Sentiment analysis of ChatGPT Android App

Objective:

To analyze user reviews and ratings of the ChatGPT Android App using data analysis techniques and basic machine learning models. The project aims to clean and preprocess the data, normalize textual content, and extract insights about user engagement, sentiment patterns, temporal trends, and behavioral characteristics. This analysis provides a structured understanding of user feedback to support data-driven evaluations and improvements.

Dataset Description:

The dataset utilized for this project was sourced from Kaggle, contributed by Ashish Kumar. It contains a collection of daily-updated user reviews and ratings for the ChatGPT Android App, along with metadata such as review content, user scores, timestamps, app versions, and relevancy information. The dataset provides a rich foundation for exploring user feedback and conducting sentiment and trend analyses. Access to the dataset is available through the Kaggle link: ChatGPT Reviews Dataset.

And the dataset consisted of the following columns:

reviewID: Unique identifier for each review.

userName: Name or alias of the user providing the review.

content: Text of the user's review.

score: Rating given by the user (1-5).

thumbsUpCount: Number of upvotes received for the review.

reviewCreatedVersion: App version at the time of review.

at: Timestamp indicating the date and time of the review.

appVersion: Detailed app version information.

This data was collected and updated dynamically to capture user feedback.

Tools and Technologies Used:

Languages and Libraries:

Python (pandas, numpy, matplotlib, seaborn, re, nltk, BeautifulSoup, TextBlob).

Frameworks: NLP processing for sentiment analysis.

Visualization Tools: Matplotlib and Seaborn for plotting graphs and showing trends.

Team Structure and Roles:

The project was executed collaboratively using **Asana**, which served as a centralized tool for workflow optimization, task prioritization, and seamless communication. Each team member contributed to specific project areas while maintaining alignment with overall objectives through effective task management and real-time updates.

1. **Dineshbabu**

    A. **Tasks**: Data Quality, User Engagement, and Temporal Trends Analysis.

    B. **Contributions**:

    - Handled missing values and removed duplicate reviews to ensure data quality.
    - Explored score distributions and analyzed review patterns by app version.
    - Examined trends across dates and correlated them with app updates.

2. **Omkar Dodamani**

   A. **Tasks**: Text Normalization, Sentiment Analysis, and User Behavior Analysis.

   B. **Contributions**:

   - Addressed punctuation and special characters in review content.
   - Performed polarity-based sentiment analysis and visualized changes over time.
   - Analyzed reviewer types and their scoring patterns.

Collaboration Highlights:

- **Task Prioritization**: Asana was used to define critical project milestones, ensuring timely completion of high-impact tasks.

- **Workflow Optimization**: Dependencies between tasks were managed effectively to streamline preprocessing and analysis workflows.

- **Risk Mitigation**: Bottlenecks such as handling inconsistent data and refining analytical approaches were resolved collaboratively through real-time updates and discussions.

- **Transparency**: Continuous tracking and reporting ensured clarity on progress, responsibilities, and deadlines.

The collaborative approach, facilitated by **Asana**, enhanced the team's ability to manage tasks efficiently, maintain accountability, and achieve project goals effectively.

Methodology :

1. **Data Preprocessing and Cleaning:**

- Addressed missing values in columns like userName, content, and reviewCreatedVersion.

- Removed duplicate reviews to enhance dataset quality.

- Normalized text in the content column by removing special characters, HTML tags, and redundant spaces.

2. Feature Engineering**:**

- Derived new temporal features from the at column, such as year, month, and weekday.
- Extracted major app versions from the appVersion column.

3. Sentiment Analysis:

- Used polarity scores to classify reviews into positive, negative, or neutral categories.
- Analyzed the frequency of key terms for each sentiment type using text tokenization and filtering.

4. User Behavior Analysis:

- Differentiated between first-time reviewers and repeat reviewers based on reviewID and userName.
- Studied consistency in ratings for frequent reviewers.

5. Trend Analysis:

- Mapped temporal patterns in review frequency and sentiment shifts using the at column.
- Evaluated the impact of app updates on user ratings and thumbs-up counts.

Key Insights and Results:

- **Rating Distribution**: Most users rated the app positively, but a subset of reviews indicated dissatisfaction, often correlating with specific app versions.
- **Common Words:** Positive reviews frequently highlighted "usability" and "accuracy," while negative reviews cited "errors" and "lags."

- **Temporal Patterns**: Review frequency spiked post-major app updates, with sentiments fluctuating based on feature changes.
- **User Behavior:** Repeat reviewers provided more critical feedback, while first-time reviewers were generally more lenient.

Challenges and Limitations:

1. **Data Quality and Missing Values:**

   Addressed incomplete values in critical columns like at and appVersion.

2. **Preprocessing Complexities:**

   Handling sarcasm and mixed sentiments in text reviews required additional manual adjustments.

3. **Scalability Issues:**

   Efficiently processing large datasets without compromising on speed and accuracy.

Conclusion and Future Scope:

- This project successfully identified critical user sentiments and behavioral trends, providing actionable insights for improving the ChatGPT Android App.
- In future sentiment detection accuracy can be enhanced by incorporating advanced **NLP models like BERT(bidirectional Encoder representations from Transformers).**
- Additional data like user demographics could provide deeper insights into user experiences.

Acknowledgment

We express our gratitude to Kaggle and Ashish Kumar for providing the comprehensive dataset that formed the foundation of this analysis. Special thanks to the collaborative efforts of team members: Omkar Dodamani, who contributed to text normalization, sentiment analysis, and user behavior studies, and Dineshbabu, who handled data cleaning, user engagement analysis, and temporal trends exploration. Their combined expertise and dedication were instrumental in overcoming challenges and successfully completing this project.

Project code:

import Libraries

```
[1]: import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
```

Read Data

```
[2]: df = pd.read_csv("chatgpt_reviews.csv")
     df.head()
     df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 272672 entries, 0 to 272671
Data columns (total 8 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   reviewId              272672 non-null  object
 1   userName              272670 non-null  object
 2   content               272663 non-null  object
 3   score                 272672 non-null  int64
 4   thumbsUpCount         272672 non-null  int64
 5   reviewCreatedVersion  248638 non-null  object
 6   at                    272672 non-null  object
 7   appVersion            248638 non-null  object
dtypes: int64(2), object(6)
memory usage: 16.6+ MB
```

1.Data Quality

Find Duplicates

```
[3]: df.duplicated().sum()

[3]: np.int64(2509)
```

Remove Duplicates

```
[4]: df = df.drop_duplicates()
```

Handling Missing Values

```
[5]: missing_values = df.isnull().sum()
     missing_values

[5]: reviewId                    0
     userName                    2
     content                     9
     score                       0
     thumbsUpCount               0
     reviewCreatedVersion    23904
     at                          0
     appVersion              23904
     dtype: int64
```

```
[6]: df['userName'] = df.userName.fillna('Unknown')

     df['content'] = df.content.fillna('')

     df['reviewCreatedVersion'] = df.reviewCreatedVersion.fillna('Unknown')

     df['appVersion'] = df.appVersion.fillna('Unknown')
```

Handling Datatypes

```
[7]: df['at'] = pd.to_datetime(df['at'], errors = 'coerce')
```

```
df['majorVersion'] = pd.to_numeric(df.majorVersion, errors = 'coerce')
df['majorVersion'] = df['majorVersion'].fillna(0)
```

```
[10]: filter = df[(df.majorVersion == 2023) & (df.year == 2024)]
filter.head()
```

5102	dd0fa11d-f493-41fb-a98c-5505b0160d7d	Mr Yaseen	amazing	5	0	1.2023.263	2024-11-10 02:38:33	1.2023.263	2024	Sunday	November	2024-11
7530	7f8ea406-6d28-404f-a1dd-0c0039d14587	John Lumpkin	This app has changed alot and I've learned to ...	4	1	1.2023.313	2024-11-07 05:10:49	1.2023.313	2024	Thursday	November	2024-11
9122	ed0d0aeb-b001-4b28-87ea-f5ba018efe6c	Taiwo Yusuf	I love it	5	0	1.2023.242	2024-11-05 07:40:19	1.2023.242	2024	Tuesday	November	2024-11

```
[11]: df.loc[(df.majorVersion == 0) & (df.year == 2023), 'majorVersion'] = 2023
df.loc[(df.majorVersion == 0) & (df.year == 2023), 'majorVersion'] = 2023
```

```
[11]: df.loc[(df.majorVersion == 0) & (df.year == 2023), 'majorVersion'] = 2023
df.loc[(df.majorVersion == 0) & (df.year == 2023), 'majorVersion'] = 2023
```



```
[12]: df.isnull().sum()
```

```
[12]: reviewId                0
userName                0
content                 0
score                   0
thumbsUpCount           0
reviewCreatedVersion    0
at                      0
appVersion              0
year                    0
day_of_week             0
month                   0
year_month              0
majorVersion            0
dtype: int64
```

```
[13]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 270163 entries, 0 to 272671
Data columns (total 13 columns):
```

```
[13]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 270163 entries, 0 to 272671
Data columns (total 13 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   reviewId              270163 non-null  object
 1   userName              270163 non-null  object
 2   content               270163 non-null  object
 3   score                 270163 non-null  int64
 4   thumbsUpCount         270163 non-null  int64
 5   reviewCreatedVersion  270163 non-null  object
 6   at                    270163 non-null  datetime64[ns]
 7   appVersion            270163 non-null  object
 8   year                  270163 non-null  int32
 9   day_of_week           270163 non-null  object
 10  month                 270163 non-null  object
 11  year_month            270163 non-null  period[M]
 12  majorVersion          270163 non-null  float64
dtypes: datetime64[ns](1), float64(1), int32(1), int64(2), object(7), period[M](1)
memory usage: 27.8+ MB
```

