Multivariate Time Series Forecasting

Long Short-Term Memory (LSTM)

Based on Jason Brownlee's tutorial: [Multivariate Time Series Forecasting with LSTMs in Keras (https://machinelearningmastery.com/multivariate-time-series-forecasting-lstms-keras/)](https://machinelearningmastery.com/multivariate-time-series-forecasting-lstms-keras/)

In [1]:

```
from math import sqrt
import pandas as pd
from datetime import datetime
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:

```
parse = lambda x: pd.datetime.strptime(x, '%Y %m %d %H')
df = pd.read_csv('pollution.csv', \
                 parse_dates =[['year', 'month', 'day', 'hour']], \
                 skiprows=25, \
                 usecols=[1,2,3,4,5,6,7,8,9,10,11,12], \
                 names = ["year","month","day", "hour","pollution","dew","temp","pre
ss", "wnd_dir","wnd_spd","snow", "rain"], \
                 date_parser = parse, \
                index_col=0)

df.index.name = 'date'
# mark all NA values with 0
df['pollution'].fillna(0, inplace=True)
```

In [3]:

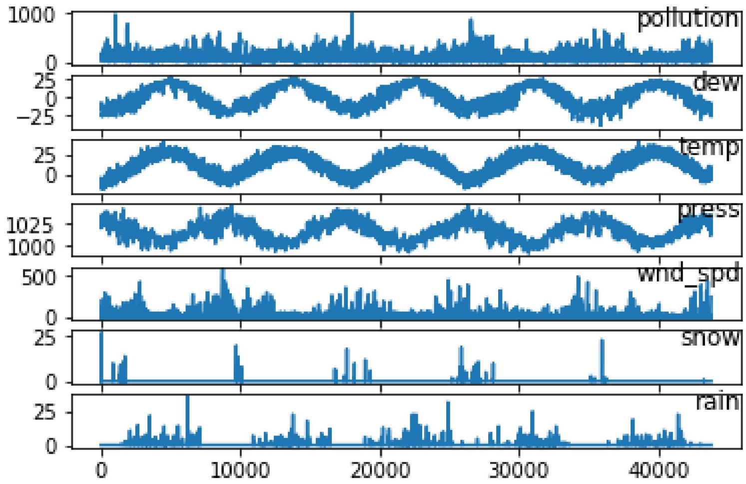
```
df.head()
```

Out[3]:

	pollution	dew	temp	press	wnd_dir	wnd_spd	snow	rain
date								
2010-01-02 00:00:00	129.0	-16	-4.0	1020.0	SE	1.79	0	0
2010-01-02 01:00:00	148.0	-15	-4.0	1020.0	SE	2.68	0	0
2010-01-02 02:00:00	159.0	-11	-5.0	1021.0	SE	3.57	0	0
2010-01-02 03:00:00	181.0	-7	-5.0	1022.0	SE	5.36	1	0
2010-01-02 04:00:00	138.0	-7	-5.0	1022.0	SE	6.25	2	0

In [4]:

```
# plots each series as a separate subplot
values = df.values
# specify columns to plot
groups = [0, 1, 2, 3, 5, 6, 7]
i = 1
# plot each column
plt.figure()
for group in groups:
    plt.subplot(len(groups), 1, i)
    plt.plot(values[:, group])
    plt.title(df.columns[group], y=0.5, loc='right')
    i += 1
plt.show()
```



In [5]:

```
df.dtypes
```

Out[5]:

```
pollution    float64
dew            int64
temp         float64
press        float64
wnd_dir       object
wnd_spd      float64
snow           int64
rain           int64
dtype: object
```

In [6]:

```
# Encode the categorical columns
# in this case, we have only wnd_dir
# df --> data
from sklearn.preprocessing import LabelEncoder

encs = dict()
data = df.copy()  #.sample(frac=1)
for c in data.columns:
    if data[c].dtype == "object":
        encs[c] = LabelEncoder()
        data[c] = encs[c].fit_transform(data[c])
```

In [7]:

```
data.dtypes
```

Out[7]:

```
pollution    float64
dew            int64
temp         float64
press        float64
wnd_dir        int32
wnd_spd      float64
snow           int64
rain           int64
dtype: object
```

In [8]:

```
# ensure all data is float
values = data.values.astype('float32')
```

In [9]:

```
# normalize features
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler(feature_range=(0, 1))
scaled = scaler.fit_transform(values)
```

In [10]:

```
# 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 = pd.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 = pd.concat(cols, axis=1)
    agg.columns = names
    # drop rows with NaN values
    if dropnan:
        agg.dropna(inplace=True)
    return agg


# specify the number of lag hours
n_hours = 3
n_features = 8
# frame as supervised learning
reframed = series_to_supervised(scaled, n_hours, 1)
```

In [11]:

```
# To understand this function, run each code below in a cell
#reframed[['var1(t)', 'var1(t-1)','var1(t-2)','var1(t-3)']]
#pd.DataFrame(scaled).head()
#0,129779
```

In [12]:

```
# split into train and test sets
values = reframed.values
n_train_hours = 365 * 24
train = values[:n_train_hours, :]
test = values[n_train_hours:, :]


# split into input and outputs
n_obs = n_hours * n_features
train_X, train_y = train[:, :n_obs], train[:, -n_features]
test_X, test_y = test[:, :n_obs], test[:, -n_features]
print(train_X.shape, len(train_X), train_y.shape)
```

```
(8760, 24) 8760 (8760,)
```

In [13]:

```
# reshape input to be 3D [samples, timesteps, features]
train_X = train_X.reshape((train_X.shape[0], n_hours, n_features))
test_X = test_X.reshape((test_X.shape[0], n_hours, n_features))
print(train_X.shape, train_y.shape, test_X.shape, test_y.shape)
```

```
(8760, 3, 8) (8760,) (35037, 3, 8) (35037,)
```

In [14]:

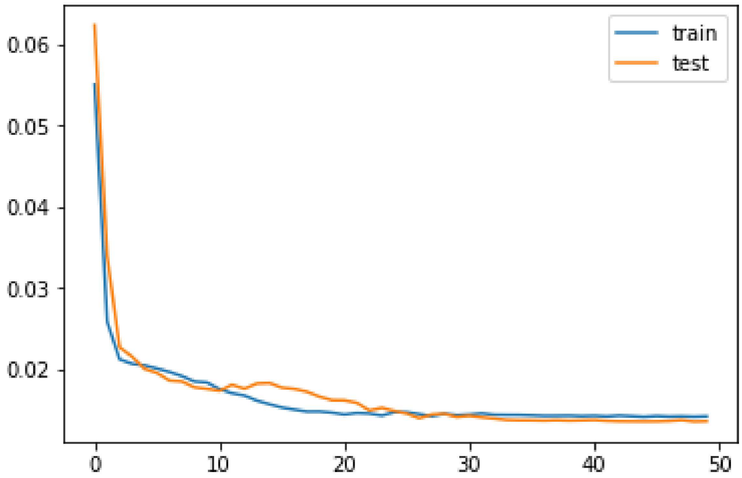
```
from sklearn.metrics import mean_squared_error
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM

# design network
model = Sequential()
model.add(LSTM(50, input_shape=(train_X.shape[1], train_X.shape[2])))
model.add(Dense(1))
model.compile(loss='mae', optimizer='adam')
# fit network
history = model.fit(train_X, train_y, epochs=50, batch_size=72, validation_data=(tes
t_X, test_y), verbose=2, shuffle=False)
# plot history
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```

```
C:\Users\Ricardo\Anaconda3\lib\site-packages\h5py\__init__.py:36: Future
Warning: Conversion of the second argument of issubdtype from `float` to
`np.floating` is deprecated. In future, it will be treated as `np.float6
4 == np.dtype(float).type`.
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
```

```
Train on 8760 samples, validate on 35037 samples
Epoch 1/50
 - 1s - loss: 0.0551 - val_loss: 0.0624
Epoch 2/50
 - 0s - loss: 0.0259 - val_loss: 0.0340
Epoch 3/50
 - 0s - loss: 0.0212 - val_loss: 0.0227
Epoch 4/50
 - 0s - loss: 0.0207 - val_loss: 0.0215
Epoch 5/50
 - 0s - loss: 0.0205 - val_loss: 0.0200
Epoch 6/50
 - 0s - loss: 0.0201 - val_loss: 0.0195
Epoch 7/50
 - 0s - loss: 0.0197 - val_loss: 0.0186
Epoch 8/50
 - 1s - loss: 0.0192 - val_loss: 0.0185
Epoch 9/50
 - 0s - loss: 0.0185 - val_loss: 0.0178
Epoch 10/50
 - 0s - loss: 0.0184 - val_loss: 0.0176
Epoch 11/50
 - 0s - loss: 0.0175 - val_loss: 0.0173
Epoch 12/50
 - 0s - loss: 0.0170 - val_loss: 0.0181
Epoch 13/50
 - 0s - loss: 0.0167 - val_loss: 0.0176
Epoch 14/50
 - 0s - loss: 0.0161 - val_loss: 0.0182
Epoch 15/50
 - 1s - loss: 0.0157 - val_loss: 0.0183
Epoch 16/50
 - 1s - loss: 0.0153 - val_loss: 0.0177
Epoch 17/50
 - 1s - loss: 0.0150 - val_loss: 0.0176
Epoch 18/50
 - 1s - loss: 0.0148 - val_loss: 0.0172
Epoch 19/50
 - 1s - loss: 0.0148 - val_loss: 0.0166
Epoch 20/50
 - 1s - loss: 0.0146 - val_loss: 0.0162
Epoch 21/50
 - 0s - loss: 0.0144 - val_loss: 0.0162
Epoch 22/50
 - 0s - loss: 0.0146 - val_loss: 0.0158
Epoch 23/50
 - 0s - loss: 0.0145 - val_loss: 0.0149
Epoch 24/50
 - 0s - loss: 0.0143 - val_loss: 0.0152
Epoch 25/50
 - 1s - loss: 0.0147 - val_loss: 0.0148
Epoch 26/50
 - 0s - loss: 0.0147 - val_loss: 0.0145
Epoch 27/50
 - 0s - loss: 0.0145 - val_loss: 0.0140
Epoch 28/50
 - 0s - loss: 0.0142 - val_loss: 0.0144
Epoch 29/50
 - 0s - loss: 0.0145 - val_loss: 0.0145
Epoch 30/50
 - 0s - loss: 0.0143 - val_loss: 0.0141
```

```
Epoch 31/50
 - 0s - loss: 0.0144 - val_loss: 0.0143
Epoch 32/50
 - 0s - loss: 0.0145 - val_loss: 0.0141
Epoch 33/50
 - 0s - loss: 0.0144 - val_loss: 0.0139
Epoch 34/50
 - 0s - loss: 0.0144 - val_loss: 0.0137
Epoch 35/50
 - 0s - loss: 0.0144 - val_loss: 0.0137
Epoch 36/50
 - 0s - loss: 0.0143 - val_loss: 0.0137
Epoch 37/50
 - 0s - loss: 0.0142 - val_loss: 0.0137
Epoch 38/50
 - 0s - loss: 0.0143 - val_loss: 0.0137
Epoch 39/50
 - 0s - loss: 0.0143 - val_loss: 0.0137
Epoch 40/50
 - 0s - loss: 0.0142 - val_loss: 0.0137
Epoch 41/50
 - 0s - loss: 0.0143 - val_loss: 0.0137
Epoch 42/50
 - 0s - loss: 0.0142 - val_loss: 0.0136
Epoch 43/50
 - 0s - loss: 0.0143 - val_loss: 0.0136
Epoch 44/50
 - 0s - loss: 0.0142 - val_loss: 0.0136
Epoch 45/50
 - 0s - loss: 0.0141 - val_loss: 0.0135
Epoch 46/50
 - 0s - loss: 0.0142 - val_loss: 0.0136
Epoch 47/50
 - 0s - loss: 0.0142 - val_loss: 0.0136
Epoch 48/50
 - 0s - loss: 0.0142 - val_loss: 0.0137
Epoch 49/50
 - 0s - loss: 0.0141 - val_loss: 0.0135
Epoch 50/50
 - 0s - loss: 0.0142 - val_loss: 0.0136
```



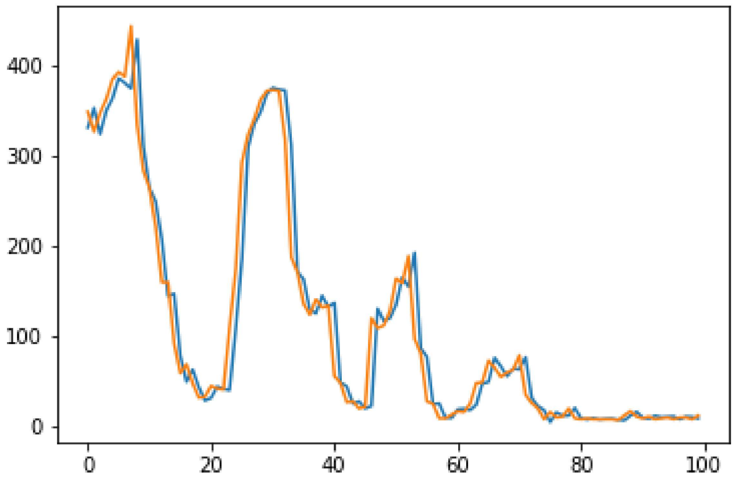
In [15]:

```
# make a prediction
yhat = model.predict(test_X)
test_X = test_X.reshape((test_X.shape[0], n_hours*n_features))
# invert scaling for forecast
inv_yhat = np.concatenate((yhat, test_X[:, -7:]), axis=1)
inv_yhat = scaler.inverse_transform(inv_yhat)
inv_yhat = inv_yhat[:,0]
# invert scaling for actual
test_y = test_y.reshape((len(test_y), 1))
inv_y = np.concatenate((test_y, test_X[:, -7:]), axis=1)
inv_y = scaler.inverse_transform(inv_y)
inv_y = inv_y[:,0]
# calculate RMSE
rmse = sqrt(mean_squared_error(inv_y, inv_yhat))
print('Test RMSE: %.3f' % rmse)
```

```
Test RMSE: 26.464
```

In [16]:

```
# The predictions look like persistence value(t) = value(t-1)
plt.plot(inv_yhat[-100:])
plt.plot(inv_y[-100:])
plt.show()
```



In [ ]: