A Survey on Cross-Lingual Aspect-Based Sentiment Analysis

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Abstract

Aspect-based sentiment analysis (ABSA), which aims to study and interpret people's sentiment at the aspect level, has attracted substantial interest in the recent decade as an important fine-grained sentiment analysis topic. To handle ABSA in diverse contexts, multiple tasks for assessing distinct sentiment elements and their relationships, such as the aspect term, aspect category, opinion term, and sentiment polarity, have been created. Cross-lingual sentiment analysis (CLSA) uses one or more source languages to assist low-resource languages in sentiment analysis. As a result, the issue of a shortage of annotated corpora in many non-English languages may be addressed. CLSA has received a lot of interest in the subject of sentiment analysis, and there has been a lot of study in this area during the previous decade. In the literature, several techniques and evaluation criteria have been offered. This paper critiques the research context of aspect-based sentiment analysis and cross-lingual sentiment analysis. The paper elaborates on the following points in depth: (1) Different ABSA tasks such as aspect term extraction and aspect polarity classification; (2) CLSA based on cross-lingual word embedding; and (3) CLSA based on multilingual-BERT and other pre-trained models. We go through their key concepts, approaches and flaws related to different techniques for handling the ABSA and CLSA tasks.

1 Problem Statement

Many languages have limited or no training data to train aspect-level sentiment classification models (low resource languages). Pre-trained multilingual language models (like mBERT and XLM-R) have alleviated the low resource problem to a certain extent as they are able to generalize across languages. The key to successful cross-lingual transfer learning is the ability to learn semantically rich language-agnostic representations. The objective of this study is to explore the current cross-lingual aspect-based sentiment analysis approaches and aspect-based sentiment analysis tasks. We want to explore how the methodologies for tackling the ABSA and CLSA tasks are able utilize the available resources, transfer the knowledge across languages and overcome the problem of limited resources.

2 Motivation

Aspect level sentiment and emotion analysis gives us the information about the sentiment and emotion labels or values associated with particular aspects in an entity. The document level sentiment analysis fails to capture the finer-grained details as different aspects can have conflicting sentiments. Aspect-based sentiment analysis is done in phases such as aspect term identification, aspect category identification and aspect sentiment classification. Aspect-based sentiment analysis gives us more in-depth knowledge towards different aspects of an entity and what is the sentiment towards each of the sentiment. Although there is a lot of work done on aspect-based sentiment analysis on English language but there are many languages whose training data or a labelled corpus is not sufficient or not at all available for training. Cross-lingual sentiment analysis (CLSA) uses one or more source languages (often resource-rich languages like English) to assist low-resource languages (referred to as target languages) in performing sentiment analysis tasks. CLSA is a type of sentiment analysis that mines subjective information in texts to discover sentimental tendencies (e.g., positive or negative). The majority of extant sentiment analysis methods are supervised learning approaches that use a large number of annotated corpora to predict and assess the sentiment polarity of unlabeled data. However, sentiment-annotated corpora are difficult to come by, especially for languages other than English. The English language has amassed a wealth of sentiment resources, including annotated corpora and a sentiment lexicon. However, research on sentiment analysis and sentiment annotated materials for other languages is quite limited.

3 Aspect-Based Sentiment Analysis Tasks

In this part, we will explore ABSA tasks, which aim to forecast a single sentiment component exclusively.

3.1 Aspect Term Extraction

One of the main goals of ABSA is to get clear aspect phrases through which people express their sentiment in the provided review. For example, the aspect words "ambience" and "waitstaff" should be extracted for the sample statement "The ambience is amazing, but the waitstaff is really rude."
Since the expected aspect terms are usually present as a single word or a phrase in a sentence, the supervised ATE problem is frequently expressed as a token-level classification task given the labelled ATE data. As a consequence, techniques for CRF (Yin et al., 2016), RNN (Liu et al., 2015), and CNN-based sequence tagging have been developed. Aspect term extraction often require the information about the domain to help predict the aspect term boundary. Due to this reason, the research area is also focused on developing better word embeddings for different domains. For learning better word representations, Yin et al. (2016) make use of the dependency route. The dependency route helps to reduce the distance between the word vectors in the embedding space. The supervised approaches for aspect term extraction need large quantities of training data as the neural network based models are data hungry. The lack of good quality training data is a concern for the ATE task, and hence the trend is shifted towards unsupervised and semi-supervised learning. Data augmentation has proven to be an effective solution when there is presence of both labelled data and a large quantity of unlabelled data for aspect term extraction. Other techniques include progressive self training, sequence-to-sequence creation, etc.

