PS7 Yuming Liu

In [1]:
```
import numpy as np
import pandas as pd
import statsmodels.api as sm
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split, LeaveOneOut, KFold
from sklearn.metrics import classification_report
import matplotlib.pyplot as plt
from scipy.interpolate import LSQUnivariateSpline

import warnings
warnings.filterwarnings("ignore")
```

Problem 1(a)

In [2]:
```
df = pd.read_csv('data/strongdrink.txt')

X = df[['alco','malic','tot_phen','color_int']]
y = df['cultivar']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, ra
ndom_state=20)

result = LogisticRegression(solver='lbfgs',multi_class='multinomial').fit(X_tr
ain, y_train)

Results = pd.DataFrame({"j = 1":np.append(result.intercept_[0],result.coef_[0
]),
               "j = 2":np.append(result.intercept_[1],result.coef_[1])},
                index=["beta_0","beta_1",'beta_2','beta_3','beta_4'])
print(Results)

y_pred = result.predict(X_test)

print(classification_report(y_test, y_pred))
```

```
            j = 1      j = 2
beta_0 -24.027617  22.780733
beta_1   1.701734  -1.466297
beta_2  -0.265788  -0.332951
beta_3   1.224101   0.663556
beta_4   0.022507  -0.922682
              precision    recall  f1-score   support

           1       0.87      1.00      0.93        13
           2       1.00      0.90      0.95        21
           3       1.00      1.00      1.00        10

    accuracy                           0.95        44
   macro avg       0.96      0.97      0.96        44
weighted avg       0.96      0.95      0.96        44
```

From the report, the error rates for the above groups are 13%, 0%, and 0%. Based on the f1-score, we have that $j = 3$ is the best model for prediction.

In [3]:
```
MSE = (y_test != y_pred).mean()
print('The MSE from the test set is ', MSE)
```

```
The MSE from the test set is  0.045454545454545456
```

Problem 1(b)

In [4]:
```
X = df[["alco","malic","tot_phen","color_int"]].values
y = df["cultivar"].values

N_loo = X.shape[0]
loo = LeaveOneOut()
loo.get_n_splits(X)
MSE_vec = np.zeros(N_loo)

ypred = np.zeros(X.shape[0])

for train_index, test_index in loo.split(X):
    X_train, X_test = X[train_index], X[test_index]
    y_train, y_test = y[train_index], y[test_index]
    LogReg = LogisticRegression(solver='lbfgs',multi_class='multinomial')
    LogReg.fit(X_train, y_train)
    y_pred = LogReg.predict(X_test)
    ypred[test_index] = y_pred
    if y_test == y_pred:
        MSE_vec[test_index] = 0
    else:
        MSE_vec[test_index] = 1
```

In [5]:
```
print(classification_report(y, ypred))
MSE_loo = MSE_vec.mean()
print('The estimate MSE loocv of the test =', MSE_loo)
```

```
              precision    recall  f1-score   support

           1       0.90      0.93      0.92        59
           2       0.91      0.90      0.91        71
           3       0.96      0.93      0.95        46

    accuracy                           0.92       176
   macro avg       0.92      0.92      0.92       176
weighted avg       0.92      0.92      0.92       176

The estimate MSE loocv of the test = 0.07954545454545454
```

From the report, the error rates for the above groups are 10%, 9%, and 4%. The rates are higher than those from (a). Based on the f1-score, we have that $j = 3$ is the best model for prediction.

Problem 1(c)

In [6]:
```
kf = KFold(n_splits=4, shuffle=True, random_state=10)
kf.get_n_splits(X)

MSE_vec_kf = np.zeros(4)

k_ind = int(0)
ypred = np.zeros(X.shape[0])

for train_index, test_index in kf.split(X):
    X_train, X_test = X[train_index], X[test_index]
    y_train, y_test = y[train_index], y[test_index]
    LogReg = LogisticRegression()
    LogReg.fit(X_train, y_train)
    y_pred = LogReg.predict(X_test)
    ypred[test_index] = y_pred
    MSE_vec_kf[k_ind] = ((y_test - y_pred) ** 2).mean()
    k_ind += 1
```

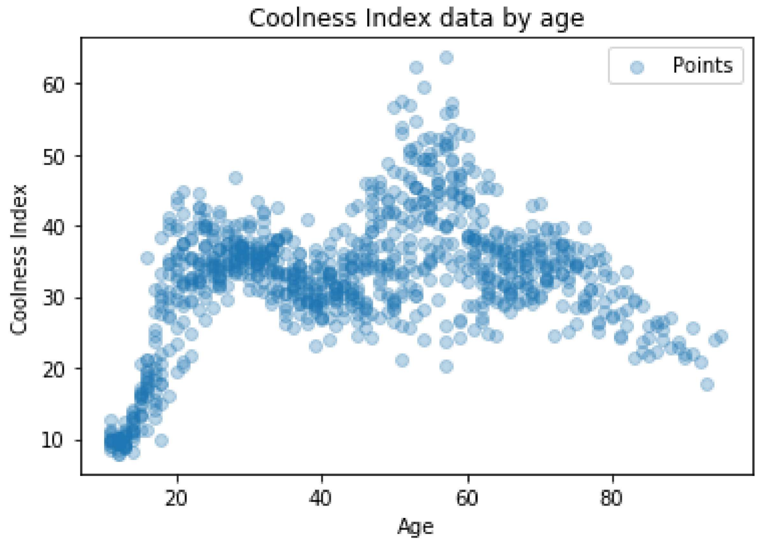
In [7]:
```
MSE_kf = MSE_vec_kf.mean()
print(classification_report(y, ypred))
print('The estimate MSE loocv of the test =', MSE_kf)
```

```
              precision    recall  f1-score   support

           1       0.87      0.93      0.90        59
           2       0.91      0.87      0.89        71
           3       0.96      0.93      0.95        46

    accuracy                           0.91       176
   macro avg       0.91      0.91      0.91       176
weighted avg       0.91      0.91      0.91       176

The estimate MSE loocv of the test = 0.10795454545454546
```

From the report, the error rates for the above groups are 13%, 9%, and 4%. The rates of 2 and 3 are higher than those from (a). The rate of 1 is higher than which from (b). The rates of 2 and 3 are possiblely the same from (b). Based on the f1-score, we have that $j = 3$ is the best model for prediction.

Problem 2(a)

In [8]:
```
df2 = pd.read_csv("data/CoolIndex.txt",names=["Age","Cool"])

plt.scatter(x =df2['Age'], y =df2['Cool'], alpha=0.3, label="Points")
plt.title('Coolness Index data by age')
plt.legend()
plt.xlabel('Age')
plt.ylabel('Coolness Index')
plt.show()
```



Problem 2(b)

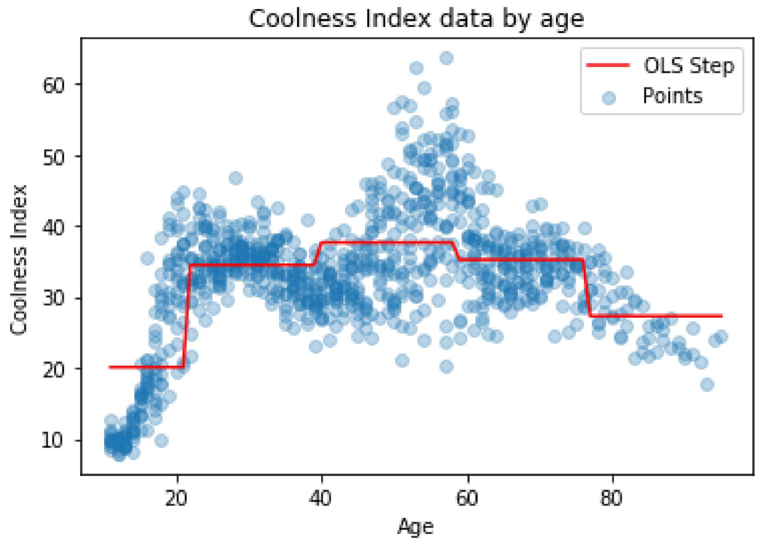
In [9]:
```
df2["bin1"]=np.where((df2.Age>=11) & (df2.Age<22),1,0)
df2["bin2"]=np.where((df2.Age>=22) & (df2.Age<40),1,0)
df2["bin3"]=np.where((df2.Age>=40) & (df2.Age<59),1,0)
df2["bin4"]=np.where((df2.Age>=59) & (df2.Age<77),1,0)
df2["bin5"]=np.where((df2.Age>=77) & (df2.Age<=95),1,0)
```

In [10]:
```
X = df2[["bin1", "bin2", "bin3", "bin4", "bin5"]]
y = df2['Cool']
res = sm.OLS(y, X, missing='drop').fit()
```

In [11]:
```
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                   Cool   R-squared:                       0.42
9
Model:                            OLS   Adj. R-squared:                  0.42
7
Method:                 Least Squares   F-statistic:                     178.
7
Date:                Tue, 25 Feb 2020   Prob (F-statistic):          3.73e-11
4
Time:                        15:25:31   Log-Likelihood:                -3214.
5
No. Observations:                 956   AIC:                             643
9.
Df Residuals:                     951   BIC:                             646
3.
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
bin1          20.1025      0.562     35.746      0.000      18.999      21.20
6
bin2          34.4758      0.431     80.006      0.000      33.630      35.32
1
bin3          37.6351      0.424     88.814      0.000      36.804      38.46
7
bin4          35.2254      0.485     72.560      0.000      34.273      36.17
8
bin5          27.2964      0.936     29.175      0.000      25.460      29.13
2
==============================================================================
=
Omnibus:                       80.102   Durbin-Watson:                   1.23
6
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              101.71
8
Skew:                           0.714   Prob(JB):                     8.17e-2
3
Kurtosis:                       3.719   Cond. No.                         2.2
1
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

In [12]:
```
plt.scatter(df2['Age'], df2['Cool'], alpha=0.3, label='Points')
plt.plot(df2['Age'], res.predict(), 'r', label='OLS Step')
plt.legend()
plt.xlabel('Age')
plt.ylabel('Coolness Index')
plt.title('Coolness Index data by age')
plt.show()
```



In [13]:
```
print('The predicted coolness of a 73-year old from the step function is', res
.params[3])
```

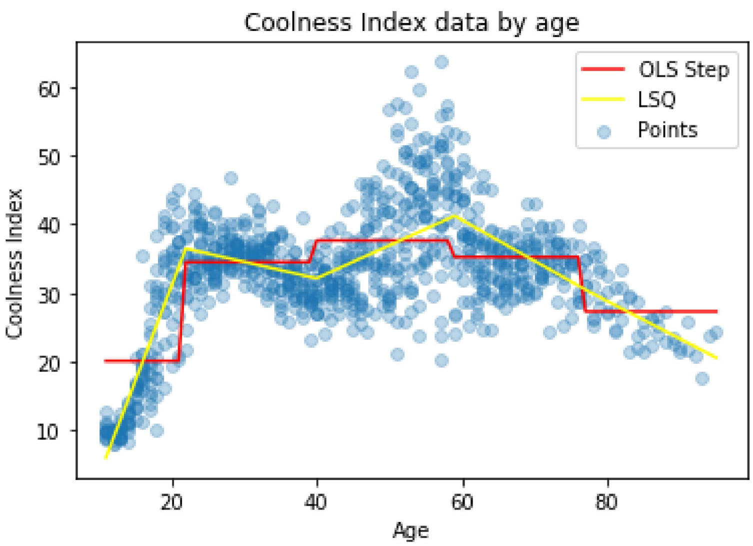
```
The predicted coolness of a 73-year old from the step function is 35.22540004
024275
```

Problem 2(c)

In [14]:
```
df3 = df2.groupby('Age').mean()
df3['Age']=df3.index
```

In [15]:
```
lsq = LSQUnivariateSpline(np.array(df3['Age']), np.array(df3['Cool']), t = [22
,40,59,77], k = 1)
```

In [16]:
```
plt.scatter(df2['Age'], df2['Cool'], alpha=0.3, label='Points')
plt.plot(df2['Age'], res.predict(), 'r', label='OLS Step')
plt.plot(df3['Age'], lsq(df3['Age']), 'yellow', label='LSQ')
plt.legend()
plt.xlabel('Age')
plt.ylabel('Coolness Index')
plt.title('Coolness Index data by age')
plt.show()
```



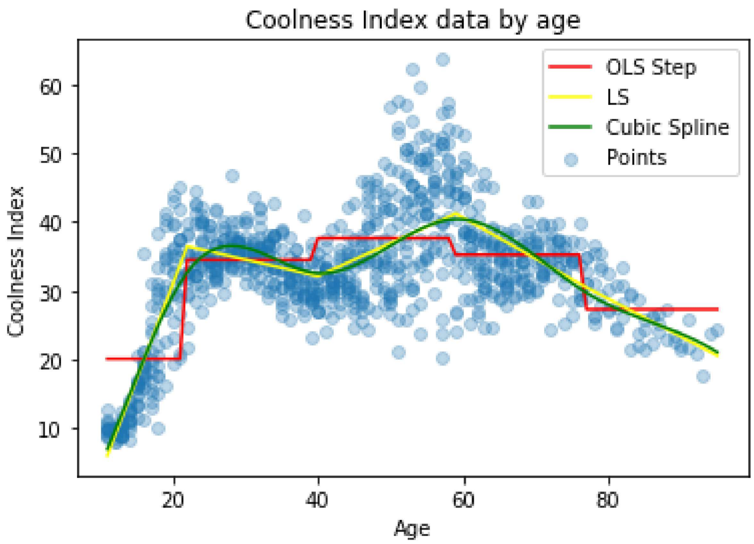
In [17]:
```
print('The predicted coolness of a 73-year old from the step function is', lsq
(73))
```

```
The predicted coolness of a 73-year old from the step function is 32.86784862
349653
```

Problem 2(d)

In [18]:
```
lsq_new=LSQUnivariateSpline(np.array(df3['Age']), np.array(df3['Cool']), t=[22
,40,59,77], k=3)
```

In [19]:
```
plt.scatter(df2['Age'], df2['Cool'], alpha=0.3, label='Points')
plt.plot(df2['Age'], res.predict(), 'r', label='OLS Step')
plt.plot(df3['Age'], lsq(df3['Age']), 'yellow', label='LS')
plt.plot(df3['Age'], lsq_new(df3['Age']), 'green', label='Cubic Spline')
plt.legend()
plt.xlabel('Age')
plt.ylabel('Coolness Index')
plt.title('Coolness Index data by age')
plt.show()
```



In [20]:
```
print('The predicted coolness of a 73-year old from the step function is', lsq_new(73))
```

```
The predicted coolness of a 73-year old from the step function is 32.64230106
6279764
```