In [0]:
```
#importing all necessary libraries

import numpy as np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn import datasets
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.tree import DecisionTreeRegressor
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.datasets import load_digits
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
from sklearn import model_selection
from sklearn.ensemble import RandomForestRegressor
from sklearn import metrics
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_predict
```

In [0]:
```
#loading boston house pricing dataset

boston = datasets.load_boston()
print(boston.data.shape, boston.target.shape)
print(boston.feature_names)
```

```
(506, 13) (506,)
['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATI
O'
 'B' 'LSTAT']
```

In [0]:
```
#creating dataframe for the dataset
```

```
data = pd.DataFrame(boston.data,columns=boston.feature_names)
data = pd.concat([data,pd.Series(boston.target,name='MEDV')],axis=1)
```

In [0]:
```
X = data.iloc[:,:-1]
y = data.iloc[:,-1]
```

In [0]:
```
x_training_set, x_test_set, y_training_set, y_test_set = train_test_spl
it(X,y,test_size=0.20,random_state=42,
shuffle=True)
```

In [0]:
```
#Model: Decision Tree Regressor

dtc =  DecisionTreeRegressor(max_depth=5, random_state=0)
dtc.fit(x_training_set, y_training_set)
```

Out[0]:
```
DecisionTreeRegressor(criterion='mse', max_depth=5, max_features=None,
                      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,
                      presort=False, random_state=0, splitter='best')
```

In [0]:
```
#Decision Tree Regressor's Errors and Variance

model_score = dtc.score(x_training_set,y_training_set)
# Have a look at R sq to give an idea of the fit ,
# Explained variance score: 1 is perfect prediction
print('coefficient of determination R^2 of the prediction.:' ,model_sco
re)
y_predicted = dtc.predict(x_test_set)
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test_set, y
_predicted))
# The mean squared error
print("Mean squared error: %.2f"% mean_squared_error(y_test_set, y_pred
icted))
# Explained variance score: 1 is perfect prediction
print('Test Variance score: %.2f' % r2_score(y_test_set, y_predicted))
```

```
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_
test_set, y_predicted)))
```

```
coefficient of determination R^2 of the prediction.: 0.9185171013474737

Mean Absolute Error: 2.606196032019045
Mean squared error: 20.36
Test Variance score: 0.72
Root Mean Squared Error: 4.511791166025231
```

In [0]:

```
# Model: Random Forest Regressor

x_training_set, x_test_set, y_training_set, y_test_set = train_test_spl
it(X,y,test_size=0.20,random_state=42,
shuffle=True)

rfc = RandomForestRegressor(max_depth=5, random_state=0)
rfc.fit(x_training_set,y_training_set)
# predictions
y_pred = rfc.predict(x_test_set)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:245:
FutureWarning: The default value of n_estimators will change from 10 in
version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

In [0]:

```
#Random Forest Regressor's Errors and Variance

model_score = rfc.score(x_training_set,y_training_set)
# Have a look at R sq to give an idea of the fit ,
# Explained variance score: 1 is perfect prediction
print('coefficient of determination R^2 of the prediction.:' ,model_sco
re)
y_predicted = rfc.predict(x_test_set)
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test_set, y
_predicted))
# The mean squared error
print("Mean squared error: %.2f"% mean_squared_error(y_test_set, y_pred
icted))
```

```
# Explained variance score: 1 is perfect prediction
print('Test Variance score: %.2f' % r2_score(y_test_set, y_predicted))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_
test_set, y_predicted)))
```

```
coefficient of determination R^2 of the prediction.: 0.9263154828659765
Mean Absolute Error: 2.2154207274115483
Mean squared error: 10.71
Test Variance score: 0.85
Root Mean Squared Error: 3.272561805256446
```

In [0]:

```
#Learning curve function

def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None, n_j
obs=1,\
                        train_sizes=np.linspace(.1, 1.0, 5), scoring='r
2'):

    plt.figure(figsize=(10,6))
    plt.title(title)

    if ylim is not None:
        plt.ylim(*ylim)

    plt.xlabel("Training examples")
    plt.ylabel(scoring)

    train_sizes, train_scores, test_scores = learning_curve(estimator,
X, y, cv=cv, scoring=scoring, n_jobs=n_jobs, train_sizes=train_sizes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)

    plt.grid()

    plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
\
                     train_scores_mean + train_scores_std, alpha=0.1, \
```

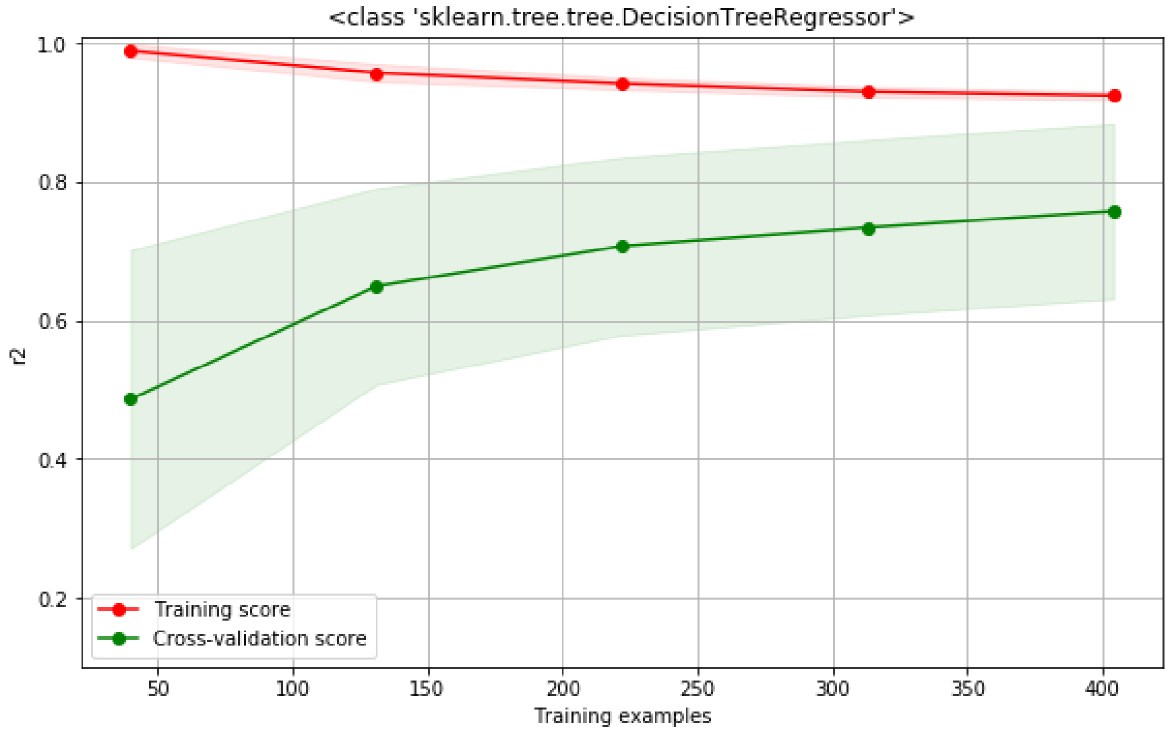
```
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,\
                     test_scores_mean + test_scores_std, alpha=0.1, col
or="g")

    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",label="Tra
ining score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g", label="Cro
ss-validation score")
    plt.legend(loc="best")

    return plt
```

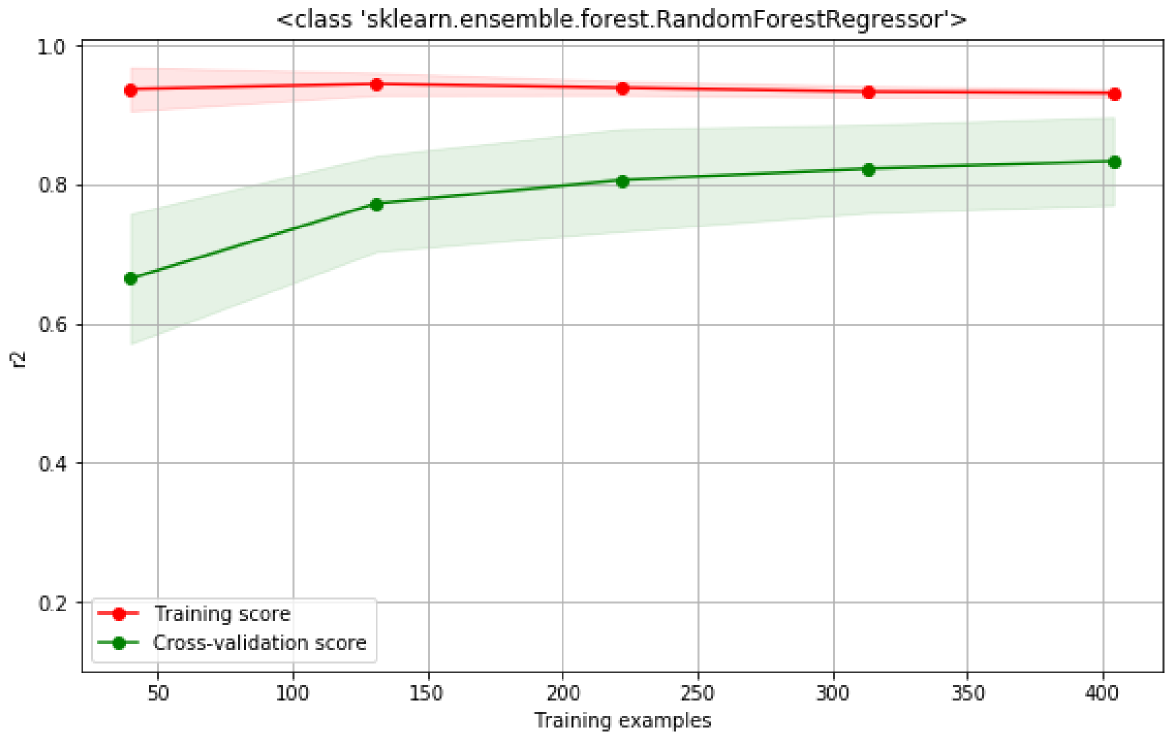
In [0]:

```
# Cross validation with 100 iterations to get smoother mean test and tr
ain
# score curves, each time with 20% data randomly selected as a validati
on set.
cv = ShuffleSplit(n_splits=100, test_size=0.2, random_state=0)

#rfc =  RandomForestRegressor(max_depth=5, random_state=0)
plot_learning_curve(dtc, DecisionTreeRegressor, X, y, ylim=(0.1, 1.01),
 cv=cv, n_jobs=4)
plot_learning_curve(rfc, RandomForestRegressor, X, y, ylim=(0.1, 1.01),
 cv=cv, n_jobs=4)
```

Out[0]:

```
<module 'matplotlib.pyplot' from '/usr/local/lib/python3.6/dist-packa
ges/matplotlib/pyplot.py'>
```


<class 'sklearn.tree.tree.DecisionTreeRegressor'>
1.0
0.8
0.6
0.4
0.2
r2
Training score
Cross-validation score
50
100
150
200
250
300
350
400
Training examples



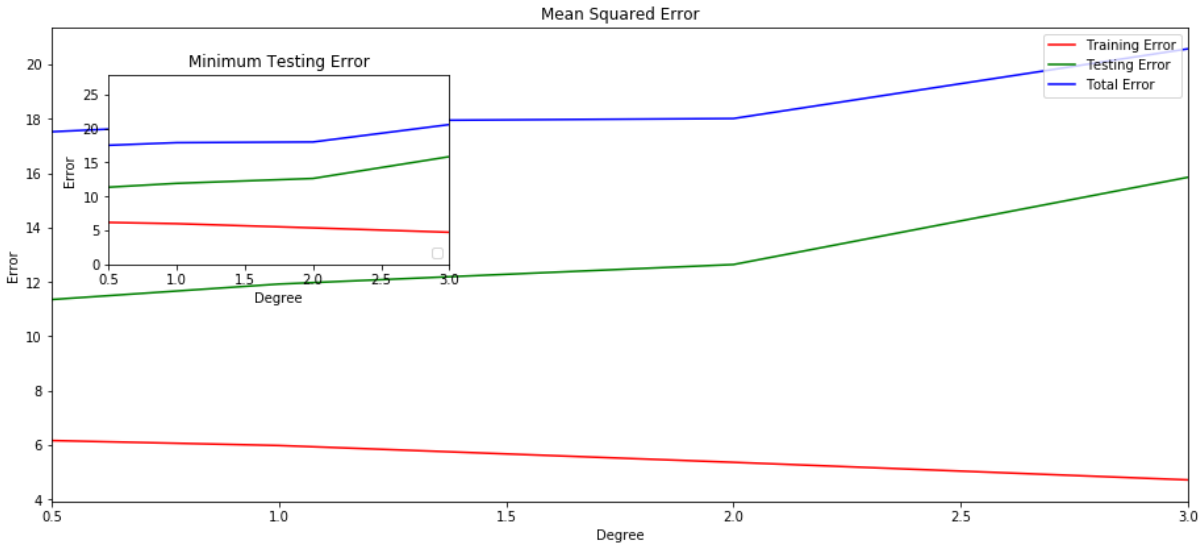
In [0]:
```
#Error Plot for Decision Tree Regressor

steps = np.arange(1,5,1)

trainErr = np.zeros(steps.shape)
testErr = np.zeros(steps.shape)

for i, step in enumerate(steps):
    # Generate polynomial features
    poly = PolynomialFeatures(step, interaction_only=True)
    pX_train = poly.fit_transform(x_training_set)
```

```
    pX_test = poly.transform(x_test_set)

    # Rescale the features with mean = 0, std = 1 for numerical stabili
ty
    scaler = StandardScaler()
    pX_train = scaler.fit_transform(pX_train)
    pX_test = scaler.transform(pX_test)

    # Create model instance
    model = RandomForestRegressor(max_depth=5, random_state=0)

    # Train model
    model.fit(pX_train, y_training_set)

    # Make Predictions
    y_train_pred = model.predict(pX_train)
    y_test_pred = model.predict(pX_test)

    # Calculate Error
    trainErr[i] = mean_squared_error(y_training_set, y_train_pred)
    testErr[i] = mean_squared_error(y_test_set, y_test_pred)


    fig = plt.figure(figsize=(12,5))

totalErr = trainErr + testErr

#test_loss_min = testErr.min()
#deg_min = testErr.argmin() + steps[0]

#plt.annotate('Minimum Test Loss (%.4f) w/ %.0f degrees' % (test_loss_m
in, deg_min),xy=(deg_min,test_loss_min),xytext=(deg_min,test_loss_min-5
0),arrowprops=dict(width=1,headwidth=2,facecolor='r',shrink=0.05))

axes1 = fig.add_axes([0, 0, 1, 1]) # main axes
axes2 = fig.add_axes([0.05, .5, .3, .4]) # inner axes

axes1.plot(trainErr,'r',label='Training Error')
axes1.plot(testErr,'g',label='Testing Error')
```

```
axes1.plot(totalErr, 'b', label='Total Error')

axes1.set_title("Mean Squared Error")
axes1.set_xlabel("Degree")
axes1.set_ylabel("Error")
axes1.set_xlim(0.5,steps[-2])
axes1.legend(loc=1)

axes2.plot(trainErr,'r')
axes2.plot(testErr,'g')
axes2.plot(totalErr,'b')
axes2.set_xlim(0.5,steps[-2])
axes2.set_ylim(0, totalErr[1]+10)
axes2.set_title("Minimum Testing Error")
axes2.set_xlabel("Degree")
axes2.set_ylabel("Error")

plt.legend(loc=4)
print ('min value:', np.abs(pX_train).min())
print ('max value:', np.abs(pX_train).max())
print ('difference in scale:', np.abs(pX_train).max() / np.abs(pX_train
).min())
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:245:
FutureWarning: The default value of n_estimators will change from 10 in
version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:245:
FutureWarning: The default value of n_estimators will change from 10 in
version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:245:
FutureWarning: The default value of n_estimators will change from 10 in
version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:245:
FutureWarning: The default value of n_estimators will change from 10 in
version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
No handles with labels found to put in legend.
```

```
min value: 0.0

max value: 17.721917521525185
difference in scale: inf

/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:67: Runtim
eWarning: divide by zero encountered in double_scalars

<Figure size 864x360 with 0 Axes>

<Figure size 864x360 with 0 Axes>

<Figure size 864x360 with 0 Axes>
```



In [0]:

```
#Error Plot for Random Forest Regressor Model

steps = np.arange(1,5,1)

trainErr = np.zeros(steps.shape)
testErr = np.zeros(steps.shape)

for i, step in enumerate(steps):
    # Generate polynomial features
```

```
    poly = PolynomialFeatures(step, interaction_only=True)
    pX_train = poly.fit_transform(x_training_set)
    pX_test = poly.transform(x_test_set)

    # Rescale the features with mean = 0, std = 1 for numerical stabili
ty
    scaler = StandardScaler()
    pX_train = scaler.fit_transform(pX_train)
    pX_test = scaler.transform(pX_test)

    # Create model instance
    model = DecisionTreeRegressor(max_depth=5,random_state=0)

    # Train model
    model.fit(pX_train, y_training_set)

    # Make Predictions
    y_train_pred = model.predict(pX_train)
    y_test_pred = model.predict(pX_test)

    # Calculate Error
    trainErr[i] = mean_squared_error(y_training_set, y_train_pred)
    testErr[i] = mean_squared_error(y_test_set, y_test_pred)

    fig = plt.figure(figsize=(12,5))

totalErr = trainErr + testErr

#test_loss_min = testErr.min()
#deg_min = testErr.argmin() + steps[0]

#plt.annotate('Minimum Test Loss (%.4f) w/ %.0f degrees' % (test_loss_m
in, deg_min),xy=(deg_min,test_loss_min),xytext=(deg_min,test_loss_min-5
0),arrowprops=dict(width=1,headwidth=2,facecolor='r',shrink=0.05))

axes1 = fig.add_axes([0, 0, 1, 1]) # main axes
axes2 = fig.add_axes([0.05, .5, .3, .4]) # inner axes

axes1.plot(trainErr,'r',label='Training Error')
```

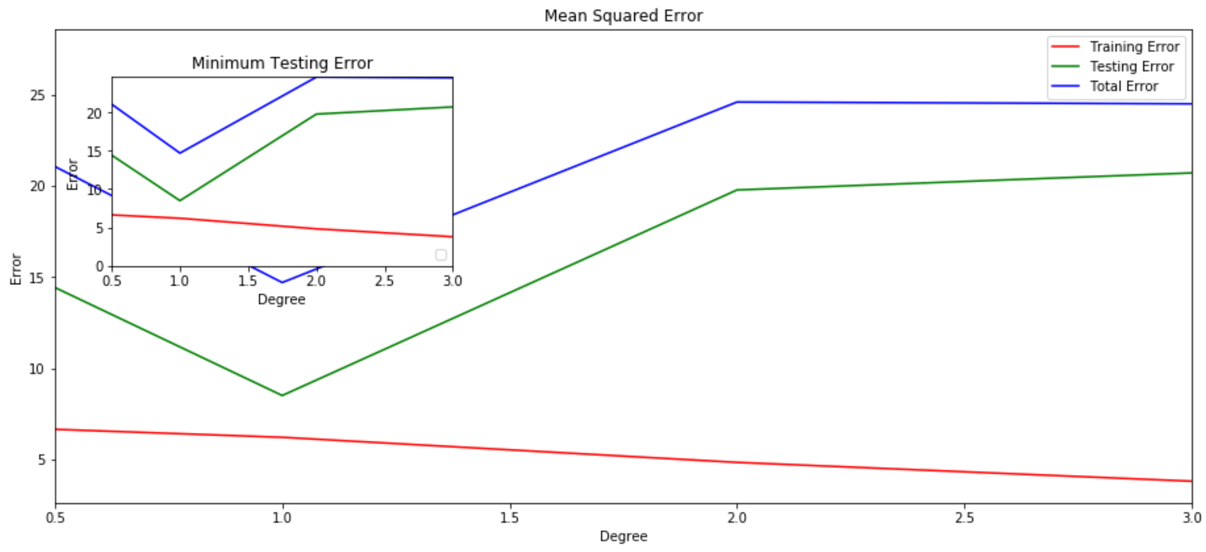
```
axes1.plot(testErr,'g',label='Testing Error')
axes1.plot(totalErr, 'b', label='Total Error')

axes1.set_title("Mean Squared Error")
axes1.set_xlabel("Degree")
axes1.set_ylabel("Error")
axes1.set_xlim(0.5,steps[-2])
axes1.legend(loc=1)

axes2.plot(trainErr,'r')
axes2.plot(testErr,'g')
axes2.plot(totalErr,'b')
axes2.set_xlim(0.5,steps[-2])
axes2.set_ylim(0, totalErr[1]+10)
axes2.set_title("Minimum Testing Error")
axes2.set_xlabel("Degree")
axes2.set_ylabel("Error")

plt.legend(loc=4)

print ('min value:', np.abs(pX_train).min())
print ('max value:', np.abs(pX_train).max())
print ('difference in scale:', np.abs(pX_train).max() / np.abs(pX_train
).min())
```

```
No handles with labels found to put in legend.
```

```
min value: 0.0
max value: 17.721917521525185
difference in scale: inf
```

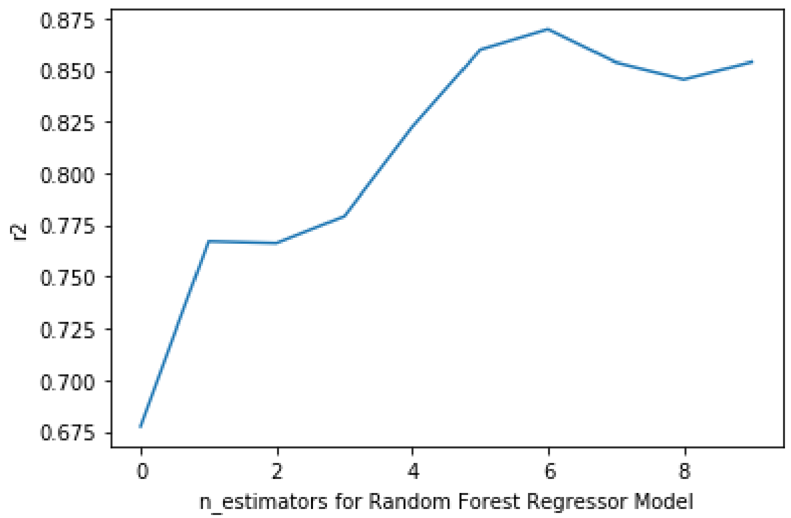
```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:67: Runtim
eWarning: divide by zero encountered in double_scalars
```

```
<Figure size 864x360 with 0 Axes>

<Figure size 864x360 with 0 Axes>

<Figure size 864x360 with 0 Axes>
```



In [0]:

```
# plot showing incresing R² as n_estimators is increased from 1 to 9 fo
r Random Forest Regressor Model.
preds = np.stack([t.predict(x_test_set) for t in rfc.estimators_])
preds[:,0], np.mean(preds[:,0])
plt.ylabel("r2")
plt.xlabel("n_estimators for Random Forest Regressor Model")
plt.plot([metrics.r2_score(y_test_set, np.mean(preds[:i+1], axis=0)) fo
r i in range(10)]);
```

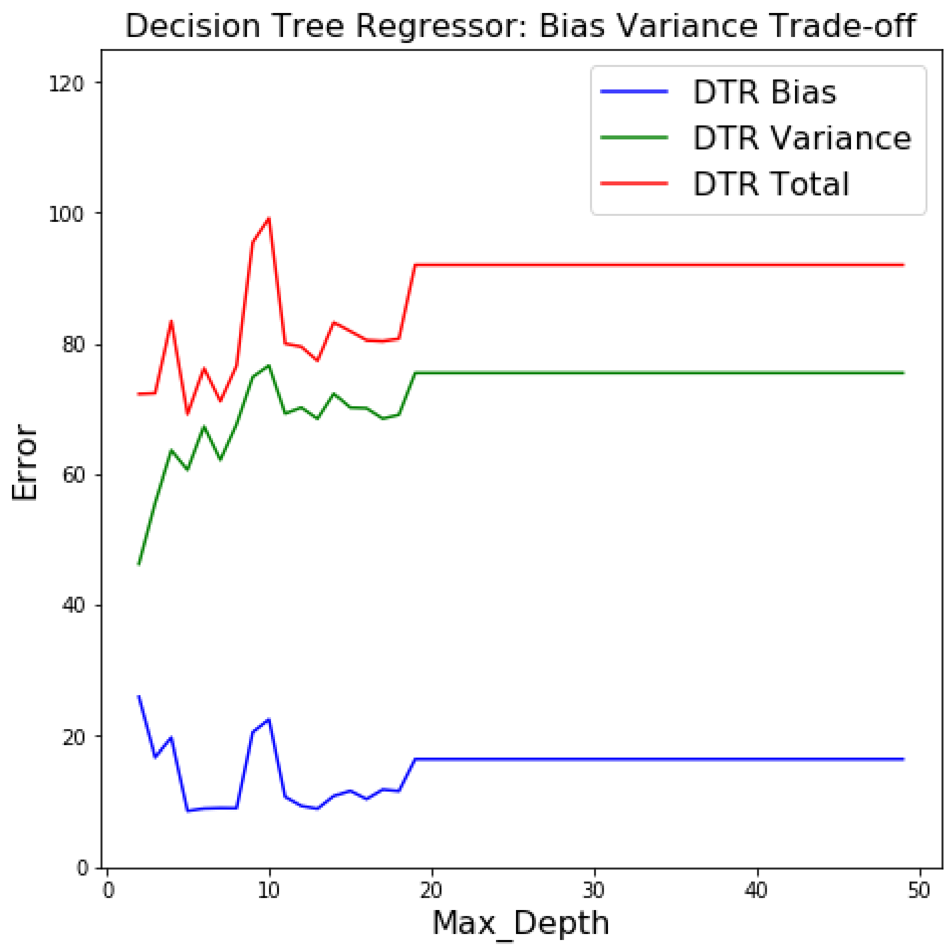


Decision Tree Regressor Bias and Variance

In [0]:
```
# Bias and Variance functions

def bias(y_predict,y):
    y_predict = np.array(y_predict)
    return np.average(np.power((y_predict-y),2))

def variance(y_predict):
    y_predict = np.array(y_predict)
    return np.var(y_predict)

# Parameters for bias and variance
max_depth_DTR = np.arange(2,50)
accuracy_DTR_score_list = []
bias_DTR_list = []
var_DTR_list = []
total_DTR_list = []
err_DTR_list_test = []
err_DTR_list_training = []
err_tot_DTR_list = []
```

```
model_DTR = DecisionTreeRegressor(random_state=42)

for entry in max_depth_DTR:

    # model fit and predict
    model_DTR.set_params(max_depth=entry)
    model_DTR.fit(x_training_set, y_training_set)
    predicted_y_DTR_test = model_DTR.predict(x_test_set)
    predicted_y_DTR_train = model_DTR.predict(x_training_set)

    # bias and variance estimate
    bias_variable = bias(predicted_y_DTR_test, y_test_set)
    variance_variable = variance(predicted_y_DTR_test)
    bias_DTR_list.append(bias_variable)
    var_DTR_list.append(variance_variable)
    total_DTR = bias_variable + variance_variable
    total_DTR_list.append(total_DTR)

    # training and test estimate
    err_DT_test_variable =mean_squared_error(y_test_set,predicted_y_DTR
_test)
    err_DT_training_variable = mean_squared_error(y_training_set, predi
cted_y_DTR_train)
    err_DT_tot_variable = err_DT_test_variable + err_DT_training_variab
le
    err_DTR_list_test.append(err_DT_test_variable)
    err_DTR_list_training.append(err_DT_training_variable)
    err_tot_DTR_list.append(err_DT_tot_variable)

    # Plot bias vs variance from changing the depth of the tree
plt.figure(figsize=(7.5,7.5))
plt.plot(max_depth_DTR, bias_DTR_list,color = 'b')
plt.plot(max_depth_DTR, var_DTR_list,color = 'g')
plt.plot(max_depth_DTR, total_DTR_list,color = 'r')
plt.legend(['DTR Bias', 'DTR Variance', 'DTR Total'], loc='upper right'
,fontsize = 16)
plt.title('Decision Tree Regressor: Bias Variance Trade-off',fontsize =
 16)
```

```
plt.ylabel('Error',fontsize = 16)
plt.xlabel('Max_Depth',fontsize = 16)
plt.ylim(0,125)
plt.show()
```

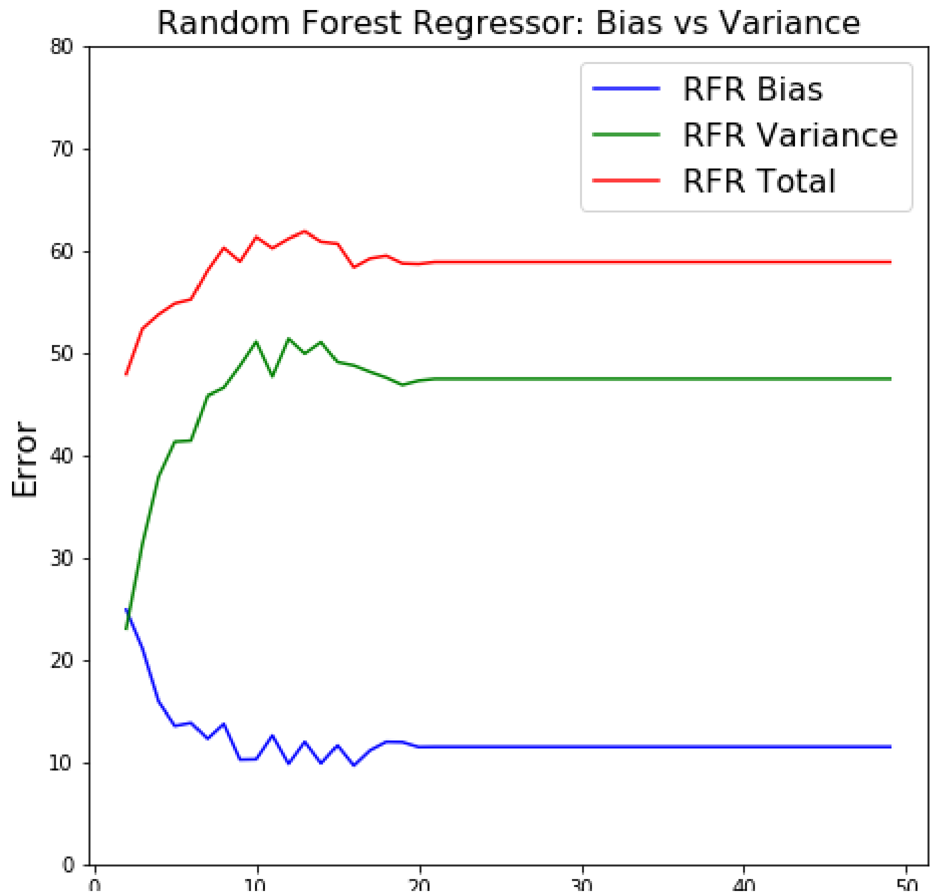


Random Forest Regressor Bias and Variance

In [0]:
```
# Parameters for Bias and Variance
```

```
max_depth_RFR = np.arange(2,50)
bias_RFR_depth_list = []
var_RFR_depth_list = []
total_RFR_depth_list = []
err_RFR_list_test = []
err_RFR_list_training = []
err_tot_RFR_list = []

model_RFR = RandomForestRegressor(random_state=42,oob_score=True)
model_RFR.set_params(max_depth= 20,
                        max_features= 'sqrt',
                        n_estimators=20,
                        oob_score = True,
                        criterion = 'mse')

for entry in max_depth_RF_regression:

    #model fit and predict
    model_RFR.set_params(max_depth=entry)
    model_RFR.fit(x_training_set,  np.ravel(y_training_set))
    predicted_y_RFR_test = model_RFR.predict(x_test_set)
    predicted_y_RFR_train = model_RF_regressor.predict(x_training_set)
    bias_variable = bias(predicted_y_RFR_test, y_test_set)
    variance_variable = variance(predicted_y_RFR_test)
    bias_RFR_depth_list.append(bias_variable)
    var_RFR_depth_list.append(variance_variable)
    total_RFR = bias_variable + variance_variable
    total_RFR_depth_list.append(total_RFR)

    # training and test estimate
    err_RF_test_variable =mean_squared_error(y_test_set,predicted_y_RFR
_test)
    err_RF_training_variable = mean_squared_error(y_training_set, predi
cted_y_RFR_train)
    err_RF_tot_variable = err_RF_test_variable + err_RF_training_variab
le
    err_RFR_list_test.append(err_RF_test_variable)
    err_RFR_list_training.append(err_RF_training_variable)
    err_tot_RFR_list.append(err_RF_tot_variable)
```

```
# Plot bias vs variance from changing the depth of the tree
plt.figure(figsize=(7.5,7.5))
plt.plot(max_depth_RFR, bias_RFR_depth_list,color = 'b')
plt.plot(max_depth_RFR, var_RFR_depth_list,color = 'g')
plt.plot(max_depth_RFR, total_RFR_depth_list,color = 'r')
plt.legend(['RFR Bias', 'RFR Variance', 'RFR Total'], loc='upper right'
,fontsize = 16)
plt.title('Random Forest Regressor: Bias vs Variance',fontsize = 16)
plt.ylabel('Error',fontsize = 16)
plt.xlabel('Max_Depth',fontsize = 16)
plt.ylim(0,80)
plt.show()
```



In [0]: