

## Customer Sentimental Analysis

Objective: As a Data Analyst at Flipkart, analyze customer sentiment towards model by evaluating reviews using sentiment analysis. The goal is to gain insights into public perception, identify product strengths and weaknesses, and support decision-making.

Literaries and Tools: Selenium: Web scraping automation. BeautifulSoup: HTML parsing. Pandas: Data cleaning and analysis. TextBlob: Sentiment analysis. Matplotlib/Seaborn: Data visualization.

- Data Collection (Web Scraping): Tools: Selenium, BeautifulSoup Steps: Use Selenium to scrape at least 300 reviews from Flipkart's page. Extract Username, Rating, and Review Text. Handle pagination to collect reviews from multiple pages.

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In [2]: # Import the necessary libraries
import requests
import time
import pandas as pd
from bs4 import BeautifulSoup
from selenium import webdriver
from selenium.webdriver.common.by import By
from selenium.webdriver.common.keys import Keys

In [7]: # Create empty lists to store the user data such as Name, City, Date of Purchase, Review & Rating
Names = []
Cities = []
Dates = []
Reviews = []
Ratings = []

# Assign the url of the flipkart website and use selenium to scrape data
url = "https://www.flipkart.com/apple-iphone-15-blue-128-gb/product-reviews/itmfi4ef54645d?pid=MODGTAGPAQNV72YzVilid=LS7NMBGTAGPAQNV72YzVILPQCO&marketplace=FLIPKART"
driver = webdriver.Chrome()
driver.get(url)

while len(Names) < 320:
    time.sleep(2)
    soup = BeautifulSoup(driver.page_source, "html.parser")

    # Extract names
    names_elements = soup.find_all("p", {"class": "f_2N8daF AW5ICA"})
    for name in names_elements:
        Names.append(name.text)

    # Extract cities
    city_elements = soup.find_all("p", {"class": "MntJpV"})
    for city in city_elements:
        Cities.append(city.text)

    # Extract dates
    dates_elements = soup.find_all("p", {"class": "r_28d0d8"})
    for date in dates_elements:
        Dates.append(date.text)
    Actual_Dates = Dates[1:12]

    # Extract reviews
    reviews_elements = soup.find_all("div", {"class": "ZmyKco"})
    for review in reviews_elements:
        Reviews.append(review.text)

    # Extract ratings
    ratings_elements = soup.find_all("div", class_ = "XQ88bG Gal8K")
    for ratings in ratings_elements:
        Ratings.append(ratings.text)

    # Try to click the "Next" button
    try:
        next_button = driver.find_element(By.XPATH, "//span[text()='Next']")
        next_button.click()
        time.sleep(3)
    except:
        break

In [9]: # Combine data into a DataFrame
df = pd.DataFrame({
    "Name": Names[1:],
    "City": Cities[1:],
    "Date": Actual_Dates[1:],
    "Review": Reviews[1:],
    "Ratings": Ratings[1:]
})

2. Data Cleaning and Preprocessing:
3. Tool: Pandas Steps: Remove duplicates and handle missing values. Text Preprocessing: Convert text to lowercase, remove special characters, and extra spaces. Tokenize text, remove stop words, and apply lemmatization.
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In [4]: # Check the basic info of the dataframe
df.info()

Out[6]:
Out[7]:
In [8]: # Clean data of City column by removing unwanted characters/ part of string
df['City'] = df['City'].str.replace("Certified Buyer, ", "", regex=False).str.strip()
df1.head()

Out[8]:
In [9]: # Clean data of Review column by removing unwanted characters/ part of string and converting to lowercase
df['Review'] = df['Review'].str.lower().str.replace("read more", "", regex=False)
df1.head()

Out[9]:
3. Sentiment Analysis: Tool: TextBlob Steps: Analyze sentiment using TextBlob's polarity score (-1 to +1). Classify sentiment: Positive: Polarity > 0.1 Negative: Polarity < 0.1 Store sentiment classification in the dataset.
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In [10]: # Import libraries for Sentimental analysis of review sentences
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import stopwords
from nltk.tokenize import word_tokenize
from textblob import TextBlob
import string

nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')

