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SENTICOG: CROSS-PLATFORM SENTIMENT ANALYSIS VIA CAUSAL GRAPH ENCODING AND MULTI-MODAL FUSION

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Abstract:

In order to provide reliable and broadly applicable sentiment predictions, this study presents SENTICOG, a cross-platform sentiment analysis system that utilises Causal Graph Encoding and Multi-Modal Fusion. By merging textual features, graph-encoded causal linkages, and auxiliary metadata into a single latent representation, SENTICOG is able to capture deep semantic structures. Within the framework, two fundamental variations are investigated: CGR-MLP (Causal Graph Representation with Multi-Layer Perceptron) and CGR-ZSG (Causal Graph Representation with Zero-Shot Generalisation). CGR-ZSG achieves 89.6%, 93.23%, and 95.6% accuracy across benchmark datasets, allowing for generalisation to unknown domains without the need for retraining. CGR-MLP further improves classification performance with accuracies of 90%, 96.87%, and 97.78%, respectively, after being tuned for supervised tasks. These findings demonstrate the benefits of combining multi-modal learning and causal reasoning for scalable, cross-domain sentiment analysis.

Keywords— Causal Graph Encoding, Multi-Modal Fusion, Cross-Platform, CGR-MLP, CGR-ZSG, Zero-Shot Generalisation, Textual Features, Metadata Integration.

I. Introduction:

Sentiment analysis has become as a crucial problem in natural language processing (NLP) due to the rapid expansion of user-generated information on social networking platforms, online reviews, and forums. However, domain transitions, cross-platform heterogeneity, and the requirement for large amounts of labelled data frequently pose challenges for traditional sentiment classification algorithms. The scalability and generalisability of sentiment analysis systems in practical applications are hampered by these issues.

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A significant amount of heterogeneity is introduced by the variations in vocabulary, syntax, context, and sentiment expression among different online platforms. Large volumes of labeled data from a single domain or platform are necessary for supervised learning approaches, which are frequently the mainstay of traditional sentiment analysis models. When these models are exposed to data from a new or unknown area, they usually do not generalize effectively. Additionally, the majority of current models are unable to comprehend the causal links present in the data, which results in poor interpretability and a vulnerability to erroneous correlations. SENTICOG tackles these issues by combining multi-modal fusion and Causal Graph Encoding in a unique way.

A potent technique that enables models to recognize and take advantage of cause-and-effect links between textual components and sentiment outputs is causal reasoning. SENTICOG learns deeper semantic and logical connections by integrating causal graph structures into the model, which goes beyond pattern recognition. This enhances the model's interpretability in addition to its accuracy. For example, knowing that terms like "because of the terrible service" are causally associated with negative sentiment aids the model in making more accurate predictions, particularly when dealing with complicated sentence patterns.

Two main model variations are introduced by the SENTICOG framework to accommodate various application scenarios:

Causal Graph Representation with Zero-Shot Generalization, or CGR-ZSG, is a variation that can classify sentiment on unseen platforms without the need for more training data. It makes use of domain-invariant characteristics and causal mechanisms to generalize across various data kinds. This is especially helpful when labeled data for the target domain is hard to come by or unavailable.

Causal Graph Representation using Multi-Layer Perceptron, or CGR-MLP: This version uses supervised learning to attain high accuracy and is designed for settings with labeled data. Applications requiring high precision can benefit from the MLP-based design's ability to understand intricate non-linear correlations between features.

Another essential element of SENTICOG is Multi-Modal Fusion, which makes it possible to integrate diverse data formats. In addition to textual content, sentiment is frequently conveyed through contextual metadata (such as timestamps and user profiles) and structural relationships (such as graph-based interactions). To create a cohesive representation, SENTICOG integrates textual embeddings (from transformer-based models using DistilBertModel), graph embeddings (from a Graph Neural Network), and auxiliary metadata. This comprehensive approach greatly improves the model's comprehension and categorization of sentiment on many platforms.

The demand for sentiment analysis systems that can function well in cross-platform, real-world settings is what drove the development of SENTICOG. When used in living systems, traditional models that function well in lab settings frequently deteriorate, mostly because of the diversity.

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In addition to empirical performance, we also emphasize interpretability and transparency in sentiment predictions. Using SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations), SENTICOG provides explanations for each prediction, highlighting which features—textual phrases, causal elements, or graph relationships—contributed most significantly to the final sentiment decision. This is particularly valuable in domains such as healthcare or finance, where trust and accountability are paramount.

II. Related Work:

By utilising multilingual sentiment lexicons, a unique zero-shot sentiment analysis technique is put forth to solve the difficulties given by low-resource languages. By using PanLex to expand the NRC-VAD vocabulary, the methodology makes it possible to train multilingual models without depending on sentence-level annotations. When compared to big language models, this method performs competitively while requiring less resources and having wide applicability across a variety of languages. The lack of aspect-level sentiment analysis, a strong dependence on lexicon quality, and a possible incapacity to account for cultural subtleties in sentiment interpretation are some of the drawbacks [1]. Mahajan et al. investigate zero-shot causal model learning, seeking to estimate structural causal models directly from observational data. This strategy minimises the requirement for retraining on each new dataset and promotes generalization in unforeseen scenarios. Its capacity to forecast causal consequences with little oversight is its main strength. However, the framework's complexity and dependence on the proper causal graph structure continue to be significant drawbacks. [2].

A syntactic-graph-based sentiment analysis technique utilising graph neural networks was presented by L. Wu et al. The authors hope to enhance sentiment categorisation by capturing syntactic relations by transforming parse trees into adjacency matrices. The primary benefit is improved contextual comprehension through graph topologies; but, when used on very large datasets, it may suffer from scalability and interpretability issues [3].S. Poria et al. discusses issues in sentiment analysis, including as domain adaptation, multimodal fusion, and sarcasm detection. It describes new guidelines and standards. Its thorough analysis and future roadmap are its advantages, however it is devoid of implementation specifics for practical use.[4].In order to extract aspect-level thoughts from product reviews, this study investigates explainable sentiment analysis using causal graph embeddings. By mapping sentiment correlations across product features, it improves interpretability. Although explainability is enhanced by the use of causal graphs, scalability and graph construction difficulty continue to be major drawbacks[5].

Applying statistical methods to the extraction of causal sentiment correlations from noisy online data. This method works well in practical situations and lowers noise-induced mistakes. However in assessments that are vague or snarky, the model might not be accurate [6]. GNN framework that improves sentiment classification at the aspect level by combining syntactic and semantic information. In terms of extracting opinion-aspect pairs, the model

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performs better than conventional RNN-based systems. Even though it is accurate, it needs a lot of fine-tuning and might not translate well to other fields [7]. This paper investigating CNN, RNN, LSTM, and Transformer models for deep learning-based sentiment analysis. [8].

The article introduces SIF, a dynamic graph structural framework that integrates textual semantic and structural information for implicit sentiment identification. Among SIF's advantages are its all-encompassing method of text analysis, its capacity for dynamic graph learning, its enhanced performance on various datasets, and its decreased reliance on domain knowledge. The framework's ability to capture intricate semantic linkages and contextual information is demonstrated by its superior performance over other graph-based techniques and popular NLP methods. The article does, however, also highlight certain shortcomings. If noisy edges are not successfully eliminated during dynamic learning, they may still be introduced during the construction of static initial graphs and have an impact on performance. Furthermore, the original graph's quality structures and the efficiency of the fusion process may have an effect on the model's performance.[9]

Provides a benchmark dataset for Kurdish sentiment analysis , Explores data augmentation techniques to address data scarcity, Evaluates multiple ML and neural network models and Analyzes the impact of emojis on sentiment classification. Limited to only three sentiment classes (positive, negative, neutral),Relatively small dataset size, even after augmentation, Does not explore more advanced deep learning models or transformers [10].

This article presents S^2GSL, a novel approach for Aspect-based Sentiment Analysis (ABSA). In order to overcome the shortcomings of earlier approaches, the model integrates syntax-based latent graph learning and segment-aware semantic graph learning. S^2GSL outperforms baselines on four benchmarks, demonstrating effectiveness in handling complex sentences with multiple aspects. The model shows improved accuracy and macro-F1 scores across datasets, particularly for Laptop, Restaurant, and MAMS. However, S^2GSL's performance on the Twitter dataset, while strong, does not significantly outperform some existing methods, possibly due to the dataset's simpler sentence structures. The model's design, while effective, introduces additional complexity compared to simpler approaches.[11] It compares collaborative filtering methods like SVD, MFB, and DPMF. The research finds as DPMF with transfer learning performs best, achieving improved RMSE and MAE scores in both single-domain and cross-domain settings. This work demonstrates the potential of transfer learning in enhancing recommendation quality across different domains, particularly when dealing with sparse data.[12] This study proposes a sentiment analysis framework for online news articles. With the lowest Mean Squared Error (MSE) and a high classification accuracy of 99.83%, the SCG-optimized BNN model performed the best. TextBlob is used by the framework to extract subjectivity and polarity features from the text, which are then fed into the neural network. It also beat the ANFIS and traditional machine learning models. The study does, however, point out that in order to improve scalability for extensive, real-time news analytics, hybrid models must be investigated. Overall, the suggested architecture

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shows how well SCG-optimized BNNs perform sentiment analysis of online news; however, scalability issues need to be addressed in future research. [13]

Domain Generalization (DG) overcomes the drawbacks of models that depend on the assumption by addressing the problem of generalizing to out-of-distribution (OOD) data using just source domain data. Using techniques like domain alignment, meta-learning, and data augmentation, DG research has spread during the last ten years into fields computer vision, NL processing, and medical . A thorough analysis of DG techniques, theories, and applications is provided in this study, along with insights on the field's development and future prospects.[14]

RICE (Regularized training with Invariance on Causal Essential set) for improving out-of-distribution (OOD) generalization. Theoretically show that if all CITs are known, then a model trained to be invariant to these CITs can achieve minmax optimality across different domains. Further, they show that it is sufficient to know only a subset of CITs, called the causal essential set. Empirically, the proposed RICE algorithm demonstrates improved OOD generalization on synthetic and real-world datasets compared to existing baselines. Pros: Provides a theoretical framework for OOD generalization without explicitly recovering the causal features, Requires less restrictive assumptions compared to prior causality-based approaches, and empirically shows improved OOD performance even with a limited set of CITs. Cons: The method relies on the availability of CITs, which may not be easy to obtain in all applications, theoretical results assume the causal mechanism is known to be invariant across domains, which may not always hold in practice.[15]

Yang et al. an approach to emotional analysis by integrating large language models (LLMs) with contrastive prompt learning. Their method enhances sentiment classification in low-resource settings through data augmentation, contrastive embedding training, and iterative self-training. The study demonstrates significant performance improvements over traditional models using minimal labeled data. This work highlights the potential of LLM-guided learning for scalable and adaptive emotion understanding.[16]

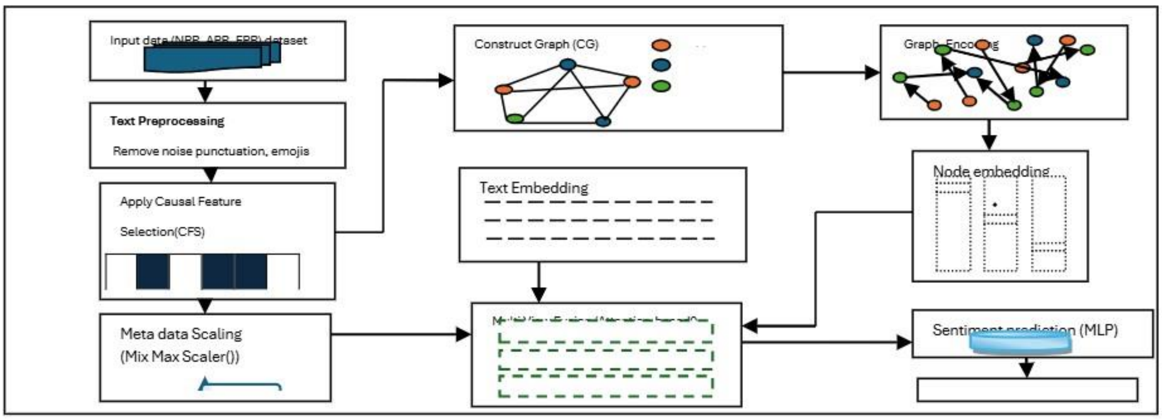

Fig.1. SENTICOG framework for sentiment analysis

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III. Methodology:

A. *Dataset Description:*

Three different datasets were gathered from the well-known Indian and international e-commerce sites Nykaa, Flipkart, and Amazon for this study. 3,222 user evaluations of cosmetics and personal hygiene goods make up the Nykaa dataset, which includes structured elements such reviewer name, review description, star rating, verification status, and review timestamps. About 189,874 product records with product names, prices, ratings, user-written reviews, and succinct summaries are included in the Flipkart dataset. Lastly, there are almost 700,000 items in the Amazon beauty review dataset, each with comprehensive metadata such as Unix timestamps, helpful vote counts, review titles and texts, numeric ratings, and confirmed purchase status.

B. *Senticog Architecture:*

The SENTICOG framework for sentiment analysis that integrates multiple advanced techniques, including causal inference, graph neural networks (GNNs), and zero-shot learning. The pipeline begins with raw text input, typically user-generated reviews. This text is processed through a causal feature selection module that identifies features with genuine causal impact on sentiment, filtering out spurious correlations. Simultaneously, a heterogeneous user–product–review graph is constructed to model real-world interactions. This graph is encoded using a GNN, producing embeddings that reflect relational and behavioural patterns.

These embeddings are fused with textual and metadata-based features in a multi-view fusion layer, where an attention mechanism highlights the most relevant components. The fused representation is then fed into a zero-shot sentiment classification module, which enables generalization to unseen domains without retraining. Finally, the model incorporates an explanation layer using tools like SHAP, offering interpretability by showing which features most influenced the sentiment prediction. The SENTICOG architecture is thus robust, scalable, and transparent, making it suitable for real-world sentiment analysis applications.

C. *Data Preprocessing:*

To ensure consistency and improve the quality of sentiment analysis, all review texts $T = \{t_1, t_2, ..., t_n\}$, where each t_i is a review text string. The preprocessing pipeline transforms each t_i into a cleaned version t_i' through a sequence of operations.

Lowercasing and Cleaning: $C(t_i)$ = lowercase and remove noise from t_i, where C removes HTML tags, punctuation, numbers, and emojis.

Tokenization: $T(C(t_i)) = [w_1, w_2, \ldots\ldots, w_m]$, where w_j is a word token in the cleaned review.

Stopword Removal: $S\left(T\left(C(t_i)\right)\right) = \{w_i \notin \text{Stopwords}\}$, where common, semantically weak words are removed.

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Lemmatization: $L(S(\dots)) = \{w_i \in S(\dots)\}$,which maps each word to its canonical form(e.g., “running”->”run”).

Final Representation:$t_i' = L\left(S\left(T(C(t_i))\right)\right)$,

This yields the cleaned corpus: $T' = \{t_1', t_2', \dots, t_n'\}$.

The preprocessing ensures semantic consistency, reduces dimensionality, and improves both model interpretability and performance

D. *Causal Feature Selection:*

Causal feature selection aims to identify input features that have direct affect the intended variable, rather than mere statistical correlation. Given a set of preprocessed reviews and their associated outcomes (e.g., sentiment labels or ratings) the goal is to extract a subset of features from the full feature set X such that:

$$P(do(F)) \neq P(Y)$$

Here, do(F) represents an intervention on the feature set F, as per Pearl’s do-calculus, which models a change in the feature values as if caused externally. A feature $f_j \in X$ is considered causally relevant if it satisfies:

$$P(do(f_i)) \neq P(do(f_i = null))$$

E. *Graph construction:*

This means changing the value of f_j would lead to a significant change in the prediction distribution of Y. In practice, this is estimated using tools like propensity score matching, inverse probability weighting, or causal graphs constructed via structural equation modeling (SEM). The selected set of causal features F is then used to train interpretable or robust predictive models.

In this step, we construct a heterogeneous graph to model the interactions between users, reviews, and products. Let the graph be defined as G = (V, E), where V represents the set of nodes and E represents the set of edges.

The nodes include:
-$U = \{u_1, u_2, \dots, u_m\}$: users (available in Amazon),
- $P = \{p_1, p_2, \dots, p_k\}$: products,
- $R = \{r_1, r_2, \dots, r_n\}$: reviews.
Thus, the total node set is:

$$V = U \cup P \cup R$$

We define edges based on known relationships:
- Review-to-Product edges: $(r_i, p_j) \in E$ if review r_i is written about product p_j
- User-to-Review edges: $(u_i, r_j) \in E$ if user u_i wrote review r_j

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- Product similarity edges: $(p_i, p_j) \in E$ if products p_i and p_j share similar categories or attributes
- Optional user similarity edges: $(u_i, u_j) \in E$ if users u_i and u_j have similar behavior (Amazon only)

Each node $v \in V$ is assigned a feature vector x_v, which can include:
- Textual embeddings for reviews
- Product metadata
- Aggregated behaviour metrics for users

The resulting graph $G = (V, E, X)$, where $X = \{v \in V\}$, is passed to a Graph Neural Network (GNN) for learning joint embeddings that capture complex multi-entity interactions relevant for downstream sentiment classification.

