Sentiment Analysis for E-Commerce

Scenario: An e-commerce platform wants to understand customer sentiments from product reviews to enhance user experience and improve product offerings.

- **Objective**: Develop a sentiment analysis model to classify reviews as positive, negative, or neutral.
- **Data**: Collect reviews from the website, focusing on text data along with metadata (ratings, timestamps).
- **Challenges**: Handling sarcasm, managing domain-specific vocabulary, and addressing language variations (e.g., slang).
- **Implementation**: Use a combination of pre-trained models (like BERT) and fine-tune them on the collected review dataset.
- **Evaluation**: Use accuracy, precision, recall, and F1-score to assess model performance. Additionally, implement A/B testing to evaluate user engagement based on sentiment insights.

To develop a sentiment analysis model for an e-commerce platform, you can follow a structured approach that addresses the specific challenges and objectives you outlined.

1. Data Collection and Preprocessing

- **Source Reviews**: Collect product reviews from the e-commerce platform, including text data (e.g., review text, title) and metadata (e.g., ratings, timestamps).
- **Data set** : Women Clothing E-Commerce.csv
- **Preprocess Data**: Clean and preprocess the review data:
    - Remove unnecessary characters.
    - Normalize the text (lowercase, stemming, lemmatization).
    - Handle domain-specific vocabulary (e.g., product names, industry terms).

    - Detect and handle slang or informal language using language models or custom dictionaries.

2. Handling Challenges

- **Sarcasm**: Sarcasm detection is challenging. Pre-trained language models like BERT may capture some nuances, but specialized fine-tuning with annotated sarcastic examples would improve results.
- **Domain-Specific Vocabulary**: Fine-tuning pre-trained models like BERT on your e-commerce dataset will allow the model to learn domain-specific terms and expressions that may not be found in general corpora.
- **Language Variations**: Use transfer learning from multilingual models or fine-tune the model on reviews that include slang, abbreviations, and emojis specific to your target audience.

3. Model Selection

- **Pre-trained Models**: Start with BERT (Bidirectional Encoder Representations from Transformers) or its variants like DistilBERT (a smaller version of BERT) or RoBERTa (Robustly optimized BERT pretraining approach).
    - BERT is well-suited for text classification tasks due to its bidirectional attention mechanism, making it effective at understanding context.
    - Fine-tune the model on your labeled sentiment data (positive, negative, neutral).
- **Fine-tuning**: Fine-tune the pre-trained model on the e-commerce reviews dataset using transfer learning to improve its ability to understand sentiment in your specific domain.

4. Model Training

- **Text Vectorization**: Use tokenizers to convert text into tokens that the model can process.

- BERT uses WordPiece tokenization to break down words into subword units, helping the model handle rare words or misspellings.

- **Train the Model**: Split the data into training, validation, and test sets. Train the model using the training set, validate it during training, and test its performance on unseen data.
    - Use the metadata (ratings, timestamps) as additional features, if relevant, to improve model predictions.

5. Evaluation Metrics

- **Accuracy**: Measure the percentage of correctly classified reviews.
- **Precision**: Evaluate how many of the positive/negative reviews predicted by the model are actually positive/negative.
- **Recall**: Measure how many of the actual positive/negative reviews were correctly identified by the model.
- **F1-Score**: Harmonic mean of precision and recall, providing a balance between them.
- **Confusion Matrix**: Visualize the true positives, true negatives, false positives, and false negatives.

6. A/B Testing and User Engagement

- **A/B Testing**: Implement A/B testing on the platform, where users are shown product recommendations or personalized content based on sentiment insights from the model.
    - For example, positive sentiment reviews can be prioritized, or users can be shown more neutral reviews for balanced perspectives.

Below code contains what are all the logic implemented in Sentiment analysis for Ecommerce

Data set used : Women Clothing E-Commerce.csv

In [1]:
```
#!pip install seaborn
#!pip install nltk
#!pip install wordcloud
#!pip install vaderSentiment
#!pip install scikit-learn
#!pip install xgboost
#!pip install lightgbm
#!pip install catboost
```

In [2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [3]:
```
import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
from matplotlib.colors import LinearSegmentedColormap
import seaborn as sns
%matplotlib inline

# Set color palette for Seaborn
colors = ["#26536f", "#3b96b7", "#749ca8", "#b6a98d", "#c78a4d", "#854927"]
sns.set_palette(colors)
```

In [4]:
```
# Text Processing Libraries
import string
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from wordcloud import WordCloud
from collections import Counter
from nltk import ngrams
```

In [5]:
```
!pip install vaderSentiment
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
# Download required NLTK data
nltk.download('stopwords')
nltk.download('punkt')
```

```
Collecting vaderSentiment
  Downloading vaderSentiment-3.3.2-py2.py3-none-any.whl.metadata (572 bytes)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages
(from vaderSentiment) (2.32.3)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.1
0/dist-packages (from requests->vaderSentiment) (3.4.0)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packag
es (from requests->vaderSentiment) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-
packages (from requests->vaderSentiment) (2.2.3)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-
packages (from requests->vaderSentiment) (2024.8.30)
Downloading vaderSentiment-3.3.2-py2.py3-none-any.whl (125 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0.0/126.0 kB ? eta -:--:--
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╸ 122.9/126.0 kB 4.5 MB/s eta 0:00:01
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 126.0/126.0 kB 3.2 MB/s eta 0:00:00
Installing collected packages: vaderSentiment
Successfully installed vaderSentiment-3.3.2
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

Out[5]: True

In [6]:
```
#Machine Learning Libraries
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import LabelEncoder, label_binarize
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import (
    AdaBoostClassifier, GradientBoostingClassifier, RandomForestClassifier
)
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
# catboost import CatBoostClassifier

