Individual "Profiling": Understanding and Predicting Users' Behaviors in Online Communities

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INTRODUCTION

As social networks have grown considerably in the last decade, the prevalence of online communities has similarly skyrocketed and influenced the dynamics of social networking. Sites like Facebook and Reddit foster, both inherently through their designs and easily through built-in features, ways for people who have similar interests to form "communities". These communities lead to "intracommunity" interactions between members of the same community and "intercommunity interactions", where members of one community engage with members of another [1].

Research indicates that an individual's actions and activity within communities is particularly interesting, where users often show great "loyalty" to them, adopt their lexicon and attitudes towards topics, and play certain roles that influence the group dynamic (leader, follower, etc.). Because members of the same community tend to show "similarity" in thought, communities can often become "Echo Chambers" where community members only receive opinions that are similar to their own, creating a "hive-mind" mentality [2]. Additionally, through analysis of "viral" diffusion online we know that certain "nodes" (be it communities or individuals) tend to hold influence much larger than comparable nodes.

REASON BEHIND RESEARCH

Therefore, because these online communities are so nuanced and influential online, they can provide information with regards to an individual's feelings on certain topics, how strongly they care about them, and how influential they are on their fellow community members.

I would like to utilize these findings in predicting not only how individuals feel about certain topics or communities but also what kind of role they would play in that community. Based on an aggregate of an individual's habits (actions and activity) in their favorite communities, I would like to survey and weigh how loyal they are to each community, how much influence they possess in that community, and their sentiments towards other communities amongst other characteristics in building a way to create individual user "profiles". These profiles would then be used in predicting how they would feel about communities foreign to them, how strongly they would feel about them, and what role they would play if they possibly joined. In doing so, I hope to gain understanding of individuals based upon their most "intimate" interactions, which could be more telling than just tracking their most visited sites.

CURRENT RESEARCH AND APPROACHES

In recent years, research on online communities and their interplay with their members has revealed a deep relationship. Communities are highly correlated with influencing a user's thoughts (measured through sentiment analysis of their contributions), actions (where actions become more similar to the group "norm" over time), and individuals they interact with (where communities are often composed of highly "similar" individuals). I will be discussing research that lays the foundation for my research proposal.

Loyalty

According to Hamilton et. al, "loyalty" within an online community refers to the "preferences and commitments of active, engaged users" in the context of "multi-community dynamics" [3]. "Loyal users" proportionally visit and engage more with this community compared to the others they visit, and they often "use language that signals collective [community] identity" [3]. Additionally, "loyal communities" retain a high proportion of loyal users and structurally they exhibit less network fragmentation, fewer triadic closures, and denser interaction networks, indicating that they are more "tight-knit and cohesive" [3].

When studying individual loyalty to online communities, Hamilton et. al classified Reddit users based on their post history as "loyal" or "vagrant". Loyal users statistically preferred "esoteric", or community-specific, content where "esotericity" was computed using the Inverse Document Frequency (IDF) of that phrase in the corpus of that community's content. Moreover, they were able to predict future loyalty of an individual by the first few posts they contributed to the community. Using a random forest classifier and features defined by the community's linguistics, predicted loyal users had "intrinsic affinities for particular elements" of language of the community at much higher rates than future vagrant users [3]. Ultimately, Hamilton et. al were able to understand the relationship between user loyalty and community-specific characteristics, predict future user loyalty, and learn why certain communities fostered loyal bases.

Online Community Influences

Influence on Individual's Beliefs (Sentiments)

In their paper "Collective Emotions Online", Chmiel et. al study the changes in "emotional valence", or general emotional classification, towards topics/posts from the perspectives of both individuals and the overall community. By categorizing every comment on BBC Forums as positive

(1), negative (-1), or neutral (0) using sentiment analysis software, they found "clusters" of like-minded individuals and tracked their growth. Modeling the probability of finding a cluster of length n individuals that share the same emotion as $P_{i.i.d.}{}^{(e)}(\geq n) = p(e)^{n-1}$ (where *p(e)* is the probability of a negative or positive emotion), they found that these clusters followed the power law [4]. Namely, as clusters of similar emotion get larger, they have a higher chance of becoming bigger, indicating that communities tend to foster "sub-groups" that become more influential and can influence sentiments on a large scale.

This phenomenon is similar to results seen by Mitrovic et. al who found "singular events corresponding to propagations of emotions in bipartite networks of blogs" [5]. Another interesting trend Chmiel et. al found was that "[users] tended to express emotions that have been recently used in the discussion", indicating that individuals exhibit time bias as well [4]. By understanding this aspect of online communities, one could infer whether an individual would "join" the majority in the community based on his past actions or sentiments towards related topics.

Influence on Individual's Actions (Behaviors)

Similarly, research indicates that online communities can also affect an individual's behavior. Crandall et. al present the "Feedback Effect", which suggests that individuals tend to interact with those who are similar to them and then interactions between them lead to further similarity [6]. To model this effect and show its prevalence in online communities, they tracked edits made in Wikipedia over time, noting the communication network of each editor and relating their activity vectors to times before and after interactions. They found that the similarity of two nodes (individuals) can be calculated by the "weighted Jaccard coefficient", $Jac(\vec{x}, \vec{y}) = \frac{\sum_{j=1}^{m} \zeta_j \min(x_j, y_j)}{\sum_{j=1}^{m} \zeta_j \max(x_j, y_j)}$ where $\vec{x}$ $and \vec{y}$ are the individuals' respective activity vectors [6].

Therefore, using this measurement of similarity they were able to accurately predict an individual's future behavior based on the actions of those in their previously existing "friendship links" and those who are "similar" in the overall network. They did this by utilizing an "urn process" that chose discretely from actions in the past, and like Chmiel et. al they found that this phenomenon too abided by the power law, where an individual's actions tended to become more similar to the actions performed by most of those around them [6]. Ultimately, this paper illuminated a well-known fact seen in the real world: that we tend to act similarly to those we are around the most.

Individual Relationship with Online Community

Commitment to Online Community

Like Hamilton et. al, Danescu et. al studied online community interaction through the lens of language, but instead of focusing on user "loyalty" they tracked user "commitment" to the community by looking at their language with regards to the community norm over time. Because members of online communities tend to join and leave at any time, looking at the language of those who stay for some period of time can be indicative of who will stay longer and who will not. In this paper, Danescu et. al calculated the "entropy" of an individual's posts over time, $H\big(p, SLM_{m(p)}\big) = -\frac{1}{N} \sum_i \log P_{SLM_{m(p)}}(b_i)$ where a post p's entropy is calculated according to a snapshot language model (SLM) [7]. Higher post entropy indicates more deviation from the community's language norm at that time.

By analyzing two beer forums, they discovered an interesting "two-stage lifecycle", where (1) new users align with the language community during the "linguistic innovative learning phase" then (2) users stop responding to changes in community norms during the "conservative phase" [7]. After seeing just a few posts and calculating their entropies, they were able to accurately predict how committed individuals would be in the future, but among those who were committed they found that most deviated from the norm at some time. Although this phenomenon is indicative of who will be committed for at least some time to the community, it could also inform how influential an individual is based on when they deviate and how the rest respond to it.

Role in Online Community

Finally, by studying Twitter discussion groups (TDGs) Ellis et. al were able to not only learn the role of individuals in their overall communities but also predict the longevity of these communities based on the role relationships within them. Using a mixed membership stochastic block model, they extended the interactions between users in the TDGs to represent the exchange of attention among the participants. Individuals were then given certain "archetypes" based on the ratio of interactions that were directed towards them versus the interactions they initiated towards others. Individuals of archetype "A" received the most attention while individuals of archetype "B" gave the most attention, and archetype "C" were the least active [8].

When predicting future "influence" they found that an individual's given archetype was highly correlated to the influence they possessed. Moreover, they characterized each community based on the community's levels of "equality" and "mobility", where high equality means attention is divided evenly among its participants and high mobility allows different levels of attention per member from session to session [8]. One measure of equality, similar to fairness seen in class, is measured by the proportion of the top 10% of individuals who hold the most "weight" compared to the whole network, calculated as so: $Top10_k = \frac{\sum_{i \in S} \pi_i(k)}{\sum_{i \in N} \pi_i(k)}$. Ellis et. al found that higher mobility and lower inequality create and predict "healthier", or longer-lasting, communities. Therefore, this paper provides good background to understand how to draw an individual's role in a community from his interactions and predict what kind of members a community needs in order to ensure its longevity.

RESEARCH PROPOSAL

Although the above papers touch upon the inferences I would like to make, none of them combine an individual's community characteristics (loyalty, influence, similarity network, etc.) to predict a user's future sentiment and behavior holistically as I would.

Overall Goal

In aggregating over a user's interactions within their "favorite" communities, or ones they are most loyal to, I hope to weigh each "heuristic" (characteristic defined above) properly in creating an overall "profile" of an individual that correctly predicts future actions and behaviors in "new" (to the individual) communities. For example, if I were to look at the activity and post history of Reddit user "neilKumar" in his top 10 favorite subReddits (communities eg. "NBA", "HipHop", "Nintendo", etc.), I would like to see if I can predict his emotional valence (feelings), loyalty and commitment, and role he would play in a community that is "foreign" (or non-visited) to him, such as "ForeignCinema".

By "user profile", I consider a set of classifiers that have been trained on the user's activity (pages visited) and actions (post history). In my classifiers, I also hope to utilize sub-heuristics that capture nuances in online communities that are not always captured in researched models. For example, if a user holds a position of power, such as being a moderator, I would like to encapsulate that into his "influence" sub-heuristic which would then inform his predicted role in another community. In "The Structural Virality of Online Diffusion" by Goel et. al, they deduce that "structural virality", or quantified information cascade in online communities, is closely tied to the "size of the largest broadcasts", or the influence of the most "powerful" nodes (individuals or groups) as measured by the infection model [9]. When looking at an individual's predicted role, I can also be informed by the size and influence of the community he currently holds power in, where someone of archetype "A" in a very influential community (eg. "The_Donald") would probably hold a similar role in a less-influential community. Therefore, I would also like to weigh each community an individual is in in context of the influence of the others, where holding a position of power in a relatively weakly influential community does not predict the user to be influential in another.

Data Collection

Because Reddit has public user data, communities that are specific-enough to demonstrate user loyalty and commitment, and volumes of post history per individual, it serves as a good basis to scrape data from and derive the desired models.

Reddit user behavior can be broken down into activities (reactions (upvotes/downvotes), communities visited) and actions (post history). Additionally, because I would need a significant amount of data per individual (thousands of tracked posts and reactions), I want to limit my number of studied individuals to a significant number that is not overwhelming (say 10,000). Regarding the number of communities I am looking at per individual, since I am initially targeting individuals who already exhibit high activity on the site, I want to study their interactions in only the top 10-20% of the communities they are most loyal to. Although this process might be time-consuming (hundreds of hours), I believe it would not cost a dime and provide useful data. Ultimately, for each individual I would like to create a database populated by textual post history and reaction activity tied to the community they come from.

Methods of Analysis

Since I am measuring "characteristics" of individuals that already have research-backed methods, I will be employing tactics utilized in the aforementioned papers to build my model. For example, since I will have lots of post history per individual, I will employ the three steps of sentiment analysis, (a) separate objective from subjective texts, (b) predict the polarity of the subjective texts, and (c) detect the sentiment target as seen in Chmiel et. al to derive a user's sentiment towards a community [4]. To measure the user's loyalty and commitment, I will calculate the user's post history "esotericity" and "entropy" with regards to the community norm over time, respectively. Additionally, based on interactions between an individual and a community, using a mixed membership stochastic block model and analysis of his similarity network, I can characterize generally what role a user has played and how influential or influenced he is in his community interactions.

In an effort to build upon past research, I will be incorporating methods that might enhance this process. The paper "DeepWalk" by Perozzi et. al suggests a better way to understand social interactions by utilizing an unsupervised learning algorithm to model social representations [10]. Instead of characterizing individuals solely on the amount of "attention" they give and receive, they quantify how "adaptable" and "community-aware" individuals are alongside how "powerful" they are to give a more nuanced understanding of role. Additionally, Belák et. al, in their research on cross-community influence, found a way to characterize different communities based on how "influential" or "dependent" they are in a cluster analysis of the whole network [11]. Incorporating this would more accurately inform the role an individual would play because being influential in a more "dependent" community might not mean as much.

Once the above methods of data collection and analysis are in place, I would like to create my set of classifiers that would produce both quantitative and qualitative profiles of individuals. Given a "new" community to test against, I would predict a user's sentiment towards it (-1 to 1 where -1 is extremely negative and 1 is extremely positive), how loyal and committed they would be to it (0 to 1 where 1 signifies full loyalty or commitment), and what role they would play (qualitative data such as archetype based upon a pre-set categorization I derive). To measure the accuracy and progress of this model, I would track the individuals I chose histories' and compare my predictions to their actions, where I would characterize their actions in new communities and see if they align with what my model would predict. Additionally, to optimize my model I would run modified gradient descent or similar techniques to re-weigh the heuristics and maximize prediction capability. Compared to the previously shown research, I believe my research would build upon all of them successfully because it aggregates key quality features from each of them in a novel way. For example, understanding current user loyalty might be indicative of future loyalty, but Hamilton et. al could have incorporated an understanding of "commitment" based on the user's posts to accurately predict the user's future drop off in activity. Similarly, if we know that a user is loyal (in terms of time) to a community, but his overall similarity network exhibits much different beliefs and behaviors, he might not be as interested in this community as his loyalty figures would indicate. Therefore, because I believe all of the above characteristics are helpful in understanding and predicting an individual's online presence, I think my model would solve my proposal effectively.

IMPLICATIONS OF RESEARCH

Advertising

If I were to succeed in being able to accurately predict how much an individual would like and interact with a community, it would be a major change to the advertising industry. Although companies now advertise to users based on their activity (sites visited) and the activity of those similar to them (based on recommendation systems), I do not think any of them currently target individuals based on their most intimate interactions, online community posts and activity. Because people tend to put the most time in topics they are interested in, if companies could harness this data and present to them products or posts related to communities that appeal to them and seem like they would invest time in, they could target individuals much more effectively. Additionally, companies could utilize an individual's perceived role among different communities and market to individuals that would make their community more "equal" and "mobile", so if a Coca-Cola subReddit needs more content the company would target more "influential" users who also would probably enjoy the product. Utilizing this research would not only allow companies to target individuals more effectively, but it would also allow them to strengthen their online presence and balance their own communities.

Social Network Theory & Research

Many of the above phenomena can be explained by widely seen social networking models including power law, infection in networks, clustering influence, similarity in networks, and more. Although my research does not suggest anything entirely innovative, it encapsulates approaches to track slightly different qualities of individuals in online communities and combines them in a way to minimize reliance on any one metric. If others were to build off my research proposal, they could understand characteristics of online communities and individuals within them even further. For example, by understanding an individual's likes, loyalty, and general role, we could perhaps predict whether they would create a new community to serve their own interests. Overall, I believe this proposal opens up many avenues from which to work off and understand online communities further.

CONCLUSION

Understanding the relationship between an individual and his actions in online communities is not straightforward, where ambiguities in perceived meaning, activity, and influence can never truly be verified because of the inherent randomness of the Internet. Although someone's online presence may give a glimpse into what they enjoy and do, there will always be some disconnect in predicting their future actions because our models cannot predict the tangibility of how a user actually acts and feels in real-life. With the advent of fake internet personas and "trolling", a user's actions may be highly distinct from their real life. Ultimately, however, I believe my proposal suggests an interesting solution in understanding a popular facet of social networks in a new way.

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