Topic: Identifying Helpful and Representative Reviews Using Machine Learning

Objective

This project aims to assess the helpfulness of product reviews on Amazon by combining textual analysis, metadata engineering, and machine learning. Specifically, we focus on:

- Predicting whether a review is helpful (HelpfulBinary) using XGBClassifier.
- Identifying the most representative review per product using BERT-based semantic similarity.
- Evaluating whether these representative reviews tend to be helpful

Dataset

The dataset consists of Amazon product reviews, with fields including review text, timestamp, score, and helpfulness information (numerator and denominator). Reviews without any helpfulness votes were flagged and separated for later prediction. https://www.kaggle.com/datasets/snap/amazon-fine-food-reviews

Key Steps

1. Data Cleaning and Feature Engineering

- Created a helpfulness_ratio (numerator / denominator).
- Flagged reviews with zero denominator as no_helpfulness for later use.
- Generated a binary label HelpfulBinary (1 if ratio > 0.5, else 0).
- Created recency weights based on review timestamps.
- Cleaned review text using tokenization, stopword removal, and lemmatization.

2. Representativeness Scoring

- Used a pre-trained BERT model to compute cosine similarity of each review against others within the same product.
- Assigned a cosine_avg_sim score to quantify how representative a review is.
- Selected the most representative review per product based on this score.

3. Dimensionally reduction -- SVD

- Compress the TF-IDF features into 100 dimensions using TruncatedSVD

- Apply standardization (StandardScaler) to ensure that all features are on the same scale.

4. Model Training

- Trained an XGBoost classifier to predict HelpfulBinary using TF-IDF text features, cosine_avg_sim, and recency_weight.
- Built scale_pos_weight to solve imbalanced problem
- For data with SVD, achieved approximately 85% accuracy on the test set.
- For data without SVD, achieved approximately 79% accuracy on the test set.

5. Post-Training Analysis

- Applied the trained model_svd to reviews that lacked helpfulness labels (zero denominator).
- Analyzed whether the most representative reviews (for each product) were predicted to be helpful.
- Compared the helpfulness of Most representative reviews, all reviews, and random reviews (1 per product)
- Representative reviews are truly more useful

Key Takeaways

- Semantic similarity is a strong signal of review quality.
- Machine learning can effectively predict helpfulness, even in the absence of user votes.
- Most representative reviews are not only central in meaning—but often truly helpful.

Conclusion

This project demonstrates a hybrid approach: combining semantic similarity (BERT-based) with traditional supervised learning to enhance review helpfulness prediction. It also highlights the practical value of identifying "representative reviews" to improve user experience in platforms like e-commerce or review aggregators.

import and install pakages

In [5]:
```
#!pip install datasets -U transformers -U sentence_transformers pandas sc
```

In [4]:
```
import numpy as np
from sentence_transformers import SentenceTransformer
from sklearn.metrics.pairwise import cosine_similarity
import pandas as pd
```

```
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.sparse import hstack

# for S3
import hashlib
import boto3
from botocore.exceptions import NoCredentialsError, PartialCredentialsErr

## for cosine_similarity
from sentence_transformers import SentenceTransformer
from sklearn.metrics.pairwise import cosine_similarity
import numpy as np
import pandas as pd
from tqdm import tqdm
import csv
import os
```

Upload to S3

In [3]:
```
# Initialize S3 Client
s3 = boto3.client("s3")
bucket_name = "is597-group10"  # bucket name
region = "us-east-1"  # AWS region
```

In [4]:
```
def print_result_1(message):
    print("=" * 80)
    print(message)
    print("=" * 80)
```

In [5]:
```
file_path = "Reviews.csv"  # Replace with a local file path
object_key = "data/Reviews.csv"

# Upload an Object
try:
    s3.upload_file(file_path, bucket_name, object_key)
    print_result_1(f"File '{file_path}' uploaded as '{object_key}'.")
except FileNotFoundError:
    print("The file was not found.")
except NoCredentialsError:
    print("Credentials not available.")
```

```
==========================================================================
======
File 'Reviews.csv' uploaded as 'data/Reviews.csv'.
==========================================================================
======
```

Fetches data directly from S3 to use cleaned data

In [6]:
```
download_path = "Reviews.csv"
object_key = "data/Reviews.csv"
try:
    s3.download_file(bucket_name, object_key, download_path)
    print(f"File '{object_key}' downloaded to '{download_path}'.")
```

```
except Exception as e:
    print(f"Error downloading file: {e}")
```

```
File 'data/Reviews.csv' downloaded to 'Reviews.csv'.
```

Data Loading and Cleaning

We begin by loading the dataset, handling duplicates, and converting the review timestamps into a numerical format for recency analysis.

In [7]:
```
df = pd.read_csv('Reviews.csv')
```

In [8]:
```
#Missing values
df.isnull().sum()
```

Out[8]:
```
Id                         0
ProductId                  0
UserId                     0
ProfileName               26
HelpfulnessNumerator       0
HelpfulnessDenominator     0
Score                      0
Time                       0
Summary                   27
Text                       0
dtype: int64
```

In [9]:
```
# Filling missing values
df['ProfileName'].fillna('Unavailable')
df.drop(columns='Summary',inplace=True)
```

In [10]:
```
# remove duplications
df.drop_duplicates(inplace=True)
df = df.dropna(subset=['Text'])
```

Recency Weight Calculation

To prioritize newer reviews, we compute a **recency weight** based on the date of each review:

- First, calculate the number of days since each review:

$$\text{days\_since} = \text{latest\_date} - \text{review\_date}$$

- Then, compute the recency weight:

$$\text{recency\_weight} = \frac{1}{\text{days\_since} + 1}$$

Interpretation:

- **Newer reviews** (smaller days_since) will have a **higher weight**.

