Support Vector Machine Vs. Ridge Regression

In this problem, we compare linear SVM and Ridge Regression in the task of classification. As we shall see, formulating the problem as different optimization problems (here SVM and Ridge Regression) makes a difference in performance. There are three places with todos, follow the todos to complete this problem.

In [21]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.linear_model import Ridge
from sklearn.metrics import accuracy_score
import pdb
```

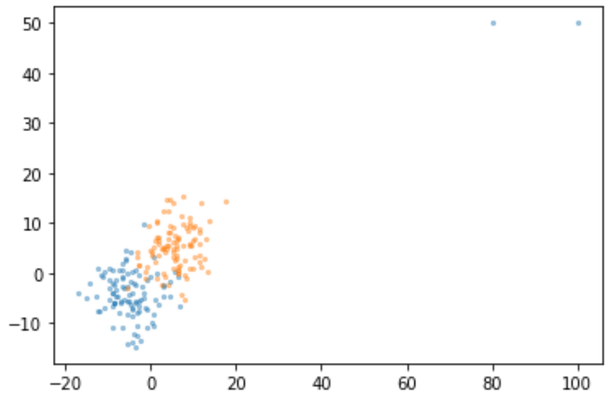
In [7]:
```
# Helper function for visualization. No todo here.
# Usage: plot_boundry(X, y, fitted_model)
#     X: your features, where each row is a data sample
#     y: your labels, can be 0/1 or -1/1
#     fitted_model: a scipy TRAINED model, such as sklearn.svm.SVC
#
def plot_boundry(X, y, fitted_model):

    plt.figure(figsize=(9.8,5), dpi=100)

    for i, plot_type in enumerate(['Decision Boundary']):
        plt.subplot(1,2,i+1)

        mesh_step_size = 0.5  # step size in the mesh
        x_min, x_max = X[:, 0].min() - .1, X[:, 0].max() + .1
        y_min, y_max = X[:, 1].min() - .1, X[:, 1].max() + .1
        x_max = 110
        y_max = 60
        xx, yy = np.meshgrid(np.arange(x_min, x_max, mesh_step_size), np.ar
ange(y_min, y_max, mesh_step_size))
        if i == 0:
            Z = fitted_model.predict(np.c_[xx.ravel(), yy.ravel()])
            Z = np.sign(Z)
        else:
            try:
                Z = fitted_model.predict_proba(np.c_[xx.ravel(), yy.ravel
()])[:,1]
            except:
                plt.text(0.4, 0.5, 'Probabilities Unavailable', horizontala
lignment='center',
                     verticalalignment='center', transform = plt.gca().tran
sAxes, fontsize=12)
                plt.axis('off')
                break
        Z = Z.reshape(xx.shape)
        plt.scatter(X[y==0,0], X[y==0,1], alpha=0.4, label='Edible', s=5)
        plt.scatter(X[y==1,0], X[y==1,1], alpha=0.4, label='Posionous', s=
5)
        plt.imshow(Z, interpolation='nearest', cmap='RdYlBu_r', alpha=0.15,
                   extent=(x_min, x_max, y_min, y_max), origin='lower')
        plt.title(plot_type)
        plt.gca().set_aspect('equal');

    plt.tight_layout()
    plt.subplots_adjust(top=0.9, bottom=0.08, wspace=0.02)
```

In [11]:
```
# load the data
train_data = np.load("ridge_vs_svm_data_train.npy")
X_train = train_data[:, 1:]
y_train = train_data[:, 0]

test_data= np.load("ridge_vs_svm_data_test.npy")
X_test = test_data[:, 1:]
y_test = test_data[:, 0]
```

Here we visualize the training data to get a sense of the distribution. Note the outliers.

In [12]:
```
plt.scatter(X_train[y_train==0,0], X_train[y_train==0,1], alpha=0.4, s=5)
plt.scatter(X_train[y_train==1,0], X_train[y_train==1,1], alpha=0.4, s=5)
```

Out[12]: `<matplotlib.collections.PathCollection at 0x7f7f1dc70fd0>`

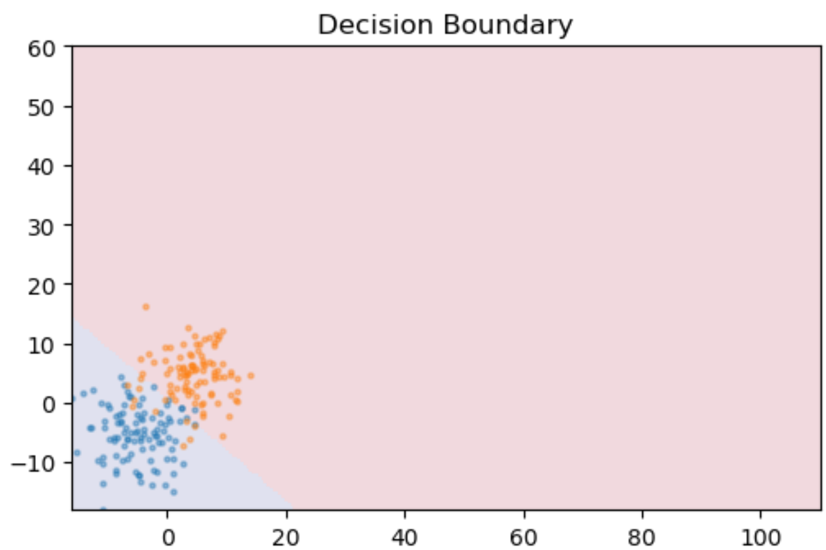


SVM

Fill in the code below to run a **linear** svm to classify the data.

In [36]:
```
fitted_model = None # your trained model (as trained by scipy)
y_pred = None # the prediction of your trained model on the testing data

########## Your beautiful code starts here ##########
# todo: Write code to train an SVM, and generate prediction y_pred.
# Optional: Try using a linear kernel and a polynomial kernel.  How does th
e value of C matter?

# svc = SVC(kernel='poly',gamma='auto')
svc = SVC(kernel='linear')
fitted_model = svc.fit(X_train, y_train)

########## Your beautiful code ends here ##########

y_pred = svc.predict(X_test)
accuracy = accuracy_score(y_pred, y_test)
print("Test Accuracy: {}".format(accuracy))

plot_boundry(X_test, y_test, fitted_model)
```

```
Test Accuracy: 0.92
```

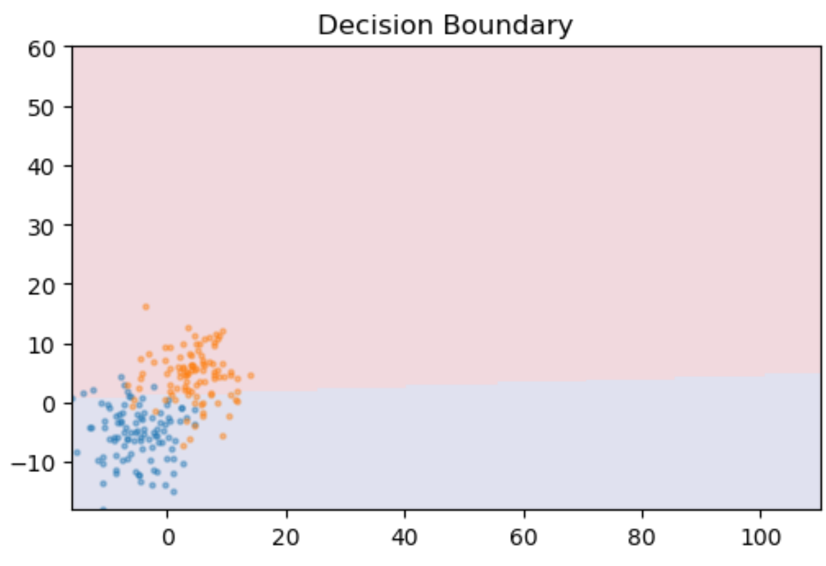


Ridge Regression

Fill in the code below to run ridge regression to classify the data.

In [37]:
```
fitted_model = None # your trained model (as trained by scipy)
y_pred_sign = None # the prediction of your trained model on the testing da
ta

# convert the labels from 0 and 1 to -1 and 1
y_train_sign = np.array(y_train)
y_test_sign = np.array(y_test)
y_train_sign[y_train_sign == 0] = -1
y_test_sign[y_test_sign == 0] = -1

# for the regularization parameter lambda, you can try something around 0.1
:)
# Optional: try choosing different parameters
llambda = 0.1

########## Your beautiful code starts here ##########
# todo: train a fitted_model and run prediction to generate y_pred_sign
clf = Ridge(alpha=llambda)
fitted_model = clf.fit(X_train, y_train_sign)
y_pred_sign = clf.predict(X_test)
y_pred_sign[y_pred_sign < 0] = -1
y_pred_sign[y_pred_sign > 0] = 1
# pdb.set_trace()
########## Your beautiful code ends here ##########

accuracy = accuracy_score(y_pred_sign, y_test_sign)
print("Test Accuracy: {}".format(accuracy))

plot_boundry(X_test, y_test, fitted_model)
```

```
Test Accuracy: 0.85
```



Why Do We See SVM Outperforming Ridge Regression?

In the above, we saw that SVM outperforms ridge regression because SVM is more robust to outliers. The data was actually synthetically generated from two Gaussians --- but remember the two outliers? Can you see how they are impacting the classifer?

The support vector machine finds a line that seperates the data whereas ridge regression is a penalized least squares. So the decision boundary is drawn based on how far away points are rather than how well it seperates the data.

How the Data was produced

In [38]:
```
# Optional: Try changing the positions of the outliers to see how they impa
ct the performanace

n = 100
cov = np.eye(2) * 20

pos = np.hstack([
    np.ones(n).reshape([-1, 1]),
    np.random.multivariate_normal([5, 5], cov, size=n),
])
neg = np.hstack([
    np.zeros(n).reshape([-1, 1]),
    np.random.multivariate_normal([-5, -5], cov, size=n),
])

syn = np.vstack([pos, neg])

outliers = np.array([
    [0, 80, 50,],
    [0, 100, 50,],
])
syn = np.vstack([pos, neg, outliers])
np.random.shuffle(syn)
np.save("ridge_vs_svm_data_train.npy", syn)


pos_test = np.hstack([
    np.ones(n).reshape([-1, 1]),
    np.random.multivariate_normal([5, 5], cov, size=n),
])
neg_test = np.hstack([
    np.zeros(n).reshape([-1, 1]),
    np.random.multivariate_normal([-5, -5], cov, size=n),
])

syn = np.vstack([pos_test, neg_test])

np.random.shuffle(syn)
np.save("ridge_vs_svm_data_test.npy", syn)
```

Credit

Spring 2019: Mong H. Ng, Prof. Ranade
Plotting function from https://github.com/devssh/svm/blob/master/SVM%20Python/Classifier%20Visualization.ipynb (https://github.com/devssh/svm/blob/master/SVM%20Python/Classifier%20Visualization.ipynb)