

Sentiment Analysis on Patient Drug Reviews

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Problem Description and project objectives

The Problem:

Patient drug reviews contain valuable emotional and clinical feedback, but the language is often vague and subjective.

Importance:

Analyzing sentiment in unstructured reviews can support pharmacovigilance and drug satisfaction tracking.

It can also help drug companies further understand the problems of medications.

Challenges:

- Emotion is not directly tied to keywords.
- Neutral reviews are ambiguous and harder to detect.
- Labeling is indirect (based on 1–10 rating).

Objectives:

- Evaluate and compare traditional vs. LLM-based classifiers.
- Test whether embedding + regression can predict numeric rating.
- Extracting side effects from negative classified comments.

Formal Task Specification

Task	Sentiment analysis	Rating regression	Side effects extraction
Input	Review embeddings	Review embeddings	Text of reviews with negative sentiment
Output	Labels: Positive, Negative, Neutral	Value between 1 to 10	Side Effects
Metrices	Accuracy, Precision	MAE, MSE, R ²	RAG Evaluation

Project Plan

Data Labeling:

- Convert numerical ratings into labels: Positive, Negative, Neutral.
- Perform class balancing with two different approaches.
- Basic cleaning and encoding reviews using S-BERT and OpenAI embeddings.

Task	Sentiment analysis	Regression	Side effects extraction
Model Training	Logistic Regression, Few-Shot Classification and XGBooster.	Linear Regression, KNN and testing regularization.	Prompt-based LLM and RAG
Evaluation	Accuracy and Precision.	MAE, MSE, R2	Precision, consistency and reliability

Previous Work

Sentiment Analysis on Drug Reviews is a common task..

<u>Drugs X Review - Sentiment III</u>

- Data: The Drug Review Dataset UCI Machine Learning Repository.
- Classifying to positive and negative reviews.
- Vectorization: TF-IDF.
- Machine Learning models: LightGBM.
- Evaluation Metrics: Accuracy, Precision, Recall and F1 score.
- Accuracy: 90%.

<u>Deep learning-based method for sentiment analysis for patients' drug reviews</u>

- Data: Drugs.com (Drug Review dataset) + WebMD dataset
- Classifying to positive, neutral and negative reviews.
- Using GloVe.6B.300d embeddings.
- Models: Bi-LSTM + CNN
 - Accuracy: 96% without GloVe, 88% with GloVe.



Previous Work

<u>BERT-based language model for accurate drug adverse event extraction from social</u> <u>media: implementation, evaluation, and contributions to pharmacovigilance practices</u>

- Data: ADE-Corpus-V2, SMM4H dataset.
- Extracting side effects from social media posts.
- Removal of characters in text and tokenization for embeddings.
- Using RRF + TF-IDF and ARF.
- Fine tuning a BERT based uncased model with the dataset ADE-Corpus-V2.
- F1 score: 0.9 for internal categories, 0.8 for external validation.

Methodology

Data Description

Source dataset: Patient Insights: 2.8Lakh Drug & Condition Reviews

Variables: 'Drug Name', 'Condition', 'User', 'Date', 'Rating', 'Content'.

New fields: 'Sentiment'.

Data Properties:

- Number of Samples: Approximately 280,000 self-reported reviews.
- Average Review Length: 91 ± 50 words.
- Rating Distribution: Skewed towards higher ratings.
- Unique Conditions: 965
- Unique Drugs: 1021

Labeling Processing:

- Each review is labeled with a numeric rating →
- Sentiment labels were created based on the rating: Positive (7–10), Neutral (4–6), Negative (1–3).

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Sentiment Analysis Task

Model	Label balancing	Test / Train split	Embeddings	Evaluation
	None			
Logistic Regression	'class_weight='balanced	80% train	SBERT – all-MiniLM-L6-v2	Accuracy and Precision for
	Over Sampling	20% test		Negative
Model	Label balancing	Test / Train splitting	Tokenizer	Evaluation
Model Few Shot Classification (nreimers/MiniLM-L	Label balancing Stratified		Tokenizer Auto Tokenizer	Evaluation Accuracy and Precision for

Sentiment Analysis Task

Model	Label balancing	Test / Train split	Embeddings	Evaluation
XGBoost Classifier				
Learning rate = 0.3	None			
		80% Train 20% Test	SBERT all-MiniLM-L6-v2'	Accuracy and Precision for
XGBoost Classifier	class_weight= 'balanced'	20% 1000	GII IVIII ILIVI LO VZ	Negative
Learning rate = 0.1	Over Sampling			

Sentiment Analysis Task

	Model	Label balancing	Test / Train split	Embeddings	Evaluation
J		class_weight="balanced"			
	Logistic Regression	Oversampling	80% train 20% test	Text-embedding -3-small OpenAl	Accuracy and Precision for Negative
		None			

Review Regression Task

Model	Label balancing	Train / Test split	Embeddings	Evaluation
Linear Regression Ridge alpha=1.0	None	80% Train	SBERT	MAE
Linear Regression	None	20% Test	all-MiniLM-L6-v2'	IVIAE
KNN (Non linear)				

Platform: Google Collab

Configuration: GPU T4, L4, A100

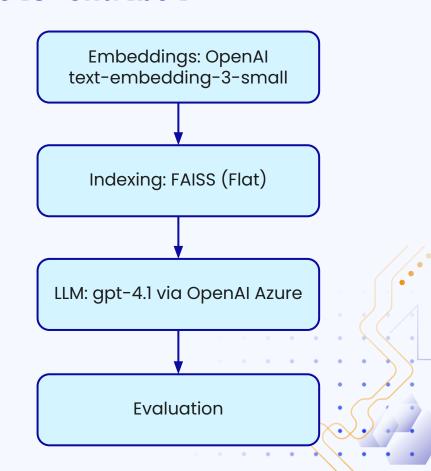
RAG - Side Effects Chatbot

Retrieval Parameters:

- k = 5: Number of documents retrieved per query.
- <u>Index Type:</u> faiss.IndexFlat 2.
- <u>Embedding Dimension:</u> 1536
- <u>Distance metric:</u> Euclidean distance

Evaluation Criteria:

- Consistency across repeated queries.
- Informativeness and fluency of the generated answer.
- Relevance to the question



Code Organization

<u>GitHub Repository:</u> https://github.com/Nikol-J/PharmaFeel



Folder/File	Description
graphs/EDA/	Exploratory Data Analysis graphs (e.g., rating distribution, review length).
graphs/results/	Final result graphs for model performance (accuracy, precision heatmaps).
notebooks/	Jupyter Notebooks: full workflow + EDA notebook.
presentations/	Project proposal, interim presentation slides and final presentation.
src/	Source code files (models, preprocessing, etc.).
README.md	Project description, goals, and link to data.



Results

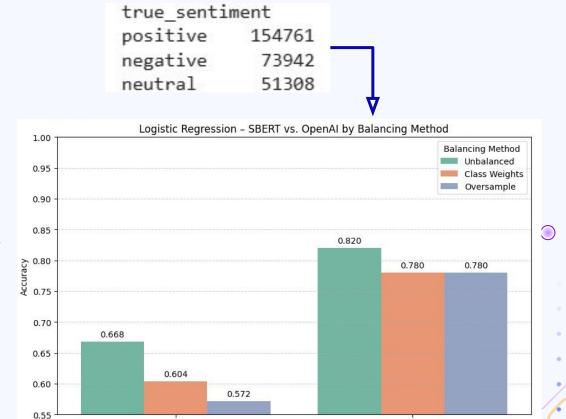
Intermediate Results - Sentiment Analysis

Objective: Evaluate logistic regression performance with different embedding methods and balancing strategies.

Best performance: OpenAI embeddings without balancing – Accuracy = 0.820

OpenAI embeddings outperformed SBERT across all balancing methods.

Both class weighting and oversampling led to lower accuracy, likely due to the highly imbalanced nature of the dataset.



Embedding Method

OpenAl

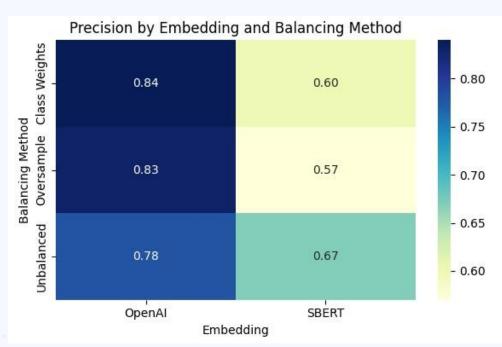
SBERT

Main Results - Sentiment Analysis

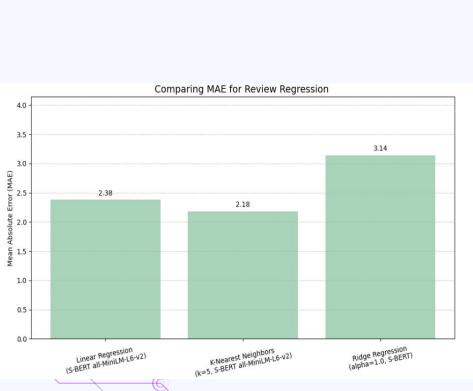
OpenAI embeddings are robust and benefit from class balancing.

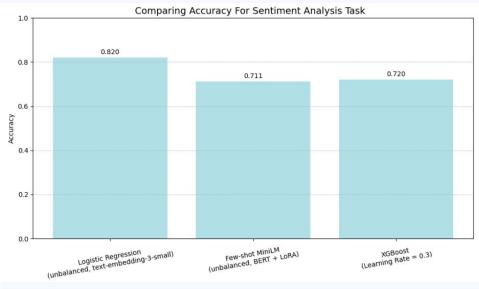
SBERT embeddings perform best when left unbalanced.

In our case, embedding quality plays a major role in how balancing techniques affect model performance.



Main Results - Sentiment Analysis





RAG Main Results

Question = "What are the side effects of Levonorgestrel?"

Answer:

Based on the provided reviews, the reported side effects of Levonorgestrel include:

```
- **Severe abdominal pain**
- **Nausea and vomiting**
- **Headache**
- **Dizziness and feeling faint**
- **Heavy bleeding**
- **Extreme tiredness/fatigue**
- **Hot flushes**
- **Bloating**
- **Loss of appetite**
- **Feeling generally unwell**
- **Weight gain**
- **Mood swings and dramatic mood changes**
- **Sore or tender breasts**
- **Vaginal soreness or itchiness**
- **Pain in the ovary**
- **Delayed or irregular periods**
- **Cramping**
- **Spotting (bleeding between periods)**
- **Sweating and high temperature**
- **Hair loss (increased hair shedding)**
- **Oily skin and acne**
```

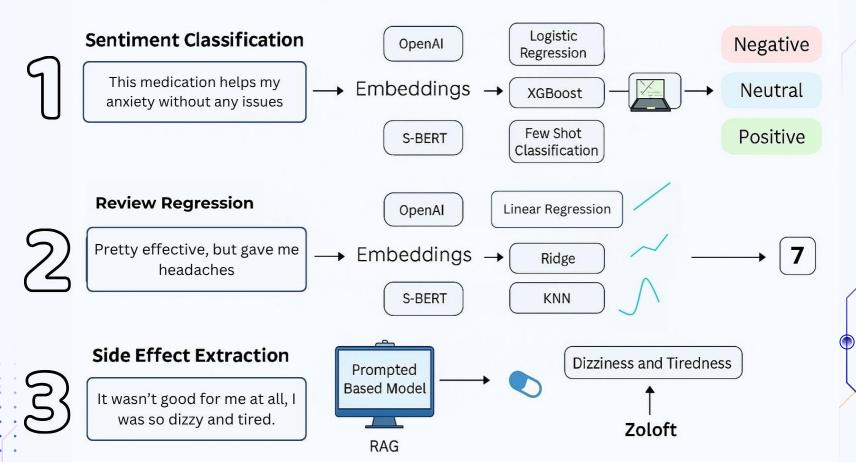
- **Decreased or uncertain libido**

Some users also reported that the insertion of levonorgestrel-containing IUDs (like Liletta or

**Note: ** Not everyone experiences these side effects, and some people may tolerate the medical

Precision: 0.83

PharmaFeel



Thank You!