Aspect based sentiment classification using BERT and context embeddings

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PROBLEM ABSTRACT

In general, sentiment analysis aims to determine the underlying emotion or intent of a given text.
Traditional sentiment analysis methods treat a piece of text as a whole and determine a single sentiment score (or polarity label) for the entire text. However, this approach can be inadequate due to various reasons like ambiguity, subjectivity, cultural and linguistic nuances as well as tonalities like irony and sarcasm.
Aspect Based Sentiment Analysis (ABSA) is a technique to identify various aspects in a text, as well as the sentiment associated with each aspect, thus providing a more granular understanding of the text.

INPUT:

"Its performance is ideal, I wish I could say the same about the price."

OUTPUT:

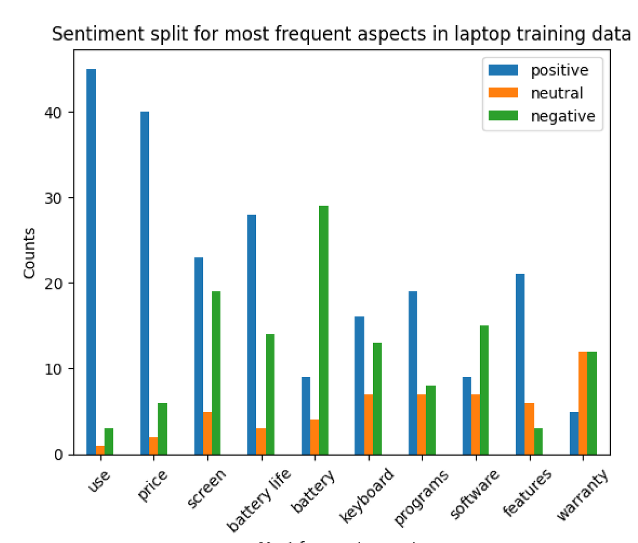
Aspect extraction:
- **performance**
- **price**

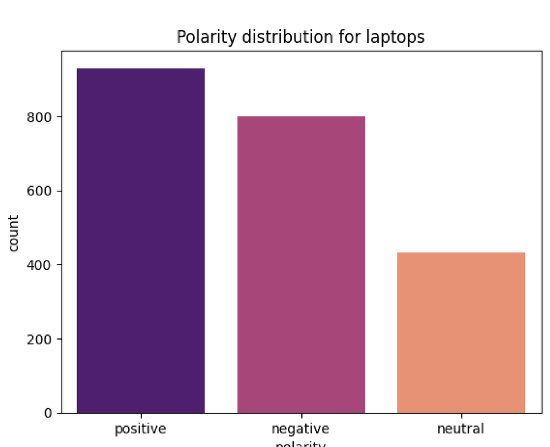
Aspect sentiment classification:
- **performance: positive**
- **price: negative**

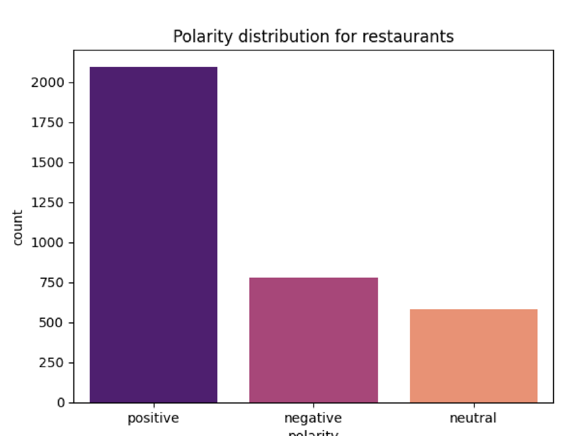
DATA/EDA

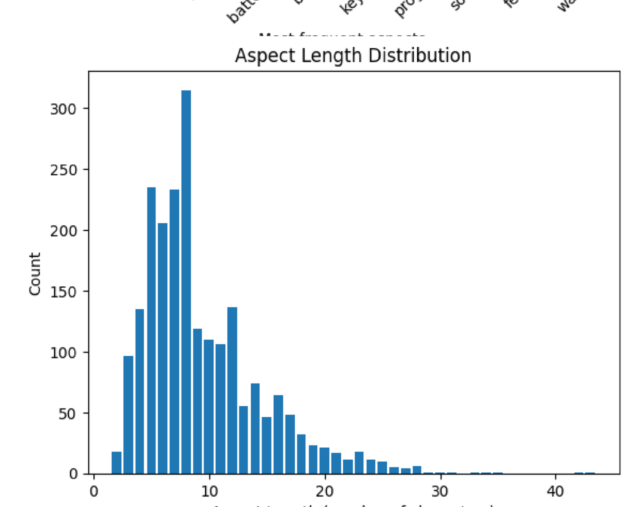
The dataset used was Semeval 2014 Task 4, The data split for the train dev and test set is described below

	LAPTOP	REST
Train	2163	3452
Test (used for cross domain)	638	1120
Dev (Used for same domain)	150	150









APPROACH

We used the BERT architecture for aspect sentiment classification. The proposed methodology consists of two main steps: aspect tagging using Named Entity Recognition (NER) and sentiment classification using aspect and context embeddings.

As the core novelty for sentiment classification, we use two embeddings for final classification: **aspect embeddings** and **context embeddings**.

- Aspect embeddings -> **mean** of BERT's final encoder token embeddings for the 'Aspect' part of the sentence,
- Context embeddings -> Final encoder embeddings of the CLS token which capture the whole context of the input sequence

