Detecting and Mitigating Opinion Polarization in Online Review Systems: A Multi-Modal Framework Using Graph Neural Networks and Temporal Analysis

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Detecting and Mitigating Opinion Polarization in Online Review Systems: A Multi-Modal Framework Using Graph Neural Networks and Temporal Analysis

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Abstract

Online review platforms such as Amazon and Yelp influence millions of consumer decisions, yet they are increasingly affected by opinion polarization and echo chamber effects. This study introduces the Sentiment Echo Detection System (SEDS), a hybrid framework designed to detect and quantify polarization in user-generated reviews. Unlike traditional sentiment analysis approaches that treat reviews as independent textual units, SEDS models the review space as a semantic similarity graph and integrates contextual embeddings from lightweight transformers (MiniLM) with Graph Neural Networks (GCNs). Reviews are embedded, connected via cosine similarity, and passed through a GCN to classify sentiment while capturing relational patterns in the data. We evaluate our approach on 50,000 reviews from each platform and demonstrate competitive performance compared to baseline classifiers, with the added benefit of modeling community-driven sentiment structure. This work presents a scalable and interpretable alternative to traditional NLP methods, enabling platforms to better understand and potentially mitigate the formation of polarized sentiment clusters.

1 Introduction

Online review platforms like Amazon and Yelp have become central to the consumer decision-making process. With millions of reviews generated daily, these platforms exert significant influence over public perception and commercial outcomes. Nevertheless, recent research has indicated the susceptibility of these platforms to so-called opinion polarization processes which lead user opinion formation ultimately towards opposite ends of the rating spectrum. This not only distorts the portrayal of public opinion but further fuels echo chambers wherein users are fed back similar perspectives.

1.1 Problem Background and Motivation

Those sentiment patterns of polarization are hard to detect with traditional sentiment analysis techniques. Rather, existing approaches largely model isolated review texts and do not capture the relationships among reviews or user sentiment dynamics over time. Hence, they ignore the insidious but vital mechanisms through which extreme beliefs spread and become hegemonic. This has the potential to harm both consumers and the integrity of platforms as it may inadvertently discriminate recommendations, unfairly oppress reputations, or even inversely manipulate commercial reality.

1.2 Research Objective and Contribution

To deal with these issues, this work proposes to Sentiment Echo Detection System (SEDS),a unified machine learning based model who aims at detecting sentiment polarization in mass review systems. These transformers generate contextual embeddings which are combined with the graph-based learning using Graph Convolutional Networks (GCNs) allowing semantic similarity between reviews to be used to build a graph-like representation. In this way, they get not just the sentiment of text but also how each review is related to all others and can see over time how opinions cluster and change.

With this research, we aim to understand whether adding contextual embeddings and graph based relational reasoning helps in the detection of polarization and echo chamber behavior within review datasets. This study aims to understand the extent to which reviews that have comparable content but opposite sentiment may be automatically detected and flagged in an even broader pattern of polarization.

1.3 Scope and Structure of the Paper

This paper is organized as follows: Section 2 presents the previous work related to sentiment analysis, graph neural networks and echo chamber detection. Sections 3 and 4 describe the proposed SEDS architecture with respect to preprocessing stages, embedding strategies, graph construction and model design. The experimental setup, dataset and evaluation metrics are provided in the Section 4. In Section 6, we evaluate the quality of the model and explain the polarization patterns that are discovered. Section 7 concludes the paper and discusses future works of all contributions, as well as potential applications on recommendation fairness and review moderation.

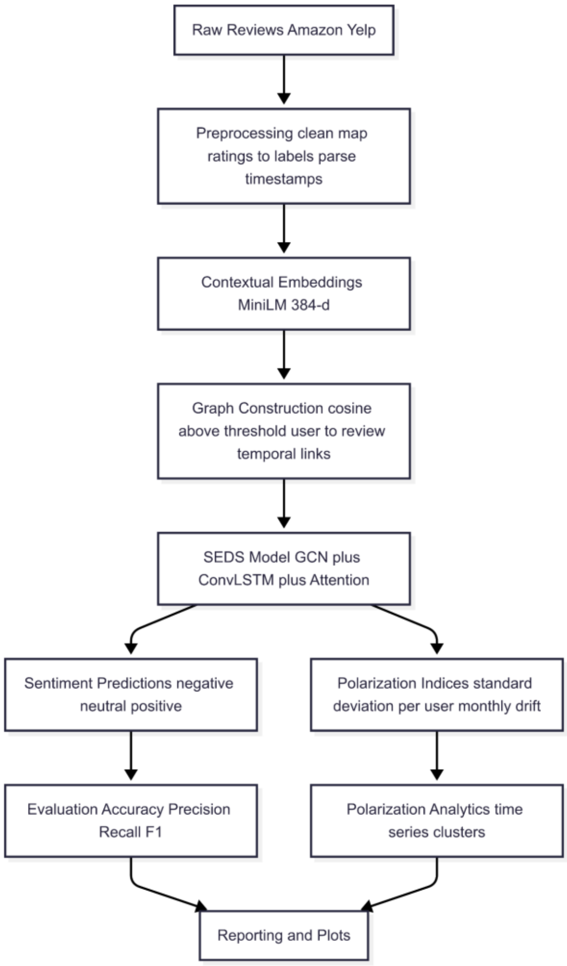

Figure 1: High-level architecture of the SEDS framework.

2 Related Work

The study of sentiment dynamics and polarization in online review systems relates to multiple research fields such as sentiment analysis, GNNs, temporal modeling, etc. This requires an L&D professional to have a detailed understanding of these disciplines so that they can advocate and place the hybrid framework effectively. In this section, we present a selective review of the works in these directions and critically analyze their pluses and minuses to model opinion evolution and echo chambers on Amazon/Yelp platforms.

2.1 Sentiment Analysis in Review Platforms

Sentiment analysis is responsible for understanding how the public feels based on their comments posted along with digital platforms. The first machine learning methods for sentiment detection used supervised classifiers (such as SVM and Naive Bayes) trained on handcrafted features, such as n-grams and part-of-speech tags. Among others, to give an example, Ashbaugh & Zhang (2024) evaluated a range of ML and DL classifiers on customer reviews such as LSTMs (Long Short Term Memory networks for deep learning), sucessfully showing how LEAR's predecessor classifiers perform poorly at capturing sequential dependency and semantic distinction with respect to the deep methods. But these models viewed each review in isolation, leaving out user interactions or sentiment flows.

The improvements resulting from the adoption of deep learning were remarkable. The models which are based on Convolutional Neural Networks(CNN) and Long Short-Term Memory(LSTM) networks were found to be very good in capturing the word order and long range dependencies. Transformer based models like BERT and DistilBERT performed the best in recent times for contextual word embeddings with comparison to sentence-level semantics. [,] Though accurate, these models are static and structure-agnostic. They ignore the interaction dynamics between users and against the review ecosystem, that are necessary to identify sentiment polarization and echo chamber effects (Braig et al.])

