Deep learning for text processing

STAT 4710

November 29, 2022

Acknowledgement: Material drawn from Stanford's CS 224n class (http://web.stanford.edu/class/cs224n/index.html)

Where we are

- **Unit 1:** R for data mining
- **Unit 2:** Prediction fundamentals
- **Unit 3:** Regression-based methods
- **Unit 4:** Tree-based methods
- **Unit 5:** Deep learning

Lecture 1: Deep learning preliminaries

Lecture 2: Neural networks

Lecture 3: Deep learning for images

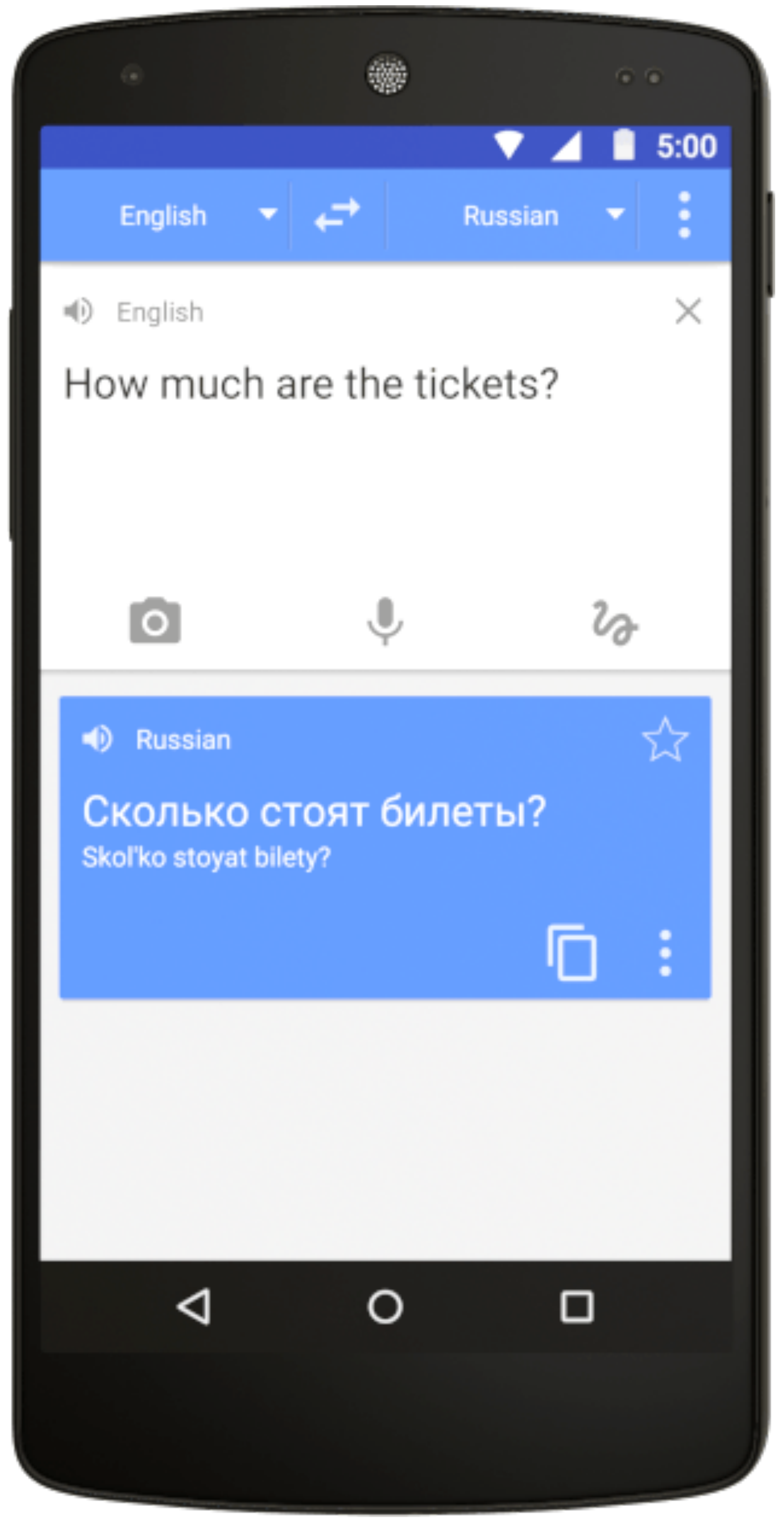
Lecture 4: Deep learning for text

Lecture 5: Unit review and quiz in class

Applications of natural language processing

Applications of natural language processing

Machine translation



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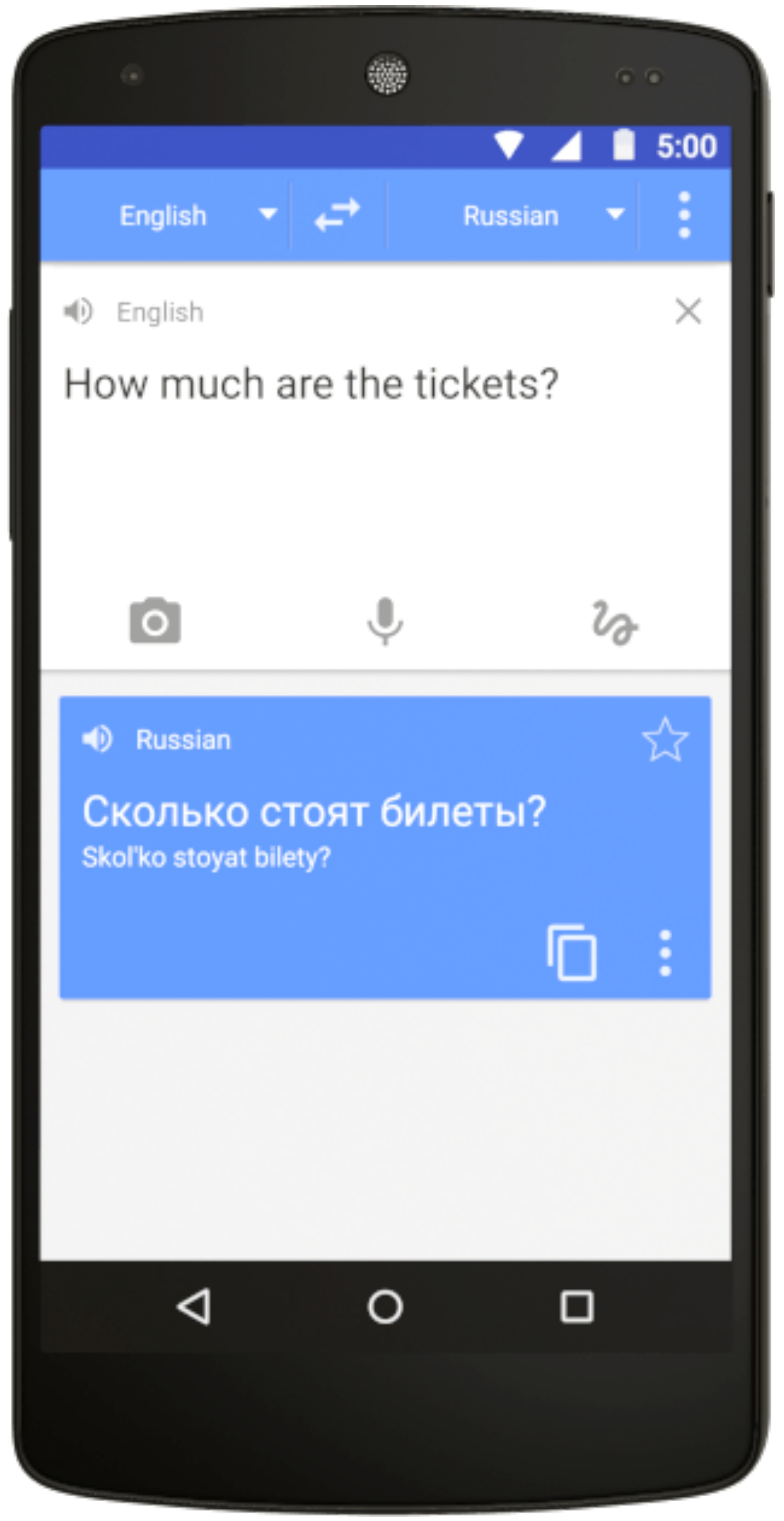

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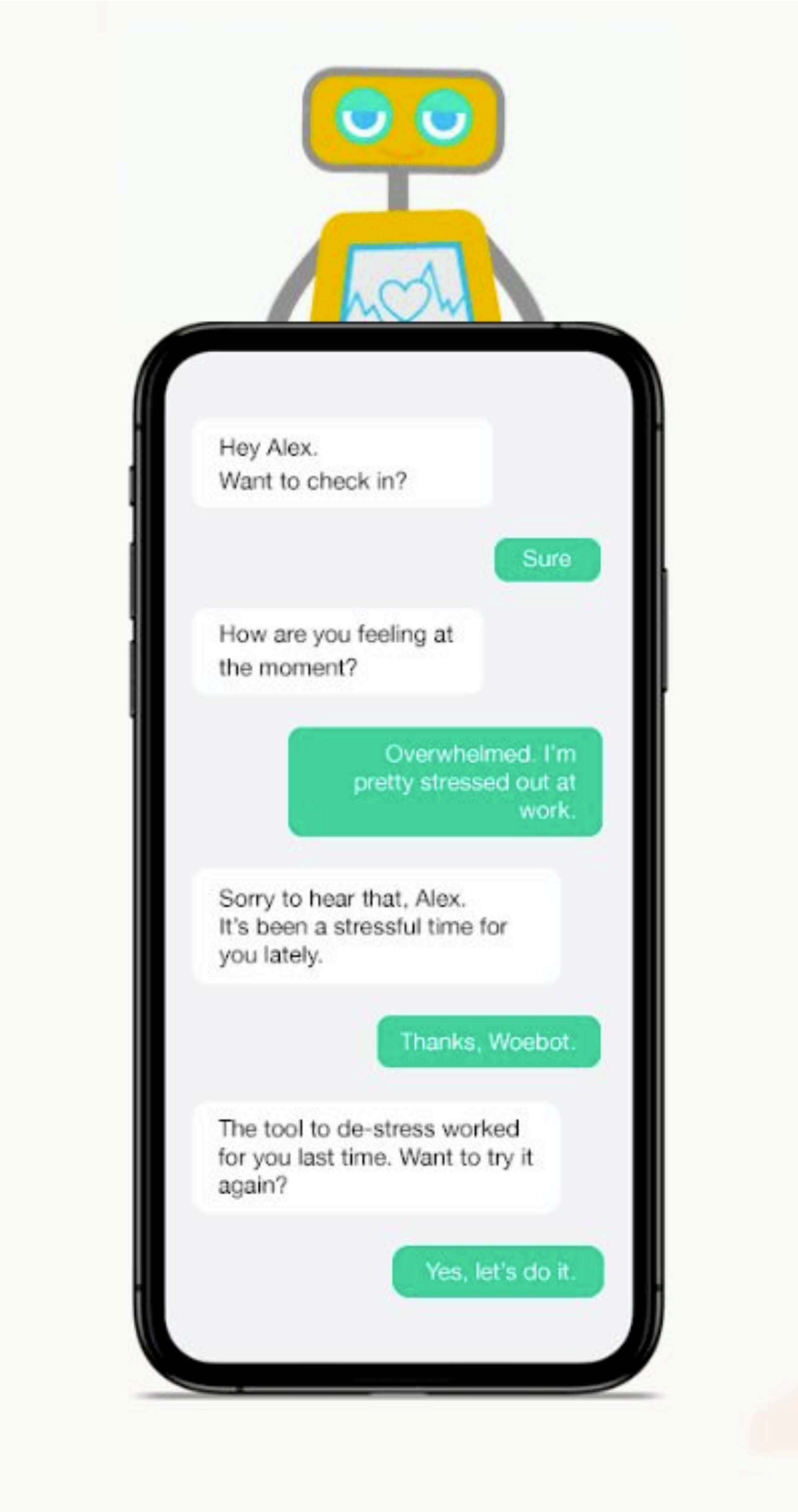
Chatbots



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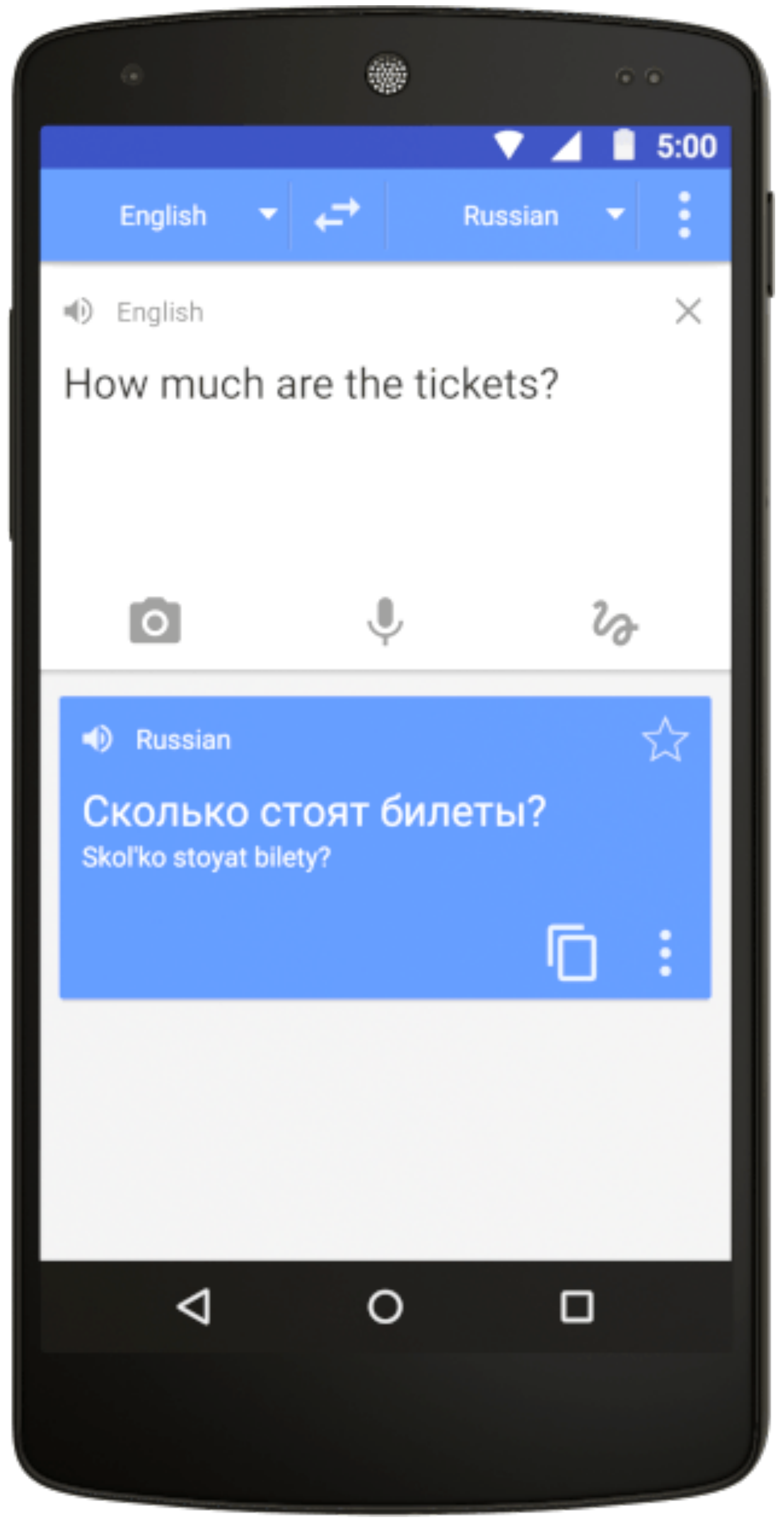

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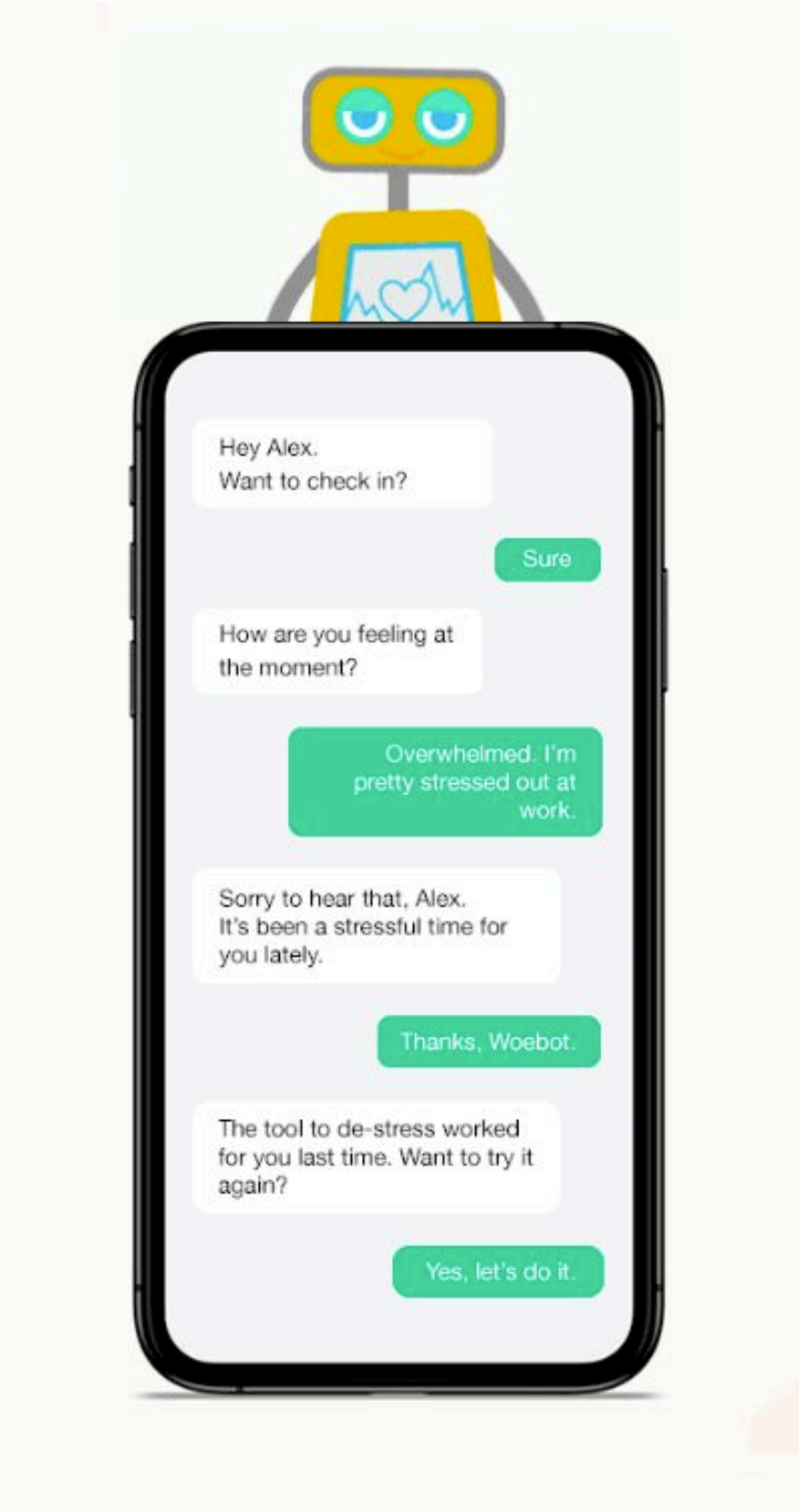

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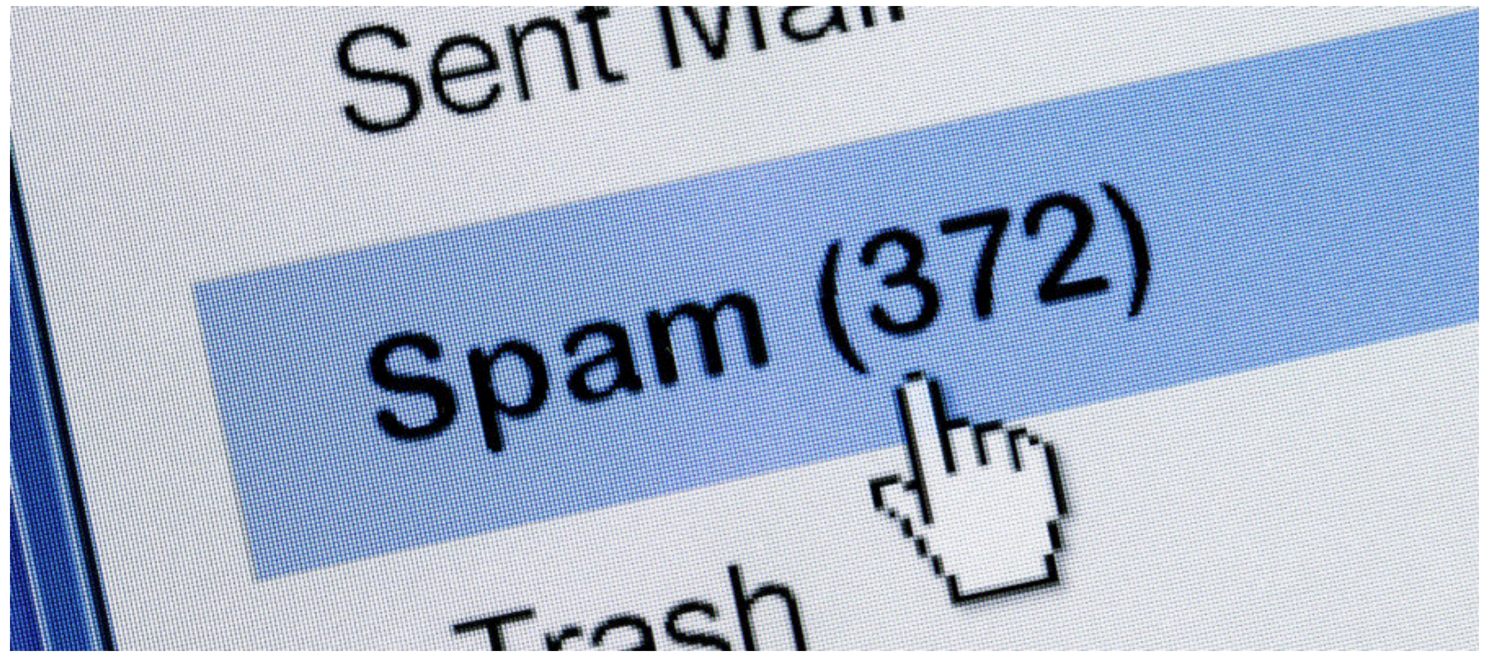

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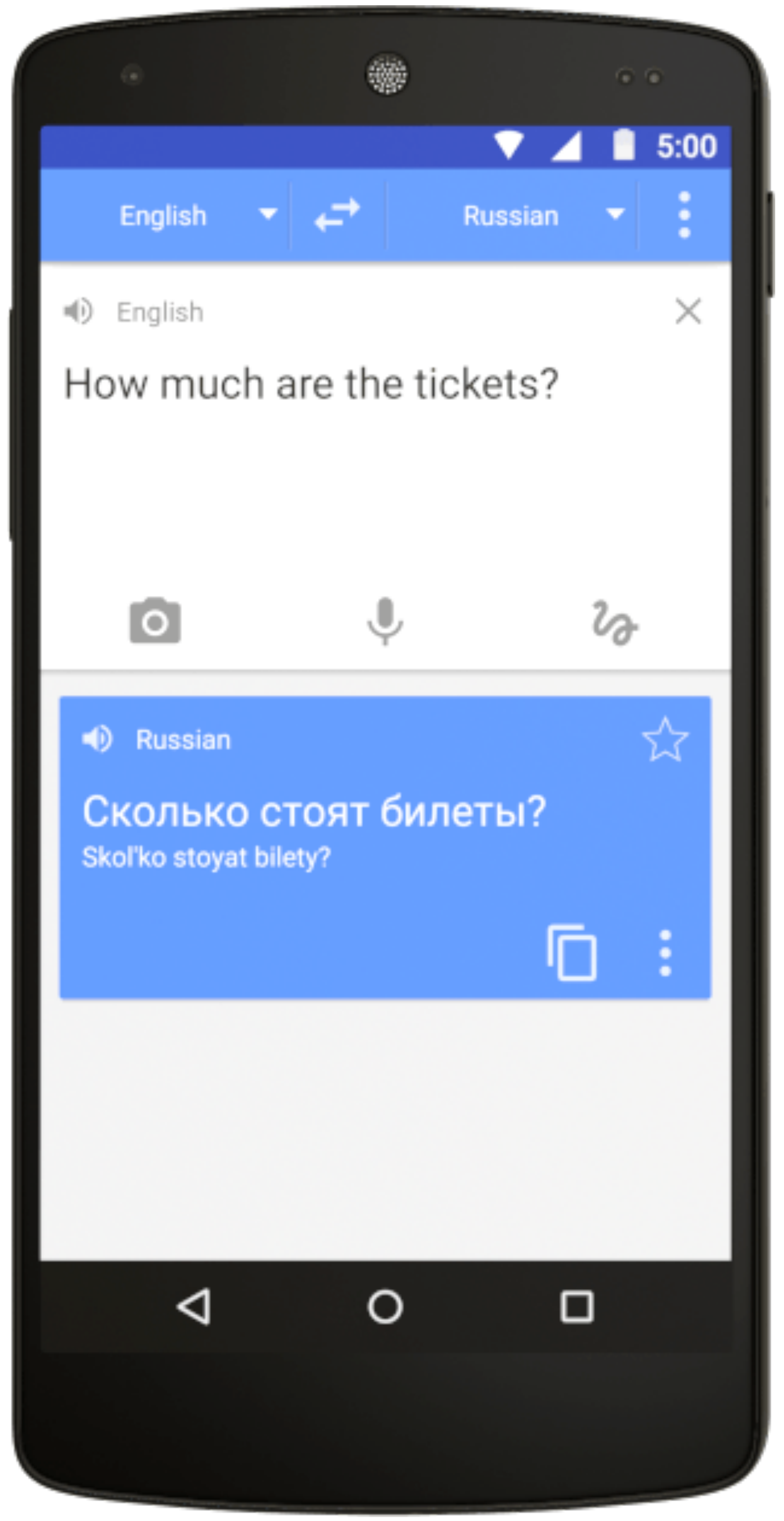

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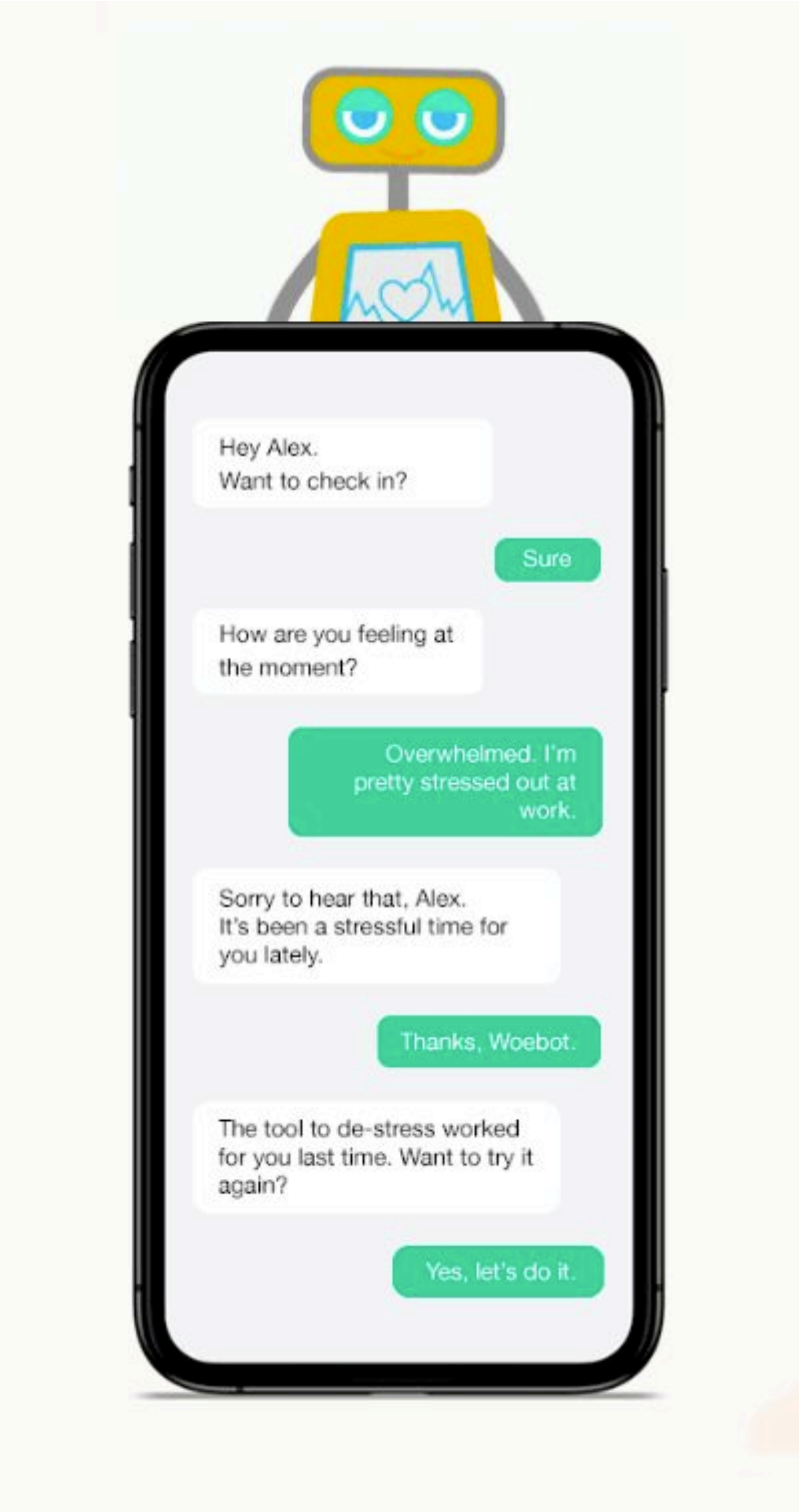

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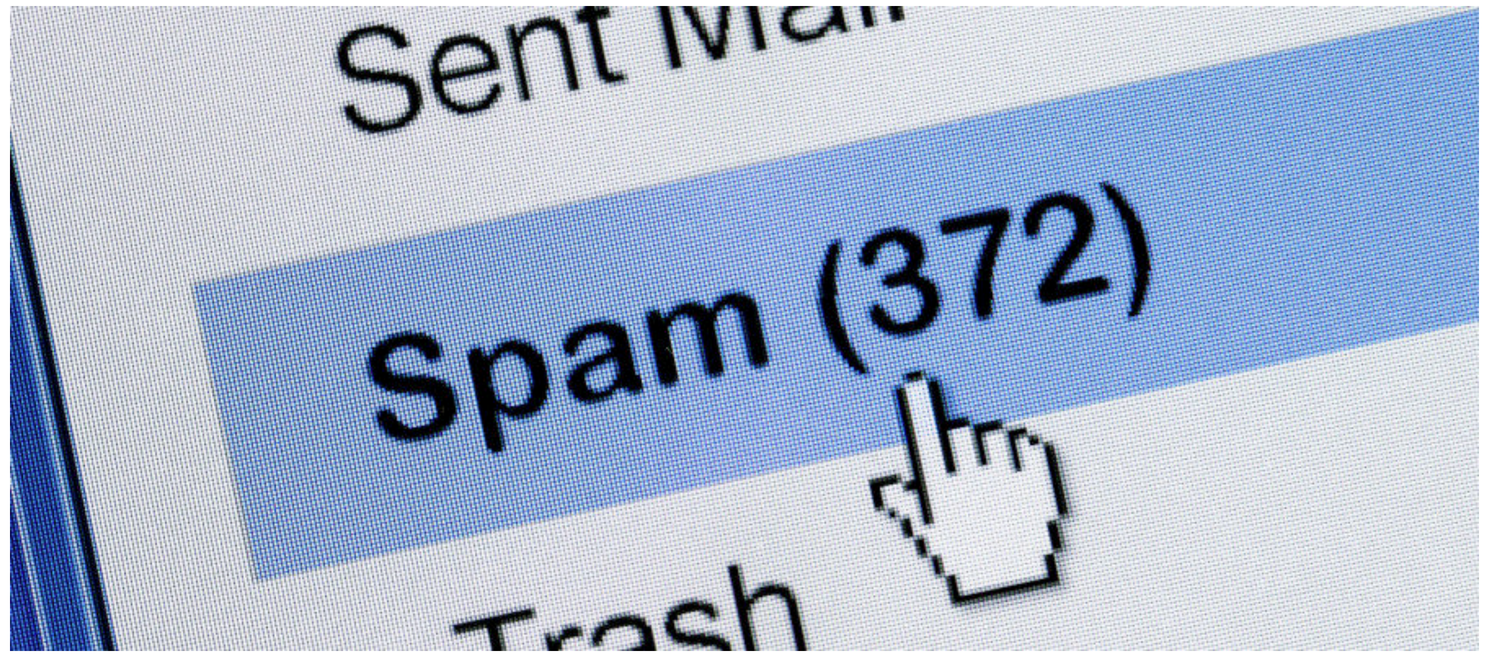

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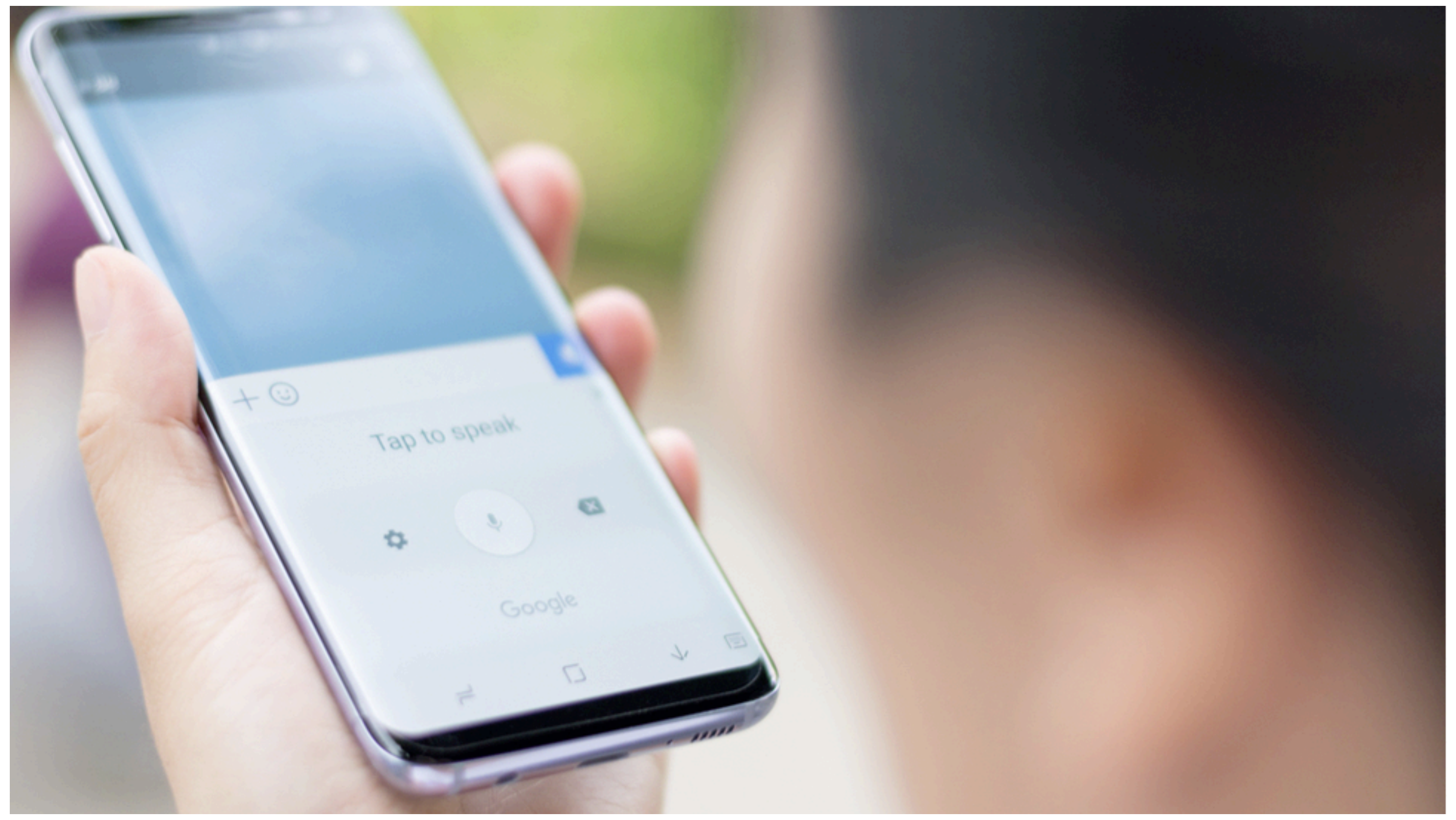

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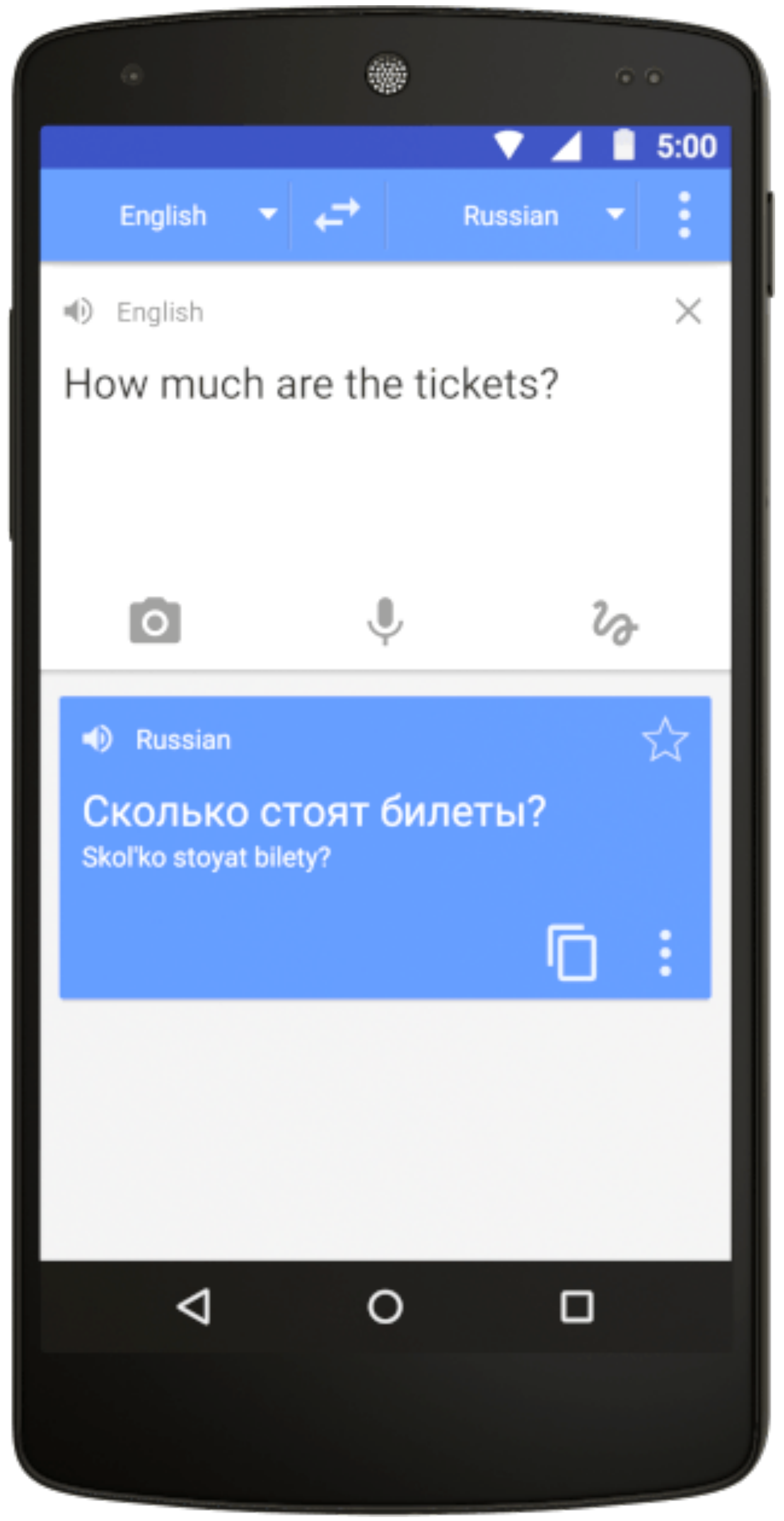

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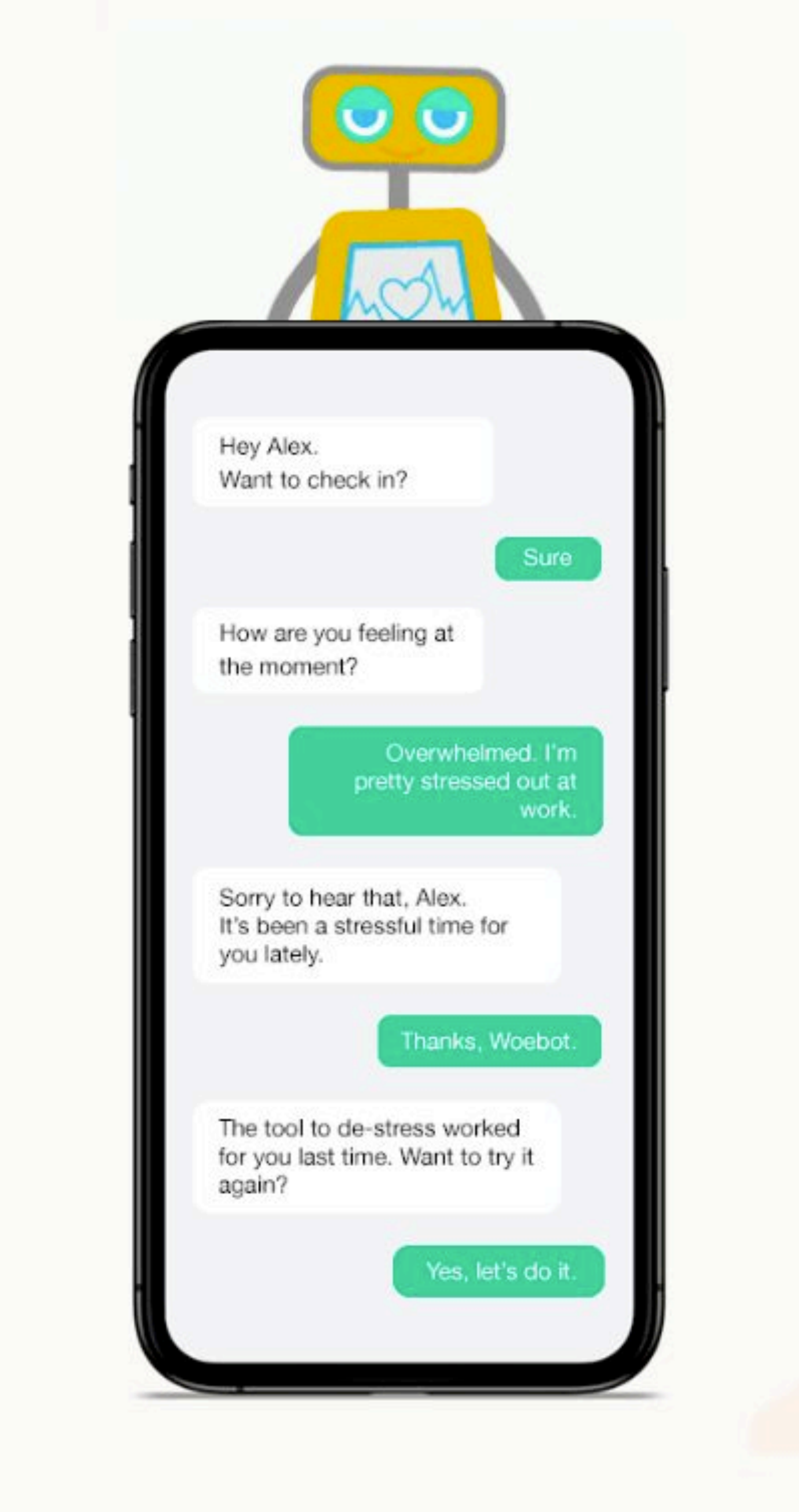

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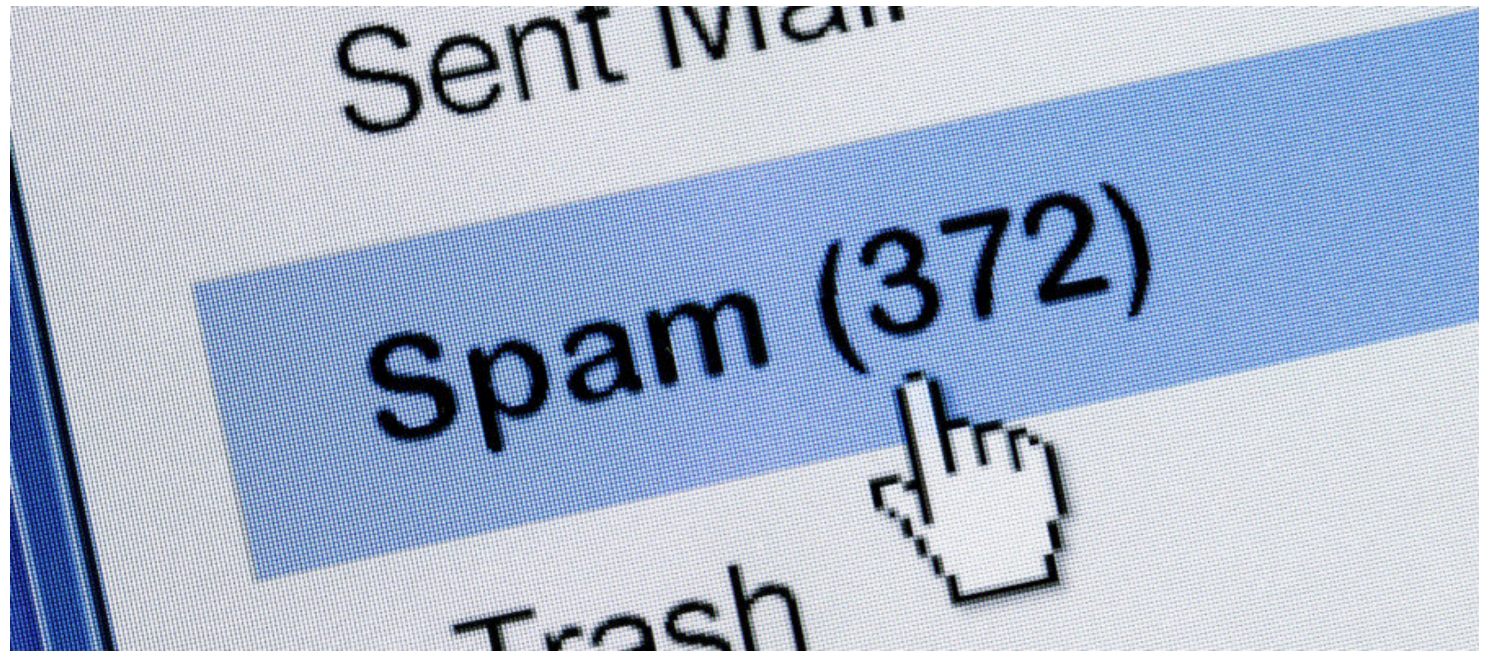

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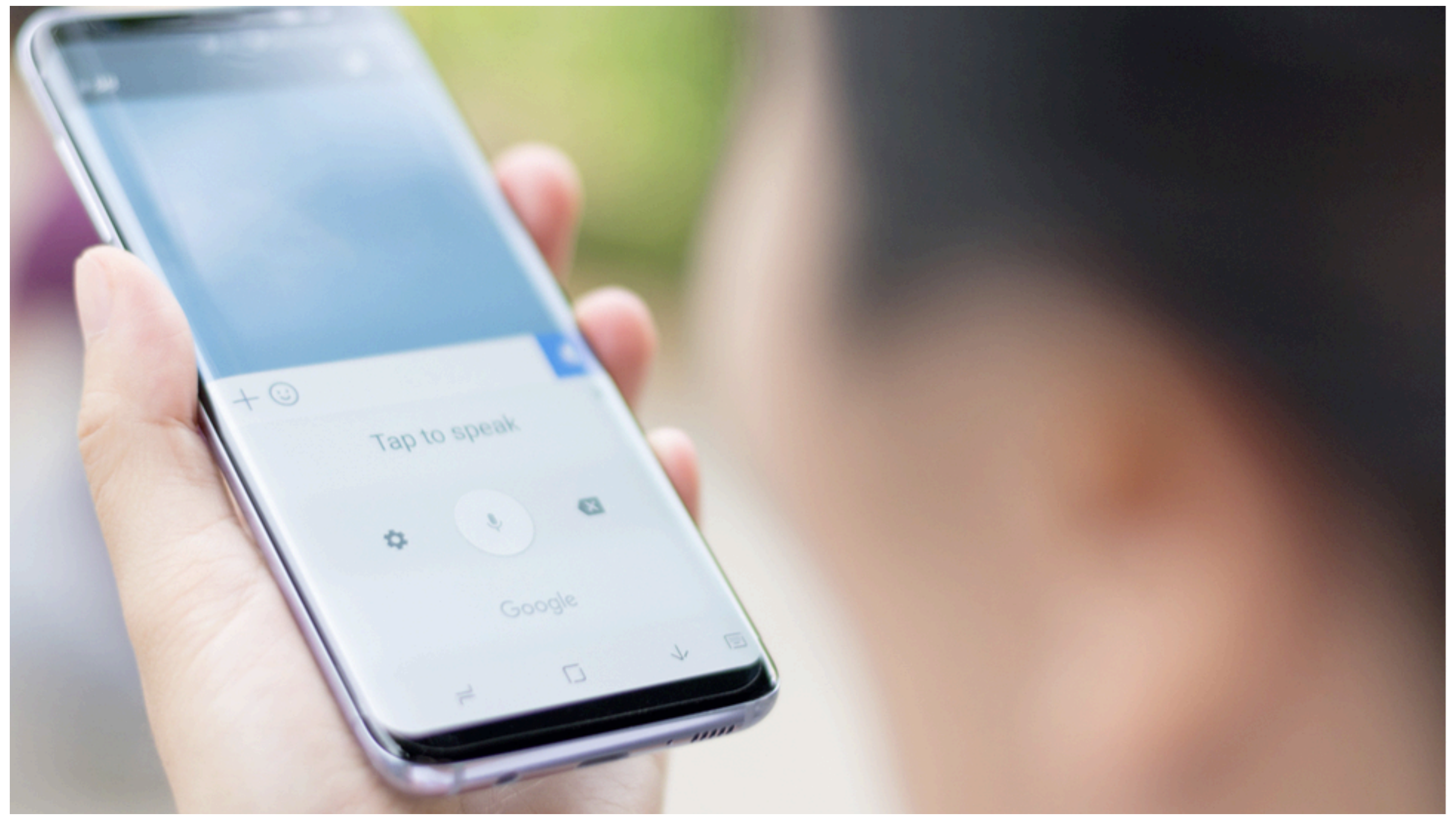

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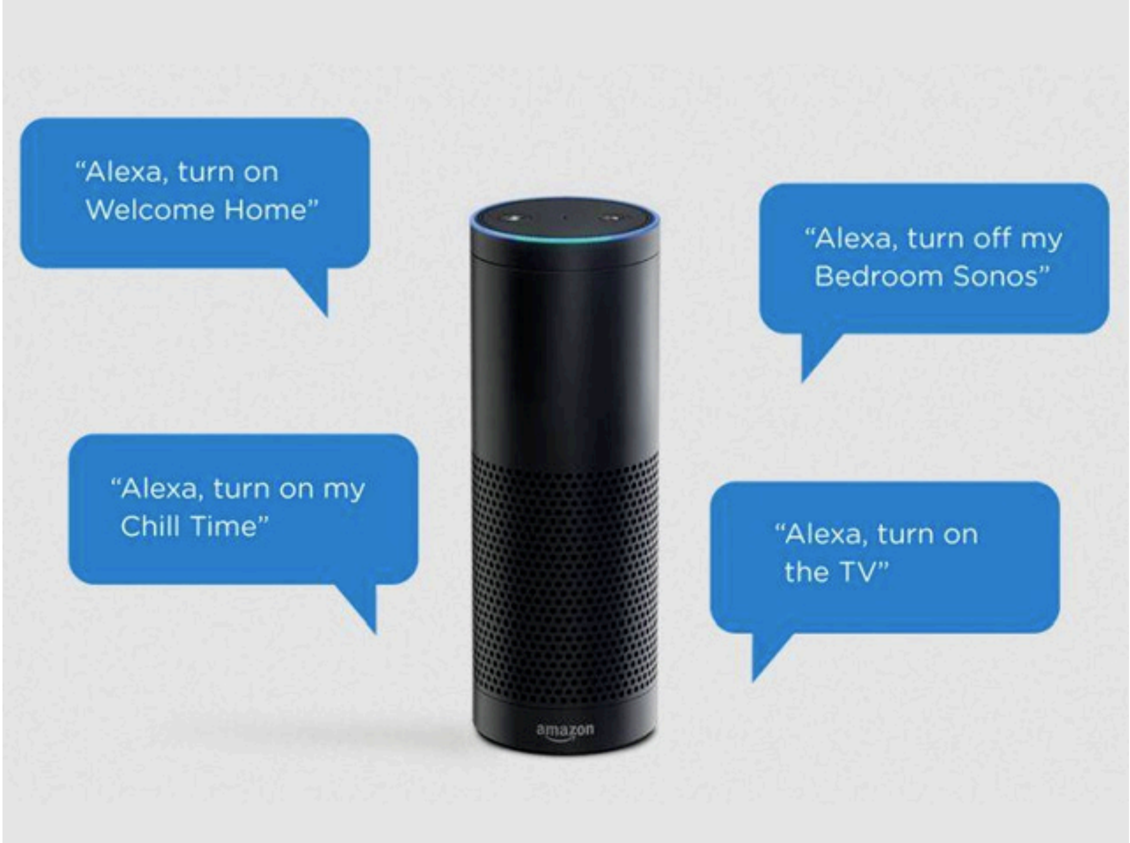

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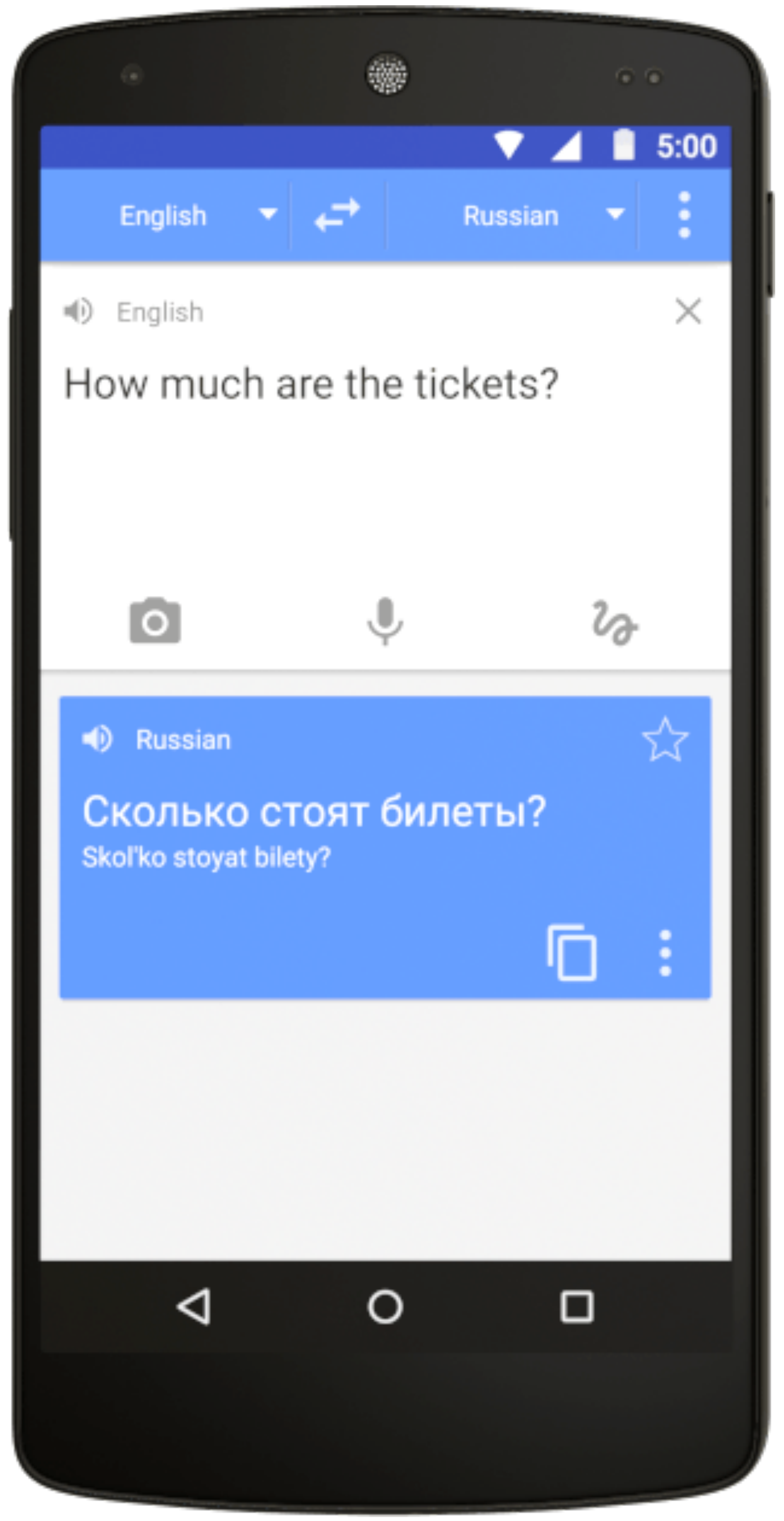

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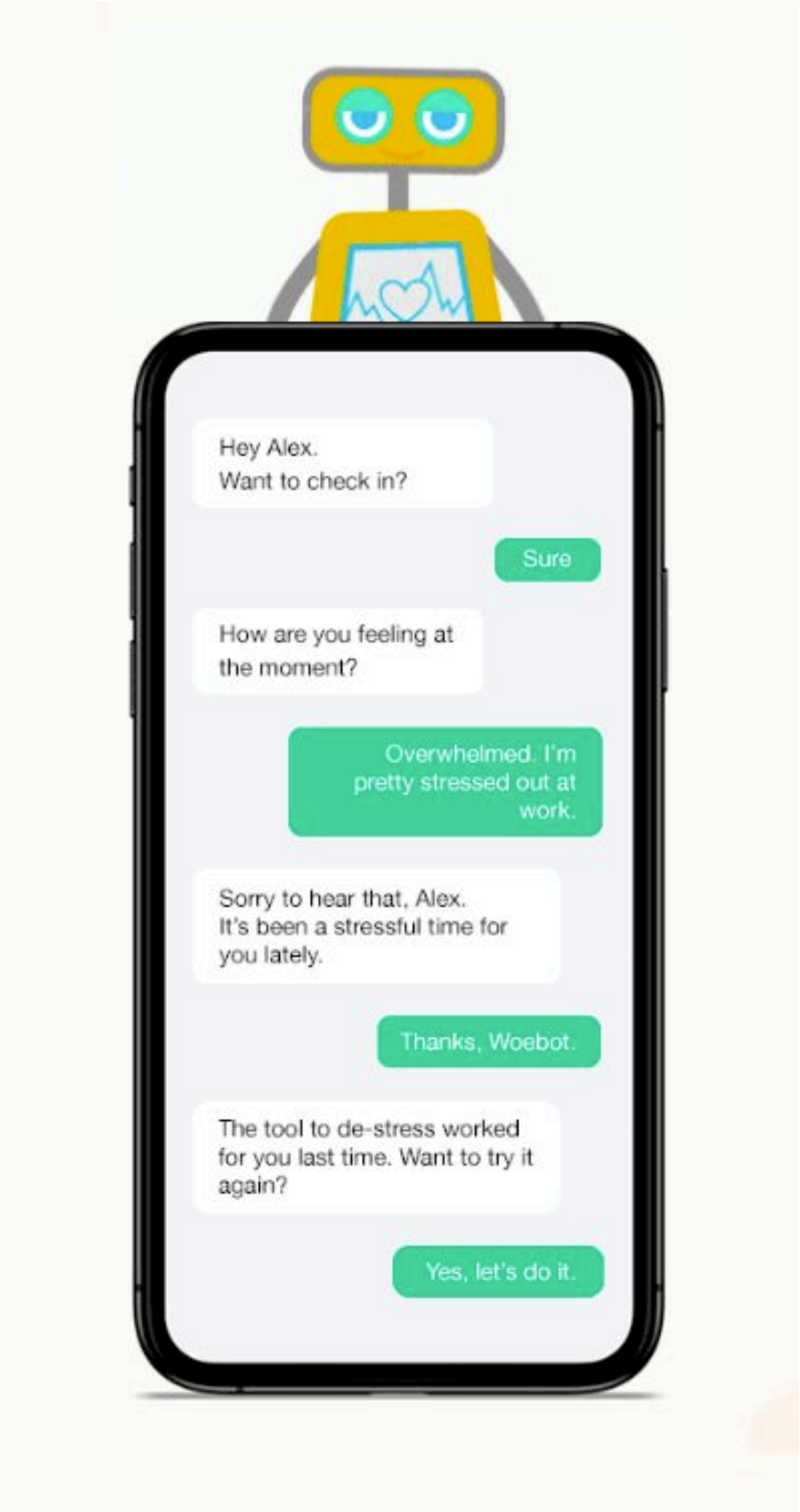

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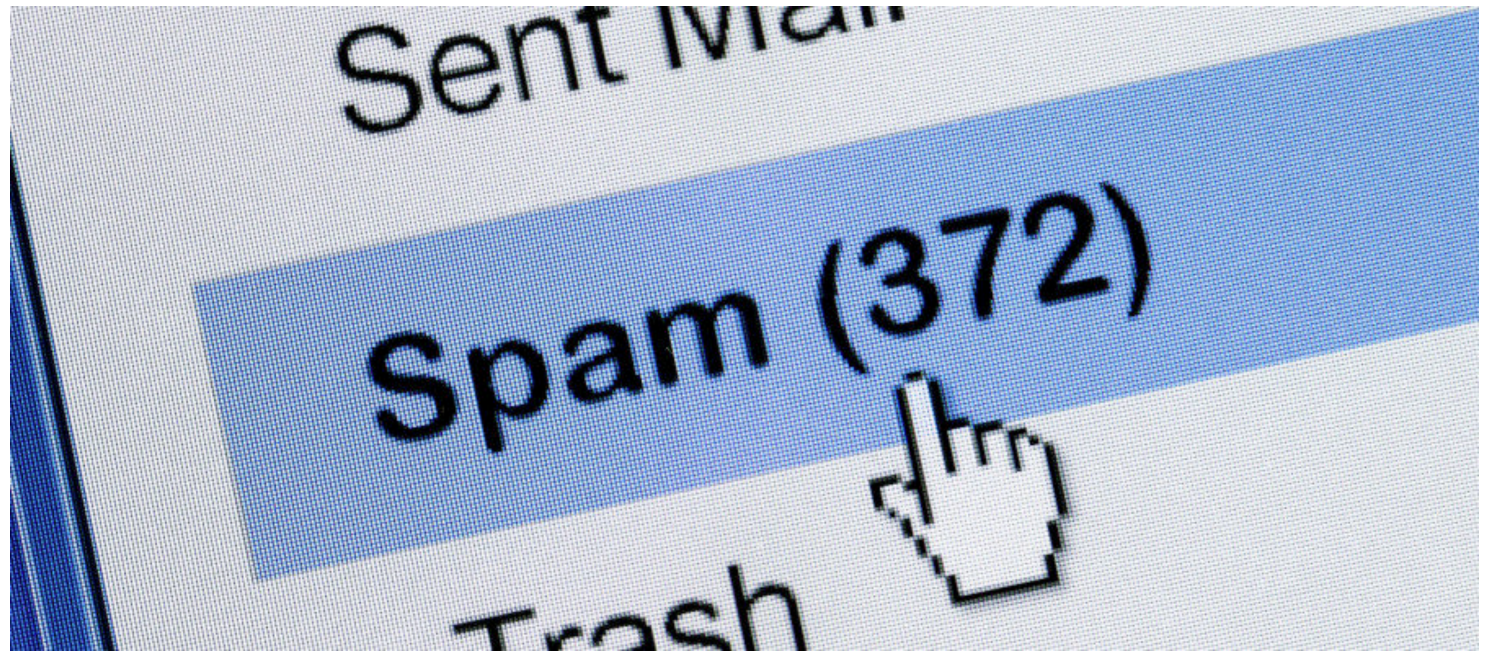

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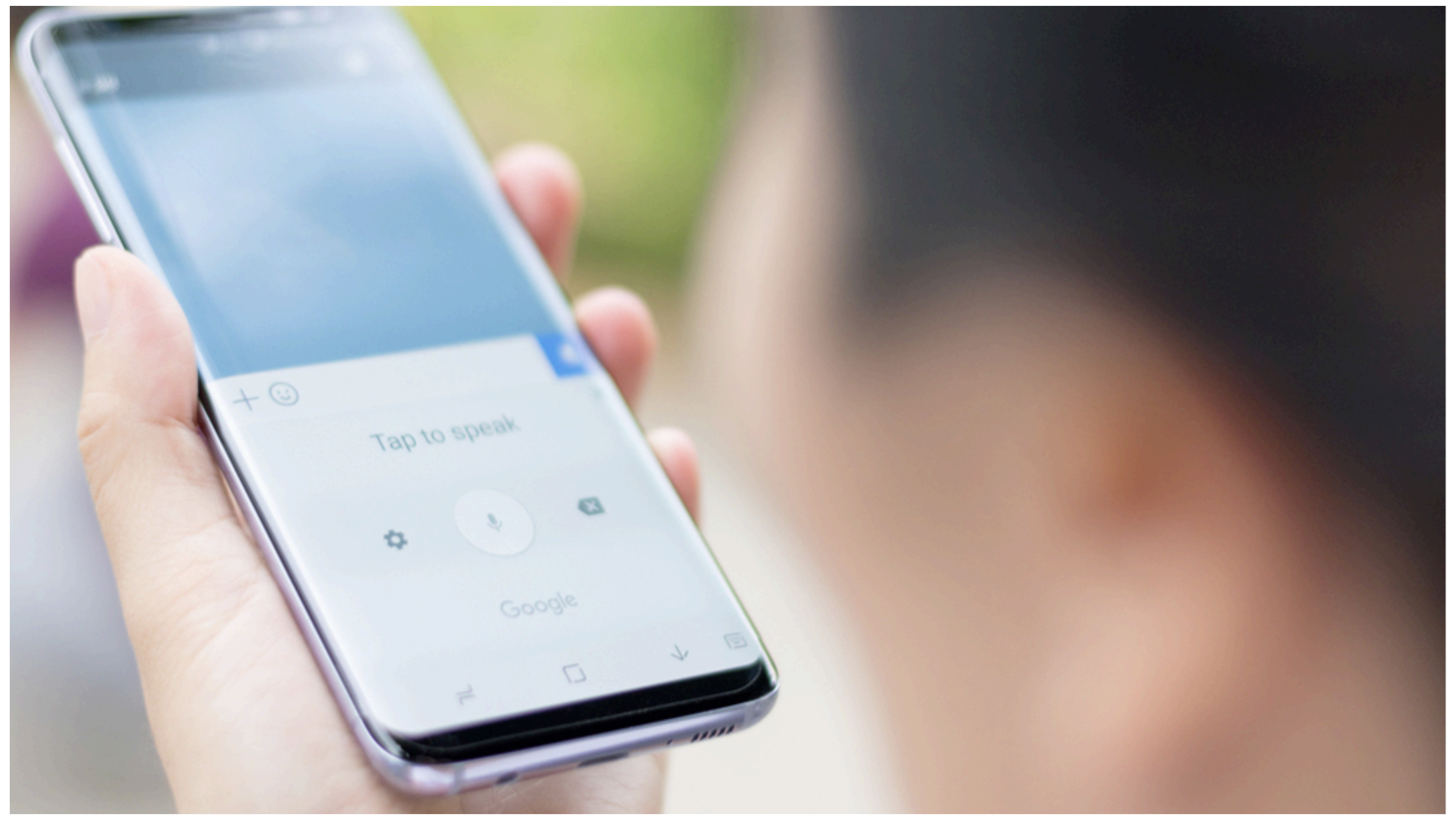

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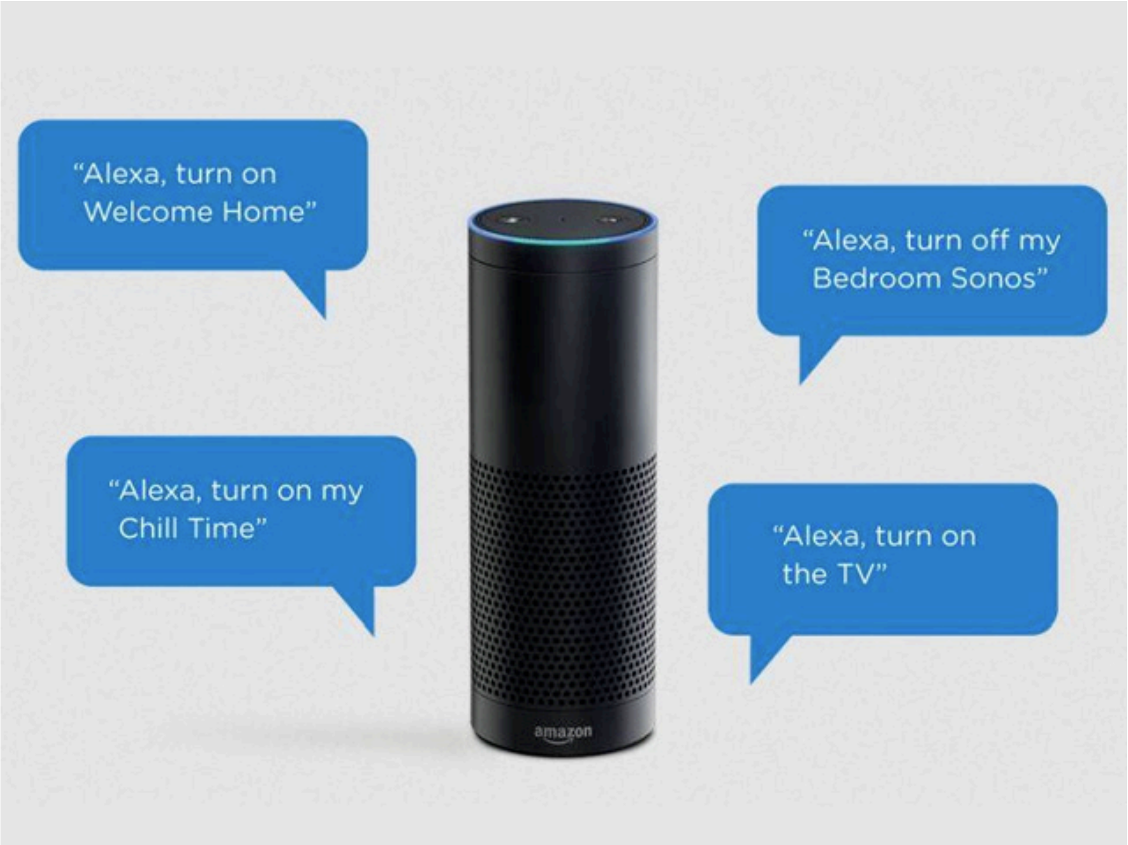

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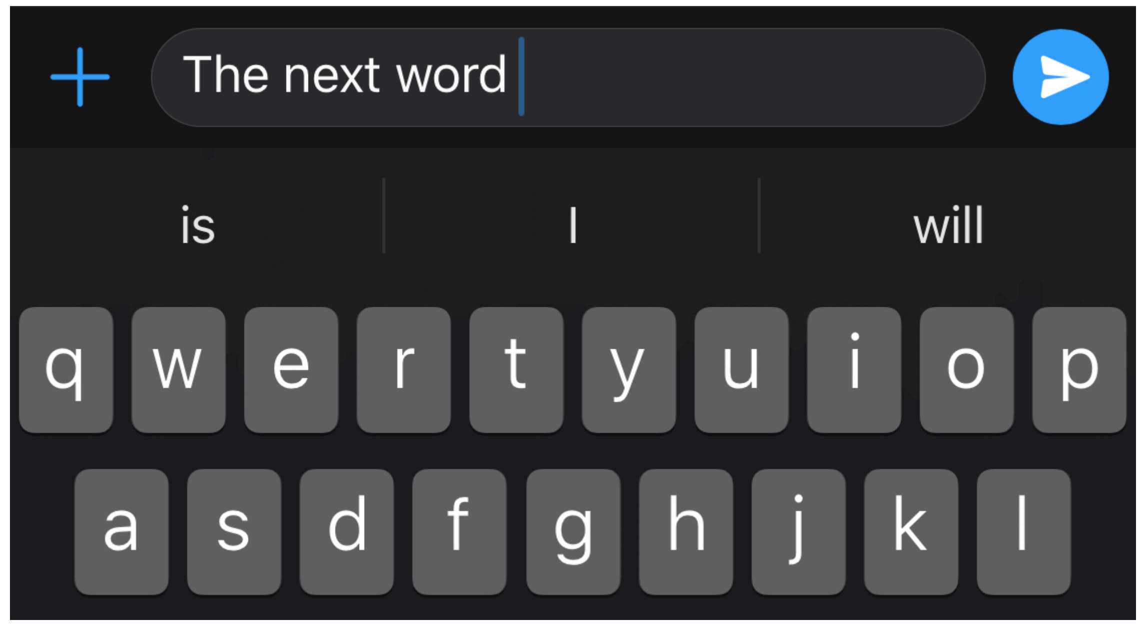
Auto-complete



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Word vectors

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On the other hand, the basic units of language are words, which do not come with a pre-packaged vector representation.

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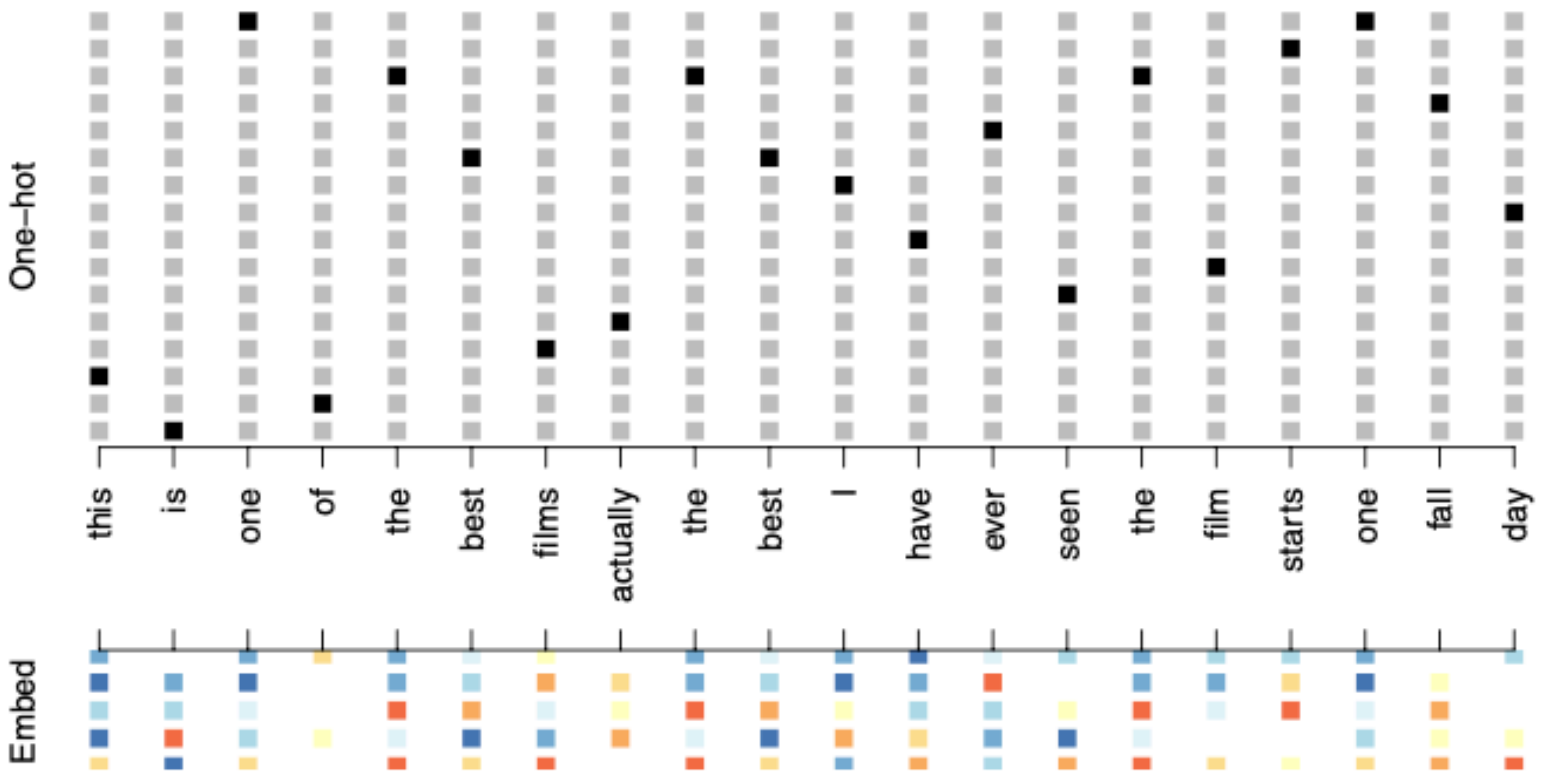
On the other hand, the basic units of language are words, which do not come with a pre-packaged vector representation.

A common first step in deep learning for NLP is to encode each word using a word vector, e.g.

$$v_{\text{man}} = (0.2, 1.6, 2.5, \ldots, 4.1)$$

Word vectors are useful if they capture the meaning of the words they represent.



Source: ISLRv2

Constructing word vectors

Example: word2vec

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Suppose for a word w_1, we model the relative frequencies of nearby words w_2 as

$$\mathbb{P}[w_2 \mid w_1] = \frac{\exp(v_1^T v_2)}{\sum_{\text{all word vectors } v} \exp(v_1^T v)}.$$

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Can then train the word vectors $v_1, v_2, \ldots$ based on a text corpus by maximizing the likelihood of all the word co-occurrence probabilities.

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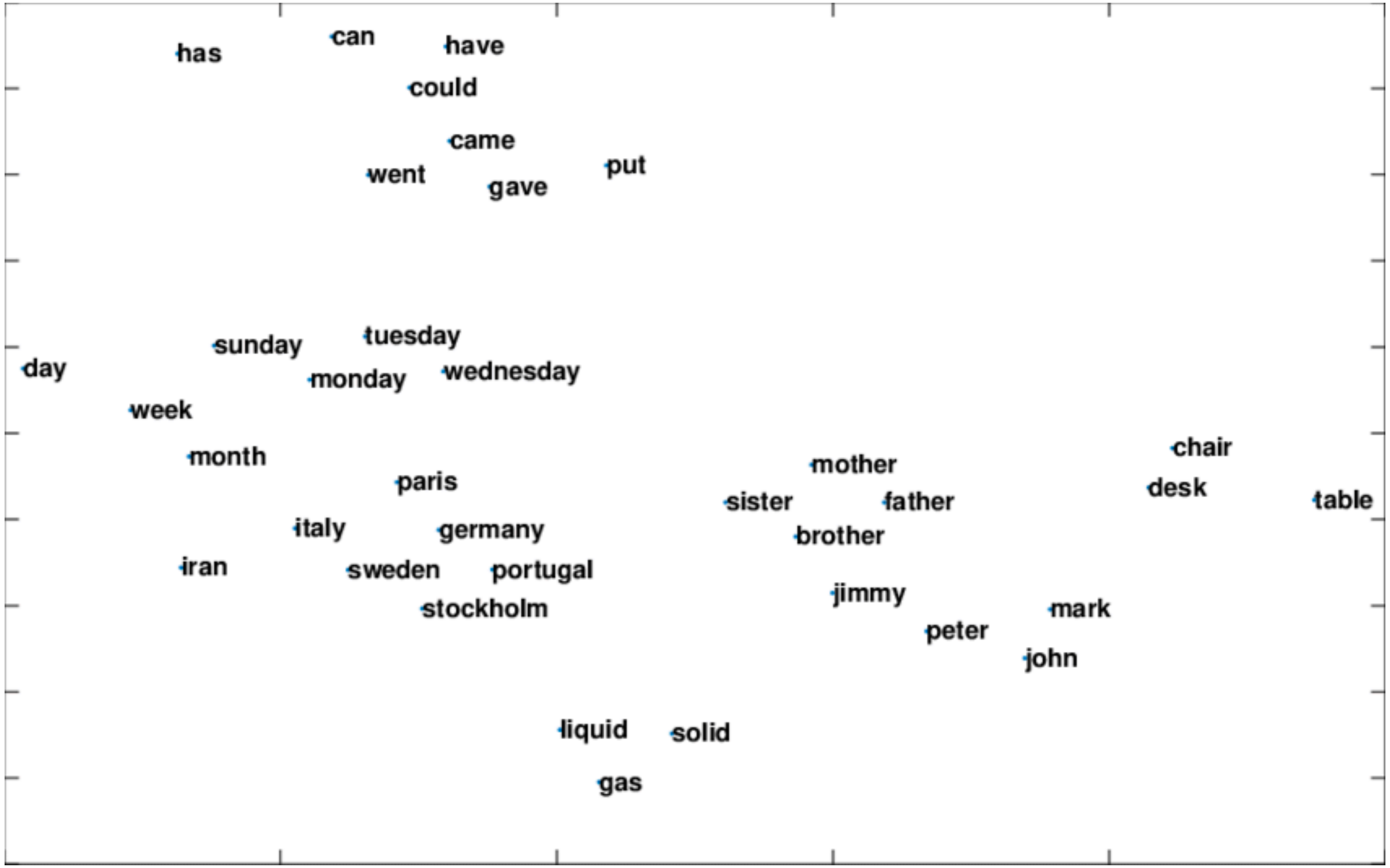
Word vectors need to be trained only once (for each language), and can be reused thereafter. For example, word2vec vectors for a few dozen languages can be downloaded at http://vectors.nlpl.eu/repository/.

Word vectors capture semantic relationships



https://www.researchgate.net/figure/A-two-dimensional-representation-of-word-embeddings-Words-with-similar-meanings-are_fig1_327074728

Case study 1: Named entity classification

Task: Classify the word in the middle of a window as either a person, location, organization, or other, e.g.

"…museums in Paris are amazing…"

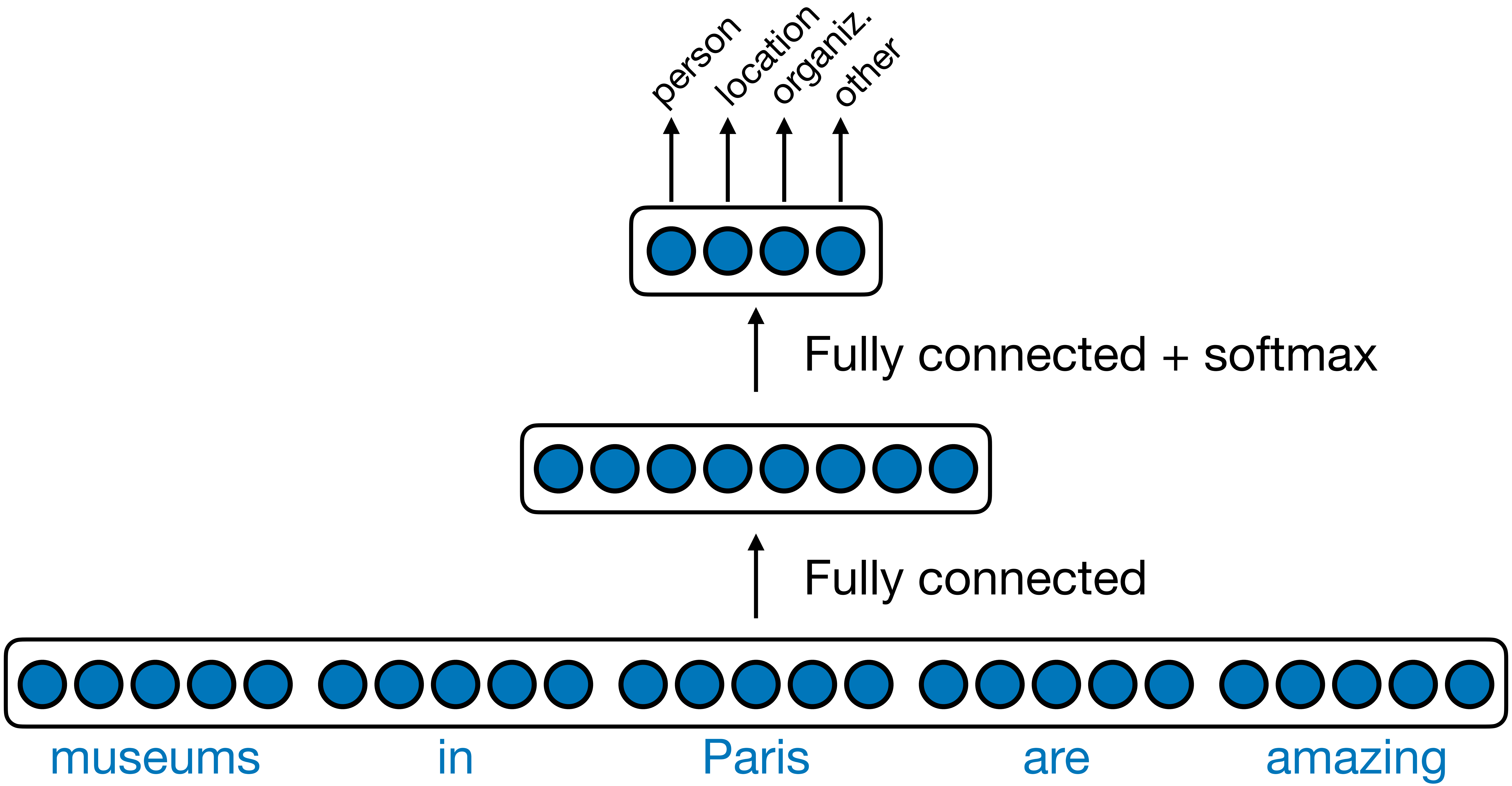
In this context, does Paris refer to Paris Hilton (person) or Paris, France (location)?

This is a kind of word sense disambiguation.

Example from https://www.youtube.com/watch?v=8CWyBNX6eDo&list=PLoROMvodv4rOhcuXMZkNm7j3fVwBBY42z&index=3

Case study 1: Named entity classification

Using word vectors, can create a fully-connected neural network:



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Advantages of fine-tuning word vectors:

- Can give better predictions if there is enough data
- Recommended for large training data sets

From fixed length to variable length

While images are usually a fixed size (e.g. 128x128 pixels), natural language chunks like sentences can have variable length. Using a fixed window size forces you to artificially chop your input. Outputs might also have variable length.

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We need a neural network architecture to handle variable-length inputs and outputs.

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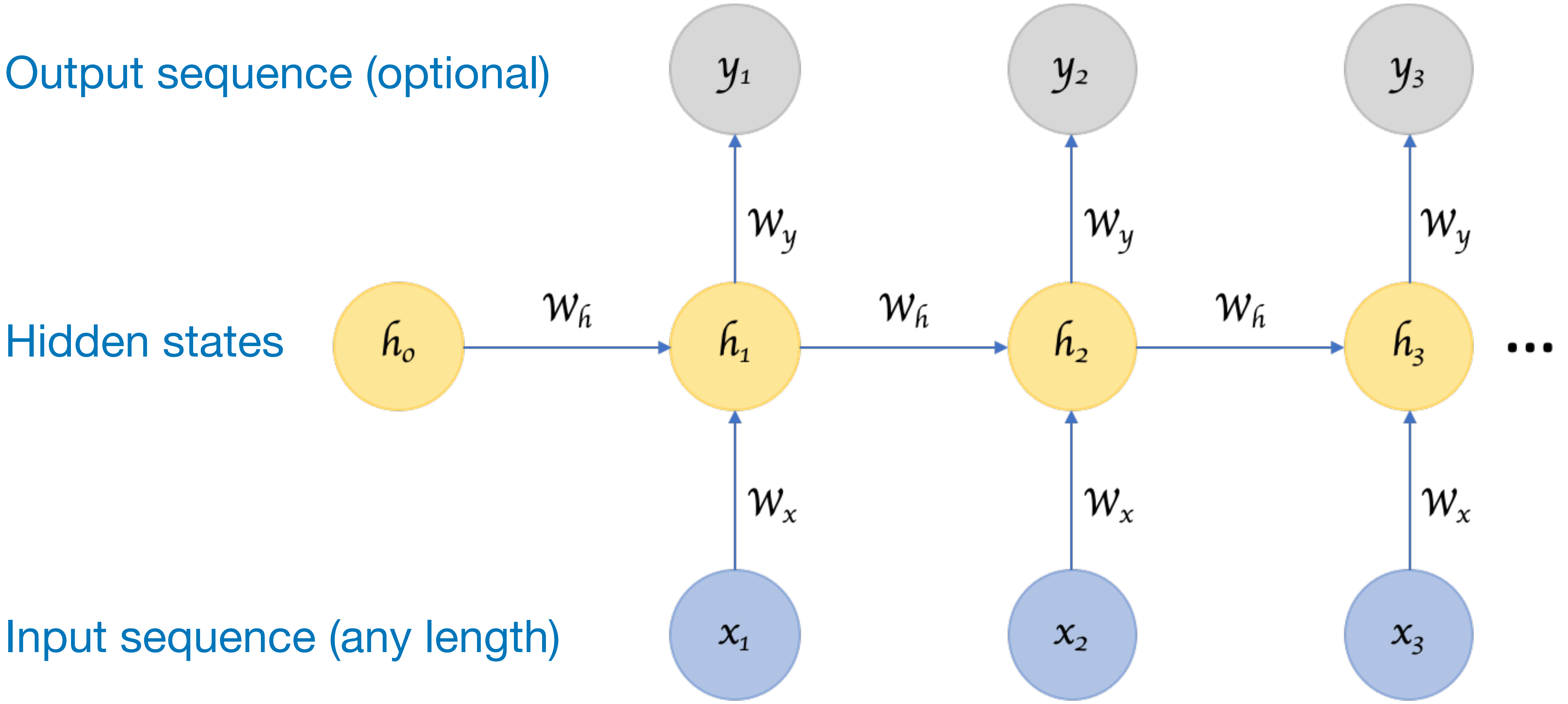

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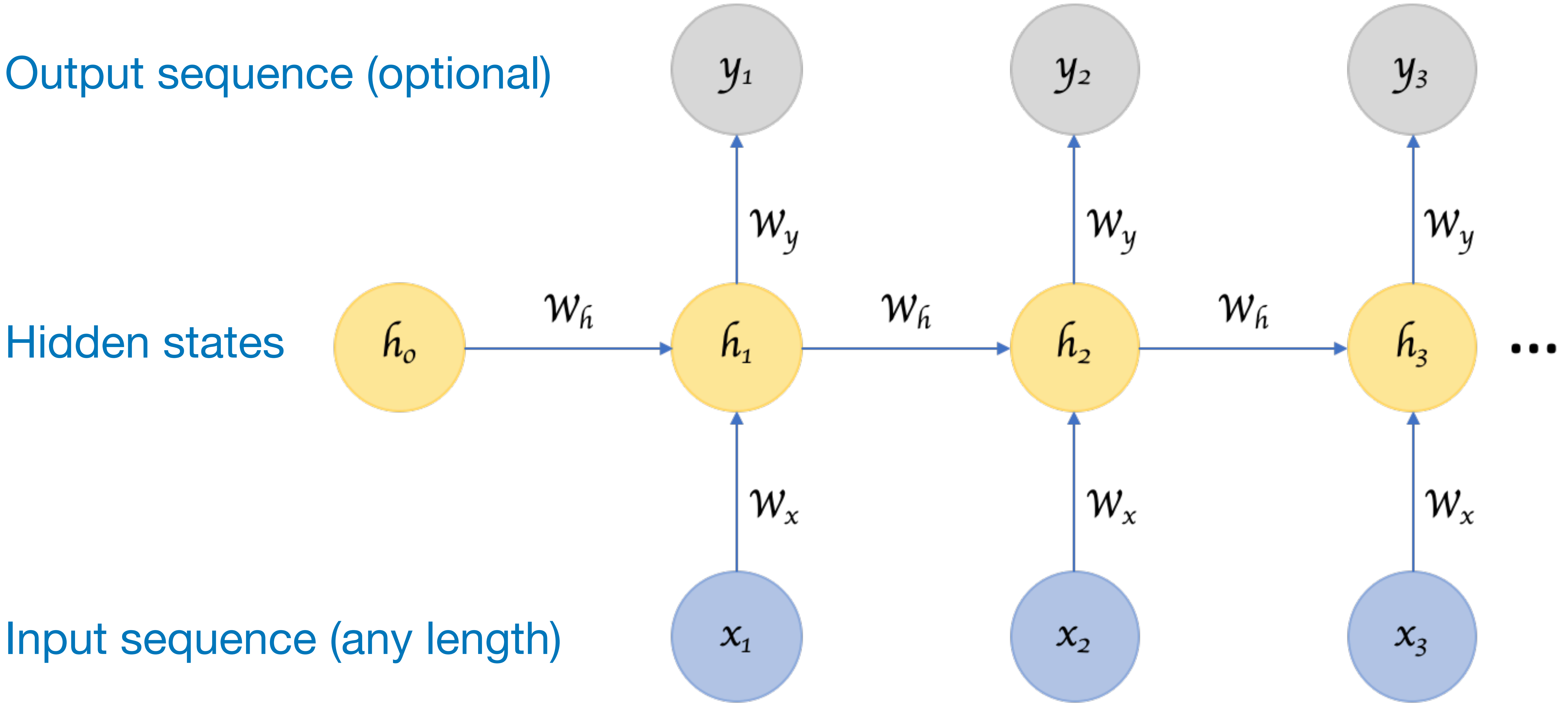

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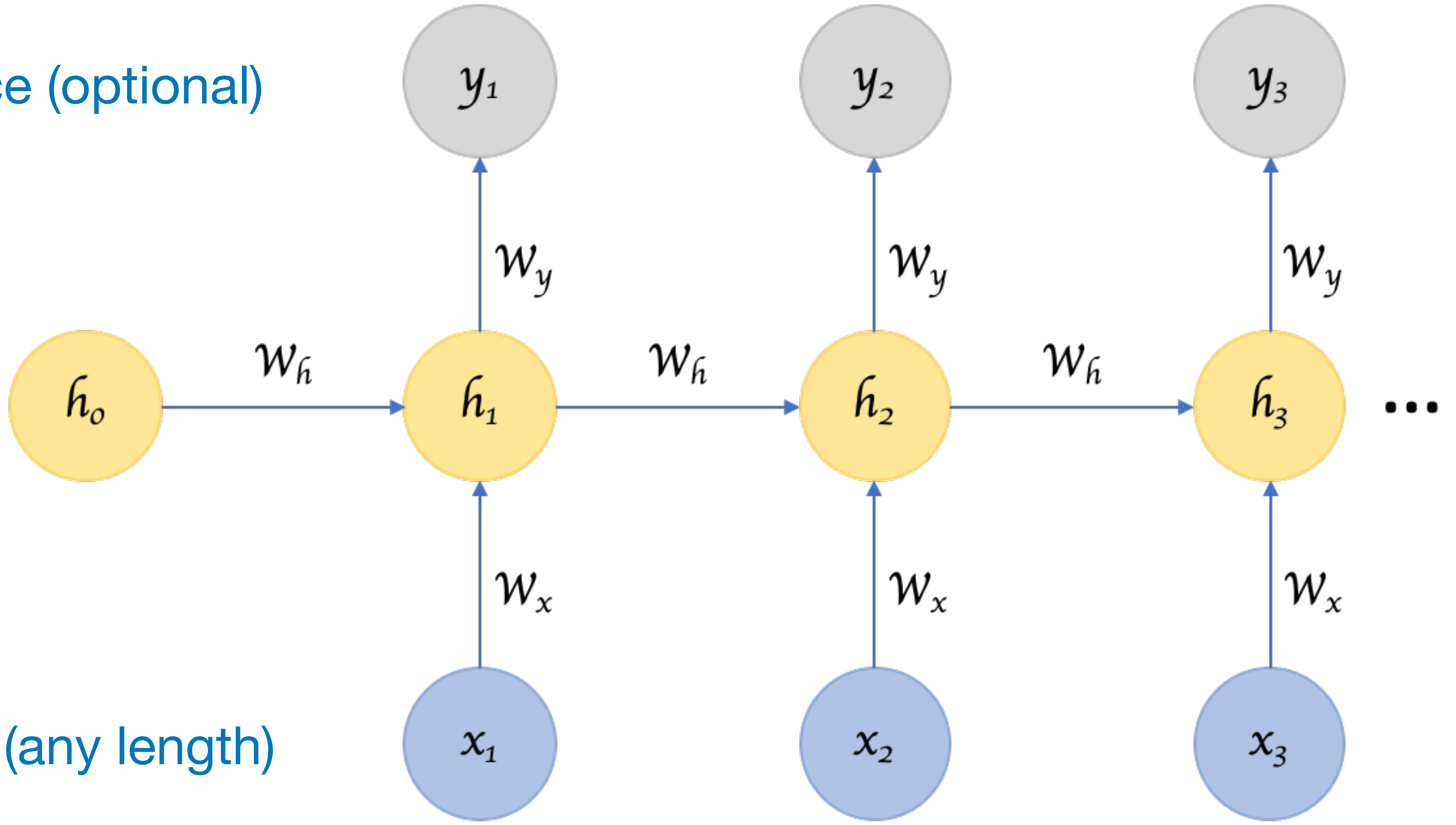
$$h_t = \sigma(W_h h_{t-1} + W_x x_t).$$

Output sequence (optional)

Hidden states

Input sequence (any length)



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All arrows represent fully connected layers

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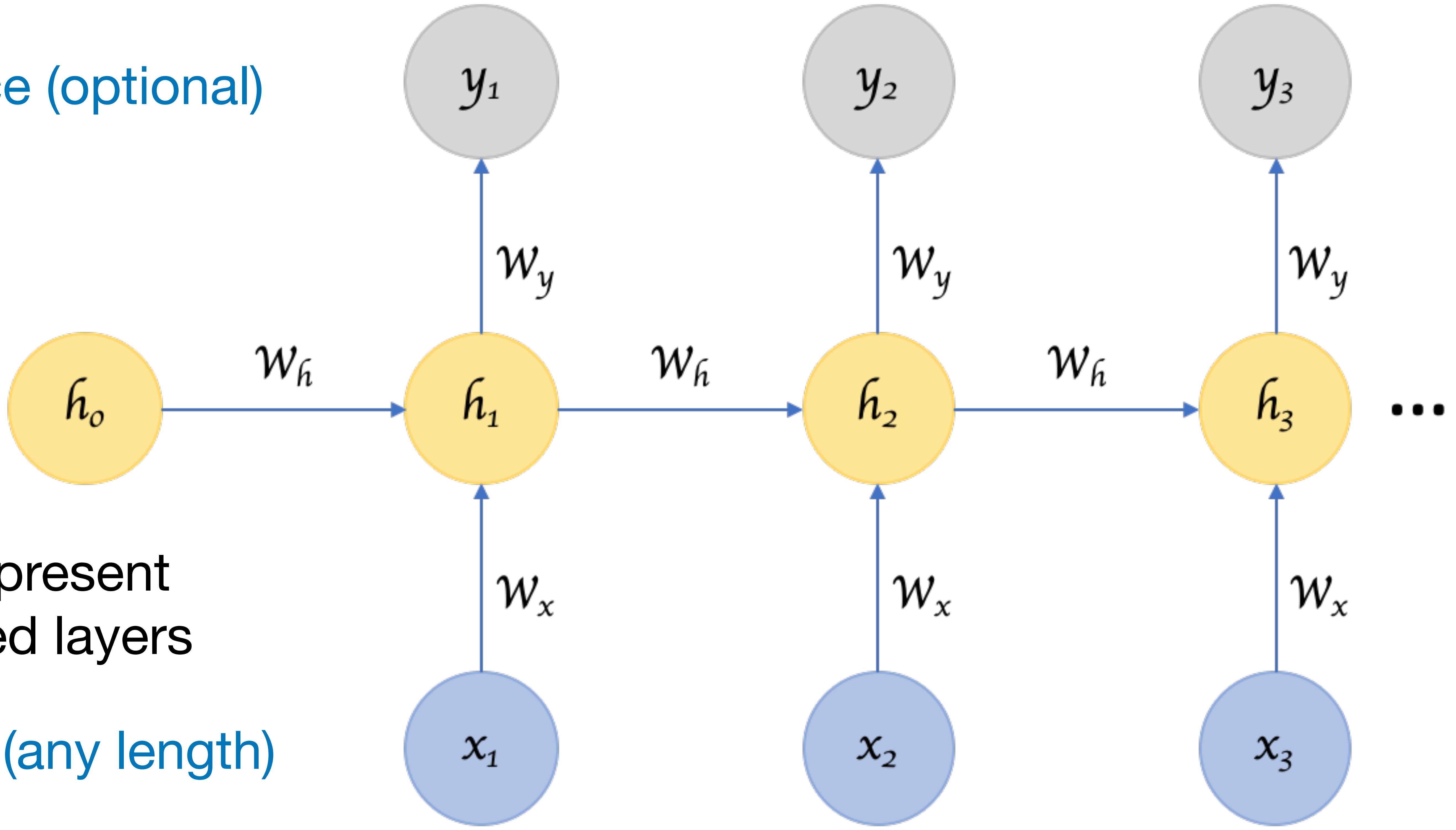

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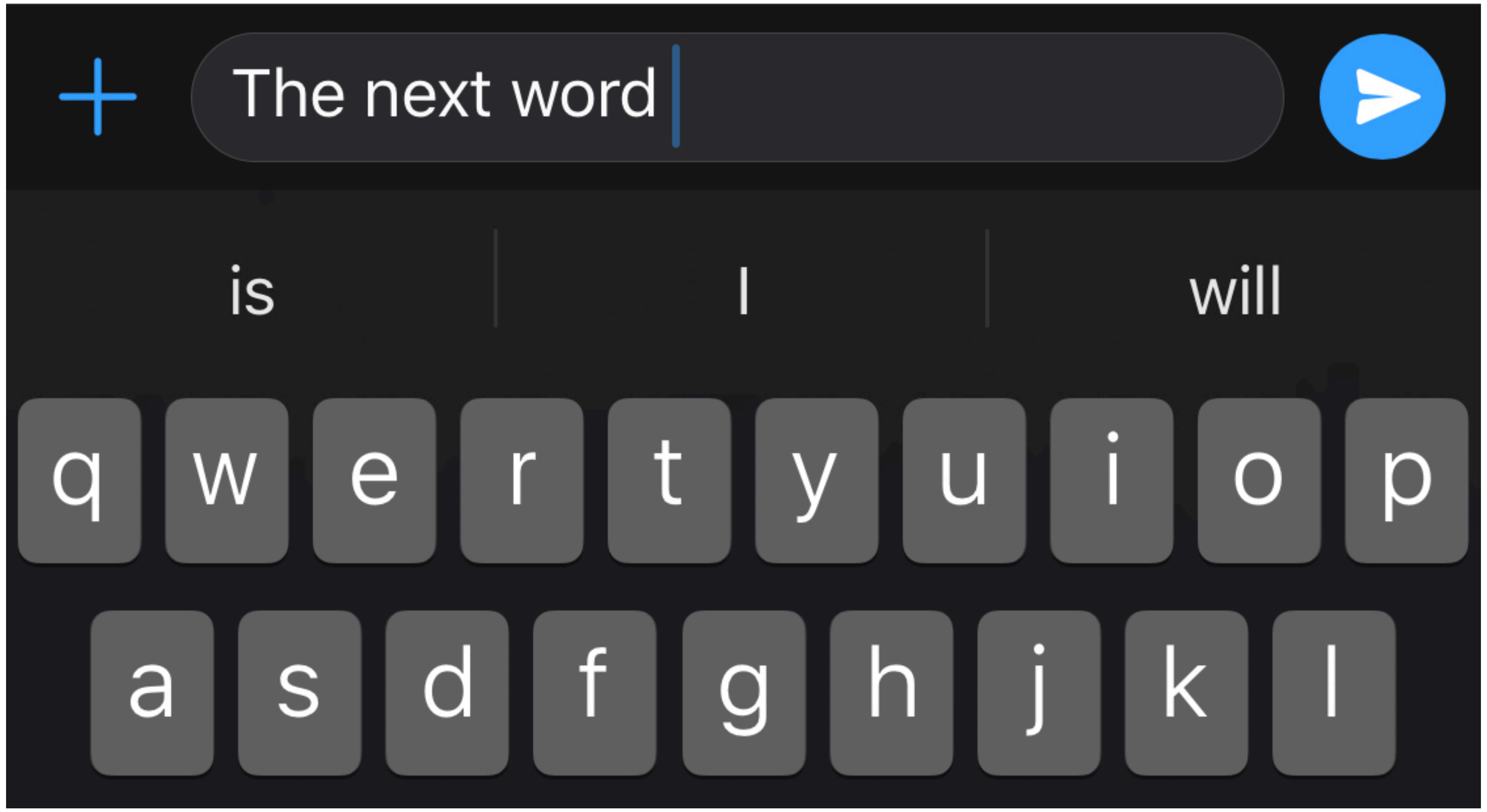
Case study 2: Language modeling

Given a sequence of words, calculate probabilities of what the next word will be.



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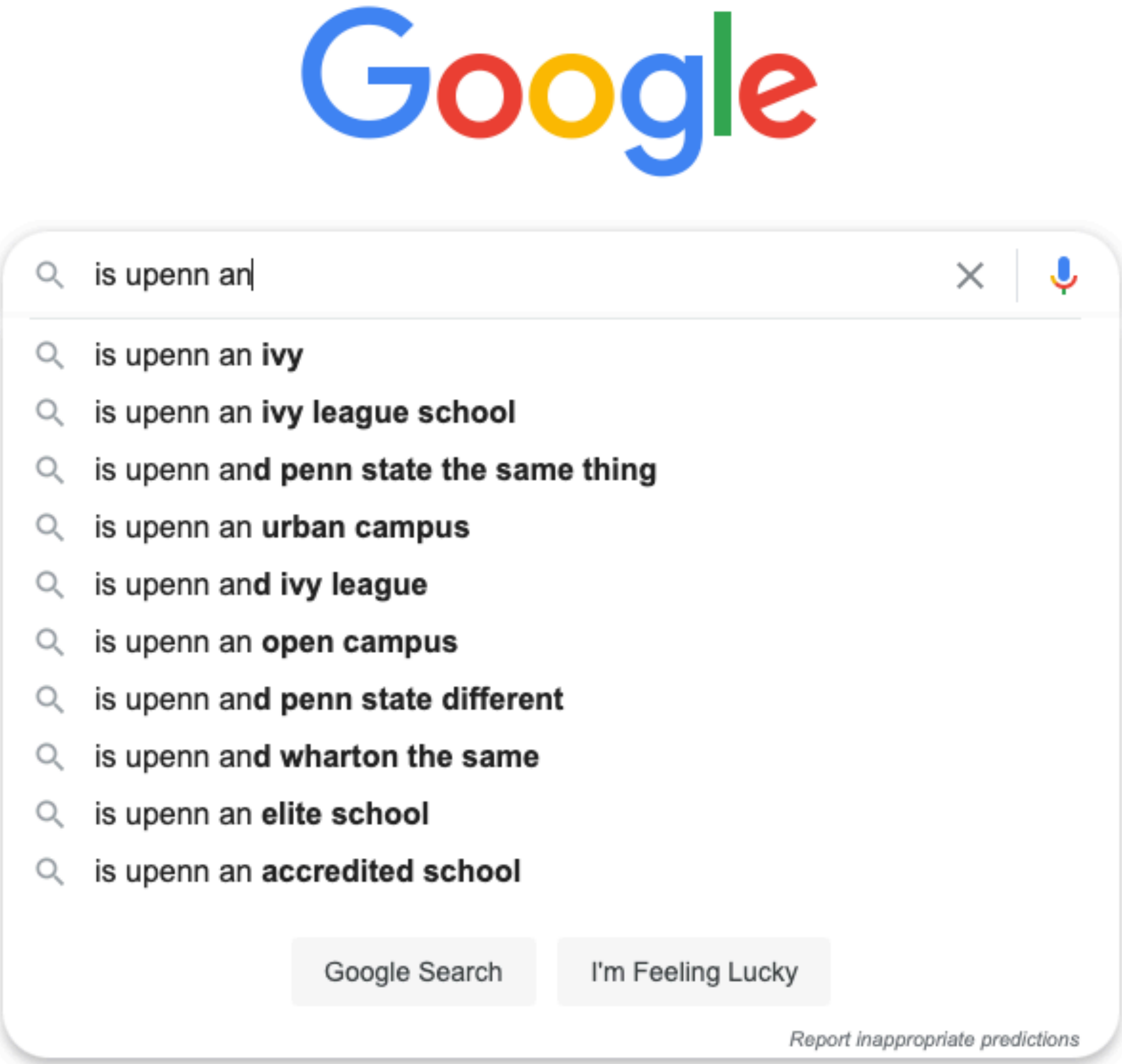

RNN for language modeling

- Initialize h_0 to zero vector.
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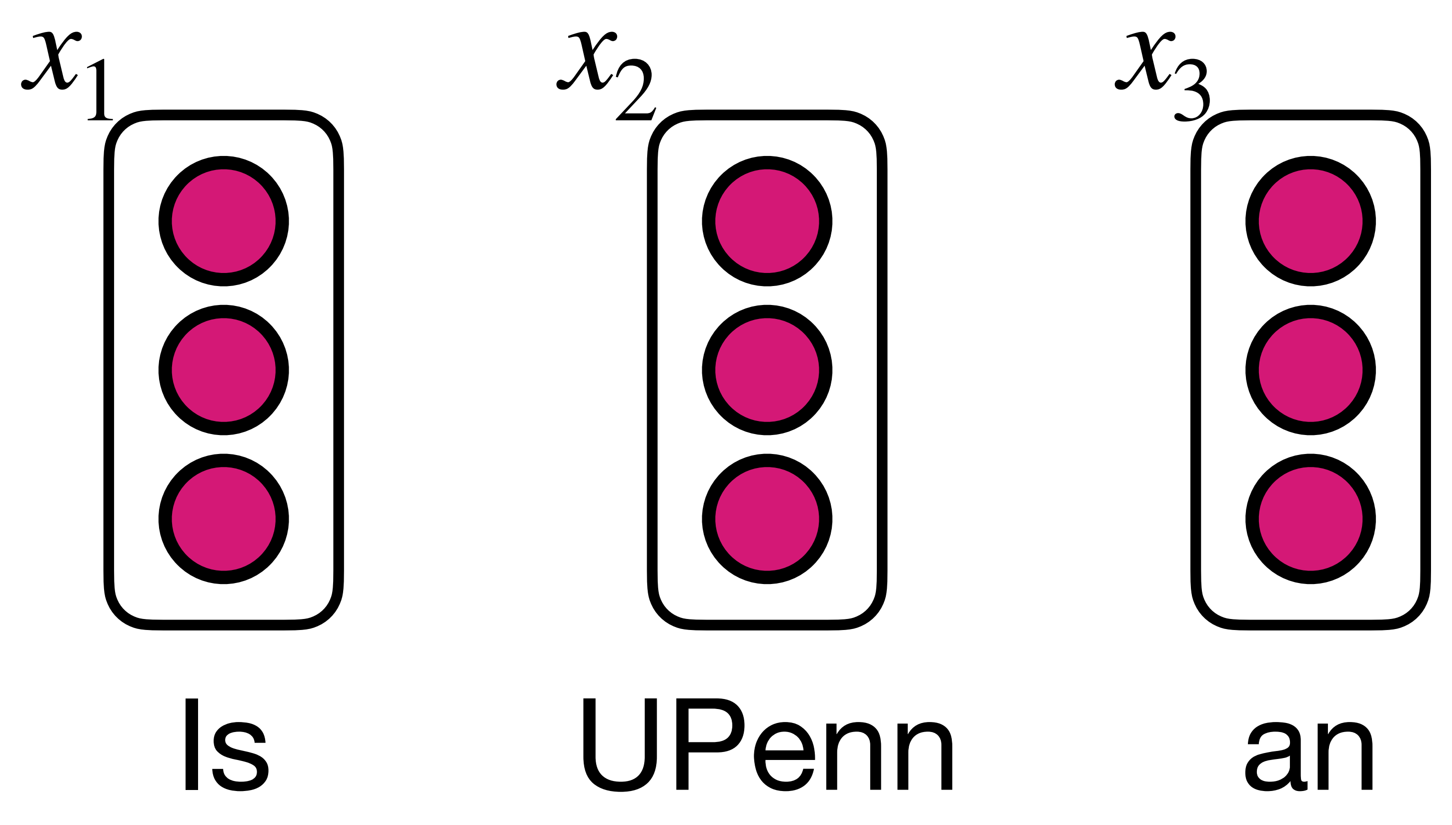

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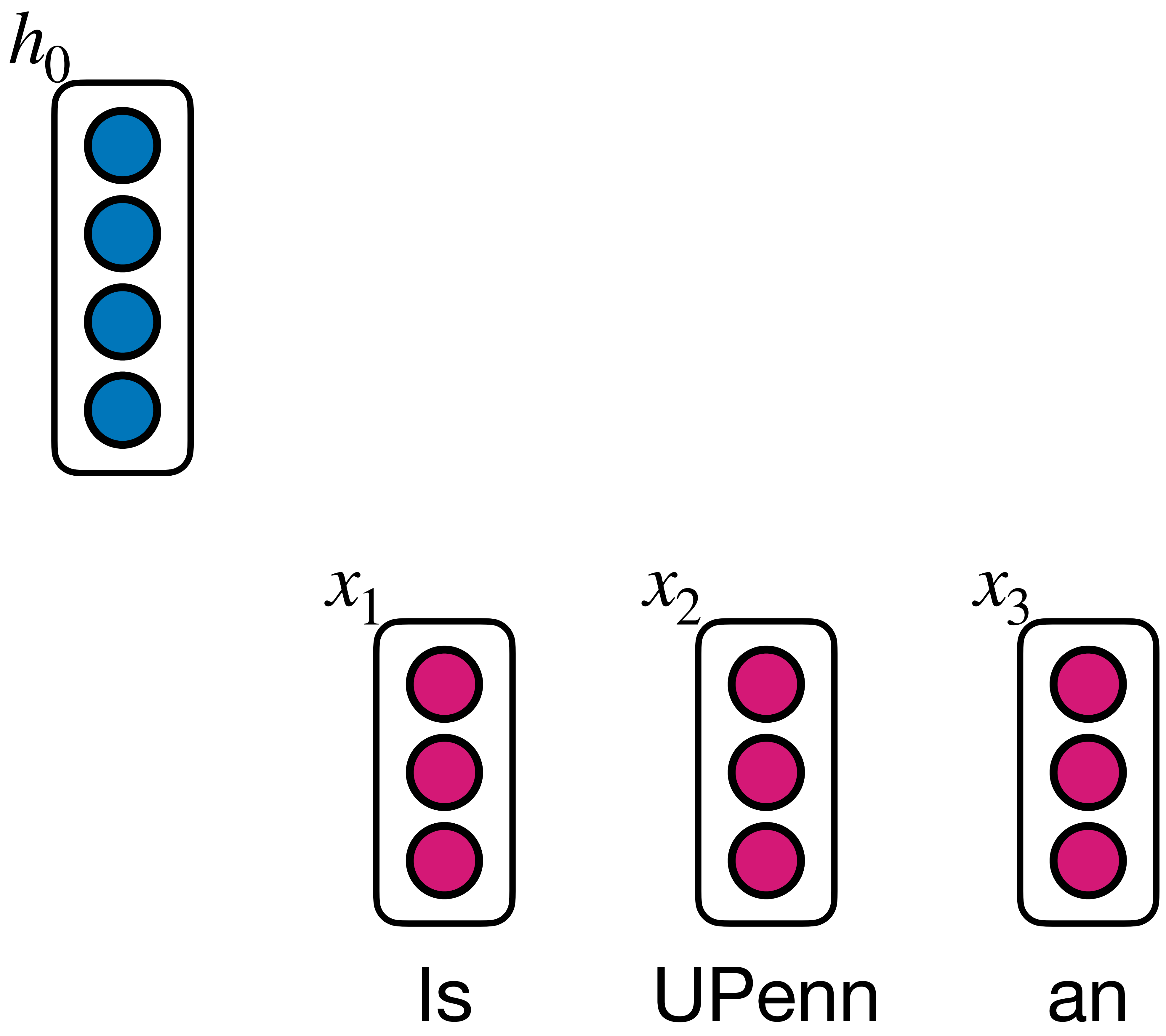

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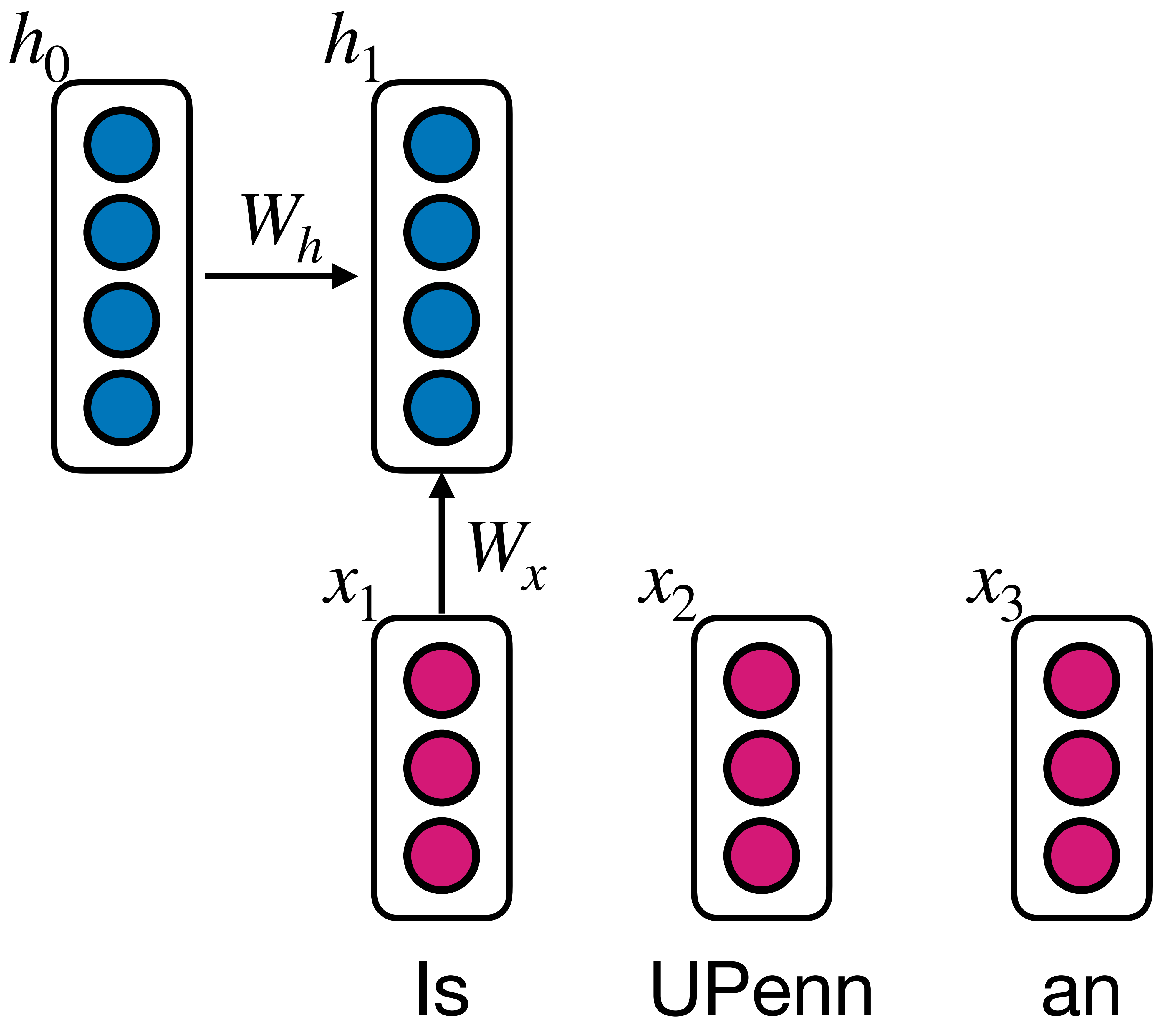

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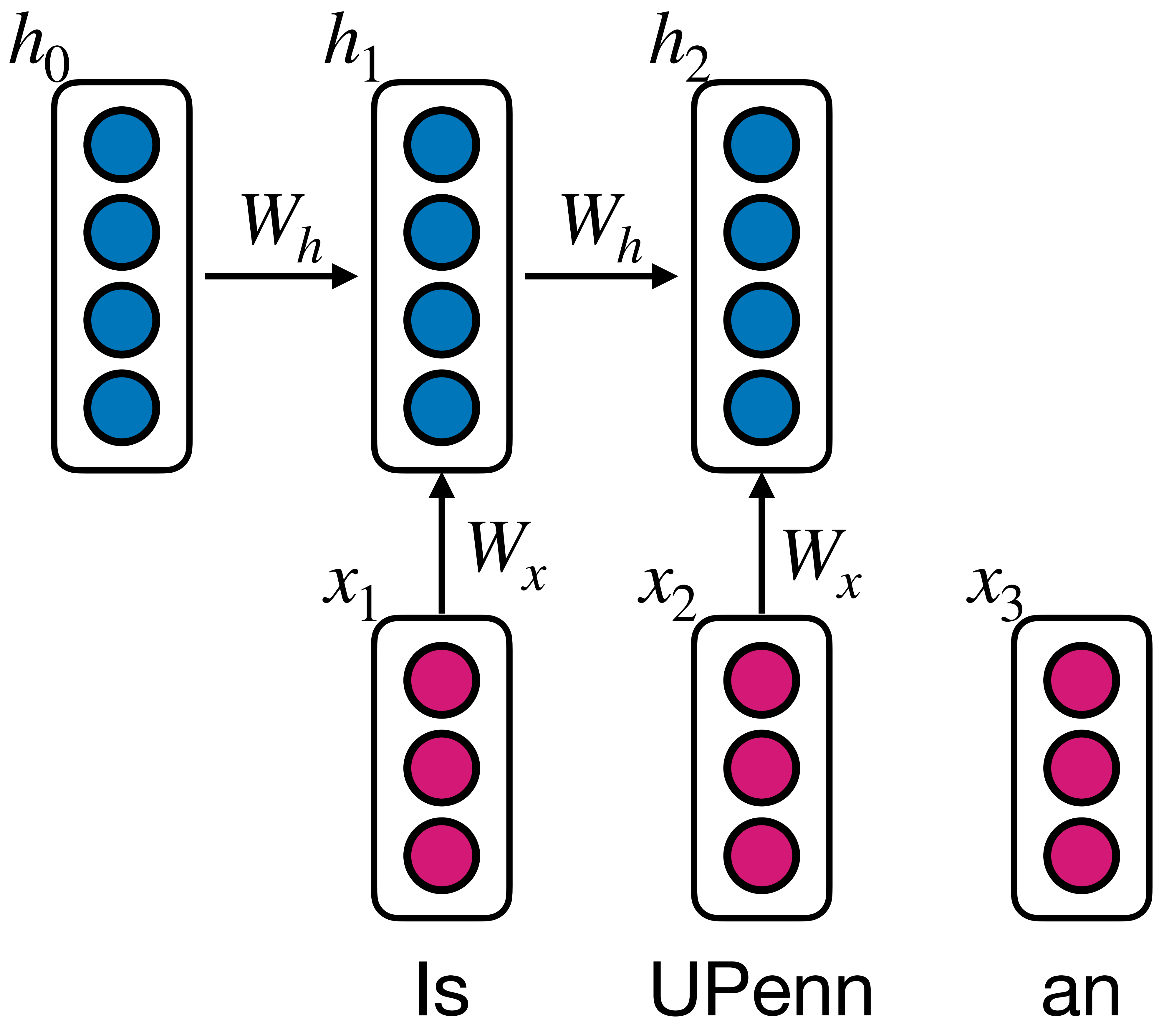

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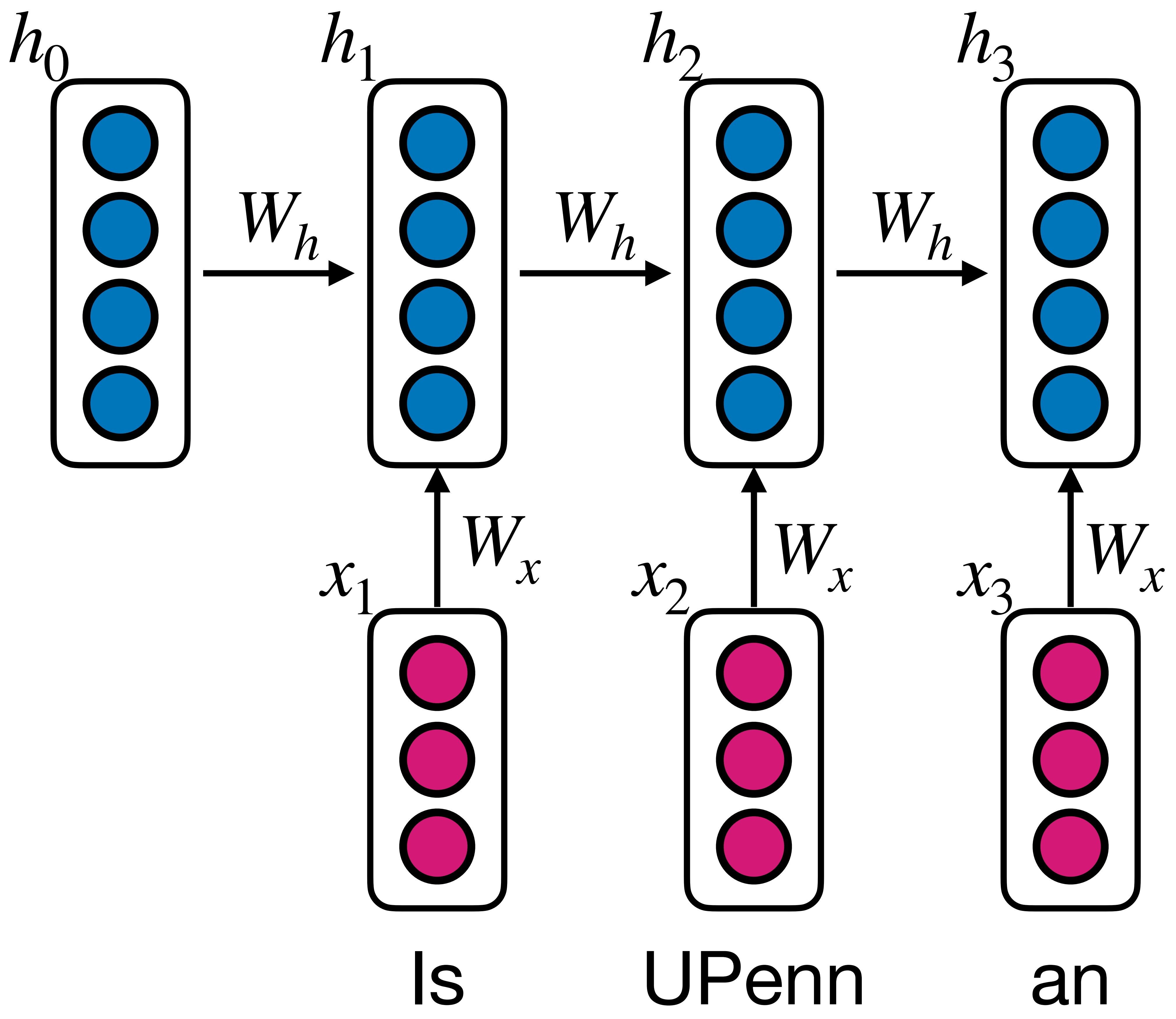

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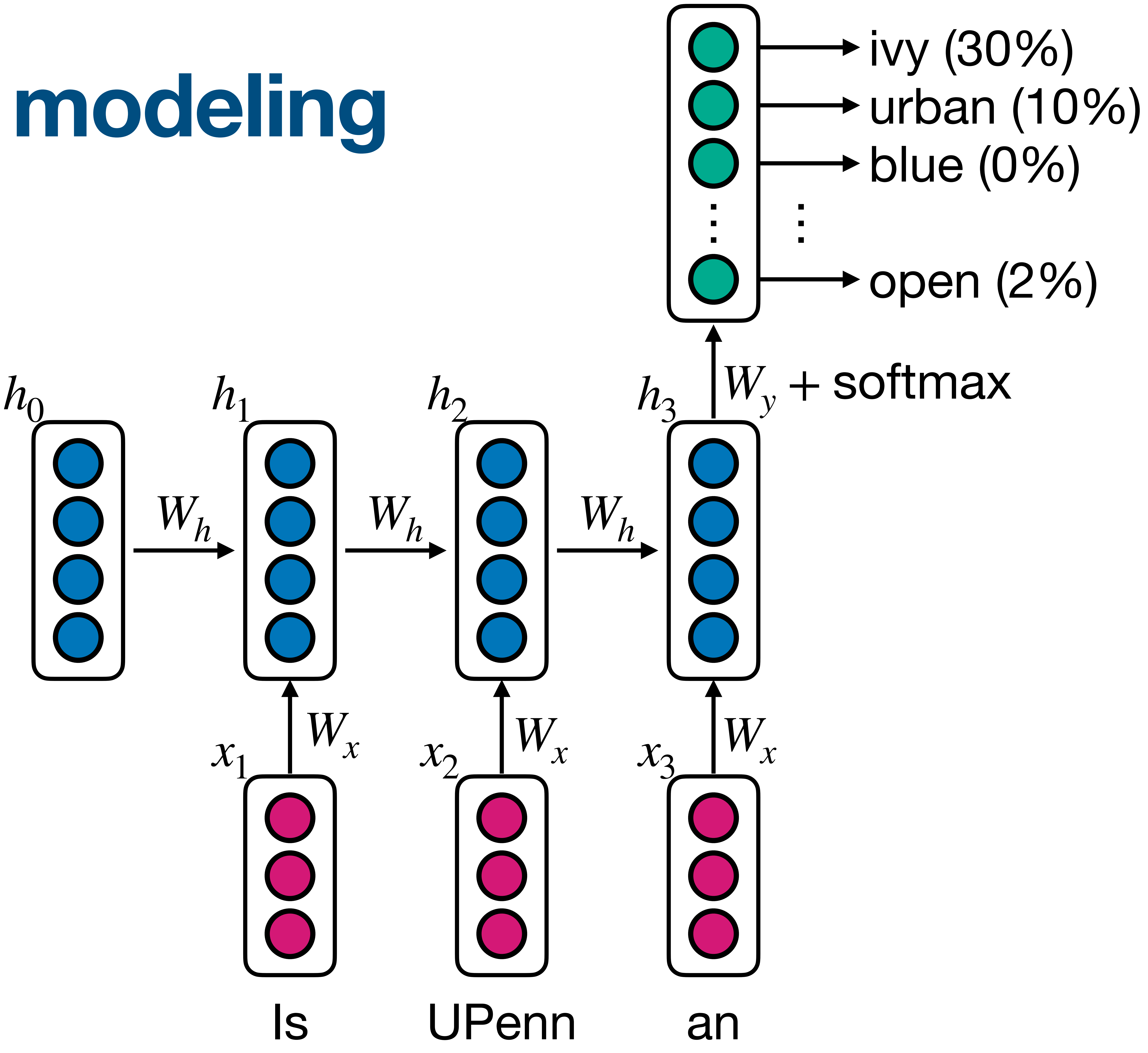
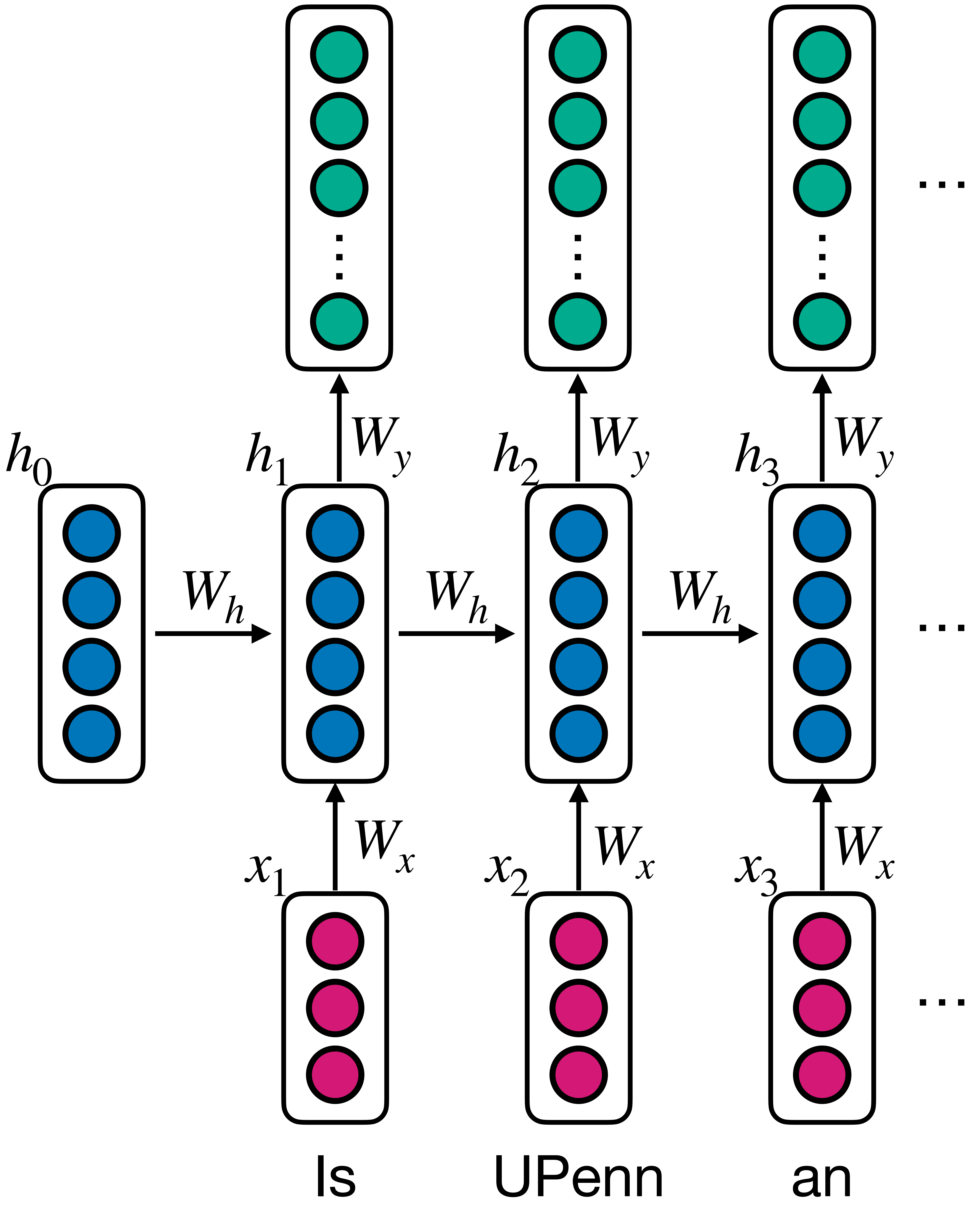


Training an RNN

- Get a big corpus of text, like Wikipedia.
- For any set of parameters, can predict each word based on all previous ones.
- Using the cross-entropy loss function averaged over all words, backpropagate through time to learn W_x, W_h, W_y.



RNNs can also generate text

Example: RNN trained on Barack Obama's speeches

https://medium.com/@samim/obama-rnn-machine-generated-political-speeches-c8abd18a2ea0

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“Good afternoon. God bless you.

The United States will step up to the cost of a new challenges of the American people that will share the fact that we created the problem. They were attacked and so that they have to say that all the task of the final days of war that I will not be able to get this done. The promise of the men and women who were still going to take out the fact that the American people have fought to make sure that they have to be able to protect our part. It was a chance to stand together to completely look for the commitment to borrow from the American people. And the fact is the men and women in uniform and the millions of our country with the law system that we should be a strong stretch of the forces that we can afford to increase our spirit of the American people and the leadership of our country who are on the Internet of American lives.

Thank you very much. God bless you, and God bless the United States of America.”

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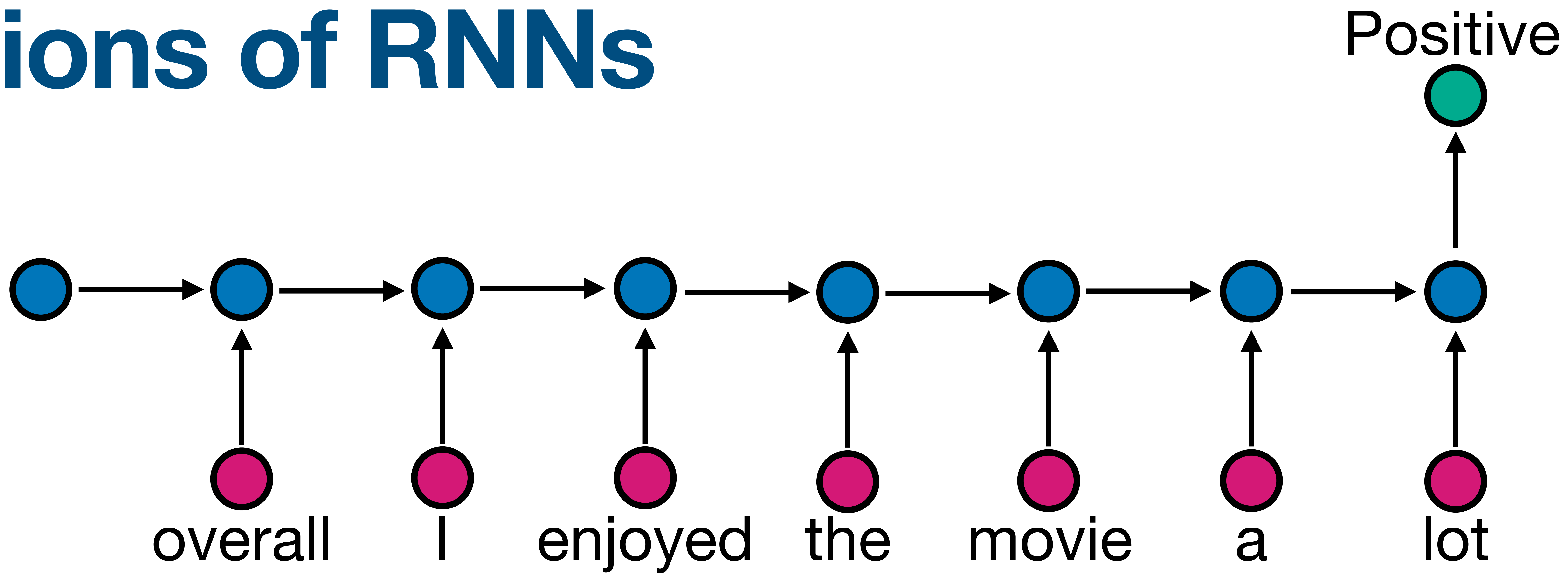
Other applications of RNNs

Sentiment analysis



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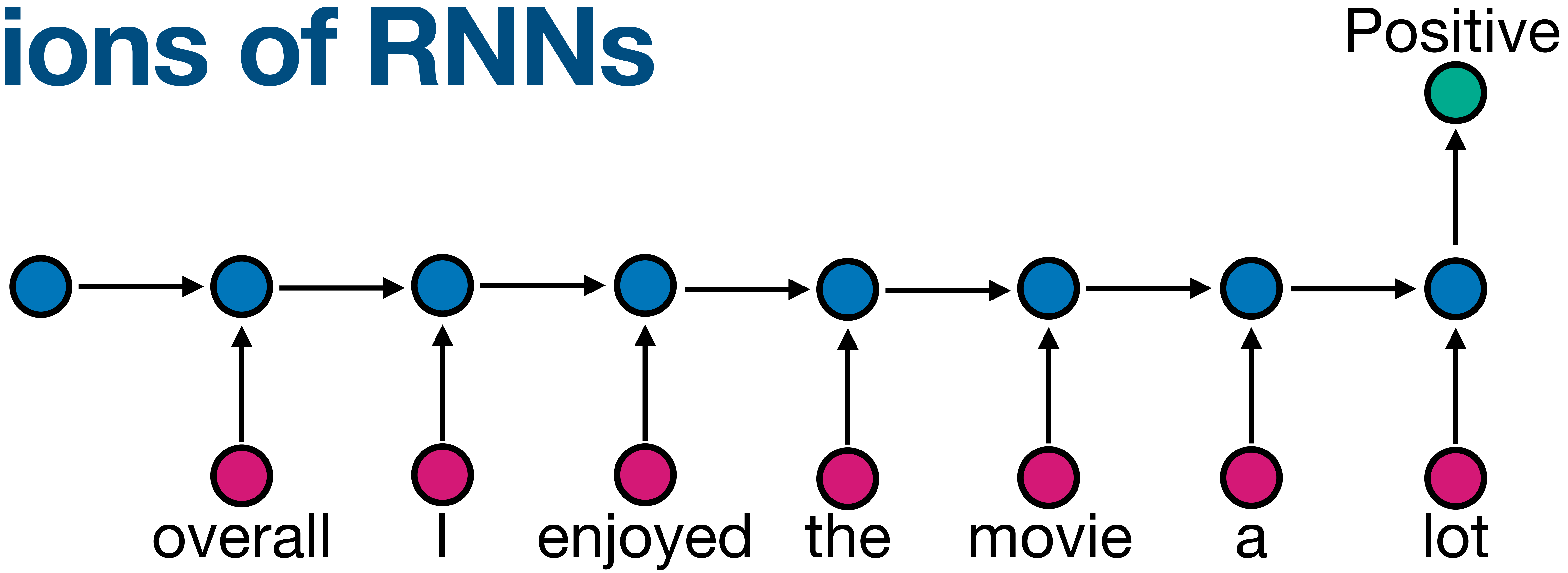
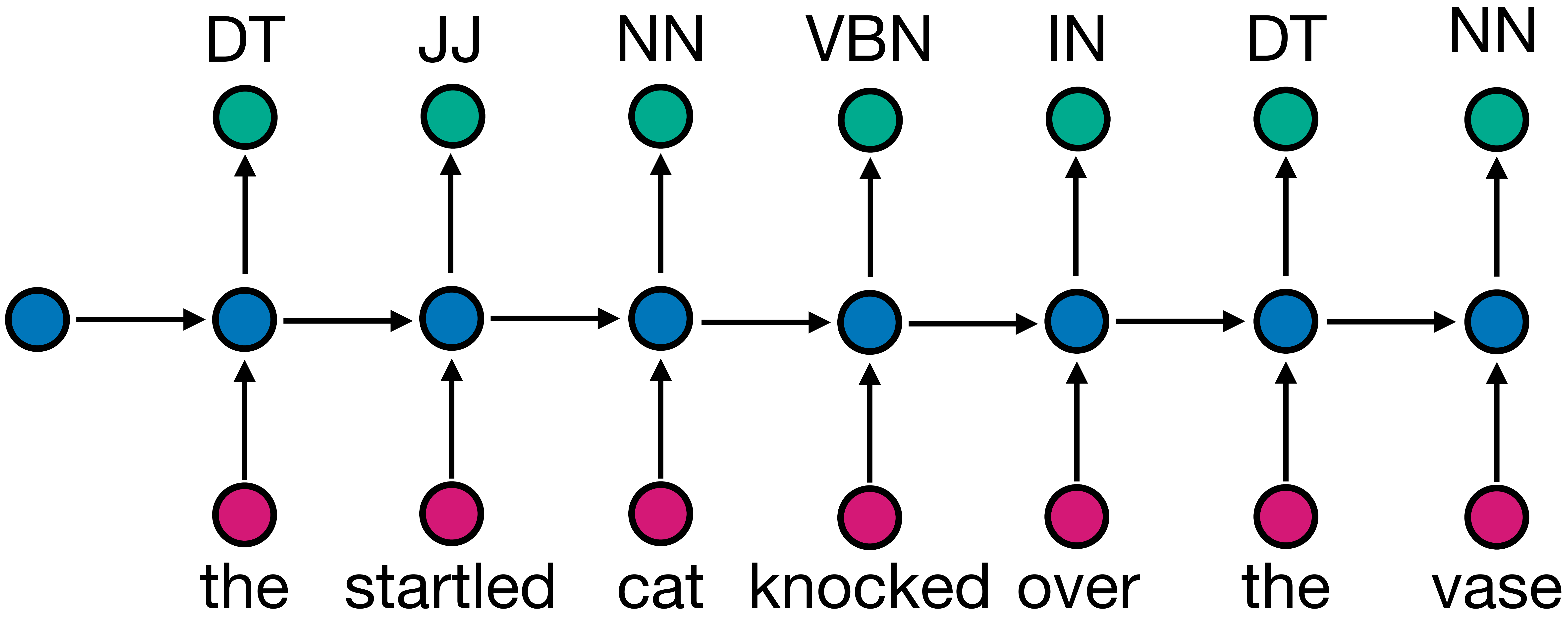


Part-of-speech tagging



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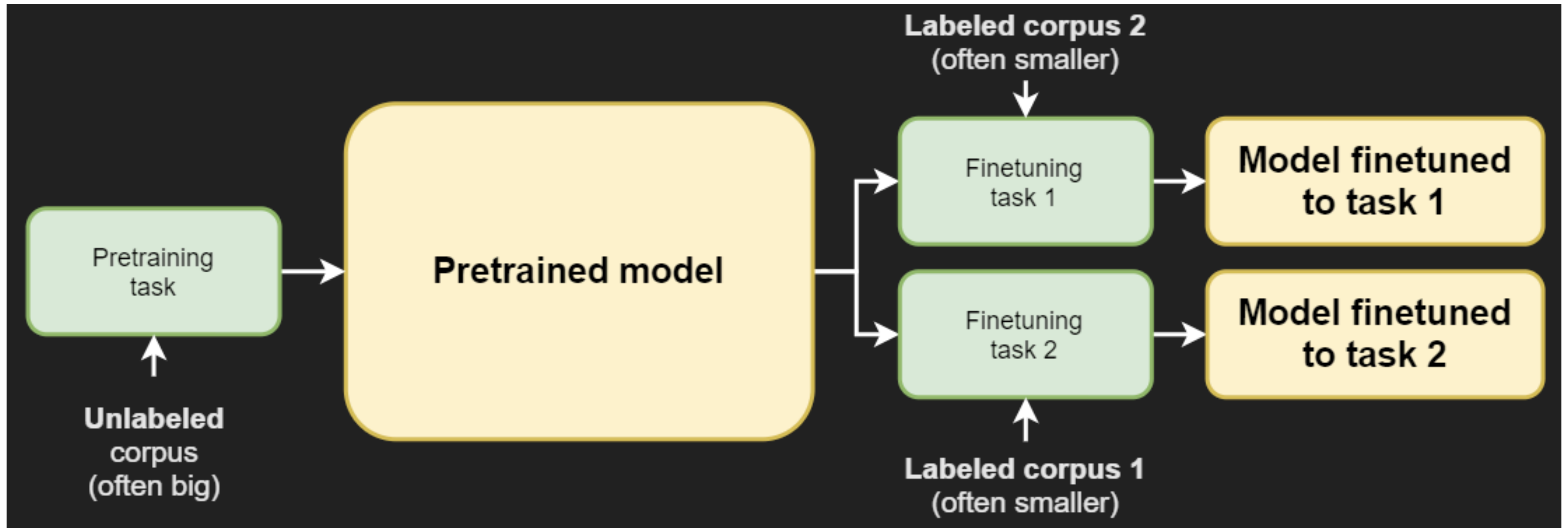

https://www.machinecurve.com/index.php/2021/01/04/intuitive-introduction-to-bert/

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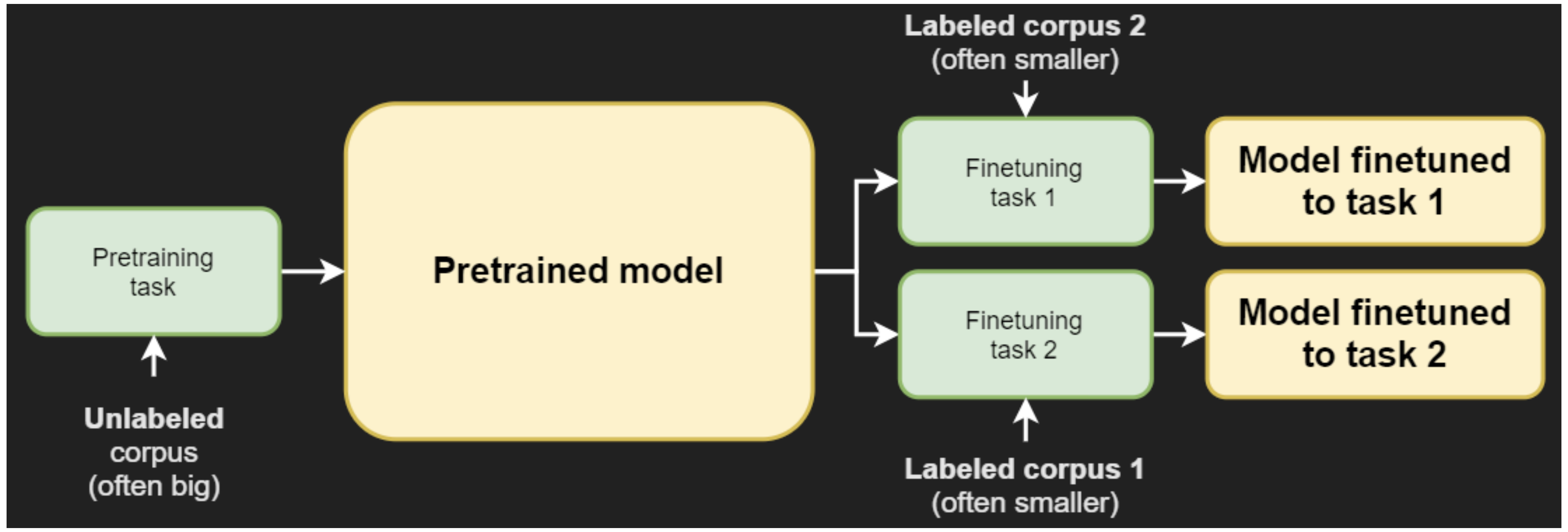

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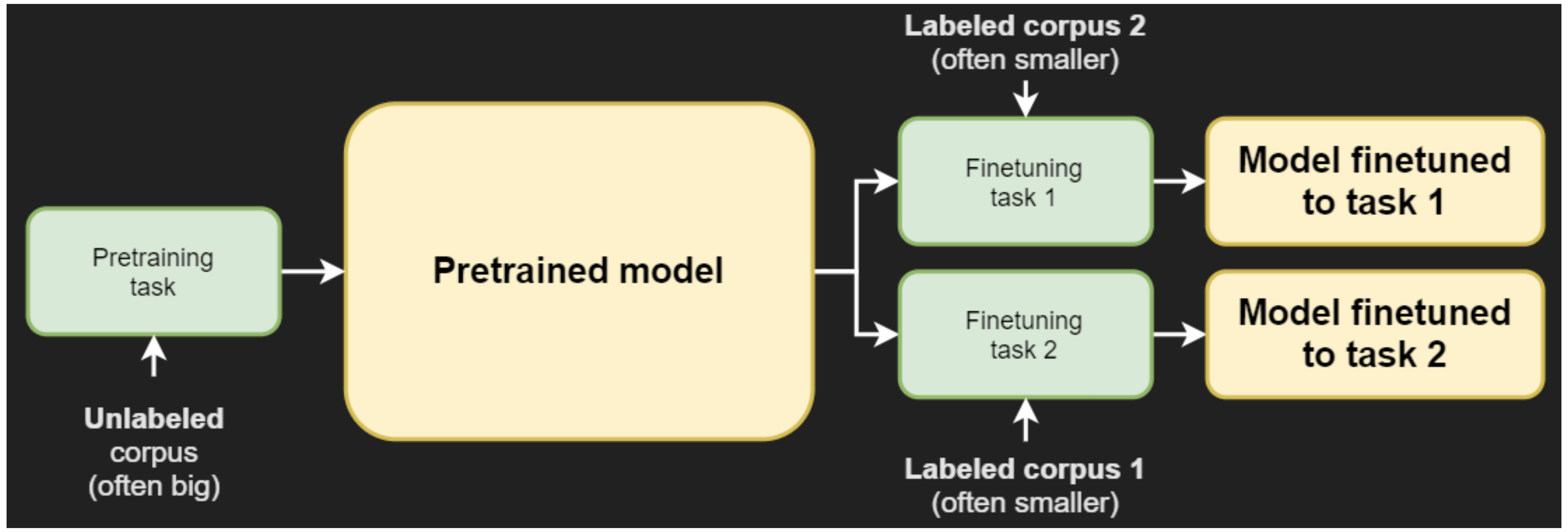

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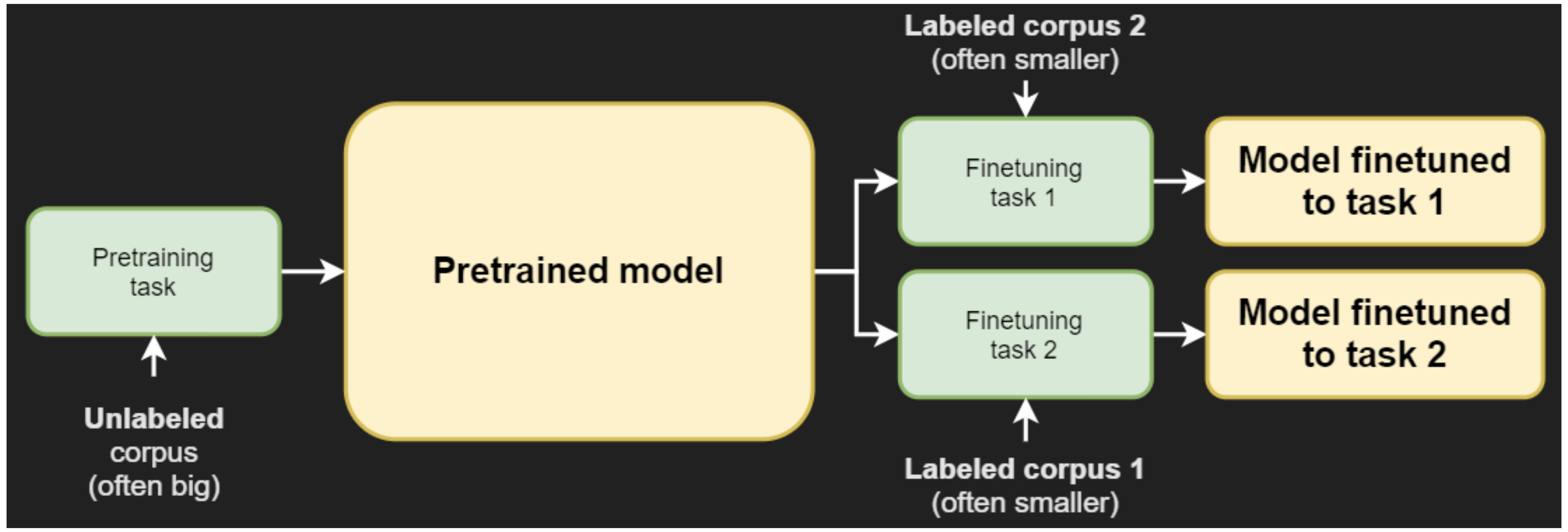

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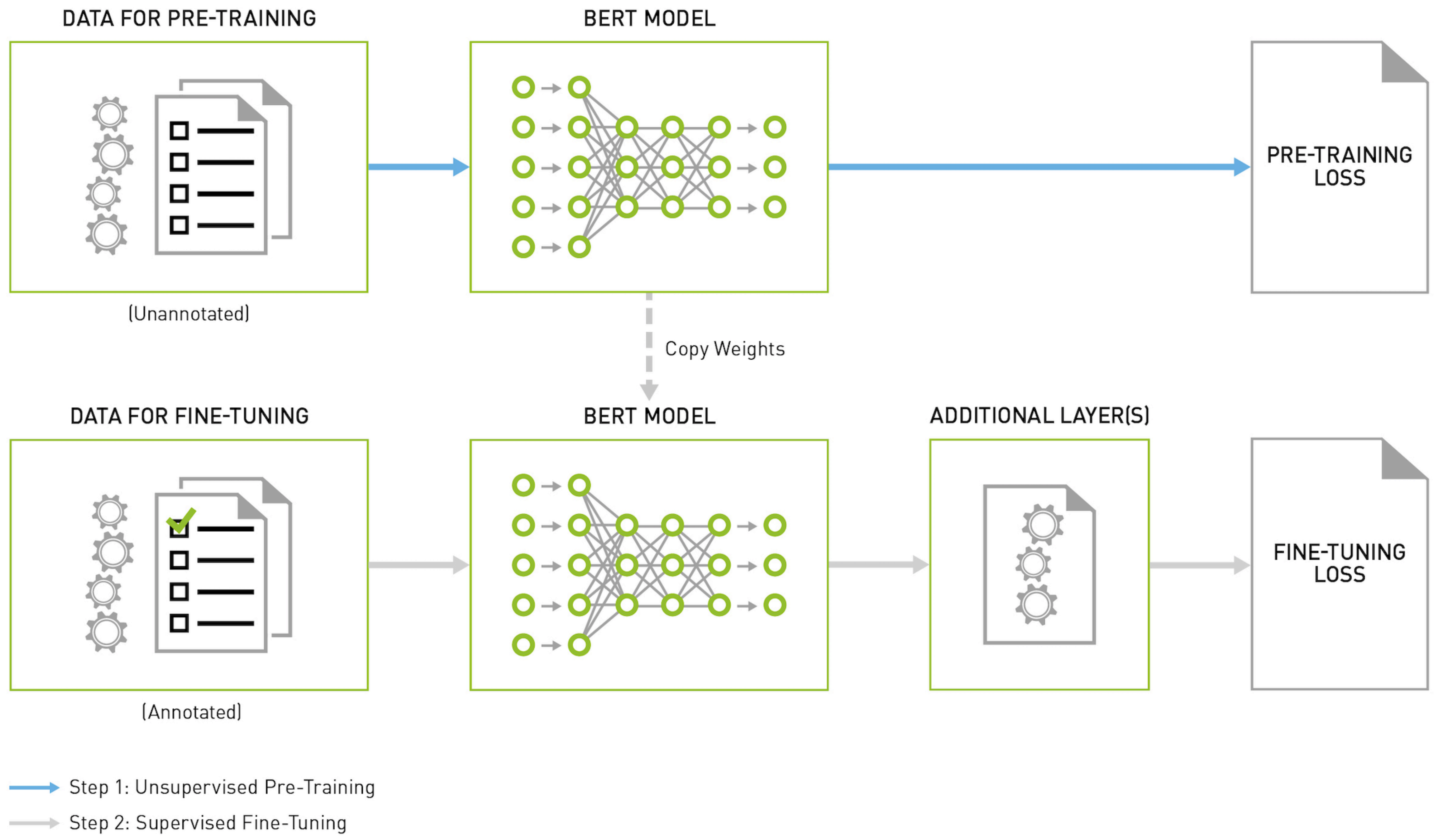

https://medium.com/future-vision/bert-meets-gpus-403d3fbed848

Summary

- Word vectors used to translate words into numbers for predictive modeling.
- Usual fully connected architecture can be paired with word vectors for window-based tasks like named entity classification.
- New architectures, such as recurrent neural networks, needed for variable-length inputs and outputs.
- RNNs work by processing the input sequence one word at a time, updating a hidden representation of the input using a fixed set of weights.
- RNNs can be applied to a diverse range of predictive tasks, like language modeling or sentiment analysis.
- The hard work of training deep learning models can be recycled through the pre-training and fine-tuning paradigm (applies not just to NLP).

Quiz Practice