WINE DATASET(UCL REPOSITORY)

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

link to dataset: https://archive.ics.uci.edu/ml/datasets/wine (https://archive.ics.uci.edu/ml/datasets/wine)

In [2]:
```
data=pd.read_csv('wine_data.csv',names=["Type","Alcohol",
"Malic acid",
"Ash",
"Alcalinity of ash",
"Magnesium",
"Total phenols",
"Flavanoids",
"Nonflavanoid phenols",
"Proanthocyanins","Color intensity","Hue","OD280/OD315 of diluted wines","Prol
ine"])
data.head()
```

Out[2]:

	Type	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proant
0	1	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	
1	1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	
2	1	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	
3	1	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	
4	1	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	

Steps to be followed

```
1.understand data
    Meaning of features
    importance of each
2.Make assumptions based on understanding
    Trying to check assumptions using visualization
    making few more assumptions and making decision about features
3.Modelling data
```

In [3]:
```
data.describe()
```

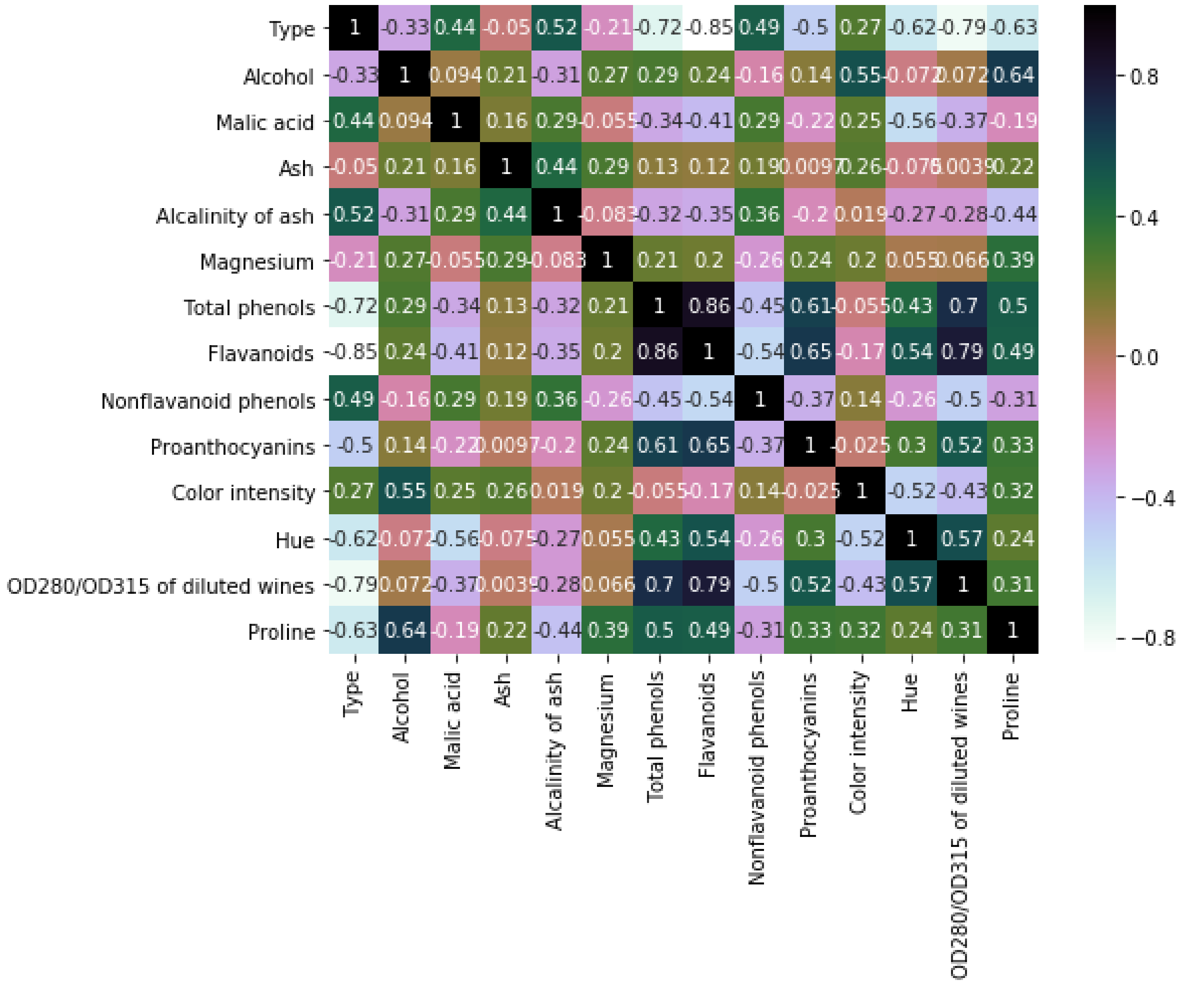
Out[3]:

	Type	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Fla
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178
mean	1.938202	13.000618	2.336348	2.366517	19.494944	99.741573	2.295112	2
std	0.775035	0.811827	1.117146	0.274344	3.339564	14.282484	0.625851	0
min	1.000000	11.030000	0.740000	1.360000	10.600000	70.000000	0.980000	0
25%	1.000000	12.362500	1.602500	2.210000	17.200000	88.000000	1.742500	1
50%	2.000000	13.050000	1.865000	2.360000	19.500000	98.000000	2.355000	2
75%	3.000000	13.677500	3.082500	2.557500	21.500000	107.000000	2.800000	2
max	3.000000	14.830000	5.800000	3.230000	30.000000	162.000000	3.880000	5

In [4]:
```
data.columns
```

Out[4]:
```
Index(['Type', 'Alcohol', 'Malic acid', 'Ash', 'Alcalinity of ash',
       'Magnesium', 'Total phenols', 'Flavanoids', 'Nonflavanoid phenols',
       'Proanthocyanins', 'Color intensity', 'Hue',
       'OD280/OD315 of diluted wines', 'Proline'],
      dtype='object')
```

In [5]:
```python
plt.figure(figsize=(8,6))
sns.heatmap(data.corr(),annot=True,cmap='cubehelix_r') #draws  heatmap with in
put as the correlation matrix calculted by(iris.corr())
plt.show()
```



In [6]:
```python
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score

x=data[[ 'Alcohol', 'Malic acid',  'Alcalinity of ash',
       'Total phenols', 'Flavanoids', 'Nonflavanoid phenols',
        'Color intensity', 'Hue',
       'OD280/OD315 of diluted wines', 'Proline']]
y=data['Type']

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.33,random_state
=44)
print("training data set:",x_train.shape)
print("testing data set:",x_test.shape)
```

```
training data set: (119, 10)
testing data set: (59, 10)
```

In [7]:
```
results=pd.DataFrame(columns=['Classifier','r2score','MSE'])
results.head()
```

Out[7]:

Classifier	r2score	MSE

In [8]:
```
from sklearn.linear_model import LogisticRegression

lr = LogisticRegression(random_state=0,C=1.0, solver='lbfgs',multi_class='mult
inomial')
lr.fit(x_train, y_train)
yhat=lr.predict(x_test)
r2score=r2_score(yhat,y_test)
mse=mean_squared_error(yhat,y_test)
print("r2score",r2score)
print('Mean squared error:',mse)
results=results.append(pd.Series(['Logistic Regression',r2score,mse],index=res
ults.columns ),ignore_index=True)
print("score:",lr.score(x_train, y_train))
```

```
r2score 0.9447047797563262
Mean squared error: 0.03389830508474576
score: 0.9495798319327731

C:\Users\vivek\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\li
near_model\logistic.py:758: ConvergenceWarning: lbfgs failed to converge. Inc
rease the number of iterations.
  "of iterations.", ConvergenceWarning)
```

In [9]:
```
from sklearn.linear_model import LinearRegression

lm=LinearRegression()
lm.fit(x_train,y_train)
yhat=lm.predict(x_test)
r2score=r2_score(yhat,y_test)
mse=mean_squared_error(yhat,y_test)
print("r2score",r2score)
print('Mean squared error:',mse)
results=results.append(pd.Series(['Regression',r2score,mse],index=results.colu
mns ),ignore_index=True)
```

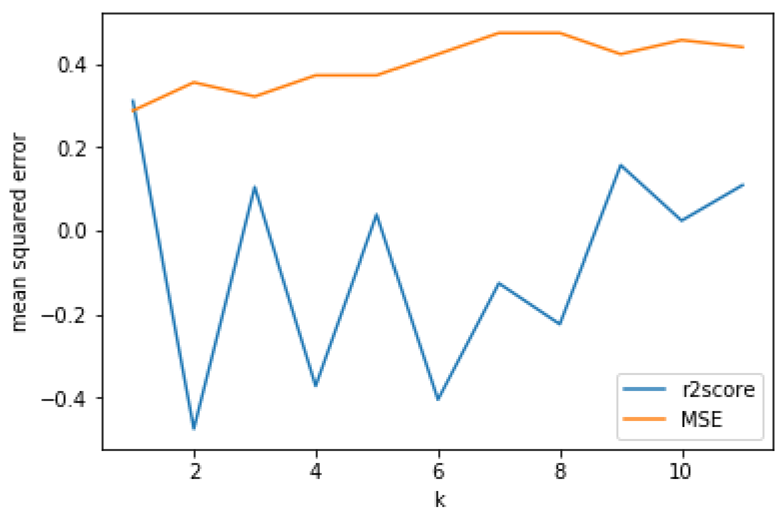
```
r2score 0.907843271302634
Mean squared error: 0.048823160144306516
```

In [10]:
```
from sklearn.neighbors import KNeighborsClassifier
import matplotlib.pyplot as plt

x1axes,x2axes=[],[]

for i in range(1,12):
    neigh = KNeighborsClassifier(n_neighbors=i)
    neigh.fit(x_train,y_train)
    yhat=neigh.predict(x_test)
    x1axes.append(r2_score(yhat,y_test))
    x2axes.append(mean_squared_error(yhat,y_test))

plt.plot(list(range(1,12)),x1axes,label="r2score")
plt.plot(list(range(1,12)),x2axes,label="MSE")
plt.xlabel('k')
plt.ylabel('mean squared error')
plt.legend()
plt.show()
```



In [11]:
```
results=results.append(pd.Series(['K nearest neighbours',max(x1axes),min(x2axe
s)],index=results.columns ),ignore_index=True)
```

In [12]:
```
from sklearn.tree import DecisionTreeClassifier

clf = DecisionTreeClassifier(random_state=0)
clf.fit(x_train,y_train)
yhat=clf.predict(x_test)
r2score=r2_score(yhat,y_test)
mse=mean_squared_error(yhat,y_test)
print("r2score",r2score)
print('Mean squared error:',mse)
print("cross val score:",cross_val_score(clf, x_train, y_train, cv=10).mean())
results=results.append(pd.Series(['Decision Tree',r2score,mse],index=results.c
olumns ),ignore_index=True)
```

```
r2score 0.8894095595126523
Mean squared error: 0.06779661016949153
cross val score: 0.8916899766899767
```

In [13]:
```
print(yhat)
print(y_test.values)
```

```
[1 2 1 3 3 1 2 2 1 2 1 1 2 1 2 2 2 2 1 1 1 3 1 1 1 1 3 3 3 2 2 3 2 2 3 1 1
 3 3 1 2 2 1 1 2 3 3 2 3 1 2 2 1 2 2 1 2 3 3]
[1 2 1 3 3 1 2 2 1 2 1 2 2 1 2 2 2 1 1 1 1 3 2 1 1 1 3 3 3 2 2 3 2 2 2 1 1
 3 3 1 2 2 1 1 2 3 3 2 3 1 2 2 1 2 2 1 2 3 3]
```

In [14]:
```
from sklearn.svm import SVC

svc = SVC(gamma='auto')
svc.fit(x_train, y_train)
yhat=svc.predict(x_test)
r2score=r2_score(yhat,y_test)
mse=mean_squared_error(yhat,y_test)
print("r2score",r2score)
print('Mean squared error:',mse)
results.append(pd.Series(['SVC',r2score,mse],index=results.columns ),ignore_in
dex=True)
```

```
r2score -3.009708737864077
Mean squared error: 0.4745762711864407
```

Out[14]:

	Classifier	r2score	MSE
0	Logistic Regression	0.944705	0.033898
1	Regression	0.907843	0.048823
2	K nearest neighbours	0.311126	0.288136
3	Decision Tree	0.889410	0.067797
4	SVC	-3.009709	0.474576

conclusion on model performance:

- regression model are performing better
- REASON: Contionous data

In [ ]: