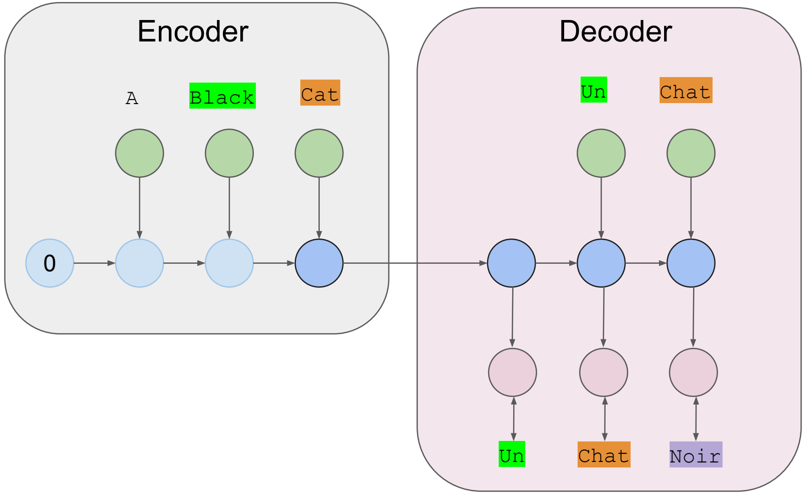
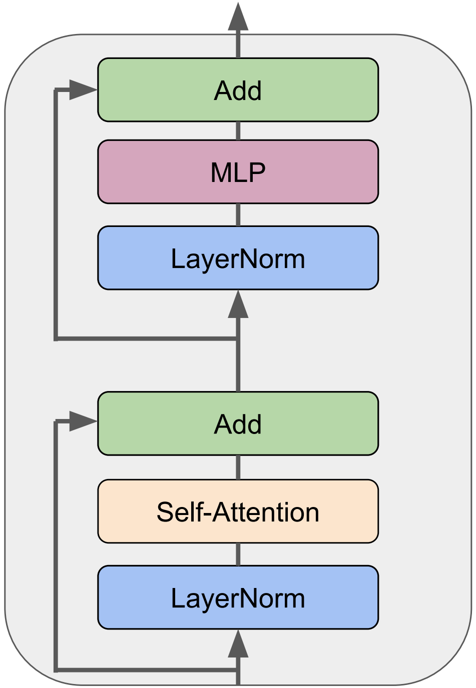
# NYU CS-GY 6923
# Machine Learning

