Individual_Project

December 1, 2019

0.1 Goal:

1. This project is going to predict the number of points based on wine reviews:

```
f: X -> y
```

- X will be the input reviews
- y will be value of points

0.2 ##### 2. And construct a small recommendation system to recommend 5 wineries for a customer.

0.3 Roadmap:

1. Import data: this project is done on Google Colab, I save the raw dataset downloaded from Kaggle website on Google Drive and then import it to Google Colab.

2. Data exploration:

- Overall dataset analysis: check number of missing values, data type of each features;
- Numerical features: descriptive stats, distribution, correlation analysis;
- Categorical features: unique value, distribution analysis.

3. Data preprocessing:

- Missing data imputation;
- Drop columns;
- Categorical features: convert long sentences feature to its length, One-hot encoding;
- Reduce dimensionality: PCA.

4. Model training and validation:

- KNN: 5-fold cross validation, tuning parameter K;
- CatBoost: feature importance discussion, reduce data dimensionality by dropping unimportant features;

5. **Small recommendation system – colaborative filtering:**

-

0.4 Cosine similarity calculation: KNN.

0.5 Results

- KNN model regression analysis: when k = 30, the RMSE of testing data is 2.112;
- CatBoost model: the RMSE of testing data is 1.844, and after dropping unimportant features, the RMSE of testing data is 1.868 (doesn't change much);
- KNN recommendation system: this model only works on customers who have already reviewed on any wines, but doesn't work on new customers.

1 Part 0: Setup Google Drive Environment

[0]:
```
!pip install -U -q PyDrive

from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

[0]:
```
link = 'https://drive.google.com/open?id=1JU1ROzMJktzwvgdbajWOHZMEFzKi8ZDI'
fluff, id = link.split('=')
file = drive.CreateFile({'id':id})
file.GetContentFile('winemag-data_first150k.csv')
```

2 Part 1: Data Exploartion

2.0.1 Part 1.1: Understand the Raw Dataset

[0]:
```
import warnings
warnings.filterwarnings('ignore')

import pandas as pd
import numpy as np
import imblearn
```

```python
# will show all the columns
pd.set_option('display.max_columns', None)

wine_df = pd.read_csv('winemag-data_first150k.csv')
```

[0]:
```python
wine_df = wine_df.drop('Unnamed: 0', axis = 1)
wine_df.head()
```

[0]:
```
    country                                        description  \
0     Italy  Aromas include tropical fruit, broom, brimston…
1  Portugal  This is ripe and fruity, a wine that is smooth…
2        US  Tart and snappy, the flavors of lime flesh and…
3        US  Pineapple rind, lemon pith and orange blossom …
4        US  Much like the regular bottling from 2012, this…

                         designation  points  price           province  \
0                       Vulkà Bianco      87    NaN  Sicily & Sardinia
1                           Avidagos      87   15.0              Douro
2                                NaN      87   14.0             Oregon
3                Reserve Late Harvest     87   13.0           Michigan
4  Vintner's Reserve Wild Child Block     87   65.0             Oregon

             region_1           region_2         taster_name  \
0                Etna                NaN       Kerin O’Keefe
1                 NaN                NaN          Roger Voss
2   Willamette Valley  Willamette Valley        Paul Gregutt
3 Lake Michigan Shore                NaN  Alexander Peartree
4   Willamette Valley  Willamette Valley        Paul Gregutt

  taster_twitter_handle                                              title  \
0          @kerinokeefe                  Nicosia 2013 Vulkà Bianco  (Etna)
1            @vossroger      Quinta dos Avidagos 2011 Avidagos Red (Douro)
2           @paulgwine       Rainstorm 2013 Pinot Gris (Willamette Valley)
3                   NaN  St. Julian 2013 Reserve Late Harvest Riesling …
4           @paulgwine   Sweet Cheeks 2012 Vintner's Reserve Wild Child…

          variety               winery
0     White Blend              Nicosia
1  Portuguese Red  Quinta dos Avidagos
2      Pinot Gris            Rainstorm
3        Riesling           St. Julian
4      Pinot Noir         Sweet Cheeks
```

[0]:
```python
print ("Num of rows: " + str(wine_df.shape[0])) # row count
print ("Num of columns: " + str(wine_df.shape[1])) # col count
```

```
Num of rows: 129971
```

```
Num of columns: 13
```

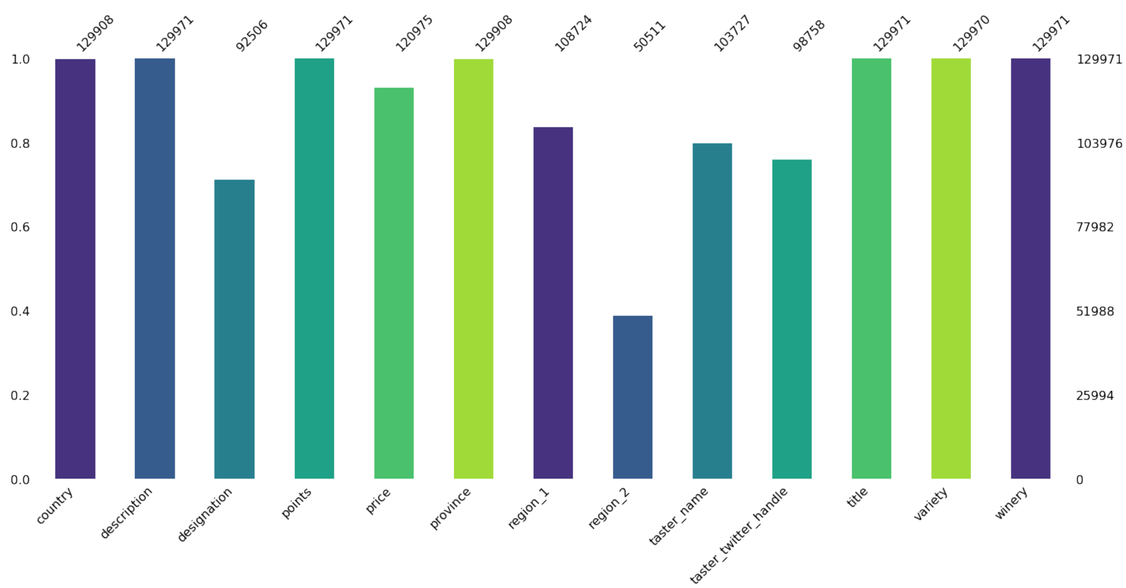
[0]:
```python
wine_df.dtypes
```

[0]:
```
country                  object
description              object
designation              object
points                    int64
price                   float64
province                 object
region_1                 object
region_2                 object
taster_name              object
taster_twitter_handle    object
title                    object
variety                  object
winery                   object
dtype: object
```

Some columns contain missing values, let's see the number of non-missing values in each column:

[0]:
```python
# Some columns contain missing values, let's see the number of non-missing␣
↪values in each column:
wine_df.describe(include='all',).T
import missingno as msno
import seaborn as sns
msno.bar(wine_df,color= sns.color_palette('viridis'))# missing values
```

[0]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f22b6fdd0b8>
```



2.1 Part 1.2 Understand the Features

2.1.1 Part 1.2.1 Descriptive Statistics of Numeric Features

[0]:
```
wine_df.describe()
```

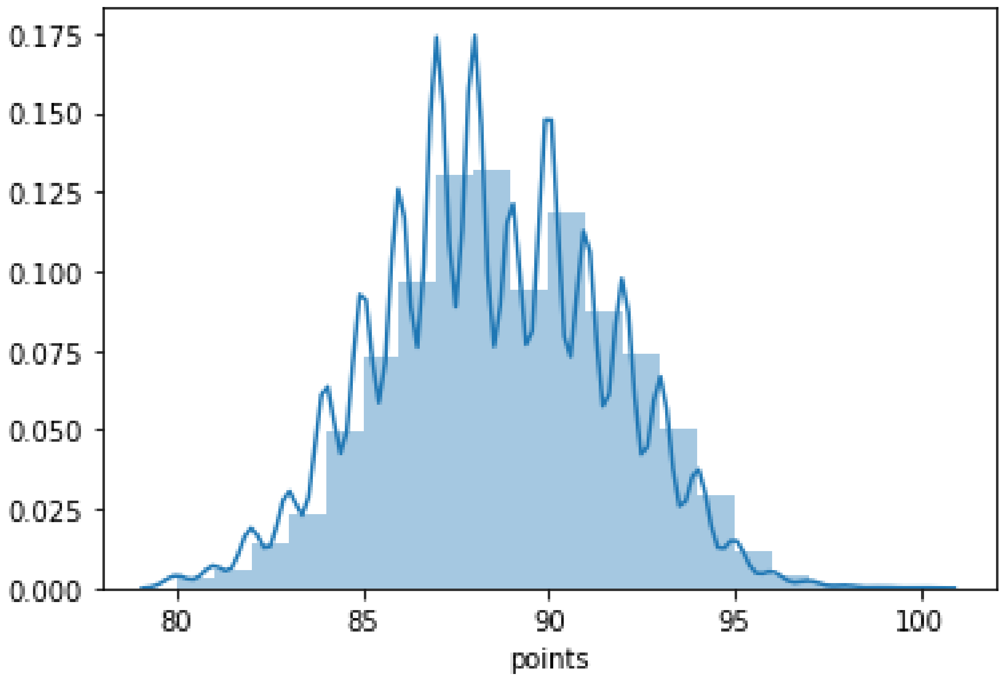
[0]:

	points	price
count	129971.000000	120975.000000
mean	88.447138	35.363389
std	3.039730	41.022218
min	80.000000	4.000000
25%	86.000000	17.000000
50%	88.000000	25.000000
75%	91.000000	42.000000
max	100.000000	3300.000000

[0]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns

# Check distribution of 'points':
sns.distplot(wine_df['points'], bins = 20)
```

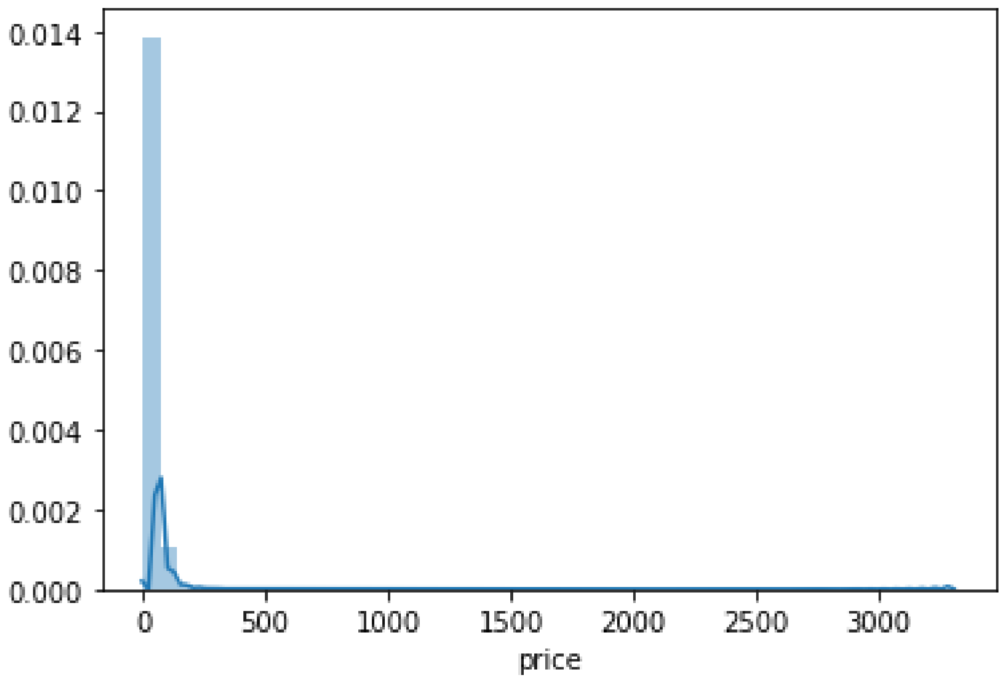
[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f22ba3445c0>



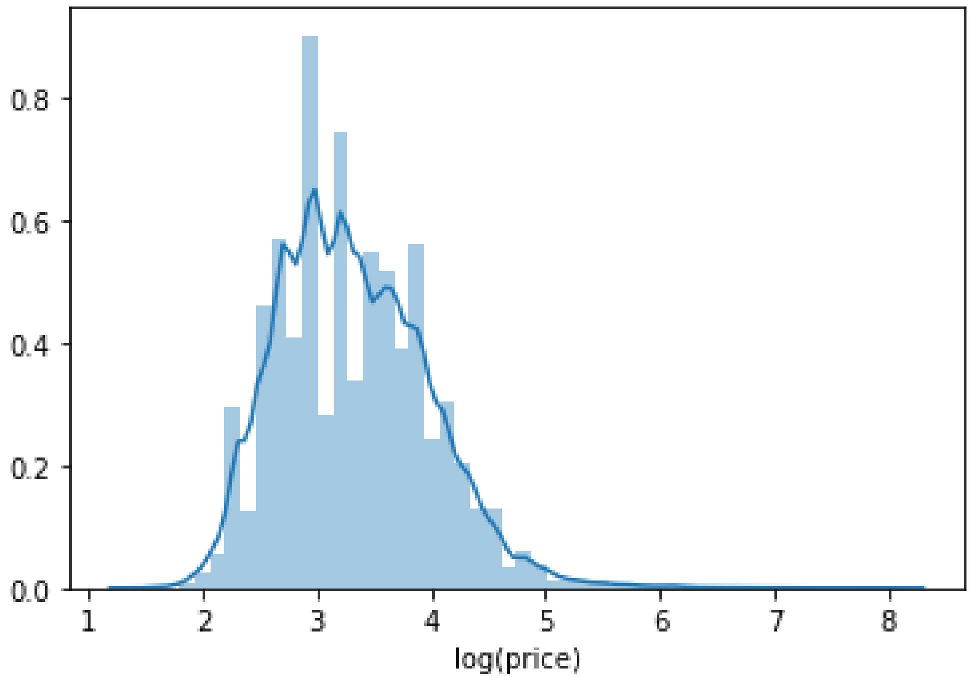
The range of points is in [80, 100],most of the wines have points less than 90.

[0]:
```
# Distribution of 'price':
sns.distplot(wine_df['price'].dropna())
```

[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f22b6ea6d68>

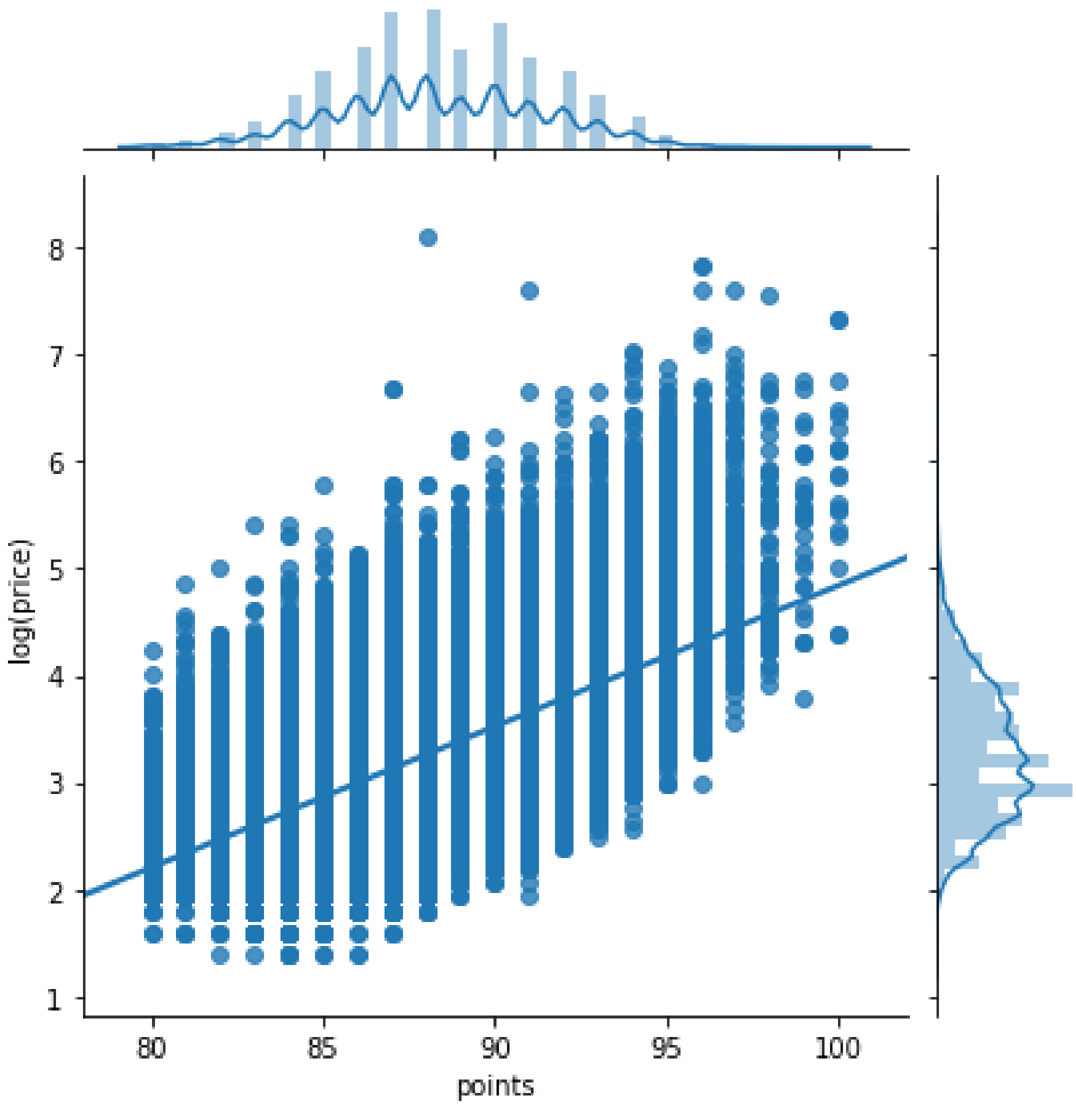


[0]:
```
# Distribution of log transformed 'price'
ax = sns.distplot(np.log(wine_df['price']).dropna())
ax.set(xlabel = 'log(price)')
plt.show()
```



The range of 'price' is in [4, 3300], however, only a small number of wines have price higher than 45. After log trasformation, the distribution seems closer to normal distribution.

[0]:
```
# Correlation between 'points' and 'log(price)':
df_plot = pd.DataFrame(data={'points': wine_df['points'], 'log(price)': np.
 ↪log(wine_df['price'])})
sns.jointplot(x = 'points', y = 'log(price)', data = df_plot, kind = 'reg');
```



Generally speaking, expensive wines tend to have higher points.

2.1.2 Part 1.2.2 Distribution of Categorical Features

1. Check number of unique values in each column

[0]:
```
wine_df.nunique()
```

[0]:
```
country                  43
description          119955
designation           37979
points                   21
```

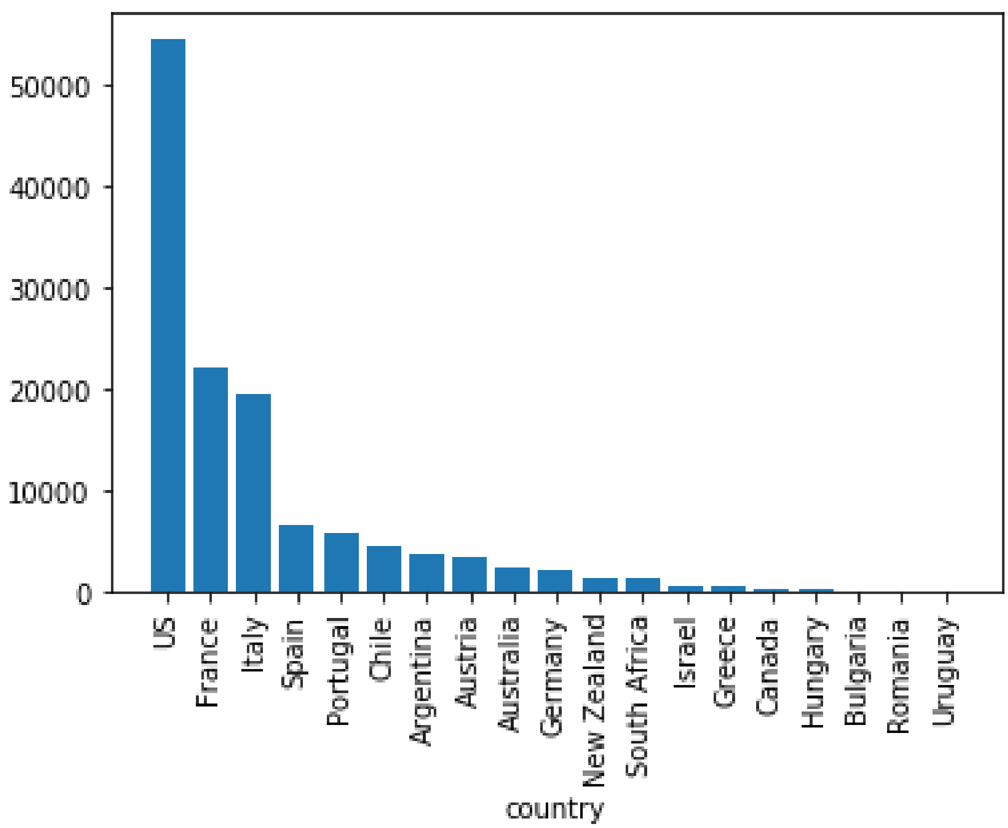
```
price                        390
province                     425
region_1                    1229
region_2                      17
taster_name                   19
taster_twitter_handle         15
title                     118840
variety                      707
winery                     16757
dtype: int64
```

'description' and 'title' columns have more than 91% unique values which are not informative. Thus I remove them in data preprocessing part later.

2. Due to limited space, only some of the categorical variables are displayed here. I use barplot to display the top 20 frequent values for each variable.

[0]:
```
plt.bar(x = wine_df['country'].value_counts()[0:19].index, height =␣
 ↪wine_df['country'].value_counts()[0:19].values)
plt.xticks(rotation=90)
plt.xlabel('country')
```

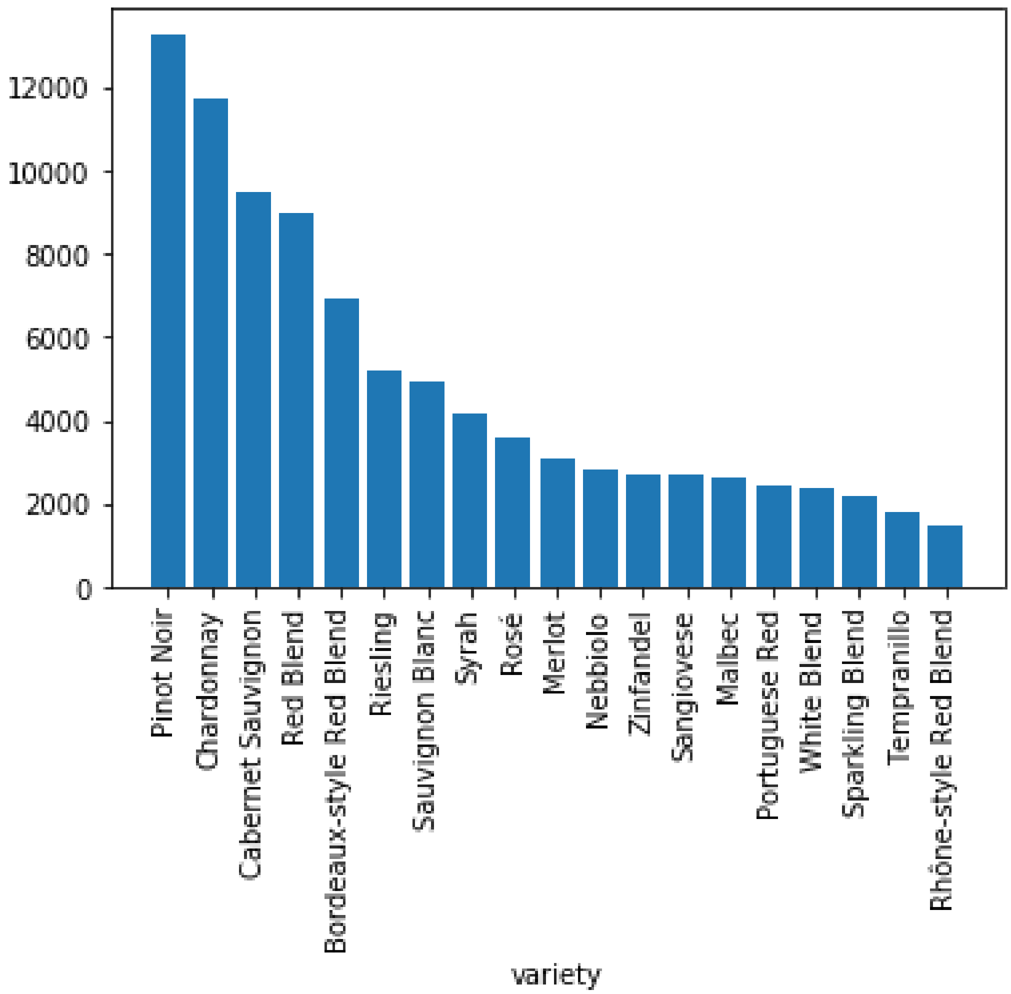
[0]:
```
Text(0.5, 0, 'country')
```



US, France and Italy are the three main countries where the wines come from.

[0]:
```
plt.bar(x = wine_df['variety'].value_counts()[0:19].index, height =␣
↪wine_df['variety'].value_counts()[0:19].values)
plt.xticks(rotation=90)
plt.xlabel('variety')
```

[0]:
```
Text(0.5, 0, 'variety')
```

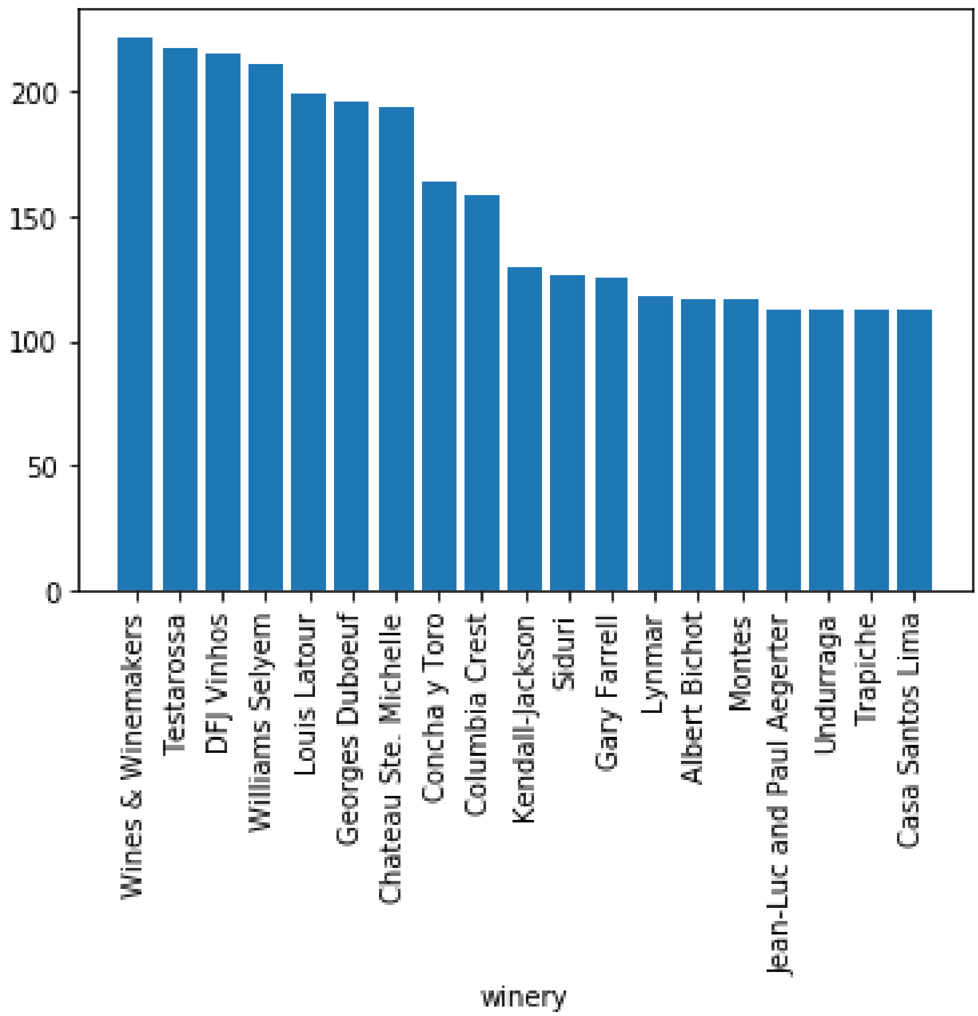


Pinot Noir is the most popular variety, and chrdonnay is the second popular one.

[0]:
```
plt.bar(x = wine_df['winery'].value_counts()[0:19].index, height =␣
↪wine_df['winery'].value_counts()[0:19].values)
plt.xticks(rotation=90)
```

```
plt.xlabel('winery')
```

[0]: Text(0.5, 0, 'winery')



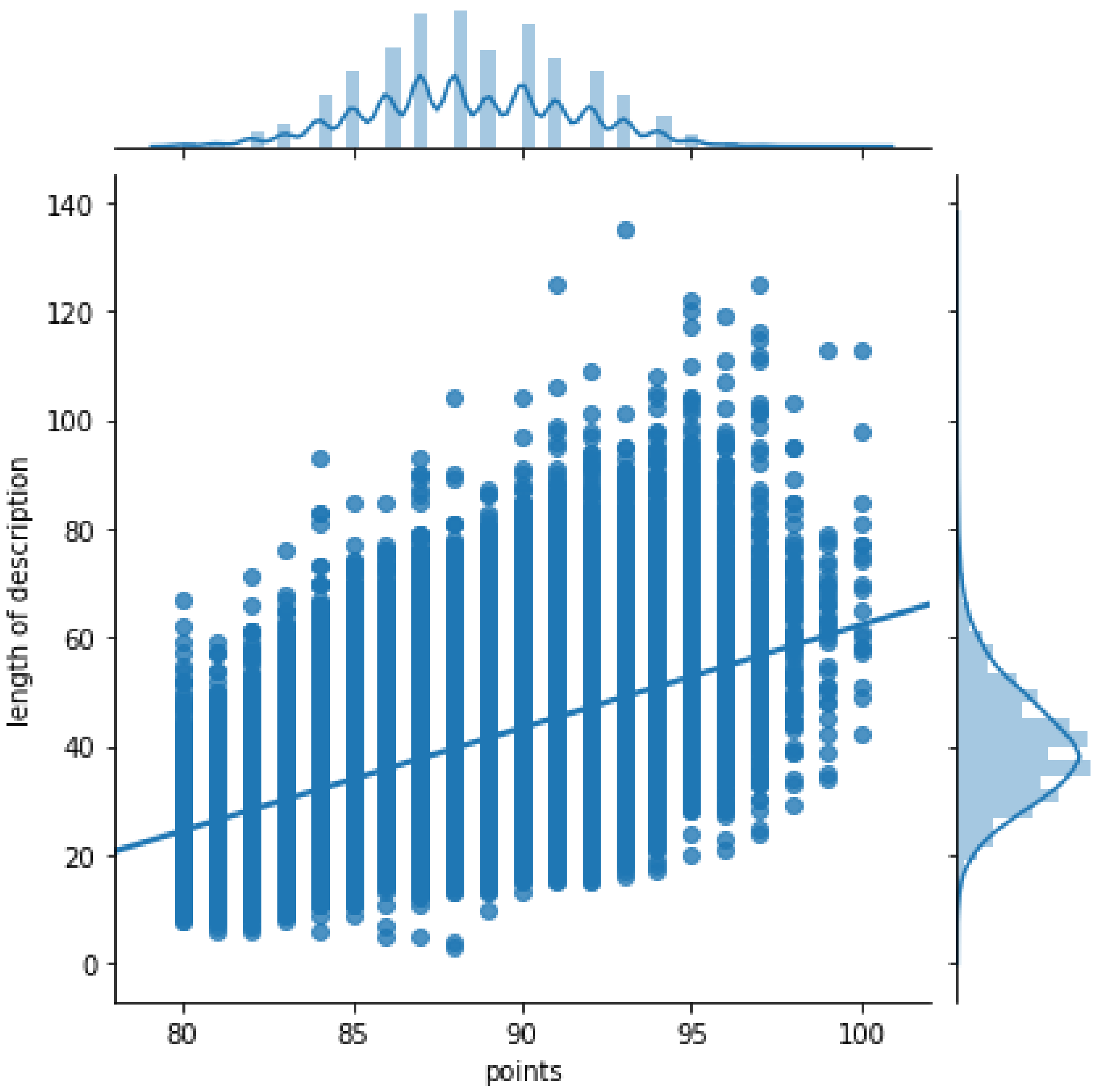
There are many unique values in column 'winery', most of them occur less than 200 times. Thus this is not a very informative column.

2.1.3 Part 1.2.3 Descriptive Statistics of a Special Column: 'description'

I tend to convert description column to its length (a new numeric column) in Part 1.2.3, before doing that, let's analyze if there is any correlation between length of descriptions and points.

[0]:
```
description_to_plot = wine_df['description'].apply(lambda x: len(x.split()))
desription_plot = pd.DataFrame(data={'points': wine_df['points'], 'length of␣
↪description': description_to_plot})
```

```
sns.jointplot(x = 'points', y = 'length of description', data =␣
↪desription_plot, kind = 'reg');
```



3 Part 2 Data Preprocessing

I preprocess **2** groups of data ([X, y] and [X2, y2]): 1. The first group of data [X, y] is for **KNN** model training. Generally speaking, I perform One-Hot Encoding on categorical variables and then apply Principle Component Analysis on that high dimensional data. 2. Another group of data [X2, y2] is for the second model. Because this dataset contains a lot of categorical variables, the second model I choose is **Catboost**, which is a utility model relates to a gradient lifting algorithm library, and can deal with class type features well.

3.1 Part 2.1 Preprocess Data for KNN Model

3.1.1 Part 2.1.1 Drop Columns

Remove the first index column and columns 'designation', 'region_2', 'taster_name', 'taster_twitter_handle' which have more than 20% missing values. Also, remove 'title' and 'description' columns which have more than 91% unique values.

[0]:
```
wine_prep = wine_df
to_drop = ['designation','region_2','taster_name','taster_twitter_handle',␣
↪'title', 'description']
wine_prep = wine_prep.drop(to_drop, axis=1)
```

3.1.2 Part 2.1.2 Preprocess Numeric Features

1. replacing missing values in column 'points' and 'price'.

[0]:
```
wine_prep['points'] = (wine_prep['points'].fillna(wine_df['points'].mean())).
↪astype('int64')
wine_prep['price'] = (wine_prep['price'].fillna((wine_df['price'].mean()))).
↪astype('float64')
wine_prep.head()
```

[0]:
```
    country  points      price           province             region_1  \
0     Italy      87  35.363389  Sicily & Sardinia                 Etna
1  Portugal      87  15.000000              Douro                  NaN
2        US      87  14.000000             Oregon    Willamette Valley
3        US      87  13.000000           Michigan  Lake Michigan Shore
4        US      87  65.000000             Oregon    Willamette Valley

          variety               winery
0     White Blend              Nicosia
1  Portuguese Red  Quinta dos Avidagos
2      Pinot Gris           Rainstorm
3        Riesling          St. Julian
4      Pinot Noir         Sweet Cheeks
```

3.1.3 Part 2.1.3 Preprocess Categorical Features

1. replacing values that don't appear frequently with 'others'
2. applying One-Hot Encoding on categorical features
3. applying PCA on features to reduce feature dimension

[0]:
```
# Replace non-frequent values with 'Others':
def others(x):
  to_replace = x.value_counts().index[(x.value_counts() < 100)]
```

```
    x[x.apply(lambda x_1: x_1 in to_replace)] = 'Others'
    return x
enc_cols = wine_prep.drop(['price', 'points'], axis = 1)
enc_cols = enc_cols.apply(others)

# One-Hot encoding:
dummies = pd.get_dummies(enc_cols)

# Combined with 'price':
wine_encoded = pd.concat([wine_prep['price'], dummies], axis = 1)
```

3.1.4 Part 2.1.4 Replace Feature 'description' with Its Length

[0]:
```
description_len = wine_df['description'].apply(lambda x: len(x.split()))
wine_encoded = pd.concat([wine_encoded, description_len], axis = 1)
```

3.1.5 Part 2.1.5 Principal Component Analysis

Because the dimension of encoded dataset for KNN model is very high, the training speed will be slow. After applying PCA method, the final training dataset contains 50 features.

[0]:
```
from sklearn import decomposition

X = wine_encoded
y = wine_df['points']

# PCA
pca = decomposition.PCA(n_components=50)
pca.fit(X)
X = pca.transform(X)
print('The dimension of the first training dataset is:')
X.shape
```

```
The dimension of the first training dataset is:
```

[0]:
```
(129971, 50)
```

3.2 Part 2.2 Preprocess Data for Catboost

[0]:
```
wine_prep2 = wine_df
y2 = (wine_prep2['points'].fillna(wine_df['points'].mean())).astype('int64')
wine_prep2['price'] = (wine_prep2['price'].fillna((wine_df['price'].mean()))).
 ↪astype('float64')
to_drop = ['description', 'points']
```

```
wine_prep2 = wine_prep2.drop(to_drop, axis=1)
X2 = pd.concat([wine_prep2, description_len], axis = 1)
X2=X2.fillna(-1)
print('The dimension of the second training dataset is:')
X2.shape
```

```
The dimension of the second training dataset is:
```

[0]:
```
(129971, 12)
```

4 Part 3: Regression Model Analysis

4.1 Part 3.1 K-Nearest Neighbors

4.1.1 Part 3.1.1 Split Dataset

[0]:
```
# Split data into training and testing
from sklearn import model_selection

# Reserve 20% for testing
X_train, X_test, y_train, y_test = model_selection.train_test_split(X, y,␣
↪test_size=0.2)

print('training data has %d observation with %d features'% X_train.shape)
print('test data has %d observation with %d features'% X_test.shape)
```

```
training data has 103976 observation with 50 features
test data has 25995 observation with 50 features
```

4.1.2 Part 3.1.2 Model Training and Validation

[0]:
```
# Build model
from sklearn.neighbors import KNeighborsRegressor

# K Nearest Neighbors
regressor_KNN = KNeighborsRegressor()
```

Use 5-fold Cross Validation to get the mean squared error for KNN:

[0]:
```
# Use 5-fold Cross Validation to get the mean squared error for different models
model_names = ['KNN']
model_list = [regressor_KNN]
count = 0
```

