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Abstract Retweeting is the core mechanism of information **diffusion** [1] *(Diffusion)* on Twitter, few studies have investigated the subjective motivation of a user to retweet a message . In this paper , in the light of psychological theory , we assume that a tweet is more likely to be retweeted by a user because of similar subjectivity, and propose a subjectivity model to **combine** [2] *(Combine)* both the **topics** [3] *(questions, issues, arguments)* and opinions to **model** [4] *(shape)* subjectivity. With state-of-the-art topic model and sentiment analysis techniques , we establish subjectivity model by finding topics **and** [5] *(Moreover\, , Also\, , So)* determining opinions towards these **topics** [6] *(issues)* from **usergenerated** [7] *(user generated, regenerated, degenerated, unregenerate)* content simultaneously . We evaluate our model in the retweeting analysis problem to verify its impact on **retweeting** [8] ***(Retweeting)*** **and effectiveness in the retweeting prediction performance .** [9] Keywords Twitter subjectivity retweeting behavior LDA sentiment analysis 1 Introduction Twitter is well-known for its freedom of publishing short message (i.e. tweet), and viral spreading of information across **complex** [10] *(Complex)* social networks . In addition to large amounts of User-Generated Content (UGC), Twitter provides its social **network** [11] *(Network)* functions for connection , communication and information diffusion by allowing users to message one another directly and follow one another publicly . The complex **networks** [12] *(systems)* and large content volume of Twitter provide reSongxian Xie **school of computer , National University of Defense Technology** [13] Tel.: +86-0731-84574627 E-mail: xsongx@nudt.edu.cn Jintao Tang Jttang@nudt.edu.(...) insights into people 's social behaviors on a **scale** [14] *(Scale)* **that** [15] has never been possible [32]. Information diffusion is a challenging problem which might be investigated on Twitter, because retweeting convention and complex networks of Twitter have provided an **unprecedented** [16] *(Unprecedented)* mechanism for the spread of information despite the restricted length of tweets [15]. Actually almost 25% of the tweets published by users are retweeted from **others** [17] *(Others)* [39]. Therefore , it is important to understand how retweeting behavior works so as to help **study** [18] *(research)* information **diffusion** [19] *(Diffusion)* on Twitter. Although several works have concentrated on analyzing retweeting habits and influencing factors [4, 17, 33], most of **them** [20] ***(Them)*** [21] *(They)* are generic , not user-oriented. From the point of a user, retweeting is a process that includes reading the tweet, estimating the content and deciding to share , and the crucial part of the process is to estimate whether a tweet contains information interesting to the user who might find it worthy to **be** [22] *(Be)* shared . **Therefore in this study we focus specifically on** [23] analyzing the retweeting behavior from the user modelling perspective . Previous studies on retweeting analysis have shown that **an** [24] *(An)* enriched user model gives coherent and consistent explanation for retweeting motivation [1, 19, 9]. Specifically , researchers have tried to model users from four types of information : profile features ("Who you are"), tweeting behavior ("How you tweet"), linguistic content ("What you tweet") **and** [25] *(Moreover\, , Also\, , So)* social network ("Who you tweet") [25]. Despite demographic profile , tweeting habits and network structure might determine the source and scope of information users could be exposed to, topics of interest encapsulated in rich linguistic content have been proved consistently dependable for retweeting behavior explanation . For example , whether a tweet will be propagated largely depends on its identification with the interests of users [26, 11]. However , beyond merely publishing news and events , Twitter has become a platform 2 Songxian Xie et al. where different opinions are presented and exchanged by allowing users publish subjective messages on topics they are interested **in** [26] . Existing researches **demonstrated** [27] *(showed, proved, confirmed)* that UGC with rich sentimental information can trigger more attention , feedback or participation [32], and tweets with high emotional diversity have a better chance of being retweeted [27]. Most studies have tried to find whether and how sentiment of a tweet will influence its spreading , but none of them realize that although users receive thousands of tweets on different **topics** [28] *(issues, subjects)* every day , whether a tweet will be retweeted **will** [29] *(Will)* depend on the subjective choice of users. Subjective initiative nature of human determines that his **behavior** [30] *(Behavior)* pattern is subjectivity driven . Psychologist have identified subjectivity as the underlying factor that influences **taking** [31] *(Taking)* what behaviors to process incoming **stimul** [32] *(stimuli, stimulus, stimulon, st imu)* [21]. According to theory of Biased Assimilation, people are prone **to choose and diffuse information according to their own biased subjectivity [14, 34].** [33] In this study we explore the UGC of Twitter to **model** [34] *(shape)* the subjectivity of users, and investigate **whether** [35] *(Whether)* the subjectivity model could benefit the retweeting behavior analysis . Intuitively, subjectivity can be represented as **topics**

36 (questions) and opinions articulated in the information generated 37 (Generated) by users on Twitter. We use the state-of-the-art topic model to find 38 (determine) the topics users are talking about, and sentiment analysis techniques to determine user's opinions towards these topics from UGC simultaneously . We evaluate our model on the retweeting analysis problem to verify its 39 (Its) impact on retweeting behavior . Modelling subjectivity on Twitter is a challenging task because 40 (Because) of the sparsity of textual information and the dynamic of topics 41 (issues, questions) and opinions . However , we are interested in understanding retweeting behavior at a local level rather than 42 (then) at a global level, since most of time retweeting pertains to a local 43 (a social) network consisting of the tweet publisher and followers , and the relatively tiny size and topic homophily of local 44 (Local) 45 (social) network 46 (system) lower 47 (lowers) the impact of sparsity. Given the biased nature of subjectivity, while new information may arise and old information may change their meaning , biased subjectivity is likely to be more consistent and less 48 prone to external perturbations , therefore subjectivity model of a user is less likely to be influenced by changes of topics and opinions on Twitter. Our work aims to define and establish the subjectivity model and identify the role of subjectivity in the processes of information diffusion on Twitter. 49 Our contributions can be summarized as follows : – In the light of psychological theory , we firstly put forward formal definition of subjectivity model for users and 50 (Moreover\, , Also\, , So) tweets which 51 (that) model both the topics 52 (questions, issues, arguments) and opinions simultaneously . – Based on the state-of-the-art topic model and sentiment analysis techniques , we build subjectivity model from UGC on Twitter and apply it to the retweeting behavior analysis problem . – We 53 systematically evaluate the effectiveness of the subjectivity model . It is demonstrated 54 (shown) that our model outperforms other UGC-based models in rewteeting 55 (rewriting, retreating, retweeting) prediction and 56 (Moreover\, , Also \, , So) gives the most significant improvement over an offthe 57 (off the, office, offtake) -shelf predicting model . The rest of the paper is organized as follows : section 2 58 gives the related 59 (relevant) works to our research , the proposed subjectivity model is defined and specified in section 3, the qualitative and quantitative evaluation is described in section 4, and Section 5 summarizes the paper and points out 60 future work . 2 Related Work Retweeting Analysis. A lot of works have analyzed the characteristics of retweeting, examining factors that lead to increased retweetability 61 (repeatability, respectability) and designing models to estimate the probability 62 (Probability) 63 (Probability) of being retweeted. As for factors influencing retweetability 64 (repeatability, respectability) , Suh et al. [33] found that tweets with URLs and 65 (Moreover\, , Also\, , So) hashtags were more likely to be retweeted. 66 Macskassy and Michelson [19] found that models derived from tweet content 67 (Content) could explain most of 68 (the) retweeting behaviors . Comarela et al. [7] found previous response to the tweeter, the tweeters sending rate , the freshness of information , the length of tweet 69 (Tweet) could affect followers 70 (follower's) response to retweet. Starbird and Palen [30] found that tweets with topical keywords were more 71 (More) likely to be retweeted. There are also many works extending the analysis to build retweeting prediction model . Osborne and Lavrenko [26] introduced 72 (added) features such as novelty of a tweet and the number of times the author is listed to train a model 73 with a passive aggressive 74 (passive-aggressive) algorithm, and found that tweet features added a substantial boost to the performance . Jenders et al. [15] analyzed the " obvious " and " latent " features from structural , content-based, and sentimental aspects and found a combination of features covering all aspects was the key to high prediction quality . Naveed et al. [23, 22] introduced interestingness based on such features as sentiments and topics to predict the probability of retweeting 75 (Retweeting) for an individual tweet. Feng and Wang [9] proposed a feature-aware factorization model to rerank 76 (rank, reran, re rank) the tweets according 77 (According) to their probability of being retweeted. Pfitzner et al. [27] proposed 78 (introduced) a new measure called emotional divergence and showed that high emotional diverse tweets have higher 79 (Higher) chances of being retweeted. All papers introduced 80 (presented, submitted) above tried to answer the question of "Whether and why a tweet will be retweeted by anyone

". [81] (.") But they are weak to capture "Whether a tweet is retweetable [82] (rewritable, regrettable, retractable, resettable) from a user-centric perspective considering the interests and opinions [83] (Opinions) ". [84] (.") In this paper , we will try to answer [85] this question by building a subjectivity model which can capture both the interests [86] (Interests) and opinions of users. Resonance Elicits Diffusion: Modeling Subjectivity for Retweeting Behavior Analysis 3 User [87] (is , was) Modelling. With the popularity of social media , researchers have begun to pay close attention to model users on the massive amount of UGC. [88] These studies provide researchers with insights into user online behaviors . Hannon et al. [10] proposed [89] (suggested) that Twitter users can be modeled by tweets [90] (Tweets) [91] (Tweets) content and the relation of Twitter social network . Macskassy and Michelson [19] discovered user's interests by leveraging Wikipedia as external knowledge to determine a common [92] (a standard) set of high-level categories that covers [93] entities in UGC. Ramage et al. [28] made use of topic models to analyze tweets at the level of individual users with 4S dimensions, showing improved performance on tasks such as post [94] (Post) filtering and user recommendation . Xu et al. [38] proposed a mixture model which incorporated three important [95] (famous) factors , namely breaking news , friends ' timeline and user interest [96] (Interest) , to explain user posting behavior . Pennacchiotti and Popescu [25] proposed a comprehensive method to model users for user classification , and confirmed the value of indepth [97] (in-depth, in depth, depth, indent, indepthly) features by exploiting the UGC, which reflect a deeper understanding [98] (Understanding) of the Twitter user and the user network structure . Few of work have identified the correlation between the opinions of users and their behaviors , motivated by the observation , we put forward subjectivity model to combine both [99] (Both) interests and opinions to model [100] (shape) a [101] (___) user. Sentiment Analysis. Sentiment analysis is a popular [102] (a modern, a traditional, a famous) research area [103] (Area) [104] (Area) and previous researches [105] (researchers) have mainly focused on reviews or news comments . Recently , researchers began to pay [106] (Pay) more and more attention to social media such as Twitter. Hu et al. [12] interpreted emotional signals available in tweets for unsupervised sentiment analysis by providing a unified [107] (Unified) way to model two main categories of emotional signals : emotion indication and emotion correlation . Jiang et al. [16] focused on target-dependent Twitter sentiment classification , and proposed a method [108] (a plan) to improve performance by taking target-dependent features and related tweets into consideration . Asiaee T. et al. [2] presented a cascaded classifier framework for per-tweet sentiment analysis by extracting tweets about a desired target subject , separating tweets with [109] (With) [110] (the , a) sentiment , and setting apart positive from negative tweets. Hu emphet [111] (nymphet, emmet) al. [13] extracted sentiment relations between tweets [112] (Tweets) based on social theories , and proposed a novel sociological approach to utilize sentiment relations between messages to facilitate sentiment classification . Motivated by sociological theories that humans tend to have consistently biased opinions , Calais Guerra et al. [5] addressed challenges of topic-based real-time sentiment analysis by proposing a novel transfer learning approach with a suitable source task of opinion holder bias prediction . Thelwall et al. [36, 35] designed SentiStrength, an algorithm for extracting sentiment strength from informal English text by exploiting the grammar [113] (Grammar) and spelling styles in typical social media text . In this paper , we adopt SentiStrength for sentiment analysis to build our subjectivity model , because the fine-grain sentiment strength it outputs could give us more detailed opinion than binary labels . 