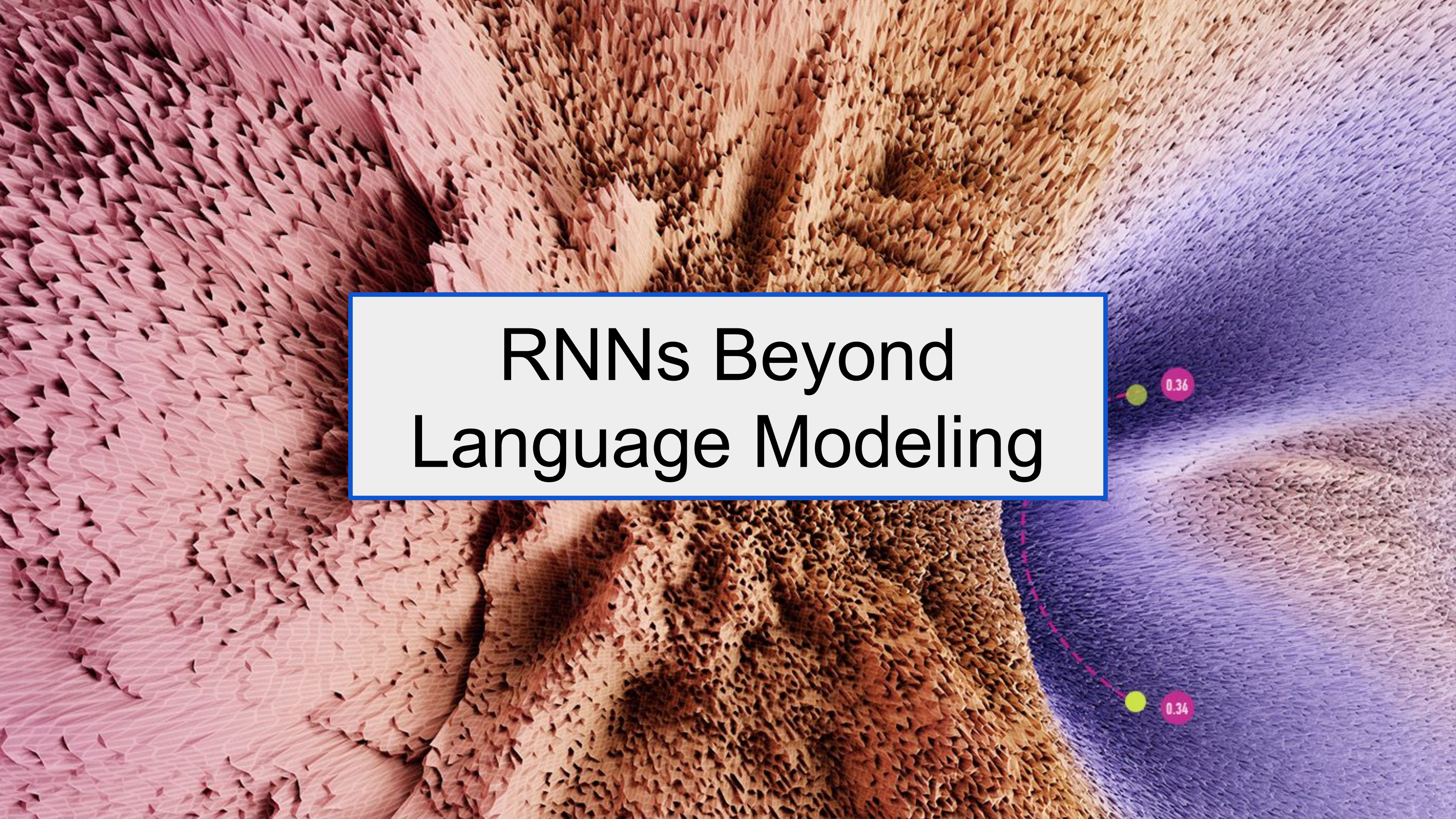
Prof. Pavel Izmailov

# Today

- RNNs beyond language modeling
- Transformers
- Post-Training



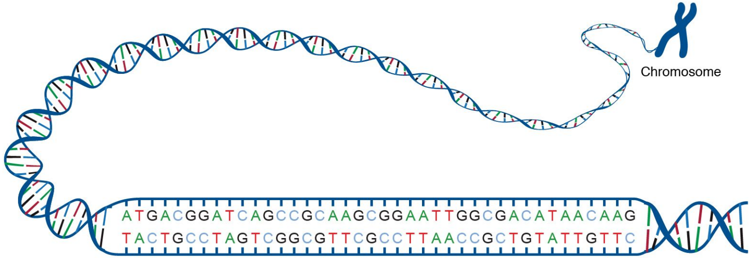





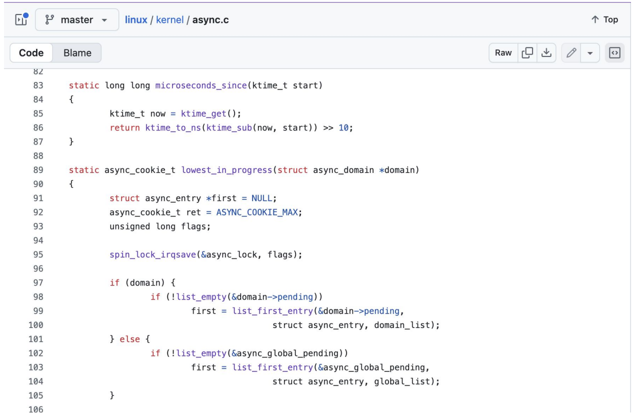

# RNNs Beyond Language Modeling

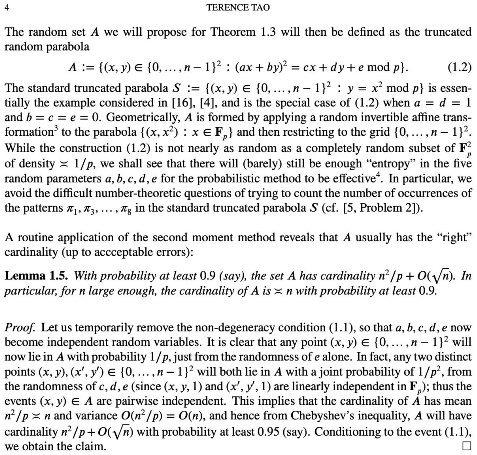
# Sequence Modeling

Last week we talked about language modeling







4 TERENCE TAO

The random set $A$ we will propose for Theorem 1.3 will then be defined as the truncated random parabola

$$A := \{(x, y) \in \{0, \dots, n-1\}^2 : (ax+by)^2 = cx + dy + e \bmod p\}. \qquad (1.2)$$

The standard truncated parabola $S := \{(x, y) \in \{0, \dots, n-1\}^2 : y = x^2 \bmod p\}$ is essentially the example considered in [16], [4], and is the special case of (1.2) when $a = d = 1$ and $b = c = e = 0$. Geometrically, $A$ is formed by applying a random invertible affine transformation[3] to the parabola $\{(x, x^2) : x \in \mathbf{F}_p\}$ and then restricting to the grid $\{0, \dots, n-1\}^2$. While the construction (1.2) is not nearly as random as a completely random subset of $\mathbf{F}_p^2$ of density $\asymp 1/p$, we shall see that there will (barely) still be enough "entropy" in the five random parameters $a, b, c, d, e$ for the probabilistic method to be effective[4]. In particular, we avoid the difficult number-theoretic questions of trying to count the number of occurrences of the patterns $\pi_1, \pi_3, \dots, \pi_8$ in the standard truncated parabola $S$ (cf. [5, Problem 2]).