3.2 Opinion Term Extraction

Identification of opinion terms or phrases about a particular topic from a given statement is termed as opinion term extraction (OTE). Since opinion term and aspect words occur simultaneously, the related aspect is also taken into account for the extraction of opinion term. Due to this co-occurrence of aspect term and opinion term, aspect words are seen in majority of OTE research.

Aspect and opinion extraction is formulated as a token classification problem. two label for aspect and opinion helps to extract aspect and opinion terms separately, or a unified label set to extract both sentiment elements simultaneously. Since aspect and opinion terms are closely related, the main challenge in OTE research is to represent the relationship between aspect and opinion terms. To capture the aspect-opinion link, several models have been developed, including dependency-tree based models, attention-based models, and models that explicitly constrain prediction using syntactic structures.

Another area of OTE research focuses on opinion word extraction but in a target oriented way. Given some aspect word or phrase, the aim is to find corresponding matching opinion words and terms in the statement. The problem is formulated as a token classification problem. The main focus of this research area revolves around the modelling of aspect representations with respect to the input statement so as to get the related views.

Fan et al. (2019) introduce the IOG neural model that incorporates aspect information through an Inward-Outward LSTM. This model constructs the aspect-fused context. Later approaches manage to improve extraction accuracy in different ways: Wu et al. (2020) make use of a generic sentiment analysis dataset. This dataset helps to transfer latent opinion information.

3.3 Aspect Polarity Classification

Aspect polarity classification seeks to predict sentiment polarity for a particular component inside a statement or a review. The aspect can be interchangeably used to denote either an aspect category or an aspect word. Due to this interchangeable nature in the definition of aspect, two APC problems are formulated: aspect term-based polarity classification and aspect category-based polarity classification. The differences between the two problems are very subtle. For example in category-based classification the category is not explicitly mentioned in the statement while in aspect term-based classification the aspect term is explicitly mentioned in the statement. Both of these problems are formulated as sequence classification problems.

The main research question in both settings is essentially similar: how to efficiently use the link between the aspect (term/ category) and the context from the review to determine the polarity. In real scenarios, some studies tackle the two tasks in a multi-task way and using the same model. Due to this we do not differentiate between these two subtasks. For both aspect category as well as aspect term we use the term "aspect". In recent times, Deep learning-based aspect polarity classification is seen to be on the rise.

Various kind of neural network-based models are suggested which help in getting some significant performance gains. The state-of-the-art neural model make use of very simple yet effective strategies such as fusion and concatenation techniques to model the relationship between aspect terms and the context in which they appear (Tang et al., 2015). For getting the aspect-based feature representations, attention mechanisms are often used. The attention mechanism is based on the idea that different parts of the sentence provide some weightage to each aspect which influence the final prediction of the model. The attention-based LSTM, introduced by Wang et al. (2016) made use of the aspect embeddings. The network was able to calculate the attention weight by using the aspect embeddings concatenated with the word embedding vector in the input review. These embeddings were then used to predict the final polarity associated with aspect term. The following approaches which we will list below make use of sophisticated attention networks and mechanisms. The attention mechanism helps in learning the aspect relationship with opinion terms in a better way. IAN (Ma et al., 2017) is able to learn the attention weights for the aspect and the statement in an independent way. IAN method is able to provide a representation for aspect term as well as the statement. In combination with the LSTM network, many other attention mechanisms have been studied. Some of these techniques are gated network or memory networks. Recent success of the pre-trained models have made them standard language models for the task of aspect polarity classification. However Sun et al. (2019a) formulated the APC task as a a sentence pair classification problem. He added auxiliary sentences which allowed BERT to better exploit its sentence pair modelling capabilities.

Other areas of aspect polarity classification research focuses on the syntactic structure of the phrase. Using the syntactic structure, the association between the aspect term and it's polarity is useful in making predictions about the overall sentiment. Previous research which used the machine learning models to tackle the APC problem used dependency trees as the main characteristic for classification. However, dependency parsing itself is a challenging task in the field of natural language processing. Aspect polarity classifiers with bad dependency parsers would not be able to perform better than other approaches. Better dependency parsing techniques have shown to be able to get better results for aspect polarity classification using dependency trees. The gains through dependency parsing-based aspect polarity classification has resulted in advancements for deep learning based neural dependency parsing. graph neural networks (GNNs) were used by Sun et al. (2019b) and Zhang et al. (2019) for making dependency trees. The dependency trees created through GNNs made use of the syntactical knowledge and the dependencies of words with each other. Seeing the improvement in performance using dependency trees, various GNN-based techniques have been suggested for the APC task which takes advantage of the syntactical knowledge in the dependency trees. Not only the syntactical structure but structural information of the sentence is also used to develop methods for aspect polarity classification. Modelling of the association between different statements and review phrases, under the assumption that different phrases explain and develop on each other and are connected, was done by Ruder et al. (2016)

3.4 End-to-End ABSA

The main goal of End-to-End ABSA (E2E-ABSA) is to simultaneously extract the aspect term and the polarity associated with that aspect term in a given statement or review. E2E-ABSA extracts the aspect and polarity tuples. Hence the E2E-ABSA task is further divided into two sub-tasks of aspect term extraction and aspect polarity classification. An immediate solution for E2E-ABSA task would be to perform aspect term extraction and aspect polarity classification in a pipe lined way, one after another. For example, take the sentence "I hate the iphone". The context information of the word "hate" suggests a negative sentiment and also signals that the next word "iphone" is the opinion target. Many approaches have been suggested to tackle the E2E-ABSA tasks, but they can be broadly classified into two groups: i) joint techniques ii) unified techniques. The joint techniques make use of the association between the two tasks (aspect term extraction and aspect polarity classification). The joint techniques train both tasks in parallel in a multi-task fashion. Two set of labels, aspect boundary label and polarity label, are used in the joint framework. The final result is obtained by using the results from both the tasks The second approach deals with E2E-ABSA task in a unified way. There is no explicit distinction between the two tasks (aspect term extraction and aspect polarity classification). The labels of both the tasks are combined to form single task labels. These token label denote both the aspect term and opinion in a unified way (B,I,O-Neg,Pos,Neutral).

Whatever technique is suggested for E2E-ABSA task, some of the overall ideas and approaches are shared across various models. For example, the association and the relationship between the aspect terms and their corresponding polarity has been shown to be important for getting the correct terms and polarity pairs. The sentiment terms in the review provide important clues for the position of the aspect term in review. Due to the relationship between aspect terms and opinions, opinion term extraction is performed as a parallel task for E2E-ABSA tasks. Chen and Qian (2020) introduced a relation-aware collaborative learning (RACL) model. The network was able to model the interactive relationship of various opinion extraction tasks with the help of a propagation mechanism which helped in coordination of different tasks.

3.5 Aspect Category Sentiment Analysis

Detection of a particular category from a given set of categories and finding the polarity associated with that category in a review is the goal of aspect category sentiment analysis (ACSA). End-to-end ABSA task and aspect category sentiment analysis appears to be almost similar but the difference lies in the format of the aspect term and category. The aspect category need not be mentioned explicitly in the review under consideration. Due to this the aspect category sentiment analysis is adopted extensively in industries. Again an immediate solution for the task would be to perform aspect category detection and then associate a polarity with it. However, finding multiple aspect categories in the review is not at all a trivial task. The errors from the first part in the pipeline would go to the later stages and would reduce overall efficacy of the system. If the association and relationship between the two subtasks is not taken into consideration then the system again suffers with a decrease in performance. Performing both the tasks in a multi-task fashion has proven to be of immense help in terms of achieving significant performance gains for individual tasks. Quite a few research now focus on the task of aspect category sentiment analysis in a structured way. The task of aspect category detection is formulated as a multi-label classification task where each category is considered as a label. However, for the task of aspect polarity classification, it was formulated as a multi-class classification task where each polarity is considered as a class. The field of aspect category sentiment analysis is broadly divided into four kinds: (i) Cartesian product, (ii) Add-one-dimension, (iii) Hierarchical classification, and (iv) Seq2Seq modelling. With the help of cartesian product, the technique lists all possible combinations of category and polarity tuples. After getting all the pairs, the model takes both the review and polarity and then the model predicts a boolean value indicating whether such a pair of category and sentiment is present in the review or not (Wan et al., 2020). The downside of this approach is that the training data created through the strategy is several fold larger than the original data. The large dataset thus creates high computational costs. An alternative to this approach would be to add a separate dimension for aspect category detection. The previous models had three options for an aspect category, namely, positive, negative, and neutral. A new label "N/A" was introduced by Schmitt et al. (2018). The "N/A" label provides the information about the presence of category in the review. This label in turn allows to solve the aspect category sentiment classification in a unified way.

