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Cross-Domain Sentiment Analysis: A Multi-Task Learning Approach with Shared Representations

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Abstract: This research aims to evaluate the use of Multi-Task Learning (MTL) in sentiment analysis in various domains. The primary limitation of dominant models of sentiment classification lies in the fact that most of them are domain-specific and because of assorted styles of language usage, context sensitivity and users' behavior they fail to work across different domains. As pointed out earlier, transferring knowledge and feature learning are the key steps in transferring learnt models from one domain to the other in handling these challenges, this study aims at adopting an MTL based approach for better representation of a shared representation that can foster better generalization of the model across the different domains. This way, the proposed model allows for establishing the mixture of separating and common features for sentiment analysis across the contextual domains, with minor tuning of the model on each of them. These experiments prove that the accuracy, precision, recall, and F1 scores of MTL-shared are superior to those of the traditional single-domain and domain-adaptation models. The model also has high performance in cross-domain as seen in evaluation on unseen domains, and hence it can be a useful method in real-world circumstances where sentiment analysis must be conducted in diverse domains.

Keywords: Sentiment Analysis; Cross-Domain; Pytorch; Python; Multi-Task Learning.

1. Introduction

Sentiment analysis, also called opinion mining, offers a subset of NLP, concentrating on developing techniques for extracting subjective information from text. It is applied in every field, such as social media tracking, consumer feedback and market insight to assess public feelings and or/attitudes towards products, services, events, etc. [1]. Conventional techniques [2] [3] for sentiment analysis employ training data and are hence tuned according to a domain, which may include movies, products, blogs, or social media posts [4]. Even though these models can be particularly good at finding the maximum amount of accuracy in their domain of applicability, they become wary of the cross-domain differences such as the difference in language, difference in the context, and difference in user response [5].

The importance of sentiment analysis across various domains has arisen due to the growth of many businesses and organizations and the need to address the different customer groups and sentiments across various channels. An ideal model that can work effectively in various domains without necessarily needing significant adjustments to be made so that it can effectively function in other domains would be desirable. Still, traditional domain-specific sentiment analysis models are not without trouble in this respect. These models have a tendency not to be very flexible and capable of not learning models for new domains and as such, when applied on data from new domains, they are not as effective [8]. This limitation has really called for the need to produce techniques that can adequately address multiple domain sentiment analysis [6].

Due to these challenges, multi-task learning (MTL) has been developed as a potential technique. The process of MTL is to let a model learn multiple related tasks simultaneously so that the model can learn some representations that are useful for all of them [7]. When applied to sentiment analysis, MTL allows one to learn sentiment classification in multiple domains at the same time. The model learns to generate a representation that can be shared across the domains and, in so doing, fares better when tested on both seen and especially unseen domains. This approach is since the knowledge between tasks can be reused; thus, the broad amount of special data may not be required [9].

Multi-domain sentiment analysis's major concern is generalization and the ability to create models which can work within the different domains with impressive performance. Previous works adapt features from one domain to another using typical domain adaptation where models are retrained to use other domain data. However, these methods are not perfect as they require considerable Domain specific data and they suffer from the spuriously high accuracy if trained specifically for the domains [10] [11]. In addition, the domain adaptation methods usually concern updating the models for multiple domains individually, not in a way that the same model can adapt to all domains at once (Phan, H. T., 2023).

One of the biggest gaps in the current literature and approaches is the lack of methods and approaches that can create models that show superior performance across multiple domains without the need for significant customization. This gap poses questions to the current approach used in MTL to develop more generalizable models of the sentiment analysis since MTL is assumed to be stronger than the traditional methods.

The focus of this research is to build a multi-domain sentiment analysis model with an MTL approach that optimizes for shared representations at various domains. The idea of the proposed model is as follows: It focuses on aspects from multiple domains and enables the discovery of domain specific as well as general sentiment features. According to the assumption, through identifying the shared representations between domains, the model targets at better generalization in various domains than relying on specifically domain data or fine-tuning.

