Detection of Biased Broadcast Sports Video Highlights by Attribute-Based Tweets Analysis

Takashi Kobayashi[1,⋆], Tomokazu Takahashi[2], Daisuke Deguchi[3], Ichiro Ide[1], and Hiroshi Murase[1]

[1] Graduate School of Information Science, Nagoya University, Japan
{ide,murase}@is.nagoya-u.ac.jp
[2] Faculty of Economics and Information, Gifu Shotoku Gakuen University, Japan
ttakahashi@gifu.shotoku.ac.jp
[3] Information and Communications Headquarters, Nagoya University, Japan
ddeguchi@is.nagoya-u.ac.jp

Abstract. We propose a method for detecting biased-highlights in a broadcast sports video according to viewers' attributes obtained from a large number of tweets. Recently, Twitter is widely used to make real-time play-by-play comments on TV programs, especially on sports games. This trend enables us to effectively acquire the viewers' interests in a large mass. In order to make use of such tweets for highlight detection in broadcast sports video, the proposed method first performs an attribute analysis on the set of tweets issued by each user to classify which team he/she supports. It then detects biased-highlights by referring to the number of tweets made by viewers with a specific attribute.

Keywords: Twitter, broadcast sports video, highlight detection, play-by-play comments.

1 Introduction

Today, due to the enormous amount of programs broadcast on TV, video summarization techniques are needed. Many methods have been proposed on summarizing various types of broadcast videos, such as news [1], sports [2], and cooking [3]. In these works, videos were mostly summarized based only on the audio-visual information that could be extracted from the video contents themselves. This approach is simple, but its output does not always match a viewer's interest, for example, a viewers' interest in a sports game may only be on their favorite team. This drawback was mostly due to the difficulty in establishing a general framework to obtain information on such interests only from the video content itself.

On the other hand, a micro-blogging service "Twitter[1]" is rapidly growing the number of its users. A post on Twitter "tweet" consists of a user name, a

⋆ Presently with Canon Inc.
[1] http://twitter.com/

S. Li et al. (Eds.): MMM 2013, Part II, LNCS 7733, pp. 364–373, 2013.

comment (maximum 140 characters), and a time stamp. It is said, as of 2012, over 100 million people use this service as a real-time communication tool because of its ease of use. Recently, as one style of Twitter usage, tweeting while watching TV is becoming popular. This enables us to exchange play-by-play comments on contents of a TV program in real-time with many other users sharing the experience while watching the same program. In case of popular programs, tens of thousands of tweets are posted during the broadcast. These tweets reflect the viewers' interests, opinions, and comments to the TV program and its contents.

Our goal is the summarization of TV programs from the viewers' viewpoints. Aiming at this goal, in this paper, we propose a method for biased-highlights detection from a broadcast sports video referring to information on user attributes obtained by analyzing their tweets. We considered that compared to other kinds of video contents, in case of team sports, viewers' interests are relatively simple; which of the two teams they support. The proposed method first performs an attribute analysis on the set of tweets issued by each user to classify which team he/she supports. It then detects biased-highlights by referring to the number of tweets made by viewers with a specific attribute. The benefit of the viewer classification is that the proposed method can provide different sets of highlights biased by supporters of each team, whereas using all tweets without the viewer classification only provides a set of highlights for both teams.

2 Related Work

Miyamori et al. [4] have proposed a broadcast video summarization method based on viewer's perspectives posted on a live chat forum in a Japanese BBS; 2-channel[2]. However, a live chat forum is not sufficient to obtain interests of general viewers in a large community because only limited users in a small community participate.

On the other hand, tweets posted on Twitter are recently focused as a resource to obtain the viewers' interests on a TV program. There is already a commercial service that visualizes tweets posted on current TV programs and ranks them in real-time according to their popularity. Shamma et al. [5] analyzed the viewers' attention of a TV debate from the contents and the number of tweets during the broadcast. In order to summarize broadcast TV videos, only few researches [6,7] made use of Twitter up to now, but even they do not consider the difference of viewers' interests.

3 Proposed Method

In this paper, we focus on video highlight detection of team-sports where two teams participate in a game, such as baseball and soccer. Therefore, we expect to obtain two different sets of highlight scenes biased according to the viewer's interest; which team he/she supports.

[2] `http://2ch.net/`

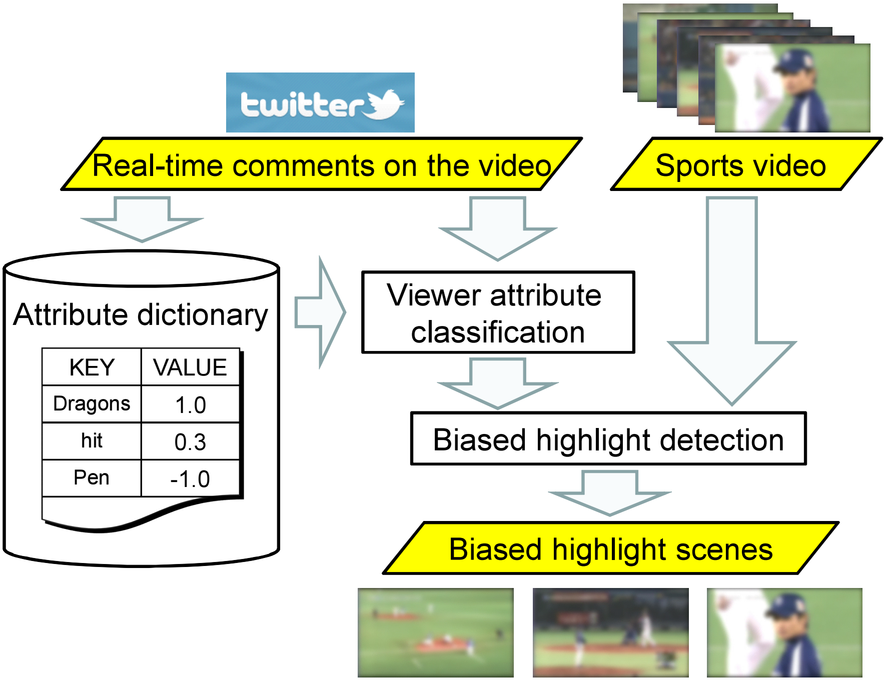

Fig. 1. The flow diagram of the proposed method

Below, we explain the proposed algorithm in the case of a game between teams A and B. Before the main process, a preprocessing is applied to tweets obtained during the period of the broadcast, in order to filter-out real-time comments by Twitter users who are presumably not watching the program.

Figure 1 shows the flow diagram of the proposed method. The proposed method detects biased-highlights of the video by an attribute-based analysis of the tweets, by mainly the following three steps:

- Creation of an attribute dictionary
- Viewer attribute classification based on their tweets
- Biased highlight detection

Below, we describe the above process in detail.

3.1 Preprocessing

First, tweets related to the actual game are extracted by using their time stamps, keywords including team names, player names, and hash-tags. We consider that the Twitter users whose tweets were included in the extracted tweets are candidates of viewers. Then the bag-of-words obtained from the set of tweets issued by each user is input to a SVM (Support Vector Machine) classifier that is trained to classify viewers and non-viewers. The classifier is trained from tweets on other games.

3.2 Creation of an Attribute Dictionary

This process creates an attribute dictionary that is needed to classify the attribute of each viewer; which team he/she supports. The dictionary consists of pairs of a term and its attribute value. The attribute value is defined in proportion to the frequency of the corresponding term that appeared in tweets by viewers supporting one of the two teams.

Here, the dictionary is renewed per short time period in the video that is being analyzed, because the meanings of a term greatly change according to the context of each game and the plays that occur in it. To create this, we make use of the SO-PMI (Semantic Orientation from Pointwise Mutual Information) method [8], which is a method for unsupervised learning of semantic orientation of a phrase. In this method, the authors classified reviews of products (recommended / not recommended), using semantic orientations of phrases in the reviews that were learned with only two initial given terms; "excellent" for positive orientation and "poor" for negative orientation.

Meanwhile, Twitter users sometimes include hash-tags in the form of "#*topic*" in their tweets for the purpose of informing other users the topic of their tweets. In case of sports, team names that they support are very often used as hash-tags. Therefore, the hash-tags including the team names were used as the initial terms for the SO-PMI method for the creation of the dictionary in our method. Here, we set the attribute values of hash-tags including team names of A and B to 1 and -1, respectively. The values of other terms w are calculated by the following equations:

$$V_A(w) = \frac{F_A(w) - F_B(w)}{F_A(w) + F_B(w)} \tag{1}$$

$$F_A(w) = \sum_{T_A \in D_{t,s}} W_{T_A}(w) \tag{2}$$

$$W_{T_A}(w) = \begin{cases} 1 & w \in T_A \\ 0 & \text{otherwise} \end{cases}, \tag{3}$$

where T_A represents a tweet including team A's hash-tags, and $D_{t,s}$, the set of all the viewers' tweets posted in a short time period (s seconds starting from time t). The value $F_B(w)$ is calculated by replacing A of Eqs. (2) and (3) with B. Thus, a term with positive values ($V_A(w) > 0$) could be used for a term supporting team A, and that with negative values ($V_A(w) < 0$), for team B. Although there are many common terms used to support both teams, the values of these terms become small by Eq. (1).

3.3 Viewer Classification Based on the Attribute Analysis on Their Tweets

Using the attribute dictionary, the attribute of each viewer is classified according to the set of their tweets during a certain period. The attribute of each viewer u is judged by the following equations:

$$L(u) = \begin{cases} A & N_A(u) > 0 \\ B & N_A(u) < 0 \\ Neutral & N_A(u) = 0 \end{cases} \tag{4}$$

$$N_A(u) = \sum_{T_u \in D} \text{sign} \sum_{w \in T_u} V_A(w), \tag{5}$$

where T_u represents a tweet by viewer u, and D, the set of all the viewers' tweets posted in the game. The viewers that post tweets including terms with positive values ($V_A(w) > 0$) are classified as team A's supporters.

3.4 Biased Highlight Detection

Based on the viewer attribute classification result, this process first divides the tweets into two sets. Each set contains tweets made by viewers labeled as supporting the same team. For each set of tweets, this process then finds the local maxima of the temporal change of the number of the tweets during each short time range as candidates of highlights. The biased highlight scenes are then detected as video segments around the candidates where the number of the tweets is greater than a threshold.

4 Experiment

We applied the proposed method to the fifth game of the annual Japanese baseball championships between "Chunichi Dragons (Hereafter, Dragons)" and "Lotte Marines (Hereafter, Marines)" on November 4, 2011. A total of 20,524 real-time tweets made by 1,424 viewers were obtained after the preprocessing of the proposed method introduced in section 3.1.

4.1 Highlight Detection Accuracy

To evaluate the detection accuracy, we compared the results obtained by the proposed method with the actual highlight scenes that were edited and broadcasted by a local broadcasting station supporting one of the teams; Dragons, their local team.

Figure 2 shows the highlights biased towards the Dragons supporters' viewpoints that were detected by the proposed method. The horizontal axis represents elapsed times from the play-ball, and the vertical axis represents the number of tweets that were posted around the time by users classified as Dragons' supporters. The blue circles and the red triangles represent the biased highlights detected by the proposed method and the broadcasted highlights, respectively. Two of three actually broadcasted highlights were successfully detected by the proposed method when a certain value was used for the detection threshold. Although we determined the threshold manually in this experiment, we will develop a method for automatic determination of the threshold in the future.

