Sentiment analysis: Measuring sentiment strength of call centre conversations

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Sentiment Analysis: Measuring Sentiment Strength of Call Centre Conversations

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Abstract – **Measuring sentiment strength can be considered as one of the key areas of sentiment analysis. The existing sentiment word scoring functions are based on the intensity of adjectives in the sentences. To date, there is a very minimal work has been done for measuring sentiment strength based on adverb and adjective combinations. This research proposes a sentiment word scoring method considering the adverb-adjective combinations of a given sentence. This is subject oriented hence this approach is proposed for a call centre domain. We use the linguistic analysis of adverbs of degree to satisfy the adverb-adjective scoring. Then a new approach has been introduced to calculate the sentence wise sentiment score by enhancing the existing sentence level sentiment scoring algorithm. Authors propose the way of determining the total sentiment strength of a given sentence. We describe the results of our experiments on set of 100 call centre conversation audio files between the call centre agent and customer and compare our algorithms with the existing sentiment scoring algorithms. It can be concluded that these enhancements have an accuracy of 74% in precision.**

Keywords: Sentiment strength, adverb-adjective scoring, sentiment analysis, word scoring, adverbs of degree

I. INTRODUCTION

Sentiment scoring for a given opinion word, can be considered as a growing research area. Scientists are interested in what the general public demand. Politicians are interested in how the media's opinion on their actions. One country is interested in how other countries are representing their actions. There are many applications which have the capability of understanding the opinion expressed in it and the strength of it [1]. But many are depended on legacy experiments and theories where lead to more errors.

The current mechanism is to find out how the sentiment analysis focusses on assigning the polarity and strength to subjective expressions or topics. Obtaining the sentiment polarity and determining the sentiment strength are two different mechanisms where measuring strength of an opinion has to be done in much accurate and systematic manner. Even there are methods to evaluate the strength of a given opinion, due to the subjectivity, the sentiment strength would be vary. Here the authors talk only about the opinions of call centre conversations which is the target domain. It is a straight forward way of obtaining the sentiment polarity as positive, neutral or negative of texts in a document [2].

Though much work has been done on determining the term orientation on the parts-of-speech, verbs and adjectives, but still almost no work has been conducted to determine a word scoring mechanism based on the combination of adverbs and adjectives. There are some researches focus on the phrase or sentence level sentiment scoring based on an adjective-adverb combination but still those are based on adjective intensity word scoring as the foundation [3]. Adverbs also can generate a huge impact for word scoring as same as adjectives do.

- He is a good technician
- He is a very good technician

Considering the above two opinions, the second one has more weight than the prior one. But we have to consider the weight which derives considering the entire sentence as well as considering word by word. The word scoring has been determined considering the intensive of adjectives of the considered document and based on this, a word bank has been developed [3] [4]. This word bank is used for determining the phrase or sentence level sentiment scoring also [3]. So there is a demand for a word bank considering the adjective-adverb intensity rather than considering only adjectives. This improved word bank can be used to enhance the existing sentence level sentiment scoring functions and the entire document level scoring procedure.

The important thing is since we are dealing with call centre conversations as our dataset, we have to transcribe the speech to text before analyzing the sentiment strength. For the transcribing, CMU Sphinx-4, a pure java speech recognition library has been used. The accuracy level of the speech recognition engine is around 42% [5]. Since our goal is to evaluate the sentiment strength in this research, we introduce only the sentiment scoring methods used.

This paper presents a linguistic approach to the problem of sentiment analysis. The goal of the study is to determine a unique method to obtain the sentiment score for a given word on the basis of adjective-adverb intensity. This method will be used to evaluate the sentence level and document level sentiment scoring. So the score range for a given conversation between the call center agent and customer will be from -1 to +1 based on the adjective-adverb combinations. A score -1 reflects a maximum negative opinion regarding the conversation and +1 indicates a maximum positive opinion regarding the conversation.

The main contributions of this research which determine sentiment scoring can be summarized as follows.

1. A new way of determining the word sentiment strength of a conversation considering *adjective-adverb intensity* on a -1 to +1 scale. This will be an enhancement of the existing adjective intensity word sentiment scoring [3]. Based on the new mechanism, a new word bank scoring algorithm is introduced, which is *Enhanced Pseudo Standard Deviation Scoring* (ESDS). This method can be used to determine the word sentiment score. The interesting thing is any sentiment score function can be plugged with this method to calculate the sentiment score for a given word. This new method has been tested with 30 conversations which are different from the training 70 conversations set between call centre agent and customer. The algorithms are described in section 2.

2. A new sentence level sentiment scoring method based on the adverb-adjective combinations (AAC). Here we used the word scoring axioms of adverbs for the *adverbs of degree* [4]. We introduced *Enhanced Adjective Priority Scoring* (EAPS) algorithm to determine the sentiment score of a given sentence. The authors have enhanced the existing *Adjective Priority Scoring* (APS) algorithm by using the novel word scoring function, *Hybrid Evaluation Method* (HEM) [3]. Both APS and EAPS have been compared with respect to human subjects in terms of performance and accuracy and concluded as EAPS performed better than APS. The Enhanced Adjective Priority Scoring method will be described in section 3.

3. A new scoring function to calculate the sentiment strength of a whole conversation. This is based on the standard deviation and mean values of the scores of the sentences in a given conversation. This derives a value where can be used as the opinion of the entire conversation for a particular customer matter. This method is described in section 4.

4. Finally it is described the experimental results which have been obtained based on 100 call centre conversations between the call center agent and a customer. The annotations were done by 10 call centre supervisors, who were responsible in evaluating the call centre agents and the technical supporting staff. The results show that the Enhanced Adjective Priority Scoring *(EAPS)* (r=0.35) produces the best results in Pearson correlation coefficient with a value of 0.579345 while Adjective Priority Scoring *(APS)* (r=0.35) has only a value of 0.473917. These experimental results are described in section 5.

II. ENHANCED PSEUDO STANDARD DEVIATION SCORING

There are existing word scoring methods such as *Pseudo Expected Value Scoring* and *Pseudo Standard Deviation Adjective Scoring* [3]. But the thing here is still the researchers have developed these functions on the basis of only taking care of adjectives. Since we are considering a call centre domain, it is not sufficient to consider only adjectives but we have to consider about the adverbs as well. So for this purpose, we have modified the existing word scoring algorithm and generated a new function for evaluating the word sentiment score. In obtaining the function there are some definitions which have to be focused.

Definition 1: ($\mathrm{n}\ (w,\ d)$), we use this notation to denote the number of occurrences of either particular word w or a synonym of in the text conversation d.

Definition 2: ($\mathrm{sds}^k(d)$) suppose $\mathcal{D}_{\mathrm{test}}$ is a set of test call centre conversation text documents, and $\mathrm{H} = \{h_1,\dots,h_m\}$ is a set of call centre supervisors , each of whom renders a quantitative score $\mathrm{h_i}(d)$ about the conversation texts d. Let μ be the mean value of all these scores and let α be the standard deviation. Let $k \geq 1$ be any integer value. We set $\mathrm{sds}^k(d)$ to be the mean of the multiset of conversation texts.

This whole definition can be described in a simple manner as follows. When assigning a score to an opinion expressing word, we start the scoring procedure by evaluating the scores assigned to call centre text conversations by human subjects. We obtain the mean and the standard deviation of these sentiment scores. Then we eliminate the sentiment scores which are more or less than k standard deviation away from the mean, and then take the average score of the rest scores. As an example if it is assumed as about 96% of all the values in a set lie within four standard deviations of the mean. So if that is the case, then k equals to 4.

Definition 3: Given any text conversation or corpus d and any collection $\mathcal{D}$ of the text conversations or corpus, we use the notation $\mathrm{oeaa}(d)$ and $\mathrm{oeaa}(\mathcal{D})$ to respectively denote the set of all opinion expressing adjectives and adverbs with their synonyms occurring in text conversation d and $\mathcal{D}_{\mathrm{test}}$. Then by using all these definitions we suggest the Enhanced Pseudo Standard Deviation Scoring formula as,

$$esds^{k}(d)=\frac{\sum_{d\in D_{test}}\left(sds^{k}(d)\times\frac{n(w,d)}{\sum_{w'\in oeaa(D_{test})}n(w',d)}\right)}{\sum_{d\in D_{test}}sds^{k}(d)} \tag{1}$$

By using the above enhanced pseudo standard scoring formula, now it can be generated an algorithm to calculate the sentiment score for a given opinion word. We wish to score the call centre conversation texts *d* in some collection $\mathcal{D}$ of corpus. Now we can present the enhanced algorithm which can be used to obtain the sentiment score for a given word in the test corpus or the conversation texts. This is a Hybrid Evaluation Method (HEM) which can be plugged not only the enhanced scoring function described earlier but also all the scoring functions including *pseudo value scoring function*, *pseudo standard deviation adjective scoring function* etc. the HEM associates with each conversation *d*, a vector of length *m* for some integer *m*. this consists of functions $ds = (ds_1,\ldots,ds_m)$ to assign scores to the conversation text. The same procedure will also be applied to all the conversation texts in $\mathcal{D}_{test}$.

So using this enhanced word sentiment scoring function, a new word bank can be introduced. This word bank concept sprang up with the implementation of the existing word scoring function, which was an adjective centric approach. So the existing word bank also can be enhanced using the new word sentiment scoring function.

III. ENHANCED ADJECTIVE PRIORITY SCORING

Authors have enhanced the existing two word scoring functions and use a hybrid algorithm to derive a quantitative score for the phrases or sentences. Again in obtaining the total sentiment score of the whole text conversation (if it consists with more than two sentences), we developed a new quantitative sentiment scoring algorithm using the standard deviation and mean as the foundation.

First to obtain the phrase of sentence score, *Adjective Adverb Combination* (AAC) method will be used. In this method we will again enhance the *Adjective Priority Scoring* algorithm using the sentiment score which is gained by using the enhanced pseudo standard deviation ($esds^k(d)$) formula [4]. For obtaining the phrase of sentence sentiment score authors use this Enhanced Adjective Priority Scoring algorithm (EAPS).

Suppose *adv* is an adverb and *adj* is an adjective. Here, special adverb scoring axioms which are described earlier will be used and let *STRONG*, *WEAK* and *DOUBT* respectively be the sets of adverbs of strong intensity, adverbs of weak intensity and adverbs of doubts. Authors experience the results are vary when the *r* value gets vary.

$$
\begin{array}{l}
\textit{function } EAPS(sc(adv), sc(adj), sp, r)\\
\textit{sp is the sentiment polarity}\\
\textit{r is the nature of conversation opinions}\\
\textit{sc is the sentiment score}\\
\\
\textit{begin}\\
result \leftarrow 0\\
\quad \textit{if } adv \in STRONG \textit{ then}\\
\quad\quad result \leftarrow (sc(adj) + r \times sc(adv))\\
\quad \textit{end if}\\
\quad \textit{if } adv \in WEAK \textit{ then}\\
\quad\quad result \leftarrow (sc(adj) - r \times sc(adv))\\
\quad \textit{end if}\\
\quad \textit{if } adv \in DOUBT \textit{ then}\\
\quad\quad result \leftarrow (sc(adj) - r \times sc(adv))\\
\quad \textit{end if}\\
\\
\textit{return result}\\
\textit{end}
\end{array}
$$

Fig. 1. Pseudo code for EPAS Algorithm

IV. SCORING THE STRENGTH OF SENTIMENT IN A CONVERSATION

Now we have obtained the sentiment score for a given phrase or a sentence. Now it is the final phase of this whole procedure, which is the sentiment score generator for the whole converted text document. For this purpose authors have developed a quantitative sentiment scoring algorithm using the standard deviation and mean values. First we have to calculate all the sentiment scores of the sentences one by one using EAPS.

There is another important aspect which have to be taken care of when obtaining the sentiment score of a particular sentence. Since this research has been done considering the call centre domain, it is a must to take care of the customer and call centre agent conversations more effective manner.

Question: Were the technical staff able to solve your problem on time sir?

Answer 1: Yes they did.

Answer 2: Yes but your people didn't fix my phone on time in last week.

Considering the above question which has been raised by a call centre agent and the two answers provided by customers, *Answer 1,* is the probable answer to the question and *Answer 2* can be taken as a previous experience but not about the given question. When obtaining sentiment scores for the given two answers, prior one will gain more score than the latter. If the *Answer 2* would be considered as the customer response to the particular question, the sentiment score of the answer could be misled us. So it is a must to consider only the statements which are in the scope and remove others which are out of the scope. This is much important since authors consider the call centre conversations as the domain. For accomplishing this task, an Ontology has been introduced.

For developing the Ontology, we have used 70 different call center agent – customer conversation voice clips based on different problems and analyze them to understand the domain to build up a knowledge base. This knowledge base was developed to identify the keywords, phrases, situations and word bank which would help to derive an ontology. This knowledge base can be used to determine the answer of customer and to derive an indicator for the relevancy.

Resource Development Framework (RDF) is used to decompose information into small pieces with some simple rules about the semantics of each one of these pieces [6]. So generating the RDF would be the first step in this process. Then using Jena Framework, which is a free and open source Java framework for building semantic web and linked data applications, this ontology can be connected to the main application using Web Ontology Language (OWL) API [7].

```
function readRDFModel(RDF_FILE, statements)
RDF_FILE - is the location variable
statements - is the object of class StmtIterator
begin
   result ← 0
   value ← 0
     if (!model)
        ModelFactory_createDefaultModel
     foreach
        value ← RDF_FILE
     end foreach
     end if
     while(statements.hasNext())
        statement ← statements(next)
        subject ← statements(subject)
        result ← (statement, subject)
     if (subject = null)
     End While
return result
end
```

Fig. 2. Pseudo code for understanding RDF

Then using the OWL and RDF, the ontology model will be created. Finally this will be used for accomplishing the process.

After considering the statements which are in the scope, Let $\mathrm{Con}(t)$ be the set of all sentences in the given conversation corpus in d that directly or indirectly reference the relevant matter m. For each sentence s in $\mathrm{Con}(t)$, $H+(s)$ or $H-(s)$ be the multiset of all AACs occurring in s that are positively or negatively applicable to the matter m. So the total strength of sentences can be gained as,

$$\sum_{s\in Con(t)}\sum_{w\in H_{+}(s)} score(w) - \sum_{s\in Con(t)}\sum_{w'\in H_{-}(s)} score(w') \quad (2)$$

After gaining the individual sentence scores then calculate the mean value of the set. And calculate the standard deviation. Then according to the distribution of results, determine a value for k to remove the outliers of the scores. Next step is to take the number of sentences which are remaining, denotes by N and obtain the total strength of the remaining scores (T). We then divide this T by N, to obtain an average strength, which can be used as the sentiment strength of the whole conversation text (T_{con}).

$$T_{con} = T/N \quad (3)$$

As the conclusion, these experiments and enhancements have moved the authors to develop three (3) new main algorithms by enhancing existing algorithms to be used for obtaining the sentiment strength. This is tested for a telecommunication and call centre domain, using test data sets and can be used for more domains as well. Especially the Hybrid Evaluation Method (HEM) can be used with every sentiment scoring function.

V. IMPLEMENTATION AND EXPERIMENTATION

Authors have implemented the suggested opinion scoring system which is the three new algorithms to calculate the sentiment word scoring, sentiment sentence scoring and sentiment paragraph level scoring. We then conducted two sets of experiments such as experimentation on Word Sentiment Score generator and experimentation on Total Sentiment Score generator.

A. Experimentation on Word Sentiment Score Generator

Authors have developed new formula for obtaining sentiment score of word, which is the Enhanced Pseudo Standard Deviation Scoring formula ($\mathrm{ESDS}^k(d)$). We have to compare this formula with the earlier scoring function, *Pseudo Standard Deviation Adjective Scoring* function ($\mathrm{SDAS}^k(d)$). Specifically we were interested in finding the value of k which makes $ESDS^k(d)$ and $SDAS^k(d)$ provide the best performance.

The performance of such algorithm or a function is based on the use of Pearson correlation coefficients between the sentiment scores or the opinion scores returned by the algorithm and the opinion scores which are provided by the human subjects, for our domain it is the supervisors. So in this scenario, the main focus is to determine the best sentiment word scoring function out of the existing *Pseudo Standard Deviation Adjective Scoring* function and the function what the authors introduced, *Enhanced Pseudo Standard Deviation Scoring* function. So to accomplish this purpose, first we collected 100 set of call centre conversations which included different types of conversations with the score assigned to each conversation by the call centre supervisors. Then we calculate the sentiment scores for those conversations using both the existing and enhanced sentiment scoring functions. Then we obtained two sets of Pearson correlation coefficients between the sentiment score returned by each function and the opinion scores for conversations which were provided by the call centre supervisors.

The goal in this experiment is to determine the way of these two functions behave as we vary the value of k. So it can be experienced that the scores obtained using each function will be varied when the k value get changed. The graph shows how the Pearson correlation coefficient of each algorithm with respect to the opinion scores given by the supervisors for each conversation.

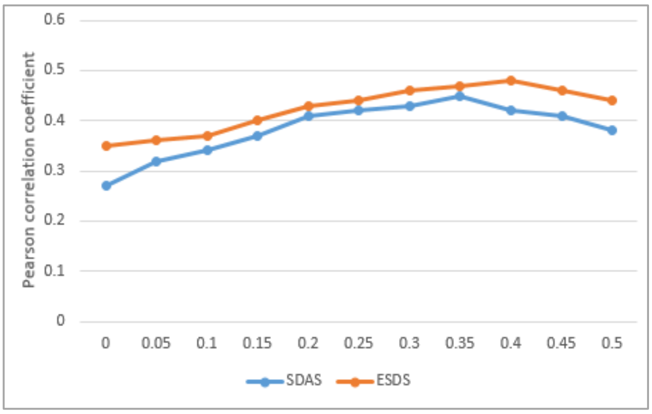

Fig. 3. Pearson correlation coefficient for $SDAS^k$ and $ESDS^k$

Then another experiment has been conducted with human subjects. These are based on the human subjects which are described in detailed manner earlier. According to this when the k value takes 0.4, the highest Pearson correlation coefficient will be derived for the enhanced sentiment scoring function (ESDS). For the existing sentiment scoring function the highest Pearson Correlation Coefficient will be obtained when the k value takes 0.35. So it can be concluded that $ESDS^{0.4}$ has the highest Pearson correlation coefficient when compared to human subjects. The following table shows the scores assigned to some words using both functions.

TABLE 1. SENTIMENT WORD SCORES USING BOTH FUNCTIONS

Word	$SDAS^k$	$ESDS^k$
Good	0.751	0.742
Aggressive	-0.391	-0.472
Late	-0.471	-0.473
Fast	0.372	0.37
Sharp	0.687	0.693

Measuring accuracy also will play a major role here. We have to measure the accuracy in terms of evaluating the precision of the Hybrid Evaluation Method (HEM) scoring algorithm of the Enhanced Sentiment Scoring function. Authors used a set of 10 supervisors, who didn't participate in developing the word bank earlier, to evaluate given different 30 call centre conversation audio files. These were not used in the training dataset and these were very new set of conversations. The rating scale was 0 to 10.

We ran the developed algorithm and evaluate the precision of them as follows. Let ConText(thr, alg) be the set of all the converted audio conversations retrieved by the function $ESDS^k$ denoted by alg which has a score that exceeds a given threshold sentiment score. Let User(thr) be the set of all the converted text files that the users say has a score over thr. We can then determine the precision of an algorithm for a given threshold to be,

$$precision^{thr}(a\lg) = \frac{|ConText(thr, a\lg) \cap User(thr)| \times 100}{|ConText(thr, a\lg)|} \quad (4)$$

When considering the threshold is between 6 and 8 the best algorithm in terms of precision is Distance weighted topic focused (DWTF) algorithm, which is one of the word scoring algorithms [3]. But for any other threshold, HEM shows the best performance. So in terms of accuracy, the HEM algorithm performs the best results by defeating the existing scoring algorithms such as DWTF, Topic Focused (TF) or Template based (TB) algorithms [3].

Since the algorithm introduced, Enhanced Sentiment Word Score generator, is a HEM and the enhanced sentiment word scoring function would behave in a very same manner in the precision trend. So it can be determined that the enhanced sentiment word scoring generator would behave in terms of precision for the given threshold range as follows. This precision would determine that the enhanced word sentiment scoring function performs in more accurate manner than the existing sentiment word scoring functions for most times in the given threshold range.

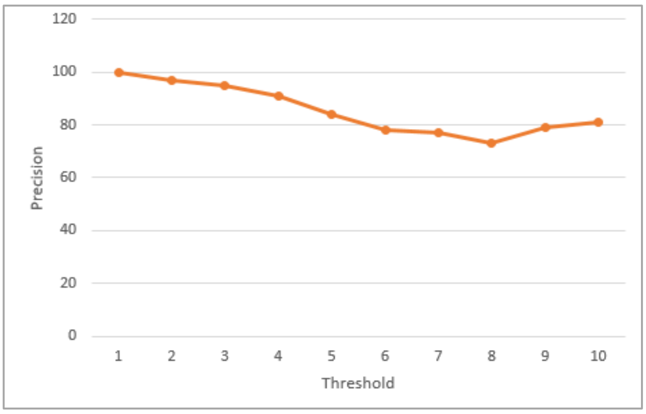

Fig. 4. Precision Trend

B. Experimentation on Total Sentiment Score Generator

Here we are measuring the performance of the algorithms which we have developed to calculate the sentiment score for a given phrase or sentence. In this mechanism, Adjective Priority Scoring (*AAC*) function is used, which is based on the Pseudo standard deviation adjective word scoring function, and the enhanced function, which is developed by us, the Enhanced Pseudo Standard Deviation Scoring function. As we did earlier, we measure the performance of each two on the basis of Pearson Correlation Coefficient with respect to the human subjects and derive the best algorithm as well as we measure the computation time to measure the performance of each algorithms.

The main two sentence level scoring algorithms are named as the AAC^r and the enhanced version of $EAAC^r$. The two algorithms are derived from the APC scoring mechanism for scoring phrases or sentences. The goal is to determine the two algorithms behave when we vary the value *r*. For accomplishing this task again the previous training conversation audio files dataset have been used and also another 30 files were used to test and evaluate the new findings. First we used the dataset which have been assigned the scores by the call centre supervisors. Then for each conversation file, the sentiment score was calculated using the existing sentence level sentiment scoring function and the enhanced sentence level sentiment scoring function. We have experienced different scores for both functions as we varied the value *r*.

As the last step, the Pearson Correlation Coefficient was determined by considering each values from the existing and enhanced sentence level sentiment scoring functions with respect to the scores which have given by the supervisors. So each two sentence level sentiment scoring functions were compared with the particular human subjects and experienced the behavior for each as follows.

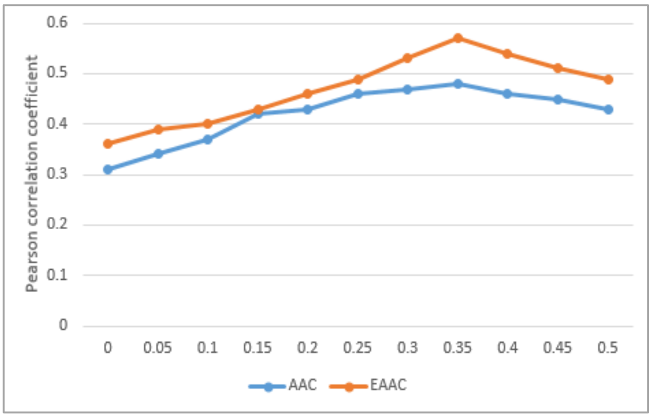

Fig. 5. Pearson correlation coefficient for AAC^r and $EAAC^r$

It can be concluded as the $EAAC^r$ will take the maximum Pearson correlation coefficient with respect to the human subjects than AAC^r with respect to the human subjects when we take the *r* value as 0.35.

Another aspect is the computation time of the scoring functions. Computation time determines the efficiency of execution of an equation, a function or an algorithm. Here in this context it is important to consider this factor since it provides a clue of the performance of each sentence level sentiment scoring or paragraph level sentiment scoring algorithms. Further it enhances the whole procedure of obtaining sentiment score of a particular call centre conversation. It is measured the performance of the existing and enhanced sentiment sentence level scoring functions based on the computation time.

First the number of conversation text regarding a particular customer issue m have been varied from 0 to 100. Figure 6 shows the result and $EAAC^r$ has less computation time than AAC^r where $EAAC^r$ is the best one out of these two algorithms in terms of both performance and computation time.

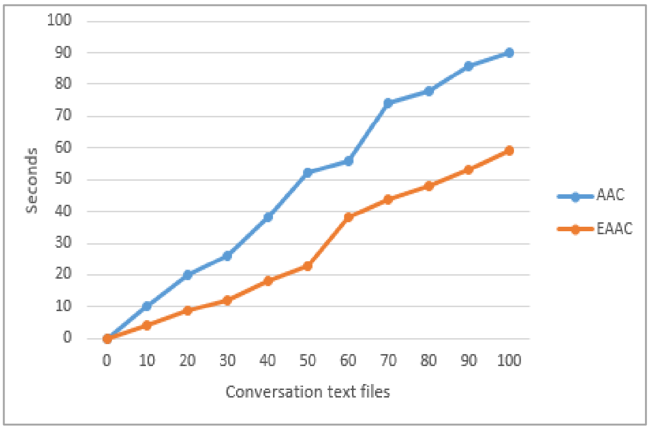

Fig. 6. Computation Time Comparison

VI. DISCUSSION AND CONCLUSION

As the final phase it can be summarized the findings again. We have enhanced the existing sentiment scoring algorithms and introduced a new way of obtaining sentiment strength. This has been specially done for telecommunication call centre domain. The authors have introduced new sentiment scoring function based on HEM algorithm. Using this function, the existing sentiment scoring function has been enhanced to obtain the sentiment score for a given sentence. These enhancements are performing well than the existing sentiment scoring mechanisms. These enhancements have been tested using 30 audio conversations. Considering Pearson correlation coefficient values, it has been proven the new sentiment scoring mechanism performs better results than the existing function with respect to human subjects. Here the performance of each algorithm has been derived with respect to the scores given by call centre supervisors so that the comparison of the algorithms has been done considering with respect to human subjects. Then authors have introduced new function for obtaining sentiment score of a given document. This enhancement also has been tested using 30 test audio files. Enhanced document level scoring function performs best results in high performance level and low computation execution time than the existing function.

It can be concluded that these enhancements are performing better than the existing methodologies. Though these have been developed based on the telecommunication call centre domain, those can be enhanced further for the suitability of more domains in future.

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