Handling Puntuations and symbols

```
[29]: from bs4 import BeautifulSoup
import re

def clean_df(text):
    text = BeautifulSoup(text, "html.parser").get_text()
    text = re.sub(r'[^A-Za-z\s]', '', text)
    text = re.sub(r'#\w+', '', text)
    return text.lower().strip()

df['content'] = df.content.apply(clean_df)
```

```
C:\Users\OM\AppData\Local\Temp\ipykernel_11648\987094038.py:5: MarkupResemblesLocatorWarning: The input looks more like a filename than marku
p. You may want to open this file and pass the filehandle into Beautiful Soup.
  text = BeautifulSoup(text, "html.parser").get_text()
```

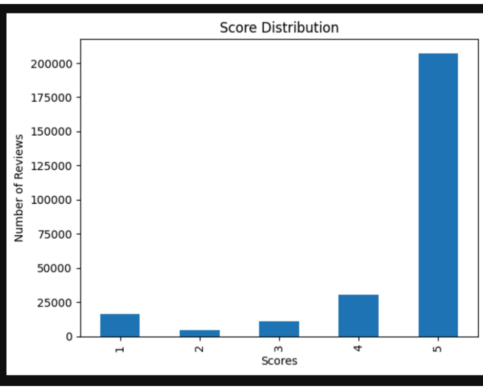
3.User Engagement

Distribution of Overall Score

[15]:
```python
score_distribution = df['score'].value_counts().sort_index()
score_distribution_proportion = df['score'].value_counts(normalize=True) * 100
distribution_table = pd.concat([score_distribution, score_distribution_proportion], axis=1, keys=['Counts', 'Proportions'])
score_distribution.plot(kind='bar', title='Score Distribution')
plt.xlabel('Scores')
plt.ylabel('Number of Reviews')
distribution_table
```

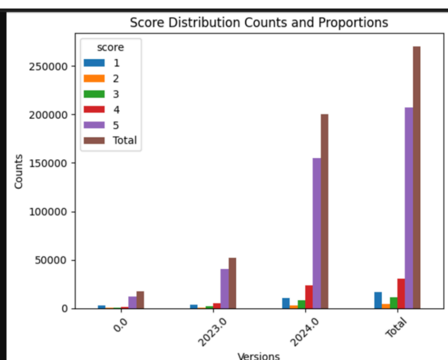
[15]:

score	Counts	Proportions
1	16513	6.112236
2	4725	1.748944
3	11099	4.108261
4	30715	11.369062
5	207111	76.661497



Distribution of each Score by versions

[16]:
```python
score_distribution_byVersion = df.groupby('majorVersion')['score'].value_counts().sort_index()

score_counts = pd.crosstab(df['majorVersion'], df['score'], dropna=False, margins=True, margins_name="Total")

score_counts_proportions = pd.crosstab(df['majorVersion'], df['score'], dropna=False, margins=True, margins_name="Total", normalize=True)*100

score_counts_combined = pd.concat([score_counts, score_counts_proportions], axis=1, keys=['Counts', 'Proportions'])

score_counts_combined['Counts'].plot(kind='bar', stacked=False, title='Score Distribution Counts and Proportions')
plt.xlabel('Versions')
plt.ylabel('Counts')
plt.xticks(rotation=45)
plt.show()

score_counts_combined
```

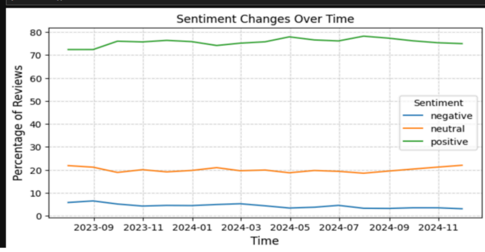


[16]:

	Counts						Proportions					
score	1	2	3	4	5	Total	1	2	3	4	5	Total
majorVersion												
0.0	2568	512	769	1632	12356	17837	0.950537	0.189515	0.284643	0.604080	4.573535	6.602310
2023.0	3687	928	2002	5574	40206	52397	1.364732	0.343496	0.741034	2.063199	14.882127	19.394588
2024.0	10258	3285	8328	23509	154549	199929	3.796967	1.215933	3.082583	8.701784	57.205835	74.003102
Total	16513	4725	11099	30715	207111	270163	6.112236	1.748944	4.108261	11.369062	76.661497	100.000000

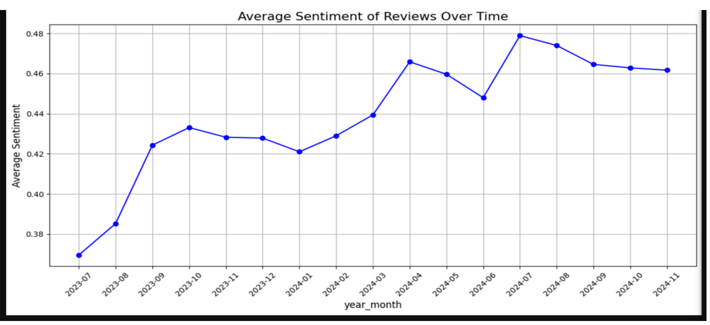
Sentiment Changes over time

[32]:
```
sentiment_over_time = df.groupby(pd.Grouper(key='at', freq='ME'))['sentiment'].value_counts().unstack(fill_value=0)

sentiment_percentages = sentiment_over_time.div(sentiment_over_time.sum(axis=1), axis=0) * 100

plt.figure(figsize=(8, 4))
for sentiment in sentiment_percentages.columns:
    plt.plot(sentiment_percentages.index, sentiment_percentages[sentiment], label=sentiment)

plt.title('Sentiment Changes Over Time', fontsize=12)
plt.xlabel('Time', fontsize=12)
plt.ylabel('Percentage of Reviews', fontsize=12)
plt.legend(title='Sentiment', fontsize=10)
plt.grid(visible=True, linestyle='--', alpha=0.6)
plt.show()
```



Polarity Changes over time

[21]:
```
monthly_sentiment = df.groupby('year_month')['polarity'].mean().reset_index()

plt.figure(figsize=(12, 6))
plt.plot(monthly_sentiment['year_month'].astype(str), monthly_sentiment['polarity'], marker='o', linestyle='-', color='blue')
plt.title('Average Sentiment of Reviews Over Time', fontsize=16)
plt.xlabel('year_month', fontsize=12)
plt.ylabel('Average Sentiment', fontsize=12)
plt.xticks(rotation=45)
plt.grid()
plt.tight_layout()
plt.show()

# Identify periods of notable shifts
monthly_sentiment['sentiment_change'] = monthly_sentiment['polarity'].diff()
```



5.Temporal Trends

Specific date when user given more reviews

[22]:
```
# Group by date and count reviews
reviews_per_date = df.groupby(df['at'].dt.date).size()
# Sort by review count in descending order and get the top 5
top_five_dates = reviews_per_date.sort_values(ascending=False).head(5)
reviews_per_day_of_week = df.groupby(df['day_of_week']).size().sort_values(ascending=False).head(3)
reviews_per_day_of_month = df.groupby(df['month']).size().sort_values(ascending=False).head(5)
# Display the top 5 dates with their review counts
print("\nTop 5 Review Date:\n",top_five_dates,
      "\n\nTop 3 Review Dates by Week:\n", reviews_per_day_of_week,
      "\n\nTop 3 Review Dates by month:\n",reviews_per_day_of_month)
```

```
Top 5 Review Date:
 at
2023-07-25    3132
2023-07-26    1993
2024-10-08    1786
2024-05-17    1237
2024-05-14    1166
dtype: int64

Top 3 Review Dates by Week:
 day_of_week
Tuesday      44185
Wednesday    41347
Thursday     38494
dtype: int64

Top 3 Review Dates by month:
 month
September    35621
August       34801
October      33932
July         33542
May          25816
dtype: int64
```

Average Score by Versions

[23]:
```python
ratings_by_version = df.groupby('majorVersion')['score'].mean()

print("Average ratings by app version:")
ratings_by_version
```

```
Average ratings by app version:
```

[23]:
```
majorVersion
0.0       4.160285
2023.0    4.482604
2024.0    4.544578
Name: score, dtype: float64
```

Average Polarity by Versions

[24]:
```python
sentiment_by_version = df.groupby('majorVersion')['polarity'].mean()

print("Average sentiment by app version:")
sentiment_by_version
```

```
Average sentiment by app version:
majorVersion
0.0       0.380982
2023.0    0.414434
2024.0    0.467800
Name: polarity, dtype: float64
```

Changes in Score After Update by Date

[25]:
```python
from datetime import datetime

#input perticukar date for get the avaerage rating before and after update
date_input = input("Enter date (YYYY-MM-DD): ")

update_date = datetime.strptime(date_input, "%Y-%m-%d")

print(update_date)

before_update = df[df['at'] < update_date]
after_update = df[df['at'] >= update_date]

before_update_avg_rating = before_update['score'].mean()
after_update_avg_rating = after_update['score'].mean()

print(f"Average rating before update: {before_update_avg_rating}")
print(f"Average rating after update: {after_update_avg_rating}")
```

```
Enter date (YYYY-MM-DD):  2023-12-5
2023-12-05 00:00:00
Average rating before update: 4.468131132342716
Average rating after update: 4.513742154133453
```

6.User Behaviours

Users with multiple reviews vs first-time reviewers

Relationship between username and review scores

26]:
```python
import pandas as pd

user_review_counts = df.groupby('userName')['reviewId'].count().reset_index()
user_review_counts.rename(columns={'reviewId': 'review_count'}, inplace=True) # rename the coulumn name 'reviewId' to 'review_count'
# Merge the counts back into the main dataset
data = df.merge(user_review_counts, on='userName')
# Categorize users
data['user_type'] = data['review_count'].apply(lambda x: 'Multiple Reviews' if x > 1 else 'First-Time Reviewer')
# Calculate average scores for each user type
average_scores = data.groupby('user_type')['score'].mean().reset_index()
print("Average scores by user type:")
print(average_scores)

# Calculate average score per user
user_avg_scores = data.groupby('userName')['score'].mean().reset_index()
user_avg_scores.rename(columns={'score': 'average_score'}, inplace=True)
# Find users with consistently high or low scores
consistent_users = user_avg_scores[user_avg_scores['average_score'].isin([user_avg_scores['average_score'].max(),
                                                                          user_avg_scores['average_score'].min()])]
print("------------------------------------------")
print("Users with the highest and lowest average scores:")
consistent_users
```

```
Average scores by user type:
             user_type     score
0  First-Time Reviewer  4.524795
1     Multiple Reviews  4.386209
---------------------------------------------
Users with the highest and lowest average scores:
```

[26]:

	userName	average_score
0	# &	5.0
1	# Amit #	5.0
2	# HASIM	5.0
3	# JACK	5.0
4	# Kratos #	5.0
...	...	...
247068	조연우	5.0
247069	조은혜	5.0
247072	탱탱탱탱탱탱	5.0
247073	하니	5.0
247074	해운대금강영어	5.0

201520 rows × 2 columns

Count of User given multiple review

[27]:
```python
user_review_counts['review_count'].value_counts().sort_index()
```

[27]:
```
review_count
1     235837
2       7507
3       1711
4        756
5        388
6        224
7        176
8        105
9         79
10        40
11        42
12        34
13        25
14        24
15        25
16        12
17        11
18         4
19         8
20         7
22         3
23         5
24         6
25         1
26         3
```

```
32        8
33        1
34        1
35        2
36        3
37        1
40        2
41        1
43        1
44        2
48        2
51        2
53        2
54        1
56        1
57        1
61        1
Name: count, dtype: int64
```

[28]:
```python
data.to_csv('updated_chatgpt_reviews_analysis.csv', index=False)
```

References:
Python Documentation:https://www.python.org/doc/
pandas: https://pandas.pydata.org/
TextBlob: https://textblob.readthedocs.io/
NLTK: https://www.nltk.org/
BeautifulSoup: https://www.crummy.com/software/BeautifulSoup/