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# A Comprehensive Review of Multi-Domain Sentiment Analysis: Techniques, Models and Future Directions

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**Abstract**

The increase in user-generated content on online platforms has underscored the significance of advanced sentiment analysis methods that can effectively function across various fields. Sentiment analysis, a component of natural language processing (NLP) focuses on recognising and organising subjective information within text data. While there have been strides in domain-specific sentiment analysis, developing models that can excel across diverse domains remains a notable challenge. This comprehensive review of 19 research papers aims to summarise the current status of research on sentiment analysis spanning multiple domains examining the strategies, models and datasets employed to enhance performance across various areas. Techniques like domain adaptation, including transfer learning and adversarial training have shown promise by refining trained models such as BERT with target domain data thereby improving their capacity to generalise across domains. The study also sheds light on future research directions concerning domain shift, feature variations and lexical and semantic aspects to optimise multi-domain sentiment classification.

**Keywords**: multi-domain sentiment classification, cross-domain sentiment classification, transfer learning

## 1. Introduction

In the digital age, the surge in user-generated content across various online platforms such as social media, e-commerce, and review sites has created an overwhelming amount of data. This influx presents both an opportunity and a challenge for the field of natural language processing (NLP). One of the most prominent applications of NLP is sentiment analysis, which aims to automatically extract and classify the underlying emotions and opinions expressed in natural language texts (Shilpa et al., 2021). User-generated content provides a platform for people to voice their thoughts and stories while taking part in conversations that accelerate opportunities for everyone to share their perspectives – a transformation that has moved influence away from established media authorities and empowered individuals to impact conversations. User-generated content is important for businesses as it has an impact on brand reputation and consumer choices. Public perception is shaped by reviews, testimonials and social media posts. Positive user-generated content can enhance a brand’s trustworthiness while negative user-generated content can harm its reputation. User-generated content promotes community engagement by creating a sense of belonging and trust among participants who are actively involved in crafting content (Vincent et al., 2019).

This active participation benefits platforms by boosting user retention and interaction levels. User-generated content also offers companies and researchers a wealth of information regarding user preferences, trends and consumer habits. Analysing this data can yield insights for enhancing product offerings, strategising marketing campaigns and overall business enhancement. Sentiment analysis can help understand the attitudes, preferences and feelings of individuals or groups towards various entities, such as products, services, topics, events or issues. It can also reveal the polarity, intensity and subjectivity of the sentiments, as well as the aspects or features that trigger them.

Sentiment classification, which focuses on identifying and categorising subjective information expressed in text, plays a pivotal role in understanding public opinion, market trends and user feedback. Traditional sentiment classification methods have predominantly concentrated on single-domain applications, leading to models finely tuned for specific contexts but often faltering when applied to different domains (Gaikar et al., 2019). The difficulty with multi-domain sentiment classification is ensuring consistent accuracy and dependability across various content types, each presenting distinct language subtleties and contextual differences (Al-Moslmi et al., 2017). This review seeks to consolidate existing research on multi-domain sentiment classification. It will delve into the approaches, frameworks and datasets created to manage the challenges of cross-domain sentiment analysis. By providing a comprehensive examination of the strategies employed to manage domain variability, this review will shed light on the successes and limitations encountered by researchers. Furthermore, it aims to identify promising avenues for future research, offering insights into the development of more robust and adaptable sentiment classification systems. Identified challenges and issues are also discussed.

## 2. Methodology

The PRISMA systematic review research methodology was undertaken by identifying relevant studies on Google Semantic Scholar. The primary search terms we used were "*multi-domain sentiment analysis*" and "*cross-domain sentiment analysis*." These key terms were primarily focused on finding articles related to multiple domain sentiment analysis. Research papers after 2019 that focused on multiple domain sentiment analysis and explored various tools and methods in this field were included. Only research studies that specifically contained "multi/cross-domain sentiment analysis/classification" in the title were included. Furthermore, only studies that performed domain sentiment analysis in English and that used accuracy as the primary evaluation metric were included in this study. Based on the research methodology, 19 studies were included in this review. The systematic review process shown in Fig. 1 was followed to conduct research into the area of multi-domain sentiment classification.

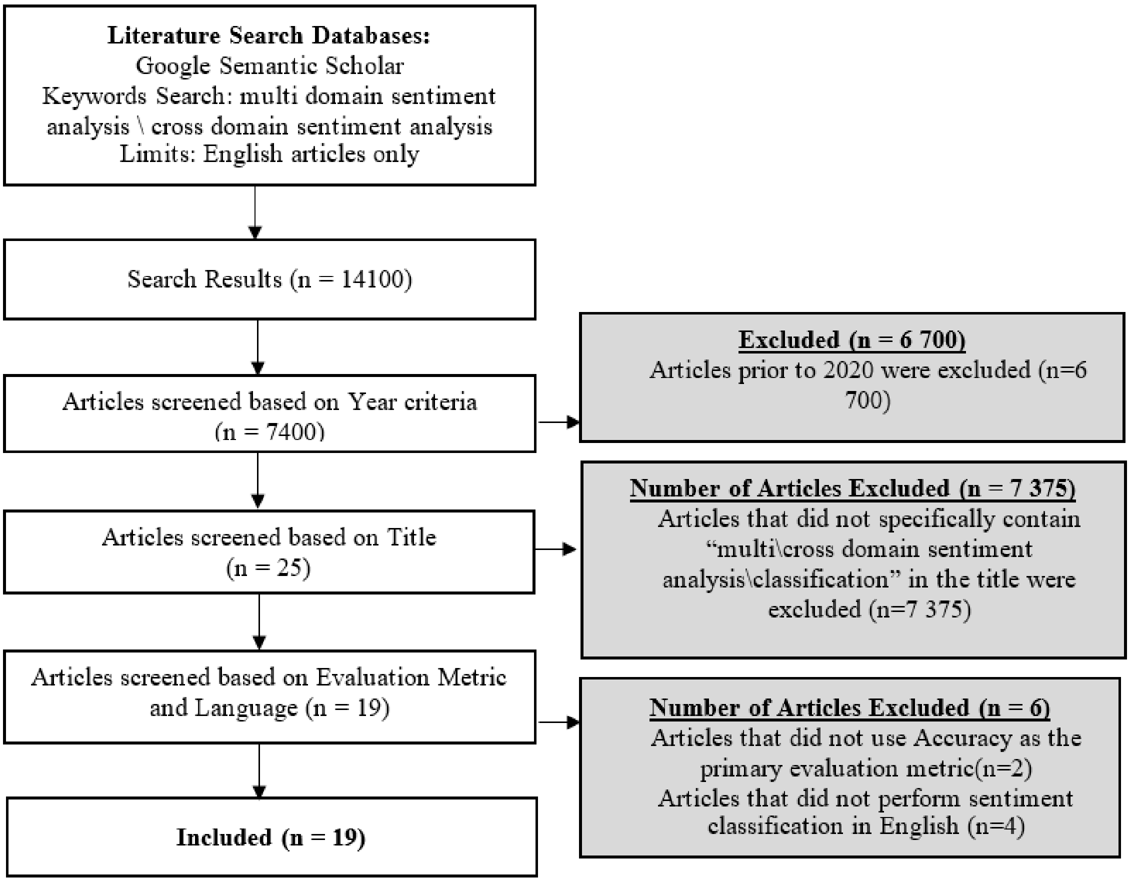

Figure 1. PRISMA systematic review research methodology

## 3. Related Works

In recent years, multi-domain sentiment analysis has gained considerable attention due to the growing need for robust sentiment classification systems that can generalise across different textual domains. Traditional sentiment analysis models often experience difficulty when applied to domains outside their training data, leading to a significant drop in accuracy (Al-Moslmi et al., 2017). To address this issue, researchers have explored various methods to enhance the multi-domain adaptability of sentiment models. This section reviews the related work in this field, focusing on the contributions of transfer learning, domain adaptation techniques, the use of large pre-trained language models, and innovative strategies for leveraging domain-specific data to optimise sentiment analysis across diverse textual landscapes.

Research conducted by Peng and Zhang (2020) proposes a novel framework called Weighted Domain-Invariant Representation Learning (WDIRL) to improve multi-domain sentiment analysis. The study found that traditional Domain-Invariant Representation Learning (DIRL) can be ineffective when the label distribution varies significantly between domains. WDIRL addresses this by introducing a class weight to align label distributions before applying domain-invariant learning. This approach aims to reduce the influence of label distribution shifts when aligning conditional feature distributions. The model was applied to the Amazon reviews (DVD, Books, Electronics, Kitchen) dataset and achieved 84% accuracy.

A study explored by Kong et al. (2023) proposes a novel method called feature projection and multi-source attention (FPMA) for multi-domain sentiment analysis. FPMA leverages feature projection and a multi-source attention mechanism to improve classification accuracy. The model was applied to the Amazon reviews (DVD, Books, Electronics, Kitchen) and online shopping datasets and achieved 84% accuracy. The FPMA method addresses the negative transfer problem through a multi-source selection strategy. It uses this strategy to identify and focus on source domains that are highly transferable and closely align with the target domain. This helps to mitigate the negative impact of using data from less relevant source domains, which could impact performance.

Research by Mousa et al. (2021) proposes a new approach for multi-domain sentiment analysis that uses a weighted ensemble of deep neural networks. The study applied convolutional neural network (CNN), long short-term memory (LSTM), gated recurrent units (GRU) each trained on data from a specific domain. A weighted scoring system to combine the predictions of the individual models was applied, with the weights being determined by the similarity between the training domain and the target domain. This approach led to improved accuracy in sentiment analysis, with an average increase of over 3% compared to other state-of-the-art approaches.

A study conducted by Geethapriya and Valli (2021) proposes a new feature extraction technique for multi-domain sentiment analysis. This technique refines feature extraction by merging synonyms and replacing negative polarity terms with antonyms, which improves the mapping of domain-specific words. The model was applied to the Amazon reviews (DVD, Books, Electronics, Kitchen) dataset and achieved 81% accuracy.

Research undertaken by Aggarwal (2021) explores sentiment analysis on Amazon reviews to classify them as positive or negative. The study focuses on three product domains: books, DVDs, and kitchen appliances. Supervised machine learning methods like Naïve Bayes, Support Vector Machines, and decision trees to classify the sentiments were applied to the dataset using feature vectors. The significance of this feature vector is that it transforms text into a format understandable by machine-learning algorithms. These algorithms can then identify patterns in the word frequencies to determine if a review carries a positive or negative sentiment. Naïve Bayes and SVM outperformed decision trees with each achieving 85% accuracy.

Studies conducted by Gunasekar et al. (2023) proposes a new model called Collaborative Word Attention Network (CWAN) for multi-domain sentiment analysis. CWAN leverages attention networks to learn domain-invariant features by focusing on both the aspects and overall sentiment of sentences. The CWAN model focuses on improving multi-domain sentiment analysis by creating new sentence and aspect vectors that contain both sentiment and domain-specific information. This is achieved by using two collaboratively operating attention networks. The model was applied to the Amazon reviews (DVD, Books, Electronics, Kitchen) dataset and achieved 82% accuracy.

Research by Lyu et al. (2023) proposes a novel model called Global-Local Dynamic Adversarial Learning (GLDAL) to address the challenge of multi-domain sentiment analysis, particularly in scenarios with limited labelled data. GLDAL uses a dynamic adversarial learning approach that leverages both global and local domain discriminators. This allows the model to effectively reduce discrepancies in both the marginal and conditional probability distributions between source and target domains. The model was applied to multiple datasets and achieved 62% average accuracy.

Work by Dai et al. (2020) proposes two novel frameworks for sentiment analysis using multi-source unsupervised domain adaptation. The first framework, Weighting Scheme based unsupervised domain adaptation (WS-UDA), combines source classifiers to generate pseudo-labels for target instances. The second, Two-Stage Training based unsupervised domain adaptation (2ST-UDA), leverages these pseudo-labels to train a target-specific extractor. Both frameworks use adversarial training with a discriminator to measure the relationship between target instances and source domains, informing the weighting scheme for source classifiers. The model was applied to multiple datasets and achieved 87% average accuracy. The study demonstrated the effectiveness of WDIRL through empirical studies on various multi-domain sentiment analysis tasks. The results showed performance improvements compared to traditional DIRL methods.

A study conducted by Ijaz et al. (2024) explores sentiment analysis using transfer learning. The study uses a multi-domain sentiment classification technique with BERT, RoBERTa, ELECTRA, and ULMFiT models to improve sentiment analysis performance. They tested these models on five datasets: Hotel Reviews, Movie Reviews, Sentiment140 Tweets, Citation Sentiment Corpus, and Bioinformatics Citation Corpus.

The study found that transfer learning, particularly with transformer models, can enhance sentiment analysis. The main advantage of using transfer learning in sentiment analysis is that it allows researchers to overcome domain-related difficulties. The research points out that traditional machine learning techniques for sentiment analysis, which rely on textual features or sentiment lexicons, often fail when applied to new domains. Transfer learning helps to address this by enabling models to learn from labelled data in one domain and apply that knowledge to unlabelled data in a different but related domain. This is particularly useful when there is limited labelled data available for the target domain, as it reduces the need for extensive data labelling. Transfer learning models performed relatively well compared to other deep-learning models.

Research conducted by Rostami et al. (2021) proposes a new domain adaptation method for sentiment analysis that increases the separation between classes in an embedding space. This method helps to reduce the impact of "domain shift" on classifier performance in the target domain. Inducing large margins between classes in the source domain helps to improve the generalisation ability of a sentiment classifier when applied to a different, but related, target domain. Essentially, by creating a larger separation between classes in the source domain, the model is better able to handle the natural variations in language and sentiment expression that occur across different domains. This makes it more robust than the phenomenon known as "domain shift," where a model's performance deteriorates when applied to data from a different domain than the one it was trained on.

Work done by Li et al. (2023) suggests a novel active learning approach to address the challenge of domain adaptation in sentiment classification, particularly when there is a significant difference between the source and target domains. This approach involves training two separate classifiers: one on labelled source domain data and another on a small amount of actively selected labelled data from the target domain. These classifiers, enhanced by leveraging unlabelled target domain data through label propagation, are then used to strategically select informative samples from the target domain using a Query-By-Committee strategy. Finally, the two classifiers are combined to make the final classification decision. The results demonstrate that this approach significantly outperforms existing state-of-the-art methods. Notably, using only 200 labelled documents from the target domain, their method achieved comparable performance to in-domain classifiers trained on 1 600 labelled documents.

Study conducted by Jambhulkar et al. (2014) proposes a multi-domain sentiment analysis methodology. It addresses the challenge of domain generalisation by creating a "sentiment glossary". This glossary uses labelled data from a source domain and unlabelled data from both source and target domains to handle feature mismatch problems. The study uses pointwise mutual information and the distributional hypothesis to cluster semantically similar words in the glossary. This helps improve the classifier's performance on the target domain. The model was applied to the Amazon reviews (DVD, Books, Electronics, Kitchen) dataset and achieved 80% accuracy.

### Transfer Learning

Transfer learning is a powerful machine learning technique that involves leveraging knowledge from one domain (source domain) to improve performance in another domain (target domain) (Oquab et al., 2014). In the context of multi-domain sentiment analysis, transfer learning helps models generalise better by using the information learned from multiple domains to enhance sentiment classification in a new or less represented domain (Bollegala et al., 2013).

During domain adaptation, it is essential to have a source domain and a target domain. The source domain should consist of sufficient labelled datasets with sentiment knowledge in comparison to the target domain. By leveraging this assumption, a transfer learning model can be created to facilitate the transfer of sentiment knowledge from the source domain to the target domain. Hence, a domain adaptation technique employing the transfer learning method needs to pinpoint common features across the domains in order to connect the source and target domains effectively. Transfer learning involves training a model on a large dataset from one or more source domains and then fine-tuning or adapting the model to a target domain. This approach takes advantage of the rich feature representations and knowledge acquired during the initial training phase, making it easier for the model to adapt to new, unseen domains (Wu &. Huang, 2016). Depending on how the source domain relates to the target domain, transfer learning methods can be categorised into three groups: instance-based transfer learning, model-parameter-based transfer learning and feature-based transfer learning. Instance-based transfer learning is a straightforward method where relevant examples from the source domain are chosen to supplement the training set of the target domain, enhancing the overall migration effect. Model-parameter-based transfer learning focuses on sharing model parameters between the source and target domains. Essentially, a neural network model is pre-trained using a significant amount of data from the source domain and then directly applied to the target task with potential reuse of some or all model parameters. Feature-based transfer learning involves two approaches: feature-extraction-based and feature-mapping-based methods (Weiss et al., 2016) .

The feature-extraction-based transfer method involves repurposing pre-trained local networks from the source domain and incorporating them into a deep network in the target domain. On the other hand, the feature-mapping-based transfer method aligns instances from both source and target domains into a new data space where their data distributions become similar. This alignment is beneficial for the joint deep neural network. Adjusting the data distribution allows for an expanded training set, leading to enhanced transfer effectiveness (Rodríguez et al., 2017).

## 4. Data Collection

In order to determine the relevant models, datasets and evaluation metrics within the context of multi-domain sentiment classification, 19 deep learning sentiment classification studies were reviewed. Table 1. indicates the findings from the study.

Table 1. Key outcomes from the studies selected

| # | ***Reference*** | ***Year*** | ***Model*** | ***Dataset and Domains*** | ***Evaluation Metrics*** |
|---|---|---|---|---|---|
| 1 | (Du et al., n.d.) | 2020 | BERT with Adversarial Training | Amazon reviews (DVD, Books, Electronics, Kitchen) | Accuracy |
| 2 | (Zhou et al., n.d.) | 2020 | Sentiment Masking and Sentiment Aware Language Model | Amazon reviews (DVD, Books, Electronics, Kitchen) | Accuracy |
| 3 | (Peng & Zhand, 2020) | 2020 | Adversarial-learning-based domain adaptation model | Amazon reviews (DVD, Books, Electronics, Kitchen) | Accuracy |
| 4 | (Li et al., 2020) | 2020 | Contrastive Learning | Amazon reviews (DVD, Books, Electronics, Kitchen) | Accuracy |

| # | *Reference* | *Year* | *Model* | *Dataset and Domains* | *Evaluation Metrics* |
|---|---|---|---|---|---|
| 5 | (Patel et al., 2021) | 2021 | Neural Network with Improved Grey Wolf Optimisation | Amazon reviews (DVD, Books, Electronics, Kitchen) | Accuracy, Precision, Recall, F1 Measure, Negative Predictive Value |
| 6 | (Yuan et al., 2021) | 2021 | BERT with Adversarial Feature Learning | Amazon reviews (DVD, Books, Electronics, Kitchen), Amazon FDU-MTL (16 domains) | Accuracy |
| 7 | (Aggarwal, 2021) | 2021 | SVM, Naïve Bayes, Decision Tree | Amazon reviews (DVD, Books, Electronics, Kitchen) | Accuracy, Precision, Recall |
| 8 | (Geethapriya & Valli 2021) | 2021 | Cross-Domain Sentiment Analysis by Refining Feature Extraction | Amazon reviews (DVD, Books, Electronics, Kitchen) | Accuracy |
| 9 | (Mousa et al. 2021) | 2021 | CNN, LSTM, GRU | Amazon (DRANZIERA) Review | Accuracy, Precision, Recall, F1 Measure |
| 10 | (Wu & Shi, 2022) | 2022 | Adversarial Soft Prompt Tuning method | Amazon reviews (DVD, Books, Electronics, Kitchen) | Accuracy |
| 11 | (Luo et al., 2022) | 2022 | Contrastive learning on BERT (COBE) | Amazon reviews (DVD, Books, Electronics, Kitchen), Amazon FDU-MTL (16 domains) | Accuracy |
| 12 | (Fu et al., 2022) | 2022 | Contrastive transformer-based domain adaptation | Amazon reviews (DVD, Books, Electronics, Kitchen), Amazon FDU-MTL (16 domains) | Accuracy |
| 13 | (Li et al., 2023) | 2023 | Sentiment-Driven Semantic Graph | Amazon reviews (DVD, Books, Electronics, Kitchen), YELP reviews | Accuracy |
| 14 | (Gunasekar et al., 2023) | 2023 | CWAN (Collaborative Word Attention Network) | Amazon reviews (DVD, Books, Electronics, Kitchen) | Accuracy |
| 15 | (Katsarou et al., 2023) | 2023 | BiLSTM-based stacked Autoencoder | Amazon reviews (DVD, Books, Electronics, Kitchen), Amazon FDU-MTL (16 domains) | Accuracy |
| 16 | (Wang & Luo, 2023) | 2034 | RolePlaying (RP) prompting strategy, Chain-of-thought (CoT) strategy and RP-CoT prompting | IMDB, FiQA, Amazon reviews | Accuracy |
| 17 | (Lyu et al., 2023) | 2023 | Global-Local Dynamic Adversarial Learning (GLDAL) | Amazon, IMDB, Covid Review, SST-5,SST-2 | Accuracy |
| 18 | (Kong et al., 2023) | 2023 | Feature projection and multi-source attention (FPMA) | Amazon reviews (DVD, Books, Electronics, Kitchen), online_shopping_10_cats | Accuracy |

| # | *Reference* | *Year* | *Model* | *Dataset and Domains* | *Evaluation Metrics* |
|---|---|---|---|---|---|
| 19 | (Wang et al., 2024) | 2024 | BERT with Invariant Representation Learning via Backdoor Adjustment | Amazon reviews (DVD, Books, Electronics, Kitchen), Restaurant, Airline, IMDB revies | Accuracy |

## 5. Evaluation and Discussion

Based on this study it is evident that numerous methods and deep learning algorithms are being applied to address the problem of multi-domain sentiment analysis including leveraging advancements in NLP and machine learning. Domain adaptation techniques, such as transfer learning, have proven effective by fine-tuning pre-trained models like BERT on target domain data, thereby enhancing their ability to generalise across domains. Transfer learning adaptations have played a role in tackling the complexities of analysing sentiments across various domains. Researchers have effectively improved the performance of trained language models such as BERT, GPT and RoBERTa by customising them for specific target domains. This customisation process enables the models to maintain their linguistic and contextual understanding while adjusting to the distinct vocabularies and expressions of sentiment within the target domain.

Cutting edge techniques in domain adaptation like domain training and Maximum Mean Discrepancy have been applied to align feature distributions between different domains. This helps reduce the impact of changes in domains. Moreover, strategies such as data augmentation, which involves creating data using methods like back translation and synonym replacement are used to tackle issues related to limited and unbalanced data. Multitask learning, where models are trained on related tasks simultaneously has also shown effectiveness, in improving the resilience and generalisation abilities of sentiment analysis models across a variety of domains. These changes in transfer learning have significantly enhanced the precision, dependability, and usefulness of sentiment analysis systems across domains. Techniques like creating data through back translation and generating domain-specific synthetic data assist models in grasping domain-specific traits more efficiently. Moreover, training models across domains simultaneously known as multi-domain training ensures the creation of sturdy and adaptable models. Employing methods that merge predictions, from various models trained on diverse domains or subsets of data also boosts model resilience and accuracy.

Different forms of learning have greatly pushed forward the realm of multi-domain sentiment analysis by skilfully tackling domain shift and feature disparities. In this method, domain neural networks (DANN) are used to reduce the gap between feature distributions in the original and target domains. By adding a domain discriminator to the model, adversarial learning strives to ensure that the sentiment classifier learns features that are consistent regardless of the domain. This involves teaching the feature extractor to generate representations that are not specific to any domain, thereby improving the model's capacity to adapt across various domains.

In addition, methods like gradient reversal layers are applied in training to better match the source and target domain distributions during training. These techniques push the model to grasp features that are not tied to any single domain enhancing its performance on unfamiliar domains. Moreover, adversarial learning has been expanded to tackle scenarios involving domains by including various domain discriminators, each specialising in a different domain and using ensemble approaches to merge their results. These adjustments have been successful in addressing the challenges posed by domain variations resulting in precise and dependable sentiment analysis across various domains. Multi-domain sentiment analysis faces several significant challenges that need to be addressed to improve its effectiveness and reliability. These challenges arise due to the inherent differences between domains, variations in language use, and the limitations of current methodologies. Below are the detailed challenges associated with multi-domain sentiment analysis:

### Domain Shift

Handling domain shift presents a challenge in multi-domain sentiment analysis. It involves the differences in data distributions among domains, which can impact the performance of sentiment analysis models. Domain shift occurs when there are variations in data distribution between the source domain (where the model is trained) and the target domain (where it is applied or tested). These differences can manifest in ways, such as variations in vocabulary usage writing styles topics covered or how sentiments are expressed. Models trained on one domain may encounter challenges when applied to another due to discrepancies, in usage writing styles and expressions of sentiment.

**Data Sparsity and Imbalance**

Insufficient labelling of data in fields is referred to as data sparsity. This means that there is not enough training data to fully capture the characteristics and emotional nuances of the specific area. Data imbalance occurs when there is a distribution of sentiment categories (such as positive, negative and neutral) in the dataset. For example, a dataset may contain more positive reviews than negative ones. This imbalance can lead to models that struggle to generalise effectively across various areas, especially those with limited available data. In situations where data-scarce models may fail to grasp the subtle nuances and unique patterns specific to the target domain, this may result in less than optimal performance.

**Feature Mismatch**

Feature discrepancy occurs when the attributes (such as words, phrases, and sentence structures) used in the domain (where the model is trained) significantly differ from those in the new domain (where the model is applied). These differences can lead to misunderstandings or incomplete interpretation of emotional signals in the new domain. Models may find it challenging to recognise characteristics or misinterpret emotional nuances due to feature discrepancy.

**Lexical and Semantic Variability**

Analysing sentiments across domains faces obstacles due to the diversity in language usage, vocabulary choices and interpretations. Sentiment analysis algorithms may struggle with accuracy because of the linguistic characteristics in different domains. For instance, technical assessments include industry terms while film reviews focus on storyline details and actor portrayals. When algorithms encounter sector-specific phrases, diverse lexicons and interpretations can lead to inaccurate sentiment evaluations.

**Developing Multi-Domain Sentiment Benchmarks**

Developing benchmarks and datasets for analysing sentiments across various domains will necessitate a joint endeavour involving researchers in collaboration with industry stakeholders and platform providers.

To establish a comprehensive sentiment benchmark across domains, it is essential to gather datasets from various sectors, such as healthcare, finance, politics and online commerce. This collaboration may require working with platform providers, governments and researchers to guarantee that the datasets accurately reflect real world sentiments. Establishing guidelines and standards for annotation and labelling is crucial to maintain the quality and comparability of datasets across different sources of information data sets. Effective evaluation criteria are crucial for evaluating the effectiveness of sentiment analysis models that operate across domains. The criteria need to extend beyond accuracy and should also measure contextual comprehension and emotional richness along with the ability to generalise across various domains.

## 6. Conclusion and Future Work

Multi-domain sentiment analysis has the potential to improve the accuracy and usefulness of sentiment classification systems in different areas. By using data from multiple domains, models can become more versatile and perform better tackling of issues like lack of data and differences in language across domains. This approach expands the applications of sentiment analysis and ensures more reliable predictions in diverse situations. A detailed examination is conducted in this review on the methods and progress in multi-domain sentiment classification focusing on challenges such as changes in domain lack of data, variations in meaning and differences in features. The review also discusses techniques such as transfer learning adapting to different domains and using pre-trained language models, like BERT.

Creating benchmarks and datasets for analysing sentiments across various domains has the potential to advance the field significantly. These tools can help in evaluating and comparing models in areas which may lead to innovation and fairness. The ultimate goal is to develop sentiment analysis models that are robust and adaptable enough to handle the nuances of content, in different fields. Future work in multi-domain sentiment classification can be explored on advanced domain adaptation techniques, such as contrastive transfer learning and domain-invariant feature extraction, which are needed to mitigate the issues relating to domain shift. Techniques such as data augmentation, semisupervised learning, and leveraging unlabelled data can help address data sparsity and imbalance. Developing domain-specific feature extraction methods and using domain adaptation frameworks to align features across domains. Using pre-trained language models with a broad understanding of language and fine-tuning them on specific domains can improve handling of lexical and semantic variability.

## 7. References

Aggarwal, S. (2021). Multi-domain sentiment analysis. *International Journal of Computer Trends and Technology*, *69*(3), 85–89. doi: 10.14445/22312803/ijctt-v69i3p115

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

Bollegala, D., Weir, D., & Carroll, J. (2013). Cross-domain sentiment classification using a sentiment sensitive thesaurus. *IEEE Transactions on Knowledge and Data Engineering*, *25*(8), 1719–1731. doi: 10.1109/TKDE.2012.103

Dai, Y., Liu, J., Ren, X., & Xu, Z. (2020). *Adversarial training based multi-source unsupervised domain adaptation for sentiment analysis*. Retrieved October 12, 2024 from http://arxiv.org/abs/2006.05602

Du, C., Sun, H., Wang, J., Qi, Q., & Liao, J. (n.d.). Adversarial and domain-aware BERT for cross-domain sentiment analysis. In *Proceedings of the 58th annual meeting of the Association for Computational Linguistics* (pp. 4019-4028). Retrieved 12 October 2024, from: https://aclanthology.org/2020.acl-main.370/

Fu, Y., & Liu, Y. (2022). Contrastive transformer based domain adaptation for multi-source cross-domain sentiment *Knowledge-Based Systems*, *245*, 108649.

