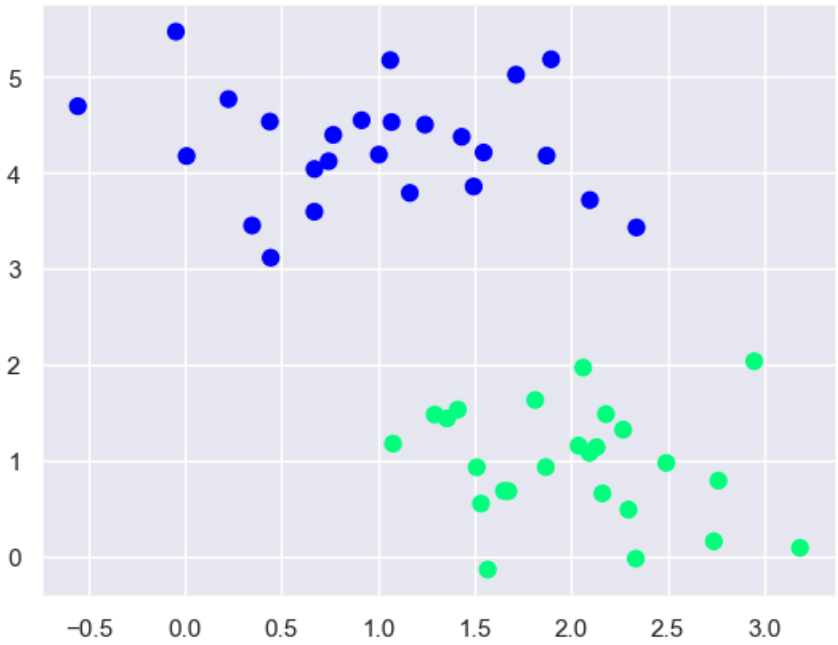
In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split , GridSearchCV
from sklearn.metrics import accuracy_score , confusion_matrix , roc_auc_score , roc_curve
```

In [2]:
```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
from scipy import stats

# use seaborn plotting defaults
import seaborn as sns; sns.set()
```

Working with Perfectly Linear Dataset

In [3]:
```
from sklearn.datasets import make_blobs
X, y = make_blobs(n_samples=50, centers=2,
                  random_state=0, cluster_std=0.60)
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='winter')
```

Out[3]:
```
<matplotlib.collections.PathCollection at 0x1c3c18cd2d0>
```



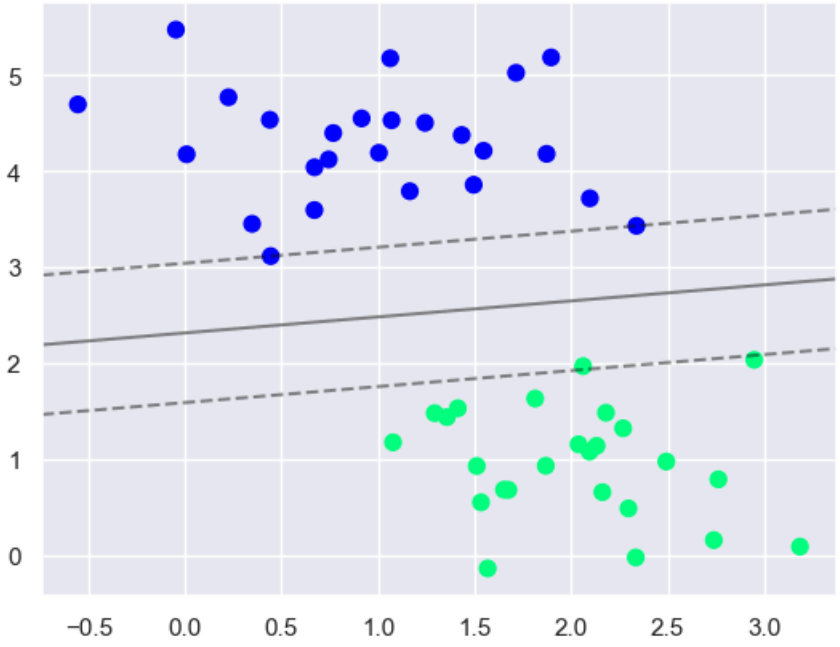
In [4]:
```
from sklearn.svm import SVC # "Support vector classifier"
model = SVC(kernel='linear', C=1)
model.fit(X, y)
```

Out[4]:
```
SVC(C=1, kernel='linear')
```

In [5]:
```
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 model
    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)
```

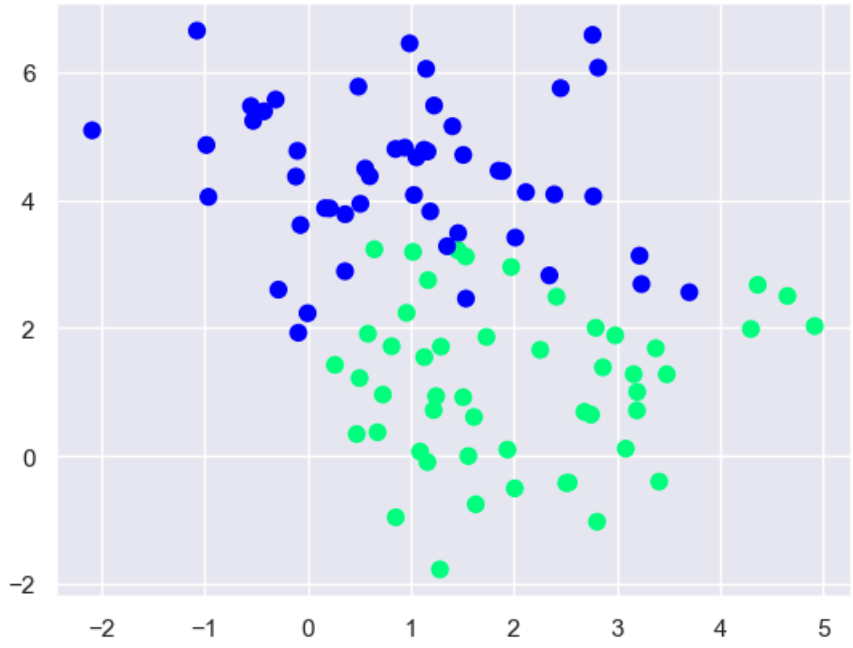
```
    # plot decision boundary and margins
    ax.contour(X, Y, P, colors='k',
               levels=[-1, 0, 1], alpha=0.5,
               linestyles=['--', '-', '--'])

    # plot support vectors
    if plot_support:
        ax.scatter(model.support_vectors_[:, 0],
                   model.support_vectors_[:, 1],
                   s=300, linewidth=1, facecolors='none');
    ax.set_xlim(xlim)
    ax.set_ylim(ylim)
```

In [6]:
```
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='winter')
plot_svc_decision_function(model);
```

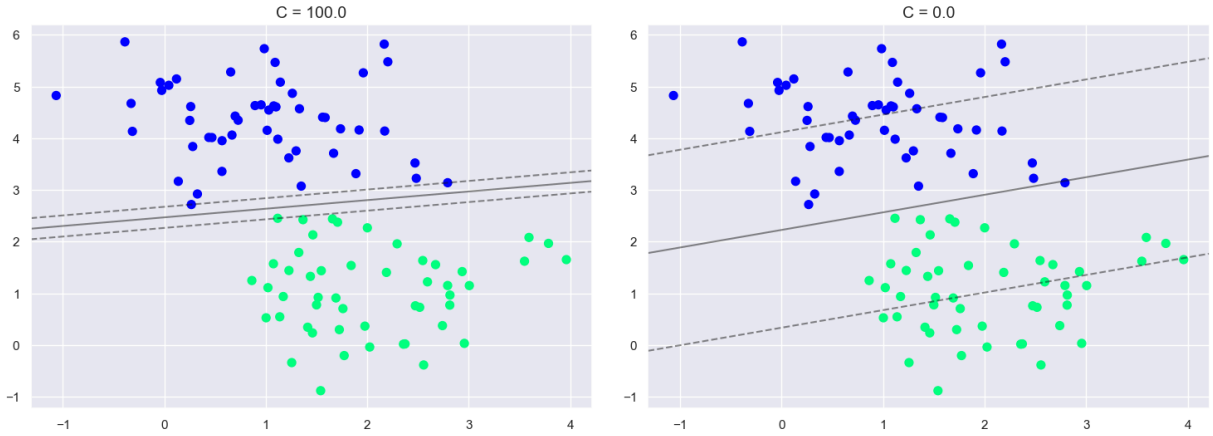


Almost Linearly Separable Dataset

In [7]:
```
X, y = make_blobs(n_samples=100, centers=2,
                  random_state=0, cluster_std=1.2)
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='winter');
```



In [8]:
```
X, y = make_blobs(n_samples=100, centers=2,
                  random_state=0, cluster_std=0.8)

fig, ax = plt.subplots(1, 2, figsize=(16, 6))
fig.subplots_adjust(left=0.0625, right=0.95, wspace=0.1)

for axi, C in zip(ax, [100.0, 0.01]):
    model = SVC(kernel='linear', C=C).fit(X, y)
    axi.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='winter')
    plot_svc_decision_function(model, axi)
    axi.scatter(model.support_vectors_[:, 0],
                model.support_vectors_[:, 1],
                s=300, lw=1, facecolors='none');
    axi.set_title('C = {0:.1f}'.format(C), size=14)
```



Mushroom Dataset

In [9]:
```
data = pd.read_csv('mushrooms.csv')
```

In [10]:
```
data.shape
```

Out[10]: (8124, 23)

In [11]:
```
X = data.drop(columns='class')
```

In [12]:
```
y = data['class']
```

In [13]:
```
from sklearn.preprocessing import LabelEncoder

encoder = LabelEncoder()
```

In [14]:
```
import pandas as pd

def encode_features(data, encoder):
    df_encoded = pd.DataFrame()
    for column in data.columns:
        if column != 'class':  # Exclude the target variable if it exists
            df_encoded[column] = encoder.fit_transform(data[column])
    return df_encoded

df_encoded = encode_features(data, encoder)
df_encoded['class'] = data['class']

# Now df_encoded contains all encoded features along with the target variable 'class'
```

In [15]:
```
df2=df_encoded
```

In [16]:
```
df2
```

Out[16]:

	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	stalk-shape	...	stalk-color-above-ring	stalk-color-below-ring	veil-type	c
0	5	2	4	1	6	1	0	1	4	0	...	7	7	0	
1	5	2	9	1	0	1	0	0	4	0	...	7	7	0	
2	0	2	8	1	3	1	0	0	5	0	...	7	7	0	
3	5	3	8	1	6	1	0	1	5	0	...	7	7	0	
4	5	2	3	0	5	1	1	0	4	1	...	7	7	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
8119	3	2	4	0	5	0	0	0	11	0	...	5	5	0	
8120	5	2	4	0	5	0	0	0	11	0	...	5	5	0	
8121	2	2	4	0	5	0	0	0	5	0	...	5	5	0	
8122	3	3	4	0	8	1	0	1	0	1	...	7	7	0	
8123	5	2	4	0	5	0	0	0	11	0	...	5	5	0	

8124 rows × 23 columns

In [17]:
```
X = df2.drop(columns='class')
y = df2['class']
```

In [18]:
```
x_train , x_test, y_train,y_test = train_test_split(X,y,random_state = 20)
```

In [19]:
```
from sklearn.svm import SVC
```

In [20]:
```
svc= SVC()
svc.fit(x_train,y_train)
```

Out[20]:
SVC
SVC()

In [21]:
```
svc.score(x_test,y_test)
```

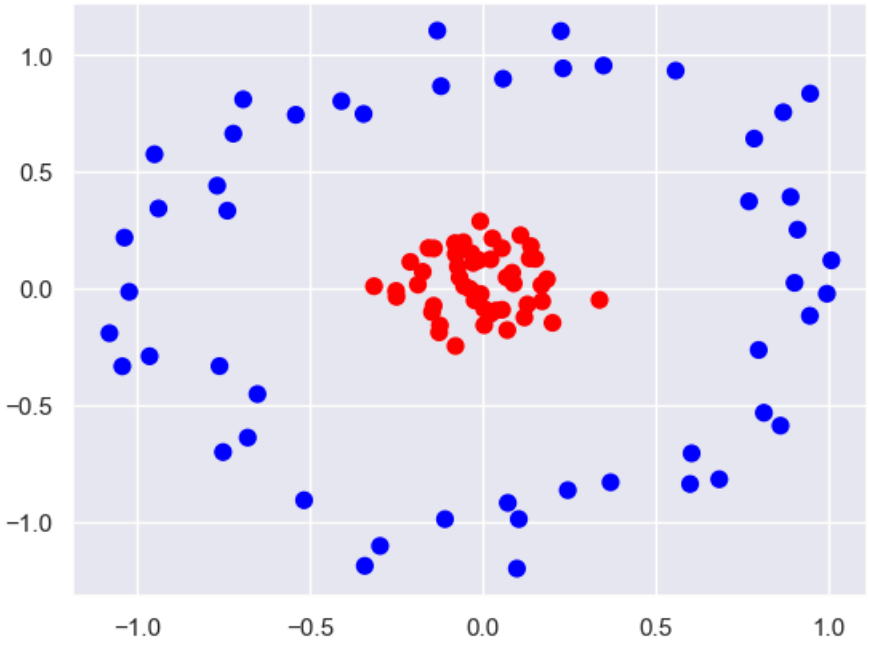
Out[21]:
```
0.9911373707533235
```

In [22]:
```
#sns.pairplot(df2, hue='class')
```

In [23]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.axes._axes import _log as matplotlib_axes_logger
from mpl_toolkits import mplot3d
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from matplotlib.colors import ListedColormap
```

In [24]:
```
from sklearn.datasets import make_circles
X, y = make_circles(100, factor=.1, noise=.1)

plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='bwr')
```

Out[24]:
```
<matplotlib.collections.PathCollection at 0x1c3c2ff24d0>
```



In [25]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20)
```

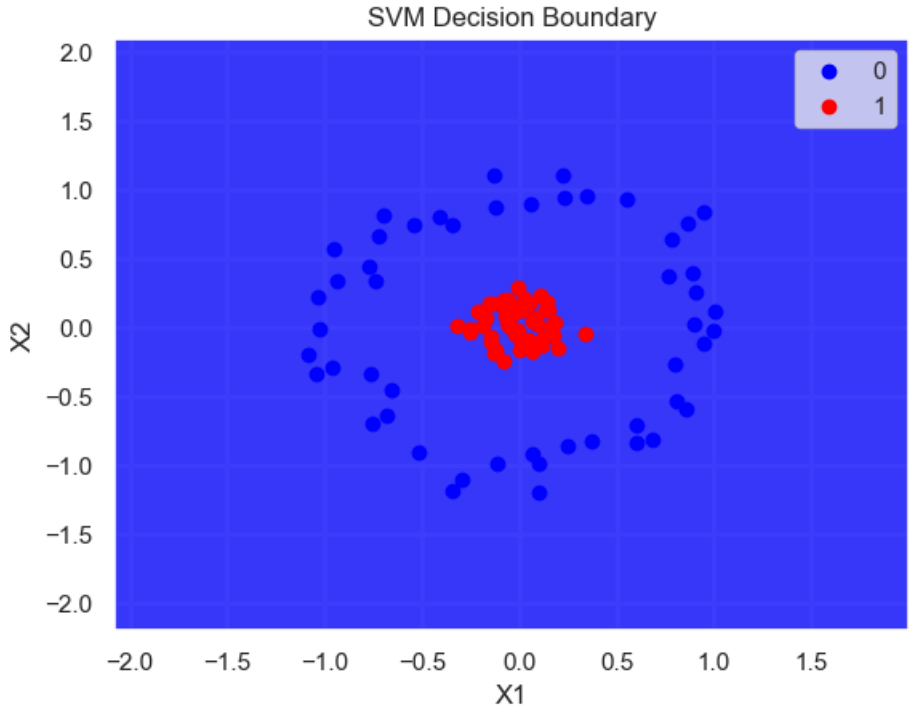
In [26]:
```
classifier = SVC(kernel="linear")
classifier.fit(X_train, y_train.ravel())
y_pred = classifier.predict(X_test)
```

In [27]:
```
from sklearn.metrics import accuracy_score
accuracy_score(y_test, y_pred)
```

Out[27]: 0.4

In [28]:
```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from sklearn.svm import SVC

# Define colormap
zero_one_colourmap = ListedColormap(['blue', 'red'])

def plot_decision_boundary(X, y, clf):
    X_set, y_set = X, y
    X1, X2 = np.meshgrid(np.arange(start=X_set[:, 0].min() - 1,
                                   stop=X_set[:, 0].max() + 1,
                                   step=0.01),
                         np.arange(start=X_set[:, 1].min() - 1,
                                   stop=X_set[:, 1].max() + 1,
                                   step=0.01))

    plt.contourf(X1, X2, clf.predict(np.array([X1.ravel(),
                                               X2.ravel()]).T).reshape(X1.shape),
                 alpha=0.75,
                 cmap=zero_one_colourmap)
    plt.xlim(X1.min(), X1.max())
    plt.ylim(X2.min(), X2.max())
    for i, j in enumerate(np.unique(y_set)):
        plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                    c=[zero_one_colourmap(i)], label=j)
    plt.title('SVM Decision Boundary')
    plt.xlabel('X1')
    plt.ylabel('X2')
    plt.legend()
    return plt.show()

# Example usage:
# X and y should be your data and labels, and clf should be your trained SVM classifier
# plot_decision_boundary(X, y, clf)
```

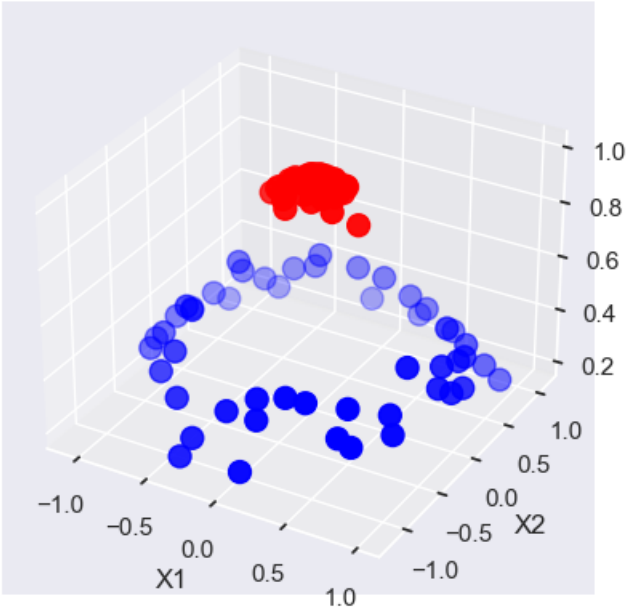
In [29]:
```
plot_decision_boundary(X, y, classifier)
```



In [30]:
```
def plot_3d_plot(X, y):
 r = np.exp(-(X ** 2).sum(1))
 ax = plt.subplot(projection='3d')
 ax.scatter3D(X[:, 0], X[:, 1], r, c=y, s=100, cmap='bwr')
 ax.set_xlabel('X1')
 ax.set_ylabel('X2')
 ax.set_zlabel('y')
 rbf_classifier = SVC(kernel="rbf")
 rbf_classifier.fit(X_train, y_train)
 y_pred = rbf_classifier.predict(X_test)
 return ax, rbf_classifier
```

In [31]:
```
plot_3d_plot(X,y)
```

Out[31]:
```
(<Axes3D: xlabel='X1', ylabel='X2', zlabel='y'>, SVC())
```

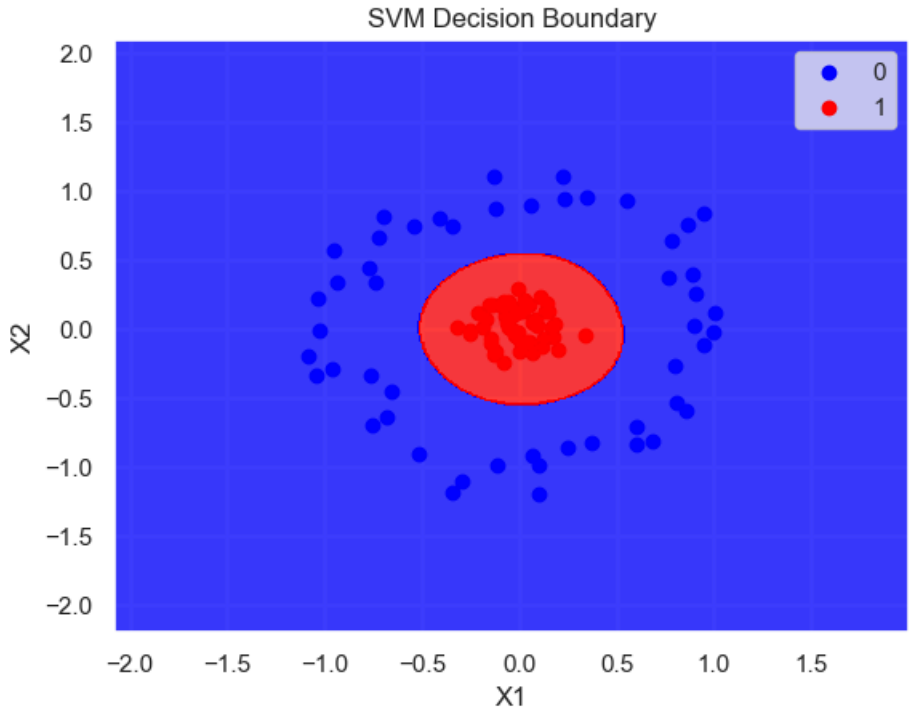


In [32]:
```
rbf_classifier = SVC(kernel="rbf")
rbf_classifier.fit(X_train, y_train)
y_pred = rbf_classifier.predict(X_test)
```

In [33]:
```
accuracy_score(y_test, y_pred)
```

Out[33]: 1.0

In [34]:
```
plot_decision_boundary(X, y, rbf_classifier)
```

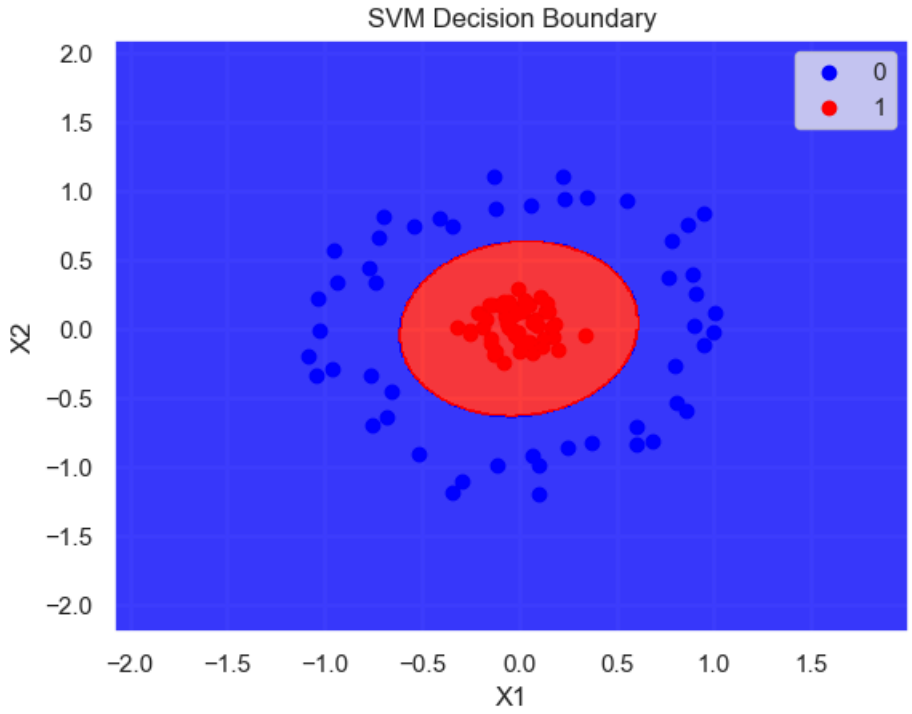


In [35]:
```
poly_classifier = SVC(kernel="poly",degree=2)
poly_classifier.fit(X_train, y_train)
y_pred = poly_classifier.predict(X_test)
```

In [36]:
```
accuracy_score(y_test, y_pred)
```

Out[36]: 1.0

In [37]:
```
plot_decision_boundary(X, y, poly_classifier)
```



In [38]:
```
X
```

Out[38]:
```
array([[-0.05459277,  0.00936684],
       [ 0.34857064,  0.95506157],
       [-0.05670649,  0.19724758],
       [-1.0429529 , -0.33499484],
       [ 0.1036395 , -0.99044455],
       [ 0.05506533,  0.1716154 ],
       [ 0.33705316, -0.04997426],
       [-0.1575562 ,  0.1722407 ],
       [-0.12131066,  0.86670968],
       [ 0.60326485, -0.70817826],
       [-0.25009257, -0.0367961 ],
       [ 0.17109976, -0.05624441],
       [-0.14262689, -0.07534606],
       [ 0.78437177,  0.64184551],
       [-0.25126585, -0.01176522],
       [-0.94986812,  0.5746776 ],
       [ 0.55713931,  0.93318911],
       [-0.0222478 , -0.02084216],
       [-0.20997505,  0.1127114 ],
       [-0.0283663 ,  0.10835236],
       [ 0.79722014, -0.26489652],
       [-0.03354415,  0.1499092 ],
       [ 0.22528645,  1.10310681],
       [ 0.24521034, -0.86642411],
       [ 0.9460335 ,  0.83519091],
       [-0.02430975, -0.05201834],
       [ 0.05810961,  0.89819136],
       [ 0.07183052, -0.9209024 ],
       [-0.12468264, -0.15950227],
       [-0.1882019 ,  0.01531838],
       [-0.517231  , -0.90929173],
       [-0.14182731,  0.1708185 ],
       [-0.34173802, -1.19096394],
       [ 0.90093786,  0.02306242],
       [ 0.00358216, -0.1585581 ],
       [-0.40953454,  0.8024751 ],
       [-0.69342221,  0.81020169],
       [-0.29759568, -1.10561218],
       [ 0.23165798,  0.9430881 ],
       [-0.00639656, -0.02489196],
       [-0.96403262, -0.291832  ],
       [ 0.16910716,  0.01318175],
       [-0.72196857,  0.66315031],
       [ 0.0551566 , -0.09240157],
       [ 0.15171333,  0.12589384],
       [ 0.94515868, -0.11838466],
       [ 0.86027141, -0.58966617],
       [-0.54131172,  0.74380239],
       [ 0.99453007, -0.02355977],
       [ 0.1285493 , -0.06951388],
       [ 0.11983372, -0.12553949],
       [-0.34529593,  0.74766033],
       [-0.08106786,  0.19355119],
       [-0.07906372,  0.14623284],
       [-0.73915442,  0.3325979 ],
       [ 0.02731885,  0.21362514],
       [-1.08009862, -0.19305061],
       [ 0.86831021,  0.75492859],
       [-0.65218216, -0.45416766],
       [-0.07281996,  0.09342769],
       [ 0.08439898,  0.06646807],
       [ 0.03759959, -0.09541964],
       [-0.12686022, -0.18943662],
       [-0.03856823, -0.00243158],
       [-0.13205965,  1.105014  ],
       [ 0.02208938,  0.12374184],
       [ 0.06826826,  0.04629369],
       [ 0.02118351, -0.11029007],
       [-0.17427442,  0.07025589],
       [-0.06776513,  0.04621474],
       [-0.76857808,  0.43983801],
       [-0.00789938,  0.28707928],
       [-0.75161258, -0.70297432],
       [ 0.76920406,  0.37248299],
       [ 0.10834282,  0.22710232],
```

