Model Prediction

Data preparation

In [ ]:
```
import matplotlib.pyplot as plt
import numpy as np
import datetime as dt
import pandas as pd
raw = pd.read_csv("austin_dockless.csv", low_memory=False)
```

In [2]:
```
# plotly
import plotly.plotly as py
from plotly.offline import iplot, init_notebook_mode
import plotly.graph_objs as go
import plotly.io as pio
import plotly.tools
plotly.tools.set_credentials_file(username='AsherMeyers', api_key='x6WJxUVsTsMwhr5MNLcZ')
```

In [187]:
```
test = raw.copy()
test["Start Time"] = pd.to_datetime(test["Start Time"], format = "%m/%d/%Y %I:%M:%S %p")
test["End Time"] = pd.to_datetime(test["End Time"], format = "%m/%d/%Y %I:%M:%S %p")
test["hour"] = test["Start Time"].map(lambda x: x.hour)
```

In [188]:
```
test = test[test["Origin Cell ID"] != 'OUT_OF_BOUNDS']
test = test[test["Destination Cell ID"] != 'OUT_OF_BOUNDS']
test = test[np.isfinite(test['Start Latitude'])]
test = test[np.isfinite(test['End Latitude'])]
test = test[np.isfinite(test['Council District (Start)'])]
test = test[pd.notnull(test['Origin Cell ID'])]

test = test[test["Start Latitude"] != 0]
#test = test[:100000]  # same as df.head(10)
# 8 months of data
```

In [189]:
```
test['datestart'] = test["Start Time"].apply(lambda x: x.date())
```

In [74]:
```
raw.columns
```

Out[74]:
```
Index(['ID', 'Device ID', 'Vehicle Type', 'Trip Duration', 'Trip Distance',
       'Start Time', 'End Time', 'Modified Date', 'Month', 'Hour',
       'Day of Week', 'Council District (Start)', 'Council District (End)',
       'Origin Cell ID', 'Destination Cell ID', 'Year', 'Start Latitude',
       'Start Longitude', 'End Latitude', 'End Longitude'],
      dtype='object')
```

In [6]:
```
def f(x):
    d = {}
    d['CountID'] = x['ID'].count()
    d['TripDurMean'] = x['Trip Duration'].mean()
    d['TripDistMean'] = x['Trip Distance'].mean()
    #d['StartMean'] = x['Start Time'].mean()
    #d['EndMean'] = x['End Team'].mean()
    return pd.Series(d, index=['CountID', 'TripDurMean', 'TripDistMean'])
```

In [7]:
```
scooters = test.groupby('datestart').apply(f)
```

In [8]:
```
from pandas import DataFrame
from pandas import concat
scooters = DataFrame(scooters)
scooters = scooters.reset_index()
```

In [37]:
```
scooters = scooters[scooters.CountID > 100]
```

In [38]:
```
scooters.head()
```

Out[38]:

	datestart	CountID	TripDurMean	TripDistMean
2	2018-04-05	112.0	1198.633929	2238.776786
3	2018-04-06	351.0	1118.914530	2616.518519
4	2018-04-07	222.0	970.707207	1815.882883
5	2018-04-08	360.0	1727.847222	3497.075000
6	2018-04-09	225.0	1559.311111	3118.777778

In [40]:
```
scooters.to_csv('scooters.csv')
```

Model Preparation

In [41]:
```
from pandas import DataFrame
from pandas import concat

def series_to_supervised(data, n_in=1, n_out=1, dropnan=True):
    """
    Frame a time series as a supervised learning dataset.
    Arguments:
    data: Sequence of observations as a list or NumPy array.
    n_in: Number of lag observations as input (X).
    n_out: Number of observations as output (y).
    dropnan: Boolean whether or not to drop rows with NaN values.
    Returns:
    Pandas DataFrame of series framed for supervised learning.
    """
    n_vars = 1 if type(data) is list else data.shape[1]
    df = DataFrame(data)
    cols, names = list(), list()
    # input sequence (t-n, ... t-1)
    for i in range(n_in, 0, -1):
        cols.append(df.shift(i))
        names += [('var%d(t-%d)' % (j+1, i)) for j in range(n_vars)]
    # forecast sequence (t, t+1, ... t+n)
    for i in range(0, n_out):
        cols.append(df.shift(-i))
        if i == 0:
            names += [('var%d(t)' % (j+1)) for j in range(n_vars)]
        else:
            names += [('var%d(t+%d)' % (j+1, i)) for j in range(n_vars)]
    # put it all together
    agg = concat(cols, axis=1)
    agg.columns = names
    # drop rows with NaN values
    if dropnan:
        agg.dropna(inplace=True)
    return agg
```

In [42]:
```
sample = scooters[['datestart','CountID']]
```

In [51]:
```
sample.head()
```

Out[51]:

	datestart	CountID
2	2018-04-05	112.0
3	2018-04-06	351.0
4	2018-04-07	222.0
5	2018-04-08	360.0
6	2018-04-09	225.0

sample.head()

In [52]:
```
values = DataFrame(sample.CountID)
dataframe = concat([values.shift(1), values], axis=1)
dataframe.columns = ['t-1', 't+1']
print(dataframe.head(5))
```

```
     t-1    t+1
2    NaN  112.0
3  112.0  351.0
4  351.0  222.0
5  222.0  360.0
6  360.0  225.0
```

In [53]:
```
X = dataframe.values
train_size = int(len(X) * 0.66)
train, test = X[1:train_size], X[train_size:]
train_X, train_y = train[:,0], train[:,1]
test_X, test_y = test[:,0], test[:,1]
```

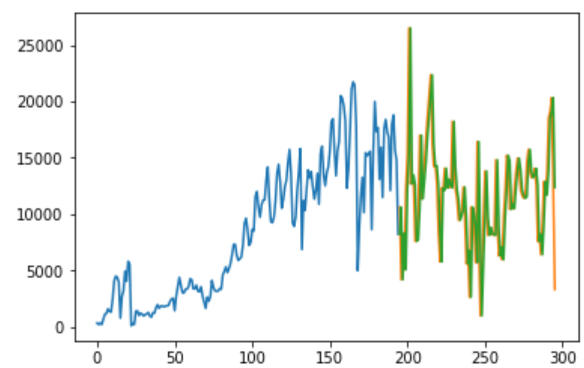
In [54]:
```
# persistence model
def model_persistence(x):
    return x
```

In [55]:
```
# walk-forward validation
from sklearn.metrics import mean_squared_error
from matplotlib import pyplot
predictions = list()
for x in test_X:
    yhat = model_persistence(x)
    predictions.append(yhat)
test_score = mean_squared_error(test_y, predictions)
print('Test MSE: %.3f' % test_score)
```

```
Test MSE: 15683278.277
```

Walk Forward Graphic

In [56]:
```
pyplot.plot(train_y)
pyplot.plot([None for i in train_y] + [x for x in test_y])
pyplot.plot([None for i in train_y] + [x for x in predictions])
pyplot.show()
```



LTSM Univariate MODEL

In [57]:
```
#LTSM Model

import numpy
import matplotlib.pyplot as plt
import pandas
import math
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
```

In [58]:
```
numpy.random.seed(7)

dataset = DataFrame(sample.CountID)
```

In [59]:
```
# normalize the dataset
scaler = MinMaxScaler(feature_range=(0, 1))
dataset = scaler.fit_transform(dataset)


# split into train and test sets
train_size = int(len(dataset) * 0.67)
test_size = len(dataset) - train_size
train, test = dataset[0:train_size,:], dataset[train_size:len(dataset),:]
print(len(train), len(test))
```

```
198 99
```

In [60]:
```
def create_dataset(dataset, look_back=1):
    dataX, dataY = [], []
    for i in range(len(dataset)-look_back-1):
        a = dataset[i:(i+look_back), 0]
        dataX.append(a)
        dataY.append(dataset[i + look_back, 0])
    return numpy.array(dataX), numpy.array(dataY)
```

In [62]:
```
# reshape into X=t and Y=t+1
look_back = 1
trainX, trainY = create_dataset(train, look_back)
testX, testY = create_dataset(test, look_back)
print(len(trainX), len(testX), len(trainY), len(testY))
```

```
196 97 196 97
```

In [63]:
```
# reshape input to be [samples, time steps, features]
trainX = numpy.reshape(trainX, (trainX.shape[0], 1, trainX.shape[1]))
testX = numpy.reshape(testX, (testX.shape[0], 1, testX.shape[1]))
```

In [64]:
```
print(len(trainX), len(testX))
```

```
196 97
```

In [65]:
```
# create and fit the LSTM network
model = Sequential()
model.add(LSTM(4, input_shape=(1, look_back)))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')
model.fit(trainX, trainY, epochs=100, batch_size=1, verbose=2)
```

```
Epoch 1/100
 - 1s - loss: 0.0831
Epoch 2/100
 - 0s - loss: 0.0360
Epoch 3/100
 - 0s - loss: 0.0270
Epoch 4/100
 - 0s - loss: 0.0216
Epoch 5/100
 - 0s - loss: 0.0165
Epoch 6/100
 - 0s - loss: 0.0125
Epoch 7/100
 - 0s - loss: 0.0099
Epoch 8/100
 - 0s - loss: 0.0086
Epoch 9/100
 - 0s - loss: 0.0079
Epoch 10/100
 - 0s - loss: 0.0075
Epoch 11/100
 - 0s - loss: 0.0074
Epoch 12/100
 - 0s - loss: 0.0074
Epoch 13/100
 - 0s - loss: 0.0073
Epoch 14/100
 - 0s - loss: 0.0073
Epoch 15/100
 - 0s - loss: 0.0073
Epoch 16/100
 - 0s - loss: 0.0074
Epoch 17/100
 - 0s - loss: 0.0074
Epoch 18/100
 - 0s - loss: 0.0074
Epoch 19/100
 - 0s - loss: 0.0073
Epoch 20/100
 - 0s - loss: 0.0073
Epoch 21/100
 - 0s - loss: 0.0074
Epoch 22/100
 - 0s - loss: 0.0073
Epoch 23/100
 - 0s - loss: 0.0074
Epoch 24/100
 - 0s - loss: 0.0073
Epoch 25/100
 - 0s - loss: 0.0072
Epoch 26/100
 - 0s - loss: 0.0072
Epoch 27/100
 - 0s - loss: 0.0072
Epoch 28/100
 - 0s - loss: 0.0072
Epoch 29/100
 - 0s - loss: 0.0072
Epoch 30/100
 - 0s - loss: 0.0072
Epoch 31/100
 - 0s - loss: 0.0071
Epoch 32/100
 - 0s - loss: 0.0072
Epoch 33/100
 - 0s - loss: 0.0071
Epoch 34/100
 - 0s - loss: 0.0071
Epoch 35/100
 - 0s - loss: 0.0072
Epoch 36/100
 - 0s - loss: 0.0069
Epoch 37/100
 - 0s - loss: 0.0070
Epoch 38/100
 - 0s - loss: 0.0071
```

```
Epoch 39/100
 - 0s - loss: 0.0070
Epoch 40/100
 - 0s - loss: 0.0071
Epoch 41/100
 - 0s - loss: 0.0071
Epoch 42/100
 - 0s - loss: 0.0070
Epoch 43/100
 - 0s - loss: 0.0072
Epoch 44/100
 - 1s - loss: 0.0070
Epoch 45/100
 - 0s - loss: 0.0071
Epoch 46/100
 - 0s - loss: 0.0070
Epoch 47/100
 - 0s - loss: 0.0070
Epoch 48/100
 - 0s - loss: 0.0070
Epoch 49/100
 - 0s - loss: 0.0070
Epoch 50/100
 - 0s - loss: 0.0070
Epoch 51/100
 - 0s - loss: 0.0069
Epoch 52/100
 - 0s - loss: 0.0070
Epoch 53/100
 - 0s - loss: 0.0070
Epoch 54/100
 - 0s - loss: 0.0069
Epoch 55/100
 - 0s - loss: 0.0070
Epoch 56/100
 - 0s - loss: 0.0068
Epoch 57/100
 - 0s - loss: 0.0068
Epoch 58/100
 - 0s - loss: 0.0069
Epoch 59/100
 - 0s - loss: 0.0068
Epoch 60/100
 - 0s - loss: 0.0070
Epoch 61/100
 - 0s - loss: 0.0069
Epoch 62/100
 - 0s - loss: 0.0068
Epoch 63/100
 - 0s - loss: 0.0068
Epoch 64/100
 - 0s - loss: 0.0067
Epoch 65/100
 - 0s - loss: 0.0069
Epoch 66/100
 - 0s - loss: 0.0068
Epoch 67/100
 - 0s - loss: 0.0069
Epoch 68/100
 - 0s - loss: 0.0069
Epoch 69/100
 - 0s - loss: 0.0068
Epoch 70/100
 - 0s - loss: 0.0069
Epoch 71/100
 - 0s - loss: 0.0068
Epoch 72/100
 - 0s - loss: 0.0068
Epoch 73/100
 - 0s - loss: 0.0068
Epoch 74/100
 - 0s - loss: 0.0069
Epoch 75/100
 - 0s - loss: 0.0068
Epoch 76/100
 - 0s - loss: 0.0068
Epoch 77/100
```

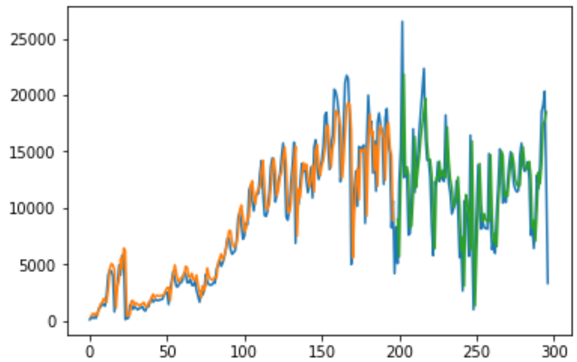
```
 - 0s - loss: 0.0069
Epoch 78/100
 - 0s - loss: 0.0069
Epoch 79/100
 - 0s - loss: 0.0068
Epoch 80/100
 - 0s - loss: 0.0066
Epoch 81/100
 - 0s - loss: 0.0069
Epoch 82/100
 - 0s - loss: 0.0068
Epoch 83/100
 - 0s - loss: 0.0068
Epoch 84/100
 - 0s - loss: 0.0069
Epoch 85/100
 - 0s - loss: 0.0068
Epoch 86/100
 - 0s - loss: 0.0067
Epoch 87/100
 - 0s - loss: 0.0068
Epoch 88/100
 - 0s - loss: 0.0068
Epoch 89/100
 - 0s - loss: 0.0068
Epoch 90/100
 - 0s - loss: 0.0068
Epoch 91/100
 - 0s - loss: 0.0068
Epoch 92/100
 - 0s - loss: 0.0067
Epoch 93/100
 - 0s - loss: 0.0068
Epoch 94/100
 - 0s - loss: 0.0067
Epoch 95/100
 - 0s - loss: 0.0068
Epoch 96/100
 - 0s - loss: 0.0067
Epoch 97/100
 - 0s - loss: 0.0067
Epoch 98/100
 - 0s - loss: 0.0067
Epoch 99/100
 - 0s - loss: 0.0067
Epoch 100/100
 - 0s - loss: 0.0067
```

Out[65]:
```
<keras.callbacks.History at 0x127e4f9b0>
```

In [66]:
```python
# make predictions
trainPredict = model.predict(trainX)
testPredict = model.predict(testX)
# invert predictions
trainPredict = scaler.inverse_transform(trainPredict)
trainY = scaler.inverse_transform([trainY])
testPredict = scaler.inverse_transform(testPredict)
testY = scaler.inverse_transform([testY])
# calculate root mean squared error
trainScore = math.sqrt(mean_squared_error(trainY[0], trainPredict[:,0]))
print('Train Score: %.2f RMSE' % (trainScore))
testScore = math.sqrt(mean_squared_error(testY[0], testPredict[:,0]))
print('Test Score: %.2f RMSE' % (testScore))
```

```
Train Score: 2145.48 RMSE
Test Score: 3582.74 RMSE
```

In [67]:
```
# shift train predictions for plotting
trainPredictPlot = numpy.empty_like(dataset)
trainPredictPlot[:, :] = numpy.nan
trainPredictPlot[look_back:len(trainPredict)+look_back, :] = trainPredict
# shift test predictions for plotting
testPredictPlot = numpy.empty_like(dataset)
testPredictPlot[:, :] = numpy.nan
testPredictPlot[len(trainPredict)+(look_back*2)+1:len(dataset)-1, :] = testPredict
# plot baseline and predictions
plt.plot(scaler.inverse_transform(dataset))
plt.plot(trainPredictPlot)
plt.plot(testPredictPlot)
plt.show()
```



In [68]:
```
trainPredict[-3:]
```

Out[68]:
```
array([[15380.596],
       [14676.66 ],
       [ 8898.599]], dtype=float32)
```

In [69]:
```
testPredict[-3:]
```

Out[69]:
```
array([[17350.73],
       [17742.7 ],
       [18499.16]], dtype=float32)
```

LTSM Multivariate MODEL

In [190]:
```
test2 = test.copy()
```

In [191]:
```
def g(x):
    d = {}
    d['CountID'] = x['ID'].count()
    d['TripDurMean'] = x['Trip Duration'].mean()
    d['TripDistMean'] = x['Trip Distance'].mean()
    d['Day of Week'] = x['Day of Week'].mean()
    #d['StartMean'] = x['Start Time'].mean()
    #d['EndMean'] = x['End Team'].mean()
    return pd.Series(d, index=['CountID', 'TripDurMean', 'TripDistMean','Day of Week'])
```

In [193]:
```
mvscooters = test2.groupby('datestart').apply(g)
```

In [194]:
```
mvscooters.head()
```

Out[194]:

	CountID	TripDurMean	TripDistMean	Day of Week
datestart				
2018-04-03	1.0	943.000000	419.000000	2.0
2018-04-04	3.0	1360.333333	5691.333333	3.0
2018-04-05	112.0	1198.633929	2238.776786	4.0
2018-04-06	351.0	1118.914530	2616.518519	5.0
2018-04-07	222.0	970.707207	1815.882883	6.0

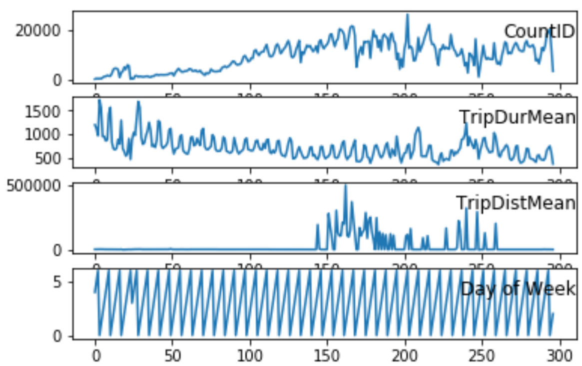
In [195]:
```
mvscooters = mvscooters[mvscooters.CountID > 100]
```

In [196]:
```
mvscooters.head()
```

Out[196]:

	CountID	TripDurMean	TripDistMean	Day of Week
datestart				
2018-04-05	112.0	1198.633929	2238.776786	4.0
2018-04-06	351.0	1118.914530	2616.518519	5.0
2018-04-07	222.0	970.707207	1815.882883	6.0
2018-04-08	360.0	1727.847222	3497.075000	0.0
2018-04-09	225.0	1559.311111	3118.777778	1.0

In [197]:
```
from pandas import read_csv
from matplotlib import pyplot
values = mvscooters.values
# specify columns to plot
groups = [0, 1, 2, 3]
i = 1
# plot each column
pyplot.figure()
for group in groups:
    pyplot.subplot(len(groups), 1, i)
    pyplot.plot(values[:, group])
    pyplot.title(mvscooters.columns[group], y=0.5, loc='right')
    i += 1
pyplot.show()
```



In [199]:
```
from sklearn.preprocessing import LabelEncoder

# convert series to supervised learning
def series_to_supervised(data, n_in=1, n_out=1, dropnan=True):
        n_vars = 1 if type(data) is list else data.shape[1]
        df = DataFrame(data)
        cols, names = list(), list()
        # input sequence (t-n, ... t-1)
        for i in range(n_in, 0, -1):
                cols.append(df.shift(i))
                names += [('var%d(t-%d)' % (j+1, i)) for j in range(n_vars)]
        # forecast sequence (t, t+1, ... t+n)
        for i in range(0, n_out):
                cols.append(df.shift(-i))
                if i == 0:
                        names += [('var%d(t)' % (j+1)) for j in range(n_vars)]
                else:
                        names += [('var%d(t+%d)' % (j+1, i)) for j in range(n_vars)]
        # put it all together
        agg = concat(cols, axis=1)
        agg.columns = names
        # drop rows with NaN values
        if dropnan:
                agg.dropna(inplace=True)
        return agg

# load dataset
dataset = mvscooters.copy()
values = dataset.values
# integer encode direction
encoder = LabelEncoder()
values[:,3] = encoder.fit_transform(values[:,3])
# ensure all data is float
values = values.astype('float32')
# normalize features
scaler = MinMaxScaler(feature_range=(0, 1))
scaled = scaler.fit_transform(values)
# frame as supervised learning
reframed = series_to_supervised(scaled, 1, 1)
# drop columns we don't want to predict
reframed.drop(reframed.columns[[5,6,7]], axis=1, inplace=True)
print(reframed.head())
```

```
   var1(t-1)  var2(t-1)  var3(t-1)  var4(t-1)   var1(t)
1   0.000000   0.612108   0.008915   0.666667  0.009055
2   0.009055   0.553677   0.009673   0.833333  0.004168
3   0.004168   0.445048   0.008065   1.000000  0.009396
4   0.009396   1.000000   0.011441   0.000000  0.004281
5   0.004281   0.876470   0.010682   0.166667  0.021900
```

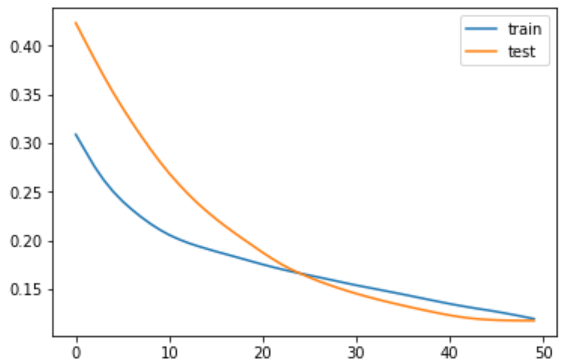
In [221]:
```
# split into train and test sets
numpy.random.seed(8)
values = reframed.values
n_train_hours = int(len(values) * 0.66)
#train = values[0:n_train_hours, :]
#test = values[n_train_hours:len(values), :]
train = values[0:n_train_hours, :]
test = values[n_train_hours:len(values), :]
# split into input and outputs
train_X, train_y = train[:, :-1], train[:, -1]
test_X, test_y = test[:, :-1], test[:, -1]
# reshape input to be 3D [samples, timesteps, features]
train_X = train_X.reshape((train_X.shape[0], 1, train_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)


#X = dataframe.values
#train_size = int(len(X) * 0.66)
#train, test = X[1:train_size], X[train_size:]
#train_X, train_y = train[:,0], train[:,1]
#test_X, test_y = test[:,0], test[:,1]
```

```
(195, 1, 4) (195,) (101, 1, 4) (101,)
```

In [224]:
```
# design network
model2 = Sequential()
model2.add(LSTM(50, input_shape=(train_X.shape[1], train_X.shape[2])))
model2.add(Dense(1))
model2.compile(loss='mae', optimizer='adam')
# fit network
history = model2.fit(train_X, train_y, epochs=50, batch_size=72, validation_data=(test_X, t
est_y), verbose=2, shuffle=False)
# plot history
pyplot.plot(history.history['loss'], label='train')
pyplot.plot(history.history['val_loss'], label='test')
pyplot.legend()
pyplot.show()
```

```
Train on 195 samples, validate on 101 samples
Epoch 1/50
 - 2s - loss: 0.3088 - val_loss: 0.4232
Epoch 2/50
 - 0s - loss: 0.2924 - val_loss: 0.4046
Epoch 3/50
 - 0s - loss: 0.2760 - val_loss: 0.3863
Epoch 4/50
 - 0s - loss: 0.2621 - val_loss: 0.3687
Epoch 5/50
 - 0s - loss: 0.2503 - val_loss: 0.3519
Epoch 6/50
 - 0s - loss: 0.2404 - val_loss: 0.3363
Epoch 7/50
 - 0s - loss: 0.2319 - val_loss: 0.3214
Epoch 8/50
 - 0s - loss: 0.2242 - val_loss: 0.3072
Epoch 9/50
 - 0s - loss: 0.2172 - val_loss: 0.2937
Epoch 10/50
 - 0s - loss: 0.2111 - val_loss: 0.2808
Epoch 11/50
 - 0s - loss: 0.2058 - val_loss: 0.2690
Epoch 12/50
 - 0s - loss: 0.2015 - val_loss: 0.2581
Epoch 13/50
 - 0s - loss: 0.1977 - val_loss: 0.2480
Epoch 14/50
 - 0s - loss: 0.1945 - val_loss: 0.2386
Epoch 15/50
 - 0s - loss: 0.1917 - val_loss: 0.2301
Epoch 16/50
 - 0s - loss: 0.1888 - val_loss: 0.2222
Epoch 17/50
 - 0s - loss: 0.1862 - val_loss: 0.2148
Epoch 18/50
 - 0s - loss: 0.1836 - val_loss: 0.2077
Epoch 19/50
 - 0s - loss: 0.1809 - val_loss: 0.2010
Epoch 20/50
 - 0s - loss: 0.1782 - val_loss: 0.1943
Epoch 21/50
 - 0s - loss: 0.1756 - val_loss: 0.1877
Epoch 22/50
 - 0s - loss: 0.1731 - val_loss: 0.1815
Epoch 23/50
 - 0s - loss: 0.1707 - val_loss: 0.1757
Epoch 24/50
 - 0s - loss: 0.1685 - val_loss: 0.1706
Epoch 25/50
 - 0s - loss: 0.1664 - val_loss: 0.1663
Epoch 26/50
 - 0s - loss: 0.1644 - val_loss: 0.1622
Epoch 27/50
 - 0s - loss: 0.1624 - val_loss: 0.1584
Epoch 28/50
 - 0s - loss: 0.1604 - val_loss: 0.1549
Epoch 29/50
 - 0s - loss: 0.1583 - val_loss: 0.1517
Epoch 30/50
 - 0s - loss: 0.1562 - val_loss: 0.1486
Epoch 31/50
 - 0s - loss: 0.1542 - val_loss: 0.1457
Epoch 32/50
 - 0s - loss: 0.1524 - val_loss: 0.1430
Epoch 33/50
 - 0s - loss: 0.1505 - val_loss: 0.1404
Epoch 34/50
 - 0s - loss: 0.1487 - val_loss: 0.1380
Epoch 35/50
 - 0s - loss: 0.1468 - val_loss: 0.1357
Epoch 36/50
 - 0s - loss: 0.1449 - val_loss: 0.1335
Epoch 37/50
 - 0s - loss: 0.1429 - val_loss: 0.1313
Epoch 38/50
```

```
 - 0s - loss: 0.1410 - val_loss: 0.1292
Epoch 39/50
 - 0s - loss: 0.1390 - val_loss: 0.1272
Epoch 40/50
 - 0s - loss: 0.1371 - val_loss: 0.1253
Epoch 41/50
 - 0s - loss: 0.1352 - val_loss: 0.1235
Epoch 42/50
 - 0s - loss: 0.1334 - val_loss: 0.1219
Epoch 43/50
 - 0s - loss: 0.1318 - val_loss: 0.1206
Epoch 44/50
 - 0s - loss: 0.1302 - val_loss: 0.1197
Epoch 45/50
 - 0s - loss: 0.1287 - val_loss: 0.1190
Epoch 46/50
 - 0s - loss: 0.1272 - val_loss: 0.1185
Epoch 47/50
 - 0s - loss: 0.1254 - val_loss: 0.1182
Epoch 48/50
 - 0s - loss: 0.1236 - val_loss: 0.1181
Epoch 49/50
 - 0s - loss: 0.1218 - val_loss: 0.1179
Epoch 50/50
 - 0s - loss: 0.1199 - val_loss: 0.1179
```



Evaluate

In [225]:
```
from keras.layers import Concatenate
# make a prediction
yhat = model2.predict(test_X)
test_X = test_X.reshape((test_X.shape[0], test_X.shape[2]))
```

In [242]:
```
# invert scaling for forecast
inv_yhat = np.concatenate((yhat, test_X[:, 1:]), axis=1)
inv_yhat = scaler.inverse_transform(inv_yhat)
inv_yhat = inv_yhat[:,0]
```

In [248]:
```
import math
# invert scaling for actual
test_y = test_y.reshape((len(test_y), 1))
inv_y = np.concatenate((test_y, test_X[:, 1:]), axis=1)
inv_y = scaler.inverse_transform(inv_y)
inv_y = inv_y[:,0]
# calculate RMSE
rmse = math.sqrt(mean_squared_error(inv_y, inv_yhat))
print('Test RMSE: %.3f' % rmse)
```

```
Test RMSE: 3919.988
```

In [252]:
```
yhat[-3:]
```

Out[252]:
```
array([[0.5585367 ],
       [0.4273869 ],
       [0.34198684]], dtype=float32)
```

In [251]:
```
test_X[-3:]
```

Out[251]:
```
array([[0.7200773 , 0.25287703, 0.00854635, 1.        ],
       [0.76584697, 0.28505477, 0.00755182, 0.        ],
       [0.46459287, 0.17767489, 0.00722205, 0.16666667]], dtype=float32)
```