Standalone LSTM Encoder - Decoder Model

In this model, we first create an LSTM-based encoder-decoder model and then extract out the standalone encoder. Recurrent neural networks, such as a long short-term memory (LSTM) networks, are specifically designed to model sequences of input data. In this neural network architecture, the encoder reads the input sequence time step, by time step. After digesting the entire time step sequence, it's output, or hidden state, is a compressed representation of the input sequence as a fixed length vector. The vector is then provided as input to the decoder which interprets each time step of the output sequence as its generated.

Once a satisfactory encoder-decoder model has been created, one that accurately depicts the reconstruction of the input sequence, we can separate the encoder model as a standalone model. The standalone encoder will contain only those layers up to creation of the fixed length vector. The encoder model can then be used as a learned, compressed representation of the input features to feed into other models.

Here we take a multivariate sequence containing six numbers per time step (6 features per time step) and feed the LSTM model a block of 12 time steps at once for analysis. We use a batch size of 20.

In [1]:
```
# import libraries
import pandas as pd
import numpy as np
import random as rn
import tensorflow as tf
from tensorflow import set_random_seed
from math import sqrt
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from keras.models import Model
from keras.layers import Input, LSTM, Dense, Dropout, Bidirectional, TimeDistributed, RepeatVector
from keras.callbacks import ModelCheckpoint, TensorBoard
from keras import regularizers
from keras.optimizers import Adam, RMSprop
```

```
Using TensorFlow backend.
```

In [2]:
```
# set the random seed
tf.logging.set_verbosity(tf.logging.ERROR)
sd = 777
np.random.seed(sd)
rn.seed(sd)
set_random_seed(sd)
```

In [3]:
```
# load dataset
series = pd.read_csv('data/sequence.csv', engine='python', header=None)
series.head(10)
```

Out[3]:

	0	1	2	3	4	5
0	3	15	20	21	36	40
1	7	18	28	35	38	42
2	12	22	23	26	27	43
3	14	19	23	34	36	41
4	11	12	20	30	32	44
5	8	13	19	28	39	41
6	2	10	22	24	27	41
7	18	20	23	25	35	39
8	8	15	24	36	38	40
9	6	21	26	27	33	39

In [4]:

```
# drop columns if needed
df = series.drop([], axis=1)
print("Dataset length:", len(df))
df.head(10)
```

```
Dataset length: 2156
```

Out[4]:

	0	1	2	3	4	5
0	3	15	20	21	36	40
1	7	18	28	35	38	42
2	12	22	23	26	27	43
3	14	19	23	34	36	41
4	11	12	20	30	32	44
5	8	13	19	28	39	41
6	2	10	22	24	27	41
7	18	20	23	25	35	39
8	8	15	24	36	38	40
9	6	21	26	27	33	39

In [5]:

```
# extract the values
data = df.values
data = data.astype('float64')
```

In [6]:

```
# normalize the data
scaler = MinMaxScaler(feature_range=(0, 1))
data_scaled = scaler.fit_transform(data)
print("The scaled dataset shape is: " + str(data_scaled.shape))
print(data_scaled)
```

```
The scaled dataset shape is: (2156, 6)
[[0.07142857 0.38235294 0.44736842 0.44736842 0.80555556 0.86666667]
 [0.21428571 0.47058824 0.65789474 0.81578947 0.86111111 0.93333333]
 [0.39285714 0.58823529 0.52631579 0.57894737 0.55555556 0.96666667]
 ...
 [0.14285714 0.32352941 0.44736842 0.86842105 0.86111111 0.86666667]
 [0.14285714 0.41176471 0.44736842 0.63157895 0.63888889 0.93333333]
 [0.         0.         0.10526316 0.15789474 0.44444444 0.33333333]]
```

In [7]:
```
def reverse_scale_predictions(scaler, input_set):
    scaled_set, temp = list(), list()
    for i in range(len(input_set)):
        row = input_set[i]
        row = np.reshape(row, (input_set.shape[1], input_set.shape[2]))
        out = scaler.inverse_transform(row)
        out2 = np.around(out).astype(int)
        temp.append(out2)
    temp2 = np.array(temp).tolist()
    while temp2:
        scaled_set.extend(temp2.pop(0))
    return scaled_set
```

In [8]:
```
# split a multivariate sequence into samples
def split_sequences(sequences, n_steps):
    X, y = list(), list()
    for i in range(len(sequences)):
        # find the end of this pattern
        end_ix = i + n_steps
        # check if we are beyond the dataset
        if end_ix > len(sequences)-1:
            break
        # gather input and output parts of the pattern
        seq_x, seq_y = sequences[i:end_ix, :], sequences[end_ix, :]
        X.append(seq_x)
        y.append(seq_y)
    return np.array(X), np.array(y)
```

In [9]:
```
# create features and targets
n_steps = 12
X, y = split_sequences(data_scaled, n_steps)
print("Input shape: " + str(X.shape))
print("Target shape: " + str(y.shape))
```

```
Input shape: (2144, 12, 6)
Target shape: (2144, 6)
```

In [10]:

```
# modify for batch sizing
X = X[4:]
y = y[4:]
print("Revised input shape: " + str(X.shape))
print("Revised target shape: " + str(y.shape))
```

```
Revised input shape: (2140, 12, 6)
Revised target shape: (2140, 6)
```

In [11]:

```
# define the Autoencoder model
def autoencoder_model(X, batch_size):
    inputs = Input(batch_shape=(batch_size, X.shape[1], X.shape[2]))
    enc1 = LSTM(512, activation='relu', return_sequences=True)(inputs)
    enc2 = LSTM(256, activation='relu', return_sequences=True)(enc1)
    enc3 = LSTM(128, activation='relu', return_sequences=False)(enc2)
    dec1 = RepeatVector(X.shape[1])(enc3)
    dec2 = LSTM(128, activation='relu', return_sequences=True)(dec1)
    dec3 = LSTM(256, activation='relu', return_sequences=True)(dec2)
    dec4 = LSTM(512, activation='relu', return_sequences=True)(dec3)
    output = TimeDistributed(Dense(X.shape[2]))(dec4)
    model = Model(inputs=inputs, outputs=output)
    return model
```

In [12]:
```
# create the LSTM Autoencoder model
batch_size = 20
autoencoder = autoencoder_model(X, batch_size)
autoencoder.compile(optimizer='adam', loss='mse')
autoencoder.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_1 (InputLayer)         (20, 12, 6)               0         
_________________________________________________________________
lstm_1 (LSTM)                (20, 12, 512)             1062912   
_________________________________________________________________
lstm_2 (LSTM)                (20, 12, 256)             787456    
_________________________________________________________________
lstm_3 (LSTM)                (20, 128)                 197120    
_________________________________________________________________
repeat_vector_1 (RepeatVecto (20, 12, 128)             0         
_________________________________________________________________
lstm_4 (LSTM)                (20, 12, 128)             131584    
_________________________________________________________________
lstm_5 (LSTM)                (20, 12, 256)             394240    
_________________________________________________________________
lstm_6 (LSTM)                (20, 12, 512)             1574912   
_________________________________________________________________
time_distributed_1 (TimeDist (20, 12, 6)               3078      
=================================================================
Total params: 4,151,302
Trainable params: 4,151,302
Non-trainable params: 0
_________________________________________________________________
```

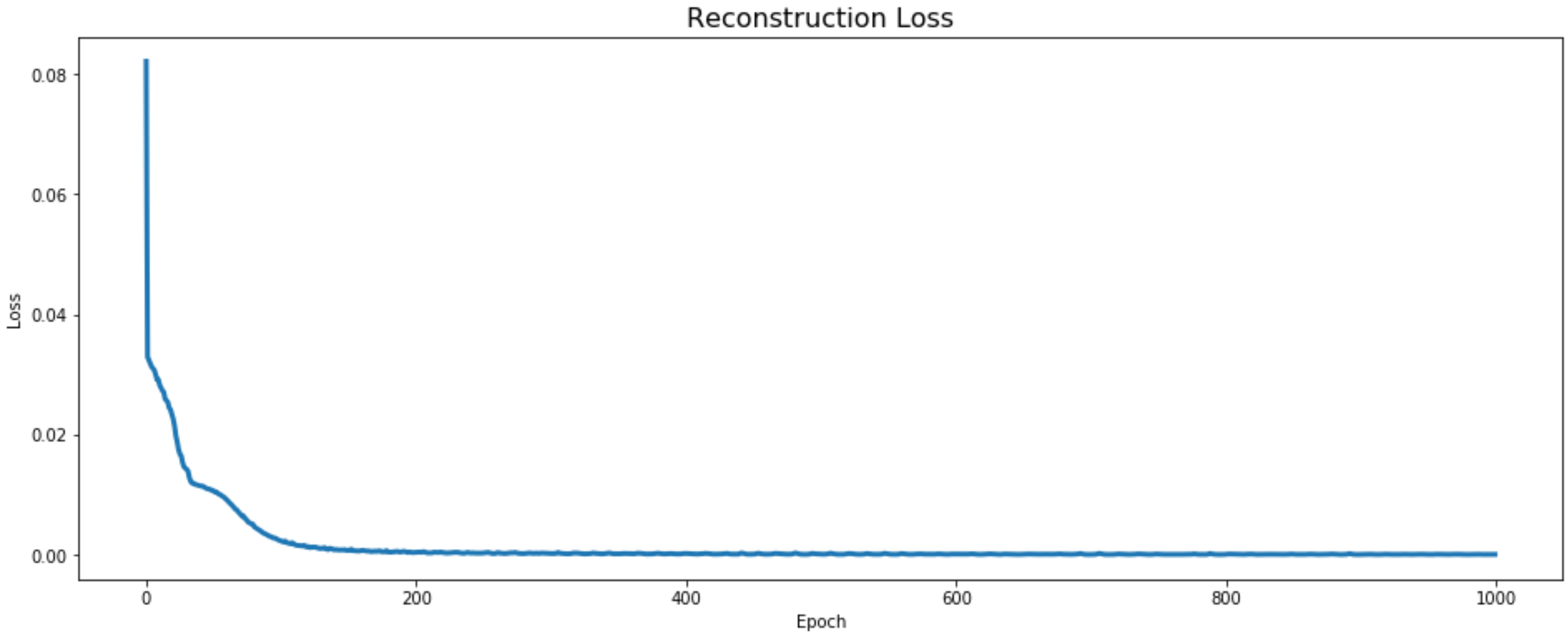
In [13]:
```
# fit the model
nb_epochs = 1000
history = autoencoder.fit(X, X, epochs=nb_epochs, batch_size=batch_size).history
```

```
Epoch 1/1000
2140/2140 [==============================] - 35s 17ms/step - loss: 0.0821
Epoch 2/1000
2140/2140 [==============================] - 32s 15ms/step - loss: 0.0329
Epoch 3/1000
2140/2140 [==============================] - 32s 15ms/step - loss: 0.0323
Epoch 4/1000
2140/2140 [==============================] - 32s 15ms/step - loss: 0.0317
Epoch 5/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0313
Epoch 6/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0310
Epoch 7/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0307
Epoch 8/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0300
Epoch 9/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0291
Epoch 10/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0291
Epoch 11/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0282
Epoch 12/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0277
Epoch 13/1000
2140/2140 [==============================] - 31s 15ms/step - loss: 0.0273
Epoch 14/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0270
Epoch 15/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0259
Epoch 16/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0256
Epoch 17/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0254
Epoch 18/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0244
Epoch 19/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0241
Epoch 20/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0234
Epoch 21/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0226
Epoch 22/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0214
Epoch 23/1000
2140/2140 [==============================] - 30s 14ms/step - loss: 0.0198
```

In [14]:
```
# validate autoencoder
yhat = autoencoder.predict(X, batch_size)
baseline = reverse_scale_predictions(scaler, X)
predictions = reverse_scale_predictions(scaler, yhat)
for i in range(10):
    print("actual: %s, predicted: %s" % (baseline[i], predictions[i]))
```

```
actual: [11, 12, 20, 30, 32, 44], predicted: [11, 12, 20, 30, 32, 44]
actual: [8, 13, 19, 28, 39, 41], predicted: [8, 14, 19, 27, 39, 41]
actual: [2, 10, 22, 24, 27, 41], predicted: [2, 10, 22, 24, 27, 41]
actual: [18, 20, 23, 25, 35, 39], predicted: [18, 20, 23, 24, 34, 39]
actual: [8, 15, 24, 36, 38, 40], predicted: [8, 15, 24, 36, 38, 40]
actual: [6, 21, 26, 27, 33, 39], predicted: [6, 21, 26, 27, 32, 39]
actual: [11, 14, 15, 18, 21, 40], predicted: [11, 14, 15, 18, 21, 40]
actual: [12, 26, 27, 28, 33, 39], predicted: [12, 26, 27, 28, 33, 39]
actual: [6, 11, 14, 24, 27, 37], predicted: [6, 11, 14, 24, 27, 37]
actual: [19, 33, 37, 39, 41, 44], predicted: [19, 34, 37, 39, 41, 44]
```

In [15]:
```
# plot the model loss
plt.figure(figsize=(16,6))
plt.plot(history['loss'], linewidth=3)
plt.title('Reconstruction Loss', fontsize=16)
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.show()
```



In [16]:
```
# create stand alone encoder
encoder = Model(inputs=autoencoder.inputs, outputs=autoencoder.layers[3].output)
encoder.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (20, 12, 6)               0
_________________________________________________________________
lstm_1 (LSTM)                (20, 12, 512)             1062912
_________________________________________________________________
lstm_2 (LSTM)                (20, 12, 256)             787456
_________________________________________________________________
lstm_3 (LSTM)                (20, 128)                 197120
=================================================================
Total params: 2,047,488
Trainable params: 2,047,488
Non-trainable params: 0
_________________________________________________________________
```

In [18]:
```
# validate encoder output
encoder_output = encoder.predict(X, batch_size)
print("Encoder output shape:", encoder_output.shape)
print(encoder_output)
```

```
Encoder output shape: (2140, 128)
[[0.         0.01816534 0.         ... 0.01122764 0.         0.        ]
 [0.         0.0544333  0.         ... 0.01204368 0.         0.22154157]
 [0.         0.03412243 0.         ... 0.03304881 0.         0.        ]
 ...
 [0.         0.02169593 0.         ... 0.         0.         0.17469828]
 [0.         0.00356639 0.         ... 0.00160127 0.         0.07961552]
 [0.         0.5866183  0.         ... 0.01417389 0.         0.56231415]]
```

In [19]:
```
# spacer
```

In [20]:

```
# save model in YAML format and weights in HDF5
model_yaml = encoder.to_yaml()
with open("encoder_standalone_20x12x6.yaml", "w") as yaml_file:
    yaml_file.write(model_yaml)
print("Model saved")
encoder.save_weights("encoder_standalone_20x12x6.hdf5")
print("Model weights saved")
```

```
Model saved
Model weights saved
```

In [ ]: