Exploring RoBERTa model for cross-domain suggestion detection in online reviews

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ABSTRACT
Detecting suggestions in online review requires contextual understanding of review text, which is an important real-world application of natural language processing. Given the disparate text domains found in product reviews, a common strategy involves fine-tuning bidirectional encoder representations from transformers (BERT) models using reviews from various domains. However, there hasn't been an empirical examination of how BERT models behave across different domains in tasks related to detecting suggestion sentences from online reviews. In this study, we explore BERT models for suggestion classification that have been fine-tuned using single-domain and cross-domain Amazon review datasets. Our results indicate that while single-domain models achieved slightly better performance within their respective domains compared to cross-domain models, the latter outperformed single-domain models when evaluated on cross-domain data. This was also observed for single-domain data not used for fine-tuning the single-domain model and on average across all tests. Although fine-tuning single-domain models can lead to minor accuracy improvements, employing multi-domain models that perform well across domains can help in cold start problems and reduce annotation costs.

Keywords: Cross-domain generalization, Natural language processing, Suggestion mining, Transfer learning, Transformers

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1. INTRODUCTION
Online services such as Suggestion Forums and TripAdvisor have review systems where users can provide comments and suggestions for products, offering valuable information to both buyers and companies as shown in Figure 1. Analysing the large volume of review data manually is impractical, so companies use data science and machine learning to extract knowledge efficiently [1]. An important task in review understanding is suggestion sentences classification, akin to sentiment analysis [2], where the text of a review is used to determine the corresponding sentiment. The task of suggestion mining from online reviews and forums, termed as Task 9 [3] was introduced at the International Workshop on Semantic Evaluation 2019. Suggestion sentence detection aids in identifying the suggestion conveyed by the customer along with the sentiment expressed in the text, addressing potential improvements for a product or a service [4]-[6] have used Ensemble classifier (Logistic, GRU, FFA, CNN), with BERT and achieved an F1 score of 85%. Goldberg et al. [7] achieved a score of 81% with Ensemble classifier CNN and LSTM. BERT. Wicakseno and Myaeng [8] reported a score of 64.8% by implementing Ensemble classifier with Attention sentence

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encoder, BERT and CNN based word encoder technique. In today's digital age, a vast volume of textual content floods online platforms such as reviews and discussion forums. These platforms serve as invaluable resources for gauging public opinions on products or services [9]. The insights gleaned from such sources not only benefit readers but also provide crucial suggestions for stakeholders [10], [11]. These suggestions can be instrumental in enhancing product quality or offering pertinent recommendations [12]. However, sifting through numerous reviews or comments to pinpoint useful suggestions demands considerable time and effort. Additionally, the unstructured nature of online texts complicates the task further [11]. Consequently, the automated extraction of suggestions from such texts poses a significant and challenging endeavor [10].


Markov and Clergerie [15] suggested that cross-domain sentiment analysis needs huge training data to fine tune BERT models. Work done showed fine-tuned BERT models are more efficient over state-of-the-art domain adaptation methods [16], [17] performed a comprehensive empirical investigation into single- and multiscource domain adaptation, both unsupervised and supervised, as well as the development of a sentiment-sensitive thesaurus that accurately captures words conveying similar sentiments.

Pecar et al. [18] on domain-specific knowledge distillation for conversational commerce is closely related to this work. Knowledge distillation addresses the issue of large and computationally expensive models being too costly to be deployed through a “teacher-student” training approach, in which a trained "teacher" model facilitates the training of a smaller "student" model [18], [19] show knowledge distillation can both reduce model size and adapt models to a specific domain. In this work, we show that BERT base models are capable of adapting to a domain through fine-tuning on domain-specific, instead of knowledge distillation. However, we also show that, compared to single-domain models, cross-domain models, though incurring a slight accuracy penalty, still retain high performance towards a broad range of data. We also propose multi-domain models as an alternative solution to cost of computation. Multidomain models and knowledge distillation could be used in tandem to further reduce computational resources, using knowledge distillation to train a "student" model with a broad spectrum of data domains, creating a model that is both small in size and applicable to multiple domains.

Bidirectional encoder representations from transformers (BERT) models [20], renowned for their prowess in natural language understanding, possess the capability to undergo fine-tuning to classify suggestion sentences in online reviews [6]. BERT leverages a transformer architecture, which enables the simultaneous processing of entire sequences of text, thereby capturing intricate contextual dependencies among words [21]. Comprising stacked transformer encoder layers equipped with self-attention mechanisms, BERT undergoes pre-training on two primary tasks: masked language modelling and next sentence prediction. Following a phase of general pre-training, BERT is fine-tuned for specific downstream tasks by incorporating task-specific layers and adjusting neural network parameters based on labeled data [22], with suggestion classification being an important downstream task. The presence of diverse domains poses a significant challenge for extracting suggestion reviews. Platforms such as Amazon encompass a wide array of product categories, necessitating models to analyse reviews specific to each domain separately. Despite endeavours to devise cross-domain models, it remains uncertain whether a single model can efficiently perform across all domains [23], [24]. In addressing this challenge, BERT can undergo fine-tuning using domain-specific training sets or a combination of training sets spanning various domains [25]. Fine-tuning with data tailored to specific domains enables models to concentrate on predicting relevant information encountered within their domain, thus avoiding the counterproductive task of predicting information irrelevant to the domain at hand. However, training distinct domain-specific models involves extra resource consumption compared to training a unified model for multiple domains, under the assumption that the multi-domain model exhibits satisfactory performance across diverse domains. To comprehend the trade-offs between a domain-specific versus a generalized approach for multiple domains, conducting an empirical investigation analysing RoBERTa’s cross-domain behaviours in the realm of review comprehension becomes crucial.

In practical scenarios, the domain-specific nature of suggestion mining frequently poses challenges when there isn't enough data available for a particular domain to adequately train a high-performing single-domain model. This issue is commonly addressed through domain adaptation, where a model is trained on data from a relevant secondary domain and then applied to the primary, data-deficient domain. Previous studies have demonstrated that fine-tuned BERT models outperform state-of-the-art domain adaptation methods [15]. Our research similarly highlights the ability of cross-domain models to adapt to different domains.

This research conducted a comprehensive empirical analysis of RoBERTa’s cross-domain behaviors in Suggestion classification, contributing novel insights into model performance and domain adaptation strategies. The subsequent sections will delve into the proposed model, the methodology, experimental results, and implications of the study, demonstrating its relevance in advancing the field of suggestion mining and informing practical applications in consumer feedback analysis.
Exploring RoBERTa model for cross-domain suggestion detection in online reviews (Anuradha Nandula)
Suggestion classification using deep learning models, the textual data input is transformed into a numerical representation using RoBERTa tokenizer. An assessment is conducted after obtaining the textual representation and then fine tuning RoBERTa pretrained model for Indomain and Cross-Domain scenarios with electronics and hotel review datasets.

3.1. Robustly optimized BERT pretraining approach

Figure 3 shows RoBERTa by [26], is an enhancement of Google's BERT model from 2018. It modifies key hyperparameters, eliminating the next-sentence pretraining objective, and utilizes larger mini-batches and learning rates during training. RoBERTa shares the architecture of BERT but employs a byte-level byte-pair encoding (BPE) tokenizer, similar to GPT-2, and adopts a distinct pretraining approach. Unlike BERT, RoBERTa does not utilize token_type_ids, eliminating the need to specify segment tokens; segments are separated using the separation token tokenizer.sep_token (or </s>). It incorporates improved pretraining techniques similar to BERT, including dynamic masking, where tokens are masked differently in each epoch, contrary to BERT's fixed masking. Furthermore, RoBERTa combines sentences to reach 512 tokens, enabling sentences to span multiple documents, and trains with larger batches. Also, it utilizes BPE with bytes as subunits instead of characters due to the presence of Unicode characters.

![Figure 3. RoBERTa pretrained model](image)

4. RESULTS AND DISCUSSION

4.1. Datasets

Two review datasets provided by [13], software forum and trip advisor with mutually dissimilar domains were chosen to fine-tune RoBERTa Model. Statistics of Electronics review data (Electronics), Hotel review data (Hotel) datasets are as shown in Table 1. Our pipeline process from data sampling to model evaluation is shown in Figure 4. Data for model training dataset Software reviews was random sampled to overcome class imbalance. Since the original Electronics domain data is significantly larger than the other datasets, 1,600 reviews were sampled from each domain for model fine-tuning, remedying domain imbalance. To reduce class imbalance, for Electronics domain, 1,600 training reviews consisting of 800 suggestion and 800 non suggestion reviews were randomly sampled. Validation set from hotel review is taken as training set for TripAdvisor domain. The test datasets provided for each domain are used for testing the model.

<table>
<thead>
<tr>
<th></th>
<th>Electronics</th>
<th></th>
<th>Hotel</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Train</td>
<td>Eval</td>
<td>Test</td>
</tr>
<tr>
<td>Suggestions</td>
<td>2,085</td>
<td>296</td>
<td>87</td>
</tr>
<tr>
<td>Non-Suggestions</td>
<td>6,415</td>
<td>296</td>
<td>746</td>
</tr>
<tr>
<td>ALL</td>
<td>8,500</td>
<td>592</td>
<td>833</td>
</tr>
</tbody>
</table>

Table 1. Statistics of datasets
4.2. Preparing text data for RoBERTa

A RoBERTa tokenizer is used to ensure data is according to the format the model can understand. Firstly, the text is broken down into tokens using the WorldPiece model, with special tokens like [CLS] and [SEP] added for context. Then, to ensure uniformity, padding is applied by adding [PAD] tokens until each sentence reaches a set length of 128 tokens. Next, tokens are converted into unique integers using RoBERTa’s vocabulary, which contains 30,522 token-integer pairs. This process, called numericization, assigns a token ID to each token, enabling RoBERTa to process them into numeric vectors for analysis.

4.3. Suggestion classification experiments

The data in this study is categorized into two distinct domains: electronics domain and Hotel domain. The balanced electronics training dataset and Hotel review training dataset are combined to form the cross-domain dataset. Processing resulted in a final training corpus of 3,200 reviews, divided evenly among the two domains. One two-domain datasets with 1,600 train examples each were formed through taking 800 examples from each combination of two single domain datasets. The series of Experiments conducted and the setup is shown in Figure 5.

The pre-trained BERT-base-cased model, RoBERTa, was utilized as the basis for fine-tuning. Multiple sets of fine-tuned models, each with different hyperparameters, were trained for individual datasets to identify the optimal model performance tailored to each dataset. Various combinations of two learning rates (1e-5, 2e-5) and two batch sizes (8, 16) were employed, alongside a training duration of 2 epochs. It was observed that higher learning rates and batch sizes led to enhanced model performance.

After selecting the best model from each batch, each of the three models was evaluated against the test split of every dataset. The F1 score metric was used to determine the optimal model in each dataset batch and evaluate model cross-domain testing. As F1 score is proportional to the difference between true and predicted values, a higher F1 score indicates higher performance. Models were trained and tested on a GPU server of provided by google Colaboratory.

4.4. Model performance evaluation

The results of testing each model against each dataset are shown in Table 2. Each row of the table represents one model being tested on all 3 datasets; each column represents one dataset having all 3 models evaluated upon it. Performance of the models was measured using F1 score. A higher F1 score indicates higher model accuracy. Bold table values represent the highest performance achieved in each column. Considering the horizontal rows, smaller F1 score indicates more difficult dataset. Considering the vertical column, higher F1 values mean a better performing model. Within-domain performance is indicated on the table through underlining. The bottom cells contain the F1 scores of cross-domain model tested on single-domain data, with right bottom cell contain the F1 scores of cross-domain data are shown.

Table 2. F1 scores of models trained on specific dataset training pools (rows) and predicting on testing datasets (columns)

<table>
<thead>
<tr>
<th>Train on models</th>
<th>Test on datasets (F1 scores)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Electronics</td>
<td>Hotel</td>
</tr>
<tr>
<td>Electronics</td>
<td><strong>86.5</strong></td>
<td>53.1</td>
</tr>
<tr>
<td>Hotel</td>
<td>54</td>
<td><strong>92</strong></td>
</tr>
<tr>
<td>Electronics + Hotel(E+H)</td>
<td>81</td>
<td>91</td>
</tr>
</tbody>
</table>

Exploring RoBERTa model for cross-domain suggestion detection in online reviews (Anuradha Nandula)
Figure 5. Experiment schemes. Series A—fine-tuning on in-domain corpus; series B–C—fine-tuning and cross domain testing; Series D–E fine-tuning on Generalized-domain corpora, and testing the obtained model using Electronics and Hotel reviews respectively.
4.5. Discussion

The main objective of this study was to assess the advantages and disadvantages of employing specific versus general model domain scopes in RoBERTa based suggestion review classification. The disparity between the model’s F1 score was relatively minor, fluctuating around 5-10%. The F1 scores of electronic model (In domain and cross domain) are 86.5% and 54% could be attributed to the nature of classifying electronics reviews, which may heavily rely on topic-specific vocabulary. While F1 score of Hotel model is 92% for in-domain and 74% for cross-domain model. This can be attributed to the fact that reviews taken from hotel reviews may encompass different verbs, the adverbs or modal verbs used to express suggestions are often similar. The BERT models likely identified the significance of suggestion-infused verbs such as "need" try ", which are applicable across various product categories. Consequently, the Pretrained models may have prioritized more general keywords over topic-specific terms and descriptions. Also, it is important to note that suggestion mining still necessitates a certain level of domain understanding, as evidenced by our findings.

5. CONCLUSION

In this study, we’ve presented an instance of how datasets formulated in varied contexts can be reconfigured and employed toward a shared aim. We illustrated a benefit in efficacy of pre-trained language models when utilized in domains dissimilar from those they were originally trained on. The pre-trained language models appear to possess the capability to grasp the fundamental concept behind a task to a greater degree. Moreover, training the models on cross-disciplinary data enhanced resilience and somewhat boosted performance. In summary, these findings indicate that pre-trained language models exhibit numerous desirable attributes when trained on diverse datasets, rendering them an optimal tool for effective utilization of existing online reviews datasets to bolster future exploration in innovative tasks.

REFERENCES


**BIOGRAPHIES OF AUTHORS**

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