3 Subjectivity Model In this section , we firstly give the definition of subjectivity model , then describe the method of building subjectivity model [114] (design) , and finally apply subjectivity model to the retweeting analysis [115] (Analysis) problem . 3.1 Definition Subjectivity has been extensively studied by psychologists to characterize the personality of a person based on his historic [116] (historical) behaviors and remarks [8]. [117] Linguists define the subjectivity of language as the speakers always show their perspectives , attitudes and sentiments in their discourses [31]. Social media provides users a platform to express their opinions towards topics of interest to show their personal subjectivity by publishing short messages . Therefore , for the term "subjectivity " , [118] (\, ") [119]

("\ ) we refer to both **topics** [120] *(questions, issues)* and opinions articulated in the UGC. That is, we model subjectivity not only by interests of users, but also by " what they think about the **interests** [121] *(Interests)* **".** [122] *(.")* Here we firstly give our definition of subjectivity model on Twitter, while we emphasize that our model can **be** [123] *(Be)* **transfered** [124] *(transferred, transfer, transfers, transference, transferee)* to other social media platforms as well . For a set of users U on Twitter, we assume there is a topic space T containing all topics they talk about, and a sentiment valence space S evaluating their opinions towards **these** [125] *(These)* topics . As for S, it is often considered as a binary space consisted of positive and negative sentimental values , however we argue that a more fine-grained sentiment space will **indicate** [126] *(Indicate)* more detailed opinions of users. Definition 1 (Subjectivity Model For User) The subjectivity model P (u) of a user u 2 U is the combination of a set of topics ft i g the user talks about in a topic space T and the user's opinions fOi **g towards the topics .** [127] of user towards topic t i is a target-dependent sentiment distribution d u;t i (si) over sentiment valence space S, subject to å jSj i=1 d u;t i (si) **= 1.** [128] 4 Songxian Xie et al. Users express themselves by tweeting on Twitter, and each tweet generated by users can be considered subjective in that **it** [129] *(It)* also contains **topics** [130] *(questions, arguments)* and opinions . So we also give a subjectivity model definition for a tweet as follows : Definition 2 (Subjectivity Model For Tweet) The subjectivity model P (m) of a tweet m is the combination of a set of topics ft i **g it** [131] *(git)* talks about , and the opinions fo i **g** [132] ***(G)*** **it** [133] *(git)* expresses . P (m) = f(t i ; **wm** [134] *(we, am, wi, mm, rm)* (t i) ; fd m;t i (si))g ; **jt** [135] *(jet, jut, at, jot, et)* i 2 T;; si 2 Sg (2) The definition of subjectivity model given above is in an **abstract** [136] *(Abstract)* form by using latent concepts of **topics** [137] *(issues)* and opinions which need to be derived from UGC. In this paper we **combine** [138] *(Combine)* subjectivity model with retweeting analysis problem and concrete the subjectivity model in such problem settings . 3.2 Retweeting Analysis Problem Statement Retweeting is the core mechanism of information diffusion on Twitter. Many factors have been proved to influence retweeting behavior [33, 19, 7], however few **researches** [139] *(researchers)* have investigated the subjective motivation of a user to retweet a message . Therefore we will study whether subjectivity model **can** [140] ***(Can)*** [141] *(Can)* help understanding underlying reasons of a user's retweeting behavior . In fact the likelihood of a tweet to be retweeted depends on both context constraints and its content. The context such as the network of the author and the time a tweet is published **affects** [142] *(Affects)* whether the tweet will be retweeted . A tweet with only few or passive followers is less likely to be retweeted, and a tweet published in the night have less chance **to be retweeted** [143] ***(Retweeted)*** **than daytime.** [144] **Apart from the** [145] context constraints , a tweet is more likely to be retweeted by subjective users **who** [146] *(Who)* find its content worth to. Therefore , we are not interested in modelling the tweet by itself just as other **researches** [147] *(researchers)* [23, 22, 27], but **understanding** [148] *(knowing)* how the content resonate with **the** [149] *(The)* users who might want to retweet it . We put a much stronger emphasis on the content and try to model the user's subjective decision by **deriving** [150] *(driving)* latent topics and opinions from UGC. Actually , none of contextual factors has any influence on the content of a tweet, therefore we deliberately ignore context constraints to avoid introducing contextual bias into **our** [151] ***(Our)*** [152] **analysis by proposing Hypothesis 1.** [153] Hypothesis 1 (H1) A tweet is evenly visible to the followers who subscribe to it by following its publisher . The rationale behind this hypothesis is, the motivation of a user to retweet a message lies in that the user considers **only** [154] ***(Only)*** [155] *(Only)* the tweet content arousing his resonance without context perturbation . On Twitter, the " following " relationship is a strong indicator of a phenomenon called "homophily", which has **been** [156] *(Been)* observed in many social networks . Homophily is a phenomenon that people connected in a social network "are **homogeneous** [157] *(Homogeneous)* **with regard to** [158] *(about)* many socio-demographic, behavioral, and intra-personal characteristics " [20]. In other words , homophily implies that a user follows another user **because** [159] ***(Because)*** **he finds they share similar interests .** [160] According to the principle of homophily, we put forwards the concept of Local Topic Space, which could be defined as: Definition 3 (Local Topic Space) In a local network consisting of a user and his followers , all users concentrate on limited **topics** [161] *(questions, issues)* derived from their UGC, and these topics form **a** [162] *(A)* local topic space . Since most of time retweeting pertains to **a local** [163] [164] *(a social)* **network , we limit our research in understanding** [165] retweeting behavior at a local level rather than at a global level, and the relatively tiny size and topic homophily of **local** [166] *(social)* network lower the **impact** [167] *(Impact)* of data sparsity. According to our Hypothesis 1, if a tweet is published , **all** [168] *(All)* followers of its author will receive it in time , and followers are likely to retweet it if they find it worthwhile . Thus the retweeting analysis problem we study can be stated as follows : Let F; A; M denote the follower set , author set and tweet **set** [169] *(Set)* respectively . For each tweet m (m 2 M) and its listener f (f 2 F), we can define a quadruple < f ; a; m; r **f am** [170] *(fam)* > where : – a (a 2 A) is the author of the tweet m and f (f 2 F) is a **follower** [171] *(Follower)* of author a. – r **f am** [172] *(fam)* is a binary label indicating whether m is retweeted by **f .** [173] *(f.)* – Our work focuses on using subjectivity model to analyze the relation between the subjectivity of a follower f and **his** [174] *(His)* retweeting behavior . Hence we transform the quadruple into the Local Topic Space T formed by the author a and followers F , and represent f ; a; m with their subjectivity models to analyze their relations with the label r f am . 3.3 Establishment of Subjectivity Model According to the definition of subjectivity model , there are **two** [175] *(Two)* distributions to model the subjectivity: the topic distribution and the opinion distribution for each topic . Both of them need to be inferred from **historic** [176] *(historical)* content produced by users. However , content analysis on Twitter is challenging : the volume of tweets is so huge while a single tweet is very short with limit of 140 characters , and informal languages are widely used , which **make many supervised learning approaches and natural language** [177] processing techniques invalid. Hence effectively modeling content on Twitter requires techniques that can readily adapt to these challenges **and** [178] *(Moreover\, , Also\, , So)* require little supervision . With state-of-the-art topic model Resonance Elicits Diffusion: Modeling Subjectivity for Retweeting Behavior Analysis 5 and sentiment analysis techniques , we establish subjectivity **model** [179] *(example)* by identifying **topics** [180] *(issues, questions)* and opinions in an unsupervised **way** [181] *(Way)* simultaneously . 3.3.1 Topic Analysis The **topics** [182] *(issues, questions)* of a tweet are latent and have to be inferred from **its** [183] ***(Its)*** [184] *(It's, It is)* content. Previous studies have tried to identify **topics** [185] *(issues)* from tweets by finding **key words** [186] *(keywords)* [6], extracting entities [1] or linking tweets to external knowledge categories [19], however , the sparsity is a main problem for these methods because even users have **common** [187] *(standard)* **local** [188] *(social)* **topics** [189] *(issues)* they still **might refer** [190] ***(Refer)*** **to a** [191] ***(the)*** **topic** [192] ***(a problem, a text, an issue, a subject, a question)*** **with different vocabulary .** [193] Works show that topic models such as Latent Dirichlet Allocation (LDA) model and its extensions [3, 37] have been efficient ways to **characterize** [194] *(Characterize)* latent topics of large volume corpus. Topics of LDA are broader in concept , since a single **topic** [195] *(text, issue, question)* consists of **the** [196] *(The)* whole collection of related words . Therefore we adopt a user-level LDA model to find latent topics for users in their Local Topic Space **,** [197] *(___)* and the generative process can be graphically represented using plate notation in Figure 1. To disFig. 1 Plate illustration of the user-level LDA model . till the topics that users are interested in, **documents** [198] *(reports)* of LDA **should** [199] *(Should)* naturally correspond to tweets content. As our goal is to understand the **topics** [200] *(questions)* that each user is interested in rather **than** [201] *(then)* the topics each **single** [202] *(individual)* tweet talks about , we aggregate the tweets published by each user into a single document , **and** [203] *(Moreover\, , Also\, , So)* replace documents of LDA with aggregated tweet **documents** [204] *(reports)* . So **a document** [205] *(a text, a report)* stands for **a s** [206] *(as)* user in our **model** [207] *(example)* , and a user can be represented as a multinomial distribution over topics , **which corresponds to the topic distribution of the** [208] ***(The)*** [209] user's subjectivity model . Formally, given a set of users U and the number of topics K, a user u (u 2 U) could be represented by a multinomial distribution q **u** [210] *(U)* over topics with a Dirichlet prior parameterized by **a .** [211] *(a.)* A topic k (k 2 K) is represented by a multinomial distribution b k with another Dirichlet prior parameterized by **h .** [212] *(h.)* The parameters q u and each b k can be estimated by Gibbs sampling or variational inference . We use variational **inference-based** [213] ***(Inference-Based)*** [214] *(Inference-Based)* topic model package **Gensim** [215] *(Genesis)* [29]. 3.3.2 Opinion Analysis Users often express opinions towards their topics of interest by publishing topic-related tweets. In order to explore the **opinions** [216] *(Opinions)* of users, **we** [217] need to understand [218] *(the , a)* sentiment embedded in each tweet. Sentiment analysis mainly depends on **machine** [219] *(Machine)* learning or rule-based approaches . Machine learning approaches often need labelled data for the training process , which is often impossible for Twitter because of the **large** [220] *(Large)* volume of tweets and its dynamic **language** [221] *(style)* **characteristics** [222] *(features)* . Therefore we adopt rule-based approaches , which could adapt to Twitter with **good** [223] *(enough)* flexibility by changing its particular characteristics into rules [36, 12]. The SentiStrength package has been built **especially** [224] *(primarily, mainly)* to cope with sentiment analysis in short informal text of social **media** [225] *(Media)* [36]. It combines lexicon-based approaches with sophisticated linguistic rules adapted to social media , which is suitable for analyzing sentiment of tweets in our research settings. SentiStrength assigns two values to each tweet standing for sentiment strengths : a positive (within [1; 5]) and a negative (within [5; 1]) sentiment measurement, both ranging from 1 to 5 on absolute integer scales , with 1 denoting neutral sentiment and 5 denoting highest sentiment strength . Sentiment assigned by SentiStrength is not a simple binary value but a fine-grained **strength** [226] *(power)* , which can catch **fine** [227] *(Fine)* opinion distributions in a user's subjectivity model . For the convenience calculation , we map the output of SentiStrength to a single-scaled sentiment valence space [0; 8] as follows : o = 8 < : p + 3 i f j pj > jnj n + 5 i f jnj > j pj 4 i f j pj = jnj (...) Where p denotes the positive **setiment** [228] *(sentiment, sentiments, sediment, settlement, sediments)* value and n denotes **negative** [229] *(Negative)* **sentment** [230] *(sentiment, sentiments, segment, settlement, sentient)* value . In the sentiment valence space [0; 8], **value** [231] *(Value)* **4** [232] *(four)* indicates neutral sentiment , while values above **4** [233] *(four)* indicate positive sentiment and values below **4** [234] *(four)* indicate negative sentiment . With the sentiments of all tweets, we can **aggregate** [235] *(Aggregate)* opinions towards a topic as a sentiment distribution over sentiment valence space [0; 8]. 3.3.3 Concrete Subjectivity Model With statistical topic analysis and opinion analysis described above , we can concrete subjectivity model in a local network **settings** [236] *(Settings)* now . For user set U of **a local** [237] *(a social)* network , we denote tweet set published by a user u as Mu = **fmi** [238] *(mi, Fm, FM, FYI)* **ji 2 [1;** [239] *(Vocabulary)* ; N]g. Each Mu is concatenated to a single document d u to construct Local Topic Space T = ft i ji = 1; ; Kg. A topic model is built with parameter q representing the distribution of each user over topics in the Local Topic Space T , and parameter b represents the distribution of each **topic** [240] *(issue)* over the vocabulary of all tweets. SentiStrength is applied to each tweet **m in** [241] *(min)* collection Mu and outputs sentiment **strength s** [242] *(strengths)* m for tweet m. We build the subjectivity model P(u) for user u as Algorithm 1: In the algorithm, we assume the sentiment of tweet m is related to every topic it talks about in Z m for simplicity . 6 Songxian Xie et al. Algorithm 1 Establishment of subjectivity **model .** [243] *(model.)* Input : The user set of **a local** [244] *(a social)* network , U ; The tweet set published by each user u, Mu; Output : The subjectivity model for each user u, P(u); 1: Topic analysis with a user-level LDA as Section 3.3.1, getting a topic model P(q ; b jMu; U); 2: for all tweet m 2 Mu

Writing issues in this paragraph:

1	Capitalization at the beginning of a sentence
2	Capitalization at the beginning of a sentence
3	Overused word: topics
4	Overused word: model
5	Conjunction at the Beginning of Sentence
6	Overused word: topics

7 Misspelled word: usergenerated
8 Capitalization at the beginning of a sentence
9 Sentence fragment
10 Capitalization at the beginning of a sentence
11 Capitalization at the beginning of a sentence
12 Overused word: networks
13 Citation audit
14 Capitalization at the beginning of a sentence
15 Sentence fragment
16 Capitalization at the beginning of a sentence
17 Capitalization at the beginning of a sentence
18 Overused word: study
19 Capitalization at the beginning of a sentence
20 Capitalization at the beginning of a sentence
21 Object instead of subject pronoun
22 Capitalization at the beginning of a sentence
23 Citation audit
24 Capitalization at the beginning of a sentence
25 Conjunction at the Beginning of Sentence
26 Prepositions at the end of sentences
27 Overused word: demonstrated
28 Overused word: topics
29 Capitalization at the beginning of a sentence
30 Capitalization at the beginning of a sentence
31 Capitalization at the beginning of a sentence
32 Misspelled word: stimul
33 Sentence fragment
34 Overused word: model
35 Capitalization at the beginning of a sentence
36 Overused word: topics
37 Capitalization at the beginning of a sentence
38 Overused word: find
39 Capitalization at the beginning of a sentence
40 Capitalization at the beginning of a sentence
41 Overused word: topics
42 Possibly confused word: than
43 Overused word: a local
44 Capitalization at the beginning of a sentence
45 Overused word: local
46 Overused word: network
47 Incorrect verb form with singular subject
48 Citation audit
49 Sentence fragment
50 Conjunction at the Beginning of Sentence
51 “That” and “which”
52 Overused word: topics

Grammarly

53	Informal pronouns
54	Overused word: demonstrated
55	Misspelled word: rewteeting
56	Conjunction at the Beginning of Sentence
57	Misspelled word: offthe
58	Citation audit
59	Overused word: related
60	Citation audit
61	Misspelled word: retweetability
62	Capitalization at the beginning of a sentence
63	Capitalization at the beginning of a sentence
64	Misspelled word: retweetability
65	Conjunction at the Beginning of Sentence
66	Citation audit
67	Capitalization at the beginning of a sentence
68	Missing article before plural noun
69	Capitalization at the beginning of a sentence
70	Plural instead of possessive
71	Capitalization at the beginning of a sentence
72	Overused word: introduced
73	Citation audit
74	Misspelled word: passive aggressive
75	Capitalization at the beginning of a sentence
76	Misspelled word: rerank
77	Capitalization at the beginning of a sentence
78	Overused word: proposed
79	Capitalization at the beginning of a sentence
80	Overused word: introduced
81	Punctuation after quotation mark
82	Misspelled word: retweetable
83	Capitalization at the beginning of a sentence
84	Punctuation after quotation mark
85	Citation audit
86	Capitalization at the beginning of a sentence
87	Missing verb
88	Sentence fragment
89	Overused word: proposed
90	Capitalization at the beginning of a sentence
91	Capitalization at the beginning of a sentence
92	Vague word: a common
93	Citation audit
94	Capitalization at the beginning of a sentence
95	Vague word: important
96	Capitalization at the beginning of a sentence
97	Misspelled word: indepth
98	Capitalization at the beginning of a sentence

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99	Capitalization at the beginning of a sentence
100	Overused word: model
101	Redundant indefinite article
102	Vague word: a popular
103	Capitalization at the beginning of a sentence
104	Capitalization at the beginning of a sentence
105	Possibly confused word: researches
106	Capitalization at the beginning of a sentence
107	Capitalization at the beginning of a sentence
108	Overused word: a method
109	Capitalization at the beginning of a sentence
110	Missing article
111	Misspelled word: emphet
112	Capitalization at the beginning of a sentence
113	Capitalization at the beginning of a sentence
114	Overused word: model
115	Capitalization at the beginning of a sentence
116	Confused “historical” and “historic”
117	Sentence fragment
118	Punctuation after quotation mark
119	Spaces before/after punctuation marks
120	Overused word: topics
121	Capitalization at the beginning of a sentence
122	Punctuation after quotation mark
123	Capitalization at the beginning of a sentence
124	Misspelled word: transfered
125	Capitalization at the beginning of a sentence
126	Capitalization at the beginning of a sentence
127	Sentence fragment
128	Sentence fragment
129	Capitalization at the beginning of a sentence
130	Overused word: topics
131	Misspelled word: g it
132	Capitalization at the beginning of a sentence
133	Misspelled word: g it
134	Misspelled word: wm
135	Misspelled word: jt
136	Capitalization at the beginning of a sentence
137	Overused word: topics
138	Capitalization at the beginning of a sentence
139	Possibly confused word: researches
140	Capitalization at the beginning of a sentence
141	Capitalization at the beginning of a sentence
142	Capitalization at the beginning of a sentence
143	Capitalization at the beginning of a sentence
144	Sentence fragment

145	Citation audit
146	Capitalization at the beginning of a sentence
147	Possibly confused word: researches
148	Overused word: understanding
149	Capitalization at the beginning of a sentence
150	Possibly confused word: deriving
151	Capitalization at the beginning of a sentence
152	Informal pronouns
153	Sentence fragment
154	Capitalization at the beginning of a sentence
155	Capitalization at the beginning of a sentence
156	Capitalization at the beginning of a sentence
157	Capitalization at the beginning of a sentence
158	Wordiness (redundant phrases)
159	Capitalization at the beginning of a sentence
160	Sentence fragment
161	Overused word: topics
162	Capitalization at the beginning of a sentence
163	Citation audit
164	Overused word: a local
165	Citation audit
166	Overused word: local
167	Capitalization at the beginning of a sentence
168	Capitalization at the beginning of a sentence
169	Capitalization at the beginning of a sentence
170	Misspelled word: f am
171	Capitalization at the beginning of a sentence
172	Misspelled word: f am
173	Spaces before/after punctuation marks
174	Capitalization at the beginning of a sentence
175	Capitalization at the beginning of a sentence
176	Possibly confused word: historic
177	Citation audit
178	Conjunction at the Beginning of Sentence
179	Overused word: model
180	Overused word: topics
181	Capitalization at the beginning of a sentence
182	Overused word: topics
183	Capitalization at the beginning of a sentence
184	Confused possessive and contraction
185	Overused word: topics
186	Misspelled word: key words
187	Vague word: common
188	Overused word: local
189	Overused word: topics
190	Capitalization at the beginning of a sentence

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191	Indefinite instead of definite article
192	Overused word: a topic
193	Citation audit
194	Capitalization at the beginning of a sentence
195	Overused word: topic
196	Capitalization at the beginning of a sentence
197	Improper comma in compound subject
198	Overused word: documents
199	Capitalization at the beginning of a sentence
200	Overused word: topics
201	Possibly confused word: than
202	Overused word: single
203	Conjunction at the Beginning of Sentence
204	Overused word: documents
205	Overused word: a document
206	Misspelled word: a s
207	Overused word: model
208	Capitalization at the beginning of a sentence
209	Citation audit
210	Capitalization at the beginning of a sentence
211	Spaces before/after punctuation marks
212	Spaces before/after punctuation marks
213	Capitalization at the beginning of a sentence
214	Capitalization at the beginning of a sentence
215	Misspelled word: Gensim
216	Capitalization at the beginning of a sentence
217	Informal pronouns
218	Missing article
219	Capitalization at the beginning of a sentence
220	Capitalization at the beginning of a sentence
221	Overused word: language
222	Overused word: characteristics
223	Vague word: good
224	Vague word: especially
225	Capitalization at the beginning of a sentence
226	Overused word: strength
227	Capitalization at the beginning of a sentence
228	Misspelled word: setiment
229	Capitalization at the beginning of a sentence
230	Misspelled word: sentment
231	Capitalization at the beginning of a sentence
232	Numerals instead of words
233	Numerals instead of words
234	Numerals instead of words
235	Capitalization at the beginning of a sentence
236	Capitalization at the beginning of a sentence

237 Overused word: a local
238 Misspelled word: fmi
239 Capitalization at the beginning of a sentence
240 Overused word: topic
241 Misspelled word: m in
242 Misspelled word: strength s
243 Spaces before/after punctuation marks
244 Overused word: a local