In [11]: # Create a column called Reviews_t that stores tokenized sentences from the Review column using the sent_tokenize function.
df['Reviews_t'] = df['Review'].apply(sent_tokenize)
df1

Out[11]:
In [12]: # Import mean from statistics for basic statistics
from statistics import mean

# Function created for assigning Polarity to the Reviews_t column
def get_polarity(sentences):
    return [TextBlob(sentence).sentiment.polarity for sentence in sentences]

# Cells get_polarity function on the Reviews_t column to assign polarity
df['Polarity'] = df['Reviews_t'].apply(get_polarity)

# Function created to calculate the average polarity of each review (Average of polarity for each sentences in a review)
def calculate_average_polarity(polarities):
    return mean(polarities) if polarities else 0

# Cells calculate_average_polarity function on the Polarity column to assign the average polarity for each review
df['Average_Polarity'] = df['Polarity'].apply(calculate_average_polarity)
df1['Average_Polarity'] = df1['Average_Polarity'].round(2)
df1.head(10)

Out[12]:
In [13]: # Function to assign the Class to the Polarity
def sentiment_class_polarity():
    if polarity > 0.75:
        return 'extremely positive'
    elif >= polarity < 0.75:
        return 'positive'
    elif polarity == 0:
        return 'neutral'
    elif <= -0.75 < polarity < 0:
        return 'negative'
    else:
        return 'extremely negative'

# Cells sentiment_class function on the Average_Polarity column to assign the sentiment class
df['Sentiment_Class'] = df1['Average_Polarity'].apply(sentiment_class)

In [14]: df1.head()

Out[14]:
In [15]: # Calculates and prints the overall average polarity score of the entire dataset of reviews
polarity_score = df1['Average_Polarity'].mean().round(2)
print(f"Average Polarity Score : {polarity_score}")
if polarity_score > 0.75:
    print("The Average Polarity Score is Extremely Positive")
elif >= polarity_score < 0.75:
    print("The Average Polarity Score is Positive")
elif polarity_score == 0:
    print("The Average Polarity Score is Neutral")
elif <= -0.75 < polarity_score < 0:
    print("The Average Polarity Score is Negative")
else:
    print("The Average Polarity Score is Extremely Negative")

Average Polarity Score : 0.52
The Average Polarity Score is Positive
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- Data Analysis and Insights: Tools: Pandas, Matplotlib/Seaborn Steps: Sentiment Distribution: Calculate positive and negative sentiment proportions. Average Rating vs Sentiment: Analyze correlation between numeric ratings (1-5 stars) and sentiment. Word Cloud: Generate a word cloud for frequently mentioned words in positive/negative reviews. Review Length Analysis: Investigate the relationship between review length and sentiment.

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In [16]: # Imports libraries for visualization
import matplotlib.pyplot as plt
import seaborn as sns

In [17]: # Plot Figure for Sentiment Distribution based on Sentiment Category
plt.figure(figsize=(10, 6))
sns.histplot(x=df['Sentiment_Class'], color='green')
plt.title('Sentiment Distribution')
plt.xlabel('Sentiment Category')
plt.ylabel('Frequency')
plt.xticks(rotation=90)
plt.show()

Sentiment Distribution

The bar chart visualizes the distribution of sentiment categories in the dataset. The x-axis represents various sentiment categories, and the y-axis shows the frequency of occurrences in each category. The categories are as follows:

1. Positive: The most frequent sentiment, with over 200 instances.
2. Extremely Positive: This category follows, though it appears much less frequently than "Positive".
3. Neutral: Appears less often than both positive categories.
4. Negative: The least frequent sentiment in the dataset.

The chart clearly demonstrates a strong inclination towards positive sentiments, with "Positive" being the predominant category, followed by "Extremely Positive". Both neutral and negative sentiments occur much less frequently.
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In [44]: df1['Review_Length'] = df1['Review'].apply(lambda x: len(x.split()))

In [45]: # Box Plot for Review Length by Sentiment
plt.figure(figsize=(8, 6))
sns.boxplot(x='Sentiment_Class', y='Review_Length', data=df1, hue = 'Sentiment_Class', palette='Set2')
plt.title('Review Length vs Sentiment', fontsize=14)
plt.xlabel('Sentiment', fontsize=12)
plt.ylabel('Review Length (Number of Words)', fontsize=12)
plt.show()

Review Length Vs Sentiment

Correlation: Reviews with more positive sentiment tend to align with higher ratings** (e.g., 4.5-5 stars), as demonstrated by the clustering and color gradient.

Neutral Reviews: Neutral reviews are spread across various ratings**, suggesting that sentiment does not always align with the assigned star rating.

Negative Reviews: Negative and extremely negative reviews typically receive lower ratings**, but they can still vary due to individual reviewer perspectives and subjective interpretation.
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In [18]: # Plotting Ratings vs average polarity
plt.figure(figsize=(10, 6))
sns.boxplot(x='Average_Polarity', y='Ratings', data = df1, hue = 'Average_Polarity', palette='coolwarm')
plt.title('Ratings vs Average Polarity')
plt.xlabel('Average Polarity')
plt.ylabel('Ratings')
plt.xticks(rotation=90)
plt.show()

Ratings vs Average Polarity

Ratings vs Average Polarity: Positive Sentiment: Shows the widest variation in review length, with a few notable outliers. The median review length is higher than that of other sentiment categories.

Extremely Positive Sentiment: Has the shortest overall review lengths, with a tighter distribution and fewer outliers.

Neutral Sentiment: Displays a narrower range of review lengths, similar to the "Extremely Positive" sentiment group.

Negative Sentiment: Exhibits a moderate range of review lengths. The median length is shorter than "Positive" but longer than both "Extremely Positive" and "Neutral."
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Interpretation: Positive reviews are generally more detailed (longer) compared to other sentiment categories. Extremely positive and neutral reviews are typically short. Negative reviews vary in length but tend to be more concise than positive ones.

- Reporting: Summarize findings, including: Overview of data collection and cleaning. Sentiment Analysis Results: Distribution of sentiments, average sentiment per rating. Insights: Key trends, issues, and positive highlights. Recommendations: Based on sentiment, suggest areas for product improvement or marketing.
- Sentiment Analysis Report: Customer Reviews on Flipkart
- Data Collection and Cleaning Process Data Source: Customer reviews were gathered from Flipkart using web scraping techniques with tools such as Selenium and BeautifulSoup. Data Preparation: The reviews were preprocessed by removing unnecessary characters, standardizing text formatting, and eliminating excess spaces. Text data was tokenized to prepare it for further analysis. Sentiments were categorized into different labels (e.g., positive, extremely positive, neutral, negative, extremely negative) using sentiment analysis methods.
  - Sentiment Analysis Findings Sentiment Breakdown: A majority of the reviews expressed positive sentiment, followed by a smaller share of extremely positive feedback, as shown in the sentiment distribution chart. Neutral and negative reviews represented a much smaller percentage of the total feedback. Sentiment by Rating: Higher star ratings were generally associated with positive or extremely positive sentiments. Lower star ratings tended to correspond with more neutral or negative feedback, signaling dissatisfaction among those customers.
  - Key Insights Positive Aspects: Customers frequently praised the design, camera quality, and overall performance of the iPhone 15. Many reviews highlighted improvements in battery life as a notable positive feature.

Common Complaints: Neutral and negative reviews often pointed to pricing issues and occasional problems with delivery or packaging. A few customers mentioned compatibility problems with certain accessories and minor software glitches.

Recommendations Product Enhancements Address minor software glitches mentioned by users to improve overall experience. Look into compatibility issues with accessories to ensure that users have a smooth and hassle-free experience.

Marketing Suggestions Emphasize the camera quality, battery life, and sleek design in future marketing campaigns. Mitigate pricing concerns by offering EMI options, exchange offers, or time-limited discounts to make the product more accessible.

Operational Improvements Focus on enhancing delivery services to reduce complaints related to packaging or shipping delays. Keep a close eye on customer feedback to swiftly identify and resolve any new issues that arise.

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In [ ]:
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