In [1]:
```
# Module: Data Science in Finance, Evaluating models
# Version 1.0
# Topic : Evaluating models and hyperparameters.
# Example source: https://www.kaggle.com/wendykan/lending-club-loan-data
#########################################################################
# For support or questions, contact Sri Krishnamurthy at
# sri@quantuniversity.com
# Copyright 2016 QuantUniversity LLC.
#########################################################################
```

Evaluating models and hyperparameters

This notebook explains some common hyperparameters for a neural network, what they mean and how to tune them.

Imports

In [2]:
```
# for numerical analysis and data processing
import numpy as np
import pandas as pd
import itertools

from IPython.display import Image

# for Machine learning algorithms
from sklearn import preprocessing
from sklearn.cluster import KMeans
from sklearn.manifold import TSNE
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error
from scipy.spatial.distance import cdist

# for vizualizations
%matplotlib inline
import matplotlib.pyplot as plt
from matplotlib import cm as cm
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns
```

Dataset

The data set is the lending data for lendingclub from August 2011 to December 2011 for some borrowers. The feature descriptions for the data are also provided. Not all the features are required for making predictions, some features are redundant in the original data file. The provided data file

is already cleaned and only relevant features are provided. There are two types of features, numerical and categorical.

Reading the input data from csv file.

In [3]:
```
df = pd.read_csv("../data/LendingClubLoan.csv", low_memory=False)
del df['issue_d'] # removing issue date as it wont affect the prediction (redundan
df_description = pd.read_excel('../data/LCDataDictionary.xlsx').dropna()
```

Preparing categorical features - One Hot Encoding

One way of representing categrical features is called one-hot encoding. Assume a categorical feature X with possible values as [a, b, c, d]. If in some sample the value of X=c, in one hot encoding ths particular feature is represented as X=[0, 0, 1, 0]. Its a binary array representation of length equal to the number of possible feature value, with 1 for the actual value.

If X can have values a b c d, then

X=c
X=[0, 0, 1, 0]

X=a
X=[1, 0, 0, 0]

In [4]:
```
numeric_columns = df.select_dtypes(include=['float64','int64']).columns
categorical_columns = df.select_dtypes(include=['object']).columns
```

In [5]:
```
for col in categorical_columns:
    df[col] = df[col].astype('category')
```

Dictionary for categorical features.

In [6]:
```
categories={}
for cat in categorical_columns:
    categories[cat] = df[cat].cat.categories.tolist()
```

In [7]:
```
p_categories = df['purpose'].cat.categories.tolist()
s_categories = df['addr_state'].cat.categories.tolist()
df[categorical_columns] = df[categorical_columns].apply(lambda x: x.cat.codes)
```

Storing interest rate statistics

In [8]:
```
min_rate= df['int_rate'].min()
max_rate= df['int_rate'].max()
print(min_rate, max_rate, max_rate- min_rate)
```

```
5.42 24.11 18.689999999999998
```

Preparing the dataset

We will require theses while making predictions

In [9]:
```
df_max = df.max()
df_min = df.min()
```

Normalize the data set for ease of calculations so that all features have values between 0 and 1.

In [10]:
```
df=(df-df.min())/(df.max()-df.min())
```

Randomize the dataset so that any ordered patterns dont influence the prediction. (We have already skipped date as an influencing factor)

In [11]:
```
df = df.iloc[np.random.permutation(len(df))]
```

The data is split into training and testing data. x represents the input features whereas y represents the output i.e. the interest rate.As a rule of thumb, we split the data into 80% training data and 20% testing or validation data.

In [12]:
```
y = df.iloc[:,df.columns.isin(["int_rate"])]
x = df.loc[:, ~df.columns.isin(["int_rate"])]

total_samples=len(df)
split = 0.8

x_train = x[0:int(total_samples*split)]
x_test = x[int(total_samples*split):total_samples]
y_train = y[0:int(total_samples*split)]
y_test = y[int(total_samples*split):total_samples]
```

Some helper functions

In [13]:
```
def mean_absolute_percentage_error(y_true, y_pred):
    '''
    Calculates mean absolute error of the true and predicted values.
    '''
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    count = 0
    sum = 0
    for a, p in zip(y_true, y_pred):
        if(a!=0):
            sum+=(abs(a-p)/a)
            count+=1
    return (sum/count) * 100
```

In [14]:
```
def view_metrics(y_test, predictions, algorithm, samples, total_samples):
    '''
    Plots the true and predicted values and prints RMS, MAE and MAPE metrics.
    '''
    fig = plt.figure(figsize=(18,5))
    plt.scatter(x=[i for i in range(samples)], y=[x for x in predictions[0:samples
    plt.scatter(x=[i for i in range(samples)], y=[x[0] for x in y_test.values[0:sa
    plt.title('True and Predicted values for test dataset - %s' % algorithm)
    plt.legend()
    plt.show()

    fig = plt.figure(figsize=(18,5))
    plt.scatter(x=[i for i in range(total_samples)], y=[x for x in predictions], l
    plt.scatter(x=[i for i in range(total_samples)], y=[x[0] for x in y_test.value
    plt.title('True and Predicted values for test dataset - %s' % algorithm)
    plt.legend()
    plt.show()

    RMS =  np.sqrt(mean_squared_error(y_test, predictions, multioutput='raw_values
    MAE = mean_absolute_error(y_test, predictions, multioutput='raw_values')
    MAPE = mean_absolute_percentage_error(y_test, predictions)
    print("Root Mean Squared Error:", RMS)
    print("Mean Absolute Error", MAE)
    print("Mean Absolute Percentage Error", MAPE)
    return RMS, MAE, MAPE
```

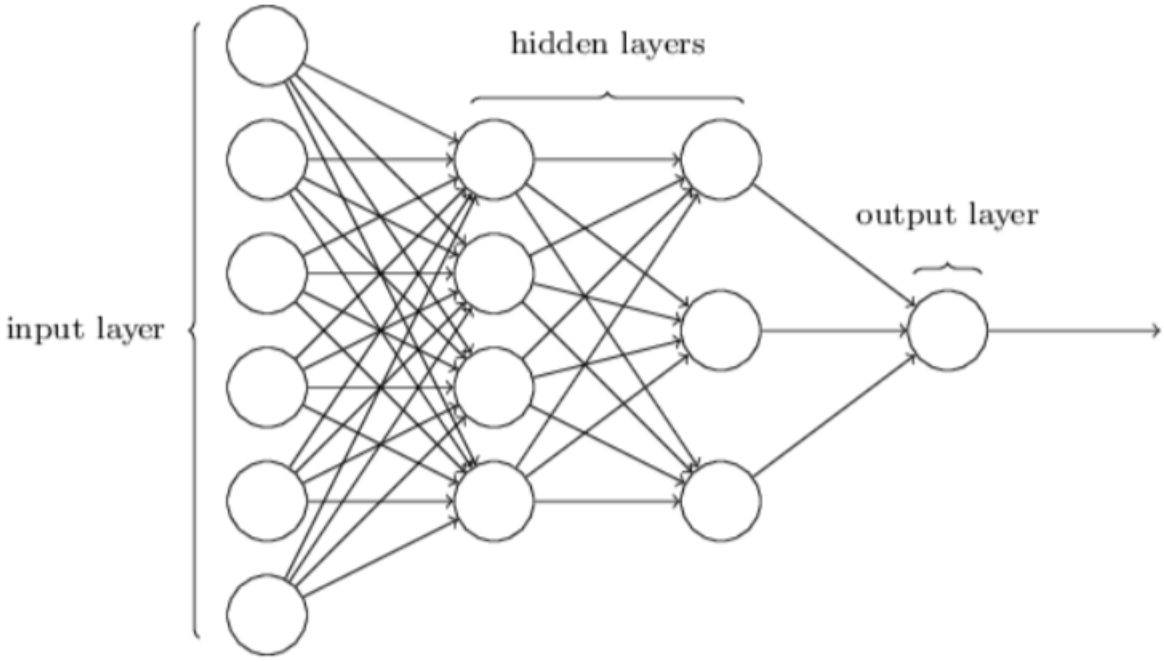
In [15]:
```
def view_metrics2(y_true, predictions, algorithm, samples, total_samples):
    '''
    Plots the true and predicted values and prints RMS, MAE and MAPE metrics.
    '''
    plt.scatter(x=[x for x in predictions[0:samples]], y=[x[0] for x in y_true.val
    plt.title('True vs Predicted values- %s' % algorithm)
    plt.xlabel('Predictions')
    plt.ylabel('True values')
    plt.show()

    RMS =  np.sqrt(mean_squared_error(y_true, predictions, multioutput='raw_values
    MAE = mean_absolute_error(y_true, predictions, multioutput='raw_values')
    MAPE = mean_absolute_percentage_error(y_true, predictions)
    print("Root Mean Squared Error:", RMS)
    print("Mean Absolute Error", MAE)
    print("Mean Absolute Percentage Error", MAPE)
    return RMS, MAE, MAPE
```

In [16]:
```
import warnings
warnings.filterwarnings('ignore')

def tune_learning_rate(learning_rates):
    models = []
    i=0
    for lr in learning_rates:
        nn_model = MLPRegressor(hidden_layer_sizes=(10,4),
                                            activation='relu', # activation functi
                                            solver='adam', # optimizer algorithm
                                            learning_rate='constant',
                                            learning_rate_init=lr, # initial learn
                                            max_iter=300, # max iterations to trai
                                            tol = -1, # tolerance for when to stop
                                            shuffle=True,
                                            random_state = 3,
                                            verbose=False) # show details at each
        nn_model = nn_model.fit(x_train, y_train.values.ravel())
        models.append(nn_model)
        print("Model",i,",For learning rate %s, loss is %.5f" % (lr, nn_model.loss
        i = i+1;
    return models
```

Neural Network Regression Model

Neural networks have a lot of hyperparameters that show their immediate effects on the learning curve, so we will choose this as a means to study hyperparameters.

The entire neural network can be considered as a non linear mathematical function with many parameters, which are called weights of the neural network. The features are the inputs of the neural network. The circles here represent neurons in the neural network, each with its own weights (coefficients).



Layers, Weights, and Backpropagation in Neural Networks

For our data set, the number of features are 16. Each layer between the input layer (where we enter the dataset) and output layer (where we obtain our predicted value) is called as a hidden layer of the neural network. Usually, but not always, higher number of layers tend to capture more nuances in the data and fit the training data better.

When we pass in the labels(y) and the features(X) to a training model, the weights in these layers act as coefficients and multiply the value of the feature and ultimately gives out a single value (can be multi-dimensional output as well) at the output layer.

This value is checked against the actual value or label that we pass, the difference in the actual and predicted value gives us a loss. This loss is then distributed back in all the layers to accommodate for it. This is done using various algorithms, most prominently **back propagation algorithm**. The rate at which these changes occur can be regarded as learning rate.

For our initial model, the learning rate was selected to be 0.001. The number of iterations, 300 in our case, specify for how many iterations should the forward pass and the backpropagation process continue. There are 10 neurons in the first hidden layer and 4 in the next.

Hyperparameters vs Parameters

```
As discussed above, parameters of a neural network are the weights associated
with the neurons that are actually involved in the calculations.
Hyperparameters on the other hand are factors that determine how the model will
be trained, like the number of iterations, the algorithms to be used, penalties
to be applied and so on.
```

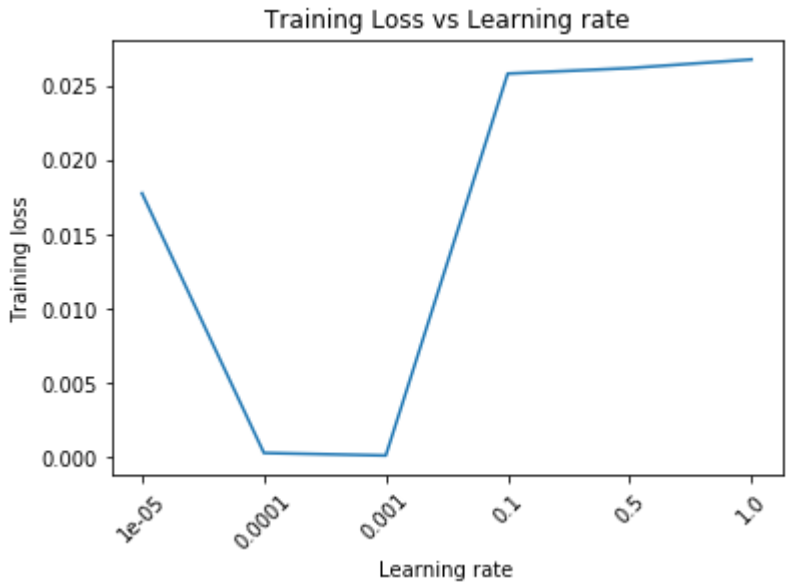
Hyperparameter tuning - Learning Rate

We will try to run the training for different values of the learning rate and see the changes. Based on the lowest loss, we will select the learning rate.

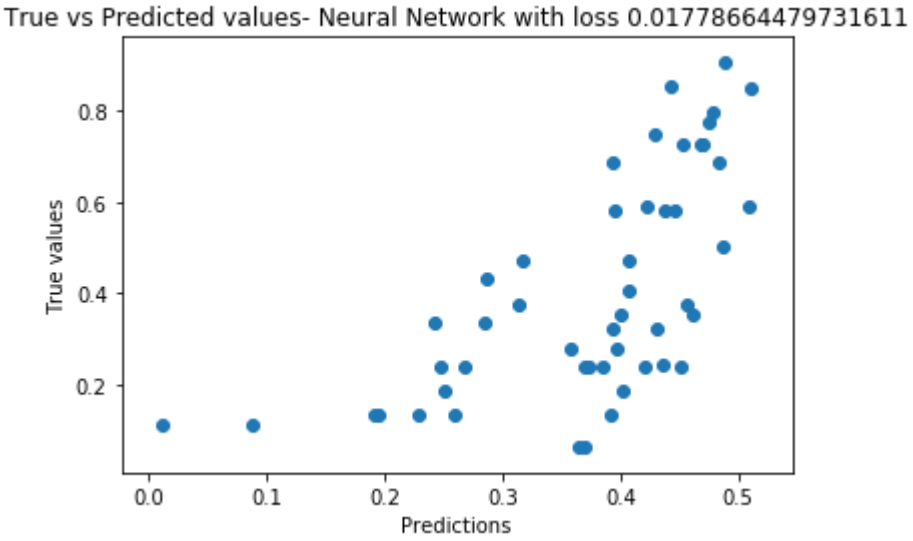
In [17]:
```
# this cell may take a few seconds to run
learning_rates = np.array([0.00001, 0.0001, 0.001, 0.1, 0.5, 1])
models = tune_learning_rate(learning_rates)
```

```
Model 0 ,For learning rate 1e-05, loss is 0.01779
Model 1 ,For learning rate 0.0001, loss is 0.00030
Model 2 ,For learning rate 0.001, loss is 0.00013
Model 3 ,For learning rate 0.1, loss is 0.02584
Model 4 ,For learning rate 0.5, loss is 0.02622
Model 5 ,For learning rate 1.0, loss is 0.02680
```

In [18]:
```
fig, axes = plt.subplots(nrows=1, ncols=1)
axes.plot([m.loss_ for m in models])
axes.set_title('Training Loss vs Learning rate')
axes.set_xlabel('Learning rate')
axes.set_ylabel('Training loss')
axes.set_xticks(np.arange(len(learning_rates)))
axes.set_xticklabels(learning_rates, rotation = 45)
plt.show()
```



