Support for Recalling Past Events Using X Posts

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Abstract— **Recalling past events is important for self-understanding and action planning. However, human memory is unreliable. Fortunately, social networking services (SNSs) can provide useful information for recalling past events. We investigate how to obtain useful information from SNS posts to support the recall of past events. This research presents a method for ranking X posts by their order of usefulness for recalling past events. We propose a method that assigns an importance score to X posts based on their content, including sentiment analysis and reactions from others, and sort them using importance scores. Experimental results demonstrated the effectiveness of our proposed method.**

Keywords— social media, X, sentiment analysis, event recall

I. Introduction

Although recalling past events is important for self-understanding and action planning, unfortunately, our human memories are unreliable. As time passes, our ability to recall past events deteriorates. On the other hand, with the spread of smartphones and tablets, such social networking services (SNSs) as X (formerly Twitter) and Instagram can provide useful information for recalling past events. We investigate how to obtain useful information from SNS posts to support the recall of past events. Our research presents a method that ranks X posts by their order of usefulness for recalling past events. Murakami et al. [1] developed a system that visualized past sentiments in Twitter posts using Google Cloud Natural Language API's sentiment analysis (Google sentiment analysis) and displayed logs sorted by date and sentiment scores. It focused on sentiment analysis to support self-understanding. In this research, we propose a method that assigns an importance score to X posts based on their content, including sentiment analysis and reactions from others, and sorts them by importance scores.

II. Related Work

Research has been conducted on scoring X posts and ranking them accordingly. For example, a ranking model [2] employed deep learning to display posts of interest to users by focusing on reposted posts, replied posts, and their timestamps. Harakawa and Iwahashi [3] suggested an easy way to obtain important information about COVID-19 by detecting tweet communities with similar topics and ranking the communities according to their importance. Montangero and Furini [4] introduced a ranking scheme called TRank, which identifies the most influential users on a particular topic with metrics like the number of followers, likes, and reposts. A machine learning method [5] calculated user influence scores based on such factors as the number of followers and followings, the number of likes and reposts of a post, and the sentiment of its text. Although this research uses X postings, it differs from previous work by focusing on individual users and only includes their own posts. Moreover, it aims to support the recall of past events.

III. Proposed Method

First, the post history in the X archive is retrieved, and such key features as number of characters, likes, reposts, and the presence of media are extracted. Next Google sentiment analysis is applied to the text of the posts. Sentiment analysis results are represented by a *score* (-1.0 to 1.0, indicating sentiment polarity) and a *magnitude* (> = 0.0, representing sentiment intensity). We use the above information to assign an importance score to a post to represent the degree to which it is useful for recalling the event and sort X posts with such scores.

The formula for calculating importance scores (I_score) is as follows:

$$I\_score = E\_score + L\_score + R\_score + C\_score + M\_score \quad (1)$$

$$E\_score = \begin{cases} score * magnitude & \text{if } score > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$L\_score = \begin{cases} \dfrac{like - like_{\min}}{like_{\max} - like_{\min}} & \text{if } like > 0 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

$$R\_score = \begin{cases} \dfrac{repost - repost_{\min}}{repost_{\max} - repost_{\min}} & \text{if } repost > 0 \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

$$C\_score = \begin{cases} \dfrac{char - char_{\min}}{char_{\max} - char_{\min}} & \text{if } char > 0 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

$$M\_score = \begin{cases} 1 & \text{if any media} \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

Equation (1) is the overall formula for I_Score (importance), and Equations (2) through (6) yield specific values for E_score (emotion), L_score (likes), R_score (reposts), C_score (characters), and M_score (media). The *score* and *magnitude* variables are derived from Google sentiment analysis; *like* represents the number of likes, *repost* indicates the number of reposts, and *char* refers to the number of characters in the posted text. Equation (2) defines the E_score, calculated by multiplying *score* and *magnitude* when the former is positive. This approach is based on findings that negatively-rated texts are less useful than positively-rated ones [1]. Equations (3), (4), and (5) represent the normalized values of likes, reposts, and the number of characters in a posted text, within a range from 0 to 1. If one or more type of media is attached, the M_score becomes 1 (6).

Table I shows an example of user posting logs arranged in a timeline order, and Table II illustrates an importance ranking rearranged using our proposed method (importance scores).

TABLE I. EXAMPLE OF TIMELINE ORDER

Date	Text	I_score	Rating
8/1	Million Arthur seems to be ...	0.38	2
8/2	This weapon is quite strong.	0.11	1
8/2	Postponing the start of ...	0.34	4

TABLE II. EXAMPLE OF IMPORTANCE RANKING (PROPOSED METHOD)

Date	Text	I_score	Rating
8/3	That was Toadette.	2.07	5
8/3	No limit!	2.01	5
8/22	Got the first number.	2.01	4

In importance rankings, observe that highly-rated posts (See Experiment) are displayed at the top, such as the top two posts on August 3 about visiting Universal Studios. The importance score for the top post was 2.07: 0.01 (E_score) + 1 (L_score) + 0 (R_score) + 0.06 (C_score) + 1 (M_score) = 2.07. In this case, likes and media, followed by text length and sentiment, contributed to the importance score.

IV. EXPERIMENT

We experimentally evaluated how effectively our proposed method recalled past events. Eight people, whose ages ranged from 21 to 24, rated the posts of August 2022 on a 5-point scale (5: very useful; 1: not useful) by answering the following question: "Is each post useful for recalling events?" Twelve methods were compared: I_score (importance score; proposed method), five scores that comprise I_score, four variations of E_score (*score*, |*score*|, |*score*| × *magnitude*, *magnitude*), timeline, and timeline reverse (baseline). The top 10 results for each method were evaluated using NDCG, a typical evaluation metric in information retrieval, where the subjects' rating values were considered relevant. Kendall's correlation analysis of each variable and each user rating was also performed (except for timeline and timeline reverse).

NDCG@10 was calculated for each subject. The mean values are shown in Table III. Table IV shows the Kendall's correlation coefficients calculated with the user ratings by the data from all the posts (**: $p < .01$, *: $p < .05$).

The importance score of the proposed method was highest at NDCG@10, confirming that it effectively recalled past events. The correlation analysis result was also the highest. However, the *magnitude* outperformed the E_score for both the NDCG and the correlation coefficient. Therefore, we additionally checked the importance score by changing the E_score to *magnitude*, and NDCG@10 became 0.636, which did not change the superiority of the proposed method.

V. CONCLUSIONS

To assist users recall past events, we proposed an importance score and a ranking function based on the content analysis of posted texts and reactions from others using posting history on X. Experimental results demonstrated the effectiveness of the proposed method. Future work will explore ways to enhance the accuracy of importance scores, such as analyzing the linguistic features of posted texts. Furthermore, we will develop a system that supports the user recall of past events using importance rankings and evaluate it.

TABLE III. NDCG@10

Method	NDCG@10
I_score (importance: proposed method)	0.681
C_score (characters)	0.622
L_score (likes)	0.616
magnitude	0.603
M_score (media)	0.592
E_score (emotion)	0.590
|*score*| * *magnitude*	0.570
R_score (reposts)	0.557
|*score*|	0.546
score	0.533
Timeline (baseline)	0.529
Timeline reverse (baseline)	0.483

TABLE IV. CORRELATION COEFFICIENTS WITH USER RATING

Variable	Correlation
I_score (importance: proposed method)	0.2459**
C_score (characters)	0.2372**
M_score (media)	0.1135**
L_score (likes)	0.0940**
magnitude	0.0868**
|*score*| * *magnitude*	0.0522**
R_score (reposts)	0.0512**
E_score (emotion)	0.0499**
Score	0.0416*
|*score*|	0.0281

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