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...

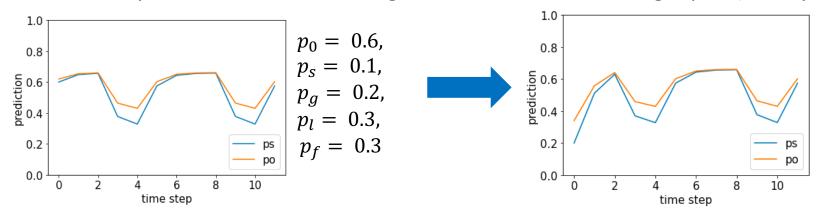
This KT model uses the # of opportunities the student had per skill and treats prior successes and failures the same.

- 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)?



- a) p_q (guess probability)
- c) p_0 (initial probability)

- b) p_l (probability of learning)
- d) p_f (forget probability)



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

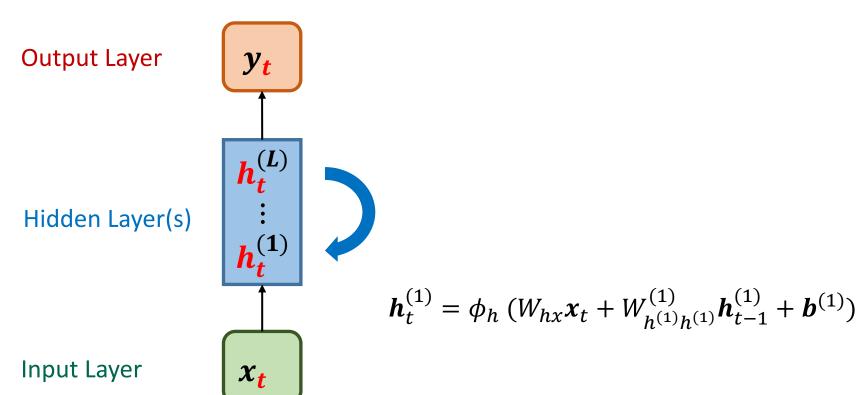
1 2 ··· n n+1
0 0 1 0 1 ?

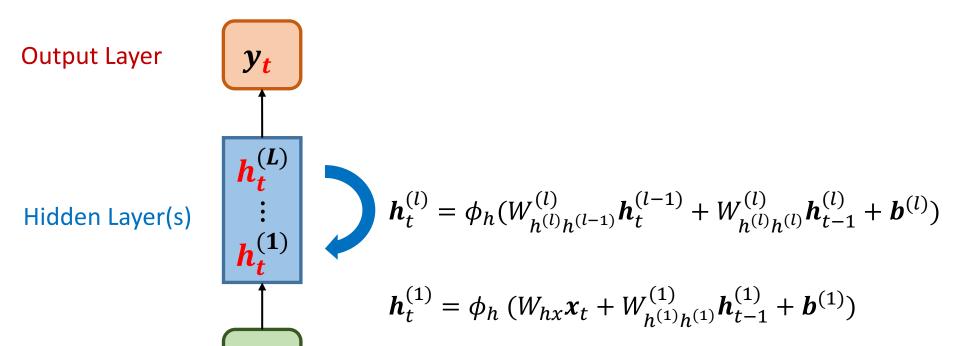
Today – Recurrent Neural Networks

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

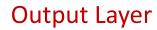
Neural Networks

- Neural networks are able to represent non-linear functions, i.e. $y_n \approx f(x_n)$ can be non-linear
- Neural networks are able to *learn* the features and the weights (parameters) from the data
- Tutorial: http://neuralnetworksanddeeplearning.com/