Geethapriya, A., & Valli, S. (2021). An enhanced approach to map domain-specific words in cross-domain sentiment analysis. *Information Systems Frontiers*, 1-15.

Luo, Y., Guo, F., Liu, Z., & Zhang, Y. (2022). *Mere Contrastive Learning for Cross-Domain Sentiment Analysis*. Retrieved October 12, 2024 from: http://arxiv.org/abs/2208.08678

Lyu, J., Zhang, Z., Chen, S., & Fan, X. (2023). Global-local dynamic adversarial learning for cross-domain sentiment analysis. *Mathematics*, *11*(14). doi: 10.3390/math11143130

Mousa, R., Shoukhcheshm, R., Moradizadeh, E., Hamian, M., Abadi, A. K., & Safari, L. (2021). Weighted deep neural network ensemble approach for multi-domain sentiment analysis. *Journal of Applied Research on Industrial Engineering*. doi: 10.22105/jarie.2021.288364.1332

Oquab, M., Bottou, L., Laptev, I., & Sivic, J. (2014). *Learning and transferring mid-level image representations using convolutional neural networks*. Retrieved October 12, 2024 from: https://openaccess.thecvf.com/content_cvpr_2014/papers/Oquab_Learning_and_Transferring_2014_CVPR_paper.pdf

Patel, D., & Amin, K. (2021). Multi-source domain adaptation in sentiment analysis using optimized neural network and cross-domain semantic library. *International Journal of Intelligent Engineering and Systems*, *14*(5), 539–549. doi: 10.22266/ijies2021.1031.47

Peng, M., & Zhang, Q. (2020). Weighed domain-invariant representation learning for cross-domain sentiment analysis. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 251–265, Barcelona, Spain. Retrieved October 12, 2024 from: https://aclanthology.org/2020.coling-main.22/

Rodríguez, P., Cucurull, G., Gonfaus, J. M., Roca, F. X., & Gonzàlez, J. (2017). Age and gender recognition in the wild with deep attention. *Pattern Recognition*, *72*, 563–571. doi: 10.1016/j.patcog.2017.06.028

Rostami, M., & Galstyan, A. (2021). *Domain adaptation for sentiment analysis using increased intraclass separation*. Retrieved October 12, 2024 from: http://arxiv.org/abs/2107.01598

Shilpa, P. C., Shereen, R., Jacob, S., & Vinod, P. (2021). Sentiment analysis using deep learning. *Proceedings of the 3rd International Conference on Intelligent*

*Communication Technologies and Virtual Mobile Networks, ICICV 2021*, 930–937. doi: 10.1109/ICICV50876.2021.9388382

Vincent, N., Johnson, I., Sheehan, P., & Hecht, B. (2019). *Measuring the importance of user-generated content to search engines*. Retrieved October 12, 2024 from https://github.com/nickmvincent/you-geo-see

Wang, S., Zhou, J., Chen, Q., Zhang, Q., Gui, T., & Huang, X. (2024). *Domain generalization via causal adjustment for cross-domain sentiment analysis*. Retrieved October 12, 2024 from http://arxiv.org/abs/2402.14536

Wang, Y., & Luo, Z. (2023, December). Enhance multi-domain sentiment analysis of review texts through prompting strategies. In *2023 International Conference on High Performance Big Data and Intelligent Systems (HDIS)* (pp. 1-7). IEEE.

Weiss, K., Khoshgoftaar, T. M., & Wang, D. D. (2016). A survey of transfer learning. *Journal of Big Data*, *3*(1). doi: 10.1186/s40537-016-0043-6

Wu, F., & Huang, Y. 2016, August). *Sentiment domain adaptation with multiple sources*. *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)* (pp. 301-310).

Wu, H., & Shi, X. (2022, May). Adversarial soft prompt tuning for cross-domain sentiment analysis. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)* (pp. 2438-2447).

Yuan, J., Zhao, Y., Qin, B., & Liu, T. (2021). *Learning to share by masking the non-shared for multi-domain sentiment classification*. Retrieved October 12, 2024 from http://arxiv.org/abs/2104.08480

Zhou, J., Tian, J., Wang, R., Wu, Y., Xiao, W., & He, L. (n.d.). *SENTIX: A sentiment-aware pre-trained model for cross-domain sentiment analysis*. Retrieved October 12, 2024 from https://github.com/12190143/SentiX