

9th November 2022

ML 4 Time-series: Recurrent Neural Networks

Dr. Andrew P. Creagh | Dr. Anshul Thacker | Prof. David A. Clifton

Institute of Biomedical Engineering (IBME),
Department of Engineering Science,
Old Road Campus Research Building (ORCRB),
University of Oxford

CDT in Health Data Science

**Mathematician
studying deep
learning**



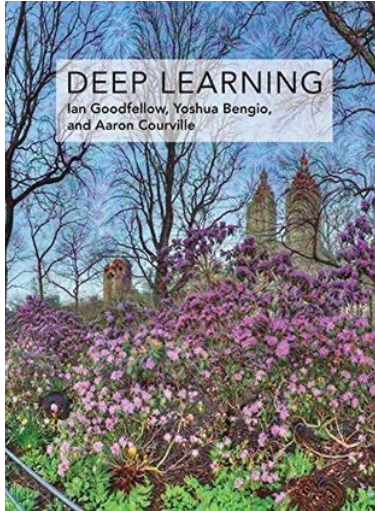
Boy, am I glad I studied linear algebra, numerical optimisation, measure theory, and convex optimisation during my undergrad. This sure would be difficult without it

**Deep learner
studying the maths**



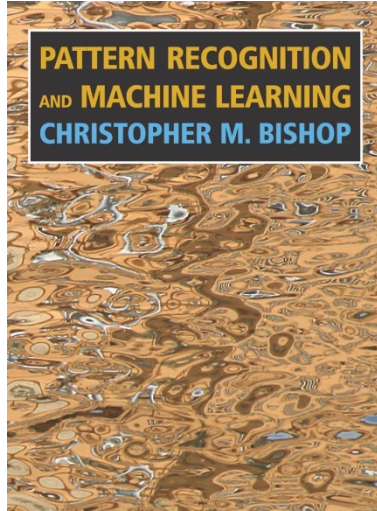
Wot's chaim rool?

Resources



A well-written introduction to all things deep learning (DL), from leaders in the field of theoretical DL.

Very light maths



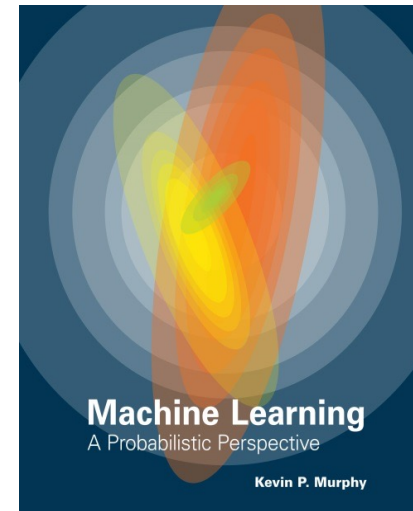
A core classic describing most non-DL algorithms. Very good for one's general understanding.

Reasonably "maths-y"



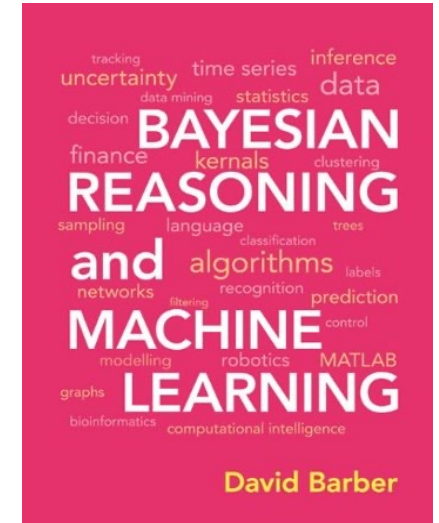
Another core classic, from one of the field's (sadly departed) foundational thinkers – good, even though it's from Cambridge

Reasonably "maths-y"



Seriously comprehensive, one of the best books for general machine learning. Excellent examples.

Really rather "maths-y"



Big, bad, and Bayesian. Everything you'd like to know about Bayesian machine learning. Great for time-series analysis.

Seriously "maths-y"

mild

medium

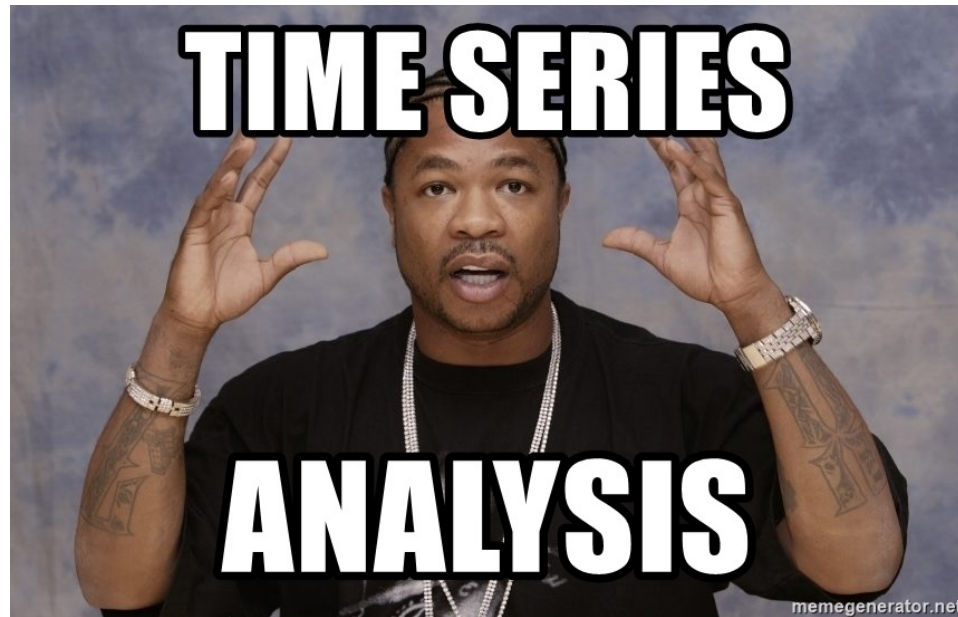
hot

extra hot



Why time?

Clinical data is **not** static: clinical measurements are often a time-series, (e.g. heart rate) or repeated measurements taken during visits to the doctor, or a stay in hospital. Clinical events can occur at a point in time (e.g. a heart attack) or can even be causal. These events generally evolve over time (known as **Stochastic processes**)



time



Choosing your model

Models that don't consider time (i.i.d.)

- Linear / Logistic Regression
- Support Vector Machines (SVM)
- Classification and Regression Trees (CART) (e.g. Random Forest)
- eXtreme Gradient Boosting (XGBoost)
- Deep Neural Networks
- Etc.

Need to incorporate time through the features instead!

Choose your fighter!



[Image Credit](#)

Choosing your model

Models that don't consider time (i.i.d.)

- Linear / Logistic Regression
- Support Vector Machines (SVM)
- Classification and Regression Trees (CART) (e.g. Random Forest)
- eXtreme Gradient Boosting (XGBoost)
- Deep Neural Networks
- Etc.

Need to incorporate time through the features instead!

Models that consider time (non i.i.d)

- Markov Chains
- Autoregressive Processes
- Hidden Markov Models (HMM)
- **Recurrent Neural Networks (RNN) /
Long-Short Term Memory (LSTM)**
- Transformers,
- Etc.

Choose your fighter!



[Image Credit](#)

Choosing your model

Choose your fighter!



[Image Credit](#)

Models that don't consider time (i.i.d)

- Linear / Logistic Regression
- Support Vector Machines (SVM)
- Classification and Regression Trees (CART) (e.g. Random Forest)
- eXtreme Gradient Boosting (XGBoost)
- Deep Neural Networks
- Etc.

Need to incorporate time through the features instead!

Models that consider time (non i.i.d)

- Markov Chains
- Autoregressive Processes
- Hidden Markov Models (HMM)
- **Recurrent Neural Networks (RNN) /
Long-Short Term Memory (LSTM)**
- Transformers,
- Etc.

Is a more complex model *necessary*?

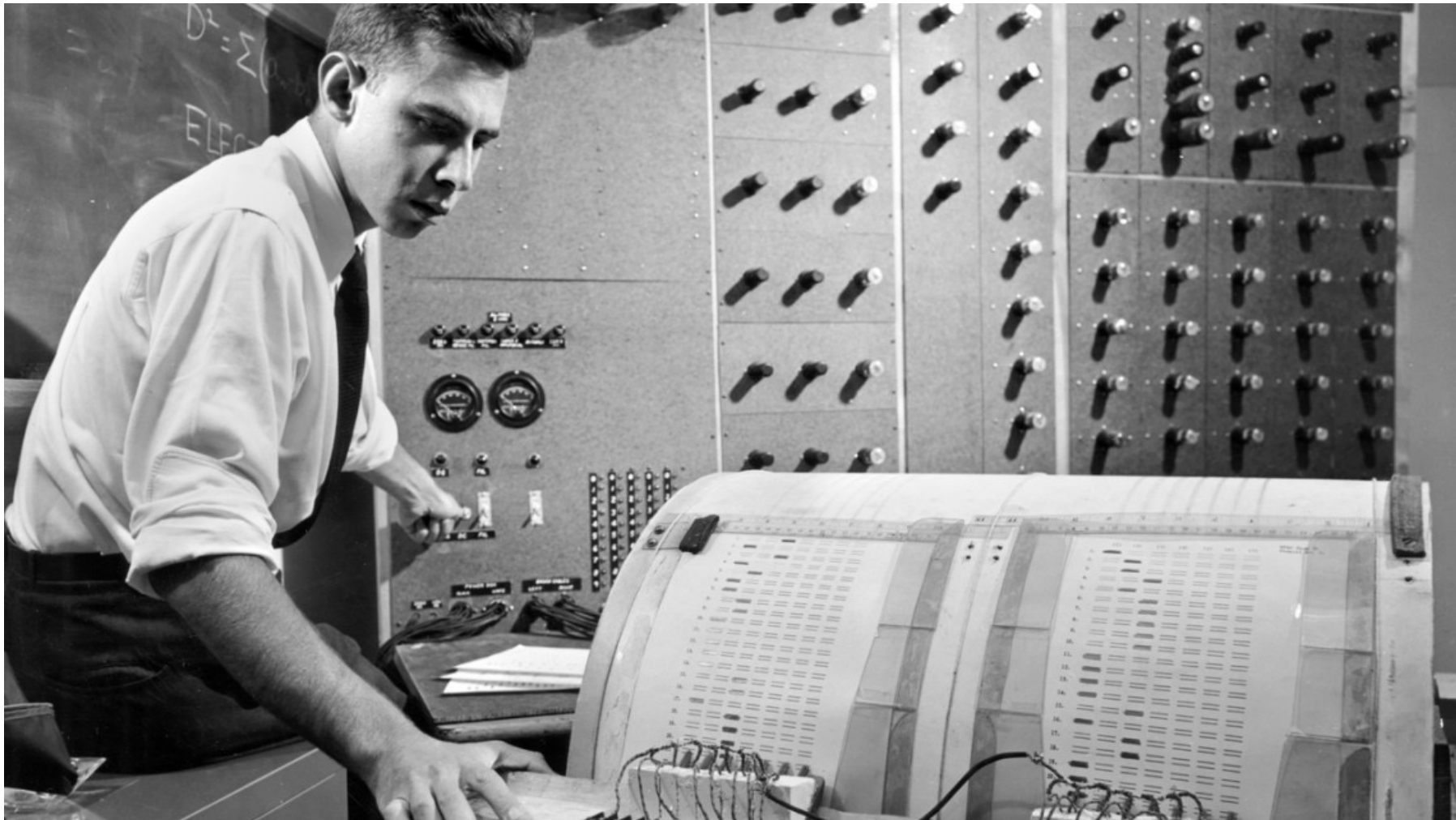


The importance of data curation, cleaning, and pre-processing are often overlooked

Recurrent Neural Networks (RNNs)

Sequential learning using memorisation

- From perceptron to multi-layer perceptron
- Neurons with recurrence
- RNNs
- The problems with long-term dependencies
- Gating to memorize long-term dependencies
- LSTMs
- Sequence processing



Frank Rosenblatt 1950, Ph.D. 1956, works on the “perceptron” – what he described as the first machine “capable of having an original idea.”

The Perceptron



DEPARTMENT OF
ENGINEERING
SCIENCE



REPORT NO. 85-460-1

THE PERCEPTRON
A PERCEIVING AND RECOGNIZING AUTOMATON
(PROJECT PARA)

January, 1957

Prepared by: Frank Rosenblatt

Frank Rosenblatt,
Project Engineer

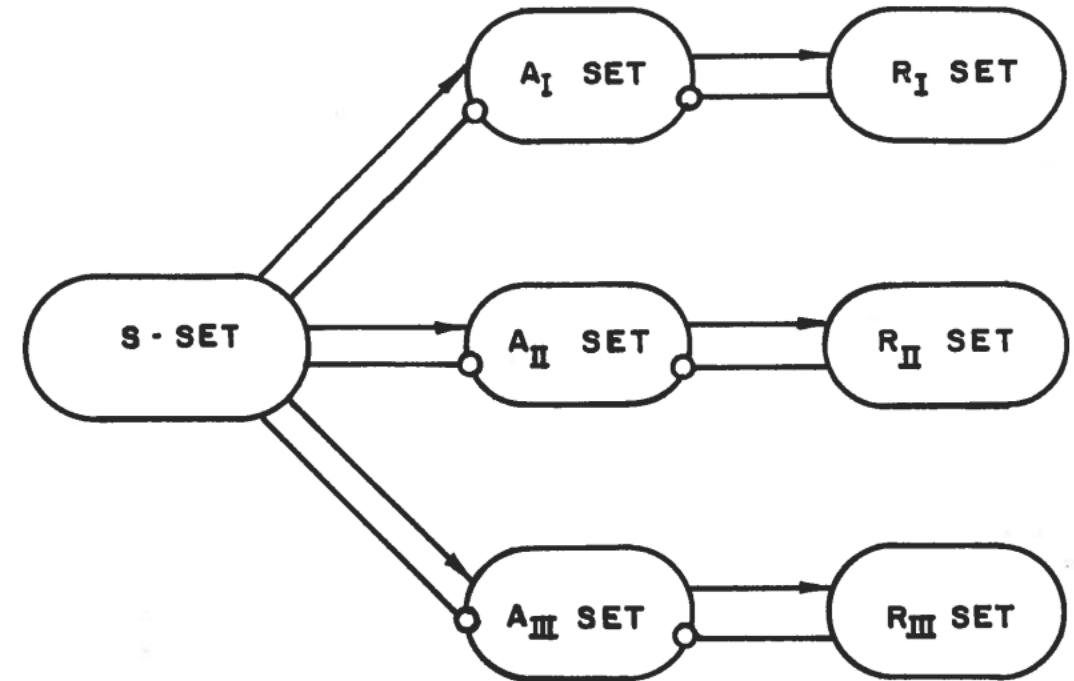
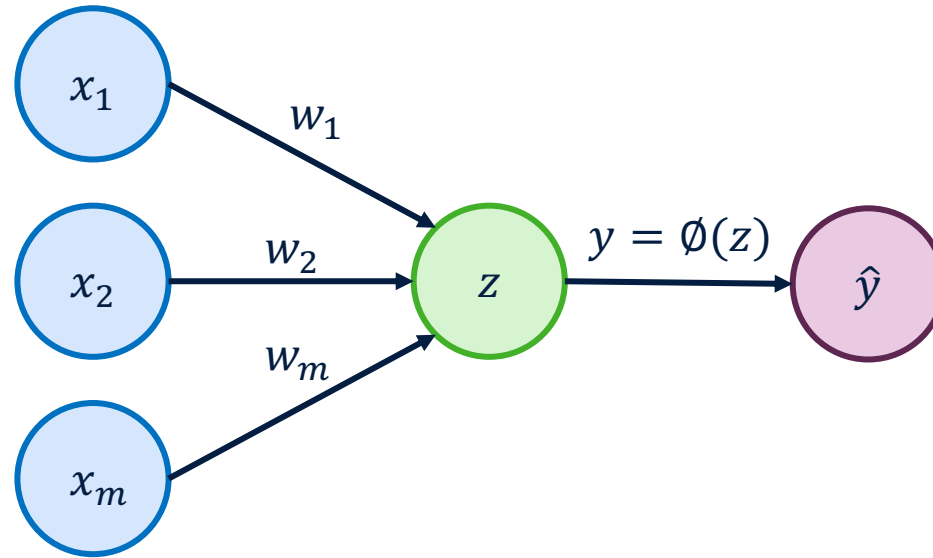


FIGURE 2

ORGANIZATION OF A PERCEPTRON WITH
THREE INDEPENDENT OUTPUT-SETS

The Perceptron

The perceptron is the building block to modern day feed-forward deep networks. A perceptron layer takes a weighted linear combination (sum) of the inputs $\mathbf{x} \in \mathbb{R}^m$ and transform this to an output through some (often non-linear) positive and monotonically increasing activation function $\phi(\cdot)$ to yield a prediction or output \hat{y}



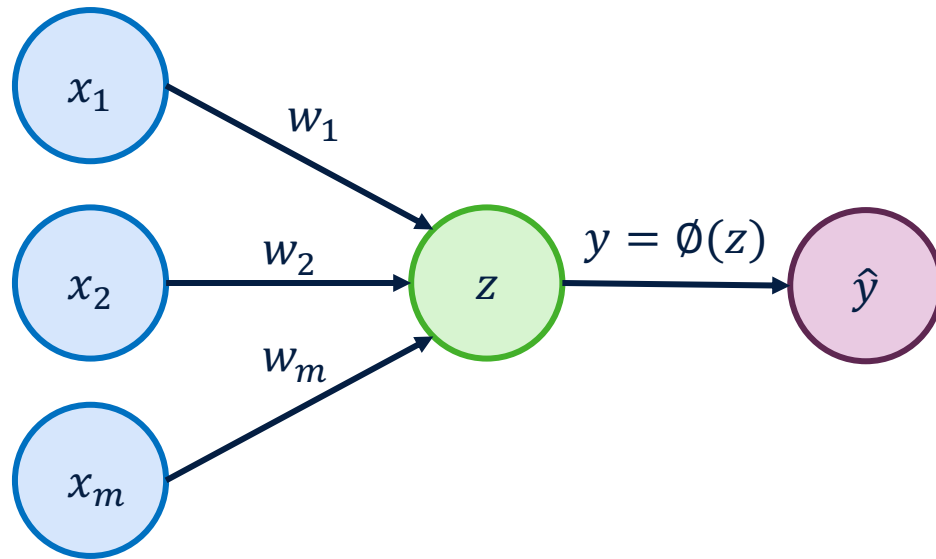
$$\mathbf{x} \in \mathbb{R}^m$$

$$z = \mathbf{w}^T \mathbf{x}$$

$$\hat{y} = \phi(\mathbf{w}^T \mathbf{x})$$

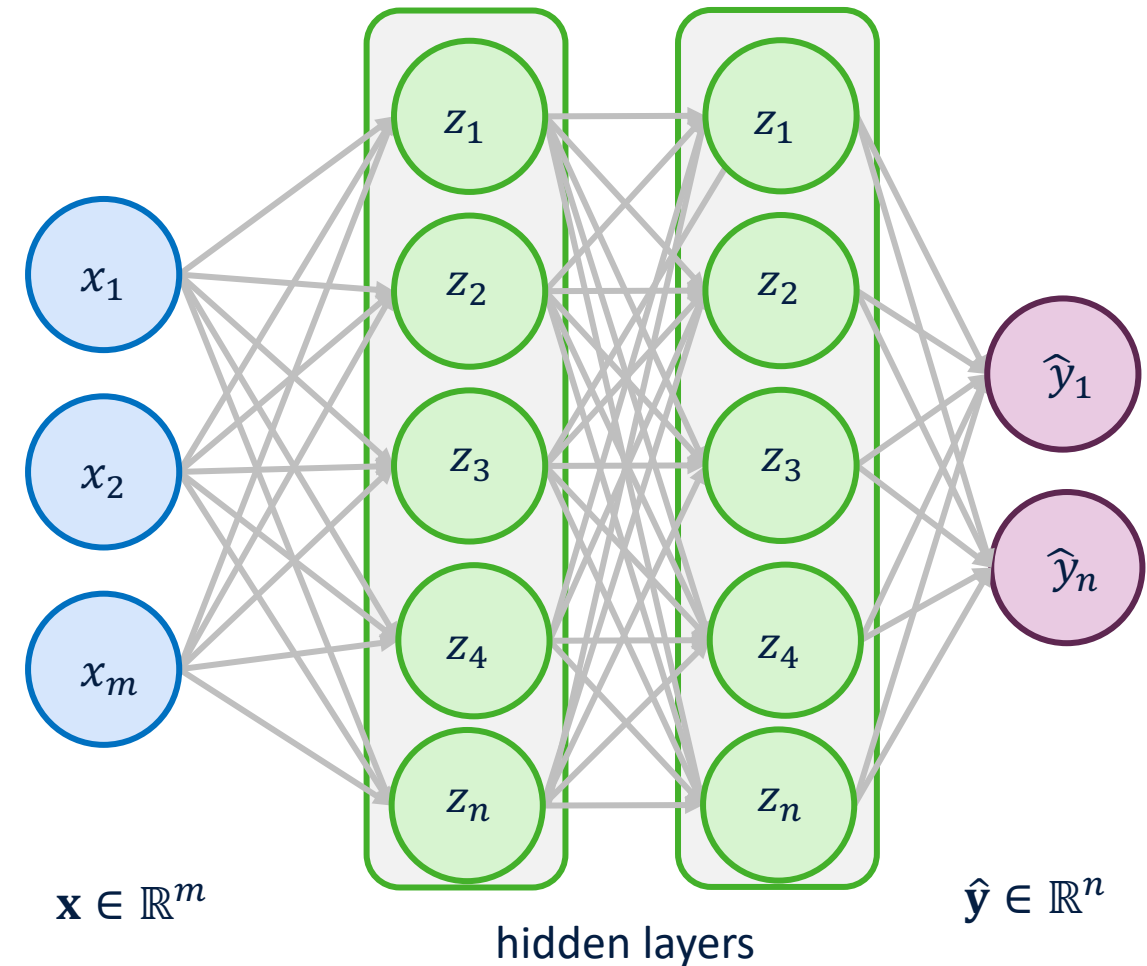
Advancing towards deep networks

the perceptron

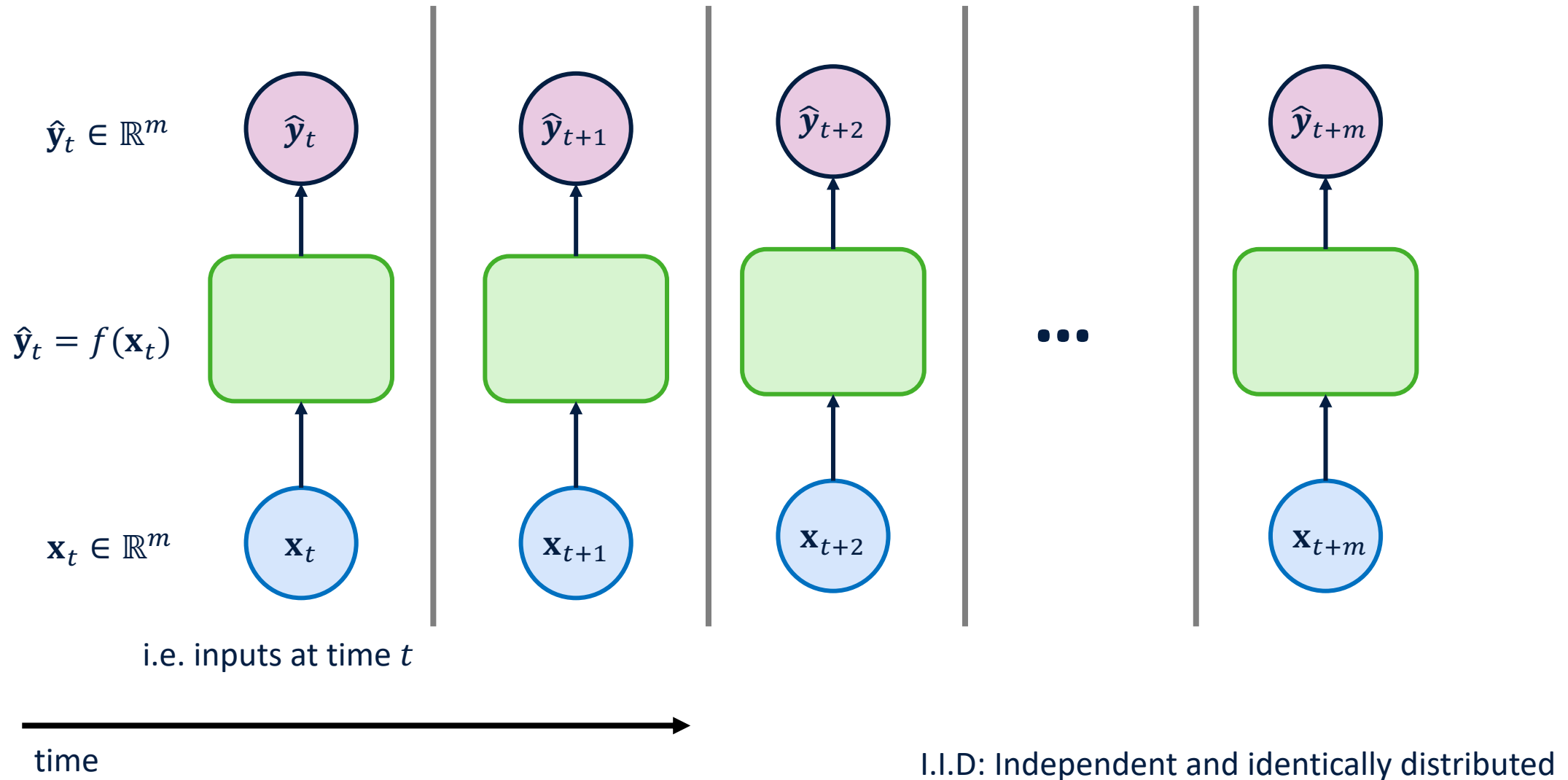


Deep learning typically describes multi-layer perceptron (MLP) blocks that are stacked in cascading architectural arrangements, consisting of a number of (often non-linear) functions successively layered together, which map an input \mathbf{x} to some output \mathbf{y}

MLP, feed forward networks

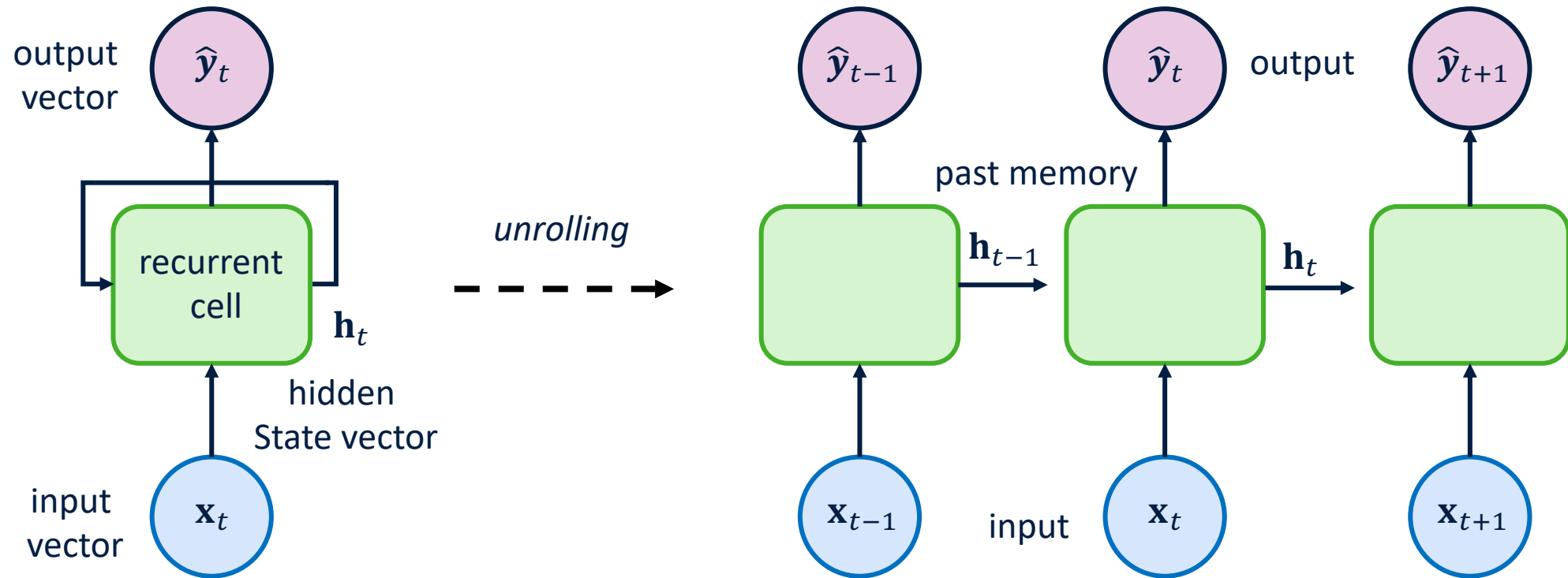


Treating individual time-steps as I.I.D.



Neurons with Recurrence

Apply a recurrence cell step at every time step to process a sequence



RNNs have a state \mathbf{h}_t , that is updated at each time step as a sequence is processed

1) **rolled** network

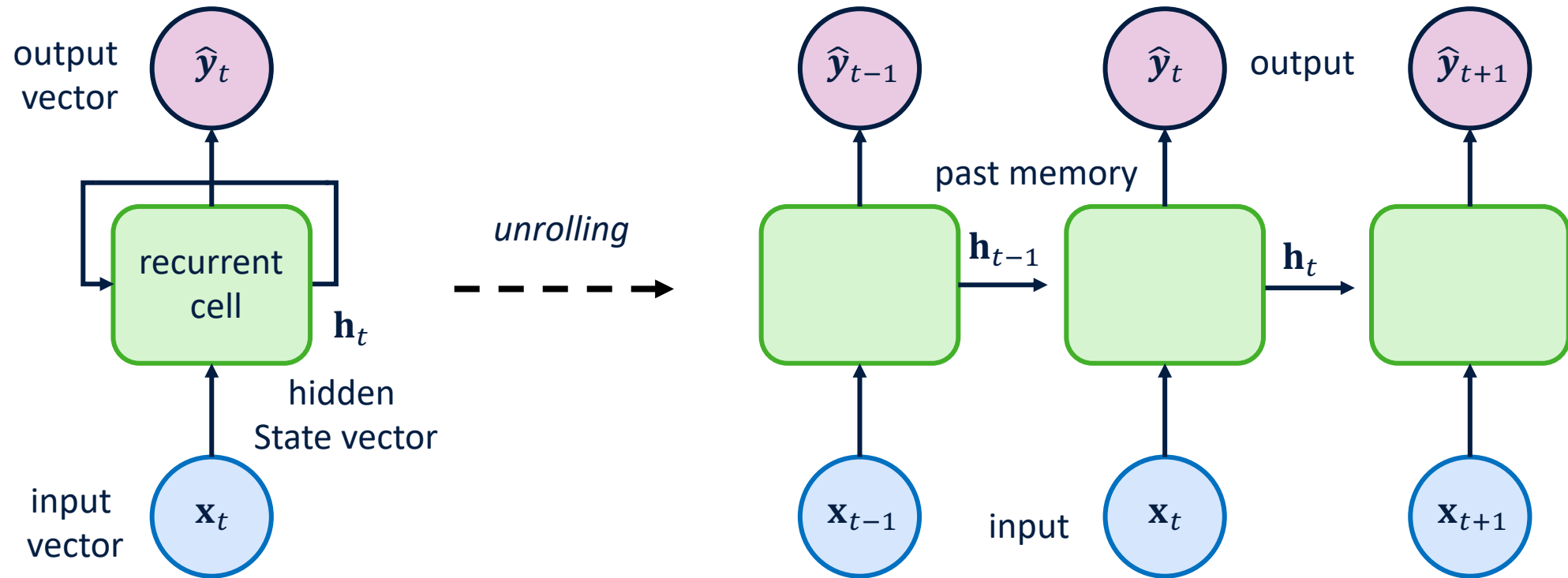
$$\hat{\mathbf{y}}_t = f(\mathbf{x}_t, \mathbf{h}_t)$$

output input past memory

2) **unrolled** network

Neurons with Recurrence

Apply a recurrence cell step at every time step to process a sequence



RNNs have a state \mathbf{h}_t , that is updated at each time step as a sequence is processed

$$\hat{\mathbf{y}}_t = f(\mathbf{x}_t, \mathbf{h}_t)$$

output input cell memory

$$\mathbf{h}_t = f_{\mathbf{w}}(\mathbf{x}_t, \mathbf{h}_{t-1})$$

cell state update the hidden state using function with weights \mathbf{w}

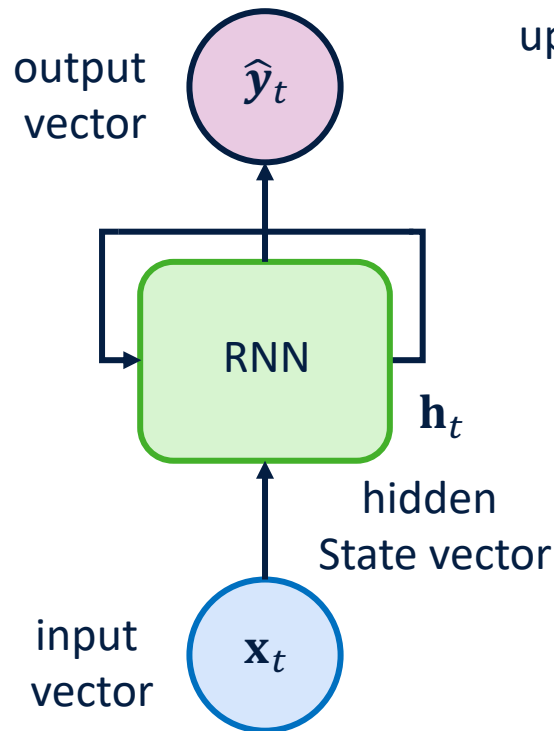
Recurrent Neural Networks (RNNs)

Apply a recurrence cell step at every time step to process a sequence

\mathbf{W}_{hh} : recurrent weights

\mathbf{W}_{hy} : hidden weights

\mathbf{W}_{xh} : input weights



update the hidden state using function with weights \mathbf{w}

$$\mathbf{h}_t = f_{\mathbf{w}}(\mathbf{x}_t, \mathbf{h}_{t-1})$$

cell state input previous state

$$\mathbf{h}_t = \tanh(\mathbf{W}_{hh}^T \mathbf{h}_{t-1} + \mathbf{W}_{xh}^T \mathbf{x}_t)$$

$$\hat{\mathbf{y}}_t = \mathbf{W}_{hy}^T \mathbf{h}_t \quad (\text{output vector})$$

RNNs have a state \mathbf{h}_t , that is updated at each time step as a sequence is processed

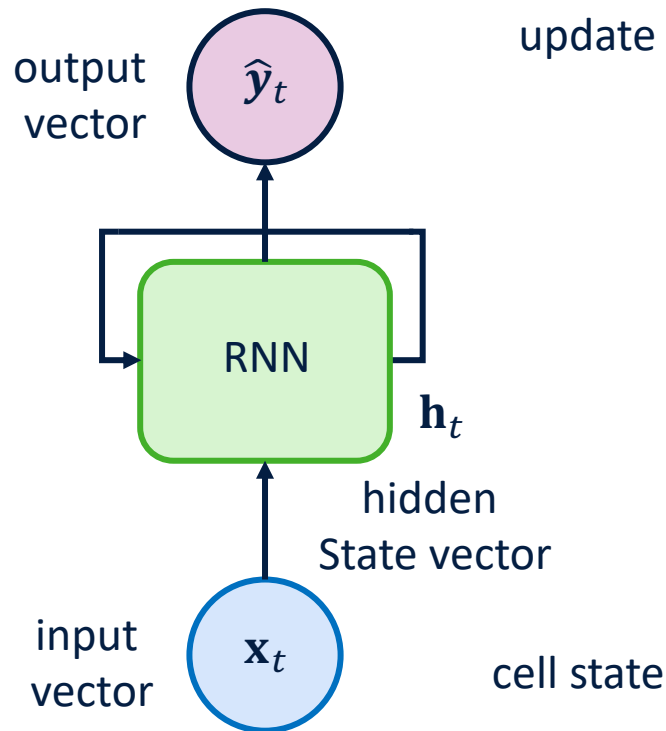
Recurrent Neural Networks (RNNs)

Apply a recurrence cell step at every time step to process a sequence

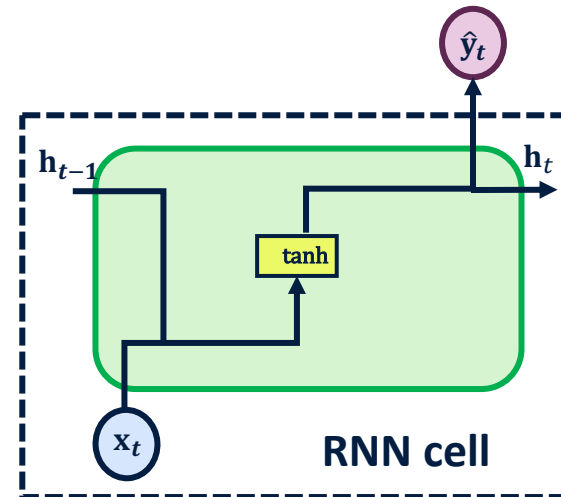
\mathbf{W}_{hh} : recurrent weights

\mathbf{W}_{hy} : hidden weights

\mathbf{W}_{xh} : input weights



update the hidden state using function with weights \mathbf{w}



$$\mathbf{h}_t = f_{\mathbf{w}}(\mathbf{x}_t, \mathbf{h}_{t-1})$$

$$\mathbf{h}_t = \tanh(\mathbf{W}_{hh}^T \mathbf{h}_{t-1} + \mathbf{W}_{xh}^T \mathbf{x}_t)$$

$$\hat{\mathbf{y}}_t = \mathbf{W}_{hy}^T \mathbf{h}_t \quad (\text{output vector})$$

RNNs have a state \mathbf{h}_t , that is updated at each time step as a sequence is processed

Recurrent Neural Networks (RNNs)

Apply a recurrence cell step at every time step to process a sequence

update the hidden state using function with weights \mathbf{w}

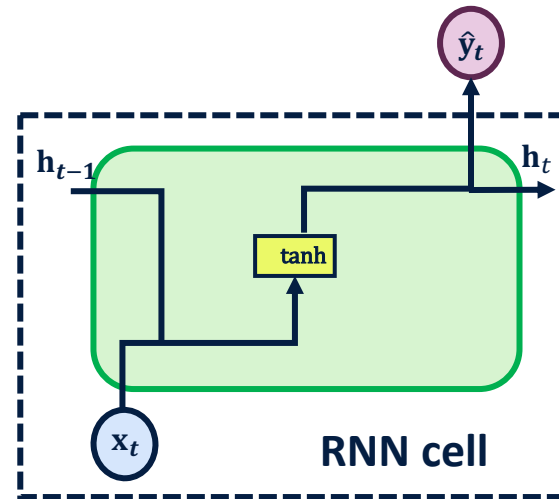
\mathbf{W}_{hh} : recurrent weights

\mathbf{W}_{hy} : hidden weights

\mathbf{W}_{xh} : input weights

minimal code example

```
class RNN:
    # ...
    def step(self, x):
        # update the hidden state
        self.h =
        np.tanh(np.dot(self.W_hh, self.h)
        + np.dot(self.W_xh, x))
        # compute the output vector
        y = np.dot(self.W_hy, self.h)
        return y
```



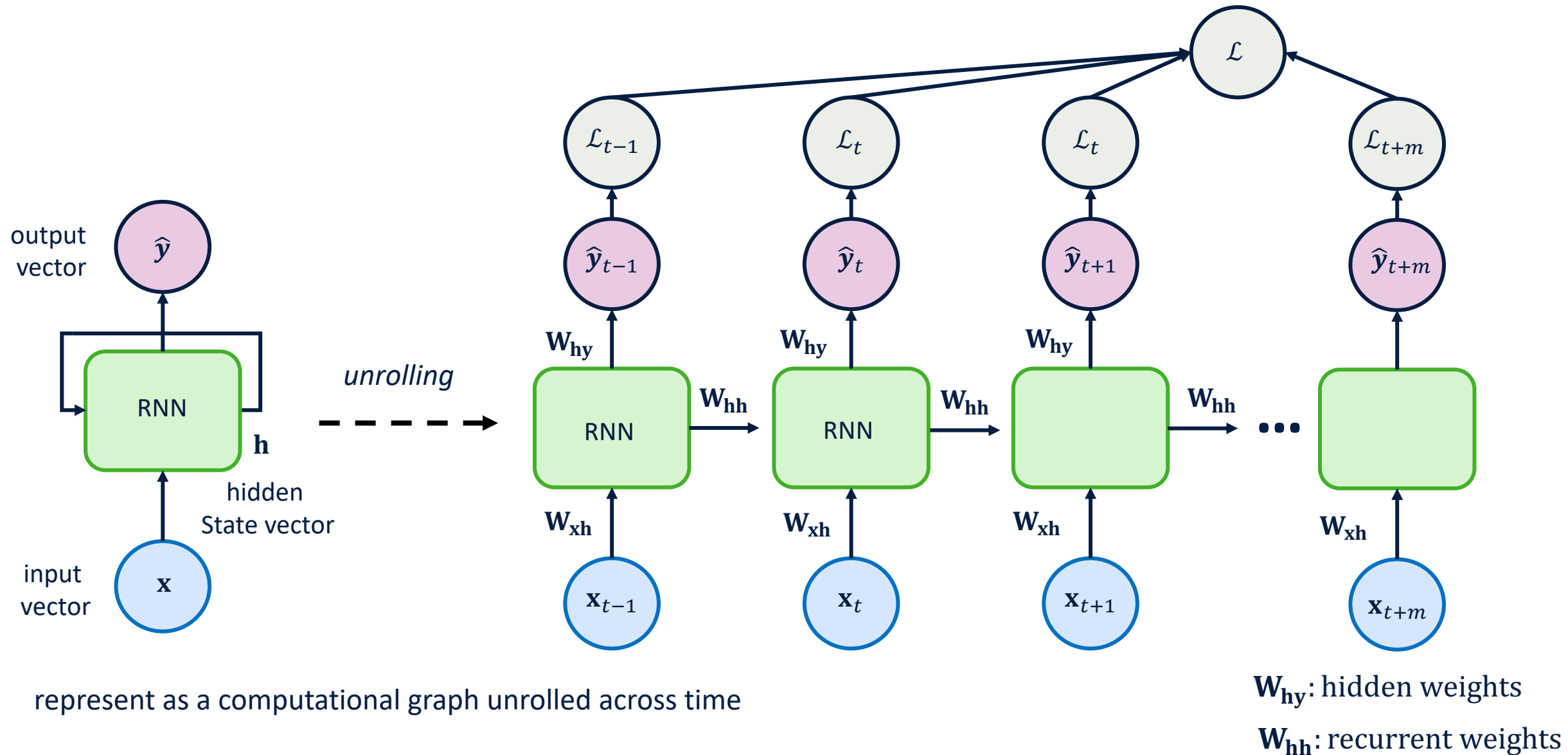
$$\mathbf{h}_t = f_{\mathbf{w}}(\mathbf{x}_t, \mathbf{h}_{t-1})$$

$$\mathbf{h}_t = \tanh(\mathbf{W}_{hh}^T \mathbf{h}_{t-1} + \mathbf{W}_{xh}^T \mathbf{x}_t)$$

$$\hat{\mathbf{y}}_t = \mathbf{W}_{hy}^T \mathbf{h}_t \quad (\text{output vector})$$

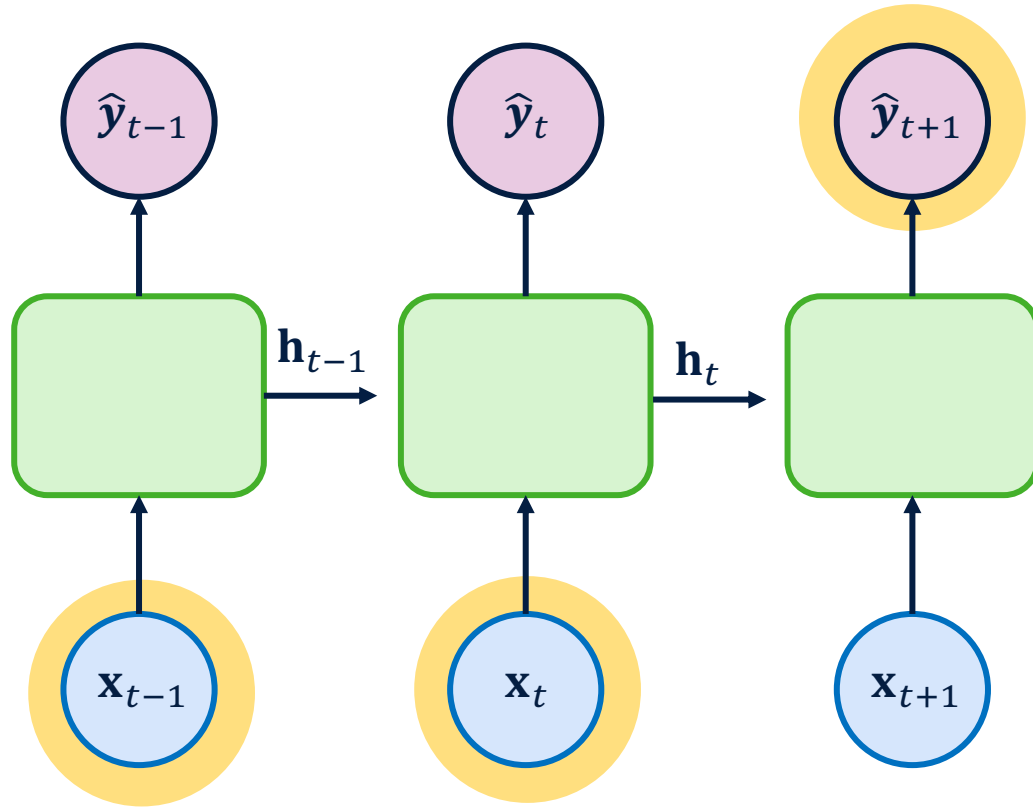
RNNs have a state \mathbf{h}_t , that is updated at each time step as a sequence is processed

Recurrent Neural Networks (RNNs)



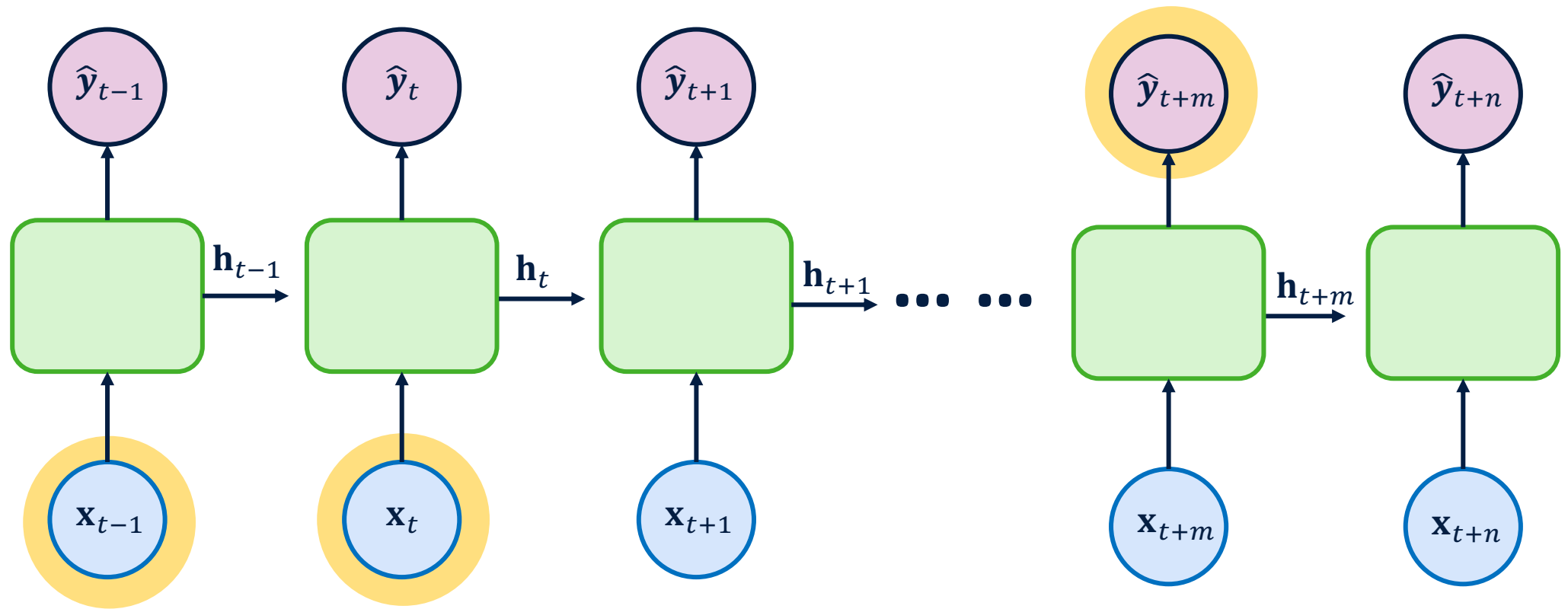
The Problem of Long-Term Dependencies

In cases certain cases, such as where the gap between the relevant information and the place that it's needed is small, RNNs can learn to use the past information.



"The clouds are in the ____"

The Problem of Long-Term Dependencies



“I grew up in France,, and I speak fluent _____”

The Problem of Long-Term Dependencies

Problems of long-term information flow...

Exploding and Vanishing Gradients: Computing the gradient ∇ (to train the model) w.r.t. \mathbf{h}_t often requires many factors of \mathbf{W}_{hh} and repeated gradient computation!

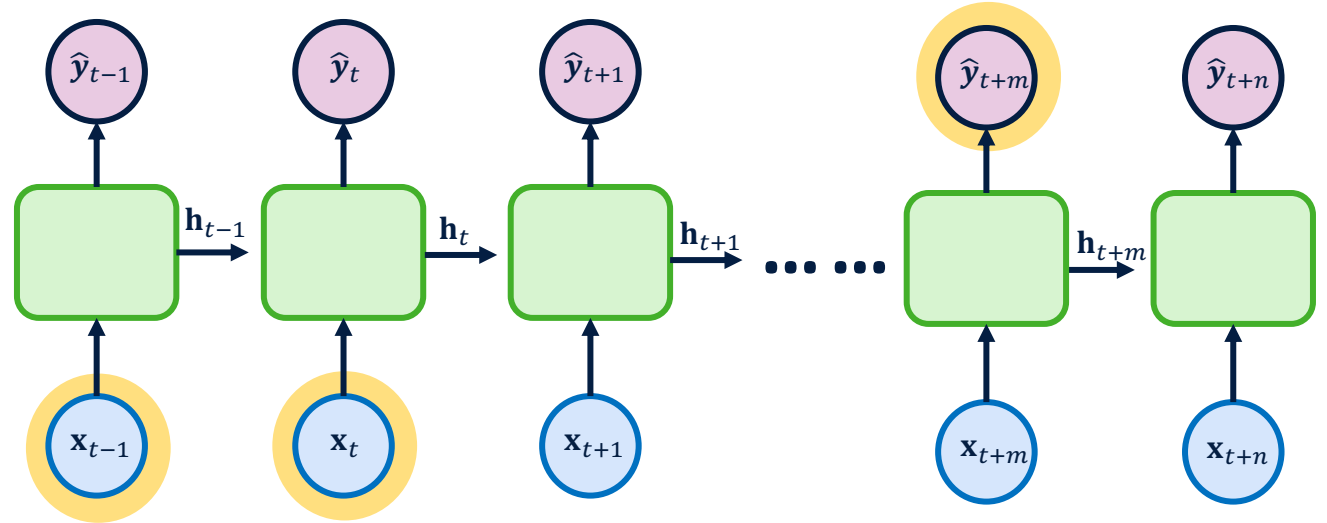
many values of:

$$\nabla_{\mathbf{h}_t} \gg 1$$

$$\nabla_{\mathbf{h}_t} \ll 1$$

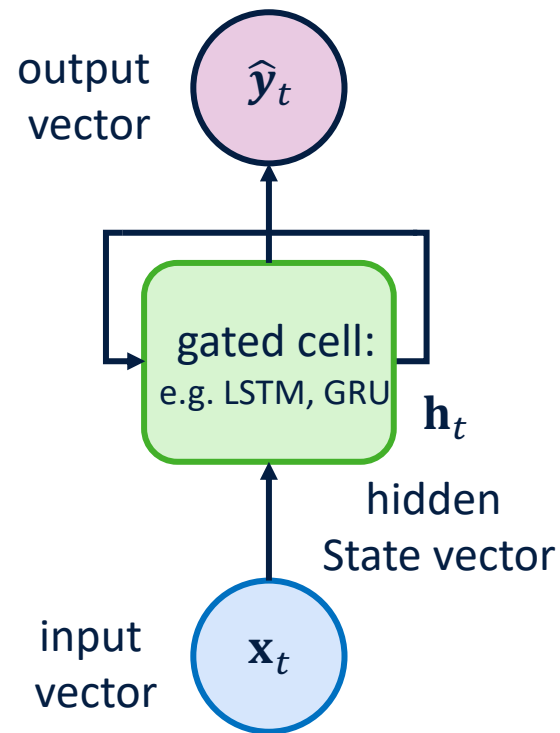
exploding gradients

vanishing gradients

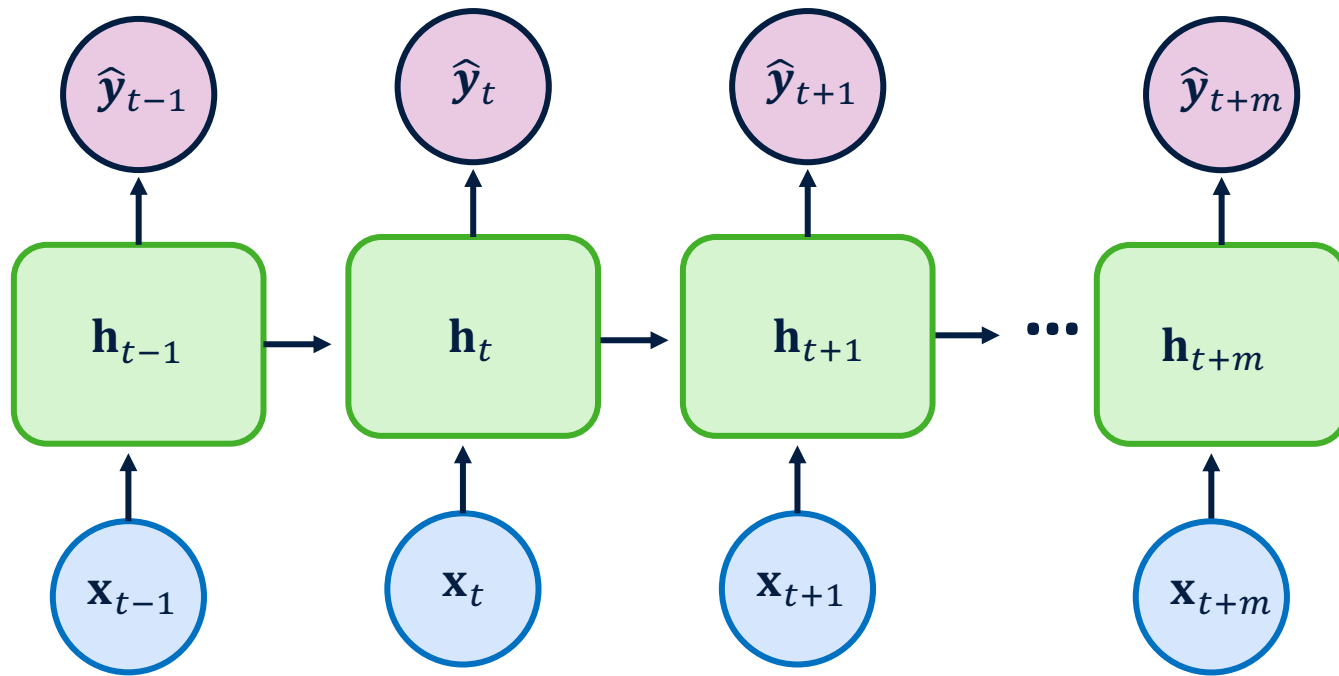


...multiply many small numbers together \rightarrow errors due to further back time steps have smaller and smaller gradients \rightarrow bias parameters to capture short-term dependencies

