Intro to Neural Nets

Session 6: RNNs for Forecasting

Session Agenda

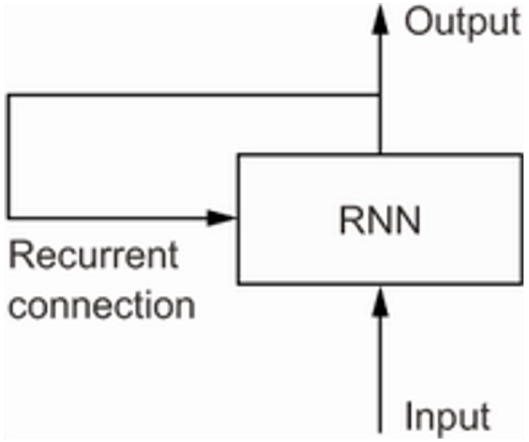
Sequence Data

- Recurrent Neural Networks (RNNs):
  - SimpleRNN
  - LSTM (Long Short-Term Memory)
  - GRU (Gated Recurrent Unit)
- Bidirectional RNN

RNN: Processing /w Memory

Incorporating Memory into a NN

- We include a feedback loop, where output feeds back into the same layer alongside the next input in the sequence (each gets its own separate set of weights, and they are able to interact with one another.



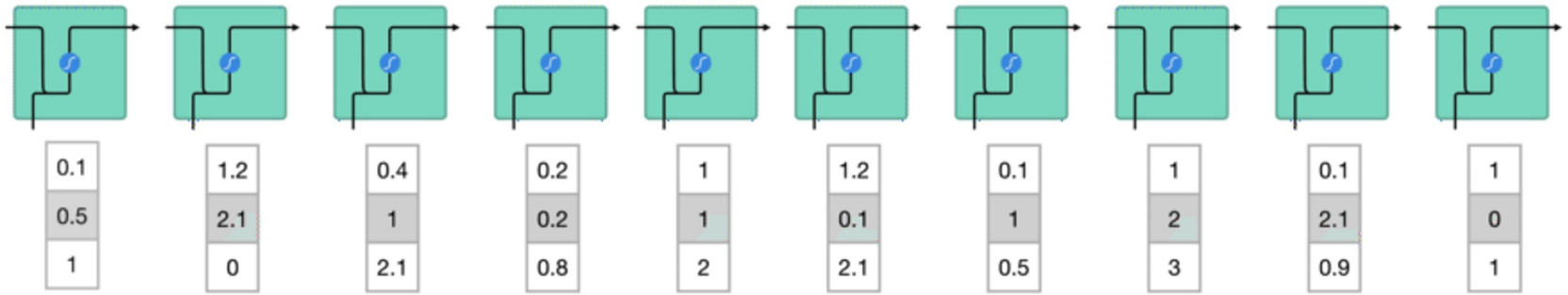
Listing 10.14 More-detailed pseudocode for the RNN

```
state_t = 0
for input_t in input_sequence:
    output_t = activation(dot(W, input_t) + dot(U, state_t) + b)
    state_t = output_t
```

Keras RNN Layers

SimpleRNN

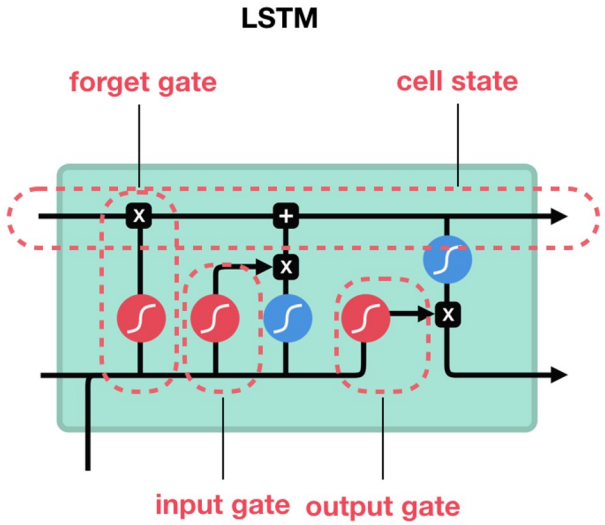
- We can, in practice, unroll an RNN layer into a series as follows.
- This is just a large Dense network with many inputs and many outputs. The inputs are arranged to interact with each other based on their temporal sequencing in the data.



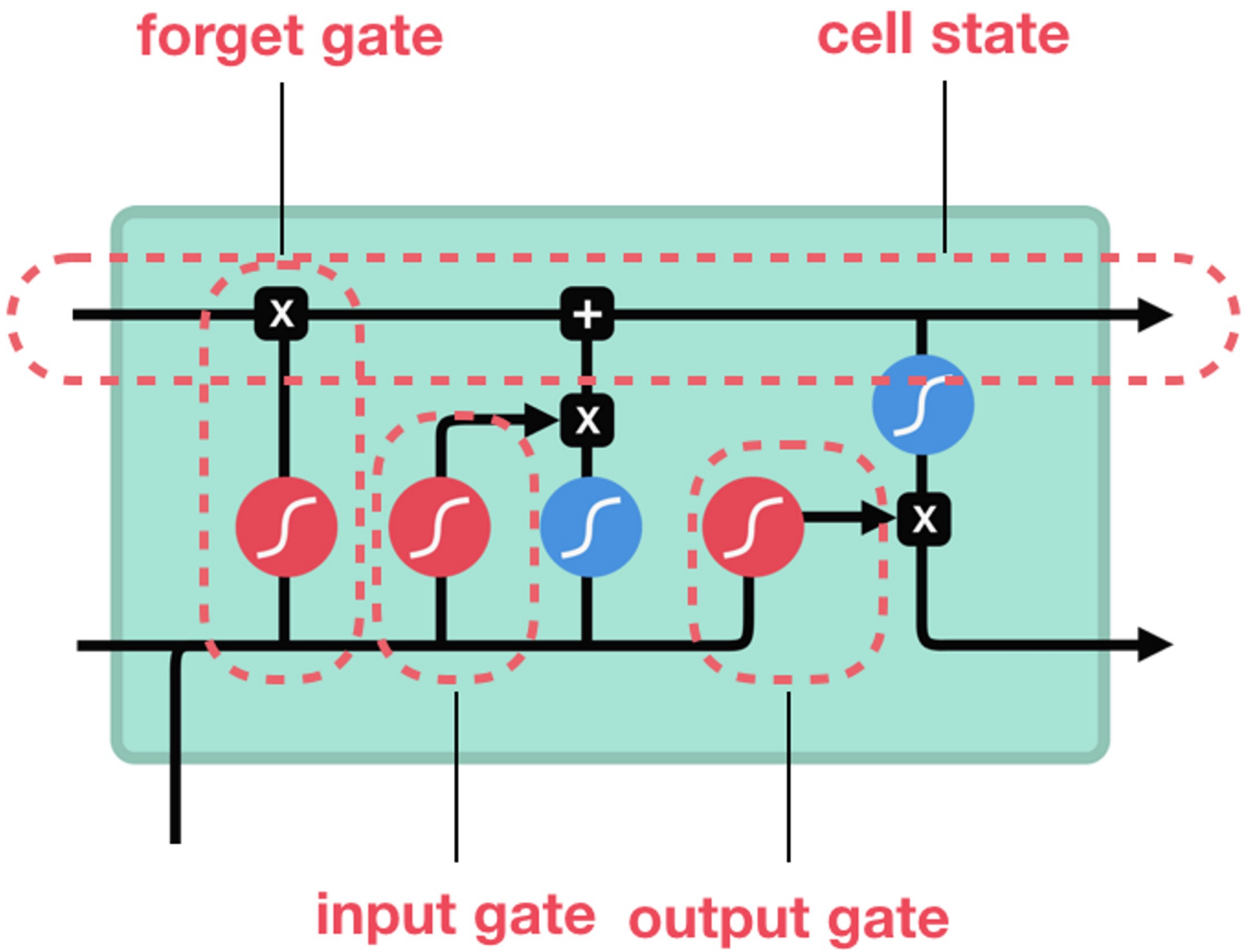
Keras RNN Layers

Long Short-Term Memory (LSTM)

- In practice, we cannot use SimpleRNNs to achieve meaningful memory (vanishing gradients arise quickly). We add what's called a "carry track" – this is an additional connection that combines output at step t, inputs at step t, and the last carry track's output. The topology means your network can 'learn' to use these connections as passthroughs for old info, or it can learn to 'block' that information in favor of more recent information (whatever is useful for accurate prediction).
- Carry tracks are basically just another degree of freedom for learning how to use lagged information.
- These ideas inspired the design of LSTM units, but nothing guarantees that these gates serve these functions..



LSTM



Keras RNN Layers

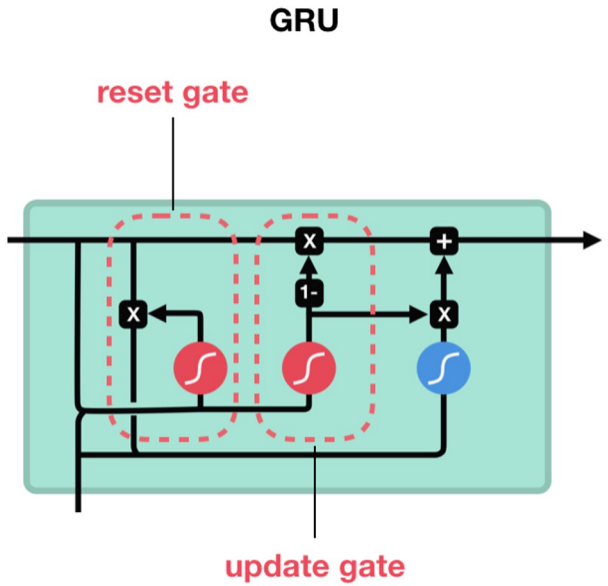
Long Short-Term Memory (LSTM)

```
>>> inputs = tf.random.normal([32, 10, 8])
>>> lstm = tf.keras.layers.LSTM(4)
>>> output = lstm(inputs)
>>> print(output.shape)
(32, 4)
>>> lstm = tf.keras.layers.LSTM(4, return_sequences=True, return_state=True)
>>> whole_seq_output, final_memory_state, final_carry_state = lstm(inputs)
>>> print(whole_seq_output.shape)
(32, 10, 4)
>>> print(final_memory_state.shape)
(32, 4)
>>> print(final_carry_state.shape)
(32, 4)
```

Keras RNN Layers

Gated Recurrent Unit (GRU)

- Less complex than an LSTM. Combines elements of the LSTM into simpler gated structure.
- Fits more quickly, with less data, but memory tends to be shorter.
- More common in NLP tasks, e.g., because “within sentence” or “within paragraph” memory is often sufficient.



Stacking RNN Layers

Stacked Layers (LSTM or GRUs)

- Same as other 'layer' types, but we need to pass the entire sequence of outputs (not just the last output). We do this with the 'return_sequences=True' argument to the layer.

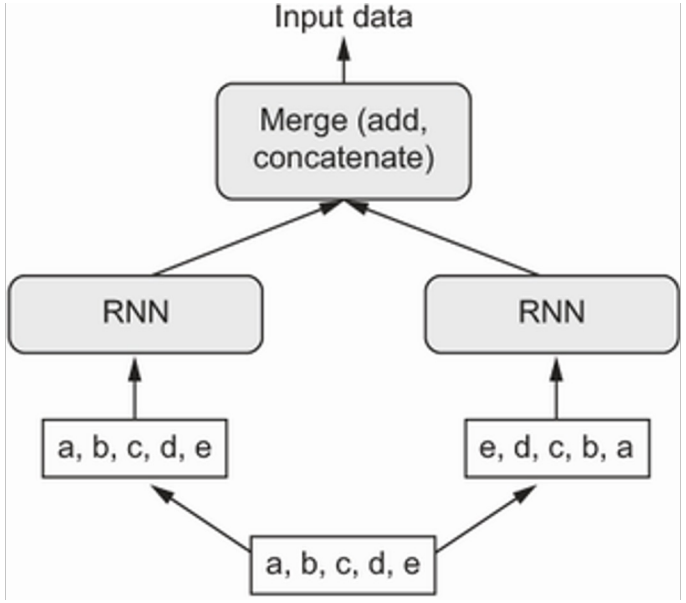
Listing 10.23 Training and evaluating a dropout-regularized, stacked GRU model

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.GRU(32, recurrent_dropout=0.5, return_sequences=True)(inputs)
x = layers.GRU(32, recurrent_dropout=0.5)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)
```

Bidirectional RNNs

Some Sequences Yield Information in Both Directions

- Consider that, in language, words that come later in a sentence can be predictive of what came before.
- Bidirectional RNNs implement a standard RNN, but they also incorporate a parallel layer implementation that takes the sequence ordered in reverse.



Questions?