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RESEARCH ARTICLE

Temporality Based Sentiment Analysis Using Linguistic Rules and Meta-Data

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Abstract Internet is frequently used as a medium for exchange of information and opinion. The raw data available over the web is refined for the use in automated decision support system. Present day sentiment analysis generates Sentiscore by giving equal weightage to all the reviews without considering the temporal aspect. This somehow degrades the reliability of decision support system. In this paper, temporal sentiment analysis is proposed based on meta-data in conjunction with the linguistic context of words. An algorithm is also developed for evaluating Tempo-Sentiscore, which is a numeric value used to capture the temporal sentiment analysis. The proposed algorithm is evaluated on benchmark product review data. The experimental results based on temporality show high performance levels with precision, recall over 90%. The performance of the system demonstrates the effectiveness of the technique using human annotation. This paper also shows how the star rating is affected when Tempo-Sentiscore is considered in place of Sentiscore. This new star rating is close to the real scenario, i.e. Human Annotation.

Keywords Sentiment analysis · Temporal tagging · Sentistrength · Natural language processing · Meta-data · Linguistic rules · Opinion mining

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1 Introduction

Nowadays, a large number of users express their views for the products over various online platforms. These reviews are useful for potential consumers and manufacturers. However, huge raw data available over the web, makes it a hard task to take any decision for any product. Therefore, the analysis of product reviews based on natural language processing is of great value. This type of analysis is called as sentiment analysis or opinion mining.

Sentiment analysis [1] (SA) is a quintuplet consisting, 'e' is an entity, 'a' is an aspect of the entity, 's' is the sentiment on aspect, 'h' is opinion holder, 't' is time of opinion.

i.e. $SA = \{e,a,s,h,t\}$

It involves building a system for collecting and categorizing the documents into positive, negative or neutral. Although, many researchers have worked to deal with various aspects of sentiment analysis. Still, many of the aspects need attention. Temporality is one of them. Time plays an inevitable role in all spheres of our lives, still real time has long been a forgotten dimension in state of the art sentiment analysers that perform automatic analysis of the reviews. Generally, with time the opinion of people is changed about any entity. Therefore, sentiment analysers should capture the temporal factor in the analysis. Present day sentiment analysers takes the time explicitly, i.e. date of post takes into consideration [2].

Temporality in real time sentiment analysis is achieved by formulating rules based on metadata as well as the linguistic context of words. Present sentiment analysers evaluate the overall Sentiscore [3] of any entity irrespective to the document creation time or review posted time.

SentiStrength [1] uses a lexical approach that exploits a list of sentiment-related terms and standard linguistic rules and methods to express sentiment. It generates Sentiscore by giving equal weightage to all the reviews without considering the temporal aspect. Therefore, takes the outdated reviews equally important as the present day reviews for the Sentiscore generation process. This somehow degrades the reliability of the sentiment analysers because the importance of bygone reviews varies with time depending on the query.

For Example,

Query 1: *Is ford car a good car?*

For above mentioned query, the reviews of present (2016/2017) should be given more weightage. The reviews from the years other than 2016/2017 should be taken as bygone or outdated reviews. Hence, less importance should be given to these.

Query 2: *Was ford car a good car in 2006?*

In this, the reviews of present (2016/2017) should be considered unimportant. These may be assigned zero weightage in the overall opinion generation. On the other hand, the reviews of 2006 should be given high weightage.

It was observed that there is a need of analysers which can work with temporality in sentiment generation. In this paper, the proposed technique generates Sentiscore by focusing on temporality. It uses a linguistic approach to exploit the temporal behaviour of words along with metadata. This type of Sentiscore generated is termed as Tempo-Sentiscore.

1.1 Motivation and Contribution

Outdated reviews may result in biased sentiment analysis, which may or may not represent the current scenario. To remove this limitation, we are trying to implement temporal sentiment analysis of reviews by providing appropriate weightage to the reviews. The proposed algorithm addresses the challenge of real time query based sentiment analysis. The focus of this research is to devise an algorithm which gives the real essence of sentiments in the textual communication. Our main contribution in this paper is the inclusion of temporality i.e. Temporal tag in sentiment analysis by categorizing the documents in present, past or future. It is designed using: (a) linguistic rules by employing the semantic context of words in English; (b) Meta-Data associated with each review in the dataset. The effect of these rules is shown using the standard dataset.