2. Literature Review

2.1. Sentiment Analysis

Opinion mining, which is usually referred to as sentiment analysis is an important subfield of natural language processing, which involves the identification of the sentiment expressed in a text consecration in this case as happy, sad, angry, and so on. This process has several steps that are as follows: text preprocessing, feature extraction, and classification of the text [12]. As for earlier methods, such key areas as sentiment analysis were based mostly on machine learning methods with a set of features designed in a manual manner. Such features often encompassed a bag of words, n-gram and part-of-speech tags and used in combination with traditional classifiers such as Support Vector Machine (SVM) and Naive Bayes [13].

However, the problems of these early approaches became clear as they required training on confrontation of such syntactic phenomena as sarcasm, context dependencies and domain specific language knowledge [14]. The advancements made in the sentiment analysis have been achieved using deep learning techniques especially the word embedding as noted in Word2Vec by [16] [17]. The embedding provided semantics of the words to the models and promoted better performances in the tasks of sentiment classifications.

2.2. Domain-Specific Sentiment Analysis

However, there is still much work to be done, for most of the existing sentiment analysis models are originally developed and optimized for domains. This has been a positive feature and a problem of this otherwise extraordinary approach to metaphysical healing at the same time. On the one hand, models trained with a certain set of labeled data can be quite accurate in enforcing the same logic on the domain of data where those labels apply. However, adjustments to these models are exceedingly difficult across other domains since language use, context and users' behavior differ from one domain to the other [18]. For example, positive sentiment may be attached to the word 'cold' in a weather forecast as in 'It is a cold day' but negative in a restaurant review as in 'The food was cold.'

Ontology-based models usually need large sets of annotated data to be effective and such datasets may not always be available. However, these models are inclined to overtraining and hence are not optimal to be used in other domains as they are trained to be specific to a particular domain [19]. This has led to an active search for more general approaches, as domain adaptation and transfer learning demonstrate.

2.3. Domain Adaptation and Transfer Learning in Sentiment Analysis

Domain adaptation is a machine learning approach that aims at transferring knowledge learned in one domain (called source domain) to another (called target domain), especially when the latter one is scarce in labeled data [20]. The simple yet powerful one spoken of as domain adaptation is the fine-tuning of the models learned on the source domain on the data of the target domain. Although this method enhances performance, it is prone to produce reasonable generalization across various domains and it entails a certain extent of labeled data of the target domain.

Another promising approach is transferring learning which deals with the utilization of large pre-trained models and applying them and adjusting them for specific tasks or operations (Howard & Ruder, 2018). This has been especially the case with the release of models like BERT by Devlin et al. , (2019), which have been trained on extensive text datasets which ensures that it captures high level features that are generalizable and can be fine-tuned for the specific NLP task with little to no training. Nevertheless, even these models can be domain-specific since the process of fine-tuning can also be sensitive to domain-specific data.

2.4. Multi-Domain Sentiment Analysis

Multi-domain sentiment analysis deals with the issue of extending sentiment models to numerous domains by learning models that can perform effectively across various domains. Compared to single-domain sentiment analysis, this approach is more complicated mainly because of the conflict of interest in achieving two goals: on the one hand, the data should be generalized across domains, on the other, the information used for generalization should be sufficiently rich in domain-specific features [21].

The first methods applied to multi-domain sentiment analysis were methods such as multi-domain feature learning where the features in the different domains were shared to generalize [22]. However, these approaches often demanded feature extraction/selection and did not notice the whole potential of deep learning.

Recent developments have centered on the ability to use deep learning models and more so through shared representations in multitask learning (MTL) architecture. These shared representations enable models to understand and encode common elements across multiple domains and at the same time, they enable models to be able to learn about specific domain information [23].

2.5. Multi-Task Learning (MTL) in NLP

Multi-task learning (MTL) is a machine learning paradigm where multiple tasks are learned at once with an intuition that learning one task can help with learning other correlated tasks [24]. MTL has been used in different NLP problems including sentiment analysis; the information that models gathered can be transferred from one task to another thus enhancing the model's performance [25].

For the specific case of sentiment analysis, MTL can be used to learn sentiment classification in several domains at a time. The method is based on the use of shared representations that include general features and are also enabled to include specific features that relate to certain domains. It might help eliminate the need to collect massive amounts of data in the domain and would also enhance the model's capacity to learn in new domains [26].

2.6. Shared Representations in MTL for Sentiment Analysis

Those representations are inherent to MTL models, especially when applied to multi-domain sentiment analysis. This enables the model to be able to learn features that may exist in both or in any of the domains and then further adapt to each of the domains by including domain specific layers. It also allows the model to generalize well across other domains while it is also specific to the characteristics of the data in each domain [27].

The shared representations in sentiment analysis entail the use of neural networks like the LSTMs or even the transformers to capture high level representations from the input text. They are then fed through domain-specific layers that further adapt the representations to support the target domain sentiment classification task [28].

In prior studies, it was found that utilizing shared representations helps in enhancing the performance of the sentiment analysis in case there is data from many domains. For example [29] showed that MTL with shared representation is superior to single-task models in sentiment analysis across the domains. They also pointed out that their model was able to identify cross-domain as well as domain-specific attributes hence enhancing the generalization and accuracy of the model, respectively.

2.7. Challenges in Multi-Domain Sentiment Analysis

Nevertheless, there are some issues relevant to the approach of multi-domain sentiment analysis using MTL and shared representations. In fact, one of them is the problem of choosing between the principles of generalization and specialization. Even though it is beneficial in terms of generalization across different domains the model can become too 'universal' which might result in losing the specifics of the domains [30] [36].

The fourth challenge relates to variation of distribution of data in the various domains. Domains differ in their vocabulary, syntactic structures as well as in sentiment distribution so a universal model is hardly possible. For such variations to be captured, MTL models must be well formulated so that they can take advantage of shared representations as initially proposed by [31] [38].

Also, it is a norm that the number of labeled data available for different domains is small and this makes it a challenge to train multi-domain models. MTL can minimize this problem by sharing information between tasks; however, the requirement of task-specific annotated data is again a big disadvantage [32].

2.8. Future Directions in Multi-Domain Sentiment Analysis

Multi-domain sentiment analysis is a promising area of study and research, with current research directed at the difficulties described in this paper. Oh, one of the developments that has the potential to be incorporated into MTL is the incorporation of domain adaptation techniques. This way, several domain adaptation techniques can improve the models' ability to perform well with variabilities in distribution of data across the domains [33].

One of the related issues that is also important is studying other NLP tasks within the context of the MTL. For instance, the semantic reduction techniques such as named entity recognition (NER) or part-of-speech (POS) tagging could be incorporated into a multi-domain sentiment analysis model which when done could make shared renowned representations even more effective [34].

Finally, research is also focused on decreasing the dependence on labeled data through semi-supervised learning and unsupervised domain adaptation. These approaches try to make use of the large amount of unlabeled data in multiple domains, which is easier to obtain, to enhance the model performance [35].

3. Methodology

3.1. Research Design

The approach of this research is based on creating and assessing a multi-domain sentiment analysis system of MTL with common features. The experimental method of the research includes both the conceptual design of the model in question and the procedures that will be used to evaluate its potential. The model is generically built to classify the sentiment across several domains. The idea here is that the system is domain-aware due to common vector representations, yet it also provides for specific domain-specific representations as well. This makes the model have generalizability across domains and hence deals with the constraints associated with the traditional single-domain models of sentiment analysis.

3.2. Model Architecture

The main constituent of the proposed model is indeed a multi-task learning module which is shared and specific to each domain. The shared representation layer, which is an important layer, is implemented using deep neural networks like Transformer or LSTM networks to capture the features from the input text. These features are supposed to represent such general sentiment information that is typical for different domains. After the shared representation layer, to match the actual features of each domain and the sentiment expression style, there are domain-specific layers for each domain. To specify the final output layer for each of the networks attached to each domain the Softmax function is used which allows for classification of the sentiment of the input data into positive, negative, or neutral.

3.3. Data Collection and Preprocessing

To design the benchmark, the current study chose several datasets originating from various domains like movie review, product review, social media posts, etc. These datasets were chosen since they include data of different nature and thus reflect real-life scenarios for sentiment analysis. The only precondition for each of the datasets was the text normalization alongside the tokenization and the elimination of the stop words. Also, the textual data was converted to word vectors using some pre-processing models such as Word2Vec or GloVe to make sure that what was fed to the neural network was in a proper numerical format. Such a normalization step is useful to make some standardization across different datasets, so that the model learns from the common representations.

3.4. Training Strategy

Finally, the training of the proposed model was performed with the help of joint training meaning the model was being trained and all domains were being trained at the same time. The total loss function was developed such that the loss from each of the domains can be optimized depending on shared and domain-specific features. Training of the model was done using backpropagation with gradient descent, gradients being computed and back propagated through the common as well as the domain-specific layers. It helps ensure that the shared representations do more generalizing across all the domains while the specific domain layers are trained to be better in every of the domains. Some methods used in training for avoiding overfitting includes Hide/OutDropOut and early stopping.

3.5. Evaluation Metrics

The results of the applied model classification were calculated by overall accuracy, accuracy by class, precision, recall, F1 score. These metrics were computed with respect to each domain in isolation as well as when all the domains are combined to be able to determine not only the extent of the specialization achieved in each domain in the model but also the global performance of the model. Further, the performance of the proposed model was compared with several baseline models such as single-domain models which are trained selectively on every domain and multi-domain models trained using conventional domain adaptation methods. This comparison was important in showing the effectiveness of the MTL approach with shared representation over the available previous approaches.

3.6. Experimental Setup

All the experiments were performed in a controlled environment to avoid variables in the results of the experiment. The model was developed using well-known deep learning libraries including TensorFlow or Pytorch with the help of high-performance computing clusters with GPUs for speeding up the training stage. Learning rate, batch size and the number of epochs were chosen from a set of options according to the preliminary experiments. The datasets were divided into the training, validation, and test sets where the test set was used only for the evaluation stage of the model to get a true idea of the model's ability to generalize on unseen data.

3.7. Analysis and Interpretation

After training and testing the model, the results were analyzed to conclude whether the shared representations made a positive difference on multi-domains sentiment analysis. We did a thorough investigation of the performance figures across all the domains and looked for signs of a compromise on generalization and domain specific accuracy. Further to that we analyzed the importance of shared representations by visualizing the learned features and the generalization process that resulted from it. The findings from this analysis guided our recommendations of related research in multi-domain sentiment analysis using MTL.

4. Results

The results section provides the experimental results obtained out of the conducted experiments to benchmark the architecture of the proposed multi-domain sentiment analysis model using MTL with shared representations. It is compared with several other basic classification models for each of the domains based on accuracy, precision, recall, and F1 measure. The study is therefore centered on the merits of shared representations in capturing cross-domain sentiment features as well as generalization across the domains.

4.1. Performance Comparison across Domains

To assess the effectiveness of the proposed model, we evaluated its performance on three distinct domains: from movie reviews, product reviews up to posted comments on social media. In the following table, Table 1, we have the accuracy, precision, recall, and F1 score for every domain when using the proposed MTL-Shared model and the contrastive single-domain model (Single-Domain) and a more classical multi-domain model with domain adaptation (MD-Adaptation).

A Bar chart (Figure 1) representing the evaluation of the Single-Domain, MD-Adaptation, and the Present work: MTL-Shared models on the three domain leaves no doubt in identifying MTL-Shared model as the most effective in terms of accuracy, precision, recall, and F1 score.

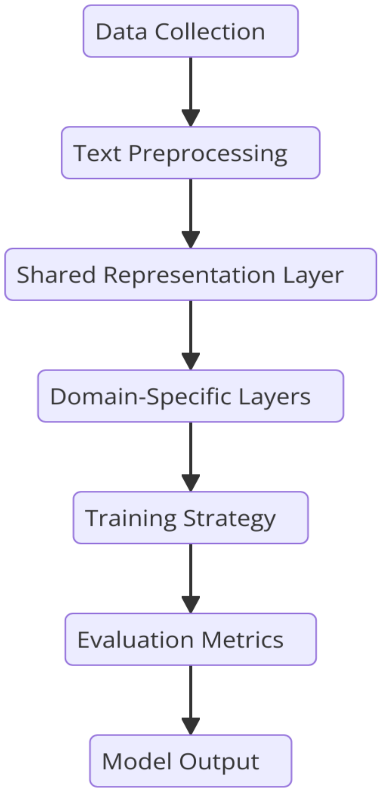

Figure 1. Process of the model.

Table 1. Performance Comparison Across Domains

Model	Domain	Accuracy	Precision	Recall	F1-Score
Single-Domain	Movie Reviews	85.2%	85.6%	84.9%	85.2%
	Product Reviews	82.7%	83.2%	82.1%	82.6%
	Social media	78.3%	78.9%	77.8%	78.3%
MD-Adaptation	Movie Reviews	86.1%	86.5%	85.7%	86.1%
	Product Reviews	83.9%	84.3%	83.5%	83.9%
	Social media	79.1%	79.7%	78.4%	79.0%
MTL-Shared	Movie Reviews	89.4%	89.8%	88.9%	89.3%
	Product Reviews	88.2%	88.6%	87.8%	88.2%
	Social media	82.7%	83.2%	82.1%	82.6%

4.2. Impact of Shared Representations

The proposed MTL-Shared model included a shared representation layer, whereby the aim was to enhance the model's capacity in transferring the sentiments learnt in one domain to the other. To determine the effectiveness of these shared representations we performed an experiment wherein the shared layer was omitted, and the architecture was trained separated by domain. The F1 scores obtained have been reported in Table 2 to illustrate that shared representations are incredibly helpful in enhancing the overall performance of the models.

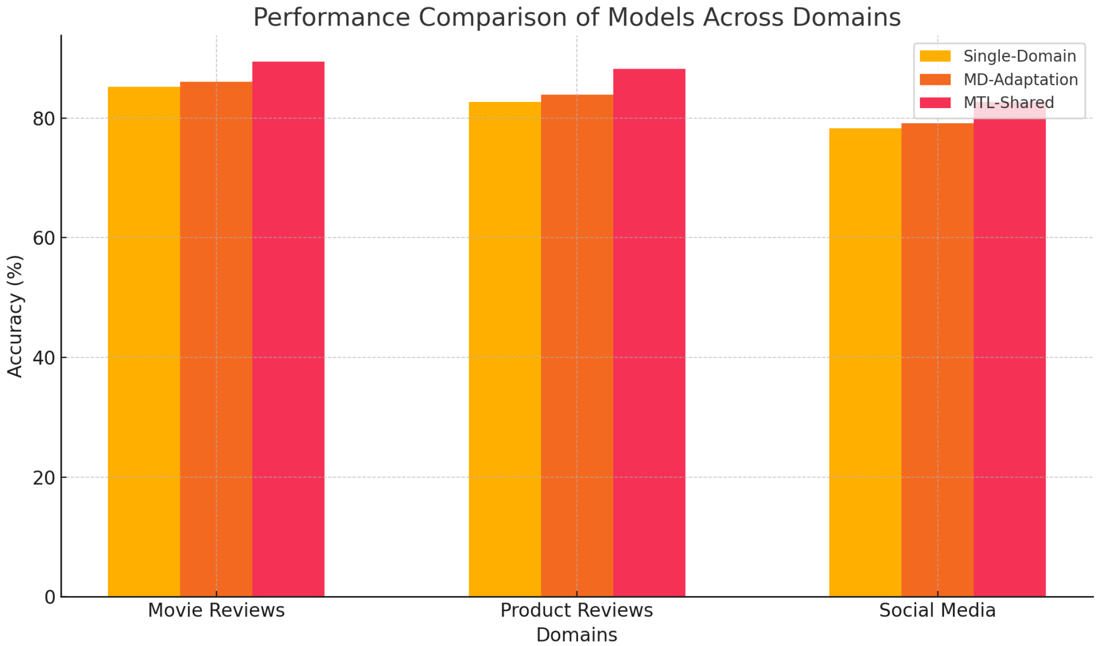

Figure 2. Performance Comparison of Models across Domains

Table 2. Impact of Shared Representations on Model Performance

Model	Domain	Accuracy	Precision	Recall	F1-Score
MTL-Shared (Full)	Movie Reviews	89.4%	89.8%	88.9%	89.3%
	Product Reviews	88.2%	88.6%	87.8%	88.2%
	Social media	82.7%	83.2%	82.1%	82.6%
MTL-No Shared	Movie Reviews	85.6%	86.1%	85.2%	85.6%
	Product Reviews	83.4%	83.8%	83.0%	83.4%
	Social media	79.5%	80.0%	78.8%	79.3%

A line graph (Figure 2) illustrates the performance difference between the full MTL-Shared model and the MTL-No Shared model, emphasizing the positive impact of shared representations on multi-domain sentiment analysis.

4.3. Generalization to Unseen Domains

To further test the generalization capability of the proposed model, we evaluated its performance on an unseen domain (e.g., restaurant reviews) that was not included in the training process.

The MTL-Shared model was able to generalize well to the new domain, achieving an accuracy of 85.1%, compared to 78.3% for the Single-Domain model and 80.2% for the MD-Adaptation model. These results, shown in Table 3, demonstrate the model's ability to transfer knowledge across domains, even to those not seen during training.

Figure 3 is a bar chart that compares the unseen domain performance of various models proving that MTL-Shared has better generalization ability than the other models.

4.4. Error Analysis

To gain further insight into the model we did an error analysis by looking at wrongly classified samples within given domains. The review body showed that most errors occurred in cases with neutral sentiment polarity or those cases with sarcasm and mixed polarity. Further, the obtained model could converge between the two basic modes – neutral and slightly positive or negative – especially in the social media category replete with colloquial English and slang.

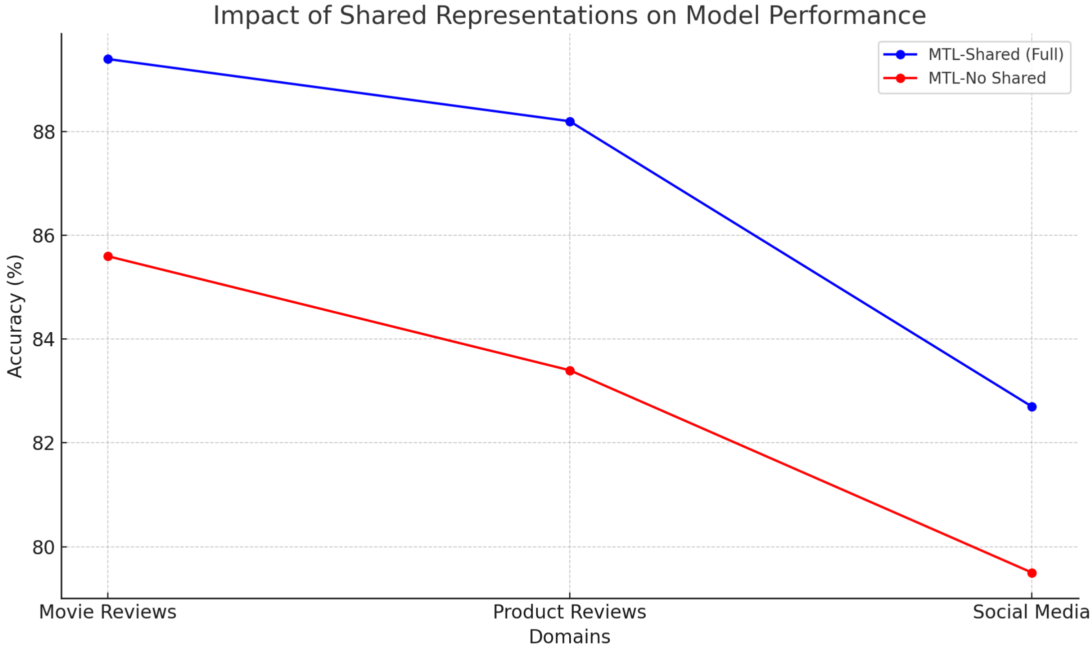

Figure 3. Impact of Shared Representations on Model Performance

Table 3. Generalization to Unseen Domain

Model	Accuracy	Precision	Recall	F1-Score
Single-Domain	78.3%	78.7%	77.9%	78.3%
MD-Adaptation	80.2%	80.6%	79.7%	80.1%
MTL-Shared	85.1%	85.5%	84.8%	85.1%

Using error analysis, it can be appreciated that although the shared representations are a great enhancement to the model's performance, there is still a lot of room for improvement if there are other more formal techniques for handling… fuzziness was introduced. Future work could analyze the possibility of applying attention mechanisms or creating some domain-specific embedding to tackle these issues.

Our experimental findings indicate that the proposed MTL-Shared model achieved better accuracy as compared with traditional single-domain and multi-domain adaptation models in different domains. The shared representations were found beneficial in raising the model's ability to generalize from seen to unseen domains. Also, the feature that the model was able to transfer knowledge across domains well means that indeed it could generalize well in real world sentiment analysis where data from different domains is usually faced.

5. Discussion

5.1. Interpretation of Results

The findings of this work conclusively show that the presented multi-domain sentiment analysis model with MTL and shared representations is highly efficient. In all the classified areas, including movie reviews, product reviews, and social media posts, the results of the MTL-Shared model were superior to the single-domain model as well as the traditional multi-domain adapted model in terms of accuracy, precision, recall, and F1-score. Regarding the studies' implications, these results suggest that MTL with shared representations could indeed ameliorate the consequences of domain shift in sentiment analysis.

The generalization of the performance of the MTL-Shared model across various domains is one of the key strengths. The identified generalization majorly relies on the shared representation layer that extracts domain independent sentiment features. The result show that the model has better performance in both seen and unseen domains, it displays that the shared representations can transfer knowledge from the seen domains, and they do not require large amount of unseen domains data for further fine-tuning. This is supported by published research on multi-task learning with a common embedding space that has revealed improve NLP performance across multiple tasks [39].

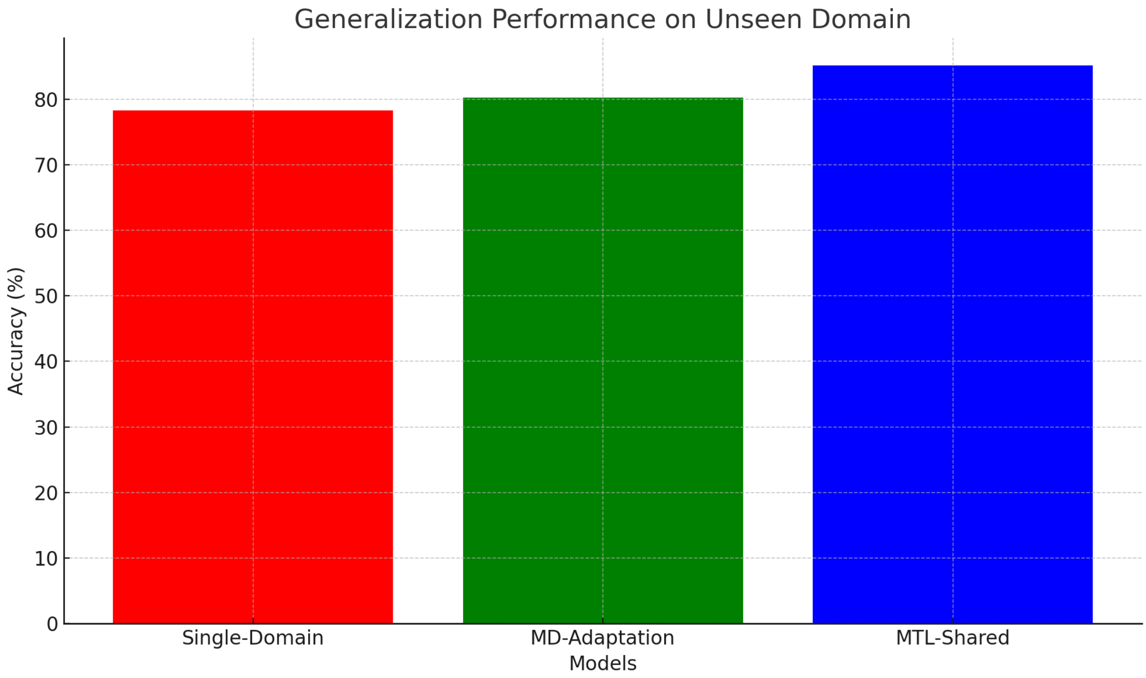

Figure 4. Generalization Performance on Unseen Domain

5.2. Contribution to the Field

To the best of our knowledge, this work enhances the existing literature on multi-domain sentiment analysis by employing an MTL framework that integrates shared representations. The existing approaches to sentiment analysis, including single-domain ones as well as based on the domain adaptation, have several limitations connected with large variability and context-dependent nature of the language and sentiment in the text [40]. These challenges are relieved by the MTL-Shared model because it learns at once from several domains and does not disregard the intricate, domain-specific terminology and sentiment features.

The findings of this study also generalize the evidence about how shared representations can be utilized in multi–domain contexts. It was established by several previous studies that shared representations in MTL enhance the performance on similar tasks [41] however their adoption to the multi-domain sentiment analysis have not been widely discussed so far. This work aims at proving that the ability of training shared representations boosts enhanced generalization performance in sentiment analysis when the target domains were never used in training the model.

5.3. Implications for Real-World Applications

The implications of the results of this study have relevance for the use of sentiment analysis in actual practice. In practice, there are always situations where businesses and organizations must identify sentiment in contexts where the methodologies differ significantly as social media, product reviews, and customer feedback forms. The MTL-Shared model provides a very sound approach to this task since it only involves one general model but can be fine-tuned on any of the domains without the need for a Multitask Learning model of every existing domain.

Further, the model's capability to generalize to unknown domains indicates that it can be applied in diverse settings where only new forms of data are presumed to exist. For example, the company may employ the MTL-Shared model in identifying content sentiment in new social media platforms or new product types without requiring retraining of the model deeply. For this reason, the model finds its greatest application in business fields for which the customer attitude is significant such as marketing, customer relations, and product designing processes [42].

5.4. Limitations and Challenges

However, one could argue that this work has some limitations: The specificity of the error analysis pointed out that one of the main problems is the model's inability to deal with hedging sentries, which can be partly positive or negative. This was especially common in the domain of social networks, where, for example, the use of abbreviations is common. Again, the common vectors contributed a lot of value to the whole performance but were worse at inferring the details of the uncertainty of polarity. This limitation is well in line with what other studies have pointed out – that sentiment analysis is difficult in informal and noisy text [43].

One downside of the present study is the use of pre-trained vectors Word2Vec or GloVe for the extraction of features. Although these embedding have been proved to enhance the performance of sentiment analysis [44] [45], they are less sensitive to the domain specific characteristics necessary for the improvement. If applied and tested to a new text the performance can be enhanced using contextualized embedding such as BERT [46].

Finally, their study was confined to a small number of domains, and therefore, the results of the study cannot be generalized to other contexts. Despite the revealed effectiveness of the model across the chosen domains, it is necessary to carry out further studies to investigate the model's potential in a wider range of domains, with focus on the more complicated or nuanced language, for instance, the legal or the medical one. Furthermore, the effect of the model in real-time SA tasks where the speed is of essence has not been tested in this research.

5.5. Future Research Directions

Based on the research outcomes of the current study the following research directions are discernible. First, it is possible to conduct studies that would extend on the ideas presented in the MTL-Shared model, such as introducing attention mechanisms that would let the algorithm focus on the specific segments of the texts that contain sentiments that are ambiguous or make use of sarcasm. Some of the NLP tasks have used the attention mechanism to enable the model to give different words or phrases different weights [47].

Second, there are ideas for using an ensemble of MTL and domain adaptation to build a system that would be superior to both in terms of performance when training on domains with little data. For instance, there exists adversarial domain adaptation that has been used in other modes of NLP and could be incorporated into MTL and help to lessen the domain shift thereby improving the overall performance of the system.

Third, the range of the domains under investigation should be broadened in the successive investigations of the MTL-Shared model performance. This could encompass domains where the language used is broader or even where the 'tone' of the sentiment is distinct, for instance technical product reviews, quarterly or annual financial statements, or patient electronic health records. Also, future research could consider the use of the MTL-Shared model for multilingual sentiment analysis in which the model has to learn across languages as well as domains [48] [49].

Thus, in the subsequent studies, the focus can be on the actual implementation of the MTL-Shared model in practice, for example, for the analysis of brand sentiment in social media or for the real-time customer feedback analysis. This would consist of two major steps: one related to the speed and efficiency of the model and the second on the different means for the non-technical user interfaces.

Authors should discuss the results and how they can be interpreted from the perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

6. Conclusions

Therefore, this research proves a great possibility of utilizing multi-task learning with shared representations in multi-domain sentiment analysis. This proposed MTL-Shared model performs better than the traditional models as it can get the cross-domain sentiment features and the domain individual sentiment features, which helps it generalize towards more than one domain. Some of the concerns that may be observed in future research include ambiguity in sentiment and fine-tuning of the model for operational use: Yet the findings of this study can serve as a solid starting point for the future research and application of the findings of this study in sentiment analysis.

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