Problem Set 7

Fulin Guo

1

a

In [176]:

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split,LeaveOneOut, KFold
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
```

In [177]:

```
wines=pd.read_csv('/Users/fulinguo/Desktop/persp-model-econ_W19/ProblemSets/PS7/
data/strongdrink.txt')
```

In [178]:

```
X=wines[['alco','malic','tot_phen','color_int']]
y=wines['cultivar']
X_train, X_test, y_train, y_test = \
    train_test_split(X, y, test_size = 0.25, random_state=20)
LogReg = LogisticRegression(multi_class='multinomial',solver='newton-cg')
LogReg.fit(X_train, y_train)
print('The intercept for j=1:',LogReg.intercept_[0])
print('The coefficients for j=1:',LogReg.coef_[0])
print('The intercept for j=2:',LogReg.intercept_[1])
print('The coefficients for j=2:',LogReg.coef_[1])
```

```
The intercept for j=1: -24.011331526271427
The coefficients for j=1: [ 1.70043264 -0.26560971  1.22389447  0.02
274778]
The intercept for j=2: 22.801680361781052
The coefficients for j=2: [-1.46798523 -0.33305092  0.66400603 -0.92
270882]
```

In [179]:

```
y_pred=LogReg.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              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

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

The error rate for category 1 is 0.13, for category 2 is 0, for category 3 is also 0

The model predicts category 3 best since its precision, recall, and f1-score are the highest among the three categories.

In [180]:

```
print('The number of observations with cultivar =1:',np.sum(wines['cultivar']==1
))
print('The number of observations with cultivar =2:',np.sum(wines['cultivar']==2
))
print('The number of observations with cultivar =3:',np.sum(wines['cultivar']==3
))
print('The number of observations with cultivar =1 in the training set:',sum(y_t
rain==1))
print('The number of observations with cultivar =2 in the training set:',sum(y_t
rain==2))
print('The number of observations with cultivar =3 in the training set:',sum(y_t
rain==3))
```

```
The number of observations with cultivar =1: 59
The number of observations with cultivar =2: 71
The number of observations with cultivar =3: 46
The number of observations with cultivar =1 in the training set: 46
The number of observations with cultivar =2 in the training set: 50
The number of observations with cultivar =3 in the training set: 36
```

Therefore, the most accurately predicted category is not the one with the most observations since category 3 has the least number of observations.

In [181]:

```
MSE=np.sum((y_test!=y_pred)**2)/len(y_pred)
print('The MSE from the test set =',MSE)
```

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

b

In [182]:

```
Xv=X.values
yv=y.values
N_loo=len(Xv)
loo=LeaveOneOut()
loo.get_n_splits(Xv)
MSE_vec=np.zeros(N_loo)
```

In [183]:

```
yp=[]
yt=[]
for train_index, test_index in loo.split(Xv):
    X_train, X_test=Xv[train_index], Xv[test_index]
    y_train, y_test=yv[train_index], yv[test_index]
    LogReg=LogisticRegression(multi_class='multinomial',solver='newton-cg')
    LogReg.fit(X_train, y_train)
    y_pred=LogReg.predict(X_test)
    yp.append(y_pred)
    yt.append(y_test)
    MSE_vec[test_index]=(y_test!=y_pred)**2
```

In [184]:

```
print(classification_report(yt, yp))
```

```
              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

   micro avg       0.92      0.92      0.92       176
   macro avg       0.92      0.92      0.92       176
weighted avg       0.92      0.92      0.92       176
```

The error rate for category 1 is 0.10, for category 2 is 0.09, for category 3 is 0.04

We can note that category 3 has the least error rate, which is the same as part (a). Another finding is that roughly speaking, the error rates are larger in part (b) than that in part (a). In particular, the error rates for category 2 and 3 are larger than their corresponding error rates in part (a). The error rate for category 1 is smaller than that in part(a).

In [185]:

```
MSE_loo = MSE_vec.mean()
```

In [186]:

```
print('The LOOCV estimate for the test MSE is:', MSE_loo)
```

```
The LOOCV estimate for the test MSE is: 0.07954545454545454
```

c

In [187]:

```
k=4
kf = KFold(n_splits=4, shuffle=True, random_state=10)
kf.get_n_splits(Xv)
MSE_vec_kf = np.zeros(k)
k_ind = int(0)
ypk=[]
ytk=[]
for train_index, test_index in kf.split(Xv):
    X_train, X_test = Xv[train_index], Xv[test_index]
    y_train, y_test = yv[train_index], yv[test_index]
    LogReg = LogisticRegression(multi_class='multinomial',solver='newton-cg')
    LogReg.fit(X_train, y_train)
    y_pred = LogReg.predict(X_test)
    MSE_vec_kf[k_ind] = ((y_test != y_pred) ** 2).mean()
    k_ind += 1
    ypk.extend(y_pred)
    ytk.extend(y_test)
print(classification_report(ytk, ypk))
```

```
              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

   micro avg       0.91      0.91      0.91       176
   macro avg       0.91      0.91      0.91       176
weighted avg       0.91      0.91      0.91       176
```

The error rate for category 1 is 0.13, for category 2 is 0.09, for category 3 is 0.04

We can note that category 3 has the least error rate, which is the same as part (a) and (b). Another finding is that roughly speaking, the error rates in part (c) are larger than that in part (a), and are slightly larger than that in part (b). In particular, the error rates for the three categories in part (c) are larger than their corresponding error rates in part (a) except that category 1's error rates are the same in these two parts. The error rate for category 1 is larger than its error rate in part (b), and the error rates for category 2 and 3 in part (c) are (roughly) the same as that in part (b).

In [188]:

```
MSE_kf = MSE_vec_kf.mean()
print('The k-fold estimate for the test MSE is:', MSE_kf)
```

```
The k-fold estimate for the test MSE is: 0.09090909090909091
```

2

a

In [189]:

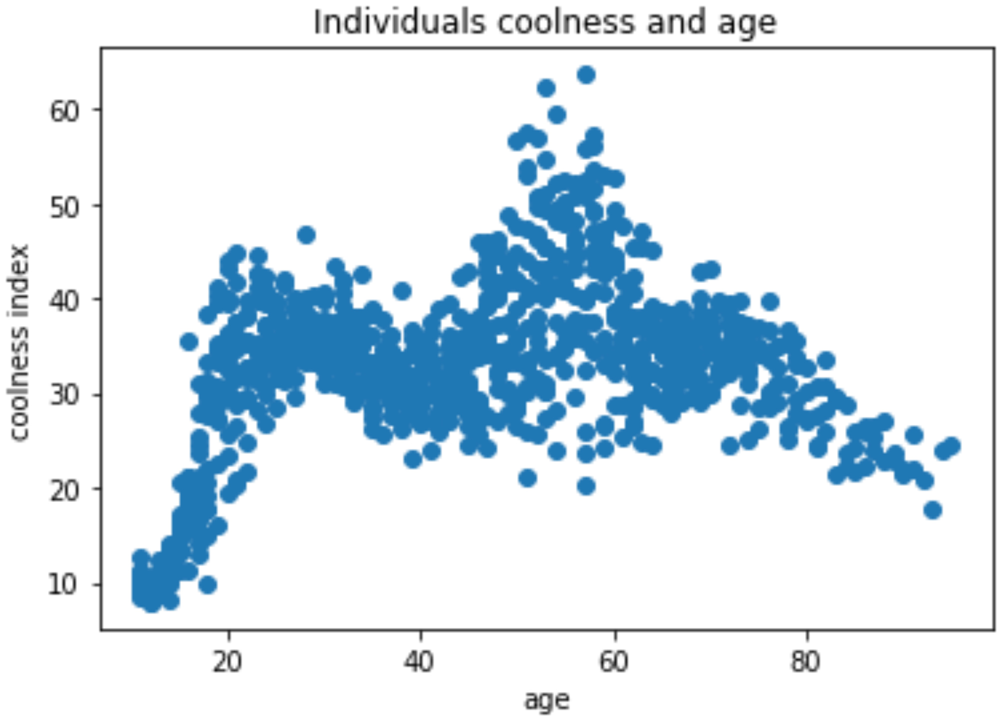
```
import matplotlib.pyplot as plt
data2=pd.read_csv('/Users/fulinguo/Desktop/persp-model-econ_W19/ProblemSets/PS7/data/CoolIndex.txt',
                  header=None,names=['age','cool'])
```

In [190]:

```
plt.scatter(data2['age'],data2['cool'])
plt.xlabel('age')
plt.ylabel('coolness index')
plt.title('Individuals coolness and age')
```

Out[190]:

```
Text(0.5, 1.0, 'Individuals coolness and age')
```



b

In [191]:

```
data2['age11']=((data2['age']>=11) & (data2['age']<22))
data2['age22']=((data2['age']>=22) & (data2['age']<40))
data2['age40']=((data2['age']>=40) & (data2['age']<59))
data2['age59']=((data2['age']>=59) & (data2['age']<77))
data2['age77']=((data2['age']>=77) & (data2['age']<=95))
data2['age11'][data2['age11']]=1
data2['age22'][data2['age22']]=1
data2['age40'][data2['age40']]=1
data2['age59'][data2['age59']]=1
data2['age77'][data2['age77']]=1
```

```
/Users/fulinguo/anaconda3/lib/python3.6/site-packages/ipykernel_laun
cher.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy

/Users/fulinguo/anaconda3/lib/python3.6/site-packages/ipykernel_laun
cher.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  import sys
/Users/fulinguo/anaconda3/lib/python3.6/site-packages/ipykernel_laun
cher.py:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy

/Users/fulinguo/anaconda3/lib/python3.6/site-packages/ipykernel_laun
cher.py:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  if __name__ == '__main__':
/Users/fulinguo/anaconda3/lib/python3.6/site-packages/ipykernel_laun
cher.py:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  # Remove the CWD from sys.path while we load stuff.
```

In [192]:

```
import statsmodels.api as sm
reg1 = sm.OLS(endog=data2['cool'], exog=data2[['age11','age22','age40','age59','
age77']])
results = reg1.fit()
print(results.summary())
```

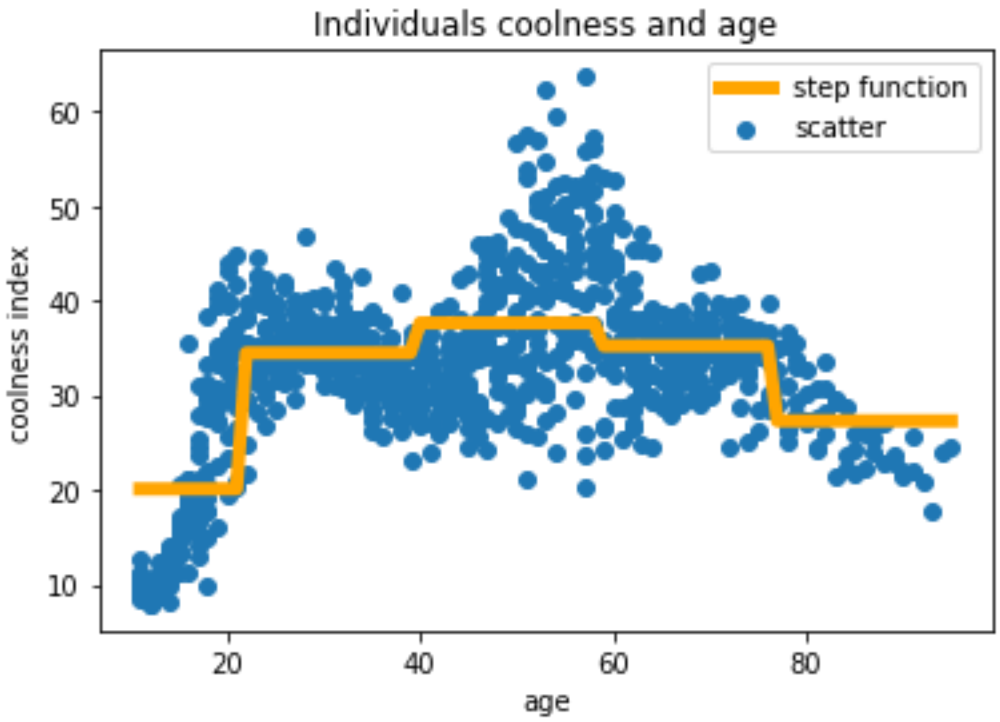
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   cool   R-squared:
0.429
Model:                            OLS   Adj. R-squared:
0.427
Method:                 Least Squares   F-statistic:
178.7
Date:                Wed, 27 Feb 2019   Prob (F-statistic):
3.73e-114
Time:                        01:05:23   Log-Likelihood:
-3214.5
No. Observations:                 956   AIC:
6439.
Df Residuals:                     951   BIC:
6463.
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
age11        20.1025      0.562     35.746      0.000      18.999
21.206
age22        34.4758      0.431     80.006      0.000      33.630
35.321
age40        37.6351      0.424     88.814      0.000      36.804
38.467
age59        35.2254      0.485     72.560      0.000      34.273
36.178
age77        27.2964      0.936     29.175      0.000      25.460
29.132
==============================================================================
Omnibus:                       80.102   Durbin-Watson:
1.236
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
101.718
Skew:                           0.714   Prob(JB):
8.17e-23
Kurtosis:                       3.719   Cond. No.
2.21
==============================================================================

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

In [193]:

```
pre_cool=results.predict(exog=data2[['age11','age22','age40','age59','age77']])
plt.scatter(data2['age'],data2['cool'],label='scatter')
plt.plot(data2['age'],pre_cool,'orange', lw=5,label='step function')
plt.xlabel('age')
plt.ylabel('coolness index')
plt.title('Individuals coolness and age')
plt.legend()
```

Out[193]:

```
<matplotlib.legend.Legend at 0x1c1a7aff60>
```



In [194]:

```
print('The estimated step function values for each bin:')
print(results.params)
```

```
The estimated step function values for each bin:
age11    20.102457
age22    34.475788
age40    37.635105
age59    35.225400
age77    27.296378
dtype: float64
```

In [195]:

```
pre=results.predict(exog=[0, 0, 0, 1, 0])[0]
print('The predicted coolness of a 73-year old from the stepwise function is:',p
re)
```

```
The predicted coolness of a 73-year old from the stepwise function i
s: 35.22540004024275
```

c

In [196]:

```
from scipy.interpolate import LSQUnivariateSpline
```

In [197]:

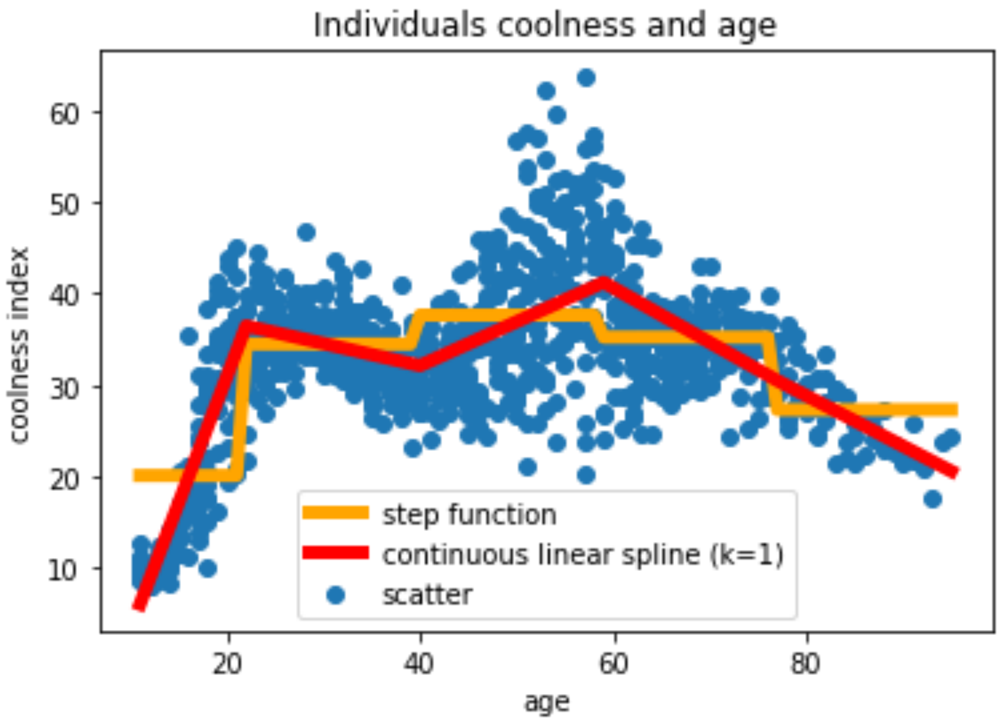
```
t=np.array([22,40,59,77])
age0=data2['age'][0]
incre_age=[age0]
incre_cool=[]
a=0
for i in range(1,len(data2['age'])):
    if data2['age'][i]!=age0:
        incre_age.append(data2['age'][i])
        incre_cool.append(sum(data2['cool'][a:i])/(i-a))
        a=i
    age0=data2['age'][i]
    if i==len(data2['age'])-1:
        incre_cool.append(sum(data2['cool'][a:i+1])/(i-a+1))
incre_age=np.array(incre_age)
incre_cool=np.array(incre_cool)
ans=LSQUnivariateSpline(incre_age, incre_cool, t,k=1)
```

In [198]:

```
plt.scatter(data2['age'],data2['cool'],label='scatter')
plt.plot(data2['age'],pre_cool,'orange', lw=5, label='step function')
plt.plot(incre_age, ans(incre_age), 'r-', lw=5,label='continuous linear spline (
k=1)')
plt.xlabel('age')
plt.ylabel('coolness index')
plt.title('Individuals coolness and age')
plt.legend()
```

Out[198]:

```
<matplotlib.legend.Legend at 0x1c1a672198>
```



In [199]:

```
pre2=ans(73)
print('The predicted coolness of a 73-year old from the stepwise function is:',p
re2)
```

```
The predicted coolness of a 73-year old from the stepwise function i
s: 32.86784862349653
```

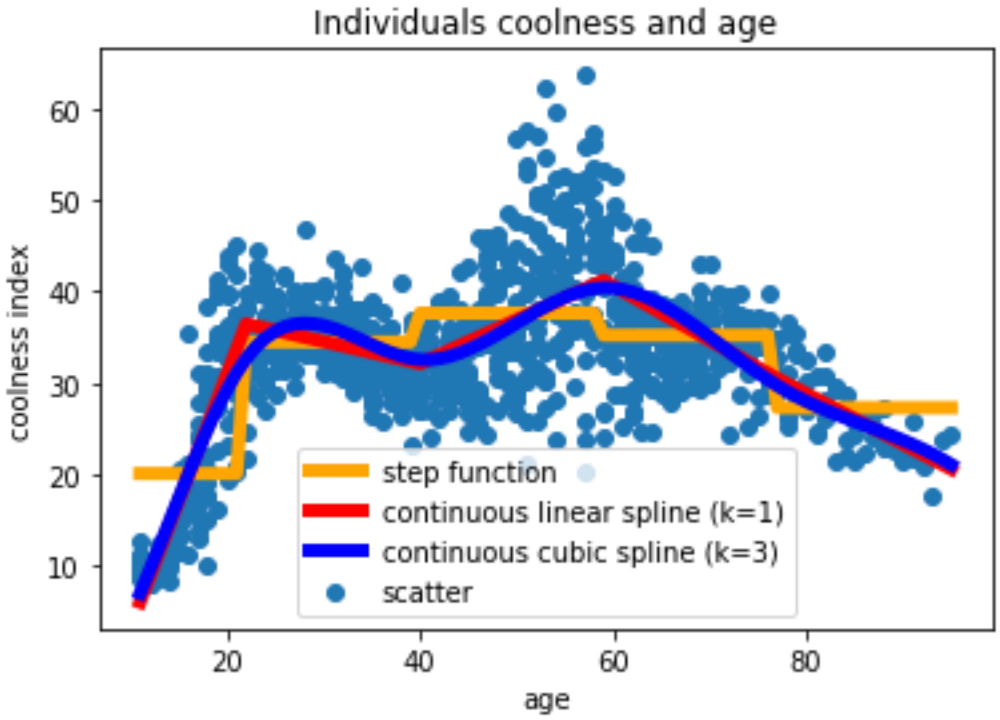
d

In [200]:

```
ans2=LSQUnivariateSpline(incre_age, incre_cool, t,k=3)
plt.scatter(data2['age'],data2['cool'],label='scatter')
plt.plot(data2['age'],pre_cool,'orange', lw=5, label='step function')
plt.plot(incre_age, ans(incre_age), 'r-', lw=5,label='continuous linear spline (
k=1)')
plt.plot(incre_age, ans2(incre_age), 'b-', lw=5,label='continuous cubic spline (
k=3)')
plt.xlabel('age')
plt.ylabel('coolness index')
plt.title('Individuals coolness and age')
plt.legend()
```

Out[200]:

```
<matplotlib.legend.Legend at 0x1c1a7560f0>
```



In [201]:

```
pre3=ans2(73)
print('The predicted coolness of a 73-year old from the stepwise function is:',p
re3)
```

```
The predicted coolness of a 73-year old from the stepwise function i
s: 32.642301066279764
```

In [ ]: