Recurrent Neural Networks

Machine Learning for Behavioral Data

April 17, 2023

Today's Topic

Week	Lecture/Lab
8	Spring Break
9	Time Series Prediction
10	Unsupervised Learning
11	Unsupervised Learning
12	Ethical Machine Learning
13	Ethical Machine Learning
14	Project Presentations
15	Whit Monday

Supervised learning on time series:

- **Probabilistic graphical models**
- **Neural networks: LSTM, GRU, etc.**

Getting ready for today's lecture…

- **If not done yet**: clone the repository containing the Jupyter notebook and data for today's lecture into your Noto workspace.
- SpeakUp room for today's lecture:

https://go.epfl.ch/speakup-mlbd

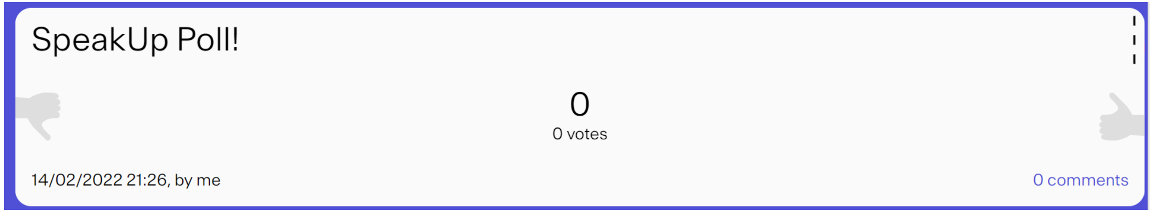
Short quiz about the past…

This KT model uses the # of opportunities the student had per skill and treats prior successes and failures the same.

a) Additive Factors Model (AFM)

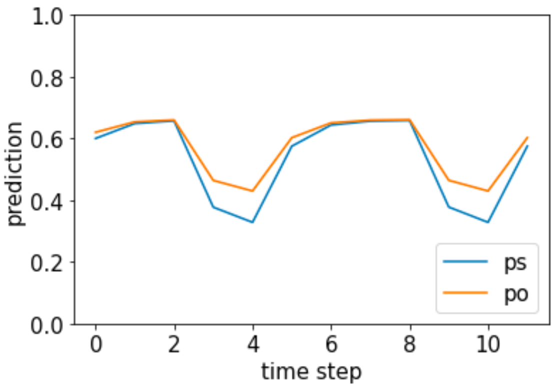
b) Performance Factors Analysis (PFA)

c) Bayesian Knowledge Tracing (BKT)

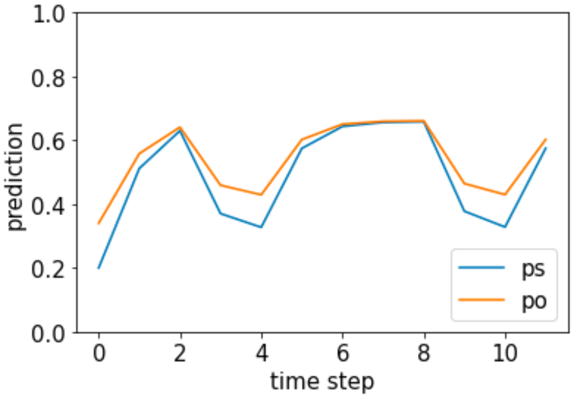


Short quiz about the past…

Which BKT parameter has been changed between the left and right plot (exactly one)?



$$p_0 = 0.6,\quad p_s = 0.1,\quad p_g = 0.2,\quad p_l = 0.3,\quad p_f = 0.3$$

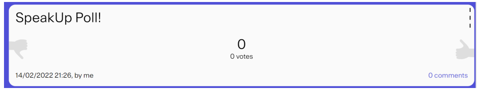


a) p_g (guess probability)

b) p_l (probability of learning)

c) p_0 (initial probability)

d) p_f (forget probability)



https://go.epfl.ch/speakup-mlbd

Short quiz about the past...

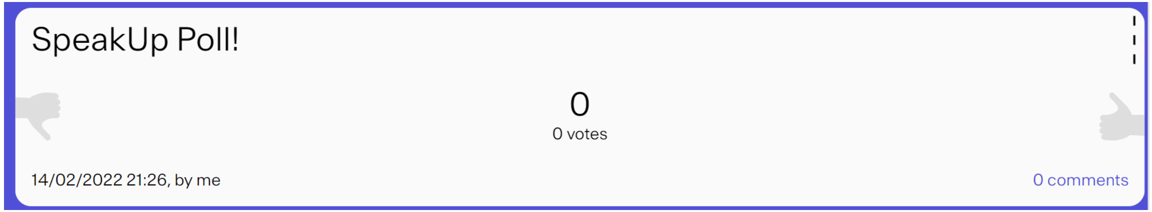
Which of the following statements about Pearson's correlation is true?

a) If two variables X, Y have correlation = 0, then X, Y are dependent.

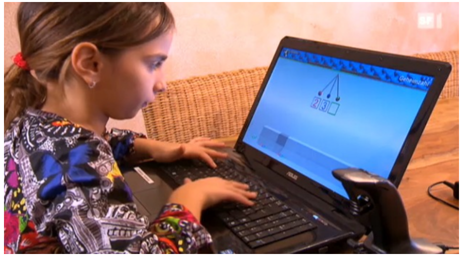
b) If two variables X, Y have correlation = 0, then X, Y are independent.

c) If X, Y are dependent variables, then their correlation = 0.

d) If X, Y are independent variables, then their correlation = 0.



Knowledge Tracing – Predicting Future Performance



Subtraction 0-100

1	2		…		n	n+1
0	0	1	0	1	1	?

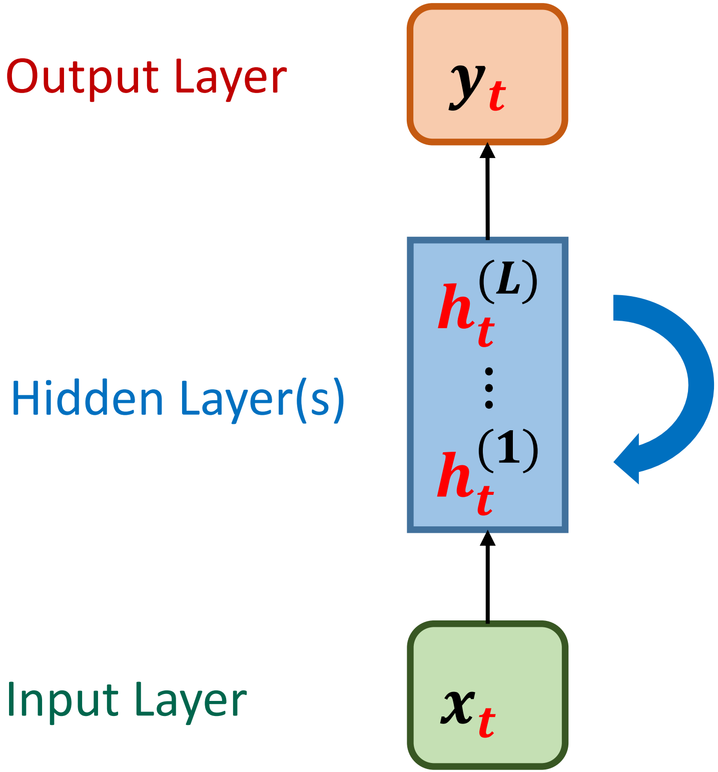
Today – Recurrent Neural Networks

- **Deep Knowledge Tracing**
- Parameters and hyperparameter tuning
- Different architectures
- Different tasks:
  - "Many-to-many" versus "Many-to-one"
  - Classification versus Regression

Neural Networks

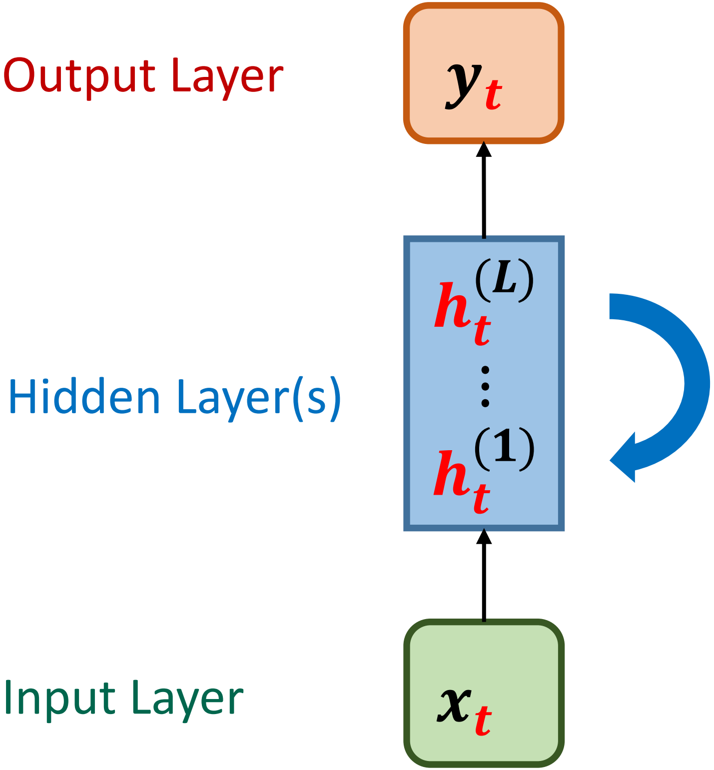
- Neural networks are able to represent non-linear functions, i.e. $y_n \approx f(\boldsymbol{x}_n)$ can be non-linear
- Neural networks are able to *learn* the features and the weights (parameters) from the data
- Tutorial: https://go.epfl.ch/tutorial-nn

Recurrent Neural Network



$$\boldsymbol{h}_t^{(1)} = \phi_h \left(W_{hx}\boldsymbol{x}_t + W^{(1)}_{h^{(1)}h^{(1)}}\boldsymbol{h}_{t-1}^{(1)} + \boldsymbol{b}^{(1)} \right)$$

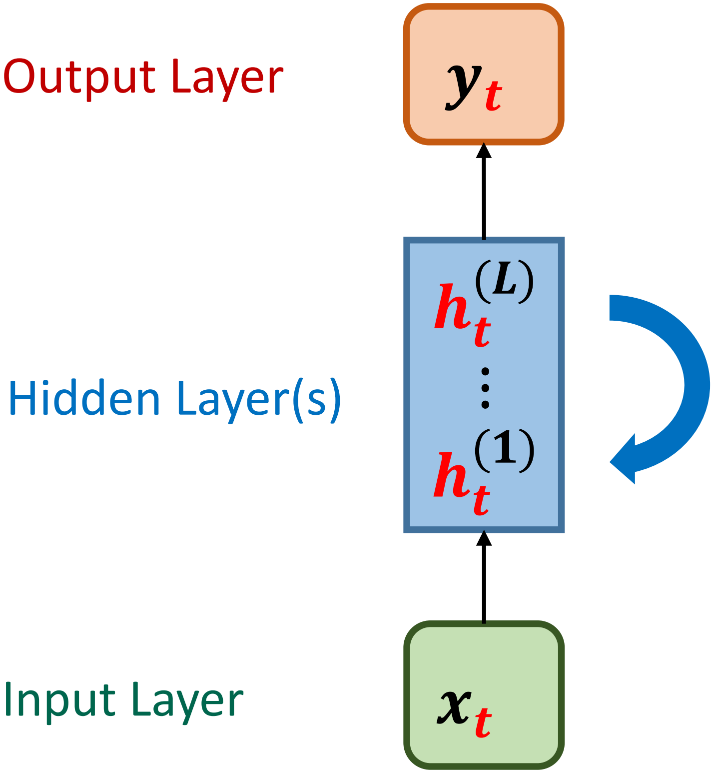
Recurrent Neural Network



$$\boldsymbol{h}_t^{(l)} = \phi_h(W^{(l)}_{h^{(l)}h^{(l-1)}}\boldsymbol{h}_t^{(l-1)} + W^{(l)}_{h^{(l)}h^{(l)}}\boldsymbol{h}_{t-1}^{(l)} + \boldsymbol{b}^{(l)})$$

$$\boldsymbol{h}_t^{(1)} = \phi_h\left(W_{hx}\boldsymbol{x}_t + W^{(1)}_{h^{(1)}h^{(1)}}\boldsymbol{h}_{t-1}^{(1)} + \boldsymbol{b}^{(1)}\right)$$

Recurrent Neural Network

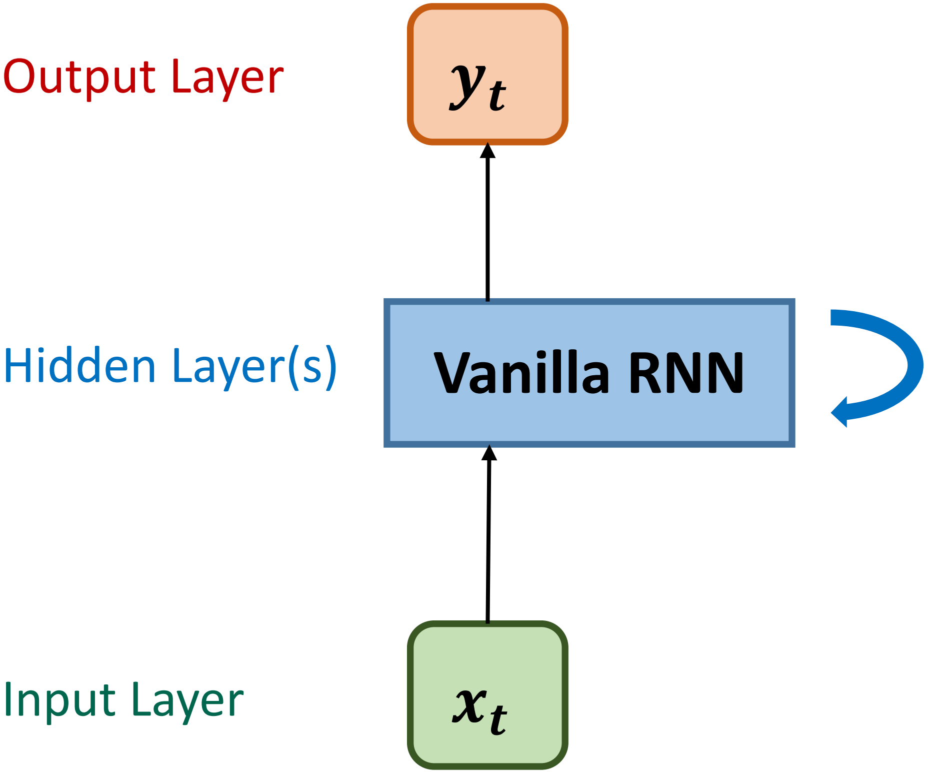


$$\boldsymbol{y}_t = \phi_y(W_{yh}\boldsymbol{h}_t^{L} + \boldsymbol{b}^{(y)})$$

$$\boldsymbol{h}_t^{(l)} = \phi_h(W^{(l)}_{h^{(l)}h^{(l-1)}}\boldsymbol{h}_t^{(l-1)} + W^{(l)}_{h^{(l)}h^{(l)}}\boldsymbol{h}_{t-1}^{(l)} + \boldsymbol{b}^{(l)})$$

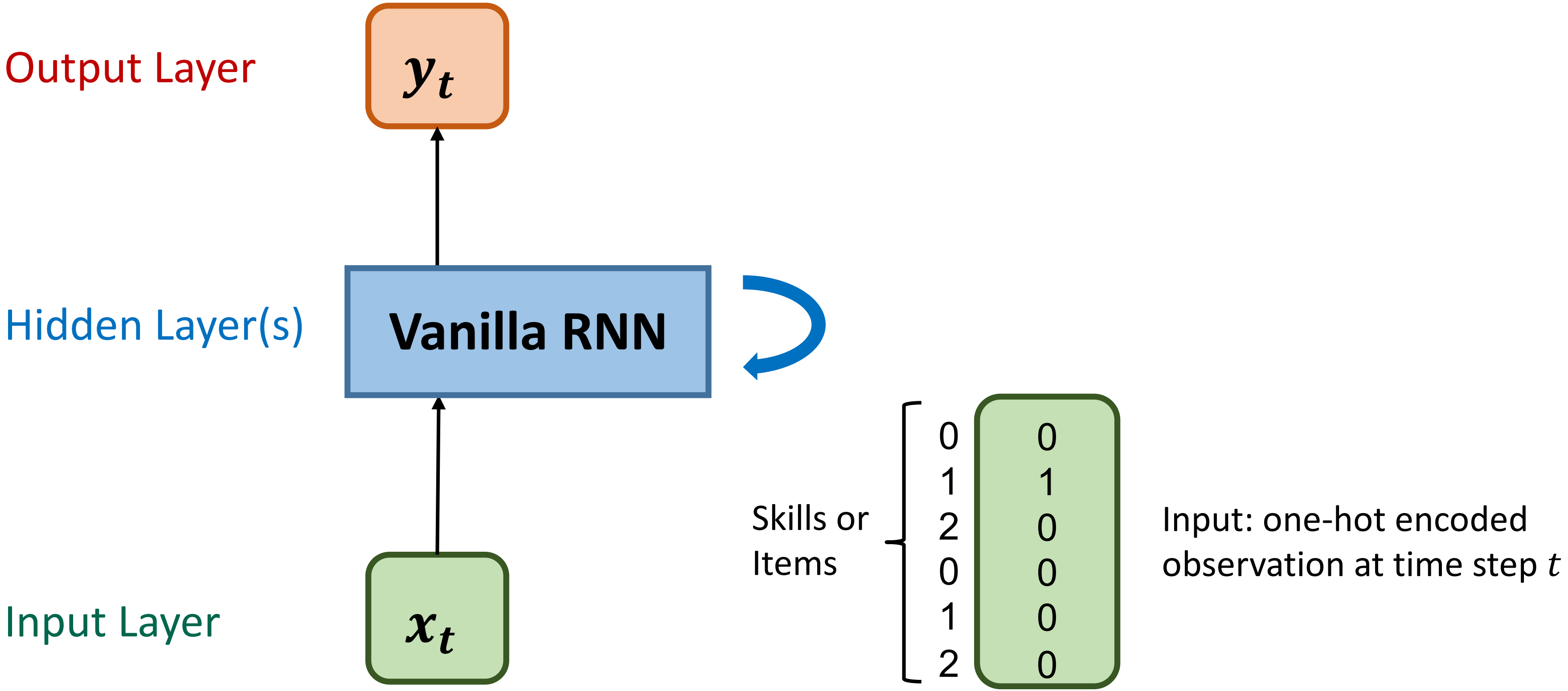
$$\boldsymbol{h}_t^{(1)} = \phi_h\,(W_{hx}\boldsymbol{x}_t + W^{(1)}_{h^{(1)}h^{(1)}}\boldsymbol{h}_{t-1}^{(1)} + \boldsymbol{b}^{(1)})$$

Deep Knowledge Tracing



[*Deep Knowledge Tracing*, Piech et al., NIPS 2015]

Deep Knowledge Tracing



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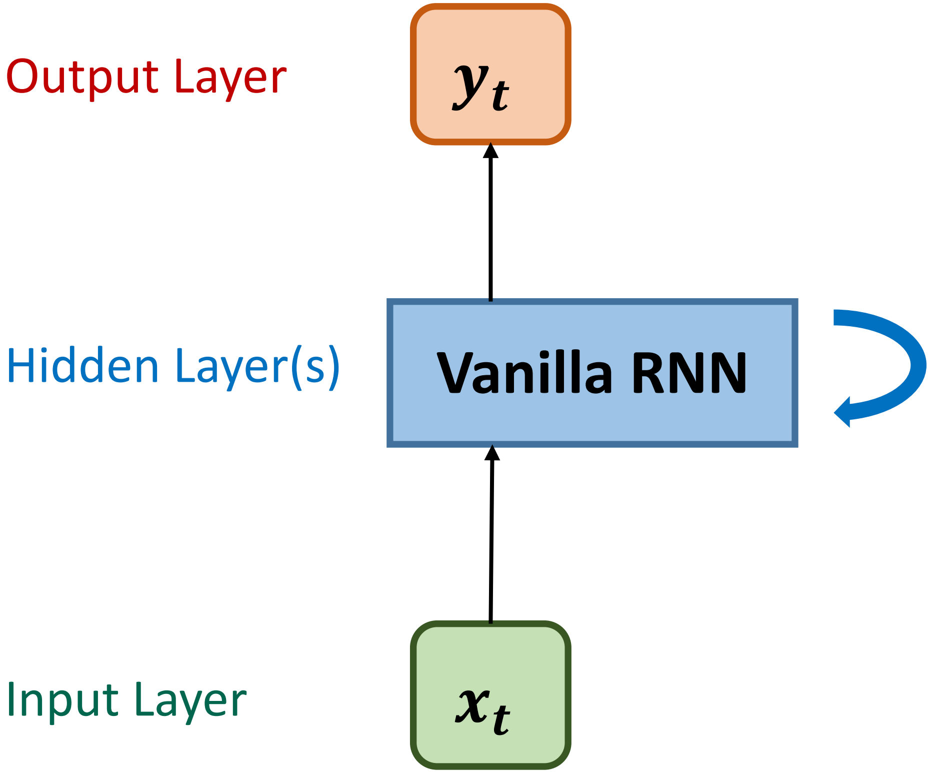
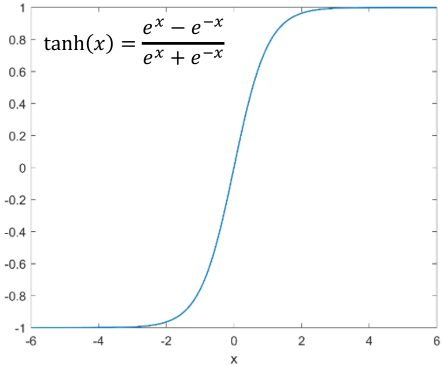
Deep Knowledge Tracing



$$\boldsymbol{h_t} = \tanh(W_{hx}\boldsymbol{x_t} + W_{hh}\boldsymbol{h_{t-1}} + \boldsymbol{b_h})$$



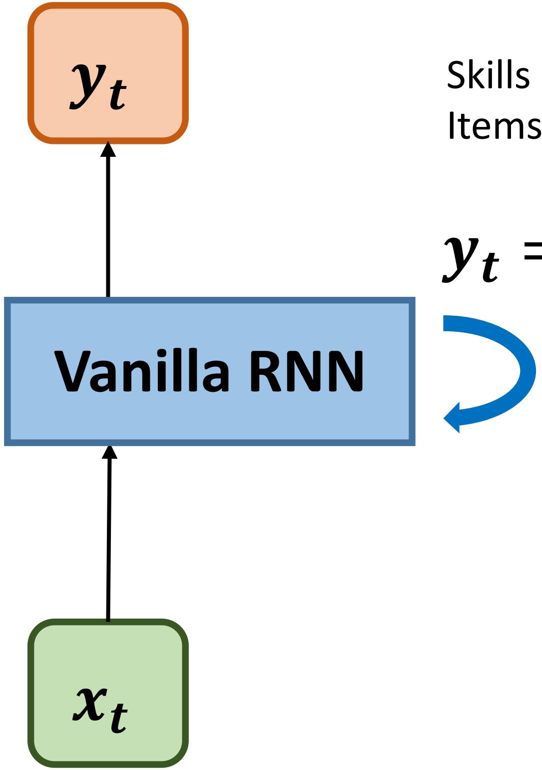
[*Deep Knowledge Tracing*, Piech et al., NIPS 2015]

Deep Knowledge Tracing

Output Layer

Hidden Layer(s)

Input Layer

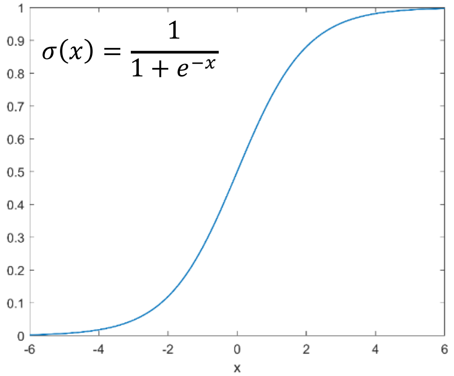


Skills or Items

$$\left\{\begin{array}{c|c} 0 & 0.3 \\ 1 & 0.5 \\ 2 & 0.7 \end{array}\right.$$

Output: probability for answering skill (or item) correct at time step t

$$\boldsymbol{y_t} = \sigma(W_{yh}\boldsymbol{h_t} + \boldsymbol{b_y})$$



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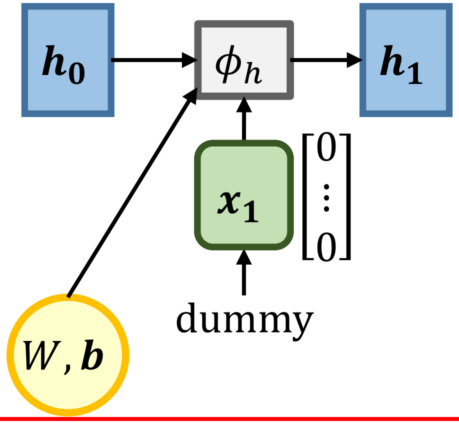
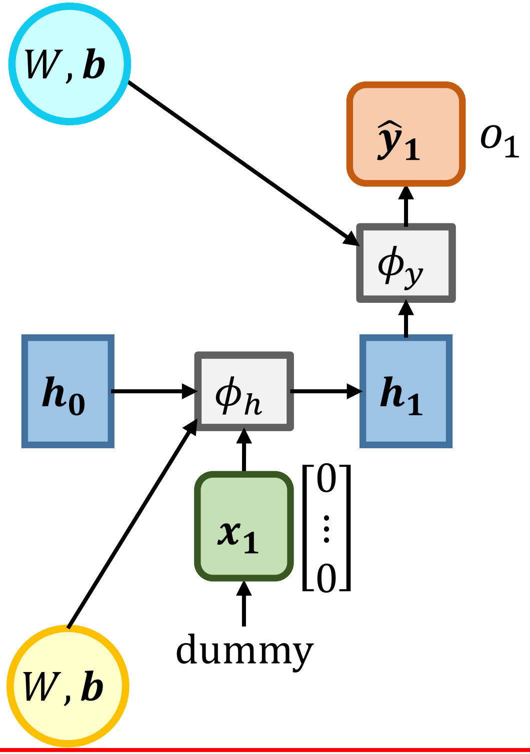
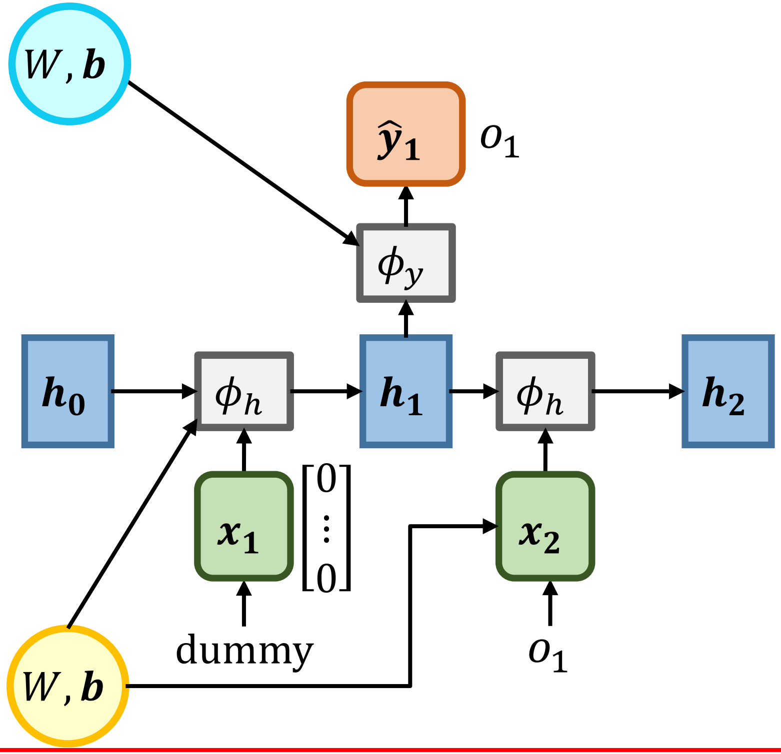
Deep Knowledge Tracing – Computational Graph



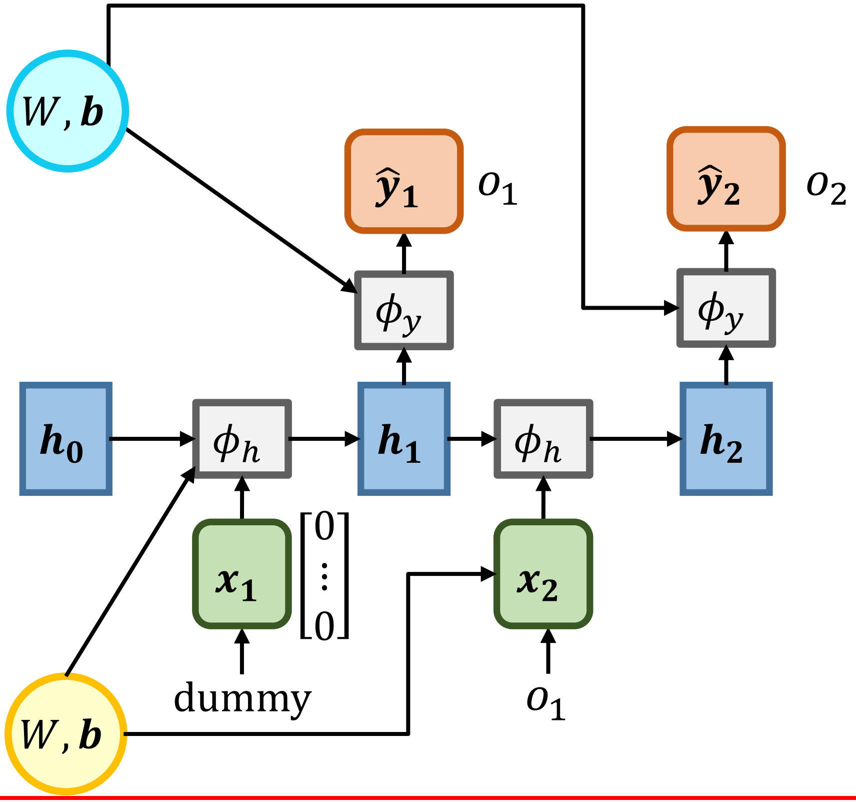
Deep Knowledge Tracing – Computational Graph



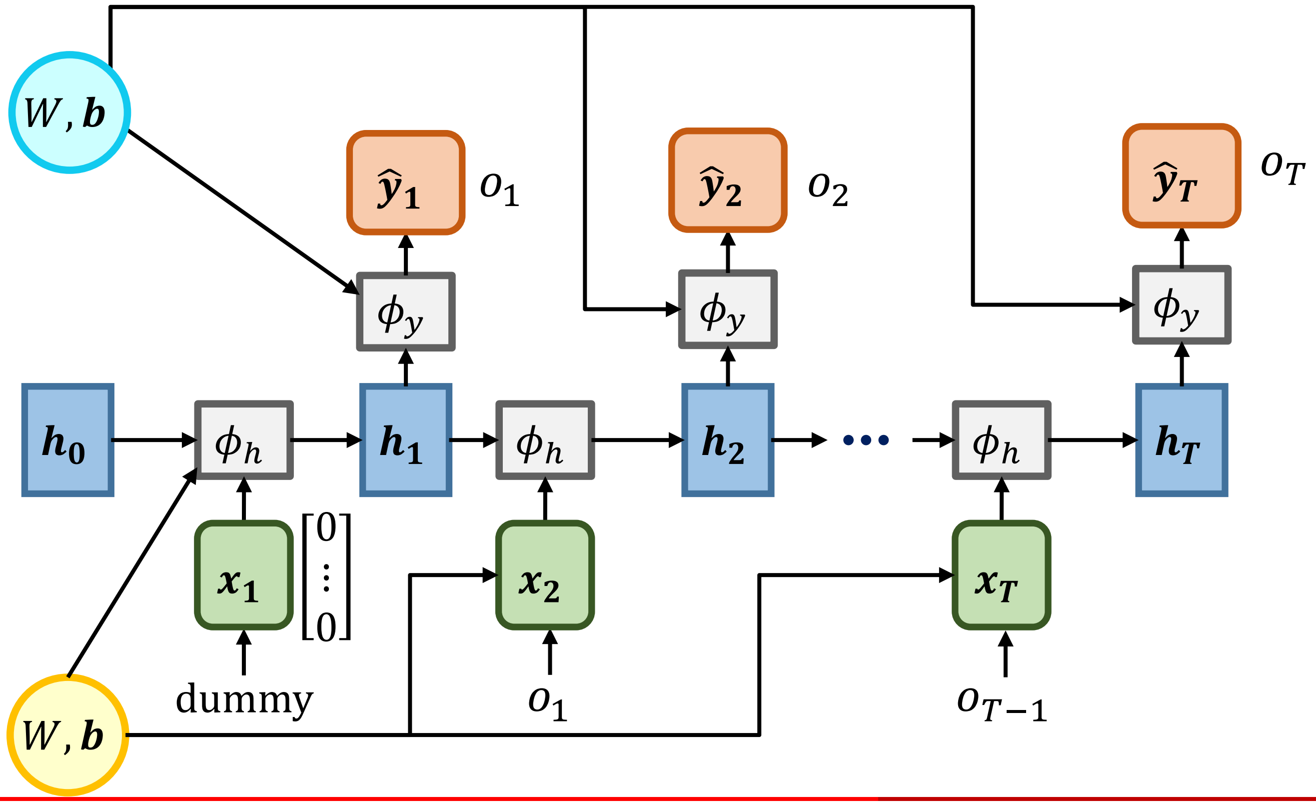
Deep Knowledge Tracing – Computational Graph



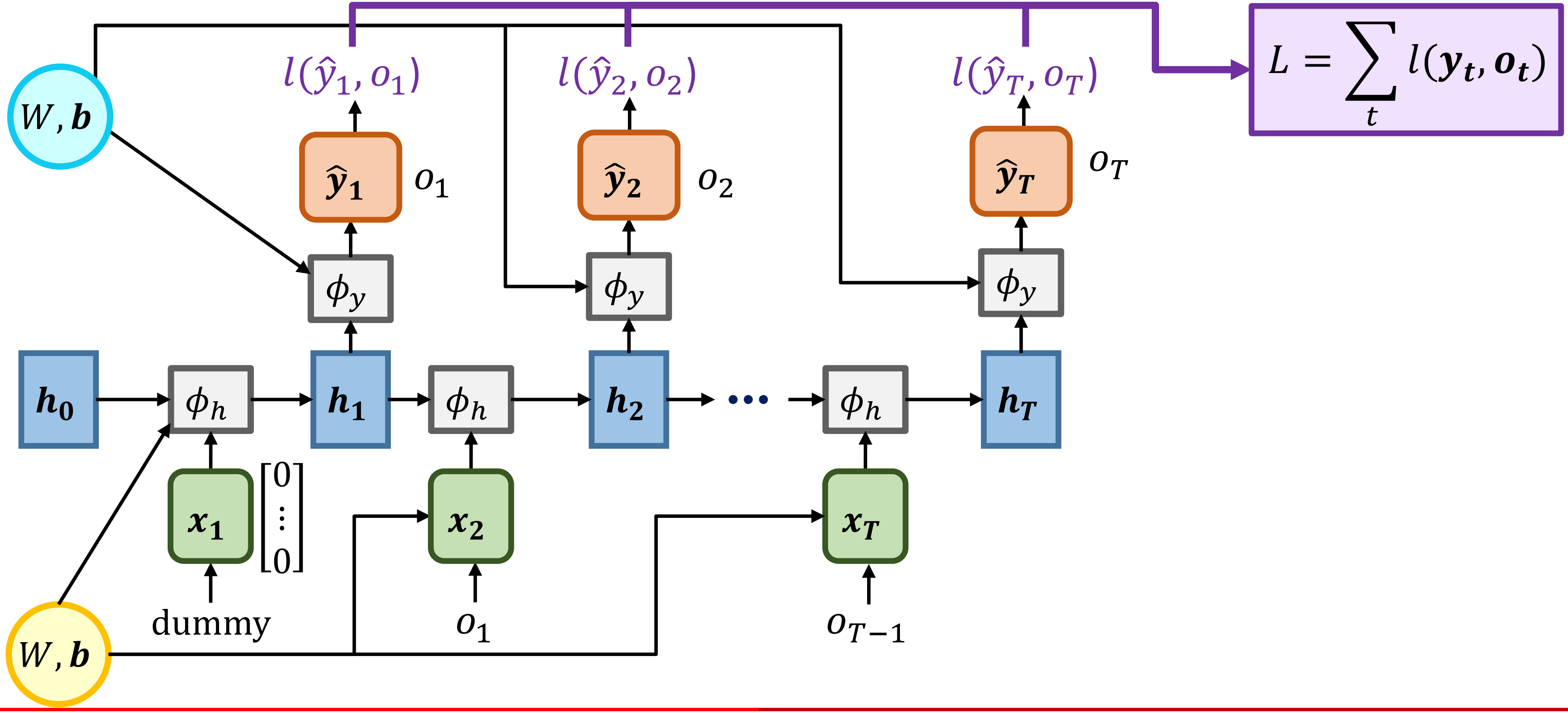
Deep Knowledge Tracing – Computational Graph



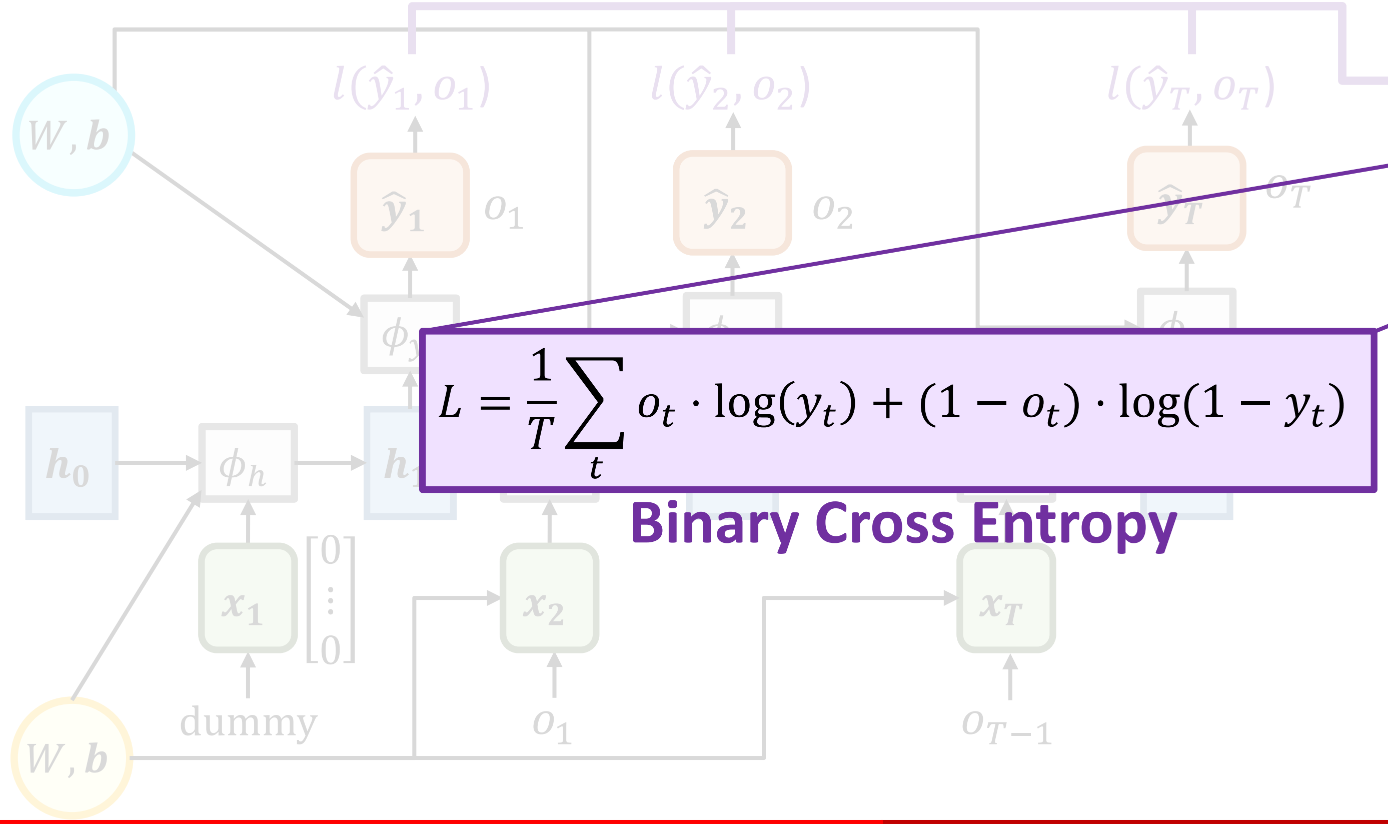
Deep Knowledge Tracing – Computational Graph



Deep Knowledge Tracing – Computational Graph



Training a DKT model: Binary Crossentropy Loss



$$L = \sum_t l(\boldsymbol{y_t}, \boldsymbol{o_t})$$

$$L = \frac{1}{T} \sum_t o_t \cdot \log(y_t) + (1 - o_t) \cdot \log(1 - y_t)$$

Binary Cross Entropy

Training and Prediction using DKT

- Training: gradient descent
- Prediction: compute inference in the network (see computational graph)

Today – Recurrent Neural Networks

- Deep Knowledge Tracing
- **Parameters and hyperparameter tuning**
- Different architectures
- Different tasks:
  - "Many-to-many" versus "Many-to-one"
  - Classification versus Regression

RNNs – Specifying Parameters

```
[ ]  # Specify the model hyperparameters. Full descriptions included in the demo notebook!
     params = {}

     params['batch_size'] = 32
     params['mask_value'] = -1.0
     params['verbose'] = 1
     params['best_model_weights'] = 'weights/bestmodel'
     params['optimizer'] = 'adam'
     params['recurrent_units'] = 16
     params['epochs'] = 20
     params['dropout_rate'] = 0.1
```

RNNs – Tuning hyperparameters

```
[ ]  # Specify the model hyperparameters. Full descriptions included in the demo notebook!
     params = {}

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     params['optimizer'] = 'adam'
     params['recurrent_units'] = 16
     params['epochs'] = 20
     params['dropout_rate'] = 0.1
```

RNNs – Tuning hyperparameters

- Optimal number of epochs can be found using callbacks
- Other parameters can be tuned using for example:
  a) Train-Validation-Test split
  b) Train-Test split, using a k-fold cross validation on the training data to determine the optimal parameters

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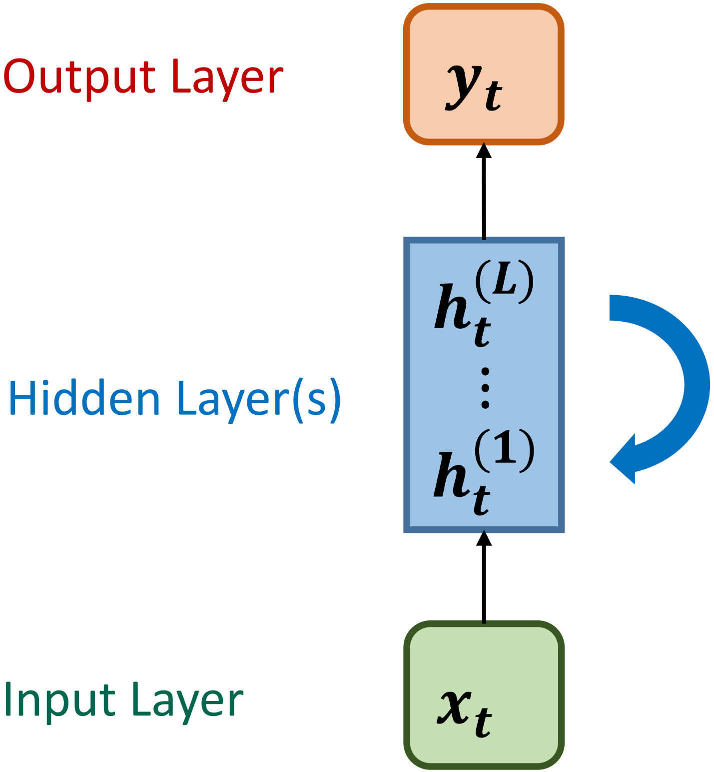
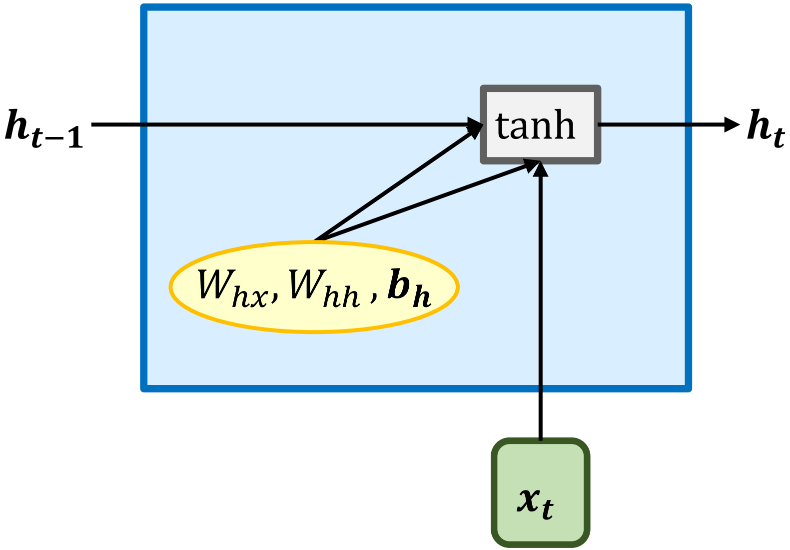
Recurrent Neural Network

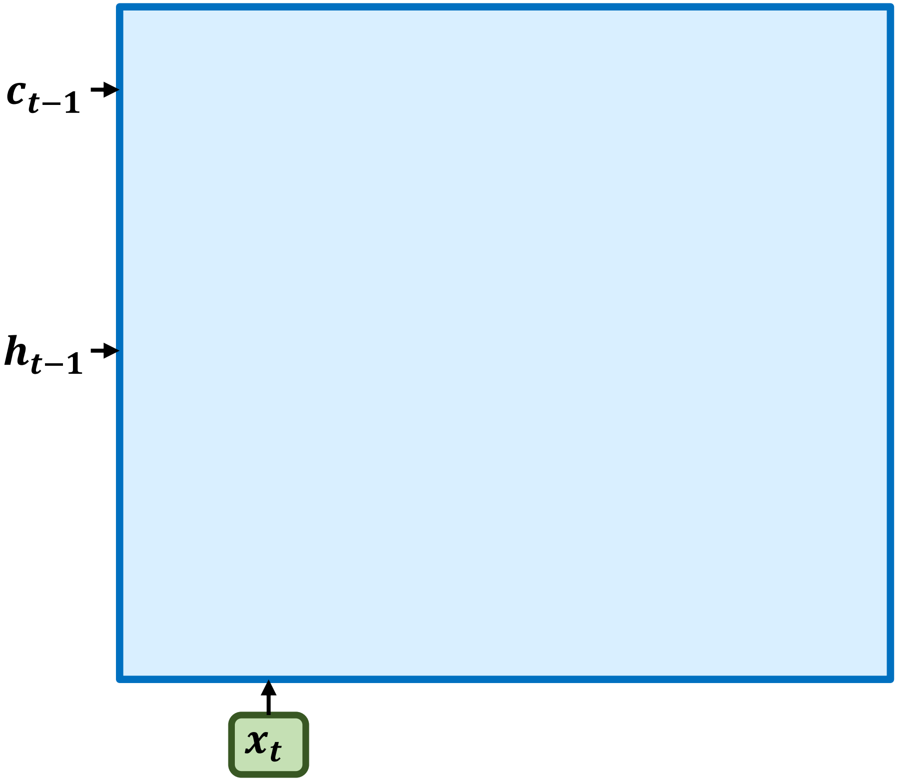


Vanilla RNN - revisited



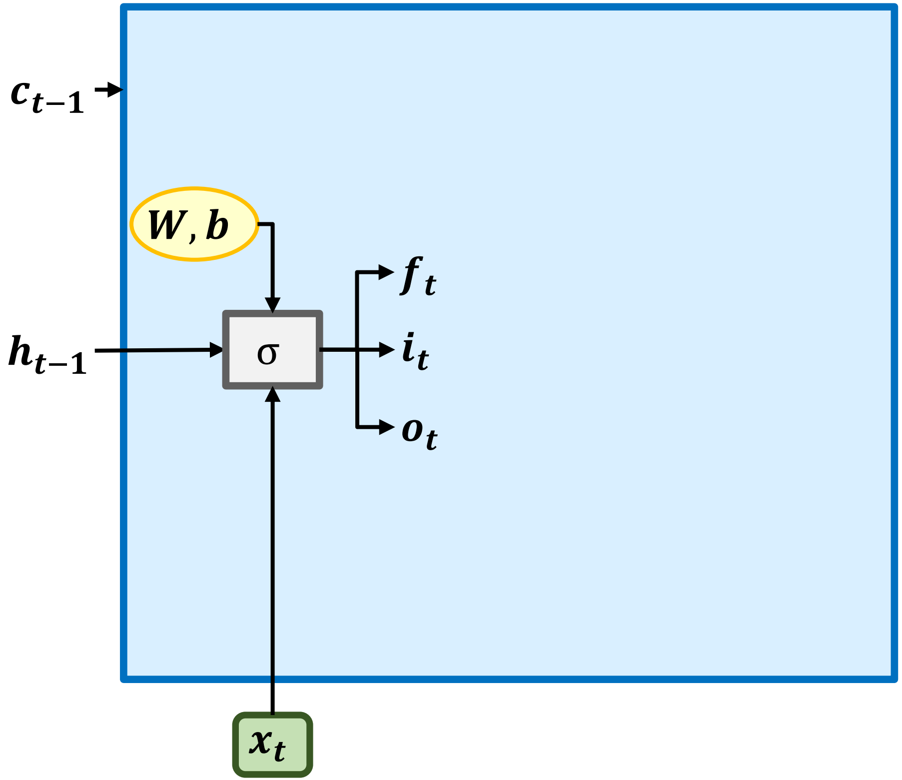
$$\boldsymbol{h_t} = \tanh(W_{hx}\boldsymbol{x}_t + W_{hh}\boldsymbol{h_{t-1}} + \boldsymbol{b_h})$$

Long-Short Term Memory Network (LSTM)



- Two states:
  - Hidden state $\boldsymbol{h_{t-1}}$
  - Cell state $\boldsymbol{c_{t-1}}$

Long-Short Term Memory Network (LSTM)



① Updating the gates:

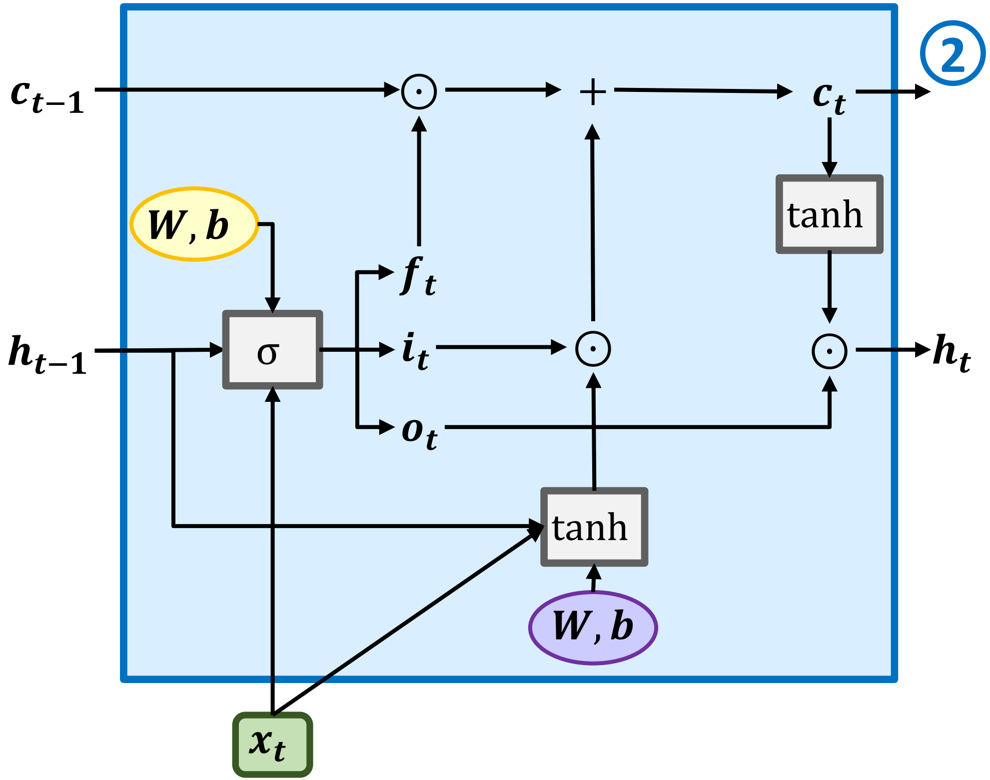
- $\boldsymbol{f}$ forget gate: whether to erase cell
- $\boldsymbol{i}$ input gate: whether to write to cell
- $\boldsymbol{o}$ output gate: how much to reveal cell

$$\boldsymbol{f}_t = \sigma(W_{fx}\boldsymbol{x_t} + W_{fh}\boldsymbol{h_{t-1}} + \boldsymbol{b_f})$$

$$\boldsymbol{i_t} = \sigma(W_{ix}\boldsymbol{x_t} + W_{ih}\boldsymbol{h_{t-1}} + \boldsymbol{b_i})$$

$$\boldsymbol{o_t} = \sigma(W_{ox}\boldsymbol{x_t} + W_{oh}\boldsymbol{h_{t-1}} + \boldsymbol{b_o})$$

Long-Short Term Memory Network (LSTM)

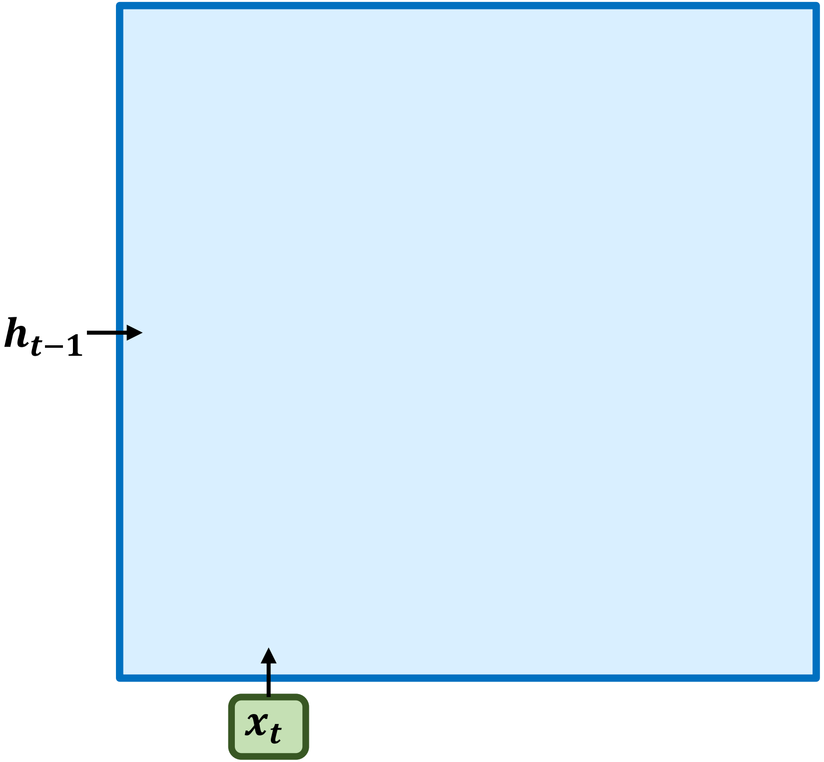


② Updating the states:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_{cx} x_t + W_{ch} h_{t-1} + b_c)$$

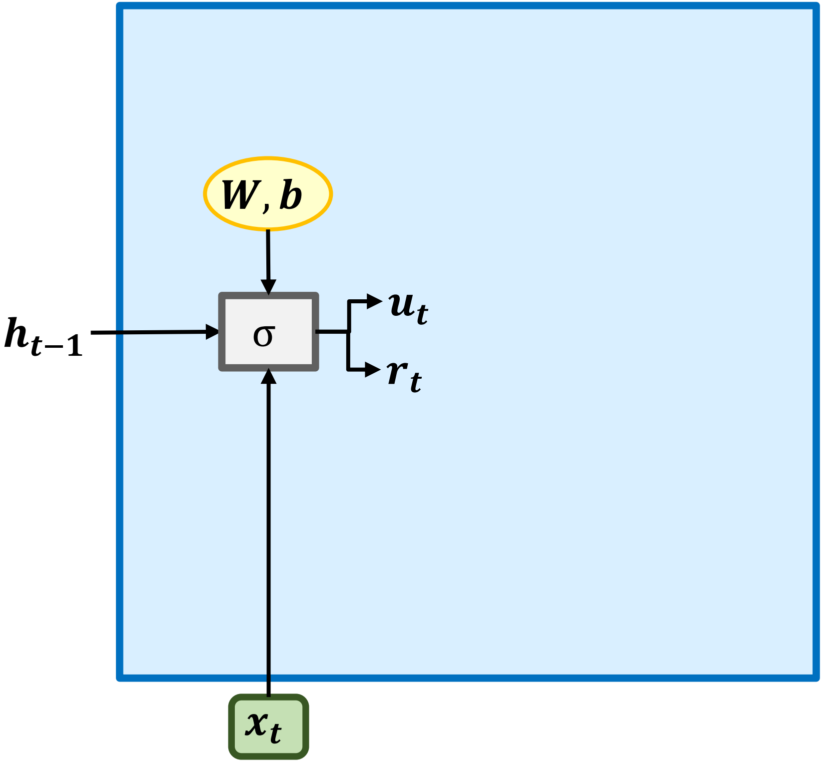
$$h_t = o_t \odot \tanh(C_t)$$

Gated Recurrent Units (GRU)



- Only one state (got rid of cell):
  - Hidden state $\boldsymbol{h_{t-1}}$

Gated Recurrent Units (GRU)



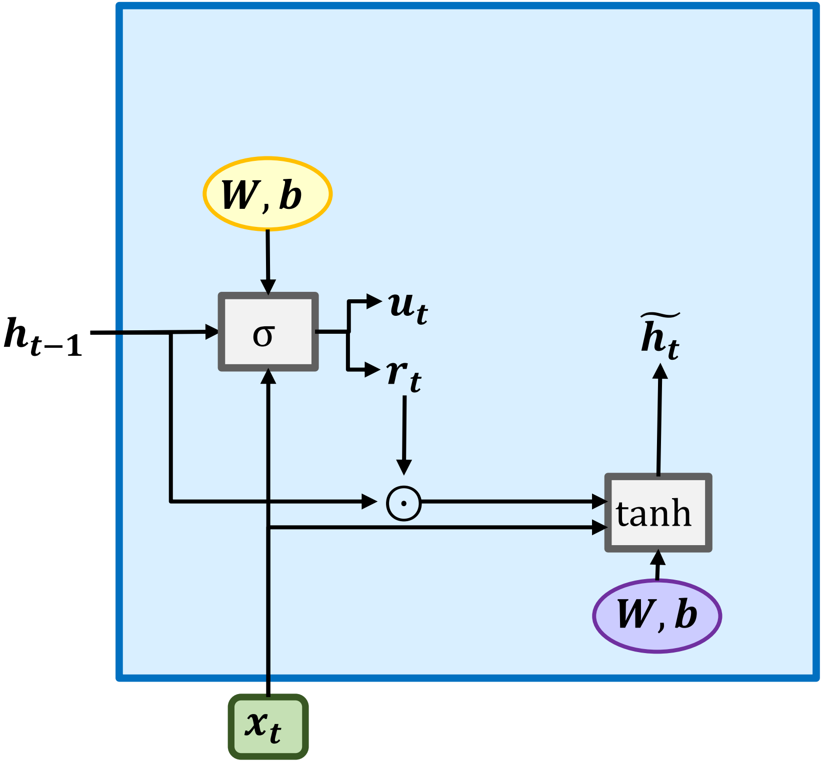
1 Updating the gates:

- $\boldsymbol{r}$ reset gate: how much of the previous state to remember
- $\boldsymbol{u}$ update gate: how much of the new state is just a copy of the old state

$$\boldsymbol{r}_t = \sigma(W_{rx}\boldsymbol{x}_t + W_{th}\boldsymbol{h}_{t-1} + \boldsymbol{b}_r)$$

$$\boldsymbol{u}_t = \sigma(W_{ux}\boldsymbol{x}_t + W_{uh}\boldsymbol{h}_{t-1} + \boldsymbol{b}_u)$$

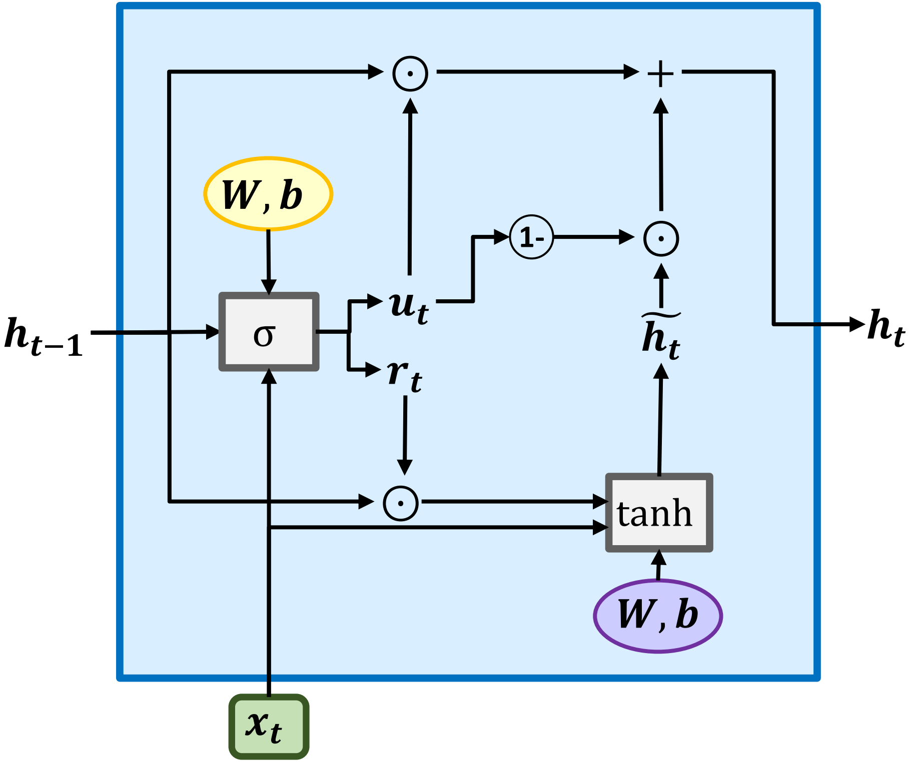
Gated Recurrent Units (GRU)



② Get candidate hidden state:

$$\widetilde{\boldsymbol{h_t}} = \tanh(W_{hx}\boldsymbol{x_t} + W_{ht}(r_t \odot \boldsymbol{h_{t-1}}) + \boldsymbol{b_h})$$

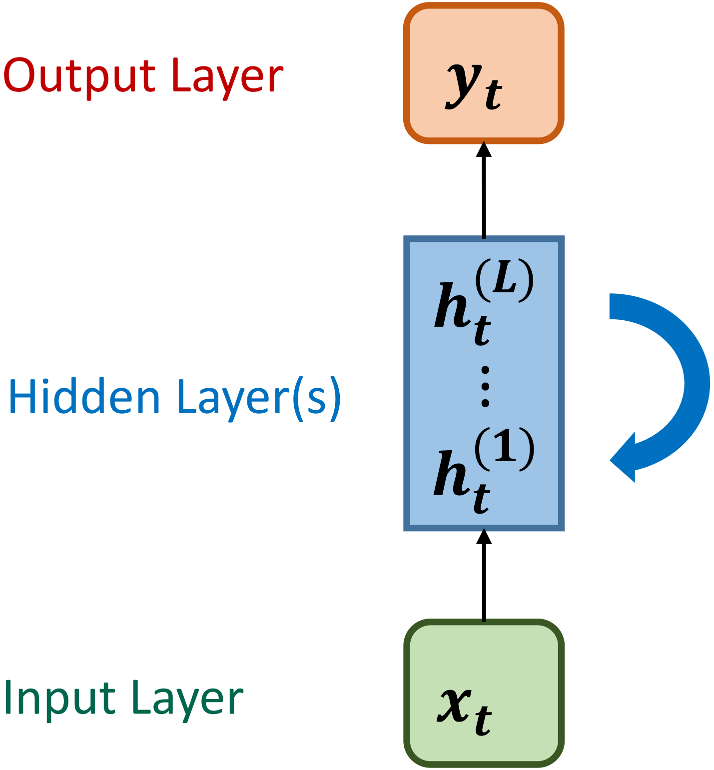
Gated Recurrent Units (GRU)



③ Updating the state:

$$h_t = u_t \odot h_{t-1} + (1 - u_t) \odot \widetilde{h_t}$$

Same input/output – different architectures



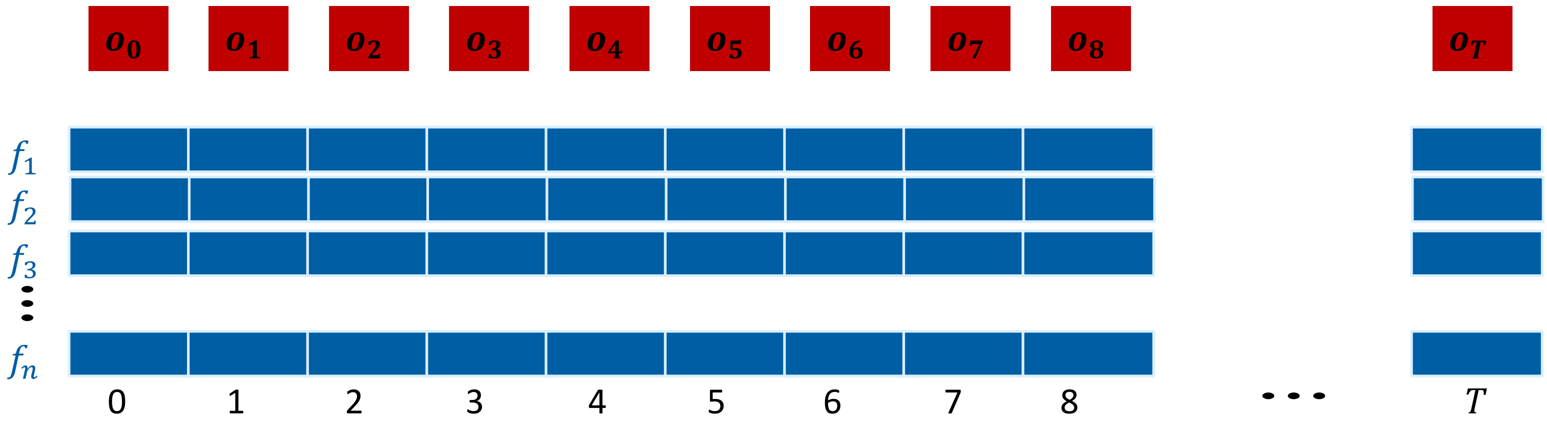
- Vanilla RNN
- LSTM
- GRU

Today – Recurrent Neural Networks

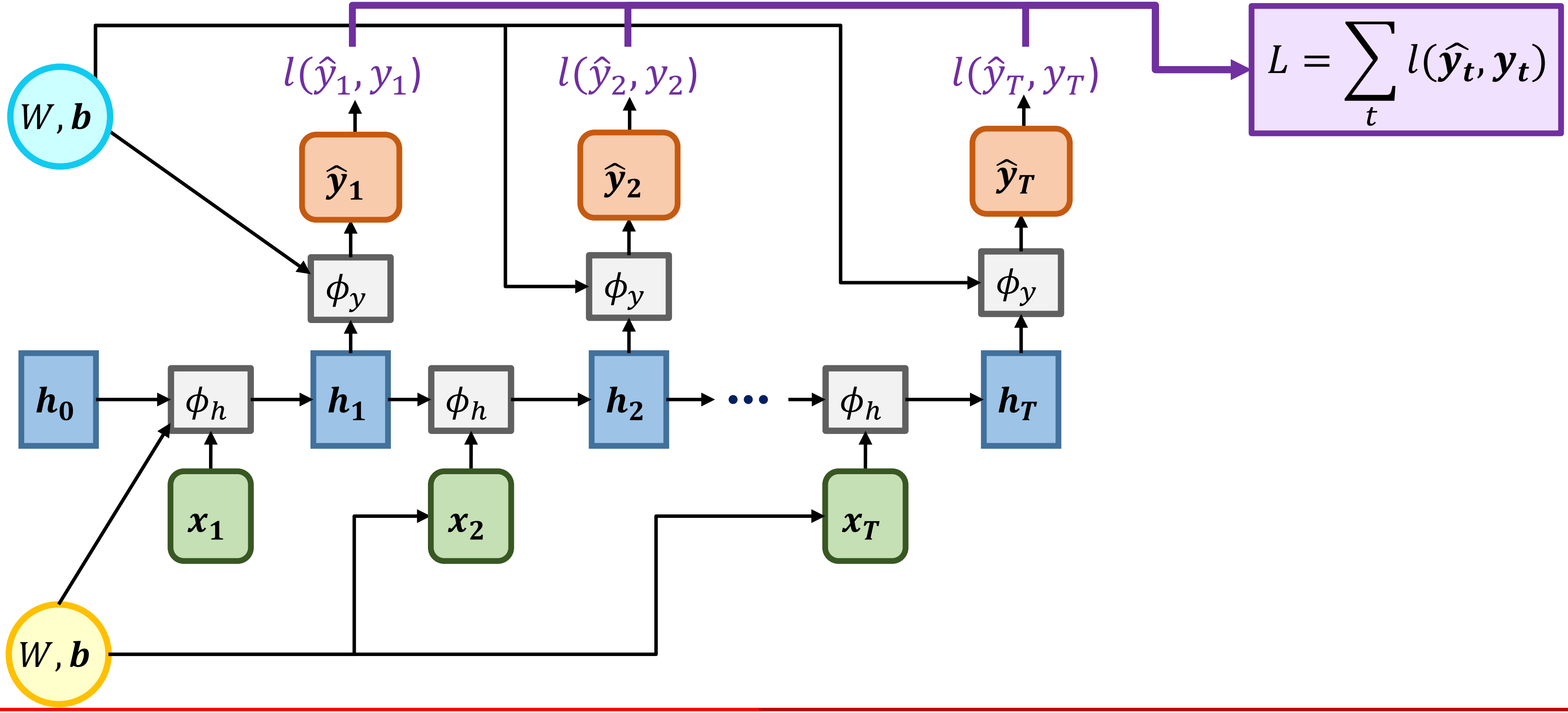
- Deep Knowledge Tracing
- Parameters and hyperparameter tuning
- Different architectures
- **Different tasks**:
  - **“Many-to-many” versus “Many-to-one”**
  - Classification versus Regression

Many-to-many aka the Tracing Task

- Prediction of a target variable o_t at each time step t

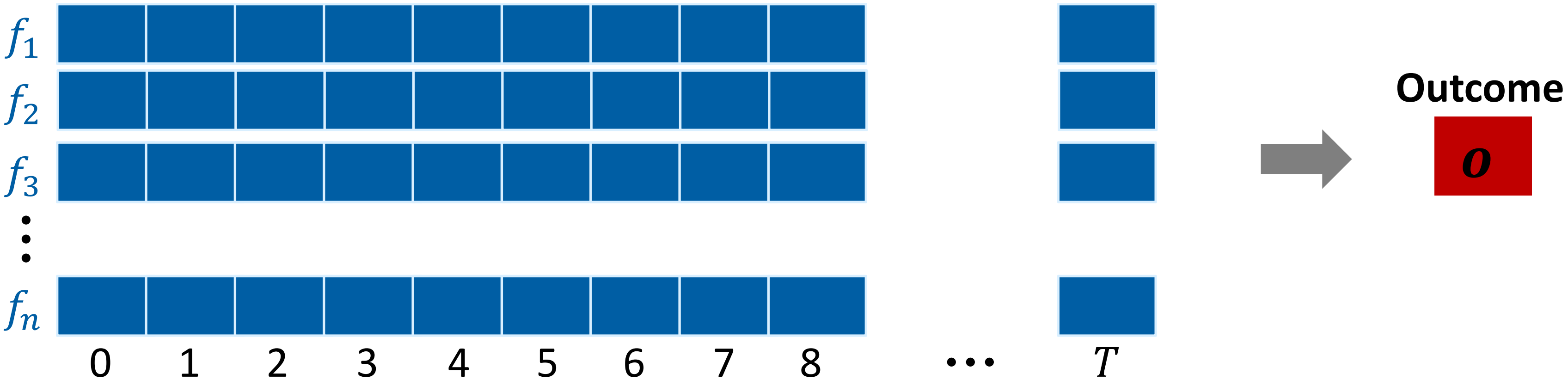


Computational Graph – Many-to-many

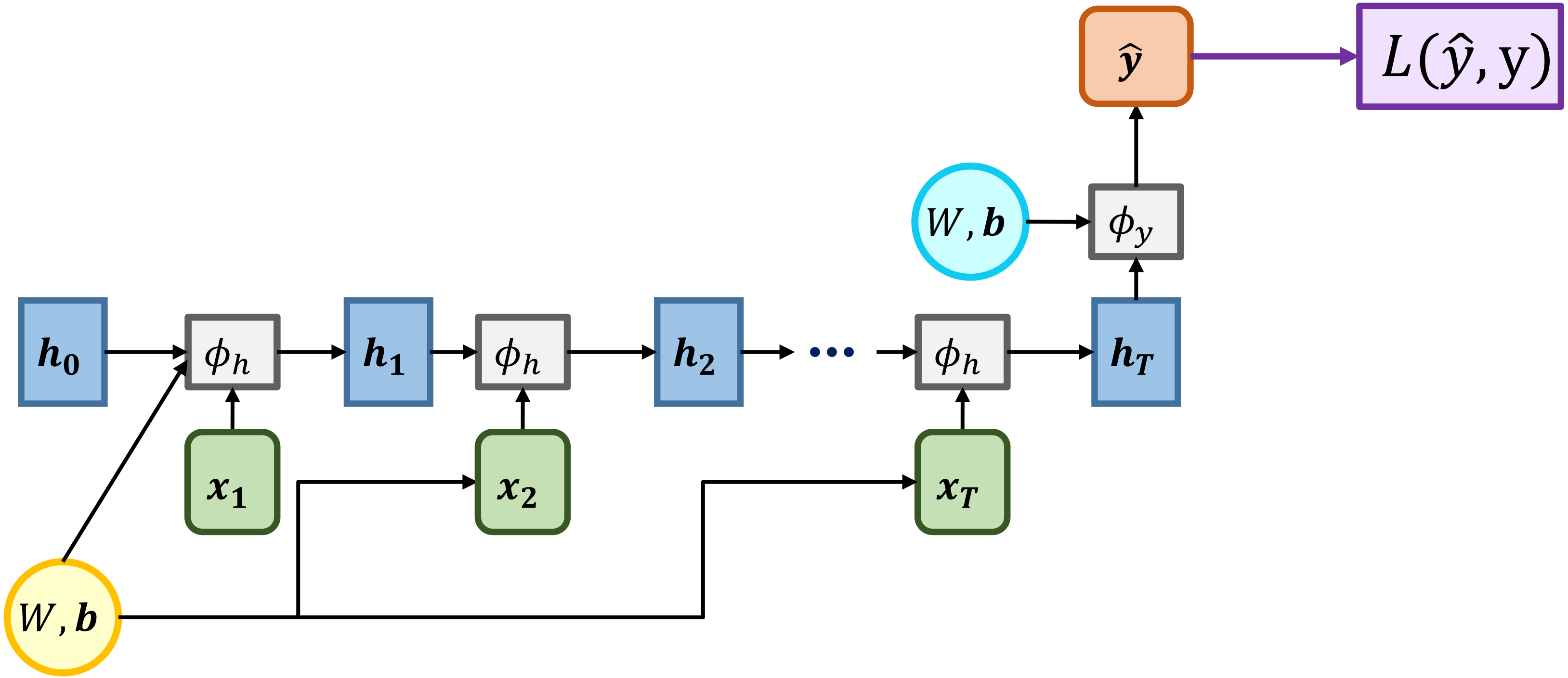


Many-to-one aka the Time-Series Prediction Task

- Prediction of a target variable $\boldsymbol{o}$ after $t \leq T$ time steps, where T is the total number of time steps



Computational Graph – Many-to-one



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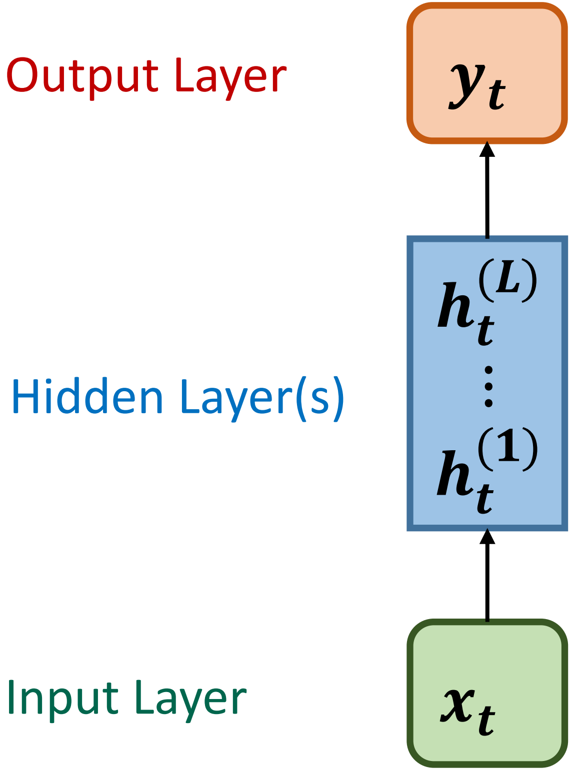
  - **Classification versus Regression**

Classification vs. Regression



$$\boldsymbol{y_t} = \phi_y(W_{yh}\boldsymbol{h}_t^L + \boldsymbol{b}^{(y)})$$

$$\boxed{L(\widehat{\boldsymbol{y_t}}, \boldsymbol{y_t})}$$

Classification vs. Regression: Output Layer

Output Layer $\boldsymbol{y_t}$

Hidden Layer(s) $\boldsymbol{h_t^{(L)}}$ $\vdots$ $\boldsymbol{h_t^{(1)}}$

Input Layer $\boldsymbol{x_t}$

$$\boldsymbol{y_t} = \phi_y(W_{yh}\boldsymbol{h}_t^L + \boldsymbol{b}^{(y)})$$

$$\boxed{L(\widehat{\boldsymbol{y_t}}, \boldsymbol{y_t})}$$

Classification

Regression

Sigmoid activation:

$$\boldsymbol{y_t} = \sigma(W_{yh}\boldsymbol{h}_t^L + \boldsymbol{b}^{(y)})$$

Linear activation:

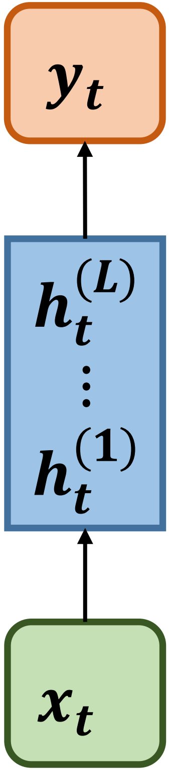
$$\boldsymbol{y_t} = W_{yh}\boldsymbol{h}_t^L + \boldsymbol{b}^{(y)}$$

Classification vs. Regression: Training Loss

Output Layer

Hidden Layer(s)

Input Layer



$$\boldsymbol{y_t} = \phi_y(W_{yh}\boldsymbol{h}_t^L + \boldsymbol{b}^{(y)})$$

$$L(\widehat{\boldsymbol{y_t}}, \boldsymbol{y_t})$$

Classification

- Binary crossentropy
- Categorical crossentropy

Regression

Mean squared error

Your Turn

- Given:
  - Data from a MOOC
  - An LSTM for predicting quiz performance of a student for every week of the course (tracing task)
- Your Task:
  1) Adjust the create_model function in order to predict pass/fail after 5 weeks of the course (time series prediction task) and send us the binary accuracy + AUC
     - Hint 1: return_sequences=False
     - Hint 2: what does TimeDistributed(…) do?
  2) Tune hyperparameters of your choice and send us binary accuracy and AUC

Summary

- Deep Knowledge Tracing
- Parameters and hyperparameter tuning
- Different architectures
- Different tasks:
  - "Many-to-many" versus "Many-to-one"
  - Classification versus Regression