Wine quality score prediction through reviews sentiment analysis and regression models Notebook

March 1, 2021

[1]:
```
import pandas as pd
import numpy as np
import nltk
import matplotlib.pyplot as plt
from nltk import word_tokenize
from nltk import pos_tag
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords

from nltk.corpus import wordnet as wn
from nltk.stem.wordnet import WordNetLemmatizer
from nltk import word_tokenize, pos_tag
from collections import defaultdict

from sklearn.feature_extraction import DictVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
from scipy.sparse import hstack
from sklearn.utils import shuffle
from sklearn import metrics
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.neural_network import MLPRegressor
from sklearn.svm import SVR
from sklearn.model_selection import cross_val_score
from wordcloud import WordCloud,STOPWORDS
import time
import seaborn as sns
```

[2]:
```
nltk.download('wordnet')
nltk.download('punkt')
nltk.download('stopwords')
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     /home/bigdata-01QYD/s259444/nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     /home/bigdata-01QYD/s259444/nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     /home/bigdata-01QYD/s259444/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[2]:
```
True
```

[3]:
```
column_names=["country", "description", "designation", "province", "region_1",␣
 ↪"region_2", "variety", "winery", "quality"]
wine_df = pd.read_csv('dev.tsv', sep='\t', header=1, names = column_names)
wine_df.head()
```

[3]:
```
       country                                        description designation  \
0           US  Simple and dry, this Cabernet has modest black…         NaN
1           US  This lovely wine captures the floral, perfumed…         NaN
2     Portugal  The aromas are the thing here, as so often wit…         NaN
3        Italy  This is an interesting, outright strange wine …        Natì
4  New Zealand  Classic gooseberry and pink grapefruit notes f…         NaN

         province           region_1           region_2             variety  \
0      California        Paso Robles      Central Coast  Cabernet Sauvignon
1          Oregon  Willamette Valley  Willamette Valley      Gewürztraminer
2      Alentejano                NaN                NaN    Touriga Nacional
3  Southern Italy           Pompeiano                NaN       Coda di Volpe
4     Marlborough                NaN                NaN     Sauvignon Blanc

               winery  quality
0         Castle Rock     31.0
1      Château Bianca     35.0
2  Herdade do Esporão     41.0
3          Sorrentino     37.0
4          Cloudy Bay     48.0
```

[4]:
```
wine_df.shape
```

[4]:
```
(120743, 9)
```

The dataset has 120743 rows and 9 columns. For the columns we have the country from where the vine has been produced, the province and the two regions. So the province inlcudes the regions, and the country includes the province.

Then there is the designation that is the name give to the wine by the produce, the variety describes the type of grapes that are used, then the winery from which is produced.

Then there's the description provided by the reviewer, and also the quality scores.

All the attributes are categorical and nominal, exeception made for the quality one, that is numerical and ordinal too.

[5]:
```
wine_df.describe()
```

[5]:
```
             quality
count  120743.000000
mean       46.277863
std        11.924830
min         0.000000
25%        38.000000
50%        46.000000
75%        55.000000
max       100.000000
```

from the table above, we can see the mean and the standard deviation, and also understand partially its distribution thanks to the percentiles.

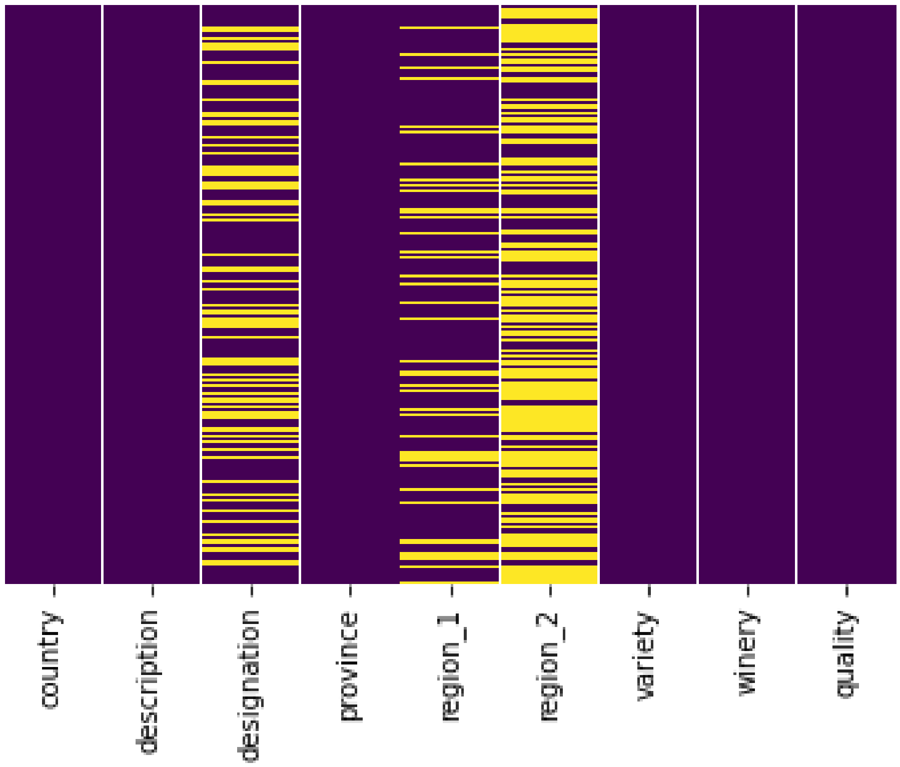
[6]:
```
wine_df.isnull().values.any()
```

[6]:
```
True
```

[7]:
```
wine_df.isnull().sum()
```

[7]:
```
country            5
description        0
designation    36518
province           5
region_1       20008
region_2       72007
variety            0
winery             0
quality            0
dtype: int64
```

[8]:
```
ax = sns.heatmap(wine_df.isnull(), yticklabels=False,cbar=False,cmap='viridis')
ax.figure.savefig('null_heatmap.png')
```



The table and plot show that region_2 has more than the half of null values, region_1 20000 records and designation 30000. There also some records (5) that have also the country value null. So as first solution, designation, region_1 and region_2 columns are dropped, and also the 5 rows with country value null.

[4]:
```
wine_df = wine_df.dropna(how="any", subset=["winery", "country", "variety",␣
 ↪"province"])
wine_df = wine_df.drop(["designation", "region_1", "region_2"], axis=1)
```

[10]:
```
wine_df.shape
```

[10]:
```
(120738, 6)
```

Let's now do a brief cardinality analysis of the attributes of the dataset.

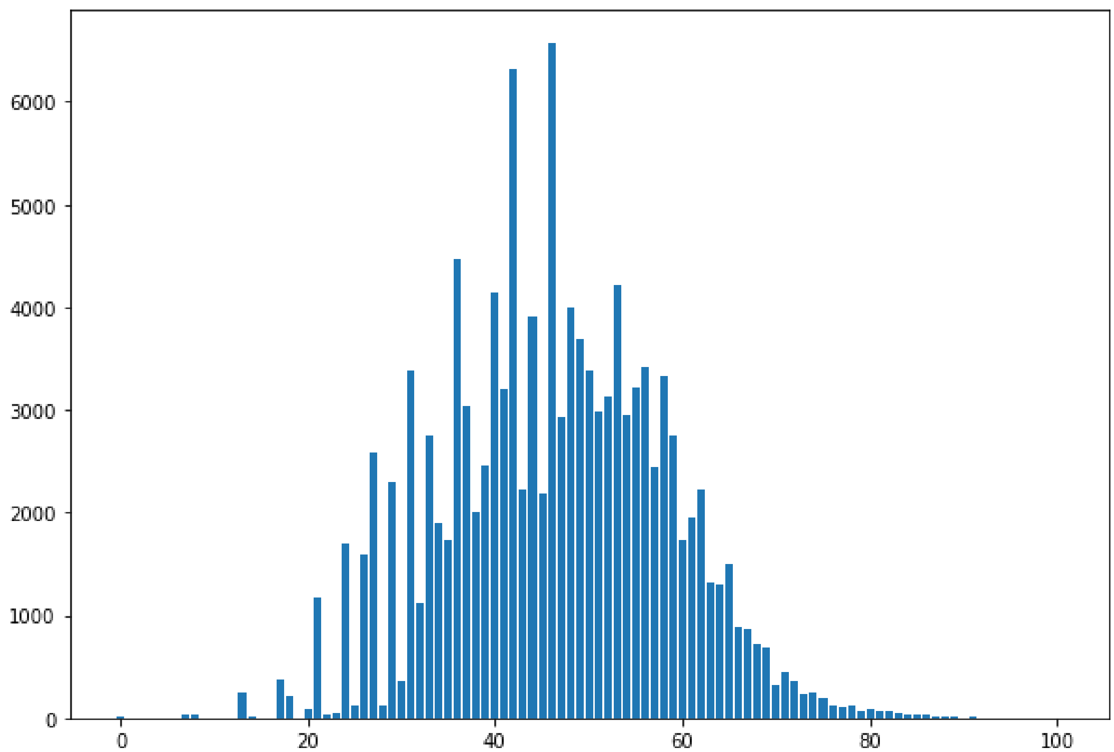
[11]:
```
for column in wine_df.columns:
    uniq = np.unique(wine_df[column])
    print('{}: {} distinct values\n'.format(column,len(uniq)))
```

```
country: 48 distinct values

description: 85001 distinct values
```

```
province: 444 distinct values

variety: 603 distinct values

winery: 14104 distinct values

quality: 86 distinct values
```

It's kind of funny to notice that only half of the descriptions are unique.

[12]:
```
votes = wine_df.groupby(['quality']).size()
indexes = votes.index
fig, ax = plt.subplots(figsize=(10,7))
ax.bar(indexes, votes)
plt.show()
fig.savefig('score_distribution.png')
```



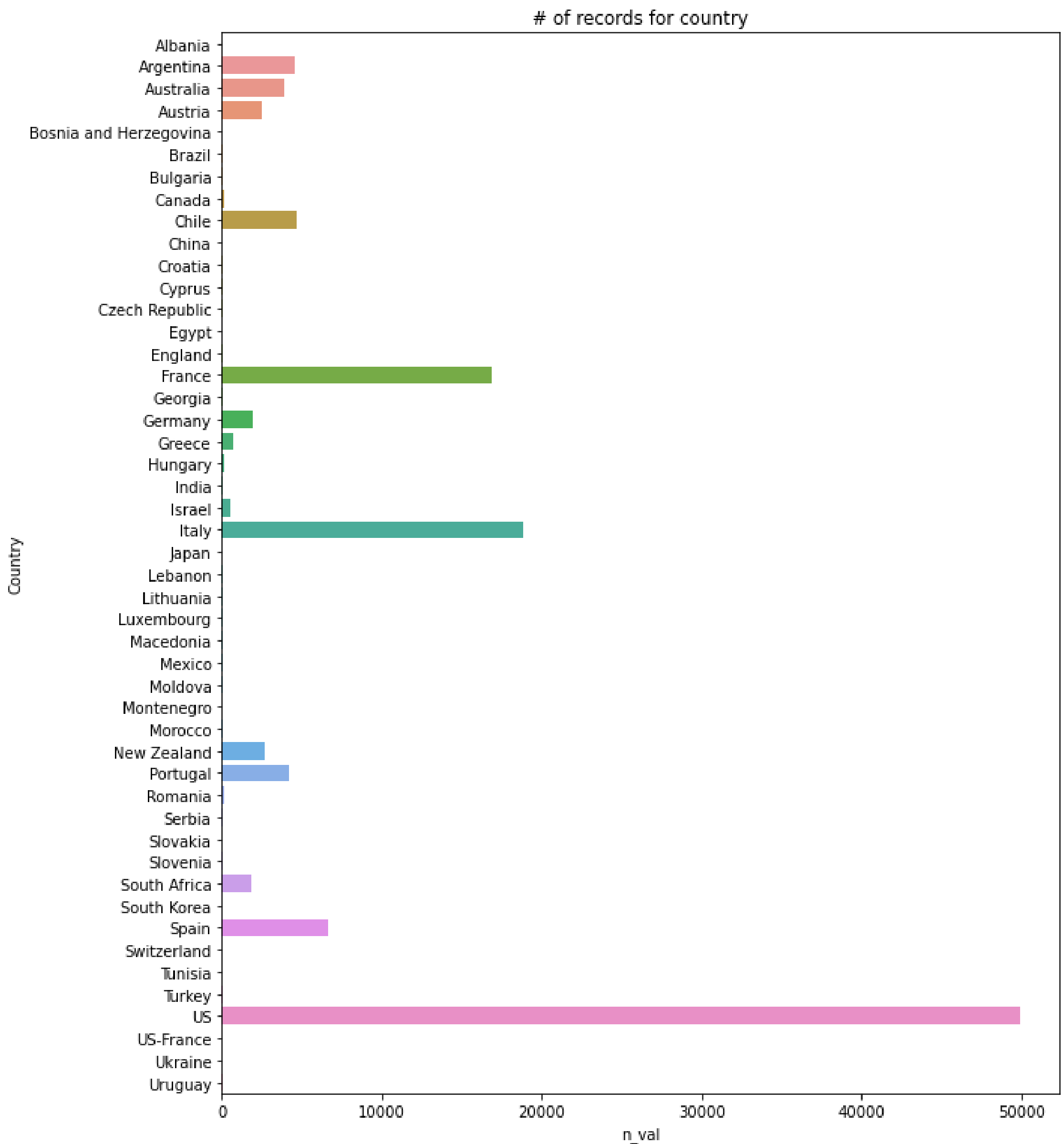
This is the distribution of the quality score. It's very close to a normal one, with 46,27 as mean.

Now just out of curiosity, let's investigate on how many zeros there are in the quality scores. Because if someone gives 0 in a range of 100 to the scores, the wine must not be wine but winegar. So we can consider them like kinda of outlier

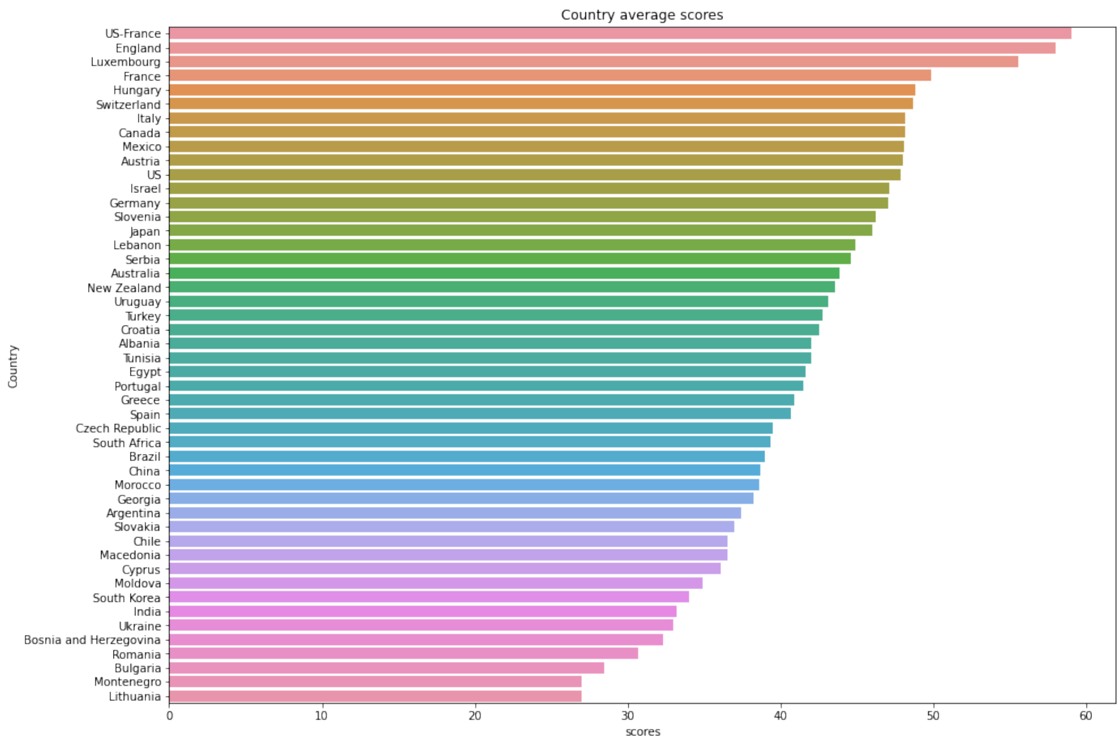
[13]:
```
print("There are {} evaluations were the score assigned is 0" .format(votes.
↪iloc[0]) )
```

```
There are 15 evaluations were the score assigned is 0
```

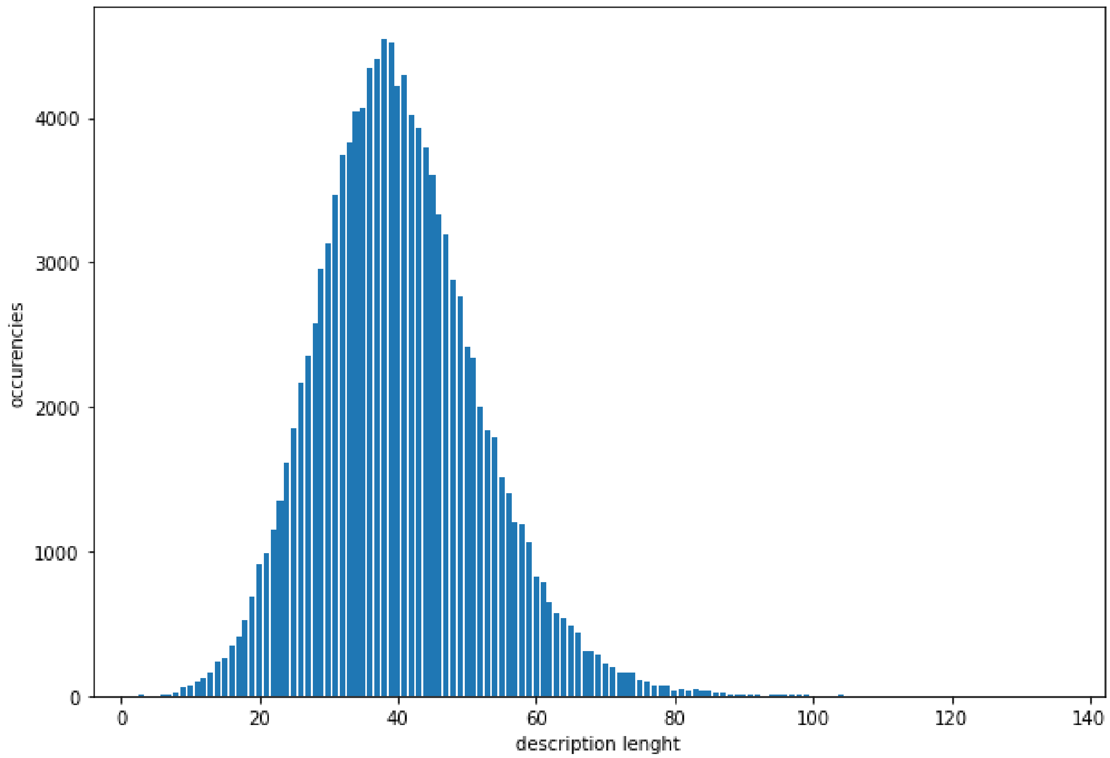
[19]:
```
val_for_country = wine_df.groupby('country').size()
plt.figure(figsize=(10,13))
ax = sns.barplot(x=val_for_country, y=val_for_country.index)
plt.title('# of records for country')
plt.xlabel('n_val')
plt.ylabel('Country')
ax.figure.savefig('records_for_country.png')
```



[23]:
```
country_avg = wine_df.groupby('country').mean()['quality'].
 ↪sort_values(ascending=False).to_frame()
plt.figure(figsize=(15,11))
ax = sns.barplot(x=country_avg['quality'], y=country_avg.index)
plt.title('Country average scores')
plt.xlabel('scores')
plt.ylabel('Country')
ax.figure.savefig('country_average_scores.png')
```



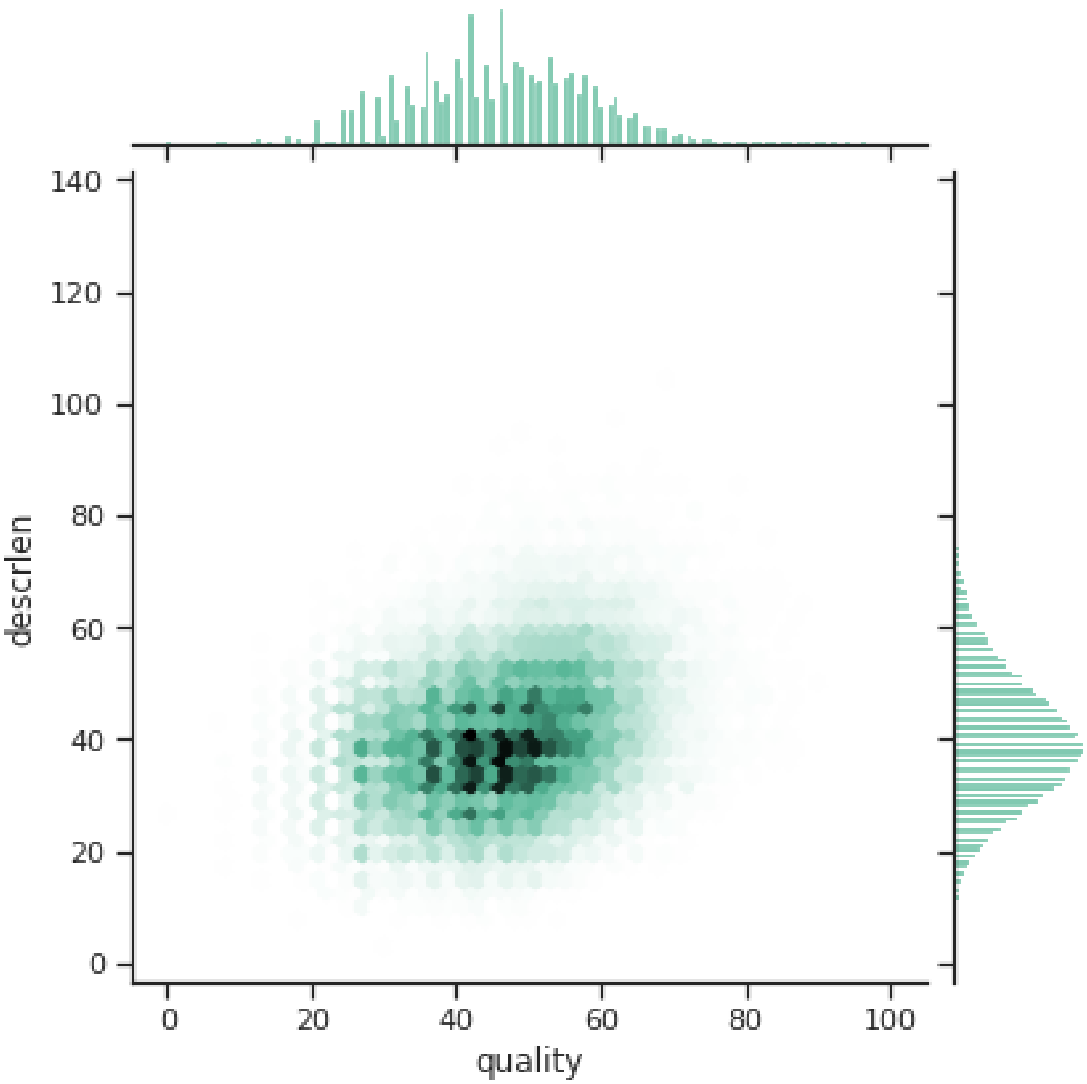
[16]:
```
wine_df['descrlen'] = wine_df['description'].apply(lambda descr:len(descr.
 ↪split()))
len_series = wine_df.groupby('descrlen').size()
fig, ax = plt.subplots (figsize = (10,7))
ax.bar(len_series.index, len_series)
ax.set_xlabel('description lenght')
ax.set_ylabel('occurencies')
plt.show()
plt.savefig('descrlen_distribution.png')
```




```
<Figure size 432x288 with 0 Axes>
```

The plot shows the distribution of the description lenghts, to be interpreted as number of words for description. This one too is a normal distribution, with averagea around 40.

[17]:
```
sns.set_theme(style='ticks')
ax = sns.jointplot(x=wine_df['quality'], y=wine_df['descrlen'], kind='hex',␣
↪color="#4CB391")
ax.fig.savefig('descrlen-quality_jointplot.png')
```



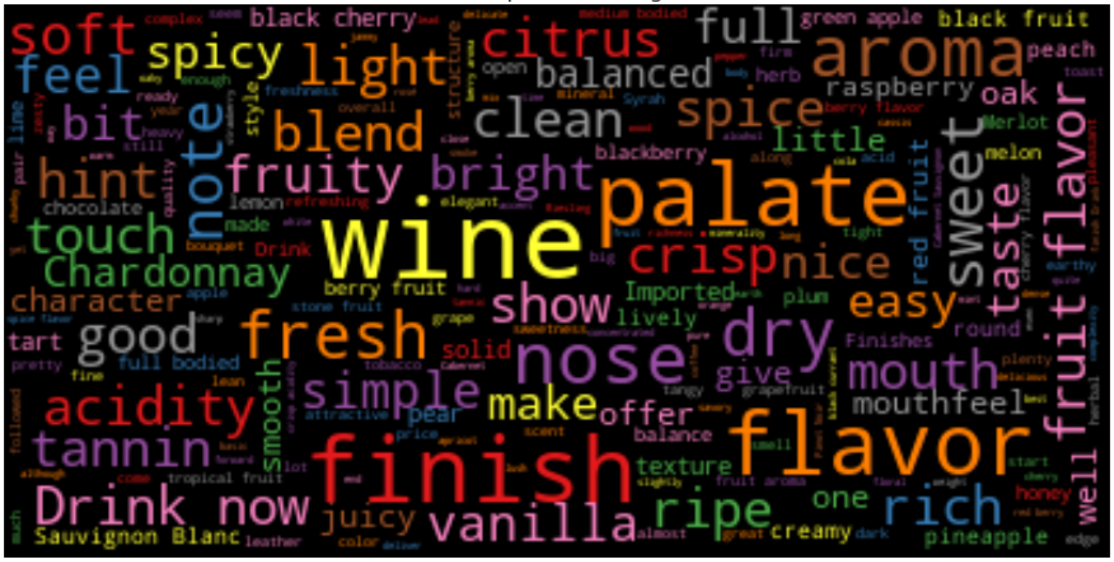
Now, let's divide the scores in 5 equal ascending categories. For computing the division we use percentiles. So we have five percentiles and for the grades: Average one, then discending loe grade rated, and bad rated, while ascending from the average grade, we have descrete and great rated. So let's plot the word clouds just to make and idea of what the descriptions tell for the different gradeds.

[18]:
```
ix = [p for p in range(20,120,20)]
perc = [np.percentile(wine_df['quality'], p) for p in range(20,120,20)]
categories=['bad', 'low-grade', 'average', 'discrete', 'great']
sns.set_context("talk")
for i,p in enumerate(perc):
  print("")
  plt.figure(figsize= (16,8))
```

```python
stringa = "WC_" + categories[i] + "_rated.png"
stringa= str(stringa)
plt.title('Word cloud of Description of {} rated wine' .format(categories[i]))
wc = WordCloud(max_words=1000,max_font_size=40,background_color='black', stopwords = STOPWORDS,colormap='Set1')
wc.generate(' '.join(wine_df[wine_df['quality']<p]['description']))
plt.imshow(wc,interpolation="bilinear")
plt.axis('off')
plt.show()
plt.savefig(stringa)
```


```
<Figure size 432x288 with 0 Axes>
```

Word cloud of Description of low-grade rated wine



<Figure size 432x288 with 0 Axes>

Word cloud of Description of average rated wine

<Figure size 432x288 with 0 Axes>

Word cloud of Description of discrete rated wine


```
<Figure size 432x288 with 0 Axes>
```

Word cloud of Description of great rated wine


```
<Figure size 432x288 with 0 Axes>
```

[5]:
```python
wnl = WordNetLemmatizer()
stop_words = set(stopwords.words('english'))
```

```python
tag_map = defaultdict(lambda : wn.NOUN)
tag_map['J'] = wn.ADJ
tag_map['V'] = wn.VERB
tag_map['R'] = wn.ADV

def tolemmas(text):
    tokens = word_tokenize(text)
    lemma_function = WordNetLemmatizer()
    lemmas = ""
    for token, tag in pos_tag(tokens):
        lemma = lemma_function.lemmatize(token, tag_map[tag[0]])
        #if not lemma in stop_words:
        lemmas = lemmas + lemma + " "
    return lemmas
```

```python
[6]: wine_df['description'] = wine_df['description'].replace('[^a-zA-Z0-9]', ' ',␣
     ↪regex = True)
     wine_df['description'] = wine_df['description'].str.lower()
     wine_df['description'] = wine_df['description'].map(lambda sentence:
     ↪tolemmas(sentence))
```

In the two cells above starts the preprocessing of the description attribute. The categorical attributes cannot be given to the machine learning model as they are. Because those models only works with numbers. So first thing first, punctuaction marks are removed, then all the text is converted to lower letters. The next important step is to lemmatize words. From wikipedia, lemmatisation is the process of grouping together the inflected forms of a word so they can be analysed as a single item, identified by the word's lemma, or dictionary form. Unlike stemming, lemmatisation depends on correctly identifying the intended part of speech and meaning of a word in a sentence, as well as within the larger context surrounding that sentence, such as neighboring sentences or even an entire document. This is why, in the function defined above, nouns, verbs, adverbs and pronoun are mapped. So some examples can be was->be mice->mouse ->meeting->meet. This is different from stemming that is the process of reducing inflected words to their word stem, base or root form—generally a written word form.

After doing this, each description, that is a vector of words, is encoded with Tfidf. Deeply analyzed during the course, Tfidf is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. The tf–idf value increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word, which helps to adjust for the fact that some words appear more frequently in general. One important thing to be aware is that the model with this encoding does not learn the "meaning" of the words, for that there are other types of encoding and models.

After doing different simulations, I decided to not remove stop words, because they can bring additional value to the model, in fact the r2 score is higher with stopword than without. This I think is more valid also for a different model, that I will not explore in this notebook, because was only mentioned in theory lessons of the course, but not deeply analyzed.

[7]:
```
vect_tfidf = TfidfVectorizer(min_df=5)
descrtfidf = vect_tfidf.fit_transform(wine_df['description']).toarray()

vect_1hot = DictVectorizer(sparse=False, dtype=int)
wine_df_tohot = wine_df.filter(['country', 'province', 'variety', 'winery'],␣
↪axis=1)
data = wine_df_tohot.to_dict('records')
cat_1hot = vect_1hot.fit_transform(data)

X_dev = np.concatenate([descrtfidf, cat_1hot], axis=1)
y_dev = wine_df['quality']
X_dev, y_dev = shuffle(X_dev, y_dev, random_state=0)
```

For the other categorical attributes, one-hot encoding is used.

For the developement dataset in both tfidf and one-hot encoding fit_transform is used, so this means that the distribution of the data is fitted and then the same data is transformed to the encoding

In the cell above, the evaluation dataset is loaded, and the same preprocessing steps are made. Here no rows are dropped, cause these missing lines would obviously cause issues with the submission. The difference with the developement set is that here for both tfidf and one-hot encoding we use first the fit method and then the transform one. This because the dev set is way more larger than the evaluation one, so "reality" can be better rappresented.

[8]:
```
column_names_ev=["country", "description", "designation", "province",␣
↪"region_1", "region_2", "variety", "winery"]
wine_df_ev = pd.read_csv('eval.tsv', sep='\t', header=0, names =␣
↪column_names_ev)
wine_df_ev = wine_df_ev.drop(["designation", "region_1", "region_2"], axis=1)

wine_df_ev['description'] = wine_df_ev['description'].replace('[^a-zA-Z0-9]', '␣
↪', regex = True)
wine_df_ev['description'] = wine_df_ev['description'].str.lower()
wine_df_ev['description'] = wine_df_ev['description'].map(lambda sentence:
↪tolemmas(sentence))

vect_tfidf = TfidfVectorizer(min_df=5)
vect_tfidf.fit(wine_df['description'])
descr_ev_tfidf = vect_tfidf.transform(wine_df_ev['description']).toarray()

wine_df_ev_tohot = wine_df_ev.filter(['country', 'province', 'variety',␣
↪'winery'], axis=1)
data_ev = wine_df_ev_tohot.to_dict('records')
vect_1hot = DictVectorizer(sparse=False, dtype=int)
vect_1hot.fit(data)
cat_1hot_ev = vect_1hot.transform(data_ev)
```

```
X_ev = np.concatenate([descr_ev_tfidf, cat_1hot_ev], axis=1)
```

[23]:
```
ridge_params = {'alpha': [0.1, 0.2, 0.7]}
```

[24]:
```
clf = Ridge(alpha=0.1)
scores = cross_val_score(clf, X_dev, y_dev, cv=4)
print(scores)
```

```
[0.7107029  0.71915213 0.71570793 0.71326291]
```

[25]:
```
clf = Ridge(alpha=0.2)
scores = cross_val_score(clf, X_dev, y_dev, cv=4)
print(scores)
```

```
[0.71754641 0.72590613 0.72302613 0.72092031]
```

Since the r2 scores of the cross validation has no large variance, and since the RAM resources of the account at Jupyter Polito are limited, the other hyperparameter setting of alpha will be explored without cross validation. Also because for now, no PCA for dimensionality reduction is applied.

[10]:
```
seed=1234
X_train, X_val, y_train, y_val = train_test_split(X_dev, y_dev, test_size = 0.
↪2, random_state=seed)
```

[26]:
```
clf = Ridge(alpha=0.5)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_val)
y_true = y_val
r2 = r2_score(y_true, y_pred)
print("r2 score for alpha=0.5: {}".format(r2))
```

```
r2 score for alpha=0.5: 0.7339390879492909
```

[27]:
```
clf = Ridge(alpha=0.7)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_val)
y_true = y_val
r2 = r2_score(y_true, y_pred)
print("r2 score for alpha=0.7: {}".format(r2))
```

```
r2 score for alpha=0.7: 0.7344847198556729
```

[28]:
```
clf = Ridge(alpha=0.5)
clf.fit(X_dev, y_dev)
y_pred = clf.predict(X_ev)

pred_df = pd.DataFrame()
pred_df['Id'] = wine_df_ev.index
```

```
pred_df['Predicted'] = y_pred

pred_df.to_csv('Final_sub_ridge_0.5.csv', header=True, index=None)
```

After trying to predict the score with lasso model, it's time to change to **MLPRegressor** used also in lab8. This is a module supplied by scikit learn. It's based on neural network. So with respect to the previous model we lose the "interpretability" of the model but we gain in performance. In fact it's known that NN are kinda of the best in perfomances. What scikit learn does, is to provide like a wrapper to construct the multi layer perceprton regressor, with just a line of code, and this is an advantage. The disadvantage is that with scikit learn is no possible to use GPUs. In fact GPUs perform way better than CPUs for this kind of matrix computations. Good news is that my account on Jupyter.polito is not enabled to use GPUs, so nothing would be changed. Otherwise, the solution would have been implementing the MLPRegressor from scratch with Pytorch, or there are also some libraries that wraps Pytorch with scikit-learn. Combining the advantages of the two.

For this reason no cross validation was applied for this model. But, different setting of some of the hyperparameters were explored in a diffent notebook, for avoiding a kernel restart.

I have decided to add **two hidden layers**. For the activation function the **rectified linear unit** has been choosen. This function is defined like:

$$R(x) = \begin{cases} x \text{ if } x > 0 \\ 0 \text{ if } x <= 0 \end{cases}$$

The biggest advantage of Relu function is that there is no saturation of the gradients. This speed up a lot the stochastic gradient discent, with respect to the tanh and sigmoid fucntions

Learning rate: It is a hyper-parameter that controls how much we are adjusting the weights of our network with respect the loss gradient. The lower the value, the slower we travel along the downward slope. Using a low learning rate might be a good idea, in terms of making sure we do not miss any local minimum, but it can also mean that it will take a lot of time to converge, expecially working with CPUs and not GPUs, especially if we get a stuck in sort of plateau region. There is a lot of research in this field how to initialize the weights and how to adjust the learning rate, also because sometimes is difficult to know how big is the "wall" that gets the model stuck in a local minima.

(form B.Caputo Machine Learning and Deep Learning 2020).

In this project the **lr** is set to the default value 0.001. Other values has been tried (e.g. 0.01) with the adaptive mode (i.e. the lr is divided by 2 if the loss does not improve for the epochs in n_iter_no_change), the classifier gets stuck in a sort of local minimum, so it finds a sub optimal solution, and the perfomances are worst than setting the intial lr to 0.001 and not adaptive.

Number of epochs i.e. max_iteration is set to 180, because after that there no significant improvement on the loss.

[27]:
```
clf = MLPRegressor(hidden_layer_sizes=(128,64), activation='relu',␣
 ↪verbose=True, solver='sgd', max_iter=180, tol=0.01, n_iter_no_change=25)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_val)
y_true = y_val
```

```python
r2 = r2_score(y_true, y_pred)
print("r2 score for MLPregressor: {}".format(r2))
```

