Deep Learning for Language Understanding

Learning Outcomes

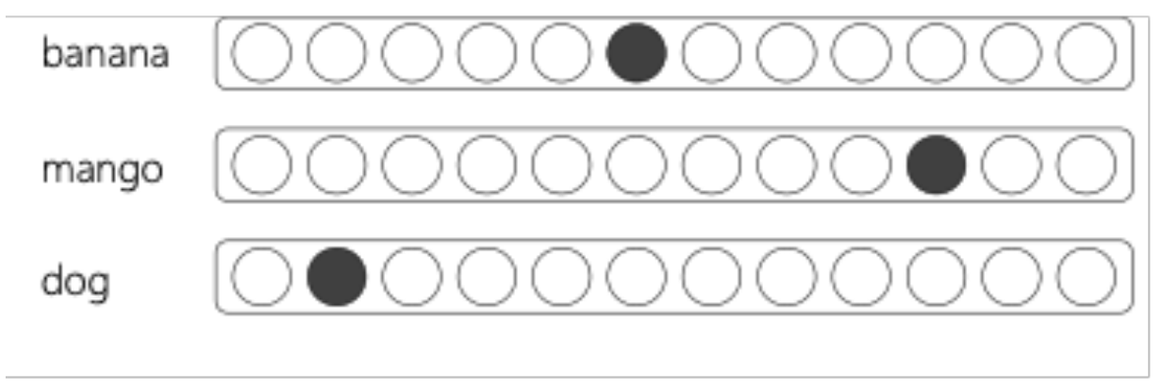
- Word2Vec distributed representation of words
- Language models using Recurrent Neural Networks
- Neural Machine Translation using Seq2Seq models
- Attention mechanisms
  - Encoder decoder attention
  - Self attention
  - Multi-head attention
  - Transformer model

How to Represent Text

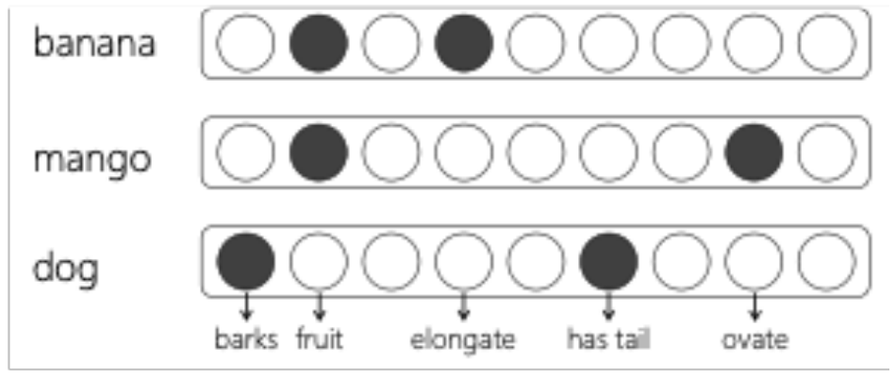
- Humans understand natural language
- Machines understand numbers
- How to represent natural language text in numbers?
- E.g, how to represent "banana is a fruit" as numbers?
  - One-hot-encoding: [0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
  - Other solutions?

Word Representations

One-hot encoding vs distributed representation



Local representations (1-hot)



Distributed representations

Limitations?

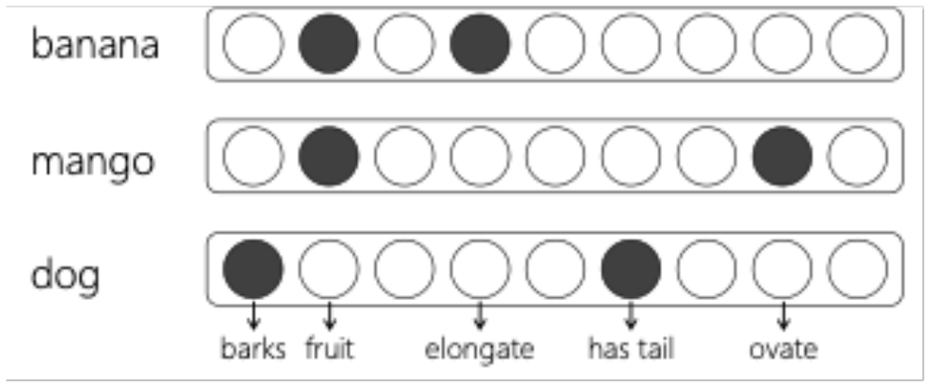
Sparseness: Lot's of 0s and few 1s

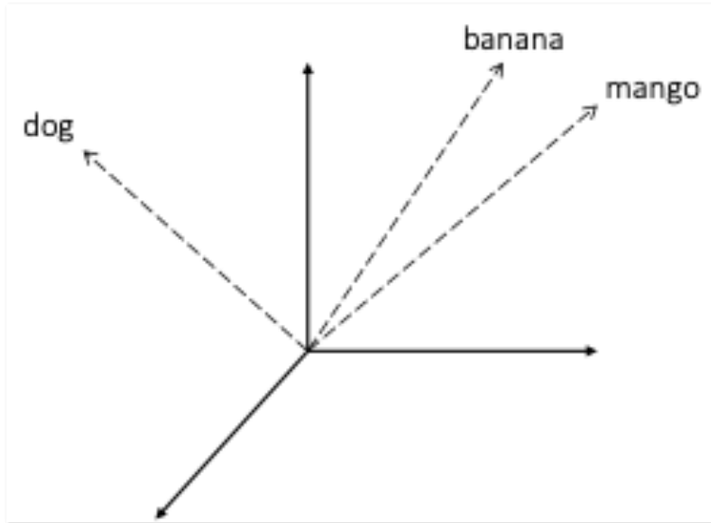
High dimensionality: 20K (speech) – 50K (PTB) – 500K (big vocab) – 13M (Google 1T)

Distributed Representation

- You can get a lot of value by representing a word by means of its neighbors "You shall know a word by the company it keeps" — (J. R. Firth 1957: 11)

Distributed Representation



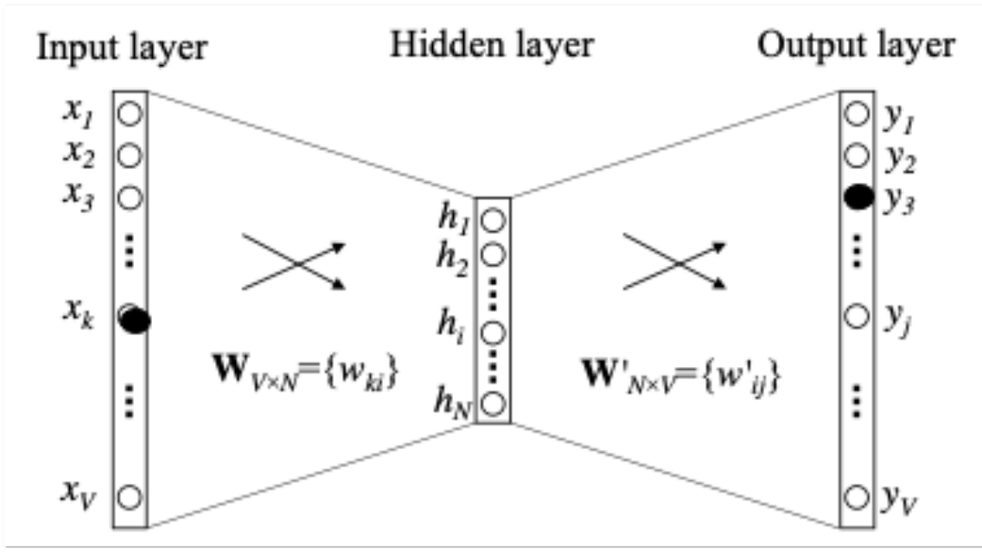


…government debt problems turning into banking crises as has happened in…
…..saying that Europe needs unified banking regulation to replace the hodgepodge…

↖ These words will represent *banking* ↗

Word Embeddings

- Goal: Given one-hot encodings of words and their context represent them in dense lower dimension space
  - Considers learning word embeddings as a prediction task
  - Training context : "Norway wins gold in Olympics"
  - **Continuous Bag of Words Model (CBOW):**
    - Guess the central word in the context
    - "norway wins X in Olympics"
    - Training data (Norway, gold), (wins, gold), (in, gold), (olympics, gold), (olympics, gold),
  - **Skip-gram**
    - Guess the context given the central word
    - "X X gold X X"
    - Training data (gold, Norway), (gold, wins), (gold, in), (gold, Olympics)



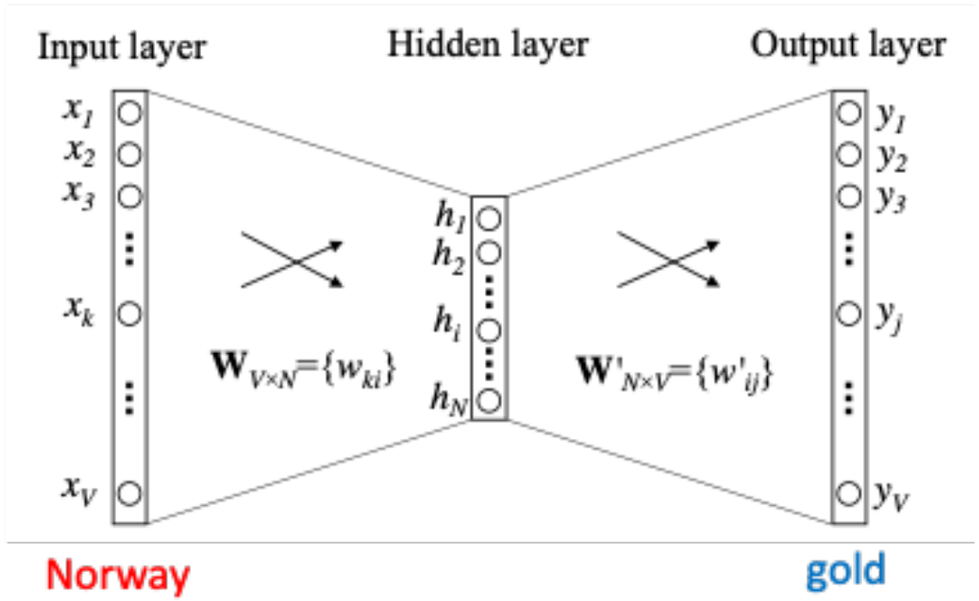
Norway gold

Is it a regression or a classification problem ?

Word2Vec

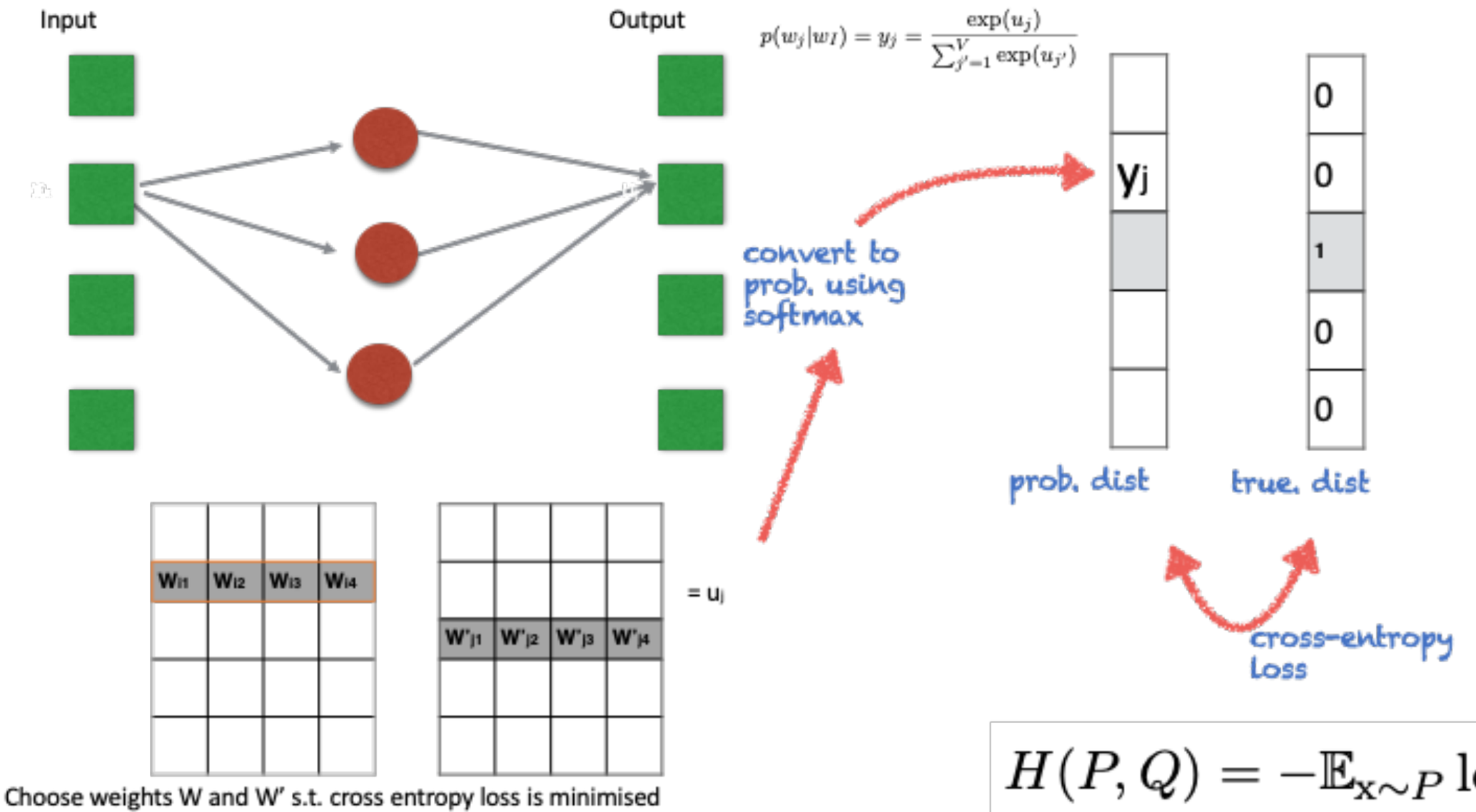
- Input and Output dimensions are size V (vocabulary), hidden layer N << V

- Input representation : **h** in the hidden space
- Output representation : **h.W'**



- Central question: how do we learn the parameters of this model (weights) given training examples from text
- What is cosine distance between output and input representation ?

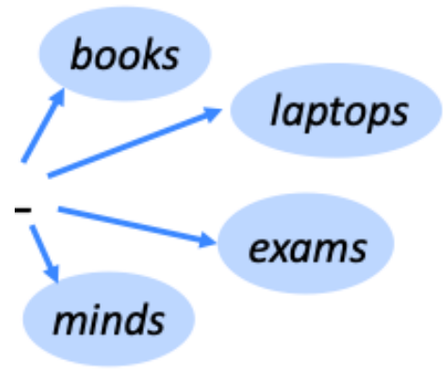
Word2Vec Forward Pass



$$H(P, Q) = -\mathbb{E}_{x \sim P} \log Q(x)$$

Language Modeling Task

- Language Modeling is the task of predicting what word comes next.
- the students opened their _____



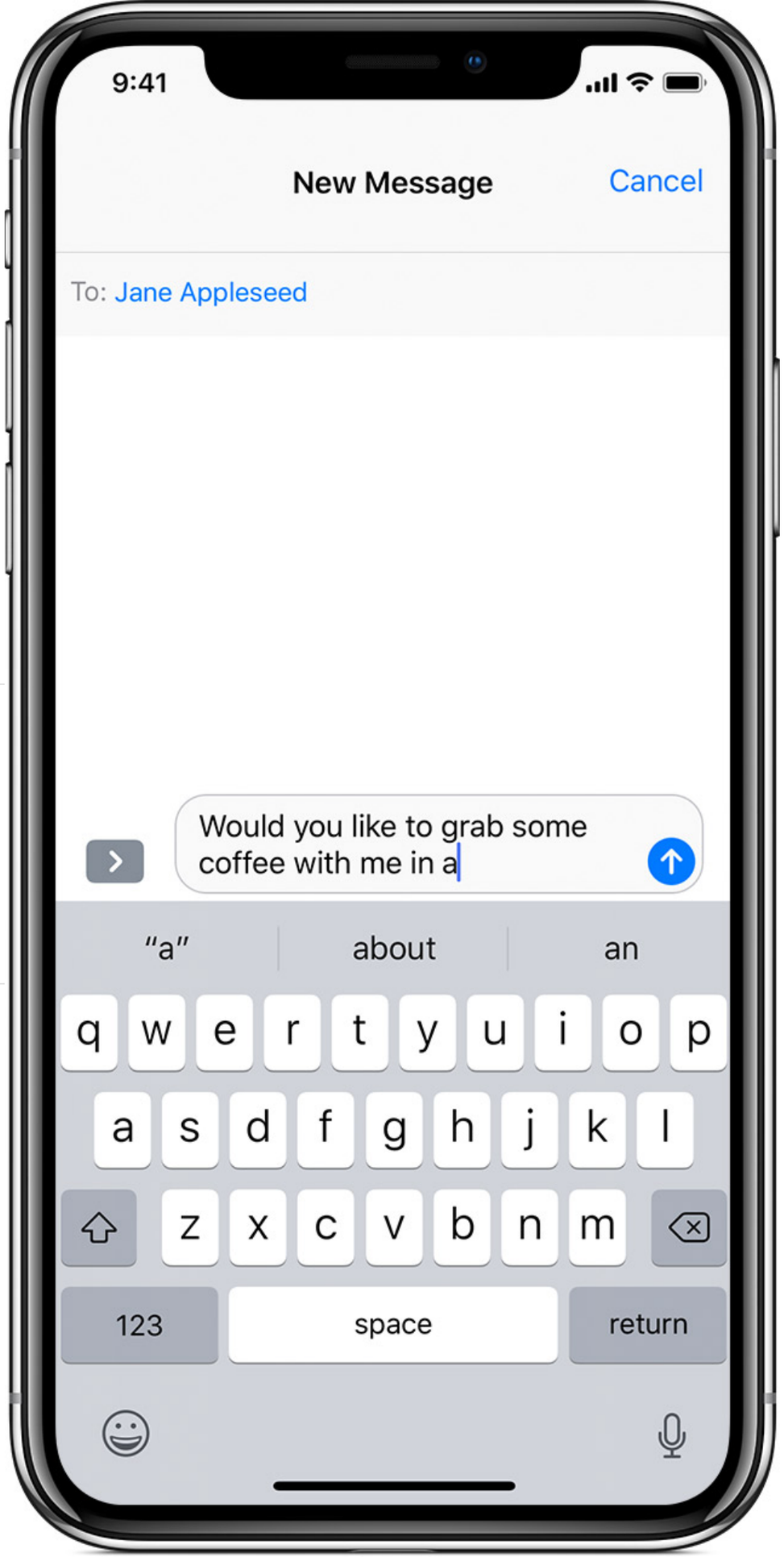
- More formally: given a sequence of words $\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \ldots, \boldsymbol{x}^{(t)}$ compute the probability distribution of the next word $\boldsymbol{x}^{(t+1)}$

$$P\left(\boldsymbol{x}^{(t+1)} | \boldsymbol{x}^{(t)}, \ldots, \boldsymbol{x}^{(1)}\right)$$

  Where $\boldsymbol{x}^{(t+1)}$ can be any word in the vocabulary $V = \{\boldsymbol{w}_1, \ldots, \boldsymbol{w}_{|V|}\}$

- A system which can compute this is called a "Language Model"

You use Language Models every day!



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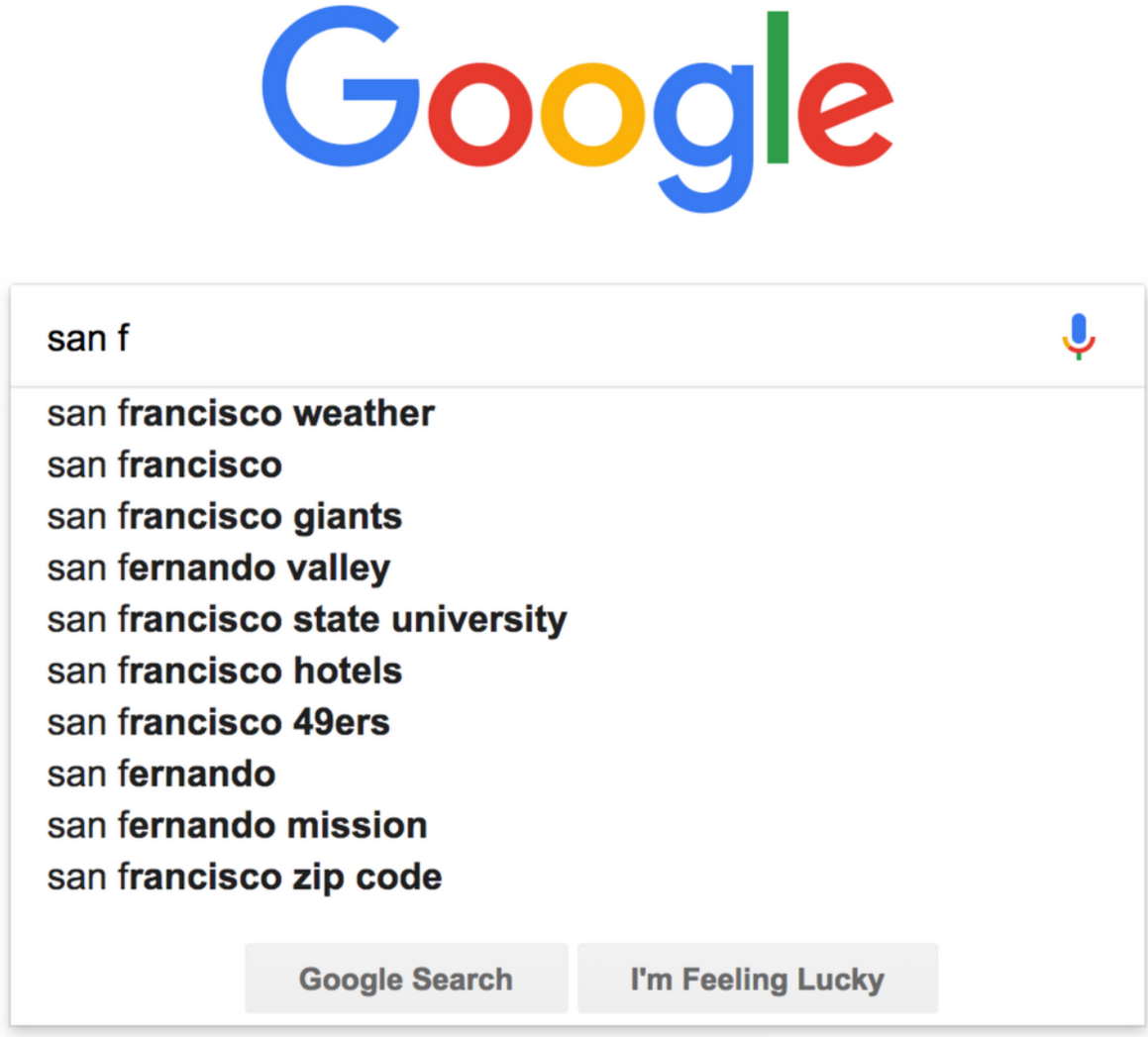


Statistical Language Models

- Pre-deep learning era: Statistical language models were used

> Idea: Collect statistics about how frequently different word sequences (n-grams) occur and use that to predict next word

Definition: *An n-gram is a chunk of n consecutive words.*

- unigrams: “the”, “students”, “opened”, ”their”
- bigrams: “the students”, “students opened”, “opened their”
- trigrams: “the students opened”, “students opened their”
- 4-grams: “the students opened their”

Statistical Langauge Models

- Learning language models from large text corpora
  - Given a large text corpus – say all sentences in Wikipedia

- Count frequency of occurrence of words – unigrams, bigrams, tri-grams ,…

$$p(w_1) = \frac{\text{count}(w_1)}{\sum \text{count}(w_i)} \qquad p(w_2|w_1) = \frac{\text{count}(w_1, w_2)}{\text{count}(w_1)} \qquad p(w_3|w_1, w_2) = \frac{\text{count}(w_1, w_2, w_3)}{\text{count}(w_1, w_2)}$$

- Why is more context better ?
  - Tri-gram > Bi-gram > Unigram

- Typically have a Markovian assumption

P(hot summer the has been)

P(hot the summer has been)

P(the summer has been hot)

$$P(w_1, \ldots, w_m) = \prod_{i=1}^{m} P(w_i|w_1, \ldots, w_{i-1}) \approx \prod_{i=1}^{m} P\left(w_i|w_{i-(n-1)}, \ldots, w_{i-1}\right)$$

Problems with Statistical LM

What comes next ? students opened their X

Sparsity Problem 1

Problem: What if *"students opened their* w_j*"* never occurred in data? Then w_j has probability 0!

(Partial) Solution: Add small δ to count for every $w_j \in V$. This is called *smoothing*.

$$p(w_j \mid \text{students opened their}) = \frac{\text{count(students opened their } w_j)}{\text{count(students opened their)}}$$

Sparsity Problem 2

Problem: What if *"students opened their"* never occurred in data? Then we can't calculate probability for *any* w_j!

(Partial) Solution: Just condition on *"opened their"* instead. This is called *backoff*.

Problems with Statistical LM

- Sparsity
  - Need lot of data to estimate long-length n-grams
  - Assume |V| = 10^5. What is the number of contexts for 4-grams ?

$$p(w_3|w_1, w_2) = \frac{\text{count}(w_1, w_2, w_3)}{\text{count}(w_1, w_2)}$$

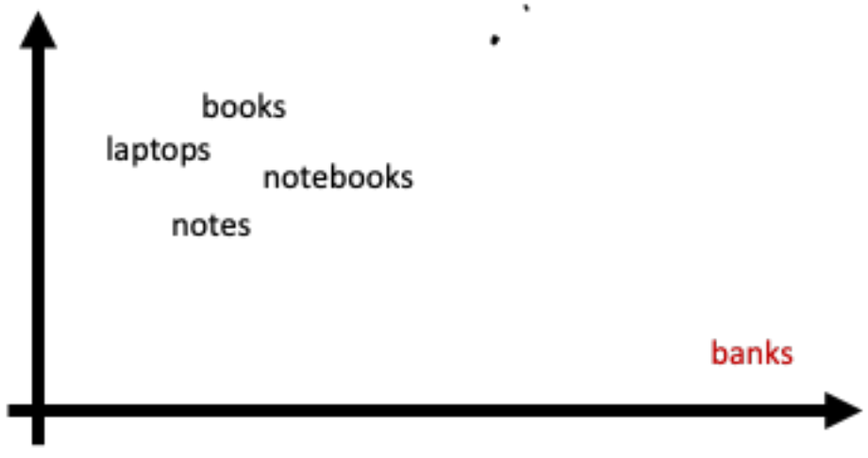
Most of them are not seen

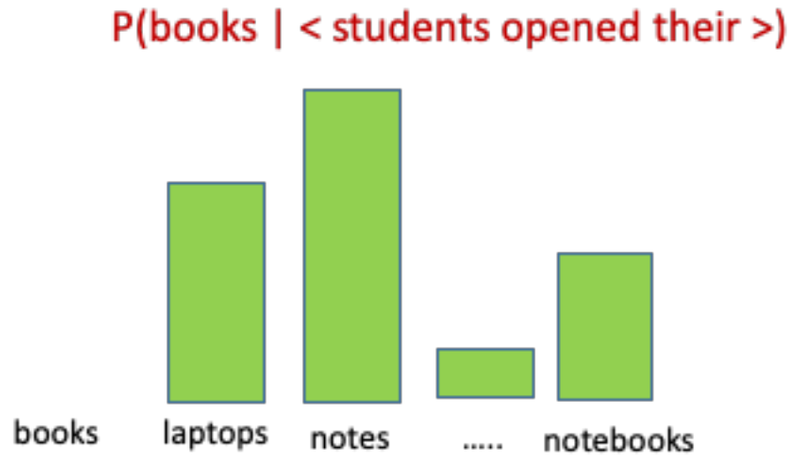
- Insufficient context
  - Markovian assumption imposes a computational limit on the context

- What is needed ?
  - We could estimate the probabilities for n-grams better by exploiting word similarity
  - Why not let a Neural Network estimate these probabilities automatically ?

Neural Language Models

- How does neural LM solve the sparsity problem ?
  - Words as dense distributed vectors so there can be sharing of statistical weight between similar words
  - Doing just this solves the sparseness problem of conventional n-gram models
    - **students opened their** {books, laptops, notes, notebooks, ….}
    - Even if books is not observed or P(books | < **students opened their** >) = 0

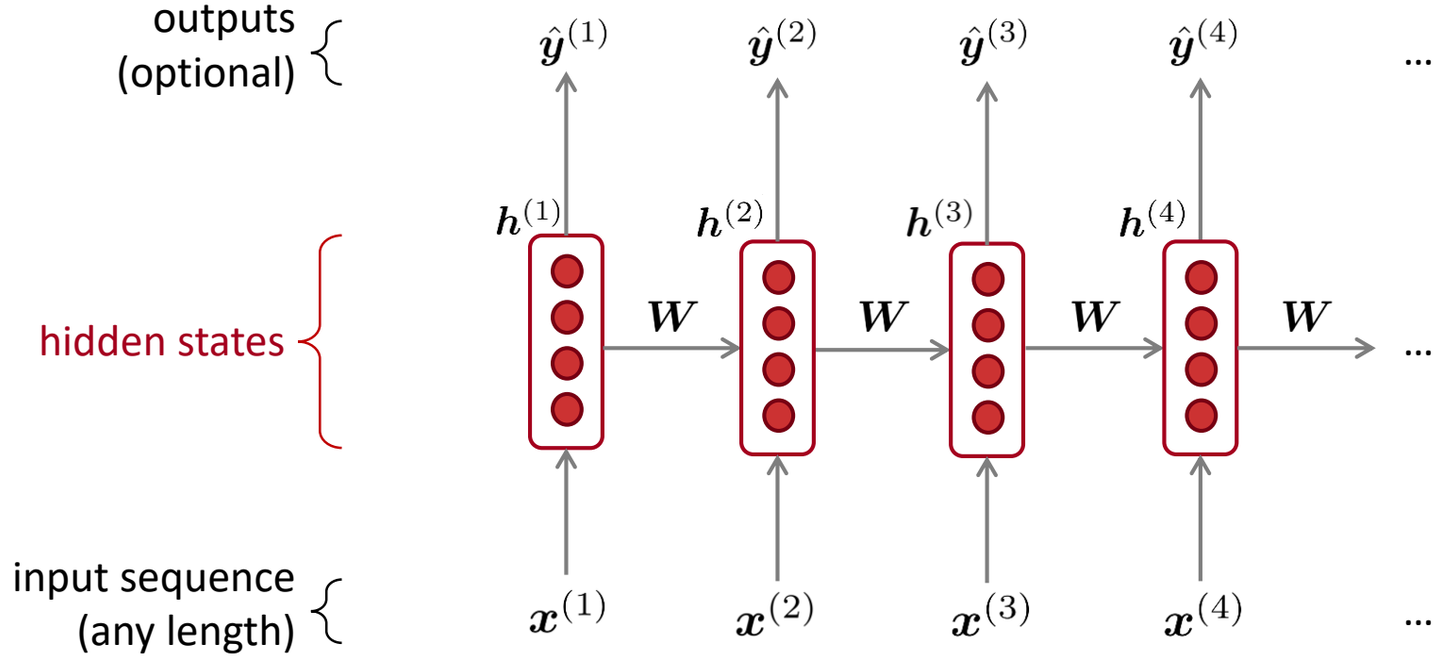




Recap: Recurrent Neural Networks

- Given a function f: $h^{(i)}, y^{(i)} = f(h^{(i-1)}, x, W)$

$h^{(i)}$ and $h^{(i-1)}$ are vectors with the same dimension

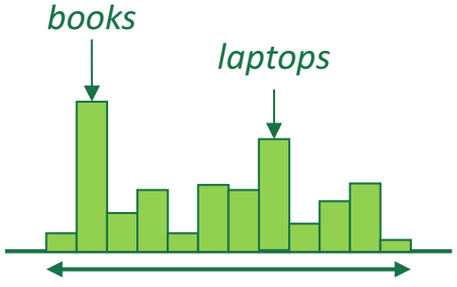


Core idea: Apply same function f with same weights W repeatedly

RNN Language Models

- Input
  - Word sequence represented as **word2vec embeddings** or **one-hot encodings**

$$\hat{\boldsymbol{y}}^{(4)} = P\left(\boldsymbol{x}^{(5)}|\text{ the students opened their }\right)$$



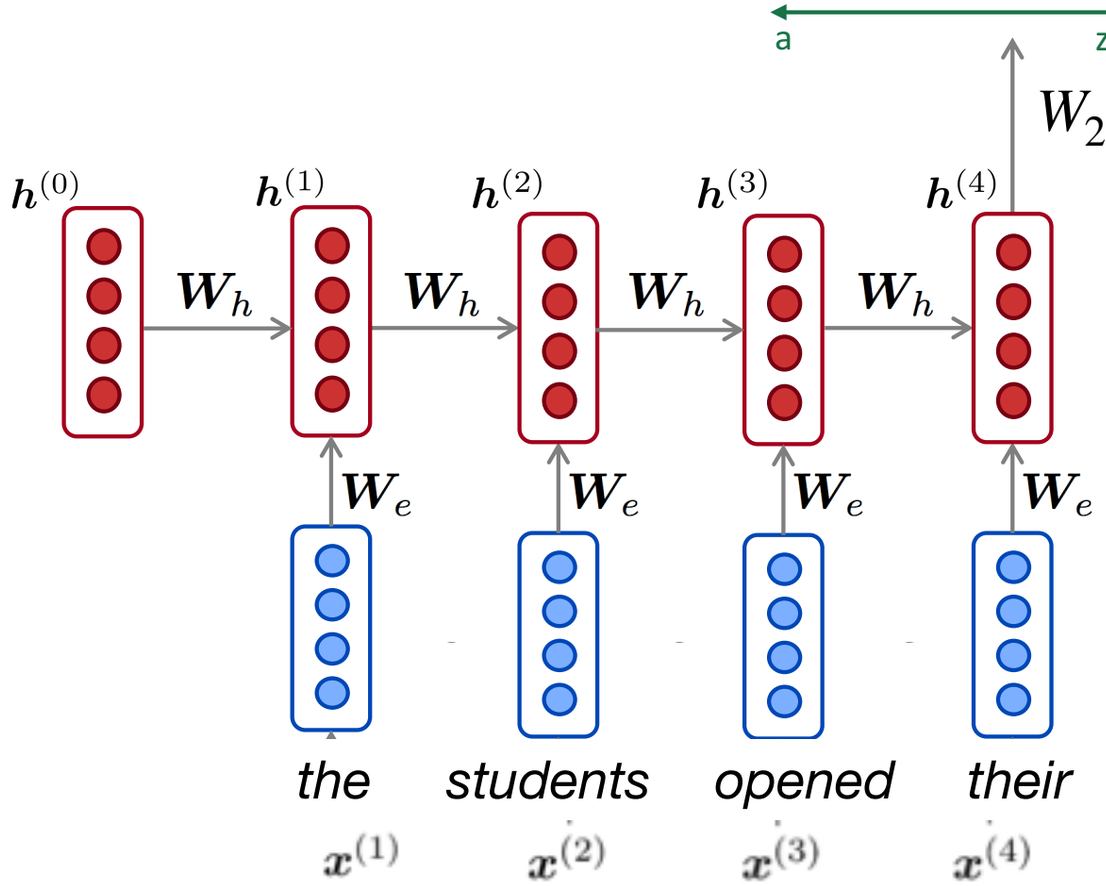
- hidden states

$$\boldsymbol{h}^{(t)} = \sigma\left(\boldsymbol{W}_h\boldsymbol{h}^{(t-1)} + \boldsymbol{W}_e\boldsymbol{e}^{(t)} + \boldsymbol{b}_1\right)$$

$\boldsymbol{h}^{(0)}$ Initial hidden state

- Output

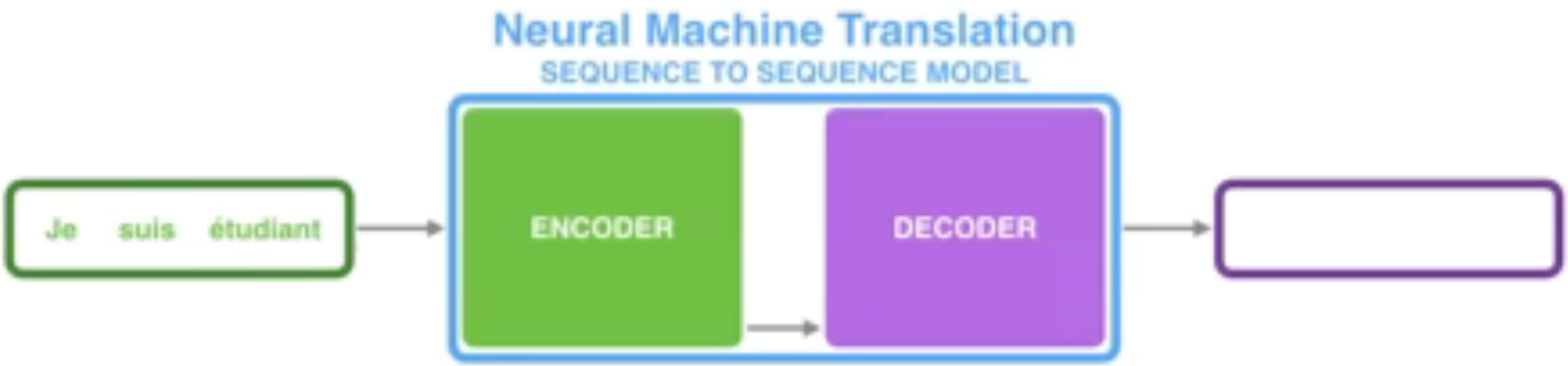
$$\hat{\boldsymbol{y}}^{(t)} = \text{softmax}\left(\boldsymbol{U}\boldsymbol{h}^{(t)} + \boldsymbol{b}_2\right) \in \mathbb{R}^{|V|}$$



Sequence-to-Sequence Models

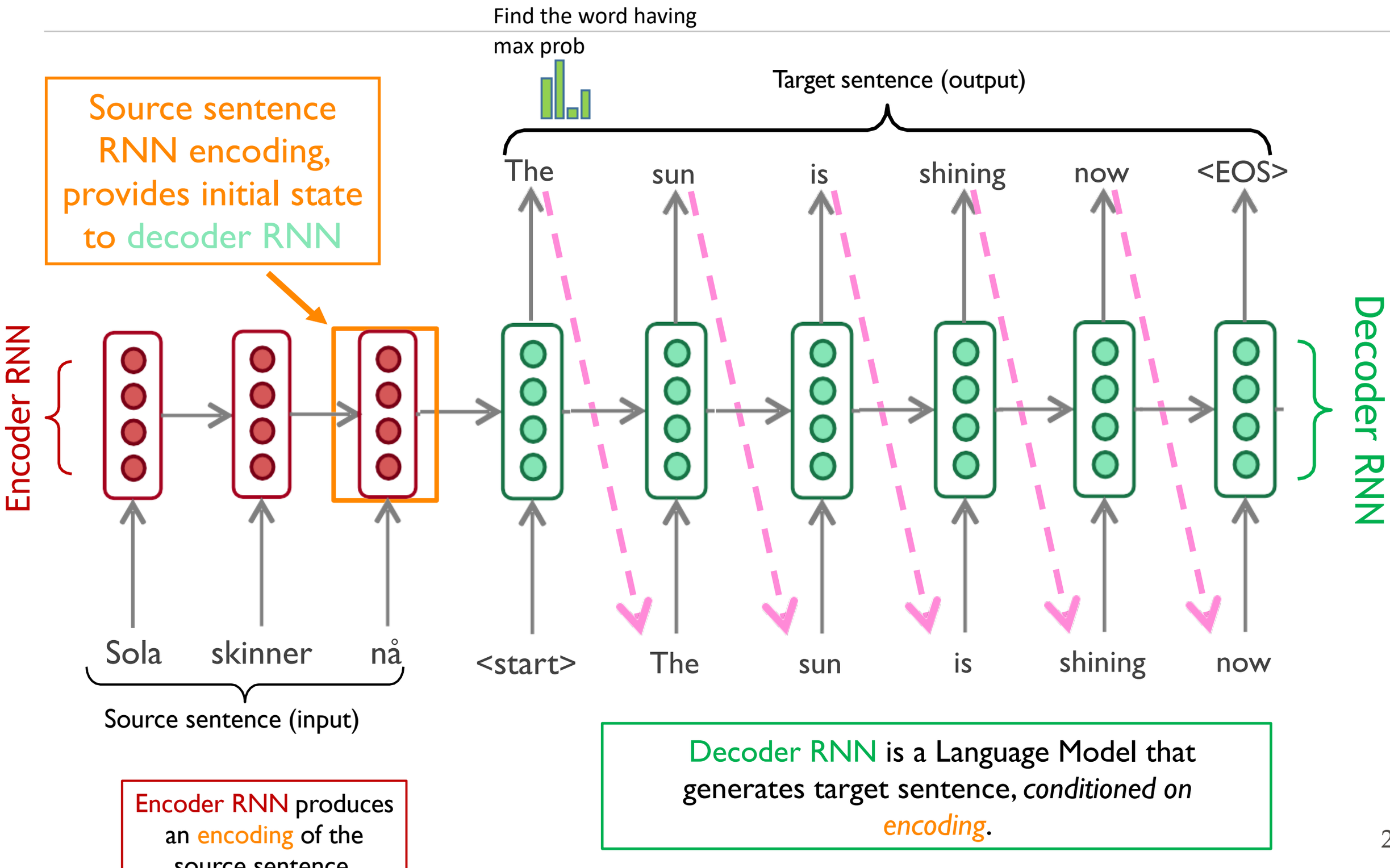
- Seq2Seq turns one sequence into another sequence
- Many NLP tasks can be phrased as Seq2Seq:
  - Summarization (long text → short text)
  - Dialogue (previous utterances → next utterance)
  - Parsing (input text → output parse as sequence)
  - Neural Machine Translation (Norwegian → English)

Seq2Seq Neural Machine Translation



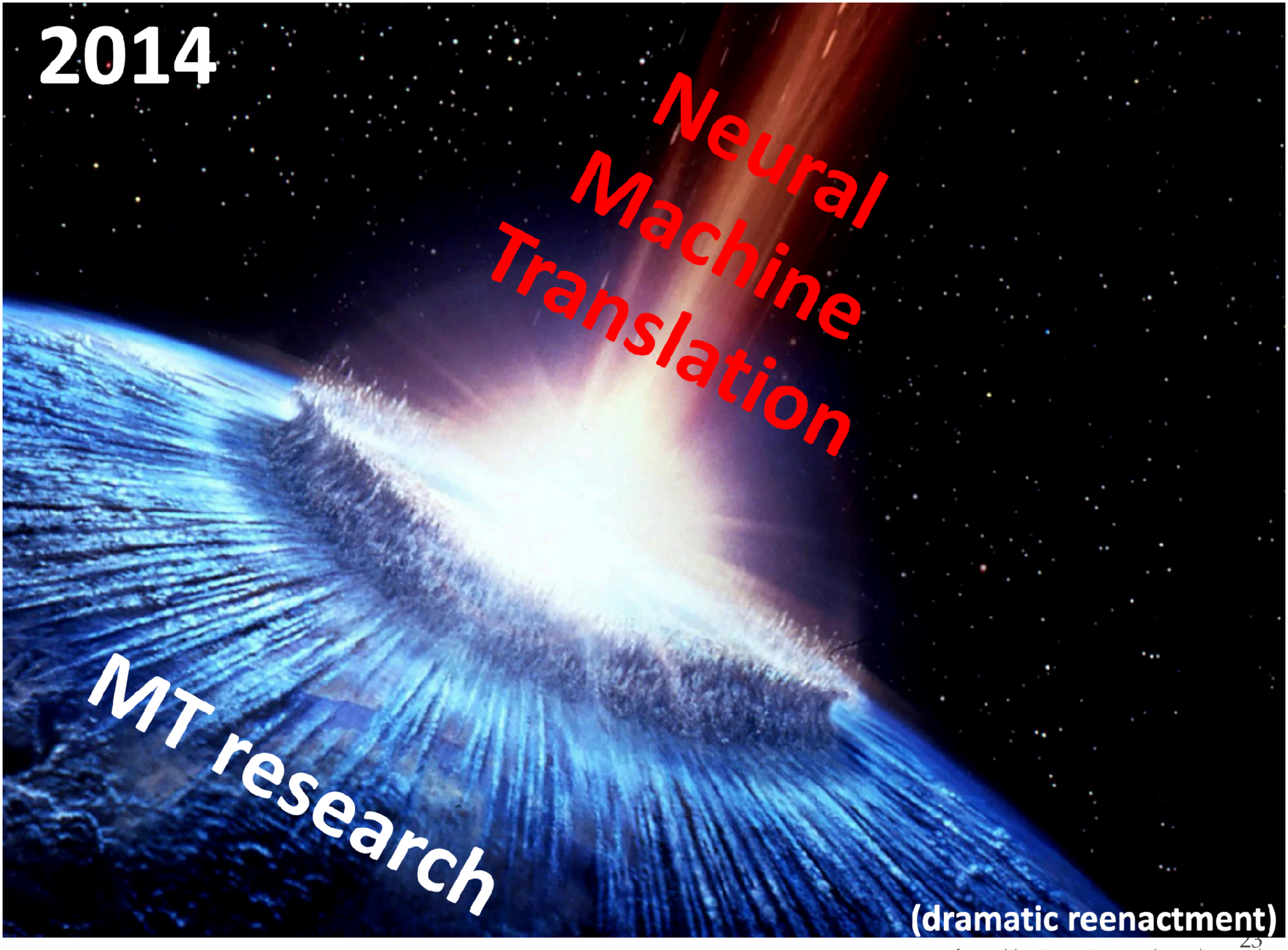
Source: http://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

RNN Neural Machine Translation



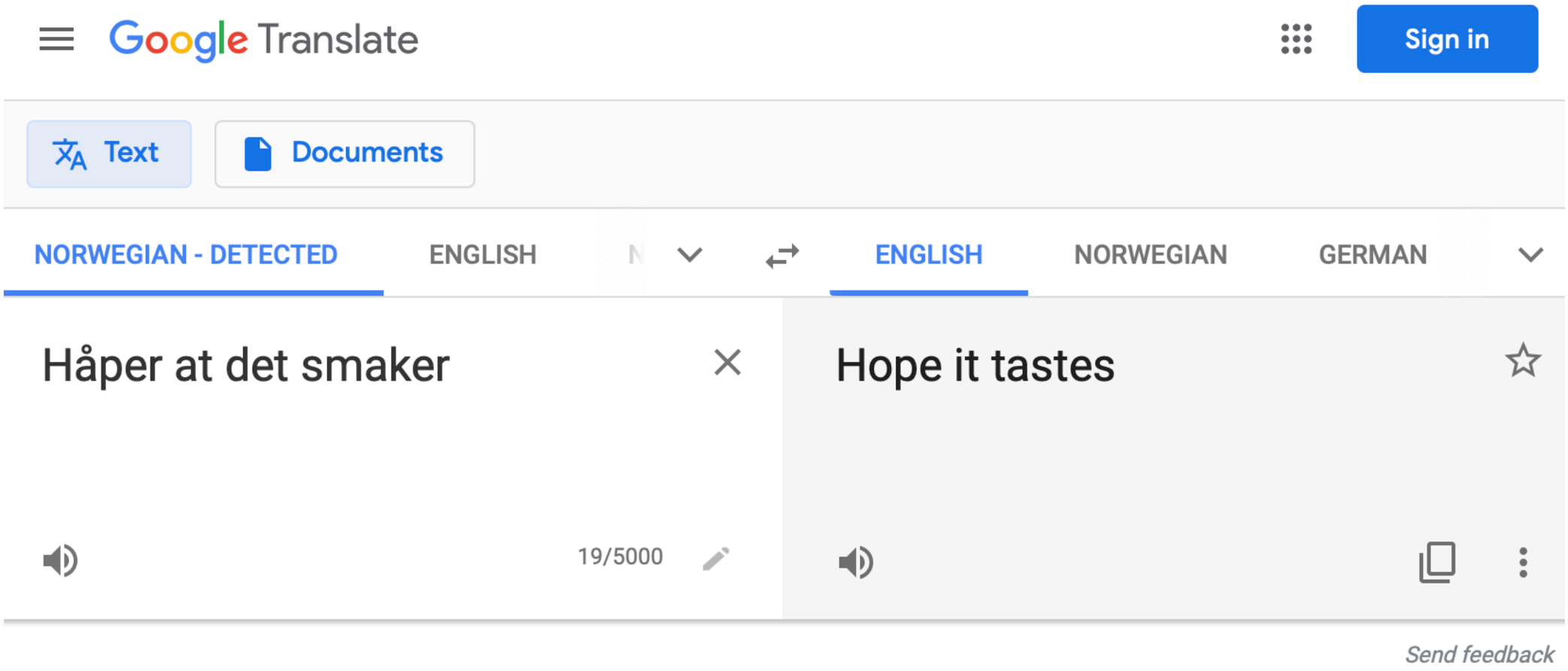
Encoder RNN produces an encoding of the source sentence.

Decoder RNN is a Language Model that generates target sentence, *conditioned on encoding*.



Source: https://web.stanford.edu/class/cs224n/

Is Machine Translation Solved?



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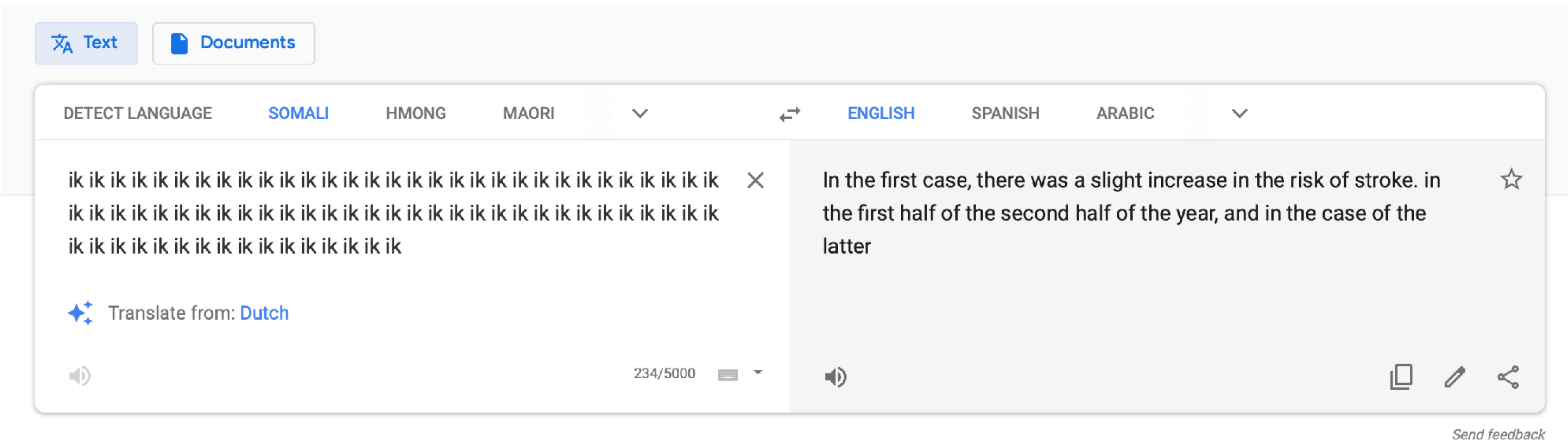

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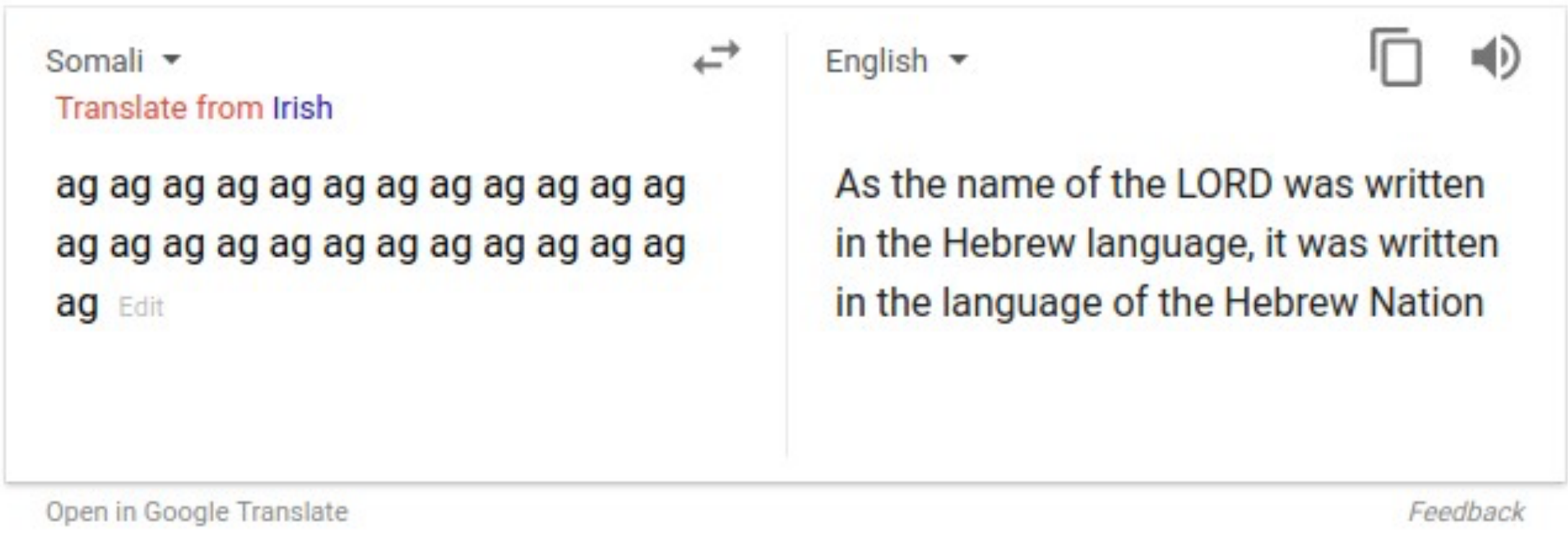
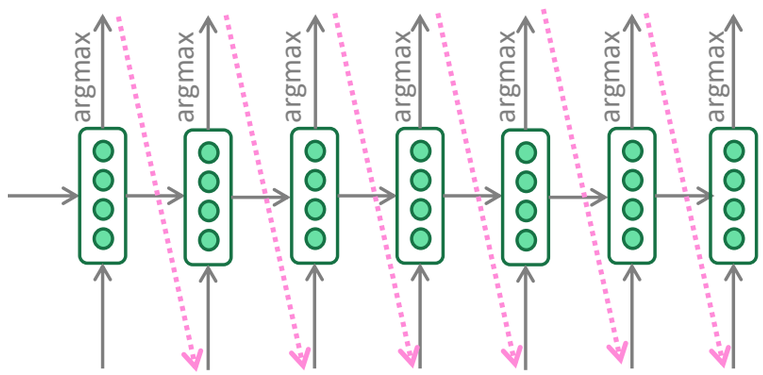
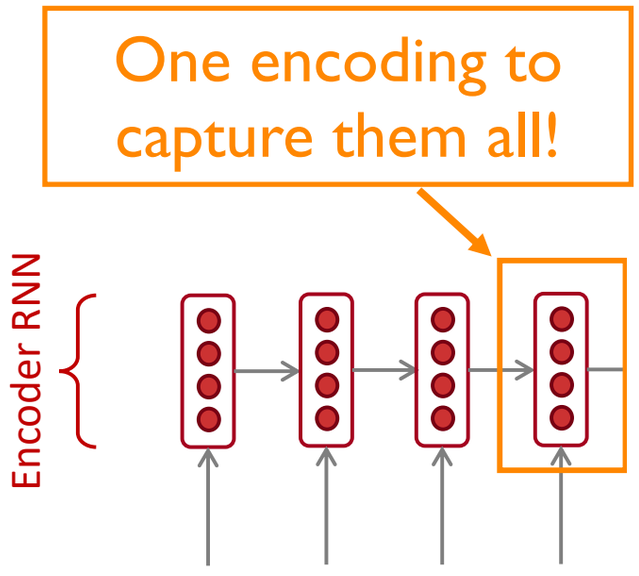


Source: https://www.skynettoday.com/briefs/google-nmt-prophecies

Problems with RNN NMT

- Decoding problem: is choosing best candidate at each time step optimal ?
  - Problem of decoding – argmax not good enough
    - Solution: **Beam search** (beyond the scope for today)
- Bottleneck problem: Encoding everything into one vector
  - **Long sentences and distant contexts**





Seq-to-Seq Bottleneck Problem

"You can't cram the meaning of a whole %&!$ing sentence into a single $&!*ing vector!"

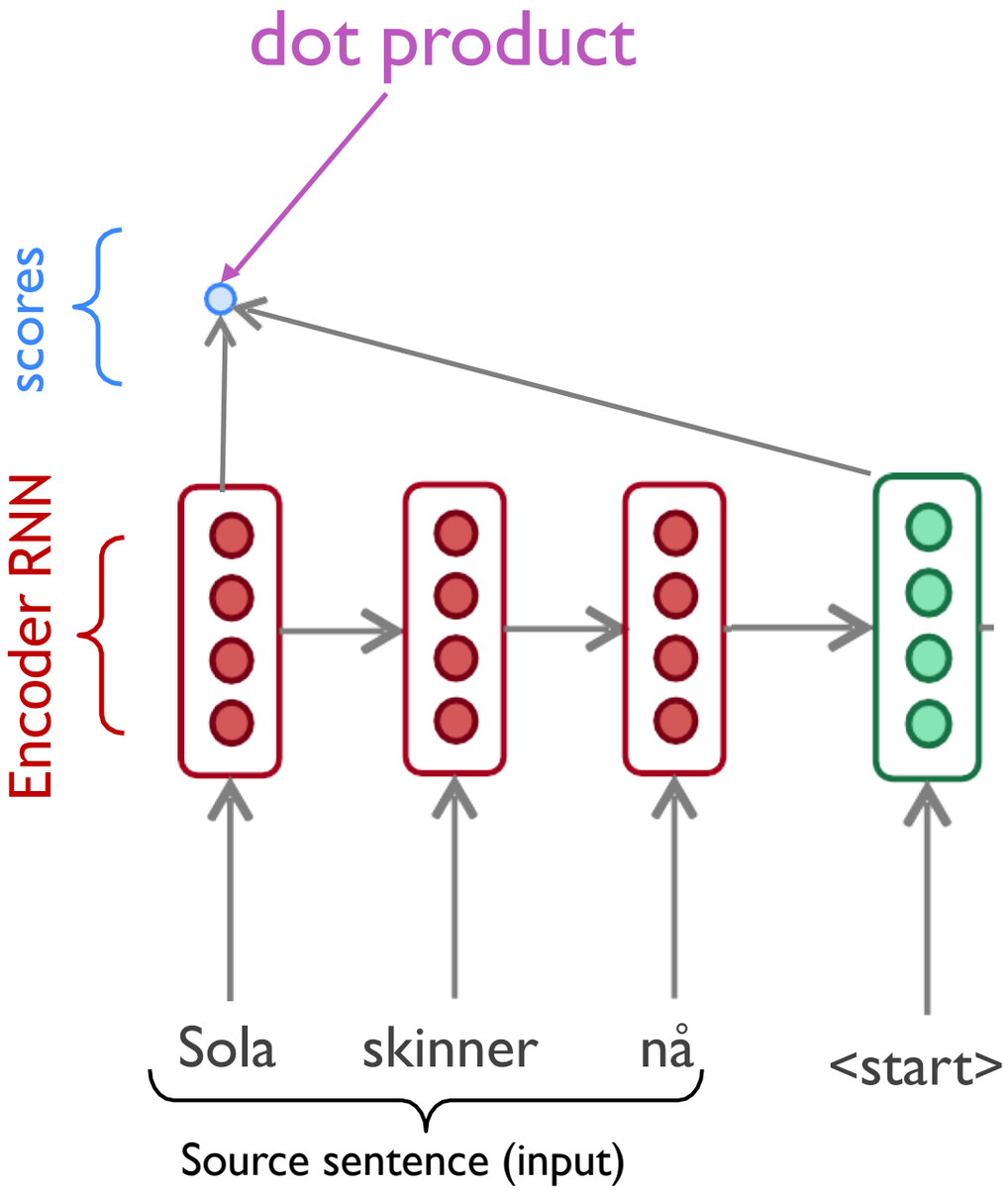
Ray Mooney

- How to solve the bottleneck problem?
  - Given an already decoded output we should be able to refer back to the original statement
- Problem of memory
  - Decoder can't remember all the information from the single encoding of the source sentence

Attention Mechanism

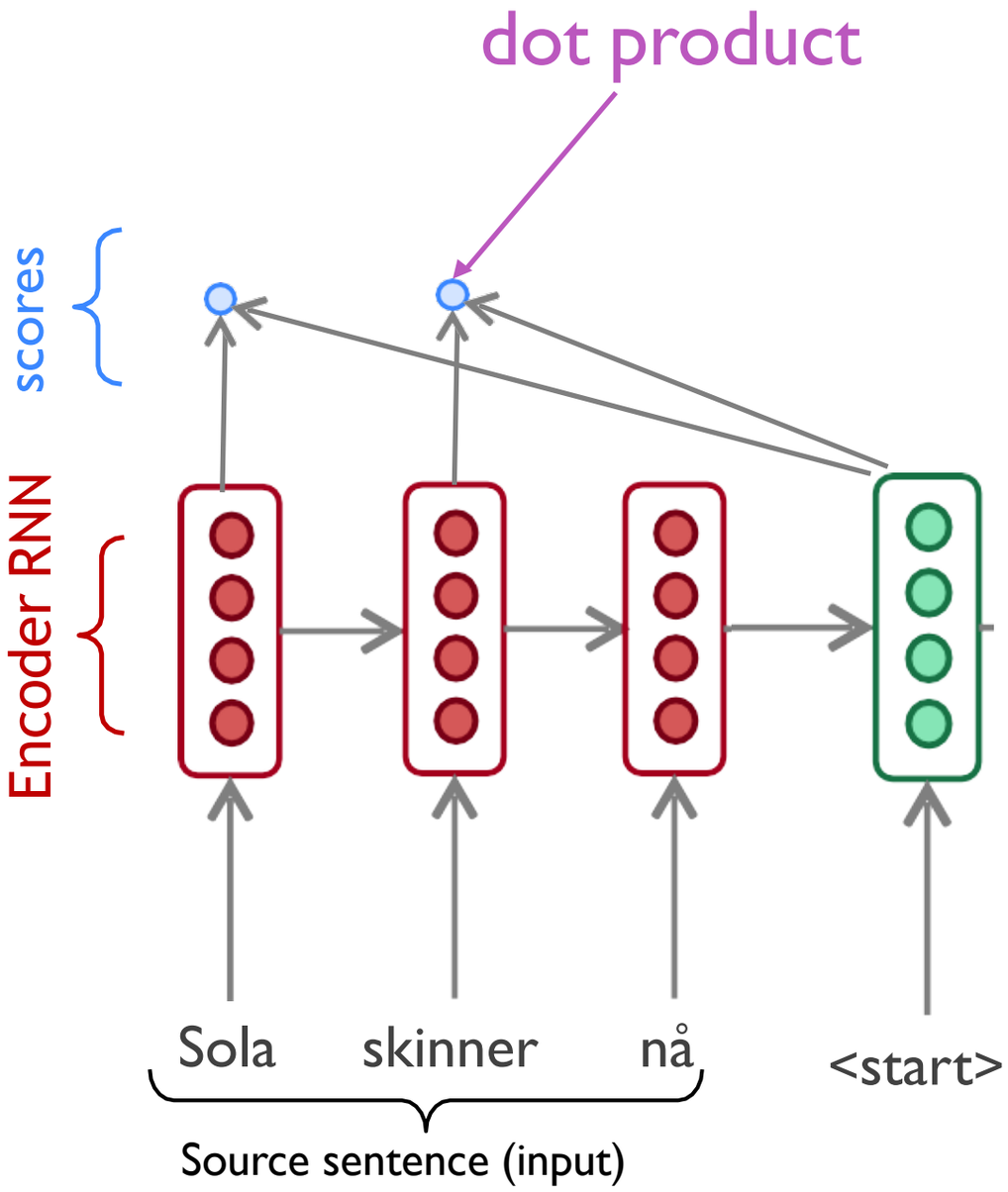
- Attention research is an enormous field with a long history in **cognitive neuroscience**
  - Humans do not process all sensory inputs to make a decision
  - We **focus on small fraction of inputs**
- **Attention mechanism in seq2seq models**
  - Provides solution to the bottleneck problem
  - Allows the decoder to **focus on part of the source sequence** at each time step

Seq2Seq with Attention



Encoder RNN produces an encoding of the source sentence.

Seq2Seq with Attention



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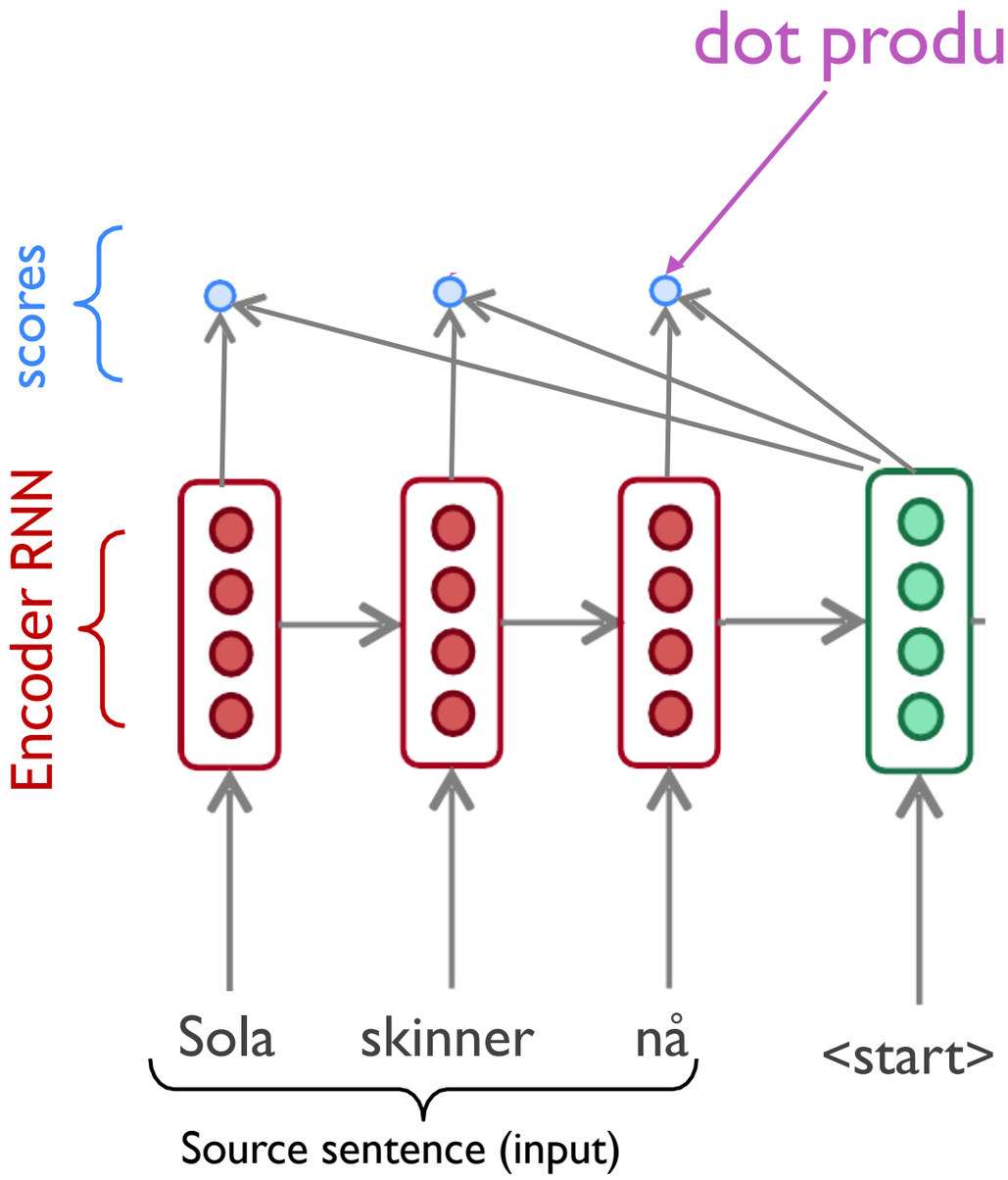

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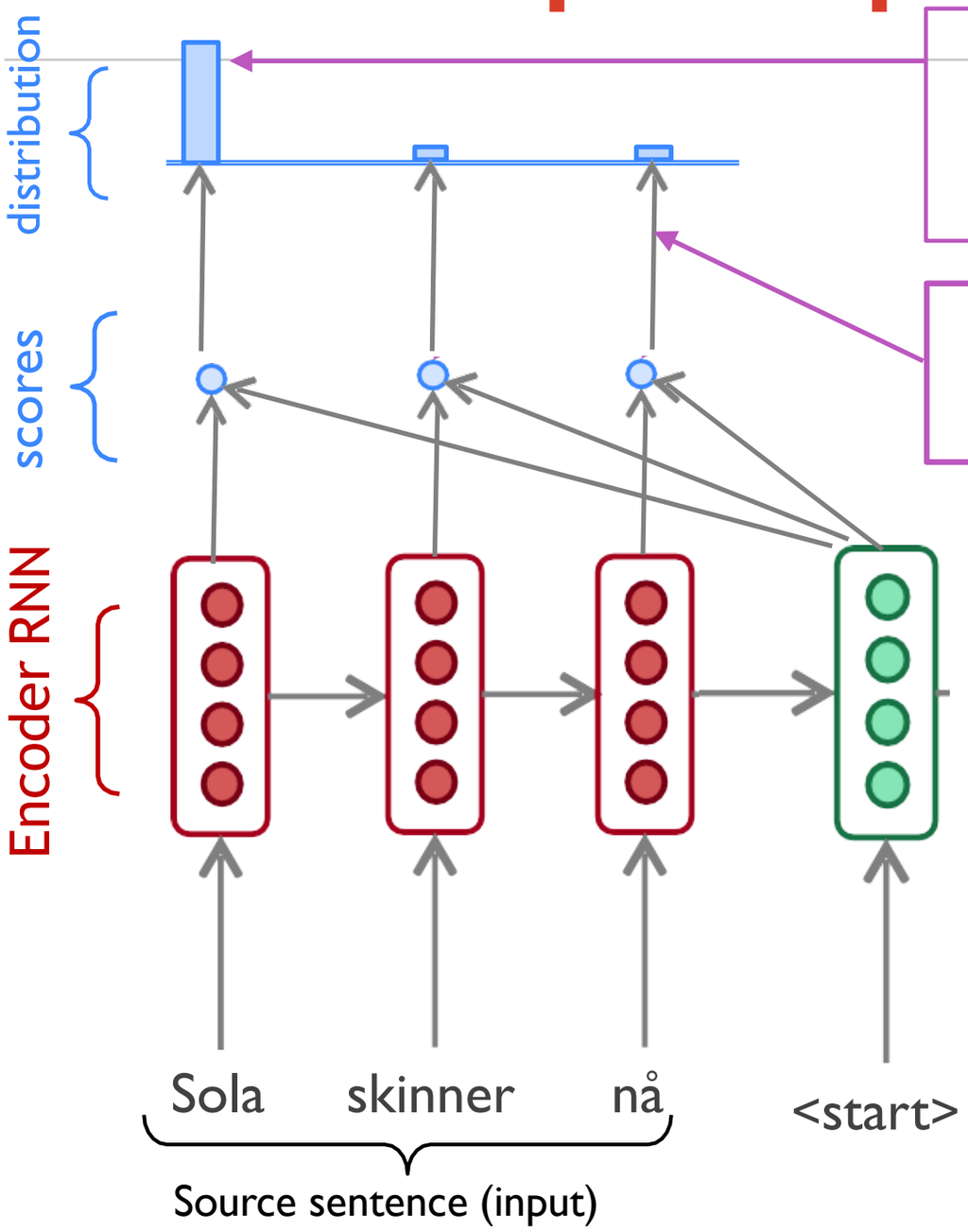
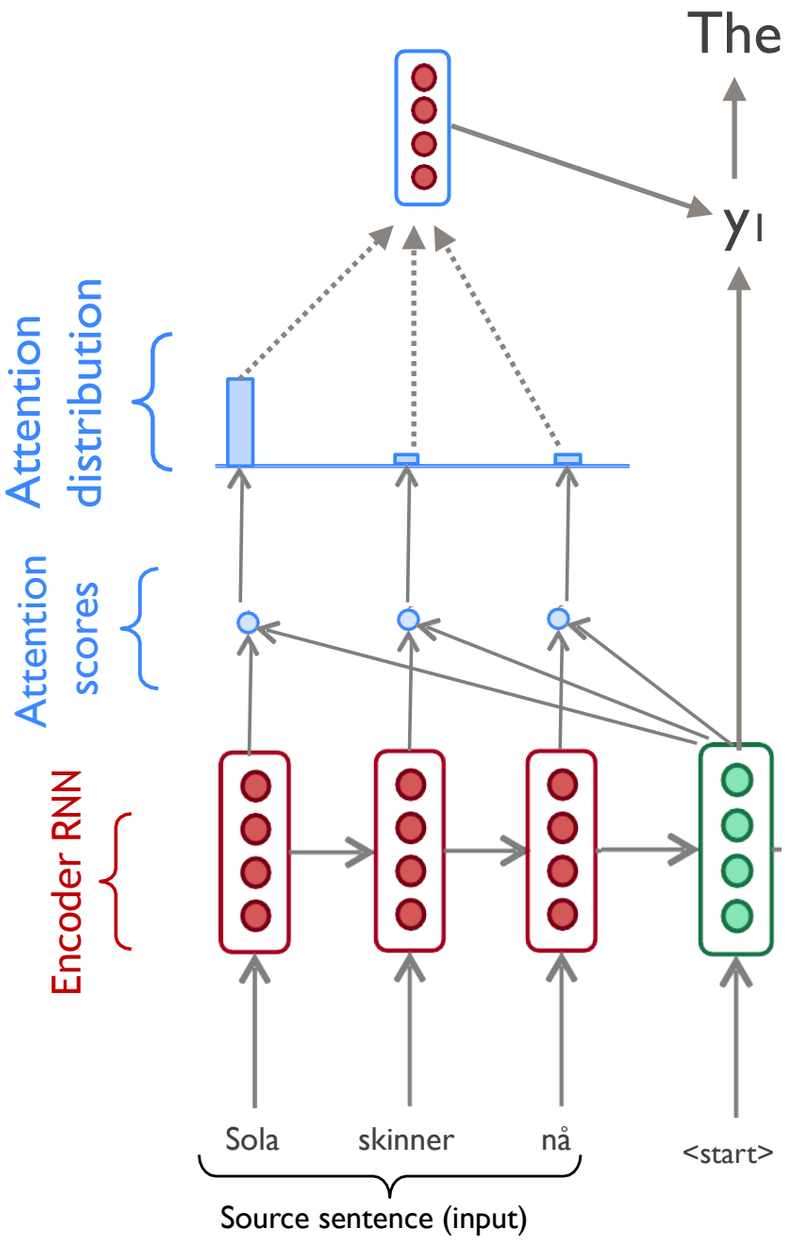


On this decoder timestep, we're mostly focusing on the first encoder hidden state (*"The sun"*)

Take softmax to turn the scores into a probability distribution

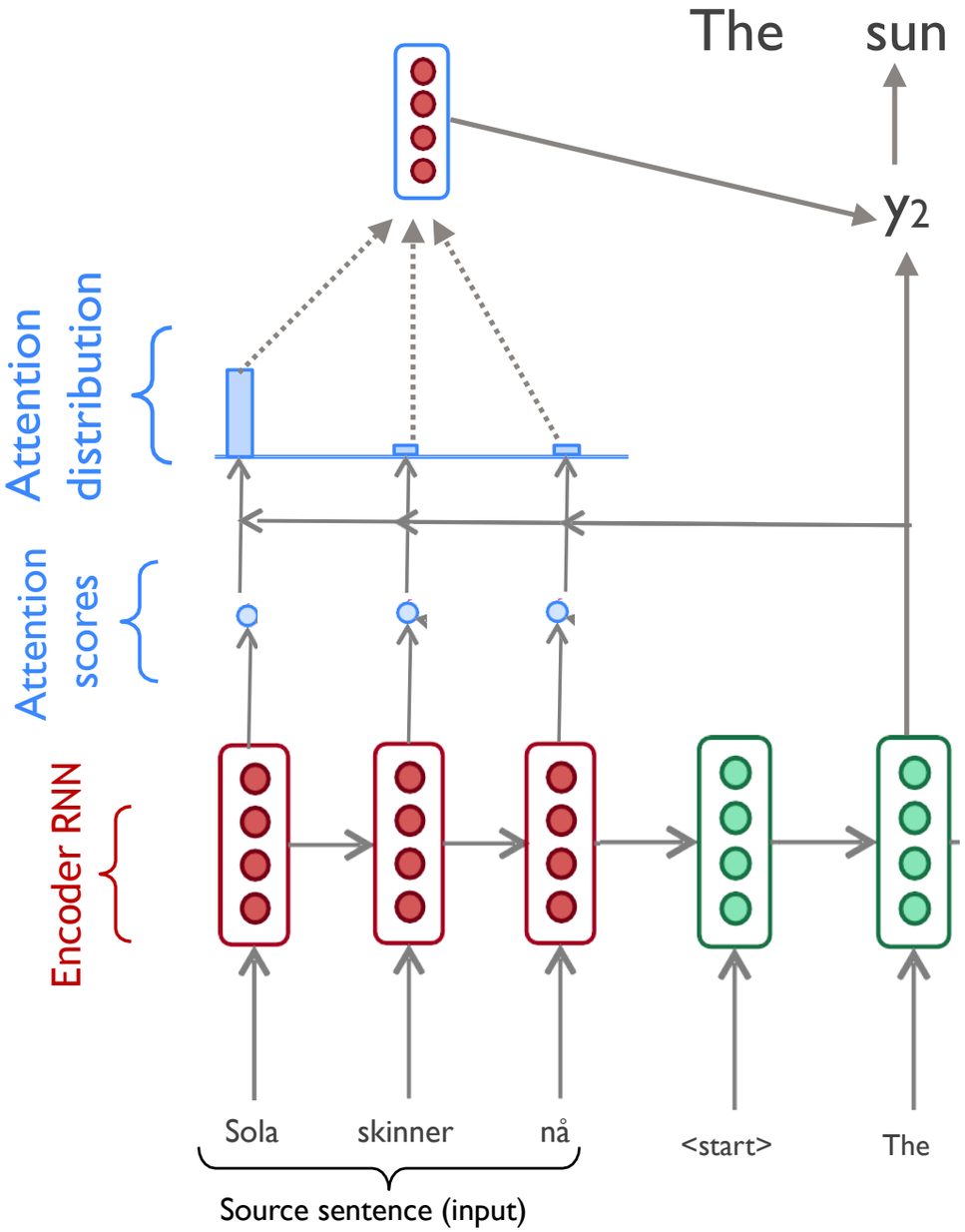
Encoder RNN produces an encoding of the source sentence.

Seq2Seq with Attention



Concatenate attention output with decoder hidden state, then use to compute as before

Seq2Seq with Attention



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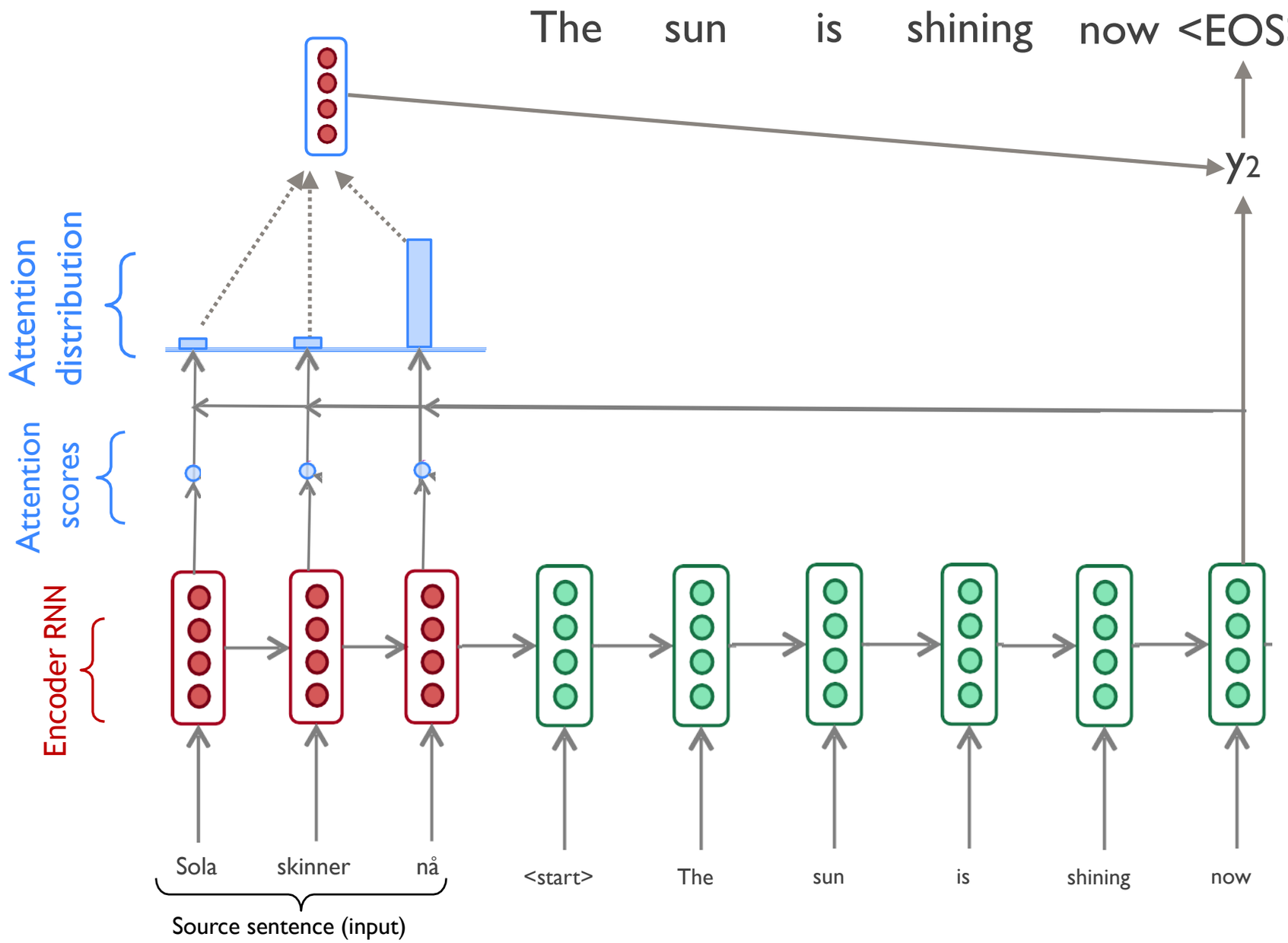


Attention in General Deep Learning

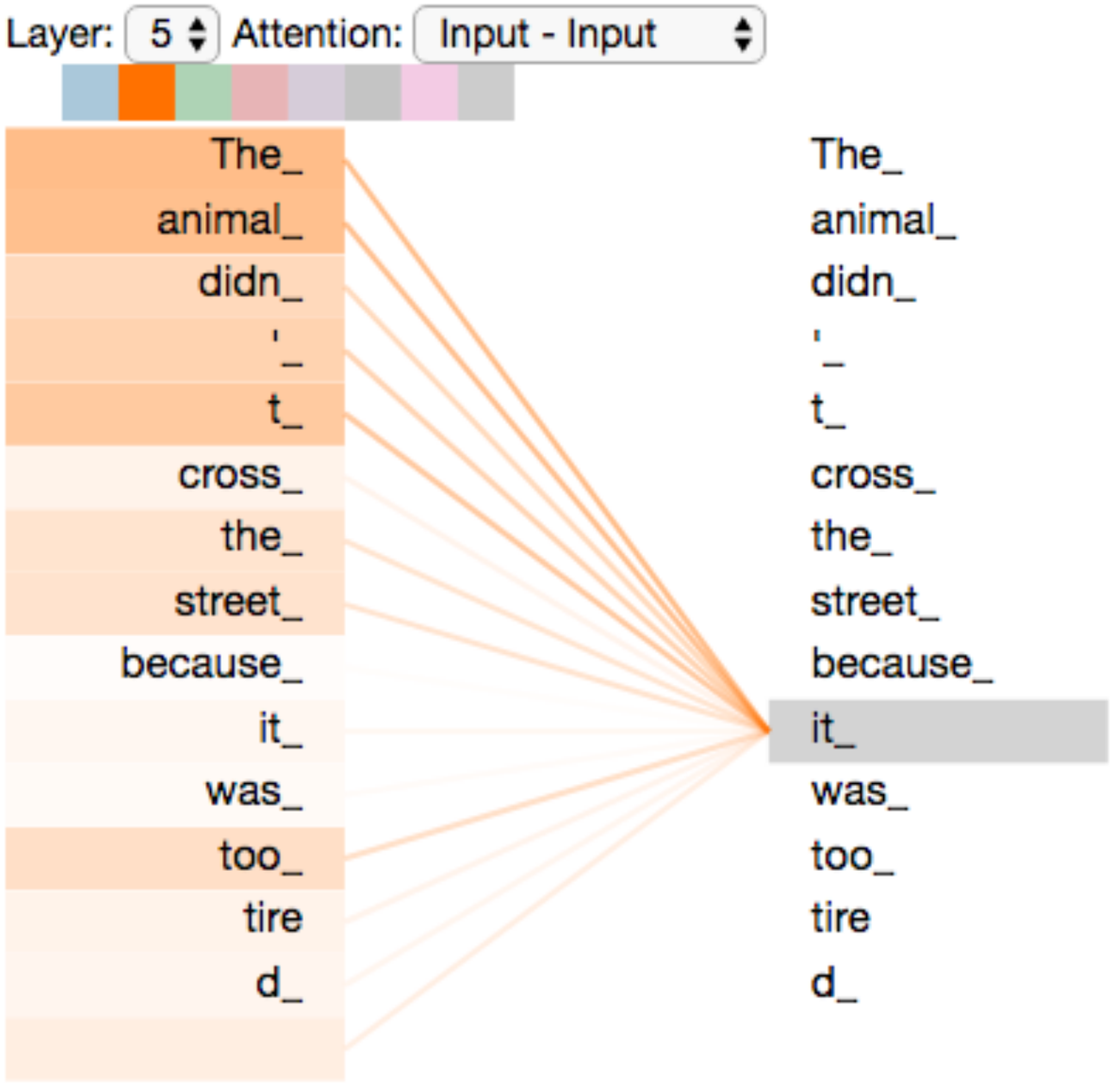
- Attention is not specific to Seq-to-Seq models or NMT tasks
- General Definition

> Given a set of vector values, and a vector query, attention is a technique to compute a weighted sum of the values, dependent on the query.

