# Improving a model with Grid Search

In this mini-lab, we'll fit a decision tree model to some sample data. This initial model will overfit heavily. Then we'll use Grid Search to find better parameters for this model, to reduce the overfitting.

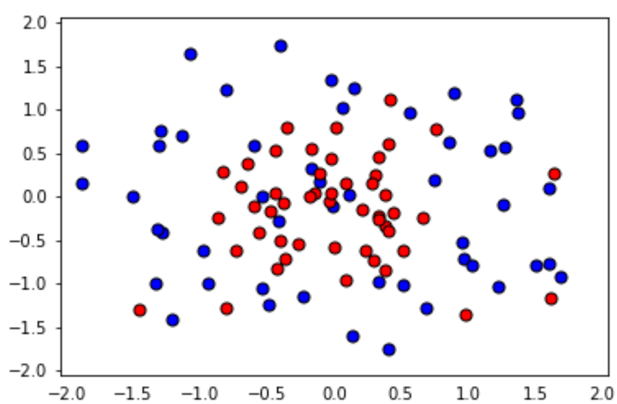
First, some imports.

In [2]:
```
%matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

## 1. Reading and plotting the data

Now, a function that will help us read the csv file, and plot the data.

In [3]:
```
def load_pts(csv_name):
    data = np.asarray(pd.read_csv(csv_name, header=None))
    X = data[:,0:2]
    y = data[:,2]

    plt.scatter(X[np.argwhere(y==0).flatten(),0], X[np.argwhere(y==0).flatten(),1]
,s = 50, color = 'blue', edgecolor = 'k')
    plt.scatter(X[np.argwhere(y==1).flatten(),0], X[np.argwhere(y==1).flatten(),1]
,s = 50, color = 'red', edgecolor = 'k')

    plt.xlim(-2.05,2.05)
    plt.ylim(-2.05,2.05)
    plt.grid(False)
    plt.tick_params(
    axis='x',
    which='both',
    bottom='off',
    top='off')

    return X,y

X, y = load_pts('data.csv')
plt.show()
```



This function will help us plot the model.

In [4]:
```
def plot_model(X, y, clf):
    plt.scatter(X[np.argwhere(y==0).flatten(),0],X[np.argwhere(y==0).flatten(),1],
s = 50, color = 'blue', edgecolor = 'k')
    plt.scatter(X[np.argwhere(y==1).flatten(),0],X[np.argwhere(y==1).flatten(),1],
s = 50, color = 'red', edgecolor = 'k')

    plt.xlim(-2.05,2.05)
    plt.ylim(-2.05,2.05)
    plt.grid(False)
    plt.tick_params(
    axis='x',
    which='both',
    bottom='off',
    top='off')

    r = np.linspace(-2.1,2.1,300)
    s,t = np.meshgrid(r,r)
    s = np.reshape(s,(np.size(s),1))
    t = np.reshape(t,(np.size(t),1))
    h = np.concatenate((s,t),1)

    z = clf.predict(h)

    s.shape = (np.size(r),np.size(r))
    t.shape = (np.size(r),np.size(r))
    z.shape = (np.size(r),np.size(r))

    plt.contourf(s,t,z,colors = ['blue','red'],alpha = 0.2,levels = range(-1,2))
    if len(np.unique(z)) > 1:
        plt.contour(s,t,z,colors = 'k', linewidths = 2)
    plt.show()
```

## 2. Splitting our data into training and testing sets

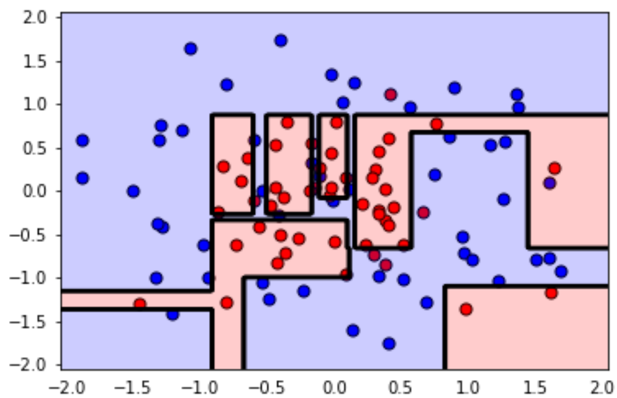
In [5]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import f1_score, make_scorer

#Fixing a random seed
import random
random.seed(42)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_st
ate=42)
```

## 3. Fitting a Decision Tree model

In [6]:
```
from sklearn.tree import DecisionTreeClassifier

# Define the model (with default hyperparameters)
clf = DecisionTreeClassifier(random_state=42)

# Fit the model
clf.fit(X_train, y_train)

# Make predictions using the unoptimized and model
train_predictions = clf.predict(X_train)
test_predictions = clf.predict(X_test)
```

Now let's plot the model, and find the testing f1_score, to see how we did.

In [7]:
```
plot_model(X, y, clf)
print('The Training F1 Score is', f1_score(train_predictions, y_train))
print('The Testing F1 Score is', f1_score(test_predictions, y_test))
```




```
The Training F1 Score is 1.0
The Testing F1 Score is 0.7
```

Woah! Some heavy overfitting there. Not just from looking at the graph, but also from looking at the difference between the high training score (1.0) and the low testing score (0.7).Let's see if we can find better hyperparameters for this model to do better. We'll use grid search for this.

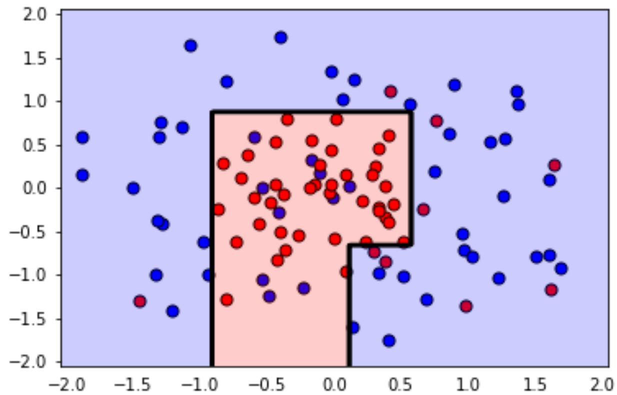
## 4. (SOLUTION) Use grid search to improve this model.

In here, we'll do the following steps:

1. First define some parameters to perform grid search on. We suggest to play with `max_depth`, `min_samples_leaf`, and `min_samples_split`.
2. Make a scorer for the model using `f1_score`.
3. Perform grid search on the classifier, using the parameters and the scorer.
4. Fit the data to the new classifier.
5. Plot the model and find the f1_score.
6. If the model is not much better, try changing the ranges for the parameters and fit it again.

In [8]:
```
from sklearn.metrics import make_scorer
from sklearn.model_selection import GridSearchCV

clf = DecisionTreeClassifier(random_state=42)

# TODO: Create the parameters list you wish to tune.
parameters = {'max_depth':[2,4,6,8,10],'min_samples_leaf':[2,4,6,8,10], 'min_sampl
es_split':[2,4,6,8,10]}

# TODO: Make an fbeta_score scoring object.
scorer = make_scorer(f1_score)

# TODO: Perform grid search on the classifier using 'scorer' as the scoring method
.
grid_obj = GridSearchCV(clf, parameters, scoring=scorer)

# TODO: Fit the grid search object to the training data and find the optimal param
eters.
grid_fit = grid_obj.fit(X_train, y_train)

# Get the estimator.
best_clf = grid_fit.best_estimator_

# Fit the new model.
best_clf.fit(X_train, y_train)

# Make predictions using the new model.
best_train_predictions = best_clf.predict(X_train)
best_test_predictions = best_clf.predict(X_test)

# Calculate the f1_score of the new model.
print('The training F1 Score is', f1_score(best_train_predictions, y_train))
print('The testing F1 Score is', f1_score(best_test_predictions, y_test))

# Plot the new model.
plot_model(X, y, best_clf)

# Let's also explore what parameters ended up being used in the new model.
best_clf
```

```
The training F1 Score is 0.814814814815
The testing F1 Score is 0.8
```




```
Out[8]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=4,
                    max_features=None, max_leaf_nodes=None,
                    min_impurity_decrease=0.0, min_impurity_split=None,
                    min_samples_leaf=2, min_samples_split=2,
                    min_weight_fraction_leaf=0.0, presort=False, random_state=42,
                    splitter='best')
```

### 5. Conclusion

Note that by using GridSearch we improved the F1 Score from 0.7 to 0.8 (and we lost some training score, but this is ok). Also, if you look at the plot, the second model has a much simpler boundary, which implies that it's less likely to overfit.