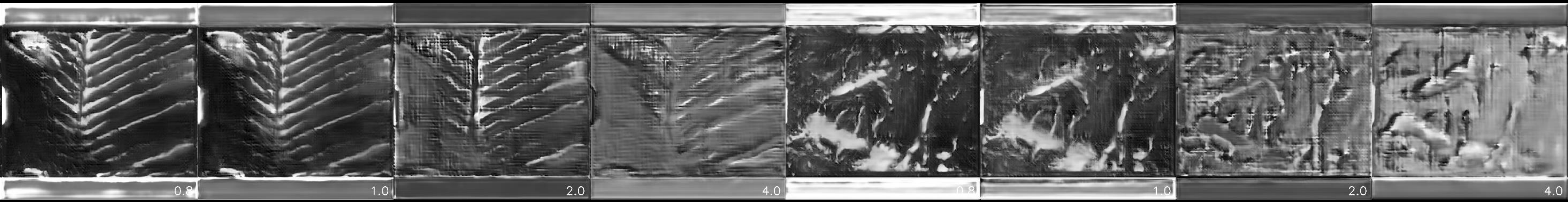
Exploring Machine Intelligence

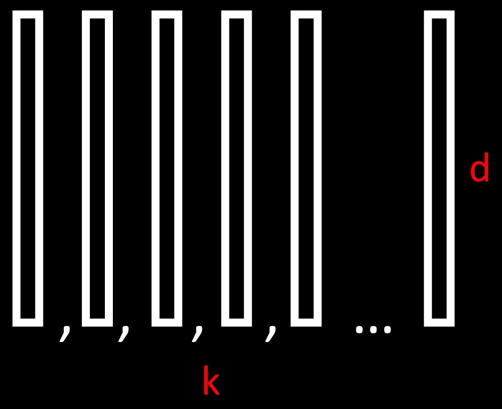
Week 7, Sequential Modelling



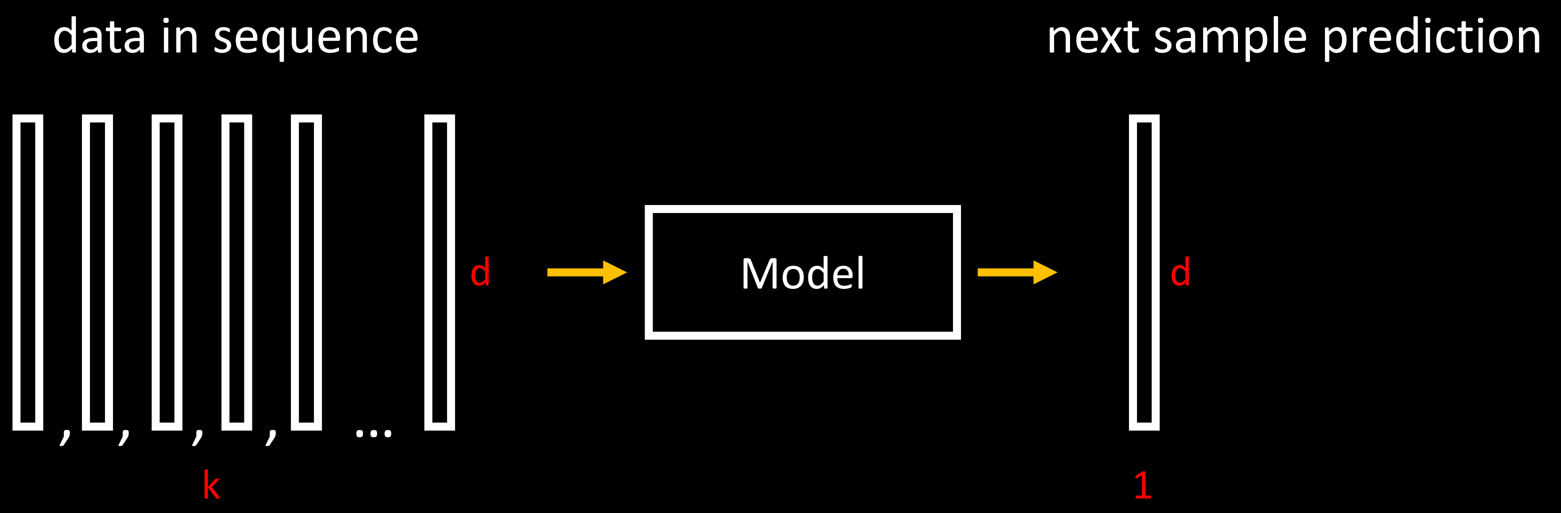
~ Vítek Růžička

Motivation for today

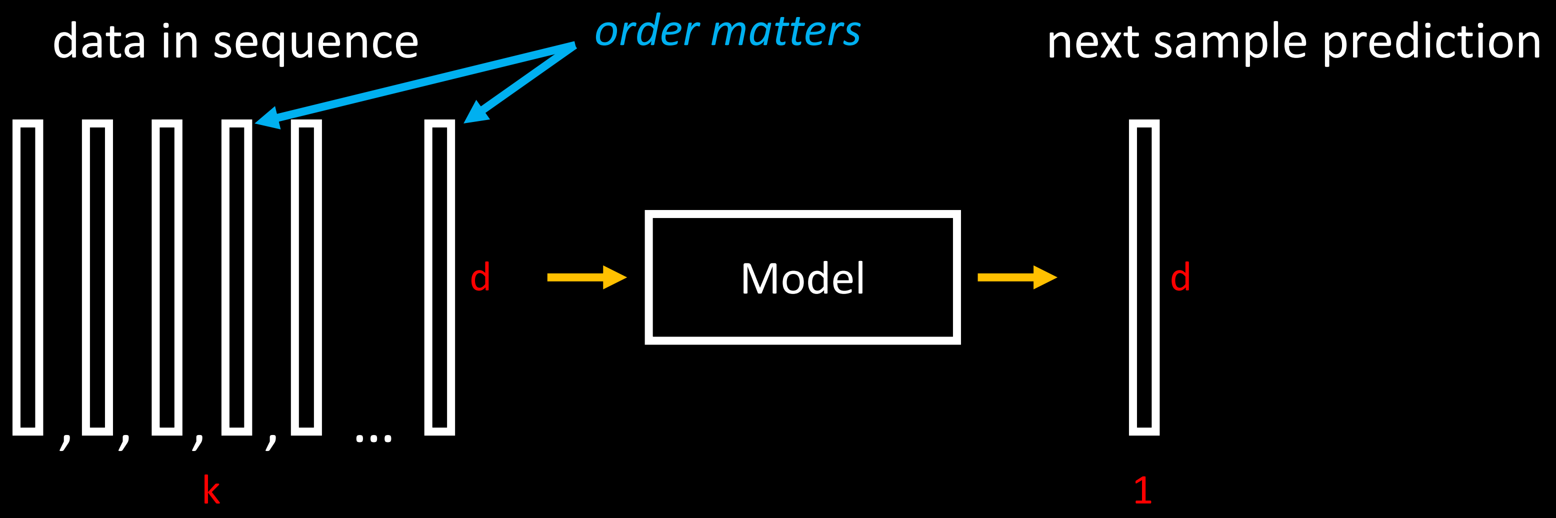
data in sequence



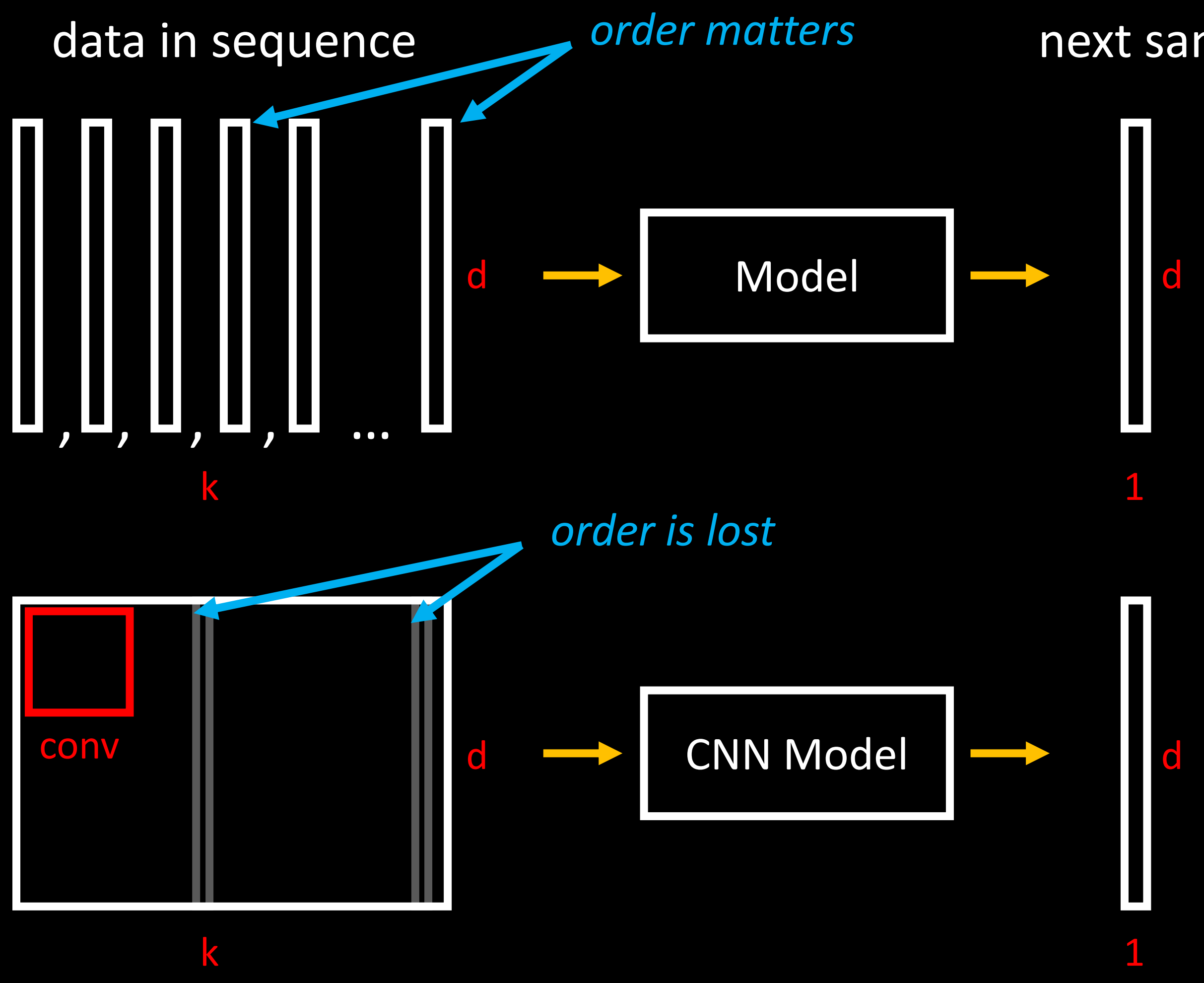
Motivation for today



Motivation for today



Motivation for today

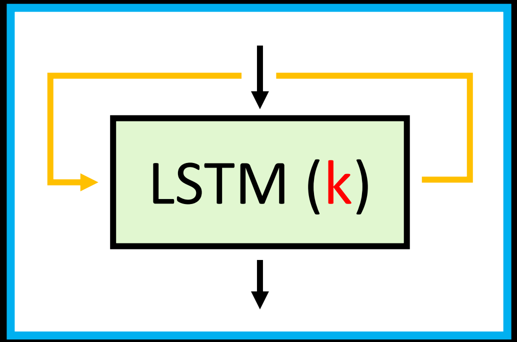


We could use any model we talked about (*CNN, fully connected NN*) to map this data – but there is a **type of models which is designed with sequential data in mind** and maps this sequentiality better.

Today

Sequential Modelling

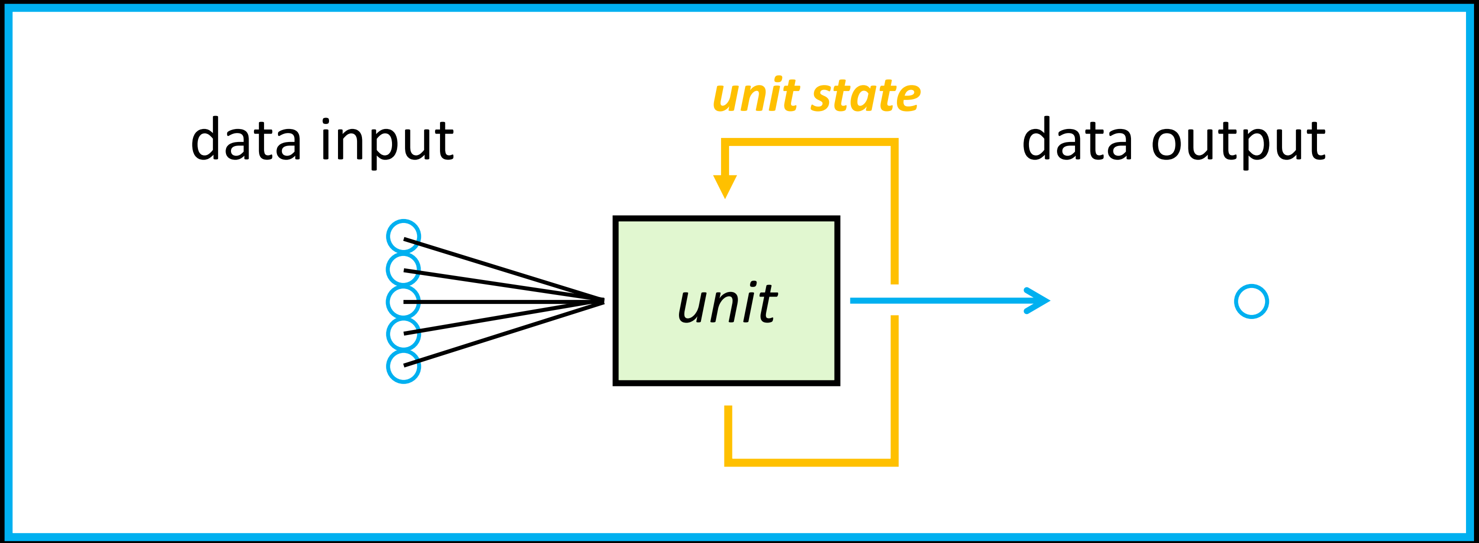
- Creating networks from **units with memory**
- Plugging in **textual and musical data**



Practical session:

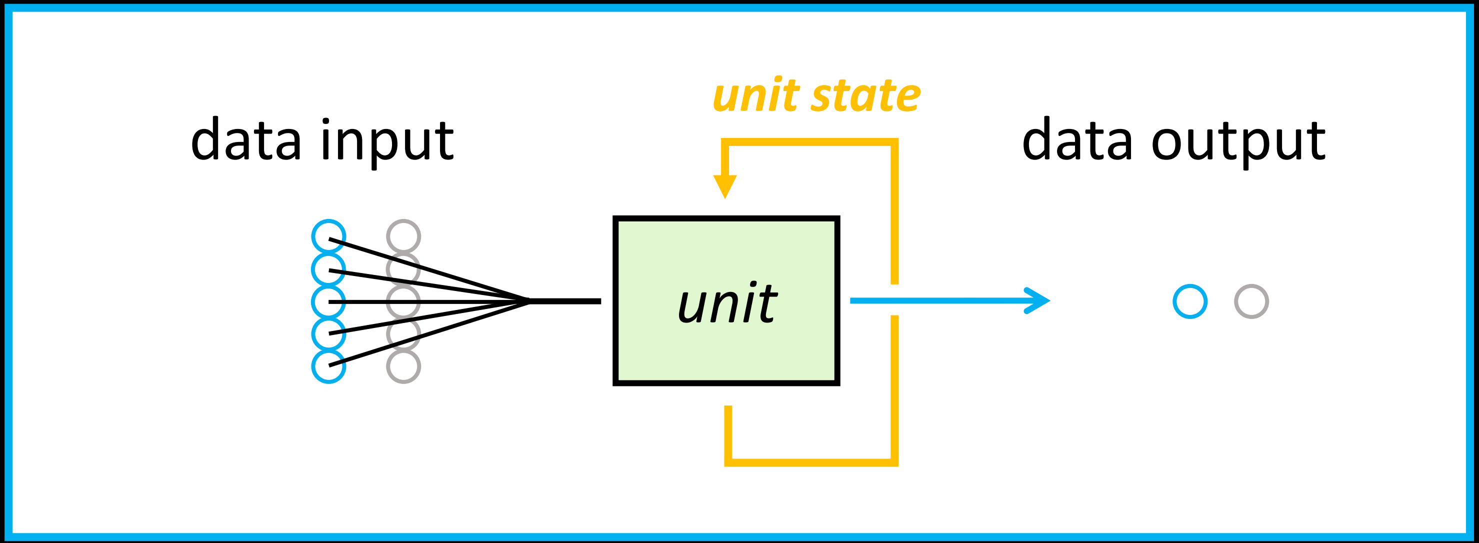
- **Q&A session** for the Final Exam

Unit with a memory



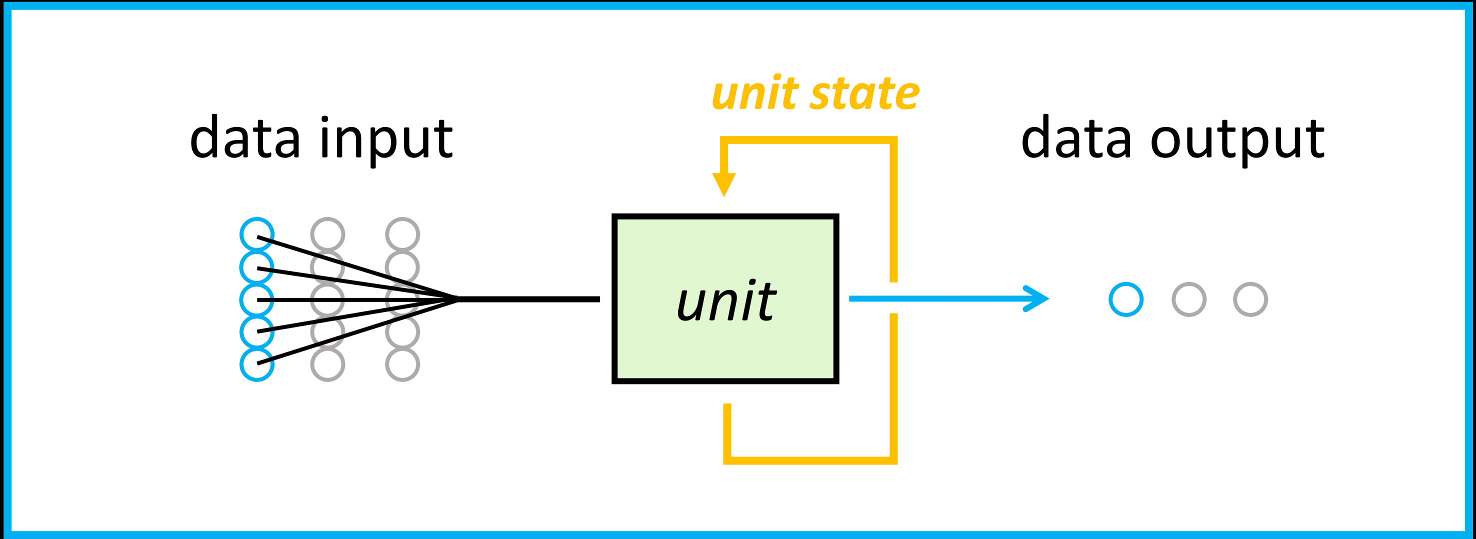
- Not only we **produce some output from the input**, we also **alter the unit state** (memorize some data from the next input in sequence)
- How both of this happens is something we **learn from the structure of data**

Unit with a memory



- Not only we **produce some output from the input**, we also **alter the unit state** (memorize some data from the next input in sequence)
- How both of this happens is something we **learn from the structure of data**

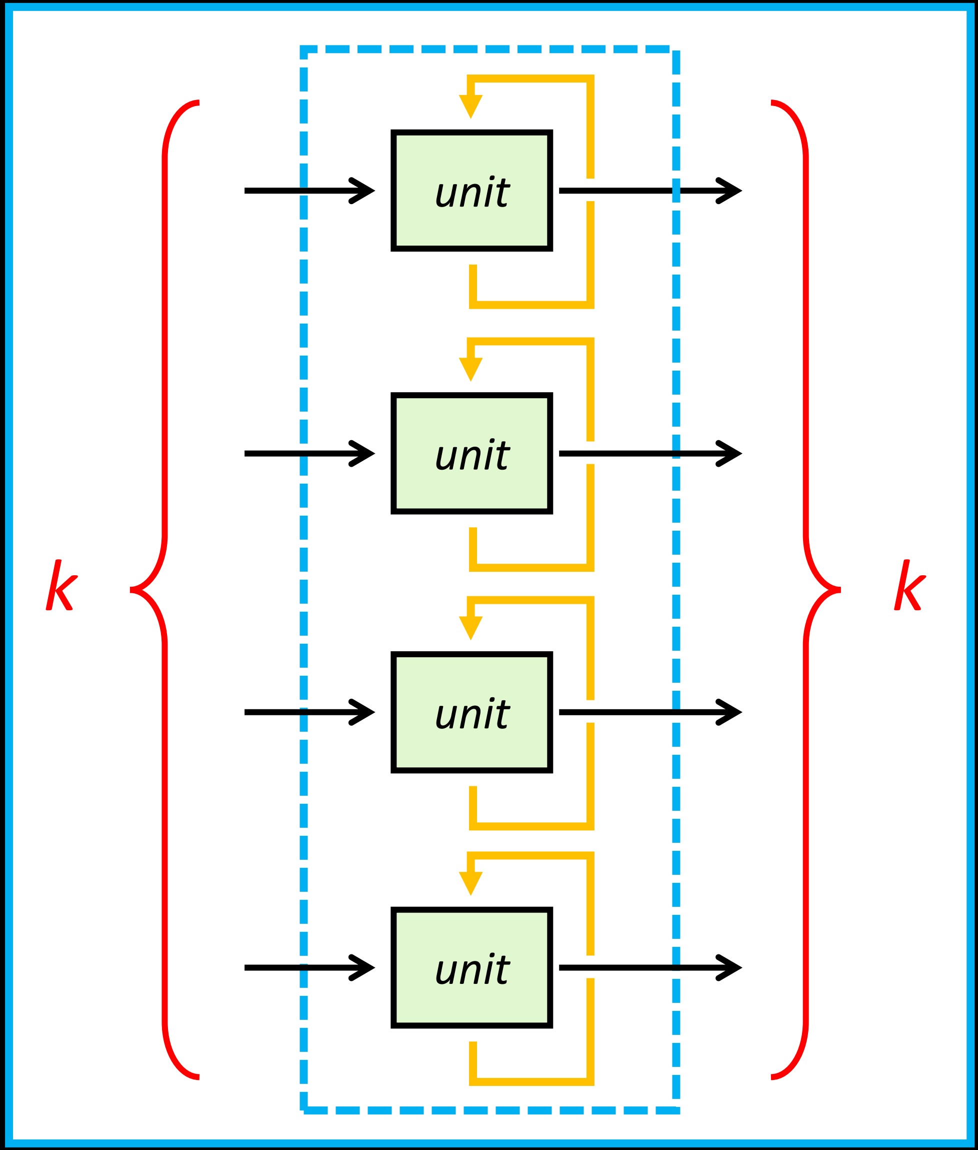
Unit with a memory



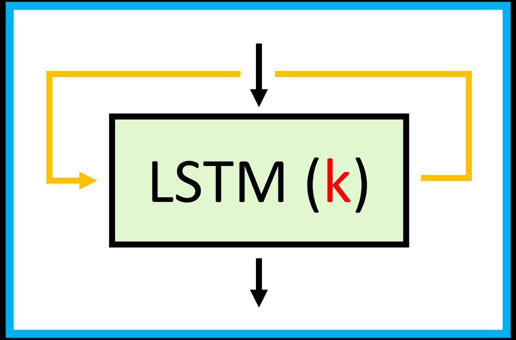
- Not only we **produce some output from the input**, we also **alter the unit state** (memorize some data from the next input in sequence)
- How both of this happens is something we **learn from the structure of data**

Recurrent layer

- These **recurrent units** with memory can be put into **layers**

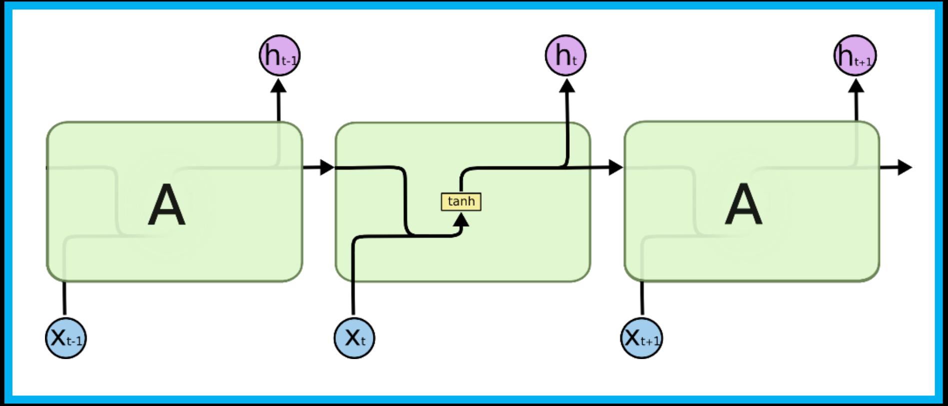


- Single **LSTM layer** with **k** units is usually simplified as:



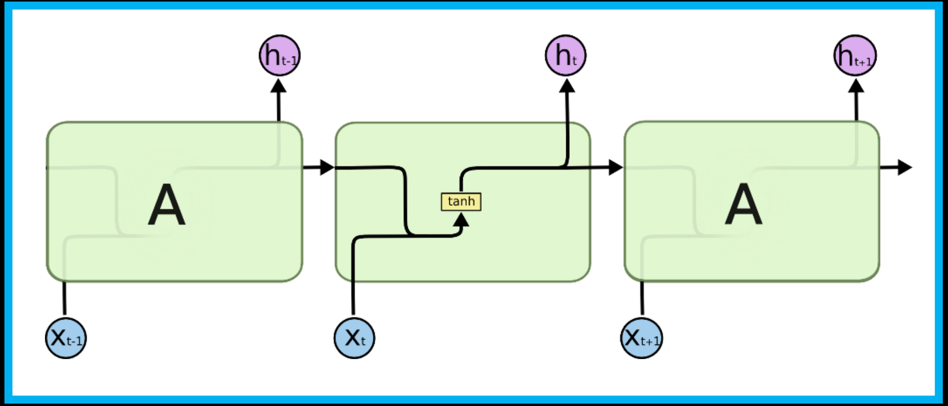
Unit types: RNNs and LSTMs

- **Recurrent Neural Networks** (RNN):
  - Simpler unit design



Unit types: RNNs and LSTMs

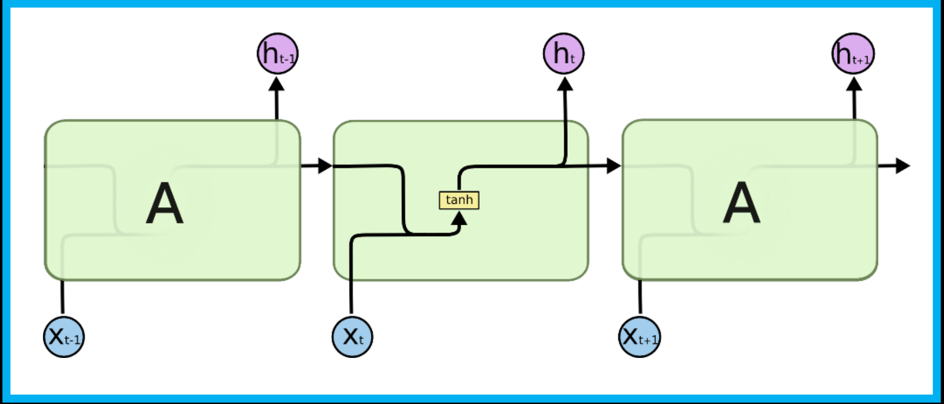
- **Recurrent Neural Networks** (RNN):
  - Simpler unit design



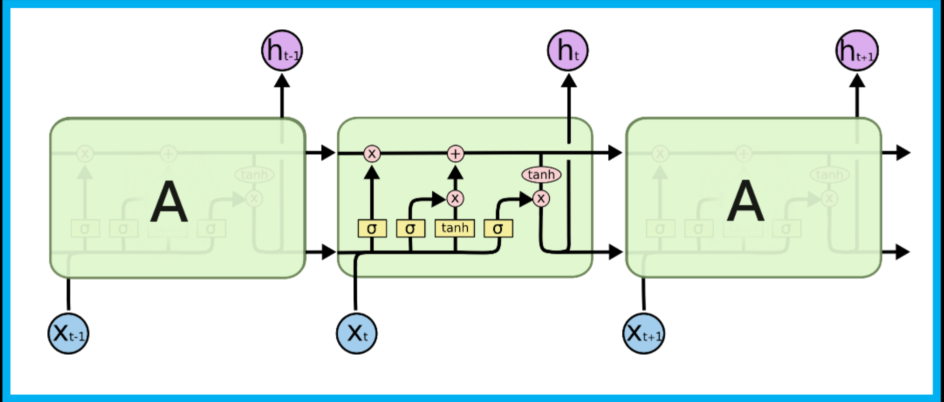
"I grew up in France… I speak fluent French."

Unit types: RNNs and LSTMs

- **Recurrent Neural Networks** (RNN):
  - Simpler unit design



- **Long-Short Term Memory** (LSTM):
  - More complex unit design, made to **remember longer dependencies** inside the data



^ forget and input gates controlled by learned parameters (hence needs more of them)

"I grew up in France… I speak fluent French."

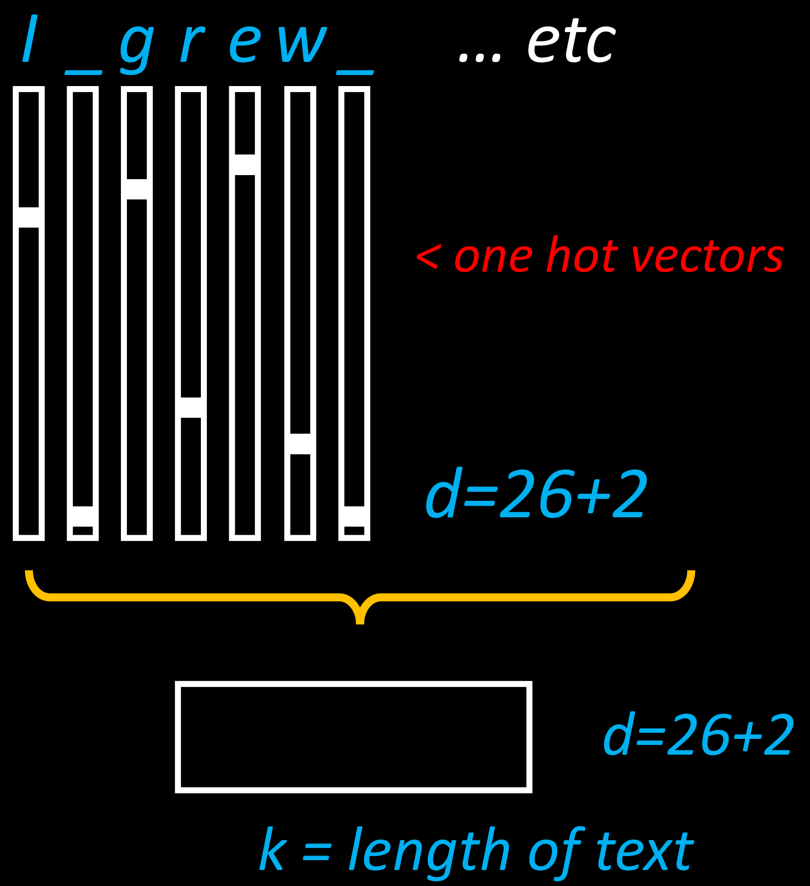
Plugging in text data

“I grew up in France… I speak fluent French.”

- **Vectorize text using a dictionary**

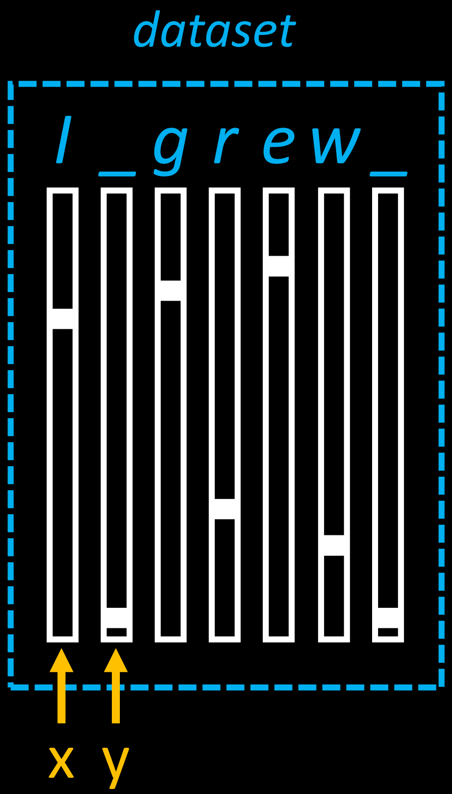
Plugging in text data

"I grew up in France... I speak fluent French." *< original data*

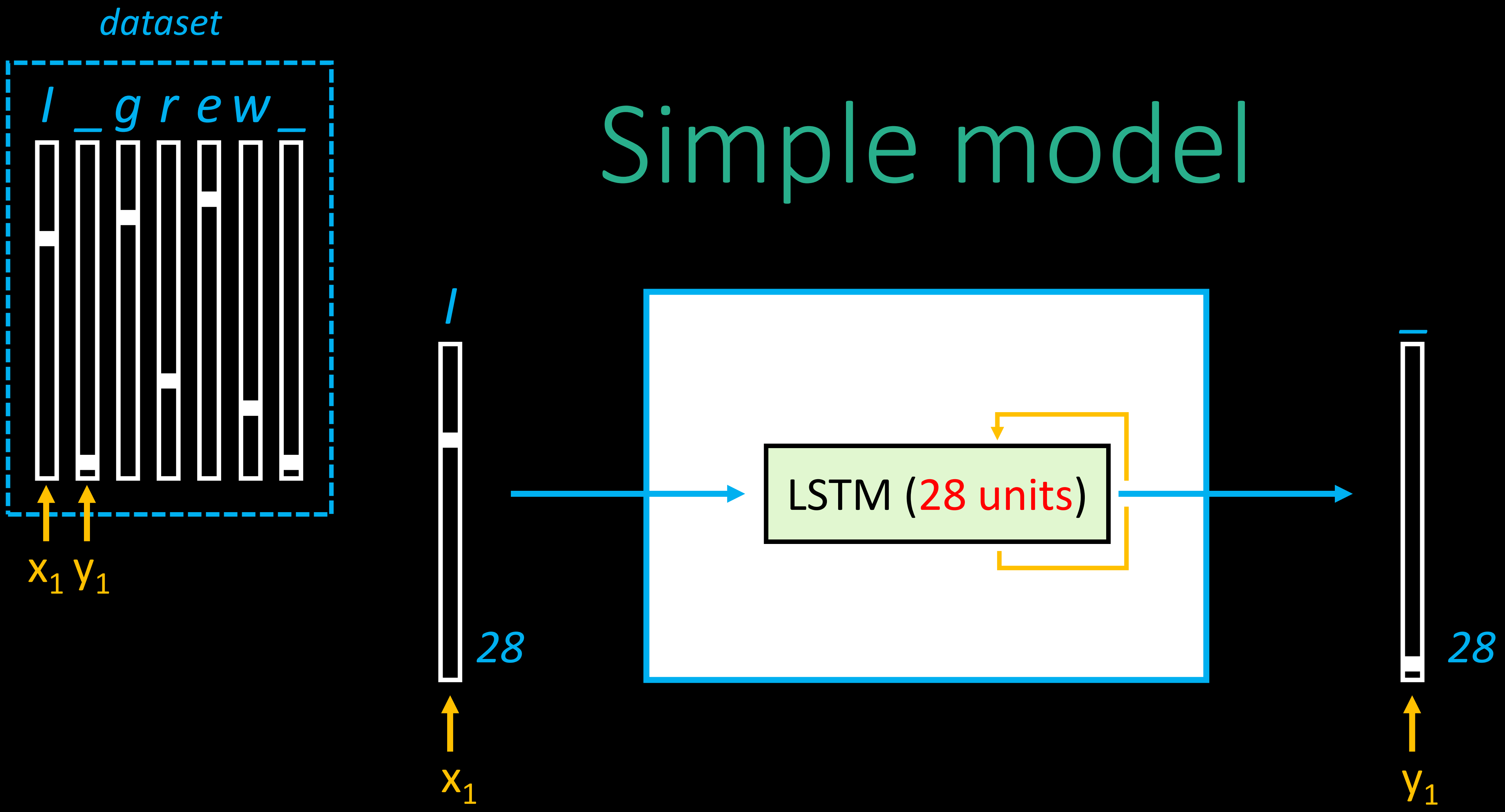


- **Vectorize text using a dictionary**
- Each letter is **encoded as a one-hot vector** using alphabet as dictionary (or full words using a word dictionary)
- We can **later decode the predictions** looking into that dictionary

Simple model

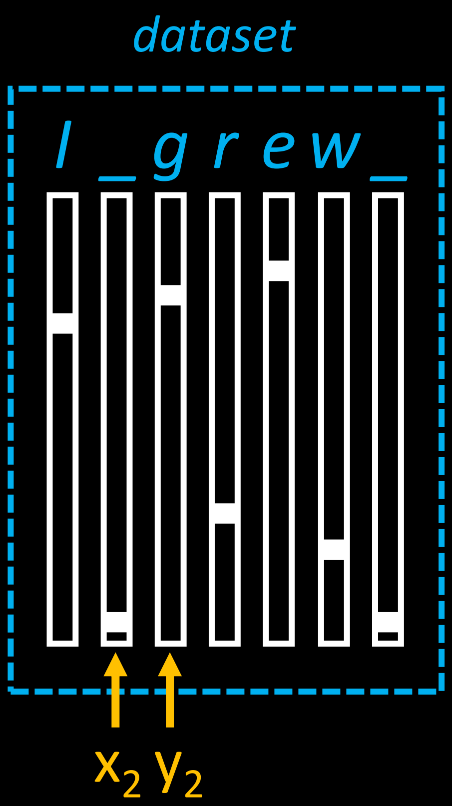


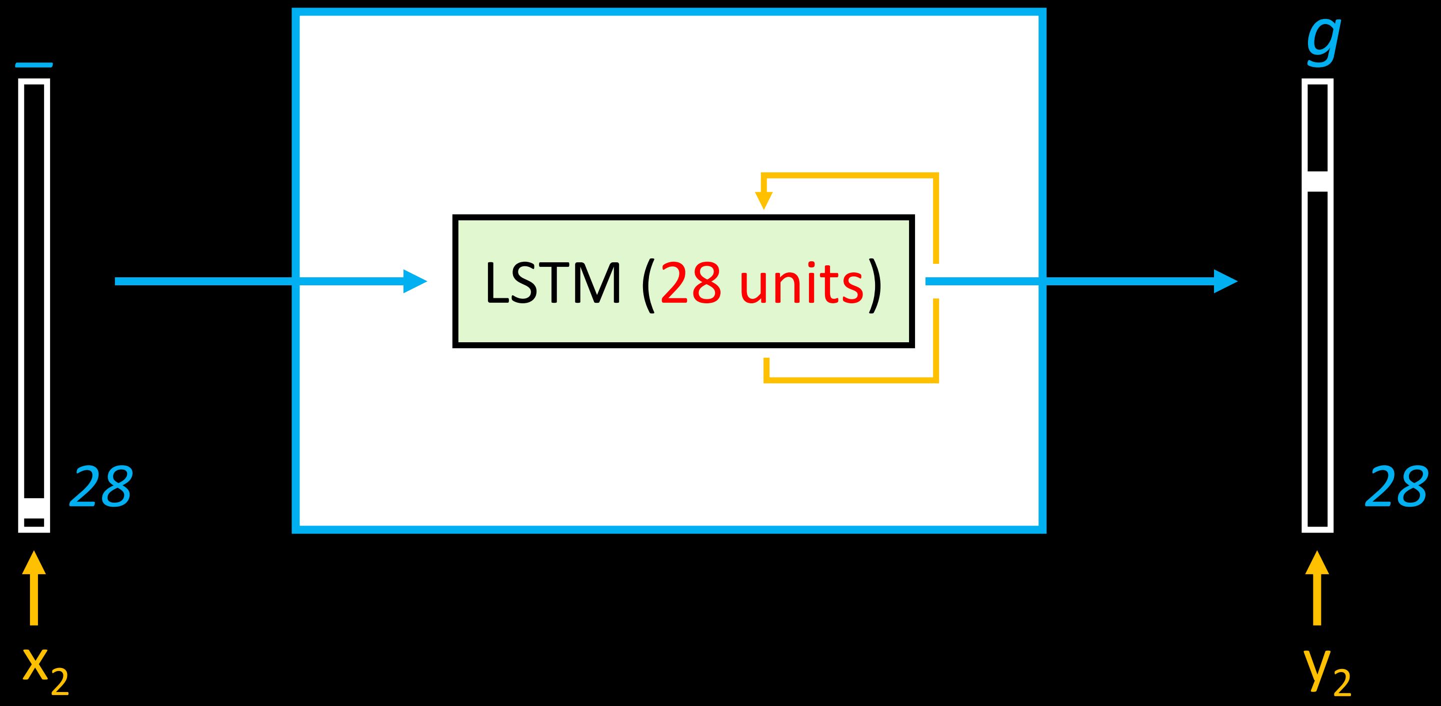
Simple model



- We are **training the model** to **learn the transformation x -> y** while it also **learns what** is useful **to save** inside the 28 units (what preceded before this x).

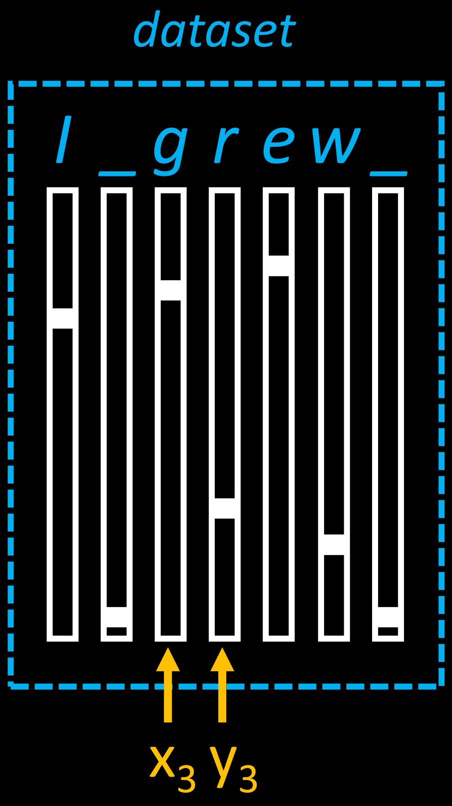
Simple model

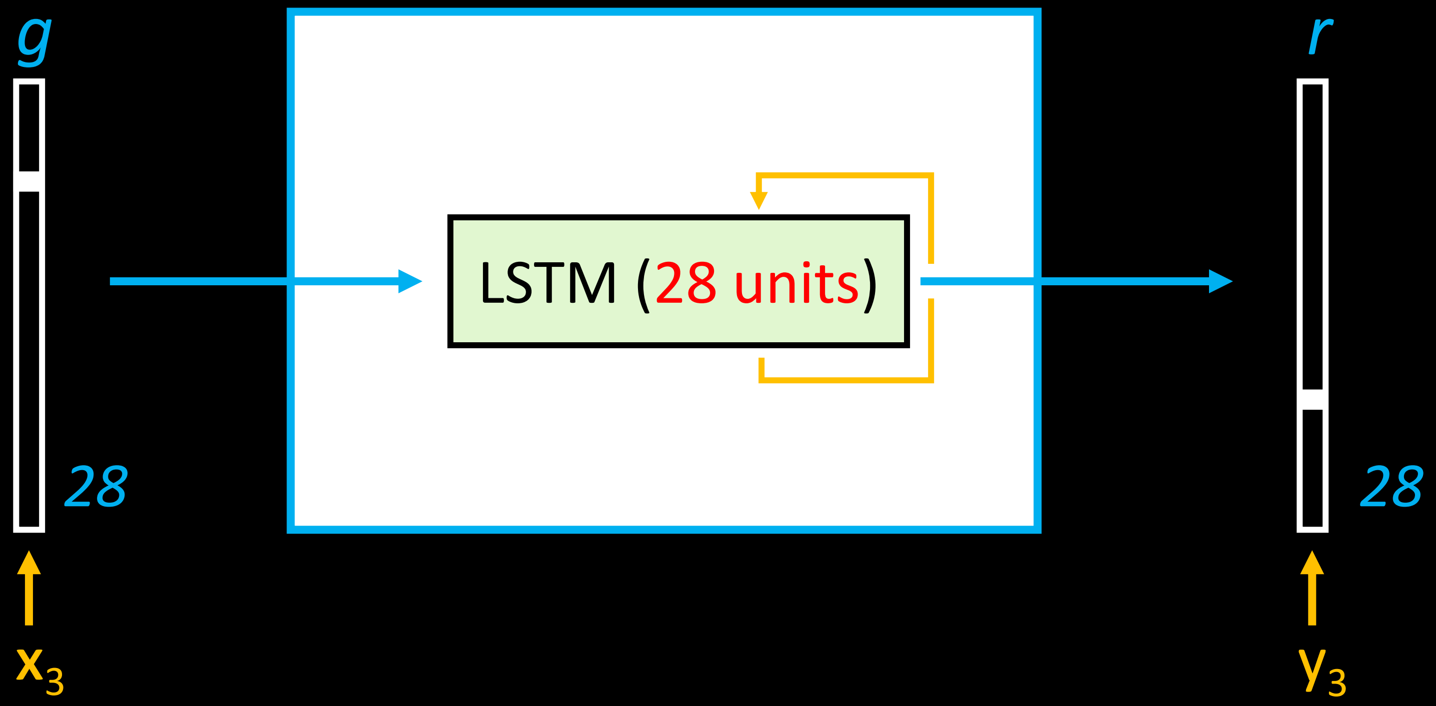




- We are **training the model** to **learn the transformation x -> y** while it also **learns what** is useful **to save** inside the 28 units (what preceded before this x).

Simple model





- We are **training the model** to **learn the transformation x -> y** while it also **learns what** is useful **to save** inside the 28 units (what preceded before this x).

Text data

- Example:

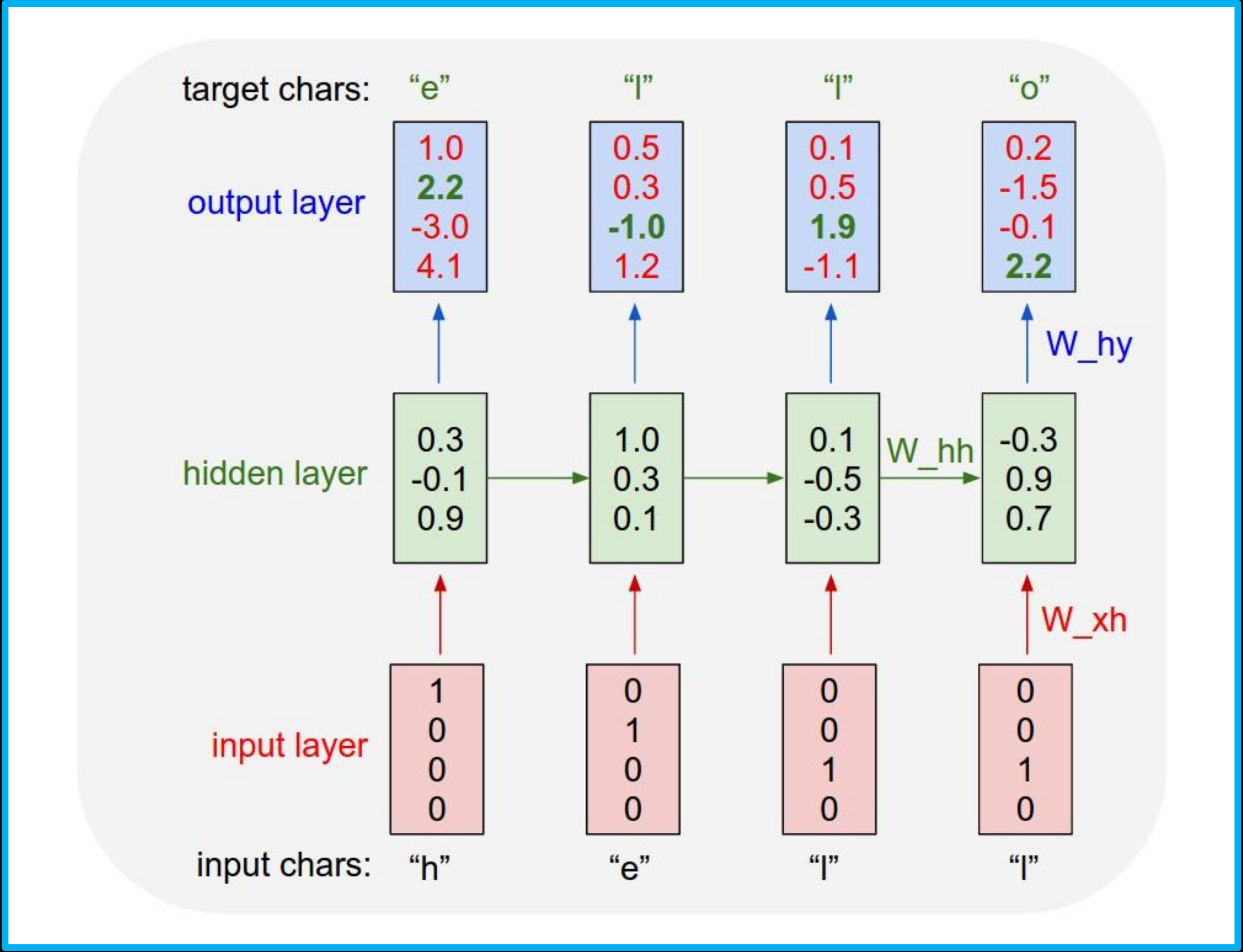
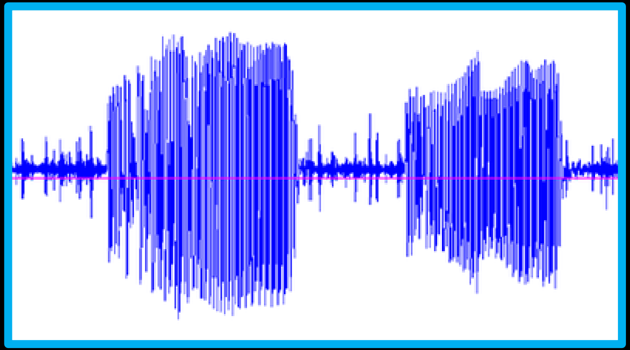


Illustration: [blog]

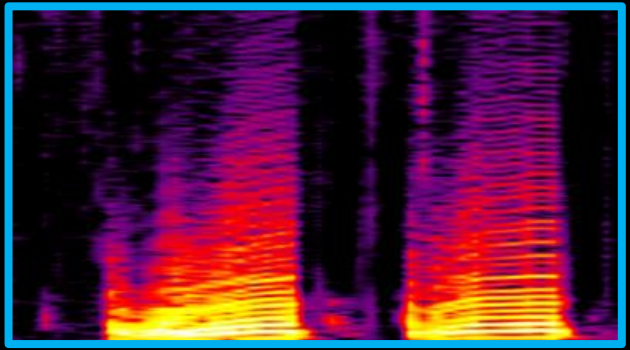
Plugging in music data

original data



fft

spectrograms

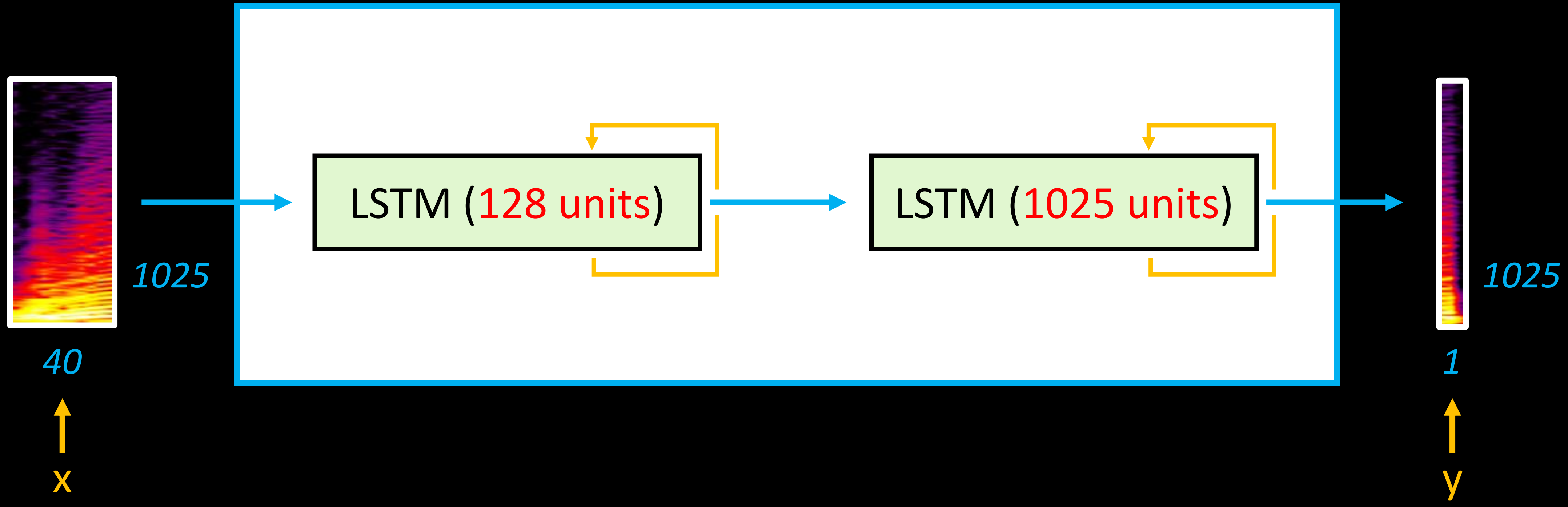


d *= 1025*

k *= number of frames*

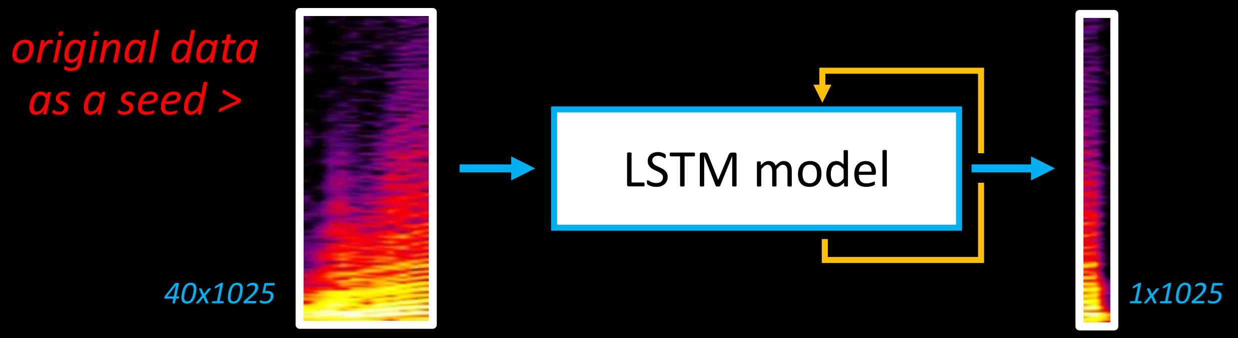
- **Encode music using the Fourier Transform** (*fft*) to get **spectrogram** (which can be considered as image representation)
- We can **later decode the predictions** using the *inverse fft*

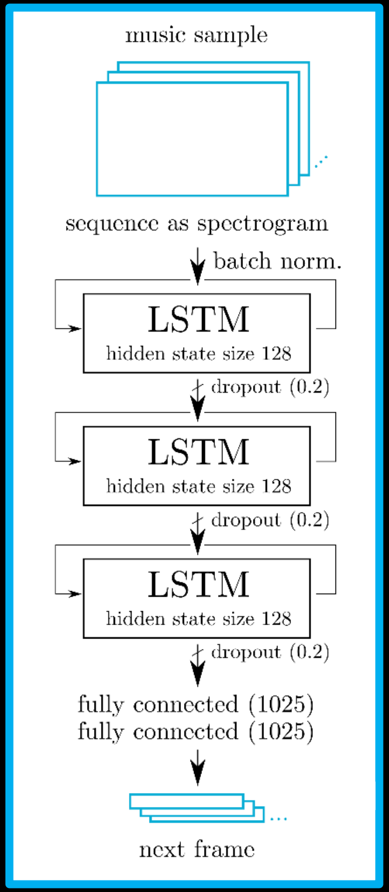
Larger model



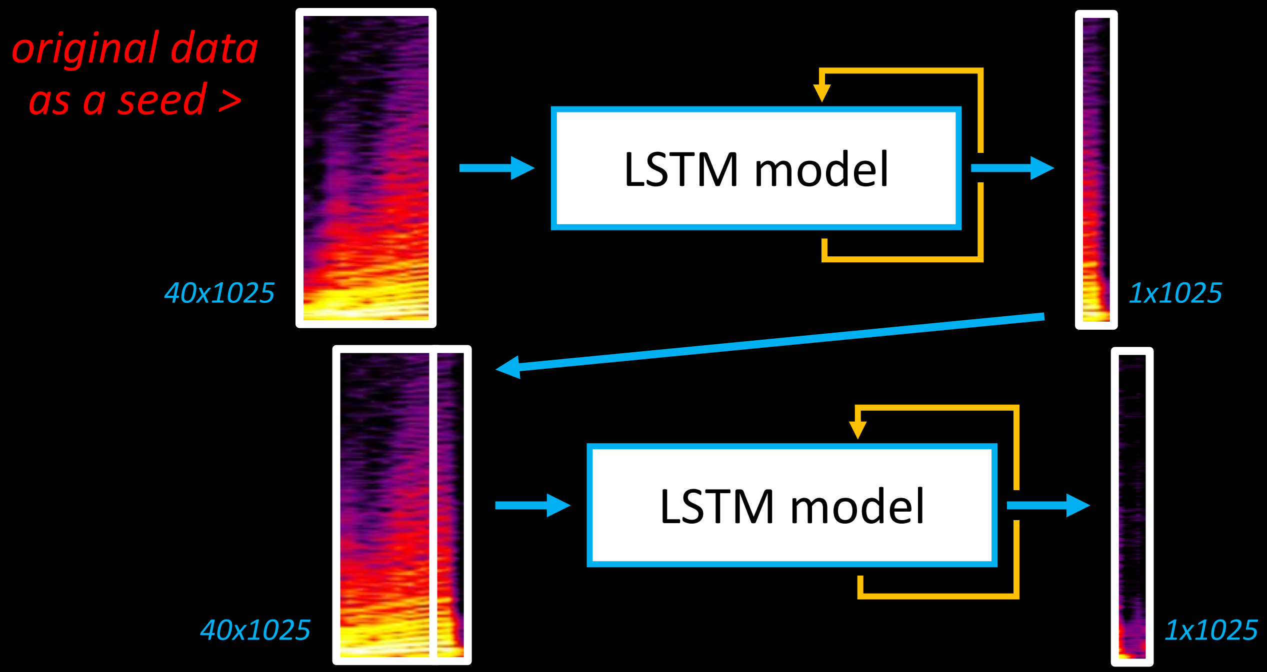
- We are **training the model** on a longer sequence of data (*"many to one"*), the model still **learns the transformation** of **x -> y**.

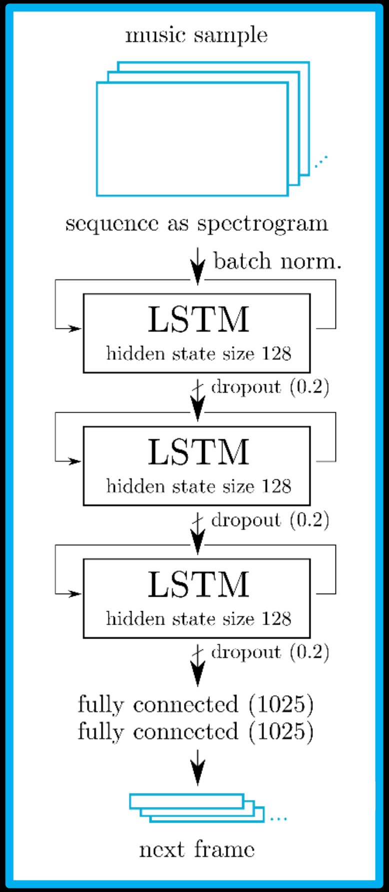
Using a trained LSTM model:



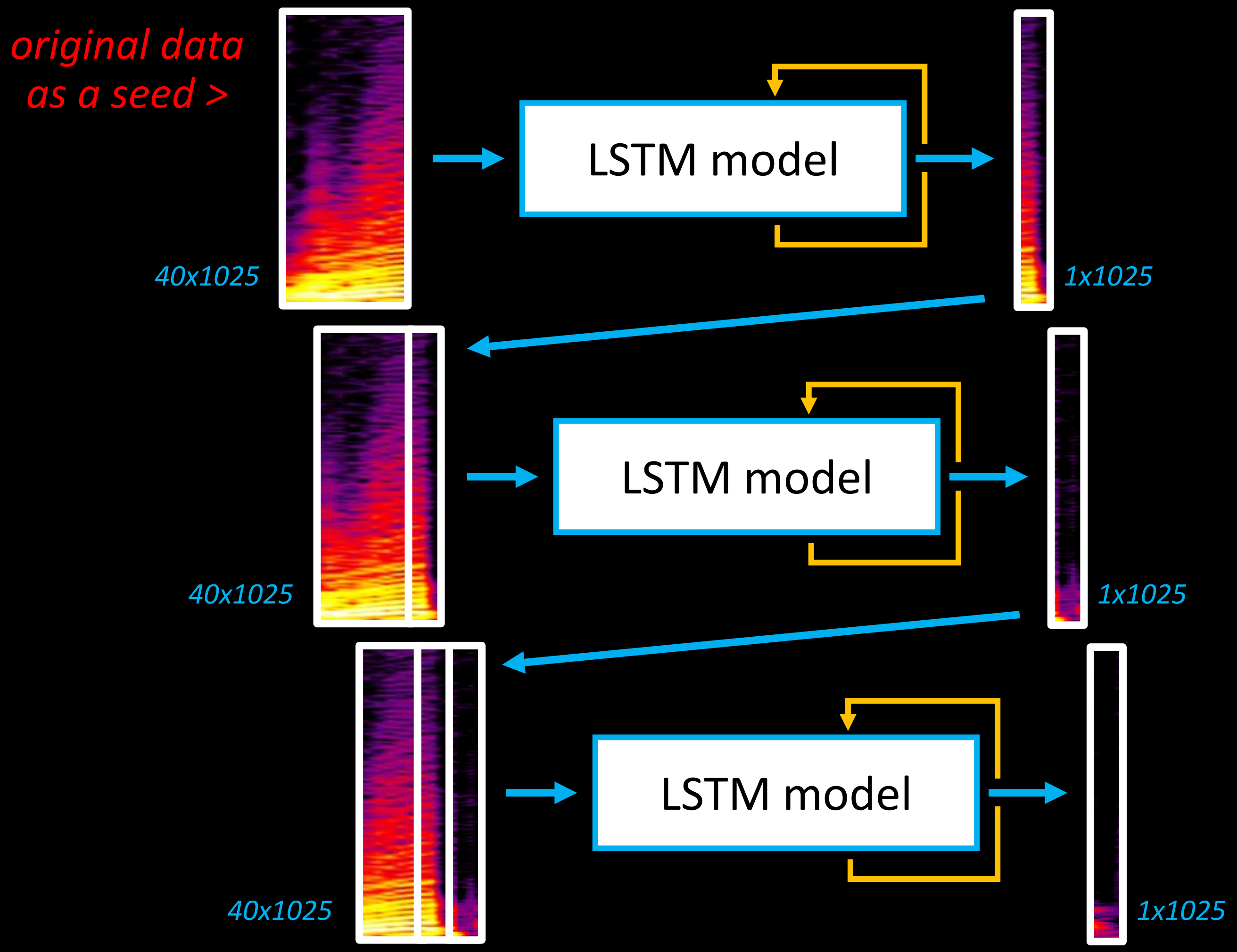


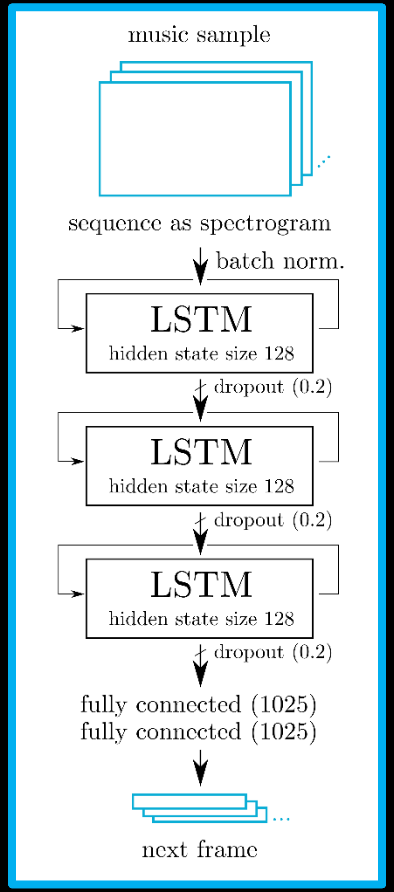
Using a trained LSTM model:



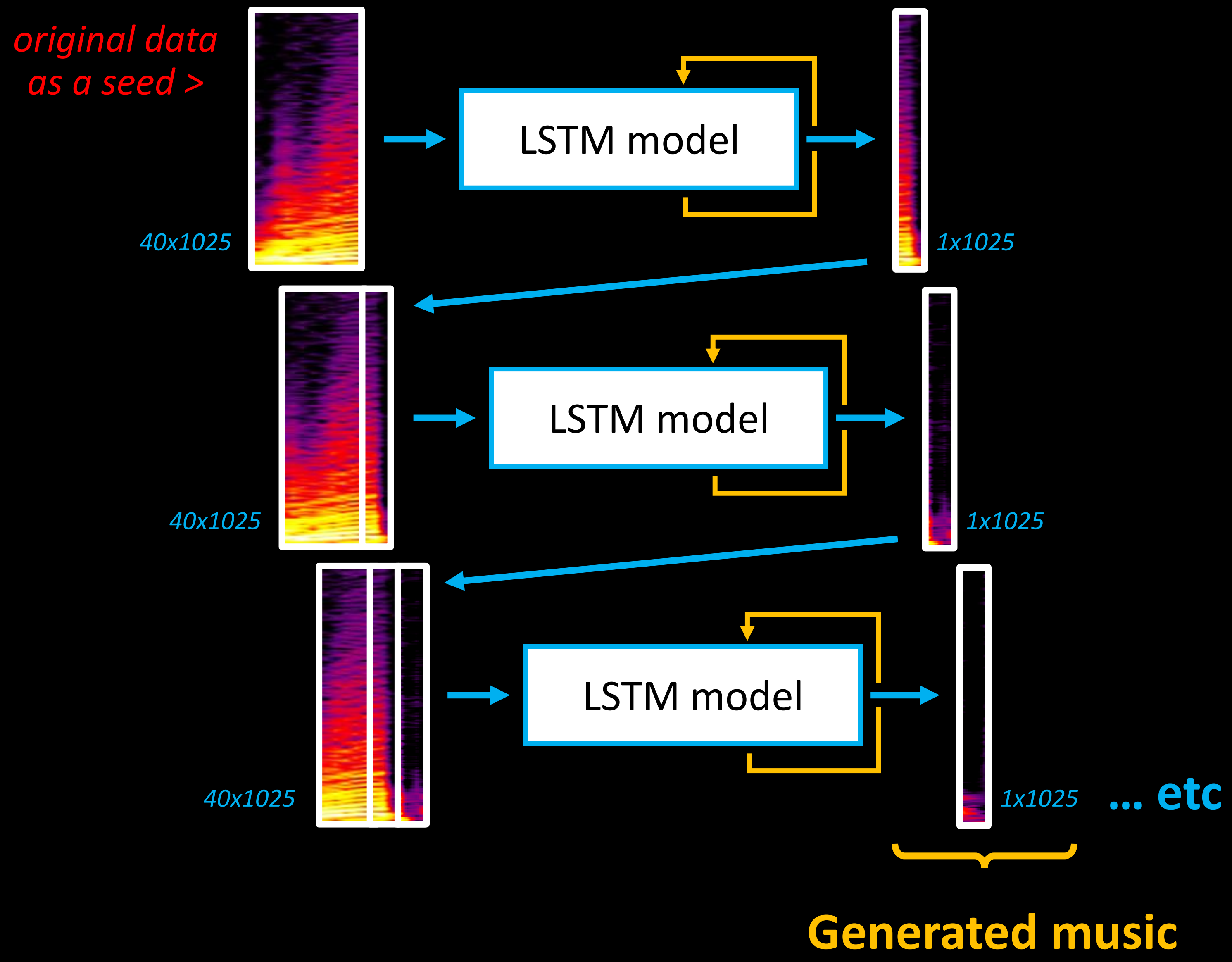


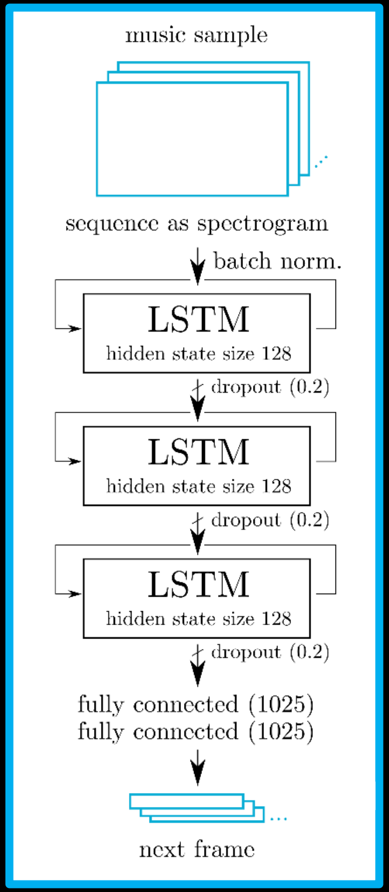
Using a trained LSTM model:





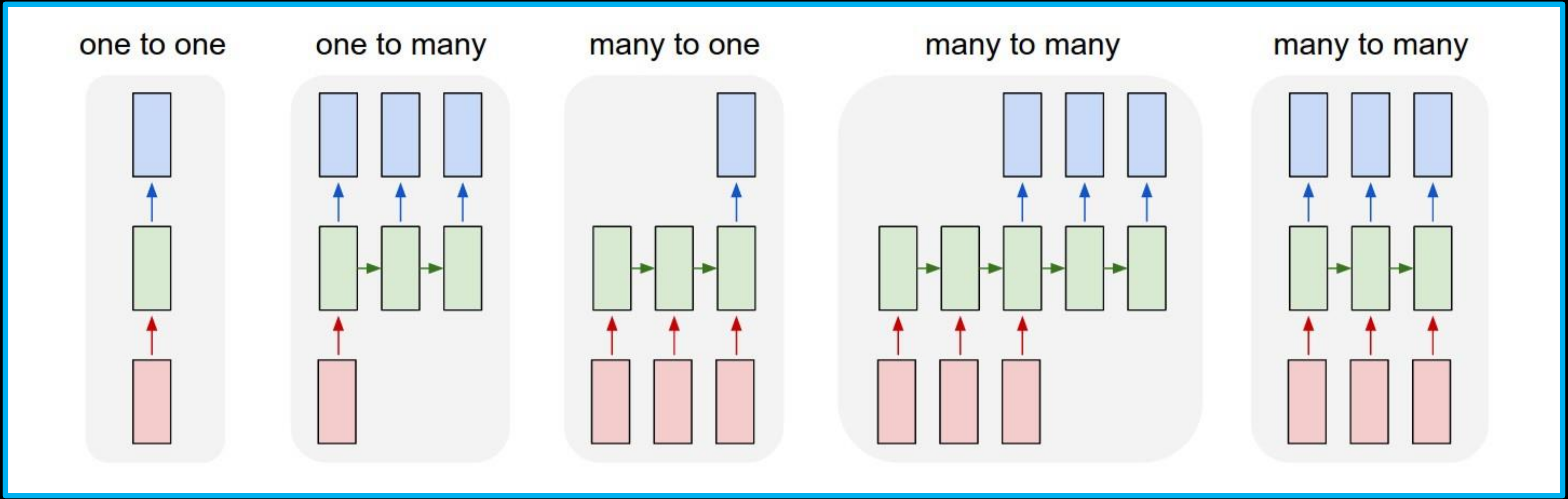
Using a trained LSTM model:





- Check the **generated music sample**: ml-jazz-meanderings-ml-generated-sounds-1

Types of models and data schemes



- The movement to the right on this illustration means **moving one timestep further** (next sample in the sequence)

Illustration: [blog]

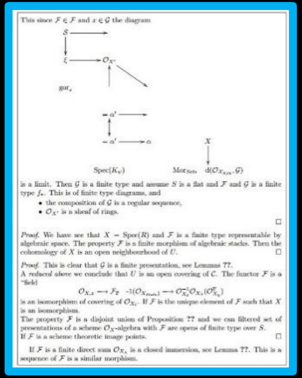
Practicum live session

- This week's live session will be organized as a **Q&A session** about all the material that we went through in the class
- **Assessment requirements** details – on our moodle page

Links and additional readings:

- **Bonus readings:**
  - **Andrej Karpathy blog** “The Unreasonable Effectiveness of Recurrent Neural Networks” – rnn-effectiveness
    - Citation: *There’s something magical about Recurrent Neural Networks (RNNs). … This post is about sharing some of that magic with you. We’ll train RNNs to generate text character by character and ponder the question “how is that even possible?”*
  - **Blog** “Understanding LSTM Networks” - Understanding-LSTMs

- **Code samples:**
  - **WordRNN**: Working repository for training and using a multilayer RNN and LSTM models – word-rnn-tensorflow
  - **Text analysis**: Gensim library examples


This since $\mathcal{F} \in \mathcal{F}$ and $x \in \mathcal{G}$ the diagram

$\mathrm{Spec}(K_\psi)$ Mor_{Sets} $d(\mathcal{O}_{X_{X/k}}, \mathcal{G})$

is a limit. Then $\mathcal{G}$ is a finite type and assume S is a flat and $\mathcal{F}$ and $\mathcal{G}$ is a finite type f_*. This is of finite type diagrams, and

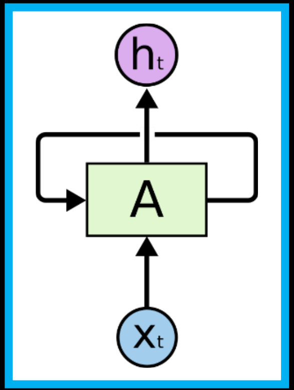
- the composition of $\mathcal{G}$ is a regular sequence,
- $\mathcal{O}_{X'}$ is a sheaf of rings.

Proof. We have see that $X = \mathrm{Spec}(R)$ and $\mathcal{F}$ is a finite type representable by algebraic space. The property $\mathcal{F}$ is a finite morphism of algebraic stacks. Then the cohomology of X is an open neighbourhood of U.

Proof. This is clear that $\mathcal{G}$ is a finite presentation, see Lemmas ??.
A *reduced above* we conclude that U is an open covering of $\mathcal{C}$. The functor $\mathcal{F}$ is a “field

is an isomorphism of covering of $\mathcal{O}_{X_i}$. If $\mathcal{F}$ is the unique element of $\mathcal{F}$ such that X is an isomorphism.
The property $\mathcal{F}$ is a disjoint union of Proposition ?? and we can filtered set of presentations of a scheme $\mathcal{O}_X$-algebra with $\mathcal{F}$ are opens of finite type over S.
If $\mathcal{F}$ is a scheme theoretic image points.

If $\mathcal{F}$ is a finite direct sum $\mathcal{O}_{X_\lambda}$ is a closed immersion, see Lemma ??. This is a sequence of $\mathcal{F}$ is a similar morphism.



The end