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Improving the Cross-Domain Classification of Short Text Using the Deep Transfer Learning Framework

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Abstract

With the advent of user-generated text information on the Internet, text sentiment analysis plays an essential role in online business transactions. The expression of feelings and opinions depends on the domains, which have different distributions. In addition, each of these domains or so-called product groups has its vocabulary and peculiarities that make analysis difficult. Therefore, different methods and approaches have been developed in this area. However, most of the analysis involved a single-domain and few studies on cross-domain mood classification using deep neural networks have been performed. The aim of this study was therefore to examine the accuracy and transferability of deep learning frameworks for the cross-domain sentiment analysis of customer ratings for different product groups as well as the cross-domain sentiment classification in five categories “very positive”, “positive”, “neutral”, “negative” and “very negative”. Labels were extracted and weighted using the Long Short-Term Memory (LSTM) Recurrent Neural Network. In this study, the RNN LSTM network was used to implement a deep transfer learning framework because of its significant results in sentiment analysis. In addition, two different methods of text representation, BOW and CBOW were used. Based on the results, using deep learning models and transferring

weights from the source domain to the target domain can be effective in cross-domain sentiment analysis.

Keywords: Sentiment Analysis, Cross-Domain Sentiment Classification, Transfer Learning, Deep Learning, Deep Neural Networks

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Introduction

With the development of the Internet and Web 2.0, providers of online shopping platforms and social networks have become increasingly popular among users. In addition, providing such context allows users to express their feelings and opinions about products from sites like Amazon, IMDB, etc. (Abdullah et al., 2019; Zola et al., 2019; Haque et al., 2018; Piryani et al., 2017; Liu et al., 2013). This has generated a huge amount of valuable data for business owners and online shopping sites (Liu et al., 2013). Of course, customer ratings do not only refer to a specific product group, but can cover a wide range of products and services; therefore, the expression of feelings and opinions is domain-dependent, and different domains have different distributions. In addition, each of these domains or the so-called product group has its vocabulary and characteristics, which make analysis difficult (Sun et al., 2017). Sentiment Analysis (SA) is an emerging trend to understand the emotions of people in different situations in their daily life (Babu & Kanaga, 2022). The purpose of SA, or opinion mining, is to use automated tools to discover subjective information such as opinions, attitudes, and feelings expressed in the text (Lin & He, 2009). Although SA is an important area and currently has a wide range of applications, it is not an easy task and brings with it many challenges associated with natural language processing (NLP) (Dang, et al., 2020). Extreme domain dependency is the most technical and major challenge in cross-domain SA. In the cross-domain situation, the differences between the different domains will lead to different performances of the class trained in one domain compared to another domain (Abdullah et al., 2019; Bengio, 2012; Wei et al., 2017). In other words, a method that works well in one area may not work in another. This problem is particularly challenging in machine learning (Sun et al., 2017). The usual premise of machine learning algorithms is based on an even data distribution of the source domain (training data) and the target domain (testing data) (Semwal et al., 2018; Zhao et al., 2017; Yang et al., 2015). Therefore, it has always been problematic to train a classifier on one or more domain data and apply it to other domain data (Abdullah et al., 2019; Sun et al., 2017; Bengio, 2012; Wei et al., 2017). To solve this problem, an approach called transfer learning or domain adaptation, which examines a model's ability to transfer knowledge across different domains, has been proposed. In this way, the model trains data from one domain (source domain) and tries to make accurate predictions from data from another domain (destination domain) (Semwal et al., 2018; Zhao et al., 2017).

Various approaches for domain matching have been proposed so far, but among them, the deep learning approach has been the most popular among researchers in recent years; because a neural network can automatically learn the correct representation without feature engineering (Zhao et al., 2017). This approach attempts to perform hierarchical learning using the structure of deep neural networks so that the best possible representative learning takes place. The purpose of representative learning is to find a space to represent the data such that the classifier trained on the training data in that space can also achieve acceptable performance for classifying the test data (Lei et al., 2018). While the choice of these models can have a major impact on the final result, the implications of data representation, the pre-processing, and pre-training steps should not be overlooked (Lei et al., 2018). Therefore, these questions arise, what is the impact of the data representation on the performance of the model? And how to improve the accuracy of cross-domain classification using the deep transfer learning approach?

Studies conducted in this field show that although the deep learning approach has been used in various investigations to solve the domain matching problem and has yielded favorable results, there are still challenges in using this approach. These include the choice of network architecture, the depth of the network, and the creation and selection of features. Furthermore, according to recent studies, deep neural networks have attracted the attention of many researchers in the field of textual SA due to their recent results and achievements in the field of machine teaching (Yuan et al., 2018). Meanwhile, deep learning models such as convolutional neural networks and recurrent neural networks have been successfully used to transfer learning in the field of computer vision and speech recognition, while the effectiveness of these models in the field of natural language processing is still debated. The aim of this study is therefore to examine the effectiveness of these models in transferring learning and adapting the domain in the mentioned field to customer opinions in different product groups. Additionally, this study attempts to improve the accuracy of cross-domain classification to some extent by using a deep transfer learning framework.

The rest of the study is organized as follows: After reviewing the research literature, the method used in the research, and the results of the data analysis are discussed. Finally, the conclusions, implications of the study, and suggestions for future research are presented.

