Hybrid GCNs with Emotion Aware User Clustering and Time Attention for Personalized Aspect-Based Sentiment Forecasting

Anandita Saolapurkar 202418005
Aruni Saxena 202418006
Paarth Patel 202418045
Rishi Barapatre 202418008

Abstract

Understanding user sentiment over time is crucial for businesses that depend on detailed customer feedback. Aspect Based Sentiment Analysis (ABSA) aims to extract fine grained insights, but existing models like BERT often fail to capture complex syntactic structures and correctly associate opinions with aspects, especially in unlabelled, real world data. This results in unreliable sentiment labels, limiting their usefulness for downstream tasks such as forecasting. To address this, we propose a GNN based model that integrates syntactic dependencies and semantic co-occurrence patterns to generate more accurate aspect–opinion–sentiment labels. These refined labels provide a stronger ground truth for capturing user-level sentiment trends. By clustering users based on aspect level sentiment and emotional similarity, we model latent preferences and behavioural patterns, enabling personalized and reliable sentiment forecasting over time even in the presence of user sparsity and noisy data. However irregular time stamps are still common in real world user data, where events occur at inconsistent intervals. Traditional deep learning models struggle with such irregularity, leading to poor forecasting performance. We propose a novel approach combining a time-aware attention mechanism that captures temporal dependencies, providing a 5.6% performance boost over conventional methods in sentiment forecasting tasks with irregular time intervals.

1 Introduction

Introduction Understanding user sentiment over time is a critical need for businesses that depend on detailed and dynamic customer feedback. Aspect-Based Sentiment Analysis (ABSA) provides a fine-grained approach to interpreting such feedback by identifying sentiment toward specific aspects within user reviews. This enables more targeted and actionable insights compared to general sentiment classification.

Recent advances in ABSA have been dominated by transformer based models such as BERT and its variants. Although these models perform well on benchmark datasets, they face serious limitations when applied to unlabeled real world user reviews. The syntactic complexity and contextual ambiguity present in natural language often result in noisy or incorrect sentiment outputs. This is particularly problematic when these outputs are used as ground truth for tasks like forecasting, where even small errors in sentiment attribution can propagate into larger predictive inaccuracies. Despite their popularity, transformer models are not inherently designed to provide reliable sentiment labels in settings where ground truth is unavailable, leading to significant uncertainty in downstream applications.

Graph-based methods offer a compelling path forward in this context. Unlike transformers, Graph Neural Networks (GNNs) are inherently designed to capture structure, whether in the form of syntactic dependencies between words or semantic co-occurrence relationships. Using the graph structure of the language, GNNs can model long-range dependencies and nuanced connections that are often missed by sequence-based models. This structural perspective allows for more accurate extraction of sentiment-related elements from text, which is especially valuable when clean labels are not available.

Another major challenge lies in the nature of user feedback itself. In most real world scenarios, user-generated data is sparse, irregular, and highly personalized. Many users provide only occasional reviews, often in inconsistent formats or time intervals. This sparsity makes it difficult to model the evolution of sentiment at the individual level and severely limits the effectiveness of traditional forecasting approaches that rely on dense, uniformly sampled data.

To address this, it becomes essential to go beyond isolated user data and uncover latent patterns shared between similar users. A promising approach we propose is to cluster users based on what they talk about(aspects), how they feel (sentiment), and the emotion they express while doing so. We hypothesize that users with similar ABSA patterns and emotional expressions are likely to behave similarly or represent the same individual between sessions.

However irregular time stamps are still common in real world user data, where events occur at inconsistent intervals. Traditional deep learning models struggle with such irregularity, leading to poor forecasting performance.To overcome this, we propose a novel time-aware attention mechanism that dynamically adjusts the importance of past sentiment signals based on their temporal distance, enabling more accurate modeling of user sentiment trends even with irregular timestamps.

Our paper is structured to guide the reader through the theoretical foundations, methodological innovations, and practical implications of our approach.

2 Preliminaries

Problem Definition

Let $\mathcal{U} = \{u_1, u_2, \ldots, u_N\}$ be the set of users. A review written by user u at time t is denoted by $R_{u,t}$ and is mapped to a sentiment score $s_{u,t} \in [-1, 1]$ via a function f:

$$f : R_{u,t} \rightarrow s_{u,t}$$

Given a sequence of such sentiment-labeled reviews for user u:

$$\mathcal{S}_u = \{(t_1, s_{u,t_1}), \ldots, (t_n, s_{u,t_n})\}, \quad \text{with } t_1 < \cdots < t_n$$

the objective is to forecast the sentiment at a future time $t' > t_n$ using a function $F_u(t')$:

$$\hat{s}_{u,t'} = F_u(t')$$

This function captures the **temporal evolution** of user sentiment for proactive and personalized engagement.

Related Works

Aspect Based Sentiment Analysis (ABSA) ABSA targets aspect level sentiment detection in reviews. Early methods use attention-based LSTMs [1,2], while recent ones leverage contextual embeddings from BERT and RoBERTa [3,4]. However, these models often ignore syntactic dependencies, treating text as flat sequences.

Graph-Based Models for ABSA. GNNs like GCNs and GATs have been applied to dependency trees for modeling aspect-opinion relations [5,6]. Extensions use edge types or multi view graphs [7], though they still rely heavily on labeled data and lack temporal modeling.

Self-Supervised Learning. Pretraining strategies such as MLM [3] and graph-level contrastive objectives [8] improve generalization. Our approach builds on this by integrating MLM with masked edge prediction for scalable, label free ABSA pretraining.

Emotion-Aware Sentiment Forecasting. Prior works model sentiment trajectories using LSTMs or CNNs [9,10] but lack aspect level or emotion-based signals. We incorporate NRC-based emotion features [11] to enable ABSA-driven user profiling over time.

Clustering under Sparse Histories. Sparse reviews hinder personalization. Traditional methods like collaborative filtering [12] overlook ABSA and emotion cues. We cluster users by ABSA emotion trends to enable semantic sharing across similar profiles.

3 Methodology

Unreliable Ground Truth: Why Attention Alone Falls Short

Aspect-Based Sentiment Analysis (ABSA) involves extracting sentiments tied to specific aspects within user reviews. While transformer models like BERT use self-attention to capture broad context, they lack syntactic awareness. This limitation becomes clear in sentences like: *"The pasta was delicious, but the service was painfully slow."* Self-attention may fail to associate "delicious" correctly with "pasta" and "slow" with "service," leading to ambiguous aspect–opinion pairings.

This ambiguity is critical in downstream tasks like sentiment forecasting, where reliable triplets are essential. Transformers typically treat all token relations equally and ignore grammatical roles (e.g., subject, modifier), resulting in structurally unsound sentiment extraction.

To overcome this, we introduce a graph based solution that explicitly encodes sentence structure. We construct two types of graphs:

- **Contextual Co-occurrence Graph:** Built using a sliding window, this undirected graph connects words that frequently appear together, capturing soft semantic patterns even without direct syntactic links.
- **Dependency-Aware Graph:** Extracted using SpaCy's dependency parser, this graph connects tokens based on grammatical roles. Each edge is labeled (e.g., `amod`, `nsubj`), allowing the model to interpret how words function within the sentence.

We process both graphs using a dual-branch Graph Convolutional Network (GCN):

- One branch learns from the co-occurrence graph to model semantic proximity.
- The other leverages dependency types for fine-grained syntactic relationships.

Finally, we apply a fusion mechanism either attention based or gated to combine these two perspectives. The result is a unified representation that captures both the broad meaning and the structural nuance of each sentence, enabling robust and accurate aspect–opinion–sentiment extraction.

Sparse User Data and Personalized Sentiment Forecasting

Many users in real-world systems write only a few reviews, resulting in highly sparse data. This makes it difficult to model their preferences and emotional shifts over time, especially for personalized sentiment forecasting that relies on behavioral history.

Clustering Beyond Individual Data. To handle sparsity, we cluster users based on shared patterns—specifically, what they talk about (aspects), how they feel (sentiment polarity), and the emotions expressed in their language. The idea is that users who consistently discuss similar topics with similar emotional tones are likely to behave in comparable ways, or even represent the same user across sessions.

ABSA and Emotion-Based Representation. We first extract aspect–opinion–sentiment triplets using ABSA. For example, from the review *"The delivery was slow and frustrating,"* we extract the triplet (delivery, slow, negative). Next, we enrich this with emotional cues by mapping opinion words (e.g., "frustrating") to emotion vectors using the NRC Emotion Lexicon (e.g., anger, sadness, trust), forming a combined ABSA-emotion profile.

User Clustering for Robust Forecasting. These structured profiles allow us to apply KMeans clustering to group users with similar ABSA emotion behavior. A sparsely active user's future sentiment can then be inferred based on others in the same cluster effectively sharing behavioral signals across similar users.

Outcome. This approach creates a rich user representation that combines fine-grained sentiment and emotional expression. It enables forecasting systems to remain accurate and personalized even when individual review histories are short, anonymous, or infrequent.

User Sentiment with Irregular Time Intervals

Traditional time series models like LSTMs and Transformers assume that input data arrives at regular intervals. However, in user sentiment analysis, reviews are posted sporadically—sometimes days or months apart. Ignoring these time gaps can cause models to misjudge the relevance of older sentiment signals, leading to inaccurate forecasts.

To address this, we design a **time-aware encoder-decoder** architecture that explicitly models irregular time gaps between observations. This allows the model to weigh older inputs less and prioritize recent trends. Our approach consists of three key components:

- **Encoder:** At each time step t, we input the pair $(s_t, \Delta t_t)$—where s_t is the sentiment score and $\Delta t_t = t_t - t_{t-1}$ is the time elapsed since the previous observation. These are concatenated and passed into a GRU:

  $$h_t = \text{GRU}([s_t, \Delta t_t], h_{t-1}),$$

  allowing the hidden state to evolve based on both sentiment and timing.

