Feature Selection

VarianceThreshold

Step 1: Import Necessary Libraries

•

In [526...

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Step 2: Create or Load the Dataset

•

In [529...

df = pd.read_csv(r"C:\Users\HP\Documents\Naresh IT\Data file\winequality_red.csv
df

Out[529...

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulph
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	
•••										
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	

1599 rows × 12 columns

Step 3: Splits X-y column

•

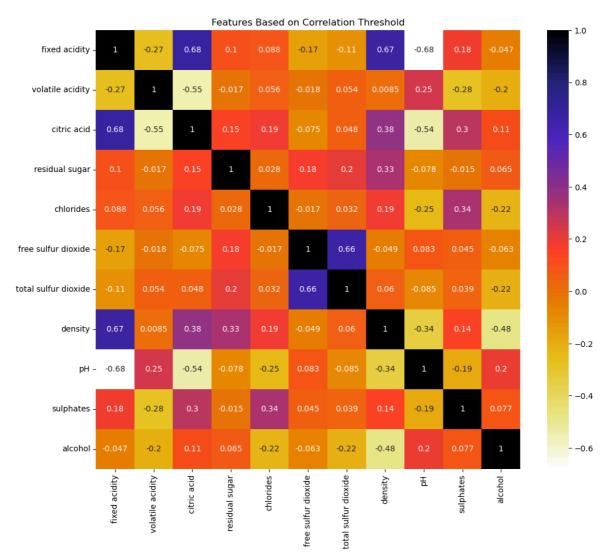
```
X=df.drop('quality',axis=1) # select the input columns
In [532...
          y=df['quality'] # select the output
          df.shape,X.shape,y.shape
Out[532... ((1599, 12), (1599, 11), (1599,))
          Apply Variance Threshold
In [535...
          from sklearn.feature_selection import VarianceThreshold
          vt=VarianceThreshold(threshold=0.3)
In [537...
         vt.fit(X)
Out[537...
                 VarianceThreshold
          VarianceThreshold(threshold=0.3)
In [539...
         vt.variances_
Out[539... array([3.02952057e+00, 3.20423261e-02, 3.79237511e-02, 1.98665392e+00,
                  2.21375732e-03, 1.09346457e+02, 1.08142564e+03, 3.55980179e-06,
                  2.38202742e-02, 2.87146470e-02, 1.13493717e+00])
In [541... vt.get_support()
Out[541... array([ True, False, False, True, False, True, False, False,
                 False, True])
```

Feature Selection-How To Drop Features Using Pearson Correlation

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	
fixed acidity	1.000000	-0.267924	0.679876	0.104657	0.087915	-0.168020	-0.108836	
volatile acidity	-0.267924	1.000000	-0.550238	-0.017290	0.056300	-0.018207	0.054028	
citric acid	0.679876	-0.550238	1.000000	0.148050	0.188716	-0.074663	0.047871	
residual sugar	0.104657	-0.017290	0.148050	1.000000	0.027555	0.177538	0.201606	
chlorides	0.087915	0.056300	0.188716	0.027555	1.000000	-0.016669	0.031555	
free sulfur dioxide	-0.168020	-0.018207	-0.074663	0.177538	-0.016669	1.000000	0.661843	-
total sulfur dioxide	-0.108836	0.054028	0.047871	0.201606	0.031555	0.661843	1.000000	
density	0.669151	0.008512	0.378511	0.332520	0.190066	-0.049243	0.059614	
рН	-0.680823	0.247491	-0.537238	-0.077903	-0.245936	0.082737	-0.084805	-
sulphates	0.183105	-0.280754	0.300356	-0.014920	0.335765	0.045379	0.038650	
alcohol	-0.046890	-0.202691	0.109209	0.065280	-0.223375	-0.062984	-0.216920	-
-								•

In [548...

```
plt.figure(figsize=(12,10))
plt.title('Features Based on Correlation Threshold')
sns.heatmap(corr,annot=True, cmap=plt.cm.CMRmap_r)
plt.savefig('Features Based on Correlation Threshold.png')
plt.show()
```



```
In [550...
           def correlation(dataset, threshold):
               col corr=set()
               corr_mateix = dataset.corr()
               for i in range(len(corr_mateix.columns)):
                   for j in range(i):
                       if abs(corr_matrix.iloc[i,j])>threshold:
                           colname = corr_mateix.columns[i]
                           col corr.add(colname)
               return col_corr
In [552...
           corr_features = correlation(X_train,0.7)
           len(set(corr_features))
           corr_features
Out[552...
           set()
In [554...
          X_train.drop(corr_features,axis=1)
```

X_test.drop(corr_features,axis=1)