F. *Graph encoding:*

It involves encoding the nodes into dense vector representations using a Graph Neural Network (GNN). The node embeddings are computed iteratively across layers of the GNN. At each layer l, the embedding of a node v is updated based on its neighbors and the types of edges connecting them. The R-GCN update rule is defined as:

Where:

-$h\_v^{(l)}$: node embedding v at layer l
- r : collection of relation types (e.g., User-Review, Review-Product)
-$N_r(v)$:collection of neighboring nodes of v under relation r
- $W_r^{(l)}$: Transformation matrix specific to relation r at layer l
-$W_{self}^{(l)}$: self-loop transformation weight
-$c\_\{v, r\}$: normalization constant
- σ: non-linear activation function

The final output $H = \{h\_v \mid v \in V\}$ is a set of learned node embeddings that encapsulate structural relationships, semantic context from causally selected features, and the influence of neighboring entities.

G. *Textual Embedding:*

After causal feature selection, each cleaned and filtered review $t_i' \in T'$ is transformed into a dense vector representation using DistilBERT. This process encodes the semantic meaning of the text in a high-dimensional space suitable for downstream tasks like sentiment classification.

Let the embedding function of the language model be denoted as:

$LM : T' \rightarrow R^d$

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Algorithm 1: Heading

Input:
- Raw reviews
$T = \{t_1, t_2, \dots t_n\}$

- Metadata

- Causal selection engine (CausalSel)

Output:
- Sentiment predictions
$S = \{s_1, \dots\dots s_n\}$

- Explanation scores
$E = \{e_1, \dots\dots, e_n\}$

Steps:
1
$\forall\, t_i \in T$:

a. Clean:
$C(t_i)$

$\rightarrow$
remove
noise,
punctuation,
emojis

b. Tokenize:
$\left(C(t_i)\right)$

c. Remove stopwords:
$\left(T\left(C(t_i)\right)\right)$

d. Lemmatize:
$L\left(S(\dots)\right) \rightarrow t_i'$

2. Apply causal selector:

3. Construct graph
$G = (V, E)$:

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a.
$V = U \cup P \cup R$

b.

4. Encode graph using GNN

5

6. Multi-View Fusion (preferred: Attention-based):

7. Predict sentiment:

8. Explain prediction (preferred: SHAP):
$e_i = \mathrm{SHAP}(z_i, s_i)$

9. Return S and E

Then, for each review:

$$e_i = LM(t_i')$$

Where:
- t_i' is the preprocessed and causally filtered text of the i-th review,
- $e_i \in R^d$ is the embedding vector of dimension d.

The entire embedding matrix for all reviews is:
$E = \{e_1, e_2, \dots, e_n\}$ where $E \in R^{nxd}$ represents textual features for all n reviews.

H. *Multi-view-fusion:*

The goal of multi-view fusion is to integrate diverse representations — textual embeddings, graph-based node features, and optional metadata — into a unified latent representation that enhances sentiment prediction. Each review or data instance is characterized by multiple modalities:

- Graph embeddings from the GNN: $h_i \in R^d$
- Textual embeddings from the pre-trained LM: $e_i \in R^d$
- Metadata features $m_i \in R^k$

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To combine them, a fusion vector z_i is computed using an attention mechanism or simple concatenation:

$$z_i = Fusion(h_i, e_i, m_i)$$

A common approach is attention-based fusion:

$$z_i = Attention(W_1 h_i, W_2 e_i, W_3 m_i)$$

Where:
- W_1, W_2, W_3 are learnable projection matrices,
- Attention is a multi-head or scaled dot-product attention function that learns the importance of each view.

The resulting fused vector $z_i \in R^{d'}$ captures relational, semantic, and contextual cues, and becomes the final feature used for sentiment prediction.

I. MLP

Once the unified representation $z_i \in R^{d'}$ is computed from the fused views, it is passed through a Multi-Layer Perceptron (MLP) for sentiment classification. The MLP acts as a non-linear function approximator that maps the high-dimensional feature vector into a probability distribution over sentiment classes.

The computation can be expressed as: $\hat{y}_i = Softmax(W_2.\sigma(W_1 \cdot Z_i + b_1) + b_2)$
Where:
- $z_i \in R^{d'}$: the fused feature vector for the i[th] instance,
- $W_1 \in R\hat{}\{h \times d'\}, W_2 \in R\hat{}$: learnable weight matrices,
- b_1, b_2: corresponding bias vectors,
- $\sigma(\cdot)$: activation function, typically ReLU,
- C: number of sentiment classes
- $\hat{y}_i \in R^c$: output probability distribution from softmax.

The model is trained using a cross-entropy loss between the predicted distribution $\hat{y}_i$ and the ground-truth label y_i:

$$L\_CE = -\sum\_\{i = 1\}\hat{}N\sum\_\{c = 1\}\hat{}C y_i\hat{}\{(c)\} \cdot log\ log\ (\hat{y}_i)\ \hat{}\{(c)\}$$

This classification head enables the framework to learn optimal boundaries in the fused latent space, capturing the interplay of graph structure, semantics, and user-product metadata for robust sentiment prediction.

J. Zero-shot Generalization(NSG)

In this step, the fused representation vector z_i for each review is passed to a zero-shot sentiment classifier to predict the sentiment label without requiring task-specific labeled training data.

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Let $Z = \{z_1, z_2, \ldots \ldots z_n\}$ be the set of multi-view fused vectors derived from graph embeddings, textual features, and metadata. The sentiment classifier f maps each fused vector to a sentiment label:

$s_i = f(z_i)$

In zero-shot classification, f evaluates the compatibility between z_i and each sentiment label hypothesis using entailment probabilities: $s_i = argmax\_\{y \in Y\}\, P(z_i,\ LM)$

Where:

- Y = {positive, neutral, negative} P(y | z_i, LLM) is the probability that z_i entails hypothesis y

This method allows the system to generalize to unseen sentiment tasks by expressing sentiment classification as a textual entailment problem, leveraging the contextual strength of large pre-trained models.

K. *Interpretability Layer*

The interpretability layer provides transparency into how each feature contributes to the sentiment classification decision. After predicting sentiment labels S = {s_1, s_2, ..., s_n} from the fused feature representations Z = {z_1, z_2, ..., z_n}, interpretability methods such as SHAP (SHapley Additive exPlanations) are used to compute feature-level importance scores.

Let (z_i, s_i) be the explanation function, then: $e_{i=\varepsilon(z_i, s_i)}$

Where:

- z_i is the fused vector for review i
- s_i is the predicted sentiment
- $e_{i=\{(f_1,\emptyset_1),(f_2,\emptyset_2),\ldots\ldots,(f_k\emptyset_k)\}}$ is a set of tuples representing feature f_j and its contribution score ϕ_j

For SHAP, the explanation is grounded in cooperative game theory:

$$\emptyset_i = \textstyle\sum\_\{S \subseteq F\ \{f_i\}\}\ (|S|!\,(|F|\ - |S| - 1)!/|F|!)\ [f(S\ U\ \{f_i\}) - f(s)]$$

Where F is the set of input features, and ϕ_j is the Shapley value for feature f_j.

The result E = {e_1, e_2, ..., e_n} provides human-interpretable insights into which features (text, graph, or metadata) were most influential for each sentiment prediction, improving transparency and trust in the model.

IV. Experimental Result

To examine the efficacy of the proposed SENTICOG framework, experiments were carried out using review datasets from three distinct e-commerce platforms: Amazon, Nykaa, and Flipkart. These datasets represent diverse linguistic patterns, product categories, and user behaviors among the dataset.

A key aspect of the evaluation focused on analyzing causal feature correlations—how strongly specific textual cues influence sentiment labels across domains. By applying Causal

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Graph Encoding, the model successfully identified domain-invariant causal features such as "late delivery", "value for money", and "damaged product", which consistently impacted sentiment polarity across all three datasets.

To understand the influence of linguistic and metadata features on user ratings, In Fig.2 we conducted a causal feature correlation analysis for both the Amazon , Nykaa and filpkart review datasets. For the Amazon dataset, text polarity exhibited a strong positive correlation with ratings (r = 0.55), indicating that reviews with more positive sentiment were generally associated with higher star ratings. Subjectivity (r = 0.26) also showed a moderate positive relationship, suggesting that more emotionally expressive reviews tended to be rated higher. Interestingly, features such as verified purchase and helpful votes had weak or slightly negative correlations with rating, implying that they may not directly influence the score but still contribute to context.

```
=== Causal Feature Correlation with Rating (Nykaa Dataset) ===
polarity         0.227550
subjectivity     0.052670
review_length   -0.060568
verified         0.043539
likes_count     -0.040344
Name: rating, dtype: float64

=== Causal Feature Correlation with Rating (Amazon) ===
polarity             0.551686
subjectivity         0.260506
review_length        0.012809
verified_purchase   -0.027534
helpful_vote        -0.033444
Name: rating, dtype: float64

=== Causal Feature Correlation with Rating (Flipkart) ===
polarity         0.658248
subjectivity     0.205100
review_length   -0.074086
Price_clean      0.070702
Name: Rate, dtype: float64
```

Fig.2. Show the Result of Causal Feature Correlation

In contrast, the Nykaa dataset showed a lower polarity– rating correlation (r = 0.23), possibly due to more diverse expression patterns or shorter reviews. Subjectivity remained weakly correlated (r = 0.05), and review length had a slight negative correlation (r = -0.06), which may indicate that longer reviews often contained criticism. Verified purchase and likes count again showed minimal correlation with rating, consistent with the Amazon findings. Overall, polarity remained the most reliable causal predictor in both platforms, validating its inclusion in downstream sentiment models. In the flipkart datasets show the polarity of reviews showed a moderate positive correlation (0.65), indicating that sentiment scores align well with the overall emotional tone expressed in the text. Subjectivity exhibited a weaker correlation (0.205), suggesting that many reviews remain factual or mixed in tone. Interestingly, review length had a strong negative correlation (-0.70) with sentiment classification, implying that longer reviews often contained more critical or mixed opinions. Additionally, the price_clean

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feature showed a very low positive correlation (0.07), suggesting that price alone has minimal direct influence on sentiment in Flipkart reviews.

Fig.3. A heatmap visualization was used to illustrate the strength of causal feature correlations across the Amazon, Nykaa, and Flipkart datasets. The color intensity clearly highlights consistent patterns—such as strong negative correlation between review length and sentiment, and moderate positive correlation between polarity and sentiment.

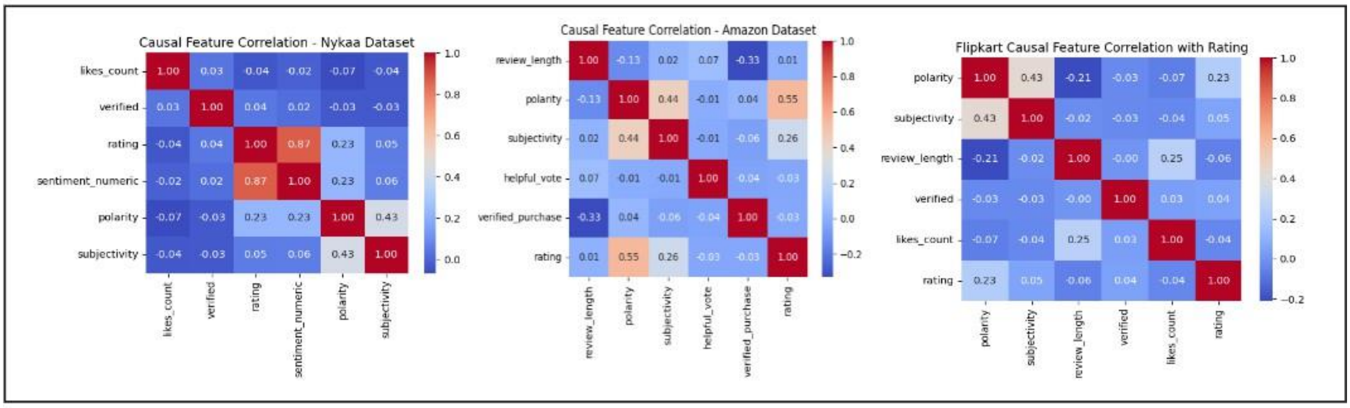

Table I: shows For every e-commerce dataset, heterogeneous graphs were created to illustrate the links between users, reviews, and products. User, product, and review nodes together up 11,289 nodes and 10,000 edges in the Amazon dataset. Written (user → review) and about (review → product) are examples of edges that capture both authorship and product relevance. With 5,606 and 5,017 nodes, respectively, the Nykaa and Flipkart graphs were relatively smaller and mostly contained review and product node types.

Table I: Graph Statistics Across E-Commerce Datasets

Metric	Amazon_DS	Nykaa_DS	Flipkart DS
Total Nodes	11289	5,606	5017
Total Edges	10000	6,444	5000
Node Types	Users, Reviews, Products.		Reviews, Products
Edge Types	wrote, about.		About

Table II: Every dataset (Nykaa, Amazon, Flipkart) is subjected to multi-view representation learning in this framework. With PyTorch Geometric, a GCN (GraphConv) layer is used for graph encoding, resulting in node-level embeddings of size 64. The DistilBERT transformer is used to encode textual data from product reviews, and the contextualised summary of each review is captured by the CLS token. Scikit-learn's MinMaxScaler is used to extract scaled metadata features including polarity, subjectivity, and review length. The fused feature matrix Z of dimension 835 is created by concatenating these three views (graph, text, and metadata).

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Table II: Torch Tensor Dimensions for Pipeline Components by Dataset

Component	Method/Tool	Nykaa_DS	Amazon_DS	Flipkart_DS	Description
Graph Encoding	GCN (GraphConv) PyTorch Geometric	([5606, 64])	([5017,64])	([11289,64])	Node embeddings learned from graph (GNN layer)
Text Embedding	transformers, DistilBertModel	([3222, 768])	([5000,768])	([5000, 768])	CLS token representation for each review
Metadata Features	scikit-learn MinMaxScaler()	([3222, 3])	([5000,3])	([5000,3])	Scaled metadata:(polarity, subjectivity, review)
Multi-View Fusion	torch.cat([...], dim=1)	([3222, 835])	([5000, 835])	([5000, 835])	Final multi-view vector (64 + 768 + 3 = 835 features)

Fig. 3, shows For graph-based analysis, a causal interaction network was constructed using review data from the e-commerce datasets. A representative subgraph of 200 nodes was extracted and visualized using a force-directed networkx.spring layout to reveal structural relationships. Node coloring based on entity type—such as product, user, and review—helped distinguish clusters and highlighted key causal pathways influencing sentiment flow across the dataset.

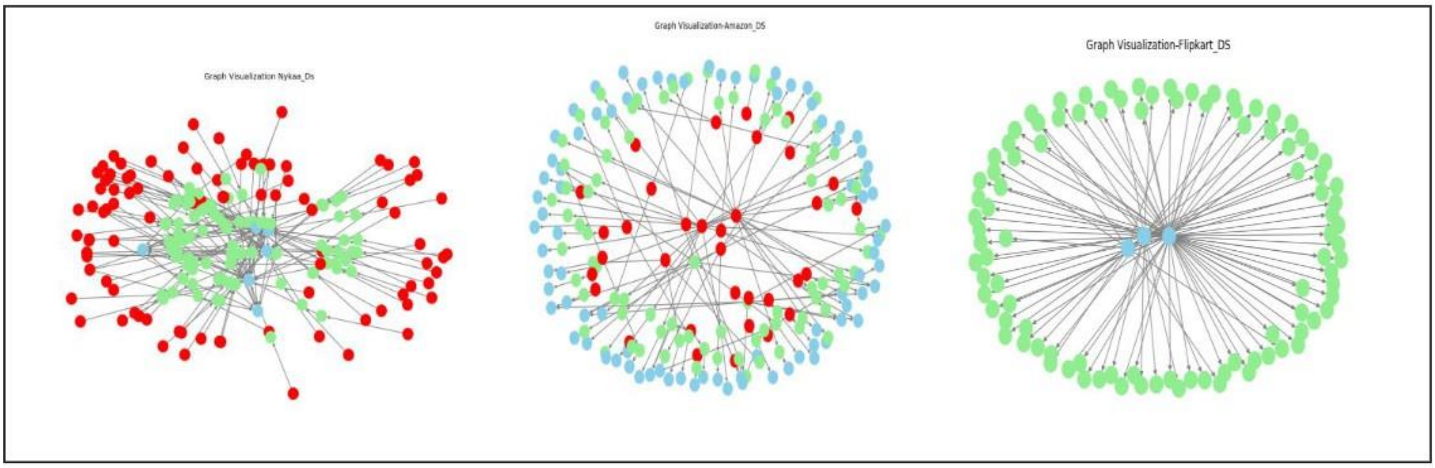

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Table III: The performance of the proposed SENTICOG model was compared to more conventional machine learning approaches, including Linear Regression, CNN, and ANN, across three datasets: Nykaa (NDS), Flipkart (FDS), and Amazon (ADS). Linear Regression achieved moderate accuracy with scores of 78.34% (NDS), 80% (FDS), and 83.65% (ADS). CNN outperformed Linear Regression slightly, with accuracies of 80.67%, 83.45%, and 86.46% respectively. ANN demonstrated further improvement, reaching 86.43% on NDS, 88.89% on FDS, and 92.45% on ADS. In contrast, the proposed SENTICOG framework significantly surpassed all baseline models: CGR-ZSG achieved 89.6% (NDS), 93.23% (FDS), and 95.6% (ADS), while CGR-MLP yielded the highest performance at 90% (NDS), 96.87% (FDS), and 97.78% (ADS). These results highlight SENTICOG's superior ability to generalize sentiment analysis through causal graph representation and multi-modal fusion.

