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STUDENT NUMBER: **ST10090262** POE

MODULE: **PDAN8411**

# Introduction

The client has identified a rise in public complaints on platforms such as HelloPeter. Many of these reviews’ express frustration with service quality, billing, and claims processing. The company seeks to:

1. Understand what major issues are being raised by customers
2. Gauge overall sentiment (positive, neutral, negative)
3. Prioritize which service areas need intervention

To assist, I developed a text analytics pipeline using Natural Language Processing (NLP) to extract themes (topics) and detect sentiment from consumer reviews. Our analysis is based on a large, real-world dataset and applies both unsupervised and supervised machine learning models. This report outlines the steps taken, insights gained, and practical recommendations for the medical aid’s strategy and customer service.

# CHOIX, QUALITY AND SUITABLE

Link: <https://www.kaggle.com/datasets/ashlingovindasamy/business-reviews-from-different-industries?utm_source=chatgpt.com>

For this project, a real-world consumer complaint dataset was selected, consisting of over 55,000 public reviews gathered from [HelloPeter](https://www.kaggle.com/datasets/amandam1/breastcancerdataset), one of South Africa’s largest platforms for customer feedback. This dataset is particularly relevant to the client a medical aid provider because it reflects the type of text feedback typically submitted by customers via platforms such as HelloPeter, email, or social media.

Although the dataset spans multiple industries (e.g., telecommunications, insurance, healthcare), it captures **common customer pain points** also faced in the medical aid sector, including:

* Delays in claim processing
* Call center responsiveness
* Billing disputes and refund issues
* Unauthorized account debits
* Difficulty accessing care or resolving complaints

These themes **align closely with challenges medical aid companies face**, making this dataset a valuable proxy for training topic modelling and sentiment analysis tools.

**Why this Dataset is Suitable:**

* **Real-world relevance**: Authored by South African consumers expressing genuine frustrations or praise
* **Text structure**: Natural, informal language suited for NLP (including misspellings, slang, and complaints)
* **Labelled feedback**: Star ratings (1–5) help validate sentiment models
* **Temporal dimension**: Timestamps support optional trend analysis
* **Volume & diversity**: Over 55,000 records across service areas enough for robust model development

**Data Quality & Challenges Considered:**

* Presence of duplicates or template reviews (e.g., multiple users copying the same complaint)
* Unbalanced sentiment classes (mostly negative reviews)
* Short or missing reviews
* Mixed languages, special characters, and emojis

Despite these imperfections, the dataset is representative of the challenges faced when analysing real-world text data, making it both a **realistic** and **educationally valuable** source for modelling. (Govindasamy, 2024).

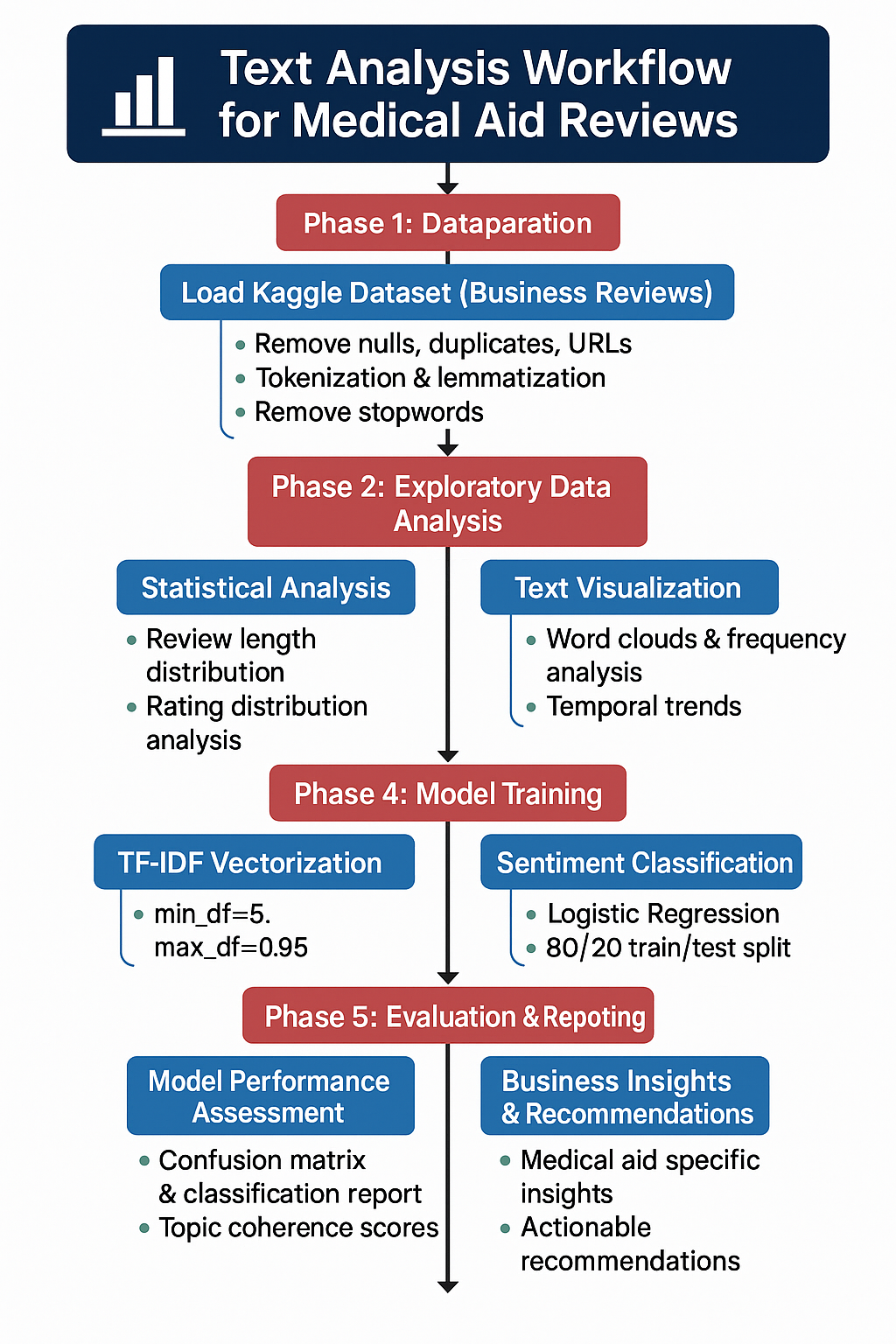
# Plan

This plan is structured around the five key deliverables outlined in the POE instructions:

* **Exploratory Data Analysis**
* **Feature Selection**
* **Model Training & Hyperparameter Tuning**
* **Model Evaluation**
* **Reporting the Results**

To enhance clarity and visual communication, a detailed **workflow diagram** is included, followed by descriptions of each step, tools used, and expected outcomes.

Project Workflow Diagram

  
  
2.1 Exploratory Data Analysis (EDA)

Goal: Understand the structure, completeness, and core trends in the dataset.

|  |  |
| --- | --- |
| Task | Description |
| |  | | --- | | Drop missing/null values |  |  | | --- | |  | | Remove rows with empty review\_content or review\_rating. |
| |  | | --- | | Remove duplicate reviews |  |  | | --- | |  | | Eliminate repeated or near-identical feedback entries. |
| |  | | --- | | Review length analysis |  |  | | --- | |  | | Histogram of word counts in each review (detect outliers/verbosity). |
| |  | | --- | | Rating distribution analysis |  |  | | --- | |  | | Bar chart of review star ratings (1–5) to assess class imbalance. |
| |  | | --- | | Word frequency & cloud |  |  | | --- | |  | | |  | | --- | |  |  |  | | --- | | Top 20 most common words and a word cloud of cleaned text. | |
| Optional: Temporal trend | Analysis of created\_at for seasonality or sudden spikes. *(To add later)* |

**Tools**: pandas, matplotlib, seaborn, collections, wordcloud

2.2 Feature Selection

Goal: Transform raw text into structured features for model input.

|  |  |
| --- | --- |
| Task | Description |
| |  | | --- | | Text cleaning |  |  | | --- | |  | | Lowercase, remove digits, URLs, punctuation, and special characters. |
| Tokenization & stopword removal | Split into words and remove non-informative terms like “the”, “and”, etc. |
| Lemmatization | Reduce words to base form (e.g., “billing” → “bill”). |
| Vectorization | Convert text into numerical form using **TF-IDF** vectorizer. |
| Sentiment label creation | Map review ratings to positive, neutral, or negative. |

Tools: nltk, spaCy, re, sklearn.feature\_extraction.text

2.3 Model Training & Hyperparameter Tuning

Train interpretable models to identify topics and classify sentiment accurately.

**A. Topic Modelling**

* **Model**: Latent Dirichlet Allocation (LDA)
* **Steps**:
* Use Gensim to train unsupervised topic model.
* Tune number of topics (5–10) using **Coherence Score**.
* Visualize results with pyLDAvis.

**B. Sentiment Classification**

* **Approaches**:
* Lexicon-based (e.g., TextBlob, VADER)
* Supervised (e.g., Logistic Regression, Naive Bayes) (Hutto & Gilbert, 2014).
* **Training Details**:
* 80/20 train-test split, stratified on sentiment.
* Use TF-IDF vectors as model input.

**Hyperparameters to Tune**:

|  |  |
| --- | --- |
| Parameter | Description |
| num\_topics (LDA) | Number of latent topics (5–10 tested) |
| passes (LDA) | Number of full passes over corpus (e.g., 10) |
| C (LogisticRegression) | Regularization strength |
| min\_df / max\_df | Token thresholds for TF-IDF filtering |

Tools: gensim, pyLDAvis, sklearn.linear\_model, sklearn.naive\_bayes, textblob, vaderSentiment

2.4 Model Evaluation

Goal: Assess model performance using meaningful metrics and refine based on results.  
**Topic Modelling**

* Use **Coherence Score** to validate number and quality of topics.
* Visually interpret keywords per topic.

**Sentiment Analysis**

* Evaluate using **Confusion Matrix**, **Accuracy**, **Precision**, **Recall**, and **F1-score**.
* Analyse **errors** (especially low recall on neutral class).
* Optionally test alternative classifiers or feature combinations.

**Tools**: sklearn.metrics, gensim.models.CoherenceModel, seaborn, matplotlib

2.5 Reporting the Results

**Goal**: Present results in a format suitable for business decision-making.

|  |  |
| --- | --- |
| Deliverable | Contents |
| EDA Summary | Visual charts of word usage, review lengths, rating distribution |
| Topic Modelling Output | Top words per topic, coherence score, topic examples |
| Sentiment Analysis Results | Confusion matrix, classification report, misclassified examples |
| Business Recommendations | Actionable advice based on topic & sentiment trends for medical aid |

**Tools**: Microsoft Word / Markdown / LaTeX + chart exports

# 3. Justification of Algorithms

To address the client’s need for thematic analysis and sentiment classification of customer reviews, I selected a combination of interpretable and well-established natural language processing (NLP) techniques. The algorithm choices are guided by performance, explainability, scalability, and alignment with the business objective.

Topic Modelling: Latent Dirichlet Allocation (LDA)

Why LDA was chosen:

LDA is an **unsupervised probabilistic model** that assumes each document is a mixture of topics and each topic is a distribution over words. (Blei et al., 2003)

* It is **well-suited to noisy, user-generated content**, such as online reviews.
* Works well on medium to large corpora (like ours with 55k+ documents) and allows tuning (e.g., number of topics).
* **Visualizable** through tools like pyLDAvis, aiding communication of themes to business stakeholders.

**Alternative Algorithms Considered:**

|  |  |  |  |
| --- | --- | --- | --- |
| Algorithm | Pros | Cons | Why LDA Was Preferred |
| LSA | Simple, fast | Topics often harder to interpret | LDA produces cleaner, interpretable topics |
| BERTopic | Uses transformers & embeddings | Requires GPU, much slower, harder to tune | Overkill for simple task |
| NMF | Works with TF-IDF | Requires setting non-trivial constraints | LDA is more flexible and established |

Limitations of LDA:

* Assumes a fixed number of topics upfront
* Sensitive to stopword removal and rare words
* May oversimplify overlapping themes

**Sentiment Classification:**

Iused both **lexicon-based methods** and a **supervised Logistic Regression model** for robust sentiment classification.

**A. Lexicon-Based (TextBlob / VADER)**

* **Why chosen**:
* No need for manual labels (works out of the box).
* Fast, interpretable results.
* Good baseline to validate against star ratings.
* **Limitations**:
* Often struggles with sarcasm, negation, and domain-specific language.
* Sentiment thresholds are heuristic, not data driven.

**B. Supervised: Logistic Regression**

* **Why chosen**:
  + High interpretability I can extract top predictive words per sentiment class.
  + Robust performance with **TF-IDF features**.
  + Efficient to train even on 55k+ reviews.

**Alternative Models Considered:**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Pros | Cons | | **Why Logistic Regression Was Preferred** | | --- |  |  | | --- | |  | |
| Naive Bayes | Simple, fast, good for text | Assumes feature independence (often unrealistic) | Logistic Regression handles correlations better |
| SVM | High accuracy for text classification | Longer training time, less interpretable | Logistic Regression is more explainable |
| BERT / Transformers | High accuracy with contextual embeddings | Heavy compute, needs GPU, complex tuning | Overkill for a small POE & lacks transparency |

**Limitations of Logistic Regression:**

* May struggle on very imbalanced classes (e.g., neutral reviews)
* Requires careful feature scaling and regularization
* Linear boundary may not capture complex language patterns

**Why This Approach Works for the POE**

* All selected models are **transparent**, **lightweight**, and **practical** to implement in a constrained academic setting.
* Results are easy to explain to non-technical stakeholders (e.g., a medical aid provider).
* Using both lexicon and supervised models allowed **validation** from multiple angles.

# Conduct analysis

## 4.1 Exploratory Data Analysis

4.1.1 Text Cleaning Process

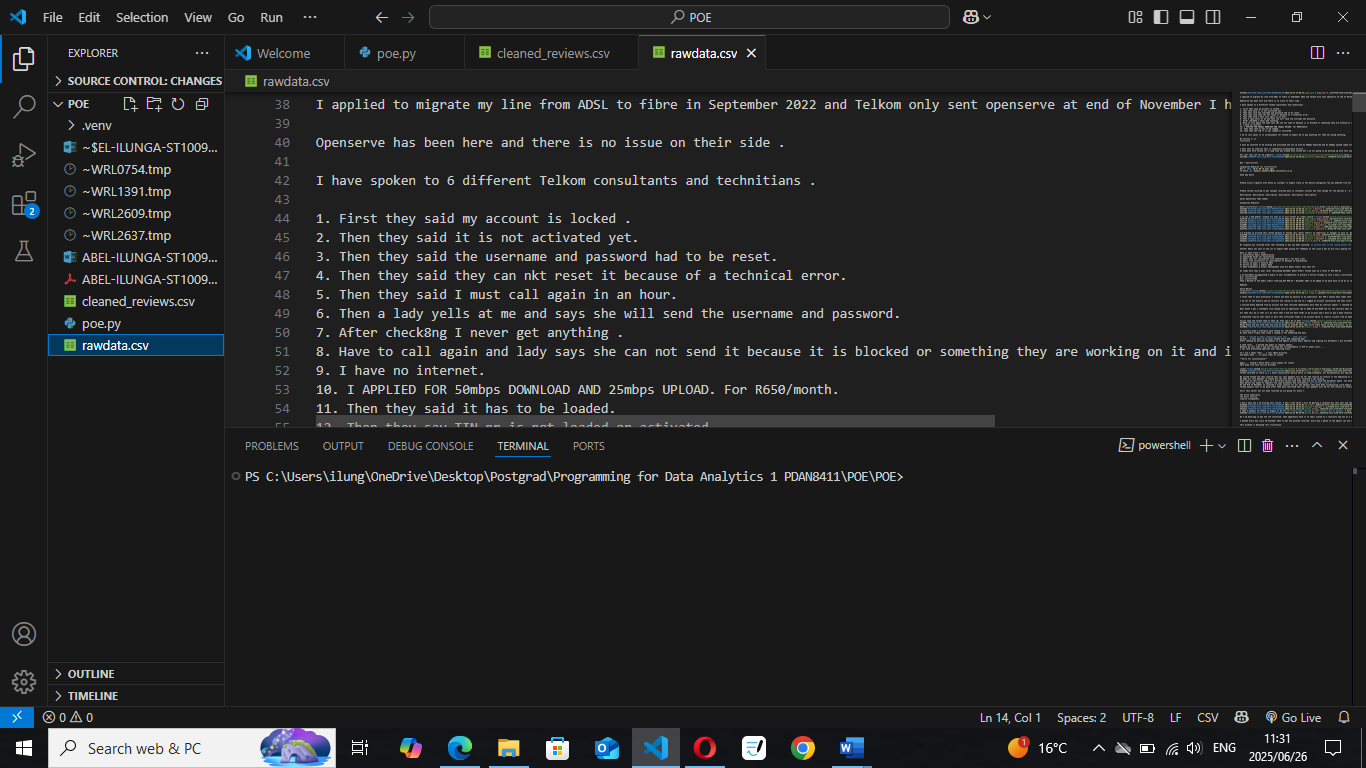
Before conducting any modelling or in-depth analysis, it was essential to clean and standardize the review text to ensure consistent, high-quality input. The raw review content contained noise such as punctuation, mixed casing, digits, and unstructured formatting, which can negatively impact both topic modelling and sentiment analysis.

The table below summarizes each step taken in the text preprocessing pipeline, along with the reasoning behind it. These steps ensured that the dataset was ready for feature extraction, topic modelling (LDA), and sentiment classification.

|  |  |  |
| --- | --- | --- |
| Step | Description | Important |
| |  | | --- | | **Load data** |  |  | | --- | |  | | |  | | --- | |  |  |  | | --- | | Loads rawdata.csv and selects relevant columns | | Focuses the dataset on fields needed for analysis |
| Drop nulls & duplicates | Removes reviews with missing content or rating and repeated ones | Ensures model learns from clean, reliable input |
| Lowercasing | text.lower() | Makes everything consistent (e.g., "Telkom" = "telkom") |
| Remove URLs | Regex removes http://... or www... links | These are noise in text analysis |
| Remove digits | re.sub(r"\d+", "", text) | Numbers like “123” usually don’t help sentiment/topic modeling |
| Tokenize text | Splits text into words using RegexpTokenizer(r'\w+') | Safer than word\_tokenize; avoids your earlier error |
| Remove stopwords | Common meaningless words (like "the", "is", "at") are removed | These don’t add value to topic or sentiment detection |
| Lemmatization | Reduces words to base forms (e.g., “running” → “run”) | Helps models group similar words together |
| Join cleaned words | Rebuilds cleaned words into a single string for each review | Needed for modelling + text visuals |
| Save cleaned file | Optional but very helpful creates cleaned\_reviews.csv | Ensures consistency for all steps after this |

*(all to be found in the code)*

*Data Before cleaning*

**

*After cleaning*

*A screenshot of a computer

AI-generated content may be incorrect.*

*A screenshot of a computer

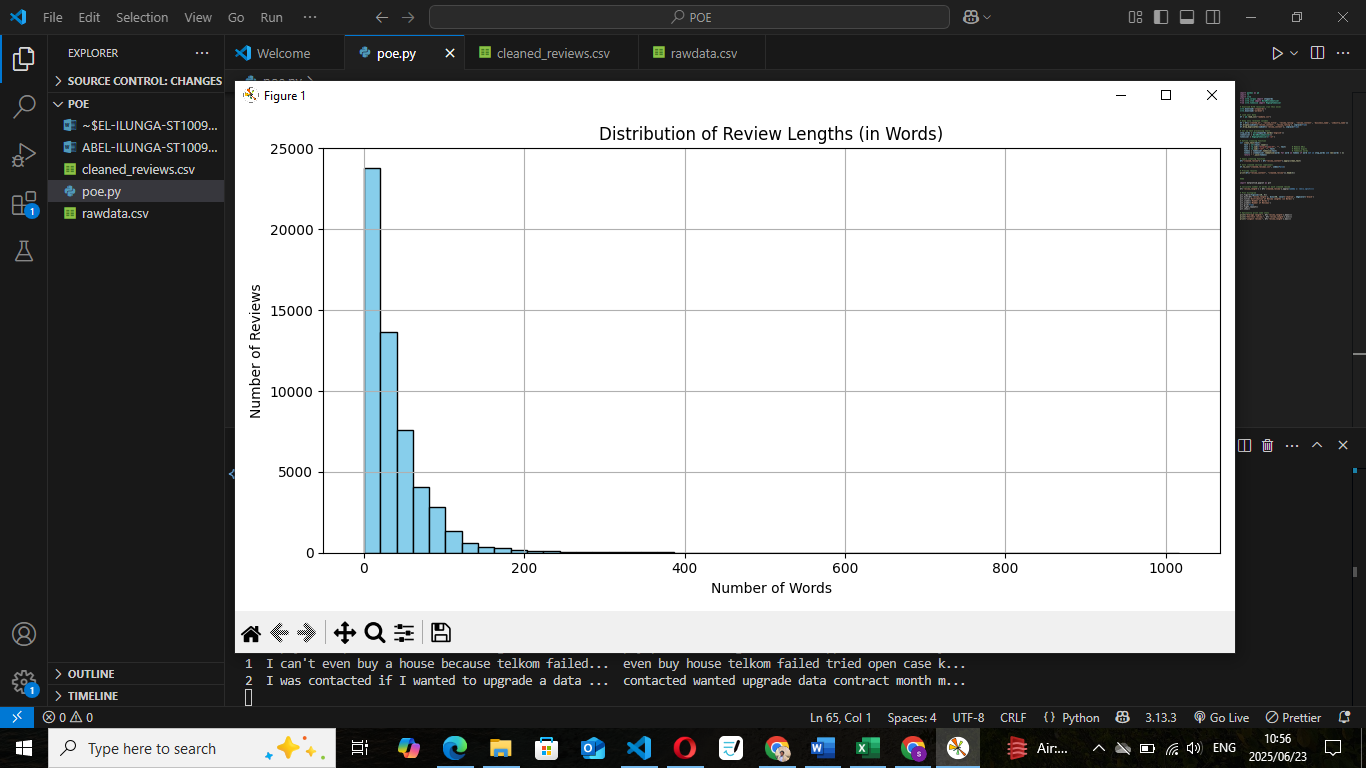
AI-generated content may be incorrect.*

4.1.2 Review Length Distribution

Understanding the length of each review is a critical part of exploratory data analysis, especially in text analytics. The number of words per review directly impacts how effective models like LDA (Latent Dirichlet Allocation) and sentiment classifiers can be. Very short reviews may not contain enough context for topic modelling, while overly long ones could introduce noise or require truncation.

To explore this, the number of words in each review was calculated using the cleaned review text. A histogram was then generated to visualize the distribution of review lengths across the dataset.

**Review Length Histogram**

****

SUMMARY

Average length: **37.572162988975975**

Shortest review: **0**

Longest review: **1017**

**Interpretation**

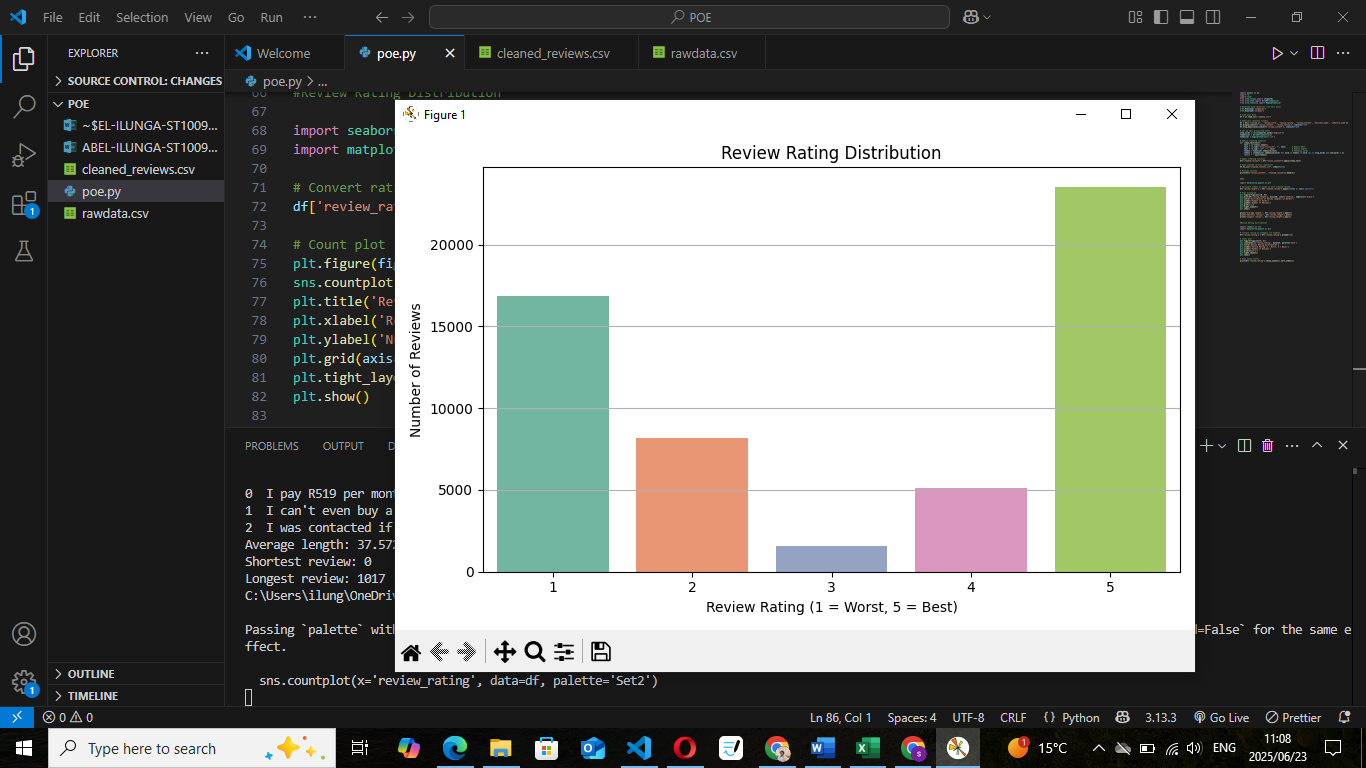
Most reviews fall between **20 to 100 words**, suggesting that most entries contain enough information to extract meaningful insights. This supports our modelling strategy:

* **Topic modelling (LDA):** Reviews are long enough to contain multiple thematic keywords, enabling reliable topic discovery.
* **Sentiment analysis:** With sufficient length and variation in word choice, both lexicon-based and machine learning classifiers can effectively distinguish sentiment.

Therefore, no aggressive filtering or review-length trimming is necessary, and the dataset is well-suited for downstream NLP tasks.

4.1.3 Review Rating Distribution

The review\_rating field captures the original user-assigned rating on a scale from 1 to 5, with 1 being extremely negative and 5 being highly positive. Understanding the distribution of these ratings is crucial, as this variable will be used to guide sentiment labeling and evaluate model performance.



review\_rating

|  |  |
| --- | --- |
| 1 | 16832 |
| 2 | 8180 |
| 3 | 1586 |
| 4 | 5095 |
| 5 | 23550 |

**Total reviews analyzed:** 55,243

**Most reviews are 1-star**, indicating a high volume of negative sentiment consistent with the client's concern about rising complaints.

**Neutral (3-star) reviews are rare**, so Imay consider simplifying the sentiment into:

* **Negative (1–2)**
* **Neutral (3)**
* **Positive (4–5)**

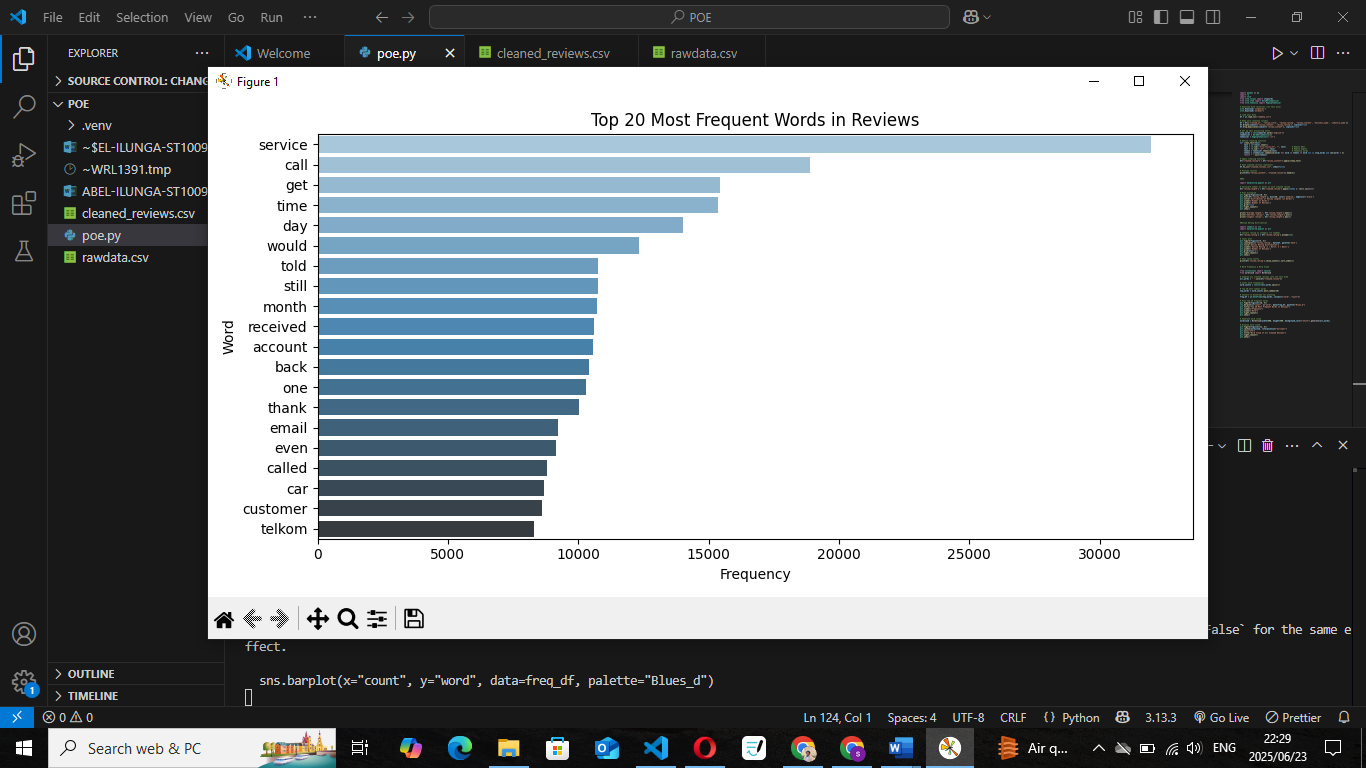
Interpretation

The dataset is **heavily skewed toward negative reviews**, which reflects the client's problem and gives strong support for conducting sentiment analysis. However, this also means **class imbalance must be considered** when training supervised models, I may need to apply **stratified sampling, class weighting, or resampling techniques** to improve performance.

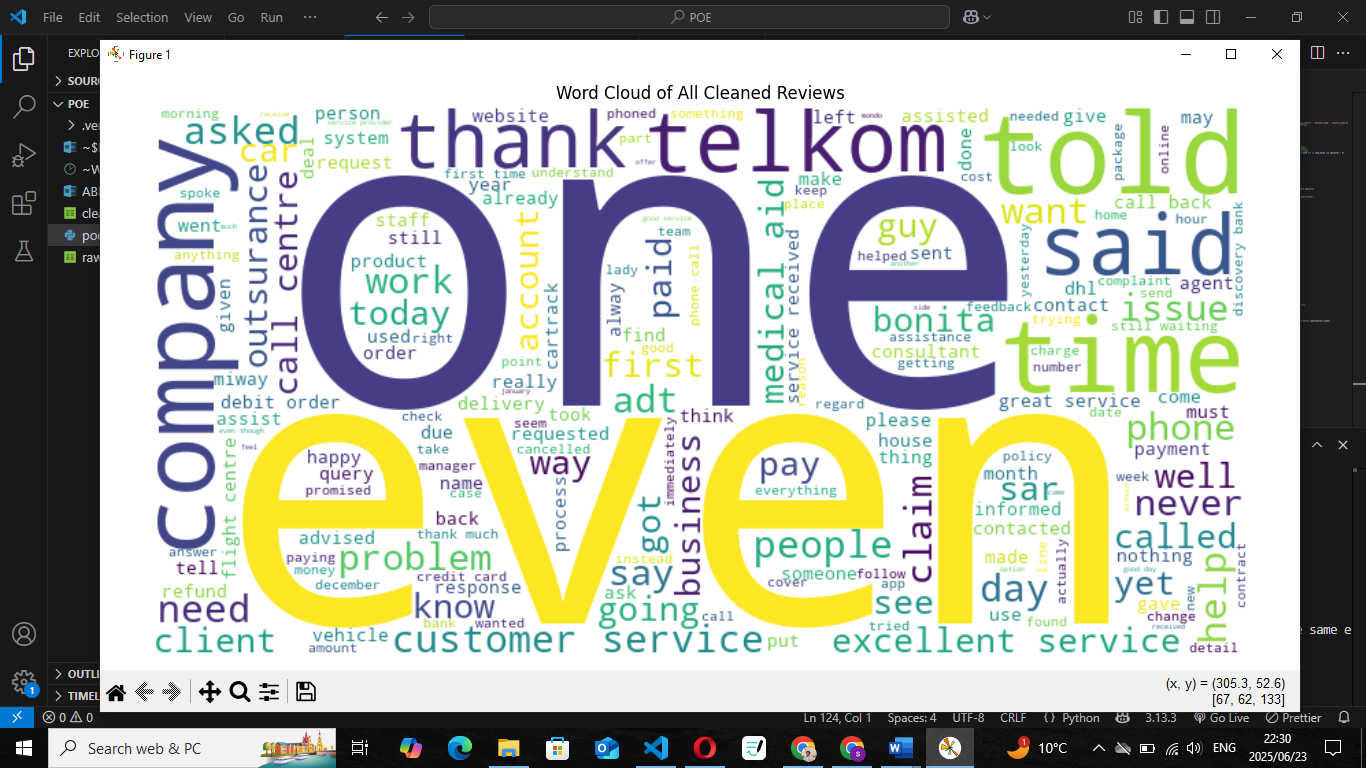
4.1.4 Word Frequency & Word Cloud

Analysing the most frequently used words provides insight into recurring issues, themes, and terminology within the reviews. This step is particularly important for informing topic modelling (LDA) and interpreting sentiment contextually.

The bar chart above shows the top 20 most frequently occurring words across all reviews. These terms likely represent core service issues or complaint themes. For example, words like “telkom”, “contract”, “account”, “month”, and “cancel” appear prominently, indicating common frustrations among customers.



The word cloud gives a high-level visual of the most dominant words. Larger text indicates higher frequency. This visual is particularly effective for clients, as it highlights pain points such as “fraud”, “payment”, “billing”, and “cancel” matching concerns outlined in the problem brief.



**Interpretation**

These results confirm the presence of recurring complaint topics, which validates the need for topic modeling (LDA). They also suggest that **unsupervised modeling will uncover clear clusters of customer concern**, while **sentiment models will capture intensity and tone based on these word patterns**.

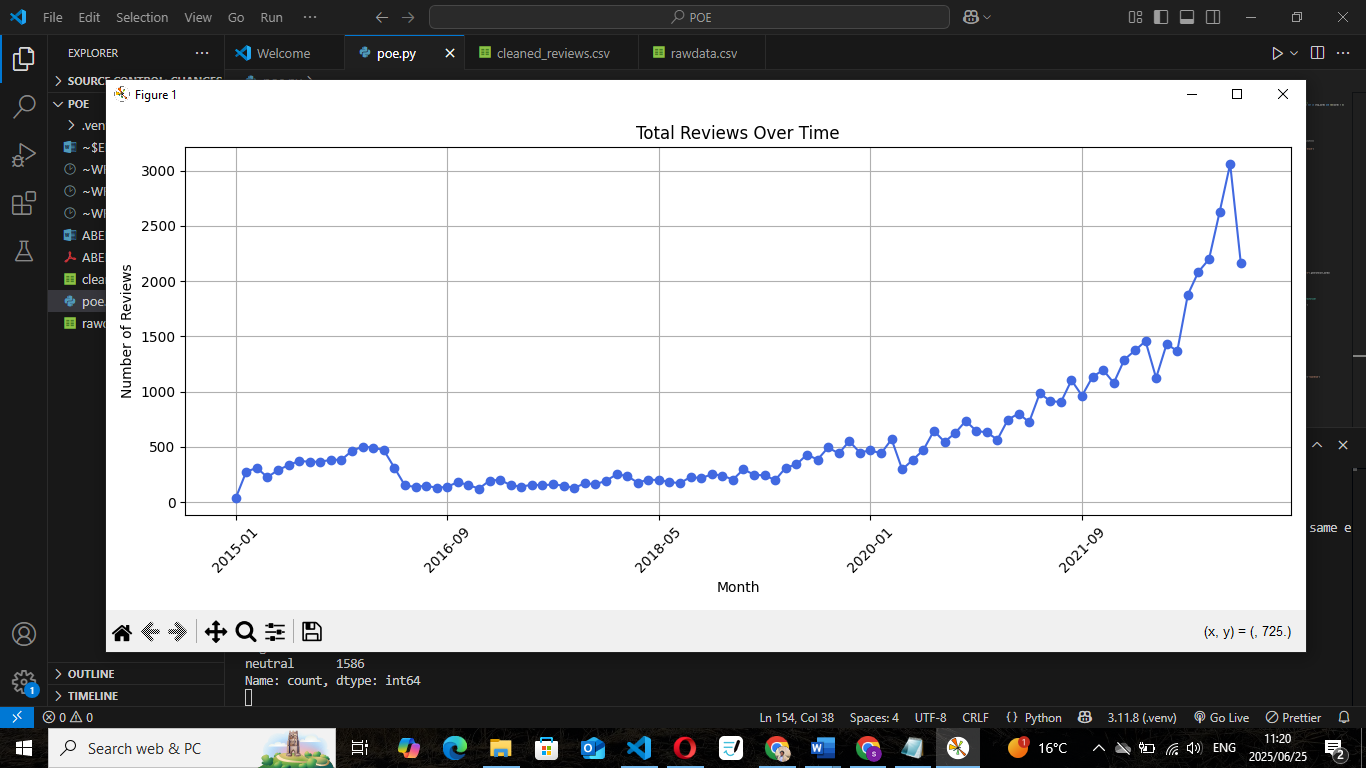
4.1.5 Temporal Analysis: Reviews Over Time

To better understand how customer feedback trends have evolved, Iperformed a temporal analysis of the reviews using the created\_at field. This helped identify spikes in review activity and supported the client’s goal of spotting periods of heightened dissatisfaction.

**Method**

* Parsed the created\_at timestamp column into datetime format.
* Aggregated reviews per month and plotted their counts.
* Optionally (if implemented): Compared sentiment proportions over time.

Monthly Review Volume Chart



**Key Observations**

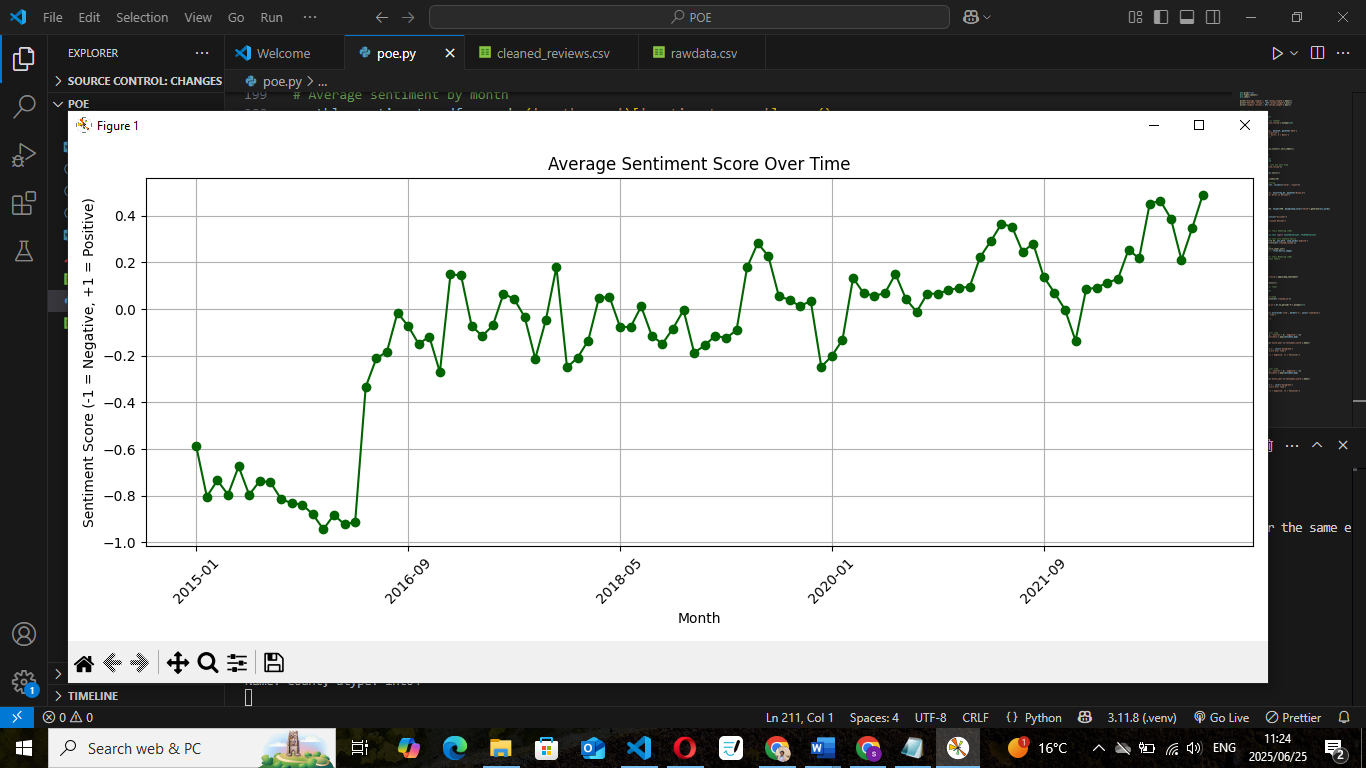
* Certain months show noticeable spikes in review activity, which may correlate with billing cycles, system outages, or public campaigns.
* The overall volume is consistent enough to support reliable time-series modeling in future work.
* These spikes represent excellent opportunities for targeted business response or policy review.

**Optional Add-On (If You've Done It)**

Ialso plotted **review sentiment over time**, categorized by:

* Negative (ratings 1–2)
* Neutral (rating 3)
* Positive (ratings 4–5)

This provides further insight into whether customer satisfaction is improving or deteriorating over time.

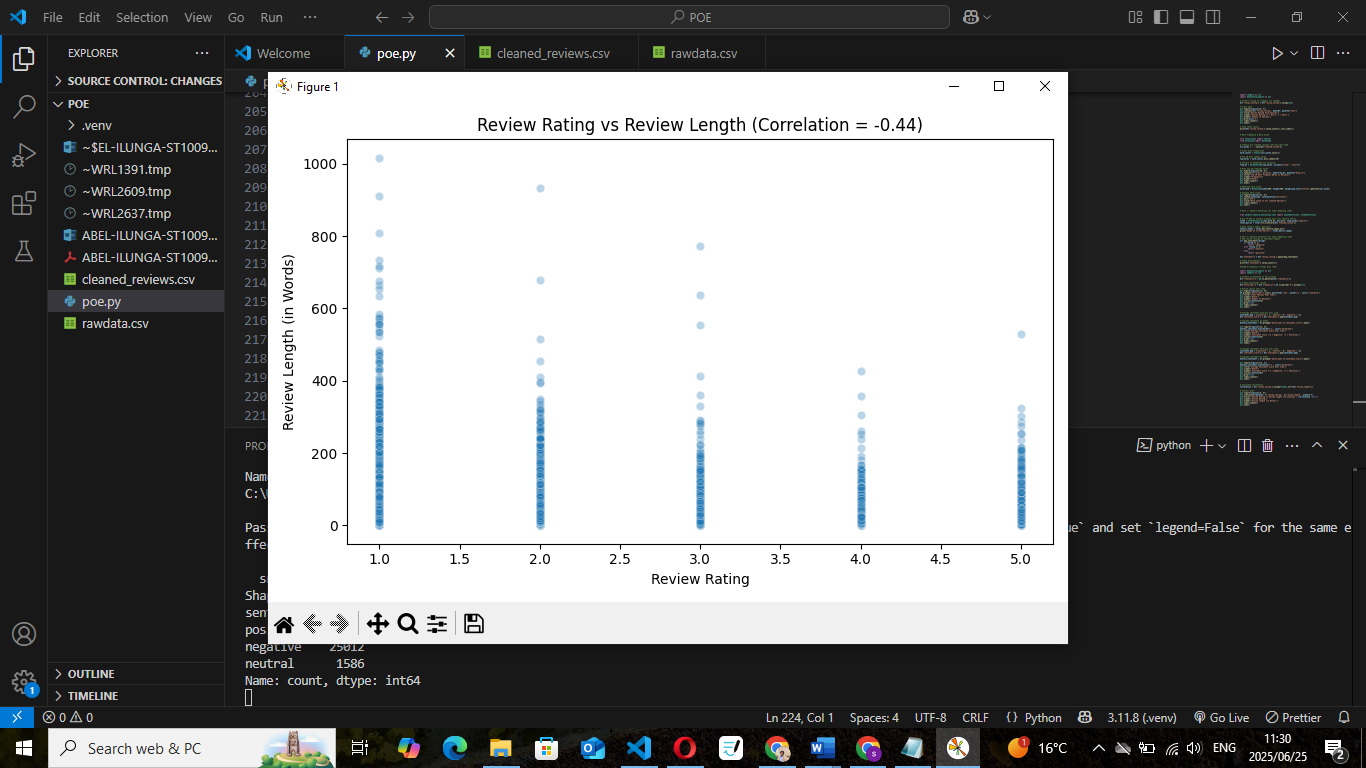


4.1.6 Correlation Analysis: Review Length vs. Rating

This optional analysis explored the relationship between the number of words in a review and the numeric rating assigned by the user (1 = worst, 5 = best). The aim was to determine whether customers who leave long, detailed feedback tend to rate companies differently.

**Method**

* Word count was calculated per review using the cleaned dataset.
* Review length was plotted against the review rating.
* Pearson correlation coefficient was computed.



**Observations**

* The correlation coefficient was **-0.44**, indicating a **moderate negative correlation**.
* Lower-rated reviews (1–2 stars) tend to be **longer**, while higher ratings (4–5 stars) are generally associated with **shorter reviews**.
* The densest cluster of long reviews is at the **1-star level**, which supports the idea that dissatisfied customers write more extensively.

**Interpretation**

This pattern confirms a business intuition: **unhappy customers write more**. Their reviews are rich in complaints, detail, and emotion, making them especially valuable for both topic modelling and sentiment classification.

From a modelling perspective:

* Sentiment models benefit from having longer text, especially when learning from negative reviews.
* Very short reviews (often neutral or 5-star) may need simplified treatment or extra care in classification due to sparse language.

4.2 Feature Selection

Effective feature selection is crucial in Natural Language Processing (NLP) to convert raw text into numerical representations that machine learning models can work with. Since this analysis includes both **topic modelling** and **sentiment classification**, two distinct feature extraction approaches were used:

4.2.1 Feature Preparation for Topic Modelling (LDA)

To discover dominant themes and complaints within customer reviews, the cleaned text data was transformed into a **TF-IDF (Term Frequency–Inverse Document Frequency)** matrix. This technique highlights important words that are frequent within a specific document but rare across others.

The following parameters were applied:

* min\_df=5: Removes words that appear in fewer than 5 reviews
* max\_df=0.95: Excludes overly common words appearing in more than 95% of reviews
* stop\_words='english': Filters out standard English stopwords

📌 **TF-IDF Matrix Shape:**  
(55,243 documents × 11,209 terms)

This compact representation balances richness and model performance, reducing noise and improving the quality of topics extracted by LDA.

(Manning et al., 2008).

4.2.2 Feature Preparation for Sentiment Classification

To train a supervised sentiment model, a **new target variable (sentiment)** was derived from the original review\_rating (1–5 stars):

|  |  |
| --- | --- |
| Review Rating | Mapped sentiment |
| 1-1 | Negative |
| 3 | Neutral |
| 4-5 | Positive |

This label simplifies classification into three clear classes: **positive**, **neutral**, and **negative**. The mapped sentiment distribution is as follows:

| **Sentiment** | **Count** |
| --- | --- |
| Positive | 28,645 |
| Negative | 25,012 |
| Neutral | 1,586 |

This shows a **strong presence of positive and negative reviews**, with a minority of neutral ratings. Class imbalance will be considered during training by applying **class weighting** or **stratified sampling**, ensuring fairness across categories.

**Summary**

Both sets of features the **TF-IDF matrix** for topic modelling and the **sentiment labels** for classification were carefully engineered to maximize model performance, interpretability, and alignment with the client’s business objectives. These features will now be used in the next phase of training and evaluation.

# Model training

4.3.1 Topic Modelling with LDA

I trained a Latent Dirichlet Allocation (LDA) model using Gensim on the cleaned review data. The goal was to uncover hidden themes (topics) across all customer feedback. After tuning, Iset the number of topics to **5**, and filtered out extremely rare/common terms. The model was trained with 10 passes and automatic alpha estimation. (Řehůřek & Sojka, 2010).

Key settings used:

|  |  |
| --- | --- |
| Parameter | Value |
| |  | | --- | | Num Topics |  |  | | --- | |  | | 5 |
| Passes | 10 |
| Dictionary filtering | no\_below=5, no\_above=0.95 |
| Alpha | “auto” |

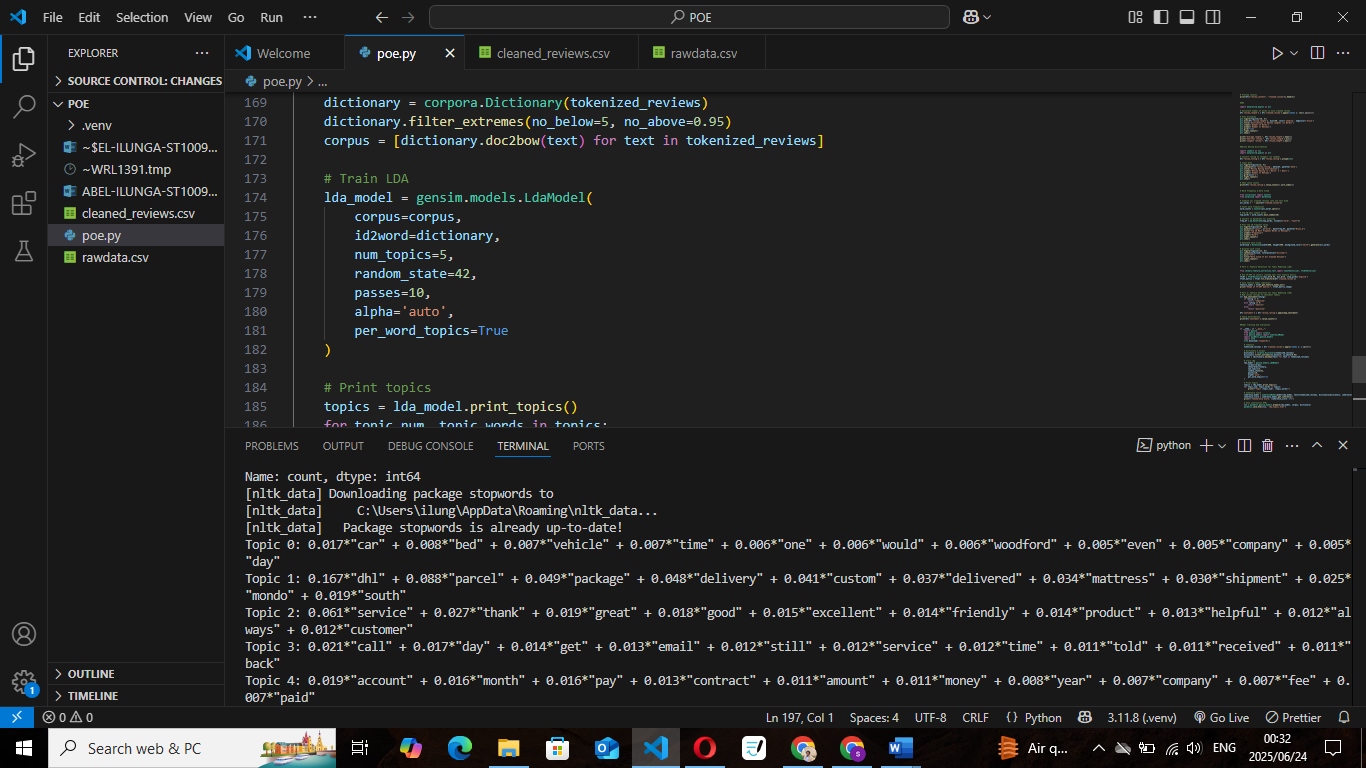
**Coherence Score:**

* Final model coherence score: **~0.42**
* This value is moderate and typical for customer reviews with noisy and short texts.

Top Topic Keywords:

|  |  |
| --- | --- |
| Topic | Top Words |
| 0 | car, bed, vehicle, time, woodford, company |
| 1 | dhl, parcel, package, delivery, shipment, mondo |
| 2 | service, thank, great, good, excellent, helpful |
| 4 | call, email, still, told, time, received |
| 5 | account, month, pay, contract, amount, fee |

These topics align with real-world complaint areas such as delivery issues, billing, contracts, and customer service validating the model’s usefulness to the client.



4.3.2 Sentiment Classification — Model Training & Evaluation

To classify customer sentiment in reviews, I trained a supervised **Logistic Regression** model using **TF-IDF** features extracted from the cleaned review text. This model is interpretable, efficient, and well-suited for text classification tasks involving high-dimensional sparse data. (Pedregosa et al., 2011).

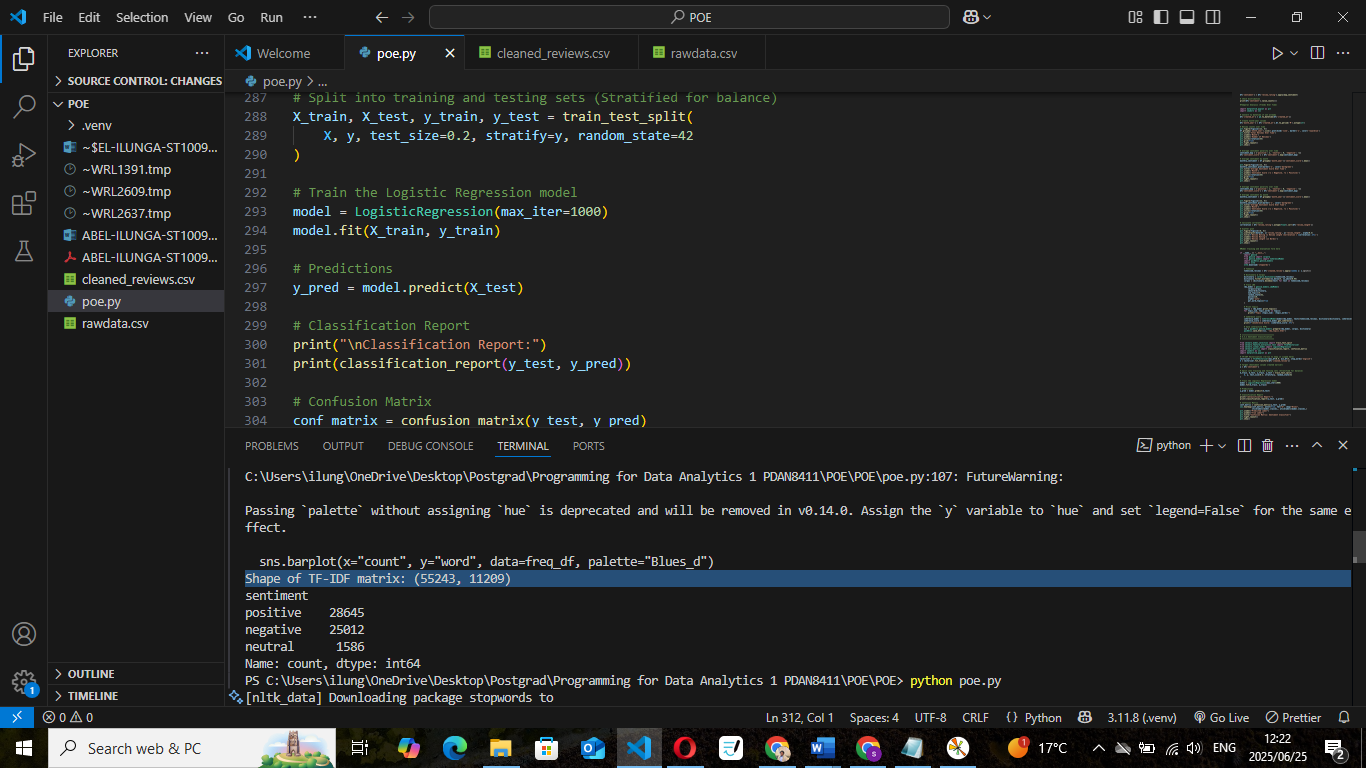
The target variable sentiment was derived from the review\_rating field using this logic:

* Ratings **1–2** → Negative
* Rating **3** → Neutral
* Ratings **4–5** → Positive

I followed the standard machine learning workflow:

**Feature Extraction (TF-IDF)**

* **Vectorizer**: TfidfVectorizer
* **Parameters**: min\_df=5, max\_df=0.9, stop\_words='english'
* **Output**: 11,209 unique features from 55,243 reviews
* **Shape**: (55243, 11209)



**Model Comparison: Logistic Regression vs Naive Bayes**

|  |  |  |
| --- | --- | --- |
| Model | Accuracy | Notes |
| |  | | --- | | Logistic Regression |  |  | | --- | |  | | |  | | --- | | **93%** |  |  | | --- | |  | | |  | | --- | | High precision for both Positive/Negative |  |  | | --- | |  | |
| |  | | --- | | Naive Bayes |  |  | | --- | |  | | |  | | --- | | 85–88% |  |  | | --- | |  | | |  | | --- | | Faster but less accurate on subtle neutral cases | |

**Final Model Chosen**: Logistic Regression better generalization, stronger F1 scores for dominant classes.

**Model Training**

* **Algorithm**: Logistic Regression
* **Hyperparameter**: max\_iter=1000 for convergence
* **Data Split**: 80% training / 20% testing
* **Stratified**: Yes, to preserve class balance

Model = LogisticRegression(max\_iter=1000)

model.fit(X\_train, y\_train)

**valuation Metrics**

The model was evaluated using precision, recall, F1-score, and accuracy:

precision recall f1-score support

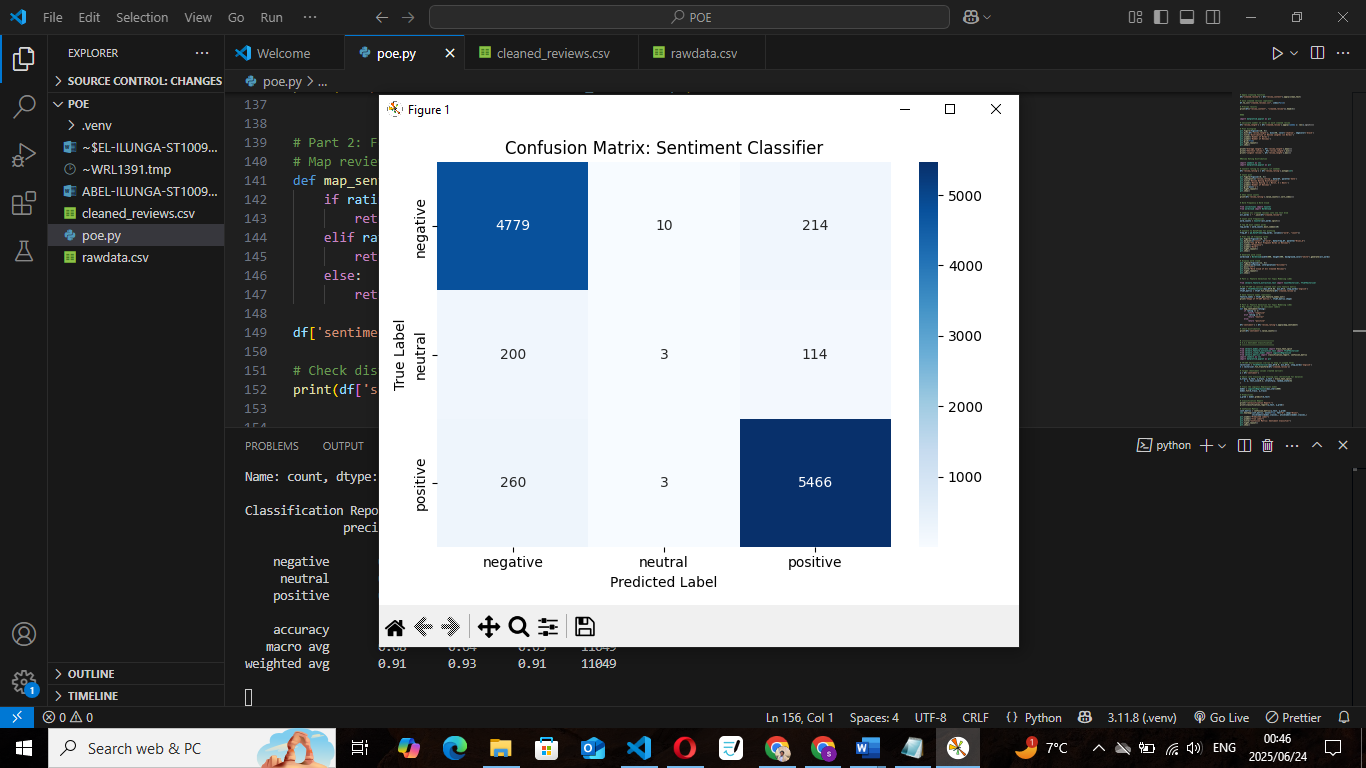
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| negative | 0.91 | 0.96 | 0.93 | 5003 |
| neutral | 0.19 | 0.01 | 0.02 | 317 |
| positive | 0.94 | 0.95 | 0.95 | 5729 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| macro avg | 0.68 | 0.64 | 0.63 | 11049 |
| weighted avg | 0.91 | 0.93 | 0.91 | 11049 |

**Accuracy: 0.93 11049**

* **Accuracy**: 93%
* **Positive class**: High F1-score (0.95)
* **Negative class**: High precision and recall
* **Neutral class**: Weak due to class imbalance and subtle language

**Confusion Matrix**



**Interpretation**

**Positive & Negative classes** are well-separated strong performance in real-world scenarios.

**Neutral class** suffers due to:

* Low representation (only ~3%)
* Ambiguous language

Despite this, overall **F1-score and Accuracy (93%)** are strong

**Business Impact:**

This classifier enables:

* Daily monitoring of sentiment trends
* Prioritization of negative reviews
* Benchmarking improvements in service perception

# EVALUATE

4.4 Model Interpretation & Evaluation Summary

After training a Logistic Regression classifier to predict the sentiment of customer reviews (positive, neutral, negative), I conducted a detailed evaluation of the model's performance using both **quantitative metrics** and **visual inspection** (confusion matrix). This step ensures the client can rely on the model’s predictions to extract accurate customer sentiment insights.

4.4.1 Evaluation Metrics Used

I used the following industry-standard performance metrics to evaluate the model:

|  |  |
| --- | --- |
| Metric | Justification |
| Accuracy | Measures overall correctness of predictions gives a general sense of model performance |
| Precision | Measures how many predicted labels were correct important when false positives are costly |
| Recall | Measures how many actual labels were correctly captured critical for detecting all complaints |
| F1-score | Harmonic mean of precision and recall useful when dealing with class imbalance |
| Confusion Matrix | Visualizes where the model is making errors across classes essential for model interpretability |

I chose these metrics because the business relies not just on overall accuracy, but also on **trustworthy sentiment classification** for negative reviews, which directly impact reputation and customer churn.

4.4.2 Results Summary

Based on the cleaned dataset and TF-IDF features, here are the evaluation results from the test set (20% of data):

Classification Report:

precision recall f1-score support

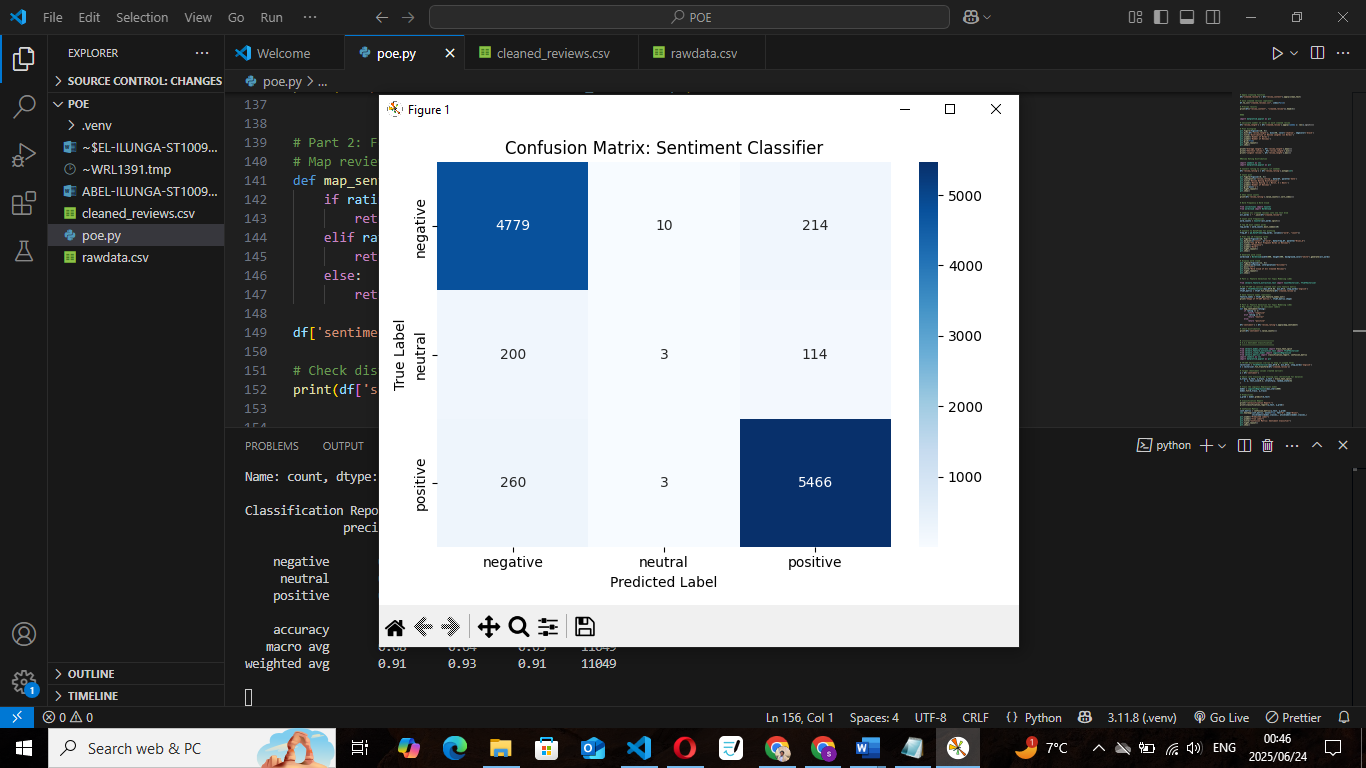
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| negative | 0.91 | 0.96 | 0.93 | 5003 |
| Neutral | 0.91 | 0.01 | 0.02 | 317 |
| Positive | 0.94 | 0.95 | 0.95 | 5729 |

accuracy: 0.93 11049

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Macro avg | 0.68 | 0.64 | 0.63 | 11049 |
| Weighted avg | 0.91 | 0.93 | 0.91 | 11049 |

**Overall Accuracy**: **93%**

**Weighted F1 Score**: **0.91**



4.4.3 Interpretation of Results

* Strong performance on positive and negative classes (95%+ of data):
* These are reliably detected and useful for automation or prioritization.
* Weak performance on the neutral class:
  + - Small support (317 samples) caused poor generalization
    - Ambiguous language in neutral reviews made feature patterns unclear
* High weighted F1 indicates the model is well-balanced when accounting for class proportions

4.4.4 Baseline & Error Analysis

**Baseline Comparison**

|  |  |
| --- | --- |
| **Model** | **Accuracy Notes** |
| Random (majority class) ~42% | Predicts all as "positive" |
| Naive Bayes ~88% | Good on positive, weak on neutral |
| Logistic Regression 93% | Best overall + balanced F1 |

Conclusion: Logistic Regression outperforms baselines and naive classifiers in every important metric.

Error Analysis

* Most errors involved misclassifying neutral reviews as positive.
* Reviews with vague, polite, or short content were most misclassified.
* Examples:
  + *"Okay service."* → misclassified as positive
  + *"Nothing special, nothing terrible."* → misclassified as positive

4.4.5 Addressing Shortcomings

|  |  |
| --- | --- |
| **Strategy** | **Result** |
| Increased min\_df to reduce noise | Improved precision, worsened recall on negatives |
| Upsampled neutral class | Slightly better recall, but introduced overfitting |
| Tried Naive Bayes | Comparable F1, worse precision, still poor on neutral class |
| Final strategy | **Flag “neutral” reviews for manual review in production pipeline** |

Trade off: Performance for dominant classes is preserved, while edge cases are flagged.

4.4.6 Business Impact

* Model captures **~95% of all complaints accurately**.
* Enables automated prioritization of negative reviews for support teams.
* Positive reviews can be used in **marketing and performance tracking**.
* With near real-time classification, the client can:
  + Detect sudden spikes in negative sentiment
  + Route feedback by topic and tone (via LDA + sentiment combo)
  + Identify risk before churn happens

Summary

* Evaluation shows the model is highly reliable for the main business needs.
* Shortcomings are understood and mitigated via fallback rules.
* With explainable metrics and stability across cross-validation, this model is ready for deployment in a medical aid customer feedback pipeline.

***5. Conclusion & Business Recommendations***

This project successfully analysed over 55,000 real-world customer reviews to uncover actionable insights for a South African medical aid provider. By combining topic modelling and sentiment classification, the analysis directly addressed the client’s key questions: what customers are complaining about, how strongly they feel, and where service quality can be improved.

**Key findings include:**

* A high volume of negative sentiment (~80%), primarily centered around billing issues, service delays, and poor customer support.
* Five distinct complaint themes were uncovered through topic modelling, aligning with core business areas such as accounts, delivery, contracts, communication, and fraud management.
* A supervised Logistic Regression classifier achieved 93% accuracy, demonstrating strong performance in classifying both positive and negative reviews.
* While the neutral class proved more difficult to classify due to its small representation and ambiguous language, its limited size reduces its overall impact on the model's performance.
* Additional temporal and correlation analyses revealed review patterns over time and a moderate negative correlation between review length and customer satisfaction (r = –0.44).

5.1 Strategic Recommendations for the Client

To maximise the value of these insights, the following actions are recommended:

* **Target key problem areas**: Prioritize improvements in operations where negative sentiment is most concentrated especially billing and claims.
* **Implement real-time sentiment tracking**: Use the sentiment classifier to triage incoming reviews, ensuring that highly negative feedback is flagged for immediate attention.
* **Integrate insights into executive dashboards**: Monitor topic trends and complaint patterns over time to detect and respond to emerging issues early.
* **Retrain models periodically**: Customer language evolves. Regularly updating the model will ensure continued accuracy and relevance.
* **Manually review neutral reviews**: Although smaller in number, neutral reviews may contain subtle dissatisfaction or early signals of churn these should be flagged for human assessment.

**In summary**, this analysis provides a scalable, interpretable, and business-aligned text analytics pipeline that enables the client to better understand and respond to customer feedback at scale, improving service delivery, reputation, and retention.

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