		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulph
	688	7.7	0.660	0.04	1.6	0.039	4.0	9.0	0.99620	3.40	
	961	7.1	0.560	0.14	1.6	0.078	7.0	18.0	0.99592	3.27	
	726	8.1	0.720	0.09	2.8	0.084	18.0	49.0	0.99940	3.43	
	537	8.1	0.825	0.24	2.1	0.084	5.0	13.0	0.99720	3.37	
	1544	8.4	0.370	0.43	2.3	0.063	12.0	19.0	0.99720 3.37 0.99550 3.17 		
	•••										
	351	9.1	0.795	0.00	2.6	0.096	11.0	26.0	0.99940	3.35	
	415	8.6	0.725	0.24	6.6	0.117	31.0	134.0	1.00140	3.32	
	564	13.0	0.470	0.49	4.3	0.085	6.0	47.0	1.00210	3.30	
	1124	6.5	0.580	0.00	2.2	0.096	3.0	13.0	0.99557	3.62	
	147	7.6	0.490	0.26	1.6	0.236	10.0	88.0	0.99680	3.11	

320 rows × 11 columns

Select Features Using Information Gain

•

it is a method of selecting the most relevent features for a model by meansuring how much each feature contributes to the target variable

```
In [558...
```

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

df = pd.read_csv(r"C:\Users\HP\Documents\Naresh IT\Data file\winequality_red.csv
df.head()
```

Out[558...

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphate
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.6
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56
4										•

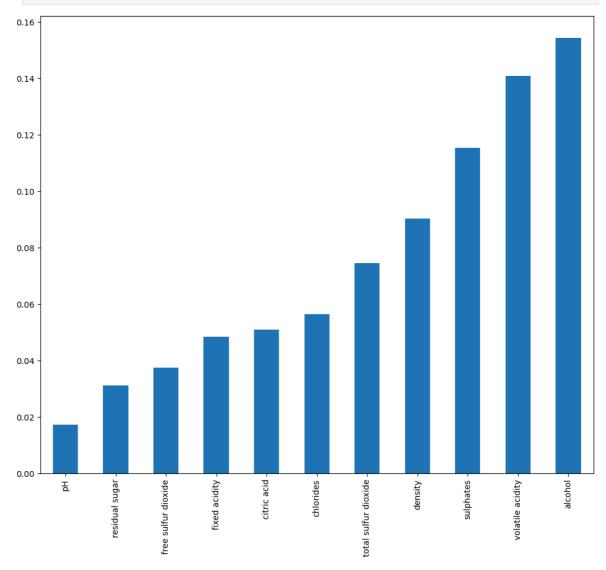
in [560... df['fixed acidity'].unique()

```
Out[560... array([7.4, 7.8, 11.2, 7.9, 7.3, 7.5, 6.7, 5.6, 8.9, 8.5, 8.1,
                 7.6, 6.9, 6.3, 7.1, 8.3, 5.2, 5.7, 8.8, 6.8, 4.6, 7.7,
                 8.7, 6.4, 6.6, 8.6, 10.2, 7., 7.2, 9.3, 8., 9.7, 6.2,
                 5., 4.7, 8.4, 10.1, 9.4, 9., 8.2, 6.1, 5.8, 9.2, 11.5,
                 5.4, 9.6, 12.8, 11., 11.6, 12., 15., 10.8, 11.1, 10., 12.5,
                 11.8, 10.9, 10.3, 11.4, 9.9, 10.4, 13.3, 10.6, 9.8, 13.4, 10.7,
                 11.9, 12.4, 12.2, 13.8, 9.1, 13.5, 10.5, 12.6, 14., 13.7, 9.5,
                 12.7, 12.3, 15.6, 5.3, 11.3, 13., 6.5, 12.9, 14.3, 15.5, 11.7,
                 13.2, 15.9, 12.1, 5.1, 4.9, 5.9, 6., 5.5])
In [562...
         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
           volatile acidity
                                1599 non-null float64
         1
         2
            citric acid
                                 1599 non-null float64
                                1599 non-null float64
            residual sugar
         3
            chlorides
                                 1599 non-null float64
            free sulfur dioxide 1599 non-null float64
         6 total sulfur dioxide 1599 non-null float64
                                 1599 non-null float64
         7
            density
         8
                                 1599 non-null float64
            рΗ
         9
             sulphates
                                 1599 non-null float64
                                  1599 non-null float64
         10 alcohol
                                  1599 non-null int64
         11 quality
        dtypes: float64(11), int64(1)
        memory usage: 150.0 KB
 In [ ]:
 In [ ]:
 In [ ]:
         X=df.drop('quality',axis=1) # select the input columns
In [567...
         y=df['quality'] # select the output
         df.shape,X.shape,y.shape
Out[567... ((1599, 12), (1599, 11), (1599,))
In [569...
         from sklearn.model_selection import train_test_split
         X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=
         print(X_train.shape,X_test.shape,y_train.shape,y_test.shape)
        (1279, 11) (320, 11) (1279,) (320,)
         from sklearn.feature selection import mutual info classif
In [571...
         mutual_info = mutual_info_classif(X_train,y_train)
         mutual_info
Out[571... array([0.04846914, 0.14095619, 0.05092167, 0.03110906, 0.05635836,
                 0.03748618, 0.07452345, 0.09033489, 0.01726703, 0.11533924,
                 0.15444002])
```

```
In [573...
          mutual_info = pd.Series(mutual_info)
          mutual_info.index = X_train.columns
          mutual_info.sort_values(ascending=False)
           alcohol
                                    0.154440
Out[573...
```

volatile acidity 0.140956 sulphates 0.115339 density 0.090335 total sulfur dioxide 0.074523 chlorides 0.056358 citric acid 0.050922 fixed acidity 0.048469 free sulfur dioxide 0.037486 residual sugar 0.031109 0.017267 рΗ dtype: float64

In [575... mutual_info.sort_values(ascending=True).plot.bar(figsize=(12,10)) plt.savefig('Information Gain.png')



SelectKBest

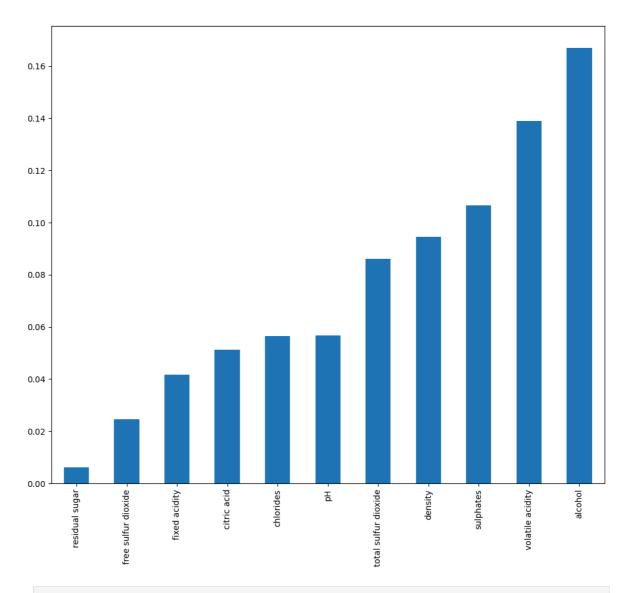
```
In [580...
           sel five cols = SelectKBest(mutual info classif, k = 5)
           sel_five_cols.fit(X_train.fillna(0),y_train)
           X_train.columns[sel_five_cols.get_support()]
           Index(['volatile acidity', 'chlorides', 'density', 'sulphates', 'alcohol'], dty
Out[580...
           pe='object')
           Feature Selection-Perform Feature Selection Using Information Gain For Regression In
           ML
In [583...
           import pandas as pd
           import numpy as np
           import seaborn as sns
           import matplotlib.pyplot as plt
           df = pd.read_csv(r"C:\Users\HP\Documents\Naresh IT\Data file\winequality_red.csv
           df.head()
Out[583...
                                                           free
                                                                   total
               fixed volatile citric residual
                                                                  sulfur density
                                              chlorides
                                                          sulfur
                                                                                   pH sulphates
              acidity
                      acidity
                               acid
                                       sugar
                                                        dioxide dioxide
           0
                  7.4
                         0.70
                               0.00
                                          1.9
                                                  0.076
                                                            11.0
                                                                    34.0
                                                                           0.9978 3.51
                                                                                             0.56
                  7.8
                         0.88
                               0.00
                                          2.6
                                                  0.098
                                                            25.0
                                                                    67.0
                                                                           0.9968 3.20
                                                                                             0.68
           2
                 7.8
                         0.76
                               0.04
                                          2.3
                                                  0.092
                                                            15.0
                                                                    54.0
                                                                           0.9970 3.26
                                                                                             19.0
           3
                 11.2
                         0.28
                               0.56
                                          1.9
                                                  0.075
                                                            17.0
                                                                    60.0
                                                                           0.9980 3.16
                                                                                             0.58
           4
                 7.4
                         0.70
                               0.00
                                          1.9
                                                  0.076
                                                            11.0
                                                                    34.0
                                                                           0.9978 3.51
                                                                                             0.56
In [585...
           df.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 1599 entries, 0 to 1598
         Data columns (total 12 columns):
          #
             Column
                                      Non-Null Count Dtype
         --- -----
              fixed acidity
          0
                                                       float64
                                      1599 non-null
          1
              volatile acidity
                                      1599 non-null
                                                       float64
          2
              citric acid
                                      1599 non-null
                                                       float64
                                                       float64
          3
              residual sugar
                                      1599 non-null
          4
              chlorides
                                      1599 non-null
                                                       float64
                                                       float64
          5
              free sulfur dioxide
                                      1599 non-null
              total sulfur dioxide 1599 non-null
                                                       float64
          6
          7
               density
                                      1599 non-null
                                                       float64
                                      1599 non-null
                                                       float64
          8
               рΗ
               sulphates
                                      1599 non-null
                                                       float64
          10 alcohol
                                      1599 non-null
                                                       float64
                                      1599 non-null
                                                       int64
          11 quality
         dtypes: float64(11), int64(1)
         memory usage: 150.0 KB
In [587...
           numeric_lst=list(df.select_dtypes(exclude='object').columns)
```

