A PROFICIENT HEALTH MANAGEMENT SYSTEM FOR SOCIAL NETWORKING

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Abstract: *Web based life has turned into a noteworthy hotspot for breaking down all parts of day by day life. Because of committed inert theme examination strategies, for example, the Ailment Topic Aspect Model (ATAM), general wellbeing would now be able to be seen on Twitter. In this work, we are keen on utilizing web based life to screen individuals' wellbeing after some time. The utilization of tweets has a few advantages including quick information accessibility at basically no expense. Early observing of wellbeing information is correlative to post-factum contemplates and empowers a scope of utilizations, for example, estimating conduct hazard factors and activating wellbeing efforts. We plan two issues: wellbeing change recognition and wellbeing progress forecast. We initially propose the Temporal Ailment Topic Aspect Model (TM– ATAM), another dormant model devoted to taking care of the primary issue by catching advances that include wellbeing related themes. TM– ATAM is a non-evident expansion to ATAM that was intended to extricate wellbeing related subjects. It learns wellbeing related point advances by limiting the expectation mistake on subject circulations between back to back posts at various time and geographic granularities. To tackle the second issue, we create T– ATAM, a Temporal Ailment Topic Aspect Model where time is treated as an irregular variable locally inside ATAM. Our investigations on a 8-month corpus of tweets demonstrate that TM– ATAM beats TM– LDA in assessing wellbeing related changes from tweets for various geographic populaces. We analyze the capacity of TM– ATAM to recognize advances because of atmosphere conditions in various geographic districts. We at that point show how T– ATAM can be utilized to foresee the most essential change and furthermore contrast T– ATAM and CDC (Center for Disease Control) information and Google Flu Trends.*

Keywords: Ailments, Temporal Ailment Topic Aspect Model, Health Transition Prediction.

I. INTRODUCTION

Web based life has turned into a noteworthy wellspring of data for breaking down all parts of every day life. Specifically, Twitter is utilized for general wellbeing observing to separate early pointers of the prosperity of populaces in various geographic locales. Twitter has turned into a noteworthy wellspring of information for ahead of schedule observing and forecast in zones, for example, wellbeing [1], fiasco the executives [2] and governmental issues [3]. In the wellbeing area, the capacity to display advances for infirmities and distinguish proclamations like "individuals talk about smoking and cigarettes prior to discussing respiratory issues", or "individuals talk about cerebral pains and stomach throb in any request", benefits syndromic observation and helps measure social hazard factors and trigger general wellbeing efforts. In this paper, we define two issues: the wellbeing progress location issue and the wellbeing progress forecast issue. To address the discovery issue, we create TM– ATAM that models worldly changes of wellbeing related points. To address the forecast issue, we propose T– ATAM, a novel strategy which reveals dormant sickness inside tweets by treating time as an irregular variable locally inside ATAM [4]. Treating time as an irregular variable is critical to anticipating the inconspicuous change in wellbeing related talk on Twitter. Basic afflictions are generally observed by gathering information from medicinal services offices, a procedure known as sentinel reconnaissance. Such assets limit observation, most particularly for ongoing criticism. Consequently, the Web has turned into a wellspring of syndromic observation, working on a more extensive scale, close ongoing and at for all intents and purposes no cost. Our difficulties are: (I) recognize wellbeing related tweets, (ii) decide when wellbeing related talks on Twitter advances starting with one subject then onto the next, (iii) catch diverse such advances for various geographic areas.

To be sure, notwithstanding developing after some time, illness conveyances likewise advance in space. In this manner, to accomplish adequacy, we should cautiously display two key granularities, transient and geographic. A worldly granularity that is too-fine may result in meager and fake advances though a too-coarse one could miss significant illness advances. So also, a too-fine geographic granularity may deliver false positives and a too-coarse one may miss important changes, e.g., when it concerns clients living in various atmospheres. For instance, exchanges on hypersensitivity break at various periods in various states in the USA [4]. In this manner, handling all tweets starting from the USA together will miss atmosphere varieties that influence individuals' wellbeing. We contend for the need to think about various time granularities for various districts and we wish to distinguish also, show the advancement of affliction conveyances between diverse fleeting granularities [8]. While several latent topic modeling methods such asProbabilistic Latent Semantic Indexing (pLSI) [5] and LatentDirichlet Allocation (LDA) [6], have been proposedto effectively cluster and classify general-purpose text, ithas been shown that dedicated methods such as the AilmentTopic Aspect Model (ATAM) are better suited forcapturing ailments in Twitter [4]. ATAM extends LDA tomodel how users express ailments in tweets. It assumes thateach health-related tweet reflects a latent ailment such asflu and allergies. Similar to a topic, an ailment indexes aword distribution. ATAM also maintains a distribution oversymptoms and treatments. This level of detail provides amore accurate model for latent ailments.

On the other hand, while pLSI and LDA have beenshown to perform well on static documents, they cannotintrinsically capture topic evolution over time. Temporal-LDA (TM–LDA) was proposed as an extension to LDA formining topics from tweets over time [7]. To address thehealth transition detection problem, we propose TM–ATAMthat combines ATAM and TM–LDA. A preliminary versionof TM–ATAM was described in a short paper [8]. We showhere that it is able to capture transitions of health-relateddiscussions in different regions (see Figure 1). As a result, the early detection of a change in discourse in Nevada, USAinto allergies can trigger appropriate campaigns.

In each geographic region, TM–ATAM learns transitionparameters that dictate the evolution of health-related topicsby [9], minimizing the prediction error on ailment distributionsof consecutive pre-specified periods of time. Our secondproblem, the health transition prediction problem, is toautomatically determine those periods. We hence proposeT–ATAM, a different and new model that treats time as arandom variable in the generative model. T–ATAM discoverslatent ailments in health tweets by treating time as a variablewhose values are drawn from a corpus-specific multinomial distribution. Just like TM–LDA, TM–ATAM and T–ATAMare different from dynamic topic models [9], [10], [11], as they are designed to learn topic transition patterns fromtemporally-ordered posts, while dynamic topic models focuson changing word distributions of topics over time.

Our experiments on a corpus of more than 500K healthrelatedtweets collected over an 8-month period, show thatTM–ATAM outperforms [12], TM–LDA in estimating temporaltopic transitions of different geographic populations. Ourresults can be classified in two kinds of transitions. Stabletopics are those where a health-related topic is mentioned continuously. One-Way [13], transitions cover the case where sometopics are discussed after others. For example, our studyof tweets from California revealed many stable topics suchas headaches and migraines. On the other hand, tweetingabout smoking, drugs and cigarettes is followed by tweetingabout respiratory ailments. Figure 1 shows example onewaytransitions we extracted for different states and cities inthe world. Such transitions are often due to external factorssuch as climate, health campaigns, and nutrition and lifestyle ofdifferent world populations.

II RELATED WORK

Proliferation of social media platforms such as Twitter, pinterest, facebook, tumblr has led to their application to a wide array of tasks including mental health assessment [14], [15], [16], inferring political affiliation [17], [18], [19], [20], brand perception [21], [21] etc. Social media, especially Twitter, are good sources of personal health [3], [4], [5], [6]. Previous studies on public health surveillance have attempted to uncover ailment topics on online discourse [4], [7] or model the evolution of general topics [7]. In this paper, we combine the best of both worlds which leads to the discovery of disease-change-points for social-media active regions. We model the evolution of diseases within change-points and obtain significant improvement over the state-of-the-art for public health surveillance using social media.

Just like TM-LDA, TM-ATAM and T–ATAM learn topic transitions over time and not topic trends. Such transitions the purpose of answering questions such as people talk about fever before talking about stomach ache. Other complementary approaches that learn the dynamicity of word distributions or topic trends have been proposed. That is the case of [9] that models topic evolution over time as a discrete chain-style process where each piece is modeled using LDA. In [11], the authors propose a method that learns changing word distributions of topics over time and in [10], the authors leverage the structure of a social network to learn how topics temporally evolve in a community. TM–ATAM and T–ATAM are however different from dynamic topic models such as [9] and [10], and from the work of Wang et al. [11], as they are designed to learn topic transition patterns from temporally-ordered posts, while dynamic topic models focus on changing word distributions of topics over time. TM–ATAM learns transition parameters that dictate the evolution of health-related topics by minimizing the prediction error on ailment distributions of consecutive periods at different temporal and geographic granularities. T–ATAM on the other hand discovers latent ailments in health tweets by treating time as a corpus-specific multinomial distribution. Classical approaches [18] have been applied to mining topics for inferring citations. Other discriminative approaches [19], [20] have been applied to do an empirical study on topic modeling and time-based topic modeling respectively. None of those are directly applicable to health data.

EXISTING SYSTEM

In the existing system, the authors propose a method that learns changing word distributions of topics over time and in the system, the authors leverage the structure of a social network to learn how topics temporally evolve in a community. TM–ATAM and T–ATAM are however different from dynamic topic models such as [9] and [10], and from the work of Wang et al. [11], as they are designed to learn topic transition patterns from temporally-ordered posts, while dynamic topic models focus on changing word distributions of topics over time. TM–ATAM learns transition parameters that dictate the evolution of health-related topics by minimizing the prediction error on ailment distributions of consecutive periods at different temporal and geographic granularities. T–ATAM on the other hand discovers latent ailments in health tweets by treating time as a corpus-specific multinomial distribution. Classical approaches have been applied to mining topics for inferring citations. Other discriminative approaches have been applied to do an empirical study on topic modeling and time-based topic modeling respectively. None of those are directly applicable to health data.

Disadvantages

- There is no Mapping Tweets to Documents.
- There is Uncovering Health Topics with ATAM.

II PROPOSED SYSTEM

In the proposed system, the system formulates and solves two problems: the health transition detection problem and the health transition prediction problem. To address the detection problem, the system develops TM–ATAM that models temporal transitions of health-related topics. To address the prediction problem, we propose T–ATAM, a novel method which uncovers latent ailment inside tweets by treating time as a random variable natively inside ATAM. Treating time as a random variable is key to predicting the subtle change in health-related discourse on Twitter.

Advantages

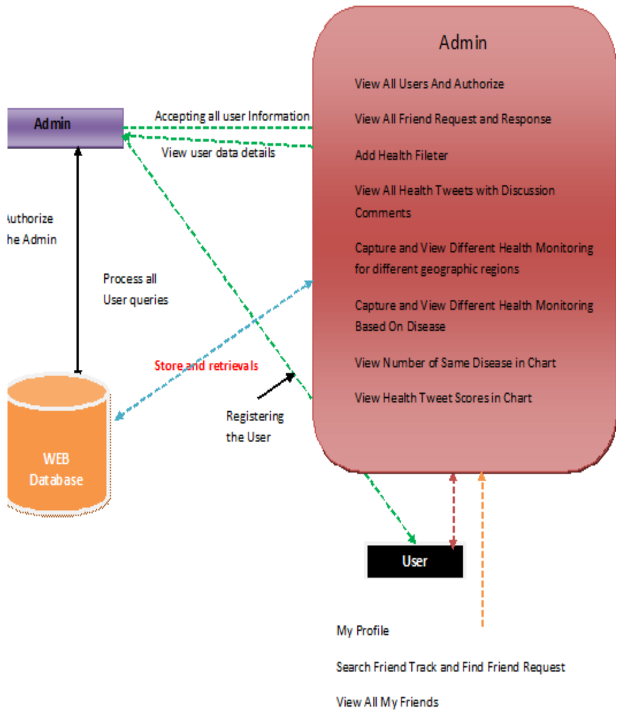
➢ TM–ATAM, a model able to detect health-related tweets and their evolution over time and space. TM–ATAM learns, for a given region, transition parameters by minimizing the prediction error on ailment distributions of pre-determined time periods.

➢ T–ATAM, a new model able to predict health-related tweets by treating time as a variable whose values are drawn from a corpus-specific multinomial distribution.

➢ Extensive experiments that show the superiority of T–ATAM for predicting health transitions, when compared against TM–LDA and TM–ATAM, and its effectiveness against a ground truth.

IV METHODOLOGY

TM–ATAM assumes that there is a common linear relation between all the aggregate topic distributions at a given period t and the one at the period just before. TM–ATAM fails to perform optimally when operated in regions where there are no substantial transitions in health topics. In particular, TM–ATAM does not take into account the potential seasonality effect, which maybe very different according to the disease of interest. Also, in TM–ATAM, we need to do post processing in order to come up with homogeneous time periods, with respect to health-topics discussed in tweets.



Admin

In this module, the Admin has to login by using valid user name and password. After login successful he can perform some operations such as View All Users And Authorize, View All Friend Request and Response, Add Health Filter, View All Health Tweets with Discussion Comments, Capture and View Different Health Monitoring for different geographic regions, Capture and View Different Health Monitoring Based On Disease, View Number of Same Disease in Chart, View Health Tweet Scores in Chart

Friend Request & Response

In this module, the admin can view all the friend requests and responses. Here all the requests and responses will be displayed with their tags such as Id, requested user photo, requested user name, user name request to, status and time &

date. If the user accepts the request then the status will be changed to accept or else the status will remains as waiting.

User

In this module, there are n numbers of users are present. User should register before performing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Verify finger print and Login Once Login is successful user can perform some operations like My Profile, Search Friend Track and Find Friend Request, View All My Friends, Create Your Health Tweet, View All My Health Tweets, View and Monitor All My Friends Health Tweets.

<u>Searching Users to make friends</u>

In this module, the user searches for users in Same Network and in the Networks and sends friend requests to them. The user can search for users in other Networks to make friends only if they have permission.

An Alternative Model: Time-Aware Ail-Ment Topic Aspect Model (T–ATAM)

TM–ATAM assumes that there is a common linear relation between all the aggregate topic distributions at a given period t and the one at the period just before. TM–ATAM fails to perform optimally when operated in regions where there are no substantial transitions in health topics, as also shown in Section 5. In particular, TM–ATAM does not take into account the potential seasonality effect, which maybe very different according to the disease of interest. Also, in TM–ATAM, we need to do post processing in order to come up with homogeneous time periods, with respect to health-topics discussed in tweets.

We now introduce a second time-aware model, coined the term, T–ATAM, where the timestamp t of each tweet is considered as a random variable, depending on the ailment associated to the post. Note that since time is now a random variable, we shall now aggregate our tweets only by region and run our new model on the different sets of posts P_g to have a deep understanding on the time evolution of the health-related content of our set of tweets. It is highly expected there is a strong dependence of the content of our posts with respect to time but also to the ailment of interest. For example, tweets associated to flu are probably mainly concentrated in winter and that those associated to sunburns mainly posted in summer whereas some ailments maybe non seasonal ones. T–ATAM learns homogeneous time periods by itself and no post-processing is needed in order to come up with change-point in ailments being discussed in tweets. This is because, in generative process, time-stamp is generated conditioned on the ailment as-signed to the tweet. Therefore, ailments learned are already time (season)-aware after the model has run its course. Fig-ure 6 shows the graphical representation of T–ATAM. This model adds three extra random variables to the graphical model of ATAM.

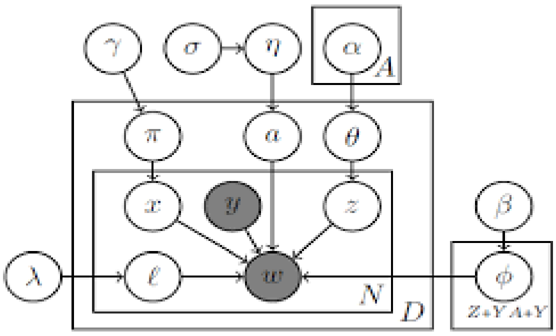


Fig: Time-Aware Ailment Topic Aspect Model

Let us now describe the generative process of T–ATAM. Basically, the generative process of each document is exactly the same as that of ATAM, except that now a time stamp is generated for each document depending on the ailment associated to the considered tweets. Time stamp is an observed random variable. To generate the time stamp associated to a given tweet, we first generate one time-distribution per ailment f_a; a 2 Ag (step (3)). Thereafter, depending on the ailment a associated to the concerned document, we generate its time stamp according to a multinomial distribution with parameter $_a$. Additionally, $_a$ is drawn from a Dirichlet distribution parameterized by a vector $_a$, specific to each ailment. This is intuitive because different ailments have their own specific chance of breaking out at different time periods. We summarize the generative process of our new model T–ATAM just below

Generative Process

(1) Set the background switching binomial

(2) Draw an ailment distributionDir( )

(3) Draw A multinomials $_A$ Dir( )

(4) Draw word multinomials Dir( ) for the topic, ailment, and background distributions

(5) For each message 1 m D

(I) Draw a switching distribution Beta($_0$; $_1$)

(II) Draw an ailment a Mult( )

(III) Draw a time stamp t Mult($_a$)

(IV) Draw a topic distributionDir($_a$)

(V) For each word w_i 2 N_m

(A) Draw aspect y_i 2 f0; 1; 2g(observed)

Draw background switcher l 2 f0; 1g Bi( )

(C) if l == 0:

(i) Draw w_i M ult($_{B;y}$)(a background)

(D) Else:

(i) Draw x_i 2 f0; 1g Bi( )

(ii) If x_i == 0 :(Draw word from topic z)

(a) Draw topic z_i M ult( )

(b) Draw w_i M ult($_z$)

(iii) Else:(draw word from ailment a aspect y)

(a) Draw w_i M ult($_{a;y}$)

It should be noted that token level sampling for **y**, **x** and l for T–ATAM stays the same as ATAM. Document-level sampling for ailment a for T–ATAM changes and is given by following equation:

P ($a_m$ja $_m$; **w**; **t**; **y**; **x**; l)

∞P ($a_m$ja $_m$)P ($t_m$jt $_m$; **a**;)

$\Pi^N{}_m$ p($w_{m;n}$j**a**; w $_{(m;n)}$; **y**; **x**; l) n

Factor which is to be multiplied with existing factors at document level sampling of ATAM for posterior distribution of ailment a: P ($t_m$jt $_m$; **a**;)

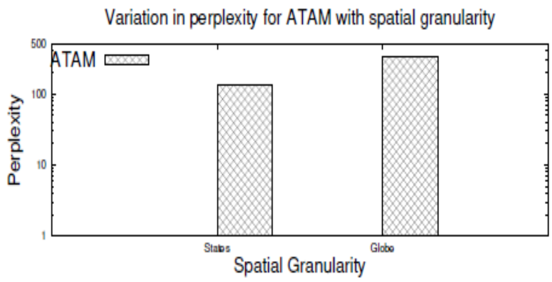
$$P(t_m j t_{m}; \mathbf{a};) = \frac{n^{i;t}{}_m{}^m + \mu}{n^i{}_m + T\mu}$$

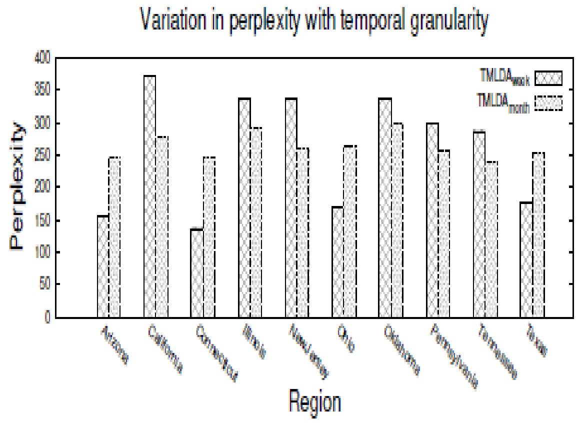
Superscript i indexes over ailments. In particular, n^i denotes number of times an ailment occurs in the corpus and $n^{i;t}m$ denotes number of times an ailment occurs with a time stamp t_m.

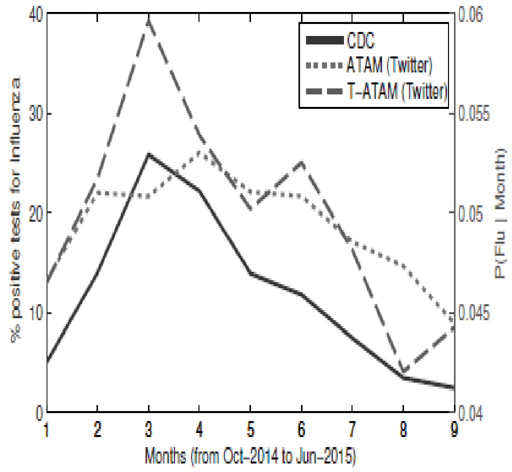
As proved in the experimental results, this new model is much more accurate than the previous one both in terms of perplexity measure and in agreement with ground truth. This model also beats ATAM in many of the regions where there are no substantial health topic transitions. Note that in the case of T–ATAM, we can infer change-point and transitions as in the case of TM–ATAM

V ANALYSIS

We conduct experiments to judge the performance of TM–ATAM and T–ATAM on universe knowledge. The experimental setup as well as the datasets and test-bench. We have a tendency to compare TM–ATAM and T–ATAM against progressive approaches. That is followed by a close study of the behavior of TM–ATAM and a chemical analysis of TM–ATAM's results. Then the impact of changing parameters in T–ATAM is studied. Finally, we study the correlations between T–ATAM's results with federal agency data and Google respiratory illness Trends in for the flu rates in U.S... Finally, we have a tendency to highlight the key insights drawn from our experiments.







VI RESULT

By modeling transitions within the same homogenous time period, TM–ATAM systematically outperforms TM–LDA in predicting health topics altogether social-media active regions. We analyze the performance of TM–ATAM by dynamical spatio-temporal parameters. Specifically, we discover that prediction accuracy for health topics is higher once operational TM–ATAM on finer s patial g ranularity a nd s horter time periods. Further, we have a tendency to persist to get fascinating region-specific intra and inter-homogeneous period of time healthrelated transitions. Whereas learning these transitions, we find that homogeneous time periods are continuous time periods that folks within the same region tweet about similar health problems. once those homogenous time periods finish, we have a tendency to found that ailments mentioned in Twitter transition into alternative disorder topics. These results show that it's a lot of logical to predict future ailments concerning folks at intervals an equivalent homogenous time period of a part than on any random health tweets. By outperforming TM–LDA in predicting future health topics, we have a tendency to show that it's essential to use an infatuated methodology that separates health-related topics from alternative topics. Since in T–ATAM, time is taken into account a variable following multinomial distribution, we have a tendency to expect it to outgo other models, TM–LDA and TM–ATAM in predicting health topics victimization confusion live. After analyzing T–ATAM's performance by dynamical various spatio-temporal parameters, we discover that (as in the case of TM–ATAM) the prediction accuracy for health topics is higher once operational T–ATAM on finer spatial granularity and shorter time periods. Finally, T–ATAM shows smart correlations with the CDC's contagion information (the rates of the positive tests of flu measured by the middle of malady management and interference in the US) and Google contagion Trends information for a syndromic surveillance study.

VII CONCLUSION

In this paper, we develop methods to uncover ailments over time from social media. We formulated health transition detection and prediction problems and proposed two models to solve them. Detection is addressed with TM–ATAM, a granularity-based model to conduct region-specific analysis that leads to the identification of time periods and characterizing homogeneous disease discourse, per region. Prediction is addressed with T–ATAM, that treats time natively as a random variable whose values are drawn from amultinomial distribution. The fine-grained nature of T–ATAM results insignificant improvements in modeling and predicting transitions of health-related tweets. We believe our approach is applicable to other domains with time-sensitive topics such as disaster management and national security matters.

VIII REFERENCES

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