# Evaluation Metrics
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score, classification_report,
    confusion_matrix, roc_curve, roc_auc_score, ConfusionMatrixDisplay, auc
)
```

```
/usr/local/lib/python3.10/dist-packages/dask/dataframe/__init__.py:42: FutureWarnin
g:
Dask dataframe query planning is disabled because dask-expr is not installed.

You can install it with `pip install dask[dataframe]` or `conda install dask`.
This will raise in a future version.

  warnings.warn(msg, FutureWarning)
```

In [7]:
```
df=pd.read_csv('sample_data/Womens Clothing E-Commerce.csv')
```

In [8]:
```
df.head()
```

Out[8]:

	Unnamed: 0	Clothing ID	Age	Title	Review Text	Division Name	Department Name	Class Name
0	0	767	33	NaN	Absolutely wonderful - silky and sexy and comf...	Initmates	Intimate	Intimates
1	1	1080	34	NaN	Love this dress! it's sooo pretty. i happene...	General	Dresses	Dresses
2	2	1077	60	Some major design flaws	I had such high hopes for this dress and reall...	General	Dresses	Dresses
3	3	1049	50	My favorite buy!	I love, love, love this jumpsuit. it's fun, fl...	General Petite	Bottoms	Pants
4	4	847	47	Flattering shirt	This shirt is very flattering to all due to th...	General	Tops	Blouses

In [9]:
```
df.shape
```

Out[9]: (23486, 8)

In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23486 entries, 0 to 23485
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   Unnamed: 0       23486 non-null  int64 
 1   Clothing ID      23486 non-null  int64 
 2   Age              23486 non-null  int64 
 3   Title            19676 non-null  object
 4   Review Text      22641 non-null  object
 5   Division Name    23472 non-null  object
 6   Department Name  23472 non-null  object
 7   Class Name       23472 non-null  object
dtypes: int64(3), object(5)
memory usage: 1.4+ MB
```

In [11]:
```
df.isna().sum()
```

Out[11]:

	0
Unnamed: 0	0
Clothing ID	0
Age	0
Title	3810
Review Text	845
Division Name	14
Department Name	14
Class Name	14

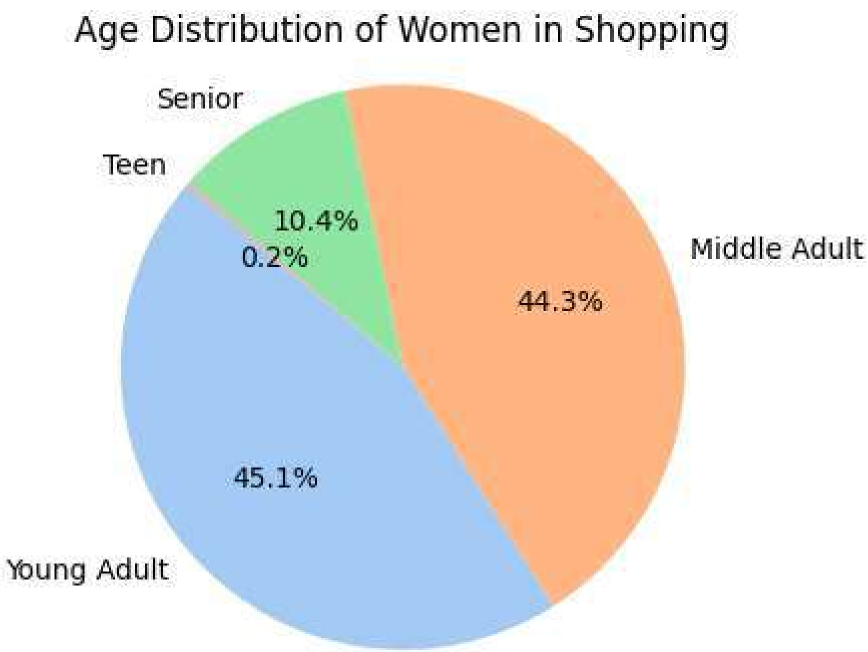
dtype: int64

In [12]:
```
print('Min Age :',df['Age'].min())
print('Max Age :',df['Age'].max())
```

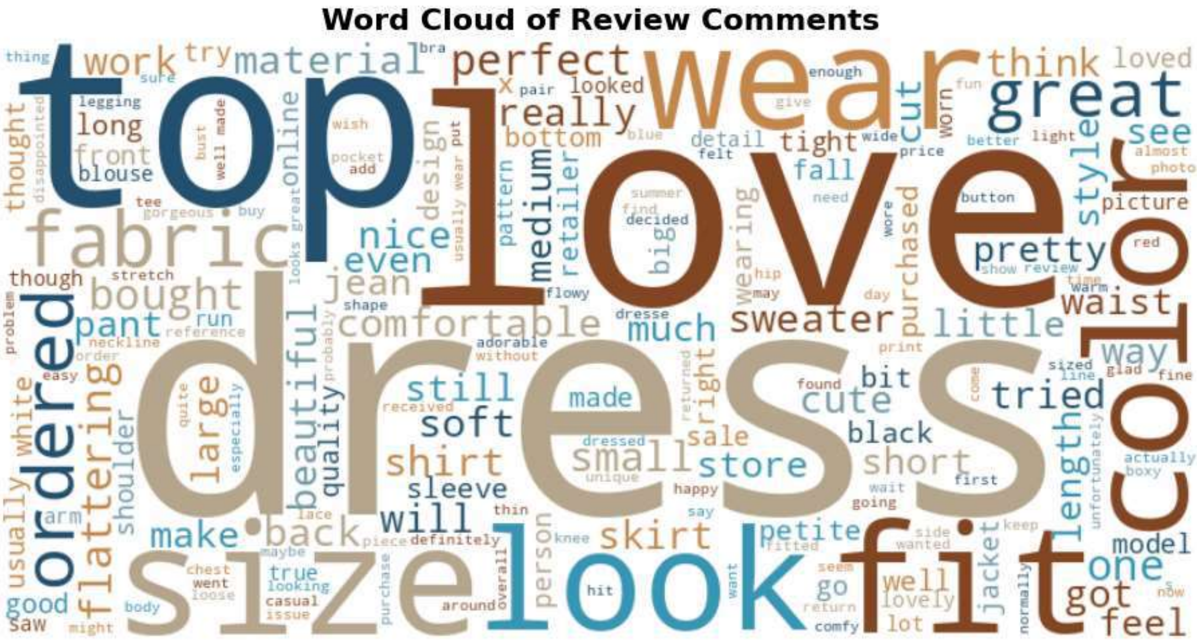
```
Min Age : 18
Max Age : 99
```

In [13]:
```
# Create age categories
bins = [ 0,19, 39, 60, 99]
labels = [ 'Teen','Young Adult', 'Middle Adult', 'Senior']
df['Age Category'] = pd.cut(df['Age'], bins, labels=labels)

# Count the number of occurrences for each category
age_counts = df['Age Category'].value_counts()

# Plot pie chart
plt.figure(figsize=(4,4 ))
plt.pie(age_counts, labels=age_counts.index, autopct='%1.1f%%', startangle=140, col
plt.title('Age Distribution of Women in Shopping')
```

```
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
plt.show()
```



In [14]:
```
# Define a color function
def color_func(word, font_size, position, orientation, random_state=42, **kwargs):
    return random.choice(colors)

# Example: Word cloud from review comments
plt.figure(figsize=(10, 5))

wordcloud = WordCloud(width=800, height=400, background_color='white', color_func=c
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')  # Hide axes
plt.title('Word Cloud of Review Comments', fontsize=16, fontweight='bold')

plt.tight_layout()
plt.show()
```



Natural Language Processing (NLP)

In [15]:
```
nlp_df=df[['Title','Review Text','Class Name']]
```

In [16]:
```
nlp_df
```

Out[16]:

	Title	Review Text	Class Name
0	NaN	Absolutely wonderful - silky and sexy and comf...	Intimates
1	NaN	Love this dress! it's sooo pretty. i happene...	Dresses
2	Some major design flaws	I had such high hopes for this dress and reall...	Dresses
3	My favorite buy!	I love, love, love this jumpsuit. it's fun, fl...	Pants
4	Flattering shirt	This shirt is very flattering to all due to th...	Blouses
...	...	...	...
23481	Great dress for many occasions	I was very happy to snag this dress at such a ...	Dresses
23482	Wish it was made of cotton	It reminds me of maternity clothes. soft, stre...	Knits
23483	Cute, but see through	This fit well, but the top was very see throug...	Dresses
23484	Very cute dress, perfect for summer parties an...	I bought this dress for a wedding i have this ...	Dresses
23485	Please make more like this one!	This dress in a lovely platinum is feminine an...	Dresses

23486 rows × 3 columns

In [17]:
```
nlp_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23486 entries, 0 to 23485
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Title        19676 non-null  object
 1   Review Text  22641 non-null  object
 2   Class Name   23472 non-null  object
dtypes: object(3)
memory usage: 550.6+ KB
```

In [18]:
```
print(f"There are {nlp_df['Class Name'].nunique()} product categories  in the Data
```

```
There are 20 product categories  in the Data set
 ['Intimates' 'Dresses' 'Pants' 'Blouses' 'Knits' 'Outerwear' 'Lounge'
 'Sweaters' 'Skirts' 'Fine gauge' 'Sleep' 'Jackets' 'Swim' 'Trend' 'Jeans'
 'Legwear' 'Shorts' 'Layering' 'Casual bottoms' nan 'Chemises']
```

In [19]:
```
# Calculating the total number of NaN values in each column of the DataFrame 'nlp_d
nan_counts = nlp_df.isna().sum()
nan_counts
```

Out[19]:

	0
Title	3810
Review Text	845
Class Name	14

dtype: int64

In [20]:
```
# Calculating the total number of NaN values in the 'review_comment_message' column
nan_count_review_comment_message = nlp_df['Review Text'].isna().sum()
print(nan_count_review_comment_message)
```

845

In [21]:
```
def remove_dup_nlp_df(nlp_df, column_name='Review Text'):

    #remove duplicates
    nlp_df=nlp_df.drop_duplicates(subset=[column_name],keep='first' )
    # Display the total entries after removing duplicates
    print(f"Total entries after removing duplicates in '{column_name}': {nlp_df.sha
    return nlp_df

nlp_df = remove_dup_nlp_df(nlp_df, 'Review Text')
nlp_df.head()
```

```
Total entries after removing duplicates in 'Review Text': 22635
```

Out[21]:

	Title	Review Text	Class Name
0	NaN	Absolutely wonderful - silky and sexy and comf...	Intimates
1	NaN	Love this dress! it's sooo pretty. i happene...	Dresses
2	Some major design flaws	I had such high hopes for this dress and reall...	Dresses
3	My favorite buy!	I love, love, love this jumpsuit. it's fun, fl...	Pants
4	Flattering shirt	This shirt is very flattering to all due to th...	Blouses

In [22]:
```
def clean_reviews(df):

    # Remove rows where 'review_comment_message' is empty
    df = df.dropna(subset=['Title','Review Text','Class Name']).reset_index(drop=Tr

    # Remove duplicate rows
    df = df.drop_duplicates(subset=['Review Text'])

    return df
```

```python
# Assuming 'nlp_df' is your dataframe
df_cleaned = clean_reviews(nlp_df)

# Display the first records to check
df_cleaned.head()
```

Out[22]:

	Title	Review Text	Class Name
0	Some major design flaws	I had such high hopes for this dress and reall...	Dresses
1	My favorite buy!	I love, love, love this jumpsuit. it's fun, fl...	Pants
2	Flattering shirt	This shirt is very flattering to all due to th...	Blouses
3	Not for the very petite	I love tracy reese dresses, but this one is no...	Dresses
4	Cagrcoal shimmer fun	I aded this in my basket at hte last mintue to...	Knits

Text Preprocessing

In [23]:

```python
# Define Portuguese stopwords
STOP_WORDS = set(stopwords.words('english'))

# Helper function to clean and tokenize text
def clean_and_tokenize(text):
    # Ensure the text is a string
    if not isinstance(text, str):
        return "", []

    # Convert to lowercase, remove punctuation, and split into words
    cleaned_text = text.lower().translate(str.maketrans('', '', string.punctuation)
    words = cleaned_text.split()

    # Remove stopwords and create tokens
    filtered_words = [word for word in words if word not in STOP_WORDS]
    return " ".join(filtered_words), filtered_words

# Main function to preprocess and clean the dataframe
def preprocess_nlp_df(df):
    # Clean, remove stopwords, and tokenize comments
    df[['Review Text clean', 'Review Text tokens']] = df['Review Text'].apply(
        lambda text: pd.Series(clean_and_tokenize(text))
    )

    # Remove rows with NaN values in key columns
    df.dropna(subset=['Title', 'Review Text'], inplace=True)

    # Drop duplicate rows based on the 'review_comment_message' and 'review_comment
    df.drop_duplicates(subset=['Review Text', 'Title'], inplace=True)

    return df.reset_index(drop=True)
```

```python
# Preprocess the dataset
nlp_df = preprocess_nlp_df(nlp_df)

# Display the first records to check
nlp_df[['Review Text', 'Review Text clean', 'Review Text tokens']].head()
```

```
<ipython-input-23-885d31dc77bb>:21: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
ser_guide/indexing.html#returning-a-view-versus-a-copy
  df[['Review Text clean', 'Review Text tokens']] = df['Review Text'].apply(
<ipython-input-23-885d31dc77bb>:21: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
ser_guide/indexing.html#returning-a-view-versus-a-copy
  df[['Review Text clean', 'Review Text tokens']] = df['Review Text'].apply(
<ipython-input-23-885d31dc77bb>:26: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
ser_guide/indexing.html#returning-a-view-versus-a-copy
  df.dropna(subset=['Title', 'Review Text'], inplace=True)
<ipython-input-23-885d31dc77bb>:29: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
ser_guide/indexing.html#returning-a-view-versus-a-copy
  df.drop_duplicates(subset=['Review Text', 'Title'], inplace=True)
```

Out[23]:

	Review Text	Review Text clean	Review Text tokens
0	I had such high hopes for this dress and reall...	high hopes dress really wanted work initially ...	[high, hopes, dress, really, wanted, work, ini...
1	I love, love, love this jumpsuit. it's fun, fl...	love love love jumpsuit fun flirty fabulous ev...	[love, love, love, jumpsuit, fun, flirty, fabu...
2	This shirt is very flattering to all due to th...	shirt flattering due adjustable front tie perf...	[shirt, flattering, due, adjustable, front, ti...
3	I love tracy reese dresses, but this one is no...	love tracy reese dresses one petite 5 feet tal...	[love, tracy, reese, dresses, one, petite, 5, ...
4	I aded this in my basket at hte last mintue to...	aded basket hte last mintue see would look lik...	[aded, basket, hte, last, mintue, see, would, ...

In [24]:

```python
# Initialize the Sentiment Analyzer once
analyzer = SentimentIntensityAnalyzer()

def classify_sentiment(df, column_name='Review Text clean'):
    # Vectorized function to get sentiment classification
    def get_sentiment_classification(text):
```

```
        scores = analyzer.polarity_scores(text)
        if scores['compound'] >= 0.05:
            return 'Positive'
        elif scores['compound'] <= -0.05:
            return 'Negative'
        else:
            return 'Neutral'

    # Apply sentiment analysis using map for faster iteration
    df[f'{column_name}_sentiment'] = df[column_name].map(get_sentiment_classificati
    return df

# Classify sentiment in 'nlp_df' based on the 'review_comment_message_clean' column
nlp_df = classify_sentiment(nlp_df, 'Review Text clean')

# Display the sentiment results
nlp_df[['Review Text clean', 'Review Text clean_sentiment']].head()
```

Out[24]:

	Review Text clean	Review Text clean_sentiment
0	high hopes dress really wanted work initially ...	Positive
1	love love love jumpsuit fun flirty fabulous ev...	Positive
2	shirt flattering due adjustable front tie perf...	Positive
3	love tracy reese dresses one petite 5 feet tal...	Positive
4	aded basket hte last mintue see would look lik...	Positive

In [25]:

```
# Concatenate all non-null texts from the 'cleaned_text' column into a single strin
text_combined = " ".join(nlp_df['Review Text clean'].dropna())

# Generate the word cloud
wordcloud = WordCloud(width=800, height=400, background_color='white', color_func=c

# Display the word cloud
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.title("Word Cloud - Clean Text")
plt.axis("off")  # Remove the axes
plt.show()
```

Word Cloud - Clean Text

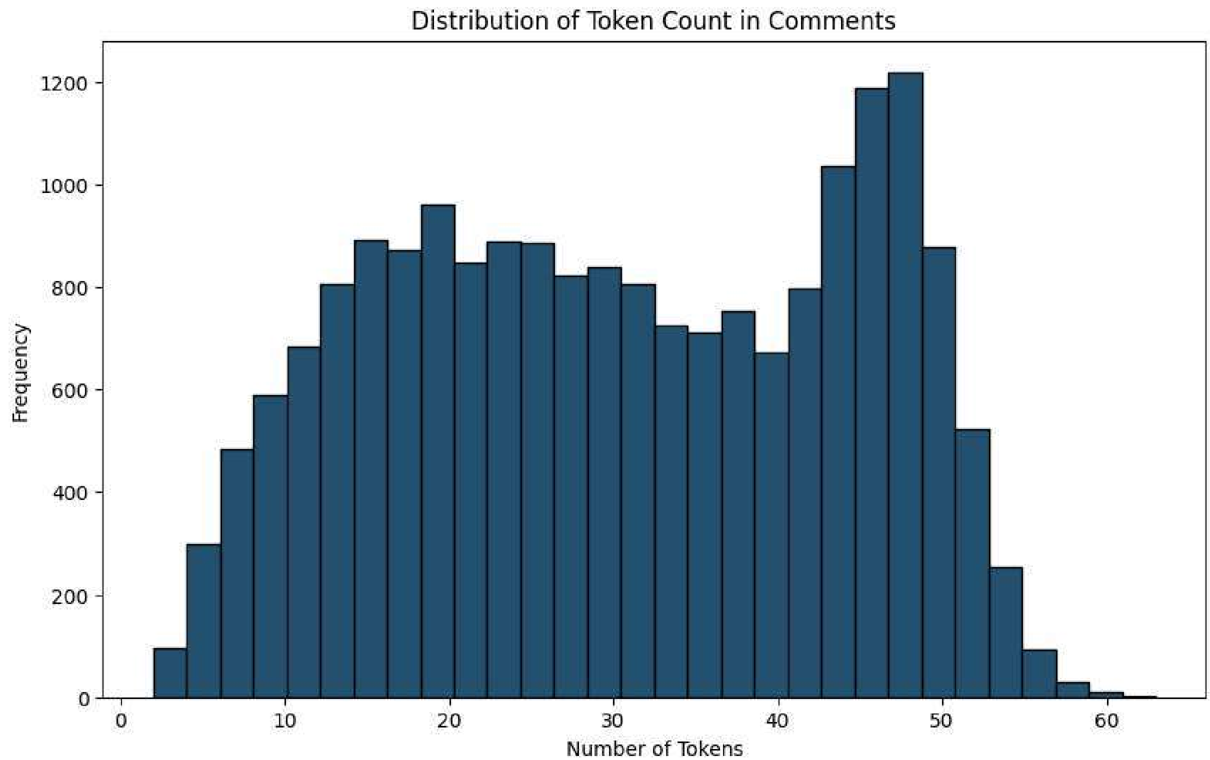
In [26]:
```python
def plot_word_clouds_by_sentiment(df, text_column='Review Text clean', sentiment_co
    # Filter text by sentiment
    sentiments = ['Positive', 'Neutral', 'Negative']

    for sentiment in sentiments:
        # Filter data by current sentiment
        text_data = " ".join(df[df[sentiment_column] == sentiment][text_column].dro

        # Generate the word cloud
        wordcloud = WordCloud(width=800, height=400, background_color='white', colo

        # Plot the word cloud
        plt.figure(figsize=(10, 5))
        plt.imshow(wordcloud, interpolation='bilinear')
        plt.axis('off')
        plt.title(f'Word Cloud for {sentiment} Sentiment')
        plt.show()

# Generate word clouds based on sentiment for the specified columns
plot_word_clouds_by_sentiment(nlp_df, 'Review Text clean', 'Review Text clean_senti
```

Word Cloud for Positive Sentiment

Word Cloud for Neutral Sentiment

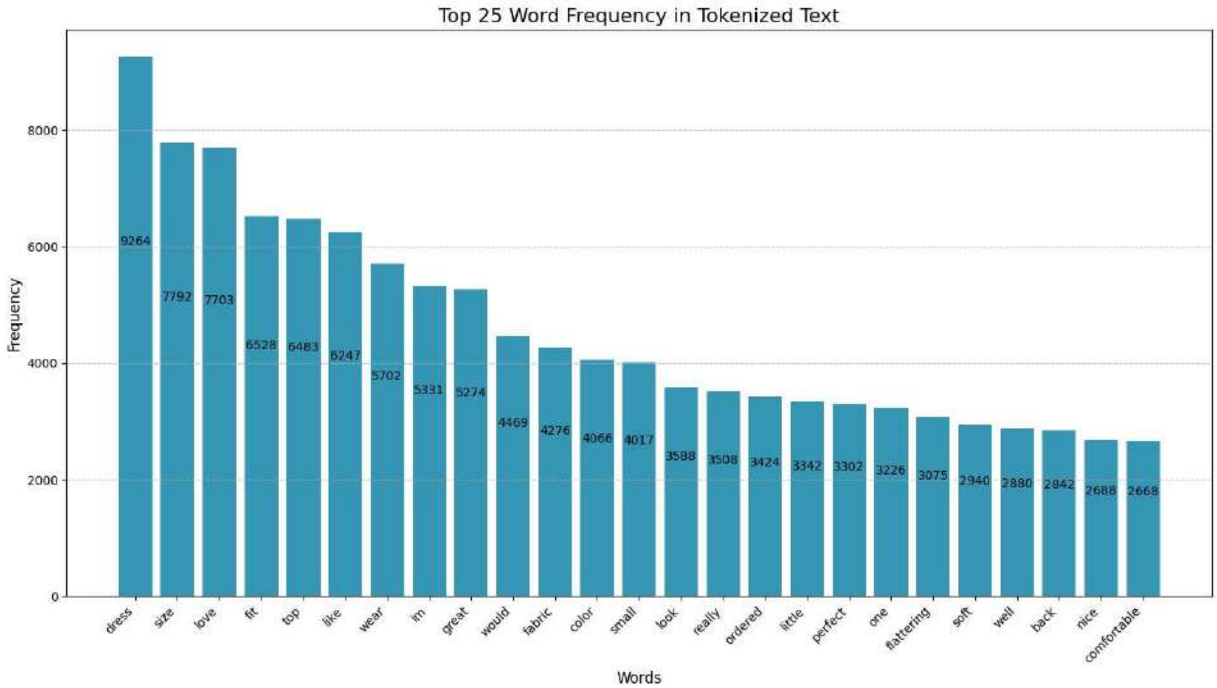
Word Cloud for Negative Sentiment


```python
In [27]: def plot_token_count_distribution(df, token_column='Review Text tokens'):
    # Calculate the number of tokens for each entry
    df['token_count'] = df[token_column].apply(len)

    # Plot the distribution of token counts
    plt.figure(figsize=(10, 6))
    plt.hist(df['token_count'], bins=30, edgecolor='black')
    plt.xlabel('Number of Tokens')
    plt.ylabel('Frequency')
    plt.title('Distribution of Token Count in Comments')
    plt.show()

# Generate the token count distribution plot
plot_token_count_distribution(nlp_df, 'Review Text tokens')
```



