Deep Learning

Lecture 7: Sequential Models

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Lecture Overview

❶ Recurrent neural networks

- Definition and implementation
- Backpropagation through time
- vanishing/exploding gradients

❷ Long short-term memory

- Definition
- Properties
- Seq2Seq
- Attention

❸ Transformers

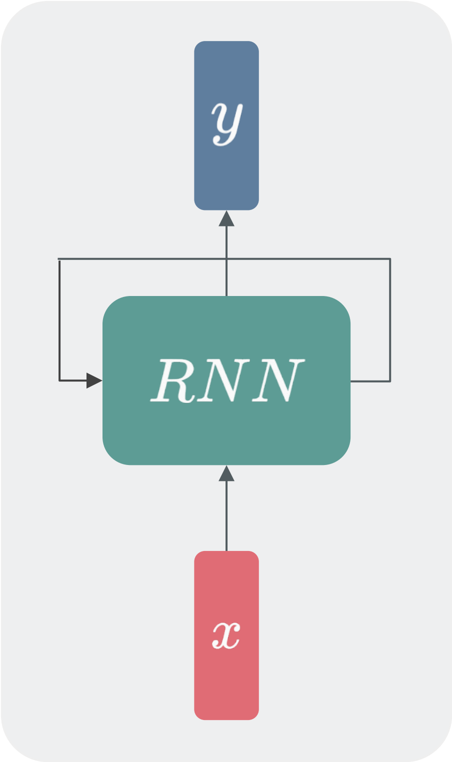
- Self-Attention
- End-to-end object detection
- GPT
- DALL-E

Recurrent Neural Networks Definition

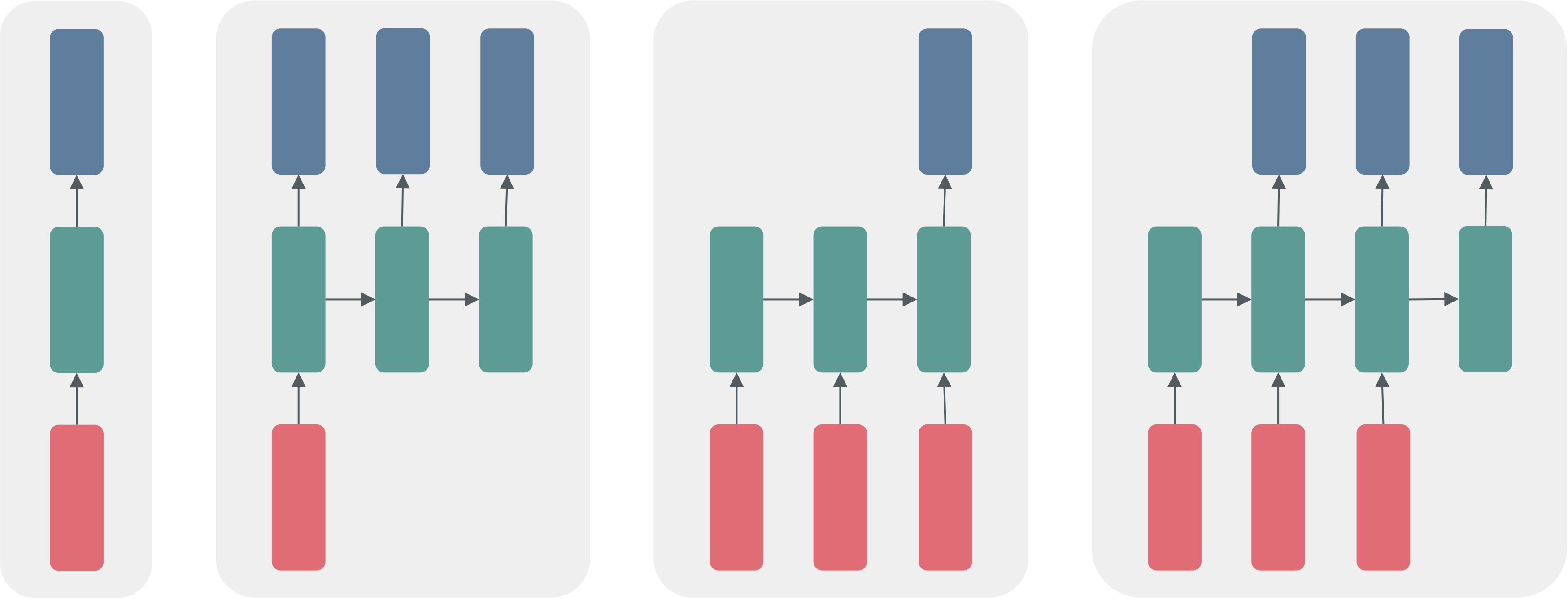
Definition: recurrent neural networks

A function applied to nodes on a directed graph. *Unlike* one-way directed graphs (e.g. text, audio), sequential data is modelled using a cyclic connection that allows information to be stored [Rumelhart et al., 1986]. The same function f is applied to inputs at each time step, updating a hidden state vector h which acts as the network's memory:

$$h_{t+1} = f_\theta(h_t, x_t)$$



Computational Graphs



One-to-One

Feedforward network

One-to-Many

e.g., image captioning

Many-to-One

e.g., sentence classification

Many-to-Many

seq2seq

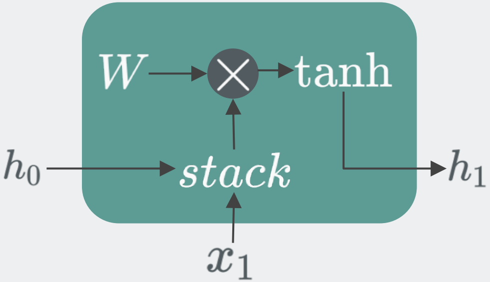
Recurrent Neural Networks Implementation

Example: RNN

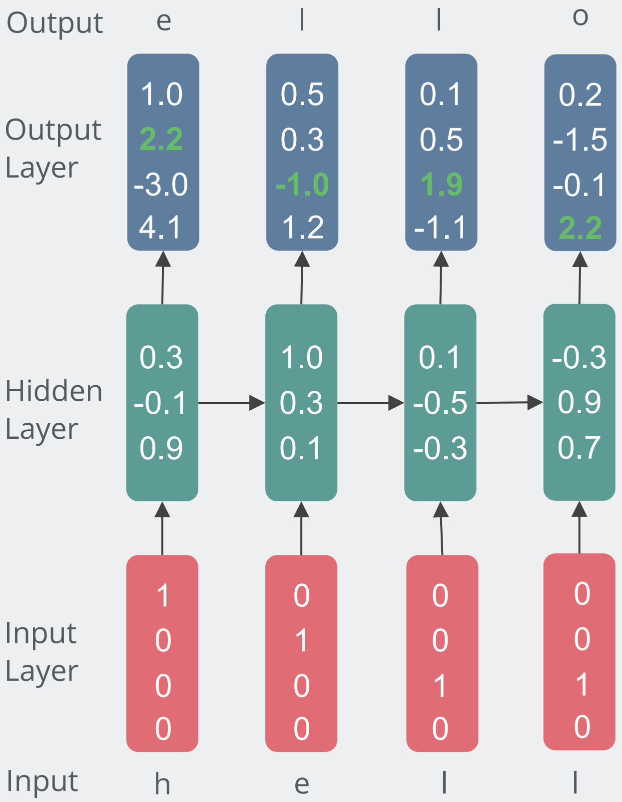
A simple implementation is:

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

which is visually interpreted as a "cell":



$$P(\mathbf{x}) = \prod_t P(x_t | x_{t-1}, x_{t-2}, \ldots, x_1)$$



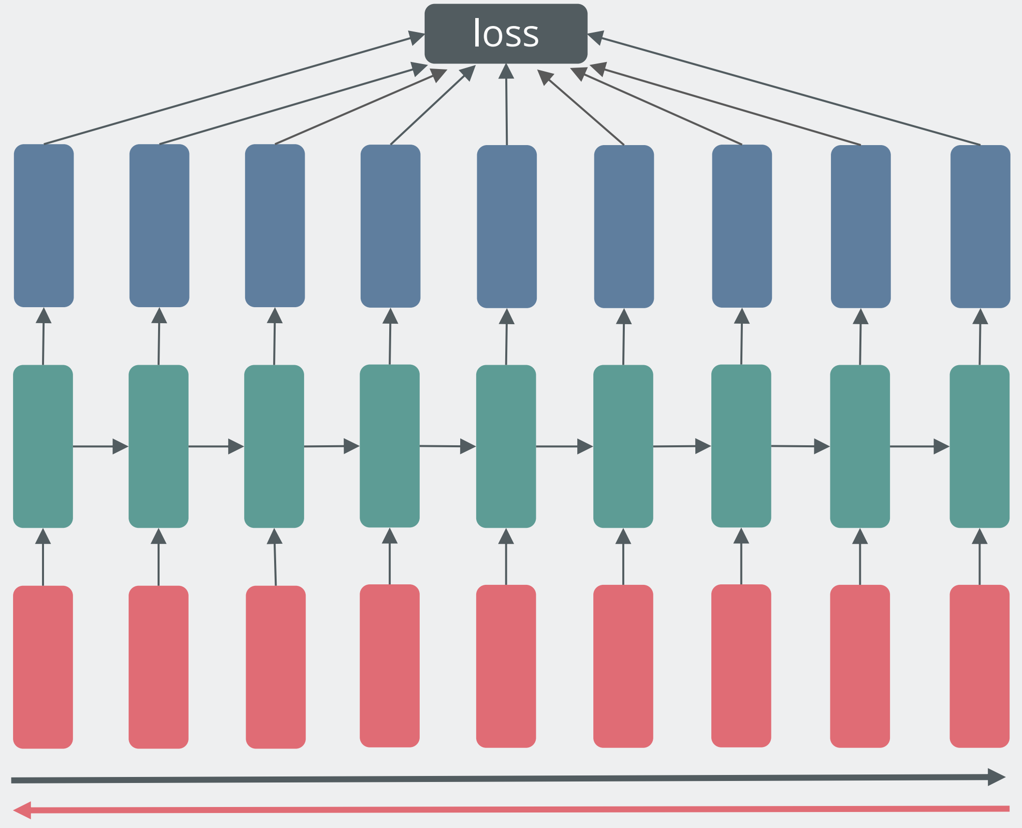
Recurrent Neural Networks Backpropagation

Definition:

Backpropagation applied to an **unrolled** RNN is called backprop through time (BPTT). Gradients accumulate in W additively:

$$\frac{\partial \mathcal{L}_T}{\partial W} = \sum_{t \leq T} \frac{\partial \mathcal{L}_T}{\partial h_t} \frac{\partial h_t}{\partial W}$$

Long sequences use truncated BPTT where sequences are split into batches but hidden connections remain.



Let's Look at Some Code!

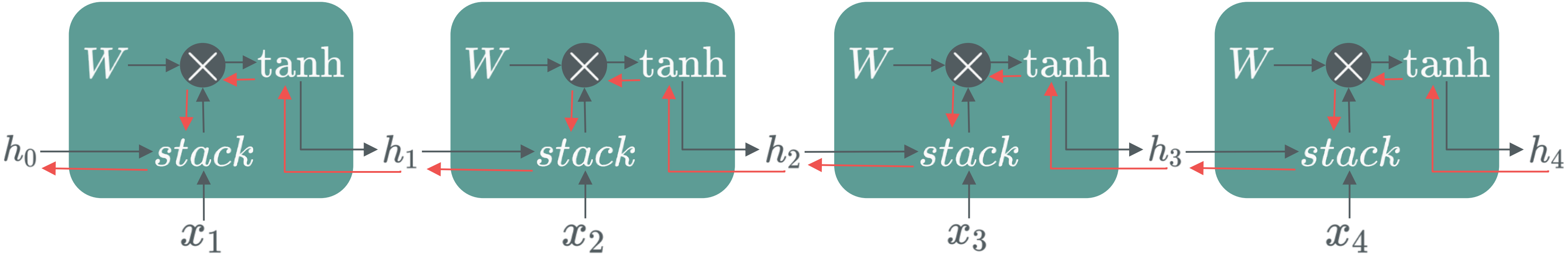
Simple RNN Example for Text Classification

Code on GitHub : https://github.com/atapour/dl-pytorch/blob/main/RNN_Sentiment_Analysis/RNN_Sentiment_Analysis.ipynb

Code on Colab: https://colab.research.google.com/github/atapour/dl-pytorch/blob/main/RNN_Sentiment_Analysis/RNN_Sentiment_Analysis.ipynb

Recurrent Neural Networks

Exploding and Vanishing Gradients



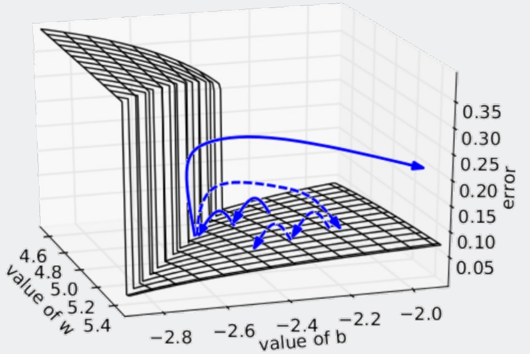
Why do gradients vanish/explode?

The gradient of involves many factors of W (and tanh).

The product of T matrices converges to 0 (or grows to infinity) at an exponential rate in T [2].

$$\frac{\partial \mathcal{L}_T}{\partial W} = \sum_{t \leq T} \frac{\partial \mathcal{L}_T}{\partial h_t} \frac{\partial h_t}{\partial W} = \sum_{t \leq T} \frac{\partial \mathcal{L}_T}{\partial h_T} \boxed{\frac{\partial h_T}{\partial h_t}} \frac{\partial h_t}{\partial W}$$

Solution to exploding gradients: **clip gradients**



Long Short-Term Memory

Preventing Vanishing Gradient

Definition: long short term memory

LSTMs [Hochreiter et al., 1997] learn longer sequences than vanilla RNNs using better gradient flow. Backpropagation from c_t to c_{t-1} has no direct matrix multiplication by W.

Gates determine how much information passes through.

Always adding new information to the hidden state can be overwhelming.

Sometimes we want to forget things!

Gates control how much information is passed through using a sigmoid function and an element-wise multiplication.

Example: LSTM cell

Long Short-Term Memory

Properties

LSTM Properties

Main Strengths

- Allows for variable length sequences
- Efficient parameter usage
- Theoretically able to store arbitrarily old information

Main Limitations

- Practically unable to store very long term dependencies
- Limited by fixed size of hidden state
- Slow training and synthesis

Further Reading:

https://karpathy.github.io/2015/05/21/rnn-effectiveness/

Seq2Seq Architecture

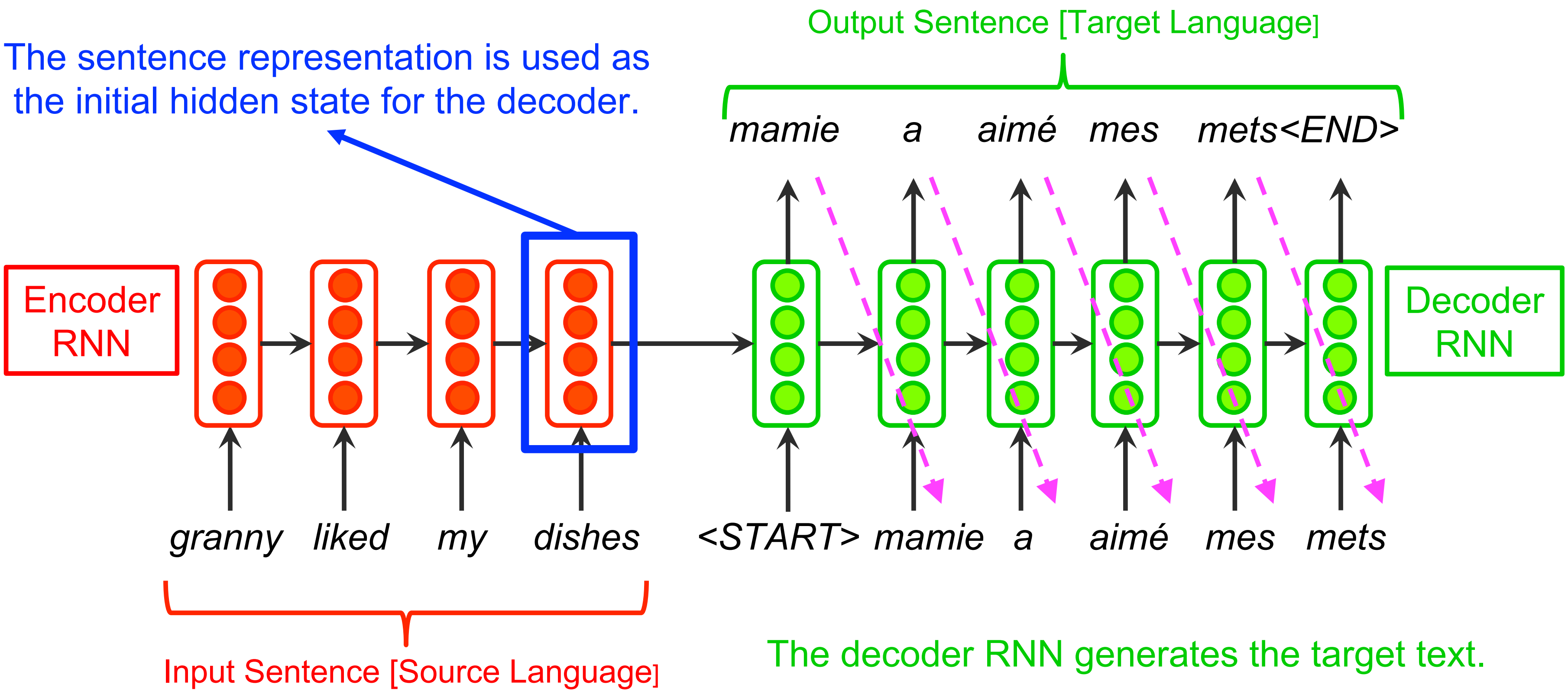
Natural Language Processing

- Seq2Seq (sequence to sequence) receives a sentence as the input and produces a sentence as the output.
- Seq2Seq will include two networks, one encoder and one decoder.
- An example of this would be "**Machine Translation**":

Source Sentence	(English)	*granny liked my dishes.*
		↓
Target Sentence	(French)	*mamie a aimé mes mets.*

Seq2Seq Architecture Machine Translation

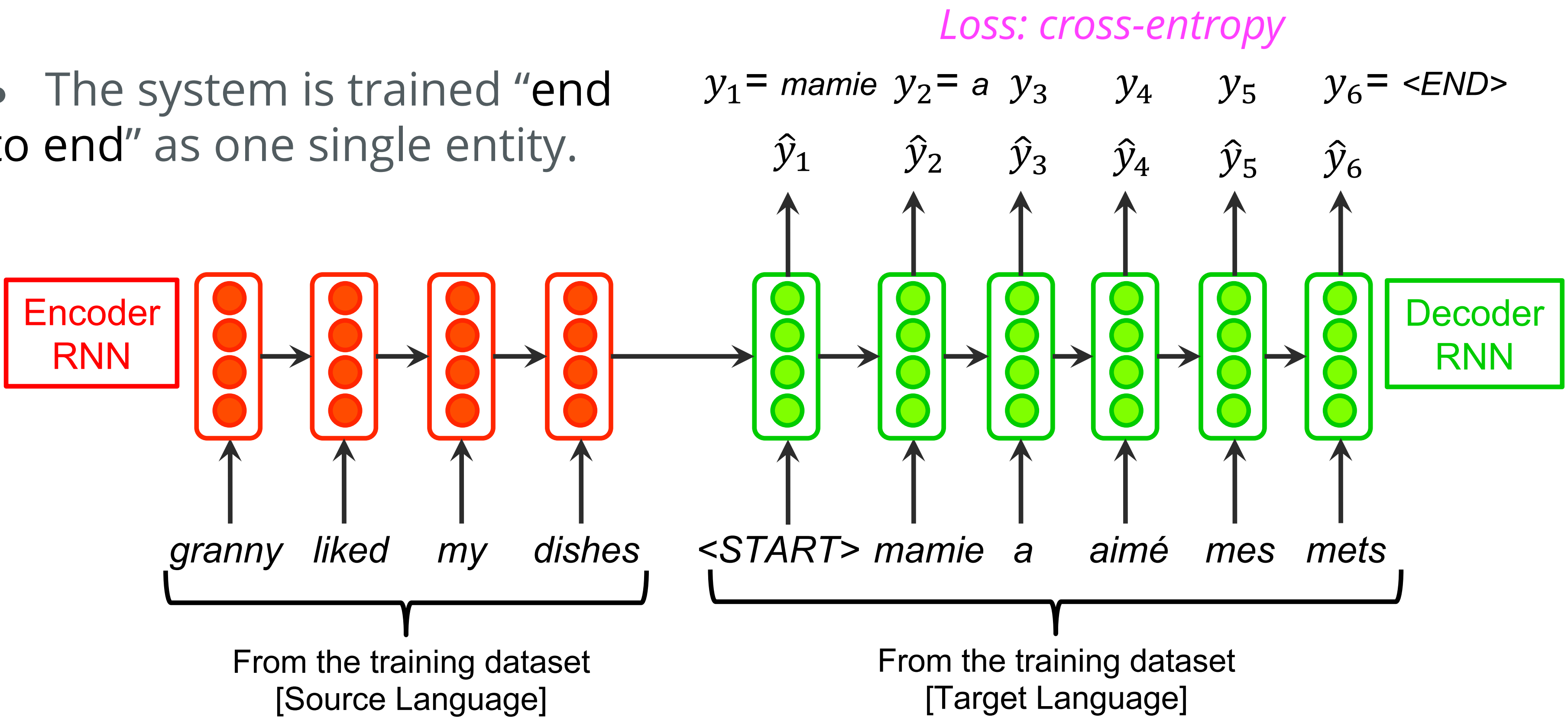
- Let's see how inference works. We will take about the training later.



Seq2Seq Architecture
Machine Translation

- Now, let's see how we would train this.

- The system is trained "end to end" as one single entity.

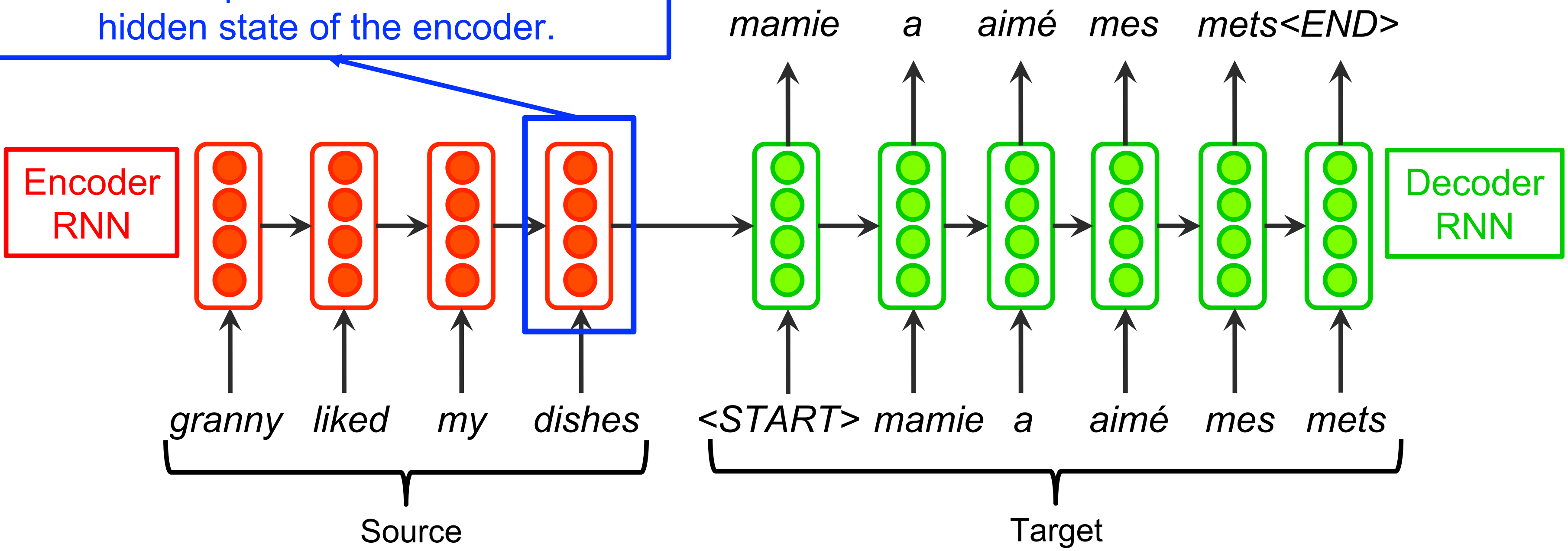


Seq2Seq Architecture Issue

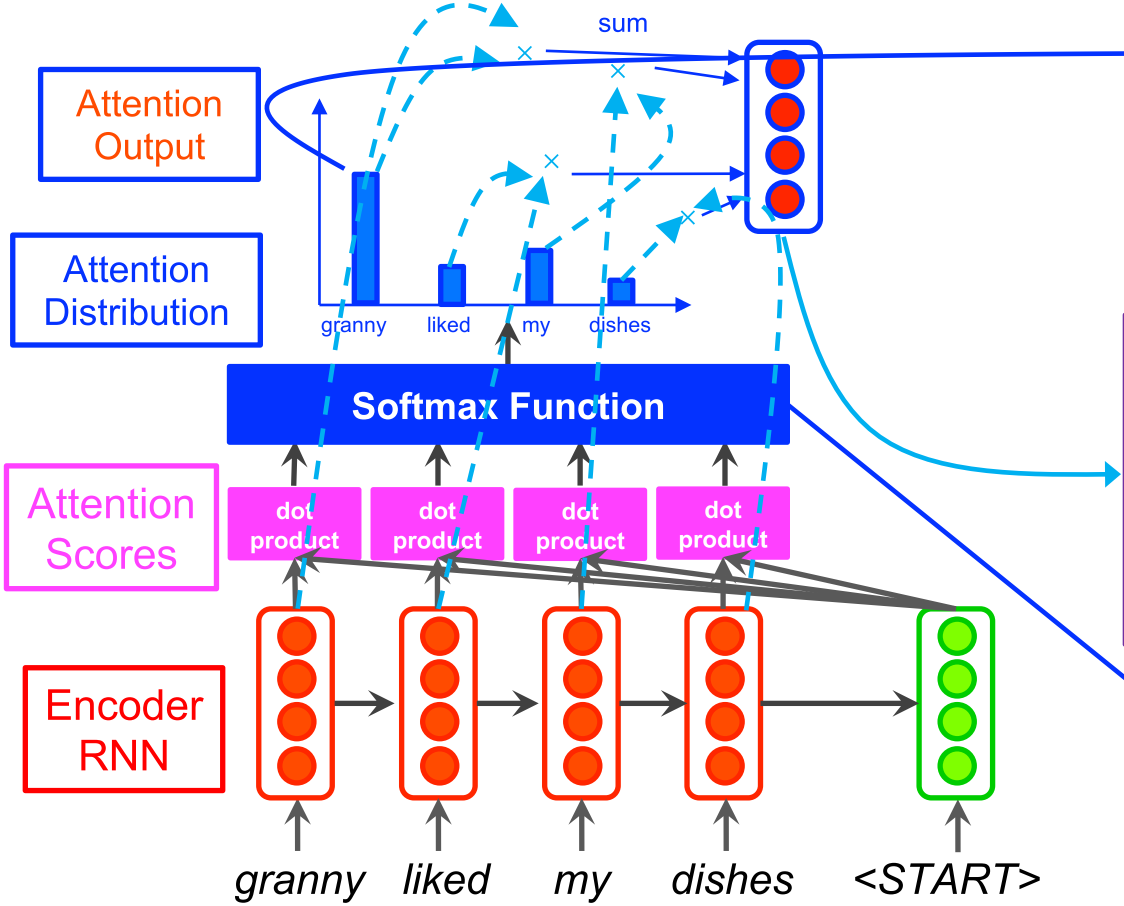
Solution: **Attention**

Informational Bottleneck:
too much pressure on a single vector

The entirety of the source sentence should be represented within the final hidden state of the encoder.



Seq2Seq with Attention

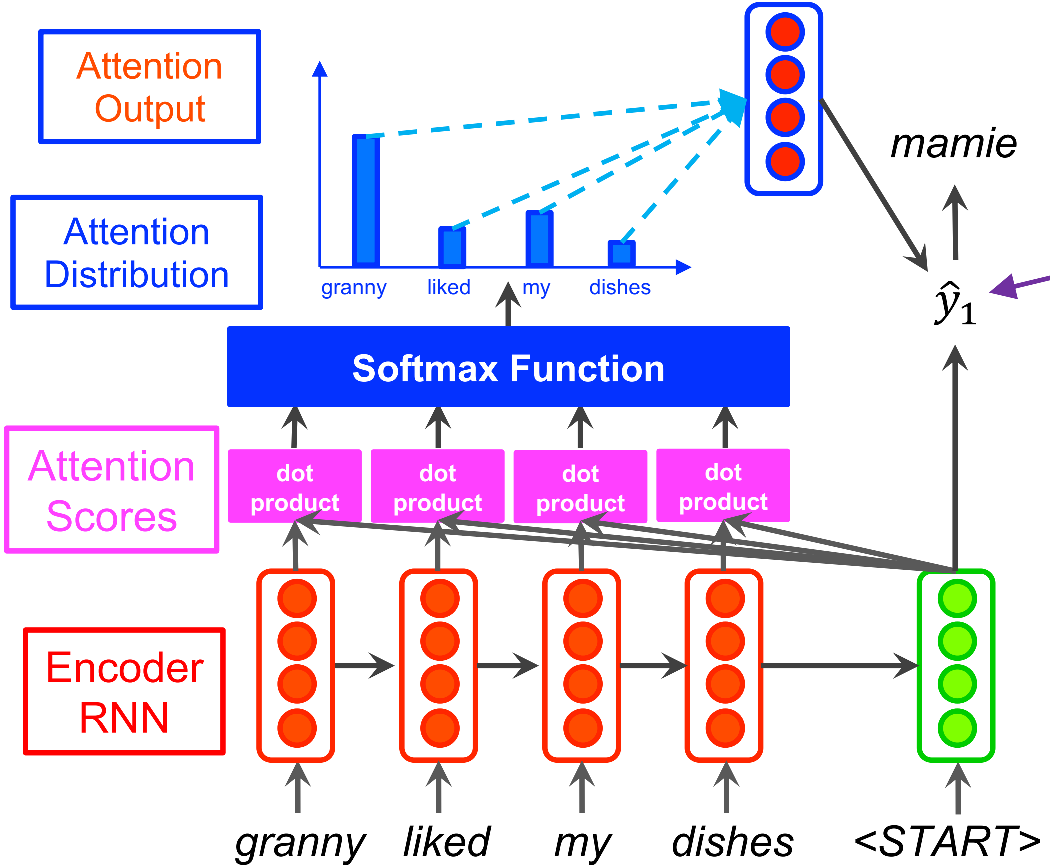


At this timestep, the decoder is **focusing** more on "granny" but could depend on information from other words as well.

Use the attention distribution to take a **weighted sum** of the encoder hidden states. Most of the information comes from hidden states that received higher attention levels.

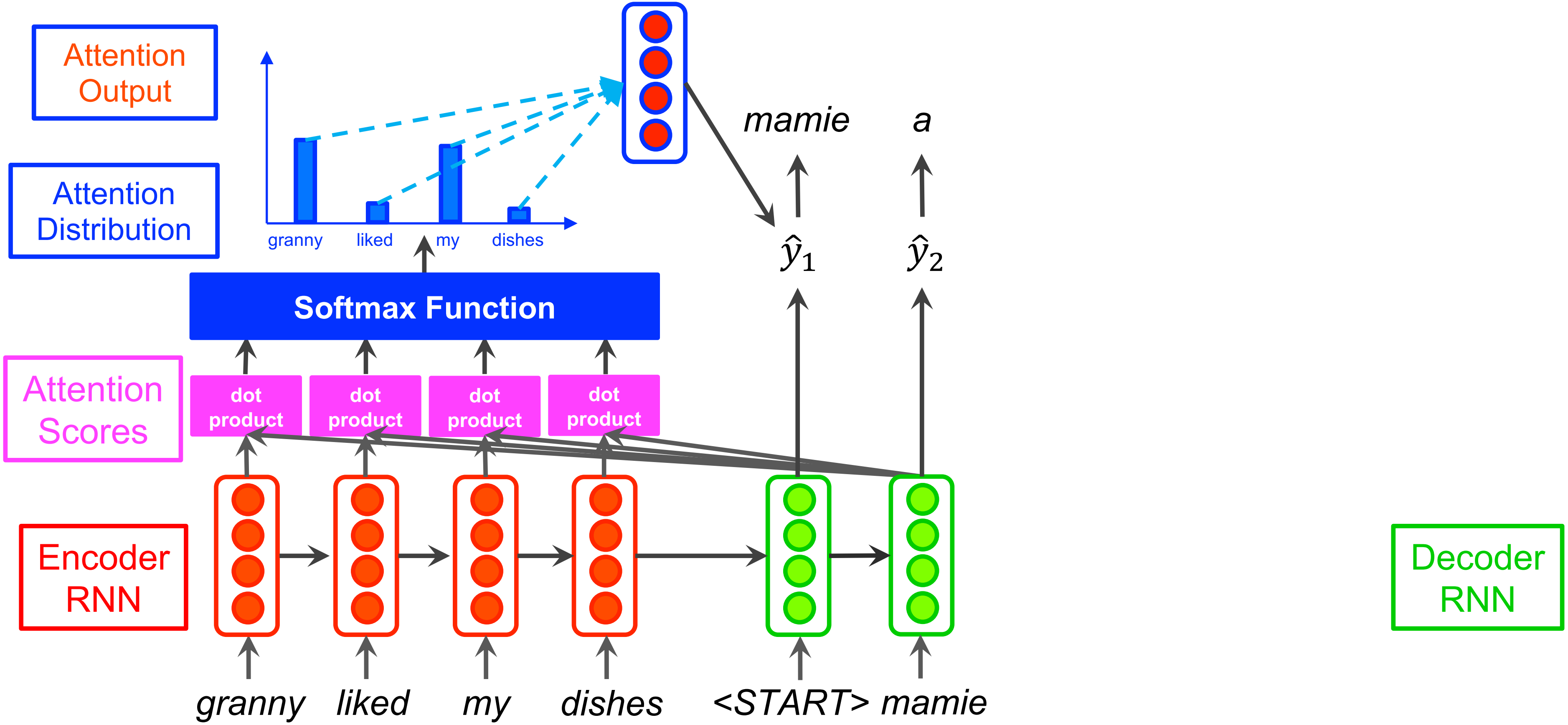
The scores are turned into a probability distribution.

Seq2Seq with Attention

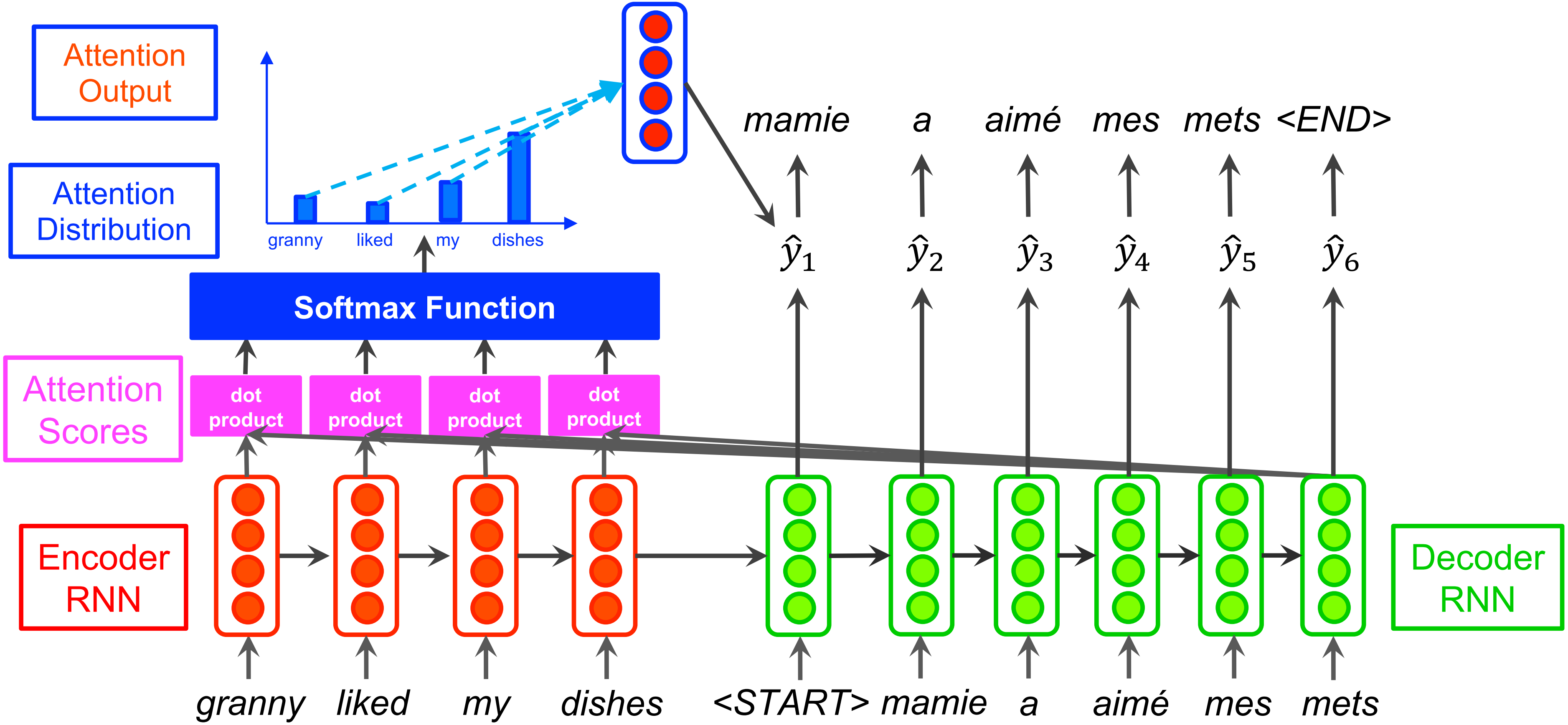


We concatenate the attention output with the decoder hidden state and use the result to obtain $\hat{y}_1$ as we did before.

Seq2Seq with Attention



Seq2Seq with Attention



Attention

Definition and Calculation

1. Encoder hidden states: $h_1, \dots, h_N \in \mathbb{R}^h$
2. At timestep t, decoder hidden state: $s_t \in \mathbb{R}^h$
3. Attention scores at timestep t: $e^t = [s_t^T h_1, \dots, s_t^T h_N] \in \mathbb{R}^N$
4. Softmax to get attention distribution: $\alpha^t = \text{softmax}(e^t) \in \mathbb{R}^N$
5. Use α^t to take a weighted sum of the encoder hidden states to get the attention output: $a_t = \sum_{i=1}^{N} \alpha_i^t h_i \in \mathbb{R}^h$
6. Concatenate attention output a_t with the decoder state s_t and continue with the rest of model training: $[a_t; s_t] \in \mathbb{R}^{2h}$

Encoder hidden states: $h_1, \dots, h_N$ Decoder hidden state: s_t

Definition: Given a set of vectors *values* and a vector *query*, attention is a weighted sum of the values, dependant on the query.

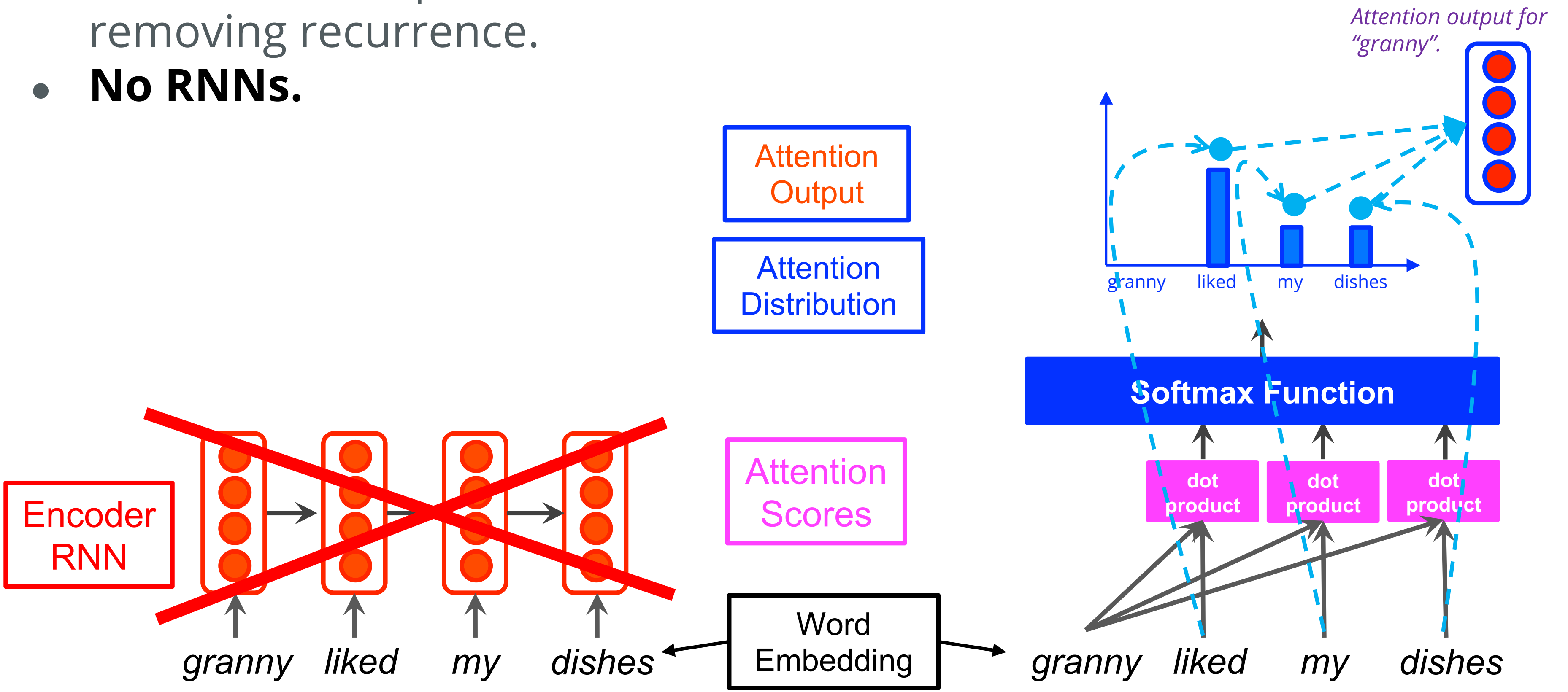
Attention types: ◦ Dot product ◦ Additive ◦ Multiplicative

Further reading: **https://arxiv.org/pdf/1703.03906.pdf**

Attention Is All You Need - Transformers

[Vaswani et al., 2017]

- **Self-Attention** provided a route to removing recurrence.
- **No RNNs.**



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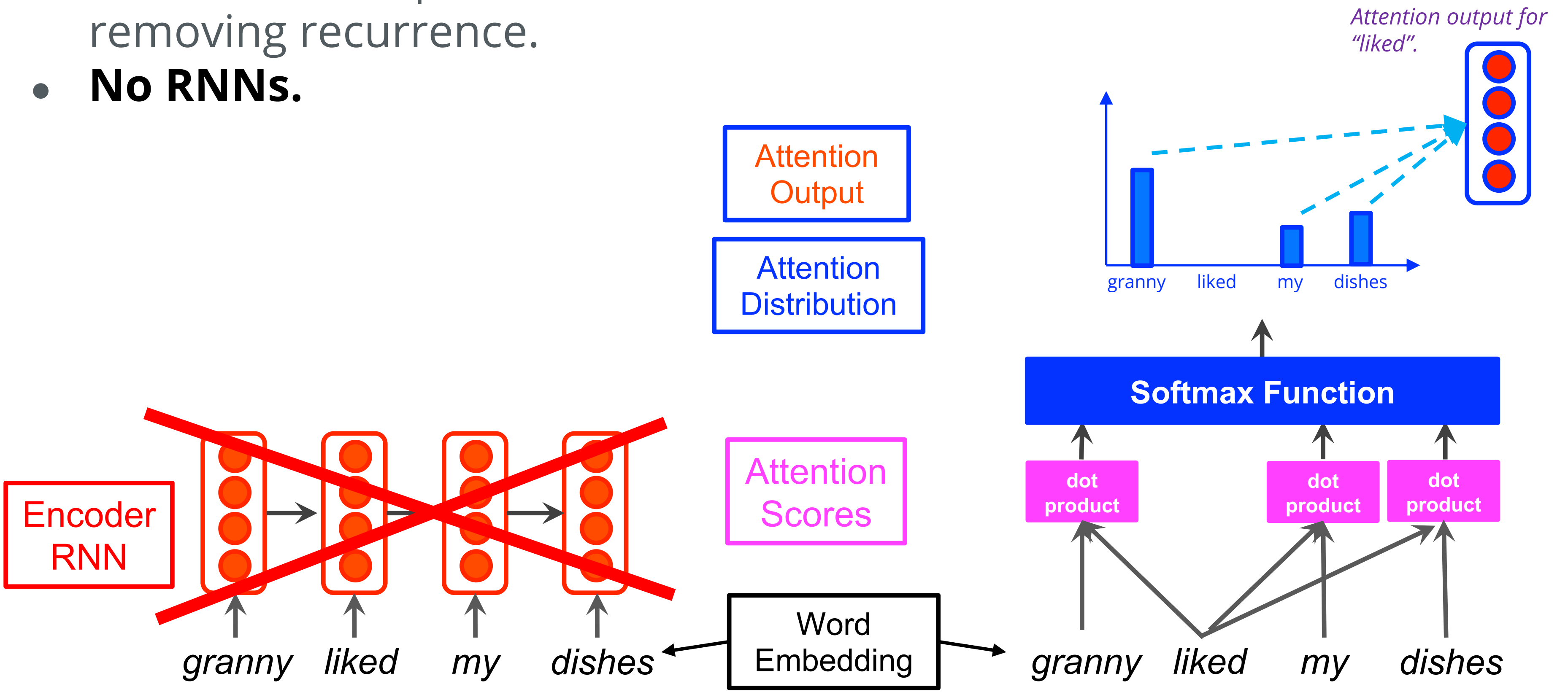

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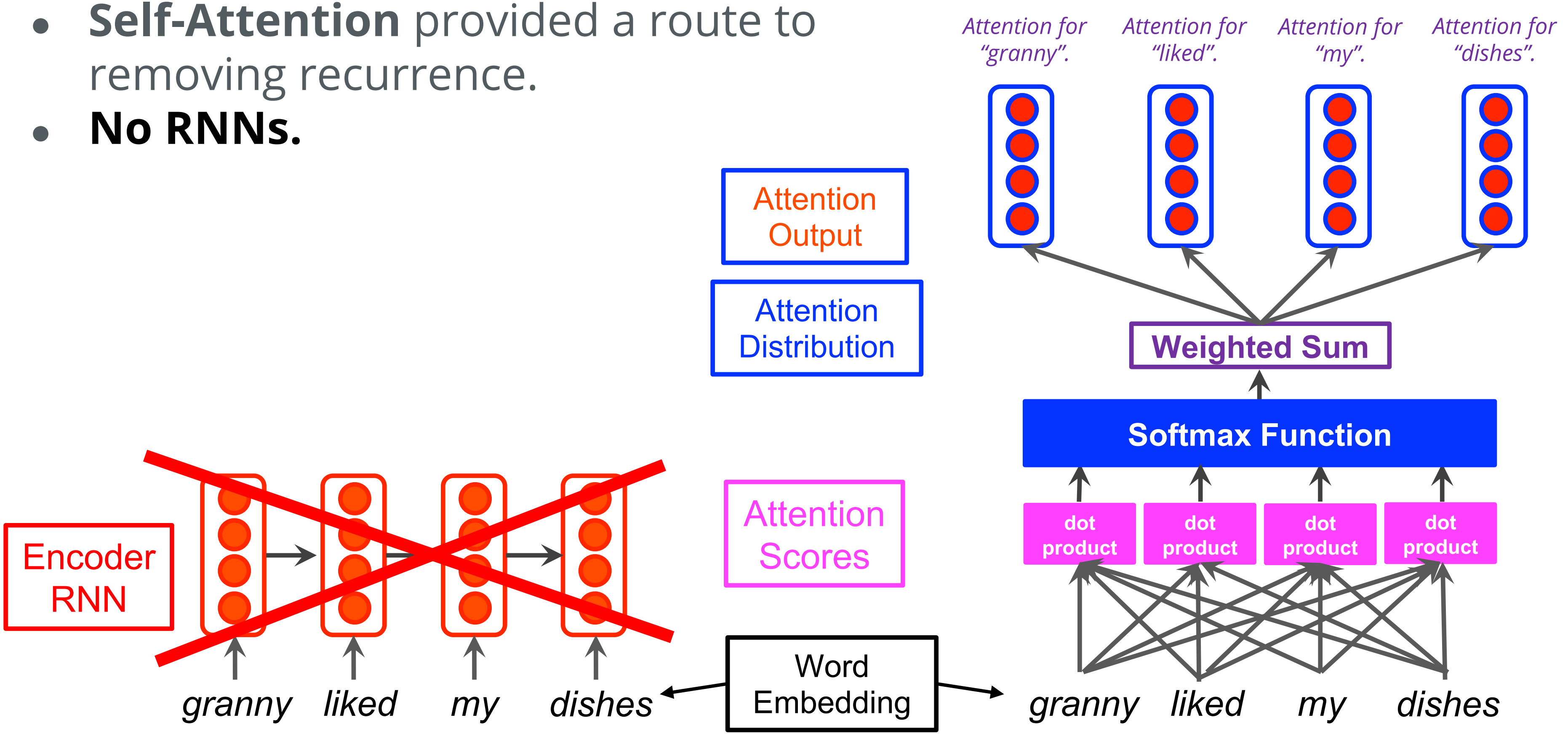
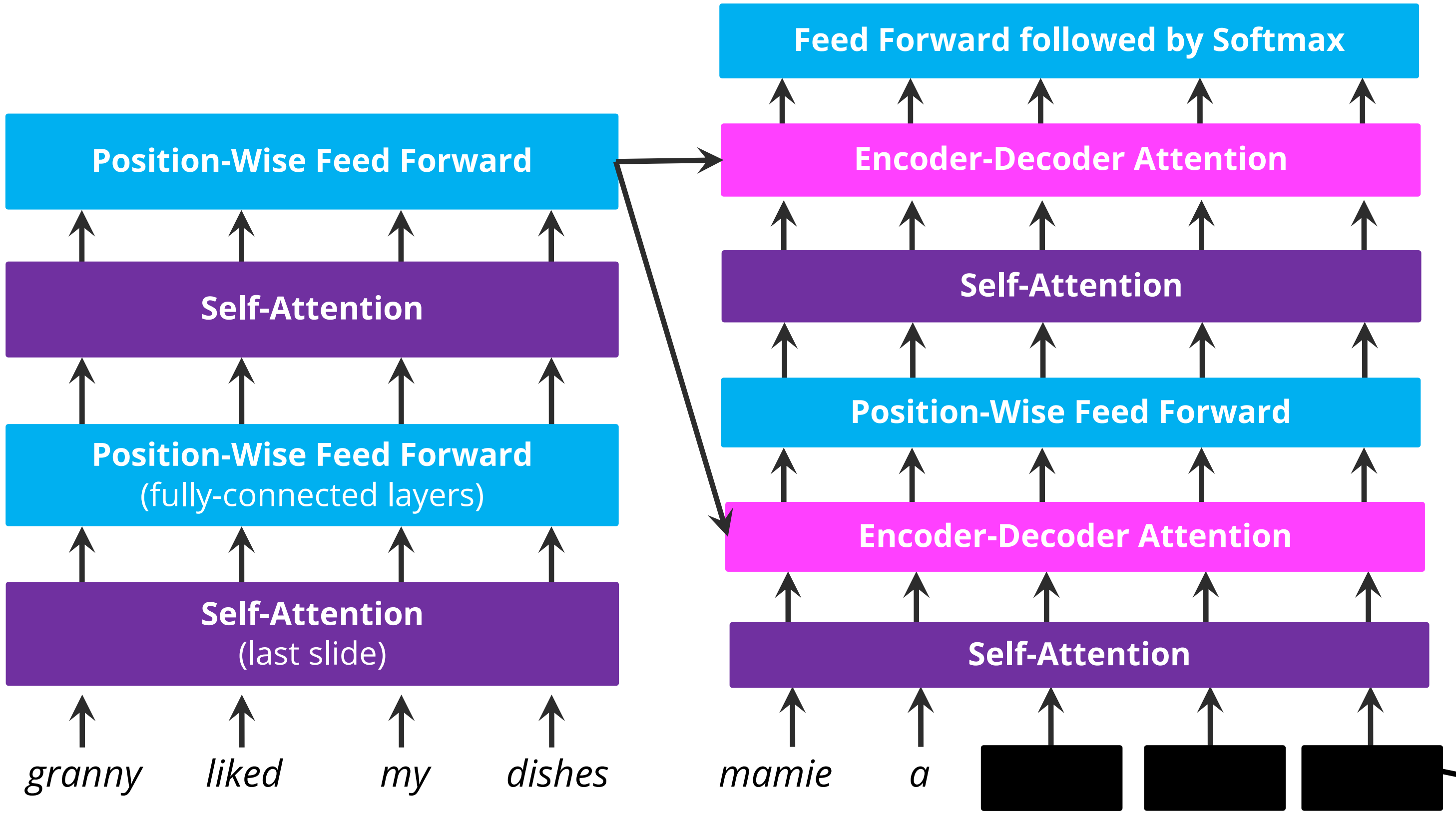


Attention Is All You Need - Transformers

[Vaswani et al., 2017]

Parallelisable

Transformers offer improvements in performance and efficiency.



In the decoder, we **mask out** words that the model is not supposed to have seen yet.

Transformers
GPT

GPT Training and Evaluation

GPT-3 [Brown et al., 2020]**:**
- 175B parameters (96 layers with 96 heads each with 12,228 neurons)
- Batch size 3.2M. Input length of 2048
- Petabytes of data from the internet

GPT-4:
- **ChatGPT**: much larger (probably)

Evaluation Tasks
- Few shot translation
- Reading comprehension (Q&A)
- Closed book question & answering
- Natural language inference
- News article writing
- Dialogue generation

Example: ChatGPT article

ChatGPT

Title: United Methodists Agree to Historic Split

Subtitle: Those who oppose gay marriage will form their own denomination

The United Methodist Church, one of the largest Protestant denominations in the United States, has reached a pivotal moment in its history. After years of internal conflict and debate over LGBTQ+ rights, particularly the issue of gay marriage and the ordination of LGBTQ+ clergy, the denomination has agreed to a historic split. This decision will see the formation of a new, conservative denomination by members who oppose gay marriage.

The schism is the culmination of a long-standing rift within the church, reflecting broader societal

Alternative LLMs

- Google AI's BARD
- Meta AI's LlaMA
- Falcon
- …

Transformers

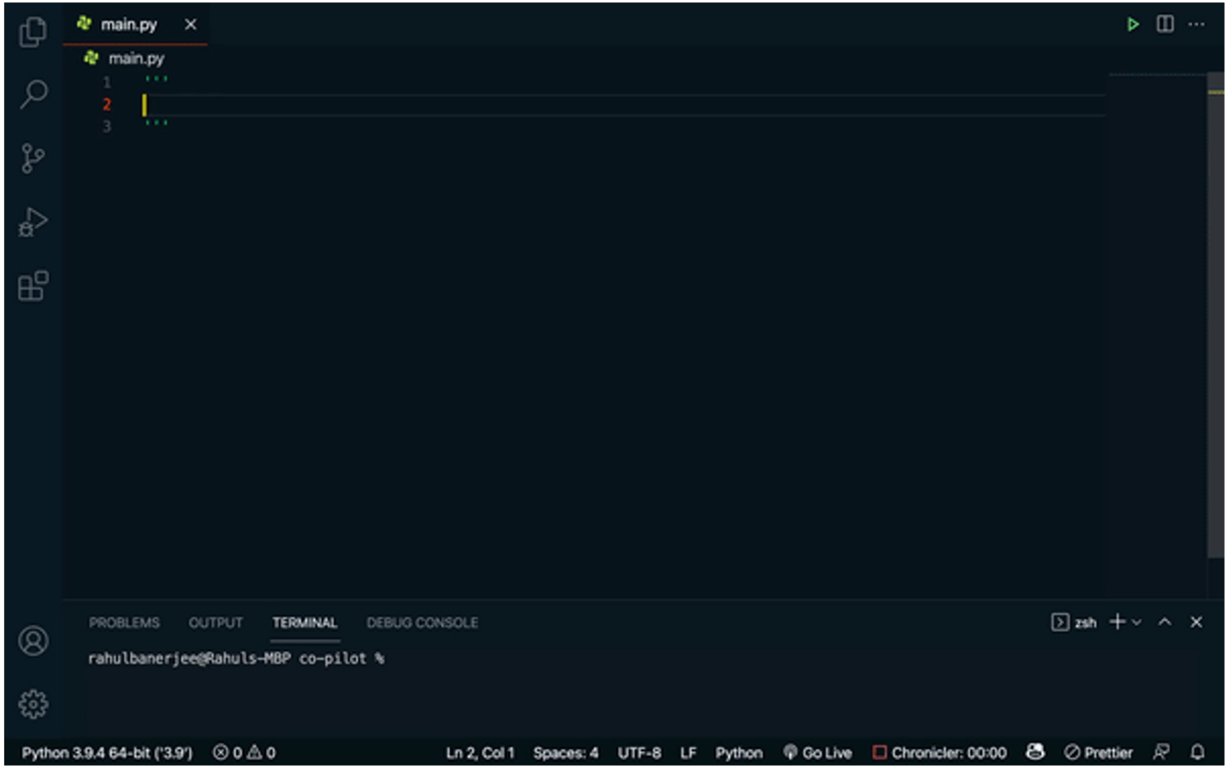
GPT-3: Codex

Example: Codex

Codex is GPT-3 trained on multiple datasets based on millions of GitHub repositories [one 2020 dataset consisted of 54 million public repos].

Available as an extension for Visual Studio Code and other IDEs.

Output still contains bugs and errors but improving.



Transformers DALL-E

DALL-E Training

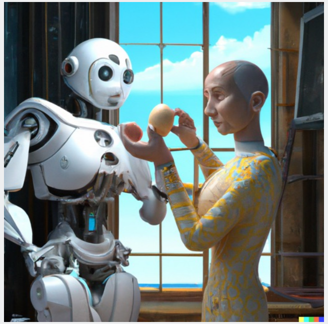
DALL-E [Ramesh et al., 2021]**:**

- 12-billion parameter version of GPT-3
- Generate images from detailed text descriptions
- **DALL·E 2**, and **DALL·E 3**

Capable of anthropomorphized versions of animals and objects, combining unrelated concepts in plausible ways, rendering text, and applying transformations to existing images

Example: DALL-E Image

A robot teaching his grandmother to suck eggs.



Good-looking man with golden hair and big bushy beard.

Transformers

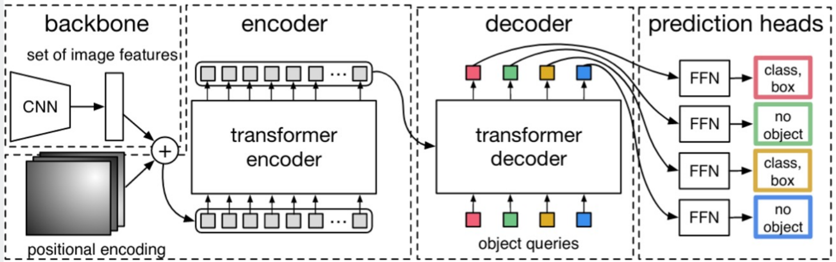
End-to-End Object Detection

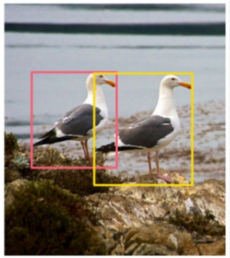
DEtection TRansformer

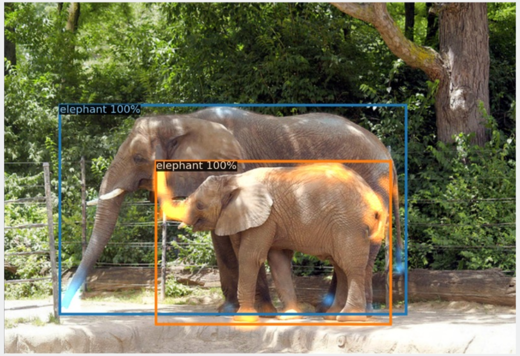
Fast object detection is crucial for many tasks including self-driving cars. Training end to end is difficult due to the discrete nature of objects.

DETR [Carion et al., 2020] enables global search and ‘query’ of the image for information. Attention matrices can also be used to make segmentation maps.

Example: architecture and examples







What we learned today!

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