02_stacked_lstm_with_feature_embeddings

September 29, 2021

1 Stacked LSTMs for Time Series Classification with TensorFlow

We'll now build a slightly deeper model by stacking two LSTM layers using the Quandl stock price data. Furthermore, we will include features that are not sequential in nature, namely indicator variables for identifying the equity and the month.

1.1 Imports

[1]:
```
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
%matplotlib inline

from pathlib import Path
import numpy as np
import pandas as pd
from scipy.stats import spearmanr
from sklearn.metrics import roc_auc_score

import tensorflow as tf
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, LSTM, Input, concatenate, Embedding,␣
↪Reshape, BatchNormalization
import tensorflow.keras.backend as K

import matplotlib.pyplot as plt
import seaborn as sns
```

[3]:
```
gpu_devices = tf.config.experimental.list_physical_devices('GPU')
if gpu_devices:
    print('Using GPU')
    tf.config.experimental.set_memory_growth(gpu_devices[0], True)
else:
    print('Using CPU')
```

```
Using CPU
```

[4]:
```
idx = pd.IndexSlice
sns.set_style('whitegrid')
np.random.seed(42)
```

[5]:
```
results_path = Path('results', 'lstm_embeddings')
if not results_path.exists():
    results_path.mkdir(parents=True)
```

1.2 Data

Data produced by the notebook build_dataset.

[6]:
```
data = pd.read_hdf('data.h5', 'returns_weekly')
```

[7]:
```
data['ticker'] = pd.factorize(data.index.get_level_values('ticker'))[0]
```

[8]:
```
data['month'] = data.index.get_level_values('date').month
data = pd.get_dummies(data, columns=['month'], prefix='month')
```

[9]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 1167341 entries, ('A', Timestamp('2009-01-11 00:00:00')) to ('ZUMZ',
Timestamp('2017-12-31 00:00:00'))
Data columns (total 67 columns):
 #   Column       Non-Null Count    Dtype
---  ------       --------------    -----
 0   fwd_returns  1167341 non-null  float64
 1   1            1167341 non-null  float64
 2   2            1167341 non-null  float64
 3   3            1167341 non-null  float64
 4   4            1167341 non-null  float64
 5   5            1167341 non-null  float64
 6   6            1167341 non-null  float64
 7   7            1167341 non-null  float64
 8   8            1167341 non-null  float64
 9   9            1167341 non-null  float64
 10  10           1167341 non-null  float64
 11  11           1167341 non-null  float64
 12  12           1167341 non-null  float64
 13  13           1167341 non-null  float64
 14  14           1167341 non-null  float64
 15  15           1167341 non-null  float64
 16  16           1167341 non-null  float64
 17  17           1167341 non-null  float64
 18  18           1167341 non-null  float64
 19  19           1167341 non-null  float64
```

```
 20  20          1167341 non-null  float64
 21  21          1167341 non-null  float64
 22  22          1167341 non-null  float64
 23  23          1167341 non-null  float64
 24  24          1167341 non-null  float64
 25  25          1167341 non-null  float64
 26  26          1167341 non-null  float64
 27  27          1167341 non-null  float64
 28  28          1167341 non-null  float64
 29  29          1167341 non-null  float64
 30  30          1167341 non-null  float64
 31  31          1167341 non-null  float64
 32  32          1167341 non-null  float64
 33  33          1167341 non-null  float64
 34  34          1167341 non-null  float64
 35  35          1167341 non-null  float64
 36  36          1167341 non-null  float64
 37  37          1167341 non-null  float64
 38  38          1167341 non-null  float64
 39  39          1167341 non-null  float64
 40  40          1167341 non-null  float64
 41  41          1167341 non-null  float64
 42  42          1167341 non-null  float64
 43  43          1167341 non-null  float64
 44  44          1167341 non-null  float64
 45  45          1167341 non-null  float64
 46  46          1167341 non-null  float64
 47  47          1167341 non-null  float64
 48  48          1167341 non-null  float64
 49  49          1167341 non-null  float64
 50  50          1167341 non-null  float64
 51  51          1167341 non-null  float64
 52  52          1167341 non-null  float64
 53  label       1167341 non-null  int64
 54  ticker      1167341 non-null  int64
 55  month_1     1167341 non-null  uint8
 56  month_2     1167341 non-null  uint8
 57  month_3     1167341 non-null  uint8
 58  month_4     1167341 non-null  uint8
 59  month_5     1167341 non-null  uint8
 60  month_6     1167341 non-null  uint8
 61  month_7     1167341 non-null  uint8
 62  month_8     1167341 non-null  uint8
 63  month_9     1167341 non-null  uint8
 64  month_10    1167341 non-null  uint8
 65  month_11    1167341 non-null  uint8
 66  month_12    1167341 non-null  uint8
dtypes: float64(53), int64(2), uint8(12)
```

```
memory usage: 507.7+ MB
```

1.3 Train-test split

To respect the time series nature of the data, we set aside the data at the end of the sample as hold-out or test set. More specifically, we'll use the data for 2017.

[10]:
```
window_size=52
sequence = list(range(1, window_size+1))
ticker = 1
months = 12
n_tickers = data.ticker.nunique()
```

[11]:
```
train_data = data.drop('fwd_returns', axis=1).loc[idx[:, :'2016'], :]
test_data = data.drop('fwd_returns', axis=1).loc[idx[:, '2017'],:]
```

For each train and test dataset, we generate a list with three input arrays containing the return series, the stock ticker (converted to integer values), and the month (as an integer), as shown here:

[12]:
```
X_train = [
    train_data.loc[:, sequence].values.reshape(-1, window_size , 1),
    train_data.ticker,
    train_data.filter(like='month')
]
y_train = train_data.label
[x.shape for x in X_train], y_train.shape
```

[12]:
```
([(1035424, 52, 1), (1035424,), (1035424, 12)], (1035424,))
```

[13]:
```
# keep the last year for testing
X_test = [
    test_data.loc[:, list(range(1, window_size+1))].values.reshape(-1,␣
 ↪window_size , 1),
    test_data.ticker,
    test_data.filter(like='month')
]
y_test = test_data.label
[x.shape for x in X_test], y_test.shape
```

[13]:
```
([(131917, 52, 1), (131917,), (131917, 12)], (131917,))
```

1.4 Define the Model Architecture

The functional API of Keras makes it easy to design architectures with multiple inputs and outputs. This example illustrates a network with three inputs, as follows:

- A two stacked LSTM layers with 25 and 10 units respectively
- An embedding layer that learns a 10-dimensional real-valued representation of the equities
- A one-hot encoded representation of the month

This can be constructed using just a few lines - see e.g., - the general Keras documentation, - the LSTM documentation.

Make sure you are initializing your optimizer given the keras-recommended approach for RNNs

We begin by defining the three inputs with their respective shapes, as described here:

[14]:
```
K.clear_session()
```

[15]:
```
n_features = 1
```

[16]:
```
returns = Input(shape=(window_size, n_features),
                name='Returns')

tickers = Input(shape=(1,),
                name='Tickers')

months = Input(shape=(12,),
               name='Months')
```

1.4.1 LSTM Layers

To define stacked LSTM layers, we set the `return_sequences` keyword to `True`. This ensures that the first layer produces an output that conforms to the expected three-dimensional input format. Note that we also use dropout regularization and how the functional API passes the tensor outputs from one layer to the subsequent layer:

[17]:
```
lstm1_units = 25
lstm2_units = 10
```

[18]:
```
lstm1 = LSTM(units=lstm1_units,
             input_shape=(window_size,
                          n_features),
             name='LSTM1',
             dropout=.2,
             return_sequences=True)(returns)

lstm_model = LSTM(units=lstm2_units,
             dropout=.2,
             name='LSTM2')(lstm1)
```

1.4.2 Embedding Layer

The embedding layer requires the `input_dim` keyword, which defines how many embeddings the layer will learn, the `output_dim` keyword, which defines the size of the embedding, and the `input_length` keyword to set the number of elements passed to the layer (here only one ticker per sample).

To combine the embedding layer with the LSTM layer and the months input, we need to reshape (or flatten) it, as follows:

[19]:
```
ticker_embedding = Embedding(input_dim=n_tickers,
                             output_dim=5,
                             input_length=1)(tickers)
ticker_embedding = Reshape(target_shape=(5,))(ticker_embedding)
```

1.4.3 Concatenate Model components

Now we can concatenate the three tensors and add fully-connected layers to learn a mapping from these learned time series, ticker, and month indicators to the outcome, a positive or negative return in the following week, as shown here:

[20]:
```
merged = concatenate([lstm_model,
                      ticker_embedding,
                      months], name='Merged')

bn = BatchNormalization()(merged)
hidden_dense = Dense(10, name='FC1')(bn)

output = Dense(1, name='Output', activation='sigmoid')(hidden_dense)

rnn = Model(inputs=[returns, tickers, months], outputs=output)
```

The summary lays out this slightly more sophisticated architecture with 29,371 parameters, as follows:

[21]:
```
rnn.summary()
```

```
Model: "model"
________________________________________________________________________________
__________________
Layer (type)                    Output Shape         Param #     Connected to
================================================================================
==================
Returns (InputLayer)            [(None, 52, 1)]      0

________________________________________________________________________________
__________________
Tickers (InputLayer)            [(None, 1)]          0

________________________________________________________________________________
__________________
LSTM1 (LSTM)                    (None, 52, 25)       2700        Returns[0][0]

________________________________________________________________________________
__________________
embedding (Embedding)           (None, 1, 5)         12445       Tickers[0][0]

________________________________________________________________________________
__________________
```

```
LSTM2 (LSTM)                    (None, 10)           1440         LSTM1[0][0]
--------------------------------------------------------------------------------
------------------
reshape (Reshape)               (None, 5)            0            embedding[0][0]
--------------------------------------------------------------------------------
------------------
Months (InputLayer)             [(None, 12)]         0
--------------------------------------------------------------------------------
------------------
Merged (Concatenate)            (None, 27)           0            LSTM2[0][0]
                                                                  reshape[0][0]
                                                                  Months[0][0]
--------------------------------------------------------------------------------
------------------
batch_normalization (BatchNorma (None, 27)           108          Merged[0][0]
--------------------------------------------------------------------------------
------------------
FC1 (Dense)                     (None, 10)           280
batch_normalization[0][0]
--------------------------------------------------------------------------------
------------------
Output (Dense)                  (None, 1)            11           FC1[0][0]
================================================================================
==================
Total params: 16,984
Trainable params: 16,930
Non-trainable params: 54
--------------------------------------------------------------------------------
------------------
```

1.5 Train the Model

We compile the model to compute a custom auc metric as follows:

[22]:
```
optimizer = tf.keras.optimizers.RMSprop(lr=0.001,
                                        rho=0.9,
                                        epsilon=1e-08,
                                        decay=0.0)
```

[23]:
```
rnn.compile(loss='binary_crossentropy',
            optimizer=optimizer,
            metrics=['accuracy',
                     tf.keras.metrics.AUC(name='AUC')])
```

[24]:
```
lstm_path = (results_path / 'lstm.classification.h5').as_posix()

checkpointer = ModelCheckpoint(filepath=lstm_path,
                               verbose=1,
```

```
                                monitor='val_AUC',
                                mode='max',
                                save_best_only=True)
```

[25]:
```
early_stopping = EarlyStopping(monitor='val_AUC',
                               patience=5,
                               restore_best_weights=True,
                               mode='max')
```

[26]:
```
training = rnn.fit(X_train,
                   y_train,
                   epochs=50,
                   batch_size=32,
                   validation_data=(X_test, y_test),
                   callbacks=[early_stopping, checkpointer],
                   verbose=1)
```

```
Epoch 1/50
32356/32357 [============================>.] - ETA: 0s - loss: 0.6892 -
accuracy: 0.5375 - AUC: 0.5504
Epoch 00001: val_AUC improved from -inf to 0.61860, saving model to
results/lstm_embeddings/lstm.classification.h5
32357/32357 [==============================] - 335s 10ms/step - loss: 0.6892 -
accuracy: 0.5375 - AUC: 0.5504 - val_loss: 0.6701 - val_accuracy: 0.5826 -
val_AUC: 0.6186
Epoch 2/50
32354/32357 [============================>.] - ETA: 0s - loss: 0.6855 -
accuracy: 0.5493 - AUC: 0.5680
Epoch 00002: val_AUC improved from 0.61860 to 0.63500, saving model to
results/lstm_embeddings/lstm.classification.h5
32357/32357 [==============================] - 338s 10ms/step - loss: 0.6855 -
accuracy: 0.5493 - AUC: 0.5680 - val_loss: 0.6668 - val_accuracy: 0.5902 -
val_AUC: 0.6350
Epoch 3/50
32352/32357 [============================>.] - ETA: 0s - loss: 0.6857 -
accuracy: 0.5488 - AUC: 0.5671
Epoch 00003: val_AUC improved from 0.63500 to 0.63709, saving model to
results/lstm_embeddings/lstm.classification.h5
32357/32357 [==============================] - 308s 10ms/step - loss: 0.6857 -
accuracy: 0.5488 - AUC: 0.5671 - val_loss: 0.6732 - val_accuracy: 0.5825 -
val_AUC: 0.6371
Epoch 4/50
32352/32357 [============================>.] - ETA: 0s - loss: 0.6831 -
accuracy: 0.5471 - AUC: 0.5660
Epoch 00004: val_AUC did not improve from 0.63709
32357/32357 [==============================] - 254s 8ms/step - loss: 0.6831 -
accuracy: 0.5471 - AUC: 0.5660 - val_loss: 0.6747 - val_accuracy: 0.5803 -
```

```
val_AUC: 0.6361
Epoch 5/50
32353/32357 [============================>.] - ETA: 0s - loss: 0.6807 -
accuracy: 0.5487 - AUC: 0.5676
Epoch 00005: val_AUC improved from 0.63709 to 0.67301, saving model to
results/lstm_embeddings/lstm.classification.h5
32357/32357 [==============================] - 253s 8ms/step - loss: 0.6807 -
accuracy: 0.5486 - AUC: 0.5676 - val_loss: 0.5795 - val_accuracy: 0.6061 -
val_AUC: 0.6730
Epoch 6/50
32357/32357 [==============================] - ETA: 0s - loss: 0.6798 -
accuracy: 0.5489 - AUC: 0.5687
Epoch 00006: val_AUC improved from 0.67301 to 0.68151, saving model to
results/lstm_embeddings/lstm.classification.h5
32357/32357 [==============================] - 251s 8ms/step - loss: 0.6798 -
accuracy: 0.5489 - AUC: 0.5687 - val_loss: 0.5815 - val_accuracy: 0.6175 -
val_AUC: 0.6815
Epoch 7/50
32355/32357 [============================>.] - ETA: 0s - loss: 0.6780 -
accuracy: 0.5508 - AUC: 0.5718
Epoch 00007: val_AUC did not improve from 0.68151
32357/32357 [==============================] - 254s 8ms/step - loss: 0.6780 -
accuracy: 0.5508 - AUC: 0.5718 - val_loss: 0.6432 - val_accuracy: 0.6144 -
val_AUC: 0.6721
Epoch 8/50
32355/32357 [============================>.] - ETA: 0s - loss: 0.6814 -
accuracy: 0.5497 - AUC: 0.5694
Epoch 00008: val_AUC did not improve from 0.68151
32357/32357 [==============================] - 255s 8ms/step - loss: 0.6814 -
accuracy: 0.5497 - AUC: 0.5694 - val_loss: 0.5745 - val_accuracy: 0.6122 -
val_AUC: 0.6757
Epoch 9/50
32353/32357 [============================>.] - ETA: 0s - loss: 0.6759 -
accuracy: 0.5525 - AUC: 0.5750
Epoch 00009: val_AUC did not improve from 0.68151
32357/32357 [==============================] - 254s 8ms/step - loss: 0.6759 -
accuracy: 0.5525 - AUC: 0.5750 - val_loss: 0.5710 - val_accuracy: 0.6176 -
val_AUC: 0.6813
Epoch 10/50
32352/32357 [============================>.] - ETA: 0s - loss: 0.6760 -
accuracy: 0.5529 - AUC: 0.5758
Epoch 00010: val_AUC did not improve from 0.68151
32357/32357 [==============================] - 246s 8ms/step - loss: 0.6760 -
accuracy: 0.5529 - AUC: 0.5758 - val_loss: 0.5733 - val_accuracy: 0.6151 -
val_AUC: 0.6765
Epoch 11/50
32346/32357 [============================>.] - ETA: 0s - loss: 0.6743 -
accuracy: 0.5537 - AUC: 0.5768
```

```
Epoch 00011: val_AUC did not improve from 0.68151
32357/32357 [==============================] - 141s 4ms/step - loss: 0.6743 -
accuracy: 0.5537 - AUC: 0.5768 - val_loss: 0.5703 - val_accuracy: 0.6161 -
val_AUC: 0.6797
```

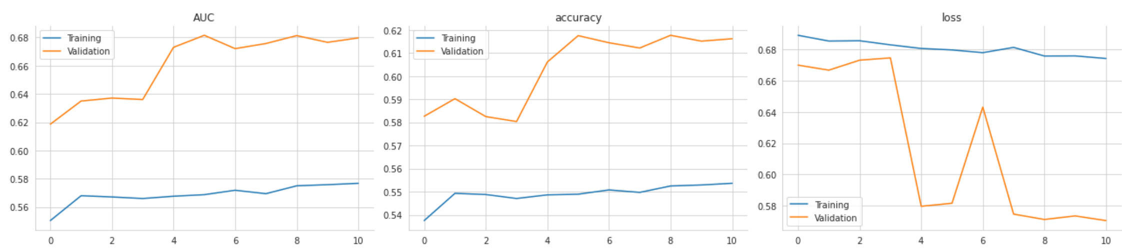
Training stops after 18 epochs, producing a test area under the curve (AUC) of 0.63 for the best model with 13 rounds of training (each of which takes around three minutes on a single GPU).

[27]:
```python
loss_history = pd.DataFrame(training.history)
```

[28]:
```python
def which_metric(m):
    return m.split('_')[-1]
```

[29]:
```python
fig, axes = plt.subplots(ncols=3, figsize=(18,4))
for i, (metric, hist) in enumerate(loss_history.groupby(which_metric, axis=1)):
    hist.plot(ax=axes[i], title=metric)
    axes[i].legend(['Training', 'Validation'])

sns.despine()
fig.tight_layout()
fig.savefig(results_path / 'lstm_stacked_classification', dpi=300);
```



1.6 Evaluate model performance

[30]:
```python
test_predict = pd.Series(rnn.predict(X_test).squeeze(), index=y_test.index)
```

[31]:
```python
roc_auc_score(y_score=test_predict, y_true=y_test)
```

[31]: 0.6815303447045473

[32]:
```python
((test_predict>.5) == y_test).astype(int).mean()
```

[32]: 0.6174943335582223

[33]:
```python
spearmanr(test_predict, y_test)[0]
```

[33]: 0.3105869204256358