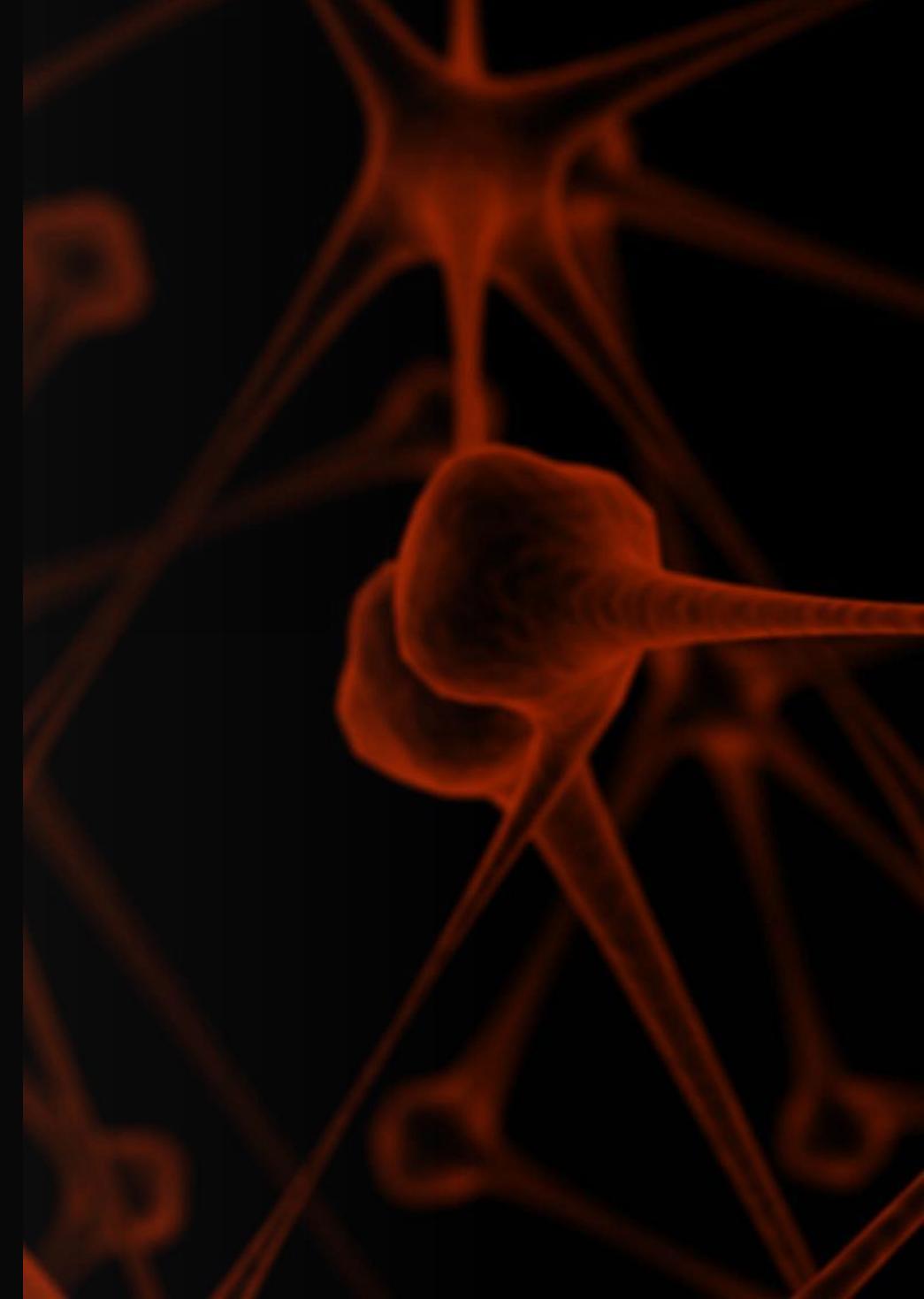




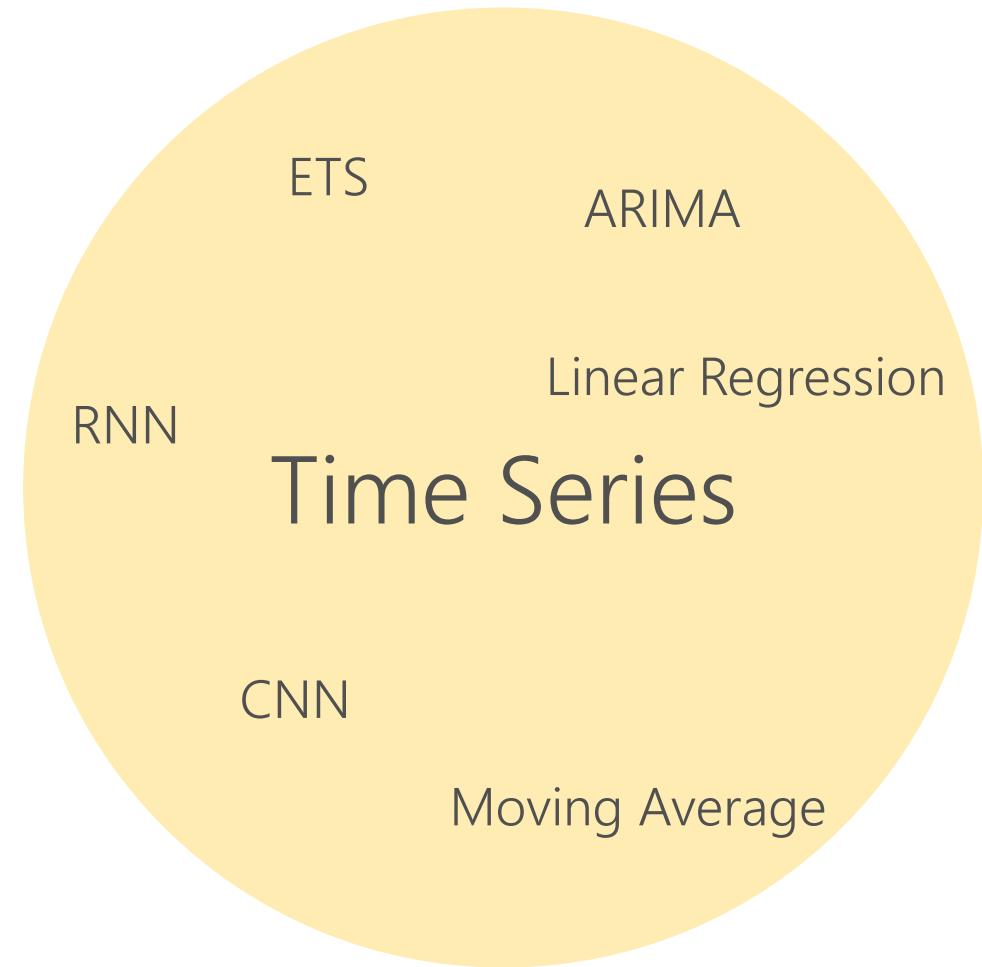
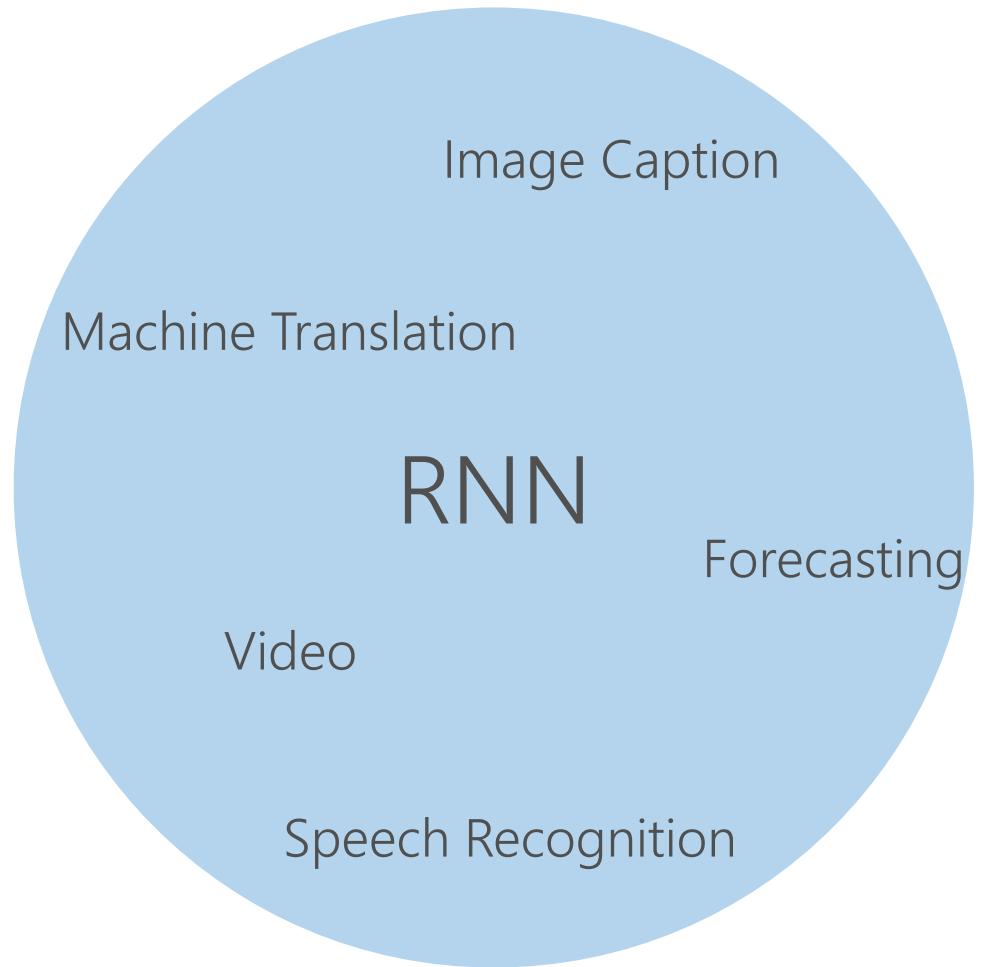
Recurrent Neural Networks for Time Series Forecasting

Yijing Chen, Dmitry Pechyoni, Angus Taylor, Vanja Paunic

Tutorial Introduction



Tutorial Introduction

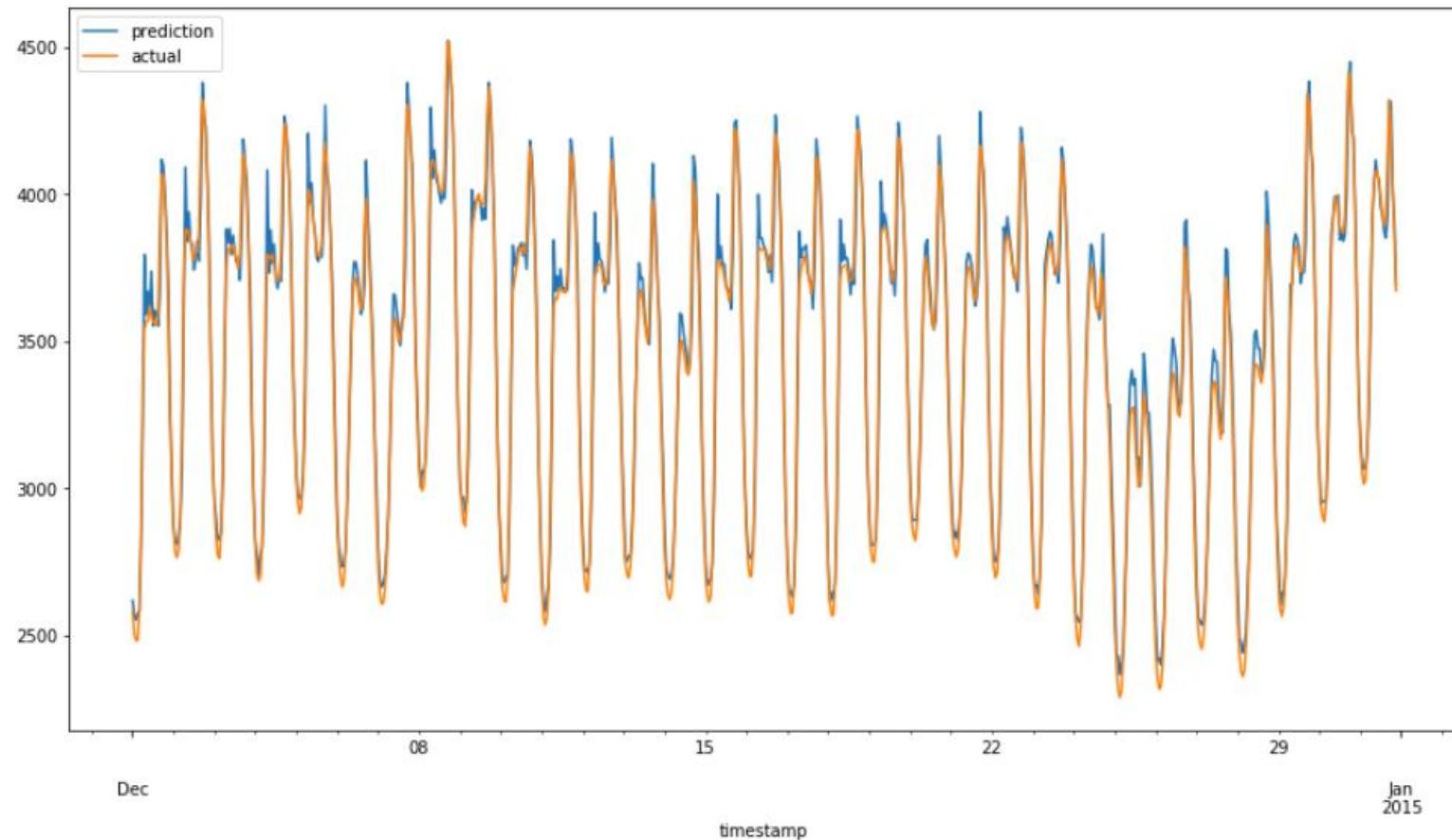


Tutorial Goals

- Understand the basics of recurrent neural networks (RNN) and advanced RNN architectures including LSTM and GRU
- Know how to use Keras to build RNN model for time series forecasting
- Know a number of techniques and tricks that are important for building successful RNN-based time series forecasting models

Tutorial Goals

By the end of this tutorial, you will have the knowledge to build RNN model to forecast New England energy consumption.



Why RNN?

- RNN has been shown perform well in many scenarios
 - 2014 Global Energy Forecasting Competition ([link](#))
 - 2016 CIF International Time Series Competition ([link](#))
 - 2017 Web Traffic Time Series Forecasting ([link](#))
 - 2018 Corporación Favorita Grocery Sales Forecasting ([link](#))
- RNN is non-parametric, that greatly simplifies learning
- Any exogenous feature can be easily injected into the model
- RNN is a natural extension of well-studied ARIMA models, but much more flexible and expressive

Target Audience

- 200 level
- Know the basics of Python
- You need to understand the basic concepts of machine learning and have some experience of building machine learning models
- No prior experience with time series or neural networks is required

Please provide feedback to help us improve!

aka.ms/rnnfeedback

Learning Path

Agenda	Time (mins)
Tutorial Introduction + Pre-requisite Setup	15
Introduction to feedforward neural network(NN) model	10
How to apply feedforward NN model to time series forecasting	20
Introduction to recurrent neural network(RNN) model	20
How to apply RNN to one step time series forecasting	20
How to apply RNN to multi-step time series forecasting	20
Other successful RNN model + Conclusion	5
Q&A	5

- Hands-on lab and quizzes
- Q&A during break or in the end

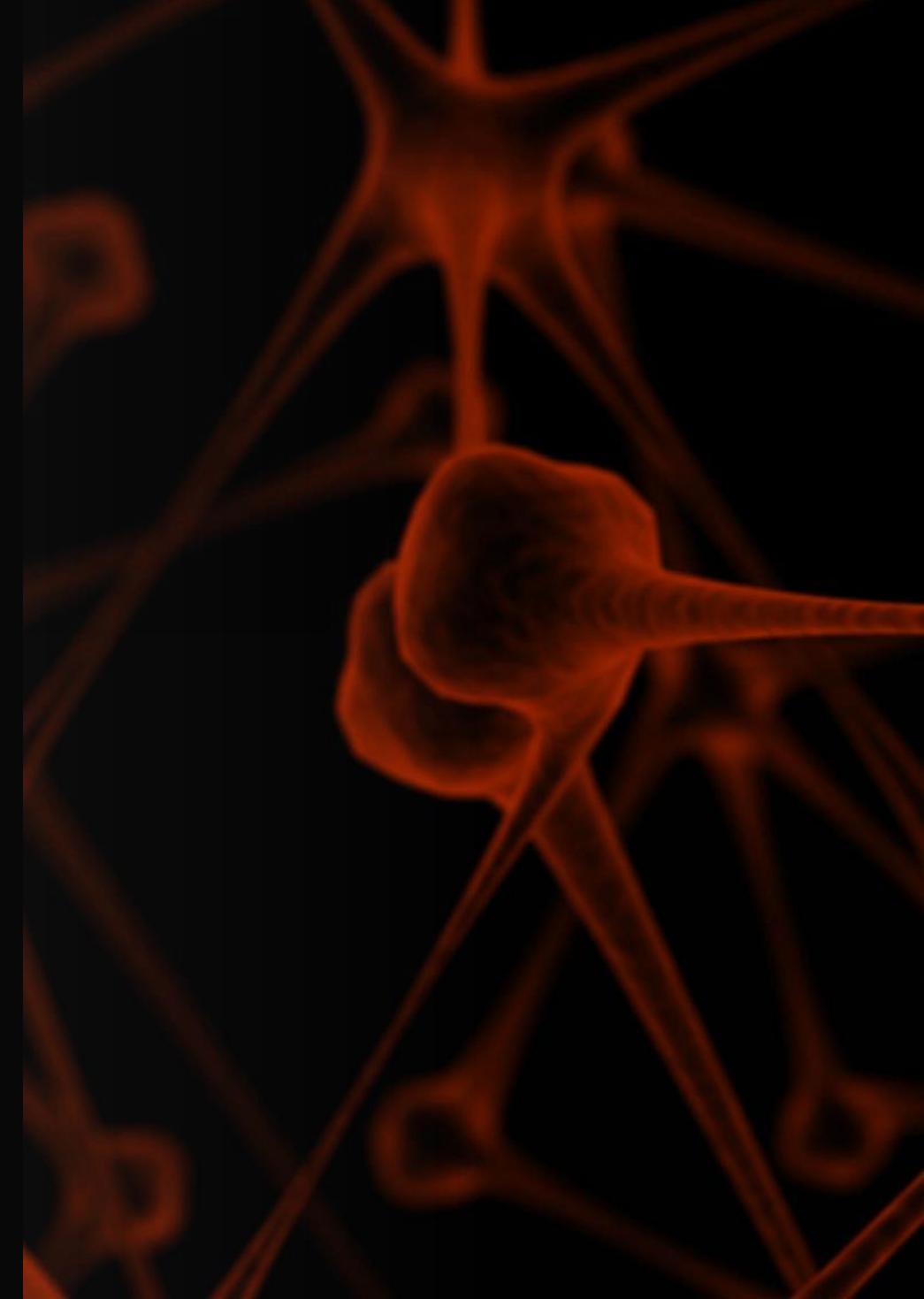
Hands-on Lab

- Form a team of 2-3
- Help your teammates
- We are here to help as well, just raise your hand
- Introduce yourself to your neighbor
- Ice breaker question: what's your favorite ice-cream flavor?

Pre-requisite Setup

aka.ms/rnntutorial

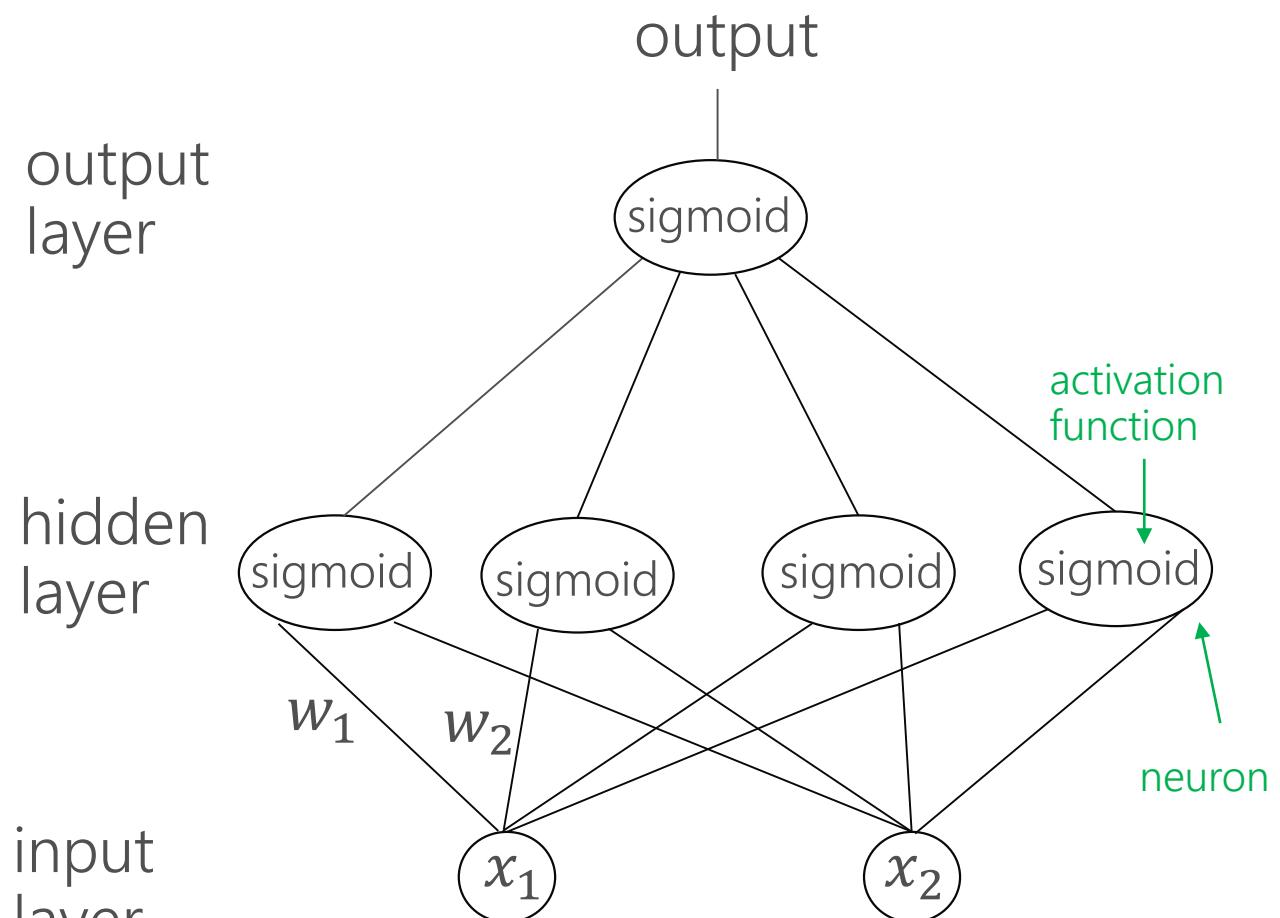
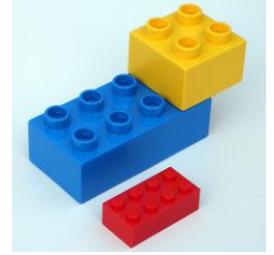
Introduction to Feedforward Neural Networks



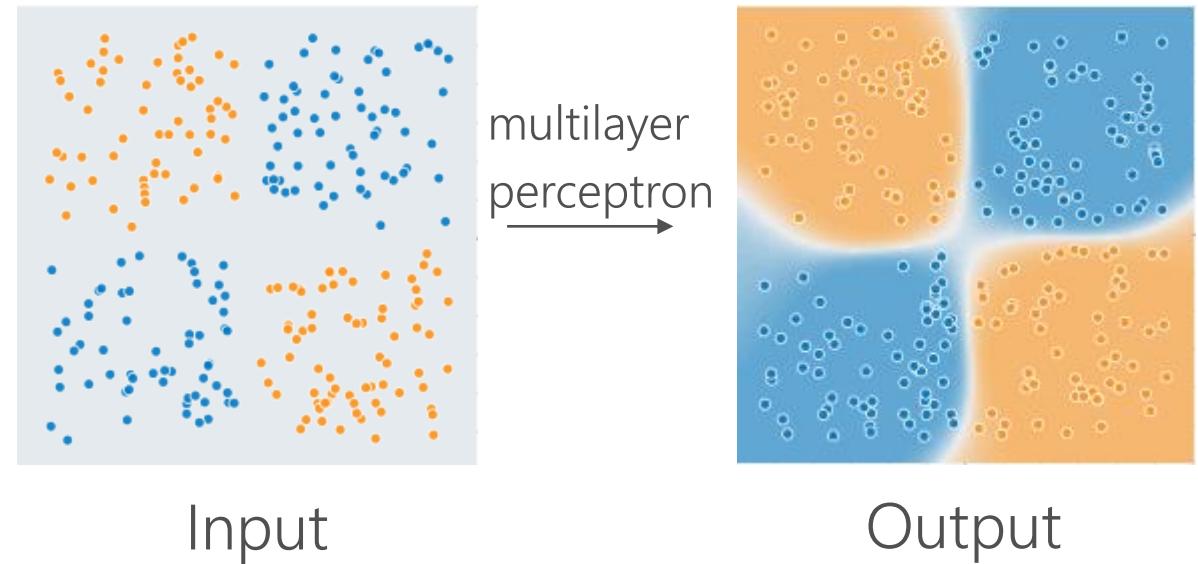
Agenda

- Architecture of Feed-forward Neural Network
- Feed-forward Neural Network Training
 - Loss function
 - Gradient descent (stochastic, batch, mini-batch gradient descent)
 - Backpropagation

Feed-forward Neural Network



$$\hat{y} = \begin{cases} 1 & \text{if output} > \text{threshold} \\ 0 & \text{otherwise} \end{cases}$$

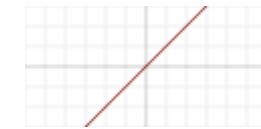


Activation Functions

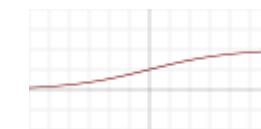
https://en.wikipedia.org/wiki/Activation_function

Applied over $x' = w \cdot x + b$

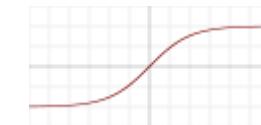
Identity $f(x') = x'$



Sigmoid $f(x') = \sigma(x') = \frac{1}{1+e^{-x'}}$



tanh (hyperbolic tangent) $f(x') = \frac{e^{x'} - e^{-x'}}{e^{x'} + e^{-x'}}$



Rectifier linear unit (ReLU) $f(x') = \begin{cases} 0 & \text{for } x' < 0 \\ x' & \text{for } x' \geq 0 \end{cases}$



Parametric rectifier linear unit (PReLU) $f(x') = \begin{cases} \alpha x' & \text{for } x' < 0 \\ x' & \text{for } x' \geq 0 \end{cases}$

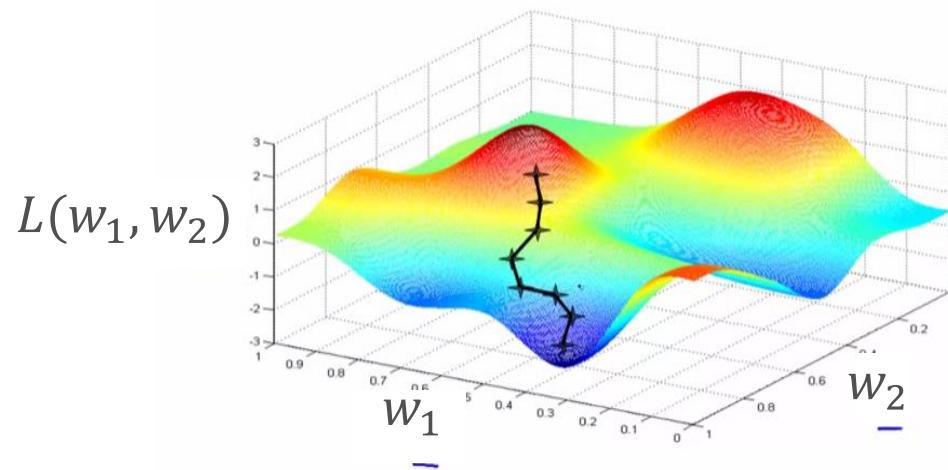


Training: overview

Use training examples to find good weights and biases of the network.

Main components:

- Loss function $L(\text{weights}, \text{biases})$ that measures discrepancy between predicted and true values
- Optimization algorithm that finds weights and biases minimizing the loss function



Examples of loss function

Commonly used loss functions in time series forecasting:

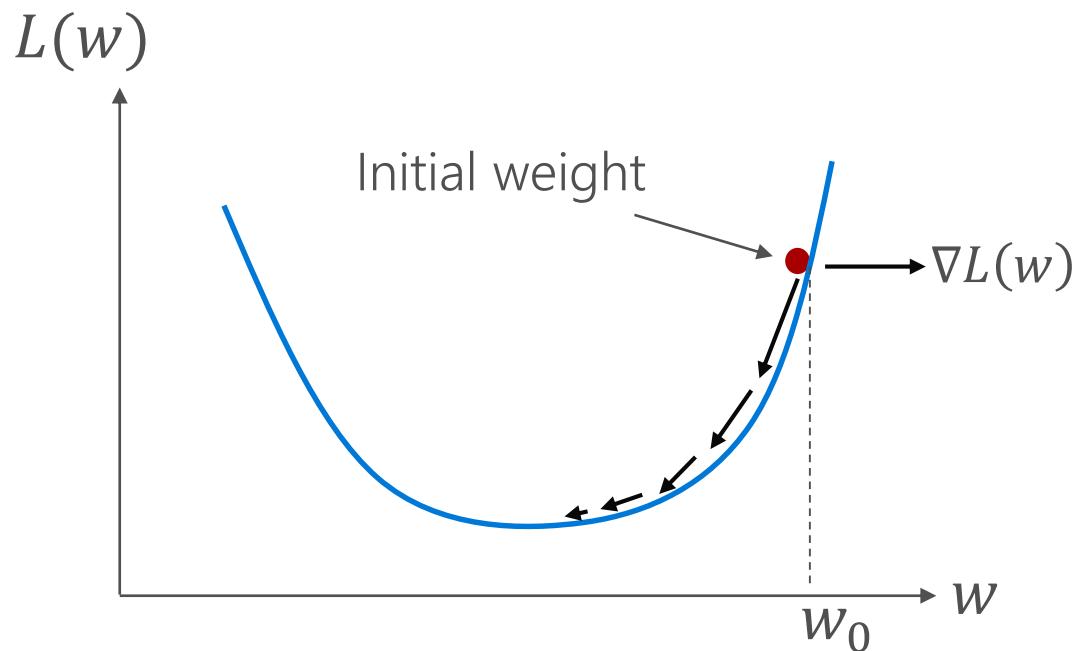
- Mean-squared-error (MSE): $\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$
- Mean Absolute Percentage Error (MAPE): $\frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right|$
- Symmetric MAPE (sMAPE): $\frac{100}{N} \sum_{i=1}^N \frac{|y_i - \hat{y}_i|}{(|y_i| + |\hat{y}_i|)/2}$

\hat{y}_i is a function of weights w and biases b .

Optimization algorithm: (Batch) gradient descent

Gradient $\nabla L(w) = \left(\frac{\partial L(w)}{\partial w_1}, \frac{\partial L(w)}{\partial w_2}, \dots, \frac{\partial L(w)}{\partial w_d} \right)$ - direction of the maximal increase of $L(w)$

1D example: $\nabla L(w) = \left(\frac{\partial L(w)}{\partial w} \right)$



Optimization algorithm

Initialization: $w = w_0$

While stopping criterion not met:

$$w = w - \alpha \cdot \nabla L(w)$$

learning rate

Minibatch Stochastic Gradient Descent

Initialization: $w = w_0$

While stopping criterion not met:

 Shuffle examples randomly

 Partition examples into batches of size m

 For minibatch = 1 ... N/m

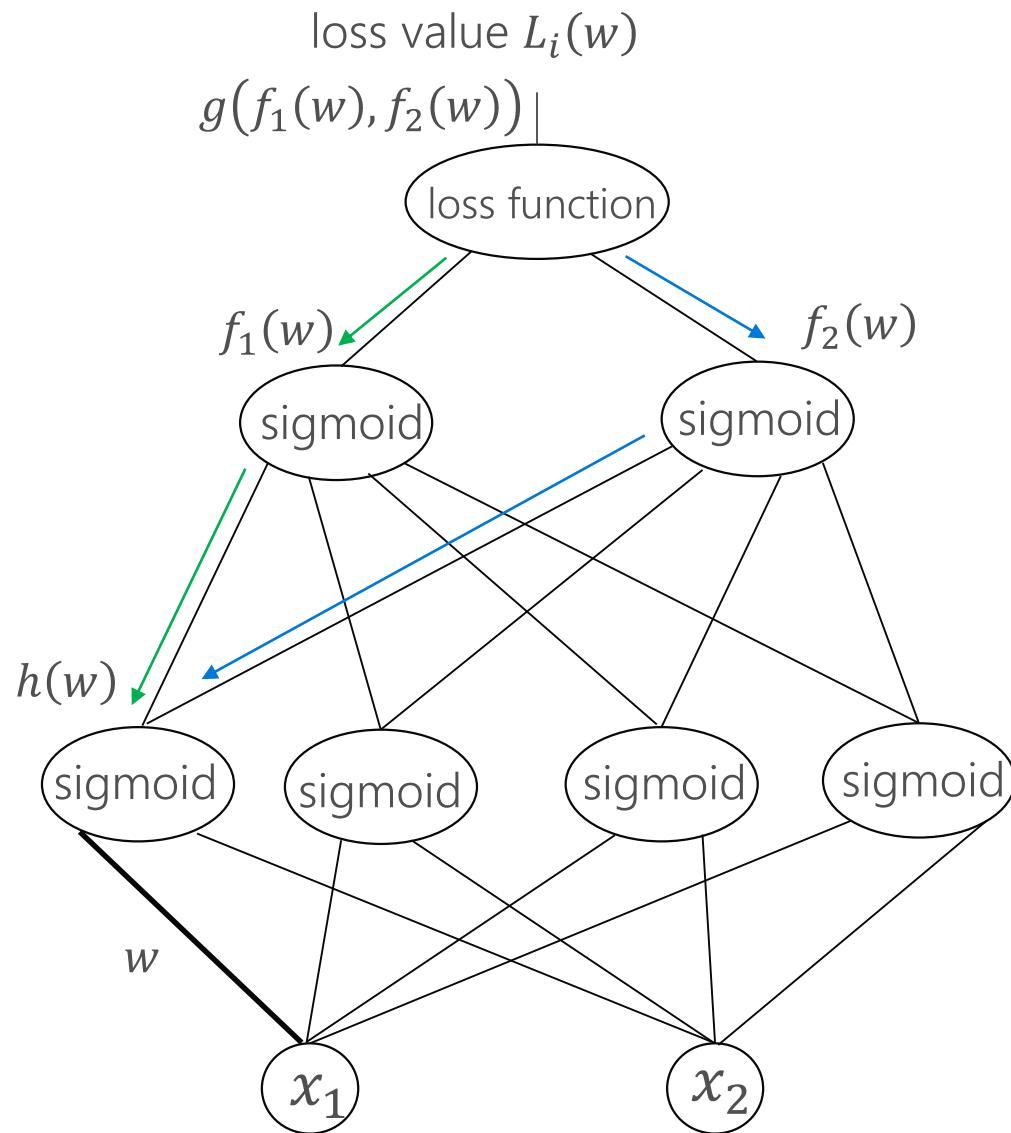
$$w = w - \frac{\alpha}{m} \sum_{i=1}^m \nabla L_i(w)$$

} epoch

gradient from the i -th
example in minibatch

m – mini-batch size (default value 32 in Keras)

Computation of gradients in NN: Backpropagation



Computation of $L'(w)$

Chain rule

$$L(w) = g(f_1(w))$$

$$L'(w) = g'(f_1(h(w))) \cdot f'_1(h(w)) \cdot h'(w)$$

$$L'(w) = g'(f_2(h(w))) \cdot f'_2(h(w)) \cdot h'(w)$$

Total derivative

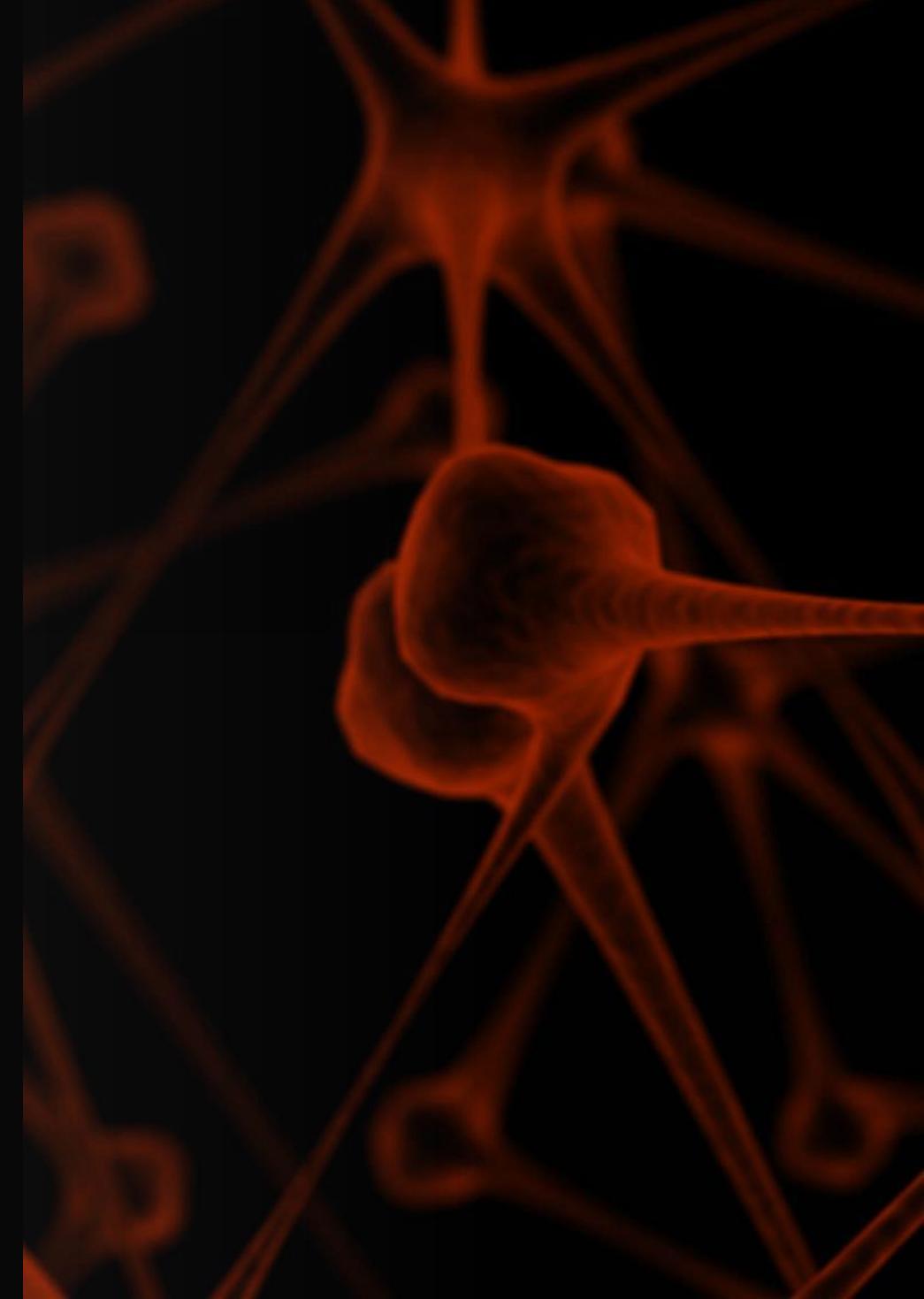
$$L(w) = g(f_1(w), f_2(w))$$

$$L'(w) = L'(w) + L'(w)$$

Training tricks

- Early stopping
- Tuning hyperparameters
- Weight Initialization [cs231n class notes](#)
- Weight regularization [Regularization for deep learning](#)
- Dropout [Dropout: A simple way to prevent neural networks from overfitting](#), [Zoneout: Regularizing RNNs by randomly preserving hidden activations](#)
- Batch normalization [Batch normalization: Accelerating deep network training by reducing internal covariate shift](#), [Recurrent batch normalization](#)
- Learning rate decay [Learning rate schedules and adaptive learning rate methods for deep learning](#)
- Advanced optimization algorithms [An overview of gradient descent optimization algorithms](#)

