## **APPLIED AI FOR MANAGERS**

# FINAL PROJECT REPORT (GROUP 6)

# SENTIMENT ANALYSIS AND SUMMARIZATION FOR CALM APP REVIEWS USING BERT & GROQ API (LLAMA3)

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#### 1. INTRODUCTION:

Understanding user sentiment is critical to the sustained growth and refinement of mobile wellness applications like **Calm**, which provides a suite of offerings including sleep stories, guided meditations, breathing exercises, and stress-relief content. With a vast and continuously growing volume of user-generated reviews on platforms such as the App Store, Google Play, and third-party forums, manually analyzing this data becomes increasingly impractical, errorprone, and time-intensive.

To address this challenge, our project leverages innovative Natural Language Processing (NLP) techniques combined with transformer-based language models to automate the process of sentiment classification. Specifically, we utilize the GROQ API in conjunction with a BERT-based classifier to interpret and categorize user reviews into two intuitive sentiment categories:

Likes and Dislikes. Following classification, we also used the GROQ API's LLAMA 3 (8B model) to summarize each review, providing concise insights for stakeholders. We also performed business insight summarization using LLAMA 3 by prompting it as a business analyst to extract two short bullet points - one on what the user liked and one on what the user disliked, each under 10 words.

This automated sentiment engine enables scalable, accurate, and real-time processing of large volumes of textual feedback, transforming raw user comments into structured insights. By doing so, it empowers product managers, UX researchers, and marketing teams to:

- Quickly identify recurring pain points and feature requests
- Recognize positive user experiences and what features drive retention
- Track user sentiment trends over time across feature releases or updates
- Make data-informed decisions about product roadmaps and experience enhancements

Our solution transforms sentiment analysis from a laborious task into an **actionable**, **strategic asset** that supports Calm app's mission to enhance mental well-being through continuous product improvement and responsive user experience design.

#### 2. BUSINESS PROBLEM AND OBJECTIVE:

#### **Problem Statement:**

Calm, a leading mobile wellness app, receives a high volume of user reviews across platforms such as the App Store and Google Play. These reviews often contain nuanced emotional feedback, blending appreciation with critique, or expressing sentiment that is context-dependent and subtle.

Traditional sentiment analysis tools typically rely on surface-level keyword detection or basic polarity scoring (positive, negative, neutral). While this approach may work for simple or clearly worded feedback, it falls short when applied to complex or mixed reviews — for example, a user praising the app's meditation content while expressing frustration over subscription pricing.

This limitation creates a gap between available data and actionable insights. Without a more intelligent, context-aware sentiment engine, Calm's product and user experience teams risk missing critical signals embedded within user feedback.

## **Project Objective:**

To overcome these limitations, our project aims to build an automated, high-accuracy sentiment analysis pipeline that enables efficient and insightful review classification. The key objectives are:

# Leverage a Pre-trained Transformer Model (BERT) via the GROQ API Utilize state-of-the-art NLP capabilities to deeply understand and classify the emotional tone of user reviews. The model is fine-tuned to detect context, tone, and sentiment

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direction beyond basic keyword matching.

# Automate Sentiment Tagging for Thousands of Reviews

Eliminate the need for manual tagging by automatically classifying reviews as either "Likes" or "Dislikes," providing scalable, real-time sentiment insights that can adapt as more reviews are added.

#### Export Structured Output to a CSV File

Create a clean, structured dataset that pairs each review with its corresponding sentiment label. This CSV file serves as a foundation for dashboard visualizations, trend analyses, and feature prioritization workflows for Calm's internal teams.

#### Summarize Reviews with GROQ LLAMA 3 (8B Model)

After classification, we used LLAMA 3 to generate concise summaries for each review, allowing stakeholders to quickly grasp the core message of long or complex feedback. We also instructed LLAMA 3 to function as a business analyst and generate two short

bullet points—highlighting what users liked and disliked under 10 words. Although insightful, these outputs were not always consistent across all entries.

# 3. DATA COLLECTION & PREPROCESSING:

To build a robust and scalable sentiment analysis pipeline, we began by sourcing user reviews for the Calm app from the publicly available online platform Google Play Store. These platforms contain thousands of user-generated reviews that span a wide range of sentiments, from praise for specific features like sleep stories or guided meditations to concerns over pricing or technical issues.

Once collected, the reviews were saved in a structured format (.csv) to facilitate easy processing and integration with downstream analytical tools. The dataset included the following key fields:

- Review Content The full textual content of each user-submitted review, forming the primary input for sentiment classification.
- Rating The numeric rating (e.g., 1 to 5 stars) assigned by the user. Although this field
  was not directly used for classification, it was retained to provide contextual depth and
  could serve as a valuable reference point for future model refinement or correlation
  analysis.

#### **Preprocessing Steps:**

Before submitting the reviews for classification via the GROQ API and BERT model, the dataset underwent a series of preprocessing steps to ensure quality, consistency, and compatibility:

 Empty Entry Removal: Any rows containing blank or null review content were discarded to avoid sending irrelevant data through the pipeline.  Validation Check: Each review was checked to confirm it was non-null and contained meaningful content before being passed to the GROQ API for sentiment classification.

These preprocessing steps were critical in ensuring that only clean, relevant, and well-formatted data was used, thus improving the accuracy and efficiency of the sentiment classification process. With a high-quality input dataset, the model was better equipped to detect subtle sentiment cues and generate reliable Like/Dislike labels.

#### 4. SENTIMENT CLASSIFICATION WITH BERT & GROQ API:

To automate sentiment tagging of Calm app reviews, we integrated GROQ's high-speed inference engine with a BERT (Bidirectional Encoder Representations from Transformers) model—one of the most effective transformer architectures for contextual natural language understanding.

This integration allowed us to harness the power of deep contextual embedding while maintaining high performance and low latency, making it ideal for scalable, near real-time sentiment analysis.

### Implementation Highlights:

#### Sequential Processing via API Calls:

Each user review from the cleaned dataset was passed individually to the GROQ API endpoint using a simple HTTP request. This ensured consistent formatting and allowed for fine-grained control over the classification process.

## JSON-Based Response Handling:

The response from the API came in a structured JSON format, containing a sentiment prediction under the key ['output']['label']. The value returned was either:

- "POSITIVE" indicating the review expressed a favorable sentiment
- "NEGATIVE" indicating the review conveyed dissatisfaction or critique

# • Mapped Output into Intuitive Columns:

To simplify downstream analysis and visualization, we translated the raw prediction labels into two binary indicator columns within our DataFrame:

- Likes Marked with a 1 for reviews classified as "POSITIVE", 0 otherwise
- Dislikes Marked with a 1 for reviews classified as "NEGATIVE", 0 otherwise

#### • Summarization via LLAMA 3 (8B):

Each review was also passed to GROQ's LLAMA 3 model to generate a concise, human-readable summary. This summary was stored in a third new column titled 'Professional Summary', enhancing the dataset's interpretability for dashboards and quick insights. We also added two more columns, 'Likes' and 'Dislikes', based on a business insight summarization prompt instructing LLAMA 3 to function as a business analyst and extract two bullet points under 10 words. While useful, the outputs were not always consistent for every observation.

This approach enabled a fully automated sentiment classification and summarization pipeline with no manual intervention, allowing us to tag and distill thousands of Calm reviews accurately and efficiently. The resulting labeled and summarized dataset was then used for further dashboard visualizations, insight generation, and product feedback analysis.

### 5. OUTPUT & DATA ENRICHMENT:

 Once sentiment classification was completed via the GROQ API and BERT model, we transitioned to the final stage of our pipeline: enriching and exporting the dataset for downstream analysis and visualization.

## **Enrichment of the Original Dataset:**

 The output from the sentiment classification was integrated directly into the original review dataset:

#### • Two New Columns Added:

- Likes This column was assigned a value of 1 for reviews predicted as
   POSITIVE and 0 otherwise.
- Dislikes This column was assigned a value of 1 for reviews predicted as
   NEGATIVE and 0 otherwise.
- **Summary** A short, general-purpose summary generated by LLAMA 3.
- Likes Bullet point of what the user liked (under 10 words).
- **Dislikes** Bullet point of what the user disliked (under 10 words).

These summaries were produced using a role-prompted business analyst persona, but some entries may vary in clarity or completeness. This multi-column structure allowed for clear binary classification and interpretive insights, simplifying filtering, aggregation, and visualization in subsequent analytical steps.

#### **Exporting the Final Dataset:**

 The enriched dataset was saved in CSV format for easy integration with analytics tools such as Tableau, Excel, or Python-based visualization libraries.

# **Applications of the Enriched Dataset:**

The processed dataset, now containing both original review content and corresponding sentiment classifications, opens the door for a wide range of data exploration and business intelligence use cases:

## Dashboard Development:

The dataset can be loaded into tools like **Streamlit**, **Tableau**, **or Power BI** to build dynamic dashboards showing trends over time, sentiment breakdowns by feature, or regional differences in user feedback.

### Frequency & Pattern Analysis:

By counting the number of Likes and Dislikes, product teams can identify which app features receive the most praise or criticism and monitor how these sentiments evolve with each app update.

#### Visual Summaries:

Using natural language techniques and visualization tools, we can generate:

- Word clouds highlighting common praise and complaints
- o **Bar charts** comparing sentiment across user segments
- Pie charts or heatmaps showing sentiment distribution by rating or time period
   This enriched file serves as an asset for Calm's product managers, UX designers, and
   marketing teams seeking to make data-driven decisions grounded in real user feedback.