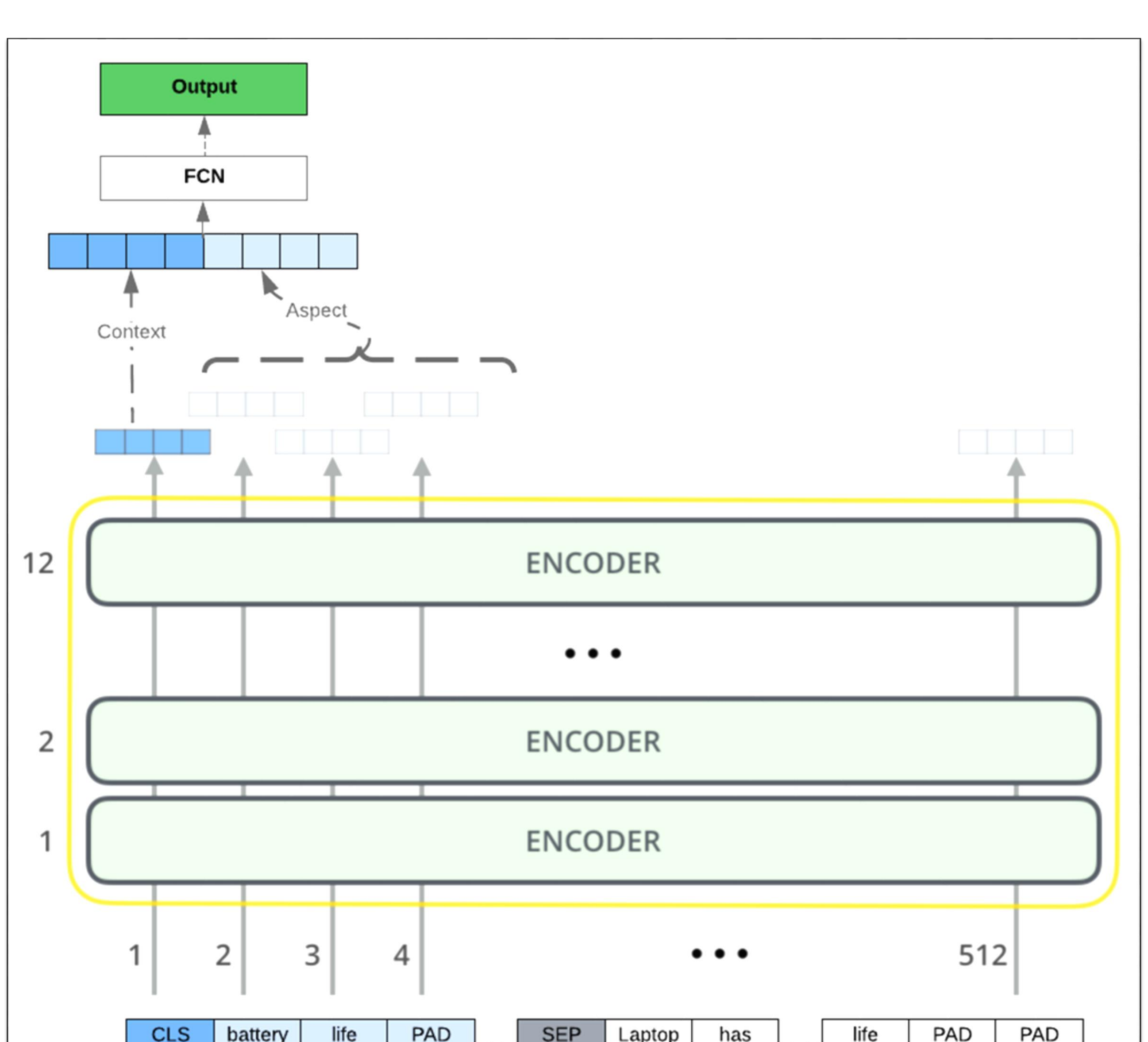


Fig 1: BERT aspect architecture

RESULTS

The tables presents the accuracies of different methods for the task of aspect sentiment classification. The evaluation was performed on two domains: Laptop and Rest14. Six distinct methods were considered: BERT aspect + NER pretraining, BERT aspect, BERT Adversarial [1], CNN based method, SVM and Word2vec+MLP approach

Domain	Laptop	Rest14
Methods	Accuracy	Accuracy
BERT aspect + NER pretraining	**82.0**	**77.3**
BERT aspect	80.6	74.6
BERT Adversarial	81.3	74.6
CNN-CRF	80.8	74.1
SVM	63.0	61.0
Word2vec + MLP	68.2	75.1

Table 1: Performance comparison of difference methods for the same domain

Cross Domain	Laptop	Rest14
Methods	Accuracy (Rest14)	Accuracy (Laptop)
BERT aspect + NER pretraining	**81.42**	77.58
BERT aspect	81.42	77.58
BERT Adversarial	80.53	**77.74**

Table 2: Ablation study of cross domain performance

ANALYSIS AND CONCLUSION

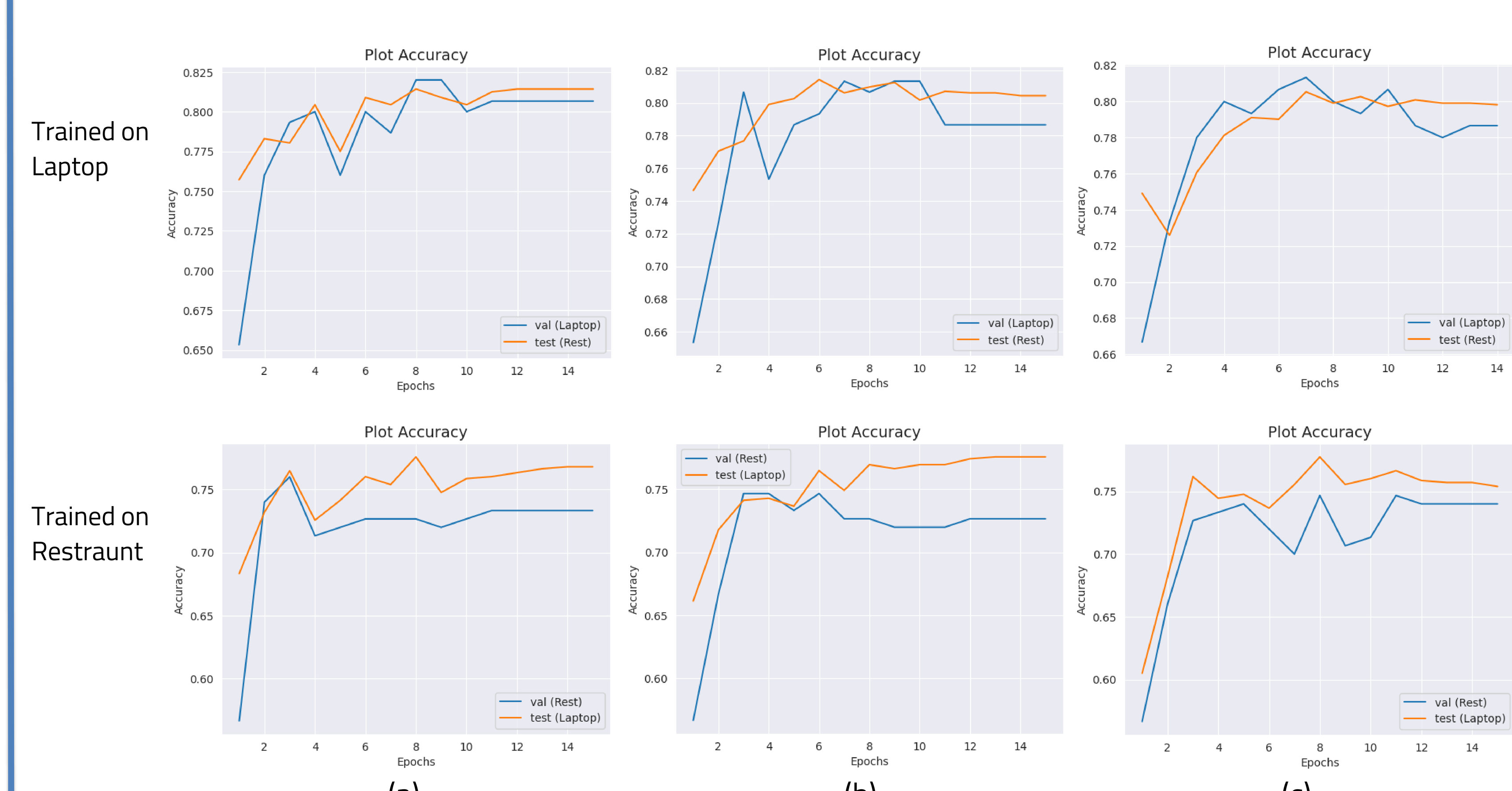


Fig 2: Accuracy plots for (a) BERT+aspect with NER pretraining (b) BERT+aspect (c) BERT with adversarial loss [1]

- Using traditional ML methods or the pre-trained Word2Vec word-embedding-based approach may not be as good as BERT for ABSA as they do not capture the contextual information.
- We also see that the data is imbalanced.
  - Sentiment classes are not equally represented
  - Some aspects are much more frequent than others and they have their own class imbalance. This could lead to a biased model

- In the both same and cross domain settings we see that the BERT based models yielded competitive accuracies for aspect sentiment classification, but a few observations to note
- In same domain, BERT aspect + NER pretraining outperforms all methods
- In cross domain, models are closely comparable

REFRENCES

1. Karimi, A., Rossi, L. and Prati, A. (2020) *Adversarial training for aspect-based sentiment analysis with bert*, *arXiv.org*. Available at: https://arxiv.org/abs/2001.11316v4 (Accessed: 05 July 2023).
2. Hu Xu, Bing Liu, Lei Shu, and Philip S. Yu. 2018. Double Embeddings and CNN-based Sequence Labeling for Aspect Extraction. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 592–598, Melbourne, Australia. Association for Computational Linguistics.