Input Layer



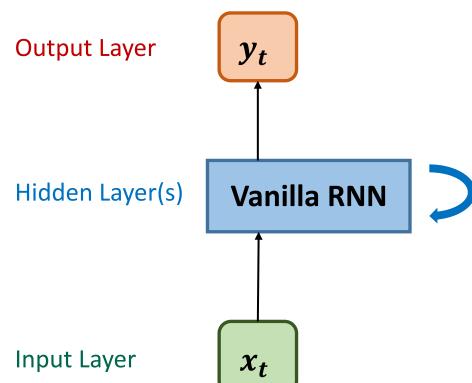
Hidden Layer(s) $\begin{array}{|c|} \hline \boldsymbol{h_t^{(L)}} \\ \vdots \\ \boldsymbol{h_t^{(1)}} \\ \hline \boldsymbol{h_t^{(1)}} \\ \end{array}$ $\boldsymbol{h_t^{(l)}} = \phi_h(W_{h^{(l)}h^{(l-1)}}^{(l)}\boldsymbol{h_t^{(l-1)}} + W_{h^{(l)}h^{(l)}}^{(l)}\boldsymbol{h_{t-1}^{(l)}} + \boldsymbol{b}^{(l)})$

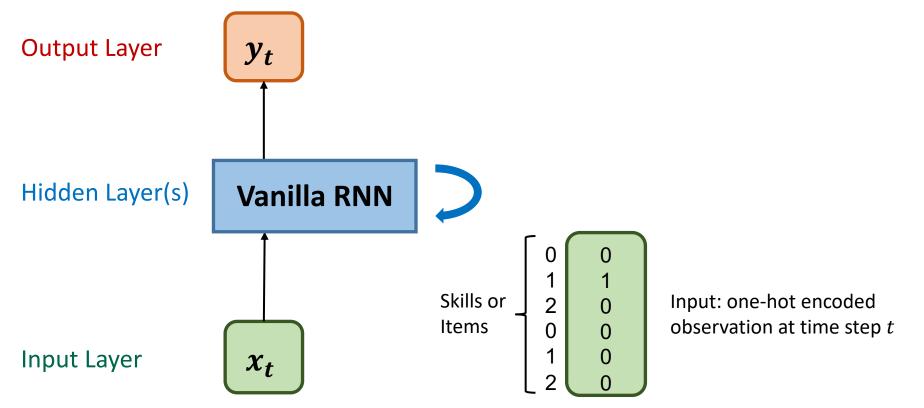
Input Layer

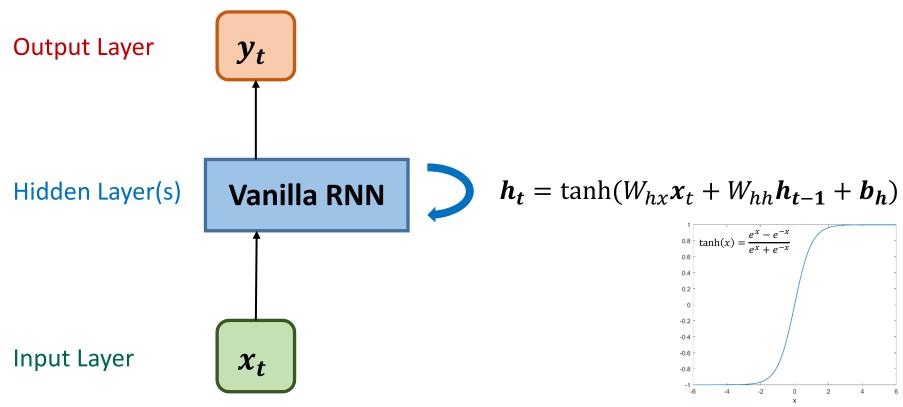
$$\boldsymbol{y_t} = \phi_y(W_{yh}\boldsymbol{h}_t^L + \boldsymbol{b}^{(y)})$$