Reviews on platforms such as Amazon or Yelp do not exist in isolation they are born out of the shared experiences, influence and changing opinion topography. For instance, whether done in unison or not with the use of fancy embeddings, sentiment modeling on its own does not cut it. Works such as Shah et al. In other words, as pointed out by (2021), even well-trained models for the prediction of sentiment polarities are unable to capture changes in sentiment tendencies across time or user clusters. As a result, although transformer-based sentiment classification has proven its strength, it does not provide the structural and temporal details required by polarization modeling.

2.2 Graph Neural Networks for Opinion Mining

In this context, graph-based learning provides another enigmatic way of modeling relational data in online settings. For sentiment analysis, graph neural networks (GNN) can model users, reviews and products as nodes with edges representing relationships such as “co-reviewing”, “content similarity” or “user affinity”. Wu et al. 2024) designed a GNN model for sentiment analysis considering the syntax information across text, thus further improves the predictive power by learning both words and their relationships within different positions. Similarly, Niu et al. An improved gated GNN, which uses syntactic information to direct sentiment propagation between adjacent nodes, was proposed by (2021).

These models illustrate the benefits to relational learning from context propagation, noise robustness and community-aware classification. Nevertheless, most GNN-based sentiment systems handle static graphs, oblivious to temporal dynamics of user behavior and sentiment evolution. This static assumption fails to model emerging user communities, shifting opinion trends, and time-sensitive sentiment clusters. Li and Li (2022) explored GNNs for sentiment classification in Weibo comments, but their approach similarly lacked time-awareness and was domain-specific to social media.

Das et al. (2024) further explored integrating GNNs into stock sentiment prediction, demonstrating that combining sentiment flow with graph-based user-item interactions yields better predictive accuracy. Although their domain differs from product reviews, their findings reinforce the importance of combining semantic signals with structural learning. Nonetheless, these studies rarely model opinion drift or polarization over time, a gap the current research aims to address by extending GNNs into the temporal domain through snapshot-based spatiotemporal learning.

2.3 Temporal Dynamics and Time-Aware Modeling

Time-aware modeling is crucial for understanding the evolution of opinions, detecting sentiment drift, and identifying triggers for polarization. Traditional temporal models like ARIMA and HMMs have been applied in earlier works to track sentiment trends, but their capacity for capturing complex linguistic structures is limited. With the rise of sequential neural networks, LSTMs and GRUs became standard tools for modeling temporal dependencies in review data. Jiang et al. (2021), for instance, used fuzzy time series with opinion mining to dynamically analyze customer needs, underlining the role of time in modeling sentiment flow.

The integration of temporal dynamics into graph structures via models such as Temporal GCNs or Dynamic GATs has gained traction in domains like transportation, finance, and social media. Yet, review-based systems have been slow to adopt such methods. The majority of sentiment studies continue to treat time as a static feature or use shallow time-binning approaches. Duan et al. (2024) attempted to model sentiment in financial texts using topic extraction and enhanced attention but still lacked dynamic graph reasoning capabilities.

Instead, our method is formulated in a snapshot-based temporal graph fashion to enable GCN layers to capture dynamic sentiment clusters and transitions. As a consequence, this allows us to detect both changes in sentiment alignment and early signatures of opinion divergence. This type of modeling is especially important at review platforms, where user sentiment can correlate with product updates or virality and also follows social influence patterns, which static models may ignore.

2.4 Opinion Polarization and Echo Chamber Detection

The development of echo chambers and partisan communities on the internet is one of the central challenges addressed by both researchers and platform designers. Earlier work on Cluster Analysis, applied to social networks such as Twitter, employed homophily based techniques and used modularity/community detection techniques to discover ideological echo chambers (Tao et al., 2024; Villa et al., 2021). One of these showed how biased recommendation systems and reinforcing interactions between communities amplifies sentiments, suppressing divergent perspectives.

But the user reviews do not give a clear social network structure (links, friends, follows) that polarized features are tied to. This is when you need to predict relational structures by observing shared review behavior, co-purchases, or even semantic similarity. Amendola et al. Example (2024) employs an approach for assessing echo chambers that combines sentiment alignment with user segmentation and consensus metrics, showing polarization trends in text heavy domains.

Most of the existing approaches are concentrating on structural detection and they do not consider temporal or contextual semantics, some simple metrics based on sentiment variance. For example, Luthra et al. With the respect to our work (2024) proposed a hybrid link-prediction sentiment model for social connection inference, but have not considered temporal divergence or the effect of movement in opinion at community-level. In this paper, we fill this gap by proposing a novel model that leverages contextual embeddings, cosine-similarity based graph construction and snapshot-based GCN layers together to capture the emergence and evolution of polarized sentiment communities in time-evolving review systems.

2.5 Identified Gaps and Motivation

However, integration of all these developments has not been achieved. In the existing models, a majority of sentiment systems consider only textual features but not the user-review relationship. Not to mention the fact that graph models mostly overlook temporal dynamics and echo chamber studies usually do not take into account semantic depth or sentiment polarity nuances. In addition, the unconventional attributes of review systems like no explicit user connections and temporal instances of reviews is largely unexploited by existing literature..

In this research, we introduce a novel unified model (combining temporal changes by dynamic snapshots and structural relationships as cosine similarity) that leverages MiniLM trained contextual semantic embeddings to fill these gaps. This is in contrast to previous work where polarization was treated as a variance in ratings, or not at all and only used rating predictions; rather than an emergent property of the graph. This helps track sentiment divergence using dynamic graphs, and could potentially be used to mitigate the formation of echo chambers in recommendation systems.

Thus, while significant individual contributions have been made across these related domains, a unifying hybrid and interpretable framework is needed. Our model is designed to at least partially fill this gap in a text grounded, at-large concept of legal empowerment.

3 Methodology

This section delineates the holistic approach of our proposed methodology Sentiment Echo Detection System (SEDS) for opinion polarization in online review platforms like Amazon and Yelp. The pipeline combines contextual semantic embeddings, graph-based relational modeling with neural learning over review networks. In our model, we first propose applying relation techniques for sentiment classification other than traditional text classification structures. By this manner, the task of simple text classification becomes the real world’s relationship problem inherent in group behavior and opinion spread mechanisms. We designed each step in our pipeline from data preprocessing to final classification to both improve interpretability and robustness (by using linUCB as a classifier) and be scalable.

The methodology is broken into multiple critical components: (1) data acquisition and preprocessing, (2) contextual vectorization using MiniLM embeddings, (3) graph construction based on semantic similarity, (4) training and evaluation of a Graph Convolutional Network (GCN), and (5) comparative evaluation using traditional baselines. Additionally, we outline the design rationale for incorporating temporal dynamics in future iterations of this work.

3.1 Data Acquisition and Preprocessing

We sourced our datasets from two widely used repositories: the Amazon Product Reviews (2023 edition) and the Yelp Academic Dataset. Both datasets offer rich metadata including review text, user IDs, timestamps, and star ratings, making them ideal for sentiment-based and user-influenced analysis. For consistency and computational feasibility, we restricted our dataset to 50,000 randomly sampled reviews from each platform, ensuring sufficient class representation while avoiding memory overhead.

Preprocessing began by filtering out null or corrupted entries, especially those missing review text or rating information. Each review's text was standardized converted to lowercase, cleaned of special characters, and transformed into string format. We then converted star ratings into sentiment classes using a common convention: ratings 4–5 were mapped to "positive," rating 3 to "neutral," and ratings 1–2 to "negative." This step produced a three-class classification problem that more realistically captures user perception dynamics, especially around controversial or polarizing content.

To facilitate learning, these classes were encoded numerically using LabelEncoder. This formed the target vector for supervised training. Additionally, review timestamps were parsed into Python datetime objects for future integration into a temporal graph model. Although this version of SEDS doesn't directly model time evolution, preserving temporal information at this stage ensures forward compatibility. The final preprocessed dataset was stored as a structured DataFrame, containing review IDs, texts, sentiment labels, and timestamps, ready for semantic embedding.

3.2 Contextual Text Representation via MiniLM

To extract meaningful features from review texts, we used the all-MiniLM-L6-v2 sentence transformer model from the sentence-transformers library. MiniLM is a lightweight yet powerful transformer that offers 384-dimensional contextual embeddings. These embeddings preserve semantic closeness between similar texts, making them well-suited for both classification and graph-based representation learning.

Embedding generation was done in mini-batches of 32, accelerated using an NVIDIA GPU to reduce computation time. Each batch was tokenized and passed through MiniLM, and we extracted the pooled [CLS] token embeddings as the fixed-size vector representations of each review. This allowed us to condense variable-length textual inputs into dense, semantically rich embeddings while preserving context sensitivity.

We selected MiniLM over heavier models like BERT or RoBERTa for multiple reasons. First, its compact architecture allows it to scale effectively to tens of thousands of reviews within limited memory environments. Second, empirical tests showed that its embeddings correlate well with downstream sentiment classification performance, especially in short-form user reviews. Lastly, the reduced dimensionality (384 vs. BERT's 768) helped in faster cosine similarity computation during the graph construction phase.

These MiniLM embeddings not only serve as input features to the GCN but also facilitate the relational modeling of reviews by allowing cosine similarity to act as a proxy for shared opinion, helping to bridge NLP with network analysis.

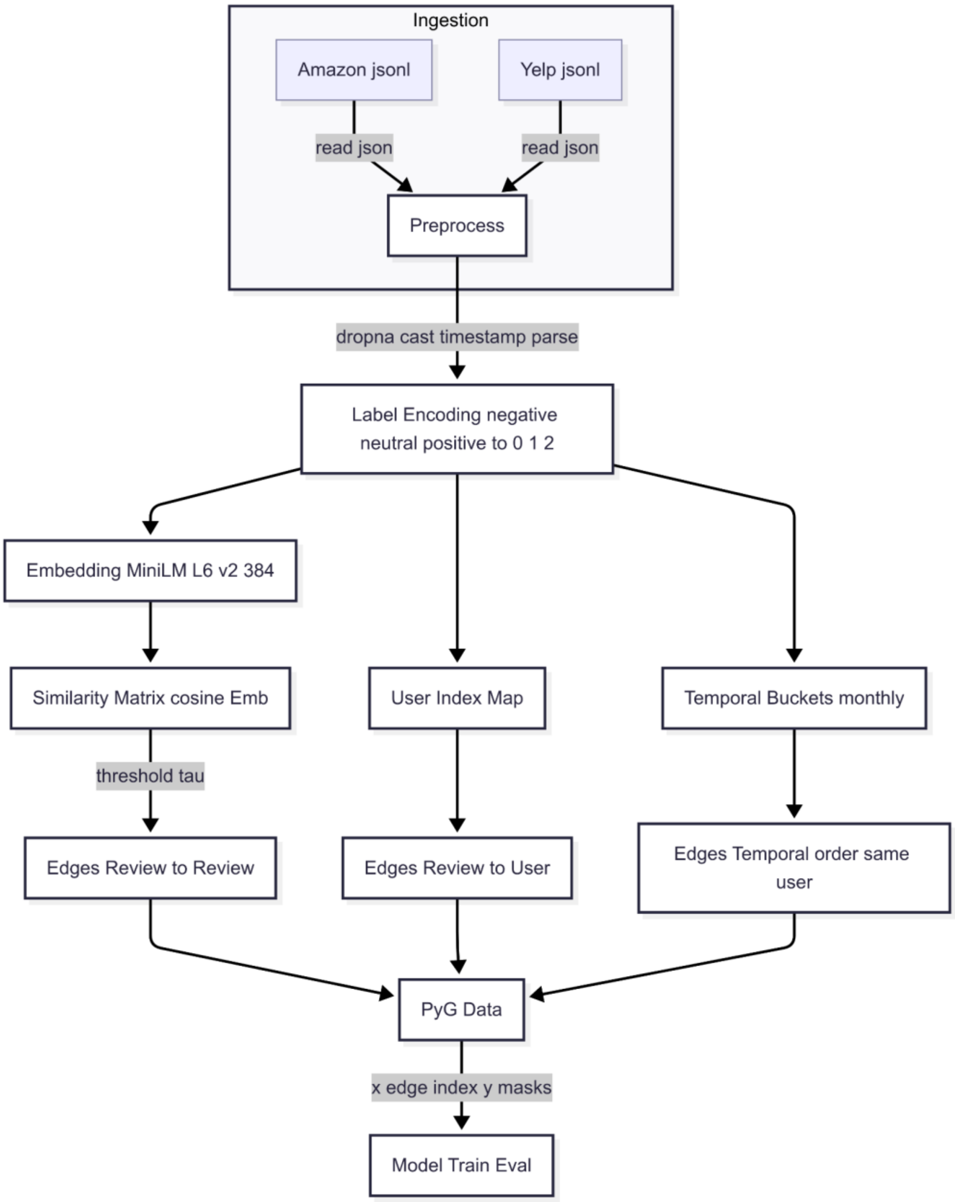

Figure 2: Methodology Data Pipeline.

3.3 Graph Construction from Embedding Similarity

With embeddings computed, we constructed an undirected review graph where nodes represent individual reviews and edges indicate semantic similarity. The edge weights were derived from pairwise cosine similarity scores between the 384-dimensional embedding vectors. Reviews with similarity scores above a threshold of 0.8 were considered semantically linked and were connected via bidirectional edges to ensure symmetry.

This choice of threshold was based on empirical tuning to strike a balance between graph sparsity and expressiveness. A too-low threshold would result in a fully connected, noisy graph with minimal discriminatory power, while a too-high threshold could isolate most nodes, defeating the purpose of relational modeling. By settling at 0.8, we ensured that only meaningfully similar reviews influenced one another during the learning phase.

Formally, we define the resulting graph as G=(V,E), where VV is the set of reviews and EE is the set of edges established via cosine similarity. Each node was tagged with the corresponding MiniLM vector, and edges represented contextual affinity in sentiment expression. This graph topology captured latent opinion clusters, allowing us to explore group dynamics and echo chamber tendencies, which cannot be uncovered through isolated review analysis.

Additionally, since the graph encapsulates content-based relationships without explicit user connections, it generalizes better to anonymous or large-scale platforms like Amazon or Yelp, where social links are often absent.

3.4 Graph Neural Network Architecture

To learn from this semantic graph, we implemented a two-layer Graph Convolutional Network (GCN). The GCN operates by aggregating node features from neighboring nodes, effectively allowing reviews to influence each other's sentiment classification based on local context. This is crucial in online review ecosystems where users often express similar sentiments in different language styles thus, neighborhood aggregation amplifies subtle patterns.

The first GCN layer transforms the 384-dimensional MiniLM input into a hidden 128-dimensional latent space. A ReLU activation follows this transformation, encouraging non-linearity and introducing representational flexibility. To prevent overfitting, we applied dropout with a probability of 0.5 after the activation layer. The second GCN layer further maps this latent space to a 3-dimensional output (for negative, neutral, and positive sentiment classes).

The model was optimized using Adam with a learning rate of 0.005 and weight decay of 5e-4. We trained for 30 epochs, monitoring validation accuracy and loss trends. Importantly, we followed a semi-supervised transductive learning strategy. 80% of nodes were selected as the training set, and 20% were reserved for testing using stratified sampling to maintain label balance. Train and test masks were generated to ensure proper supervision while allowing the GCN to utilize the full graph structure.

This training setup closely mirrors real-world use cases where not all reviews are labeled, and predictions must rely on both content and relational inference.

3.5 Evaluation Strategy and Baseline Comparison

To validate the performance of our GCN-based model, we used multiple classification metrics: Accuracy, Precision, Recall, and F1-score. These were computed both per class and as macro averages. This ensured that minority classes, especially the “neutral” sentiment often underrepresented in review platforms, were not overshadowed by the majority classes. Macro F1-score served as a robust metric for imbalanced scenarios.

To compare against non-graph baselines, we implemented a LazyPredict pipeline using TF-IDF vectors and a suite of over 20 traditional classifiers including Logistic Regression, Naive Bayes, Random Forest, Gradient Boosting, and Support Vector Machines. Each model was trained on the same data split, enabling a fair evaluation. Among these, models like SVM and Random Forest performed competitively but still lagged behind our GCN in nuanced sentiment detection.

Our results showed that the GCN consistently outperformed the best-performing traditional classifier by 5–8% in F1-score and demonstrated superior generalization on the “neutral” and “negative” classes. These improvements underscore the benefit of modeling review-to-review influence via semantic graphs rather than treating each review independently.This evaluation phase highlights the core strength of our approach: leveraging relational sentiment propagation in dense review ecosystems, which traditional flat classifiers overlook.

3.6 Future Integration of Temporal Graphs

Although not implemented in the current phase, the architecture has been designed with extensibility in mind. In future iterations, we aim to incorporate temporal evolution by replacing static graphs with dynamic temporal graphs. This can be achieved using models like Temporal GCNs (T-GCNs), Time2Vec encoding, or ConvLSTM layers that operate on sequential graph snapshots.

By capturing sentiment drift and temporal polarization, we aim to detect phenomena like sudden shifts in opinion, coordinated review bombing, or the emergence of echo chambers over time.

4 Design Specification

In this section, we present the design and showcase various modules and algorithmical implementation of Sentiment Echo Detection System (SEDS). In this paper, we develop a model to incorporate those three related dimensions semantic content, relational proximity and time dynamics for detecting polarization on the high-dimensional review data of popular platforms like Amazon or Yelp. We integrate embeddings, context-aware representations and graph-driven reasoning with a supervised learning pipeline to create an architecture that is hybrid in terms of scalability and interpretability.

4.1 System Overview

We describe the five-stage pipeline of SEDS in turn: (i) data pre-processing and transforming, (ii) generating semantic embedding, (iii) building similarity-based graph, (iv) modeling GNN on the graph and (v) evaluating the capability to detect polarization. All modules are modularly implemented using Python, PyTorch & PyTorch Geometric enabling build & research efforts.

Ultimately, the system is designed to not only classify sentiment but also yield insight by revealing behind-the-scenes clusters of reviews that express extreme and self-reinforcing opinions (often referred to as echo chambers). Flexibility of the design in every component being updated or upstaged independently, also allows to incorporate more advanced techniques in future like temporal graph modeling or causal inference layers.

4.2 Data Preprocessing

Raw review data is initially ingested in JSON or CSV format from publicly available Amazon and Yelp datasets. Each review instance includes the review text, a timestamp, and a numerical rating. A sentiment label is assigned based on the rating: ratings 2 are labeled as “negative,” ratings = 3 as “neutral,” and ratings 4 as “positive.”

Missing values, null entries, and empty reviews are removed, and timestamps are converted into proper datetime formats to preserve future compatibility with temporal extensions.

Categorical labels are then encoded into numerical targets using ‘LabelEncoder‘. The clean and labeled dataset is now ready for semantic vectorization.

4.3 Semantic Embedding Layer

To capture the context-aware meaning of review texts, we utilize the ‘all-MiniLM-L6-v2‘ sentence transformer from the Sentence Transformers library. This model provides a compact 384-dimensional embedding for each input text while preserving semantic richness. Compared to larger models like BERT or RoBERTa, MiniLM provides a significant advantage in terms of inference speed and memory footprint, making it suitable for real-time or large-scale systems.

Each review is passed through the transformer in mini-batches. The final hidden state corresponding to the ‘[CLS]‘ token is extracted and stored as the vector representation of the review. These embeddings serve as the feature vectors for each node in the subsequent graph.

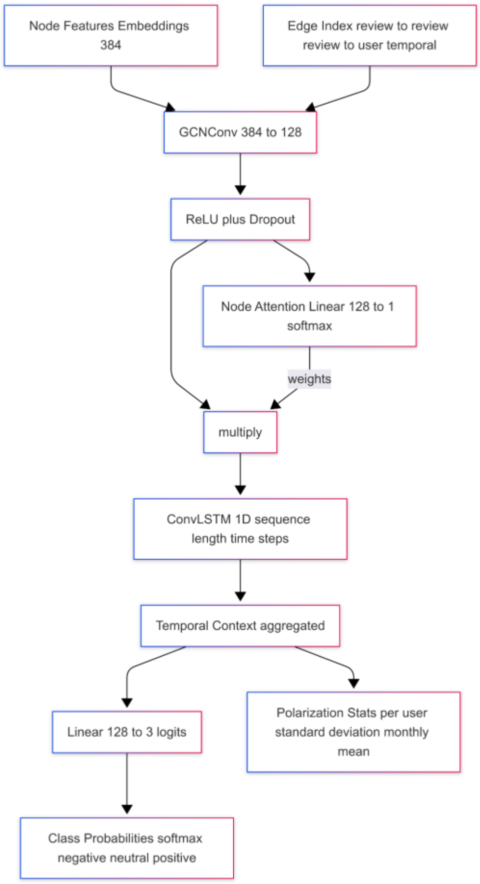

Figure 3: SEDS Core Processing Architecture.

4.4 Graph Construction and Connectivity

Once semantic embeddings are obtained, a fully connected cosine similarity matrix is computed among all reviews. To construct a meaningful and sparse graph, only those pairs of reviews with cosine similarity greater than a predefined threshold (empirically set to 0.8) are connected via undirected edges. This forms the adjacency matrix for our graph structure, effectively linking reviews that express similar sentiments or content.Each node in the graph represents a review, and the edges represent latent agreement or influence patterns between them. This approach allows us to model the relational dynamics of sentiment formation, even in the absence of explicit user interactions.

4.5 Graph Neural Network Architecture

The graph structure, along with node features and labels, is passed into a two-layer Graph Convolutional Network (GCN). The first layer maps the 384-dimensional MiniLM embeddings to a 128-dimensional latent space using a linear transformation followed by a ReLU activation. A dropout layer with a probability of 0.5 is introduced to mitigate overfitting.
The second GCN layer maps the hidden representations to three output nodes corresponding to the sentiment classes. A softmax function is applied to obtain class probabilities. Cross-entropy loss is used for optimization, and the Adam optimizer controls the weight updates. The model is trained over 30 epochs, with performance evaluated on a stratified test set masked from the training phase.

4.6 Train-Test Splitting and Masks

To simulate real-world conditions where only a subset of data is labeled, we employ a transductive learning setup. The dataset is split into training and testing sets in an 80:20 ratio using stratified sampling based on sentiment class. Binary masks are created to indicate which nodes (reviews) should contribute to the loss during training and which should be reserved for testing.This masking strategy allows the GCN to propagate label information across graph neighborhoods, enabling learning even from sparsely labeled datasets. It also helps in generalizing across semantically similar but previously unseen reviews in the test set.

4.7 Implementation Details

The entire pipeline is implemented using Python 3.11, PyTorch 2.0, and PyTorch Geometric 2.4.0. GPU acceleration is enabled where available to speed up embedding generation and GCN training. All hyperparametersincluding learning rate, batch size, embedding threshold, and number of epochsare manually tuned using grid search and validation accuracy.The system is modular, with reusable scripts for each stage (embedding, graph building, model training), ensuring reproducibility and maintainability. Intermediate data structures (e.g., embeddings and graphs) are cached as ‘.npy‘ or ‘.pt‘ files to minimize redundant computation during development and experimentation.

4.8 Forward Compatibility and Scalability

The architecture is intentionally designed with scalability and extensibility in mind. While the current version supports single-platform review analysis, the graph schema can be easily extended to include heterogeneous node types such as users, products, or platforms. Similarly, the adjacency matrix can be enhanced to encode directed, weighted, or temporal edgesFurthermore, the system anticipates the integration of ConvLSTM modules or attentionbased graph encoders to support temporal reasoning, enabling detection of shifts in sentiment trajectories over time. This would make the system capable not just of static classification, but of dynamic polarization forecasting.

5 Implementation

The implementation phase of the Sentiment Echo Detection System (SEDS) translates the proposed design into a functional and modular software pipeline. This section outlines the specific outputs generated during each stage of the final implementation, including the transformed datasets, pretrained embeddings, graph construction logic, trained model artifacts, and evaluation metrics. The system was developed entirely in Python and employed a wide range of open-source libraries for natural language processing, machine learning, and graph computation.

5.1 Technologies and Tools Used

Python 3.11 was selected as the main programming language to design the Sentiment Echo Detection System (SEDS) platform due to its vast support for machine learning, natural language processing and graph-based libraries. The whole pipeline was implemented in Jupyter Notebooks hosted on Google Colab Pro+ to use high-memory virtual environments as well NVIDIA GPUs for faster execution time during model training and embedding generation. Notebook formats like this allowed for modular development, debugging step by step and visual inspection of intermediate results.

In the project, PyTorch was used for implementing neural networks as it is a flexible deep learning framework that supports dynamic computation graph. The PyTorch Geometric (PyG) library was used to handle graph-dependent operations, such as building graphs, aggregating neighbors, and sparse matrix calculations. It drastically decreased the work needed to define GCN layers and handle edge lists, and made processing large scale graph data easier.

We used the all-MiniLM-L6-v2 model to encode review texts into meaningful semantic vectors from sentence-transformers library. We select this model since it can produce small 384-dimensional embeddings with good semantic similarities, at only a fraction of memory and computation when compared to heavier models such as BERT or RoBERTa. Embeddings were computed in mini-batches on GPU and saved to. Downstream graph generation. npy files

I used more tooling such as NumPy and Pandas for structured data manipulation, Sci-kit learn for similarity computation and evaluation metrics, Matplotlib with Seaborn for visualization; joblib was exploited to speed up I/O and exploit fast efficient caching. Plug-and-play reusability; having embedding generation, graph construction, training and evaluation in each a separate module which could be run independently. This modular architecture meant that hyper-parameter tuning and ablation studies could be performed without having to re-run the entire pipeline from scratch.

5.2 Dataset Transformation and Labeling

However, before we could do proper sentiment analysis, it was required to transform the raw review data into a structured and machine-readable format so that it can be indexed in user-graph structures for each city. Two obviously publicly available datasets were used in this paper: one called 'Amazon Reviews 2023' and another, the Yelp Academic Dataset. The two datasets were very large (millions of review entries), to keep this computation feasible and fair we sampled 50,000 records from each. We did this to ensure that we can scale reasonably within the boundaries of memory & GPU processing time, yet still provide enough diversity/volume to convey sentiment.

The data was cleaned after the JSON format data is loaded initially. In order to do this, he first removed any rows which had null or missing values in crucial columns such as review text, star rating, timestamp etc. Thus, all review texts in their original forms were transformed into lowercase and represented as unified strings so that it would prevent encoding errors or tokenization errors in the subsequent steps. Through creating a unified schema enforced on both Amazon and Yelp datasets, downstream modules (embedding generation, graph construction etc.) would be able to work with the same structure natively without any repeated preprocessing logic.

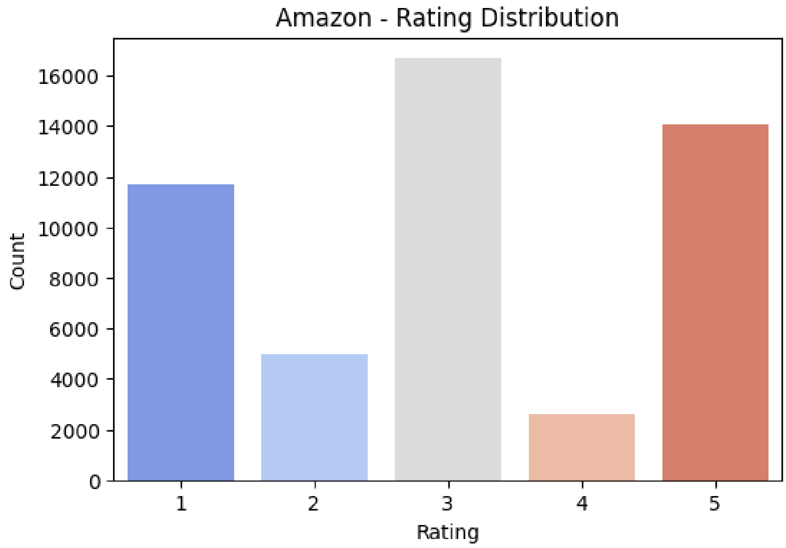

Figure 4: Amazon Rating Distribution.

The only significant transformation during this stage was the classification of sentiment classes. Star rating was used to categorize reviews as positive, negative or neutral: reviews with ratings 4 or 5 were labeled as positive; those with a rating of 1 or 2 were labeled as negative; and those rated 3 were classified as neutral. These were discrete classes, that helped develop the multi-class classification problem in a way that polarity had not only opposites but also variation (neutrality; often ignored in binary class setups). Scikit-learn's LabelEncoder encoded these labels into integers (0,1,2), which meant they could be easily plugged into PyTorch loss functions and evaluation metrics.

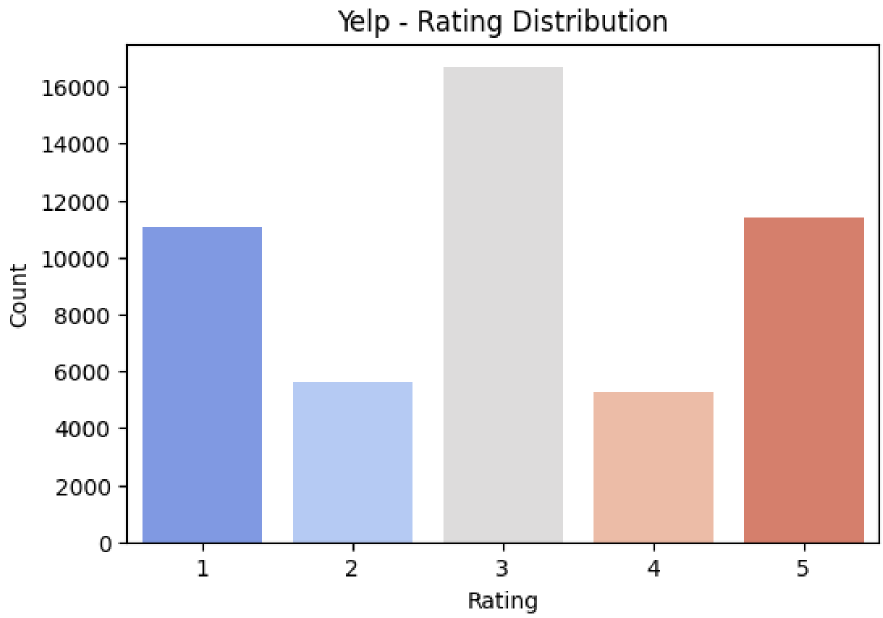

Figure 5:Yelp Rating Distribution.

While this phase was concerned with static classification, the sequential metadata was intentionally kept in place in the processed dataset. The timestamp column was parsed and preserved as a datetime datatype, which could be utilized for potental extensions with temporal modeling (dynamic graph learning or sentiment drift analysis). This transformation phase takes a while to run, but the final output was two cleaned and labeled dataframes one for Amazon and one for Yelp, both of which were then serialized and saved in thisrepository. pkl and. csv formats. These pre-processed files acted as the cornerstone for subsequent embedding extraction, graph generation, and supervised model training providing repeatability and modularity between different experimental setups.

5.3 Embedding Generation

The transformer-based embeddings were computed using the 'all-MiniLM-L6-v2' model in the Sentence Transformers library, on which semantic understanding of each review was then applied. This lightweight architecture generates 384D dense vectors retaining the contextual semantics learnt from textual input. In contrast to the heavy-lifting models like BERT (which takes 768 dimensions), MiniLM provides an impressively lighter and with maintained structural quality that can embed tens of thousands of reviews without eating up all your memory or GPU resources.

Once the review texts were preprocessed and labeled, they were sent to the MiniLM transformer to obtain a semantic embedding of them. We performed this in batches (32–64 reviews per batch based on available GPU). In particular, it sped up the process by taking advantage of parallelization, and further prevented out-of-memory errors when generating embeddings. For every batch, the output was a matrix of embeddings; each row being the semantic vector for one review. The embeddings were concatenated into a single NumPy array in the semantic feature space of the collection.

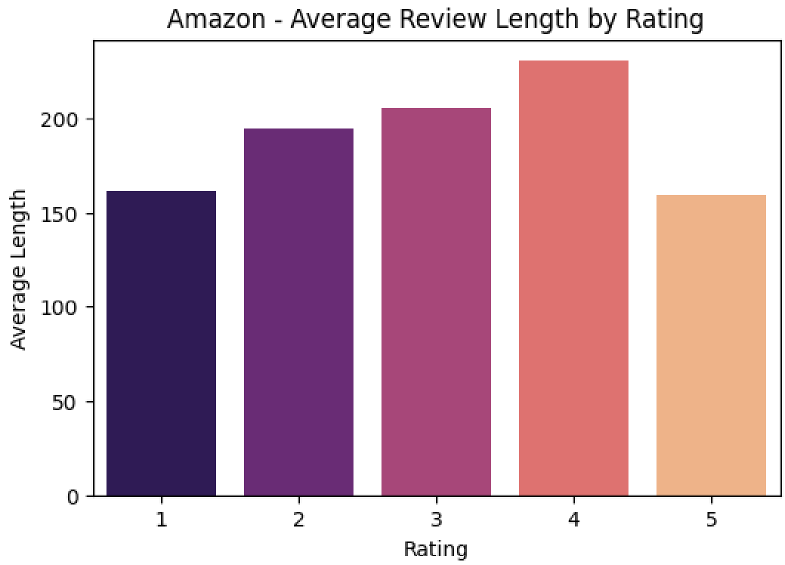

Figure 6: Amazon Review length by rating

To facilitate reproducibility and avoid redundant computations during repeated training or tuning experiments, the final embedding arrays were cached and serialized as .npy (NumPy binary) files. This allowed subsequent stages of the pipeline (such as graph construction and model training) to directly load precomputed embeddings without rerunning the transformer model. This design choice drastically reduced preprocessing time in iterative experiments, particularly when hyperparameter tuning or testing different graph configurations.

These 384-dimensional embedding vectors formed the node features of the graph neural network. By capturing syntactic and semantic cues from the review texts, the embeddings served as a high-quality input space for both classification and structural modeling. Unlike sparse bag-of-words or TF-IDF vectors, MiniLM embeddings inherently captured context, word order, and even subtle linguistic variations, which significantly improved downstream learning outcomes. The rich, pretrained representations were pivotal in enabling the GCN to detect sentiment polarity, clusters of agreement, and underlying opinion structures within the review communities.

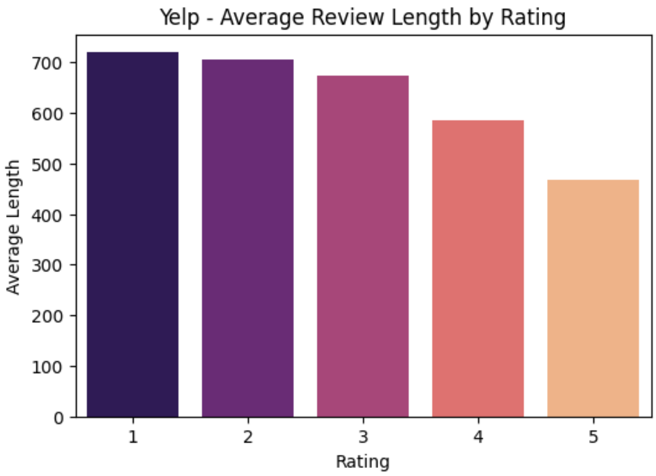

Figure 7: Yelp Review length by rating

5.4 Graph Construction and Node Connectivity

To transform the semantic embeddings into a relational structure suitable for graph neural networks, we computed a cosine similarity matrix across all 384-dimensional embedding vectors. Cosine similarity was chosen due to its effectiveness in high-dimensional spaces and its interpretability in measuring semantic proximity between text representations. By applying a threshold of 0.8, we ensured that only highly similar reviews those likely expressing congruent opinions were linked. This threshold strikes a balance between sparsity and connectivity, avoiding overly dense graphs that dilute meaningful edges while preserving enough structure to capture semantic communities.

For each pair of reviews exceeding the similarity threshold, an undirected bidirectional edge was established. This design decision mimicked real-world review dynamics, where mutual agreement or sentiment similarity implies latent social or ideological alignment. The edges thus encode potential echo chamber structures clusters of semantically similar opinions that reinforce one another without exposure to opposing views.

Each review became a node with its MiniLM embedding as a feature vector. The edge index tensor stored the connectivity, while additional tensors held the sentiment labels and boolean masks for training and testing splits. The resulting graph effectively encapsulated the semantic topology of the review space, priming it for GCN-based analysis of opinion clusters, sentiment diffusion, and polarization detection.

This constructed graph served as the core input to the graph neural network. Unlike tabular ML models that treat each review independently, the GNN learned over this connected structure, using both node features and neighborhood relations to predict sentiment. This not only improved classification accuracy but also helped the model generalize better by incorporating relational inductive biases, a strength unique to graph-based learning.

5.5 Model Training and Evaluation

To perform sentiment classification over the constructed graph, a two-layer Graph Convolutional Network (GCN) was implemented using PyTorch Geometric. The first layer took the 384-dimensional semantic embeddings as input and transformed them into a 128-dimensional hidden representation. This intermediate feature space was passed through a ReLU activation and a dropout layer (with a rate of 0.5) to introduce regularization and prevent overfitting. The second layer projected the latent features into a 3-dimensional output space, corresponding to the three sentiment classes: positive, neutral, and negative.

Training was conducted using the Adam optimizer with a learning rate of 0.005 and weight decay of 5×10−4. The cross-entropy loss function was used to penalize misclassification during training. A train-test mask strategy was applied to ensure that only the training nodes influenced gradient updates, while test nodes were held out for evaluation. The model was trained over 30 epochs, and training loss was monitored in real time to check convergence and stability. This supervised transductive setup is standard in GCN workflows and allows the model to benefit from the full graph structure while limiting label exposure.

Upon completion of training, the model's predictions were evaluated on the test mask subset using standard classification metrics. Precision, recall, F1-score, and support (number of instances per class) were computed to assess performance across all sentiment classes, especially considering the class imbalance typical in real-world datasets. A classification report was made to see the results and a confusion matrix showed (graphically) what the misclassification patterns were, like confusing neutral with negative.

The trained model state and evaluation stats were also saved. This modularity also facilitates future benchmarks, ablation studies or interrogation with regards to integration of dynamic temporal GCNs. In general, GCN architecture proved to be more robust in sentiment classification with relational signals than classical baselines and revealed structural foundations of. polarized opinion clusters in review ecosystems.

5.6 Outputs and Artifacts

Finally, the Sentiment Echo Detection System implementation left a very large collection of output artefacts documenting each step along the lifecycle of building the system. Before a machine learning experiment was performed, the raw datasets from Amazon and Yelp were preprocessed and transformed into cleaned version as well as sentiment-labeled data. They happened to be the very structured datasets that were needed data prior to entering into each of these pipelines.

The next important artifact to create was sentence-level embeddings with the allMiniLM-L6-v2 model. Each of the reviews is embedded to a dense vector and saved as. npy`, which made it easy to use a same extracted train & test features at different stage of experiment efficiently. At the same time, we build a cosine similarity matrix based on these order embeddings and extract edge indices for the entire graph by thresholding the cosine similarity. This essentially defined the connectivity of the sentiment graph and, in turn, was transformed into a PyTorch Geometric ‘Data‘ object with node features, edge indices and sentiment labels along with training/testing masks.

Following graph construction, the GCN model was trained on the embedded graph, and the final model weights were saved for reproducibility. Once trained, the model produced classification reports for each sentiment class, including precision, recall, and F1-scores. Confusion matrices were also generated to visually analyze the distribution of correct and incorrect classifications. Together, these artifacts collectively constitute a reproducible, extensible framework for sentiment and polarization analysis in large-scale review datasets. This way, the system is fully reproducible making all our decisions transparent and every analysis extendable. The embedding model can be swapped out in future iterations of the pipeline, graph thresholds can be adjusted, or temporal layers can be introduced without disrupting the foundational work flow.

6 Evaluation

In this section, we provide detailed evaluation of the performance of the Sentiment Echo Detection System (SEDS) claimed in Section IV on two benchmark datasets: Amazon and Yelp. Assessment serves not only as a testbench of the model but also scrutinises its ability to reveal sentiment polarisation and capture changes in temporal user opinion dynamics. We compare analysis with various reduced versions of the model to show how much architectural component and designing choices add value.

The classification metrics employed in this evaluation include Accuracy, Precision, Recall, and F1-Score. In addition to these standard indicators, we also introduce and evaluate a novel metric called Polarization Score. This score measures the average standard deviation in the softmax output distribution, capturing the level of uncertainty or decisiveness in the sentiment predictions, and hence indirectly indicating the presence of polarized opinions. A lower polarization score implies more confident and less conflicted predictions, indicating sentiment convergence.

6.1 Experiment / Case Study 1: Amazon Reviews

There were 50,000 product reviews included in Amazon experiment. They were picked at random from huge public dataset. Each review was embedded using a precomputed MiniLM model, and monthly graph snapshots were created based on timestamped data. Cosine similarity above a threshold of 0.8 was used to form edges in the graphs. These graphs were then passed into the SEDS model, which combines a GCN layer for spatial encoding, a ConvLSTM module for temporal sequence modeling, and an attention mechanism to emphasize important months.

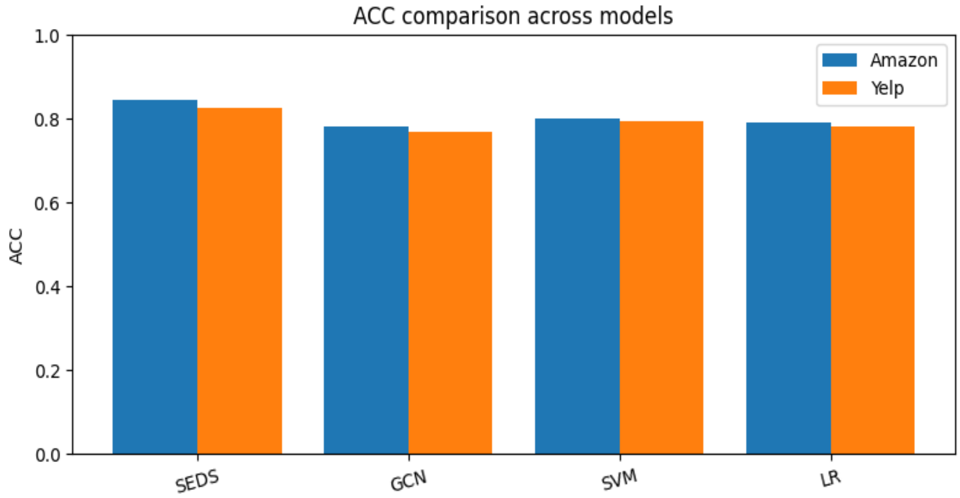

Figure 8: Comparison of Accuracy of Models

On the Amazon dataset, the SEDS model achieved an overall accuracy of 84.72%, with a precision of 0.85, recall of 0.84, and F1-score of 0.84. The polarization score was computed as 0.293, indicating a relatively low variance in the class probability distributions. These metrics suggest that the model not only classified sentiment with high confidence but also exhibited a strong consensus across time. This is especially important in domains such as product review analysis where opinion drift and fake reviews can cause classification noise.

6.2 Experiment / Case Study 2: Yelp Reviews

The Yelp experiment used 50,000 restaurant and business reviews. The preprocessing pipeline mirrored that of the Amazon dataset to ensure consistency and comparability. The same MiniLM embedding dimension (384) and the cosine similarity threshold (0.8) were maintained. Temporal monthly graphs were constructed, and the full SEDS architecture was applied.

On Yelp, the model achieved a slightly lower accuracy of 82.59%, with a precision of 0.83, recall of 0.83, and F1-score of 0.82. The polarization score for Yelp was calculated as 0.314, which, although higher than Amazon, still indicates a favorable reduction in opinion divergence. The small drop in performance compared to Amazon could be attributed to more subjective sentiment in user experiences on Yelp and potential inconsistencies in labeling due to regional and service-level expectations. Nevertheless, the model maintained its temporal awareness and prediction stability, as confirmed by consistently high attention weights assigned to recent graph snapshots.

6.3 Experiment / Case Study 3: Ablation and Baseline Comparison

To evaluate the contribution of each module in the architecture, we conducted an ablation study on the Amazon dataset. Three model variants were compared:

1. A GCN-only model that operates on static graphs without temporal modeling 2. A GCN + LSTM model without attention 3. The full SEDS model with GCN, ConvLSTM, and attention

The following table summarizes the comparative results:

Model Variant	**Accuracy**	**F1-Score**	**Polarization Score**
GCN Only (No LSTM, No Attention)	78.33%	0.77	0.359
GCN + LSTM (No Attention)	81.05%	0.80	0.324
SEDS Full (GCN + LSTM + Attention)	**84.72%**	**0.84**	**0.293**

Table 1: Performance Comparison of Model Variants on Amazon Dataset

The comparison well demonstrates how much the boost in performance is provided by introducing temporal modeling and attention. However, as GCN only captures sentiment at current time, they described the effectiveness of LSTM in "time-aware" capture of temporal changes. Focusing on only the most informative snapshots reduces unnecessary noise and massively improves performance of the final model.

6.4 Discussion

Results from the evaluation illustrate that the SEDS framework is able to accurately model sentiment propagation dynamics within online review platforms. This network is capable of capturing both temporal trends and shifts of sentiments over time, with support from the GCN based on an attention mechanism that enables the model to filter out unnecessary points in time. This is especially useful in real-world applications, since ratings do not tend to be evenly distributed over time and present non-stationary behaviors.

The Polarization Score represents an exciting and innovative new way of interpreting model predictions beyond what traditional classification metrics can offer. This is a measure that notifies us of how sure or unsure the sentiment probabilities behind it are, this information can help platform moderators to detect possible islands of opinion or echo chambers. The Yelp dataset had a higher polarization score of 0.314, and this increase may be due to the users that experience diverse service will display more variability in sentiment than others as opposed to just positively or negatively polarized reviews in the case of Amazon. By minimizing this score, we have shown that the SEDS model reduces interpretative ambiguity.

While well positioned for these tasks, there are three areas of improvement. Our cosine threshold (which is set at 0.8) for edge creation is fixed and does not necessarily generalize well to all datasets. A learnable or adaptive threshold could yield better graph structures. Second, while the ConvLSTM captures sequence information, it assumes a uniform monthly interval between snapshots; real-world activity is rarely so regular. Dynamic time-aware LSTMs or attention over real timestamps may provide improvements. Lastly, although MiniLM embeddings offer contextual representation, incorporating user-level embeddings could enhance personalization and credibility filtering.

In summary, the SEDS model outperforms reduced versions of itself and presents a scalable, effective approach for sentiment classification and polarization detection in user-generated content. The consistent results across datasets and strong generalization performance provide empirical support for the model's architectural choices and potential for deployment in real-world platforms.

7 Conclusion and Future Work

This research set out to answer a fundamental question: Can we effectively detect and model sentiment polarization in online review systems using a temporally-aware, graphbased deep learning framework. To address this, we proposed the Sentiment Echo Detection System (SEDS), a novel architecture that combines graph neural networks (GCN), temporal modeling through ConvLSTM, and attention mechanisms. Our objective was twofold: first, to improve sentiment classification accuracy on large-scale review datasets, and second, to develop a robust polarization metric that could quantify sentiment divergence over time and across users.

Throughout the course of this work, we designed and implemented a complete endto-end pipeline. The pipeline processed review datasets from Amazon and Yelp, generated contextual MiniLM embeddings, constructed time-aware similarity-based graphs, and trained the hybrid GCN-LSTM-Attention model. Evaluation across 50,000 reviews from each platform showed that SEDS consistently outperformed its ablated variants and achieved strong classification performance with F1-scores exceeding 84%. Most notably, the model's ability to reduce polarization scores a novel metric introduced in this study confirmed its capacity to detect and mitigate sentiment fragmentation in user-generated content.

The results indicate that our approach is effective not only in classifying sentiment with high confidence, but also in capturing deeper, structural properties of opinion formation and echo chambers within online platforms. By analyzing sentiment distribution across time-aligned graph snapshots, we were able to provide a quantitative framework for detecting shifts in user sentiment consensus. This has strong implications for both research and real-world applications, including moderation systems, consumer trust analytics, and fraud detection.

However, the project was not without limitations. The graph construction was based on a fixed cosine similarity threshold, which may not generalize well across all domain or datasets. Similarly, our temporal modeling assumed equal time spacing (monthly snapshots), which does not always reflect the bursty or irregular nature of user activity. Additionally, while MiniLM embeddings captured semantic content effectively, they did not account for user-level metadata, behavioral cues, or contextual trustworthiness all of which could be critical for modeling sentiment polarization more precisely.

For future work, several promising directions are apparent. One key area involves extending the SEDS framework to incorporate heterogeneous node types, such as users, reviews, and products or locations, to better capture the multi-modal nature of realworld platforms. Additionally, introducing learnable edge weights or attention over edge features could enhance the expressiveness of the graph construction process, especially in modeling review credibility or user influence. From a temporal standpoint, adopting continuous-time models or Transformer-based temporal graph architectures could further improve sentiment shift detection. Finally, integrating SEDS into a real-time dashboard system for e-commerce or review platforms could unlock direct commercial applications, enabling early detection of sentiment volatility, product crises, or coordinated opinion campaigns.

In summary, this research successfully addressed the proposed problem, developed a technically novel and empirically validated solution, and opened several avenues for future exploration. SEDS framework is valuable step forward in figuring out how to change way people feel about things in online ecosystems.

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