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Unifying Adversarial Adaptation and Maximum Mean Discrepancy for Enhanced Cross-Domain Aspect Sentiment Classification

[1]Sampathirao Suneetha, [2] Prof. S. Viziananda Row

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Abstract: Cross-domain sentiment analysis is a fundamental challenge in NLP with applications in diverse areas such as product reviews, customer feedback, and social media monitoring. In this paper, we propose a comprehensive approach for Cross-Domain Aspect-Based Sentiment Analysis (CD-ABSA) that integrates aspect extraction and sentiment classification. Leveraging pre-trained Bidirectional Encoder Representations from Transformers (BERT) models, our methodology presents a novel framework that utilizes Adversarial Domain Adaptation, incorporating Maximum Mean Discrepancy (MMD) to facilitate the adaptation of sentiment classifiers from one domain to another, specifically in the restaurants, laptops, books, and clothes domains. Our approach ensures accurate sentiment analysis across diverse domains by reducing the distribution gap through adversarial domain adaptation and MMD(ADA-MMD). We evaluate our model using accuracy and F1-Scores and show its superior performance compared to existing methods. This research represents a significant step towards domain-agnostic sentiment analysis by combining aspect extraction and sentiment classification within a unified framework, providing practical solutions for scenarios with limited or no domain-specific labeled data.

Keywords: *Cross-Domain Aspect based Sentiment Analysis, Aspect Extraction, Sentiment Classification, Adversarial Domain Adaptation, Maximum Mean Discrepancy.*

1. Introduction:

Sentiment analysis, a branch of NLP, has gained significant attention in recent years due to its potential applications in understanding and extracting sentiment or opinions from textual data. This technology has numerous real-world applications, ranging from market research to social media monitoring and customer feedback analysis. One of the essential aspects of sentiment analysis is the extraction of aspects or specific topics within text documents to determine the sentiment associated with those aspects [[1]]. Aspect Based Sentiment Analysis (ABSA) takes sentiment analysis a step further by considering the sentiment expressed towards specific aspects or features within a text [[2]]. ABSA provides a more fine-grained understanding of opinions, making it particularly valuable for domains like product reviews and customer feedback where opinions are expressed about multiple aspects of a product or service [[3]].

1Research Scholar, 2Professor

1,2Department of CS&SE, AUCE, Andhra University, Visakhapatnam, AP, India.

1Corresponding author: email: sampath.suneetha@gmail.com

However, real-world sentiment analysis applications often involve multiple domains. In such scenarios, the performance of sentiment analysis models can degrade when applied to domains that were not seen during training, as they may exhibit differences in language, sentiment expression, or topic distribution. This challenge gave rise to the need for cross-domain sentiment analysis [[4]], where models are designed to handle data from different domains effectively.

The idea of CD-ABSA required us to address two key components: aspect extraction and sentiment classification. Firstly, the aspect extraction task was addressed in our previous work [[5]] leveraging adversarial domain adaptation with BERT [[6]]. In this paper, we advance this domain adaptation further by integrating MMD with adversarial domain adaptation, refining our approach for improved cross-domain sentiment classification.

In CD-ABSA, an aspect is a specific feature or attribute of a product or service that the user expresses their opinion on. For example, in the sentence “The battery life is amazing, but the camera quality is poor”, the aspects are “battery life” and “camera quality”, and the sentiments are “positive” and “negative”, respectively. To perform CD-ABSA, we combine our model with the cross-domain aspect extraction using adversarial domain adaptation model that we developed in our previous paper [[5]]. The cross-domain aspect extraction model can identify and extract the aspects from the text. We then feed the extracted aspects and the text to our model discussed in this paper and predict the sentiment labels for each aspect. The flow of CD-ABSA is shown in Figure 1. This way, we can obtain a more fine-grained and comprehensive analysis of the user opinions across different domains.

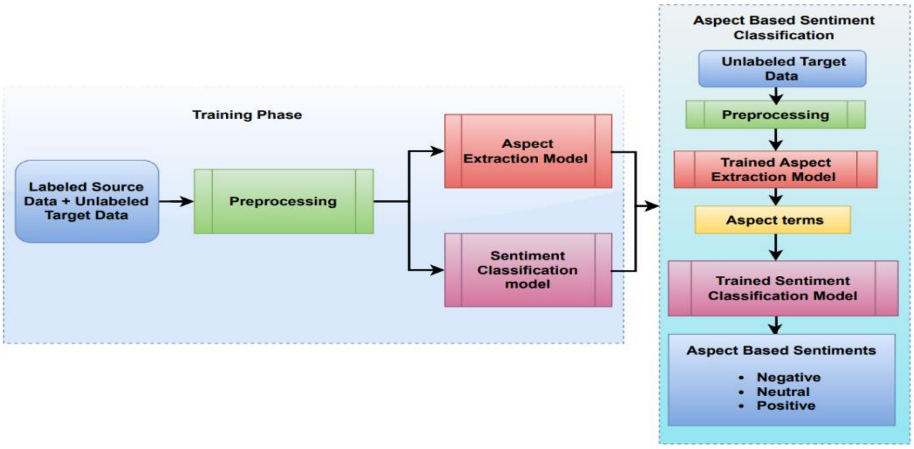

Fig 1: Cross Domain ABSA

Adversarial domain adaptation is a technique that helps align the feature distributions of different domains, reducing the domain shift problem [[7]]. By incorporating adversarial learning, we aim to make our model domain-agnostic, enabling it to perform well in unseen domains. MMD [[8]], on the other hand, provides an effective way to measure the dissimilarity between distributions [[9]], helping us further improve cross-domain performance.

Our model is meticulously designed to bolster the generalizability of sentiment classification across diverse domains while concurrently delving into the granular analysis of aspect-based sentiments. By enhancing domain adaptation through the fusion of MMD and adversarial domain adaptation techniques, we aim to elevate the effectiveness and robustness of sentiment classification in various domain-specific contexts.

To evaluate the effectiveness of our approach, we conduct experiments in four diverse domains: restaurants, laptops, books, and clothes reviews. We measure the performance of our model using accuracy and F-scores, shedding light on how well it adapts and generalizes to different domains. Our results provide insights into the challenges and solutions involved in cross-domain aspect-based sentiment analysis, with potential implications for various applications where understanding nuanced opinions is essential. The contributions of this paper can be summarized as follows:

- Integration of BERT for efficient feature extraction, and incorporation of previously extracted aspects from our previous work [[5]], allowing for a comprehensive understanding of sentiment at the aspect level across different domains.
- Introduction of a novel framework for cross-domain aspect-based sentiment analysis, combining adversarial domain adaptation and MMD techniques, improving cross-domain sentiment analysis capabilities.

2. Related Work:

In the realm of ABSA, several models have emerged for fine-grained sentiment analysis, leveraging supervised learning methods. Mitchell et al. [[10]] utilized handcrafted features and conditional random fields for aspect identification and sentiment polarity. Zhang et al. [[11]] combined word embeddings with automated features for ABSA. Li et al. [[12]] proposed a holistic framework encompassing aspect extraction, sentiment classification, and sentiment consistency regularization. He et al. [[13]] introduced an interactive multi-task learning network, while Zhou et al. [[14]] presented a span-based model for joint aspect extraction and sentiment classification. Despite their promise, these supervised models often demand extensive annotated data, posing challenges in real-world applications.

In the domain of cross-domain sentiment analysis, several researchers primarily have concentrated on domain adaptation for coarse-grained sentiment classification, lacking the fine-grained aspect identification needed for ABSA. Li et al. [[15]] employed history attention and selective transformation for aspect term extraction. He et al. [[16]] proposed effective attention modeling for aspect-level sentiment classification, while Li et al. [[17]] introduced a unified model for opinion target extraction and sentiment prediction. Zhang et al. [[18]] explored aspect and opinion terms co-extraction based on partially-supervised word alignment. Jakob et al. [[19]] focused on extracting opinion targets in both single- and cross-domain settings using conditional random fields, whereas Li et al. [[20]] delved into learning to identify review spam. Ding et al. [[21]] introduced a lexicon-based approach to opinion mining, and Wang et al. [[22]] utilized recursive neural networks for aspect and opinion term co-extraction in multi-domain adaptation. UDA [[23]], an approach that unifies feature-based and instance-based adaptation techniques for cross-domain ABSA; FMIM [[24]], a feature-based domain adaptation method employing fine-grained mutual information maximization; CDRG [[25]], a cross-domain review generation approach that utilizes labeled source-domain reviews to generate labeled target-domain reviews based on masked language models; DA^2LM [[26]], a cross-domain Data Augmentation framework based on Domain Adaptive Language Modeling (DA^2LM), which contains three key stages to automatically generate sufficient target-domain labeled data, including Domain-Adaptive Pseudo Labeling, Domain-Adaptive Language Modeling, and Target-Domain Data Generation; Li et al. [[27]] introduced selective adversarial learning for cross-domain ABSA.

Expanding upon Li et al.'s [[27]] approach, our work integrates adversarial domain adaptation and MMD techniques to facilitate cross-domain sentiment analysis. Additionally, we incorporate the cross-domain aspect extraction task outlined in our previous work [[5]], thereby achieving comprehensive cross-domain ABSA.

3. Problem Statement:

The study focuses on addressing cross-domain aspect sentiment classification, where labeled data D_S from a source domain and unlabeled data D_T from a target domain are available. The objective is to predict sentiment polarities for aspect terms within text inputs lacking labeled sentiment information in the target domain. Domain adaptation techniques such as MMD and adversarial domain adaptation employing BERT as the feature extractor to bridge the domain gap between D_S and D_T have been addressed in our present work. In the source domain D_S , the dataset comprises pairs of input texts x_i^s and their corresponding aspect-related sentiment labels y_i^s . Conversely, the target domain D_T consists of text inputs x_i^t with aspect terms but devoid of labeled sentiment polarities. The challenge lies in effectively transferring knowledge from D_S to D_T to accurately predict sentiment polarities for aspect terms in the absence of labeled target domain data.

Notations:

$D_S = \{(x_i^s, y_i^s)\}_{i=1}^{n_s}$: Labeled source domain dataset.

x_i^s: Input text with aspect terms.

y_i^s: Corresponding sentiment polarity labels for aspect terms in x_i^s.

$D_T = \{x_i^t\}_{i=1}^{n_t}$: Unlabeled target domain dataset.

x_i^t: Input text with aspect terms but without labeled sentiment polarities.

$A = \{a_1, a_2, ..., a_m\}$: Extracted aspect terms from x_i^s and x_i^t.

Objective: Predict sentiment polarities $Y = \{y_1, y_2, ..., y_m\}$ corresponding to aspect terms in D_T utilizing D_S knowledge, domain adaptation techniques, and BERT feature extraction.

The research methodology involves developing a model that can generalize sentiment predictions for aspect terms in the target domain by effectively using labeled data from the source domain. By employing domain adaptation techniques such as MMD and adversarial domain adaptation, the feature distributions between the source and target domains are aligned, addressing domain shift issues. Utilizing BERT as the feature extractor allows the model to encode contextual information of aspect terms and their surroundings in both D_S and D_T . Consequently, the model learns representations that facilitate sentiment classification for aspect terms in the target domain despite the absence of labeled sentiment information.

4. Methodology Of Cross-Domain Sentiment Classification:

4.1 Pre-processing: In this initial phase, we undertake data preprocessing to prepare it for the training process. This preprocessing encompasses several essential tasks [[28]]. Firstly, we convert all the text data to lowercase to maintain uniformity in representations. Furthermore, we eliminate punctuation marks, such as periods, commas, and quotation marks, from the text to prevent them from affecting the learning process. Next, we tokenize the text by breaking it down into individual tokens or words. This division allows us to capture finer linguistic nuances and empowers the model to process the text at the token level.

A key part of our preprocessing involves associating tokens with sentiment labels. However, before assigning sentiment tags, we first compare each token with a set of predefined aspect labels. If a token matches an aspect label, we assign it a sentiment value that corresponds to its related sentiment (0 for negative, 1 for neutral, and 2 for positive). If the token does not correspond to an aspect term, we assign it a value of -1. This approach helps us more accurately determine the sentiment related to specific aspects within the text.

Following tokenization and sentiment tagging, we transform the text into a numerical format. We create a vocabulary of unique tokens and assign a unique index to each. These indices replace the original tokens in the text, thus converting it into a numerical representation that is suitable for machine learning algorithms. This process ensures that our model not only understands the sentiment of each part of the text but also recognizes the specific aspects these sentiments are associated with.

Lastly, we set up data loaders to manage the loading and preprocessing of data in batches during training. Data loaders enhance training speed and optimize memory usage by efficiently handling the batch processing of the data. To guarantee that all input sentences share the same length, we carry out sequence padding. Sentences shorter than the maximum sequence length is extended with special padding tokens, while longer sentences are truncated. This step ensures efficient batch processing during training and maintains consistent input dimensions for the model.

4.2 Feature Extraction: Selecting an appropriate Feature Extraction model is crucial for effective cross-domain sentiment analysis. Our choice of BERT is driven by its ability to capture complex linguistic patterns due to its bidirectional training and extensive pre-training on diverse corpora, making it highly suitable for analyzing varied linguistic structures in cross-domain sentiment analysis.

BERT transforms an input sequence into contextual embeddings, where each token is represented as a vector that encodes its meaning in the context of the entire sequence. Mathematically, BERT transforms a sequence of input embeddings X = $[x_1, x_2, ..., x_n]$ into a sequence of contextual embeddings H = $[h_1, h_2, ..., h_n]$.

4.3 Learning procedure: The learning procedure in a neural network typically involves a process called training, where the network learns to perform a task by adjusting its parameters based on the input data and expected outputs.

Sentiment Classifier and Sentiment Loss: After obtaining BERT embeddings, a linear classifier [[29]] is employed to map the high-dimensional BERT embeddings to sentiment labels. After obtaining the BERT embeddings, a linear classifier can be represented in equation (1).

$$y=W. x + b \tag{1}$$

where, **y** is the predicted sentiment label, **W** is the weight matrix, **x** is the BERT feature vector, **b** is the bias term. The sentiment loss is calculated using a standard cross-entropy loss function [[30]] as in equation (2), which quantifies the difference between the predicted sentiment labels and the true labels in the source domain.

$$L_{sentiment} = -\sum_{i=1}^{n} y_s^i log(f(X_s^i)) \tag{2}$$

where, $\boldsymbol{y_s^i}$ is the true label for the i-th sample from source domain, $\boldsymbol{f}(\boldsymbol{X_s^i})$is the predicted probability distribution over sentiment classes. Back-propagating the gradients through the layers of the model to update the sentiment classifier parameters(**θ**) is done using the formula in equation (3):

$$\boldsymbol{\theta_{Snew} = \theta_{Sold} - \alpha * \nabla\theta L_{sentiment}} \tag{3}$$

Here, **α** represents the learning rate, which determines the step size for parameter updates during optimization.

Domain Discriminator: In cross-domain sentiment classification, a domain discriminator is utilized as part of domain adaptation techniques to address the challenge of sentiment analysis across different domains. The main role of a domain discriminator in domain adaptation frameworks, is to facilitate the learning of domain-invariant features. It acts as a critical component within adversarial learning setups, working alongside a feature extractor or classifier to discern and differentiate between different domains present in the data. By doing so, it encourages the feature extractor to learn representations that are not specific to any single domain but instead capture shared, transferable information across domains. The domain discriminator essentially guides the model to develop robust, generalized features that are applicable and effective when applied to diverse domains, enhancing the model's ability to adapt and perform well on new, unseen data distributions.

Source and Target Domain Loss: The source domain loss is calculated by applying the domain discriminator to source domain features. It encourages the model to correctly identify source domain samples. Conversely, the target domain loss discourages the model from misclassifying target domain samples as source domain. These losses are theoretically motivated by adversarial domain adaptation, where the discriminator's task is to distinguish between source and target domain features, while the feature extractor BERT aims to counter the discriminator's objective. We compute source domain loss and target domain loss using the formulas in equation (4) and (5):

$$L_{source} = -\sum_{i=1}^{N_s} D_s^i \log(D(X_s^i)) \quad (4)$$

$$L_{target} = -\sum_{i=1}^{N_t} D_t^i \log(D(X_t^i)) \quad (5)$$

where, $\mathbf{N_s}$ is the number of samples in the source domain, $\mathbf{N_t}$ is the number of samples in the target domain, $\boldsymbol{D_s^i}$ is the ground-truth domain class for the i[th] sample in the source data, and $\boldsymbol{D_t^i}$ is the ground-truth domain class for the i[th] sample in the target data.

The domain loss $\boldsymbol{L_{dom}}$ can be calculated as in equation (6):

$$L_{dom} = L_{dom_s} + L_{dom_t} \quad (6)$$

Gradient Reversal Layer: The gradient reversal layer is introduced to enhance the influence of the domain discriminator during training [[31]]. It is theoretically justifiable because it reverses the gradients during backpropagation, essentially maximizing the domain loss while optimizing the overall model. The tunable parameter' **λ'** allows fine-grained control over the trade-off between the sentiment and domain loss. The gradient reversal operation is defined as in equation (7):

$$\nabla\theta L_{dom} = -\lambda \frac{\partial L_{dom}}{\partial \theta_{\mathrm{dom}}} \quad (7)$$

where **λ** is the gradient reversal coefficient. Back-propagate the gradients through the layers of the model to update the parameters of domain discriminator as in equation (8):

$$\theta_{Dnew} = \theta_{Dold} - \alpha * \nabla\theta L_{\mathrm{dom}} \quad (8)$$

Maximum Mean Discrepancy: MMD is a statistical measure used to quantify the dissimilarity between two probability distributions based on their respective samples. It calculates the discrepancy or difference between these distributions by comparing their means in a high-dimensional space through a kernel function. MMD aims to find a representation of the distributions where similar samples from different distributions have a small discrepancy while different samples have a larger one. By minimizing this discrepancy, MMD allows for effective domain adaptation and transfer learning by encouraging models to learn representations that capture relevant information across different domains while emphasizing differences between them.

MMD Loss: MMD loss is a theoretical concept borrowed from domain adaptation literature. It aims to minimize the distributional shift between the source and target domains [[32]]. By using a kernel function, it measures the similarity between distributions in a high-dimensional feature space. The theoretical foundation for MMD lies in the idea that reducing the MMD distance aligns the source and target domain feature distributions, which is crucial for domain adaptation. The formula for MMD for different kernel functions is defined as in equation (9):

$$MMD(P,Q)\begin{cases} \mathrm{E_P[x] - 2E_{P,Q}[X,Y] + E_Q[Y]} & \text{if kernel} = \text{'linear'} \\ \mathrm{((E_P[x] - 2E_{P,Q}[X,Y] + E_Q[Y]) + b)^d} & \text{if kernel} = \text{'poly'} \\ \frac{1}{n^2}\sum_{i,j=1}^{n} k(x_i, x_j) + \frac{1}{m^2}\sum_{i,j=1}^{m} k(y_i, y_j) + \frac{1}{nm}\sum_{i=1}^{n}\sum_{j=1}^{m} k(x_i, y_j) & \text{if kernel} = \text{'rbf'} \end{cases} \quad (9)$$

Here, $\boldsymbol{P}$ and $\boldsymbol{Q}$ are the source and target representations, respectively. $\boldsymbol{E_P[x]}$ is the expected mean value of the source domain features. $\boldsymbol{E_Q[Y]}$ is the expected mean value of the target domain features. $\boldsymbol{E_{P,Q}[X,Y]}$ is the joint expected mean value of the source and target domain features. This term captures the relationship between the source and target domains. '$\boldsymbol{b}$' is the bias term in the polynomial kernel, added to control the influence of higher-order terms in the kernel and to ensure numerical stability and the degree '$\boldsymbol{d}$' determines the complexity of the interactions between features captured by the kernel. A higher degree allows for capturing more complex, higher-order interactions.

For rbf kernel, k is the Gaussian kernel function $\boldsymbol{k}$ $\boldsymbol{(u, v)}$=$\boldsymbol{exp}$ $(-\frac{||\boldsymbol{u}-\boldsymbol{v}||^2}{2\sigma^2})$ where σ is the kernel width parameter, and **n** and **m** are the number of samples in the source and target representations respectively. $||\boldsymbol{u}-\boldsymbol{v}||^2$ represents the squared Euclidean distance between vectors $\boldsymbol{u}$ and $\boldsymbol{v}$.

CDASC-MMD Training: The Figure 2 represents a machine learning workflow for cross-domain aspect sentiment classification using MMD. Initially, both data (labeled source and unlabeled target) are preprocessed to prepare them for feature extraction. Subsequently, BERT extracts feature from the preprocessed text. These features are then fed into a sentiment classifier that predicts the sentiment of the source data, the accuracy of which is quantified by the sentiment loss.

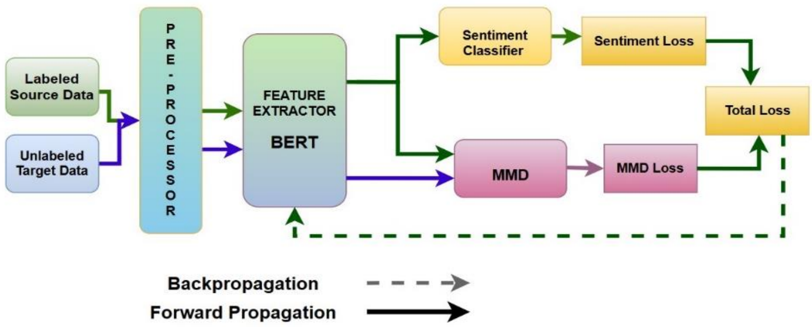

Fig 2: Learning procedure for CDASC-MMD

Alongside this, a domain adaptation technique known as MMD is employed to minimize the distributional differences between the source and target data, resulting in the MMD loss. The total loss of the model is the aggregate of sentiment loss and MMD loss, and it guides the backpropagation process to adjust the model parameters. Through iterative training, the model aims to accurately classify sentiment in the source domain while also generalizing to the target domain, despite the lack of labels in the latter, achieving cross-domain sentiment classification.

CDASC-ADA Training: Due to MMD's limitations in handling high-dimensional spaces and sensitivity to kernel choices, our methodology transitions to CDASC-ADA, which employs adversarial domain adaptation to address these challenges and enhance the model's adaptability to complex domain shifts. The Figure 3 illustrates a learning procedure for cross-domain aspect sentiment classification using adversarial domain adaptation. Initially, both (labeled source and unlabeled target) datasets undergo preprocessing to prepare for feature extraction. The preprocessed data is then input into BERT to extract features. The extracted features serve two main functions: they are input into a sentiment classifier to predict sentiment, and they are also fed into a domain discriminator.

The sentiment classifier aims to determine the sentiment of specific aspects within the text and its performance is measured by calculating the sentiment loss against known labels in the source data. Concurrently, the domain discriminator attempts to distinguish between source and target domain data, contributing to the source domain loss and target domain loss calculations. These losses are instrumental for the model to not only improve in sentiment classification but also to generalize its applicability across different domains.

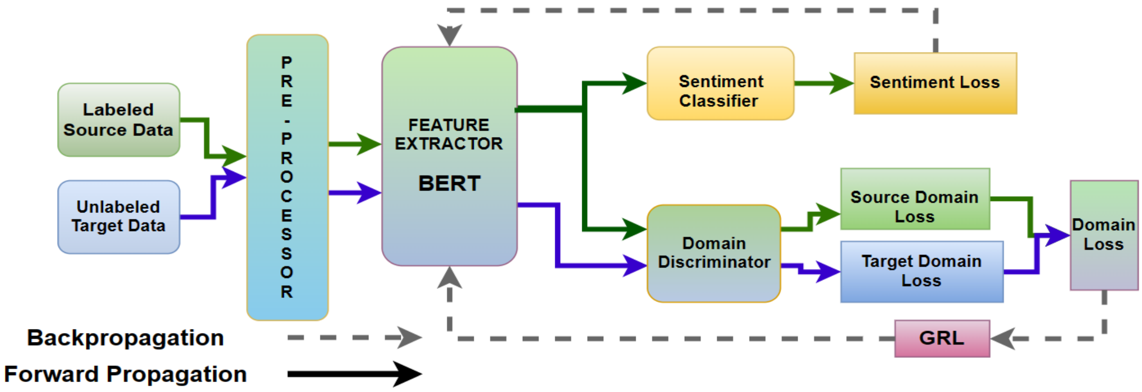

Fig 3: Learning procedure for CDASC-ADA

A key component in this process is the GRL, which reverses the gradient flowing from the domain discriminator during backpropagation. This encourages the feature extractor to generate domain-agnostic features, improving the model's ability to classify sentiment without being confounded by domain differences. The forward and backward propagation arrows depict the training process, where the model iteratively learns from the gradient descent to update its parameters, thereby refining its ability to accurately classify sentiments on seen data and generalize this capability to new, unseen domains.

CDASC-ADA-MMD Training: Building upon the limitations faced by ADA, specifically in achieving complete domain invariance and disentangling complex domain shifts, the methodology further integrates MMD techniques to supplement adversarial adaptation's efforts in aligning source and target domains and reducing distributional discrepancies for more robust cross-domain sentiment classification. The Figure 4 illustrates the architecture of a machine learning process designed to perform aspect sentiment classification across different domains. The process employs both adversarial adaptation and MMD techniques to enhance the model's ability to classify sentiment in a target domain using labeled data from a source domain. Initially, labeled data from the source domain and unlabeled data from the target domain are preprocessed to standardize their format. Then, these data pass through a feature extraction phase, where a BERT model is used to transform the text into numerical features that capture the semantic meanings.

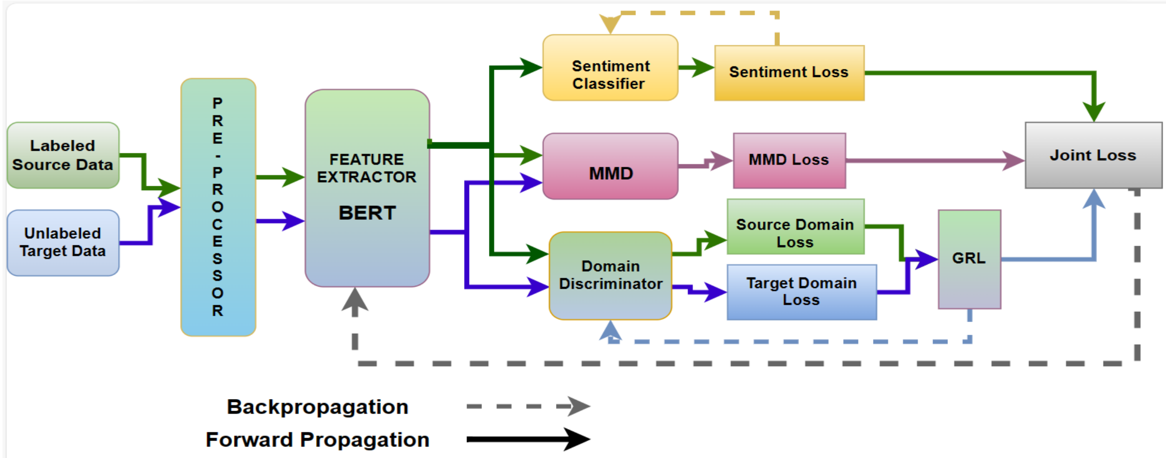

Fig 4: Learning procedure for CDASC-ADA-MMD

A sentiment classifier is trained on the source data to identify sentiment, while the MMD component calculates the discrepancy between the source and target data distributions to minimize this difference, thereby aligning the two domains more closely. Additionally, a domain discriminator is used to make the feature extractor generate domain-invariant features that are indistinguishable between the source and target domains, using adversarial training signaled by the GRL. The model optimizes multiple loss functions concurrently: sentiment loss for classification accuracy, MMD loss to minimize distribution discrepancy, and domain loss to enhance domain invariance. These loss components are then combined into a joint loss that the model aims to minimize. During training, the model uses backpropagation to update the weights, indicated by the dashed lines in the figure, to improve its performance iteratively. The end goal is to create a model that can accurately classify sentiment in the target domain despite the lack of labeled data in that domain.

Algorithm 1 shows the learning procedure of CDASC-ADA-MMD. We use the adam optimizer to update network weights. In the algorithm ∇F, ∇C and ∇D represent partial derivatives of F, C and D respectively.

Algorithm 1: Learning procedure of CDASC-ADA-MMD

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Input: source data x_s, source labels y_s, target data x_t, hyperparameters λ and γ, learning rate α.

Output: target labels y_t

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Step 1: Initialize feature extractor F, label classifier C, domain discriminator D

Step 2: Initialize MMD loss LMMD, classification loss LC, domain loss LD

Step 3: Initialize hyperparameters λ and γ, learning rate α.

Step 4: Repeat the following steps until convergence:

- Sample a mini-batch of source data (x_s, y_s) and target data x_t
- Compute source and target features: $f_s = F(x_s)$, $f_t = F(x_t)$
- Compute source and target labels: $\widehat{y_s}= C(f_s)$, $\widehat{y_t}= C(f_t)$
- Compute source and target domain labels: $d_s = D(f_s)$, $d_t = D(f_t)$
- Compute MMD loss: LMMD = MMD (f_s, f_t)
- Compute classification loss: LC = CrossEntropy($\widehat{y_s}$, y_s)$=-\sum_{i=1}^{n} y_s^i \log(F(X_s^i))$
- Compute domain loss: LD = BinaryCrossEntropy(d_s, 1) + BinaryCrossEntropy(d_t, 0) = $-\sum_{i=1}^{N_s} D_s^i \log\left(D(X_s^i)\right) - \sum_{i=1}^{N_t} D_t^i \log(D(X_t^i))$

Update F by descending its gradient: F = F - α * ((γ*LMMD + LC - λ *LD) *∇F)

Update C by descending its gradient: C = C - α * (LC * ∇C)

Update D by descending its gradient: D = D - α * ((-**λ** *LD) * ∇D)

Step 5: Return $\widehat{y_t}$ as yt

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Joint Training: In the joint training phase of our model, we integrate multiple loss components to calculate the total loss, which is a critical step in the training process. The total loss is a combination of multiple components that serve distinct purposes. The sentiment loss ensures that the model performs well on the sentiment classification task. The source and target domain losses are critical for domain adaptation, while the MMD loss further aids in aligning the feature distributions. Tunable hyperparameter **γ** controls the relative importance of MMD during training, enabling a fine balance between sentiment classification and domain adaptation. The total loss can be defined as the weighted sum of the individual losses as in equation (10)) and (11):

$$L_{total}=L_{sentiment} + L_{source} + L_{target} + L_{MMD} \qquad (10)$$

$$L= -\sum_{i=1}^{n} y_s^i log(f_s(X_s^i))+(-\lambda(-\sum_{i=1}^{n} D_s^i log(g_s(X_s^i)) - \sum_{i=1}^{m} D_t^i log(g_t(X_t^i)))) + \gamma(\mathrm{MMD}(F(X_s^i), F(X_t^i))) \qquad (11)$$

Then backpropagate the total loss L_{total} and update the parameters of feature extractor.

This comprehensive approach integrates advanced techniques from sentiment analysis and domain adaptation to create a model that is practically effective for cross-domain sentiment analysis. ADA-MMD training enriches the model's ability to align feature distributions across domains, resulting in robust and accurate sentiment analysis in previously unseen domains.

4.4 Classification:

After the training phase, the model is applied to unlabeled data from the target domain for classification purposes shown in Figure 5. Initially, the target unlabeled data undergoes preprocessing steps outlined in Section 4.1 to ensure uniformity and readiness for analysis. Once preprocessed, the trained model extracts aspect terms from this data. Aspect extraction involves identifying and isolating specific attributes or features within the text, such as 'battery life' or 'camera quality.' These extracted aspects are then channeled into the sentiment analysis task, where the model further analyzes each aspect to discern sentiments associated with them. This sentiment analysis aims to categorize sentiments as positive, negative, or neutral, providing a nuanced understanding of sentiments pertaining to individual features or attributes mentioned within the text. This process enables a more detailed and insightful analysis of sentiments across various aspects within the target domain's unlabeled data.

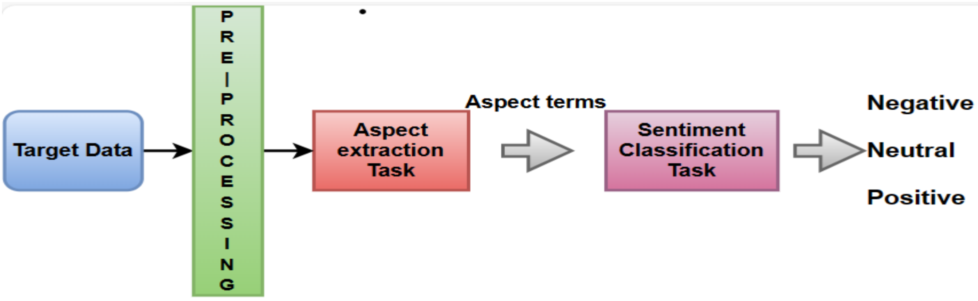


Fig 5: Aspect Sentiment Classification

5. Experiments And Result Analysis:

5.1 Datasets: In our research, we perform experiments using the SemEval 2014 dataset [[33]] comprising reviews from two distinct categories: Restaurants and Laptops. To broaden the scope and evaluate the cross-domain performance of our model, we have expanded our dataset to include two more domains: Clothes and Books. Therefore, our dataset now encompasses reviews from four categories: Restaurants, Laptops, Books and Clothes denoted respectively R, L, B and C. These reviews are categorized into three sentiment polarities: positive, neutral, and negative.

To evaluate the cross-domain performance of our model, we establish pairings between these data domains represented as (L, R), (R, L), (C, B) and (B, C). Within each domain, we partition the data into two separate subsets, which are subsequently divided into train and test sets. A summarized overview of these datasets can be found in Table 1, and the Figure 6 provides a sample representation of the preprocessed data.

Table 1: Description of different domain datasets

Dataset	Description	Total	Train	Test
R	**Restaurants**	**5,841**	**4,673**	**1168**
L	**Laptops**	**3,845**	**2,364**	**590**
B	**Books**	**4,509**	**3,609**	**900**
C	**Clothes**	**3,416**	**2,780**	**636**

1	Tokens	Tags	Polarities
2	['Boot', 'time', 'is', 'super', 'fast', ',', 'around', 'anywhere', 'from', '35', 'seconds', 'to', '1', 'minute', '.']	[1, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	[2, 2, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1]
3	['tech', 'support', 'would', 'not', 'fix', 'the', 'problem', 'unless', 'I', 'bought', 'your', 'plan', 'for', '$', '150', 'plus', '.']	[1, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	[0, 0, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1]
4	['Set', 'up', 'was', 'easy', '.']	[1, 2, 0, 0, 0]	[2, 2, -1, -1, -1]
5	['Did', 'not', 'enjoy', 'the', 'new', 'Windows', '8', 'and', 'touchscreen', 'functions', '.']	[0, 0, 0, 0, 0, 1, 2, 0, 1, 2, 0]	[-1, -1, -1, -1, -1, 0, 0, -1, -1, -1, -1]

Fig 6: Sample Preprocessed data from laptops domain

5.2 Implementation: In our experiments, we follow the standard evaluation protocol for DA according to [[11]] and [[27]]. In CDASC-ADA-MMD, we standardized our parameters, setting λ (GRL coefficient) at 0.01 and γ (MMD coefficient) at 0.1 consistently across all experimental setups. To implement the Transformer model, we utilized bert-base model provided by Hugging Face [[34]], and fine-tuned to our datasets [[35]]. The classifier and domain discriminator are trained from scratch involving backpropagation, with a learning rate of 2e-5 using the Adam optimizer. For our CDASC-ADA-MMD model experiments, we opted for a batch size of 16 to maintain consistency across evaluations. These experiments were conducted on a system running a Windows operating system, equipped with an 11th Gen Intel Core i5 CPU, 8GB of RAM, and a GPUP100 for computational support.

5.3 Hyper-parameters and training: In our experiments, we focused on optimizing hyperparameters for BERT in cross-domain sentiment classification, specifically targeting restaurants and laptops data, as well as books and clothes domains. The results, illustrated in various subplots shown in Figure 7, reveal how different dropout values (0.0, 0.1, 0.2, 0.3, 0.4, 0.5) over 1 to 5 training epochs impact model performance across these domains.

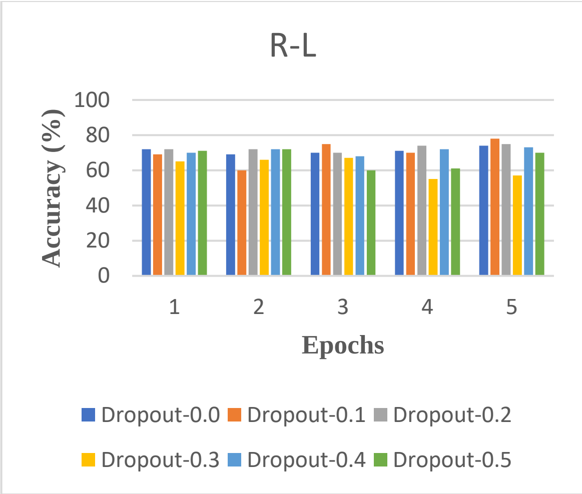
Across diverse domain adaptations ranging from restaurants to laptops, laptops to restaurants, books to clothes, and clothes to books. The impact of dropout rates and epochs in domain adaptation processes is multifaceted and pivotal in determining the model's performance and adaptability to new domains. The transition from the restaurants to laptops domain reveals dropout 0.1 as a standout choice, showcasing its peak accuracy of 78 at the fifth epoch, signifying its efficacy for adaptation. Moreover, dropout 0.2 emerges as consistently optimal, displaying an increasing trend in accuracies across epochs, suggesting an effective adaptation process. Conversely, rates of 0.3 and 0.5 demonstrate notably lower accuracies, highlighting their inadequacy for this specific adaptation.

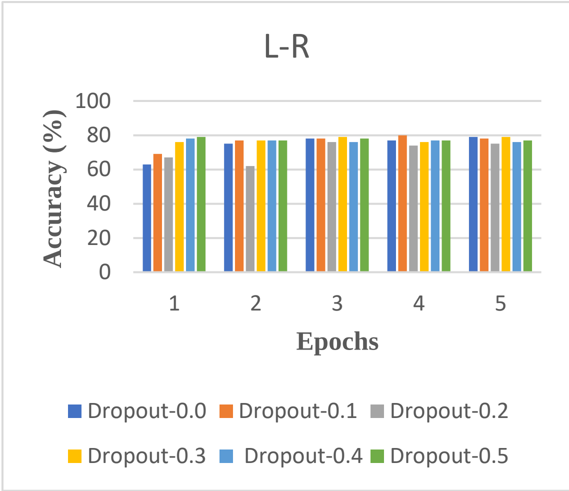
Shifting focus to the laptops to restaurants adaptation, dropout 0.1 at the fourth epoch presents a notable accuracy peak of 80, marking it as a potentially optimal configuration. However, while dropout 0.5 attains the highest average accuracy, it stabilizes early (at epoch 3), limiting its sensitivity to further training epochs. Lower dropout rates of 0.0 and 0.1 exhibit continuous accuracy improvements with increasing epochs, indicating the benefit of prolonged training for these rates.

When transitioning from books to clothes, dropout 0.1 at epoch 3 also showcases a peak accuracy of 80, maintaining 70 to 80 accuracies consistently across epochs.

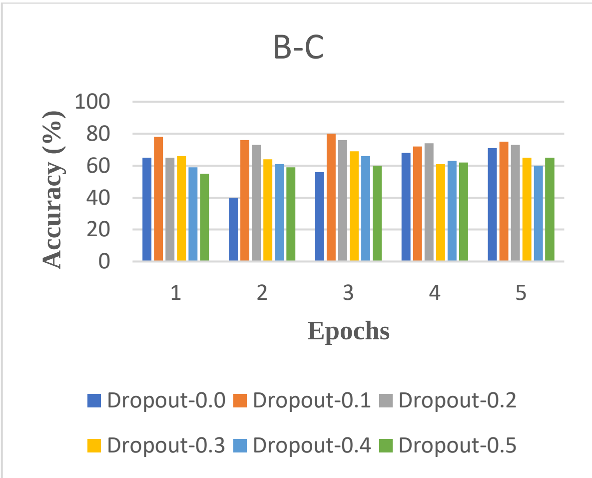
Lastly, adapting from clothes to books emphasizes the efficacy of moderate dropout rates (0.1 and 0.2), consistently delivering higher accuracies within the range 70 to 80 across epochs. Notably, dropout 0.1 at epoch 3 achieves a remarkable accuracy of 83, exemplifying its effectiveness in capturing domain-specific features during this adaptation.

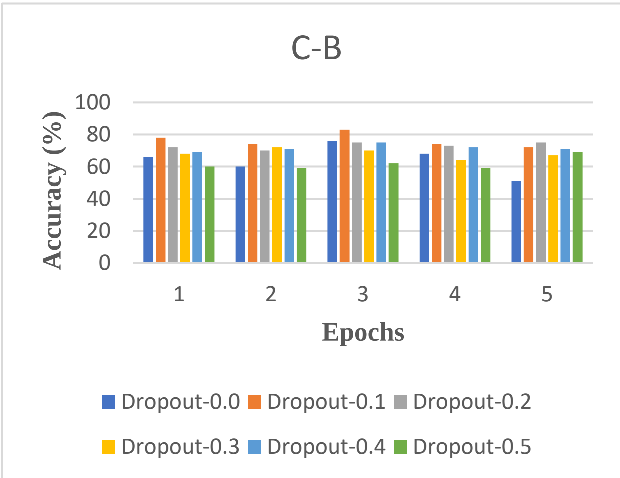
In summary, while the optimal dropout rate and epoch for maximal accuracy might vary across different domain shifts, the observations collectively underline the significance of moderate dropout rates, particularly 0.1, in facilitating better adaptation. The right combination of dropout rates and epochs can facilitate efficient adaptation by capturing relevant domain-specific information without overfitting or sacrificing generalizability.





(a) (R, L) **(b) (L, R)**





(c) (B, C) **(d) (C, B)**

Fig 7: Accuracy vs. Epochs for Different Dropout Values for different Domain Adaptations

In the context of the ADA-MMD framework applied to our datasets, two additional hyperparameters are considered: γ, which affects the MMD balance and λ, which influences the domain discriminator in ADA. Specifically, γ governs the influence of the MMD loss (M (f_s, f_t)), while λ regulates the impact of the domain discriminator loss (L_d).

To systematically investigate the sensitivity of the model to these hyperparameters, a comprehensive analysis was conducted by varying γ and λ across the set {0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1}. The results are presented in Table 2 and Table 3, illustrating the F1-Scores and accuracy of the model under different γ and λ values for the (L, R), (R, L), (B, C) and (C, B) categories.

Table 2: Influence of Gamma value (γ) on Model Performance

Gamma value (γ)	(L, R)		(R, L)		(B, C)		(C, B)	
	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score	Accuracy
0.001	44	55	43	53	55	62	57	72
0.005	46	58	51	62	61	70	61	75
0.01	52	65	56	65	63	74	64	79
0.05	69	74	59	70	69	78	69	81
0.1	75	80	74	78	71	80	72	83
0.5	69	73	67	72	59	63	62	75
1.0	38	40	37	37	38	52	39	51

Upon examining the tables, several observations can be made. The consistent decrease in both F1 score and accuracy across all category pairs when varying γ away from 0.1 indicates the sensitivity of the model's performance to the MMD balance. Likewise, the pattern observed with λ, where deviations from 0.01 lead to a consistent decline in performance, highlights the crucial role of the domain discriminator in the ADA framework. The emphasis on optimal performance at specific values (0.1 for γ and 0.01 for λ) reinforces the importance of careful hyperparameter tuning for achieving peak model effectiveness within the applied framework.

Table 3: Influence of Lambda value(λ) on Model Performance

Lambda value(λ)	(L, R)		(R, L)		(B, C)		(C, B)	
	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score	Accuracy
0.001	66	77	67	73	59	70	58	75
0.005	68	76	70	74	67	79	60	76
0.01	75	80	74	78	71	80	72	83
0.05	72	76	73	75	65	78	71	81
0.1	72	76	73	74	69	77	71	80
0.5	61	63	56	60	63	70	65	74
1.0	38	41	36	36	29	51	36	58

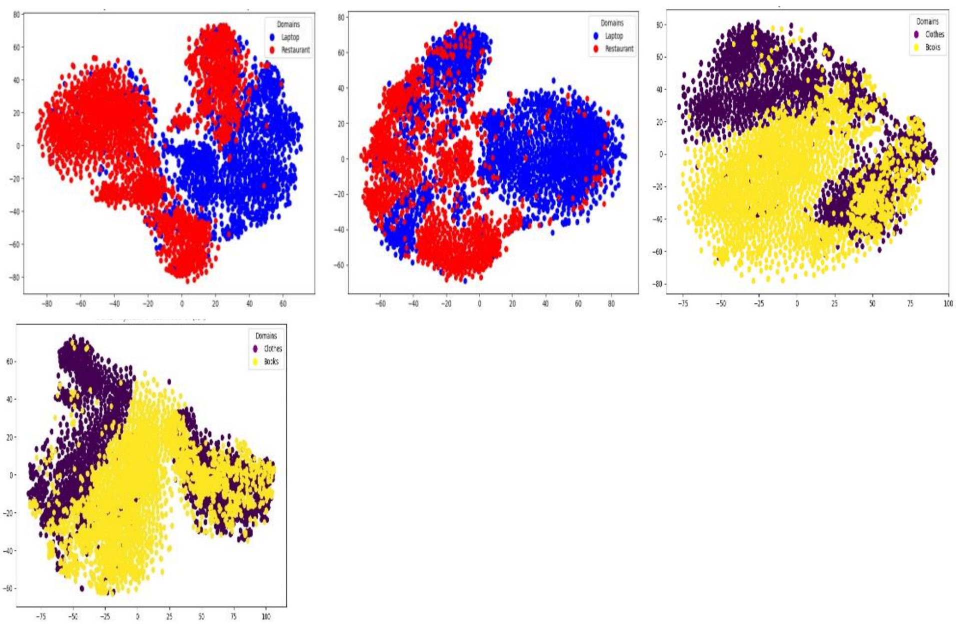
Table 4: Influence of MMD-Kernal Function on Model Performance

MMD-Kernal Function	(L, R)		(R, L)		(B, C)		(C, B)	
	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy
Linear	**69**	**74**	**67**	**73**	**67**	**77**	**69**	**80**
Polynomial	**54**	**68**	**52**	**61**	**69**	**80**	**71**	**78**
Gaussian (RBF)	**75**	**80**	**74**	**78**	**71**	**80**	**72**	**83**

The analysis of the influence of different MMD kernel functions on model performance, as detailed in Table 4, shows distinct patterns across various category pairs. The analysis reveals that the Gaussian (RBF) kernel is the most effective MMD kernel function, consistently achieving the highest F1-scores and accuracies across all category pairs. The Linear kernel also performs well but is slightly less effective than the Gaussian. In contrast, the Polynomial kernel shows mixed results, performing better in certain categories but weaker in others. This indicates the Gaussian kernel's superiority in handling non-linear features and the importance of selecting the right kernel function for optimal model performance.

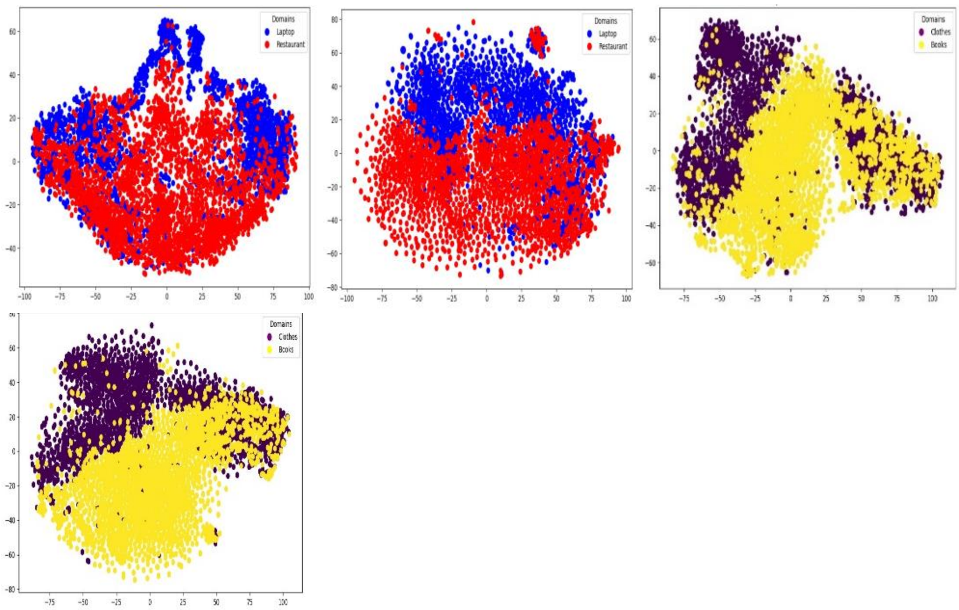
5.4 t-SNE Projections: t-SNE (t-distributed Stochastic Neighbor Embedding) projections is to visualize high-dimensional data in a way that can be easily interpreted. Given that high-dimensional datasets are difficult to explore and visualize, t-SNE helps to reduce the number of dimensions to two or three while attempting to maintain the relative distances between data points. Figure 8 represents the t-SNE projections of sentiment embeddings from domain adaptation methods, showing Laptops-to-Restaurants (L-R) and Restaurants-to-Laptops transitions with blue (Laptops) and red (Restaurants) points, and Books-to-Clothes (B-C) and Clothes-to-Books (C-B) transitions with purple (Clothes) and yellow (Books) points. Figures 8a, 8b, 8c and 8d show t-SNE projections for MMD based adaptation. MMD aims to minimize the statistical distance between the source and target domains, which is observed in the degree of overlap between the clusters in the respective figures.

CDASC-MMD:



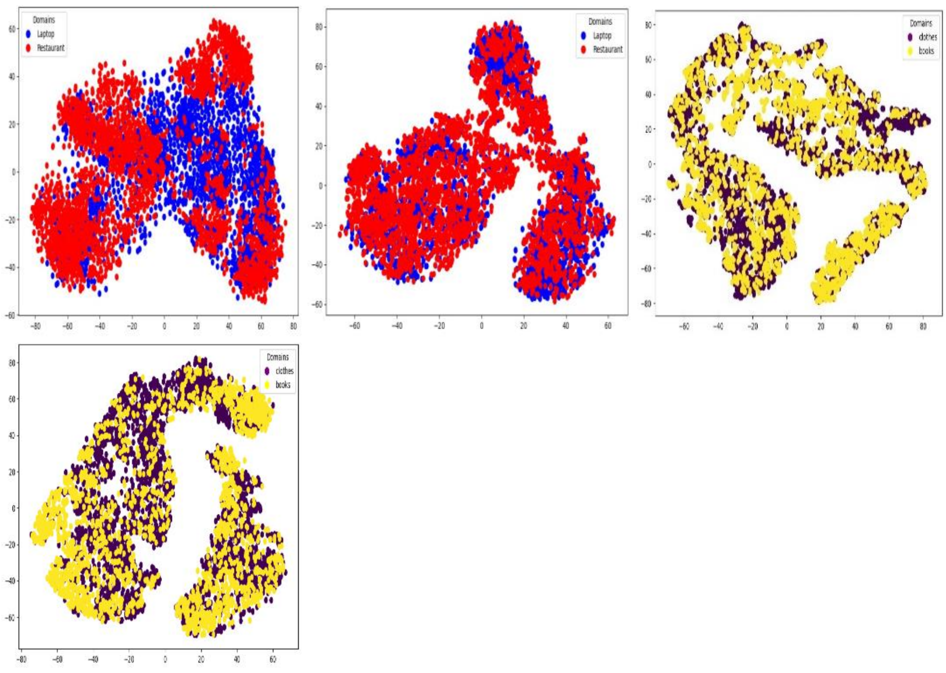
a) L- R **b) R-L** **c) B-C** **d) C-B**

CDASC-ADA:



e) L-R **f) R-L** **g) B-C** **h) C-B**

CDASC-ADA-MMD:



i) L-R **j) R-L** **k) B-C** **l) C-B**

Fig 8: Visualization of t-SNE Projections of Final Hidden State Embeddings of Sentiments Generated by Domain Adaptation Methods.

Figures 8e, 8f, 8g and 8h present the results of CDASC-ADA, where adversarial training is used to align the source and target domains in both adaptation directions. ADA typically yields more domain-invariant features, which is visually reflected in a more homogeneous mix of the clusters in the figures. Finally, Figures 8i, 8j, 8k and 8l show a hybrid approach combining Adversarial Domain Adaptation with MMD (ADA-MMD), potentially revealing the most integrated clusters due to the combined strengths of both techniques. Across these figures, the success of the domain adaptation is visually indicated by the mixing of the blue and red data points for laptops and restaurants, and purple and yellow data points for clothes and books. The more indistinguishable the clusters are from each other, the more effective the adaptation, suggesting that the model has developed an understanding of features that are invariant across both domains.

5.5 Comparative Analysis: To evaluate the effectiveness of our ADA-MMD approach in the context of Cross-Domain Aspect-Sentiment Classification (CDASC), we compare it against several competitive domain adaptation methods discussed in section 2. Specifically, the comparative analysis involves BERT [[36]], as a baseline method. Additionally, UDA, FMIM, CDRG, and DA^{2}LM are included in our comparisons. The results of our methods for CDASC task against the other methods are summarized in Table 5.

Table 5: F1-Scores of our experiment against others

Model	**(L, R)**	**(R, L)**	**(B, C)**	**(C, B)**
BERT	**37.38**	**32.69**	**54.87**	**52.05**
UDA	**49.52**	**43.95**	**-**	**-**
FMIM	**53.24**	**38.20**	**-**	**-**
CDRG	**57.96**	**45.66**	**-**	**-**
DA^{2}LM	**60.39**	**42.91**	**-**	**-**
CDASC-MMD	**66.52**	**65.02**	**63.41**	**59.98**
CDASC-ADA	**70.52**	**68.73**	**65.25**	**68.18**
CDASC -ADA-MMD	**75.16**	**74.38**	**70.89**	**72.16**

The table presents a detailed comparison of various adaptation techniques for the Cross-Domain Aspect-Sentiment Classification task, with a specific focus on four domains: restaurants (R), laptops (L), books (B), and clothes (C). The F1-scores are provided for each technique across these domains.

A noticeable trend is the consistent improvement in performance from BERT to more advanced techniques like CDASC-ADA-MMD. BERT, the baseline model, shows moderate performance with scores ranging from 32.69 to 54.87 across different evaluation settings.

The introduction of Unsupervised Data Augmentation (UDA) and other methods like FMIM and CDRG shows incremental improvements and the DA^{2}LM model further enhances performance, especially in the laptops and restaurants domains, but the most significant advancements are observed in the CDASC series. The absence of scores for books and clothes in UDA, FMIM, DA^{2}LM and CDRG suggests these models were not evaluated in these domains.

We extensively evaluated CDASC-MMD and CDASC-ADA models to optimize parameters for CDASC-ADA-MMD as discussed in section 5.3. For CDASC-MMD, we explored various γ values from 0.01 to 1.0, with the model achieving its peak performance at γ=0.1, signifying its optimal value. Alternatively, CDASC-ADA which was considered for examination with λ values from 0.001 to 1.0 has given better performance at λ=0.01 over CDASC-MMD. Integrating these determined parameters (γ=0.1 and λ=0.01), our CDASC-ADA-MMD model notably outperformed other configurations. This choice of parameters remained consistent even when evaluating for an extensive range of γ and λ values from {0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1} for the combined CDASC-ADA-MMD model.

5.6 Cross-Domain ABSA Results:

The Tables 6 and 7 show sample results of our aspect-based sentiment analysis conducted across different domains: from laptops to restaurants, restaurants to laptops, clothes to books and from books to clothes.

Table 6: Cross-Domain ABSA Results for Laptops and Restaurants domains

Input Text	Predicted Aspects (Laptops to Restaurants)	Aspect Sentiment Class	Predicted Aspects (Restaurants to Laptops)	Aspect Sentiment Class
For the price you pay this product is very good. However, battery life is a little lack-luster coming from a MacBook Pro.	['price', 'battery life']	['price'] -Positive ['battery life']-Negative	['price', 'battery life', 'mac']	['price'] --Positive ['battery life']- Negative ['mac'] - Neutral
Not was the food outstanding, but the little 'perks' were great.	['food', '##ks']	['food'] -Neutral ['##ks']-Neutral	['food', 'per', '##ks']	['food']- Negative ['per'] -Positive ['##ks'] -Neutral
The food is uniformly exceptional, with a very capable kitchen which will proudly whip up whatever you feel like eating, whether it's on the menu or not.	['food', 'kitchen']	['food'] -Positive ['kitchen'] -Positive ['menu']-Negative	['food', 'kitchen', 'menu']	['food'] -Positive ['kitchen'] -Positive ['menu'] Neutral
I charge it at night and skip taking the cord with me because of the good battery life.	['cord', 'battery life']	['cord']-Neutral ['battery life'] -Positive	['cord', 'battery life']	['cord']- Negative ['battery life'] -Positive

Table 7: Cross-Domain ABSA Results for Books and Clothes domains

Input Text	Predicted Aspects (Books to Clothes)	Aspect Sentiment Class	Predicted Aspects (Clothes to Books)	Aspect Sentiment Class
It is a bit larger than I expected but I love the color and feel of the fabric.	[‘color’]	[‘color’]- Positive	[‘color’, ‘fabric’]	[‘color’]- Positive [‘fabric’]- Positive
The material and the exact fix and I would recommend this product to all my friends and will continue to buy this brand	[‘material’, ‘product’]	[‘material’]- Neutral [‘product’]- Positive	[‘material’, ‘product’, ‘brand’]	[‘material’]- Negative [‘product’]- Positive [‘brand’]- Positive
This is the 6th book in series and i have read all that preceded although the mystery is decent the behavior of the characters is getting both redundant and unpleasant	[‘book’, ‘mystery’, ‘behavior of the characters’]	[‘book’]- Neutral [‘mystery’]- Neutral [‘behavior of the characters’]- Negative	[‘book’, ‘behavior of the characters’]	[‘book’]- Neutral [‘behavior of the characters’]- Negative

In my opinion she has become a page-turner author and I just could not put this book down!	[‘author’, ‘book’]	[‘author’] -Positive [‘book’]- Neutral	[‘book’]	[‘book’]- Positive

These tables show how the model's ability to generalize and adapt to different domains affects the prediction of aspects and sentiment classes. The variations in sentiment for the same aspect across domains underscore the importance of domain-specific training for accurate sentiment analysis. This cross-domain application is crucial for understanding and improving sentiment analysis models, making them more versatile and reflective of the real-world scenarios where they are applied.

6. Conclusion

In this paper, we presented a groundbreaking approach to Cross-Domain Aspect-Based Sentiment Analysis (CD-ABSA), effectively integrating aspect extraction and sentiment classification. Utilizing pre-trained BERT models, our methodology innovatively combines Adversarial Domain Adaptation with MMD for cross-domain aspect sentiment classification task, a technique we refer to as CDASC-ADA-MMD. This approach is particularly tailored to bridge the distribution gap between diverse domains, such as restaurants, laptops, books, and clothes considered in our work. Our model's unique capability lies in its robust performance across various domains, especially in scenarios where domain-specific labeled data is scarce or non-existent. By incorporating aspect extraction from our previous research, we achieved a comprehensive analysis of sentiments at an aspect level, marking a notable advancement in the domain of sentiment analysis.

Our experiments, conducted using the restaurants, laptops, books, and clothes review datasets, clearly demonstrate the superiority of our model over existing methods. The CDASC-ADA-MMD approach not only excelled in accuracy and F1-Scores but also showcased exceptional adaptability and generalization across different domains. This is a substantial contribution to sentiment analysis, particularly beneficial for applications like market research, social media monitoring, and customer feedback analysis, where understanding detailed opinions across varied domains is essential. The success of our model, as evidenced by t-SNE projections, underscores the effectiveness of our domain adaptation strategies. In conclusion, this research significantly advances the field of sentiment analysis, providing a scalable and effective solution for cross-domain sentiment challenges and setting a foundation for future exploration in other domains and enhanced aspect-sentiment integration.

Future work could explore extending our approach to multiple source adaptations. This enhancement would harness diverse data inputs, potentially improving the model's accuracy and robustness in cross-domain sentiment analysis. Such an expansion would align with emerging trends in machine learning, addressing the complexities of real-world data variations.

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Declaration:

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationship that could have appeared to influence the work reported in this paper.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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