Recurrent Neural Networks

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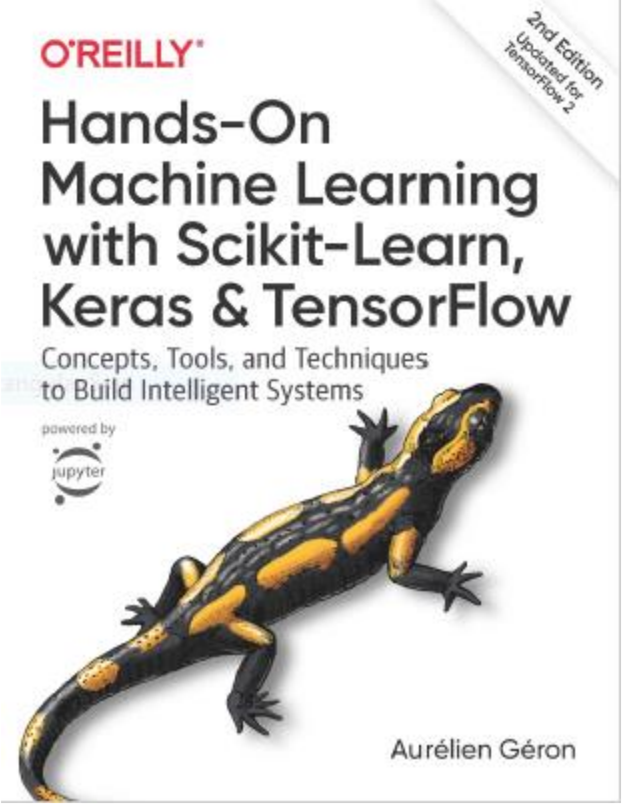
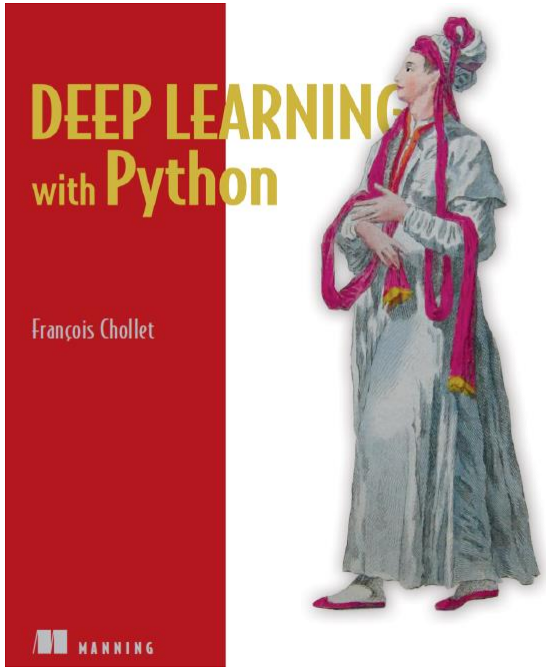
Reference



- Chapter 15: **Processing Sequences Using RNNs and CNNs**

- Aurélien Géron, **Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow**, O'Reilly, 2nd Edition, 2019
  - Material: https://github.com/ageron/handson-ml2

Reference



- **Deep Learning with Python**, by François Chollet, Manning Pub. 2018

Outline

1. Introduction
2. Recurrent neurons and layers
3. Training RNNs
4. Forecasting a time series
    1. Implementing a simple RNN
    2. Deep RNNs
    3. Forecasting Several Time Steps Ahead
5. Handling long sequences
    1. LSTM cell
    2. GRU cell
6. Exercises

Introduction

- YouTube Video: **Deep Learning with Tensorflow - The Recurrent Neural Network Model** from Cognitive Class

https://youtu.be/C0xoB8L8ms0

1. Introduction

- **Recurrent neural networks (RNNs)** are used to handle time series data or sequences.
- **Applications**:
  - Predicting the future (stock prices)
  - Autonomous driving systems (predicting trajectories)
  - Natural language processing (automatic translation, speech-to-text, or sentiment analysis)
  - Creativity (music composition, handwriting, drawing)
  - Image analysis (image captions)