Another contribution is an algorithm which is designed to generate Tempo-Sentiscore. To test the performance of Tempo-Sentiscore, the Gold standard is used. This Tempo-Sentiscore allows us to have a more precise measure of the impact of the temporality of the sentiment classification task.

The objective is to better understand the impact of the temporality on the sentiment analysis. This paper shows how the star rating gets affected by considering Tempo-Sentiscore instead of Sentiscore, Using Tempo-Sentiscore, we get the star rating closer to the real scenario.

2 Related Work

Many researchers worked in the area of sentiment analysis or opinion mining. Thelwall et al. [2] developed various algorithms for the identification of subjective or objective nature of the textual data. These subjective clues are further classified as positive or negative. They developed algorithm to detect sentiment strength in addition to sentiment polarity from the structured sentences. Strapparava et al. [4] worked for the differentiation of emotions as mild or strong, this is same as deduced by humans. With the passage of time, researchers found much of the textual data is informal and unstructured in nature. The need to tackle with this informal text for sentiment analysis was aroused. Thelwall et al. [5] devised a technique for calculating the actual sentiment strength from unstructured and informal text, i.e. short sentences. Most of the sentiment analysis work is based on WordNet [6] which is the electronic dictionary used for various linguistic tasks and SentiWordNet [7] is another lexicon which holds a numeric value given to various words contributing for calculating the actual magnitude or strength of the opinion.

Temporal properties in natural language processing has not gotten the proper attention in sentiment analysis.

Inclusion of time in the field of sentiment analysis also made it more valuable in decision support systems. Temporal aspect in sentiment analysis based on metadata (explicit) was considered by O'Connor [2]. They counted all instances of positive-sentiment and negative-sentiment through topic keyword during the specific time as mentioned explicitly in the query. Thelwall et al. [8] in their work considered time associated for the analysis of sentiments. They have found the popularity of any event by taking time, event and its corresponding sentiment from the online reviews. Again in their work, they used the metadata for each review i.e. date of post.

Han et al. [9] gave a two-level constraint-based framework, one is for processing and second is based on reasoning over temporal information in natural language. Chang [10] devised an algorithm for temporal tagging, which not only recognise, but also normalize temporal expressions in English. Tempo-WordNet [11] has generated using various linguistic rules for the classification of sentences as temporal/Atemporal [11]. Sentiment analysis based on the temporal nature of the document considering metadata along with linguistic rules is yet not considered by the existing systems. Razavi et al. [12] worked for deducing the sentiment of the text containing the dreaming content. They used short textual data for sentiment analysis of dreams. Fukuhara et al. [13] proposed a sentiment analyser for analyzing temporal trends of sentiments and topics from texts with respect to time. They had shown the impact of sentiment corresponding to a particular topic at a specific time. In their work, they had used various news articles and data collected from weblogs. Other researchers [14] used images which contained geographical information. They had used that information for embedding temporality and for sentiment analysis, they used images. The effect of temporality was analysed [15] by showing their effect over communities. Along with it, the effect of preprocessing was also associated with sentiment analysis [16]. Results were found better in case of SVM from the state of the art. To reduce high dimensionality in processing through bag-of-words, a system was proposed [17], which minimizes the dimensionality by eliminating irrelevant features and noisy text. Arabic social media data [18] was considered to broaden the work in the area of sentiment analysis. Again in their research they had taken care of temporality of the reviews. Recently, temporal characteristics [19] has used for sentiment analysis of travel blogs over time, i.e. explicit temporality. Temporal sentiment analysis has used for person recommendation [20].

The brief description of sentiment analysis based on explicit and implicit temporal tag is given in Table 1.

It can be summarized from Table 1 that temporal expressions hidden in the linguistic context of words are not considered by sentiment analysers. Although researchers consider explicit time in the form of metadata to deduce the sentiments.

We have proposed a system that generates the sentiment analysis of the documents based on metadata as well as temporality of the word linguistically. The architecture of the system is as shown in Fig. 1.

For Example

The lens quality was good. Posted on: 01/01/2016

It contains two aspects

(1) According to the metadata (date of post), the given review is in present.

(2) According to the linguistic rules (was,were, etc. -→ past), here the presence of the word 'was' make the given review fall in past category.

3 Proposed Definition of Tempo-Sentiscore

It is the measure of subjectivity and opinion from the textual data. It usually captures a modified potency of the Sentiscore. It is a triplet comprising, 's' is Sentiscore associated with each document, 't' is the temporal tag (present, past or future) based on implicit and explicit tag assigned to each document, 'c' is the weightage given to each temporal tag, i.e. c ε c1, c2, c3 where 'c1' is weightage given to present, 'c2' is the weightage given to past and 'c3' is weightage given to the future.

i.e. $\mathrm{TS} = \{s,t,c\}$

The aggregated Tempo-Sentiscore of any entity is defined by the Eq. (1).

$$\mathrm{TS} = \left(\begin{array}{r} \sum_{i=1}^{n} \mathrm{Sentiscore}(\mathrm{TempTag}_{\mathrm{present}}) * c1+ \\ \sum_{i=1}^{n} \mathrm{Sentiscore}(\mathrm{TempTag}_{\mathrm{past}}) * c2+ \\ \sum_{i=1}^{n} \mathrm{Sentiscore}(\mathrm{TempTag}_{\mathrm{future}}) * c3 \end{array} \right) \Big/ n \tag{1}$$

where 'Sentiscore($\mathrm{TempTag}_{\mathrm{present}}$)' magnitude of the sentiment score using SentiWordNet for the document in present. 'Sentiscore($\mathrm{TempTag}_{\mathrm{past}}$)' magnitude of the

Table 1 Summarized work in sentiment analysis based on explicit temporal tag

Sr. no.	Author	Explicitly mention of topic keyword	Implicitly deduce topic keyword	Handling the geographical dispersion of time	Fore-cast analysis	Weightage hinged to reviews w.r.t. time
1	Brendan O'Connor [7]	✔	×	×	✔	×
2	Mike Thelwall [2]	✔	×	✔	×	×
3	Amir H. Razavi [12]	✔	×	×	×	×
4	Dias [11]	✔	✔	×	×	×
5	Fukuhara [13]	✔	×	×	×	×

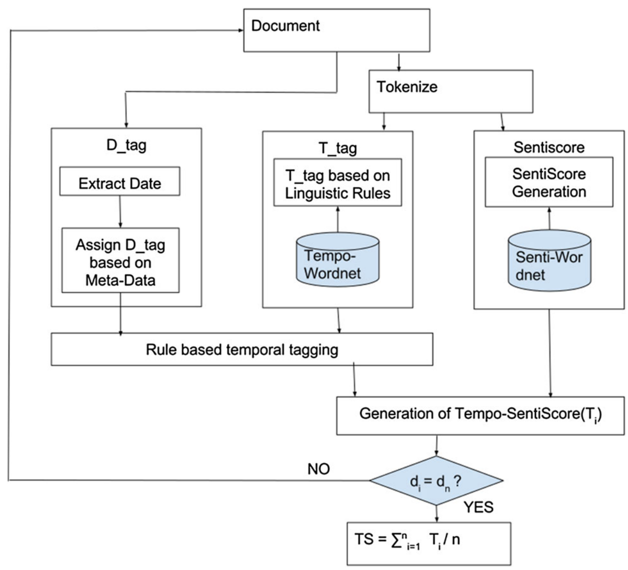

Fig. 1 System architecture of proposed sentiment analyser

sentiment score using SentiWordNet for the documents in past. 'Sentiscore($TempTag_{future}$)' magnitude of the sentiment score using SentiWordNet for the documents in future. c1, c2 and c3 are the variables whose value depends on the temporal(present/past/future) tag of the document. From Eq. (1), Tempo-Sentiscore (TS) is calculated based on the formulated rules for the temporal tag mentioned in Table 2. It includes T_tag and D_tag based on linguistic rules and metadata respectively.

4 Proposed System Design

The methodology of the proposed system involves

(1) Tokenization
(2) Tagging
(3) Sentiscore Generation
(4) Tempo-Sentiscore generation.

The detail description of each is as follows

(1) *Tokenization*

Pre-processing of the text includes tokenization. It is a process of dividing the whole text into segments based on word boundaries or a delimiter depending on the language used. It binds the characters into semantic units. The origin of this approach is from Penn Treebank Project [6]

Test sentence: *He is very happy with the products of this company.*

Tokens Generated:	*He*
	is
	very
	happy
	with
	the
	products
	of
	this
	company.

(2) Tagging

It comprises of 3 different phases,

(a) Implicit Tagging
(b) Explicit Tagging
(c) Generation of Temp_tag

(a) *Implicit Tagging (T_tag)*: In this phase the temporal tag is assigned to documents based on various linguistic rules. The linguistic rules targeting the most used general terms of temporal expressions. TempoWordNet is used for having temporal-tag [11] i.e.

was/were/had/…etc. → past
is/am/are/…etc. → present
will/shall/…etc. → future

For Example

Review 1: Ford car was a good car. It was very comfortable.

Table 2 Rules for the temporal tag of a document

Rules	T_tag	D_tag	Temp_tag
Rule 1	Present	Past	Past
Rule 2	Present	Present	Present
Rule 3	Past	Past	Past
Rule 4	Past	Present	Past
Rule 5	Future	Past	Past
Rule 6	Future	Present	Future

Posted on: 02/05/2017

T_tag = past (implicit)

For above mentioned query, the review talks about the past opinion of the car. Although it is posted in present. *Review 2: The food of this restaurant is awful.*
Posted on: 08-09-2014

T_tag = present (implicit)

Linguistically the post is considered as present opinion. However, it is written in the past year.

(b) *Explicit Tagging (D_tag)*: It is metadata based tagging phase. In this phase, the D_tag is assigned to each document. It is based on the document creation time or date of post. If the number of days exceeds the given threshold value, then D_tag is present and if it is below the threshold value then D_tag is past. The reviews from the year 2016and 2017 are taken as present before 2016 every review is counted in the past.

For Example

(1) *Ford car is a good car. It is very comfortable.*
Date of post: 12/08/2004

D_tag = past(explicit)

In the above example, this review is considered in past category.(2) *The food of this restaurant was awful.*
Date of post:08-07-2017

D_tag = present(explicit)

According to the date of post of the review, the given review is in present.

(c) *Generation of Temp_tag*: Rules for the Temp_tag are formulated with the help of three linguistic experts. They were instructed to read D_tag and T_tag to annonate Temp_tag as present, Past and Future. With the rules as defined in Table 2, Temporal tag is assigned to each document.

4.1 Rules for the Assignment of Temporal Tag to Each Document

Semantic Structure of rules

{ruleType: "tokens",pattern: (/D_tag?/,/T_tag?/),Temp_tag: ?}, Where '?' is replaced by present, past and future as by different temporal expressions.

(3) *Sentiscore Generation*

SentiWordNet is the base for getting the actual magnitude of the sentiment for a document. For our work, we have used SentiWordNet [7]. The Sentiscore(w_i) is calculated using the core Senti-strength algorithm [3].

Test sentence

Her happiness is increased by having this cellphone.

$$Sentiscore(w) = 0.271$$

After the completion of all the three phases, we get the following

(i) Sentiscore
(ii) D_tag (metadata based)
(iii) T_tag (linguistic rules)
(iv) Temp_tag

(4) *Tempo-Sentiscore Generation*

In this step, the Tempo- Sentiscore is to be calculated which captures the real essence of the sentiment.

The Tempo-Sentiscore is calculated as follows

$$\mathrm{TS}_i = [w_i] * \mathrm{c}$$

where, 'TS_i' is the new magnitude of the opinion according to the temporal tag for 'ith' document.

'w_i' holds the magnitude of Sentiscore by using SentiWordNet for 'i^{th}' document.

The value of 'c' depends on the temporal tag, i.e. present/past/future

For Example,

If *Temp_tag = present*, then c = c1
If *Temp_tag = past*, then c = c2
If *Temp_tag = future*, then c = c3

c1 + c2 + c3 = 1

Finally, Tempo-Sentiscore of any entity is calculated as an aggregation of Tempo-Sentiscore associated with each document (i) using Eq. (2).

$$\mathrm{TS} = \left(\sum_{i=1}^{n} t_i\right)/\mathrm{n} \tag{2}$$

5 Proposed Algorithm

Based on the above discussion, an algorithm is devised as shown in Fig. 2. It follows the simple method given in Sect. 3. The input is a collection of documents and the output is a Tempo-Sentiscore (TS) for an entity. The algorithm is simplified for presentation clarity.

```
Input
Directory containing documents D = {D1, ..., Dn}
'n' is the total no. of documents
'c1' the magnitude to be multiplied with the Sentiscore, where the temp_tag = present and 0<c1>1
'c2' the magnitude to be multiplied with the Sentiscore where the temp_tag = past and 0<c2>1
'c3' the magnitude to be multiplied with the Sentiscore where the temp_tag = future and 0<c3>1
        c1+c2 +c3= 1
Output
Aggregated Tempo-Sentiscore 'TS'

Algorithm
1.  Set i to 1
2.  for each document(di) in D
3.      Tokenization
        //Apply the rules
4.      Apply the linguistic rules for temporal tagging using TempoWordNet
5.      Calculate frequency count( past, present ,future)
6.      T_tag:= max(present, past, future)
7.      D_tag := past/present    // based on threshold values for past/present
8.      If (T_tag = null) then
9.          Temp_tag := D_tag
10.     endif
11.     Calculate the Sentiscore 'wi'
// Case:1-- update the temp_tag as present
12.     if (T_tag = present) then
13.         if (D_tag = past) then
14.             temp_tag := past
15.         elseif(D_tag = present) then
16.             temp _tag:= present
17.         endif
18.     endif
//Case 2: update the temp_tag as past
19.     if (T_tag= past) then
20.         if (D_tag =past) then
21.             temp_tag := past
22.         elseif (D_tag = present) then
23.             temp_tag := past
24.         endif
25.     endif
//Case 3: update the temp_tag as future
26.     if (T_tag = future ) then
27.         if (D_tag = past) then
28.             temp_tag:= past
29.         elseif(D_tag = present) then
30.             temp _tag:= future
31.         endif
32.     endif
//Apply the rules for updating the magnitude of Sentiscore 'w'
33.     If (temp_tag = present) then
34.         t_i = c1*w_i
35.     elseif (temp_tag = past ) then
36.         t_i = c2*w_i
37.     elseif (temp_tag = future) then
38.         t_i = c3*w_i
39. i := i+1
40. if (i<= n ) then goto step 1
41. End for
42. Tempo-Sentiscore (TS) = (∑_{i=1}^{n} t_i )/n
```

◀**Fig. 2** Proposed algorithm

6 Experimental Setup

The experiment is held at document level. It contains the following components to deploy the proposed algorithm.

6.1 Dataset

We have used the standard dataset [21]. The version of the dataset consists 2745 reviews of ford car collected during the year 2007, 2008 and 2009. These reviews are collected from the social sites, i.e. Edmunds. In our proposed algorithm, we assumed the reviews collected in 2009 as present for temporal tagging based on metadata. It contains the review, date of post and entity about which the review is expressed.

As shown in Table 3, column heading D_tag which is based on metadata or date of post., T_tag values are based on linguistic context of words, temp_tag contains the total number of review fall in each category (present/past/future).

