Grammarly

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Spelling Correction	48 issues	× Spelling (42) × Commonly confused words (1) × Unknown words (5)
Grammar	7 issues	× Passive voice use (7)
Grammar	12 issues	× Use of articles (6) × Use of nouns (2) × Subject and verb agreement (2) × Verb form use (2)
Punctuation	4 issues	× Punctuation within a clause (3) × Punctuation between clauses (1)
Sentence Structure	6 issues	× Sentence fragment (6)
Enhancement Suggestion	32 issues	× Vocabulary use (32)
Style Check	73 issues	× Usage of colloquial speech (20) × Improper formatting (51) × Wordiness (2)

do 3: Sentiment analysis as Section 3.3.2, outputting sentiment of m, s m ; 4: **end** [1] *(point)* for 5: for user u 2 U do 6: the topic distribution is the corresponding component of parameter q , q u; 7: the topics he tweets about are Z u = ft j p (t jq u) > 0; t 2 T g; 8: **end** [2] *(point)* for 9: for tweet m 2 Mu do 10: **topics** [3] *(issues, questions)* of m can be identified by the topic model , Z m = ft j p (t jq ; b ; Z u) > 0; t 2 T g; 11: **end** [4] *(point)* for 12: for each topic t 2 Z u do 13: for sentiment **value s** [5] *(values)* 2 S do 14: count the number of tweets which talk about topic t with sentiment value s, Ns = åm2Mu I (s m) ; **i f** [6] *(if)* s m = s&t 2 Z m ; 15: **end** [7] *(point)* for 16: calculating **opinion** [8] *(view)* towards topic t , **Ot** [9] *(Or, Out, On, At, OR)* = n Ns ås2S Ns o ; 17: **end** [10] *(point)* for 18: establishing subjectivity model of user u, P (u) = n t ; p (t **jq** [11] *(jg, sq, Sq, JV, JP)* u) ; n Ns ås2S Ns o **jt** [12] *(jet, at, It, jot, jat)* 2 Z u; s 2 S o ; 19: return P(u); Accordingly subjectivity model P (m) for tweet **m as** [13] *(mas)* : P (m) = f(t ; p (t jq ; b) ; d m;t

(s)) = 1:0jt 2 Z m ; s 2 Sg (4) Noting that , the opinion towards each topic is a distribution **of** [14] *(Of)* 1:0 on a single sentiment **value s** [15] *(values)* of tweet m. 3.4 Retweeting Analysis With Subjectivity Model To understand the underlying reasons why a user retweet a message , we try to simulate the subjective decision-making **procedure** [16] *(Procedure)* by investigating the relationship among the subjectivity models of a tweet, its author and followers . We assume that a user retweet a message because the user not only finds its **topics** [17] *(subjects)* interesting but also shares similar opinions towards these topics . In other words , if the subjectivity models of a tweet and a user are similar enough , the user will **have** [18] *(Have)* a very high probability to retweet. We call this phenomenon as " resonance ", and assume that the resonance between a tweet and users will elicit retweeting behavior . With the subjectivity models built for users and tweets, we can define a similarity measurement to quantify the resonance among them. Formally, for a tweet m, the corresponding author a, and a list of followers F = f f ! (6) where – l is the coefficient used to control the proportions of **topic** [19] *(Topic)* similarity and opinion similarity in the holistic subjective similarity . We initiate it by setting l = 0:5, and adjust its value in the range of [0; 1] to optimize the best **performance** [20] *(Performance)* of **our** [21] model . – Dist() is the similarity **measurement** [22] *(measure)* between two distribution , we choose cosine distance in our research among different **measurements** [23] *(sizes, measures, analyses)* because of its effectiveness. **We** [24] also assume that a user might retweet another user because of their subjective resonance . Accordingly we define similarity between author a and follower f i as: Sim (a; f i) = l Dist p (t jq a; Z a) ; **p t** [25] *(pt)* **jq** [26] *(jg, sq, Sq, JV, JP)* f i ; Z f i +(1 l) å t 2T Dist (Oa;t ; O **fi** [27] *(i, fit, fin, fa, fr)* ; t) ! (7) 4 Experiment In this section , we investigate whether subjectivity model **can** [28] ***(Can)*** [29] *(Can)* help retweeting analysis on **an** [30] *(a)* Twitter dataset. 4.1 Dataset We adopt an off-the-shelf Twitter dataset of previous work [18], which was created with Twitter API 1 . To **form** [31] *(create, build, construct)* the dataset, 500 randomly selected English target tweets were monitored in the next few days to find followers who would retweet them. Also each target tweet was chosen as starting point to **collect** [32] ***(Collect)*** **historical data of its author and followers .** [33] Overall, there are 45,531 followers and 6,277,736 tweets, and 5214 **followers** [34] *(Followers)* who have retweeted at least one target tweet during the monitored period . Summary statistics of the dataset **are** [35] *(Are)* listed in Table 1. The relations among a target tweet, its **author** [36] *(founder)* and followers are illustrated in Figure 2. There is a local network structure for each target tweet as figure shows , consisting of **its** [37] ***(Its)*** [38] *(It's, It is)* author and followers . 1 https://dev.twitter.com/ Resonance Elicits Diffusion: Modeling Subjectivity for Retweeting Behavior Analysis 7 Table 1 Retweet Dataset Statistics Tatget tweets 500 Average number of followers per target tweet 89 Total **retweeters** [39] *(retweets, retweeted, tweeters, tweeter, retweet)* 5214 Total non- **retweeters** [40] *(tweeters, retweets, retweeted, tweeter, retweet)* 40317 Fig. 2 Relations among a target tweet, its **author** [41] *(founder)* and followers . 4.2 Impact Evaluation of Different Factors In Section 3.4, **we** [42] model retweeting probability with subjectivity model in the form of similarity **measurements** [43] *(measures)* 6,7. By setting different value to l , the measurements can be transformed into different versions to model **different** [44] *(various)* factors that might influence user's retweeting behavior , which are: – TTF: Topic similarity between Tweet and Follower (l = **1** [45] *(One)* in **measurement** [46] *(size)* 6). – OTF: Opinion similarity between Tweet and Follower (l = 0 in measurement 6). – STF: Subjective similarity between Tweet and Follower (l 2 (0; 1) in measurement 6). – TAF: Topic similarity between Publisher and Follower (l = 1 in measurement 7). – OAF : Opinion similarity between Publisher and Follower (l = 0 in measurement 7). – SAF: Subjective similarity between Publisher and Follower (l 2 (0; 1) in measurement 7). The six similarity measurements could be grouped into two aspects . One is consisted of TTF, OTF and STF, which is direct and explicit by modelling the tweet and its followers ; **the** [47] *(The)* other **is consisted of TAF, OAF and SAF, which is indirect and implicit by modelling the author and follower** [48] *(consists of TAF \, OAF and SAF\, which is indirect and implicit by modelling th(...))* . The two aspects reflect **properly** [49] *(correctly)* the local information diffusion **structure** [50] *(Structure)* of Twitter at micro-level as illustrated in Figure 2. To evaluate the impact of **different** [51] *(various)* factors on retweeting behavior , **we** [52] compare six average similarity scores between 5214 **retweeters** [53] *(retweets, tweeters, tweeter, retweeted, retweet)* and 5214 randomly selected **nonretweeters** [54] . The values of l for STF and SAF are tuned to produce the largest value difference between **retweeters** [55] *(retweets, retweeted, tweeters, tweeter, retweet)* **and** [56] *(Moreover\, , Also\, , So)* non- **retweeters** [57] *(tweeters, retweets, tweeter, retweeted, retweet)* , which are l = 0:5 on **our** [58] dataset. Figure 3 shows the result . As the figure illustrated , the **similarities** [59] ***(similarity's)*** [60] *(similarity)* scores of **retweeters** [61] *(retweets, tweeters, tweeter, retweeted, retweet)* are obviously higher than **nonretweeters** [62] for all six factors . Specifically : – TTF score shows that a tweet is more likely to be retweeted by followers who find topics it talks about interesting to them, which is consistent with other studies [19]; Fig. 3 Impact of different factors on retweeting behavior . – OTF score shows that opinions in a tweet is an important indicator to be retweeted by by followers who hold similar opinions , although other studies [27, 22] have shown that sentiment in tweet has impact on retweeting behavior , they have n't consider the opinions of followers and opinion similarity **betweet** [63] *(between, tweet, betwixt, retweet, retweets)* tweet and followers ; – STF score shows the subjective similarity is the most distinguishable feature among the six factors with the largest value difference , which proves the importance of subjectivity model ; – TAF score gives another perspective for retweeting analysis from the topic similarity between author and followers , indicating that followers are more likely to retweet author with similar interests , which verifies the homophily principle of following relation ; – OAF score indicates that similar opinions also **influence** [64] *(change)* followers ' decision of retweeting another user, which **proves** [65] ***(Proves)*** [66] *(declares, demonstrates, determines)* [67] *(the , an)* opinion homophily of following [68] *(the , a)* relation . – SAF score is interesting in that it implies that subjective similarity between author and followers might cause retweeting, and we call this phenomenon " tight homophily" of following [69] *(the , a)* relation because [70] *(\ )* it requires both topic homophily and opinion homophily. 4.3 Performance of Retweeting Prediction The main purpose of retweeting analysis is to help users find interesting information from the overwhelming information streams . Retweeting is an important signal of interestingness because users are prone to broadcast their favorite messages to their followers . Thus , the performance of retweeting prediction is a suitable evaluation for the utility of subjectivity **model** [71] *(Model)* in retweeting analysis problem . In our experiment , we evaluate the subjectivity model in supervised machine **learning** [72] *(Learning)* framework . As Section 3.2 introduced , the retweeting analysis problem could be formulated as a quadruple < f ; a; c; r **f am** [73] ***(is)*** [74] *(fam)* >. For retweeting prediction , we need to estimate the label r f am 8 Songxian Xie et al. **when** [75] *(When)* m; [76] *(___)* a; and f are known . There are 5,214 **retweeters** [77] *(retweets, tweeters, tweeter, retweeted, retweet)* in our dataset who retweet at least one target tweet, so we extract 5214 quadruples as positive instances with their label r f am = 1. For the other 40,317 non- **retweeters** [78] *(retweets, tweeters, retweeted, tweeter, retweet)* , we also extract quadruples as negative instances with label r f am = 0. **To a** [79] *(They)* void **unbalance** [80] *(unbalancing)* bias of training data, **we** [81] randomly sample 5,214 negative instances into the test dataset. 4.3.1 Comparison With Other User Models Firstly the comparison between our model with other UGCbased user models (TF-IDF model [18], entity-based model **and** [82] ***(Moreover\, , Also\, , So)*** **hashta** [83] *(Calculated)* g-based model [1]) in retweeting prediction is investigated . As defined in Section 4.2, the six similarities derived from our model are used for comparison , because they model different factors that **influence** [84] *(affect)* retweeting **baehavior** [85] *(behavior, behaviour, behaviors)* . For the comparing models , cosine similarities are calculated between tweets and followers . We use the logistic **regression** [86] ***(Regression)*** **classifier of Scikit-learn machine learning package [24], with 5-fold cross-validation on our** [87] **balance dataset.** [88] Accuracy is **our** [89] evaluation metric. Performances of our model **and** [90] *(Moreover\, , Also\, , So)* all other models are shown in Figure 4. Figure 4 also Fig. 4 Comparison of different models . shows that the impact of topic number of LDA on the predicting accuracy , our model arrives its peak when the number is set to 60, so we fix the topic number as 60 in all our experiment . As Figure 4 illustrates , the best accuracy of 68.67% is achieved by the STF (Subjective similarity between tweet **and** [91] *(Moreover\, , Also\, , So)* followers). The accuracies of

TF-IDF model and entitybased [92] (entity based) model are 63.45% and 62.12%, which are very close to TTF (Topic similarity between Tweet and Followers, 63.88%) and [93] (Moreover\, , Also\, , So) OAF (Opinion similarity between Publisher and Followers, 62.96%). While for hashtag-based model , its accuracy **is** [94] ***(Is)*** **50.76 % ,** [95] ***(%\ )*** **which is only a little better than random selection (50%)** [96] ***(\ )*** **but not significant .** [97] The reason might lie in Table 2 Prediction Accuracy of Different Models. Significant improvement over baseline with star ( ) and LUO' model with dagger (‡) (p<0.05). Feature Set Accuracy(%) RB 60.85 LUO 68.76 SM6 69.12 LUO( )+TTF 69.20 LUO( )+TAF (...) **a** [98] ***(A)*** [99] *(A)* very low usage of [100] *(the , an)* hashtag in our [101] data. The accuracies of the other three model are OTF (Opinion similarity between Tweet and Followers, 64.80%), TAF (Topic similarity between Publisher and Followers, 62.58%) and SAF (Subjective similarity between Publisher and Followers, 66.95%) model . The results show that subjectivity model can better help understanding retweeting behavior than the other user models . 4.3.2 Comparison with Other Factors In this section , we feed the six similarities of our model as features into a retweeting classification framework [102] *(structure)* to verify **the** [103] ***(The)*** **effectiveness of subjectivity model .** [104] We compare the performance of our model with method of Luo et al. [18] which uses four feature families : Retweet History (follower who retweeted a user before is likely to retweet the user again), Follower Status (for a follower , the number of tweets, followers , friends , being listed [105] *(recorded)* and whether he is verified), Follower Active Time (the time users interact with others) and Follower Interests (common interests between tweet and followers , TF-IDF model). We use LinearSVM of Scikit-learn package to build a retweeting prediction framework , leveraging two different features [106] *(Features)* sets [107] *(set)* . One includes the six features derived from subjectivity model (marked as "SM6"). The other is the feature **set** [108] ***(Set)*** [109] *(Set)* from Luo et al. [18] (marked as "LUO"). We use the same dataset as Section 4.3.1 with 5-fold cross-validation, and [110] *(Moreover\, , Also\, , So)* accuracy as evaluation metric. In addition , we set a baseline (marked as "RB"), for which followers who have retweeted the author 's previous tweets are predicted as retweeters [111] *(retweets, tweeters, tweeter, retweet, retweeted)* of current [112] *(Current)* [113] *(is , was)* tweet. The result is listed in Table 2. The accuracy of baseline is 60.85%, and two prediction models (LUO and **our** [114] ***(Our)*** [115] ***(Our)*** [116] SM6) both outperform the baseline significantly. But the prediction [117] *(Prediction)* model based on our [118] feature set shows no significant improvement over LUO feature set . The reason might be that our model only tries to reflect the retweeting motivation of users based on content, whereas other important [119] *(essential)* factors associated with retweeting behavior are not consid [120] *(consider, cons, consist, consign, onside)* - Resonance Elicits Diffusion: Modeling Subjectivity for Retweeting Behavior Analysis 9 ered [121] *(red, ere, reed, erased, eared)* , such as network topology and tweeting habit of the user [122] *(User)* , etc [123] . Since it is proved that subjectivity model outperforms TF-IDF model in Section 4.3.1, which is used in LUO feature set , we propose that retweeting prediction performance could [124] *(Could)* be improved by using features derived from subjectivity model . As denoted by "LUO( )+" in the table , the Follower Interests features of LUO are replaced with our six [125] *(Six)* features one by one. The accuracies are all improved . It shows that our [126] model is of great importance for retweeting prediction . Noticing that , the most significant improvement (LUO( ) +STF [127] , 72.86% versus 68.76%) is the subjective similarity feature between tweet and followers , which verifies our assumption that subjective resonance between **tweet** [128] ***(Tweet)*** [129] *(Tweet)* and followers can be considered as the underlying reason that elicits retweeting behavior . Besides, the improvement by adding subjective similarity features between aauthor [130] *(author, authors, a author)* and followers (LUO( ) +SAF [131] , 72.05% versus 68.76%) is also obvious in that the resonance between author and follower [132] *(Follower)* indicates the tight homophily between them. Finally , the last row of table is the complete combination of two sets of features (LUO( )+All) by adding all six features into LUO feature set . The performance shows no significant improvement over adding STF feature only , in that subjectivity model combines both topic and opinion information , and STF is a integral feature to model both topic similarity and opinion similarity between tweet and followers , so it is

redundant [133] *(Redundant)* to add other separate parts . 4.4 Case Study In this section we give an vivid example to illustrate the subjectivity model and its ability in explaining the retweet behavior . The subjectivity models for one of the 500 target tweets, its author , and two followers (one **retweeter** [134] *(tweeter, retweet, retweeted, retweets, retweeting)* , the other **non- retweeter** [135] ***(retweets, retweet, tweeter, retweeted, retweeting)*** [136] *(Non-Retweeter)*) are shown as Figure 5. The right part of each **sub-figure** [137] *(Sub-Figure)* illustrates topic distribution and the left part illustrates opinions towards each topic . It is the 14 **th** [138] *(the, tah, Thu, tho, THC)* topic that **the** [139] *(The)* tweet talks about in the local topic space . Figure 6 shows top words of the 14 **th** [140] *(the, tah, Thu, tho, THC)* topic , the tweets of author and two followers in a word cloud 2 . Content of the tweet is: Tweet: "Sometimes the right person for you was there all along . You just **didnt** [141] *(didn't, did, dint, didst, dent)* see it because the wrong one was blocking the sight " The topic of this tweet is about " love between people " and the **opinion** [142] *(view)* is neutral , which is in accordance with the 14 **th** [143] *(the, tah, Thu, tho, THC)* topic word cloud in Figure 6 and subjectivity model of tweet in **Firgure** [144] *(Figure, Figures)* 5. The author concentrates on the 14 **th** [145] *(the, tah, Thu, tho, THC)* topic with 208 tweets **,** [146] *(___)* and his opinions are mainly neutral (as Figure 5, 6 demonstrate). As for two followers , the **retweeter** [147] *(retweet, retweets, tweeter, retweeted, retweeting)* 2 We use TagCrowd (http://tagcrowd.com/) to produce word cloud. Fig. 6 Word cloud of 14 **th** [148] *(the, tah, Thu, tho, THC)* **topic** [149] ***(Topic)*** [150] *(text, subject)* , author and followers . has published 250 tweets about two **topics** [151] *(issues, questions)* (the 14 **th** [152] *(the, tah, Thu, tho, THC)* and 52 nd **topic** [153] *(text, question, problem)*) uniformly and his opinions towards the two topics are **mainly** [154] *(Mainly)* neutral . While the other one, the non- **retweeter** [155] *(retweet, tweeter, retweeted, retweets, retweeting)* has also talked about two **topics** [156] *(issues)* (14 **th** [157] *(the, tah, Thu, tho, THC)* and 56 **th** [158] *(the, tah, Thu, tho, THC)* topic) with 188 tweets, but he is mainly interested in the 14 **th** [159] *(the, tah, Thu, tho, THC)* topic and his **opinion** [160] *(Opinion)* is positive . Although two followers have same interest (the 14 **th** [161] *(the, tah, Thu, tho, THC)* topic), their different opinions elicit their different decision , which verifies subjectivity model can help better understanding the retweeting behavior not only from **topics** [162] ***(Topics)*** [163] *(questions)* but also opinions . 5 Conclusion In this paper , we propose a subjectivity model to analyze **user** [164] *(User)* retweeting behavior on Twitter. We assume that retweeting should be elicited by the subjective resonance between **the** [165] *(The)* tweet and its followers . We define the subjectivity model formally as the combination of **topics** [166] *(issues)* and opinions , and we put forward an algorithm to establish the subjectivity model **leveraging** [167] *(Leveraging)* statistical topic model and sentiment analysis techniques . We demonstrate the effectiveness of our model for retweeting analysis problem and show that subjectivity model **is** [168] ***(Is)*** **able to** [169] ***(Can)*** [170] ***(Can)*** **reach better understanding of retweeting behavior .** [171] **Our** [172] future work mainly lie in two directions . Firstly, **the** [173] *(The)* subjectivity model is established through simple combination of **topics** [174] *(issues)* and opinions . It is an interesting direction to establish it under the framework of generative **topicsentiment** [175] model , which has been applied in reviews and citation network . Secondly , we will apply subjectivity model to other social media analysis task such as connection prediction and friend recommendation .

Writing issues in this paragraph:

1	Overused word: end
2	Overused word: end
3	Overused word: topics
4	Overused word: end
5	Misspelled word: value s
6	Misspelled word: i f
7	Overused word: end

8	Overused word: opinion
9	Misspelled word: Ot
10	Overused word: end
11	Misspelled word: jq
12	Misspelled word: jt
13	Misspelled word: m as
14	Capitalization at the beginning of a sentence
15	Misspelled word: value s
16	Capitalization at the beginning of a sentence
17	Overused word: topics
18	Capitalization at the beginning of a sentence
19	Capitalization at the beginning of a sentence
20	Capitalization at the beginning of a sentence
21	Informal pronouns
22	Overused word: measurement
23	Overused word: measurements
24	Informal pronouns
25	Misspelled word: p t
26	Misspelled word: jq
27	Misspelled word: fi
28	Capitalization at the beginning of a sentence
29	Capitalization at the beginning of a sentence
30	The use of <i>a</i> versus <i>an</i>
31	Overused word: form
32	Capitalization at the beginning of a sentence
33	Sentence fragment
34	Capitalization at the beginning of a sentence
35	Capitalization at the beginning of a sentence
36	Overused word: author
37	Capitalization at the beginning of a sentence
38	Confused possessive and contraction
39	Misspelled word: retweeters
40	Misspelled word: retweeters
41	Overused word: author
42	Informal pronouns
43	Overused word: measurements
44	Overused word: different
45	Numerals instead of words
46	Overused word: measurement
47	Capitalization at the beginning of a sentence
48	Intransitive verb in passive voice
49	Vague word: properly
50	Capitalization at the beginning of a sentence
51	Overused word: different
52	Informal pronouns
53	Misspelled word: retweeters

54	Unknown word: nonretweeters
55	Misspelled word: retweeters
56	Conjunction at the Beginning of Sentence
57	Misspelled word: retweeters
58	Informal pronouns
59	Plural instead of possessive
60	Incorrect noun form
61	Misspelled word: retweeters
62	Unknown word: nonretweeters
63	Misspelled word: betweet
64	Overused word: influence
65	Capitalization at the beginning of a sentence
66	Overused word: proves
67	Missing article
68	Missing article
69	Missing article
70	Missing comma after introductory phrase
71	Capitalization at the beginning of a sentence
72	Capitalization at the beginning of a sentence
73	Incorrect verb form with singular subject
74	Misspelled word: f am
75	Capitalization at the beginning of a sentence
76	Redundant indefinite article
77	Misspelled word: retweeters
78	Misspelled word: retweeters
79	Capitalization at the beginning of a sentence
80	Infinitive instead of gerund
81	Informal pronouns
82	Conjunction at the Beginning of Sentence
83	Capitalization at the beginning of a sentence
84	Overused word: influence
85	Misspelled word: baehavior
86	Capitalization at the beginning of a sentence
87	Informal pronouns
88	Sentence fragment
89	Informal pronouns
90	Conjunction at the Beginning of Sentence
91	Conjunction at the Beginning of Sentence
92	Misspelled word: entitybased
93	Conjunction at the Beginning of Sentence
94	Capitalization at the beginning of a sentence
95	Spaces before/after punctuation marks
96	Missing comma in compound sentence
97	Missing subject
98	Capitalization at the beginning of a sentence
99	Capitalization at the beginning of a sentence

100 Missing article
101 Informal pronouns
102 Overused word: framework
103 Capitalization at the beginning of a sentence
104 Sentence fragment
105 Overused word: listed
106 Capitalization at the beginning of a sentence
107 Incorrect verb form with plural subject
108 Capitalization at the beginning of a sentence
109 Capitalization at the beginning of a sentence
110 Conjunction at the Beginning of Sentence
111 Misspelled word: retweeters
112 Capitalization at the beginning of a sentence
113 Missing verb
114 Capitalization at the beginning of a sentence
115 Capitalization at the beginning of a sentence
116 Informal pronouns
117 Capitalization at the beginning of a sentence
118 Informal pronouns
119 Vague word: important
120 Misspelled word: consid
121 Misspelled word: ered
122 Capitalization at the beginning of a sentence
123 “Etc.” and “So On” in formal writing
124 Capitalization at the beginning of a sentence
125 Capitalization at the beginning of a sentence
126 Informal pronouns
127 Unknown word: +STF
128 Capitalization at the beginning of a sentence
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130 Misspelled word: aauthor
131 Unknown word: +SAF
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139 Capitalization at the beginning of a sentence
140 Misspelled word: th
141 Misspelled word: didnt
142 Overused word: opinion
143 Misspelled word: th
144 Misspelled word: Firgure
145 Misspelled word: th

146	Improper comma in compound subject
147	Misspelled word: retweeter
148	Misspelled word: th
149	Capitalization at the beginning of a sentence
150	Overused word: topic
151	Overused word: topics
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153	Overused word: topic
154	Capitalization at the beginning of a sentence
155	Misspelled word: retweeter
156	Overused word: topics
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162	Capitalization at the beginning of a sentence
163	Overused word: topics
164	Capitalization at the beginning of a sentence
165	Capitalization at the beginning of a sentence
166	Overused word: topics
167	Capitalization at the beginning of a sentence
168	Capitalization at the beginning of a sentence
169	Wordiness (redundant phrases)
170	Wordiness (circumlocutions)
171	Missing subject
172	Informal pronouns
173	Capitalization at the beginning of a sentence
174	Overused word: topics
175	Unknown word: topicsentiment