Chapter 4
A Survey of Transformer-Based Stance Detection

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ABSTRACT

Stance detection systems are built in order to determine the position of text authors using the text that they produce and other contextual information. As the result of the stance detection procedure, the position of the text producer is determined as favor, against, or none. On the other hand, transformer-based technologies are reported to perform well for various natural language processing tasks. These are deep learning-based models that also incorporate attention mechanism. BERT and its variants are among the most popular transformer-based models proposed so far. In this chapter, the authors provide a plausible literature review on stance detection studies that are based on transformer models. Also included in the current chapter are important further research directions. Stance detection and transformer-based models are significant and recent problems in natural language processing and deep learning, respectively. Hence, they believe that this chapter will be an important guide for related researchers and practitioners working on these topics of high impact.

INTRODUCTION

Stance detection has emerged as a significant problem which has its roots in natural language processing (NLP), social media analysis, and information retrieval (Küçük and Can, 2020; Küçük and Can, 2021; Küçük and Can, 2022). Stance detection is also closely related to the problems in affective computing such as sentiment analysis. In stance detection, the main objective is to automatically infer the position (stance) of the text author towards a target where the output of this procedure is usually 'favor' or 'against' (Küçük and Can, 2020).

On the other hand, deep learning approaches dominate the methods used in many application domains including NLP, speech processing, and computer vision. Transformer-based methods are among these popular deep-learning methods (Yay et al., 2020). As is the case for many tasks related to NLP, a high percentage of recent work on stance detection employ transformer-based deep learning approaches,

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including but not limited to Bidirectional Encoder Representations of Transformers (BERT) (Devlin et al., 2018).

In this book chapter, we present a survey of transformer-based stance detection studies. We also address future research opportunities and provide pointers to related outstanding issues. Stance detection is an important research problem and is beneficial in many application settings including polling, predictions for elections and referendums, and Web search. Hence, a survey of transformer-based stance detection studies will have both theoretical and application-oriented contributions to the related literature.

Stance Detection

Stance detection is commonly considered as a classification task requiring two inputs, a piece of text and a target, and the stance (position) of the text author towards the target is expected at the end of the stance detection procedure (Küçük and Can, 2020). Stance detection is usually considered within the scope of *affective computing* and sometimes considered as a subproblem of *sentiment analysis*.

There are several subproblems of stance detection including *multi-target stance detection*, *cross-target stance detection*, and *contextual stance detection* (Küçük and Can, 2021; Küçük and Can, 2022). In multi-target stance detection, there is a set of (usually interrelated) targets instead of a single one. In cross-target stance detection, the training dataset is available for one target although the test dataset is about another target (Küçük and Can, 2020). In contextual stance detection, in addition to the text under consideration, contextual features can also be used such as retweets, user information and other inter-relationships in case of social media posts (Cignarella et al., 2020). Another relevant research problem is *stance quantification* (Küçük, 2022), where the percentages of pieces of text items classified as f*avor*, *against*, *neutral*, or *none* are expected instead of the individual classification results for the input text items.

Other and more application-specific subproblems of stance detection are *fake news stance detection* and *rumour stance detection*. In fake news stance detection, a news headline and news body are provided and the stance of the body towards the headline is expected, usually in the form of a class label as *agrees*, *disagrees*, *discusses*, and *unrelated* (Küçük and Can, 2020; Umer et al., 2020). On the other hand, in rumour stance detection, we have a piece of text and a rumour as input, and the position of the text towards the rumour is expected, usually as *supporting*, *denying*, *querying*, and *commenting* (Zubiaga et al., 2018).

Stance detection research problem and its subproblems are shown schematically in Figure 1, based on the related figure given in (Küçük and Can, 2020).

There are a number of stance detection competitions that have been carried out (Küçük and Can, 2020). The initial and most prominent of these competitions is *SemEval-2016 Shared Task on Stance Detection* (Mohammad et al., 2016) performed on English tweets. This competition and its followers for other languages help stance detection researchers by providing annotated datasets and up-to-date information about the performance rates of various approaches applied to the problem.

Various approaches have been applied to the stance detection problem so far, such as rule-based methods, machine learning-based models, deep learning-based models, and hybrid approaches (Küçük and Can, 2022). Transformer learning models fall under the deep-learning methods. Since they are central to main topic of our current survey, they are described in details in the following subsection.

Important machine learning models tested for stance detection include SVM (Mohammad et al., 2016) and neural networks (). Ensemble models such as random forest are also tested for the problem. Considering deep learning approaches, RNN, LSTM, CNN, and transformer-based models are also