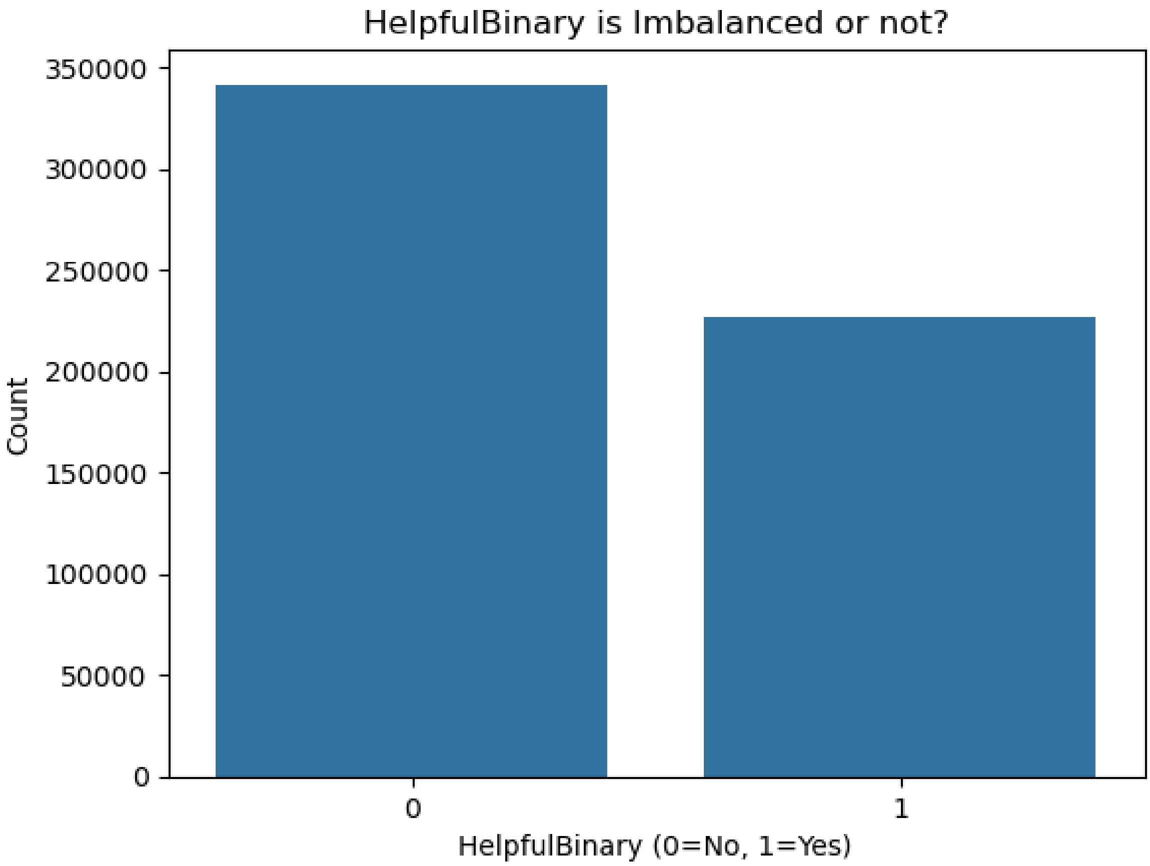
- **Older reviews** (larger days_since) will have a **lower weight**.
- Adding (+1) in the denominator prevents division by zero and stabilizes the calculation.

This method ensures that **recent reviews contribute more** when training and prediction models.

In [11]:
```
# time preprocessing
df['Time'] = pd.to_datetime(df['Time'], unit='s')
latest_date = df['Time'].max()
df['days_since'] = (latest_date - df['Time']).dt.days
df['recency_weight'] = 1 / (df['days_since'] + 1)
```

In [12]:
```
# make ReviewIdx for furthering usage
df['ReviewIdx'] = df.groupby("ProductId").cumcount()

# We create a helpfulness ratio and define a binary label `HelpfulBinary`
df['helpfulness_ratio'] = df['HelpfulnessNumerator'] / df['HelpfulnessDen
df['HelpfulBinary'] = (df['helpfulness_ratio'] > 0.5).astype(int)
```

In [13]:
```
sns.countplot(data=df, x='HelpfulBinary')
plt.title("HelpfulBinary is Imbalanced or not?")
plt.xlabel("HelpfulBinary (0=No, 1=Yes)")
plt.ylabel("Count")
plt.show()
```



It's slightly imbalanced, we'll solve imbalanced problem in model training step.

In [14]:
```
df[df['HelpfulnessDenominator'] > 0]["HelpfulBinary"].value_counts()
```

Out[14]:
```
HelpfulBinary
1    226666
0     71736
Name: count, dtype: int64
```

In [15]:
```
len(df)
```

Out[15]:
```
568454
```

In [16]:
```
len(df["ProductId"].unique())
```

Out[16]:
```
74258
```

In [17]:
```
# Among 568454 products review, has 74258 products, but only 24739 produc
(df["ProductId"].value_counts() > 3).sum()
```

Out[17]:
```
24739
```

It suggests that among 568454 products review, has 74258 products, but only 24739 products have more than three reviews

In [18]:
```
df = df[['ProductId', 'Text', 'helpfulness_ratio', 'recency_weight', 'Tim
#df_unlabeled = df_unlabeled[['ProductId', 'Text', 'recency_weight', 'Tim
df.head()
```

Out[18]:

	ProductId	Text	helpfulness_ratio	recency_weight	Time	HelpfulBinar
0	B001E4KFG0	I have bought several of the Vitality canned d...	1.0	0.001821	2011-04-27	
1	B00813GRG4	Product arrived labeled as Jumbo Salted Peanut...	NaN	0.020000	2012-09-07	
2	B000LQOCH0	This is a confection that has been around a fe...	1.0	0.000653	2008-08-18	
3	B000UA0QIQ	If you are looking for the secret ingredient i...	1.0	0.001992	2011-06-13	
4	B006K2ZZ7K	Great taffy at a great price. There was a wid...	NaN	0.166667	2012-10-21	

In [19]:
```
len(df)
```

Out[19]: 568454

Find most representative review by calculate semantic Representativeness (cosine_avg_sim)

Using `sentence-transformers`, we compute the average cosine similarity of each review to other reviews within the same product. This represents how "representative" each review is in its group.

In [20]:
```
# Optimized Version: Incremental writing with automatic checkpoint recove
#(to prevent kernel crashes and allow seamless restarts)
# I do it while there's no no_helpfulness column. That is, I run the algo

#  Filter and keep only products with more than 3 reviews
pid_counts = df['ProductId'].value_counts()
```

```
df_filtered = df[df['ProductId'].isin(pid_counts[pid_counts > 3].index)].

# Initialize the BERT model
model = SentenceTransformer("all-MiniLM-L6-v2")

# Attempt to load existing results to chek with ProducIds have already be
done_pids = set()
if os.path.exists("cosine_avg_sim_results.csv"):
    try:
        done_df = pd.read_csv("cosine_avg_sim_results.csv")
        done_pids = set(done_df['ProductId'].unique())
    except:
        pass

# Write to file in append mode(without overwriting existing data)
with open("cosine_avg_sim_results.csv", "a", newline="") as f:
    writer = csv.writer(f)
    if os.stat("cosine_avg_sim_results.csv").st_size == 0:
        writer.writerow(["ProductId", "ReviewIdx", "cosine_avg_sim"])

    for pid, group in tqdm(df_filtered.groupby("ProductId")):
        if pid in done_pids:
            continue  # Skip products that have already been processed

        texts = group["Text"].fillna("").tolist()
        if len(texts) < 3:
            for i in range(len(texts)):
                writer.writerow([pid, i, 0])
            continue

        embeddings = model.encode(texts, batch_size=32, show_progress_bar
        sim_matrix = cosine_similarity(embeddings)
        avg_sim = sim_matrix.mean(axis=1)

        for i, sim in enumerate(avg_sim):
            writer.writerow([pid, i, sim])
```

```
100%|██████████| 24739/24739 [00:00<00:00, 33982.52it/s]
```

In [21]:

```
df_filtered = pd.read_csv("cosine_avg_sim_results.csv")

# merge ProductId + ReviewIdx
merged_df = df.merge(df_filtered, on=['ProductId', 'ReviewIdx'], how='lef
merged_df = merged_df.dropna(subset=['cosine_avg_sim']).reset_index(drop=
merged_df
```

Out[21]:

	ProductId	Text	helpfulness_ratio	recency_weight	Time	Helpf
0	B006K2ZZ7K	Great taffy at a great price. There was a wid...	NaN	0.166667	2012-10-21	
1	B006K2ZZ7K	I got a wild hair for taffy and ordered this f...	NaN	0.009346	2012-07-12	
2	B006K2ZZ7K	This saltwater taffy had great flavors and was...	NaN	0.007752	2012-06-20	
3	B006K2ZZ7K	This taffy is so good. It is very soft and ch...	NaN	0.005650	2012-05-03	
4	B001GVISJM	good flavor! these came securely packed... the...	1.0	0.001385	2010-11-05	
...	...	...	...	...	...	
492913	B001EO7N10	You can make this mix yourself, but the Star A...	1.0	0.001037	2010-03-08	
492914	B001EO7N10	I had ordered some of these a few months back ...	NaN	0.003861	2012-02-11	
492915	B001EO7N10	Hoping there is no MSG in this, this tastes ex...	NaN	0.003003	2011-11-29	
492916	B001EO7N10	My only complaint is that there's so much of i...	NaN	0.002000	2011-06-15	
492917	B001EO7N10	Great for sesame chicken..this is a good if no...	NaN	0.001672	2011-03-09	

492918 rows × 8 columns

In [22]:
```
# Identify the highest cosine_avg_sim review for each product
high_reviews = merged_df.loc[df_filtered.groupby('ProductId')['cosine_avg

# suggesting whole content
pd.set_option('display.max_colwidth', None)
high_reviews[['ProductId', 'Text', 'cosine_avg_sim']].head(10)
```

Out[22]:

	ProductId	Text	cosin
0	B006K2ZZ7K	I got a wild hair for taffy and ordered this five pound bag. The taffy was all very enjoyable with many flavors: watermelon, root beer, melon, peppermint, grape, etc. My only complaint is there was a bit too much red/black licorice-flavored pieces (just not my particular favorites). Between me, my kids, and my husband, this lasted only two weeks! I would recommend this brand of taffy -- it was a delightful treat.	
1	B001UJEN6C	I have tried other energy shots and this one is the only one that really makes me feel good and energized without any other sides effects at all, its also the best taste, others taste like medicine, this one has a tea fresh taste. I love it.	
2	B000G6RYNE	These potato chips are excellent.There are no trans fats. They taste absolutely delicious.Whenever I am in the mood for potatoe chips, Kettles is the brand I buy. A great product that anyone should enjoy and I highly recommend them! Enjoy!	
3	B000G6RYNE	These chips are nasty. I thought someone had spilled a drink in the bag, no the chips were just soaked with grease. Nasty!!	
4	B000G6RYNE	I bought these when on sale through Amazon. Nice crispy thick chips. Definitely a great buy if you can catch them on sale.	
5	B0030C9A60	I bought these chocolate liquor cups for a party! It was a big hit. They are high quality and a good buy.	
6	B001GCVLXG	If you like Shortbread you will really like these. Walkers always makes the best Shortbread. Walkers Shortbread Highlander Shortbread Portion Pack, 1.4 Ounce Units (Pack of 24)	
7	B0025ULYKI	Not as thick as kettle chips we have had in the past, definitely more like a potato chip and the college crowd loves it. Interestingly enough they feel more 'gourmet' when eating these. The flavor is not heavily garlic while you can easily taste the cheese.	
8	B0025ULYKI	I LOVE Old Dutch Ketchup chips but they are no where to be found in the US and pricey on eBay. I tried Herr's but they were dull - very ketchupy but not the tangy-vinigary ketchup bite that Old Dutch has (makes your mouth hurt in a good way if you eat too many!). Uncle Rays are decent - more of a kick - many "loaded" chips which I like, still, not the addictive bite I love. So - if you love Herr's these may be too much for you. If you love Old Dutch give these a shot. I am still on my quest for something equal to Old Dutch!!	
9	B004IF3TAQ	I don't know whether it was a fault in the packaging or if they were just past their prime, but they were rock hard and the flavor was not strong enough.	

In [23]:
```
# Identify the lowest cosine_avg_sim review for each product
least_rep_reviews = merged_df.loc[
    merged_df.groupby('ProductId')['cosine_avg_sim'].idxmin()
].reset_index(drop=True)

# suggesting whole content
pd.set_option('display.max_colwidth', None)
least_rep_reviews[['ProductId', 'Text', 'cosine_avg_sim']].head(10)
```

Out[23]:

	ProductId	Text	cosine_avg_sim
0	0006641040	It was a great price, but I can't read it to my class. It is like a little travel brochure.	0.303209
1	7310172001	Love this faucet. My husband had installed the same one in our old house so when our current faucet was leaking I told him not to fix it and we would buy the same one. It was easy enough for him to install but he did need my assistance a few times to help hold some things in place. Looks great and works great.	0.030737
2	7310172101	Love this faucet. My husband had installed the same one in our old house so when our current faucet was leaking I told him not to fix it and we would buy the same one. It was easy enough for him to install but he did need my assistance a few times to help hold some things in place. Looks great and works great.	0.030737
3	B00002N8SM	This sly trap is attractive to look at, works well, and has no odor. I recommend it!	0.446163
4	B00004CI84	i got this cause i love the more. the quality is okay but i guess it would look nicer on a 120hz tv	0.126864
5	B00004CXX9	When Amazon sells something directly, you get it on time if not earlier. I originally placed the order with one of their advertised Marketplace vendors who advertised 3-4 days. the order acknowledgement indicated devlivery within 3 weeks (via USPS). I immediately cancelled that order and ordered from Amazon. Got it in 3 days.	0.024058
6	B00004RAMS	Cut my hand the first time I tried to set set it. Hard as hell to set. Cant use it when the ground is wet. I didn't like this sucker at all	0.205461
7	B00004RAMV	The screw on top does not screw onto the container provided. There is no way the item can be hung from the top loop because the jar would fall. Mismatched top and jar. Disappointed with quality	0.237008
8	B00004RAMX	I am outside with product open and there is absolutely nothing here to show me how to use this. Now I must go inside, search online, print or make notes to have something with me as I use this product. Why not one printed sheet to use at worksite? No value here--I'm losing half an hour.	0.063595
9	B00004RAMY	It arrived on time with out any problems. The only problem is my sister (who purchased it) and her neighbor could not get it to work.	0.066076

Feature Engineering for Modeling

We prepare TF-IDF vectors from cleaned text, and combine them with numerical features such as:

- cosine_avg_sim

- recency_weight
- (optionally) helpfulness_ratio

In [24]:
```
#Cleaning the text
from nltk.corpus import stopwords
import nltk
from nltk.stem import WordNetLemmatizer
import re
nltk.download('wordnet')
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()

# Simple contraction expansion
def expand_contractions(text):
    contraction_map = {
        "can't": "cannot", "won't": "will not", "n't": " not", "'re": " a
        "'s": " is", "'d": " would", "'ll": " will", "'t": " not", "'ve":
    }
    for c, e in contraction_map.items():
        text = re.sub(c, e, text)
    return text

def clean_text(text):
    text = expand_contractions(text)
    text = re.sub(r'[^a-zA-Z\s]', '', str(text))
    tokens = text.lower().split()
    tokens = [lemmatizer.lemmatize(word) for word in tokens if word not i
    return " ".join(tokens)

merged_df['CleanedText'] = merged_df['Text'].apply(clean_text)
```

```
[nltk_data] Downloading package wordnet to /home/ec2-user/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     /home/ec2-user/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [25]:
```
df_unlabeled = merged_df[merged_df['helpfulness_ratio'].isna()]
df_labeled = merged_df[merged_df['helpfulness_ratio'].notna()]
df_unlabeled = df_unlabeled[['ProductId', 'Text', 'recency_weight', 'Time
```

In [26]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
import xgboost as xgb
# Make TF-IDF feature
vectorizer = TfidfVectorizer(max_features=1000)
X_text = vectorizer.fit_transform(df_labeled['CleanedText'])

# Other numerical value
X_extra = df_labeled[['cosine_avg_sim', 'recency_weight']].values

# merge all numerical feature we'll use for training XGBoost model
from scipy.sparse import hstack, csr_matrix
X = hstack([X_text, csr_matrix(X_extra)])
y = df_labeled['HelpfulBinary'].values
```

```
/home/ec2-user/anaconda3/envs/python3/lib/python3.10/site-packages/xgboos
t/core.py:377: FutureWarning: Your system has an old version of glibc (<
2.28). We will stop supporting Linux distros with glibc older than 2.28 af
ter **May 31, 2025**. Please upgrade to a recent Linux distro (with glibc
>= 2.28) to use future versions of XGBoost.
Note: You have installed the 'manylinux2014' variant of XGBoost. Certain f
eatures such as GPU algorithms or federated learning are not available. To
use these features, please upgrade to a recent Linux distro with glibc 2.2
8+, and install the 'manylinux_2_28' variant.
  warnings.warn(
```

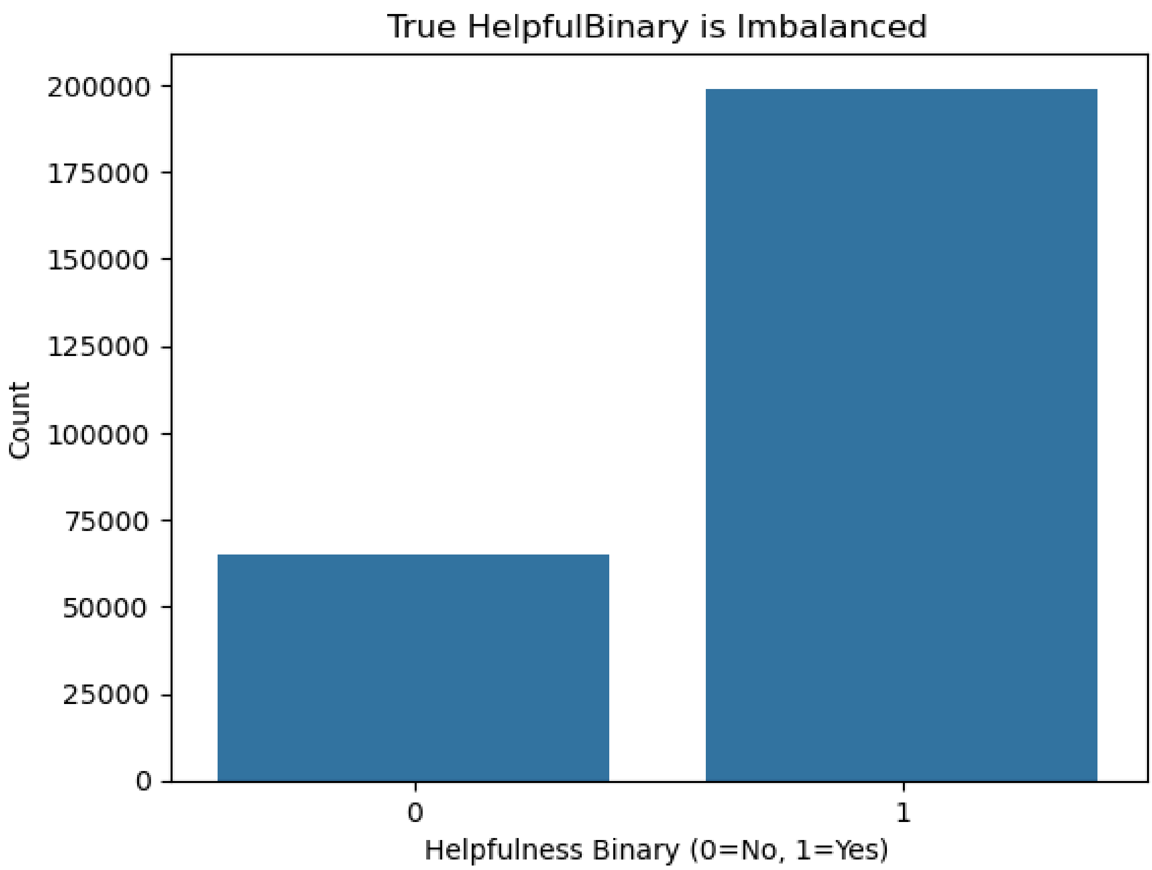
In [27]:
```
df_labeled['HelpfulBinary'].value_counts()
```

Out[27]:
```
HelpfulBinary
1    199061
0     64932
Name: count, dtype: int64
```

In [28]:
```
print("HelpfulBinary = 1:", len(df_labeled[df_labeled['HelpfulBinary'] ==
print("HelpfulBinary = 0:", len(df_labeled[df_labeled['HelpfulBinary'] ==
```

```
HelpfulBinary = 1: 0.7540389328504923
HelpfulBinary = 0: 0.24596106714950774
```

In [29]:
```
sns.countplot(data=df_labeled, x='HelpfulBinary')
plt.title("True HelpfulBinary is Imbalanced")
plt.xlabel("Helpfulness Binary (0=No, 1=Yes)")
plt.ylabel("Count")
plt.show()
```



In [30]:
```
# combine TF-IDF
X_text_sparse = X_text  # TF-IDF is sparse
X_extra_dense = X_extra  # cosine / recency / ratio are dense
```

```
# For merging successfully, we transform dense array into sparse format.
X = hstack([X_text_sparse, csr_matrix(X_extra_dense)])
```

XGBoost Training for Helpfulness Classification(with dimensionally reduction -- SVD)

We use TruncatedSVD to compress the sparse TF-IDF matrix into a smaller dense feature space, preserving important information while reducing memory and computational costs.

we apply TruncatedSVD to reduce the dimensionality of sparse TF-IDF features. TruncatedSVD (Truncated Singular Value Decomposition) compresses a high-dimensional sparse matrix into a lower-dimensional dense matrix while preserving the main variance in the data. This helps reduce computational cost and improves the stability and efficiency of model training.

We first compress the TF-IDF features into 100 dimensions using TruncatedSVD, and then apply standardization (StandardScaler) to ensure that all features are on the same scale.

Using TruncatedSVD is particularly suitable for text analysis tasks, because TF-IDF matrices are typically sparse, and TruncatedSVD can directly operate on sparse inputs without converting them into dense format, thus avoiding memory issues.

In [31]:
```
from sklearn.pipeline import make_pipeline
from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import StandardScaler
from scipy.sparse import hstack, csr_matrix

# transform X_extra into sparse
X_extra_sparse = csr_matrix(X_extra)

# merge two sparse matrix
X_sparse_all = hstack([X_text, X_extra_sparse])  # all of them are sparse

# TruncatedSVD + scaling in pipeline
pipeline = make_pipeline(
    TruncatedSVD(n_components=100, random_state=42),
    StandardScaler()  # optional, if needed by XGBoost
)

X_reduced = pipeline.fit_transform(X_sparse_all)
```

In [32]:
```
# use X_reduced which is dimension reducted feature to train
X_train, X_test, y_train, y_test = train_test_split(X_reduced, y, test_si

# make processed file
df_X_train = pd.DataFrame(X_train)
df_X_test = pd.DataFrame(X_test)
df_y_train = pd.DataFrame(y_train)
df_y_test = pd.DataFrame(y_test)

# Save train and test set to local CSV files
```

```
df_X_train.to_csv('X_train_processed.csv', index=False)
df_X_test.to_csv('X_test_processed.csv', index=False)
df_y_train.to_csv('y_train_processed.csv', index=False)
df_y_test.to_csv('y_test_processed.csv', index=False)

print("Data reformatted for XGBoost and saved to CSV files locally.")
```

```
Data reformatted for XGBoost and saved to CSV files locally.
```

In [11]:

```
# Upload train/test data to S3
import sagemaker
import boto3

# Initialize SageMaker session
sagemaker_session = sagemaker.Session()
role = sagemaker.get_execution_role()
bucket = "is597-group10"
prefix = "model_training"

# Upload CSVs
X_train_s3_path = sagemaker_session.upload_data(
    path='X_train_processed.csv',
    bucket=bucket,
    key_prefix=f'{prefix}/train'
)

y_train_s3_path = sagemaker_session.upload_data(
    path='y_train_processed.csv',
    bucket=bucket,
    key_prefix=f'{prefix}/train'
)

X_test_s3_path = sagemaker_session.upload_data(
    path='X_test_processed.csv',
    bucket=bucket,
    key_prefix=f'{prefix}/test'
)

y_test_s3_path = sagemaker_session.upload_data(
    path='y_test_processed.csv',
    bucket=bucket,
    key_prefix=f'{prefix}/test'
)

print(f"Training data uploaded to: {X_train_s3_path}")
print(f"Testing data uploaded to: {y_train_s3_path}")
print(f"Testing data uploaded to: {X_test_s3_path}")
print(f"Testing data uploaded to: {y_test_s3_path}")
```

```
/home/ec2-user/anaconda3/envs/python3/lib/python3.10/site-packages/pydanti
c/_internal/_fields.py:172: UserWarning: Field name "json" in "MonitoringD
atasetFormat" shadows an attribute in parent "Base"
  warnings.warn(
[05/14/25 23:01:10] INFO     Found credentials from IAM Role:
                             BaseNotebookInstanceEc2InstanceRole
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/
sagemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2
-user/.config/sagemaker/config.yaml
```

```
[05/14/25 23:01:12] INFO     Found credentials from IAM Role:
                             BaseNotebookInstanceEc2InstanceRole
```

```
[05/14/25 23:01:13] INFO     Found credentials from IAM Role:
                             BaseNotebookInstanceEc2InstanceRole
```

```
Training data uploaded to: s3://is597-group10/model_training/train/X_train_processed.csv
Testing data uploaded to: s3://is597-group10/model_training/train/y_train_processed.csv
Testing data uploaded to: s3://is597-group10/model_training/test/X_test_processed.csv
Testing data uploaded to: s3://is597-group10/model_training/test/y_test_processed.csv
```

In [34]:

```python
from sklearn.decomposition import TruncatedSVD
from sklearn.metrics import classification_report, confusion_matrix
# calculate weight between HelpfulBinary = 0 and HelpfulBinary = 1 to sol
neg, pos = np.bincount(y)
scale_pos_weight = neg / pos # weight between HelpfulBinary = 0 and Helpf

# Train model
model_svd = xgb.XGBClassifier(
    n_estimators=1000,
    max_depth=8,
    learning_rate=0.1,
    scale_pos_weight=scale_pos_weight  # add weight deal with imbalance c
)
model_svd.fit(X_train, y_train)

# Evaluate model
y_svd_pred = model_svd.predict(X_test)
print(classification_report(y_test, y_svd_pred))
```

```
              precision    recall  f1-score   support

           0       0.73      0.60      0.66     12887
           1       0.88      0.93      0.90     39912

    accuracy                           0.85     52799
   macro avg       0.81      0.77      0.78     52799
weighted avg       0.84      0.85      0.84     52799
```

In [37]:

```python
# Save model locally as a file
model_svd.save_model('helpful_svd_xgb_model.json')

object_key = 'model_training/model/helpful_svd_xgb_model.json'
# Upload model to S3
s3.upload_file('helpful_svd_xgb_model.json', bucket_name, object_key)
```

XGBoost Training for Helpfulness Classification(without dimensionally reduction)

We use XGBoost to predict the `HelpfulBinary` label. Since the dataset is imbalanced, we apply `scale_pos_weight` to give more importance to the minority class (helpful reviews).

In [34]:
```
# Train XGBClassifier
from sklearn.metrics import classification_report, confusion_matrix
#neg, pos = np.bincount(y) # we do that in previous cells
#scale_pos_weight = neg / pos

# split train and test data
X2_train, X2_test, y2_train, y2_test = train_test_split(X, y, test_size=0

# train XGBoost
model = xgb.XGBClassifier(n_estimators=1000, max_depth=7, learning_rate=0
model.fit(X2_train, y2_train)

# prediction and evaluation
y_pred = model.predict(X2_test)
print(classification_report(y2_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.55      0.71      0.62     12887
           1       0.90      0.81      0.85     39912

    accuracy                           0.79     52799
   macro avg       0.72      0.76      0.73     52799
weighted avg       0.81      0.79      0.79     52799
```

NOTE: I try to use n_estimators=1000, max_depth=8, learning_rate=0.1 for this model as well, but kernal die. Therefore, I only can compare these parameter with model_svd n_estimators=1000, max_depth=8, learning_rate=0.1

Model Evaluation

We evaluate the classifier's performance using precision, recall, and F1-score. The model achieves good accuracy, especially in identifying helpful reviews.

In [35]:
```
# Evaluate model
y_svd_pred = model_svd.predict(X_test)
print("Evaluate the model with SVD")
print(classification_report(y_test, y_svd_pred))

# prediction and evaluation
y_pred = model.predict(X2_test)
print(classification_report(y2_test, y_pred))
```

```
Evaluate the model with SVD
              precision    recall  f1-score   support

           0       0.73      0.60      0.66     12887
           1       0.88      0.93      0.90     39912

    accuracy                           0.85     52799
   macro avg       0.81      0.77      0.78     52799
weighted avg       0.84      0.85      0.84     52799

              precision    recall  f1-score   support

           0       0.55      0.71      0.62     12887
           1       0.90      0.81      0.85     39912

    accuracy                           0.79     52799
   macro avg       0.72      0.76      0.73     52799
weighted avg       0.81      0.79      0.79     52799
```

Comparison Between Models With and Without Dimensionality Reduction (TruncatedSVD)

To evaluate the effect of dimensionality reduction, we compared two models:

- **Model 1: With TruncatedSVD (dimensionality reduction)**
- **Model 2: Without dimensionality reduction (using full TF-IDF features)**

Metric	With SVD	Without SVD
Precision (class 0)	0.73	0.55
Recall (class 0)	0.60	0.71
F1-score (class 0)	0.66	0.62
Precision (class 1)	0.88	0.90
Recall (class 1)	0.93	0.81
F1-score (class 1)	0.90	0.85
Macro avg F1-score	0.78	0.73
Weighted avg F1-score	0.84	0.79
Accuracy	0.85	0.79

Interpretation:

- After applying TruncatedSVD, **the model's overall performance improved**.
- **F1-score**, which balances precision and recall, **increased** after using SVD, meaning the model became better at both identifying helpful reviews and avoiding false positives.
- **Accuracy** also improved from 0.79 to 0.85.
- **Macro average F1-score** (which treats both classes equally) increased, indicating that the model handles both helpful and non-helpful reviews more

fairly after dimensionality reduction.

- This shows that applying TruncatedSVD **helped simplify the feature space** without losing important information, and **also reduced overfitting** by removing noisy or redundant features.

Therefore, we decide to use Model 1 (the one with SVD) to do prediction

In data with helpfulnessBinary gound truth, does most representative data more helpful?

In [36]:
```
# True helpfulness for training data(for most representative data)
high_true_reviews = df_labeled.loc[
    df_labeled.groupby('ProductId')['cosine_avg_sim'].idxmax()
].reset_index(drop=True)
high_true_reviews['HelpfulBinary'].value_counts()
```

Out[36]:
```
HelpfulBinary
1    20300
0     3528
Name: count, dtype: int64
```

In [37]:
```
## for most representative review
print("HelpfulBinary = 1:", len(high_true_reviews[high_true_reviews['Help
print("HelpfulBinary = 0:", len(high_true_reviews[high_true_reviews['Help
```

```
HelpfulBinary = 1: 0.8519388954171563
HelpfulBinary = 0: 0.14806110458284372
```

In [38]:
```
## for all reviews
print("HelpfulBinary = 1:", len(df_labeled[df_labeled['HelpfulBinary'] ==
print("HelpfulBinary = 0:", len(df_labeled[df_labeled['HelpfulBinary'] ==
```

```
HelpfulBinary = 1: 0.7540389328504923
HelpfulBinary = 0: 0.24596106714950774
```

We found most representative reviews are indeed more helpful than normal reviews

Predicting Helpfulness for Unlabeled Reviews

We use the trained model_svd to predict whether reviews without any helpfulness votes are likely to be helpful. This simulates a real-world setting where feedback hasn't been collected yet.

Are Representative Reviews More Helpful?

To verify whether representative reviews are truly more useful, we compare the helpfulness of:

- Most representative reviews
- All reviews
- Random reviews (1 per product)

In [38]:
```
# Predict Helpfulness for Most representative reviews
high_rep_reviews = df_unlabeled.loc[
    df_unlabeled.groupby('ProductId')['cosine_avg_sim'].idxmax()
].reset_index(drop=True)

# Make TF-IDF feature
X_text_hrep = vectorizer.fit_transform(high_rep_reviews['CleanedText'])

# Other numerical value
X_extra_hrep = high_rep_reviews[['cosine_avg_sim', 'recency_weight']].val


# transform X_extra into sparse
X_extra_hrep_sparse = csr_matrix(X_extra_hrep)

# merge two sparse matrix
X_hrep_sparse_all = hstack([X_text_hrep, X_extra_hrep_sparse])  # all of

# TruncatedSVD + scaling in pipeline
pipeline = make_pipeline(
    TruncatedSVD(n_components=100, random_state=42),
    StandardScaler()  # optional, if needed by XGBoost
)

X_hrep_reduced = pipeline.fit_transform(X_hrep_sparse_all)

# Predict
hrep_pred = model_svd.predict(X_hrep_reduced)
high_rep_reviews['PredictedHelpful'] = hrep_pred
```

In [43]:
```
# Predict Helpfulness for All Reviews
# only predict for all df_unlabeled

# Make TF-IDF feature
X_text_all = vectorizer.transform(df_unlabeled['CleanedText'].fillna(""))

# Other numerical value
X_extra_all = df_unlabeled[['cosine_avg_sim', 'recency_weight']].fillna(0

# Transform X_extra into sparse
X_extra_all_sparse = csr_matrix(X_extra_all)

# Merge two sparse matrix
X_all_sparse = hstack([X_text_all, X_extra_all_sparse])

# Apply the same pipeline (TruncatedSVD + Scaling)
X_all_reduced = pipeline.fit_transform(X_all_sparse)

# Predict
all_pred = model_svd.predict(X_all_reduced)
df_unlabeled['PredictedHelpful_All'] = all_pred
```

In [44]:
```
# Predict Helpfulness for Random Reviews (1 per Product)
#

import numpy as np

# Randomly sample 1 review per ProductId
random_reviews = df_unlabeled.groupby('ProductId').apply(lambda x: x.samp
```

```
# Make TF-IDF feature
X_text_random = vectorizer.transform(random_reviews['CleanedText'].fillna

# Other numerical value
X_extra_random = random_reviews[['cosine_avg_sim', 'recency_weight']].fil

# Transform X_extra into sparse
X_extra_random_sparse = csr_matrix(X_extra_random)

# Merge two sparse matrix
X_random_sparse = hstack([X_text_random, X_extra_random_sparse])

# Apply the same pipeline (TruncatedSVD + Scaling)
X_random_reduced = pipeline.fit_transform(X_random_sparse)

# Predict
random_pred = model_svd.predict(X_random_reduced)
random_reviews['PredictedHelpful_Random'] = random_pred
```

```
/tmp/ipykernel_7111/1196998240.py:7: DeprecationWarning: DataFrameGroupBy.
apply operated on the grouping columns. This behavior is deprecated, and i
n a future version of pandas the grouping columns will be excluded from th
e operation. Either pass `include_groups=False` to exclude the groupings o
r explicitly select the grouping columns after groupby to silence this war
ning.
  random_reviews = df_unlabeled.groupby('ProductId').apply(lambda x: x.sam
ple(1, random_state=42)).reset_index(drop=True)
```

In [45]:

```
# 📊 Summarize Predicted Helpfulness Rates

# calculate predict ratio per group
rate_all = df_unlabeled['PredictedHelpful_All'].mean()
rate_random = random_reviews['PredictedHelpful_Random'].mean()
rate_rep = high_rep_reviews['PredictedHelpful'].mean()

# make a DataFrame
summary_df = pd.DataFrame({
    'Type of Review': ['All Reviews', 'Random Review per Product', 'Most
    'Predicted Helpful Rate': [rate_all, rate_random, rate_rep]
})

print(summary_df)
```

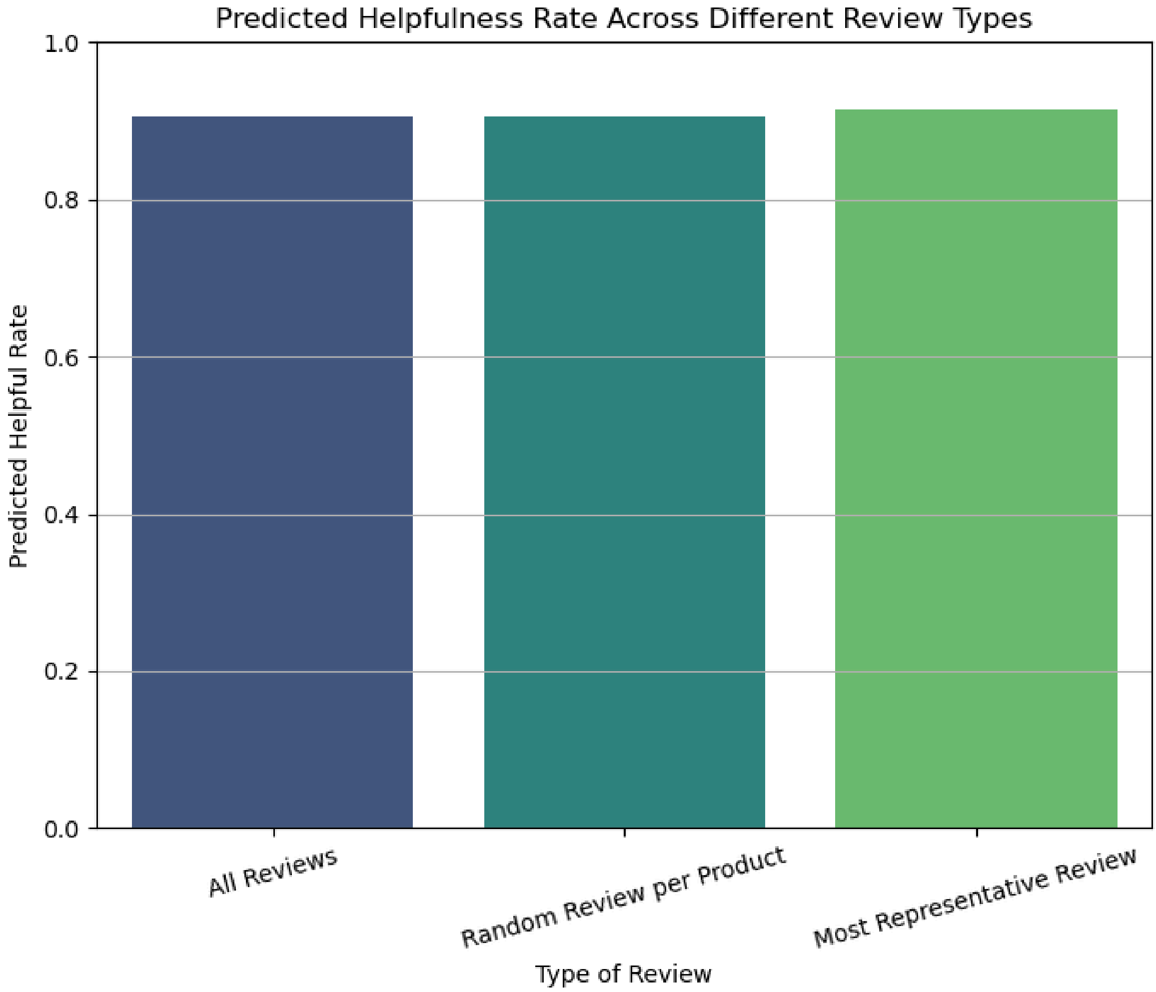
```
                  Type of Review  Predicted Helpful Rate
0                    All Reviews                0.905235
1      Random Review per Product                0.906284
2   Most Representative Review                0.914828
```

In [46]:

```
# Visualize Predicted Helpfulness Rates

import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(8, 6))
sns.barplot(x='Type of Review', y='Predicted Helpful Rate', data=summary_
plt.title('Predicted Helpfulness Rate Across Different Review Types')
plt.ylabel('Predicted Helpful Rate')
plt.xticks(rotation=15)
plt.ylim(0, 1)
```

```
plt.grid(axis='y')
plt.show()
```

```
/tmp/ipykernel_7111/322214116.py:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for
the same effect.

  sns.barplot(x='Type of Review', y='Predicted Helpful Rate', data=summary
_df, palette="viridis")
```



Summary: Are Representative Reviews More Helpful?

Most representative reviews achieved the highest predicted helpful rate (91.48%), compared to random reviews (90.63%) and all reviews (90.52%).

Although the differences are not extremely large, the trend consistently shows that reviews selected based on higher semantic representativeness are slightly more likely to be helpful.

This suggests that the representativeness score, which was based on average cosine similarity and recency weighting, successfully captures meaningful review quality to some extent.

Additionally, it matches with ground truth of data with HelpfulnessBinary, making the conclusion more convincing.

Future Work

- Explore deep learning models (e.g., fine-tuned BERT with numeric fusion).
- Incorporate additional metadata (e.g., reviewer reputation or review length).
- Extend the analysis to other domains (e.g., app reviews, hotel feedback).
- Use AWS SageMaker in-built monitoring tools and AWS SageMaker-built models after we get permission.