Hierarchical methods are also used to solve the task of ACSA. for solving the problem of aspect category sentiment analysis, Cai et al. (2020) present a hierarchical classification method. The aspect categories are detected using a hierarchical graph convolutional network. The model then predicts the associated polarity with each of the detected categories in the review. The hierarchical approach helps in modelling the intimate relationship between the aspect categories as well as the relationship between different aspect categories and the polarity. In a similar way, for tackling the data deficiency issue, Yang et al. (2020) introduced the use of a shared layer for polarity prediction between the aspect categories. The sequence-to-sequence paradigm was explored by Liu et al. (2021) for tackling the aspect category sentiment classification. The authors made us of the natural language statements and phrases. The phrases were able to describe the expected prediction of the system. This helped in getting sgnificant performance gains when compared to the previous classification models based on pre-trained models

4 Cross-domain ABSA

Within a specific domain, the supervised ABSA models have been well developed. In real-world scenarios which contains texts from disparate or unknown areas the models are likely to fail and give inaccurate answers. The primary cause for this is that the features associated with the opinion target from many domains are often quite diverse, and the models may lack prior knowledge about commonly-used terms in undiscovered regions. A straightforward solution would be to produce labelled data for these domains and then retrain new models. Given that ABSA problems need fine-grained annotations, acquiring a large volume of tagged data can be expensive, if not impossible.

Domain adaptation approaches are used to give alternate strategies for well generalising ABSA systems to other domains, allowing for cross-domain ABSA predictions at a cheaper cost. The main research areas in this field can be divided into the following: data-based transfer and feature-based transfer The vast majority of these efforts may be divided into two categories:

The data-based transfer tries to improve the generalisation ability of the ABSA model to the target domain by adjusting the distribution of the training data. Ding et al. (2017) produce pseudo-labeled data in the target domain using high-precision syntactic patterns and domain-independent opinion phrases. The newly created data which is pseudo-labeled is provided to the training set (consisting of the source domain data). The model is now trained on the mixed data which helps in cross-domain transfer. A similar method was used by Li et al. (2012). The authors made the new target-domain pseudo-labeled data. They further used the data and for giving different weightage to the source domain data. Apart from making predictions on unlabeled data from the target domain, Yu et al. (2021) takes labeled sentences data from the source domain as input. The authors make an aspect-constrained (opinion-constrained) masked language model. The authors then perform the conversion of the opinion term from the source domain data to target domain data. The newly constructed data can be used a silver standard dataset. Learning domain-agnostic representations is the main school of thought and reasoning backing the feature-based transfer for ABSA tasks. Jakob and Gurevych (2010) and Chernyshevich (2014) includes various syntactic features which are not dependent on the domain into a Conditional Random Field-based tagger. The tagger performs the task of aspect term extraction for cross-domain setting. The creation of edge prediction task for dependency trees was explored by Wang and Pan (2018) and Wang and Pan (2020). This helped the research area which focused on syntactically-aware representations. The representations helped in reducing the domain shift. Other secondary tasks such as aspect-polarity relationship prediction, opinion term extraction and categorization are used for better alignment of representations. Using domain-agnostic representations in combination with weighted token-level instance through various auxiliary tasks was explored by Gong et al. (2020). For domain adaptation task in a cross-domain end-to-end ABSA setting, this technique was used to combine both data-based and feature-based transfer.

5 Cross-Lingual Sentiment Analysis

Cross-lingual Sentiment Analysis (CLSA) is the technique of sentiment analysis in which we use the resources from languages on which extensive work is done (resource rich languages) and try to solve the problem on a language where there is unavailability of such a labelled corpora or resource. The task is to train a sentiment analysis model on a source language A for which labelled corpora is available and use that model and data to test the system on another language B for which training data is not available. The main challenge in this approach is reduce the language gap between different languages.

5.1 Traditional Approaches

Singhal and Bhattacharyya (2016) utilised polarity words and word embeddings in the English language for doing the task of sentiment analysis for Indian languages like Hindi and Marathi as well as for European languages. The training data was first converted into the English language with the help of Google translation tool. The English words in the translated sentence is then mapped to the pre-trained word embeddings for English. Using these representation a CNN based network was trained for the sentiment classification. In another approach (Singhal and Bhattacharyya, 2016) the English polarity words are appended in the training data. This approach helped in learning the correct patterns in a sentence and improving prediction on the negative label. (Balamurali et al., 2012) in their work used the WordNet senses in place of the words to train the bilingual embeddings. By adding words from the synsets of the source language, the WordNet for the target language was created. Now the words, in both source and target language, which have similar context will have the same synset identifier. A sentiment classifier was trained on the created dataset.

5.2 Cross-lingual Word Embeddings

Word embeddings have become and integral part in almost all NLP tasks and cross-lingual sentiment analysis is no exception to that. The rise in research towards multilingual models have motivated the research in cross-lingual embeddings as well. Cross-lingual embeddings are word representations of two or more languages in a common vector space such that the words with similar context and semantics are closer to each other. For example the English word *"sad"* and the Hindi word *"dukhi"* should be closer to each other in the combined vector space.
In a cross-lingual setting, (Barnes et al., 2016) used multilingual word embeddings for sentiment categorization. (Akhtar et al., 2018) used bilingual word embeddings learnt from a parallel corpus to reduce the influence of data sparsity. The cross-lingual word embeddings may then be fed into any model to do the task at hand, such as sentiment analysis.

6 Deep Learning Based Aspect-based Sentiment Analysis

Deep learning approaches are dominating the performance on the task of aspect-based sentiment analysis. The state-of-the-art approaches are using the Transformer (Vaswani et al., 2017) and the BERT (Devlin et al., 2019) pre-trained models for achieving high performance. We will discuss some of the recent approaches using BERT architecture for the ABSA task.

6.1 Exploiting BERT for End-to-End Aspect-based Sentiment Analysis

In the work by (Li et al., 2019) , the authors makes the task of the aspect-based sentiment analysis in the form of a sequence labelling task. The authors use the BERT model (Devlin et al., 2019). SemEval ABSA dataset (Pontiki et al., 2016) were used for training. The input is a sentence which is processed by the BERT model which produces a contextualized representation of the input sentence in the final layers. The contextualized representation is taken and a linear classification layer is added on top of the BERT model. This task specific layer is used to classify the input tokens. The output tag can be B-POS, B-NEG, B-NEU, I-POS, I-NEG, I-NEU, E-POS, E-NEG, E-NEU, or O. B,I,E and O represents the beginning, inside, end, and outside respectively. Each tag denoting positive, negative or neutral sentiment if it is a part of the aspect. This was one of the first works to show the effectiveness of BERT model for the sentiment analysis task and how it tackles the problem of overfitting.

6.2 Aspect-Based Sentiment Analysis Using BERT

The authors of Hoang et al. (2019) attempt to address the challenge of Aspect-Based Sentiment Analysis using the SemEval-2016 dataset. The authors suggest a novel ABSA job for out-of-domain categorization of sentences and texts. They present a combination model that solves aspect classification and sentiment classification concurrently using only one phrase pair classifier model from BERT.

The authors create three models using BERT (Devlin et al., 2019) which are:

1. Aspect classification model:
   (a) This model is similar in structure to that of a Sentence Pair classifier
   (b) text and the aspect are taken as the input
   (c) Using the labels 'related' and 'unrelated,' the model tries to find if aspects are related to the text or not.
   (d) It is feasible to handle out-of-domain aspects using the aspect as input, i.e. aspects that are not part of the collection of aspects on which the model was trained.
2. Sentiment polarity classification model
   (a) for estimating polarity on a text based on a specified element

(b) The Sentence Pair categorization model's architecture was used to implement the model

(c) Input: The first input is the review to be examined, and the second is the aspect on which the text will be evaluated

(d) This model's output will be one of the following: 'positive,' 'negative,' 'neutral,' or 'conflict.'

3. Combined model for both aspect and sentiment classification

(a) The task is designed as a multi-class classifier that predicts both the aspect and polarity.

(b) The Sentence Pair categorization model's architecture was used to implement the model

(c) The model is fed the review and the aspect term and. The model predicts a polarity label if the aspect is connected to the text. Otherwise the model predicts irrelevant label.

6.3 Does syntax matter? A strong baseline for Aspect-based Sentiment Analysis with RoBERTa

(Dai et al., 2021) shows the use of dependency trees combined with the RoBERTa model for the task of aspect-based sentiment analysis. The authors contend that dependency trees can significantly increase ABSA performance. They offer an induced tree technique based on a pre-trained model (PTM). The induced tree is taken as an input to the model that take dependency trees as input and output the polarity for a particular aspect. The tree structure may be inferred from the BERT models' final levels. The authors begin by comparing the induced trees from PTMs and the dependency parsing trees on many prominent ABSA models. As input, the ABSA models use dependency trees. The fine-tuned RoBERTa-induced tree outperforms the parser-provided tree. The fine-tuned RoBERTa Induced Tree is more sentiment-word focused and may help the ABSA assignment. Because it implicitly contains task-oriented syntactic information, a pure RoBERTa-based model can exceed or approximate past state-of-the-art results on six datasets spanning four languages.

6.4 A Multi-task Learning Model for Chinese-oriented Aspect Polarity Classification and Aspect Term Extraction

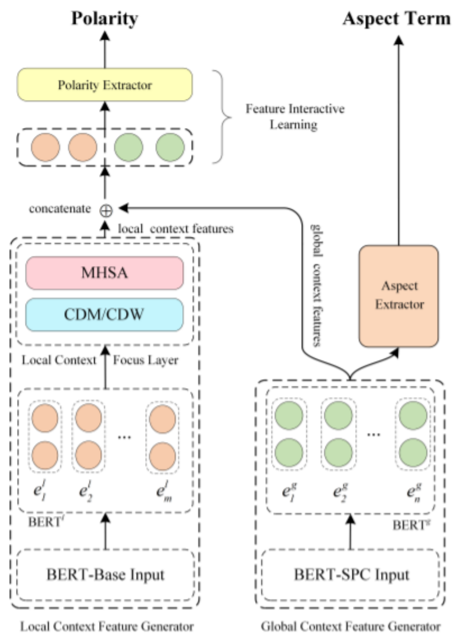

Figure 1: Network Architecture of LCF based BERT model (Yang et al., 2021)

For the job of aspect extraction and classification, (Yang et al., 2021) employs the multi-task framework in conjunction with the BERT model. The model employs a Local Context Focus (LCF) mechanism over the BERT model, which recognises local and global context features and uses the context feature vectors derived by BERT models to execute aspect extraction and classification tasks. The model has produced cutting-edge results on a variety of sentiment analysis datasets and has been effective in combining multilingual models with the assistance of the mBERT model.

7 Summary

In this work, we evaluate wide range of ABSA tasks, CLSA's current research and thoroughly expand on its development process. It should be highlighted that the ultimate purpose of CLSA is to assist target languages in doing sentiment analysis using source languages. CLSA is an interesting topic to pursue because of the high number of languages with limited resources. The original aim of CLSA will be breached if the cost of knowledge transmission needed by the CLSA model is too high, or even considerably exceeds the cost of people and material resources required by the monolingual sentiment analysis. At the same time, it is one of the key markers for determining if the CLSA model can be used in large-scale languages in the future.

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