## textanalysi

June 29, 2025

## 1 Data importation

#### 1.1 Understanding the Data

```
import pandas as pd
# Show all columns
pd.set_option('display.max_columns', None)

# Show all rows (be careful with large data!)
pd.set_option('display.max_rows', None)

# Don't truncate column contents
pd.set_option('display.max_colwidth', None) # For pandas >= 1.0
# Prevent scientific notation for numbers
pd.set_option('display.float_format', '{:.2f}'.format)
data = pd.read_csv("~/Downloads/week5_customer_reviews.csv")
data.columns
```

# 2 What are the main columns in the dataset and what does each represent?

Column			
Name	Description		
review_id	A unique identifier for each review. Useful for referencing or tracking specific reviews.		
customer_name and an analyzing repeat			
	reviewers or customer behavior.		
raw_reviewThe original review text exactly as written by the customer. May include typos,			
	punctuation, emojis, etc.		
product	The name or ID of the product being reviewed. Helps group or compare reviews		
	across different products.		
rating	The numerical rating given by the customer (e.g., from 1 to 5). Useful for sentiment		
	analysis or quality scoring.		

Column		
Name	Description	
date	The date when the review was written. Useful for time-based analysis or trends.	
cleaned_revilew processed version of raw_review, typically cleaned by removing stopwords,		
	punctuation, and applying lowercasing, etc. This is what you'd usually use for NLP	
	or modeling.	
review_lengthe number of words or characters in the cleaned review. Useful for analyzing		
	verbosity or filtering short/long reviews.	

#### 2.1 What are some examples of messy elements in the raw\_review column?

Row Messy Elements	Explanation
<pre>0 han\@; d 1 emplo\(yee on. 2 p~{}#layer 3 missi: =" '#_on 4 m~,(! @!:~y</pre>	Emojis (, ), special characters (\@,;), garbled Unicode Escape characters (\(), likely a typo or broken word Mixed special characters (~, {}, #), corrupted text Emojis (, ), strange punctuation mix (:="'#_) Heavy use of punctuation and symbols (~,(!@!:~), emoji (), broken words

#### 2.2 How many unique products are reviewed in the dataset?

#### 2.2.1 7 unique products:

- 1. Toaster
- 2. Smartwatch
- 3. Phone Case
- 4. Headphones
- 5. Shoes
- 6. Blender
- 7. Mug

#### 3 Cleaning Tasks

## 3.1 How can you remove all special characters, emojis, and numbers from the raw\_review column using Python?

You can clean the raw\_review column in your DataFrame by removing all special characters, emojis, and numbers using regular expressions in combination with Python string processing tools like re.

Here's a complete example:

#### 3.1.1 Cleaning Function

```
import re

def clean_text(text):
    if pd.isnull(text):
        return ""

# Remove emojis and non-ASCII characters
    text = text.encode('ascii', 'ignore').decode('ascii')

# Remove special characters and numbers (keep only letters and spaces)
    text = re.sub(r'[^A-Za-z\s]', '', text)

# Remove extra spaces and lowercase everything
    text = re.sub(r'\s+', '', text).strip().lower()
    return text
```

#### 3.1.2 Apply It to raw\_review Column

data['cleaned\_review'] = data['raw\_review'].apply(clean\_text)

- 3.2 Write a function in Python that strips extra spaces and lowercases the review text.
  - 1. Removes extra spaces (leading, trailing, and multiple spaces in between words)
  - 2. Converts all characters to lowercase

#### 3.2.1 Function: Strip Extra Spaces & Lowercase

```
def clean_basic(text):
    if pd.isnull(text):
        return ""

# Remove leading/trailing whitespace and reduce multiple spaces to one cleaned = ' '.join(text.strip().split())

# Convert to lowercase return cleaned.lower()
```

#### 3.2.2 Apply to Your DataFrame

```
data['cleaned_review'] = data['raw_review'].apply(clean_basic)
```

3.3 What is the difference between raw\_review and cleaned\_review after text cleaning? Illustrate with 3 examples

```
[39]: import re
      def clean_text(text):
          if pd.isnull(text):
              return ""
          # Remove emojis and non-ASCII characters
          text = text.encode('ascii', 'ignore').decode('ascii')
          # Remove special characters and numbers (keep only letters and spaces)
          text = re.sub(r'[^A-Za-z\s]', '', text)
          # Remove extra spaces and lowercase everything
          text = re.sub(r'\s+', ' ', text).strip().lower()
          return text
      data['cleaned_review'] = data['raw_review'].apply(clean_text)
[40]: def clean_basic(text):
          if pd.isnull(text):
              return ""
          # Remove leading/trailing whitespace and reduce multiple spaces to one
          cleaned = ' '.join(text.strip().split())
          # Convert to lowercase
          return cleaned.lower()
```

#### 3.4 1. Compute Number of Words in Each Review

To compute the number of words in each cleaned\_review:

```
# Ensure NaNs don't cause errors
data['review_length'] = data['cleaned_review'].fillna('').apply(lambda x: len(x.split()))
This counts how many space-separated tokens (words) are in each review.
```

#### 3.5 2. Categorize Reviews as Positive / Neutral / Negative

data['cleaned\_review'] =data['cleaned\_review'].apply(clean\_basic)

