

Deep Learning for Predictive Maintenance

In [41]: `import keras`

In [42]: `import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from keras.layers import Dense, Dropout, GRU, Input,Conv1D, MaxPooling1D, Flatten, concatenate
%matplotlib inline
from keras.models import Model`

In [43]: `train_data = pd.read_csv('train_data.txt')
train_data`

Out[43]:

	id	cycle	setting1	setting2	setting3	s1	s2	s3	s4	s5	...	s16	s17	s18	s19	s20	s21	RUL	label1	label2	cycle_norm	
	0	1	1	0.459770	0.166667	0.0	0.0	0.183735	0.406802	0.309757	0.0	...	0.0	0.333333	0.0	0.0	0.713178	0.724662	191	0	0	0.000000
	1	1	2	0.609195	0.250000	0.0	0.0	0.283133	0.453019	0.352633	0.0	...	0.0	0.333333	0.0	0.0	0.666667	0.731014	190	0	0	0.002770
	2	1	3	0.252874	0.750000	0.0	0.0	0.343373	0.369523	0.370527	0.0	...	0.0	0.166667	0.0	0.0	0.627907	0.621375	189	0	0	0.005540
	3	1	4	0.540230	0.500000	0.0	0.0	0.343373	0.256159	0.331195	0.0	...	0.0	0.333333	0.0	0.0	0.573643	0.662386	188	0	0	0.008310
	4	1	5	0.390805	0.333333	0.0	0.0	0.349398	0.257467	0.404625	0.0	...	0.0	0.416667	0.0	0.0	0.589147	0.704502	187	0	0	0.011080

20626	100	196	0.477011	0.250000	0.0	0.0	0.686747	0.587312	0.782917	0.0	...	0.0	0.750000	0.0	0.0	0.271318	0.109500	4	1	2	0.540166	
20627	100	197	0.408046	0.083333	0.0	0.0	0.701807	0.729453	0.866475	0.0	...	0.0	0.583333	0.0	0.0	0.124031	0.366197	3	1	2	0.542936	
20628	100	198	0.522989	0.500000	0.0	0.0	0.665663	0.684979	0.775321	0.0	...	0.0	0.833333	0.0	0.0	0.232558	0.053991	2	1	2	0.545706	
20629	100	199	0.436782	0.750000	0.0	0.0	0.608434	0.746021	0.747468	0.0	...	0.0	0.583333	0.0	0.0	0.116279	0.234466	1	1	2	0.548476	
20630	100	200	0.316092	0.083333	0.0	0.0	0.795181	0.639634	0.842167	0.0	...	0.0	0.666667	0.0	0.0	0.178295	0.218172	0	1	2	0.551247	

20631 rows × 30 columns

In [44]: `test_data = pd.read_csv('test_data.txt')
test_data`

Out[44]:

	id	cycle	setting1	setting2	setting3	s1	s2	s3	s4	s5	...	s16	s17	s18	s19	s20	s21	cycle_norm	RUL	label1	label2	
	0	1	1	0.632184	0.750000	0.0	0.0	0.545181	0.310661	0.269413	0.0	...	0.0	0.333333	0.0	0.0	0.558140	0.661834	0.000000	142	0	0
	1	1	2	0.344828	0.250000	0.0	0.0	0.150602	0.379551	0.222316	0.0	...	0.0	0.416667	0.0	0.0	0.682171	0.686827	0.002770	141	0	0
	2	1	3	0.517241	0.583333	0.0	0.0	0.376506	0.346632	0.322248	0.0	...	0.0	0.416667	0.0	0.0	0.728682	0.721348	0.005540	140	0	0
	3	1	4	0.741379	0.500000	0.0	0.0	0.370482	0.285154	0.408001	0.0	...	0.0	0.250000	0.0	0.0	0.666667	0.662110	0.008310	139	0	0
	4	1	5	0.580460	0.500000	0.0	0.0	0.391566	0.352082	0.332039	0.0	...	0.0	0.166667	0.0	0.0	0.658915	0.716377	0.011080	138	0	0

13091	100	194	0.781609	0.500000	0.0	0.0	0.611446	0.619359	0.566172	0.0	...	0.0	0.500000	0.0	0.0	0.395349	0.418669	0.534626	24	1	1	
13092	100	195	0.436782	0.416667	0.0	0.0	0.605422	0.537388	0.671843	0.0	...	0.0	0.583333	0.0	0.0	0.333333	0.528721	0.537396	23	1	1	
13093	100	196	0.465517	0.250000	0.0	0.0	0.671687	0.482014	0.414754	0.0	...	0.0	0.583333	0.0	0.0	0.372093	0.429301	0.540166	22	1	1	
13094	100	197	0.281609	0.583333	0.0	0.0	0.617470	0.522128	0.626435	0.0	...	0.0	0.583333	0.0	0.0	0.403101	0.518779	0.542936	21	1	1	
13095	100	198	0.574713	0.750000	0.0	0.0	0.524096	0.666667	0.721472	0.0	...	0.0	0.666667	0.0	0.0	0.434109	0.402237	0.545706	20	1	1	

13096 rows × 30 columns

Modelling

In [45]: `# window size of 60 cycles
sequence_len = 60`

In [46]: `def gen_sequence(id_data, seq_length, seq_cols):
 data_array = id_data[seq_cols].values
 num_elements = data_array.shape[0]
 for start, stop in zip(range(0, num_elements-seq_length), range(seq_length, num_elements)):
 yield data_array[start:stop, :]`

In [47]: `sequence_cols = ['setting1', 'setting2', 'setting3', 'cycle_norm', 's1', 's2', 's3', 's4', 's5', 's6', 's7', 's8', 's9', 's10', 's11', 's12', 's13', 's14', 's15', 's16', 's17', 's18', 's19', 's20', 's21']`

In [48]: `seq_gen = (list(gen_sequence(train_data[train_data['id']==id], sequence_len, sequence_cols))
 for id in train_data['id'].unique())
seq_array = np.concatenate(list(seq_gen)).astype(np.float32)
seq_array.shape`

Out[48]: (14631, 60, 25)

In [49]: `def gen_labels(id_df, seq_length, label):
 data_array = id_df[label].values
 num_elements = data_array.shape[0]
 return data_array[seq_length:num_elements, :]`

In [50]: `label_gen = [gen_labels(train_data[train_data['id']==id], sequence_len, ['label1'])
 for id in train_data['id'].unique()]
label_array = np.concatenate(label_gen).astype(np.float32)
label_array.shape`

Out[50]: (14631, 1)

GRU Network

```
In [51]: nb_features = seq_array.shape[2]
nb_out = 1
in_shape = (sequence_len, nb_features)
input_n = Input(shape=in_shape)
input_n.shape
```

Out[51]: (None, 60, 25)

```
In [52]: # Define the sigmoid activation function
def sigmoid(x):
    return 1 / (1 + np.exp(-x))

# Define the tanh activation function
def tanh(x):
    return np.tanh(x)

# Define the derivative of the tanh function
def tanh_derivative(x):
    return 1 - np.square(np.tanh(x))
```

```
In [53]: gru1 = GRU(units=500, return_sequences=True)(input_n)
dropout1 = Dropout(0.2)(gru1)
```

```
In [54]: gru2 = GRU(units=100, return_sequences=False)(dropout1)
dropout2 = Dropout(0.2)(gru2)
```

```
In [55]: conv1 = Conv1D(filters=64, kernel_size=3, activation='relu')(input_n)
conv2 = Conv1D(filters=128, kernel_size=3, activation='relu')(conv1)
pool1 = MaxPooling1D(pool_size=2)(conv2)
flatten1 = Flatten()(pool1)
```

```
In [56]: concat = concatenate([dropout2, flatten1])
```

```
In [57]: output_n = Dense(units=nb_out, activation='sigmoid')(concat) #sigmoid (0,1) as we've used binary classification
```

```
In [58]: #our model
model = Model(inputs=input_n, outputs=output_n)
```

```
In [59]: model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

```
In [60]: print(model.summary())
```

Model: "functional_3"

Layer (type)	Output Shape	Param #	Connected to
input_layer_1 (InputLayer)	(None, 60, 25)	0	-
gru_2 (GRU)	(None, 60, 500)	790,500	input_layer_1[0]...
conv1d_2 (Conv1D)	(None, 58, 64)	4,864	input_layer_1[0]...
dropout_2 (Dropout)	(None, 60, 500)	0	gru_2[0][0]
conv1d_3 (Conv1D)	(None, 56, 128)	24,704	conv1d_2[0][0]
gru_3 (GRU)	(None, 100)	180,600	dropout_2[0][0]
max_pooling1d_1 (MaxPooling1D)	(None, 28, 128)	0	conv1d_3[0][0]
dropout_3 (Dropout)	(None, 100)	0	gru_3[0][0]
flatten_1 (Flatten)	(None, 3584)	0	max_pooling1d_1[...
concatenate_1 (Concatenate)	(None, 3684)	0	dropout_3[0][0], flatten_1[0][0]
dense_1 (Dense)	(None, 1)	3,685	concatenate_1[0]...

Total params: 1,004,353 (3.83 MB)

Trainable params: 1,004,353 (3.83 MB)

Non-trainable params: 0 (0.00 B)

None

```
In [61]: model.fit(seq_array, label_array, epochs=1, batch_size=250, validation_split=0.02, verbose=1,
callbacks = [keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0, patience=10, verbose=0, mode='auto')])
print("Model evaluation on training data:")
print("Loss: %.2f" % scores[0])
print("Accuracy: %.2f" % scores[1])
```

58/58 ----- 117s 2s/step - accuracy: 0.8587 - loss: 0.3496 - val_accuracy: 0.9181 - val_loss: 0.1710
Model evaluation on training data:
Loss: 0.13
Accuracy: 0.95

```
In [62]: # training metrics
scores = model.evaluate(seq_array, label_array, verbose=1, batch_size=200)
```

74/74 ----- 38s 509ms/step - accuracy: 0.9523 - loss: 0.1203

```
In [63]: seq_array_1 = [test_data[test_data['id']==id][sequence_cols].values[-sequence_len:]
for id in test_data['id'].unique() if len(test_data[test_data['id']==id]) >= sequence_len]
seq_array_test_last = np.asarray(seq_array_1).astype(np.float32)
seq_array_1 = np.asarray(seq_array_1).astype(np.float32)


# Filter labels for testing data
y_mask = [len(test_data[test_data['id']==id]) >= sequence_len for id in test_data['id'].unique()]
label_array_1 = test_data.groupby('id')['label1'].nth(-1)[y_mask].values
label_array_1 = label_array_1.reshape(label_array_1.shape[0],1).astype(np.float32)

print(seq_array_1.shape)
print(label_array_1.shape)
```

```
# Generate predictions for testing data
predictions = model.predict(seq_array_1)
```

(88, 60, 25)
(88, 1)
3/3  3s 1s/step

```
In [64]: scores_test = model.evaluate(seq_array_1, label_array_1, verbose=1)
print('Test Accuracy: {}'.format(scores_test[1]))
```

3/3  1s 144ms/step - accuracy: 0.9347 - loss: 0.2029
Test Accuracy: 0.9318181872367859