```
In [134]: import numpy as np
   import pandas as pd
   import matplotlib.pyplot as plt
   import seaborn as sns
   %matplotlib inline
```

In [135]: df = pd.read_csv("winequality-red.csv")

In [136]: df.head()

Out[136]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcoho
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
4											•

In [137]: df.info()

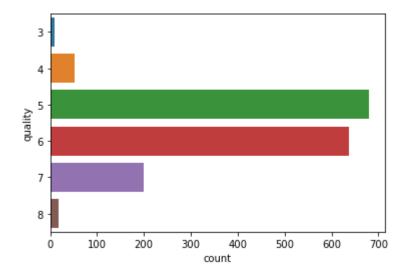
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):

	`	,	
#	Column	Non-Null Count	Dtype
0	fixed acidity	1599 non-null	float64
1	volatile acidity	1599 non-null	float64
2	citric acid	1599 non-null	float64
3	residual sugar	1599 non-null	float64
4	chlorides	1599 non-null	float64
5	free sulfur dioxide	1599 non-null	float64
6	total sulfur dioxide	1599 non-null	float64
7	density	1599 non-null	float64
8	рН	1599 non-null	float64
9	sulphates	1599 non-null	float64
10	alcohol	1599 non-null	float64
11	quality	1599 non-null	int64

dtypes: float64(11), int64(1)

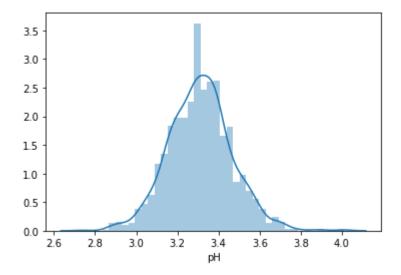
memory usage: 150.0 KB

```
In [138]: | df.columns.tolist()
Out[138]: ['fixed acidity',
            'volatile acidity',
            'citric acid',
            'residual sugar',
            'chlorides',
            'free sulfur dioxide',
            'total sulfur dioxide',
            'density',
            'pH',
            'sulphates',
            'alcohol',
            'quality']
In [139]: vc=df["quality"].value_counts()
Out[139]: 5
                681
                638
           7
                199
           4
                 53
           8
                 18
                 10
           Name: quality, dtype: int64
In [140]: | sns.countplot(data=df,y="quality")
Out[140]: <matplotlib.axes._subplots.AxesSubplot at 0x1eb91818c88>
```



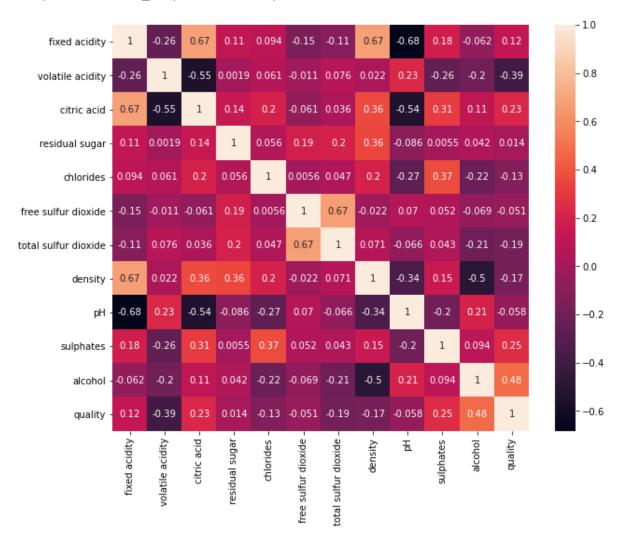
In [141]: sns.distplot(df["pH"]) # pH distribution

Out[141]: <matplotlib.axes._subplots.AxesSubplot at 0x1eb91932548>



In [142]: plt.figure(figsize=(10,8))
 sns.heatmap(df.corr(),annot=True)

Out[142]: <matplotlib.axes._subplots.AxesSubplot at 0x1eb919874c8>

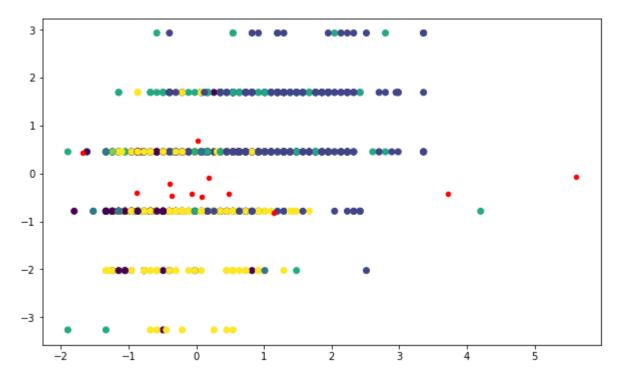


```
In [143]:
          from sklearn.preprocessing import StandardScaler
           from sklearn.model selection import train test split
           from sklearn.cluster import KMeans
In [144]: df.isnull().sum()
Out[144]: fixed acidity
                                   0
          volatile acidity
                                   0
           citric acid
                                   0
          residual sugar
                                   0
          chlorides
                                   0
           free sulfur dioxide
                                   0
          total sulfur dioxide
                                   0
          density
                                   0
          рΗ
                                   0
           sulphates
                                   0
           alcohol
                                   0
           quality
                                   0
          dtype: int64
In [145]: | ## preparing data for clustering
In [146]: | target_col = df["quality"]
In [147]: target_col
Out[147]: 0
                   5
                   5
           1
                   5
           2
           3
                   6
                   5
          1594
                   5
          1595
                   6
          1596
                   6
          1597
                   5
          1598
          Name: quality, Length: 1599, dtype: int64
In [148]: | sc = StandardScaler()
In [149]: | df_scaled = sc.fit_transform(df)
```

```
In [150]: df_scaled
Out[150]: array([[-0.52835961,
                                     0.96187667, -1.39147228, ..., -0.57920652,
                     -0.96024611, -0.78782264],
                    [-0.29854743,
                                     1.96744245, -1.39147228, ..., 0.1289504,
                     -0.58477711, -0.78782264],
                    [-0.29854743, 1.29706527, -1.18607043, ..., -0.04808883,
                     -0.58477711, -0.78782264],
                    [-1.1603431, -0.09955388, -0.72391627, ..., 0.54204194,
                      0.54162988,
                                    0.45084835],
                    [-1.39015528,
                                     0.65462046, -0.77526673, ...,
                                                                        0.30598963,
                     -0.20930812, -0.78782264],
                    [-1.33270223, -1.21684919, 1.02199944, ...,
                                                                        0.01092425,
                      0.54162988,
                                    0.45084835]])
            df scaled = pd.DataFrame(df scaled,columns=df.columns)
In [151]:
            df scaled
Out[151]:
                                                                          free
                                                                                   total
                      fixed
                              volatile
                                          citric
                                                  residual
                                                           chlorides
                                                                        sulfur
                                                                                  sulfur
                                                                                           density
                     acidity
                               acidity
                                           acid
                                                    sugar
                                                                       dioxide
                                                                                 dioxide
                  -0.528360
                             0.961877 -1.391472 -0.453218
                                                           -0.243707
                                                                     -0.466193
                                                                               -0.379133
                                                                                         0.558274
                                                                                                    1.28
                  -0.298547
                             1.967442 -1.391472
                                                 0.043416
                                                           0.223875
                                                                     0.872638
                                                                               0.624363
                                                                                         0.028261
                                                                                                   -0.7°
                  -0.298547
                             1.297065
                                      -1.186070
                                                 -0.169427
                                                           0.096353
                                                                     -0.083669
                                                                               0.229047
                                                                                         0.134264
                                                                                                   -0.3
                   1.654856
                            -1.384443
                                       1.484154
                                                 -0.453218
                                                           -0.264960
                                                                     0.107592
                                                                                         0.664277
                                                                                0.411500
                                                                                                   -0.97
                  -0.528360
                             0.961877
                                      -1.391472
                                                -0.453218
                                                           -0.243707
                                                                    -0.466193
                                                                              -0.379133
                                                                                         0.558274
                                                                                                    1.28
             1594
                  -1.217796
                             0.403229
                                      -0.980669
                                                 -0.382271
                                                           0.053845
                                                                     1.542054
                                                                               -0.075043
                                                                                         -0.978765
                                                                                                    98.0
             1595
                 -1.390155
                             0.123905
                                      -0.877968
                                                 -0.240375
                                                           -0.541259
                                                                     2.211469
                                                                               0.137820
                                                                                         -0.862162
                                                                                                    1.3
                  -1.160343
                            -0.099554
                                      -0.723916
                                                 -0.169427
                                                           -0.243707
                                                                     1.255161
                                                                               -0.196679
                                                                                         -0.533554
                                                                                                    0.70
                                                 -0.382271
             1597 -1.390155
                             0.654620
                                      -0.775267
                                                           -0.264960
                                                                     1.542054
                                                                               -0.075043
                                                                                         -0.676657
                                                                                                    1.67
             1598 -1.332702 -1.216849
                                       1.021999
                                                 0.752894
                                                          -0.434990
                                                                     0.203223
                                                                              -0.135861
                                                                                         -0.666057
                                                                                                    0.5
            1599 rows × 12 columns
In [152]:
            kmeans = KMeans(
                     n clusters=6,
                     max iter=1000,
                     random state=1,
                     init="random"
                          )
           kmeans.fit(df scaled)
In [153]:
Out[153]: KMeans(init='random', max_iter=1000, n_clusters=6, random_state=1)
```

```
In [154]:
            y km = kmeans.predict(df scaled)
In [159]:
            cluster_centre = pd.DataFrame(kmeans.cluster_centers_,columns=df.columns)
In [160]:
            cluster centre
Out[160]:
                                                                         free
                                                                                  total
                    fixed
                            volatile
                                         citric
                                                residual
                                                          chlorides
                                                                       sulfur
                                                                                 sulfur
                                                                                          density
                                                                                                         ŗ
                  acidity
                             acidity
                                         acid
                                                  sugar
                                                                      dioxide
                                                                                dioxide
             0
               -0.041842
                           0.072370
                                     0.069753
                                               -0.100205
                                                         -0.030330
                                                                    0.937458
                                                                               1.187992
                                                                                         0.264947 -0.14270
                -0.618848
                          -0.467039
                                     -0.125523
                                               -0.226296
                                                         -0.384579
                                                                    0.143304
                                                                              -0.231554
                                                                                        -1.158374
                                                                                                   0.54109
                -0.188637
                          -0.051583
                                     0.400212
                                               4.244759
                                                          0.206318
                                                                    1.589869
                                                                               1.742223
                                                                                         1.035402 -0.19454
                1.378218
                          -0.689121
                                               0.102163
                                                         -0.004633
                                                                   -0.565416
                                                                              -0.546030
                                                                                         0.799599
                                                                                                   -0.85607
             3
                                     1.153195
                0.081831
                           0.017955
                                     1.144178
                                               -0.399396
                                                          5.604731
                                                                    -0.070479
                                                                               0.474416
                                                                                         0.185803
                                                                                                   -1.6873
                -0.489153
                           0.691740
                                    -0.819240
                                              -0.214826
                                                         -0.070664
                                                                   -0.434285
                                                                              -0.419141
                                                                                        -0.087270
                                                                                                   0.43078
                                                                                                        •
            df.columns
In [161]:
Out[161]: Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
                     'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
                     'pH', 'sulphates', 'alcohol', 'quality'],
                   dtype='object')
```

Out[179]: <matplotlib.collections.PathCollection at 0x1eb9343be48>



In [186]: !pip install kneed
 from kneed import KneeLocator

Requirement already satisfied: kneed in c:\users\dhruv\anaconda3\envs\ml\lib \site-packages (0.7.0)

Requirement already satisfied: matplotlib in c:\users\dhruv\anaconda3\envs\ml \lib\site-packages (from kneed) (3.2.2)

Requirement already satisfied: scipy in c:\users\dhruv\anaconda3\envs\ml\lib\site-packages (from kneed) (1.5.2)

Requirement already satisfied: numpy>=1.14.2 in c:\users\dhruv\anaconda3\envs\ml\lib\site-packages (from kneed) (1.19.1)

Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\dhruv\anaconda3 \envs\ml\lib\site-packages (from matplotlib->kneed) (1.2.0)

Requirement already satisfied: cycler>=0.10 in c:\users\dhruv\anaconda3\envs \ml\lib\site-packages (from matplotlib->kneed) (0.10.0)

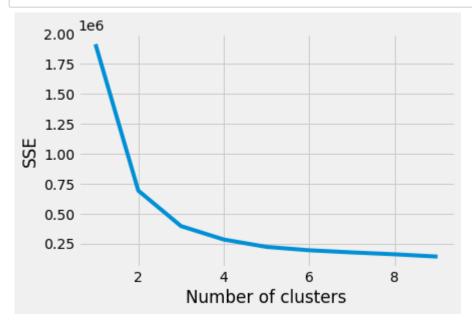
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in c:\users\dhruv\anaconda3\envs\ml\lib\site-packages (from matplotlib->kneed) (2.4.7)

Requirement already satisfied: python-dateutil>=2.1 in c:\users\dhruv\anacond a3\envs\ml\lib\site-packages (from matplotlib->kneed) (2.8.1)

Requirement already satisfied: six in c:\users\dhruv\anaconda3\envs\ml\lib\si te-packages (from cycler>=0.10->matplotlib->kneed) (1.15.0)

```
In [187]: kmeans_kwargs = {"init": "random", "n_init": 10, "max_iter": 300, "random_stat
    e": 42}

sse = []
for i in range(1,10,1):
        kmeans = KMeans(n_clusters=i, **kmeans_kwargs).fit(df)
        sse.append(kmeans.inertia_)
    plt.style.use("fivethirtyeight")
    plt.xlabel('Number of clusters')
    plt.ylabel('SSE')
    plt.plot(range(1,10,1), sse)
    plt.show()
    kl = KneeLocator(range(1, 10, 1), sse, curve="convex", direction="decreasing")
    print(kl.elbow)
```



3

In []: ## thus we successfully performed KMEANS clustering on Red-wine quality datase t.