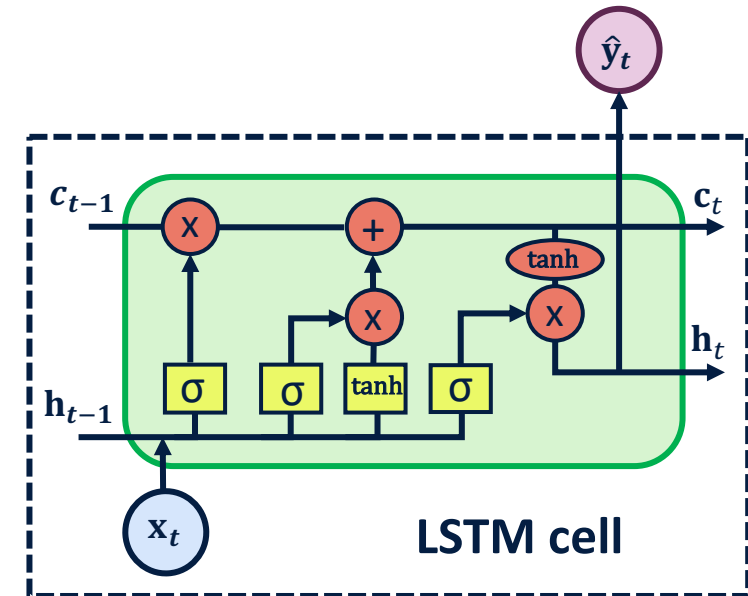
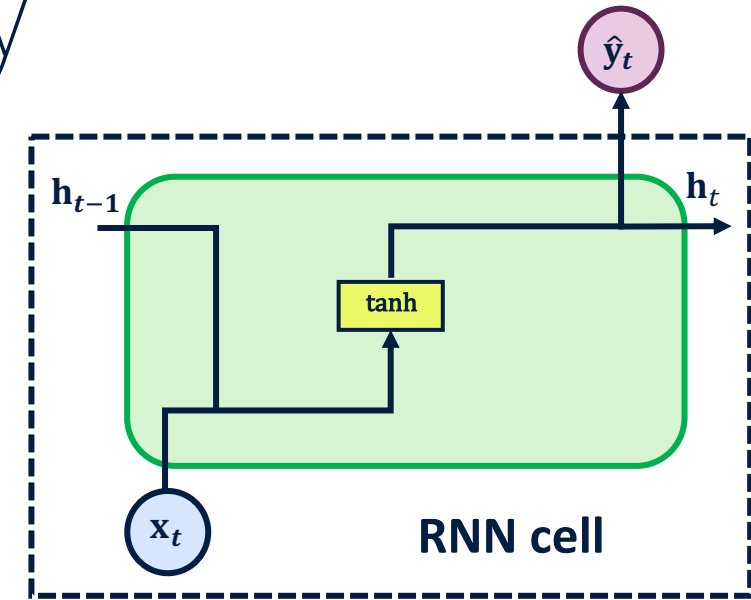
Gating to memorize long-term dependencies



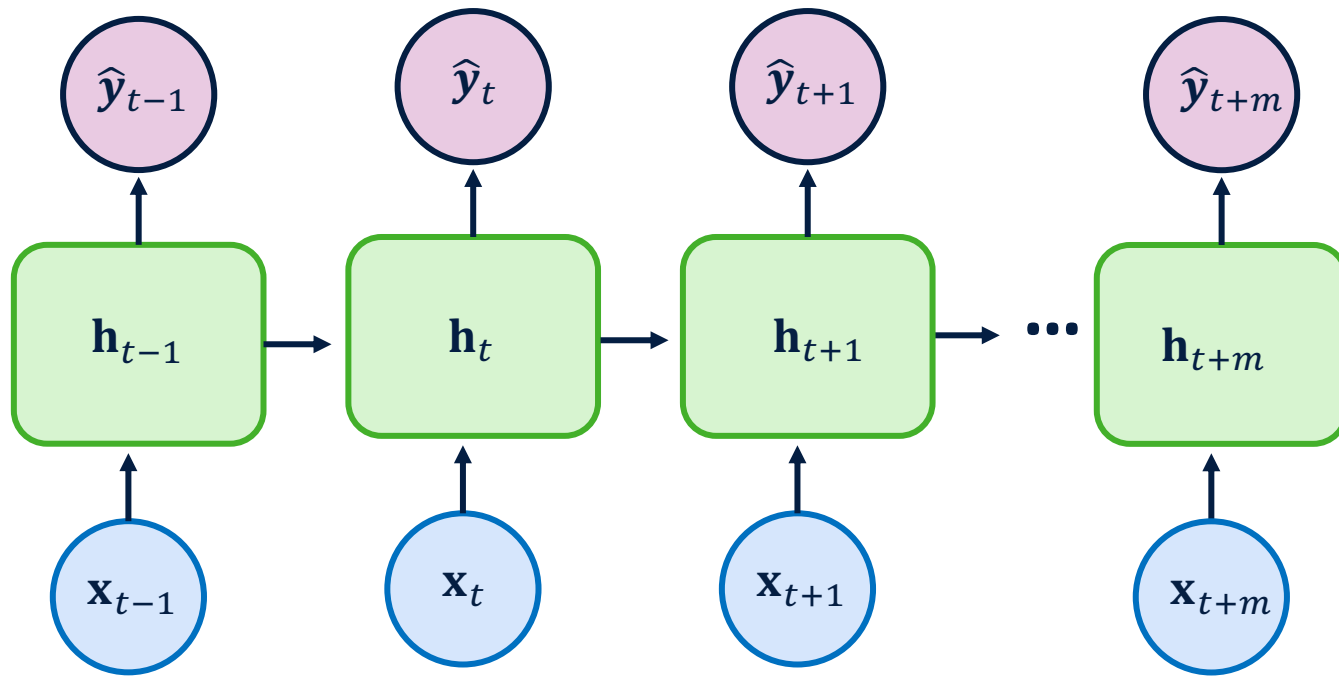
Long-Short Term Memory (LSTM)



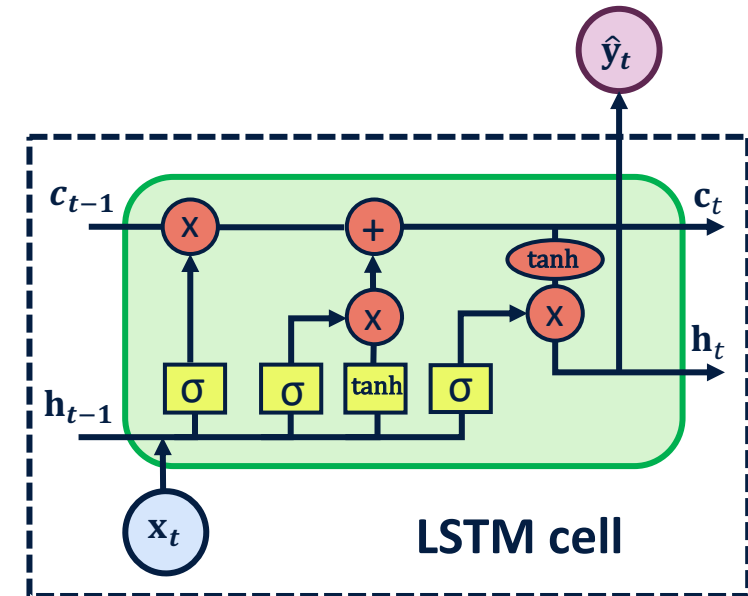
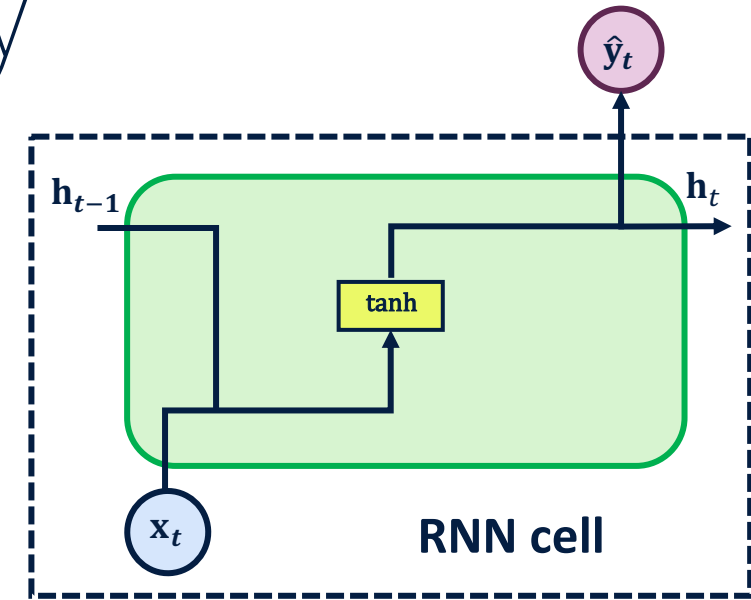
- RNN contains simple computation node
- Replace with LSTM computation block with control information flow (memory)
- LSTMs can track information over many $(t + m)$ timesteps



Long-Short Term Memory (LSTM)

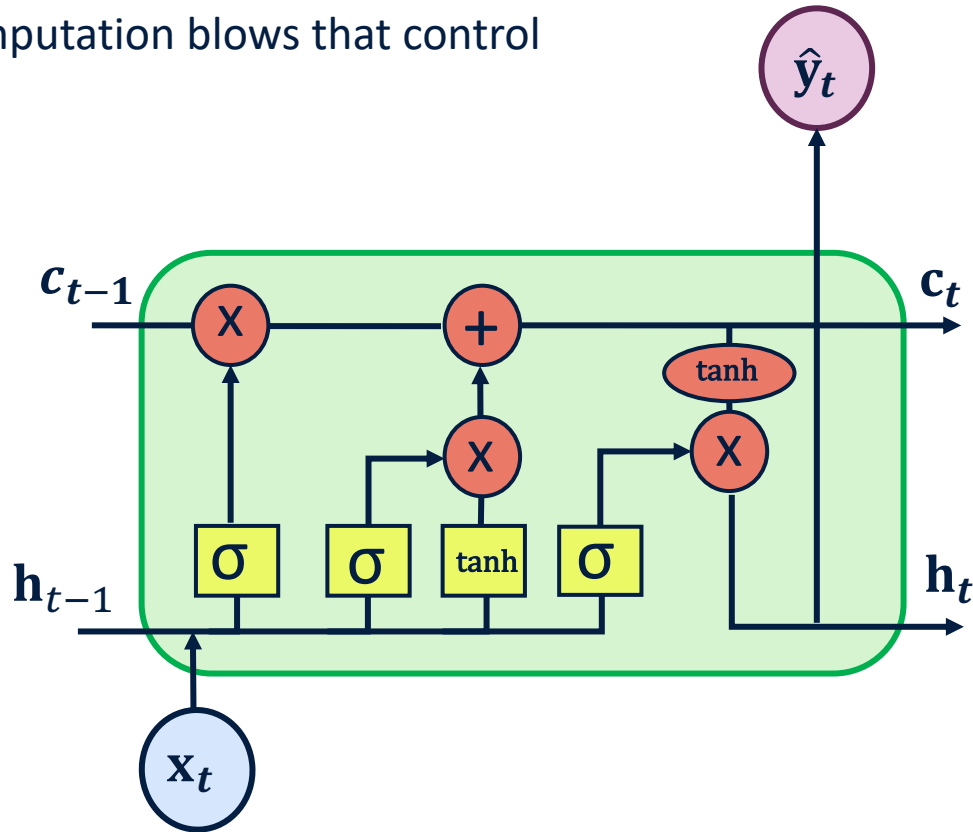


- RNN contains simple computation node
- Replace with LSTM computation block with control information flow (memory)
- LSTMs can track information over many $(t + m)$ timesteps



Long-Short Term Memory (LSTM)

LSTM modules contain computation blows that control information flow



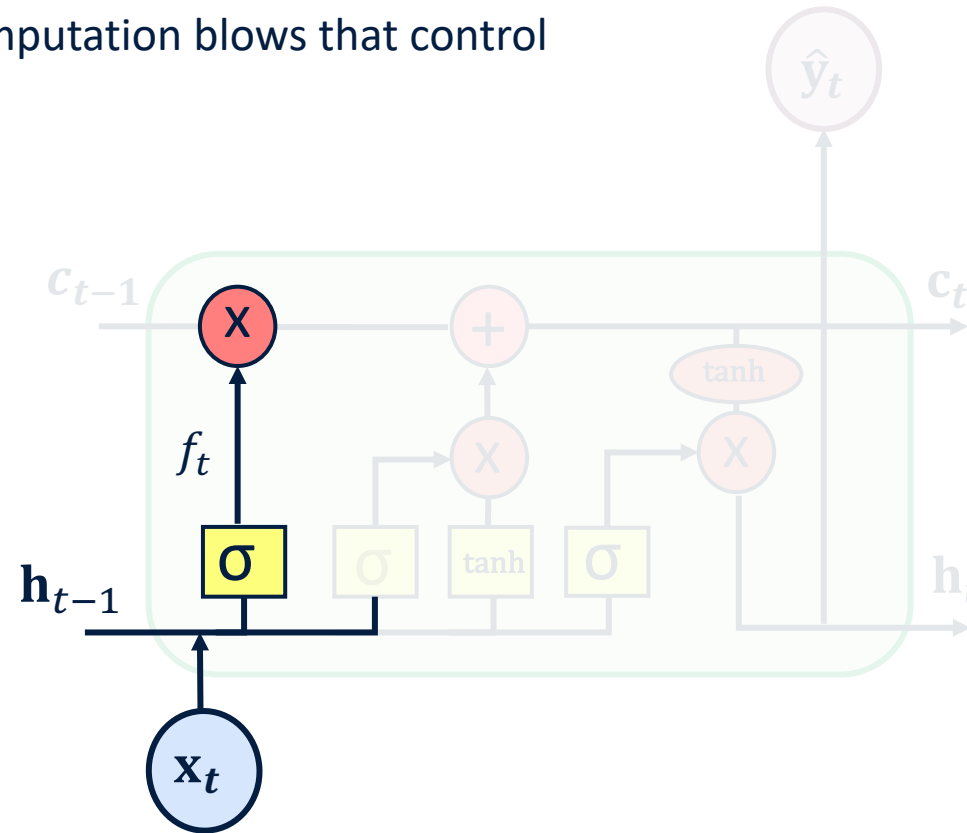
- \times : pointwise multiplication
- $+$: pointwise addition
- σ : sigmoid function
- \tanh : hyperbolic tangent function

1) Forget 2) Store 3) Update 4) Output

Long-Short Term Memory (LSTM)

LSTM modules contain computation blows that control information flow

- \times : pointwise multiplication
- $+$: pointwise addition
- σ : sigmoid function
- \tanh : hyperbolic tangent function



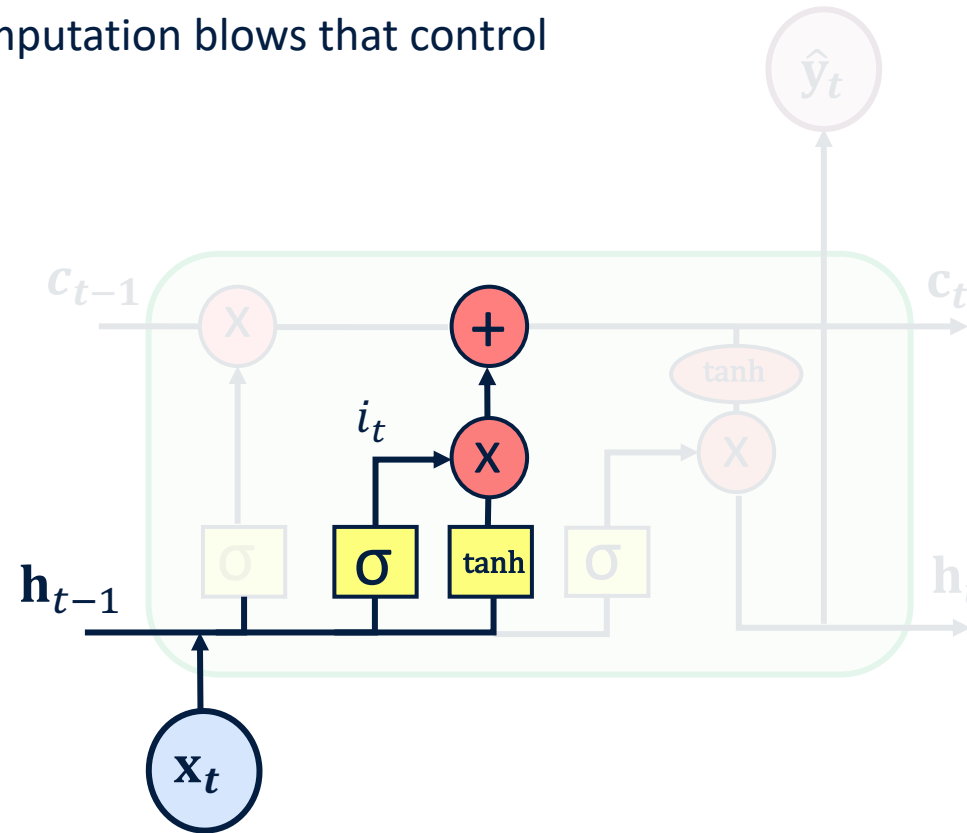
1) Forget 2) Store 3) Update 4) Output

LSTMs **forget irrelevant** parts of the previous state

Long-Short Term Memory (LSTM)

LSTM modules contain computation blows that control information flow

- \times : pointwise multiplication
- $+$: pointwise addition
- σ : sigmoid function
- \tanh : hyperbolic tangent function



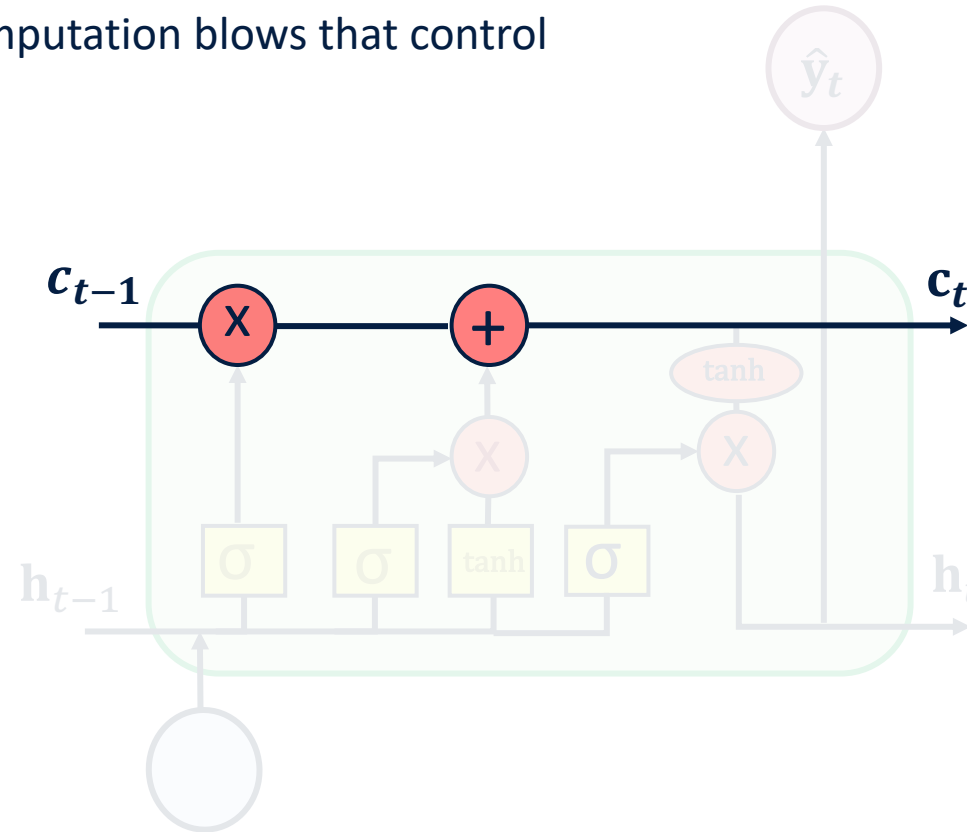
1) Forget **2) Store** 3) Update 4) Output

LSTMs **store relevant** new information into the cell state

Long-Short Term Memory (LSTM)

LSTM modules contain computation blows that control information flow

- \times : pointwise multiplication
- $+$: pointwise addition
- σ : sigmoid function
- \tanh : hyperbolic tangent function



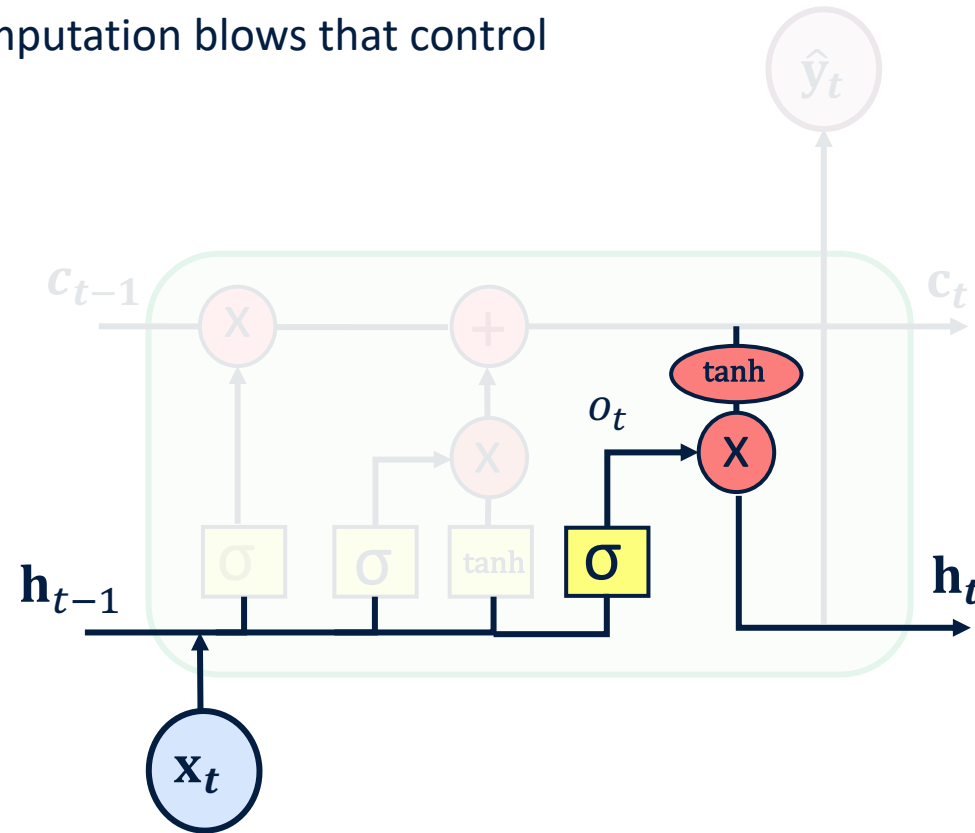
1) Forget 2) Store 3) **Update** 4) Output

LSTMs **selectively update** cell state values

Long-Short Term Memory (LSTM)

LSTM modules contain computation blows that control information flow

- \times : pointwise multiplication
- $+$: pointwise addition
- σ : sigmoid function
- \tanh : hyperbolic tangent function

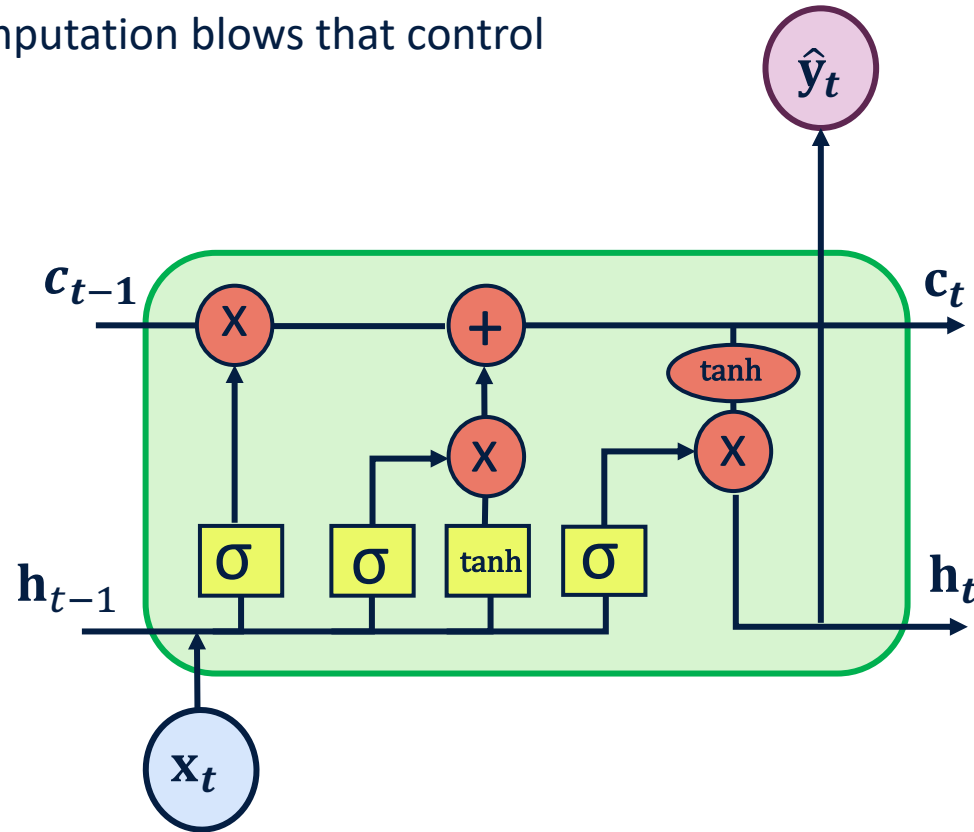


1) Forget 2) Store 3) Update 4) **Output**

LSTMs **output gate** controls what information is sent to the next step, essentially returning a filtered version of the cell state

Long-Short Term Memory (LSTM)

LSTM modules contain computation blows that control information flow



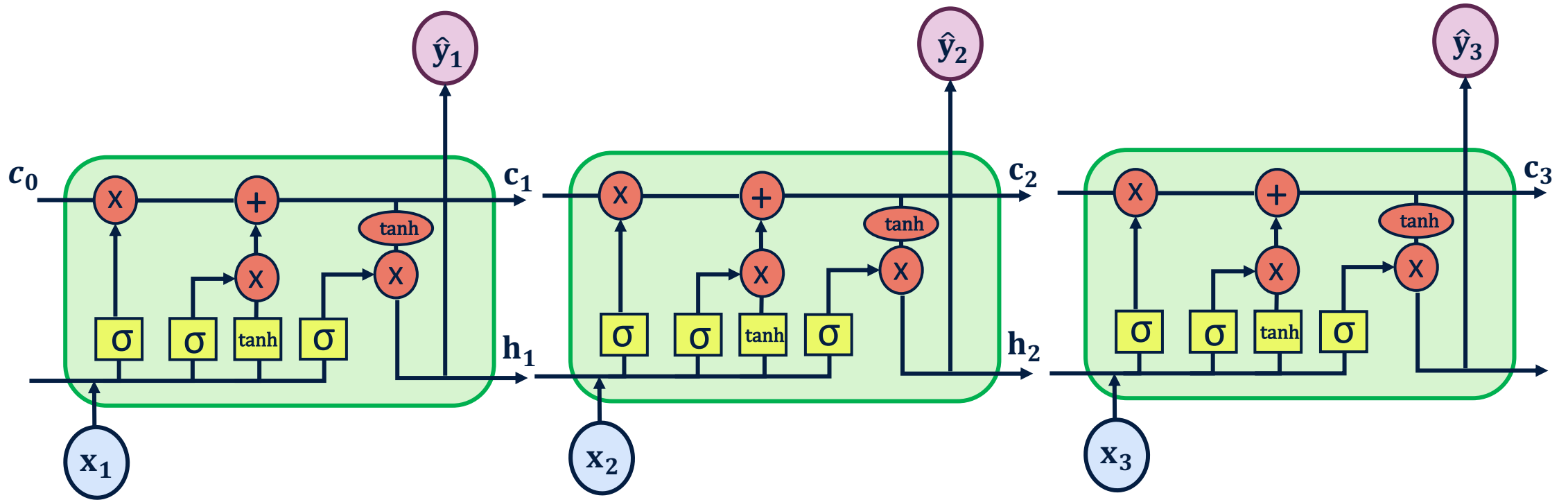
- \times : pointwise multiplication
- $+$: pointwise addition
- σ : sigmoid function
- \tanh : hyperbolic tangent function

1) Forget 2) Store 3) Update 4) Output

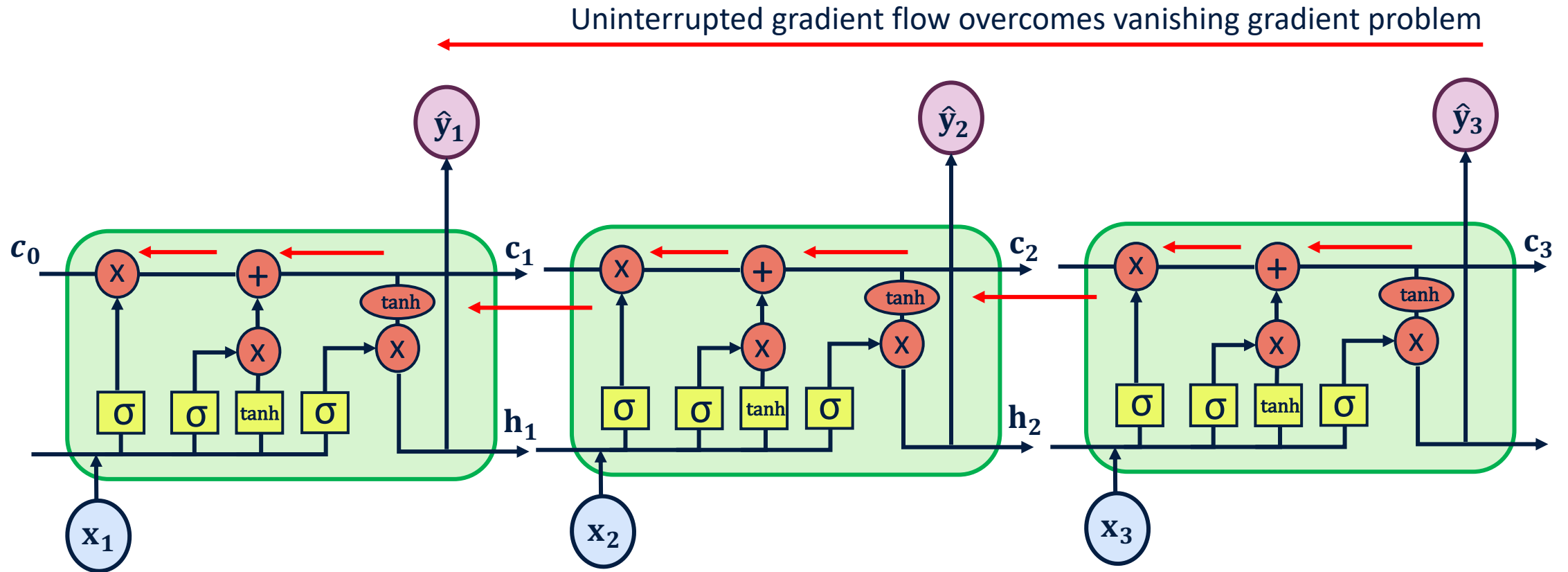
Key Concept: LSTMS maintain a separate cell state from what is outputted and uses gates to control the flow of information

Long-Short Term Memory (LSTM)

Forward pass

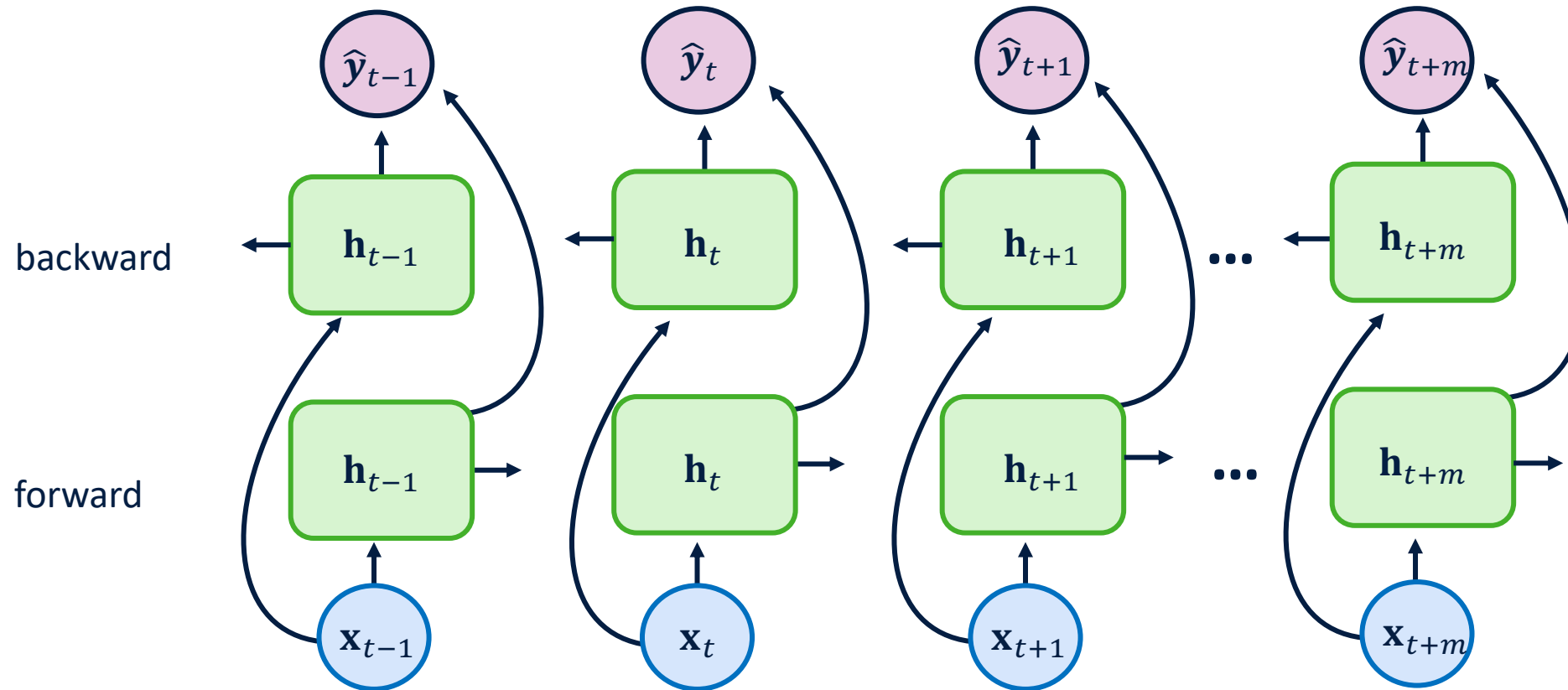


Long-Short Term Memory (LSTM)



Key Concept: No multiplication with weights matrix \mathbf{W} during backpropagation (don't worry about this too much!)
Cell state multiplied by different values of forget gate \rightarrow less prone to vanishing and exploding gradient problems

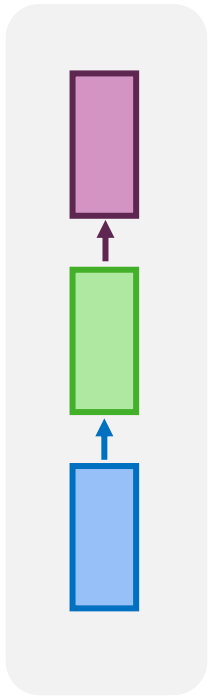
Bi-directional RNNs



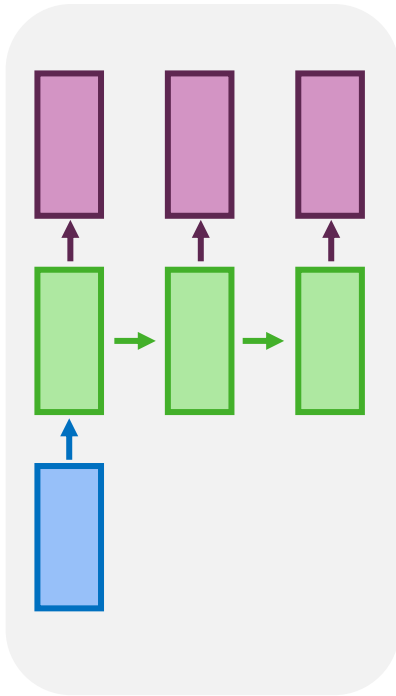
The hidden state is the concatenated result of both forward and backward hidden states so that it can capture **past** and **future** information

Sequence Processing Options

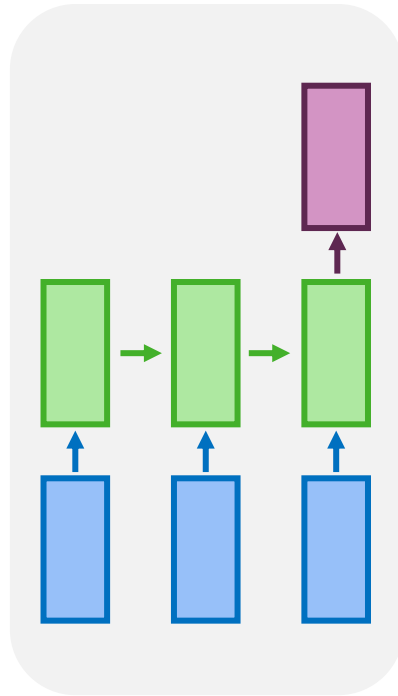
one to one



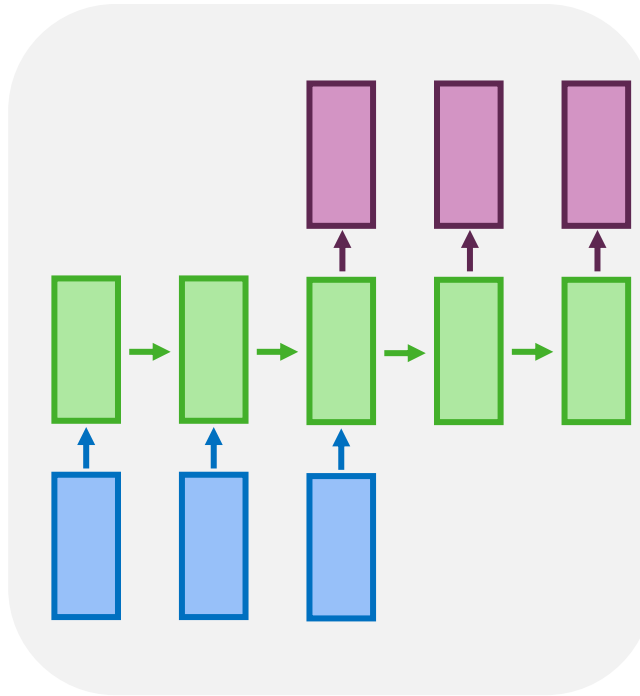
one to many



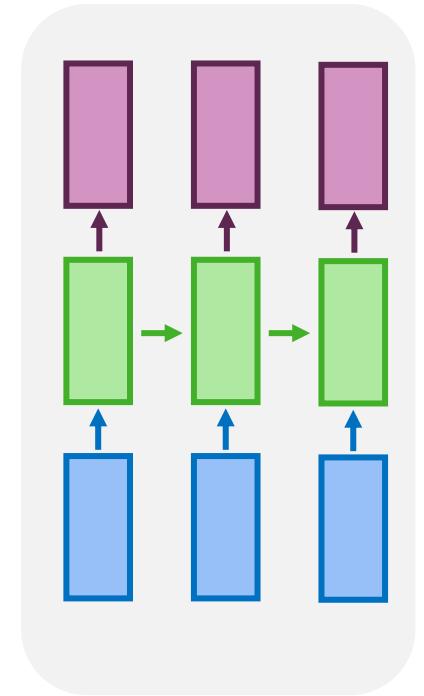
many to one



many to many



many to many



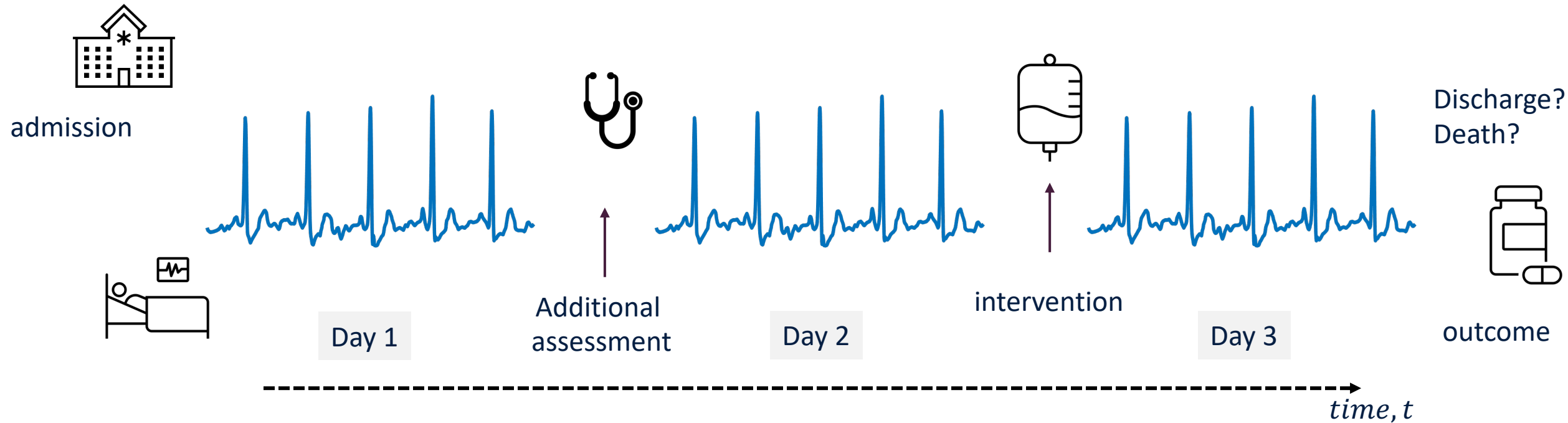
Source: <https://karpathy.github.io/2015/05/21/rnn-effectiveness/>

How to implement RNNs?

The practicalities:

1. Understanding your problem
2. Setting up your RNN
3. Picking your ML framework
4. Training your RNN
5. Avoiding overfitting
6. Your machine learning pipeline

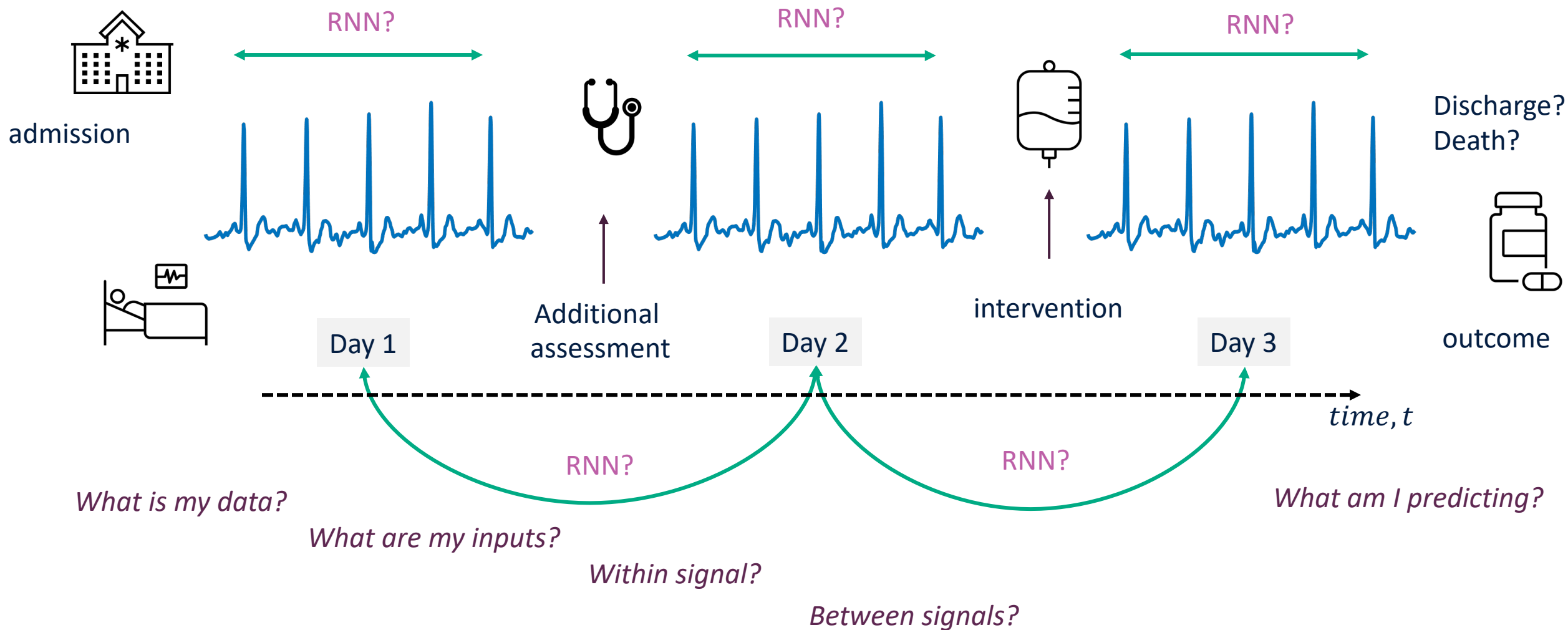
Setting up your time-series problem



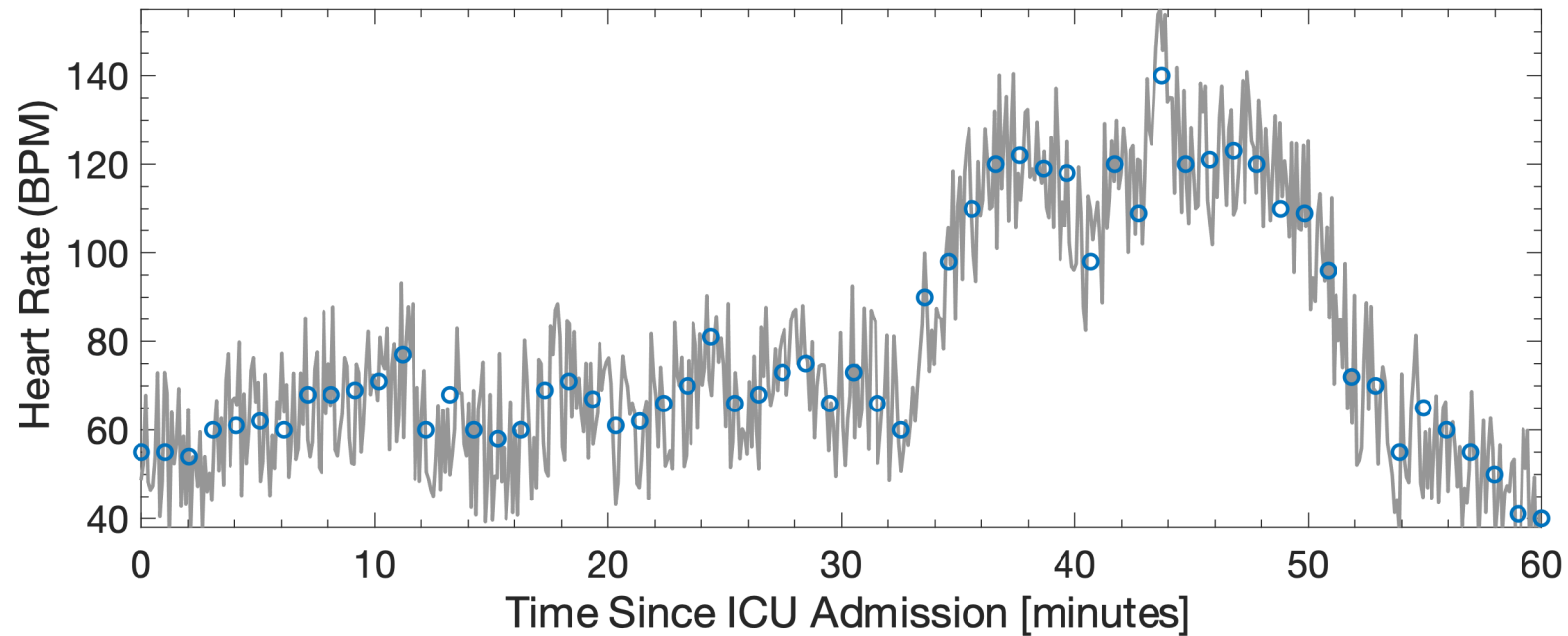
What is my data?

What am I predicting?

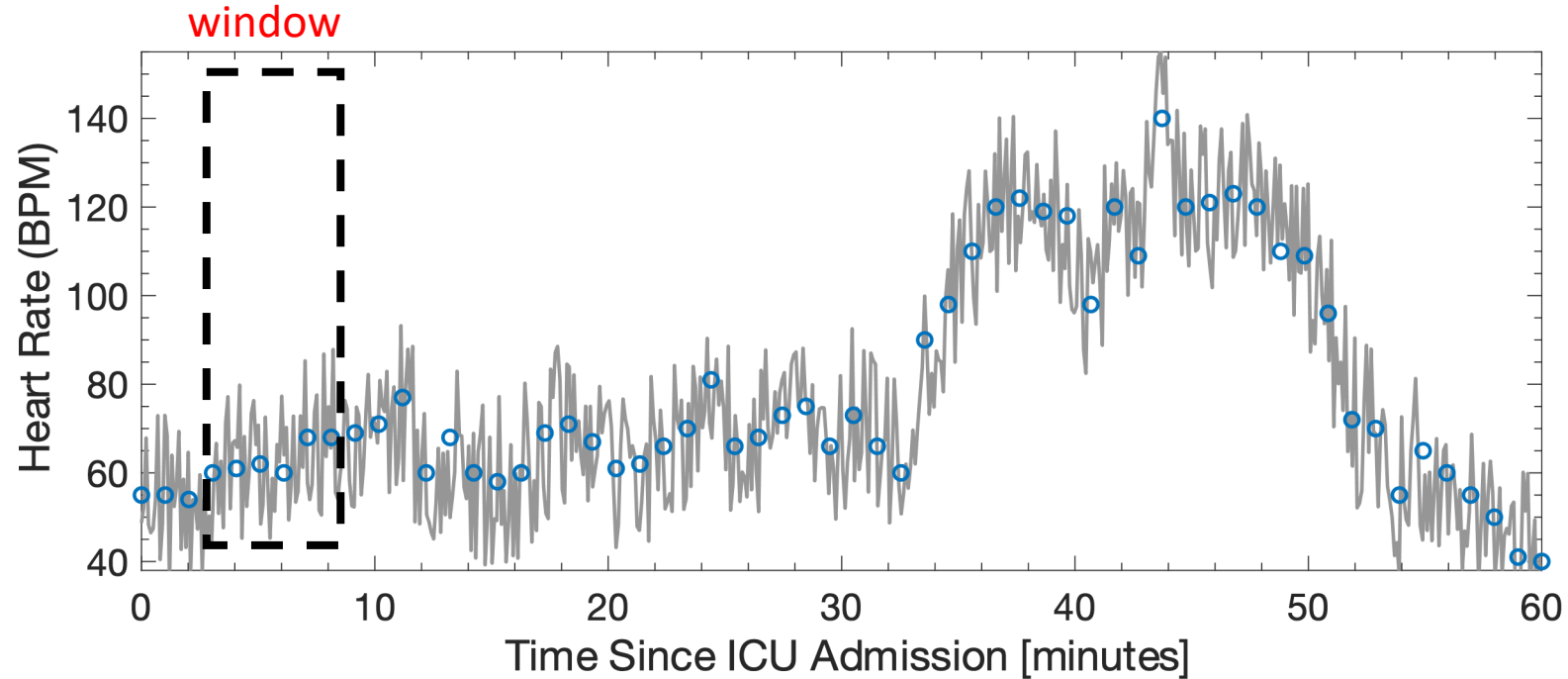
Setting up your time-series problem



Discretising Time: Windowing

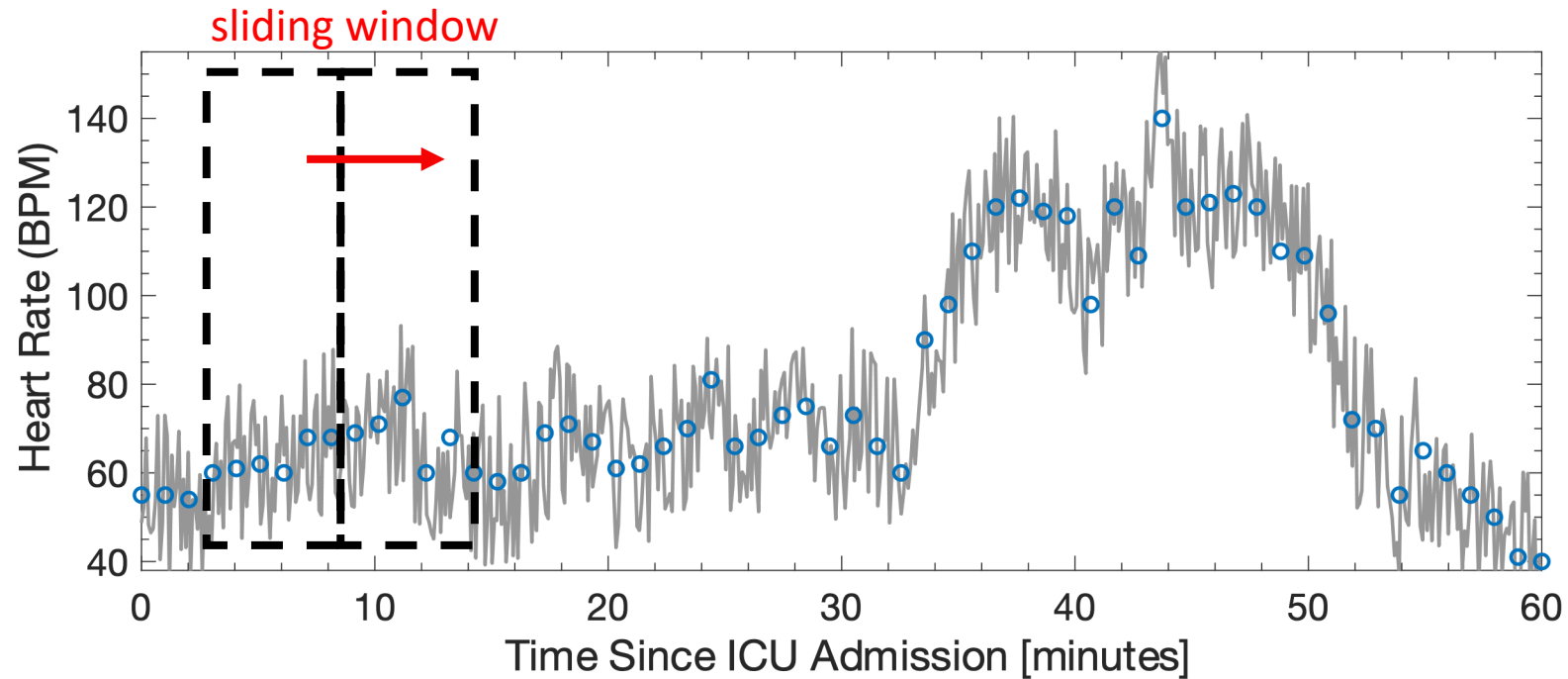


Discretising Time: Windowing



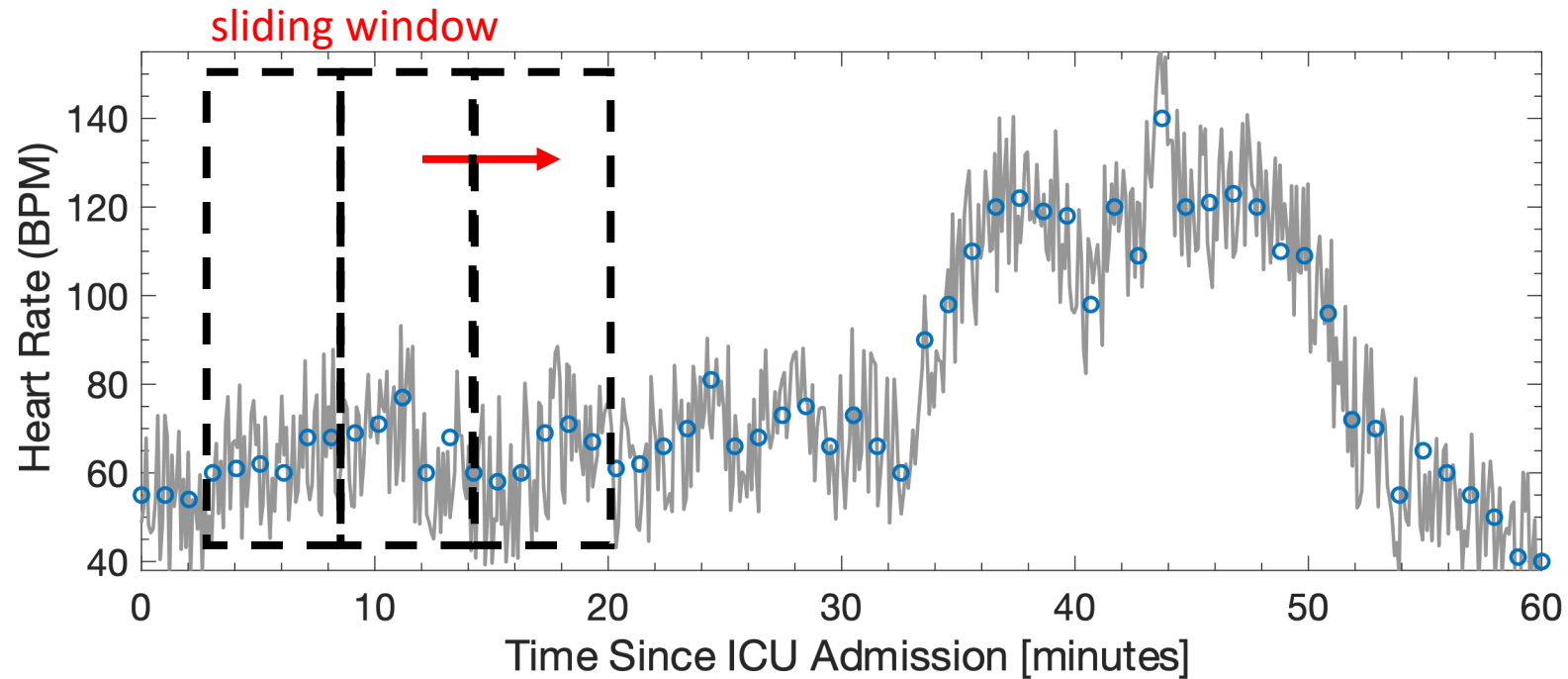
$$\mathbf{z}_1 = \begin{bmatrix} \bar{x}^{(1)} \\ \sigma^{(1)} \\ x_{min}^{(1)} \\ x_{max}^{(1)} \end{bmatrix}$$

Discretising Time: Windowing



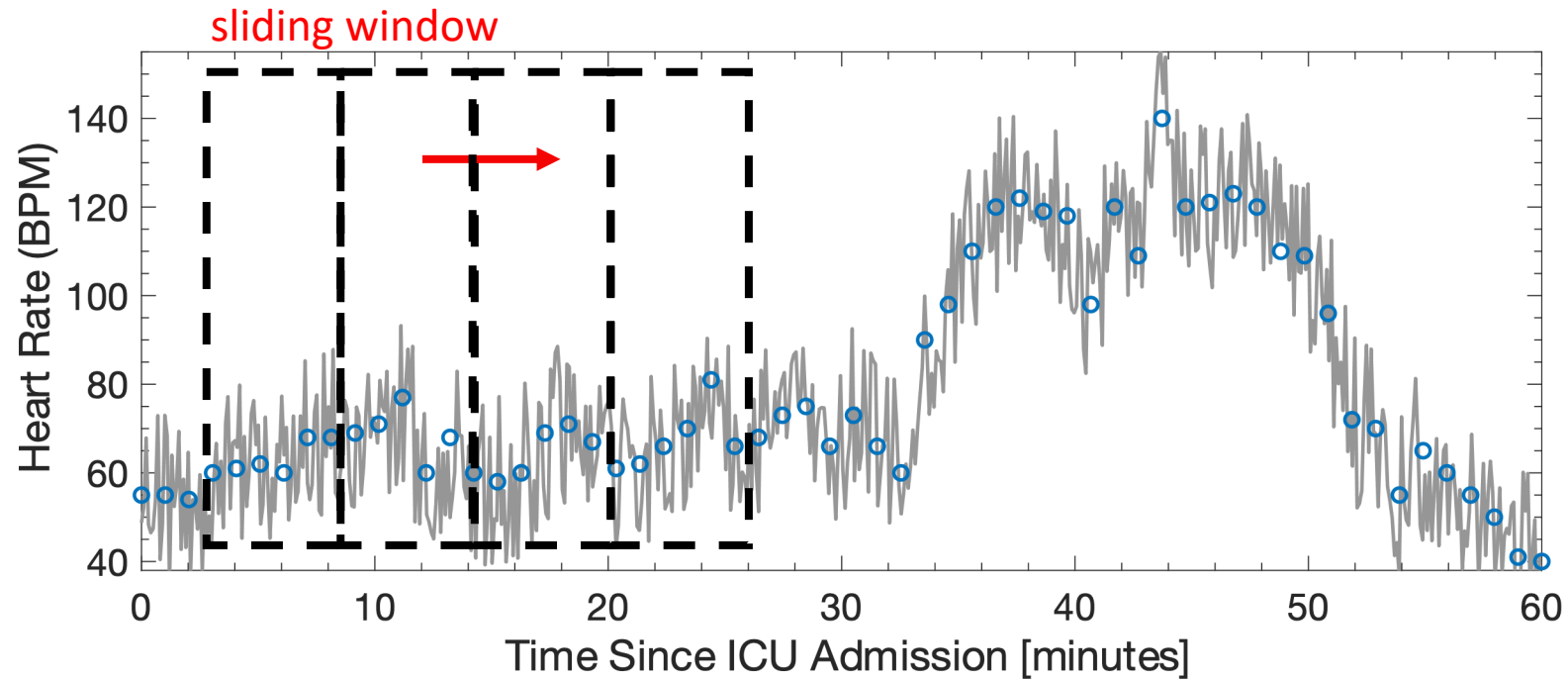
$$\mathbf{z}_2 = \begin{bmatrix} \bar{x}^{(2)} \\ \sigma^{(2)} \\ x_{min}^{(2)} \\ x_{max}^{(2)} \end{bmatrix}$$

Discretising Time: Windowing



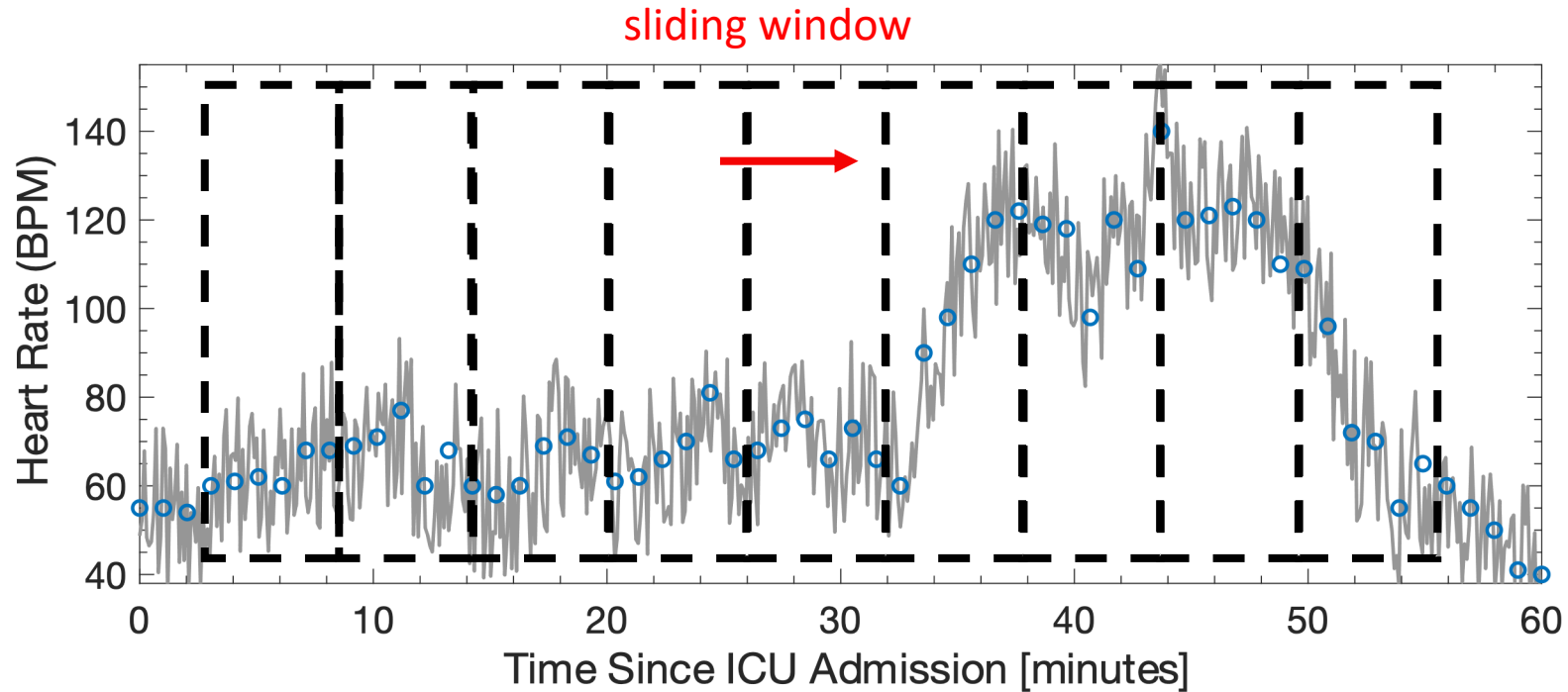
$$\mathbf{z}_3 = \begin{bmatrix} \bar{x}^{(3)} \\ \sigma^{(3)} \\ x_{min}^{(3)} \\ x_{max}^{(3)} \end{bmatrix}$$

Discretising Time: Windowing



$$\mathbf{z}_3 = \begin{bmatrix} \bar{x}^{(3)} \\ \sigma^{(3)} \\ x_{min}^{(3)} \\ x_{max}^{(3)} \end{bmatrix}$$

Discretising Time: Windowing



$$\mathbf{z}_m = \begin{bmatrix} \bar{x}^{(m)} \\ \sigma^{(m)} \\ x_{min}^{(m)} \\ x_{max}^{(m)} \end{bmatrix}$$

$$\mathbf{z}_m = \left[\bar{x}^{(m)}, \sigma^{(m)}, x_{min}^{(m)}, x_{max}^{(m)} \right]^T$$

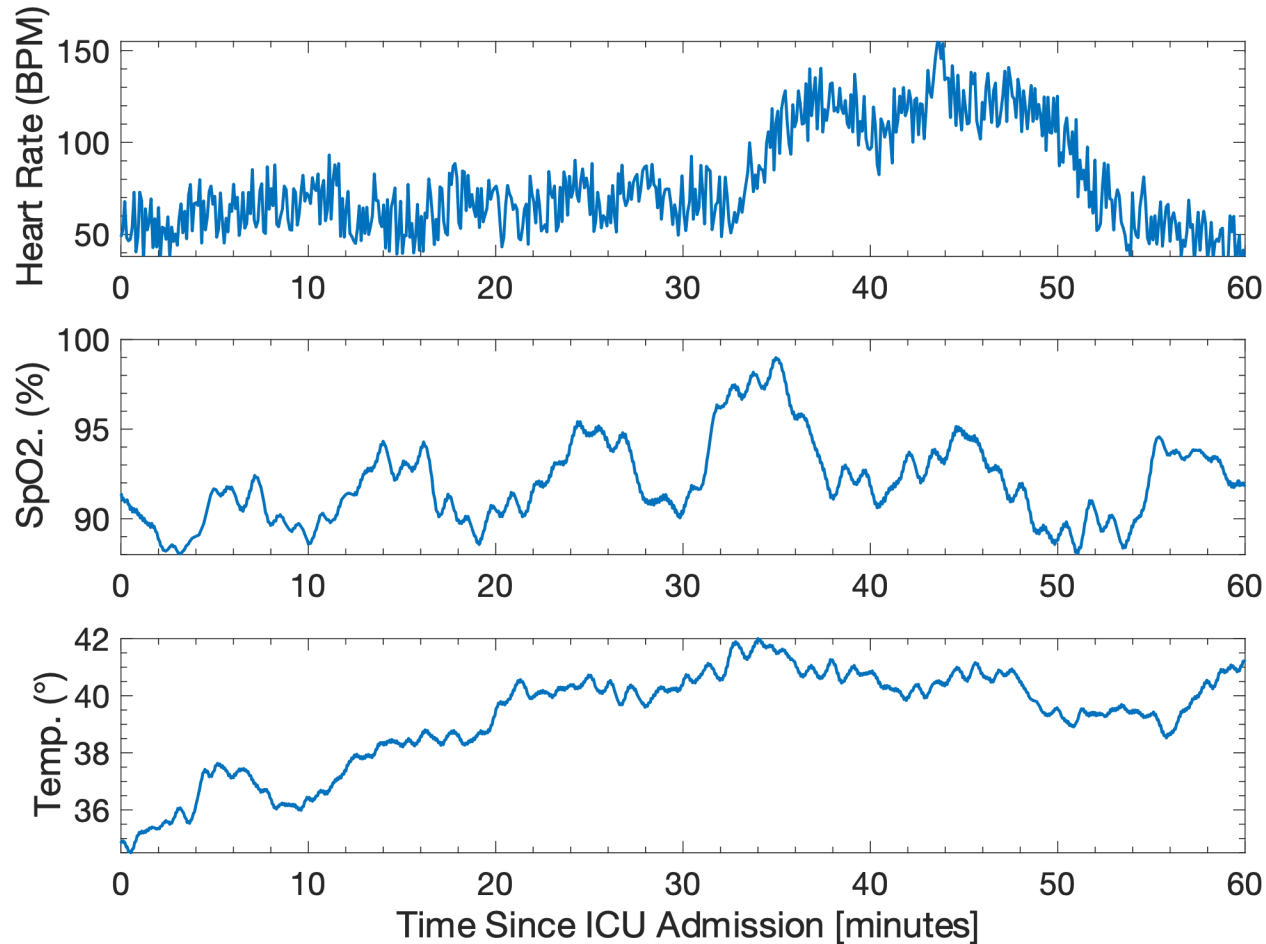
$$\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \mathbf{z}_3, \dots, \mathbf{z}_T]$$

$$\mathbf{Z} \in \mathbb{R}^{P \times T}$$

P : number of features, input channels, etc.

T : number of timesteps.

Handling Multivariate Time-Series Data



Handling uneven / irregularly sampled data:

$$\mathbf{x}_1 = \{x_1, x_2, \dots x_m\}$$

$$\mathbf{x}_2 = \{x_1, x_2, \dots x_n\}$$

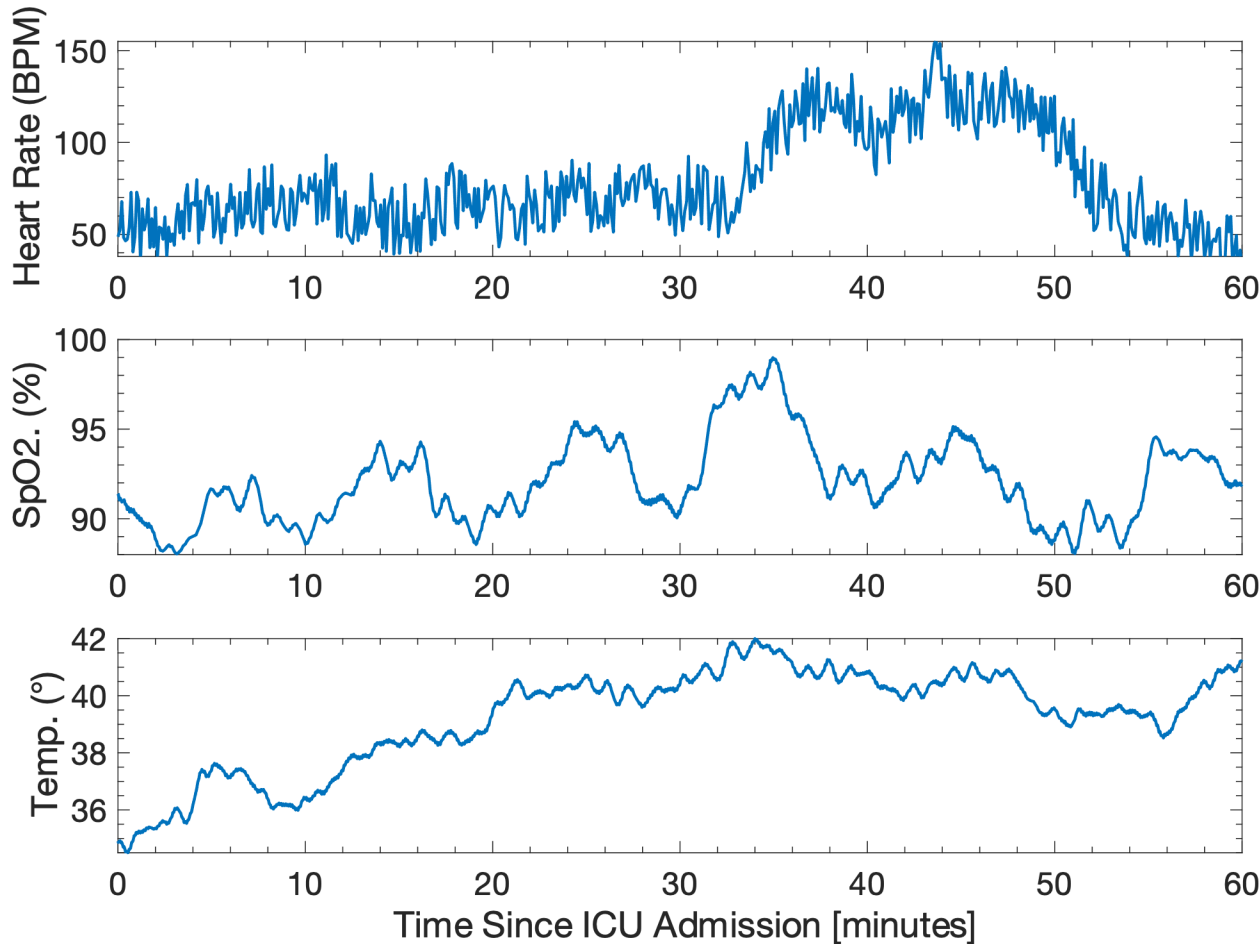
$$\mathbf{x}_3 = \{x_1, x_2, \dots x_n\}$$

$$m > n$$

Resampling

- Downsample (or window)
- Don't up-sample (if you can avoid it); you're interpolating information that you don't know, which is always dangerous

Handling Multivariate Time-Series Data



Handling uneven / irregularly sampled data:

$$\mathbf{x}_1 = \{x_1, x_2, \dots, x_m\}$$

$$\mathbf{x}_2 = \{x_1, x_2, \dots, x_n\}$$

$$\mathbf{x}_3 = \{x_1, x_2, \dots, x_n\}$$

$$m > n$$

Resampling

- Downsample (or window)
- Don't up-sample (if you can avoid it); you're interpolating information that you don't know, which is always dangerous

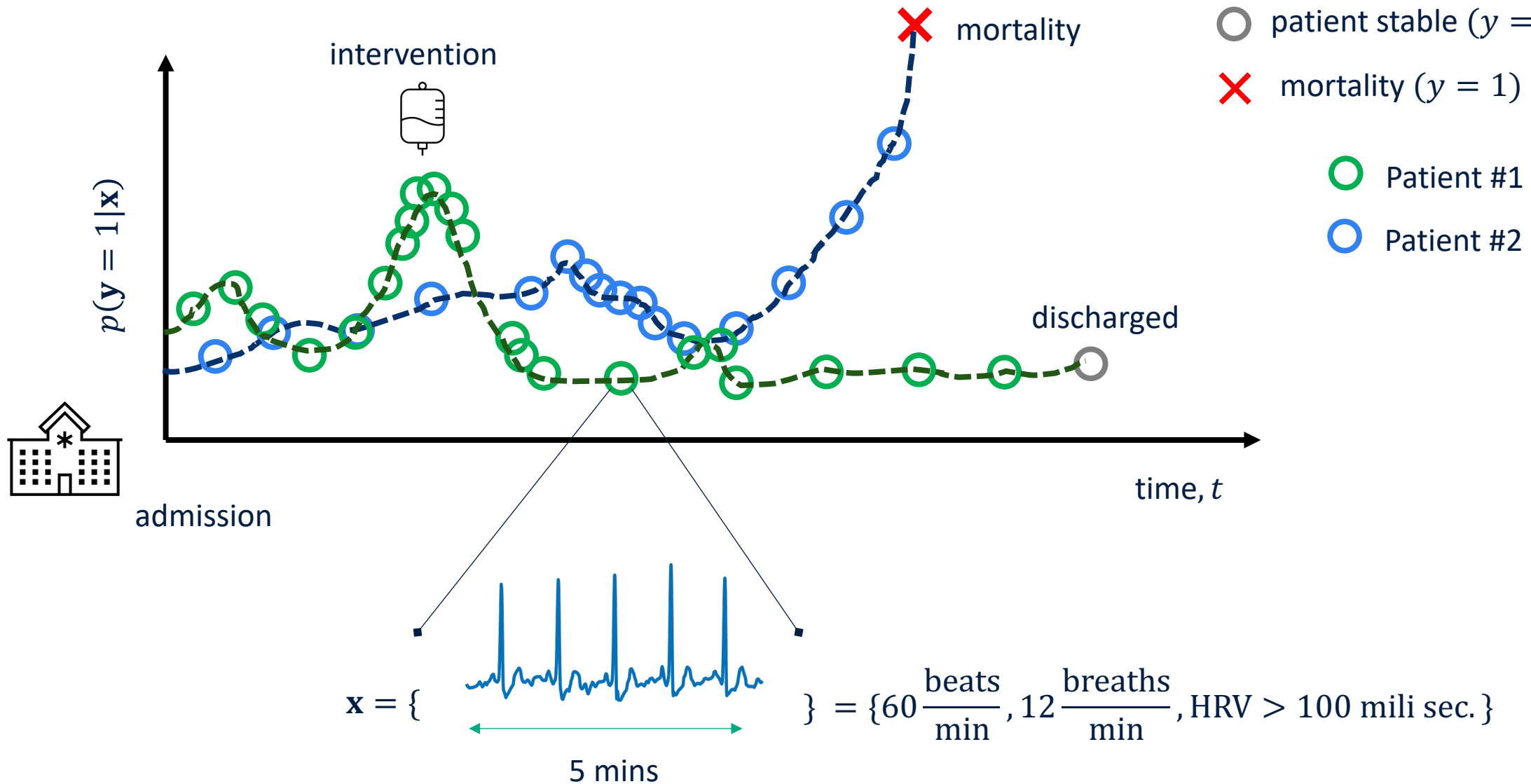
$$\mathbf{Z} \in \mathbb{R}^{P \times T}$$

for each time-series feature
(e.g. HR, SpO2, Temp.)

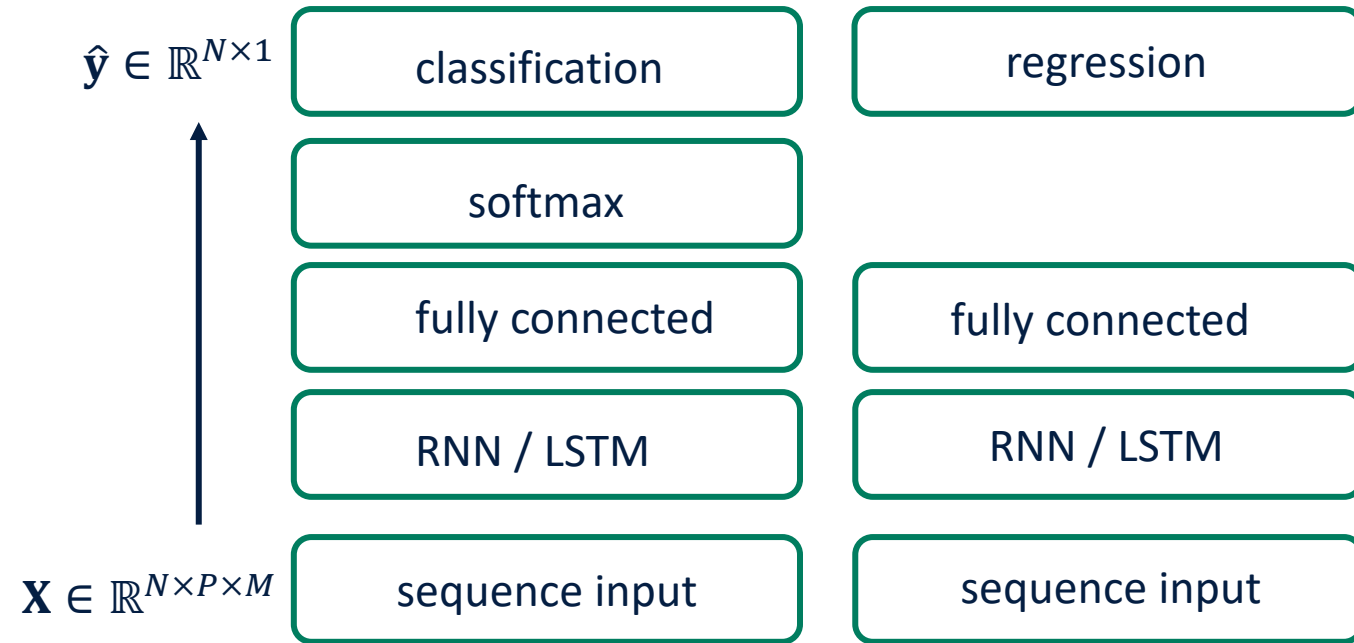
$$\mathbf{Z} \in \mathbb{R}^{(P \times 3) \times T}$$

ICU admission problem

After 3 days, is the patient alive or dead, $m = 5$ days?



Setting up your RNN



N : number of samples / observations.

M : number of timesteps.

P : number of features, input channels, etc.

Input data considerations:

LSTM networks support input data with varying sequence lengths.

- **Padding:** add values (usually zeros) to the start/end of sequences so that all the sequences have the same length as the longest/shortest sequence
- **Truncating:** make all sequences the same length as the shortest sequence. The remaining data in the sequences is discarded.
- **Splitting:** pads all the sequences to the nearest multiple of the specified length that is greater than the longest sequence length. Then, split each sequence into smaller sequences of the specified length

What framework to use?*



For some good comparison information:

<https://www.projectpro.io/article/pytorch-vs-tensorflow-2021-a-head-to-head-comparison/416>

<https://medium.com/analytics-vidhya/ml03-9de2f0dbd62d>

*we're using PyTorch in this workshop

LSTM example

$N = 500$: number of samples / observations.

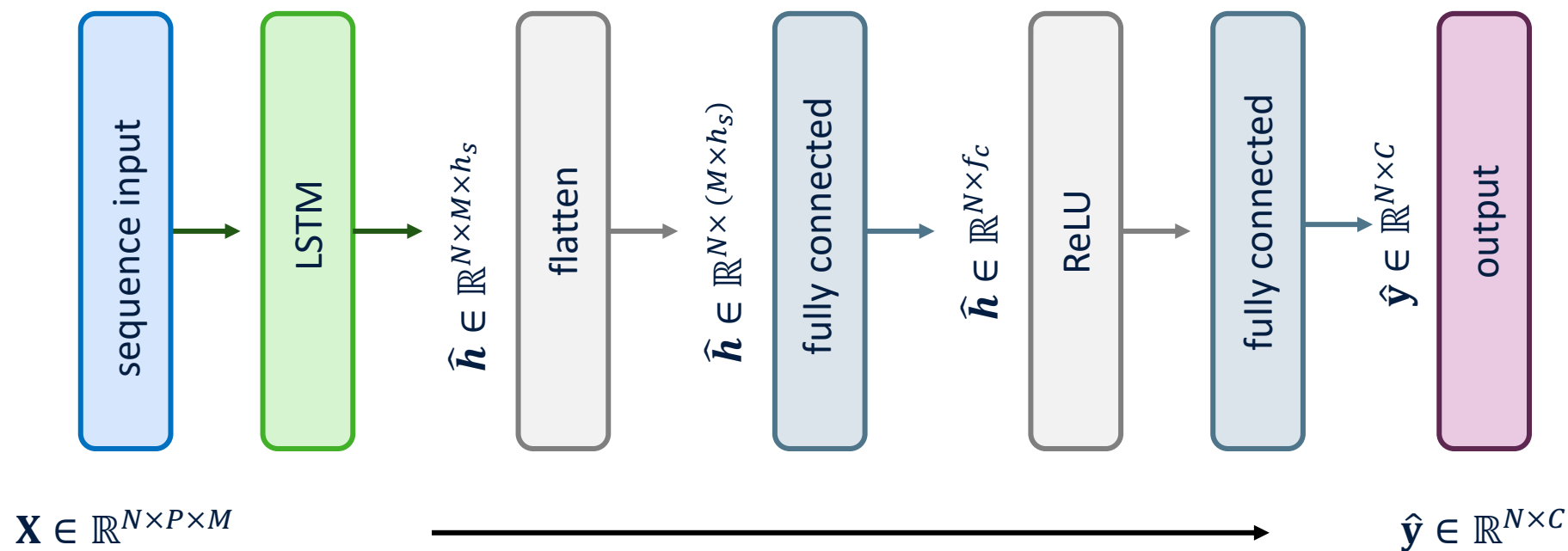
$M = 10$: number of timesteps

$P = 3$: number of features, input channels, etc.

$C = 6$: number of classes

$h_s = 128$: hidden size

$f_c = 64$: number of fully connected nodes



LSTM example code

```
import torch #pytorch
import torch.nn as nn
from torch.autograd import Variable

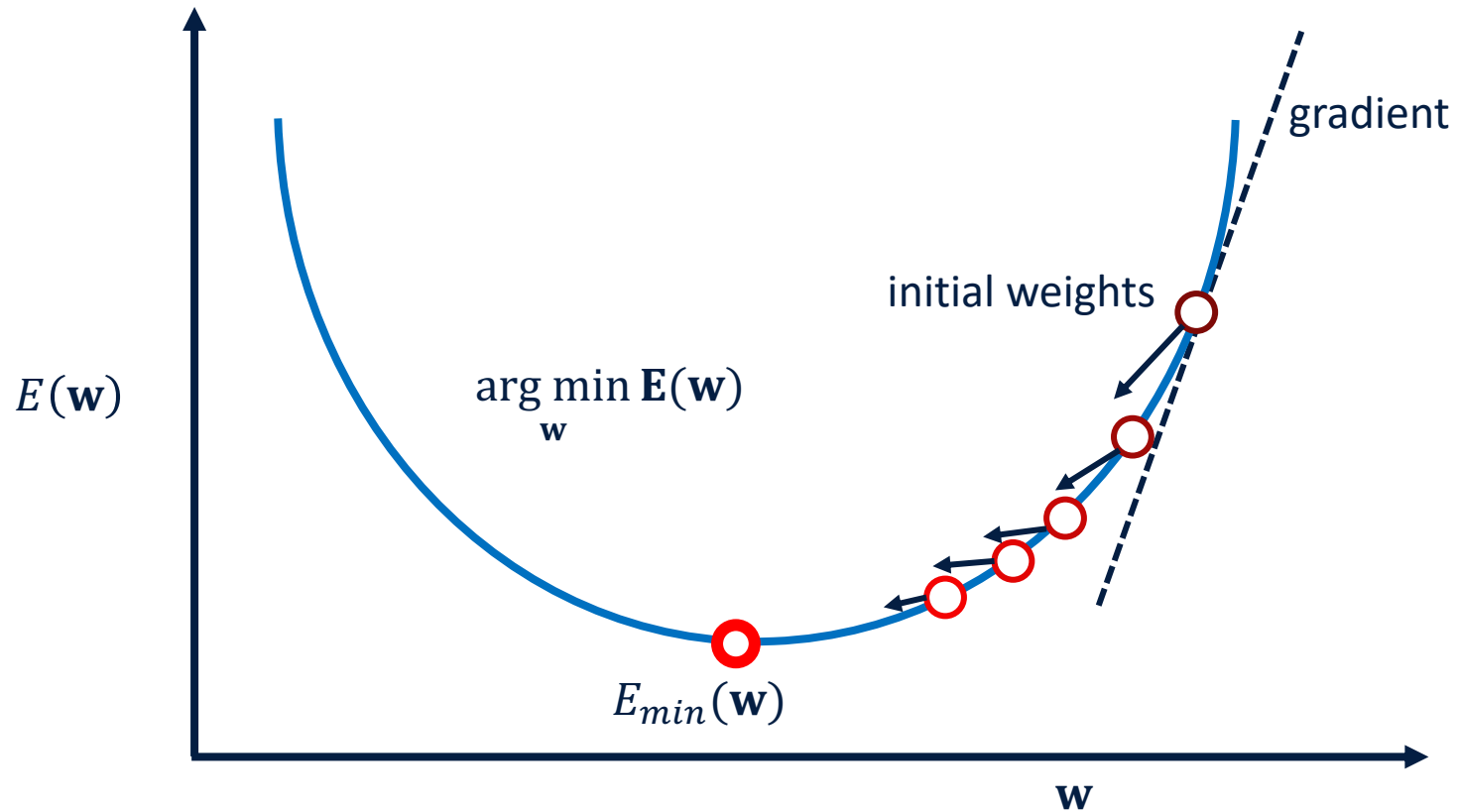
class Model(nn.Module):
    def __init__(self, num_classes=3, input_size=3, hidden_size=128, num_layers=1, seq_length=10):
        super(model, self).__init__()
        self.num_classes = num_classes #number of classes
        self.num_layers = num_layers #number of recurrent layers
        self.input_size = input_size #input size (# features / channels)
        self.hidden_size = hidden_size #hidden state
        self.seq_length = seq_length #sequence length

        self.lstm = nn.LSTM(input_size=input_size, hidden_size=hidden_size,
                             num_layers=num_layers, batch_first=True) #lstm
        self.fc_1 = nn.Linear(hidden_size, 100) #fully connected 1
        self.fc = nn.Linear(100, num_classes) #fully connected last layer

        self.relu = nn.ReLU()

    def forward(self,x):
        h_0 = Variable(torch.zeros(self.num_layers, x.size(0), self.hidden_size)) #hidden state
        c_0 = Variable(torch.zeros(self.num_layers, x.size(0), self.hidden_size)) #internal state
        # Propagate input through LSTM
        output, (hn, cn) = self.lstm(x, (h_0, c_0)) #lstm with input, hidden, and internal state
        hn = hn.view(-1, self.hidden_size) #reshaping the data for Dense layer next
        out = self.fc_1(hn) #first Dense
        out = self.relu(out) #relu
        out = self.fc(out) #Final Output
        return out
```

Machine Learning 101



Jacobian

gradient $\mathbf{J} = \frac{\partial E(\mathbf{w})}{\partial \mathbf{w}} = \nabla E(\mathbf{w})$

Hessian

$$\mathbf{H} = \frac{\partial^2 E(\mathbf{w})}{\partial \mathbf{w} \partial \mathbf{w}^\top} = \nabla^2 E(\mathbf{w})$$

We can use Newton-Raphson

$$x_{n+1} = x_n - \frac{f'(x_n)}{f''(x_n)}$$

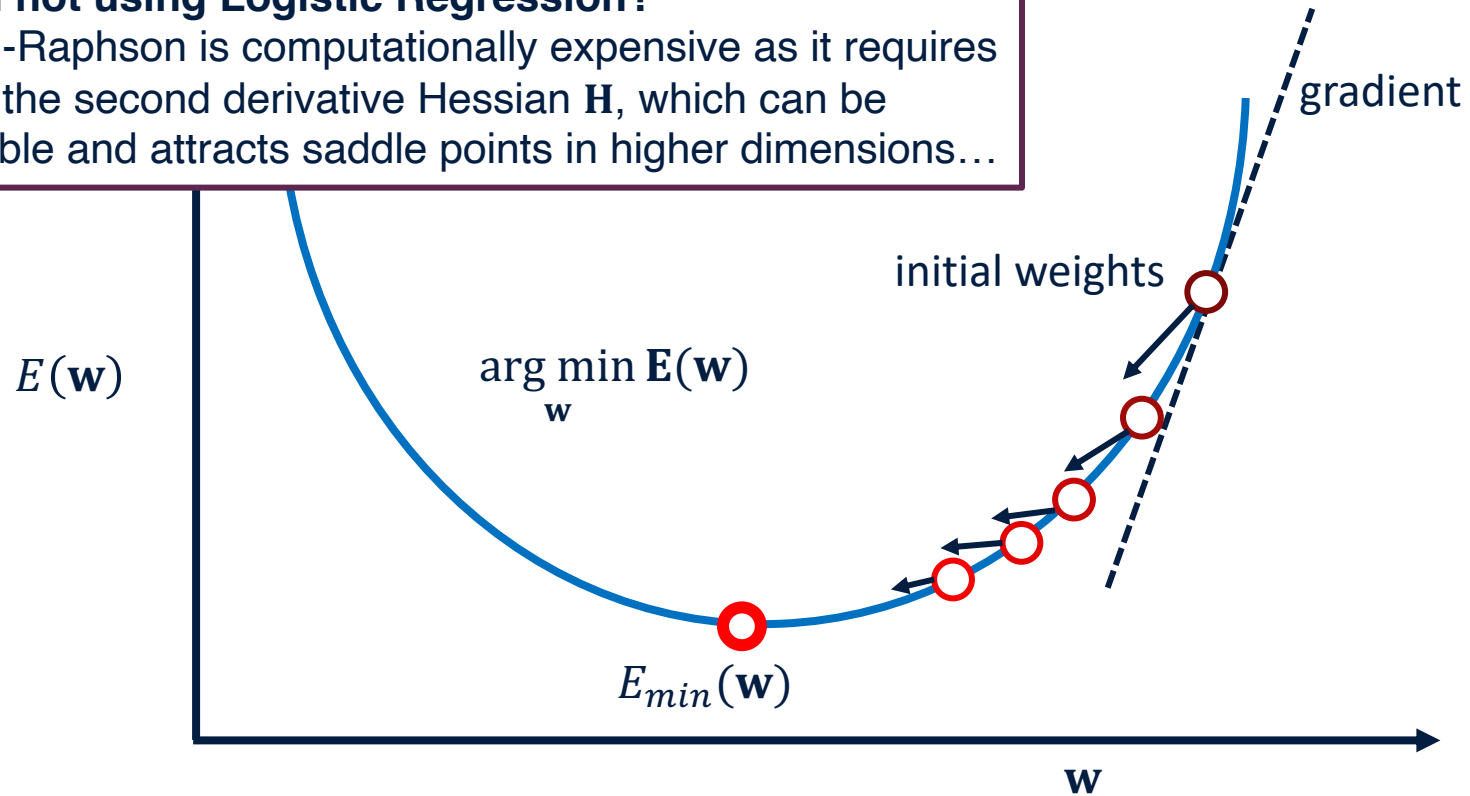
Training a model, TL;DR:

To minimise (or maximise) an objective function, take the gradient (partial derivatives) of the error function with respect to \mathbf{w} and set its derivatives to zero.

Machine Learning 101

But I'm not using Logistic Regression?

Newton-Raphson is computationally expensive as it requires solving the second derivative Hessian \mathbf{H} , which can be intractable and attracts saddle points in higher dimensions...



We can use Newton-Raphson

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t - \frac{\nabla_{\mathbf{w}_t} E(\mathbf{w}_t)}{\nabla_{\mathbf{w}_t}^2 E(\mathbf{w})}$$



Jacobian

$$\mathbf{J} = \frac{\partial E(\mathbf{w})}{\partial \mathbf{w}} = \nabla E(\mathbf{w})$$

Hessian

$$\mathbf{H} = \frac{\partial^2 E(\mathbf{w})}{\partial \mathbf{w} \partial \mathbf{w}^\top} = \nabla^2 E(\mathbf{w})$$

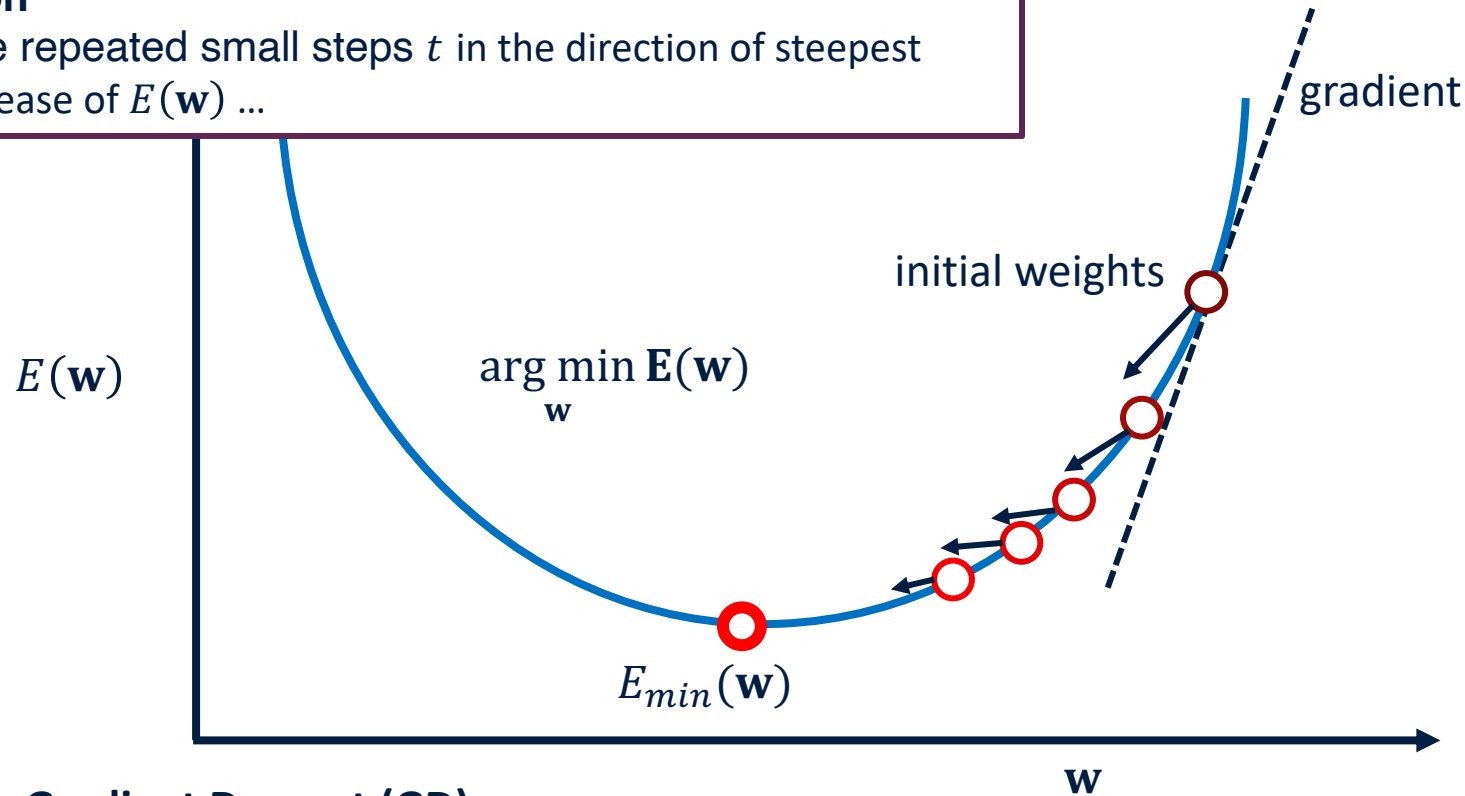
Training a model, $TL;DR$:

To minimise (or maximise) an objective function, take the gradient (partial derivatives) of the error function with respect to \mathbf{w} and set its derivatives to zero.

Machine Learning 101

Solution

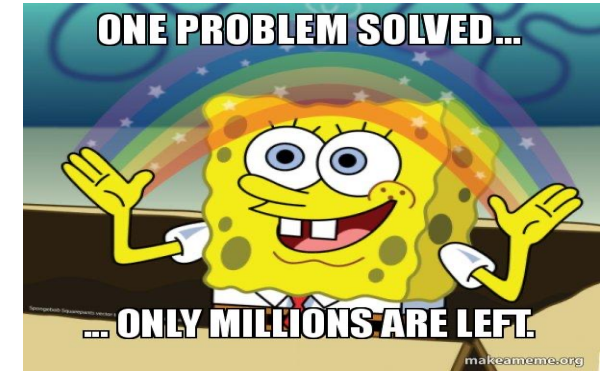
- Take repeated small steps t in the direction of steepest decrease of $E(\mathbf{w})$...



We can use **Gradient Descent (GD)**

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t - \eta_t \nabla_{\mathbf{w}_t} E(\mathbf{w}_t)$$

Where η is the learning rate, $\eta > 0$ determining the size of the step



Jacobian

$$\mathbf{J} = \frac{\partial E(\mathbf{w})}{\partial \mathbf{w}} = \nabla E(\mathbf{w})$$

~~Hessian~~

~~$$\mathbf{H} = \frac{\partial^2 E(\mathbf{w})}{\partial \mathbf{w} \partial \mathbf{w}^T} = \nabla^2 E(\mathbf{w})$$~~

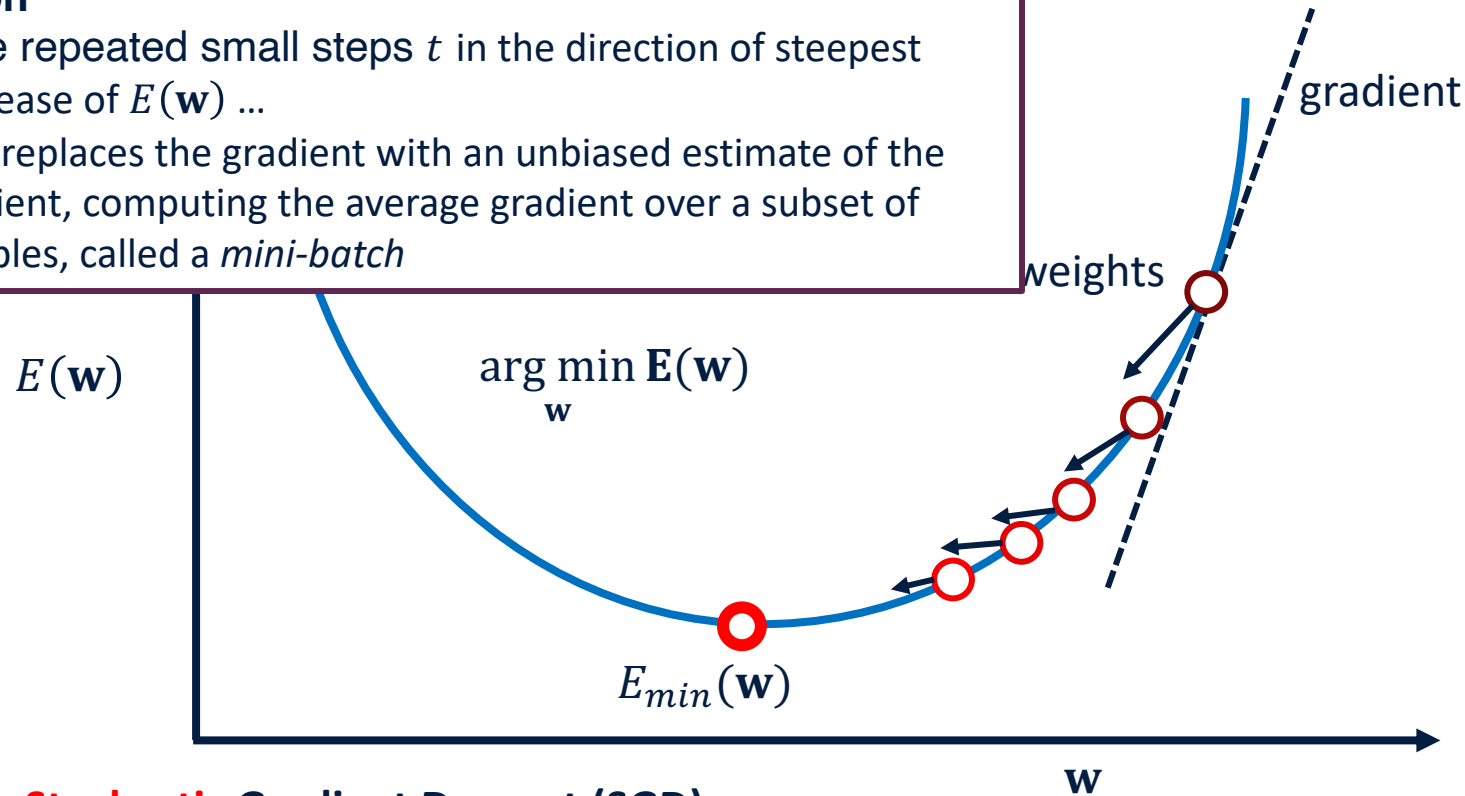
Training a model, $TL;DR$:

To minimise (or maximise) an objective function, take the gradient (partial derivatives) of the error function with respect to \mathbf{w} and set its derivatives to zero.

Machine Learning 101

Solution

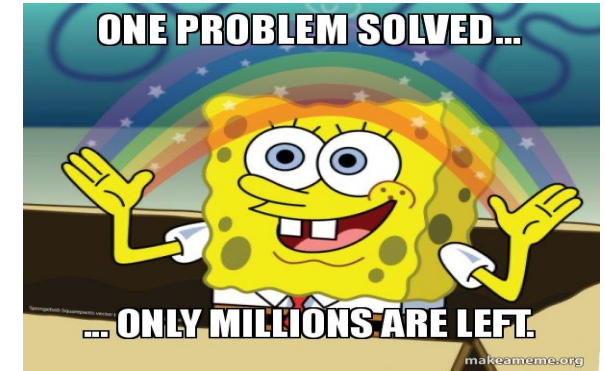
- Take repeated small steps t in the direction of steepest decrease of $E(\mathbf{w})$...
- SGD replaces the gradient with an unbiased estimate of the gradient, computing the average gradient over a subset of samples, called a *mini-batch*



We can use **Stochastic Gradient Descent (SGD)**

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t - \eta_t \frac{1}{m} \nabla_{\mathbf{w}_t} \sum_{i=1}^m E(\mathbf{w}_t)$$

Where η is the learning rate, $\eta > 0$ determining the size of the step



Jacobian

$$\mathbf{J} = \frac{\partial E(\mathbf{w})}{\partial \mathbf{w}} = \nabla E(\mathbf{w})$$

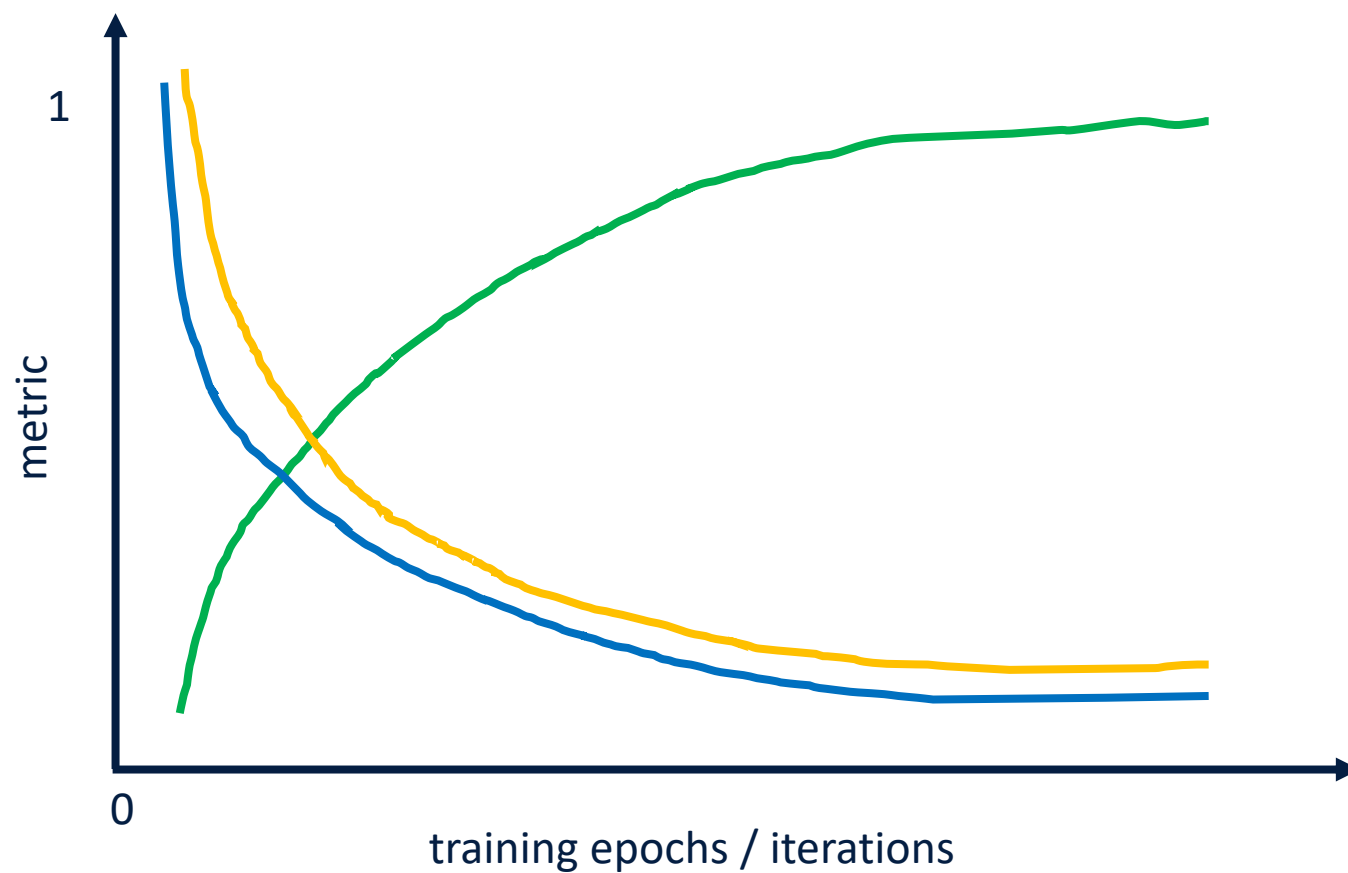
~~Hessian~~

~~$$\mathbf{H} = \frac{\partial^2 E(\mathbf{w})}{\partial \mathbf{w} \partial \mathbf{w}^T} = \nabla^2 E(\mathbf{w})$$~~

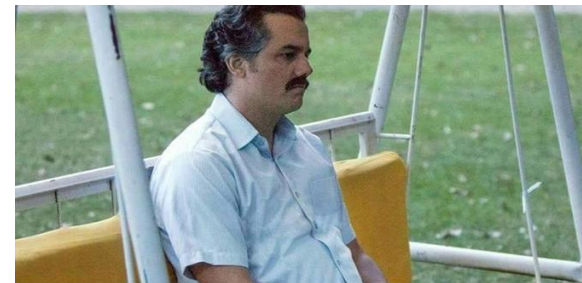
Training a model, $TL;DR$:

To minimise (or maximise) an objective function, take the gradient (partial derivatives) of the error function with respect to \mathbf{w} and set its derivatives to zero.

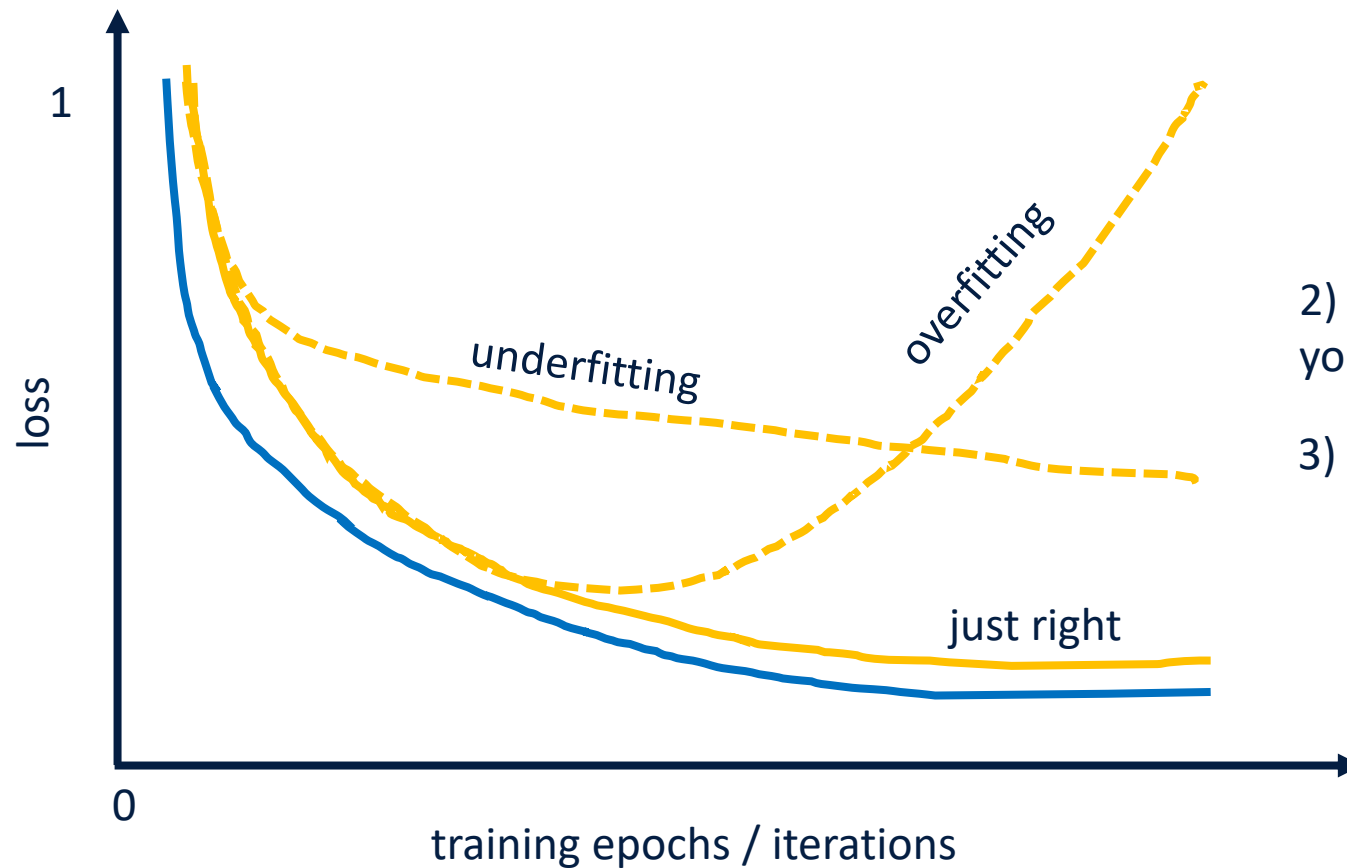
How to train your model



Waiting on your model to train



Avoiding Overfitting



Tips:

1) adjust your learning rate

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t - \eta_t \frac{1}{m} \nabla_{\mathbf{w}_t} \sum_{i=1}^m E(\mathbf{w}_t)$$

Where η is the learning rate, $\eta > 0$
determining the size of the step

2) Add regularization by penalizing
your loss function

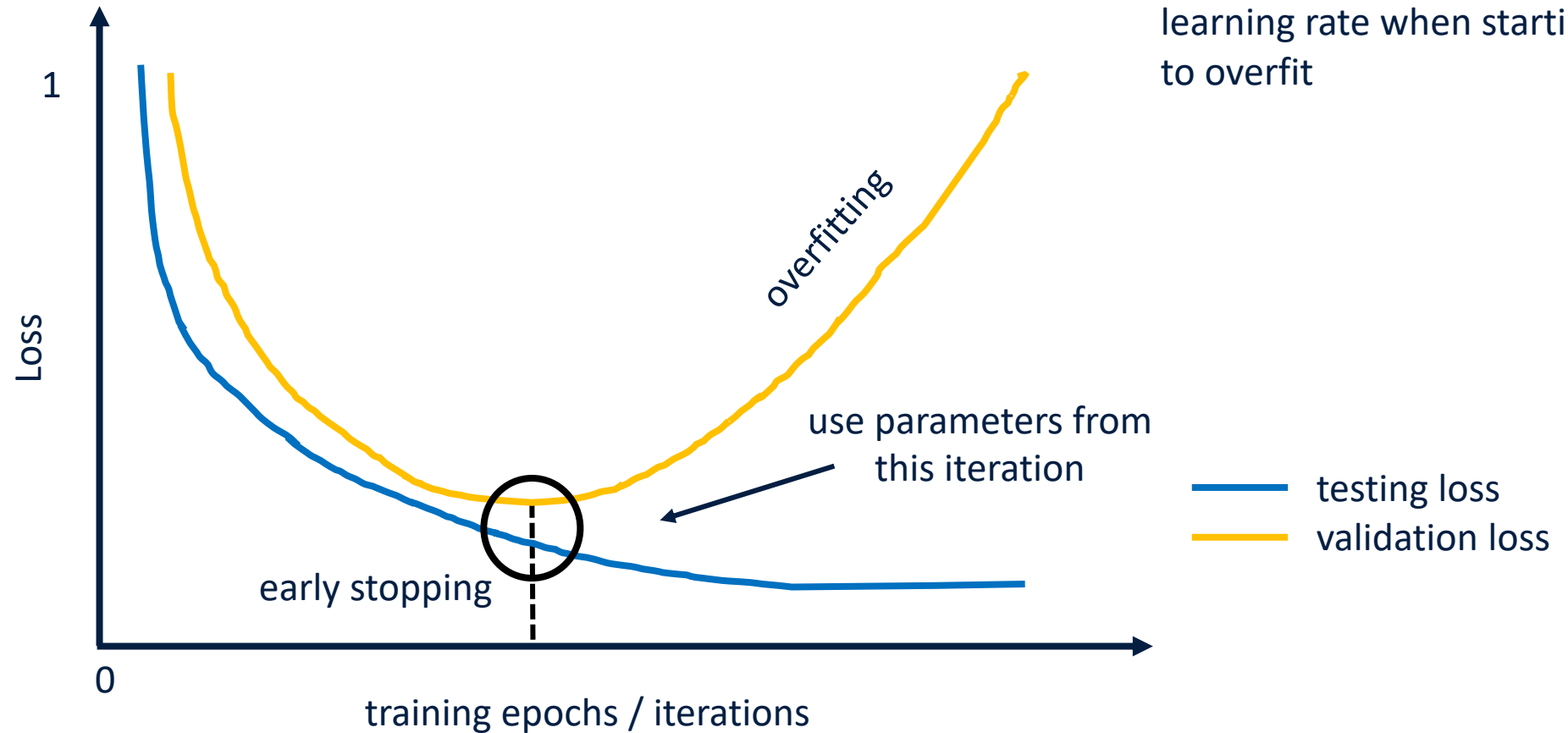
3) Add dropout to your model

— testing loss
— validation loss

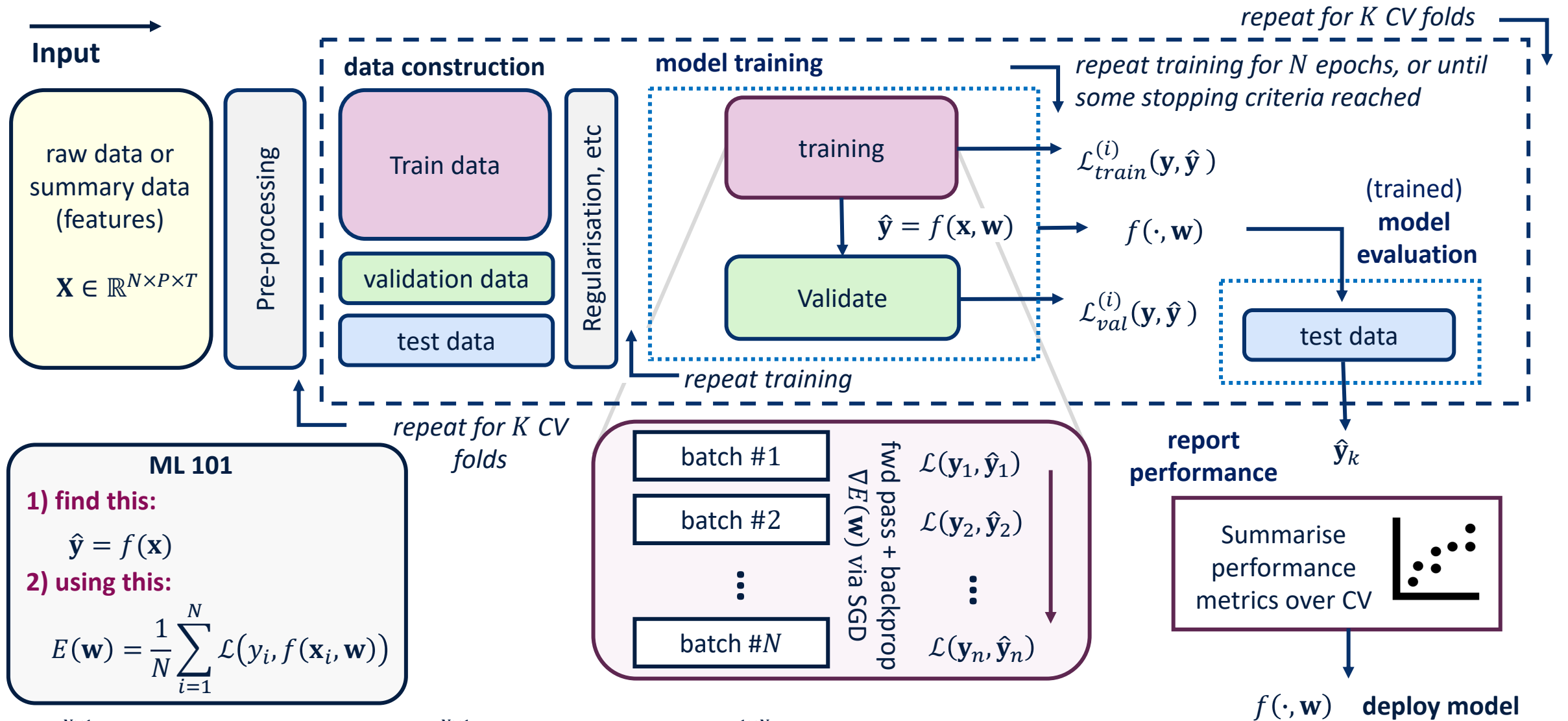
Avoiding Overfitting

Tips:

- 4) Add early stopping criteria
- 5) Dynamically lower your learning rate when starting to overfit

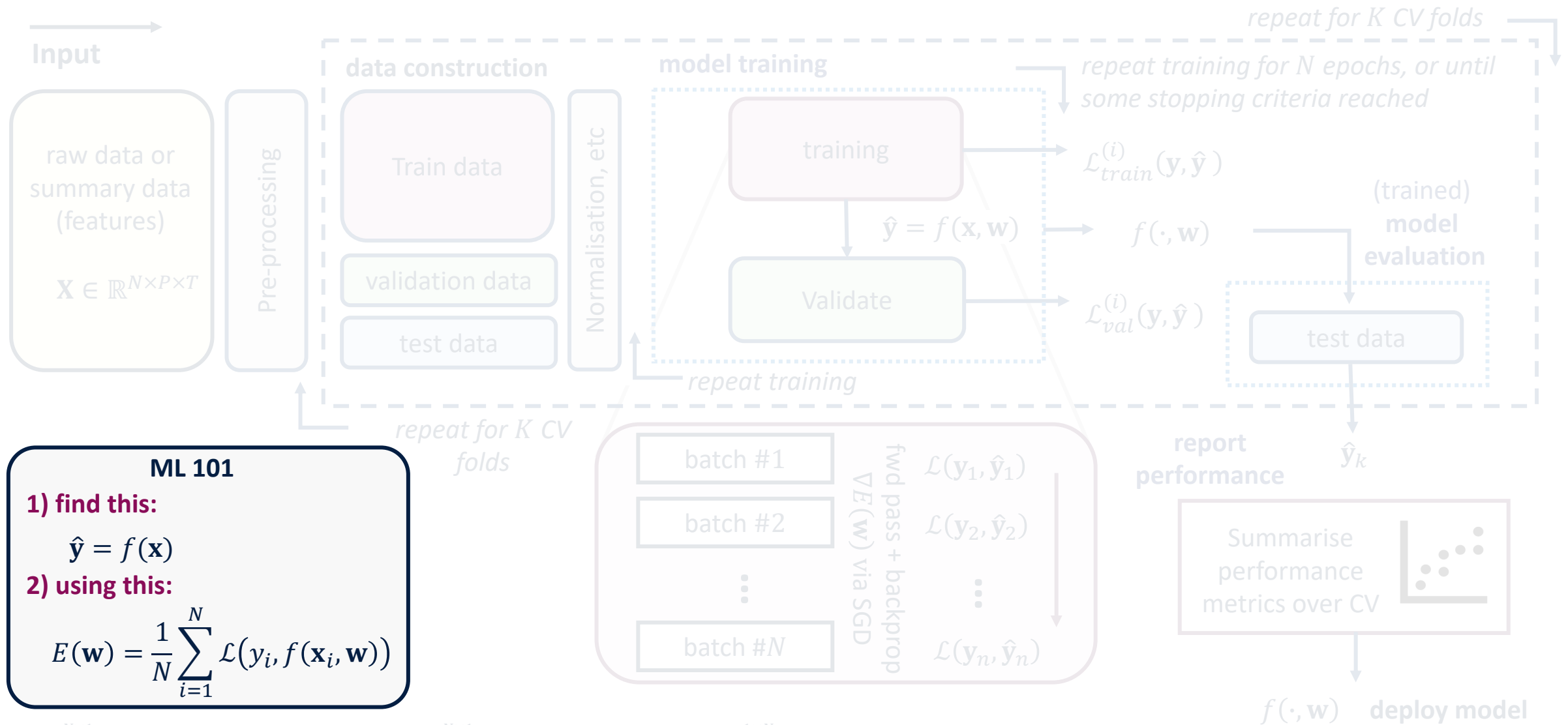


Typical Machine Learning Pipeline



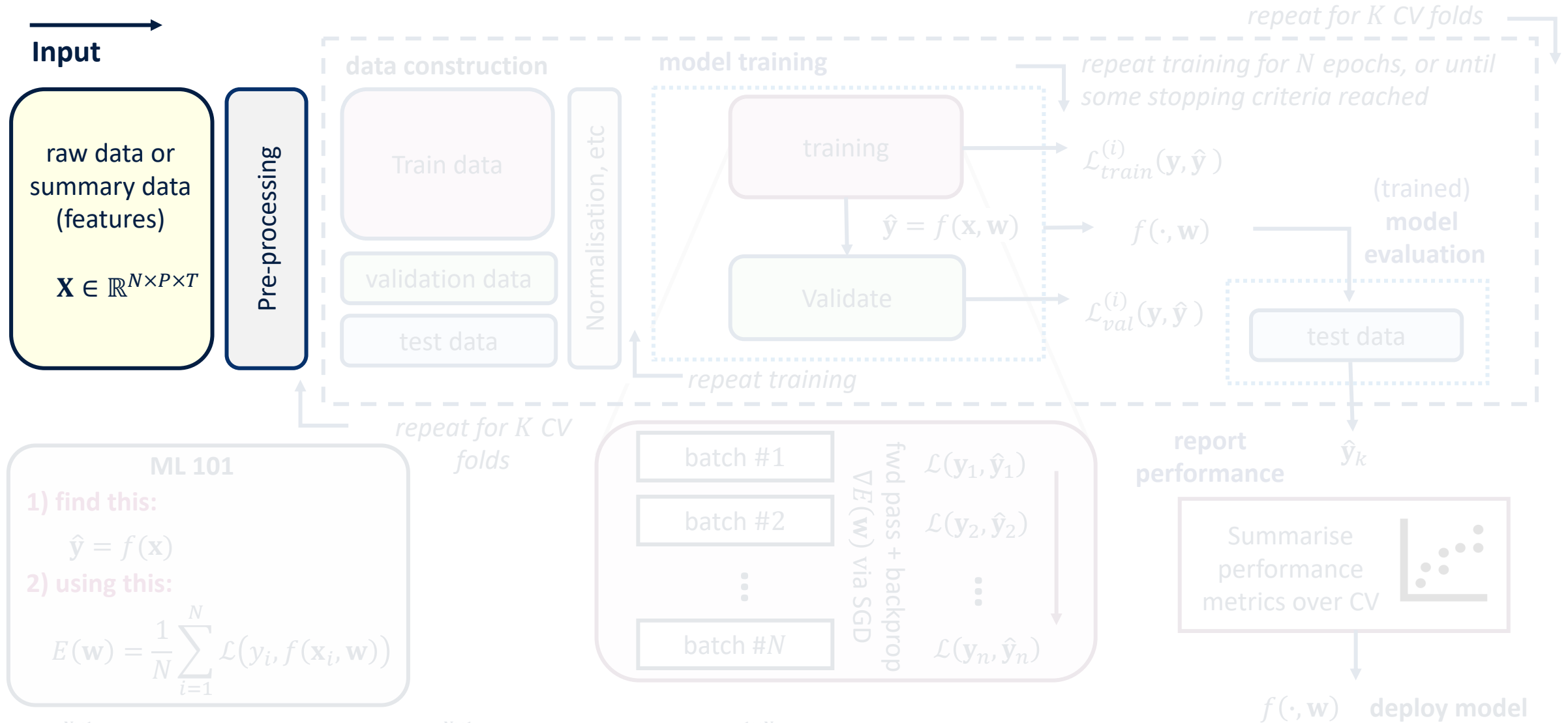
$\hat{\mathbf{y}} \in \mathbb{R}^{N \times 1}$ are the predictions / estimations; $\mathbf{y} \in \mathbb{R}^{N \times 1}$ are the response labels; $\mathbf{w} \in \mathbb{R}^{1 \times N}$ are the weights or parameters of a model
 N : number of samples / observations; T : number of timesteps; P : number of features, input channels, etc.

Typical Machine Learning Pipeline



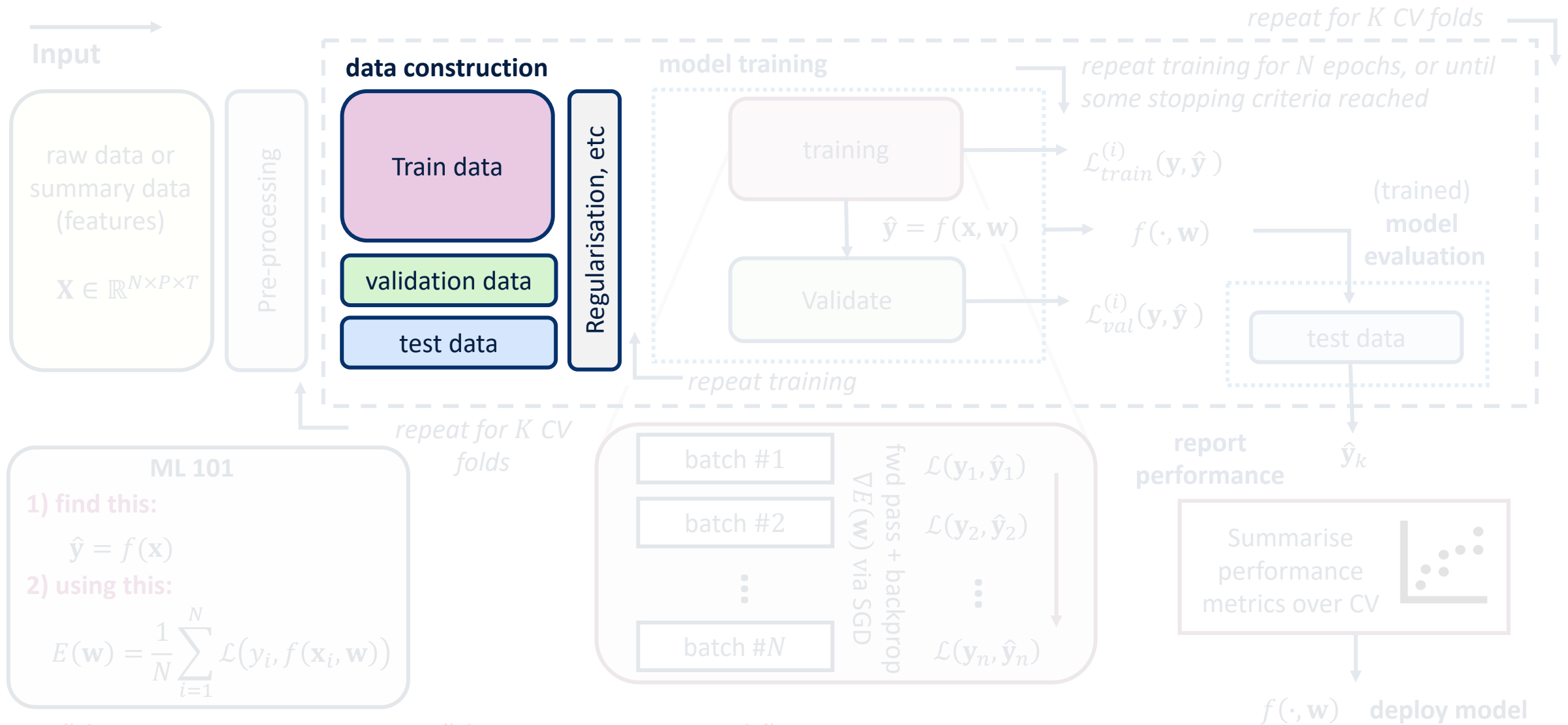
$\hat{\mathbf{y}} \in \mathbb{R}^{N \times 1}$ are the predictions / estimations; $\mathbf{y} \in \mathbb{R}^{N \times 1}$ are the response labels; $\mathbf{w} \in \mathbb{R}^{1 \times N}$ are the weights or parameters of a model
 N : number of samples / observations; M : number of timesteps; P : number of features, input channels, etc.

Typical Machine Learning Pipeline



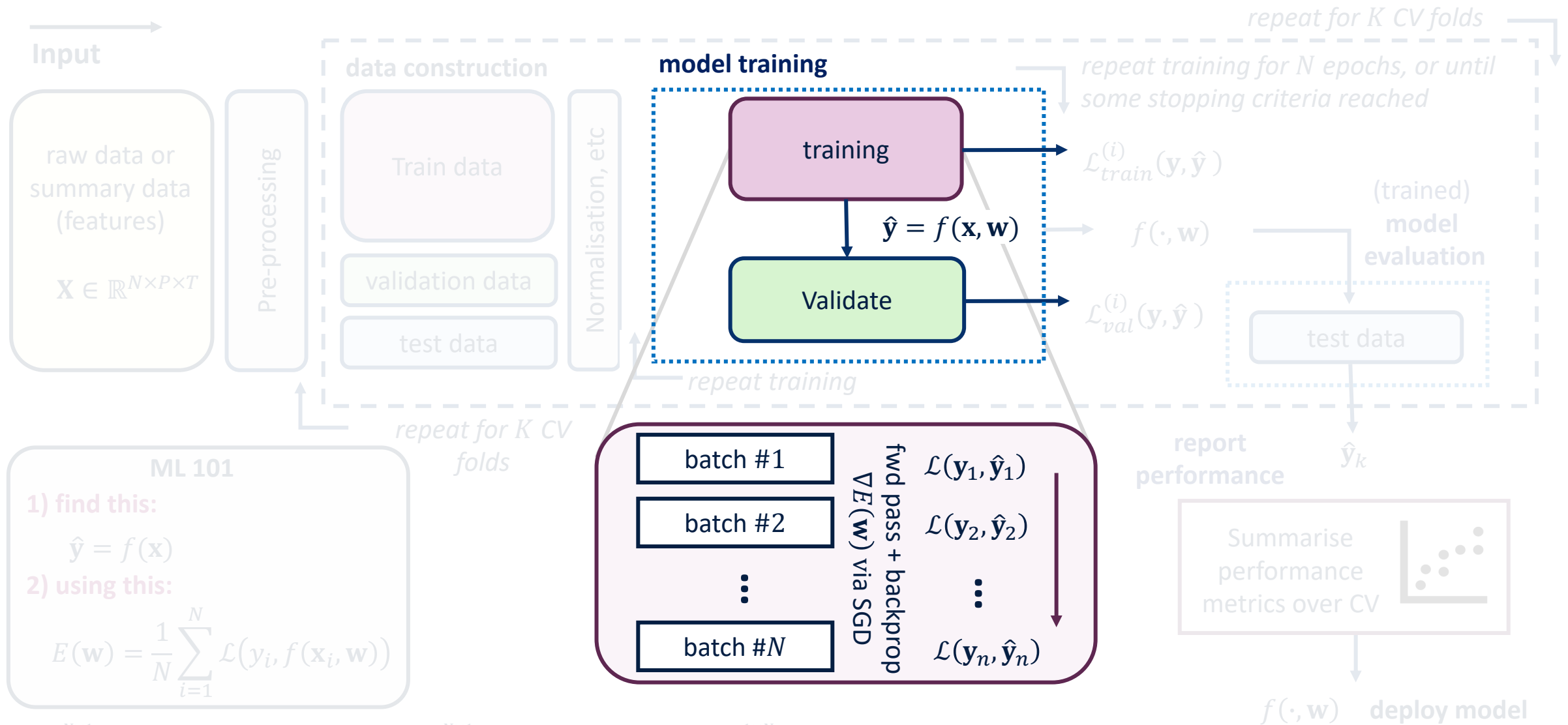
$\hat{\mathbf{y}} \in \mathbb{R}^{N \times 1}$ are the predictions / estimations; $\mathbf{y} \in \mathbb{R}^{N \times 1}$ are the response labels; $\mathbf{w} \in \mathbb{R}^{1 \times N}$ are the weights or parameters of a model
 N : number of samples / observations; M : number of timesteps; P : number of features, input channels, etc.

Typical Machine Learning Pipeline



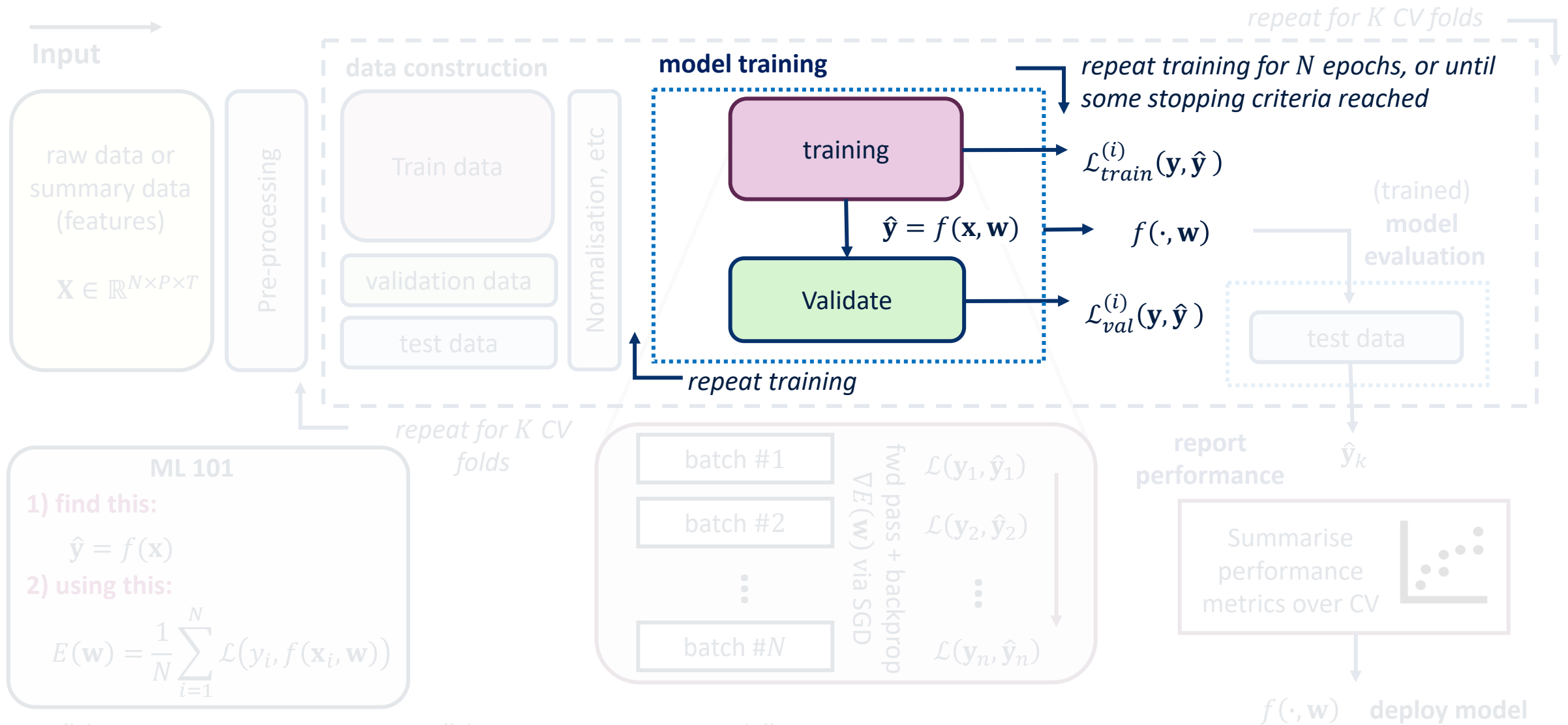
$\hat{\mathbf{y}} \in \mathbb{R}^{N \times 1}$ are the predictions / estimations; $\mathbf{y} \in \mathbb{R}^{N \times 1}$ are the response labels; $\mathbf{w} \in \mathbb{R}^{1 \times N}$ are the weights or parameters of a model
 N : number of samples / observations; M : number of timesteps; P : number of features, input channels, etc.

Typical Machine Learning Pipeline



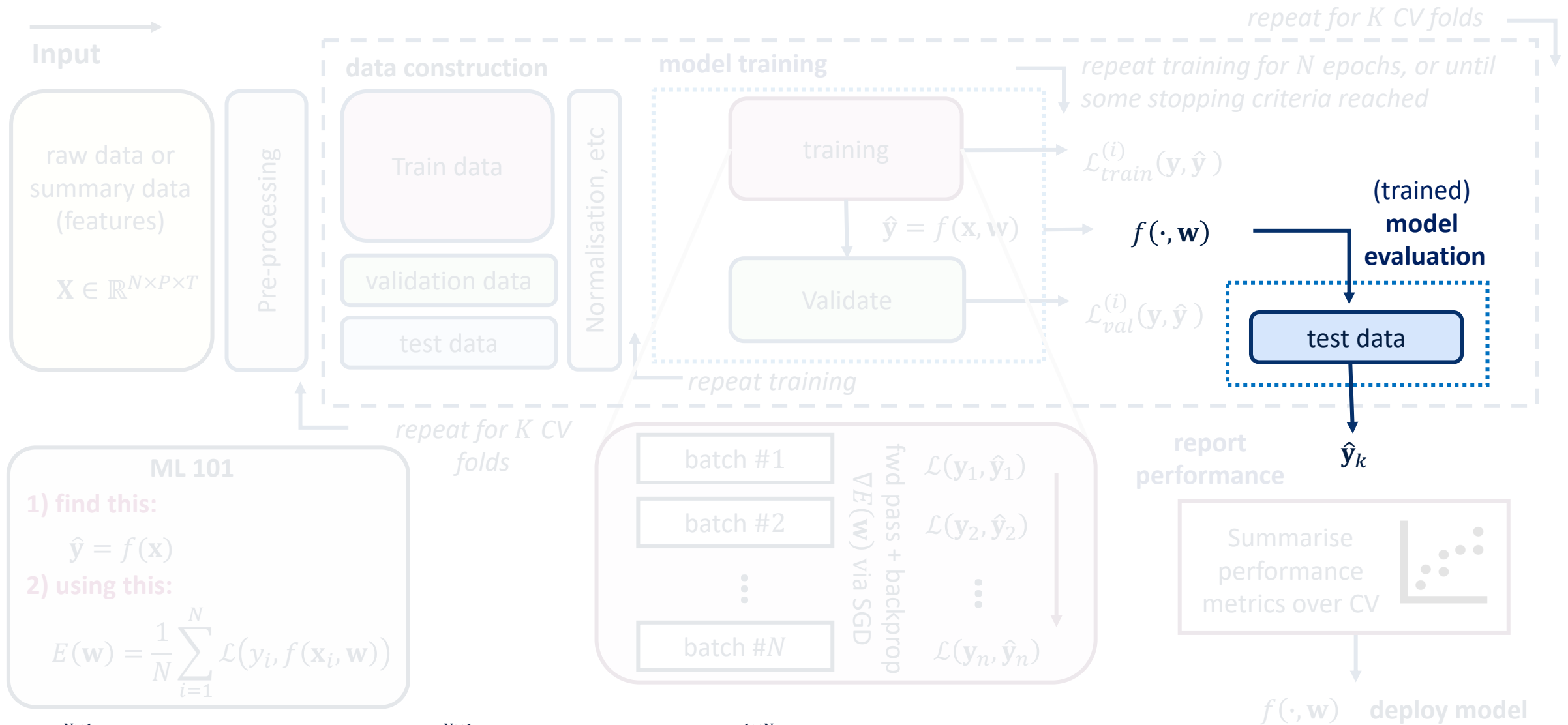
$\hat{\mathbf{y}} \in \mathbb{R}^{N \times 1}$ are the predictions / estimations; $\mathbf{y} \in \mathbb{R}^{N \times 1}$ are the response labels; $\mathbf{w} \in \mathbb{R}^{1 \times N}$ are the weights or parameters of a model
N: number of samples / observations; M: number of timesteps; P: number of features, input channels, etc.

Typical Machine Learning Pipeline



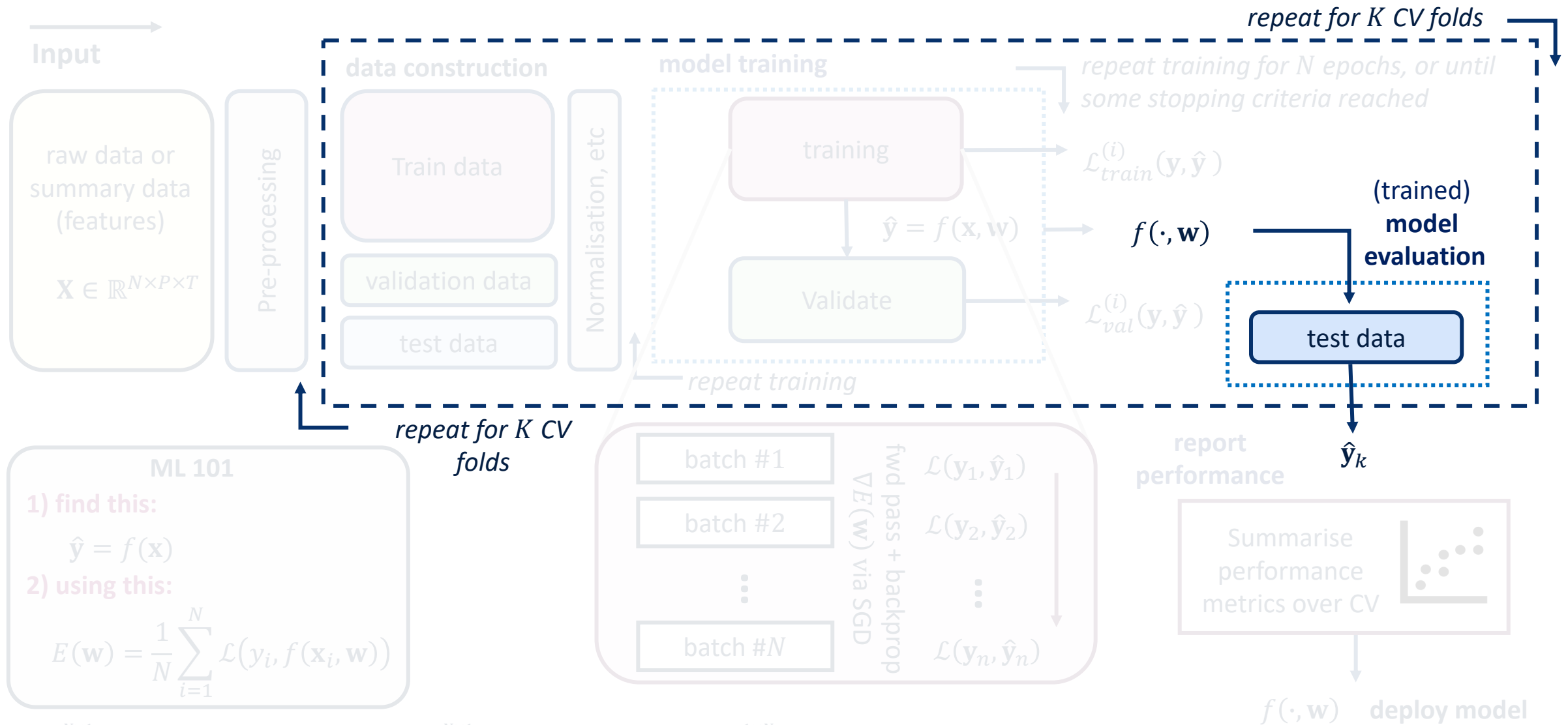
$\hat{\mathbf{y}} \in \mathbb{R}^{N \times 1}$ are the predictions / estimations; $\mathbf{y} \in \mathbb{R}^{N \times 1}$ are the response labels; $\mathbf{w} \in \mathbb{R}^{1 \times N}$ are the weights or parameters of a model
 N : number of samples / observations; M : number of timesteps; P : number of features, input channels, etc.

Typical Machine Learning Pipeline



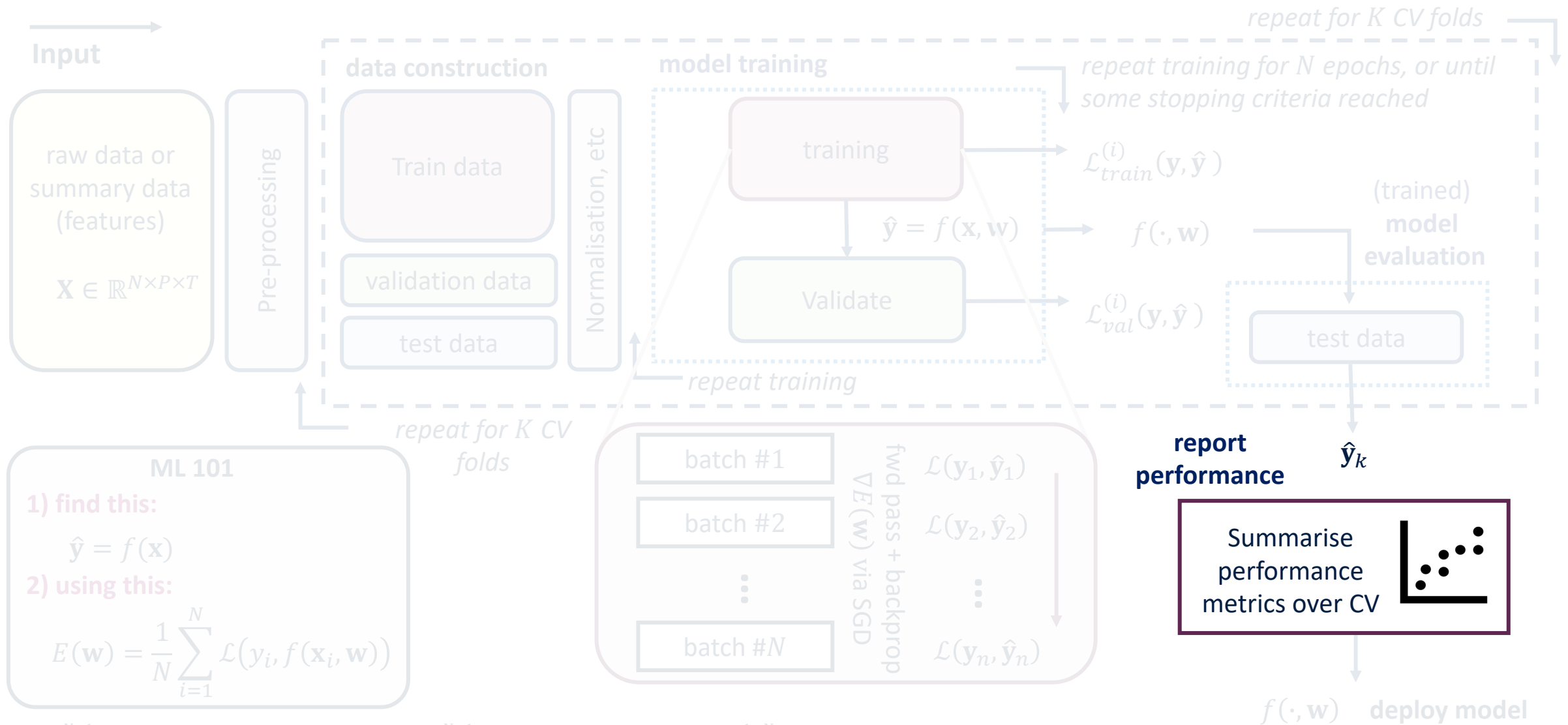
$\hat{\mathbf{y}} \in \mathbb{R}^{N \times 1}$ are the predictions / estimations; $\mathbf{y} \in \mathbb{R}^{N \times 1}$ are the response labels; $\mathbf{w} \in \mathbb{R}^{1 \times N}$ are the weights or parameters of a model
 N : number of samples / observations; M : number of timesteps; P : number of features, input channels, etc.

Typical Machine Learning Pipeline



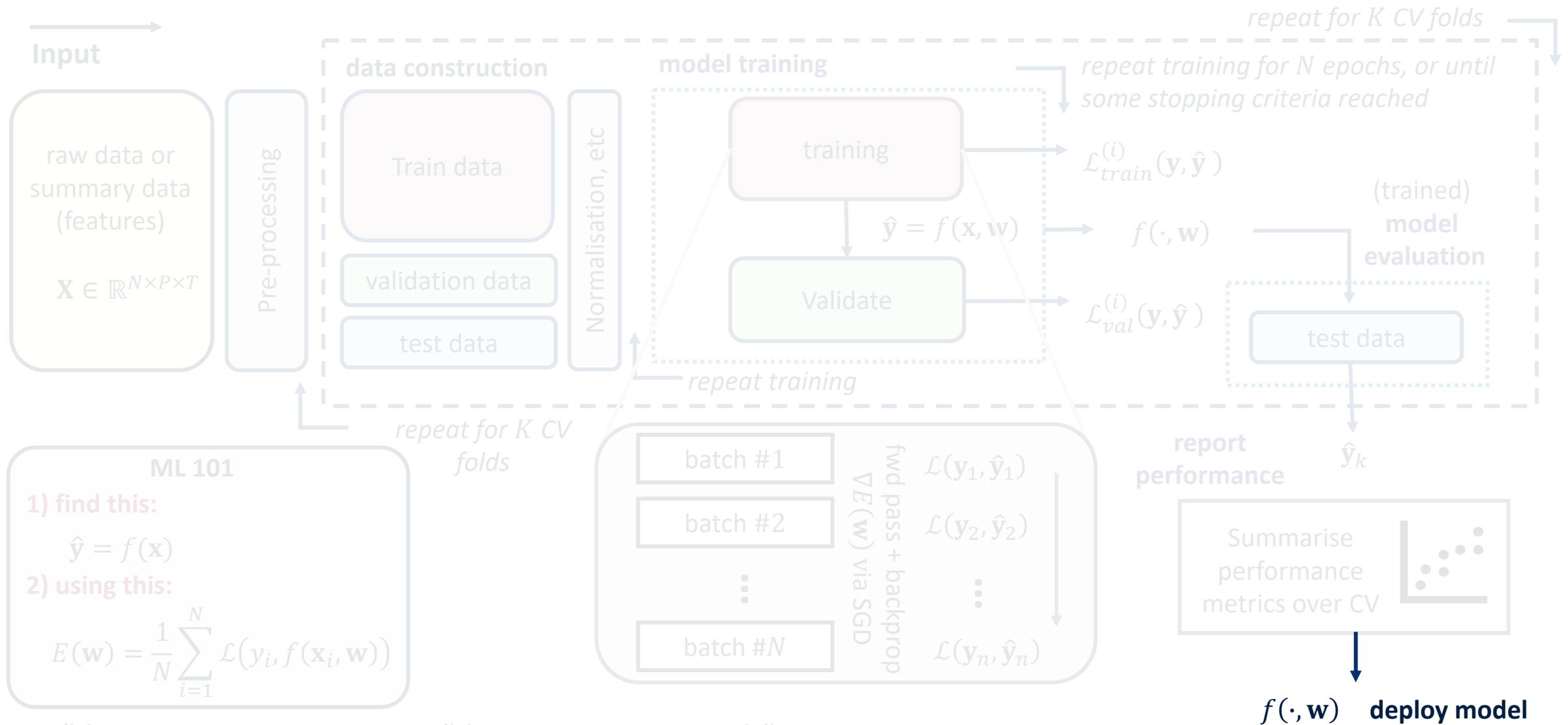
$\hat{\mathbf{y}} \in \mathbb{R}^{N \times 1}$ are the predictions / estimations; $\mathbf{y} \in \mathbb{R}^{N \times 1}$ are the response labels; $\mathbf{w} \in \mathbb{R}^{1 \times N}$ are the weights or parameters of a model
 N : number of samples / observations; M : number of timesteps; P : number of features, input channels, etc.

Typical Machine Learning Pipeline



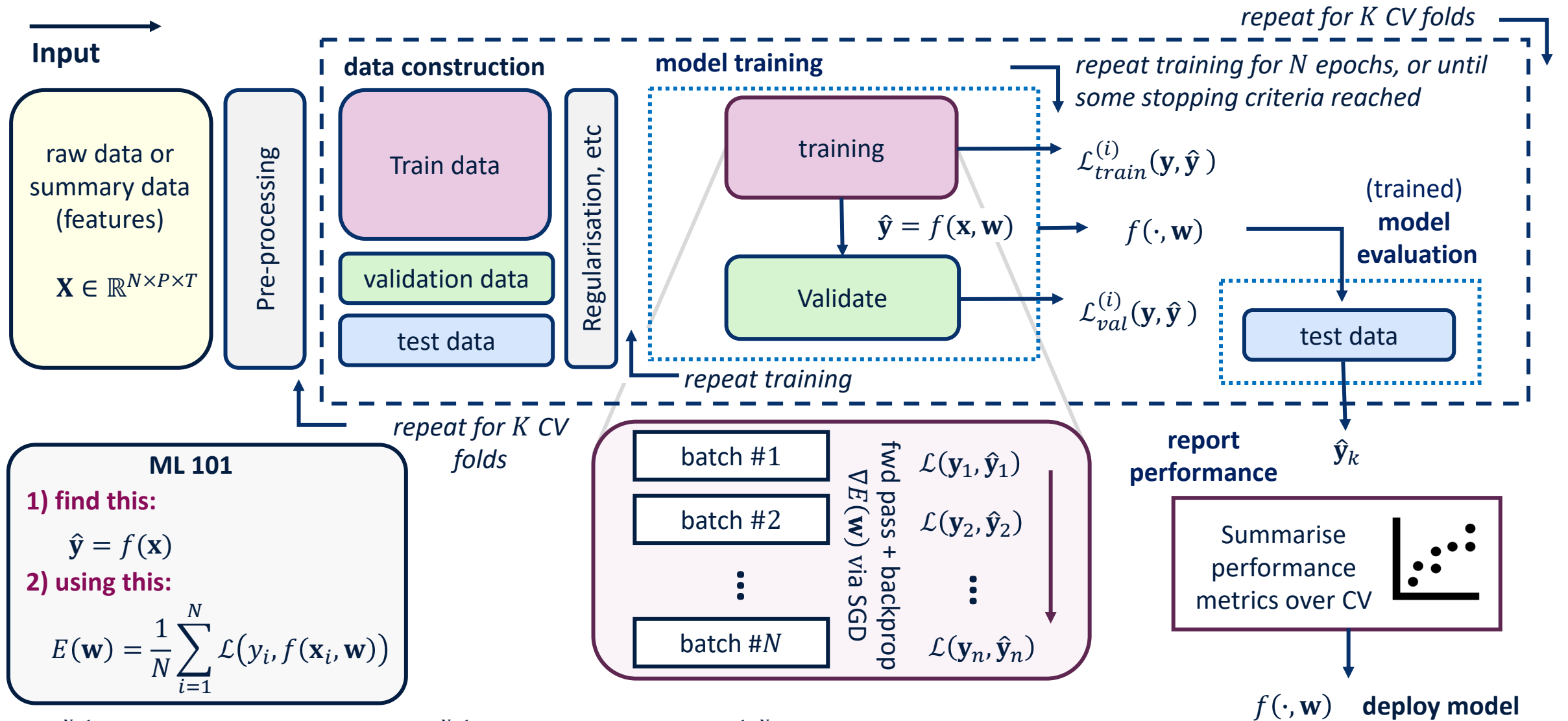
$\hat{\mathbf{y}} \in \mathbb{R}^{N \times 1}$ are the predictions / estimations; $\mathbf{y} \in \mathbb{R}^{N \times 1}$ are the response labels; $\mathbf{w} \in \mathbb{R}^{1 \times N}$ are the weights or parameters of a model
 N : number of samples / observations; M : number of timesteps; P : number of features, input channels, etc.

Typical Machine Learning Pipeline



$\hat{\mathbf{y}} \in \mathbb{R}^{N \times 1}$ are the predictions / estimations; $\mathbf{y} \in \mathbb{R}^{N \times 1}$ are the response labels; $\mathbf{w} \in \mathbb{R}^{1 \times N}$ are the weights or parameters of a model
 N : number of samples / observations; M : number of timesteps; P : number of features, input channels, etc.

Typical Machine Learning Pipeline



$\hat{\mathbf{y}} \in \mathbb{R}^{N \times 1}$ are the predictions / estimations; $\mathbf{y} \in \mathbb{R}^{N \times 1}$ are the response labels; $\mathbf{w} \in \mathbb{R}^{1 \times N}$ are the weights or parameters of a model
 N : number of samples / observations; M : number of timesteps; P : number of features, input channels, etc.

ML 4 Time-series: Recurrent Neural Networks

What have we learned?

- Assuming individual time-steps as I.I.D. is a naïve approach
- Incorporating recurrence into our networks can model temporality
- RNNs are prone to *vanishing* and *exploding* gradient problems
- Gated cells, such as LSTMS overcome these difficulties, allowing us to model long-term dependencies
- How we can implement and train RNNs/LSTMS
- What a typical machine learning pipeline should look like