Cross-target Stance Classification as Domain Adaptation

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Abstract. As in many NLP tasks, stance classification - the computational task of inferring attitudes towards a given target topic from text - often relies on supervised methods and annotated corpora. However, given the costs associated with corpus annotation, and the need to provide stance labels for every target of interest, cross-target methods (that is, the use of an existing corpus of stance towards a particular target to classify stance towards a different, previously unseen target), are of great interest. Based on these observations, in the present work we address the issue of cross-target stance classification with the aid of an existing domain adaptation method based on BERT in combination with adversarial learning and knowledge distillation, and which has been shown to be successful in the related tasks of cross-domain sentiment analysis and cross-domain author profiling. To this end, we envisage a number of experiments to compare cross-target stance classification between target pairs with different degrees of semantic relatedness, and examine how much loss is observed from single-target to cross-target stance classification settings, and attempt to identify possible ways forward.

Keywords: Natural language processing · Stance classification · Cross-target stance · Domain adaptation

1 Introduction

Stance classification [1,10] is the computational task of inferring attitudes (e.g., for/against) towards a particular target (e.g., an individual, a piece of legislation etc.) that may or may not be explicitly mentioned in the text. For instance, 'killing animals is unacceptable' may represent a stance in favour of veganism, or against a particular individual who kills animals etc. The task bears some resemblance to sentiment analysis, but stance (for/against) and sentiment (positive/negative) do not necessarily correlate [1].

Stance classifier models are usually built by making use of supervised machine learning methods that rely upon labelled training data. As in other text classification tasks of this kind, best results are usually observed in *single-target*

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settings, that is, when both train and test documents discuss the same topic of interest. Thus, for instance, single-target stance classification would normally consist of building a classifier from stances in favour and against, e.g., a target president, and would subsequently use the model to classify previously unseen stances towards the same individual.

From a machine learning perspective, single-target settings will arguably obtain optimal results but, in many practical situations, training data about the intended target may be simply unavailable. In these cases, a possible alternative to (often costly) corpus annotation is to consider a *cross-target* setting, that is, building a model from data about a certain target for which a labelled corpus happens to be available (e.g., stances towards president A), and then using it to classify stances towards a different target (e.g., president B, or presumably even a more semantically-distant target, such as a political activist, a country, a product etc.)

If compared to single-target settings, cross-target settings may of course convey a certain degree of accuracy loss, but the appeal of circumventing the need for corpus annotation (for every possible topic of interest) remains strong in the field [3,4,7,12,25,26].

Of particular interest to the present work, [18] has introduced a domain adaptation method based on pre-trained BERT language models [6] in combination with adversarial learning and knowledge distillation [9] called BERT-AAD. The method has been shown to obtain positive results in cross-domain sentiment analysis and, more recently, also in cross-domain author profiling [5], that is, the task of predicting an author's demographics (e.g., gender, age, personality etc.) based on text that he/she has written [20–22]. However, it remains unclear whether this method may also be useful for stance classification, which is arguably closer to a text inference task [1].

To shed light on this issue, the present work extends previous studies in cross-domain sentiment analysis and author profiling by applying BERT-AAD [18], possibly for the first time, to stance classification. To this end, we introduce a novel multi-topic corpus of tweets labelled with stance information in the Portuguese language, and we envisage a number of experiments to compare cross-target stance classification between target pairs with different degrees of semantic relatedness. In doing so, our main objective is to examine how much loss is observed from single-target to cross-target stance classification settings, and to identify possible ways forward.

2 Background

Existing work in stance classification has grown considerable as a result of the SemEval-2016 shared task 6 [13], which introduced supervised (task A) and unsupervised (task B) challenges, and an accompanying dataset labelled with stance information (for, against, and none) towards five topics (Atheism, Climate Change, Feminist Movement, Hillary Clinton, and Abortion Legalisation.) An additional, unlabelled topic (Donald Trump) was taken as test data for task B which, although not particularly focused on cross-target stance classification, was modelled in this way by some of the participant systems that attempted to circumvent the lack of labelled test data (about Donald Trump) by using data about the other targets. Section 2.1 describes some of these studies, and more recent approaches to cross-target stance classification. Section 2.2 focuses on the cross-domain sentiment analysis method in [18] that will be taken as the basis for the present work.

2.1 Cross-target Stance Classification

The work in [4] presents a cross-target stance classification approach that uses a feature extraction method based on auto-encoders. To this end, the encoder takes as an input a bag-of-words representation of the 50k most frequent words in the corpus, performs dimensionality reduction and then recreates the original embeddings. Stance classification proper (using Hillary Clinton train data and Donald Trump test data from Semeval-2016 task B) is performed by using logistic regression.

The work in [24] was also a participant system at SemEval-2016 task B, introducing a cross-target stance classification approach based on support vector machines (SVMs) and a range of lexical and syntactic features. First, the model identifies whether the input text conveys any stance at all and, if so, determines its polarity (for/against) by measuring the similarity between a test instance (about Trump) and other topics.

The work in [7] introduces a similar two-step model to classify stance in texts. The first step consists of detecting subjectivity, i.e., whether the text contains any stance at all. The second step, applicable only to non-neutral texts, predicts stance polarity. Classification is performed with the aid of SVMs and engineered features (e.g., sentiment, word and char n-grams, presence of target keywords in the text, among others). The models used for cross-target stance detection are trained using all available data from other topics in the SemEval-2016 corpus, and are shown to outperform previous participant systems in task B.

The work in [25] presents a deep neural network with attention mechanism for cross-target stance classification. The model architecture consists of two bidirectional LSTM networks (BiLSTMs) to encode the contextual information in the input sentence and target, an attention mechanism to focus on common aspects shared by source and target domains, and the final prediction layer. The model outperforms the best participant systems from previous SemEval-2016.

The work in [8] approaches the cross-target stance detection task by introducing a recurring neural network based on LSTM cells with a double attention mechanism (called 'target' attention and 'target towards' attention, respectively.) The model consists of a hierarchical architecture in which the first level encodes words, and the second level encodes the relevance of each sentence in the text. First level outputs are individually fed into a pooling layer and then to the second level. The model outperforms a number of existing baseline systems applied to the SemEval-2016 Task B data.

The work in [26] introduces a cross-target stance classification model comprising two main components, namely, a semantic-emotion graph (SE-graph) and a graph convolution network. The SE-graph component encodes semantics-related and emotion-related lexicons and incorporates external knowledge at the word and concept levels. Graph nodes represent either a word or an emotion tag, and edges represent the co-occurrence of two nodes. The convolution network encodes the graph structure to generate a representation of the connections between words or emotion tags. These two components are used in a knowledge-aware memory unit (KAMU) that extends a BiLSTM model and encodes the sentence, and which uses a second BiLSTM network to encode topic information. Results suggest that the model obtains SOTA accuracy for most target topics from the SemEval-2016 corpus.

The work in [2] addressed the cross-target stance detection task from a zero-shot perspective, that is, without training examples about any particular target. The work introduces a dataset called VAST and a model to perform zero-shot stance detection called Topic-Grouped Attention (TGA). This consists of a contextual conditional embedding layer followed by topic-grouped attention using generalised representations, and a feed-forward network. The conditional embedding layer is composed by two encoders that use BERT to generate representations for both topic and text. The TGA module uses scaled dot-product attention to compute the importance of each topic token.

Based on the same dataset and also focused on zero-shot settings to address the cross-target stance detection task, the work in [3] introduces TOAD (TOpic-ADversarial network). This consists of four main components. First, there is a topic-oriented document encoder, which encodes both text and topic using BiLSTM and Attention mechanisms. The second component, called topic-invariant transformation, performs domain adaptation to generate topic-invariant representations without removing stance cues. The third component is a stance classifier consisting of a two-layer feed-forward network. Finally, the fourth component is a topic discriminator, which predicts the topic of the input sentence. This module is used alongside topic-invariant transformation to train the domain adaptation model.

Finally, in [12] a neural model based on a knowledge graph and BERT is used to address the cross-target stance classification. The architecture is composed of a BERT encoder to generate both topic and text representations, and which is followed by a knowledge graph encoding with a form of Graph Convolution Network (GCN). The graph is taken to represent common sense knowledge, in which nodes represent concepts found in the document and the edges represent the relations between them.

2.2 Domain Adaptation Using BERT

The work in [18] introduces a domain adaptation method called BERT-AAD, which combines BERT pre-trained models and adversarial discriminative domain adaptation (ADDA) [23] for cross-domain sentiment analysis.

ADDA consists of mapping source and target domains into a space of shared features as an adversarial framework (comprising discriminative modelling, untied weight sharing, and GAN-based loss) as a means to transfers knowledge from a larger (teacher) model to a smaller (student) one.

Given the logits predictions z^S and z^T made by a student and teacher models, and a degree of knowledge transfer t, knowledge distillation (KD) seeks to minimise the following objective function [9,18]:

$$t^2\ x \sum_{k} -softmax(z_k^T/t)\ x\ log(softmax(z_k^S/t)) \quad (1)$$

The combination of ADDA and KD (named as AAD in [18]) is motivated by the observation that, in the case of BERT, using ADDA alone would amount to random classification due to the overly large number of model parameters. The combined BERT-AAD approach, by contrasts, operates as a regularisation method that preserves the knowledge acquired from the source domain, and enables the output model to adapt to the target domain without overfitting.

3 Materials and Method

BERT-AAD [18] has been shown to obtain results that are close to in-domain classification in both cross-domain sentiment analysis and also in cross-domain author age and gender classification [5]. In the present work, we will extend these studies by turning to the issue of cross-target stance classification. More specifically, we envisage a number of experiments intended to investigate to which extent BERT-AAD is suitable for cross-target stance classification, and how its results compare to those observed in single-target settings. We notice, however, that since cross-target settings are unlikely to outperform the single-target settings, the focus of the present work is on minimising the accuracy loss observed from single- to cross-target settings in a novel multi-target stance corpus.

3.1 Corpus

Although a number of data sets for stance classification in our language of interest - Portuguese - have been developed in previous work [16,17,19], these do not focus on cross-target settings. For that reason, we created a novel corpus of Portuguese Twitter data labelled with binary (for/against) stance information towards six targets that are popular topics of hyperpartisan discourse on Brazilian social media.

The corpus, hereby called UstanceBR r1, is organised in three polarised topic categories, each of them comprising a target generally favoured by more conservative individuals, and another target of more liberal leaning as follows.

– Presidents: Bolsonaro, Lula
– Covid-19: Hydroxychloroquine, Sinovac vaccine

Table 1. Corpus descriptive statistics.

Target	Against	For	Overall (A+F)	Words	Avg words
Bolsonaro	5,603	4,119	9,722	233,799	24.05
Lula	4,601	3,814	8,415	213,684	25.39
Hydroxychloroquine	4,007	4,018	8,025	228,617	28.49
Sinovac	4,061	3,945	8,006	227,310	28.39
Church	3,553	3,600	7,153	172,530	24.12
Globo TV	3,451	2,698	6,149	110,586	17.98
Overall	25,276	22,194	47,470	1,186,526	25.00

– Institutions: Church, Globo TV network

Table 1 presents the descriptive statistics for the six datasets.

The three target pairs were chosen so as to represent different degrees of similarity for the purpose of cross-target stance classification. The Presidents target pair is arguably the more closely related of the three, at least in the sense that many of the arguments used for/against one particular president tend to be applicable to another as well. For instance, 'X proposed a bad economic plan' works equally well as a stance against any president X. By contrast, the two Covid-19-related targets are only moderately close (e.g., 'X is a well-known Malaria medicine' is only applicable to Hydroxychloroquine), and the Institutions target pair is arguably the least related of the three. Arguments used for/against church (e.g., social work, freedom of expression etc.) are generally distinct from those that would be applicable to a TV network (e.g., editorial standards, broadcast quality etc.)

3.2 Classifier Models

We consider a number of cross-target stance classifiers that take as an input a dataset from a train domain (e.g., Bolsonaro) and attempt to perform stance classification on a different test domain. In doing so, rather than attempting every possible combination of target pairs, we shall focus on cross-target learning between more closely related targets (e.g., Bolsonaro-Lula) for brevity.

Our main approach, hereby called *CT.AAD*, is a straightforward adaptation of the AAD sentiment analysis method in [18] to stance classification. This consists of a BERT model that has been fine-tuned to the underlying (stance classification) task, and subsequently combined with the adversarial adaptation with distillation method discussed in Sect. 2.2.

As baseline alternatives to *CT.AAD*, we will consider a general architecture that leverages a BERT pre-trained language model as a token embedding generator with no fine-tuning. More specifically, we concatenate the last four layers of the language model - making a 3072-dimension vector - to represent each input token. This representation is taken as an input to a LSTM network with multi-head self-attention, and followed by a dense layer activated by a softmax function to generate the final class predictions.

By varying the way in which train and test data are used in our experiments, the general LSTM architecture gives rise to three baseline systems of interest. These are summarised as follows.

Single-target uses train and test data about the same target, and is intended as our main (and strongest) baseline system.

CT.Base uses train data from each individual source domain and test data from a different (target) domain, and it is intended to represent a standard LSTM-BERT approach to cross-target stance classification.

Finally, *CT.Replace* is a cross-target strategy similar to *CT.Base*, but in which keywords describing the source target (e.g., Lula) were replaced by their counterparts (e.g., Bolsonaro) in the target domain before actual training. Thus, for instance, given the task of classifying a stance towards Lula using training data about Bolsonaro, a source sentence as in 'I'm outraged after Bolsonaro's speech' would be converted into 'I'm outraged after Lula's speech', the underlying assumption being that replacements of this kind may narrow the gap between source and target domains, at least when these are sufficiently close (as it may be the case of our Presidents dataset), but perhaps less so in the case of more distant pairs (e.g., church and TV network.)

4 Results

Table 2 summarises single- and cross-target stance classification F1 results for the six text targets under consideration. The best cross-target strategy for each target is highlighted, and the bottom line shows the F1 loss observed between *Single-target* and the best cross-target results. Recall that cross-target models were built using only their counterpart target as training data. For instance, Bolsonaro cross-target stance classification uses data from the Lula dataset, and vice-versa.

Table 2. Single-target (top row) versus best cross-target (CT rows) stance classification F1 results.

Strategy	Presidents		Covid-19		Institutions	
	Bolsonaro	Lula	Hydroxy	Sinovac	Globo TV	Church
Single-target (ST)	0.83	0.83	0.83	0.84	0.86	0.85
CT.Base	0.59	0.57	0.47	0.47	0.69	**0.77**
CT.Replace	0.59	0.57	**0.58**	**0.62**	0.27	0.30
CT.AAD	**0.62**	**0.59**	0.41	0.35	**0.79**	0.76
(ST - CT.AAD) loss	0.21	0.24	0.25	0.22	0.07	0.08

As expected, results from Table 2 show that none of the cross-target alternatives are able to outperform *Single-target* classification. Moreover, we notice that

CT.AAD outperforms the other cross-target alternatives in only three tasks, and it performs particularly poorly in the intermediate, partially related Covid-19 target pair.

Interestingly, however, F1 losses from *Single-target* to *CT.AAD* are generally similar for the first two target pairs (i.e., within the -0.21 to -0.25 range), whereas for the third pair (Institutions) *CT.AAD* results are much closer to *Single-target*. This may in principle seem counter-intuitive as the Institutions target pair is arguably the least semantically related of the three and, as a result, less knowledge transfer should be expected between these two targets if compared to, say, the Presidents target pair. One possible explanation for this outcome may be related to the observation that the two more closely-related target pairs (Presidents and Covid-19) are also more polarised in the sense that being for/against one president or medicine often means the opposite if considering the second president or medicine. For instance, an argument in favour of a given president will almost always represent an argument against his political opponent. Thus, we hypothesise that topic polarisation, which is arguably less pronounced in the Institutions target pair, may have hindered the present domain adaptation methods to a certain extent, although more research on this issue is clearly needed. For the use of polarised political information in stance classification, we refer to, e.g., [11].

5 Final Remarks

The present work has addressed the issue of cross-target stance classification by introducing a novel stance corpus in the Portuguese language, and by investigating the use of an existing sentiment analysis domain adaptation method based on BERT in combination with adversarial learning and knowledge distillation. Our experiments compared cross-target stance classification between target pairs with different degrees of semantic relatedness, and examined how much loss is observed from single-target to cross-target stance classification settings.

Our current findings suggest that the use of the domain adaptation method for cross-target stance classification is partially successful, but results vary considerably depending on which target pair is considered. Perhaps surprisingly, best results were not those obtained by the more closely related target pairs (e.g., presidents), which suggests that other variables play a role in cross-target learning. Among these, topic polarisation (i.e., when being in favour of target A implies being against target B) may have limited the opportunities for knowledge transfer. A more detailed study along these lines is left as future work. We notice also that the present task may benefit from pronoun resolution [14,15], which is also left as future work.

The present dataset - called UstanceBR r1 - is freely available for research purposes[1].

[1] https://drive.google.com/drive/folders/1Mj22A9jCeaTcyp7FX9RLHJjMQ-II5bQ2?usp=sharing.

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