Recurrent Neural Networks

ACTL3143 & ACTL5111 Deep Learning for Actuaries

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Lecture Outline

- **Tensors & Time Series**
- Some Recurrent Structures
- Recurrent Neural Networks
- CoreLogic Hedonic Home Value Index
- Splitting time series data
- Predicting Sydney House Prices
- Predicting Multiple Time Series

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Shapes of data

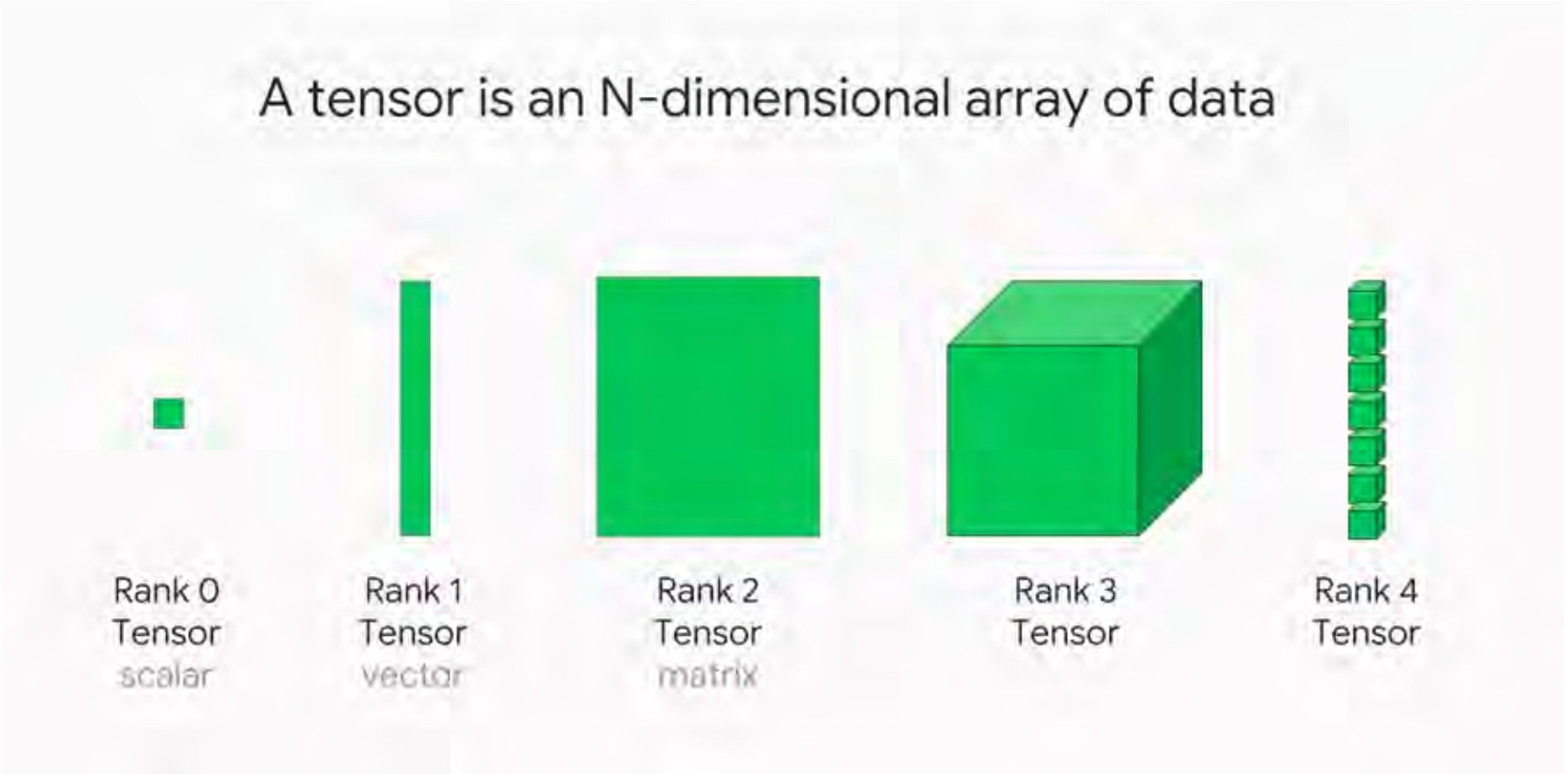

Illustration of tensors of different rank.

Source: Paras Patidar (2019), Tensors — Representation of Data In Neural Networks, Medium article.

The `axis` argument in numpy

Starting with a $(3, 4)$-shaped matrix:

```
1 X = np.arange(12).reshape(3,4)
2 X
```

```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

`axis=0`: $(3, 4) \rightsquigarrow (4,)$.

```
1 X.sum(axis=0)
```

```
array([12, 15, 18, 21])
```

`axis=1`: $(3, 4) \rightsquigarrow (3,)$.

```
1 X.prod(axis=1)
```

```
array([   0,  840, 7920])
```

The return value's rank is one less than the input's rank.

Important

The `axis` parameter tells us which dimension is removed.

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Using `axis` & `keepdims`

With `keepdims=True`, the rank doesn't change.

```
1 X = np.arange(12).reshape(3,4)
2 X
```

```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

`axis=0`: $(3,4) \rightsquigarrow (1,4)$.

```
1 X.sum(axis=0, keepdims=True)
```

```
array([[12, 15, 18, 21]])
```

```
1 X / X.sum(axis=1)
```

```
ValueError: operands could not be broadcast
together with shapes (3,4) (3,)
```

`axis=1`: $(3,4) \rightsquigarrow (3,1)$.

```
1 X.prod(axis=1, keepdims=True)
```

```
array([[   0],
       [ 840],
       [7920]])
```

```
1 X / X.sum(axis=1, keepdims=True)
```

```
array([[0.  , 0.17, 0.33, 0.5 ],
       [0.18, 0.23, 0.27, 0.32],
       [0.21, 0.24, 0.26, 0.29]])
```

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The rank of a time series

Say we had n observations of a time series $x_1, x_2, \ldots, x_n$.

This $\mathbf{x} = (x_1, \ldots, x_n)$ would have shape $(n,)$ & rank 1.

If instead we had a batch of b time series'

$$\mathbf{X} = \begin{pmatrix} x_7 & x_8 & \cdots & x_{7+n-1} \\ x_2 & x_3 & \cdots & x_{2+n-1} \\ \vdots & \vdots & \ddots & \vdots \\ x_3 & x_4 & \cdots & x_{3+n-1} \end{pmatrix},$$

the batch $\mathbf{X}$ would have shape (b, n) & rank 2.

Multivariate time series

t	x	y
0	x_0	y_0
1	x_1	y_1
2	x_2	y_2
3	x_3	y_3

Say n observations of the m time series, would be a shape (n, m) matrix of rank 2.

In Keras, a batch of b of these time series has shape (b, n, m) and has rank 3.

Note

Use $\mathbf{x}_t \in \mathbb{R}^{1 \times m}$ to denote the vector of all time series at time t. Here, $\mathbf{x}_t = (x_t, y_t)$.

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Recurrence relation

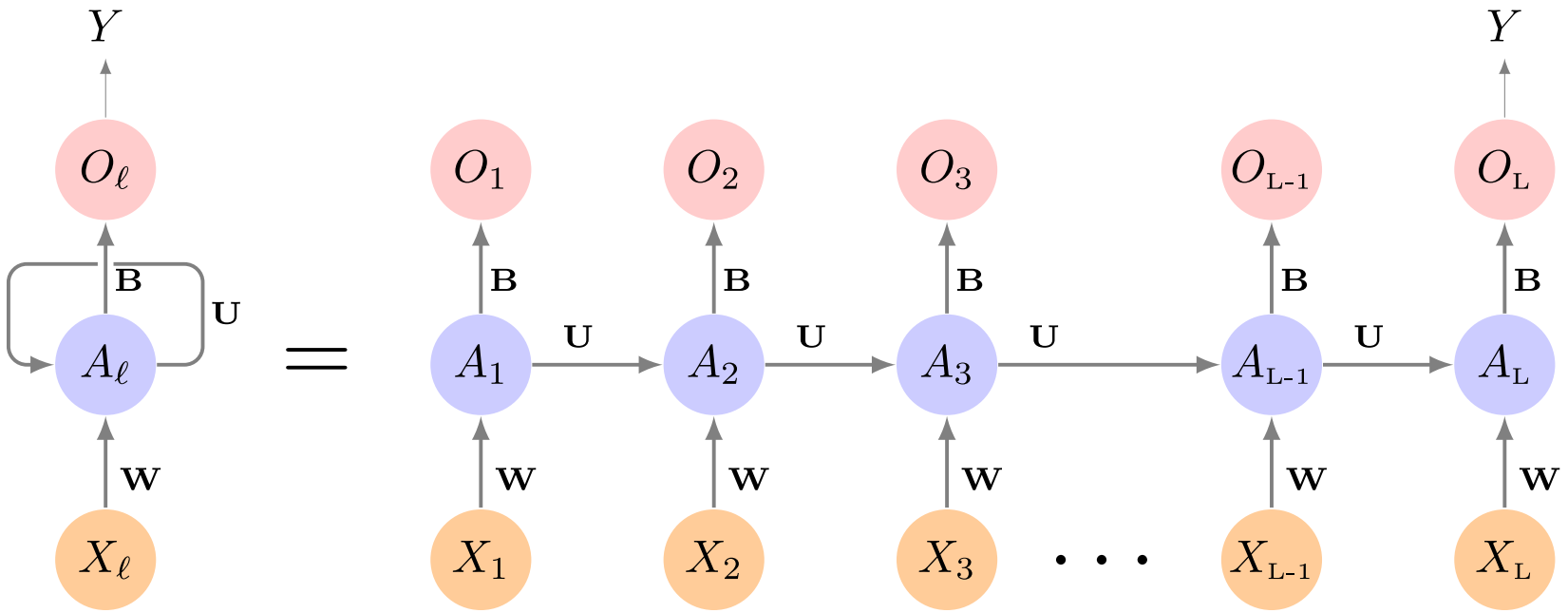
> A recurrence relation is an equation that expresses each element of a sequence as a function of the preceding ones. More precisely, in the case where only the immediately preceding element is involved, a recurrence relation has the form
>
> $$u_n = \psi(n, u_{n-1}) \quad \text{for} \quad n > 0.$$

Example: Factorial $n! = n(n-1)!$ for $n > 0$ given $0! = 1$.

Source: Wikipedia, Recurrence relation.

Diagram of an RNN cell

The RNN processes each data in the sequence one by one, while keeping memory of what came before.



Schematic of a simple recurrent neural network. E.g. SimpleRNN, LSTM, or GRU.

Source: James et al (2022), An Introduction to Statistical Learning, 2nd edition, Figure 10.12.

A SimpleRNN cell.

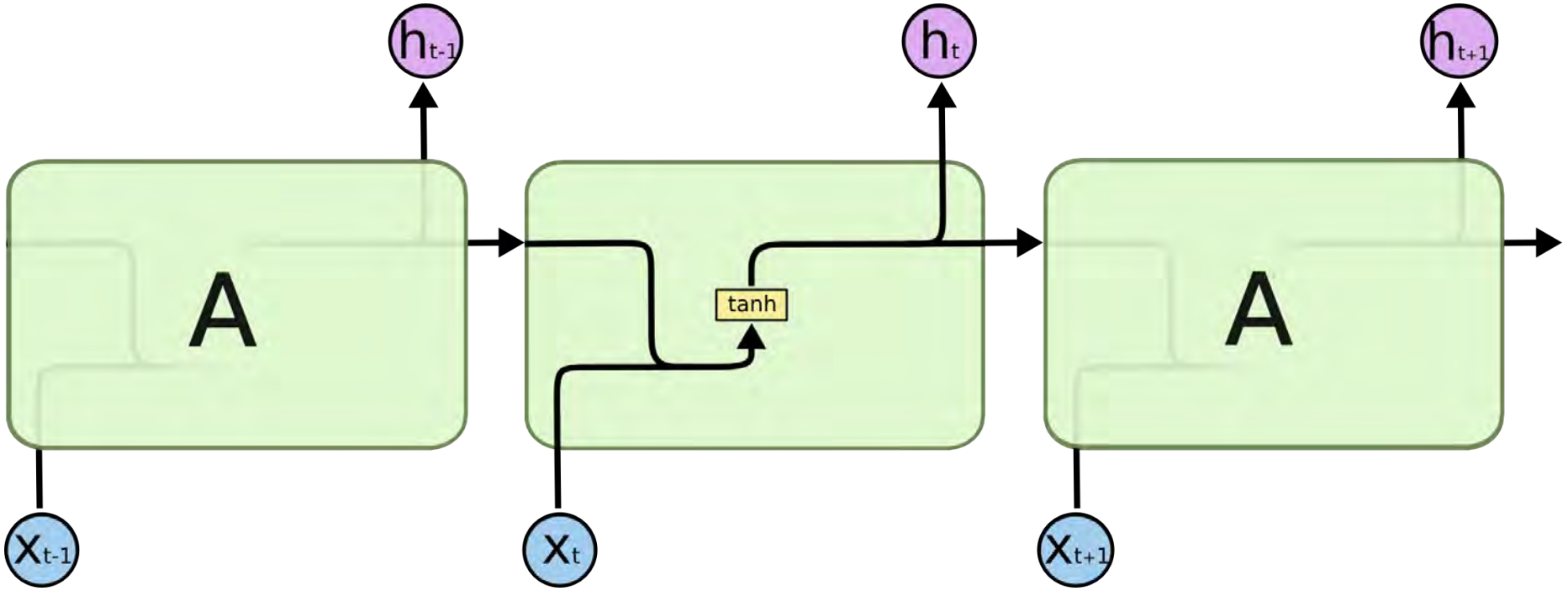


Diagram of a SimpleRNN cell.

All the outputs before the final one are often discarded.

Source: Christopher Olah (2015), Understanding LSTM Networks, Colah's Blog.

SimpleRNN

Say each prediction is a vector of size d, so $\mathbf{y}_t \in \mathbb{R}^{1\times d}$.

Then the main equation of a SimpleRNN, given $\mathbf{y}_0 = \mathbf{0}$, is

$$\mathbf{y}_t = \psi\big(\mathbf{x}_t\mathbf{W}_x + \mathbf{y}_{t-1}\mathbf{W}_y + \mathbf{b}\big).$$

Here,

$$\mathbf{x}_t \in \mathbb{R}^{1\times m}, \mathbf{W}_x \in \mathbb{R}^{m\times d},$$
$$\mathbf{y}_{t-1} \in \mathbb{R}^{1\times d}, \mathbf{W}_y \in \mathbb{R}^{d\times d}, \text{ and } \mathbf{b} \in \mathbb{R}^{d}.$$

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SimpleRNN (in batches)

Say we operate on batches of size b, then $\mathbf{Y}_t \in \mathbb{R}^{b \times d}$.

The main equation of a SimpleRNN, given $\mathbf{Y}_0 = \mathbf{0}$, is

$$\mathbf{Y}_t = \psi\big(\mathbf{X}_t \mathbf{W}_x + \mathbf{Y}_{t-1} \mathbf{W}_y + \mathbf{b}\big).$$

Here,

$$\mathbf{X}_t \in \mathbb{R}^{b \times m}, \mathbf{W}_x \in \mathbb{R}^{m \times d},$$
$$\mathbf{Y}_{t-1} \in \mathbb{R}^{b \times d}, \mathbf{W}_y \in \mathbb{R}^{d \times d}, \text{ and } \mathbf{b} \in \mathbb{R}^{d}.$$

Remember, $\mathbf{X} \in \mathbb{R}^{b \times n \times m}$, $\mathbf{Y} \in \mathbb{R}^{b \times d}$, and $\mathbf{X}_t$ is equivalent to `X[:, t, :]`.

Simple Keras demo

```
num_obs = 4
num_time_steps = 3
num_time_series = 2

X = np.arange(num_obs*num_time_steps*num_time_series).astype(np.float32) \
        .reshape([num_obs, num_time_steps, num_time_series])

output_size = 1
y = np.array([0, 0, 1, 1])
```

```
X[:2]
```

```
array([[[ 0.,  1.],
        [ 2.,  3.],
        [ 4.,  5.]],

       [[ 6.,  7.],
        [ 8.,  9.],
        [10., 11.]]], dtype=float32)
```

```
X[2:]
```

```
array([[[12., 13.],
        [14., 15.],
        [16., 17.]],

       [[18., 19.],
        [20., 21.],
        [22., 23.]]], dtype=float32)
```

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Keras' SimpleRNN

As usual, the `SimpleRNN` is just a layer in Keras.

```
from keras.layers import SimpleRNN

random.seed(1234)
model = Sequential([
  SimpleRNN(output_size, activation="sigmoid")
])
model.compile(loss="binary_crossentropy", metrics=["accuracy"])

hist = model.fit(X, y, epochs=500, verbose=False)
model.evaluate(X, y, verbose=False)
```

```
[3.1845884323120117, 0.5]
```

The predicted probabilities on the training set are:

```
model.predict(X, verbose=0)
```

```
array([[0.97],
       [1.  ],
       [1.  ],
       [1.  ]], dtype=float32)
```

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SimpleRNN weights

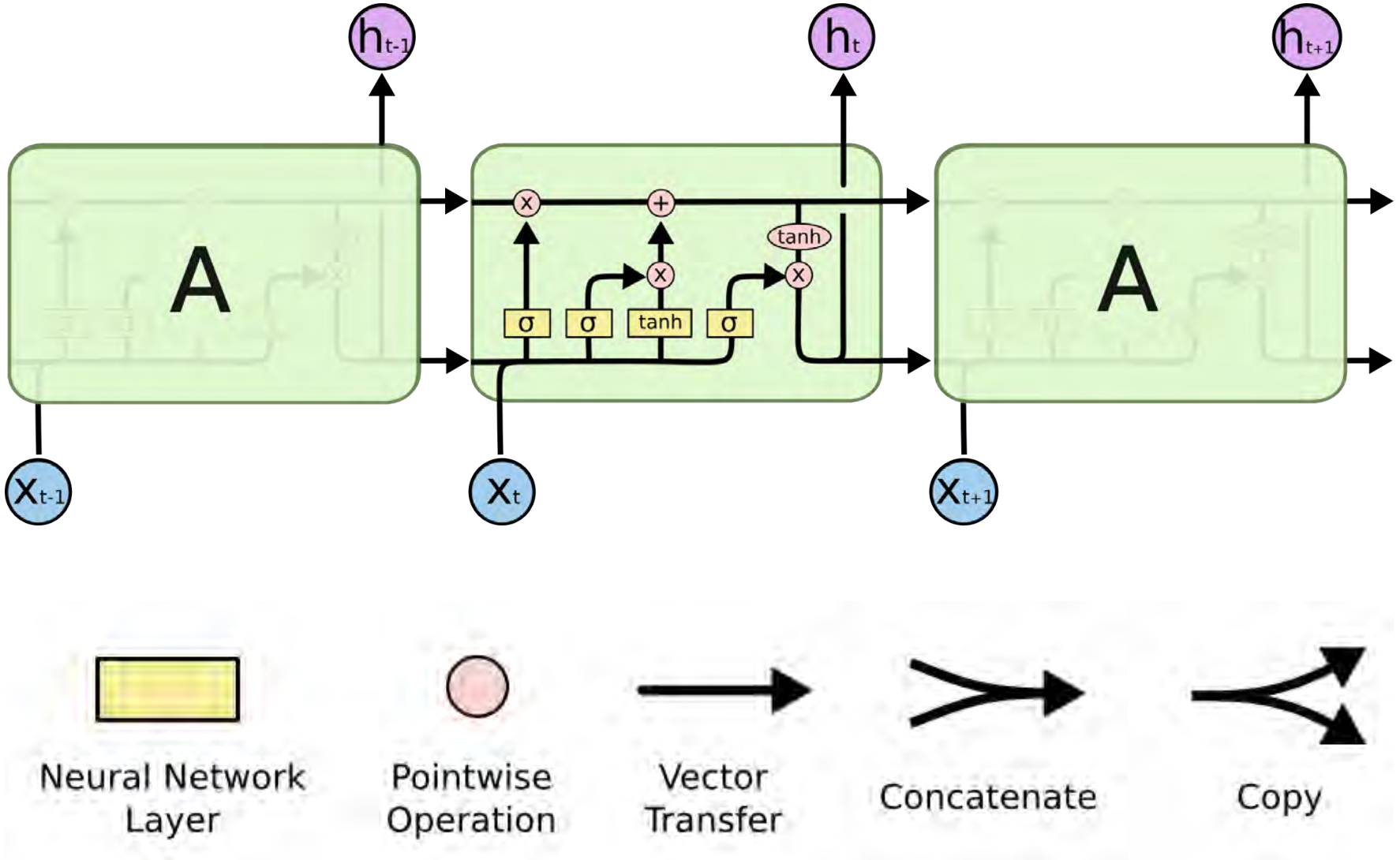
```
model.get_weights()
```

```
[array([[0.68],
        [0.21]], dtype=float32),
 array([[0.49]], dtype=float32),
 array([-0.51], dtype=float32)]
```

```
def sigmoid(x):
  return 1 / (1 + np.exp(-x))

W_x, W_y, b = model.get_weights()

Y = np.zeros((num_obs, output_size), dtype=np.float32)
for t in range(num_time_steps):
    X_t = X[:, t, :]
    z = X_t @ W_x + Y @ W_y + b
    Y = sigmoid(z)

Y
```

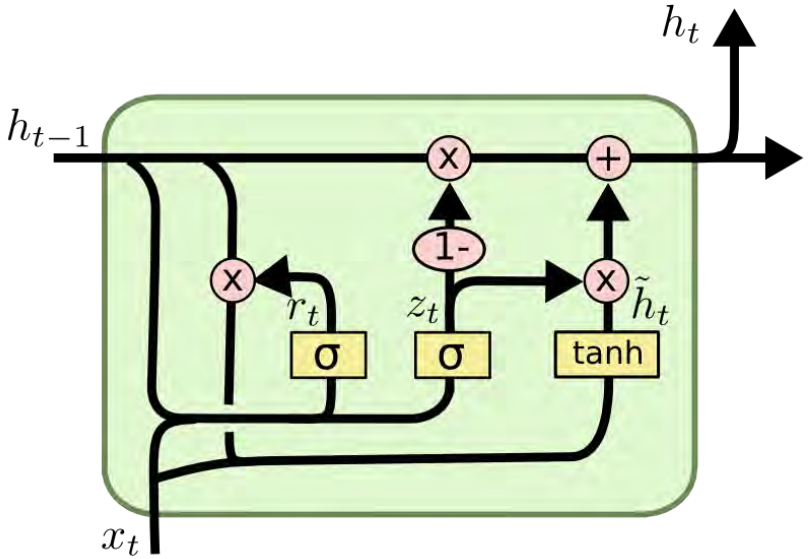
```
array([[0.97],
       [1.  ],
       [1.  ],
       [1.  ]], dtype=float32)
```

LSTM internals



Source: Christopher Olah (2015), Understanding LSTM Networks, Colah's Blog.

GRU internals



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Diagram of a GRU cell.

Source: Christopher Olah (2015), Understanding LSTM Networks, Colah's Blog.

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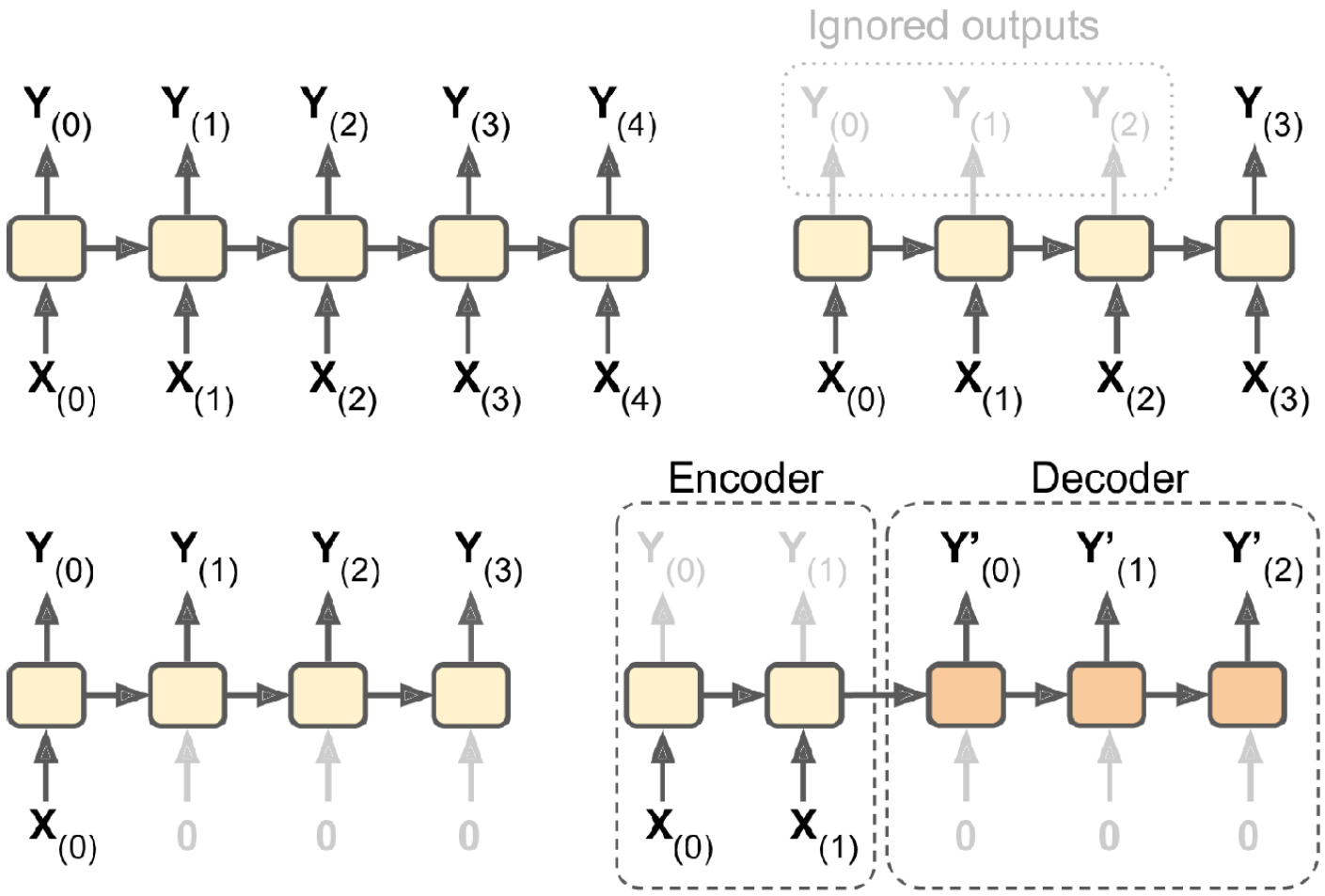
Basic facts of RNNs

- A recurrent neural network is a type of neural network that is designed to process sequences of data (e.g. time series, sentences).
- A recurrent neural network is any network that contains a recurrent layer.
- A recurrent layer is a layer that processes data in a sequence.
- An RNN can have one or more recurrent layers.
- Weights are shared over time; this allows the model to be used on arbitrary-length sequences.

Applications

- Forecasting: revenue forecast, weather forecast, predict disease rate from medical history, etc.
- Classification: given a time series of the activities of a visitor on a website, classify whether the visitor is a bot or a human.
- Event detection: given a continuous data stream, identify the occurrence of a specific event. Example: Detect utterances like “Hey Alexa” from an audio stream.
- Anomaly detection: given a continuous data stream, detect anything unusual happening. Example: Detect unusual activity on the corporate network.

Input and output sequences



Categories of recurrent neural networks: sequence to sequence, sequence to vector, vector to sequence, encoder-decoder network.

Source: Aurélien Géron (2019), *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*, 2nd Edition, Chapter 15.

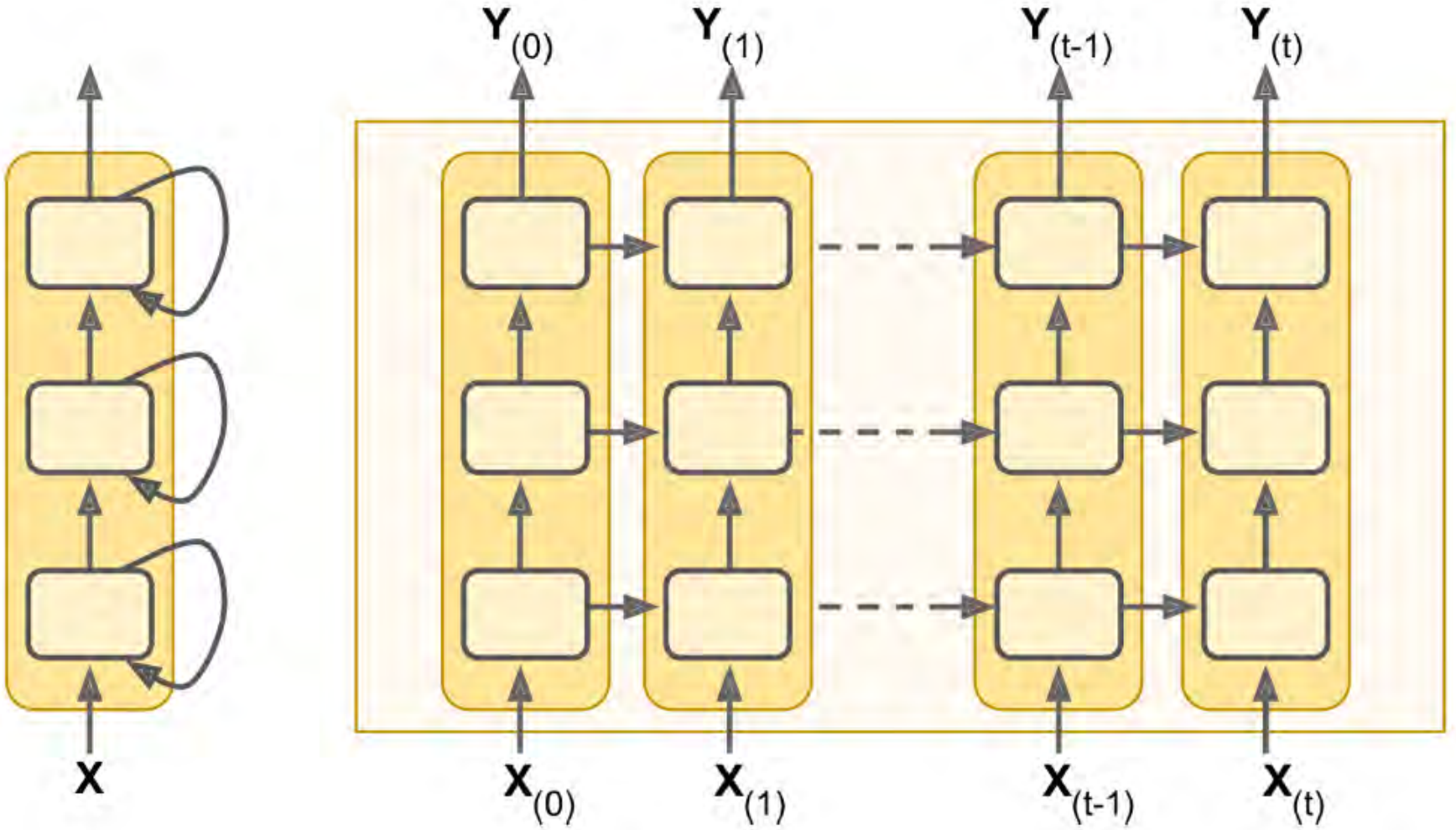
Input and output sequences

- Sequence to sequence: Useful for predicting time series such as using prices over the last N days to output the prices shifted one day into the future (i.e. from $N-1$ days ago to tomorrow.)
- Sequence to vector: ignore all outputs in the previous time steps except for the last one. Example: give a sentiment score to a sequence of words corresponding to a movie review.

Input and output sequences

- Vector to sequence: feed the network the same input vector over and over at each time step and let it output a sequence. Example: given that the input is an image, find a caption for it. The image is treated as an input vector (pixels in an image do not follow a sequence). The caption is a sequence of textual description of the image. A dataset containing images and their descriptions is the input of the RNN.
- The Encoder-Decoder: The encoder is a sequence-to-vector network. The decoder is a vector-to-sequence network. Example: Feed the network a sequence in one language. Use the encoder to convert the sentence into a single vector representation. The decoder decodes this vector into the translation of the sentence in another language.

Recurrent layers can be stacked.



Deep RNN unrolled through time.

Source: Aurélien Géron (2019), *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*, 2nd Edition, Chapter 15.

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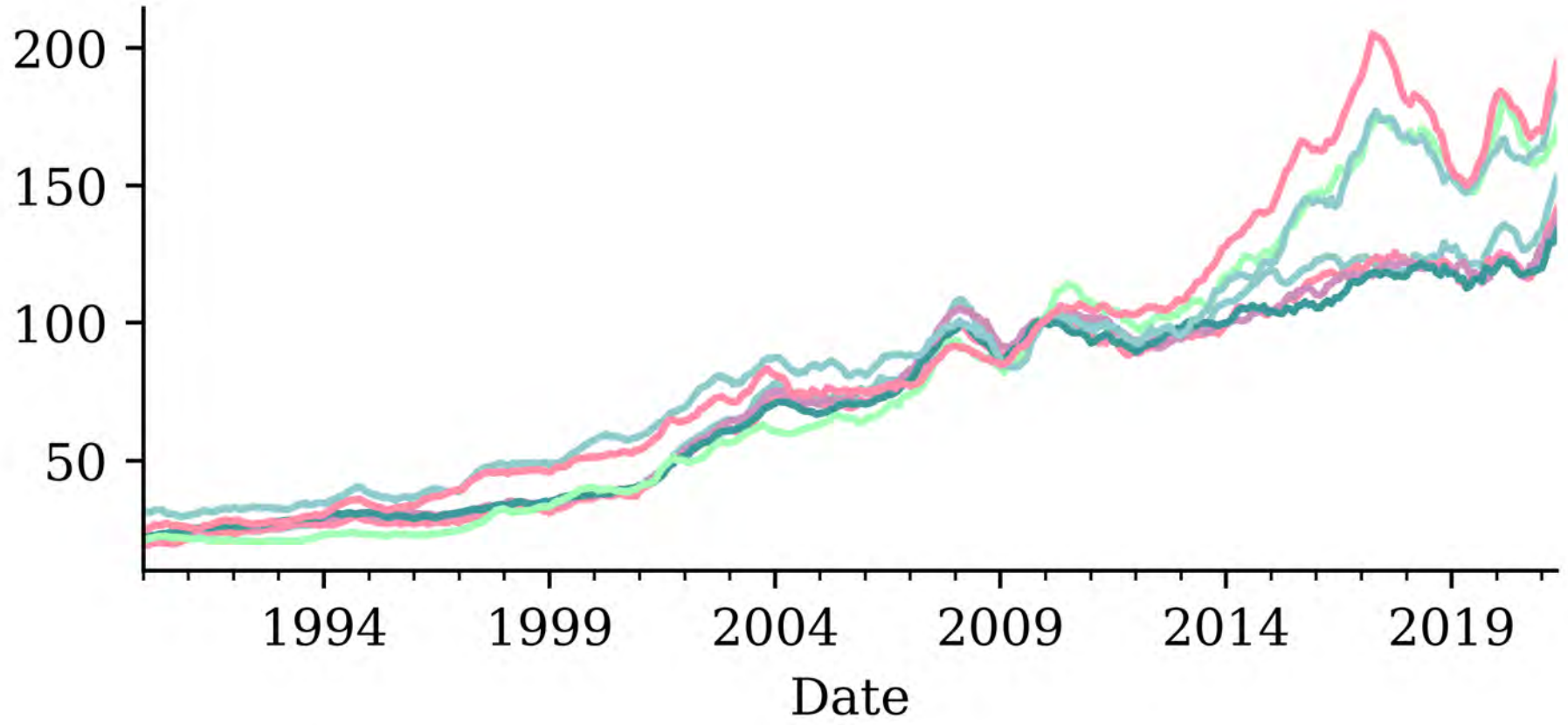
Australian House Price Indices



Percentage changes

```
changes = house_prices.pct_change().dropna()
changes.round(2)
```

Date	Brisbane	East_Bris	North_Bris	West_Bris	Melbourne	North_Syd	Sydney
1990-02-28	0.03	-0.01	0.01	0.01	0.00	-0.00	-0.02
1990-03-31	0.01	0.03	0.01	0.01	0.02	-0.00	0.03
...	...	...	...	...	...	...	...
2021-04-30	0.03	0.01	0.01	-0.00	0.01	0.02	0.02
2021-05-31	0.03	0.03	0.03	0.03	0.03	0.02	0.04

376 rows × 7 columns

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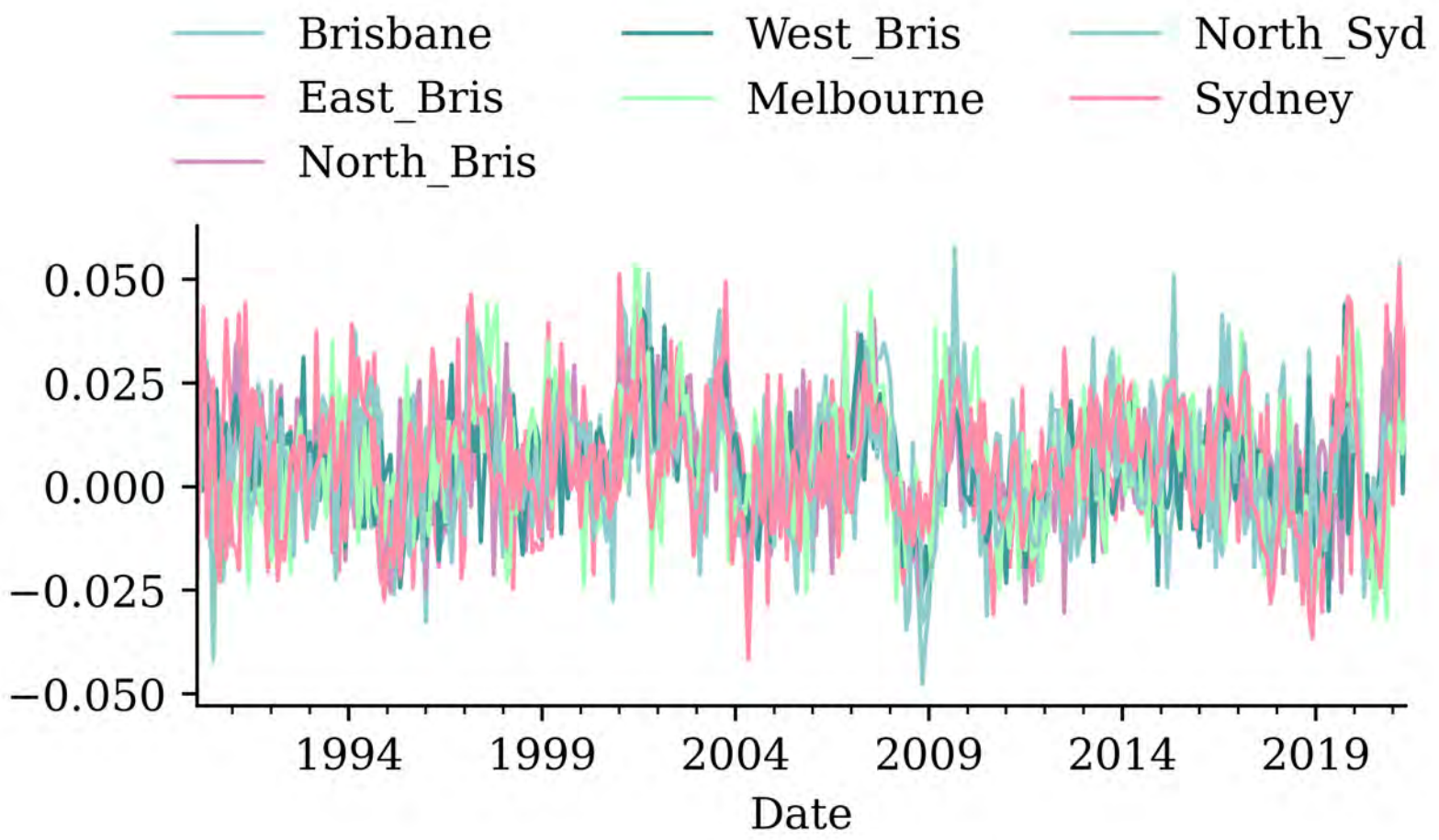
Percentage changes

```
1 changes.plot();
```



The size of the changes

```
1 changes.mean()
```

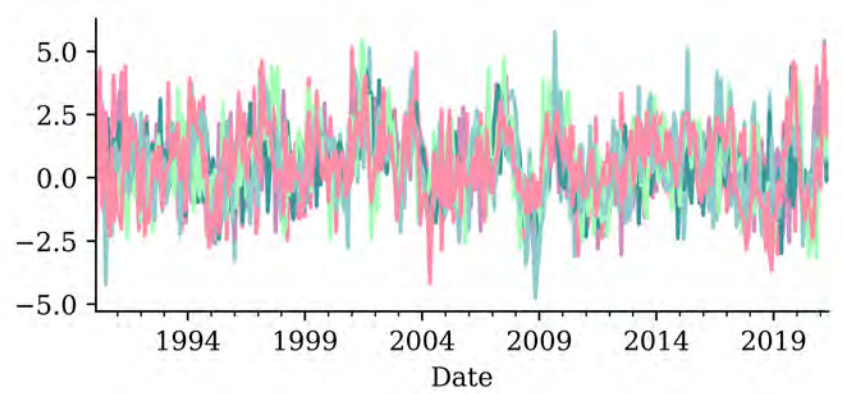
```
Brisbane      0.005496
East_Bris     0.005416
North_Bris    0.005024
West_Bris     0.004842
Melbourne     0.005677
North_Syd     0.004819
Sydney        0.005526
dtype: float64
```

```
1 changes *= 100
```

```
1 changes.mean()
```

```
Brisbane      0.549605
East_Bris     0.541562
North_Bris    0.502390
West_Bris     0.484204
Melbourne     0.567700
North_Syd     0.481863
Sydney        0.552641
dtype: float64
```

```
1 changes.plot(legend=False);
```



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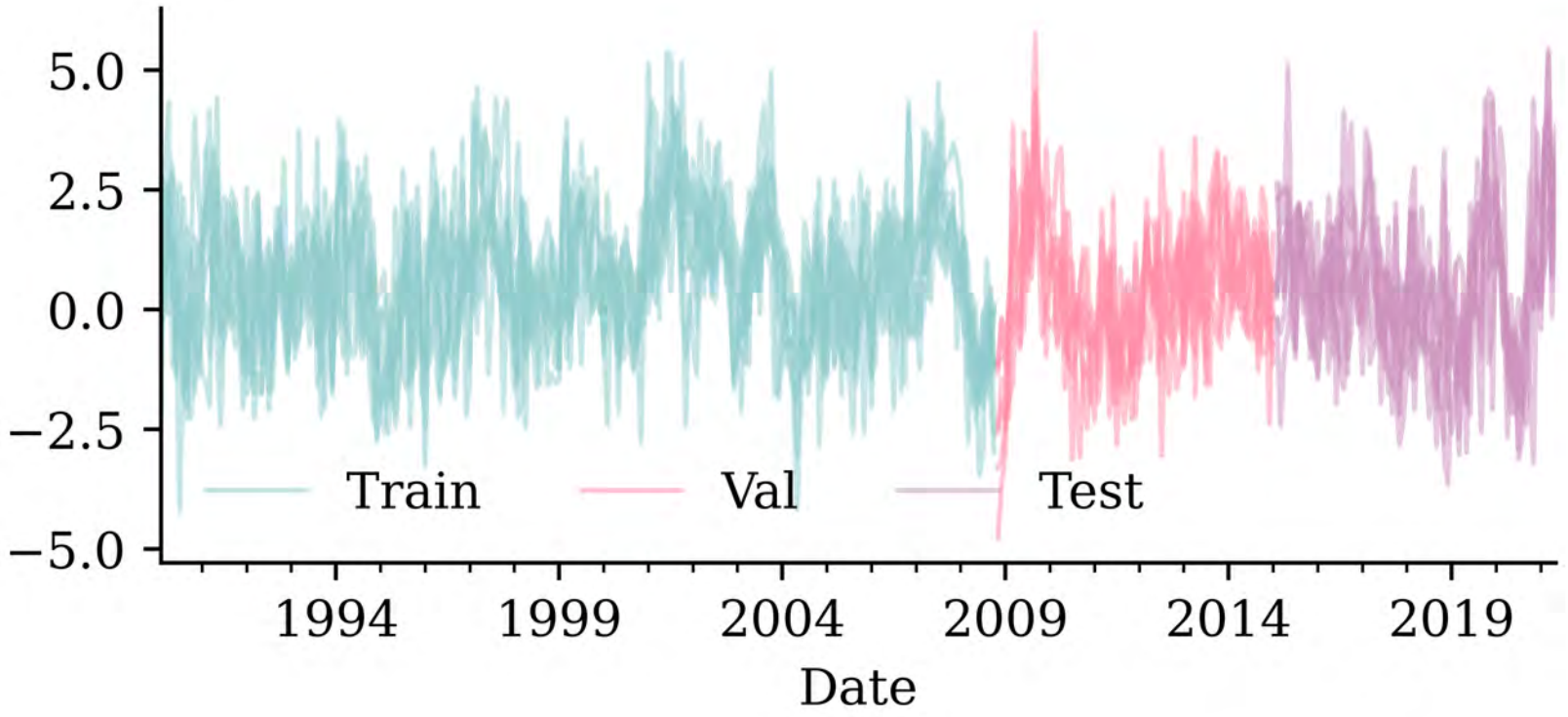
Split *without* shuffling

```
1 num_train = int(0.6 * len(changes))
2 num_val = int(0.2 * len(changes))
3 num_test = len(changes) - num_train - num_val
4 print(f"# Train: {num_train}, # Val: {num_val}, # Test: {num_test}")
```

```
# Train: 225, # Val: 75, # Test: 76
```



Subsequences of a time series

Keras has a built-in method for converting a time series into subsequences/chunks.

```python
from keras.utils import timeseries_dataset_from_array

integers = range(10)
dummy_dataset = timeseries_dataset_from_array(
    data=integers[:-3],
    targets=integers[3:],
    sequence_length=3,
    batch_size=2,
)

for inputs, targets in dummy_dataset:
    for i in range(inputs.shape[0]):
        print([int(x) for x in inputs[i]], int(targets[i]))
```

```
[0, 1, 2] 3
[1, 2, 3] 4
[2, 3, 4] 5
[3, 4, 5] 6
[4, 5, 6] 7
```

Source: Code snippet in Chapter 10 of Chollet.

On time series splits

If you have a lot of time series data, then use:

```python
from keras.utils import timeseries_dataset_from_array
data = range(20); seq = 3; ts = data[:-seq]; target = data[seq:]
nTrain = int(0.5 * len(ts)); nVal = int(0.25 * len(ts))
nTest = len(ts) - nTrain - nVal
print(f"# Train: {nTrain}, # Val: {nVal}, # Test: {nTest}")
```

```
# Train: 8, # Val: 4, # Test: 5
```

```python
trainDS = \
  timeseries_dataset_fr
    ts, target, seq,
    end_index=nTrain)
```

```python
valDS = \
  timeseries_dataset_fr
    ts, target, seq,
    start_index=nTrain,
    end_index=nTrain+nV
```

```python
testDS = \
  timeseries_dataset_fr
    ts, target, seq,
    start_index=nTrain+
```

```
Training dataset
[0, 1, 2] 3
[1, 2, 3] 4
[2, 3, 4] 5
[3, 4, 5] 6
[4, 5, 6] 7
[5, 6, 7] 8
```

```
Validation dataset
[8, 9, 10] 11
[9, 10, 11] 12
```

```
Test dataset
[12, 13, 14] 15
[13, 14, 15] 16
[14, 15, 16] 17
```

Adapted from: François Chollet (2021), *Deep Learning with Python*, Second Edition, Listing 10.7.

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On time series splits II

If you *don't* have a lot of time series data, consider:

```
X = []; y = []
for i in range(len(data)-seq):
    X.append(data[i:i+seq])
    y.append(data[i+seq])
X = np.array(X); y = np.array(y);
```

```
nTrain = int(0.5 * X.sh
X_train = X[:nTrain]
y_train = y[:nTrain]
```

```
Training dataset
[0, 1, 2] 3
[1, 2, 3] 4
[2, 3, 4] 5
[3, 4, 5] 6
[4, 5, 6] 7
[5, 6, 7] 8
[6, 7, 8] 9
[7, 8, 9] 10
```

```
nVal = int(np.ceil(0.25
X_val = X[nTrain:nTrain
y_val = y[nTrain:nTrain
```

```
Validation dataset
[8, 9, 10] 11
[9, 10, 11] 12
[10, 11, 12] 13
[11, 12, 13] 14
[12, 13, 14] 15
```

```
nTest = X.shape[0] - nT
X_test = X[nTrain+nVal:
y_test = y[nTrain+nVal:
```

```
Test dataset
[13, 14, 15] 16
[14, 15, 16] 17
[15, 16, 17] 18
[16, 17, 18] 19
```

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Creating dataset objects

```
# Num. of input time series.
num_ts = changes.shape[1]

# How many prev. months to use.
seq_length = 6

# Predict the next month ahead.
ahead = 1

# The index of the first target.
delay = (seq_length+ahead-1)
```

```
# Which suburb to predict.
target_suburb = changes["Sydney"]

train_ds = \
  timeseries_dataset_from_array(
    changes[:-delay],
    targets=target_suburb[delay:],
    sequence_length=seq_length,
    end_index=num_train)
```

```
val_ds = \
  timeseries_dataset_from_array(
    changes[:-delay],
    targets=target_suburb[delay:],
    sequence_length=seq_length,
    start_index=num_train,
    end_index=num_train+num_val)
```

```
test_ds = \
  timeseries_dataset_from_array(
    changes[:-delay],
    targets=target_suburb[delay:],
    sequence_length=seq_length,
    start_index=num_train+num_val)
```

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Converting `Dataset` to numpy

The `Dataset` object can be handed to Keras directly, but if we really need a numpy array, we can run:

```
1 X_train = np.concatenate(list(train_ds.map(lambda x, y: x)))
2 y_train = np.concatenate(list(train_ds.map(lambda x, y: y)))
```

The shape of our training set is now:

```
1 X_train.shape
```

```
(220, 6, 7)
```

```
1 y_train.shape
```

```
(220,)
```

Converting the rest to numpy arrays:

```
1 X_val = np.concatenate(list(val_ds.map(lambda x, y: x)))
2 y_val = np.concatenate(list(val_ds.map(lambda x, y: y)))
3 X_test = np.concatenate(list(test_ds.map(lambda x, y: x)))
4 y_test = np.concatenate(list(test_ds.map(lambda x, y: y)))
```

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A dense network

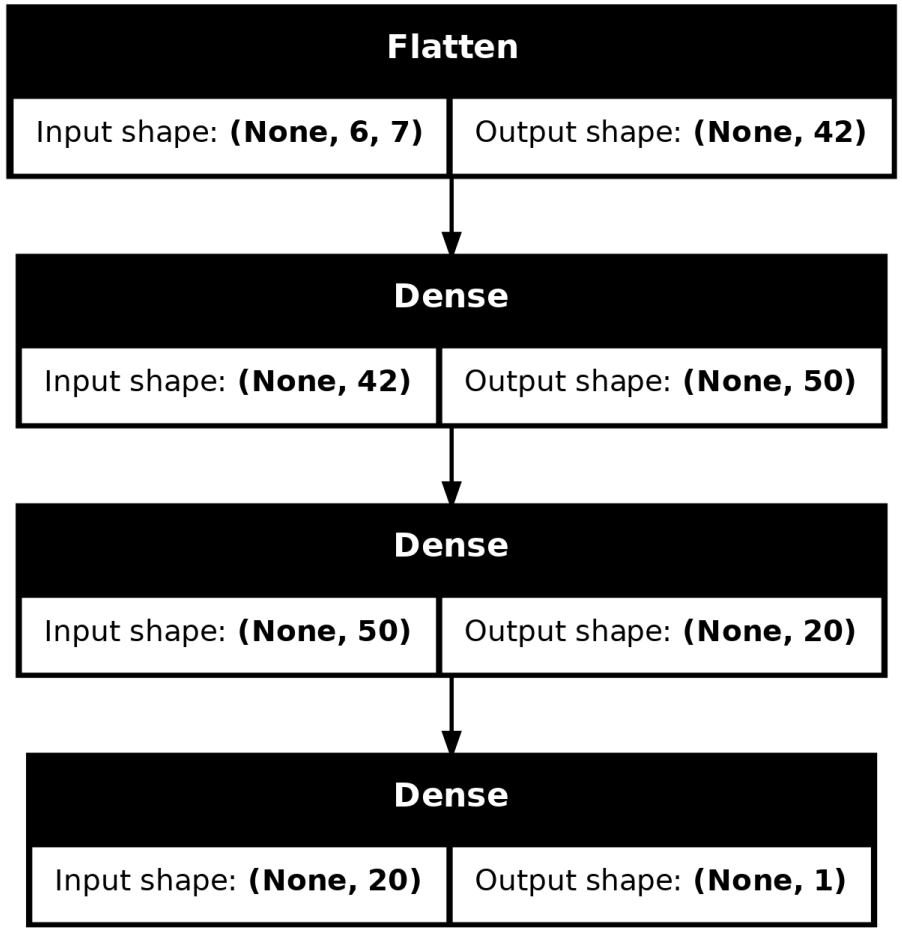
```
from keras.layers import Input, Flatten
random.seed(1)
model_dense = Sequential([
    Input((seq_length, num_ts)),
    Flatten(),
    Dense(50, activation="leaky_relu"),
    Dense(20, activation="leaky_relu"),
    Dense(1, activation="linear")
])
model_dense.compile(loss="mse", optimizer="adam")
print(f"This model has {model_dense.count_params()} parameters.")

es = EarlyStopping(patience=50, restore_best_weights=True, verbose=1)
%time hist = model_dense.fit(X_train, y_train, epochs=1_000, \
  validation_data=(X_val, y_val), callbacks=[es], verbose=0);
```

```
This model has 3191 parameters.
Epoch 57: early stopping
Restoring model weights from the end of the best epoch: 7.
CPU times: user 2.74 s, sys: 250 ms, total: 2.99 s
Wall time: 2.65 s
```

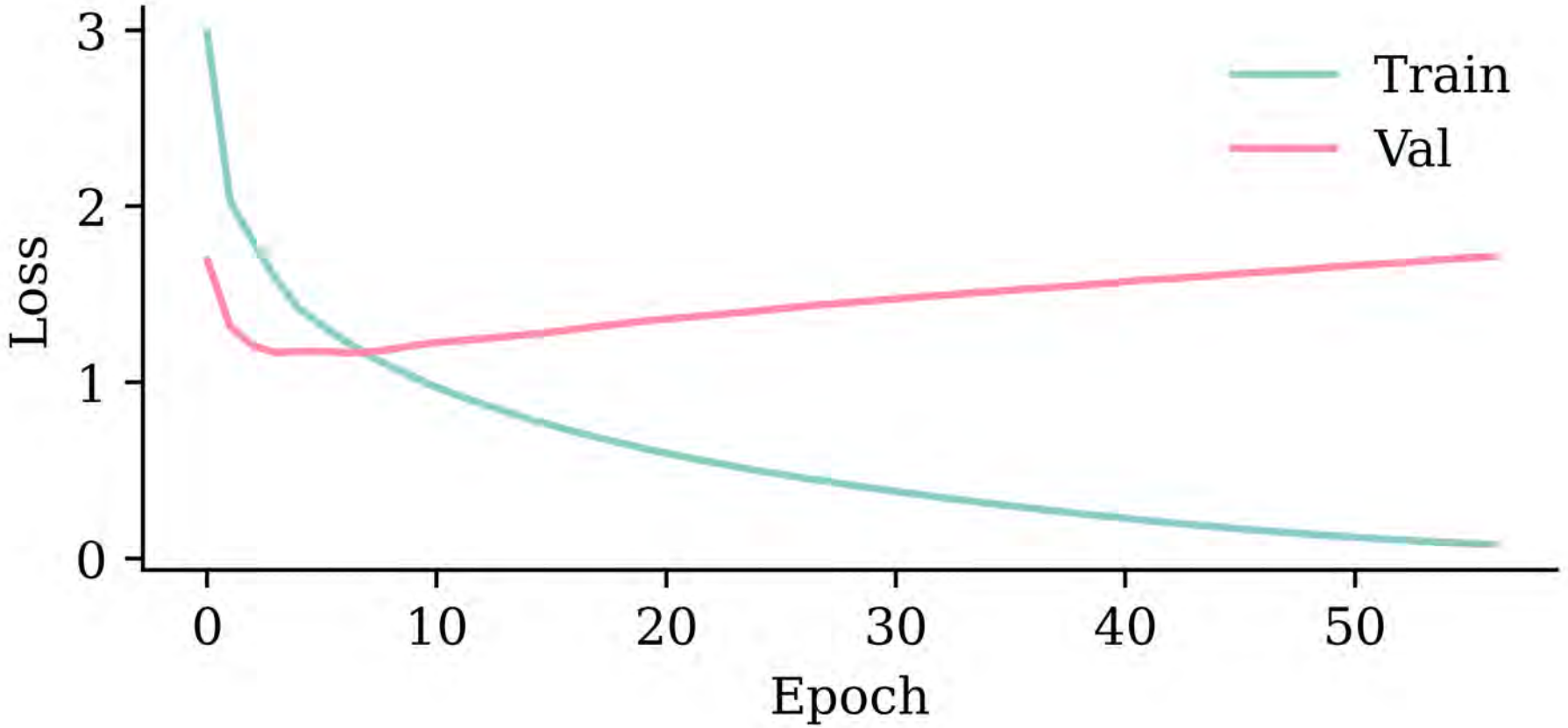
UNSW SYDNEY

Plot the model

```
1 from keras.utils import plot_model
2 plot_model(model_dense, show_shapes=True)
```



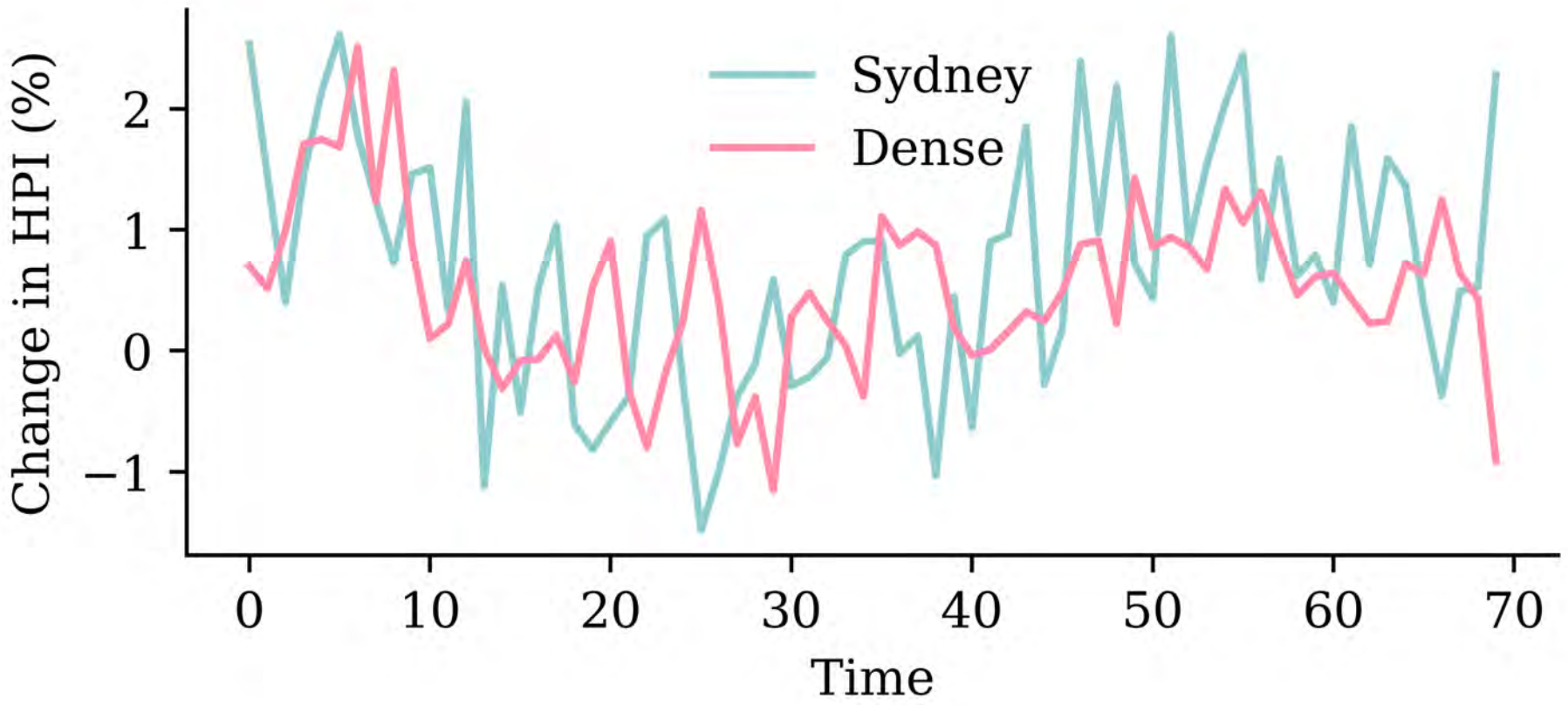
Assess the fits




```
1 model_dense.evaluate(X_val, y_val, verbose=0)
```

```
1.1644608974456787
```

Plotting the predictions



A `SimpleRNN` layer

```
random.seed(1)

model_simple = Sequential([
    Input((seq_length, num_ts)),
    SimpleRNN(50),
    Dense(1, activation="linear")
])
model_simple.compile(loss="mse", optimizer="adam")
print(f"This model has {model_simple.count_params()} parameters.")

es = EarlyStopping(patience=50, restore_best_weights=True, verbose=1)
%time hist = model_simple.fit(X_train, y_train, epochs=1_000, \
  validation_data=(X_val, y_val), callbacks=[es], verbose=0);
```

```
This model has 2951 parameters.
Epoch 62: early stopping
Restoring model weights from the end of the best epoch: 12.
CPU times: user 3.76 s, sys: 438 ms, total: 4.2 s
Wall time: 3.19 s
```

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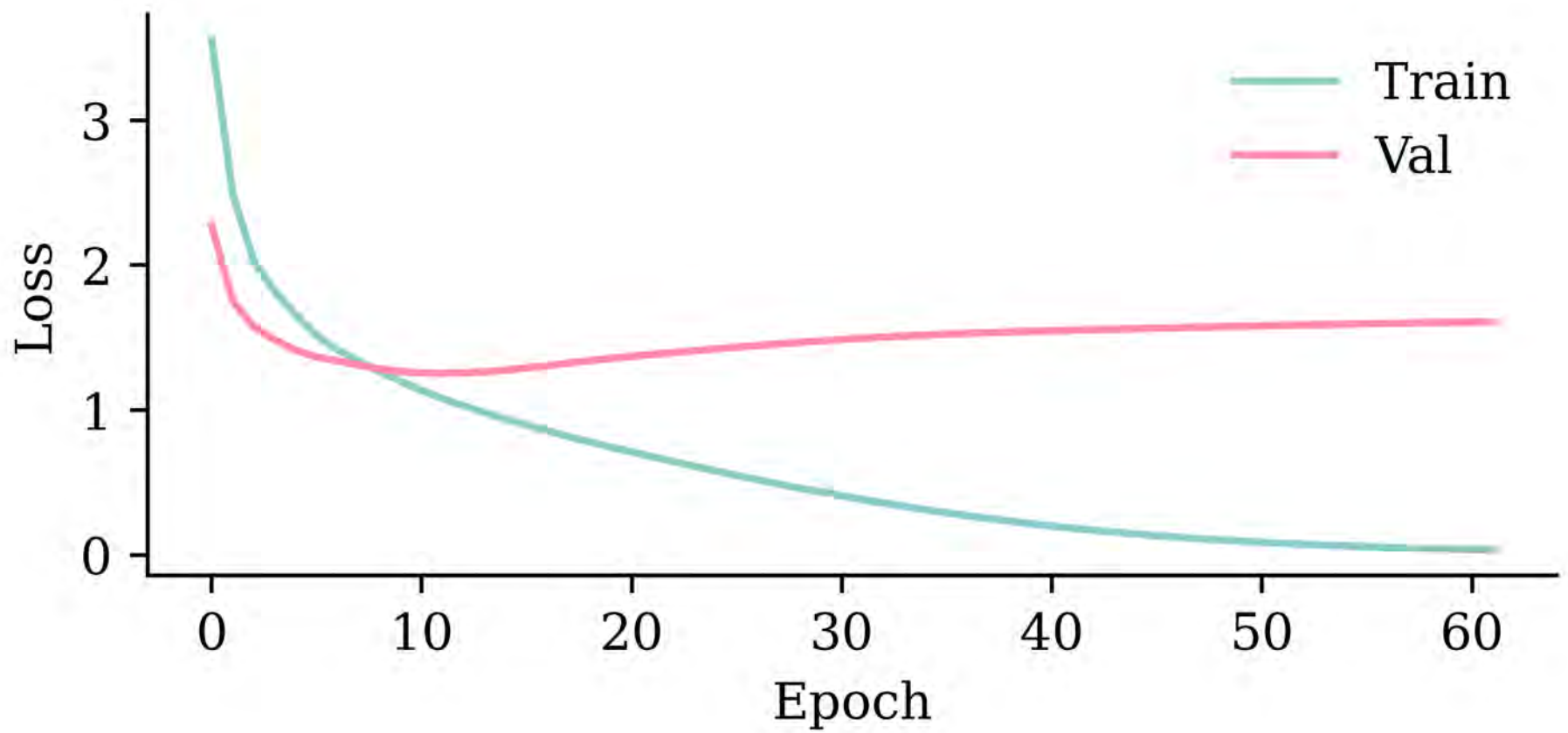
Assess the fits




```
1 model_simple.evaluate(X_val, y_val, verbose=0)
```

```
1.2507916688919067
```

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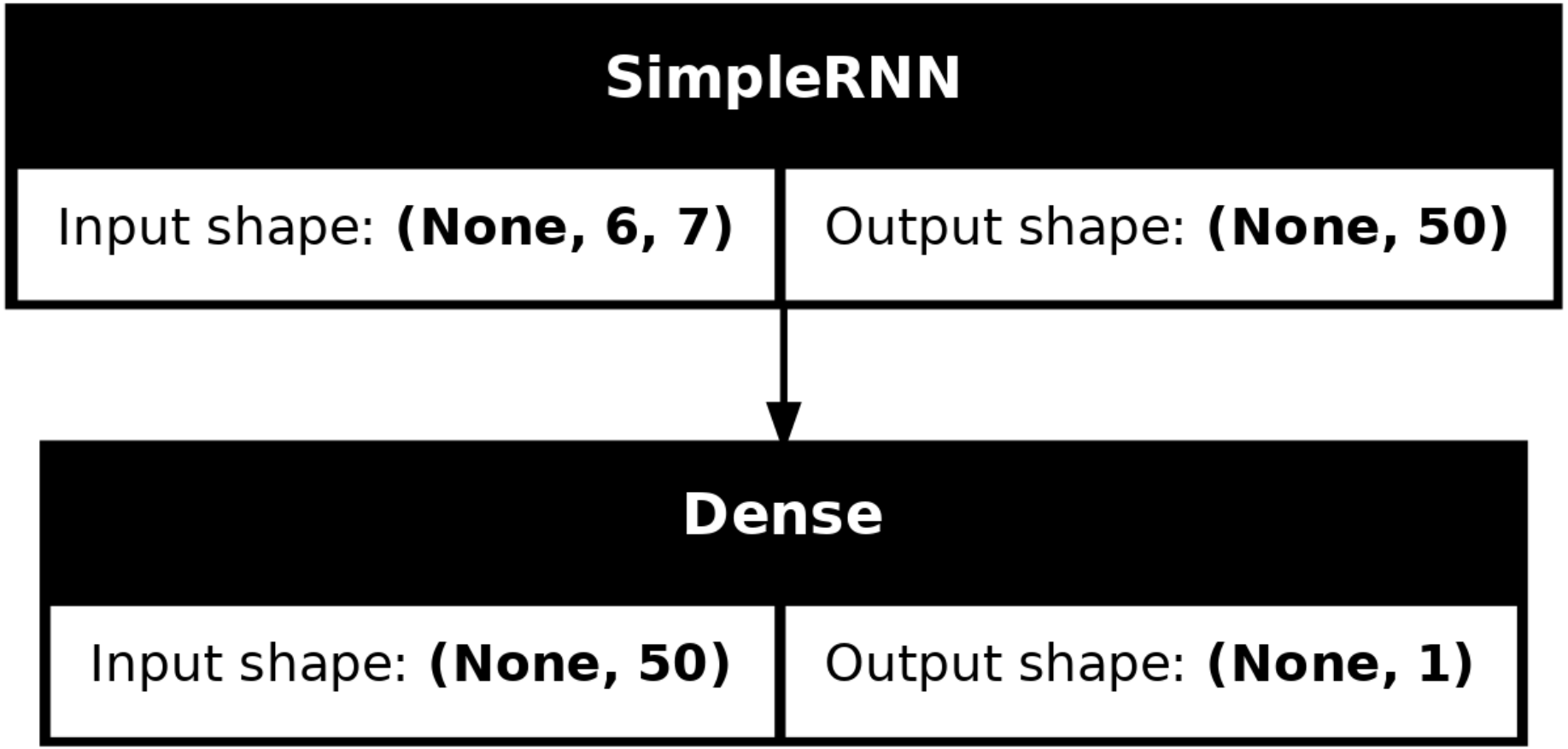
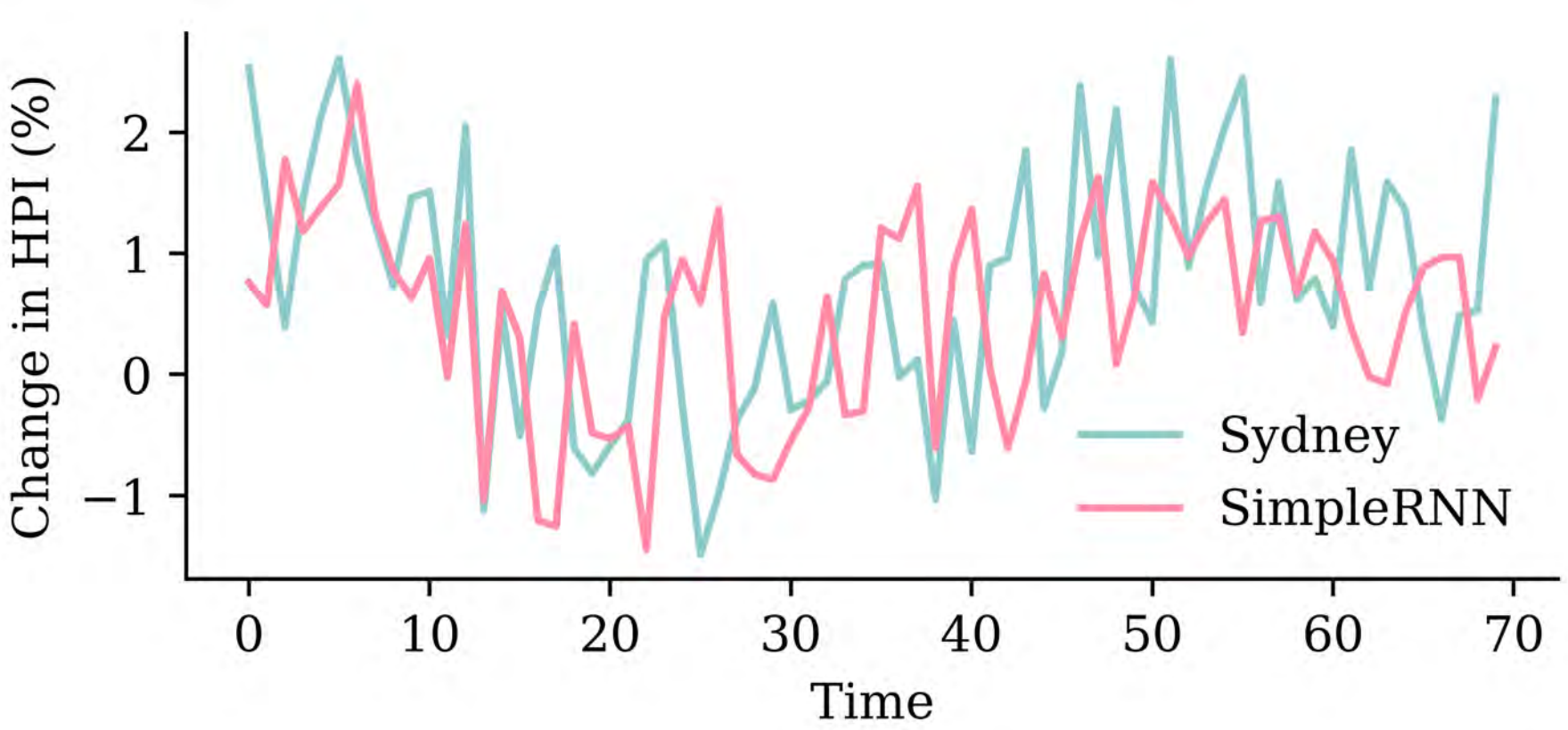
Plot the model

```
1 plot_model(model_simple, show_shapes=True)
```



Plotting the predictions

```
WARNING:tensorflow:5 out of the last 7 calls to <function TensorFlowTrainer.make_predict_function.
<locals>.one_step_on_data_distributed at 0×79eba06db4c0> triggered tf.function retracing. Tracing is expensive and the excessive
number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3)
passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has
reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for  more
details.
```



A LSTM layer

```
from keras.layers import LSTM

random.seed(1)

model_lstm = Sequential([
    Input((seq_length, num_ts)),
    LSTM(50),
    Dense(1, activation="linear")
])

model_lstm.compile(loss="mse", optimizer="adam")

es = EarlyStopping(patience=50, restore_best_weights=True, verbose=1)

%time hist = model_lstm.fit(X_train, y_train, epochs=1_000, \
  validation_data=(X_val, y_val), callbacks=[es], verbose=0);
```

```
Epoch 59: early stopping
Restoring model weights from the end of the best epoch: 9.
CPU times: user 4.38 s, sys: 548 ms, total: 4.92 s
Wall time: 3.69 s
```

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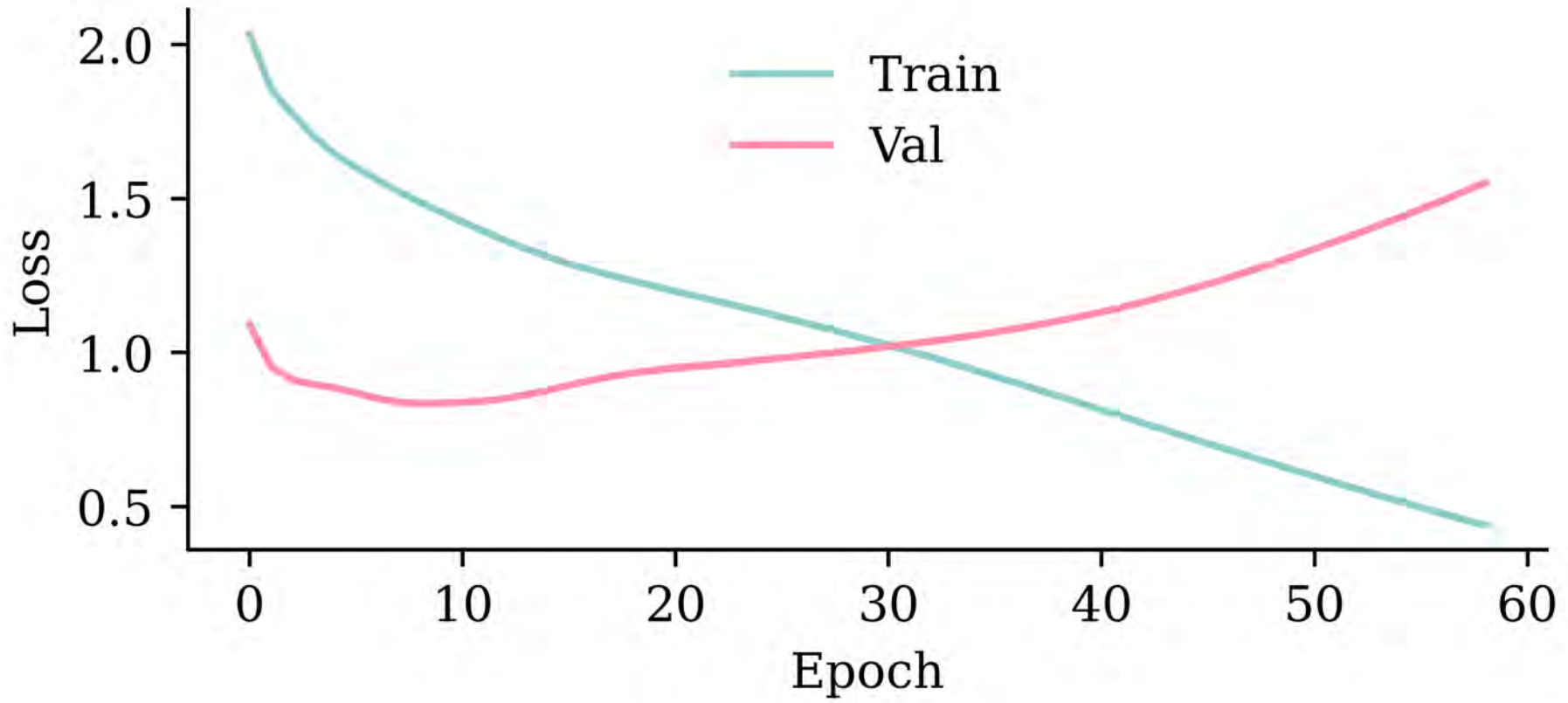
Assess the fits




```
1 model_lstm.evaluate(X_val, y_val, verbose=0)
```

```
0.8353261947631836
```

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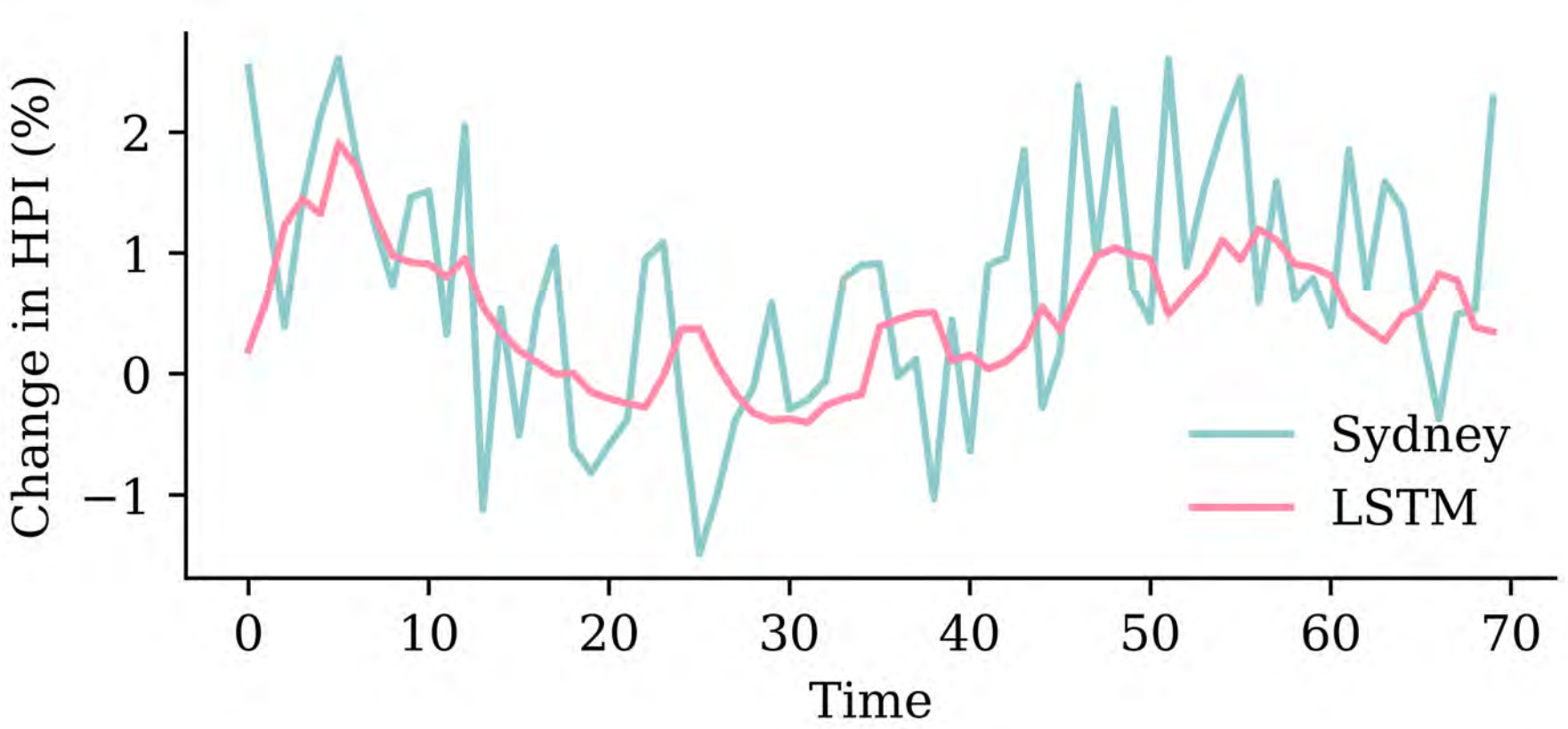
Plotting the predictions

```
WARNING:tensorflow:6 out of the last 8 calls to <function TensorFlowTrainer.make_predict_function.
<locals>.one_step_on_data_distributed at 0×79ec0c1f1bc0> triggered tf.function retracing. Tracing is expensive and the excessive
number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3)
passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has
reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for  more
details.
```



A GRU layer

```
from keras.layers import GRU

random.seed(1)

model_gru = Sequential([
    Input((seq_length, num_ts)),
    GRU(50),
    Dense(1, activation="linear")
])

model_gru.compile(loss="mse", optimizer="adam")

es = EarlyStopping(patience=50, restore_best_weights=True, verbose=1)

%time hist = model_gru.fit(X_train, y_train, epochs=1_000, \
  validation_data=(X_val, y_val), callbacks=[es], verbose=0)
```

```
Epoch 57: early stopping
Restoring model weights from the end of the best epoch: 7.
CPU times: user 4.73 s, sys: 587 ms, total: 5.32 s
Wall time: 3.73 s
```

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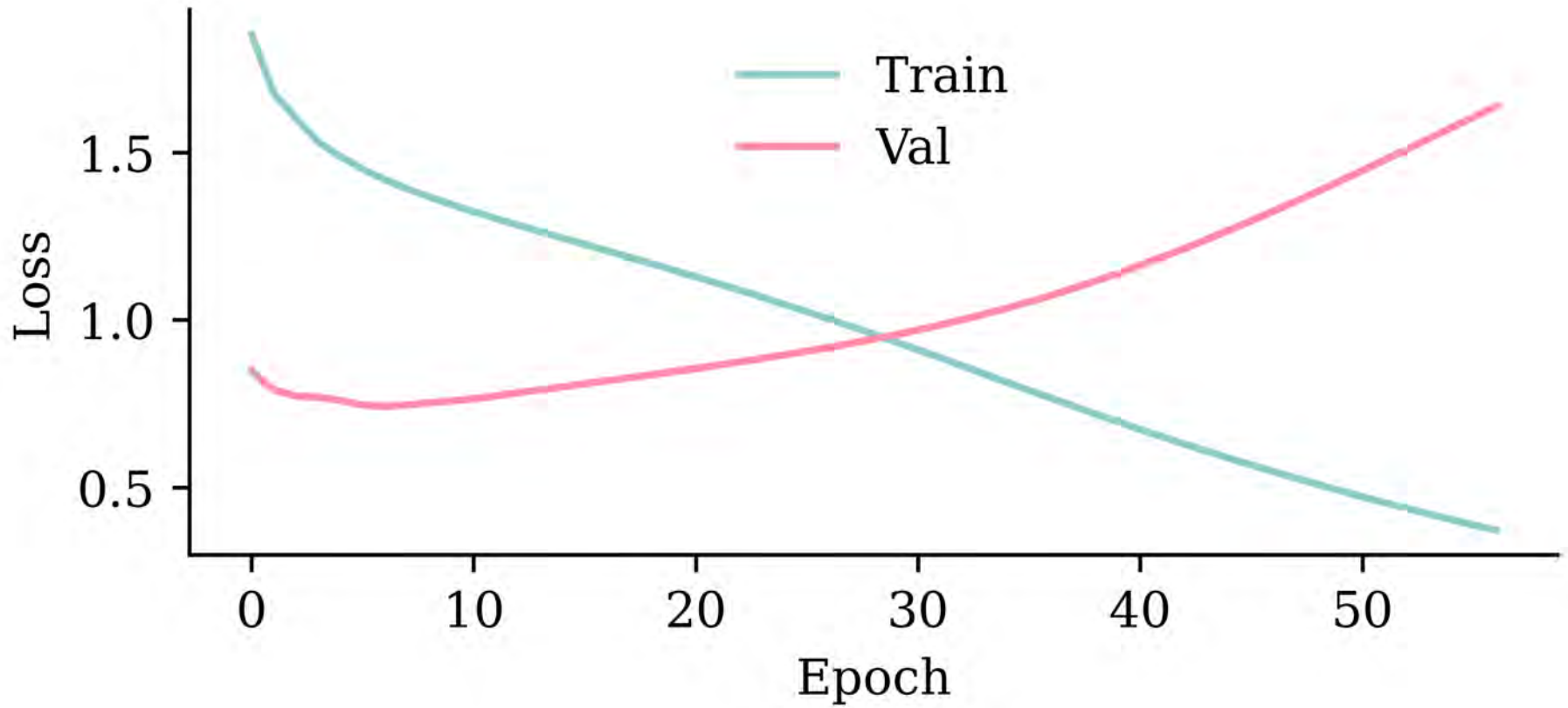
Assess the fits




```
1 model_gru.evaluate(X_val, y_val, verbose=0)
```

```
0.7435100674629211
```

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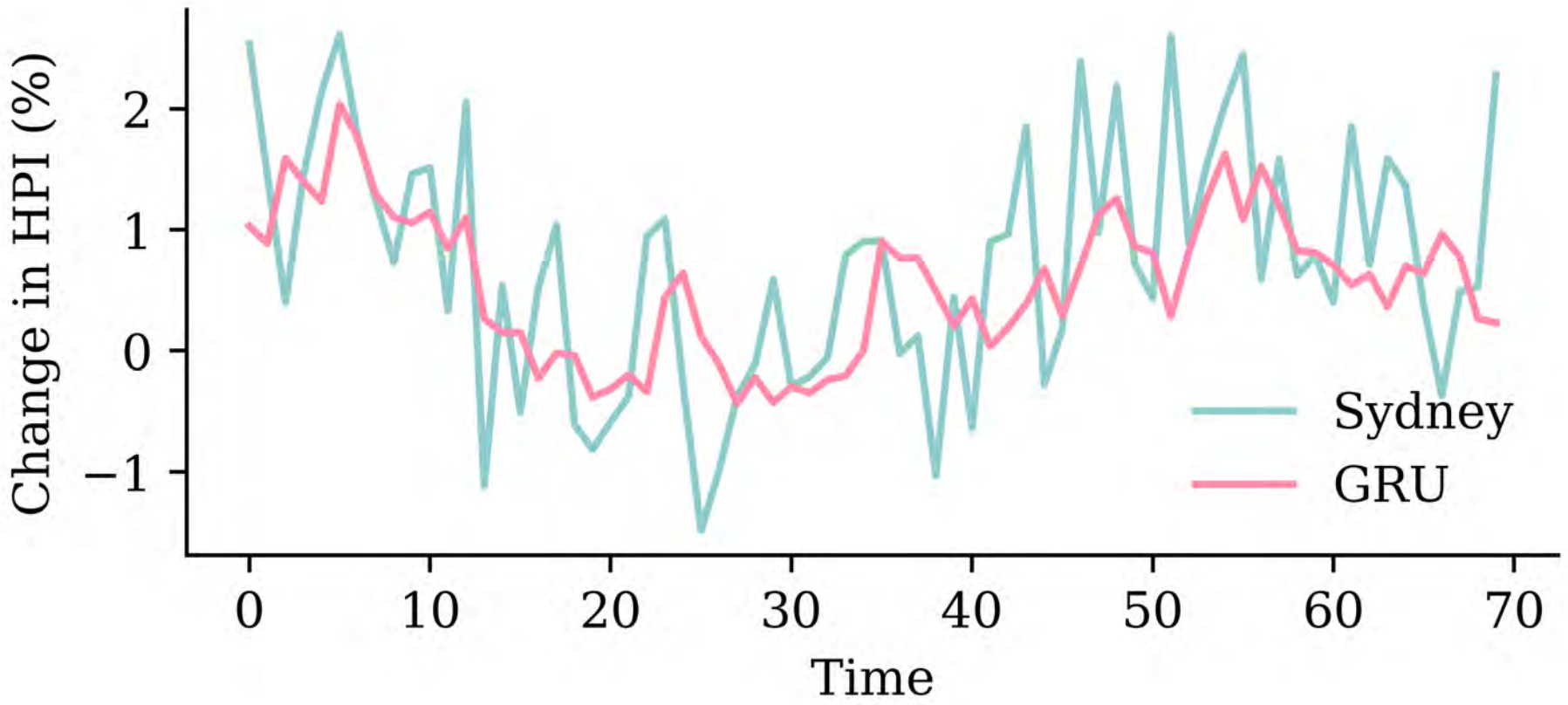
Plotting the predictions



Two GRU layers

```
random.seed(1)

model_two_grus = Sequential([
    Input((seq_length, num_ts)),
    GRU(50, return_sequences=True),
    GRU(50),
    Dense(1, activation="linear")
])

model_two_grus.compile(loss="mse", optimizer="adam")

es = EarlyStopping(patience=50, restore_best_weights=True, verbose=1)

%time hist = model_two_grus.fit(X_train, y_train, epochs=1_000, \
  validation_data=(X_val, y_val), callbacks=[es], verbose=0)
```

```
Epoch 56: early stopping
Restoring model weights from the end of the best epoch: 6.
CPU times: user 7.04 s, sys: 744 ms, total: 7.78 s
Wall time: 8.24 s
```

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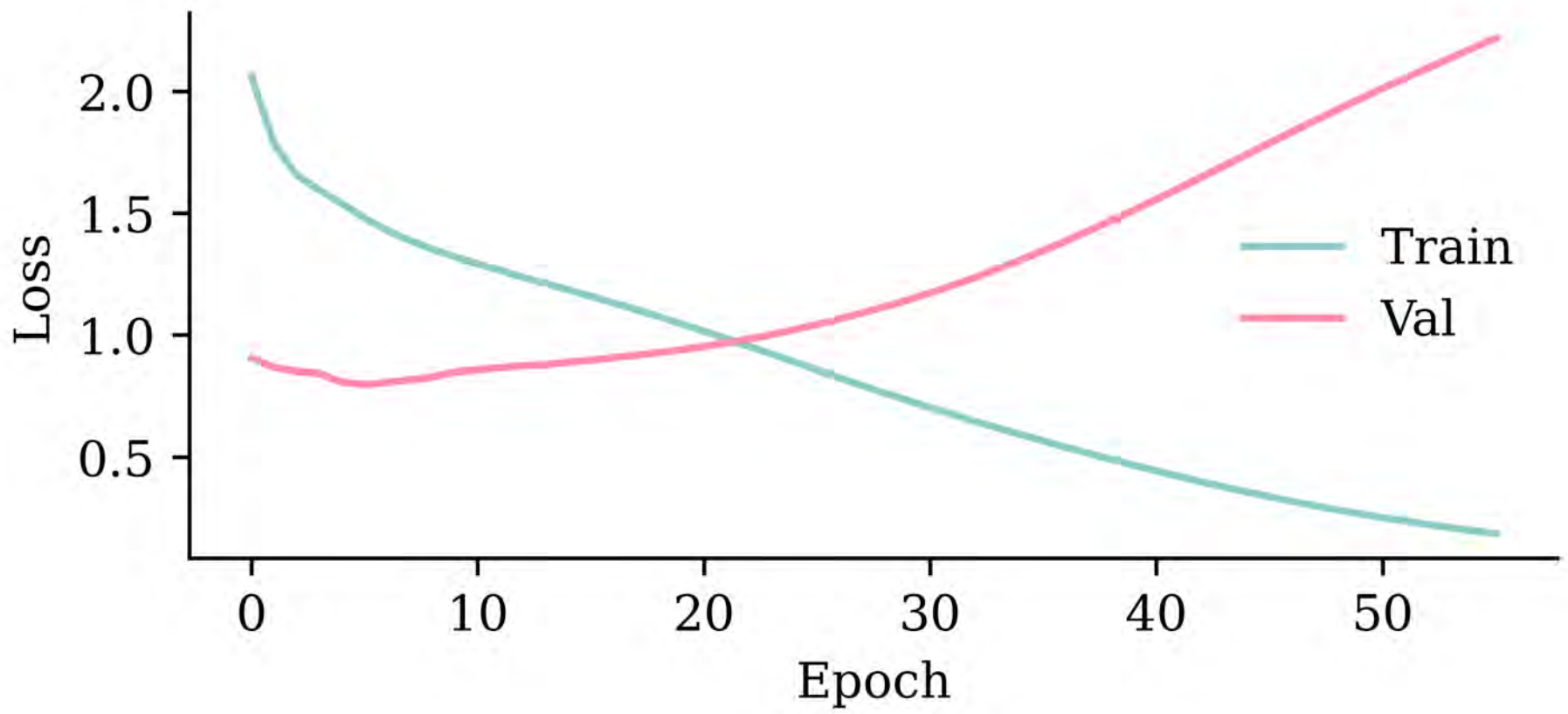
Assess the fits




```
1 model_two_grus.evaluate(X_val, y_val, verbose=0)
```

```
0.7989509105682373
```

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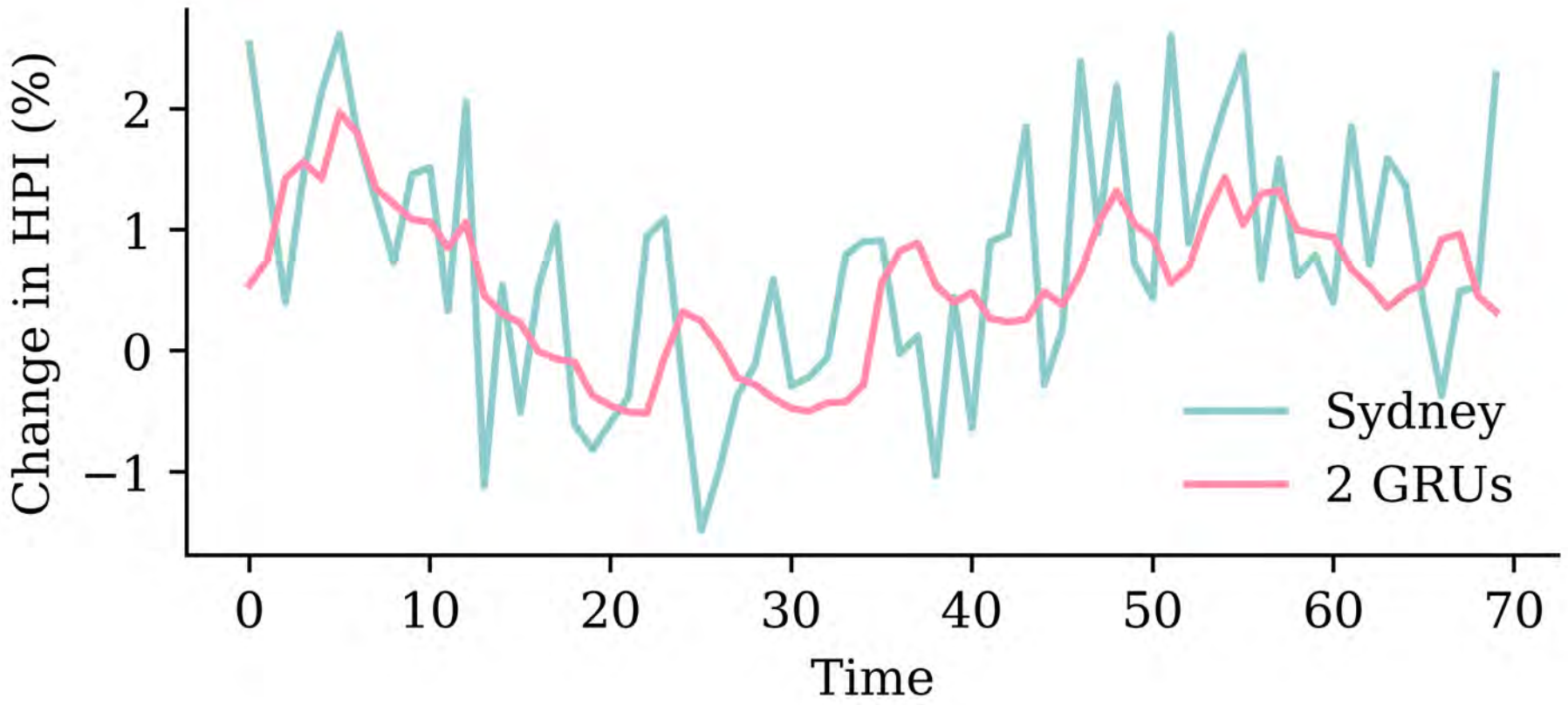
Plotting the predictions



