

TopicImpact: Improving Customer Feedback Analysis with Opinion Units for Topic Modeling and Star-Rating Prediction

Emil Häglund

Department of Computing Science
Umeå University, Sweden
emilh@cs.umu.se

Johanna Björklund

Department of Computing Science
Umeå University, Sweden
johanna@cs.umu.se

Abstract

We improve the extraction of insights from customer reviews by restructuring the topic modelling pipeline to operate on opinion units – distinct statements that include relevant text excerpts and associated sentiment scores. Prior work has demonstrated that such units can be reliably extracted using large language models. The result is a heightened performance of the subsequent topic modeling, leading to coherent and interpretable topics while also capturing the sentiment associated with each topic. By correlating the topics and sentiments with business metrics, such as star ratings, we can gain insights on how specific customer concerns impact business outcomes. We present our system’s implementation, use cases, and advantages over other topic modeling and classification solutions. We also evaluate its effectiveness in creating coherent topics and assess methods for integrating topic and sentiment modalities for accurate star-rating prediction.

1 Introduction

Understanding customer feedback is important for businesses aiming to refine their operations, uncover growth opportunities, and align with customer needs. While many organizations collect substantial amounts of text-based input from customers, employees, and other stakeholders, the primary challenge lies not in the availability of information, but in extracting insights from large volumes of unstructured data (Tavakoli et al., 2024).

We propose the analysis framework TopicImpact, which integrates neural topic modeling with an LLM-enabled preprocessing step that extracts and structures opinions. In the preprocessing step, raw reviews are transformed by an LLM into opinion units (Häglund and Björklund, 2025) – extracted phrases that encapsulate a customer’s sentiment on specific aspects. Additionally, the LLM assigns a sentiment score on a scale from 1 to 10,

where 1 indicates a very negative sentiment and 10 represents a very positive one. (See Part A of Figure 3 for examples of opinion units.) By clustering these opinion units instead of entire reviews, TopicImpact generates more coherent and interpretable topic clusters. A detailed outline of the system is provided in Section 3.

The improved topic clusters allow marketers to establish several important facts. By considering the themes of the generated clusters, they learn (1) *the topics discussed in the reviews*, and by considering the cluster sizes, also (2) *the prevalence of each topic*. Through the sentiment score of each opinion, they can infer (3) *the sentiments associated with the topics*, and by applying regression to the combination of topics and sentiments, (4) *the contribution of each topic to the business metric, both in terms of polarity (positive/negative) and degree*. By providing these four pieces of information, our solution contributes to a complete and detailed understanding of customer opinions in unstructured review text.

The proposed framework offers clear advantages over traditional topic modeling methods. Unlike approaches that cluster entire reviews, TopicImpact generates more coherent topics by clustering aspect-delineated opinion units, this is an important strategy because individual reviews often address multiple aspects. Statistical methods like Latent Dirichlet Allocation (LDA) (Blei et al., 2003b) assume that documents are mixtures of words and, similar to TopicImpact, allow reviews to belong to multiple topics. However, LDA lacks the contextual understanding provided by embeddings created with pretrained language models. While LDA represents topics using keyword lists, it offers limited insight into which specific parts of a text prompted the assignment of a review to a topic. In contrast, TopicImpact enhances interpretability by using the opinion units’ aspect-delineated label and excerpt as the clusterable document, offering clear context

for understanding the topic assignment. Additionally, metadata links back to the original review.

We can also relate topic modeling to classification, which is the appropriate approach when dealing with static and clearly defined categories. However, classification fails to capture emerging themes and niche customer concerns. Nor is classification suitable for exploratory analysis — situations where we do not know what opinions to expect in advance.

Another drawback with classification is the difficulty of adapting the level of topical abstraction. For example, shifting from analyzing general pricing concerns to examining a specific coupon code campaign would typically require retraining and relabeling datasets in traditional models. Even with LLMs that do not require extensive training data, this necessitates reclassification of all reviews, which incurs significant consumption of time, cost and compute. Topic modeling overcomes these limitations by enabling dynamic adjustments, such as setting the desired number of topics or providing seed words to refine the analysis toward specific topics. While our system also requires LLM-based preprocessing and embedding of opinion units—both of which are computationally demanding—these, are performed only once, enabling later rapid iteration and exploration of customer feedback across different levels of abstraction.

Beyond extracting insights from reviews, the applications of TopicImpact extend to other forms of opinionated free-text data, such as employee surveys, customer support interactions, course evaluations, and patient feedback. Instead of correlating topics with star ratings, we can analyse other business outcomes, such as employee or patient satisfaction, purchase likelihood or customer churn.

In the upcoming sections, we outline the implementation of TopicImpact and discuss its intended use cases. We then conduct experiments to address the following key research questions.

RQ1: Can topic modeling of opinion units generate coherent topics with regards to subject matter and sentiment? How does a sentiment-aware embedding model compare to a general-purpose embedding model in this context?

RQ2: To what extent can topics generated through topic modeling accurately predict star ratings? Furthermore, how can the integration of sentiment and topic modalities enhance prediction accuracy?

Value Proposition. TopicImpact is a fast, interpretable and cost-effective solution for iteratively exploring customer opinions. It generates coherent topic clusters, provides supporting customer quotes, and identifies the sentiment associated with each topic, as well as its correlation to business metrics.

2 Related Work

TopicImpact contributes to the field of aspect-based sentiment analysis (Zhang et al., 2022). The goal of this field is to understand which aspects are addressed in a text—such as a product review—and what sentiment the author expresses about each aspect. Early work treated the extraction of sentiments, terms, and categories in relative isolation (Liu et al., 2015; Li and Lam, 2017; Zhou et al., 2015; Luo et al., 2019). More recent studies have focused on extracting multiple factors simultaneously, capturing both the opinion aspect and its corresponding expression (Peng et al., 2020; Gao et al., 2021).

Opinion units extend aspect-sentiment pairs by including excerpts from the target text that motivate the pairing. Compared to keywords, phrase extraction offer a more complete and nuanced representation of opinions. This added context benefits downstream tasks and, as we will show, supports clustering. Evaluations on review datasets demonstrate that LLMs can accurately extract opinion units using few-shot learning, with GPT-4 achieving a recall of 85.3% and precision of 87.4% when evaluated on restaurant reviews (Häglund and Björklund, 2025). A key advantage of this approach is its flexibility: when it is not possible or desirable to adhere to a fixed aspect taxonomy, the LLM can define aspects on the fly. Opinion units have been evaluated for similarity search across academic and public review datasets, where it outperformed the traditional data segmentation strategies of sentence and passage chunking (Häglund and Björklund, 2025).

In our work, we identify topics by embedding the opinion units and clustering the resulting vectors producing grouped themes. Embedding clustering works well for the short text excerpts involved, automatically determines the number of topics, and typically yields high topic coherence (Grotenhorst, 2022a). The classical topic modeling alternative is Latent Dirichlet Allocation, which has a smaller computational footprint and produces interpretable topic representations through keyword

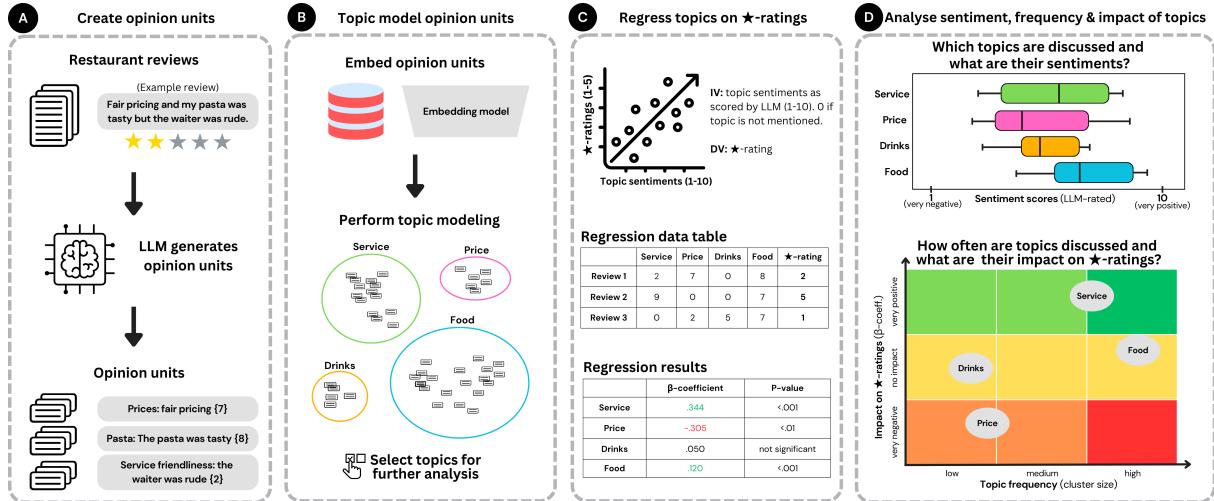


Figure 1: Overview of TopicImpact. **A:** LLM processes reviews to opinion units: *label: excerpt {sentiment 1-10}*. **B:** Embed and cluster opinion units through topic modeling. **C:** Regress topics and sentiments onto star ratings. **D:** Analyze sentiment, frequency, and topic impact.

distributions (Blei et al., 2003a). A core principle of LDA is that documents are modeled as mixtures of topics, meaning each document is assumed to cover multiple topics. This is an important property for aspect-based sentiment analysis, where texts discuss opinions on several distinct aspects. Consequently, LDA and its variants have been adopted in unsupervised aspect-based sentiment analysis implementations (Linshi, 2014; Debortoli et al., 2016; Krishnan, 2023).

A limitation of traditional embedding-based clustering, by contrast, is that each document is assigned to only one topic cluster. This restricts its ability to represent multi-aspect texts in which multiple opinions or themes coexist. At the same time, these methods benefit from the richer semantic representations of modern embeddings, producing clusters that—according to human evaluations—are more semantically coherent than those generated by LDA (Churchill and Singh, 2022). Our approach leverages the strengths of both methods by using LLM-preprocessing to segment texts into individual opinion units, each treated as a separate document for clustering. This mirrors LDA’s ability to assign multiple topics within a text, while benefiting from the richer semantic representations provided by embedding-based methods. Furthermore, LLM-preprocessing serves an additional function by filtering out non-opinionated content that is irrelevant for sentiment analysis (Häglund and Björklund, 2025), removing noise from the topic modeling.

LLMs can also be used for topic identification

in a corpus without clustering (Pham et al., 2024), but Li et al. (2025) find that this often results in overly generic topics that do not aid understanding.

3 System description

The TopicImpact system is presented in Figure 1, through four steps (A-D). In step A, individual reviews are processed into opinion units using LLMs. These opinion units consist of an opinion label, a supporting excerpt, and a sentiment score (1–10), where 1 is very negative and 10 is very positive. An example review is processed in the figure. More details on the conceptualization of opinion units and an evaluation of LLM’s ability to generate them can be found in (Häglund and Björklund, 2025). To isolate the contribution of specific topics, we instruct the LLM to tag overall sentiments towards the restaurant or experience (e.g., “we had a wonderful time”) with an “overall experience” label. Since these statements are not informative for individual topics, we remove them from the analysis.

Step B starts by embedding the opinion units label and excerpt using a word embedding model, along with relevant metadata such as review ID and sentiment score. The opinion units are clustered through topic modeling, based on the widely used BertTopic (Grootendorst, 2022b), with the number of clusters as a key parameter. The final step in this phase is to inspect the clusters and select topics for further analysis.

In Step C, the relationship between the chosen topics and a business metric (here: star rating) is analyzed using multiple linear regression (MLR).

Each review is a data point, with independent variables X representing clustered topics, each in its own column. For example, if an opinion unit linked to a review is clustered under a ‘service’ topic, the ‘service’ column for this review data point is populated with the sentiment score of the opinion unit. If there are multiple mentions of ‘service’ within the same review, an average sentiment score is calculated; if there are no mentions, the value is set to zero. The dependent variable y is the star rating which ranges from 1 to 5. This analysis provides coefficients for each topic, reflecting their strength of association with star ratings, along with p -values to assess statistical significance.

In Step D we draw insights from the analysis. The topic clusters generated in Step B allow us to identify key topics discussed- their frequency, and sentiment. Regression analysis ranks topics by their relation to star-ratings. Combining this with frequency data highlights the topics most critical to customer satisfaction, enabling the creation of a priority matrix to rank issues by importance (Slack, 1994). For example, a frequently discussed topic that negatively affects satisfaction should be urgently addressed, while a positive but infrequent topic (e.g. sustainability) may present an opportunity for product promotion, such as highlighting locally-sourced ingredients.

Regression Model. Multiple linear regression is widely used in social science and marketing research for its interpretability and ability to assess the significance of relationships (Gordon, 2015). While non-linear models may improve prediction accuracy, they often compromise explainability. Despite criticisms of applying continuous outcome regression to ordinal scales like star ratings or Likert scales (Binder et al., 2019), it remains the standard approach. Therefore, we adopt this method.

Word Embeddings. In our research questions, we ask whether coherent clusters of opinion units can be formed with respect to topic and sentiment. A key design consideration is the choice of word embedding. While general-purpose embeddings effectively capture semantic similarity, they often struggle to distinguish between opposing sentiments (Kim et al., 2024)—e.g., “the food is delicious” and “the food is disgusting” might be considered similar due to shared topical context. Recent research addresses this by fine-tuning embeddings to incorporate sentiment information (Tang et al., 2016; Yu et al., 2017; Fan et al.,

2022; Kim et al., 2024; Ghafouri et al., 2024) We compare a general-purpose embedding, all-mpnet-base-v2 (Transformers, 2024), with SentiCSE (Kim et al., 2024), a state-of-the-art, RoBERTa-based sentiment-aware model, to assess their impact on topic- and sentiment-cluster coherence. SentiCSE employs contrastive learning to separate positive and negative sentiment representations in embedding space. Through their LLM-rated sentiment metadata (1-10), opinion units offers an alternative approach to achieving sentiment-topic coherence by splitting data based on sentiment scores, then clustering using general-purpose embedding models. In our experiments, we compare these methods’ ability to predict star ratings.

4 Applications

Our system offers distinct advantages for a range of use cases. We divide these into three classes:

1. *Exploratory Analysis of Customer Feedback.* Comparative analysis of product aspects or features: Understand which aspects resonate positively or negatively with customers. Evaluate how customer sentiments towards specific aspects of the business influence metrics like satisfaction, sales, churn, or brand loyalty. This customer knowledge could allow businesses to create more personalized promotions or experiences, tailored to specific customer segments’ priorities and needs.
2. *Identification of Emerging Trends and Issues.* Real-time tracking of emerging trends in customer feedback. Businesses can quickly detect responses to new features or pinpoint emerging issues.
3. *Hypothesis-driven exploration* For targeted investigations, the system enables a non-compute-intensive, iterative approach. For example, analysts can evaluate sentiment toward a new coupon campaign, refining parameters such as cluster size and using keyword-seeded clustering to explore this predefined topic of inquiry—without the compute and time costs of classification methods.

TopicImpact is especially valuable for industries with large, diverse feedback data, such as e-commerce platforms and large retail chains, where customer preferences can vary widely and are often unpredictable. It is also beneficial for traditional service and product-based industries, including hotel and restaurant chains, fashion, automotive, or any business that gathers customer feedback.

The demand for customer opinion analysis, is also evident in academic research. Several studies,

particularly in the hotel, restaurant, and consumer-tech sectors, have focused on: (i) clustering opinions in reviews to analyze topic frequency and sentiment (e.g. (Linshi, 2014; Debortoli et al., 2016; Hu et al., 2019; Krishnan, 2023)), and (ii) correlating topics with star ratings to evaluate their impact on overall business outcomes (e.g. (Debortoli et al., 2016; Linshi, 2014; Fu et al., 2013; Pappas and Popescu-Belis, 2014; Ganu et al., 2013; Radojevic et al., 2017; Binder et al., 2019)). These articles use methods such as LDA, keyword extraction, or available metadata, and therefore lack the advancements in explorability, cluster coherence and interpretability that LLM-preprocessing enables.

5 Experiments

We describe the experiments conducted to evaluate the proposed framework and research questions.

5.1 Dataset and Preprocessing

We base our experiments on the Yelp review dataset (Yelp, 2015). Due to its vast size, we restrict ourselves to reviews from US restaurants, and focus on three gastronomic styles—Italian, Mexican, and Japanese. The filtering of reviews is based on Yelp’s metadata. This results in three distinct datasets for topic modeling and star prediction analysis. Each dataset is subsampled to 5000 reviews.

Opinion units are generated using GPT-4, with a prompt in Appendix A1. We exclude opinion units related to the overall experience, focusing instead on specific aspects as described in Section 3. On average, each review generates 5.65 opinion units.

5.2 Topic Modeling

For our experiments, we adopt the BERTopic pipeline outlined by (Grootendorst, 2022a), employing hard HDBSCAN (Campello et al., 2013) for clustering and UMAP for dimensionality reduction. We consider two alternative sentence embedding models: a general-purpose model `a11-mpnet-base-v2` (Transformers, 2024) and a state-of-the-art sentiment-aware embedding model (SentiCSE; see (Kim et al., 2024)). For our evaluation, we set the number of topics to 20 to ensure a manageable workload for human evaluation and the minimum topic size to 50 to provide sufficient data for statistical significance in regression analysis.

We then evaluate the coherence of the topic clusters and their predictive ability for star ratings. To accurately reflect system performance, we include

all topics in the analysis without any sub-selection. However, subselection is often helpful in applications to focus on the topics that are of greatest interest to the user (discussed in Sections 3 and 4).

5.3 Evaluation of Topic Modeling

We evaluate the coherence of topics clusters with regards to topic and sentiment. For each cluster, three evaluators identify a dominant topical theme and determine which opinion units align with this theme (an inclusion-based approach (Eklund et al., 2024)). The precision of a cluster is defined as the proportion of opinion units that belong to its dominant theme. Evaluators were assigned 20 randomly sampled opinion units per topic. Further details on the evaluation are provided in Appendix A2.

To assess evaluator consistency, 5 opinion units per topic were reviewed by all evaluators, allowing us to calculate inter-rater agreement as (m/n) , where m is the number of overlapping opinion units on which all evaluators agreed, and n is the number of total overlapping units.

Sentiment precision is calculated based on the distribution of LLM-assigned sentiment scores. We define it as the percentage of opinions with the dominant sentiment (positive or negative). For example, if 18/20 opinion units in a cluster have a sentiment score > 5 (positive), the precision is 90%. The same applies if 18/20 opinion units are negative (sentiment score ≤ 5).

5.4 Star Prediction: Regression analysis

After the topic modelling has been applied to the extracted opinion units, we can predict the star-rating of an individual review r through multiple linear regression (MLR). The basis for the regression is the opinion units extracted from r — their sentiment scores and their topic membership assigned through the topic modeling described in Section 5.2. The regression model is given in Equation 1, where K is the number of topics and $s_k(r)$ represents the average sentiment scores of the opinion units belonging to r that occur in topic cluster k (see Figure 1 and Section 2).

$$\text{★-rating}(r) = \beta_0 + \sum_{k=1}^K \beta_k \cdot s_k(r) \quad (1)$$

We implement three different methods for integrating topic and sentiment information to predict star ratings and compare their performance. To control for the effect of clustering granularity, we

Embedding	Dataset	% Outliers	Topic (P)		Sentiment (P)	
			Avg.	$\geq .9$	Avg.	$\geq .9$
General-Purpose	Italian	24.9	.905	79.0	.761	20.0
	Mexican	16.9	.917	79.0	.734	5.0
	Japanese	29.3	.863	63.2	.730	15.0
Sentiment-Aware	Italian	22.9	.843	55.3	.908	75.0
	Mexican	32.0	.832	60.5	.866	60.0
	Japanese	20.1	.821	52.6	.902	70.0

Table 1: Average topic and sentiment precision for cluster coherence, % of clusters with precision $\geq .9$ and % of outliers (opinion units not assigned to a cluster by BERTopic) for each embedding-dataset pair ($K = 20$).

vary the number of clusters $K \in \{10, 20, 30\}$. For each method, we conduct evaluations both with sentiment scores (as defined in Equation 1) and without sentiment scores. In the latter case, we let $s_k(r) = 1$ if topic k is mentioned in review r and 0 otherwise.

- M1.** Cluster with a general embedding model, here all-mpnet-base-v2 (Transformers, 2024).
- M2.** Cluster using a sentiment-aware embedding model, here SentiCSE (Kim et al., 2024).
- M3.** Split opinion units into negative and positive data based on LLM ratings (negative: ≤ 5 , positive: > 5), then perform topic modeling separately using the general embedding model.

For Method 3, the sentiment scores (1-10) are adjusted to a 1-5 scale. For the cluster based on the positive data split, ratings of 1-5 correspond to the previous 6-10 range on the 1-10 scale, while for the negative cluster, the ratings of 1-5 remain. Splitting the data before clustering means that positive and negative influences are weighted separately. For instance, good service might not significantly impact the star rating because it is often expected, whereas poor service can be a decisive factor in lowering the overall experience.

We evaluate the predictive performance of the regression models using R^2 and RMSE on a hold-out sample with 5-fold cross-validation.

6 Results

The alternative combinations of clustering approach and embedding model are evaluated based on (i) cluster coherence and (ii) effectiveness in predicting star ratings.

6.1 Topic and Sentiment Coherence

For the general-purpose embedding model (that is, all-mpnet-base-v2), the average topic precision over the clusters for each dataset fall in the range

86.3-91.7%, with 63.2-79.0% of topics achieving 90% precision (see Table 1), demonstrating a high topic coherence (Eklund and Forsman, 2022). The sentiment-aware model (sentiCSE) consistently performs worse across all three datasets. The results suggest that the general-purpose model largely ignores sentiment polarity when clustering, whereas the sentiment-aware model creates multiple clusters for the same topic with opposing sentiment (e.g., positive vs. negative price clusters). This focus on sentiment partly explains the lower topic precision, as it forms clusters that are cohesive in terms of sentiment but inconsistent in terms of topic. For instance, opinions about service, food quality, and cleanliness may be grouped together simply because they were all described as “okay”.

Inter-rater agreement among evaluators was 90.3%. For topics with a clear theme (e.g., precision $\geq 80\%$), agreement was 96.1%. The percentage of outliers not assigned to a cluster ranges from 17-32%. While BERTopic can optionally force documents into clusters, we believe that having outliers is valid, as some opinions naturally fall outside the larger groups. Therefore, we allowed outliers.

To answer RQ1, our topic modeling results—comparing one general and one sentiment-aware embedding—achieve high topic cohesion but not high sentiment precision simultaneously. However, the metadata of opinion units can be leveraged to create sentiment coherence. We implement this in the next section, where one of our star-rating prediction method splits the data based on sentiment-scores before topic modeling.

6.2 Star Prediction: Regression Analysis

In Table 2, we present the results of star-rating predictions using the three methods outlined in Section 5.4. The regression results show that sentiment-aware embeddings (Method 2) yield more accurate star rating predictions than general embeddings (Method 1). This improvement is expected, as topic clusters are formed based on both sentiment and topic, providing more relevant information about the customer’s overall satisfaction. Method 3, which splits the dataset based on LLM-sentiment scores into positive and negative opinion units before clustering each split separately, achieves the highest accuracy with an R^2 value of 0.726, indicating a strong model fit. When clustering with general embeddings, incorporating sentiment scores of the individual opinions as described in Section 5.4, rather than using one-hot encoding for topic

membership, enhances prediction accuracy.

The results are consistent across datasets and numbers of clusters. Table 2 shows regression outcomes averaged over the three datasets, with 5-fold cross-validation ($K=20$ clusters). Detailed results for each dataset and number of clusters ($K = 10, 20, 30$) are provided in Appendix A3.

To answer RQ2, our results show that TopicImpact accurately predicts star ratings. Topic modeling alone using general embeddings yields unsatisfactory results due to insufficient sentiment capture. However, combining topic assignment with the opinion units’ sentiment scores—by segmenting data by sentiment before clustering and incorporating sentiment scores into regression (Eq. 1)—achieves high regression accuracy.

Method	s_k scores	# Sig. β	R^2	RMSE
M1. General Embeddings	without	14.5	.113	1.31
	with	14.6	.383	1.12
M2. Sentiment-Aware Embeddings	without	14.5	.487	1.01
	with	15.3	.393	1.10
M3. Sentiment Splitting	without	11.5	.652	.825
	with	15.1	.726	.731

Table 2: Star-prediction: No. of significant β coefficients (out of 20), R^2 and RMSE ($K = 20$).

To illustrate the output from TopicImpact, we present results from the Japanese restaurant dataset using Method 3: Sentiment Splitting, with $K = 20$ clusters (10 negative and 10 positive). In Table 3 we summarize the topics ranked by their influence on star rating. For each topic, the table includes the beta coefficient, the topic size (number of assigned opinion units), and a representative opinion unit.

7 Conclusion

TopicImpact enhances the extraction of actionable insights from customer reviews by integrating topic modeling with LLM-powered segmentation of reviews into distinct opinion units—individual, separated opinions supported by text excerpts. This provides both topic coherence and interpretability, while the metadata of opinion units enables sentiment-based segmentation. By incorporating sentiment scores and correlating topics with business metrics, TopicImpact effectively predicts star ratings and reveals how customer concerns influence business outcomes. This approach offers a fast, cost-effective solution for businesses to explore and act on customer feedback.

A promising avenue for future research is integrating keyword or example-guided topic seed-

Topic	β	Size	Opinion Unit	Example
Food safety	-.121	56	Food poisoning:	The next day was spent in the bathroom for several hours getting rid of the sushi
Service	-.886	1718	Staff friendliness:	Our waiter had a very unfriendly standoffish personality
Food	-.852	2398	Food quality:	My food was awful... overcooked
Order error	-.621	76	Order accuracy:	I got the complete wrong order
Portions	-.511	73	Portion size:	The serving was pathetically small
Hibachi	-.458	363	Hibachi grill entertainment:	the chef was lacking in entertainment. I was borderline bored
Pricing	-.346	755	Sushi pricing:	Pricing was too high for a conveyor belt style. These shops are popular in Japan, Taiwan, and China yet they were charging \$11.00 a roll compared to other country’s \$1.50 a roll
Cleanliness	-.311	921	Cleanliness:	the restaurant was filthy
Drinks	-.215	170	Sake selection:	it tasted like water with a little vodka poured into it
Parking	-.161	121	Parking:	A negative is the parking spots are narrow. It would deter me from going there when it’s busy
Food	.835	7182	Sushi:	The sushi is always spot on delicious
Service	.350	1623	Service:	The service is super good. The waitresses will check on you and do refills
Price	.347	1268	Food value:	the food is very good for the price
Atmosphere	.346	182	Atmosphere:	Casual and comfortable atmosphere!
Interior	.229	758	Décor:	The decor is a simple and clean aesthetic
Noodles	.137	72	Nabeyaki udon:	The udon chicken tastes AMAZING. it hands down the best nabeyaki udon in town
Busyness	.137	248	Restaurant crowding:	Whenever we’ve gone on a weekend evening, it’s never been terribly crowded
Family friendly	n.s.	75	Suitability for families:	great for families!
Location	n.s.	337	Location:	The location of this place is actually beautiful
Views	n.s.	66	Views:	The place has wonderful views, since it’s right on the river

Table 3: *Topic* is a description of the topic, β . is the regression coefficient in star rating prediction, *Size* is the number of opinion units in the topic, and the final column provides an example opinion unit. “n.s.” indicates that the β -coefficient was not statistically significant (i.e., $p > .05$).

ing within our framework of topic modeling with LLM preprocessing. This approach could combine the predefined segmentation of classification with the exploratory, iterative, and cost-effective benefits of topic modeling. Furthermore, verifying the performance of TopicImpact in other domains, such as retail product reviews, course evaluations, or employee satisfaction surveys, could improve opinion analysis in these critical areas. The different domains could pose distinct challenges, including varied opinion lengths, increased opinion nuance, or more frequent non-opinion content. Strategies to tackle these issues might involve customizing prompts, designing fine-tuning datasets, and thoughtfully combining abstractive and extractive summarization techniques to produce clear opinion units.

8 Limitations

A limitation of LLM preprocessing is that it sometimes misses opinions in reviews or creates excerpts lacking full context (Häglund and Björklund, 2025). While the fidelity of extracted opinion units is high

using GPT-4 (Häglund and Björklund, 2025) some errors persist, which can undermine the accuracy of subsequent opinion analysis. However, preprocessing also addresses key issues in opinion clustering, such as removing non-opinionated text.

In this work, we evaluate our system’s ability to generate coherent topics and predict star ratings by comparing a general-purpose embedding model (all-mpnet-base-v2) with a sentiment-aware embedding (sentiCSE). While the comparison reveals clear trends between the general and sentiment-aware embeddings, further validation using a larger number of embedding models would enhance the reliability and generalizability of these conclusions.

Another limitation of this work is the lack of a standardized benchmark dataset for evaluating aspect-based sentiment analysis in the context of topic modeling. Benchmark datasets such as 20 Newsgroups are commonly used to assess topic models in domains like news (Churchill and Singh, 2022). However, traditional aspect-based sentiment analysis datasets, such as the SemEval restaurant reviews (Pontiki et al., 2016), consist of short, sentence-length entries that fail to capture the complexity of full-length reviews. As a result, they are ill-suited for evaluating topic models applied to real-world review data, which is the focus of our work. To address this gap, we use authentic, full-length reviews and rely on human evaluation. This enables a context-sensitive assessment of both topic relevance and sentiment—better reflecting real-world use cases. Although evaluating topic models using a labeled dataset has its issues—particularly the difficulty of aligning fixed abstraction levels with an unsupervised task—such evaluation could complement our results and support benchmarking against alternative approaches.

Another set of limitations arises not from our system evaluation, but from the inherent challenges of topic modeling itself, particularly when chosen over classification methods. When the desired topics are known in advance, classification is typically the more appropriate approach, as it offers higher performance for accurate topic segmentation. However, topic modeling is more suitable for exploratory tasks where flexibility, iteration, and cost-effectiveness are priorities. One key issue with topic modeling is the potential misalignment between generated topics and user expectations. For example, should a topic such as “tiramisu” form its own cluster, or would it be better grouped under a broader “dessert” category or even inside a general

“food” cluster? The behavior and granularity of topic formation can be influenced by settings such as the number of clusters or the use of seeded clustering techniques. However, the inability to exert complete control over topic granularity and assignment is a drawback for applications that require stable and pre-defined topic categories.

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A Appendix

A.1 Prompt template

Perform aspect-based sentiment analysis for the restaurant review provided as the input. Return each aspect-sentiment pair with a label and a corresponding excerpt from the text. Also rate the sentiment of each aspect on a scale from 1-10 where 1 is highly negative and 10 is highly positive.

Aspect-sentiment pairs should not mix opinions on different aspects. Make sure to include all aspects. An aspect should be independent and not have to rely on other aspects to be understood.

If an opinion in the review is about the restaurant or experience in general then label this aspect as “overall experience”. Opinions not related to the restaurant should not be included.

Example input: I just left Mary’s with my lovely wife. We had a very mixed experience. 3 out of 5 stars. The gorgeous outdoor patio seating was fantastic with a nice view of the ocean. First, we split a dozen oysters. They were the best I had in my life! FRESH! Delicious! The avocado toast was excellent as were the crab cakes. However, I absolutely hated the dessert we ordered and did not particularly like my cocktail. Also, the staff could have been a little friendlier.

Example output:

```
[["Overall experience", "We had a very mixed experience. 3 out of 5 stars.", 6],  
 ["Outdoor patio seating", "The gorgeous outdoor patio seating was fantastic with a nice view of the ocean", 9],  
 ["View", "a nice view of the ocean", 8],  
 ["Oysters", "we split a dozen oysters. They were the best I had in my life! FRESH! Delicious!", 10],  
 ["Avocado toast", "the avocado toast was excellent", 9],  
 ["Crab cakes", "the crab cakes were excellent", 9],  
 ["Dessert", "I absolutely hated the dessert we ordered", 1],  
 ["Cocktail", "I did not particularly like my cocktail", 3],  
 ["Staff friendliness", "the staff could have been a little friendlier", 4]]
```

Input: Review to be processed

Output:

Figure 2: Prompt template for generating opinion units.

A.2 Instructions for Evaluators Analyzing the Clustered Topics

The evaluation of topic clusters was performed by one of the authors and 2 unpaid volunteers recruited through personal outreach. They were provided the following instructions.

1. Select the Topic: Click on a topic in the topic list.
2. Review the Excerpts: Carefully read through the 20 opinions/restaurant review excerpts belonging to the selected topic.
3. Identify a Common Theme: Look for a common theme among the review excerpts. Focus only on the topic being discussed (e.g., service, desserts, cleanliness, etc.). Ignore the sentiment of the opinions—whether they are positive or negative is not relevant.

4. Name the Topic: In the Excel file, write a descriptive name for the topic in the “Topic Name” column. If there is no clear majority theme, choose the most common or representative theme based on your judgment.

5. Flag Errors: Identify any review excerpts that DO NOT FIT the topic. In the Excel file, list the IDs of these excerpts under the “Error IDs” column. Separate the IDs with commas (e.g., 5,7,15).

A.3 Additional Star Rating Regression Results.

The following tables present the detailed star rating regression results as discussed in Section 6.2. These results are shown for each dataset (Italian, Mexican, and Japanese) and when varying number of clusters (K) used in the topic modeling. Results are averages over 5-fold cross validation on a hold-out sample.

Method	s_k -ratings	K	R2	RMSE	Sig. Coeffs. (β)
M1. General Embeddings	With	10	.482	1.02	6.2/10
	Without	10	.090	1.35	8.6/10
	With	20	.380	1.12	12.6/20
	Without	20	.136	1.32	16.0/20
	With	30	.335	1.16	20.2/30
	Without	30	.145	1.31	21.2/30
	With	10	.366	1.13	8.8/10
	Without	10	.441	1.07	9.4/10
	With	20	.378	1.13	17.2/20
	Without	20	.463	1.05	17.0/20
M2.Sentiment-Aware Embeddings	With	30	.350	1.16	25.2/30
	Without	30	.456	1.06	25.4/30
	With	10	.766	.687	8.0/10
	Without	10	.671	.814	8.6/10
	With	20	.750	.712	14.4/20
	Without	20	.678	.808	15.4/20
	With	30	.728	.744	20.0/30
	Without	30	.661	.832	21.0/30
	With	40	.716	.763	31.0/40
	Without	40	.666	.827	31.0/40

Table 4: Italian restaurant dataset: Star prediction results (R^2 and RMSE) and no. of significant β -coefficients, varying the number of clusters (K).

Method	s_k -ratings	K	R2	RMSE	Sig. Coeffs. (β)
M1. General Embeddings	With	10	.544	.900	7.2/10
	Without	10	.089	1.27	8.2/10
	With	20	.364	1.06	14.8/20
	Without	20	.119	1.25	14.8/20
	With	30	.335	1.09	19.0/30
	Without	30	.136	1.25	17.8/30
	With	10	.385	1.05	8.6/10
	Without	10	.503	.945	7.2/10
	With	20	.396	1.05	12.2/20
	Without	20	.531	.922	9.8/20
M2.Sentiment-Aware Embeddings	With	30	.401	1.04	21.2/30
	Without	30	.531	.918	20.0/30
	With	10	.720	.705	8.8/10
	Without	10	.641	.797	8.8/10
	With	20	.705	.726	15.6/20
	Without	20	.635	.807	14.8/20
	With	30	.697	.736	23.4/30
	Without	30	.642	.802	21.8/30
	With	40	.695	.743	29.0/40
	Without	40	.641	.806	28.4/40
M3. Sentiment Splitting	With	10	.456	1.06	8.8/10
	Without	10	.049	1.40	8.0/10
	With	20	.326	1.18	16.4/20
	Without	20	.084	1.37	12.8/20
	With	30	.320	1.18	20.2/30
	Without	30	.125	1.34	20.6/30
	With	10	.498	1.02	6.6/10
	Without	10	.533	.985	7.6/10
	With	20	.404	1.12	16.6/20
	Without	20	.466	1.05	16.8/20
M3. Sentiment Splitting	With	30	.422	1.1	27.6/30
	Without	30	.482	1.04	25.4/30
	With	10	.727	.750	9.6/10
	Without	10	.640	.861	10.0/10
	With	20	.724	.754	15.2/20
	Without	20	.643	.859	17.2/20
	With	30	.691	.800	22.8/30
	Without	30	.627	.880	22.2/30
	With	40	.688	.807	29.6/40
	Without	40	.629	.880	30.2/40

Table 5: Mexican restaurant dataset: Star prediction results (R^2 and RMSE) Star prediction results (R^2 and RMSE) and no. of significant β -coefficients, varying the number of clusters (K).

Method	s_k -ratings	K	R2	RMSE	Sig. Coeffs. (β)
M1. General Embeddings	With	10	.456	1.06	8.8/10
	Without	10	.049	1.40	8.0/10
	With	20	.326	1.18	16.4/20
	Without	20	.084	1.37	12.8/20
	With	30	.320	1.18	20.2/30
	Without	30	.125	1.34	20.6/30
	With	10	.498	1.02	6.6/10
	Without	10	.533	.985	7.6/10
	With	20	.404	1.12	16.6/20
	Without	20	.466	1.05	16.8/20
M2.Sentiment-Aware Embeddings	With	30	.422	1.1	27.6/30
	Without	30	.482	1.04	25.4/30
	With	10	.727	.750	9.6/10
	Without	10	.640	.861	10.0/10
	With	20	.724	.754	15.2/20
	Without	20	.643	.859	17.2/20
	With	30	.691	.800	22.8/30
	Without	30	.627	.880	22.2/30
	With	40	.688	.807	29.6/40
	Without	40	.629	.880	30.2/40
M3. Sentiment Splitting	With	10	.724	.754	15.2/20
	Without	10	.643	.859	17.2/20
	With	20	.691	.800	22.8/30
	Without	20	.627	.880	22.2/30
	With	30	.688	.807	29.6/40
	Without	30	.629	.880	30.2/40
	With	40	.688	.807	29.6/40
	Without	40	.629	.880	30.2/40
	With	50	.724	.754	15.2/20
	Without	50	.643	.859	17.2/20

Table 6: Japanese restaurant dataset: Star prediction results (R^2 and RMSE) and no. of significant β -coefficients, varying the number of clusters (K).