assignment08

June 24, 2018

1 Team Members

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```
In [1]: import tensorflow as tf
        from sklearn.linear_model import LinearRegression, LogisticRegression
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.ensemble import RandomForestRegressor
        from sklearn.metrics import log_loss
        import numpy as np
        import pickle
        from sklearn.externals import joblib
        import matplotlib.pyplot as plt
        %matplotlib inline
        from sklearn.metrics import explained_variance_score, mean_squared_error
```

```
/home/ramesh/anaconda2/lib/python2.7/site-packages/h5py/__init__.py:34: FutureWarning: Conversio
  from ._conv import register_converters as _register_converters
```

```
In [2]: #Load MNIST data from tf
        from tensorflow.examples.tutorials.mnist import input_data
        mnist = input_data.read_data_sets("MNIST_data/", one_hot=False)
        # mnist_one_hot = input_data.read_data_sets("MNIST_data/", one_hot=True)
```

```
WARNING:tensorflow:From <ipython-input-2-2720d8fc3cb4>:3: read_data_sets (from tensorflow.contri
Instructions for updating:
Please use alternatives such as official/mnist/dataset.py from tensorflow/models.
WARNING:tensorflow:From /home/ramesh/anaconda2/lib/python2.7/site-packages/tensorflow/contrib/le
Instructions for updating:
Please write your own downloading logic.
WARNING:tensorflow:From /home/ramesh/anaconda2/lib/python2.7/site-packages/tensorflow/contrib/le
Instructions for updating:
```

```
Please use urllib or similar directly.
Successfully downloaded train-images-idx3-ubyte.gz 9912422 bytes.
WARNING:tensorflow:From /home/ramesh/anaconda2/lib/python2.7/site-packages/tensorflow/contrib/le
Instructions for updating:
Please use tf.data to implement this functionality.
Extracting MNIST_data/train-images-idx3-ubyte.gz
Successfully downloaded train-labels-idx1-ubyte.gz 28881 bytes.
WARNING:tensorflow:From /home/ramesh/anaconda2/lib/python2.7/site-packages/tensorflow/contrib/le
Instructions for updating:
Please use tf.data to implement this functionality.
Extracting MNIST_data/train-labels-idx1-ubyte.gz
Successfully downloaded t10k-images-idx3-ubyte.gz 1648877 bytes.
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Successfully downloaded t10k-labels-idx1-ubyte.gz 4542 bytes.
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
WARNING:tensorflow:From /home/ramesh/anaconda2/lib/python2.7/site-packages/tensorflow/contrib/le
Instructions for updating:
Please use alternatives such as official/mnist/dataset.py from tensorflow/models.
```

In [3]:
```
train_images = mnist.train.images
train_labels = mnist.train.labels
test_images = mnist.test.images
test_labels = mnist.test.labels
```

In [4]:
```
def trainRandomForest(index):
    model = RandomForestClassifier(n_estimators=index,n_jobs=4)
#     print index
#     model.random_state(index)
    model.fit(train_images, train_labels)
    return model

models = {}
for i in [3,25,77,99]:
    print i
    model = trainRandomForest(i)
    models[i] = model

# joblib.dump(models, 'random_forest_models.pkl')
# print models
```

```
3
25
77
99
```

1.5 Plot of Uncertainty:

To plot the uncertainty, we get the probabilities of a test image being classified into each class, i.e, for every image, we determine 10 probability values, each representing the probability of the test image being classified into the respective class.

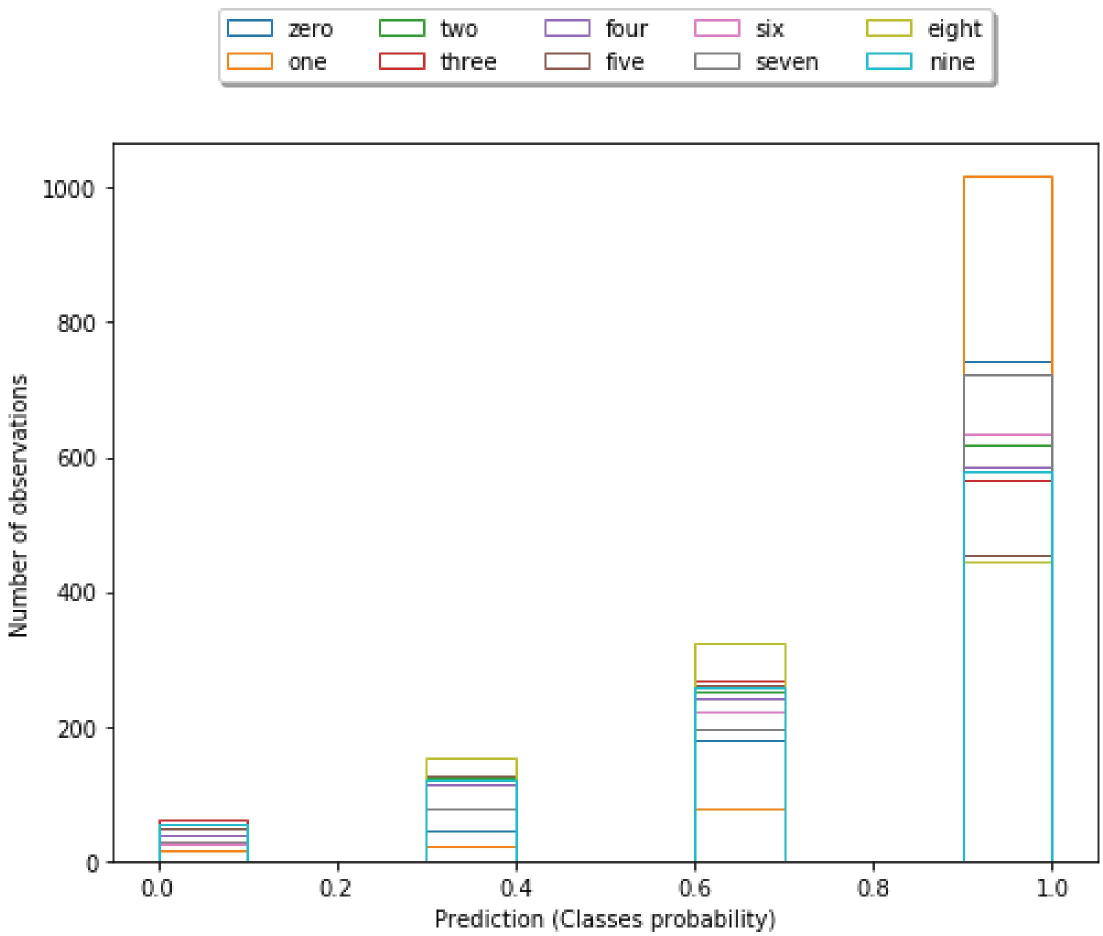
To plot the histogram, we determine the indices of each of the 10 types of digit in the test data set and then plot the probability of each type of image being classified correctly.

In other words, the x-axis of the histogram plot represents the probability that a digit is correctly classified into their respective classes and y-axis represents the number of observations that fall under these probabilities.

For example, in the plot using a model with 3 members, we observe that the digit labeled 'one' has the largest number of observations that achieve a probability of being correctly classified with a probability of 0.9-1.0.

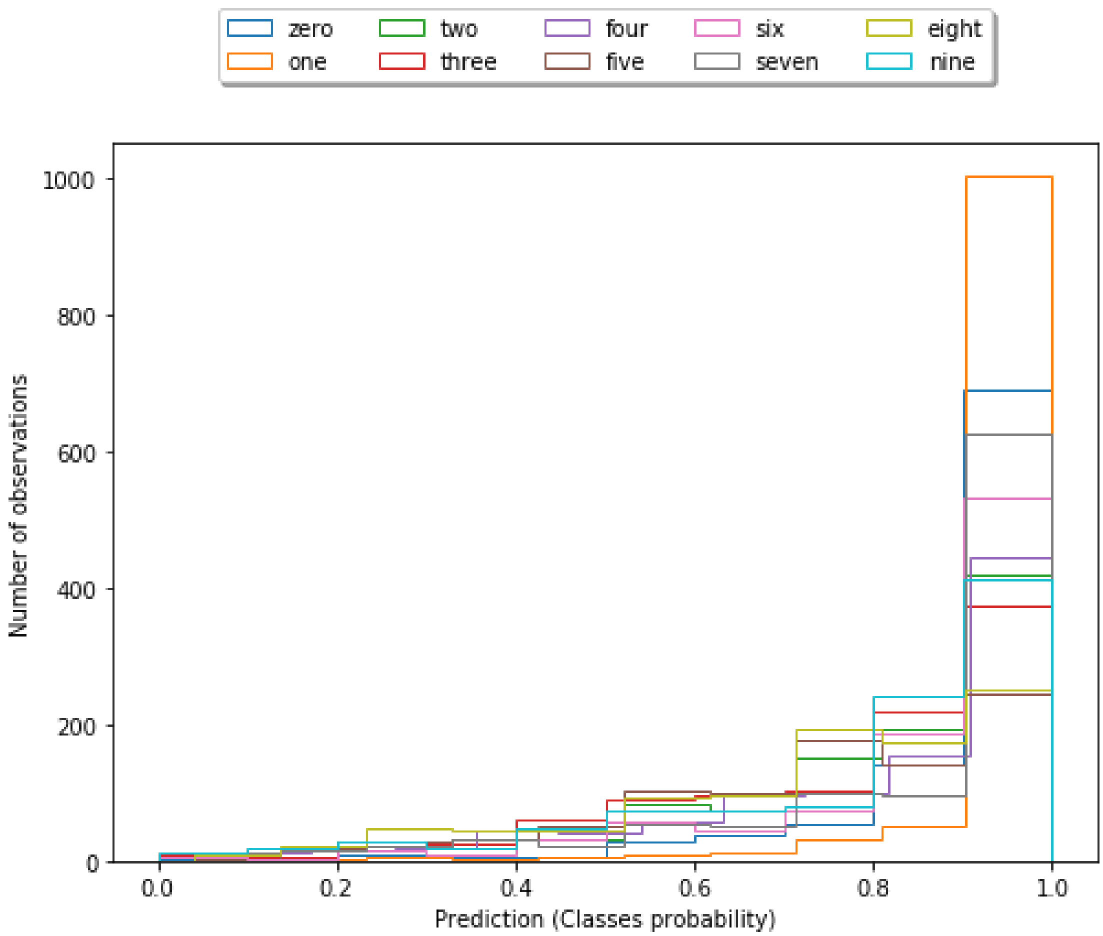
```
In [5]: def plot_uncertainty(model,test_images,test_labels):
            predicted_output = model.predict_proba(test_images)

            zero = np.where(test_labels == 0)[0]
            one = np.where(test_labels == 1)[0]
            two = np.where(test_labels == 2)[0]
            three = np.where(test_labels == 3)[0]
            four = np.where(test_labels == 4)[0]
            five = np.where(test_labels == 5)[0]
            six = np.where(test_labels == 6)[0]
            seven = np.where(test_labels == 7)[0]
            eight = np.where(test_labels == 8)[0]
            nine = np.where(test_labels == 9)[0]
            fig, ax = plt.subplots(1,figsize=(8,6))

            ax.hist(predicted_output[zero, 0], histtype='step', label='zero')
            ax.hist(predicted_output[one, 1], histtype='step', label='one')
            ax.hist(predicted_output[two, 2], histtype='step', label='two')
            ax.hist(predicted_output[three, 3], histtype='step', label='three')
            ax.hist(predicted_output[four, 4], histtype='step', label='four')
            ax.hist(predicted_output[five, 5], histtype='step', label='five')
            ax.hist(predicted_output[six, 6], histtype='step', label='six')
            ax.hist(predicted_output[seven, 7], histtype='step', label='seven')
            ax.hist(predicted_output[eight, 8], histtype='step', label='eight')
            ax.hist(predicted_output[nine, 9], histtype='step', label='nine')

            ax.legend(loc='upper center', bbox_to_anchor=(0.5, 1.2),
                      ncol=5, fancybox=True, shadow=True)

            ax.set_xlabel('Prediction (Classes probability)')
            ax.set_ylabel('Number of observations')
```

```
In [6]: plot_uncertainty(models[3],test_images,test_labels)
```



We now make histogram plots to observe the uncertainty when using models with an increasing number of members. The following figure shows the plot for a model with 25 members:

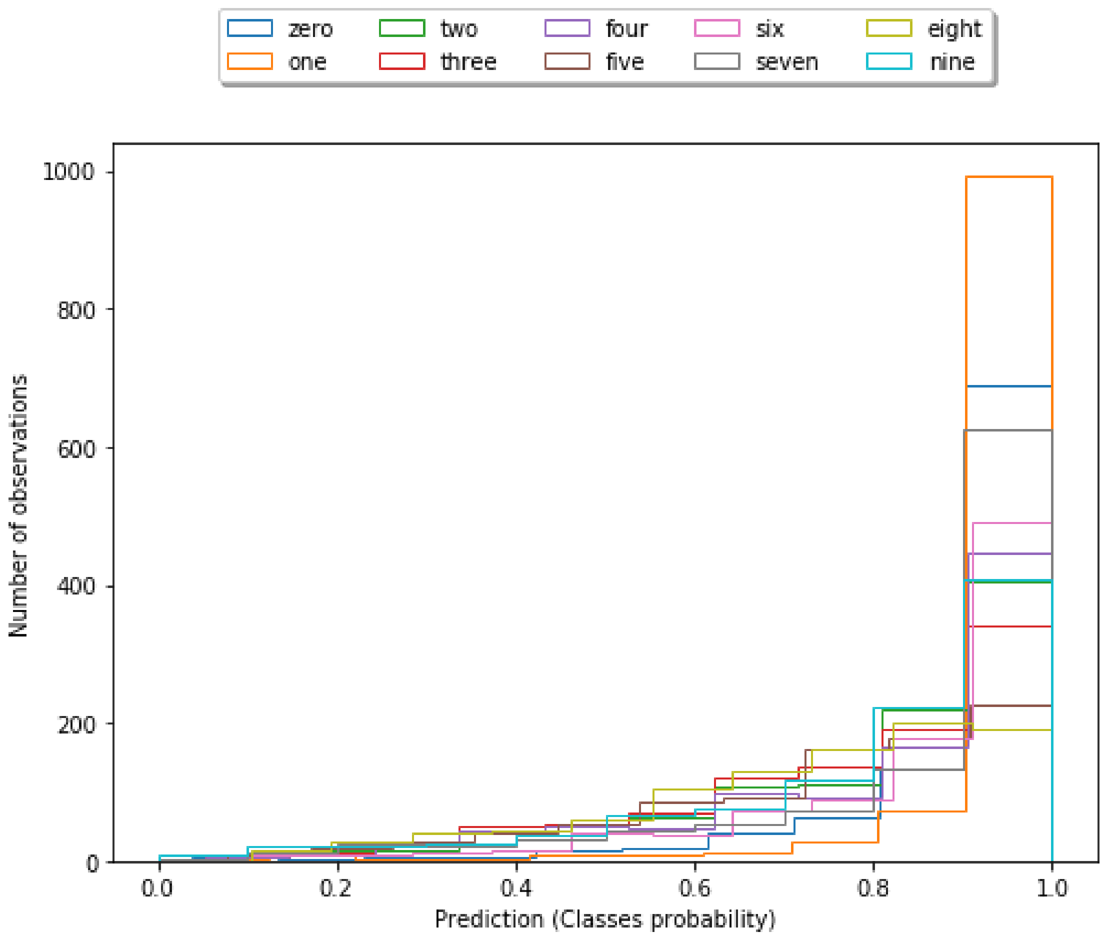
```
In [7]: plot_uncertainty(models[25],test_images,test_labels)
```



With an increase in the number of members, there are a lower number of images with a lower probability of being classified to an incorrect class. In addition, number of images of each type have an increasingly higher probability of being classified correctly.

The following figure shows a histogram plot when using a model with 77 members.

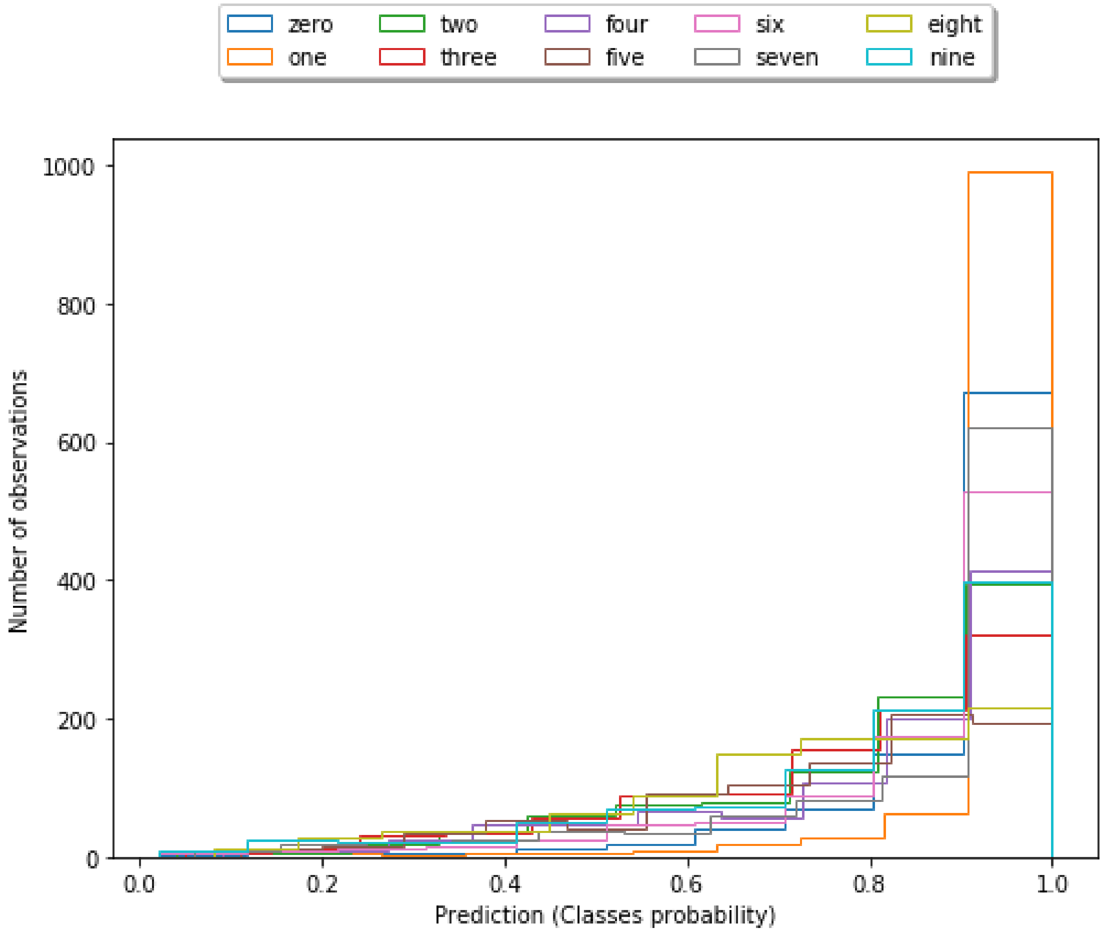
```
In [8]: plot_uncertainty(models[77],test_images,test_labels)
```



Increasing the number of members to 77 causes the plot to show a similar change as in the previous plot, but on a much lower scale. In other words, while the number of images with a higher probability score for their correct classes has increased for each type, the scale of this increase is not as high as seen when increasing the number of members from 3 to 25.

Similar results are seen when increasing the number of members from 77 to 99 as shown in the histogram plot below.

```
In [9]: plot_uncertainty(models[99],test_images,test_labels)
```



Comparison of the accuracy scores (shown below) shows that the accuracy increases with the increase in the number of members.

```
In [10]: print models[25].score(test_images,test_labels)
```

```
0.962
```

```
In [11]: print models[77].score(test_images,test_labels)
```

```
0.9669
```

```
In [12]: print models[99].score(test_images,test_labels)
```

```
0.97
```

Thus accuracy increases and the uncertainty decreases with an increase in the number of members in the ensemble.

```
In [13]: predicted_output = models[25].predict_proba(test_images)
         pred_labels = models[25].predict(test_images)

         misclassified = np.where(test_labels != pred_labels)
         mis_classified = np.asarray(misclassified)[0]
```

The above code obtains the indices of the test images that were wrongly classified as well as the predicted probabilities when using a model with 25 members. To analyze the reason for miss-classification, we take the true labels and the predicted probabilities for the first 5 misclassified examples:

```
In [14]: true = []
         prediction = []
         pred_prob = []
         for i in range(5):
             idx = mis_classified[i]
             true.append(test_labels[idx])
             prediction.append(pred_labels[idx])
             pred_prob.append(predicted_output[idx])

         print "True labels for first 5 misclassified examples :"
         print true
         print "Predicted labels for first 5 misclassified examples :"
         print prediction
```

```
True labels for first 5 misclassified examples :
[5, 4, 9, 7, 9]
Predicted labels for first 5 misclassified examples :
[2, 6, 4, 4, 8]
```

```
In [15]: print "Predicted probabilities for first 5 misclassified examples :"
         for i in range(5):
             idx = mis_classified[i]
             print predicted_output[idx]
```

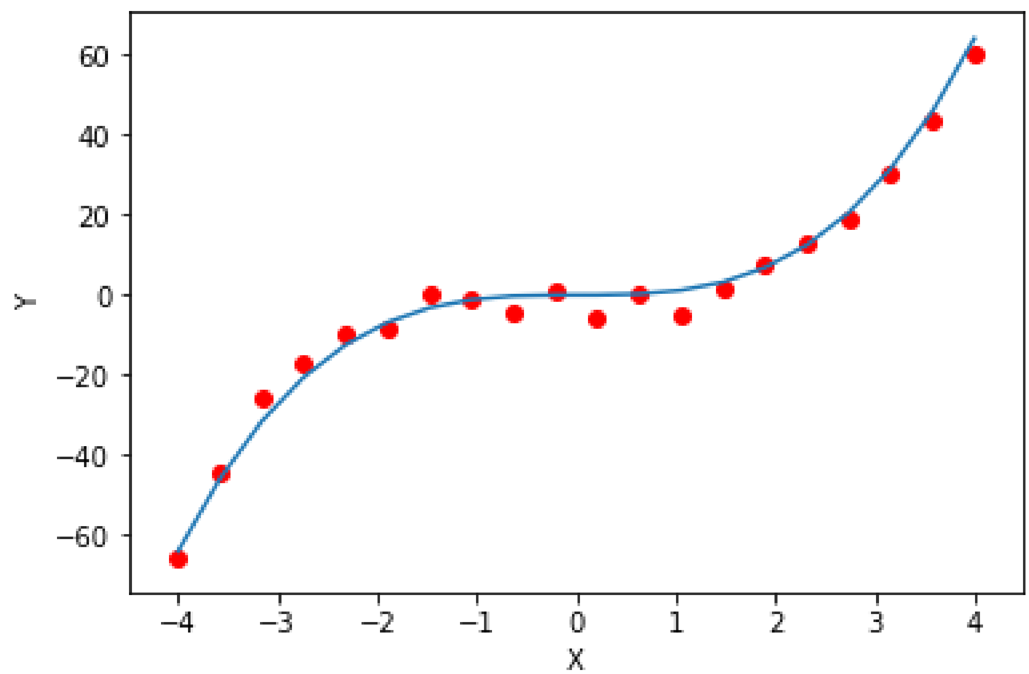
```
Predicted probabilities for first 5 misclassified examples :
[0.   0.   0.32 0.   0.16 0.16 0.04 0.08 0.12 0.12]
[0.04 0.   0.16 0.   0.2  0.2  0.32 0.   0.   0.08]
[0.   0.   0.   0.   0.32 0.12 0.08 0.12 0.12 0.24]
[0.   0.   0.   0.04 0.56 0.   0.   0.36 0.   0.04]
[0.04 0.   0.12 0.12 0.   0.2  0.   0.   0.48 0.04]
```

It can be observed from the above probabilities that the actual label for an image has been assigned a lower probability as compared to the true label. For instance, the first misclassified image has the highest probability of 0.44 assigned to label 9 whereas the true label for the image ,i.e 7 has only a probability of 0.2. Similaryly for the second misclassified example, a higher probability is assigned to label 7 as compared to the true label 9. The same holds true for the remaining misclassified examples as well.

1.6 Reproduction of figure from paper using Random forest

In [23]:
```
# Generating samples between -4 and 4 for training
num_of_data = 20
x = np.linspace(-4,4,num_of_data)

# Generating noise with mean 0 and standard deviation 3^2
noise = np.random.normal(0,3,num_of_data)

# Generating output and adding noise
y = x**3
y_noise = y + noise

# Plotting
plt.plot(x,y)
plt.xlabel("X")
plt.ylabel("Y")
plt.scatter(x,y_noise,color="red")
```

Out[23]:
```
<matplotlib.collections.PathCollection at 0x7f741c048190>
```



In [17]:
```
# Training model with 10 members in ensemble
sinmodel = RandomForestRegressor(n_estimators=10,n_jobs=4)
sinmodel.fit(x.reshape(20,1),y.reshape(20,1))
```

```
/home/ramesh/anaconda2/lib/python2.7/site-packages/ipykernel_launcher.py:3: DataConversionWarnin
  This is separate from the ipykernel package so we can avoid doing imports until
```

```
Out[17]: RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                    max_features='auto', max_leaf_nodes=None,
                    min_impurity_decrease=0.0, min_impurity_split=None,
                    min_samples_leaf=1, min_samples_split=2,
                    min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=4,
                    oob_score=False, random_state=None, verbose=0, warm_start=False)
```

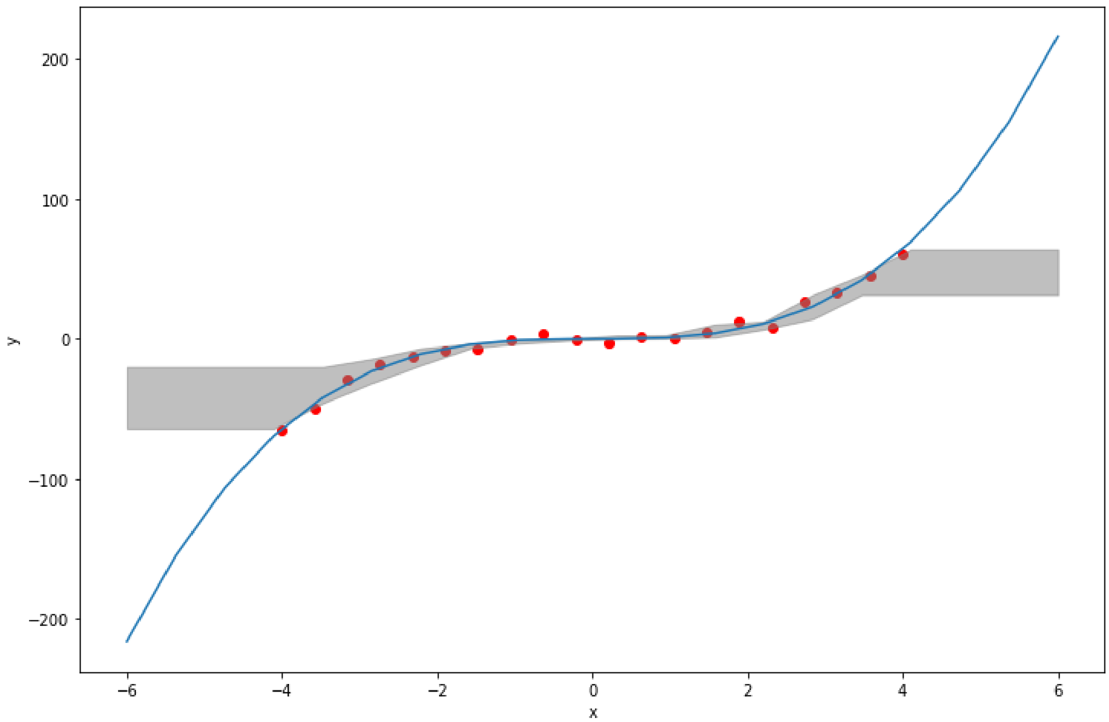
```
In [18]: # Generating test samples
         test_x = np.linspace(-6,6,20)
         test_y = test_x**3
```

```
In [19]: # Predicting the test samples
         test_predict = sinmodel.predict(test_x.reshape(20,1))
```

```
In [20]: # function to find the upper and lower error bounds for the predicted values
         def find_bounds(model, X, percentile=95):
             err_down = []
             err_up = []

             for x in range(len(X)):
                 preds = []
                 for pred in model.estimators_:
                     preds.append(pred.predict(X[x])[0])
                 err_down.append(np.percentile(preds, (100 - percentile) / 2. ))
                 err_up.append(np.percentile(preds, 100 - (100 - percentile) / 2.))

             return err_down, err_up
```

```
In [22]: lower,upper = find_bounds(sinmodel,test_x)
         plt.figure(figsize=(12,8))
         plt.plot(test_x,test_y)
         plt.scatter(x,y_noise,color="red")
         plt.xlabel("x")
         plt.ylabel("y")
         plt.fill_between(test_x, lower, upper, color='grey', alpha=0.5)
```

```
Out[22]: <matplotlib.collections.PolyCollection at 0x7f741c183f50>
```



In the above plot, the blue line represents the ground truth, with the red dots representing noisy training data points. Furthermore, uncertainty grows outside the range of (-4,4).