**Ideas**

* User posts something on social media
* Crawler crawls for posts mentioning Wells Fargo
  + If positive sentiment:
    - Get user name/email address from database
    - Get user persona and based on transaction history, recommend products for the consumer
  + If negative sentiment:
    - Comment/DM with the ticket id
    - Customer fills in details
    - Summarize and send across portal
      * Recommended remediation plan/team to reach out to from knowledge base

**Challenges**

* Generate product recommendations from knowledge base
  + Generate some products which are of the format:
* Model training
* Model refinement

**Approach**

Sentiment analysis

Sentiment Analysis is a Natural Language Processing (NLP) task that involves determining the sentiment or emotional tone expressed in a piece of text. The sentiment is typically classified into categories such as:

* Positive: The text expresses positive emotions or opinions.
* Negative: The text expresses negative emotions or opinions.
* Neutral: The text expresses a neutral sentiment, neither positive nor negative.

Sentiment analysis was done using LLM Models via OpenRouter, a platform providing APIs for genAI use cases. Below models were evaluated:

1. mistralai/mistral-small-3.1-24b-instruct:free:

Mistral Small 3.1 24B Instruct is an upgraded variant of Mistral Small 3 (2501), featuring 24 billion parameters with advanced multimodal capabilities. It provides state-of-the-art performance in text-based reasoning and vision tasks, including image analysis, programming, mathematical reasoning, and multilingual support across dozens of languages. Equipped with an extensive 128k token context window and optimized for efficient local inference, it supports use cases such as conversational agents, function calling, long-document comprehension, and privacy-sensitive deployments.

1. meta-llama/llama-3.3-70b-instruct:free: The Meta Llama 3.3 multilingual large language model (LLM) is a pretrained and instruction tuned generative model in 70B (text in/text out). The Llama 3.3 instruction tuned text only model is optimized for multilingual dialogue use cases and outperforms many of the available open source and closed chat models on common industry benchmarks.Supported languages: English, German, French, Italian, Portuguese, Hindi, Spanish, and Thai.

Out of the two, llama gave a better output since it is primarily trained for language and sentiment analysis related tasks

RAG (Retrieval Augment Generation)

RAG stands for Retrieval-Augmented Generation, which is a technique used in Natural Language Processing (NLP) to combine retrieval-based and generation-based approaches to answer questions or generate responses more effectively.

Key Concepts of RAG:

1. Retrieval: The process of searching for and retrieving relevant documents (or passages) from a large corpus of text that might contain useful information for answering a query or generating a response.
2. Augmentation: The process of augmenting the original query with the retrieved documents or passages. These documents provide context or relevant information that can help generate a better answer.
3. Generation: After retrieving the relevant documents, a generative model (typically a language model like GPT or BERT-based models) generates the final response based on the input query and the retrieved documents.

Llama3 (langchain) was used for performing RAG on a sample dataset containing financial products for recommendations. Due to limited system resources, was written on Google Colab, the ipynb notebook is attached in the GitHub repo

**Training methodology**

Pre-trained methods were used for running the models

Hyperparameter tuning

**Data**

Three datasets were prepared (attached to github repo)

1. Customer profile data

CustID

Age

Gender

Location

Interest

Preference

Income

Education

Occupation

Priority

Recommendation

1. Social media sentiment data

CustomerID

PostId

Platform

Content

Sentiment-Score

Intent

1. Available financial products for recommendation  
     
   Fields:

Product Name

Description

Type

Target Audience Age

Target Audience Income (LPA)

Annual Spends (LPA)

CIBIL Score

Rewards

**Business recommendations**

In the BFSI (Banking, Financial Services, and Insurance) sector, leveraging **sentiment analysis** powered by **Generative AI (GenAI)** provides significant opportunities to enhance customer experience, drive product recommendations, and optimize overall business operations. By analyzing customer sentiment from diverse sources such as social media, reviews, and surveys, financial institutions can better understand their customers’ needs and emotions, allowing for personalized and contextually relevant product suggestions.

For **product recommendation** use cases, sentiment analysis can serve as a valuable tool to:

* **Identify customer satisfaction levels**, allowing for targeted recommendations, whether upselling premium services or addressing dissatisfaction with alternative offerings.
* **Improve customer retention** by proactively addressing negative sentiment and offering tailored solutions that address pain points.
* **Personalize the customer journey**, by recommending the right financial products based on the user’s sentiment, creating a more engaging and trust-building experience.

By implementing a sentiment-driven recommendation system, BFSI companies can achieve:

* **Higher engagement** by presenting customers with products that align with their emotional context.
* **Improved customer satisfaction and loyalty** through timely and relevant solutions.
* **Increased revenue** by offering products and services that resonate with the customer’s emotional needs.

Ultimately, the integration of sentiment analysis and GenAI into the BFSI sector represents a powerful step toward delivering more personalized, efficient, and customer-centric services. It creates a mutually beneficial relationship between businesses and customers, empowering financial institutions to stay competitive and relevant in an increasingly digital and dynamic market.