A MODEL THAT INTEGRATES USER ACTIVITIES FOR ANALYZING USER BEHAVIOR PREDICTION IN ONLINE SOCIAL NETWORKS

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Abstract:

Among the most frequently viewed websites in recent years are social media platforms like Facebook, Twitter, and LinkedIn. There is a current flurry of activity around research on social network user relationships. Clicks, shares, likes, forwards, and comments are additional characteristics that social networks might benefit from, but current link prediction algorithms only use topological structure and node attribute information. To fill this need, we provide a mechanism for predicting links based on users' engagement with the content, such as their clicks, shares, likes, forwards, and comments. Our study presents a link prediction model that integrates measures for topological structure and user activity. To define link prediction, the suggested measure may fill a gap left by current approaches. Implementing the suggested measures on standard datasets by appropriately training the classifiers is the subject of inquiry in this work-in-progress article.

Introduction:

Google Plus, LinkedIn, Facebook, and Twitter are just a few examples of the many online social networks that have massive user bases and continue to see annual user growth[1]. Researchers from academia and business are drawn to these networks because of their varied user base and potential for economic and societal impact [2]. Predicting which users will become linked in the future is the goal of link prediction [3]. Sites like LinkedIn and Facebook's "people you may know" feature is one example of a link suggestion. Owners of social media sites make a killing by targeting ads to specific users based on their preferences (also called recommender systems in the literature, a specific instance of the link prediction problem) and the number of people who interact with those ads (like, posting, commenting, liking, forwarding, etc.) on those sites. So, it's reasonable to assume that both users and social networks gain from link suggestion and prediction services. Current link prediction approaches primarily aim at predicting the linkages with the greatest linkage probability by taking user characteristics and topological structures into account [5]. However, they fail to take into account the value of analysing the additional attribute information provided by these social networks, such shares, comments, clicks, etc., in order to forecast linkages. In light of this, it is necessary to define new measures unrelated to the topological characteristics of online social networks in order to better forecast linkages, take into account these current aspects, and provide better recommendations. With the help of millions of people throughout the globe, social networks like Twitter, citation networks, follower networks, recommendation networks, and wikipedia networks create massive amounts of data quickly and dynamically. The many different kinds of networks need user and customer categorisation for the purposes of analysis, product sales data, network performance and design upgrades, and so on.

First, it uses various clustering criteria, decision rules, and hidden flows to classify users into distinct groups. Then, it uses certain generic user activity patterns and network access patterns to its advantage. These patterns are influenced by the social network's platform, adaptability, and extensive features, which in turn drive user behaviour in general. While some of these behaviors—those that survive in our conceptualization—are readily calculable from publicly accessible social network data, others may not be so easily disclosed. Such actions are considered to be transient behaviours among social media users. The concealed data, such web server access logs and covert work flow, may be used to indirectly calculate nonpersistent behaviour.

User Behaviour Analysis

There are a number of reasons why studying user behaviour is a crucial part of computational social networks. Behaviour analysis in social networks includes tasks such as identifying illegal behaviours, detecting anomalies, studying sentiment in bigger social groups, estimating popularity, reviewing products, and so on. This case involves quantitative and qualitative analysis of user activity based on data acquired from a social network. As you can see in figure 1 down below, we have presented an architecture for behaviour analysis. I. Location The Survey's Standard In comparison to other polls, ours varies in the following respects. Following in the footsteps of [35], we go into depth on the topic of behaviour analysis and examine the origins, factors, and features of social network user activity. Instead of limiting ourselves to only statistical techniques, we also include a wide range of modern approaches to social network user behaviour analysis, including classification-based, knowledge-based, soft computing, clustering-based, etc. Additionally, we have included a number of significant research topics and unanswered questions. Similar to [7] and [5], we want to categorise the many systems, software tools, and methodologies used to analyse user activity on social networks, as well as the platforms and features of these networks. Furthermore, we do comprehensive analyses of various approaches. Additionally, similar to [6], we have included a list of research topics and unanswered questions. In contrast to [8], our survey covers a wider range of topics than only social network activity analysis and categorisation. Numerous modern techniques and approaches to analysis are included. Our study includes a thorough explanation of the several kinds of social network datasets, as well as their collection and preparation. In contrast to [19], we not only outline practical research difficulties and open tasks, but we also provide suggestions for analysing user behaviour. In contrast to [23], the emphasis of our study is on the actions of social media users, including how they are described, the techniques and systems employed for recognising and detecting them, and how they compare to one another.

