Novel Relevance Model for Sentiment Classification Based on Collision Theory

Meenakshi Sundaram Murugeshan and Saswati Mukherjee

Department of Information Science and Technology,
College of Engineering, Guindy, Anna University, Chennai, India
{msundar_26,msaswati}@yahoo.com

Abstract. The performance of an Information Retrieval system is very much dependent on the effectiveness of the relevance model being used. Motivated by the concepts in Collision Theory in Physics, this paper proposes a novel approach of identifying relevance between two text objects. The role of positive and negative features is considered in designing the relevance measure based on the transitions in Collision Theory. For evaluating the measure, we have applied our relevance model on sentiment classification.

Keywords: Relevance Measure, Sentiment Classification, Collision Theory.

1 Introduction

One of the fundamental tasks in Information Retrieval is to identify the relevance between text objects. The notion of relevance is ambiguous based on the aspects that are considered [1]. The goal of relevance measures is to identify the degree of relatedness between the information being compared. Similarity measures are widely applied for comparing textual information and their role in comparing small text objects is discussed in [2]. Relevance measures can be used for identifying the orientation of the opinion expressed about a particular feature [3]. The terms in a text object can be classified as positive or negative based on their contribution towards a particular category. In opinion classification both kinds of terms are utilized to calculate the relevance score of a particular review.

Concepts in Collision Theory deal with the interactions of various charged particles and their effect on a particular system under consideration [4]. The applicability of Collision Theory in Information Retrieval and the similarity between the unknown document and the collision system is presented in [5]. This unified framework for relevance calculation combines the advantages of similarity measures, utilizes the negative features, applies proximity information and helps in enhancing the performance of the matching process. We have used sentiment classification for testing the effectiveness of our relevance model.

This paper is organized as follows. In Section 2, we describe the related work. Section 3 describes the applicability our model for sentiment classification. In Section, 4 we discuss our experimental results and Section 5 concludes the paper.

V.V. Das and J. Stephen (Eds.): CNC 2012, LNICST 108, pp. 417–421, 2012.

2 Related Work

Authors [6] have analyzed the effectiveness of machine learning methods *viz.* Naïve Bayes, Maximum Entropy and Support Vector Machines (SVM) for sentiment classification. A term count based method that exploits negations, intensifiers and diminishers for sentiment classification is explained in [7]. A similarity based approach for classifying the factual sentences from opinion bearing sentences is proposed and discussed [8]. Authors [9] have given a detailed account of four related problems in opinion mining *Viz.* subjectivity classification, word sentiment classification, document sentiment classification and opinion extraction. The role of polarity shifting in sentiment classification is discussed in [10]. Models inspired by concepts in physics such as Quantum Theory [11], [12] and Theory of Gravitation [13] have been effectively applied in Information Retrieval.

3 Collision Model for Sentiment Classification

In sentiment classification the task is to classify the given review as positive or negative depending on the opinions expressed. Polarity terms *viz.* adjectives and adverbs affect the associated features either positively or negatively. For example, "good" is a positive polarity term, whereas "bad" is a negative polarity term. We have used the method applied in [14] for building polarity lists and identifying features from training documents.

Sentences containing features identified from the training-set are extracted from the test reviews. The factors affecting the effect of polarity terms on these features are their weights and the role of terms other than the features and polarity terms. Negations are handled by replacing the associated polarity terms with antonyms. Each polarity term is assigned an initial value from the weights obtained from the training-set. Three types of transitions *viz.* free-free, free-bound and bound-bound transitions are used to calculate the effective polarity of the associated feature as shown in the equation given below.

$$\text{Free-Free transition} = \sum_{i=1}^{n} \text{Free-Free Polarity Gain}$$

Where,

Free-Free Polarity Gain =

$$\frac{(\sqrt{pv\_high} \times e^{pv\_low}) + HV(P\_terms)}{\left|Avg\_dis\tan ce[(feature, polariry\_term1), (feature, polariry\_term2)]\right|}$$

Where $HV(P\_terms) = \frac{1}{2}(P\_terms)$

$$\text{Free-Bound transition (+ve)} = \frac{(\sqrt{pv\_high} \times e^{nv\_low})}{\left|Dis\tan ce(feature, Pos\_polariry\_term)\right|}$$

$$\text{Free-Bound transition (-ve)} = \frac{(\sqrt{nv\_high} \times e^{pv\_low})}{\left|Dis\tan ce(feature, Neg\_polariry\_term)\right|}$$

Bound-Bound transition =

$$\frac{(\sqrt{nv\_high} \times e^{nv\_low}) + HV(P\_terms)}{\left|Avg\_dis\tan ce[(feature, polariry\_term1),(feature, polariry\_term2)]\right|}$$

pv_low – Polarity weight of the positive polarity term having lower weight in a transition.
pv_high –Polarity weight of the positive polarity term having higher weight in a transition.
nv_low – Polarity weight of the negative polarity term having lower weight in a transition.
nv_high – Polarity weight of the negative polarity term having higher weight in a transition.

The distance between the features and polarity terms are calculated by considering the number of nouns and verbs that are in between the polarity term and feature(s) in a sentence. Each polarity term is reduced to half values in successive free-free and bound-bound transitions until the half-value of the previous polarity terms become less than both the polarity values in the current transition. The polarity terms on either side of the features are considered in distance measure used in these transitions as shown below.

Let us consider $\{F_1 \ldots . F_n\}$ as the set of features.

The score for a particular feature is calculated as,

Collision Score (FS_i) = PC_Score – NC_Score
Where FS_i is the score of the i^{th} feature considered.

PC_Score = Positive collision score
Defined as,
Positive collision score = Free-Free transition + Free-Bound transition (PC)
NC_Score = Negative collision score
Defined as,
Negative collision score= Free-bound transition (NC)+Bound-Bound transition
Where,
Free-bound transition (PC) – Positively contributing Free-Bound transitions
Free-bound transition (NC) – Negatively contributing Free-Bound transitions

The collision score of the overall review combines the effect of individual collision scores of all features as given below.

RS = Positive if $FS_1 + FS_2 + \ldots + FS_n > 0$
RS = Negative if $FS_1 + FS_2 + \ldots + FS_n < 0$

Where RS is the sentiment of the review.

4 Evaluation

We have used the dataset containing four products provided by [15] for our experiments. For evaluating the effectiveness of our model we have used the accuracy measure. Term count method where polarity lists are built as shown in [14] has been successfully applied for sentiment classification. Hence, we have compared the performance of our approach with the term count based method. The classification results are shown in Table 1.

Table 1. Comparison of accuracies for four categories using term count method and Collision Theory based model

Review	Class	Term Count (TC)	Collision Model
Kitchen	Positive	76.8	79.3
	Negative	62.0	67.2
Books	Positive	79.6	79.8
	Negative	72.0	78.6
Electronics	Positive	84.0	83.7
	Negative	62.0	65.6
DVD	Positive	82.0	81.2
	Negative	74.4	77.4

We can observe that for kitchen and books categories the accuracy values of both positive and negative reviews outperform that of term count based method. In electronics and DVD categories accuracies of positive reviews are marginally less. However the results of negative reviews are better than the term count method. Overall our approach has given better results in 6 out of 8 categories used in the evaluation.

5 Conclusion

In this paper, we have proposed and tested the effectiveness of the Collision Theory inspired model of relevance calculation for sentiment classification. The distribution of positive and negative polarity terms is analyzed using three types of transitions. The sentiment of the review is determined based on the difference between positive and negative collisions. The advantages of the collision model over conventional relevance method are evident from the results of our approach.

References

1. Mizzaro, S.: How many relevances in information retrieval? Interacting with Computers, 303–320 (1998)
2. Metzler, D., Dumais, S.T., Meek, C.: Similarity Measures for Short Segments of Text. In: Amati, G., Carpineto, C., Romano, G. (eds.) ECIR 2007. LNCS, vol. 4425, pp. 16–27. Springer, Heidelberg (2007)
3. Zhang, M., Ye, X.: A Generation Model to Unify Topic Relevance and Lexicon-based Sentiment for Opinion Retrieval. In: Proceedings of 31st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 411–418 (2008)
4. Harwit, M.: Astrophysical Concepts, 4th edn. Springer (2006)
5. Murugeshan, M.S., Mukherjee, S.: A Collision Theory Inspired Model for Categorization of Wikipedia Documents. European Journal of Scientific Research 56(3), 396–403 (2011)
6. Pang, B., Lee, L., Vaithyanathan, S.: Thumbs up? Sentiment Classification using Machine Learning Techniques. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP 2002), pp. 79–86 (2002)
7. Kennedy, A., Inkpen, D.: Sentiment Classification of Movie Reviews Using Contextual Valence Shifters. Computational Intelligence 22(2), 110–125 (2006)
8. Yu, H., Hatzivassiloglou, V.: Towards Answering Opinion Questions: Separating Facts from Opinions and Identifying the Polarity of Opinion Sentences. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP 2003), pp. 129–136 (2003)
9. Tang, H., Tan, S., Cheng, X.: A survey on sentiment detection of reviews. Expert Syst. Appl. 36(7), 10760–10773 (2009)
10. Li, S., Lee, S.Y.M., Chen, Y., Huang, C., Zhou, G.: Sentiment Classification and Polarity Shifting. In: Proceedings of the 23rd International Conference on Computational Linguistics (COLING 2010), pp. 635–643 (2010)
11. van Rijsbergen, C.J.: The Geometry of Information Retrieval. Cambridge University Press, New York (2004)
12. Piwowarski, B., Lalmas, M.: A Quantum-Based Model for Interactive Information Retrieval. In: Azzopardi, L., Kazai, G., Robertson, S., Rüger, S., Shokouhi, M., Song, D., Yilmaz, E. (eds.) ICTIR 2009. LNCS, vol. 5766, pp. 224–231. Springer, Heidelberg (2009)
13. Shi, S., Wen, J., Yu, Q., Song, R., Ma, W.: Gravitation-Based Model for Information Retrieval. In: Proceedings of the 28th International Conference on Research and Development in Information Retrieval (SIGIR 2005), pp. 488–495 (2005)
14. Murugeshan, M.S., Sampath, A., Ahmed, F., Ashok, B., Mukherjee, S.: Effect of Modifiers for Sentiment classification of Reviews. In: Proceedings of the 6th International Conference on Natural Language Processing (ICON 2008), pp. 157–164 (2008)
15. Blitzer, J., Dredze, M., Pereira, F.: Biographies, Bollywood, Boom-boxes and Blenders: Domain Adaptation for Sentiment Classification. In: Proceedings of the Association of Computational Linguistics (ACL), pp. 440–447 (2007)