

PS5

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

1 Q1

```
In [2]: import sklearn
from sklearn import preprocessing
from sklearn.linear_model import LogisticRegression
from sklearn.cross_validation import train_test_split
from sklearn import metrics
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import LeaveOneOut
import seaborn as sb
from sklearn.model_selection import KFold
import statsmodels.api as sm
from scipy.interpolate import LSQUnivariateSpline
```

```
/anaconda/lib/python3.6/site-packages/sklearn/cross_validation.py:41: DeprecationWarning: This module
    "This module will be removed in 0.20.", DeprecationWarning)
/anaconda/lib/python3.6/site-packages/statsmodels/compat/pandas.py:56: FutureWarning: The pandas
    from pandas.core import datetools
```

```
In [3]: sd = pd.read_csv("data/strongdrink.txt")
xvar = ["alco", "malic", "tot_phen", "color_int"]
yvar = ["cultivar"]
X_train, X_test, y_train, y_test = \
    train_test_split(sd[xvar], sd[yvar], test_size = 0.25,
        random_state=20)
MultLogReg = LogisticRegression(multi_class='multinomial',
                                solver='newton-cg')
MultLogReg.fit(X_train, y_train)
coef = pd.DataFrame(MultLogReg.coef_[0:2], index = ["cultivar = 1", "cultivar = 2"], col
coef.loc[:, "Intercept"] = MultLogReg.intercept_[0:2]
coef
```

```
/anaconda/lib/python3.6/site-packages/sklearn/utils/validation.py:578: DataConversionWarning: A
y = column_or_1d(y, warn=True)
```

```
Out [3]:
```

	alco	malic	tot_phen	color_int	Intercept
cultivar = 1	1.700368	-0.265602	1.223892	0.022762	-24.010548
cultivar = 2	-1.468065	-0.333055	0.664017	-0.922714	22.802713

```
In [4]: pd.crosstab(index = y_test["cultivar"], columns = 'count')
```

```
Out [4]: col_0    count
cultivar
1             13
2             21
3             10
```

```
In [5]: print(classification_report(y_test, MultLogReg.predict(X_test)))
```

	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
avg / total	0.96	0.95	0.96	44

Cat 2 and 3 both achieve perfect precision, but according to other scores category 3 is best at predicting, which, on the contrary to the question, has fewest observations.

1.1 b) LOOCV

```
In [6]: N = sd.shape[0]
        loo = LeaveOneOut()
        Xvars = sd[xvar].values
        yvals = sd[yvar].values
        loo.get_n_splits(Xvars)
        classify = np.empty((N, 2))
        for train_index, test_index in loo.split(sd[xvar]):
            X_train, X_test = Xvars[train_index], Xvars[test_index]
            y_train, y_test = yvals[train_index], yvals[test_index]
            LogReg = LogisticRegression(multi_class='multinomial',
                                       solver='newton-cg')
            LogReg.fit(X_train, y_train)
            y_pred = LogReg.predict(X_test)
            classify[test_index,:] = np.array([y_test, y_pred]).reshape((1,2))
```

```
/anaconda/lib/python3.6/site-packages/sklearn/utils/validation.py:578: DataConversionWarning: A
y = column_or_1d(y, warn=True)
```

```
In [7]: print(classification_report(classify[:,0], classify[:,1]))
```

	precision	recall	f1-score	support
1.0	0.90	0.93	0.92	59
2.0	0.91	0.90	0.91	71
3.0	0.96	0.93	0.95	46
avg / total	0.92	0.92	0.92	176

The precision rates for each category is in the first column. The precision is worse than that from part (a) in general, except for cat 1 the first method achieves better precision.

```
In [8]: print("The average MSE is:")
        (1 - (classify[:,0] == classify[:,1])).mean()
```

The average MSE is:

```
Out[8]: 0.07954545454545454
```

1.2 c) k-fold cross validation

```
In [9]: k = 4
kf = KFold(n_splits=k, random_state=10, shuffle=True)
kf.get_n_splits(Xvars)
classify_kf = np.empty((N, 2))
k_ind = 0
for train_index, test_index in kf.split(Xvars):
    X_train, X_test = Xvars[train_index], Xvars[test_index]
    y_train, y_test = yvals[train_index], yvals[test_index]
    LogReg = LogisticRegression(multi_class='multinomial',
                                solver='newton-cg')
    LogReg.fit(X_train, y_train)
    y_pred = LogReg.predict(X_test)
    classify_kf[test_index,0:1] = y_test
    classify_kf[test_index,1] = y_pred
```

```
/anaconda/lib/python3.6/site-packages/sklearn/utils/validation.py:578: DataConversionWarning: A
y = column_or_1d(y, warn=True)
```

```
In [10]: print(classification_report(classify_kf[:,0], classify_kf[:,1]))
```

	precision	recall	f1-score	support
1.0	0.87	0.93	0.90	59

2.0	0.91	0.87	0.89	71
3.0	0.96	0.93	0.95	46
avg / total	0.91	0.91	0.91	176

The precision rates for each category is in the first column. The precision is worse than that from part (a) and part (b) on average.

```
In [11]: print("The average MSE is:")
          (1 - (classify_kf[:,0] == classify_kf[:,1])).mean()
```

The average MSE is:

```
Out[11]: 0.090909090909090912
```

2 Q2

2.1 Scatterplot

```
In [12]: ci = pd.read_csv("data/CoolIndex.txt", names = ['age', "CI"], header = None, dtype = {
          ci.head()
          fig, ax = plt.subplots()
          ax.scatter(ci['age'], ci['CI'], c = "gray")
          ax.set_xlabel("Age")
          ax.set_ylabel("Coolness Index")
          ax.set_title("Scatter plot of Coolness Index against Age")
          fig
```

```
Out[12]:
```



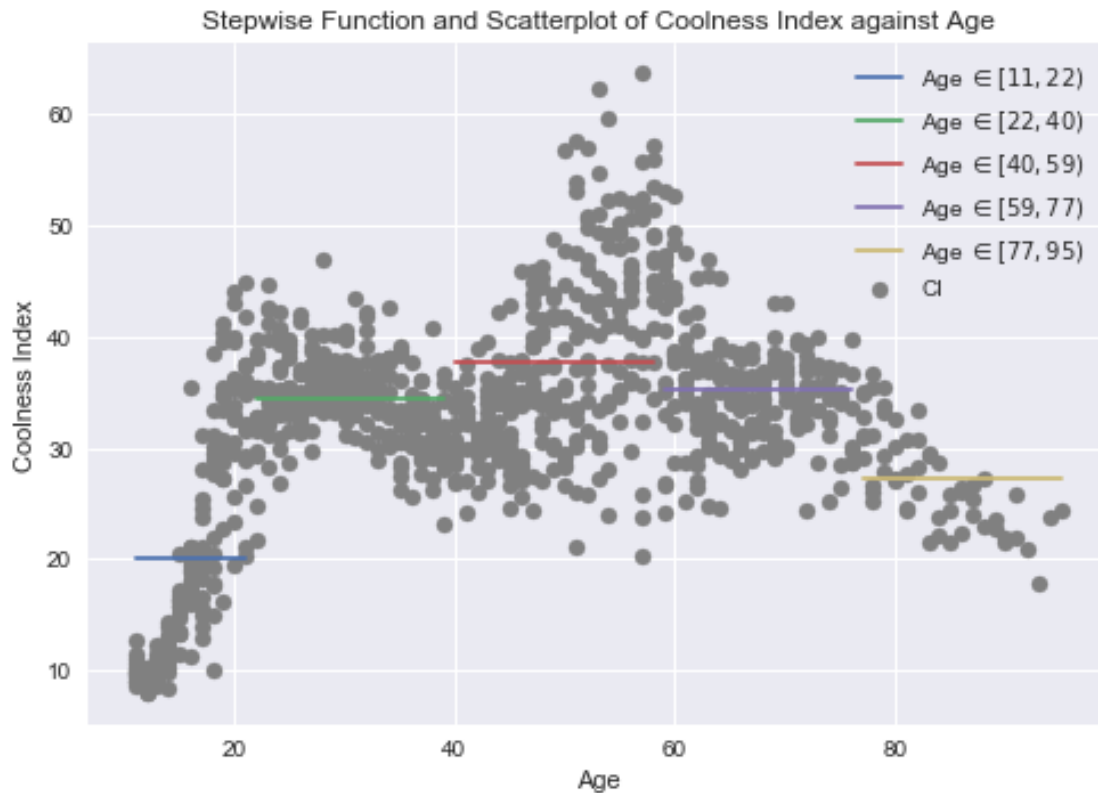
2.2 Stepwise Function

```
In [13]: cutoff = np.array([21, 39, 58, 76])
         ci.loc[:, "binnum"] = np.searchsorted(cutoff, ci.age)
         ci = pd.concat((ci,
                        pd.get_dummies(ci.binnum, prefix = "bin")),
                        axis = 1)

In [14]: reg = sm.OLS(ci.CI, ci.iloc[:, -5:]).fit()

In [15]: bins = [
            "$\in [11, 22)$",
            "$\in [22, 40)$",
            "$\in [40, 59)$",
            "$\in [59, 77)$",
            "$\in [77, 95)$"
          ]
         for i in range(5):
             ax.plot(ci.loc[ci.binnum == i, "age"], np.ones((ci.binnum == i).sum()) * reg.params[
                 label = 'Age ' + bins[i]
             ])
         ax.set_title("Stepwise Function and Scatterplot of Coolness Index against Age")
         ax.legend()
         fig
```

Out[15]:



```
In [16]: print("beta 0 to beta 5 are as follows:")  
         reg.params
```

beta 0 to beta 5 are as follows:

```
Out[16]: bin_0    20.102457  
         bin_1    34.475788  
         bin_2    37.635105  
         bin_3    35.225400  
         bin_4    27.296378  
         dtype: float64
```

```
In [17]: print("Predicted coolness of a 73-year old is")  
         reg.params[np.searchsorted(cutoff, 73)]
```

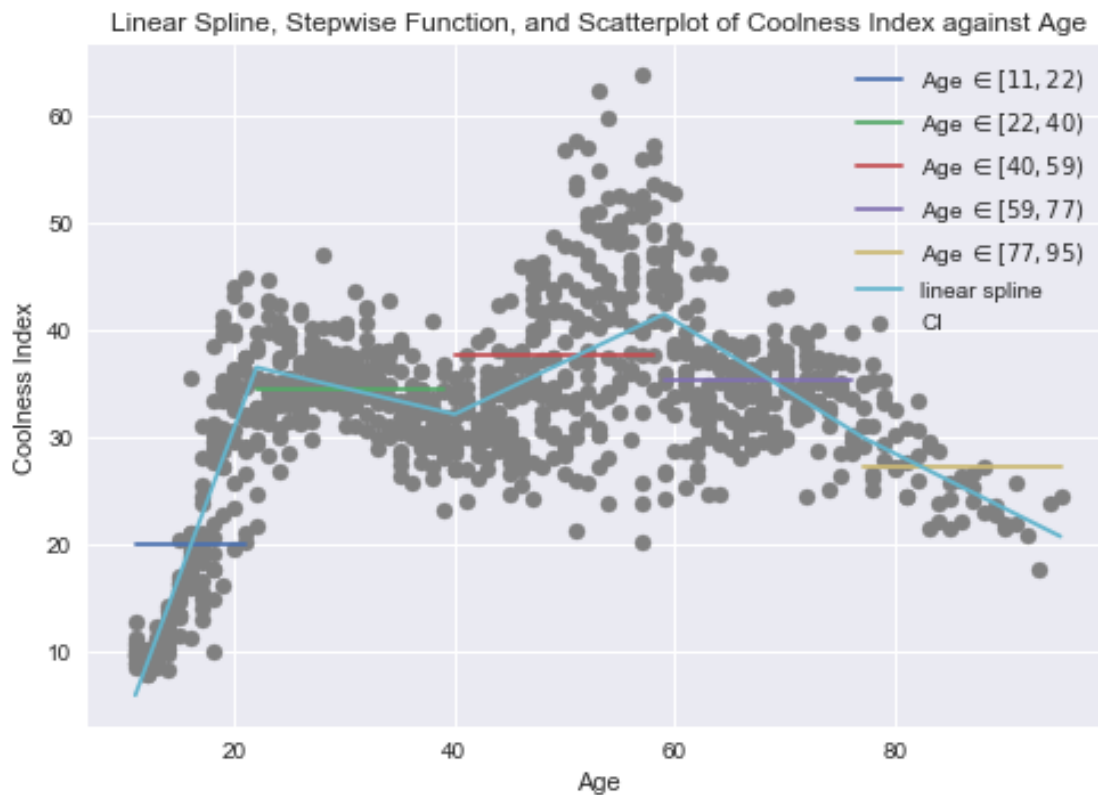
Predicted coolness of a 73-year old is

```
Out[17]: 35.225400040242754
```

```
In [18]: knots = [22, 40, 59, 77]
spl_ci = LSQUnivariateSpline(ci.age.values, ci.CI.values, knots, k=1)
age_vec = np.linspace(ci.age.values.min(), ci.age.values.max(), 1000)
ax.plot(age_vec, spl_ci(age_vec), label = "linear spline")
ax.legend()
ax.set_title("Linear Spline, Stepwise Function, and Scatterplot of Coolness Index against Age")

fig
```

Out[18]:



```
In [19]: print("Predicted coolness of a 73-year old from linear spline is")
spl_ci(73)
```

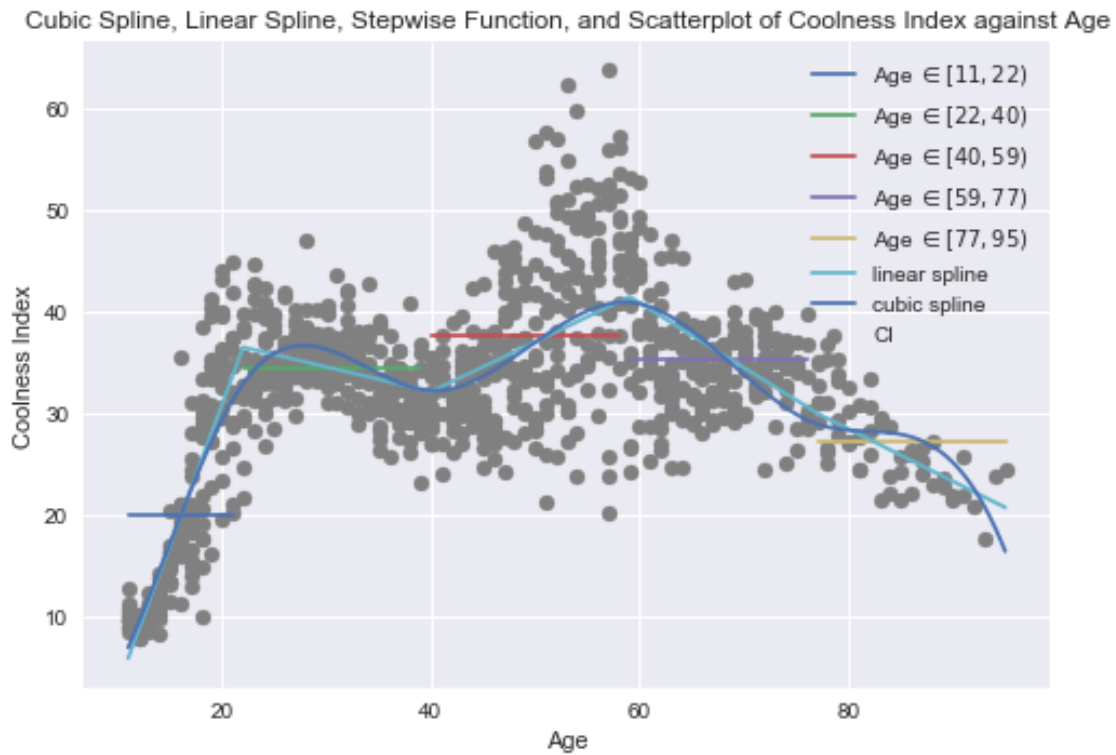
Predicted coolness of a 73-year old from linear spline is

Out[19]: array(32.536832389143306)

```
In [20]: cubspl_ci = LSQUnivariateSpline(ci.age.values, ci.CI.values, knots, k=3)
age_vec = np.linspace(ci.age.values.min(), ci.age.values.max(), 1000)
ax.plot(age_vec, cubspl_ci(age_vec), label = "cubic spline")
```

```
ax.legend()
ax.set_title("Cubic Spline, Linear Spline, Stepwise Function, and Scatterplot of Coolness Index against Age")
fig
```

Out[20]:



```
In [21]: print("Predicted coolness of a 73-year old from cubic spline is")
         cubspl_ci(73)
```

Predicted coolness of a 73-year old from cubic spline is

Out[21]: array(31.262429389257864)