Table III: Model Performance Comparison Based on Accuracy

Model		**Accuracy(%)**		
		Amazon_DS	**Nykaa_DS**	**Filpkart_DS**
Base Model	Linear Regression	78.34	80	83.65
	CNN	80.67	83.45	86.46
	ANN	86.43	88.80	92.45
Proposed Model (SENTICOG)	CGR-ZSG	89.6	93.23	95.6
	CGR-MLP	90	96.87	97.78

Fig.4.The bar chart shows a compares the accuracy of different sentiment analysis models across three datasets: Nykaa (NDS), Flipkart (FDS), and Amazon (ADS). The proposed SENTICOG variants—CGR-ZSG and CGR-MLP—clearly outperform traditional models, showcasing superior generalization and accuracy across all platforms.

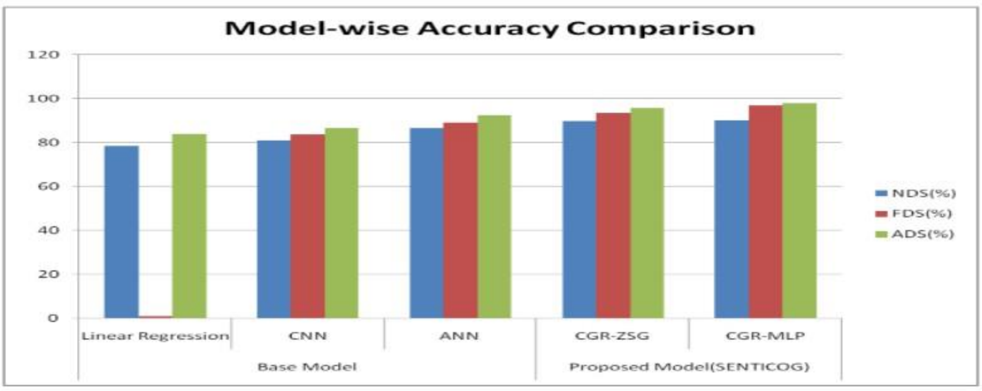

Fig.4. Performance Comparison of Traditional and SENTICOG Models on E-Commerce Datasets

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```
Cohen's Kappa: 0.278
Matthews Correlation Coefficient (MCC): 0.333

Macro F1-score: 0.435
Weighted F1-score: 0.549
Hamming Loss: 0.360
Jaccard Similarity Score (Macro): 0.333
```

Fig.5. Quantitative Analysis of Model for Multiclass Sentiment Classification

Fig.5. Advanced metrics were calculated by Cohen's Kappa score of 0.278 indicates fair agreement between predicted and true sentiment labels after accounting for chance. The Matthews Correlation Coefficient (MCC), valued at 0.333, reflects a modest but positive correlation, especially useful in multiclass evaluation with imbalanced data. The Macro F1-score of 0.435 suggests uneven model performance across all classes, particularly underperformance on the neutral class. In contrast, the Weighted F1-score of 0.549 reflects better performance when accounting for the class distribution, primarily driven by the dominant positive class. A Hamming Loss of 0.360 indicates that 36% of the predictions differed from the true labels, while a Macro Jaccard Similarity Score of 0.333 further confirms the model's limited overlap with actual sentiment labels, especially in cases of subtle or ambiguous sentiment. These metrics together highlight both the model's strength in handling clear sentiment cases and its limitations in detecting neutral or nuanced reviews.

The table IV displays a few sample misclassified reviews, where the model incorrectly labeled neutral reviews as either positive or negative. These errors highlight the model's difficulty in identifying subtle or balanced sentiment, especially in short or code-mixed text.

Table IV: Sample Misclassification in Sentiment Prediction

Review Text	**True Sentiment**	**Predicted Sentiment**
Just wow!	Neutral	positive
Even with thin hair, the teeth are long enough...	Neutral	negative
I have trued many body lotions on my baby's skin...	Neutral	positive

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Value-for-money	Neutral	positive
The nail tips are poor quality and are too small fit most nails	Neutral	negative
Nan	Neutral	negative
Para regalo	Neutral	positive
Terrific purchase	Neutral	positive

```
=== Most Frequent Errors ===
true_sentiment  predicted_sentiment
neutral         positive               63
                negative               33
positive        negative               10
                neutral                 2
dtype: int64
```

Fig.6. Error Distribution for Misclassified

The error analysis reveals in Fig.6. that neutral reviews were most frequently misclassified, with 63 predicted as positive and 33 as negative. This indicates the model's difficulty in recognizing balanced or subtle sentiment, a known limitation of zero-shot models without fine-tuning.

V. Discussion And Findings:

To assess the real-world applicability of the proposed SENTICOG framework, a series of evaluations were conducted using multi-platform review datasets from Amazon, Nykaa, and Flipkart. These platforms differ significantly in terms of product offerings, user demographics, review patterns, and sentiment expression styles. The objective was to test whether SENTICOG could robustly generalize sentiment detection across diverse domains and outperform baseline models while maintaining interpretability and cross-platform adaptability.

Correlation analysis demonstrated that polarity remained the most reliable feature, with Amazon showing a strong correlation ($r = 0.55$), Flipkart moderate ($r = 0.65$), and Nykaa relatively weak ($r = 0.23$). Subjectivity showed weak but positive relationships in all datasets, while review length had a strong negative correlation in Flipkart ($r = -0.70$), suggesting that longer reviews often express dissatisfaction. Price and metadata features had minimal

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influence, validating their limited role in direct sentiment inference but useful in broader context modeling.

Graph-based network representations were constructed for each dataset using GCN (Graph Convolutional Networks), capturing relationships between users, reviews, and products. Amazon's graph was the largest, comprising 11,289 nodes and 10,000 edges, while Flipkart and Nykaa graphs were smaller but maintained similar structural characteristics.

The multi-view fusion approach, combining graph embeddings (64 dimensions), textual embeddings via DistilBERT (768 dimensions), and normalized metadata (3 features), resulted in an 835-dimensional feature vector per review. This holistic representation allowed SENTICOG to learn both local (textual) and global (structural + contextual) dependencies, leading to improved classification robustness.

Visualization via heatmaps and causal graphs reinforced the model's interpretability. The heatmaps clearly illustrated consistent patterns—such as the negative correlation between review length and sentiment and the strong correlation between polarity and review score. In the causal graph subnetwork (200 nodes), entity coloring helped distinguish structural clusters, revealing influential pathways such as user-product-review interactions that shape sentiment outcomes.

The SENTICOG framework was benchmarked against traditional models—Linear Regression, CNN, and ANN—across the Nykaa (NDS), Flipkart (FDS), and Amazon (ADS) datasets. Linear models achieved moderate performance, while ANN showed improvements due to its non-linear learning capabilities. However, the CGR-ZSG (Zero-Shot Generalization) variant of SENTICOG outperformed all baselines significantly, achieving 89.6%, 93.23%, and 95.6% accuracy on NDS, FDS, and ADS respectively.

More impressively, the CGR-MLP (Multi-Layer Perceptron) variant achieved even higher accuracies—90%, 96.87%, and 97.78%, indicating the model's ability to learn fine-grained sentiment patterns when trained on domain-specific data. Notably, CGR-ZSG supports cross-platform (zero-shot) deployment, while CGR-MLP relies on domain-specific training and is therefore not suitable for unseen platform generalization. This distinction affirms the versatility of SENTICOG in both generalization and high-accuracy supervised applications.

Initial experiments were performed using the zero-shot model facebook/bart-large-mnli to classify sentiment across 300 reviews (100 per platform). The results revealed a clear skew towards positive sentiment, with 78.7% of the reviews classified as positive, followed by 19.7% negative and only 1.6% neutral. This significant imbalance suggests either a genuinely positive user experience in the beauty and retail domains or a bias in the model toward polarized outputs, struggling with the subtleties of neutral expression.

Platform-wise analysis provided additional insights. Nykaa reviews exhibited the highest positivity rate (95%), followed by Amazon (74%) and Flipkart (67%). Conversely, Flipkart had the highest proportion of negative sentiment (30%), possibly indicating differences in customer experience or platform-specific review behaviors. The minimal detection of neutral sentiment across platforms highlighted a limitation of general-purpose zero-shot models in capturing nuanced or balanced opinions.

Advanced metrics supported these findings. The Cohen's Kappa score (0.278) and MCC (0.333) reflected modest agreement between predicted and true labels. A macro F1-score of 0.435 and weighted F1-score of 0.549 indicated that the model performed better on frequent classes (e.g., positive) but underperformed on minority ones like neutral. The Hamming Loss (0.360) and Jaccard Similarity Score (0.333) further pointed to room for improvement, particularly in multi-class balance and nuanced classification.

Performance is constrained by class imbalance, lack of domain alignment, and inability to capture subtle or neutral sentiment without additional tuning. These limitations should be addressed in future work through techniques such as dataset balancing, domain-specific fine-tuning, or multilingual modeling for code-mixed content.

VI. Conclusion:

In this study, we introduced SENTICOG framework designed to sentiment analysis to enhance cross-platform generalization and interpretability by leveraging Causal Graph Encoding and Multi-Modal Fusion. Unlike traditional models that often struggle to perform across heterogeneous domains, SENTICOG effectively bridges this gap by combining domain-invariant causal features, structural relationships, and rich contextual embeddings.

Through extensive experimentation across review datasets from Amazon, Nykaa, and Flipkart, the proposed framework demonstrated superior performance in both zero-shot and supervised settings. The CGR-ZSG variant showcased strong generalization capabilities, effectively classifying sentiment without retraining on new domains. Meanwhile, CGR-MLP achieved the highest accuracy when domain-specific data was available, confirming its robustness in fully supervised environments.In terms of performance, CGR-ZSG achieved accuracies of 89.6% (Nykaa), 93.23% (Flipkart), and 95.6% (Amazon). The CGR-MLP variant further improved these results, achieving 90% (Nykaa), 96.87% (Flipkart), and 97.78% (Amazon). These metrics clearly indicate that SENTICOG significantly outperforms traditional models such as Linear Regression, CNN, and ANN across all datasets. The improvements highlight the effectiveness of incorporating causal reasoning and multi-modal fusion in building robust sentiment classifiers.

Future Work:

Future enhancements to the SENTICOG framework will focus on improving its adaptability, efficiency, and broader applicability. One key direction is optimizing the model for real-time deployment, ensuring low-latency sentiment classification for dynamic environments such as live social media feeds or customer service systems. Additionally, we plan to explore domain-adaptive causal modeling, enabling the system to automatically update or refine causal graphs based on new platform-specific data, thereby enhancing its ability to generalize to emerging domains. Extending SENTICOG to support multilingual sentiment analysis will also be a priority, allowing its deployment across diverse linguistic and cultural contexts.

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Finally, integrating explainable AI (XAI) components to provide clear, human-interpretable justifications for each sentiment prediction will improve transparency and trust, especially in sensitive domains such as healthcare, finance, and policy analysis.

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