```
for regressor in model_list:
  cv_score = model_selection.cross_val_score(regressor, X, y, cv=5,␣
 ↪scoring='neg_mean_squared_error')
  cv_score = np.sqrt(-cv_score)
  print(cv_score)
  print('Model RMSE of %s is: %.3f'%(model_names[count], cv_score.mean()))
```

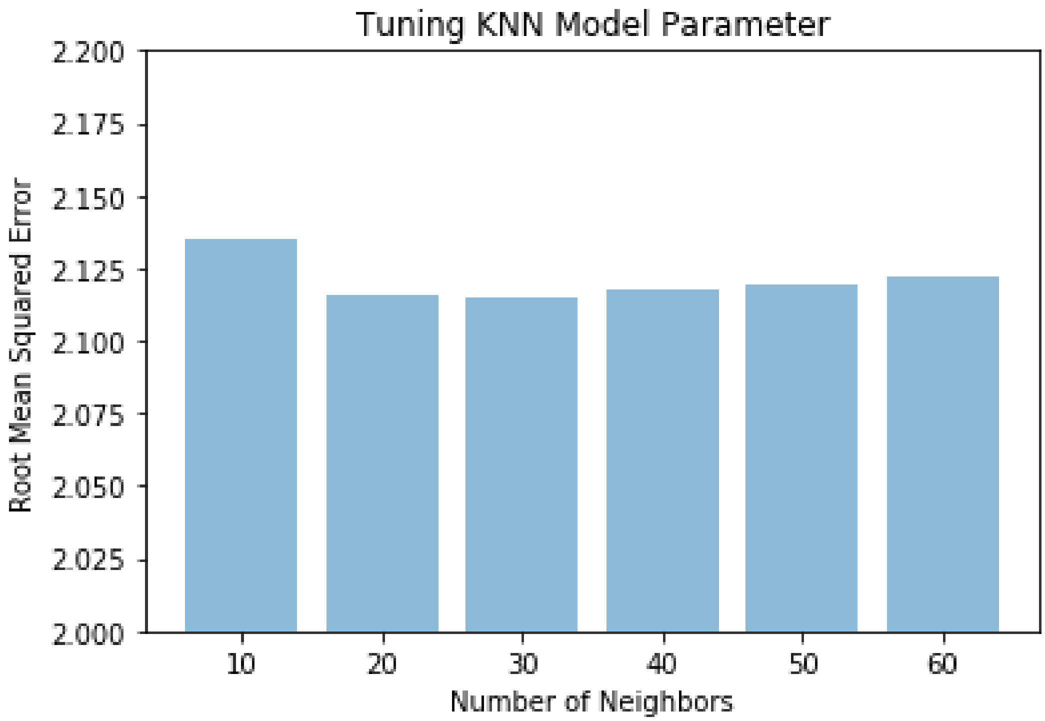
```
[2.21111219 2.22051193 2.14503297 2.2102439  2.2033381 ]
Model RMSE of KNN is: 2.198
```

4.2 Part 3.2 Tuning Model Parameters for KNN

Change the number of neighbors in the KNN model (I don't use cross validation here because it takes very long time to run):

[0]:
```
# change the number of neighbors (10, 20, 30, 40, 50, 60) in the KNN model
from sklearn.metrics import mean_squared_error
rmse_KNN = []
for n in [10, 20, 30, 40, 50, 60]:
  regressor_KNN = KNeighborsRegressor(n_neighbors = n)
  regressor_KNN.fit(X_train, y_train)
  y_predict_KNN = regressor_KNN.predict(X_test)
  rmse_KNN.append((mean_squared_error(y_test, y_predict_KNN))**0.5)

import matplotlib.pyplot as plt
plt.bar(np.arange(6), rmse_KNN, align='center', alpha=0.5)
plt.ylabel('Root Mean Squared Error')
plt.xlabel('Number of Neighbors')
plt.title('Tuning KNN Model Parameter')
plt.xticks(np.arange(6), [10, 20, 30, 40, 50, 60])
axes = plt.gca()
axes.set_ylim([2.0, 2.2])
plt.show()
print('When k = 30, KNN model has the best estimation with root mean squared␣
 ↪error = %.3f' % min(rmse_KNN) )
```




```
When k = 30, KNN model has the best estimation with root mean squared error =
2.115
```

4.3 Part 3.3 CatBoost

Cat Boost has two advantages: 1. Firstly, it deals with categorical features in the training process rather than in the pre-processing stage. 2. Secondly, the algorithm for calculating leaf nodes can avoid overfitting when choosing tree structure.

4.3.1 Part 3.3.1 Split Dataset

[0]:
```
categorical_features_indices =[0,1,3,4,5,6,7,8,9,10]

X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, test_size=0.2,
                                                        random_state=42)

X_train2, X_valid2, y_train2, y_valid2 = train_test_split(X_train2, y_train2,␣
 ↪test_size=0.2,
                                                        random_state=52)
```

4.3.2 Part 3.3.2 Cat Boost Model Training and Testing

[0]:
```
def perform_model(X_train, y_train, X_valid, y_valid, X_test, y_test):
    model = CatBoostRegressor(
        random_seed = 400,
        loss_function = 'RMSE',
        iterations=400,
    )

    model.fit(
        X_train, y_train,
        cat_features = categorical_features_indices,
        eval_set=(X_valid, y_valid),
        verbose=False
    )

    y_train_pred = model.predict(X_train)
    rmse_train = (np.mean((y_train - y_train_pred) **2)) **0.5

    y_test_pred = model.predict(X_test)
    rmse_test = (np.mean((y_test - y_test_pred) **2)) **0.5

    print("RMSE on training data: ", rmse_train)
    print("RMSE on test data: ", rmse_test)

    return model
```

[0]:
```
model=perform_model(X_train2, y_train2, X_valid2, y_valid2, X_test2, y_test2)
```

```
RMSE on training data:  1.535566132453336
RMSE on test data:  1.8444138832320554
```

4.4 Part 3.4 CatBoost Feature Importance Discussion

[0]:
```
feature_score = pd.DataFrame(list(zip(X2.dtypes.index, model.
 ↪get_feature_importance(Pool(X2, label=y2,␣
 ↪cat_features=categorical_features_indices)))),
                columns=['Feature','Score'])

feature_score = feature_score.sort_values(by='Score', ascending=False,␣
 ↪inplace=False, kind='quicksort', na_position='last')
```

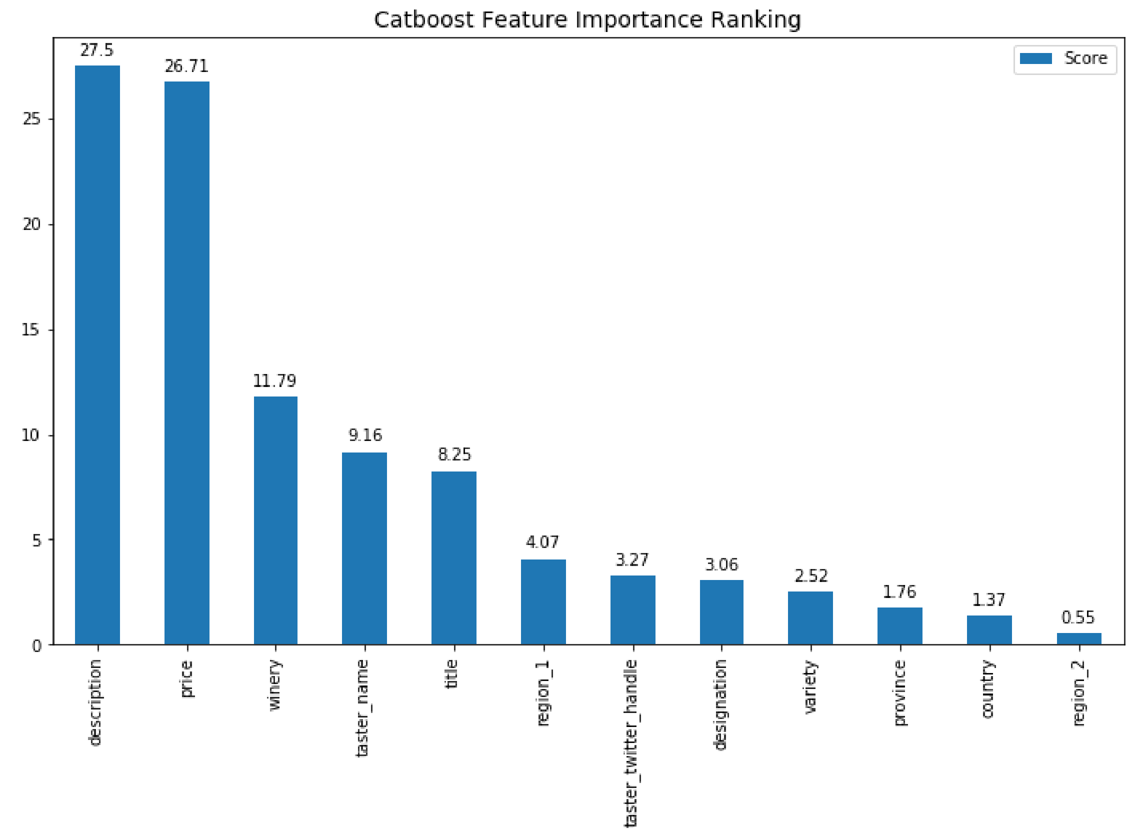
[0]:
```
plt.rcParams["figure.figsize"] = (12,7)
ax = feature_score.plot('Feature', 'Score', kind='bar')
ax.set_title("Catboost Feature Importance Ranking", fontsize = 14)
ax.set_xlabel('')
```

```
rects = ax.patches

labels = feature_score['Score'].round(2)

for rect, label in zip(rects, labels):
    height = rect.get_height()
    ax.text(rect.get_x() + rect.get_width()/2, height + 0.35, label,␣
 ↪ha='center', va='bottom')

plt.show()
```



As we can see from the feature importance plot, features 'region_2', 'country', 'province' and 'variety' are not important to CatBoost Model. Dropping those columns could decreasing training time. Let's try to drop them and see how the score changes:

[0]:
```
X2=X2.drop(columns=['country', 'province', 'region_2', 'variety'])

categorical_features_indices =[0,2,3,4,5,6]

X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, test_size=0.2,
```

```
                                                                    random_state=42)

X_train2, X_valid2, y_train2, y_valid2 = train_test_split(X_train2, y_train2,␣
 ↪test_size=0.2,
                                                                    random_state=52)
```

[0]:
```
model=perform_model(X_train2, y_train2, X_valid2, y_valid2, X_test2, y_test2)
```

```
RMSE on training data:  1.5256643813745259
RMSE on test data:  1.8679501819819297
```

The RMSE of the model after I drop 4 columns which are not important doesn't change a lot. It's feasible to drop those columns to improve model efficiency.

5 Part 4: Small Recommendation System – Collabrative Filtering

This small recommendation system is performed by KNN, the similarity between each pair of customers is represented by cosine similarity. For a customer, I would like to recommend 5 wineries which are similar to the one the customer has reviewed. And those recommended wineries were tasted by 5 other customers who gave points higher than the average:

5.1 Part 4.1 Data Preprocessing

[0]:
```
# filter the dataframe, only keep rows which satisfy the condition: 'pinot␣
 ↪noir', 'price less than 20 dollars', 'has a fruity taste' and 'points >␣
 ↪average'
def func(x):
  if 'fruity' in x:
    return True
  return False

X_re = pd.DataFrame(X[(wine_df['variety'] == 'Pinot Noir') & (wine_df['price']␣
 ↪< 20) & (wine_df['description'].apply(func)) & (wine_df['points'] >␣
 ↪wine_df['points'].mean())])
y_re = pd.DataFrame(y[(wine_df['variety'] == 'Pinot Noir') & (wine_df['price']␣
 ↪< 20) & (wine_df['description'].apply(func)) & (wine_df['points'] >␣
 ↪wine_df['points'].mean())]).reset_index(drop = True)
wine_re = wine_df[(wine_df['variety'] == 'Pinot Noir') & (wine_df['price'] <␣
 ↪20) & (wine_df['description'].apply(func)) & (wine_df['points'] >␣
 ↪wine_df['points'].mean())]
wine_re_train = pd.concat([X_re, y_re], axis = 1)
```

5.2 Part 4.2 Model Training and Recommendation

[0]:
```
from sklearn.neighbors import NearestNeighbors
from scipy.sparse import csr_matrix
from sklearn.decomposition import TruncatedSVD

knn = NearestNeighbors(n_neighbors=10,algorithm= 'brute', metric= 'cosine')
model_knn = knn.fit(wine_re_train)
```

I randomly select a customer from raw dataset 'wine_df', and try to give him/her recommendation from the model.

[0]:
```
import random
for i in range(5):
  query_index = np.random.choice(pd.concat([pd.DataFrame(X), pd.DataFrame(y)],␣
↪axis = 1).shape[0])
  distance, indice = model_knn.kneighbors(pd.concat([pd.DataFrame(X), pd.
↪DataFrame(y)], axis = 1).iloc[query_index,:].values.reshape(1,␣
↪-1),n_neighbors= 6)
  for i in range(0, len(distance.flatten())):
      if  i == 0:
          print('Recmmendation for customer {0} in dataset row {1}:\n'.
↪format(wine_df.iloc[query_index, 8],pd.concat([pd.DataFrame(X), pd.
↪DataFrame(y)], axis = 1).index[query_index]))
      else:
          print('{0}: {1} with distance: {2}'.format(i, wine_re.iloc[indice.
↪flatten()[i], 12], distance.flatten()[i]))
```

```
Recmmendation for customer nan in dataset row 13883:

1: Dr. Nägler with distance: 0.011897025262433969
2: J. Lohr with distance: 0.015233030969037276
3: Willm with distance: 0.01562148796809526
4: Balletto with distance: 0.015658968179223076
5: Villa Wolf with distance: 0.015929275688086997
Recmmendation for customer Kerin O'Keefe in dataset row 51837:

1: Willm with distance: 0.00042388708821594623
2: J. Lohr with distance: 0.0007977300452143288
3: Three Brothers with distance: 0.0011844567231310554
4: Dr. Nägler with distance: 0.0012684173846814195
5: Murphy-Goode with distance: 0.0014919488310070061
Recmmendation for customer Lauren Buzzeo in dataset row 12932:

1: Willm with distance: 0.009167540030077137
2: Balletto with distance: 0.009586663853631494
```

```
3: J. Lohr with distance: 0.013522808583615209
4: Dr. Nägler with distance: 0.01485081544373379
5: Three Brothers with distance: 0.015207288103780137
Recmmendation for customer Roger Voss in dataset row 83166:

1: Wakefield with distance: 0.04750312499019549
2: Willm with distance: 0.04791019183876277
3: Balletto with distance: 0.04878461196185424
4: J. Lohr with distance: 0.051494593165777425
5: Simonnet-Febvre with distance: 0.05534249118315393
Recmmendation for customer Roger Voss in dataset row 55800:

1: Willm with distance: 0.006986447917567529
2: Balletto with distance: 0.00722844278658219
3: Esterházy with distance: 0.009294054246720362
4: P.J. Valckenberg with distance: 0.010290199278800038
5: J. Lohr with distance: 0.010525276043425125
```

This model could give a simple recommendation for a customer who has reviewed for any wines before. The model calculate the similarity between his/her review and other customers' reviews. This is not 'new-customer-friendly' because if a customer hasn't reviewed yet, the model won't work.