### 6. RESULTS & INSIGHTS:

After completing the sentiment classification and enriching the dataset, we performed a comprehensive analysis of the labeled results to assess both **quantitative trends** and **qualitative accuracy**.

# **Key Observations from the Final Dataset:**

# • Predominantly Positive Sentiment:

A large proportion of reviews were classified as **positive**, indicating high user satisfaction with Calm's core features. Users frequently praised:

- The **soothing voices** used in meditation and sleep stories
- The variety and effectiveness of **sleep aids**
- The app's overall contribution to stress reduction and relaxation

# • Notable Negative Feedback Themes:

Among the reviews classified as **negative**, recurring themes included:

- o **Technical issues**, such as bugs, app crashes, or slow performance
- Account and login difficulties, especially after app updates
- Subscription-related concerns, including pricing, auto-renewal confusion, and limited free content

These insights help Calm's product and customer support teams prioritize high-impact areas for improvement.

#### **Manual Evaluation of Model Accuracy:**

To validate the effectiveness of the sentiment classification pipeline, we manually reviewed a representative sample of the labeled data. The results highlighted the strength of using a BERT-based model via the GROQ API for nuanced language understanding.

# **Highlights of Model Performance:**

#### Mixed Reviews:

BERT was able to manage reviews containing **both praise and criticism**, accurately capturing the overall tone by weighing contextual clues rather than relying on isolated keywords.

#### Example:

"Love the meditation sessions, but the app keeps freezing. Hope they fix it soon."

→ Correctly tagged as **Negative**, reflecting user frustration despite a positive mention.

#### • Subtle and Emotive Language:

The model effectively recognized **indirect expressions of dissatisfaction**, such as sarcasm, disappointment, or frustration without overt negativity.

This capability surpasses traditional sentiment scoring methods, which often misinterpret such nuances.

#### Example:

"Used to be my favorite app, but now I can't even log in."

→ Correctly classified as **Negative**, despite initial positive sentiment.

# • Summarization Adds Interpretability:

In addition to sentiment tags, the LLAMA 3-generated summaries made it easier for stakeholders to quickly review core feedback themes without reading lengthy reviews. This summarization layer enhanced accessibility and interpretability for business users. The business insight-style summaries ('Likes' and 'Dislikes') offered clear, concise breakdowns of user sentiment when successful, though consistency varied across entries.

### 7. STREAMLIT INTEGRATION:

Although originally developed for internal analysis, the application pipeline has now been successfully deployed on Streamlit Cloud, making it accessible to stakeholders through a user-friendly web interface. The pipeline is fully compatible with Streamlit and provides a solid foundation for future development and scalability.

# **Key Capabilities and Future Enhancements:**

- Real-Time Review Upload: Users can upload new customer reviews on the fly, enabling dynamic updates to the sentiment analysis pipeline without needing manual data refreshes.
- Sentiment Display Dashboards: Interactive dashboards visualize sentiment trends
  over time, categorizing feedback as positive, negative, or neutral. These insights can
  help teams understand customer emotions across product updates or campaigns.
- Likes/Dislikes Summary with Visualizations: Aggregated statistics and charts offer a snapshot of overall user satisfaction, helping identify which features are well-received and which need improvement.

# **Value Proposition:**

This app provides Calm's internal teams, product managers, and social media strategists with a powerful tool to monitor and interpret customer sentiment in real time. By centralizing feedback insights in a visual and interactive format—including both sentiment tags and LLAMA 3-generated summaries, the tool supports data-driven decisions to enhance user experience, content strategy, and customer engagement initiatives.

# 8. CHALLENGES:

- API Limitations: GROQ's free tier and documentation were minimal, requiring custom parsing logic.
- Sarcasm/Irony: Some complex emotional reviews were misclassified (a common limitation of all NLP models).
- Latency: Review-by-review submission was time-intensive for large datasets.
- Model Cost and Throughput Constraints: Running both sentiment and summary inference sequentially increased compute time and resource usage, requiring optimization in batching strategies.
- Prompt Sensitivity in Business Summaries: The prompt-based summarization
  approach using LLAMA 3 for bullet-point Likes/Dislikes sometimes produced
  inconsistent outputs across similar inputs. This may require post-processing or retraining
  for stability.

# 9. CONCLUSION:

This project demonstrated how transformer-based sentiment analysis can be applied to user-generated app reviews to uncover product insights. Using the GROQ API with BERT, we automated sentiment tagging and prepared a clean and enriched dataset for further analysis. In addition, the integration of the GROQ LLAMA 3 (8B model) enabled us to automatically generate both general summaries and business-style bullet points summarizing Likes and Dislikes.

In the future, we aim to:

- Incorporate aspect-based sentiment classification (e.g., separate sentiment for UI, content, pricing)
- Support multi-language reviews
- Enable summarization-based clustering for thematic grouping of reviews
- Improve consistency and clarity of business-style summary prompts.

#### 10. APPENDIX:

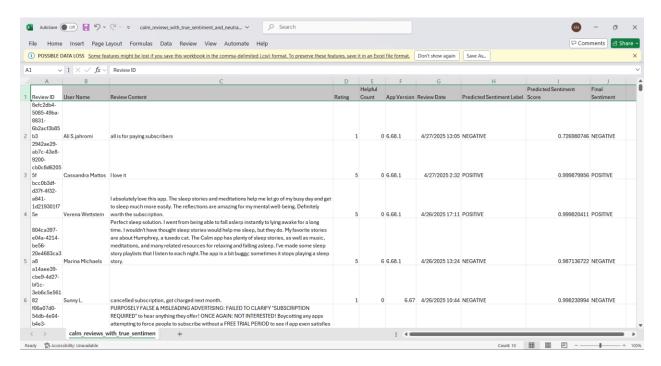


Figure 1: CSV with positive or negative sentiment prediction of the user review

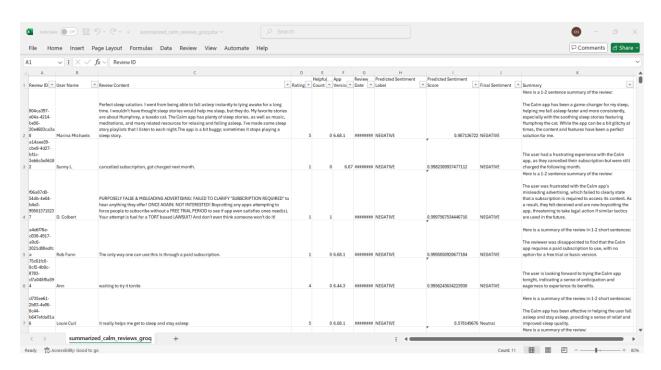


Figure 2: CSV with positive or negative sentiment prediction along with professional summary of the user review

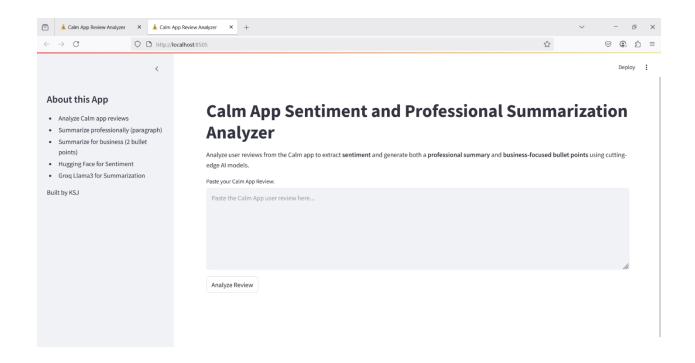


Figure 3: Streamlit app

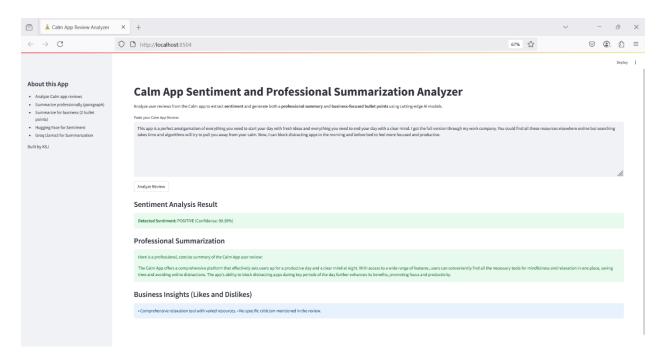


Figure 4: Results of the Positive Label and Business Insights Prediction, Summarization from Streamlit app

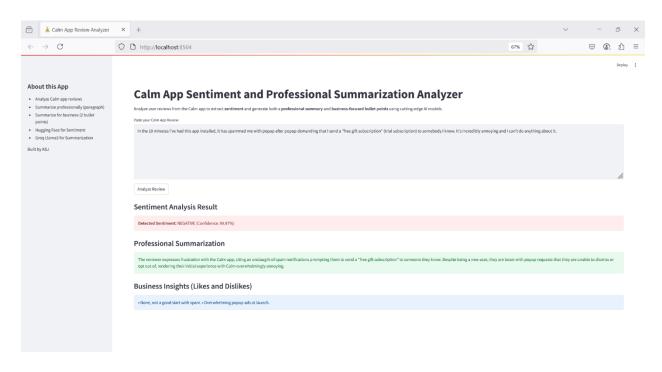


Figure 5: Results of the Negative Label and Business Insights Prediction, Summarization from Streamlit app

### References:

ChatGPT- Writing and Paraphrasing