Using Fuzzy Logic For Multi-Domain Sentiment Analysis

Mauro Dragoni[1], Andrea G.B. Tettamanzi[2], and Célia da Costa Pereira[2]

[1] FBK–IRST, Trento, Italy
[2] Université Nice Sophia Antipolis, I3S, UMR 7271, Sophia Antipolis, France
dragoni@fbk.eu andrea.tettamanzi|celia.pereira@unice.fr

Abstract. Recent advances in the Sentiment Analysis field focus on the investigation about the polarities that concepts describing the same sentiment have when they are used in different domains. In this paper, we investigated on the use of fuzzy logic representation for modeling knowledge concerning the relationships between sentiment concepts and different domains. The developed system is built on top of a knowledge base defined by integrating WordNet and SenticNet, and it implements an algorithm used for learning the use of sentiment concepts from multi-domain datasets and for propagating such information to each concept of the knowledge base. The system has been validated on the Blitzer dataset, a multi-domain sentiment dataset built by using reviews of Amazon products, by demonstrating the effectiveness of the proposed approach.

1 Introduction

Sentiment Analysis is a kind of text categorization task that aims to classify documents according to their opinion (polarity) on a given subject [1]. This task has created a considerable interest due to its wide applications. However, in the classic Sentiment Analysis the polarity of each term of the document is computed independently with respect to domain which the document belongs to. Recently, the idea of adapting terms polarity to different domains emerged [2]. The rational behind the idea of such investigation is simple. Let's consider the following example concerning the adjective "small":

1. The sideboard is **small** and it is not able to contain a lot of stuff.
2. The **small** dimensions of this decoder allow to move it easily.

In the first text, we considered the Furnishings domain and, within it, the polarity of the adjective "small" is, for sure, "negative" because it highlight an issue of the described item. On the other side, in the second text, where we considered the Electronics domain, the polarity of such adjective can be considered "positive".

In literature, different approaches related to the Multi-Domain Sentiment Analysis has been proposed. Briefly, two main categories may be identified: (i) the transfer of learned classifiers across different domains [3] [4], and (ii) the use of propagation of labels through graphs structures [5] [6]. Independently from the kind of approach, works using concepts rather than terms for representing different sentiments have been proposed.

Differently from the approaches already discussed in the literature, we address the multi-domain sentiment analysis problem by applying the fuzzy logic theory for modeling membership functions representing the relationships between concepts and domains. Moreover, the proposed system exploits the use of semantic background knowledge for propagating information represented by the learned fuzzy membership functions to each element of the network.

2 System

The main aim of the implemented system is the learning of fuzzy membership functions representing the belonging of a concept with respect to a domain in terms of both sentiment polarity as well as aboutness. The two pillars on which the system has been though are: (i) the use of fuzzy logic for modeling the polarity of a concept with respect to a domain as well as its aboutness, and (ii) the creation of a two-levels graph where the top level represents the semantic relationships between concepts, while the bottom level contains the links between all concept membership functions and the domains.

Figure 1 shows the conceptualization of the two-levels graph. Relationships between the concepts of the Level 1 (the Semantic Level) are described by the background knowledge exploited by the system. The type of relationships are the same generally used in linguistic resource: for example, concepts C_1 and C_3 may be connected through an Is-A relationship rather than the Antonym one. Instead, each connection of the Level 2 (the Sentiment Level) describes the belonging of each concept with respect to the different domains taken into account.

The system has been trained by using the Blitzer dataset[3] in two steps: first, the fuzzy membership functions have been initially estimated by analyzing only the explicit information present within the dataset (Section 2.1); then, (ii) the explicit information has been propagated through the Sentiment Level graph by exploiting the connections defined in the Semantic Level.

2.1 Preliminary Learning Phase

The Preliminary Learning (PL) phase aims to estimate the starting polarity of each concept with respect to a domain. The estimation of this value is done by analyzing only the explicit information provided by the training set. This phase allows to define the preliminary fuzzy membership functions between the concepts defined in the Semantic Level of the graph and the domains that are defined in the Sentiment one. Such a value is computed by the Equation 1

$$\mathrm{polarity}_i^*(C) = \frac{k_C^i}{T_C^i} \in [-1, 1] \qquad \forall i = 1, \ldots, n, \tag{1}$$

where C is the concept taken into account, index i refers to domain D_i which the concept belongs to, n is the number of domains available in the training set, k_C^i is the arithmetic sum of the polarities observed for concept C in the training set restricted to

[3] http://www.cs.jhu.edu/ mdredze/datasets/sentiment/

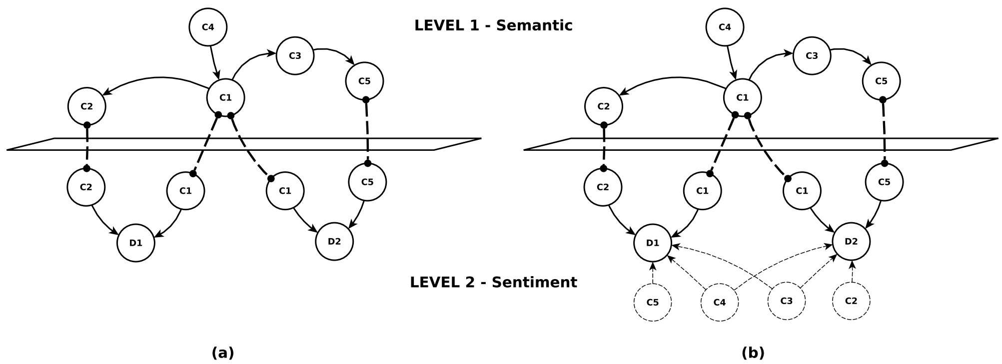

Fig. 1: The two-layer graph initialized during the Preliminary Learning Phase (a) and its evolution after the execution of the Information Propagation Phase (b).

domain D_i, and T_C^i is the number of instances of the training set, restricted to domain D_i, in which concept C occurs. The shape of the fuzzy membership function generated during this phase is a triangle with the top vertex in the coordinates $(x, 1)$, where $x = \text{polarity}_i^*(C)$ and with the two bottom vertices in the coordinates $(-1, 0)$ and $(1, 0)$ respectively. The rationale is that while we have one point (x) in which we have full confidence, our uncertainty covers the entire space because we do not have any information concerning the remaining polarity values.

2.2 Information Propagation Phase

The Information Propagation (IP) phase aims to exploit the explicit information learned in the PL phase in order to both (i) refine the fuzzy membership function of the known concepts, as well as, (ii) to model such functions for concepts that are not specified in the training set, but that are semantically related to the specified ones. Figure 1 presents how the two-levels graph evolves before and after the execution of the IP phase. After the PL phase only four membership functions are modeled: C_1 and C_2 for the domain D_1, and C_1 and C_5 for the domain D_2 (Figure 1a). However, as we may observe, in the Semantic Level there are concepts that are semantically related to the ones that were explicitly defined in the training set, namely C_3 and C_4; while, there are also concepts for which a fuzzy membership function has not been modeled for some domains (i.e. C_2 for the domain D_2 and C_5 for the domain D_1).

Such fuzzy membership functions may be inferred by propagating the information modeled in the PL phase. Similarly, existing fuzzy membership functions are refined by the influence of the other ones. Let's consider the polarity between the concept C_3 and the domain D_2. The fuzzy membership function representing this polarity is strongly influenced by the ones representing the polarities of concepts C_1 and C_5 with respect to the domain D_2.

The propagation of the learned information through the graph is done iteratively where, in each iteration, the estimated polarity value of the concept x learned during the PL phase is updated based on the learned values of the adjoining concepts. At each iteration, the updated values is saved in order to exploit it for the re-shaping of the fuzzy membership function associating the concept x to the domain i.

The resulting shapes of the inferred fuzzy membership functions will be trapezoids where the extension of the upper base is proportional to the difference between the value learned during the PL phase (V_{pl}) and the value obtained at the end of the IP phase (V_{ip}); while, the support is proportional to both the number of iterations needed by the concept x to converge to the V_{ip} and the variance with respect to the average of the values computed after each iteration of the IP phase.

3 Concluding Remarks

The system have been validated on the full version of the Blitzer dataset[4] and the results, compared with the precision obtained by three baselines, are shown in Table 1.

SVM [7] Precision (Rec. 1.0)	Naive-Bayes [8] Precision (Rec. 1.0)	Max-Entropy [8] Precision (Rec. 1.0)	MDFSA Precision	MDFSA Recall
0.8068	0.8227	0.8275	**0.8617**	0.9987

Table 1: Results obtained on the full version of the Blitzer dataset.

The results demonstrated that the modeled fuzzy membership functions may be exploited effectively for computing the polarities of concepts used in different domains.

References

1. 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), Philadelphia, Association for Computational Linguistics (July 2002) 79–86
2. Blitzer, J., Dredze, M., Pereira, F.: Biographies, bollywood, boom-boxes and blenders: Domain adaptation for sentiment classification. In Carroll, J.A., van den Bosch, A., Zaenen, A., eds.: ACL, The Association for Computational Linguistics (2007)
3. Bollegala, D., Weir, D.J., Carroll, J.A.: Cross-domain sentiment classification using a sentiment sensitive thesaurus. IEEE Trans. Knowl. Data Eng. **25**(8) (2013) 1719–1731
4. Xia, R., Zong, C., Hu, X., Cambria, E.: Feature ensemble plus sample selection: Domain adaptation for sentiment classification. IEEE Int. Systems **28**(3) (2013) 10–18
5. Ponomareva, N., Thelwall, M.: Semi-supervised vs. cross-domain graphs for sentiment analysis. In Angelova, G., Bontcheva, K., Mitkov, R., eds.: RANLP, RANLP 2011 Organising Committee / ACL (2013) 571–578
6. Tsai, A.C.R., Wu, C.E., Tsai, R.T.H., jen Hsu, J.Y.: Building a concept-level sentiment dictionary based on commonsense knowledge. IEEE Int. Systems **28**(2) (2013) 22–30
7. Chang, C.C., Lin, C.J.: Libsvm: A library for support vector machines. ACM TIST **2**(3) (2011) 27
8. McCallum, A.K.: Mallet: A machine learning for language toolkit. `http://mallet.cs.umass.edu` (2002)

[4] Detailed results and tool demo are available at http://dkmtools.fbk.eu/moki/demo/mdfsa/mdfsa_demo.html