

# IDL

## INTRODUCTION TO DEEP LEARNING

# Recurrent Neural Networks (RNNs)

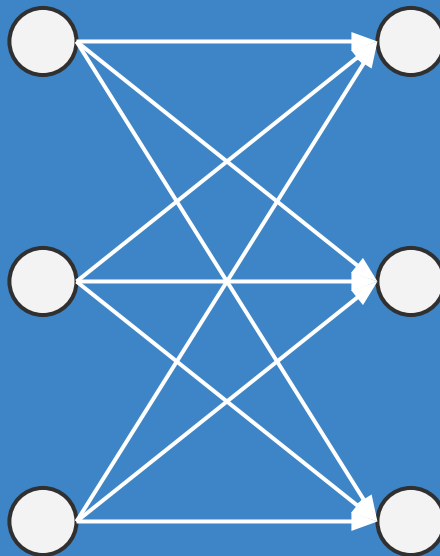
## Long Short-Term Memory (LSTM)

# What's for dinner?

day  
of the  
week

month  
of the  
year

late  
meeting



pizza



burger



fries



# What's for dinner?

pizza  
yesterday



pizza



burger  
yesterday



burger



fries  
yesterday



fries



predicted pizza for yesterday

predicted burger for yesterday

predicted fries for yesterday

pizza yesterday

burger yesterday

fries yesterday



pizza

burger

fries



# 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

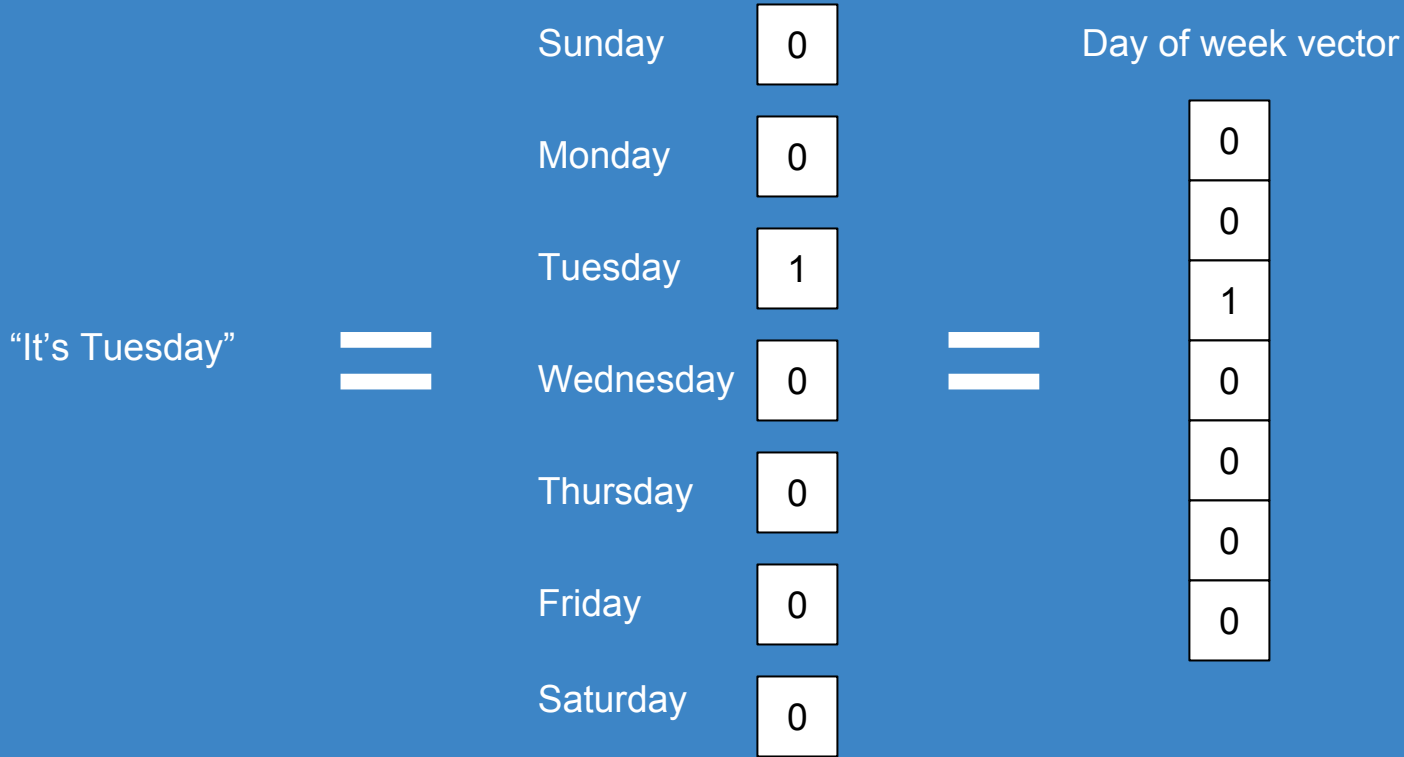
43

13

.25

.83

# A vector is a list of values



# A vector is a list of values

“Tonight I think  
we’re going to  
have sushi.”

=

Pizza

0

Burger

1

Fries

0

=

Dinner prediction vector

0

1

0



predicted pizza for yesterday

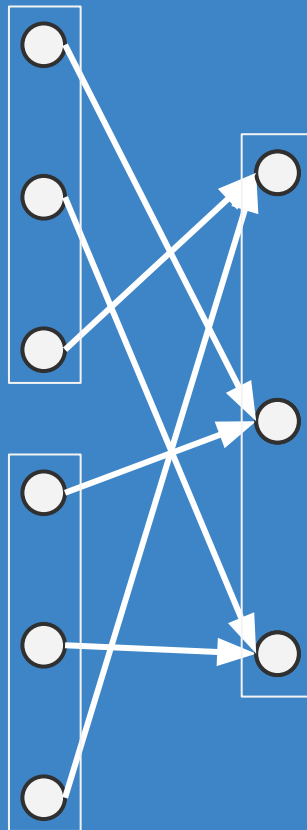
predicted burger for yesterday

predicted fries for yesterday

pizza yesterday

burger yesterday

fries yesterday



pizza

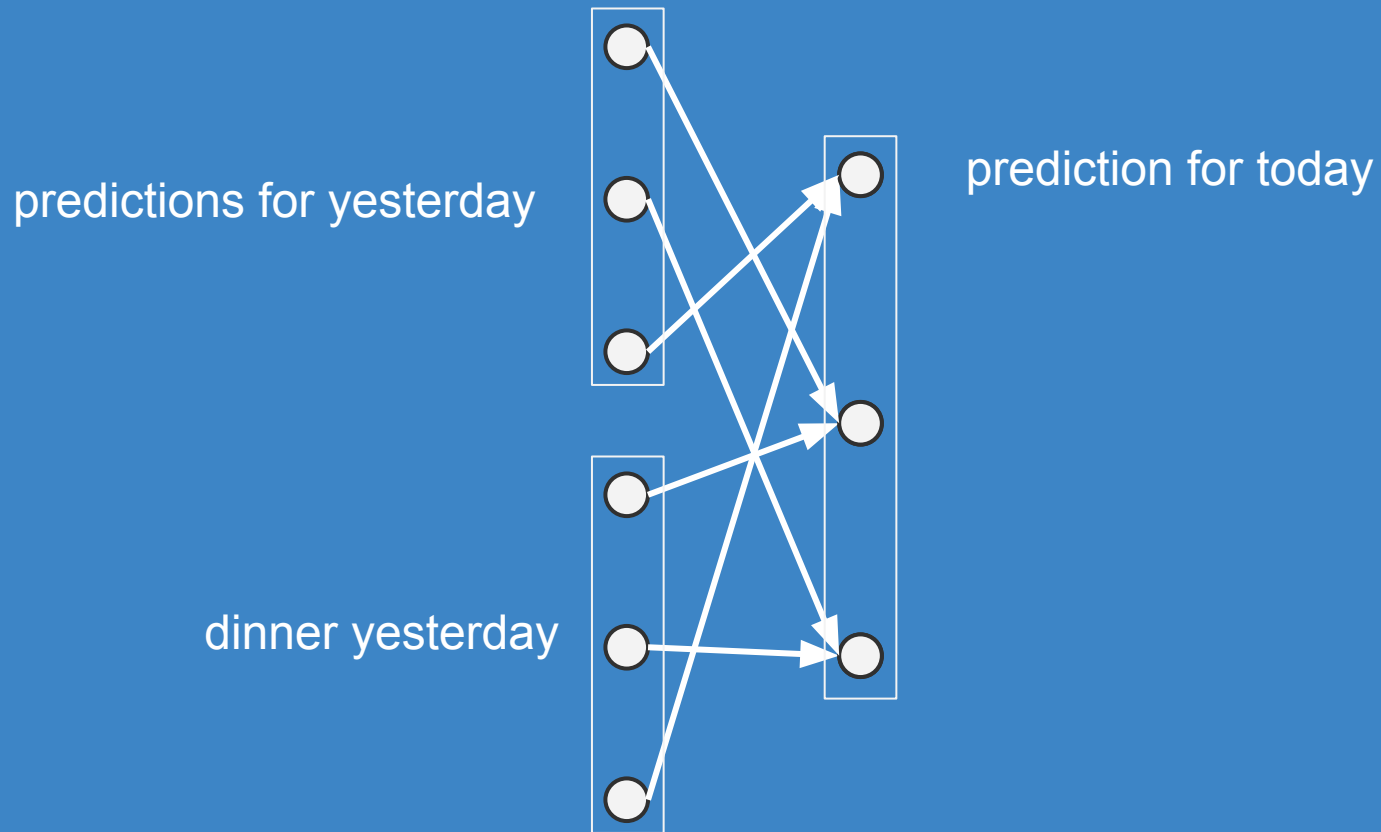


burger

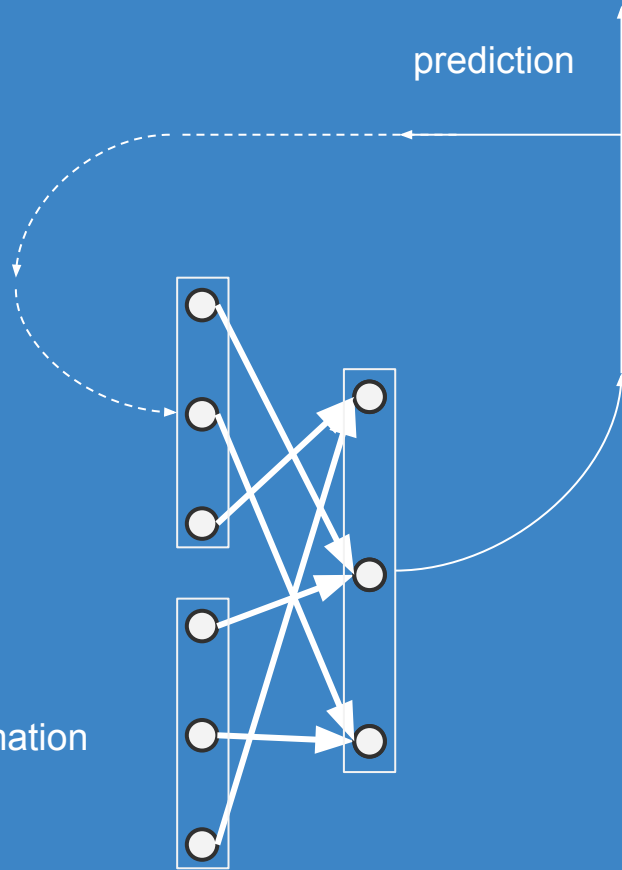


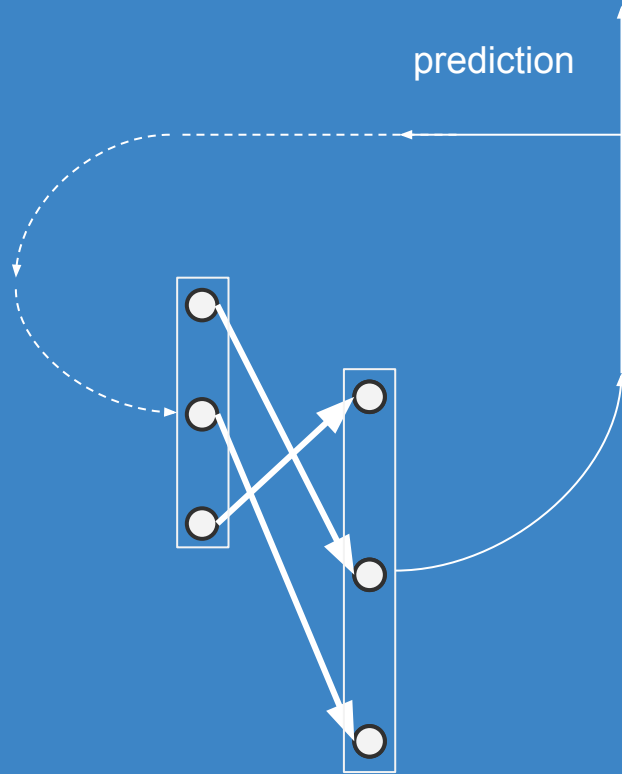
fries



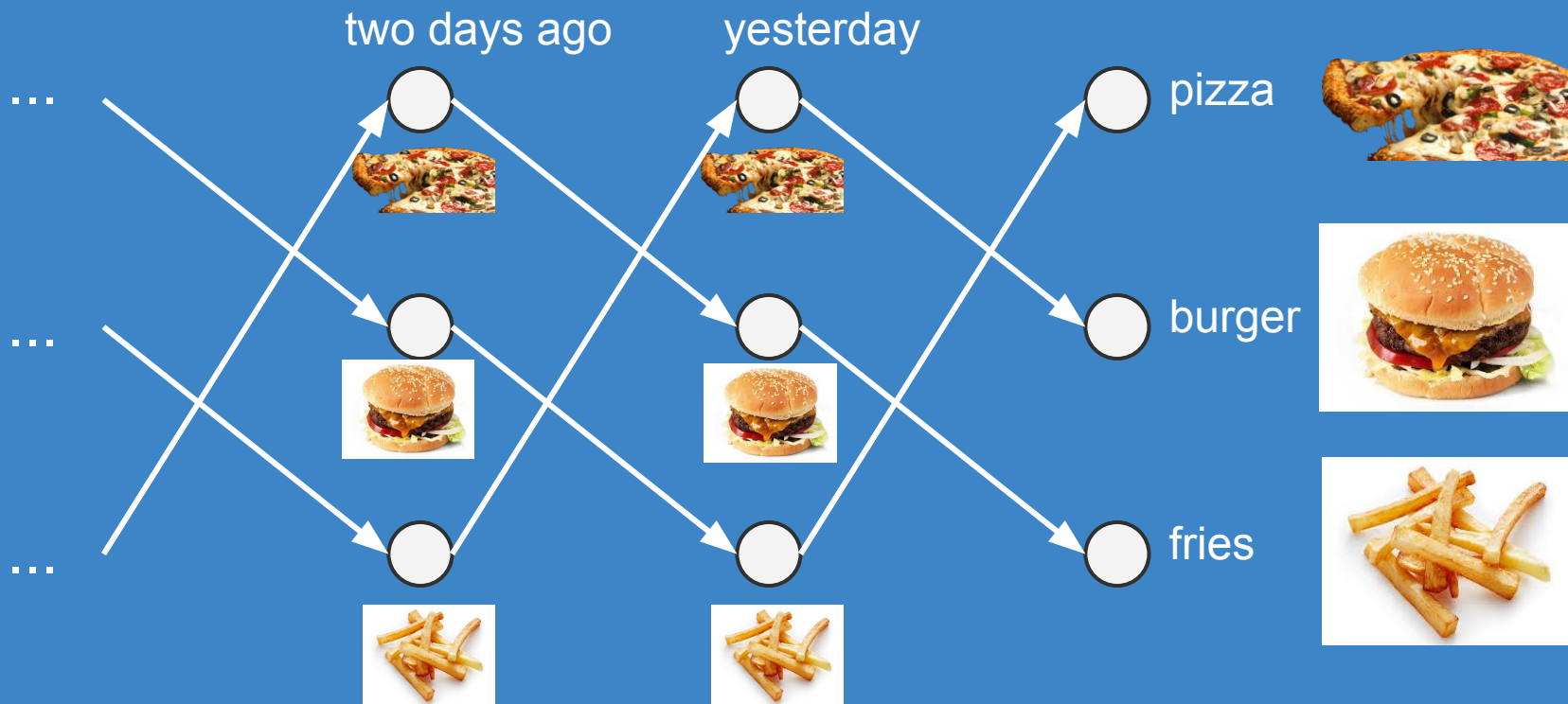


new information





# Unrolled predictions



# Write a children's book

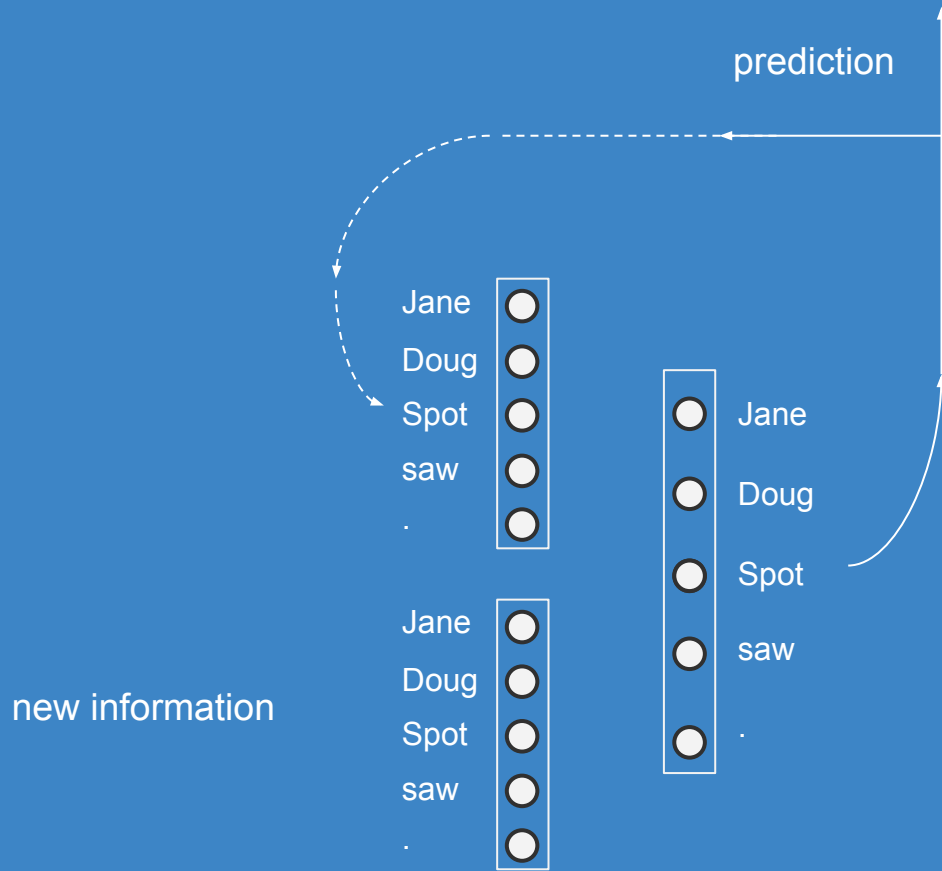
Doug saw Jane.

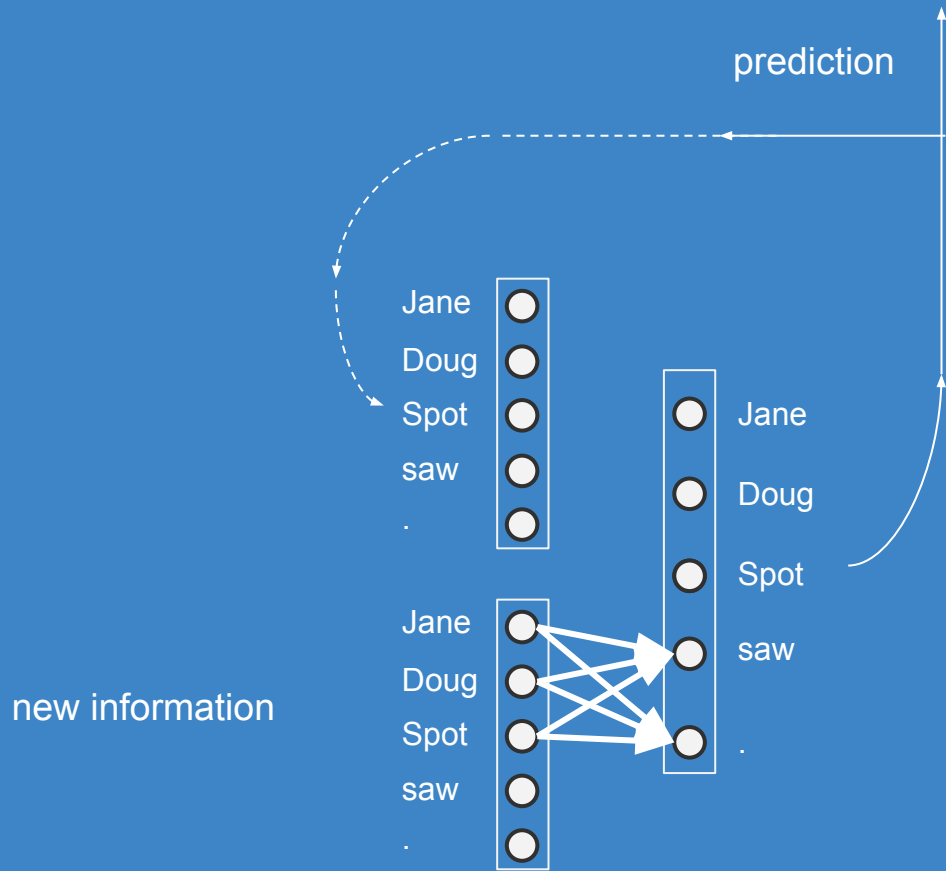
Jane saw Spot.

Spot saw Doug.

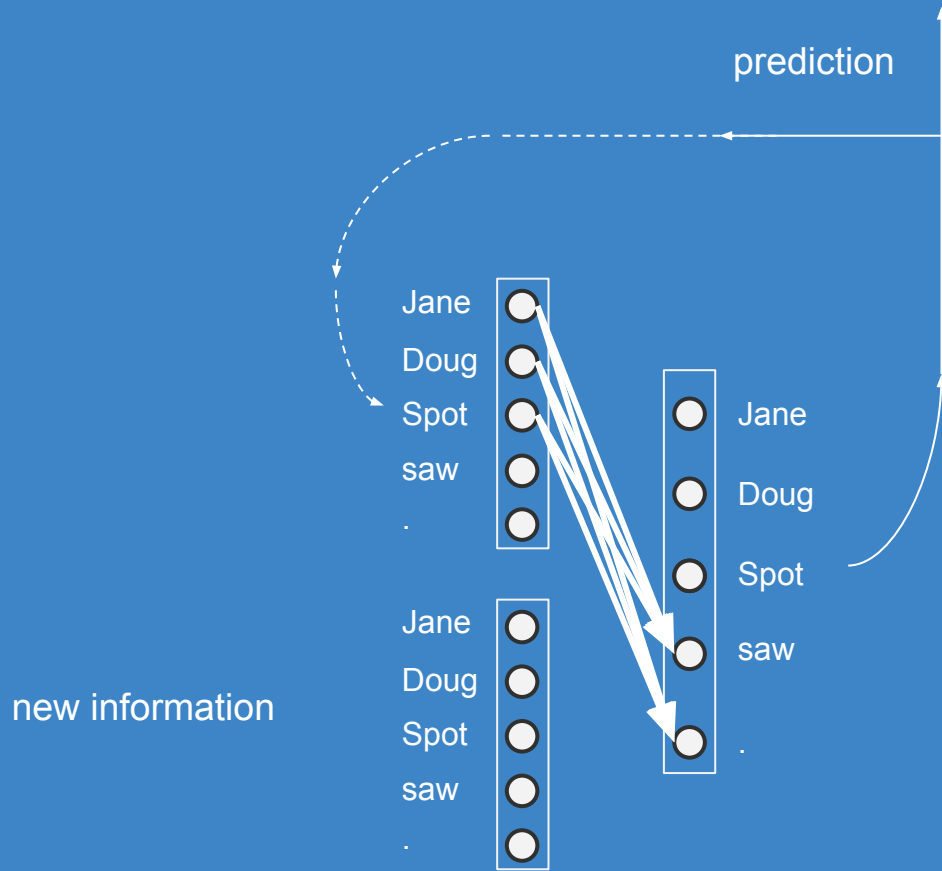
...

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

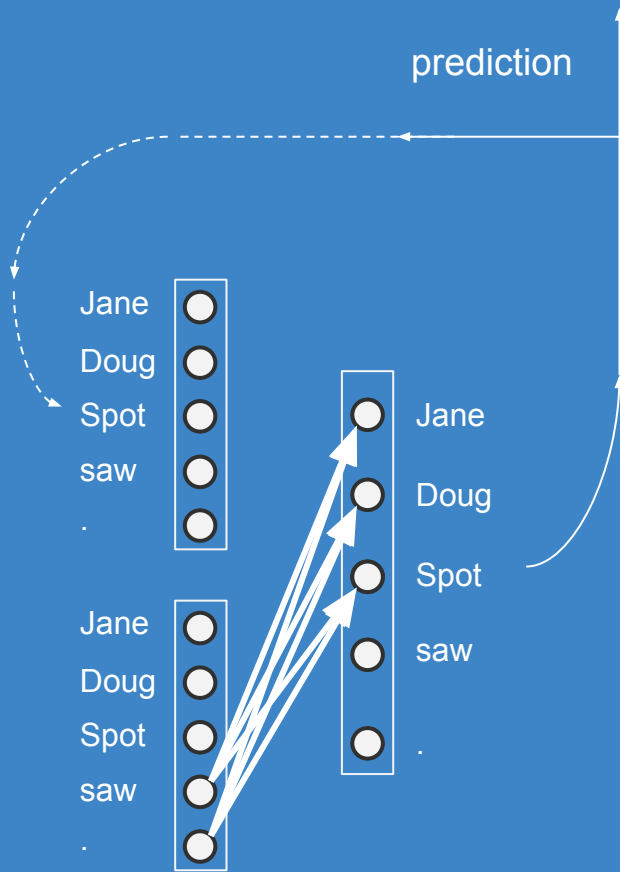




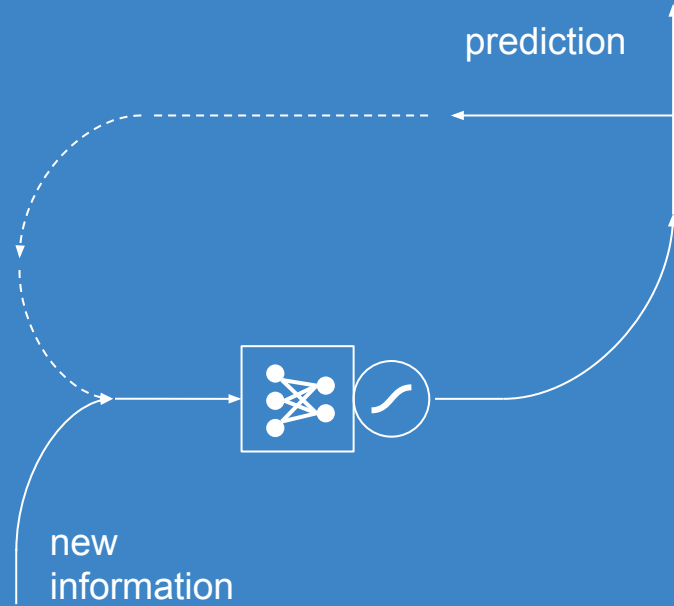




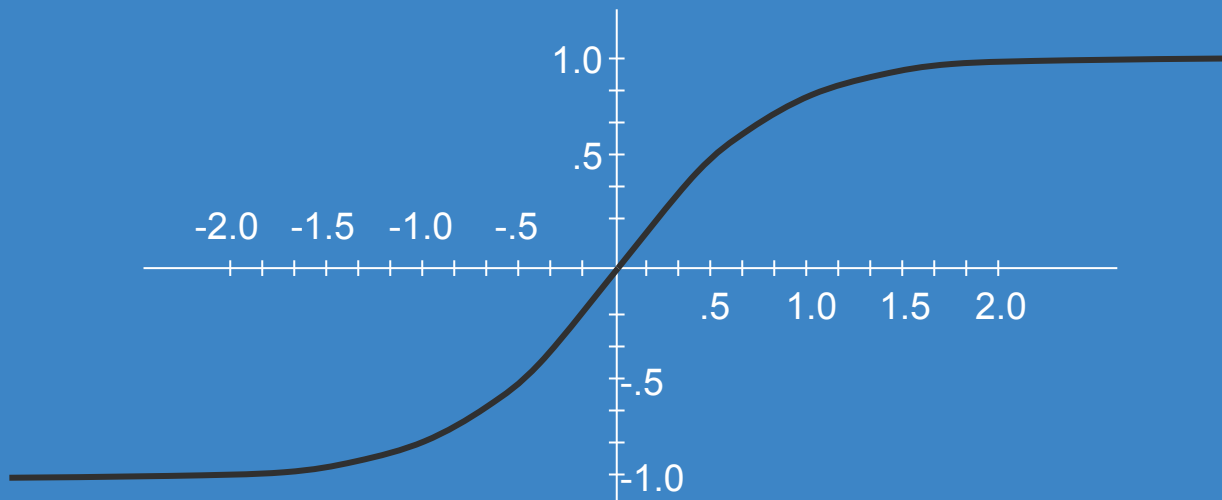
new information



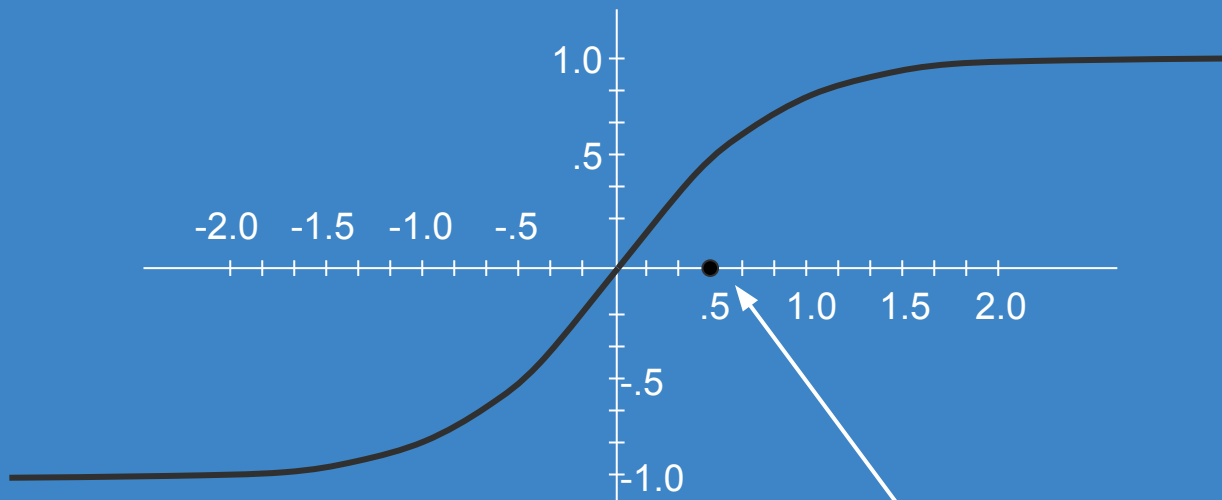
# recurrent t neural network



# Hyperbolic tangent (tanh) squashing function

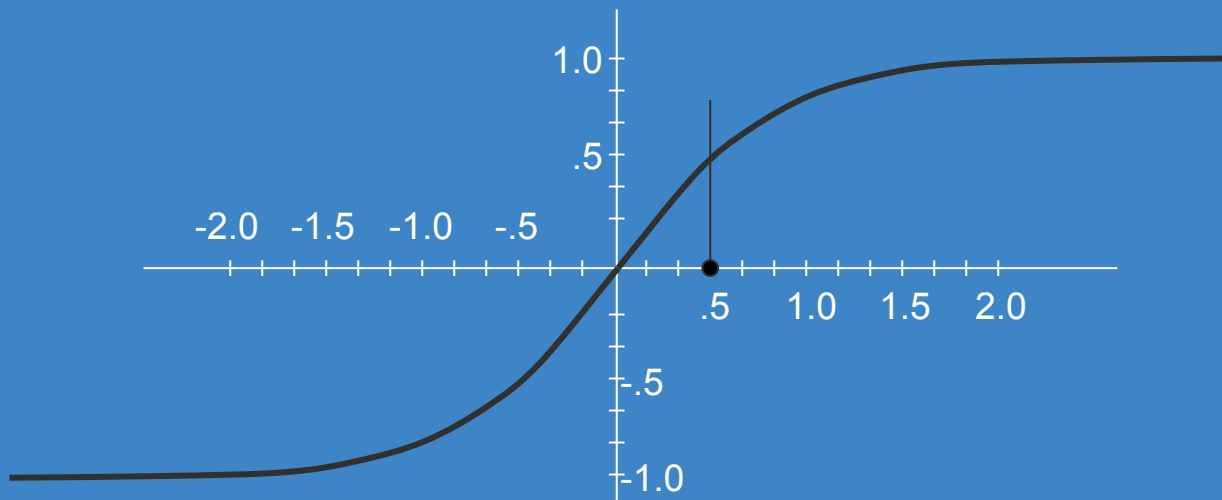


# tanh squashing function

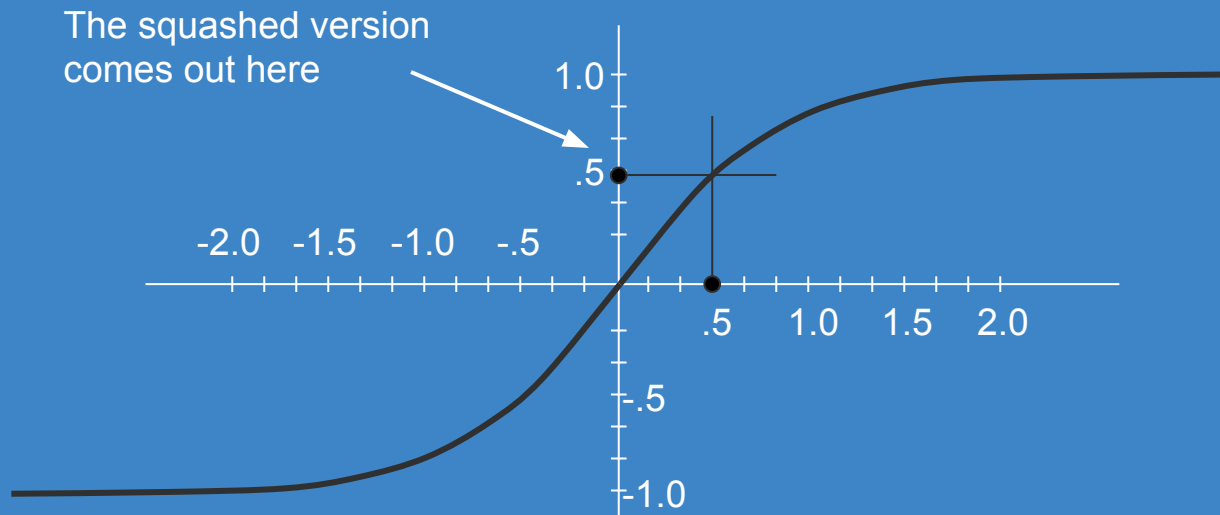


Your number goes in here

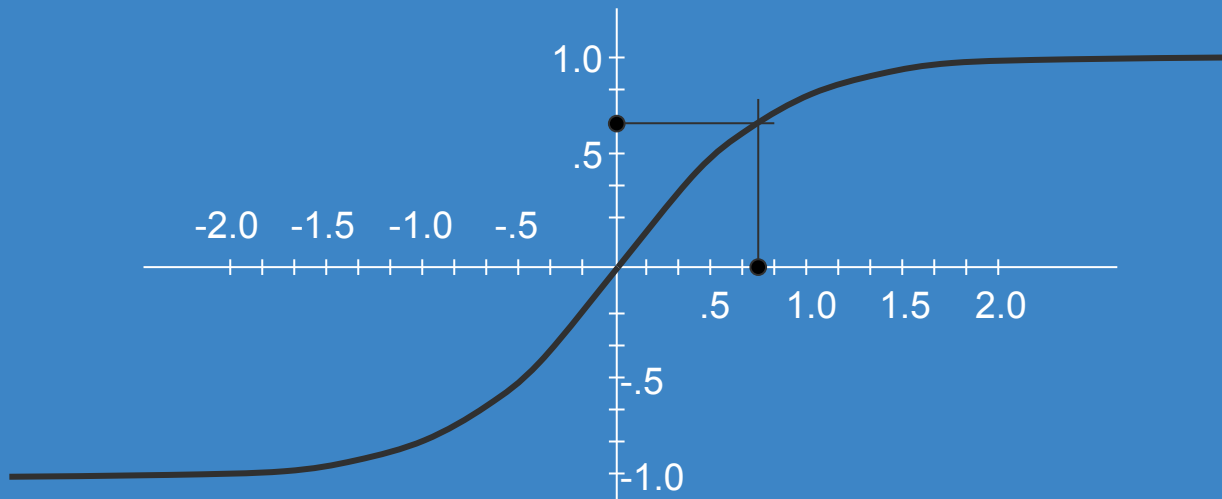
# tanh squashing function



# tanh squashing function

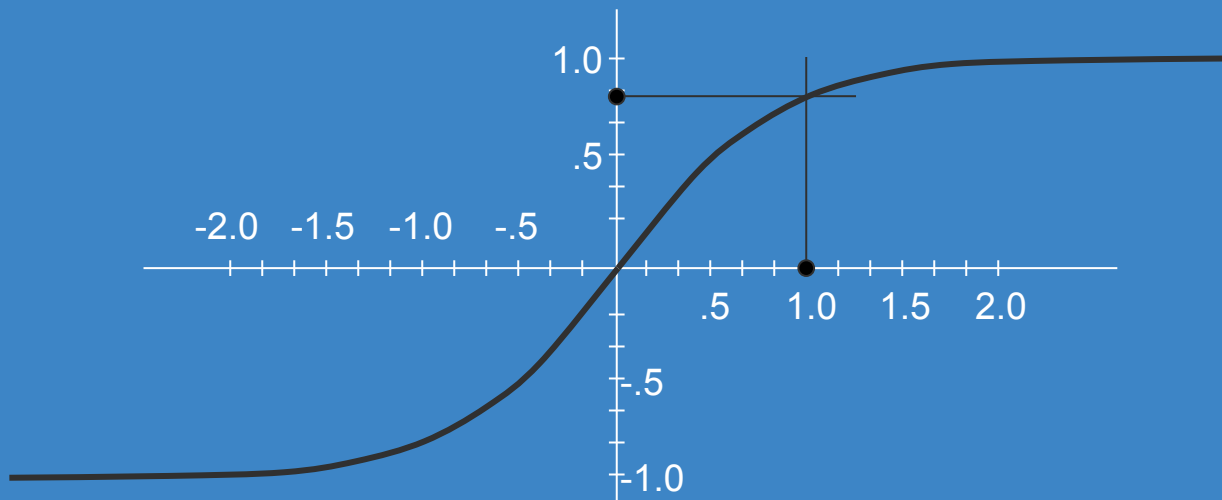


# tanh squashing function

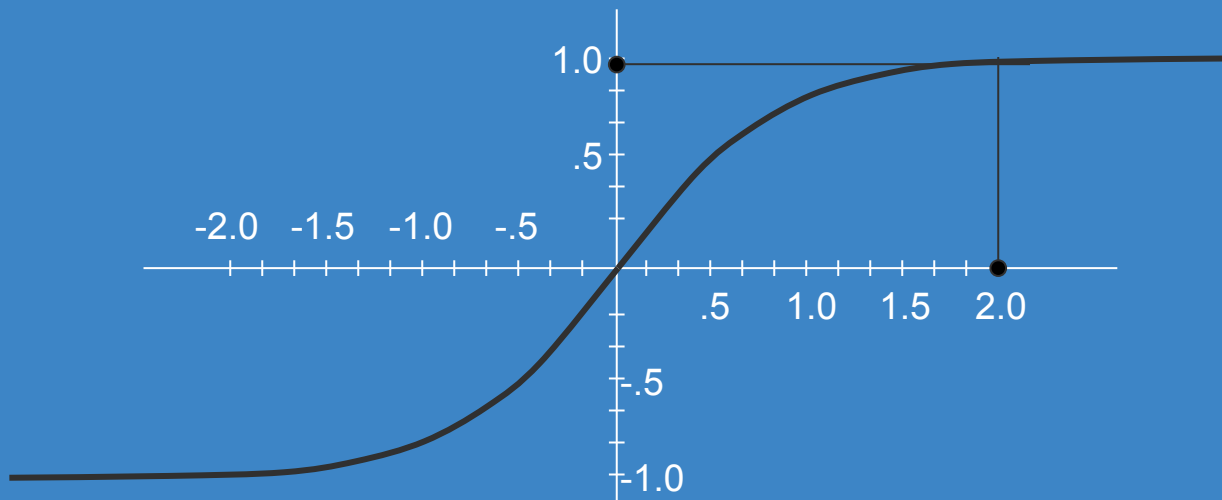




# tanh squashing function

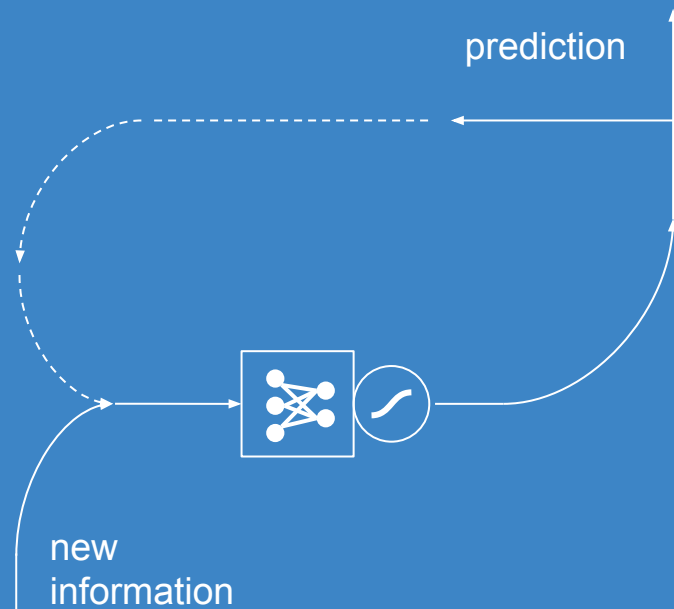


# tanh squashing function



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

# recurrent neural network



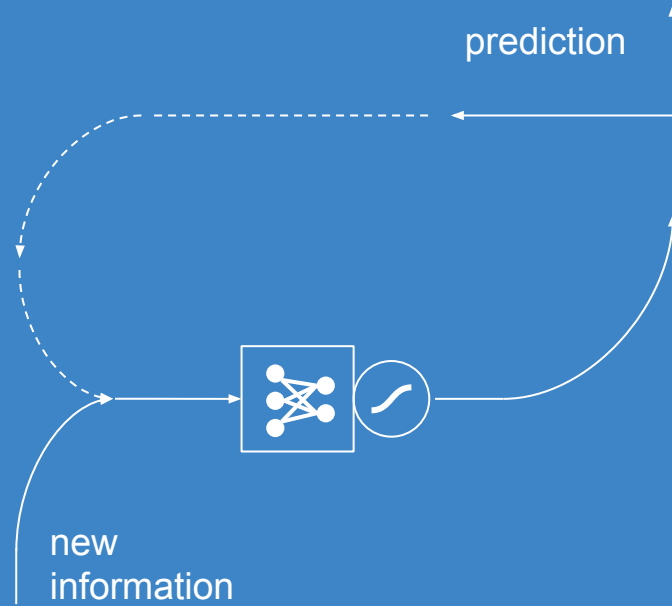
# Mistakes an RNN can make

Doug saw Doug.

Jane saw Spot saw Doug saw ...

Spot. Doug. Jane.

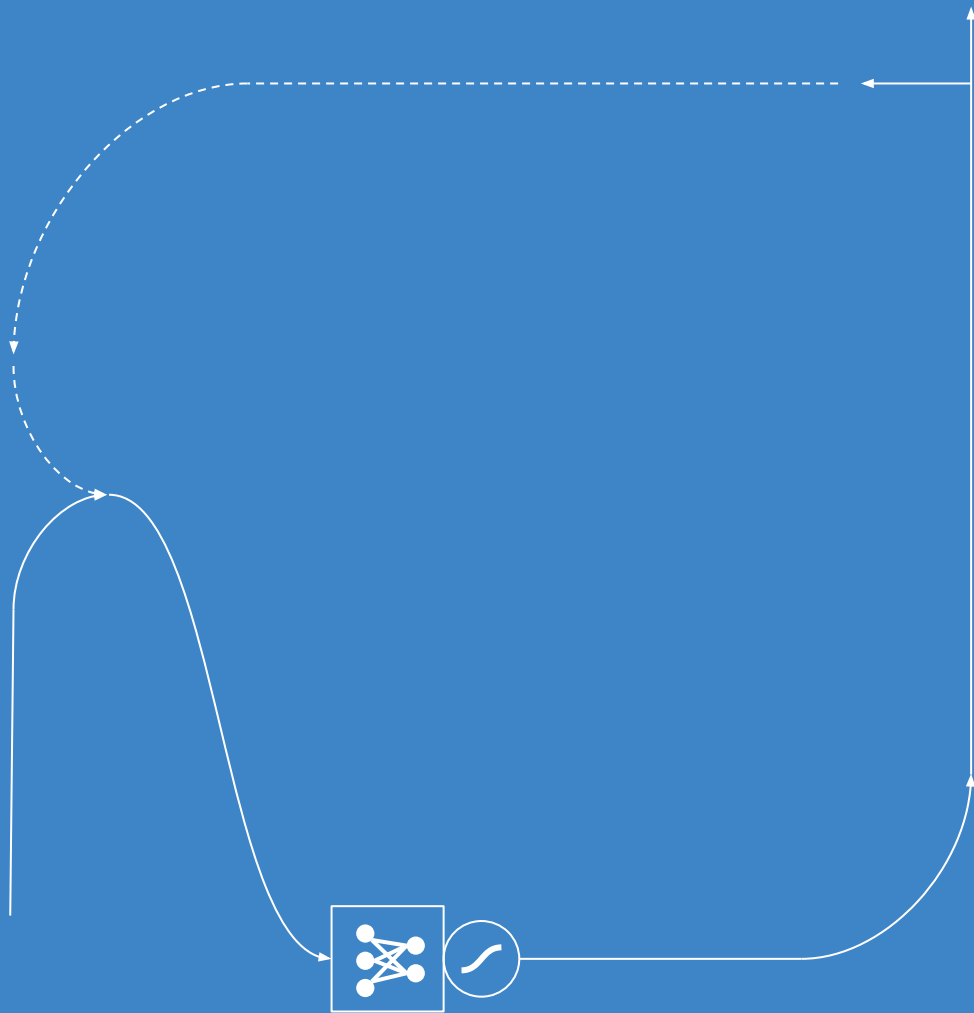
# recurrent neural network



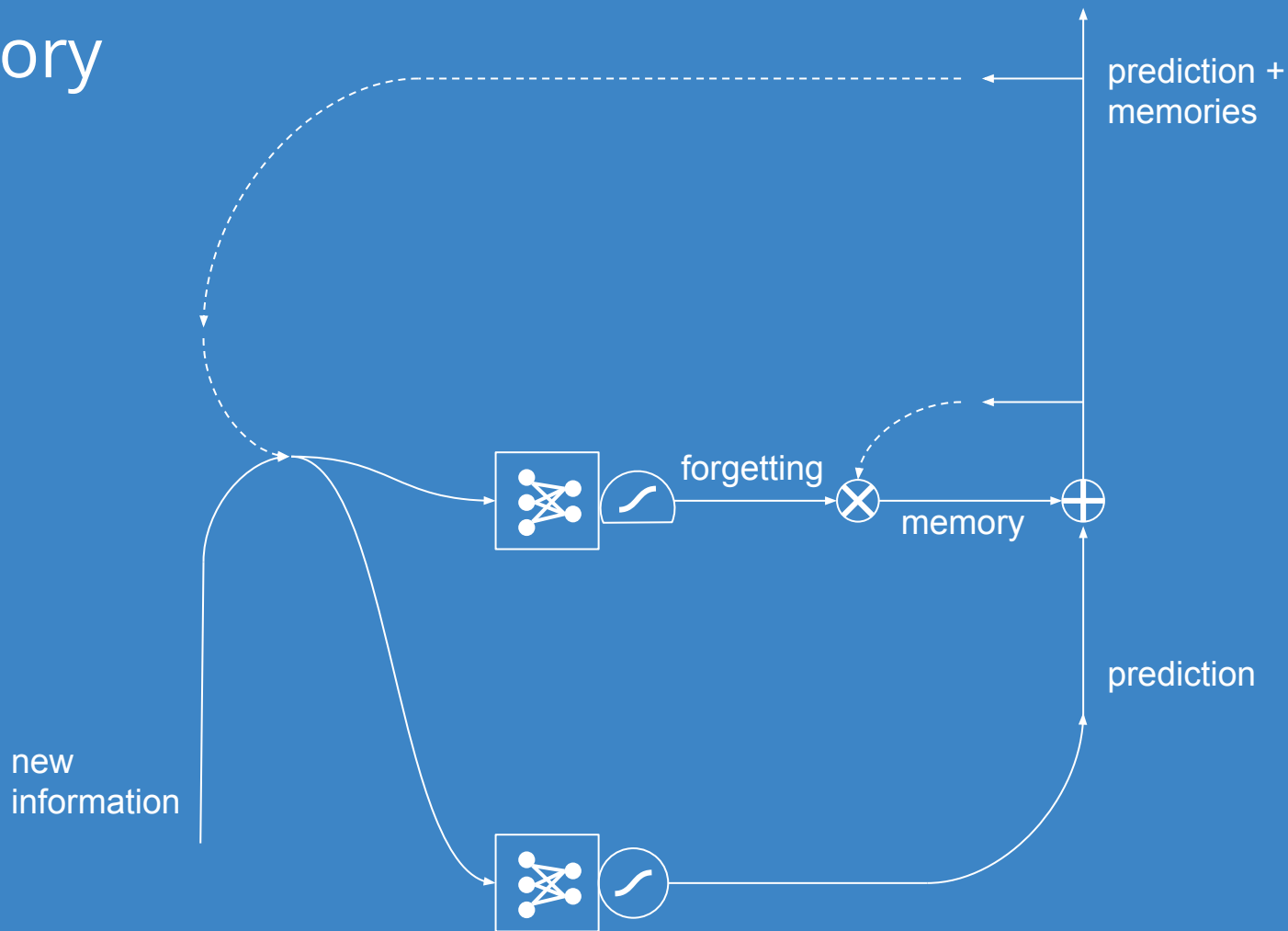
# recurrent neural network

new  
information

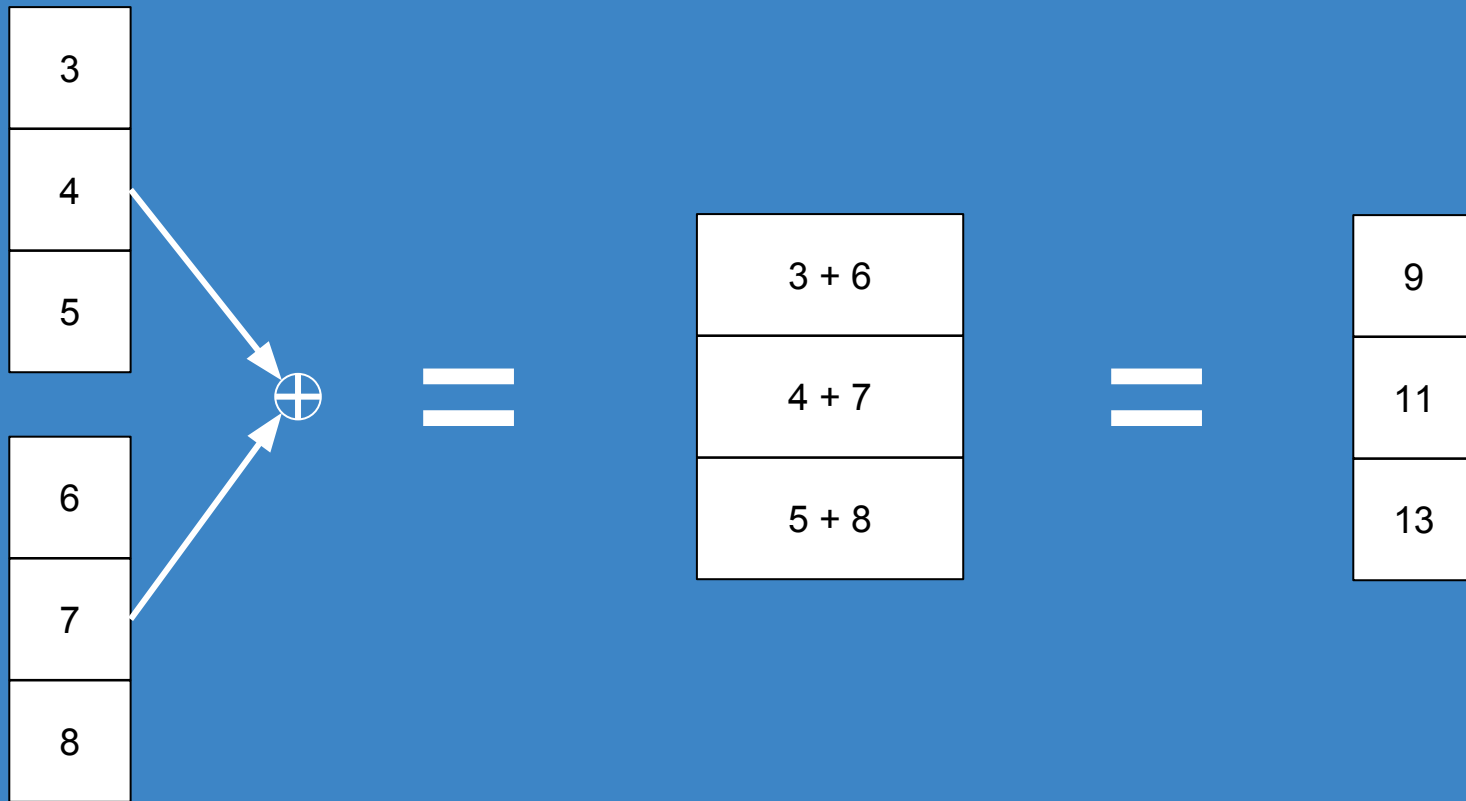
prediction



# memory

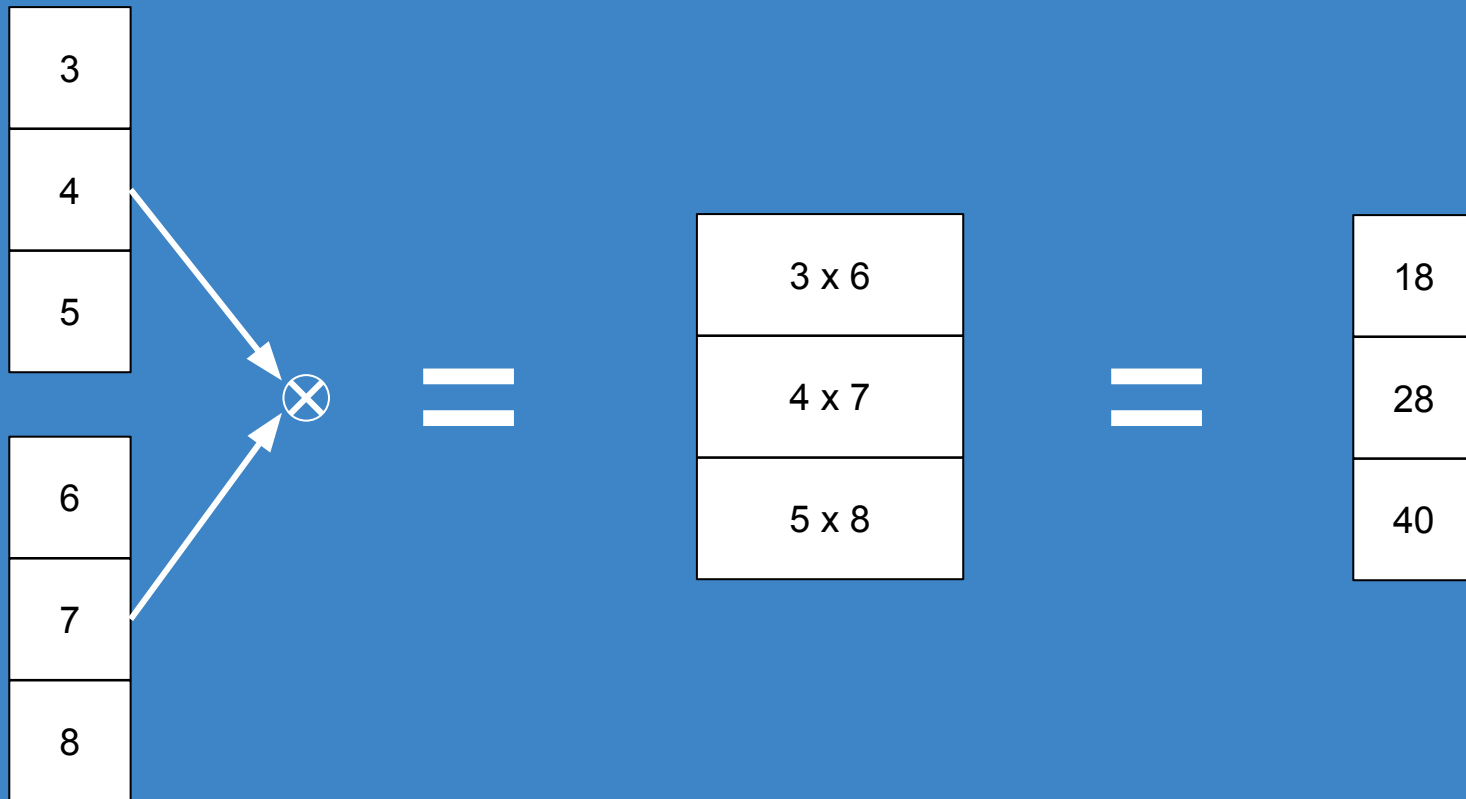


# Plus junction: element-by-element addition

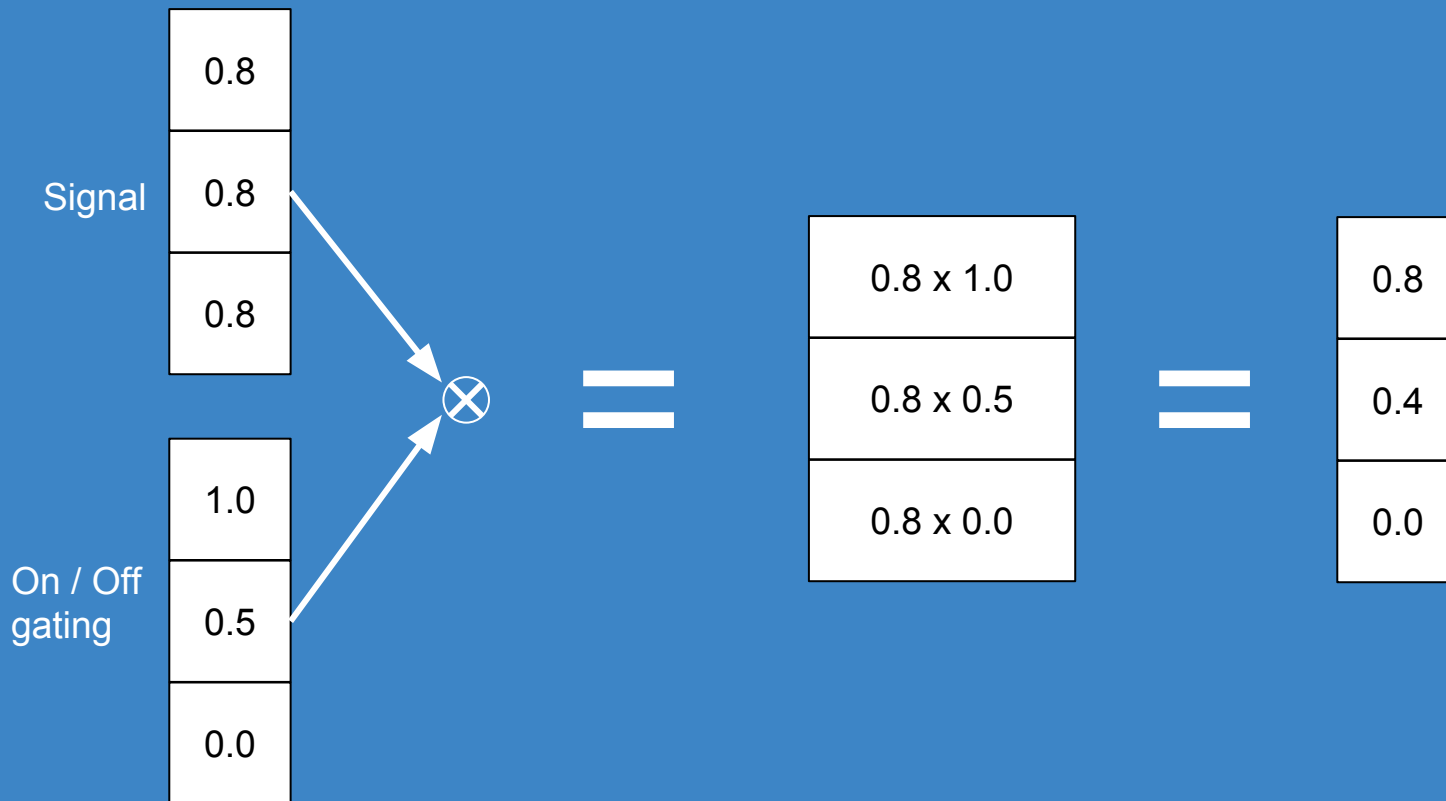




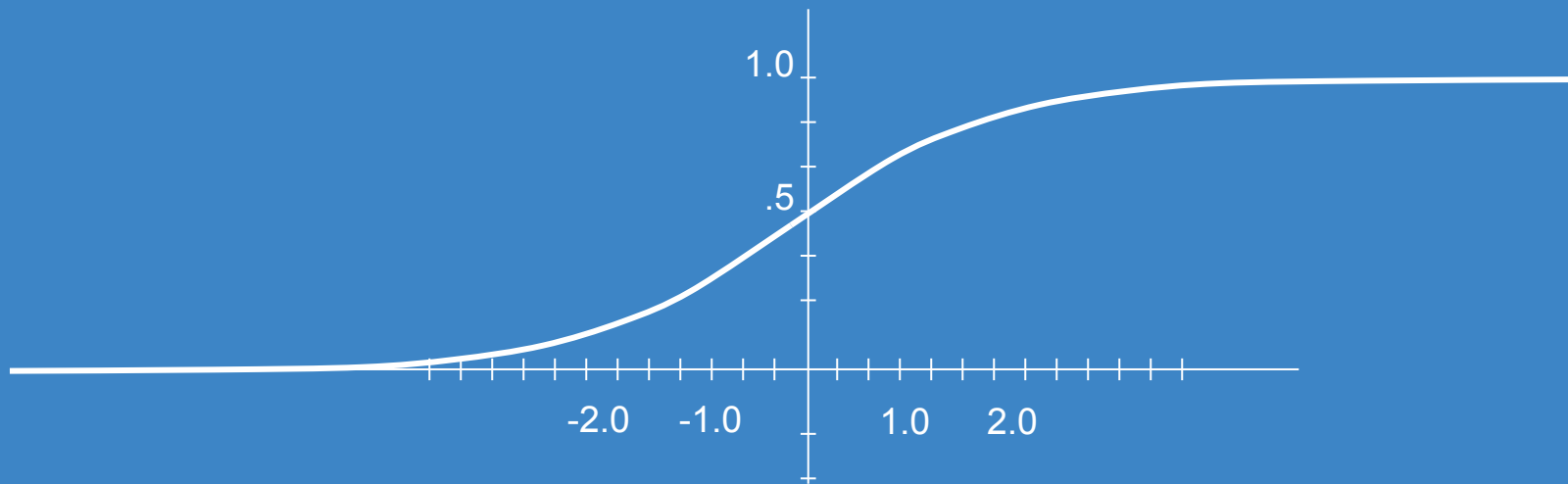
# Times junction: element-by-element multiplication



# Gating

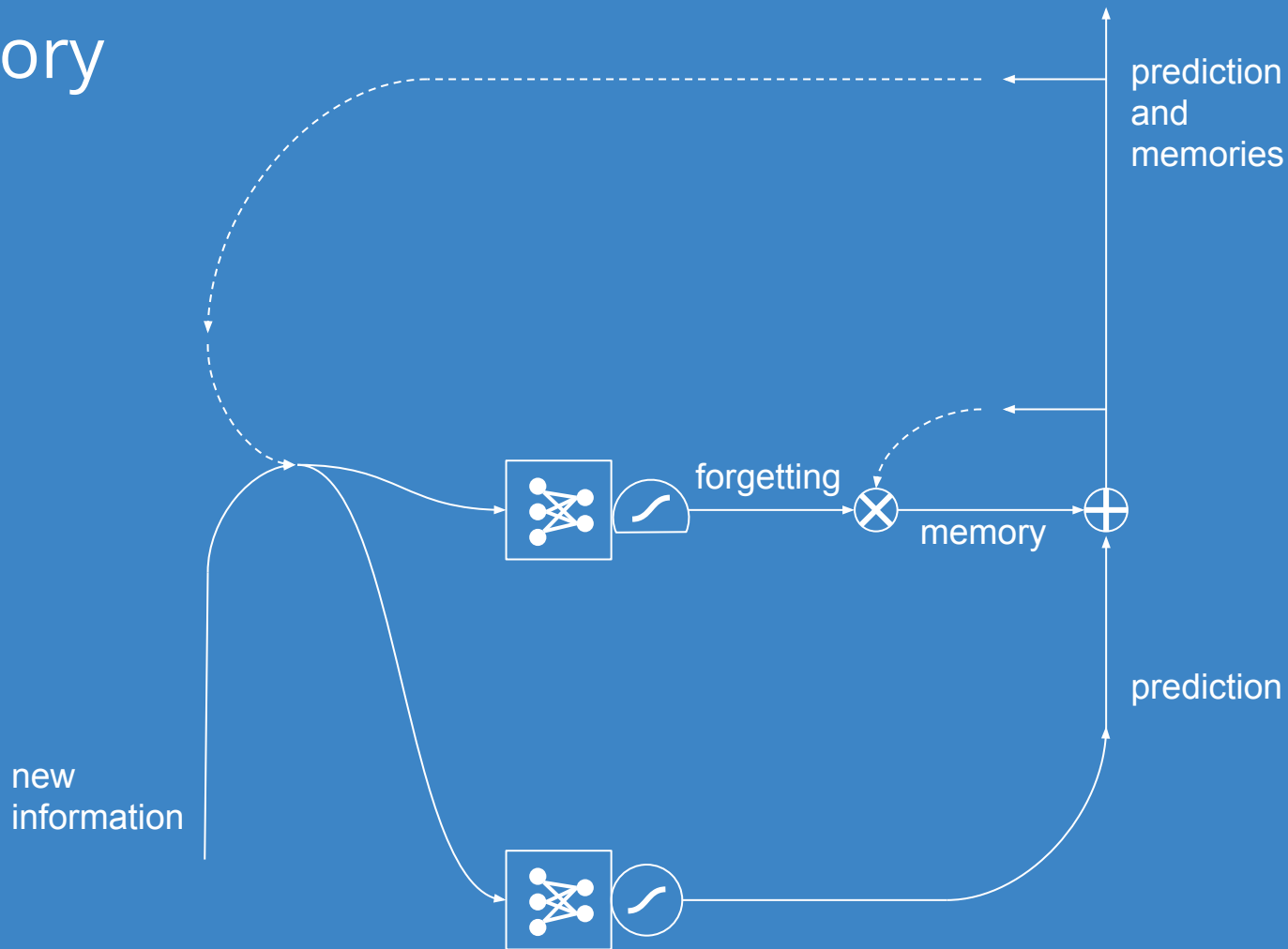


# Logistic (sigmoid) squashing function

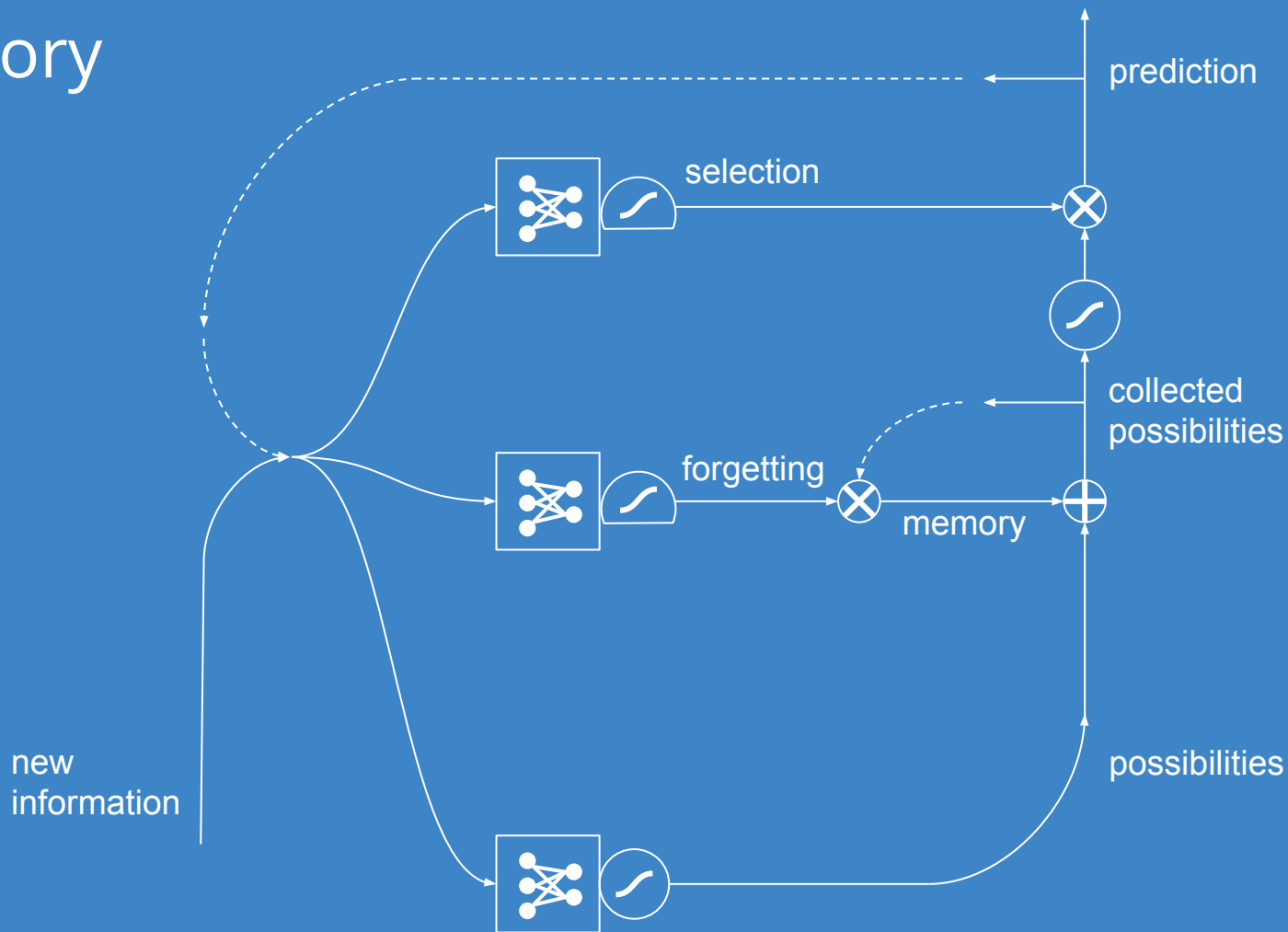


No matter what you start with, the answer stays between 0 and 1.

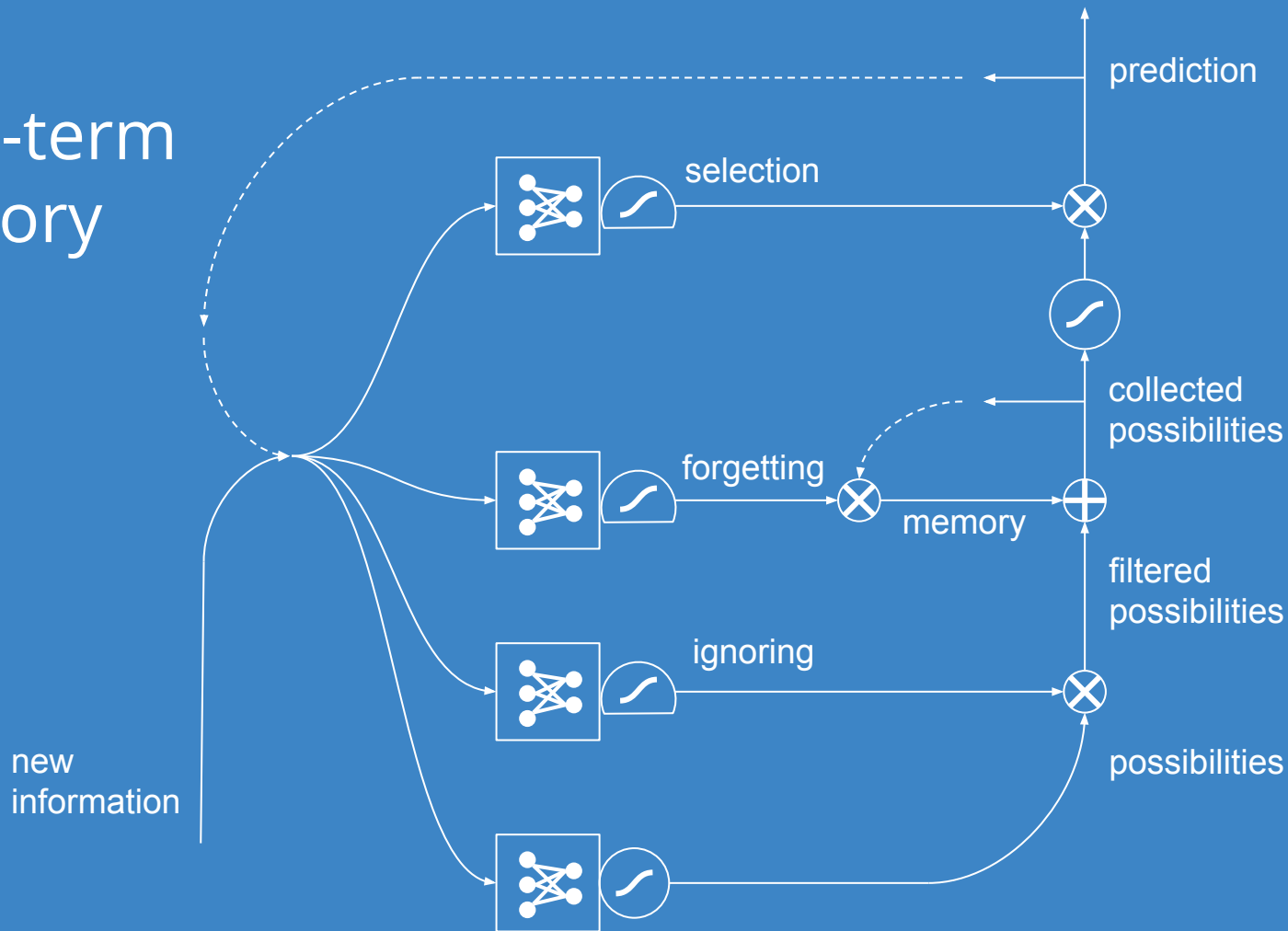
# memory



# memory

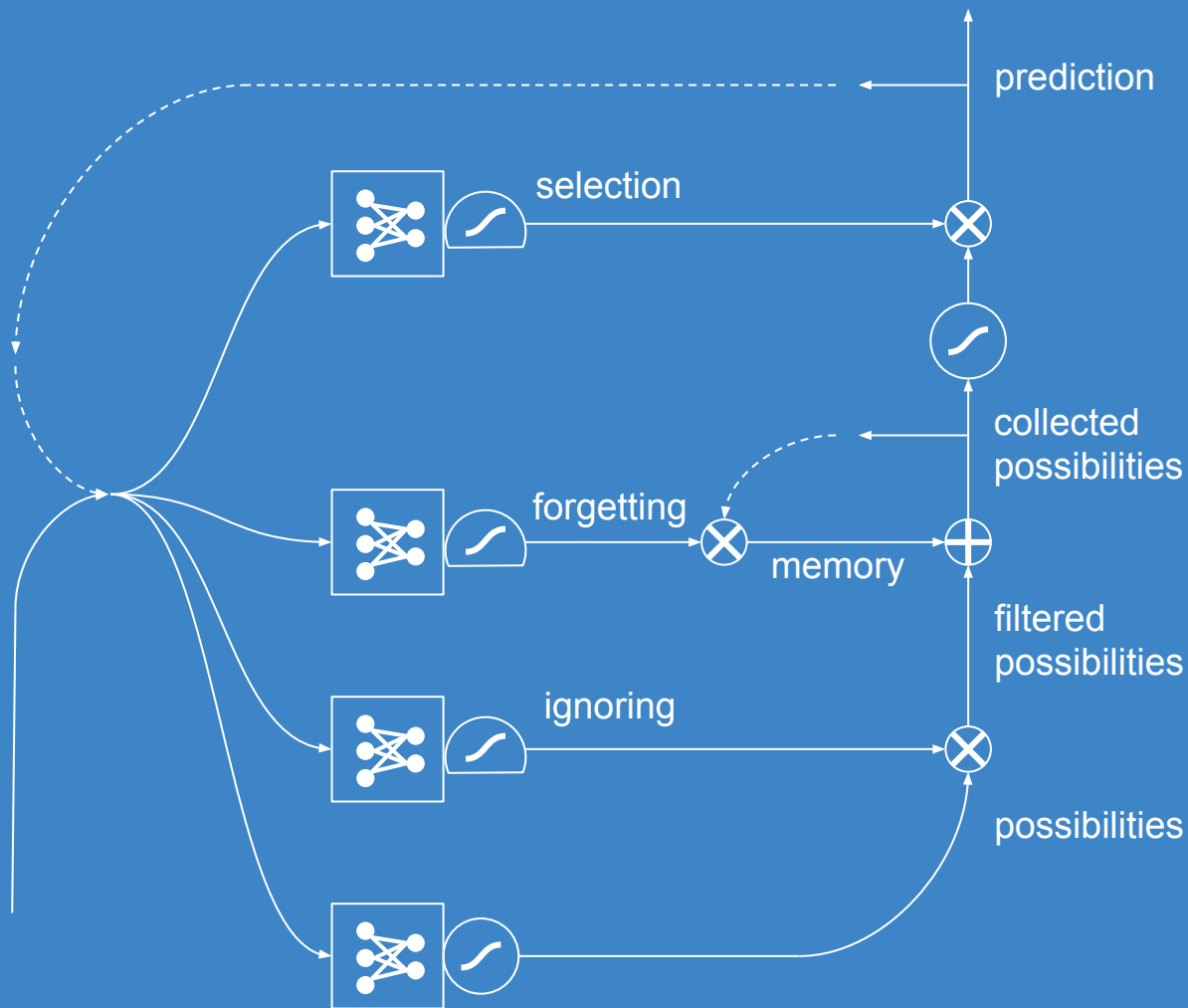


# long short-term memory



# long short-term memory

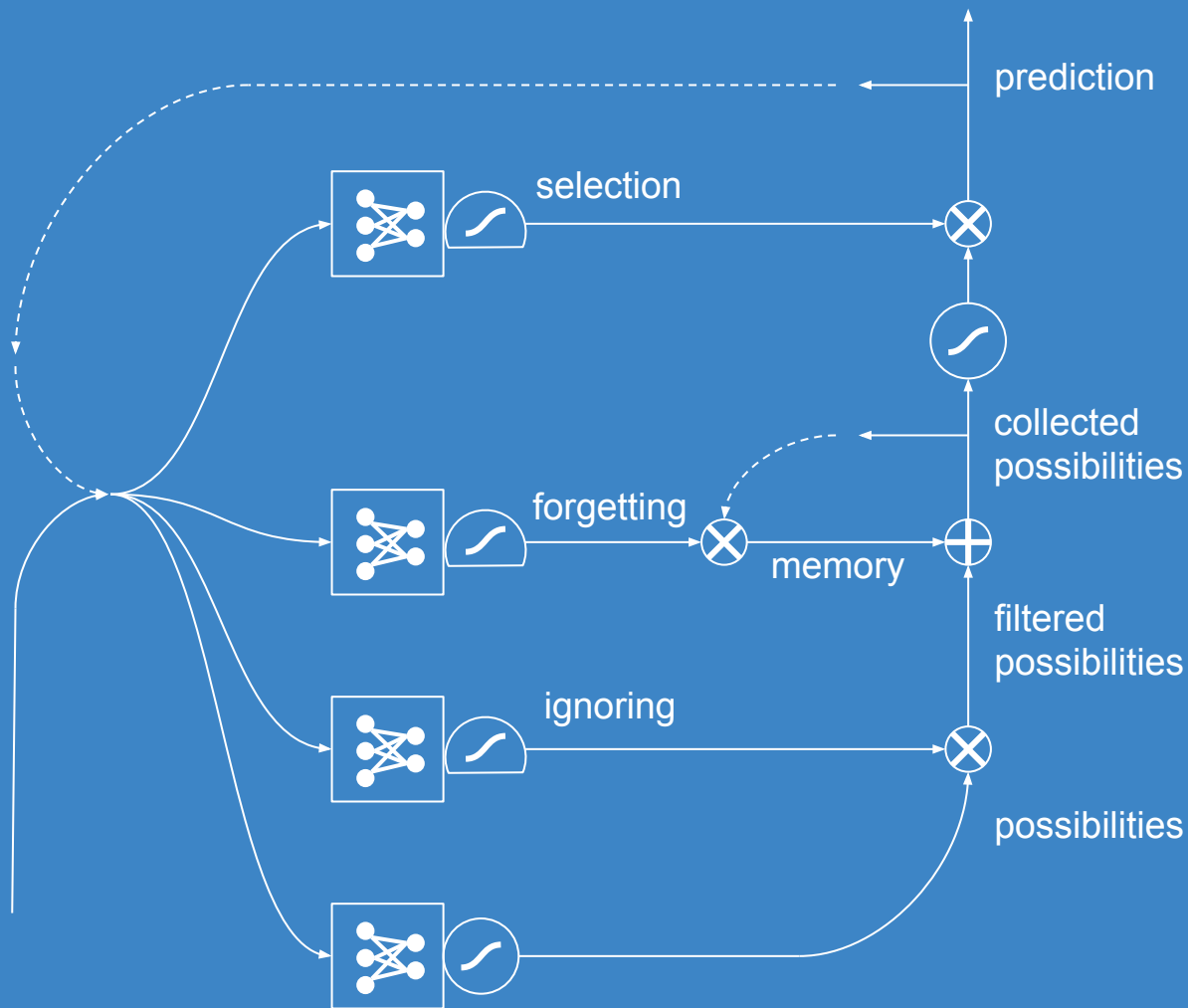
Jane saw Spot.  
Doug ...



# long short-term memory

Doug,  
Jane,  
Spot

Jane saw Spot.  
Doug ...

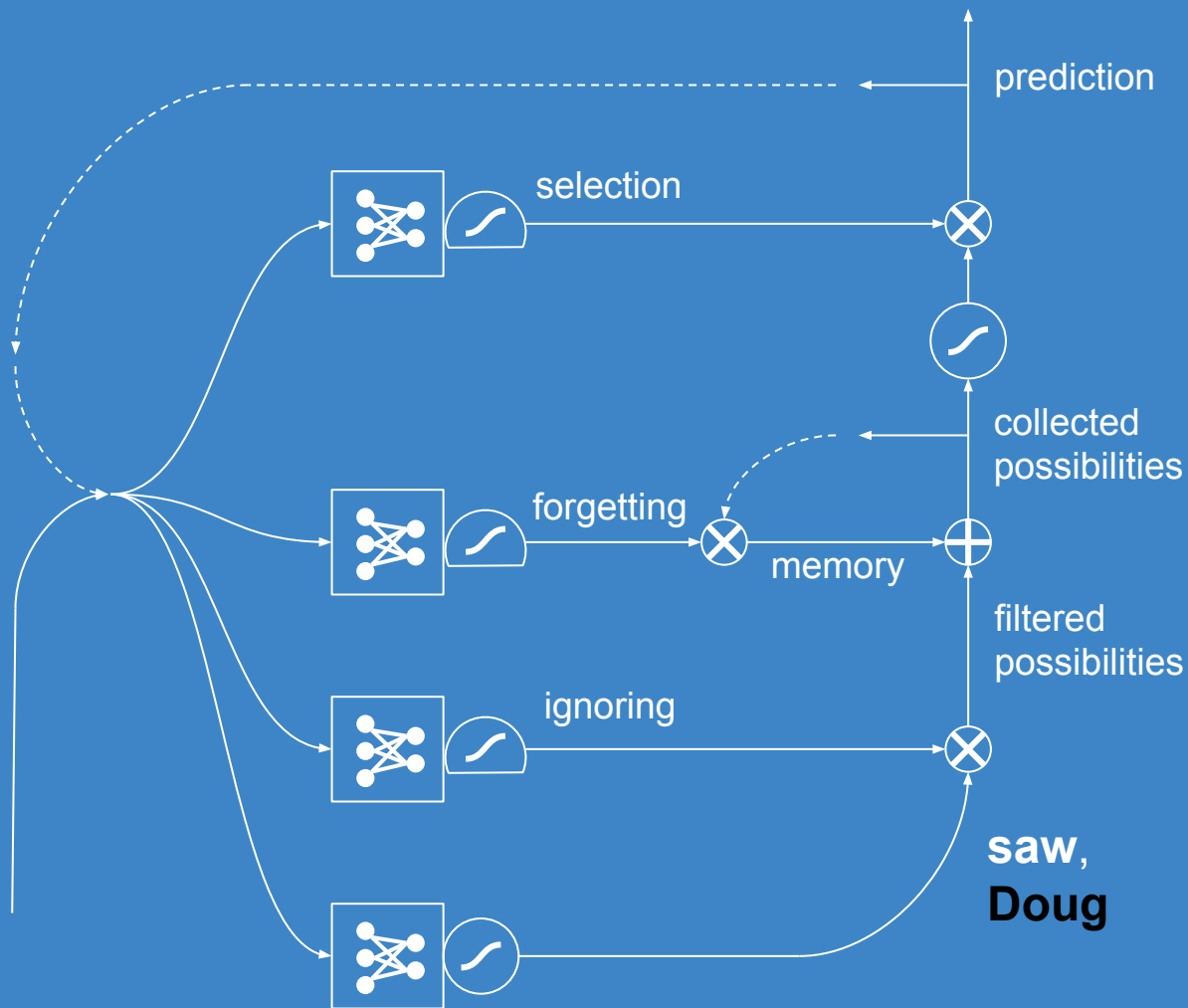




long  
short-term  
memory

Doug,  
Jane,  
Spot

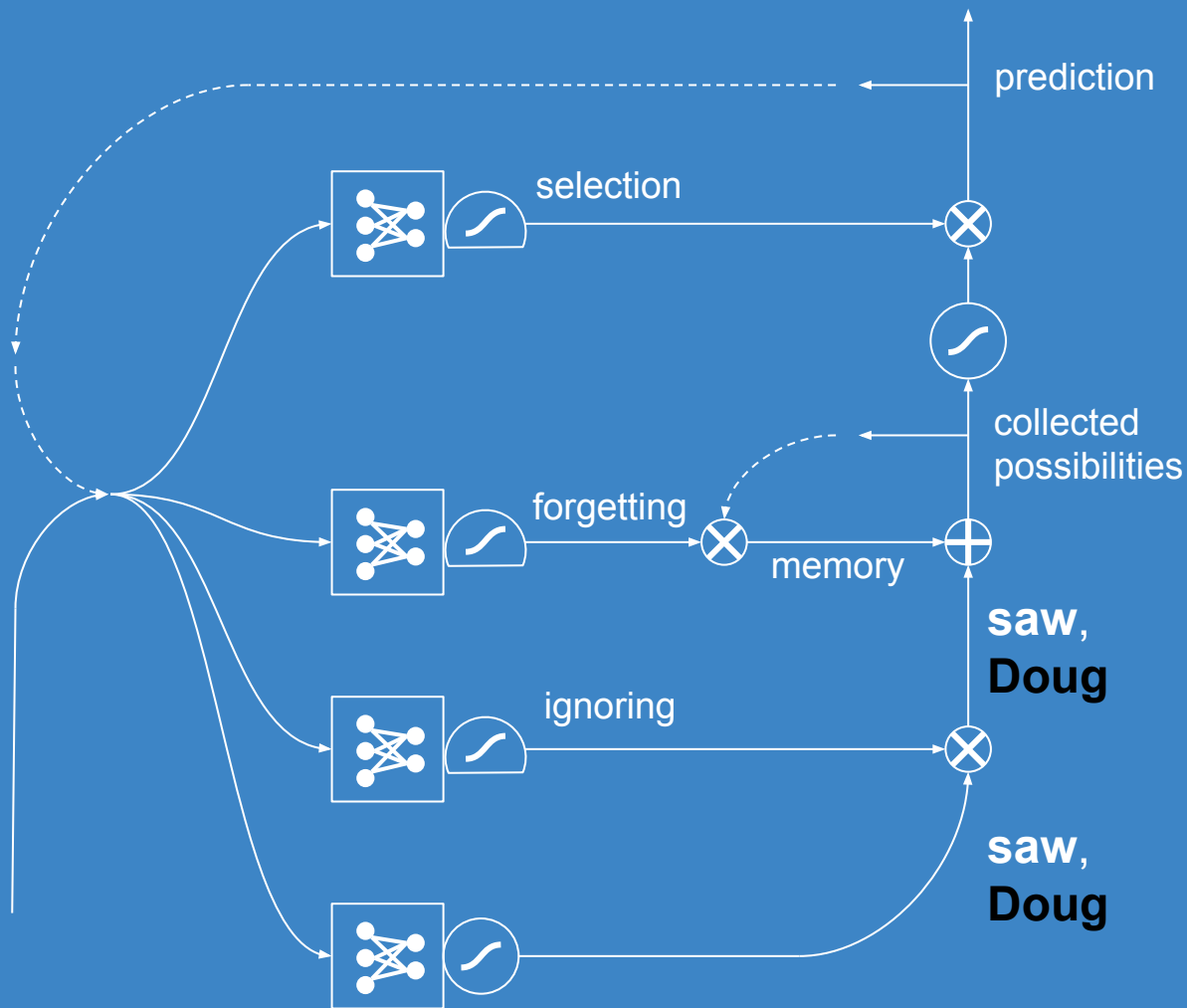
Jane saw Spot.  
Doug ...



long  
short-term  
memory

Doug,  
Jane,  
Spot

Jane saw Spot.  
Doug ...

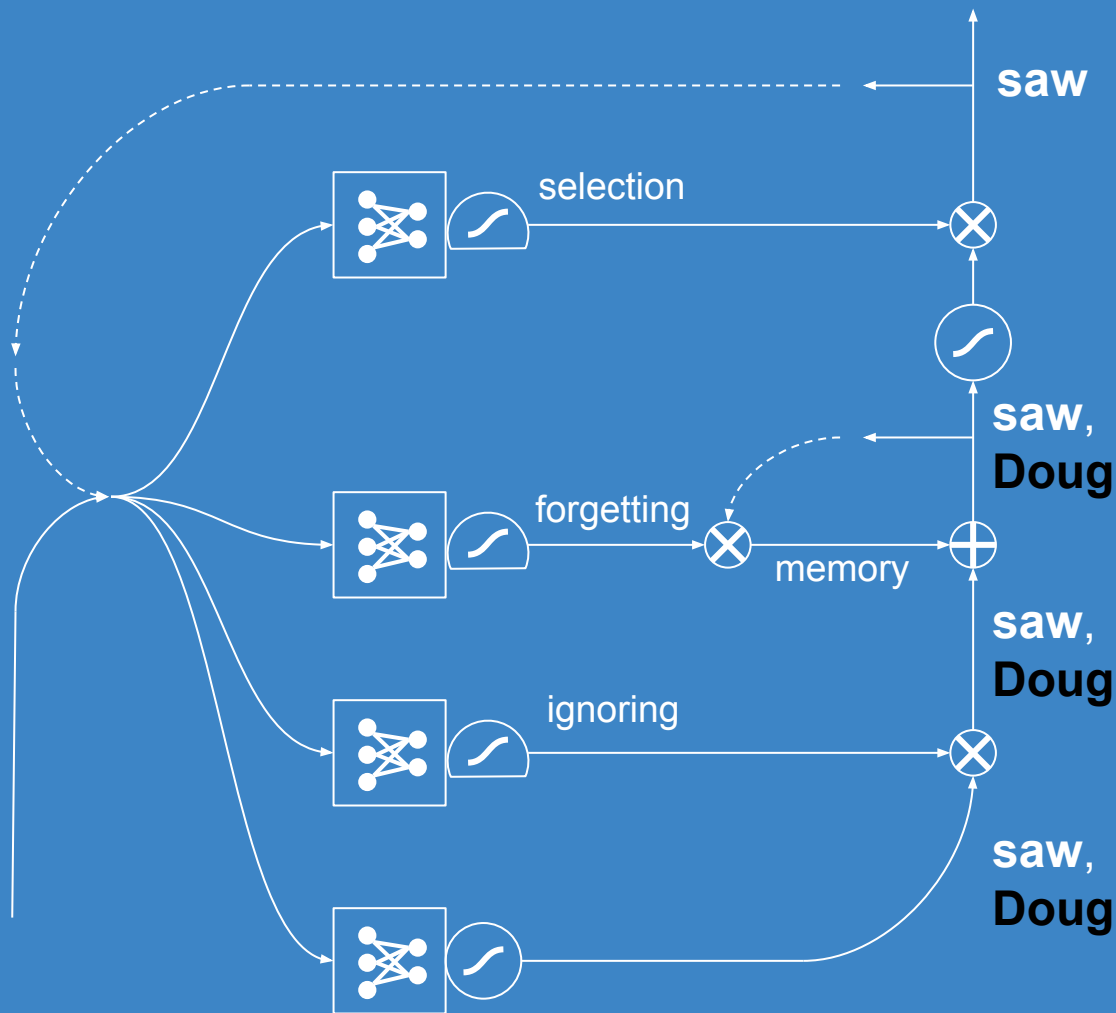




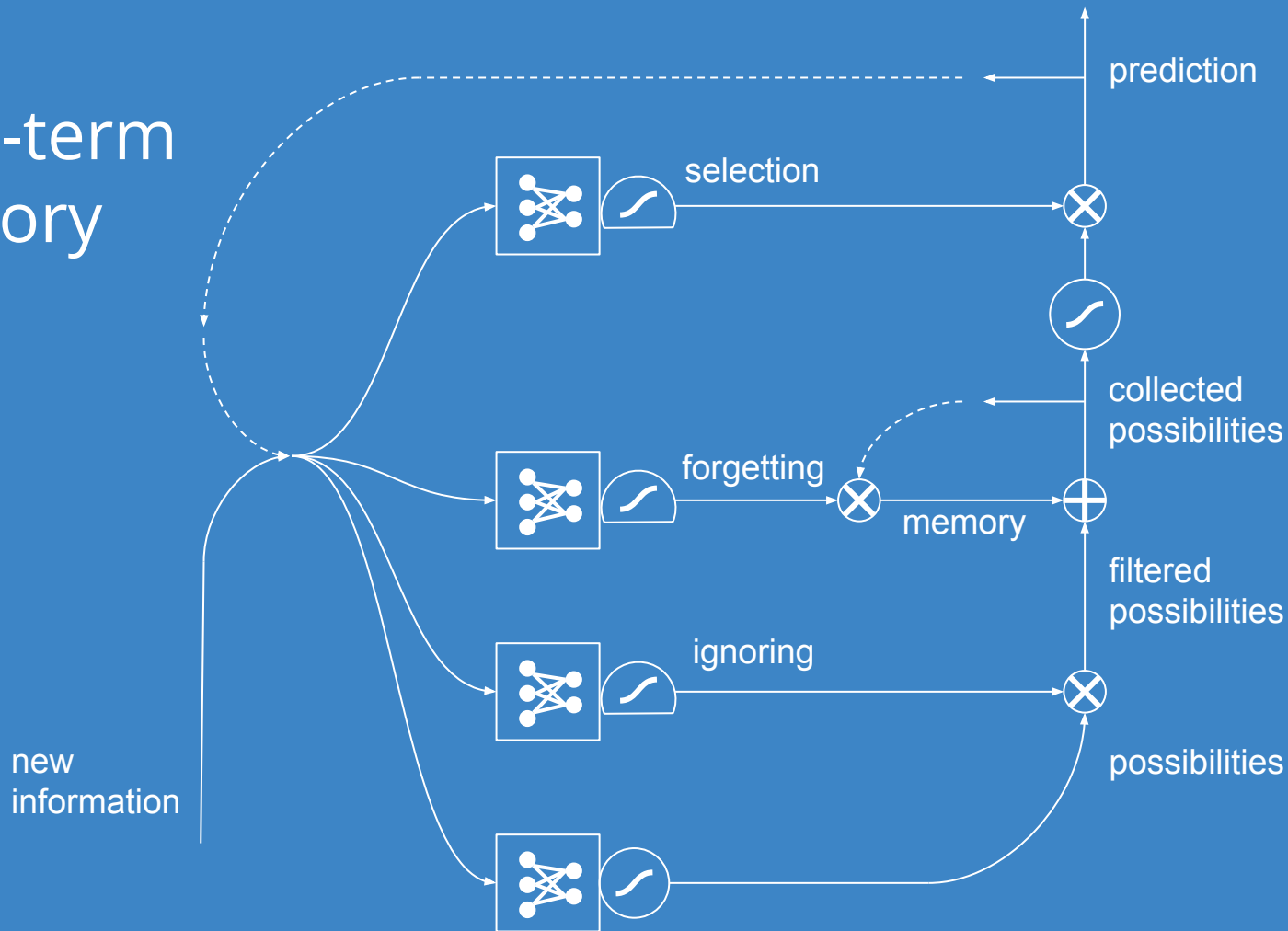
long  
short-term  
memory

Doug,  
Jane,  
Spot

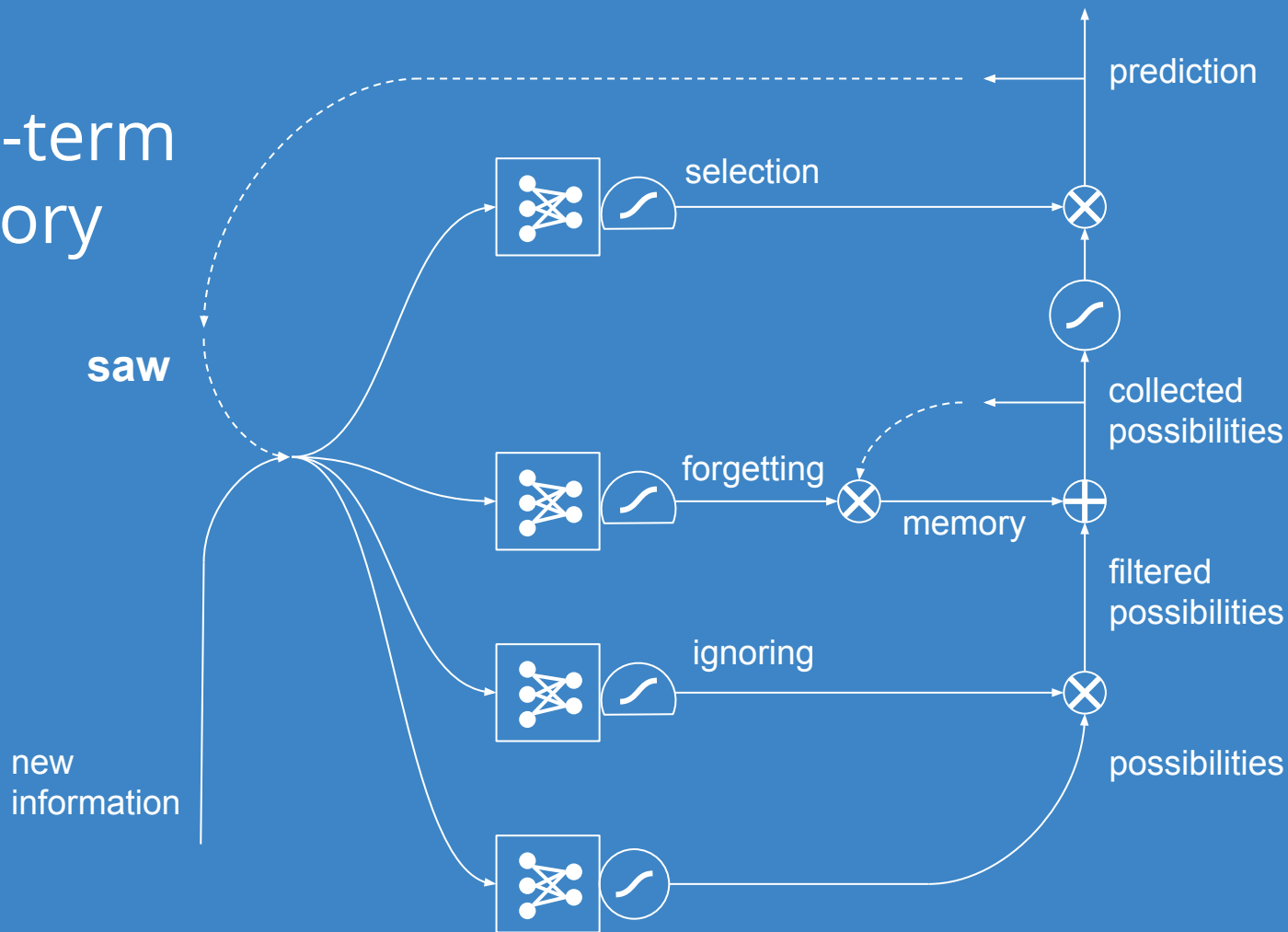
Jane saw Spot.  
Doug ...



# long short-term memory



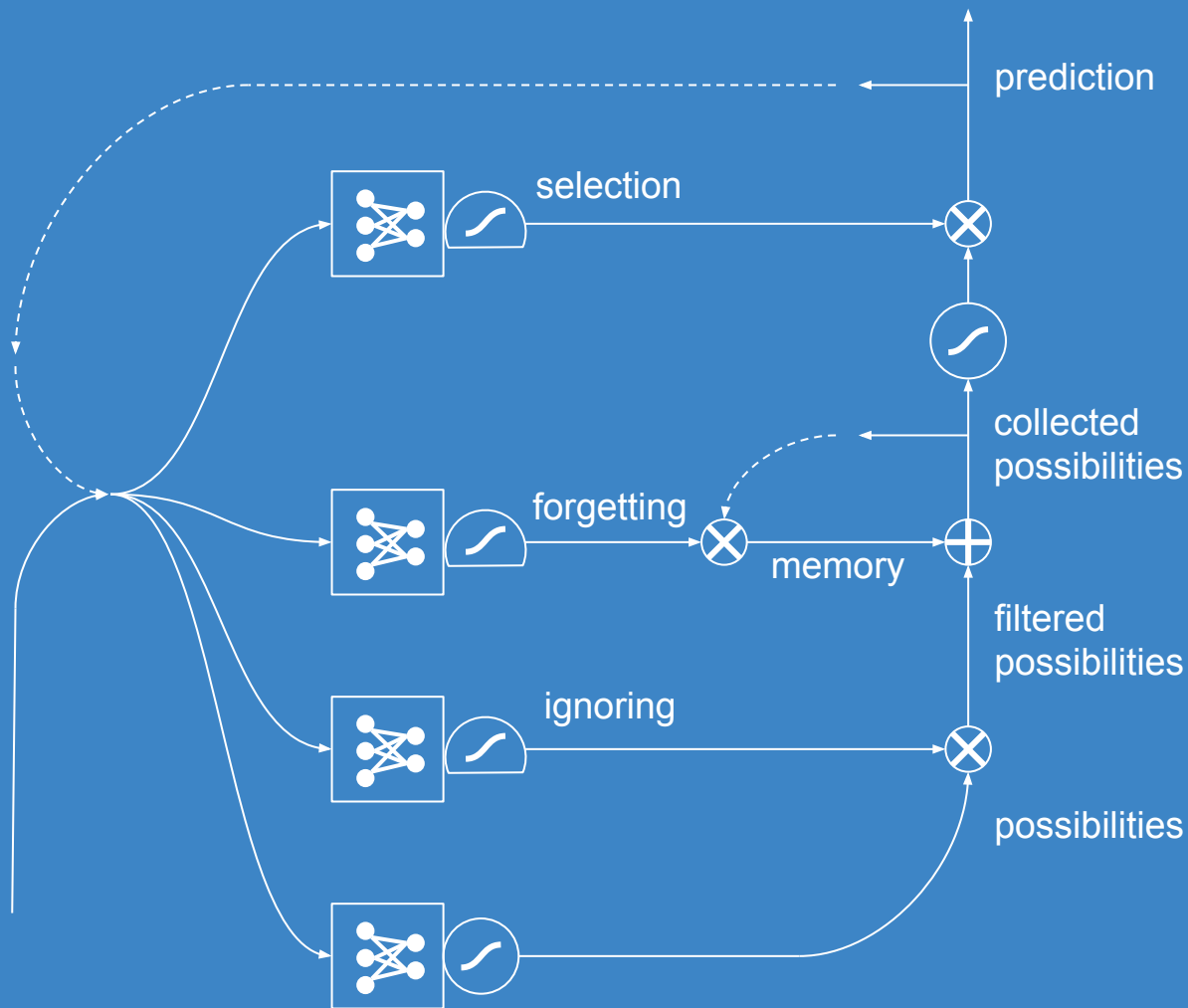
# long short-term memory



# long short-term memory

saw

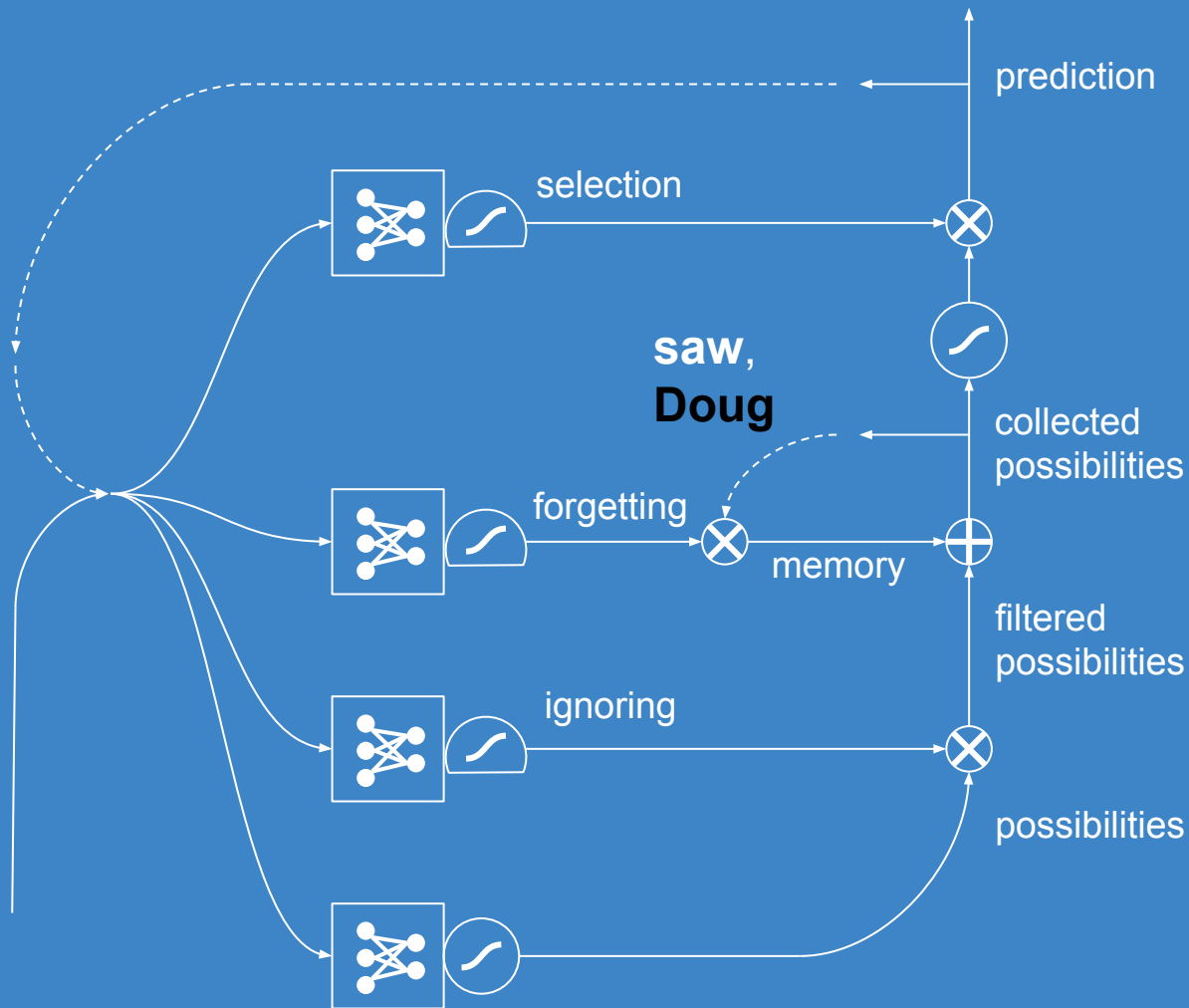
Jane saw Spot.  
Doug saw ...



# long short-term memory

Jane saw Spot.  
Doug **saw** ...

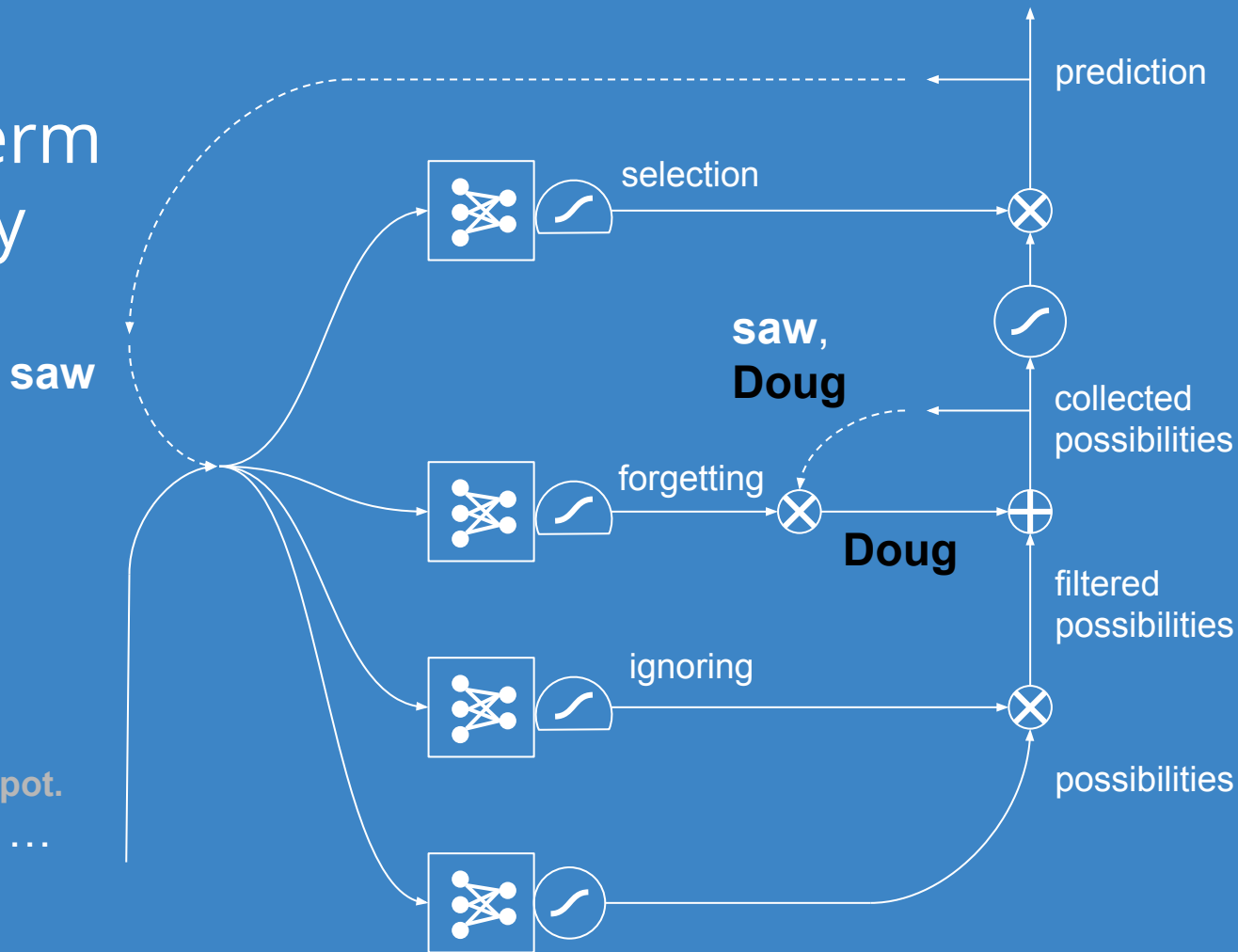
saw





# long short-term memory

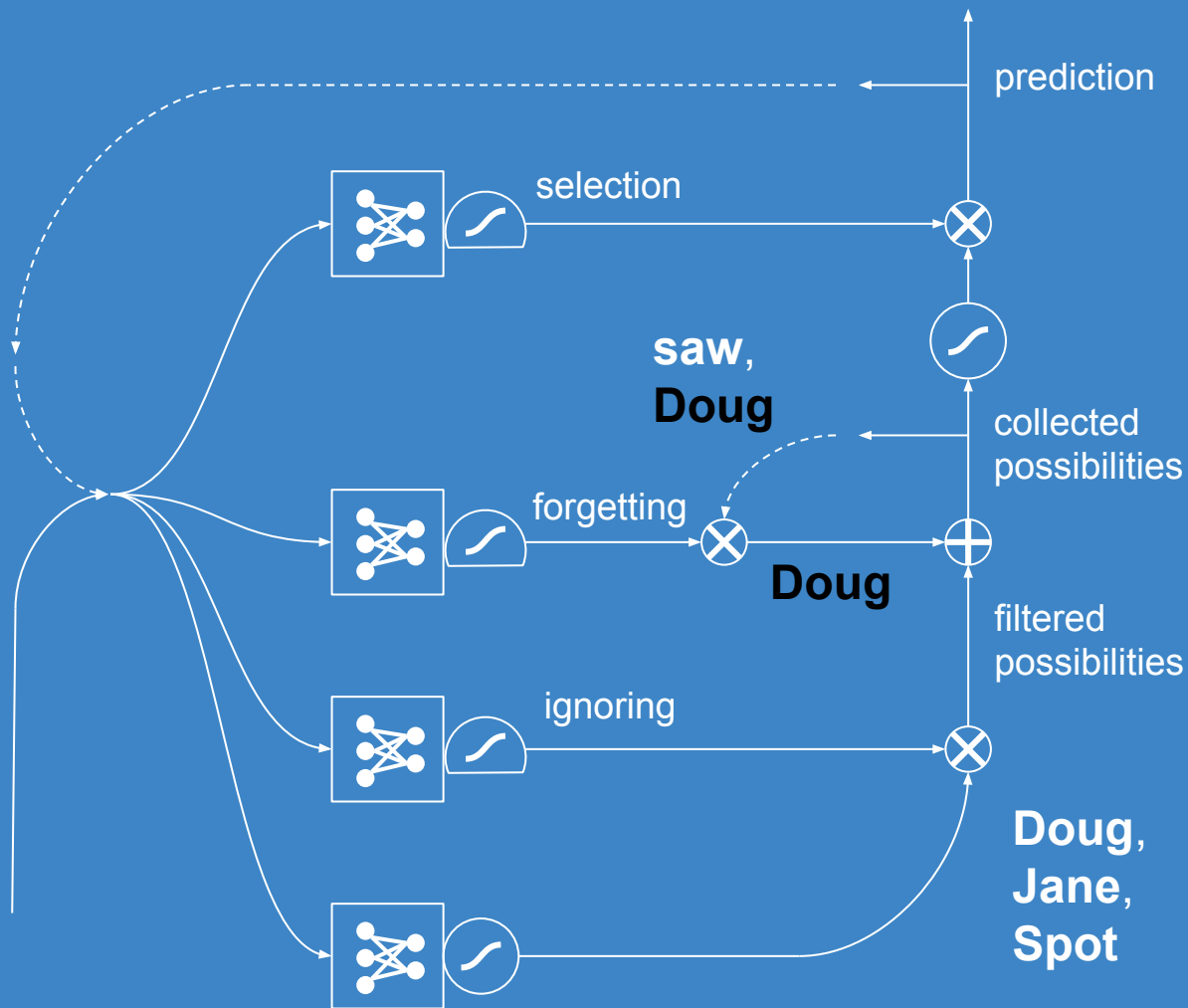
Jane saw Spot.  
Doug **saw** ...



# long short-term memory

Jane saw Spot.  
Doug **saw** ...

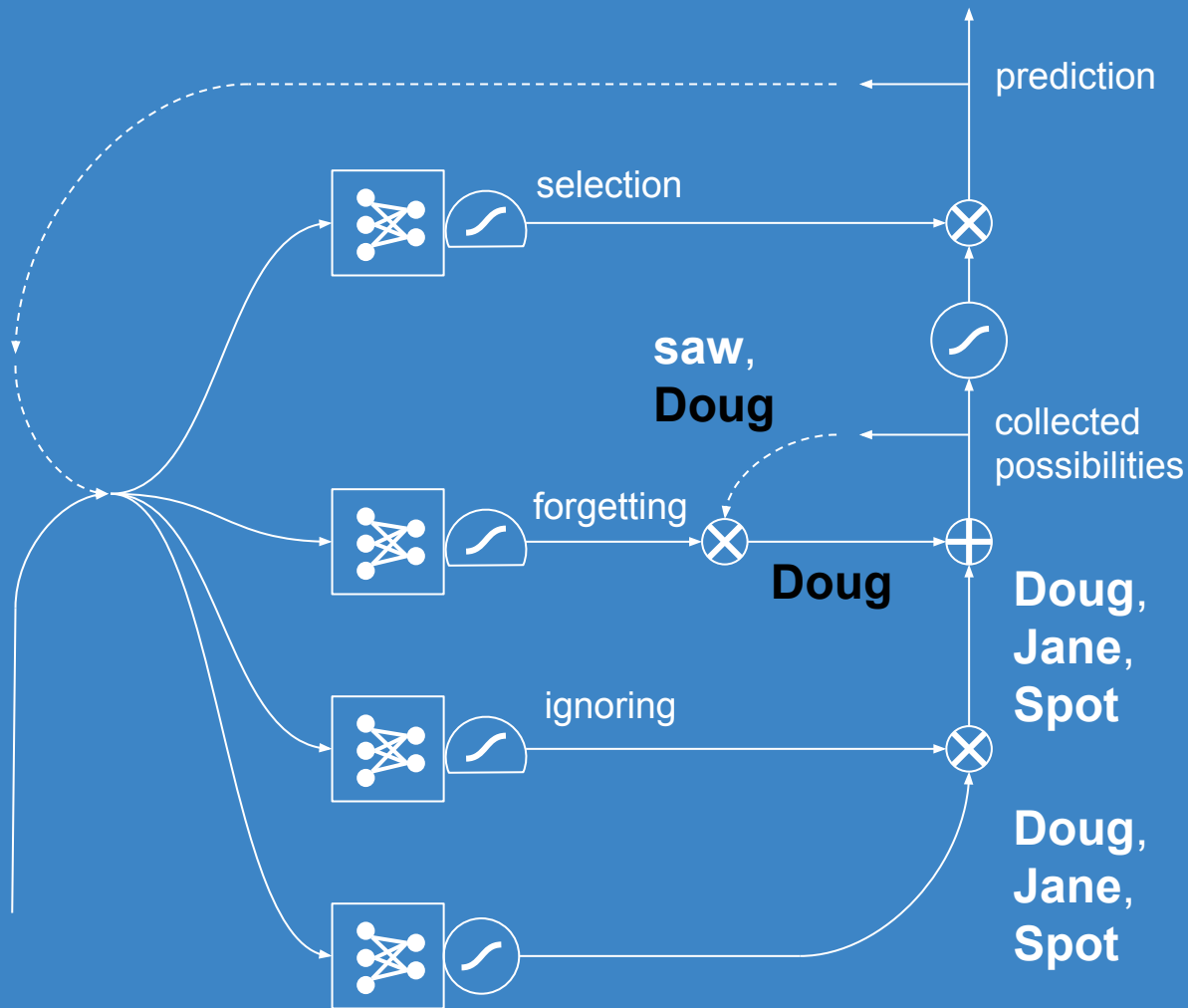
saw



long  
short-term  
memory

Jane saw Spot.  
Doug **saw** ...

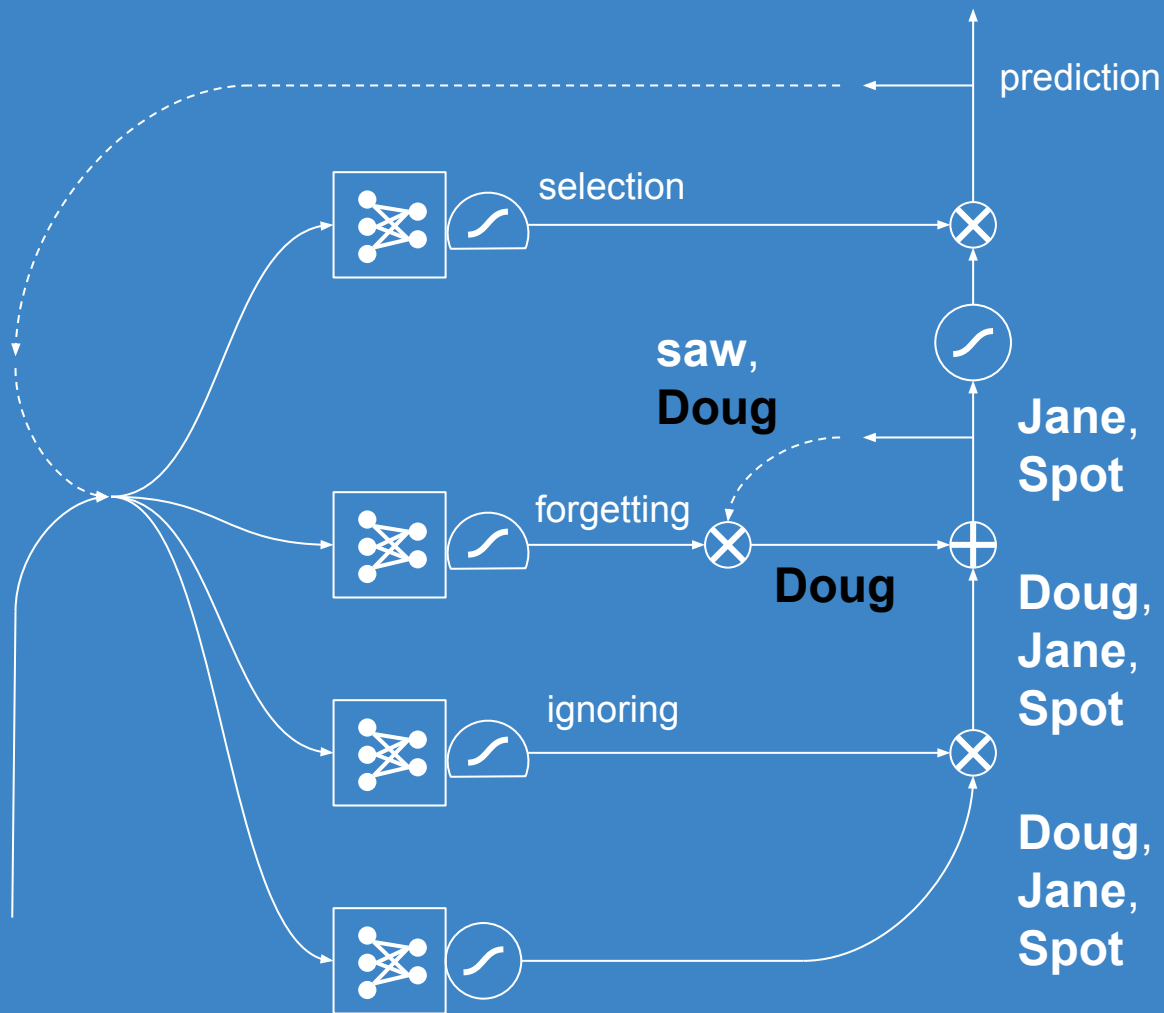
saw



long  
short-term  
memory

Jane saw Spot.  
Doug **saw** ...

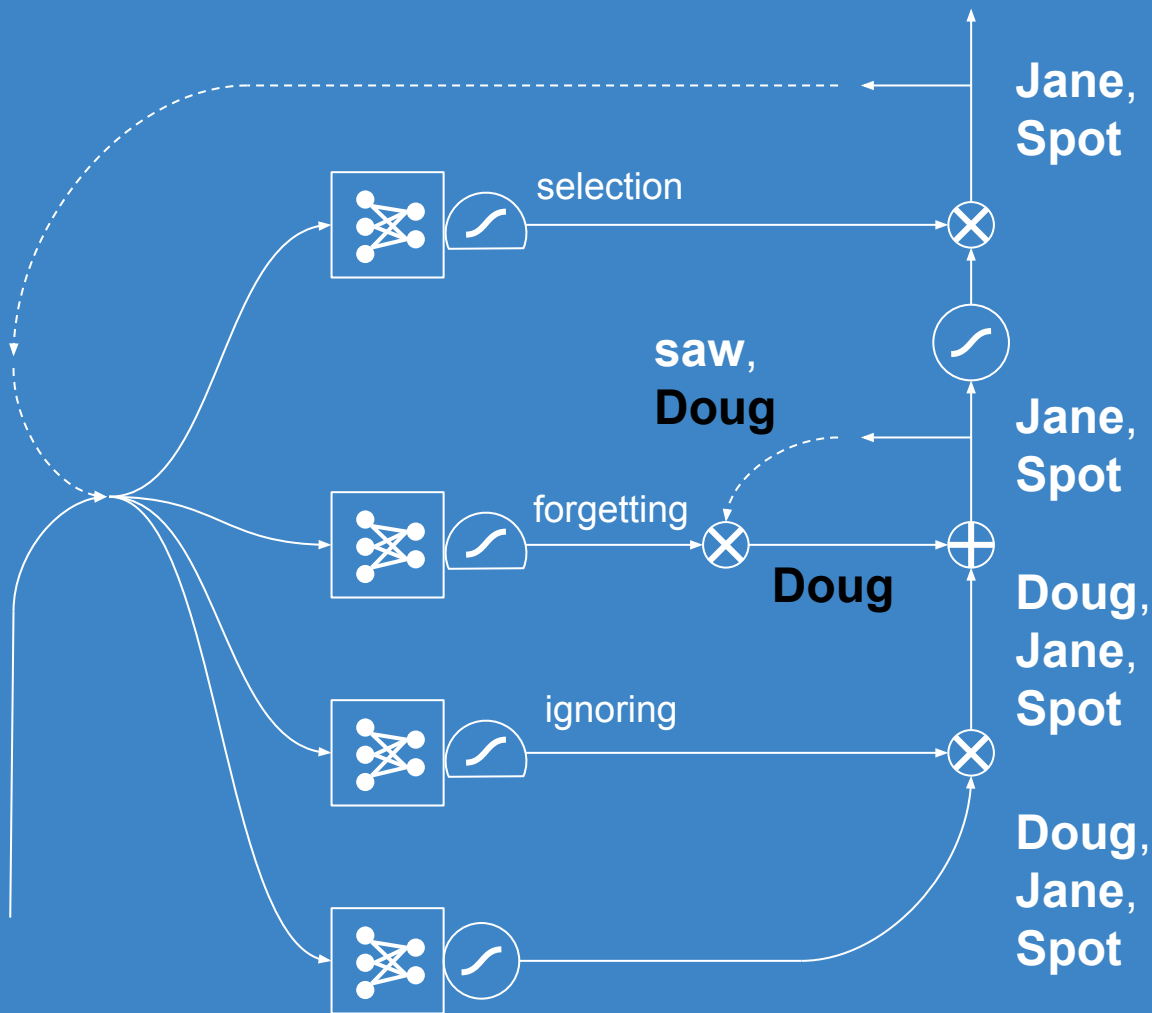
saw



long  
short-term  
memory

Jane saw Spot.  
Doug **saw** ...

saw



# Sequential patterns

Text

Speech

Audio

Video

Physical processes

Anything embedded in time (almost everything)

Traditional LSTM with forget gates.<sup>[2][3]</sup>

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

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$

$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c)$$

$$h_t = o_t \circ \sigma_h(c_t)$$

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

- $\sigma_g$ : The original is a **sigmoid function**.
- $\sigma_c$ : The original is a **hyperbolic tangent**.
- $\sigma_h$ : The original is a hyperbolic tangent, but the peephole LSTM paper suggests  $\sigma_h(x) = x$ .<sup>[18][19]</sup>