1. Introduction and Background

Nowadays, by being in the era of data explosion where around 500 million tweets are sent daily, and since people are always curious about others’ opinions, one challenge is to build a system to detect and summarize the overall sentiment of these data. Sentiment analysis is the computational study of detecting and extracting subjective information and attitudes about entities. The entity can represent individuals, events, products, or topics. The output of it is the opinion polarity. Polarity is generally expressed in different forms from two classes of POSITIVE and NEGATIVE or three classes of POSITIVE, NEUTRAL, and NEGATIVE, while at some researches, it is represented as a real number between 1-5 stars or 0-10 grade. Sentiment analysis was acknowledged in the early 2000s with Turney (2002), and Pang et al. (2002), both of them doing binary classification on reviews. Sentiment analysis is generally performed at three different levels: document-based, sentence-based, and aspect-based. At both the document and sentence levels of sentiment analysis, the main goal is to detect the polarity of a specific document or a sentence. In contrast, aspect-based sentiment analysis is focused on identifying the polarity of the targets expressed in a sentence. A target is an object, its components, attributes and features. For instance, at Liu (2010) a model is provided that identifies the polarity of product features that the reviewer has commented on. For example, in 'Food was great but the service was miserable.' There are two opinion targets, 'food' and 'service'. The reviewer has a POSITIVE sentiment polarity on 'food' and a NEGATIVE sentiment polarity on 'service'. This example shows why document-based and sentence-based systems are insufficient for this task. The superiority of aspect-based models to sentence-based and document-based models becomes vivid when manufacturers or service providers want to know which component or feature of their product is not well enough and needs improvement based on the negative reviews they get from customers. Generally, in aspect-based sentiment analysis, most of the data resources and systems built so far are tailored to English (Saedi et al., 2016) and other languages like Chinese (Zhou et al., 2021; Bu et al., 2021) and Arabic (Al-Ayyoub et al., 2017; Al-Smadi et al., 2015). There are three datasets for English, which researchers mainly use to compare the performance of their systems which are Restaurants and Laptops (Pontiki et al., 2014) and Twitter (Dong et al., 2014). The first and second datasets contain annotated data samples from comments and reviews about laptops and restaurants from SemEval-2014 task 4: Aspect-based sentiment analysis. The last one is based on collected tweets from Twitter. Moreover at Martens et al. (2021) authors gathered reviews from social media platforms like Twitter and Instagram on German language. Then, they manually annotated gathered data based on defined aspects in each review into NEGATIVE, NEUTRAL and POSITIVE categories. At last, they utilized BERT (Devlin et al., 2019) transformer model for classification. On the other hand, Farsi is the official language of Iran, Afghanistan, and Tajikistan and also is spoken in the east of Uzbekistan. Based on our knowledge, there are two datasets available for Persian language. But the service was miserable.' There are two opinion targets, 'food' and 'service'. The reviewer has a POSITIVE sentiment polarity on 'food' and a NEGATIVE sentiment polarity on 'service'. This example shows why document-based and sentence-based systems are insufficient for this task. 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this language. First, SentiPers (Hosseini et al., 2018) corpus that contains annotated data in all three levels (document-based, sentence-based, and aspect-based) with 21,375 target words and 26,996 corresponding opinion words identified from product reviews, which is highly imbalanced with more than 79% of them being labeled as POSITIVE and they claimed that have reached 63.15% score on polarity assignment in inner-annotator agreement. Second, ParsiNLU (Khashabi et al., 2021) is a Farsi benchmark for 6 various NLU tasks, which in aspect-based sentiment analysis they manually annotated 2,423 instances from reviews from two different domains of food & beverages and movies with 6 various labels from VERY POSITIVE to VERY NEGATIVE and MIXED but the class distribution reported on their paper shows that less than 5% of the annotated data was labeled as NEUTRAL.

The rest of the paper is organized as follows. In section 2 details about the data collection and annotation process are presented. In section 3 result of applying available systems for aspect-based sentiment analysis on the Pars-ABSA dataset is discussed. In section 4 we conclude and give future directions of research.

2. Dataset and annotation

This paper introduces a manually annotated aspect-based sentiment analysis corpus from customer reviews on products. It differs from past works mentioned earlier in various aspects, including the number of data instances, better inner-annotator agreement score, solving the imbalanced distribution of data, and providing reviews from different domains. Pars-ABSA dataset is available on a public repository

2.1. Annotation

The data was gathered from the website of Digikala. Digikala is the biggest e-commerce startup in Iran, and thousands of people buy goods from its website daily. Some of them submit comments about their purchased products and share their experiences with others. It is noteworthy to mention that more than 600,000 comments were scraped from the Digikala. Then, a framework based on python programming language was developed for manually annotating data instances. Furthermore, an annotation guideline was provided for annotators with a brief introduction to the task along with clearly expressed definitions of the classes and examples. Three native graduate students were employed to manually annotate the crawled data. It is important to note that all three annotators have annotated each data sample, and if two of them agree on the label, it was included in the dataset. In addition, to test the quality of their job and avoid any conflicts between annotators, after labeling the first 100 instances, a reviewer

| Item                          | Value       |
|-------------------------------|-------------|
| # of targets                  | 10,002      |
| # of targets in train set     | 8,001       |
| # of targets in test set      | 2,001       |
| # of targets with positive polarity | 5,114       |
| # of targets with negative polarity | 3,061       |
| # of targets with neutral polarity | 1,827       |
| # of unique targets with positive polarity | 1,494       |
| # of unique targets with negative polarity | 1,442       |
| # of unique targets with neutral polarity | 802         |
| # of tokens                   | 693,825     |
| # of unique words             | 18,270      |
| # of comments                 | 5,602       |
| Average # of words per comment| 123.85      |
| Average # of targets per comment| 1.785       |

Table 1: Statistics of Pars-ABSA dataset.

has been assigned to discuss the samples that they have disputes on them and fix misunderstandings.

2.2. Dataset Statistics

Statistical information about the proposed dataset is indicated in Table 1. Also, from 10,002 targets, the 30 most repetitive targets (e.g. "گوشی موبایل", "دوربین", "کیفیت" and "کیفیت" of "Qualiy" and "Camera") is presented at Figure A additionally in Figure B for each target, the number of occurrences in each category is presented. For instance, "سامسونگ" and "دوربین سلفی" targets are mostly occurred in (NEGATIVE) category, expressing these two as the most unpleasant targets. As well, "گوشی موبایل" and "طراحی" targets are usually appeared in (POSITIVE) category that demonstrate them as the two most desirable targets. At last, "کیفیت", " производства", "کیفیت ساخت" "Durability" mostly took part in (NEUTRAL) category that explains reviewers can not decide on them to be good or bad.

Afterward, in Figure A frequency distribution of comments based on their lengths is presented and confirms that user reviews mostly have the length of less than 10 to 80 tokens. Moreover, in Figure B a density chart for comment lengths based on each category is given. It can be concluded from this chart that there is a relation between sentiment polarity of targets and the length of their reviews and when a review contains more than 800 tokens, the sentiment polarity of its target is usually labeled as (NEUTRAL).

2.3. Evaluation

To evaluate the quality of annotated corpus, it is common to calculate inter-annotator agreement. Because three annotators participated in this phase, Fleiss’ (Fleiss, 1971) metric is computed as an inter-annotator agreement which is suitable for problems with more than two raters. In our case, we obtained 0.787 agreement overall annotated polarity of instances in the cor-
(a) Most repetitive targets  
(b) Stacked representation of targets in each category

Figure 1: An overview of the 30 most repetitive targets in the Pars-ABSA dataset.

(a) Frequency distribution for comment lengths  
(b) Density chart for comment lengths based on each category

Figure 2: An overview of comment lengths for each category and entirely

...pus, that according to what is mentioned in [Fleiss, 1971] is considered as a substantial agreement.

2.4. Corpus structure

Pars-ABSA dataset is stored in two formats including XML and text. In XML format which is the main format of SemEval 2014 datasets, there is a main tag named sentences that contains all of the data instances. For each review in the dataset, there is a corresponding sentence tag available inside the main tag. sentence tag encompasses two types of tags, the first is text tag that contains the review and the second is aspectTerms that consists of one or more aspectTerm tags, as long as it is possible to have more than one aspect in each sentence. Each aspectTerm tag has four attributes, including the aspect, its polarity and, starting and ending index of it inside the review. An example of stored data instances in XML format is presented at Figure 3 in Appendix. In the second format, for each aspect term, there are three corresponding lines inside the file, the review is at the first line, but the aspect term is replaced with $\text{STS}$, aspect term is written in the second line and in the third line, there is a number for sentiment polarity of the aspect term (1 for POSITIVE, 0 for NEUTRAL and -1 for NEGATIVE). An example of data instances in the text format is available in Table 2.

3. Experiments

To evaluate Pars-ABSA corpus, it was split into two sets of training with 80% and test with 20% of data.
In my opinion this speaker is in good shape and $T$ is good too. Generally its smell is good with a bad spreading and with medium $T$. 

| Model  | Multilingual | ParsBERT |
|--------|--------------|-----------|
|        | Acc | F1 | Acc | F1 |
| BERT   | 0.795 | 0.772 | 0.862 | 0.849 |
| LCF    | 0.795 | 0.78 | 0.874 | 0.863 |

Table 3: Performance of models on Pars-ABSA corpus based on Accuracy and macro-average F1 metrics.

slightly better simple linear classification over the BERT(Devlin et al., 2019) since it employs an additional mechanism to focus on local context. Also, comparing pre-trained language models reveals that ParsBERT(Farahani et al., 2021) which is a monolingual model, outperforms the multilingual BERT(Devilin et al., 2019) model because it was explicitly pre-trained on a large amount of Farsi writing materials.

4. Conclusion and future works

In this paper, Pars-ABSA, a Farsi aspect-based sentiment analysis corpus was presented; moreover, the method of collecting and annotating plus statistics of the dataset was discussed and demonstrated. At last, the corpus was evaluated with models previously used for English datasets and, their performances were analyzed.

As future plans, our goal is to extend Pars-ABSA to include different domains such as restaurants and hotels and advanced pre-processing techniques since the reviews mostly have informal writing structures.
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6. Language Resource References

A. Appendix

Figure 3: An example of data samples stored in XML format