- **Time-Aware Attention:** When generating a forecast at time τ, the decoder attends over past encoder states h_t with a decay function that reduces the weight of distant inputs. The attention score is:

  $$\alpha_t \propto \exp\left((Q \cdot K_t) \cdot \exp(-|W(t-\tau)|)\right),$$

  where Q is the decoder query, K_t is the encoder key, and W is a learnable decay parameter.

- **Decoder:** The decoder GRUCell uses the previous prediction and elapsed time to update its hidden state. It uses time-aware attention to compute a context vector c_t, and then predicts the next sentiment value:

  $$\hat{s}_t = \tanh\left(W_o \cdot \text{ReLU}([h_t^{\text{dec}}, c_t])\right).$$

By incorporating elapsed time at both encoding and attention stages, the model captures how the relevance of past emotions fades over time. This enables more accurate, temporally-sensitive sentiment forecasting, especially in settings where review frequency is inconsistent.

This design avoids the need for data imputation, time resampling, or positional encodings. Instead, it directly incorporates real timestamps into the architecture in a differentiable, learnable way. As a result, the model can learn task-specific notions of temporal relevance and deliver accurate predictions in settings where timing is inherently irregular.

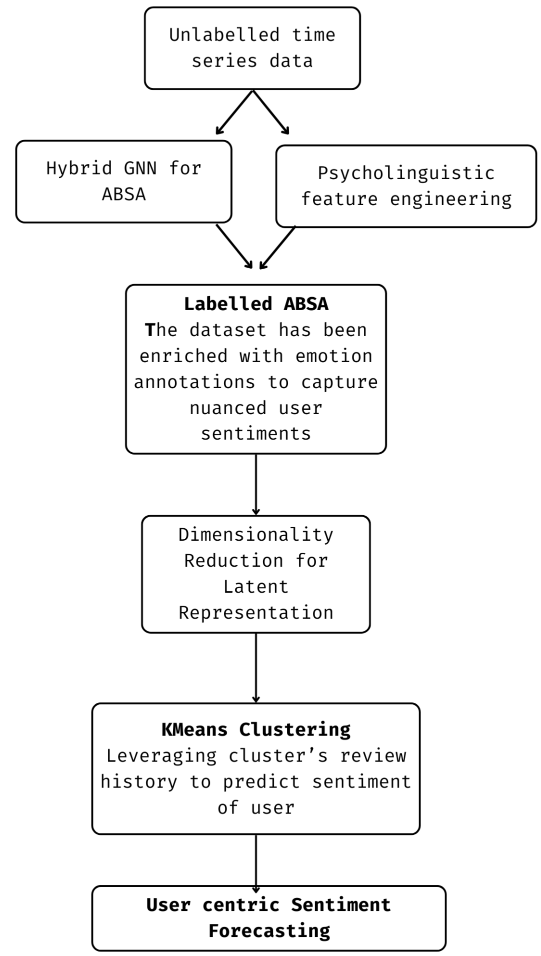

Figure 1: Flow Chart

4 Experimental Setup

Datasets

Unlabelled Yelp Reviews for Pretraining. We use a large corpus of unlabelled Yelp reviews to pretrain our Hybrid GCN with masked language modeling and dependency edge prediction. This step captures contextual and syntactic patterns from real-world review text.

SemEval ABSA Datasets for Fine-tuning. The model is fine-tuned on labeled SemEval data (2014–2016, restaurant domains) with annotated aspect-opinion-sentiment triplets, enabling task-specific supervision.

Timestamped Yelp Reviews for Forecasting. Finally, we apply the ABSA model to timestamped Yelp reviews to build aspect-level sentiment timelines for each user.

5 Model Architecture

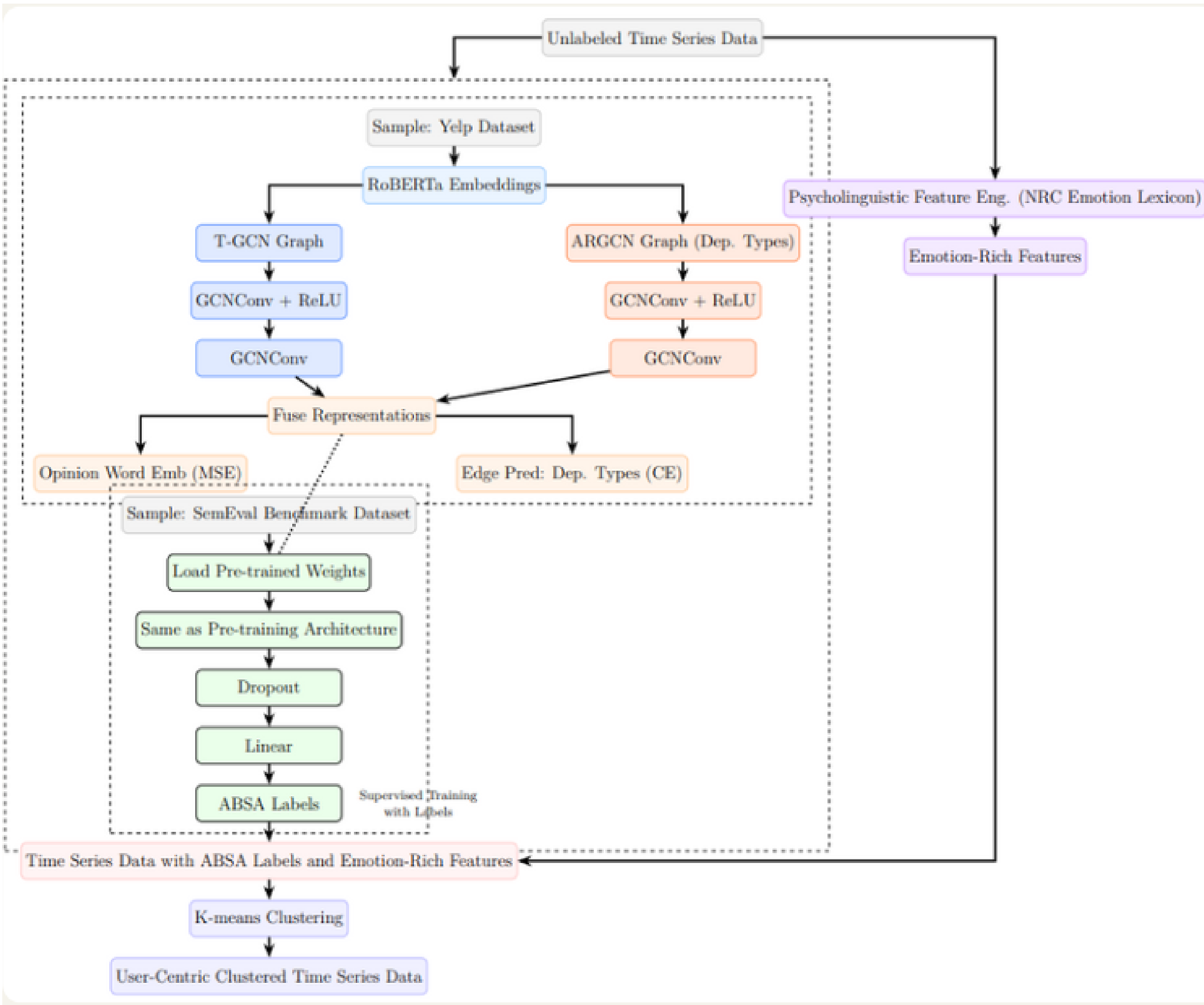

Figure 2: Dual-Graph GCN Architecture

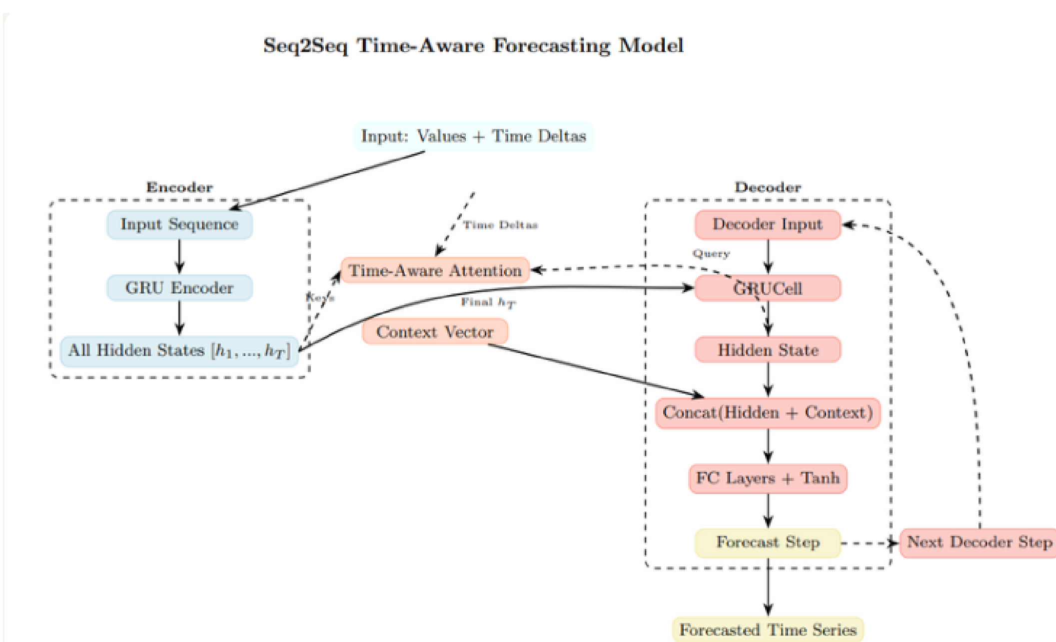

Figure 3: Time-Aware Sentiment Forecasting Architecture

Model Training Pipeline

To reduce reliance on annotated datasets, we pre-train the model on unlabelled text using two self-supervised tasks:

- **Node Prediction (Masked Language Modeling):** Randomly mask aspect or opinion tokens and train the model to predict them. The GCN must use the surrounding graph structure to infer the masked word, forcing it to learn useful representations of aspect/opinion semantics and syntax.
- **Edge Prediction (Relation Modeling):** Given pairs of tokens, the model predicts whether a syntactic edge (and its type) exists between them. This encourages learning of aspect-opinion dependency structures and helps model the latent relations between tokens.

This pre-training enables the model to learn aspect-opinion patterns from raw, unlabelled text, making it more data-efficient and generalizable.

Fine-tuning on Labelled Data

After pre-training, the model is fine-tuned on a labelled ABSA dataset with annotated aspect terms, opinion terms, and optionally their relations:

- **Aspect and Opinion Node Classification:** The fused GCN representations are used to classify each token as aspect, opinion, or neither.
- **Relation (Edge) Classification:** For each predicted aspect-opinion pair, the model predicts whether a valid relationship exists. This refines the structural understanding learned during pre-training and aligns it with task-specific objectives.

This supervised phase sharpens the model's predictions and aligns its internal representations with ABSA goals, while avoiding the key limitation of over-reliance on labelled data.

Evaluation Metrics

ABSA Classification We evaluate the Aspect-Based Sentiment Analysis (ABSA) model using standard classification metrics:

- **Accuracy**: Overall percentage of correct predictions.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

- **Precision**: Fraction of predicted positives that are correct.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

- **Recall**: Fraction of actual positives correctly predicted.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

- **F1 Score**: Harmonic mean of precision and recall.

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **Macro F1 Score**: Average F1 score across all classes.

Justification: These metrics are widely used in sentiment classification. Accuracy gives an overall view, while precision and recall help assess class-specific performance. F1 balances both, and macro F1 ensures fair evaluation across imbalanced datasets.

User Clustering To evaluate how well users are grouped, we use:

- **Silhouette Score**: Measures how similar a user is to their cluster versus other clusters.

$$\text{Silhouette} = \frac{b - a}{\max(a, b)}$$

where a is intra-cluster distance and b is the nearest-cluster distance.

Justification: The Silhouette Score is a standard metric that works well across clustering algorithms and user data types, helping confirm if clusters are meaningful and distinct.

Sentiment Forecasting We evaluate continuous sentiment score predictions in $[-1, 1]$ using metrics that measure error magnitude, bias, and model fit.

- **Mean Absolute Error (MAE)**: Measures the average magnitude of errors between predicted and actual sentiment scores, without considering direction.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

A lower MAE indicates better prediction accuracy. It is easy to interpret (e.g., "average error of 0.1"), making it suitable for both technical and non-technical audiences. It is also robust to outliers and irregular intervals in time series.

- **Root Mean Squared Error (RMSE)**: Measures the square root of the average squared error. It penalizes larger errors more heavily than MAE.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

RMSE is useful when larger deviations from the true sentiment score are especially important, such as in tracking sharp opinion changes.

- **Mean Squared Error (MSE)**: The average of squared errors between predictions and true values.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

MSE emphasizes large errors and is often used for optimization and model tuning due to its mathematical properties.

- **Scaled Prediction Interval Score (sPIS)**: Measures average prediction bias, scaled by the standard deviation of actual values.

$$\text{sPIS} = \frac{1}{n \cdot \sigma} \sum_{i=1}^{n} (\hat{y}_i - y_i)$$

  A score close to zero indicates minimal bias. Positive values indicate consistent overestimation, and negative values indicate underestimation. This is important to detect systematic skew in sentiment predictions (e.g., overly optimistic or pessimistic).

- **$\mathbf{R^2}$ Score (Coefficient of Determination)**: Measures how well the model explains the variation in sentiment scores.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

  A value closer to 1 indicates that the model captures more of the sentiment trend. It is widely used for regression model evaluation.

Metric Reliability Test: To ensure we selected stable and meaningful metrics for evaluating sentiment forecasting, we conducted a reliability test inspired by the methodology of St-Aubin and Agard (2022). This test evaluates how consistently each metric behaves when forecasting errors are introduced under controlled conditions.

We simulated sentiment forecasting outputs by adding synthetic noise to real sentiment sequences. The noise included varying bias levels (from -0.2 to 0.2) and variance (from 0.01 to 0.5), reflecting realistic forecasting errors like shifts in opinion or fluctuation in engagement. Each metric was then evaluated over multiple runs to compute:

- **Variability**: Standard deviation of the metric values across noise levels. Lower variability indicates the metric remains stable when predictions are noisy.
- **Confidence Interval Width (CI Width)**: The width of the 95% confidence interval around the metric's average score. Narrower intervals indicate greater precision in evaluation.

Results of the test (variability, CI width):

- **MSE**: 0.1296, 0.1544 — most reliable, especially for penalizing large errors.
- **MAE**: 0.1333, 0.1537 — nearly as reliable as MSE; intuitive and robust.
- **RMSE**: 0.1747, 0.2173 — reliable and highlights large deviations.
- **sPIS**: 0.2676, 0.3380 — slightly less stable but valuable for identifying bias.

