## S+P\_Week\_3\_Lesson\_4\_LSTM

## December 6, 2020

```
[]: #@title Licensed under the Apache License, Version 2.0 (the "License");
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     # WITHOUT WARRANTIES OR CONDITIONS OF ANY KIND, either express or implied.
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     # limitations under the License.
[]: !pip install tf-nightly-2.0-preview
[]: import tensorflow as tf
     import numpy as np
     import matplotlib.pyplot as plt
     print(tf.__version__)
    2.0.0-dev20190628
[]: def plot_series(time, series, format="-", start=0, end=None):
         plt.plot(time[start:end], series[start:end], format)
         plt.xlabel("Time")
         plt.ylabel("Value")
         plt.grid(True)
     def trend(time, slope=0):
         return slope * time
     def seasonal_pattern(season_time):
         """Just an arbitrary pattern, you can change it if you wish"""
         return np.where(season_time < 0.4,</pre>
                         np.cos(season_time * 2 * np.pi),
```

1 / np.exp(3 \* season\_time))

def seasonality(time, period, amplitude=1, phase=0):
 """Repeats the same pattern at each period"""

```
return amplitude * seasonal_pattern(season_time)
     def noise(time, noise_level=1, seed=None):
         rnd = np.random.RandomState(seed)
         return rnd.randn(len(time)) * noise_level
     time = np.arange(4 * 365 + 1, dtype="float32")
     baseline = 10
     series = trend(time, 0.1)
     baseline = 10
     amplitude = 40
     slope = 0.05
     noise_level = 5
     # Create the series
     series = baseline + trend(time, slope) + seasonality(time, period=365,__
     →amplitude=amplitude)
     # Update with noise
     series += noise(time, noise_level, seed=42)
     split_time = 1000
     time_train = time[:split_time]
     x_train = series[:split_time]
     time_valid = time[split_time:]
     x_valid = series[split_time:]
     window_size = 20
     batch_size = 32
     shuffle_buffer_size = 1000
[]: def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
       dataset = tf.data.Dataset.from_tensor_slices(series)
       dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)
       dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
       dataset = dataset.shuffle(shuffle_buffer).map(lambda window: (window[:-1],__
      \rightarrow window [-1])
       dataset = dataset.batch(batch_size).prefetch(1)
       return dataset
[]: tf.keras.backend.clear_session()
     tf.random.set_seed(51)
     np.random.seed(51)
     tf.keras.backend.clear_session()
     dataset = windowed_dataset(x_train, window_size, batch_size,_
      →shuffle_buffer_size)
```

season\_time = ((time + phase) % period) / period

```
model = tf.keras.models.Sequential([
 tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1),
               input_shape=[None]),
   tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32, __
 →return_sequences=True)),
 tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32)),
 tf.keras.layers.Dense(1),
 tf.keras.layers.Lambda(lambda x: x * 100.0)
])
lr_schedule = tf.keras.callbacks.LearningRateScheduler(
   lambda epoch: 1e-8 * 10**(epoch / 20))
optimizer = tf.keras.optimizers.SGD(lr=1e-8, momentum=0.9)
model.compile(loss=tf.keras.losses.Huber(),
          optimizer=optimizer,
          metrics=["mae"])
history = model.fit(dataset, epochs=100, callbacks=[lr_schedule])
Epoch 1/100
W0701 23:09:28.075649 139706394146688 deprecation.py:323] From
/usr/local/lib/python3.6/dist-
packages/tensorflow_core/python/keras/optimizer_v2/optimizer_v2.py:460:
BaseResourceVariable.constraint (from
tensorflow.python.ops.resource_variable_ops) is deprecated and will be removed
in a future version.
Instructions for updating:
Apply a constraint manually following the optimizer update step.
22.0115
Epoch 2/100
21.6472
Epoch 3/100
21.2292
Epoch 4/100
20.7798
Epoch 5/100
20.2896
Epoch 6/100
19.6838
Epoch 7/100
```

```
18.7455
Epoch 8/100
17.9816
Epoch 9/100
17.6597
Epoch 10/100
17.3525
Epoch 11/100
17.0524
Epoch 12/100
16.7591
Epoch 13/100
16.4636
Epoch 14/100
16.1633
Epoch 15/100
15.8621
Epoch 16/100
15.5677
Epoch 17/100
15.2885
Epoch 18/100
15.0166
Epoch 19/100
14.7570
Epoch 20/100
14.5246
Epoch 21/100
14.3102
Epoch 22/100
14.1009
Epoch 23/100
```

```
13.8871
Epoch 24/100
13.6703
Epoch 25/100
13.4467
Epoch 26/100
13.2158
Epoch 27/100
12.9747
Epoch 28/100
12.7263
Epoch 29/100
12.4713
Epoch 30/100
12.2018
Epoch 31/100
11.8717
Epoch 32/100
11.7775
Epoch 33/100
11.0358
Epoch 34/100
11.4071
Epoch 35/100
11.6302
Epoch 36/100
11.1067
Epoch 37/100
10.5667
Epoch 38/100
10.0461
Epoch 39/100
```

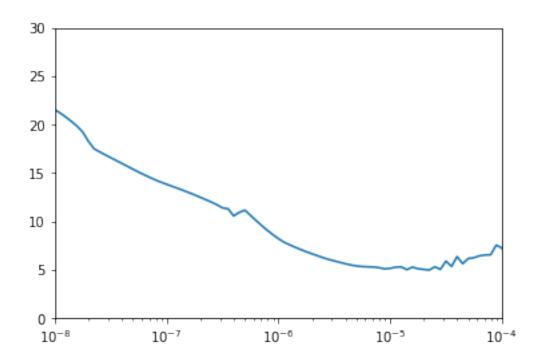
```
9.5571
Epoch 40/100
9.1088
Epoch 41/100
8.6896
Epoch 42/100
8.3230
Epoch 43/100
8.0550
Epoch 44/100
7.8007
Epoch 45/100
7.5605
Epoch 46/100
7.3303
Epoch 47/100
7.1208
Epoch 48/100
6.9241
Epoch 49/100
6.7161
Epoch 50/100
6.5433
Epoch 51/100
6.3832
Epoch 52/100
6.2375
Epoch 53/100
6.0902
Epoch 54/100
5.9581
Epoch 55/100
```

```
5.8649
Epoch 56/100
5.7960
Epoch 57/100
5.7761
Epoch 58/100
5.7588
Epoch 59/100
5.6861
Epoch 60/100
5.5644
Epoch 61/100
5.6095
Epoch 62/100
5.7408
Epoch 63/100
5.7684
Epoch 64/100
5.4791
Epoch 65/100
5.7438
Epoch 66/100
5.5727
Epoch 67/100
5.5037
Epoch 68/100
5.4332
Epoch 69/100
5.7748
Epoch 70/100
5.5061
Epoch 71/100
```

```
6.3689
Epoch 72/100
5.8189
Epoch 73/100
6.8376
Epoch 74/100
6.1061
Epoch 75/100
6.6292
Epoch 76/100
6.7193
Epoch 77/100
6.9178
Epoch 78/100
7.0080
Epoch 79/100
7.0168
Epoch 80/100
8.0238
Epoch 81/100
7.7349
Epoch 82/100
6.8037
Epoch 83/100
5.8989
Epoch 84/100
6.6115
Epoch 85/100
7.1887
Epoch 86/100
6.8992
Epoch 87/100
```

```
7.1150
 Epoch 88/100
 7.8736
 Epoch 89/100
 8.4836
 Epoch 90/100
 10.2216
 Epoch 91/100
 9.1908
 Epoch 92/100
 9.6962
 Epoch 93/100
 7.9644
 Epoch 94/100
 10.3532
 Epoch 95/100
 9.6303
 Epoch 96/100
 11.0897
 Epoch 97/100
 11.9054
 Epoch 98/100
 13.3121
 Epoch 99/100
 11.7019
 Epoch 100/100
 13.2224
[]: plt.semilogx(history.history["lr"], history.history["loss"])
 plt.axis([1e-8, 1e-4, 0, 30])
```

[]: [1e-08, 0.0001, 0, 30]



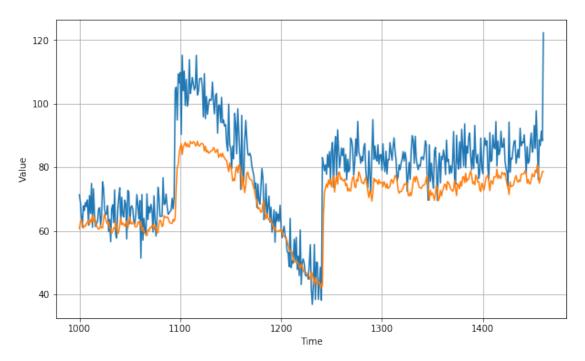
```
[]: tf.keras.backend.clear_session()
     tf.random.set_seed(51)
     np.random.seed(51)
     tf.keras.backend.clear_session()
     dataset = windowed_dataset(x_train, window_size, batch_size,_
     ⇔shuffle_buffer_size)
     model = tf.keras.models.Sequential([
       tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1),
                           input_shape=[None]),
       tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32, ___
     →return_sequences=True)),
       tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32)),
      tf.keras.layers.Dense(1),
       tf.keras.layers.Lambda(lambda x: x * 100.0)
    ])
     model.compile(loss="mse", optimizer=tf.keras.optimizers.SGD(lr=1e-5, momentum=0.
     →9),metrics=["mae"])
    history = model.fit(dataset,epochs=500,verbose=0)
```

```
[]: forecast = []
    results = []
    for time in range(len(series) - window_size):
        forecast.append(model.predict(series[time:time + window_size][np.newaxis]))

forecast = forecast[split_time-window_size:]
    results = np.array(forecast)[:, 0, 0]

plt.figure(figsize=(10, 6))

plot_series(time_valid, x_valid)
    plot_series(time_valid, results)
```



```
[]: tf.keras.metrics.mean_absolute_error(x_valid, results).numpy()
```

## []: 8.514286

```
[]: import matplotlib.image as mpimg import matplotlib.pyplot as plt

#-----
# Retrieve a list of list results on training and test data
# sets for each training epoch
#------
```

```
mae=history.history['mae']
loss=history.history['loss']
epochs=range(len(loss)) # Get number of epochs
# Plot MAE and Loss
#-----
plt.plot(epochs, mae, 'r')
plt.plot(epochs, loss, 'b')
plt.title('MAE and Loss')
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend(["MAE", "Loss"])
plt.figure()
epochs_zoom = epochs[200:]
mae_zoom = mae[200:]
loss_{zoom} = loss[200:]
# Plot Zoomed MAE and Loss
plt.plot(epochs_zoom, mae_zoom, 'r')
plt.plot(epochs_zoom, loss_zoom, 'b')
plt.title('MAE and Loss')
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend(["MAE", "Loss"])
plt.figure()
```

```
[]: tf.keras.backend.clear_session()
```

```
dataset = windowed_dataset(x_train, window_size, batch_size,_
     ⇔shuffle_buffer_size)
     model = tf.keras.models.Sequential([
       tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1),
                           input shape=[None]),
      tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32,__
     →return_sequences=True)),
      tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32)),
      tf.keras.layers.Dense(1),
      tf.keras.layers.Lambda(lambda x: x * 100.0)
    ])
     model.compile(loss="mse", optimizer=tf.keras.optimizers.SGD(lr=1e-6, momentum=0.
     →9))
     model.fit(dataset,epochs=100, verbose=0)
[]: tf.keras.backend.clear_session()
     dataset = windowed_dataset(x_train, window_size, batch_size,_
     ⇒shuffle_buffer_size)
     model = tf.keras.models.Sequential([
       tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1),
                           input_shape=[None]),
       tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32, ___
     →return_sequences=True)),
      tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32,
     →return_sequences=True)),
      tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32)),
      tf.keras.layers.Dense(1),
       tf.keras.layers.Lambda(lambda x: x * 100.0)
     ])
     model.compile(loss="mse", optimizer=tf.keras.optimizers.SGD(lr=1e-6, momentum=0.
     →9))
    model.fit(dataset,epochs=100)
```