Effect of readability of political tweets on positive user engagement

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***Abstract*—Twitter is one of the essential information environments where novel information join and diffuse through the public discourse via user engagement. Although the previous work has shed light on the role of the content in information diffusion, stylistic factors such as readability are still under-explored. We investigated the effect of the readability on positive user engagement for over 80,000 political tweets collected for a period of six months. We formulated a set of experiments involving the use of regression techniques to predict user engagement. Our findings indicate that the addition of the readability related features leads to more accurate and more robust predictions. Increase in the prediction robustness means that ease-of-read have a considerable influence on the positive engagement political tweets receive.**

I. Introduction

Micro-blogging platforms like Twitter play an essential role in the diffusion of information and spread of news, political agenda, and rumours. Users on Twitter share their views and other information via short messages that are no longer than 280 characters. This character limit at first may seem appealing because it can make tweets easy to read due to shortness. Nevertheless, it also can make the tweets harder to read compared to longer texts ubiquitous on the web (e.g. blog articles). It is because users may need to use acronyms, abbreviations, and social media-specific features and writing styles like hashtags, emojis, and mentions to convey more information using fewer characters.

Many European political actors use Twitter to communicate with their followers by tweeting daily. Followers of these accounts engage with the actors by retweeting, and liking tweets. The high number of shares and likes can be indicators of positive feedback by followers [11]. High levels of engagement not only provides feedback to the account owner but also renders the tweet more visible to the broader audience, thus making it more salient in the public sphere [36]. As such, tweets that receive large amounts of engagement can have a profound impact by enabling collective action or diffusing conspiracy theories [14].

Most of the literature on engagement with social media posts have focused on the content of the posts while mostly ignoring linguistic factors. In this paper, we propose readability of the tweet as a significant and complementary determinant of the engagement with political messages. Research in the context of user consumption hedonism indicates a positive relationship between the ease-of-read of tweets posted by top commercial brands and user engagement with them [11]. Currently, the research on the possible effects of the readability of political tweets and user engagement with these tweets is lacking. Consequently, the main focus of this research is to investigate the relationship between the readability of the tweets and user engagement levels.

We investigate the relationship in a three-step approach. First, we create a set of stylistic, twitter specific, syntactic, and readability formulas as readability measures derived from tweet texts. Then we set up and use a set of experiments where we use machine learning techniques on a dataset of tweets posted by the EU political actors. Finally, we compare the performance of learners when baseline features were augmented with readability features to the case where only baseline features were used.

Our results indicate that when readability related features are included to train prediction models, compared to when textual-only features, i.e. baseline features, both the performance and robustness of the model improved as indicated by smaller prediction errors, and lower dispersion. These results contribute to the existing research in two ways. First, the increased predictive performance of the models indicates that readability can be an empirically and theoretically well-grounded predictor of user engagement. Secondly, our application of the readability on a novel dataset shows that it can be a context-independent determinant of user engagement.

Section two introduces the related work. Section three presents the measures of user engagement which have been used in this paper. Section four describes the experimental settings, and section five provides the results and discusses the findings. Finally, section six concludes this article.

II. Related work

Readability can be defined as the extent to which the reader can understand a piece of text with ease [8], [15]. Readability depends on many things, including content related features such as length of words and sentences in the text, the complexity of the vocabulary, font size, line height, and character spacing [5], [18]. The highly readable text is less cognitively demanding to read and comprehend, thus making the text more engaging on the top of its content. Consequently, a good ease-of-read lowers the mental hurdles for the reader, thus enabling the people with lower reading comprehension to join in the audience. Moreover, high readability can mitigate the adverse effects of topical complexity on user engagement. Political issues are products of complex systems and logic. They are produced and reproduced by a multitude of actors and interests in an obscure constellation where responsibilities are unclear, and cause-effect relations are convoluted. High levels of ease-of-read then can enable those who are not extensively politically savvy to understand the issue, the message and join in the discussion.

The previous work on engagement with tweets already shows that content alone is not enough. Xu and Jawla [36] demonstrate that some of the textual features related to readability, such as the length of the text, cue containers (e.g., mentions and hashtags) positively affect the engagement levels. Davenport et al. [10] show that Flesch reading ease formula [15], can be used to analyse demographic trends. In terms of commercial communication, extant research shows that there is an essential interplay between the readability of tweets posted by commercial brands and the positive engagement of users with the tweets [2], [11]. However, the accumulated knowledge lacks insight into the role of the readability in the engagement with political tweets.

III. Determinants of user engagement

Engagement is often conceptualised as user interaction with a post on social media. For example, on Twitter in the forms of likes and retweets, and on Facebook in the form of reaction buttons and sharing. In this work, we use the number of retweets and likes to measure the engagement levels of users with posted tweets. In this section, we review the previous work on the determinants of such engagement.

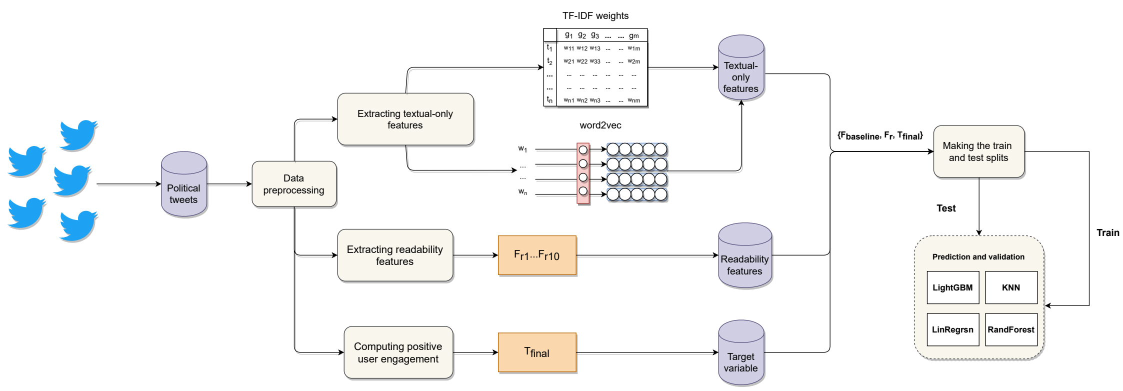
A. Drivers of retweeting

As the primary information diffusion mechanism, retweeting can have significant effects both on the public debate and the public opinion such as spreading of hoax and conspiracy theories [17]. Consequently, determinants of retweets have received considerable scholarly attention.

Previous research on retweetability points to the following three key factors: i) embedded textual features, ii) latent content features and iii) contextual features from the tweeting account. Several studies have found that embedded textual features such as URLs, hashtags increase the retweetability of the tweet [21], [33]. .

Studies focusing on latent content features such as the emotional aspect of the message and the topic have a strong influence over the likelihood of

Fig. 1: An overview of the approach



retweeting [21], [23], [31], [32], [35].For example, Kalsnes and Larsson [23] show that sensationalist softer news tends to be retweeted more.

Beyond the latent features, Rowe et al. [31] have shown that overt content features such as the number of verbs, nouns and punctuation influence the retweetability. Lastly, studies have shown that tweeting accounts popularity (number of followers and friends) has a discernible impact on the likelihood of retweeting [6], [21], [25].

B. *Drivers of liking*

Comparatively speaking, we know a lot less about the drivers of "likeability" of social media posts. Most of our scholarly knowledge on the topic comes from studies that have focused on the determinants of the number of reactions on Facebook, in particular reactions to the messages posted by populist politicians on Facebook.

Content analysis based research on Facebook points to several important content-related factors as the drivers of liking. Primary among these content-based factors is the emotional content in the political messages on Facebook.

Beyond the emotional content, the existing research also indicates that political communication style such as populist communication style, length of the text, target in the message, and issue salience of the message topic influence the number of reactions from users [4], [13], [19], [22].

IV. Features and Target

In this section, we describe the core elements in our experiments, i.e. features proxying readability and user engagement metrics. Figure 1 presents an overview of our experimental design.

A. *Tweet readability measures*

Readability of a textual message is related to its linguistic features which make it easier or harder to understand for the reader. However, the choice of the which linguistic feature to utilise is not always clear, and there are variations in preferences [12]. Motivated by the extant work on the text readability [11], [34], we create readability indicators from the textual content of tweets. We chose four categories of stylistic, platform-specific, syntactic, and readability formulas related features for this work. These features are (1) number of words (i.e. the number of tokens) per tweet, (2) average length of a word per tweet, (3) ratio of hashtags to words per tweet (4) ratio of mentions to words per tweet (5) ratio of emojis to words per tweet (6) the number of nouns in a tweet divided by the number of verbs per tweet, (7) Flesch reading ease score [15], (8) Dale-Chall readability score [9], (9) Coleman-Liau index [7], and (10) Number of difficult words.

Table I contains the names and description of readability features used in this work (represented as F_r collectively).

TABLE I: Feature names and descriptions for measures used which correspond to the readability of the (political) tweets

Feature	Description	Category
F_{r_1}	Number of words (i.e. tokens) in tweet	Stylistic
F_{r_2}	Number of characters in tweet divided by number of words per tweet	Stylistic
F_{r_3}	Number of hashtags in tweet divided by number of words	Twitter-specific
F_{r_4}	Number of mentions in tweet divided by number of words	Twitter-specific
F_{r_5}	Number of emojis in tweet divided by number of words	Twitter-specific
F_{r_6}	Number of nouns in the tweet divided by number of verbs	Syntactic
F_{r_7}	Flesch reading ease score	readability formula
F_{r_8}	Dale-Chall readability score	readability formula
F_{r_9}	Coleman-Liau index	readability formula
$F_{r_{10}}$	Number of difficult words per tweet, i.e. words that have more than two syllables	readability formula

B. User engagement measures

On Twitter, users engage with the tweets they enjoy by liking and retweeting them thus giving feedback to the author of the original tweet In this work, we compute the positive user feedback received for a tweet via measuring the values of variables T_1 and T_2 that are described in table II..

Two variables T_1 and T_2 are highly correlated (Pearson correlation=0.898), also the value of these two variables are very skewed (see table III). To reduce the noise we used a logarithmic transformation on the average value for these two variables to construct our final target variable, which is defined as follows:

$$T_{final} = Log(\frac{T_1 + T_2}{2} + 1) \tag{1}$$

Where Log is the natural logarithm function; we added 1 to the average to prevent the calculation of logarithm of zero.

V. Experimental Settings

A. Data collection

We collected tweets posted by accounts of the EU political actors and institutions for about six months [1], using Twitter's official API [2]. We first identified these accounts via the official web-pages of the European parliament [3] and the EU's public relations [4]. Initially, we identified 833 accounts on Twitter that are related to political actors and the institution of the EU. The final dataset is composed of 225,362 English tweets from 747 distinct accounts before preprocessing. We were not able to collect tweets from all of the actors' accounts since some of these accounts were inaccessible (i.e. private accounts). Some of the accounts, such as those belonging the UK members of the European Parliament, have been closed.

B. Data preprocessing

We took preprocessing steps on the complete dataset to clean the data and prepare it for feature extraction. We followed a two-phase approach in preprocessing. This way, we could utilise certain information such as hashtags and mentions from each tweet to construct the readability features. However, this information had to be omitted for feature engineering of textual features later on.

[1] from October 14th 2019 until March 16th 2020,
[2] https://developer.twitter.com/en
[3] https://www.europarl.europa.eu/meps/en/full-list
[4] https://europa.eu/european-union/contact/social-networks˙en

TABLE II: Primary measures of positive feedback. Note that the number of retweets and likes were normalised by number of followers

Variable	Description
T_1	(Number of retweets/number of followers)
T_2	(Number of favorites/number of followers)

TABLE III: Note that the number of likes and number of retweets received by the tweets are highly skewed

Variable	Min	Max	Mean	SD	Skewness
Retweet	0	21717	41.74	265.591	31.662
Like	0	87963	145.12	1104.55	32.938
T_{final}	0	5.616	0.64	0.84	1.961

1) Preprocessing phase one:

1) We removed all the retweets and duplicate tweets to reduce the noise
2) We converted all newline charters into a single space character
3) We removed any tweets where the retweet counts or like counts where not available [5]

At the end of this step, we end up with 84,321 tweets from 694 political actors. The output of this phase is further used for engineering the readability features enlisted in table I.

2) Preprocessing phase two:

1) We filtered out all the common English stop-words, such as *or*, *the*, and all the punctuation marks such as *dot*, and any non-alphabetic characters like $
2) We removed all tab characters and turned multiple spaces into single space
3) We removed all the hashtags, mentions and URLs
4) We converted all the capital letters into lowercase

We further removed the preprocessed tweets, which did not contain any words. At the end of this phase, the final dataset is composed of 83,908 tweets.

C. Extracting textual features

We used two methods for extracting the textual-only features from the political tweets. Firstly, we calculated the TF-ID [3] scores for unigrams, bi-grams, and tri-grams in the (preprocessed) tweet messages. We only calculated the TF-IDF score for grams which were in at least five tweets and not more than in 0.7 of the whole dataset. We chose the top higher scoring grams as features for building the models. This approach has been successfully used in similar problem settings for building predictive modelling of identifying extremist in social media [28]. We used Scikit-learn [6] (version 0.23.1) for calculating TF-IDF scores of the grams relative to each tweet message.

Secondly, We used Gensim [30] (version 3.8.3) and learned the 100-dimensional embedding vectors with a window size of 5 using word2vec skip-gram [27] for words in the tweets and averaged vector representations of words to aggregate as the characteristic feature of that tweet.

D. Extracting readability features

We used the output of phase one of the preprocessing to feature engineer the readability features enlisted in table II. We used a Twitter-specific POS tagger [16] to extract the information to construct the Twitter-specific features. If the POS tagger detects no verbs in a tweet, we set the value of F_{r_6} to -1 to indicate the non-existence of a verb in a tweet message.

[5] Tweets that received no engagement, i.e $T_{final} = 1$ were not removed from the data-set

[6] https://scikit-learn.org/stable/

TABLE IV: Average values of MSE for 100 runs using each set of features on four different regressors. The values stand for mean error ± dispersion, i.e. standard deviation. The better results are shown in bold.

Regressor	MSE			
	TF-IDF	TDF-IDF + F_r	Word2vec	Word2vec + F_r
Random Forests	0.701 ± 0.014	$\mathbf{0.552 \pm 0.011}$	0.619 ± 0.011	$\mathbf{0.504 \pm 0.009}$
KNN	0.752 ± 0.025	$\mathbf{0.714 \pm 0.013}$	0.675 ± 0.01	$\mathbf{0.644 \pm 0.009}$
Linear Regression	0.642 ± 0.013	$\mathbf{0.604 \pm 0.012}$	0.622 ± 0.012	$\mathbf{0.569 \pm 0.011}$
LightGBM	0.638 ± 0.013	$\mathbf{0.532 \pm 0.011}$	0.559 ± 0.011	$\mathbf{0.478 \pm 0.01}$

E. Learners

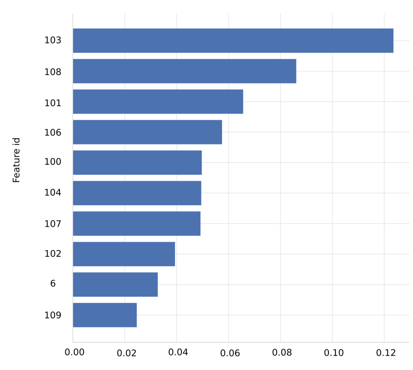
We formulated our problem as a regression problem. We used two types of textual-only features as baselines, namely top 100 grams with higher values for TF-IDF and aggregated word2vec embeddings vectors. These two sets of features were used as baseline features to train regression models to predict the target variable, which is defined in equation 1. Then we added the readability features, from table I to these baseline features, and trained the regressors with the additional features. We used lightGBM [24], linear regression, k nearest neighbours (KNN) [1], and random forests regressors [20] in our experiments. We measured the performance of the regressors by calculating the mean squared error (MSE) between the predicted values and the real values of the target variables. Lower MSE indicates a better performance. All the results in this paper are based on this metric. We used 80% of the data for training and 20% for testing. We ran our experiment 100 times with different random samples for the train and the test. In our experiment, we used Python 3 implementation of lightGBM [7] (version 2.3.1) and for three other regressors (linear regression, KNN, and random forests), we made use of Scikit-learn [29] (version 0.23.1). We used the default (hyper-)parameter settings. In addition, while training KNN, we standardised the features to *Z-scores* to accommodate KNN's sensitivity to feature scales.

VI. Results and discussion

We used two baselines, and correspondingly two augmented feature sets. We trained each regressor with these four sets of features: (1) TF-IDF only, (2) TF-IDF plus readability related features, (3) aggregated word2vec embeddings only, (4) aggregated word2vec embeddings plus readability-associated features. The results are highlighted in table IV.

Our main observation is that adding the readability related features lead to lower average prediction error and more robust results independent of the learner. Another observation is that word2vec-based features performed better than TF-IDF features. Error reduction when readability features were added for tree-based ensemble learners, i.e. random forests and lightGBM, is more considerable compared to two other learners, i.e. linear regression and KNN. This could be traced back to the fact that tree-based ensembles like random forests are better suited to model non-linear decision boundaries that could be present in a complex dataset, e.g. political tweets.

Fig. 2: top 10 TF-IDF-based features plus readability related features; feature ids from 100 and onward refer to readability features



[7] https://github.com/microsoft/LightGBM

Fig. 3: top 10 word2vec-based features plus readability related features; feature ids from 100 and onward refer to readability features

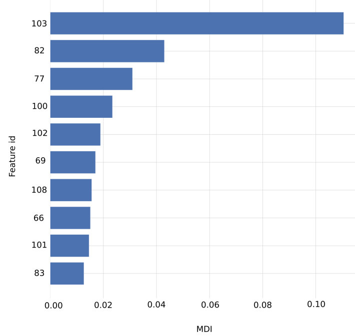


Figure 2 and 3 present the mean decrease impurity (MDI) [26] from random forests regressor [8]. We observed that F_{r_3} has the highest MDI value. Interestingly, for TF-IDF plus readability related features, 9 out of the top 10 features with higher values for gain are from readability features. Similarly, for aggregated word2vec embeddings plus readability-associated feature, 5 out of 10 top features based on higher values of gain are from the set of readability related features. This may explain why learners with readability features out-performed the baseline models. Based on the feature importance, we conjecture that adding more precise readability features which have been extracted, the tweet texts leads to better prediction accuracy.

VII. Conclusion

In this work, for the first time, we investigated the possible effect of readability of political tweets posted by a large number of Twitter accounts associated with European political actors, on the (positive) user engagement received from users and followers of these accounts. To do so, we formalised the task of measuring user engagement as a regression problem. Then we used a set of features which could proxy the readability of the text in the tweets and compared the performance of four regressors with two baselines and two augmented sets of features. Our results indicate that the inclusion of readability related features in training the prediction models used in our work significantly improves the accuracy as well as the robustness of the predictions. The results indicate the critical role of readability in user engagement of political tweets.

For future work, we consider three directions. First, effective measuring of the readability of political tweets may need further investigation, because currently, there is no consensus on which textual and linguistic features of a tweet are mainly affecting the readability. In addition, further research is necessary to extend readability measures to other languages and re-evaluate the robustness of readability as a predictor. Second, the application of deep neural networks techniques can be a promising direction of research because these models can find complex linguistic and textual interconnections between terms that can bypass the possible current limitations such as the need to extensive feature engineering. Lastly, future work can focus on the interconnections between visual materials provided in the tweets such as memes, readability and engagement levels. It is conceivable that visual materials can significantly influence ease-of-read and cognitive demands for comprehension by presenting the information via more comprehensible mediums. This, however, is beyond the scope of the current work.

[8]For example, feature id 100 refers to readability feature F_{r_1}

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