LSTM in Pytorch with Temporal Data - Lab -

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Agenda

- Jena Weather Dataset
- RNNs & LSTMs
- Build your LSTM-based model
- Train your LSTM-based model

Notebook link: https://shorturl.at/xAI37

Jena Weather Dataset

For today's lab session, we will use an openly available weather data: the Jena Weather Analysis dataset.

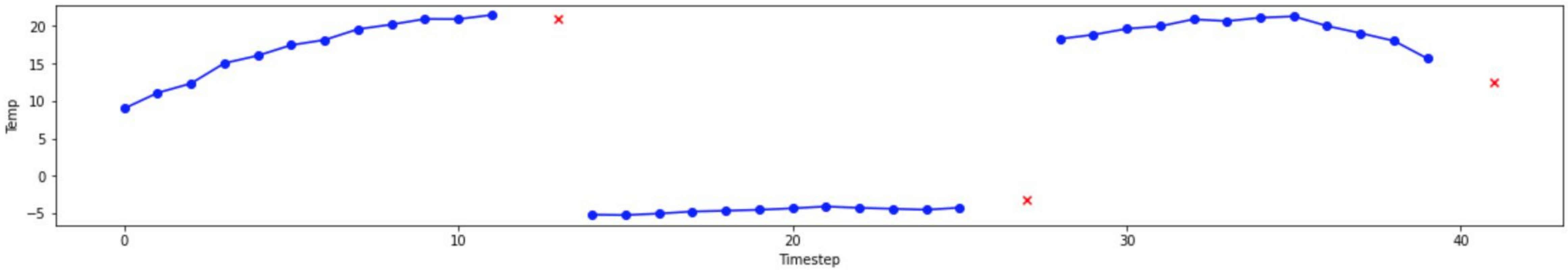
It includes 10-minute recordings of multiple weather parameters for the German city of Jena, including:

- Temperature
- Dew Point
- Relative Humidity
- Vapor Pressure
- Atmospheric Pressure
- Wind Speed
- …

Jena Weather Dataset

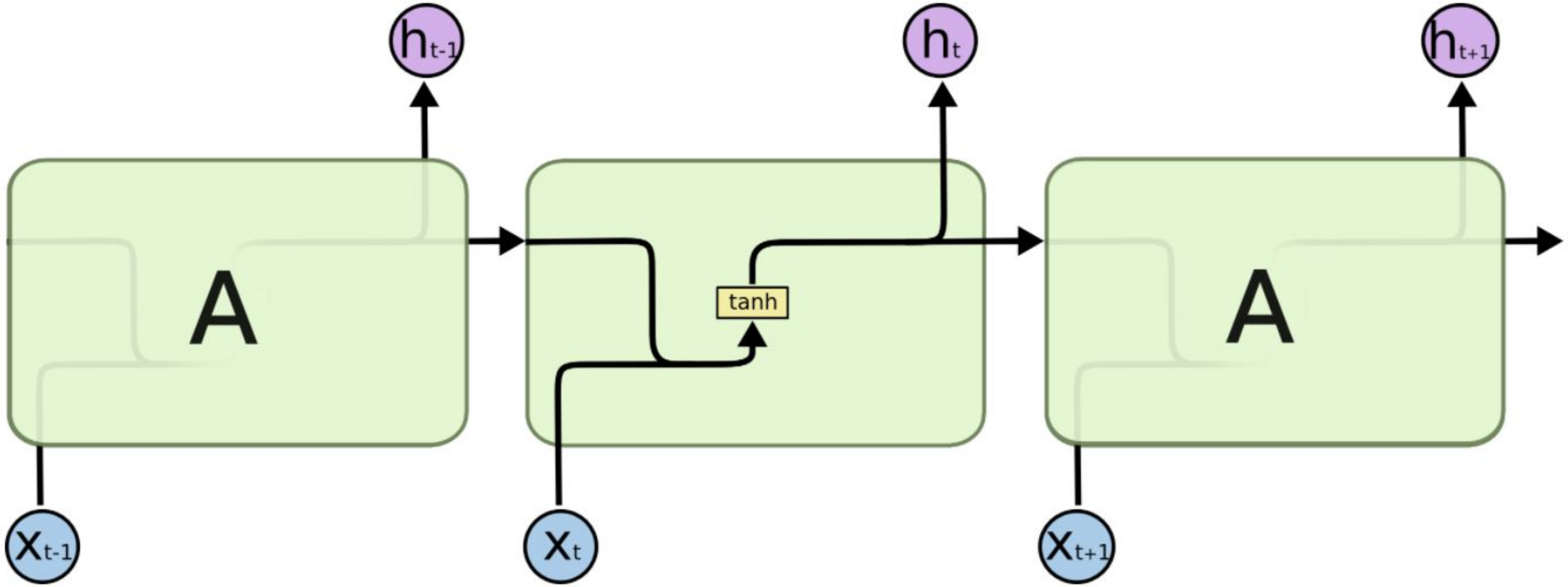
We will design a model that

- Receives a 12 hourly recordings of 19 weather variables
- Forecasts the temperature two hours into the future



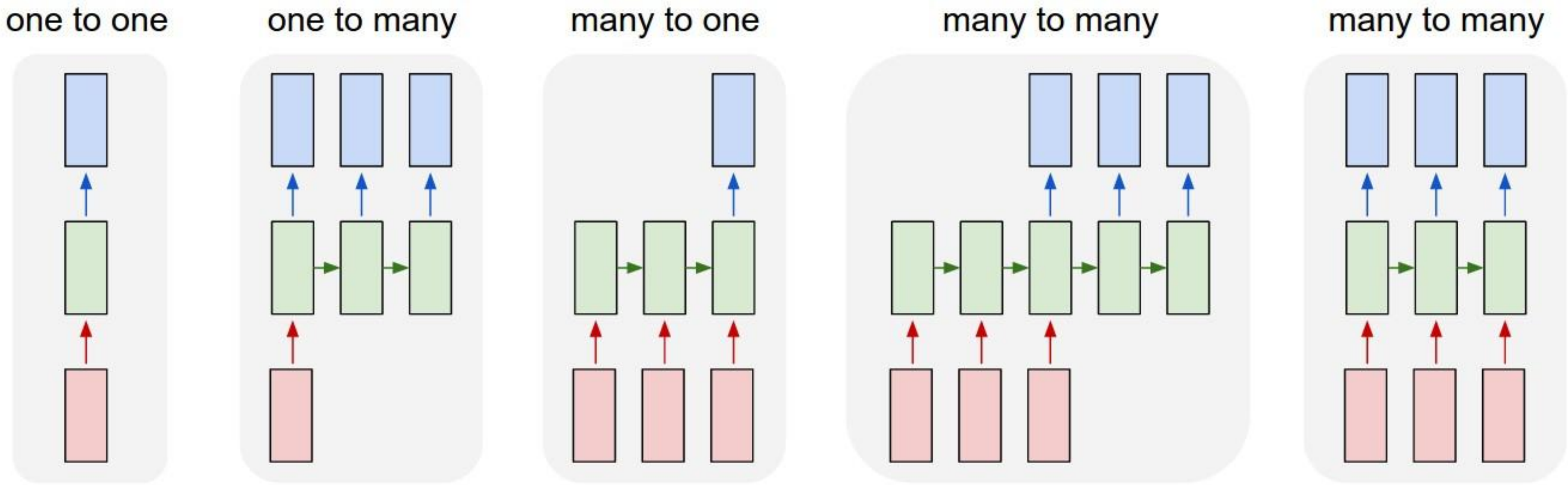
Recurrent Neural Networks

- Handle sequential data in an optimized manner
- Operation is similar to a state-machine
- Information on previous timesteps is encapsulated in the hidden state



Modes of operation

- As we deal with sequential data, there are many ways we can use RNNs

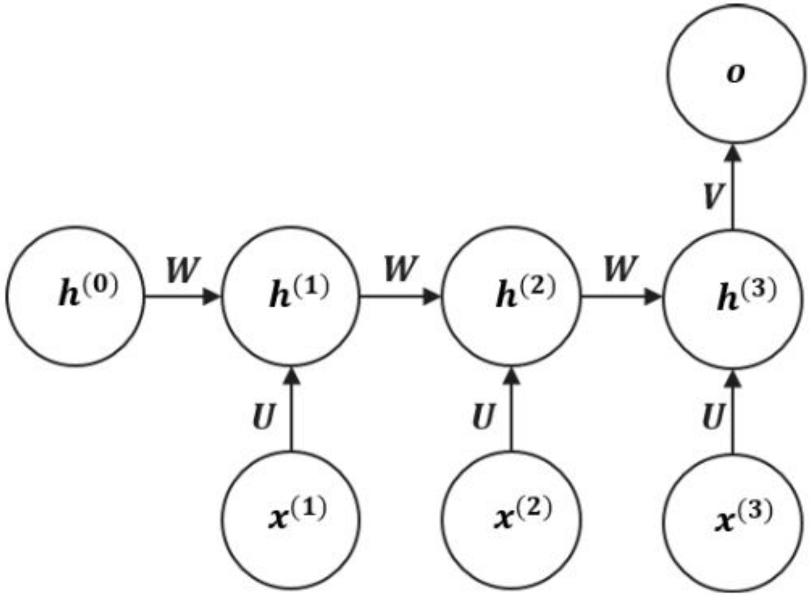


- What is our configuration for today's task?

Many to one. We want to predict a new possible timestep for a given temporal series

Backpropagation Through Time

- When applying backpropagation, we must *unroll* the computational graph
- Long-term dependencies are problematic *(vanishing gradients)!*

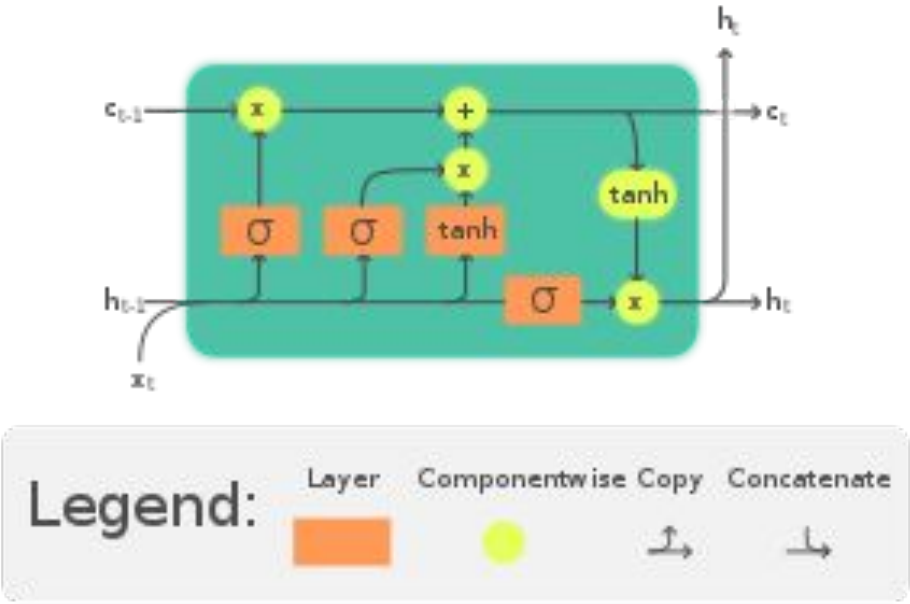


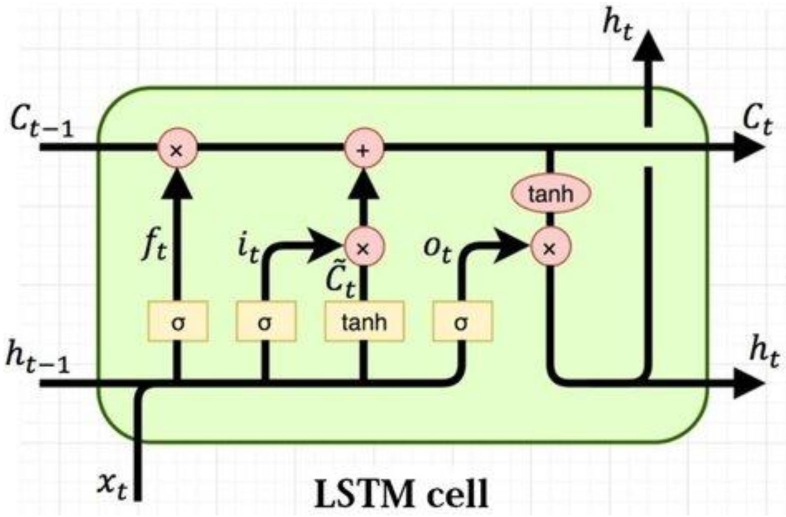
- $\frac{\partial L}{\partial \boldsymbol{V}} = \frac{\partial L}{\partial \boldsymbol{o}} \frac{\partial \boldsymbol{o}}{\partial \boldsymbol{V}}$
- $\frac{\partial L}{\partial \boldsymbol{W}} = \frac{\partial L}{\partial \boldsymbol{o}} \frac{\partial \boldsymbol{o}}{\partial \boldsymbol{h}^{(3)}} \sum_{k=0}^{3} \left(\frac{\partial \boldsymbol{h}^{(3)}}{\partial \boldsymbol{h}^{(k)}} \frac{\partial \boldsymbol{h}^{(k)}}{\partial \boldsymbol{W}} \right)$
- $\frac{\partial L}{\partial \boldsymbol{U}} = \frac{\partial L}{\partial \boldsymbol{o}} \frac{\partial \boldsymbol{o}}{\partial \boldsymbol{h}^{(3)}} \sum_{k=0}^{3} \left(\frac{\partial \boldsymbol{h}^{(3)}}{\partial \boldsymbol{h}^{(k)}} \frac{\partial \boldsymbol{h}^{(k)}}{\partial \boldsymbol{U}} \right)$

Long-Short Term Memory Networks

To compensate for this issue, we introduce LSTMs:

- They facilitate the flow of gradients through their hidden states
- Dual-track cell structure: cell state (*gradient superhighway*) + hidden state (output)
- Forget, input & output gates regulate the information flow from/to cell state
- Sigmoids vs tanhs!





$$i_t = \sigma\left(x_t U^i + h_{t-1} W^i\right)$$
$$f_t = \sigma\left(x_t U^f + h_{t-1} W^f\right)$$
$$o_t = \sigma\left(x_t U^o + h_{t-1} W^o\right)$$
$$\tilde{C}_t = \tanh\left(x_t U^g + h_{t-1} W^g\right)$$
$$C_t = \sigma\left(f_t * C_{t-1} + i_t * \tilde{C}_t\right)$$
$$h_t = \tanh(C_t) * o_t$$

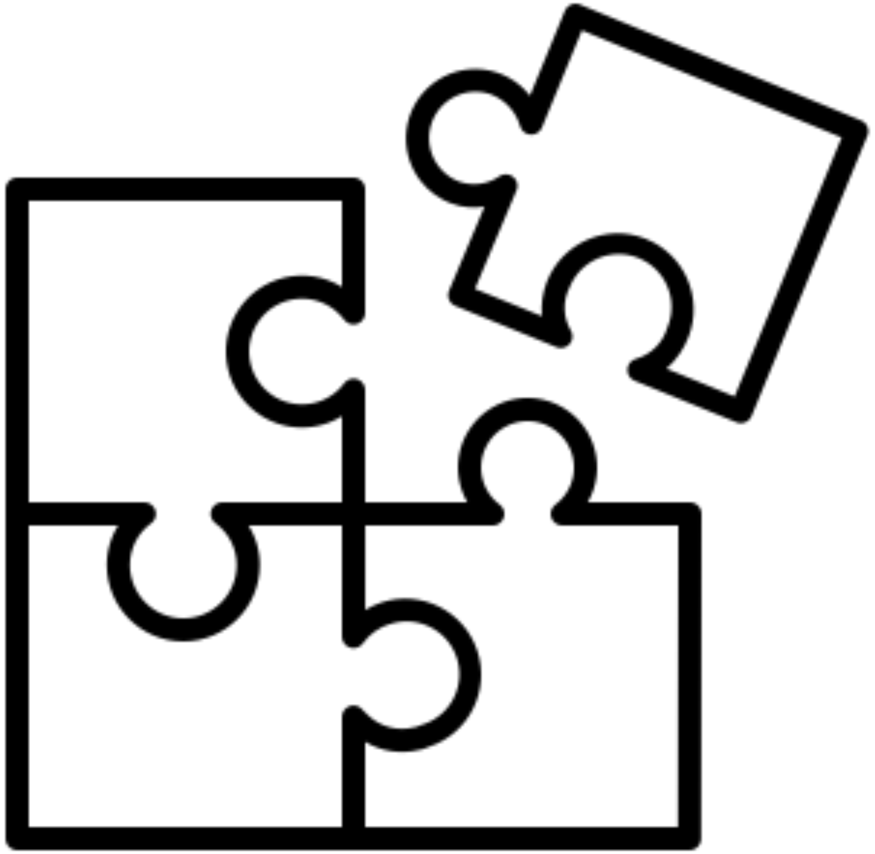
Defining our model

To build our model, we will need to combine the following classes today:

- torch.nn.Linear
- torch.nn.LSTM
- torch.nn.ReLU

Each implements a piece of the network; how can they be combined?

Follow the shapes!



LSTM → size
num-hidden
hyperparameter

MLP
- Linear
- ReLU
- Linear → 1 output for series,

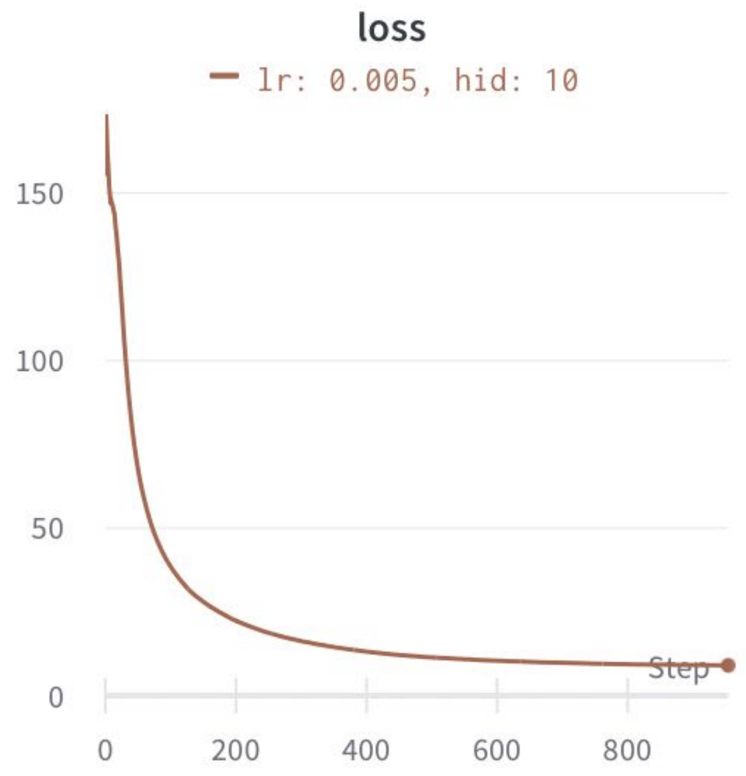
Training our model

To train our model, we:

- Feed it randomly shuffled sequences of data
- Ask it to guess the corresponding target temperature
- Compute the error (loss)
- Back-propagate the loss through the network
- Adjust parameters accordingly
- goto 1!

When do we stop?

?



Error Measures

The way we compute errors is a crucial part of the training procedure:

- Cross-Entropy Loss $\ell(x, y) = L = \{l_1, \dots, l_N\}^\top, \quad l_n = -w_{y_n} \log \frac{\exp(x_{n,y_n})}{\sum_{c=1}^{C} \exp(x_{n,c})}$
- Mean Square Error $\ell(x, y) = L = \{l_1, \dots, l_N\}^\top, \quad l_n = (x_n - y_n)^2$
- Mean Absolute Error (L1loss) $\ell(x, y) = L = \{l_1, \dots, l_N\}^\top, \quad l_n = |x_n - y_n|$

What can we use for the task at hand? Why?

Because we want the info about how many far it is y-pred from ground truth
(we don't need accuracy or evaluation parameter)

Tweaking Hyperparameters

Our model seems to be working, but can we do better?

- Trying out different optimizers
- Testing out different hidden sizes
- Changing the learning rate
- Learning rate scheduling