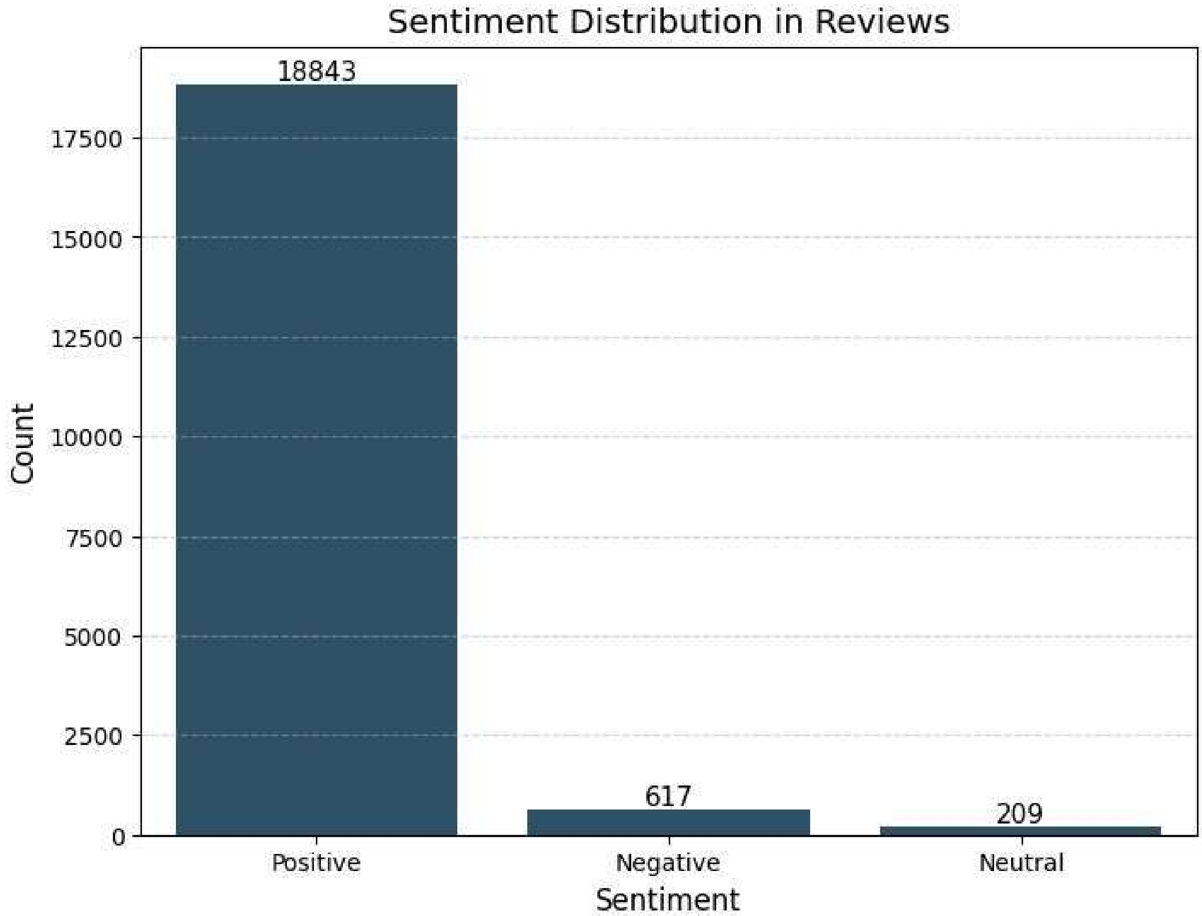
In [28]:
```
# Function to get top N tokens or n-grams
def get_top_tokens(df, token_column='Review text tokens', top_n=50):
    all_tokens = [token for tokens in df[token_column] for token in tokens]
    token_counts = Counter(all_tokens)
    return token_counts.most_common(top_n)

# Function to create a DataFrame from frequency counts
def create_frequency_df(counter, columns=['Word', 'Frequency']):
    return pd.DataFrame(counter.items(), columns=columns)

# General plotting function for bar charts
def plot_top_frequencies(df, title, xlabel, column_name):
    plt.figure(figsize=(14, 8))
    bars = plt.bar(df[column_name], df['Frequency'], color=colors[1])

    # Add labels
    for bar in bars:
        plt.text(bar.get_x() + bar.get_width() / 2., bar.get_height() - max(5, bar.
                 f'{int(bar.get_height())}', ha='center', color='black', fontsize=1

    # Customize and show plot
    plt.xlabel(xlabel, fontsize=12)
    plt.ylabel('Frequency', fontsize=12)
    plt.title(title, fontsize=16)
    plt.xticks(rotation=45, ha='right')
    plt.grid(True, axis='y', linestyle='--', alpha=0.7)
    plt.tight_layout()
    plt.show()

# Get top tokens and plot
top_50_tokens = get_top_tokens(nlp_df, 'Review Text tokens', 50)
```

```
top_50_tokens_df = create_frequency_df(dict(top_50_tokens))
plot_top_frequencies(top_50_tokens_df.head(25), 'Top 25 Word Frequency in Tokenized
```



In [29]:

```
# Plot the sentiment count
plt.figure(figsize=(8, 6))
ax = sns.countplot(x="Review Text clean_sentiment", data=nlp_df)

# Add labels and title
plt.xlabel("Sentiment", fontsize=12)
plt.ylabel("Count", fontsize=12)
plt.title("Sentiment Distribution in Reviews", fontsize=14)

# Display value labels on top of each bar
for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', fontsize=11, color='black', xytext=(0, 5)
                textcoords='offset points')

# Reduce gridline visibility for a cleaner look
plt.grid(visible=True, axis='y', linestyle='--', alpha=0.5)

plt.show()
```



Data Preprocessing

Separate Features and Labels

In [30]:
```
label_encoder = LabelEncoder()

X = nlp_df['Review Text clean'].to_list() # Text column
# Convert categorical classes
y = nlp_df['Review Text clean_sentiment'].to_list()


y1 = label_encoder.fit_transform(y)

# Check if the conversion was successful
print(f"Unique values in y_train_encoded after encoding: {y1}")
 # Target column
print(len(X))
print(len(y))
```

```
Unique values in y_train_encoded after encoding: [2 2 2 ... 2 2 2]
19669
19669
```

In [30]:

```

```

Train / Test Split

In [31]:

```
### Feature Encoding
```

BERT (Bidirectional Encoder Representations from Transformers)

In [32]:

```
X_train, X_val, y_train, y_val = train_test_split(X,y1,test_size=0.2, random_state=
#print(X_train.count())
```

In [34]:

```
# Install required libraries
# pip install transformers datasets torch scikit-learn

from transformers import BertTokenizer, BertForSequenceClassification, Trainer, Tra
from sklearn.model_selection import train_test_split
from torch.utils.data import Dataset
import torch

# Assuming X (text data) and y (labels) are already prepared as lists or arrays
# Example: X = ["Sample text 1", "Sample text 2"], y = [0, 1]

# Step 1: Define Dataset Class
class TextDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_length):
        self.texts = texts
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_length = max_length

    def __len__(self):
        return len(self.texts)

    def __getitem__(self, idx):
        text = self.texts[idx]
        label = self.labels[idx]
        encoding = self.tokenizer(
            text,
            max_length=self.max_length,
            padding="max_length",
            truncation=True,
            return_tensors="pt",
        )
        return {
            "input_ids": encoding["input_ids"].squeeze(0),
            "attention_mask": encoding["attention_mask"].squeeze(0),
```

```
            "labels": torch.tensor(label, dtype=torch.long),
        }

# Step 2: Prepare Tokenizer and Model
model_name = "bert-base-uncased"
tokenizer = BertTokenizer.from_pretrained(model_name)
model = BertForSequenceClassification.from_pretrained(model_name, num_labels=len(se

# Step 3: Split Data and Create Dataset Objects

train_dataset = TextDataset(X_train, y_train, tokenizer, max_length=128)
val_dataset = TextDataset(X_val, y_val, tokenizer, max_length=128)

# Step 4: Define Training Arguments
training_args = TrainingArguments(
    output_dir="./results",          # Directory to save model
    num_train_epochs=3,              # Number of epochs
    per_device_train_batch_size=16,  # Batch size for training
    per_device_eval_batch_size=16,   # Batch size for evaluation
    evaluation_strategy="epoch",     # Evaluate every epoch
    save_strategy="epoch",           # Save model every epoch
    logging_dir="./logs",            # Log directory
    learning_rate=2e-5,              # Learning rate
    load_best_model_at_end=True,     # Load the best model at the end
)

# Step 5: Create Trainer
trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=val_dataset,
    tokenizer=tokenizer,
)

# Step 6: Train the Model
trainer.train()

# Step 7: Evaluate the Model
results = trainer.evaluate()
print("Evaluation Results:", results)

# Optional: Save the model
trainer.save_model("./bert-finetuned")
```

```
Some weights of BertForSequenceClassification were not initialized from the model ch
eckpoint at bert-base-uncased and are newly initialized: ['classifier.bias', 'classi
fier.weight']
You should probably TRAIN this model on a down-stream task to be able to use it for
predictions and inference.
/usr/local/lib/python3.10/dist-packages/transformers/training_args.py:1568: FutureWa
rning: `evaluation_strategy` is deprecated and will be removed in version 4.46 of
🤗 Transformers. Use `eval_strategy` instead
  warnings.warn(
<ipython-input-34-cb192934b911>:63: FutureWarning: `tokenizer` is deprecated and wil
l be removed in version 5.0.0 for `Trainer.__init__`. Use `processing_class` instea
d.
  trainer = Trainer(
```

[2952/2952 19:43, Epoch 3/3]

Epoch	Training Loss	Validation Loss
1	0.183700	0.134810
2	0.088600	0.142956
3	0.045900	0.154931

[246/246 00:29]

```
Evaluation Results: {'eval_loss': 0.13481032848358154, 'eval_runtime': 29.8361, 'eva
l_samples_per_second': 131.854, 'eval_steps_per_second': 8.245, 'epoch': 3.0}
```

In [36]:

```
from sklearn.metrics import classification_report

# Get predictions
preds = trainer.predict(val_dataset)
pred_labels = torch.argmax(torch.tensor(preds.predictions), axis=1).numpy()

# Generate report
print(classification_report(y_val, pred_labels, target_names=["Negative", "Neutral"
```

```
              precision    recall  f1-score   support

    Negative       0.79      0.26      0.39       132
     Neutral       0.78      0.16      0.26        45
    Positive       0.97      1.00      0.98      3757

    accuracy                           0.96      3934
   macro avg       0.84      0.47      0.54      3934
weighted avg       0.96      0.96      0.95      3934
```

In [43]:

```
from transformers import BertTokenizer, BertForSequenceClassification
import torch

# Load saved model and tokenizer
tokenizer = BertTokenizer.from_pretrained("./sentiment_model")
model = BertForSequenceClassification.from_pretrained("./sentiment_model")

# Sentiment prediction function
def predict_sentiment(text):
```

```
    # Tokenize input text
    inputs = tokenizer(text, return_tensors="pt", truncation=True, padding=True, ma

    # Perform inference
    with torch.no_grad():
        outputs = model(**inputs)

    # Get predicted class
    logits = outputs.logits
    predicted_class = torch.argmax(logits, dim=1).item()

    # Map class to sentiment
    sentiment_map = {0: "Negative", 1: "Neutral", 2: "Positive"}
    return sentiment_map[predicted_class]

# Example usage
review = "The product quality is good! Absolutely love it."
print(f"Sentiment: {predict_sentiment(review)}")
```

```
Sentiment: Positive
```