You can categorize sentiment based on the rating column:

```
def get_sentiment(rating):
    if rating <= 2:</pre>
```

```
return 'Negative'
         elif rating == 3:
             return 'Neutral'
         else:
             return 'Positive'
     data['sentiment'] = data['rating'].apply(get_sentiment)
     3.6
            3. Which Product Got the Most Negative Reviews (rating 2)?
     You can filter and then use value_counts():
     # Filter negative reviews
     negative_reviews = data[data['rating'] <= 2]</pre>
     # Count by product
     most_negative_product = negative_reviews['product'].value_counts().idxmax()
     count = negative_reviews['product'].value_counts().max()
     print(f"The product with the most negative reviews is '{most_negative_product}' with {count} re
     If you want to see all products ranked by number of negative reviews:
     print(negative_reviews['product'].value_counts())
[41]: # Ensure NaNs don't cause errors
      data['review_length'] = data['cleaned_review'].fillna('').apply(lambda x: len(x.
       ⇔split()))
      def get_sentiment(rating):
          if rating <= 2:</pre>
              return 'Negative'
          elif rating == 3:
              return 'Neutral'
          else:
              return 'Positive'
```

```
[42]: # Filter negative reviews
negative_reviews = data[data['rating'] <= 2]

# Count by product
most_negative_product = negative_reviews['product'].value_counts().idxmax()</pre>
```

data['sentiment'] = data['rating'].apply(get\_sentiment)

```
count = negative_reviews['product'].value_counts().max()
print(f"The product with the most negative reviews is '{most_negative_product}'
with {count} reviews.")
```

The product with the most negative reviews is 'Blender' with 316 reviews.

#### 3.7 Bar Chart: Number of Reviews per Product

#### **3.7.1** Insight:

- All products have a similar number of reviews ( $\sim 700$  each).
- This balance suggests that the dataset may have been sampled evenly across products, which is good for **unbiased product comparison**.
- Products like **Headphones**, **Shoes**, and **Mugs** slightly edge out others in review count, but differences are minor.

#### 3.8 Review Length vs Rating (Boxplot)

#### **3.8.1** Insight:

- The median review length is nearly identical across all ratings (centered around 9 words).
- Some 5-star reviews have outliers on the longer end, but overall distribution is very similar.
- Conclusion: There's no strong relationship between review length and sentiment/rating.

#### 3.9 Correlation & Averages

Average review lengths:

Negative 9.64 Neutral 9.45 Positive 9.53

Correlation between review length and rating: -0.01

#### **3.9.1** Insight:

- The correlation of -0.01 confirms that review length and rating are nearly unrelated.
- Slightly longer reviews appear in negative sentiment, but the difference is marginal.

#### 3.10 Summary

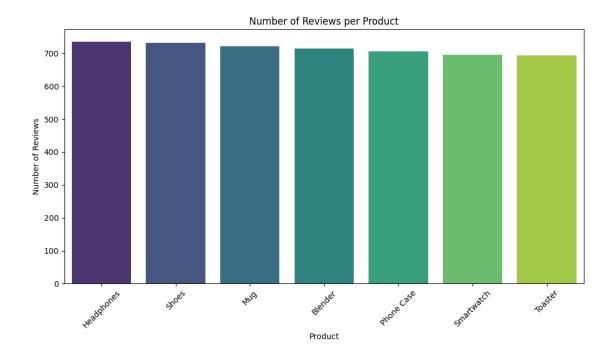
Question	Insight
Average review length by	Very similar across all: ~9.5 words
sentiment	
Most-reviewed product	Headphones (barely), but all are equally represented
Long reviews = better reviews?	No. Review length does not predict sentiment or rating

```
[43]: avg_length_by_sentiment = data.groupby('sentiment')['review_length'].mean()
      print(avg_length_by_sentiment)
     sentiment
     Negative
                9.64
     Neutral
                9.45
     Positive
                9.53
     Name: review_length, dtype: float64
[44]: import matplotlib.pyplot as plt
      import seaborn as sns
      # Count reviews per product
      product_counts = data['product'].value_counts()
      # Plot
      plt.figure(figsize=(10, 6))
      sns.barplot(x=product_counts.index, y=product_counts.values, palette='viridis')
      plt.title('Number of Reviews per Product')
      plt.xlabel('Product')
      plt.ylabel('Number of Reviews')
      plt.xticks(rotation=45)
      plt.tight_layout()
     plt.show()
```

/tmp/ipykernel\_73229/2286281743.py:9: FutureWarning:

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

sns.barplot(x=product\_counts.index, y=product\_counts.values,
palette='viridis')



```
[45]: correlation = data['review_length'].corr(data['rating'])
print(f"Correlation between review length and rating: {correlation:.2f}")
```

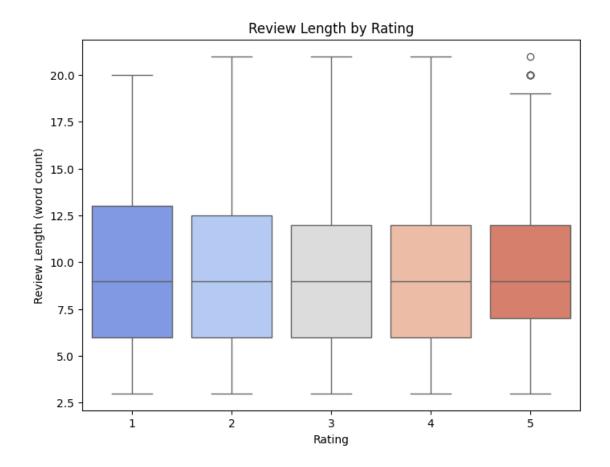
Correlation between review length and rating: -0.01

```
[46]: plt.figure(figsize=(8, 6))
    sns.boxplot(x='rating', y='review_length', data=data, palette='coolwarm')
    plt.title('Review Length by Rating')
    plt.xlabel('Rating')
    plt.ylabel('Review Length (word count)')
    plt.show()
```

/tmp/ipykernel\_73229/3781088033.py:2: FutureWarning:

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

sns.boxplot(x='rating', y='review\_length', data=data, palette='coolwarm')



[]: