TrachtPS9

March 13, 2019

1 Problem Set 9

1.1 Daniel Tracht

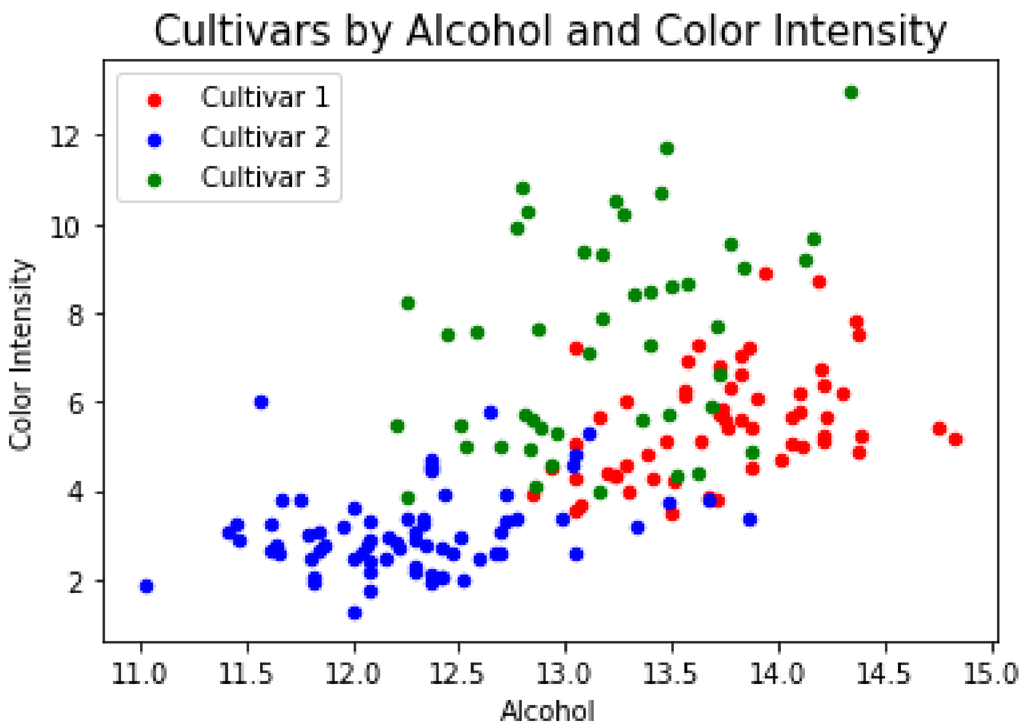
We begin with the data from the `strongdrink.txt` as we had used in Problem Set 7.

```
In [1]: import pandas as pd
        import numpy as np

        wine = pd.read_csv('data/strongdrink.txt')

        X = wine[["alco", "malic", "tot_phen", "color_int"]].values
        y = wine["cultivar"].values
```

1.2 Part a

We wish to create a scatterplot of the data where the x-variable is `alco` and the y-variable is `color_int`, where each dot has a different color denoting its `cultivar`:

```
In [7]: import matplotlib.pyplot as plt

        fig, ax = plt.subplots()
        colors = {1:"R", 2:"B", 3:"G"}
        labels = {1:"Cultivar 1", 2:"Cultivar 2", 3:"Cultivar 3"}
        grouped = wine.groupby("cultivar")
        for key, group in grouped:
            group.plot(ax=ax, kind='scatter', x="alco", y="color_int", label=labels[key],
                       color=colors[key])
        plt.title("Cultivars by Alcohol and Color Intensity", fontsize=15)
        plt.xlabel("Alcohol")
        plt.ylabel("Color Intensity")
        plt.show()
```



1.3 Part b

We wish to estimate a multinomial logistic model of `cultivar` on `alco`, `malic`, `tot_phen`, `color_int` with the specified linear predictor and report the best hyperparameters and the MSE of the optimal results

In [3]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import uniform as sp_uniform

# setting the parameter distributions over which we test as instructed
param_dist1 = {'penalty': ['l1', 'l2'],
               'C': sp_uniform(0.1, 10.0)}

# no need to add constant column to X with fit_intercept=True
logit = LogisticRegression(solver="saga", multi_class='multinomial', max_iter=1000,
                           fit_intercept=True)

random_search1 = \
    RandomizedSearchCV(logit, param_distributions=param_dist1,
                       n_iter=200, n_jobs=-1, cv=5, random_state=25,
                       scoring='neg_mean_squared_error', iid=True)
```

```
random_search1.fit(X, y)
print("Best hyperparameters for Logistic: ", random_search1.best_params_)
print("MSE from best hyperparameters for Logistic: ", -random_search1.best_score_)
```

```
Best hyperparameters for Logistic:  {'C': 1.9591123209017924, 'penalty': 'l1'}
MSE from best hyperparameters for Logistic:  0.1534090909090909


C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\sag.py:334: ConvergenceWarning
  "the coef_ did not converge", ConvergenceWarning)
```

1.4 Part c

We wish to estimate a Random Forest model of `cultivar` on the same four features as in the previous part.

In [4]:
```
from sklearn.ensemble import RandomForestRegressor
from scipy.stats import randint as sp_randint

# setting the parameter distributions over which we test as instructed
param_dist2 = {'n_estimators': [10, 200],
              'max_depth': [2, 4],
              'min_samples_split': sp_randint(2, 20),
              'min_samples_leaf': sp_randint(2, 20),
              'max_features': sp_randint(1, 4)}

random_forest = RandomForestRegressor()

random_search2 = RandomizedSearchCV(random_forest,
                                    param_distributions=param_dist2,
                                    n_iter=200,
                                    n_jobs=-1,
                                    cv=5,
                                    random_state=25,
                                   scoring='neg_mean_squared_error',
                                   iid = True)
random_search2.fit(X, y)
print("Best hyperparameters for Random Forest: \n", random_search2.best_params_)
print("MSE from best hyperparameters for Random Forest: \n",
      -random_search2.best_score_)
```

```
Best hyperparameters for Random Forest:
 {'max_depth': 4, 'max_features': 3, 'min_samples_leaf': 2, 'min_samples_split': 3, 'n_estimat
MSE from best hyperparameters for Random Forest:
 0.20363146777673888
```

1.5 Part d

We wish to estimate a SVM model using a Gaussian radial basis function kernel and the same four features as the previous two parts

```
In [5]: from sklearn import svm

        param_dist3 = {'C': sp_uniform(loc=0.1, scale=10.0),
                       'gamma': ['scale', 'auto'],
                       'shrinking': [True, False]}

        # kernel='rbf' is the default
        svm = svm.SVC()

        random_search3 = RandomizedSearchCV(svm,
                                            param_distributions=param_dist3,
                                            n_iter=200,
                                            n_jobs=-1,
                                            cv=5,
                                            random_state=25,
                                           scoring='neg_mean_squared_error',
                                           iid=True)
        random_search3.fit(X, y)
        print("Best hyperparameters for SVM: \n", random_search3.best_params_)
        print("MSE from best hyperparameters SVM: \n", -random_search3.best_score_)
```

```
Best hyperparameters for SVM:
 {'C': 3.3605112613782553, 'gamma': 'scale', 'shrinking': True}
MSE from best hyperparameters SVM:
 0.14772727272727273
```

1.6 Part e

We wish to fit a multiple hidden layer neural network model on the same data as in the previous three parts.

```
In [6]: from sklearn.neural_network import MLPClassifier

        param_dist4 = {'hidden_layer_sizes': sp_randint(1, 100),
                       'activation': ['logistic', 'relu'],
                       'alpha': sp_uniform(0.1, 10.0)}

        mlp = MLPClassifier(solver='lbfgs')

        random_search4 = RandomizedSearchCV(mlp,
                                            param_distributions=param_dist4,
                                            n_iter=200,
                                            n_jobs=-1,
```

```
                                           cv=5,
                                           random_state=25,
                                          scoring='neg_mean_squared_error',
                                          iid=True)
random_search4.fit(X, y)
print("Best hyperparameters for MLP: \n",random_search4.best_params_)
print("MSE from best hyperparameters for MLP: ", -random_search4.best_score_)
```

```
Best hyperparameters for MLP:
 {'activation': 'relu', 'alpha': 0.7965389843643799, 'hidden_layer_sizes': 91}
MSE from best hyperparameters for MLP:  0.07386363636363637
```

Of the above models, we really have only the average out-of-sample MSE using the best hyperparameters to choose which one is the best predictor. In the logistic model, we estimated an average OOS-MSE of about 0.153 (though even after 1000 iterations, it did not converge). In the random forest model, we estimated an average OOS-MSE of about 0.204. In the support vector machine model, we estimated an average OOS-MSE of about 0.148. And in the neural network, we estimated an average OOS-MSE of about 0.074. And while we don't have standard errors of these point estimates, it would likely be safe to say that our neural network from part e) is the best predictor of `cultivar`.