Compare the models

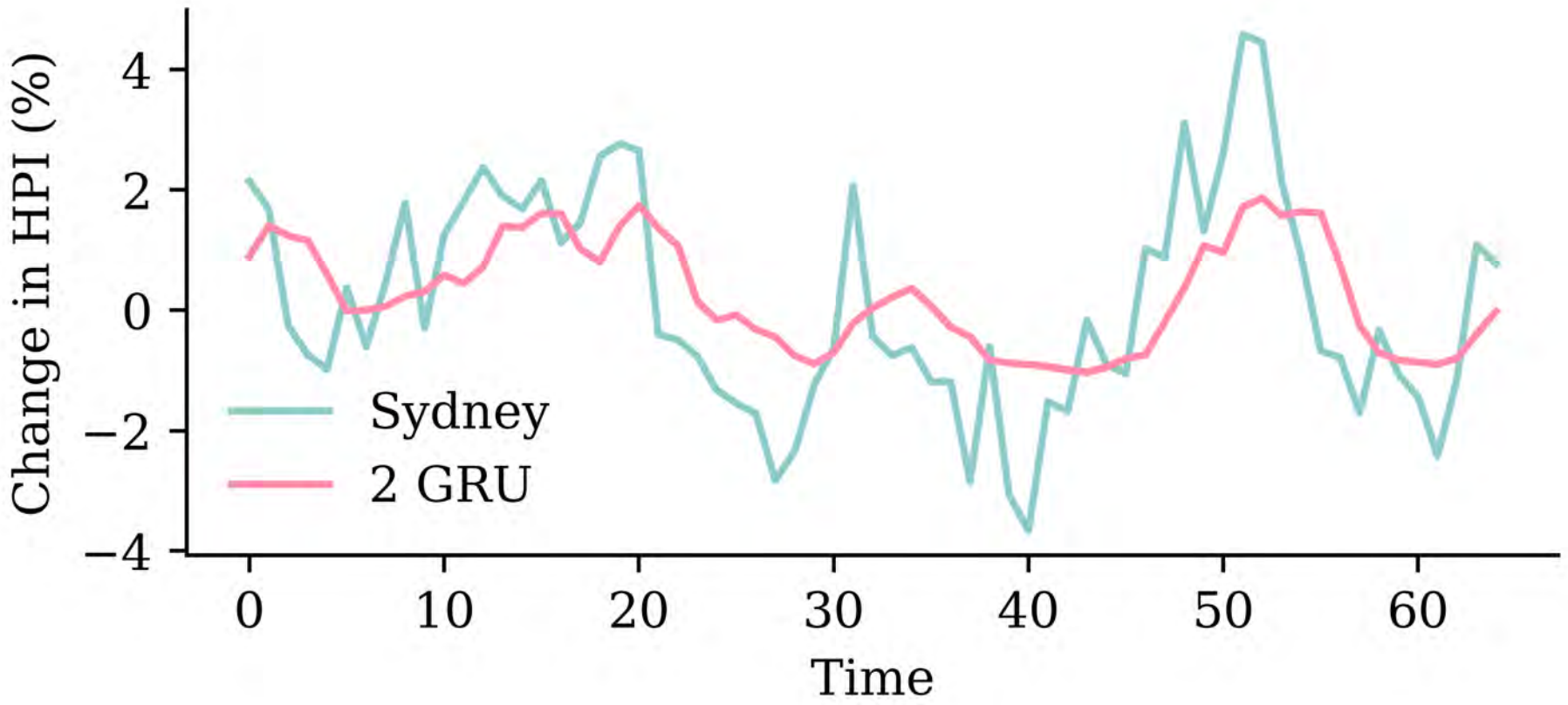
	Model	MSE
1	SimpleRNN	1.250792
0	Dense	1.164461
2	LSTM	0.835326
4	2 GRUs	0.798951
3	GRU	0.743510

The network with two GRU layers is the best.

```
1 model_two_grus.evaluate(test_ds, verbose=0)
```

```
1.8552547693252563
```

Test set



Lecture Outline

- Tensors & Time Series
- Some Recurrent Structures
- Recurrent Neural Networks
- CoreLogic Hedonic Home Value Index
- Splitting time series data
- Predicting Sydney House Prices
- **Predicting Multiple Time Series**

Creating dataset objects

Change the `targets` argument to include all the suburbs.

```
train_ds = \
  timeseries_dataset_from_array(
    changes[:-delay],
    targets=changes[delay:],
    sequence_length=seq_length,
    end_index=num_train)
```

```
val_ds = \
  timeseries_dataset_from_array(
    changes[:-delay],
    targets=changes[delay:],
    sequence_length=seq_length,
    start_index=num_train,
    end_index=num_train+num_val)
```

```
test_ds = \
  timeseries_dataset_from_array(
    changes[:-delay],
    targets=changes[delay:],
    sequence_length=seq_length,
    start_index=num_train+num_val)
```

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Converting `Dataset` to numpy

The shape of our training set is now:

```
1 X_train = np.concatenate(list(train_ds.map(lambda x, y: x)))
2 X_train.shape
```

```
(220, 6, 7)
```

```
1 y_train = np.concatenate(list(train_ds.map(lambda x, y: y)))
2 y_train.shape
```

```
(220, 7)
```

Converting the rest to numpy arrays:

```
1 X_val = np.concatenate(list(val_ds.map(lambda x, y: x)))
2 y_val = np.concatenate(list(val_ds.map(lambda x, y: y)))
3 X_test = np.concatenate(list(test_ds.map(lambda x, y: x)))
4 y_test = np.concatenate(list(test_ds.map(lambda x, y: y)))
```

A dense network

```
random.seed(1)
model_dense = Sequential([
    Input((seq_length, num_ts)),
    Flatten(),
    Dense(50, activation="leaky_relu"),
    Dense(20, activation="leaky_relu"),
    Dense(num_ts, activation="linear")
])
model_dense.compile(loss="mse", optimizer="adam")
print(f"This model has {model_dense.count_params()} parameters.")

es = EarlyStopping(patience=50, restore_best_weights=True, verbose=1)
%time hist = model_dense.fit(X_train, y_train, epochs=1_000, \
  validation_data=(X_val, y_val), callbacks=[es], verbose=0);
```

```
This model has 3317 parameters.
Epoch 75: early stopping
Restoring model weights from the end of the best epoch: 25.
CPU times: user 3.77 s, sys: 288 ms, total: 4.06 s
Wall time: 7.31 s
```

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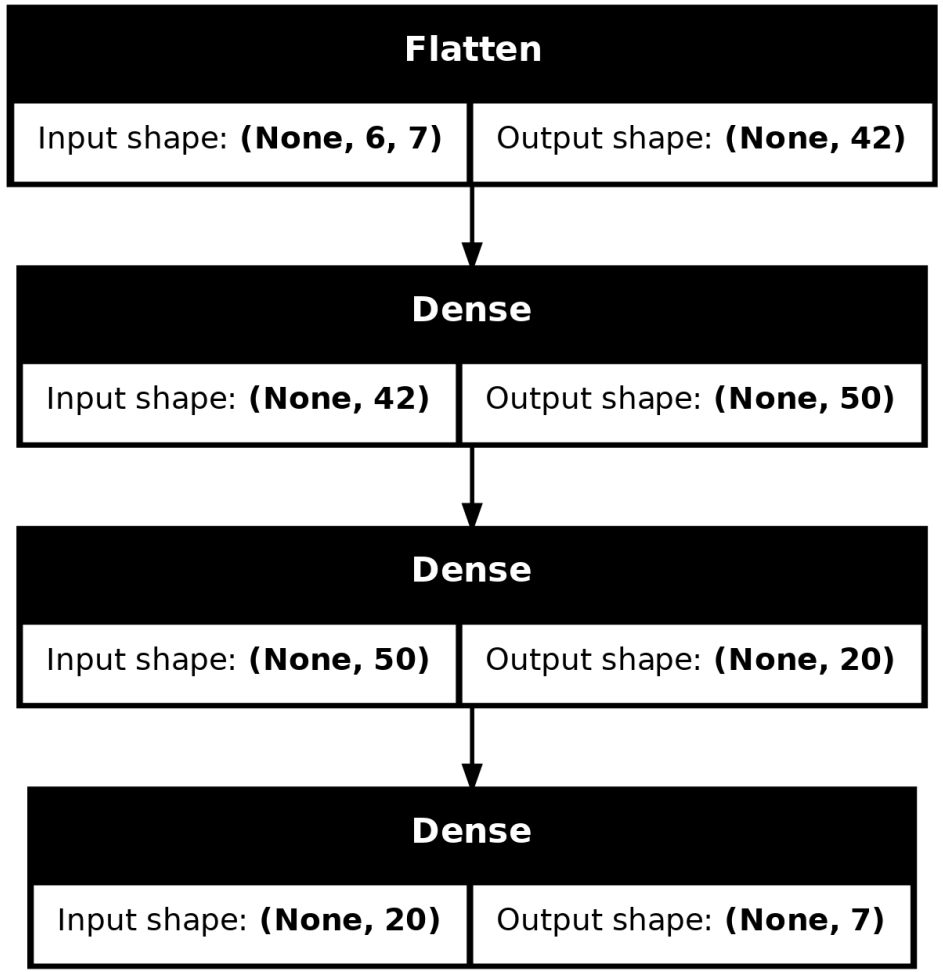
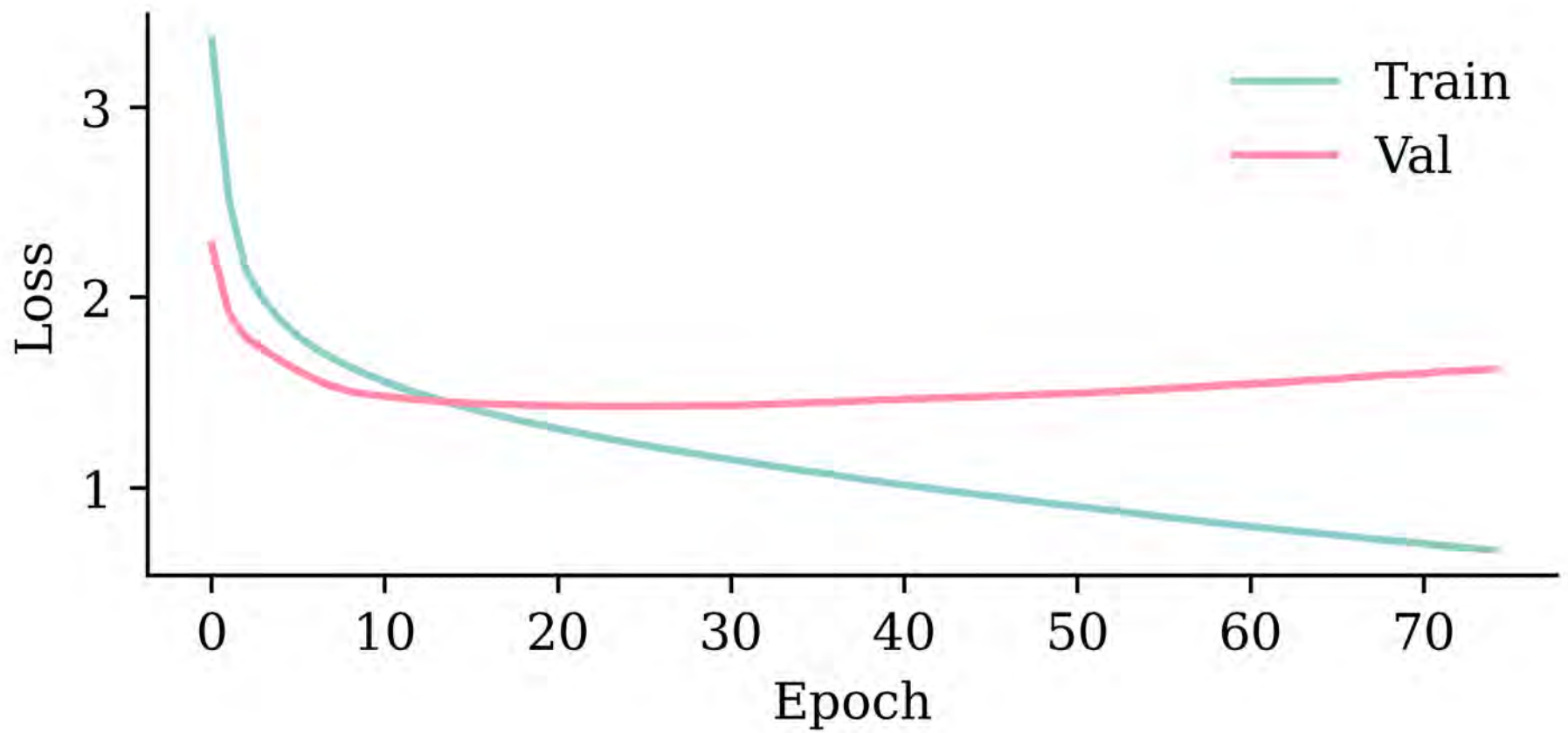
Plot the model

```
1 plot_model(model_dense, show_shapes=True)
```



Assess the fits




```
1 model_dense.evaluate(X_val, y_val, verbose=0)
```

```
1.4294650554656982
```

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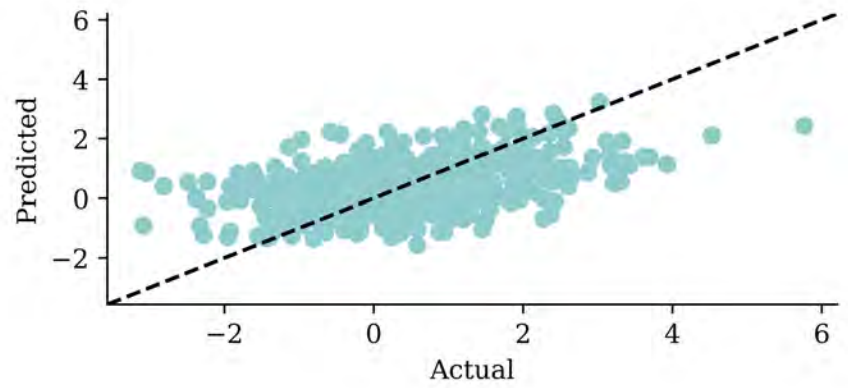
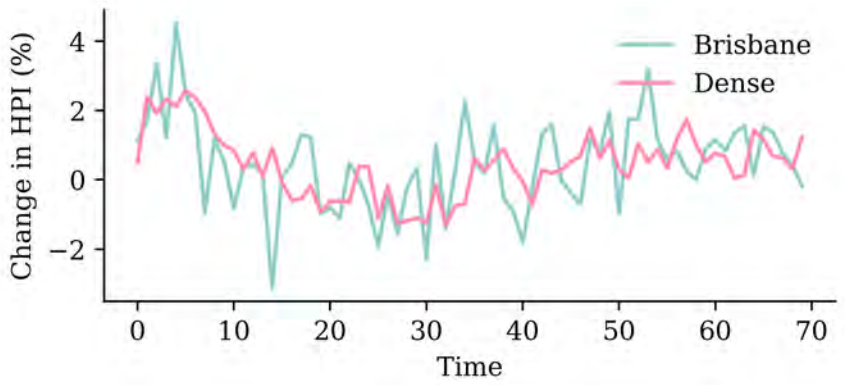
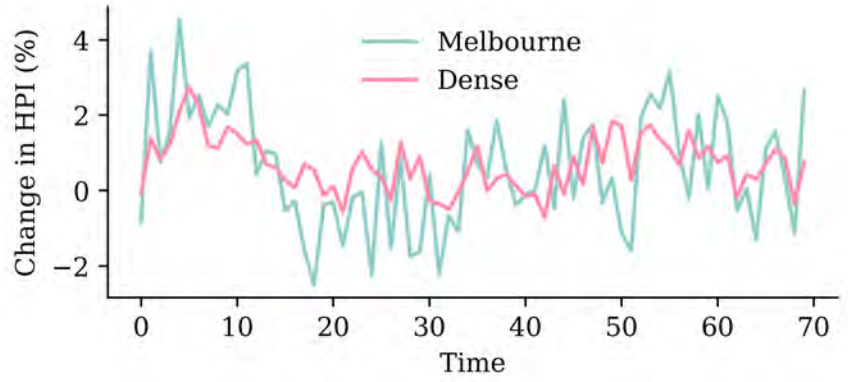
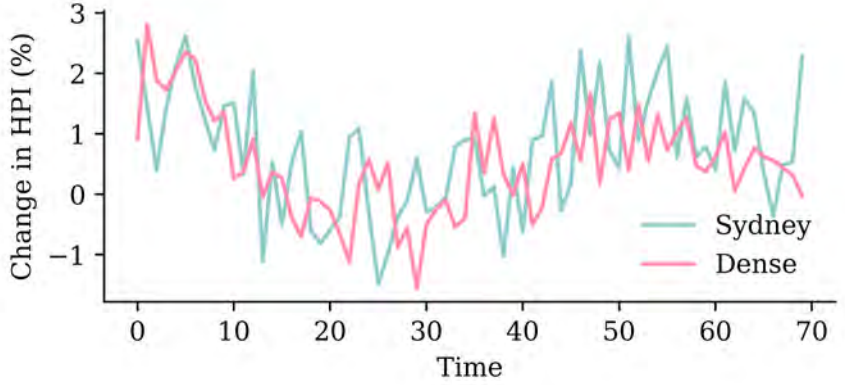
Plotting the predictions









A `SimpleRNN` layer

```
random.seed(1)

model_simple = Sequential([
    Input((seq_length, num_ts)),
    SimpleRNN(50),
    Dense(num_ts, activation="linear")
])
model_simple.compile(loss="mse", optimizer="adam")
print(f"This model has {model_simple.count_params()} parameters.")

es = EarlyStopping(patience=50, restore_best_weights=True, verbose=1)
%time hist = model_simple.fit(X_train, y_train, epochs=1_000, \
  validation_data=(X_val, y_val), callbacks=[es], verbose=0);
```

```
This model has 3257 parameters.
Epoch 70: early stopping
Restoring model weights from the end of the best epoch: 20.
CPU times: user 4.41 s, sys: 521 ms, total: 4.93 s
Wall time: 6.43 s
```

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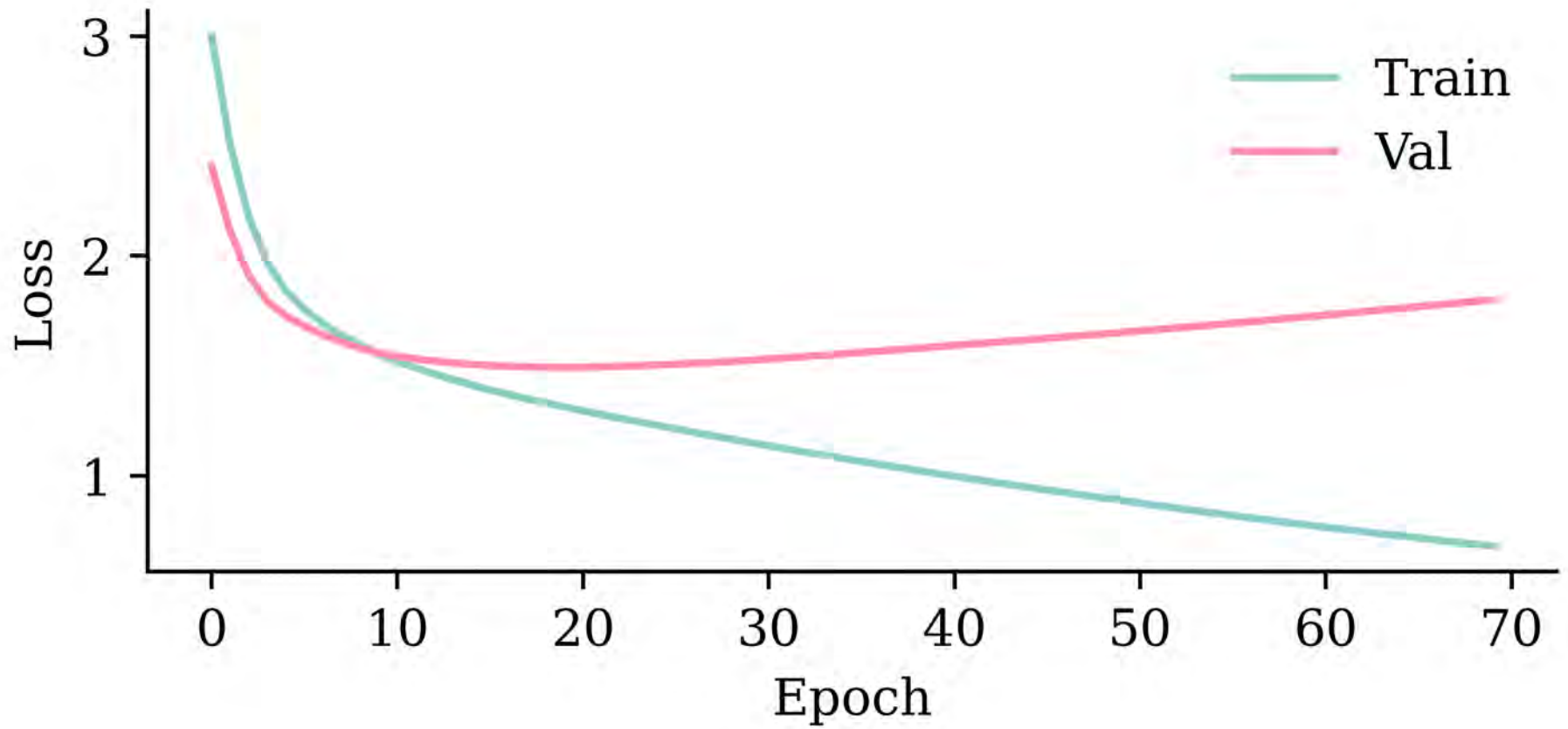
Assess the fits



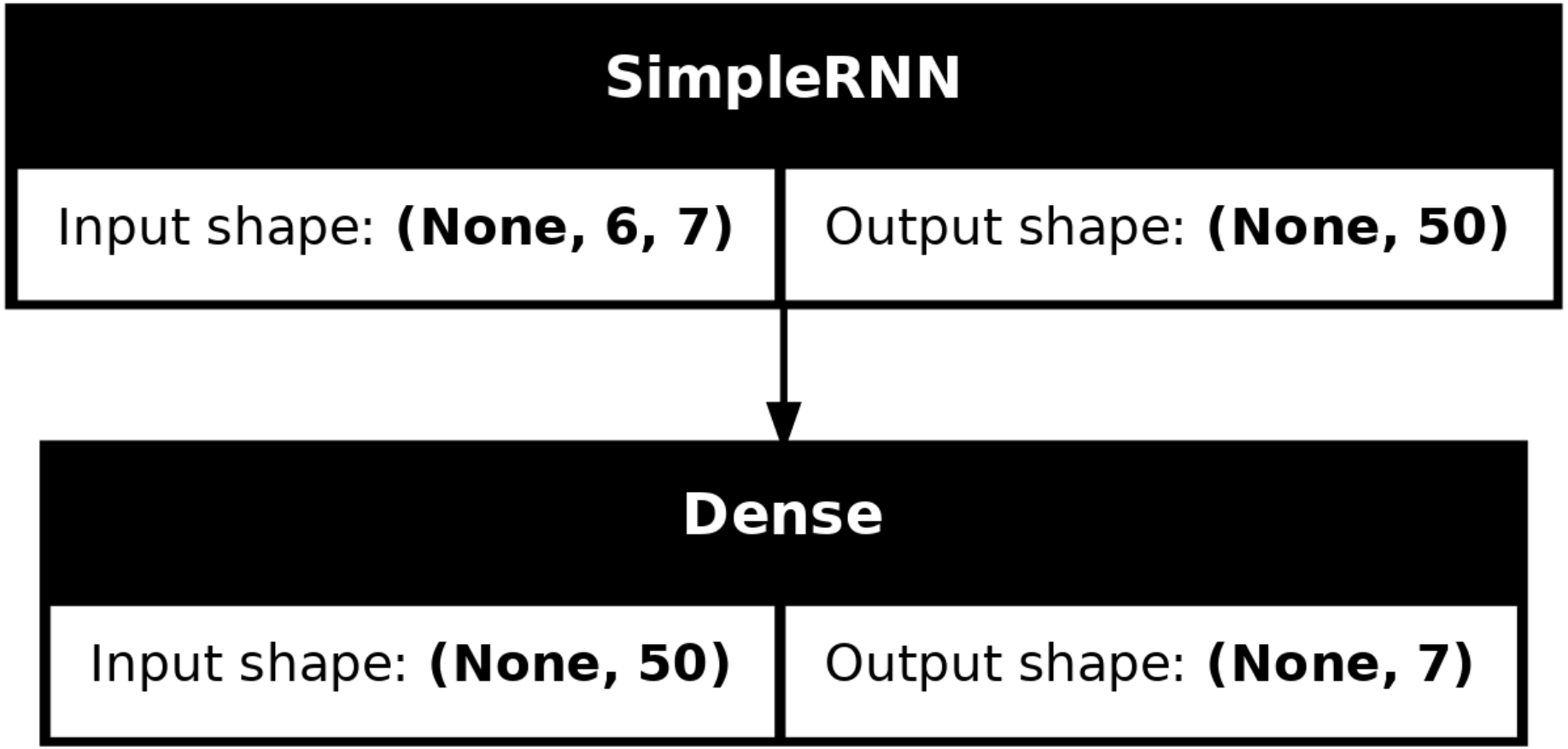

```
1 model_simple.evaluate(X_val, y_val, verbose=0)
```

```
1.4916820526123047
```

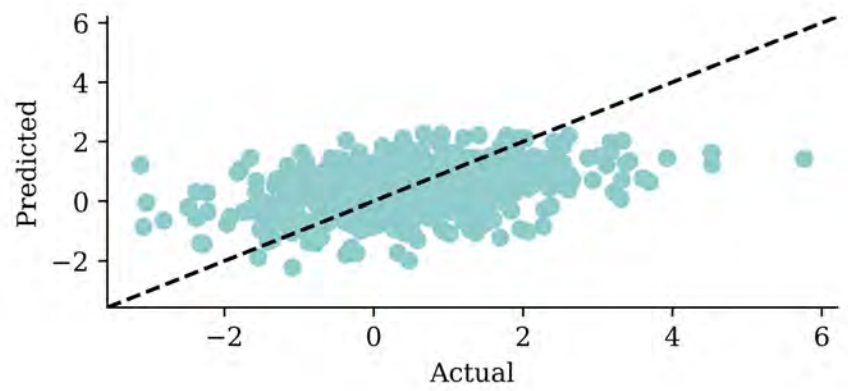
UNSW SYDNEY

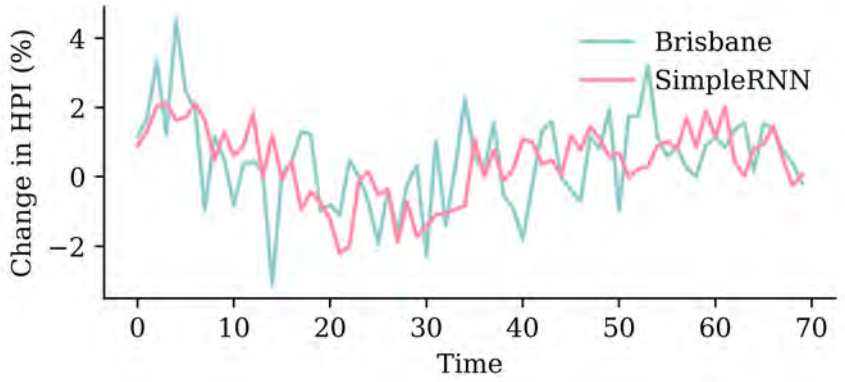
Plot the model

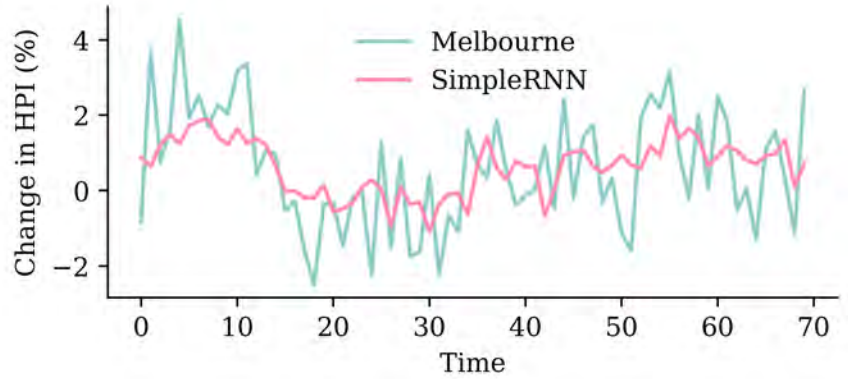
```
1 plot_model(model_simple, show_shapes=True)
```

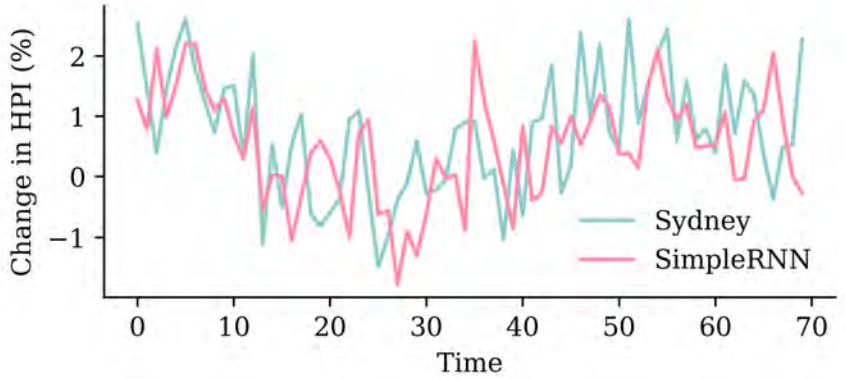


Plotting the predictions









A LSTM layer

```
random.seed(1)

model_lstm = Sequential([
    Input((seq_length, num_ts)),
    LSTM(50),
    Dense(num_ts, activation="linear")
])

model_lstm.compile(loss="mse", optimizer="adam")

es = EarlyStopping(patience=50, restore_best_weights=True, verbose=1)

%time hist = model_lstm.fit(X_train, y_train, epochs=1_000, \
  validation_data=(X_val, y_val), callbacks=[es], verbose=0);
```

```
Epoch 74: early stopping
Restoring model weights from the end of the best epoch: 24.
CPU times: user 4.59 s, sys: 531 ms, total: 5.12 s
Wall time: 3.7 s
```

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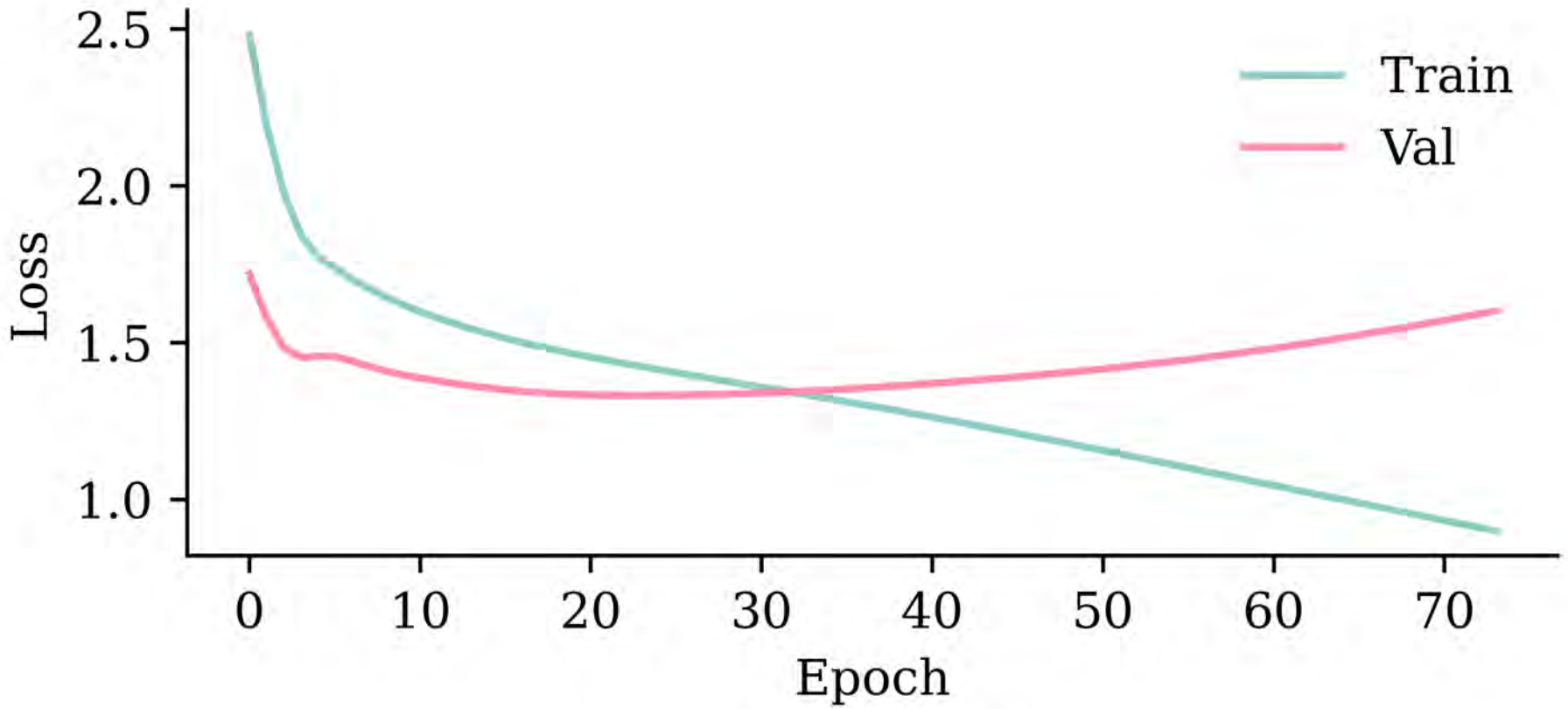
Assess the fits




```
1 model_lstm.evaluate(X_val, y_val, verbose=0)
```

```
1.3311247825622559
```

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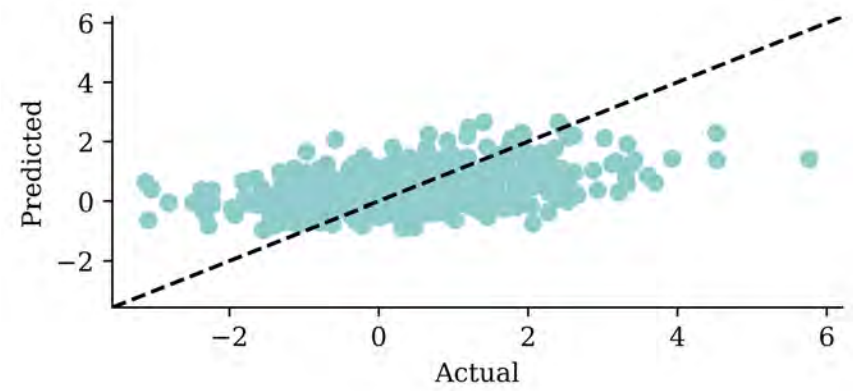
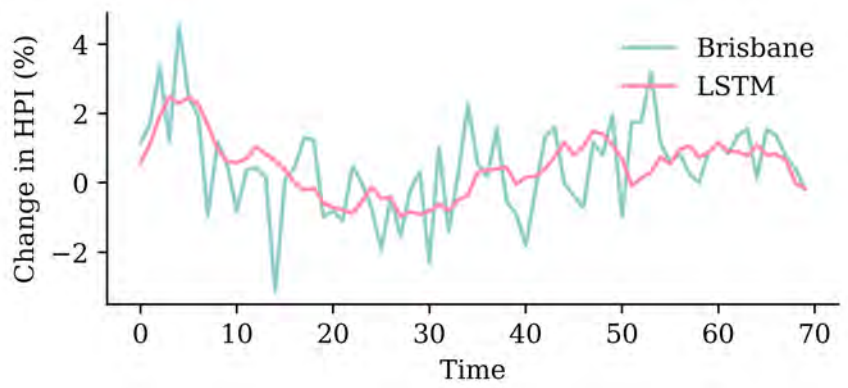
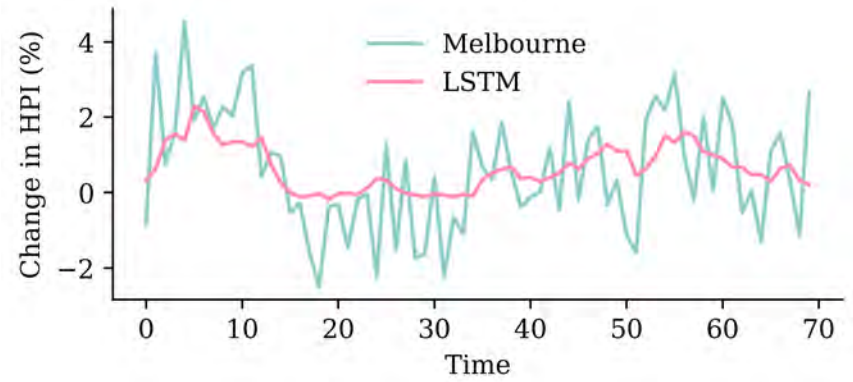
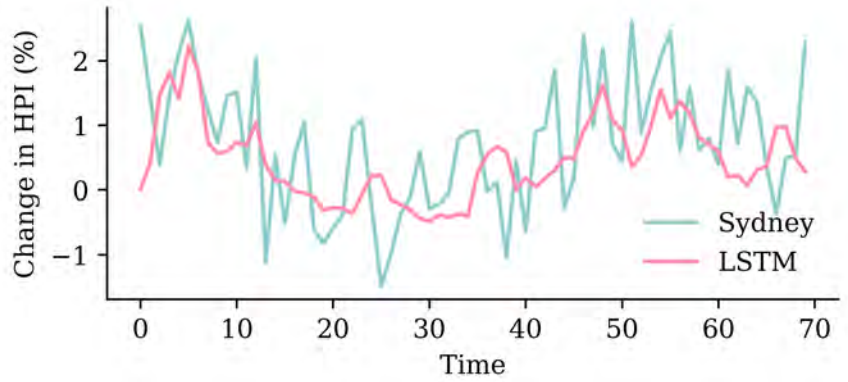
Plotting the predictions









A GRU layer

```
random.seed(1)

model_gru = Sequential([
    Input((seq_length, num_ts)),
    GRU(50),
    Dense(num_ts, activation="linear")
])

model_gru.compile(loss="mse", optimizer="adam")

es = EarlyStopping(patience=50, restore_best_weights=True, verbose=1)

%time hist = model_gru.fit(X_train, y_train, epochs=1_000, \
  validation_data=(X_val, y_val), callbacks=[es], verbose=0)
```

```
Epoch 70: early stopping
Restoring model weights from the end of the best epoch: 20.
CPU times: user 4.99 s, sys: 487 ms, total: 5.48 s
Wall time: 3.74 s
```

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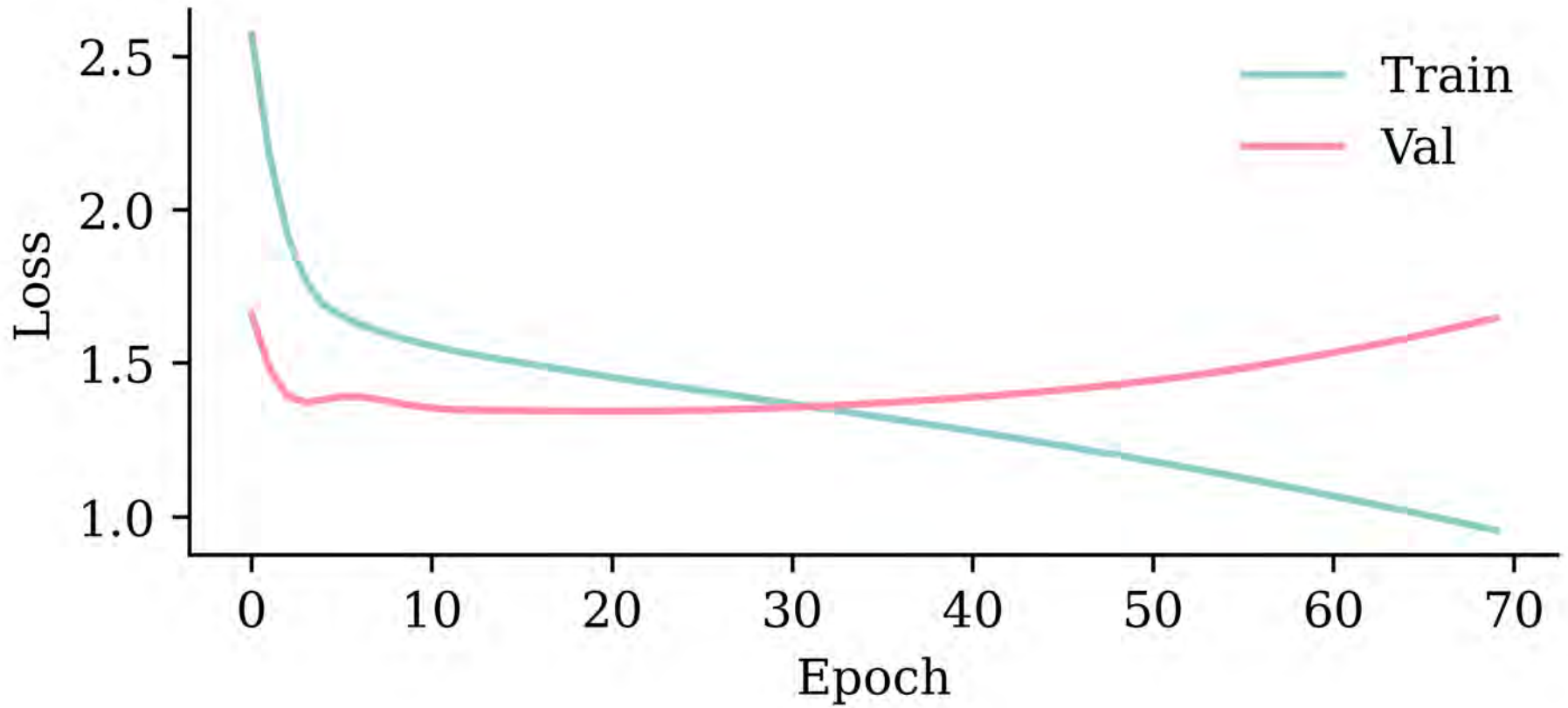
Assess the fits




```
1 model_gru.evaluate(X_val, y_val, verbose=0)
```

```
1.344503402709961
```

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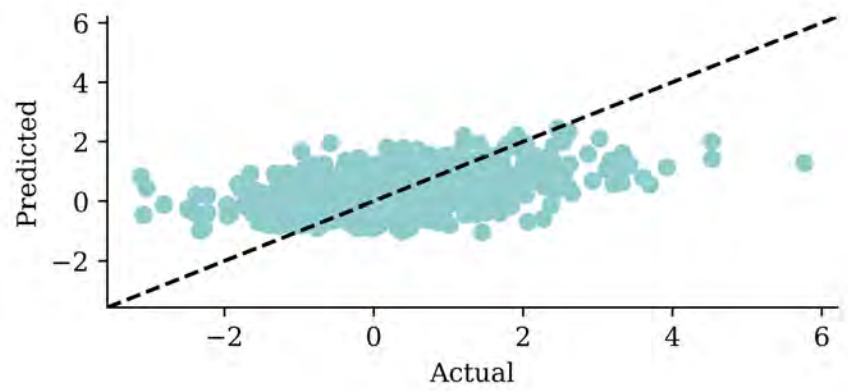
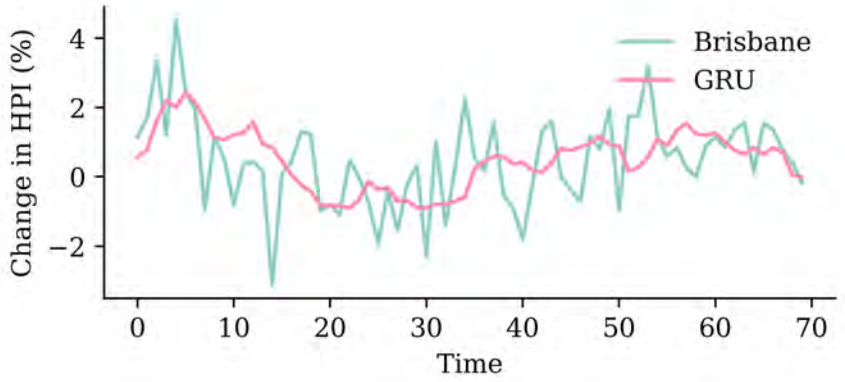
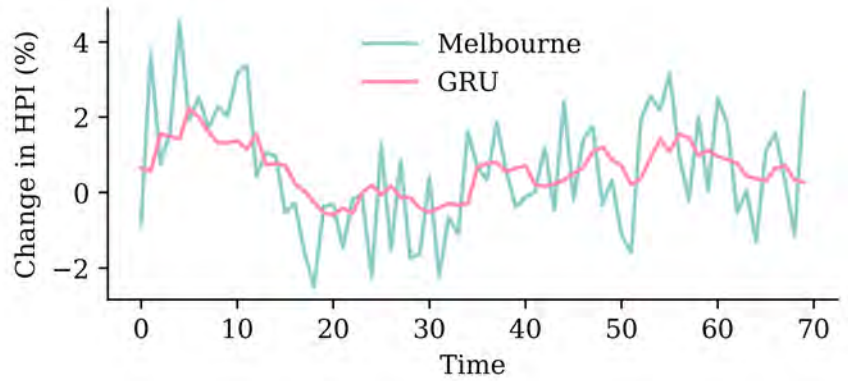
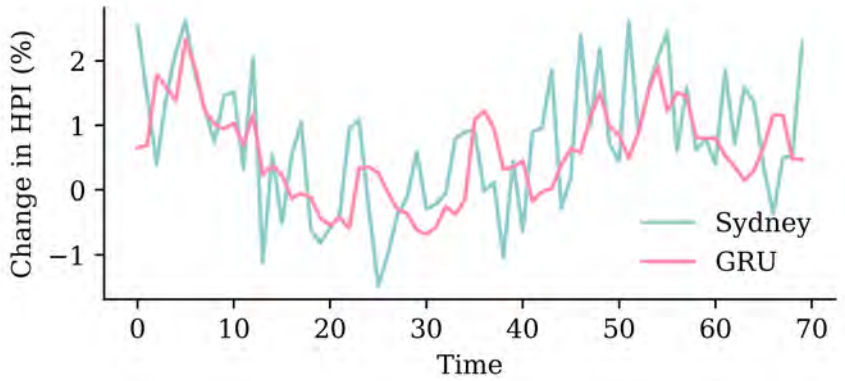
Plotting the predictions









Two GRU layers

```
random.seed(1)

model_two_grus = Sequential([
    Input((seq_length, num_ts)),
    GRU(50, return_sequences=True),
    GRU(50),
    Dense(num_ts, activation="linear")
])

model_two_grus.compile(loss="mse", optimizer="adam")

es = EarlyStopping(patience=50, restore_best_weights=True, verbose=1)

%time hist = model_two_grus.fit(X_train, y_train, epochs=1_000, \
  validation_data=(X_val, y_val), callbacks=[es], verbose=0)
```

```
Epoch 67: early stopping
Restoring model weights from the end of the best epoch: 17.
CPU times: user 7.47 s, sys: 678 ms, total: 8.15 s
Wall time: 5.06 s
```

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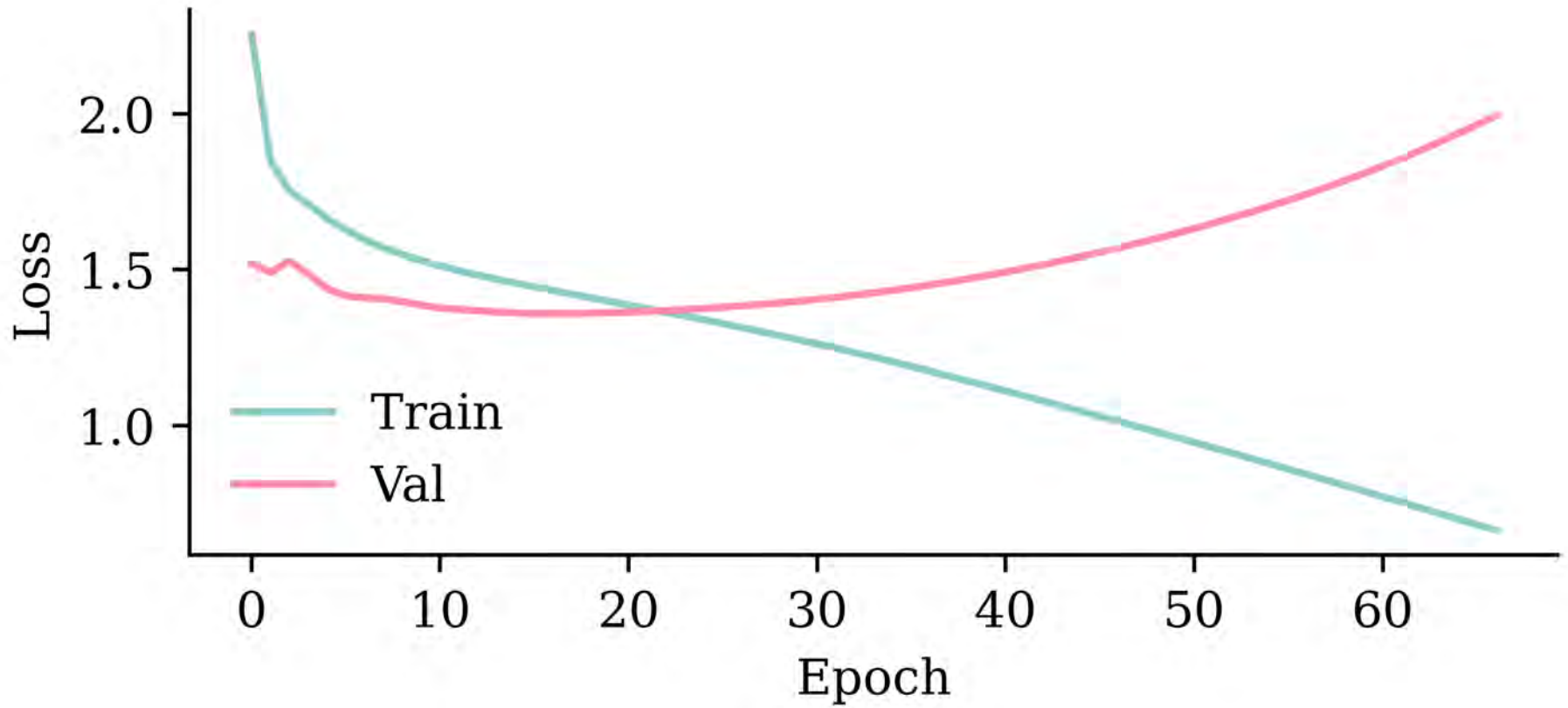
Assess the fits




```
1 model_two_grus.evaluate(X_val, y_val, verbose=0)
```

```
1.358651041984558
```

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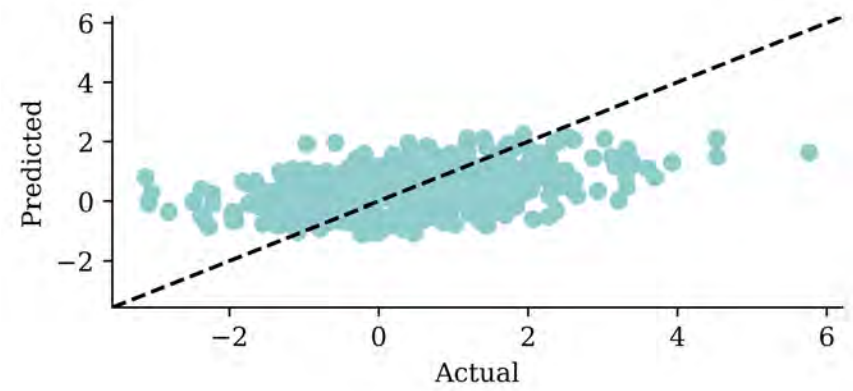
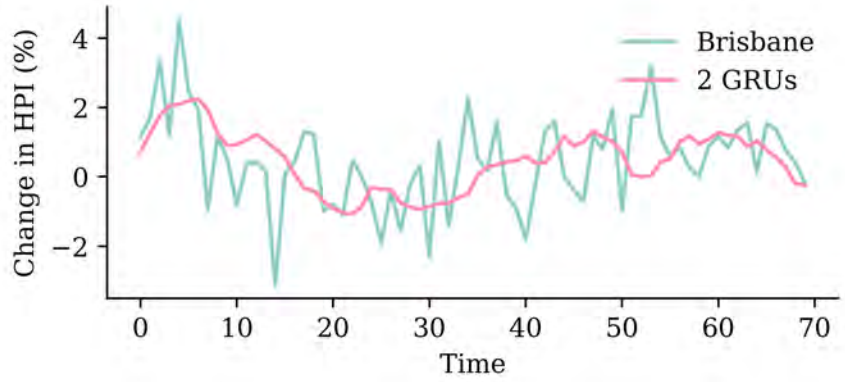
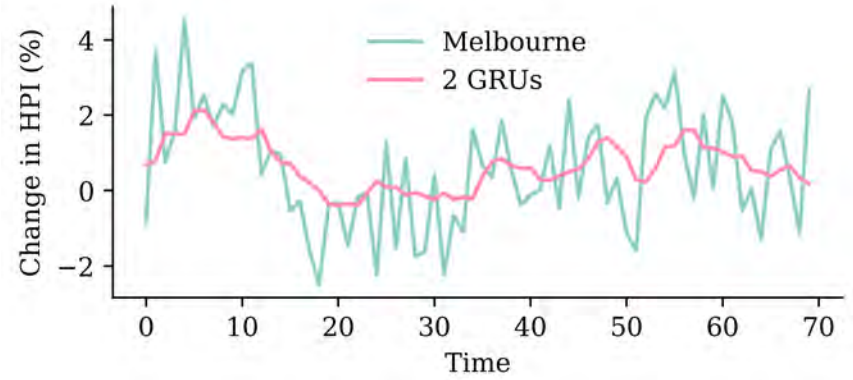
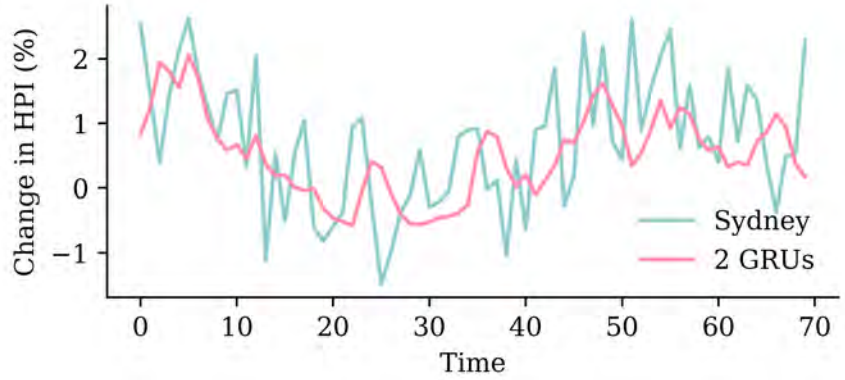
Plotting the predictions









Compare the models

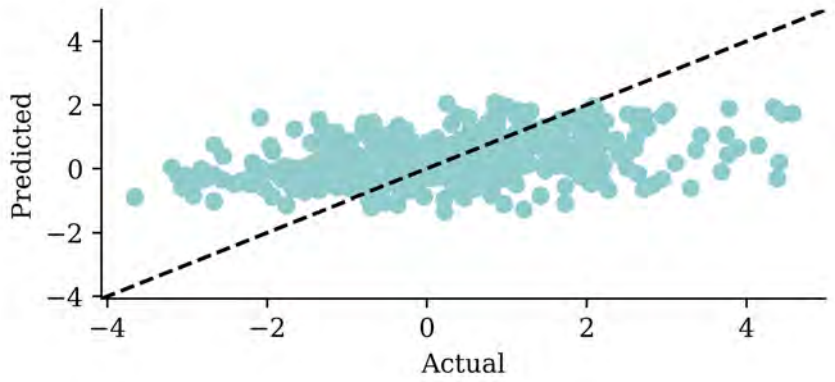
	Model	MSE
1	SimpleRNN	1.491682
0	Dense	1.429465
4	2 GRUs	1.358651
3	GRU	1.344503
2	LSTM	1.331125

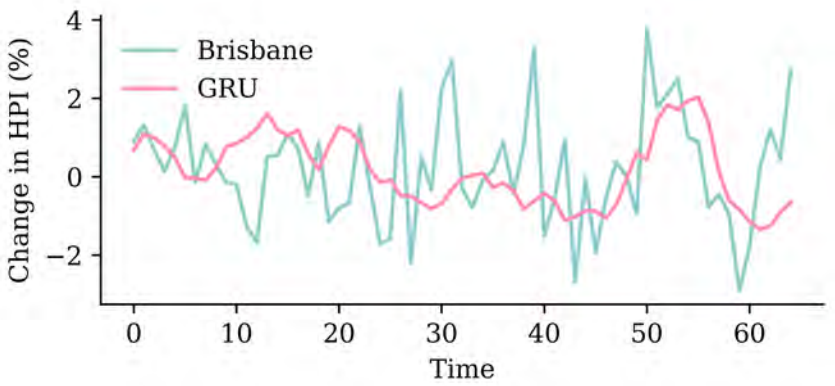
The network with an LSTM layer is the best.

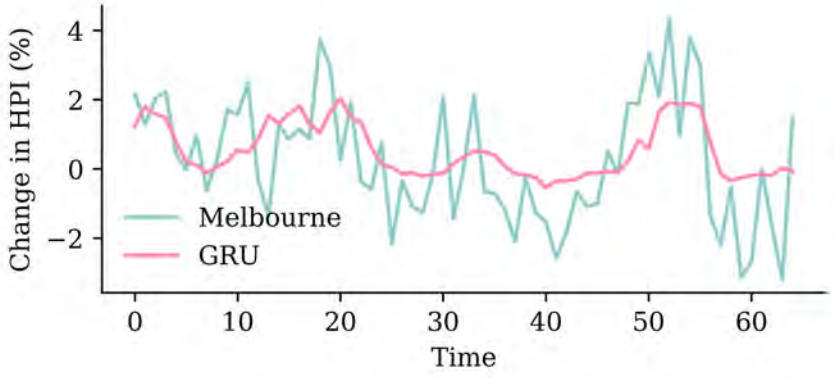
```
1 model_lstm.evaluate(test_ds, verbose=0)
```

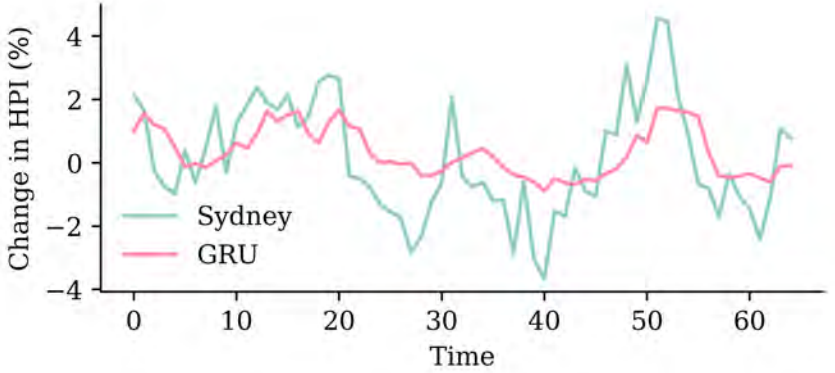
```
1.932026982307434
```

Test set









Package Versions

```
1 from watermark import watermark
2 print(watermark(python=True, packages="keras,matplotlib,numpy,pandas,seaborn,scipy,torch
```

```
Python implementation: CPython
Python version       : 3.11.9
IPython version      : 8.24.0

keras     : 3.3.3
matplotlib: 3.9.0
numpy     : 1.26.4
pandas    : 2.2.2
seaborn   : 0.13.2
scipy     : 1.11.0
torch     : 2.0.1
tensorflow: 2.16.1
tf_keras  : 2.16.0
```

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Glossary

- GRU
- LSTM
- recurrent neural networks
- SimpleRNN