How to apply feed-forward NN to time series forecasting



Time Series & Time Series Forecasting

- *Time series* are observations taken sequentially in time
- *Time series forecasting* predicts future based on the past (historical data)

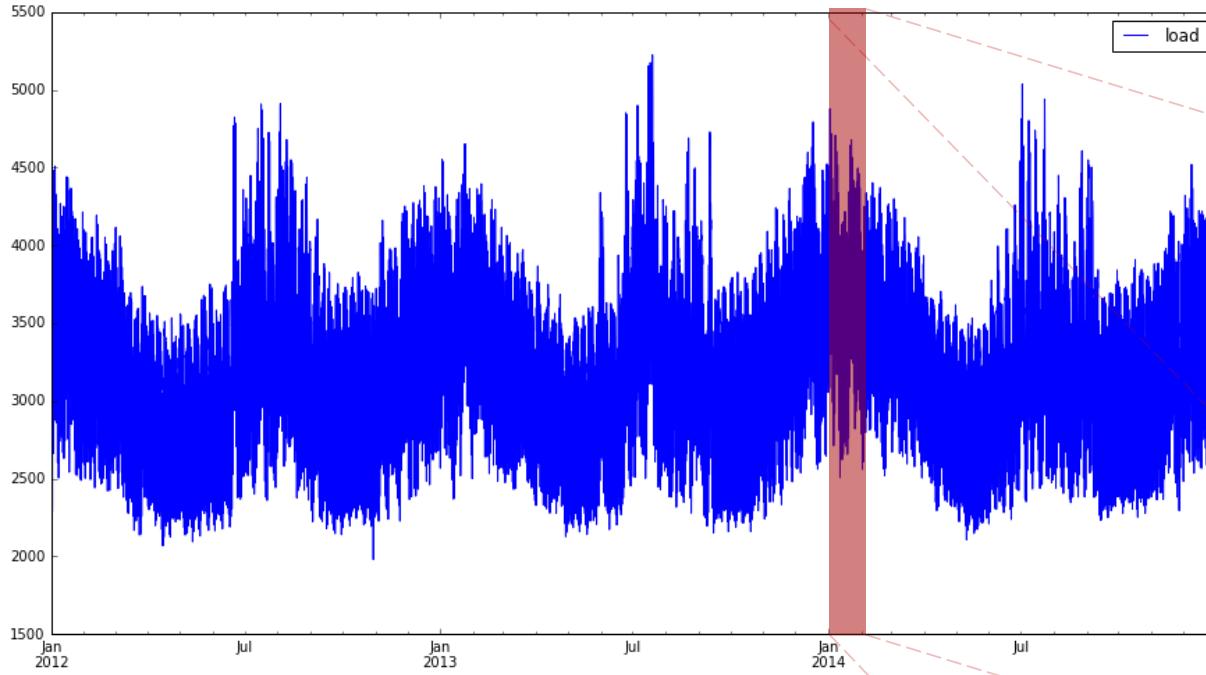
Date	Observation
2018-06-04	60
2018-06-05	64
2018-06-06	66
2018-06-07	65
2018-06-08	67
2018-06-09	68
2018-06-10	70
2018-06-11	69
2018-06-12	72
2018-06-13	?
2018-06-14	?
2018-06-15	?

The table illustrates a time series dataset. The first 10 rows represent historical data, grouped under a bracket labeled "History". The last three rows represent future data, grouped under a bracket labeled "Future". The "Date" column shows dates from June 4 to June 12, with the forecasted dates (June 13-15) showing question marks.

Scenario: energy load forecasting

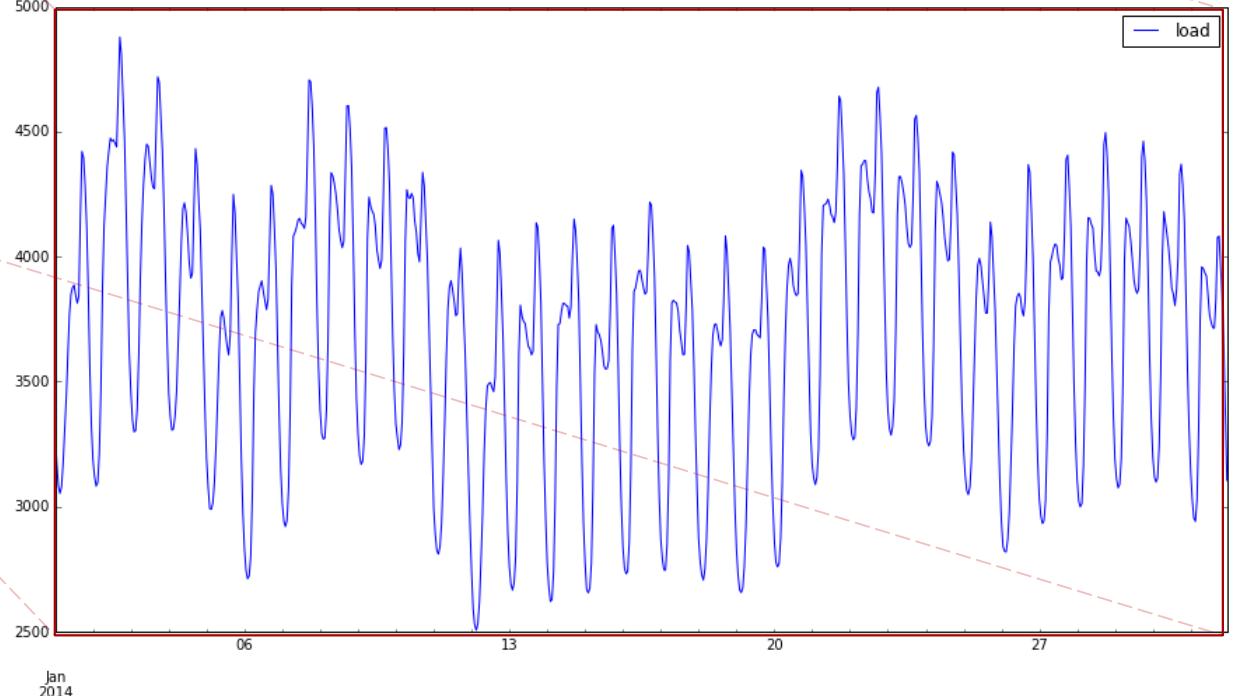
- Energy grid operators keep the supply and demand of electricity on power grids in balance
- They need short term demand forecasts to ensure the availability of the supply, and long term forecasts for planning
- Data in this example was used in the Global Energy Forecasting Competition in 2014 - GEFCom2014

New England ISO data



- 26,000 hourly load values
- Annual, weekly and daily seasonality

Tao Hong, Pierre Pinson, Shu Fan, Hamidreza Zareipour, Alberto Troccoli and Rob J. Hyndman,
"Probabilistic energy forecasting: Global Energy Forecasting Competition 2014 and beyond",
International Journal of Forecasting, vol.32, no.3,
pp 896-913, July-September, 2016.



Why Keras?

- 👍 High-level API for deep learning
- 👍 Simplified syntax for common DL tasks
- 👍 Operates over efficient backends (e.g. TensorFlow, CNTK)
- 👎 Less control over low-level operations
- 👎 Sometimes not as efficient as other frameworks

One step ahead forecasting of univariate time series using feed-forward neural network

Open 2_one_step_FF_univariate.ipynb

Hyperparameters

- Architecture
 - number of layers, number of cells in each layer, connections between cells
- Loss function
 - weight of regularization term
- Optimization
 - learning rate, mini-batch size, stopping criterion, initialization

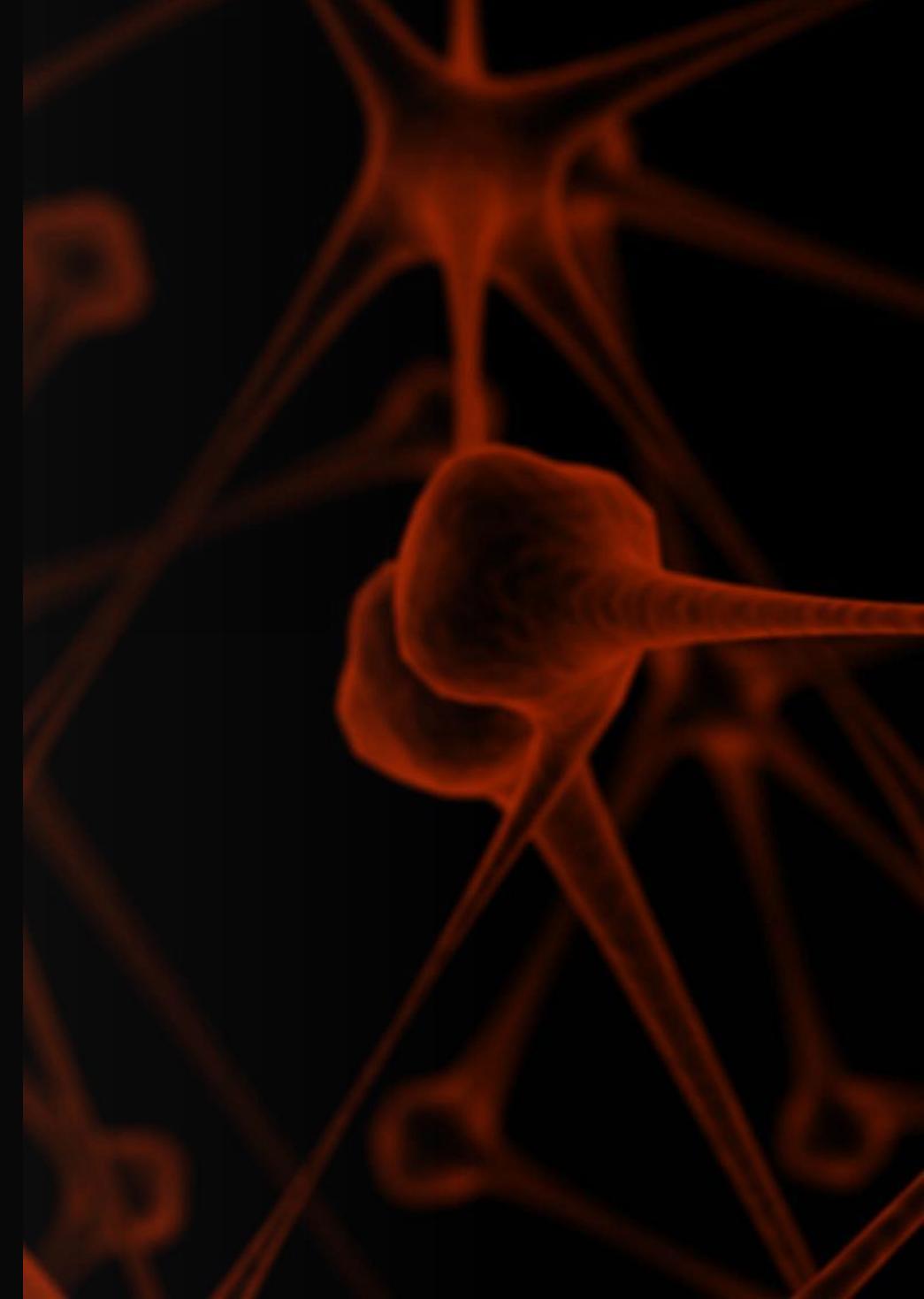
Advanced techniques for tuning hyperparameters

- Bayesian optimization [Bayesian optimization with robust Bayesian neural networks](#)
- Multi-armed bandit techniques [Hyperband: A novel bandit-based approach for hyperparameter optimization](#)
- Neural architecture search [Neural architecture search with reinforcement learning](#)
- Genetic programming [Population based training of neural networks](#)

Performance comparison

Algorithm	MAPE (Mean Absolute Percentage Error)
ARIMA	4.9
Feedforward Neural Network	4.27

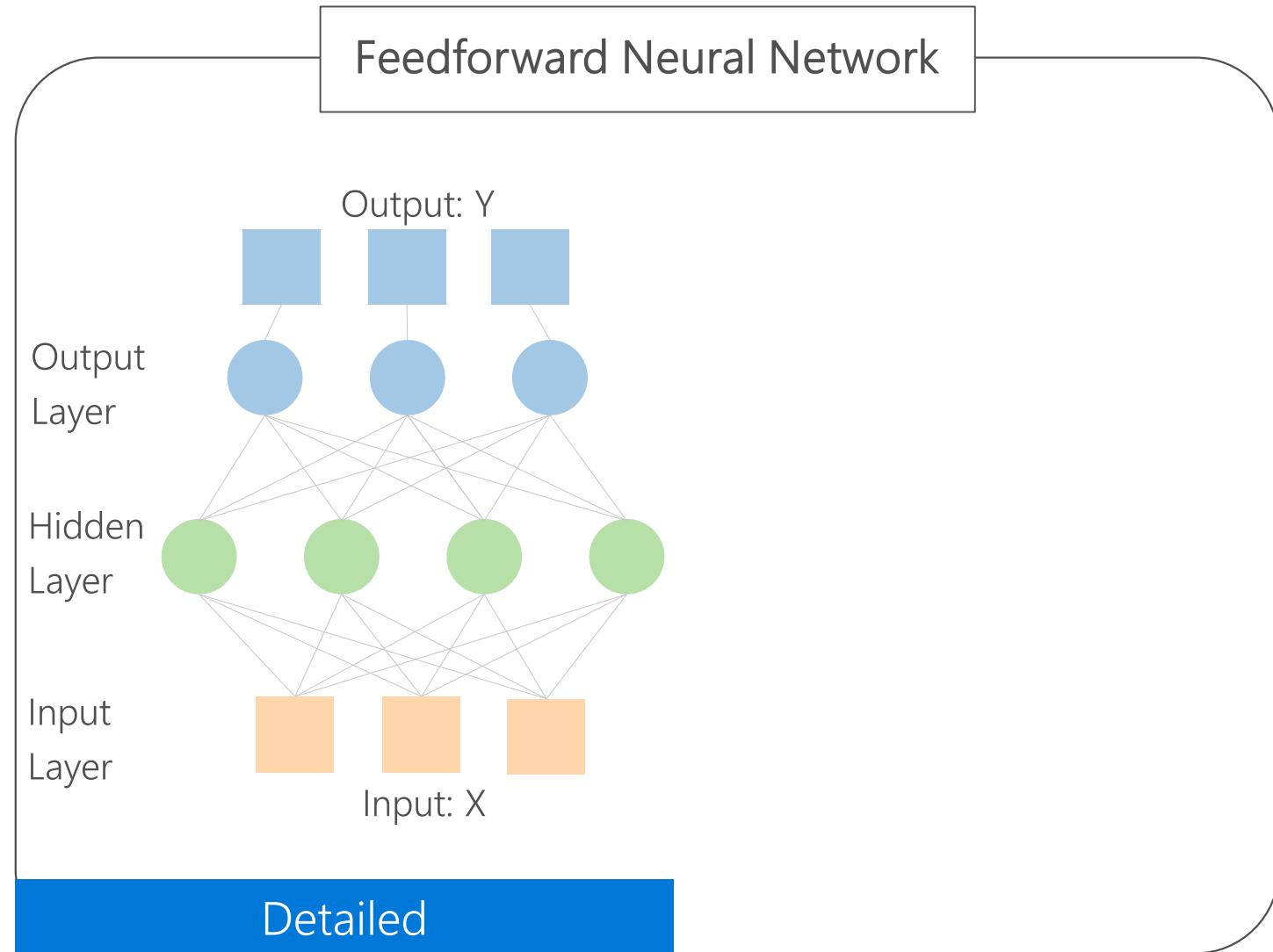
Introduction to Recurrent Neural Networks



Agenda

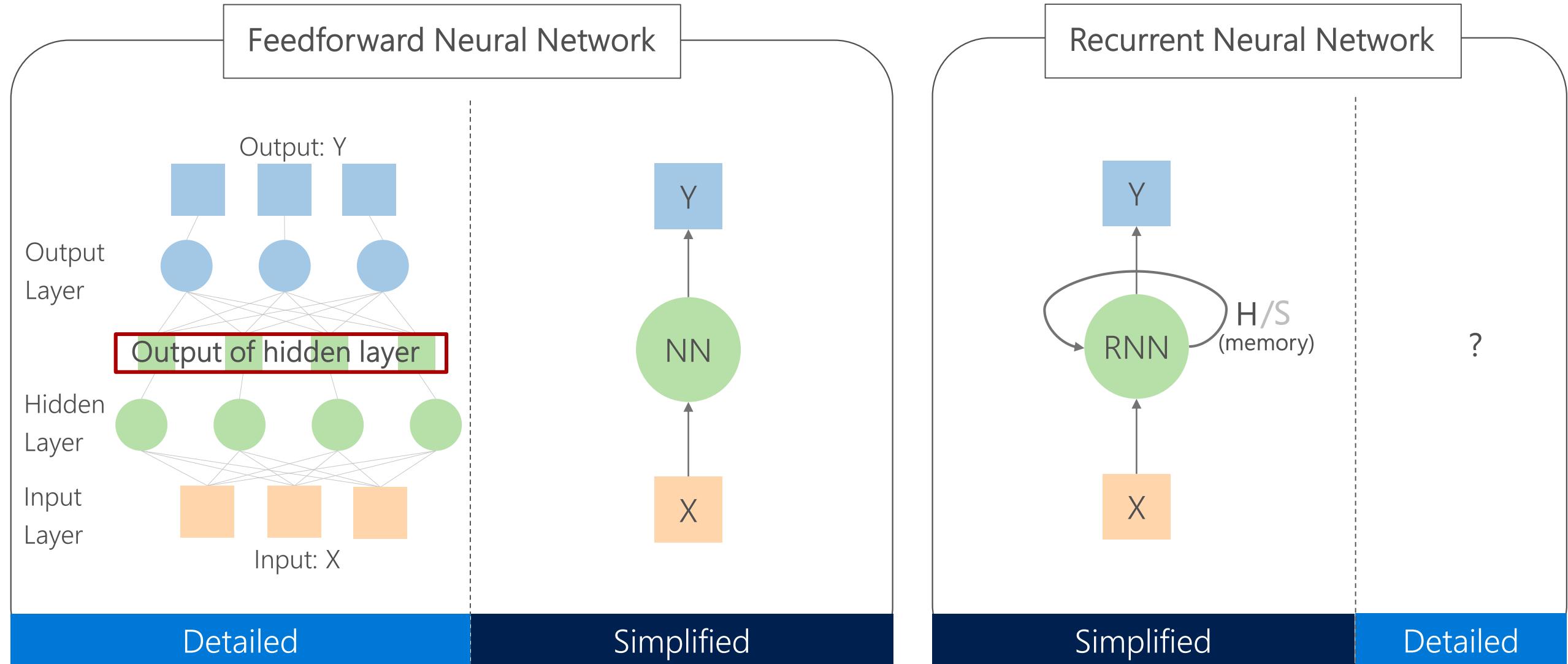
- What are RNNs?
- How RNNs are trained: Backpropagation through time (BPTT)
- Vanilla RNN and its gradient problems
- Other RNN units
 - GRU
 - LSTM
- RNN stacking

What are RNNs?



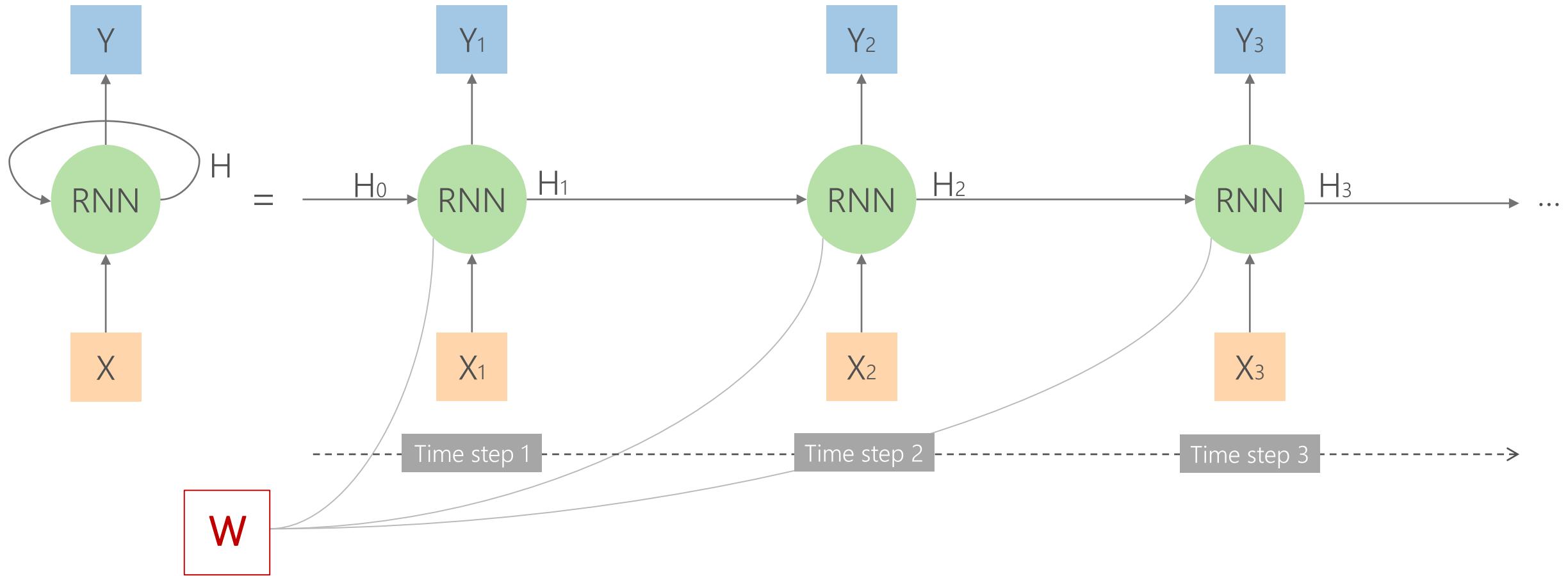
What are RNNs?

RNN has internal hidden state which can be fed back to network



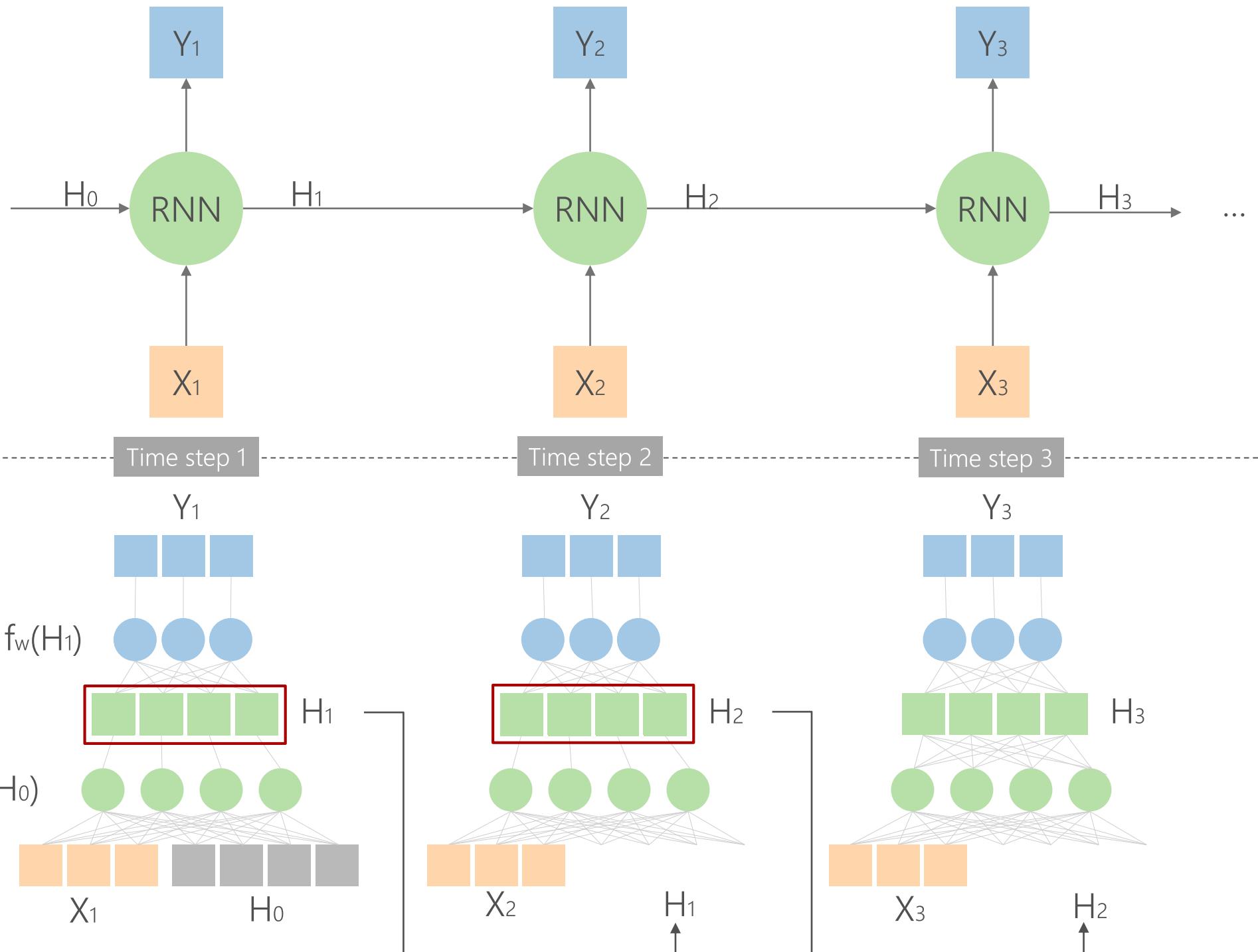
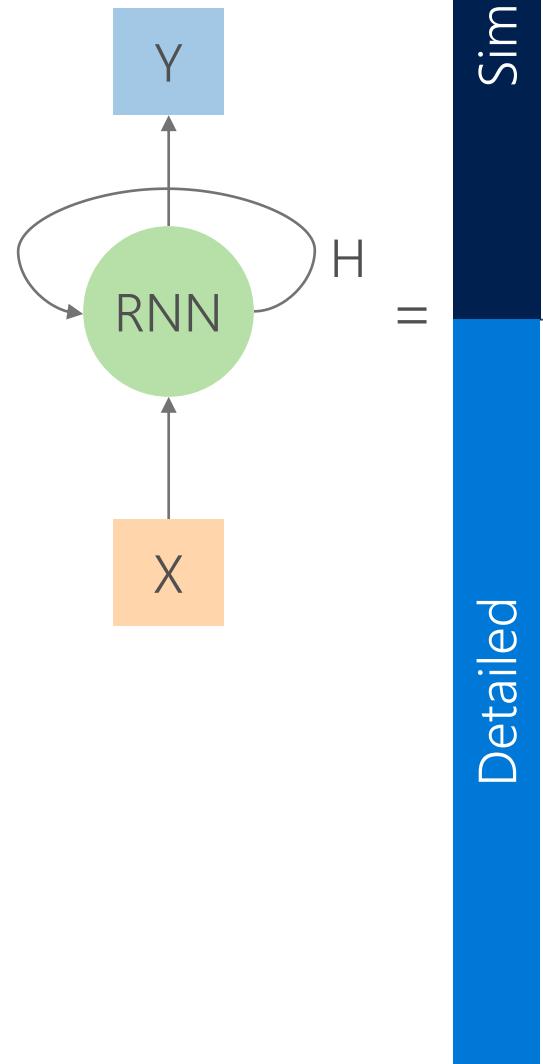
Unrolled RNN

The same weight and bias shared across all the steps



In Keras you will see “timesteps” when set data input shape

Unrolled RNN

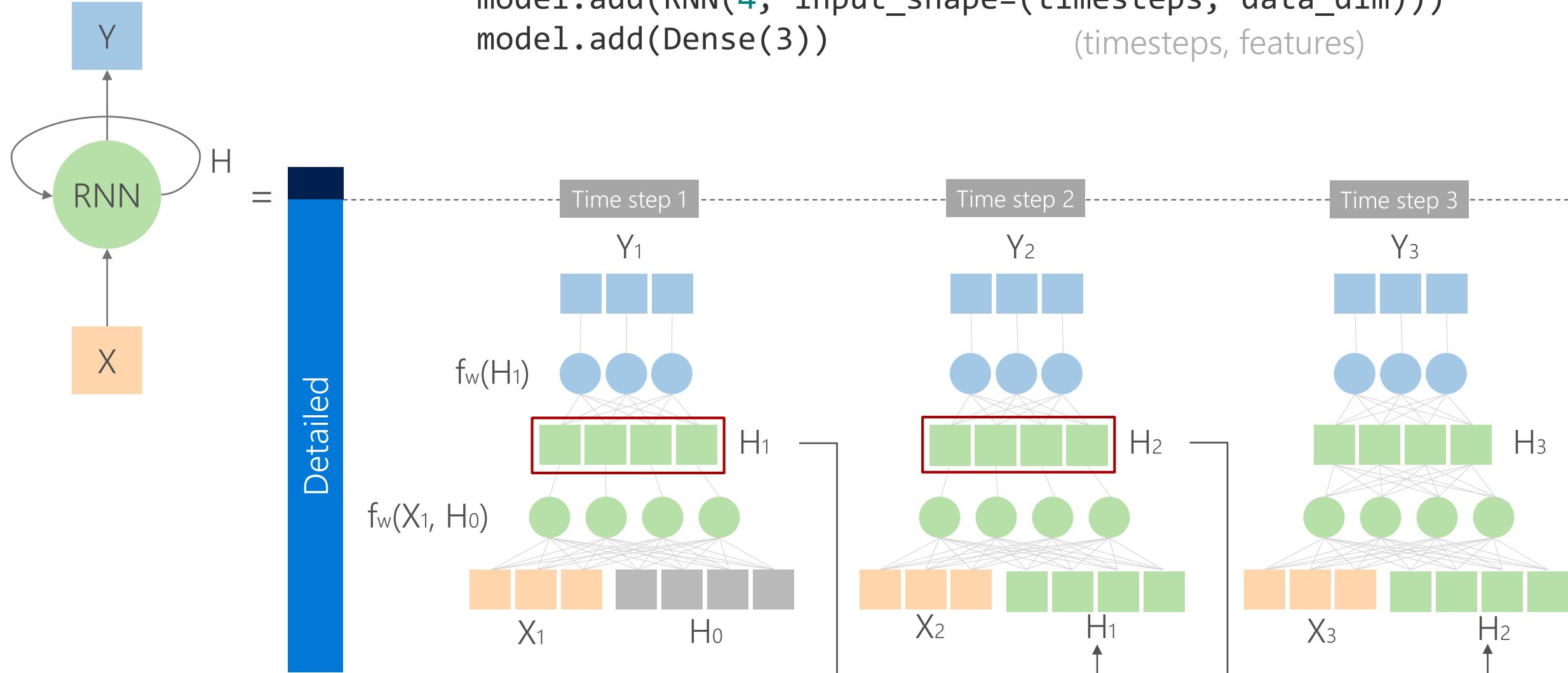


Unrolled RNN

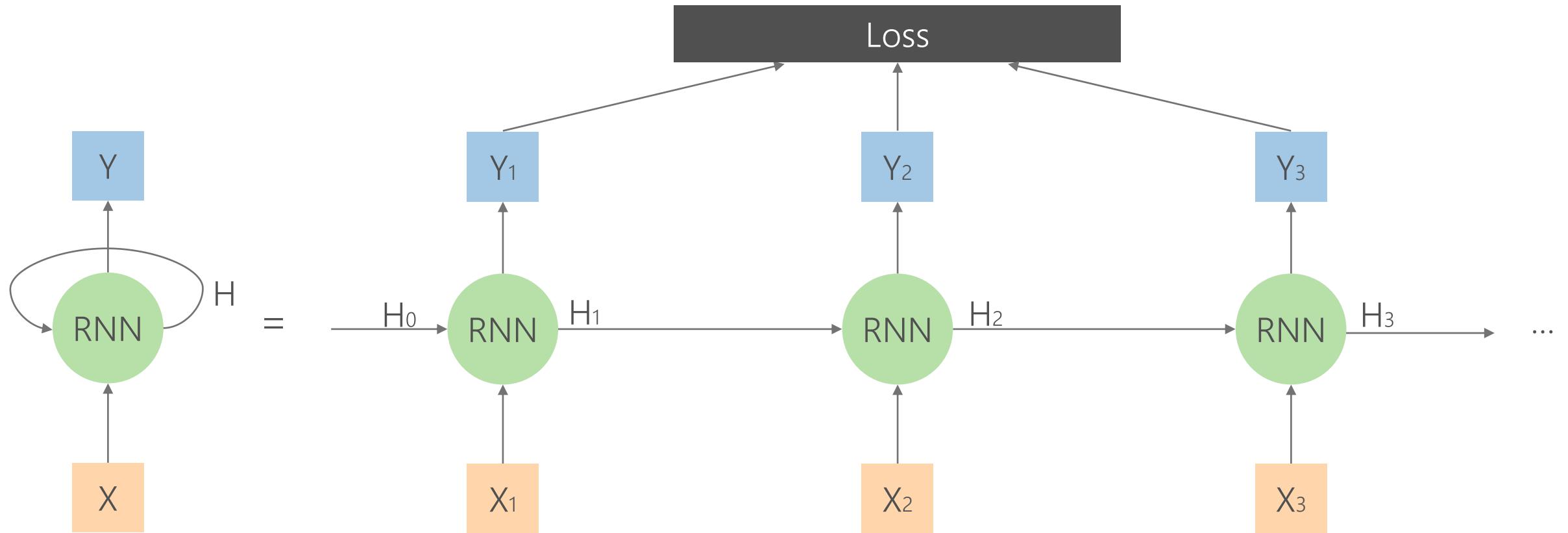
In Keras, the parameter “**units**” is dimensions of hidden state.
(Think of it as feedforward neural network number of units in hidden layer.)

```
model = Sequential()  
model.add(RNN(4, input_shape=(timesteps, data_dim)))  
model.add(Dense(3))
```

(timesteps, features)



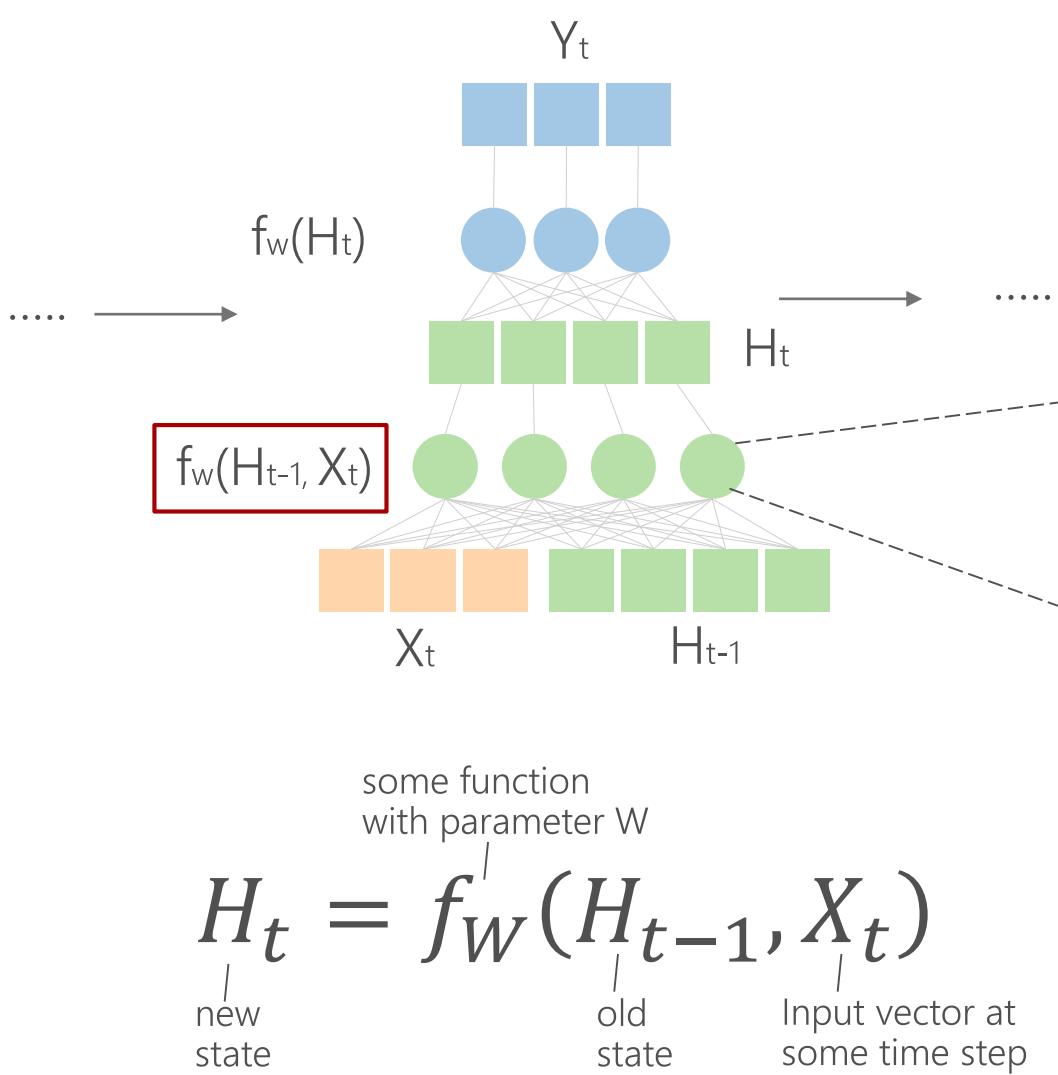
Backpropagation through time (BPTT)



Forward through entire sequence to compute loss

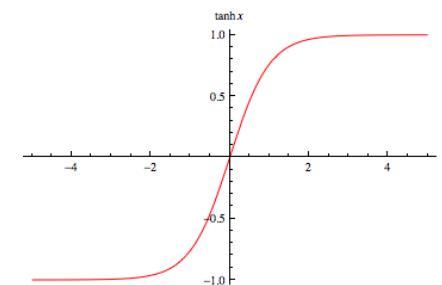
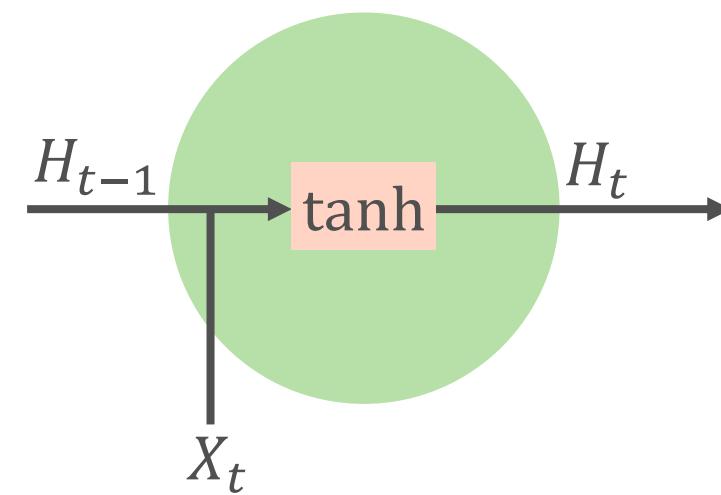
then backward through entire sequence to compute gradient

Vanilla RNN

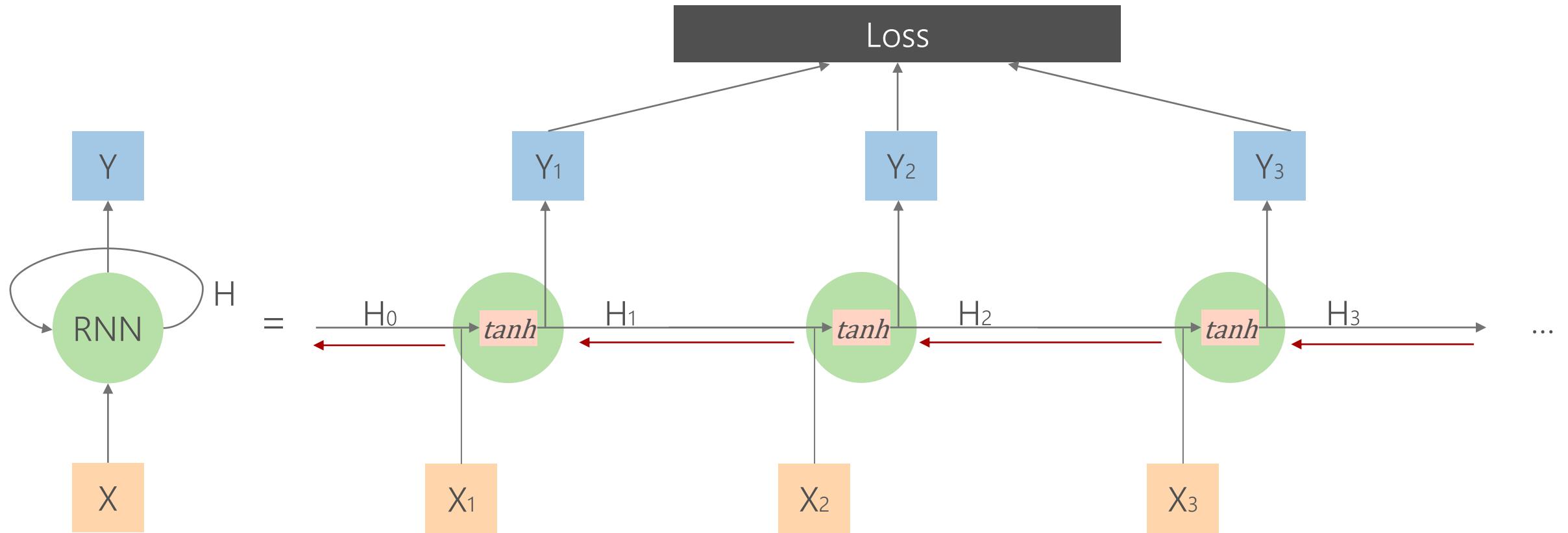


Vanilla RNN:

$$\begin{aligned} H_t &= \tanh(W_h H_{t-1} + W_x X_t) \\ &= \tanh(\mathbf{W} \cdot [H_{t-1}, X_t]) \end{aligned}$$



Vanilla RNN BPTT

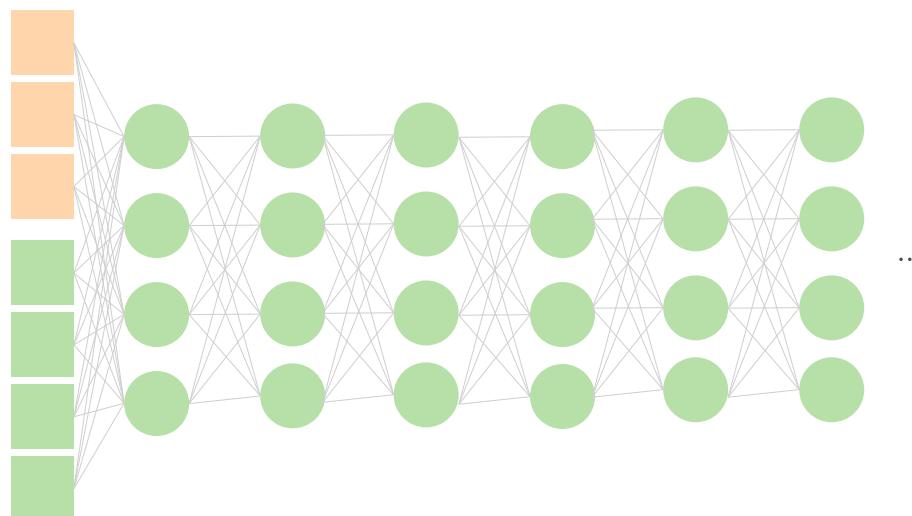


Computing gradient of h_0 involves repeated \tanh and many factors of W

Vanilla RNN Gradient Problems

Computing gradient of h_0 involves repeated tanh and many factors of W which causes:

- Exploding gradient (e.g. $5*5*5*5*5*5*.....$)
- Vanishing gradients (e.g. $0.7*0.7*0.7*0.7*0.7*0.7*.....$)



100 time steps is similar to 100 layers feedforward neural net

Exploding Gradient

- Exploding gradients are obvious. Your gradients will become NaN (not a number) and your program will crash
- Solution: Gradient clipping
Clip the gradient when it goes higher than a threshold

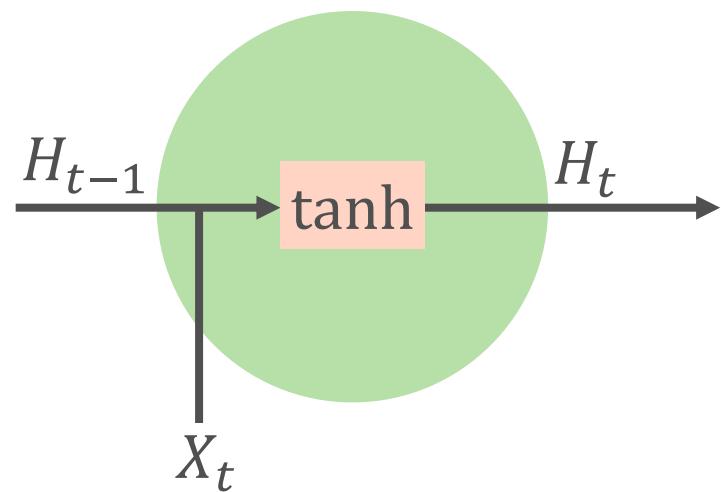
Vanishing Gradient

- Vanishing gradients are more problematic because it's not obvious when they occur or how to deal with them
- Solutions:
 - Change activation function to ReLU
 - Proper initialization
 - Regularization
 - Change architecture to LSTM or GRU

Gated Recurrent Unit (GRU)

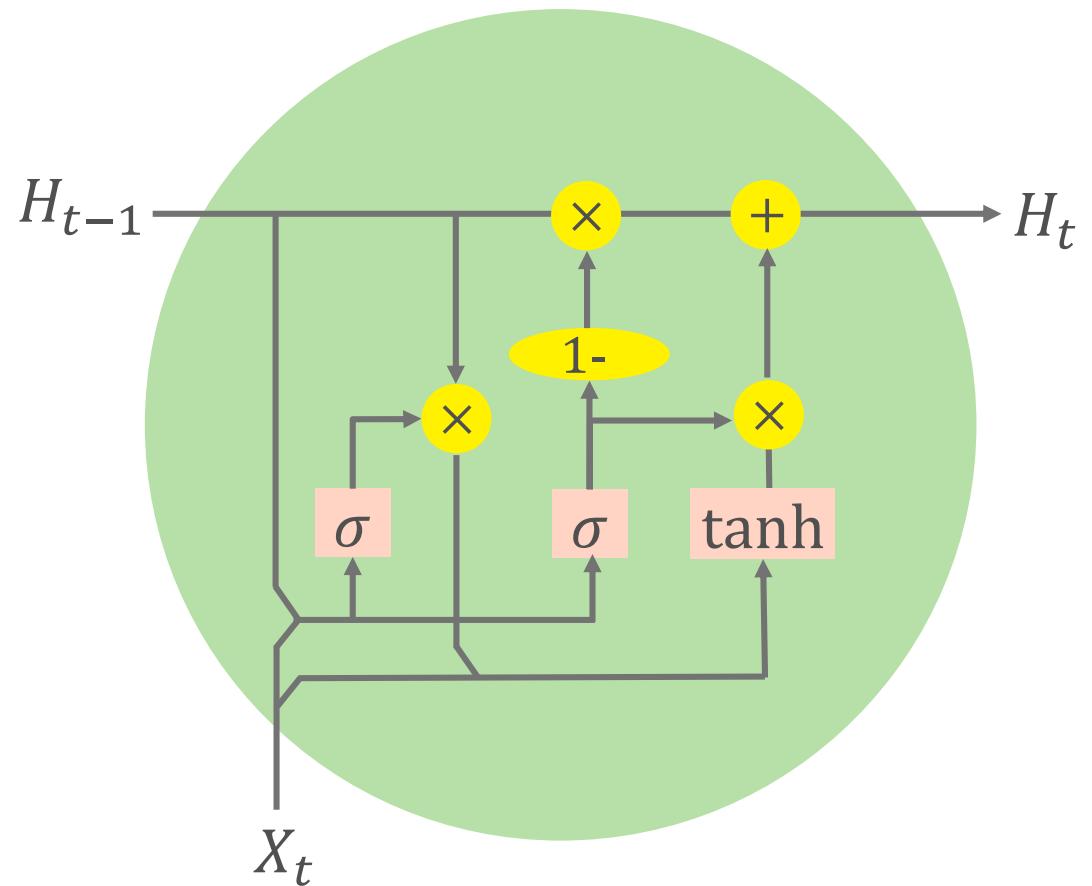
Vanilla RNN:

$$H_t = \underline{\tanh(\mathbf{W} \cdot [H_{t-1}, X_t])}$$

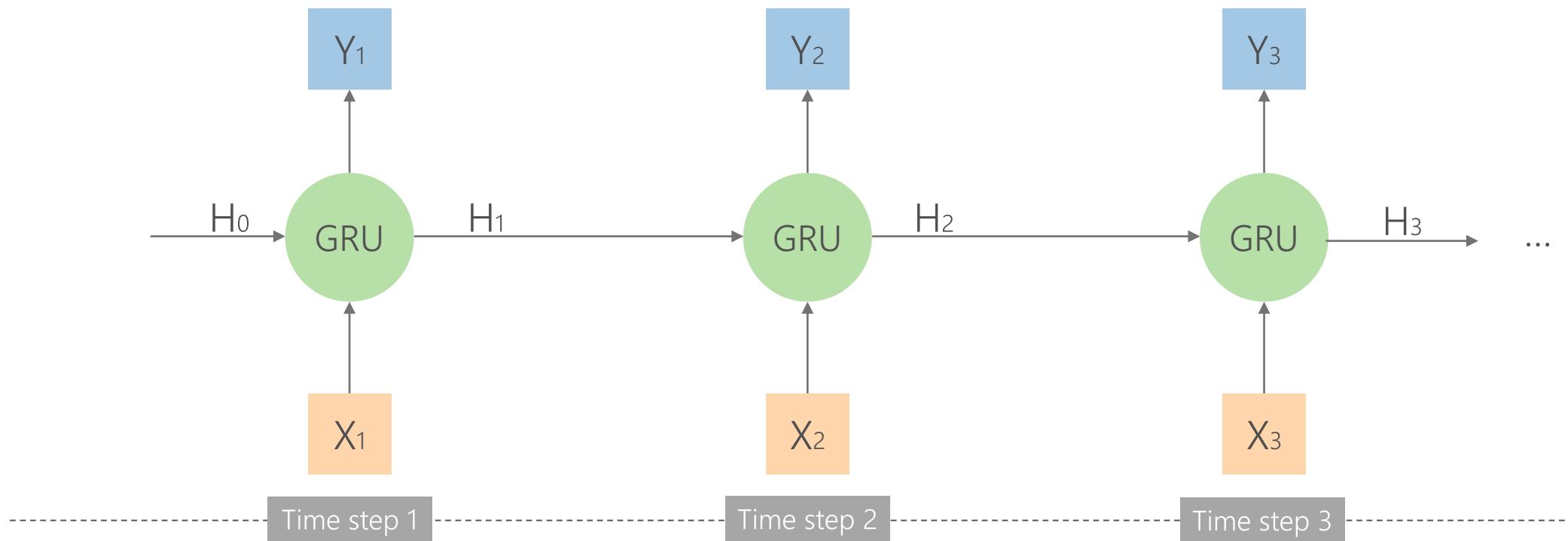


GRU:

$$H_t = \underline{(1 - z_t) \times H_{t-1} + z_t \times \tilde{H}_t}$$

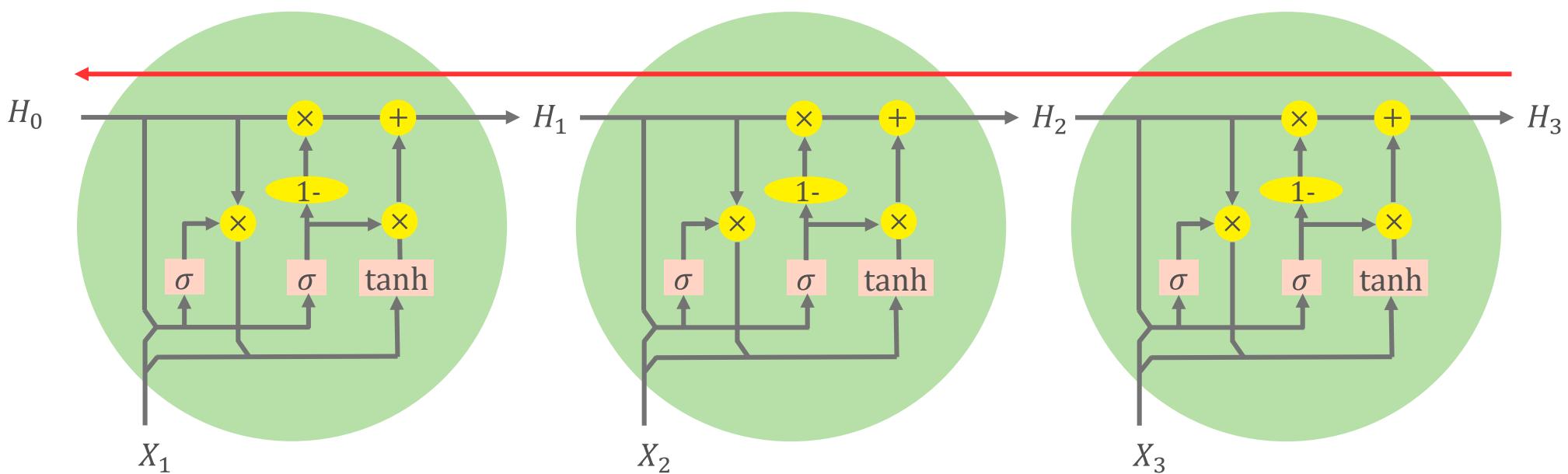


GRU

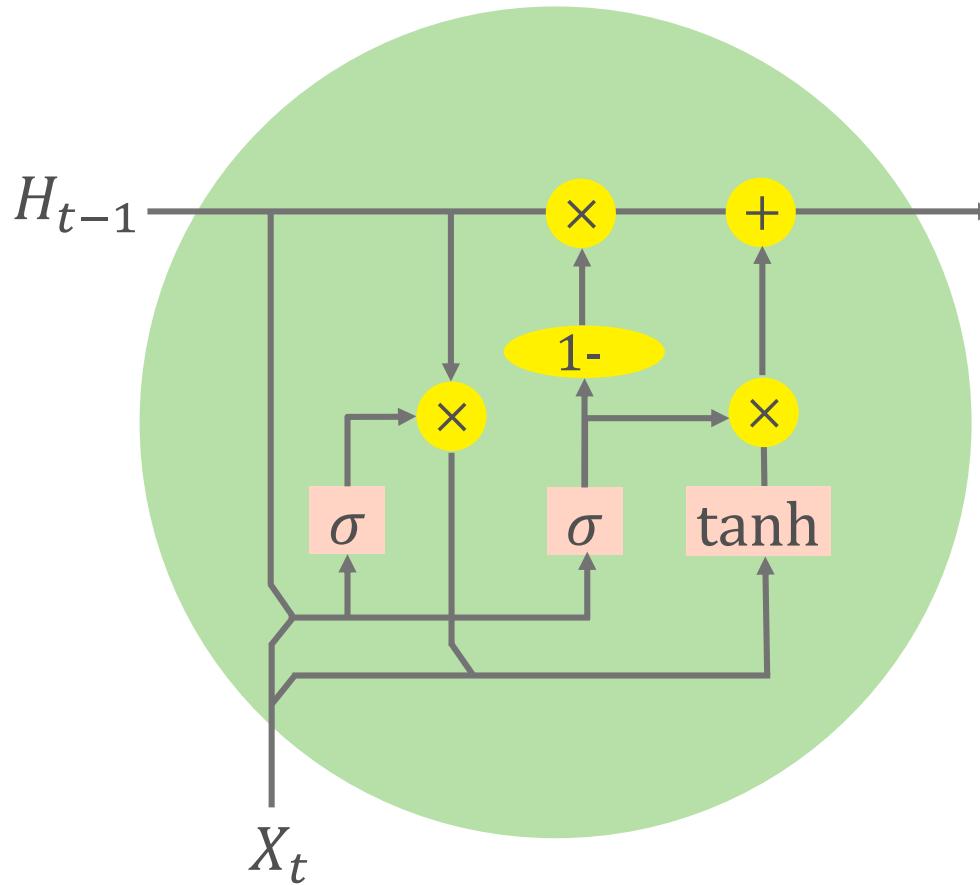


Uninterrupted gradient flow

State runs straight through the entire chain with minor linear interactions which makes information very easy to pass.



Gated Recurrent Unit (GRU)



$$\text{Hidden state: } H_t = (1 - z_t) \times H_{t-1} + z_t \times \tilde{H}_t$$

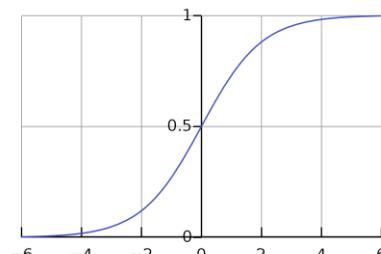
$$\text{Update gates: } z_t = \sigma(W_z \cdot [H_{t-1}, X_t])$$

$$\text{Candidate gates/states: } \tilde{H}_t = \tanh(W \cdot [r_t \times H_{t-1}, X_t])$$

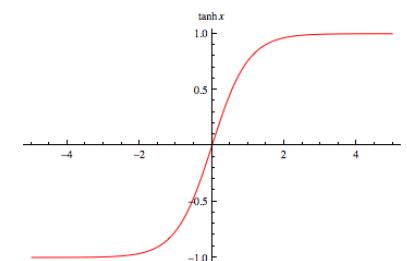
$$\text{Reset gates: } r_t = \sigma(W_r \cdot [H_{t-1}, X_t])$$

GRU [[Learning phrase representations using rnn encoderdecoder for statistical machine translation, Cho et al. 2014](#)]

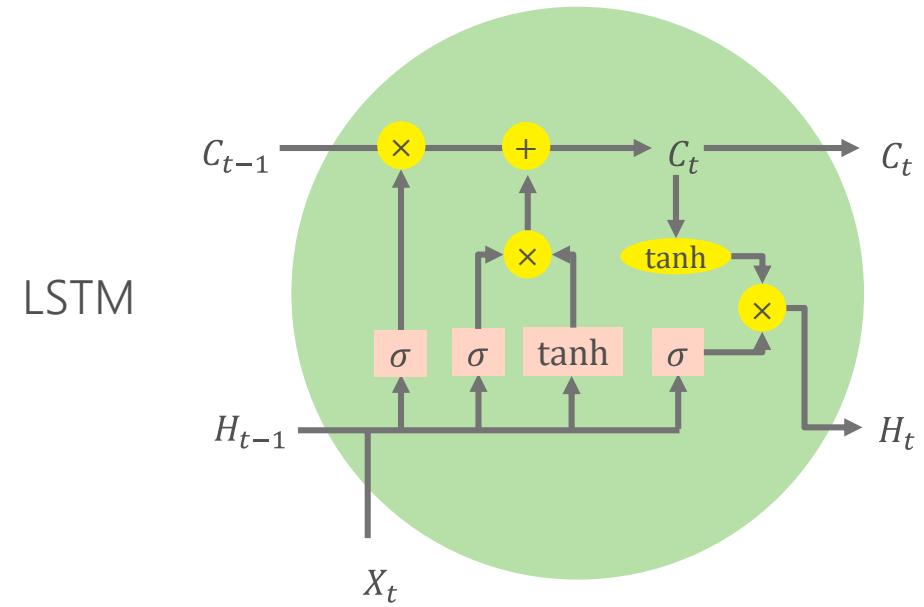
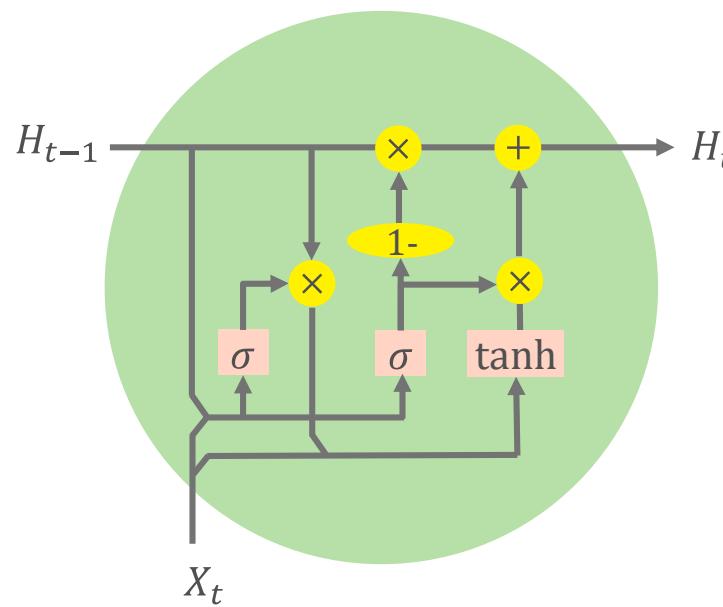
$$\sigma(0,1)$$



$$\tanh(-1, 1)$$



GRU vs LSTM (Long Short Term Memory)



Hidden state: $H_t = (1 - z_t) \times H_{t-1} + z_t \times \tilde{H}_t$

Update gates: $z_t = \sigma(W_z \cdot [H_{t-1}, X_t])$

Reset gates: $r_t = \sigma(W_r \cdot [H_{t-1}, X_t])$

Candidate gates/states: $\tilde{H}_t = \tanh(W \cdot [r_t \times H_{t-1}, X_t])$

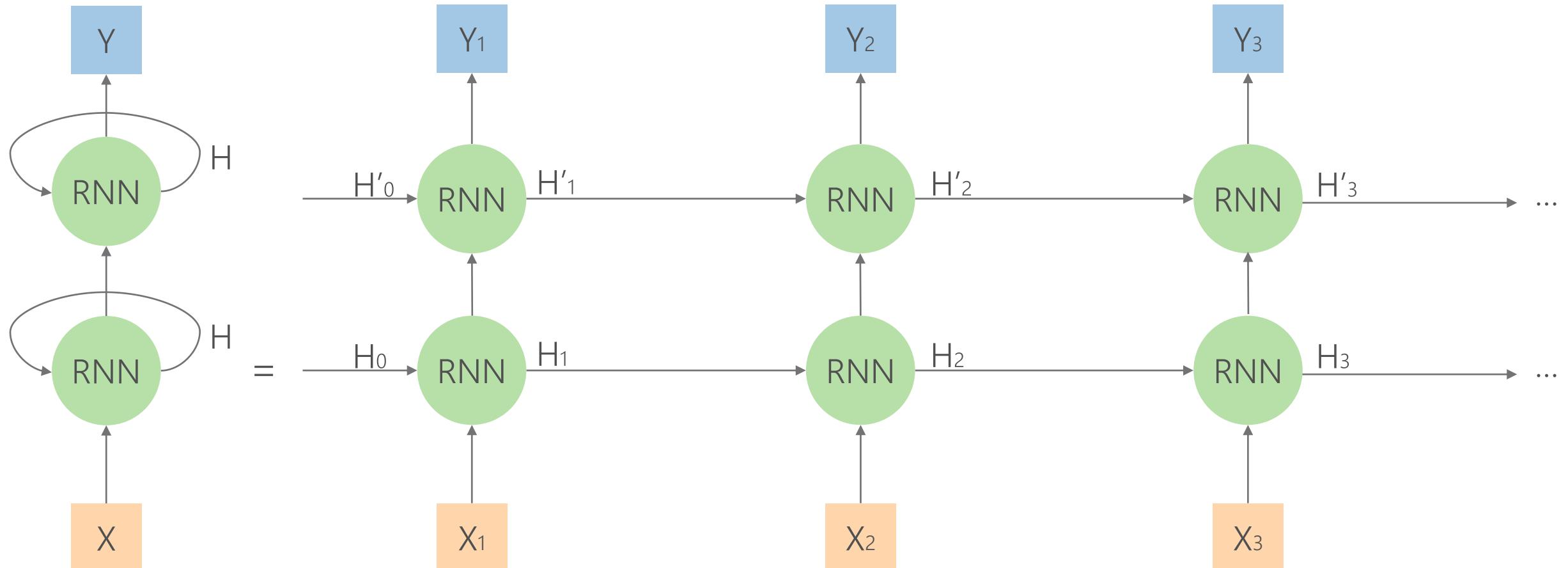
Hidden cell state: $C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t$
 Hidden state: $H_t = o_t \times \tanh(C_t)$

Forget gates: $f_t = \sigma(W_f \cdot [H_{t-1}, X_t])$
 Input gates: $i_t = \sigma(W_i \cdot [H_{t-1}, X_t])$

Candidate gates/states: $\tilde{C}_t = \tanh(W_g \cdot [H_{t-1}, X_t])$
 Output gates: $o_t = \sigma(W_o \cdot [H_{t-1}, X_t])$

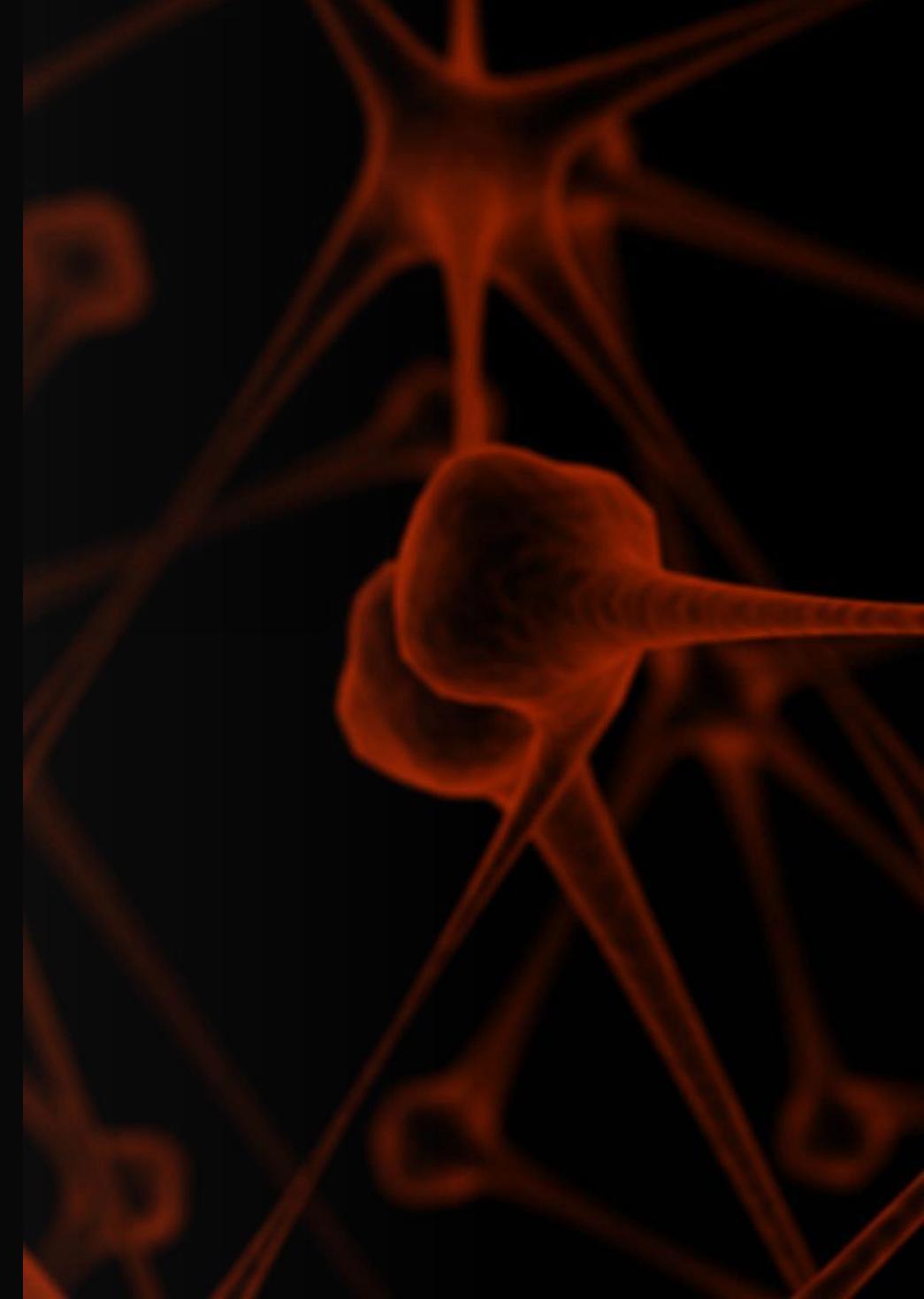
RNN Stacking

To learn more complex relationships, we can go deep by stacking the cells.



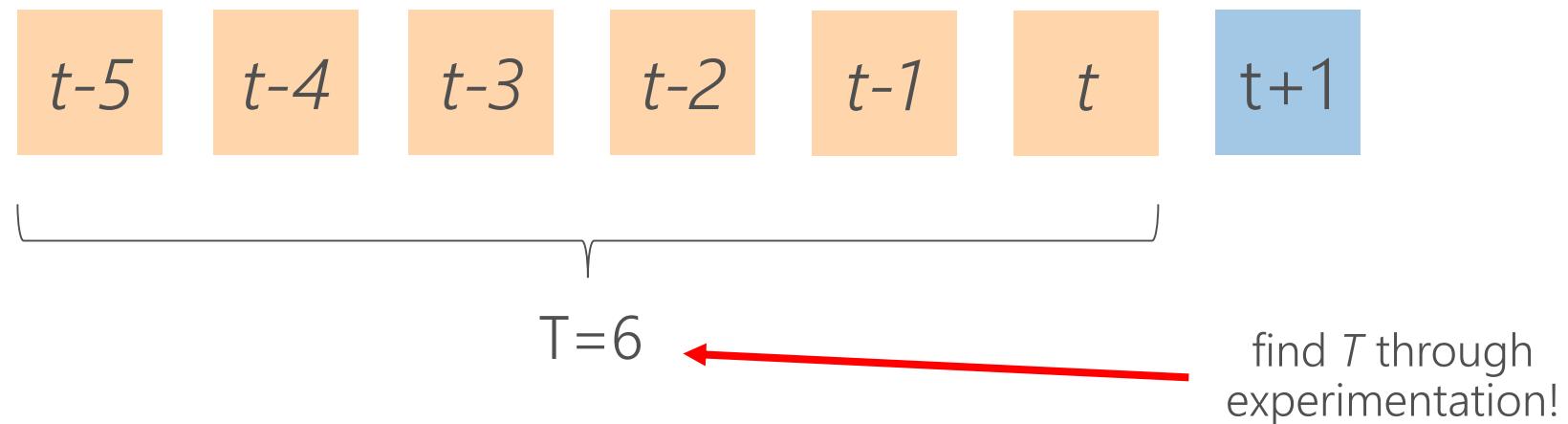
```
model = Sequential()  
model.add(RNN(4, return_sequences=True, input_shape=(timesteps, data_dim)))  
model.add(RNN(4))
```

RNN for one step
time series
forecasting



One-step forecast

- Assuming we are at time t ...
- ... predict the value at time $t+1$...
- ... conditional on the previous T values of the time series



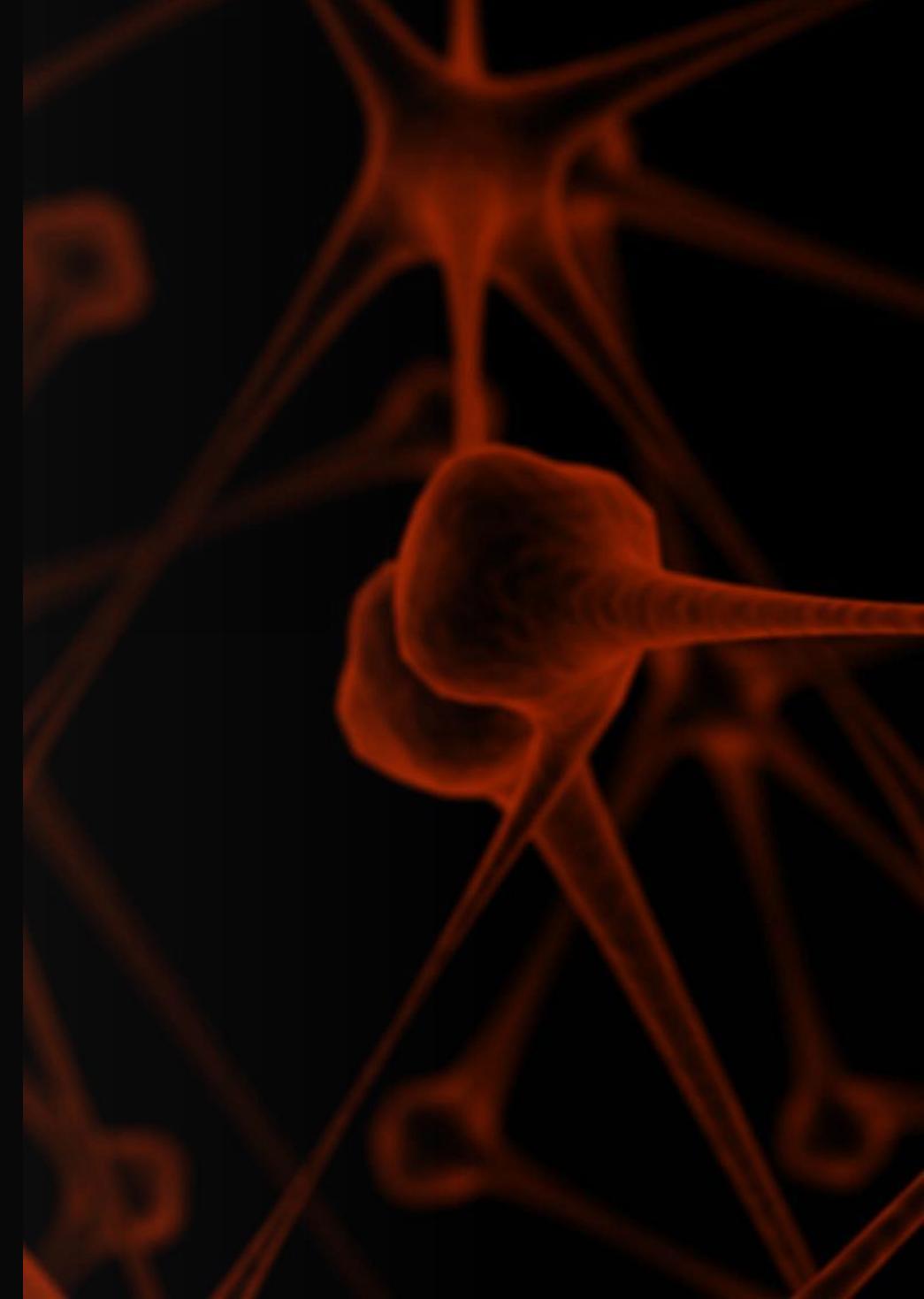
Hands-on Experiment

Open: 3_one_step_RNN_univariate.ipynb

Hands-on Quiz

Open: Quiz_one_step_RNN_multivariate.ipynb

RNN for multi-step time series forecasting

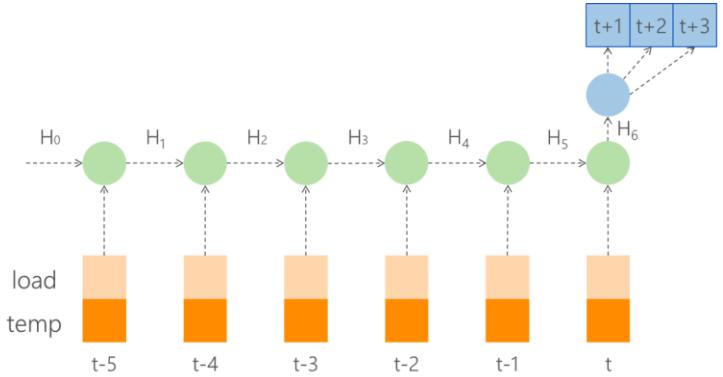


Multi-step forecast

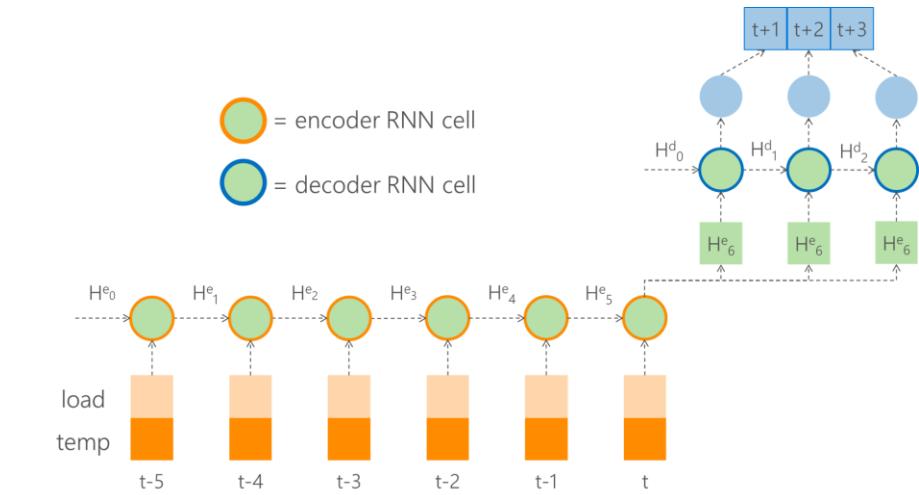
- Assuming we are at time t ...
- ... predict the values at times $(t+1, \dots, t+HORIZON)$...
- ... conditional on the previous T values of the time series



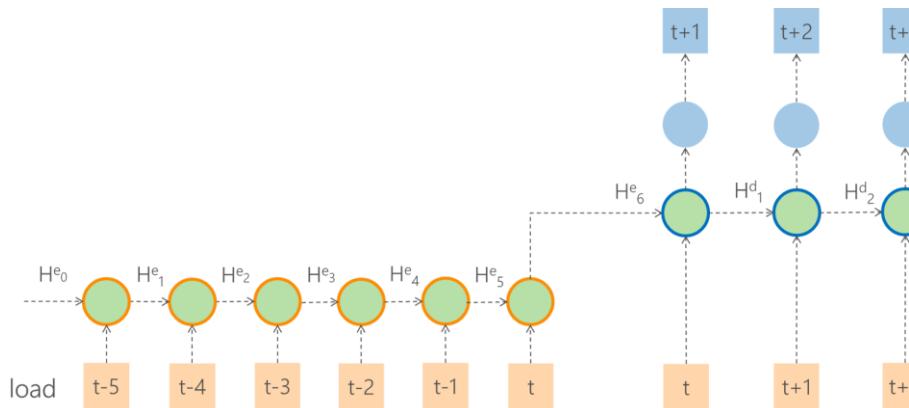
Multi-step forecast



Vector output

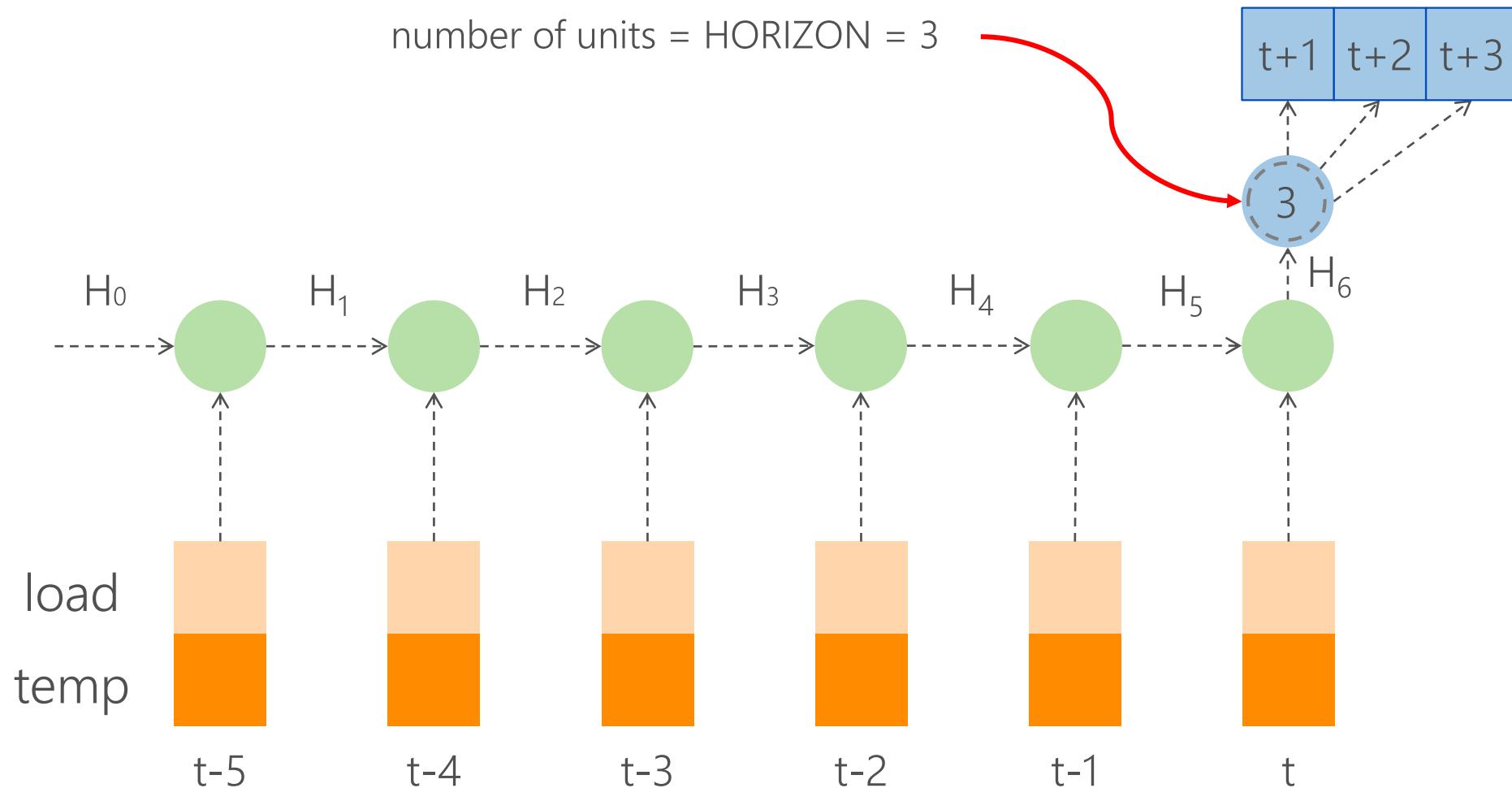


Simple encoder-decoder



Recursive encoder-decoder

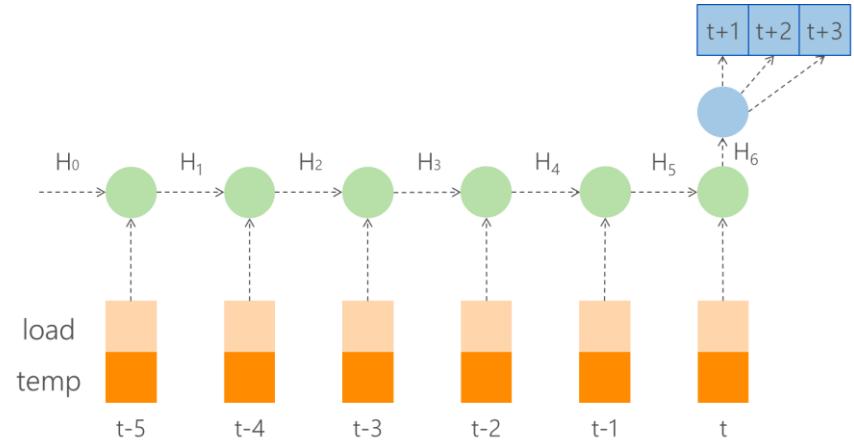
Vector output approach



Multi-step forecasting using a vector output RNN

Open 4_multi_step_RNN_vector_output.ipynb

Vector output approach



- 👍 Simplest to implement
- 👍 Fastest to train
- 👎 Does not model dependencies between predicted outputs

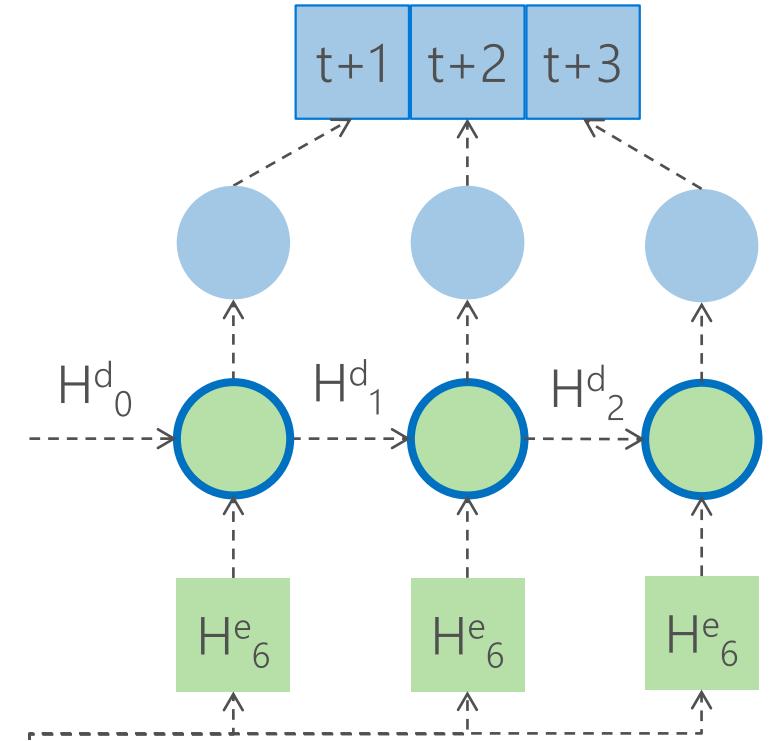
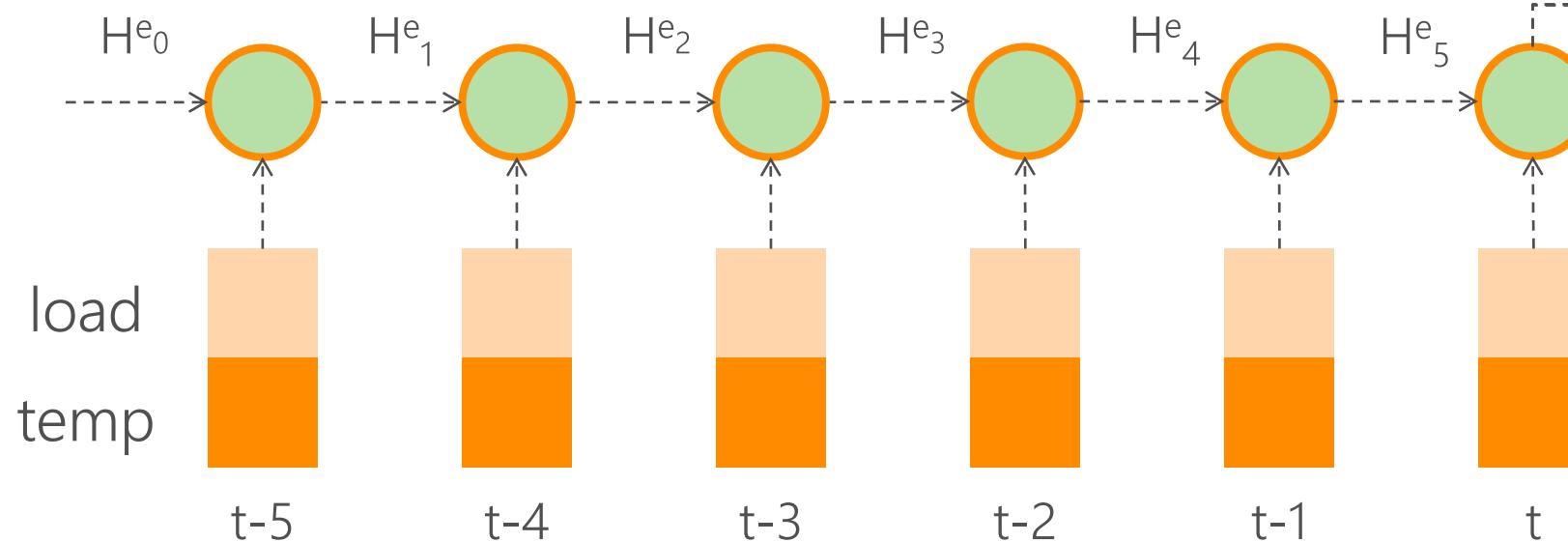
Performance comparison

Algorithm	MAPE (Mean Absolute Percentage Error)
ARIMA	4.9
Feedforward Neural Network	4.27
RNN: vector output	3.67

Simple encoder-decoder

 = encoder RNN cell

 = decoder RNN cell

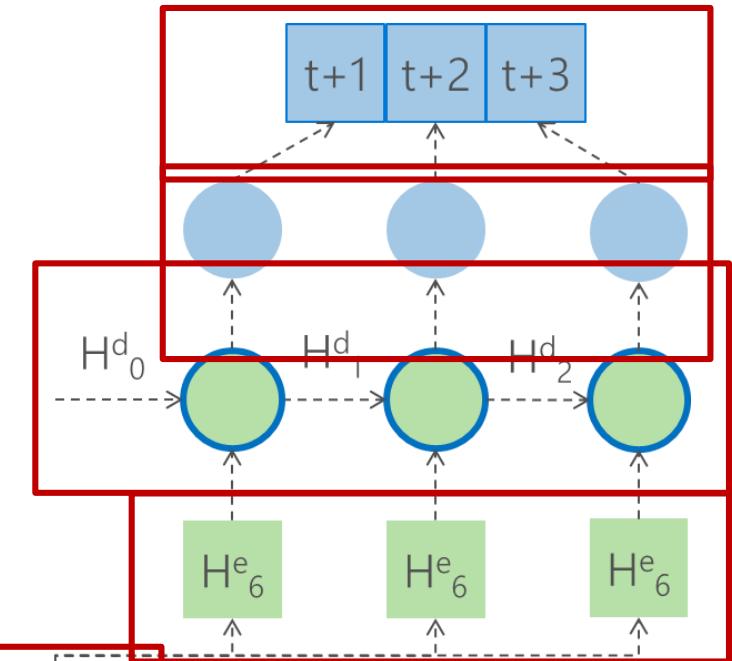
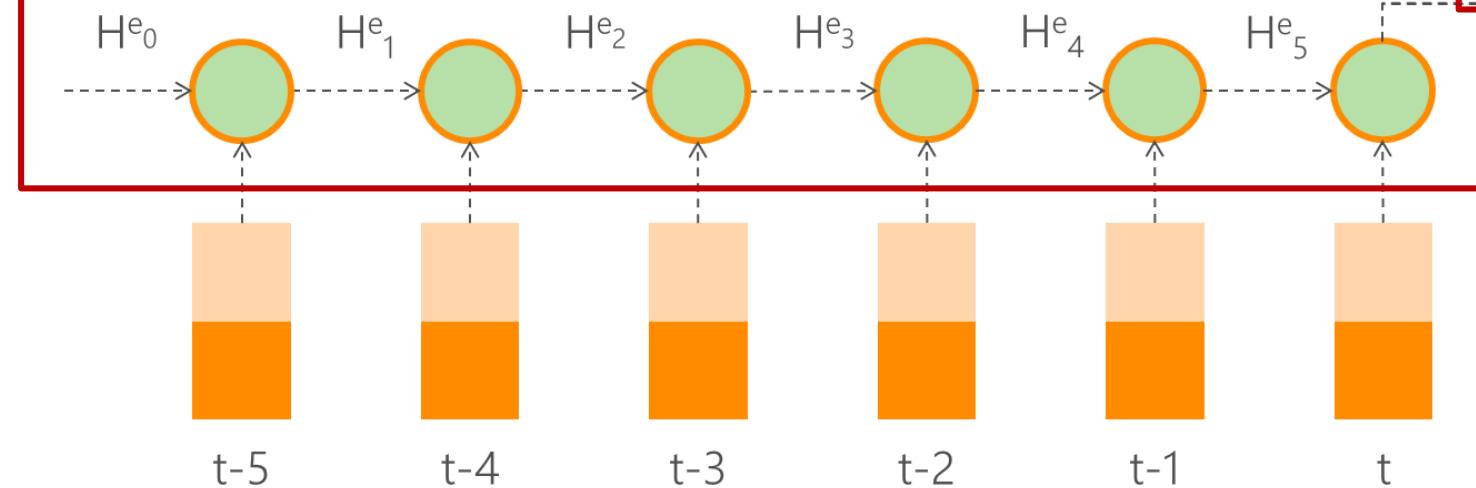


Multi-step forecasting using encoder-decoder

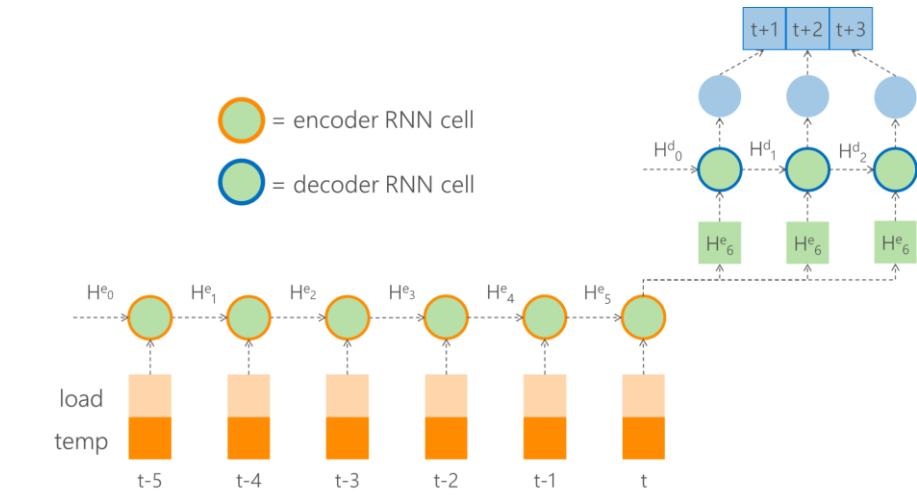
Open 5_multi_step_RNN_encoder_decoder_simple.ipynb

Simple encoder-decoder

```
model = Sequential()  
model.add(GRU(LATENT_DIM, input_shape=(6, 2))  
model.add(RepeatVector(3))  
model.add(GRU(LATENT_DIM, return_sequences=True))  
model.add(TimeDistributed((Dense(1))))  
model.add(Flatten())
```



Simple encoder-decoder

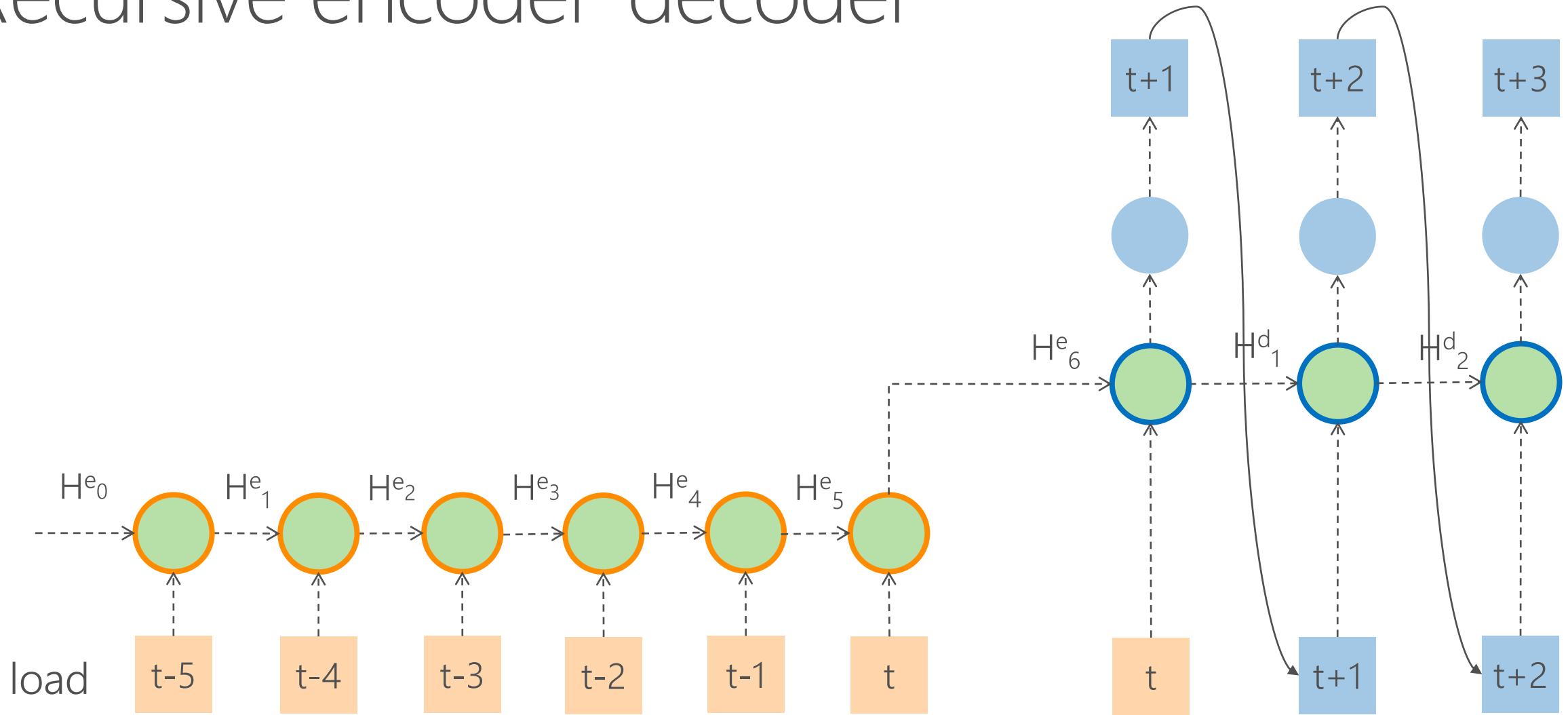


- 👍 Fairly simple to implement
- 👍 Tries to capture dependencies between forecasted time steps through decoder hidden state
- 👎 Slower to train with stacked RNN layers

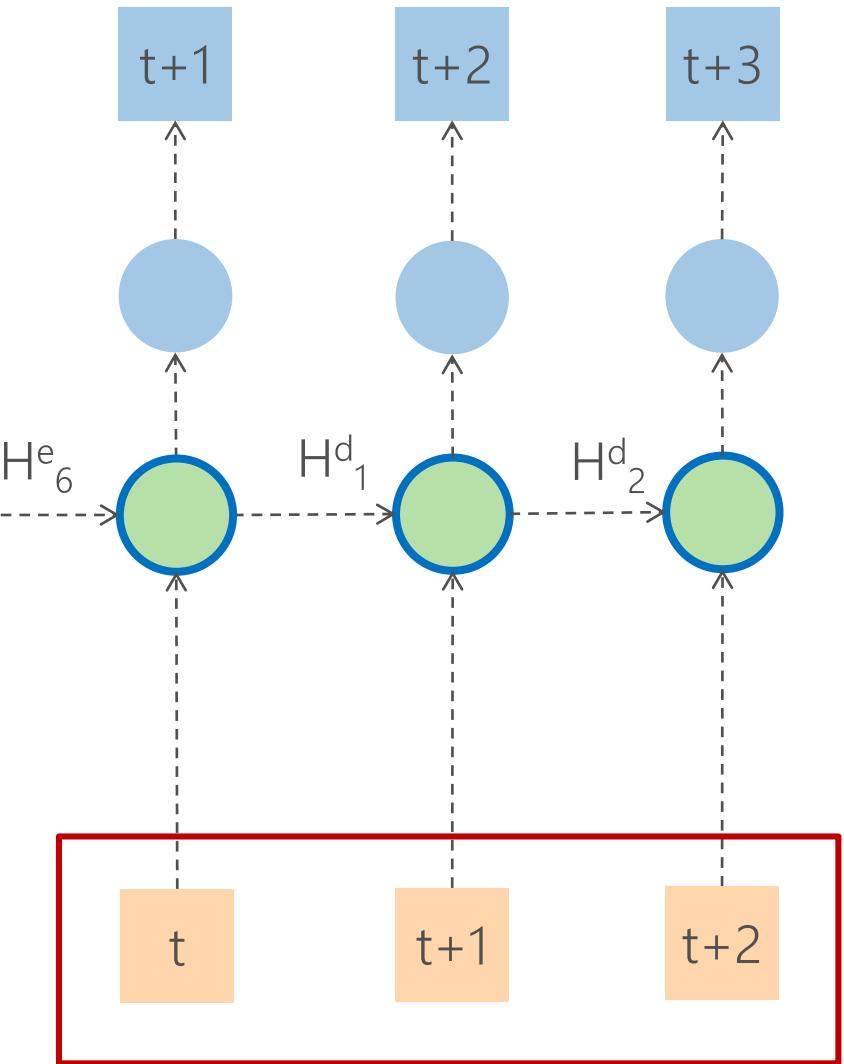
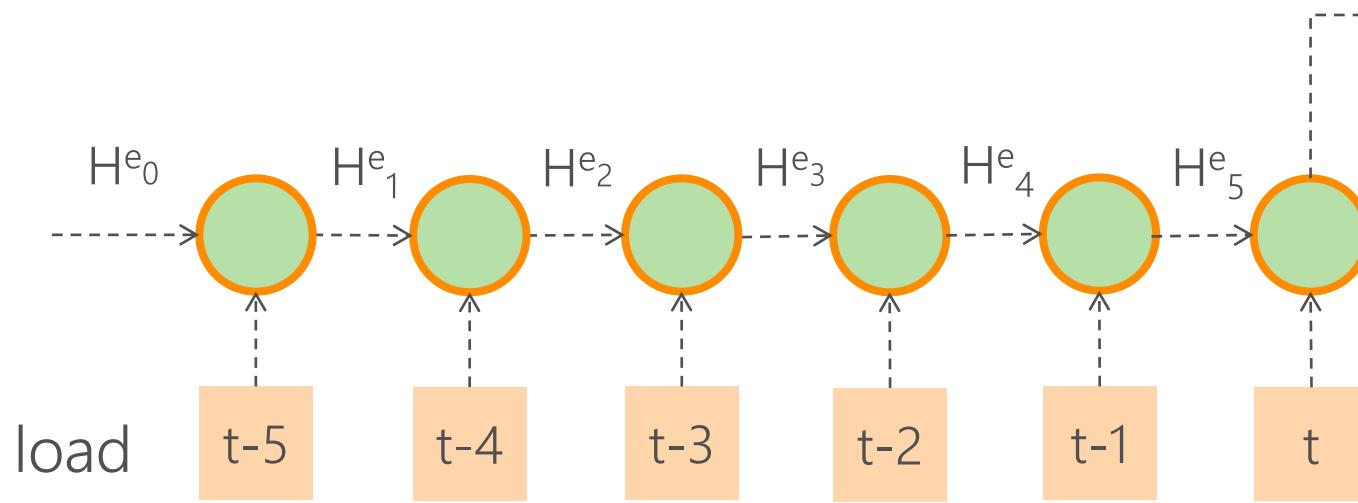
Performance comparison

Algorithm	MAPE (Mean Absolute Percentage Error)
ARIMA	4.9
Feedforward Neural Network	4.27
RNN: vector output	3.67
RNN: simple encoder-decoder	3.58
RNN: encoder-decoder with teacher forcing	4.57

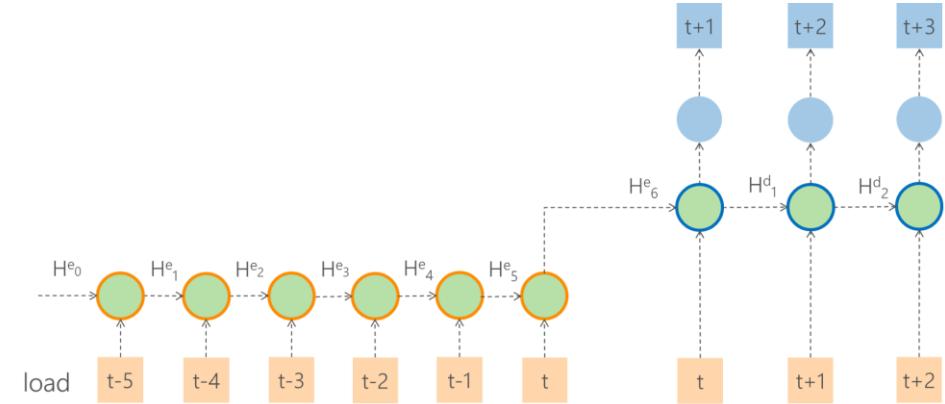
Recursive encoder-decoder



Recursive encoder-decoder (training with teacher forcing)



Recursive encoder-decoder



- 👍 Tries to capture dependencies between forecasted time steps through recursive decoder
- 👍 Variable length output (can generate forecasts of variable horizons)
- 👎 More difficult to implement
- 👎 Slower to train and slower to generate forecasts
- 👎 Error propagation due to recursive decoder

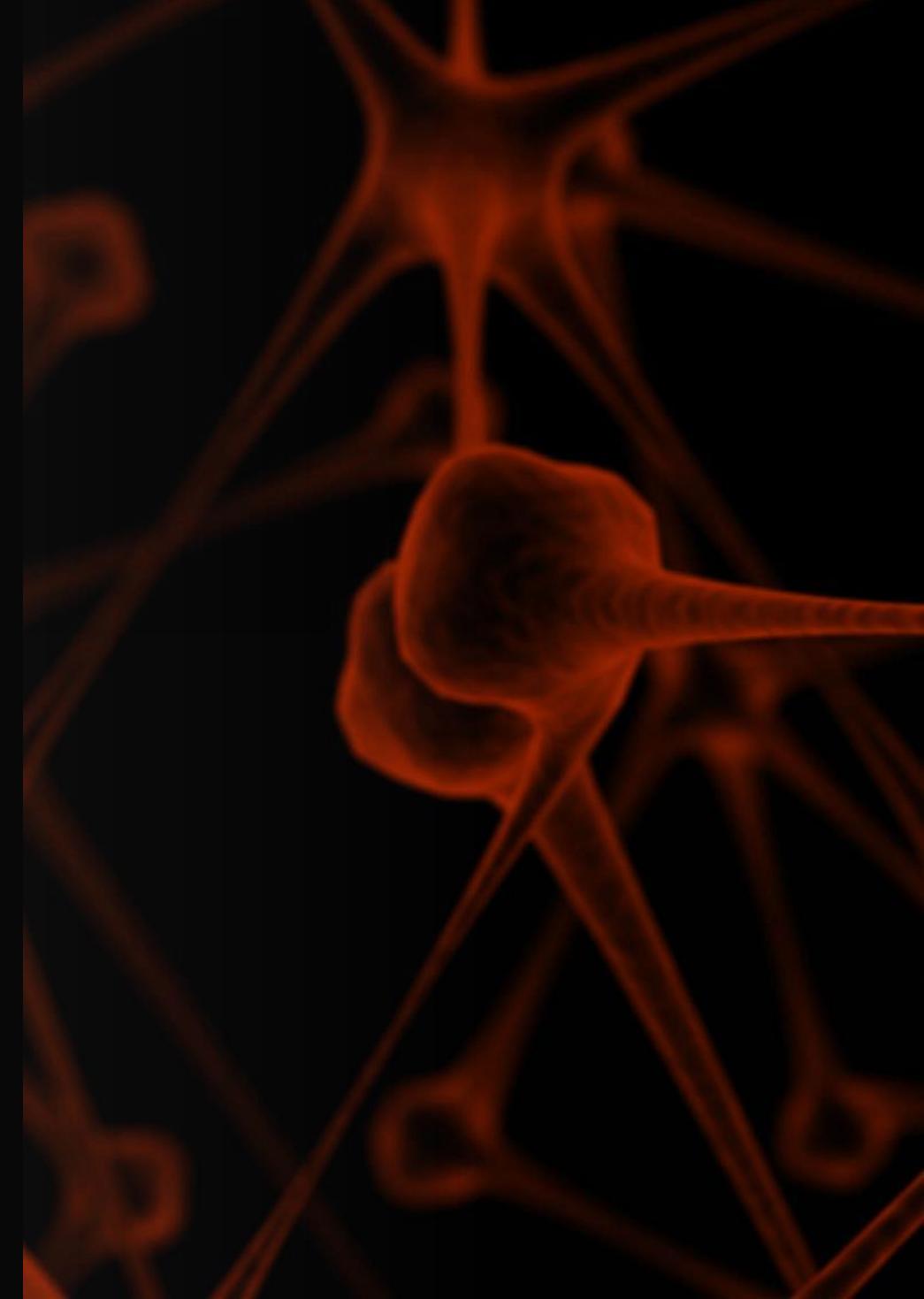
Performance comparison

Algorithm	MAPE (Mean Absolute Percentage Error)
ARIMA	4.9
Feedforward Neural Network	4.27
RNN: vector output	3.67
RNN: simple encoder-decoder	3.58
RNN: encoder-decoder with teacher forcing	4.57

Hands-on Quiz

Open Quiz_multi_step_RNN_encoder_decoder.ipynb

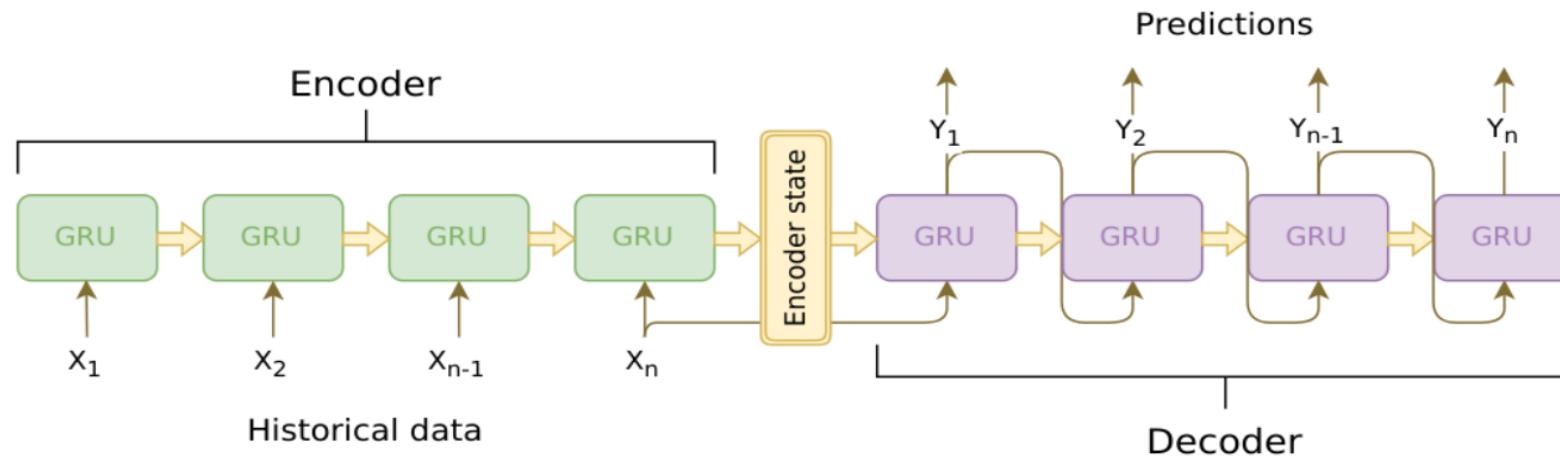
Successful RNN models



Web traffic forecasting competition

Forecast traffic of 145K Wikipedia pages

Winning solution: github.com/Arturus/kaggle-web-traffic

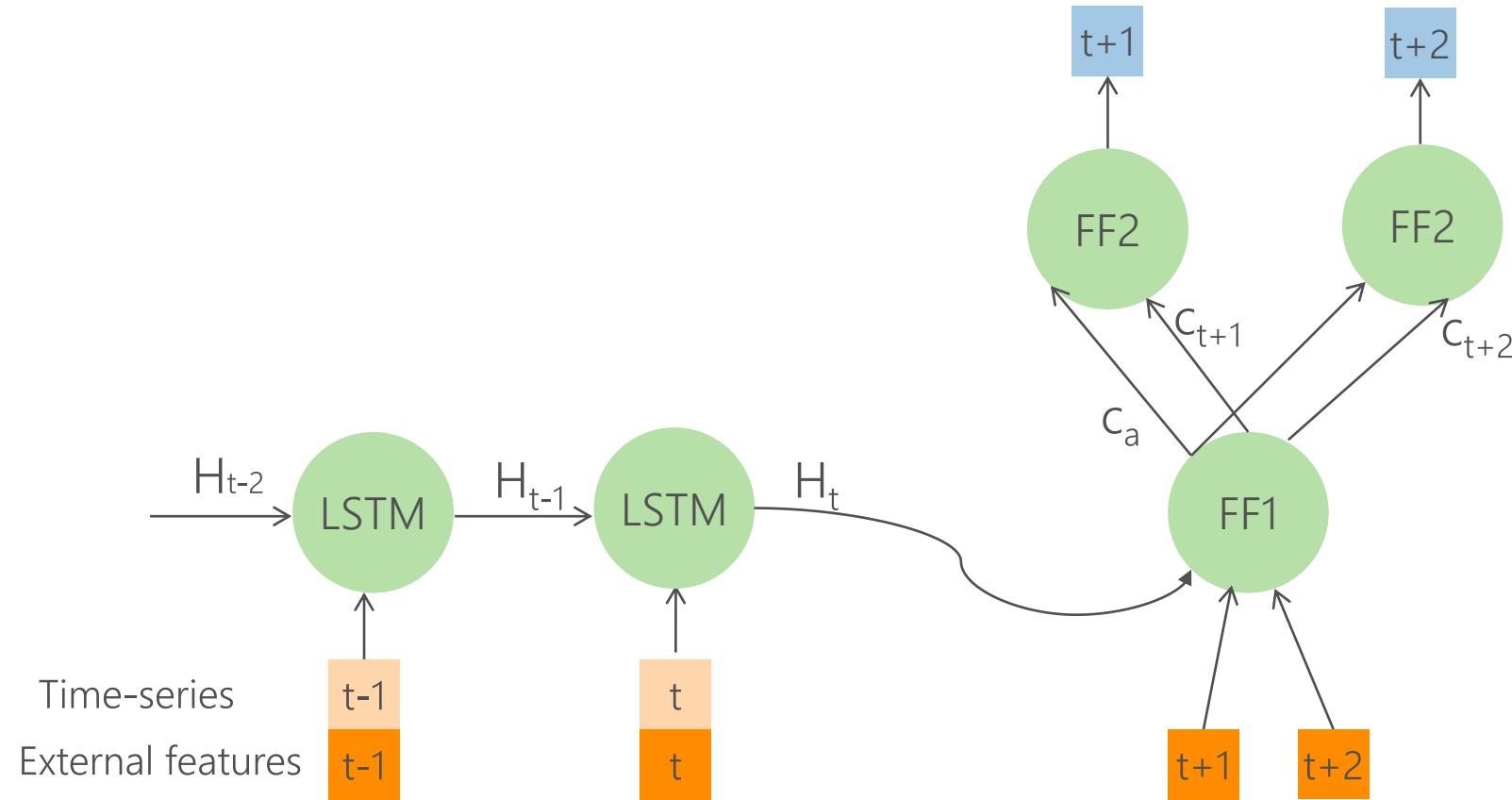


- Feature engineering: transform univariate to multivariate time series by adding seasonality features:
$$x_t \rightarrow (x_t, x_{t-\text{quarter}}, x_{t-\text{year}})$$
- COCOB optimizer that doesn't require learning rate tuning and converges considerably faster, custom implementation
- Sophisticated technique for building ensemble of RNN models, mainly for reducing model variance

GEFCom 2014 competition

Energy load and price forecasting in New England

Best model (2017): LSTM encoder + feed-forward neural network arxiv.org/abs/1711.11053



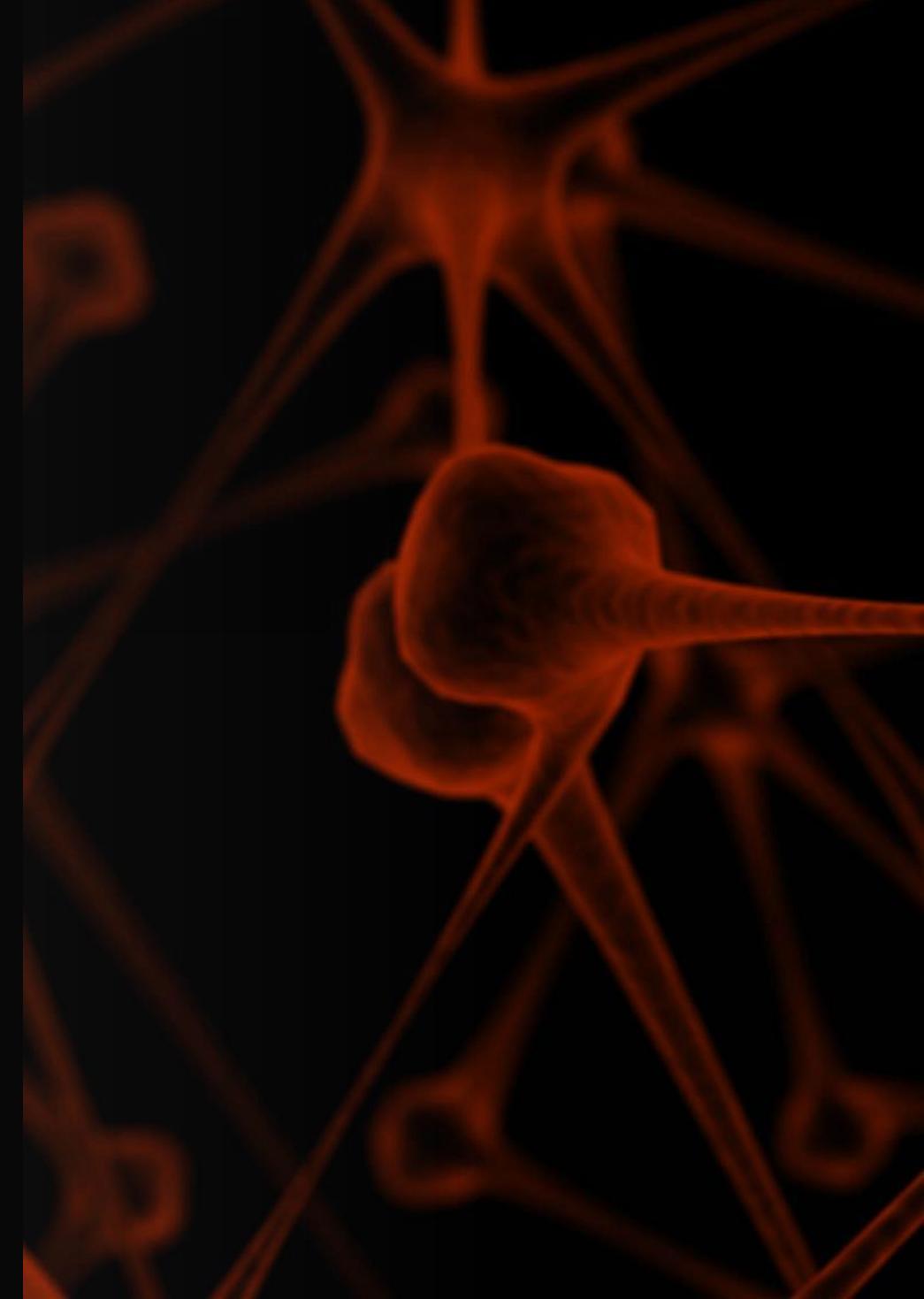
c_a - horizon-agnostic context

c_{t+i} - horizon-dependent context

FF2 has the same weights for all horizons

External features: weekday/holiday indicators, day of week, hour of the day, weather data

Conclusions



Techniques not covered

- Probabilistic prediction [Multi-horizon quantile-based forecaster](#)
- Advanced architectures
 - dropout / zoneout [Zoneout: Regularizing RNNs by randomly preserving hidden activations](#)
 - memory networks [memory networks](#)
- Advanced training techniques
 - state-of-the-art optimization algorithms
 - recurrent batch normalization [recurrent batch normalization](#)
 - stateful training [stateful training](#)
- Temporal convolutional neural networks [An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling](#)

Learning resources

- Source code of examples of how to train RNN models with Keras
URL: <https://aka.ms/rnntutorial>
- Blogs
 - machinelearningmastery.org
 - dacatay.com
- Competitions
 - Kaggle
- State-of-the-art results
 - Conferences: NIPS, ICLR, ICML
 - Hot-off-the-oven papers: arxiv-sanity.org

References

[Dropout: A simple way to prevent neural networks from overfitting,](#)

[Zoneout: Regularizing RNNs by randomly preserving hidden activations](#)

[Batch normalization: Accelerating deep network training by reducing internal covariate shift,](#)

[Recurrent batch normalization](#)

[Learning rate schedules and adaptive learning rate methods for deep learning](#)

[An overview of gradient descent optimization algorithms](#)

[Learning phrase representations using rnn encoderdecoder for statistical machine translation](#)

[LSTM: A Search Space Odyssey](#)

[Bayesian optimization with robust Bayesian neural networks](#)

[Hyperband: A novel bandit-based approach for hyperparameter optimization](#)

[Neural architecture search with reinforcement learning](#)

[Multi-horizon quantile-based forecaster](#)

[Population based training of neural networks](#)

[Memory networks](#)

[Stateful training](#)

[An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling](#)

[Winning solution of web traffic forecasting competition](#)

[Probabilistic energy forecasting: Global Energy Forecasting Competition 2014 and beyond](#)

Key Takeaways

- RNNs are very powerful models, sometimes RNNs are the most accurate models.
- RNNs share many techniques/tricks with feed-forward neural networks
- Tuning hyperparameters and other tricks are important for creating an accurate model

Q & A