The Problem of User Behaviour Analysis

The conduct is difficult to quantify mathematically since it is a qualitative phrase. According to our perspective, this may be described as the user's regular participation in social network activities. The most common pattern of social network user activity is this, to be more explicit. When people utilise social networks for real-life communication, they engage in patterns of interaction that reveal which patterns have the most impact on the whole network. These significant network patterns must be identified. The general behaviour of the social network may be inferred from these patterns. This is crucial for social networks that include the patterns of interaction between actors with many connections. Consequently, we are keen to identify the social network community's most powerful interaction structures. Considering a certain graph G that has vertex V and edge E. There are a lot of social network interaction patterns buried in G, and we need to find the most common ones, P. One user's conduct in a social network is every distinct pattern inside that network.In order to conduct a qualitative analysis of user behaviour on a certain social network platform, it is necessary to first identify the network's users' most common interaction patterns.

Our Contributions

The vast literature on the topic of social network user behaviour analysis is systematically and comprehensively reviewed in this article. The following are some of the most important findings from this survey: (a) We know a lot about how people act in online social networks, but we don't know nearly as much about how their actions correlate with one another. Using examples, we attempted to establish a basic correlation with our behaviour study of social network users. (b) Persistent and non-persistent user behaviour analysis are the two main categories we've used. This is an innovative approach to studying the habits of people on social networks. (c) We have explored a broad variety of methodologies accessible in literature up to 2016, which is more than most previous surveys do for social network user behaviour analysis. (d) When it comes to the behaviour analysis task, most surveys skip over describing and representing the conduct of social network users. In this paper, we describe and compare several methods for characterising behaviour using publicly accessible information. (e) Along with a discussion of behaviour analysis approaches, we provide many strategies to characterise the conduct of online social network users and compare them. (f) We compile a list of all the technologies that play a role in analysing user activity on social networks. (g) The datasets utilised for analysis are also described. (h) Lastly, we bring attention to a number of significant theoretical and practical research concerns and obstacles.

Behaviour Characterization

To characterise the conduct of social network users, one must utilise suitable mathematical definitions. In order to extract useful patterns of conduct from massive social network datasets, this mathematical description of behaviour will be useful. This is a very intricate depiction since human conduct differs substantially from that of social media users, who in turn vary from one social media site to another. The ways in which a person uses several social media platforms may vary greatly, and these variations impact the user's behaviour across all platforms.

In addition, there are a number of challenges associated with accurately representing data for use in models, processing complexity, and generalising behavioural characterisations into computable forms. So far, attempts have been made to categorise user behaviour according to various patterns, sets of activities, methods of social network engagement, etc. Characterising user activity across different social network platforms included a number of different approaches. "Traffic analysis and characterisation of Internet user Behaviour" [21] by Maria Kihl et. al. (2010) examined data collected from a Swedish municipal broadband access network to find patterns in user activity. Internet traffic patterns, volumes, and applications are the main topics of this article. In addition, we model and analyse user activity parameters such as session durations and traffic rate distributions. In their 2011 research article "Modelling Users Activity on Twitter Networks: Validation of Dunbars Number"[10], Bruno Goncalves et al. presented a straightforward model of user conduct that mimics actual social behaviour by using limited priority queuing and time resources. In order to determine the theoretical upper bound on the number of solid social ties, they used a dataset consisting of six months' worth of Twitter chats that included 1.7 million people. A behavioural model based on user roles in social networks was developed in a 2011 article by Radoslaw Brendel and Henryk Krawczyk, "Primary role identification in dynamic social networks" [4]. Complex structures that emerge in social networks often undergo further evolution as time passes. Consideration of this dynamic reflecting the players' behavioural traits is necessary for the description of actor roles in such frameworks. One way to think about a position is as a series of tasks. Sequence diagrams represent the ordering of various activities, whereas pattern sub-graphs represent the kinds of activities themselves. In order to give each actor's major function in a dynamic social network, a role identification process is provided for these stated roles. In 2012, researchers Erheng Zhong et al. looked at user conduct in composite ways, which is the same user's behaviour across several social media sites. Modelling user activity from a single historical user record was the basis of several prior efforts [4]. It was noted that several individuals are active on multiple social media platforms simultaneously, including Facebook, Twitter, and others. Their interests and actions in various networks impact each other, which is a crucial point. To improve user modeling's predictive capabilities and address the data sparsity issue, this opens the door to combining what is known about users' actions across networks. They defined the issue as the transmission of information across many networks as a composite network. They began by using a user-specific hierarchical Bayesian model to choose the best networks inside a composite social network. Next, they utilise the chosen networks' linkages as well as data on related behaviours to construct topic models that may predict user activity. In 2013, Francis T. Odonovan et. al. investigated users' online actions in their study titled "Characterising User Behaviour and Information Propagation on a Social Multimedia Network" [9]. The sharing of multimedia files is one example of this, and its popularity may swing wildly. They went over the preliminary results of analysing demographic and psychological profiles linked with anonymised, scraped data from willing Facebook members. Five groups of users were identified based on their shared online habits and connected profile traits. In 2013, Ryan A. Rossi presented a research article titled "Modelling Dynamic Behaviour in Large Evolving Graphs"[17] detailing their work on social network graphs and their dynamic behaviour. A big time-evolving network was the basis for their studies, which aimed to model and describe the temporal behaviours of individual nodes. They have also looked at ways to represent the patterns of nodes' behavioural transitions. To account for the changing functions of the graph's nodes, they put forth a model of temporal behaviour. The model states that computationally efficient and generalisable interpretable behavioural roles exist. Their approach can (a) use the temporal behaviour of nodes and network states to identify trends and patterns, (b) forecast when structural changes will occur, and (c) determine when there will be anomalous transitions in the temporal behaviour of nodes. In their 2013 study "Modelling Temporal Activity Patterns in Dynamic Social Networks"[24], Vasanthan Raghavan et al. created probabilistic models for social network user activity that took into account the perceived effect of the user's social network. In 2013, "Social network based microblog user behaviour analysis"[23] was released by Qiang Yan et. al. It is becoming more clear that microblogs have an impact on the dissemination of information. In this article, a microblog social network was constructed by defining the following and being followed behaviours as out-degree and in-degree, respectively. A power-law distribution for out-degree, in-degree, and total number of microblog posts was observed, along with a short average route length, a high average clustering coefficient, and a small average diameter of linked graphs. There is a negative correlation between the degree of each user and the exponent of the total number distribution of microblogs. The rate of exponentiation slows significantly as the degree increases. They highlighted that induced drive and spontaneous drive led to the behaviour of posting microblogs, and they suggested a social network based human dynamics model based on empirical study in this article. A user behaviour model was examined in a 2014 study by Zhenhua Wang et. al., "Analysis of user behaviours by mining large network data sets" [7]. Internet application design and service extension are profoundly affected by the current trend in social behaviour research, which aims to understand human intelligence via mining petabytes of network data. Additionally, the most effective social sensor for these investigations may be operational mobile networks that provide massive amounts of data. This study delves into a real-life example of social sensing assisted by mobile networks, which reveals characteristics of mobile network users' actions via intelligent processing of massive data. This article uses massive user data sets to investigate user behaviour in three areas: communication, travel, and consumption. "Characterising Group- Level User Behaviour in Major Online Social Networks"[15] was published in 2014 by Reza Motamedi et. al. They compared and contrasted the group-level actions of Facebook, Twitter, and Google+ members in a comprehensive measuring study. They zeroed in on three key metrics—user connection, user activity, and user reactions—to record user behaviour. In addition, they analysed various parts of user activity for all groups over the course of two years using temporal analysis. The following practical insights are derived from this analysis: (i) While people on Google+ and Facebook are fast to voice their opinions, Twitter users are more likely to retweet posts they've received, making them spread even farther. Even though re-sharing is commonplace on Twitter, more people are likely to repost a message from a popular Facebook user than a popular Twitter user. section II Online social networks (OSNs) with more features tend to have more active members who respond more quickly. "Modelling Temporal Activity Patterns in Dynamic Social Networks"[14] was published in 2014 by Vasanthan Raghavan et. al., which examined users' conduct across time. Incorporating the user's perception of the social network's effect, this study aims to construct probabilistic models for users' temporal activity in social networks, such as posting and tweeting. Previous research in this field has produced advanced models of user behaviour, but these models either totally disregard or subtly reflect the impact of social networks. By suggesting a linked hidden Markov model (HMM), they are able to circumvent the model's lack of network transparency on an individual scale. In this model, the user's friends' aggregate activity influences the evolution of the user's activity along a Markov chain with a hidden state.

Behaviour Recognition

It is possible to infer users' true actions from their online profiles, posts, and other data collected from social media platforms. There were a lot of attempts to uncover user activity across various social media sites. The 2009 study "Identifying User Behaviour in Online Social Networks"[20] by Marcelo Maia et al. described human conduct. They went over the many ways in which user behaviour might be described. Methods for characterising user activity that rely on unique user characteristics have not worked well for online networking sites in the past. In these settings, users may engage with the site and one other in a myriad of ways, including uploading and viewing material, selecting friends, rating content, subscribing to people, and many more. For various user groups, distinct patterns of interaction are discernible. A approach for recognising and characterising user actions in online social networks was suggested in this research. Users with comparable patterns of conduct were grouped together using a clustering method. Later on, they proved that characteristics derived from users' social interactions serve as effective discriminators and enable the detection of relevant user behaviours. In 2009, K. R. Suneetha R. Krishnamoorthi used data mining methods on web server log data to discover web access pattern behaviour in their research article "Identifying User Behaviour by Analysing Web Server Access Log File" [1]. They elaborated on how remembering a user's preferred pages allows for better personalisation. These websites may be used to learn a user's regular browsing habits and then recommend other pages based on those habits. Improving the overall performance of future accesses may be achieved by identifying essential connections based on user access activity. Web mining data is often analysed using conventional data mining techniques including association, clustering, classification, and inspection to uncover patterns of sequential user activity. In 2012, the study "Modelling and Analysis of User Behaviour in Online Communities"[23] was published by Sofia Angeletou, Matthew Rowe, and Harith Alani, who investigated online community user conduct. For the purpose of modelling and computing community behaviour online, they used statistical analysis in conjunction with a semantic model and rules. Several Boards forum communities were subjected to this model's application.i.e., to classify members' actions throughout time and document the ways in which various combinations of actions are associated with good and poor development within these communities. "Social Media Data Analysis for Revealing Collective Behaviours"[3] was published in 2012 by Aoying Zhou, Weinign Qian, and Haixin Ma, who investigated collective behaviour in social networks. They demonstrated that, with enough social media data, collective user actions could be detected, analysed, and, in some cases, predicted. Their tests used data collected from Sina Weibo and Twitter, two popular social media sites. The activities of a big number of diverse individuals that are neither conforming nor deviant constitute collective behaviours. Within the framework of social media, researchers examine a range of group behaviours. Based on their research, we know that social media exhibit a wide variety of information flow patterns, some of which are more akin to more conventional forms of media like newspapers and others which are deeply ingrained in the structure of social networks. External stimuli, the structure of social networks, and the behaviours of individual users all have a significant impact on how hotspots evolve. On top of that, social media is usually resistant to the same kinds of recurrent external stimuli.

Behaviour Prediction

Characterising and recognising user behaviour across platforms in social networks is something we have covered so far. The aforementioned tasks have made use of a variety of methodologies and algorithms. What follows is a summary of recent studies that have contributed to the field of behaviour prediction. The following is an example of how future activity may be anticipated by analysing different social network data sets and by looking at past actions. In their 2012 research article titled "Collective behaviour prediction in social media: A survey," M. Vasudevan and M. Tamilarasi surveyed users' collective behaviour in social networks [19]. The term "collective behaviour" describes the actions taken by people in a social network setting. With the availability of behaviour data for some network participants, this aggregate behaviour opens the door to predicting consumers' online actions. This research delves at the ways in which social media networks might provide light on how people tend to act and what they like. Tasks like social media advertising and suggestion, as well as patterns of behaviour seen in social media, may be better understood using this. "Human behaviour at large scale in various social networks" was the subject of Adam Sadilek's dissertation [1]. Underlying this theory is the idea of consolidating and analysing sensory input from many people, regardless of how varied, loud, or incomplete it may be. In addition, they discovered that there are several sources of raw sensory data that may be used to build robust machine learning models. These sources include users' online communication content, both explicit and implicit social interactions, and interpersonal connections. Some areas where these models might be useful include deducing people's whereabouts and social networks from their online activity, comprehending human activities, and forecasting the spread of worldwide illnesses based on people's casual conversations. In their 2012 study titled "Whats Your Next Move: User Activity Prediction in Location-based Social Networks," Jihang Ye et. al.The underlying user movement pattern was modelled using the information from the check-in category [12]. Next, they suggested a system that, using an estimated distribution of user activity categories, would employ a mixed hidden Markov model to forecast the most probable location. Modelling at the category level has many benefits, such as accurately expressing the semantic meaning of user behaviours and drastically reducing the prediction space. This research by Michal Kosinski et. al. looked at how people utilise social networks and what factors influence their website choices and activity. This study, which is based on data from one million users, looks at the correlation between individuals' personality traits and their online activity, as measured by the websites they visit and the characteristics of their Facebook profiles [24]. The findings demonstrate the existence of significant psychological connections among users' personalities, website choices, and Facebook profile characteristics. In a nutshell, they said that internet advertising, search engine optimisation, and personalised content may all benefit from personality profile prediction. You may use this idea to foretell how people will act on social media. In 2013, researchers Sharad Goel and Daniel G. Goldstein looked into the topic of individual behaviour prediction [4]. They used a communications network that included more than 100 million individuals to predict very varied actions taken by customers of an online department store. In particular, they discovered that social network data significantly enhance the prediction accuracy of baseline models when used to determine the kind of people most inclined to take action. Under the title "Predicting Individual Behaviour with Social Networks," they released their academic study. To predict user behaviour in social media, Tad Hogg et. al. released "Stochastic Models Predictive Models" in 2013. Several variables influence the amount of user-generated material in online social media [2]. Among these factors are the site's layout for new material, the user's frequency of visits, the number of friends followed, the activity level of these friends, and the user's interest in and use of the content. They unveiled a methodology for stochastic modelling that correlates user actions with specifics of the site's UI and user actions. In addition, they detailed a method for using the data at hand to estimate the model parameters. They used the algorithm to forecast the reactions of advocates' followers to their tweets on contentious issues, notably focussing on Twitter debates.

Methods & Approaches For Behaviour Analysis

In this study, we have covered three subcategories of social network user behaviour analysis: behaviour characterisation, behaviour recognition, and behaviour prediction. Users' community membership habits exhibit a high degree of consistency, even though online forums are very random and structural links are less committed. Thus, it has been said that the actions of SN users might vary according on the topic or platform. For any kind of social media platform, there is no universally accepted description of user conduct. To estimate a dynamic model of user behaviour in a social network site, Ahn Dae-Yong and Randal Watson used unique data on the daily login activity of MySpace.com users in their 2010 research article, "A Dynamic Model of User Behaviour in a Social Network Site" [2]. There are two possible outcomes (interactions, utility flow over time) of using a social networking site: (1) keeping the quality of interactions with current friends high, and (2) increasing the amount of interactions by adding new friends to the network. It is reasonable to use a model that considers customers' future behaviour to examine social media site use, as both of these impacts will lead to a greater flow of utilities. A commendable method for modelling and analysing user behaviours based on their internet activities (communication, workshop, play, etc.) was proposed by David John Robinson in his 2010 PhD thesis, "Cyber-Based Behavioural Modelling" [5]. They laid the groundwork for cyber-based behavioural modelling by presenting a framework to detect, extract, and evaluate cyber behaviours. Changes in individual and group behaviour may be studied, predicted, and detected using these methods. Internet users' actions while using proxies were examined by Kartik Bommepally et. al. in their 2010 study "Internet Activity Analysis Through Proxy Log" [15]. They also looked at how people used the Internet. Server log data allows for the analysis of user use behaviour. Researchers Laszlo Gyarmati and Tuan Anh Trinh conducted a large-scale measurement study of user activity in many major OSNs in their 2010 research article "Measuring User Behaviour in Online Social Networks" [17]. In order to track what users are up to, a measuring framework was built. We tracked over 80,000 people for six weeks by downloading over 100 million profile pages using over 500 PlanetLab nodes distributed throughout the world. They used the data to tackle two major problems with OSNs: how to characterise user actions and how to analyse use trends. The study by Pietro Panzarasa et al. on user patterns and dynamics [2] "Behaviour and Interaction: Network Analysis of an Online Community" (2010) uses a community's longitudinal network data to look at how people utilise the system, what they do socially, and what mechanisms are driving those patterns. In the online community, people gradually bond with one another via online conversations, making it a classic example of a complicated developing social network. In his 2010 PhD thesis titled "SOCIOSCOPE: Human Relationship and Behaviour Analysis"[13], Huiqi Zhang put forth a model for analysing human behaviour, social networks, and relationships using data collected from mobile phone calls. The complexity and variety of human social conduct makes it impossible for a single method to identify all of its characteristics. In order to measure social groupings, connections, and communication patterns, anticipate the strength of social ties, and identify changes in human behaviour, he employed different probability and statistical methodologies. For scenarios in which the number of other actors' choices determines the relative costs and advantages of two options, Mark Granovetter of the State University of New York at Stony Brook wrote an essay titled "Models of collective behaviour" [22]. An actor's threshold, or the fraction of other actors who must make a choice before they do so, is the central idea. Starting with a distribution of threshold frequencies, the models enable the computation of the final or equilibrium number for each choice. We take into account the stability of the equilibrium as a function of different potential threshold distribution modifications. We emphasise that accurate distributions for outcomes are very important. Because groups with comparable average preferences may produce vastly diverse outcomes, it is risky to draw conclusions about individual inclinations from group results or to attribute conduct to universally accepted standards. Riot behaviour, invention, rumour spread, strikes, voting, and migration are some of the suggested uses. Topics covered in the research include measurement, falsification, and verification.

Datasets For Behaviour Analysis

Methods for analysing user activity on social networks may make use of a number of publicly accessible datasets. What follows is a list of the most popular datasets. Practical study of social network user activity requires capturing and preprocessing of high speed communications from these networks. A variety of technologies are used to collect and analyse data pertaining to social network traffic. For the purpose of behaviour analysis, several kinds of data are used. To investigate the group dynamics of social network users in the context of the community identification issue, Krishna Das et al. [16] employed data sets that are comparable to the ones listed below. Behaviour analysis makes use of the following data types: (i) Personal Information: These are the details that a user gives when signing up for a social media account. Statistical analysis of the research article (ii) Posted Data: Information that members voluntarily provide online, including posts, comments, and messages.Due to the very sparse nature of the data, analysing datasets of this kind presents significant challenges. These, however, are very necessary for persistent behaviour analysis, which includes things like product ratings, reputation and trust assessment, sentiment analysis, and so on. ("iii") Derived Data: Information that has been "mined" or "derived" from other sources via correlation. Included in this category are data used for non-persistent behaviour analysis, such as log server data, web traces, browser history, time stamp data, etc.

Conclusion:

We examined user conduct in OSNs from three angles: characterising the behaviour, recognising it, and predicting it. The research took into account a wide variety of user behaviours on social media sites, including connection and interaction types, traffic patterns, user positioning within the network, and more. We looked at the current representative systems and suggested some ways forward. We also zeroed down on two separate but related areas of study, such as social media users' persistent and non-persistent behaviours. With the inclusion of several publications up till 2016, this survey will aid in comprehending the chronological progression of research on user behaviour analysis.

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