Generic Architecture of a Social Media-driven Intervention Support System for Smart Cities

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ABSTRACT

With the growing adoption of Internet and mobile technology, the information exchange via social media has greatly influenced both government and corporate operations. Social Media has not only become a platform for mere entertainment and communication but a great source of innovation for public services. While millions of users generate data on these social media platforms everyday, the challenge is to effectively extract and analyze information from the big social data in a productive manner for improving public services of future smart and connected communities.

In this paper, we propose a novel approach of creating an *Intervention Support System* (ISS) interface for public services of a city to easily and effectively monitor attitude trends of public for topics of interest (e.g., a cleanliness awareness campaign), while hiding all the complex functionality of collecting, processing, and mining big user-generated data from social media. We first discuss the generic architecture of ISS and its various components, followed by demonstrating the efficacy of the proposed architecture via an application design to identify intervention targets on social networks for supporting public campaigns against the key societal crisis of gender-based violence. We conclude with the challenges, limitations, and future work direction to effectively assist future smart city services via big data analytics approaches.

CCS CONCEPTS

• **Information systems → Data analytics**;

KEYWORDS

Smart Cities, Social Media Analytics, Intervention Support System, Attitude Modeling, Gender Based Violence

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1 INTRODUCTION

Social Media has become an inseparable part of our lives today. It offers not just a platform for entertainment and communication, but also a pathway to business and growth. Social media platforms have grown rapidly in the past decade along with the generation of enormous data. Tera-bytes of data is generated publicly on these platforms. Although such data is available easily, the analysis of such data for any sensemaking is a challenge due to a variety of factors including grammar-free language usage, diversity of user demographics, variety of content types, and scale of noisy-irrelevant content [13]. Albeit observing the potential of exploiting this one of the major source of big data, different types of organizations – both for-profits and non-profits – have been exploring ways to use this data for improving their workflows and services as well as public engagement [12]. With the growing development, there is an upsurge in the number of business applications that use social media data for better productivity, analysis of the target customer groups, and better customer satisfaction [16, 22]. Likewise, it provides an unconventional source of information and a novel platform for engagement with public for the governments and public services in a city as well.

Social media analytics added with a supporting intervention system is essential to adapt to the next generation data sourcing and technologies to mine that data within the smart cities context. To understand the pattern of this change is to analyze the user behavior from the user-generated content on social media platforms. As a solution to assist organizational decision makers in extracting relevant insights and manage overload of big social media data, we propose a novel data-driven approach to create an Intervention Support System (*ISS*) based on our prior system *CitizenHelper* [13]. The proposed *ISS* system design (c.f. Figure 1) consists of a pipeline of four fundamental data operators for analyzing big social data for smart city analytics: data sourcing, acquisition and filtering, distributed behavior modeling, and interactive visualization. The proposed design is well-suited for scalable, distributed computing frameworks to allow a tractable approach towards handling big social data. ISS interface helps in identification of target user candidates or groups on social media platforms for designing intervention strategies to support organizational services, such as public awareness campaign teams in the government. An *ISS* system acts as an interface between the enormous data and behavioral intelligence to inform the business workflow decisions.

The applications of *ISS* architecture can help smart city analytics within different organizations including non-governmental organizations (NGOs) with limited resources. Such applications

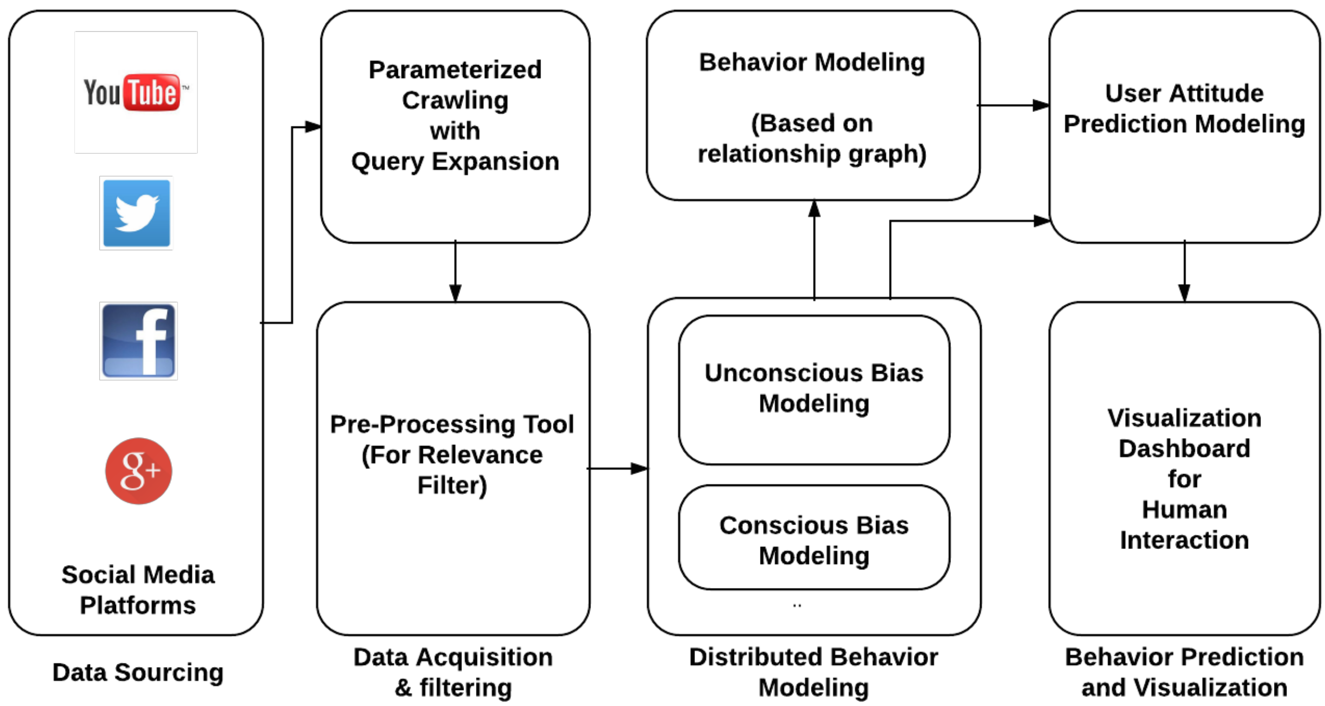

Figure 1: A generic architecture diagram for Intervention Support System

could help make decisions on the basis of intelligent insights of public participation as well as user-generated content analysis on social media to redefine the organizational actions and activities for the general benefit of the target users. This could be easily observed with the increasing number of domains adopting social media strategies. For instance, an *ISS* can be used for public health issues to predict attitude trends of public towards flu shots using Twitter data [16], or for gauging public attitude towards upcoming socio-economic policies to encourage crowd-participation in policy making through Twitter [7], or understanding public attitude towards more socially-sensitive issues like gender-based violence [19] for assisting social activist NGOs. Application of ISS-driven model can also be used by political parties to examine the pattern of voter wishes on specific issues, or by companies to analyze the effect of a new product launch and its expected reach, or by NGOs to examine the demographic groups affected by specific biases in any region.

Given that the proposed ISS design has a generic architecture, it could be customized as per the need of the end users by the domain and relevant tasks of the organizational actors. To verify and validate the proposed architecture, we demonstrate an *ISS* to assist an NGO or governmental agency in selecting a group of Twitter users for intervention related to gender-based violence, by modeling the various relational factors (c.f. Figure 2) guided by socio-psychological theories for inference of attitude of the users. This system not only aims to help the *NGOs* to put their limited resources to effective use, but also helps them to know their target customer audience, i.e. public, better based on the content posted by public on social media.

The rest of the paper is organized as follows. Section 2 provides the theories supporting the design and architecture of the model based on psychological and practical heuristic approaches. In Section 3, we describe the generic architecture of *ISS* and the characteristics of its various components. Section 4 presents details on a demonstration of the *ISS* architecture in a practical application of gender-based violence using data from Twitter micro-blogging service. Finally, section 5 presents contributions of this generic framework, limitations with the current system, and future work.

2 RELATED WORK

We discuss the related work across three different focus areas: first, the social media applications in diverse domains; second, the social media research in modeling user behavior and corresponding socio-psychological theories that are relevant to inform architecture design of an *ISS*, and lastly, the relevant software architecture paradigms.

In recent years, we have observed a new way of large-scale information exchange, where many users spread their views on social media channels like Twitter, Facebook, YouTube, Instagram etc. Over the past few years, researchers have tried to exploit social media data and extract meaningful insights for applications in various domains [20, 24]. One such application by Asur and Huberman (2010) [2] was to help predict the future with social media by exploiting Twitter data to forecast box-office revenues for movies in the entertainment domain. Similarly, Aramaki et al. (2011) and Achrekar et al. (2011) [1] exploited Twitter data for a real-time assessment to predict flu for public health domain. The model of [1] was trained with the help of the data collected by U.S. Center for Disease Control and Prevention (*CDC*) and showed that Twitter data can improve the model prediction accuracy for flu outbreaks. There are numerous other examples in which social media data has improved the reliability of the current systems, developed novel prediction models for social network analysis, and assisted identification and classification of the user demographic groups. Majority of such relevant works have potential to inform applications in the context of smart city analytics. Therefore, social media shows a promise to provide a novel information platform for intervention strategies also for end users of an organizational service in future smart cities, by modeling individual user and group level behaviors from the social media content.

Social Media is a major, unprecedented source for understanding a user's social behavior. Many research studies in the emerging field of Computational Social Science [15] have been conducted recently to use this data to model user's psychological traits [4, 6, 17], which have numerous applications in the real world. Understanding social psychological factors affecting human attitude such as unconscious bias, aggression, stereotyping, and belief with humor/sarcasm have a vital role in understanding user actions on social media. The correct identification of user and group level behaviors on social media presents a complementary approach to existing methods of survey-driven approaches for helping organizational actors intervene effectively for their end users, i.e. public in the case of smart city governments. Therefore, modeling such behavioral traits have an important role in the design of an *ISS*. We briefly describe these psychological concepts [11, 18] to better inform a reader in the following. *Attitude* is an evaluation of an object, person, act, etc. The attitude can be explicit and implicit, and can be weak or strong, positive or negative. *Stereotyping* is a thought that can be adopted about specific types of individuals or certain ways of doing things. These thoughts or beliefs may or may not accurately reflect reality. Similarly, *unconscious bias* is a construct that is created and reinforced by our environments and experiences. Our mind is constantly processing information, oftentimes without our conscious awareness and therefore, our behavior has some impact due to this psychological construct. *Microaggression* is a subtle but offensive comment or action directed at a minority or other non-dominant group that is often unintentional or unconsciously reinforces a stereotype.

To leverage the theoretical understanding of the socio-psychological concepts, recent social media mining studies enable computational modeling of some of these constructs. Gao et al. [10] have proposed a method for attitude modeling on Twitter data based on the fact that in recent years many users have spread their views on this micro-blogging site on certain topics and if a user retweets/forwards specific tweet messages, it has likely some opinions on the topic of the tweet content. The authors model attitude by defining relationship between user's opinions, sentiments, and action (the act of retweet). Using Matrix factorization, the authors successfully built a classifier model for predicting the user action of retweet. In another study, researchers used the microblogging site of Twitter to capture cultural differences in expressions of intentions [21]. In this approach, authors demonstrated a latent representation of an individual's culture derived from its intentions to explore the intersection between culture and intentions, by using the vast amount of written expressions in users' historic profile data on Twitter. The authors used hashtags as cognitive factors to represents user's intention and used naive Bayes model to develop an intention classifier. Similarly, many studies deal with subjective behavior analysis of textual data, which is a very important foundation for building an Intervention Support System. For measuring the human psychological traits through textual information, one of crucial approach to processing the raw data is user attitude towards a target, such as negative sentiment towards a product. Among the relevant approaches, [8] mined the target-based sentiments by extraction of targets from data using Wikipedia/Wiktionary and then using the construction of a lexicon for target-specific polarity adjectives. [23] developed a three-class classifier that divides the tweets with given targets into positive, negative, and neutral sentiment respectively; since the target is not randomly chosen, this approach is more reliable while not only considering the sentiments of the target, but also the sentiment of the whole sentence.

For the software design aspect of *ISS*, there are several approaches for a system software design [5]. We rely on the scenario-based software architecture analysis proposed by [3, 14], given the diverse nature of organizational needs for behavior modeling requirements in a smart city analytics context. On one hand, the latest research methods show efficiency to achieve any sensemaking of the social data, while on the other hand, there is a gap in transforming these research methods into a systematic social analytics software, which can provide the outcome of the isolated techniques of user behavior modeling into a meaningful interface for organizations of smart cities. *ISS* present one alternative for this purpose of providing a meaningful interface for complex social media analytics.

3 INTERVENTION SUPPORT SYSTEM (*ISS*): GENERIC ARCHITECTURE

This section describes a generic architecture (Figure 1) of an Intervention Support System or *ISS*, which can predict the psychological attitude trend of a user sample on social media, by modeling conscious or unconscious bias behavior and affinity of the user towards particular groups/topics. The *ISS* design assumes the social media as its primary data source and builds upon a standard data operation pipeline observed in machine learning applications. The pipeline runs to first allow collection of training data samples for building a model of user or customer behavior, followed by employing the trained model to predict user behavior on the new streaming content, in order to understand the general trend of behavior shift for a user group towards the targeted topics. The specific components of *ISS* and their connections summarized in Figure 1 are discussed below:

(1) **Data Source:** Input data for the *ISS* model is from social media platforms such as Twitter, Facebook, Google+, YouTube, etc. Since the social media sites have abundant users who

cover all the range of topics in the conversations, the data sample has sparse distribution of the relevant information for organizational services. Social media platforms provide APIs such as Twitter Streaming API[1] to collect data for the given criterion of parameters (e.g., keywords, location bounding box of a city or a region, etc.) for data collection as discussed next.

(2) **Data Acquisition and Filtering:** The second step after choosing a platform for data collection is to filter the streaming data for further use in analytical modeling of interest. The first goal is to define target users of interest as we cannot generalize the behavior of all users on social media due to different demographics, culture, and interests of users. So we start with a selection of an event (e.g., launch of a activism campaign) and all the users who have participated by posting messages related to that event will become our target users of interest. The relevant event message is filtered by a given set of keywords to define the event or a specific location bounding-box. After acquiring the users of our interest, we crawl all the historical message data in the profiles of users in our target user sample. For example, the user data in the case of Twitter platform could be all the historical tweets. For Facebook, it would be all the posts in the timeline of a user profile; for YouTube, it would be the comments and likes by the users on videos. One can limit the time frame of all the user data and the resulting data is further fed to the next module in the pipeline for an insightful analysis of user behavior.

(3) **Distributed Behavior Modeling:** The third step is the crucial step for preparing and modeling user data to extract valuable information for user behavior. The proposed design allows distributed computation of a variety of influencing factors for user behavior that are modeled on a given user's historic data. For instance, to capture conscious and unconscious (implicit) biases for a user's attitude, we use two different, parallel approaches. For the conscious bias, we define a set of topics of interest to an organization and then compute the user's attitude towards the topic, with a goal of capturing stereotyping behavior of the user for the given topics. These topics can be very generic or specific such as gender, race, religion, ethnicity, employment, and even politics. For unconscious bias, we measure a difference between the likelihood of a user's interaction with a given pair of complementary communities such as male versus female. The individual behavioral factors are combined via a machine learning model to predict whether a user will act (e.g., retweet on Twitter), given a social media message (e.g., tweet on Twitter).

(4) **Prediction Modeling and Presentation:** The final component gathers the output generated from the previous steps and predict the trend of user attitude towards the subject of interest, i.e. topics. The results are combined as per the relationship graph model designed for the application domain (see Figure 2). A dashboard is developed to represent the results using visualization tools for providing better understanding to the end user, i.e., organizational actor.

[1]https://developer.twitter.com/en/docs/tweets/filter-realtime/overview

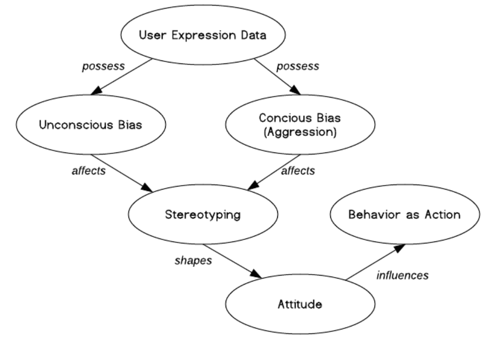

Figure 2: Relationship Graph Model.

The generic architecture described in the previous section has many applications as discussed in the introduction. We demonstrate one implementation of *ISS* for a case of NGO who wants to curb the gender-based violence problem via an online awareness campaign.

4 *ISS* FOR CAMPAIGNS AGAINST GENDER-BASED VIOLENCE

We demonstrate an instance of the generic architecture of *ISS* to build a system for assisting smart city organizations in identification of potential user targets for the interventions, in an effort to curb gender-based violence (GBV) crisis (*c.f.* Figure 3). Here, the social media platform is chosen as Twitter. If the user performs an act of 'retweet' on specific tweets containing some topics of interest for gender, we assume that the user has some opinions on the topic of the tweet. User's unconscious bias and conscious bias (aggression) are computed using user profile history collected from Twitter, and part of this collected data is used to train the model. The system can help the NGOs to understand the public attitude of a particular area and target a specific group by recommending changes to the policies for justice and protection of the group from gender-based violence in any form. We describe details of each *ISS* component in the following:

(1) *Data Source:* We use Twitter Streaming API for sourcing streaming user data for gender-based violence related events. Tweets concerning gender-based violence are collected from the API by providing the filter parameters as a set of relevant keywords [19], e.g., rape, sexual assault.

(2) *Data Acquisition and Filtering:* The collected tweets contain text as well as additional content and metadata, including videos, images, emojis, links, and special characters for the content of different languages than the organization's choice (e.g., other than English). Some of the additional metadata content as needed is removed to make this data suitable for processing in the distributed behavior modeling framework in the next step.

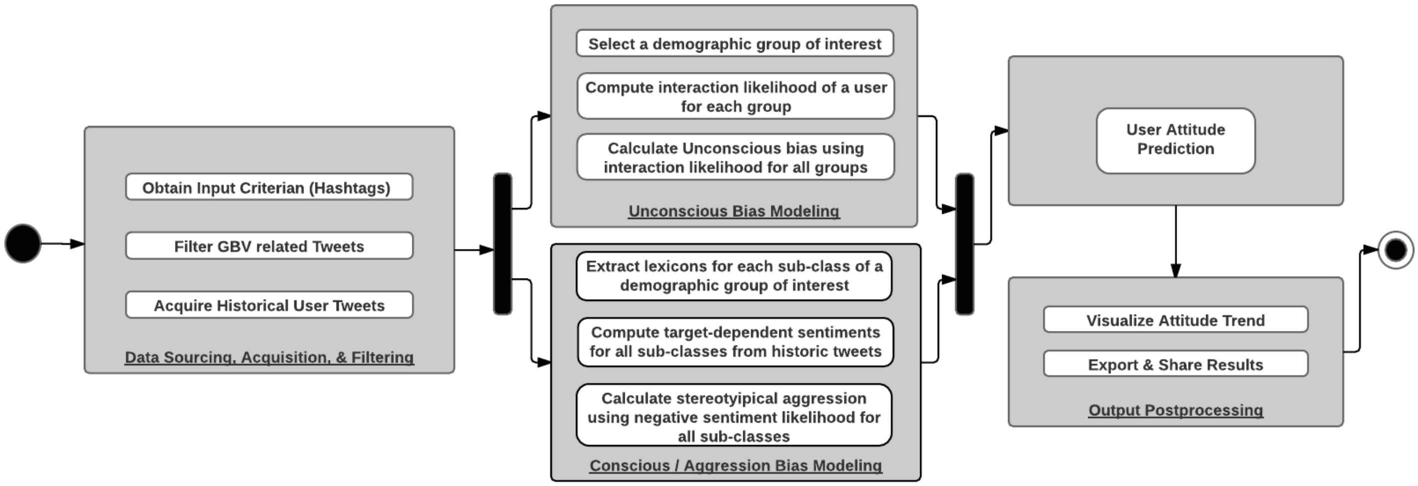

Figure 3: Activity diagram for an ISS system for assisting campaigns to curb gender-based violence

(3) *Distributed Behavior Modeling:* Our main goal is to implement the relationship between various influencing factors of a user's attitude and behavior, which in turn gets manifested by a user action, such as retweeting a strongly opinionated message about a racial stereotype. For theoretical guidance to build a relationship graph (*c.f.* Figure 2) between the socio-psychological concepts, we relied on the theory behind Implicit Association Test (IAT) [9], which provides a systematic reasoning embedded in a questionnaire given to a test subject, in order to measure its social and cognition factors including thoughts and feelings, of which the test subject may be unaware of or unable to control.

For the unconscious bias computation, we first estimate the likelihood of interaction of a user with another user from a different demographic community via tweet mentions (e.g., a male user interacting with male users often) and then, identify the data-driven pattern to suggest if the candidate user has any unconscious bias, such as for gender, race, etc. We have proposed a metric to calculate the unconscious bias of a user for interaction with a particular community of interest here as gender that is defined in equation 1 as follows:

$$U_B = Divergence(P_{male\_interaction}, P_{female\_interaction}) \quad (1)$$

where:
U_B = Unconscious Bias
$Divergence$ = Measure of probability distributional difference
$P_{male\_interaction}$ = Probability of interacting with male users (likewise for female user)

Similarly, for the conscious bias or micro-level aggression computation, we compute target-specific sentiment for the target lexical set comprised of words corresponding to a minority demographic group in a region of interest: the potential stereotypes. Our first step is to acquire target social group's representative lexicon, which is done using diverse knowledge bases including DBpedia, WordNet, SentiWordNet, Urban Dictionary, etc. We now apply the target-specific sentiment analysis on tweets (historical) of a user if a tweet contains any target lexicon word then it gets classified into 3 classes (positive, negative, or neutral) to estimate the polarity for the target lexicon word. Target-specific sentiment is then used to compute user's aggression towards the target lexicon by aggregating over all the tweets of the user with the help of a proposed measure in equation 2 as follows:

$$S_A = Divergence(P_{sc_1}, ..., P_{sc_n}) \quad (2)$$

where:
S_A = Conscious/aggression bias
$Divergence$ = Measure of probability distributional difference
P_{sc_i} = Probability of negative sentiment for a target social group lexicon sc_i

For example, if a religion is a target social group taken from IAT, then its subclass can be Christian, Hispanic, Sikh, Hindu, Muslim, etc. Now, consider a historical tweet of a user User1: "Muslims are bad and they are the cause of terrorism" has the target for subclass "Muslim" and a negative sentiment towards the same which is computed through target-specific sentiment analysis and thus, this user has a negative affinity towards Muslims, and a bias, considering a minority social group in a region. Finally, after modeling various behavioral factors in a distributed environment, we train a classifier for a predictive modeling to determine whether a user is likely to retweet/forward a given opinionated message with a stereotyped content.

(4) *Data modeling and Presentation:* User attitude trend prediction model is developed by using the results of the prior step as a rich set of features. Relationship premise for the features

is that when a user has unconscious bias and aggression or conscious bias, they form the user's stereotypical attitude observable by the behavior, i.e., user's action such as retweeting a stereotyped message on the social platform. The prediction modeling task can also help estimate the probability of shift in the attitude of users from a region in future based on the features of existing state of unconscious and conscious (aggression) bias. The prediction trend is shown by graphs in the dashboard of the end user (e.g., NGO or smart city service personnel for community welfare). Prediction trend informs the intervention strategies and the samples for intervention targets, such as how to craft the campaign event for awareness to reduce stereotypical bias and hatred towards a particular social construct (race, or religion or ethnicity).

5 DISCUSSION, FUTURE WORK AND CONCLUSIONS

The proposed generic architecture for *ISS* provides a flexible framework for designing systems to aid intervention programs in various application domains for smart city analytics. The proposed design is flexible to modify for behavioral modeling of interest to an end user organization, and accordingly, to fit into different applications/businesses. The visual analytics in the dashboard helps visualize the attitude trends of the masses and provides the organizations an ability to gain major insights affecting their customer, the public in the case of city governments, faster than traditional survey-based methods. There are, however, limitations and scope for the future work to this approach in terms of testing scalability, requirements for adaptability across diverse applications as well as specific behavior formalization for different data sources of social media (e.g., Twitter versus Instagram), given that the form of user action could vary across data sourcing platform.

The effectiveness of the generic architecture is planned to be assessed following the scenario-based design method [3]. For future work, we plan to evaluate the proposed *ISS* application for gender-based violence with an end user NGO. Identification and incorporation of further improvements – such as incorporating a feedback-driven, online learning model – are to be made to the generic architecture in several iterations. Also, a robust probabilistic graphical model could be developed based on the theoretically-motivated relationship graph proposed in this paper. Instantiation of generic architecture by implementing it in other application demonstration scenarios and with other social media platforms also will be the future work directions on the presented framework.

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