INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE

ISSN: 2057-5688

COLLABORATIVE FILTER BASED GROUP RECOMMENDATION CROWD FUNDING

[1]Dr.CH.V. PHANI KRISHNA, [2]GUJJA MANI CHANDAN, [3]GUJJA PRATHYUSHA, [4]ALETI ABHINAYA

[1]Professor, Dept.of CSE, Teegala Krishna Reddy Engineering College, Meerpet, Hyderabad,

rajani.bashaboina@gmail.com

[2,3,4]BTech Student, Dept.of CSE, Teegala Krishna Reddy Engineering College, Meerpet, Hyderabad

gujjamanichandan@gmail.com , prathyusharao2610@gmail.com , abhinayaaleti@gmail.com

Abstract: *Crowdfunding platforms are a novel method of internet fundraising. The production of data from the crowdfunding platform has increased, but the benefits of this data have not. This has led to a state of "information overload." User-specific recommendation systems driven by data mining can play an effective role in solving this problem. This study introduces a collaborative filtering system that is driven by its end-users by fusing user input with the closest neighbor technique from machine learning. The results of this test demonstrate that the algorithm can provide useful project suggestions to those who utilize the crowdfunding site.*

Keywords: *Personalized recommendation; Crowdfunding platform; Machine learning; Collaborative filtering*

I. INTRODUCTION

Crowdfunding has emerged as “the next big thing” in entrepreneurial financing. By providing the much-needed seed capital for new business ventures, it has created plenty of new job opportunities and revived lost business ventures. In 2014 alone, the crowdfunding platforms raised over $16.2 billions of dollars worldwide, thereby becoming a viable alternative to banks, brokers, and other financial intermediaries for people seeking funding to jump-start their business ventures. The concept of crowdfunding is analogous to micro-financing where the required funds are collected by pooling small amounts of money from several individuals. Since its launch in April 2009, Kickstarter has grown to become one of the most popular crowdfunding platforms. Kickstarter terms the founders of a project as creators and the investors as backers. The creators express their ideas by posting a detailed description about their project. Usually, the description contains videos, images and textual information that explains the novelty of the project. In addition, the creators provide a detailed timeline, funding goal, and the rewards for different pledge levels. The need for recommender systems in crowdfunding platforms. Although the interest in using Kickstarter for crowdfunding has been outstanding, the success rate of projects is not very impressive. Statistical reports show that only about 37% of the projects succeeded in reaching their funding goal , which means over 60% of the crowdfund- ing projects in Kickstarter have failed. One of the main reasons for these failures is the lack of publicity . We argue that recommendation systems that suggest suitable projects to crowdfunding investors can address this problem. Thus, in this paper, we propose a probabilistic recommendation.

II. LITERATURE SURVEY

Historical user activity is key for building user profiles to predict the user behavior and affinities in many web applications such as targeting of online advertising, content personalization and social recommendations. User profiles are temporal, and changes in a user's activity patterns are particularly useful for improved prediction and recommendation. For instance, an increased interest in car-related web pages may well suggest that the user might be shopping for a new vehicle.In this project we present a comprehensive statistical framework for user profiling based on topic models which is able to capture such effects in a fully \emph fashion. Our method models topical interests of a user dynamically where both the user association with the topics and the topics themselves are allowed to vary over time, thus ensuring that the profiles remain current. We describe a streaming, distributed inference algorithm which is able to handle tens of millions of users. Our results show that our model contributes towards improved behavioral targeting of display advertising relative to baseline models that do not incorporate topical and/or temporal dependencies. As a side-effect our model yields human-understandable results which can be used in an intuitive fashion by advertisers.

III. PROPOSED SYSTEM

ISSN: 2057-5688

In this section, we introduce CrowdRec, a probabilistic generative model for recommending crowdfunding projects to groups of users. The recommendation model aims to capture the following observations: A crowdfunding group may support projects from multiple topical categories, A user's backing decision is based not only on her personal preference but also on the collective preferences of her groups; A group's collective preference to support a project is strongly correlated with the personal preferences of topically authoritative users (i.e., users expertise) within the group, The dynamic status of a project im- pacts both the individual investor's personal preferences and the group's collective preferences in backing crowdfunding projects.

SYSTEM ARCHITECTURE :

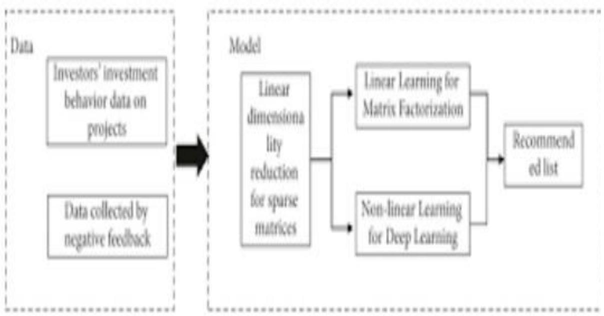


Fig.1 System architecture

MACHINE LEARNING

Before we take a look at the details of various machine learning methods, let's start by looking at what machine learning is, and what it isn't. Machine learning is often categorized as a subfield of artificial intelligence, but I find that categorization can often be misleading at first brush. The study of machine learning certainly arose from research in this context, but in the data science application of machine learning methods, it's more helpful to think of machine learning as a means of building models of data. Fundamentally, machine learning involves building mathematical models to help understand data. "Learning" enters the fray when we give these models tunable

parameters that can be adapted to observed data; in this way the program can be considered to be "learning" from the data. Once these models have been fit to previously seen data, they can be used to predict and understand aspects of newly observed data. I'll leave to the reader the more philosophical digression regarding the extent to which this type of mathematical, model-based "learning" is similar to the "learning" exhibited by the human brain.Understanding the problem setting in machine learning is essential to using these tools effectively, and so we will start with some broad categorizations of the types of approaches

CATEGORIES OF MACHINE LEANING

At the most fundamental level, machine learning can be categorized into two main types: supervised learning and unsupervised learning. Supervised learning involves somehow modeling the relationship between measured features of data and some label associated with the data; once this model is determined, it can be used to apply labels to new, unknown data. This is further subdivided into classification tasks and regression tasks: in classification, the labels are discrete categories, while in regression, the labels are continuous quantities. We will see examples of both types of supervised learning in the following section. Unsupervised learning involves modeling the features of a dataset without reference to any label, and is often described as "letting the dataset speak for itself." These models include tasks such as clustering and dimensionality reduction. Clustering algorithms identify distinct groups of data, while dimensionality reduction algorithms search for more succinct representations of the data. We will see examples of both types of unsupervised learning in the following section.

NEED FOR MACHINE LEARNING

Human beings, at this moment, are the most intelligent and advanced species on earth because they can think, evaluate and solve complex problems. On the other side, AI is still in its initial stage and haven't surpassed human intelligence in many aspects. Then the question is that what is the need to make machine learn? The most suitable reason for doing this is, "to make decisions, based on data, with efficiency and scale". Lately, organizations are investing heavily in newer technologies like Artificial Intelligence, Machine Learning and Deep Learning to get the key information from data to perform several real-world tasks and solve problems. We can call it data-driven decisions taken by machines, particularly to automate the process. These data-driven decisions can be used, instead of using programing logic, in the problems that cannot be programmed inherently. The fact is that we can't do without human intelligence, but other aspect is that we all need to solve real-world problems with efficiency at a huge scale. That is why the need for machine learning arises.

ISSN: 2057-5688

IV. RESULTS

To run this project double click on 'run.bat' file to get below screen

INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE
ISSN: 2057-5688

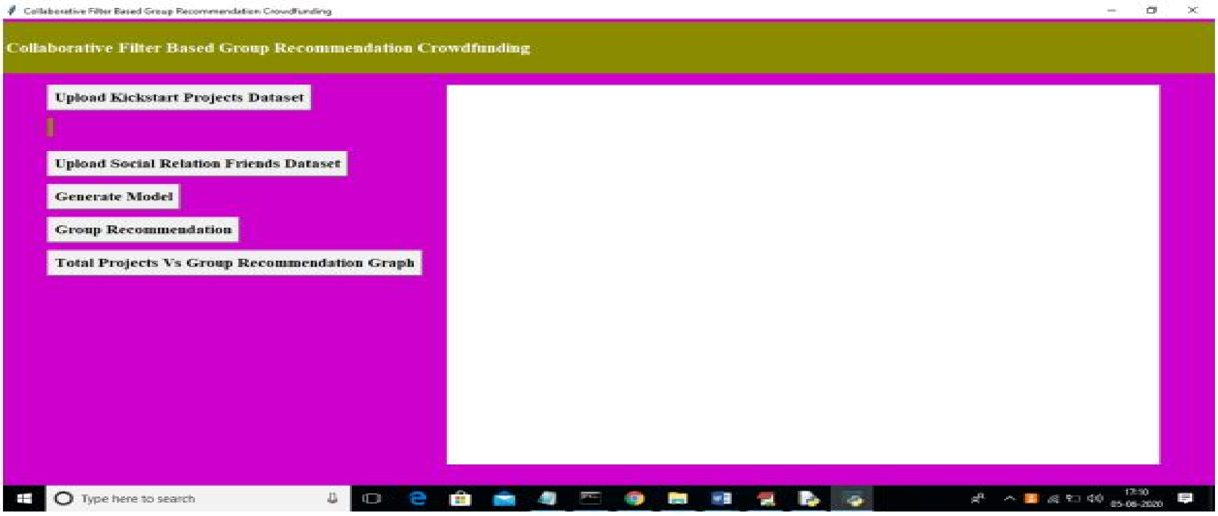


Fig.2 In above screen click on ‘Upload Kickstart Projects Dataset’ button and upload dataset

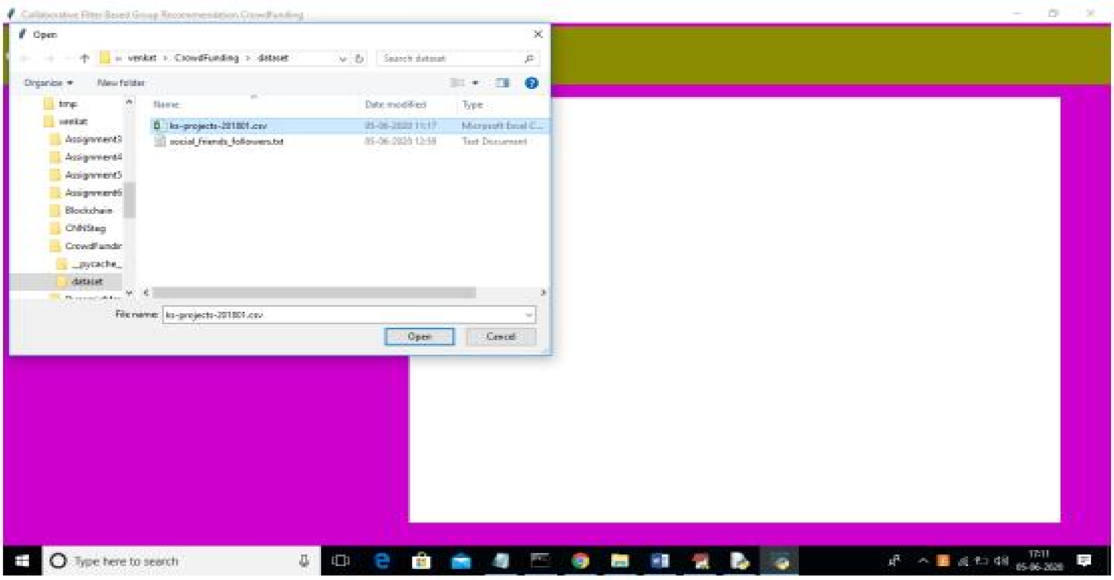


Fig.3 In above screen uploading file called ‘ks-projects-201801.csv’ kickstart dataset file and after uploading dataset will get below screen

INTERNATIONAL JOURNAL OF
TECHNO-ENGINEERING
IJTE

ISSN: 2057-5688

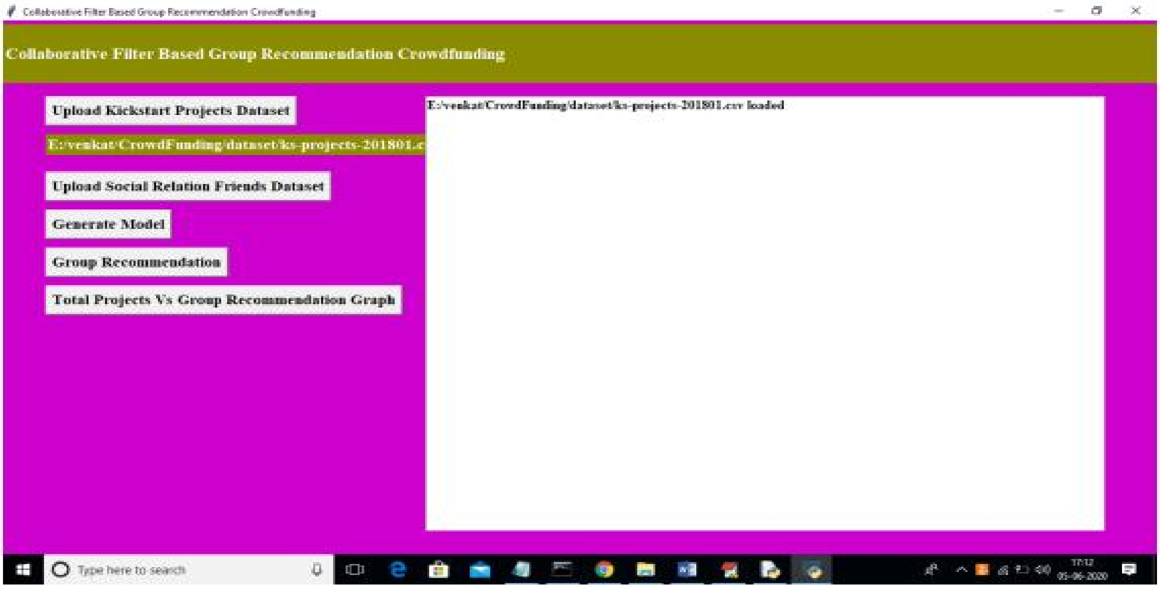


Fig.4 Now click on ‘Upload Social Relation Friends Dataset’ button and upload social link dataset file

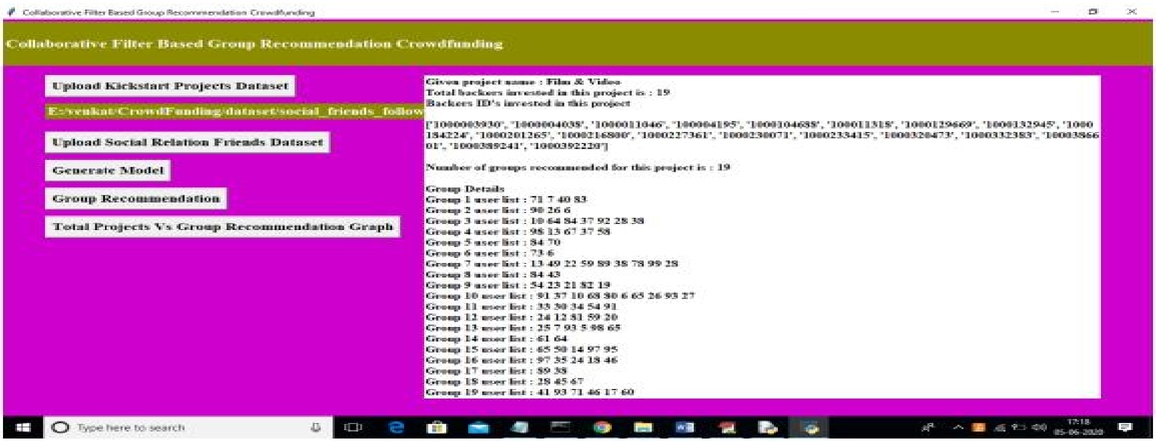
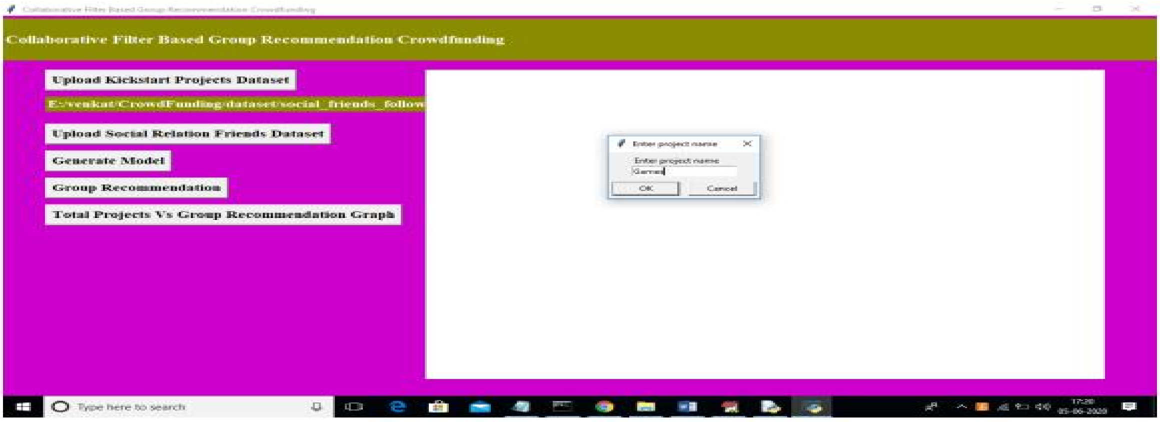


Fig.5 In above screen for ‘Film & Video’ project total 19 investors/backers invested amount and each investor will have some social group and all those groups will get recommendation of this project. In each group we can see ID’s of users separated with space will get recommendation for this project. Now we look for another project called ‘Games’



\

Fig.6 Now click OK to get below screen

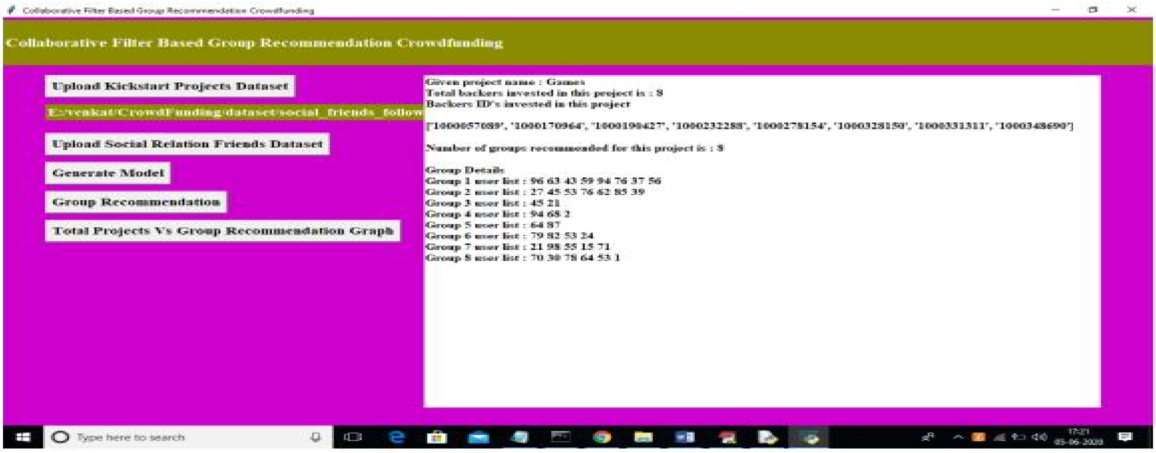


Fig.7 In above screen we can see total 8 users invested in this Games project and all groups of this user will get recommendation of this project. In square bracket we can see ID's 38 of investor/backers. Now click on 'Total Projects Vs Group Recommendation Graph' button to get below graph

ISSN: 2057-5688

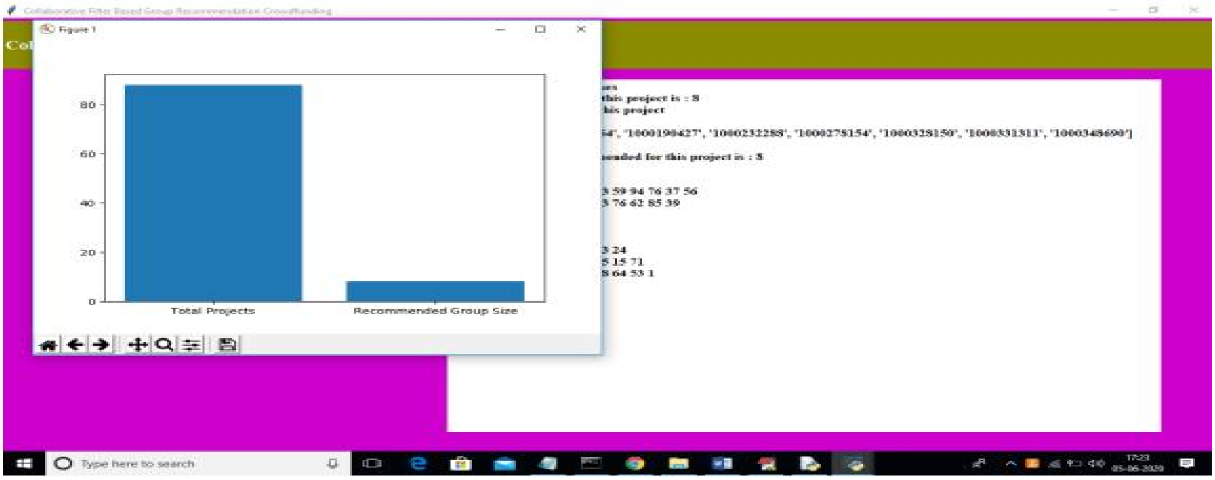


Fig.8 In above graph x-axis represents total projects and recommendation group and y-axis represents count of total projects and number of recommendation generated for given input project.

V. CONCLUSION

In this project, we introduced a recommendation frame- work for a popular crowdfunding platform, i.e., Kickstarter. We point out the challenges arising in Kickstarter, where the backing habits of its users depend on a diverse set of features, including topical, geolocation, temporal, and social traits. By exploiting the notion of groups, we proposed a recommendation model that effectively incorporates all these features when recommending projects to groups of Kickstarter users. Using a real dataset, we conducted a comprehensive evaluation to show that our model outperforms other state-of-the-art group-recommendation models in terms of a variety of performance metrics. Finally, we also studied the impact of various prior information and show that the on- going status (or popularity) of the projects plays an important role in improving the recommendation performance.

REFERENCES:

• G. Adomavicius and A. Tuzhilin. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. Knowledge and Data Engineering, IEEE Transactions on, 17(6):734–749, 2005.

• A. Ahmed, Y. Low, M. Aly, V. Josifovski, and A. J. Smola. Scalable distributed inference of dynamic user interests for behavioral targeting. In Proceedings of the

ISSN: 2057-5688

17th ACM SIGKDD international conference on Knowledge discovery and data mining, pages 114–122, 2011.

• J. An, D. Quercia, and J. Crowcroft. Recommending investors for crowdfunding projects. In Proceedings of the 23rd international conference on World wide web, pages 261–270, 2014.

• L. Baltrunas, T. Makcinskas, and F. Ricci. Group recommendations with rank aggregation and collaborative filtering. In Proceedings of the fourth ACM conference on Recommender systems, pages 119–126, 2010.

• D. Billsus and M. J. Pazzani. User modeling for adaptive news access. User modeling and user-adapted interaction, 10(2-3):147–180, 2000.

• D. Blackwell and J. B. MacQueen. Ferguson distributions via p olya urn schemes. The annals of statistics, pages 353–355, 1973.

• Y. Cha, B. Bi, C.-C. Hsieh, and J. Cho. Incorporating popularity in topic models for social network analysis. In Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval, pages 223–232, 2013.

• K. Chen, T. Chen, G. Zheng, O. Jin, E. Yao, and Y. Yu. Collaborative personalized tweet recommendation. In Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval, pages 661–670, 2012.

• W.-Y. Chen, J.-C. Chu, J. Luan, H. Bai, Y. Wang, and E. Y. Chang. Collaborative filtering for orkut communities: discovery of user latent behavior. In Proceedings of 41 the 18th international conference on World wide web, pages 681–690, 2009.

• W.-Y. Chen, D. Zhang, and E. Y. Chang. Combinational collaborative filtering for personalized community recommendation. In Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining, pages 115–123, 2008.

• J. Choo, C. Lee, D. Lee, H. Zha, and H. Park. Understanding and promoting microfinance activities in kiva. org. In Proceedings of the 7th ACM international conference on Web search and data mining, pages 583–592, 2014.

Prasadu Peddi (2018), Data sharing Privacy in Mobile cloud using AES, ISSN 2319-1953, volume 7, issue 4.