```
In [589...
           numeric_lst
Out[589...
          ['fixed acidity',
            'volatile acidity',
            'citric acid',
            'residual sugar',
            'chlorides',
            'free sulfur dioxide',
            'total sulfur dioxide',
            'density',
            'pH',
            'sulphates',
            'alcohol',
            'quality']
In [591...
          X=df.drop('quality',axis=1) # select the input columns
           y=df['quality'] # select the output
          df.shape,X.shape,y.shape
Out[591...
          ((1599, 12), (1599, 11), (1599,))
In [593...
          from sklearn.model_selection import train_test_split
          X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=
           print(X_train.shape,X_test.shape,y_train.shape,y_test.shape)
         (1279, 11) (320, 11) (1279,) (320,)
          X_train
In [595...
Out[595...
                                                              free
                                                                      total
                   fixed volatile citric residual
                                                 chlorides
                                                            sulfur
                                                                     sulfur density
                                                                                    pH sulph
                 acidity acidity acid
                                          sugar
                                                                   diovide
                                                           diovido
```

	•	•		•		dioxide	dioxide		
441	11.9	0.40	0.65	2.15	0.068	7.0	27.0	0.99880	3.06
227	9.0	0.82	0.14	2.60	0.089	9.0	23.0	0.99840	3.39
1386	7.4	0.64	0.07	1.80	0.100	8.0	23.0	0.99610	3.30
1245	7.4	0.55	0.19	1.80	0.082	15.0	34.0	0.99655	3.49
60	8.8	0.40	0.40	2.20	0.079	19.0	52.0	0.99800	3.44
•••	•••								
1228	5.1	0.42	0.00	1.80	0.044	18.0	88.0	0.99157	3.68
1077	8.6	0.37	0.65	6.40	0.080	3.0	8.0	0.99817	3.27
1318	7.5	0.63	0.27	2.00	0.083	17.0	91.0	0.99616	3.26
723	7.1	0.31	0.30	2.20	0.053	36.0	127.0	0.99650	2.94
815	10.8	0.45	0.33	2.50	0.099	20.0	38.0	0.99818	3.24

1279 rows × 11 columns

```
Out[597... fixed acidity
          volatile acidity
                                  0
          citric acid
                                  0
          residual sugar
                                  0
          chlorides
          free sulfur dioxide
                                  0
          total sulfur dioxide
                                  0
          density
                                  0
          рΗ
                                  0
          sulphates
          alcohol
          dtype: int64
In [599...
          from sklearn.feature_selection import mutual_info_regression
          mutual_regr = mutual_info_regression(X_train.fillna(0),y_train)
          mutual_regr
Out[599...
          array([0.0416753, 0.1388615, 0.05116235, 0.00617849, 0.05656146,
                 0.0246472 , 0.08607223, 0.09446549, 0.05667224, 0.10660919,
                 0.1670758 ])
In [601...
          mutual_regr = pd.Series(mutual_regr)
          mutual_regr.index = X_train.columns
          mutual_regr.sort_values(ascending=False)
Out[601...
          alcohol
                                  0.167076
          volatile acidity
                                  0.138861
          sulphates
                                  0.106609
          density
                                  0.094465
          total sulfur dioxide
                                  0.086072
                                 0.056672
          рΗ
          chlorides
                                 0.056561
          citric acid
                                 0.051162
          fixed acidity
                                 0.041675
          free sulfur dioxide 0.024647
          residual sugar
                                  0.006178
          dtype: float64
In [603...
          mutual_regr.sort_values(ascending=True).plot.bar(figsize=(12,10))
          plt.savefig('Information Gain For Regression.png')
```



In []: