SVM

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0.1 # Gahan Saraiya (18MCEC10)

1 SVM

AIM: Support Vector Machine(SVM) using linear and polynomial kernel

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Svm classifier mostly used in addressing multi-classification problems. Multi-classification problem means having more that 2 target classes to predict.

```
In [8]: # Import built-in modules
        import os
        import numpy as np # linear algebra
        import itertools
        from subprocess import check_output
        from collections import Counter
```

```
In [9]: # Import 3rd party Python packages
        import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
        import matplotlib
        import matplotlib.pyplot as plt #for plotting
        from sklearn import linear_model, exceptions
        from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
        from sklearn.svm import SVC, LinearSVC
        from sklearn import datasets
        from sklearn.preprocessing import StandardScaler
        from sklearn.datasets import make_moons
        from sklearn.pipeline import Pipeline
        from sklearn.preprocessing import PolynomialFeatures
        # dividing into train and test
        from sklearn.model_selection import train_test_split
        import seaborn as sns
        # print(check_output(["ls", "input"]).decode("utf8"))
        # %matplotlib inline
```

```
In [10]: def plot_svc_decision_boundary(svm_clf, xmin, xmax):
             w = svm_clf.coef_[0]
```

```python
    b = svm_clf.intercept_[0]

    # At the decision boundary, w0*x0 + w1*x1 + b = 0
    # => x1 = -w0/w1 * x0 - b/w1
    x0 = np.linspace(xmin, xmax, 200)
    decision_boundary = -w[0]/w[1] * x0 - b/w[1]

    margin = 1/w[1]
    gutter_up = decision_boundary + margin
    gutter_down = decision_boundary - margin

    svs = svm_clf.support_vectors_
    plt.scatter(svs[:, 0], svs[:, 1], s=180, facecolors='#FFAAAA')
    plt.plot(x0, decision_boundary, "k-", linewidth=2)
    plt.plot(x0, gutter_up, "k--", linewidth=2)
    plt.plot(x0, gutter_down, "k--", linewidth=2)

#define a function to plot the dataset
def plot_dataset(X, y, axes):
    plt.plot(X[:, 0][y==0], X[:, 1][y==0], "bs")
    plt.plot(X[:, 0][y==1], X[:, 1][y==1], "ms")
    plt.axis(axes)
    plt.grid(True, which='both')
    plt.xlabel(r"$x_1$", fontsize=20)
    plt.ylabel(r"$x_2$", fontsize=20, rotation=0)

#define a function plot the decision boundaries
def plot_predictions(clf, axes):
    #create data in continous linear space
    x0s = np.linspace(axes[0], axes[1], 100)
    x1s = np.linspace(axes[2], axes[3], 100)
    x0, x1 = np.meshgrid(x0s, x1s)
    X = np.c_[x0.ravel(), x1.ravel()]
    y_pred = clf.predict(X).reshape(x0.shape)
    y_decision = clf.decision_function(X).reshape(x0.shape)
    plt.contourf(x0, x1, y_pred, cmap=plt.cm.brg, alpha=0.2)
    plt.contourf(x0, x1, y_decision, cmap=plt.cm.brg, alpha=0.1)
```

In [15]:
```python
d = datasets.load_iris()
iris = pd.DataFrame(d.data, columns=d.feature_names)
iris['target'] = d['target']
iris['label'] = iris.target.replace(dict(enumerate(d.target_names)))
iris.head()
```

Out[15]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	\
0	5.1	3.5	1.4	0.2	
1	4.9	3.0	1.4	0.2	
2	4.7	3.2	1.3	0.2	

```
3               4.6            3.1             1.5             0.2
4               5.0            3.6             1.4             0.2

   target   label
0       0  setosa
1       0  setosa
2       0  setosa
3       0  setosa
4       0  setosa
```

```
In [16]: iris.describe()
```

```
Out[16]:        sepal length (cm)  sepal width (cm)  petal length (cm)  \
         count         150.000000        150.000000         150.000000
         mean            5.843333          3.057333           3.758000
         std             0.828066          0.435866           1.765298
         min             4.300000          2.000000           1.000000
         25%             5.100000          2.800000           1.600000
         50%             5.800000          3.000000           4.350000
         75%             6.400000          3.300000           5.100000
         max             7.900000          4.400000           6.900000

                petal width (cm)      target
         count        150.000000  150.000000
         mean           1.199333    1.000000
         std            0.762238    0.819232
         min            0.100000    0.000000
         25%            0.300000    0.000000
         50%            1.300000    1.000000
         75%            1.800000    2.000000
         max            2.500000    2.000000
```

The 4 features are

- SepalLength (Cm)
- SepalWidth (Cm)
- PetalLength (Cm)
- PetalWidth (Cm)

The flower species type is the target class and it having 3 types

- Setosa

- Versicolor
- Virginica

In [28]:
```
#print(iris)
X = d.data[:, :2]  # petal length, petal width
#print(X)

y = d['target']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
# X = X_train
# y = y_train
# setosa_or_versicolor = (y == 0) | (y == 1)
# X = X[setosa_or_versicolor]
# y = y[setosa_or_versicolor]
```

`multi-class` parameter determines the multi-class strategy if the data contains more than two classes.

`ovr` - `One-vs-the-rest (OvR)` multiclass/multilabel strategy. Also known as one-vs-all, this strategy consists in fitting one classifier per class. For each classifier, the class is fitted against all the other classes

`ovo` - `one-vs-one`

In [32]:
```
# SVM Classifier model
#the hyperparameter control the margin violations
#smaller C leads to more margin violations but wider street
#C can be inferred
svm_clf = SVC(kernel="linear",
              C=1.0,
              tol=0.0001,
              max_iter=10**9,
              decision_function_shape="ovr"
             )
svm_clf.fit(X_train, y_train)

# svm_clf.predict([[2.4, 3.1]])

#SVM classifiers do not output a probability like logistic regression classifiers

print('Accuracy of linear SVC on training set: {:.4f}'.format(svm_clf.score(X_train, y

print('Accuracy of linear SVC on test set: {:.4f}'.format(svm_clf.score(X_test, y_tes
```

```
Accuracy of linear SVC on training set: 0.8083
Accuracy of linear SVC on test set: 0.8000
```

In [31]:
```
svm_clf = SVC(kernel="linear",
              C=1.0,
```

```
                    tol=0.0001,
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                    decision_function_shape="ovo"
                   )
svm_clf.fit(X_train, y_train)

# svm_clf.predict([[2.4, 3.1]])

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```
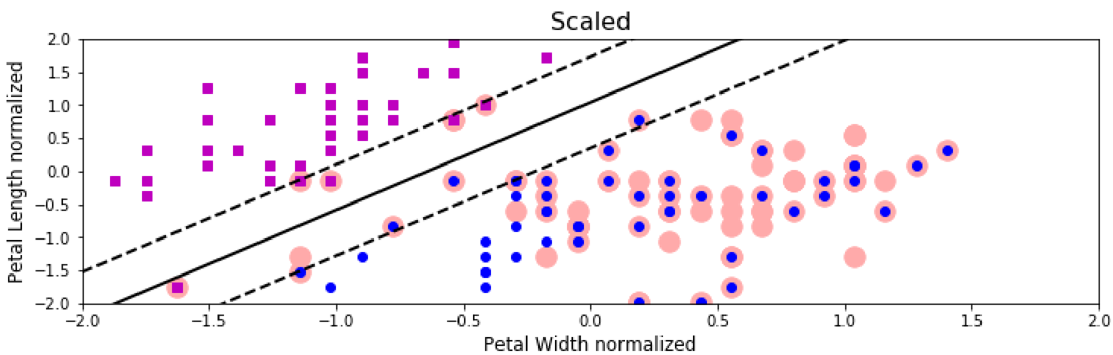

```
Accuracy of linear SVC on training set: 0.8083
Accuracy of linear SVC on test set: 0.8000
```

In [22]:
```
#plot the decision boundaries
plt.figure(figsize=(12,3.2))

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
svm_clf.fit(X_scaled, y)

plt.plot(X_scaled[:, 0][y==1], X_scaled[:, 1][y==1], "bo")
plt.plot(X_scaled[:, 0][y==0], X_scaled[:, 1][y==0], "ms")
plot_svc_decision_boundary(svm_clf, -2, 2)
plt.xlabel("Petal Width normalized", fontsize=12)
plt.ylabel("Petal Length normalized", fontsize=12)
plt.title("Scaled", fontsize=16)
plt.axis([-2, 2, -2, 2])
```

Out[22]: [-2, 2, -2, 2]



1.1 Polynomial kernel

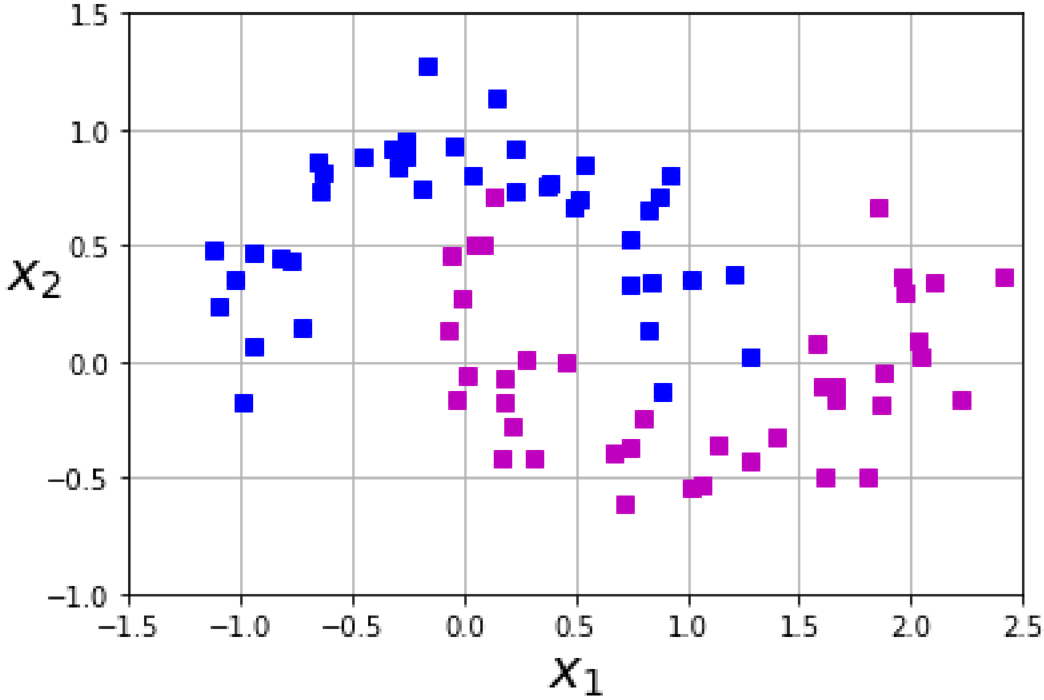
When multi-class is 'crammer_singer' it optimizes a joint objective over all classes.

```
In [35]: poly_svc = SVC(kernel="poly",
                        C=1.0,
                        tol=0.0001,
                        max_iter=10**9,
                        gamma='auto',
                        decision_function_shape="ovr"
                       )
         poly_svc.fit(X_train, y_train)

         # svm_clf.predict([[2.4, 3.1]])

         #SVM classifiers do not output a probability like logistic regression classifiers

         print('Accuracy of linear SVC on training set: {:.4f}'.format(poly_svc.score(X_train,

         print('Accuracy of linear SVC on test set: {:.4f}'.format(poly_svc.score(X_test, y_tes
```

```
Accuracy of linear SVC on training set: 0.8167
Accuracy of linear SVC on test set: 0.8000
```

1.2 Working with `make_moons` datasets

```
In [23]: X, y = make_moons(n_samples=100, noise=0.15, random_state=42)
         #Let's have a look at the data we have generated
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
         plot_dataset(X_train, y_train, [-1.5, 2.5, -1, 1.5])
         plt.show()
```

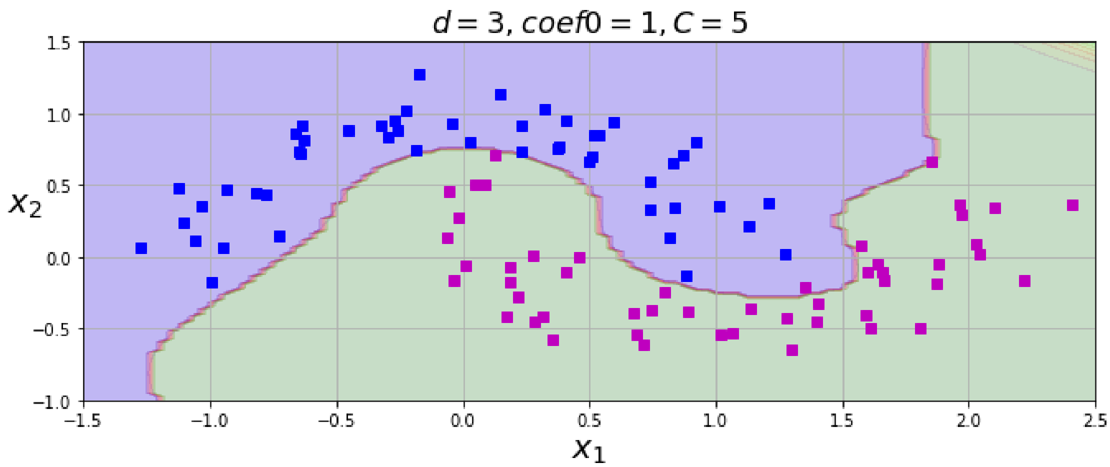


In [24]:
```
#C controls the width of the street
#Degree of data

#create a pipeline to create features, scale data and fit the model
polynomial_svm_clf = Pipeline((
    ("poly_features", PolynomialFeatures(degree=3)),
    ("scalar", StandardScaler()),
    ("svm_clf", SVC(kernel="poly", degree=10, coef0=1, C=5, max_iter=10**9, gamma="au
))

#call the pipeline
polynomial_svm_clf.fit(X_train,y_train)


print('Accuracy of linear SVC on training set: {:.2f}'.format(polynomial_svm_clf.score

print('Accuracy of linear SVC on test set: {:.2f}'.format(polynomial_svm_clf.score(X_
```

```
Accuracy of linear SVC on training set: 1.00
Accuracy of linear SVC on test set: 0.95
```

In [25]:
```
#plot the decision boundaries
plt.figure(figsize=(11, 4))
```

```python
#plot the decision boundaries
plot_predictions(polynomial_svm_clf, [-1.5, 2.5, -1, 1.5])

#plot the dataset
plot_dataset(X, y, [-1.5, 2.5, -1, 1.5])

plt.title(r"$d=3, coef0=1, C=5$", fontsize=18)
plt.show()
```



In [ ]:

In [ ]: