Multivariate Time Series Classification Problem

November 16, 2018

1 Introduction

Times plays a vital role in deciding situation in many real-world problems. For example, company sales, energy consumption, e-commerce platforms etc. align largely with festival times. Based on the consumer data for several years, a company generally decides when is the best time to select their next schemes. So, to develop software, based on time-series data to predict companies next move time series modeling is a powerful technique. Moreover, analyzing such kind of real-world problems to predict anomaly behavior also needs to design the model based on time series analysis. Before we go deep down into time series modeling with machine learning, I like to provide a brief introduction about univariate and multivariate time series.

1.1 Univariate Time series:

A univariate time series is nothing but a series with a single time-dependent variable For example, consider the example given below, where 'temperature' variable is dependent on 'time' variable. So this dataset is for univariate(temperature) time series and this dataset demands to predict a temperature given time as input.

1.2 Multivariate Time Series:

In multivariate time series, there are more than one time-dependent variable. However, each variable is not only dependent on their past values but also has some dependency on other variables. For example, consider the example below, where 'temperature' variable is dependent not only on time but also other variables such as humidity, wind, dew point, cloud cover etc. So this dataset is an example of multivariate time series which demand to predict a temperature given all other variables and time as input.

2 Time series forecasting as Supervised learning

To build a classification model based on time series data, at first, we must preprocess the dataset which will be compatible to access with machine learning algorithms. So re-framing the time series forecasting dataset as supervised learning problems, from input sequence to pairs of input and output sequence, is necessary. Before we approach the real-world time series problem, I like to show an example of how to convert a time series problem to a supervised learning problem. A supervised learning problem consists of some input patterns (X) and output patterns(Y), based on that pattern an algorithm learn how to predict an output pattern given a definite input pattern (X). For example, consider the example below:

X	Y
-10	cold
-5	cold
5	cold
10	cold
20	normal
30	normal
40	hot
45	hot

Whereas, time series data is a sequence of values which are ordered by time index. For example:

X	Y	Z
5 am	-10	cold
7 am	-5	cold
9 am	5	cold
11 am	10	cold
1 pm	20	normal
3 pm	30	normal
5 pm	40	hot
6 pm	45	hot

To convert time series data into supervised learning problem we have to add more columns of data with the present time series data to include all the data for a given lag period. This approach will serve the purpose of multivariate time series where the present output sequence is dependent on previous input and output as well as present input.
For example, if our dataset includes data (X, Y) for present time series, we need to include two more columns with the dataset given one lag period like as $X(t-1), Y(t-1), X(t), Y(t)$.

3 Methodology

For the given multivariate time series problem I chose Long Short-Time Memory(LSTM) Recurrent Neural Network(RNN) where every neuron gets the present input sequence as well as the output of previous input sequence.

3.1 Data preprocessing

The first column is for keeping an index of times series and the second column is for each time series indexing. For classification problem, we do not need these two columns. That is why I dropped these two columns. The last column in the dataset is the output column. For binary classification, I replaced '0' as 'negative and '1' and '2' as positive class. After preprocessing the reformed dataset saved.

3.2 Converting series data into supervised learning data

A function is created to convert time series data into supervised learning compatible data. I took help of pandas shift() function to create data with a particular lagging period.

3.3 Design network and fit network

As the data is sequential and the problem demands a sequential model to evaluate, an LSTM sequential model is selected for the problem. As we are designing a binary classification solution, sigmoid function chose as an activation function. Moreover, for loss calculation mean squared error is chosen and stochastic gradient descent is chosen for optimization. After choosing all the necessary features of the model, the model is fitted with training data and validation data and trained for 50 epochs.

3.4 Plotting the result

Sklearn library in python has a special library named 'history' to plot a graph of model accuracy and loss during the training process. The trained model further tested with the test data. A Receiver Operating Characteristic (ROC) curve of the testing result shown at last.

4 Two class event detection as anomaly detection

Conventional machine learning algorithm shows poor performance when faced with imbalanced dataset or dataset with a minority or anomaly class. For example, logistic regression and decision tree have a bias toward the larger of class instances. These algorithm counts minority classes data as noise and ignored most of the time during modeling. So, in regards to anomaly detection these algorithm shows high misclassification rate. For example, if a dataset has 1000 total data with 950 data instances as one class and 50 data instances as another class, a model trained with a conventional algorithm will provide high misclassification rate when tested with a minority class instance. This sort of problem can be solved by improving the classification algorithm or balancing the training dataset. The later one is easier to implement and has also wide applications. For this dataset, I will balance the training dataset using random undersampling approach rather than improving classification algorithm. An example of random undersampling approach is as below. Assume there are 1000 total data instances where 950 is in one class and 50 is in another class. So if I use 10% undersampling of the whole dataset, the algorithm will take 95 data from the first class without replacement and merge with 50 data with another class and make a dataset of 145 total instances.

5 Walkthrough of the Source Code

Importing all necessary libraries:

1.import pandas for data preprocessing
2.import numpy for array processing
3.import math to perform mathematical functions
4.import matplotlib.pyplot to draw graphs
5.import sklearn for a python machine learning library
6.import keras for high level neural network platform in python, runs on the top of TensorFlow or Theano

```
In [1]: from sklearn.metrics import confusion_matrix
        import numpy as np
        import pandas as pd
        import math
        from math import sqrt
        from numpy import concatenate
        from matplotlib import pyplot
        from matplotlib.pyplot import figure
        from pandas import read_csv
        from pandas import DataFrame
        from pandas import concat
        from sklearn.preprocessing import MinMaxScaler
        from sklearn.preprocessing import LabelEncoder
        from sklearn.metrics import mean_squared_error
        from keras.models import Sequential
        from keras.layers import Dense
        from keras.layers import LSTM
```

```
C:\Users\Sen\Anaconda3\lib\site-packages\h5py\__init__.py:36: FutureWarning: Conversion of the s
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
```

Load data as from csv file(provide the csv file name as file_name.csv)

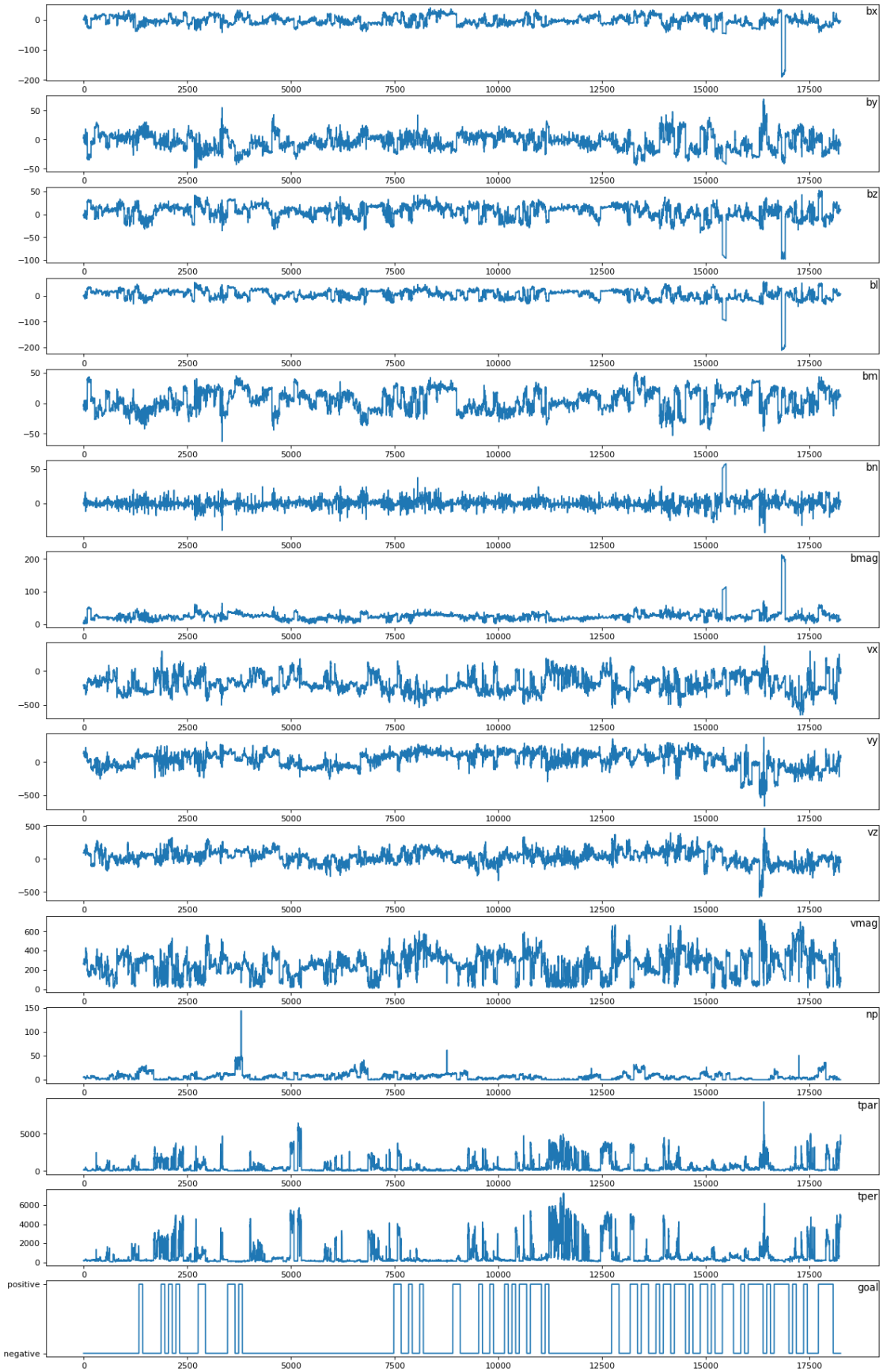
```
In [14]: #load data
         dataset = read_csv('test_problem.csv')
```

