```
In [2]: |import numpy as np
        import tensorflow as tf
        from tensorflow import keras
        import pandas as pd
        import seaborn as sns
        from pylab import rcParams
        import string
        import re
        import matplotlib.pyplot as plt
        import math
        from matplotlib import rc
        from sklearn.model selection import train test split
        from collections import Counter, defaultdict
        from bs4 import BeautifulSoup
        from sklearn.metrics import accuracy_score
        from sklearn.metrics import classification_report, confusion_matrix
        import nltk
        from nltk.corpus import stopwords
        from wordcloud import WordCloud
        %matplotlib inline
        sns.set(style='darkgrid', palette='pastel', font_scale=1.5)
        rcParams['figure.figsize'] = 14, 8
        RANDOM\_SEED = 50
        np.random.seed(RANDOM_SEED)
        nltk.download('stopwords')
        [nltk_data] Downloading package stopwords to
        [nltk_data]
                        C:\Users\esber\AppData\Roaming\nltk_data...
        [nltk_data] Package stopwords is already up-to-date!
Out[2]: True
In [7]: train = pd.read_csv("/Users/esber/Documents/PythonProjects/data/TrainDataReview.csv")
```

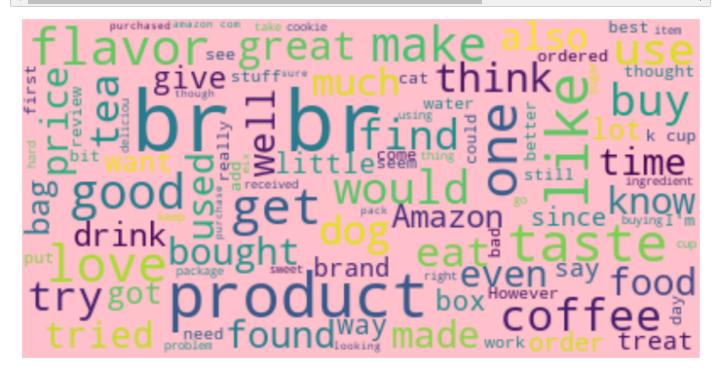
test = pd.read_csv("/Users/esber/Documents/PythonProjects/data/TestDataReview.csv")

```
In [8]: f = sns.countplot(x='sentiment', data=train)
    f.set_title("Sentiment Distribution Result")
    f.set_xticklabels(['Negative', 'Positive'])
    plt.xlabel("");
```



```
In [9]: text = " ".join(review for review in train.review)

wordcloud = WordCloud(max_font_size=50, max_words=100, background_color="pink", stopwords=:
    plt.figure()
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")
    plt.show();
```



```
In [10]: class Tokenizer:

    def clean(self, text):
        no_html = BeautifulSoup(text).get_text()
        clean = re.sub("[^a-z\s]+", " ", no_html, flags=re.IGNORECASE)
        return re.sub("(\s+)", " ", clean)

    def tokenize(self, text):
        clean = self.clean(text).lower()
        stopwords_en = stopwords.words("english")
        return [w for w in re.split("\W+", clean) if not w in stopwords_en]
```

```
In [11]: | class MultinomialNaiveBayes:
             def __init__(self, classes, tokenizer):
               self.tokenizer = tokenizer
               self.classes = classes
             def group_by_class(self, X, y):
               data = dict()
               for c in self.classes:
                 data[c] = X[np.where(y == c)]
               return data
             def fit(self, X, y):
                 self.n_class_items = {}
                 self.log_class_priors = {}
                 self.word_counts = {}
                 self.vocab = set()
                 n = len(X)
                 grouped_data = self.group_by_class(X, y)
                 for c, data in grouped_data.items():
                   self.n_class_items[c] = len(data)
                   self.log_class_priors[c] = math.log(self.n_class_items[c] / n)
                   self.word_counts[c] = defaultdict(lambda: 0)
                   for text in data:
                     counts = Counter(self.tokenizer.tokenize(text))
                     for word, count in counts.items():
                         if word not in self.vocab:
                              self.vocab.add(word)
                         self.word_counts[c][word] += count
                 return self
             def laplace_smoothing(self, word, text_class):
               num = self.word_counts[text_class][word] + 1
               denom = self.n_class_items[text_class] + len(self.vocab)
               return math.log(num / denom)
             def predict(self, X):
                 result = []
                 for text in X:
                   class_scores = {c: self.log_class_priors[c] for c in self.classes}
                   words = set(self.tokenizer.tokenize(text))
                   for word in words:
                       if word not in self.vocab: continue
                       for c in self.classes:
                         log_w_given_c = self.laplace_smoothing(word, c)
                         class_scores[c] += log_w_given_c
                   result.append(max(class_scores, key=class_scores.get))
                 return result
```

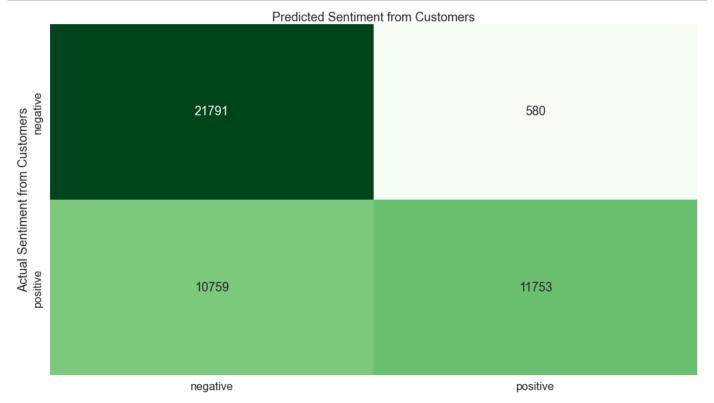
```
In [12]: X = train['review'].values
                                     y = train['sentiment'].values
                                      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDOM_state=RANDO
In [14]: | MNB = MultinomialNaiveBayes(
                                                      classes=np.unique(y),
                                                      tokenizer=Tokenizer()
                                      ).fit(X_train, y_train)
In [15]: y_hat = MNB.predict(X_test)
In [16]: | accuracy_score(y_test, y_hat)
Out[16]: 0.747365372189916
In [17]: print(classification_report(y_test, y_hat))
                                                                                                precision
                                                                                                                                                    recall f1-score
                                                                                                                                                                                                                                 support
                                                                                   0
                                                                                                                    0.67
                                                                                                                                                             0.97
                                                                                                                                                                                                     0.79
                                                                                                                                                                                                                                          22371
                                                                                   1
                                                                                                                    0.95
                                                                                                                                                             0.52
                                                                                                                                                                                                     0.67
                                                                                                                                                                                                                                          22512
                                                                                                                                                                                                     0.75
                                                                                                                                                                                                                                         44883
                                                      accuracy
                                                   macro avg
                                                                                                                   0.81
                                                                                                                                                             0.75
                                                                                                                                                                                                     0.73
                                                                                                                                                                                                                                          44883
                                                                                                                                                                                                                                         44883
                                      weighted avg
                                                                                                                    0.81
                                                                                                                                                             0.75
                                                                                                                                                                                                     0.73
In [18]: cnf_matrix = confusion_matrix(y_test, y_hat)
                                      cnf_matrix
```

Out[18]: array([[21791,

[21791, 580], [10759, 11753]], dtype=int64)

```
In [29]: class_names = ["negative", "positive"]
fig,ax = plt.subplots()

sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, fmt="d", cmap="Greens", cbar=False, xticlax.xaxis.set_label_position('top')
plt.tight_layout()
plt.ylabel('Actual Sentiment from Customers')
plt.xlabel('Predicted Sentiment from Customers');
```



In []:	
In []:	
In []:	