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| University of St. Gallen  School of Management, Economic, Law,  Social Sciences and International Affairs (HSG)  Programming with Advanced Computer Languages  Dr. Mario Silic |
| **Sentiment Analysis of Restaurant Reviews**  A Case Study |
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# Introduction

A large share of customers opts for or against a restaurant based on past reviews. Thus, it is crucial for companies to know what is written about them online. Because of increasing data availability companies struggle to gain strategic insights and track the companies’ performance (Weisskopf & Masset, 2018). Therefore, the goal of this project is to help restaurants gain real-time indications of customer satisfaction. This will allow companies to make data-based decisions to improve their performance. In the context of our project, we will analyze the sentiments of individual restaurant reviews with the help of text-mining.

# Project-setup

## 2.1 Determination of project environment

The entire project, from data acquisition to graphics creation, was written in the integrated Colaboratory development environment. Specifically, Colaboratory was chosen to create and share live code, visualizations and code documentation within the team without the need to install Python and Machine Learning tools locally on the desktop. Furthermore, the entire project was written in Python 3 in order to use the required libraries from Python.

## Determination of data set

To create a sentiment analysis and key messages based on customer reviews, we needed a restaurant record. Above all, open-source platforms such as GitHub and Kaggle offered themselves here. In the end, anonymous restaurant reviews were used to provide consistent customer reviews. The raw data used contains 1000 lines and two columns ("Review" and "Liked"). Each line corresponds to a customer review ("Review"), whereby the rating ("Liked") differentiates between negative (0) and positive (1). (Kaggle, 2018)

# Code outline

* **Line 1 – 23 Installation of required libraries:** All necessary libraries are installed and imported such as the panda data reader which is a necessity for the program to run.
* **Line 25 – 40 Data import and saving to a panda data frame:** The data is imported from the local .tsv file and saved to a data frame using the panda library. Furthermore, we check how many entries we have.
* **Line 41 – 67 Building a sentiment label**: The tagging of the data ("labeling") consists essentially of being able to train the model on the basis of tasks and their solutions to solve similar and unseen tasks (Martins, 2018). In the context of our project, the task for the model was to find the sentiment of a review. Therefore, we created a new column in the data frame that is called sentiment to represent a positive and negative experience in the restaurant. We created the column based on the “liked” column where 0 indicates negative and 1 indicates positive.
* **Line 68 – 81 Label Transformation:** To train machine learning models with the labels, the labels had to be converted into a numeric form (Mayer, 2019). Therefore, we used the label encoder to create two sentiments id (0 and 1).
* **Line 82 – 113 Helper function for Text normalisation:** As mentioned above, textual data must be represented in a numerical form for the creation of the model. Therefore, we need to tokenise data, meaning transforming the reviews text to vectors. To limit tokenization to the most important words, text normalization is applied. The normalization of the data is intended to erase unimportant information that affects the accuracy of the model. Consequently, within the framework of our project, the review data had to be normalized and then transformed into a numerical form. For reasons of efficiency, normalization was included as a helper function of tokenization. Specifically, we removed all the stopwords and applied stemming.
* **Line 119 – 161 Text normalisation and Model creation:** The tokenizer transforms the data into streams of token objects, with each token object identifying its own word or punctuation within a sentence (Porsteinsson, 2019). While there are several ways to make the tokenization of the data, we chose the "bag of words" method to measure the frequency of each token. In a next step, the tokens were converted into numbers using a vectorizer (vectorizer). As a tokenizer the CountVectorizer of Sklearn was used. (D'Souza, 2018) In a final step, the significance of a token was weighted using the TF-IDF methodology. TF-IDF stands for term frequency-inverse document frequency. The TF-IDF weight is a statistical measure of how important a word is for a document in a collection or corpus. The meaning increases in proportion to the number of occurrences of a word in the document but is balanced by the frequency of the word in the corpus. For the TF-IDF transformation also the Sklearn Library was used (D'Souza, 2018). Furthermore, we split the data between test and training data in order to make sure that we test the model with data that the model has not yet seen to make sure we rule out overfitting. In the last step, we create a model with the help of the Multinomial Naive Bayes as a check to see whether the text normalisation and test-training split have worked successfully.
* **Line 162 – 251 Model training with other classifiers:** Given the variety of classification algorithms available to create and train a model, a model evaluation was done within the work (Sidana, 2019). To be able to evaluate the models objectively, therefore, a helper function was written which standardizes the procedure per model and uses the same vectors as an argument for each model. The choice of classification algorithms to be evaluated was based on the Naive Bayes algorithm, the logistic regression, the random forest classifier, and the linear SVC.
* **Line 252 – 273 Model evaluation:** In order to determine the classification algorithm to be optimized, the accuracy value ("accuracy value") was used as the decisive criterion. In this regard, the classification algorithm having the highest accuracy value was followed up. In our case, the naive bayes was the algorithm that created the most accurate model, therefore we decided to visualize the results of the naive bayes algorithm only.
* **Line 274 – 348 Model visualisation**: In order to get a better understanding of our results we illustrated the test results graphically in a confusion matrix. This allowed us to have a better overview of the recall and precision value.

# Code

1. # -\*- coding: utf-8 -\*-
2. """Untitled1.ipynb
4. Automatically generated by Colaboratory.
6. Original file is located at
7. https://colab.research.google.com/drive/1iF5tNNoR2lhqVU4bNgQL1viJa8n6mv0Q
8. """
10. # install mglearn:
11. !pip install mglearn
12. # import libraries required:
13. **import** os
14. **import** glob
15. **from** pprint **import** pprint
17. **import** sklearn
18. **import** numpy as np # linear algebra
19. **import** pandas as pd # data processing, CSV file I/O (e.g. pd.read\_csv)
21. **from** tqdm.auto **import** tqdm
23. **import** io
25. """# Data import and Data preparation"""
27. # upload Restaurant\_Reviews.tsv from your local drive
29. **from** google.colab **import** files
30. uploaded = files.upload()
32. # Saving the dataset in a Panda Dataframe
34. df = pd.read\_csv("Restaurant\_Reviews.tsv", sep='\t')
36. df.head(100)
38. # show row length to see how much data we have
39. len(df)
41. """# Building a sentiment classifier"""
43. #New column created with help of a mapping from the values in the "Liked" column
44. df['Sentiment'] = df.Liked.map({
45. 0: 'Negativ',
46. 1: 'Positive'
47. })
48. df.head(10)
50. # drop the null values in the review column to have only clean data. check the new length
51. df.Review.isna().sum()
52. #keep the ones that are not not null
53. df = df[~df.Review.isna()]
54. len(df)
56. # show number of entries per sentiment to make sure we have a balanced dataset (roughly 50%)
57. **import** matplotlib.pyplot as plt; plt.style.use('seaborn')
59. fig = plt.figure(figsize=(8, 6))
61. df\
62. .groupby('Sentiment')['Review']\
63. .count()\
64. .plot(kind='bar', ylim=0)
66. plt.show()
68. """# Label transformation & Text normalisation"""
70. # Use LabelEncoder  to convert text labels into values/id's
71. **from** sklearn.preprocessing **import** LabelEncoder

74. lbl\_enc = LabelEncoder()
75. lbl\_enc.fit(sorted(df['Sentiment'].unique()))
77. # obtaining a numeric representation of an array
78. df['sentiment\_id'] = lbl\_enc.transform(df['Sentiment'])
80. df.head(10)
82. # Here we introduce the stemmatization function, which we use afterwards within the count vectorizer
83. # We have to describe the function separately because Sklearn does not offer a native stemming function
84. """ Helper function for Text normalisation"""

87. **import** nltk
88. **from** nltk.stem.porter **import** PorterStemmer
89. **from** textblob **import** TextBlob
90. **import** re
91. !pip install textblob
92. nltk.download('punkt')
93. SENT\_DETECTOR = nltk.data.load('tokenizers/punkt/english.pickle')

96. porter\_stemmer = PorterStemmer()
98. # Use TextBlob function in order to stem the data of the review rext
99. **def** textblob\_tokenizer(str\_input):
100. blob = TextBlob(str\_input.lower())
101. tokens = blob.words
102. words = [token.stem() **for** token **in** tokens]
103. **return** words
105. # Use NLTK's PorterStemmer
106. **def** stemming\_tokenizer(str\_input):
107. words = re.sub(r"[^A-Za-z0-9\-]", " ", str\_input).lower().split()
108. words = [porter\_stemmer.stem(word) **for** word **in** words]
109. **return** words
111. stemming\_tokenizer("I went fishing to get fishes")
112. textblob\_tokenizer("I went fishing to get fishes")
113. """# Text normalization and model creation"""
114. ## NNOTE: In this code section we transform the review data into text data. Labels have already been encoded
115. **from** sklearn.model\_selection **import** cross\_val\_score, StratifiedShuffleSplit, StratifiedKFold
116. **from** sklearn.model\_selection **import** train\_test\_split
117. **from** sklearn.feature\_extraction.text **import** CountVectorizer, TfidfTransformer, TfidfVectorizer
118. **from** sklearn.naive\_bayes **import** MultinomialNB

121. # Split data
122. train\_index, test\_index = next(StratifiedShuffleSplit(n\_splits=1, test\_size=0.2).split(df['Review'], df['sentiment\_id']))
124. # Get data
125. train\_df = df.iloc[train\_index]
126. test\_df = df.iloc[test\_index]
128. # Get data
129. X\_train = train\_df['Review'].to\_numpy()
130. X\_test = test\_df['Review']
131. y\_train\_labels = train\_df['sentiment\_id']
132. y\_test\_labels = test\_df['sentiment\_id']
133. **print**(type(X\_train))
135. # Convert labels to numbers NOTE: Here we do not convert to labels because we have done so above!!!
136. y\_train = y\_train\_labels.to\_numpy()
137. y\_test = y\_test\_labels
138. **print**(type(y\_train))

141. # Use a CountVectorizer for bag-of-words
142. count\_vect = CountVectorizer(min\_df=5, ngram\_range=(1, 2), stop\_words='english', tokenizer=textblob\_tokenizer)
143. X\_train\_counts = count\_vect.fit\_transform(X\_train)
144. X\_test\_counts = count\_vect.fit\_transform(X\_test)
146. # Use Tfidf to transform the counts into tfidf weights
147. tfidf\_transformer = TfidfTransformer(sublinear\_tf=True, norm='l2')
148. X\_train\_tfidf = tfidf\_transformer.fit\_transform(X\_train\_counts)
149. X\_test\_tfidf = tfidf\_transformer.fit\_transform(X\_test\_counts)
151. # TO GET FEATURES (get\_feature\_names()), YOU HAVE TO USE TfidfVectorizer
152. # This is the same as the two above
153. tfidf = TfidfVectorizer(sublinear\_tf=True, min\_df=5, norm='l2', ngram\_range=(1, 2), stop\_words='english')
154. X\_train\_tfidf = tfidf.fit\_transform(X\_train)
155. X\_test\_tfidf = tfidf.transform(X\_test)
157. # To test whether the transforamtion of the data worked, we insert the created variables as inputs to the multinomialNB to check if it can create a model
158. clf = MultinomialNB()
159. clf.fit(X\_train\_counts, y\_train)
161. """# Model training with other classifiers"""
163. # A reusable function that we can loop through for every single classifier
164. # import Classifiers
165. **from** sklearn.naive\_bayes **import** MultinomialNB
166. **from** sklearn.linear\_model **import** LogisticRegression
167. **from** sklearn.ensemble **import** RandomForestClassifier
168. **from** sklearn.svm **import** LinearSVC
170. # Import training utilities
171. **from** sklearn.feature\_selection **import** chi2
173. # Import metrics
174. **from** sklearn.metrics **import** accuracy\_score, precision\_recall\_fscore\_support, classification\_report, confusion\_matrix
176. #Here we create a standardised function that can be used for each classifier to create a model. this allows comparability between the effectiveness of the classifiers
177. **def** train(model, features, labels, num\_cv):
179. results = []
181. kfold = StratifiedShuffleSplit(n\_splits=num\_cv, test\_size=0.2)
183. **for** train, test **in** kfold.split(features, labels):
185. clf = sklearn.clone(model)
187. X\_train = features[train]
188. X\_test = features[test]
189. y\_train = labels[train]
190. y\_test = labels[test]
192. clf.fit(X\_train, y\_train)
194. y\_pred = clf.predict(X\_test)
196. a = accuracy\_score(y\_test, y\_pred)
197. p, r, f, \_ = precision\_recall\_fscore\_support(y\_test, y\_pred, average='macro')
198. report = classification\_report(y\_test, y\_pred)
200. results.append({
201. 'accuracy': a,
202. 'precision': p,
203. 'recall': r,
204. 'fscore': f,
205. 'report': report
206. })
208. **return** results
210. #In this code part we loop through the function above with different classifiers!!
211. #NOTE: This code has dependencies with the text representation, since we take the vectorized data from there
213. # Define the different classifier that we want to usemodels
214. models = [
215. MultinomialNB(),
216. LogisticRegression(random\_state=0, solver='liblinear', multi\_class='auto'),
217. RandomForestClassifier(n\_estimators=200, max\_depth=3),
218. LinearSVC()
219. ]
220. # trainings set is split 5 times and the results are appended to the back of the entries list
222. num\_cv = 5
224. entries = []
226. # Go over each Classifier
227. **for** model **in** models:
228. model\_name = model.\_\_class\_\_.\_\_name\_\_
230. # NOTE: the train x\_train\_tfid and y\_train are variables we created earlier! We shall not overwrite them. review data is not vectorised and the model can not analyze it!!!!!!
232. results = train(model, X\_train\_tfidf, y\_train, num\_cv)
233. #Create areport for the test results and store it to a list.
235. **for** fold\_idx, metric **in** enumerate(results):
236. entries.append({
237. 'model\_name': model\_name,
238. 'fold\_idx': fold\_idx,
239. 'accuracy': metric['accuracy'],
240. 'precision': metric['precision'],
241. 'recall': metric['recall'],
242. 'fscore': metric['fscore'],
243. 'report': metric['report']
244. })
246. # convert list to a panda dataframe
247. cv\_df = pd.DataFrame(entries)
249. cv\_df
251. """# Model evaluation"""
253. # reusable function to illustrate data with a certain type of box plot
254. **import** matplotlib.pyplot as plt; plt.style.use('seaborn')
255. **import** seaborn as sns
257. **def** plot\_metric(df, metric):
258. fig = plt.figure(figsize=(6, 8))
260. sns.boxplot(x='model\_name', y=metric, data=cv\_df[['model\_name', metric]])
261. sns.stripplot(x='model\_name', y=metric, data=cv\_df[['model\_name', metric]],
262. size=8, jitter=True, edgecolor="gray", linewidth=2)
263. plt.xticks(rotation=30, ha='right')
264. plt.show()
266. #create a plot for the accuracy values
267. plot\_metric(cv\_df, 'accuracy')
269. #overarching model evaulation. we see that MultinomialNB is the most efficient one. hence we train the entire training data with SVC to see
270. # if we can increase the scores..
271. cv\_df.groupby('model\_name')[['accuracy', 'precision', 'recall', 'fscore']].mean()
273. """# Model visualisation"""
275. # We use the MultinomialNB and train on the WHOLE training set, without k-fold.
276. model = MultinomialNB()
278. model.fit(X\_train\_tfidf, y\_train)
280. y\_pred = model.predict(X\_test\_tfidf)
282. #we want to graphically illustrate our results in more detail. true positives, false negatives
283. **from** sklearn.utils.multiclass **import** unique\_labels
284. # First, we need a function to draw the confustion matrix
285. **def** plot\_confusion\_matrix(y\_true, y\_pred, classes,
286. normalize=False,
287. title=None,
288. cmap=plt.cm.Reds, ax=None):
289. **if** **not** title:
290. **if** normalize:
291. title = 'Normalized confusion matrix'
292. **else**:
293. title = 'Confusion matrix, without normalization'
295. classes = [classes[i] **for** i **in** unique\_labels(y\_true, y\_pred)]
297. # Compute confusion matrix
298. cm = confusion\_matrix(y\_true, y\_pred)
300. **if** normalize:
301. cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
303. **if** ax **is** None:
304. ax = plt.gca()
306. im = ax.imshow(cm, cmap=cmap)
308. cb = ax.figure.colorbar(im, ax=ax)
310. tick\_marks = np.arange(len(classes))
312. ax.set\_xticks(tick\_marks)
313. ax.set\_yticks(tick\_marks)
315. ax.set\_xticklabels(classes, rotation=0, ha='right', rotation\_mode='anchor')
316. ax.set\_yticklabels(classes, rotation=0)
318. ax.set\_xlabel('Predicted class')
319. ax.set\_ylabel('True class')
321. # Loop over data dimensions and create text annotations.
322. fmt = '.2f' **if** normalize **else** 'd'
323. thresh = cm.max() / 2
324. **for** i **in** range(cm.shape[0]):
325. **for** j **in** range(cm.shape[1]):
326. ax.text(j, i, format(cm[i, j], fmt),
327. ha="center", va="center",
328. color="white" **if** cm[i, j] > thresh **else** "black")
330. #fig.tight\_layout()
331. plt.grid(False)
333. **return** ax
335. fig, ax = plt.subplots(figsize=(12, 12))
337. plot\_confusion\_matrix(y\_test, y\_pred, classes=lbl\_enc.classes\_, normalize=True)
339. ax.set\_title('Confusion Matrix (Normalized Values)')
340. plt.show()
342. fig, ax = plt.subplots(figsize=(12, 12))
344. plot\_confusion\_matrix(y\_test, y\_pred, classes=lbl\_enc.classes\_, normalize=True)
346. ax.set\_title('Confusion Matrix (Normalized Values)')
347. plt.show()

# Conclusion

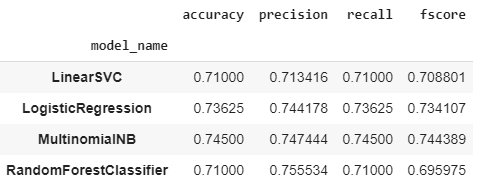


Figure 1: Accuracy of the four different models (own figure)

The table indicates that the MultionomialNB provides the highest accuracy rate of 74.5%. Therefore, we used the MultionomialNB to train the entire data set to see if we could increase the scores. Afterwards, we created a confusion matrix to visualize our model.

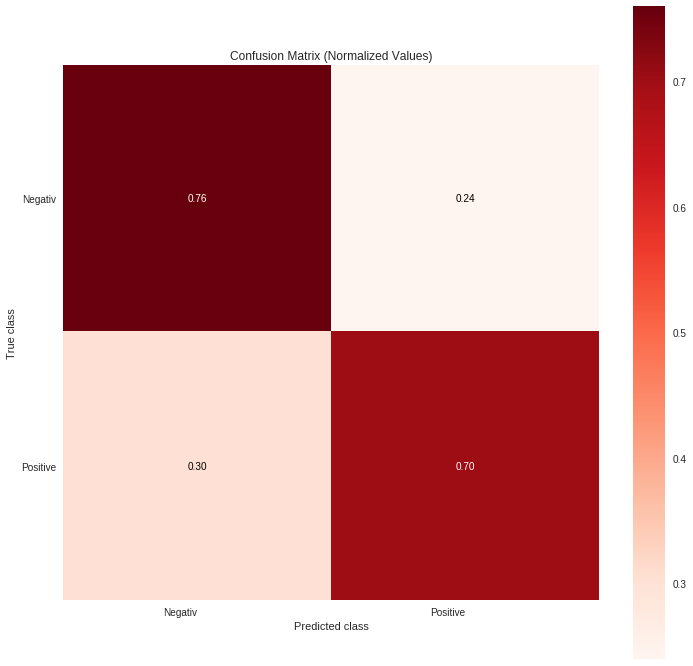


Figure 2: Confusion Matrix for the MultinomialNB (own figure)

The matrix shows that the model identified 70% of the positive ratings correctly and 76% of the negative ratings. Therefore, this model can be used by restaurants to gain a real-time overview of their current online performance with respect to customer reviews and enable them to take accurate actions to boost their performance.

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