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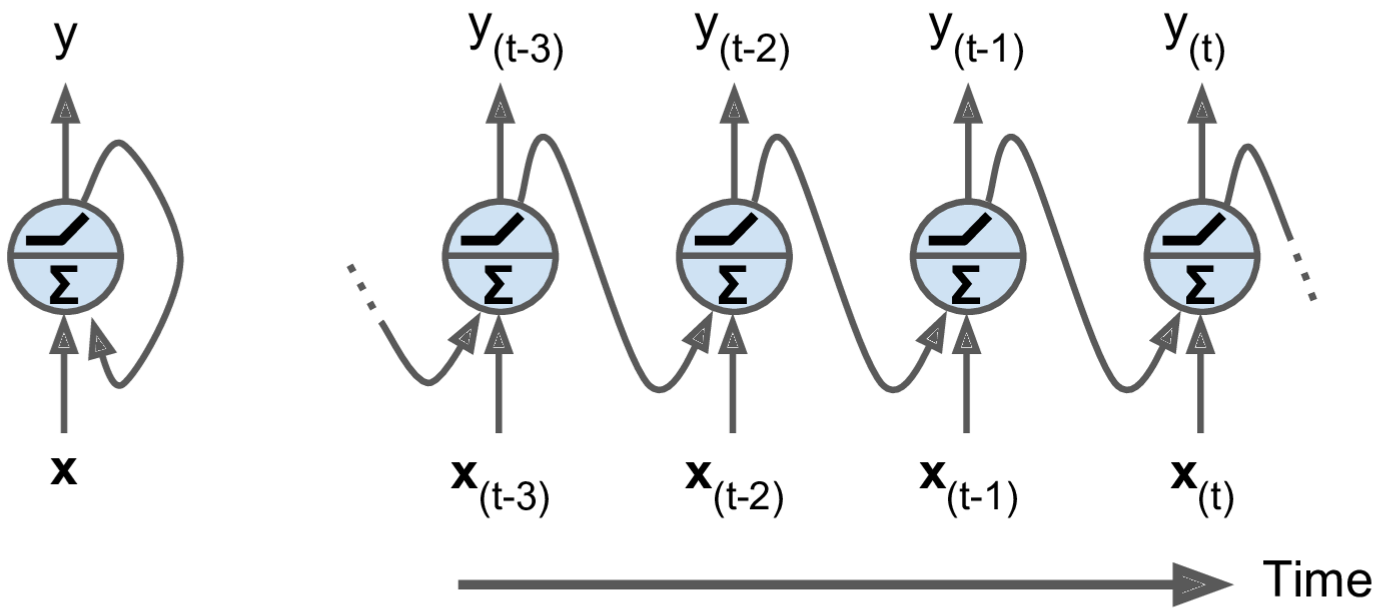
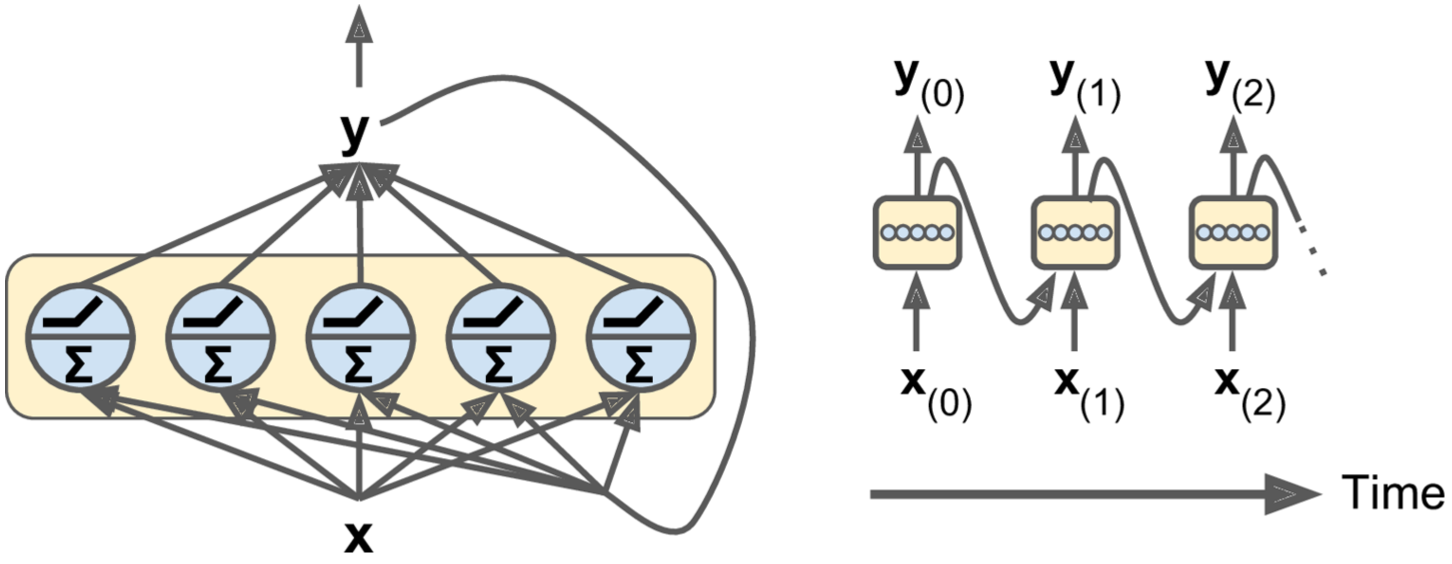
2. Recurrent Neurons and Layers

- The figure below shows a **recurrent neuron** (left), unrolled through time (right).



2. Recurrent Neurons and Layers

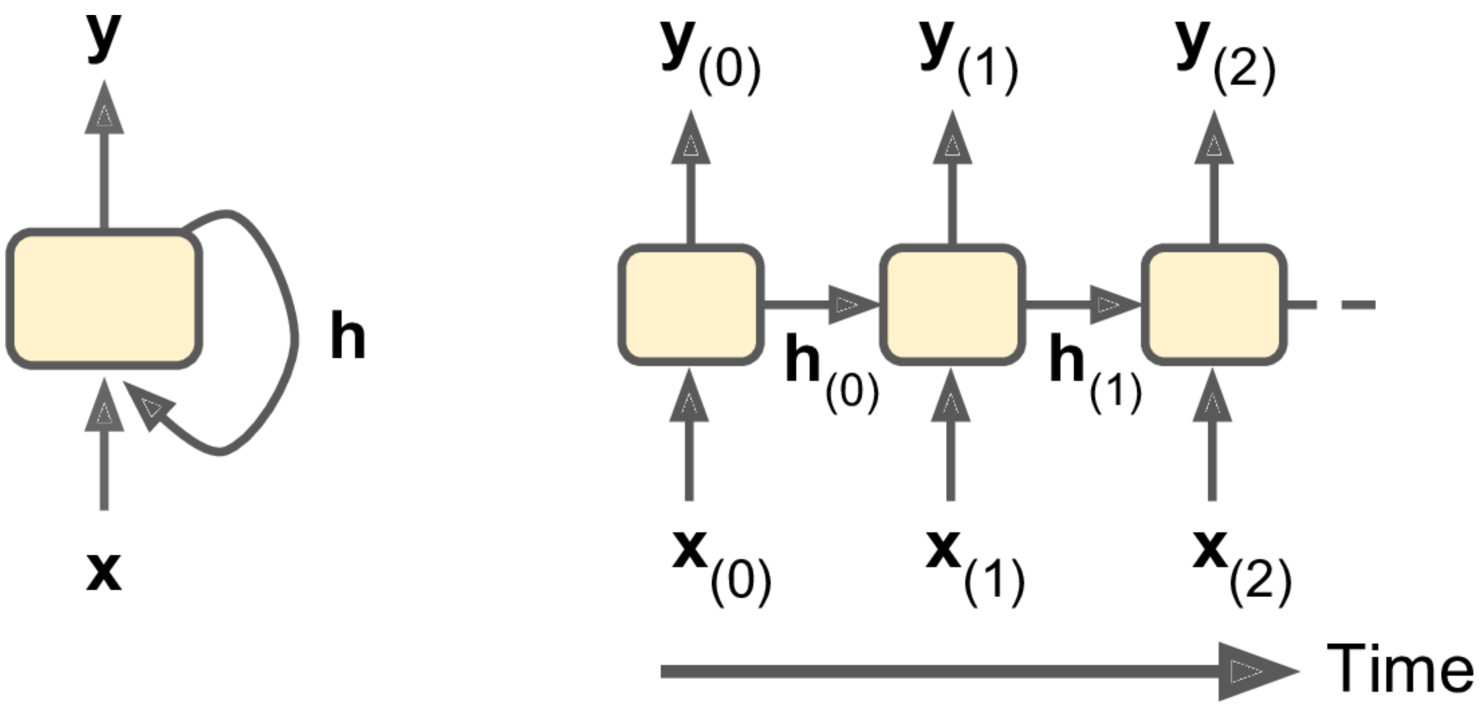
- Multiple recurrent neurons can be used in a **layer**.



- The **output** of the layer is: $\mathbf{Y}_{(t)} = \phi\left(\mathbf{X}_{(t)} \cdot \mathbf{W}_x + \mathbf{Y}_{(t-1)} \cdot \mathbf{W}_y + \mathbf{b}\right)$

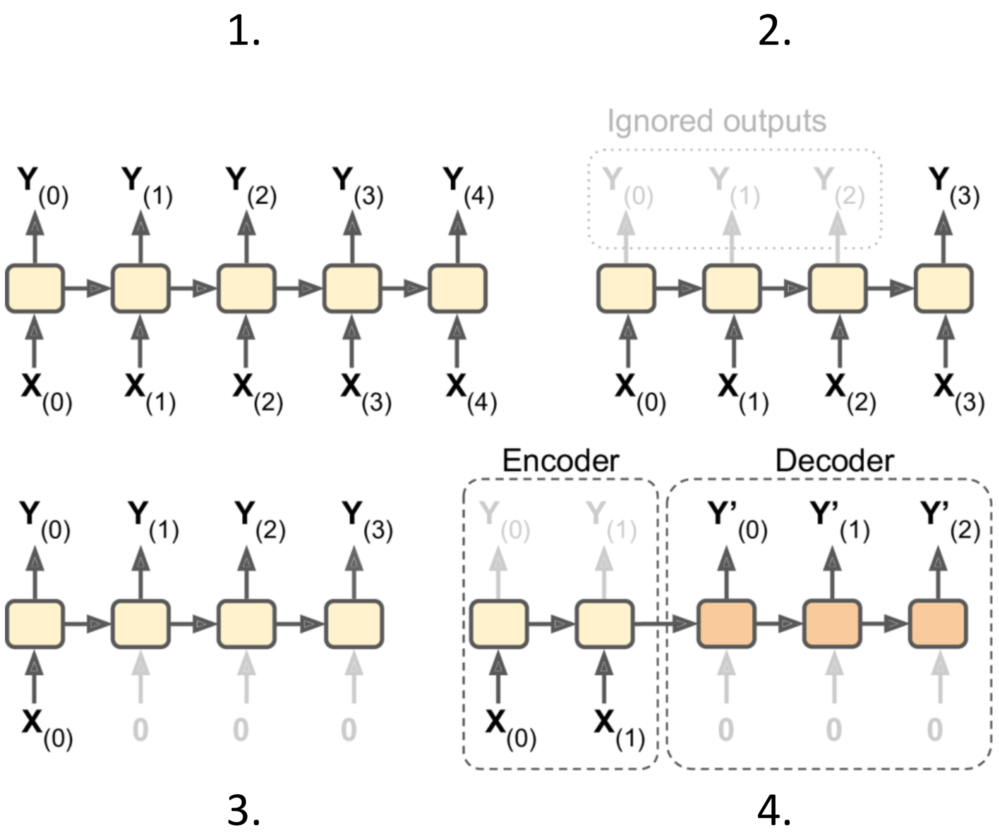
2. Recurrent Neurons and Layers

- Recurrent neurons have memory (hold state) and are called **memory cells**.
- The state $\mathbf{h}_{(t)} = f(\mathbf{h}_{(t-1)}, \mathbf{x}_{(t)})$, not always $\equiv \mathbf{y}_{(t)}$



2. Recurrent Neurons and Layers: Input and Output Sequences

1. **Seq to seq net.**: For predicting the future.
2. **Seq to vector**: For analysis, e.g., sentiment score.
3. **Vector to seq**: For image captioning.
4. **Encoder-decoder**: For sequence transcription.



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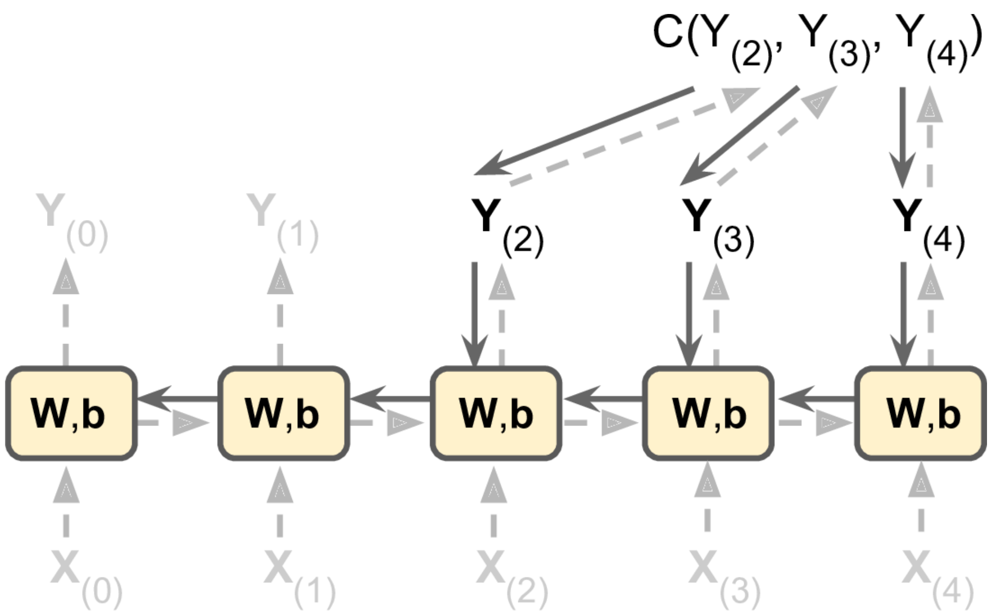
3. Training RNNs

- Training using strategy called **backpropagation through time** (BPTT).
- **Forward pass** (dashed)
- **Cost function** of the not-ignored outputs.
- **Cost gradients** are **propagated backward** through the unrolled network.



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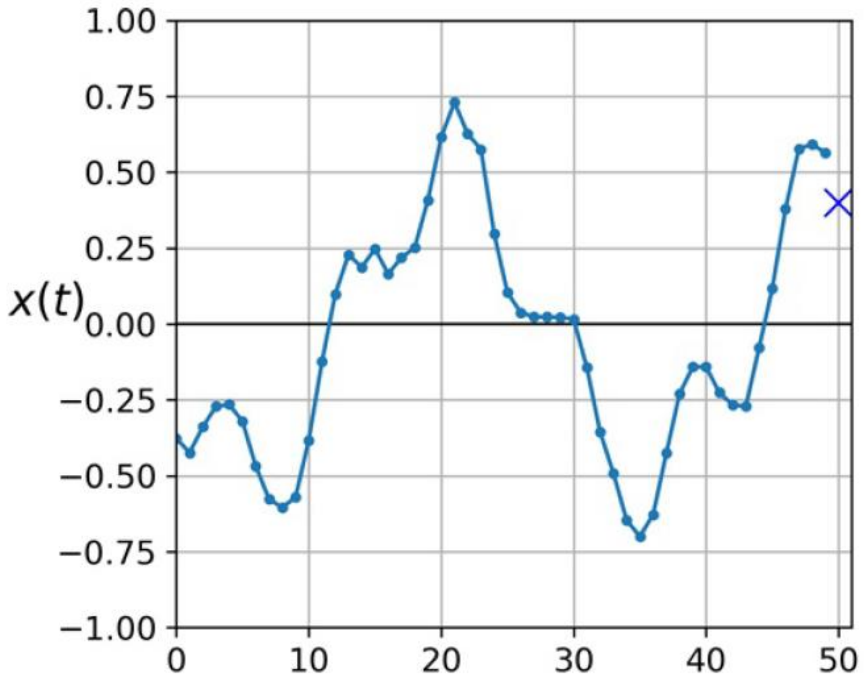
4. Forecasting a Time Series

- The data is a sequence of one or more values per **time step**.
  - **Univariate** time series
  - **Multivariate** time series
- **Forecasting**: predicting future values
  - Forecast the **next** value
  - Forecast **N next** values



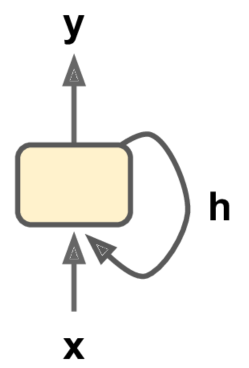
4.1 Implementing a Simple RNN

```
# Generate 10,000 time series
n_steps = 50
series = generate_time_series(10000, n_steps + 1)

# Split them 7,000 : 2,000 : 1,000
X_train, y_train = series[:7000, :n_steps], series[:7000, -1]
                # (7000, 50, 1), (7000, 1)
X_valid, y_valid = series[7000:9000, :n_steps], series[7000:9000, -1]

X_test, y_test = series[9000:, :n_steps], series[9000:, -1]
```

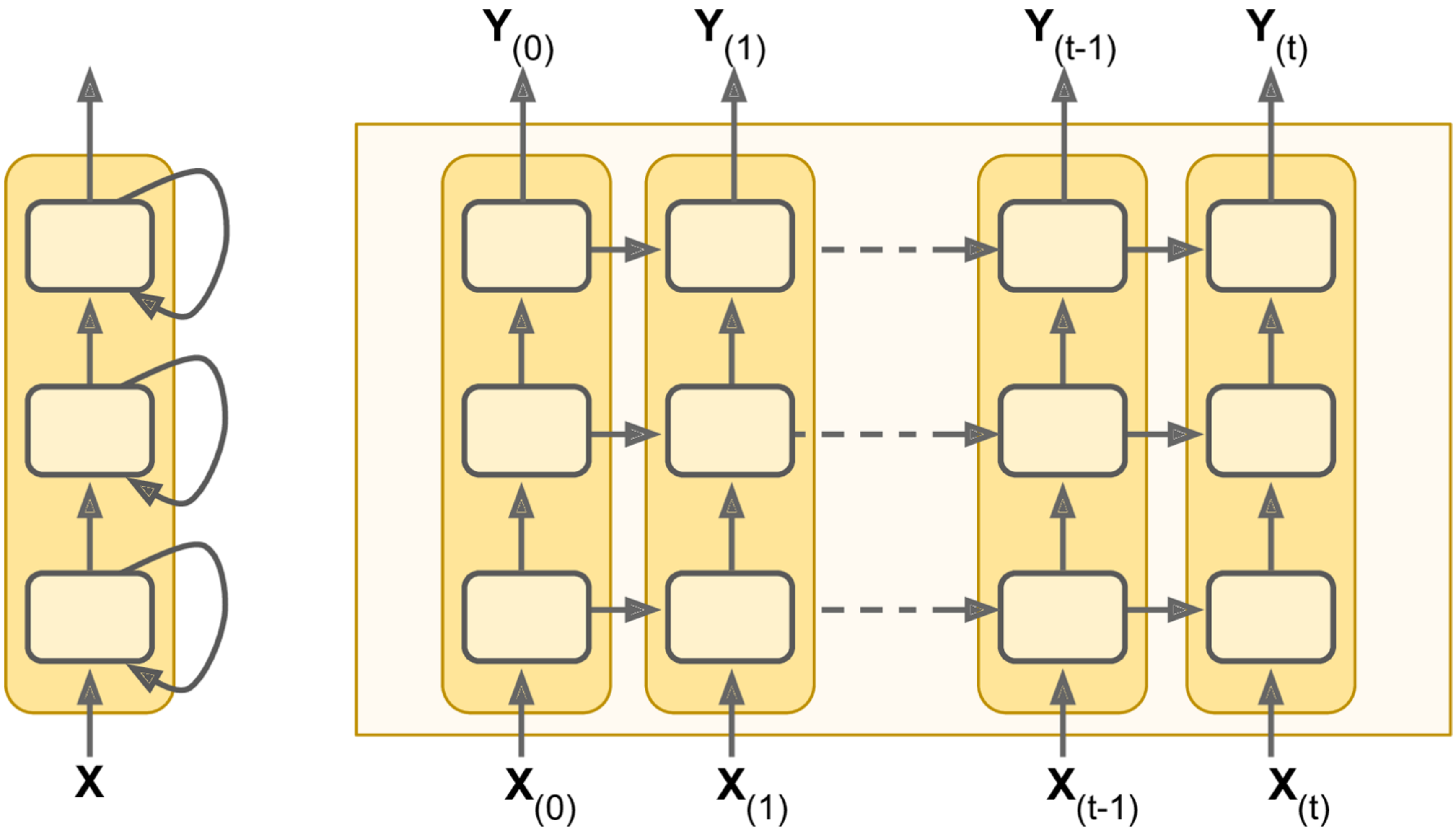
4.1 Implementing a Simple RNN

```
# Sequential model of one neuron
model = keras.models.Sequential([
        keras.layers.SimpleRNN(1, input_shape=[None, 1])
])

optimizer = keras.optimizers.Adam(lr=0.005)
model.compile(loss="mse", optimizer=optimizer)
history = model.fit(X_train, y_train, epochs=20,
                    validation_data=(X_valid, y_valid))

model.evaluate(X_valid, y_valid) # MSE = 0.011, Dense achieves 0.004
```

Uses tanh activation $h_t = y_t$



4.2 Deep RNNs

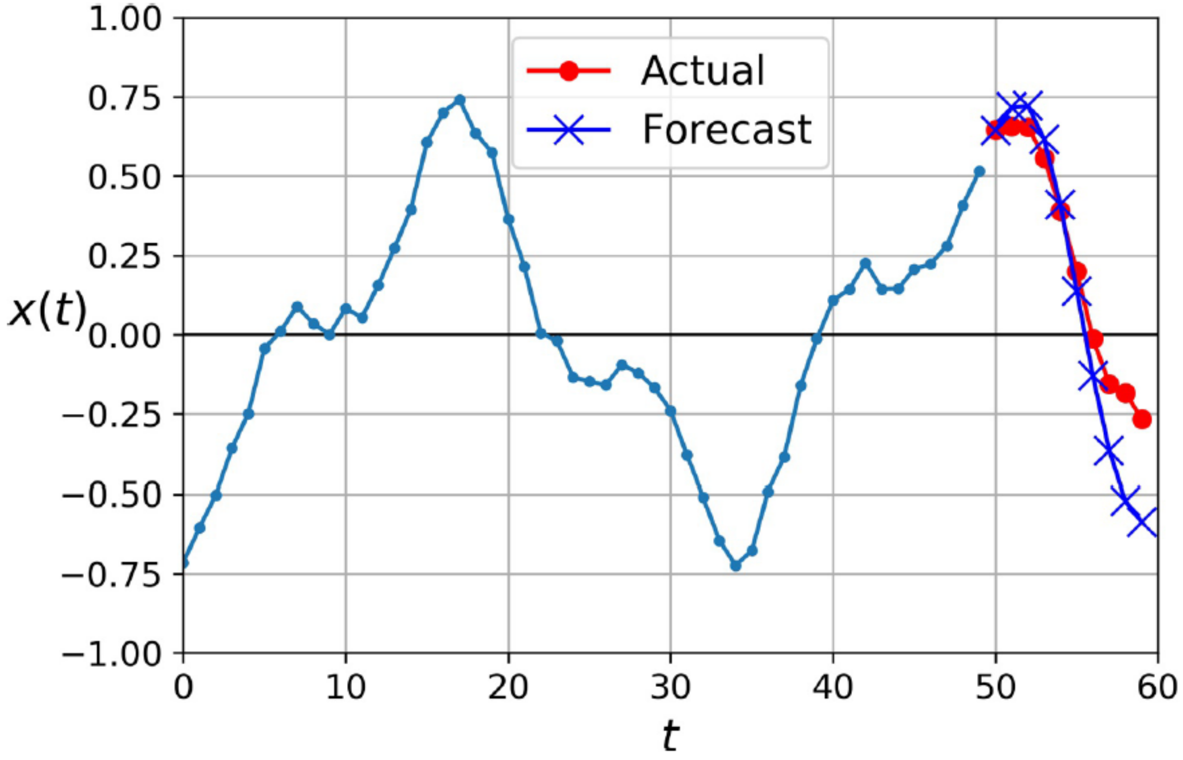


4.2 Deep RNNs

```
# Sequential model of two hidden RNN layers
model = keras.models.Sequential([
      keras.layers.SimpleRNN(20,
            return_sequences=True, # output all steps
            input_shape=[None, 1]),
      keras.layers.SimpleRNN(20),
      keras.layers.Dense(1)
])

# MSE = 0.0026
```

4.3 Forecasting Several Time Steps Ahead

- Can train an RNN to predict all **N next** values at once (sequence-to-vector model).
- The output layer should have N neurons.



4.3 Forecasting Several Time Steps Ahead

```
# Generate 10,000 time series with 10 steps ahead
series = generate_time_series(10000, n_steps + 10)

# Split them 7,000 : 2,000 : 1,000
X_train, y_train = series[:7000, :n_steps],
      series[:7000, -10:, 0] #(7000, 50, 1), (7000,10)
X_valid, y_valid = series[7000:9000, :n_steps],
      series[7000:9000, -10:, 0]
X_test, y_test = series[9000:, :n_steps],
      series[9000:, -10:, 0]
```

4.3 Forecasting Several Time Steps Ahead

```
# Sequential model of two hidden RNN layers
model = keras.models.Sequential([
        keras.layers.SimpleRNN(20, return_sequences=True,
                input_shape=[None, 1]),
        keras.layers.SimpleRNN(20),
        keras.layers.Dense(10)
])

# MSE = 0.008
```

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5. Handling Long Sequences

- Training long sequences has two major challenges:
  - Unstable gradients
  - Forgetting the first inputs in the sequence
- For the **unstable gradients**:
  - **Does not help**: ReLU activation, batch normalization
  - **Helps**: good parameter initialization, faster optimizers, dropout

```
model = Sequential()
model.add(layers.SimpleRNN(20, dropout=0.2, recurrent_dropout=0.2,
          input_shape=[None, 1]))
model.add(layers.Dense(1))
```

To fight overfitting and unstable gradients

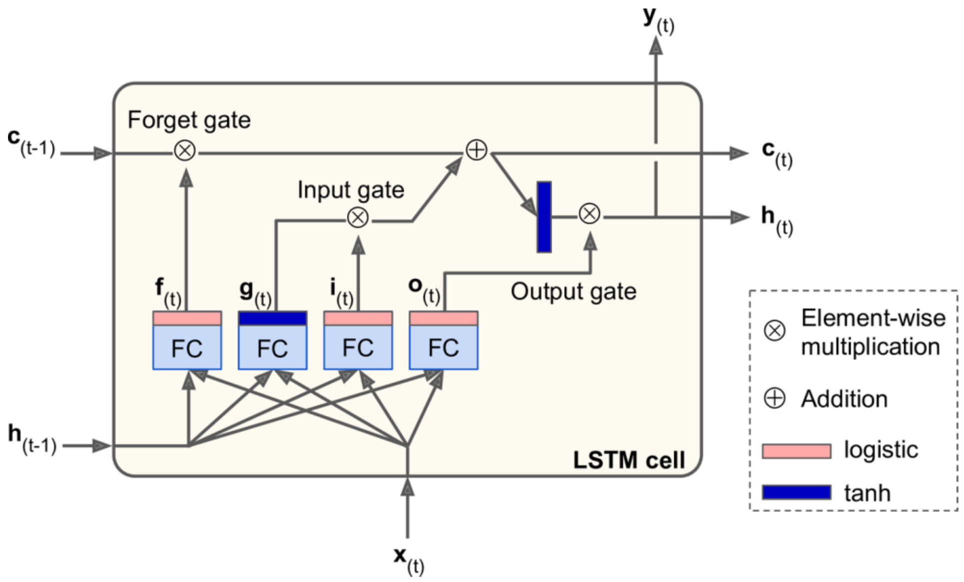
5. Handling Long Sequences

- To solve the **short-term memory problem**, use
  - **LSTM cell**
  - **GRU cell**

- These cells can be used in place of **`SimpleRNN`**

5.1 LSTM Cell

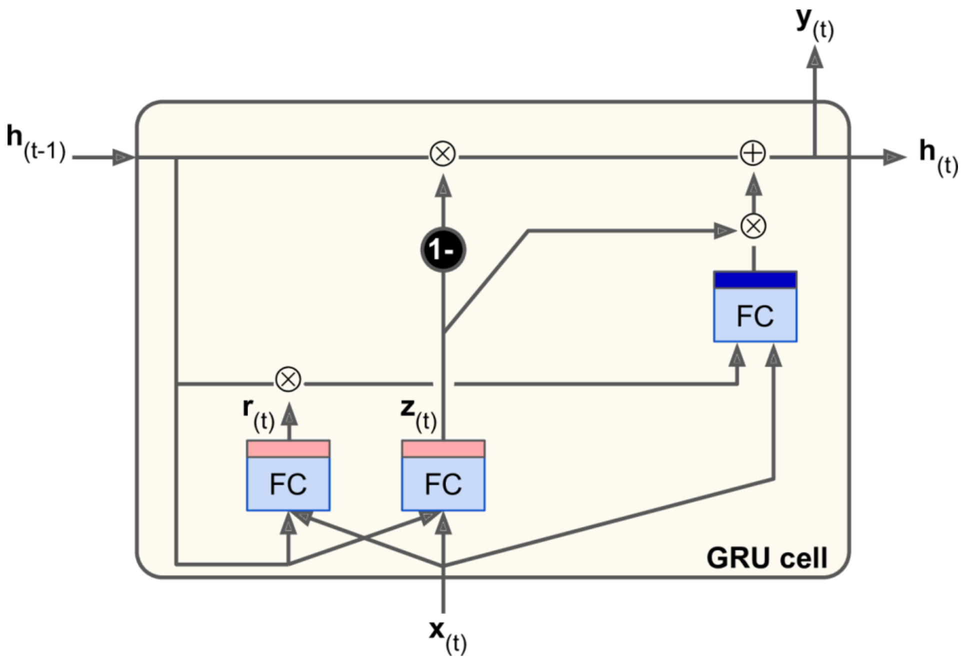
- The **Long Short-Term Memory** (LSTM) cell was proposed in 1997.
- Training converges faster and it **detects long-term dependencies** in the data.
- $\mathbf{h}_{(t)}$ as the short-term state and $\mathbf{c}_{(t)}$ as the long-term state.




```
model.add(LSTM(20))
```

5.2 GRU Cell

- The **Gated Recurrent Unit** (GRU) cell was proposed in 2014.
- **Simplified version** of the LSTM cell, performs just as well.
- A single gate controls the forget gate and the input gate.




```
model.add(GRU(20))
```

6. Exercises

15.1. Can you think of a few applications for a sequence-to-sequence RNN? What about a sequence-to-vector RNN, and a vector-to-sequence RNN?

15.2. How many dimensions must the inputs of an RNN layer have? What does each dimension represent? What about its outputs?

15.3. If you want to build a deep sequence-to-sequence RNN, which RNN layers should have return_sequences=True? What about a sequence-to-vector RNN?

15.4. Suppose you have a daily univariate time series, and you want to forecast the next seven days. Which RNN architecture should you use?

15.5. What are the main difficulties when training RNNs? How can you handle them?

15.6. Can you sketch the LSTM cell’s architecture?

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