Lecture 13

Temporal Processing and RNNs

Spring 2021
Bill Freeman, Phillip Isola

13. Temporal Processing and RNNs

- Sequence problems
- Temporal convnets
- Recurrent Neural Networks (RNNs)
- LSTMs
- Attention
- Example problems:
  - Image captioning
  - Sound prediction


kindergarden classroom

television
person
chair


“What color is the chair?”


"What color is the chair?"
red


“What will the girl do next?”

Sequences

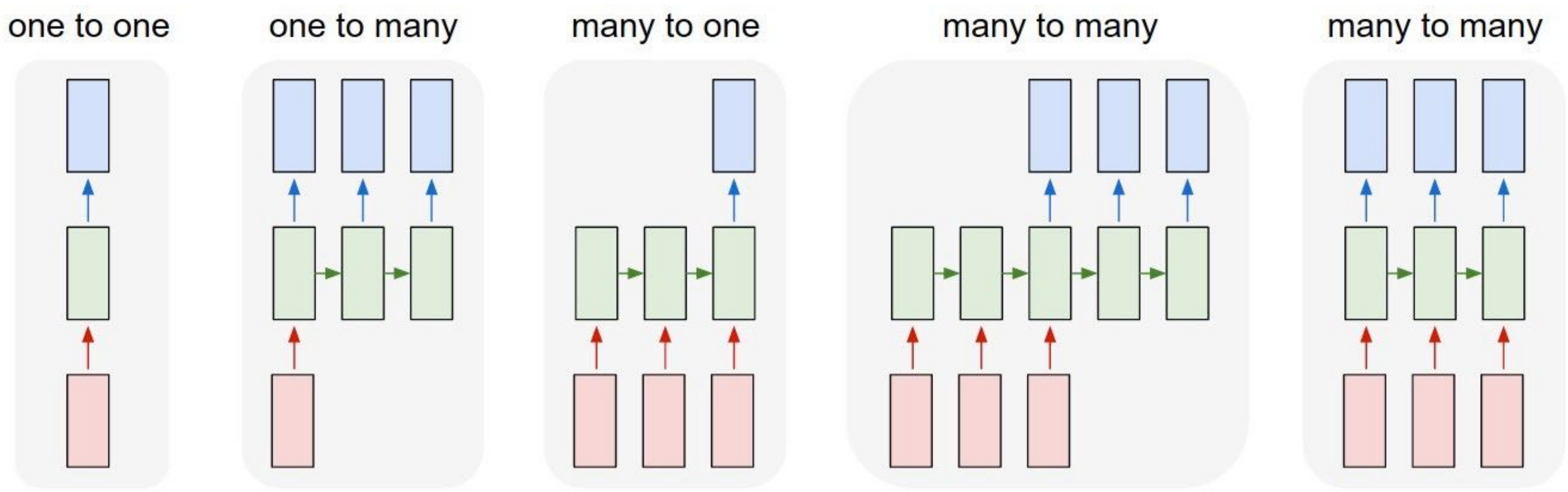
time

“An”, “evening”, “stroll”, “through”, “a”, “city”, “square”

time

time

How do we model sequences?



Input: No sequence

Output: No sequence

Example: “standard” classification / regression problems

Input: No sequence

Output: Sequence

Example: Im2Caption

Input: Sequence

Output: No sequence

Example: sentence classification, multiple-choice question answering

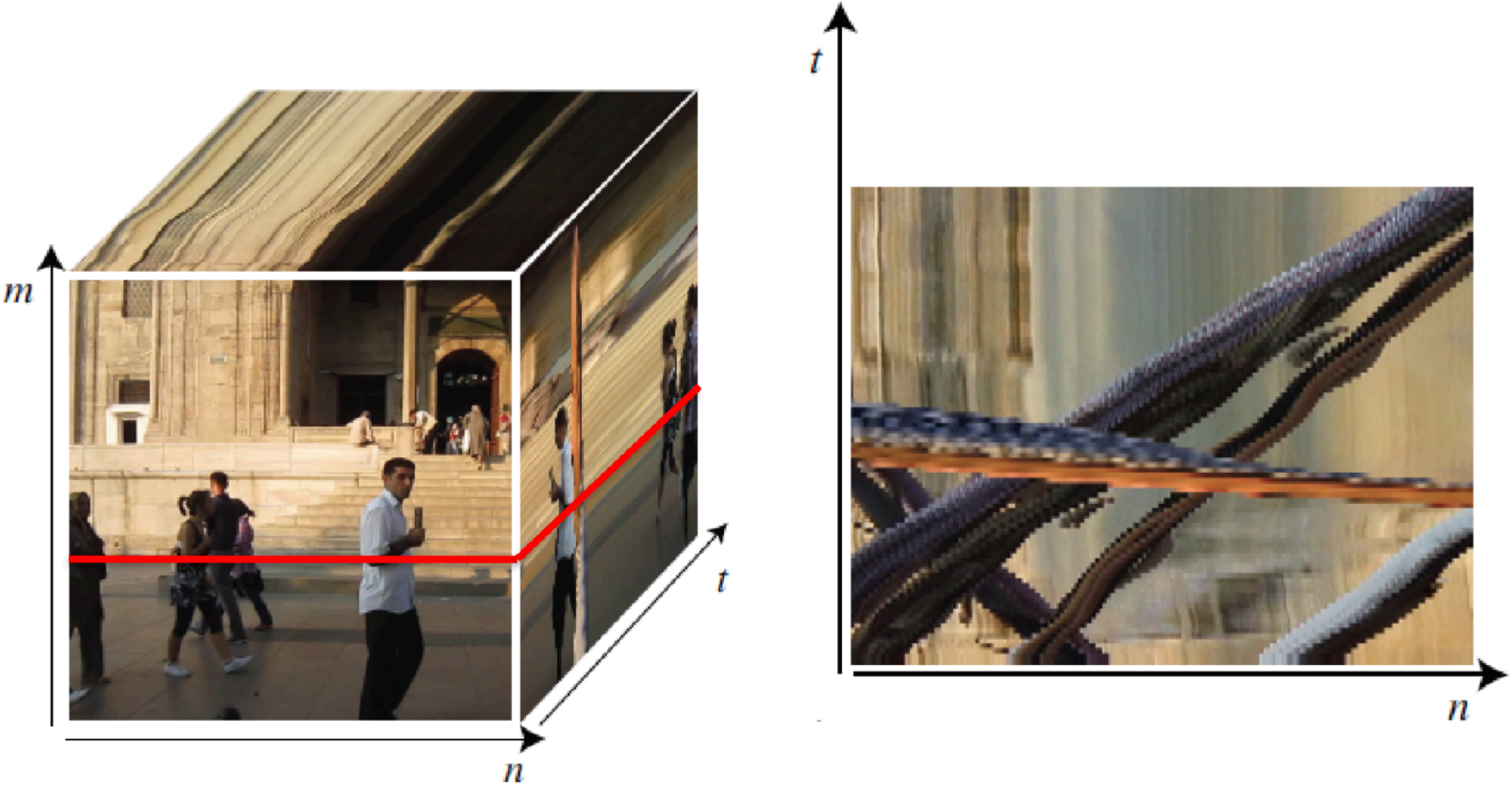
Input: Sequence

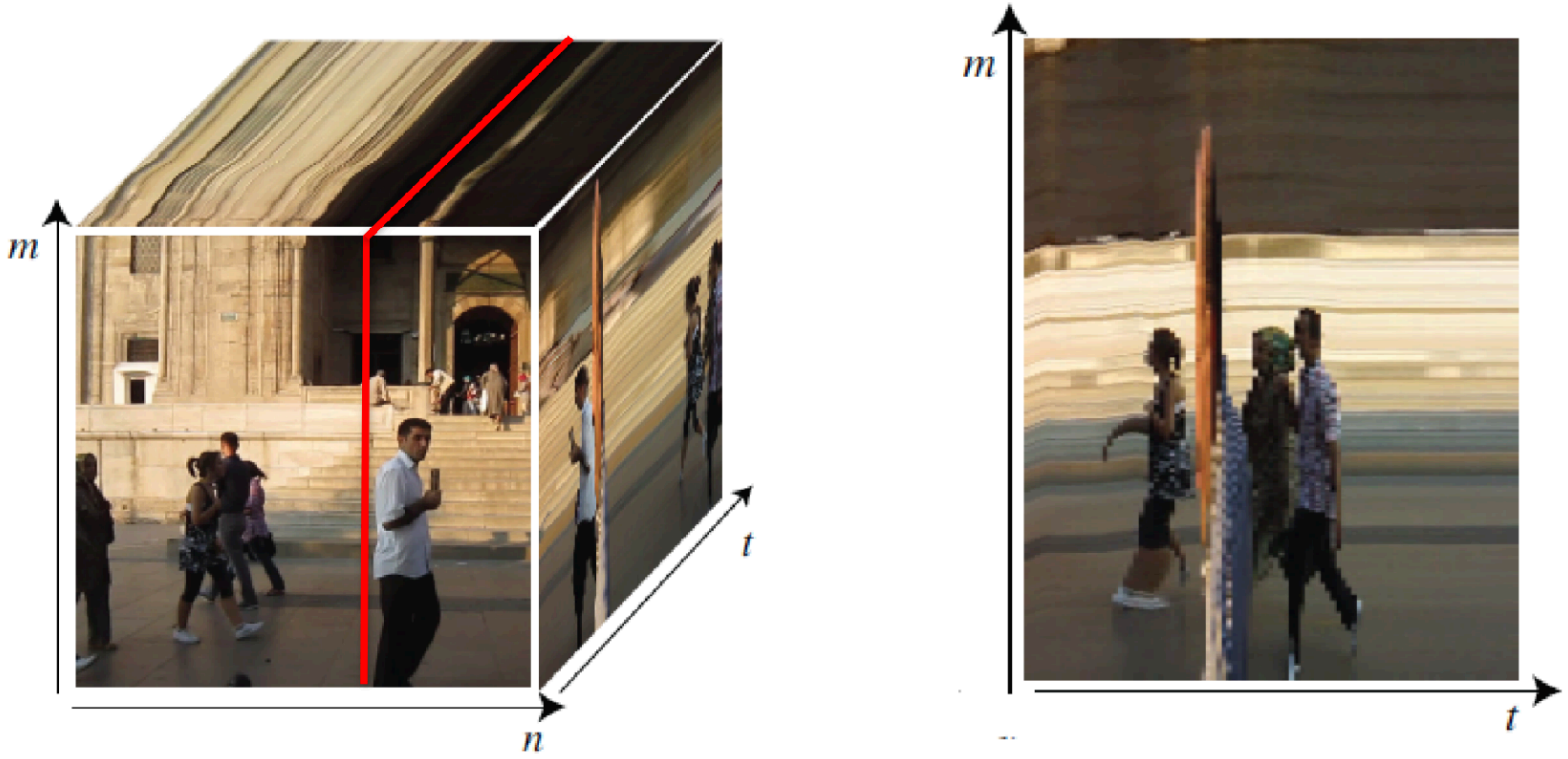
Output: Sequence

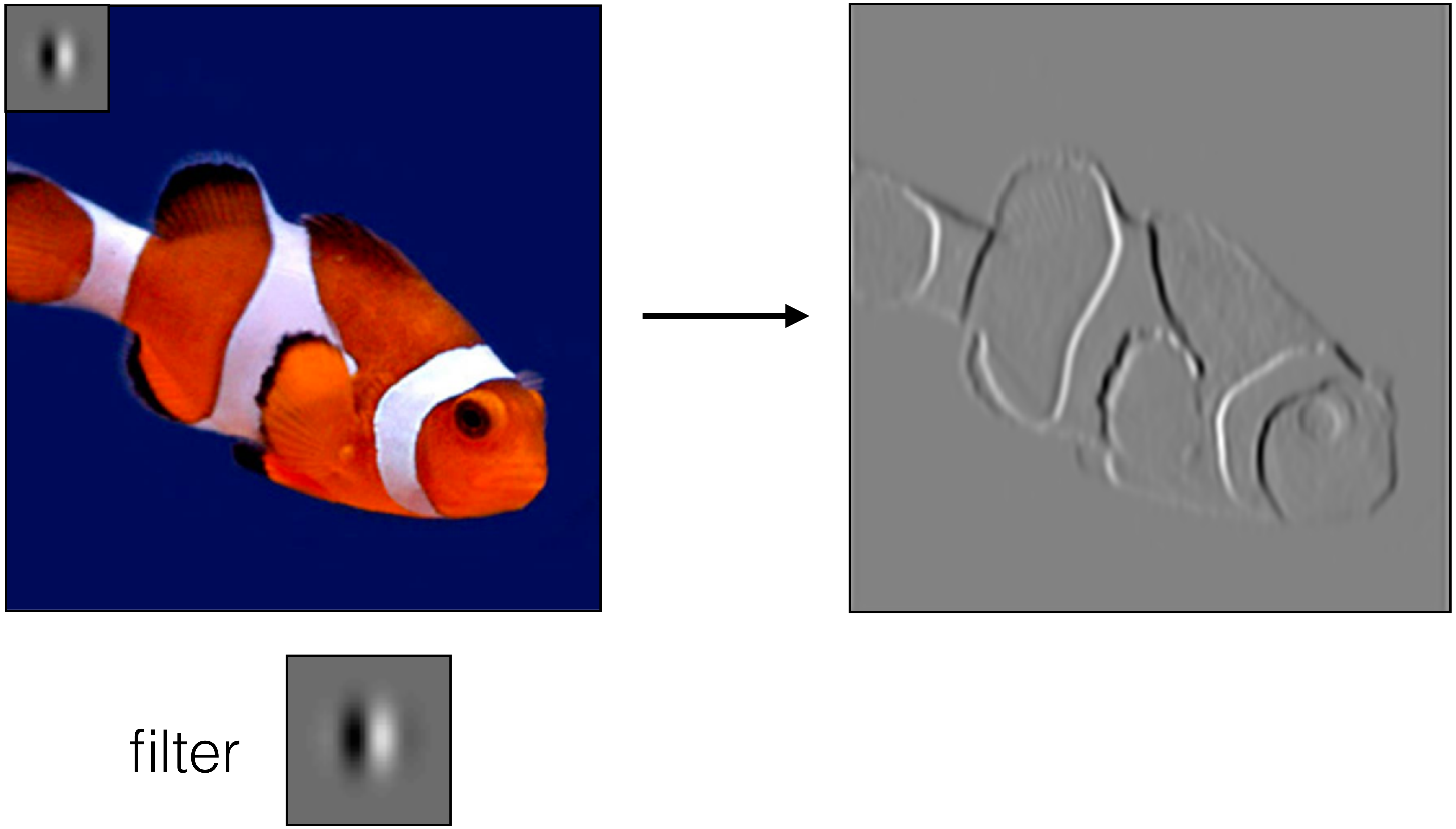
Example: machine translation, video captioning, open-ended question answering, video question answering

http://karpathy.github.io/2015/05/21/rnn-effectiveness/ Credit: Dhruv Batra, Andrej Karpathy

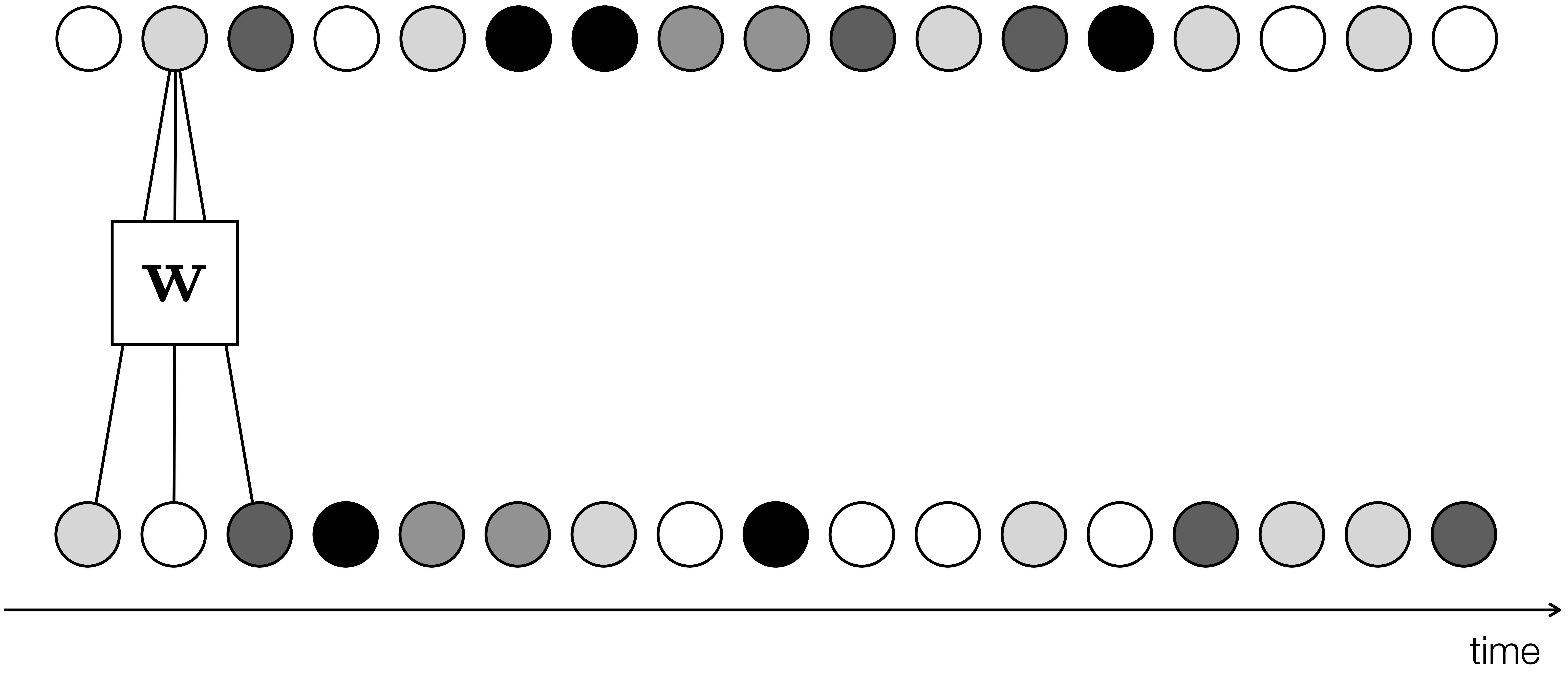

m
n
t

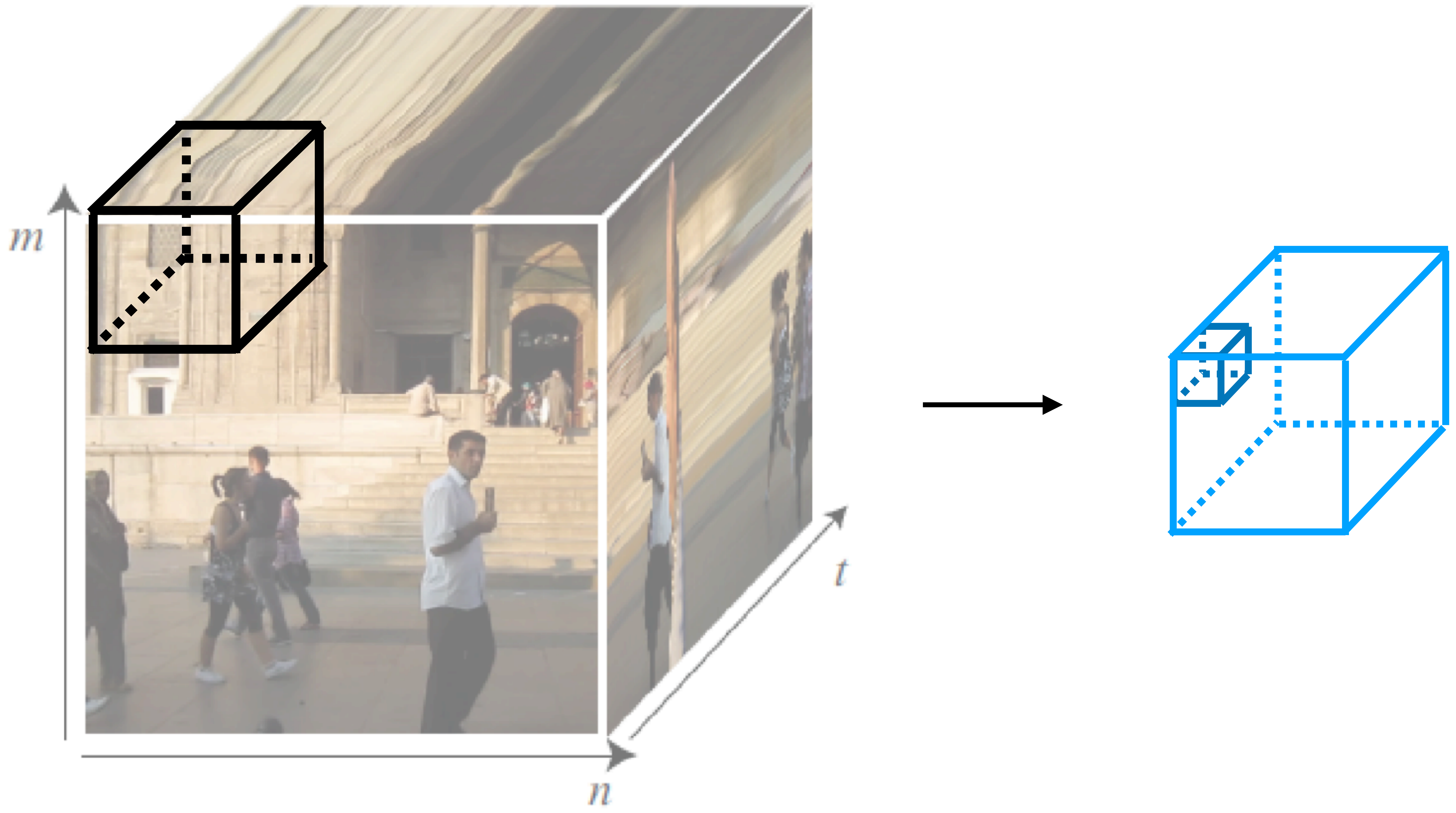

m
n
t
t
n

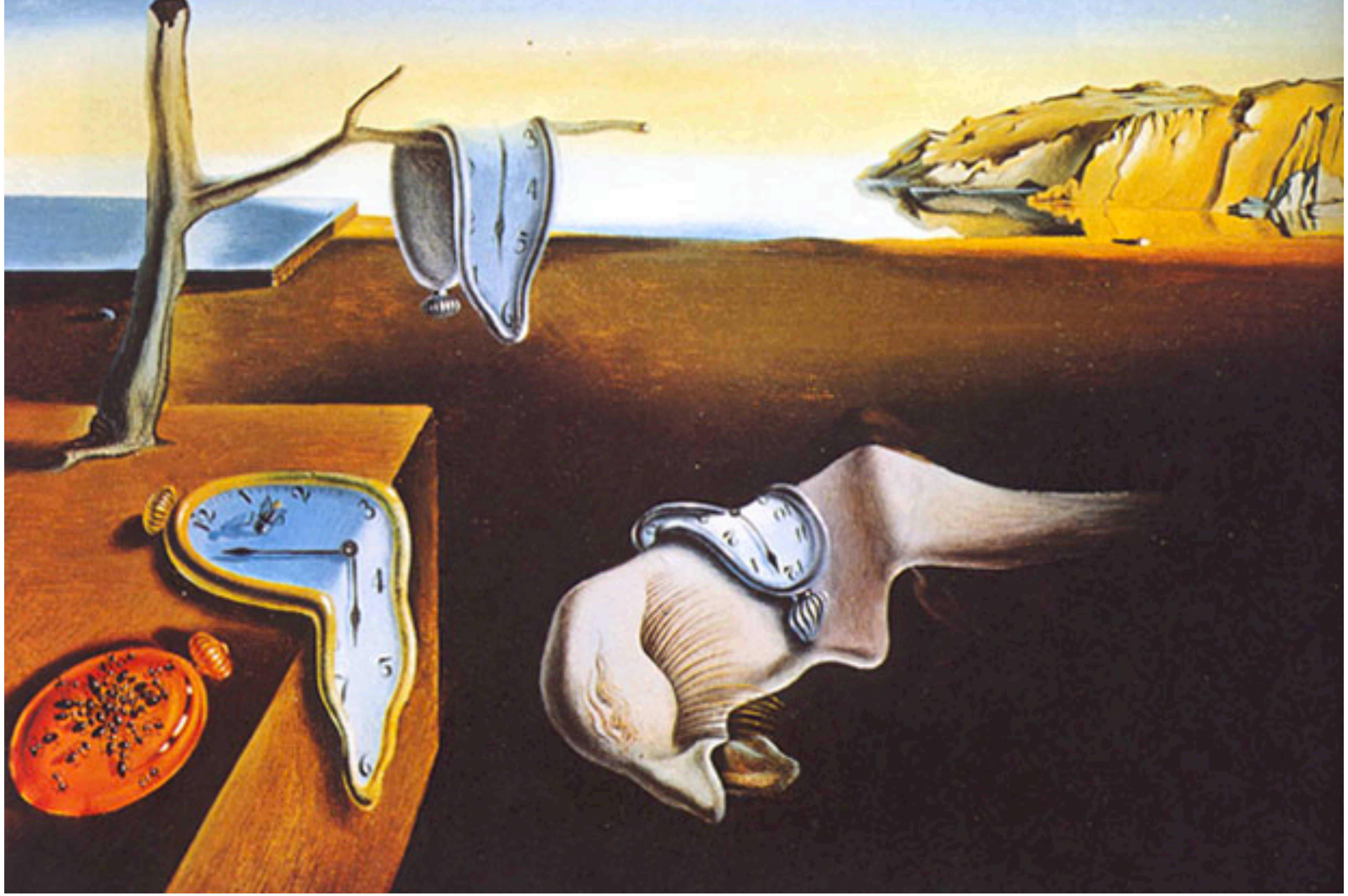

m
n
t
m
t


filter

Convolutions in time

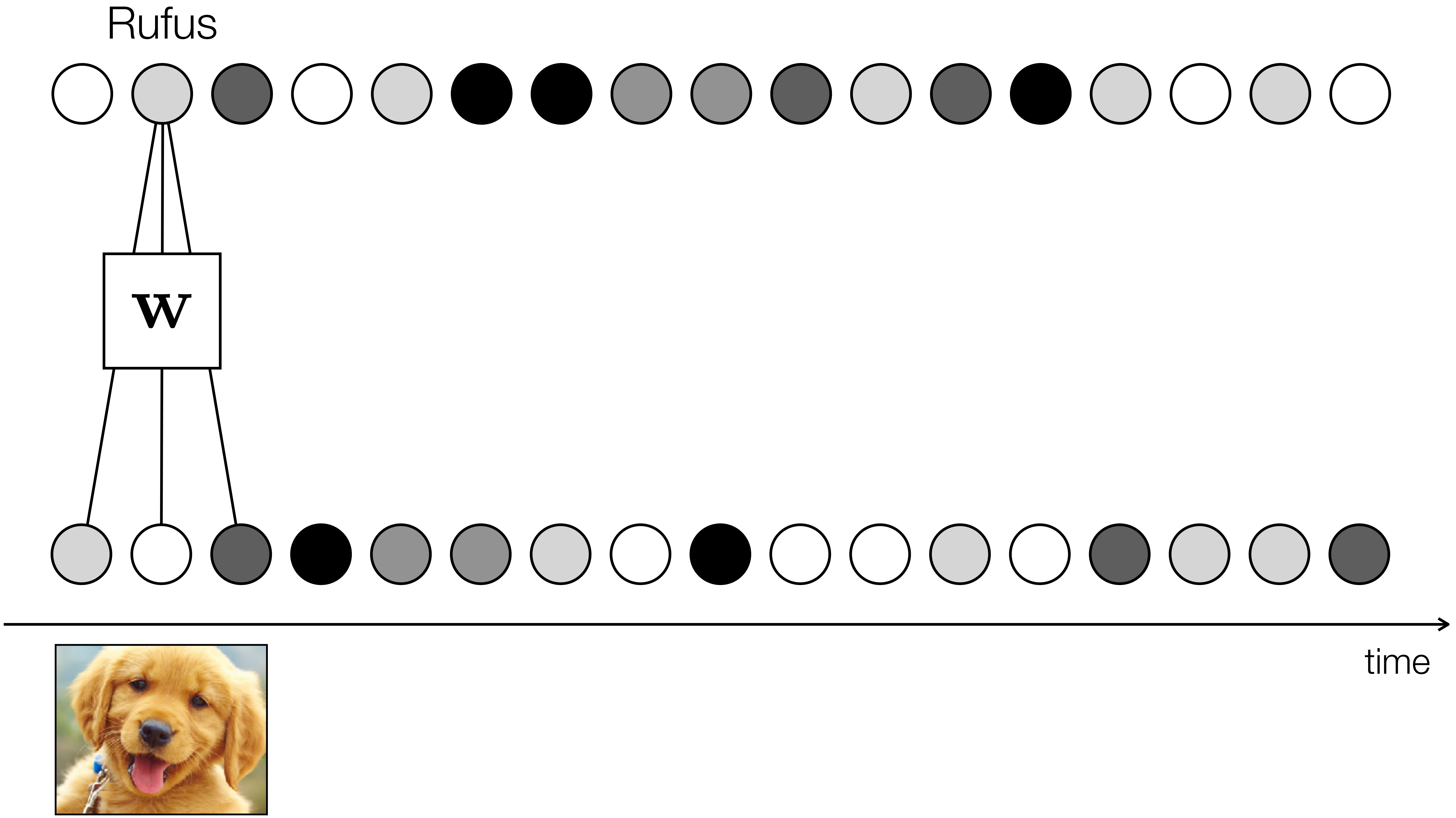


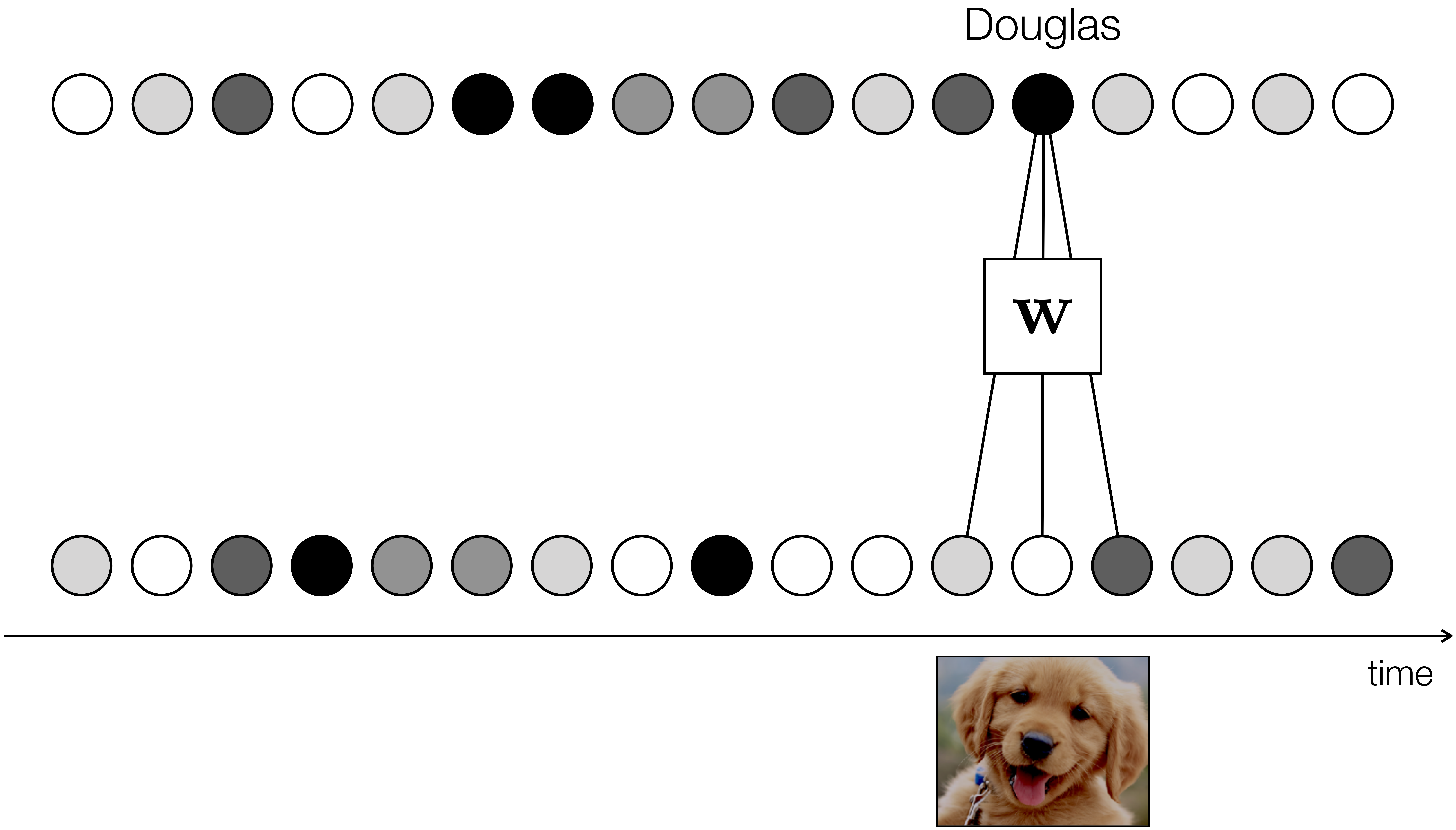

m
n
t

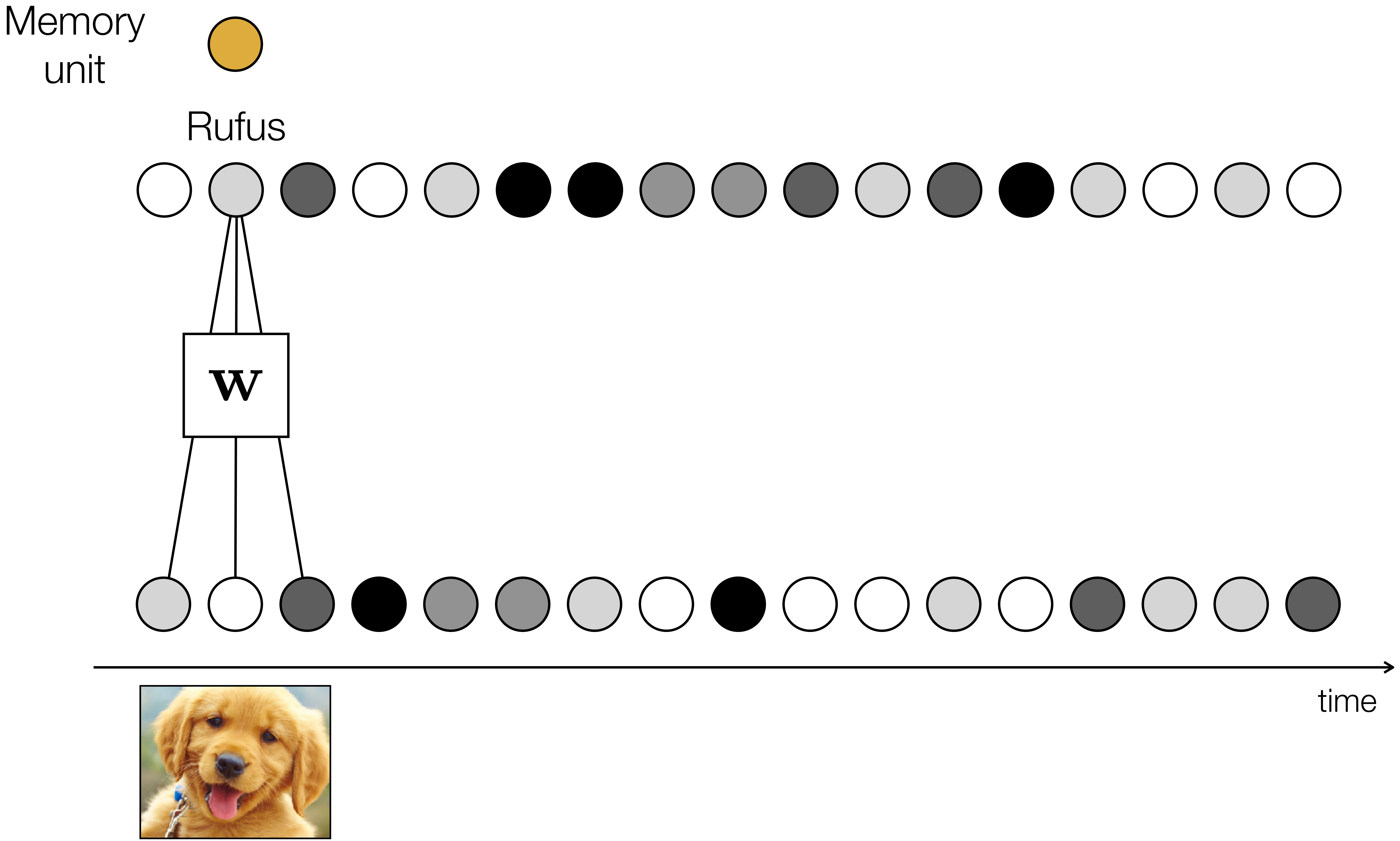


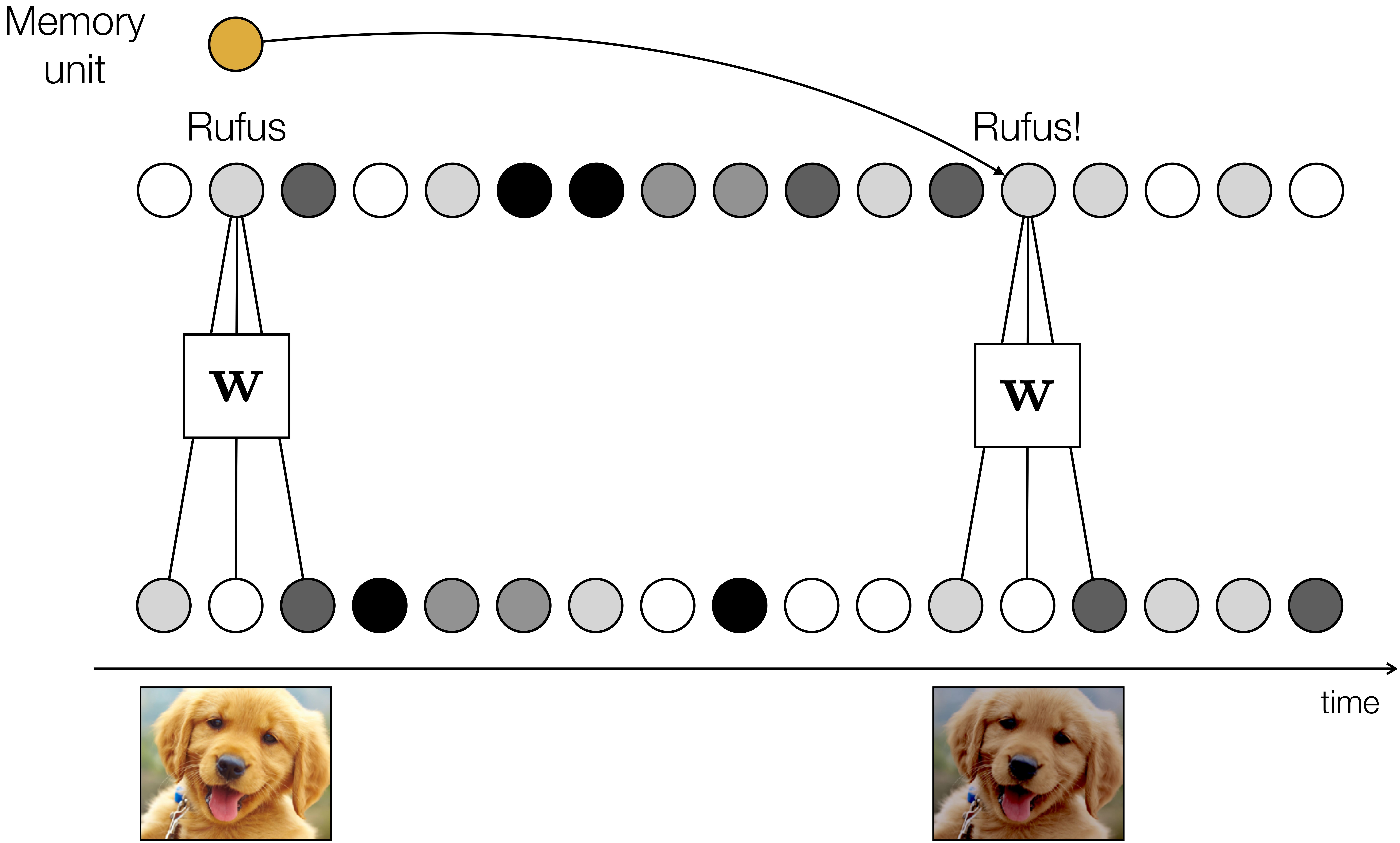
“The Persistence of Memory”, Dali 1931

It bothered him that the dog at three fourteen (seen from the side) should have the same name as the dog at three fifteen (seen from the front).
— “Funes the Memorius”, Borges 1962

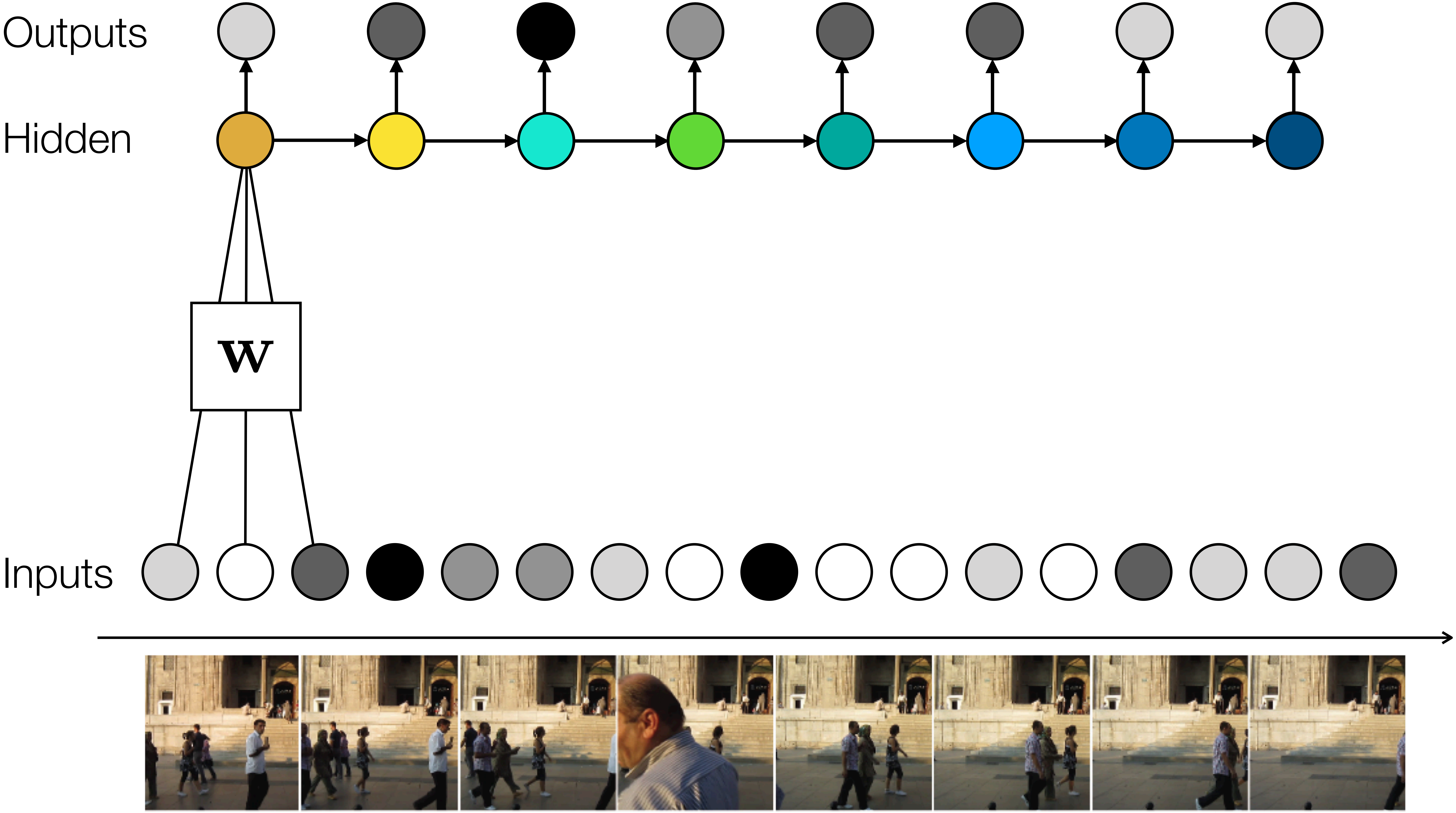

Rufus
w
time


Douglas
w
time

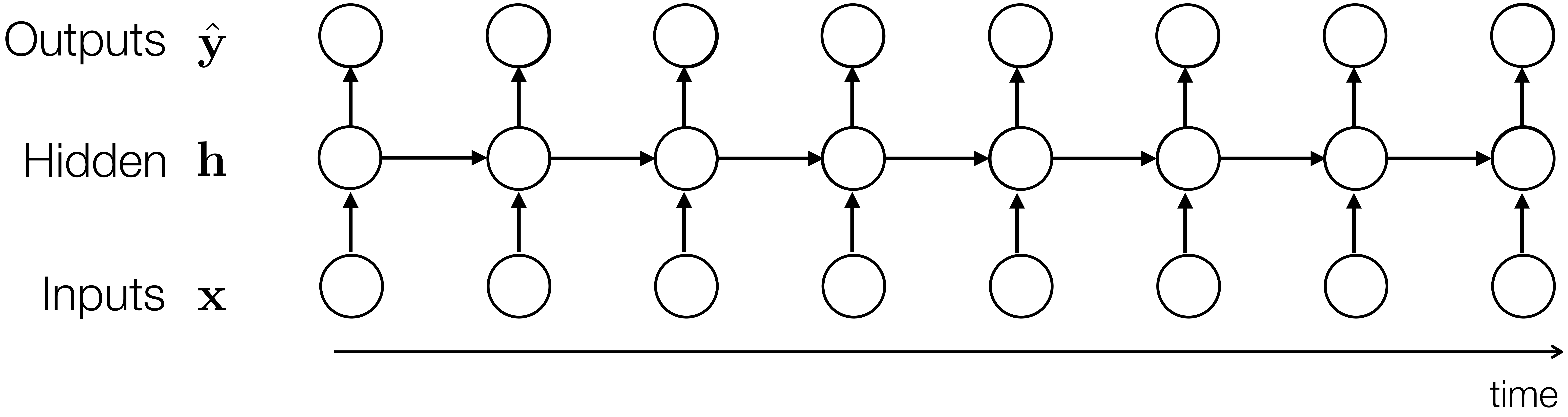

Memory unit
Rufus
w
time


Memory unit
Rufus
Rufus!
$\mathbf{w}$
$\mathbf{w}$
time

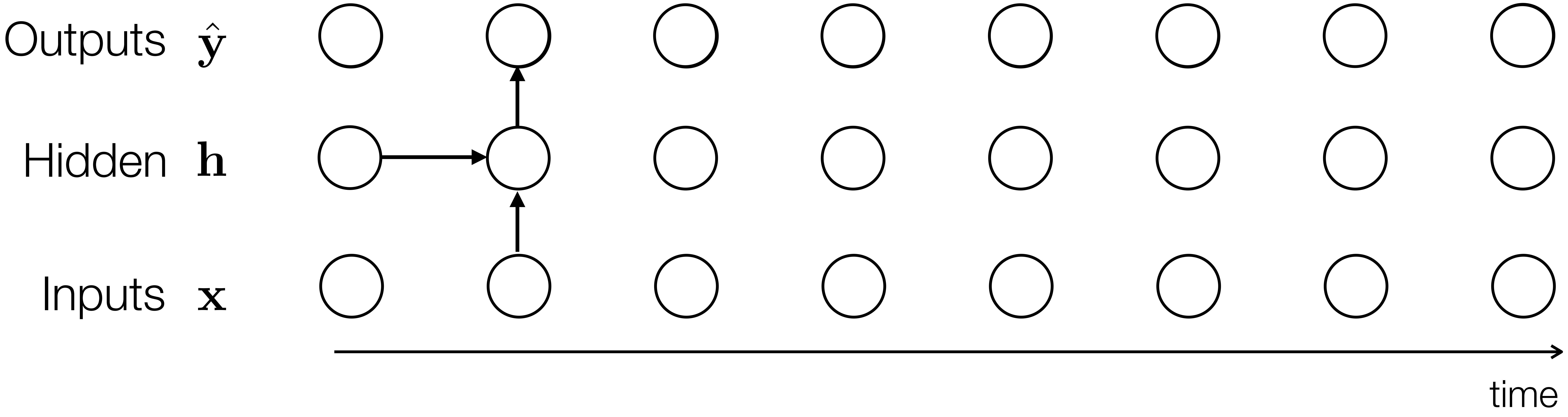
Recurrent Neural Networks (RNNs)



Recurrent Neural Networks (RNNs)



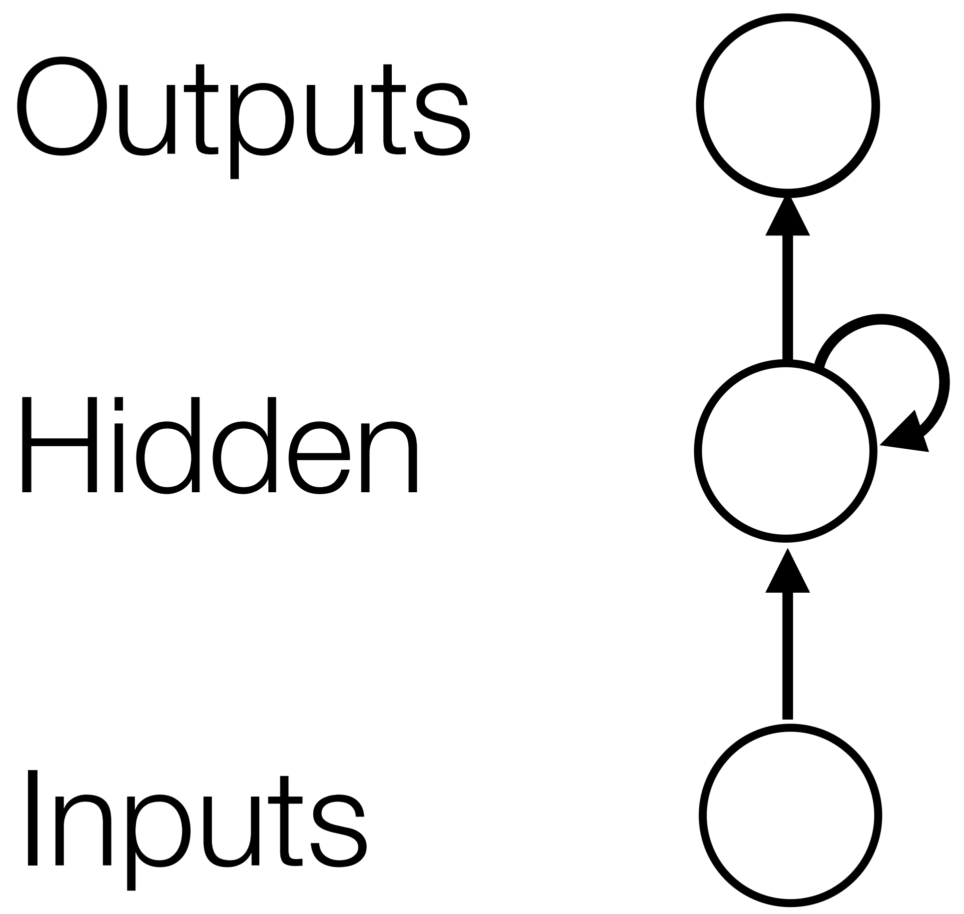
Recurrent Neural Networks (RNNs)



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

$$\mathbf{y}_t = g(\mathbf{h}_t)$$

Recurrent Neural Networks (RNNs)

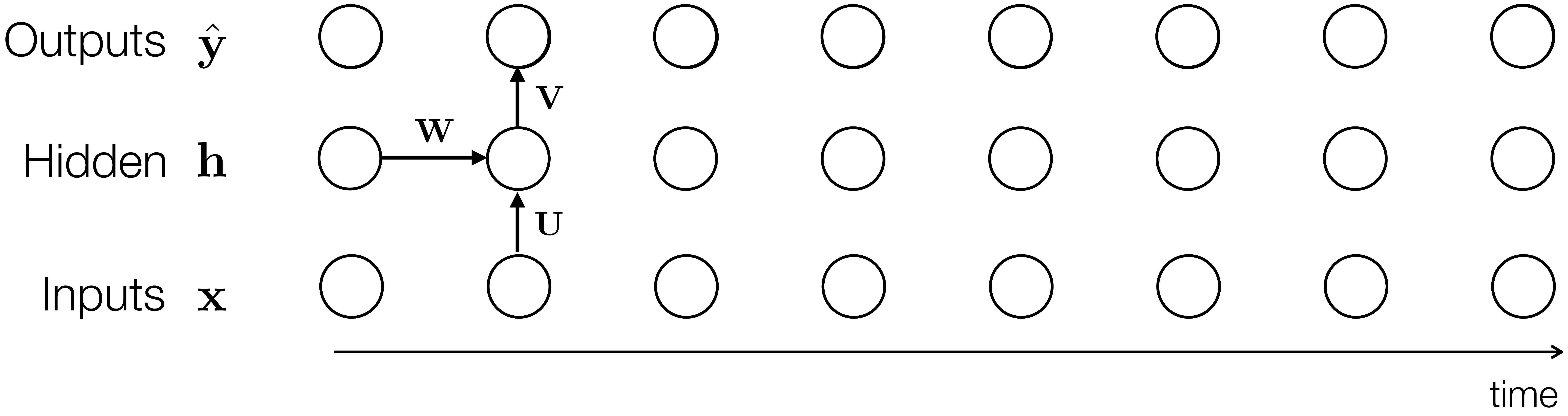


Recurrent!

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

$$\mathbf{y}_t = g(\mathbf{h}_t)$$

Recurrent Neural Networks (RNNs)



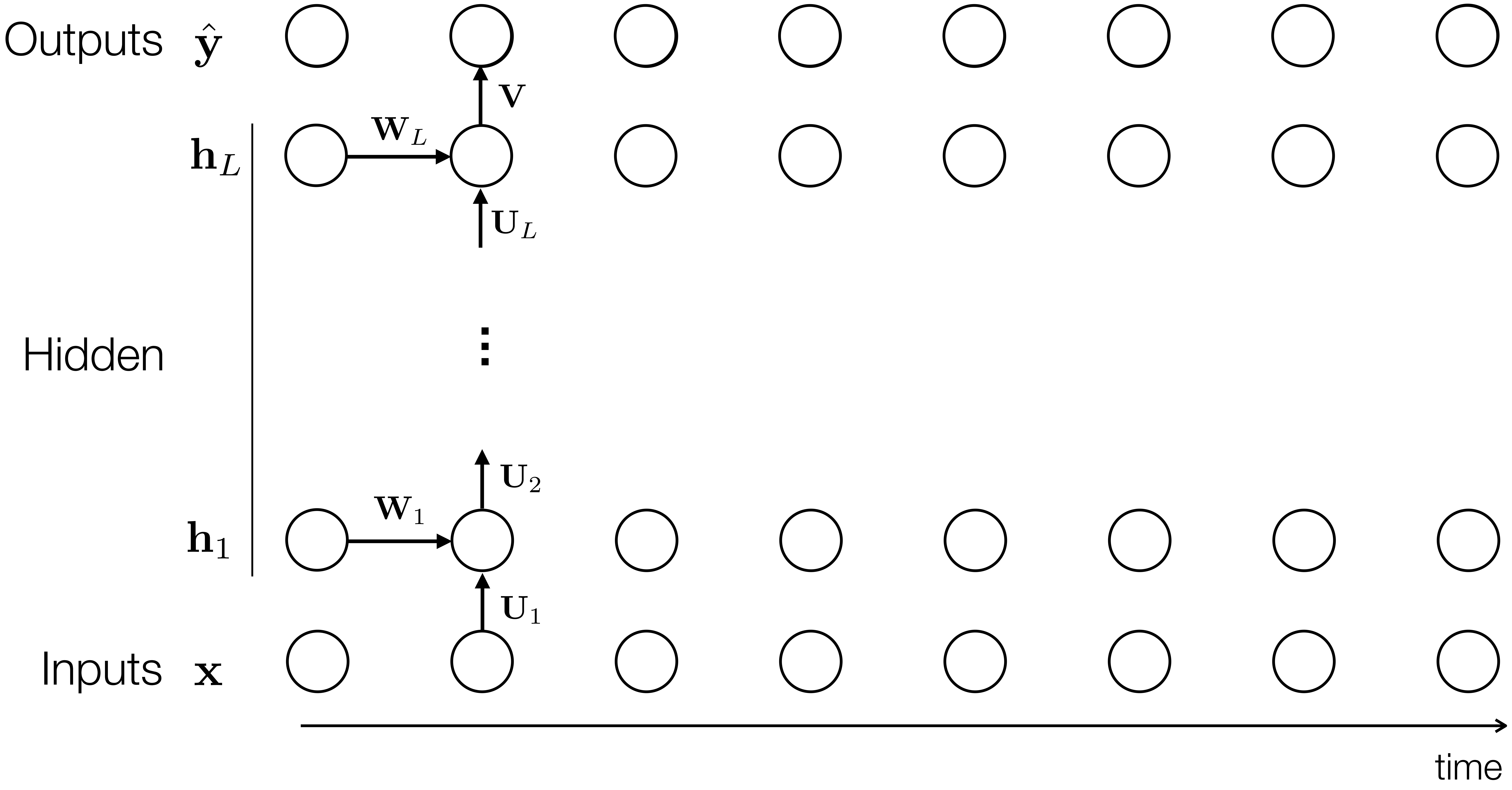
$$\mathbf{a}_t = \mathbf{W}\mathbf{h}_{t-1} + \mathbf{U}\mathbf{x}_t + \mathbf{b}$$

$$\mathbf{h}_t = \tanh(\mathbf{a}_t)$$

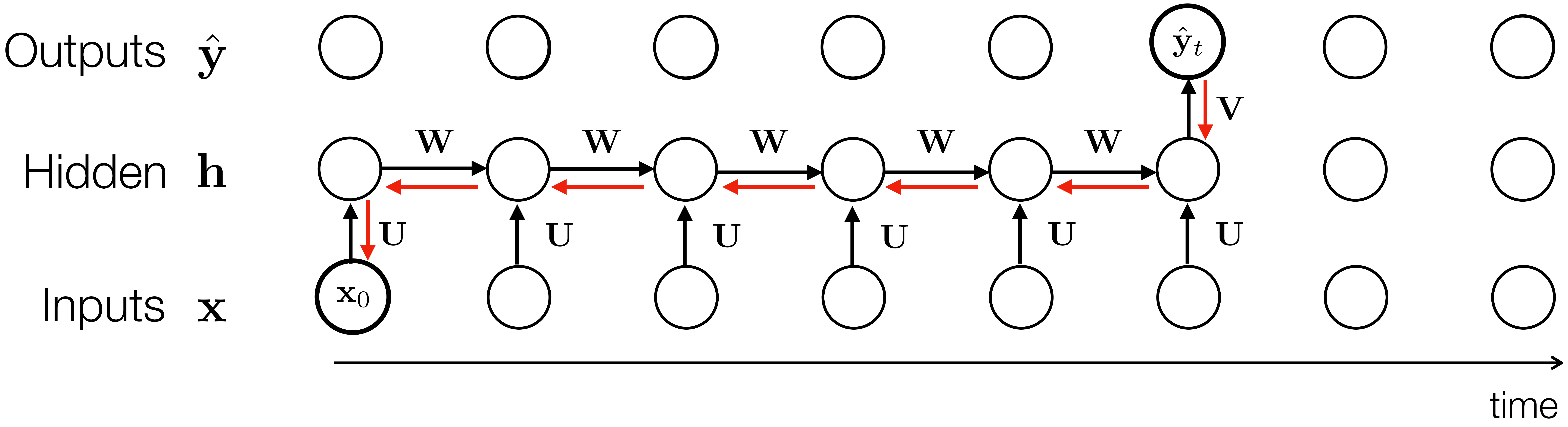
$$\mathbf{o}_t = \mathbf{V}\mathbf{h}_t + \mathbf{c}$$

$$\hat{\mathbf{y}}_t = \mathtt{softmax}(\mathbf{o}_t)$$

Deep Recurrent Neural Networks (RNNs)

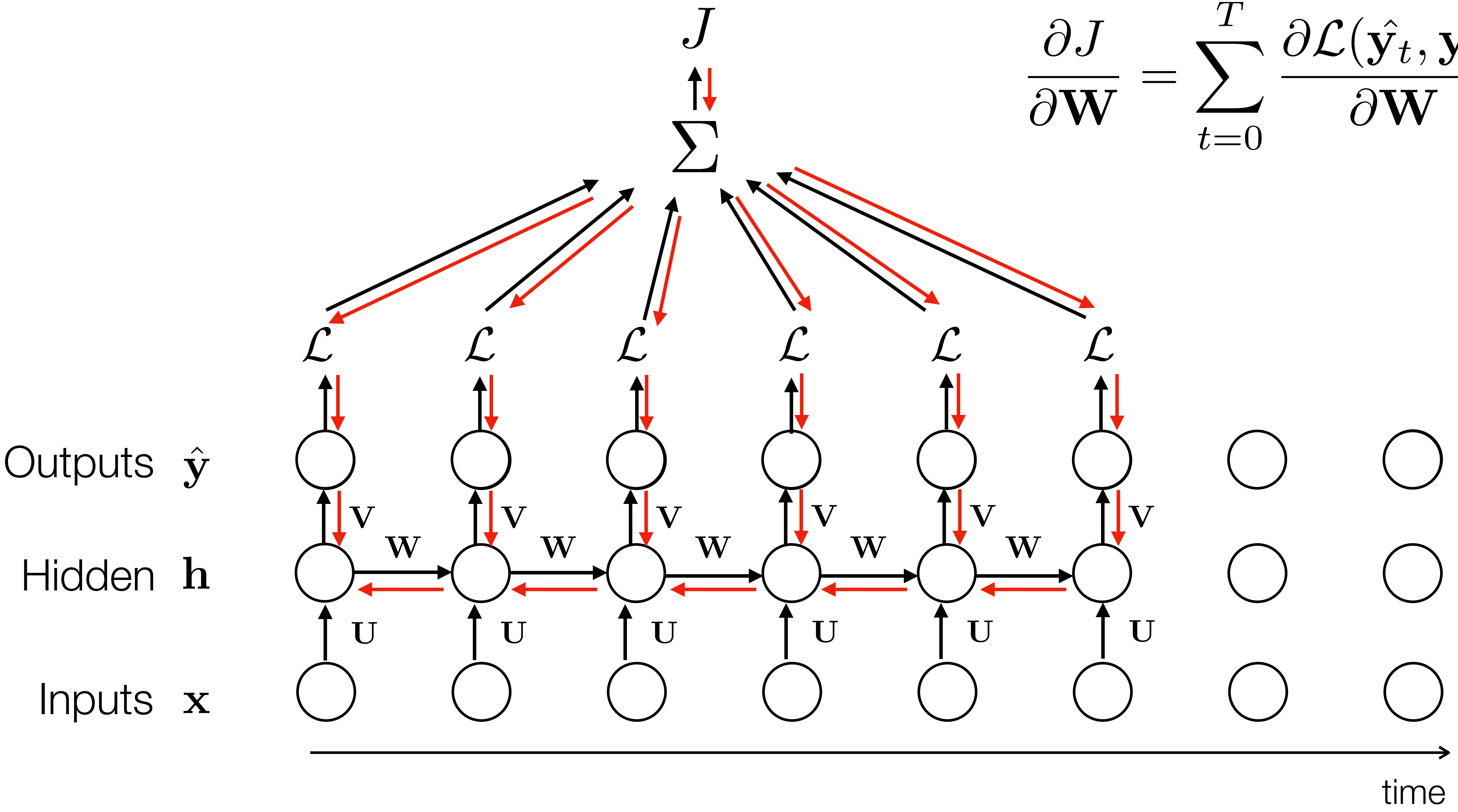


Backprop through time



$$\frac{\partial \hat{\mathbf{y}}_t}{\partial \mathbf{x}_0} = \frac{\partial \hat{\mathbf{y}}_t}{\partial \mathbf{h}_t} \frac{\partial \mathbf{h}_t}{\partial \mathbf{h}_{t-1}} \cdots \frac{\partial \mathbf{h}_1}{\partial \mathbf{h}_0} \frac{\partial \mathbf{h}_0}{\partial \mathbf{x}_0}$$

$$\frac{\partial J}{\partial \mathbf{W}} = \sum_{t=0}^{T} \frac{\partial \mathcal{L}(\hat{\mathbf{y}}_t, \mathbf{y}_t)}{\partial \mathbf{W}}$$



Recurrent linear layer

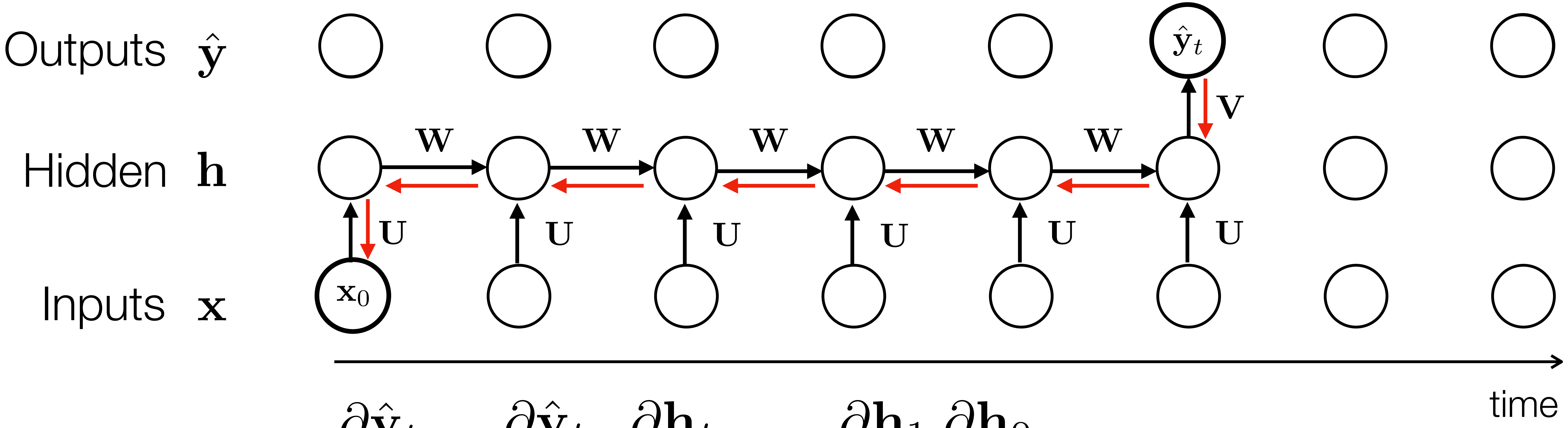
$$\frac{\partial J}{\partial \mathbf{W}} = \sum_{t=0}^{T} \frac{\partial \mathcal{L}(\hat{\mathbf{y}}_t, \mathbf{y}_t)}{\partial \mathbf{W}}$$

The problem of long-range dependences

Why not remember everything?

- Memory size grows with t
- This kind of memory is **nonparametric**: there is no finite set of parameters we can use to model it
- RNNs make a Markov assumption — the future hidden state only depends on the immediately preceding hidden state
- By putting the right info in to the hidden state, RNNs can model depedences that are arbitrarily far apart

The problem of long-range dependences



$$\frac{\partial \hat{\mathbf{y}}_t}{\partial \mathbf{x}_0} = \frac{\partial \hat{\mathbf{y}}_t}{\partial \mathbf{h}_t} \frac{\partial \mathbf{h}_t}{\partial \mathbf{h}_{t-1}} \cdots \frac{\partial \mathbf{h}_1}{\partial \mathbf{h}_0} \frac{\partial \mathbf{h}_0}{\partial \mathbf{x}_0}$$

- Capturing long-range dependences requires propagating information through a long chain of dependences.
- Old observations are forgotten
- Stochastic gradients become high variance (noisy), and gradients may **vanish** or **explode**

LSTMs

Long Short Term Memory

[Hochreiter & Schmidhuber, 1997]

A special kind of RNN designed to avoid forgetting.

This way the default behavior is not to forget an old state. Instead of forgetting by default, the network has to *learn to forget*.

[Slide derived from Chris Olah: http://colah.github.io/posts/2015-08-Understanding-LSTMs/]

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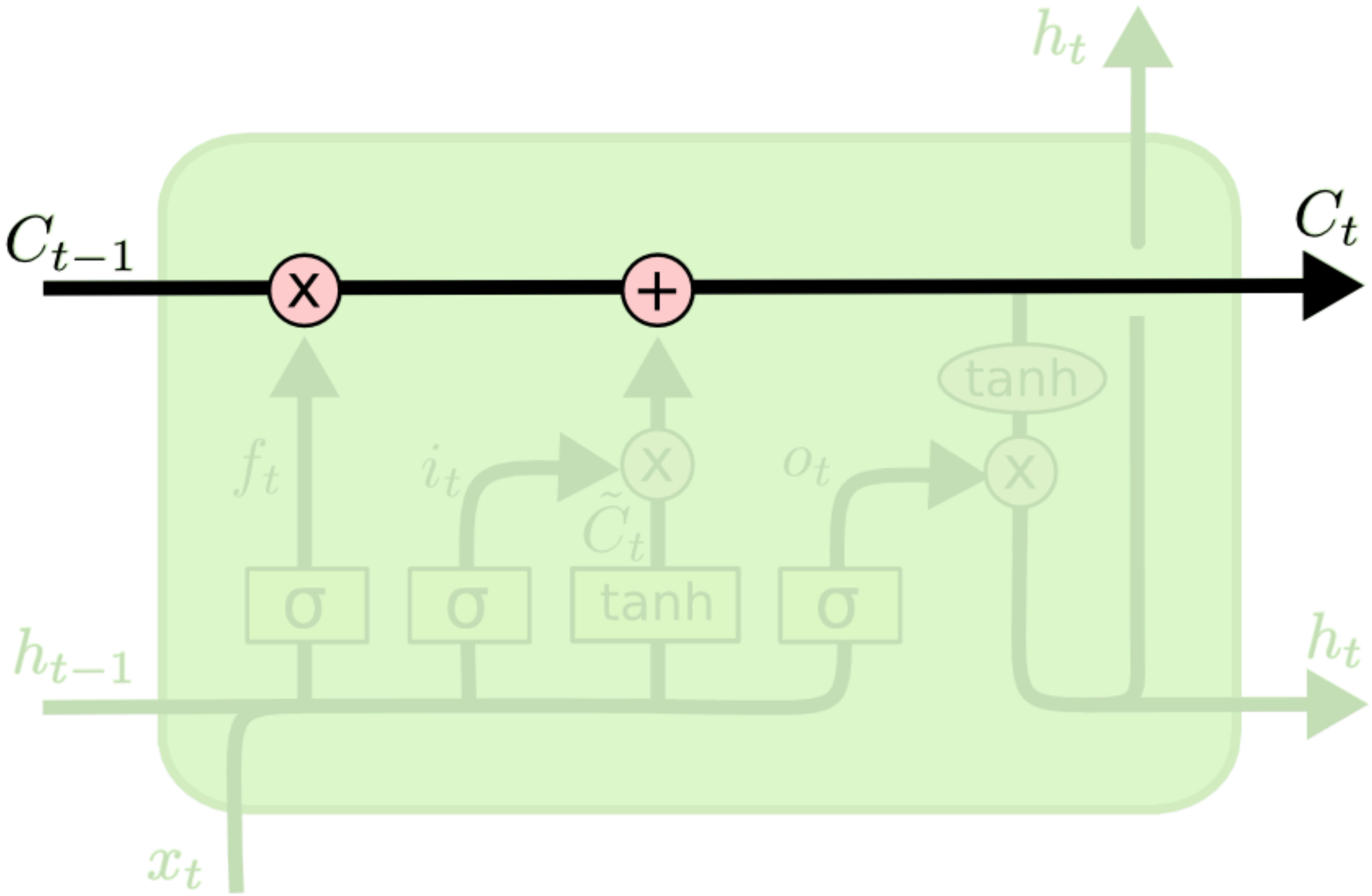
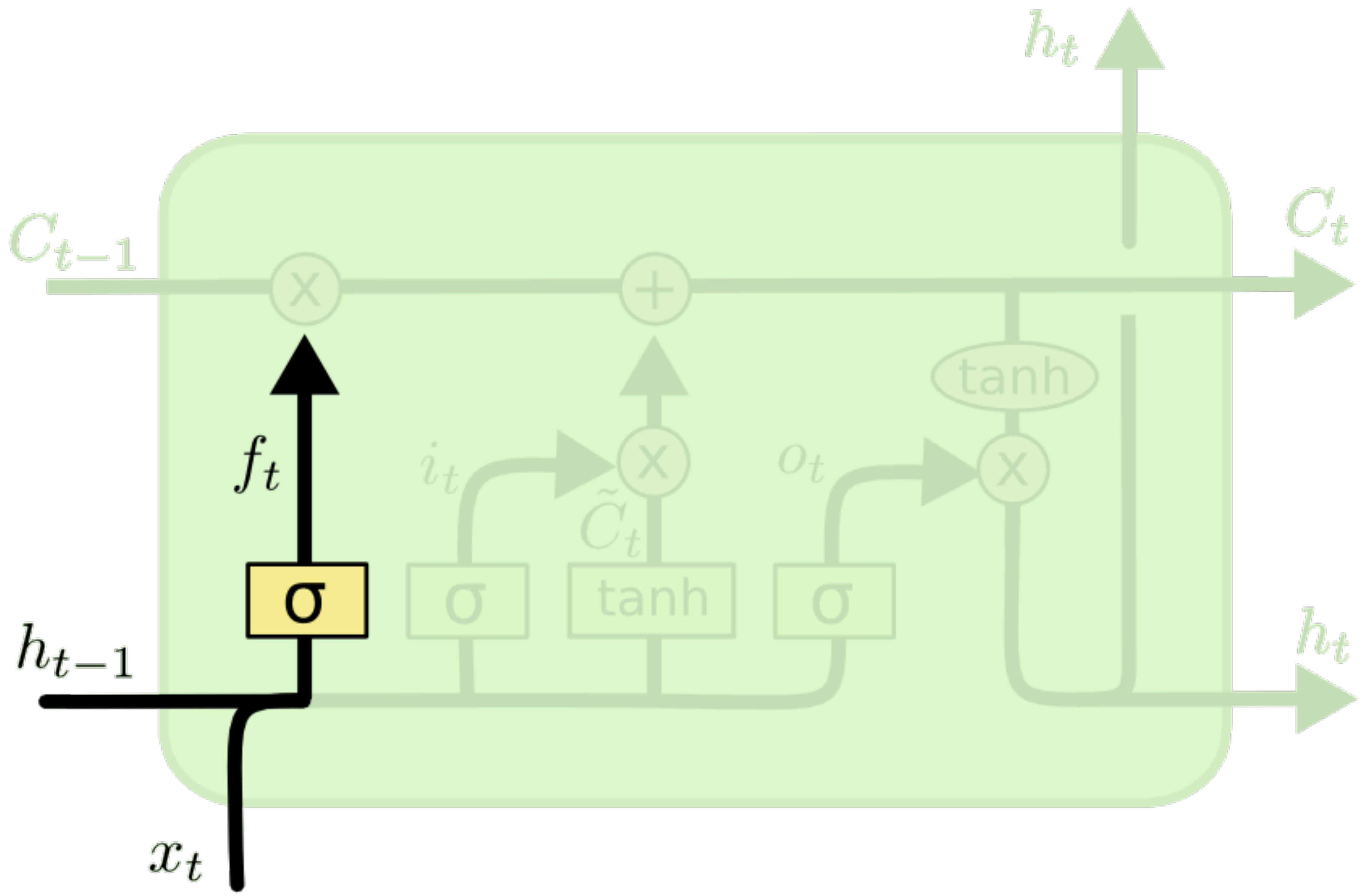
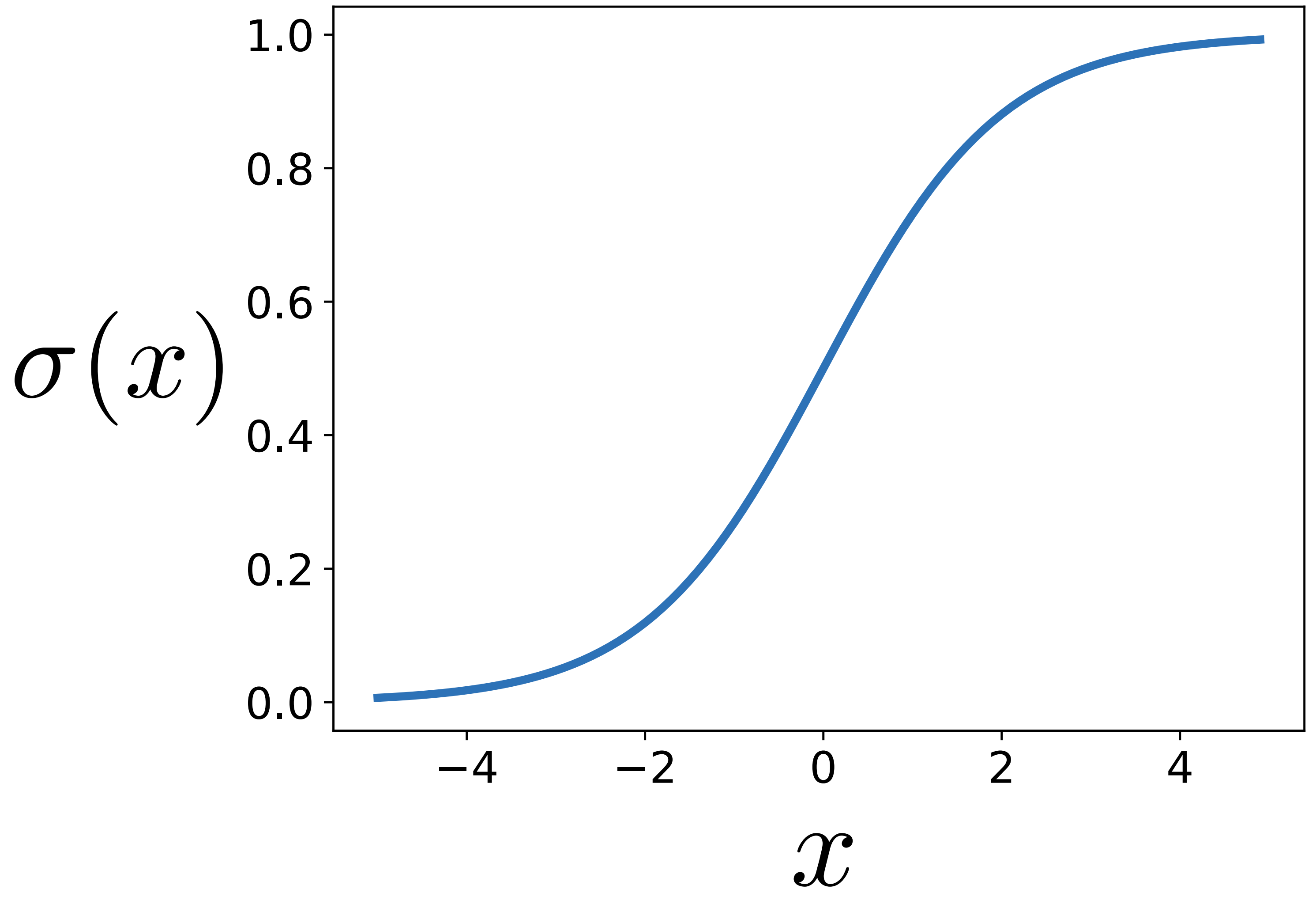


C_t = Cell state

[Slide derived from Chris Olah: http://colah.github.io/posts/2015-08-Understanding-LSTMs/]



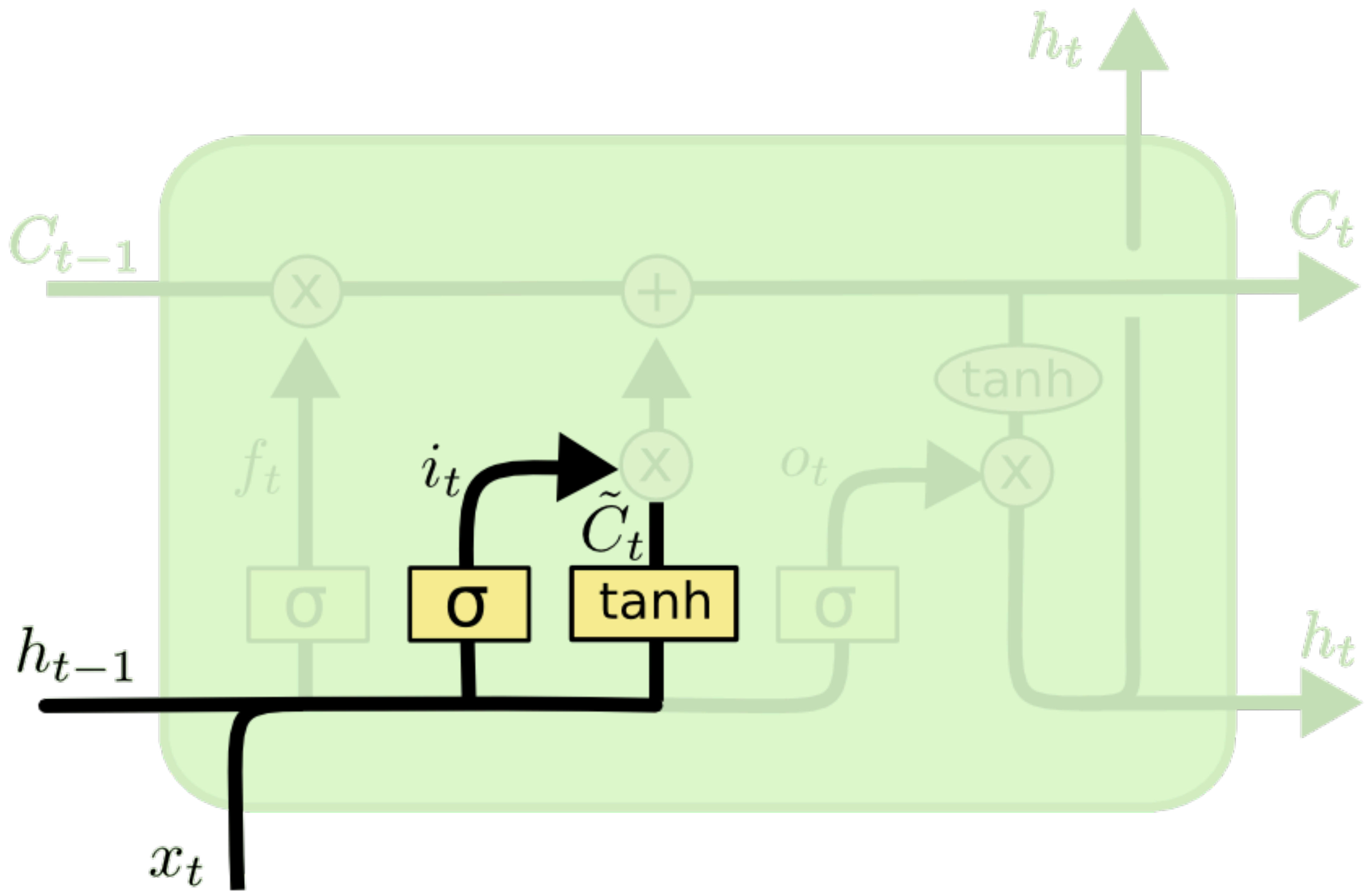


$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

Decide what information to throw away from the cell state.

Each element of cell state is multiplied by ~1 (remember) or ~0 (forget).

[Slide derived from Chris Olah: http://colah.github.io/posts/2015-08-Understanding-LSTMs/]



which indices to write to

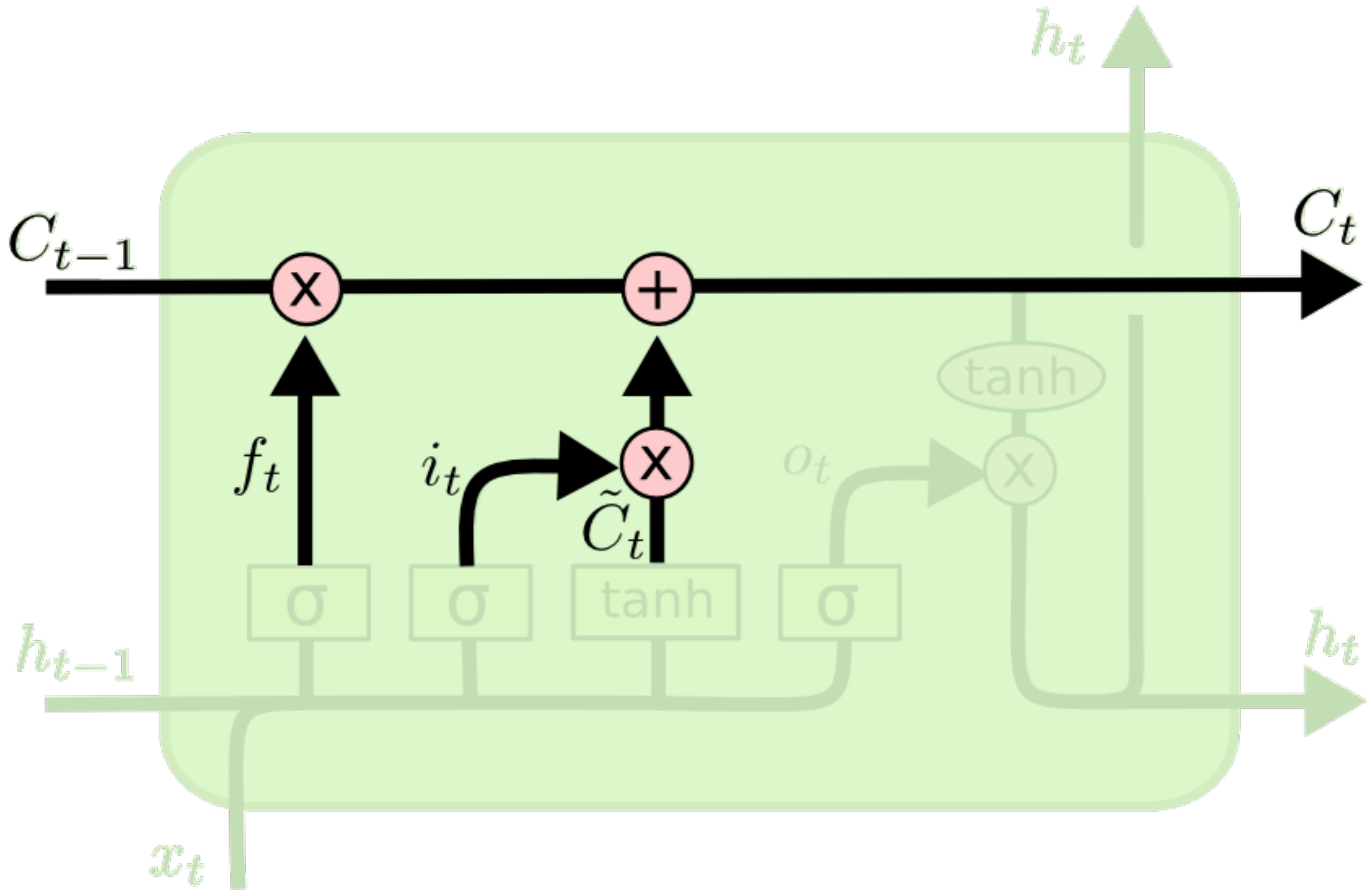
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \;+\; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \;+\; b_C)$$

what to write to those indices

Decide what new information to add to the cell state.

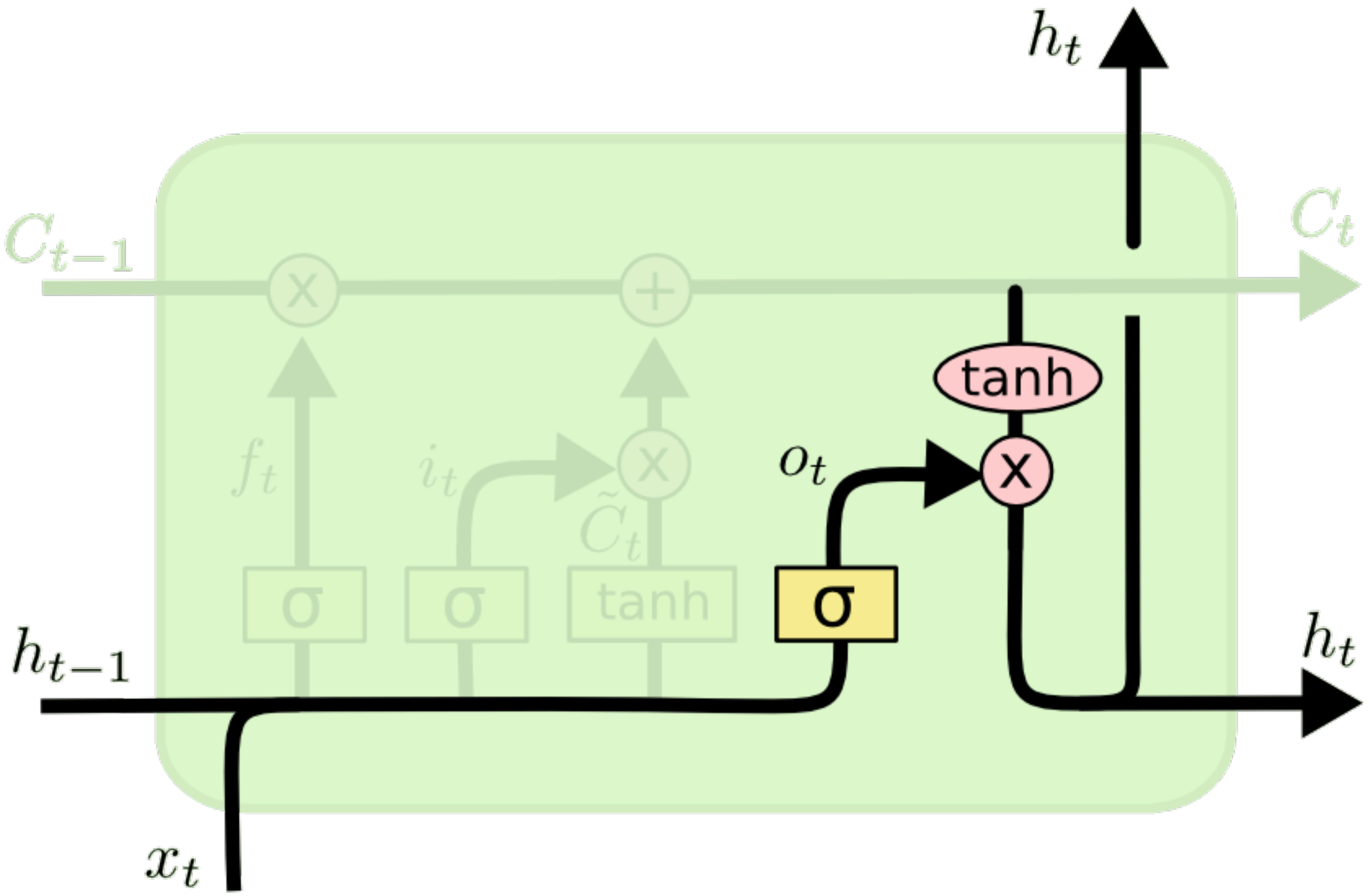
[Slide derived from Chris Olah: http://colah.github.io/posts/2015-08-Understanding-LSTMs/]



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Forget selected old information, write selected new information.

[Slide derived from Chris Olah: http://colah.github.io/posts/2015-08-Understanding-LSTMs/]



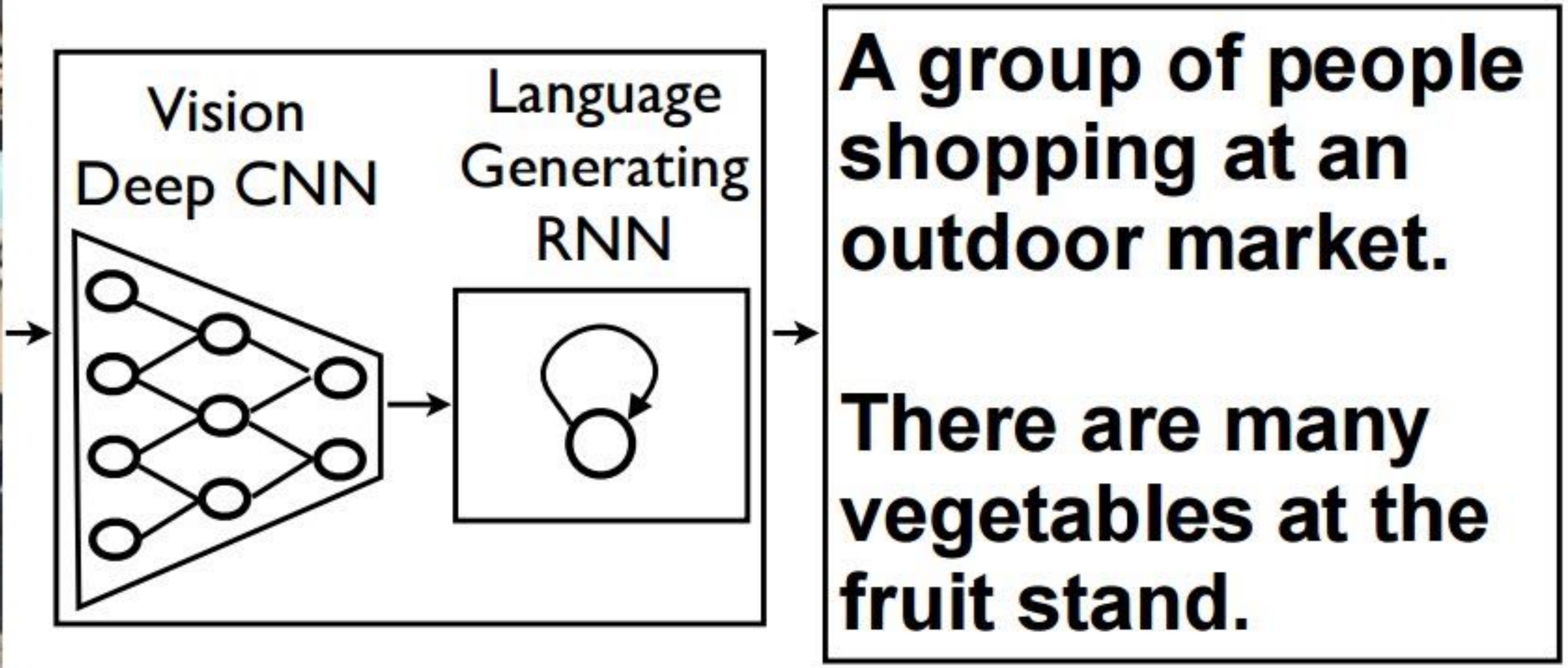
$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

After having updated the cell state's information, decide what to output.

[Slide derived from Chris Olah: http://colah.github.io/posts/2015-08-Understanding-LSTMs/]

Image Captioning



[Example above from: Vinyals, Toshev, Bengio, Erhan, CVPR 2015, https://arxiv.org/abs/1411.4555]

Recipe for deep learning in a new domain

1. Transform your data into numbers (e.g., a vector)

2. Transform your goal into a numerical measure (objective function)

3. #1 and #2 specify the “learning problem”

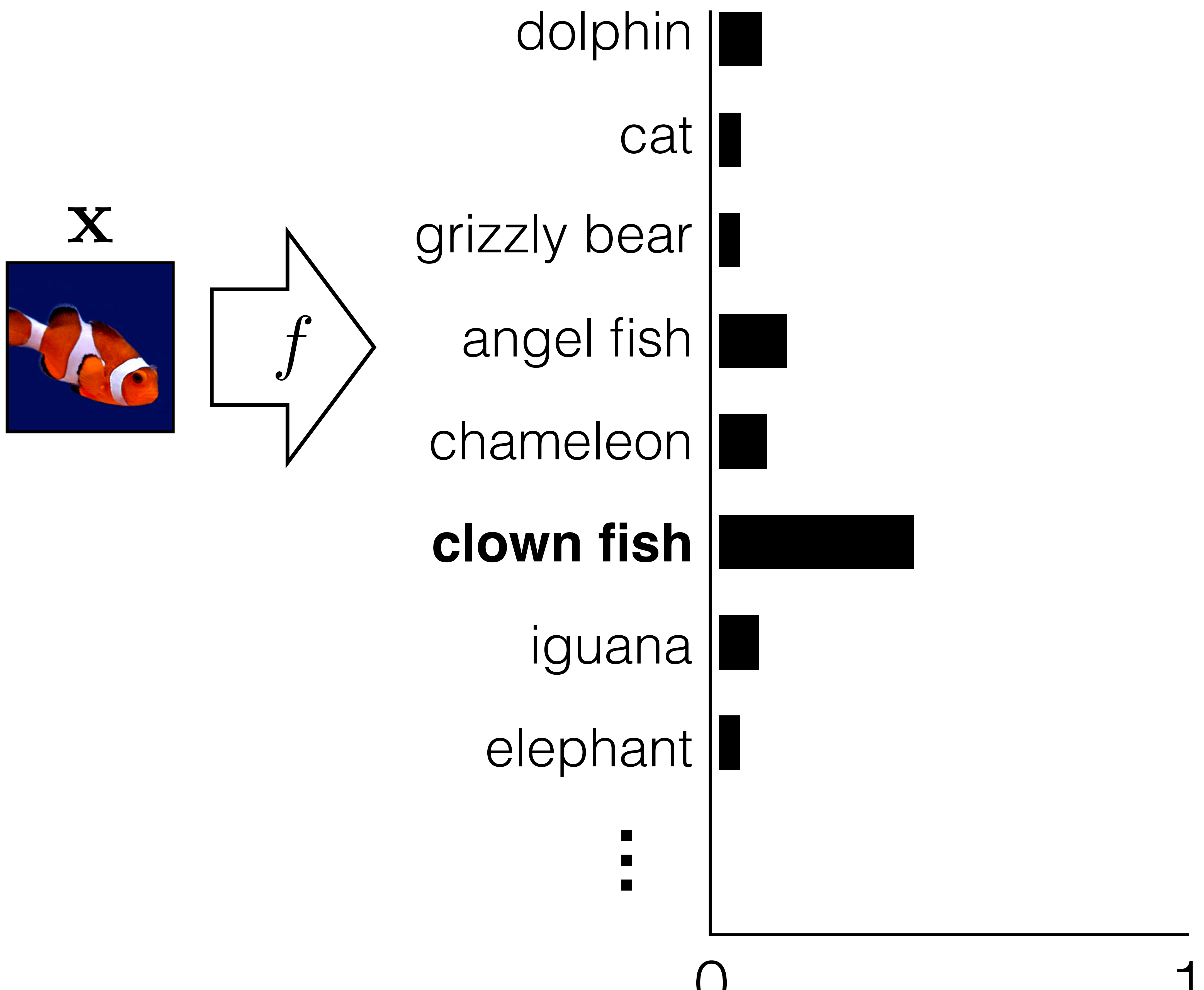
4. Use a generic optimizer (SGD) and an appropriate architecture (e.g., CNN or RNN) to solve the learning problem

How to represent words as numbers?

How to represent words as numbers?

Prediction $\hat{\mathbf{y}}$

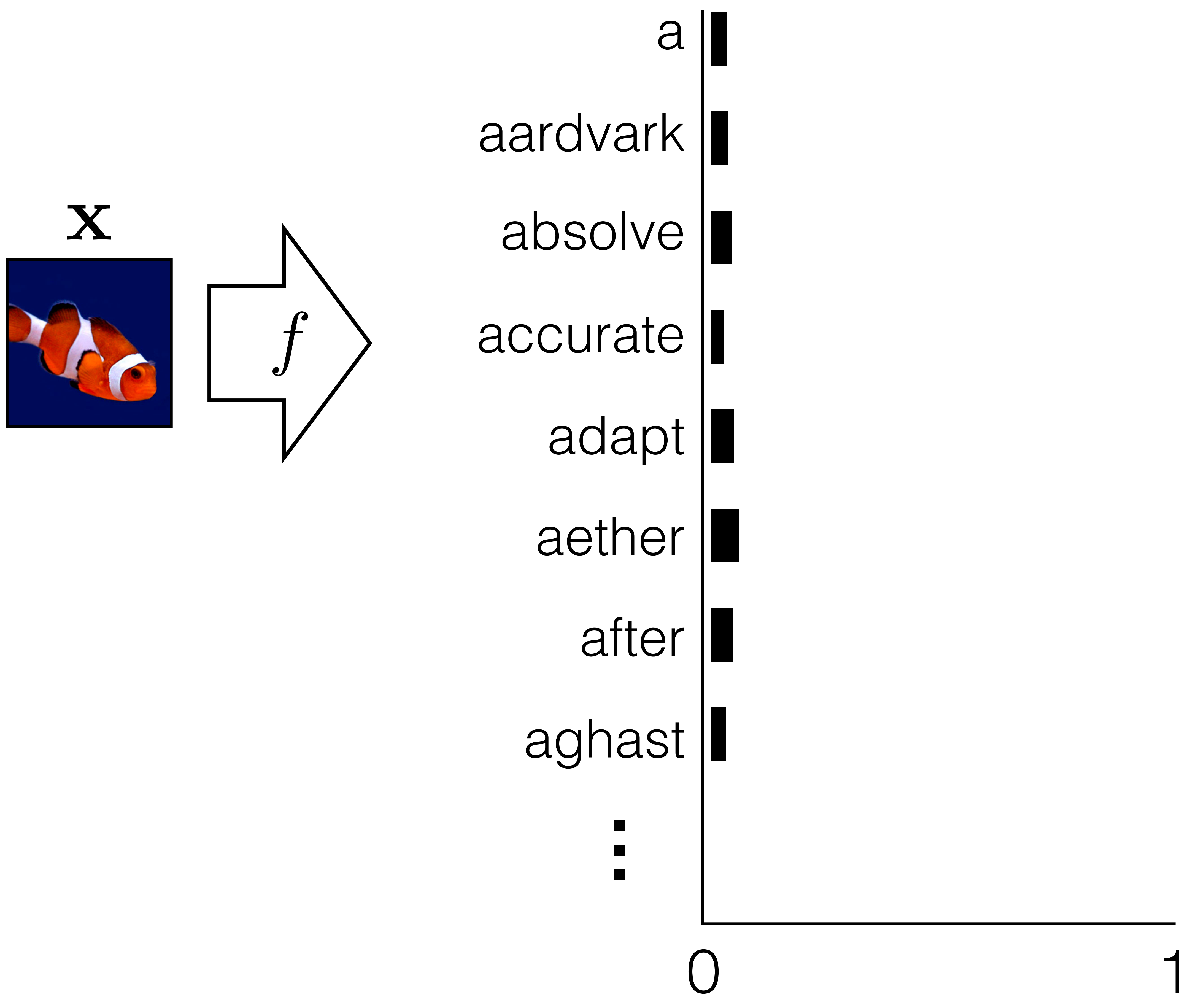
$$f_\theta : X \to \mathbb{R}^K$$



How to represent words as numbers?

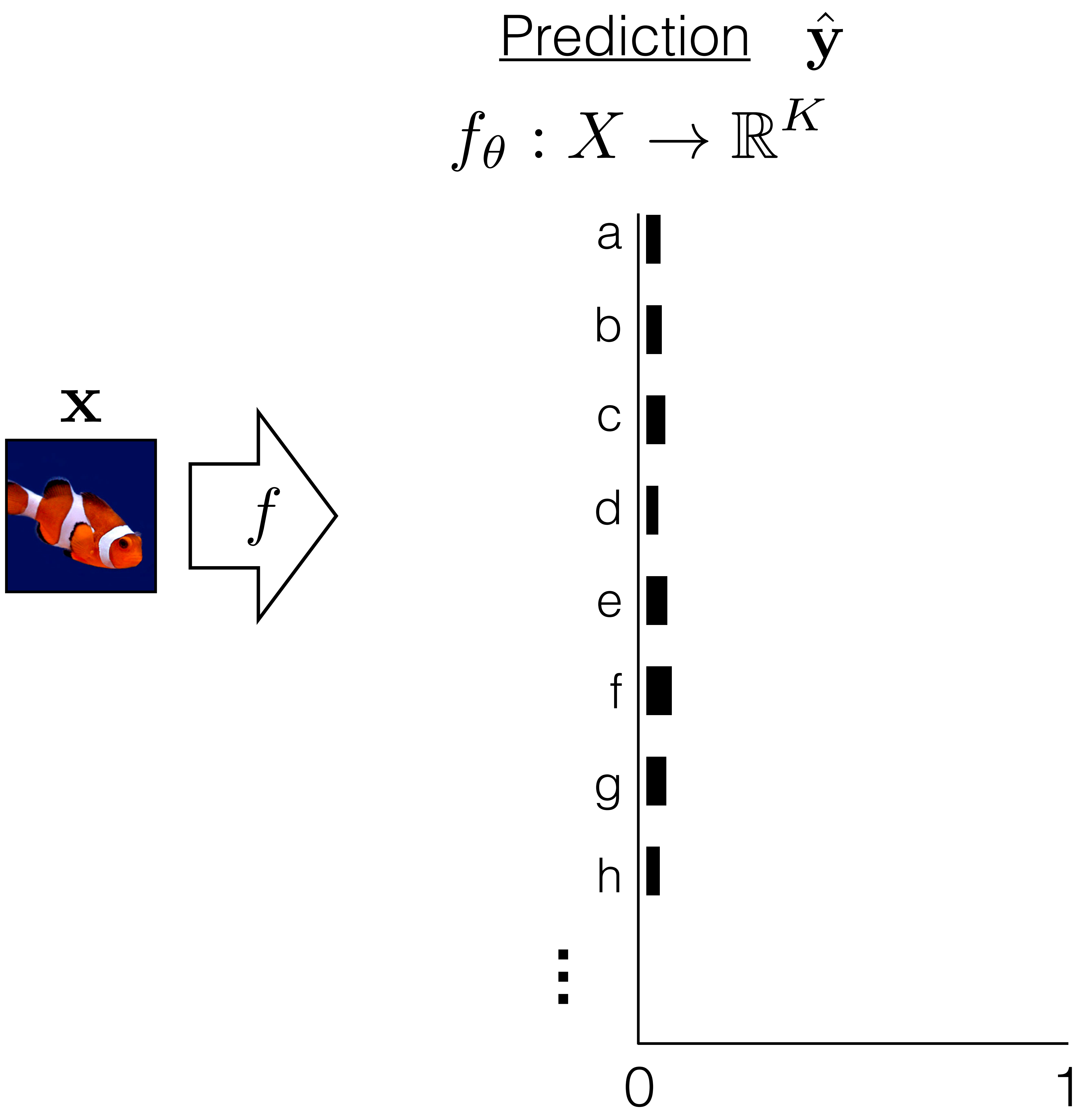
Prediction $\hat{\mathbf{y}}$

$$f_\theta : X \to \mathbb{R}^K$$



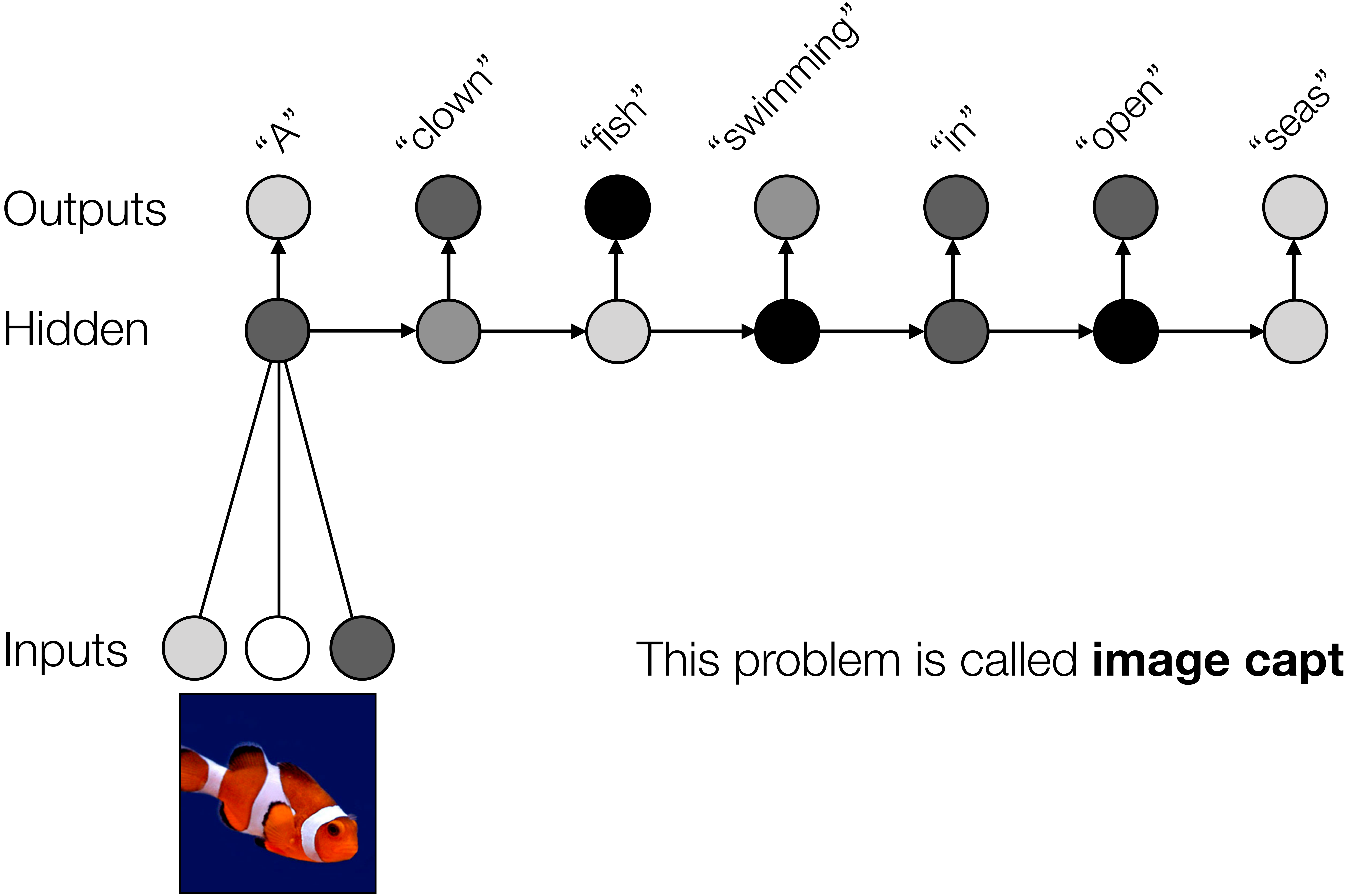
Rather than having just a handful of possible object classes, we can represent all words in a large vocabulary using a very large K (e.g., K=100,000).

How to represent words as numbers?

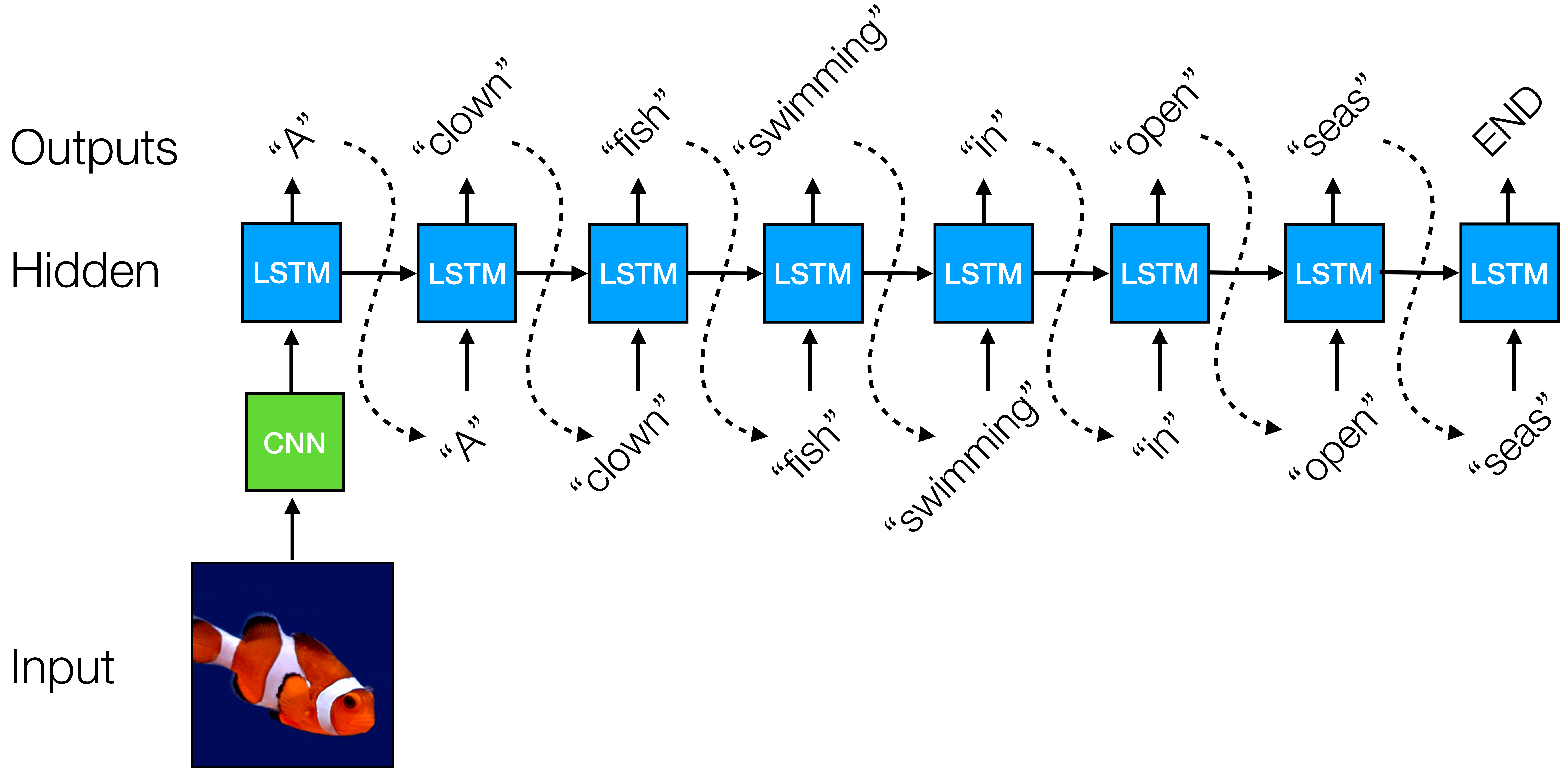


Or, represent each character as a class (e.g., K=26 for English letters),

and represent words as a sequence of characters.

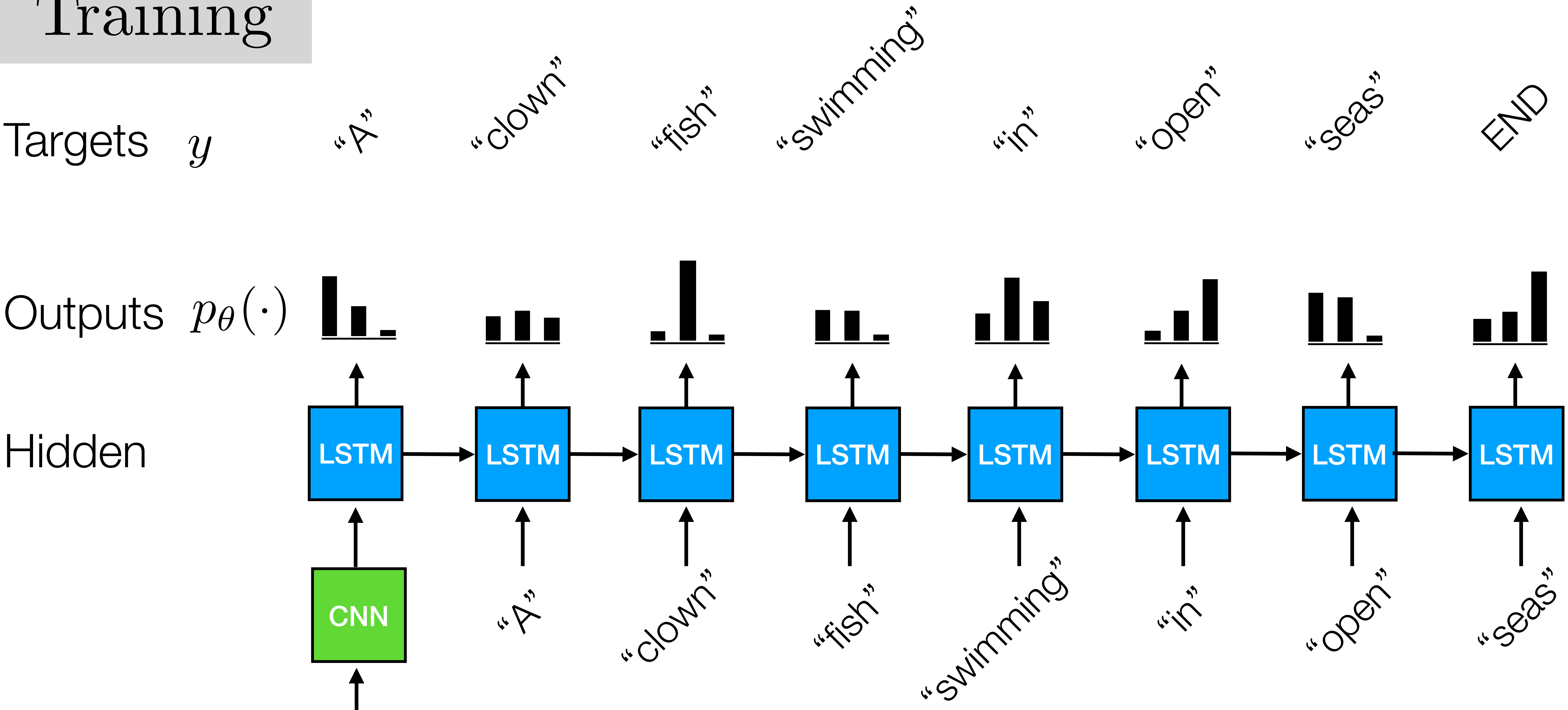


This problem is called **image captioning**



Outputs
Hidden
Input
“A”
“clown”
“fish”
“swimming”
“in”
“open”
“seas”
END
LSTM
LSTM
LSTM
LSTM
LSTM
LSTM
LSTM
LSTM
CNN
“A”
“clown”
“fish”
“swimming”
“in”
“open”
“seas”

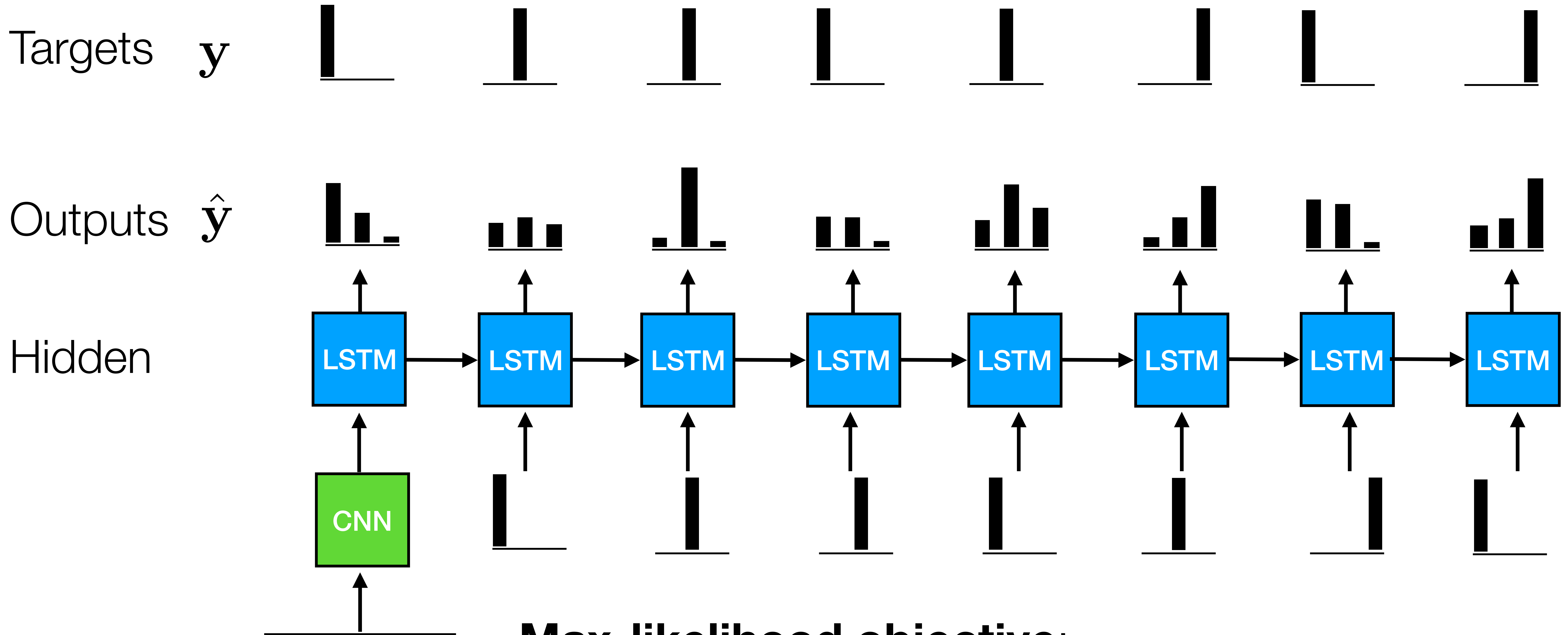
Training

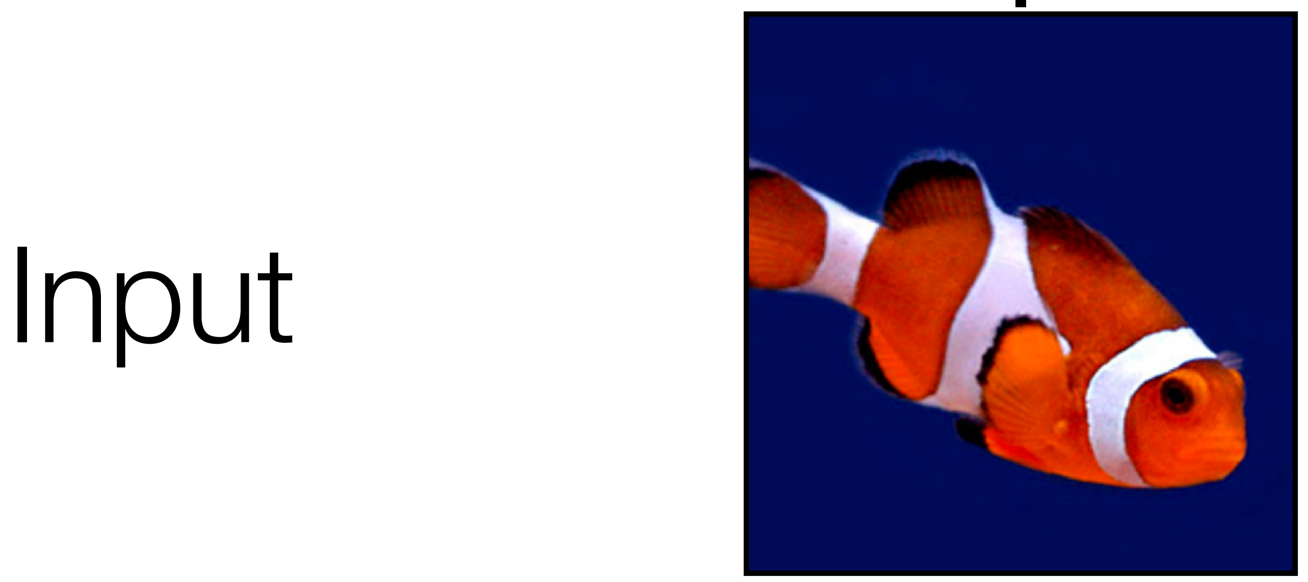


Input

Max-likelihood objective: maximize probability the model assigns to each target word: $\arg\max_\theta \log p_\theta(y)$

Training

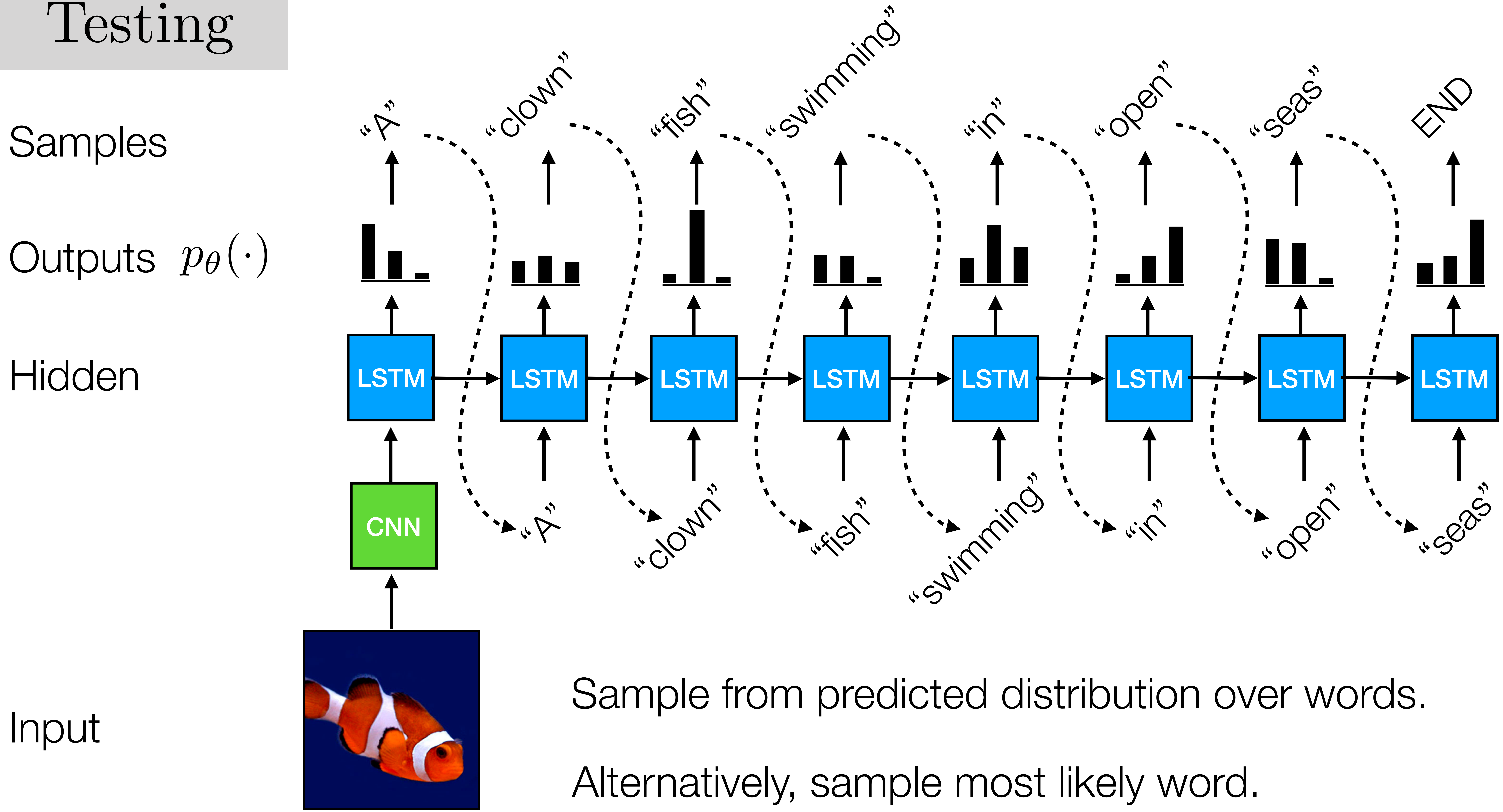




Max-likelihood objective: minimize cross-entropy between model outputs and one-hot encoded targets.

$$f^* = \arg\min_{f \in \mathcal{F}} \sum_{i=1}^{N} H(\mathbf{y}_i, \hat{\mathbf{y}}_i)$$

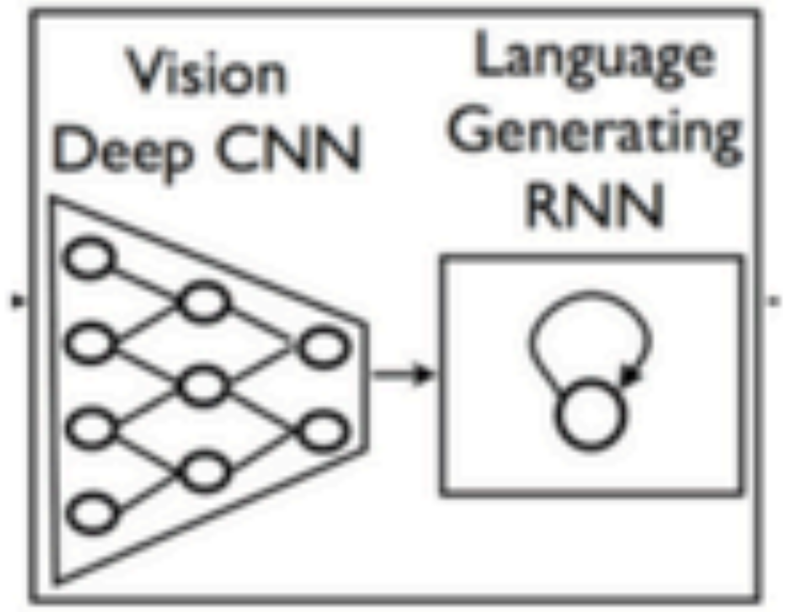
Testing



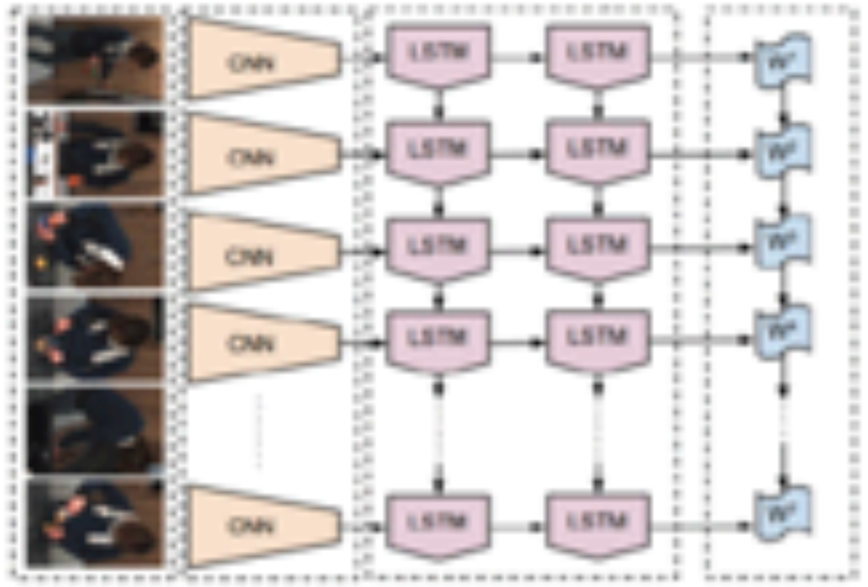
Sample from predicted distribution over words.

Alternatively, sample most likely word.

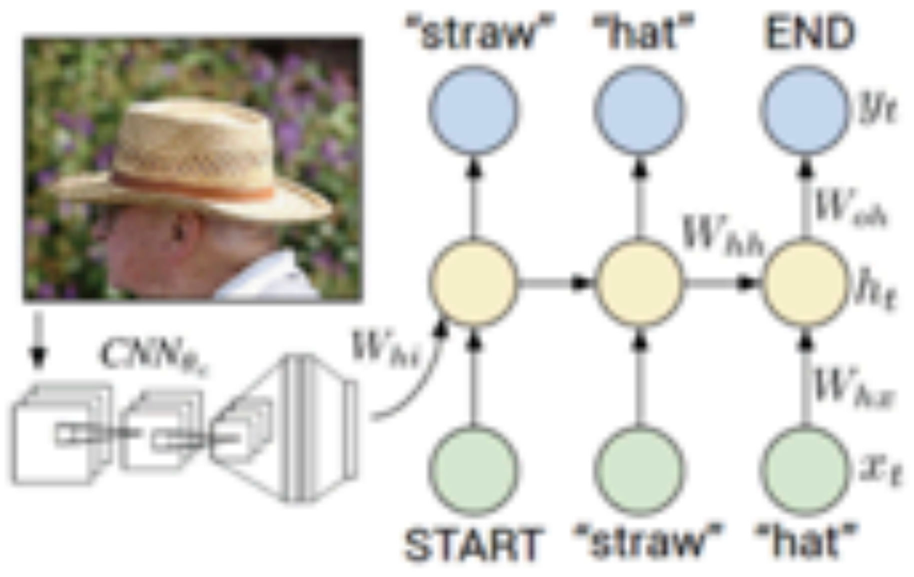
It was very popular a few years ago



Vinyals et al., 2015



Donahue et al., 2015



Karpathy and Fei-Fei, 2015

Hodosh et al., 2013

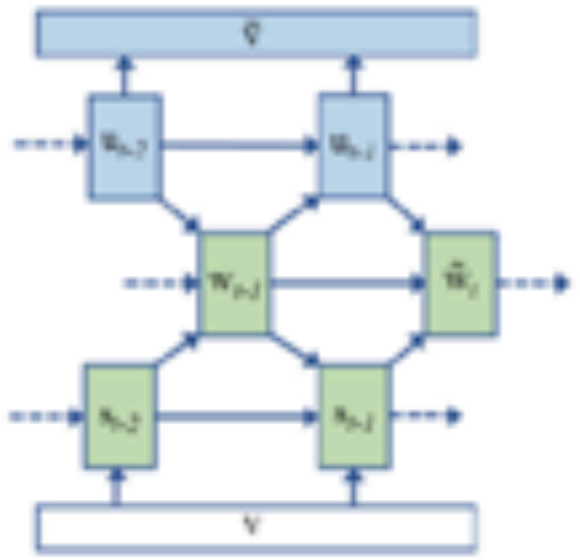
Fang et al., 2015

… and many more

Mao et al., 2015

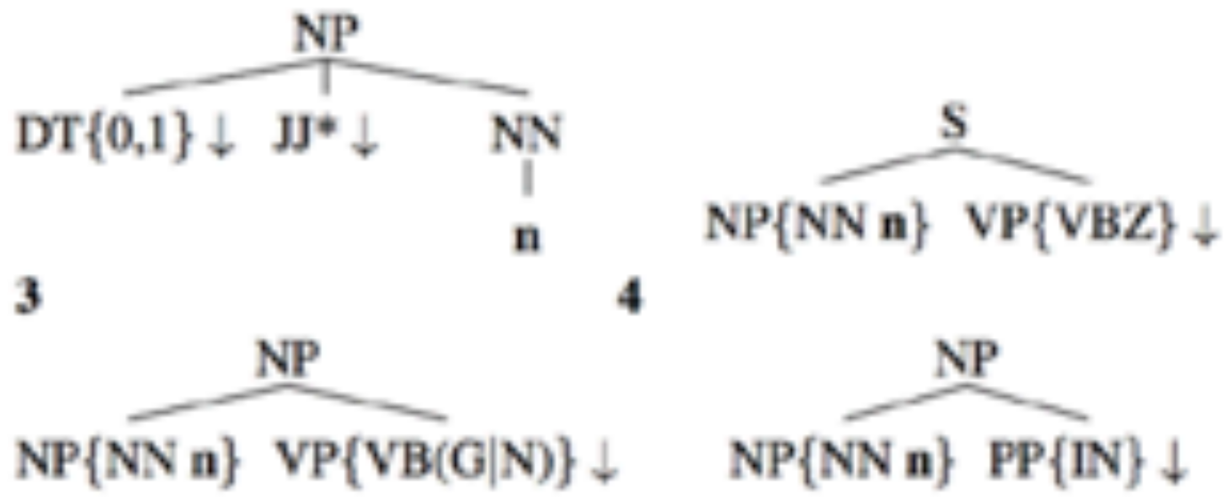
Ordonez et al., 2011

Kulkarni et al., 2011

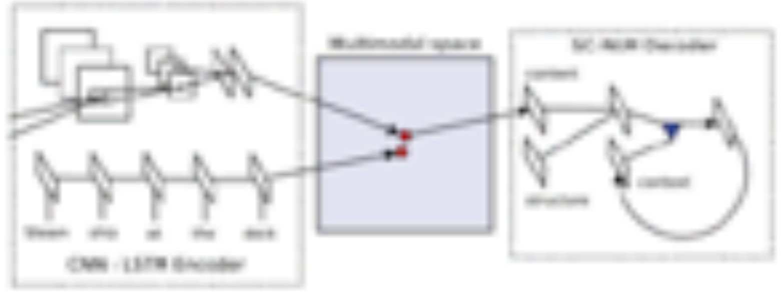


Chen and Zitnick, 2015

Farhadi et al., 2010



Mitchell et al., 2012



Kiros et al., 2015

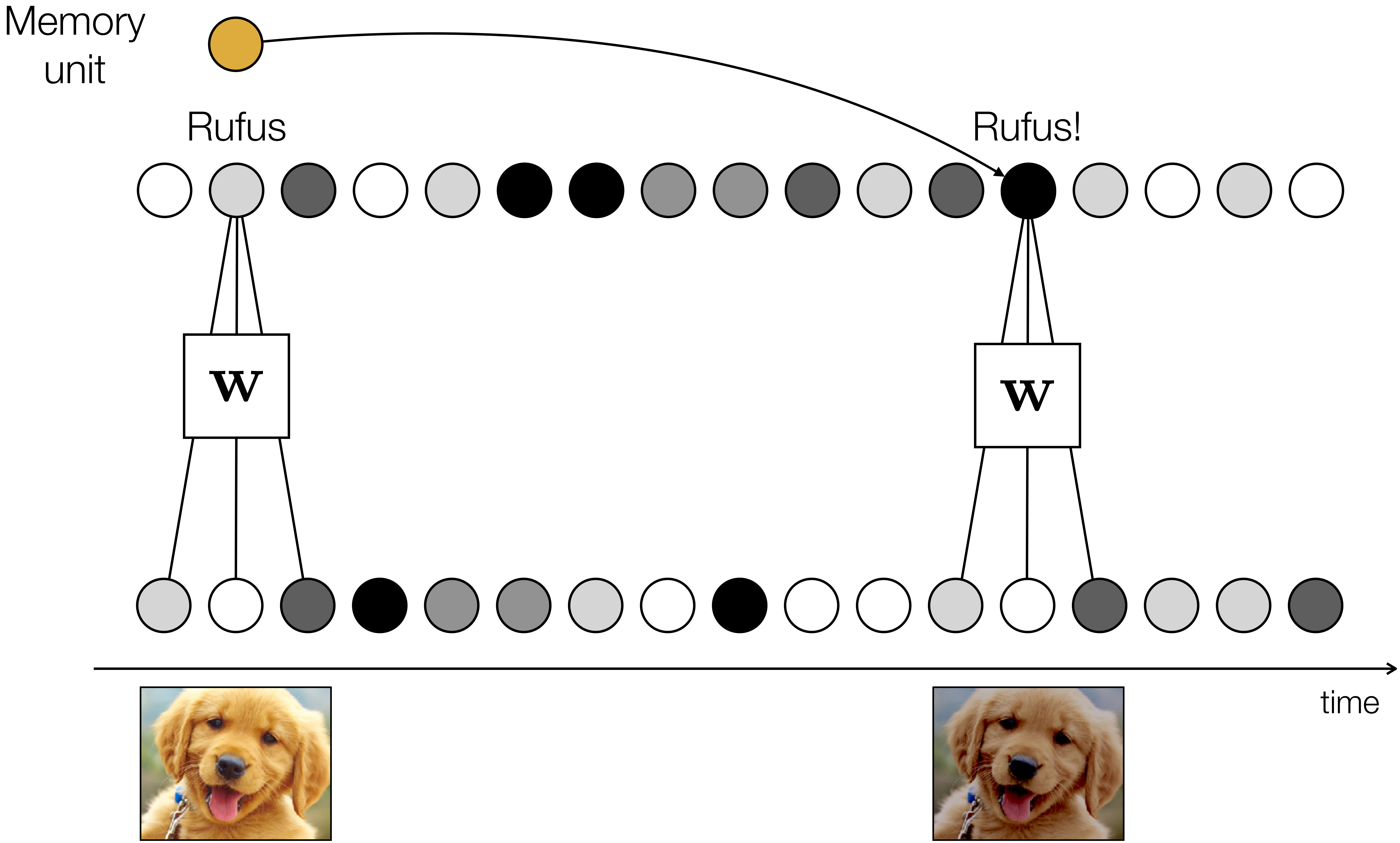
Slide credit: Devi Parikh

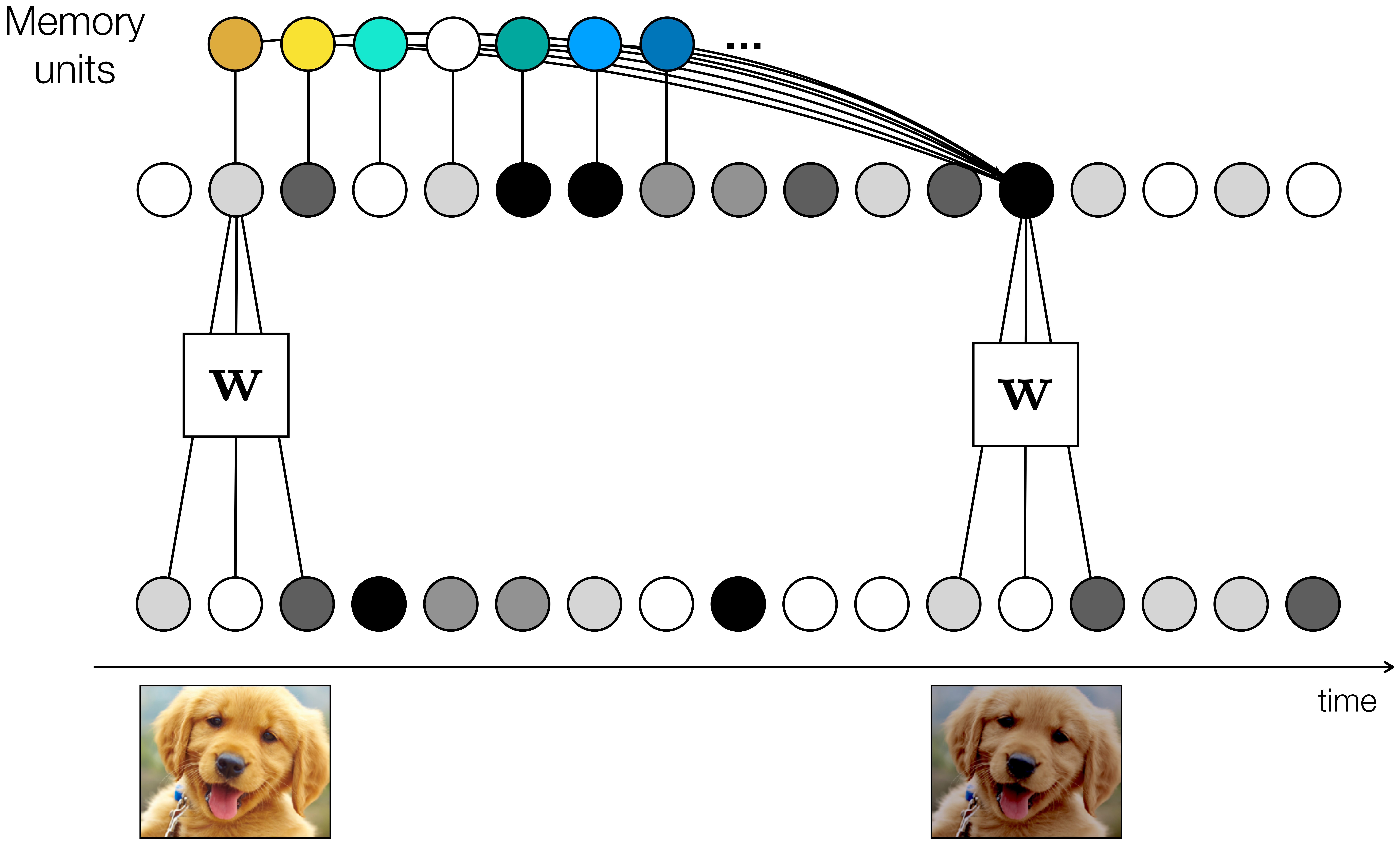

A person riding a motorcycle on a dirt road.
Two dogs play in the grass.
A skateboarder does a trick on a ramp.
A dog is jumping to catch a frisbee.
A group of young people playing a game of frisbee.
Two hockey players are fighting over the puck.
A little girl in a pink hat is blowing bubbles.
A refrigerator filled with lots of food and drinks.
A herd of elephants walking across a dry grass field.
A close up of a cat laying on a couch.
A red motorcycle parked on the side of the road.
A yellow school bus parked in a parking lot.
Describes without errors
Describes with minor errors
Somewhat related to the image
Unrelated to the image

The problem of long-range dependences

Why not remember everything?

- Memory size grows with t
- This kind of memory is **nonparametric**: there is no finite set of parameters we can use to model it
- RNNs make a Markov assumption — the future hidden state only depends on the immediately preceding hidden state
- By putting the right info in to the hidden state, RNNs can model depedences that are arbitrarily far apart


Memory unit
Rufus
Rufus!
W
W
time



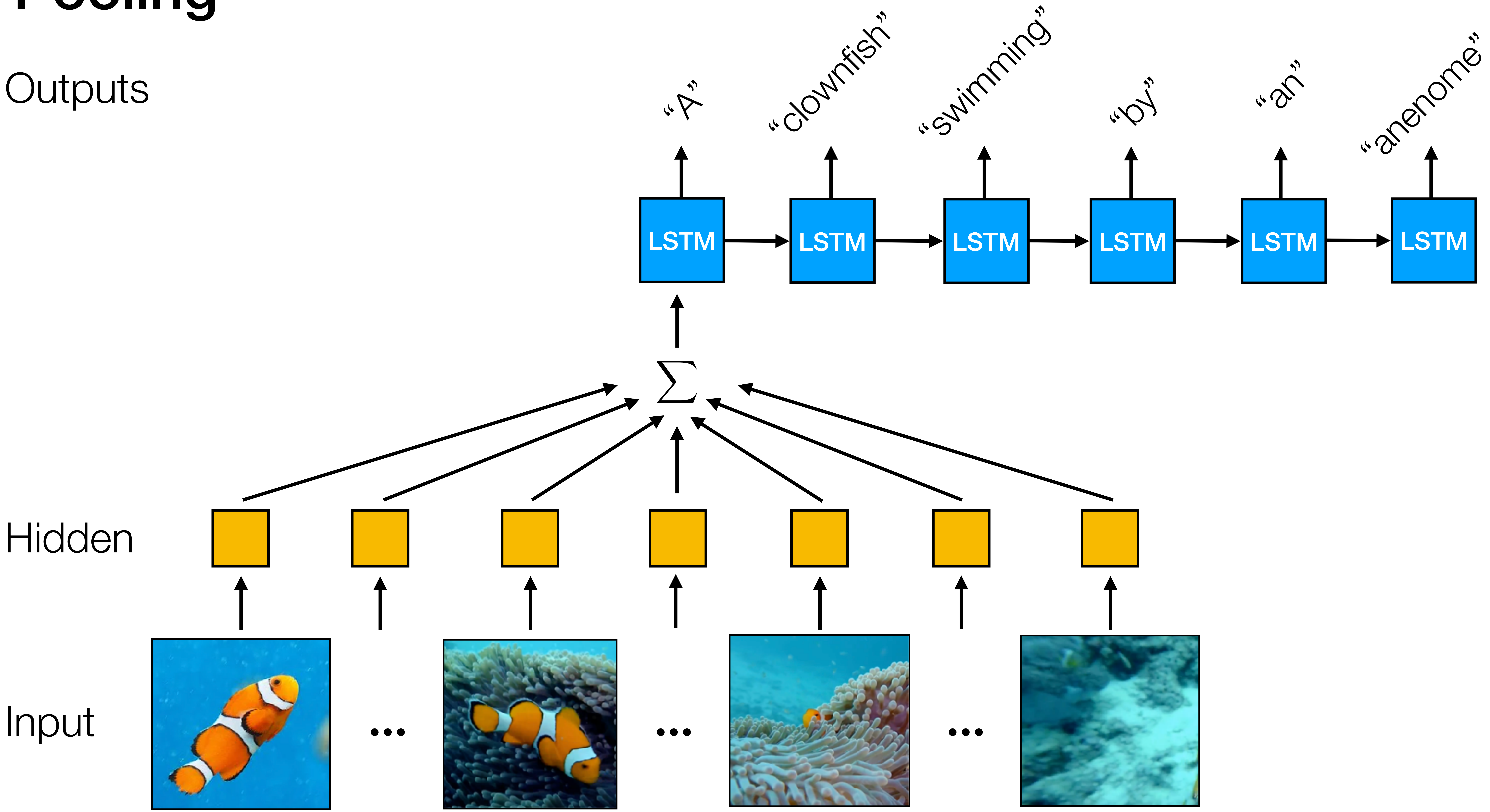
Memory units
...
W
W
time

The problem of long-range dependences

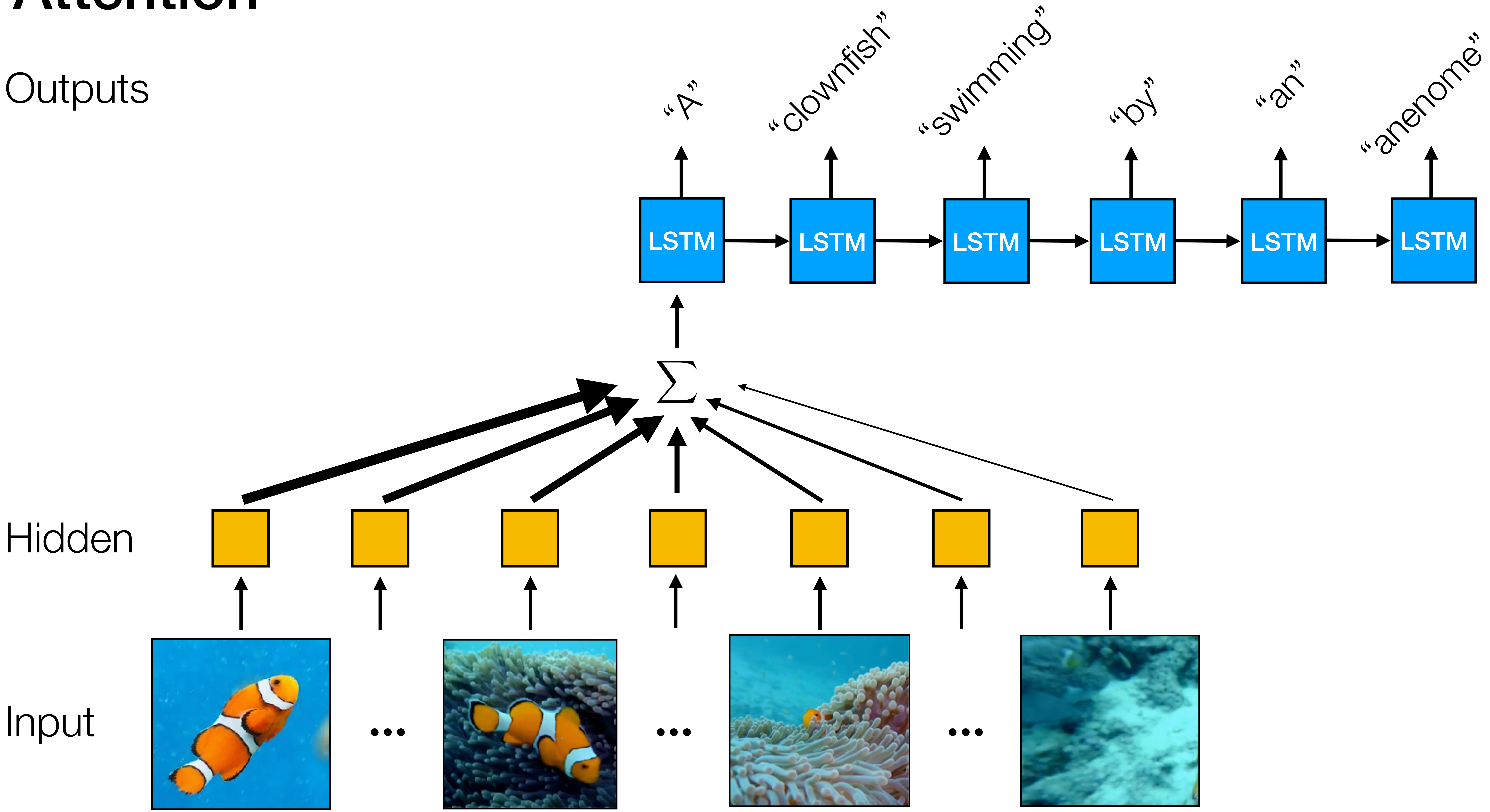
Other methods exist that do directly link old "memories" (observations or hidden states) to future predictions:

- Temporal convolutions
- Attention / Transformers (see https://arxiv.org/abs/1706.03762)
- Memory networks (see https://arxiv.org/abs/1410.3916)

Pooling


Outputs
"A"
"clownfish"
"swimming"
"by"
"an"
"anenome"
LSTM
LSTM
LSTM
LSTM
LSTM
LSTM
Σ
Hidden
Input
...
...
...

Attention


Outputs
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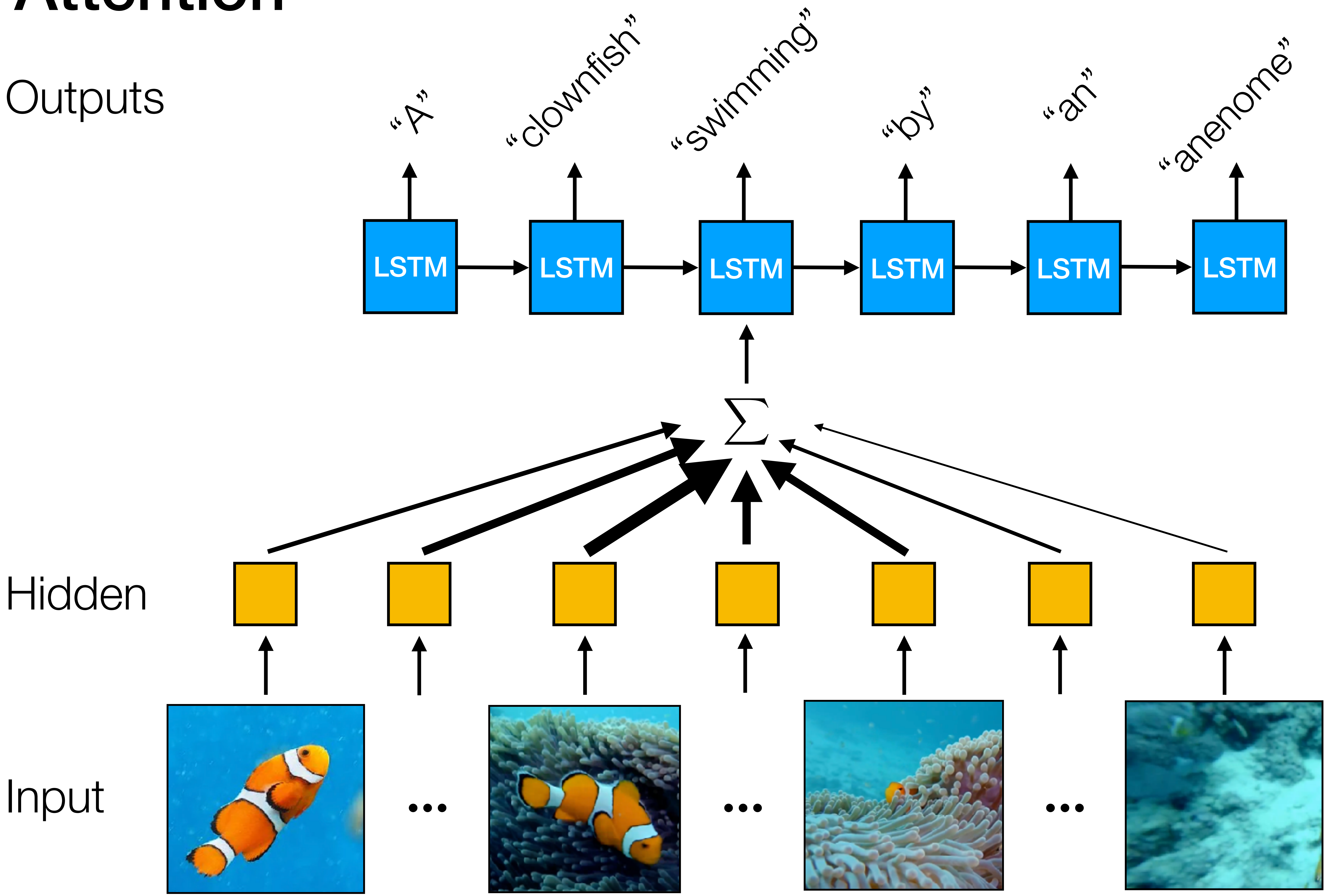
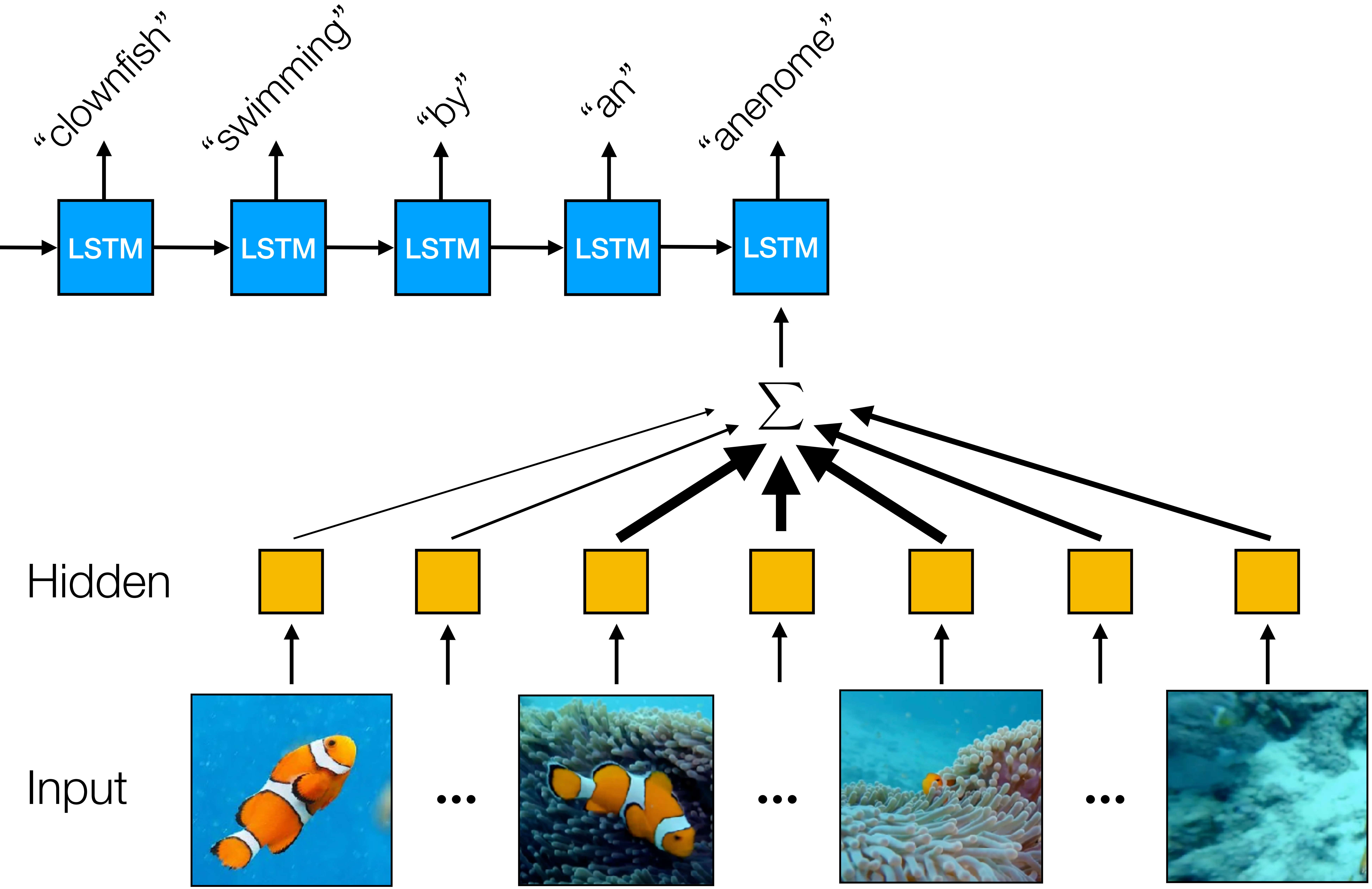
LSTM
LSTM
LSTM
LSTM
LSTM
LSTM
Σ
Hidden
Input
...
...
...

Attention

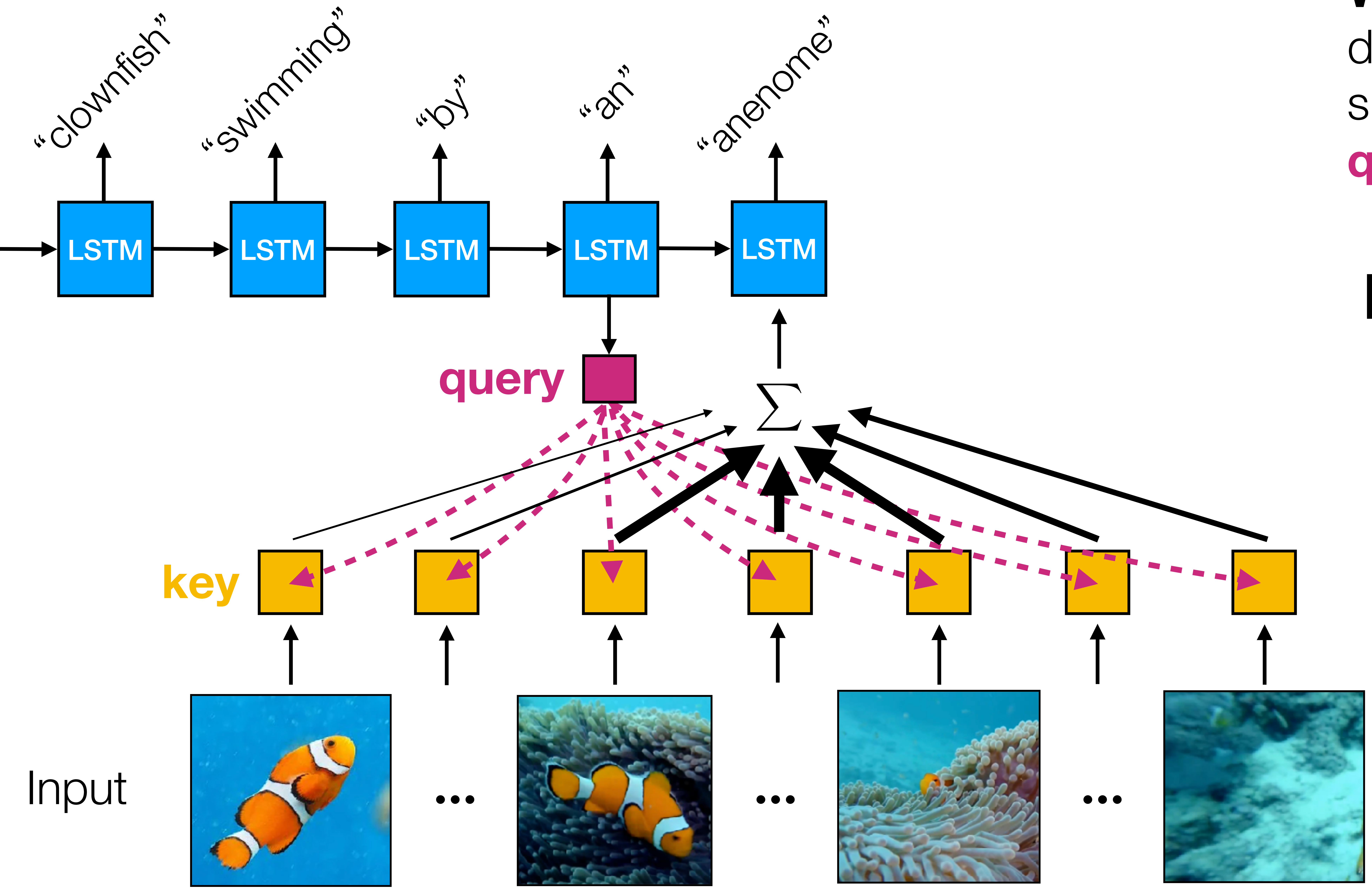

Outputs
“A”
“clownfish”
“swimming”
“by”
“an”
“anenome”
LSTM
LSTM
LSTM
LSTM
LSTM
LSTM
$\sum$
Hidden
Input
...
...
...

Attention

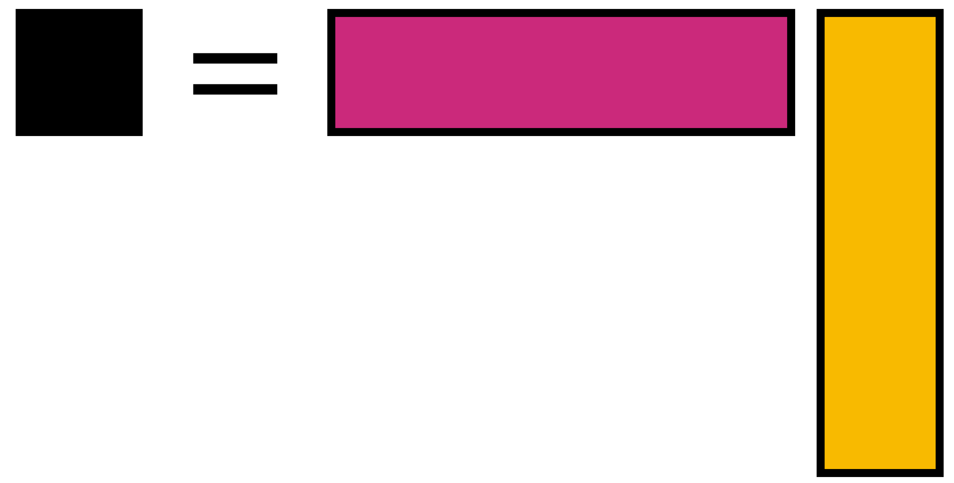


“clownfish”
“swimming”
“by”
“an”
“anenome”
LSTM
LSTM
LSTM
LSTM
LSTM
Σ
Hidden
Input
...
...
...

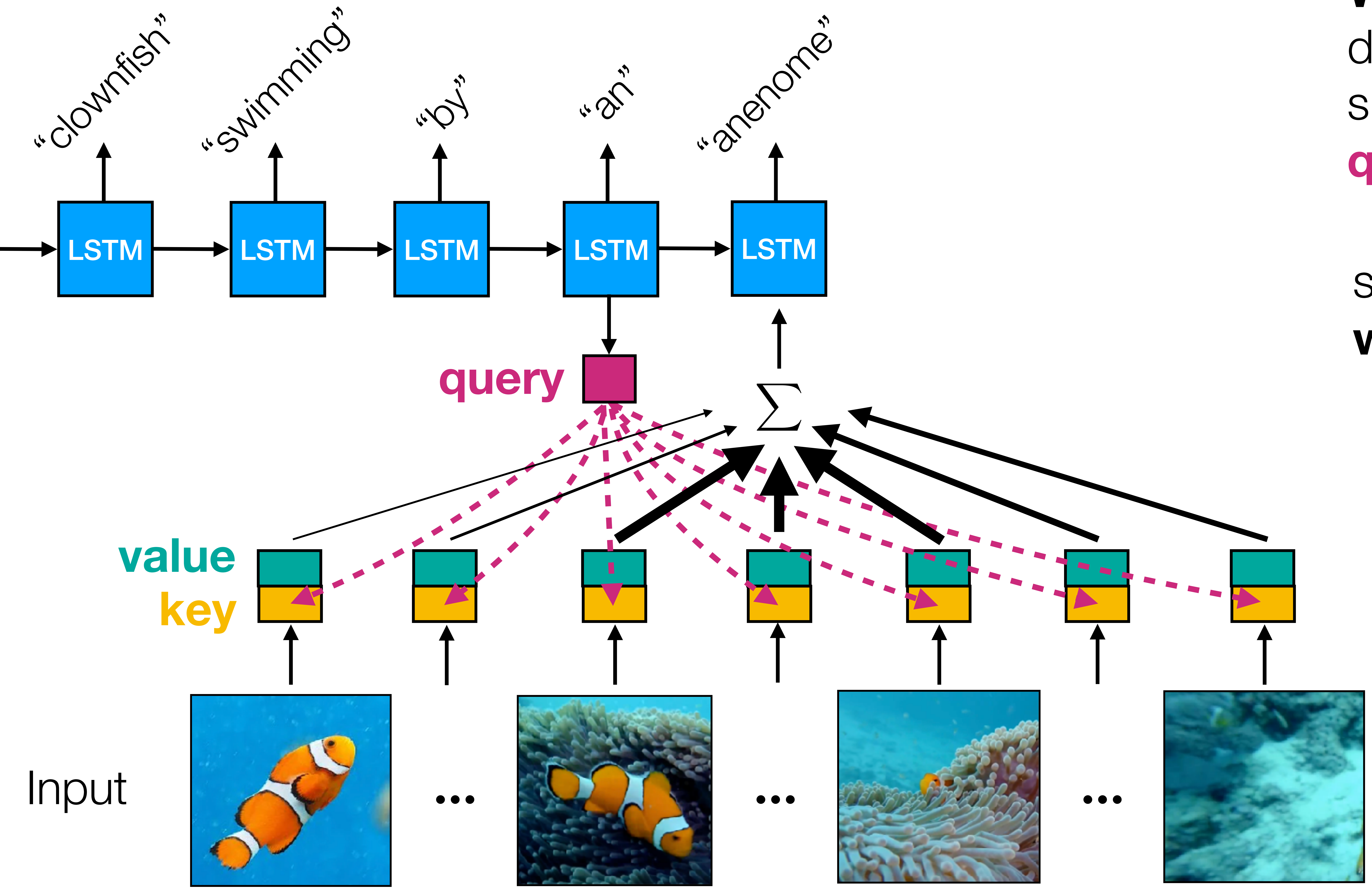
Attention



Weights are determined by similarity between **query** and **key**



Attention



Weights are determined by similarity between **query** and **key**

summation is over **weights** * **value**

Attention


arXiv:1706.03762v5 [cs.CL] 6 Dec 2017

Attention Is All You Need

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Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

1 Introduction

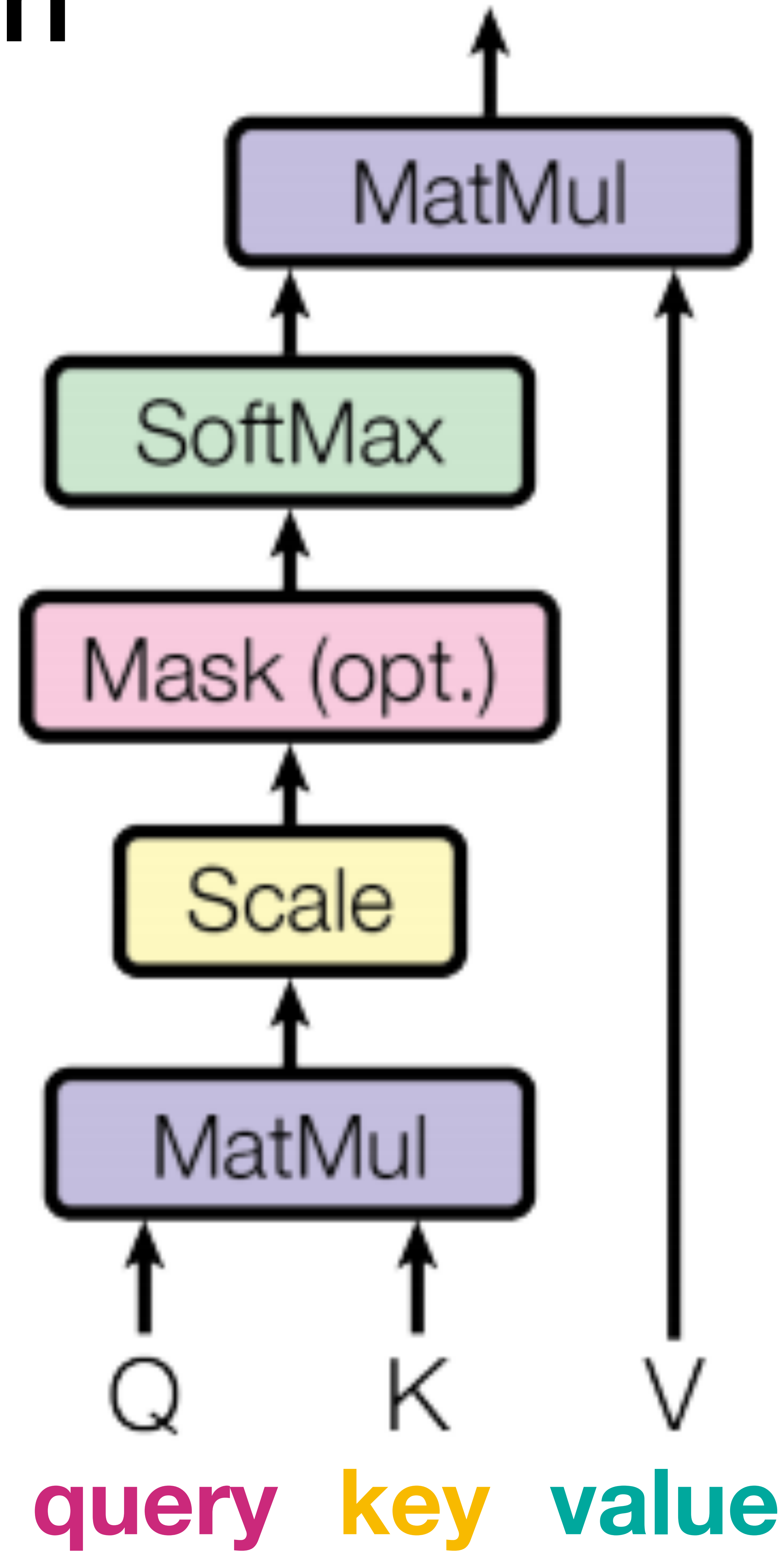
Recurrent neural networks, long short-term memory [13] and gated recurrent [7] neural networks in particular, have been firmly established as state of the art approaches in sequence modeling and

*Equal contribution. Listing order is random. Jakob proposed replacing RNNs with self-attention and started the effort to evaluate this idea. Ashish, with Illia, designed and implemented the first Transformer models and has been crucially involved in every aspect of this work. Noam proposed scaled dot-product attention, multi-head attention and the parameter-free position representation and became the other person involved in nearly every detail. Niki designed, implemented, tuned and evaluated countless model variants in our original codebase and tensor2tensor. Llion also experimented with novel model variants, was responsible for our initial codebase, and efficient inference and visualizations. Lukasz and Aidan spent countless long days designing various parts of and implementing tensor2tensor, replacing our earlier codebase, greatly improving results and massively accelerating our research.

†Work performed while at Google Brain.

‡Work performed while at Google Research.

31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.



["Attention is all you need", Vaswani et al. 2017]

Transformer

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Attention Is All You Need

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Abstract

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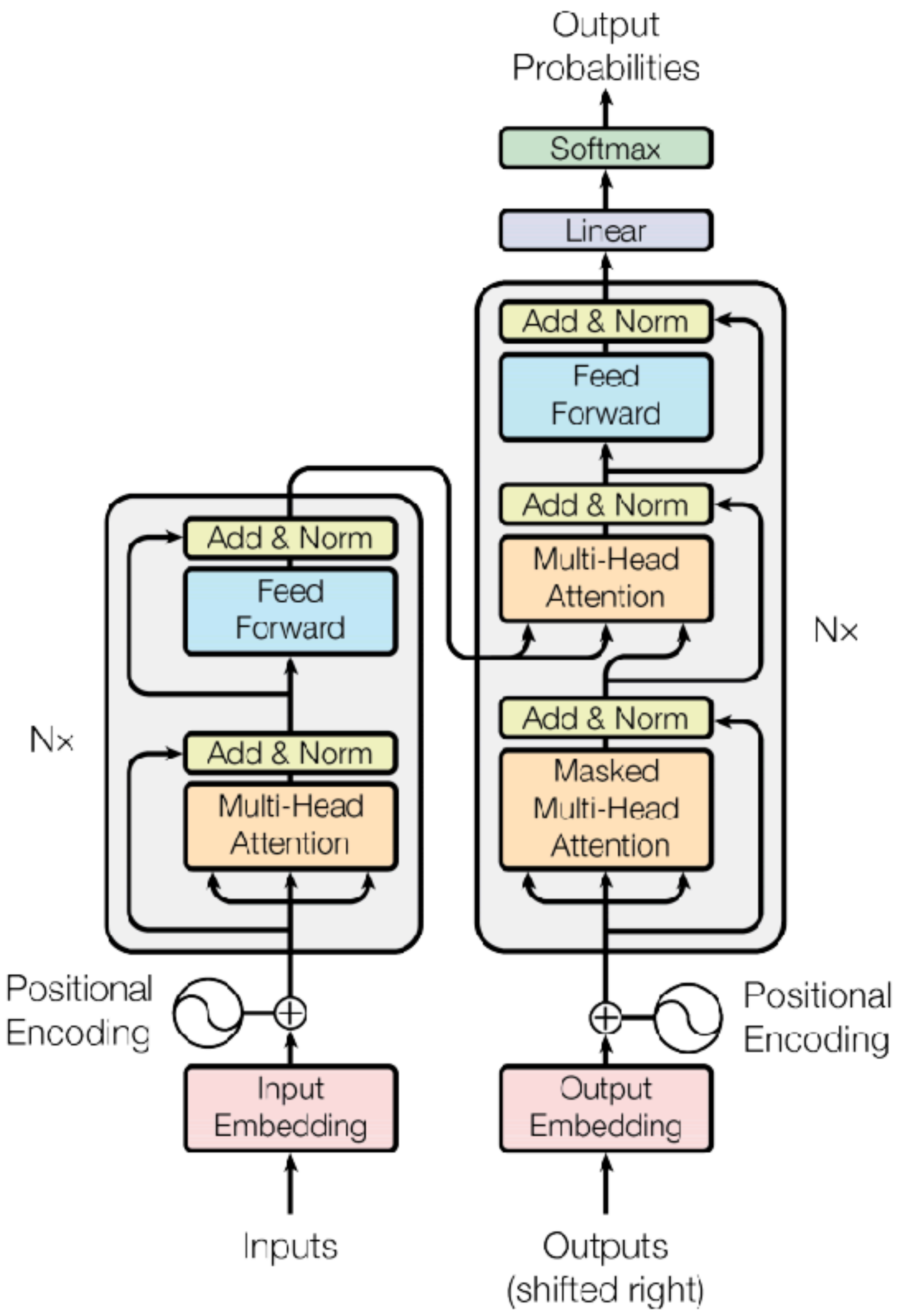
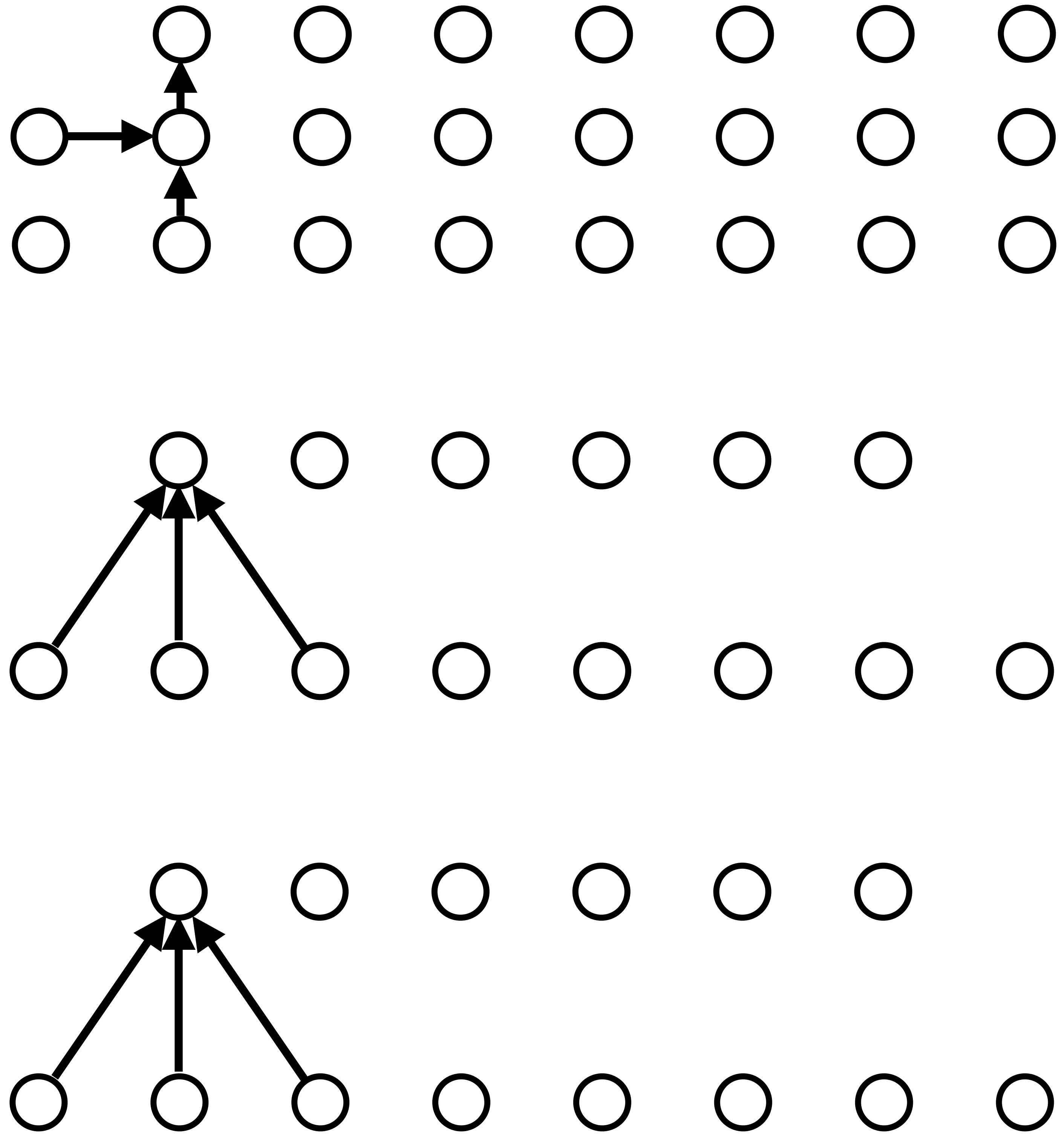


[“Attention is all you need”, Vaswani et al. 2017]

Modeling arbitrarily long sequences

- RNNs — recurrent weights are shared across time
- Convolution — conv weights are shared across time
- Attention — weights are dynamically determined



Anything you can do w.r.t. time, you can do w.r.t. space, and vice versa.

Popular right now: treat pixels as a sequence and then apply sequence modeling methods.

Generative Pretraining from Pixels

Mark Chen[1] Alec Radford[1] Rewon Child[1] Jeff Wu[1] Heewoo Jun[1] Prafulla Dhariwal[1] David Luan[1] Ilya Sutskever[1]

Abstract

Inspired by progress in unsupervised representation learning for natural language, we examine whether similar models can learn useful representations for images. We train a sequence Transformer to auto-regressively predict pixels, without incorporating knowledge of the 2D input structure. Despite training on low-resolution ImageNet without labels, we find that a GPT-2 scale model learns strong image representations as measured by linear probing, fine-tuning, and low-data classification. On CIFAR-10, we achieve 96.3% accuracy with a linear probe, outperforming a supervised Wide ResNet, and 99.0% accuracy with full fine-tuning, matching the top supervised pre-trained models. An even larger model trained on a mixture of ImageNet and web images is competitive with self-supervised benchmarks on ImageNet, achieving 72.0% top-1 accuracy on a linear probe of our features.

ported strong results using a single layer of learned features (Coates et al., 2011), or even random features (Huang et al., 2014; May et al., 2017). The approach fell out of favor as the state of the art increasingly relied on directly encoding prior structure into the model and utilizing abundant supervised data to directly learn representations (Krizhevsky et al., 2012; Graves & Jaitly, 2014). Retrospective study of unsupervised pre-training demonstrated that it could even hurt performance in modern settings (Paine et al., 2014).

Instead, unsupervised pre-training flourished in a different domain. After initial strong results for word vectors (Mikolov et al., 2013), it has pushed the state of the art forward in Natural Language Processing on most tasks (Dai & Le, 2015; Peters et al., 2018; Howard & Ruder, 2018; Radford et al., 2018; Devlin et al., 2018). Interestingly, the training objective of a dominant approach like BERT, the prediction of corrupted inputs, closely resembles that of the Denoising Autoencoder, which was originally developed for images.

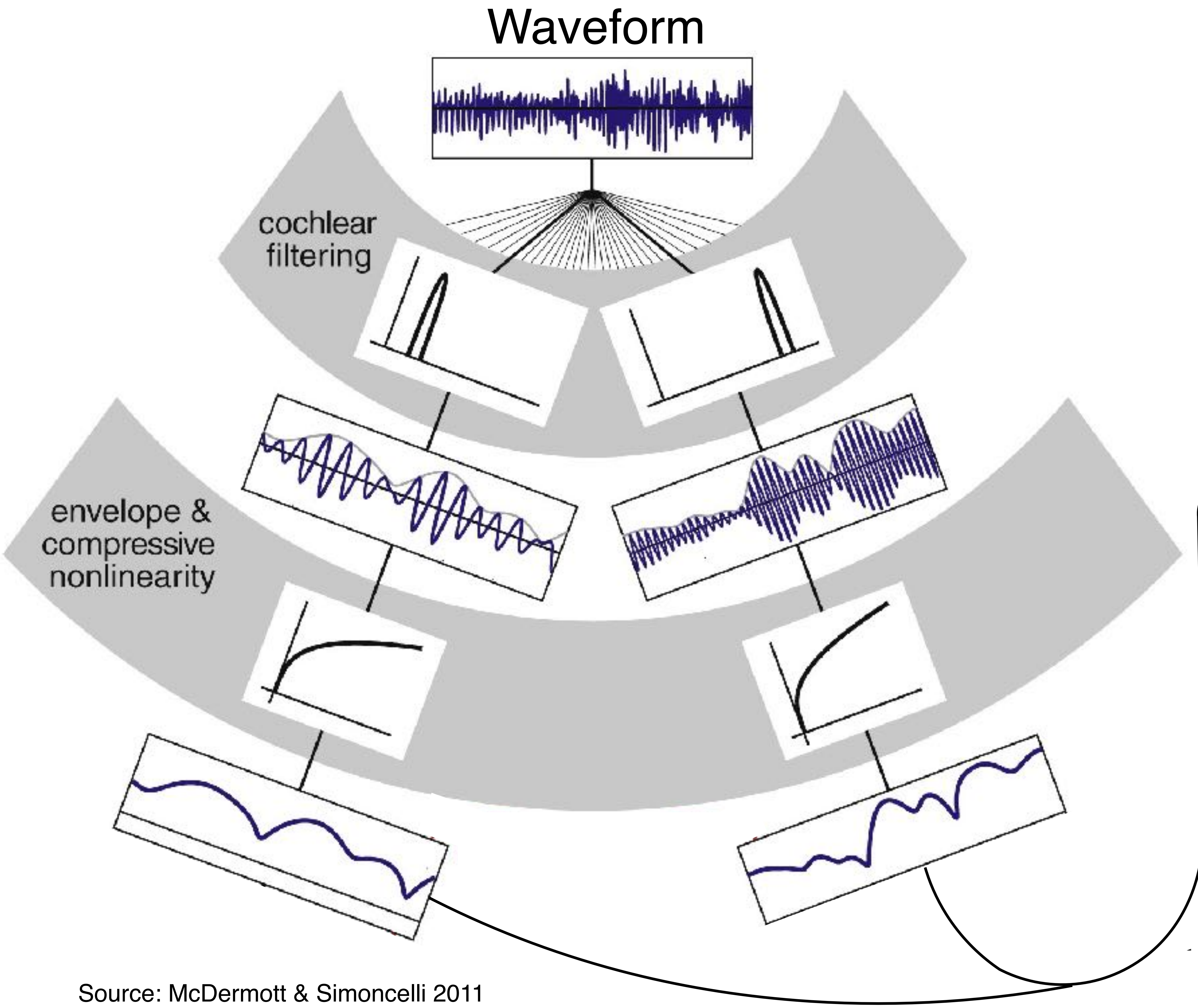

6.867
Office hour
RODE

The Greatest Hits dataset

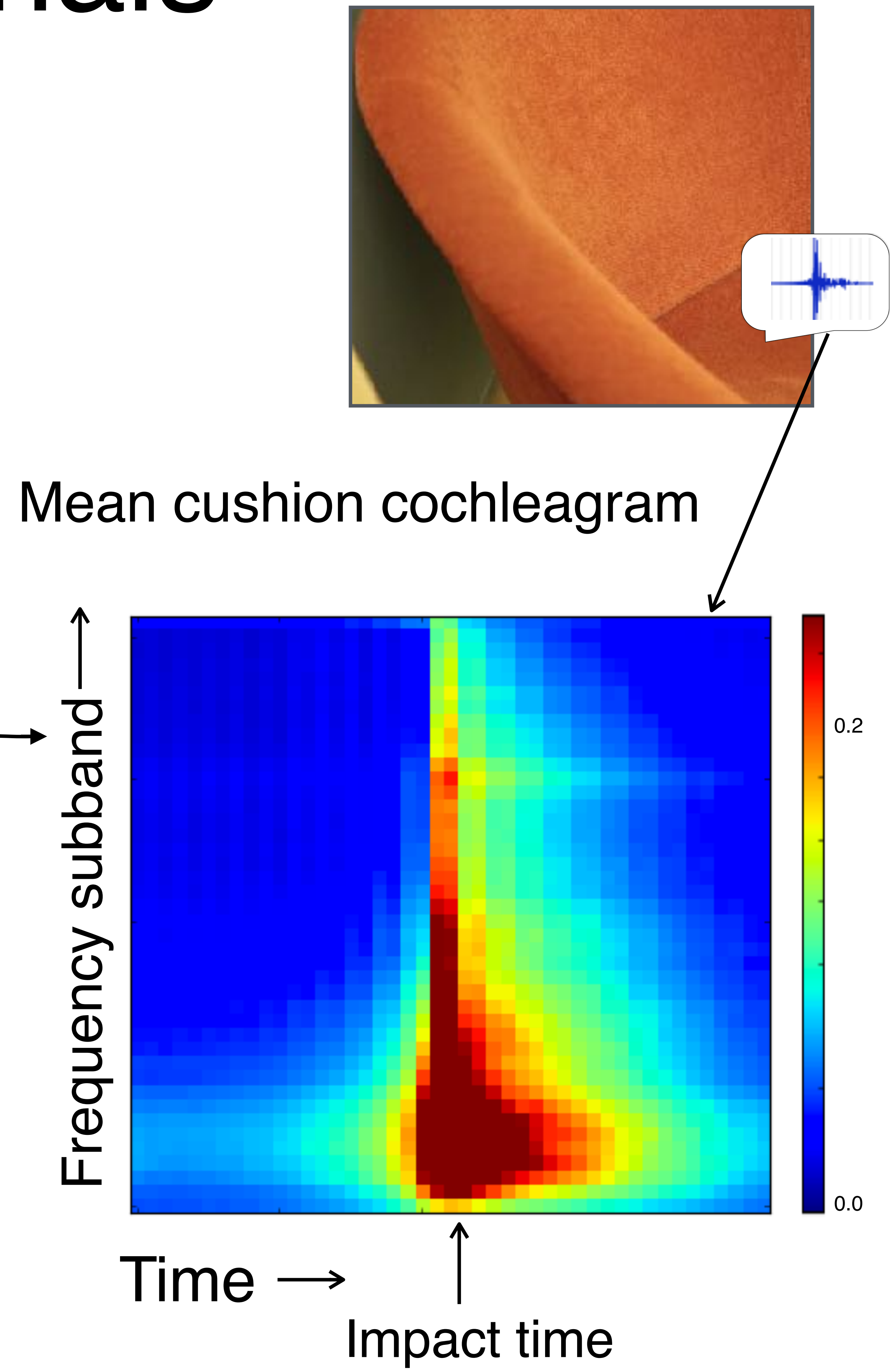
The Greatest Hits dataset

- 978 videos of people probing scenes with a drumstick
- 46,620 hits and scratches
- Material, action, and reaction labels (used for analysis)

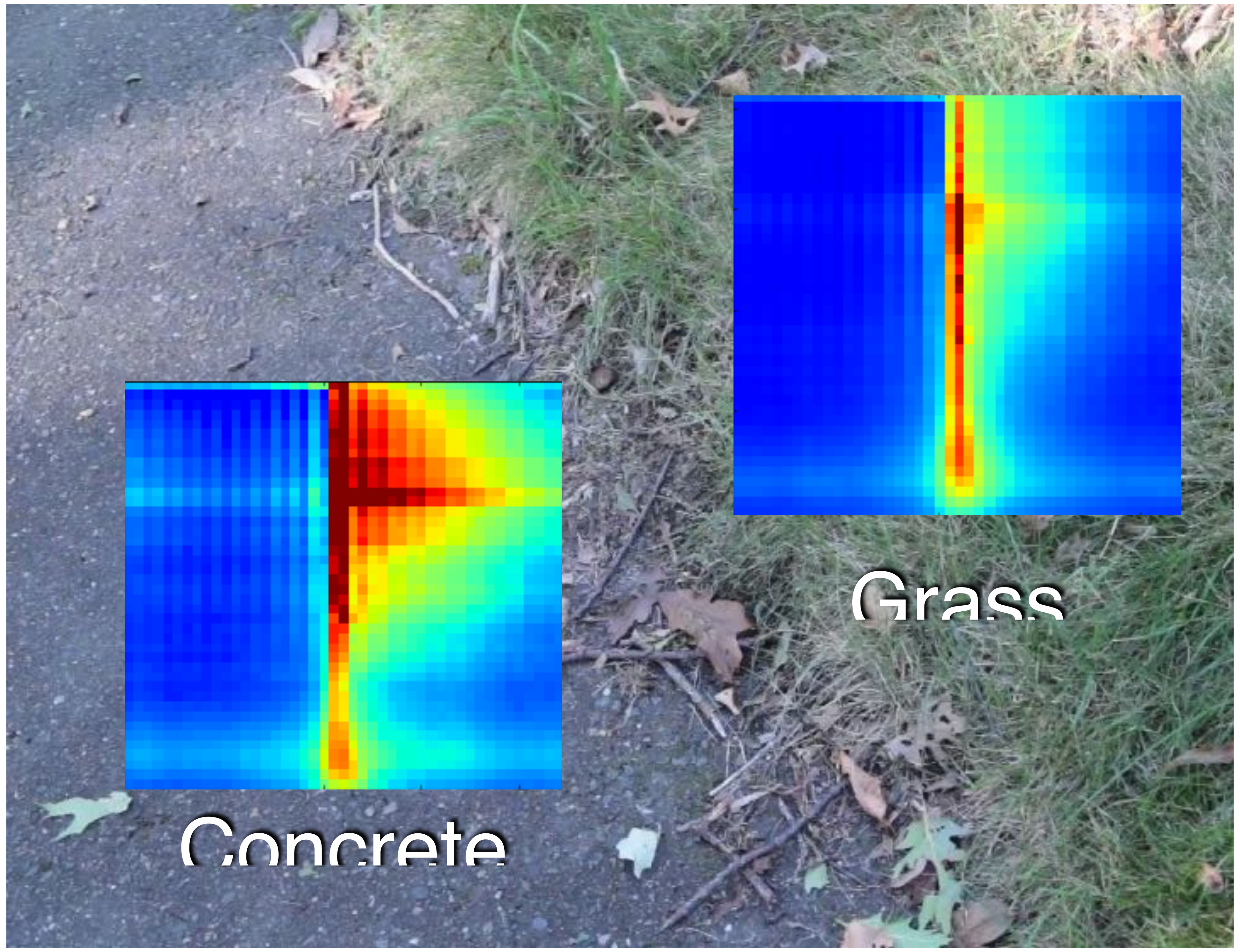
Sound and materials

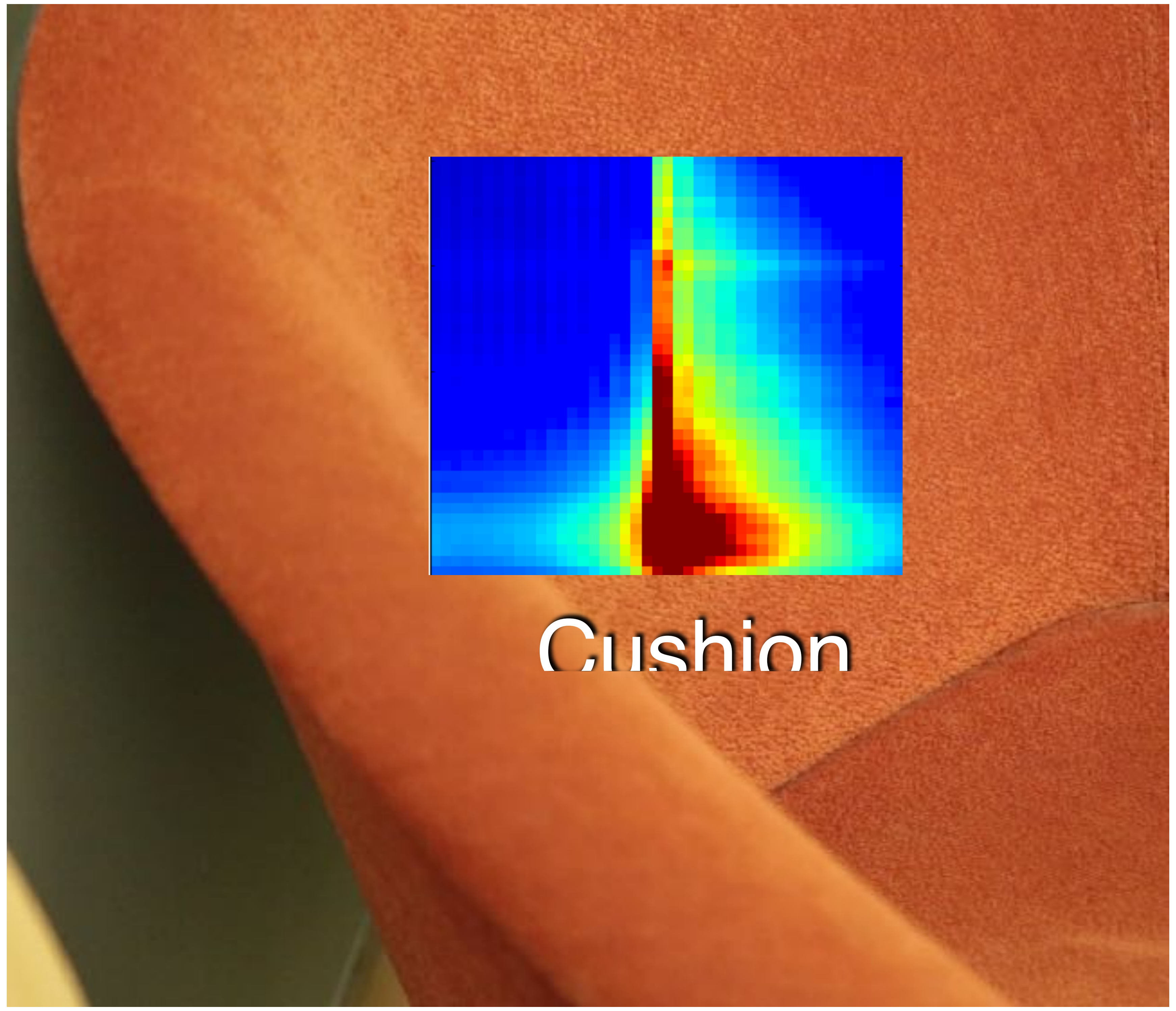


Source: McDermott & Simoncelli 2011

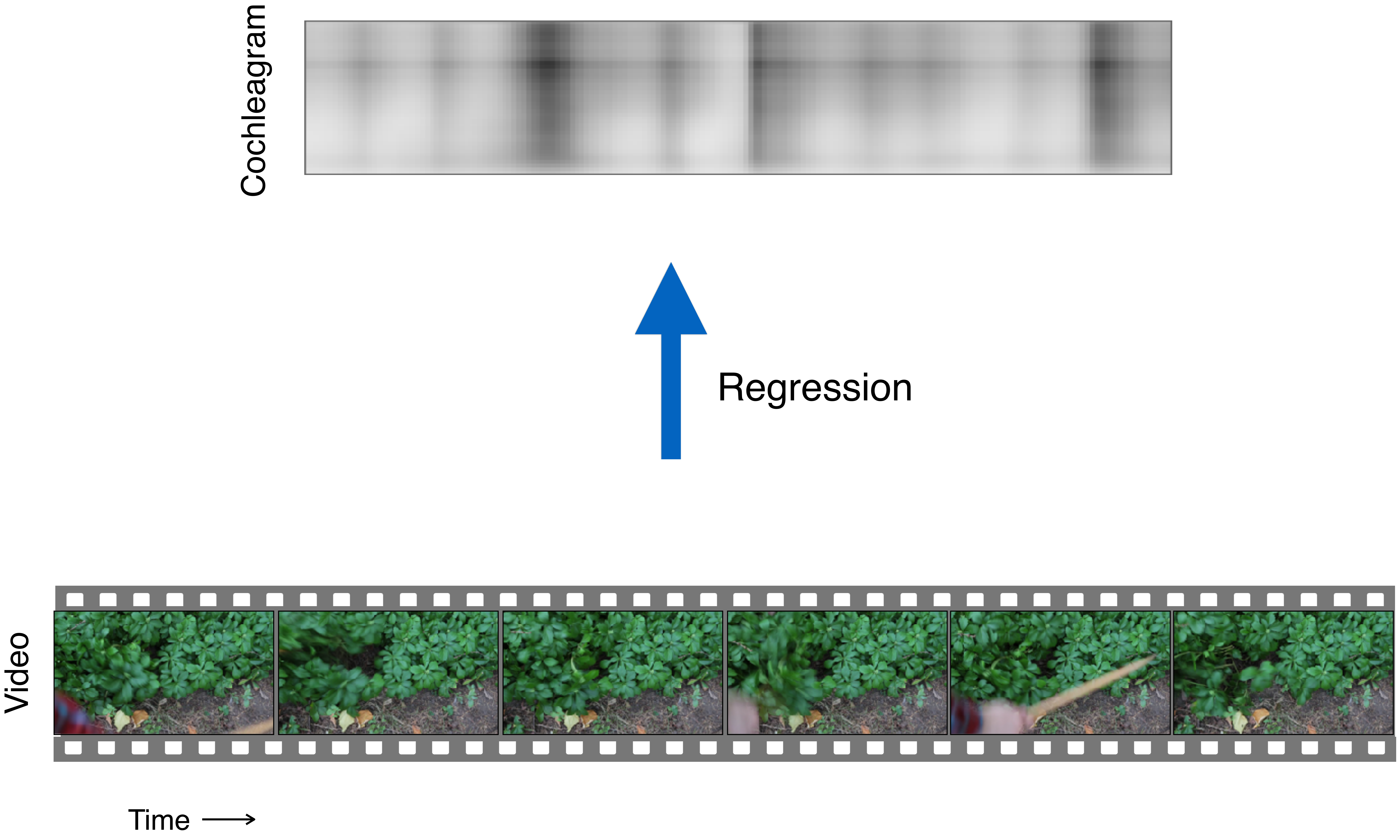


Sound and materials

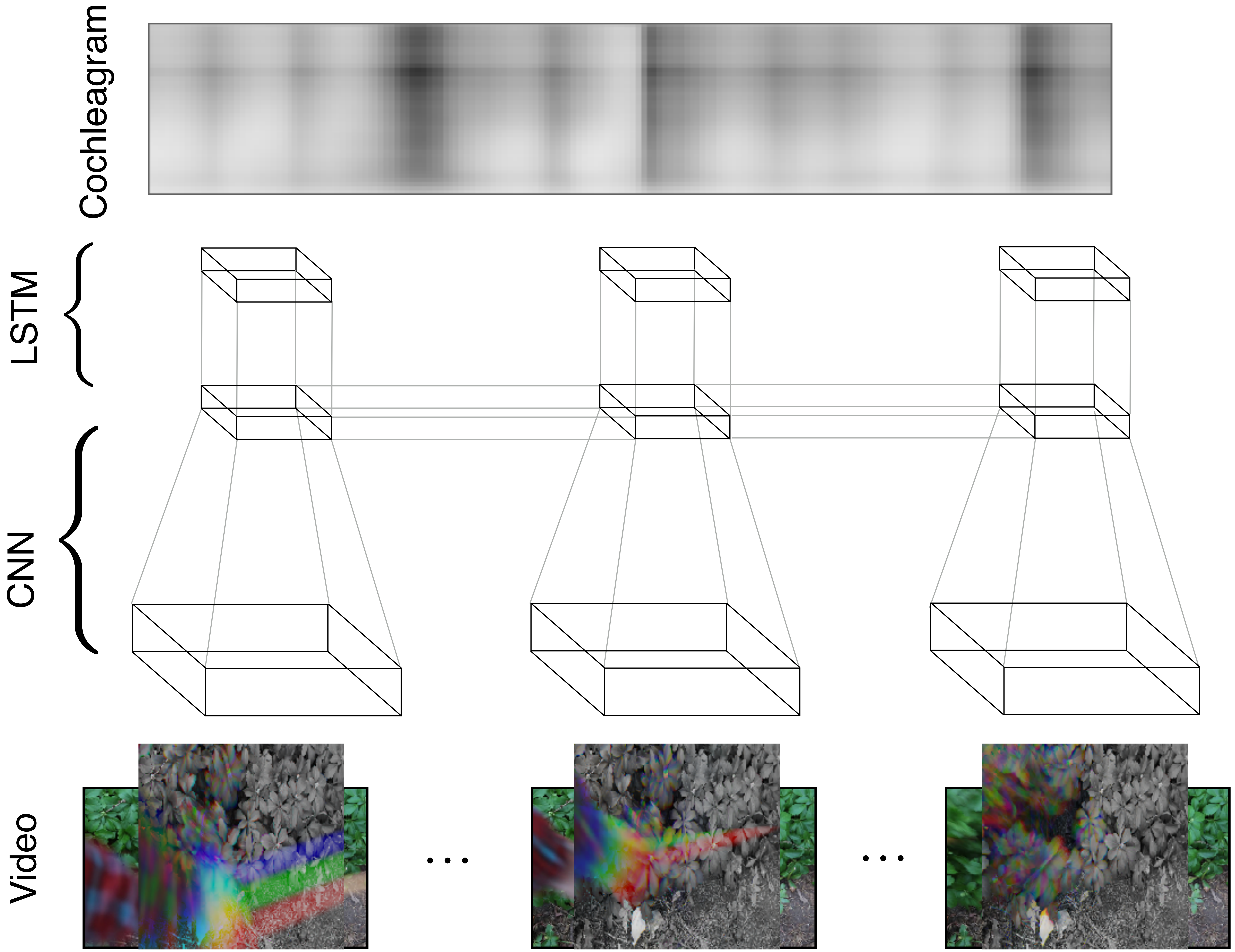




Predicting sound features

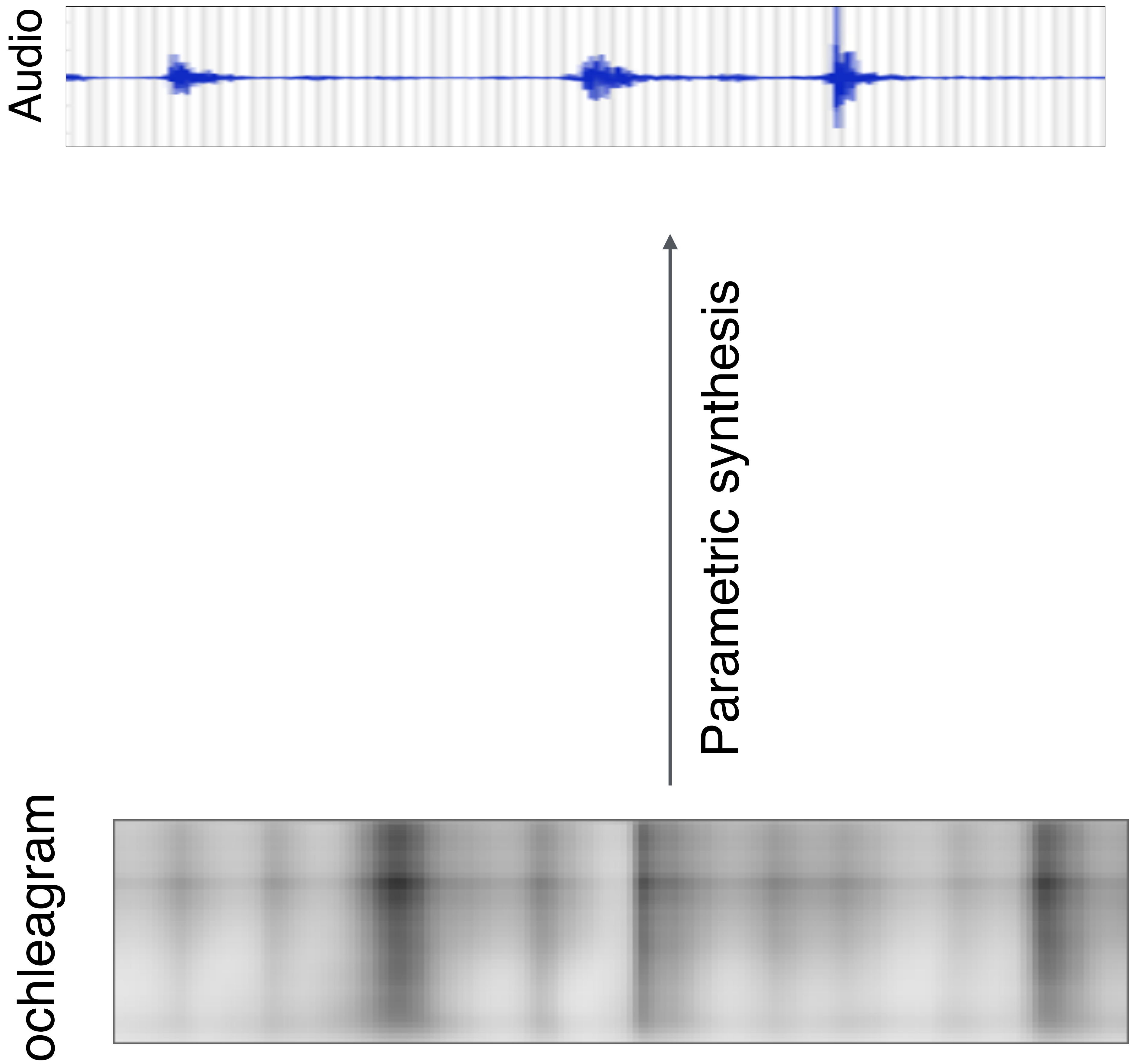


Predicting sound features



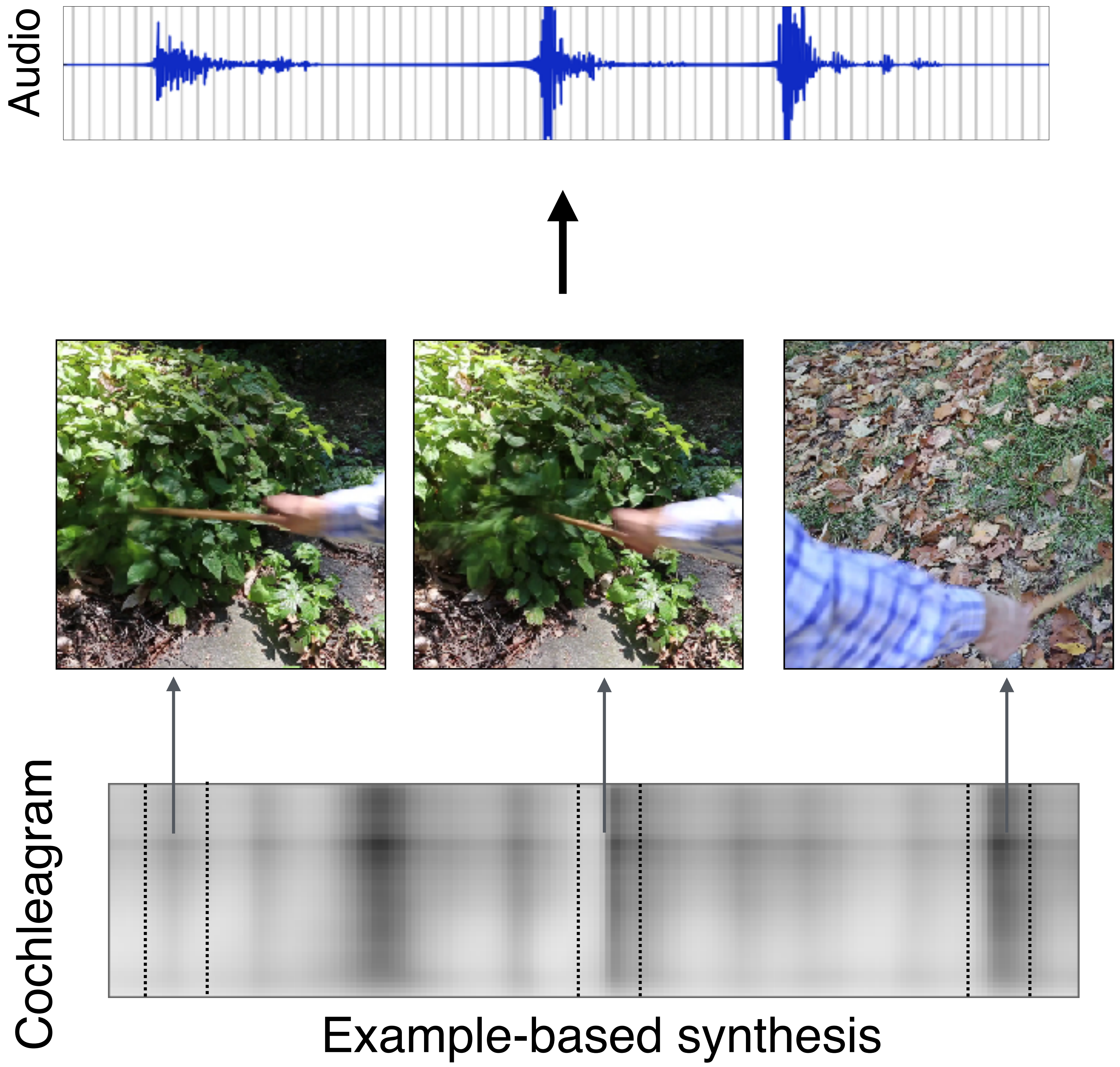
- Two-stream CNN: color + spacetime images

Generating a waveform

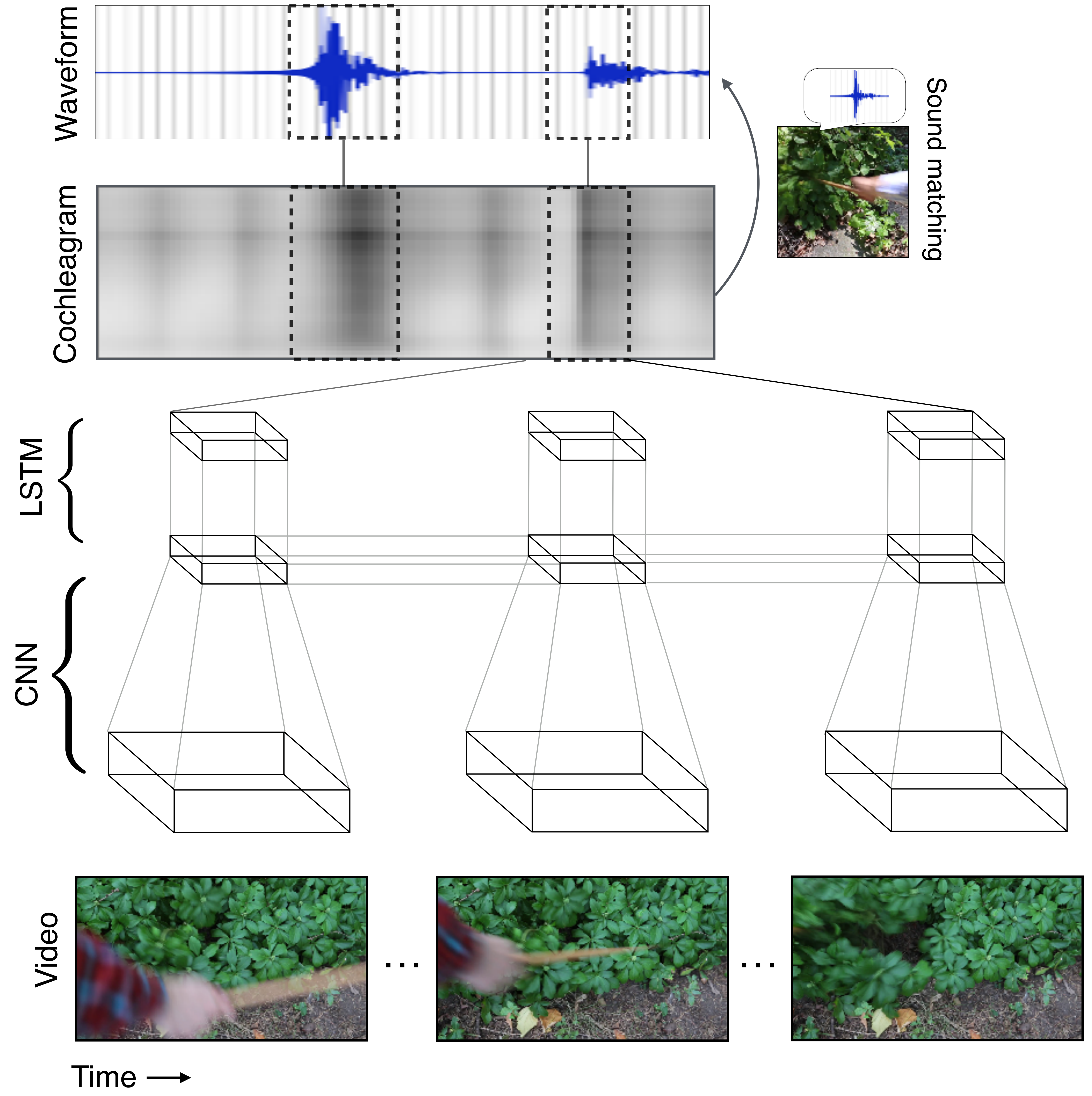


[Slaney95]

Generating a waveform



Recap: full model



Some results

Our output

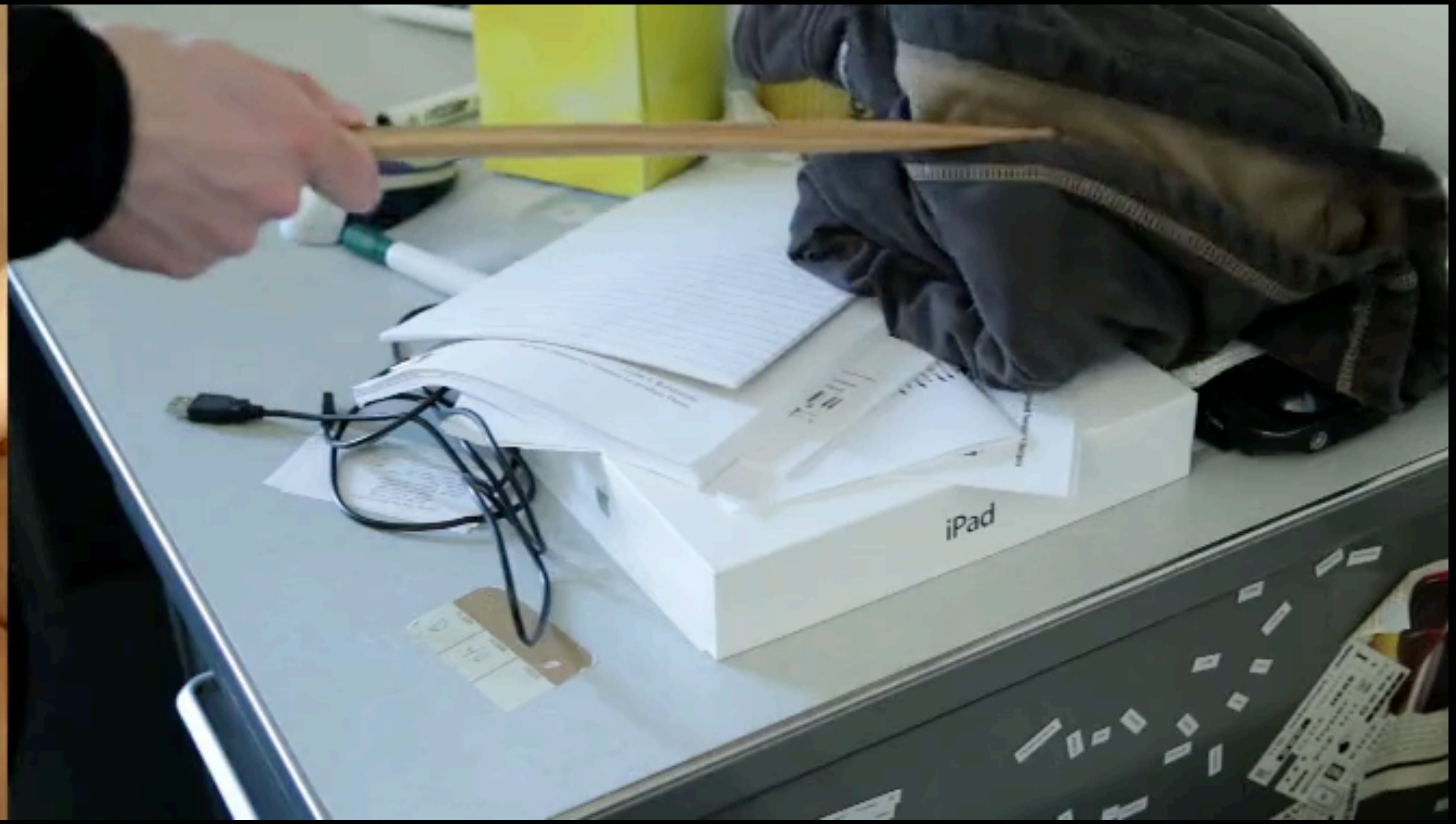
Original sound source

Our output

Original sound source

Our output

Original sound source




Predicted sound

Other actions?


Other actions?


Predicted sound

13. Temporal Processing and RNNs

- Sequence problems
- Temporal convnets
- Recurrent Neural Networks (RNNs)
- LSTMs
- Attention
- Example problems:
    - Image captioning
    - Sound prediction