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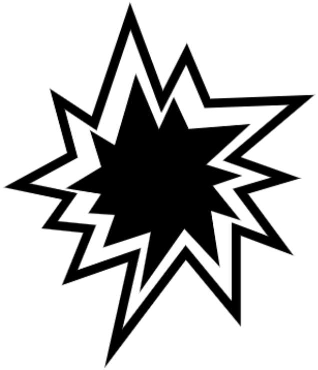
RNNs and Vanishing Gradients

Outline

- Backprop through time
- RNNs and vanishing/exploding gradients
- Solutions



RNNs: Advantages

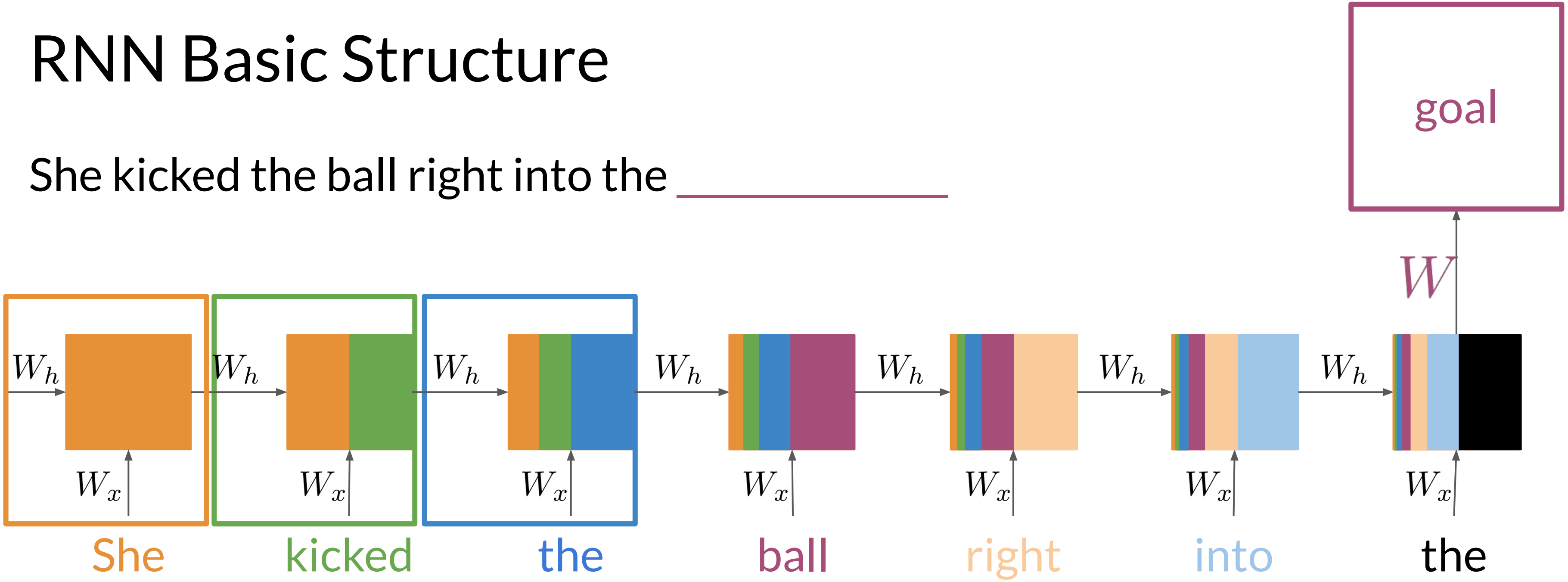
- Captures dependencies within a short range
- Takes up less RAM than other n-gram models

RNNs: Disadvantages

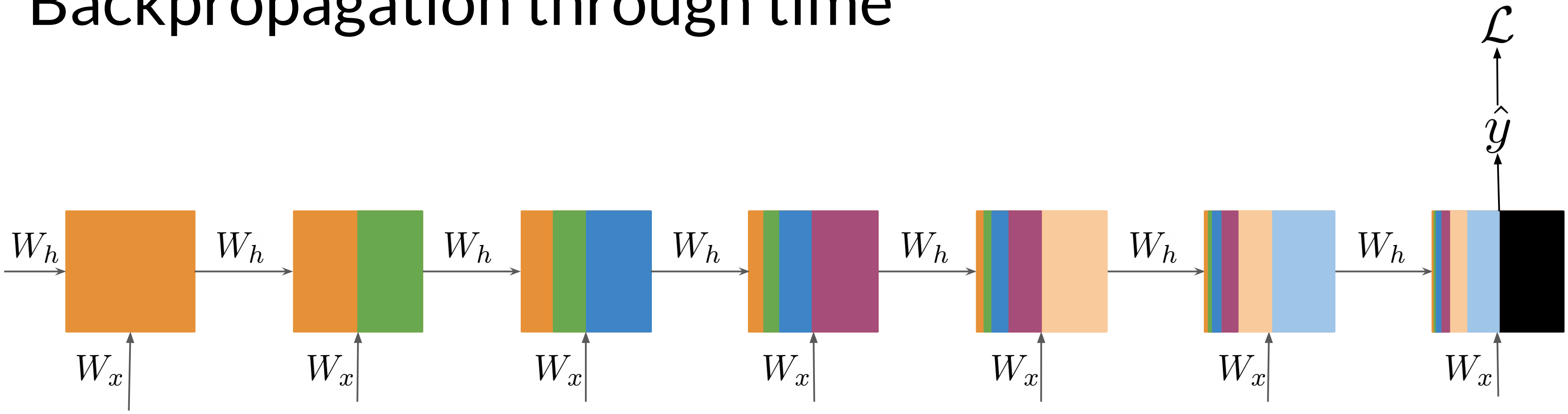
- Struggles to capture long term dependencies
- Prone to vanishing or exploding gradients

RNN Basic Structure

She kicked the ball right into the ____________



Backpropagation through time



W_x, W_h → Same at every step

$$\frac{\partial L}{\partial W_h} \propto \sum_{1 \le k \le t} \left(\prod_{t \ge i > k} \frac{\partial h_i}{\partial h_{i-1}} \right) \frac{\partial h_k}{\partial W_h}$$

Gradient is proportional to a sum of partial derivative products

Backpropagation through time

$$\frac{\partial L}{\partial W_h} \propto \sum_{1 \le k \le t} \boxed{\left(\boxed{\prod_{t \ge i > k} \frac{\partial h_i}{\partial h_{i-1}}} \right) \frac{\partial h_k}{\partial W_h}}$$

Contribution of hidden state ***k***

Length of the product proportional to how far ***k*** is from ***t***

$$\boxed{\frac{\partial h_t}{\partial h_{t-1}} \frac{\partial h_{t-1}}{\partial h_{t-2}} \frac{\partial h_{t-2}}{\partial h_{t-3}} \frac{\partial h_{t-3}}{\partial h_{t-4}} \frac{\partial h_{t-4}}{\partial h_{t-5}} \frac{\partial h_{t-5}}{\partial h_{t-6}} \frac{\partial h_{t-6}}{\partial h_{t-7}} \frac{\partial h_{t-7}}{\partial h_{t-8}} \frac{\partial h_{t-8}}{\partial h_{t-9}} \frac{\partial h_{t-9}}{\partial h_{t-10}} \frac{\partial h_{t-10}}{\partial W_h}}$$

Contribution of hidden state ***t-10***

Backpropagation through time

$$\frac{\partial L}{\partial W_h} \propto \sum_{1\le k\le t} \boxed{\left(\boxed{\prod_{t\ge i>k} \frac{\partial h_i}{\partial h_{i-1}}}\right) \frac{\partial h_k}{\partial W_h}}$$

Contribution of hidden state ***k***

Length of the product proportional to how far ***k*** is from ***t***

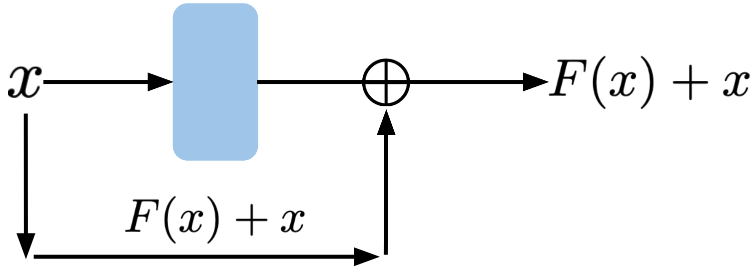
Partial derivatives <1	Contribution goes to 0	Vanishing Gradient
Partial derivatives >1	Contribution goes to infinity	**Exploding** Gradient

Solving for vanishing or exploding gradients

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

- Gradient clipping $32 \longrightarrow 25$

- Skip connections



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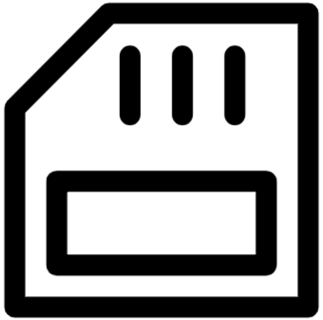
Introduction to LSTMs

Outline

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



LSTMs: a memorable solution

- Learns when to remember and when to forget
- Basic anatomy:
  - A cell state
  - A hidden state
  - Multiple gates
- Gates allow gradients to avoid vanishing and exploding

LSTMs: Based on previous understanding

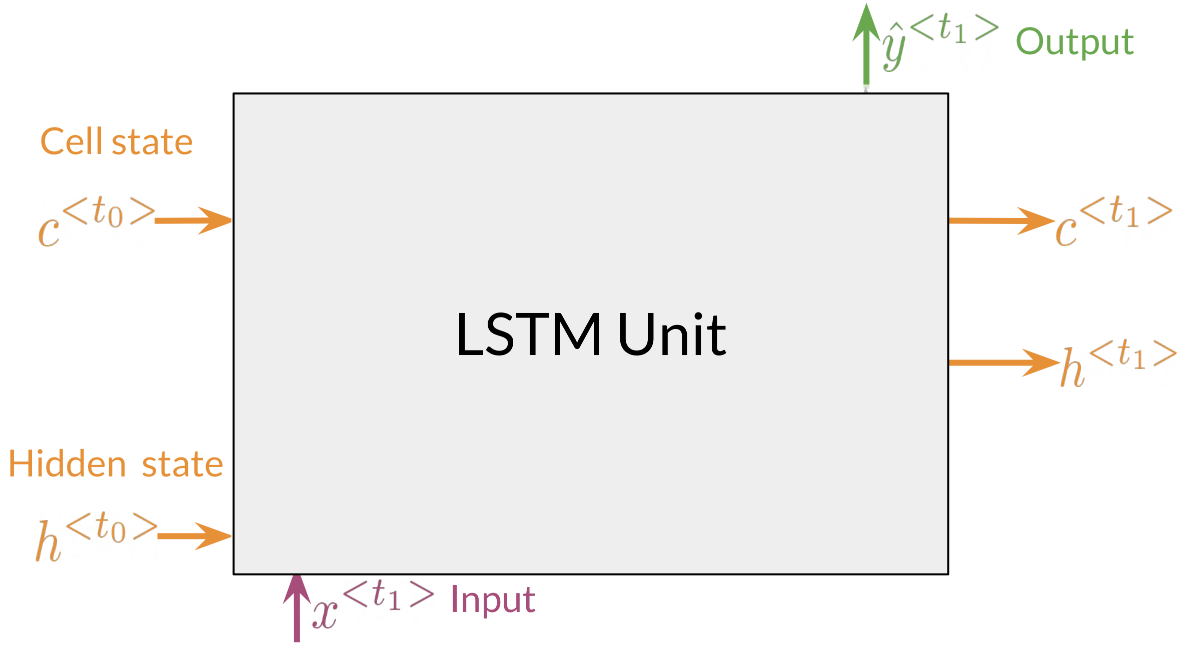
Starting point with some irrelevant information

Cell and Hidden States

- Discard anything irrelevant
- Add important new information
- Produce output

→ Gates

Gates in LSTM



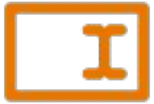
1. **Forget Gate:** information that is no longer important

2. **Input Gate:** information to be stored

3. **Output Gate:** information to use at current step

Applications of LSTMs

Next-character prediction



Chatbots

Music composition

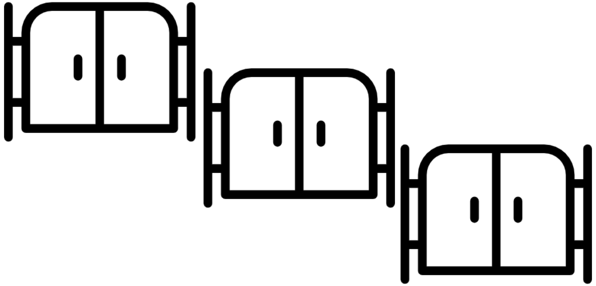
Image captioning

Speech recognition

Summary

- LSTMs offer a solution to vanishing gradients

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



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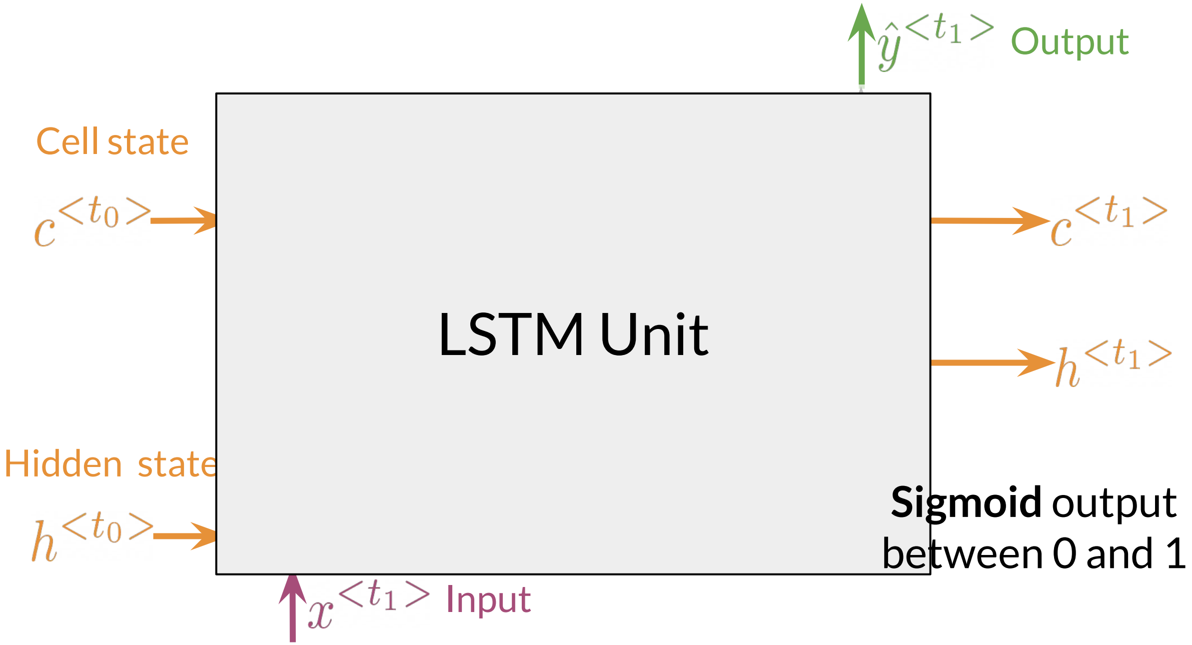
LSTM Architecture

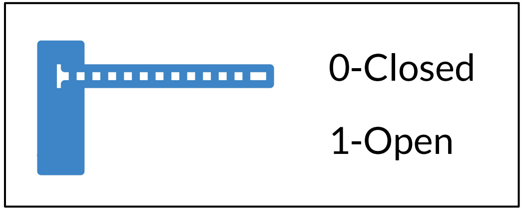
Gates in LSTM



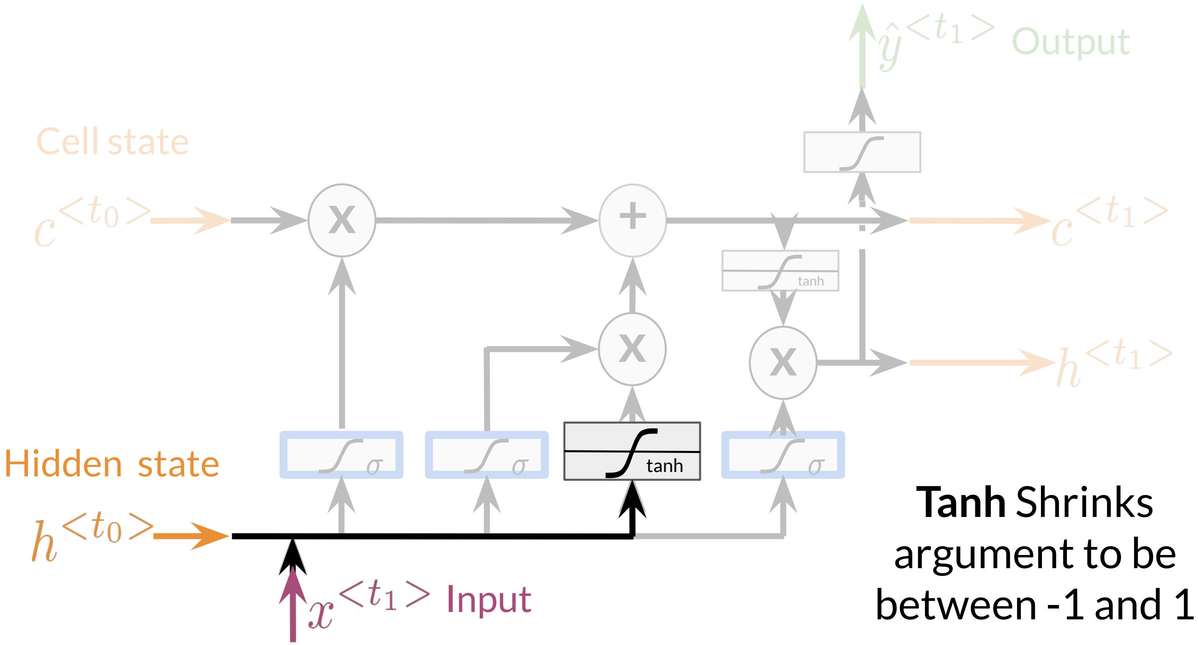
1. Forget Gate: information that is no longer important

2. Input Gate: information to be stored

3. Output Gate: information to use at current step



Candidate Cell State



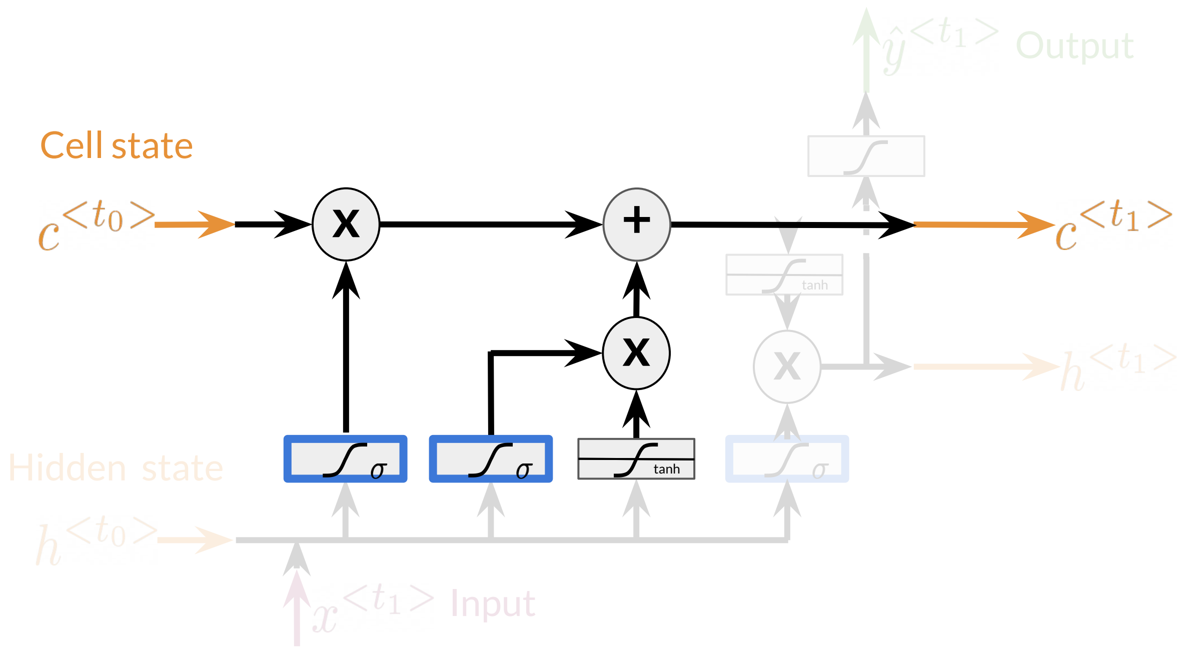
Candidate cell state

Information from the previous hidden state and current input

Tanh Shrinks argument to be between -1 and 1

Other activations could be used

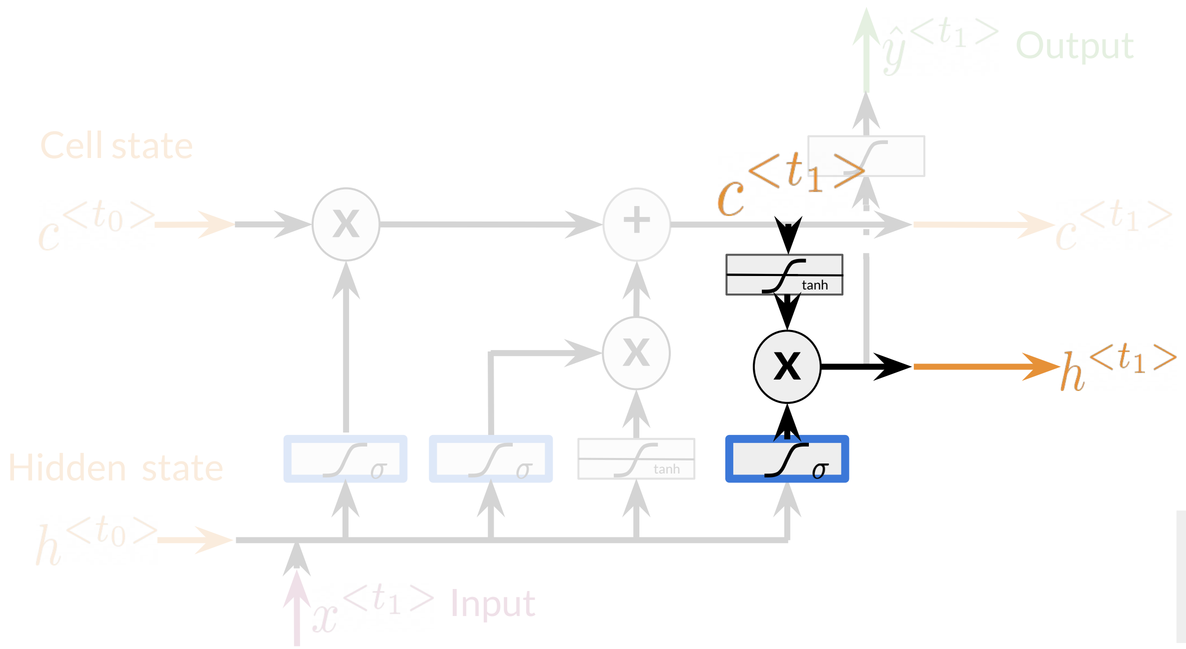
New Cell State



New Cell state

Add information from the **candidate cell state** using the **forget** and **input gates**

New Hidden State



New Hidden State

Select information from the **new cell state** using the **output gate**

The **Tanh** activation could be omitted

Summary

- LSTMs use a series of gates to decide which information to keep:
  - Forget gate decides what to keep
  - Input gate decides what to add
  - Output gate decides what the next hidden state will be

Introduction to Named Entity Recognition

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What is Named Entity Recognition?

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

Types of Entities

Thailand:
Geographical

Google:
Organization

Indian:
Geopolitical

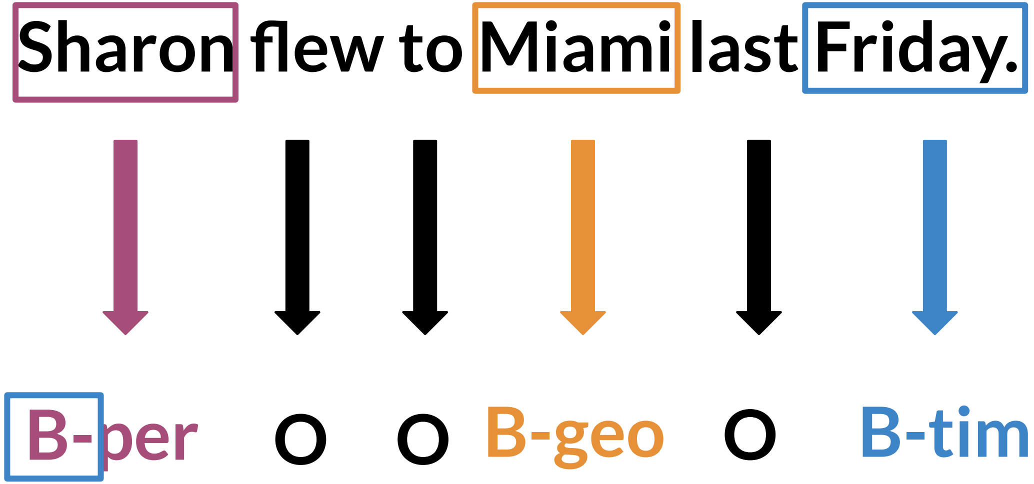
More Types of Entities

December:
Time Indicator

Egyptian statue:
Artifact

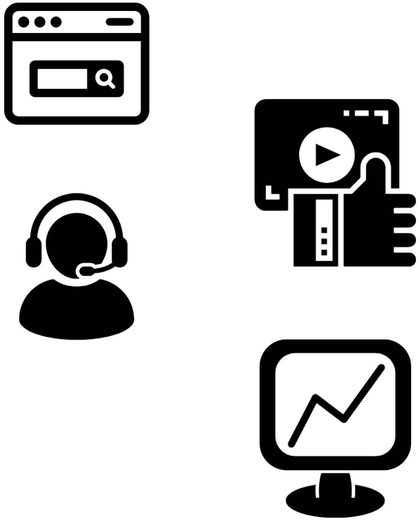
Barack Obama:
Person

Example of a labeled sentence



Applications of NER systems

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



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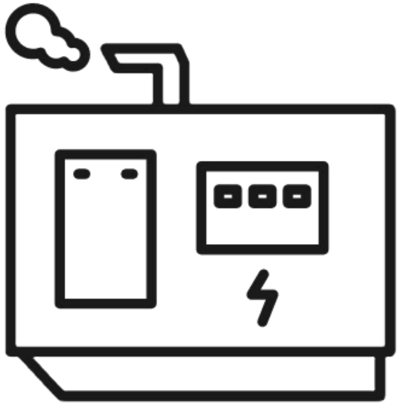
Training NERs: Data Processing

Outline

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



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]

1 2 3

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

Token padding

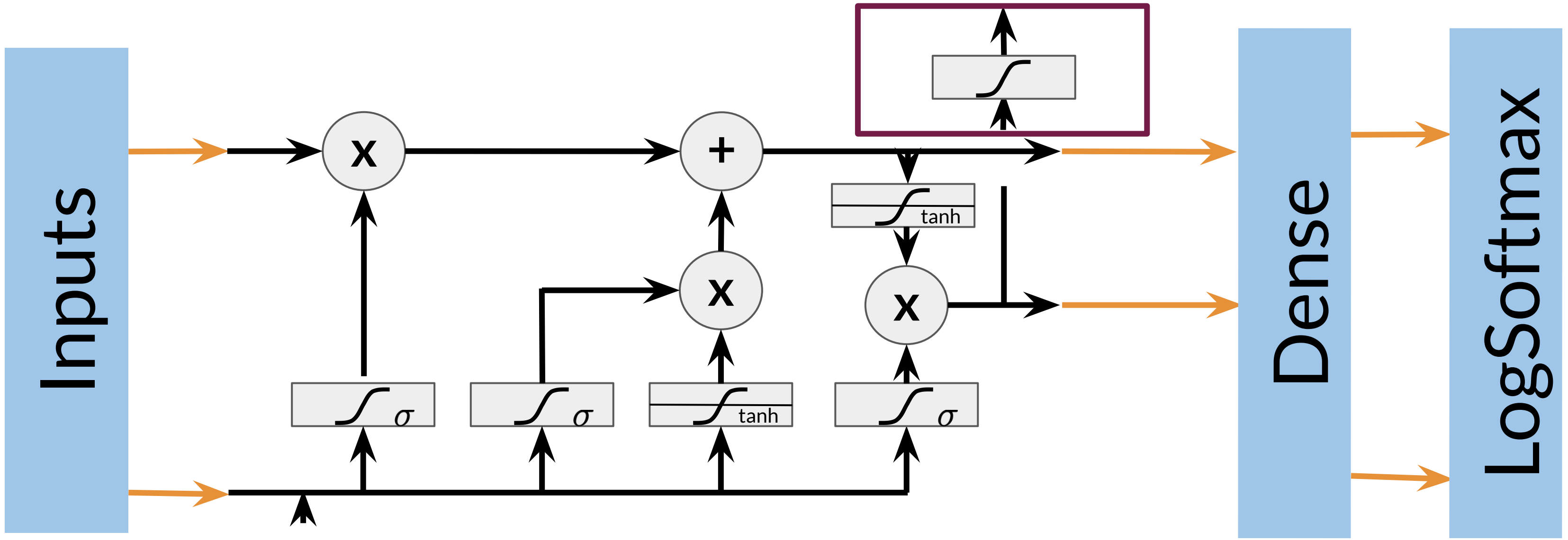
For LSTMs, all sequences need to be the same size.

- 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

Training the NER



Layers in TensorFlow

```
model = tf.keras.Sequential([
    tf.keras.layers.Embedding(),
    tf.keras.layers.LSTM(),
    tf.keras.layers.Dense(),
])
```

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

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Computing Accuracy

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 masked_accuracy(y_true, y_pred):
    mask = ...
    y_pred_class = tf.math.argmax(y_pred, axis=-1)
    matches_true_pred = tf.equal(y_true, y_pred_class)
    matches_true_pred *= mask
    masked_acc = tf.reduce_sum(acc) / tf.reduce_sum(mask)

    return masked_acc
```

Summary

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