```
       [ 0.68322226, -0.81956835],
       [-0.93837747,  0.34213203],
       [ 0.20108286, -0.14840275],
       [ 0.0032726 , -0.08794875],
       [ 0.90965539,  0.25112465],
       [ 0.36897762, -0.8326068 ],
       [ 0.08886254,  0.02051646],
       [ 0.07021886, -0.17951731],
       [ 0.0981127 , -1.20260127],
       [ 0.88936195,  0.39164269],
       [-0.31490537,  0.008492  ],
       [ 0.13862259,  0.1804244 ],
       [ 0.81227372, -0.53435842],
       [-0.10993297, -0.99071855],
       [ 0.13491927,  0.12763835],
       [-1.03660136,  0.21705684],
       [-0.76182854, -0.33405101],
       [-0.01194656,  0.12041164],
       [ 0.59879328, -0.83984171],
       [ 0.18477592,  0.03830988],
       [-0.14744198, -0.10269836],
       [-0.68029332, -0.64098467],
       [-0.07954434, -0.24786924],
       [ 1.00742389,  0.11948071],
       [-1.02297156, -0.01545247]])
```

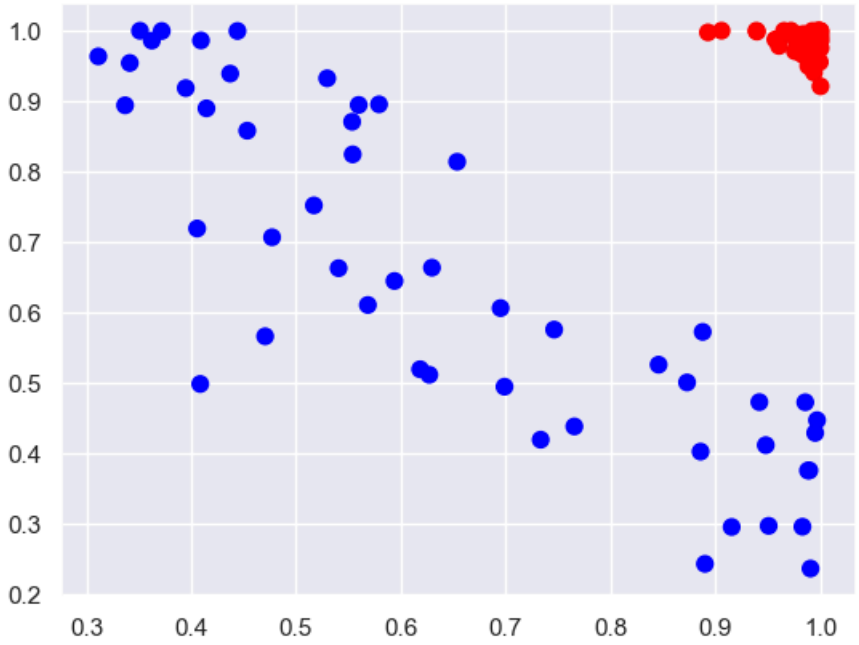
In [39]:
```
np.exp(-(X**2)).sum(1)
```

Out[39]:
```
array([1.99693633, 1.28725243, 1.95863007, 1.23081979, 1.36425966,
       1.96795003, 1.89011631, 1.94625051, 1.45719829, 1.30055248,
       1.93801654, 1.9679908 , 1.97420214, 1.20285868, 1.93867876,
       1.12439704, 1.15174952, 1.99907086, 1.94424479, 1.98752409,
       1.46187401, 1.97665329, 1.24667568, 1.41368428, 0.90642251,
       1.99670696, 1.44293619, 1.42309806, 1.95945437, 1.96496536,
       1.20271085, 1.9513286 , 1.13187884, 1.44357559, 1.97515989,
       1.37079698, 1.13696878, 1.20977413, 1.35864514, 1.99933967,
       1.31316664, 1.97163406, 1.23797026, 1.98846067, 1.96152162,
       1.39537544, 1.18338837, 1.3210908 , 1.37136005, 1.97879034,
       1.97010587, 1.45938713, 1.95668051, 1.9726114 , 1.47433763,
       1.9546439 , 1.27483731, 1.03607072, 1.46716129, 1.98602054,
       1.98849386, 1.98952369, 1.94878534, 1.99850769, 1.27763003,
       1.98431677, 1.99320948, 1.98746114, 1.96516128, 1.99328489,
       1.37803748, 1.92082776, 1.17848008, 1.42385083, 1.93806243,
       1.13785344, 1.30409077, 1.93858961, 1.99228415, 1.37603638,
       1.37267308, 1.99171371, 1.96336872, 1.2258717 , 1.31120746,
       1.90552081, 1.94893841, 1.26856969, 1.36272732, 1.96580191,
       1.29543292, 1.45409494, 1.98546293, 1.19262984, 1.96496756,
       1.96800392, 1.29259801, 1.93410283, 1.3482634 , 1.35093618])
```

In [40]:
```
X_new=np.exp(-(X**2))
```

In [41]:
```
plt.scatter(X_new[:, 0], X_new[:, 1], c=y, s=50, cmap='bwr')
```

Out[41]:
```
<matplotlib.collections.PathCollection at 0x1c3c663d390>
```


1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0