Time Series Management

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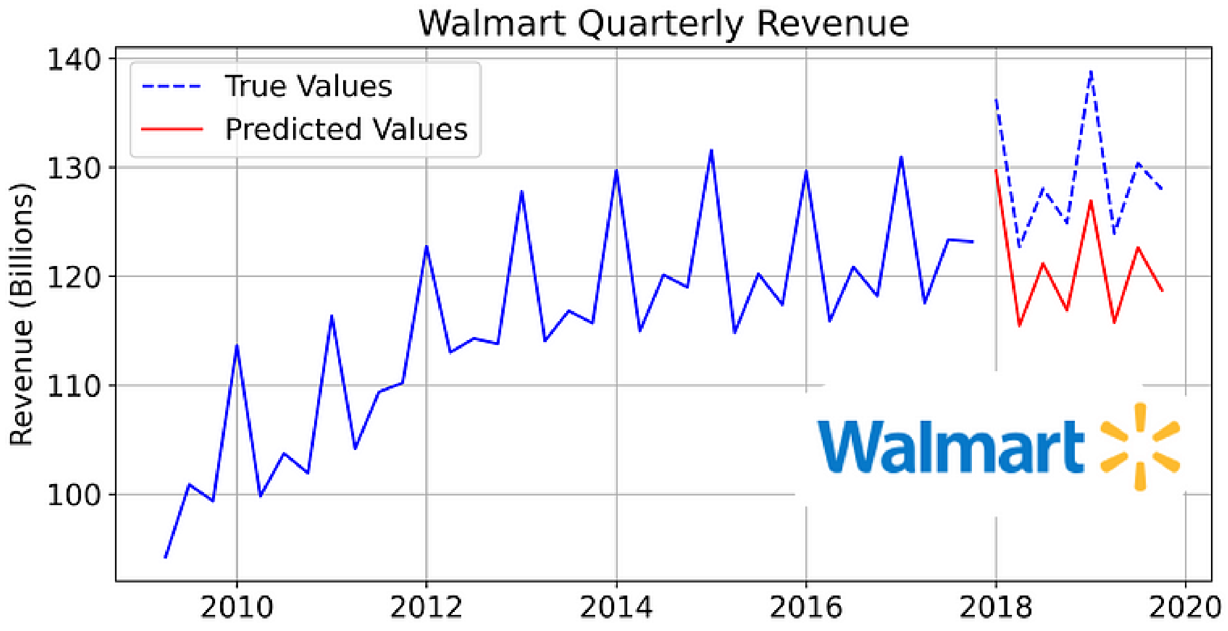
Syllabus

- Recap: Time Serie Forecasting and Deep Learning Fundamentals
- Introduction to convolutional neural networks (CNN)
- Implementation of the models with the Keras Library

Time series data… quick recap

- A **univariate time series** is a sequence of measurements of the same variable collected over time. Most often, the measurements are made at regular time intervals.



https://www.kaggle.com/code/anushkaml/walmart-time-series-sales-forecasting

Time Series Forecasting

- Predict Future (Values) based on the past (Historical Data)

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

Question to ask prior to forecast

- Can we forecast?
  - How well we understand the factor influencing the future?
  - How much data we have?*
- How far in the future (horizon) we want to forecast?
- What technique, model should we use ?

Why Deep Learning models? (1/2)

Deep learning model perform well and better than other methods in many scenarios.

Model	Features	RMSE	MAPE (%)	Run time (s)
FeedForward	Date features + Covariants	**10.73**	4.20	53.35
AutoARIMA	Baseline	11.00	**3.52**	20658.95
DeepAR	Date features	11.96	5.99	156.18
FeedForward	Baseline	12.01	3.88	78.47
SeasonalNaive	Baseline	12.47	3.86	**1.20**
FeedForward	Date features	13.93	3.95	9.37
DeepAR	Baseline	14.01	6.12	856.51
DeepAR	Date features + Covariants	17.79	6.04	781.09
TrivialIdentity	Baseline	18.20	5.09	1.30
NPTS	Baseline	82.45	19.75	25.20

https://blog.dataiku.com/deep-learning-time-series-forecasting

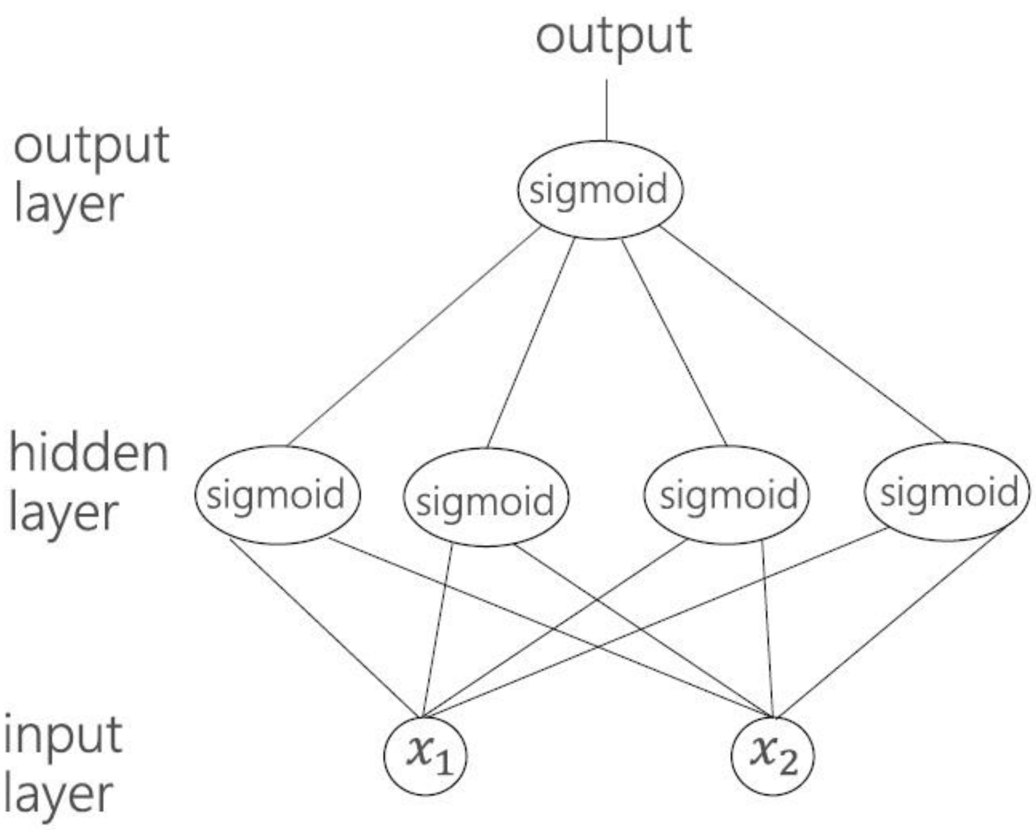
Z. Tang, P.A. Fishwik, *Feedforward Neural Nets as Models for Time Series Forecasting*, November 1993

Why Deep Learning models? (2/2)

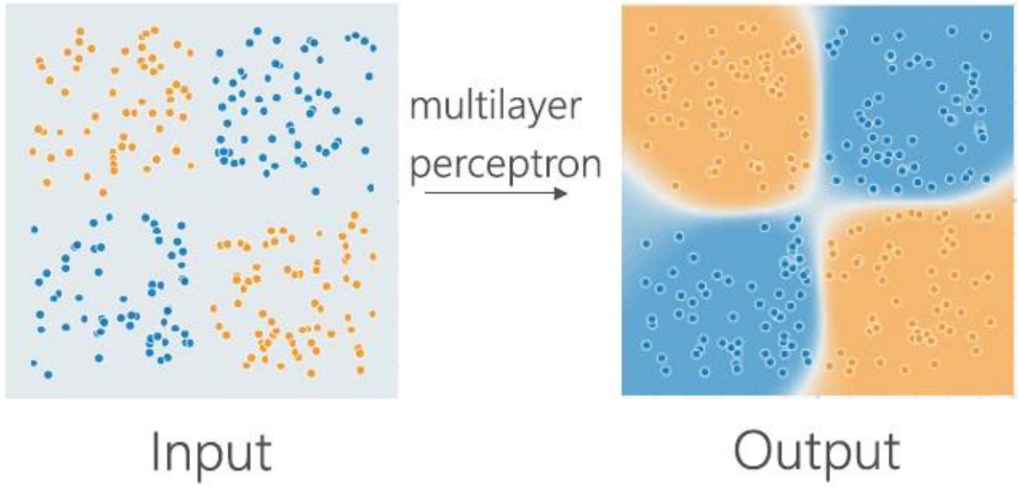
- Non-parametric
- Flexible and expressive
- Easily inject exogenous features into the model
- Learn from large time series datasets

DEEP LEARNING FUNDAMENTALS

Multilayer Perceptron



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



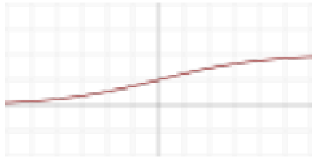
also known as Feed-Forward Neural Network and Deep Neural Network

Picture credits DeepLearningForTimeSeriesForecasting (Microsoft) https://github.com/Azure/DeepLearningForTimeSeriesForecasting

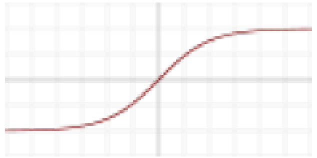
Activation Function

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

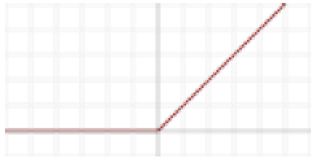
Sigmoid $f(x') = \sigma(x') = \frac{1}{1+e^{-x'}}$



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



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

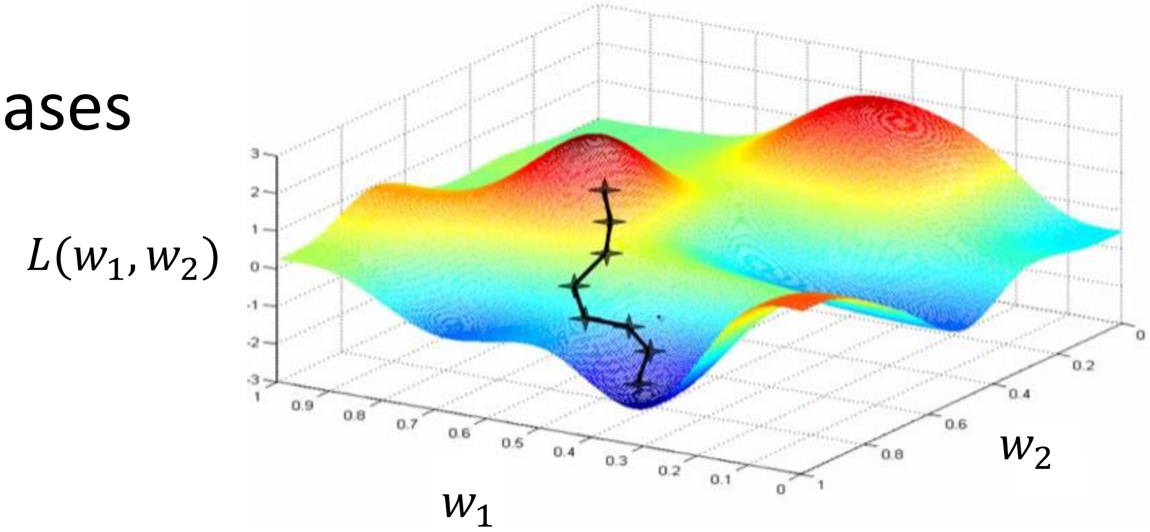


Training: overview

- Main Idea: Use training example to find proper weights and biases.

- Loss function **L(Weights, biases)** measure the discrepancy between predicted and true values

- We want to optimize weight and biases to reduce the Loss.

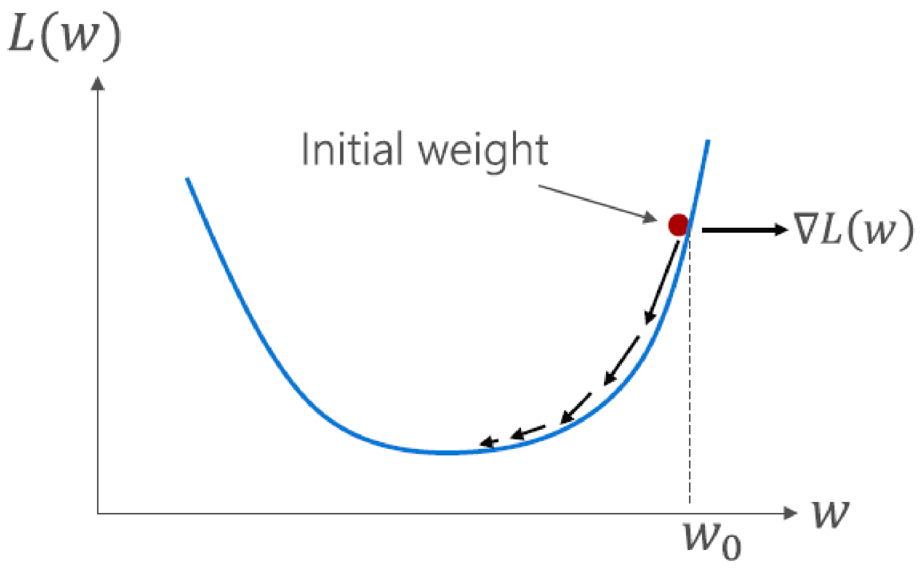


Picture credits Andrew NG, Coursera

Optimization (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: $w = w_0$

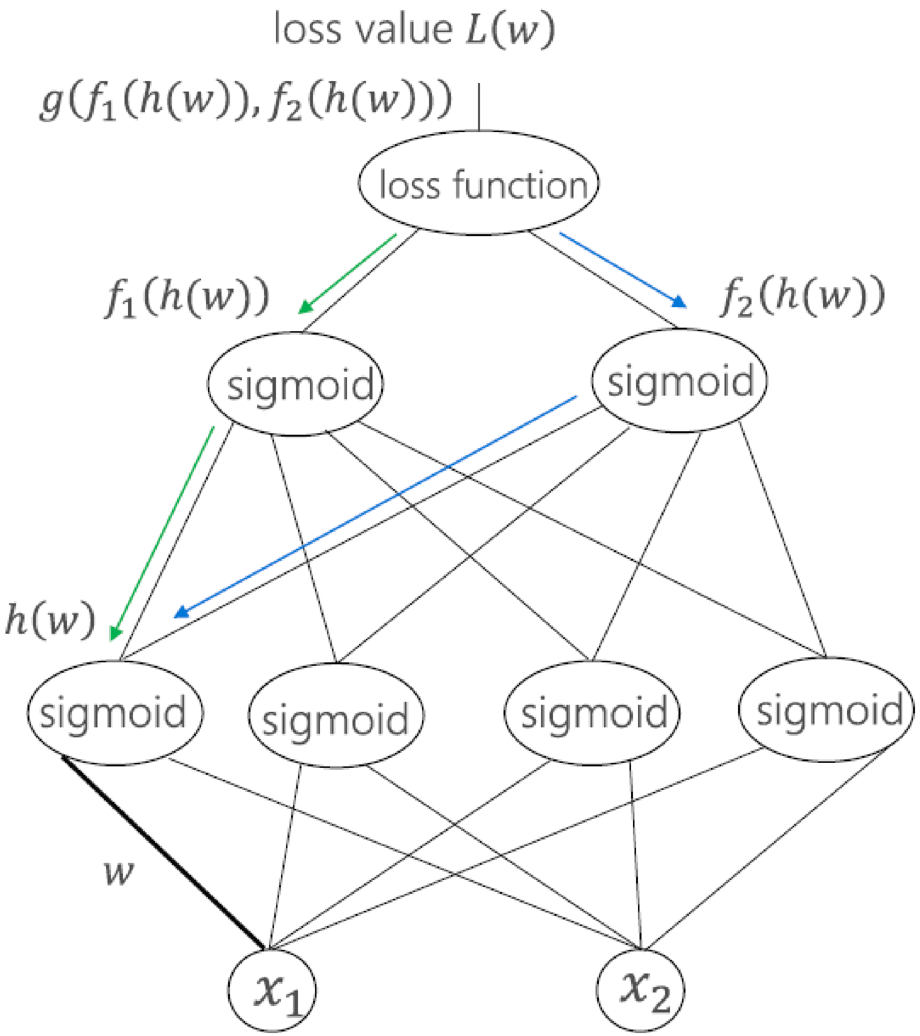
While stopping criterion not met:

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

learning rate

Picture credits DeepLearningForTimeSeriesForecasting (Microsoft) https://github.com/Azure/DeepLearningForTimeSeriesForecasting

Gradients Computation: Backpropagation



Computation of $L'(w)$

Chain rule

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

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

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

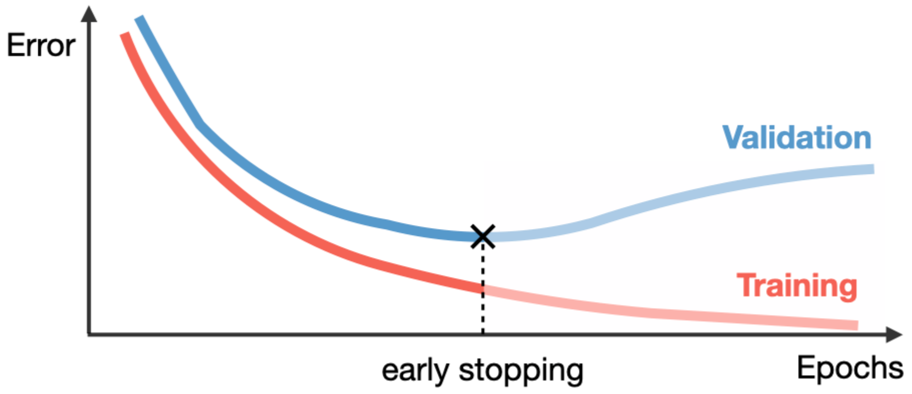
Total derivative

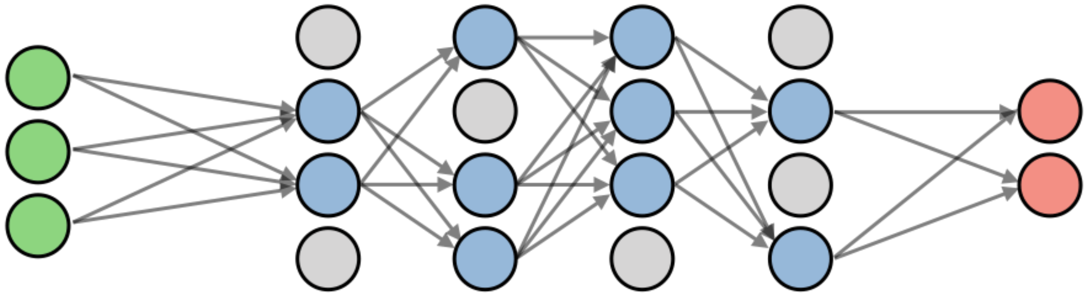
$$L(w) = g(f_1(w), f_2(w))$$

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

Training improvement strategy

- **Early stopping**
- Tuning hyperparameters
- Initialization
- Weight regularization
- **Dropout**
- **Batch Normalization**
- Learning rate decay





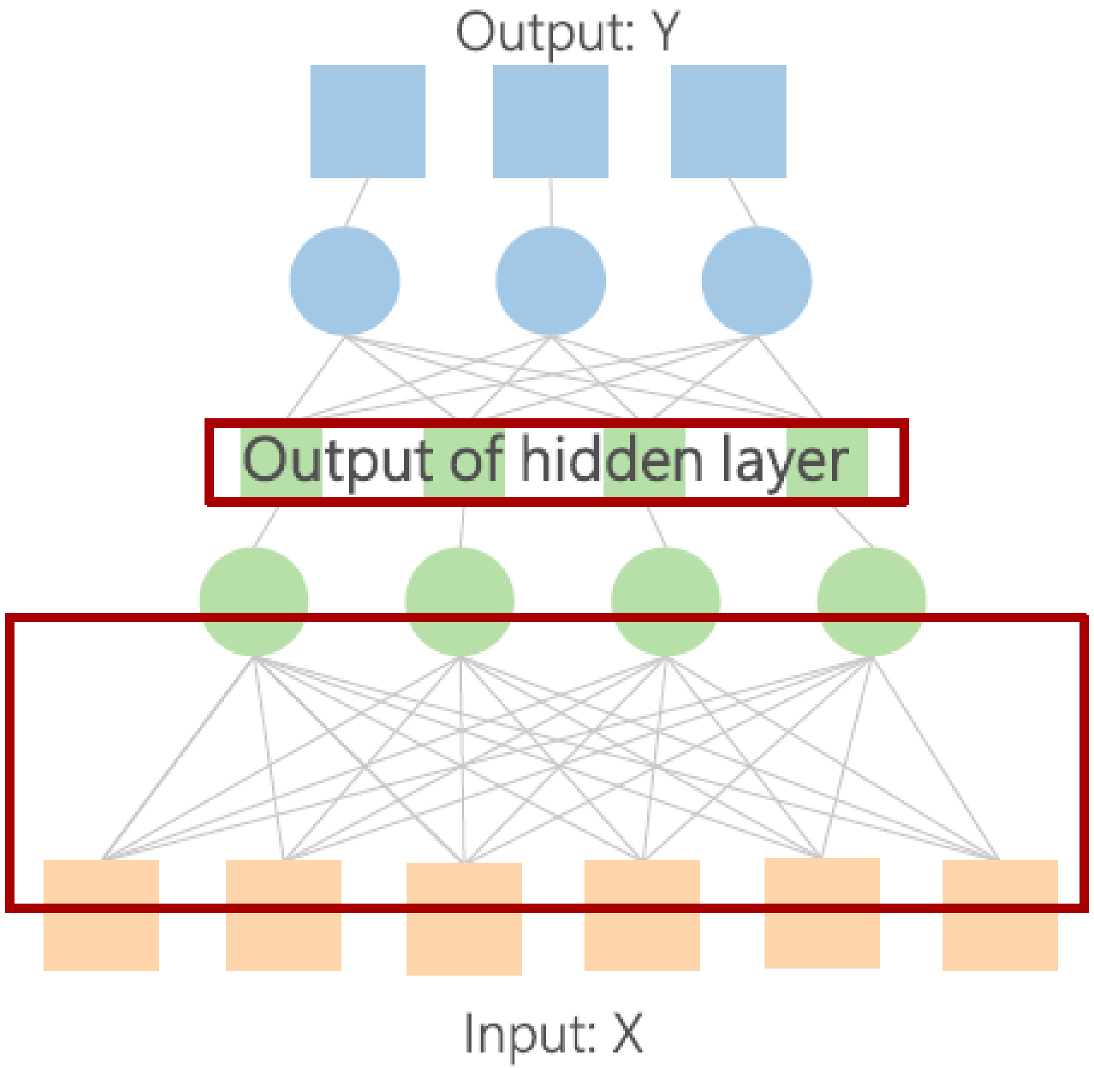
$$x_i \longleftarrow \gamma \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} + \beta$$

https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-deep-learning-tips-and-tricks

Convolutional neural networks (CNN) for Time series Forecasting

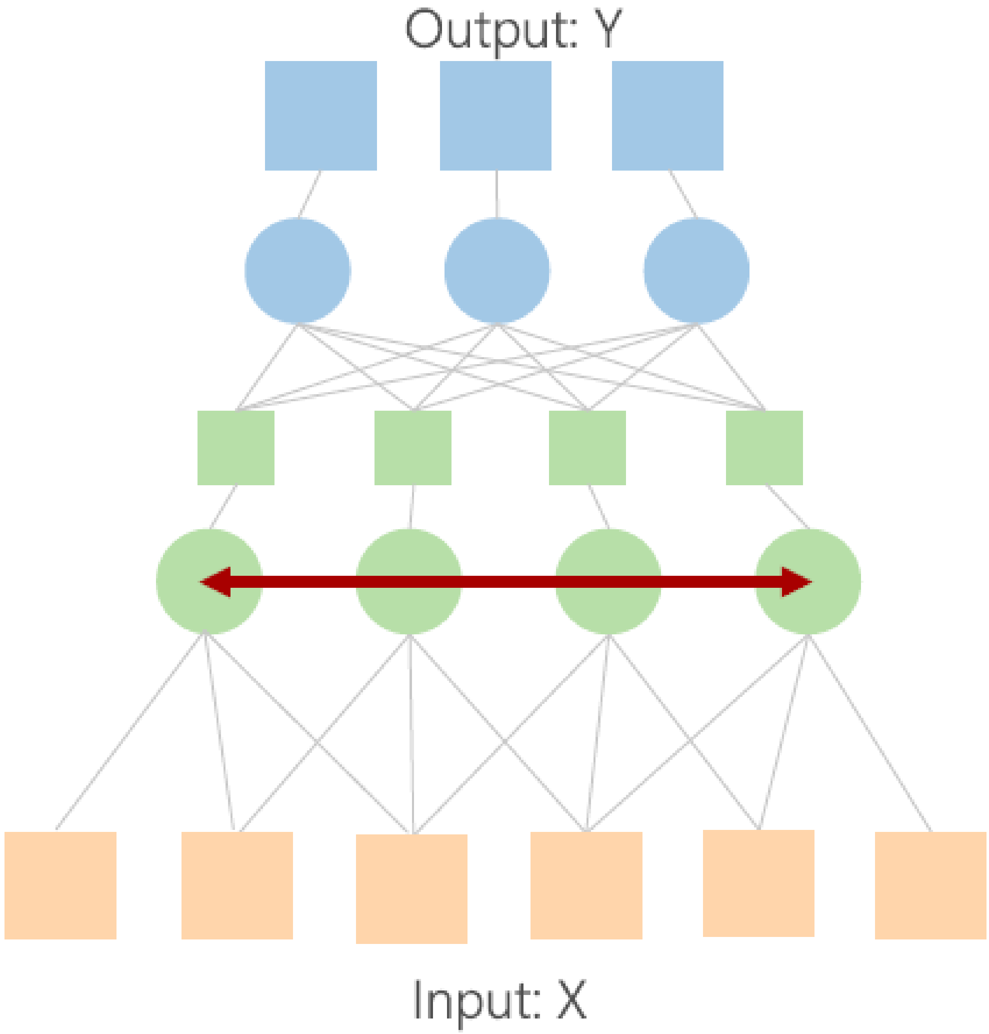
Fully connected VS Convolutional Layer

Fully Connected: Units in hidden layer are connected to every unit in previous layer.



Fully connected **VS** Convolutional Layer

Convolutional Layer: Units in hidden operate on a field of the input (the weights are shared across the input)

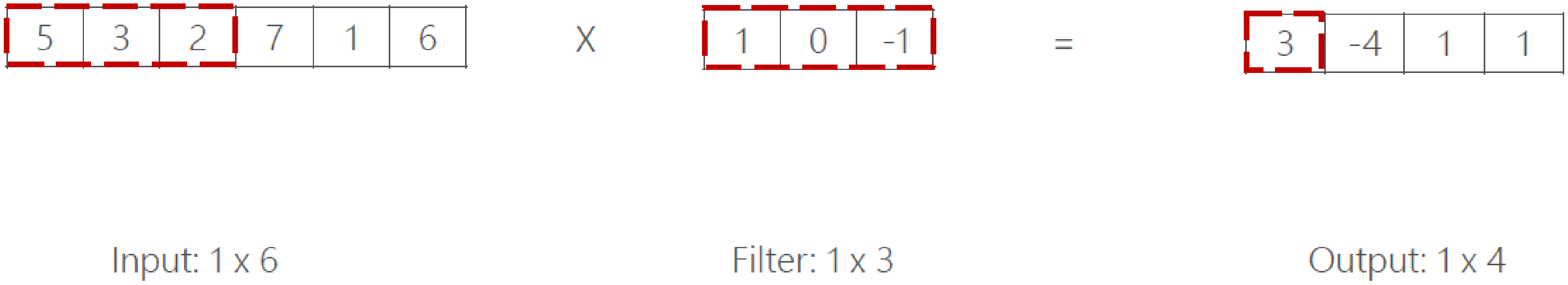


1D Convolution

- Apply a 1D filter to all elements of an input time series.

- Result: SUM of element-wise product

(5 x 1) + (3 x 0) + (2 x -1) = 3



1D Convolution

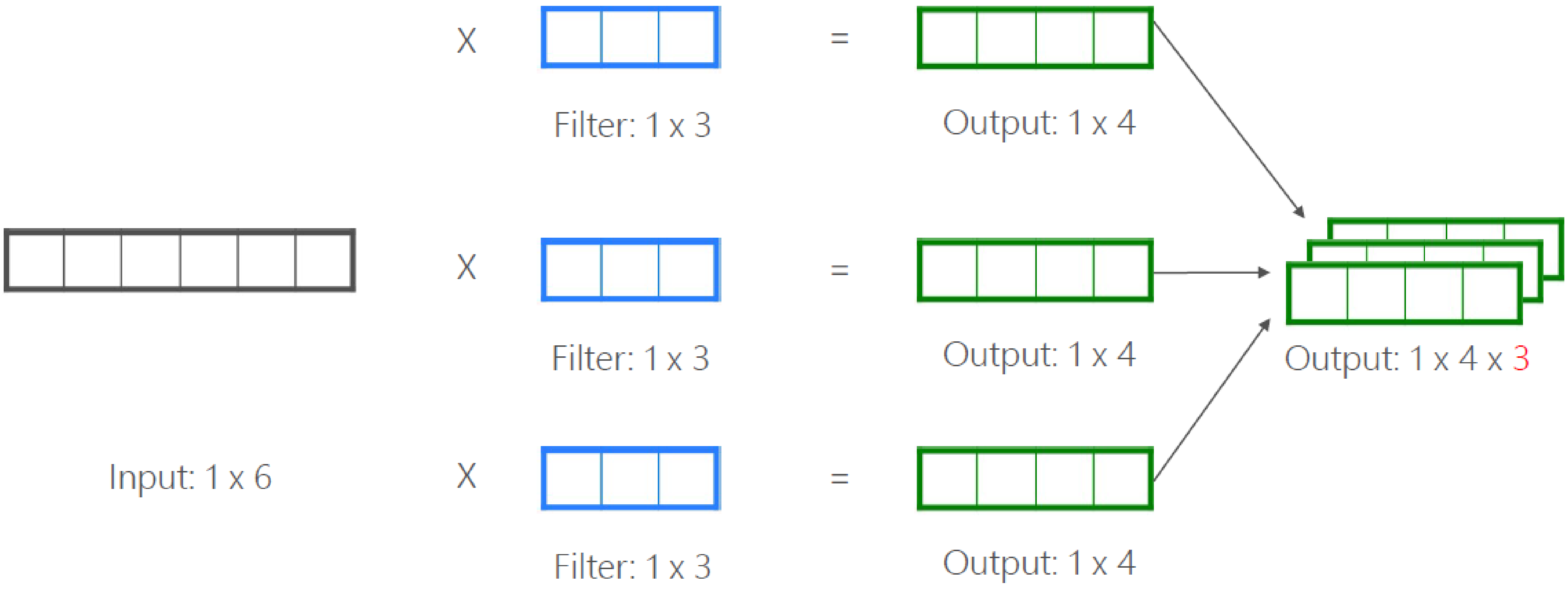
- Filters are trained to detect features in the input sequence.
- Features can be detected regardless of where they appear in the input sequence.

$$\begin{array}{|c|c|c|c|c|c|}\hline 5 & 3 & 2 & 7 & 1 & 6 \\ \hline \end{array} \quad \times \quad \begin{array}{|c|c|c|}\hline w_1 & w_2 & w_3 \\ \hline \end{array} \quad = \quad \begin{array}{|c|c|c|c|}\hline 3 & 4 & 1 & 1 \\ \hline \end{array}$$

Input: 1 x 6 Filter: 1 x 3 Output: 1 x 4

1D Convolution

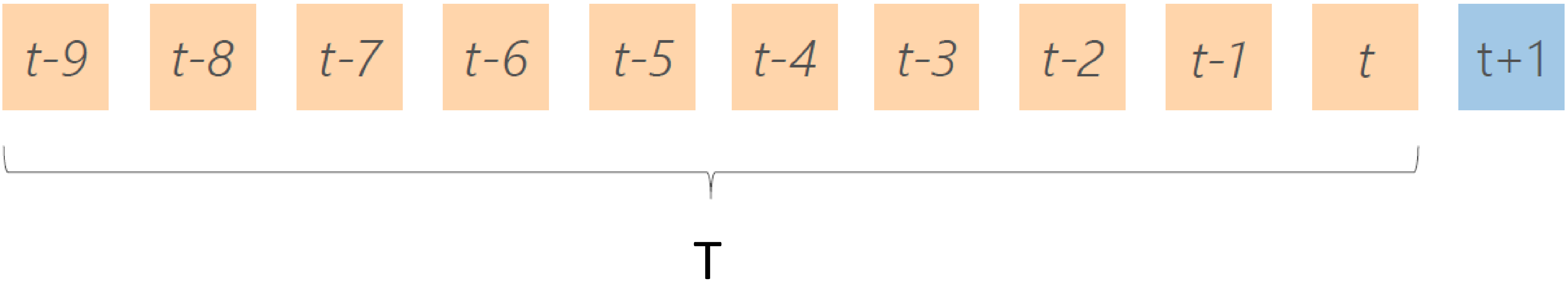
- Apply multiple filters to the input data to detect multiple features.



Apply CNN to forecasting time series

At time *t* :

1. predict the value at time *t+1*
2. Conditioned on the previous T values of the time series



Apply CNN to forecasting time series

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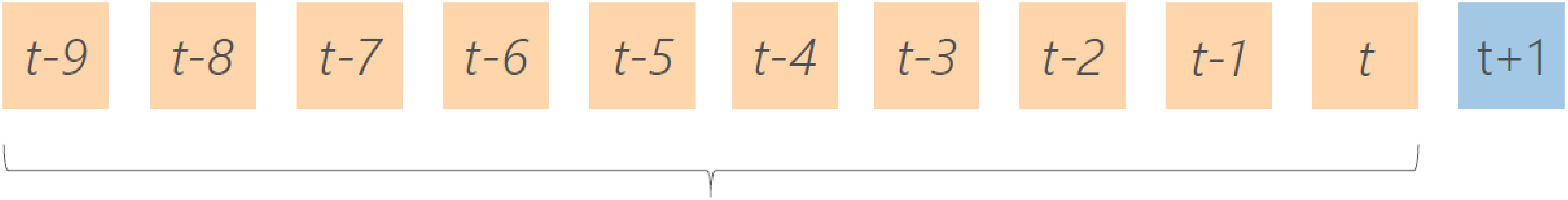
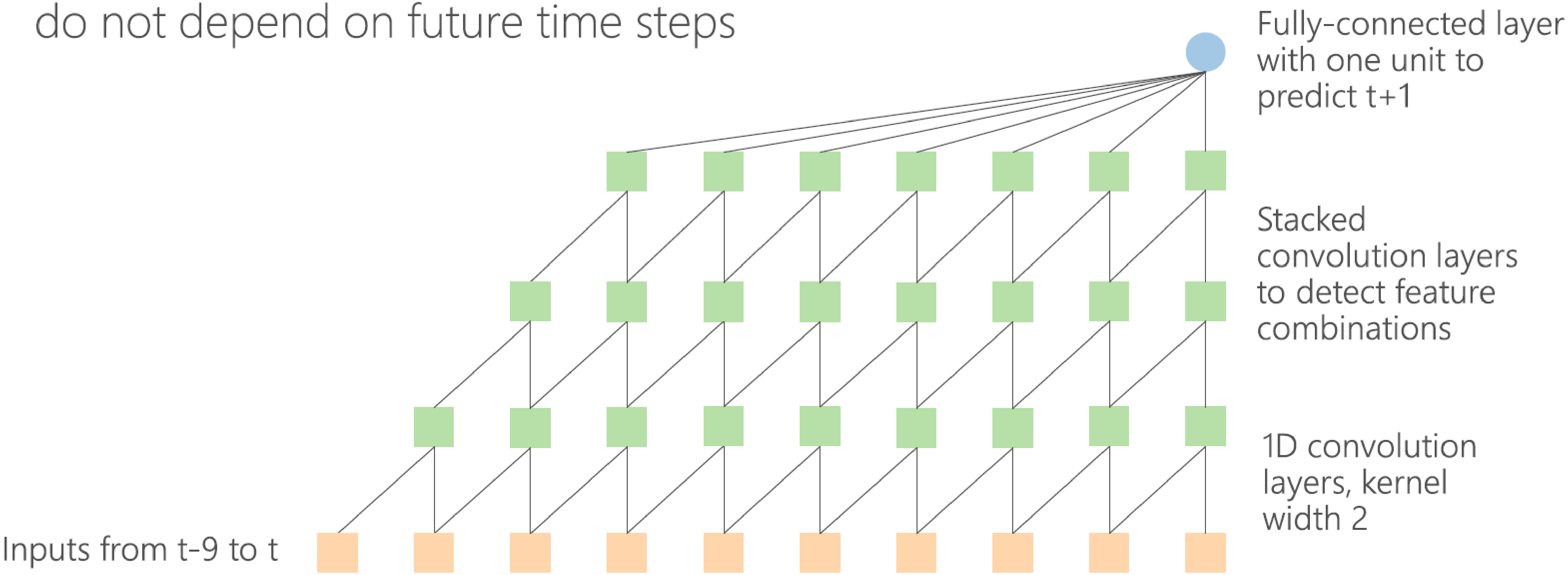


T = 10 --- Empirically selected

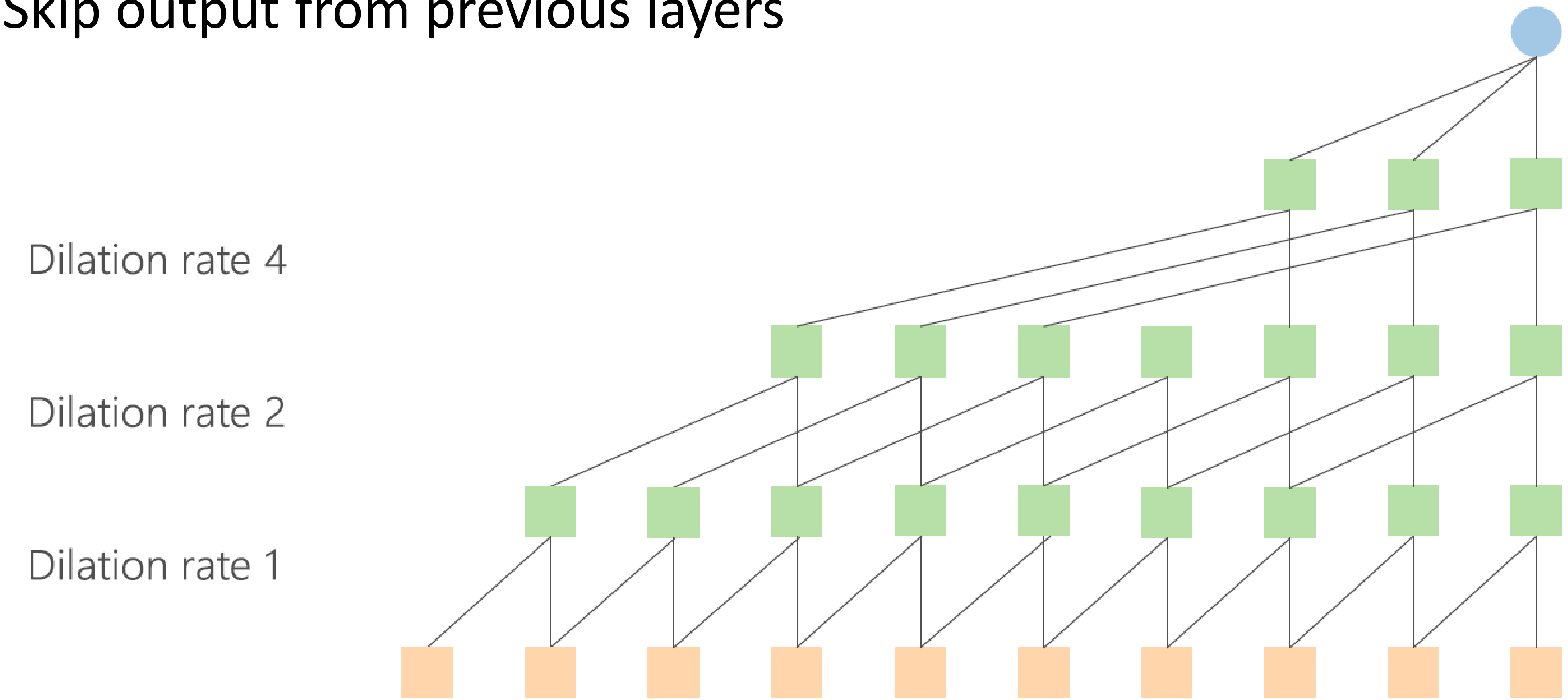
Apply CNN to forecasting time series

- Causal convolutions: the output at each time step do not depend on future time steps



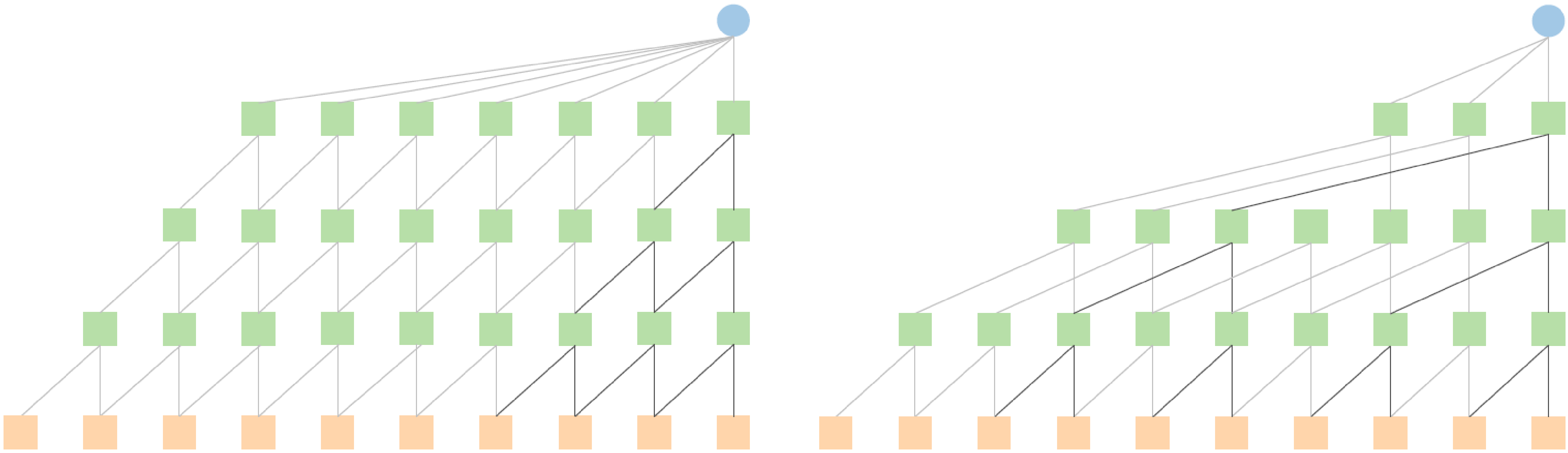
Dilated Convolutions

- Skip output from previous layers



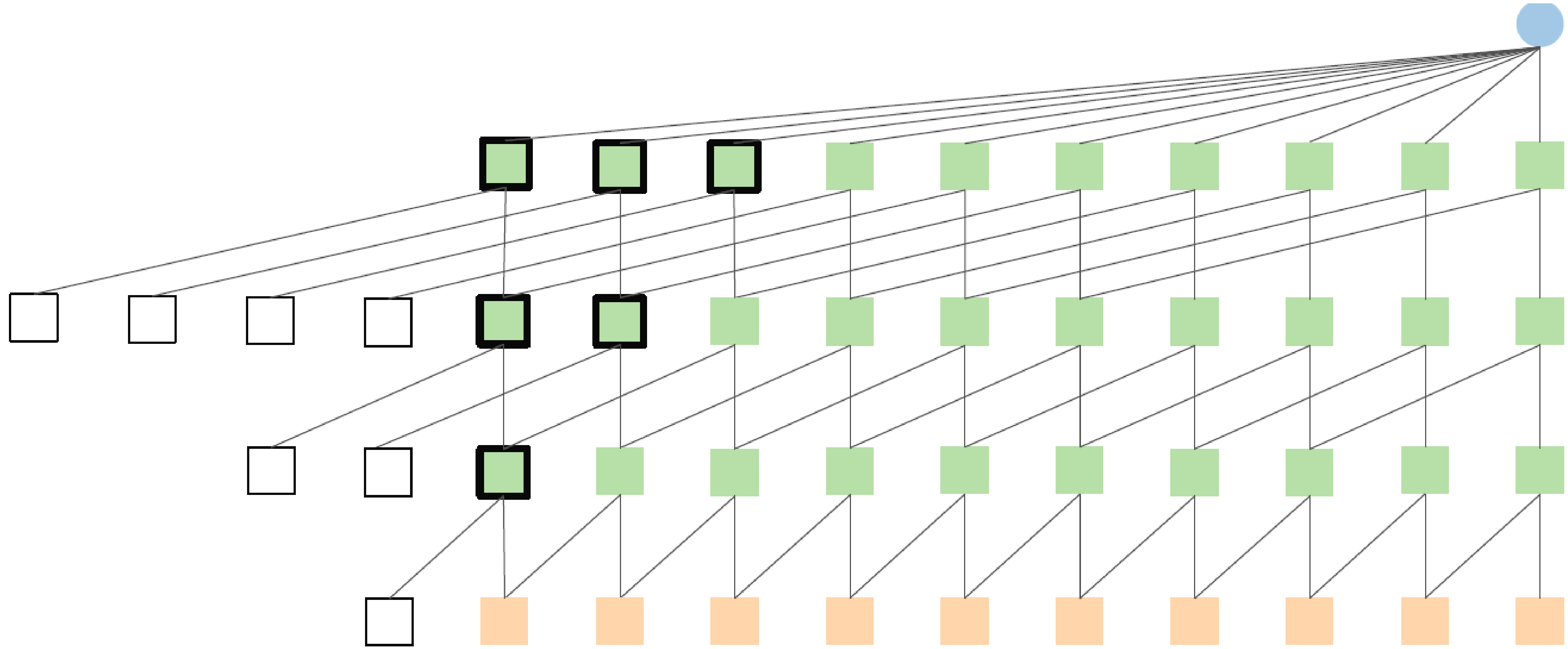
Dilated Convolutions

- Normal convolution => more connections =>more weights to train
- Reach information from more distant values in the time series (non contigous filter)



Causal padding

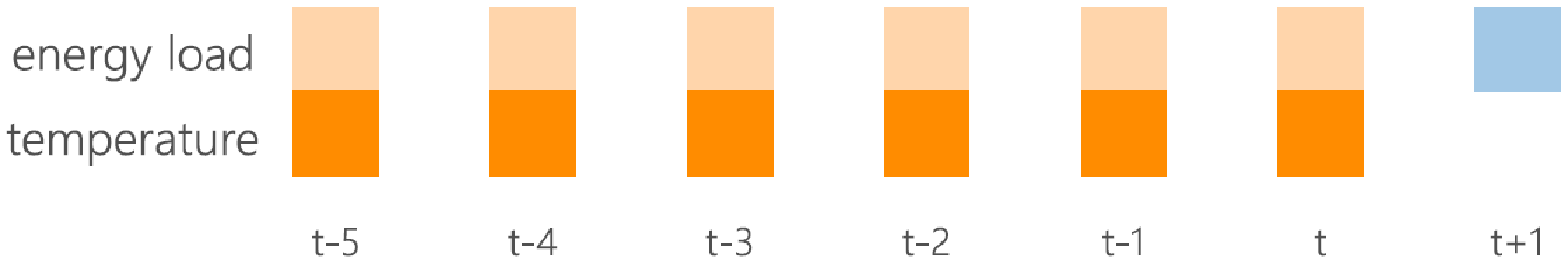
- Padding is necessary to keep the right output dimensions



Multivariate Time Series Case

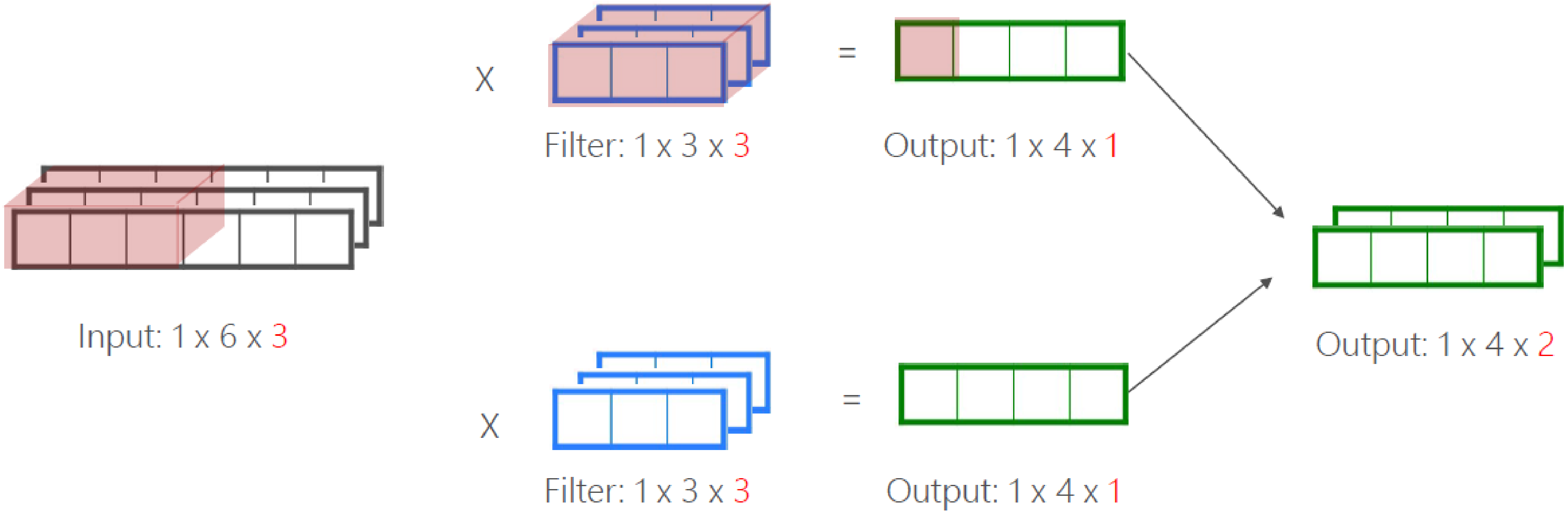
- Time series with more than 1 variable evolving along time (aka covariates)

- Example



Multivariate Time Series

- Feature extraction with multiple filters (per dimension)



Convolutional neural networks (CNN) with Keras

Imports the KERAS modules (NN components)

```
from keras.models import Model, Sequential
from keras.layers import Conv1D, Dense, Flatten
from keras.callbacks import EarlyStopping, ModelCheckpoint
```

https://keras.io/

KERAS – 1D convolutional filter

TIME SERIES PAST VALUE WINDOW (T)

```
model = Sequential()
model.add(Conv1D(FILTERS_NUMBER, kernel_size=KERNEL_SIZE,
                 padding='causal', strides=1, activation='relu',
                 dilation_rate=1, input_shape=(T, 1)))
```

https://keras.io/api/layers/convolution_layers/convolution1d/

KERAS – 1D convolutional filter

 # TIME SERIES variable (1 = univariate case)

```
model = Sequential()
model.add(Conv1D(FILTERS_NUMBER, kernel_size=KERNEL_SIZE,
                 padding='causal', strides=1, activation='relu',
                 dilation_rate=1, input_shape=(T, 1)))
```

https://keras.io/api/layers/convolution_layers/convolution1d/

Do not forget…flatten + dense layer for the final prediction

```
model.add(Flatten())
model.add(Dense(HORIZON, activation='linear'))
```

Number of predictions

https://keras.io/api/layers/reshaping_layers/flatten/

https://keras.io/api/layers/core_layers/dense/

Early stopping + best model save + training

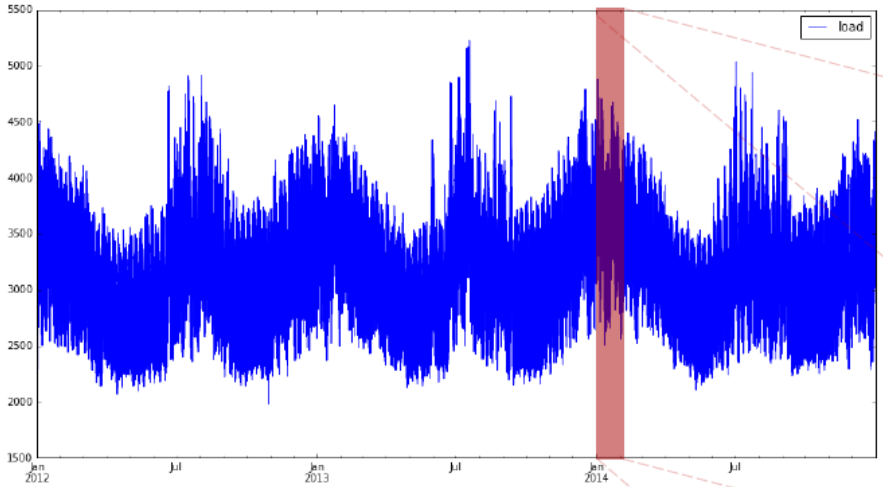
```
model.compile(optimizer='Adam', loss='mse')

earlystop = EarlyStopping(monitor='val_loss', min_delta=0, patience=5)

best_val = ModelCheckpoint('model_{epoch:02d}.keras', save_best_only=True, mode='min')

history = model.fit(X_train,
          y_train,
          batch_size=BATCH_SIZE,
          epochs=EPOCHS,
          validation_data=(X_valid, y_valid),
          callbacks=[earlystop, best_val],
          verbose=1)
```

https://keras.io/api/models/model_training_apis/
https://keras.io/api/callbacks/early_stopping/

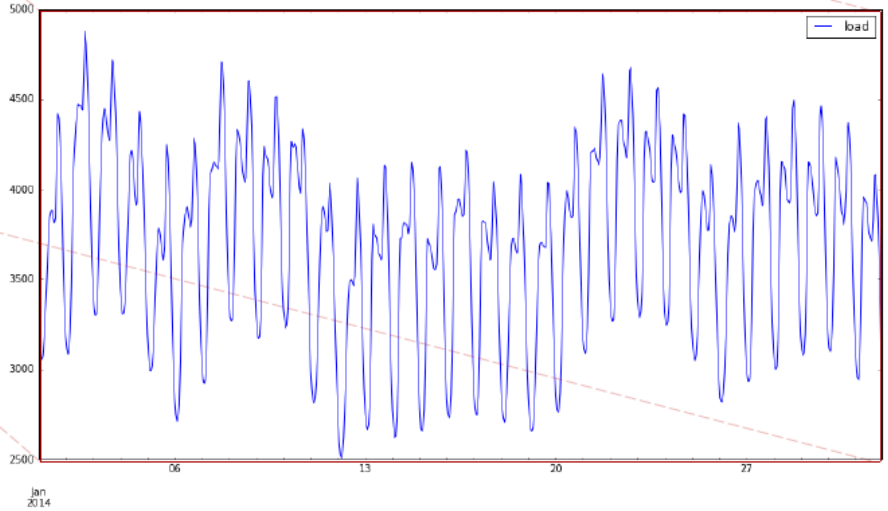
Presentation du TD

Data

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.

Notebook

- Open the file (Python Notebook):

TD_CNN_dilated_TS_FORECASTING.ipynb

- Instruction are contained in the notebook

References

- https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-deep-learning-tips-and-tricks
- **DeepLearningForTimeSeriesForecasting (Microsoft)** https://github.com/Azure/DeepLearningForTimeSeriesForecasting
- **Ben Auffarth** Machine Learning for Time-Series with Python
- https://github.com/PacktPublishing/Machine-Learning-for-Time-Series-with-Python/tree/main/chapter10