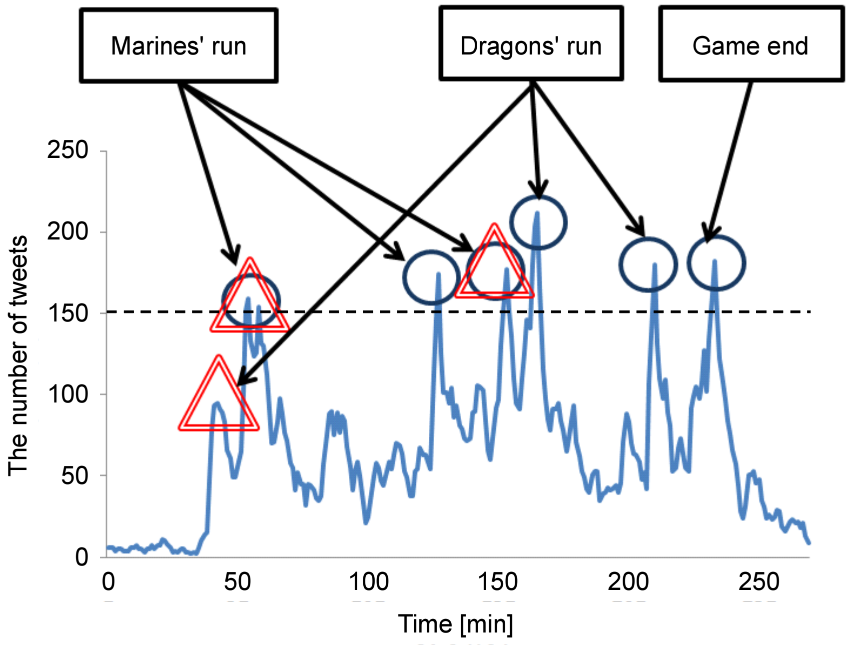

Fig. 2. The highlights biased towards the "Dragons" supporters' viewpoints obtained by the proposed method

Tables 1 and 2 describe the events that occurred around these moments. Six of the seven detected highlights corresponded to the actual runs in the game. From this, we can confirm that the proposed method successfully detected the highlights. However, the proposed method could not detect the first highlight scene "Dragons score the first run on a sacrifice fly." As one of the main reasons for this, we consider that the number of tweets around the time was fewer compared to that for other highlights. This is because, for this game, not all TV stations started broadcasting immediately after play-ball. Therefore, only a limited number of viewers that were either on-site, or had access to CATV or satellite TVs could post tweets around the time. To detect highlights accurately including such cases, a method is required that uses not only the number of tweets but also its means and variations.

4.2 Analysis of Viewers' Interests

We analyzed the difference of the viewers' viewpoints depending on the teams they support. As the result of the viewer attribute classification based on the attribute of their tweets, the 1,424 viewers were classified into 684 Dragons' supporters and 740 Marines' supporters. Figure 3 compares the transitions of the frequency of tweets issued by the viewers with each attribute. Several peaks where the tweets largely increased was observed in the case of Dragons' supporters.

Table 1. Biased highlights obtained by the proposed method for Dragons' supporters

Time	Event	Score
18:54	Marines hits with the bases full and turns the game.	4 vs. 1
18:59	Marines adds runs.	6 vs. 1
20:08	Marines hits a two-run home-run.	9 vs. 1
20:34	Marines adds a run.	10 vs. 1
20:45	Dragons adds a run.	10 vs. 2
21:31	Dragons hits a two-run home-run.	10 vs. 4
21:54	The game ends in a win for Marines.	10 vs. 4

Table 2. Highlights broadcasted by a local TV station supporting the Dragons

Time	Event	Score
18:39	Dragons scores the first run on a sacrifice fly.	0 vs. 1
18:54	Marines hits with the bases full and turns the game.	4 vs. 1
20:34	Marines adds a run.	10 vs. 1

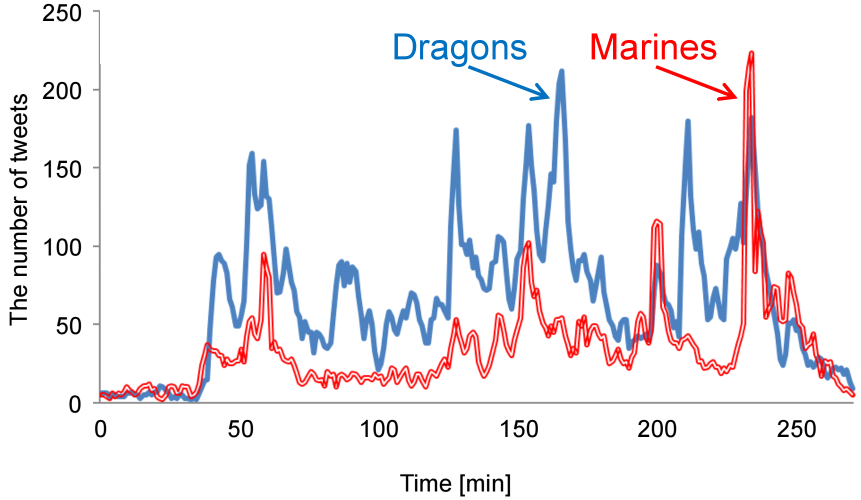

Fig. 3. The transitions of the frequency of tweets made by the viewers with each attribute

On the other hand, in the case of Marines' supporters, fewer peaks than the Dragons' supporters were observed, with many tweets observed towards the end of the game.

Figures 4 and 5 show the events that occurred around the peaks for each team. We observed that the figures show the difference of interests between the supporters of each team; the Dragons' supporters were interested in scoring scenes by both teams, whereas the Marines' supporters showed interest in scoring scenes of only their team. The reasoning of this difference could be analyzed

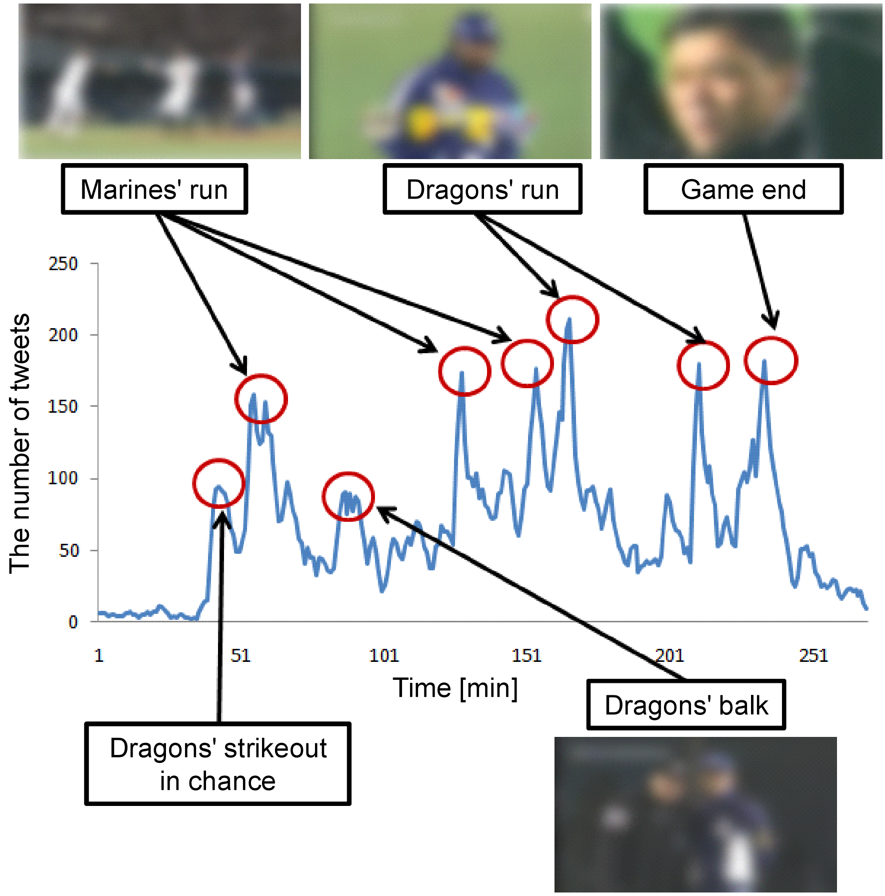

Fig. 4. Interests of the Dragons' supporters

as follows; the game resulted in that Marines won the game by 10 vs. 4 after keeping a large lead for a long time. The Marines' supporters were secure to their victory in the early stage, so they were probably interested only in the Marines' runs that strengthened their feeling of security. On the other hand, the Dragons' supporters kept their hopes on their come-from-behind victory until the last moment, so they were interested in all plays that could affect the game. From this analysis, we confirmed the effectiveness of the attribute-based viewer classification for the acquisition of the viewers' interests.

4.3 Viewer Classification Accuracy

The viewer classification accuracy is one of the most important factors that determines the performance of the proposed method. To evaluate the accuracy, we conducted the following experiment.

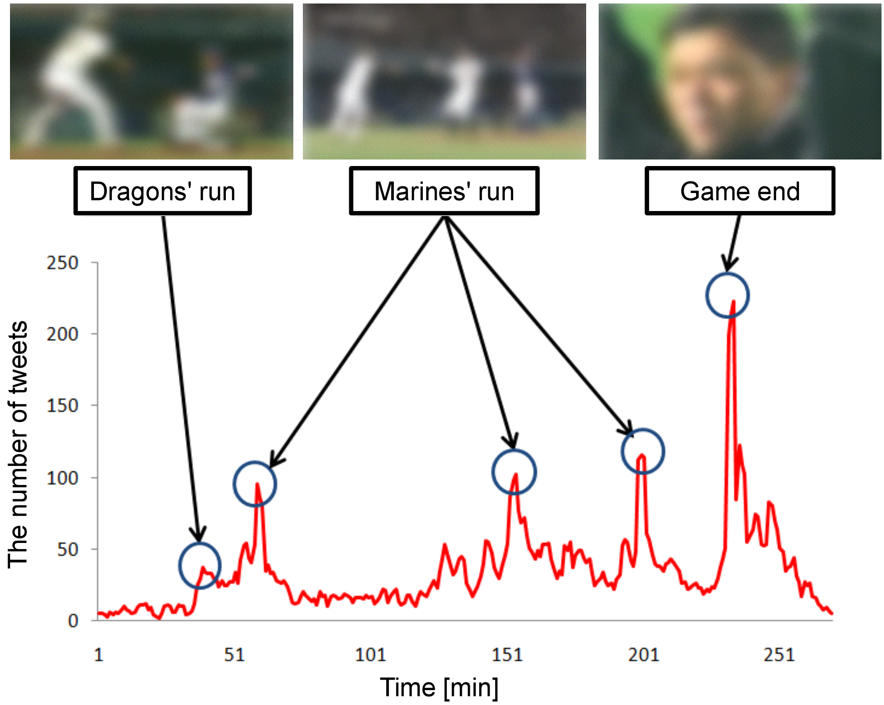

Fig. 5. Interests of the Marines' supporters

First, we chose 200 viewers at random from the 1,424 viewers, and then labeled them manually with their attributes, namely which team he/she supports. The classification accuracy was calculated while changing the unit time length s that was used in the creation of the attribute dictionary. As a result, we confirmed that the proposed method could classify the viewers with the accuracy of more than 80% when s was set to 2 seconds. Shortening s improved the accuracy because the tweets effectively reflected quick responses to each play. On the other hand, too short s sometimes reduced the number of the terms that could be registered to the dictionary, which could cause a degradation in the accuracy.

5 Summary

We proposed a method for biased highlight scene detection from a broadcast sports video based on the interests of viewers obtained through their tweets on Twitter. To acquire each viewer's interest, that is which team the viewer supports, the proposed method performed the viewer classification based on attributes of their tweets. Biased highlights were detected for each team by referring to the transition of the number of tweets by viewers supporting the team. In an experiment, we applied the proposed method to highlight detection of an actual baseball game broadcasted on TV. From the result, we confirmed that the proposed method could effectively detect highlights biased towards the viewers' interests.

Acknowledgments. Parts of this work were supported by the Grants-in-Aid for Scientific Research.

References

1. Nack, F., Ide, I.: Why did the Prime Minister resign? —generation of event explanation from large news repositories—. In: Proc. Nineteenth ACM Int. Conf. on Multimedia, pp. 313–322 (2011)
2. Chang, Y.L., Zeng, W., Kamel, I., Alonso, R.: Integrated image and speech analysis for content-based video indexing. In: Proc. Int. Conf. on IEEE Multimedia Computing and Systems 1996, pp. 306–313 (1996)
3. Miura, K., Hamada, R., Ide, I., Sakai, S., Tanaka, H.: Motion based automatic abstraction of cooking videos. In: Proc. ACM Multimedia 2002 Workshop on Multimedia Information Retrieval, pp. 21–29 (2002)
4. Miyamori, H., Nakamura, S., Tanaka, K.: Generation of views of TV content using TV viewers' perspectives expressed in live chats on the web. In: Proc. Thirteenth ACM Int. Conf. on Multimedia, pp. 853–861 (2005)
5. Shamma, D.A., Kennedy, L., Churchill, E.F.: Tweetgeist: Can the twitter timeline reveal the structure of broadcast events? In: Proc. 2010 ACM Conf. on Computer Supported Cooperative Work, pp. 589–594 (2010)
6. Hannon, J., McCarthy, K., Lynch, J., Smyth, B.: Personalized and automatic social summarization of events in video. In: Proc. Fifteenth Int. Conf. on Intelligent User Interfaces, pp. 335–338 (2011)
7. Chakrabarti, D., Punera, K.: Event summarization using tweets. In: Proc. Fifth Int. AAAI Conf. on Weblogs and Social Media, p. 154 (2011)
8. Turney, P.D.: Thumbs up? Thumbs down? Semantic orientation applied to unsupervised classification of reviews. In: Proc. 40th Annual Meeting of the Association for Computational Linguistics, pp. 417–424 (2002)