# 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

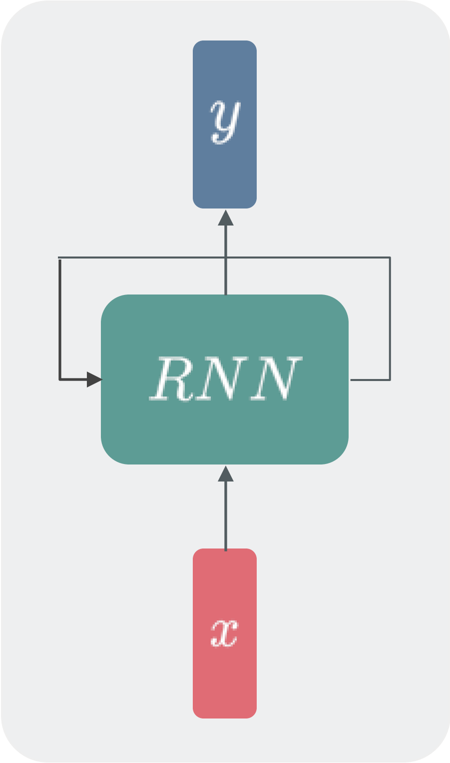
- Self-Attention
- End-to-end object detection
- GPT
- DALL-E

# Recurrent Neural Networks Definition

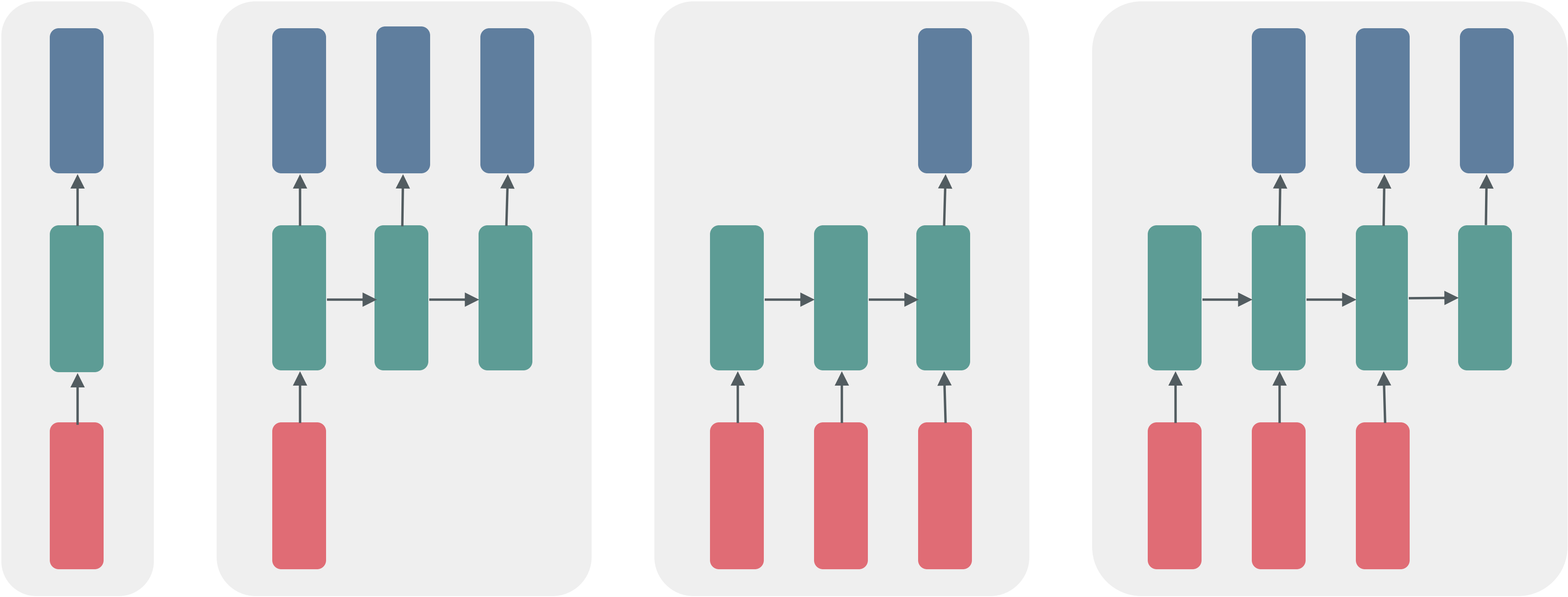
**Definition:** recurrent neural networks

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*

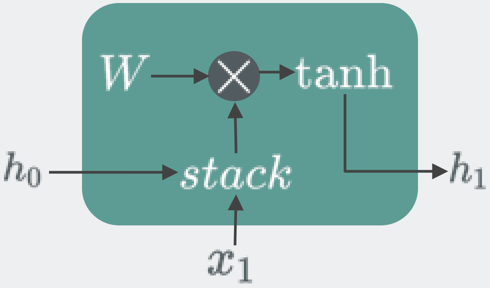
# Recurrent Neural Networks Implementation

**Example:** RNN

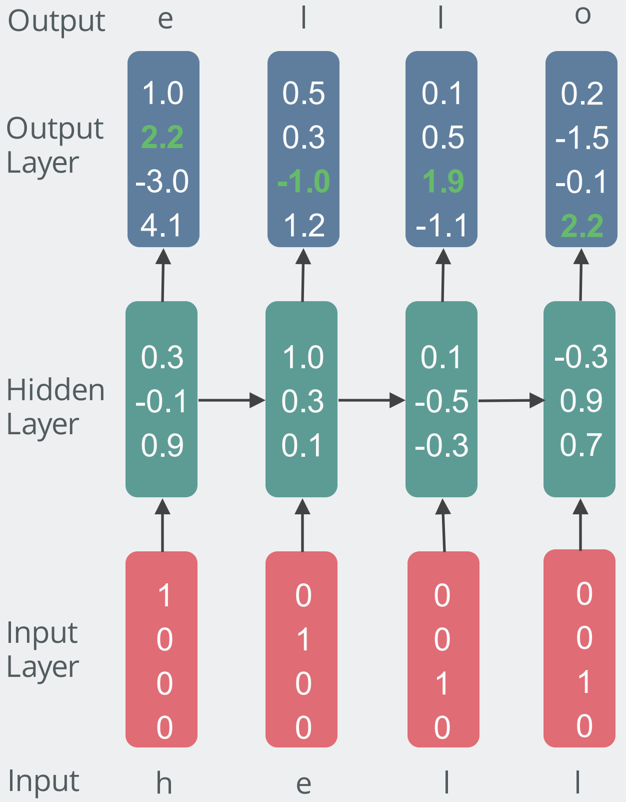
A simple implementation is:

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

which is visually interpreted as a “cell”:




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



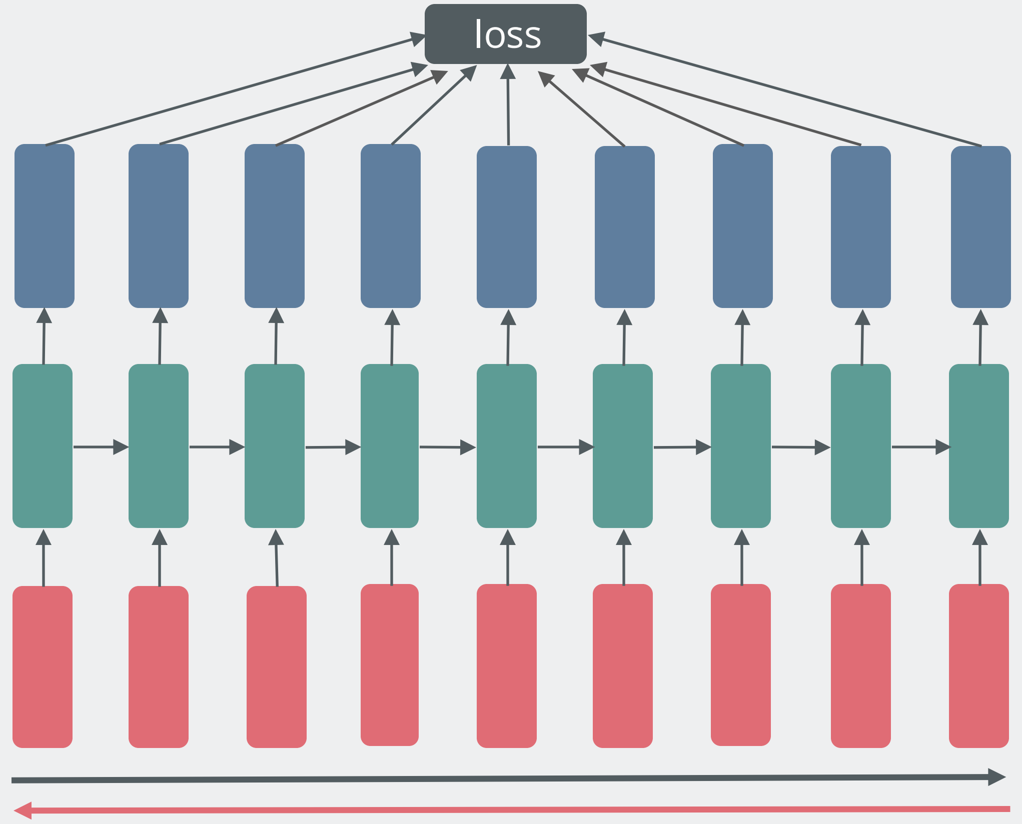
# Recurrent Neural Networks Backpropagation

**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!

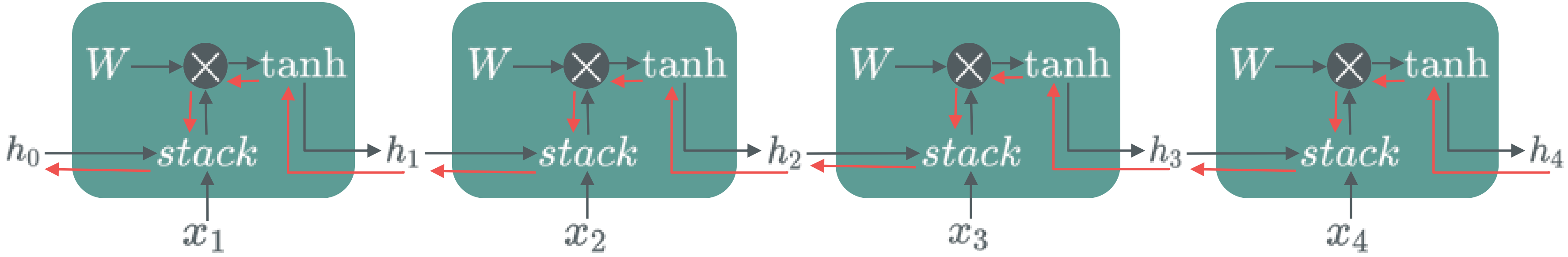
## Simple RNN Example for Text Classification

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






## Why do gradients vanish/explode?

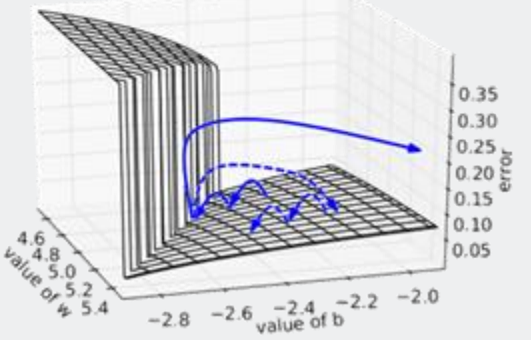
The gradient of involves many factors of $W$ (and tanh).

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

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

[Demo]

## 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!

## Example: LSTM cell


Gates control how much information is passed through using a sigmoid function and a dot product.

# Let’s Look at Some Code!

## Simple LSTM Example for Text Classification

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

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# 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

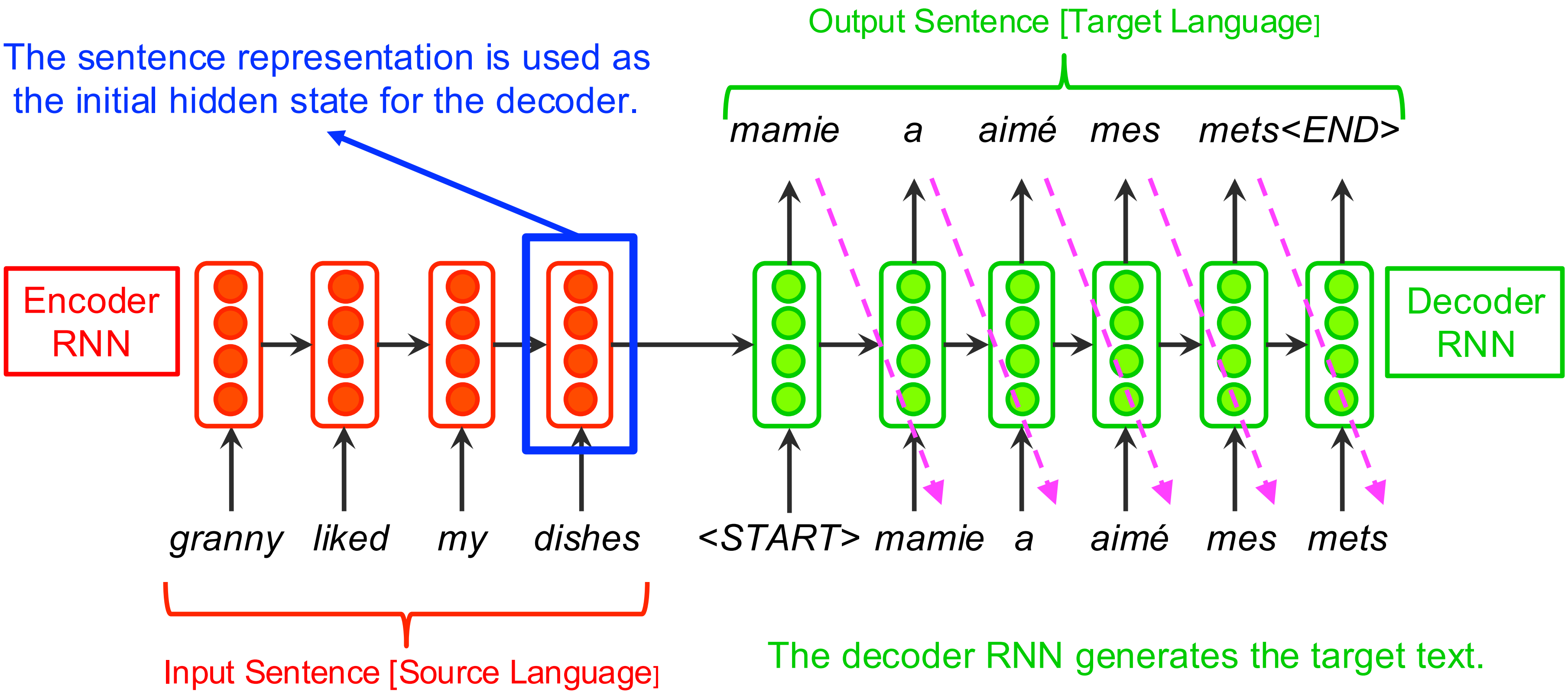


- Seq2Seq (sequence to sequence) receives a sentence as the input and produces a sentence as the output.
- Seq2Seq will include two networks, one encoder and one decoder.
- An example of this would be "**Machine Translation**":

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

# Seq2Seq Architecture Machine Translation

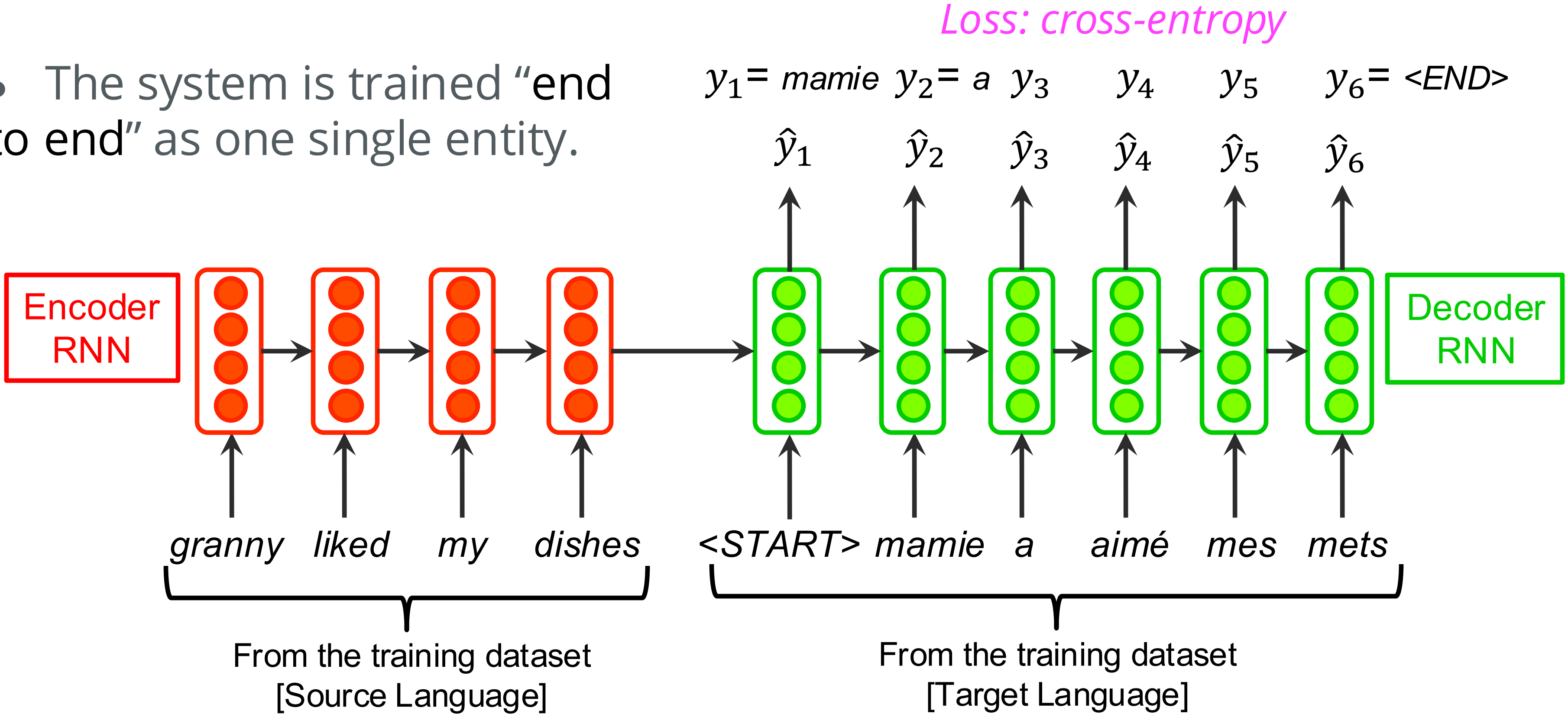
- Let's see how inference works. We will take about the training later.



# Seq2Seq Architecture Machine Translation

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

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

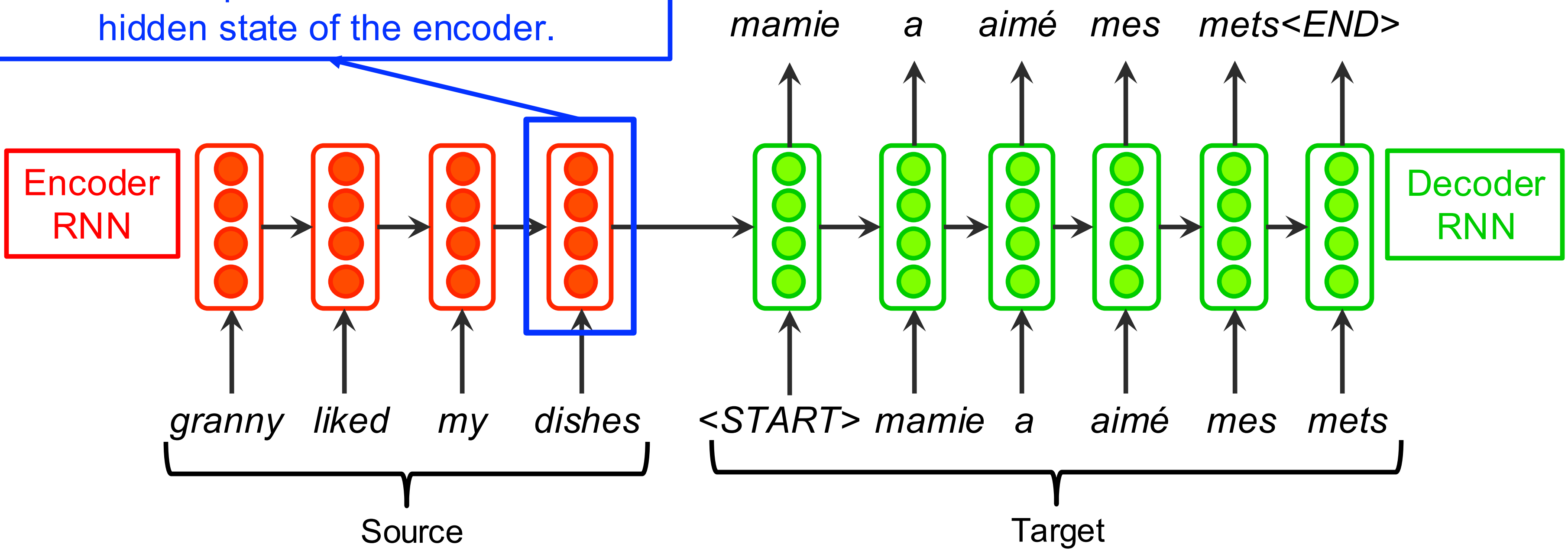


# Seq2Seq Architecture
Issue

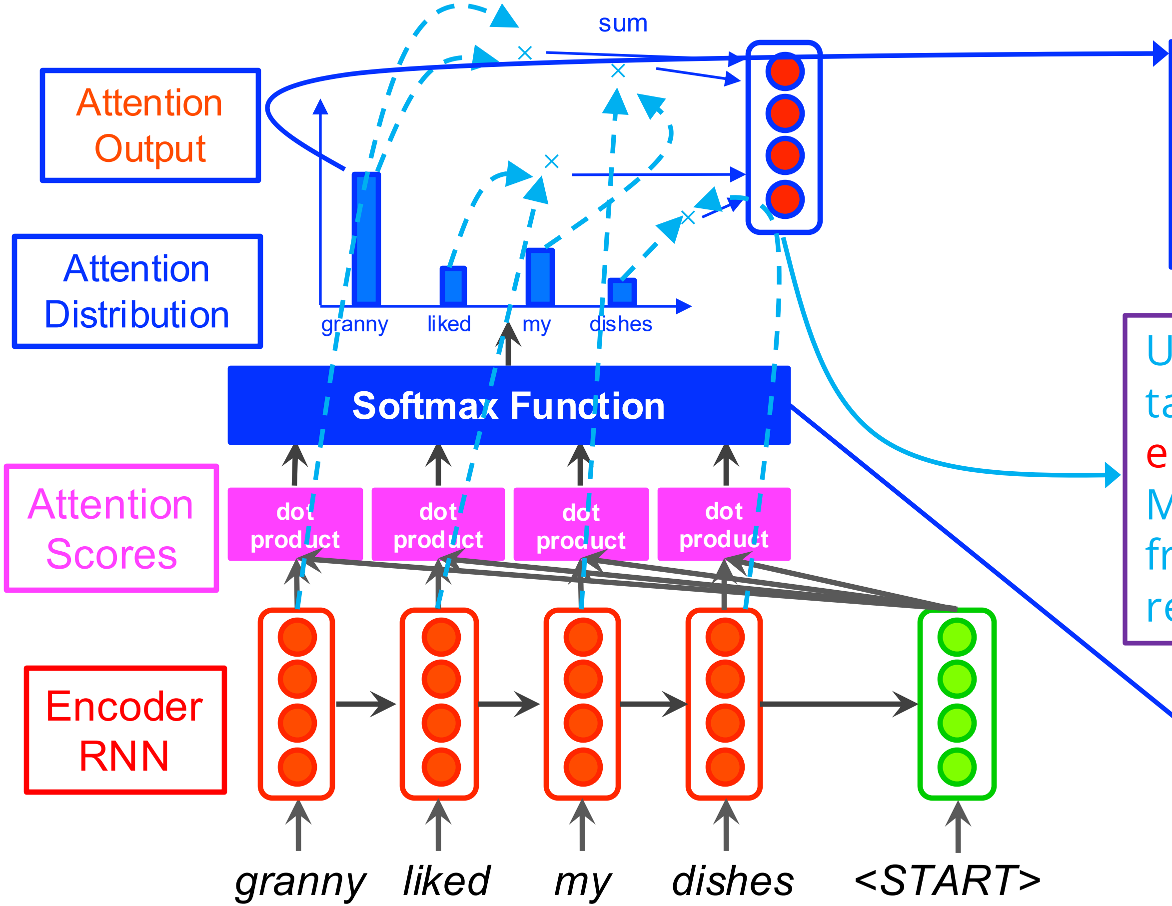
Solution: **Attention**

**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

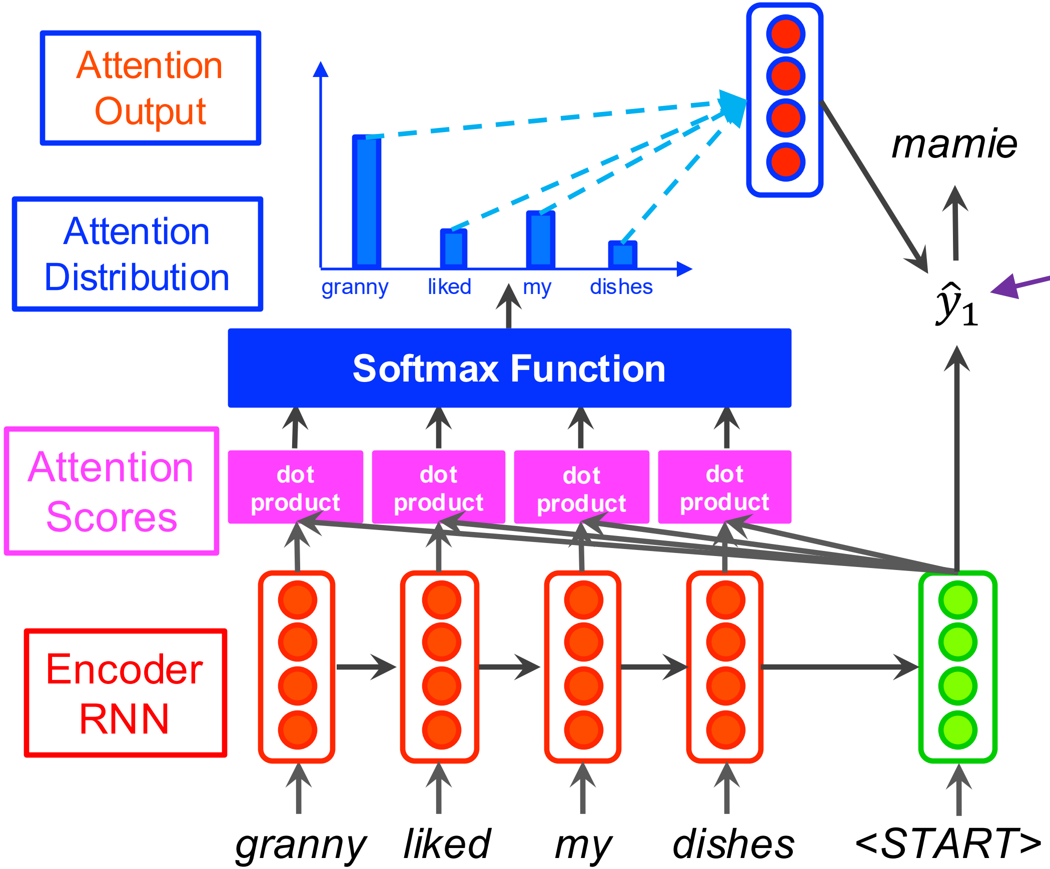



At this timestep, the decoder is **focusing** more on "granny" but could rely on information from the other words as well.

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.

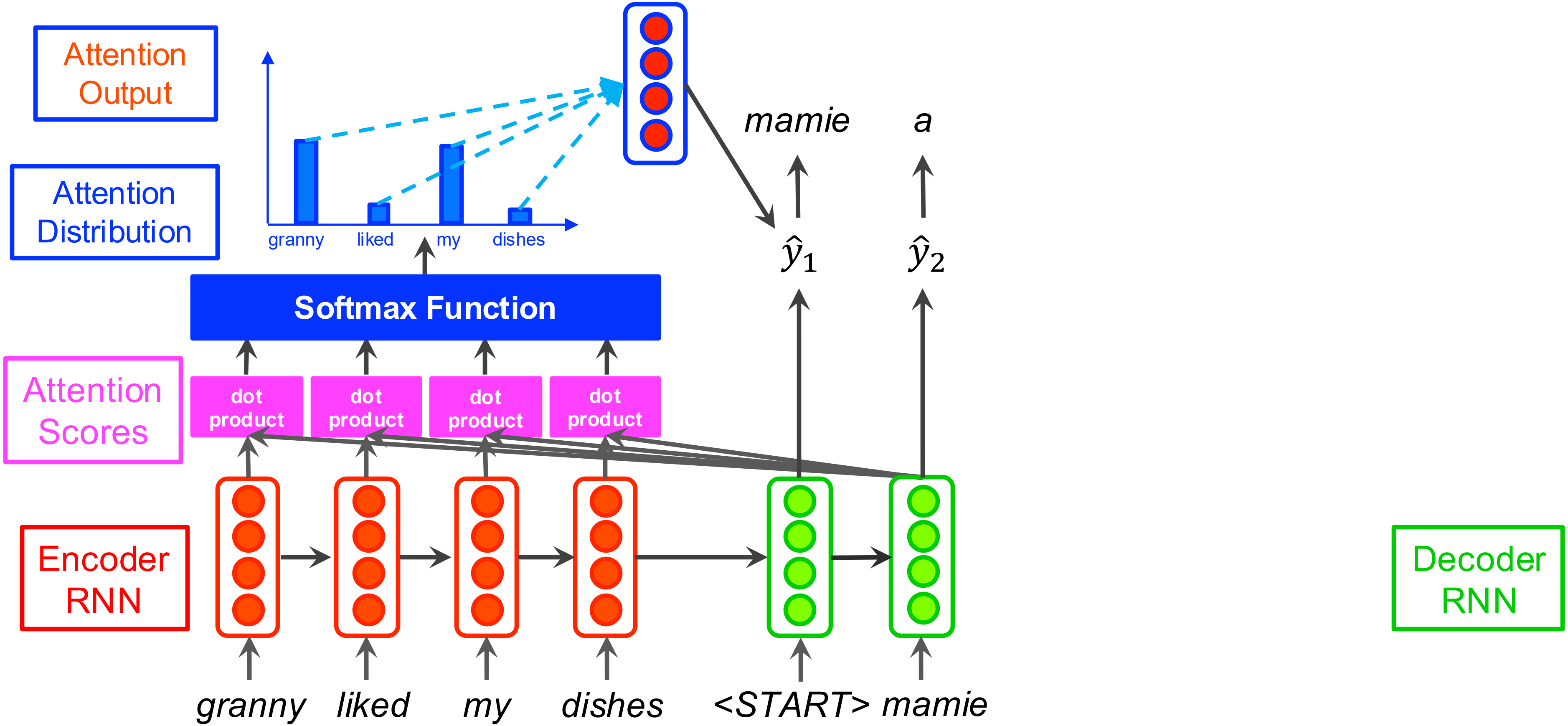
The scores are turned into a probability distribution.

# Seq2Seq with Attention

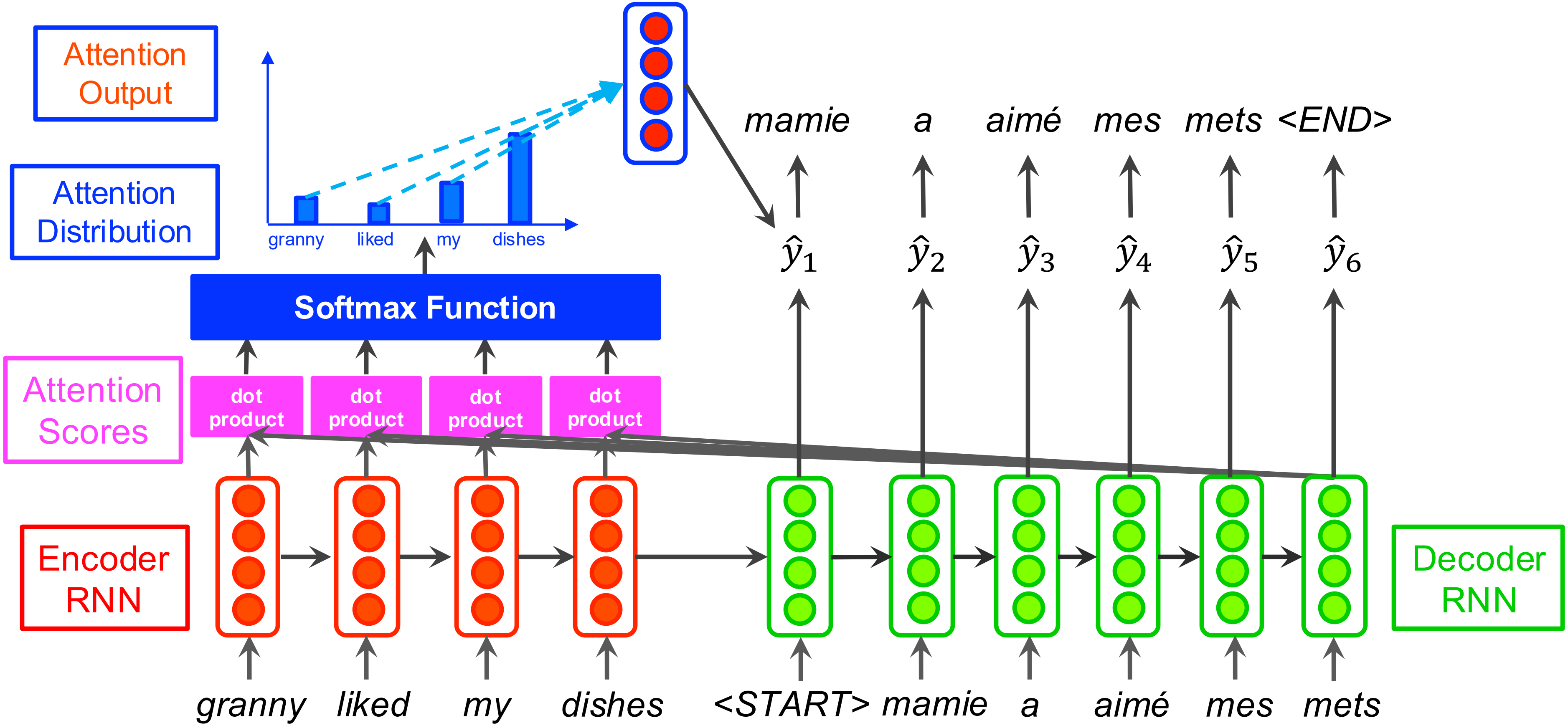



We concatenate the attention output with the decoder hidden state and use the result to obtain $\hat{y}_1$ as we did before.

# Seq2Seq with Attention



# Seq2Seq with Attention



# Attention

Definition and Calculation

1. Encoder hidden states: $h_1, \ldots, h_N \in \mathbb{R}^h$
2. At timestep $t$, decoder hidden state: $s_t \in \mathbb{R}^h$
3. Attention scores at timestep $t$: $e^t = [s_t^T h_1, \ldots, s_t^T h_N] \in \mathbb{R}^N$
4. Softmax to get attention distribution: $\alpha^t = \mathrm{softmax}(e^t) \in \mathbb{R}^N$
5. Use $\alpha^t$ 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: $h_1, \ldots, h_N$ 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.

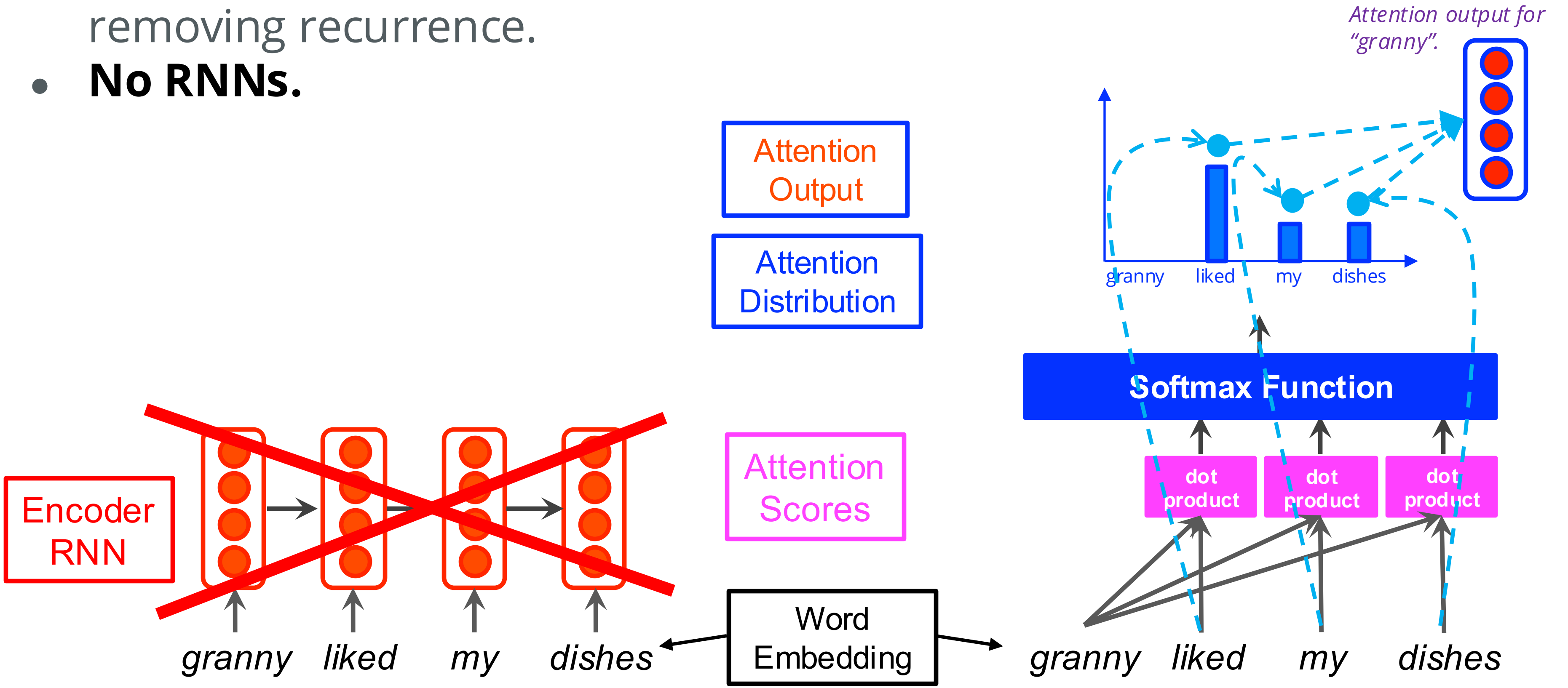
**Attention types:**
- Dot product
- Additive
- Multiplicative

Further reading: [https://arxiv.org/pdf/1703.03906.pdf](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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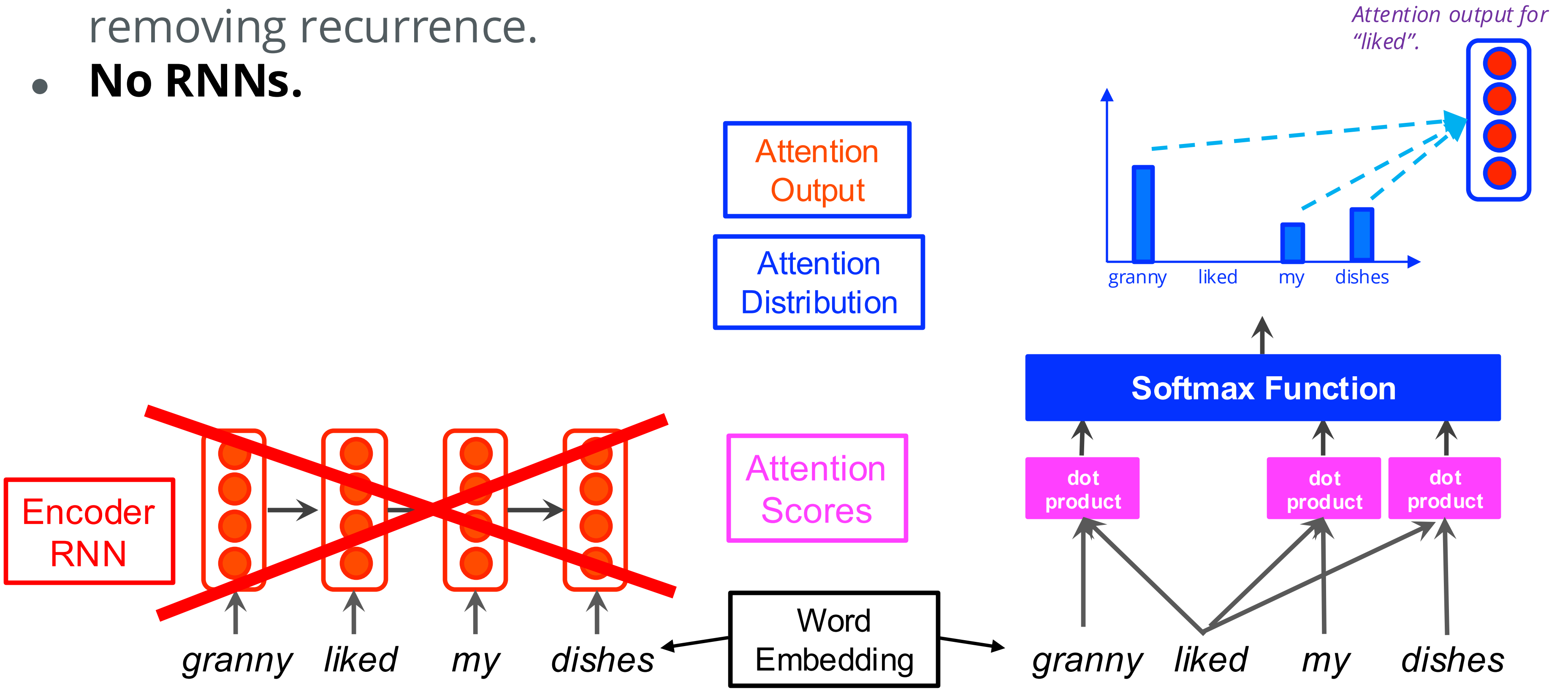

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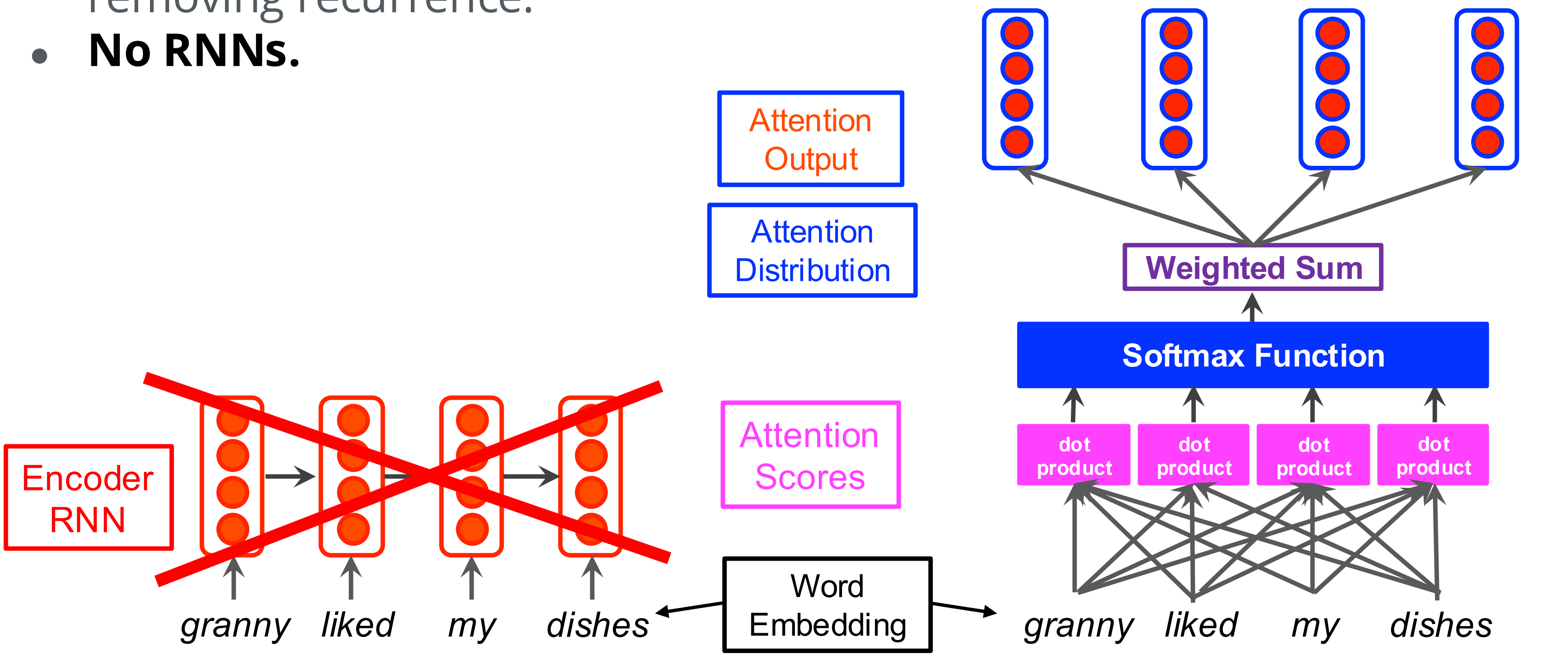
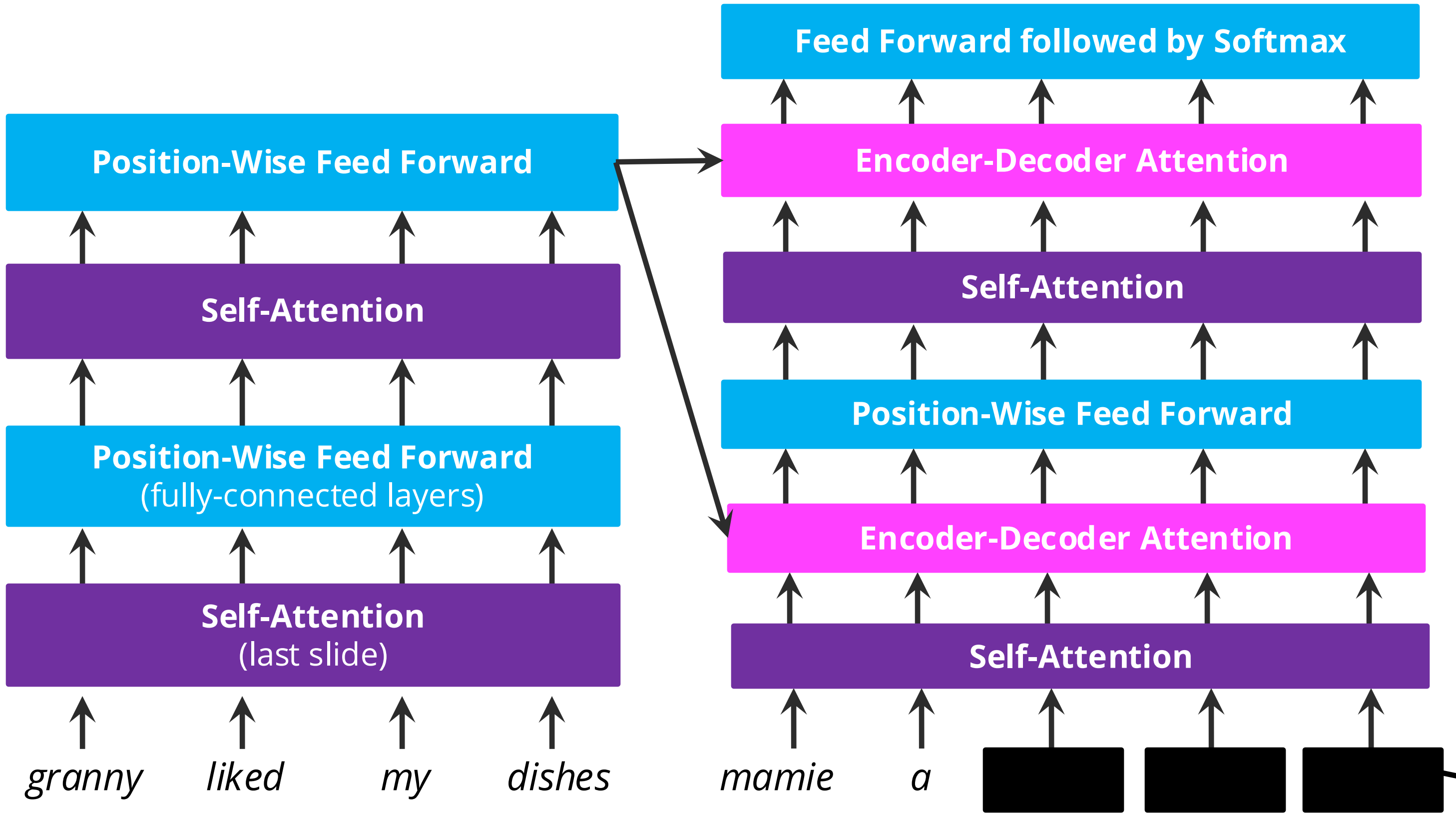


# Attention Is All You Need - Transformers

[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.

# Let’s Look at Some Code!

## Simple Transformer Example for Text Classification

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

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# 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
- Terabytes of data from the internet

**GPT-4 and GPT-5:**

- **ChatGPT**: much larger

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 Gemini
- Meta AI's LlaMA
- Anthropic's Claude
- Falcon
- …

# Transformers GPT-3: Codex

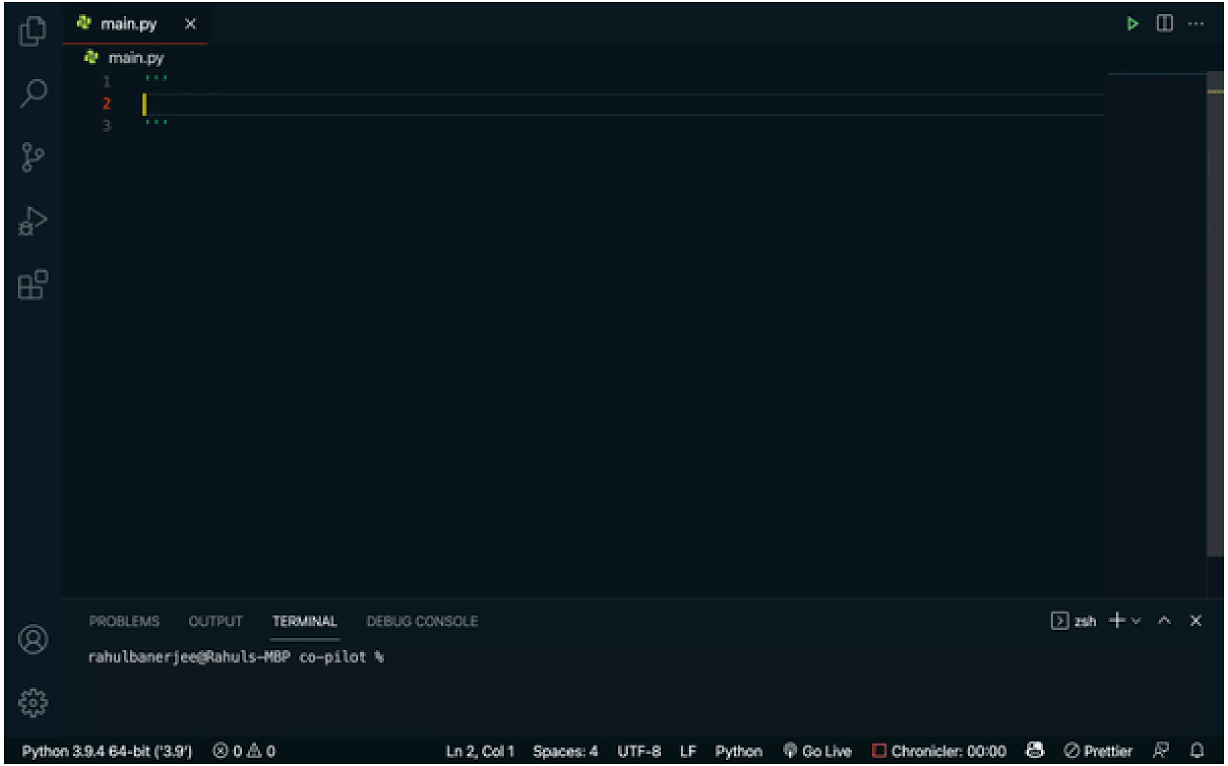
## **Example:** Codex

Codex is GPT 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.

VS Code Cursor + Sonnet 3.5

Output still contains bugs and errors but improving.



# Transformers DALL-E

## DALL-E Training

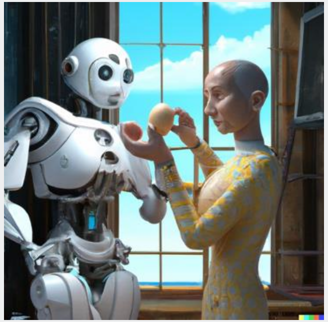
**DALL-E** [Ramesh et al., 2021]**:**

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

Capable of anthropomorphised 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

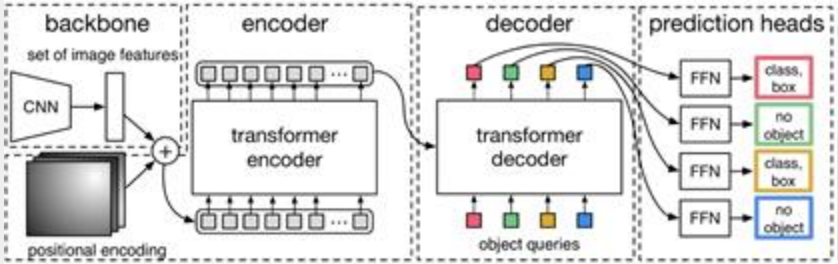
End-to-End Object Detection

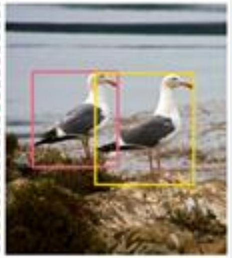
## DEtection TRansformer

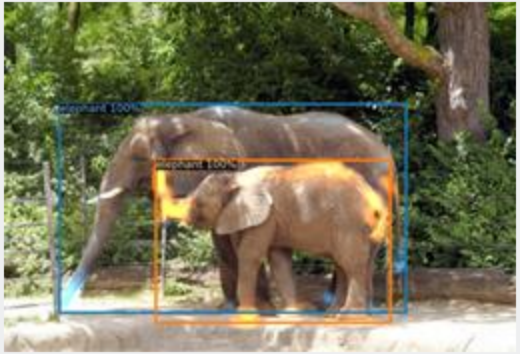
Fast object detection is crucial for many tasks including self-driving cars. Training end to end is difficult due to the discrete nature of objects.

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!

## ❶ Recurrent neural networks

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

## ❷ Long short-term memory

- Definition
- Properties
- Seq2Seq
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## ❸ Transformers

- Self-Attention
- End-to-end object detection
- GPT-3
- DALL-E