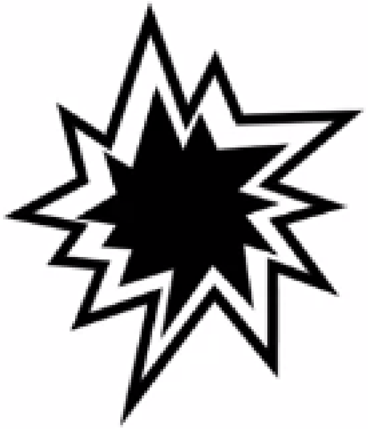
Outline

- RNNs and vanishing/exploding gradients

- Solutions



RNNs: Advantages

- Captures dependencies within a short range

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- Captures dependencies within a short range

RNNs: Advantages

➕ Captures dependencies within a short range

RNNs: Advantages

- Captures dependencies within a short range
- Takes up less RAM than other n-gram models

RNNs: Disadvantages

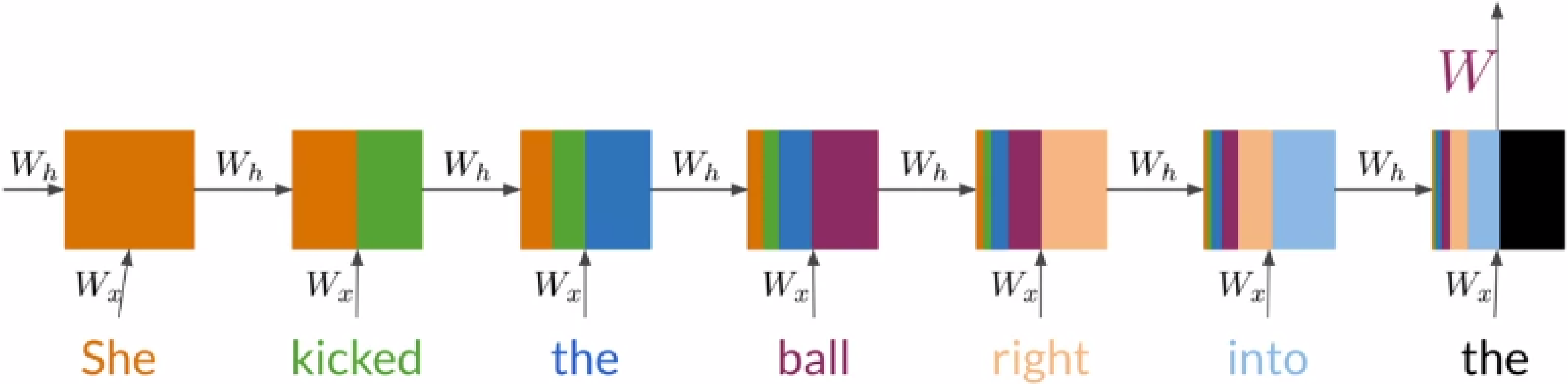
- Struggles with longer sequences

RNNs: Disadvantages

- Struggles with longer sequences
- Prone to vanishing or exploding gradients

RNN Basic Structure

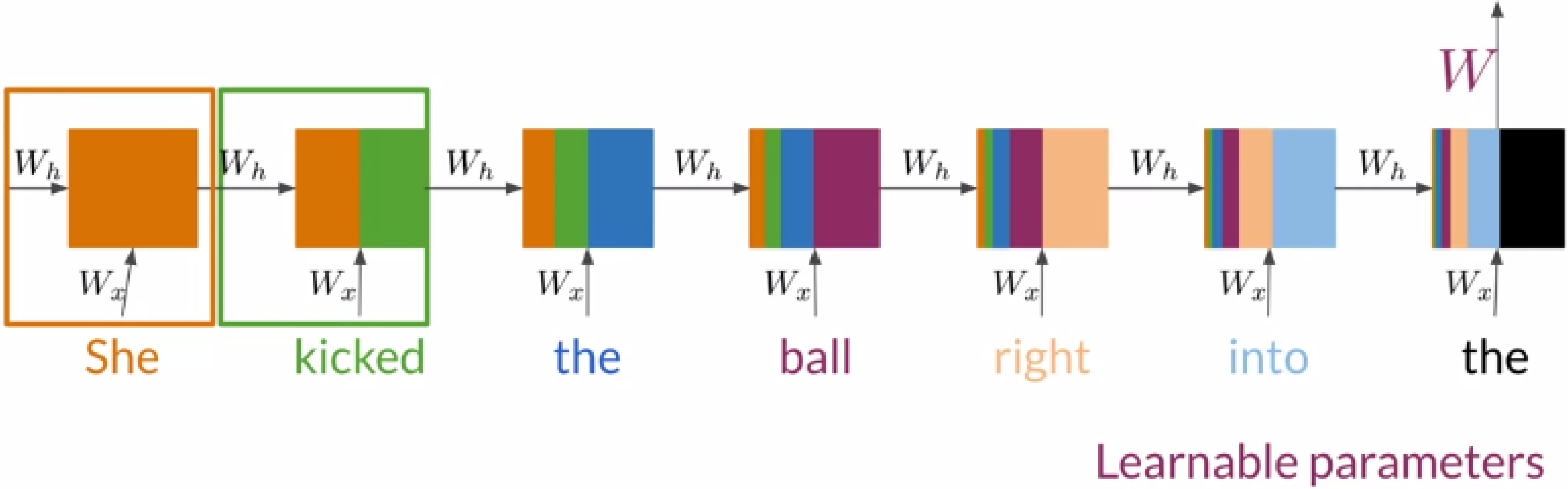
She kicked the ball right into the ____________



Learnable parameters

RNN Basic Structure

She kicked the ball right into the ____________



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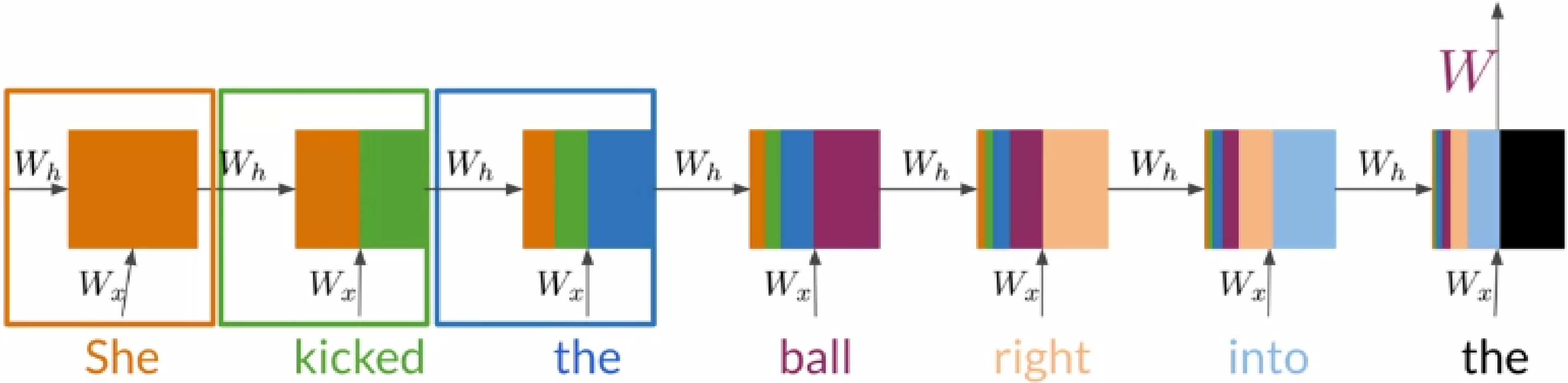

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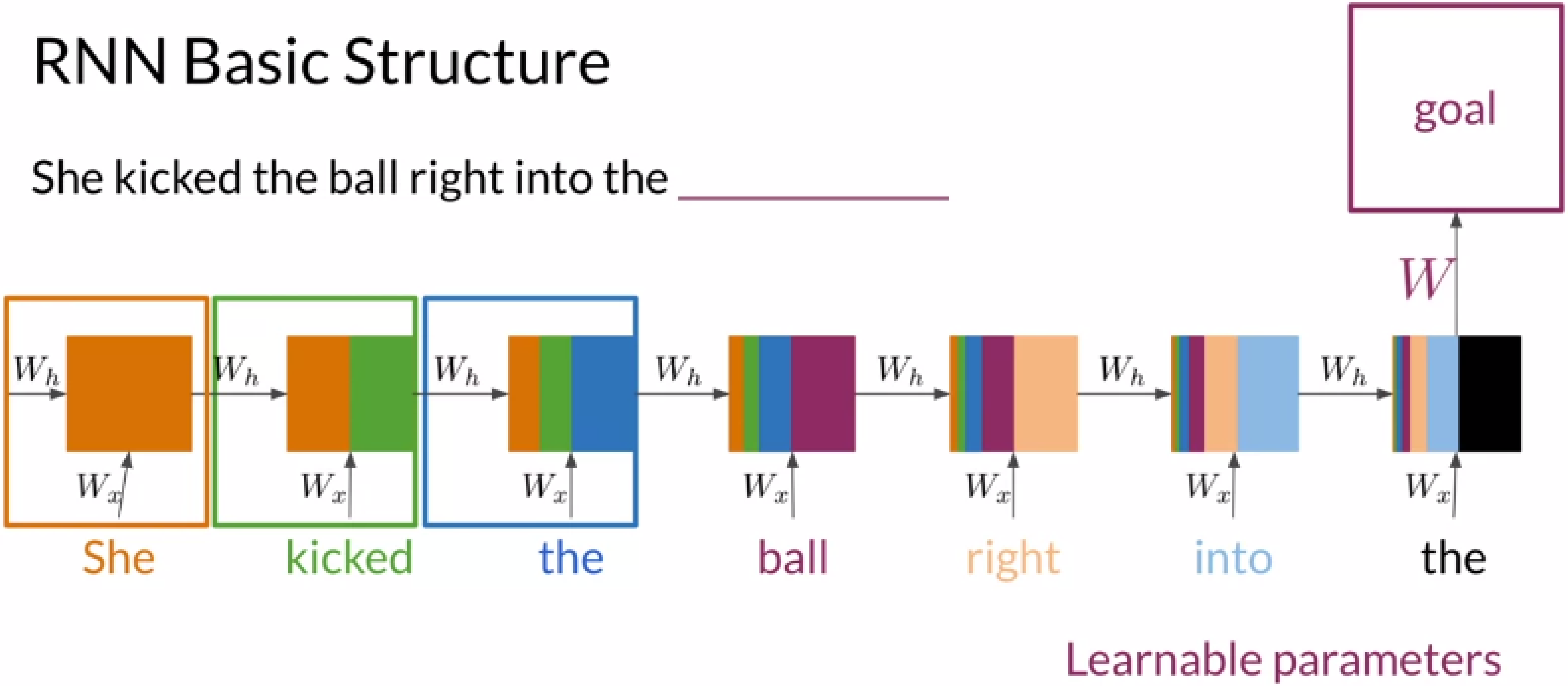

Backpropagation through time

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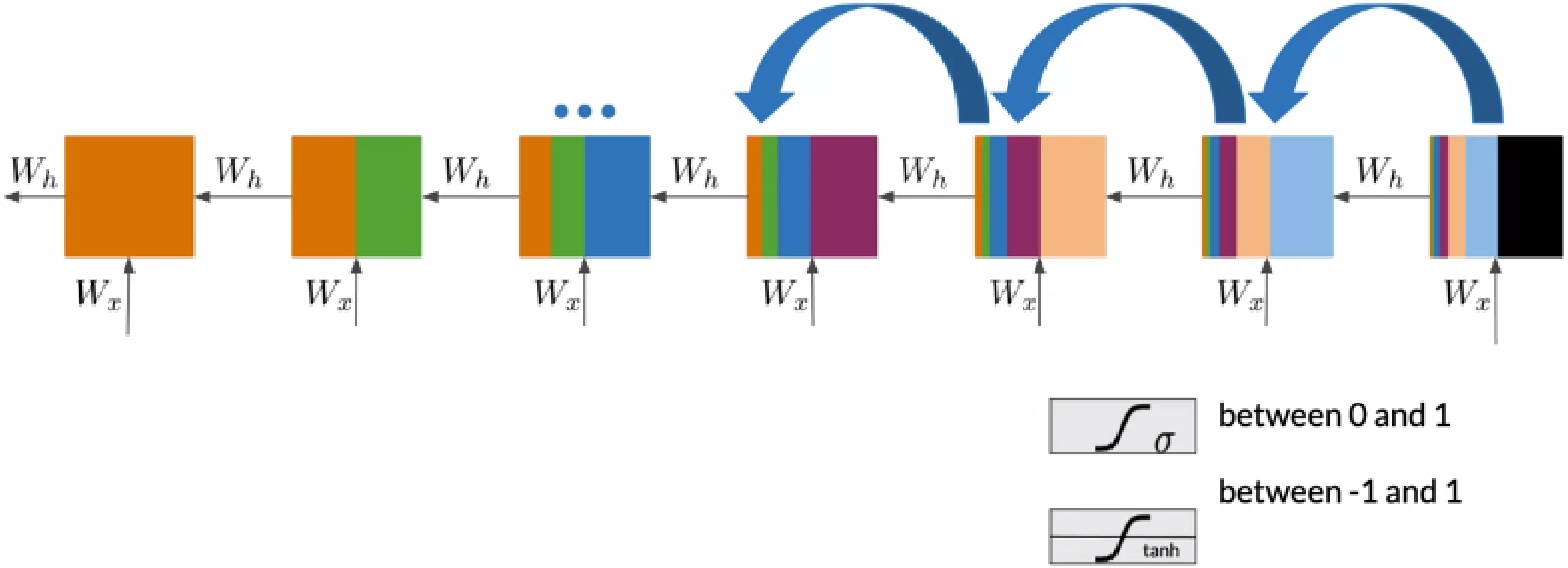
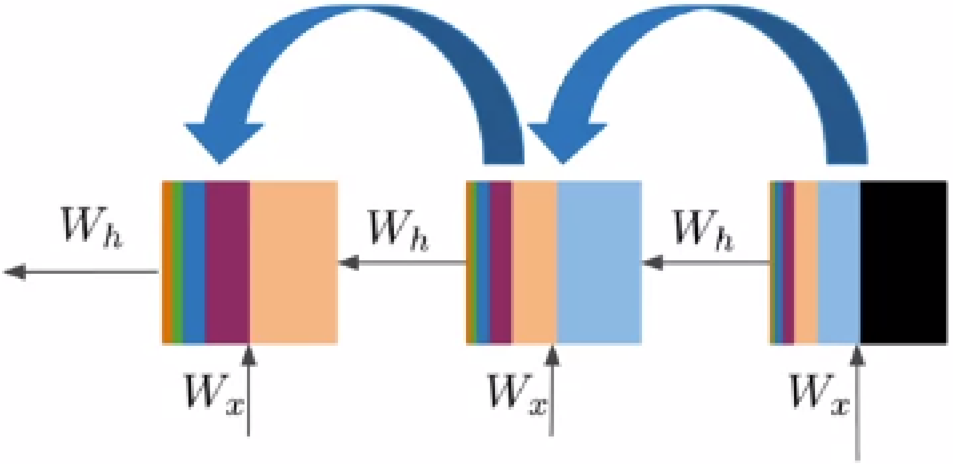


The vanishing gradient problem



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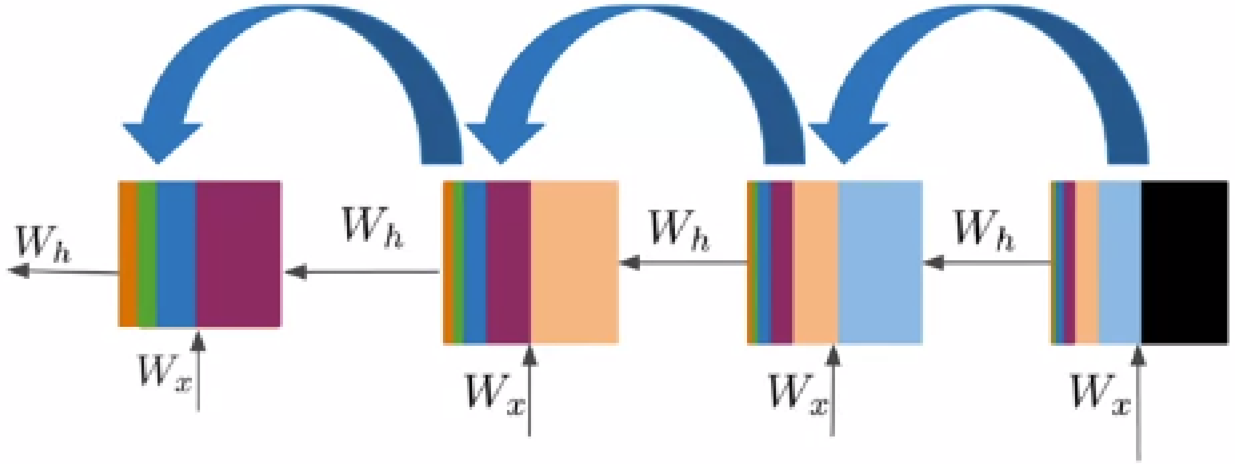

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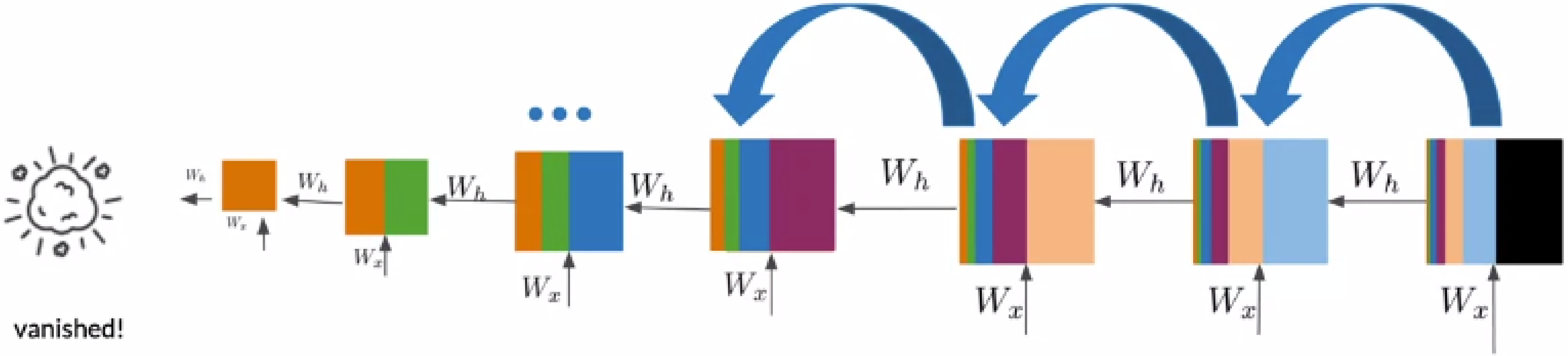

Solving for vanishing or exploding gradients

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- Identity RNN with ReLU activation $\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$ $-1 \longrightarrow 0$

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- Gradient clipping $32 \longrightarrow 25$

Solving for vanishing or exploding gradients

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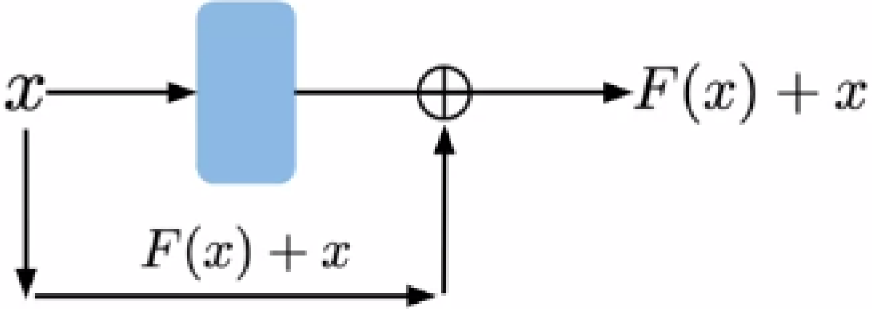
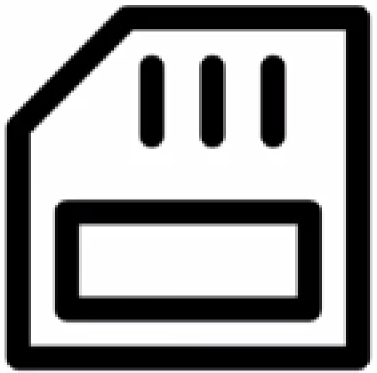
- Gradient clipping $32 \longrightarrow 25$
- Skip connections



Outline

- Meet the Long short-term memory unit!
- LSTM architecture
- Applications



LSTMs: a memorable solution

- Learns when to remember and when to forget

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- Basic anatomy:
    - A cell state
    - A hidden state with three gates
    - Loops back again at the end of each time step

LSTMs: a memorable solution

- Learns when to remember and when to forget
- Basic anatomy:
    - A cell state
    - A hidden state with three gates
    - Loops back again at the end of each time step
- Gates allow gradients to flow unchanged

LSTMs: Based on previous understanding

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Cell state = before conversation

Forget gate = beginning of conversation

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Input gate = thinking of a response
Output gate = responding

LSTMs: Based on previous understanding

Cell state = before conversation

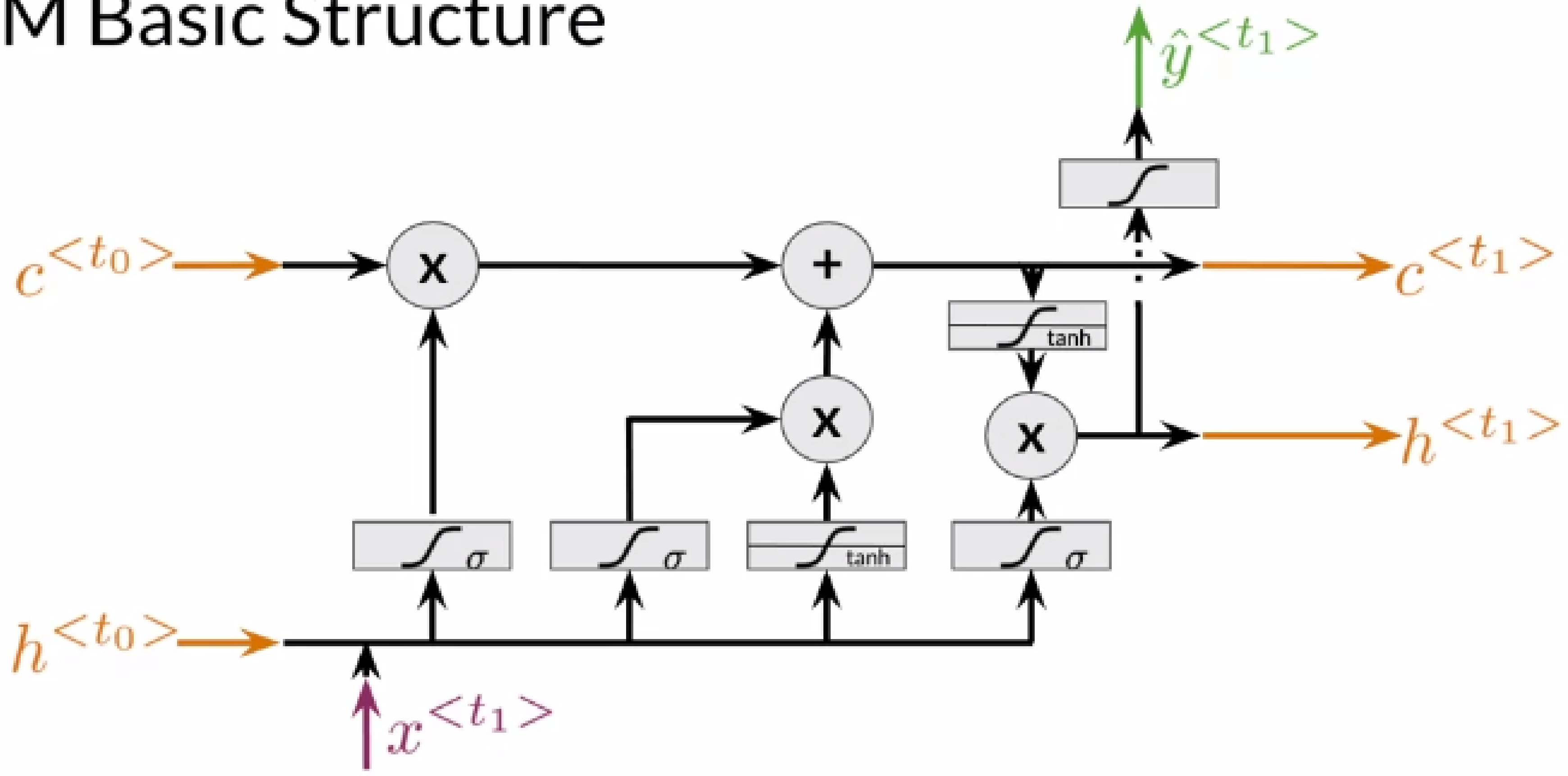
Forget gate = beginning of conversation

Input gate = thinking of a response

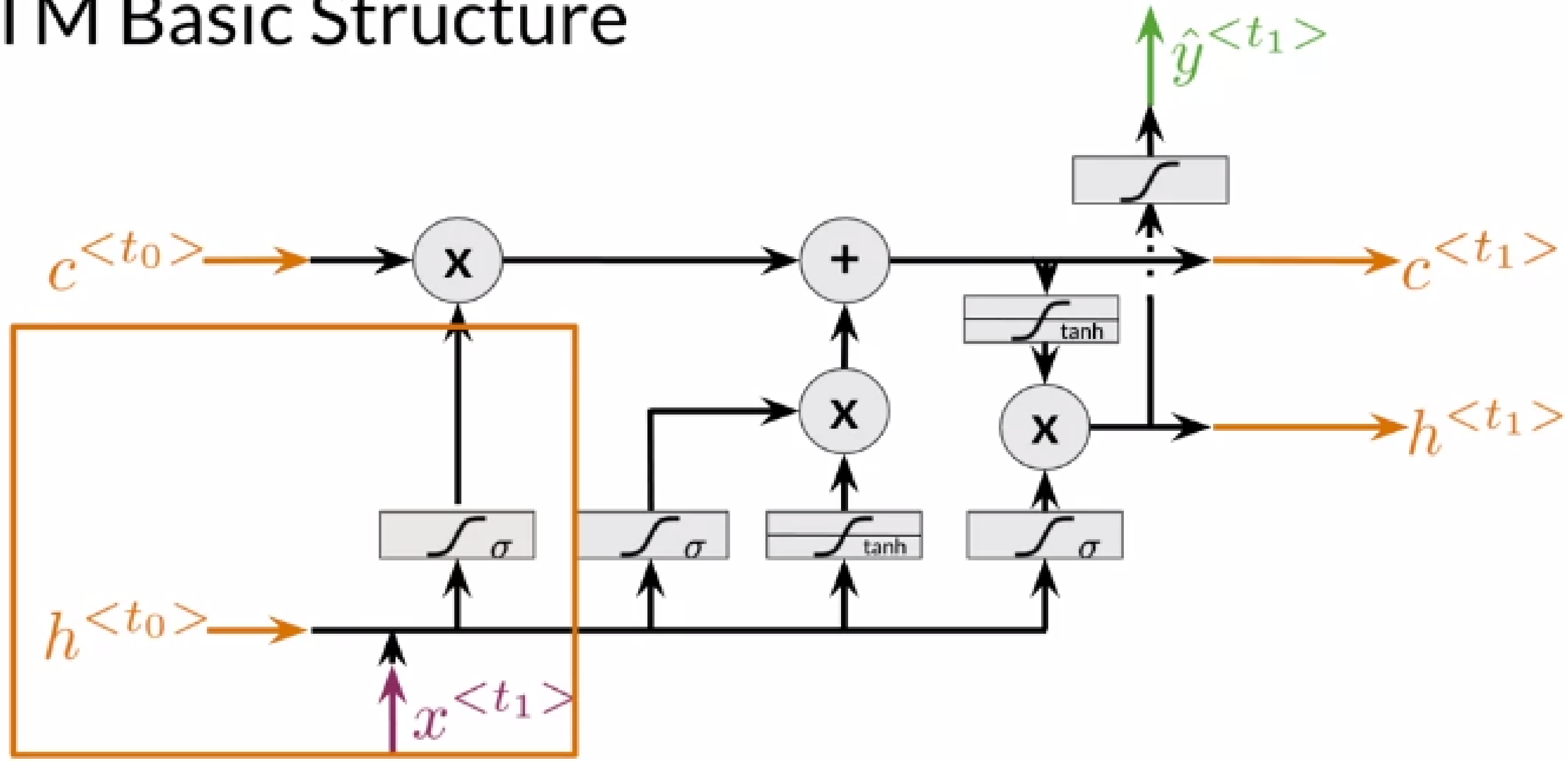
Output gate = responding

Updated cell state = after conversation

LSTM Basic Structure



LSTM Basic Structure



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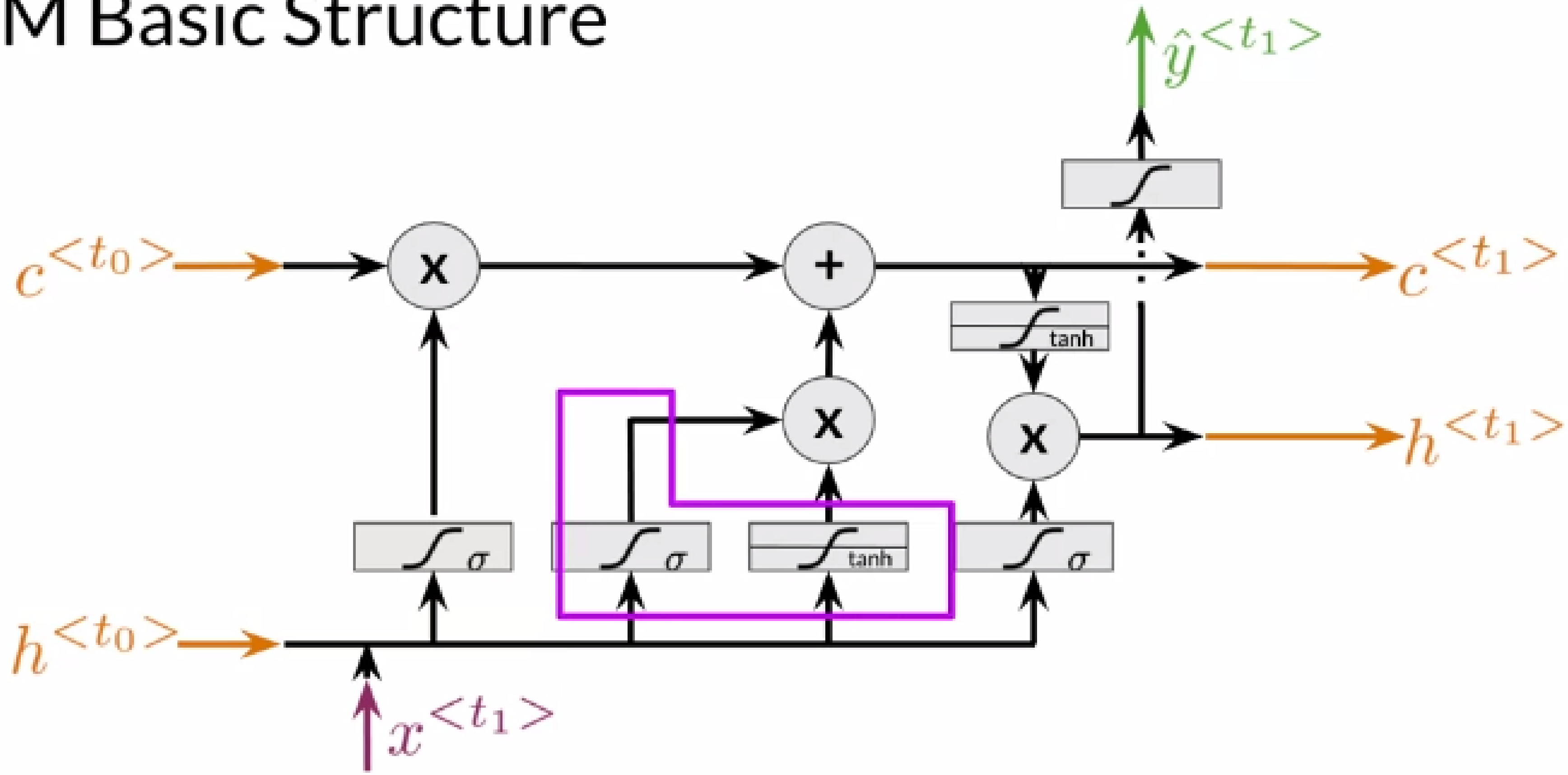

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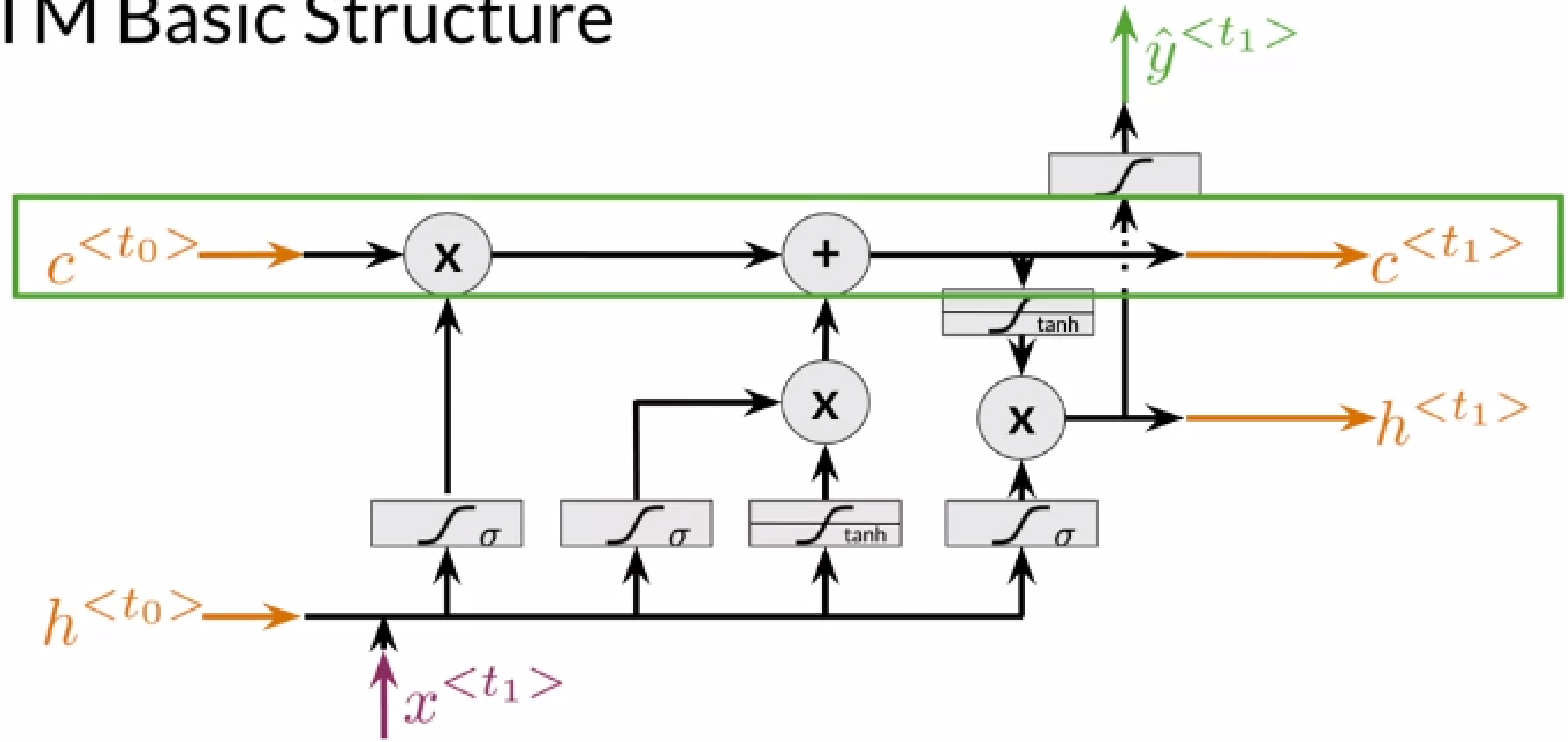
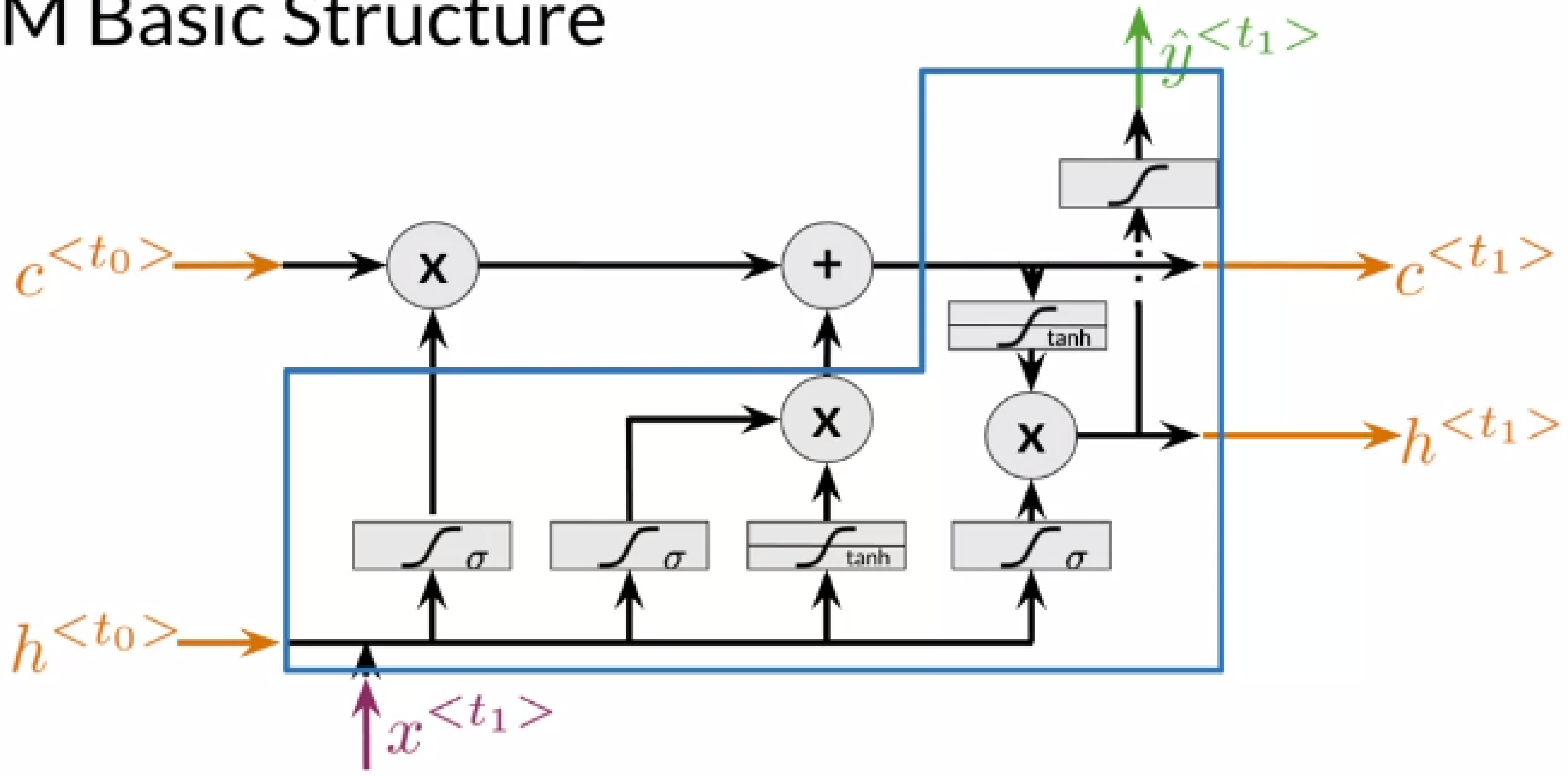
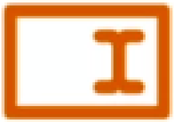


LSTM Basic Structure



Applications of LSTMs

Next-character prediction



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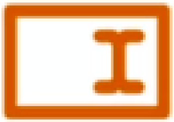
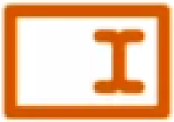


Chatbots

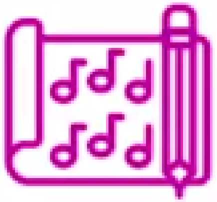
Applications of LSTMs

Next-character prediction



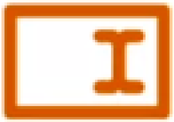
Chatbots

Music composition



Applications of LSTMs

Next-character prediction



Chatbots

Music composition

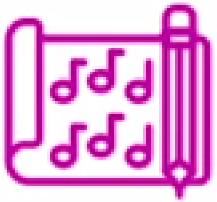
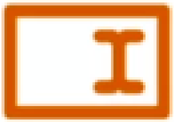


Image captioning

Applications of LSTMs

Next-character prediction



Chatbots

Music composition

Image captioning

Speech recognition

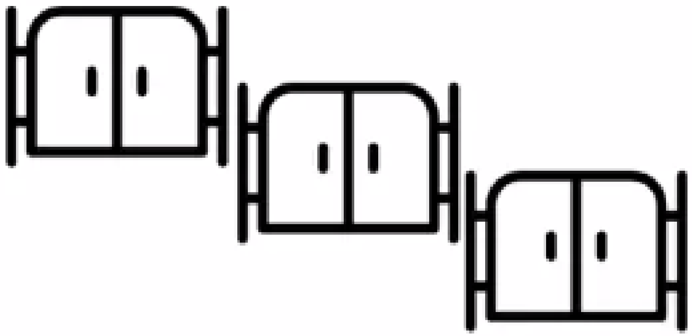
Summary

- LSTMs offer a solution to vanishing gradients

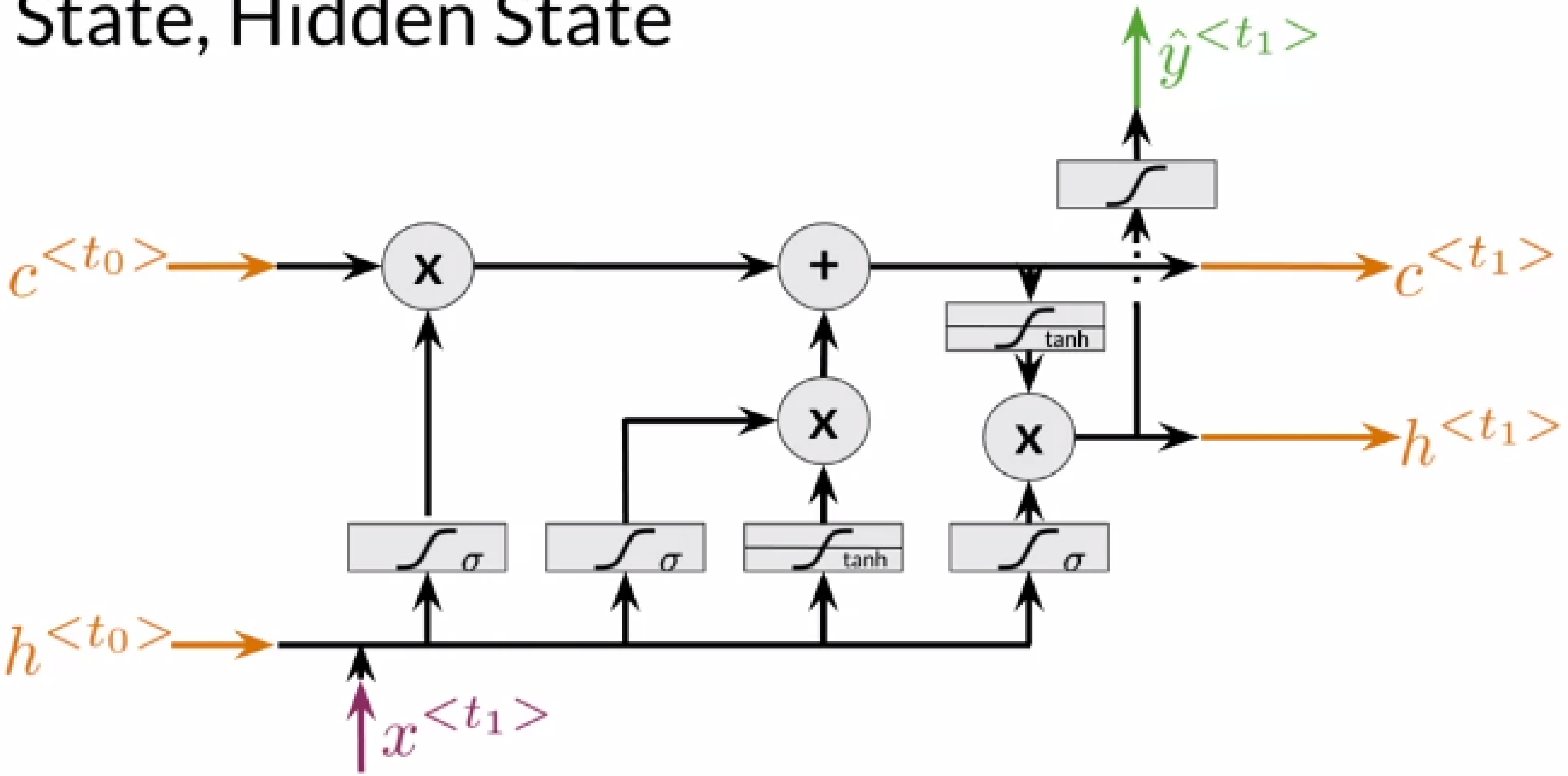
Summary

- LSTMs offer a solution to vanishing gradients

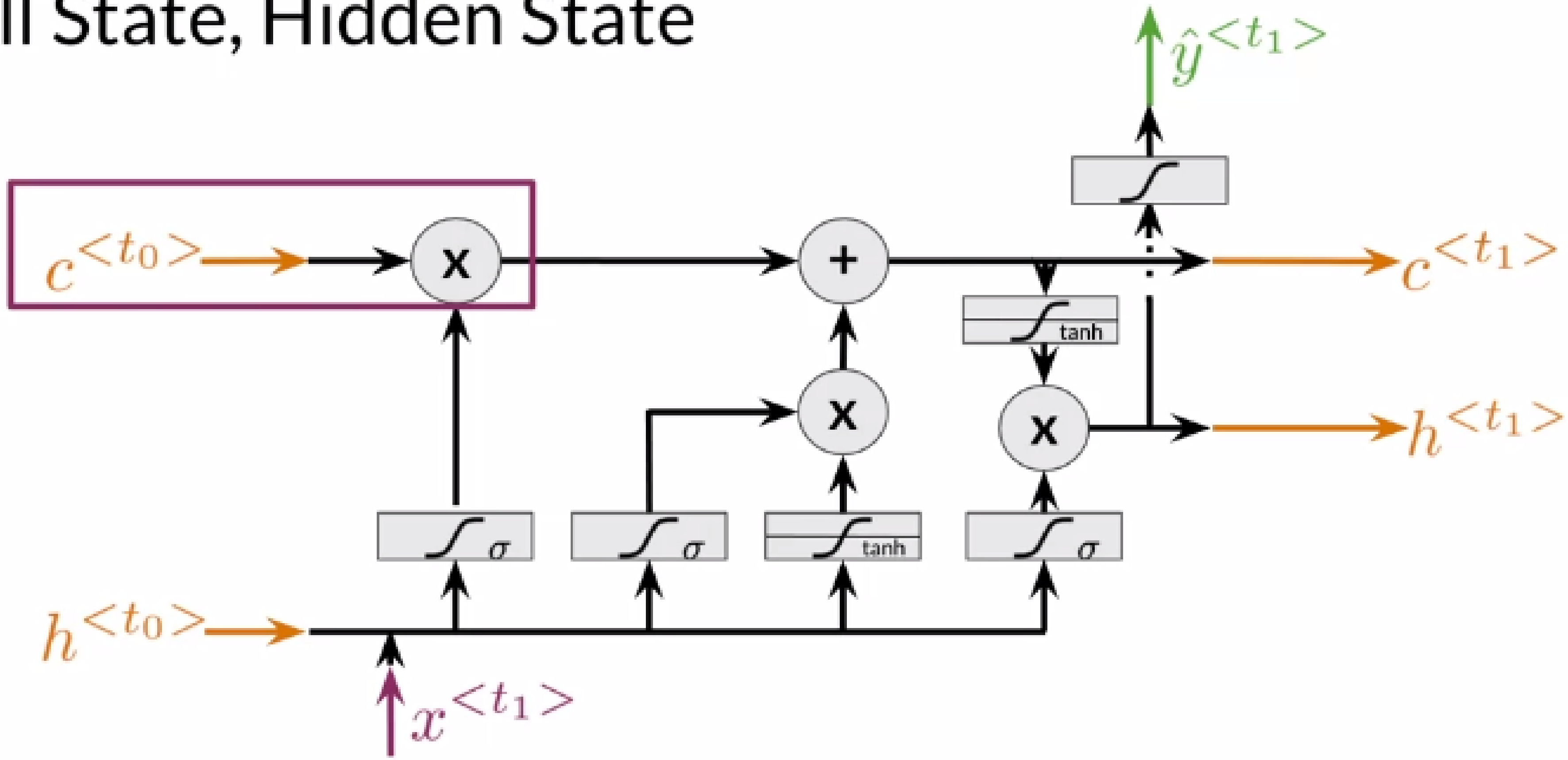
- Typical LSTMs have a cell and three gates:
    - Forget gate
    - Input gate
    - Output gate



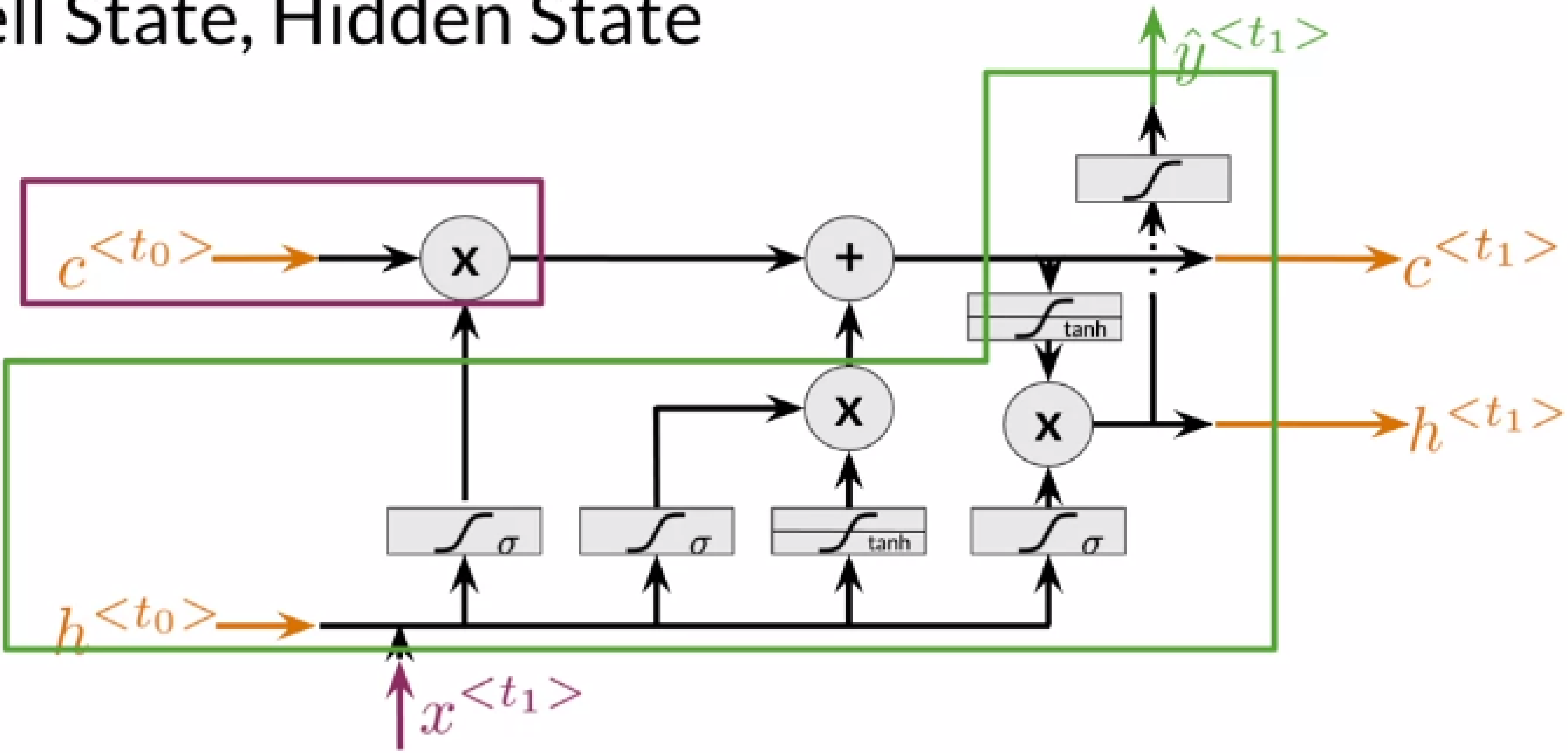
Cell State, Hidden State



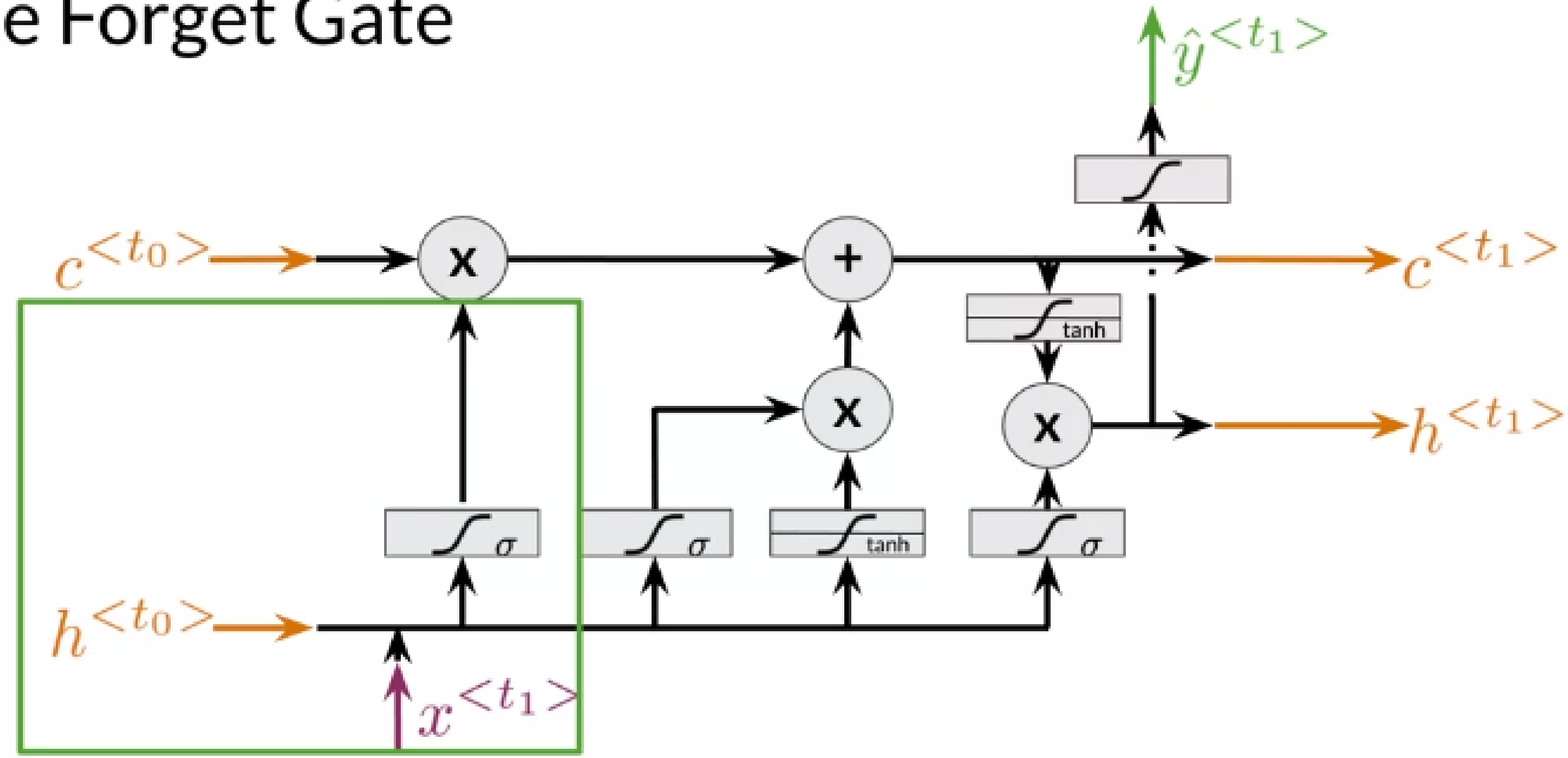
Cell State, Hidden State



Cell State, Hidden State



The Forget Gate



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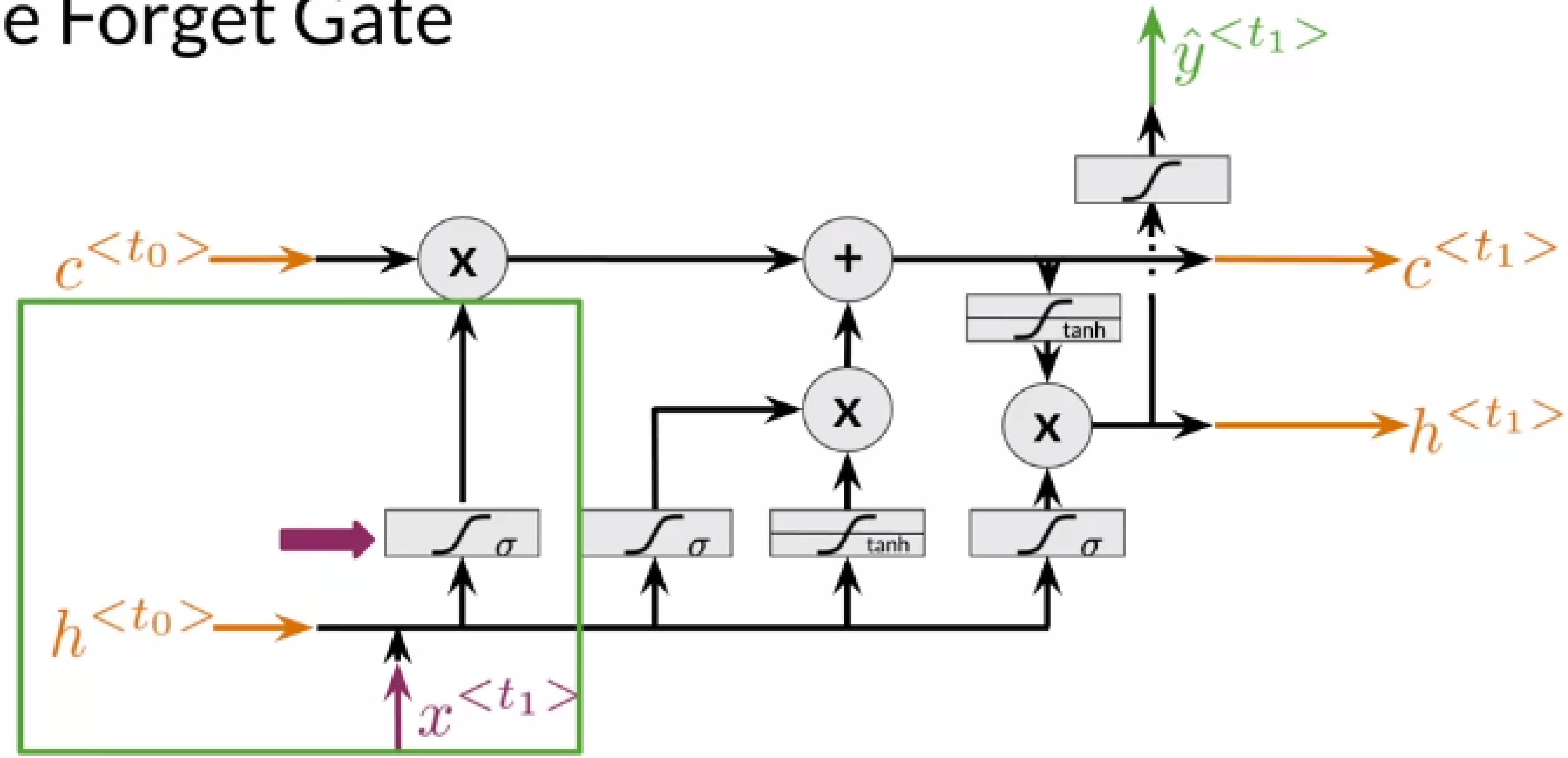
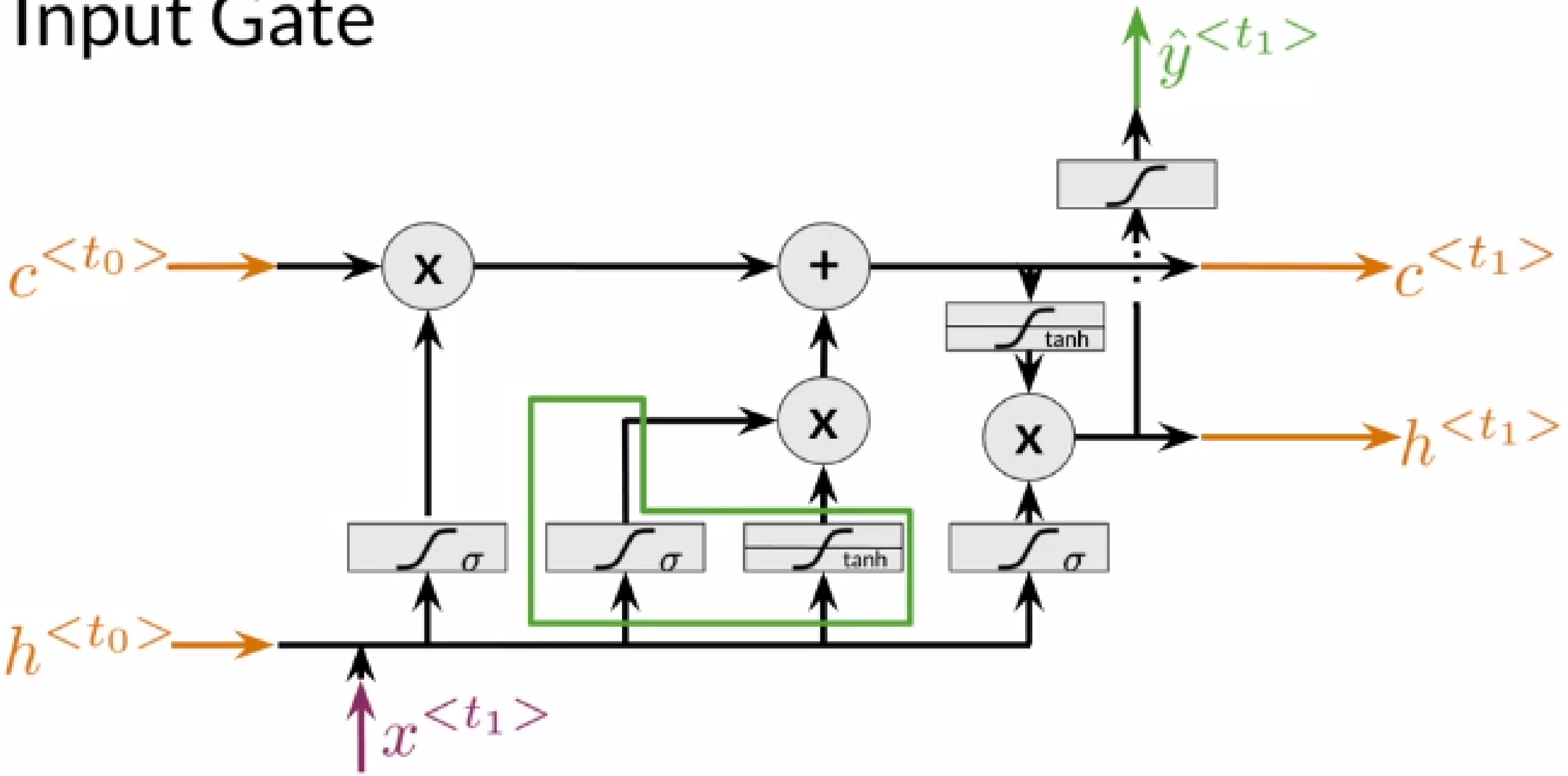


The Input Gate



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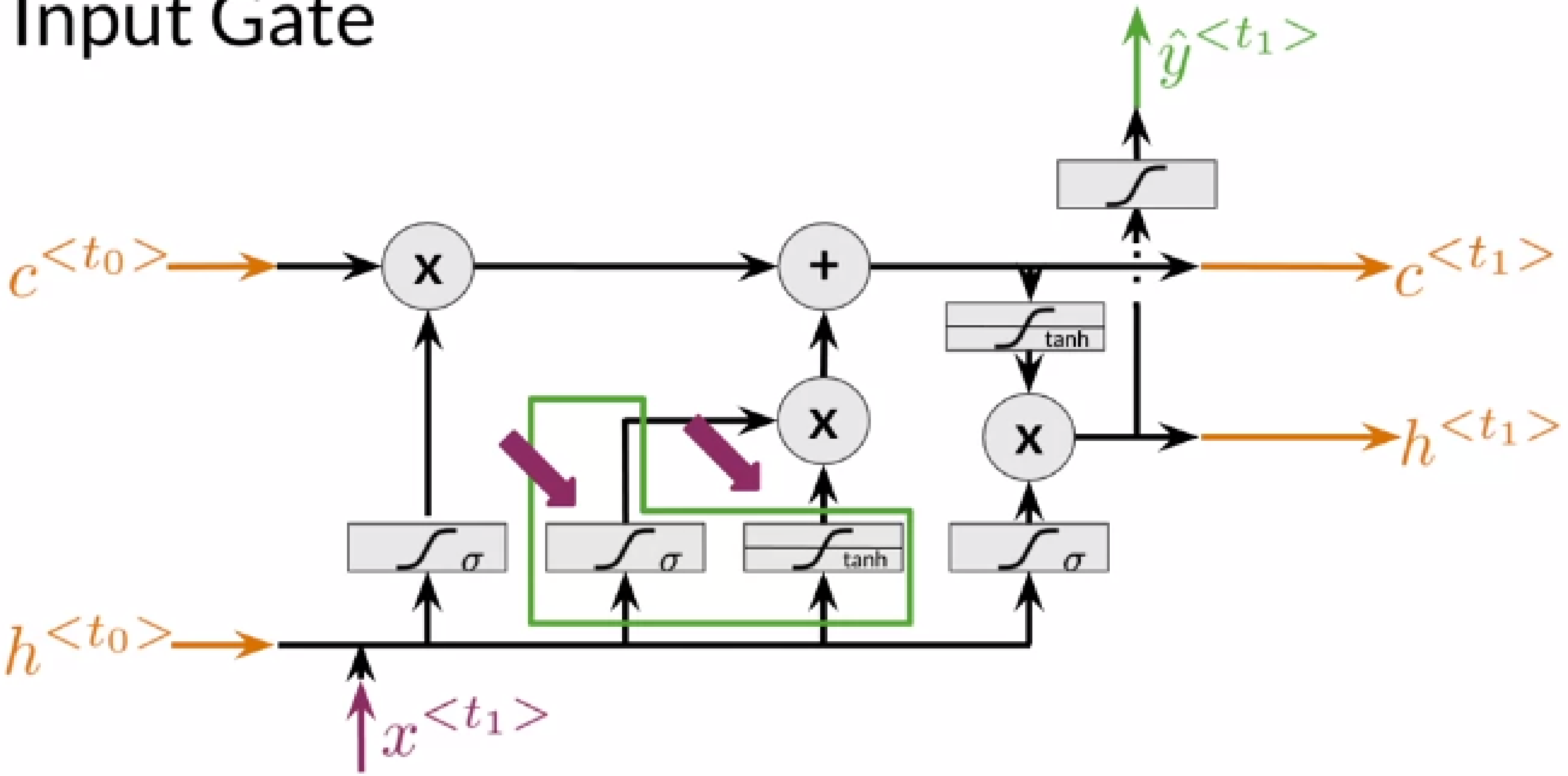

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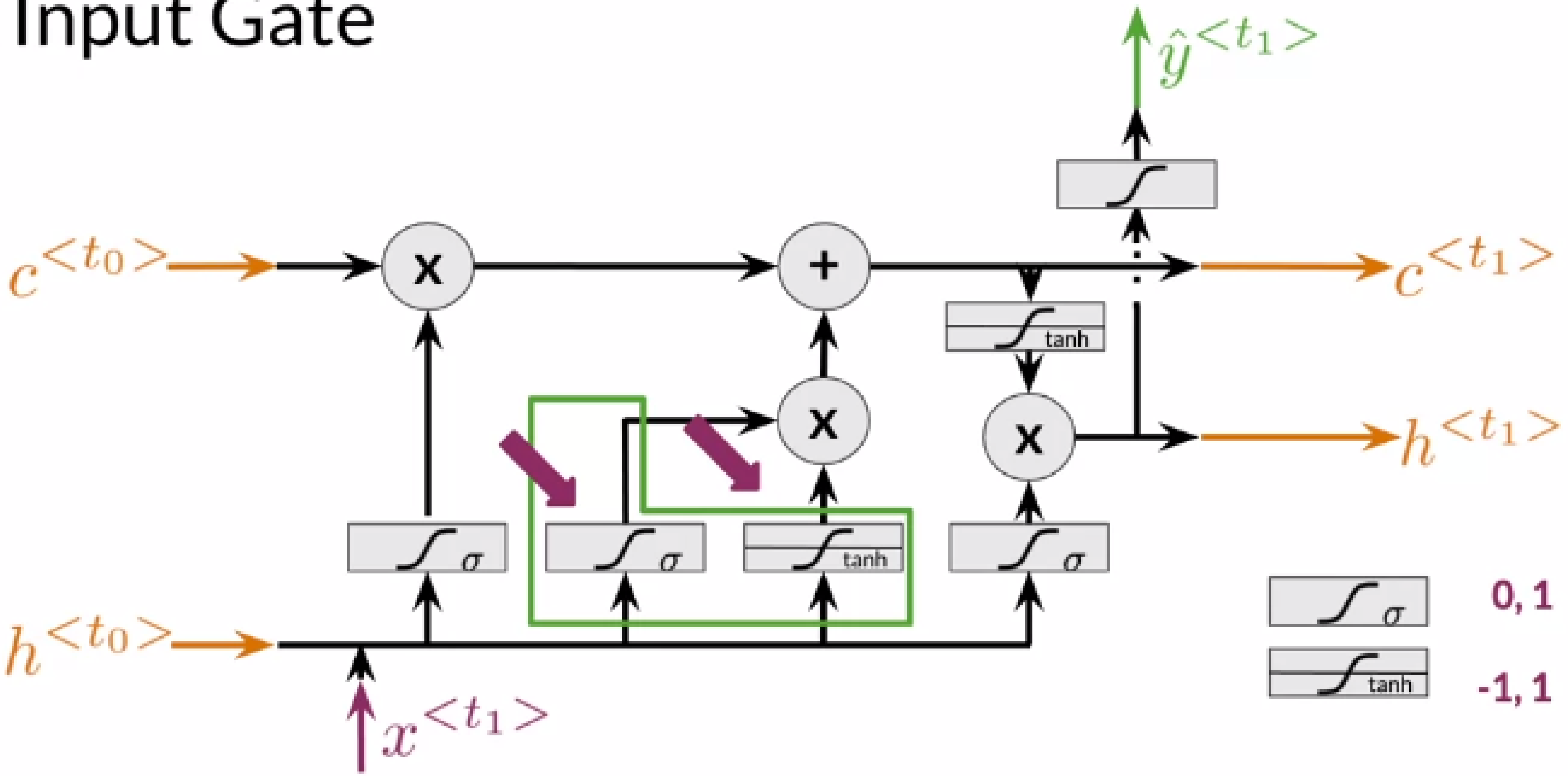

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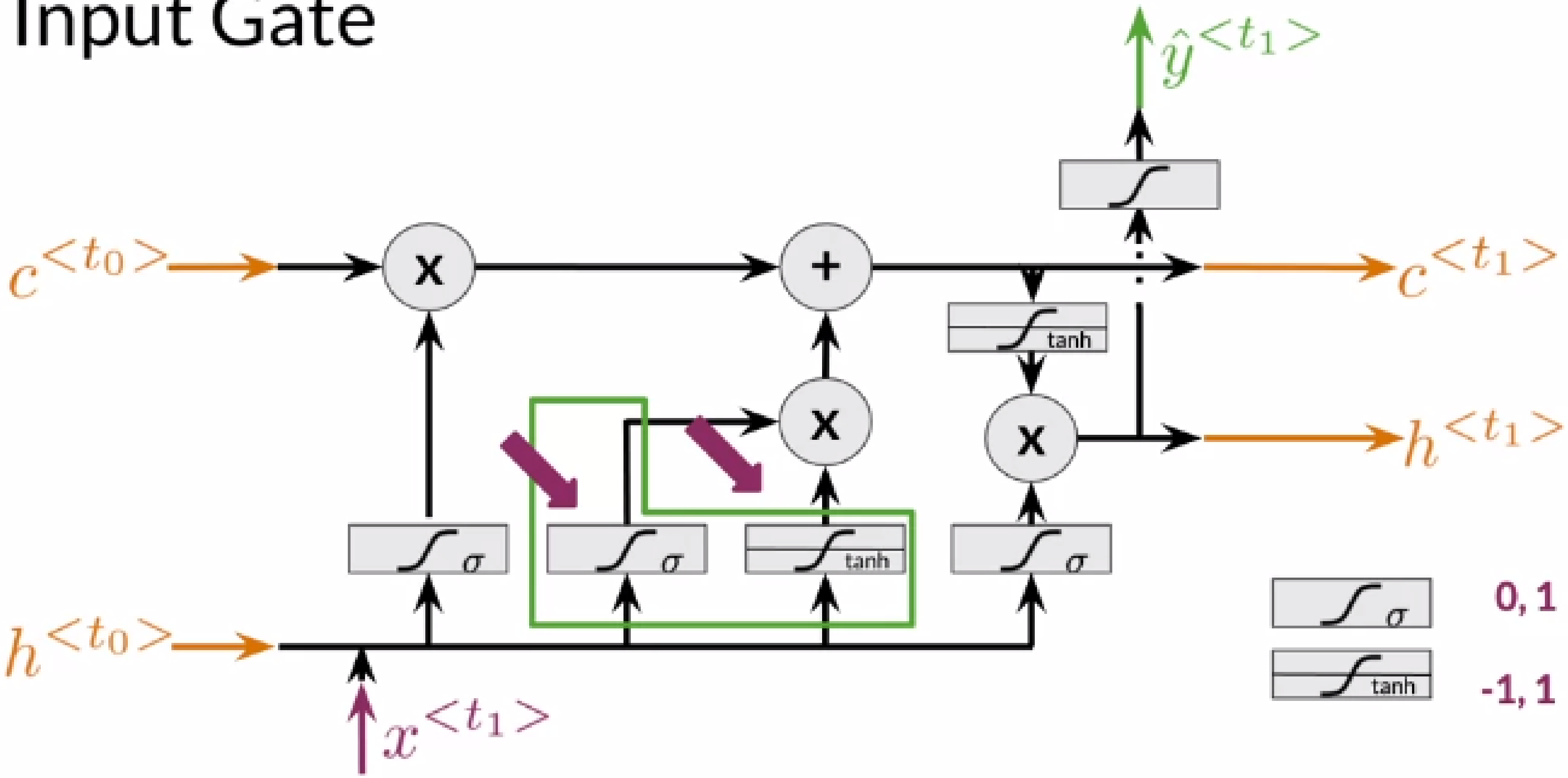

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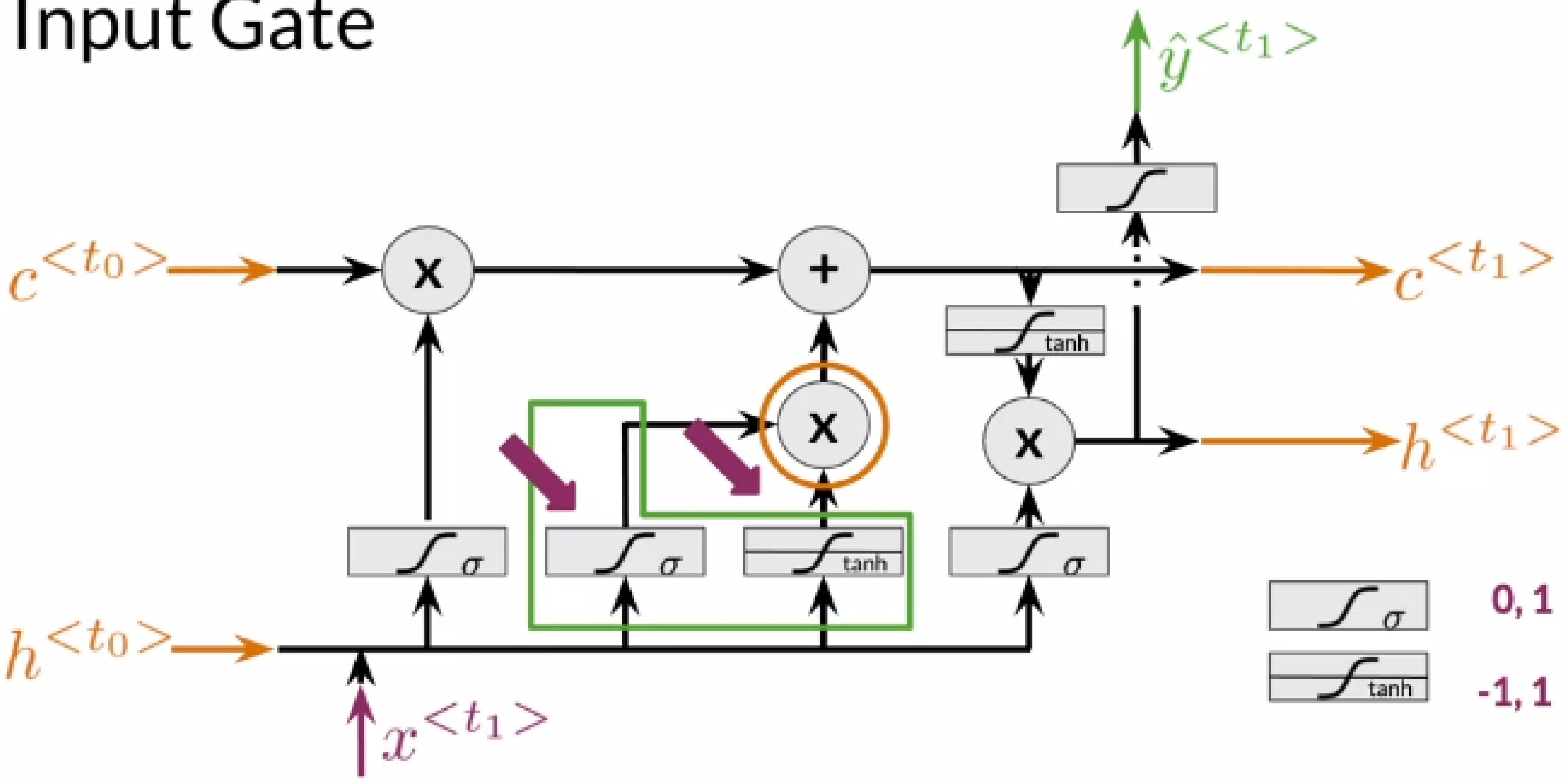
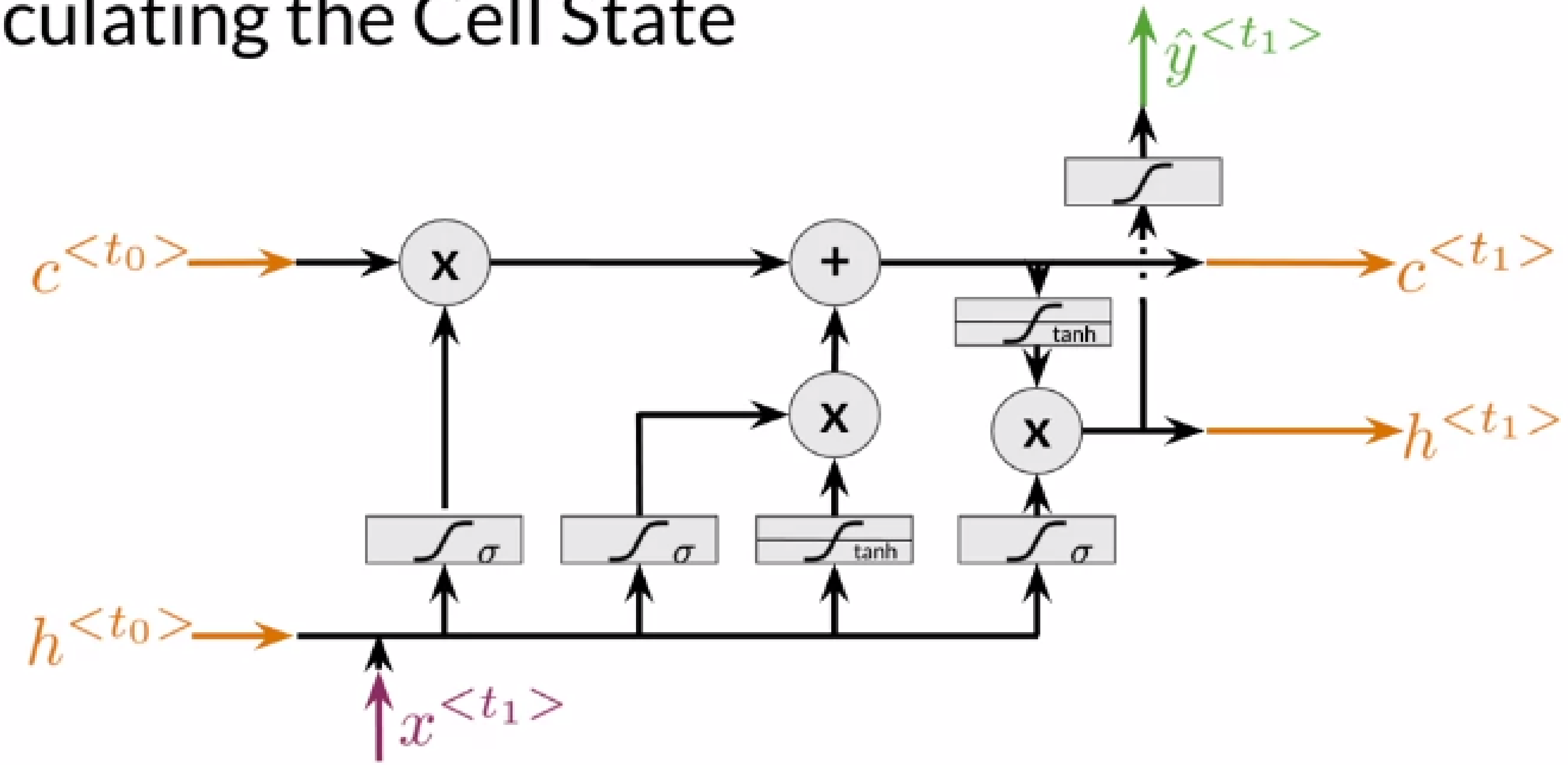


Calculating the Cell State



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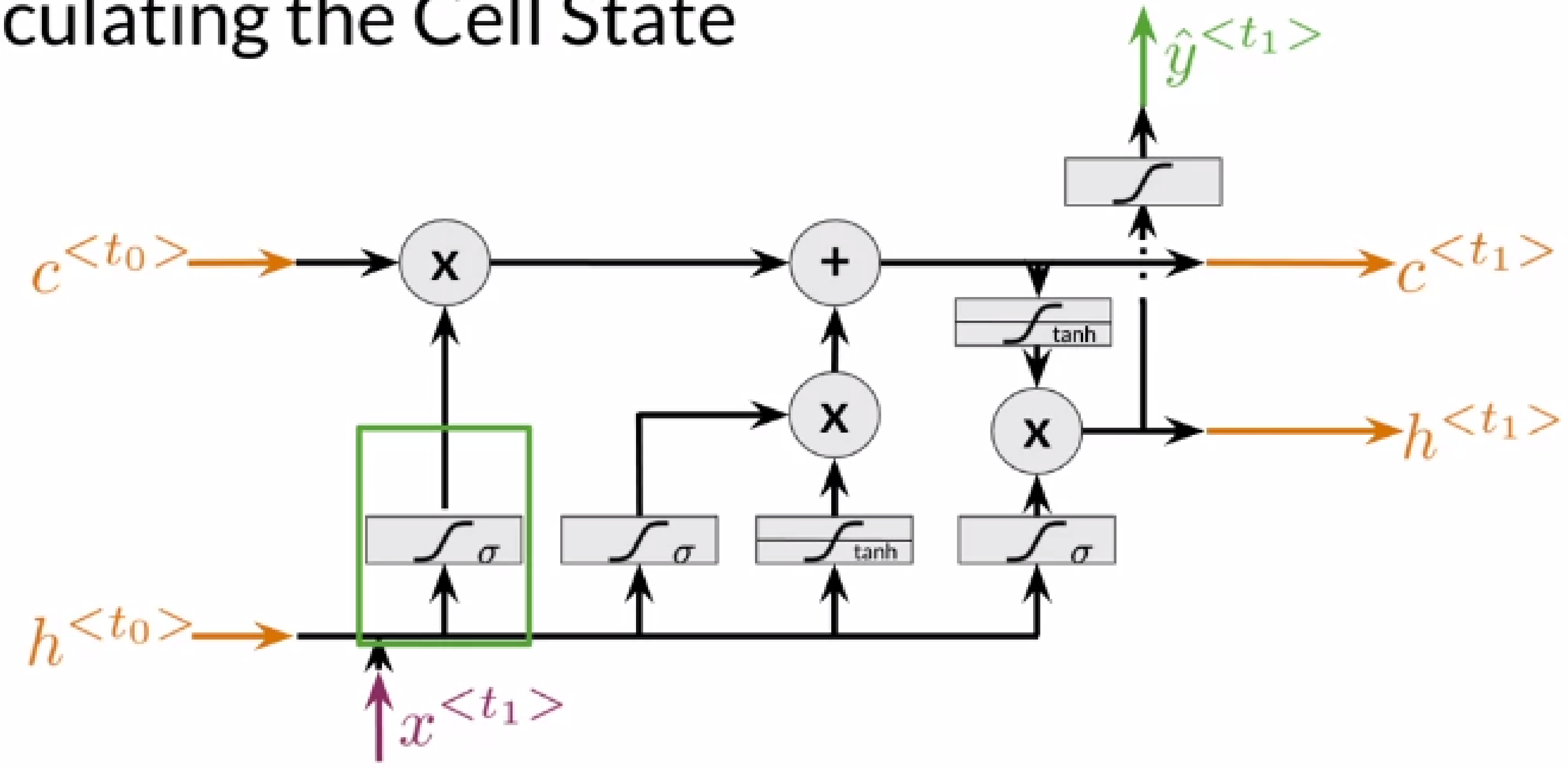

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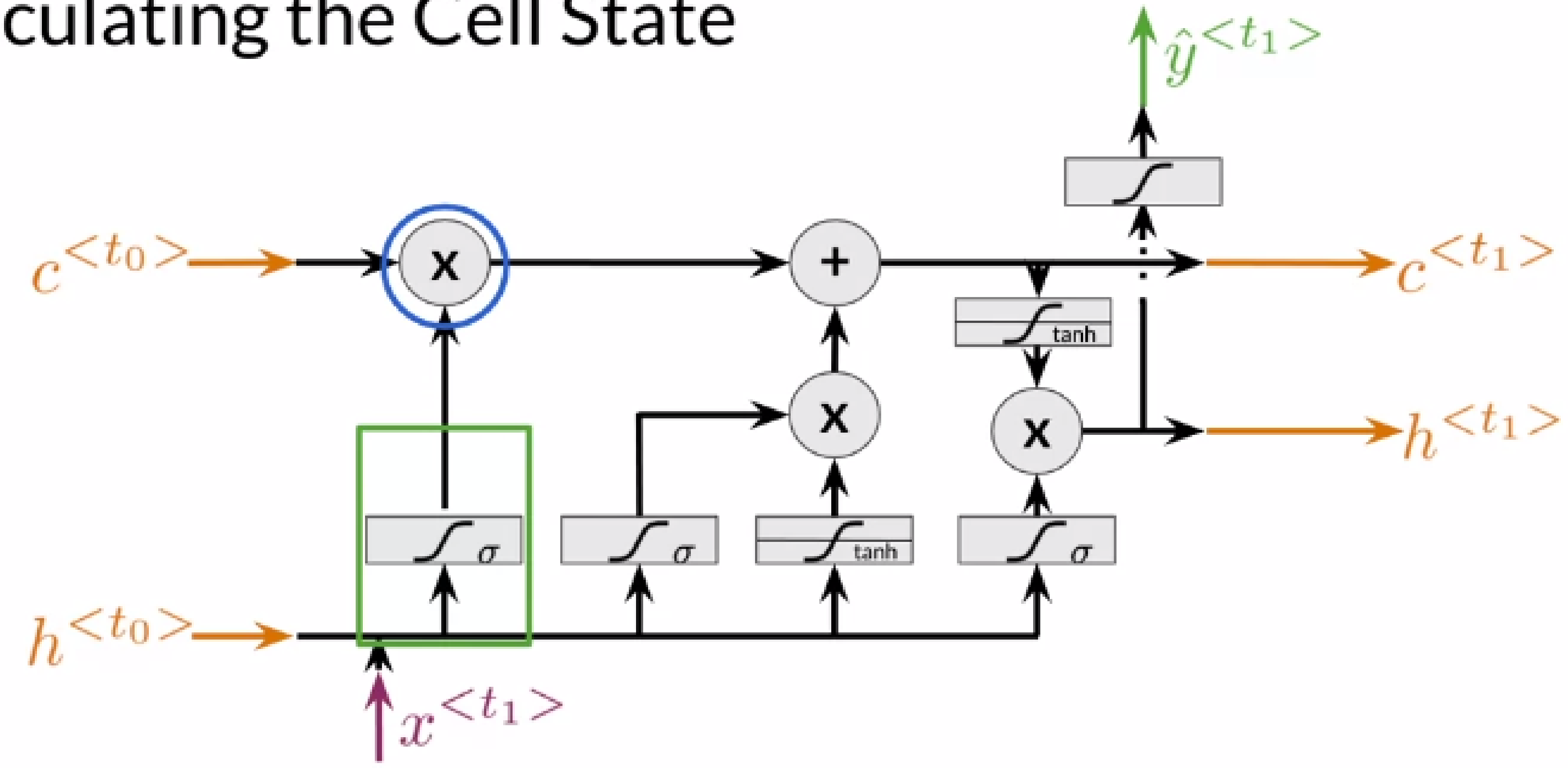

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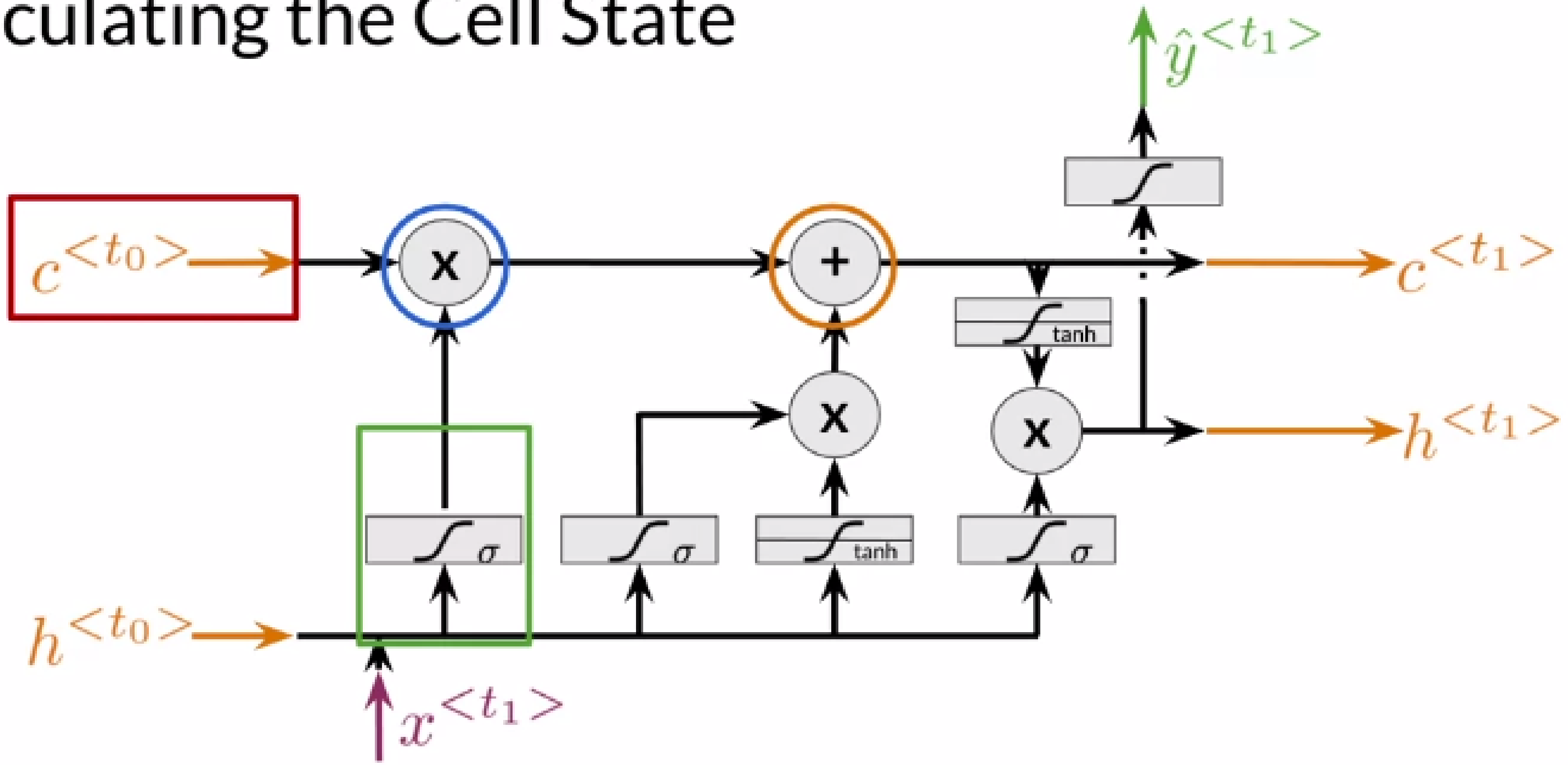
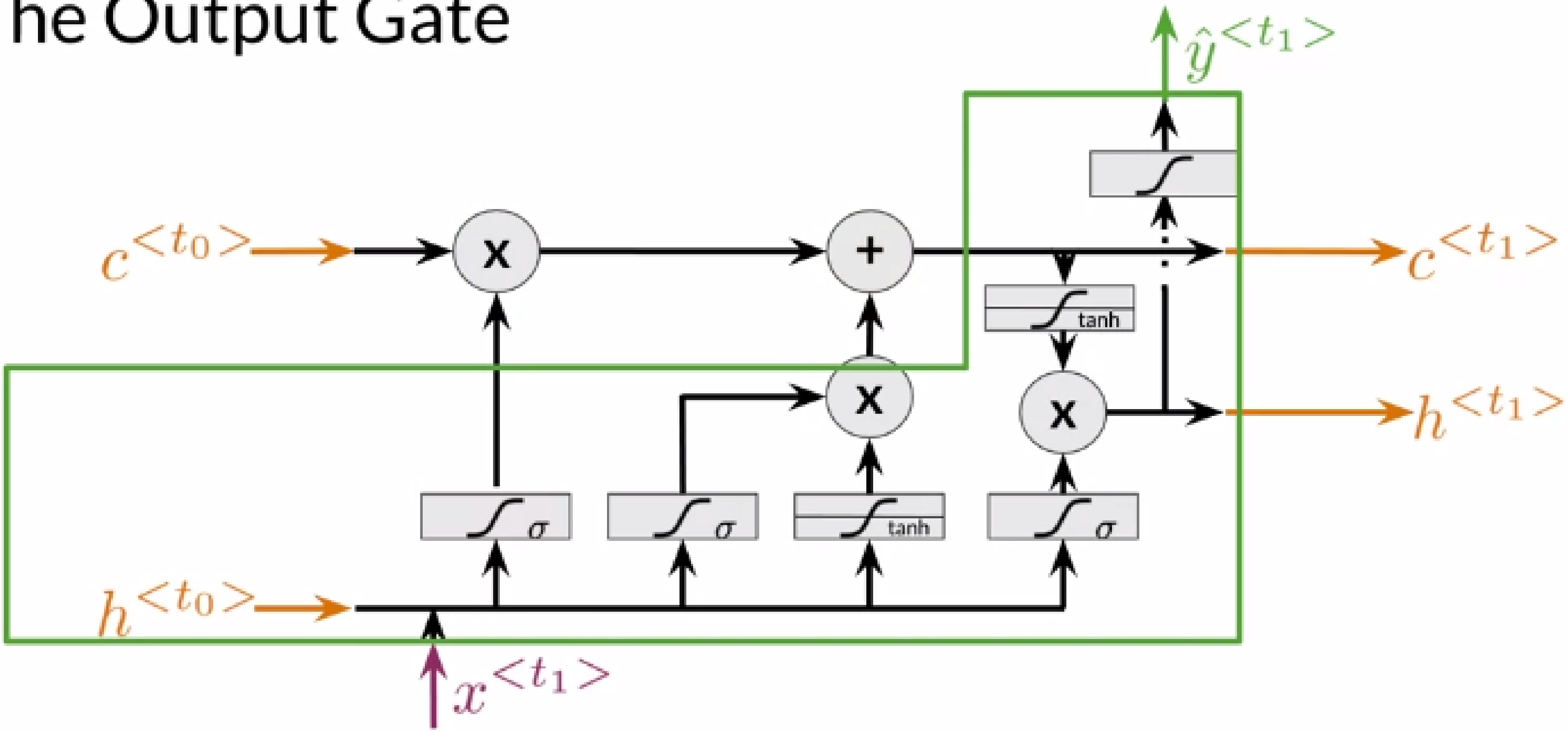


The Output Gate



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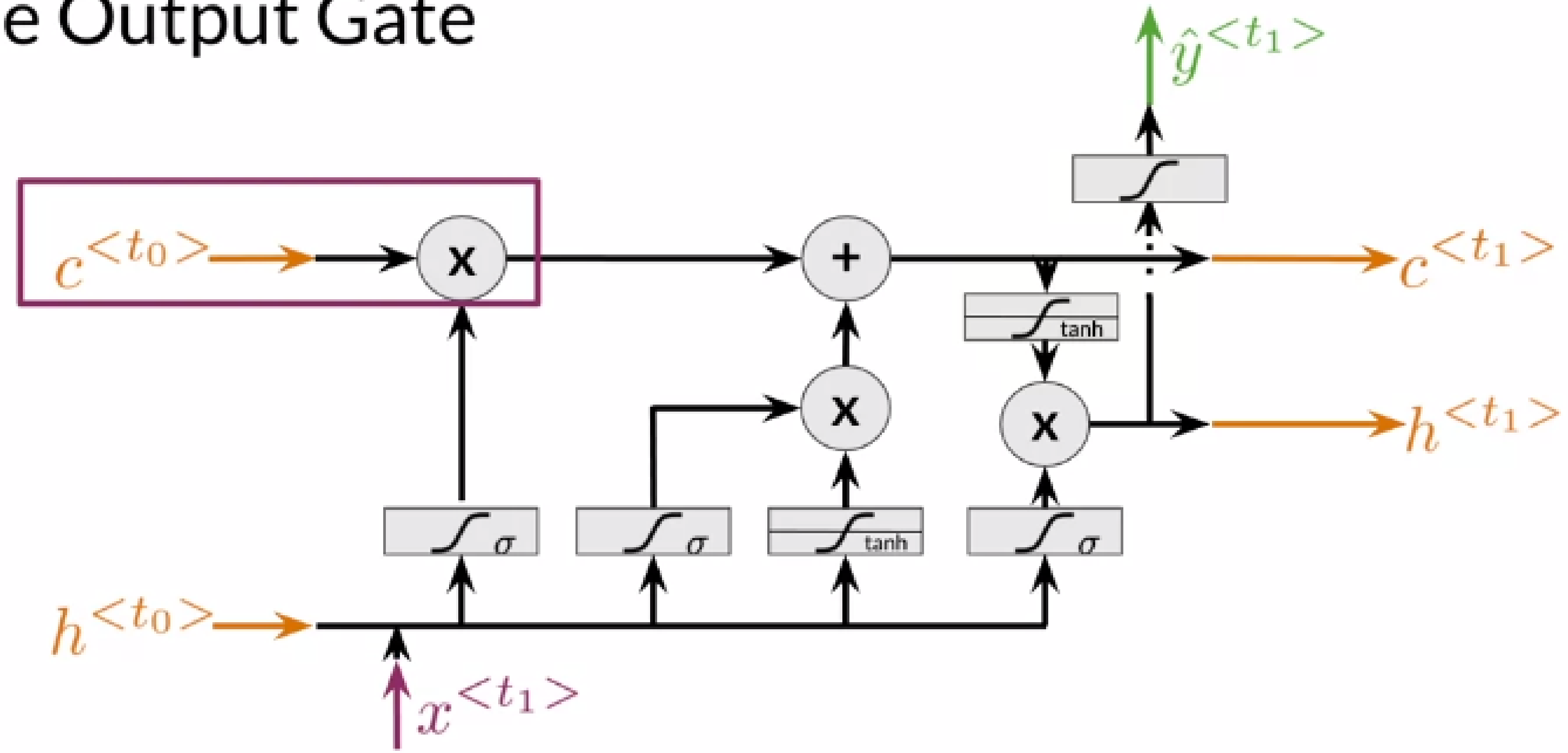

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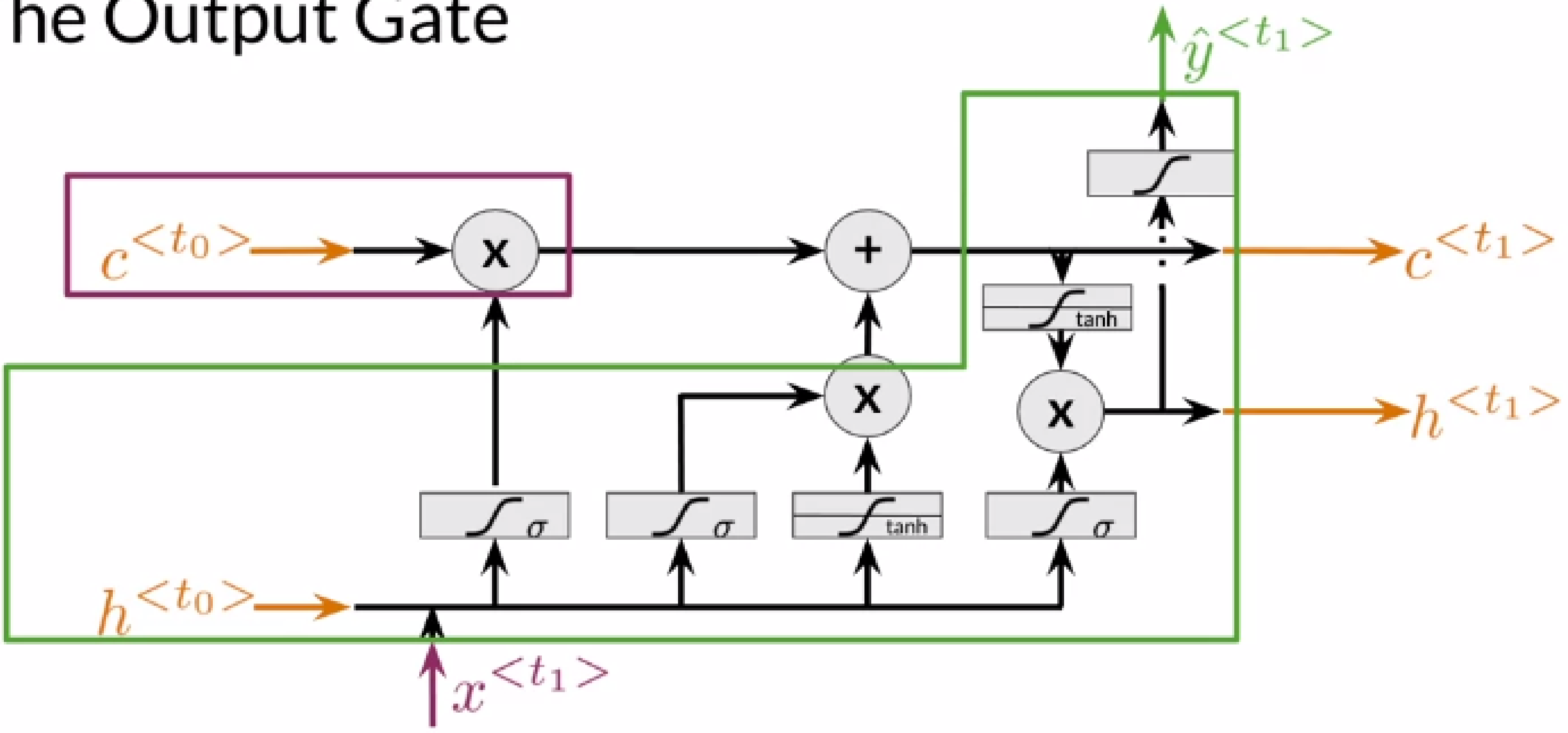

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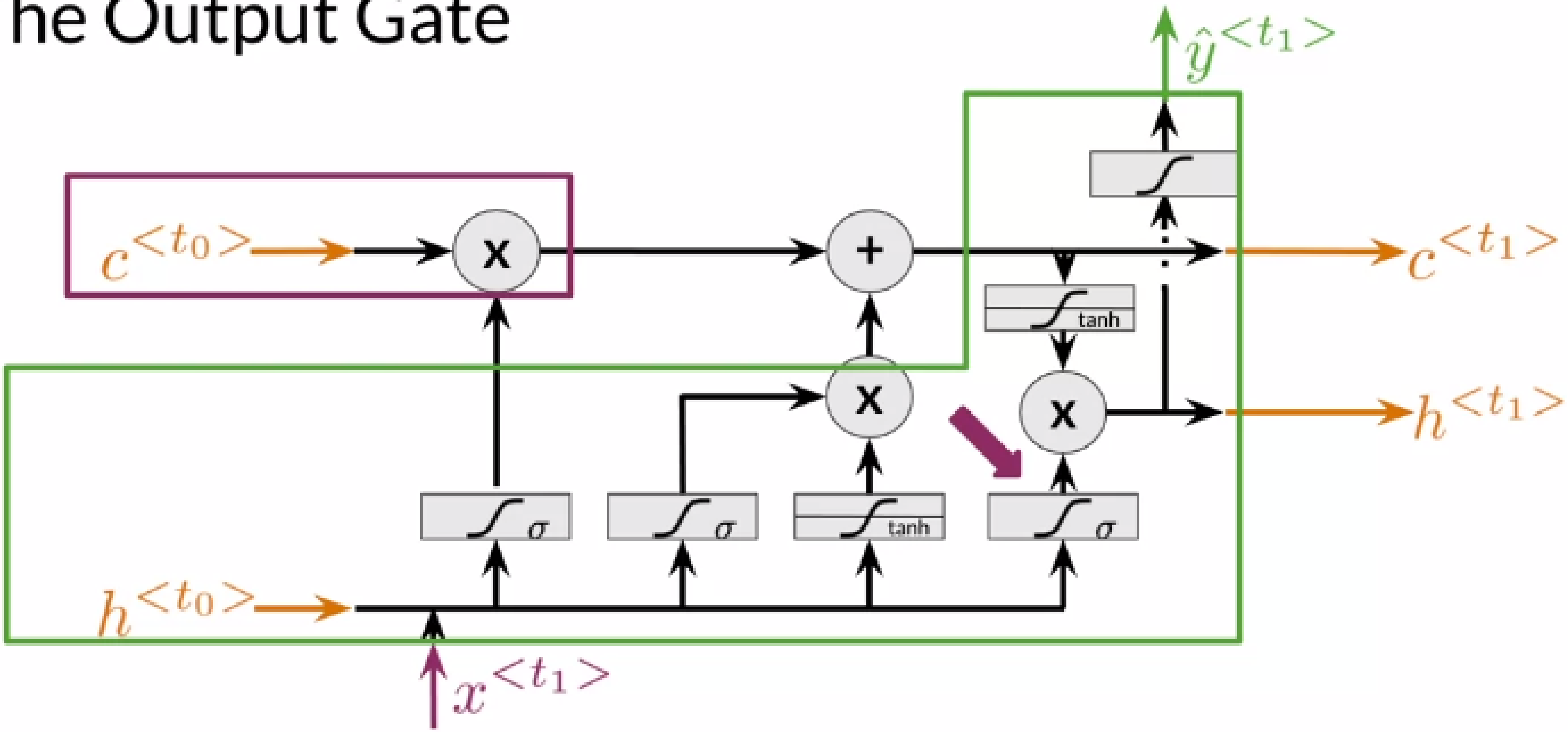

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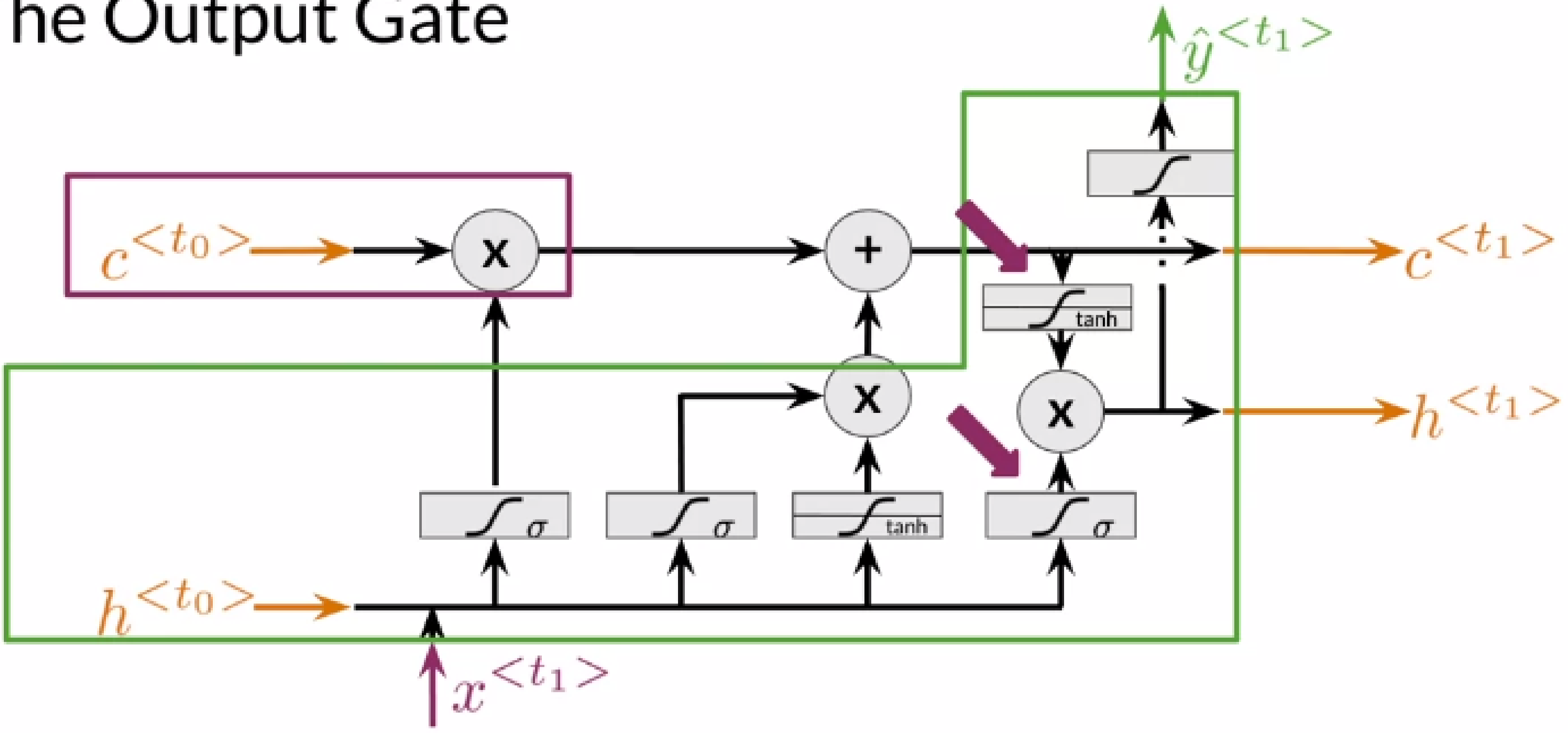

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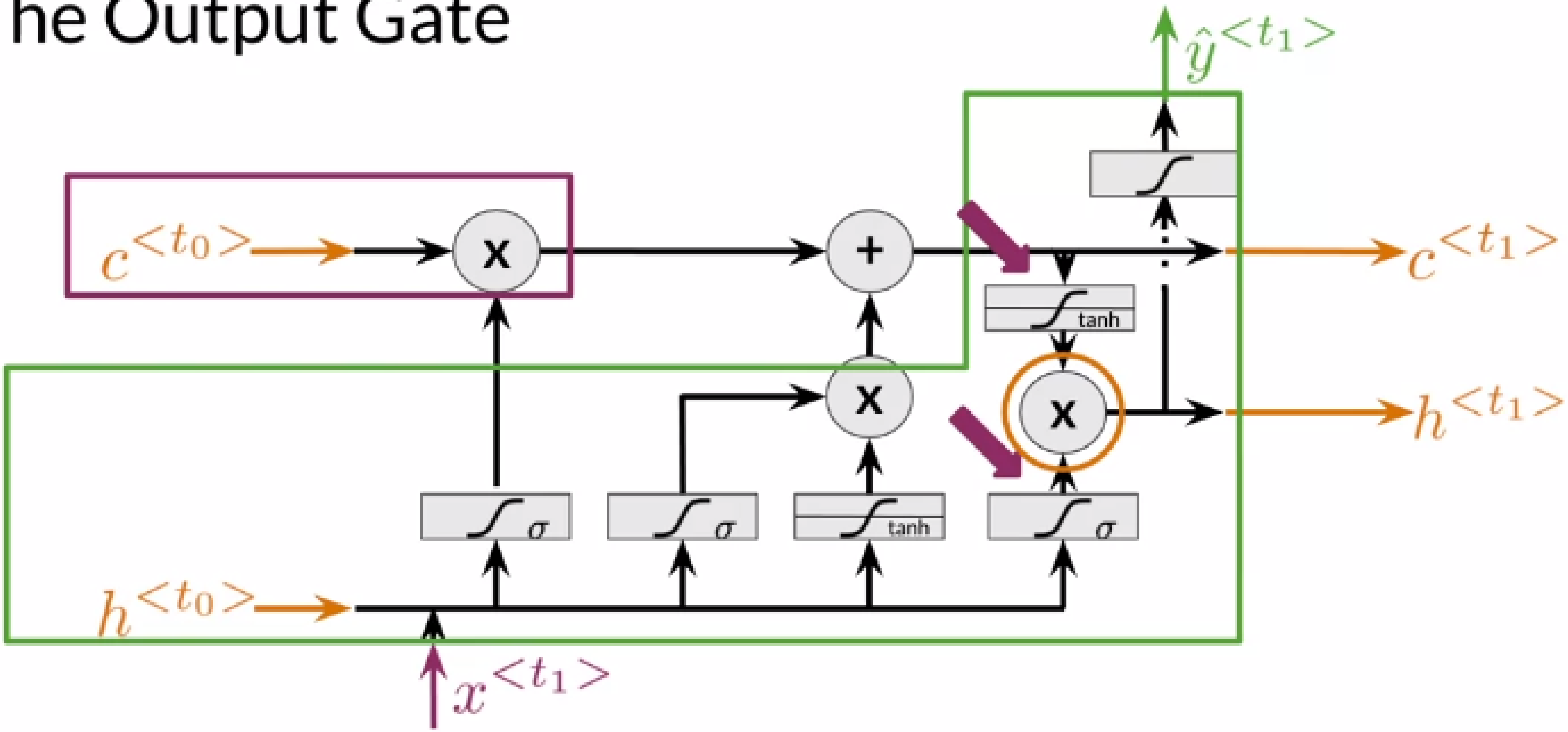

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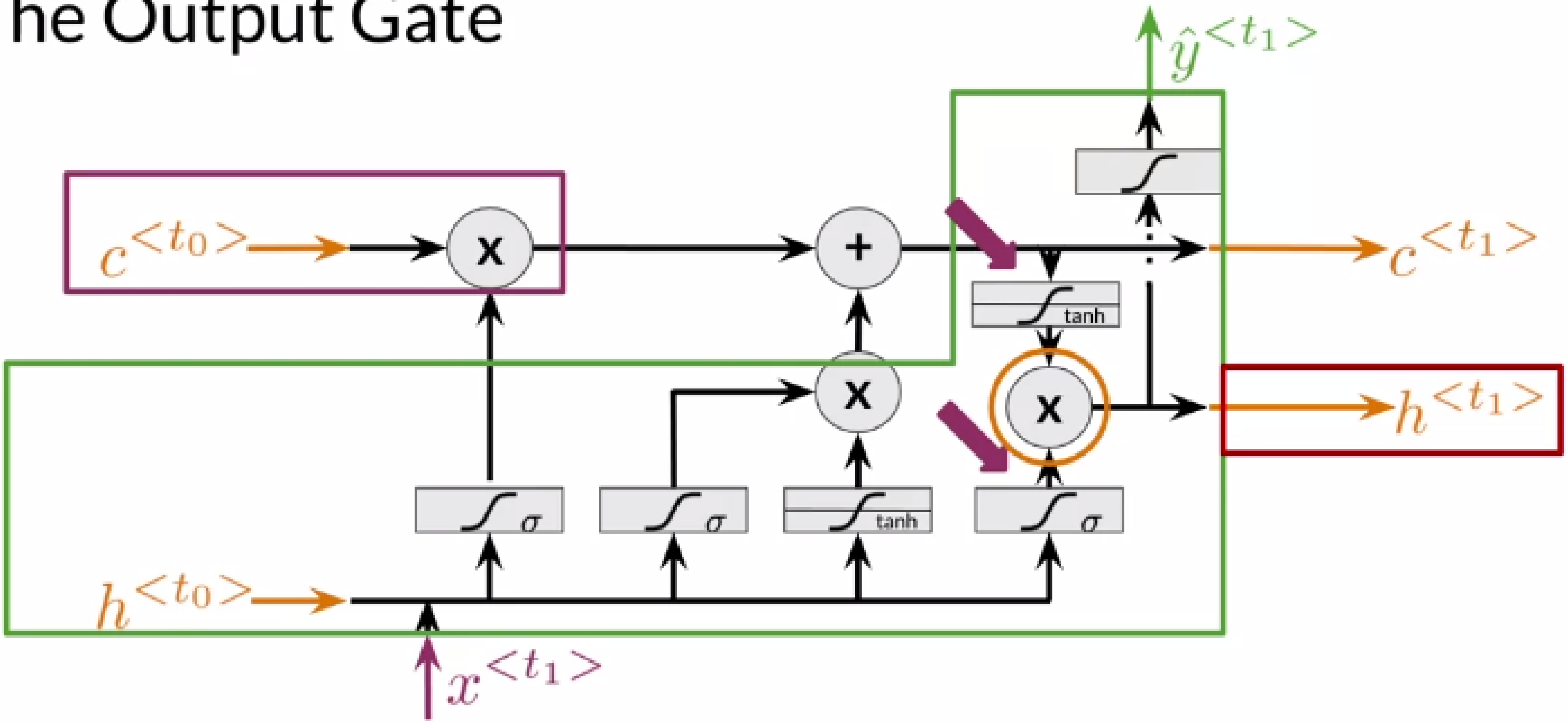

Summary

- LSTMs use a series of gates to decide which information to keep:
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- One time step is completed after updating the states

What is Named Entity Recognition?

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- Locates and extracts predefined entities from text

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- Locates and extracts predefined entities from text
- Places, organizations, names, time and dates

Types of Entities

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Thailand:
Geographical

Types of Entities

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Geographical

Google:
Organization

Types of Entities

Thailand:
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Google:
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Indian:
Geopolitical

More Types of Entities

December:
Time Indicator

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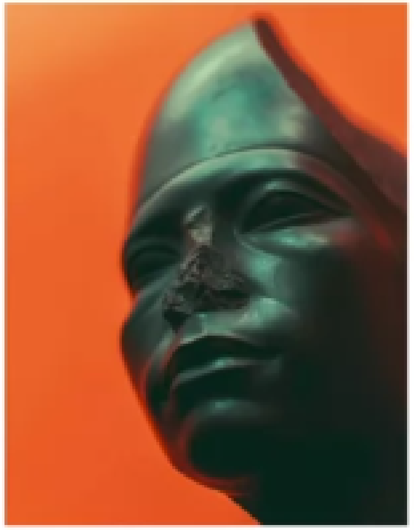
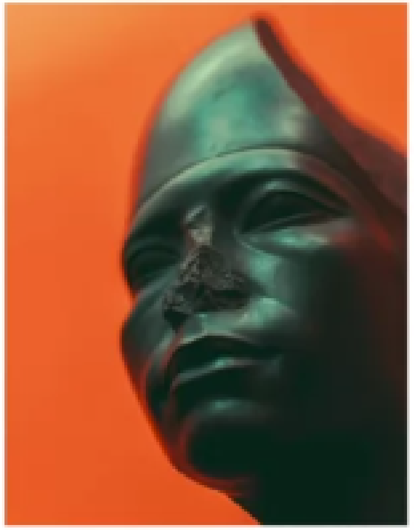


Egyptian statue:
Artifact

More Types of Entities

December:
Time Indicator



Egyptian statue:
Artifact

Barack Obama:
Person

Example of a labeled sentence

Sharon flew to Miami last Friday.

Example of a labeled sentence

$\boxed{\textbf{Sharon}}$ **flew to Miami last Friday.**

B-per

Example of a labeled sentence

Sharon flew to **Miami** last Friday.

B-per

B-geo

Example of a labeled sentence

Sharon flew to Miami last Friday.

B-per B-geo B-tim

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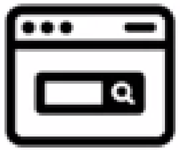
Applications of NER systems

- Search engine efficiency



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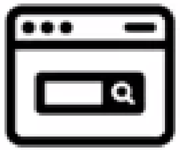

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- Search engine efficiency
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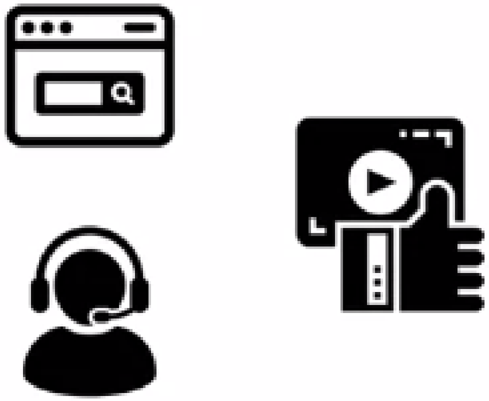


Applications of NER systems

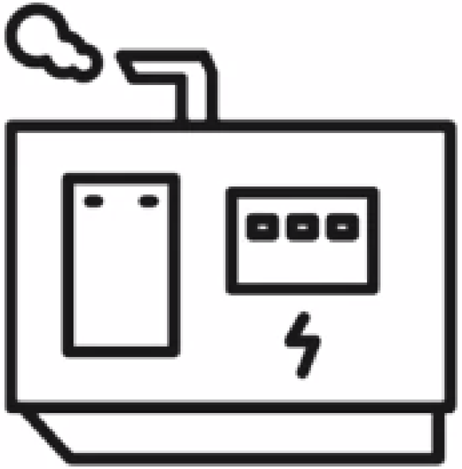
- Search engine efficiency
- Recommendation engines
- Customer service
- Automatic trading

Training NERs: Data Processing

deeplearning.ai

Outline

- Convert words and entity classes into arrays
- Token padding
- Create a data generator



Processing data for NERs

- Assign each class a number

1	2	3
B-per	B-geo	B-tim

Processing data for NERs

- Assign each class a number
- Assign each word a number

Sharon flew to Miami last Friday.

[4282, 853, 187, 5388, 2894, 7]

B-per O O B-geo O B-tim

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- Set sequence length to a certain number

Token padding

For LSTMs, all sequences need to be the same size.

- Set sequence length to a certain number
- Use the <PAD> token to fill empty spaces

Training the NER

1. Create a tensor for each input and its corresponding number
2. Put them in a batch → 64, 128, 256, 512 ...
3. Feed it into an LSTM unit
4. Run the output through a dense layer
5. Predict using a log softmax over K classes

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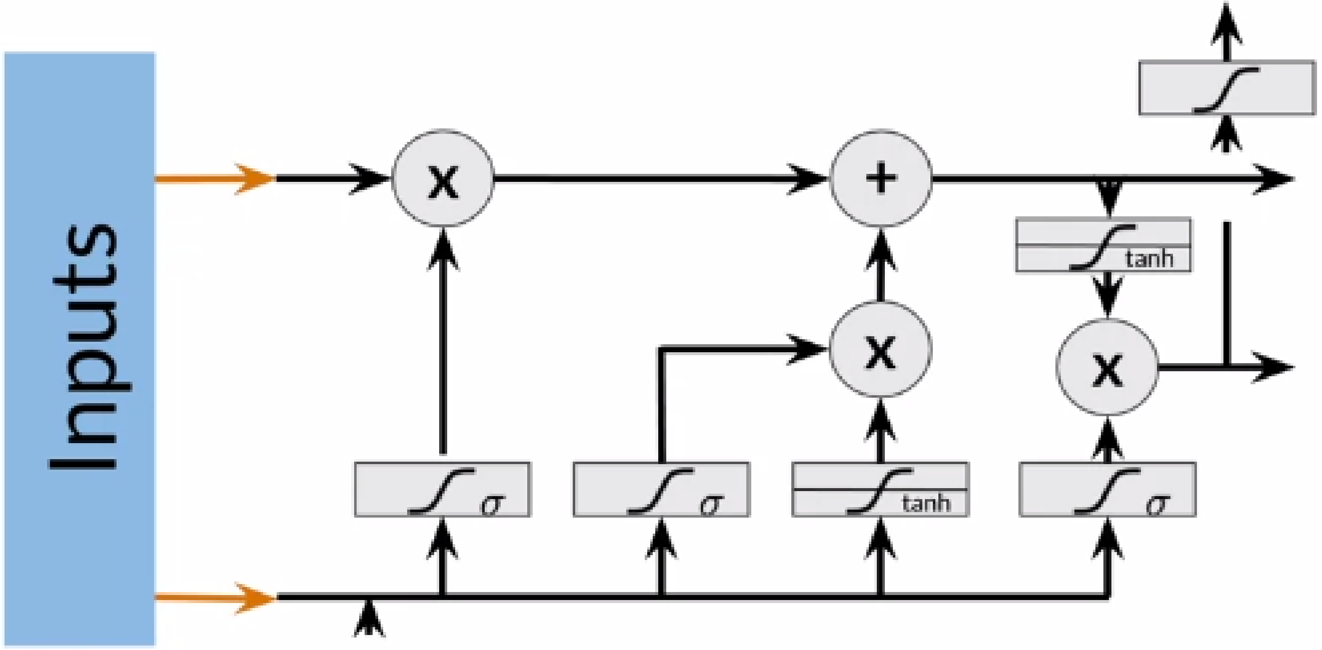

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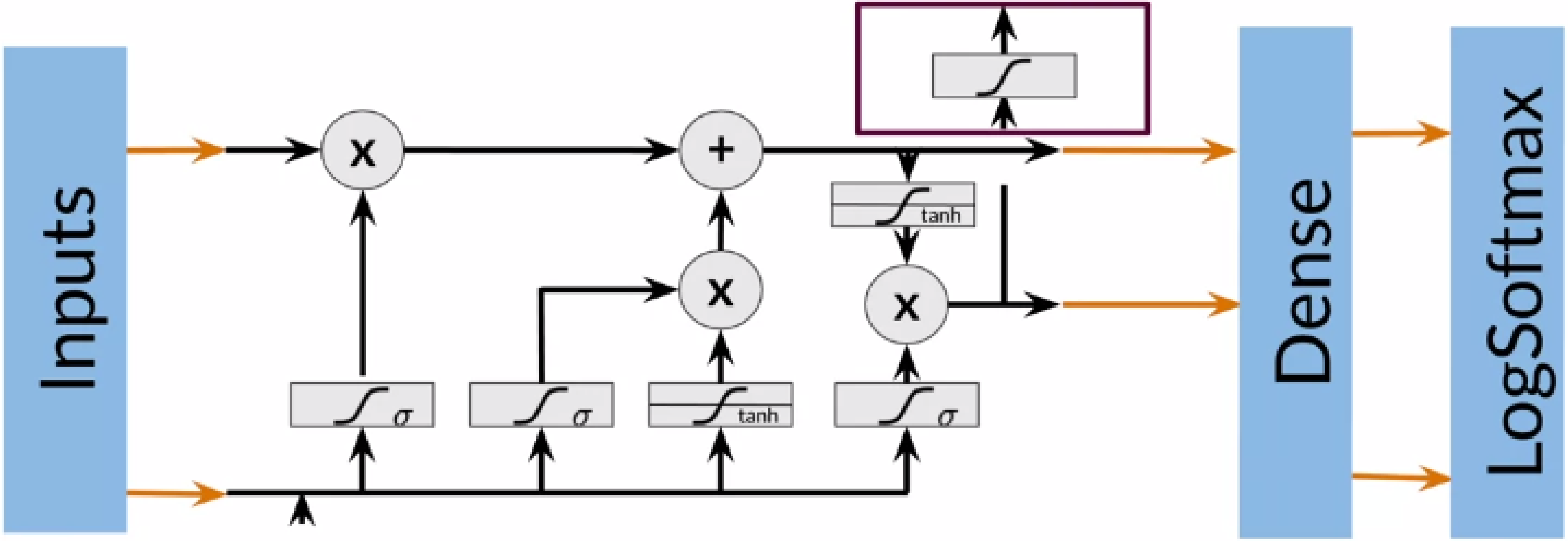

Layers in Trax

```
model = tl.Serial(
    tl.Embedding(),
    tl.LSTM(),
    tl.Dense()
    tl.LogSoftmax()
  )
```

Summary

- Convert words and entities into same-length numerical arrays
- Train in batches for faster processing
- Run the output through a final layer and activation

deeplearning.ai

Computing Accuracy

Evaluating the model

1. Pass test set through the model

Evaluating the model

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2. Get arg max across the prediction array

Evaluating the model

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3. Mask padded tokens

Evaluating the model

1. Pass test set through the model
2. Get arg max across the prediction array
3. Mask padded tokens
4. Compare outputs against test labels

Evaluating the model in Python

```python
def evaluate_model(test_sentences, test_labels, model):
    pred = model(test_sentences)
    outputs = np.argmax(pred, axis=2)
    mask = ...
    accuracy = np.sum(outputs==test_labels)/float(np.sum(mask))

    return accuracy
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Evaluating the model in Python

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```

Summary

- If padding tokens, remember to mask them when computing accuracy
- Coding assignment!