Literature Review

Natural Language Processing (NLP) is a computational approach to text analysis based on a set of theories and technologies that communicate with an intelligent system (Babu & Kanaga, 2022; Liddy, 2001). It can be used to perform many tasks in these intelligent systems (Babu & Kanaga, 2022). Many NLP researchers have focused on text classification as SA, and topic modeling (Alqarni & Rahman, 2023). Topic modeling refers to any technique that reveals the hidden semantic structure in a corpus that provides information about various topics in the texts (Dahal et al., 2019; Blei, 2012). Topic modeling is used to determine the subtopics of Twitter discussions on climate change. Sentiment analysis (SA), also known as opinion mining, is the process of identifying sentiments and opinions expressed in a given text (Dahal et al., 2019; Medhat et al. 2014). It is the study and investigation of people's attitudes, feelings, evaluations, and opinions on subjects such as services, products, people, organizations, events, problems, decisions, and issues (Başarslan & Kayaalp, 2023; Alqarni & Rahman, 2023; Babu & Kanaga, 2022; Zhang et al., 2018; Qi et al., 2016). SA is used to determine the different levels of positive and negative views on climate change in the dataset (Dahal et al., 2019). SA not only stands for polarity (positive, neutral, negative) but also for emotions (happy, sad, angry, etc.). It uses various natural language processing algorithms. SA is the text extraction of words representing a brand's social sentiment (Babu & Kanaga, 2022). It applies not only to individuals but also to organizations as organizations and business owners must find out what customers think about their products and services (Lin et al., 2017). SA also helps the company determine whether the manufactured product is in demand in the market or not (Babu & Kanaga, 2022).

One of the problems raised in SA is different domains and languages during analysis. Feelings about different topics and events are different. The distribution of words in different domains is different, leading to problems in using the information from one domain with an annotated main text to analyze sentiments in other domains with less annotated and labeled resources. Manual annotation and labeling are also costly and often impractical (Sun et al., 2017). There are three approaches to address the problem including SA vocabulary-based techniques, machine learning-based techniques, and hybrid approaches (Dang et al., 2020; Bhavitha et al., 2017). Vocabulary-based techniques were the first techniques used for SA. They fall into two approaches: dictionary-based and corpus-based (Dang et al., 2020; Salas-Zárate et al., 2017). The first type uses a dictionary for sentiment classification such as that found on SentiWordNet and WordNet. However, corpus-based SA is not based on a predefined dictionary but rather on a statistical analysis of the content of a set of documents based on k-nearest neighbors (k-NN), conditional random fields (CRF), and hidden Markov models (HMM) among others (Dang et al., 2020; Huq et al., 2017). The proposed machine learning-based techniques for SA problems can be divided into two groups of traditional models and deep learning models. Traditional models refer to classic machine learning techniques, such as naïve Bayesian classifier, the maximum entropy classifier, or support vector machines (SVM) (Dang et al., 2020; Zhang & Zheng, 2016).

Deep learning has become a powerful machine learning technique that adapts a multi-layered approach to the hidden layers of the neural network and offers advanced prediction results (Chen et al., 2020; Dang et al., 2020; Abdullah et al., 2019; Zhang et al., 2018). Deep learning models can provide better results than traditional models (Pandey et al., 2017). In traditional machine learning approaches, features are defined and extracted manually or using feature selection methods. However, in deep learning models, features are automatically learned and extracted, and higher accuracy and performance are achieved. In general, the parameters of the classifier hyper models are also measured automatically (Dang et al., 2020).

Different types of deep learning models can be used for SA, including CNN, DNN, and RNN. Such approaches address classification problems at the document, sentence, or aspect level (Pandey et al., 2017). RNN is a sequential model that takes a variable-length sequence of inputs. An RNN shares similar parameters between all-time intervals. This means the operation is the same but the input for each step is different. This technique significantly reduces the total number of parameters the network has to learn (Pal et al., 2018; Yuan & Zhou, 2015). CNN is one of the most important classes of deep neural networks. It is one of the most widely used methods of analyzing visual images. In general, a CNN network consists of three main layers, convolution, pooling, and full connection (Severyn & Moschitti, 2015).

Recently, deep learning models (including DNN, CNN, and RNN) have been used to increase the efficiency of SA tasks. For example, Yadav and Vishwakarma (2023) have proposed a Deep Multilevel Attention Network (DMLANet) that uses the correlation between image and text modalities to enhance multimodal learning. Specifically, they developed dual visual mapping along spatial and channel dimensions to maximize CNN's rendering performance. They carried out extensive evaluations on four real datasets, namely MVSA-Single, MVSA-Multiple, Flickr, and Getty Images, and confirmed the superiority of our method.

Alqarni & Rahman (2023) used deep learning techniques to implement to examine the impact on the opinions about COVID-19 in Saudi Arabia. They used CNN and BiLSTM, to rank the sentiment for tweets in Arabic.

Gulati et al. (2022) provided a comparative analysis of popular machine learning-based classifiers. They ran conducted on a dataset of tweets related to the COVID-19 pandemic. They conducted experiments on three modes, namely unigram, bigram, and trigram. Based on the results, the linear SVC, perceptron, passive-aggressive classifier, and logistic regression can achieve a maximum accuracy rating of more than 98% in classification (unigram, bigram, and trigram) and are very close in terms of performance.

In another study, Yang et al. (2020) proposed a new SA model, SLCABG, based on a sentiment lexicon, combining CNN and an attention-based bidirectional recurrent unit (BiGRU). Their experimental results show that this model can effectively improve the performance of SA-Text.

The study by Xu et al. (2019) turned attention to text data modeling and the CNN-LSTM approach at the word and sentence level to attract semantic information in images. Another study by Chen et al. (2019) used emoticons as weak labels and extracted detailed features from image and text methods using CNN and dynamic CNN. A probabilistic graphical model was used to derive the correlation between the labels predicted by different methods.

In addition, Ziser et al. (2018) proposed a representation learning model (Pivot-Based Language Model (PBLM) that processes textual information with a sequential NN (LSTM) and whose output consists of a context-dependent representation vector for each input word. They examined the cross-domain sentiment classification task over 20 domain pairs and indicated significant improvements over strong benchmarks.

Peng et al. (2018) also proposed a method to simultaneously extract domain-specific and invariant representations and to train a classifier for each of the representations. This study introduced some target domain labeled data for domain-specific learning of information and demonstrated that the proposed method could achieve better performance than more advanced methods.

Li et al. (2018) proposed a hierarchical attention transfer network for cross-domain sentiment classification that can draw attention to emotions across domains at the word and sentence level by automatically capturing pivots and non-pivots. Their method provided a better interpretation of requests that should be transmitted. In another study, Chen et al. (2017a) proposed a two-tier sentiment classification approach using BI_LSTM_CRF and CNN deep neural networks. First, using BI_LSTM_CRF, they divided the target-based sentences into three different groups of non-goal, single-goal, and multiple-goal. They then assigned each group’s sentences to a CNN for sentiment classification. Finally, the trained classifier was tested on four different datasets.

Wei et al. (2017) also used a CNN and LSTM-based transfer learning framework for domain adaptation and the classification of opinions recorded in online training forums. In this framework, feature representations are first learned for each word according to the local text feature by CNN convolution operations, then opinion representations are learned by the extracted attributes using the LSTM model that maintains long semantic feature relationships. Next, the possibility of transferring the parameters of a trained model to a training course was examined.

Given the recent advances in neural networks for text data processing, Sundström (2018) examined the ability and portability of this network to transfer knowledge from the source domain to the target domain. He also analyzed the performance of his network with different text representations and concluded that using pre-trained representations like word2vec would give better results.

In another study, Li et al. (2017) proposed an end-to-end adversarial memory network (AMN) for cross-domain sentiment classification. Their proposed framework consists of shared memory networks with two parameters, one for sentiment classification and the other for domain classification. So that, their framework can automatically capture the pivots using an attention mechanism.

Zhou et al. (2015) developed a bidirectional LSTM to improve the accuracy and performance of knowledge transfer from the source domain to the target domain by proposing a new algorithm. They first trained the BI_LSTM networks with a large amount of training data from the well-labeled source and then optimized the training data associated with the target domain. In this study, transfer strategies and fine-tuning were used for domain adaptation.

According to studies conducted in this field, although the learning approach has been used in several studies to solve the domain matching problem, further studies are needed to improve the existing work and new applications of deep learning for domain classification and matching problems to discover. Furthermore, despite the good performance of neural networks, especially CNN and RNN, in contextual sentiment analysis, transfer learning in machine vision, and speech recognition, the performance of these models in natural language processing needs further investigation (Yuan et al., 2018). Therefore, this study aims to evaluate the efficiency of these models in transferring learning and adapting the domain of customer opinions on different product groups. This study attempts to provide a framework based on the deep transfer learning approach to improve the cross-domain classification of customer reviews and more precisely classify them into five different classes within different product groups; because the existing clusters are simply restricted to the polarity of opinions into two or three positive, negative and neutral classes (Al-Moslmi et al., 2017; Severyn & Moschitti, 2015; Sundström, 2018; Tang et al., 2014).

Methodology

The objective of this study is to examine the accuracy and portability of deep learning frameworks to analyze the cross-domain sentiment of customers in different product groups (10967 laptop reviews on the Amazon website as the source domain and 1001 videos on IMDB as the target domain), as well as cross-domain sentiment ranking in five classes of “very positive”, “positive”, “neutral”, “negative” and “very negative”. Therefore, the Long Short-Term Memory (LSTM) Neural Network was used and their weights were stored and transmitted. In this study, due to its significant results in SA, the RNN network (LSTM) was used to implement a deep transfer learning framework.

In addition, three popular machine learning models, Support Vector Machine, Naive Bayes, and Maximum Entropy, which perform well in sentiment classification, were also studied and implemented as basic methods. The results of each model were evaluated against the confusion matrix and its criteria, which include accuracy, precision, recall, and F-measure. The confusion matrix is the n*n matrix, where n is the number of classes (Chen et al., 2017b; Sundström & Dahlbom, 2018).

The Python programming language and its libraries were used to analyze data.

Results

Data Pre-processing

This part cleans and processes the collected data. The input document was processed to remove redundancies and inconsistent data, word hyphenation, and rooting (Inzalkar & Sharma, 2015; Monali & Sandip, 2014).

The pre-processing phase includes the Tokenization process (splitting text or a sentence into a sequence of tokens roughly equivalent to "words"), rooting, removing stopwords, etc. In this study, the python nltk library and nltk.tokenize, nltk.corpus and nltk.stem.lancaster modules were used for data preprocessing. An example of the preprocessing code is shown in Table 1. As this table indicates after pre-processing, all words were converted to lowercase, keys, and conjunctions were removed, and the verbs were reset to their roots.

Table 1

An Example of Pre-Processed Source Domain Comments

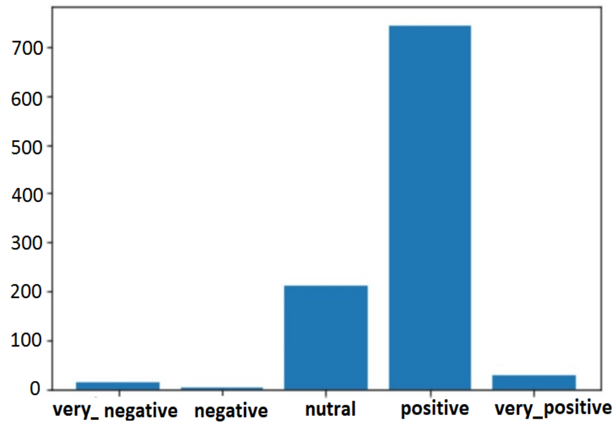
Before Pre-processing	Good basic tablet for checking email, web browsing, and reading eBooks.
After Pre-processing	good bas tablet check email web brows read eBooks

Labeling

Because the approach of this study is supervised and it aims to classify opinions into five different classes, the opinions were labeled using the TextBlob library used for natural language processing, SA, and classification. TextBlob is a Python library for processing text data. It offers a simple API to dive into common NLP tasks like part-of-speech labeling, noun phrase extraction, SA, classification, translation, and more. Polarity and subjectivity are two properties of TextBlob's mood feature. In this study, only the polarity value was used to define the labeling algorithm. Polarity is a float that lies in the range of [-1, 1], where 1 means a positive statement and -1 means a negative statement. The polarity diagram of the target domain is shown in Figure 1.

Figure 1

Polarity Distribution Diagram of the Target Domain



Text Representation

Since machine learning models cannot process unstructured texts, in this phase the unstructured data is represented and converted into numbers to make it understandable for the machine. Therefore, the Bag of Words (BOW) and Continuous Bag of Words (CBOW) model architectures, which are Word2Vec approaches to word placement, were used (Bengio, 2012). The BOW model is widely used in document classification methods where the (frequency of) occurrence of each word is used as a feature for the training classifier (McTear et al., 2016). This model is a simplifying representation in which, a text (e.g., a sentence or a document) is represented as a bag (several sentences) of its words, without considering the grammar and even the order of the words, but keeping multiplicity (Sivic & Zisserman, 2008; Bengio, 2012).

The CBOW-based Word2Vec model is essentially a neural network with an input layer, a hidden layer with linear neurons without an activation function, and an output layer with a softmax activity function, used for multi-category classifications (Alami et al., 2019). The

CBOW model architecture predicts the current target word based on the words in the source context. In the CBOW model, the modification consists of replicating the input to the hidden layer connections C times, the number of context words, and adding a divide-by-C operation to the hidden layer neurons. With this configuration for specifying C context words, each word encoded using a 1 representation of V means that the hidden layer output is the average of the word vectors corresponding to the context words in the input. After network training, the output layer is removed and the weights learned from the hidden layer represent the real vectors. The context can be a group of words instead of a word. The only difference is that the hidden layer output is the average number of input words (Chen et al., 2017b).

The result of source domain representations with two models showed better performance of CBOW than BOW. The accuracy and error plots of the source model using CBOW and BOW are shown in Figures 2 and 3, respectively.

Figure 2

Source Model Loss and Accuracy Using CBOW

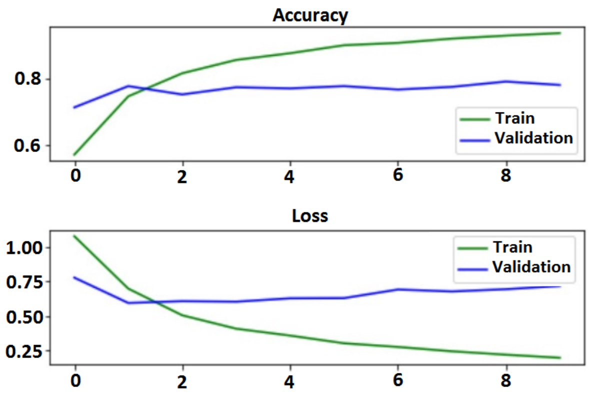
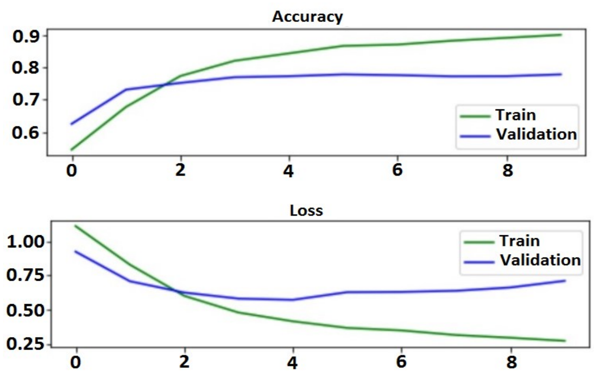


Figure 3

Source Model Loss and Accuracy Using BOW



Modeling

In this phase, the data is used for modeling. In this study, the RNN (LSTM) network was used to implement a deep transfer learning framework. Deep learning models are highly dependent on their hyperparameters. Therefore, hyperparameters must be tuned correctly to achieve optimal results and accuracy. Since, the purpose of this study is not to evaluate the performance of different architectures, after various trials and errors, the desired architecture was chosen and other possible architectures were not explored. One of the most important hyperparameters for training neural networks is the learning rate, which is used for optimization and error minimization and for which it has a value of 0.01. According to the research objective, the activity functions ReLU and Softmax activity functions were used (Lim & Lee, 2017).

The accuracy of the machine learning model in predicting the measured and estimated output using the cost function. The function measures the error between the predicted value and the actual target value. Since this study aims to make a cross-domain classification, the categorical-cross-entropy cost function was used. The Adam algorithm was also used for optimization (Zhu et al., 2017). This algorithm is originally an extended model of the gradient descent algorithm. This algorithm is suitable for a large amount of data or parameters (Kingma & Ba, 2014). It has also performed well in deep learning in computer vision, and natural language processing (Snoek, et al., 2012). The representation size was set to the default value of 300 and the data were grouped to increase the speed of the neural networks and facilitate their parallelization (Ioffe & Szegedy, 2015). Finally, 64 values were assigned to this hyperparameter. The dropout technique was used during training to avoid overfitting in deep neural networks. This technique not only avoids overfitting but also selects more valuable features (Srivastava et al., 2014).

Evaluation

In this phase, the proposed model must be evaluated according to valid criteria and its knowledge must be used in the target domain. As the present study deals with the sentiment classification into five different classes, the confusion matrix and its measures including accuracy, precision, recall, and F-measure were used to assess the performance of the model. Because there are five classes in this study, the confusion matrix becomes a multiclass matrix (5*5). Therefore, the precision, recall, and accuracy criteria were calculated based on formulas 1, 2, and 3, respectively (Manliguez, 2016):

$$\mathrm{P_i} = \frac{\mathrm{TTP_{all}}}{\mathrm{TTP_{all}} + \mathrm{TFP_i}} \tag{1}$$

$$\mathrm{R_i} = \frac{\mathrm{TTP_{all}}}{\mathrm{TTP_{all}} + \mathrm{TFN_i}} \tag{2}$$

$$\text{Overall Accuracy} = \frac{\mathrm{TTP_{all}}}{\text{Total Number of Testing Entries}} \tag{3}$$

Where Pi is precision, Ri recalls, TTP represents the number of records whose actual class is positive and their classification algorithm is correctly identified as positive. TFP is the number of records whose actual class is negative and their classification algorithm is incorrectly identified as negative; TFN is the number of records whose actual class is positive and their classification algorithm is incorrectly identified as negative.

The results of the model evaluation and the comparison with the Support Vector Machine (SVM), Naive Bayes, and Maximum Entropy are presented in Table 2. Based on the results, the CBOW method is better than the BOW method. Furthermore, the results of the implemented models show that using deep learning models and transferring f weights from the source domain to the target domain model can be effective in analyzing the cross-domain sentiment. In addition, the results indicate that deep learning models will perform better when working with a large volume of data.

Table 2.

Models Evaluation Results

Model	Accuracy	Precision	Recall	F-Measure	CPU	RAM	Time (ms)
BOW Source Domain Model	0.84	0.62	0.62	0.62	88%	7.2	6757.521
CBOW Source Domain Model	0.98	0.73	0.63	0.68	92%	8.1	8569.256
Target Domain Model	0.66	0.57	0.45	0.50	90%	7.9	656.511
Support Vector Machine	0.45	0.42	0.45	0.43	48%	2.5	440.323
Naive Bayes	0.42	0.40	0.41	0.40	49%	2.3	320.298
Maximum Entropy	0.53	0.52	0.51	0.52	63%	3.1	486.981

Conclusion

The increasing number and availability of online ratings and comments make sentiment ratings an essential part of doing business online. SA focuses on determining the polarity of sentiments. The main problem with machine learning models is their domain dependency. Therefore, various domain adaptation approaches have been proposed, where the deep learning approach has attracted the attention of many researchers due to its significant performance in computer vision and natural language processing (for domain classification). However, it is limited to the polarity of opinions in two or three categories, positive, negative, and neutral. Therefore, for the first time, this study used a deep learning framework to classify sentiment into five categories, which is the innovation of the study. Another novelty of this study is the transfer of weights from the source domain to the target domain and the classification of sentiments between domains. To do this, the LSTM neural network was used to store and transfer the text weights. Two types of text representations, BOW and CBOW, were used in this study.

Results from the two approaches indicated the effect of the text representation on improving model performance; in addition, the RNN (LSTM) network was used to implement the deep transfer learning framework. The results of the study indicate that the proposed approach plays an important role in classifying sentiments between domains.

The study attempted to improve the accuracy of classification accuracy by evaluating different architectures with different hyperparameters tuning values. To do this, after training and developing the source domain model and achieving the desired accuracy, the weights obtained from the network were stored and assigned to the target domain model. The results of the model evaluation indicated a better performance of CBOW compared to the BOW method.

Furthermore, the results of the study suggest that using a deep learning model and transferring weights from the source domain to the target domain model can be effective in cross-domain sentiment analysis. Also, deep learning models will perform better when working with large amounts of data, but on the downside, better hardware and more powerful tools are needed.

This study complements the literature on sentiment analysis with deep learning and serves as a basis for future research on the use of deep learning for cross-domain sentiment analysis.

The cross-domain text classification framework proposed in this study reduces the need to build sentiment models for each data source and requires no human effort to classify unlabeled texts. Therefore, companies can use this framework to quickly get an overview of their customers' products.

To some extent, transfer learning can reduce the dependence of learning on large datasets, thereby reducing computational resource consumption and saving training time.

This framework can also be used to examine verbatim feedback from customers whose sentiment is very negative. Similarly, managers can also view positive customer reviews to understand why those customers were satisfied with the products or services. After reading the customers' reviews and knowing the positives and negatives that led to their opinion, better decisions can be made about promoting the product or service.

In addition, managers can analyze online reviews of their products and compare them to their competitors. By analyzing sentiment, companies can identify which aspects of their competitors' products are performing the most negatively and use this to their advantage. They can also follow market trends as they emerge by analyzing official market reports and trade publications.

Transfer learning helps to save resources and improve efficiency when training new models. It also helps to train models when only unlabeled datasets are available since most of the model is already trained. The main advantages of transfer learning for machine learning are: eliminating the need for a large labeled training dataset for each new model; improved efficiency of development and deployment of machine learning for multiple models; a more general approach to troubleshooting machines using different algorithms to solve new challenges; models can be trained in simulations instead of real environments; save training data; typically, a large range variety of data is required to accurately train a machine learning algorithm; creating labeled training data takes time, effort, and expertise.

Transfer learning reduces the training data required for new machine learning models because most of the model is already trained. In many cases, large labeled datasets are not available to organizations. Transfer learning means that models can be trained on an existing labeled dataset and then applied to similar data that has not been labeled.

Transfer learning helps developers take a hybrid approach of different models to tailor a solution to a specific problem. Sharing knowledge between two different models can result in a much more accurate and powerful model. With this approach, models can be created iteratively. Transfer learning will also be a key factor in the spread of machine learning models in new regions and industries.

Limitations and Recommendations

Deep neural network architectures are very diverse and each investigation can present its new framework and architecture. Therefore, future research can explore different network architectures to improve cross-domain text classification. In addition, the classification and weighting of the labels in this study were performed using the RNN LSTM network. Therefore, it is suggested that future research conduct the same study using Generic Adversarial Networks (GANs) and compare their findings to those of this study.

The data collected in this study contained only text and no hashtags, scores, or emoji, so future research could contain more comprehensive data and examine these characteristics.

Furthermore, it is suggested that future research investigate different representations and layout layers, as well as, different and large domains. In addition, it is recommended that future research use other deep networks and verify their performance in knowledge transfer across domains.

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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References

Abdullah, N. A., Feizollah, A., Sulaiman, A., & Anuar, N. B. (2019). Challenges and Recommended Solutions in Multi-Source and Multi-Domain Sentiment Analysis. *IEEE Access, 7*, 144957-144971. https://doi.org/10.1109/ACCESS.2019.2945340

Alami, N., Meknassi, M., & En-nahnahi, N. (2019). Enhancing unsupervised neural networks-based text summarization with word embedding and ensemble learning. *Expert systems with applications*, 123, 195-211. https://doi.org/10.1016/j.eswa.2019.01.037

Al-Moslmi, T., Omar, N., Abdullah, S., & Albared, M. (2017). Approaches to cross-domain sentiment analysis: A systematic literature review. *IEEE access*, 5, 16173-16192. https://doi.org/10.1109/ACCESS.2017.2690342

Babu, N. V., & Kanaga, E. G. M. (2022). Sentiment analysis in social media data for depression detection using artificial intelligence: a review. *SN Computer Science*, 3, 1-20. https://doi.org/10.1007/s42979-021-00958-1

Başarslan, M. S., & Kayaalp, F. (2023). Sentiment analysis with ensemble and machine learning methods in multi-domain datasets. *Turkish Journal of Engineering*, *7*(2), 141-148. https://doi.org/10.31127/tuje.1079698

Bengio, Y. (2012, June). Deep learning of representations for unsupervised and transfer learning. JMLR: Workshop and Conference Proceedings 27, 17–37. http://proceedings.mlr.press/v27/bengio12a/bengio12a.pdf

Bhavitha, B. K., Rodrigues, A. P., & Chiplunkar, N. N. (2017, March). *Comparative study of machine learning techniques in sentimental analysis.* In 2017 International conference on inventive communication and computational technologies *(ICICCT) (pp. 216-221).* IEEE. https://doi.org/10.1109/ICICCT.2017.7975191

Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, 55(4), 77-84. https://doi.org/10.1145/2133806.2133826

Chen, J., Feng, J., Sun, X., & Liu, Y. (2020). Co-Training Semi-Supervised Deep Learning for Sentiment Classification of MOOC Forum Posts. *Symmetry*, 12(1), 8-32. https://doi.org/10.3390/sym12010008

Chen, T., Xu, R., He, Y., & Wang, X. (2017a). Improving sentiment analysis via sentence type classification using BiLSTM-CRF and CNN. *Expert Systems with Applications*, 72, 221-230. https://doi.org/10.1016/j.eswa.2016.10.065

Chen, L., Guan, Z., He, J., & Peng, J. (2017b). A survey on sentiment classification. *J. Comput. Res. Dev*, *54*(6), 1150-1170.

Dahal, B., Kumar, S. A., & Li, Z. (2019). Topic modeling and sentiment analysis of global climate change tweets. *Social Network Analysis and Mining*, 9(24), 1-20.

Dang, N. C., Moreno-García, M. N., & De la Prieta, F. (2020). Sentiment analysis based on deep learning: A comparative study. *Electronics*, *9*(3), 483-512. https://doi.org/10.3390/electronics9030483

Gulati, K., Kumar, S. S., Boddu, R. S. K., Sarvakar, K., Sharma, D. K., & Nomani, M. Z. M. (2022). Comparative analysis of machine learning-based classification models using sentiment classification of tweets related to COVID-19 pandemic. *Materials Today: Proceedings*, 51, 38-41 https://doi.org/10.1016/j.matpr.2021.04.364

Haque, T. U., Saber, N. N., & Shah, F. M. (2018, May). *Sentiment analysis on large scale Amazon product reviews.* In 2018 IEEE International Conference on Innovative Research and Development (ICIRD) (pp. 1-6). IEEE. https://doi.org/10.1109/ICIRD.2018.8376299

Huq, M. R., Ahmad, A., & Rahman, A. (2017). Sentiment analysis on Twitter data using KNN and SVM. *International Journal of Advanced Computer Science and Applications,* 8(6),19-25. https://pdfs.semanticscholar.org/05a8/78000170abcd0c6f8208080470858422e17c.pdf

Inzalkar, S., & Sharma, J. (2015). A survey on text mining-techniques and application. *International Journal of Research in Science & Engineering*, 24, 1-14. http://www.ttcenter.ir/ArticleFiles/ENARTICLE/3771.pdf

Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*. https://doi.org/10.48550/arXiv.1412.6980

Li, Z., Wei, Y., Zhang, Y., & Yang, Q. (2018, April). *Hierarchical attention transfer network for cross-domain sentiment classification.* In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 32, No. 1). https://doi.org/10.1609/aaai.v32i1.12055

Li, Z., Zhang, Y., Wei, Y., Wu, Y., & Yang, Q. (2017, August). *End-to-End Adversarial Memory Network for Cross-domain Sentiment Classification.* In Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence (IJCAI-17) (pp. 2237-2243). https://hsqmlzno1.github.io/assets/publications/AMN2017.pdf

Liddy, E. D. (2001). *Natural language processing. In Encyclopedia of Library and Information Science*, 2nd Ed. NY. Marcel Decker, Inc. https://surface.syr.edu/cgi/viewcontent.cgi?article=1043&context=istpub

Lim, S., & Lee, D. (2017). Stable improved softmax using constant normalization. *Electronics Letters*, 53(23), 1504-1506. https://doi.org/10.1049/el.2017.3394

Lin, C., & He, Y. (2009, November). *Joint sentiment/topic model for sentiment analysis.* In Proceedings of the 18th ACM conference on Information and knowledge management (pp. 375-384). https://doi.org/10.1145/1645953.1646003

Lin, S., Xie, H., Yu, L. C., & Lai, K. R. (2017, December). SentiNLP at IJCNLP-2017 Task 4: Customer feedback analysis using a Bi-LSTM-CNN model. *In Proceedings of the IJCNLP 2017, Shared Tasks (pp. 149-154).* https://aclanthology.org/I17-4025/

Ioffe, S., & Szegedy, C. (2015). Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167.* http://proceedings.mlr.press/v37/ioffe15.html

Liu, Y., Jin, J., Ji, P., Harding, J. A., & Fung, R. Y. (2013). Identifying helpful online reviews: a product designer's perspective. *Computer-Aided Design*, 45(2), 180-194.

https://doi.org/10.1016/j.cad.2012.07.008

McTear, M., Callejas, Z., & Griol, D. (2016). *The dawn of the conversational interface.* In The Conversational Interface (pp. 11-24). Springer, Cham. https://doi.org/10.1007/978-3-319-32967-3_2

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams engineering journal*, *5*(4), 1093-1113. https://doi.org/10.1016/j.asej.2014.04.011

Monali, P., & Sandip, K. (2014). A concise survey on text data mining. *International Journal of Advanced Research in Computer and Communication Engineering*, *3*(9), 8040-8043.

Pal, S., Ghosh, S., & Nag, A. (2018). Sentiment analysis in the light of LSTM recurrent neural networks. *International Journal of Synthetic Emotions (IJSE),* 9(1), 33-39. https://doi.org/10.4018/IJSE.2018010103

Pandey, A. C., Rajpoot, D. S., & Saraswat, M. (2017). Twitter sentiment analysis using hybrid cuckoo search method. *Information Processing & Management,* 53(4), 764-779. https://doi.org/10.1016/j.ipm.2017.02.004

Peng, M., Zhang, Q., Jiang, Y. G., & Huang, X. J. (2018, July). *Cross-domain sentiment classification with target domain specific information.* In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (pp. 2505-2513). Melbourne, Australia. https://doi.org/10.18653/v1/P18-1233

Piryani, R., Madhavi, D., & Singh, V. K. (2017). Analytical mapping of opinion mining and sentiment analysis research during 2000–2015. *Information Processing & Management*, 53(1), 122-150. https://doi.org/10.1016/j.ipm.2016.07.001

Qi, J., Zhang, Z., Jeon, S., & Zhou, Y. (2016). Mining customer requirements from online reviews: A product improvement perspective. *Information & Management*, *53*(8), 951-963. https://doi.org/10.1016/j.im.2016.06.002

Salas-Zárate, M. D. P., Medina-Moreira, J., Lagos-Ortiz, K., Luna-Aveiga, H., Rodriguez-Garcia, M. A., & Valencia-Garcia, R. (2017). Sentiment analysis on tweets about diabetes: an aspect-level approach. *Computational and mathematical methods in medicine*, *2017*. https://doi.org/10.1155/2017/5140631

Severyn, A., & Moschitti, A. (2015, August). *Twitter sentiment analysis with deep convolutional neural networks.* In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 959-962). https://doi.org/10.1145/2766462.2767830

Sivic, J., & Zisserman, A. (2008). Efficient visual search of videos cast as text retrieval. *IEEE transactions on pattern analysis and machine intelligence*, 31(4), 591-606. https://doi.org/10.1109/TPAMI.2008.111

Snoek, J., Larochelle, H., & Adams, R. P. (2012). Practical bayesian optimization of machine learning algorithms. *In Advances in neural information processing systems (pp. 2951-2959).* https://proceedings.neurips.cc/paper_files/paper/2012/hash/05311655a15b75fab86956663e1819cd-Abstract.html

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014).

Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research*, *15*(1), 1929-1958. https://www.jmlr.org/papers/volume15/srivastava14a/srivastava14a.pdf?utm_content=buffer79b43&utm_medium=social&utm_source=twitter.com&utm_campaign=buffer,

Sun, S., Luo, C., & Chen, J. (2017). A review of natural language processing techniques for opinion mining systems. *Information fusion*, 36, 10-25. https://doi.org/10.1016/j.inffus.2016.10.004

Sundström, J. (2018*). Sentiment analysis of Swedish reviews and transfer learning using convolutional neural networks.* UPTEC STS. Retrieved from http://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-339066.

Tang, D., Qin, B., & Liu, T. (2015). Deep learning for sentiment analysis: successful approaches and future challenges. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery,* 5(6), 292-303. https://doi.org/10.1002/widm.1171

Vidya, S. (2018). Cross Domain Sentiment Classification Using Natural Language Processing. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. 3(3), 348-353. https://www.researchgate.net/profile/Dr-Svidya/publication/361983484_Cross_Domain_Sentiment_Classification_Using_Natural_Language_Processing/links/62cfc802e2a5013989058038/Cross-Domain-Sentiment-Classification-Using-Natural-Language-Processing.pdf

Wei, X., Lin, H., Yang, L., & Yu, Y. (2017). A convolution-LSTM-based deep neural network for cross-domain MOOC forum post classification. *Information*, *8*(3), 92-108. https://doi.org/10.3390/info8030092

Yadav, A., & Vishwakarma, D. K. (2023). A deep multi-level attentive network for multimodal sentiment analysis. *ACM Transactions on Multimedia Computing, Communications and Applications*, *19*(1), 1-19. https://doi.org/10.3390/info8030092

Yang, L., Li, Y., Wang, J., & Sherratt, R. S. (2020). Sentiment analysis for E-commerce product reviews in Chinese based on sentiment lexicon and deep learning. *IEEE access*, *8*, 23522-23530. https://doi.org/10.1109/ACCESS.2020.2969854

Yang, X., Zhang, T., Xu, C., & Yang, M. H. (2015). Boosted multi-feature learning for cross-domain transfer. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, *11*(3), 1-18. https://doi.org/10.1145/2700286

Yuan, Z., Wu, S., Wu, F., Liu, J., & Huang, Y. (2018). Domain attention model for multi-domain sentiment classification. *Knowledge-Based Systems*, *155*, 1-10. https://doi.org/10.1016/j.knosys.2018.05.004

Yuan, Y., & Zhou, Y. (2015). Twitter sentiment analysis with recursive neural networks. *CS224D course projects*. https://cs224d.stanford.edu/reports/YuanYe.pdf

Zhang, L., Wang, S., & Liu, B. (2018). Deep learning for sentiment analysis: A survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *8*(4), e1253. https://doi.org/10.1002/widm.1253

Zhang, X., & Zheng, X. (2016, July). *Comparison of text sentiment analysis based on machine learning.* In 2016 15th international symposium on parallel and distributed computing (ISPDC) (pp. 230-233). IEEE. https://doi.org/10.1109/ISPDC.2016.39s

Zhou, G., Zhou, Y., Guo, X., Tu, X., & He, T. (2015). Cross-domain sentiment classification via topical correspondence transfer. *Neurocomputing*, *159*, 298-305. https://doi.org/10.1016/j.neucom.2014.12.006

Zhao, C., Wang, S., & Li, D. (2017, September). *Deep transfer learning for social media cross-domain sentiment classification.* In Chinese National Conference on Social Media Processing (pp. 232-243). Springer, Singapore. https://doi.org/10.1007/978-981-10-6805-819

Zhu, F., Dong, X., Song, R., Hong, Y., & Zhu, Q. (2017, November). *A multiple learning model based voting system for news headline classification.* In National CCF Conference on Natural Language Processing and Chinese Computing (pp. 797-806). Springer, Cham. https://doi.org/10.1007/978-3-319-73618-1_69

Ziser, Y., & Reichart, R. (2018, June). *Pivot based language modeling for improved neural domain adaptation.* In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers) (pp. 1241-1251). https://aclanthology.org/N18-1112/

Zola, Paola, Paulo Cortez, Costantino Ragno, and Eugenio Brentari. (2019). Social Media Cross-Source and Cross-Domain Sentiment Classification. *International Journal of Information Technology & Decision Making (IJITDM).* 18(5), 1469-1499. https://doi.org/10.1142/S0219622019500305

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