Cleaning the dataset by droping the first two coloumns as they are not necessary as features:
1.Replace the value of goal for binary classification where '0' as 'negative' class and '1' and '2' as 'positive' class.
2.Save the cleaned and process dataset into a new file name.

```
In [3]: #Droping frist two columns from the dataset
        dataset.drop('ID_TestSet', axis=1, inplace= True)
        dataset.drop('file', axis=1, inplace= True)

        # Values in the selected column to find and their replacements
        find_values = [0, 1, 2]
        replace_with = ['positive', 'negative', 'negative']

        # Find and replace values in the selected 'goal column
        dataset['goal'] = dataset['goal'].replace(find_values, replace_with)

        #save the dataset into a new csv file
        dataset.to_csv('intern_dataset_binary.csv')
```

Ploting the dataset:
1.Plot every features of the dataset using matplotlib.pyplot library in a single frame
2.Show the top five values of the new dataset

In [4]:
```
#load the new dataset, specifying first row as header and first coloum as index
dataset = read_csv('intern_dataset_binary.csv', header=0, index_col=0)

values = dataset.values
i=1
# initialize the figure size providing figure features
figure(num=None, figsize=(18, 30), dpi=80, facecolor='w', edgecolor='k')
# plot each column one by one from total 15 columns
for group in range(15):
    #subplot with 15 rows and 1 column, where i represent the row number
    pyplot.subplot(15,1,i)
    #ploting graph with the values for each coloumn
    pyplot.plot(values[:, group])
    #initializing title of the plot where the column name is in the right side
    pyplot.title(dataset.columns[group], y=0.8, loc='right')
    i+=1

pyplot.show()
#showing top 5 rows in the dataset
print(dataset.head(5))
```


bx
by
bz
bl
bm
bn
bmag
vx
vy
vz
vmag
np
tpar
tper
goal
positive
negative
0
2500
5000
7500
10000
12500
15000
17500

Data Preprocessing Steps:

1.create a function to convert time series dataset into supervised learning dataset

2.Encoding the categorical value of the 'goal' column with the help of sklearn.preprocessing

3.Normalize all the features value between 0 and 1 with the help of sklearn.preprocessing

4.framed the preprocessed times series dataset into a supervised learning dataset

5.As new column generates to frame into supervised learning dataset, further normalization is performed

```
In [5]: # function to convert time series data into supervised learning
        def time_series_to_supervised(data, lag=1, output=1, removenan=True):
            variable= 1 if type(data) is list else data.shape[1]
            data_frame= pd.DataFrame(data)
            columns, names = list(), list()
            # input sequence (t-n, t-(n-1)....t-1)
            for i in range(lag, 0, -1):
                columns.append(data_frame.shift(i))
                names = names + [('var%d(t-%d)' % (j+1, i)) for j in range(variable)]
            # sequence to forcast (t, t+1, t+2,...t+n)
            for i in range(0, output):
                columns.append(data_frame.shift(-i))
                if i==0:
                    names = names + [('var%d(t)'%(j+1)) for j in range(variable)]
                else:
                    names = names + [('var%d(t+%d)'% (j+1, i)) for j in range(variable)]
            #concatenating all columns and name
            aggregate= pd.concat(columns, axis=1)
            aggregate.columns= names
            #drop all rows which have NaN as feature values
            if removenan:
                    aggregate.dropna(inplace=True)
            return aggregate


        values = dataset.values
        # Encoding the categorical values in 'goal' column
        encoder = LabelEncoder()
        values[:,14] = encoder.fit_transform(values[:,14])
        values = values.astype('float32')
        # normalize all features between 0 and 1
        scaler = MinMaxScaler(feature_range=(0, 1))
        scaled= scaler.fit_transform(values)

        # frame as supervised learning
        reframed = time_series_to_supervised(scaled, 1, 1)
        reframed =reframed.astype('float32')
        # normalize all features(including old ones) between 0 and 1
```

```
        scaler = MinMaxScaler(feature_range=(0, 1))
        scaled = scaler.fit_transform(reframed)
        #normalized features framed into dataset
        reframed = pd.DataFrame(scaled)
        print(reframed.head(5))
        print(reframed.shape[0])
```

```
     bx    by    bz    bl    bm    bn  bmag      vx      vy     vz    vmag  \
0  0.52  3.99 -2.53  0.12 -4.74 -0.33  4.75 -212.49  126.52  94.29  264.67
1 -0.46  2.83 -0.37  1.47 -2.49 -0.08  2.89 -205.30  121.80  91.70  255.72
2  0.63  3.69 -2.23  0.10 -4.36 -0.12  4.36 -208.85  119.43  89.61  256.73
3  1.71  3.79 -1.89 -0.25 -4.46  0.94  4.57 -205.67  124.33  91.95  257.32
4  0.69  0.82  0.04  0.05 -0.80  0.72  1.08 -212.35  120.57  95.26  262.10

     np    tpar    tper      goal
0  5.51  141.67  157.74  negative
1  6.51  139.22  154.13  negative
2  6.15  144.39  151.92  negative
3  6.06  148.72  164.85  negative
4  5.97  183.88  153.38  negative
         0         1         2         3         4         5         6   \
0  0.830850  0.446224  0.631946  0.791192  0.511947  0.421807  0.017356
1  0.826580  0.436446  0.646286  0.796235  0.531711  0.424278  0.008560
2  0.831329  0.443695  0.633937  0.791117  0.515285  0.423883  0.015512
3  0.836035  0.444538  0.636195  0.789810  0.514406  0.434361  0.016505
4  0.831590  0.419504  0.649007  0.790930  0.546557  0.432187  0.000000

         7         8         9  ...        20        21        22        23  \
0  0.431023  0.764555  0.645218 ...  0.424278  0.008560  0.438072  0.759976
1  0.438072  0.759976  0.642756 ...  0.423883  0.015512  0.434592  0.757677
2  0.434592  0.757677  0.640769 ...  0.434361  0.016505  0.437709  0.762430
3  0.437709  0.762430  0.642994 ...  0.432187  0.000000  0.431161  0.758783
4  0.431161  0.758783  0.646140 ...  0.444543  0.013809  0.415143  0.777983

         24        25        26        27        28   29
0  0.642756  0.349659  0.045255  0.013365  0.020129  0.0
1  0.640769  0.351063  0.042752  0.013923  0.019825  0.0
2  0.642994  0.351884  0.042126  0.014391  0.021605  0.0
3  0.646140  0.358530  0.041501  0.018190  0.020026  0.0
4  0.647804  0.390819  0.038302  0.019689  0.020348  0.0

[5 rows x 30 columns]
18244
```

Preparing Training and Testing dataset:

1.As one time series represent 89 rows so diving all rows by 89 will provide us total number of series

2.Dividing 70% of the data into training set and 30% to test set
3.Spliting further input and output for each training set and test set

In [6]:
```
# split into train and test sets

#calculating total number of series
total_series= math.ceil(reframed.shape[0]/89)

#dividing into training set
training_set= (int)(math.ceil(total_series*0.7)*89)
values = reframed.values

#collecting values until the selected rows for training set
train = values[:training_set, :]

#the rest of the rows are for test set
n_test = values[training_set:, :]

total_series2= math.ceil(n_test.shape[0]/89)
n_validation = (int)(math.ceil(total_series2*0.5)*89)

valadation = n_test[:n_validation, :]
test = n_test[n_validation:, :]

# split into input and outputs
train_X, train_y = train[:, :-1], train[:, -1]
valadation_X, valadation_y = valadation[:, :-1], valadation[:, -1]
test_X, test_y = test[:, :-1], test[:, -1]
```

Reshaping input into 3D [samples, timesteps, features] to feed into learning model:

In [7]:
```
# reshape input to be 3D [samples, timesteps, features]
train_X = train_X.reshape((train_X.shape[0], 1, train_X.shape[1]))
valadation_X = valadation_X.reshape((valadation_X.shape[0], 1, valadation_X.shape[1]))
test_X = test_X.reshape((test_X.shape[0], 1, test_X.shape[1]))
print(train_X.shape, train_y.shape, test_X.shape, test_y.shape, valadation_X.shape, vala
```

```
(12816, 1, 29) (12816,) (2669, 1, 29) (2669,) (2759, 1, 29) (2759,)
```

Design network for the problem:
1.Initialize sequential model
2.Add Long Short-Term Memory model with 50 neurons to the model class
3.Initialize activation function as 'sigmoid'
4.Initialize loss function as 'Mean Squared Error', Optimizer as 'adam' and metrics as accuracy

In [8]:
```
# design network
model = Sequential()
model.add(LSTM(50, input_shape=(train_X.shape[1], train_X.shape[2])))
```

```
        model.add(Dense(1, activation='sigmoid'))
        model.compile(loss='mse', optimizer='adam', metrics=['accuracy'])
        print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 50)                16000
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 51
=================================================================
Total params: 16,051
Trainable params: 16,051
Non-trainable params: 0
_________________________________________________________________
None
```

Fit the design network:
1.Provide the training dataset
2.Define number of epochs
3.Define batch_size for processing
4.Provide dataset for validation

```
In [9]: # fit network
        history = model.fit(train_X, train_y, epochs=50, batch_size=267, validation_data=(valada
```

```
Train on 12816 samples, validate on 2759 samples
Epoch 1/50
 - 1s - loss: 0.1921 - acc: 0.7779 - val_loss: 0.3080 - val_acc: 0.4516
Epoch 2/50
 - 0s - loss: 0.1447 - acc: 0.8194 - val_loss: 0.3280 - val_acc: 0.4516
Epoch 3/50
 - 0s - loss: 0.1335 - acc: 0.8194 - val_loss: 0.2992 - val_acc: 0.4516
Epoch 4/50
 - 0s - loss: 0.1206 - acc: 0.8194 - val_loss: 0.2393 - val_acc: 0.4516
Epoch 5/50
 - 0s - loss: 0.0973 - acc: 0.8262 - val_loss: 0.1449 - val_acc: 0.9188
Epoch 6/50
 - 0s - loss: 0.0656 - acc: 0.9536 - val_loss: 0.0782 - val_acc: 0.9935
Epoch 7/50
 - 0s - loss: 0.0403 - acc: 0.9926 - val_loss: 0.0455 - val_acc: 0.9935
Epoch 8/50
 - 0s - loss: 0.0243 - acc: 0.9971 - val_loss: 0.0291 - val_acc: 0.9935
Epoch 9/50
 - 0s - loss: 0.0156 - acc: 0.9971 - val_loss: 0.0211 - val_acc: 0.9935
Epoch 10/50
 - 0s - loss: 0.0111 - acc: 0.9971 - val_loss: 0.0167 - val_acc: 0.9935
Epoch 11/50
```

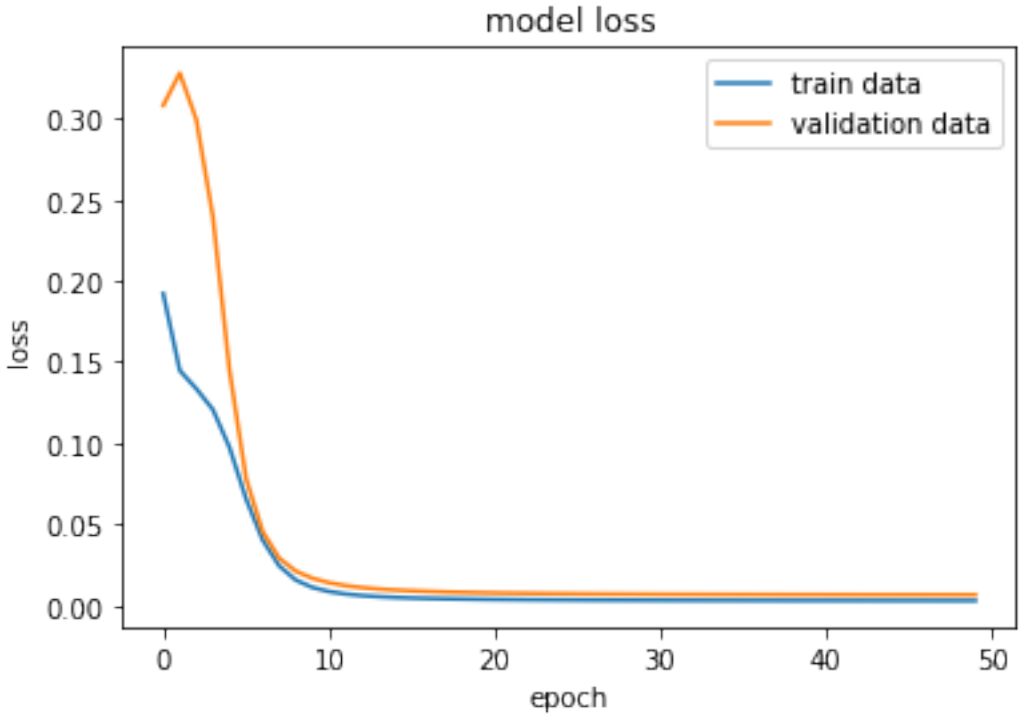
```
 - 0s - loss: 0.0086 - acc: 0.9971 - val_loss: 0.0140 - val_acc: 0.9935
Epoch 12/50
 - 0s - loss: 0.0070 - acc: 0.9971 - val_loss: 0.0122 - val_acc: 0.9935
Epoch 13/50
 - 0s - loss: 0.0061 - acc: 0.9971 - val_loss: 0.0110 - val_acc: 0.9935
Epoch 14/50
 - 0s - loss: 0.0054 - acc: 0.9971 - val_loss: 0.0101 - val_acc: 0.9935
Epoch 15/50
 - 0s - loss: 0.0049 - acc: 0.9971 - val_loss: 0.0095 - val_acc: 0.9935
Epoch 16/50
 - 0s - loss: 0.0046 - acc: 0.9971 - val_loss: 0.0090 - val_acc: 0.9935
Epoch 17/50
 - 0s - loss: 0.0043 - acc: 0.9971 - val_loss: 0.0086 - val_acc: 0.9935
Epoch 18/50
 - 0s - loss: 0.0041 - acc: 0.9971 - val_loss: 0.0083 - val_acc: 0.9935
Epoch 19/50
 - 1s - loss: 0.0039 - acc: 0.9971 - val_loss: 0.0080 - val_acc: 0.9935
Epoch 20/50
 - 1s - loss: 0.0038 - acc: 0.9971 - val_loss: 0.0078 - val_acc: 0.9935
Epoch 21/50
 - 1s - loss: 0.0037 - acc: 0.9971 - val_loss: 0.0077 - val_acc: 0.9935
Epoch 22/50
 - 1s - loss: 0.0036 - acc: 0.9971 - val_loss: 0.0075 - val_acc: 0.9935
Epoch 23/50
 - 0s - loss: 0.0035 - acc: 0.9971 - val_loss: 0.0074 - val_acc: 0.9935
Epoch 24/50
 - 0s - loss: 0.0034 - acc: 0.9971 - val_loss: 0.0073 - val_acc: 0.9935
Epoch 25/50
 - 0s - loss: 0.0034 - acc: 0.9971 - val_loss: 0.0072 - val_acc: 0.9935
Epoch 26/50
 - 0s - loss: 0.0033 - acc: 0.9971 - val_loss: 0.0071 - val_acc: 0.9935
Epoch 27/50
 - 0s - loss: 0.0033 - acc: 0.9971 - val_loss: 0.0071 - val_acc: 0.9935
Epoch 28/50
 - 0s - loss: 0.0032 - acc: 0.9971 - val_loss: 0.0070 - val_acc: 0.9935
Epoch 29/50
 - 0s - loss: 0.0032 - acc: 0.9971 - val_loss: 0.0070 - val_acc: 0.9935
Epoch 30/50
 - 0s - loss: 0.0032 - acc: 0.9971 - val_loss: 0.0069 - val_acc: 0.9935
Epoch 31/50
 - 0s - loss: 0.0032 - acc: 0.9971 - val_loss: 0.0069 - val_acc: 0.9935
Epoch 32/50
 - 0s - loss: 0.0031 - acc: 0.9971 - val_loss: 0.0069 - val_acc: 0.9935
Epoch 33/50
 - 0s - loss: 0.0031 - acc: 0.9971 - val_loss: 0.0068 - val_acc: 0.9935
Epoch 34/50
 - 0s - loss: 0.0031 - acc: 0.9971 - val_loss: 0.0068 - val_acc: 0.9935
Epoch 35/50
```

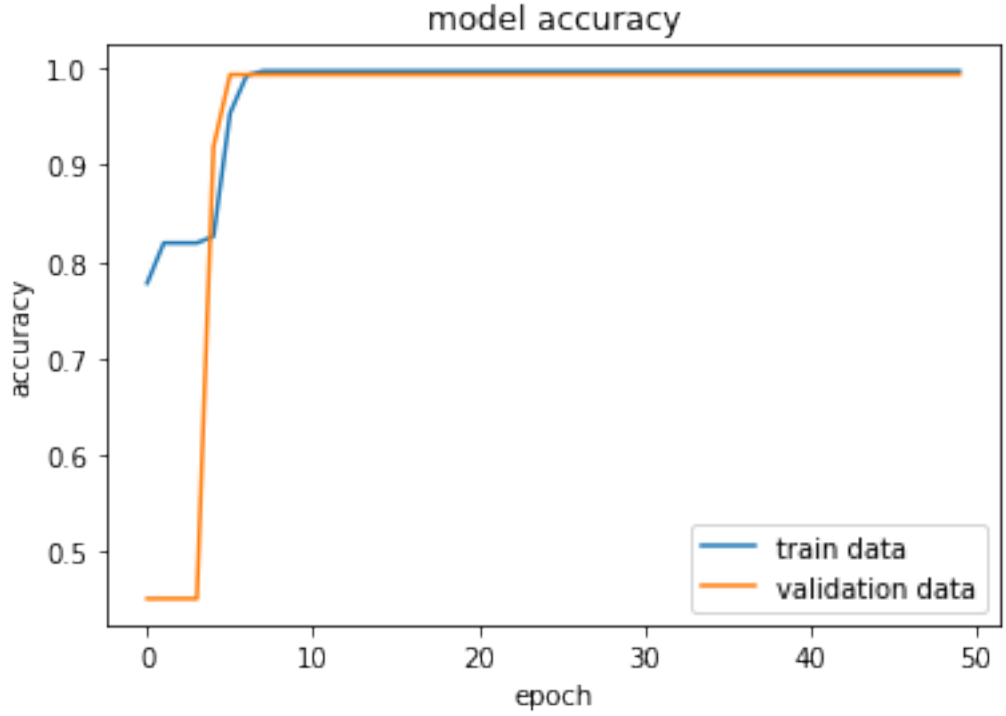
```
 - 0s - loss: 0.0031 - acc: 0.9971 - val_loss: 0.0068 - val_acc: 0.9935
Epoch 36/50
 - 1s - loss: 0.0031 - acc: 0.9971 - val_loss: 0.0068 - val_acc: 0.9935
Epoch 37/50
 - 1s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0067 - val_acc: 0.9935
Epoch 38/50
 - 1s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0067 - val_acc: 0.9935
Epoch 39/50
 - 0s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0067 - val_acc: 0.9935
Epoch 40/50
 - 0s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0067 - val_acc: 0.9935
Epoch 41/50
 - 0s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0067 - val_acc: 0.9935
Epoch 42/50
 - 0s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0067 - val_acc: 0.9935
Epoch 43/50
 - 0s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0067 - val_acc: 0.9935
Epoch 44/50
 - 0s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0066 - val_acc: 0.9935
Epoch 45/50
 - 0s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0066 - val_acc: 0.9935
Epoch 46/50
 - 0s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0066 - val_acc: 0.9935
Epoch 47/50
 - 0s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0066 - val_acc: 0.9935
Epoch 48/50
 - 0s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0066 - val_acc: 0.9935
Epoch 49/50
 - 0s - loss: 0.0030 - acc: 0.9971 - val_loss: 0.0066 - val_acc: 0.9935
Epoch 50/50
 - 0s - loss: 0.0029 - acc: 0.9971 - val_loss: 0.0066 - val_acc: 0.9935
```

Ploting graph of model loss and model accuracy for training process:

```
In [10]: # plot model loss
         pyplot.plot(history.history['loss'], label='train data')
         pyplot.plot(history.history['val_loss'], label='validation data')
         pyplot.title('model loss')
         pyplot.ylabel('loss')
         pyplot.xlabel('epoch')
         pyplot.legend()
         pyplot.show()
         # plot model accuracy
         pyplot.plot(history.history['acc'], label='train data')
         pyplot.plot(history.history['val_acc'], label='validation data')
         pyplot.title('model accuracy')
         pyplot.ylabel('accuracy')
```

```
pyplot.xlabel('epoch')
pyplot.legend()
pyplot.show()
```





Predict ouput (goal) value from the model:

```
In [11]: # Predict value of goal from input
         yhat = model.predict(test_X)
```

Accuracy Measures of the model:

```
In [12]: # Accuracy evaluation of the model with test data
         acc = model.evaluate(test_X, test_y, verbose=0)
         print("Accuracy: %.2f%%" % (acc[1]*100))
```

```
Accuracy: 99.44%
```

Root Mean Square Error(RMSE) and ROC curve for the model:

```
In [13]: # Reshape test data into 2D
         test_X = test_X.reshape((test_X.shape[0], test_X.shape[2]))

         # invert scaling for predicted data
         inv_ypred = concatenate((yhat,test_X), axis=1)

         inv_ypred = scaler.inverse_transform(inv_ypred)

         inv_ypred = inv_ypred[:,0]

         # invert scaling for actual test data
         test_y = test_y.reshape((len(test_y), 1))
         inv_y = concatenate((test_y,test_X), axis=1)

         inv_y = scaler.inverse_transform(inv_y)

         inv_y = inv_y[:,0]

         # calculate Root Mean Square Error (RMSE)
         rmse = sqrt(mean_squared_error(inv_y, inv_ypred))
         print('Root Mean Square Error (RMSE): %.3f' % rmse)

         pred=[]
         for each in inv_ypred:
             if(each+0.5>math.ceil(each)):
                 pred.append(math.ceil(each))
             else:
                 pred.append(math.floor(each))

         act=[]
         for each in inv_y:
```

```
            if(each+0.5>math.ceil(each)):
                act.append(math.ceil(each))
            else:
                act.append(math.floor(each))

        #importing roc_curve library from sklearn.metrics
        from sklearn.metrics import roc_curve

        fpr_keras, tpr_keras, thresholds_keras = roc_curve(act, pred)

        from sklearn.metrics import auc
        auc_keras = auc(fpr_keras, tpr_keras)

        pyplot.figure(1)
        pyplot.plot([0, 1], [0, 1], 'k--')
        pyplot.plot(fpr_keras, tpr_keras, label='Binary Classification (area = {:.3f})'.format(

        pyplot.xlabel('False positive rate')
        pyplot.ylabel('True positive rate')
        pyplot.title('ROC curve')
        pyplot.legend(loc='best')
        pyplot.show()
```

```
Root Mean Square Error (RMSE): 0.075
```