In [19]:
```
view_metrics2(y_train, models[0].predict(x_train),'Neural Network with loss '+str(
```

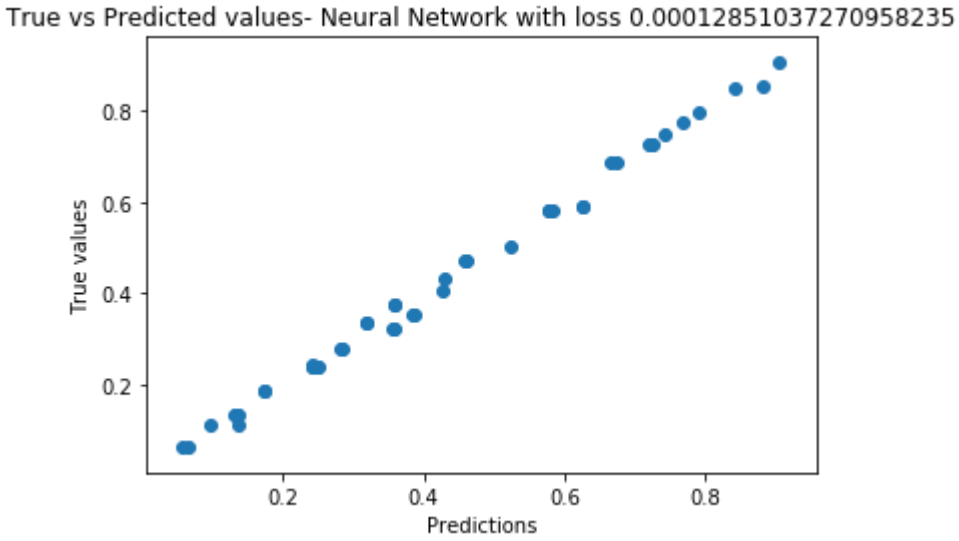



```
Root Mean Squared Error: [0.18840716]
Mean Absolute Error [0.15336086]
Mean Absolute Percentage Error [104.3745781]
```

Out[19]:
```
(array([0.18840716]), array([0.15336086]), array([104.3745781]))
```

The graph of true values vs predictions show no trends at all. This means that the predicted values are nowhere related to the true values. For a really low learning rate, there wasn't any considerable learning in 300 iterations.

In [20]:
```
view_metrics2(y_train, models[2].predict(x_train),'Neural Network with loss '+str(
```

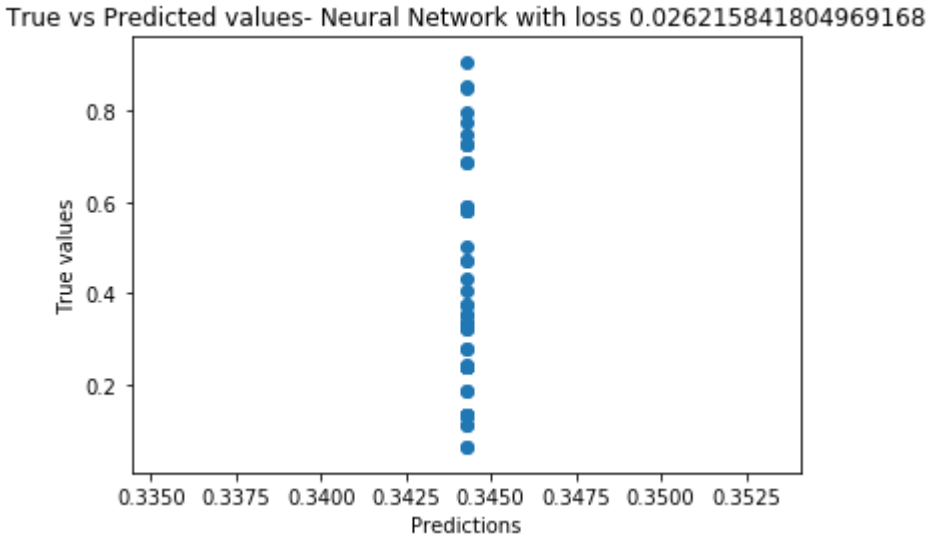



```
Root Mean Squared Error: [0.01574614]
Mean Absolute Error [0.01196708]
Mean Absolute Percentage Error [6.53190503]
```

Out[20]:
```
(array([0.01574614]), array([0.01196708]), array([6.53190503]))
```

The graph of true values vs predictions lie on a line with slope of around 45 degrees. This means that the predicted values are almost same as the true values. Had they been identical, we would have seen a single line at 45 degree. For a learning rate of 0.01 the loss is considerably low.

In [21]:
```
view_metrics2(y_train, models[4].predict(x_train),'Neural Network with loss '+str(
```

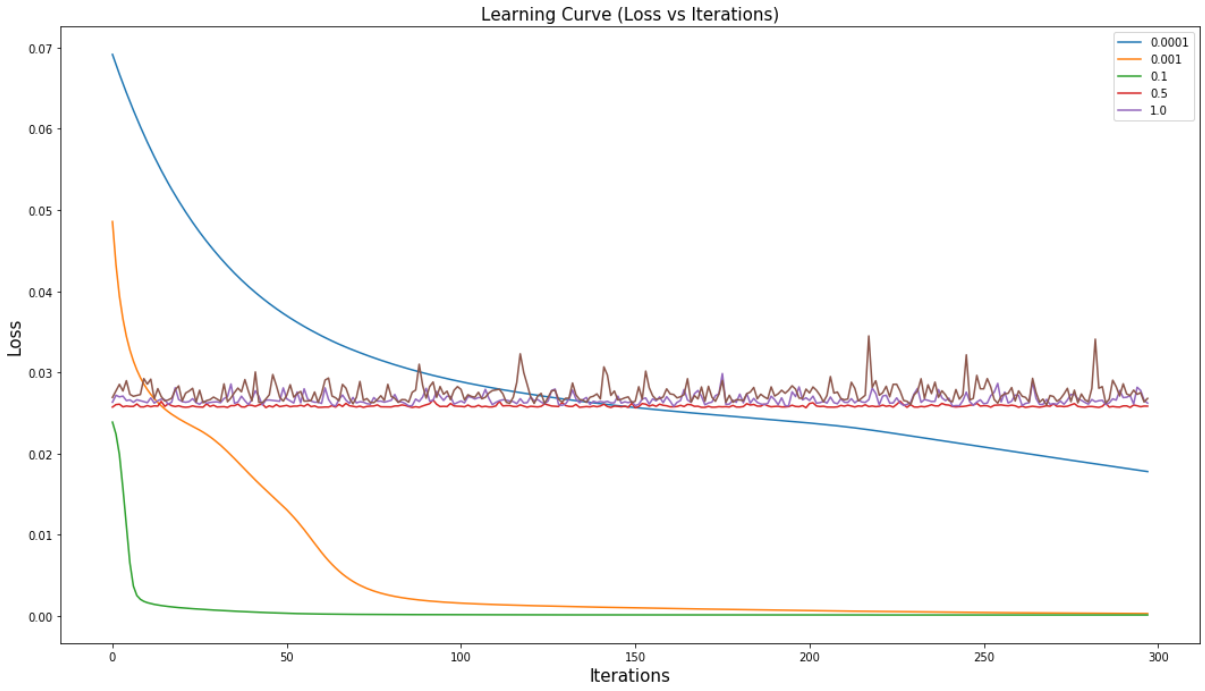



```
Root Mean Squared Error: [0.22872821]
Mean Absolute Error [0.18610802]
Mean Absolute Percentage Error [118.87584012]
```

Out[21]:
```
(array([0.22872821]), array([0.18610802]), array([118.87584012]))
```

The graph of true values vs predictions lie on a straight vertical line. This means that the model just predicted a single value for all inputs. This is a result of very very high learning rate of 0.5.

In [22]:
```
fig = plt.figure(figsize=(18,10))
for model in models:
    plt.plot(model.loss_curve_[2:])
    plt.legend(learning_rates[1:])
plt.xlabel('Iterations', fontsize=15)
plt.ylabel('Loss', fontsize=15)
plt.title('Learning Curve (Loss vs Iterations)', fontsize=15)
plt.show()
```



Convergence refers to a state when the losses do not vary much within a given tolerance and drop down to low values.

We can see that high learning rates show practically no learning from the model. Really low learning rate tend to converge very slowly. The optimal value converges really quickly.

Hyperparameter tuning - Optimization algorithm

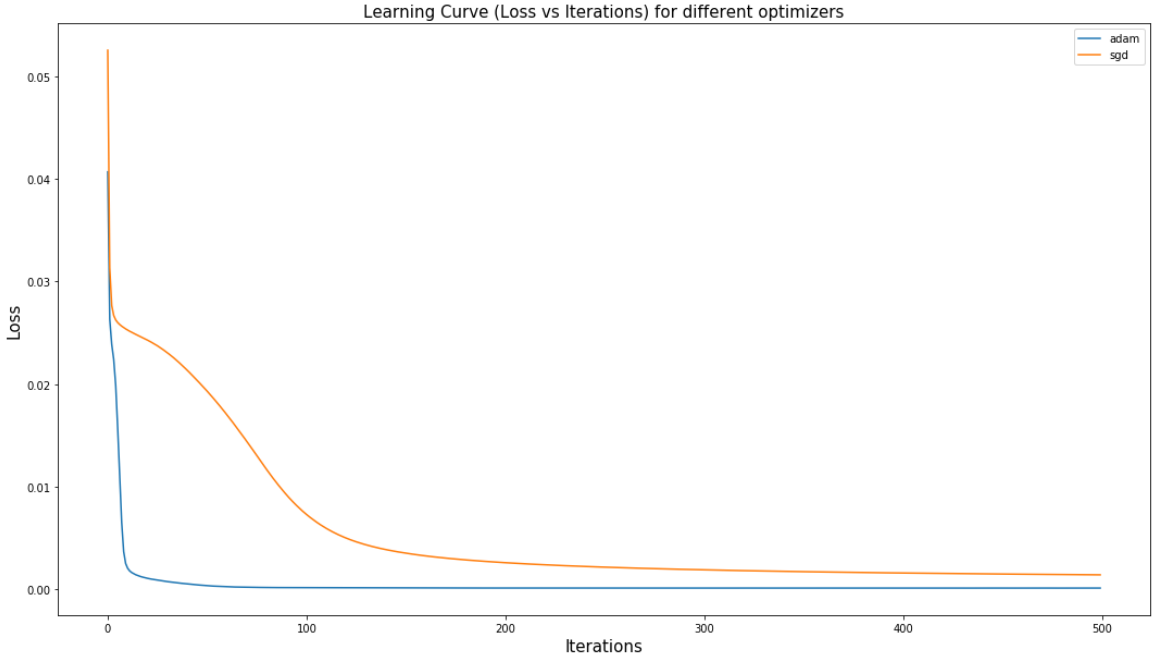
Now that we have selected the learning rate that yields lowest loss, let us see what effect does the optimization algorithm have on the model.

In [23]:
```
optimizers = ['adam', 'sgd']

def select_optimizer(optimizers):
    models = []
    i=0
    for opt in optimizers:
        nn_model = MLPRegressor(hidden_layer_sizes=(10,4),
                                            activation='relu', # activation functi
                                            solver=opt, # optimizer algorithm
                                            learning_rate='constant',
                                            learning_rate_init=0.001, # initial le
                                            max_iter=500, # max iterations to trai
                                            tol = -1, # tolerance for when to stop
                                            shuffle=True,
                                            random_state = 3,
                                            verbose=False) # show details at each
        nn_model = nn_model.fit(x_train, y_train.values.ravel())
        models.append(nn_model)
        print("Model",i,",For optimizer %s, loss is %.5f" % (opt, nn_model.loss_))
        i = i+1;
    return models
```

In [24]:
```
models = select_optimizer(optimizers)
```

```
Model 0 ,For optimizer adam, loss is 0.00013
Model 1 ,For optimizer sgd, loss is 0.00142
```

In [25]:
```
fig = plt.figure(figsize=(18,10))
for model in models:
    plt.plot(model.loss_curve_)
    plt.legend(optimizers)
plt.xlabel('Iterations', fontsize=15)
plt.ylabel('Loss', fontsize=15)
plt.title('Learning Curve (Loss vs Iterations) for different optimizers', fontsize
plt.show()
```



SGD or Stochastic Gradient Descent and Adam and Adam are two of the three popular optimization algorithms provided by the scikit-learnn package. The third one is called 'lbfgs', another from a quasi-Newton method. This one is suitable for really small datasets and doesnt provide a good learning curve.

Hyperparameter tuning - Regularization parameter

Regularization basically adds a penalty as model complexity increases. Regularization parameter (L2 alpha) penalizes all the parameters except intercept so that model generalizes the data and won't overfit and the paramters arent updated as drastically.

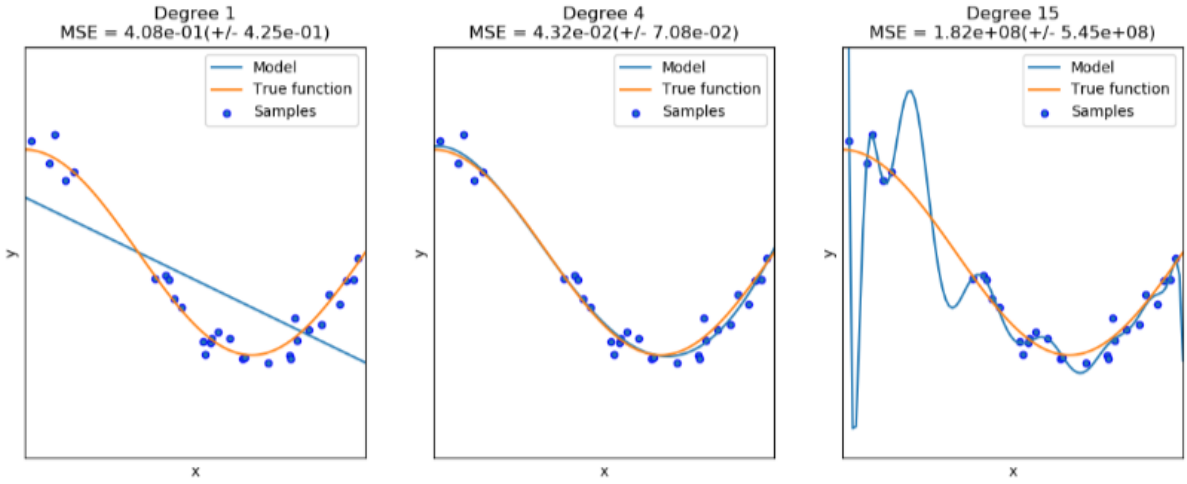
Overfitting refers to the fact that the model has fit the training data so well that it doesnt recognise outliers i.e. it has fit the noise in the training data as we. A more complex model usually tends to overfit. For example, a neural net with too many layers may fit to the training data very well but wont be able to generalize on testing or validation data set.

Overfitting causes the model to not accept new samples readily, i.e, it doesn't generalize well while making predictions.

Similarly there is **underfitting**, when the model is not able to provide a low loss even on the training data, let alone a testing dataset.

The first figure shows a sample of underfitting, the second one is a good fit and the third one is

overfitting. A higher degree polynomial is more complex than a linear model in the first case, hence it overfits.

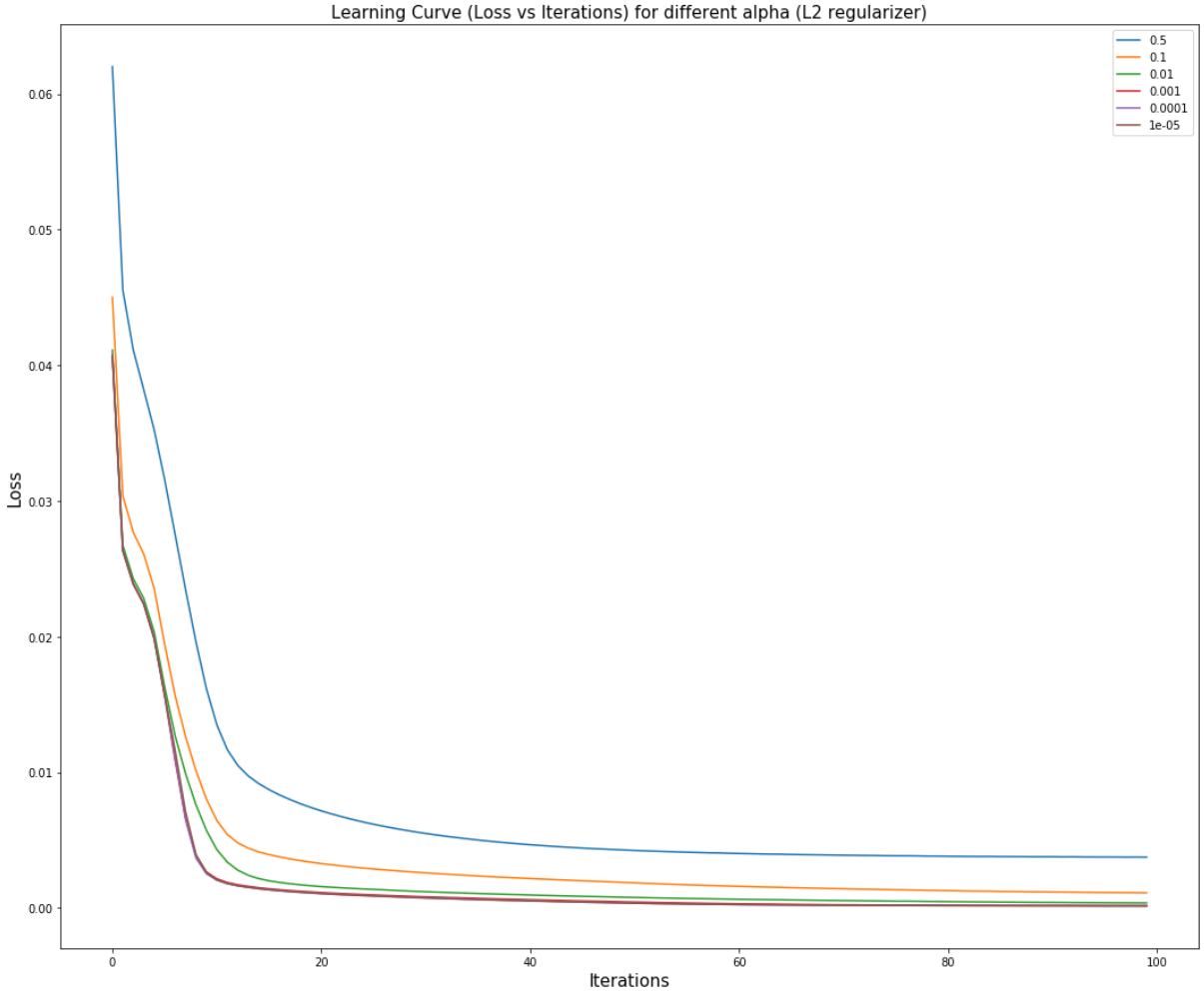


In [26]:
```
alphas = [0.5, 0.1, 0.01, 0.001, 0.0001, 0.00001]

def tune_alpha(alphas):
    models = []
    i=0
    for alpha in alphas:
        nn_model = MLPRegressor(hidden_layer_sizes=(10,4),
                                activation='relu', # activation functi
                                solver='adam', # optimizer algorithm
                                learning_rate='constant',
                                learning_rate_init=0.001, # initial le
                                max_iter=500, # max iterations to trai
                                tol = -1, # tolerance for when to stop
                                shuffle=True,
                                random_state = 3,
                                alpha = alpha,
                                verbose=False) # show details at each
        nn_model = nn_model.fit(x_train, y_train.values.ravel())
        models.append(nn_model)
        print("Model",i,",For alpha %s, loss is %.5f" % (alpha, nn_model.loss_))
        i = i+1;
    return models
```

In [27]:
```
models = tune_alpha(alphas)
```

```
Model 0 ,For alpha 0.5, loss is 0.00369
Model 1 ,For alpha 0.1, loss is 0.00099
Model 2 ,For alpha 0.01, loss is 0.00023
Model 3 ,For alpha 0.001, loss is 0.00016
Model 4 ,For alpha 0.0001, loss is 0.00013
Model 5 ,For alpha 1e-05, loss is 0.00014
```

In [28]:
```
fig = plt.figure(figsize=(18,15))
for model in models:
    plt.plot(model.loss_curve_[0:100])
    plt.legend(alphas)
plt.xlabel('Iterations', fontsize=15)
plt.ylabel('Loss', fontsize=15)
plt.title('Learning Curve (Loss vs Iterations) for different alpha (L2 regularizer
plt.show()
```



High L2 penalty causes underfitting as it doesn't allow the model to train. So the L2 alpha values have to be low.

Activation function

Activation functions are functions that introduce non linearities in the neural network. If we do not apply any non linearliy, our entire network would be just one big linear function, only transforming the input from one lyaer to another.

A Neural Network without Activation function would simply be a Linear regression Model, which has limited power as we already saw in teh last lab. We want our Neural Network to not just learn and compute a linear function but something more complicated than that.

ReLU or Rectified Linear Unit is the activation function we are using.
Mathematically: **A(x) = max(0,x)**

Finalizing our model

The configuration of the neural netowrk is referred to as its architecture . The architecutre for our network is as follows:

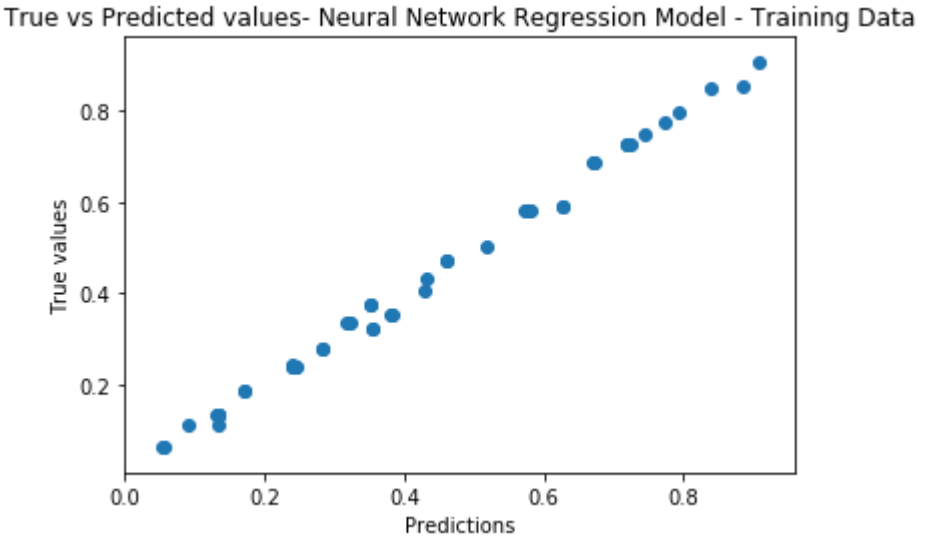
-	-
Input dimension	16
Output dimension	1
Hidden Layers	2
Neurons in Hidden Layer 1	10
Neurons in Hidden Layer 2	4
Optimier	Adam
Activation Function	ReLU
Learning rate	0.001
L2 Regularizer	0.0001

Now that we have tuned certain hyperparameters, let us go ahead a nd train the model for one last time.

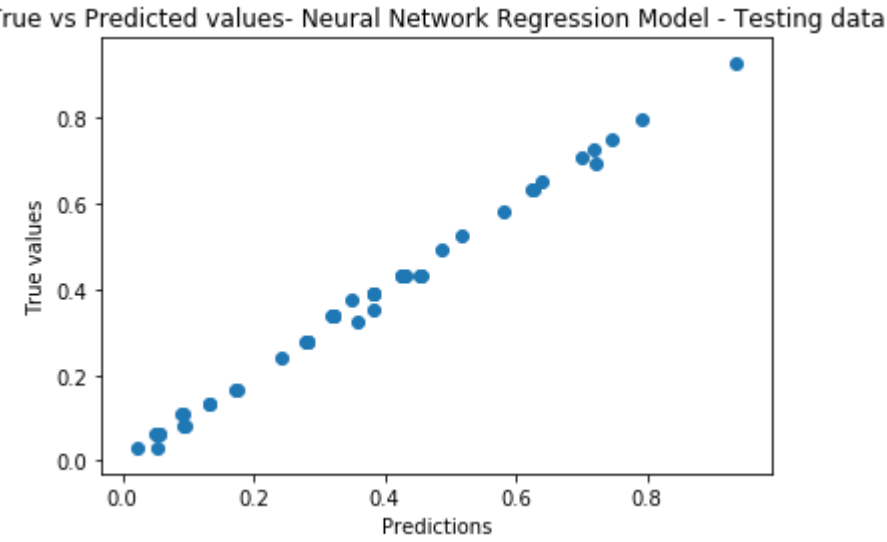
In [29]:
```
nn_model = MLPRegressor(hidden_layer_sizes=(10,4),
                                            activation='relu', # activation functi
                                            solver='adam', # optimizer algorithm
                                            learning_rate='constant',
                                            learning_rate_init=0.001, # initial le
                                            max_iter=500, # max iterations to trai
                                            tol = -1, # tolerance for when to stop
                                            shuffle=True,
                                            random_state = 3,
                                            alpha = 0.0001,
                                            verbose=False) # show details at each
nn_model = nn_model.fit(x_train, y_train.values.ravel())
```

In [30]:
```
nn_model_predictions = nn_model.predict(x_test)
nn_model_predictions_tr = nn_model.predict(x_train)
```

In [31]:
```
nn_model_metrics_tr = view_metrics2(y_train, nn_model_predictions_tr,'Neural Netwo
nn_model_metrics = view_metrics2(y_test, nn_model_predictions,'Neural Network Regr
```




```
Root Mean Squared Error: [0.01571878]
Mean Absolute Error [0.01209218]
Mean Absolute Percentage Error [6.62405243]
```




```
Root Mean Squared Error: [0.01512933]
Mean Absolute Error [0.0120668]
Mean Absolute Percentage Error [6.98240221]
```

If the MAPE for testing data is more then that for the training data, and this is fine. This indicates that the model hasnt overfit. Had it overfit, the MAPE would have been lesser for the test data and more for training data.

If there is overfitting, we can play around with the alpha values and learning rate to get rid of overfitting.

In [32]:
```
# this cell may take a few seconds to execute depending on model size

# for saving models
import pickle
# import _pickle as cPickle # try this if previous import fails

pickle.dump(nn_model, open('nn_model.model', 'wb'))
```

Random forest regressor

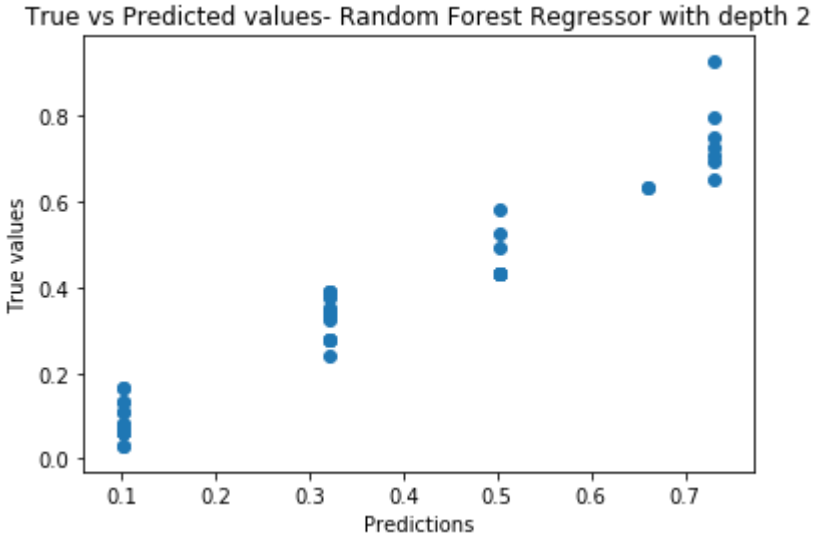
We will now try to experiment with different depths for a random forest, depth being one of the important hyperparameter.

We avoid very deep trees as they tend to overfit the data

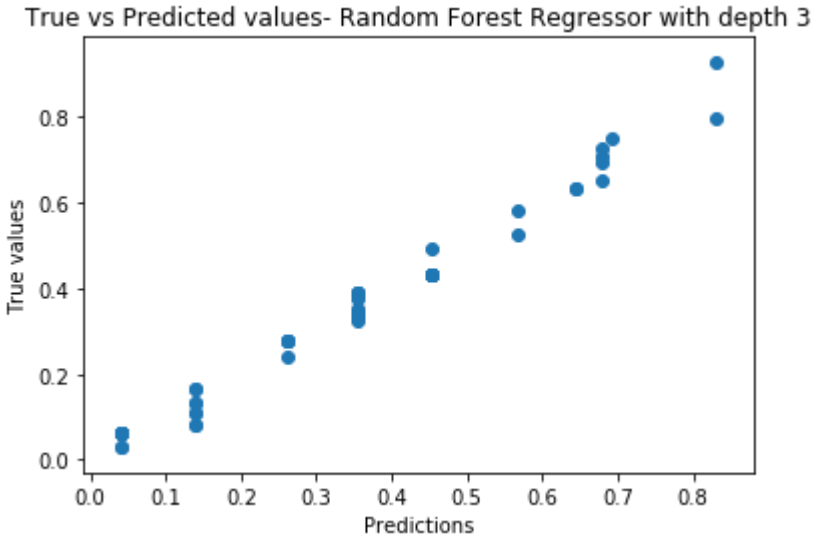
For very low depths, there is underfitting and the data points are evidently not on a diagonal line.

We can see that after depth 5, there isn't much change in the accuracy or the True vs Predicted plot.

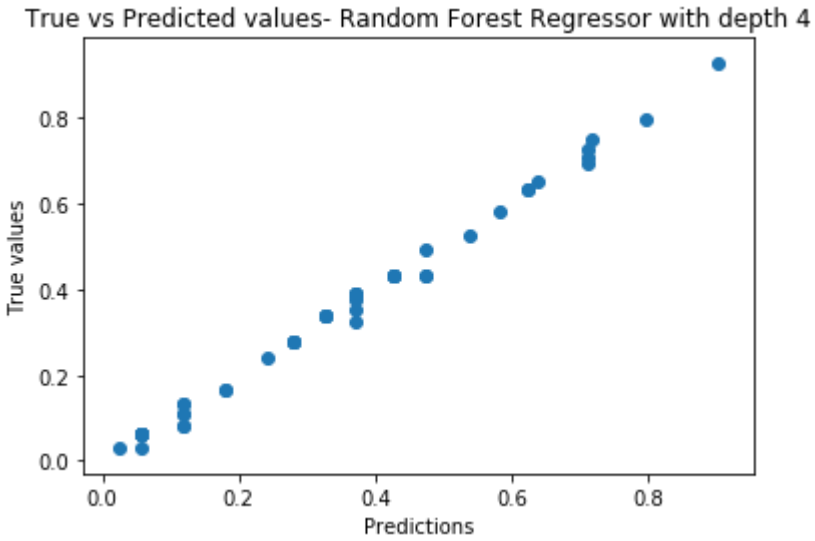
In [33]:
```
depths = [2, 3, 4, 5, 6, 8]
for d in depths:
    rand_forest_model = RandomForestRegressor(max_depth=d, random_state=0) # build
    rand_forest_model = rand_forest_model.fit(x_train, y_train.values.ravel()) # t
    feature_importance = rand_forest_model.feature_importances_
    R2 = rand_forest_model.score(x_train, y_train) # coefficient of determination
    rand_forest_model_predictions = rand_forest_model.predict(x_test) # make predi
    rand_forest_model_metrics = view_metrics2(y_test, rand_forest_model_prediction
```



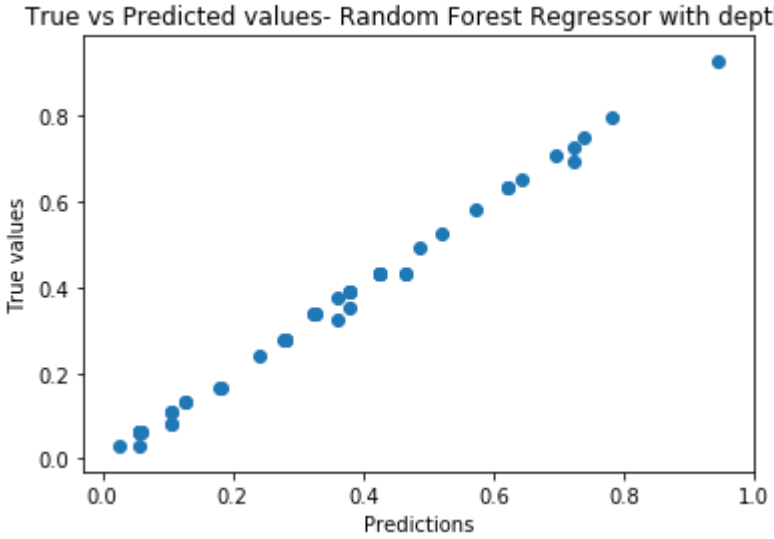

```
Root Mean Squared Error: [0.05972388]
Mean Absolute Error [0.04987512]
Mean Absolute Percentage Error [28.76100097]
```



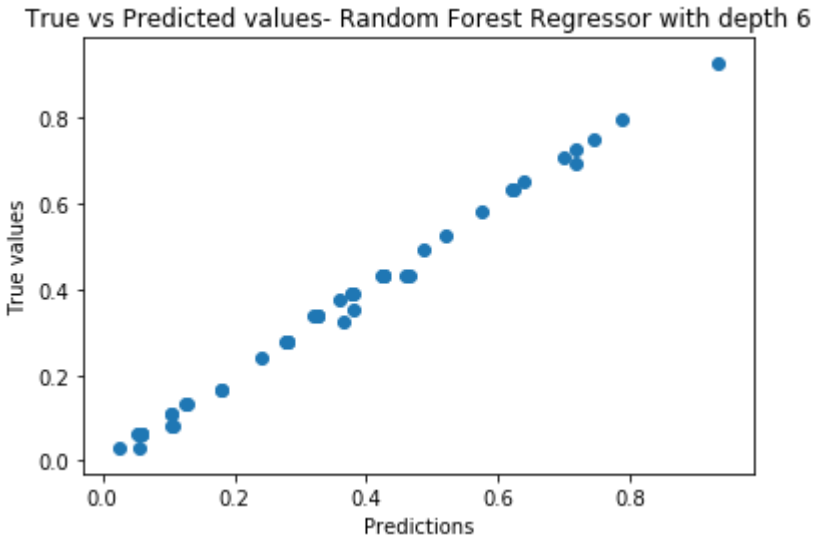

```
Root Mean Squared Error: [0.03066119]
Mean Absolute Error [0.02536055]
Mean Absolute Percentage Error [10.97024759]
```



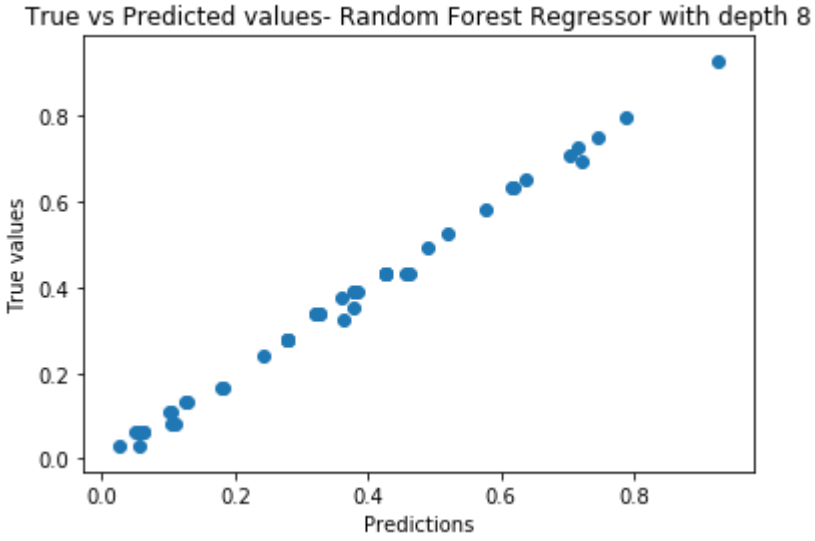

```
Root Mean Squared Error: [0.0173077]
Mean Absolute Error [0.01300879]
Mean Absolute Percentage Error [6.32871557]
```




```
Root Mean Squared Error: [0.01433295]
Mean Absolute Error [0.01131248]
Mean Absolute Percentage Error [5.68925716]
```




```
Root Mean Squared Error: [0.01400626]
Mean Absolute Error [0.0110939]
Mean Absolute Percentage Error [5.64195185]
```

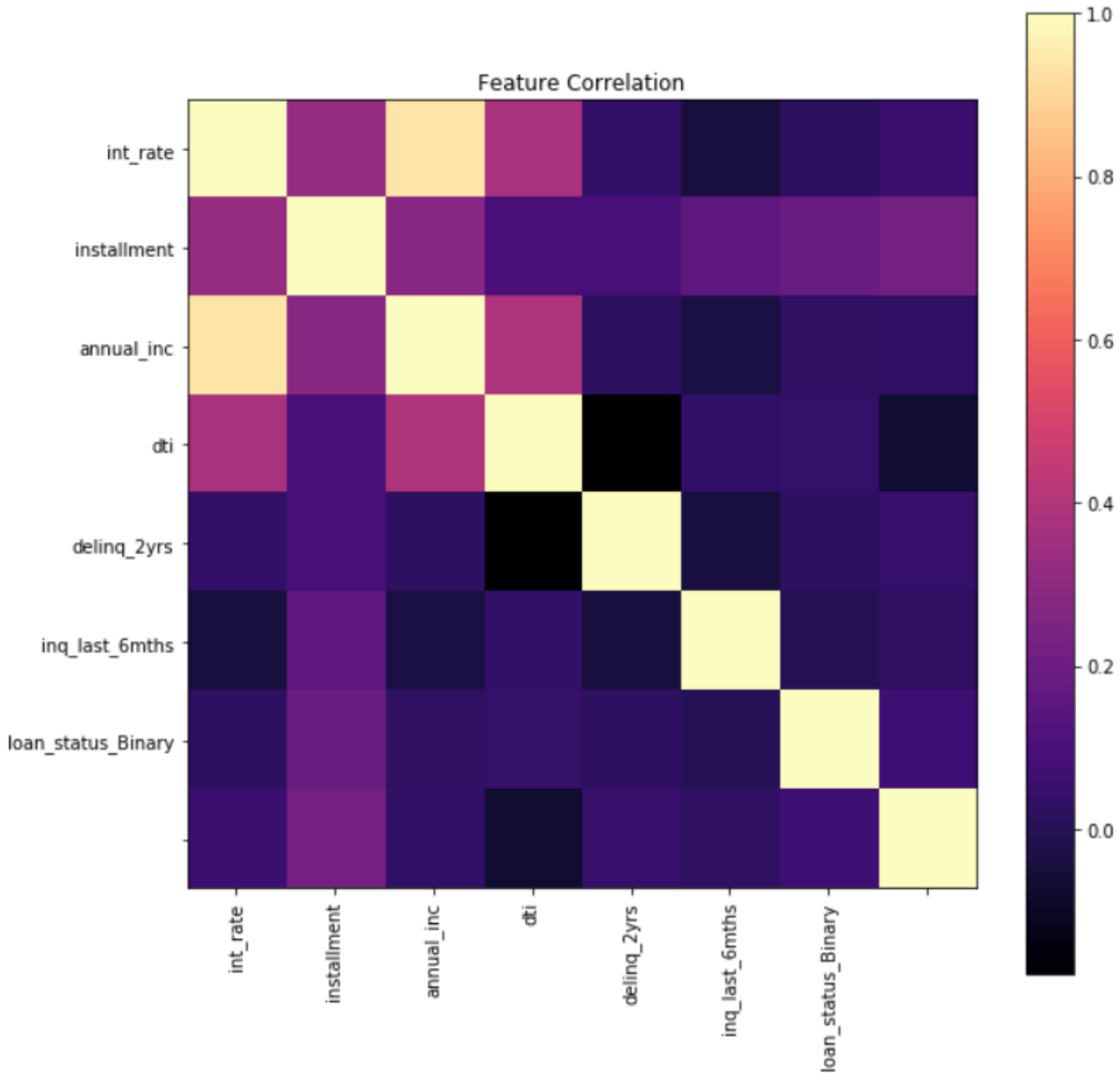



```
Root Mean Squared Error: [0.01435889]
Mean Absolute Error [0.01093468]
Mean Absolute Percentage Error [5.51871584]
```

In [34]:
```
# this cell may take a few seconds to execute depending on model size

rand_forest_model = RandomForestRegressor(max_depth=5, random_state=0) # build mod
rand_forest_model = rand_forest_model.fit(x_train, y_train.values.ravel()) # train

# for saving models
import pickle
# import _pickle as cPickle # try this if previous import fails

pickle.dump(rand_forest_model, open('rand_forest.model', 'wb'))
```

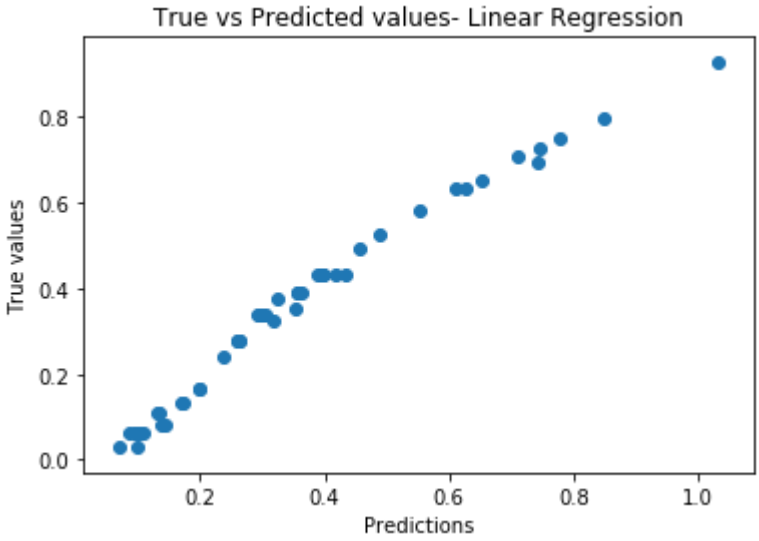
Since 'delinq_2yrs','inq_last_6mths','loan_status_Binary' have very low correlation to the interest rate (as evident from the correlation metrix), we will try to train the linear regression model excluding

these 4 features.



In [35]:
```
lin_reg_model = LinearRegression() # build model
lin_reg_model= lin_reg_model.fit(x_train, y_train) # train model


# for saving models
import pickle
# import _pickle as cPickle # try this if previous import fails

pickle.dump(lin_reg_model, open('lin_reg_model.model', 'wb'))
```

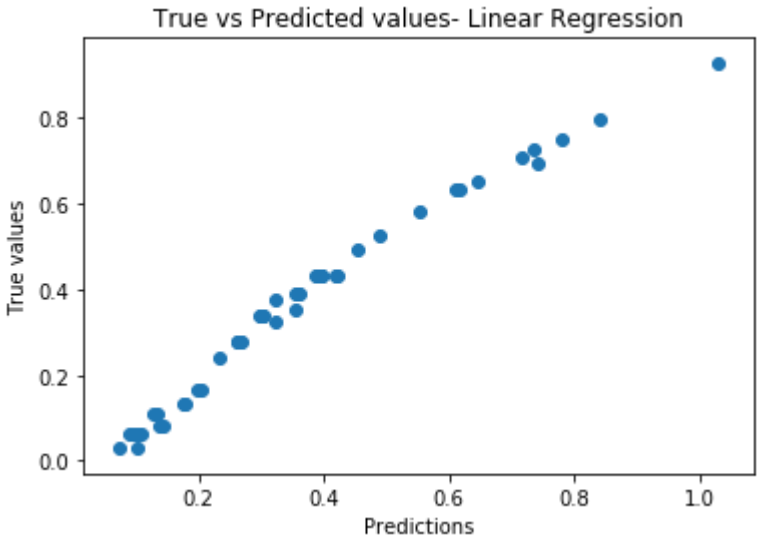
In [36]:
```
lin_reg_model_predictions = lin_reg_model.predict(x_test) # make predictions
lin_reg_model_metrics = view_metrics2(y_test, lin_reg_model_predictions,'Linear Re
```




```
Root Mean Squared Error: [0.03629574]
Mean Absolute Error [0.03076603]
Mean Absolute Percentage Error [19.78465651]
```

In [37]:
```
x_train_filtered = x_train.loc[:, ~x_train.columns.isin(['delinq_2yrs','inq_last_6
x_test_filtered = x_test.loc[:, ~x_test.columns.isin(['delinq_2yrs','inq_last_6mth
```

In [38]:
```
lin_reg_model = LinearRegression() # build model
lin_reg_model= lin_reg_model.fit(x_train_filtered, y_train) # train model
lin_reg_model_predictions = lin_reg_model.predict(x_test_filtered) # make predicti
lin_reg_model_metrics = view_metrics2(y_test, lin_reg_model_predictions,'Linear Re
```




```
Root Mean Squared Error: [0.03654826]
Mean Absolute Error [0.03109087]
Mean Absolute Percentage Error [19.99388958]
```

Looking at both the above runs, we were right in our assumption that

'delinq_2yrs','inq_last_6mths','loan_status_Binary' arent as much related to the interest rate. The percentage error didnt change much

Saving data for prediction

In [ ]:
```
# order is important
features = ["loan_amnt", "term", "installment", "grade", "sub_grade", "emp_length"
            "verification_status", "purpose", "addr_state", "dti", "delinq_2yrs",
```

In [ ]:
```
prediction_data = [rand_forest_model, df_max, df_min, categories, features]
pickle.dump(prediction_data, open('prediction_data.data', 'wb'))
```