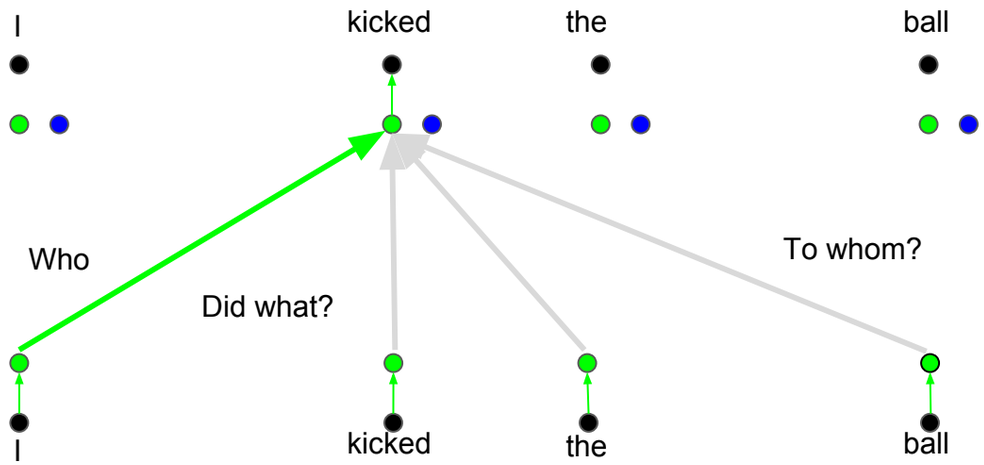
- The query attends to the values
- In Seq2Seq models each decoder hidden state (query) attend to all the encoder hidden state (values)

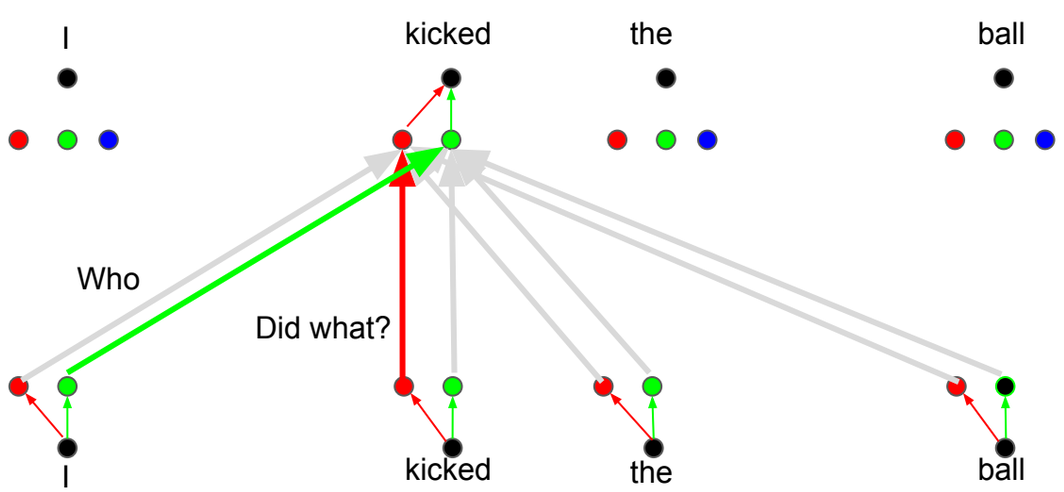
Self-Attention

- ”The animal didn't cross the street because it was too tired”
- What does “it” in this sentence refer to?



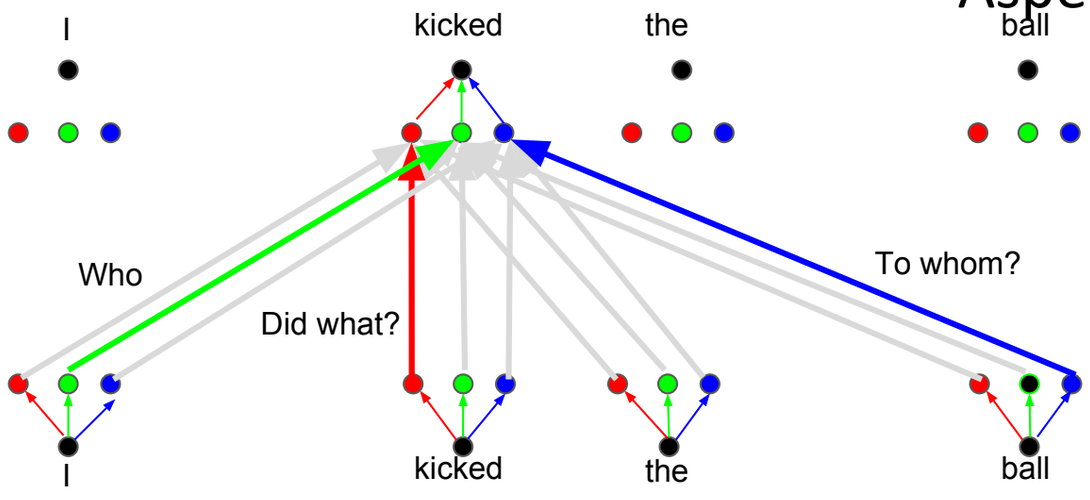
Multi-head Attention





Aspect: “who”

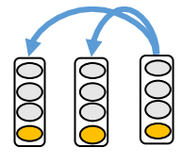
Aspect: “did what”



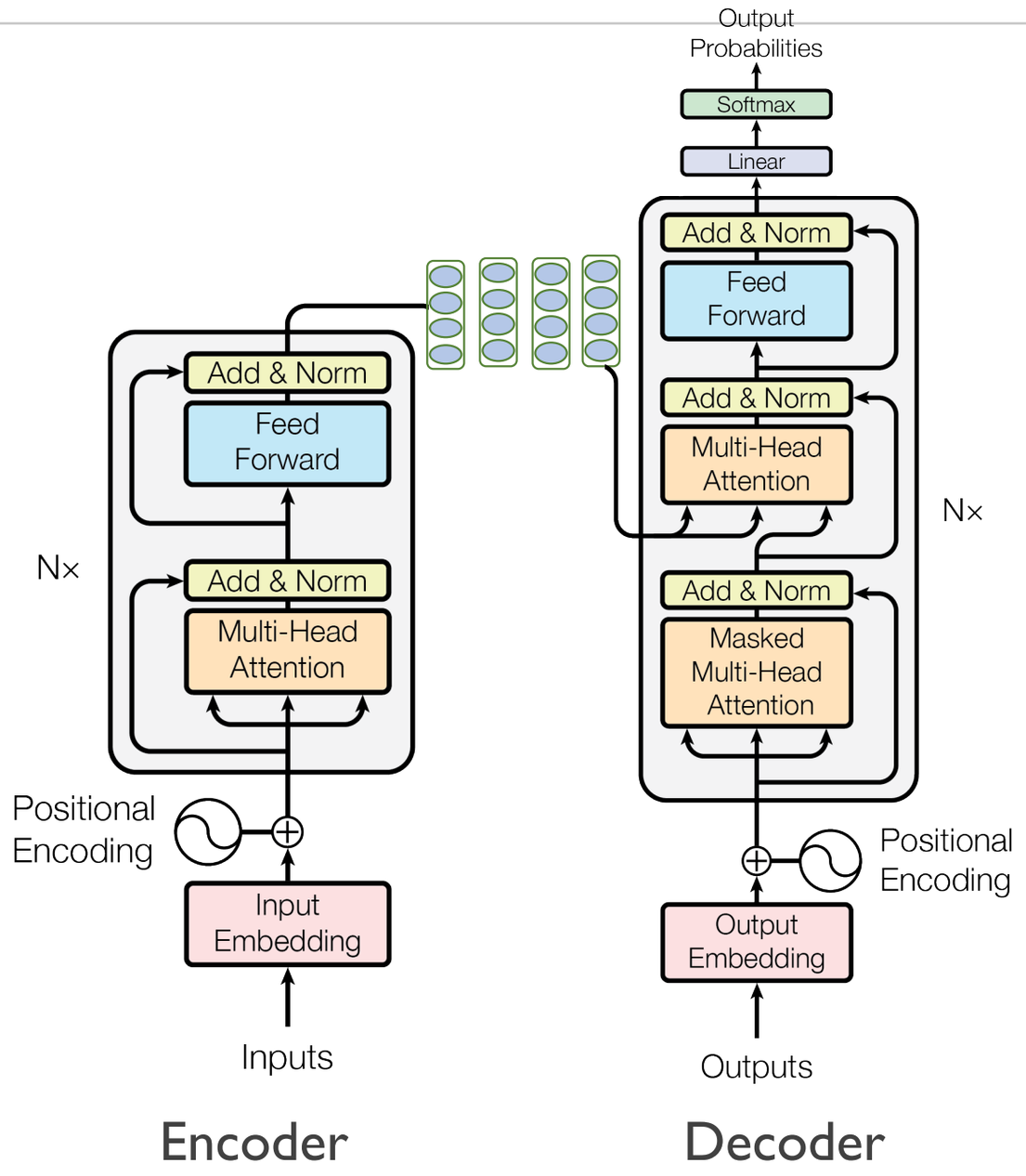
Aspect: “to whom”

Transformer Attention

- Uses three types of attention
  - Encoder-decoder attention
  - Self-attention
  - Masked attention
    - Used in decoder
    - Only attends to the past words



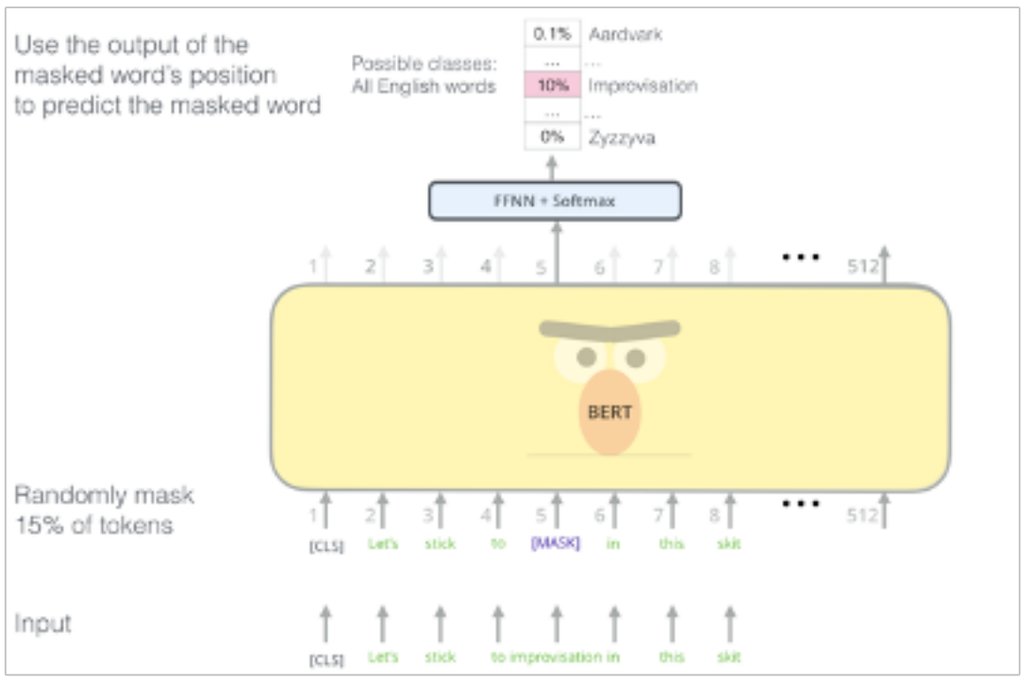
- Incorporates the position information through position encoding



BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

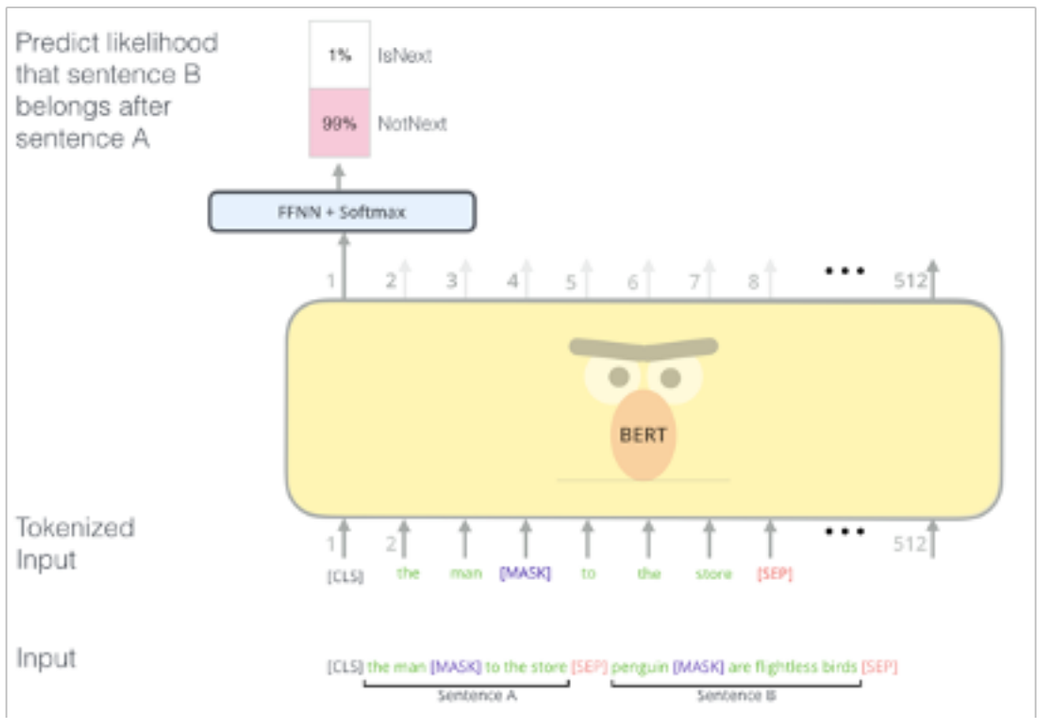
Masked word prediction

- Given a sentence with some words masked at random, can we predict them?
- Randomly select 15% of tokens to be replaced with "<MASK>"



Next sentence prediction

- Given two sentences, does the first follow the second? Teaches BERT about relationship between two sentences
- 50% of the time the actual next sentence, 50% random



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