In column D_tag, we have found the 775 reviews of present and 1970 reviews of past category. We found no review in future category. The second column (T_tag) gave the number of reviews categorized as in present, past and future based on the linguistic context of the words using Table 3. The number of reviews in present, past and future are 2459, 279 and 7 respectively. It shows that most of the people prefer writing the reviews in present. We figured out from Table 3 that number of reviews under column head (Temp_tag) changed in each category. It is observed that the consideration of linguistic context of words along with the metadata decreased the number of reviews in present, i.e. 669 and future reviews, i.e. 2. On the other hand, decreased the number of reviews fall in past category i.e. 2074. The reason is that some of these reviews were written in 2007 or 2008 which makes them to be considered in past. So, in the last column, we found the number of reviews in present and future category is reduced.

The reviews fall in the present category of metadata (D_tag) are filtered by reducing those reviews which linguistically (T_tag) talked about the past status of ford car. The number of reviews is reduced to 669. Therefore, 106 reviews actually talking about the past status of the Ford car. It is shown in Table 3.

In Fig. 3, initially according to the date of post, the reviews in the present category were 775. By analyzing these reviews thoroughly based on the rules mentioned in Table 2, we found that only 669 reviews are actually talked

Table 3 Number of reviews in each category based on meta-data(Dtag), linguistic context of words(Ttag), formulated rules based on Dtag and

Ttag	D_tag	T_tag	Temp_Tag
Past	1970	279	2074
Present	775	2459	669
Future	0	7	2
Total	2745	2745	2745

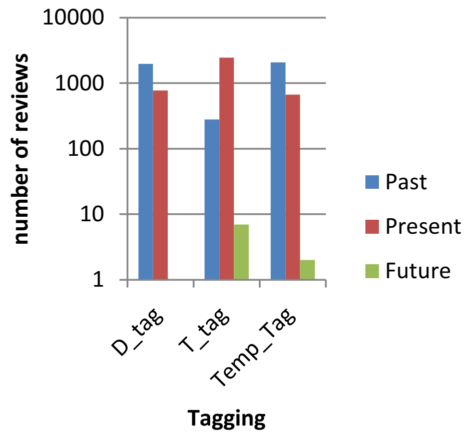

Fig. 3 Variation in number of reviews in present, past or future category

about the present scenario of the ford. For past the total number of reviews posted before 2009 were 1970. The number of reviews in this category was increased to 2074. We have found that 104 reviews which are posted in 2009 i.e. present actually described the past opinion towards the ford car. In future category, 7 reviews were found under T_tag. Further, applying the rules mention in Table 2, only 2 reviews are actually considered as predictive opinion i.e. future.

The next phase after categorization of reviews, is to generate the Tempo-Sentiscore. From Table 3, it can be seen that the data in each category are different.

To reduce the biasing between each class, we manually designed the dataset consists of 300 reviews in each category (present, past or future), i.e. 900 reviews. We took the help of 3 linguistic experts to form the Gold standard.

6.2 Performance Evaluation

We used precision and recall to measure the performance of our method.

Recall [22] is the percentage of each class present in the corpus that are found by the learning system. Recall can be calculated by the Eq. (3).

Table 4 Precision, Recall and F-measure of three classes (present, past and future)

	Recall	Precision	F-Measure
Present	92.66	92.33	92.49
Past	97.58	97.58	97.58
Future	82.35	83.05	82.69
Overall	90.86	90.98	90.92

Table 5 Sentiment Analysis Based on Temporal Tagging

Entity	Aggregated reviews based on temporal tag	Aggregated Sentiscore of reviews	Aggregated tempo-Sentiscore
Ford'07	past	0.57	0.19
Ford'07	Present	− 0.2	− 0.11
Real time Sentiscore	Past + present	0.37	0.08

Table 6 Assumption of Star Rating Based on Sentistrength and Tempo-Sentiscore

Range of sentiscore/tempo-sentiscore	Rating
0–0.2	*
0.3–0.5	**
0.6–0.7	***
0.8–0.9	****
1	*****

$$\mathrm{Recall(R)} = \mathrm{TP}/(\mathrm{TP}+\mathrm{FN}) \tag{3}$$

Precision [22] is the accurate number of classifications found by the learning system. Precision can be calculated by the Eq. (4).

$$\mathrm{Precision\ (P)} = \mathrm{TP}/(\mathrm{TP}+\mathrm{FP}) \tag{4}$$

F Measure [15] is a metric used as a tradeoff between Recall and Precision. It is calculated using Eq. (5).

$$F\text{ - }Measure = 2TP/(2TP+FP+FN) \tag{5}$$

The performance of the system for categorization of data in each class is based on the overlapping of the results with the Gold standard. The results are shown in form of Precision, Recall and F-measure in Table 4. Precision, recall and F- measure for individual class is described in Table 4. The average Precision and Recall of the proposed system over the given dataset is 90.98 and 90.86 respectively. The average F-measure is also calculated as 90.92.

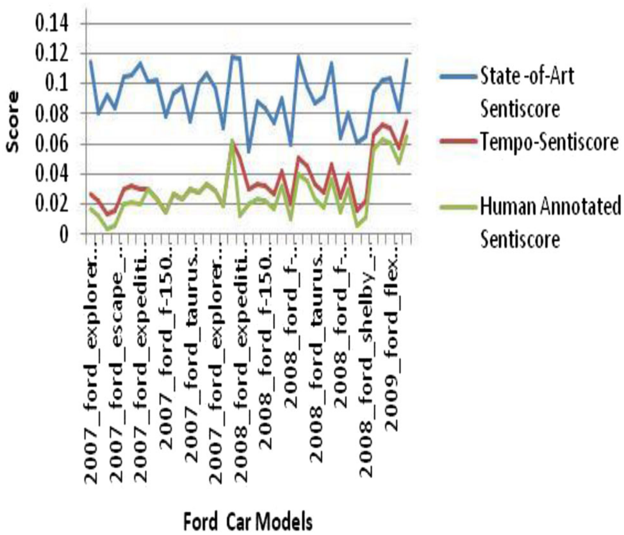

Fig. 4 Sentiment analysis based on Sentiscore vs Tempo-Sentiscore

6.3 Effectiveness of TempoSentiscore

Tempo-Sentistrength is calculated using Eq. (1). Sentiscore is calculated by the sentiment classification through term scoring using SentiWordNet. The values of c1, c2 and c3 are gathered by the survey of more than 300 responses.

The average of the weightage given by human annotators for c1, c2 and c3, i.e. present(c1), past(c2) or future(c3) is taken.

The value of c1, c2 and c3 are found as 0.75, 0.15 and 0.10 respectively as per the average of their respective values collected by the survey.

The values of c1, c2 and c3 are query based. For the query asking for the present status of the ford car, the weightage given to the present reviews is more than past or outdated reviews.

Query 1: Are people happy with the ford car?

All the reviews are taken for the analysis. Equal weightage is given to all the reviews irrespective of the temporal nature of the document.

Query 2: Were people happy with the ford car till 2007?

In this, the reviews till 2007 are gathered. The reviews of previous years (…..,2005,2006) are taken as past, 2007 reviews are taken as present, while the reviews of 2007 pointing towards the future are taken as future.

6.4 Experimental Results

The experiment for the Tempo-Sentiscore task was carried out using the manual annotation by different linguistic experts. As for the Tempo-Sentiscore, there was not any kind of baseline for the comparison. This arises the difficulty in evaluating the performance.

To evaluate the effectiveness of the proposed system, we employed the experiments to overlap with the Gold standard. The variation in the Sentiscore i.e. Tempo-Sentiscore according to temporal tags is shown in Table 5.

For the star rating of any entity, Sentiscore plays a vital role. From Table 6, it can be seen that the star rating is affected by real time Sentiscore to a great extent. If the real time Sentiscore is used without temporal tagging, then ford'07 is rated as "**". On the other hand, with temporal tagging, it is rated as "*".

The trend followed by both the Sentiscore and Tempo-Sentiscore is almost the same. The magnitude of the Tempo-Sentiscore is low as compared to the Sentiscore as shown in Fig. 4. Linguistic expert's agreement helped in showing the Tempo-Sentiscore represent the real scenario of the opinion about any entity. From Fig. 4, it is noticed that Tempo-Sentiscore is very near to the Human annotated results as compared to Sentiscore. It shows the reliability of the proposed algorithm.

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