```
Iteration 1, loss = 58.47685619
Iteration 2, loss = 25.16348556
Iteration 3, loss = 21.35660277
Iteration 4, loss = 19.19306005
Iteration 5, loss = 17.24127753
Iteration 6, loss = 15.58359859
Iteration 7, loss = 14.91037985
Iteration 8, loss = 13.53853254
Iteration 9, loss = 12.93454563
Iteration 10, loss = 12.24097862
Iteration 11, loss = 11.43025652
Iteration 12, loss = 10.72454331
Iteration 13, loss = 10.23076475
Iteration 14, loss = 9.63218890
Iteration 15, loss = 9.31063889
Iteration 16, loss = 8.60000682
Iteration 17, loss = 8.32127603
Iteration 18, loss = 7.69016729
Iteration 19, loss = 7.31025141
Iteration 20, loss = 6.92619066
Iteration 21, loss = 6.46324693
Iteration 22, loss = 6.36946246
Iteration 23, loss = 5.74046626
Iteration 24, loss = 5.46369452
Iteration 25, loss = 5.32415754
Iteration 26, loss = 4.85906767
Iteration 27, loss = 4.73114508
Iteration 28, loss = 4.20550025
Iteration 29, loss = 4.17765840
Iteration 30, loss = 3.67226107
Iteration 31, loss = 3.56727229
Iteration 32, loss = 3.28176759
Iteration 33, loss = 3.04264505
Iteration 34, loss = 2.89243722
Iteration 35, loss = 2.84081063
Iteration 36, loss = 2.66708737
Iteration 37, loss = 2.44798872
Iteration 38, loss = 2.31497093
Iteration 39, loss = 2.09649200
Iteration 40, loss = 2.08805370
Iteration 41, loss = 1.84330488
Iteration 42, loss = 1.84571495
Iteration 43, loss = 1.71104580
Iteration 44, loss = 1.60835695
```

```
Iteration 45, loss = 1.54390828
Iteration 46, loss = 1.37765020
Iteration 47, loss = 1.30599617
Iteration 48, loss = 1.23521475
Iteration 49, loss = 1.20279614
Iteration 50, loss = 1.10304504
Iteration 51, loss = 1.02341135
Iteration 52, loss = 0.96931766
Iteration 53, loss = 0.94664730
Iteration 54, loss = 0.80740347
Iteration 55, loss = 0.90174755
Iteration 56, loss = 0.83985726
Iteration 57, loss = 0.71124345
Iteration 58, loss = 0.66794968
Iteration 59, loss = 0.64766510
Iteration 60, loss = 0.62313130
Iteration 61, loss = 0.53035063
Iteration 62, loss = 0.61238340
Iteration 63, loss = 0.50913932
Iteration 64, loss = 0.55860235
Iteration 65, loss = 0.53516845
Iteration 66, loss = 0.47845537
Iteration 67, loss = 0.39624716
Iteration 68, loss = 0.39875819
Iteration 69, loss = 0.40593551
Iteration 70, loss = 0.39456990
Iteration 71, loss = 0.34928932
Iteration 72, loss = 0.34412401
Iteration 73, loss = 0.32945828
Iteration 74, loss = 0.38896205
Iteration 75, loss = 0.26433318
Iteration 76, loss = 0.30199256
Iteration 77, loss = 0.25010917
Iteration 78, loss = 0.26085895
Iteration 79, loss = 0.26162013
Iteration 80, loss = 0.26463435
Iteration 81, loss = 0.21590483
Iteration 82, loss = 0.28255589
Iteration 83, loss = 0.21021971
Iteration 84, loss = 0.21090807
Iteration 85, loss = 0.19127355
Iteration 86, loss = 0.24351502
Iteration 87, loss = 0.22158106
Iteration 88, loss = 0.13632376
Iteration 89, loss = 0.13395289
Iteration 90, loss = 0.14869901
Iteration 91, loss = 0.14590884
Iteration 92, loss = 0.14121220
```

```
Iteration 93, loss = 0.18210923
Iteration 94, loss = 0.14424816
Iteration 95, loss = 0.11852419
Iteration 96, loss = 0.09728541
Iteration 97, loss = 0.12577234
Iteration 98, loss = 0.12344787
Iteration 99, loss = 0.07134005
Iteration 100, loss = 0.08569594
Iteration 101, loss = 0.07893226
Iteration 102, loss = 0.10980140
Iteration 103, loss = 0.08785908
Iteration 104, loss = 0.11183543
Iteration 105, loss = 0.07651750
Iteration 106, loss = 0.12581083
Iteration 107, loss = 0.09440404
Iteration 108, loss = 0.09167095
Iteration 109, loss = 0.05456321
Iteration 110, loss = 0.08009692
Iteration 111, loss = 0.08122309
Iteration 112, loss = 0.05742525
Iteration 113, loss = 0.03801444
Iteration 114, loss = 0.07045892
Iteration 115, loss = 0.10070407
Iteration 116, loss = 0.03543064
Iteration 117, loss = 0.05464291
Iteration 118, loss = 0.02947829
Iteration 119, loss = 0.02396475
Iteration 120, loss = 0.03584108
Iteration 121, loss = 0.04067001
Iteration 122, loss = 0.09489499
Iteration 123, loss = 0.09842790
Iteration 124, loss = 0.06235426
Iteration 125, loss = 0.03358241
Iteration 126, loss = 0.05644204
Iteration 127, loss = 0.02853013
Iteration 128, loss = 0.03588636
Iteration 129, loss = 0.04153127
Iteration 130, loss = 0.03996616
Iteration 131, loss = 0.02651245
Iteration 132, loss = 0.02618720
Iteration 133, loss = 0.04347013
Iteration 134, loss = 0.04665164
Iteration 135, loss = 0.02895753
Iteration 136, loss = 0.02792094
Iteration 137, loss = 0.03778098
Iteration 138, loss = 0.07660478
Iteration 139, loss = 0.02431145
Training loss did not improve more than tol=0.010000 for 25 consecutive epochs.
```

```
Stopping.
r2 score for MLPregressor: 0.7966121099596044
```

[31]:
```
clf.fit(X_dev, y_dev)
y_pred = clf.predict(X_ev)

pred_df = pd.DataFrame()
pred_df['Id'] = wine_df_ev.index
pred_df['Predicted'] = y_pred

pred_df.to_csv('Final_MLP_128_64_it180_25.csv', header=True, index=None)
```

```
Iteration 1, loss = 53.36497278
Iteration 2, loss = 23.74714711
Iteration 3, loss = 20.20465267
Iteration 4, loss = 17.84762389
Iteration 5, loss = 16.19518446
Iteration 6, loss = 15.01944114
Iteration 7, loss = 13.80788894
Iteration 8, loss = 12.87584372
Iteration 9, loss = 12.01514529
Iteration 10, loss = 11.28817093
Iteration 11, loss = 10.55714273
Iteration 12, loss = 10.05196476
Iteration 13, loss = 9.38316831
Iteration 14, loss = 8.80913995
Iteration 15, loss = 8.25002876
Iteration 16, loss = 7.75291178
Iteration 17, loss = 7.23323827
Iteration 18, loss = 6.82079867
Iteration 19, loss = 6.31649001
Iteration 20, loss = 6.17899620
Iteration 21, loss = 5.64048992
Iteration 22, loss = 5.33056768
Iteration 23, loss = 5.12040676
Iteration 24, loss = 4.80308721
Iteration 25, loss = 4.60262889
Iteration 26, loss = 4.12656612
Iteration 27, loss = 3.95758679
Iteration 28, loss = 3.66749813
Iteration 29, loss = 3.39255872
Iteration 30, loss = 3.19532563
Iteration 31, loss = 2.97677860
Iteration 32, loss = 2.99294306
Iteration 33, loss = 2.60290440
Iteration 34, loss = 2.49713324
Iteration 35, loss = 2.39456139
Iteration 36, loss = 2.09070856
```

```
Iteration 37, loss = 2.13953935
Iteration 38, loss = 2.00850336
Iteration 39, loss = 1.87431733
Iteration 40, loss = 1.73788850
Iteration 41, loss = 1.60767963
Iteration 42, loss = 1.57401551
Iteration 43, loss = 1.40233436
Iteration 44, loss = 1.34060045
Iteration 45, loss = 1.28603435
Iteration 46, loss = 1.23723703
Iteration 47, loss = 1.14478686
Iteration 48, loss = 1.11825245
Iteration 49, loss = 1.03094831
Iteration 50, loss = 1.00513762
Iteration 51, loss = 0.97046801
Iteration 52, loss = 0.87110679
Iteration 53, loss = 0.85098901
Iteration 54, loss = 0.79878873
Iteration 55, loss = 0.71055517
Iteration 56, loss = 0.61121424
Iteration 57, loss = 0.65860050
Iteration 58, loss = 0.65890070
Iteration 59, loss = 0.67768782
Iteration 60, loss = 0.56628501
Iteration 61, loss = 0.55631477
Iteration 62, loss = 0.52923783
Iteration 63, loss = 0.47441832
Iteration 64, loss = 0.55229303
Iteration 65, loss = 0.43834573
Iteration 66, loss = 0.43147806
Iteration 67, loss = 0.43089906
Iteration 68, loss = 0.37876956
Iteration 69, loss = 0.45088773
Iteration 70, loss = 0.31849531
Iteration 71, loss = 0.34956557
Iteration 72, loss = 0.34015707
Iteration 73, loss = 0.26957032
Iteration 74, loss = 0.32558901
Iteration 75, loss = 0.27094952
Iteration 76, loss = 0.25944357
Iteration 77, loss = 0.31320393
Iteration 78, loss = 0.24635276
Iteration 79, loss = 0.25327411
Iteration 80, loss = 0.26853321
Iteration 81, loss = 0.18427990
Iteration 82, loss = 0.22811718
Iteration 83, loss = 0.23644565
Iteration 84, loss = 0.15789480
```

```
Iteration 85, loss = 0.23140164
Iteration 86, loss = 0.21176052
Iteration 87, loss = 0.20074138
Iteration 88, loss = 0.18211390
Iteration 89, loss = 0.13745740
Iteration 90, loss = 0.14058538
Iteration 91, loss = 0.15662598
Iteration 92, loss = 0.17309826
Iteration 93, loss = 0.16437803
Iteration 94, loss = 0.11623422
Iteration 95, loss = 0.16177184
Iteration 96, loss = 0.15461455
Iteration 97, loss = 0.08285078
Iteration 98, loss = 0.09560941
Iteration 99, loss = 0.08151446
Iteration 100, loss = 0.10533427
Iteration 101, loss = 0.09414676
Iteration 102, loss = 0.14858717
Iteration 103, loss = 0.10624442
Iteration 104, loss = 0.11834992
Iteration 105, loss = 0.11927949
Iteration 106, loss = 0.05708478
Iteration 107, loss = 0.12087947
Iteration 108, loss = 0.12409756
Iteration 109, loss = 0.07621408
Iteration 110, loss = 0.07016926
Iteration 111, loss = 0.07578335
Iteration 112, loss = 0.04543062
Iteration 113, loss = 0.04400092
Iteration 114, loss = 0.05110917
Iteration 115, loss = 0.07250740
Iteration 116, loss = 0.04395513
Iteration 117, loss = 0.04282265
Iteration 118, loss = 0.08876136
Iteration 119, loss = 0.11124681
Iteration 120, loss = 0.08364885
Iteration 121, loss = 0.04589048
Iteration 122, loss = 0.07778984
Iteration 123, loss = 0.06918949
Iteration 124, loss = 0.04321710
Iteration 125, loss = 0.02956152
Iteration 126, loss = 0.02385337
Iteration 127, loss = 0.04695742
Iteration 128, loss = 0.02987689
Iteration 129, loss = 0.05024526
Iteration 130, loss = 0.04113667
Iteration 131, loss = 0.03713177
Iteration 132, loss = 0.03088846
```

```
Iteration 133, loss = 0.03887165
Iteration 134, loss = 0.09398879
Iteration 135, loss = 0.02762025
Iteration 136, loss = 0.03349105
Iteration 137, loss = 0.02952055
Iteration 138, loss = 0.07809873
Iteration 139, loss = 0.03466393
Iteration 140, loss = 0.04561743
Iteration 141, loss = 0.02308116
Iteration 142, loss = 0.01705416
Iteration 143, loss = 0.03788704
Iteration 144, loss = 0.02327840
Iteration 145, loss = 0.06512072
Iteration 146, loss = 0.02254824
Iteration 147, loss = 0.01807213
Iteration 148, loss = 0.01649402
Iteration 149, loss = 0.02480563
Iteration 150, loss = 0.02268671
Iteration 151, loss = 0.00972559
Training loss did not improve more than tol=0.010000 for 25 consecutive epochs.
Stopping.
```

[33]:

```
clf = MLPRegressor(hidden_layer_sizes=(256,128), activation='relu',␣
↪verbose=True, solver='sgd', max_iter=180, tol=0.01, n_iter_no_change=35)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_val)
y_true = y_val
r2 = r2_score(y_true, y_pred)
print("r2 score for MLPregressor: {}".format(r2))
```

```
Iteration 1, loss = 58.39732895
Iteration 2, loss = 24.95301632
Iteration 3, loss = 21.08542204
Iteration 4, loss = 18.62028709
Iteration 5, loss = 16.87199302
Iteration 6, loss = 15.41080970
Iteration 7, loss = 14.04697074
Iteration 8, loss = 13.02643491
Iteration 9, loss = 12.32034061
Iteration 10, loss = 11.15985326
Iteration 11, loss = 10.49603342
Iteration 12, loss = 9.69375657
Iteration 13, loss = 8.95657711
Iteration 14, loss = 8.44922600
Iteration 15, loss = 7.81752241
Iteration 16, loss = 7.22114990
Iteration 17, loss = 6.60146457
Iteration 18, loss = 6.10174544
```

```
Iteration 19, loss = 5.91290717
Iteration 20, loss = 5.45381228
Iteration 21, loss = 4.66781691
Iteration 22, loss = 4.66500247
Iteration 23, loss = 4.09492473
Iteration 24, loss = 3.62670287
Iteration 25, loss = 3.77154771
Iteration 26, loss = 3.02361906
Iteration 27, loss = 3.09155965
Iteration 28, loss = 2.71649758
Iteration 29, loss = 2.61211096
Iteration 30, loss = 2.23356877
Iteration 31, loss = 2.09579770
Iteration 32, loss = 1.89527027
Iteration 33, loss = 1.85850085
Iteration 34, loss = 1.66107625
Iteration 35, loss = 1.52676013
Iteration 36, loss = 1.34920082
Iteration 37, loss = 1.23627939
Iteration 38, loss = 1.10508870
Iteration 39, loss = 0.92529400
Iteration 40, loss = 0.95863039
Iteration 41, loss = 0.92028512
Iteration 42, loss = 0.78665028
Iteration 43, loss = 0.77284990
Iteration 44, loss = 0.67728648
Iteration 45, loss = 0.61660715
Iteration 46, loss = 0.60579218
Iteration 48, loss = 0.47688840
Iteration 49, loss = 0.50901907
Iteration 50, loss = 0.40758613
Iteration 51, loss = 0.34591803
Iteration 52, loss = 0.44444928
Iteration 53, loss = 0.29357474
Iteration 54, loss = 0.34230339
Iteration 55, loss = 0.32929436
Iteration 56, loss = 0.28695597
Iteration 57, loss = 0.22179391
Iteration 58, loss = 0.27113030
Iteration 59, loss = 0.27768308
Iteration 60, loss = 0.20947748
Iteration 61, loss = 0.12855193
Iteration 62, loss = 0.16904783
Iteration 63, loss = 0.15769236
Iteration 64, loss = 0.11590922
Iteration 65, loss = 0.12900534
Iteration 66, loss = 0.13412558
Iteration 67, loss = 0.12245052
```

```
Iteration 68, loss = 0.09282799
Iteration 69, loss = 0.11977312
Iteration 70, loss = 0.06666080
Iteration 71, loss = 0.09025770
Iteration 72, loss = 0.10038424
Iteration 73, loss = 0.09566832
Iteration 74, loss = 0.07666478
Iteration 75, loss = 0.05978297
Iteration 76, loss = 0.08507549
Iteration 77, loss = 0.06519219
Iteration 78, loss = 0.04885032
Iteration 79, loss = 0.06880033
Iteration 80, loss = 0.05298001
Iteration 81, loss = 0.05457982
Iteration 82, loss = 0.03630402
Iteration 83, loss = 0.02582118
Iteration 84, loss = 0.03333586
Iteration 85, loss = 0.03759142
Iteration 86, loss = 0.02400483
Iteration 87, loss = 0.01999782
Iteration 88, loss = 0.03532774
Iteration 89, loss = 0.02538304
Iteration 90, loss = 0.05575188
Iteration 91, loss = 0.03149397
Iteration 92, loss = 0.04383536
Iteration 93, loss = 0.01573186
Iteration 94, loss = 0.01233173
Iteration 95, loss = 0.02157185
Iteration 96, loss = 0.01309035
Iteration 97, loss = 0.01869422
Iteration 98, loss = 0.00912955
Iteration 99, loss = 0.00660146
Iteration 100, loss = 0.02660913
Iteration 101, loss = 0.01106242
Iteration 102, loss = 0.00671042
Iteration 103, loss = 0.00872749
Iteration 104, loss = 0.01531431
Iteration 105, loss = 0.01143603
Iteration 106, loss = 0.00578916
Iteration 107, loss = 0.00388242
Iteration 108, loss = 0.00331832
Iteration 109, loss = 0.01524782
Iteration 110, loss = 0.00724405
Iteration 111, loss = 0.00689096
Iteration 112, loss = 0.00346474
Iteration 113, loss = 0.00406279
Iteration 114, loss = 0.00857455
Iteration 115, loss = 0.01309257
```

```
Iteration 116, loss = 0.02126272
Iteration 117, loss = 0.00831047
Iteration 118, loss = 0.00848713
Iteration 119, loss = 0.00530886
Training loss did not improve more than tol=0.010000 for 35 consecutive epochs.
Stopping.
r2 score for MLPregressor: 0.8107273215720792
```

[35]:
```
clf.fit(X_dev, y_dev)
y_pred = clf.predict(X_ev)

pred_df = pd.DataFrame()
pred_df['Id'] = wine_df_ev.index
pred_df['Predicted'] = y_pred

pred_df.to_csv('Final_MLP_256_6128_it180_35.csv', header=True, index=None)
```

```
Iteration 1, loss = 50.80821905
Iteration 2, loss = 23.64980095
Iteration 3, loss = 19.87913044
Iteration 4, loss = 17.64661621
Iteration 5, loss = 15.91735639
Iteration 6, loss = 14.39996418
Iteration 7, loss = 13.23667957
Iteration 8, loss = 12.15835192
Iteration 9, loss = 11.20425640
Iteration 10, loss = 10.24779404
Iteration 11, loss = 9.69625928
Iteration 12, loss = 9.02875421
Iteration 13, loss = 7.98453979
Iteration 14, loss = 7.59707924
Iteration 15, loss = 6.87155638
Iteration 16, loss = 6.30777028
Iteration 17, loss = 5.88038006
Iteration 18, loss = 5.27883281
Iteration 19, loss = 4.86689831
Iteration 20, loss = 4.58922743
Iteration 21, loss = 4.21002664
Iteration 22, loss = 3.82264057
Iteration 23, loss = 3.42169762
Iteration 24, loss = 3.08430172
Iteration 25, loss = 3.04422483
Iteration 26, loss = 2.49710747
Iteration 27, loss = 2.57124288
Iteration 28, loss = 2.31565225
Iteration 29, loss = 1.99655903
Iteration 30, loss = 1.90909883
Iteration 31, loss = 1.80410477
```

```
Iteration 32, loss = 1.56846713
Iteration 33, loss = 1.39675892
Iteration 34, loss = 1.30466949
Iteration 35, loss = 1.32620937
Iteration 36, loss = 1.12103703
Iteration 37, loss = 1.06943232
Iteration 38, loss = 0.93086192
Iteration 39, loss = 0.83570415
Iteration 40, loss = 0.85046081
Iteration 41, loss = 0.78904827
Iteration 42, loss = 0.62688102
Iteration 43, loss = 0.63555133
Iteration 44, loss = 0.62509318
Iteration 45, loss = 0.54208481
Iteration 46, loss = 0.52077143
Iteration 47, loss = 0.42995887
Iteration 48, loss = 0.40398845
Iteration 49, loss = 0.44171905
Iteration 50, loss = 0.37543426
Iteration 51, loss = 0.38252115
Iteration 52, loss = 0.31490101
Iteration 53, loss = 0.24523984
Iteration 54, loss = 0.21648492
Iteration 55, loss = 0.26364625
Iteration 56, loss = 0.23516137
Iteration 57, loss = 0.24701190
Iteration 58, loss = 0.16701267
Iteration 59, loss = 0.19245004
Iteration 60, loss = 0.18035415
Iteration 61, loss = 0.15497067
Iteration 62, loss = 0.15891468
Iteration 63, loss = 0.13697878
Iteration 64, loss = 0.15185686
Iteration 65, loss = 0.10094345
Iteration 66, loss = 0.16072498
Iteration 67, loss = 0.07675900
Iteration 68, loss = 0.09005880
Iteration 69, loss = 0.09482960
Iteration 70, loss = 0.11833911
Iteration 71, loss = 0.11486698
Iteration 72, loss = 0.08617822
Iteration 73, loss = 0.06263908
Iteration 74, loss = 0.05586519
Iteration 75, loss = 0.05581700
Iteration 76, loss = 0.07601347
Iteration 77, loss = 0.04439674
Iteration 78, loss = 0.04255724
Iteration 79, loss = 0.04911298
```

```
Iteration 80, loss = 0.02566921
Iteration 81, loss = 0.05461125
Iteration 82, loss = 0.05266658
Iteration 83, loss = 0.06815945
Iteration 84, loss = 0.02581990
Iteration 85, loss = 0.01987304
Iteration 86, loss = 0.01543503
Iteration 87, loss = 0.05064561
Iteration 88, loss = 0.02549609
Iteration 89, loss = 0.03389630
Iteration 90, loss = 0.03137019
Iteration 91, loss = 0.07446973
Iteration 92, loss = 0.02577530
Iteration 93, loss = 0.03165049
Iteration 94, loss = 0.02993968
Iteration 95, loss = 0.02045571
Iteration 96, loss = 0.01256603
Iteration 97, loss = 0.01242259
Iteration 98, loss = 0.00879807
Iteration 99, loss = 0.00717021
Iteration 100, loss = 0.00639579
Iteration 101, loss = 0.00826263
Iteration 102, loss = 0.01686545
Iteration 103, loss = 0.02168446
Iteration 104, loss = 0.01444169
Iteration 105, loss = 0.01008615
Iteration 106, loss = 0.00622368
Iteration 107, loss = 0.00424273
Iteration 108, loss = 0.00650476
Iteration 109, loss = 0.00457590
Iteration 110, loss = 0.00938446
Iteration 111, loss = 0.01380974
Iteration 112, loss = 0.00829920
Iteration 113, loss = 0.00610139
Iteration 114, loss = 0.01230427
Iteration 115, loss = 0.00873918
Iteration 116, loss = 0.00760680
Training loss did not improve more than tol=0.010000 for 35 consecutive epochs.
Stopping.
```