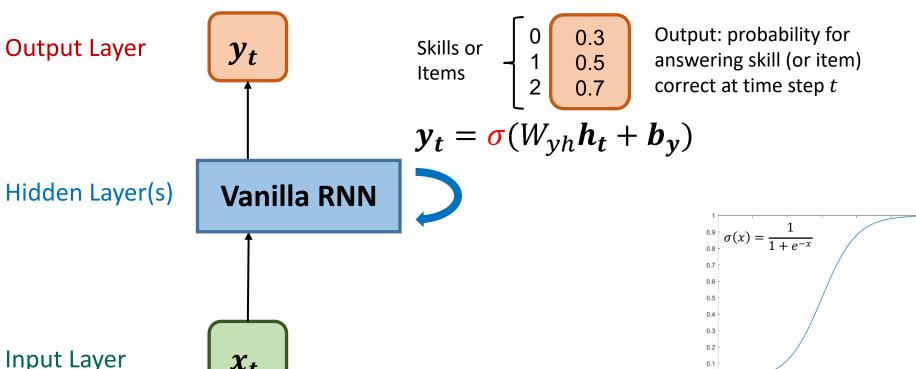
$$\boldsymbol{h}_{t}^{(l)} = \phi_{h}(W_{h^{(l)}h^{(l-1)}}^{(l)}\boldsymbol{h}_{t}^{(l-1)} + W_{h^{(l)}h^{(l)}}^{(l)}\boldsymbol{h}_{t-1}^{(l)} + \boldsymbol{b}^{(l)})$$

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

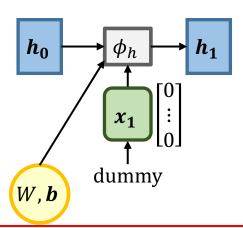


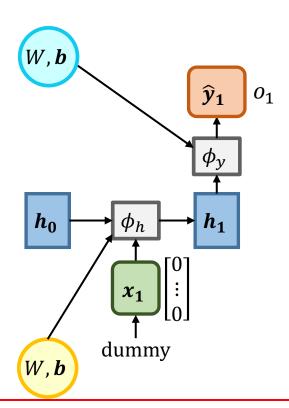


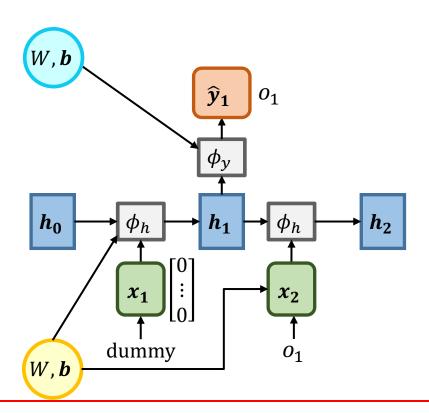


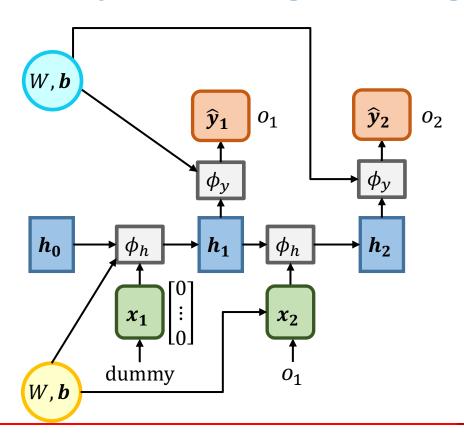


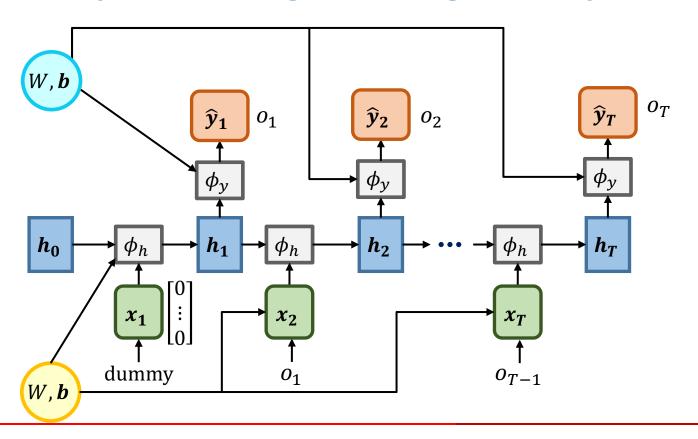
0.1

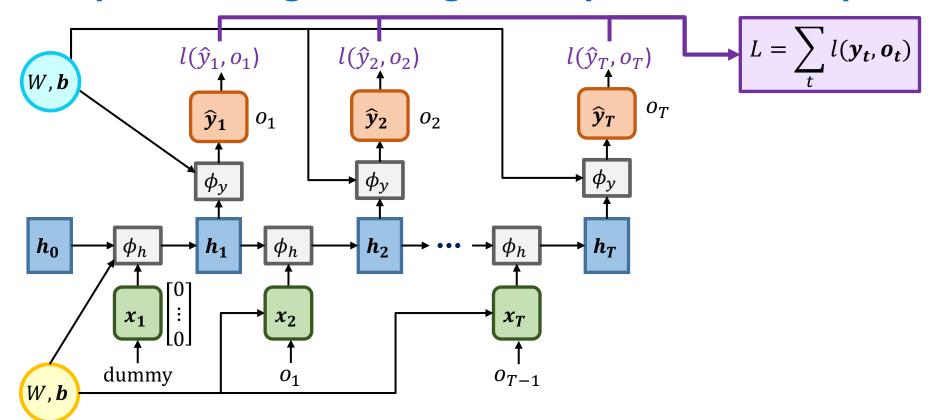




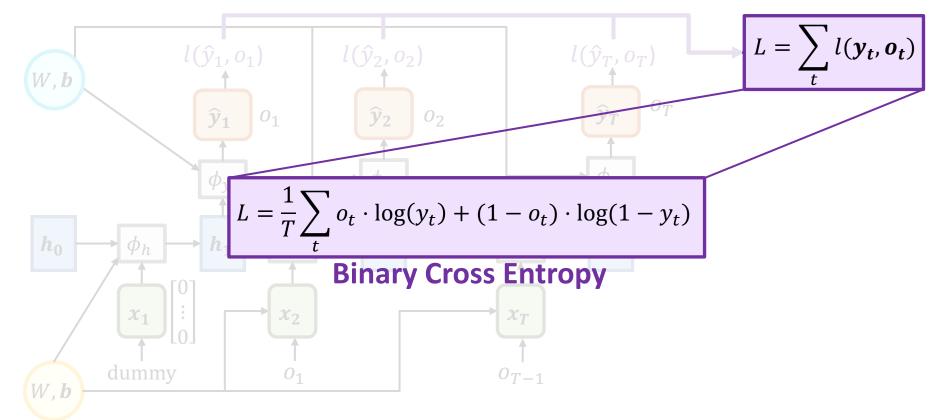








Training a DKT model: Binary Crossentropy Loss



Training and Prediction using DKT

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

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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

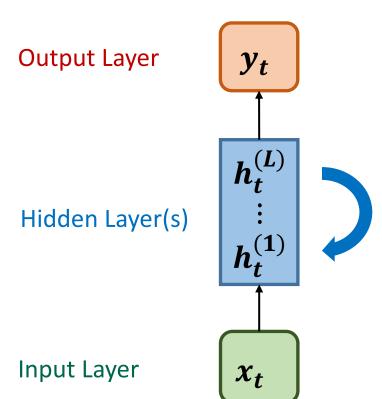
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RNNs – Tuning hyperparameters

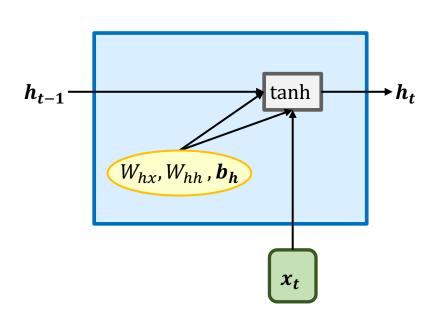
- Optimal number of epochs can be found using callbacks
- Other parameters can be tuned using for example:
 - a) Train-Validation-Test split
 - b) Train-Test split, using a k-fold cross validation on the training data to determine the optimal parameters

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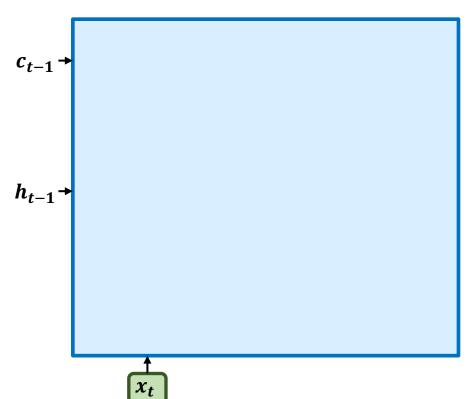


Vanilla RNN - revisited



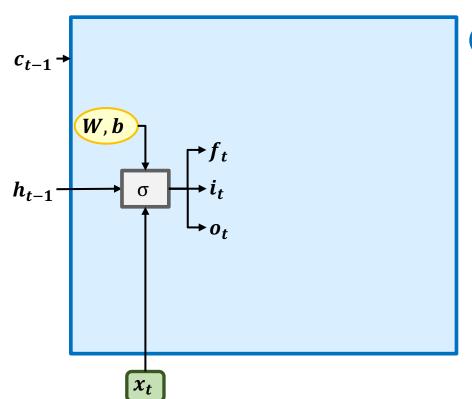
$$\boldsymbol{h_t} = \tanh(W_{hx}\boldsymbol{x_t} + W_{hh}\boldsymbol{h_{t-1}} + \boldsymbol{b_h})$$

Long-Short Term Memory Network (LSTM)



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

Long-Short Term Memory Network (LSTM)



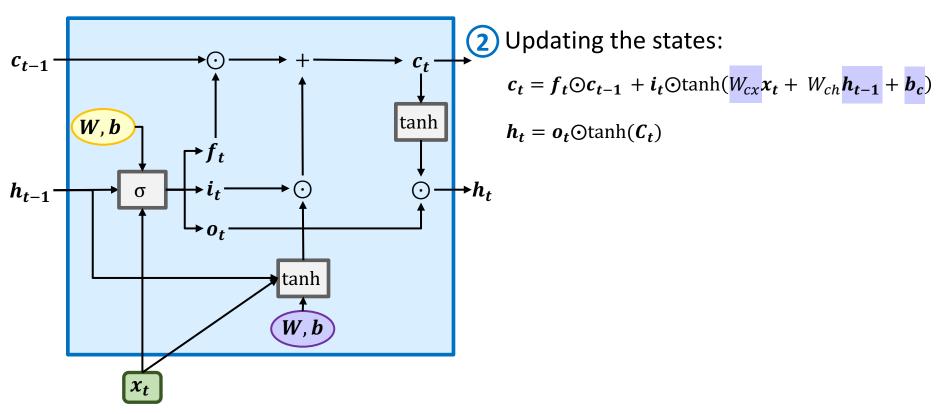
- 1 Updating the gates:
 - − f forget gate: whether to erase cell
 - -i input gate: whether to write to cell
 - o output gate: how much to reveal cell

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

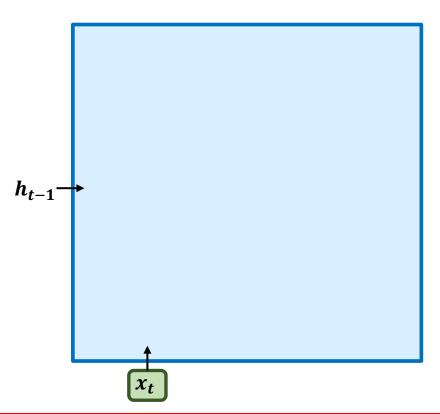
$$i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i)$$

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

Long-Short Term Memory Network (LSTM)

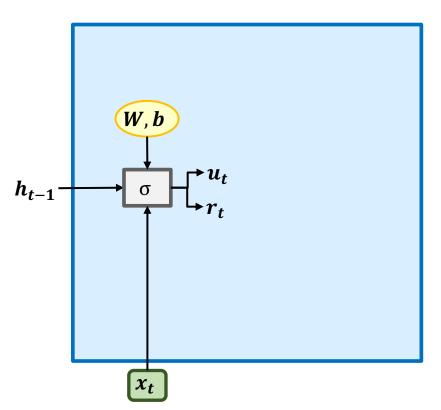


Gated Recurrent Units (GRU)



- Only one state (got rid of cell):
 - Hidden state $oldsymbol{h}_{t-1}$

Gated Recurrent Units (GRU)

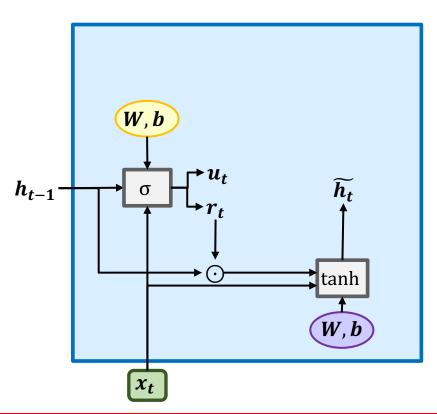


- 1 Updating the gates:
 - r reset gate: how much of the previous state to remember
 - u update gate: how much of the new state is just a copy of the old state

$$r_t = \sigma(\frac{W_{rx}}{X_t} x_t + \frac{W_{th}}{W_{th}} h_{t-1} + \frac{b_r}{V_t})$$

$$\boldsymbol{u_t} = \sigma(\boldsymbol{W_{ux}}\boldsymbol{x_t} + \boldsymbol{W_{uh}}\boldsymbol{h_{t-1}} + \boldsymbol{b_u})$$

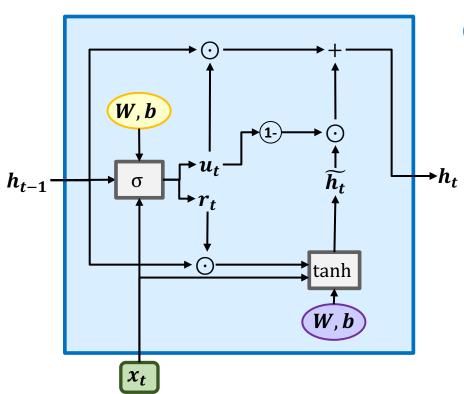
Gated Recurrent Units (GRU)



2 Get candidate hidden state:

$$\widetilde{\boldsymbol{h}_t} = \tanh(W_{hx}\boldsymbol{x}_t + W_{ht}(r_t \odot \boldsymbol{h}_{t-1}) + \boldsymbol{b}_{\boldsymbol{h}})$$

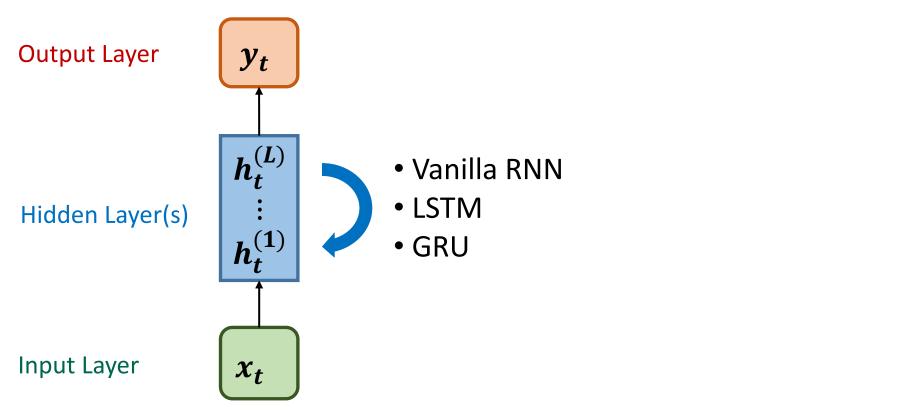
Gated Recurrent Units (GRU)



3 Updating the state:

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

Same input/output – different architectures

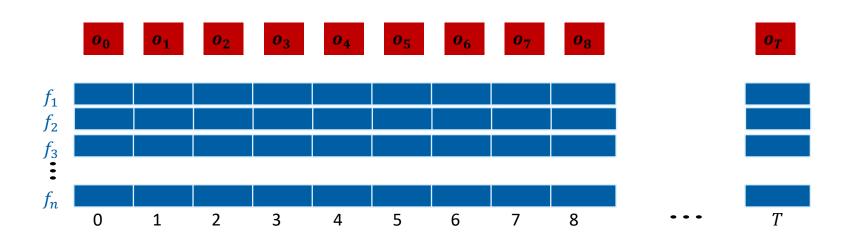


Today – Recurrent Neural Networks

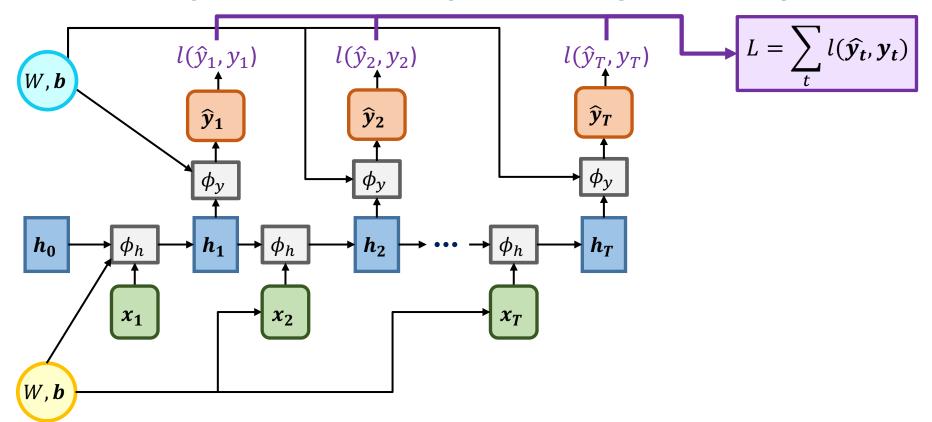
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Many-to-many aka the Tracing Task

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

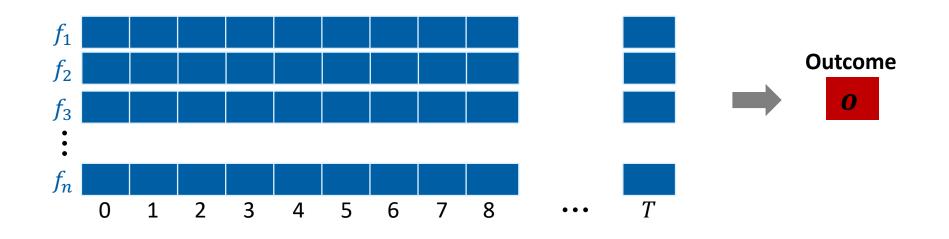


Computational Graph – Many-to-many

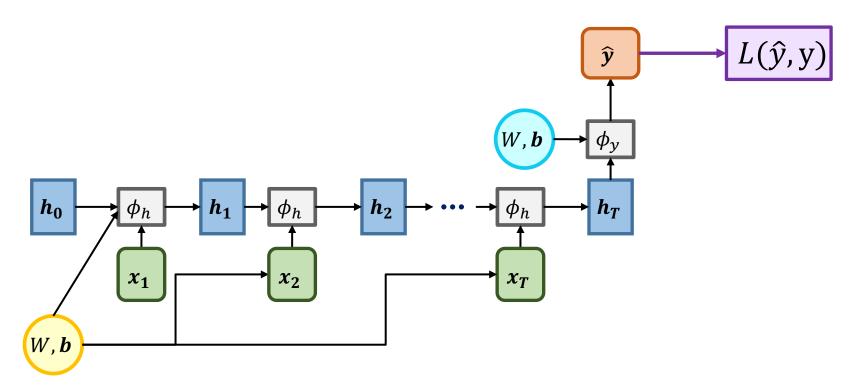


Many-to-one aka the Time-Series Prediction Task

• Prediction of a target variable o after $t \le T$ time steps, where T is the total number of time steps



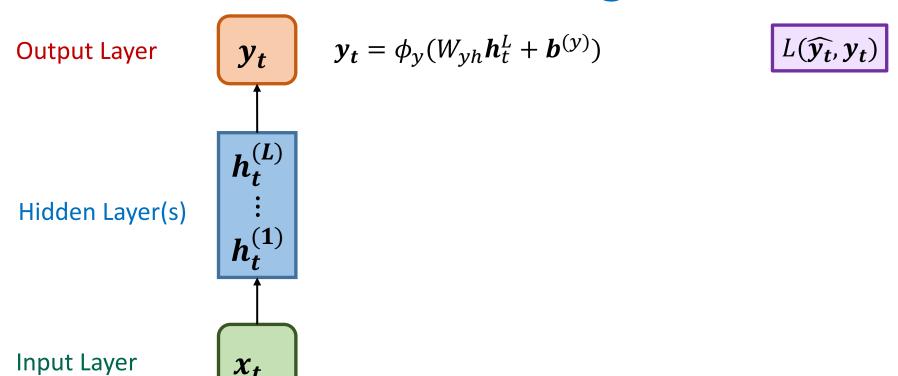
Computational Graph – Many-to-one



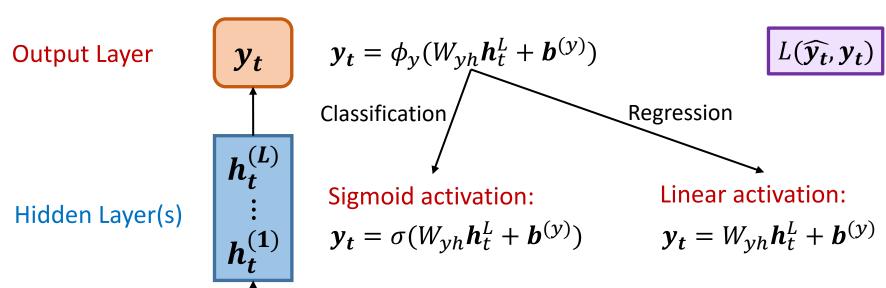
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Classification vs. Regression

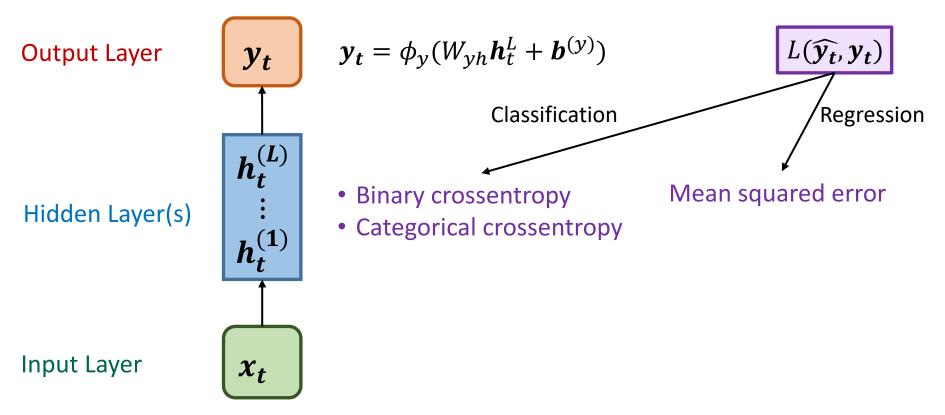


Classification vs. Regression: Output Layer



Input Layer

Classification vs. Regression: Training Loss



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:
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