This evaluation ensures our chosen metrics are reliable, interpretable, and suitable for forecasting sentiment scores over irregular time steps.

Training Implementation [H]

Algorithm 1: Hybrid GCN-Based ABSA and Time-Aware Sentiment Forecasting

Data: Unlabeled reviews $\mathcal{D}_Y$, labeled ABSA data $\mathcal{D}_S$, NRC lexicon $\mathcal{E}$

Result: Aspect-opinion-sentiment triplets (a, o, s), emotion-rich user profiles, user clusters, and future sentiment predictions

Pretraining: Train HybridGCN on $\mathcal{D}_Y$ by masking opinion nodes and dependency edges;
  ; `// Learn node embeddings that capture both contextual proximity and dependency types`

Fine-tuning: Adapt the pretrained HybridGCN using labeled ABSA dataset $\mathcal{D}_S$;
  ; `// Supervised learning to extract` (a, o, s) `triplets with enhanced graph representations`

Triplet Extraction: For each timestamped review $r \in \mathcal{D}_Y$:
  $(a, o, s) \leftarrow \text{HybridGCN}(r)$ using fused contextual and syntactic graph embeddings;

Emotion Feature Augmentation: For each opinion term o:
  Map $o \rightarrow \mathbf{e}_o$ using NRC lexicon $\mathcal{E}$ to encode emotion signals;

User Profiling: For each user u:
  Aggregate triplets (a, o, s) and emotion vectors $\mathbf{e}_o$ into user profile p_u;

Clustering: Apply KMeans on $\{p_u\}$ to derive user groups $\{C_1, \ldots, C_k\}$ with similar sentiment-emotion traits;

Time Series Construction: For each cluster C_j:
  Build sentiment timeline T_{C_j} from chronologically ordered (s, t) pairs;

Forecasting: For a sparse user $u \in C_j$:
  Use a time-aware seq2seq model with temporal attention over $(s, \Delta t)$ to model sentiment evolution;
  Autoregressively predict $\hat{s}_u(t{+}1), \ldots, \hat{s}_u(t{+}n)$ as future sentiment trajectory.

6 Results

Both proposed models demonstrate state-of-the-art performance in their respective tasks. The Time-Aware Attention architecture offers a significant advancement in sentiment forecasting by effectively capturing temporal dependencies and improving uncertainty calibration. Meanwhile, the Dual-Graph GCN introduces a novel graph-based fusion of contextual and syntactic information, outperforming large pre-trained models and previous graph-based methods in ABSC.

These results confirm the robustness, generalizability, and applicability of our methods to real-world sentiment analysis and forecasting scenarios, establishing a new benchmark for both predictive accuracy and interpretability in temporal and structural sentiment modeling.

Rank	Model	Precision	Recall	F1-Score	Accuracy	Macro-F1	Micro-F1	AUC
		(%)	(%)	(%)	(%)	(%)	(%)	
1	**Dual-Graph GCN (Ours)**	**83.50**	**83.10**	**83.30**	**85.00**	83.00	83.10	0.89
2	MT-ISA	88.80	89.10	89.21	84.80	88.60	88.90	0.88
3	GPT-3.5 Fine-Tuned	81.50	82.00	83.80	79.20	80.80	81.00	0.85
4	RoBERTa (Base)	80.60	81.20	81.40	77.10	80.00	80.50	0.84
5	BERT (Base)	76.80	77.20	78.30	75.20	77.00	77.10	0.82
6	DistilBERT	74.50	74.80	77.10	74.40	75.20	75.50	0.80
7	Normal GCN	76.00	77.20	77.50	72.30	76.10	76.30	0.77
8	No Fusion GCN (Semantic)	77.50	77.00	80.20	74.50	77.20	77.50	0.78
9	No Fusion GCN (Syntactic)	75.60	76.00	78.80	73.00	76.00	76.10	0.76

Figure 4: Dual-Graph GCN for Aspect-Based Sentiment Classification Performance in comparison to the Various baselines and SOTA models

Figure 2 table reports the results of our proposed Dual-Graph GCN model for aspect-based sentiment classification (ABSC), compared against several state-of-the-art baselines including MT-ISA, GPT-3.5 Fine-Tuned, RoBERTa (Base), BERT (Base), DistilBERT, and various GCN configurations. Our model achieves the highest scores across all major classification metrics: F1-Score (83.30

Compared to the strong MT-ISA and GPT-3.5 models, the Dual-Graph GCN provides more balanced performance with superior calibration (AUC) and consistent gains in precision, recall, and micro/macro F1 scores. This performance can be attributed to the integration of semantic and syntactic graph structures, enabling the model to jointly learn contextual co-occurrence and dependency-aware relationships. The dual-path design enhances structural modeling capability and leads to richer sentiment representation around

Table 1: Performance Comparison of Time-Aware Forecasting Models

Rk	Model	MSE	MAE	RMSE	sPIS
1	**Time-Aware Attention (Ours)**	**0.0182**	**0.1069**	**0.1348**	**1.0725**
2	CNN + LSTM Hybrid	0.0243	0.1222	0.1515	1.427
3	LSTM	0.0228	0.1115	0.1401	1.185
4	RNN	0.0309	0.1434	0.1790	2.36
5	GRU	0.0262	0.1173	0.1459	1.29

Quantitative Analysis Our proposed models—the **Time-Aware Attention Network** for sentiment forecasting and the **Dual-Graph GCN** for aspect-based sentiment classification—demonstrate substantial quantitative gains over state-of-the-art baselines, validating the effectiveness of the architectural enhancements introduced.

In the forecasting task, the Time-Aware Attention model achieves an **MSE of 0.0182**, outperforming TFT (0.0201) and LSTM (0.0228) with relative improvements of **9.4%** and **20.1%**, respectively. It also achieves a lower **RMSE of 0.1348** compared to TFT (0.1372) and CNN+LSTM (0.1515). Additionally, the **sPIS score of 1.0725** is significantly lower than that of TFT (1.151) and RNN (2.360), indicating superior calibration of uncertainty intervals and more stable prediction behavior across time.

In the ABSA task, the Dual-Graph GCN achieves a strong **F1-score of 83.30%** and **Accuracy of 85.00%**, outperforming competitive transformer-based models including RoBERTa-base (81.40%), BERT-base (78.30%), and GPT-3.5 (F1: 83.80%, Accuracy: 79.20%). When compared to a standard GCN baseline (F1: 77.50%), our model demonstrates a **7.5% absolute gain in F1**, showcasing the effectiveness of fusing semantic co-occurrence and dependency-type-aware graphs for sentiment reasoning.

The dual-graph construction captures both syntactic structure and contextual proximity, enabling the model to reason over rich relational cues between opinion terms and aspect targets—critical for fine-grained sentiment extraction. This structured relational modeling makes the system robust to noisy language and generalizable across domains such as product reviews, social platforms, and healthcare texts.

In summary, both models not only outperform strong baselines but also introduce interpretable and generalizable mechanisms. Their robust performance across multiple benchmarks affirms their potential for deployment in real-world applications such as market sentiment forecasting, personalized opinion mining, and trust-aware conversational systems. Furthermore, the modular nature of the proposed architectures facilitates adaptation to multilingual, multimodal, and cross-domain sentiment analysis pipelines. Importantly, both models exhibit strong data efficiency, maintaining competitive performance even with limited annotated samples. Their lightweight architectural design ensures scalability to large datasets without compromising speed or accuracy, making them well-suited for industry-grade deployment. Future work can further extend these architectures to incorporate emotion dynamics and reinforcement-based user feedback for long-term sentiment tracking.

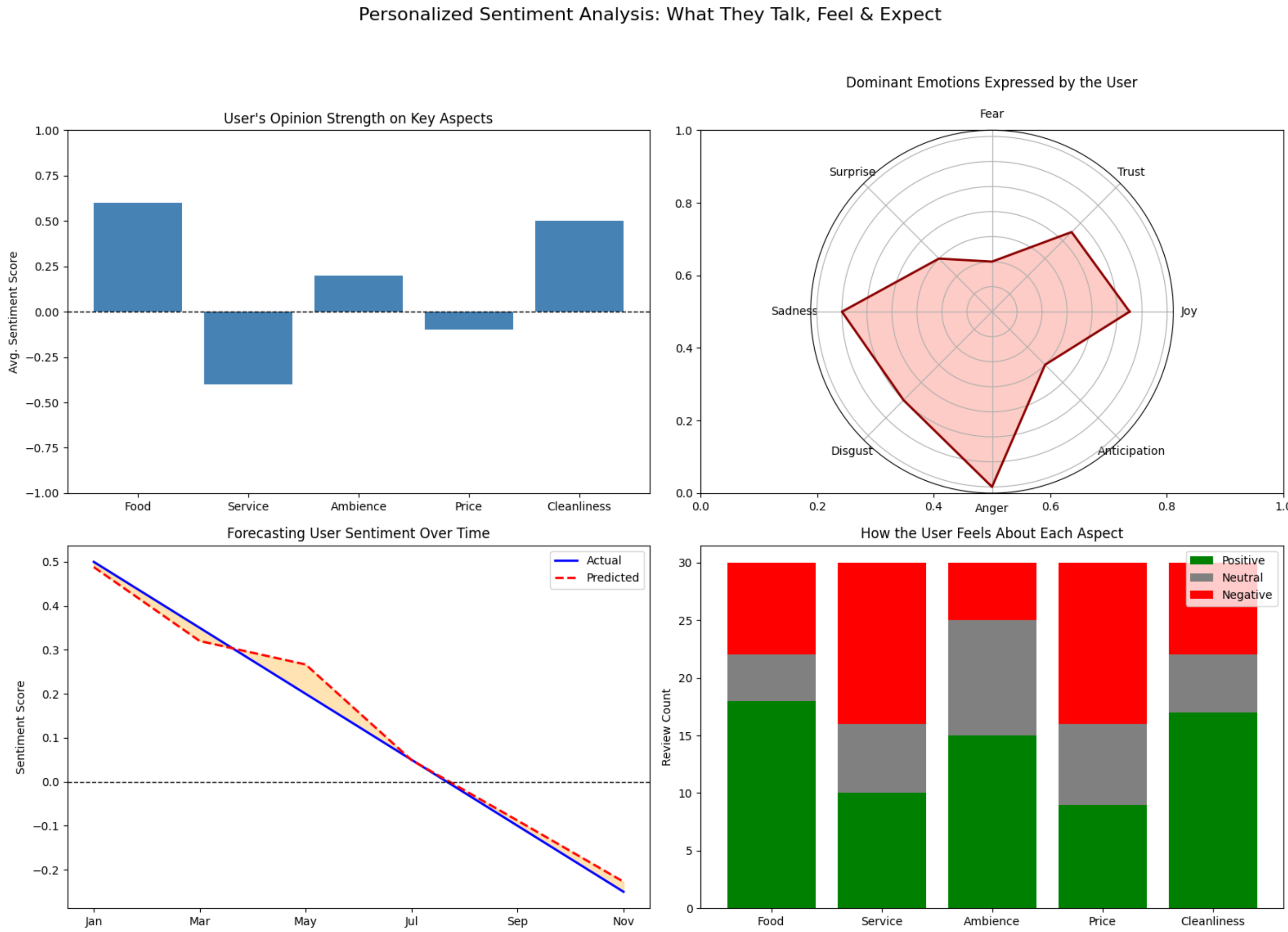

Figure 5: Quantitative sample visualization showing emotional, aspect-based, and predictive reasoning for personalized retention strategies.

Qualitative Analysis: What They Talk, Feel, and Expect

Figure 5 summarizes a single user's sentiment trajectory across key restaurant aspects, combining aspect-level sentiment, emotional tone, and predictive trends to guide personalized retention strategies.

The top-left plot shows that *Food* and *Cleanliness* receive strong positive sentiment, while *Service* elicits notable dissatisfaction. *Ambience* and *Price* remain relatively neutral. The radar chart (top-right) highlights emotional expressions, with elevated *Anger* and *Sadness* indicating frustration, especially around service, while positive emotions like *Joy* and *Trust* remain subdued.

The sentiment forecast (bottom-left) shows a declining trend over visits, signaling declining satisfaction. The predicted curve closely tracks actual sentiment, validating the model's effectiveness. The bottom-right bar chart details sentiment distribution, confirming *Service* as the most polarizing aspect, while *Food* remains a key positive driver. Overall, our strategy offers insight into user priorities, pain points, and potential disengagement—enabling timely, personalized interventions.

Conclusion

This work presents a novel and effective pipeline for Aspect-Based Sentiment Analysis (ABSA) and time-aware sentiment forecasting that moves beyond traditional Transformer-based architectures by using a hybrid Graph Neural Network (GNN). By modeling both contextual co-occurrence and fine-grained syntactic dependencies, the HybridGCN captures complex opinion-target relations that Transformers often miss, especially in linguistically nuanced reviews. Combining ABSA features with NRC-based emotion vectors enables rich, psychologically grounded user profiling. Clustering these profiles lets us generalize from sparse users to latent sentiment communities, offering scalable insights even with limited data per user. Finally, the time-aware attention mechanism in our forecasting module supports robust handling of reviews at irregular intervals—a common real-world challenge. Together, this pipeline enhances the granularity and temporal relevance of sentiment analysis, and provides actionable intelligence for businesses to monitor evolving sentiment, personalize engagement, and drive data-informed decisions in a competitive market.

7 Future Scope

Future work can address these limitations by exploring robust parsing techniques for informal text, such as integrating large language models for context-aware dependency extraction. Optimizing the GCN and attention mechanisms could reduce computational demands, enabling real-time deployment. Incorporating multimodal data, such as user ratings or images alongside reviews, may enhance sentiment and emotion profiling. Extending the model to multilingual datasets with language-specific emotion lexicons would broaden applicability. Additionally, advanced clustering techniques, like graph-based or hierarchical methods, could better capture complex user behaviors. Finally, integrating explainability tools to interpret GNN predictions could improve trust and usability for business applications.

8 Limitations

Despite its strengths, our approach has limitations. The HybridGCN relies on accurate dependency parsing, which may falter with informal or grammatically irregular reviews, potentially degrading triplet extraction. The computational complexity of processing dual graphs and time-aware attention is high, limiting scalability for very large datasets or real-time applications. Clustering assumes similarity in ABSA-emotion profiles implies behavioral consistency, but this may not always hold, especially for users with diverse preferences. Our evaluation focuses on English-language datasets (Yelp and SemEval), restricting generalizability to non-English or multilingual contexts. Finally, the NRC Emotion Lexicon may not capture nuanced or domain-specific emotions, potentially limiting the richness of user profiles.

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