Support Vector Machines

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1 Lab 7

2 Support Vector Machines

2.1 Submitted to: Prof. Sweetlin Hemlatha

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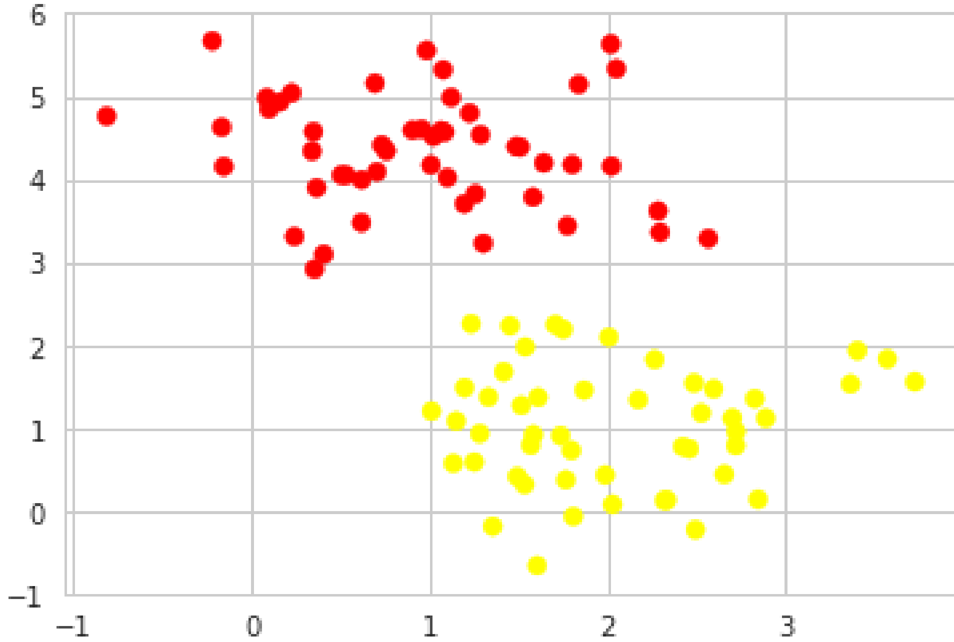
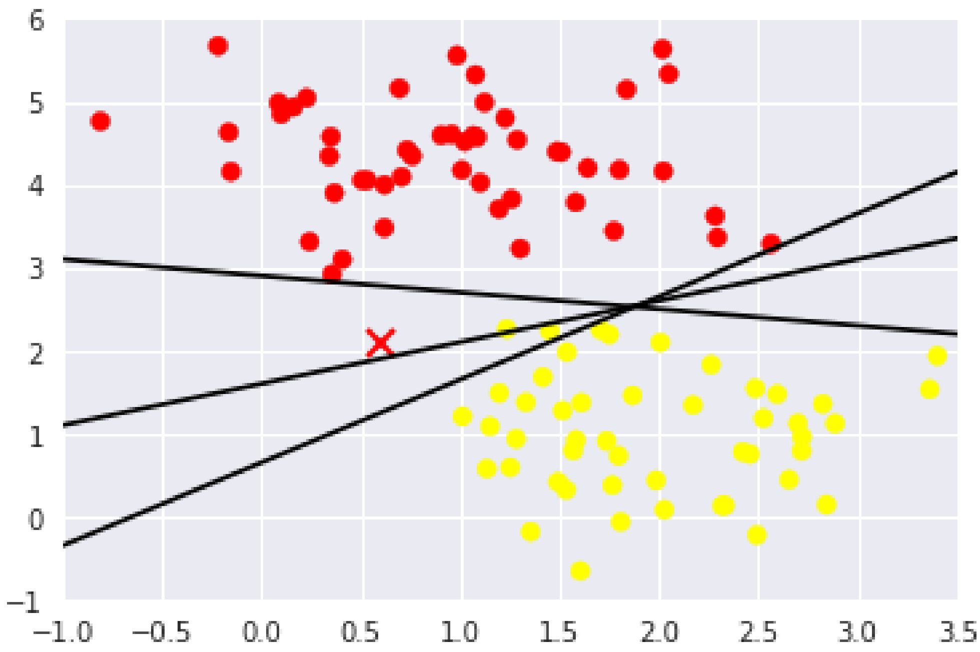
```
In [16]: import numpy as np
         import pandas as pd
         import seaborn as sns
         from scipy import stats
         from sklearn.svm import SVC
         from sklearn.utils import shuffle
         from sklearn.metrics import classification_report
         from sklearn.model_selection import train_test_split
         from sklearn.model_selection import GridSearchCV
         from sklearn.datasets.samples_generator import make_blobs

         import matplotlib.pyplot as plt
         from matplotlib.colors import ListedColormap
         %matplotlib inline

         sns.set(style='whitegrid', context='notebook', font_scale=1)
```

```
In [2]: X, y =  make_blobs(n_samples=100, centers=2, random_state =0, cluster_std=0.70)
        plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='autumn')
```

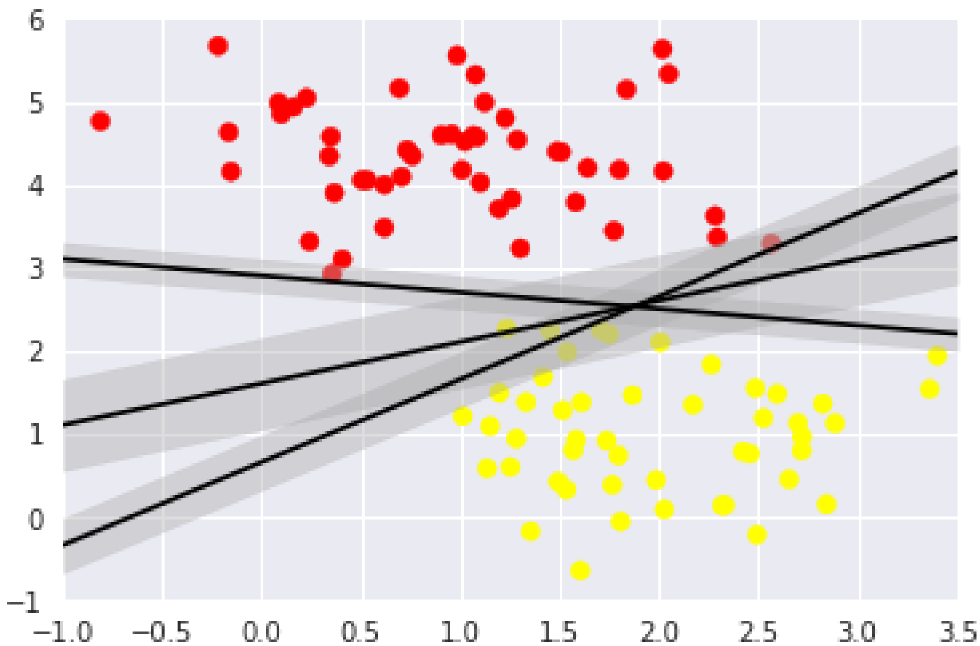
```
Out[2]: <matplotlib.collections.PathCollection at 0x7fd48abf7e10>
```




```
In [3]: xfit = np.linspace(-1, 3.5)
        plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='autumn')
        plt.plot([0.6], [2.1], 'x', color='red', markeredgewidth=2, markersize=10)

        for m, b in [(1, 0.65), (0.5, 1.6), (-0.2, 2.9)]:
            plt.plot(xfit, m*xfit +b, '-k')

        plt.xlim(-1, 3.5);
```



In [4]:
```
xfit = np.linspace(-1, 3.5)
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='autumn')

for m, b, d in [(1, 0.65, 0.33), (0.5, 1.6, 0.55), (-0.2, 2.9, 0.2)]:
    yfit = m*xfit + b
    plt.plot(xfit, yfit, '-k')
    plt.fill_between(xfit, yfit-d, yfit+d, edgecolor='none', color='#AAAAAA', alpha=0.

plt.xlim(-1, 3.5);
```



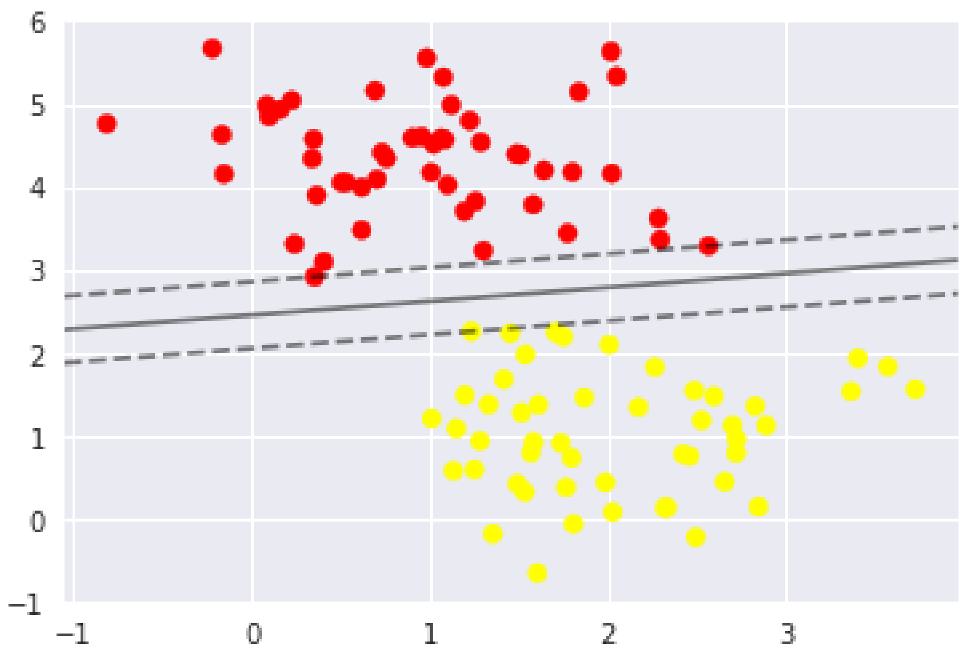
In [5]:
```
from sklearn.svm import SVC
model = SVC(kernel='linear', C=1E10)
model.fit(X, y)
```

Out[5]:
```
SVC(C=10000000000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='linear',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

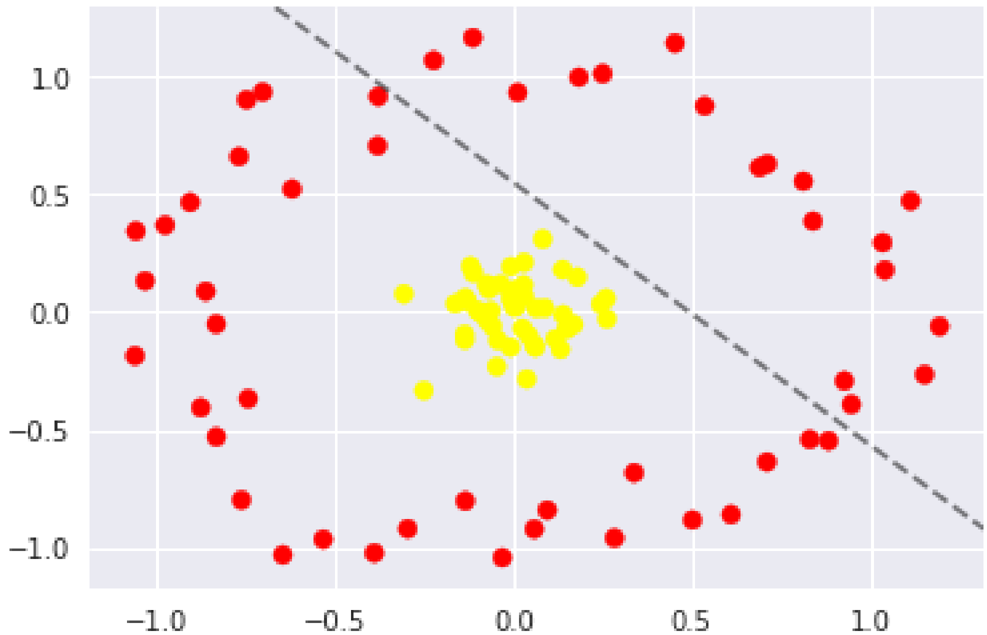
In [6]:
```
def plot_svc_decision_function(model, ax=None, plot_support=True):
    """Plot the decision function for a 2D SVC"""
    if ax is None:
        ax = plt.gca()
    xlim = ax.get_xlim()
    ylim = ax.get_ylim()

    #create grid to evaluate
    x = np.linspace(xlim[0], xlim[1], 30)
    y = np.linspace(ylim[0], ylim[1], 30)
    Y, X = np.meshgrid(y, x)
    xy = np.vstack([X.ravel(), Y.ravel()]).T
    P = model.decision_function(xy).reshape(X.shape)

    #plot decision boundaries and margins
    ax.contour(X, Y, P, colors='k', levels=[-1, 0, 1], alpha=0.5, linestyles=['--', '-
```

```
    #plot support vector machines
    if plot_support:
        ax.scatter(model.support_vectors_[:,0], model.support_vectors_[:, 1], s=300, li
    ax.set_xlim(xlim)
    ax.set_ylim(ylim)
```

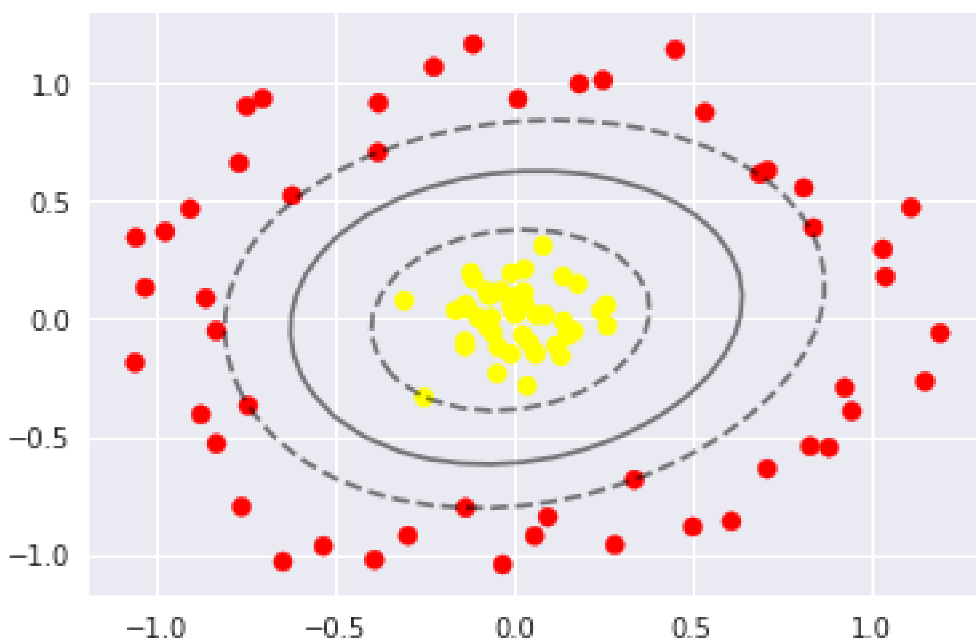
```
In [7]: plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='autumn')
        plot_svc_decision_function(model);
```




```
In [8]: from sklearn.datasets.samples_generator import make_circles
        X, y = make_circles(100, factor=.1, noise=.1)

        clf = SVC(kernel='linear').fit(X, y)

        plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='autumn')
        plot_svc_decision_function(clf, plot_support=False);
```




```
In [9]: clf = SVC(kernel='rbf', C=1E6)
        clf.fit(X, y)
        plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='autumn')
        plot_svc_decision_function(clf, plot_support=False);
```



2.2.1 On my own dataset

In [3]:
```
wine_data = pd.read_csv('../Dataset/winequality-white.csv', sep=';')
red_wine = pd.read_csv('../Dataset/winequality-red.csv', sep=';')
wine_data.append(red_wine)
wine_data.head(10)
```

Out[3]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.0              0.27         0.36            20.7      0.045
1            6.3              0.30         0.34             1.6      0.049
2            8.1              0.28         0.40             6.9      0.050
3            7.2              0.23         0.32             8.5      0.058
4            7.2              0.23         0.32             8.5      0.058
5            8.1              0.28         0.40             6.9      0.050
6            6.2              0.32         0.16             7.0      0.045
7            7.0              0.27         0.36            20.7      0.045
8            6.3              0.30         0.34             1.6      0.049
9            8.1              0.22         0.43             1.5      0.044

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 45.0                 170.0   1.0010  3.00       0.45
1                 14.0                 132.0   0.9940  3.30       0.49
2                 30.0                  97.0   0.9951  3.26       0.44
3                 47.0                 186.0   0.9956  3.19       0.40
4                 47.0                 186.0   0.9956  3.19       0.40
5                 30.0                  97.0   0.9951  3.26       0.44
6                 30.0                 136.0   0.9949  3.18       0.47
7                 45.0                 170.0   1.0010  3.00       0.45
8                 14.0                 132.0   0.9940  3.30       0.49
9                 28.0                 129.0   0.9938  3.22       0.45

   alcohol  quality
0      8.8        6
1      9.5        6
2     10.1        6
3      9.9        6
4      9.9        6
5     10.1        6
6      9.6        6
7      8.8        6
8      9.5        6
9     11.0        6
```

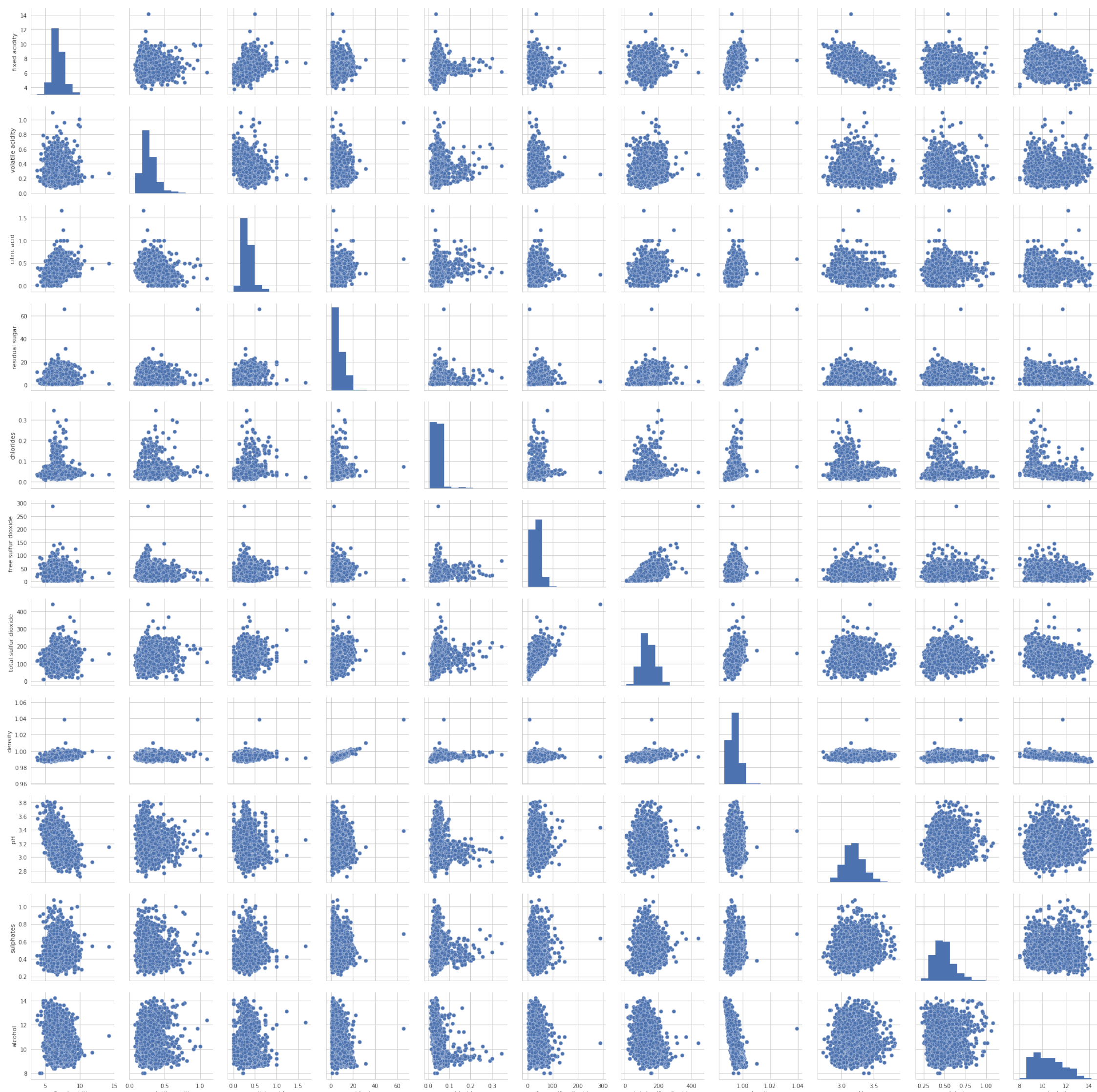
In [4]:
```
wine_data.dtypes
```

Out[4]:
```
fixed acidity           float64
volatile acidity        float64
citric acid             float64
residual sugar          float64
```

```
chlorides                float64
free sulfur dioxide      float64
total sulfur dioxide     float64
density                  float64
pH                       float64
sulphates                float64
alcohol                  float64
quality                    int64
dtype: object
```

In [5]:
```
sns.pairplot(wine_data.iloc[:,:11].dropna(), size=2.5)
```

Out[5]:
```
<seaborn.axisgrid.PairGrid at 0x7fd48ac0d550>
```



```
In [6]: X_train, X_test, Y_train, Y_test = train_test_split(wine_data.iloc[:,:11],
                                                            wine_data.iloc[:, 11],
                                                            test_size=0.2,
                                                            random_state=42)
        print('Size of training set: ', len(X_train.axes[0]))
        print('Size of test set: ', len(X_test.axes[0]))
```

```
Size of training set:  3918
Size of test set:  980
```

```
In [7]: parameters = [{'kernel': ['rbf'],
                       'gamma': [1e-4, 1e-3, 0.01, 0.1, 0.2, 0.5],
                        'C': [1, 10, 100, 1000]},
                      {'kernel': ['linear'], 'C': [1, 10, 100, 1000]}]
```

```
In [8]: clf = GridSearchCV(SVC(decision_function_shape='ovr'), parameters, cv=5)
        clf.fit(X_train, Y_train)
```

```
Out[8]: GridSearchCV(cv=5, error_score='raise',
               estimator=SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
          decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
          max_iter=-1, probability=False, random_state=None, shrinking=True,
          tol=0.001, verbose=False),
               fit_params=None, iid=True, n_jobs=1,
               param_grid=[{'kernel': ['rbf'], 'gamma': [0.0001, 0.001, 0.01, 0.1, 0.2, 0.5],
               pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
               scoring=None, verbose=0)
```

```
In [9]: print("Best parameters set found on development set:")
        print(clf.best_params_)
        print("Grid scores on training set:")
        means = clf.cv_results_['mean_test_score']
        stds = clf.cv_results_['std_test_score']
        for mean, std, params in zip(means, stds, clf.cv_results_['params']):
            print("%0.3f (+/-%0.03f) for %r"
                  % (mean, std * 2, params))
```

```
Best parameters set found on development set:
{'C': 1, 'gamma': 0.5, 'kernel': 'rbf'}
Grid scores on training set:
0.450 (+/-0.016) for {'C': 1, 'gamma': 0.0001, 'kernel': 'rbf'}
0.472 (+/-0.018) for {'C': 1, 'gamma': 0.001, 'kernel': 'rbf'}
0.490 (+/-0.025) for {'C': 1, 'gamma': 0.01, 'kernel': 'rbf'}
0.555 (+/-0.008) for {'C': 1, 'gamma': 0.1, 'kernel': 'rbf'}
0.576 (+/-0.027) for {'C': 1, 'gamma': 0.2, 'kernel': 'rbf'}
0.593 (+/-0.019) for {'C': 1, 'gamma': 0.5, 'kernel': 'rbf'}
0.479 (+/-0.035) for {'C': 10, 'gamma': 0.0001, 'kernel': 'rbf'}
0.503 (+/-0.022) for {'C': 10, 'gamma': 0.001, 'kernel': 'rbf'}
```

```
0.537 (+/-0.016) for {'C': 10, 'gamma': 0.01, 'kernel': 'rbf'}
0.556 (+/-0.018) for {'C': 10, 'gamma': 0.1, 'kernel': 'rbf'}
0.573 (+/-0.044) for {'C': 10, 'gamma': 0.2, 'kernel': 'rbf'}
0.589 (+/-0.029) for {'C': 10, 'gamma': 0.5, 'kernel': 'rbf'}
0.517 (+/-0.019) for {'C': 100, 'gamma': 0.0001, 'kernel': 'rbf'}
0.526 (+/-0.027) for {'C': 100, 'gamma': 0.001, 'kernel': 'rbf'}
0.554 (+/-0.006) for {'C': 100, 'gamma': 0.01, 'kernel': 'rbf'}
0.555 (+/-0.021) for {'C': 100, 'gamma': 0.1, 'kernel': 'rbf'}
0.573 (+/-0.044) for {'C': 100, 'gamma': 0.2, 'kernel': 'rbf'}
0.589 (+/-0.029) for {'C': 100, 'gamma': 0.5, 'kernel': 'rbf'}
0.528 (+/-0.018) for {'C': 1000, 'gamma': 0.0001, 'kernel': 'rbf'}
0.551 (+/-0.029) for {'C': 1000, 'gamma': 0.001, 'kernel': 'rbf'}
0.566 (+/-0.036) for {'C': 1000, 'gamma': 0.01, 'kernel': 'rbf'}
0.556 (+/-0.021) for {'C': 1000, 'gamma': 0.1, 'kernel': 'rbf'}
0.573 (+/-0.044) for {'C': 1000, 'gamma': 0.2, 'kernel': 'rbf'}
0.589 (+/-0.029) for {'C': 1000, 'gamma': 0.5, 'kernel': 'rbf'}
0.526 (+/-0.015) for {'C': 1, 'kernel': 'linear'}
0.526 (+/-0.018) for {'C': 10, 'kernel': 'linear'}
0.534 (+/-0.024) for {'C': 100, 'kernel': 'linear'}
0.522 (+/-0.033) for {'C': 1000, 'kernel': 'linear'}
```

In [10]:
```
print("Detailed classification report:")
print("The model is trained on the full development set.")
print("The scores are computed on the full evaluation set.")
#data_train, data_test, label_train, label_test

y_true, y_pred = Y_test, clf.predict(X_test)
print(classification_report(y_true, y_pred))
print()
```

```
Detailed classification report:
The model is trained on the full development set.
The scores are computed on the full evaluation set.
             precision    recall  f1-score   support

          3       0.00      0.00      0.00         5
          4       1.00      0.08      0.15        25
          5       0.83      0.39      0.53       291
          6       0.55      0.95      0.70       432
          7       0.91      0.39      0.55       192
          8       1.00      0.37      0.54        35

avg / total       0.73      0.63      0.60       980



/home/prateek/anaconda3/envs/dltf/lib/python3.6/site-packages/sklearn/metrics/classification.py
```

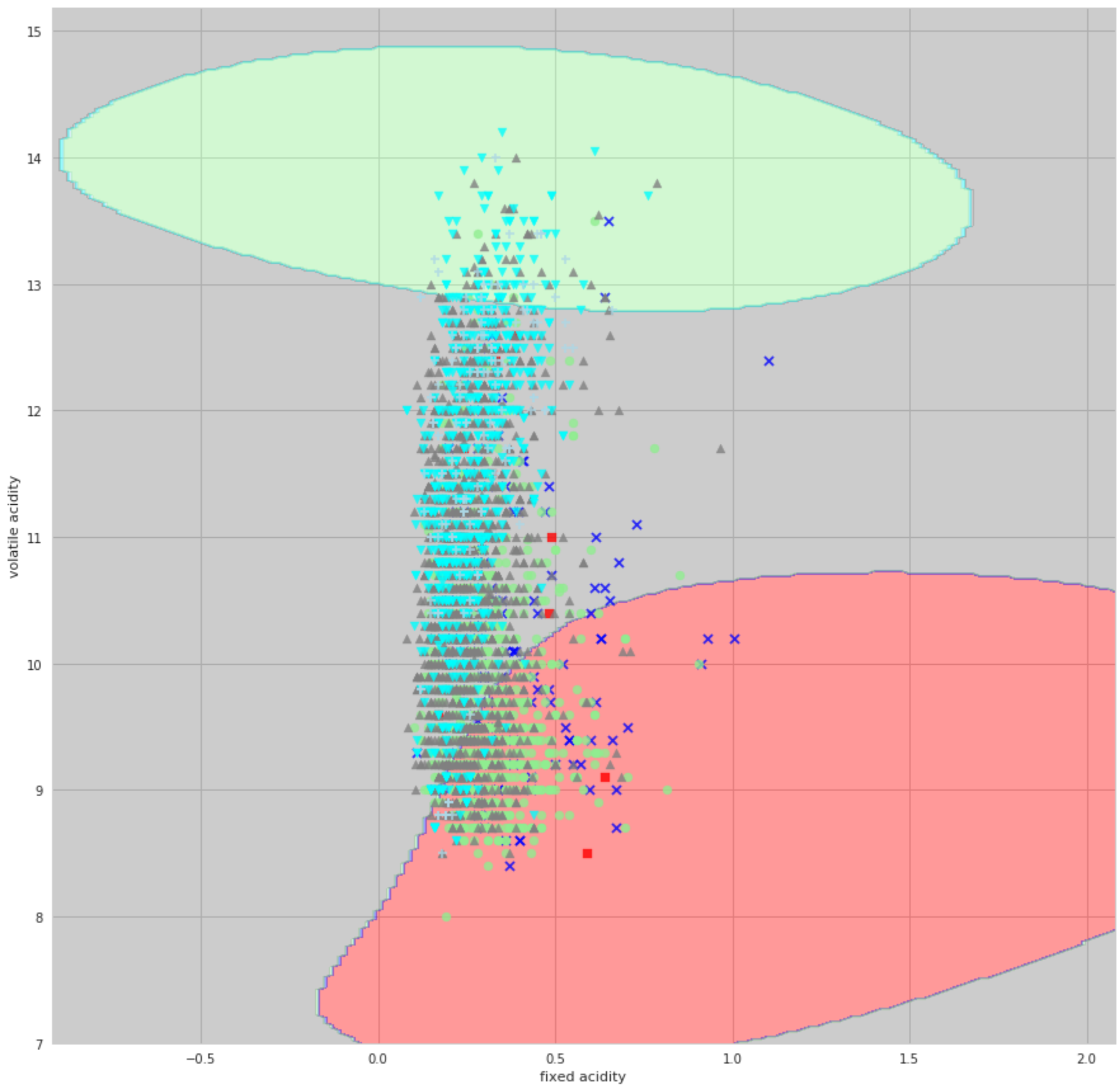
```
  'precision', 'predicted', average, warn_for)
```

```
In [21]: def plot_decision_surface(X, y, classifier, test_idx=None, resolution=0.02):

             markers = ('s', 'x', 'o', '^', 'v', '+', '.')
             colors = ('red', 'blue', 'lightgreen', 'gray', 'cyan', 'lightblue', 'lightgreen')
             cmap = ListedColormap(colors[:len(np.unique(y))])

             x1_min, x1_max = X[:, 0].min() - 1, X[:, 0].max() + 1
             x2_min, x2_max = X[:, 1].min() - 1, X[:, 1].max() + 1
             xx1, xx2 = np.meshgrid(np.arange(x1_min, x1_max, resolution), np.arange(x2_min, x2

             Z = classifier.predict(np.array([xx1.ravel(), xx2.ravel()]).T)
             Z = Z.reshape(xx1.shape)

             plt.figure(figsize=(15,15))
             plt.contourf(xx1, xx2, Z, alpha=0.4, cmap=cmap)
             plt.xlim(xx1.min(), xx1.max())
             plt.ylim(xx2.min(), xx2.max())
             plt.xlabel('fixed acidity')
             plt.ylabel('volatile acidity')

             X_test, y_test = X[test_idx, :], y[test_idx]

             for idx, cl in enumerate(np.unique(y)):
                 plt.scatter(x=X[y == cl, 0], y=X[y == cl, 1],
                 alpha=0.8, c=cmap(idx),
                 marker=markers[idx], label=cl)
                 if test_idx:
                     X_test, y_test = X[test_idx, :], y[test_idx]
                     plt.scatter(X_test[:, 0], X_test[:, 1], c='',
                     alpha=1.0, linewidth=1, marker='o',
                     s=55, label='test set')
```

```
In [22]: svc = SVC(C=1.0, kernel='rbf')
         svc.fit(X_train.iloc[:, [1, 10]], Y_train)
```

```
Out[22]: SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
           decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
           max_iter=-1, probability=False, random_state=None, shrinking=True,
           tol=0.001, verbose=False)
```

```
In [23]: a = np.array(X_train.iloc[:, [1, 10]])
         plot_decision_surface(X=a, y = np.array(Y_train.values), classifier=svc)
```


15
14
13
12
11
10
9
8
7
volatile acidity
−0.5
0.0
0.5
1.0
1.5
2.0
fixed acidity