduct experiments to demonstrate the significance of using CNMF to induce latent features for spammers and legitimate users, respectively, and validate the effectiveness of the new social interaction regularization term

### **Advantages of Proposed System**

 $\Box$  The proposed system refines the latent features with predicted label information and social interaction information with the help of svm classifier.

□ The proposed system implemented UNLABELED USER CONTENT FACTORIZATION.

### SYSTEM DESIGN

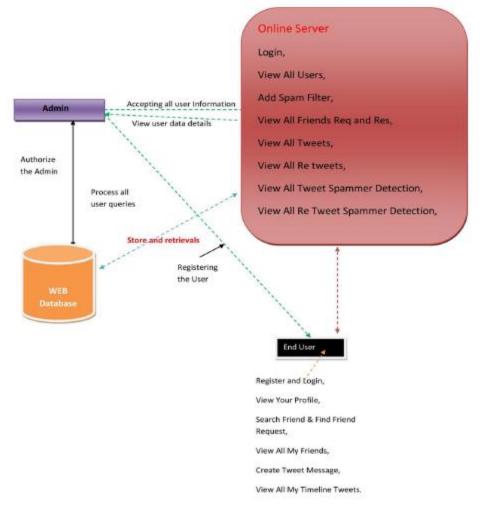
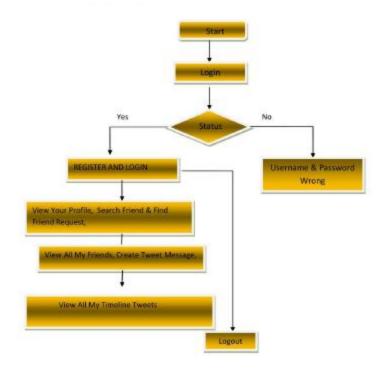


Fig-1 Block Diagram

Flow Chart 1: End User





# Hardware Requirements:

- Processor: i3 and above
- RAM: 4 GB
- Space on Hard Disk: 20 GB

# **Software Requirements:**

- Eclipse IDE
- JDK 1.8
- SQL YOG
- MYSQL
- TOMCAT

# **Operating Systems Supported:**

- Windows 7
- Windows 10
- Windows 11

# Technologies and Languages used to Develop:

- ✓ JAVA
- ✓ J2EE (JSP, Servlet)
- ✓ CSS
- ✓ HTML
- ✓ JAVA SCRIPT
- ✓ MySQL

Debugger and Emulator: ✓ Eclipse INPUT AND OUPUT DESIGN

# **INPUT DESIGN:**

Input Design plays a vital role in the life cycle of software development, it requires very careful attention of developers. The input design is to feed data to the application as accurate as possible. So inputs are supposed to be designed effectively so that the errors occurring while feeding are minimized. According to Software Engineering Concepts, the input forms or screens are designed to provide to have a validation control over the input limit, range and other related validations. This system has input screens in almost all the modules. Error messages are developed to alert the user whenever he commits some mistakes and guides him in the right way so that invalid entries are not made. Let us see deeply about this under module design.

Input design is the process of converting the user created input into a computer-based format. The goal of the input design is to make the data entry logical and free from errors. The error is in the input are controlled by the input design. The application has been developed in user-friendly manner. The forms have been designed in such a way during the processing the cursor is placed in the position where must be entered. The user is also provided with in an option to select an appropriate input from various alternatives related to the field in certain cases. Validations are required for each data entered. Whenever a user enters an erroneous data, error message is displayed and the user can move on to the subsequent pages after completing all the entries in the current page.

# **OUTPUT DESIGN:**

The Output from the computer is required to mainly create an efficient method of communication within the company primarily among the project leader and his team members, in other words, the administrator and the clients. The output of VPN is the system which allows the project leader to manage his clients in terms of creating new clients and assigning new projects to them, maintaining a record of the project validity and providing folder level access to each client on the user side depending on the projects allotted to him. After completion of a project, a new project may be assigned to the client. User authentication procedures are maintained at the initial stages itself. A new user may be created by the administrator himself or a user can himself register as a new user but the task of assigning projects and validating a new user rests with the administrator only. The application starts running when it is executed for the first time. The server has to be started and then the internet explorer in used as the browser. The project will run on the local area network so the server machine will serve as the administrator while the other connected systems can act as the clients. The developed system is highly user friendly and can be easily understood by anyone using it even for the first time.

# RESULTS



Fig-3: Output Of Home Page

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Fig-4: Admin Login Page

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Fig-5: User Login Page

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Fig-6: New User Register Page

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Fig-7: View and Authorize User from Admin

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Fig-8: Adding Spam Filters

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Fig-9: View Of All Tweet Spammer Users from Admin

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Fig-10: View Of All ReTweet Spammer Users from Admin

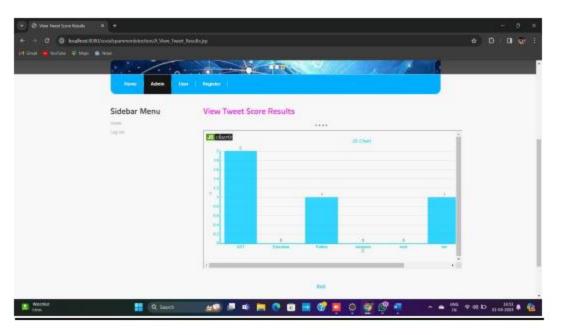


Fig-11: View Of Tweet Score results By Using Spam Filters

# **Conclusion:**

In this paper, we propose a new framework by taking advantage of content and social interaction information for social spammer detection. Different from existing methods that utilize users' the following information, the proposed method CNMFSD integrates users' interaction information based on the trained classification model. In addition, we introduce a new strategy to induce latent features using CNMF in spammers and legitimate users space for improving the performance of detecting spammers. Experimental results on a real dataset show that CNMFSD obtains better detection performance compared with existing methods. In this work, we employ Convex-NMF to learn latent user features for legitimate users and spammers, respectively. Such a fine-grained learning strategy makes the proposed model obtain accurate latent user representations, which further helps the model to achieve better performance. Besides, introducing social interaction into this task can also improve prediction performance. Although the proposed model outperforms baselines, it also has some disadvantages. First, in the classifier training stage, we do not consider the social interaction graph, which is trained solely based on the outputs from CNMF. Second, we use tf-idf to extract the user content matrices. However, spammer always posts some normal tweets to imitate the behavior of legitimate users. Thus, it is essential to distinguish the importance of tweets when we extract the user content matrix.

# **Future Enhancement:**

In future work, we will directly use raw tweets as the model input to learn user representations by distinguishing the importance of each tweet via deep learning techniques. After that, we plan to use graph neural networks to model social interactions among users.

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