Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)

adapted with permission from Brandon Rohrer

RNNs excel at analyzing sequential patterns

Text

Speech

Audio

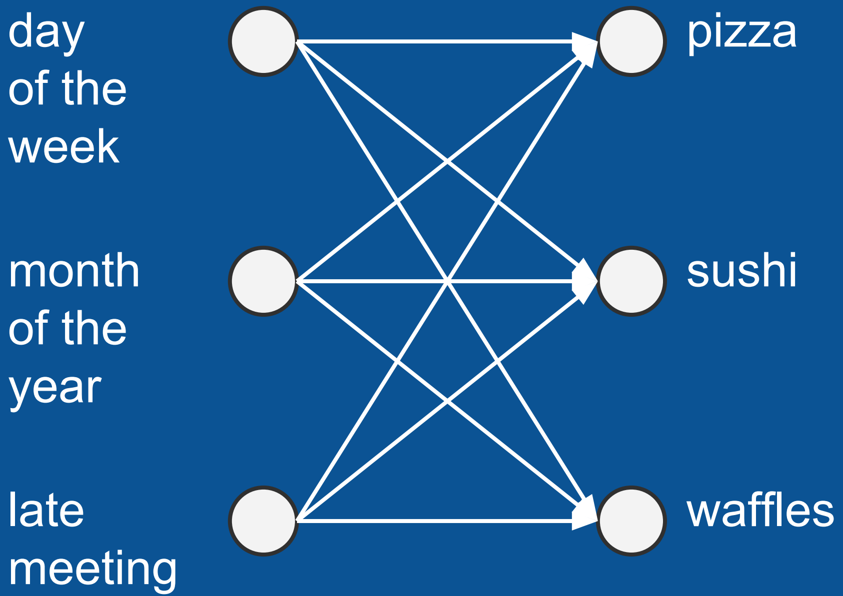
Video

Physical processes

Anything embedded in time (almost everything)

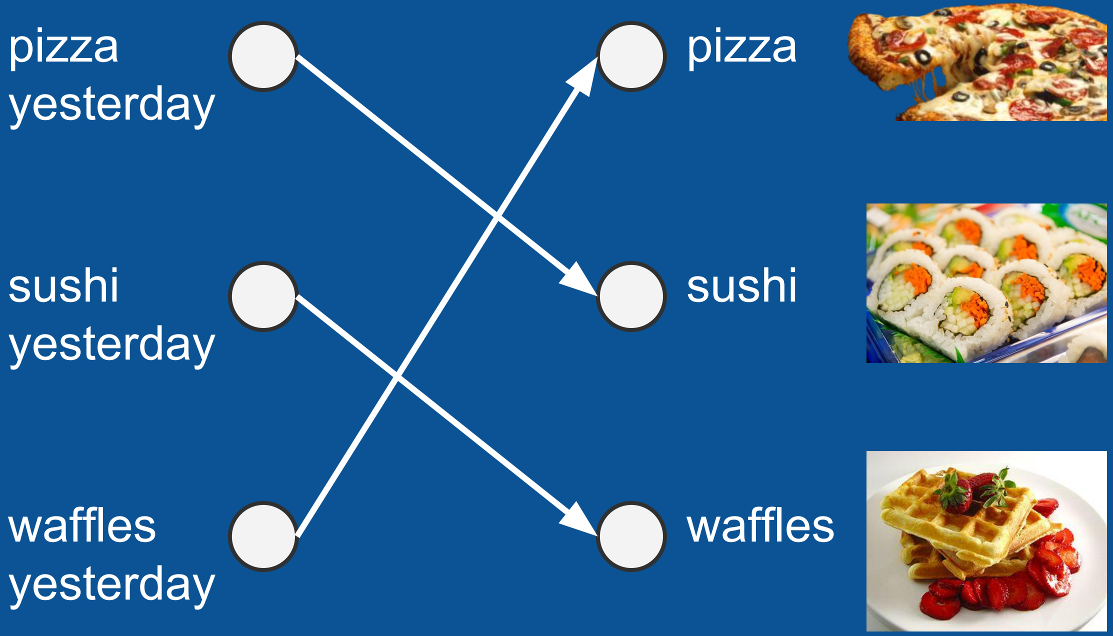
What's for dinner?

Thinking of it in a non-sequential way.

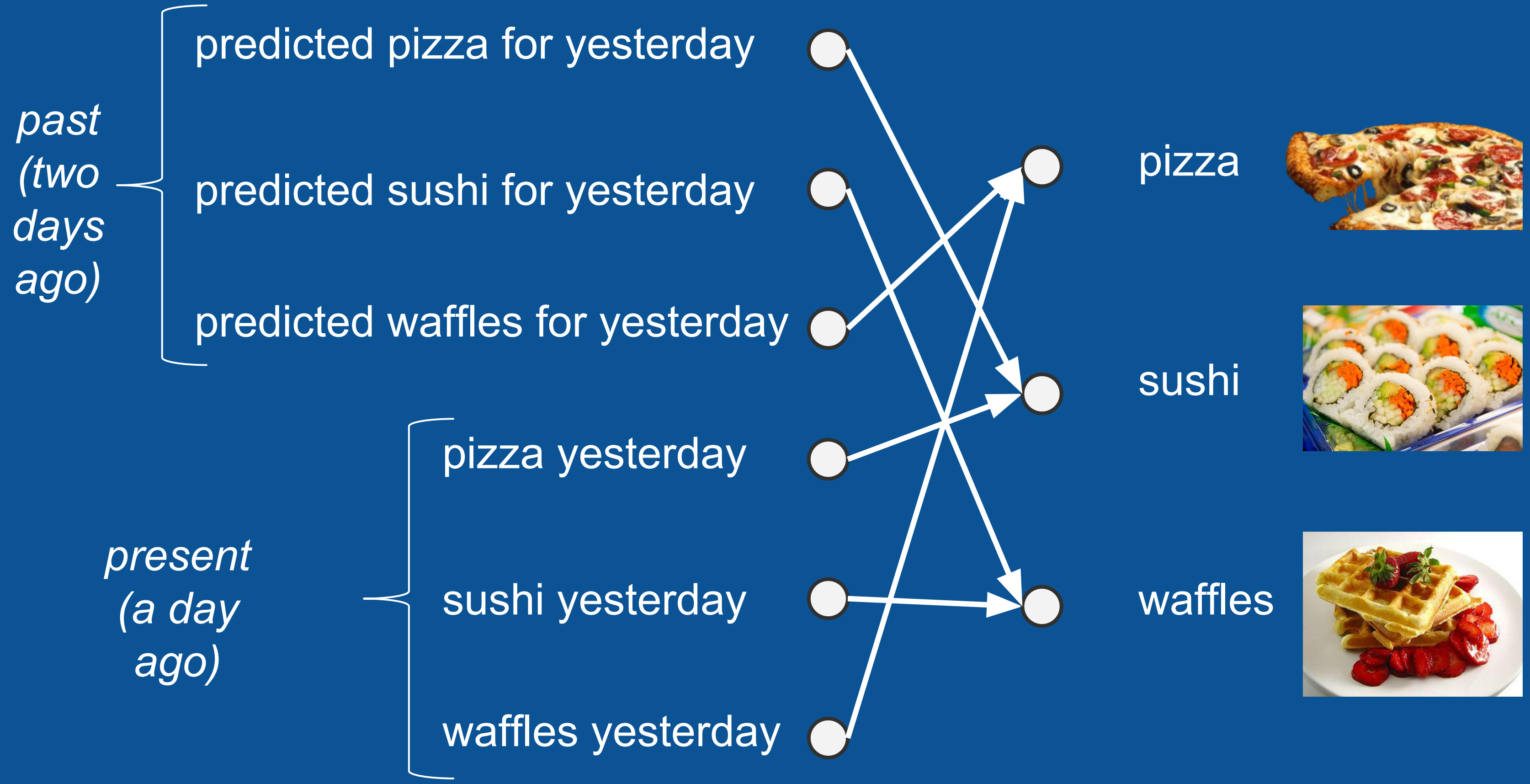


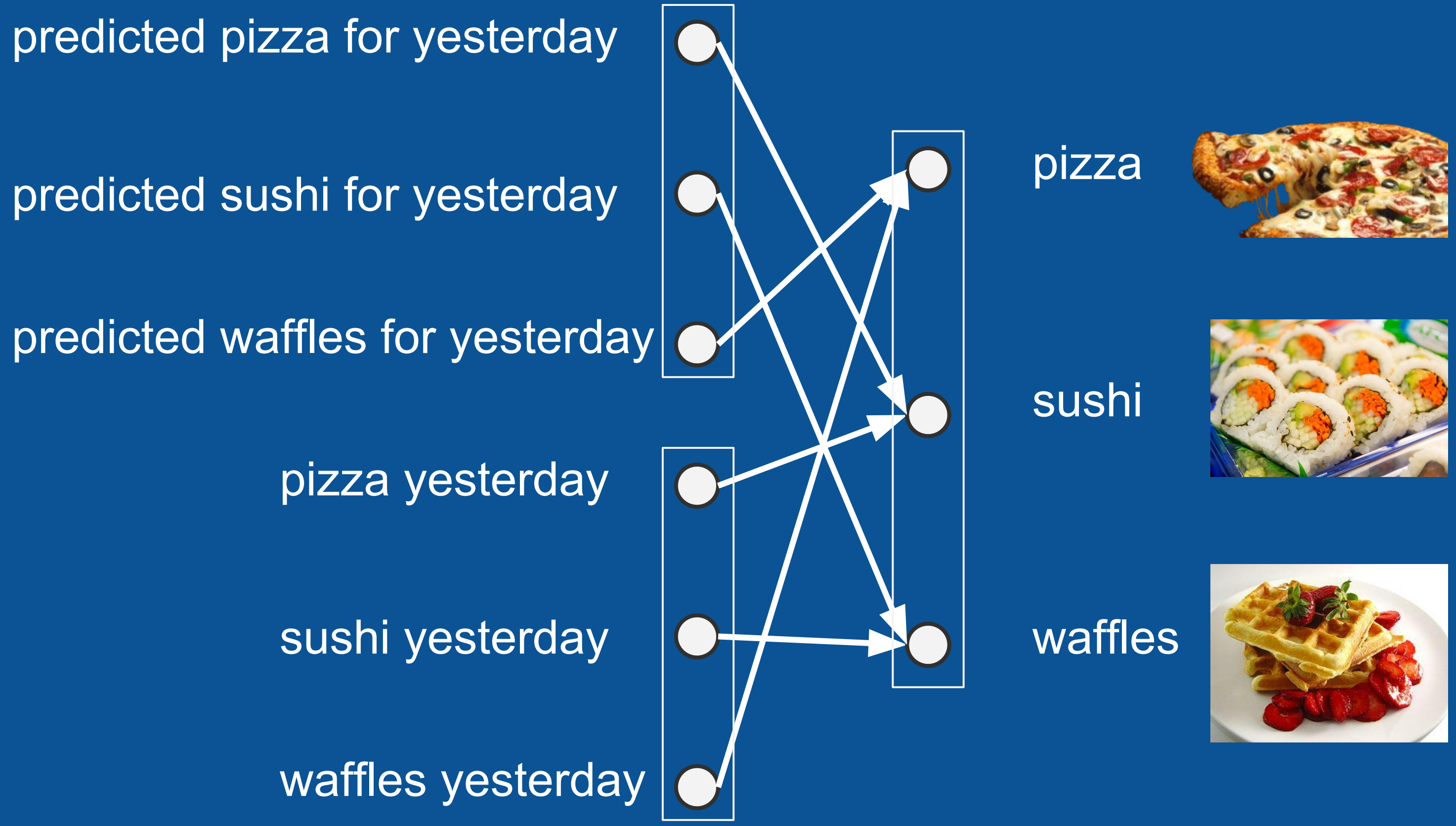
What’s for dinner?

But there probably is a sequential aspect to it.

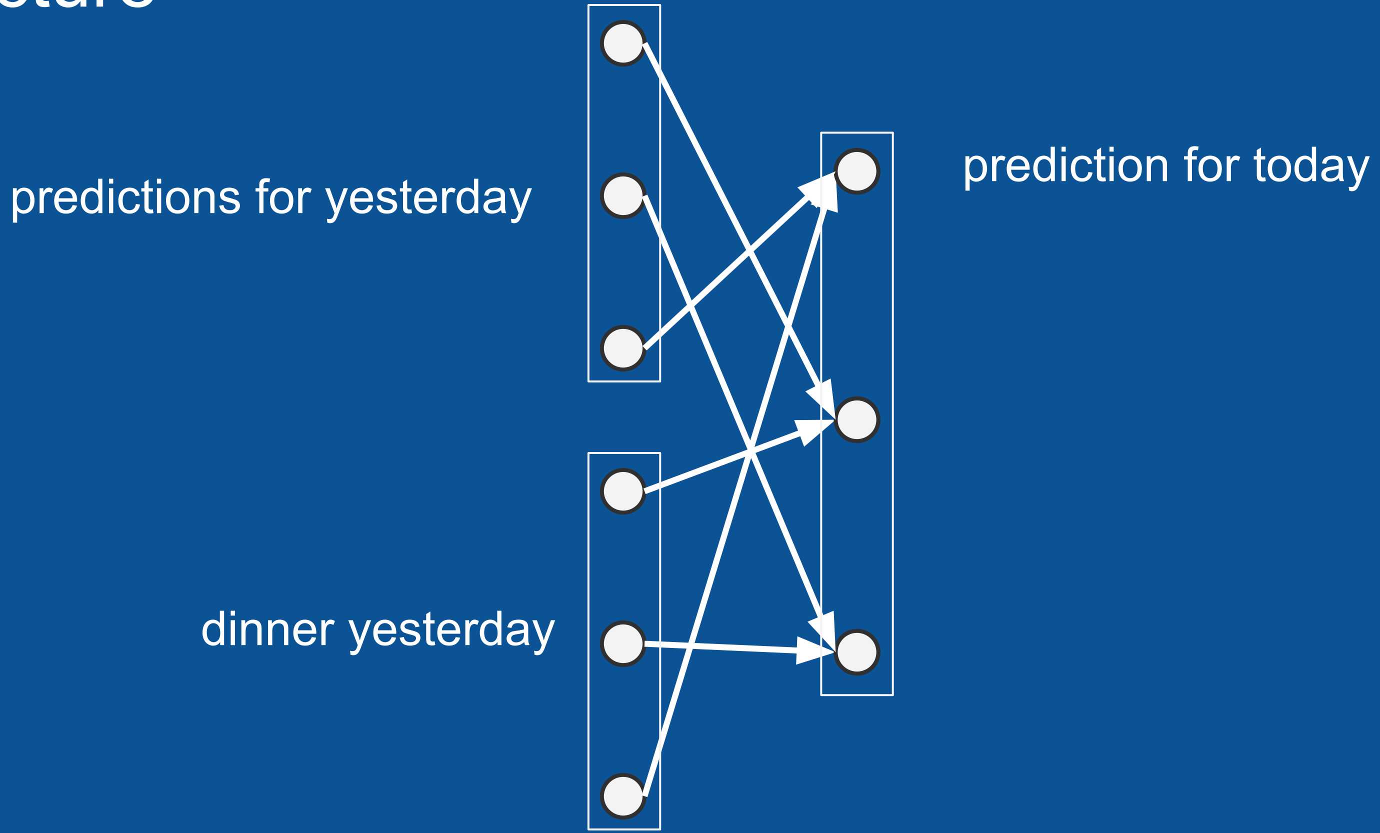



predicted pizza for yesterday
predicted sushi for yesterday
predicted waffles for yesterday
pizza yesterday
sushi yesterday
waffles yesterday
pizza
sushi
waffles

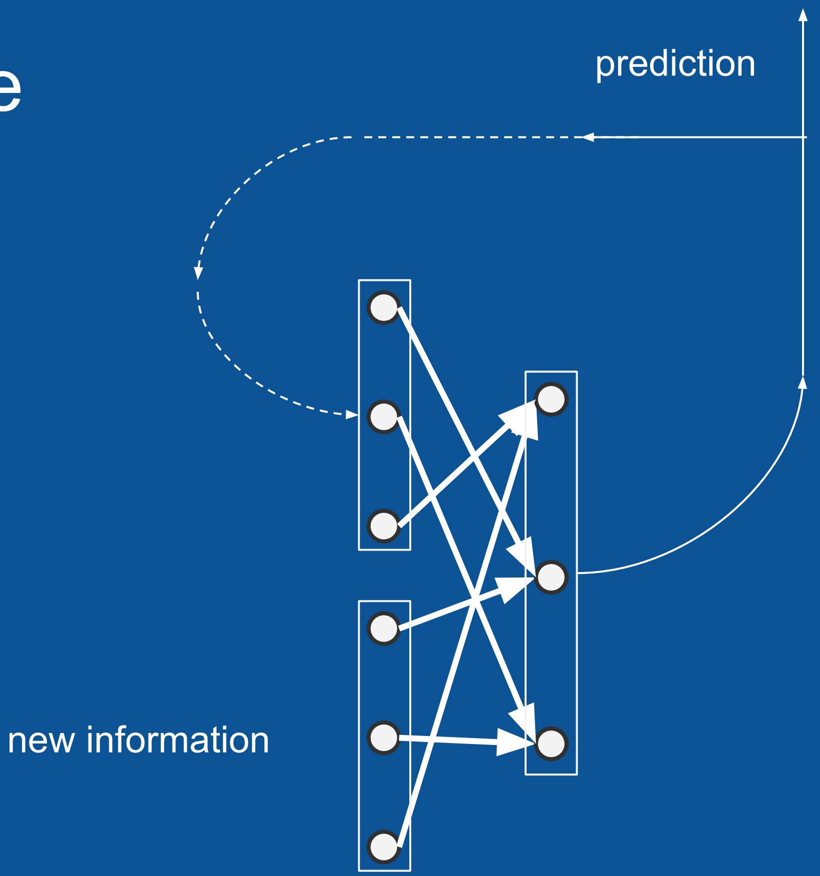

past
(two
days
ago)
predicted pizza for yesterday
predicted sushi for yesterday
predicted waffles for yesterday
present
(a day
ago)
pizza yesterday
sushi yesterday
waffles yesterday
pizza
sushi
waffles


predicted pizza for yesterday
predicted sushi for yesterday
predicted waffles for yesterday
pizza yesterday
sushi yesterday
waffles yesterday
pizza
sushi
waffles

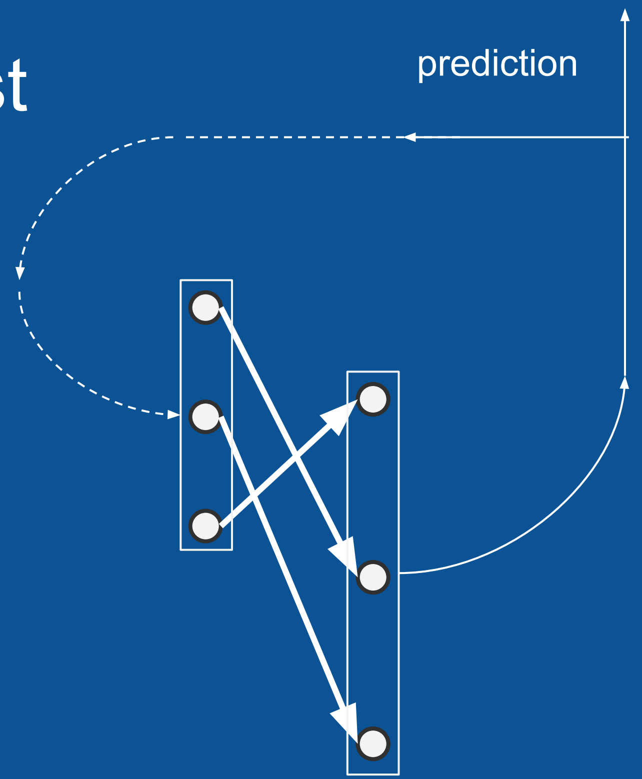
Architecture



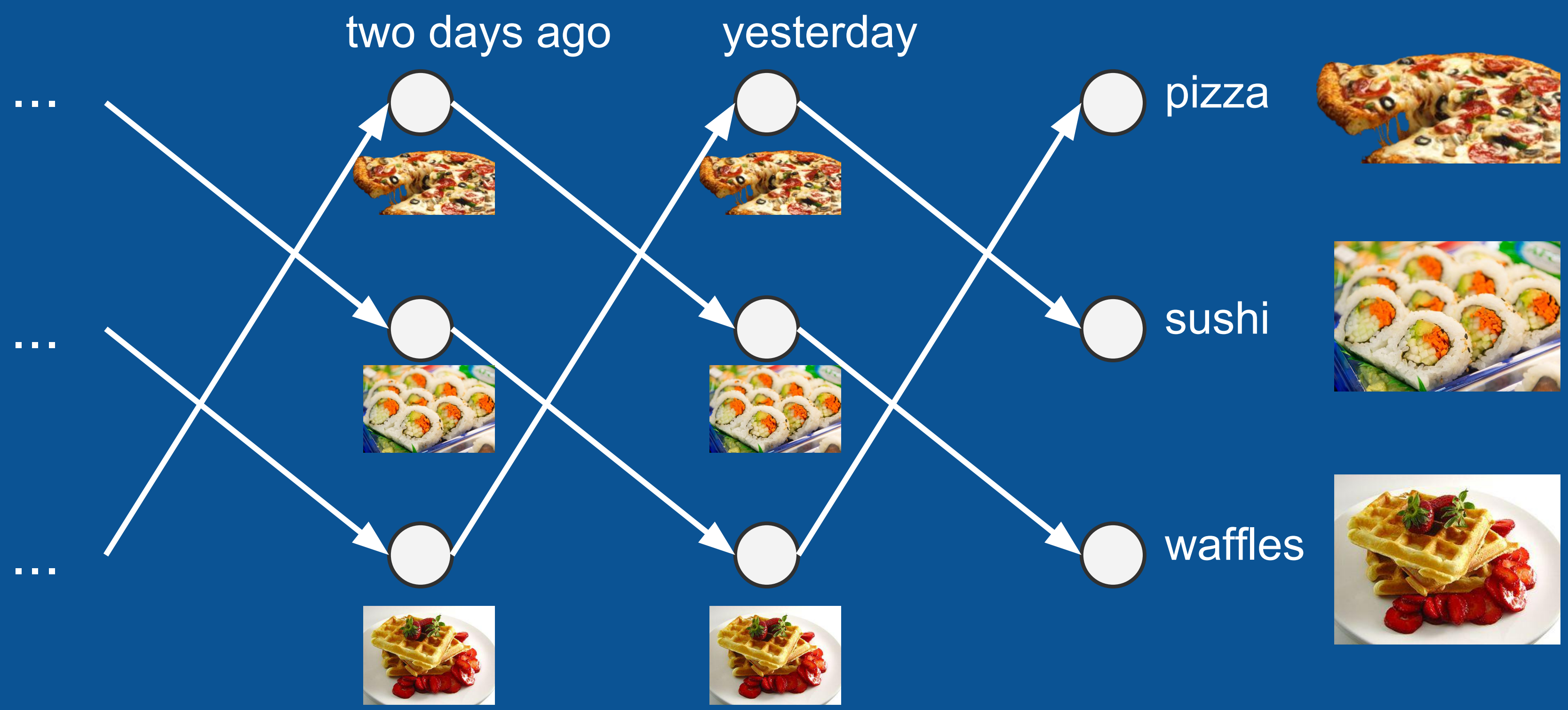
Architecture



Unrolling the past



Unrolled predictions



Another example: Write a children's book

Training data:

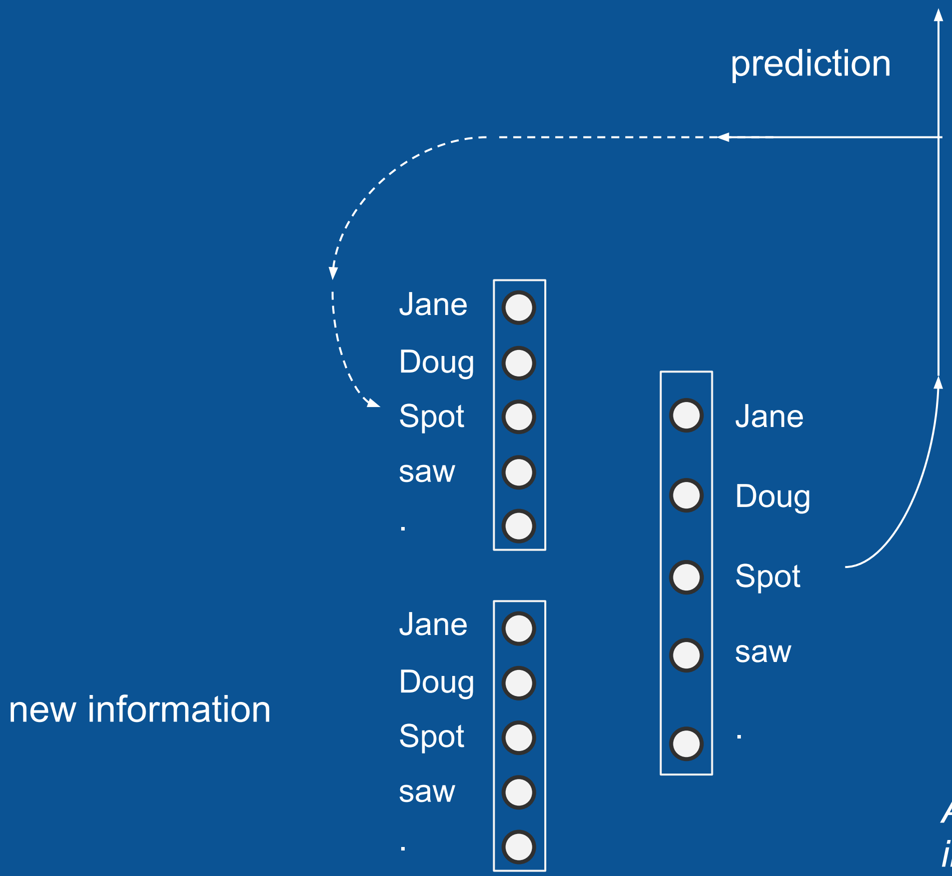
Doug saw Jane.

Jane saw Spot.

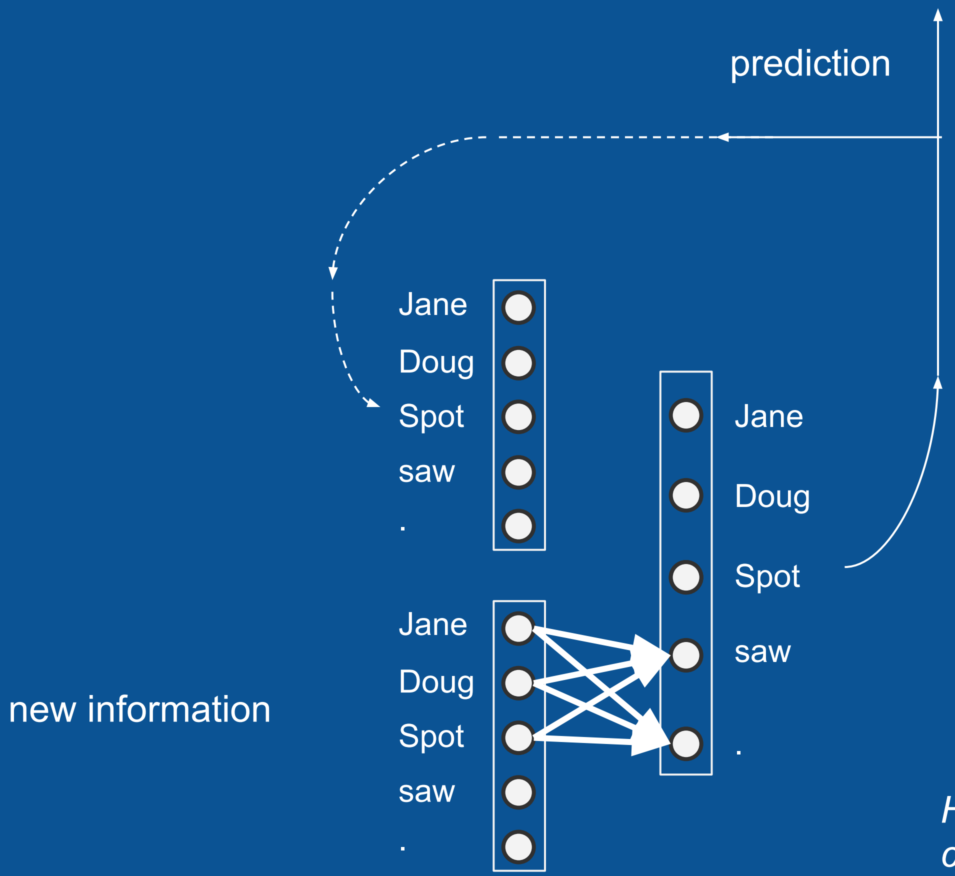
Spot saw Doug.

...

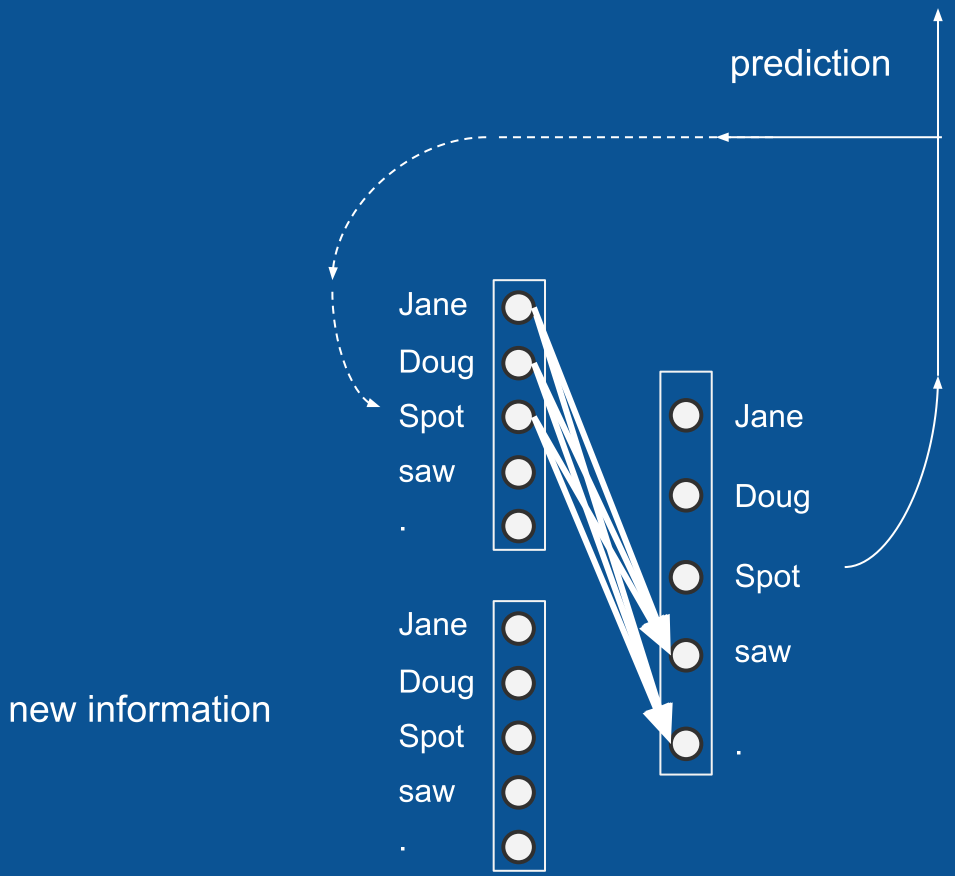
Your dictionary is small: {Doug, Jane, Spot, saw, .}

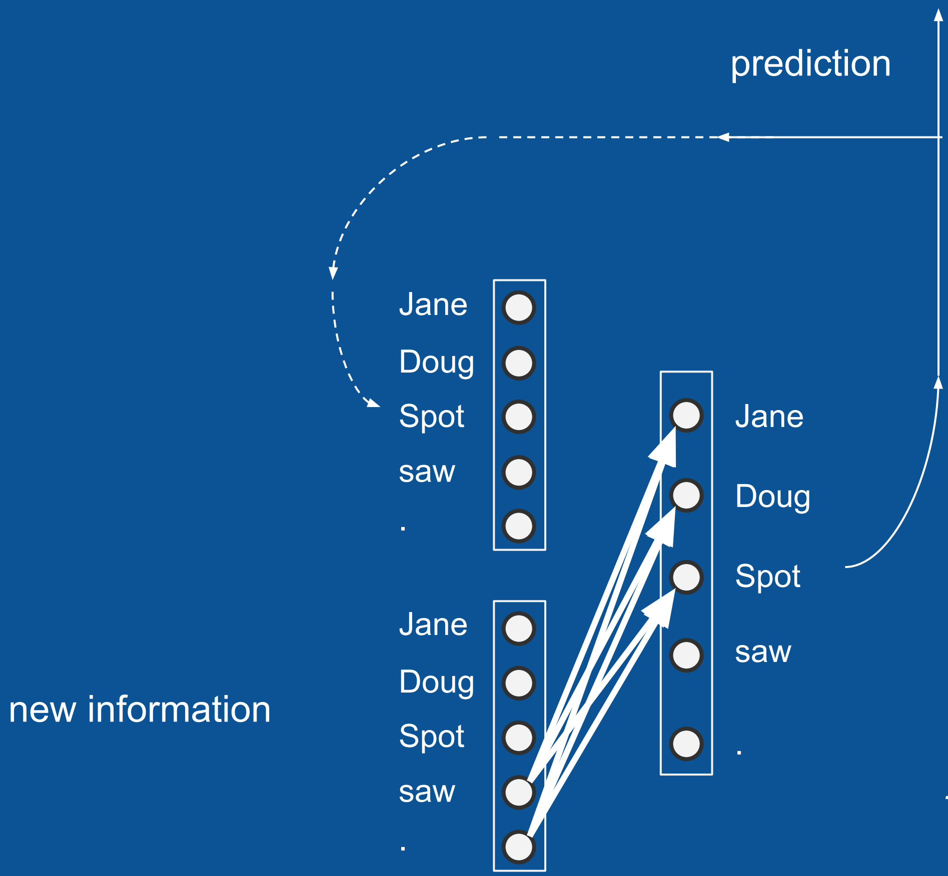


All the words can be new information, and all the words can be the prediction.



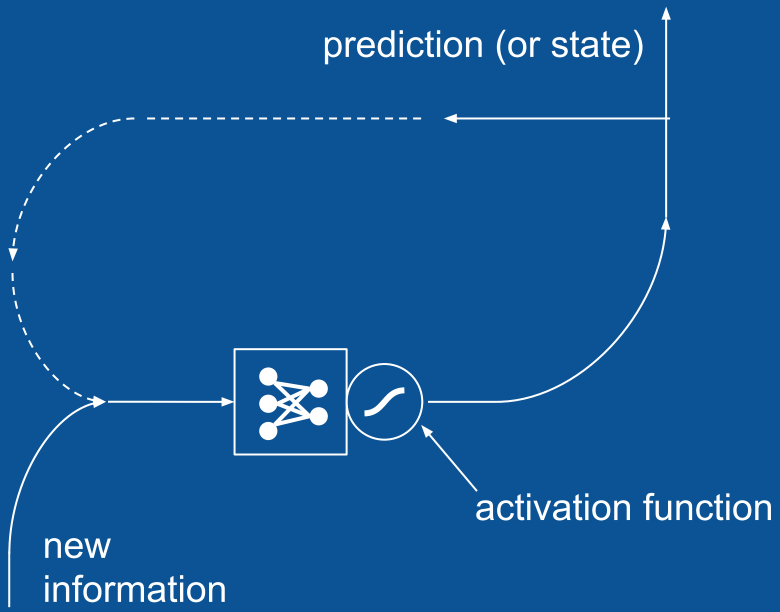
However, based on training corpus, after one of the names the next "word" is highly likely to be "saw" or "."


prediction
Jane
Doug
Spot
saw
.
Jane
Doug
Spot
saw
.
Jane
Doug
Spot
saw
.
new information

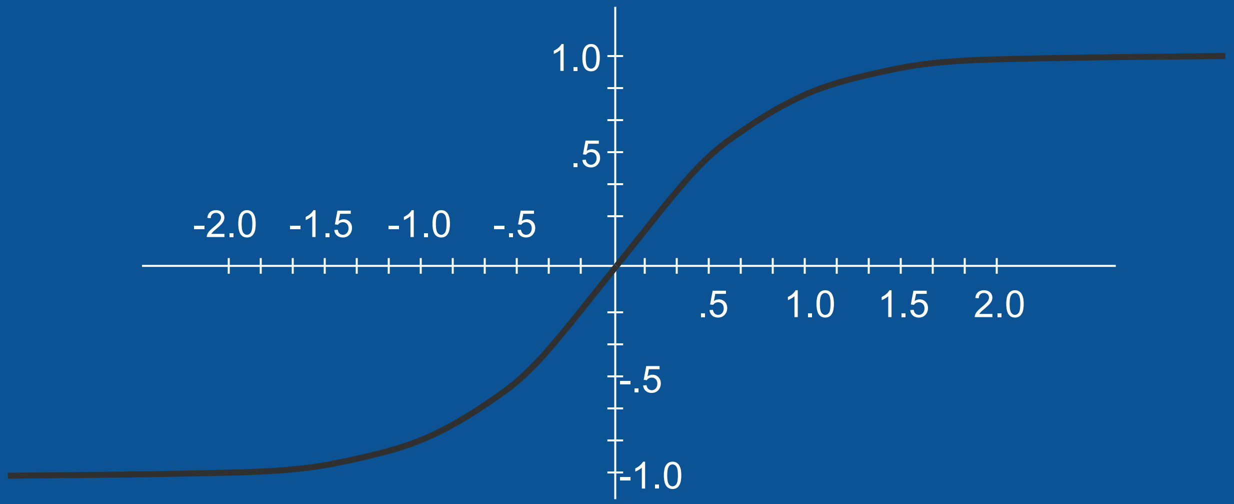


The converse is true, too.

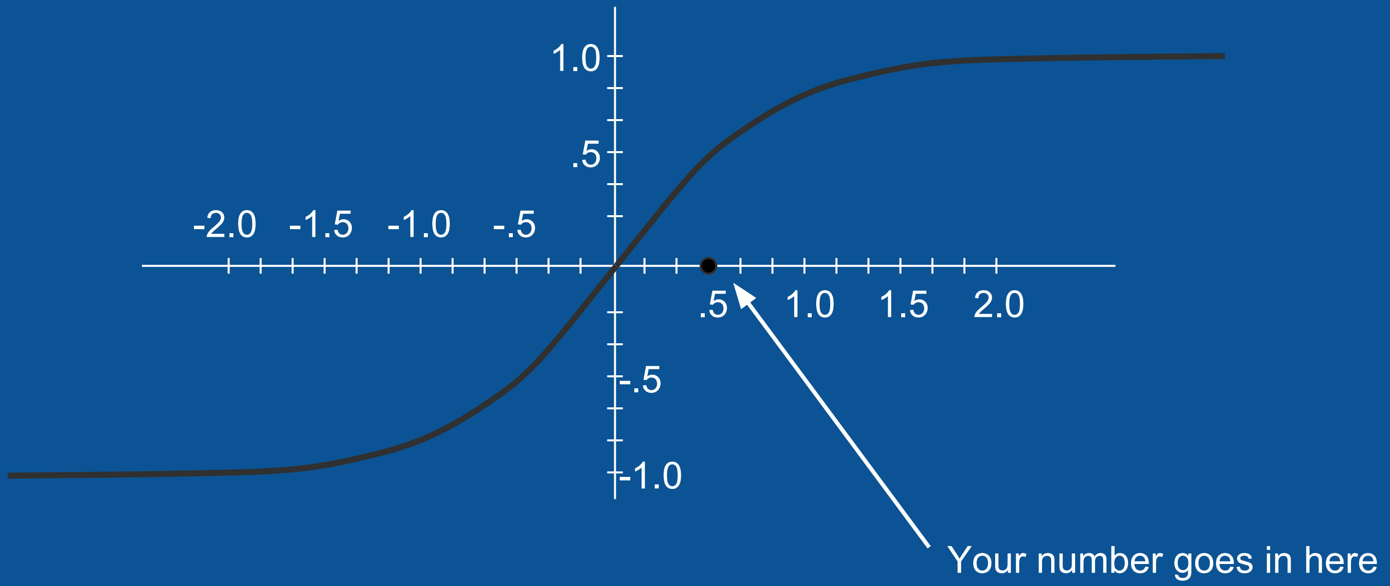
recurrent neural network



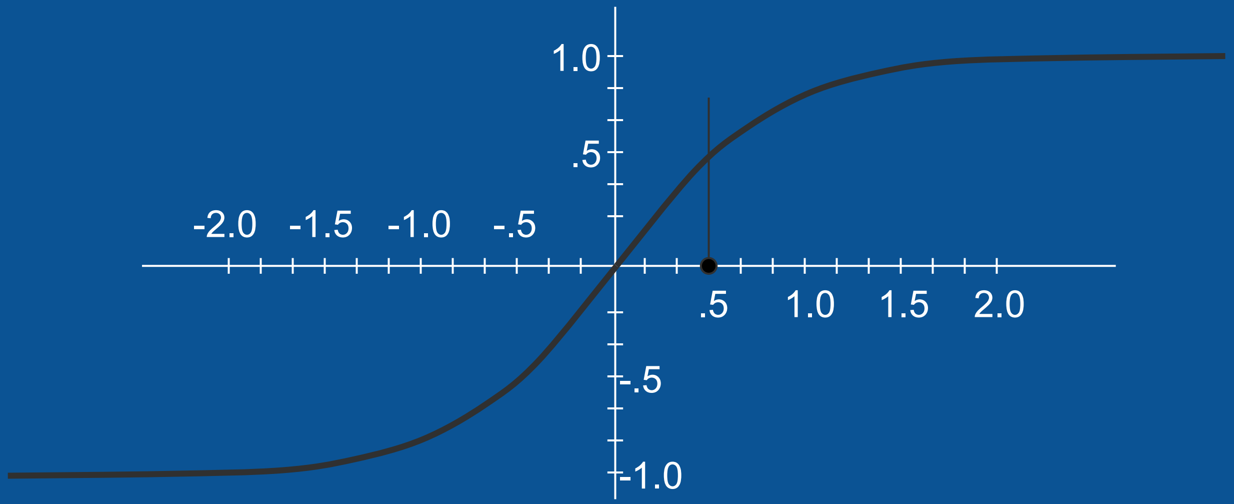
Hyperbolic tangent (tanh) activation function



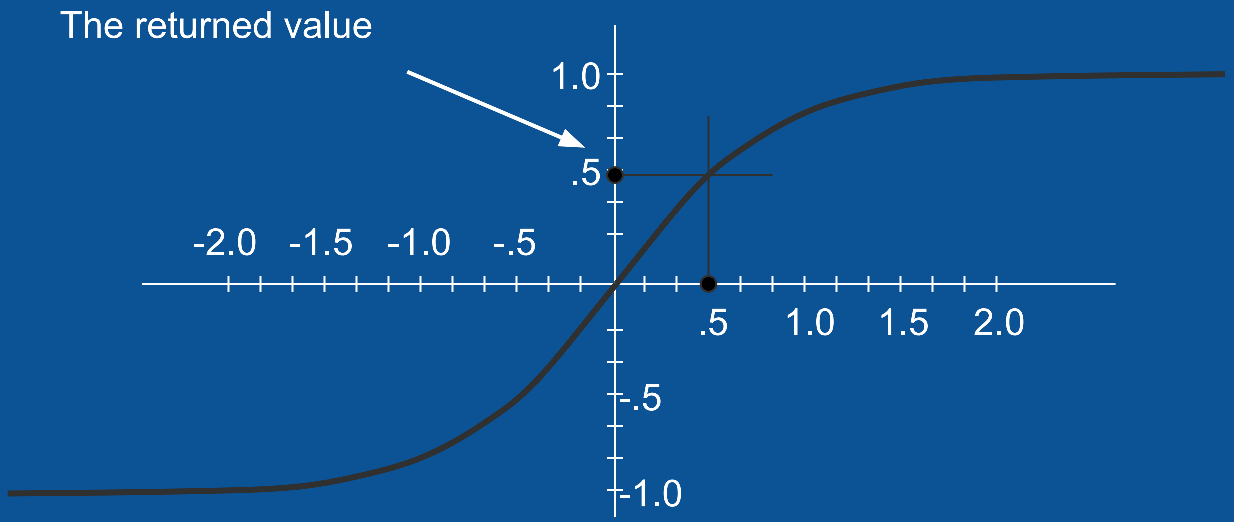
tanh activation function



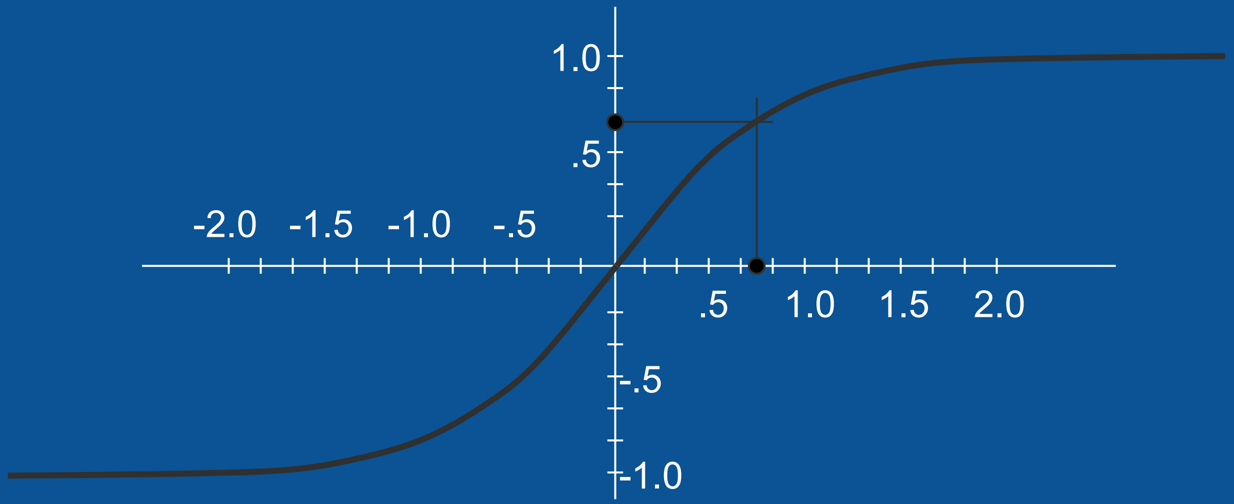
tanh activation function



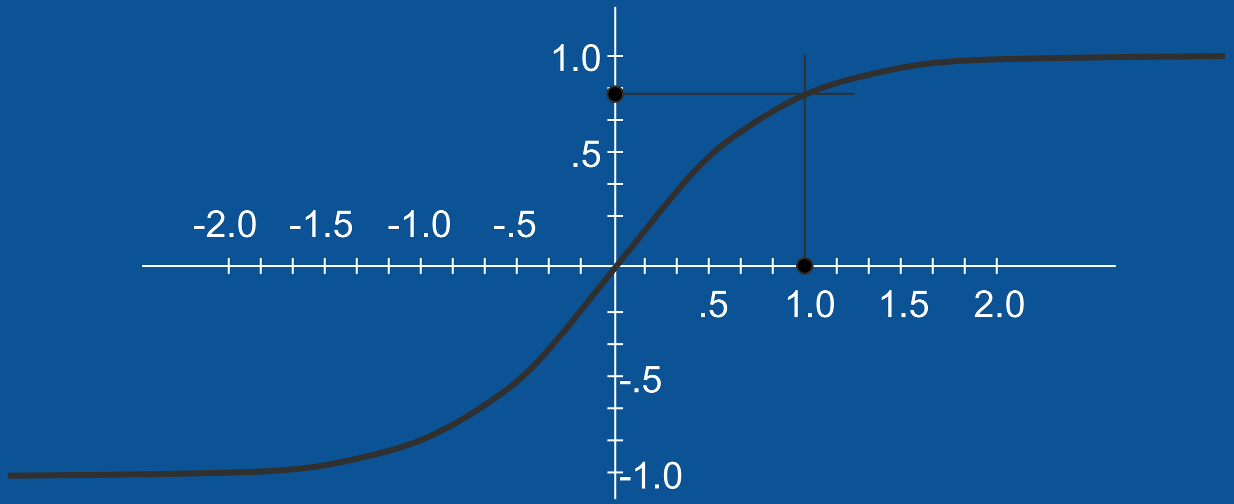
tanh activation function



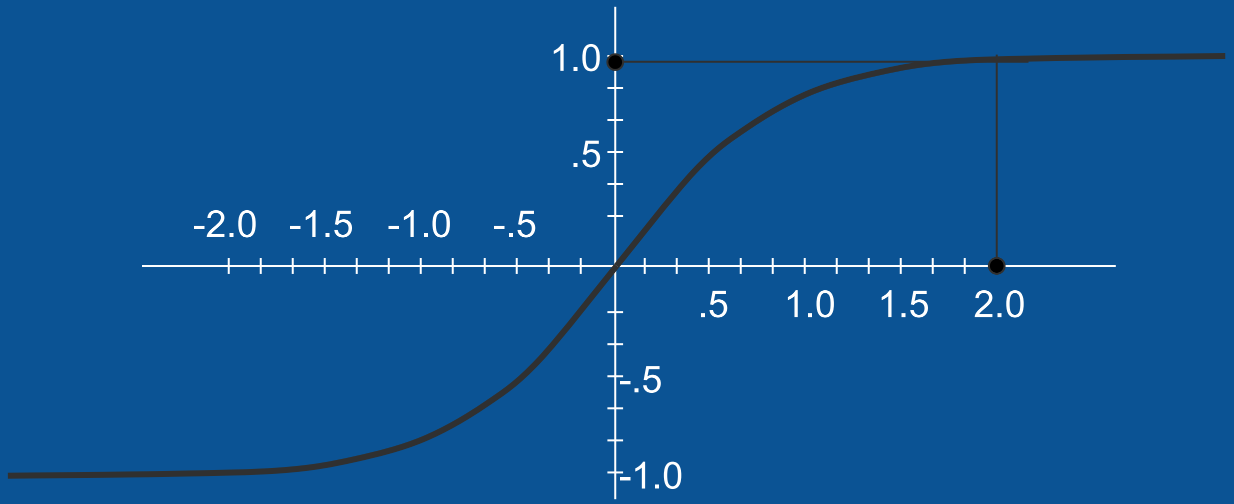
tanh activation function



tanh activation function

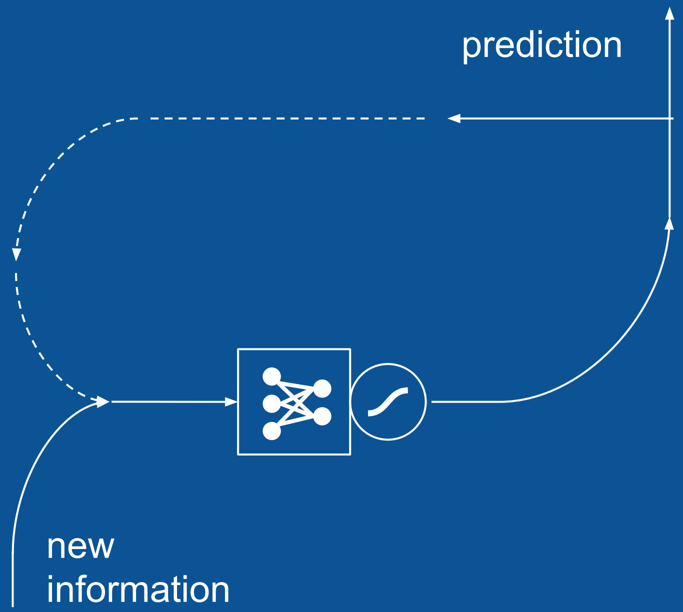


tanh activation function



No matter what you start with, the answer stays between -1 and 1.

recurrent neural network



Mistakes a simple RNN can make

Our predicted story:

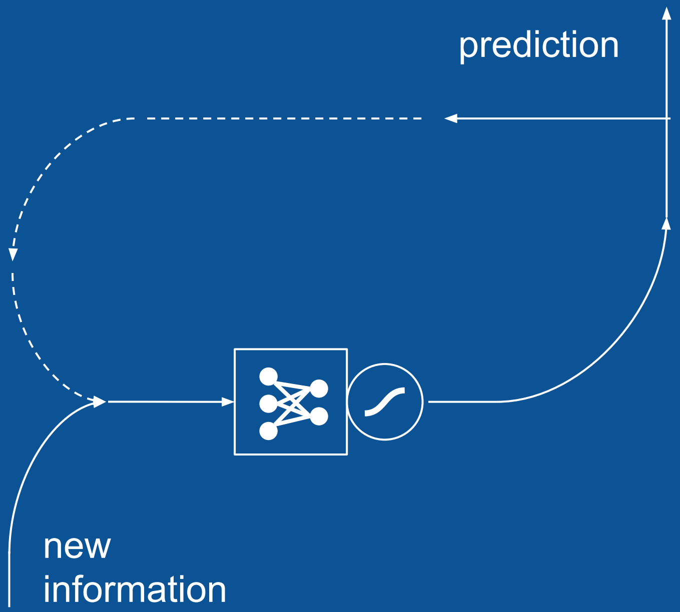
Doug saw Doug.

Jane saw Spot saw Doug saw …

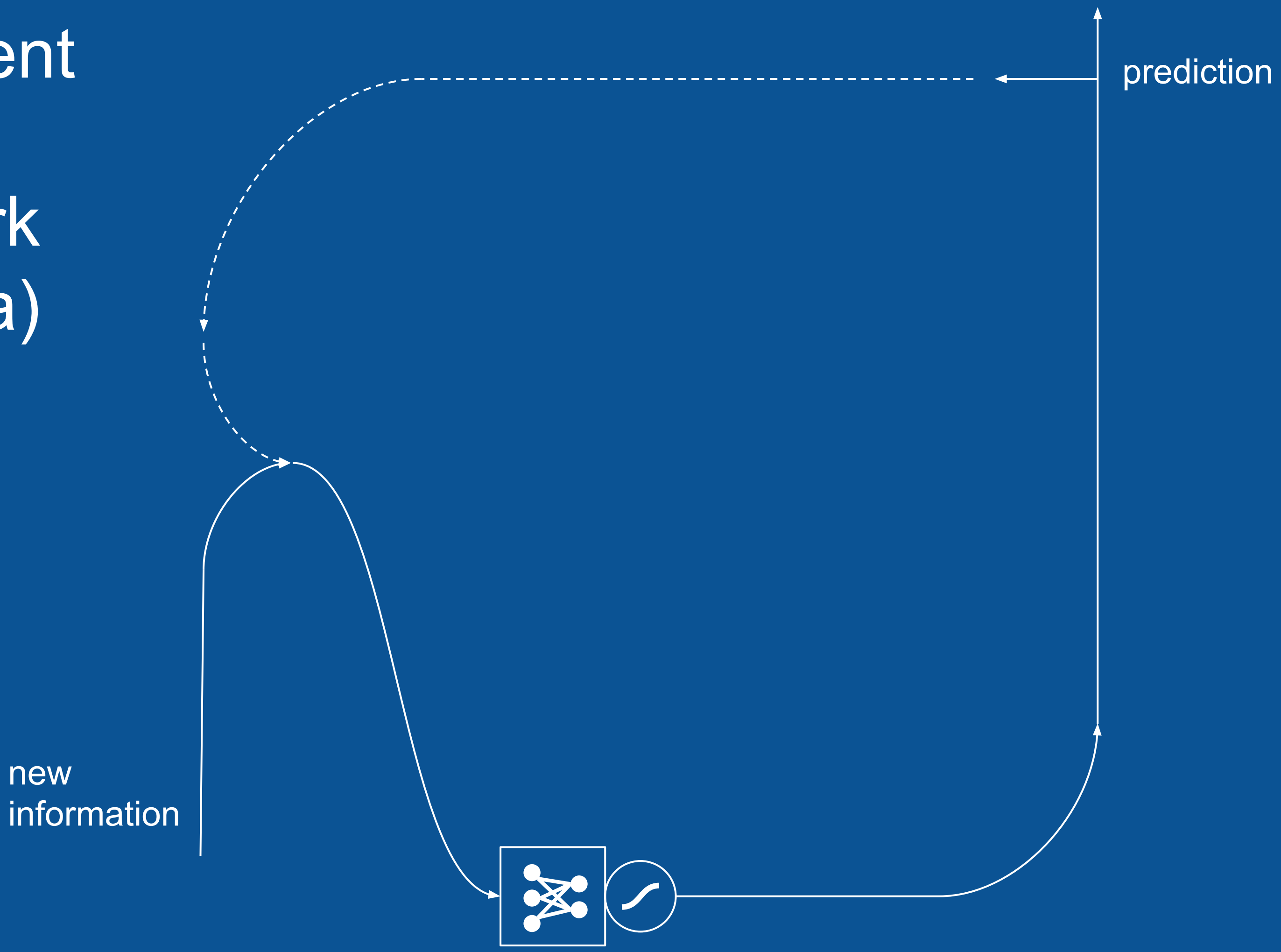
Spot. Doug. Jane.

We need to remember farther back in time, maybe make some things off-limits.
Enter the LSTM.

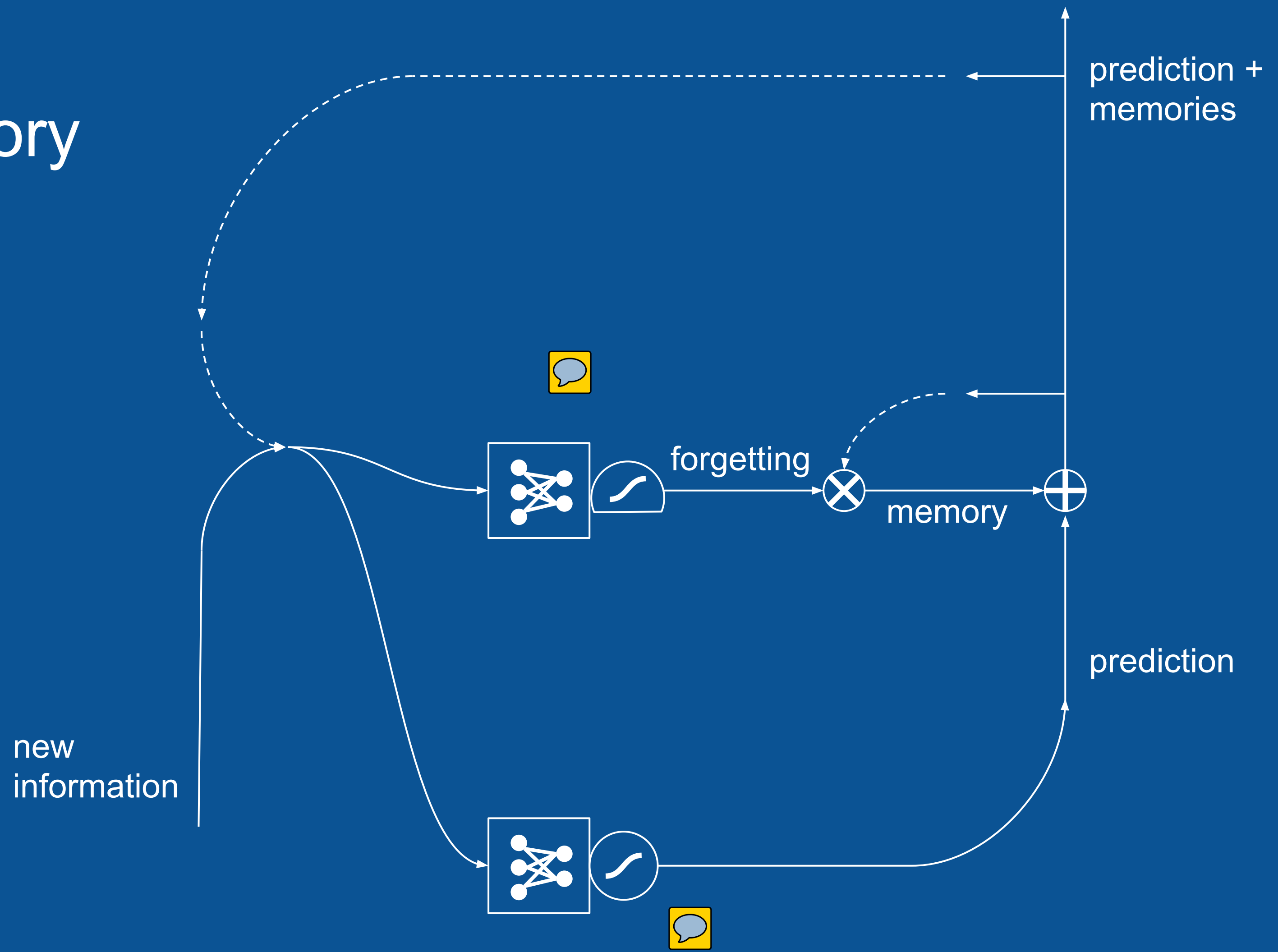
recurrent neural network (vanilla)



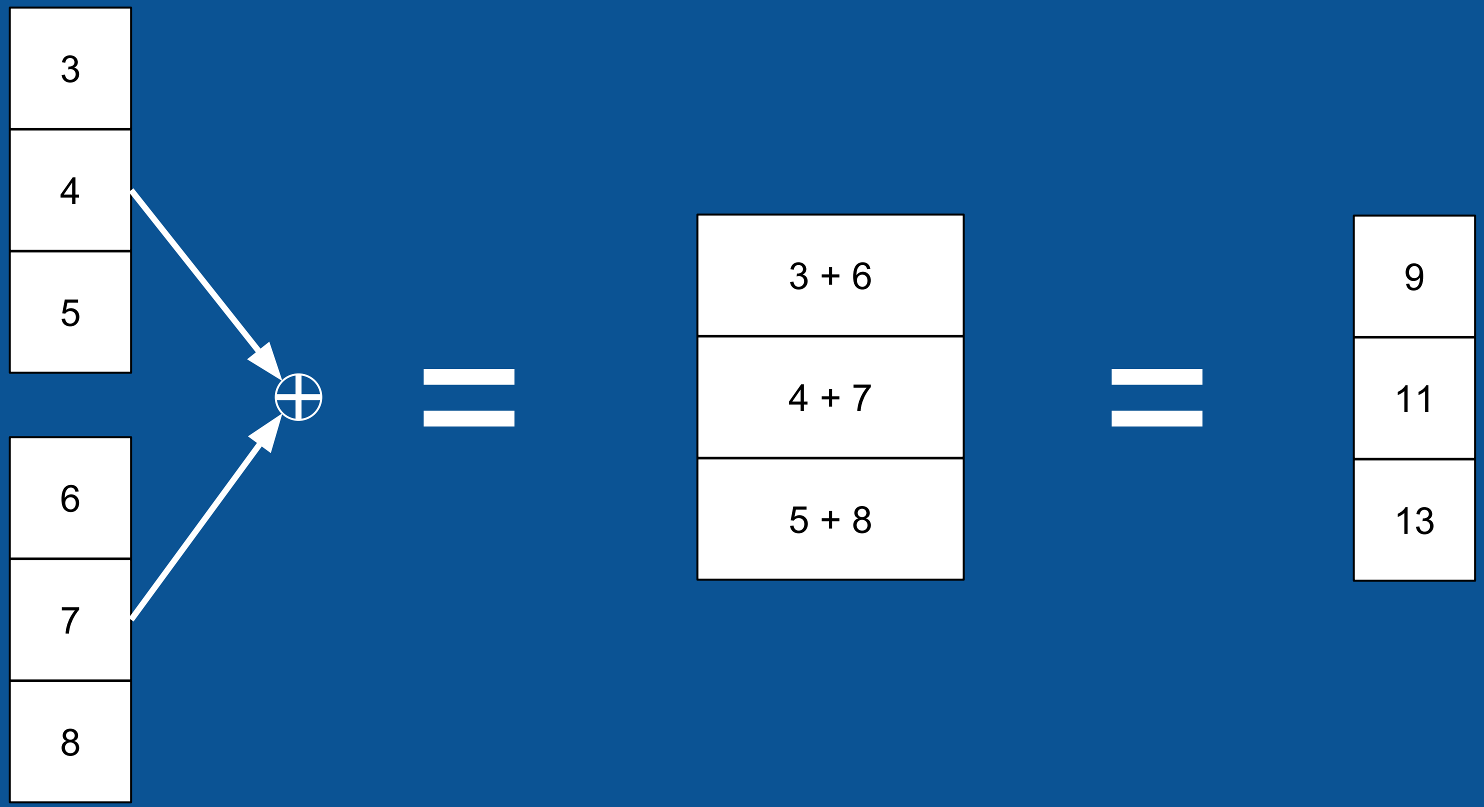
recurrent neural network (vanilla)



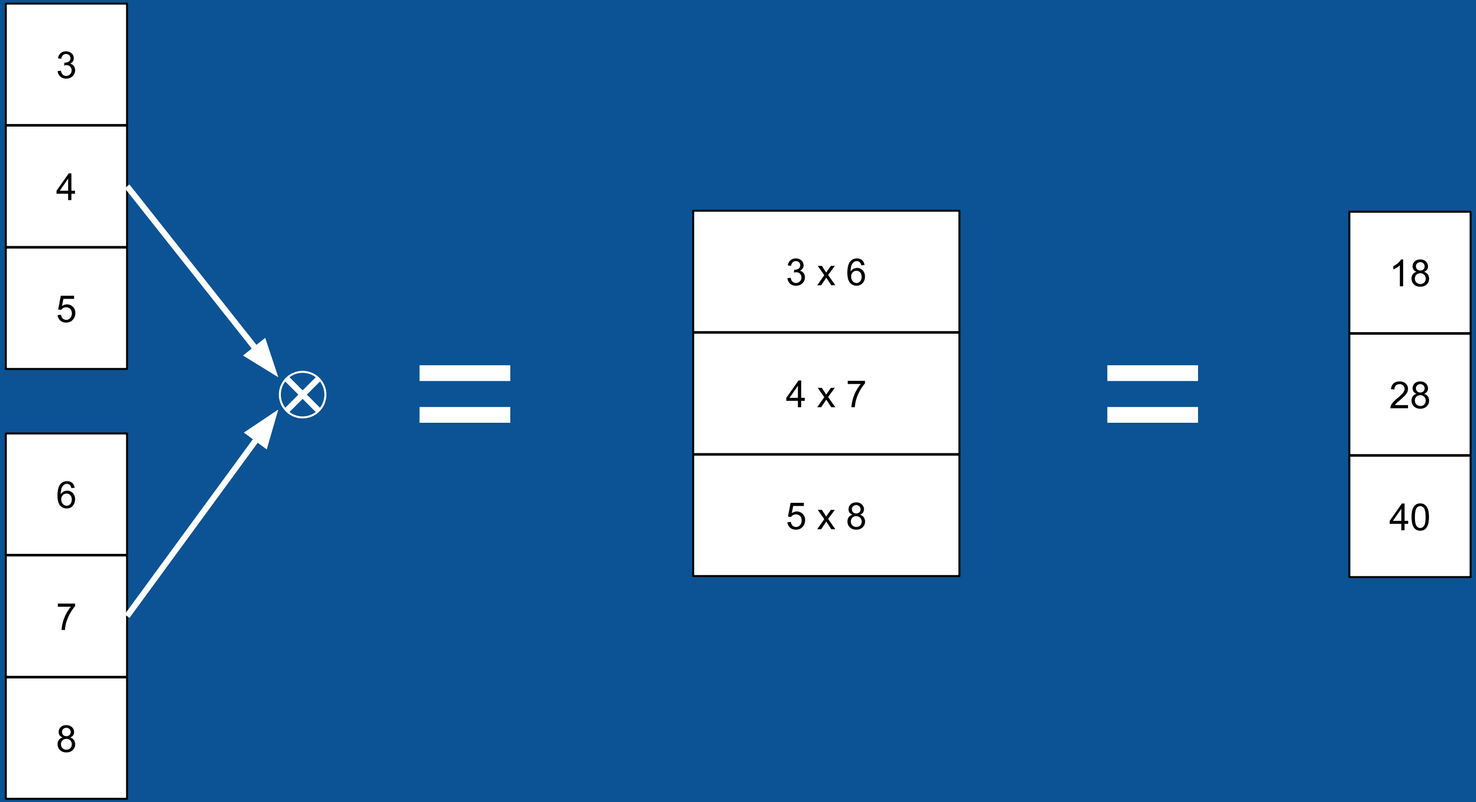
add memory and gates



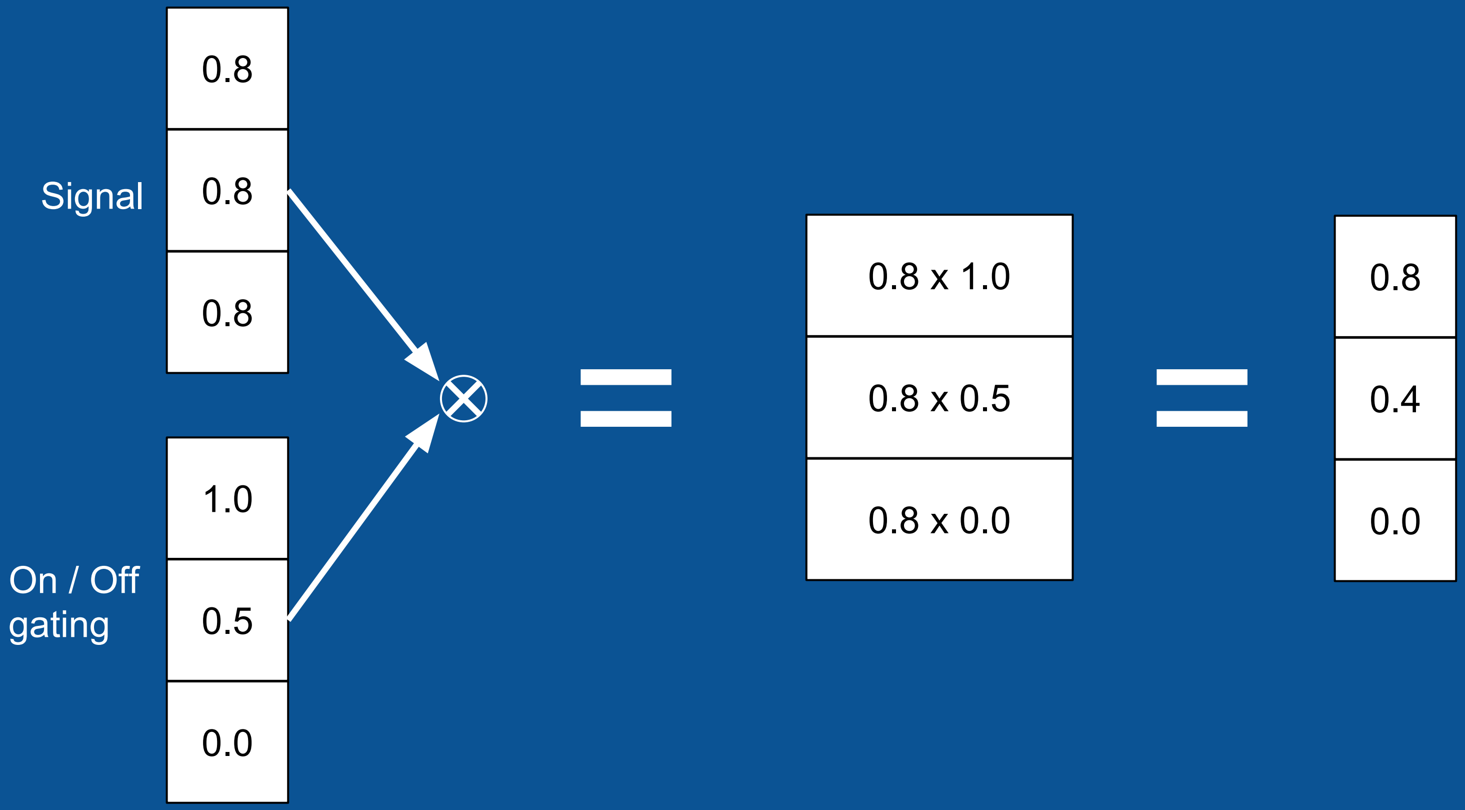
Plus junction: element-by-element addition



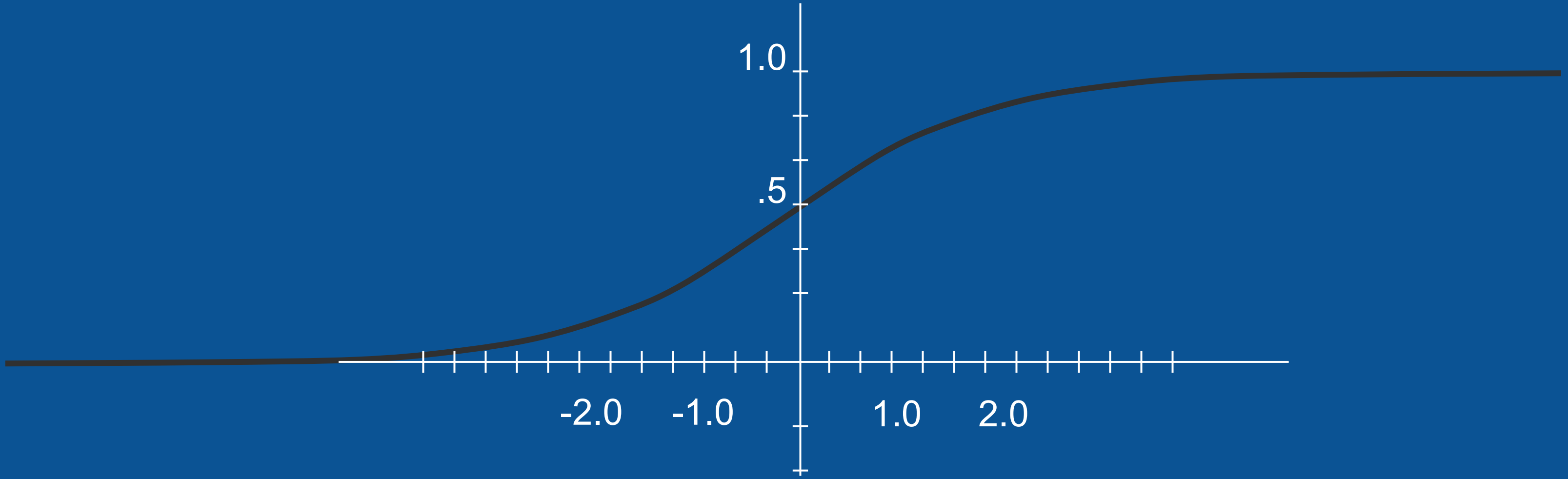
Times junction: element-by-element multiplication



Gating

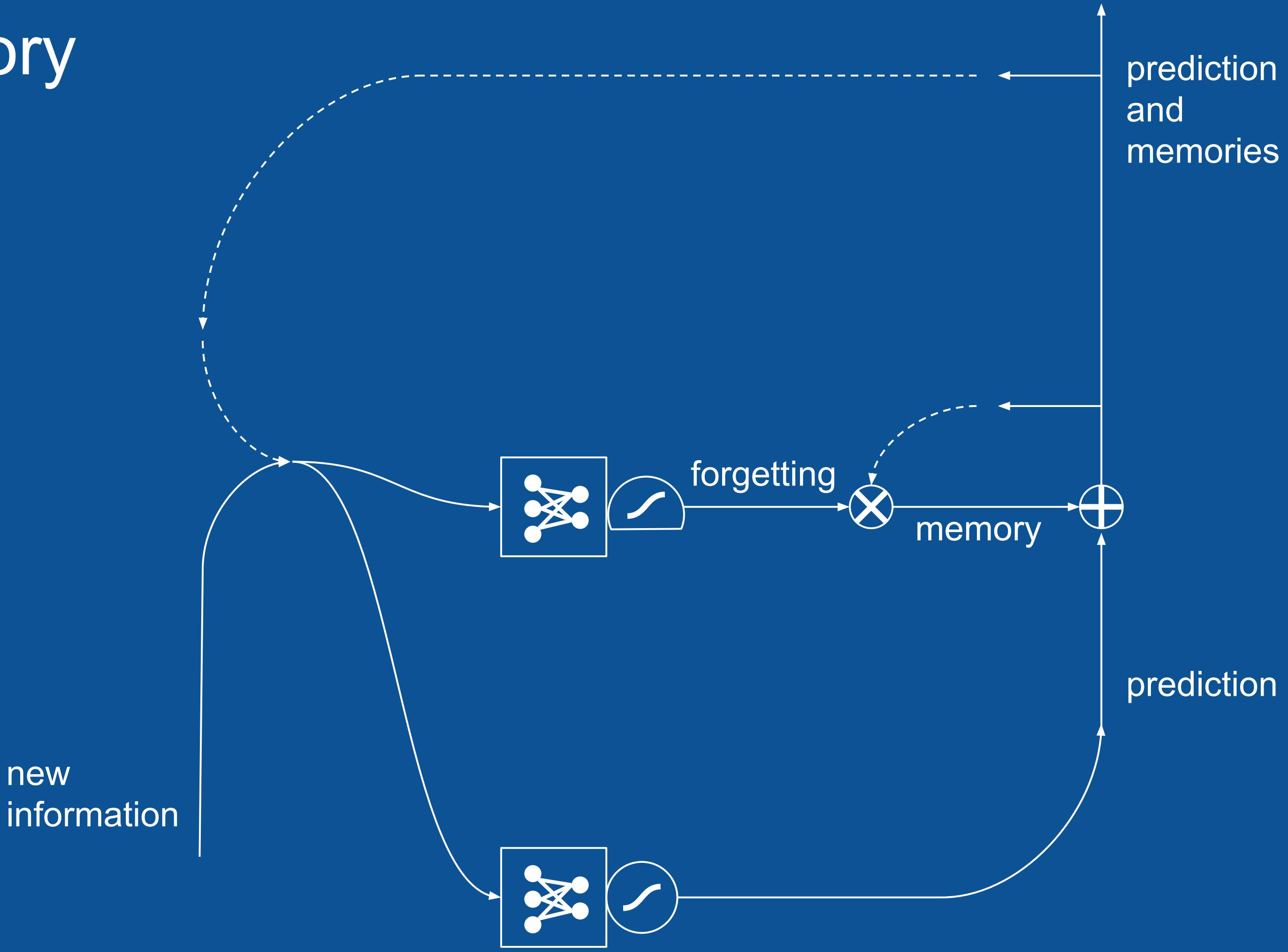

Signal
0.8
0.8
0.8
On / Off gating
1.0
0.5
0.0
0.8 x 1.0
0.8 x 0.5
0.8 x 0.0
0.8
0.4
0.0

Logistic (sigmoid) activation function



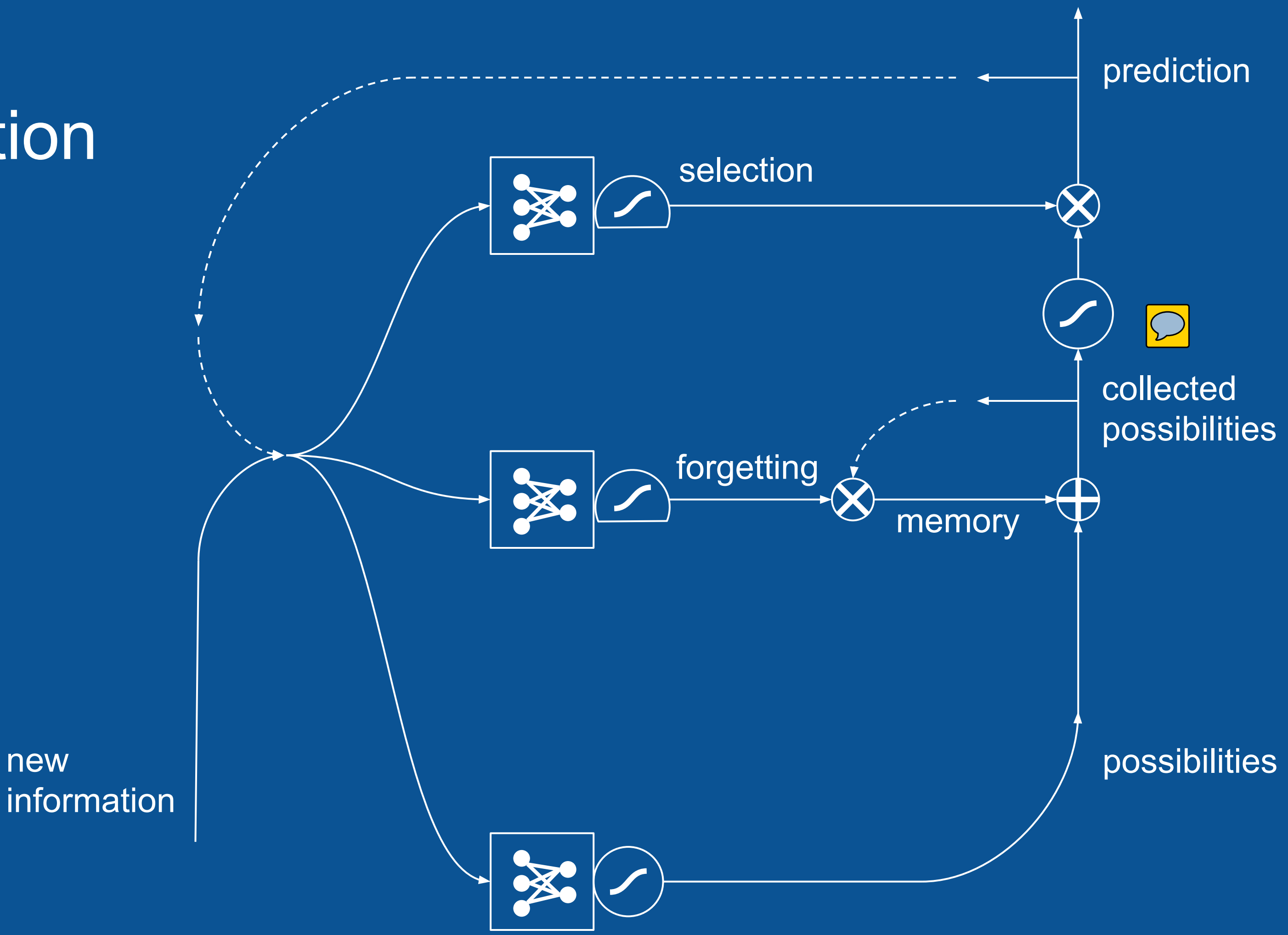
No matter what you start with, the answer stays between 0 and 1.

memory

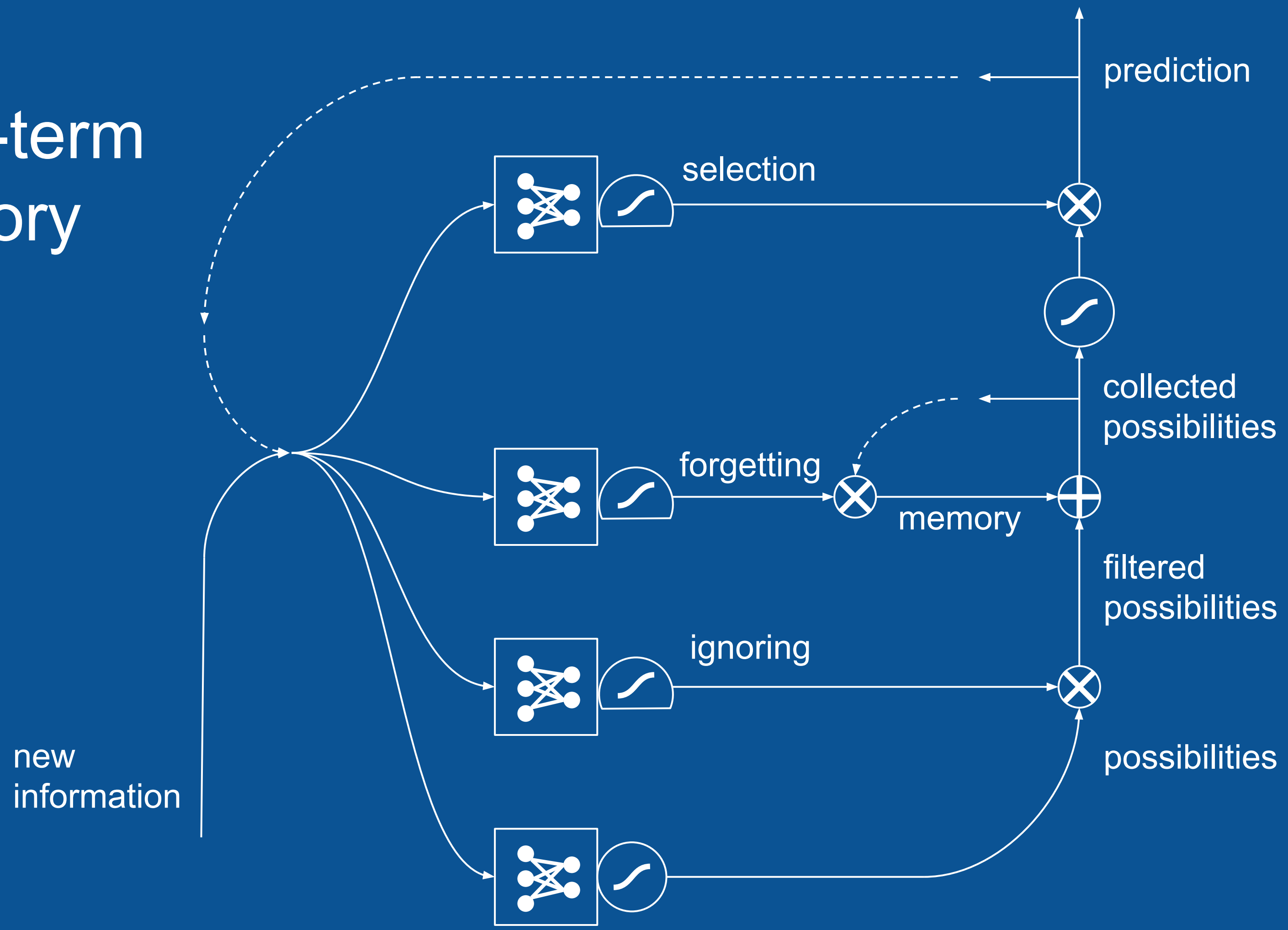


prediction
and
memories
forgetting
memory
prediction
new
information

add selection

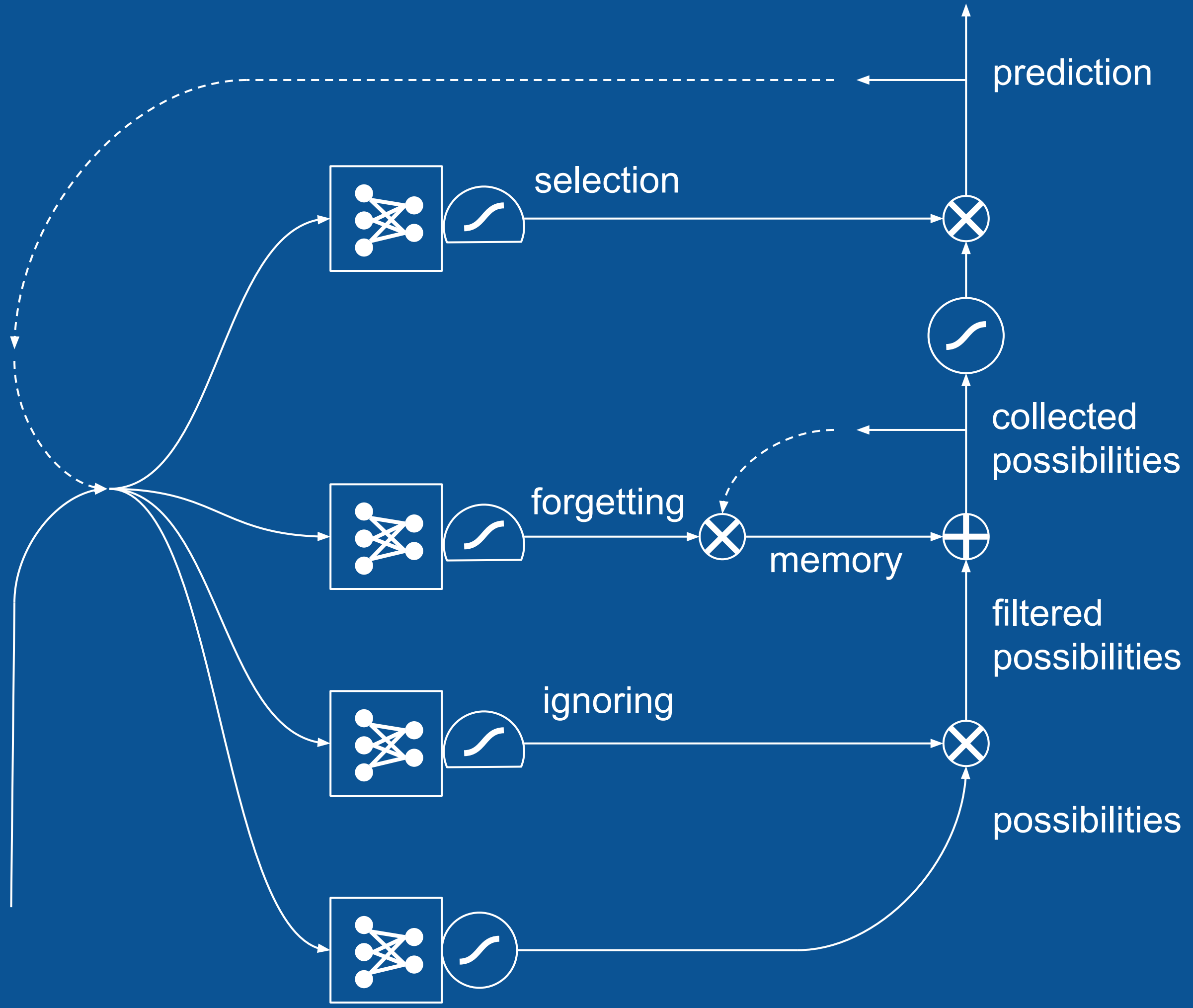


long short-term memory

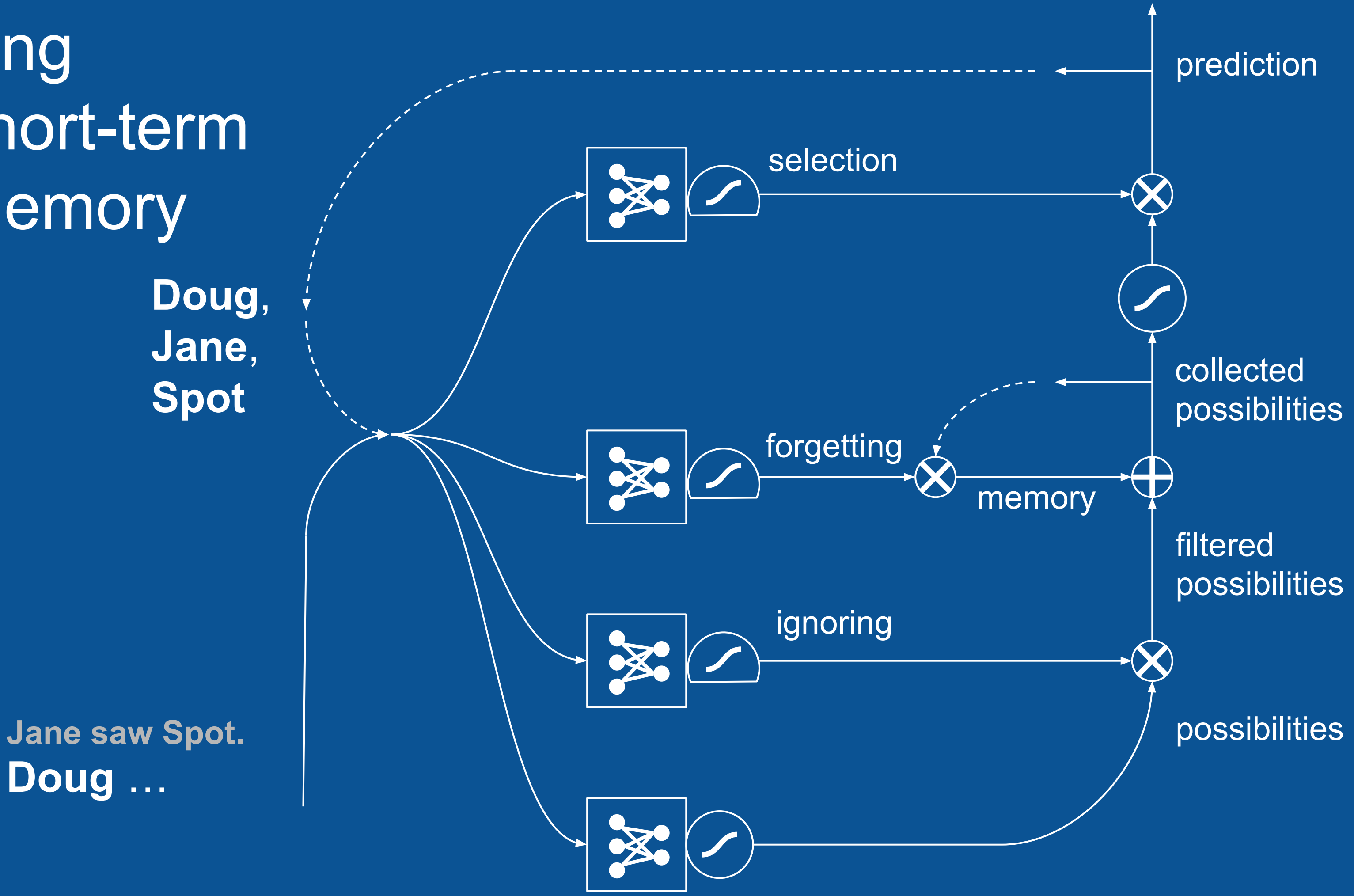


long short-term memory

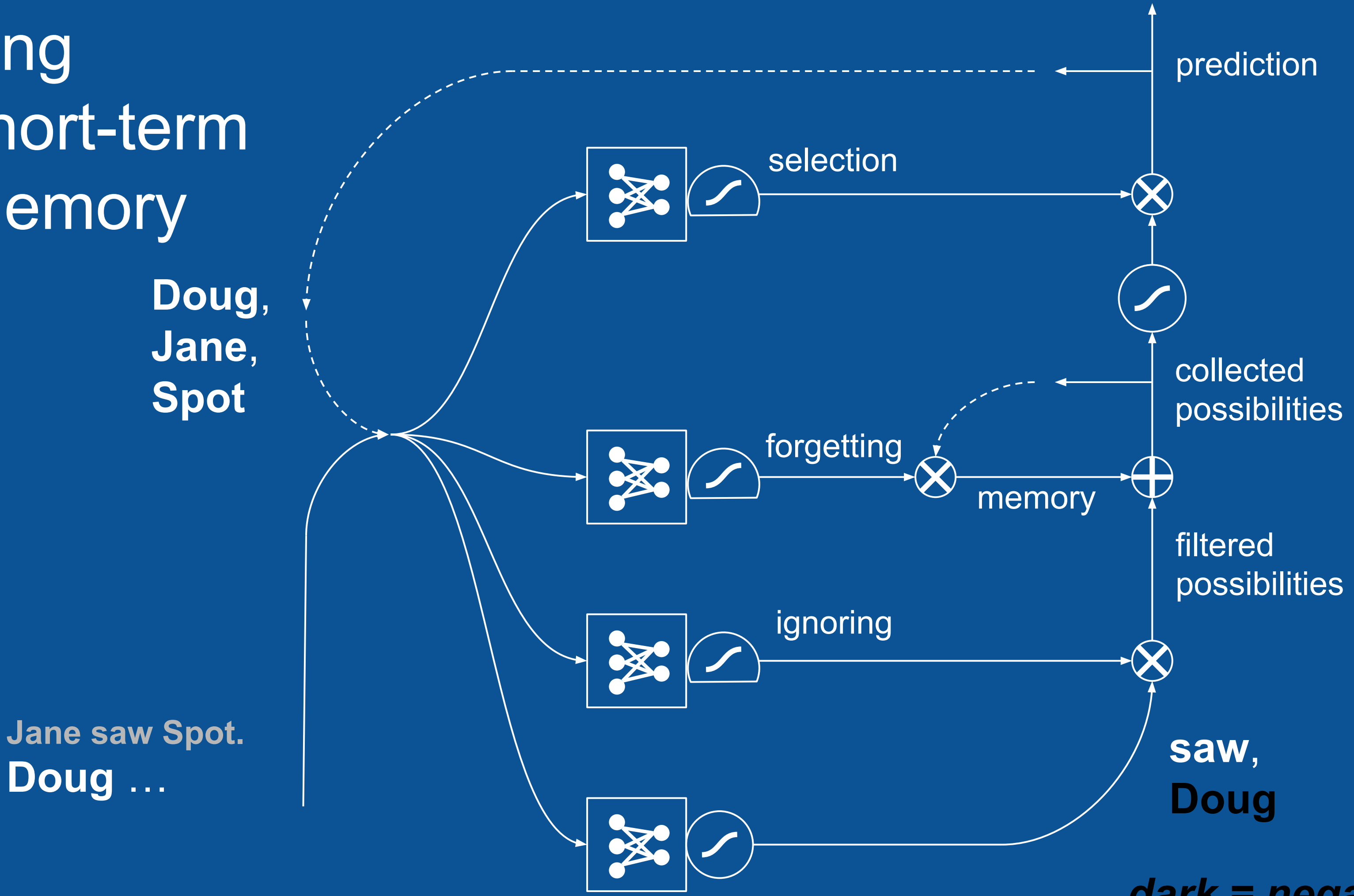
Jane saw Spot.
Doug …



long short-term memory

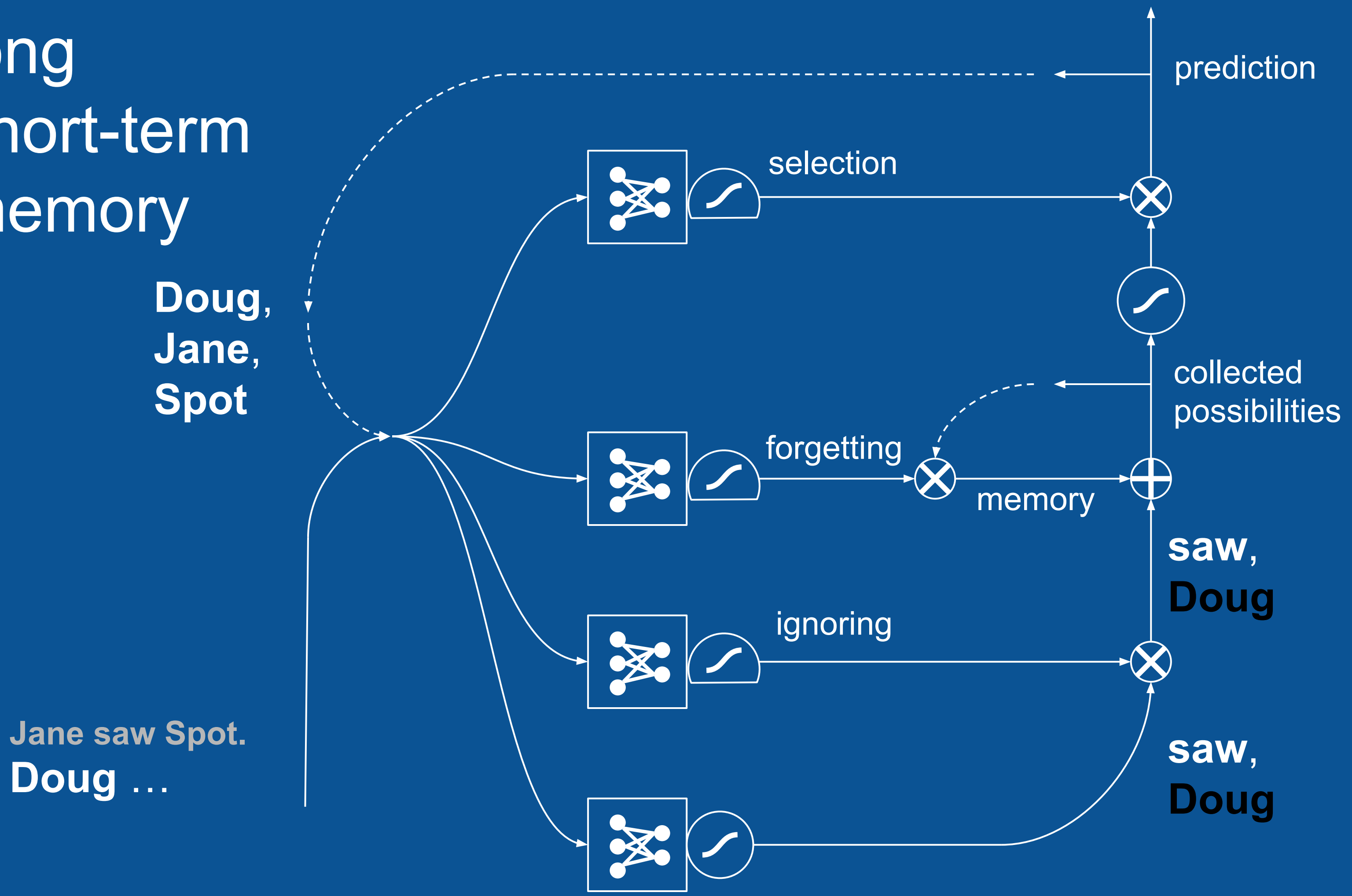


long short-term memory

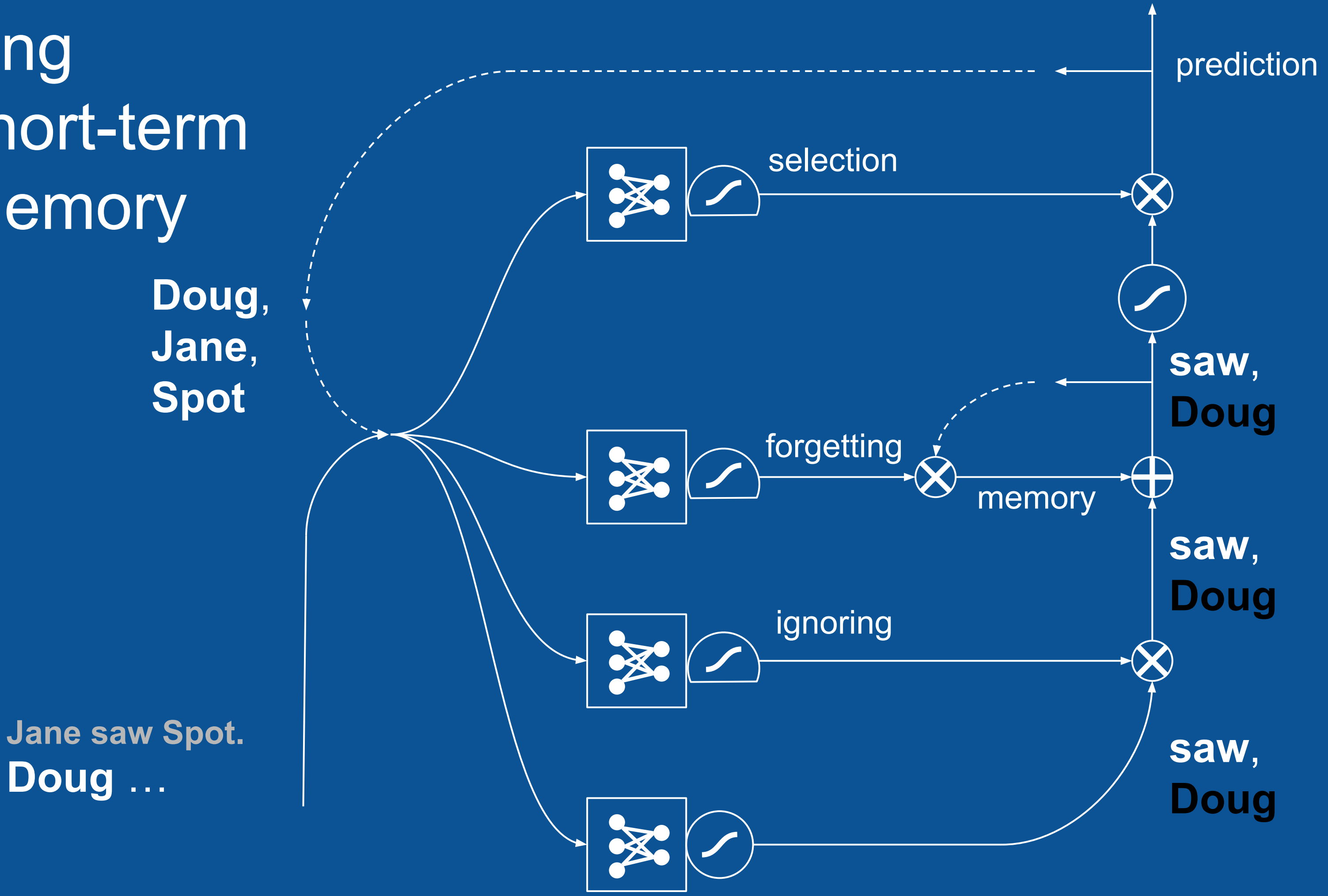


dark = negative value

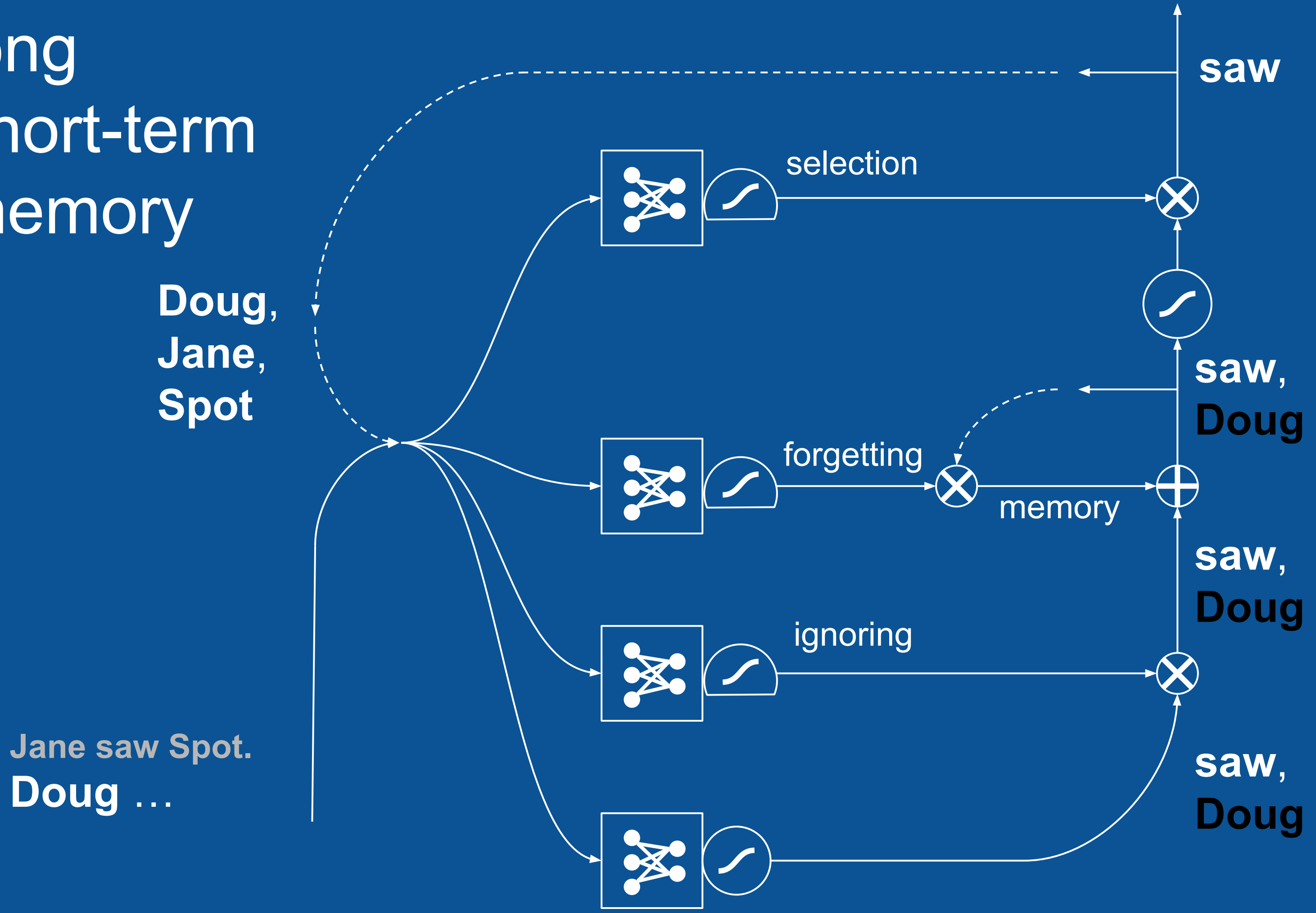
long short-term memory



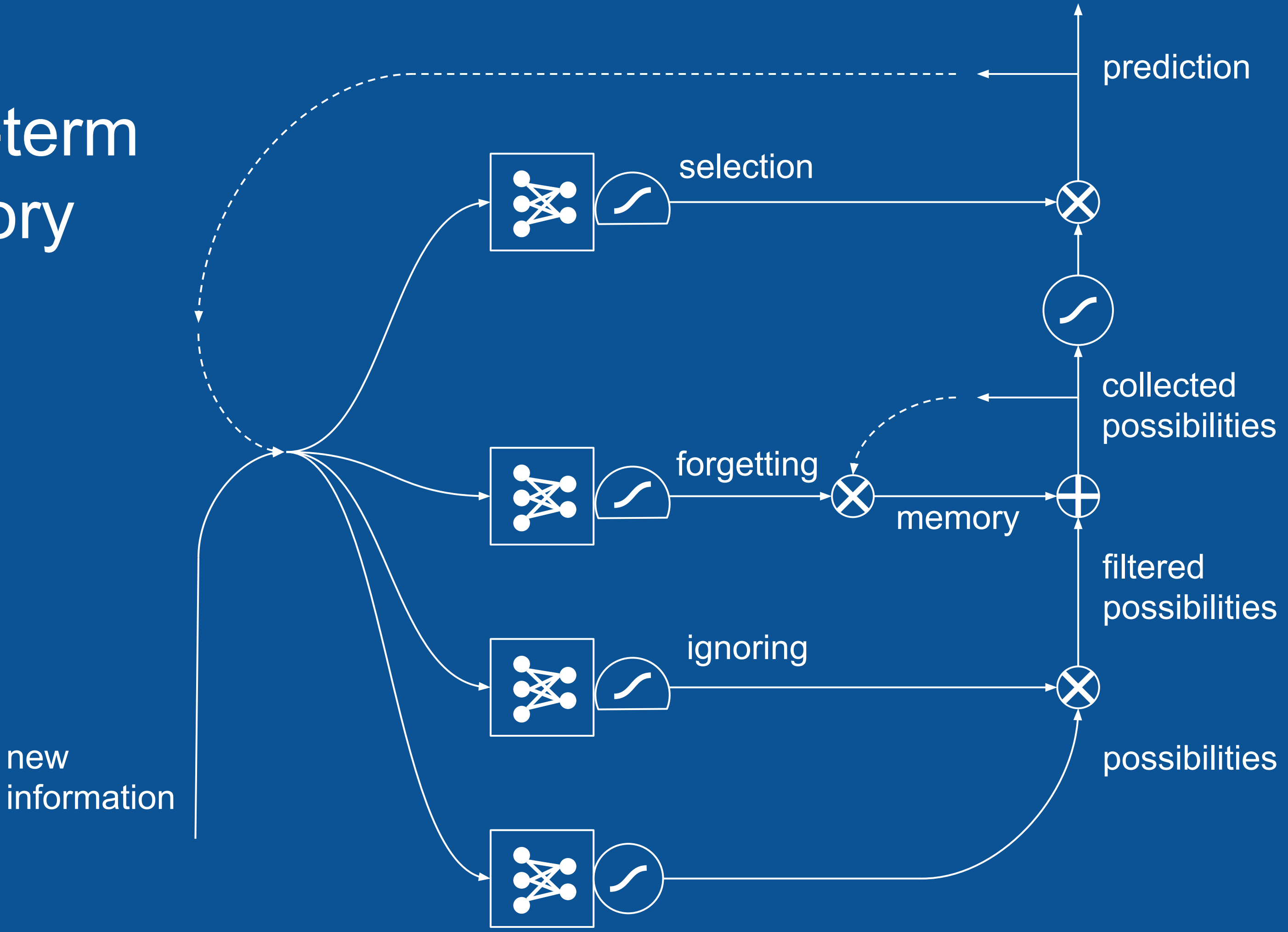
long short-term memory



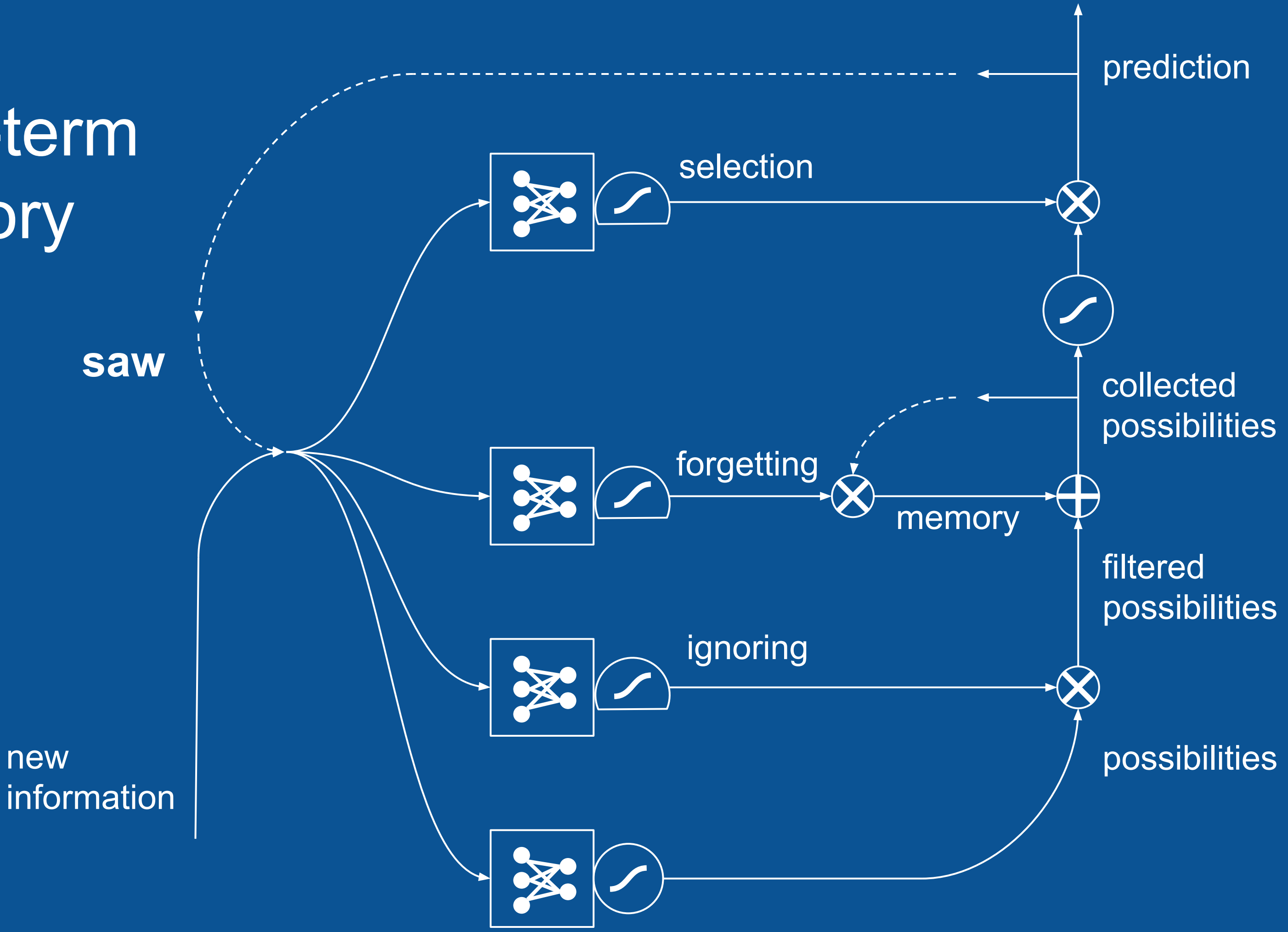
long short-term memory



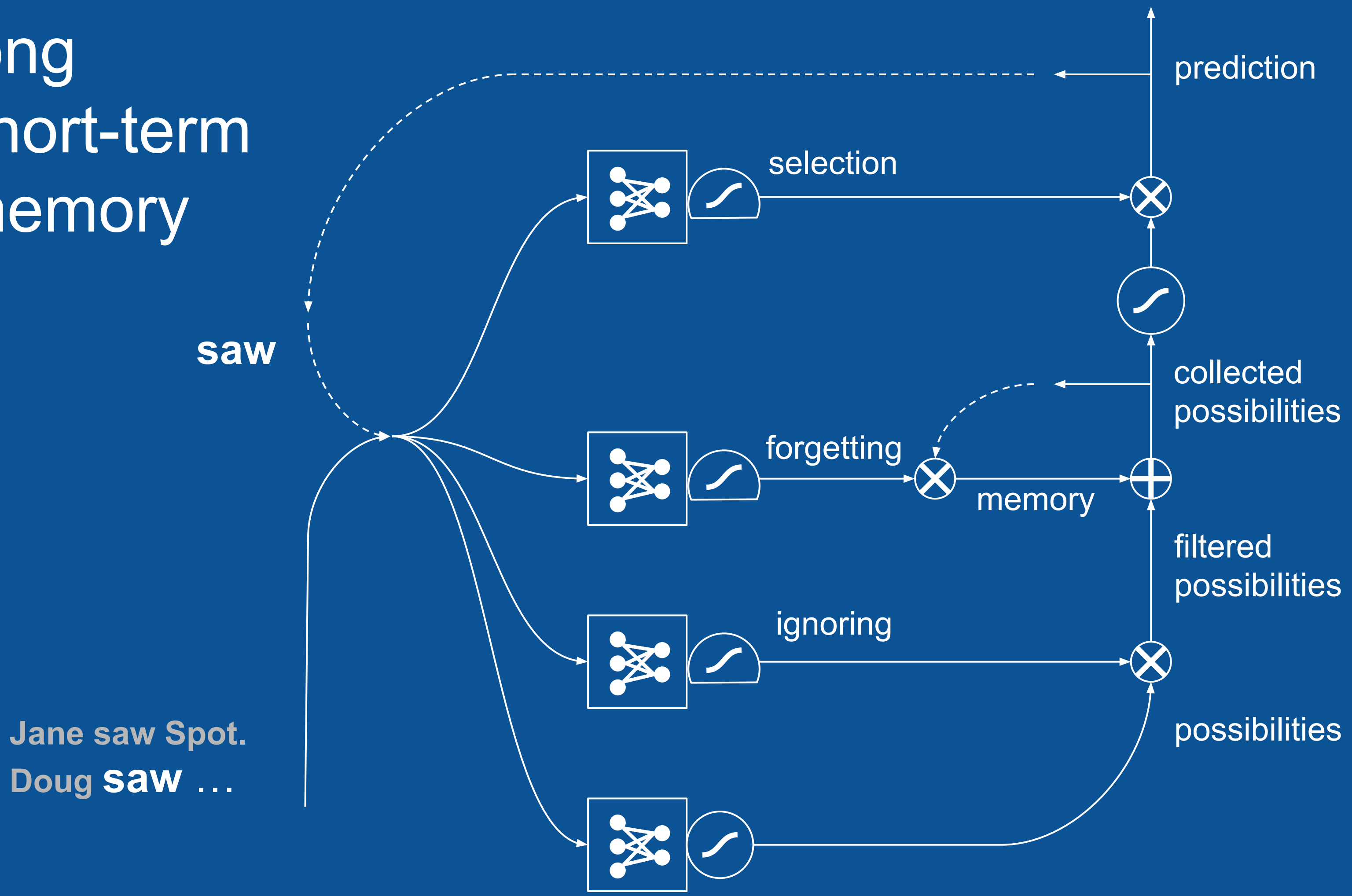
long short-term memory



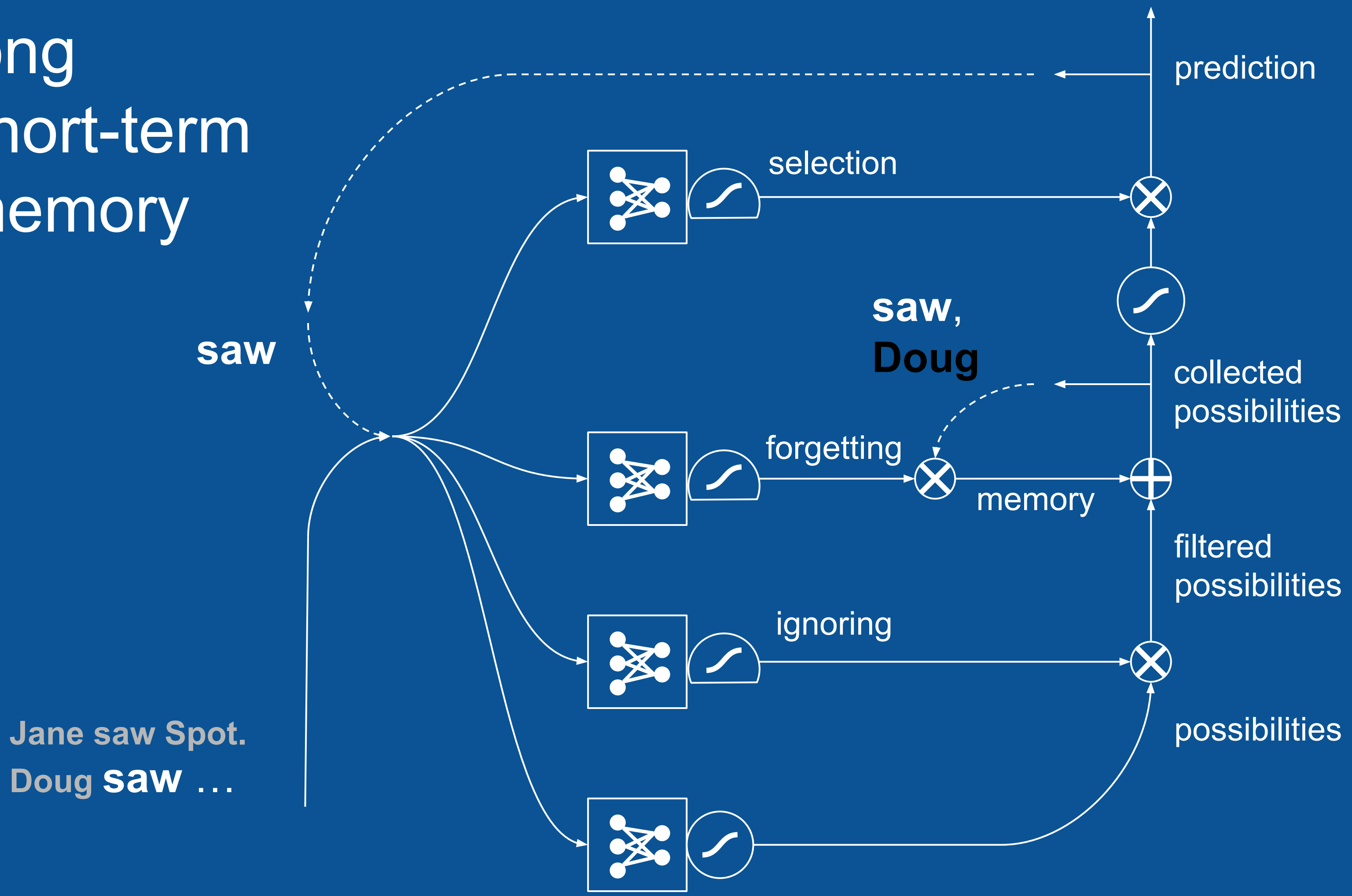
long short-term memory



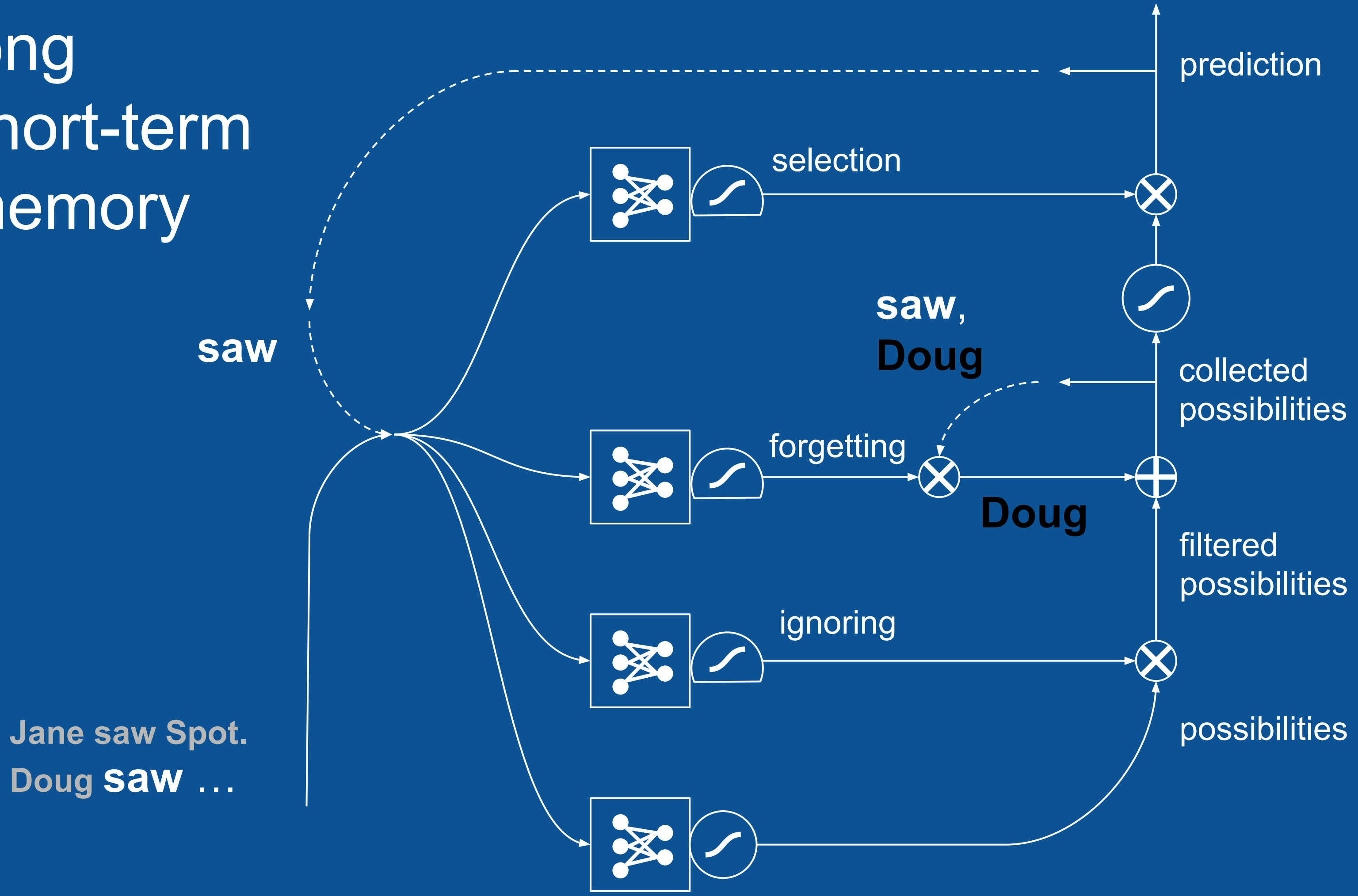
long short-term memory



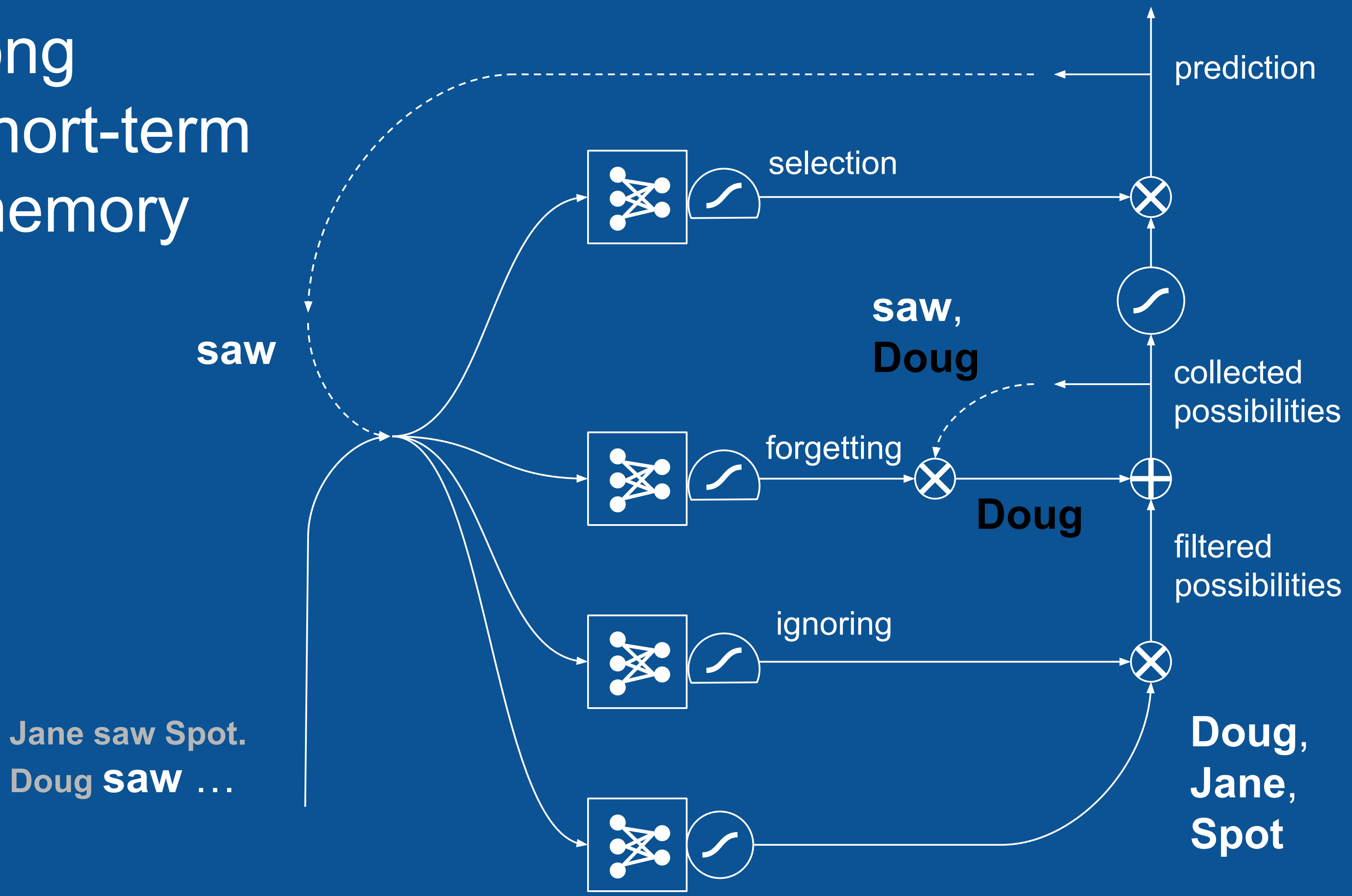
long short-term memory



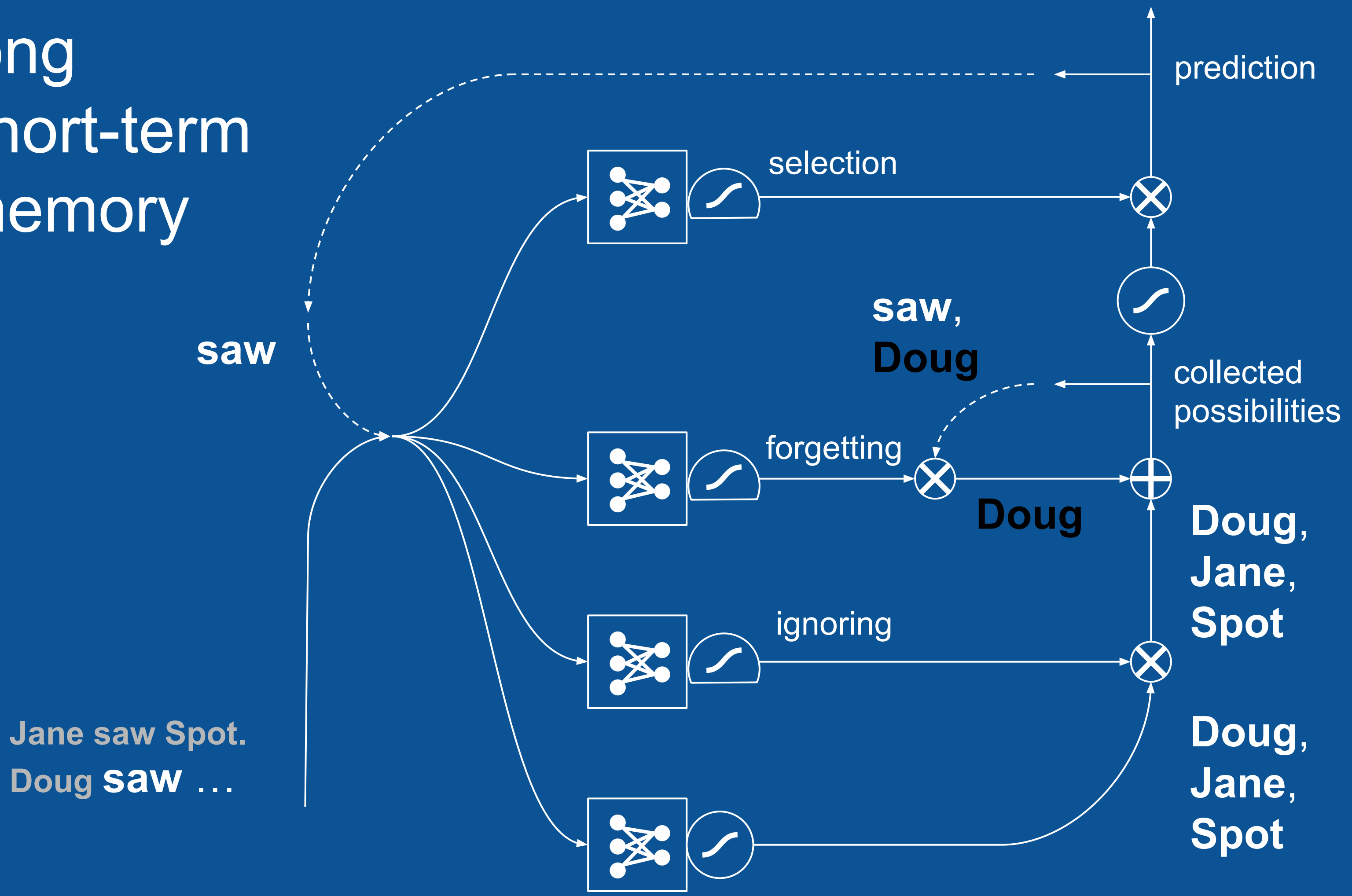
long short-term memory



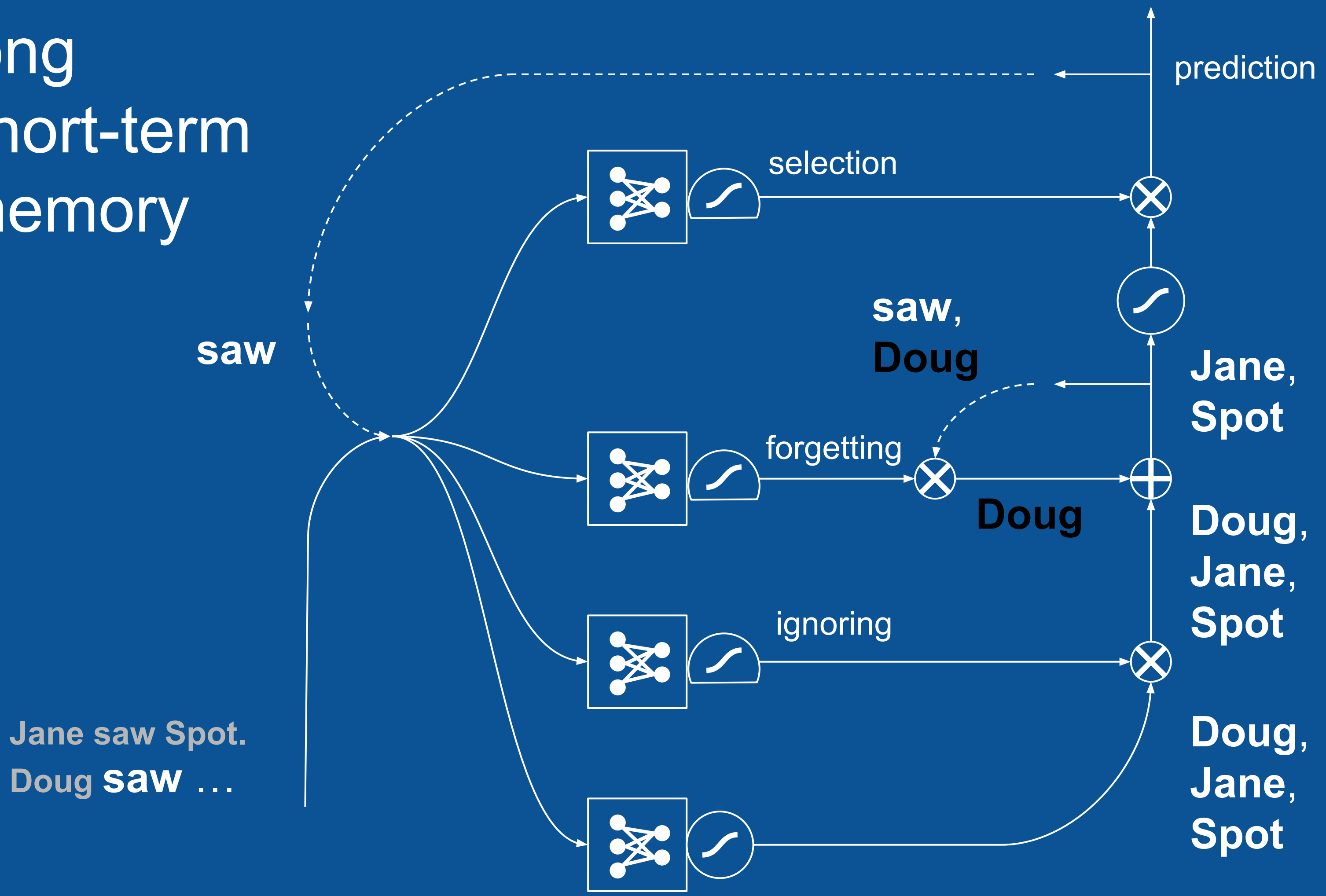
long short-term memory



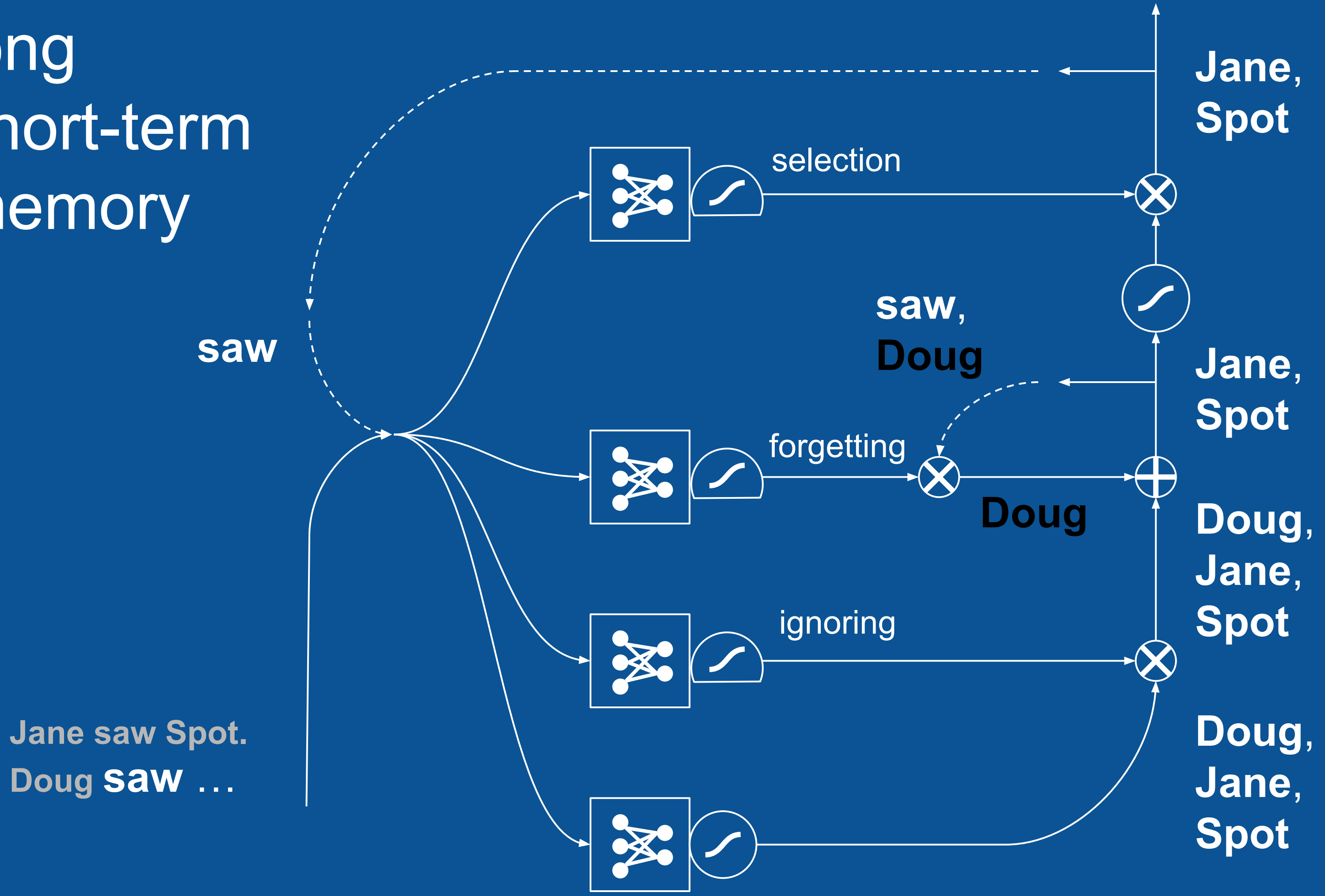
long short-term memory



long short-term memory



long short-term memory



Traditional LSTM with forget gates.[2][3]

Initial values: $c_0 = 0$ and $h_0 = 0$. The operator $\circ$ denotes the Hadamard product (entry-wise product).

$$
\begin{aligned}
f_t &= \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \\
i_t &= \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \\
o_t &= \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \\
c_t &= f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \\
h_t &= o_t \circ \sigma_h(c_t)
\end{aligned}
$$

Variables

- x_t : input vector
- h_t : output vector
- c_t : cell state vector
- W, U and b: parameter matrices and vector
- f_t, i_t and o_t : gate vectors
  - f_t : Forget gate vector. Weight of remembering old information.
  - i_t : Input gate vector. Weight of acquiring new information.
  - o_t : Output gate vector. Output candidate.

Activation functions

- σ_g : The original is a sigmoid function.
- σ_c : The original is a hyperbolic tangent.
- σ_h : The original is a hyperbolic tangent, but the peephole LSTM paper suggests $\sigma_h(x) = x$.[18][19]

source:
Wikipedia

Resources

Brandon Rohrer's blog on RNNs and LSTMs

Chris Olah's tutorial

Andrej Karpathy's

- Blog post
- RNN code
- Stanford CS231n lecture

The DeepLearning 4J tutorial has some helpful discussion and a longer list of good resources.

How Neural Networks Work [video]

Credits (all images CC0)

Pizza image

Sushi image

Waffles image

Appendix

A vector is a list of values

"Tonight I think we're going to have sushi."

=

Pizza	0
Sushi	1
Waffles	0

=

Dinner prediction vector

$$\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

A vector is a list of values

"High is 67 F.
Low is 43 F.
Wind is 13 mph.
.25 inches of rain.
Relative humidity
is 83%."

=

High temperature	67
Low temperature	43
Wind speed	13
Precipitation	.25
Humidity	.83

=

Weather vector

67
43
13
.25
.83

A vector is a list of values