# Neural Language Modeling

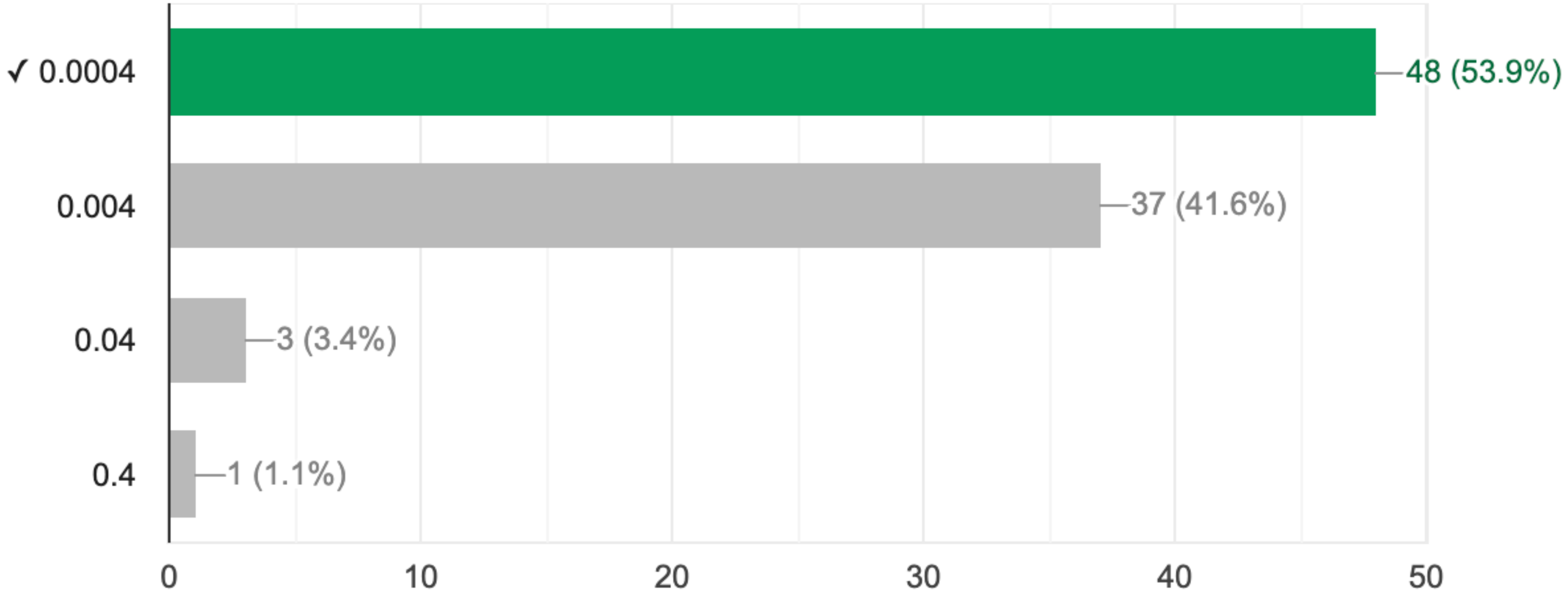
## CSCI 1460: Computational Linguistics
## Lecture 10

**Ellie Pavlick**
**Fall 2022**

Use the below corpus to train a unigram language model. Given your language model, what is the probability of the sentence "i say potato"? (Tip: You absolutely can do this by hand, but writing a short python program is easier, more fun, and you learn just as much! =D)

Copy

48 / 89 correct responses



```
[ ] corpus = [

        '<s> i say tomato </s>',
        '<s> you say tomato </s>',
        '<s> i like potatoes </s>',
        '<s> you like potatoes </s>',
        '<s> tomato tomato </s>',
        '<s> potato potato </s>'
    ]

    corpus = [s.split() for s in corpus]
    print(corpus)
```

```
ugram_probs = {}
for s in corpus:
  for w in s:
    if w not in ugram_probs:
      ugram_probs[w] = 0
    ugram_probs[w] += 1

print(ugram_probs)
total = sum(ugram_probs.values())
print(total)
```

```
{'<s>': 6, 'i': 2, 'say': 2, 'tomato': 4, '</s>': 6, 'you': 2, 'like': 2, 'potatoes': 2, 'potato': 2}
28
```

```
from math import log

new_sent = "i say potato"

prob = 1
for w in new_sent.split():
  prob *= ugram_probs[w]/total
print(prob)
```

```
0.0003644314868804664
```

Are we supposed to count <s> and </s> as words?????

```python
corpus = [

    '<s> i say tomato </s>',
    '<s> you say tomato </s>',
    '<s> i like potatoes </s>',
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```python
from math import log

new_sent = "i say potato"

prob = 1
for w in new_sent.split():
  prob *= ugram_probs[w]/total
print(prob)
```

```
0.0003644314868804664
```

usually dont include <s> and </s> in unigram models, but I had done so in computing this answer. 🤦‍♀️

# Topics

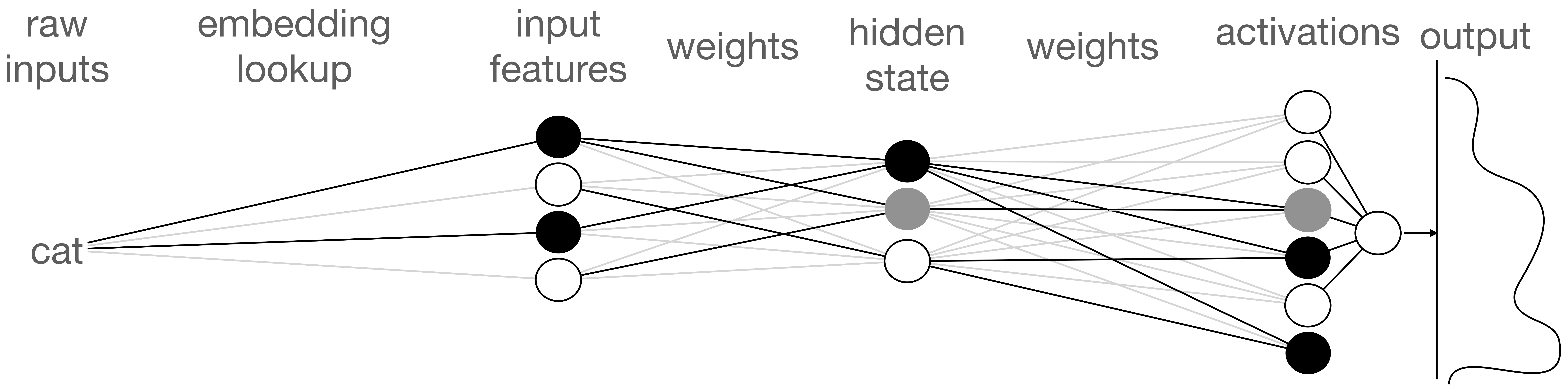
- NN Architectures for Language Modeling
  - MLP
  - Recurrent Neural Network (RNN)
  - Long-Short Term Memory Network (LSTM)
  - Transformer

# Topics

- NN Architectures for Language Modeling
  - **MLP**
  - Recurrent Neural Network (RNN)
  - Long-Short Term Memory Network (LSTM)
  - Transformer

# Multilayer Perceptron

Task: Predict the next word
Input: cat
Expected: sat



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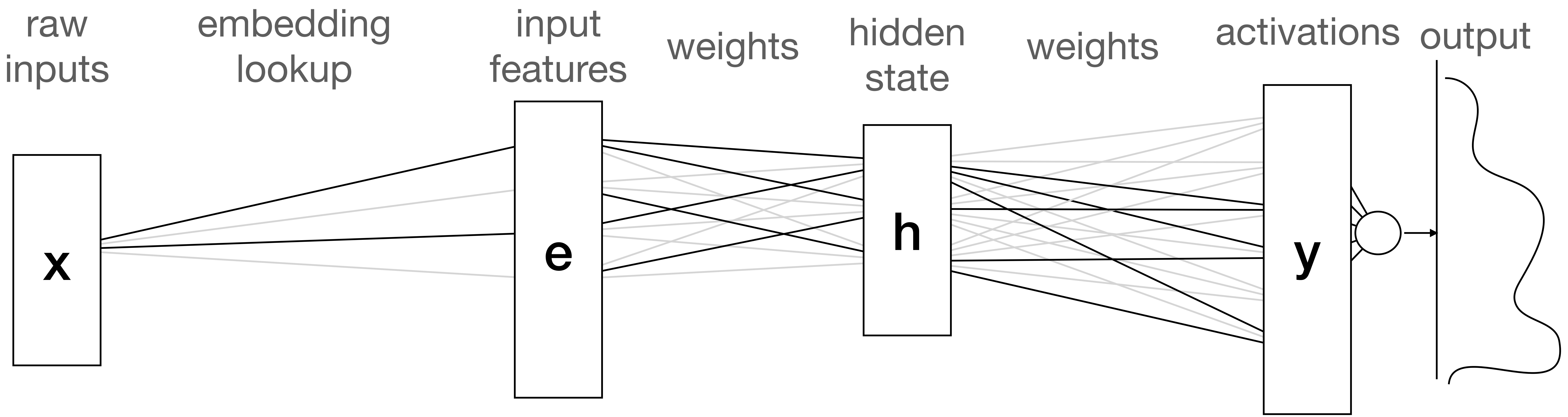
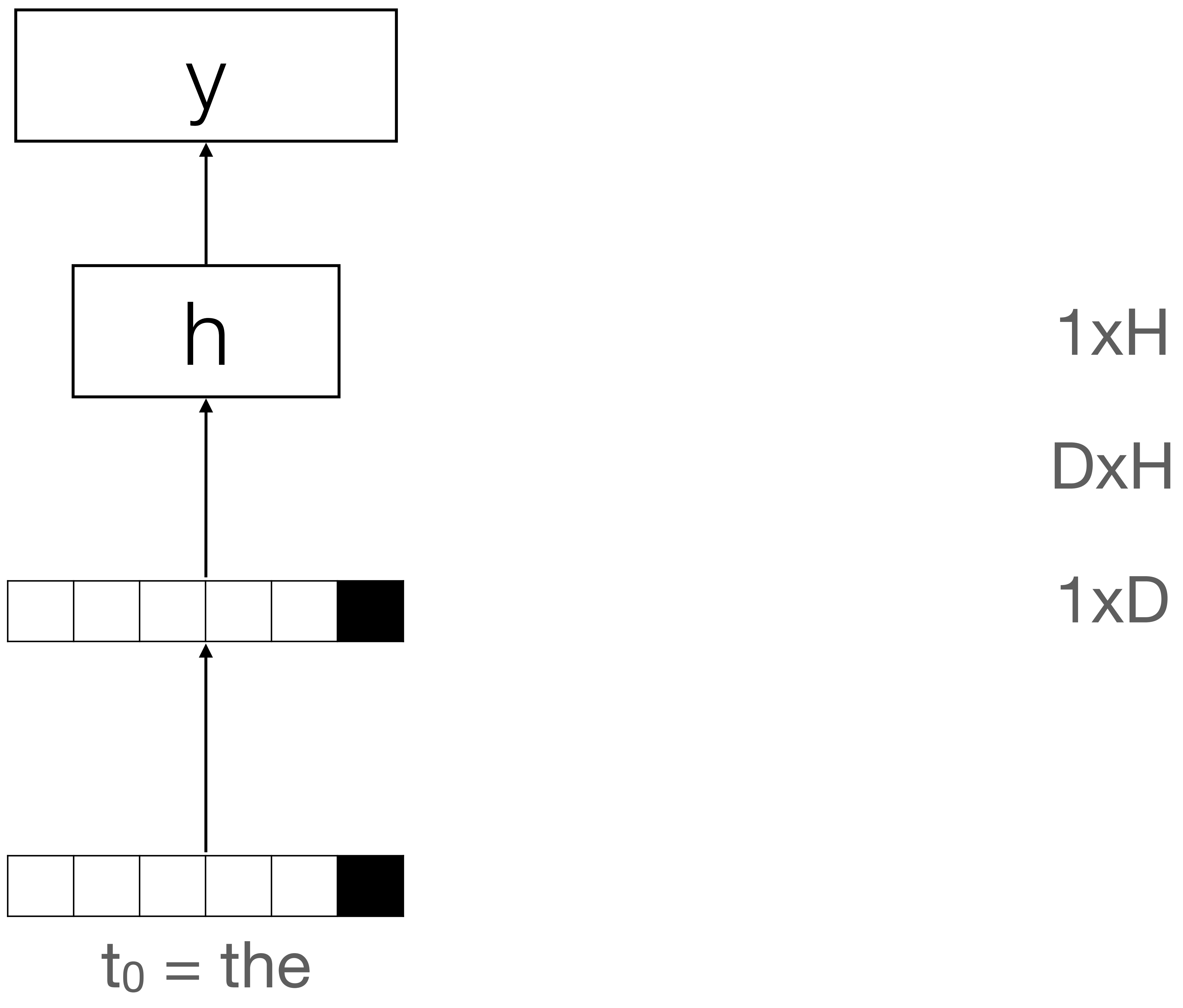


# Multilayer Perceptron
## MLP for Language Modeling

Task: Predict the next word
**Input: the**
Expected: cat



# Multilayer Perceptron

## MLP for Language Modeling

Task: Predict the next word
**Input: the cat**
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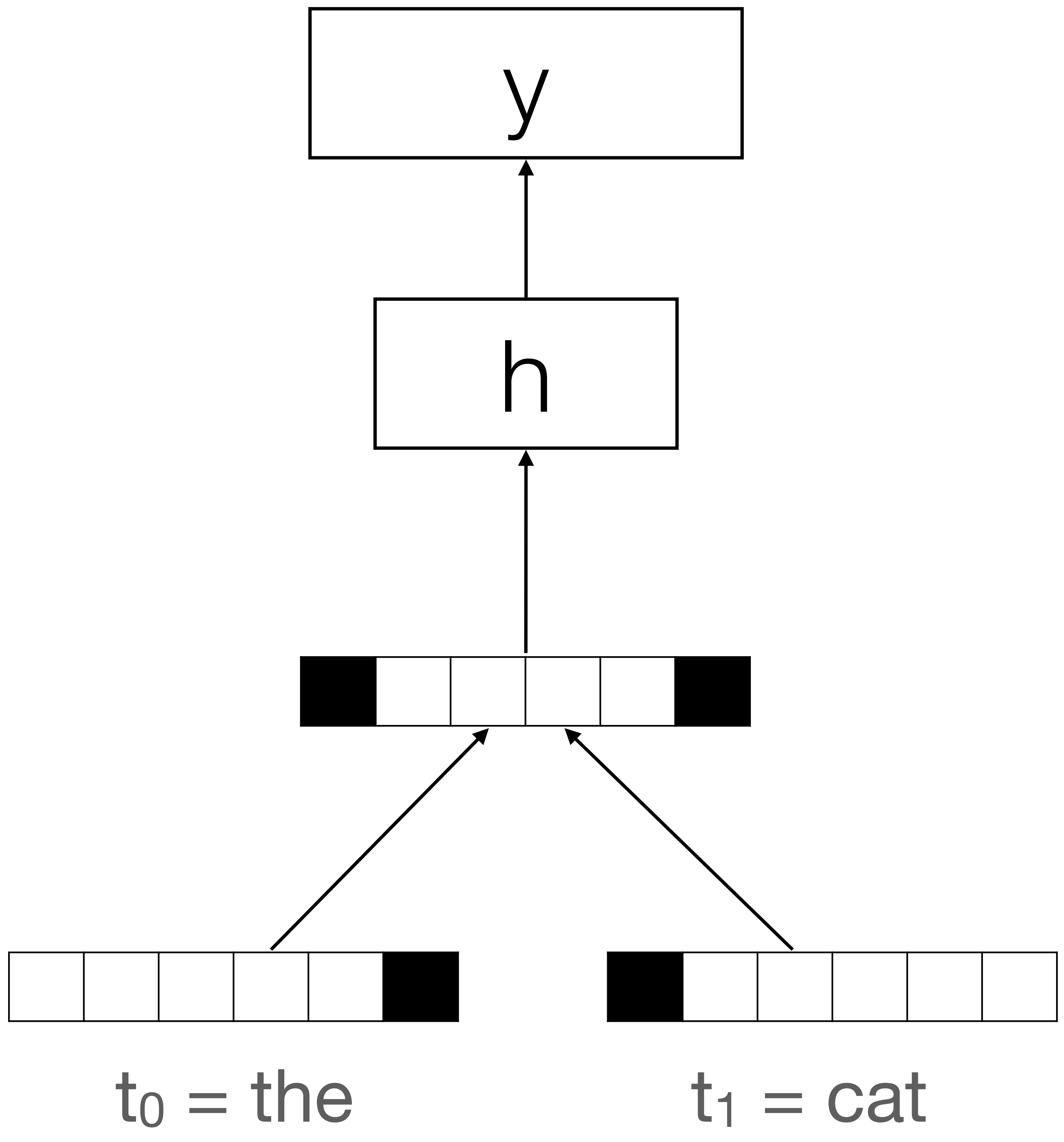


1xH

DxH

1xD

sum up the input embeddings

# Multilayer Perceptron

## MLP for Language Modeling

Task: Predict the next word
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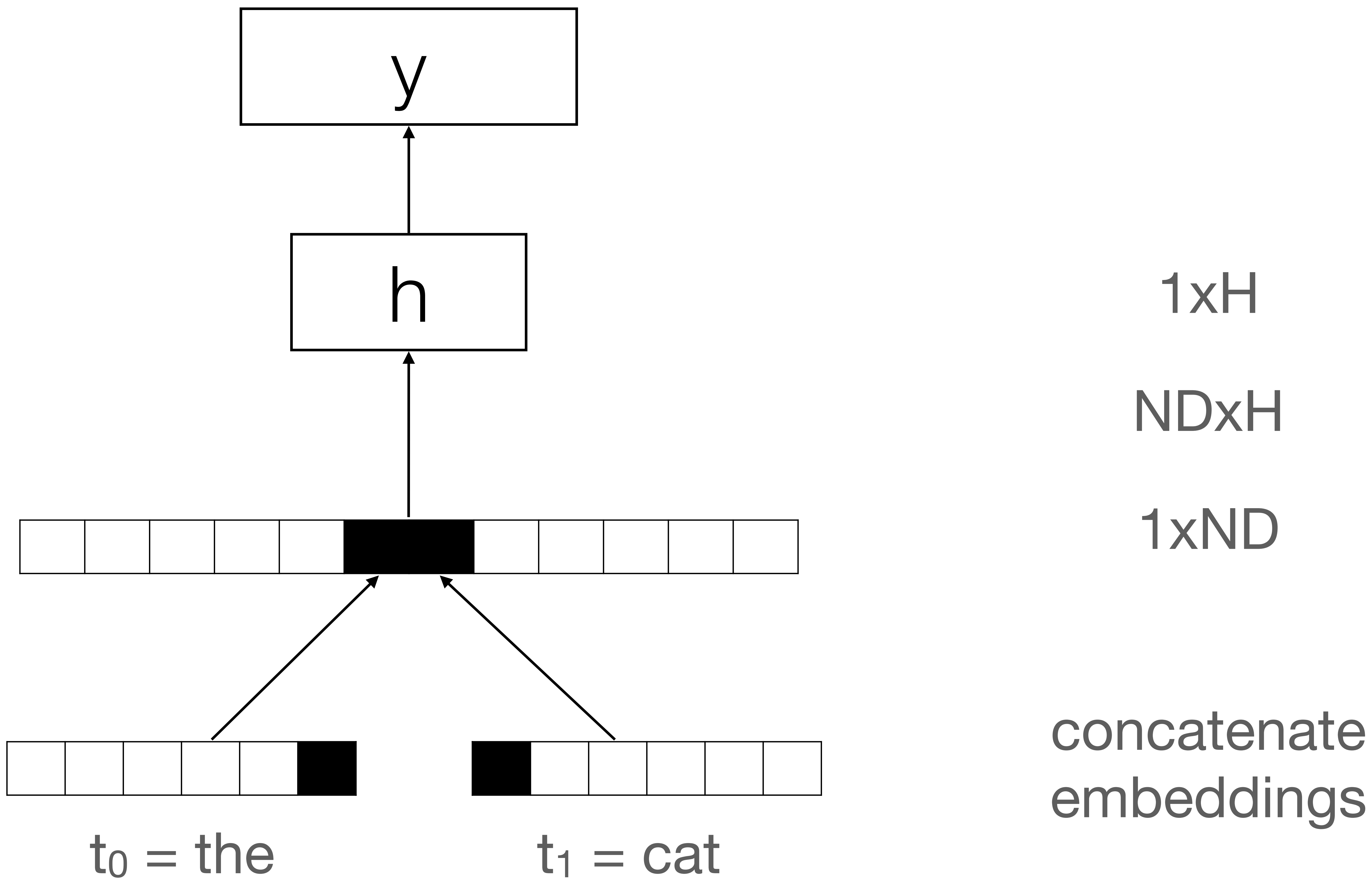


# Multilayer Perceptron

## MLP for Language Modeling

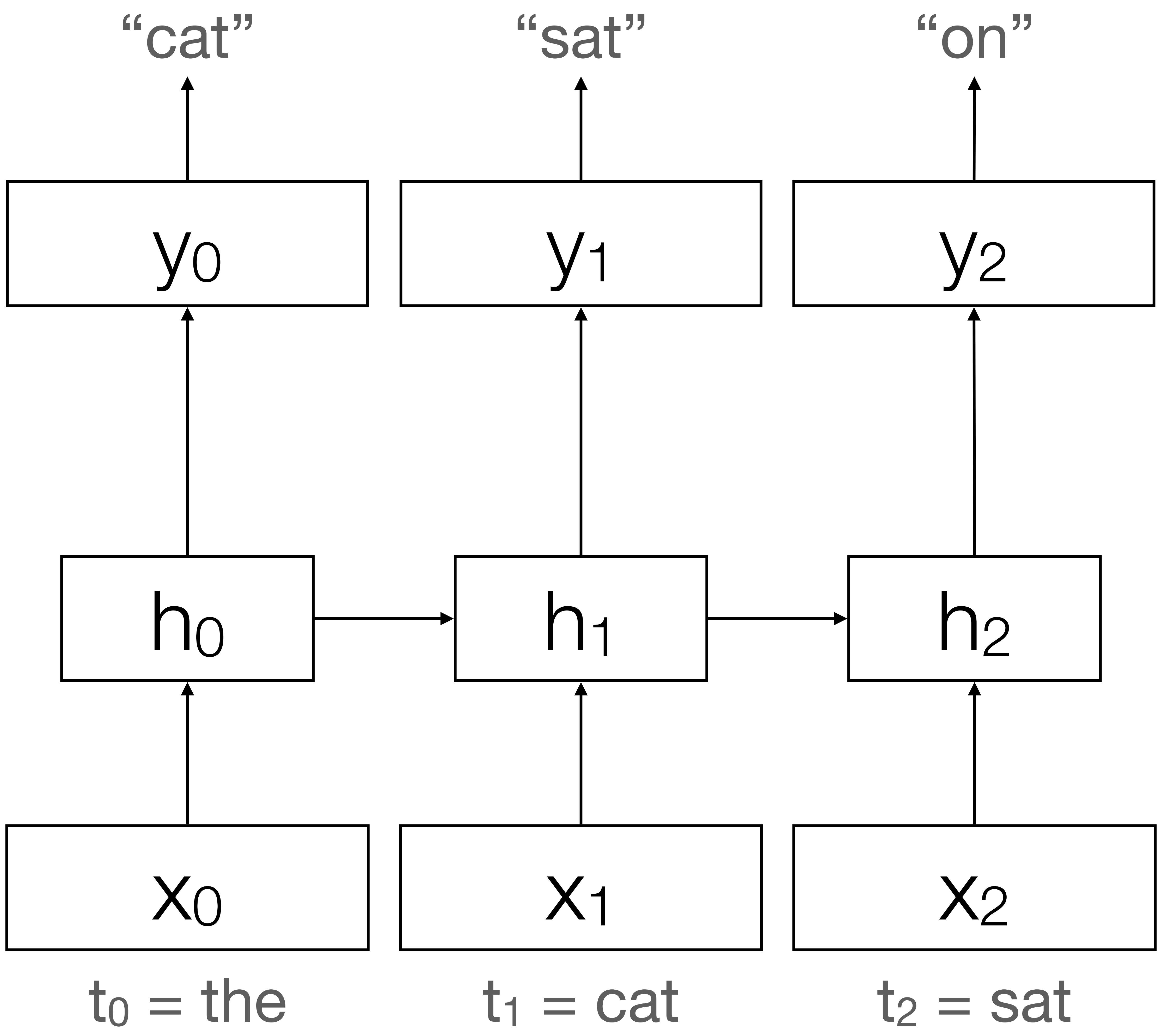
- MLP doesn’t readily support long, sequential inputs
- No way of encoding word order
    - Essentially a BOW model
- Inputs either become muddy (adding everything together, i.e., “bag of vectors”) or too large (concatenating everything)
- Still, “bag-of-vectors” classifiers are common and often work well for basic applications

# Topics

- NN Architectures for Language Modeling
  - ~~MLP~~
  - **Recurrent Neural Network (RNN)**
  - Long-Short Term Memory Network (LSTM)
  - Transformer

# Recurrent Neural Networks (RNNs)

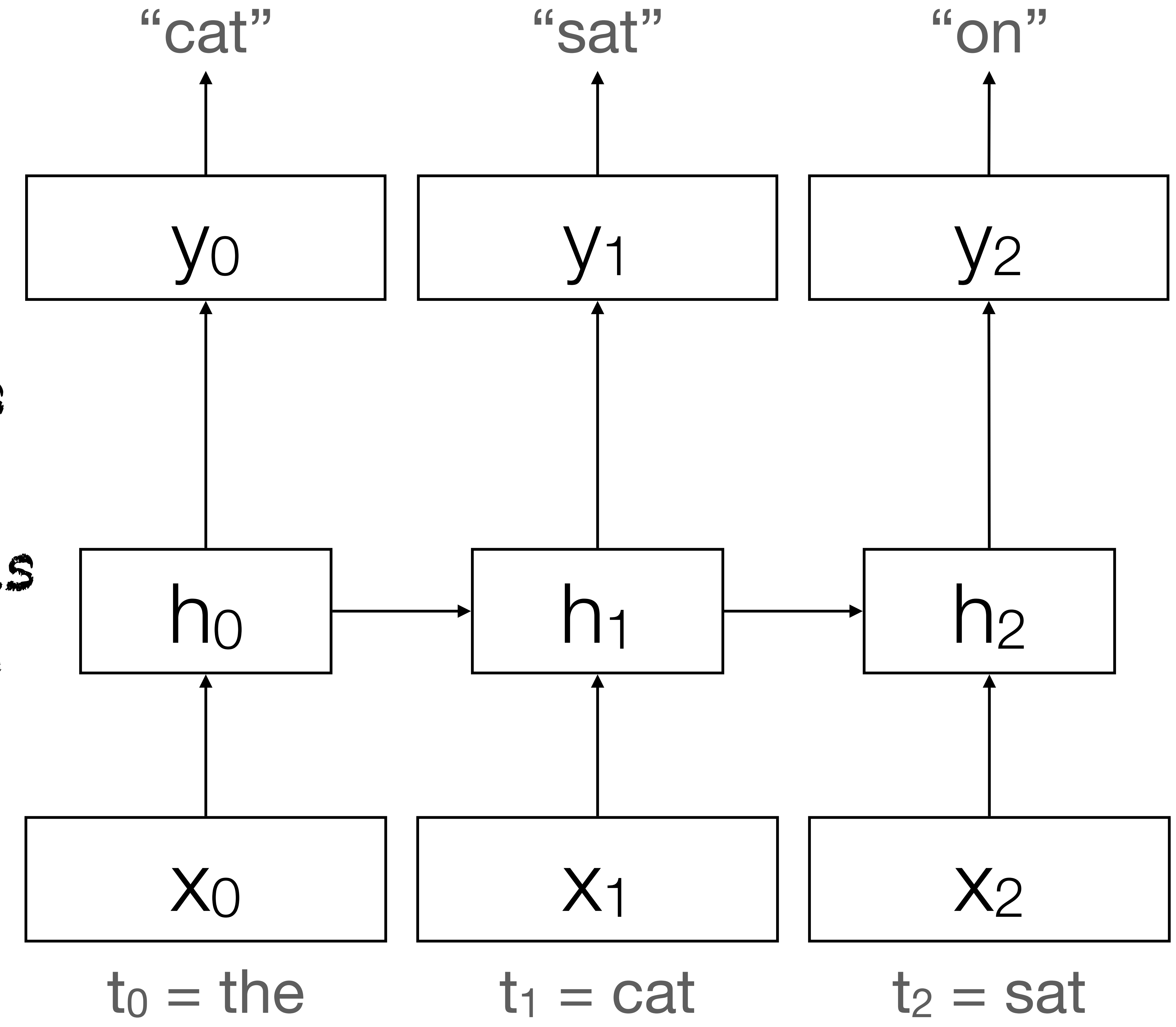
## Architecture



# Recurrent Neural Networks (RNNs)

## Architecture

Generation of word i+1 depends on word i plus "memory" of words generated up to i



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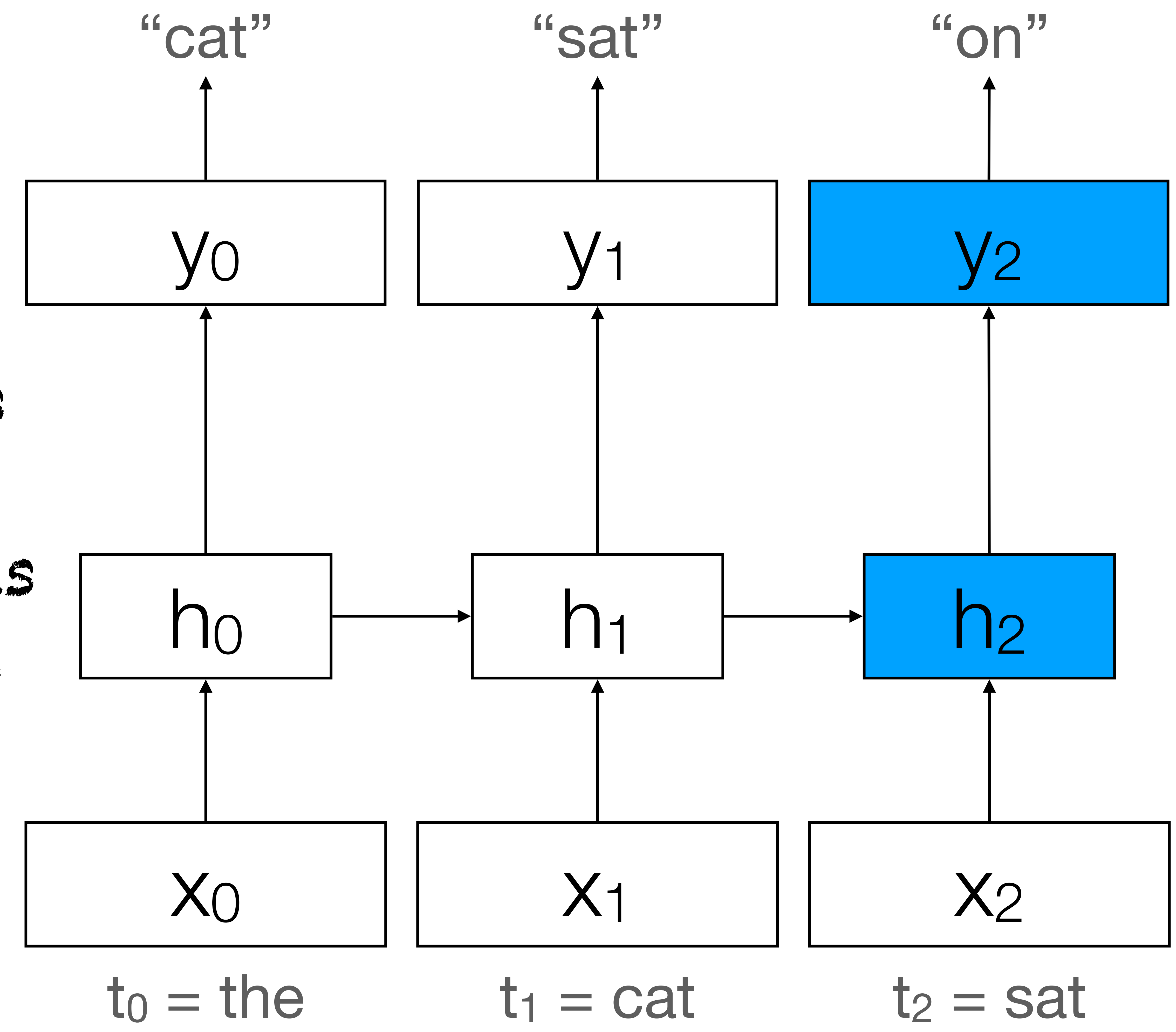

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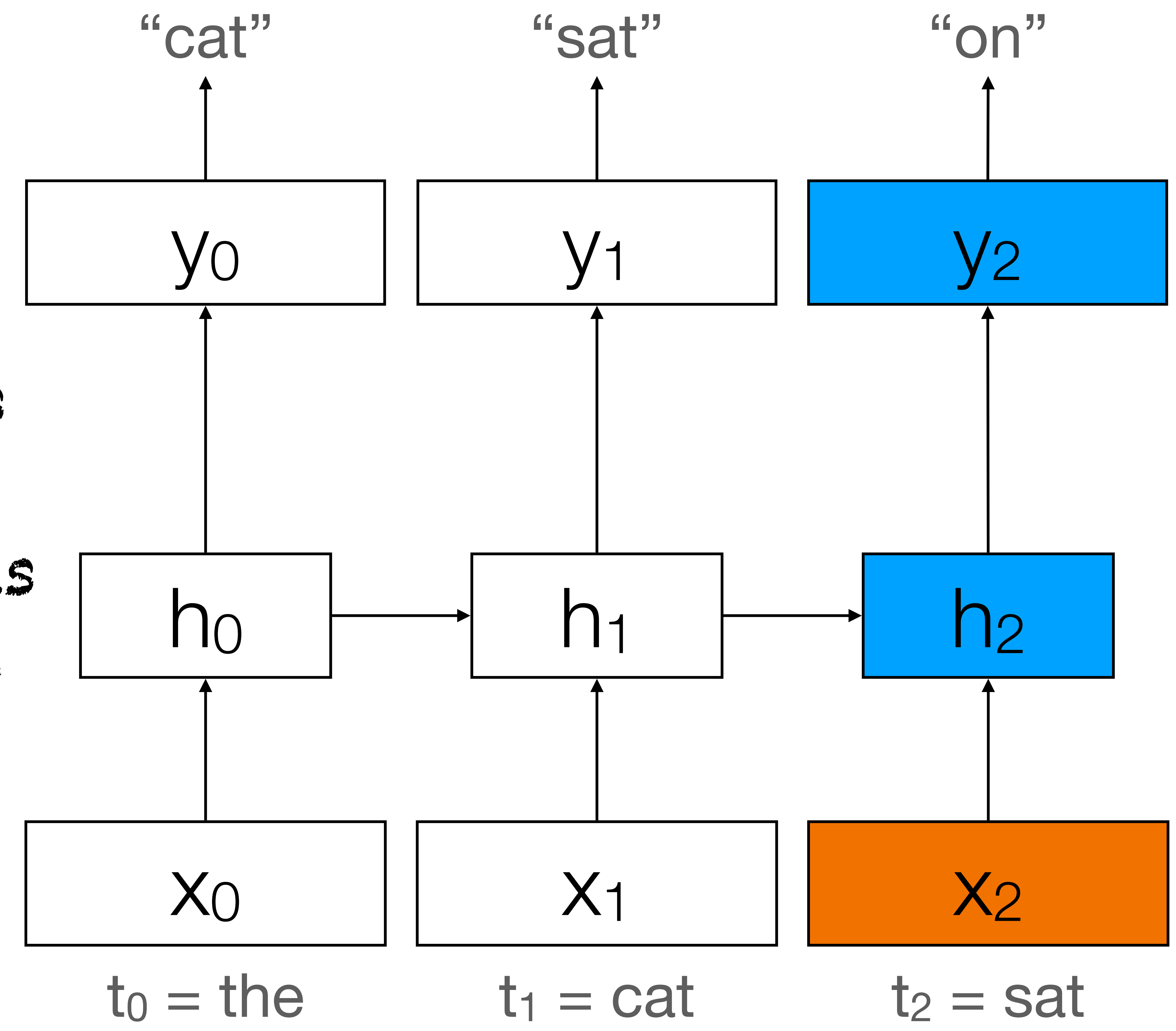

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## Architecture

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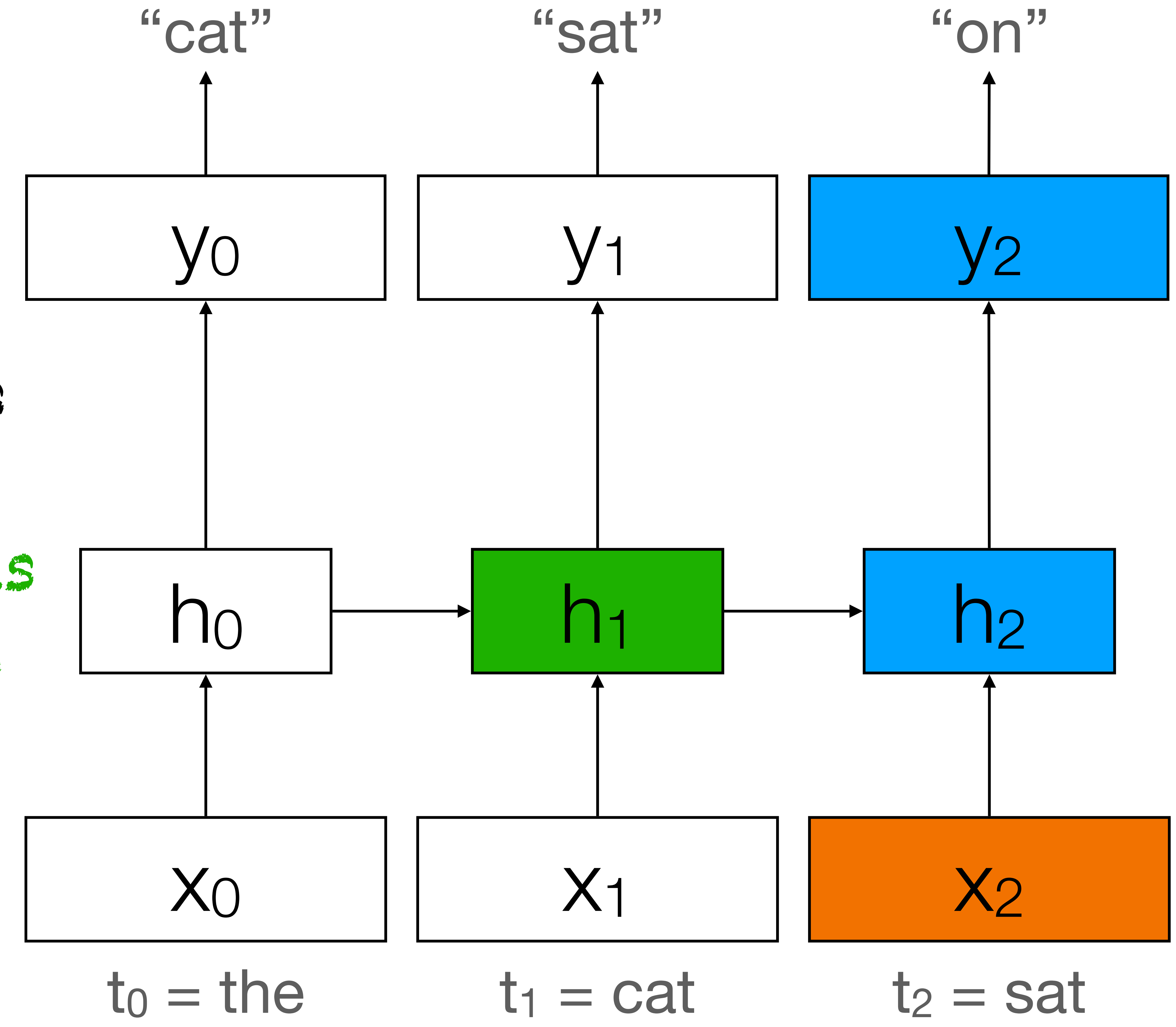
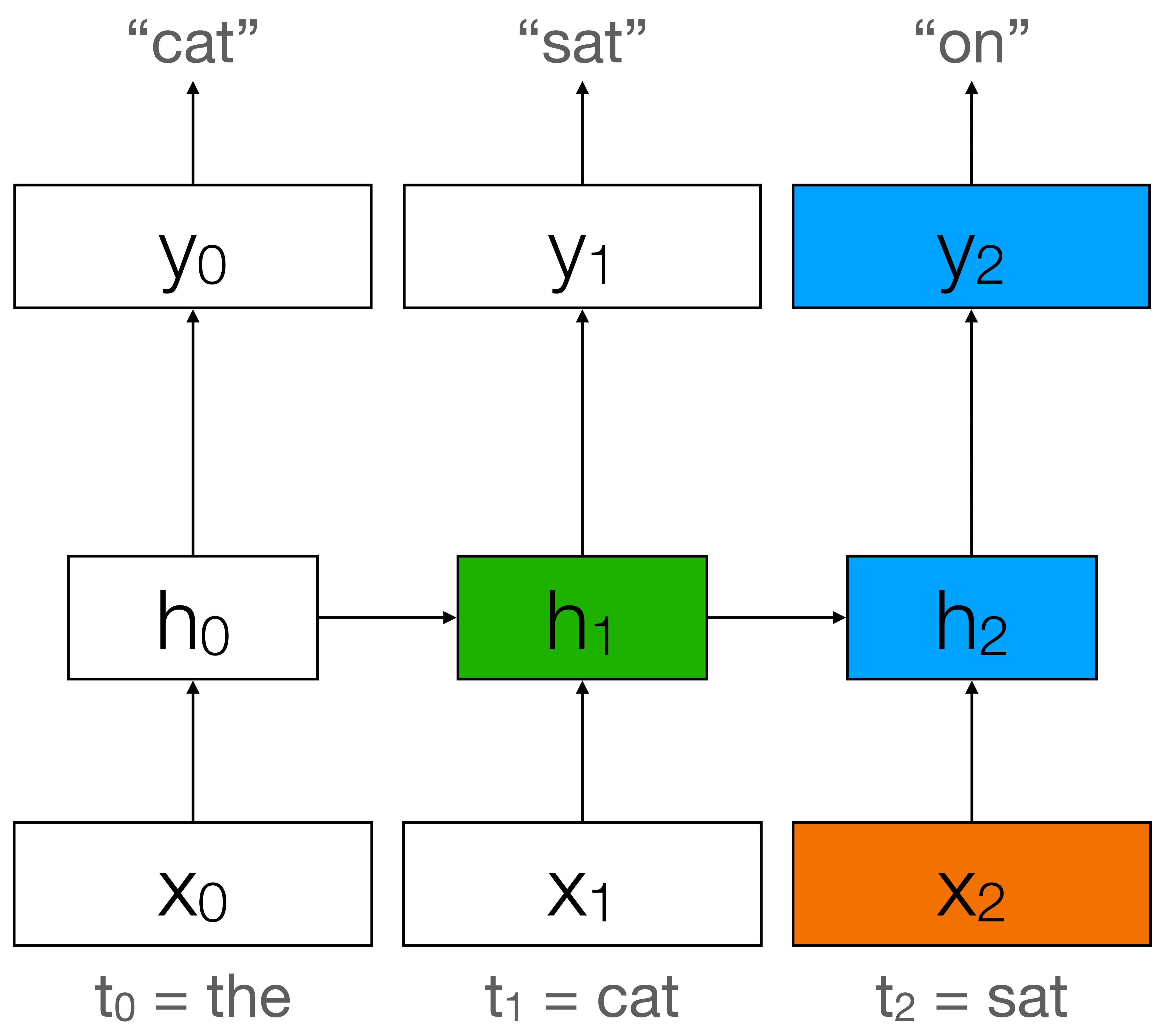


# Recurrent Neural Networks (RNNs)

## Architecture

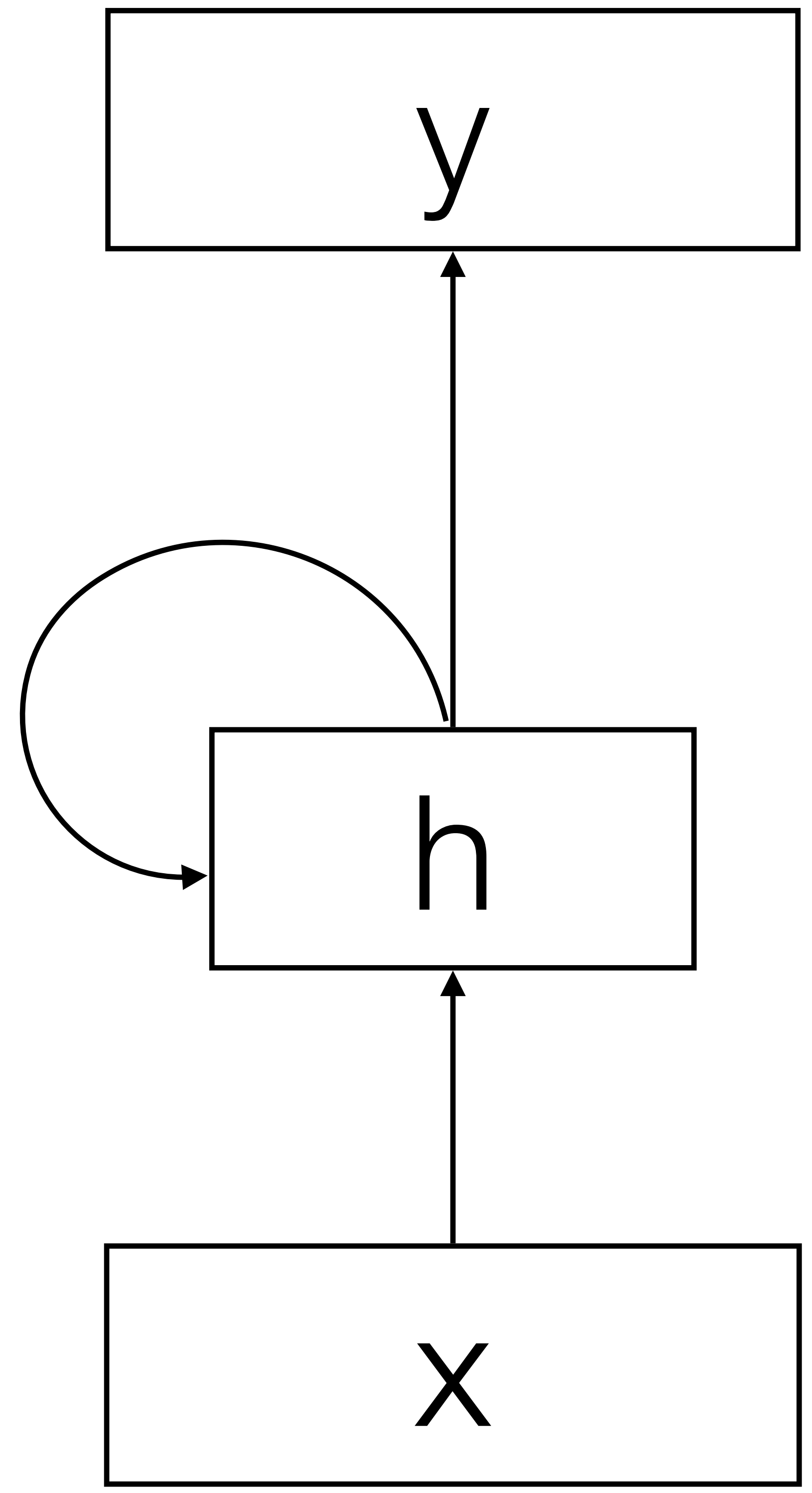
View #1:
"Unrolled"



# Recurrent Neural Networks (RNNs)

## Architecture

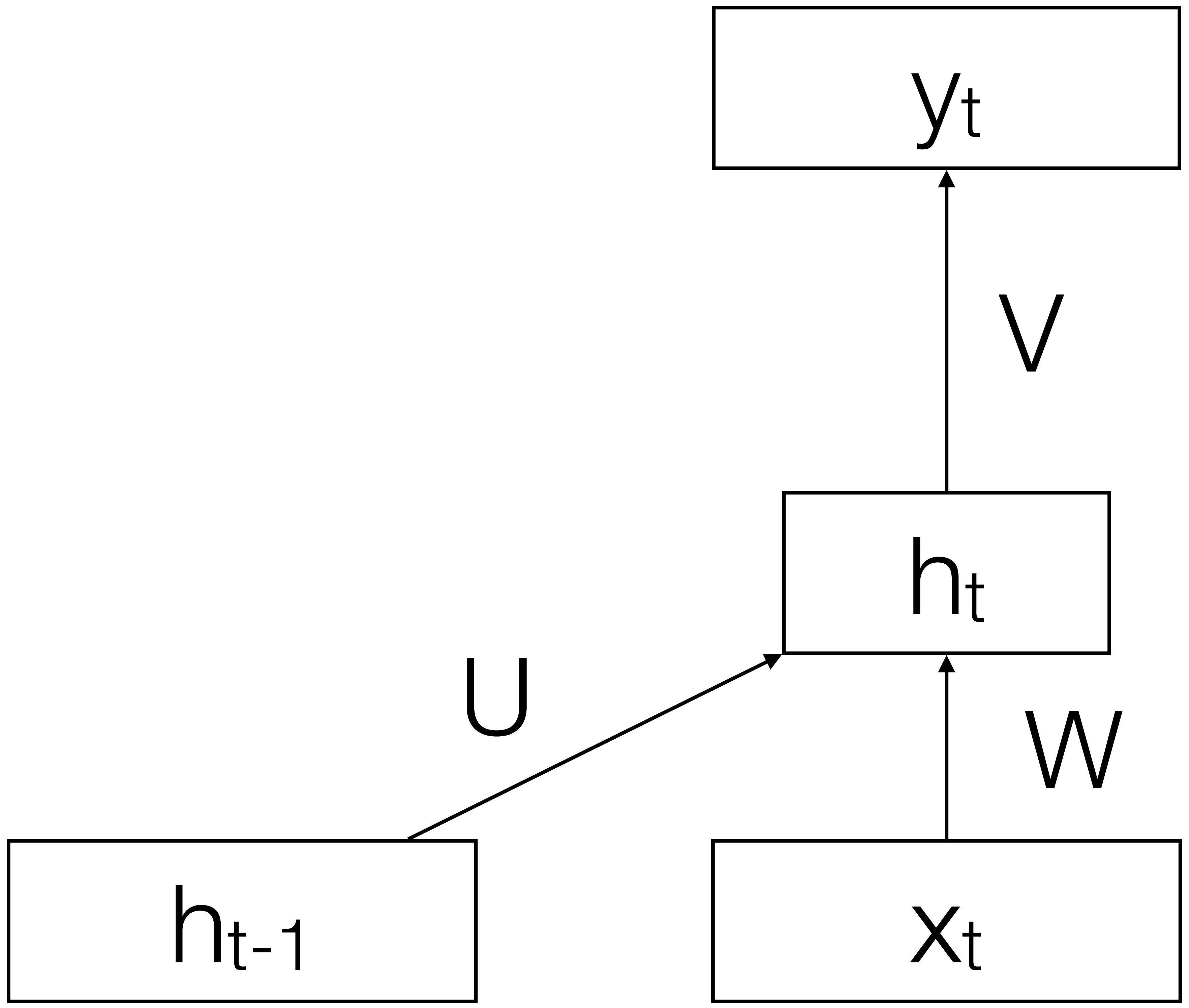
View #2:
Recurrent/
Recursive



# Recurrent Neural Networks (RNNs)

## Architecture

View #3:
(A single step of)
recurrent/recursive



# Recurrent Neural Networks (RNNs)

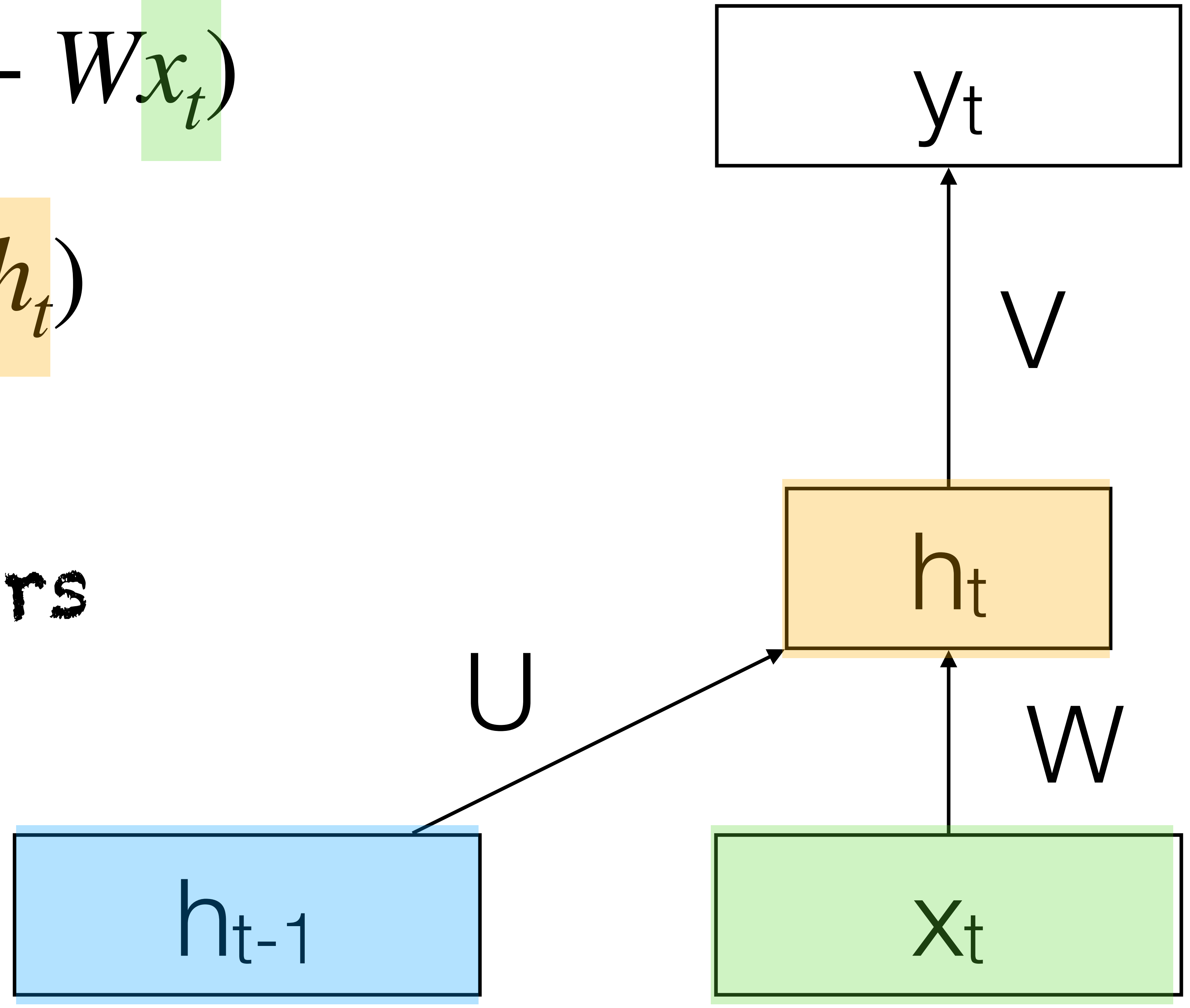
## Architecture

$$h_t = g(Uh_{t-1} + Wx_t)$$

$$y_t = f(Vh_t)$$

View #3:
(A single step of)
recurrent/recursive

Vectors



# Recurrent Neural Networks (RNNs)

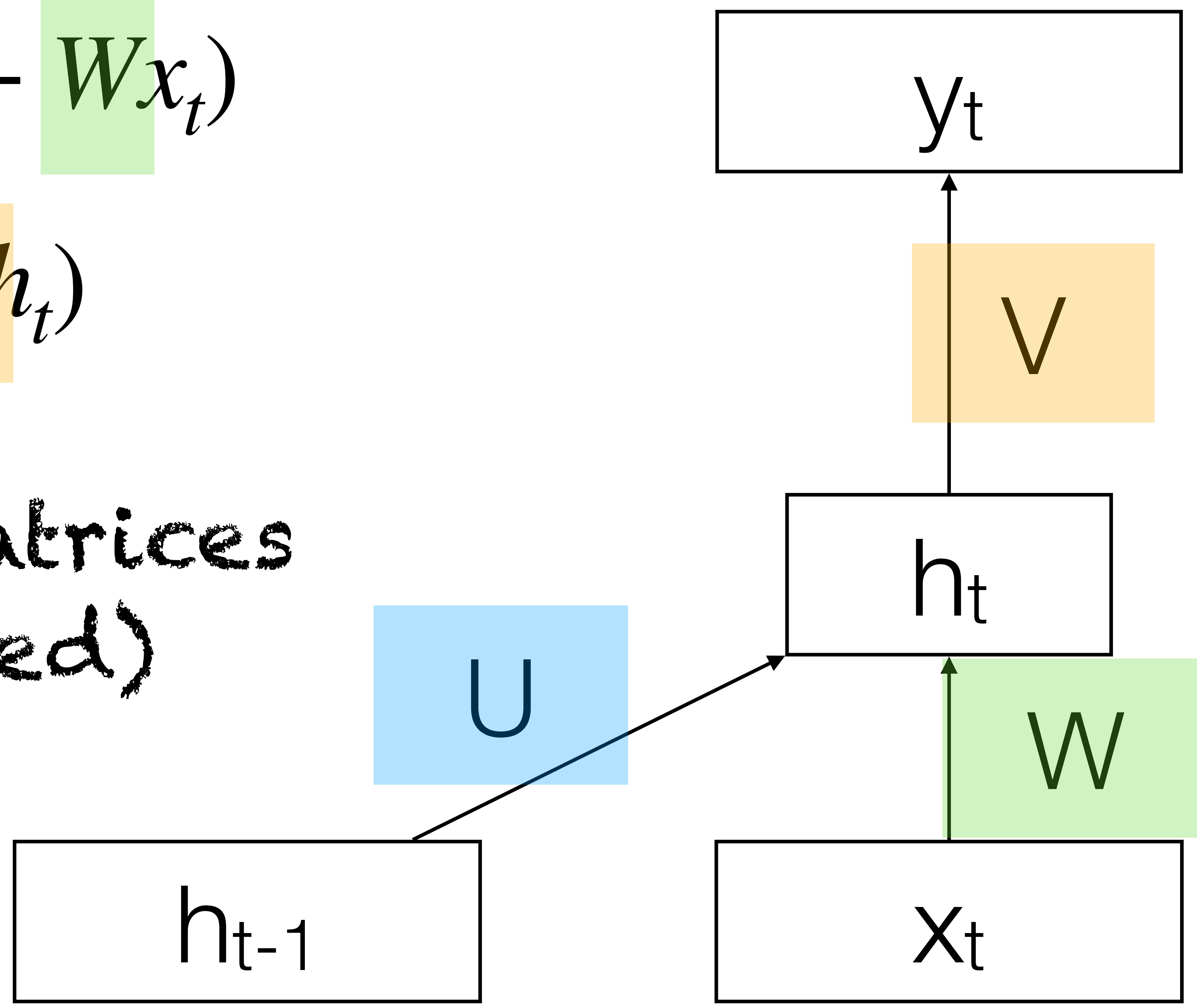
## Architecture

$$h_t = g(Uh_{t-1} + Wx_t)$$

$$y_t = f(Vh_t)$$

View #3:
(A single step of)
recurrent/recursive

Weight Matrices
(Learned)



# Recurrent Neural Networks (RNNs)

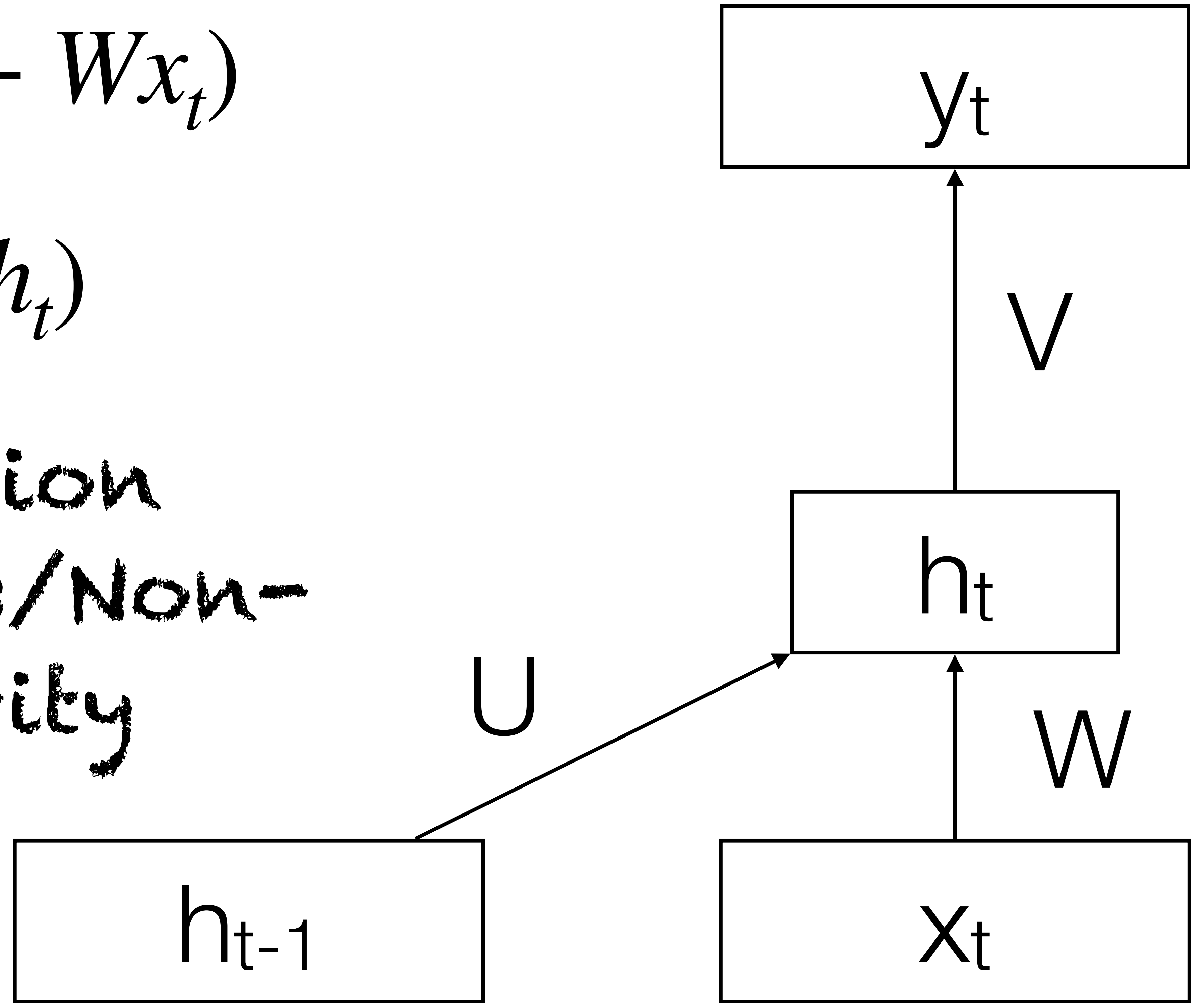
## Architecture

$$h_t = g(Uh_{t-1} + Wx_t)$$

$$y_t = f(Vh_t)$$

View #3:
(A single step of)
recurrent/recursive

Activation
Functions/Non-
Linearity



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## Architecture

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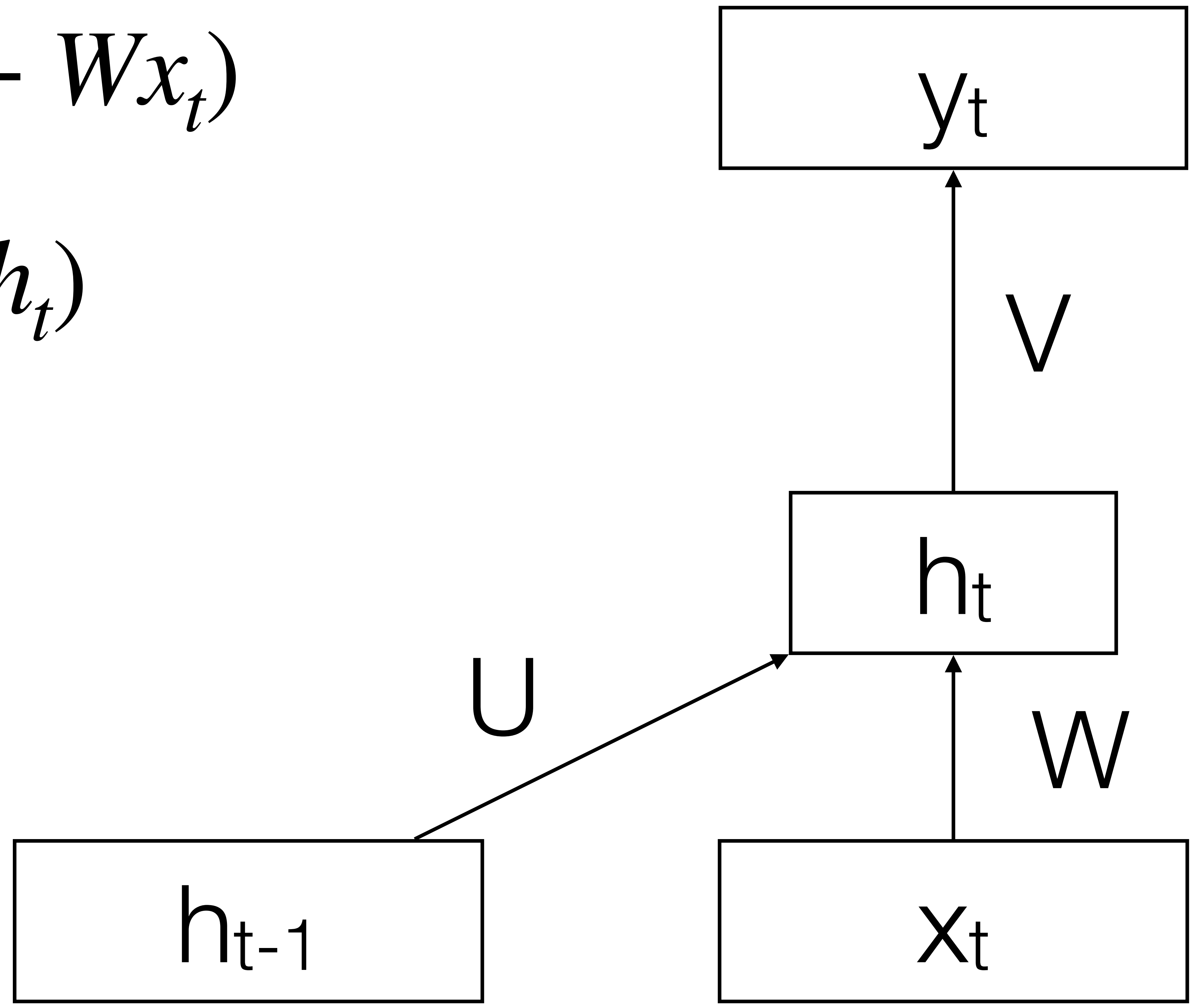
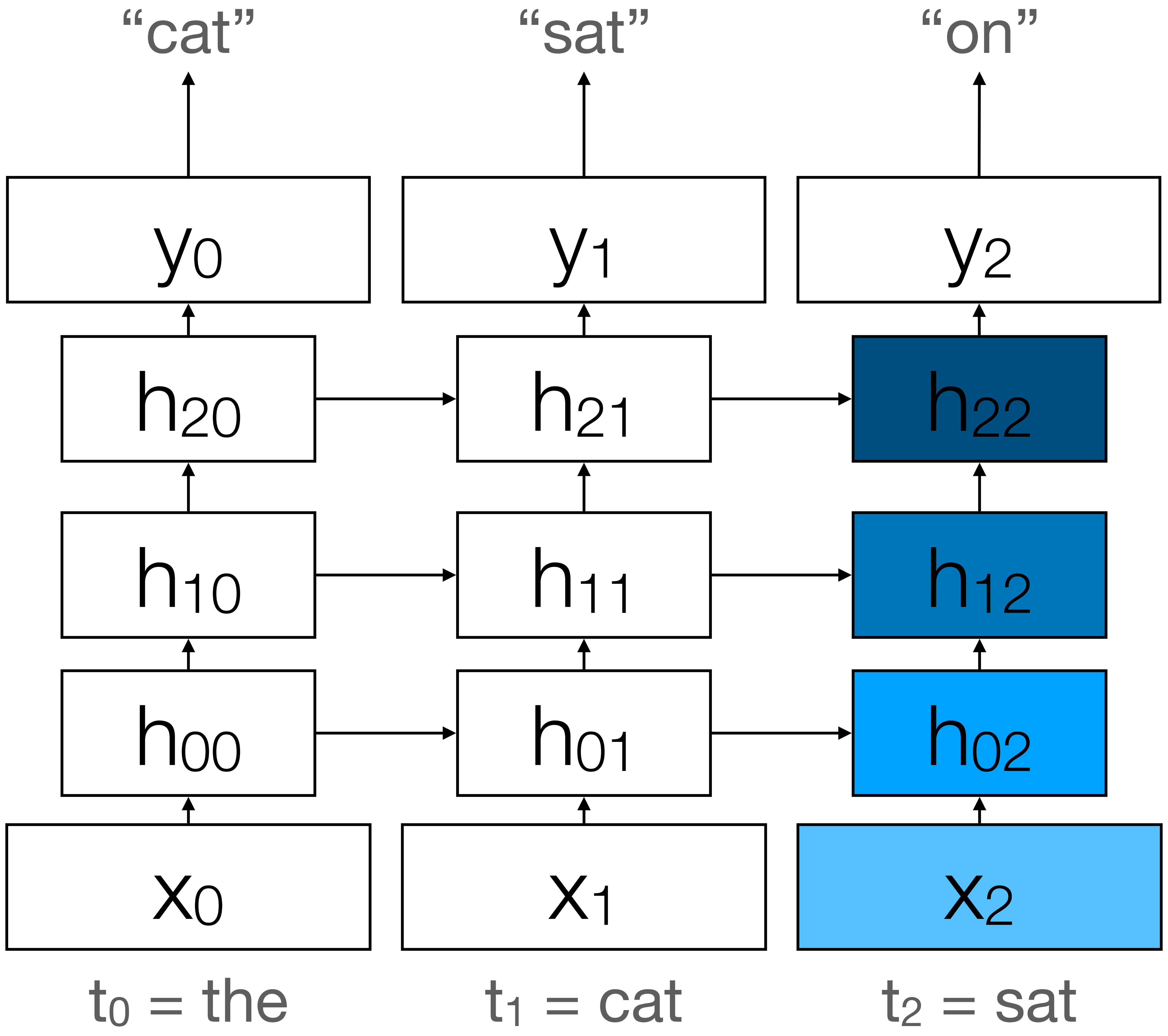



# Recurrent Neural Networks (RNNs)

## Architecture

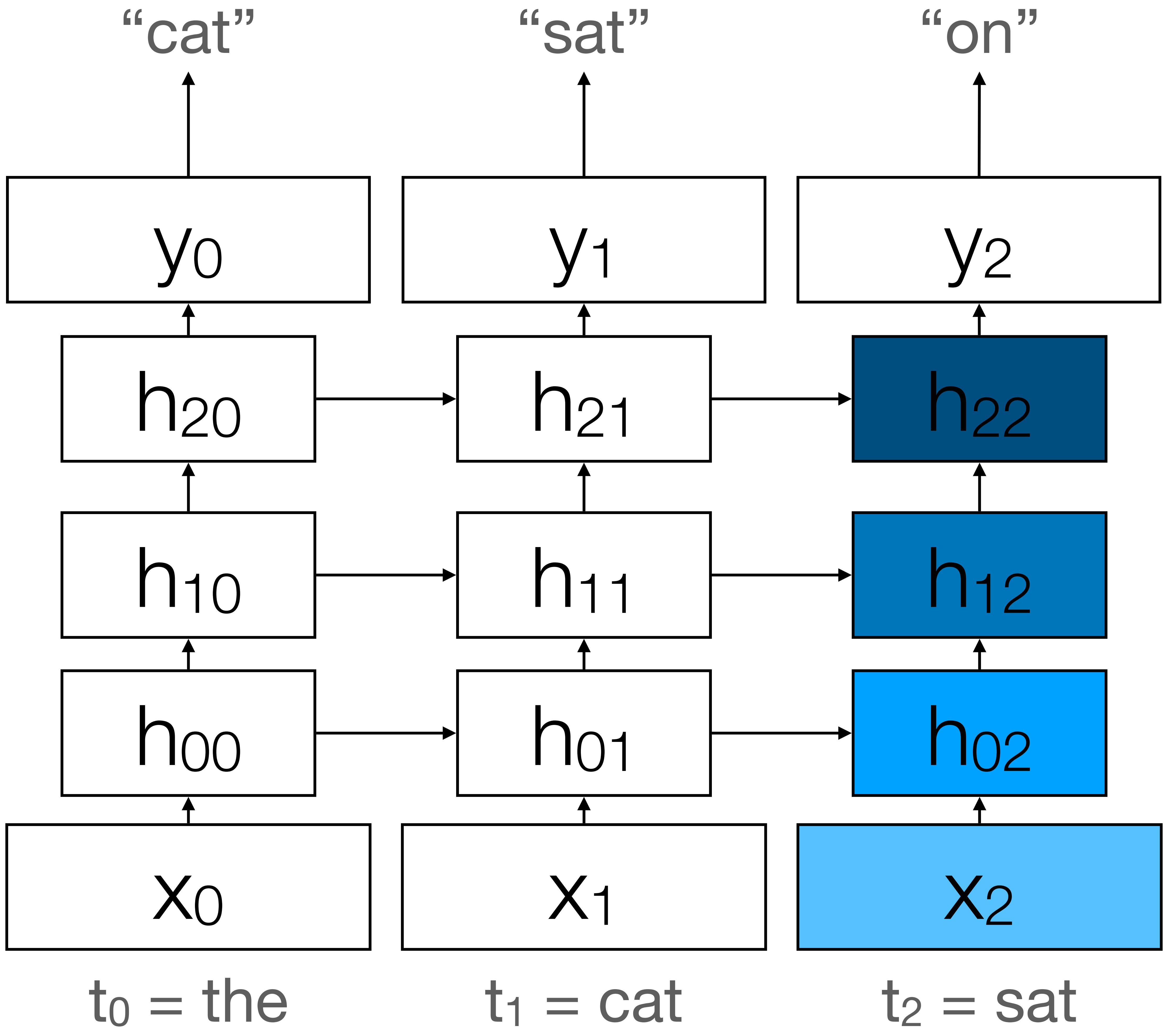
“Stacked” RNNs
(more later)



# Recurrent Neural Networks (RNNs)

## Architecture

"Stacked" RNNs (more later)




allow increasingly abstract in-context representations

# Recurrent Neural Networks (RNNs)

## Inference

**function** FORWARDRNN($\mathbf{x}$, *network*) **returns** output sequence $\mathbf{y}$

$\mathbf{h}^0 \leftarrow 0$
**for** $i \leftarrow 1$ **to** LENGTH($\mathbf{x}$) **do**
  $\mathbf{h}_i \leftarrow g(\mathbf{U}\mathbf{h}_{i-1} + \mathbf{W}\mathbf{x}_i)$
  $\mathbf{y}_i \leftarrow f(\mathbf{V}\mathbf{h}_i)$
**return** $y$

# Recurrent Neural Networks (RNNs)

## Training Considerations

- Recurrent or Unrolled? Typically, in practice, unrolled and padded to a fixed length
  - Better for batching
- “Teacher Forcing”
  - When producing word i, predict based on the *real* i-1, not the predicted i-1 (which is likely wrong)
  - Student forcing = use the predicted i-1
  - Sometimes people mix teacher and student forcing

# Topics

- NN Architectures for Language Modeling
  - ~~MLP~~
  - Recurrent Neural Network (RNN)
  - **Long-Short Term Memory Network (LSTM)**
  - Transformer

# Long-Short Term Memory Network (LSTM)

## Motivation

- RNNs struggle with “long range dependencies”
  - “The <u>flights</u> the airline was cancelling <u>were</u> ful”l
- Some challenges:
  - h trying to do too much
  - “vanishing gradients” make it hard to update early hidden states for long sequences

# Long-Short Term Memory Network (LSTM)

## Architecture

- Introduce a “gating” mechanisms which manages the hidden state/ memory
- Break this up into two processes:
    - *forget gate* which removes information no longer needed
    - *add gate* which adds new information likely to be useful in the future
- Also adds explicit previous “context” in addition to prior hidden state

# Long-Short Term Memory Network (LSTM)

## Architecture

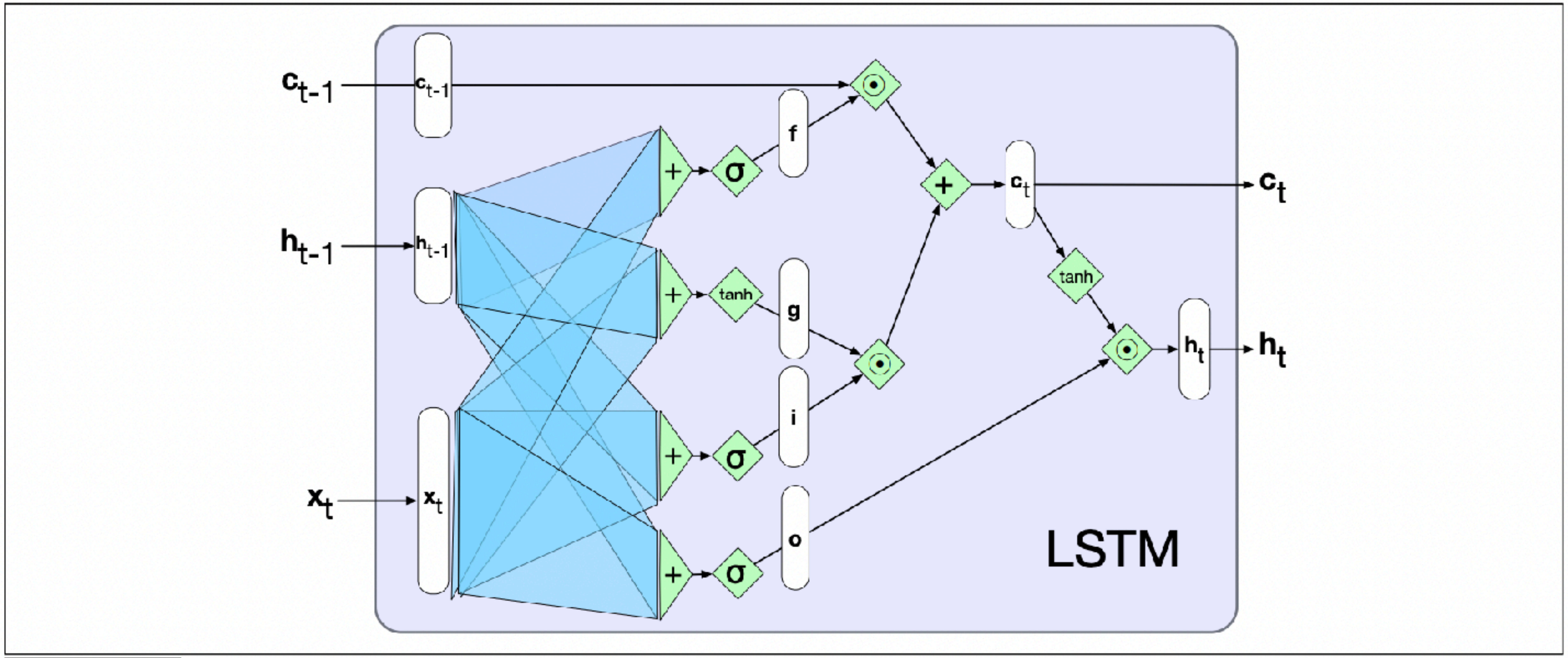
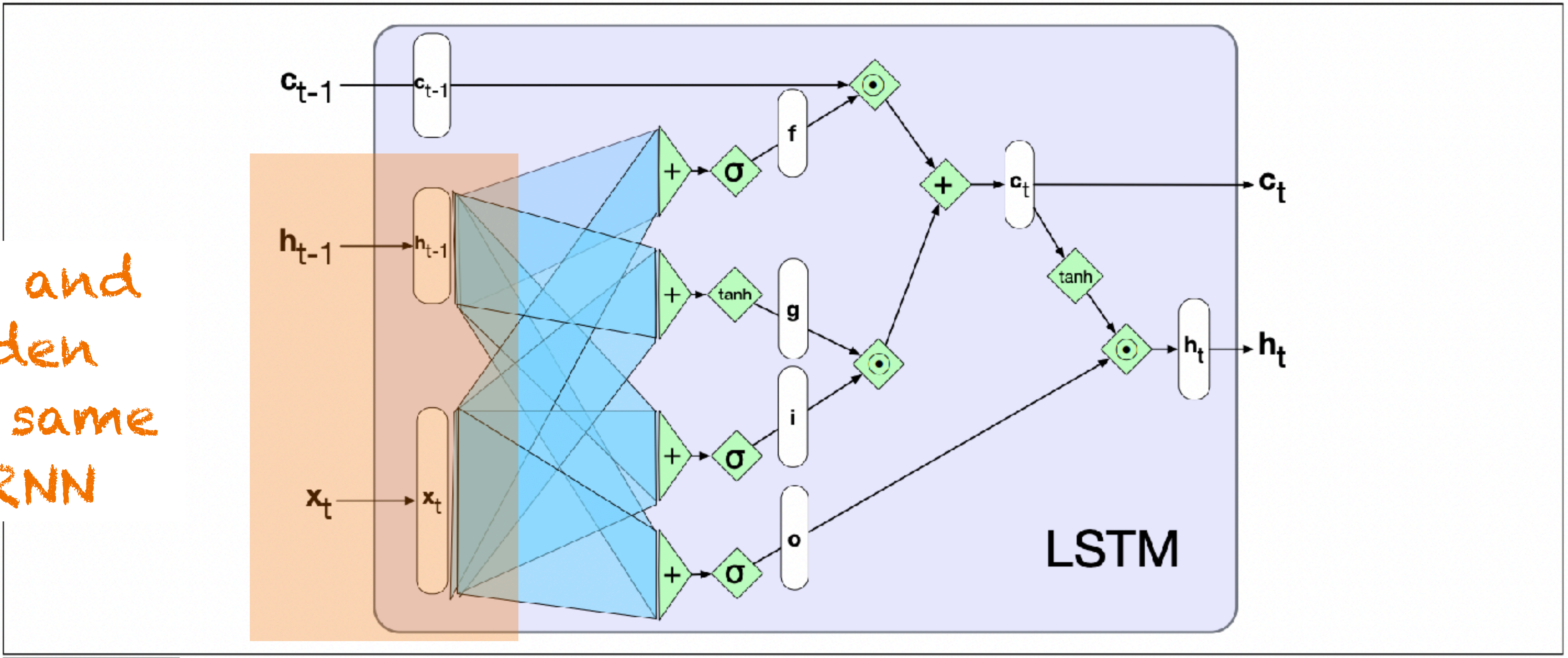



**Figure 9.13** A single LSTM unit displayed as a computation graph. The inputs to each unit consists of the current input, $x$, the previous hidden state, $h_{t-1}$, and the previous context, $c_{t-1}$. The outputs are a new hidden state, $h_t$ and an updated context, $c_t$.

# Long-Short Term Memory Network (LSTM)

## Architecture

input and hidden state, same as RNN

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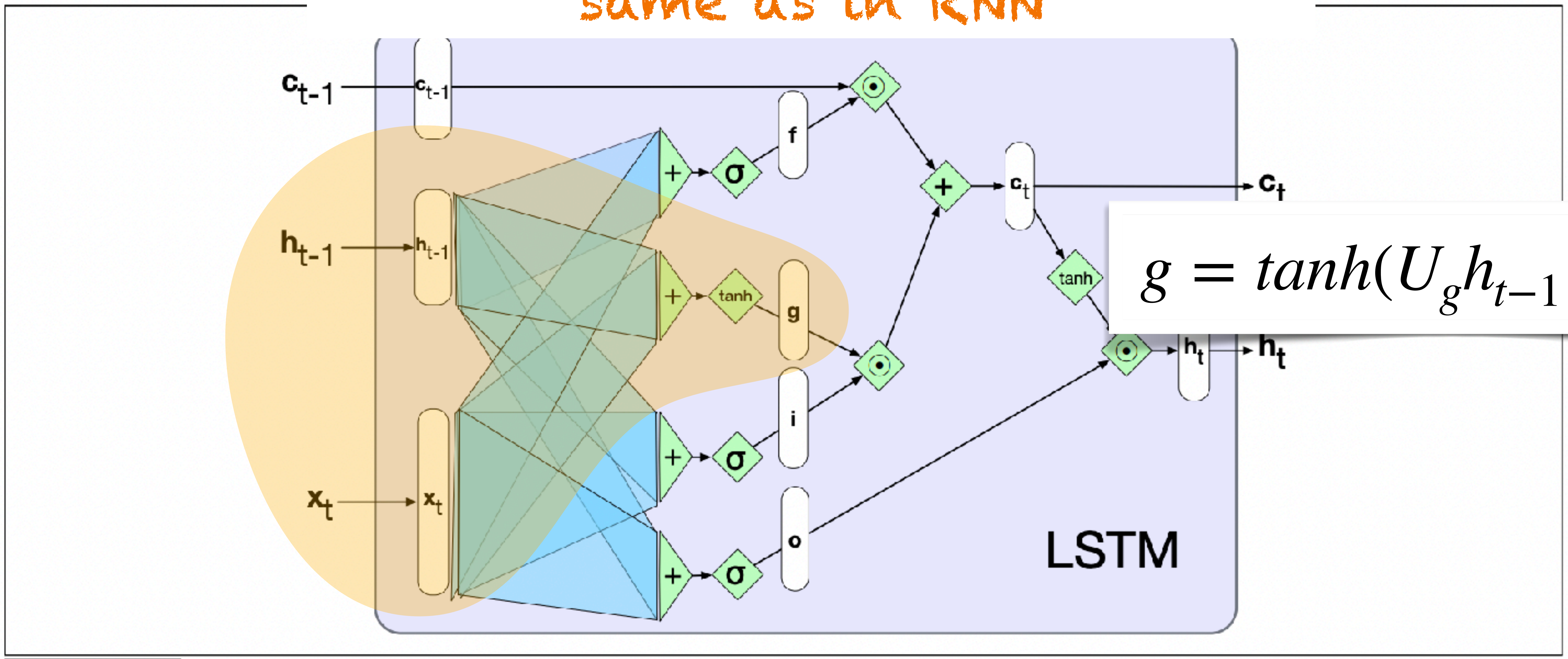
# Long-Short Term Memory Network (LSTM)

## Architecture

processing of current input,
same as in RNN




$$g = tanh(U_g h_{t-1} + W_g x_t)$$

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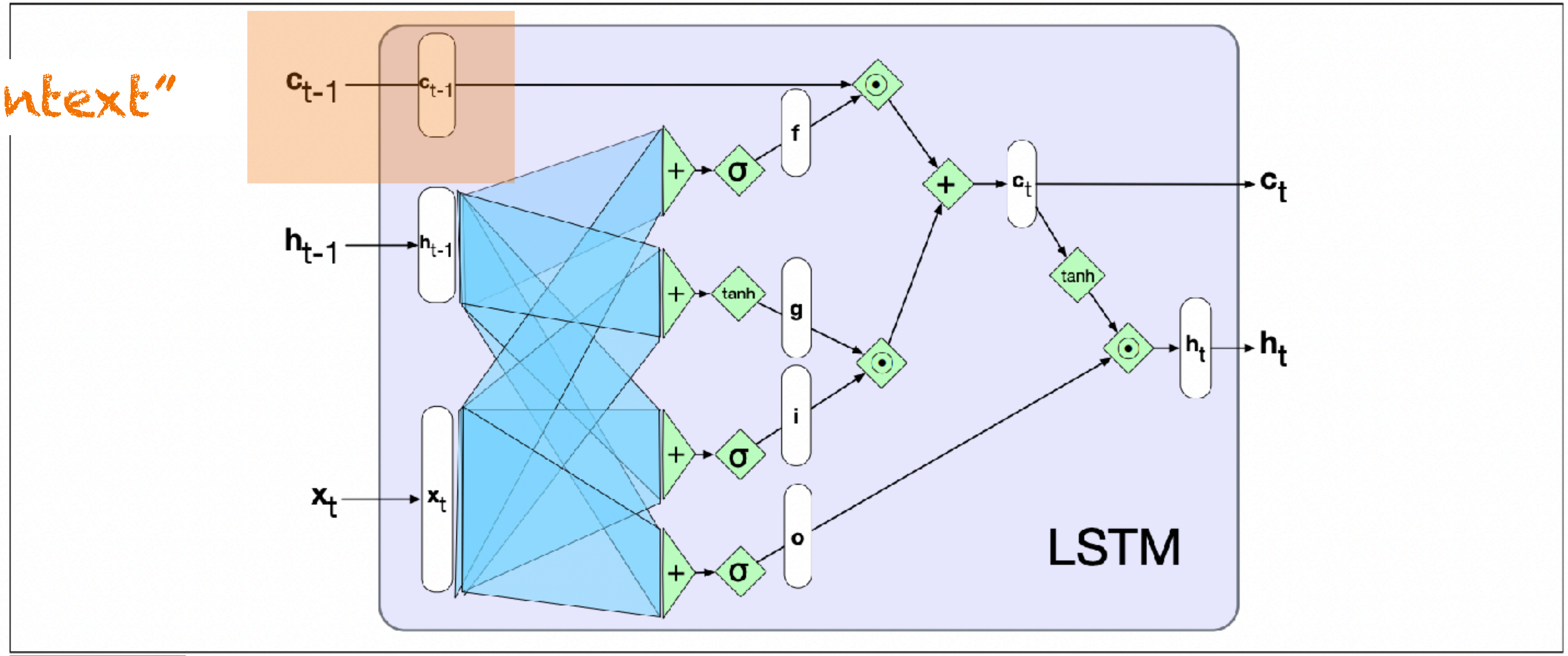
# Long-Short Term Memory Network (LSTM)

## Architecture

"Context"

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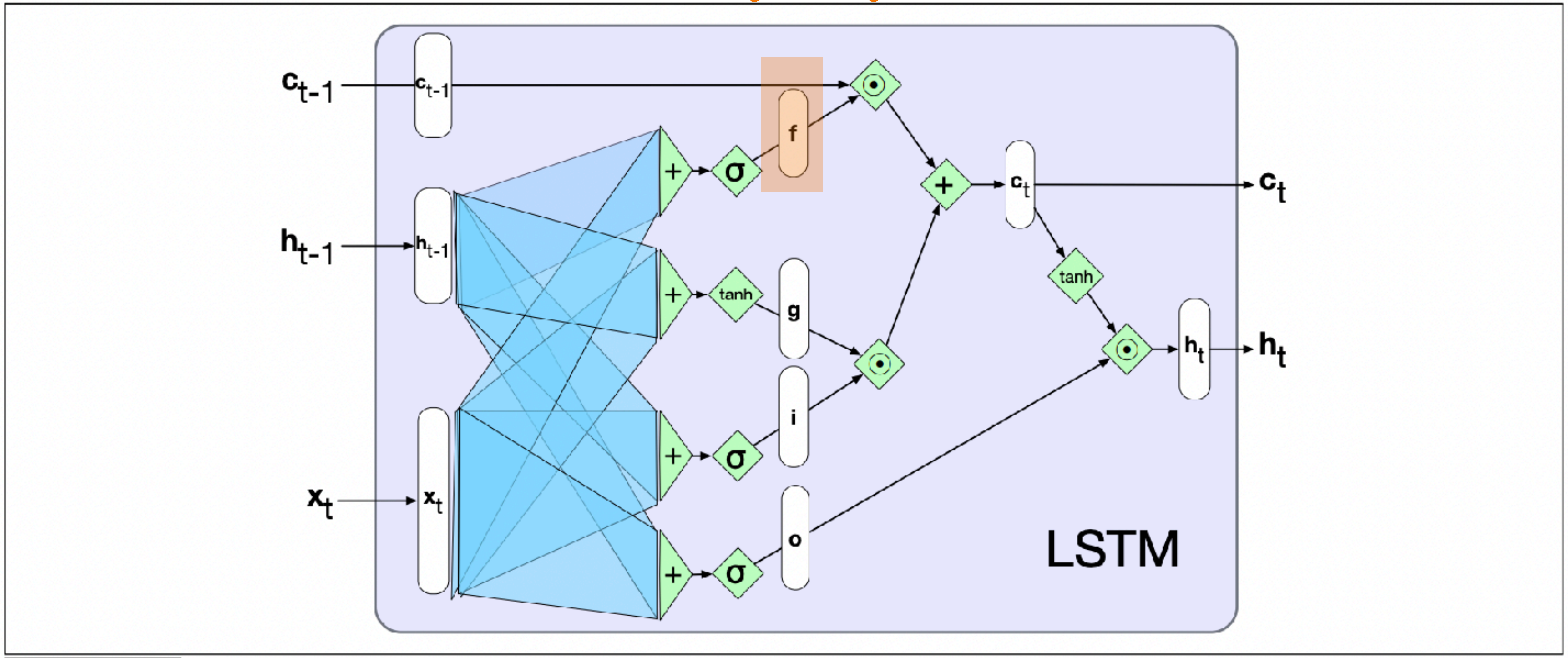
# Long-Short Term Memory Network (LSTM)

## Architecture

forget gate

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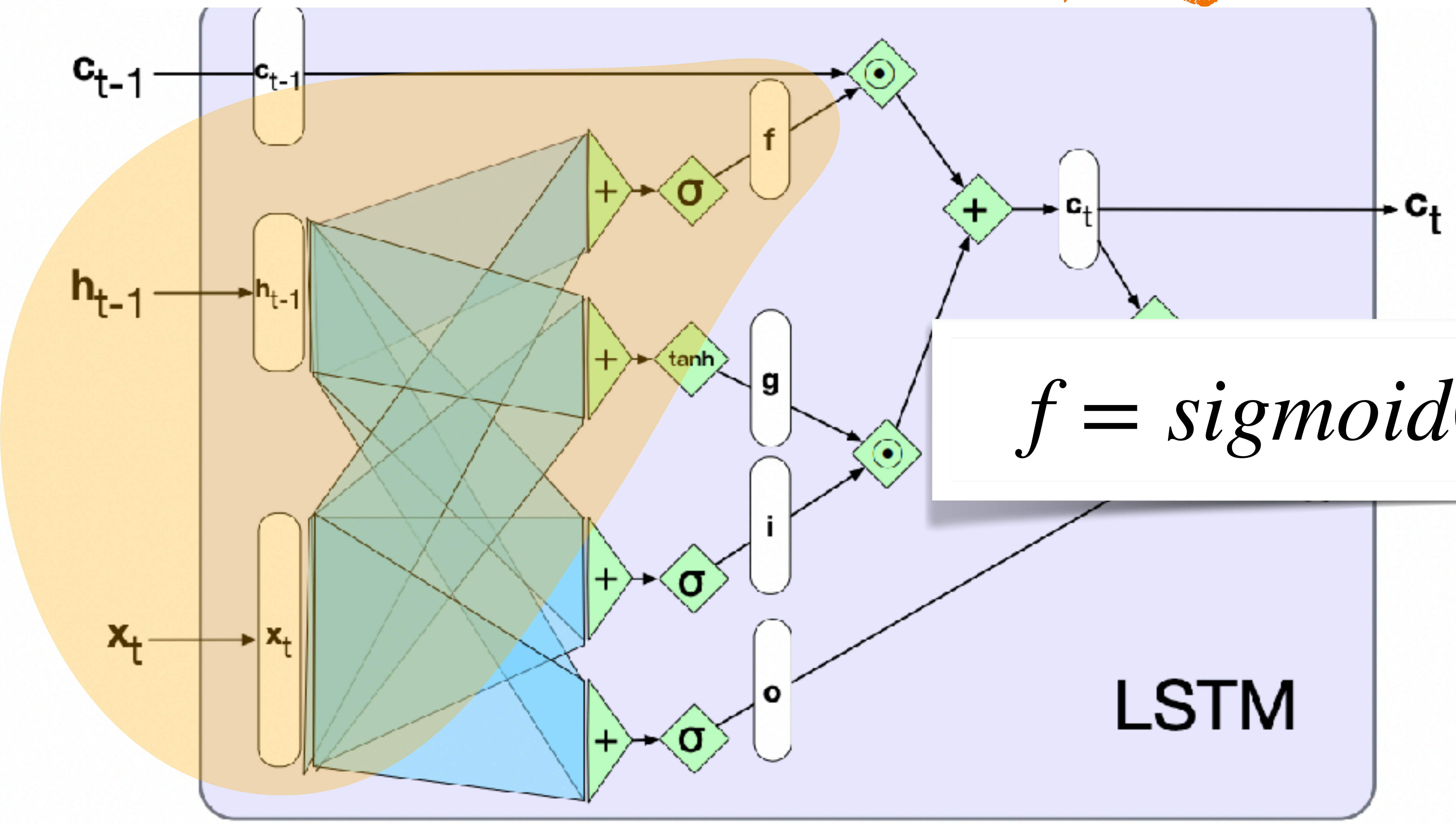
# Long-Short Term Memory Network (LSTM)

## Architecture

$h_{t-1}$ and x also used to determine what to "forget"




$$f = sigmoid(U_f h_{t-1} + W_f x_t)$$

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# Long-Short Term Memory Network (LSTM)

## Architecture

- “Gate” just means:
  - Learn some *mask* (i.e., vector)
  - Apply the mask to (i.e., elementwise multiplication aka Hadamard product) to some hidden state
- As always, mask is learned via backprop

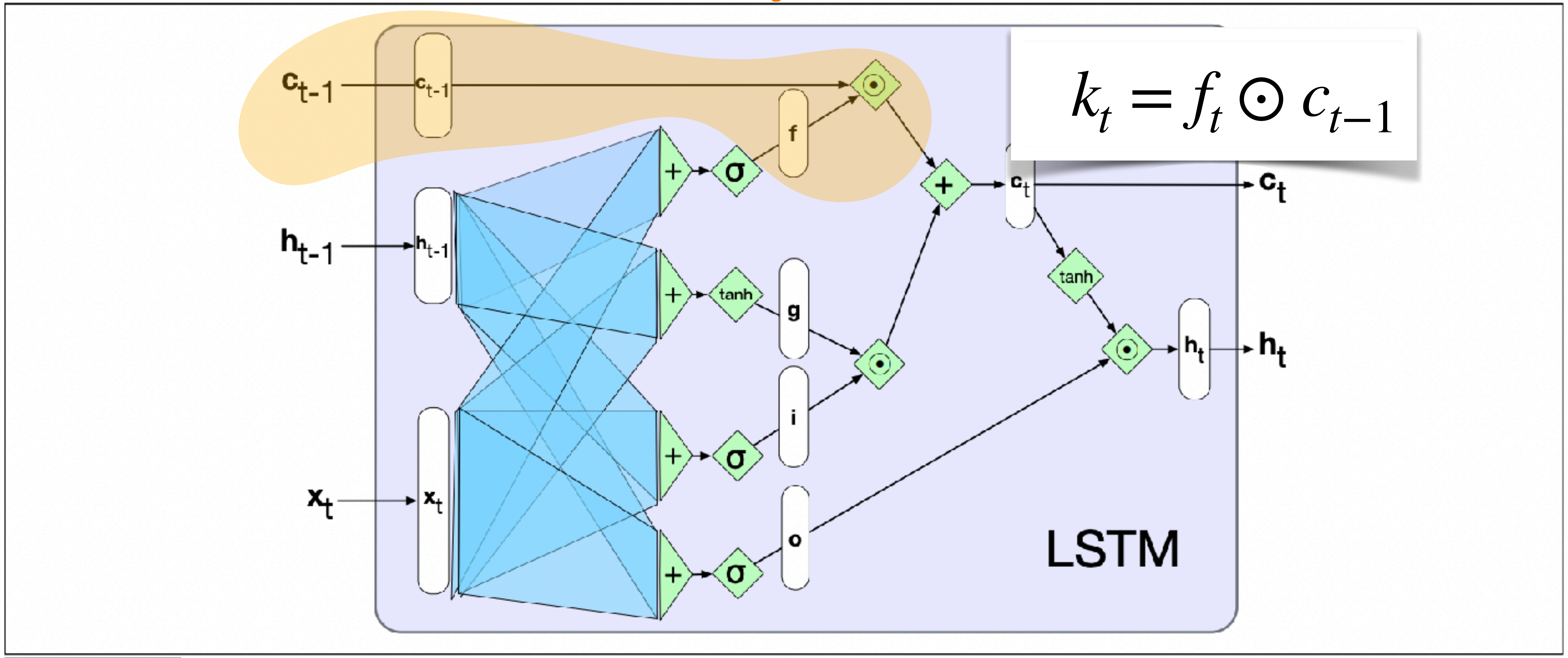
| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 7 | 2 | 9 | $\odot$ | 0.1 | 0.8 | 0.9 | 0.2 | = | 0.3 | 5.6 | 1.8 | 1.8 |
| hidden state | | | | | mask | | | | | result | | | |

# Long-Short Term Memory Network (LSTM)

## Architecture

f is used to "gate" the context

$$k_t = f_t \odot c_{t-1}$$

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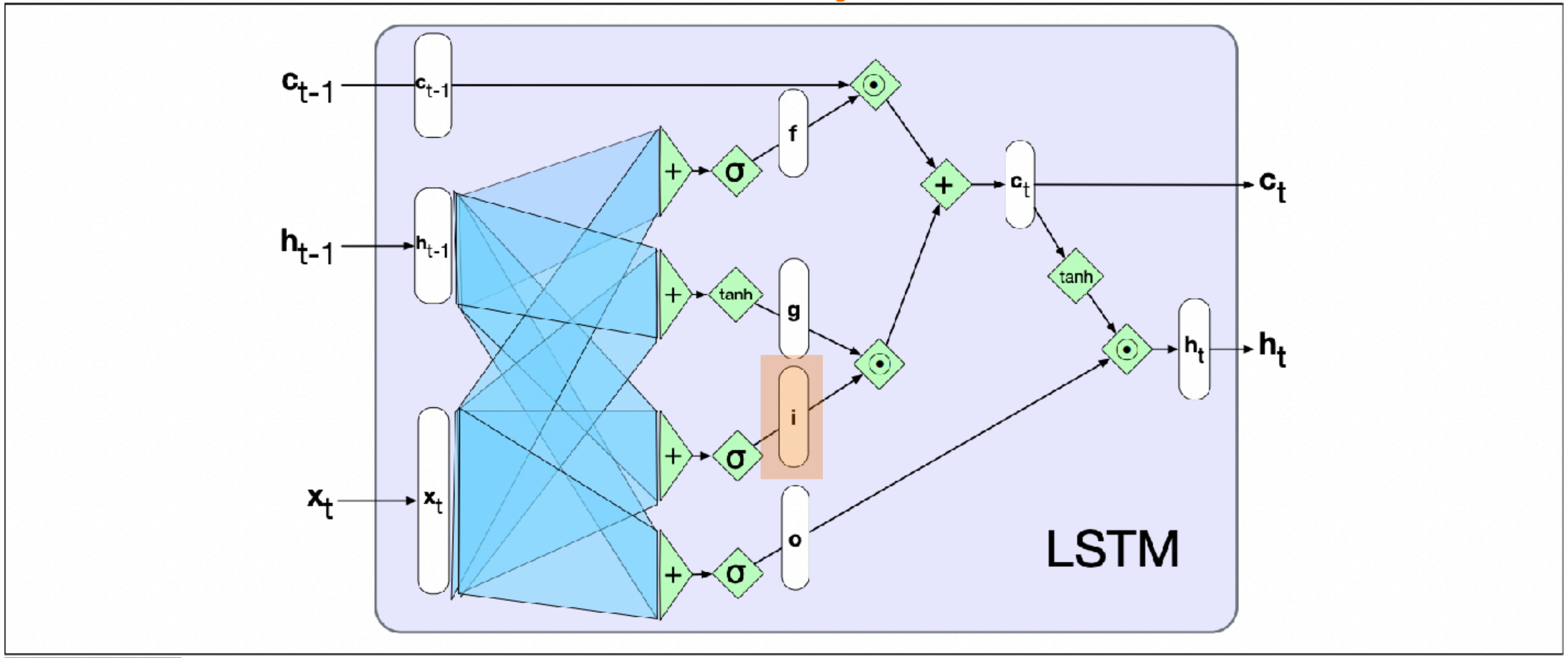
# Long-Short Term Memory Network (LSTM)

## Architecture

add gate

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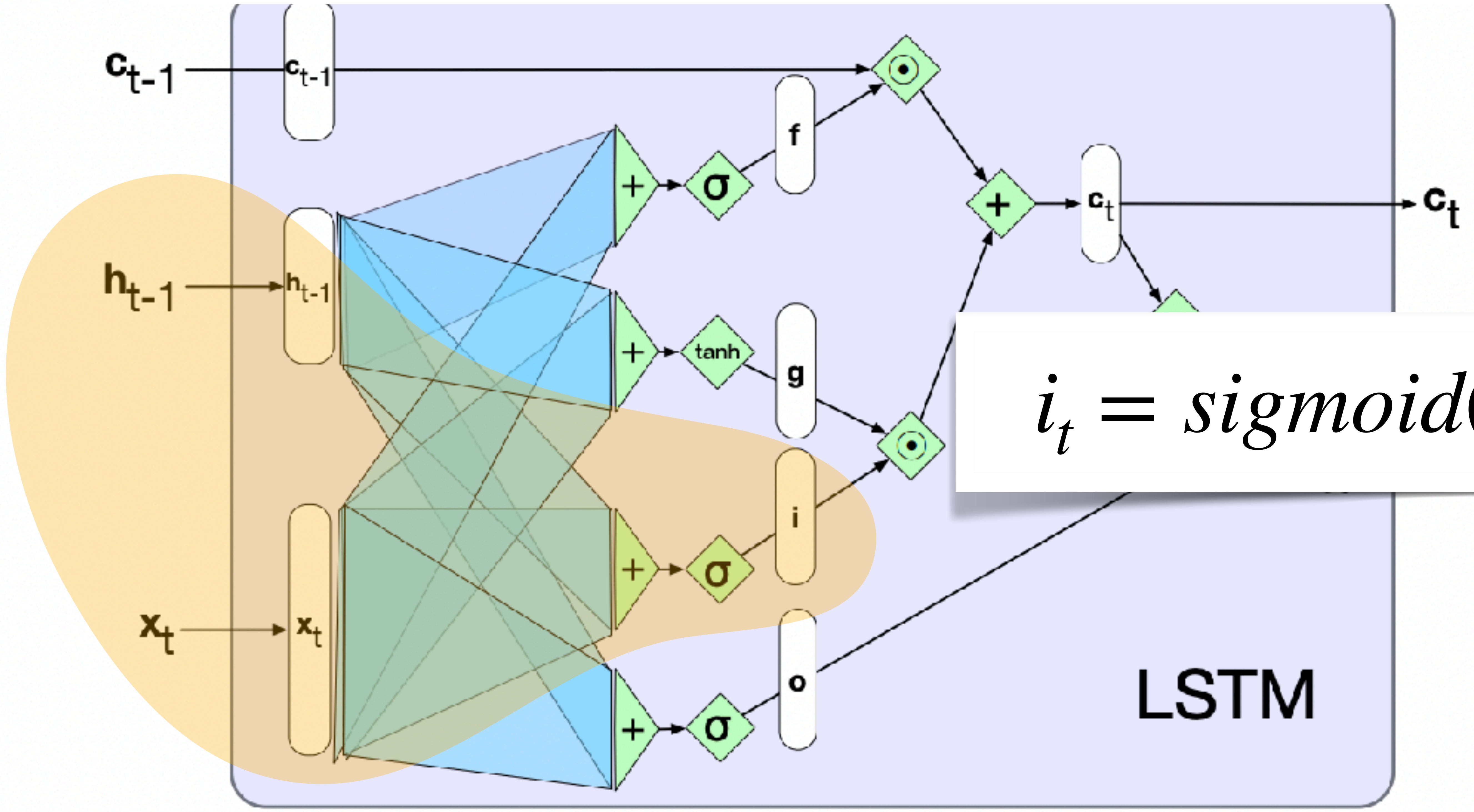
# Long-Short Term Memory Network (LSTM)

## Architecture

$h_{t-1}$ and x also used to determine what to "add"




$$i_t = sigmoid(U_i h_{t-1} + W_i x_t)$$

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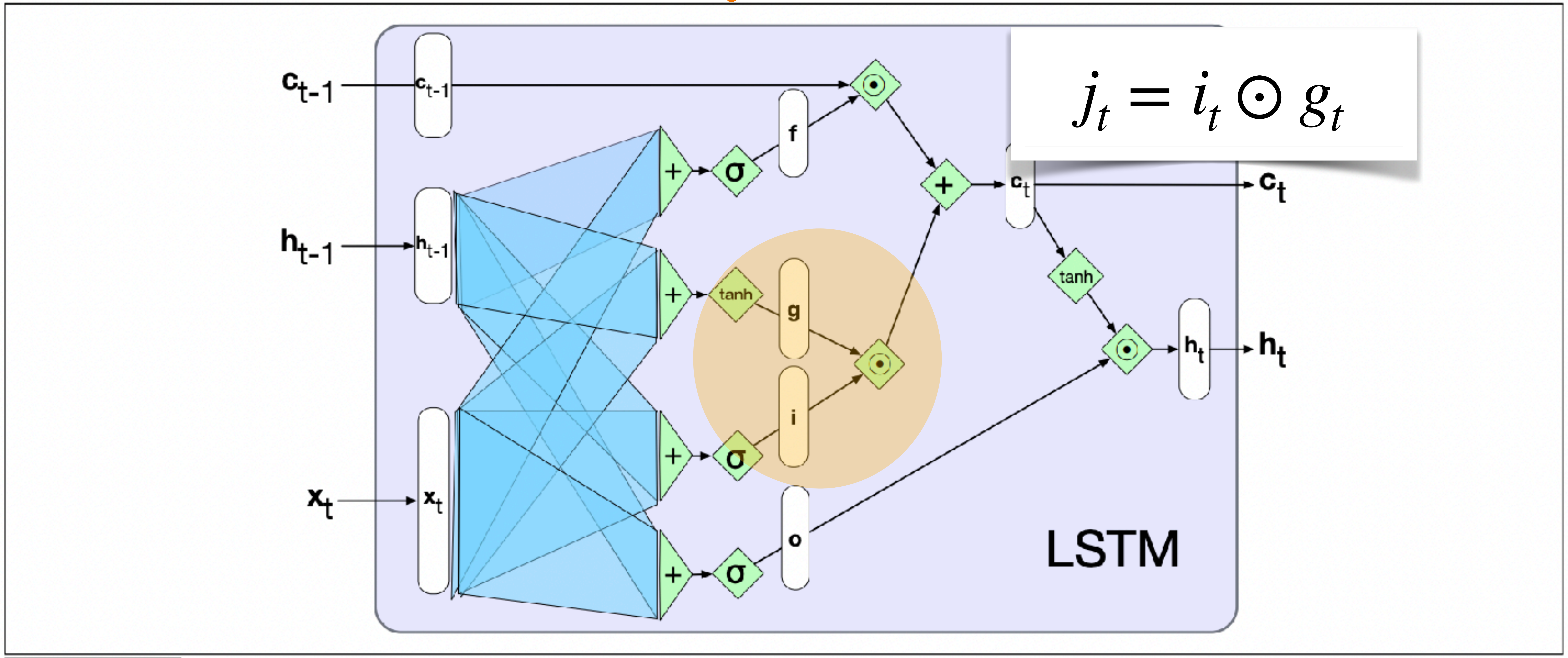
# Long-Short Term Memory Network (LSTM)

## Architecture

i is used to "gate" the current state




$$j_t = i_t \odot g_t$$

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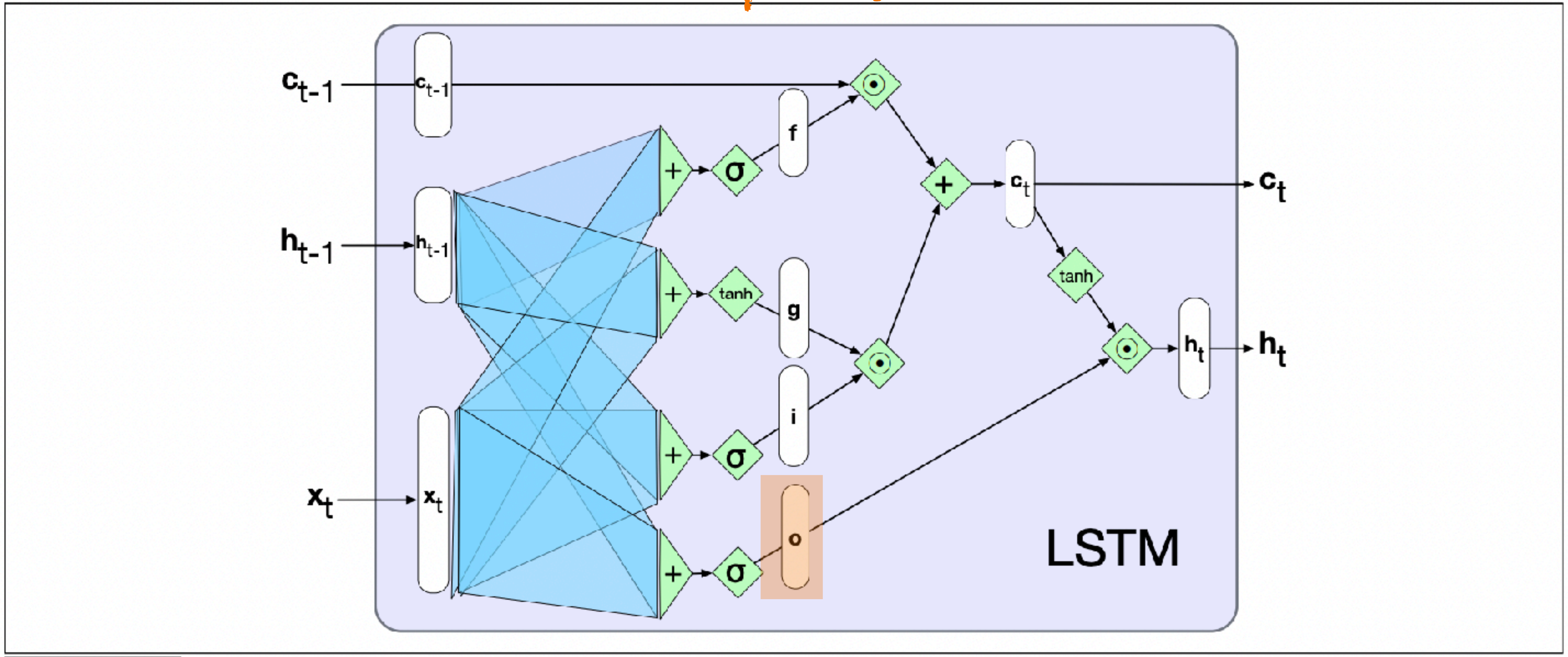
# Long-Short Term Memory Network (LSTM)

## Architecture

output gate

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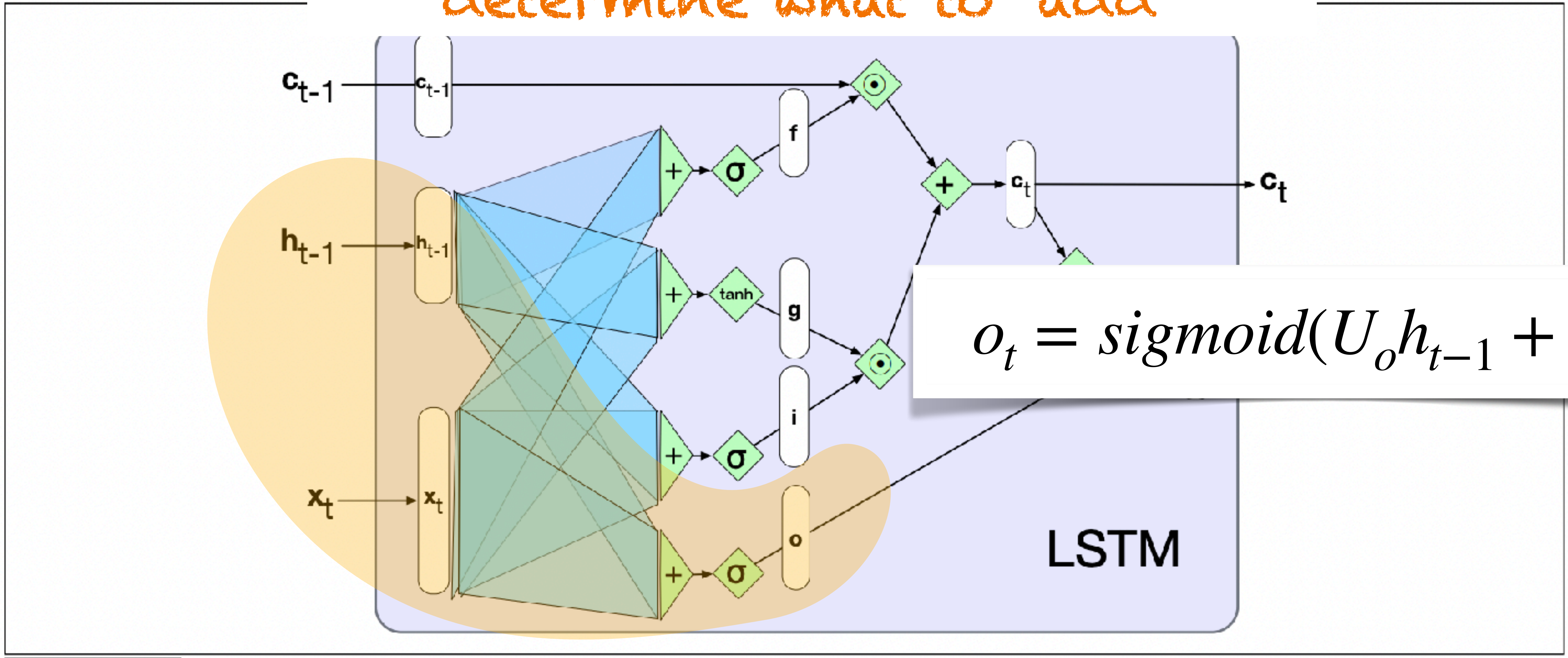
# Long-Short Term Memory Network (LSTM)

## Architecture

$h_{t-1}$ and x also used to determine what to "add"




$$o_t = sigmoid(U_o h_{t-1} + W_o x_t)$$

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# Long-Short Term Memory Network (LSTM)

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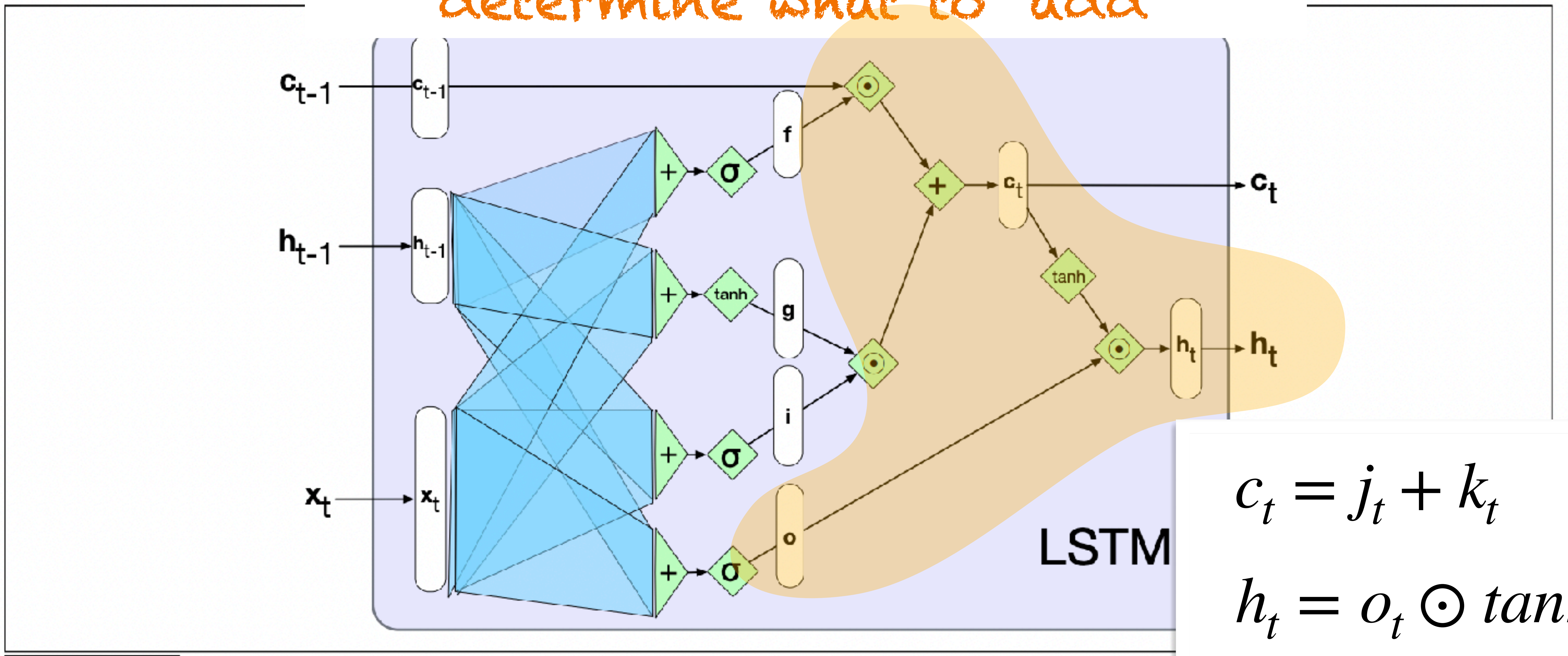


$$c_t = j_t + k_t$$

$$h_t = o_t \odot tanh(c_t)$$

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# Long-Short Term Memory Network (LSTM)

## Architecture

$$g = tanh(U_g h_{t-1} + W_g x_t)$$

$$f = sigmoid(U_f h_{t-1} + W_f x_t)$$

$$i_t = sigmoid(U_i h_{t-1} + W_i x_t)$$

$$o_t = sigmoid(U_o h_{t-1} + W_o x_t)$$

$$k_t = f_t \odot c_{t-1}$$

$$j_t = i_t \odot g_t$$

$$c_t = j_t + k_t$$

$$h_t = o_t \odot tanh(c_t)$$

# Long-Short Term Memory Network (LSTM)

## Architecture

$$g = tanh(U_g h_{t-1} + W_g x_t)$$
$$f = sigmoid(U_f h_{t-1} + W_f x_t)$$
$$i_t = sigmoid(U_i h_{t-1} + W_i x_t)$$
$$o_t = sigmoid(U_o h_{t-1} + W_o x_t)$$

compute current state, add gate, forget gate, and output gate from previous hidden state and current input

$$k_t = f_t \odot c_{t-1}$$
$$j_t = i_t \odot g_t$$
$$c_t = j_t + k_t$$
$$h_t = o_t \odot tanh(c_t)$$

# Long-Short Term Memory Network (LSTM)

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$$g = tanh(U_g h_{t-1} + W_g x_t)$$

$$f = sigmoid(U_f h_{t-1} + W_f x_t)$$

$$i_t = sigmoid(U_i h_{t-1} + W_i x_t)$$

$$o_t = sigmoid(U_o h_{t-1} + W_o x_t)$$

combine those things using Hadamard product

$$k_t = f_t \odot c_{t-1}$$

$$j_t = i_t \odot g_t$$

$$c_t = j_t + k_t$$

$$h_t = o_t \odot tanh(c_t)$$

# Long-Short Term Memory Network (LSTM)

## Architecture

$$g = tanh(U_g h_{t-1} + W_g x_t)$$
$$f = sigmoid(U_f h_{t-1} + W_f x_t)$$
$$i_t = sigmoid(U_i h_{t-1} + W_i x_t)$$
$$o_t = sigmoid(U_o h_{t-1} + W_o x_t)$$

update context and hidden state for next iteration

$$k_t = f_t \odot c_{t-1}$$
$$j_t = i_t \odot g_t$$
$$c_t = j_t + k_t$$
$$h_t = o_t \odot tanh(c_t)$$

# Long-Short Term Memory Network (LSTM)

## Architecture

$$g = tanh(U_g h_{t-1} + W_g x_t)$$

$$f = sigmoid(U_f h_{t-1} + W_f x_t)$$

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$$o_t = sigmoid(U_o h_{t-1} + W_o x_t)$$

$$k_t = f_t \odot c_{t-1}$$

$$j_t = i_t \odot g_t$$

$$c_t = j_t + k_t$$

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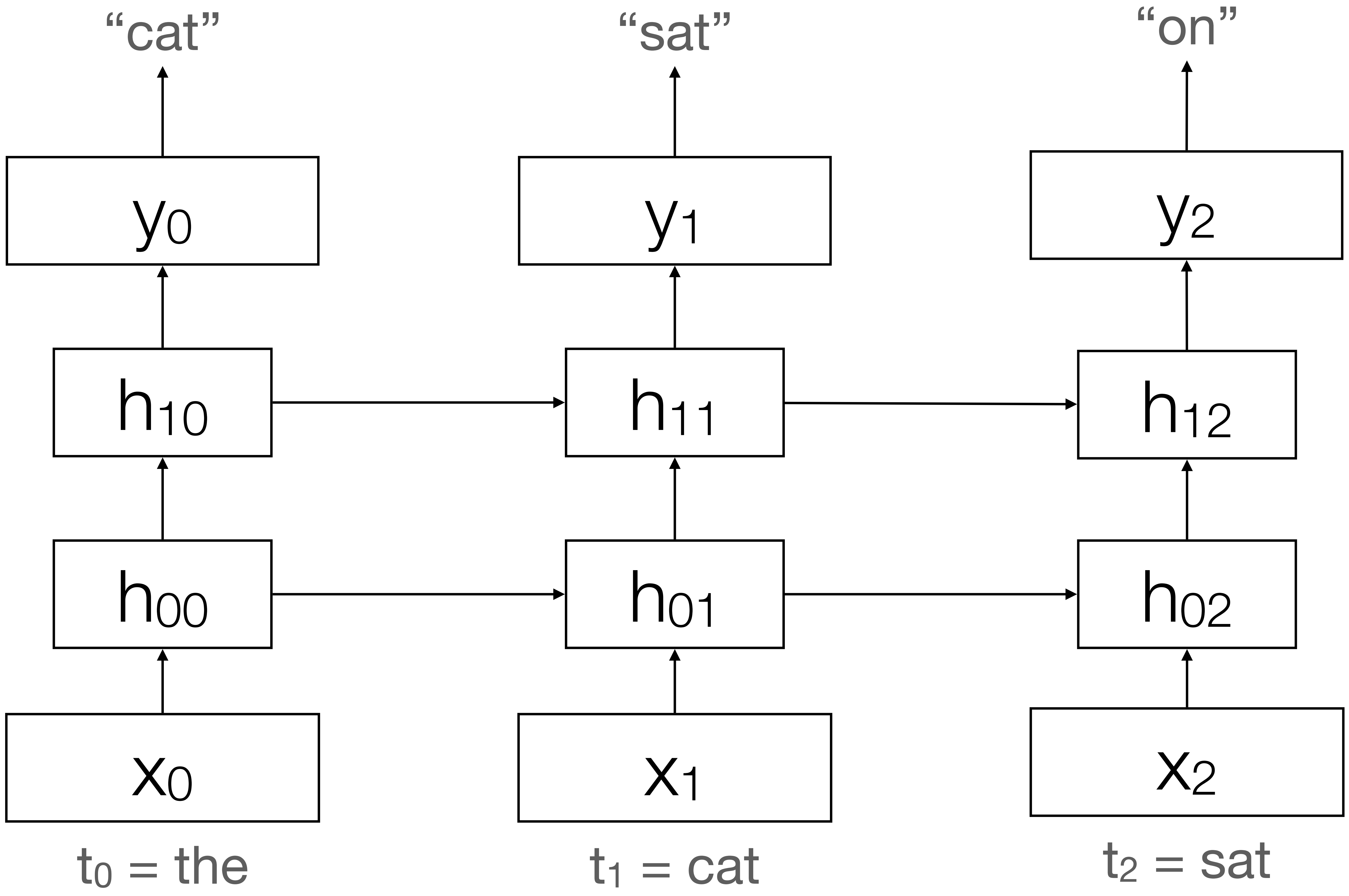
# Topics

- NN Architectures for Language Modeling
  - ~~MLP~~
  - Recurrent Neural Network (RNN)
  - Long-Short Term Memory Network (LSTM)
  - **Transformer**

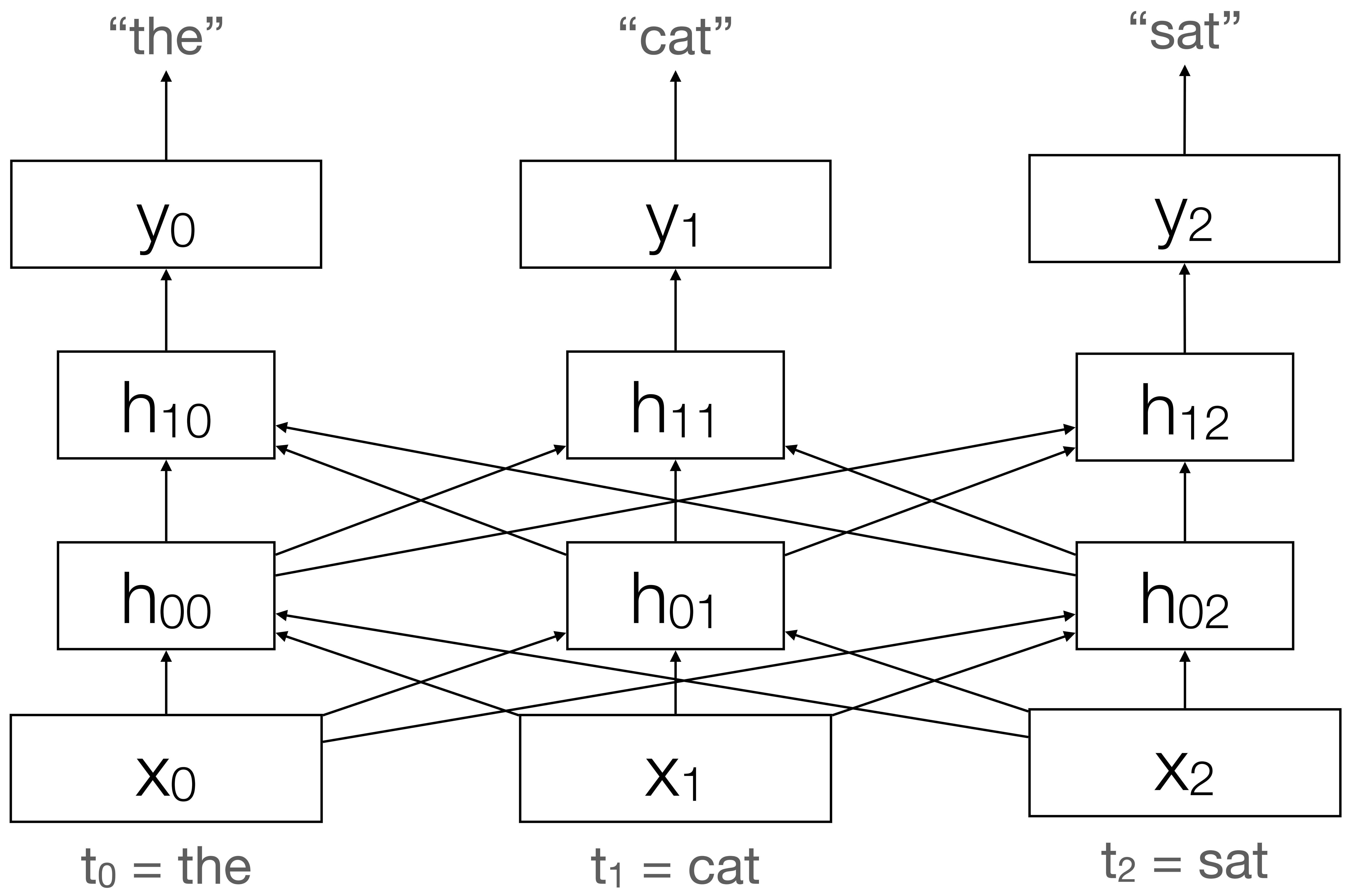
# Transformers

## Recap: Recurrent Neural Network (RNN)



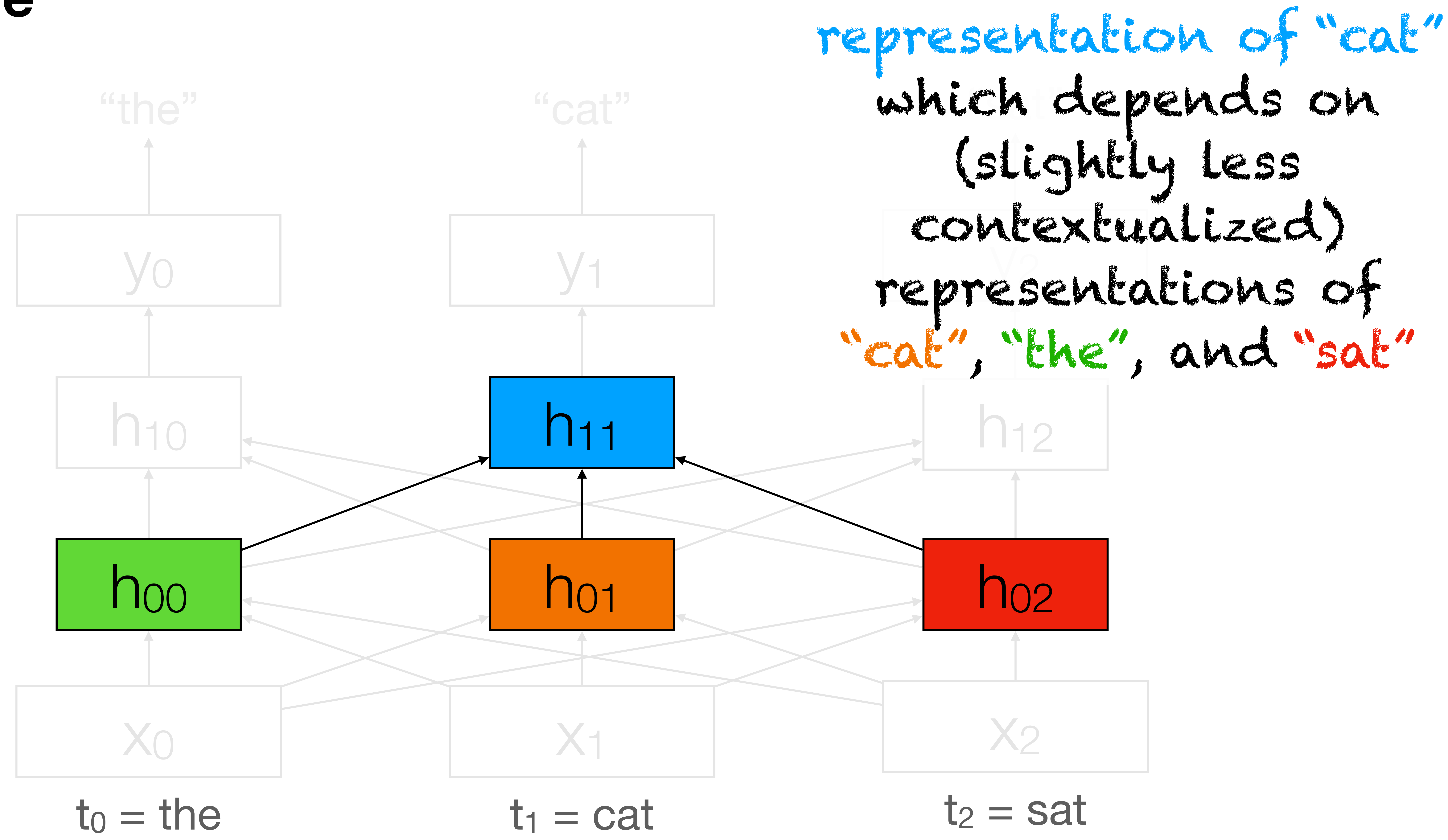
# Transformers

## Architecture



# Transformers

## Architecture



# Topics

- NN Architectures for Language Modeling
  - ~~MLP~~
  - Recurrent Neural Network (RNN)
  - Long-Short Term Memory Network (LSTM)
  - **Transformers**
    - Architecture
    - Self Attention
    - Blocks
    - Positional Encodings

# Topics

- NN Architectures for Language Modeling
  - ~~MLP~~
  - Recurrent Neural Network (RNN)
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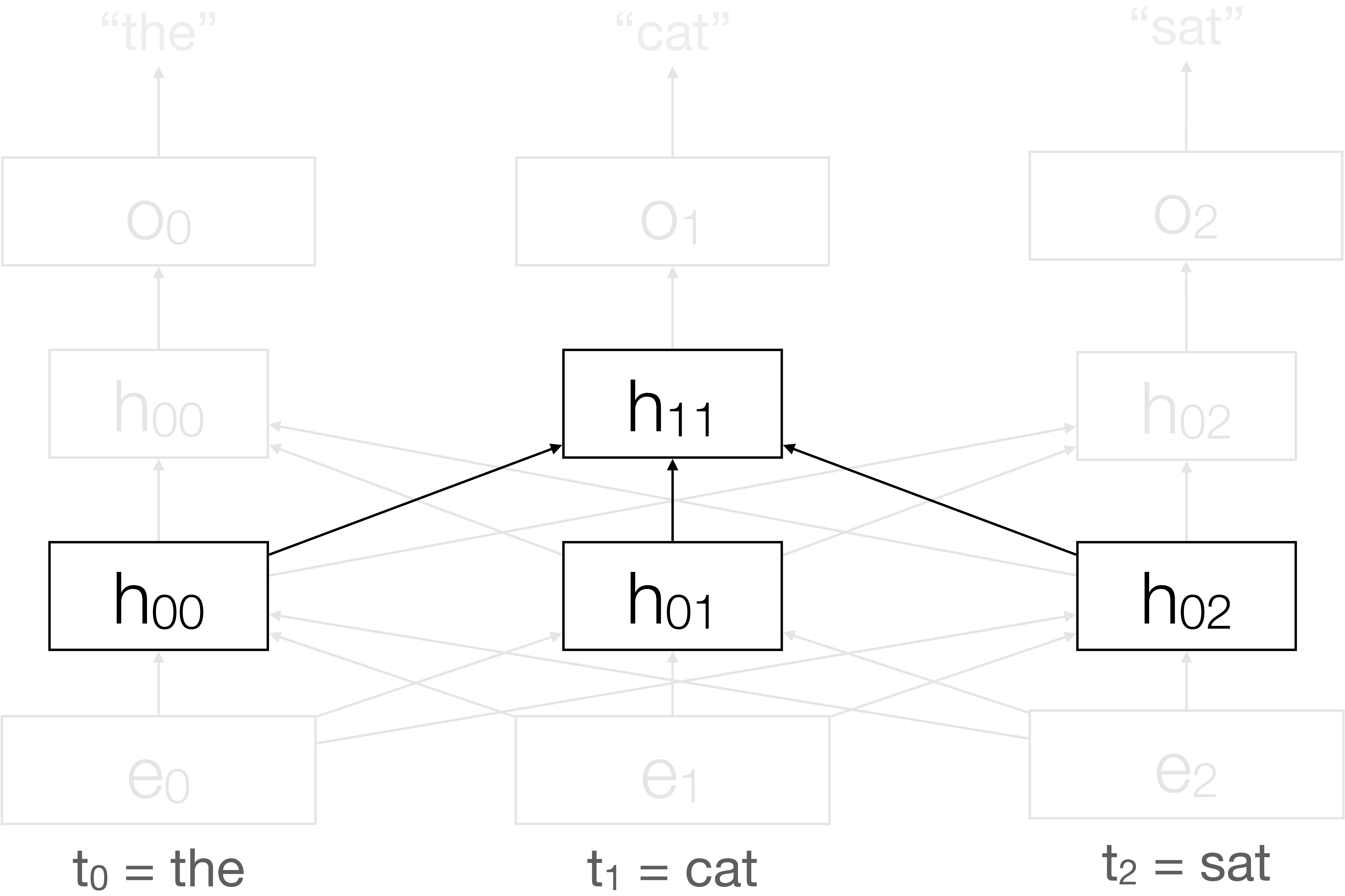
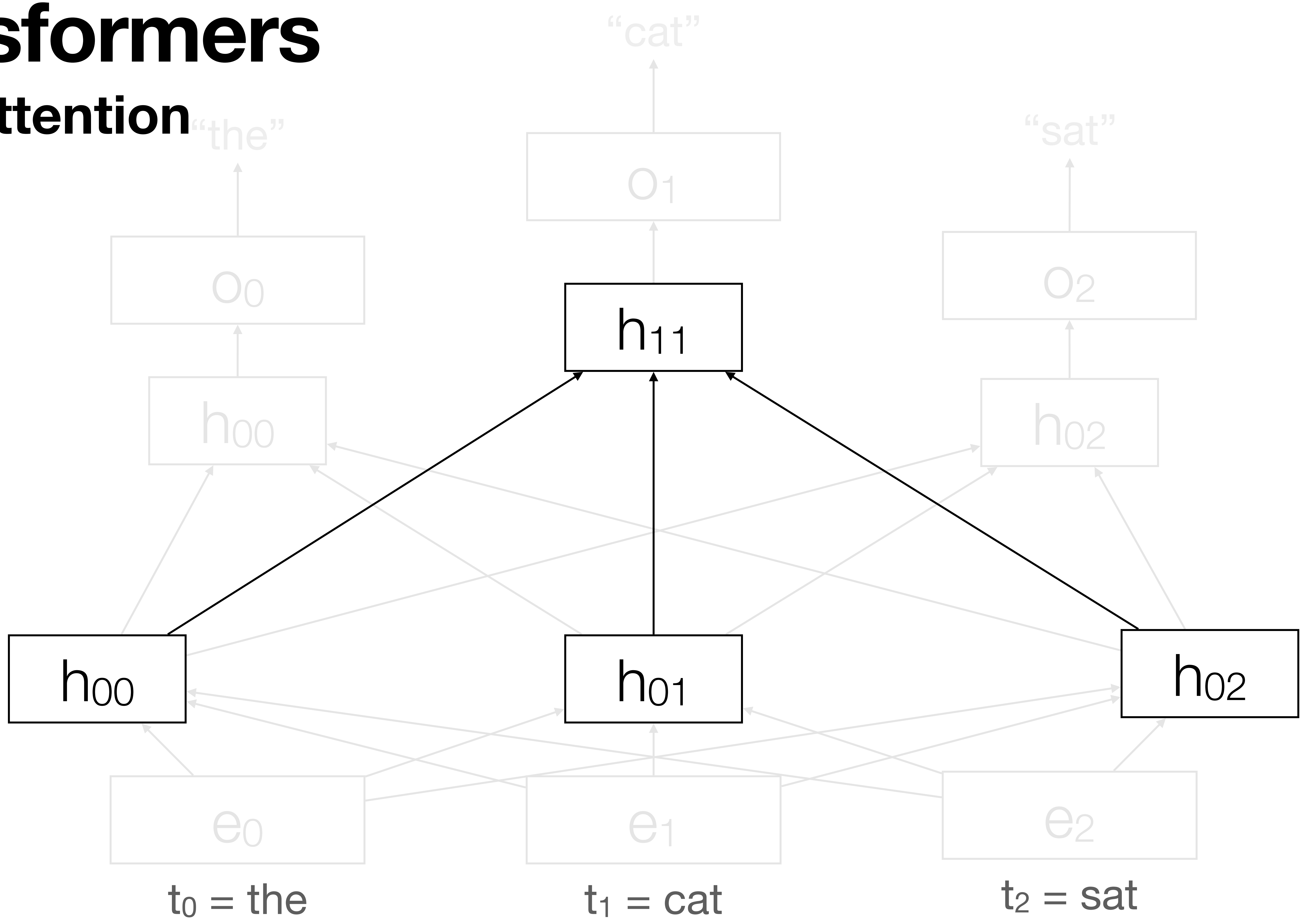
# Transformers

## (Self) Attention



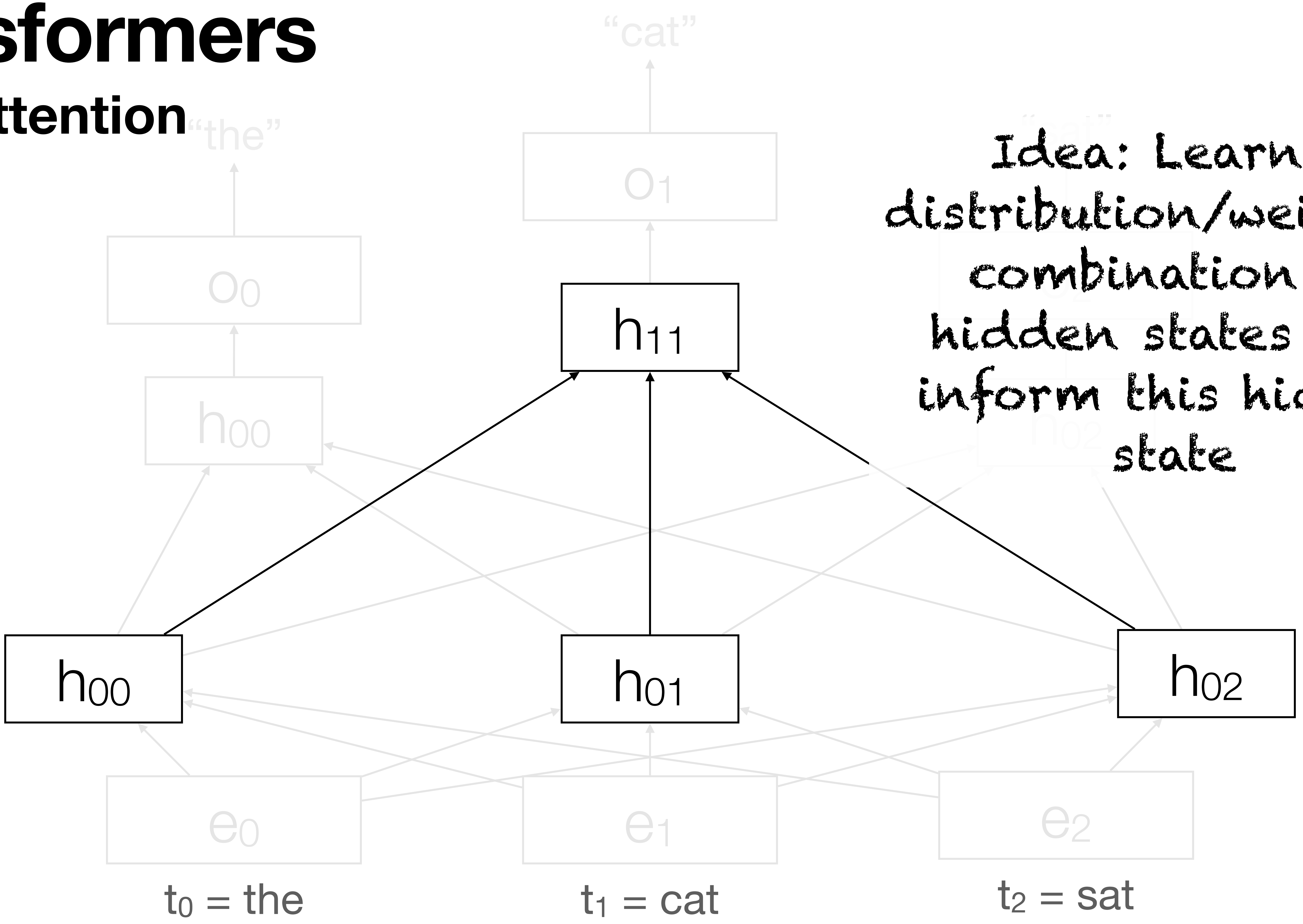
# Transformers

## (Self) Attention



# Transformers

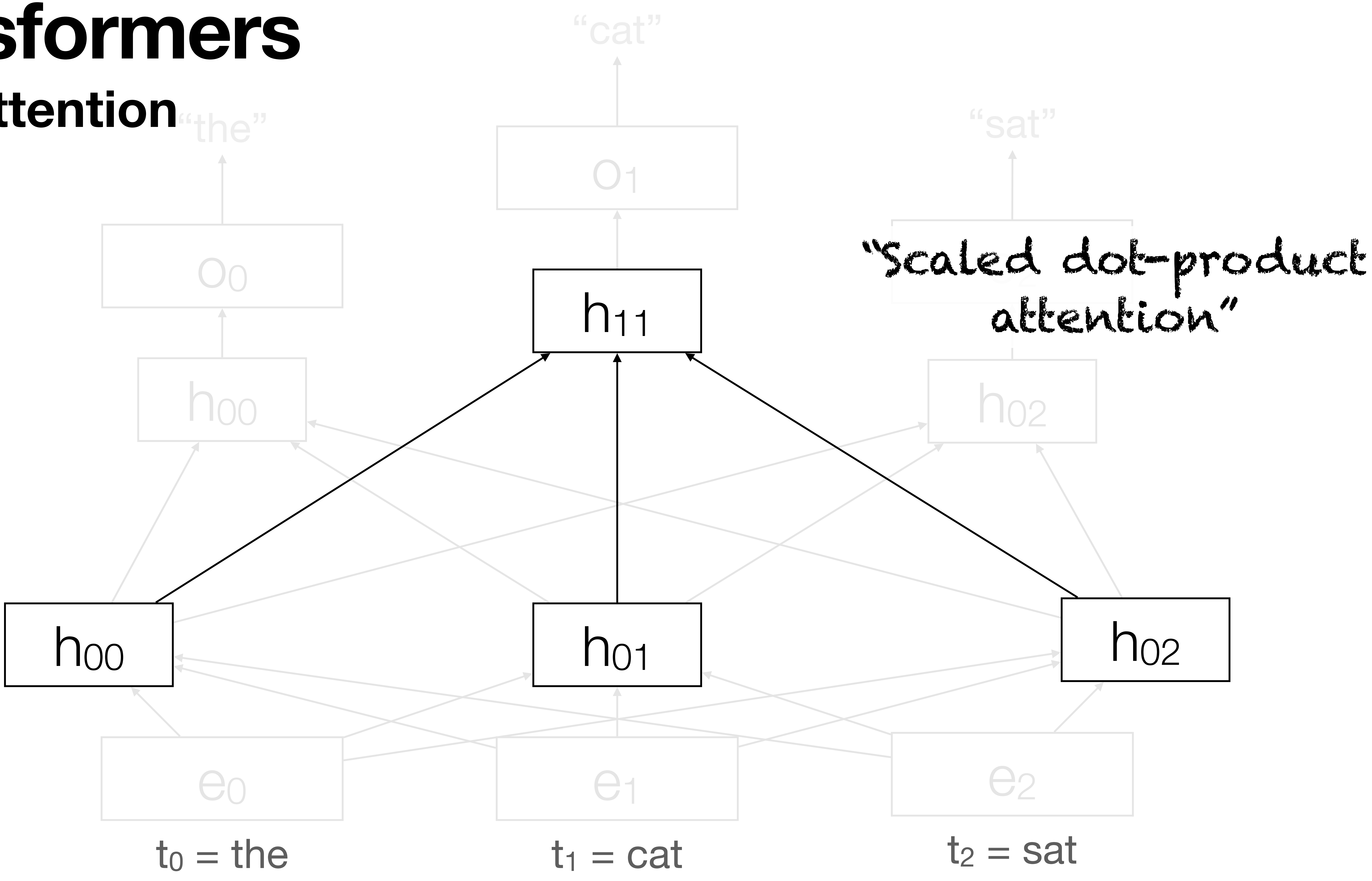
## (Self) Attention




Idea: Learn a distribution/weighted combination of hidden states that inform this hidden state

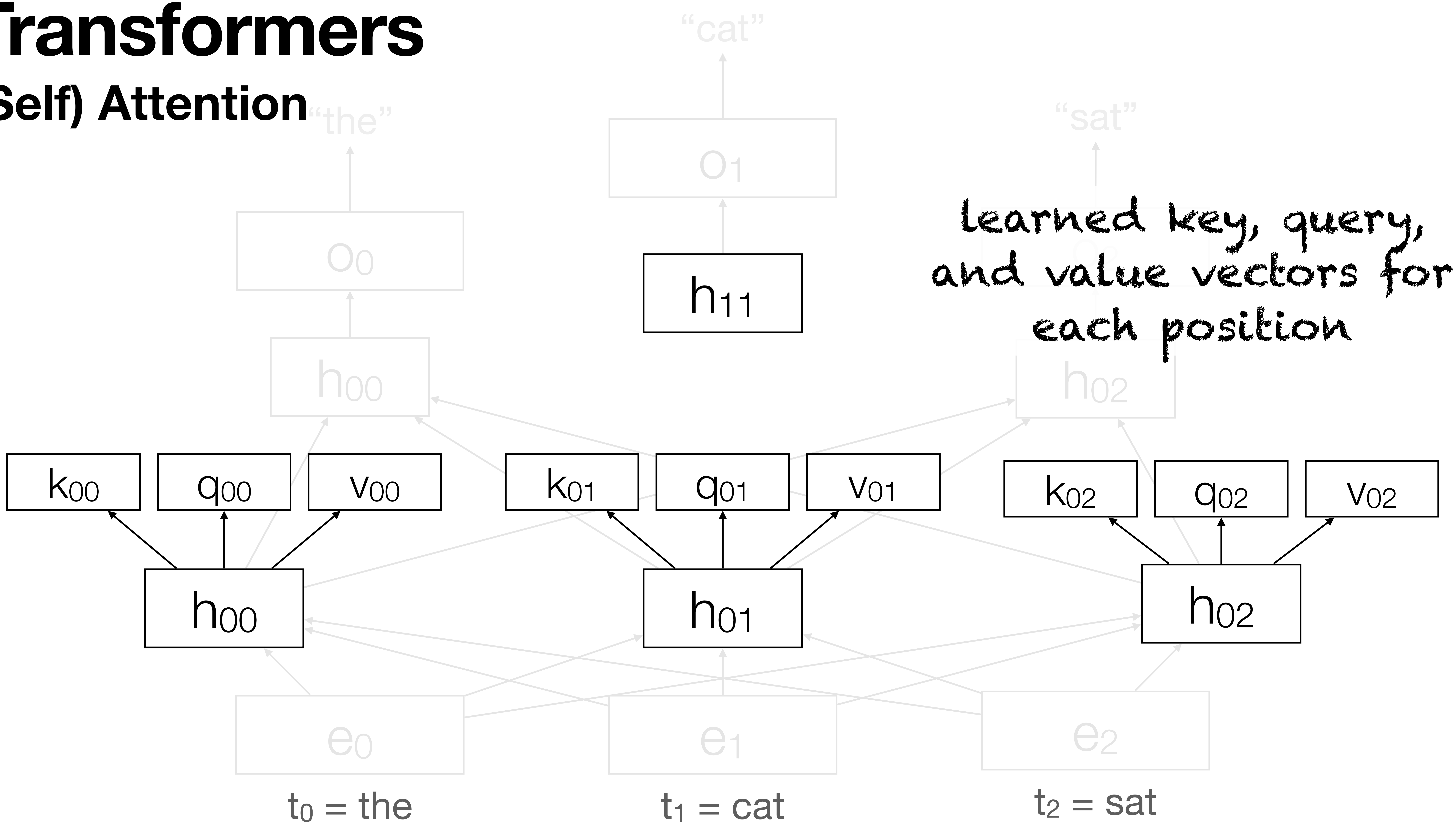
# Transformers

## (Self) Attention



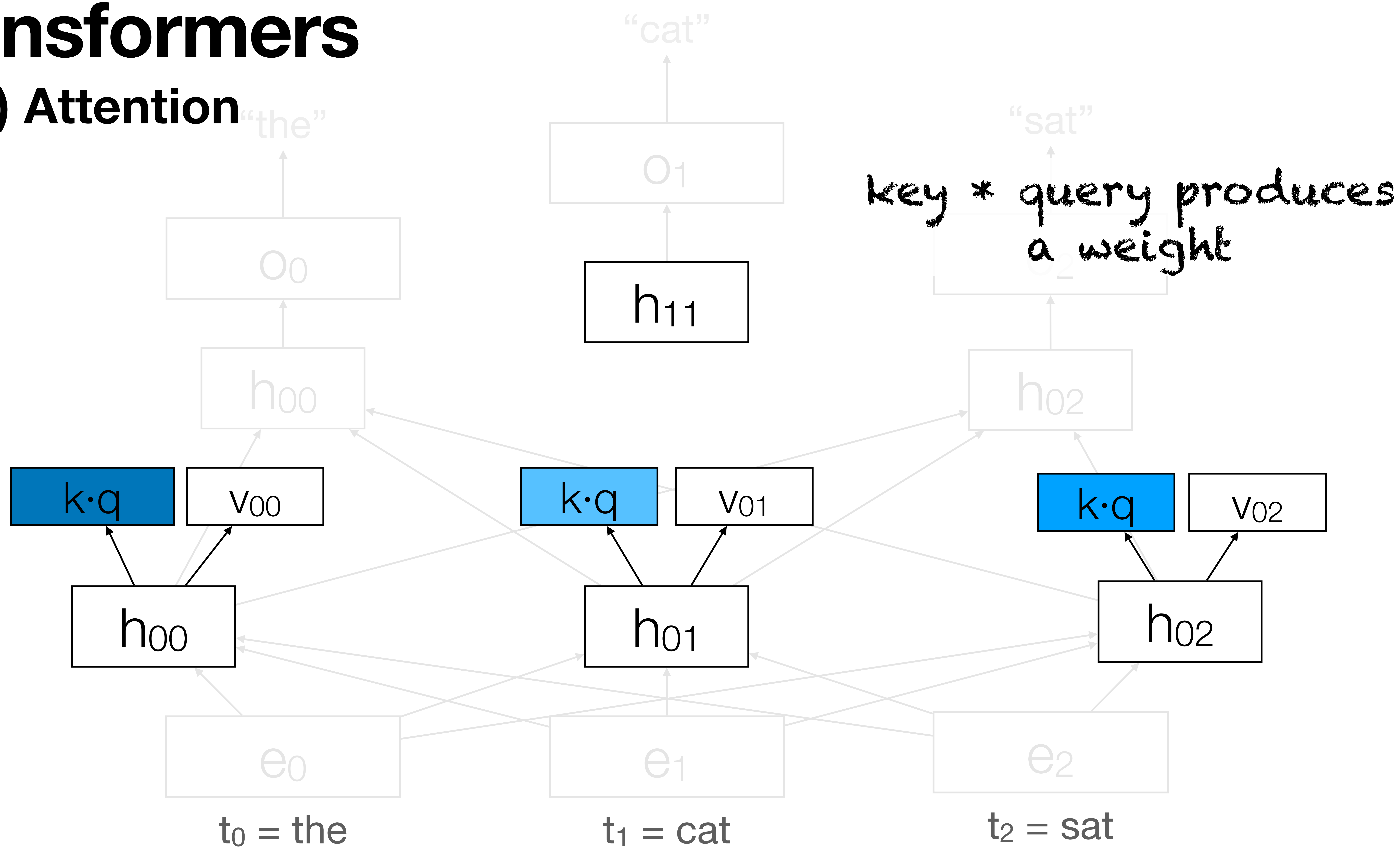
# Transformers

## (Self) Attention



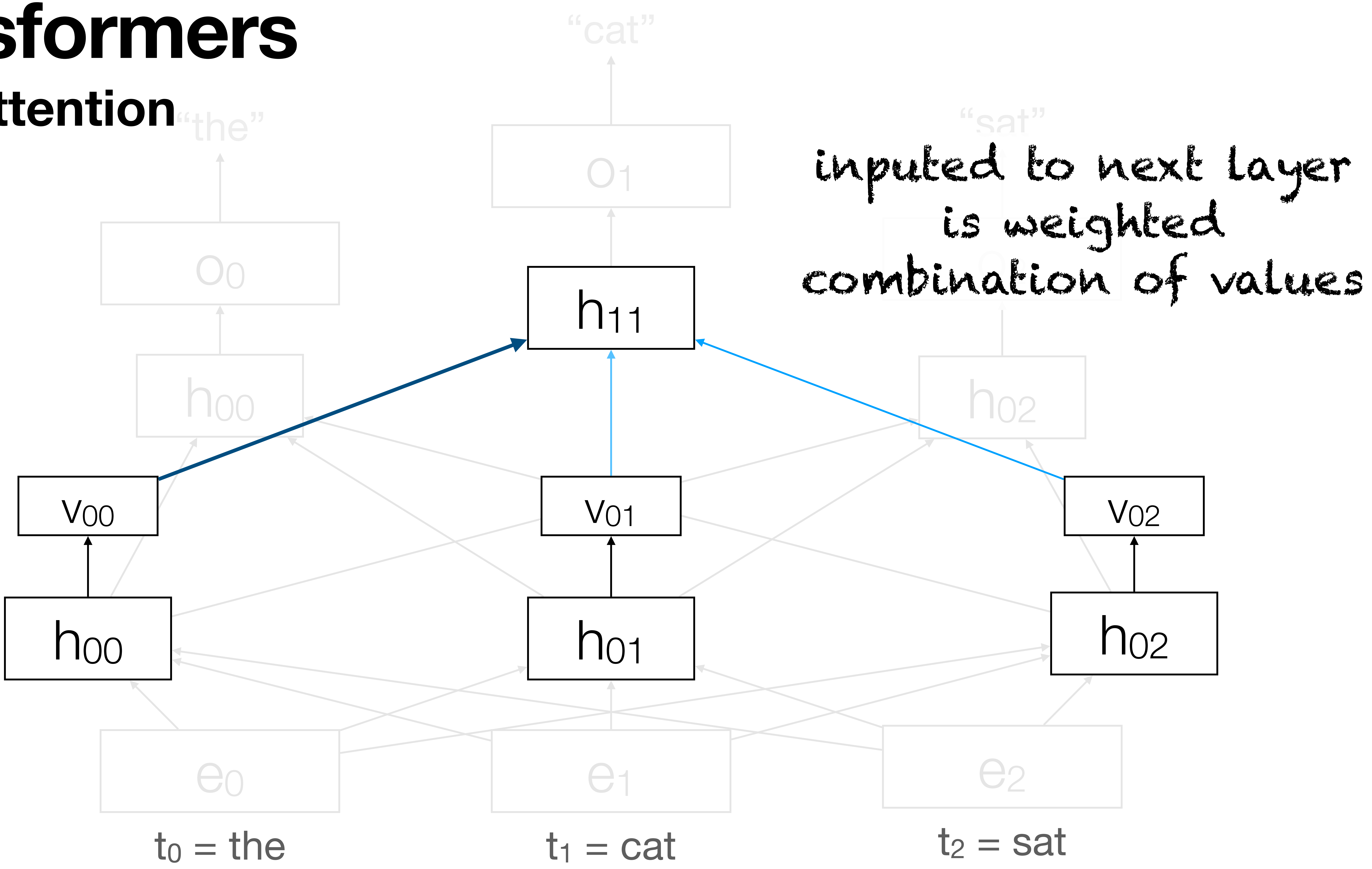
# Transformers

## (Self) Attention



# Transformers

## (Self) Attention



# Transformers

## (Self) Attention

- Each word has three roles:
  - Query: The word as the current focus. I.e., attention is trying to determine how to process this word.
  - Key: The word as a context word. I.e., attention is determining how to use this word to inform the query.
  - Value: The word as part of the output. I.e., attention is determining how to use this word, based on the key-query, to produce an output.
- Every word acts in all three roles at each timestep.
- We learn three weight matrices (Q,K,V) to cast each word into each role

# Transformers

## (Self) Attention

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- Every word acts in all three roles at each timestep.
- We learn three weight matrices (Q,K,V) to cast each word into each role

$$\mathbf{q}_i = \mathbf{W^Q}\mathbf{x}_i; \;\; \mathbf{k}_i = \mathbf{W^K}\mathbf{x}_i; \;\; \mathbf{v}_i = \mathbf{W^V}\mathbf{x}_i$$

# Transformers

## (Self) Attention

- To actually compute the attention:
  - score = dot(k,q)
  - score is just a scaler number
- y = weighted_sum of values = sum (score*v)

# Transformers

## (Self) Attention

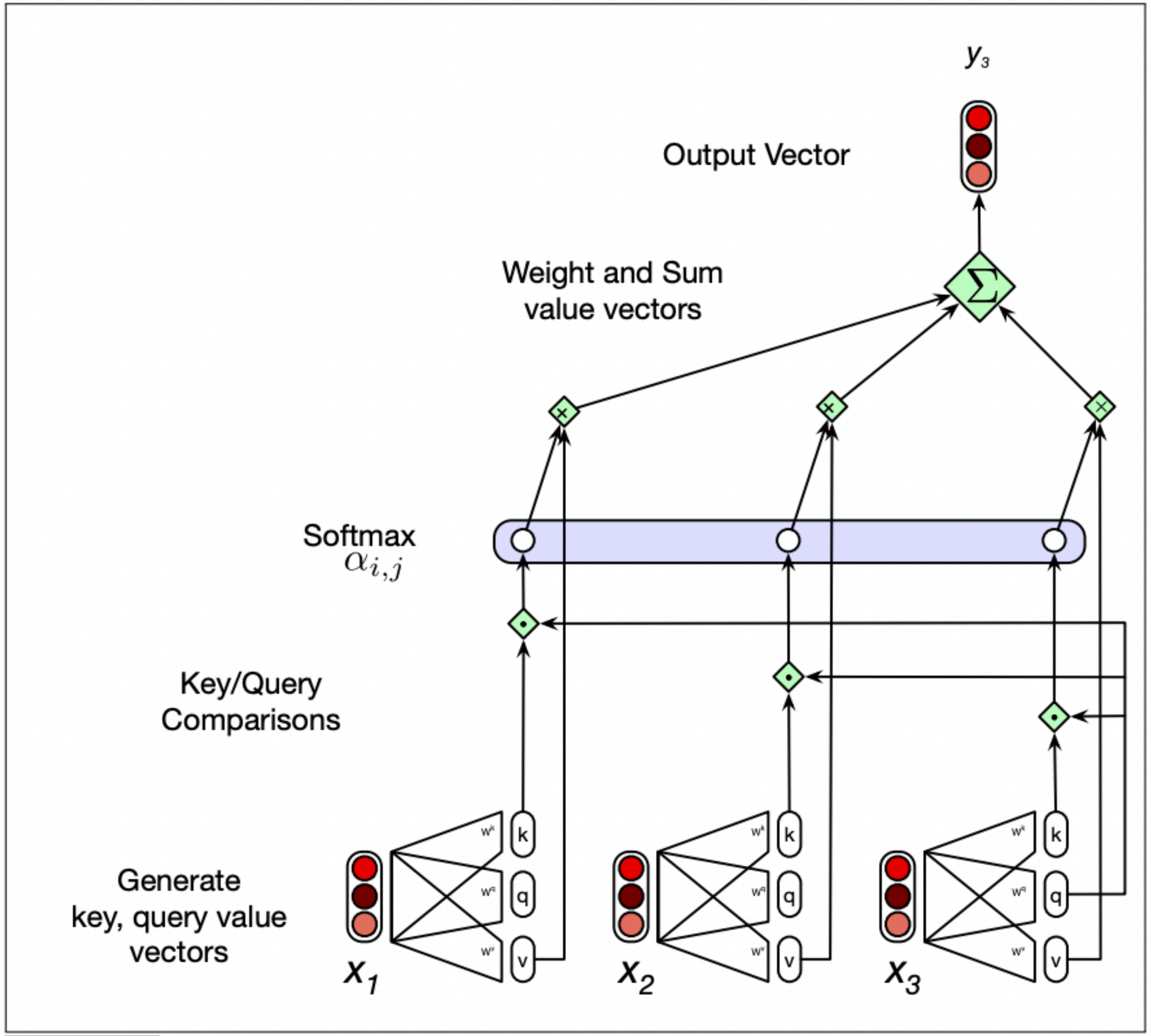



**Figure 9.16** Calculating the value of $\mathbf{y}_3$, the third element of a sequence using causal (left-to-right) self-attention.

# Transformers

## (Self) Attention

dot(q,k)

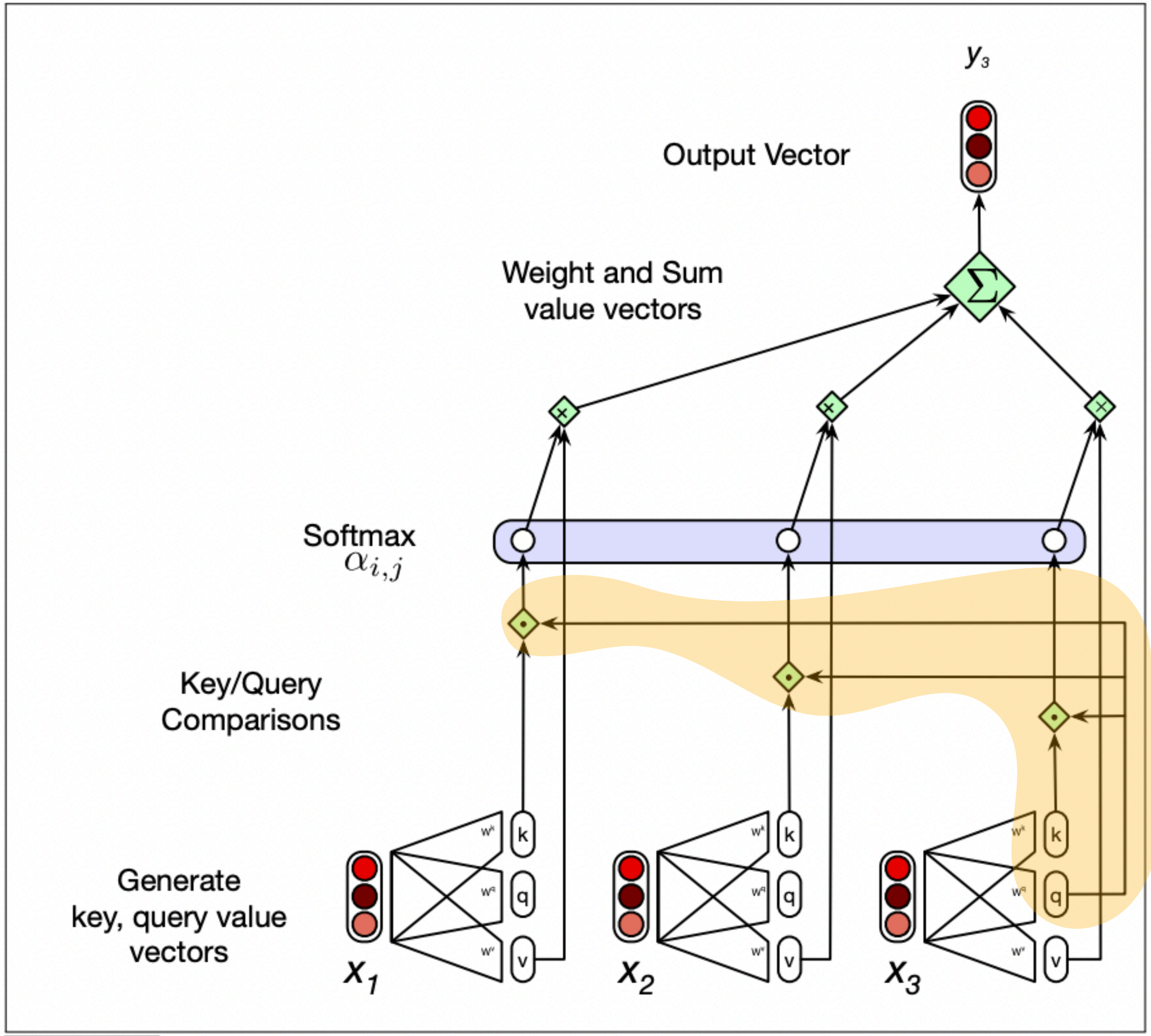



**Figure 9.16** Calculating the value of $\mathbf{y}_3$, the third element of a sequence using causal (left-to-right) self-attention.

# Transformers

## (Self) Attention

score*value

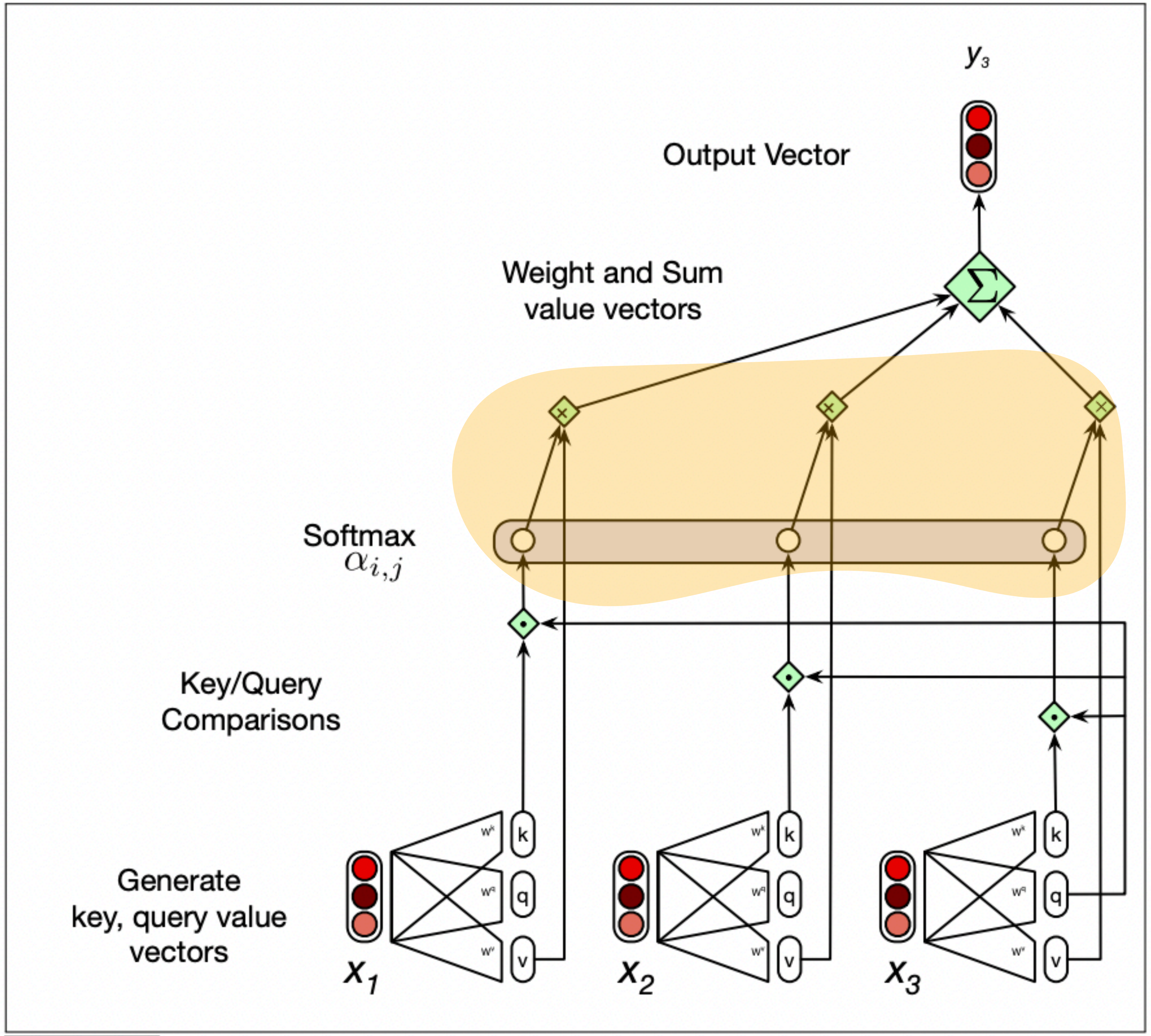
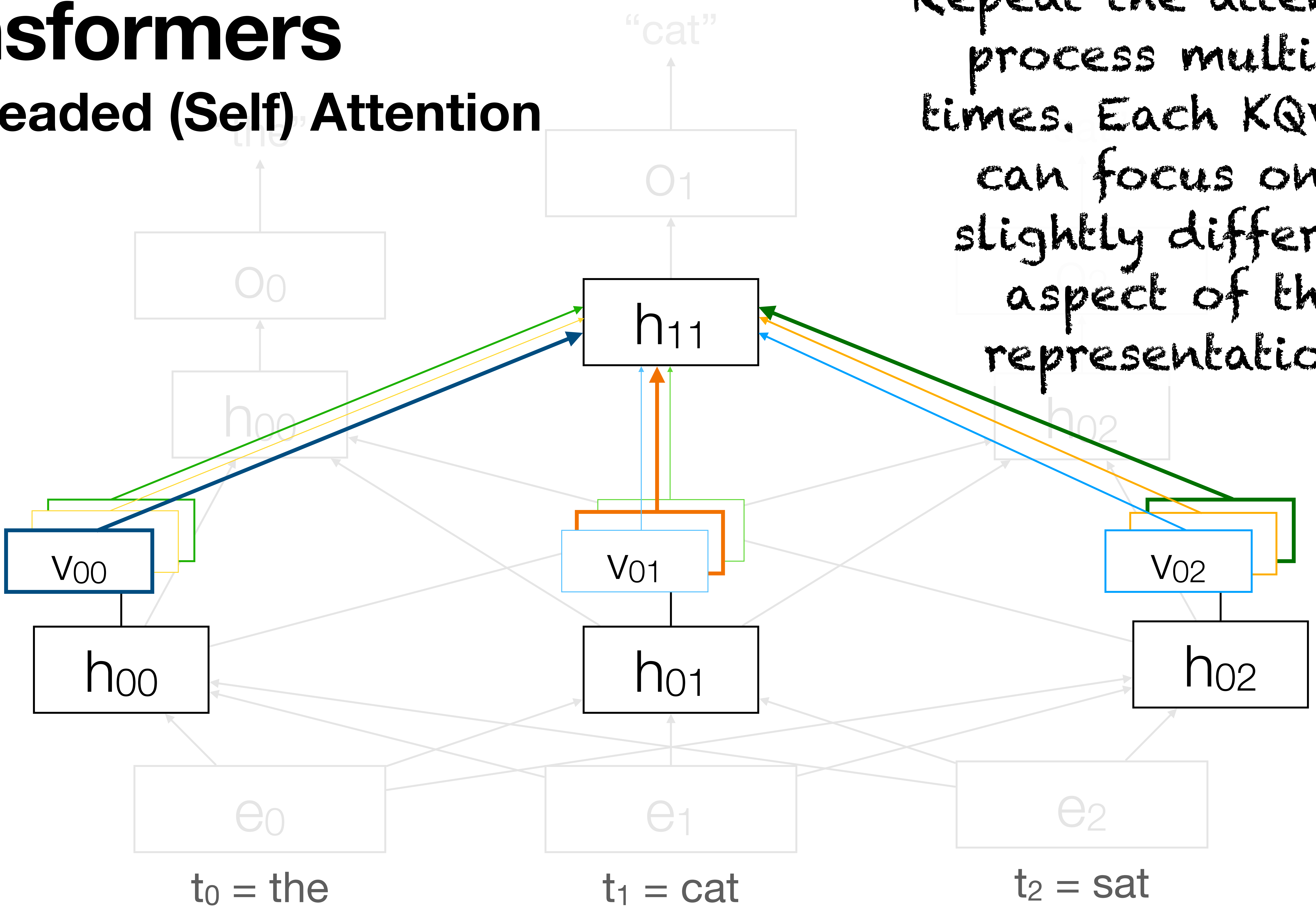



**Figure 9.16** Calculating the value of $\mathbf{y}_3$, the third element of a sequence using causal (left-to-right) self-attention.

# Transformers

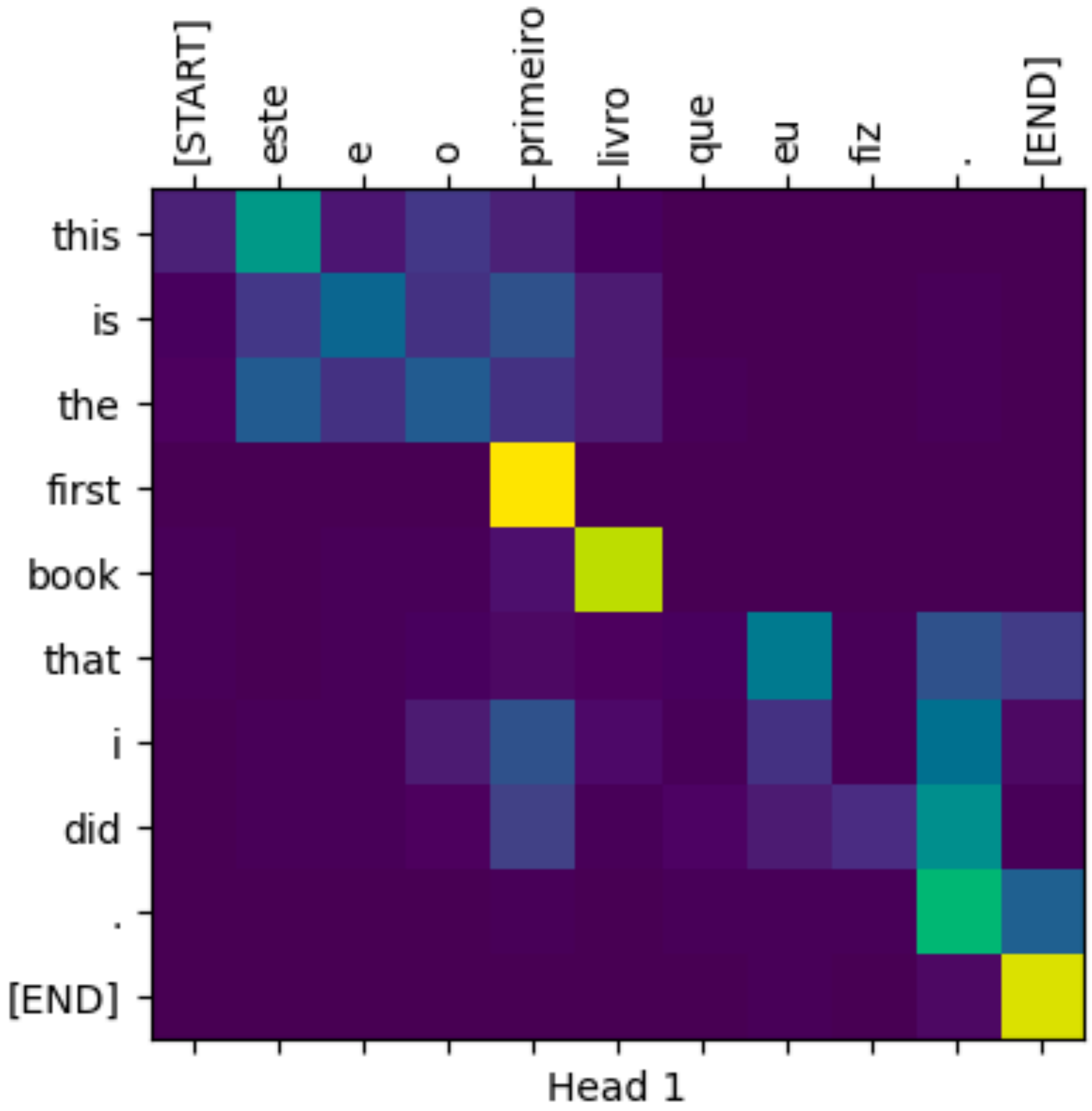
## Multiheaded (Self) Attention

Repeat the attention process multiple times. Each KQV set can focus on a slightly different aspect of the representation.

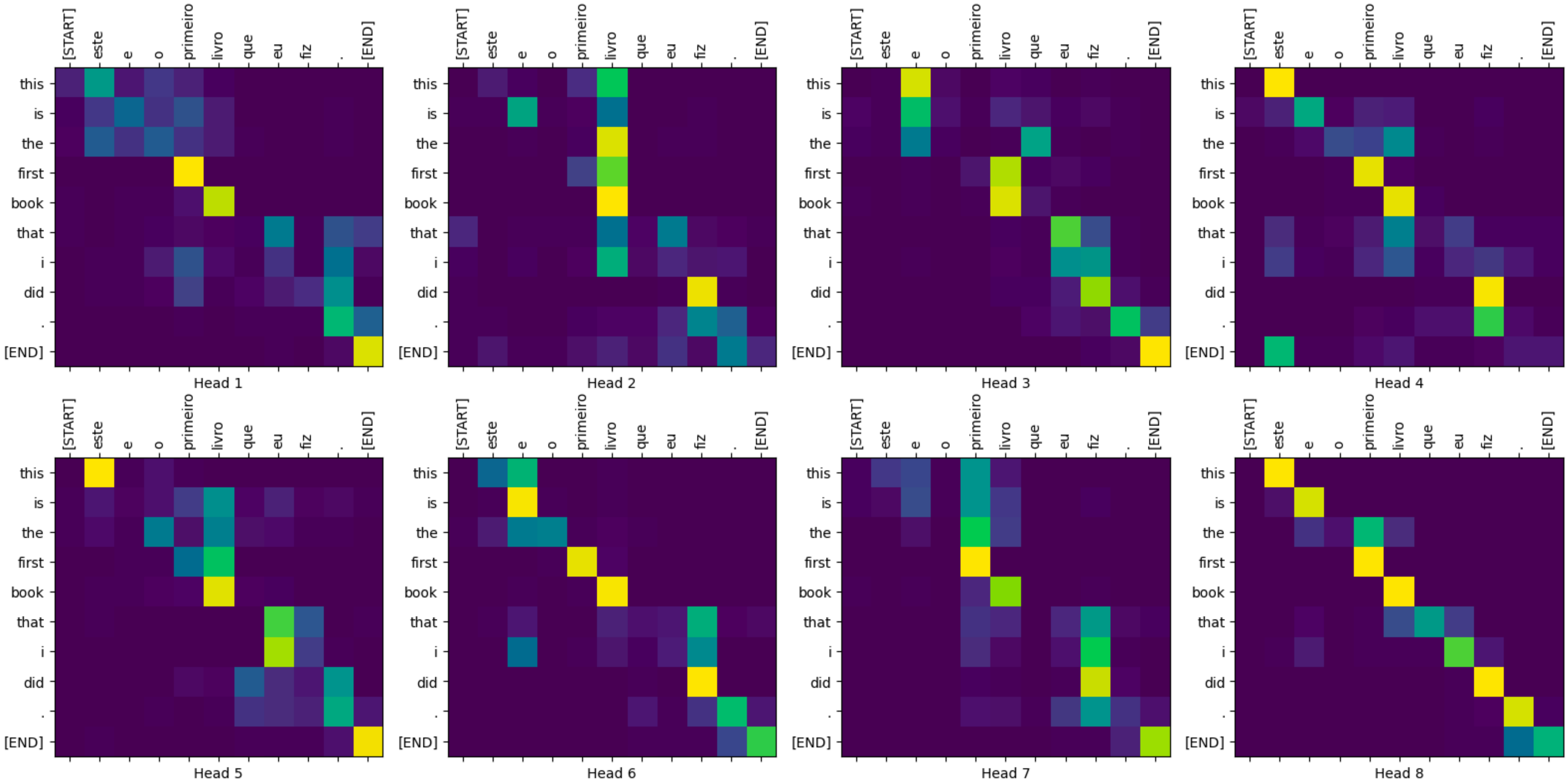


# Transformers

## Multiheaded (Se



https://www.tensorflow.org/text/tutorials/transformer

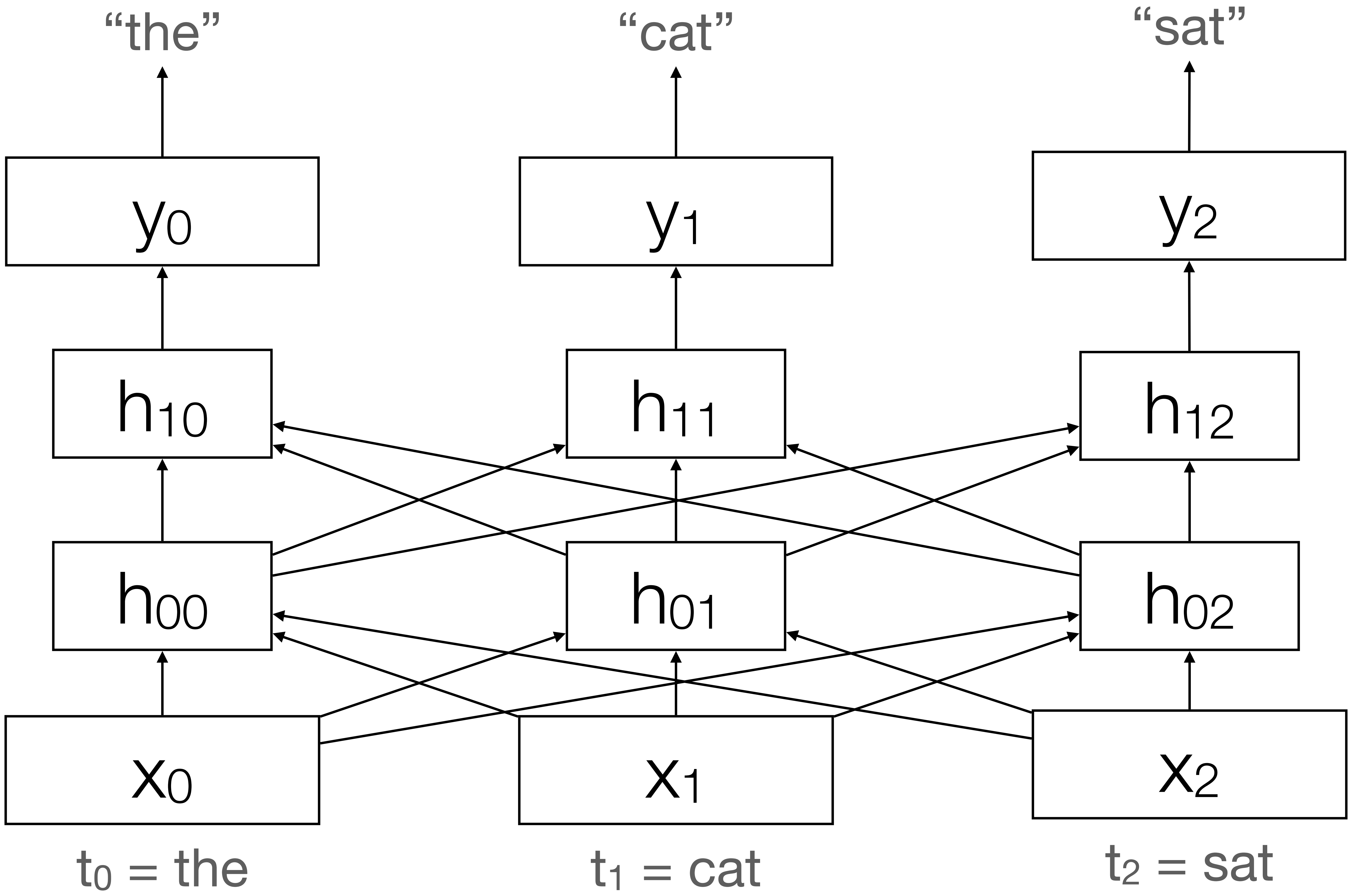


# Topics

- NN Architectures for Language Modeling
  - Recurrent Neural Network (RNN)
  - Long-Short Term Memory Network (LSTM)
  - **Transformers**
    - Architecture
    - Self Attention
    - **Blocks**
    - Positional Encodings

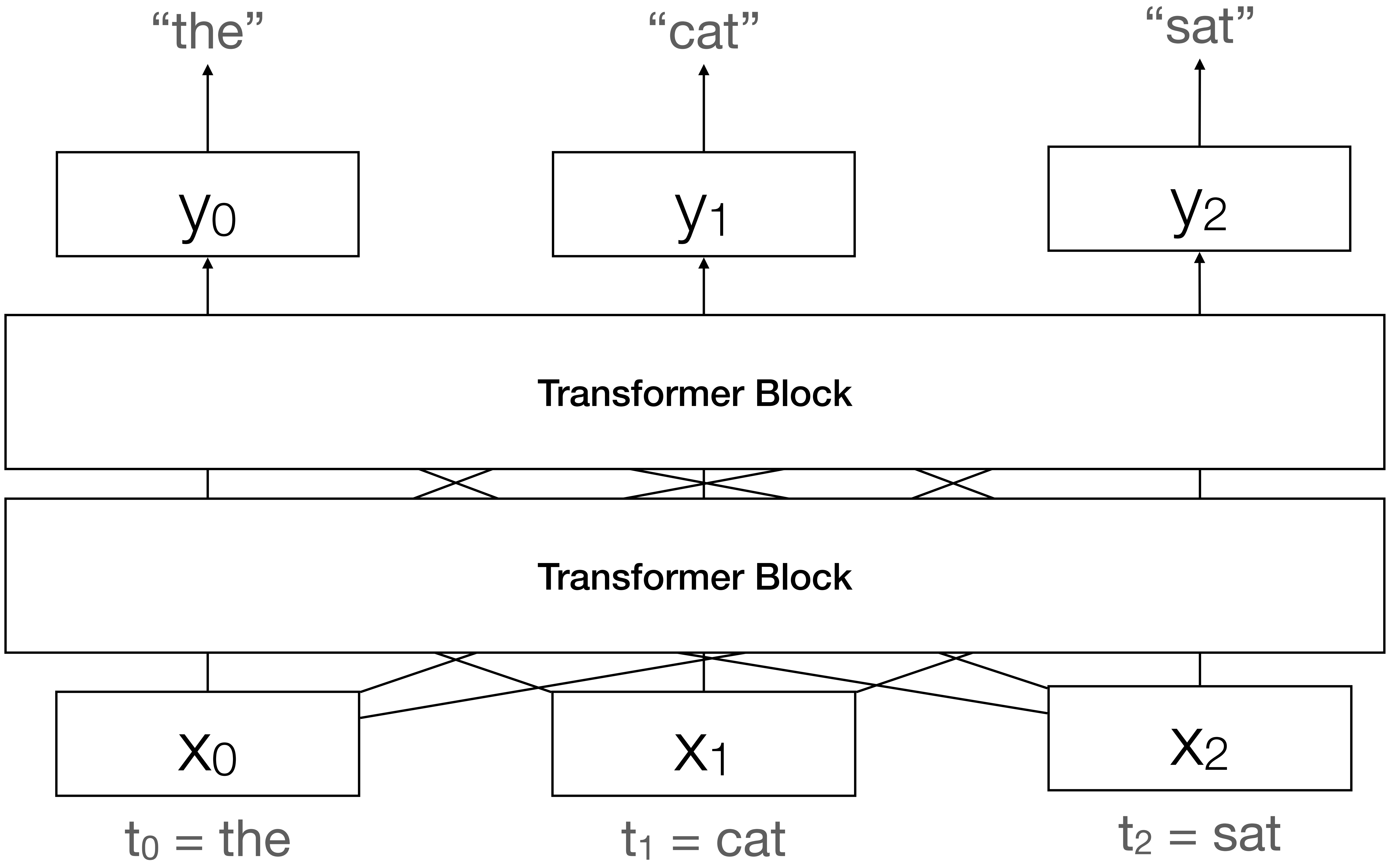
# Transformers

## Transformer Blocks



# Transformers

## Transformer Blocks



# Transformers

## Transformer Blocks

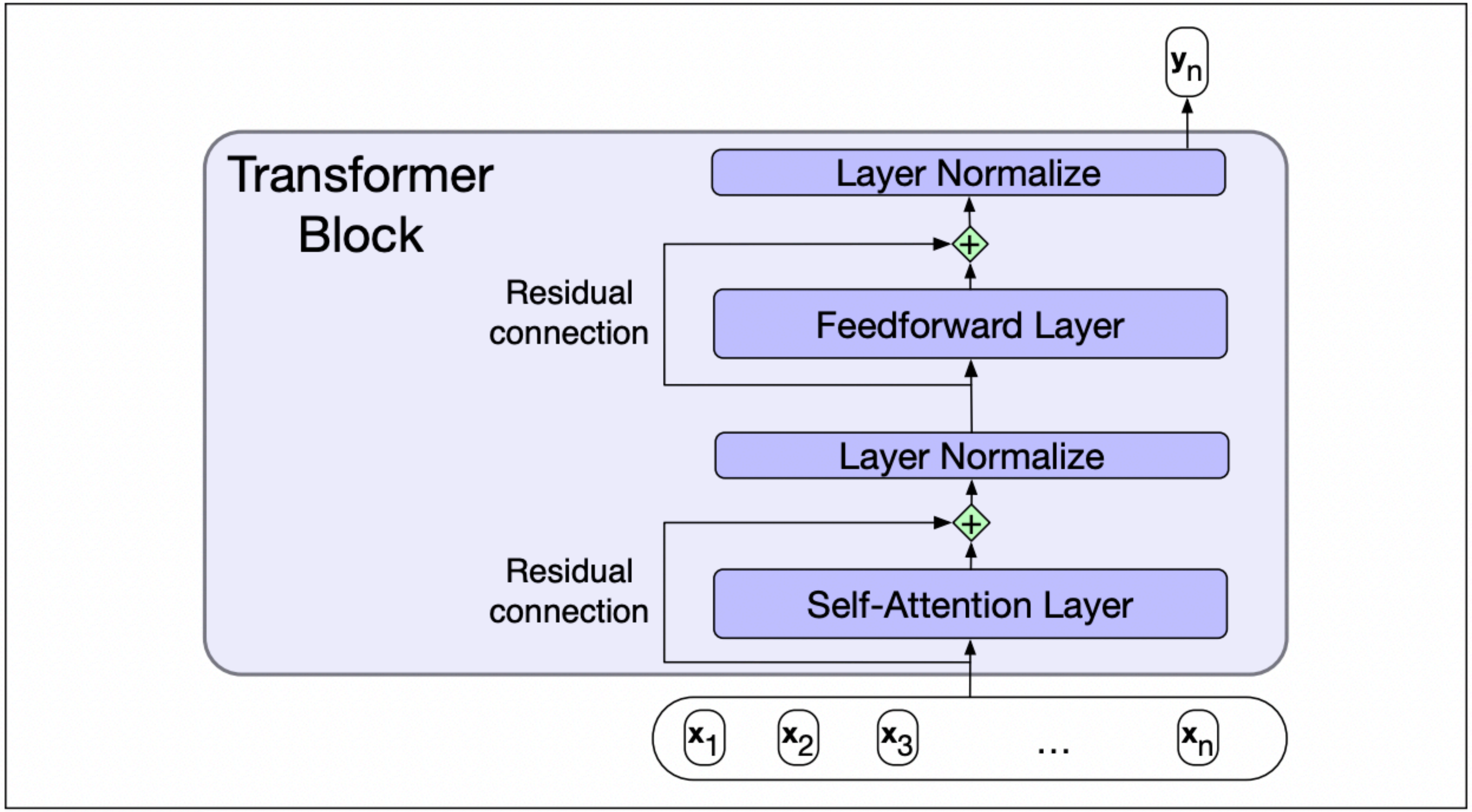



**Figure 9.18** A transformer block showing all the layers.

# Transformers

## Transformer Blocks

just add input to output, to help with training/vanishing gradients

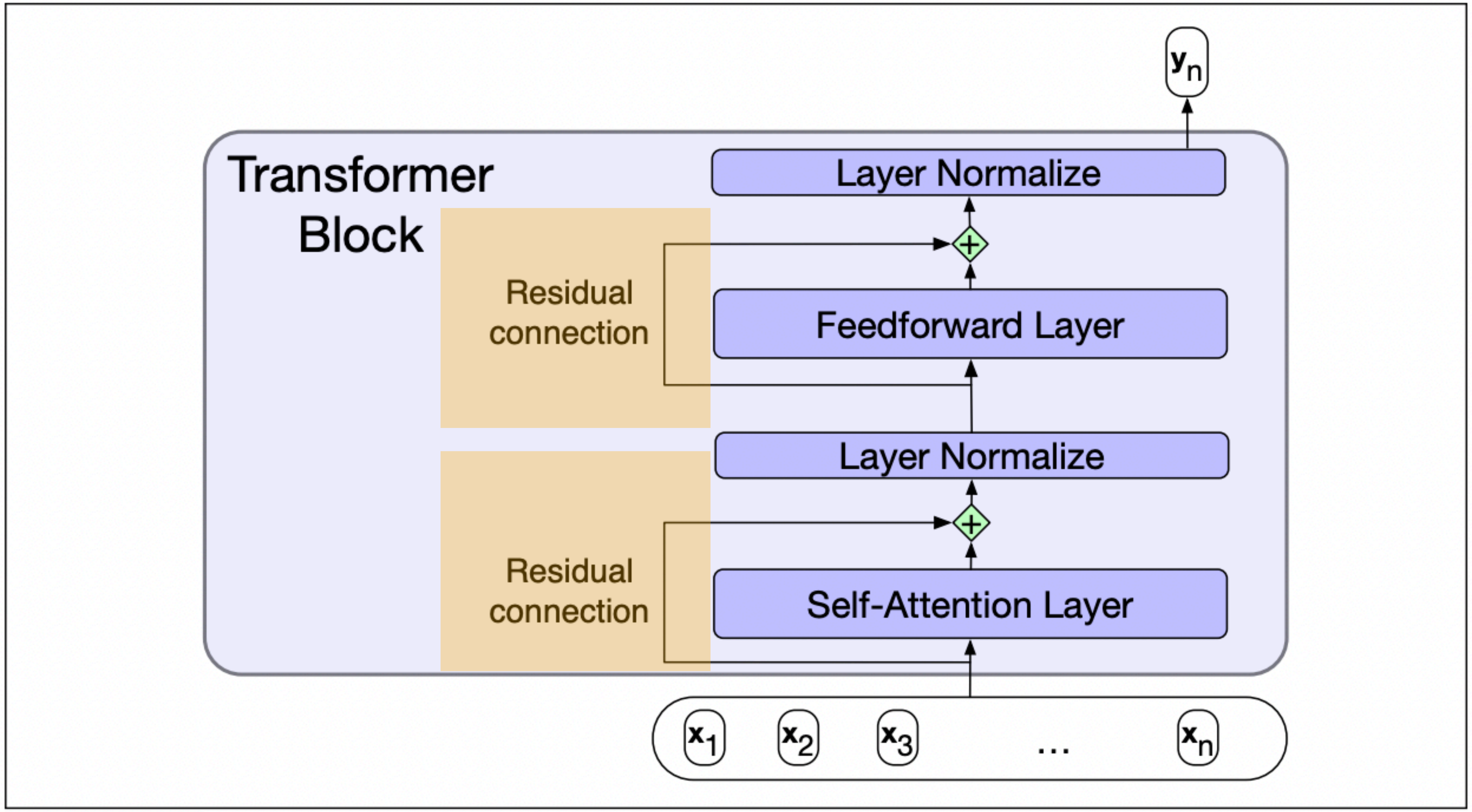



**Figure 9.18** A transformer block showing all the layers.

# Transformers

## Transformer Blocks

same idea z-score normalization: subtract mean, divide by standard deviation (with some learnable parameters, of course)

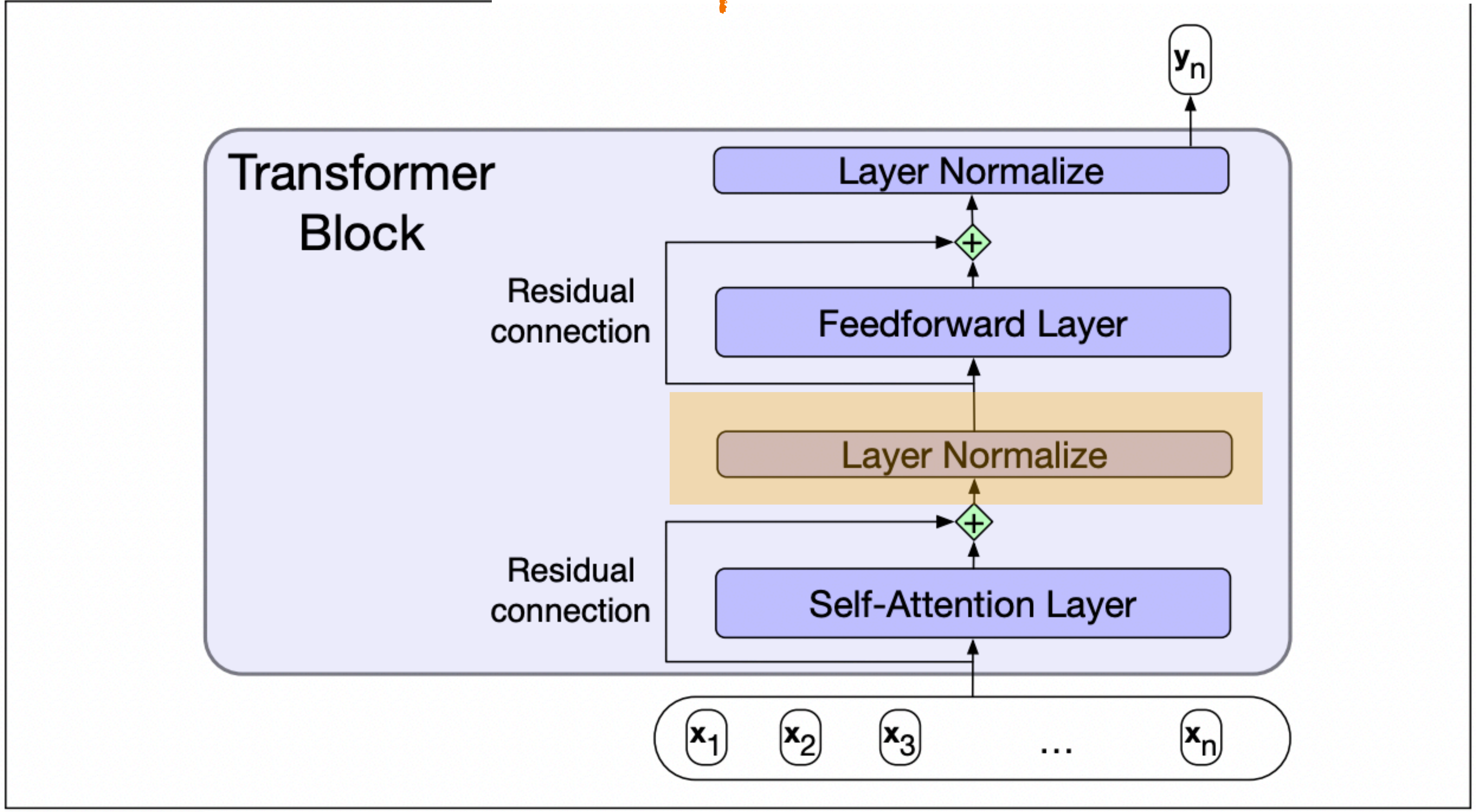



**Figure 9.18** A transformer block showing all the layers.

# Transformers

## Transformer Blocks

simple perceptron-style layer to
combine everything together

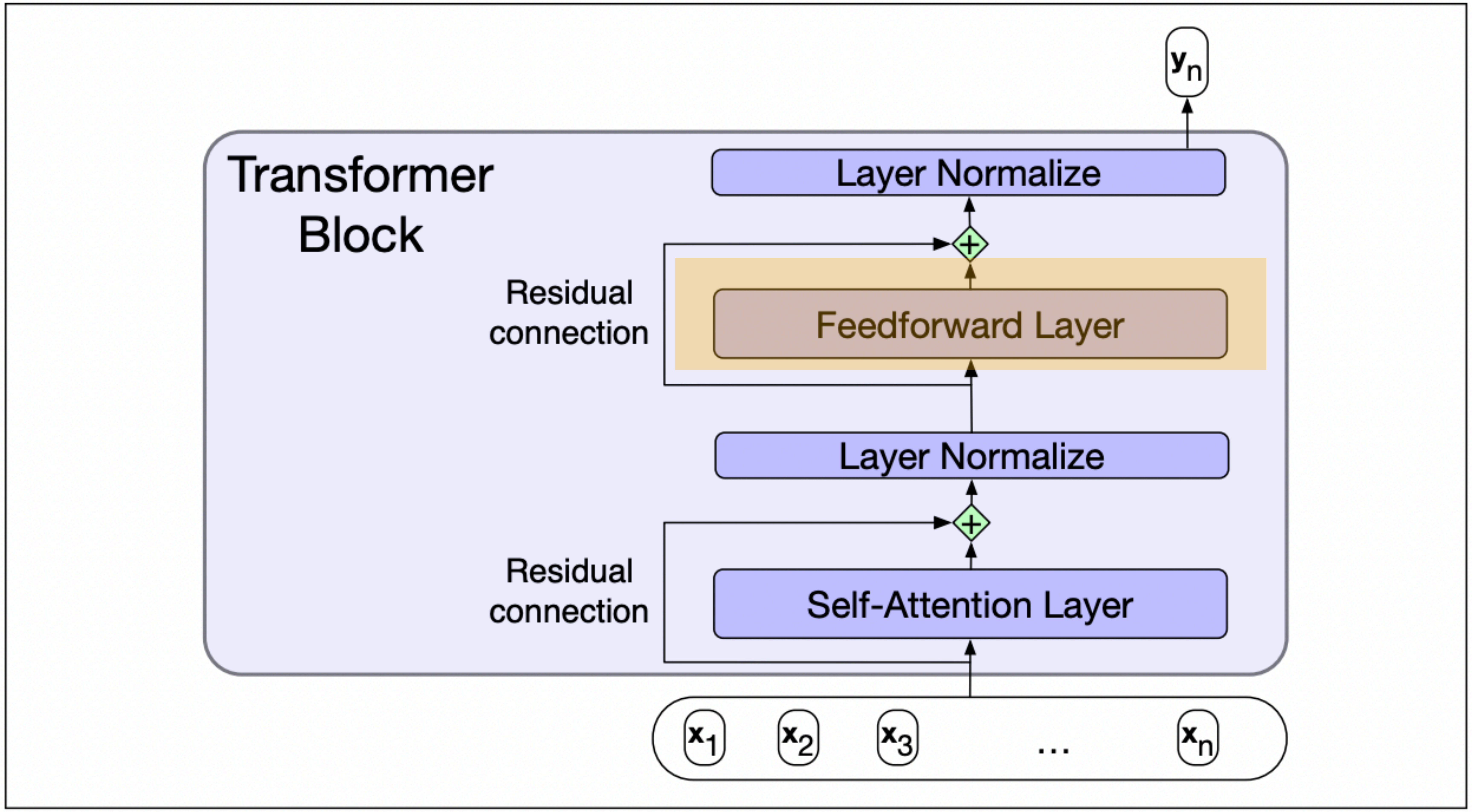



**Figure 9.18** A transformer block showing all the layers.

# Topics

- NN Architectures for Language Modeling
  - Recurrent Neural Network (RNN)
  - Long-Short Term Memory Network (LSTM)
  - **Transformers**
    - Architecture
    - Self Attention
    - Blocks
    - **Positional Encodings**

# Transformers

## Positional Encodings

- Unlike RNNs/LSTMs—Transformers aren't actually aware of the order in which words occur!
  - Essentially, they are a (very fancy) bag of words
- Solution: Positional encodings
  - Idea: Just include an input with each word saying what position it is (e.g., "cat in the 3rd position", "sat in the 4th position")

# Transformers

## Positional Encodings

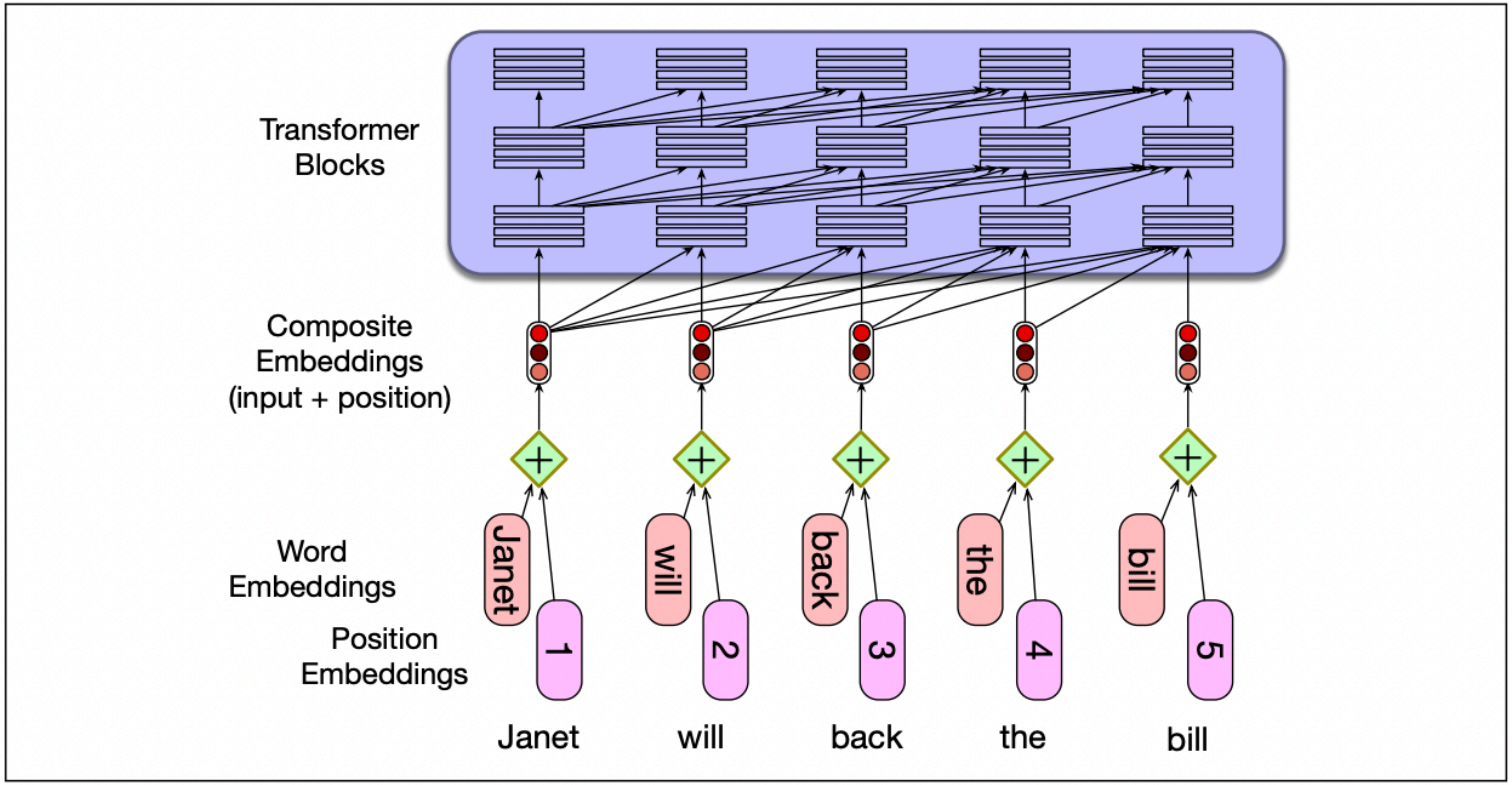



**Figure 9.20** A simple way to model position: simply adding an embedding representation of the absolute position to the input word embedding.

# Transformers

## Positional Encodings

- Problems
  - Not the same as relative/order information (which we want in language). (Later work introduces relative positional encodings instead, and they seem to work better)
  - Less supervision for later positions
  - What about language being infinitely recursive?

# Topics

- NN Architectures for Language Modeling
  - Recurrent Neural Network (RNN)
  - Long-Short Term Memory Network (LSTM)
  - **Transformers**

# Transformers

## What's the big deal?

- Attention
  - Very **minimal inductive bias**
  - Any **arbitrary graph structure** over the inputs can be learned
- Multiheadedness
  - Each "head" focuses on a **different subspace** of the input
  - E.g., one head can highlight syntactically connected words, while another finds pragmatically relevant information unconstrained by syntax
    - Ty is my cat. Yesterday while my husband and I weren't looking **he** killed a bird

# Transformers

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# Transformers

## What's the big deal?

- Also: **very scalable**!
  - At layer N, no dependency between timesteps, so can be trained completely in parallel (unlike RNNs)
  - Faster training = bigger models + more data
  - Allows for massive **pretraining**

# All done!
# More questions?