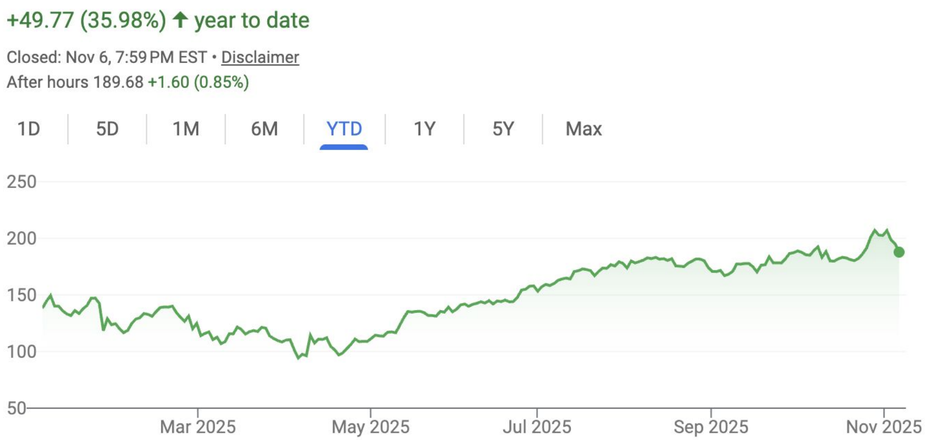
A routine application of the second moment method reveals that $A$ usually has the "right" cardinality (up to accceptable errors):

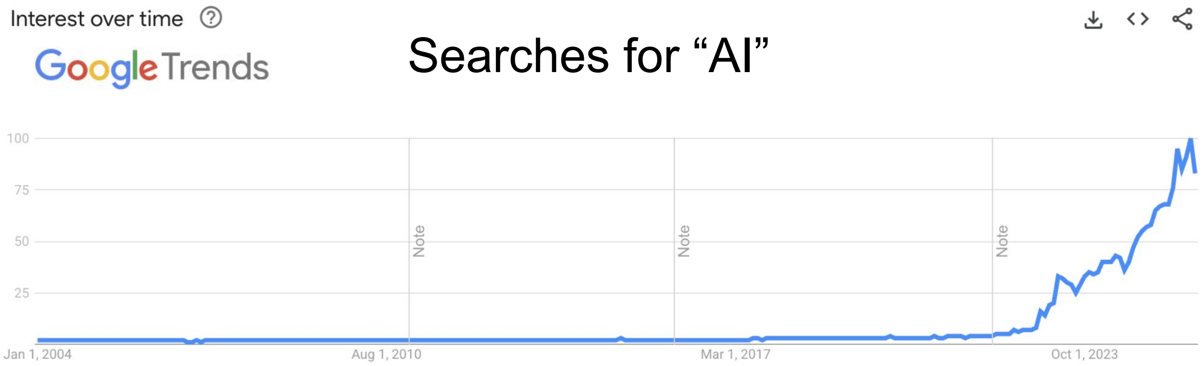
**Lemma 1.5.** *With probability at least 0.9 (say), the set $A$ has cardinality $n^2/p + O(\sqrt{n})$. In particular, for $n$ large enough, the cardinality of $A$ is $\asymp n$ with probability at least 0.9.*

*Proof.* Let us temporarily remove the non-degeneracy condition (1.1), so that $a, b, c, d, e$ now become independent random variables. It is clear that any point $(x, y) \in \{0, \dots, n-1\}^2$ will now lie in $A$ with probability $1/p$, just from the randomness of $e$ alone. In fact, any two distinct points $(x, y), (x', y') \in \{0, \dots, n-1\}^2$ will both lie in $A$ with a joint probability of $1/p^2$, from the randomness of $c, d, e$ (since $(x, y, 1)$ and $(x', y', 1)$ are linearly independent in $\mathbf{F}_p$); thus the events $(x, y) \in A$ are pairwise independent. This implies that the cardinality of $A$ has mean $n^2/p \asymp n$ and variance $O(n^2/p) = O(n)$, and hence from Chebyshev's inequality, $A$ will have cardinality $n^2/p + O(\sqrt{n})$ with probability at least 0.95 (say). Conditioning to the event (1.1), we obtain the claim. □

# Sequence Modeling

How do we model a time series?

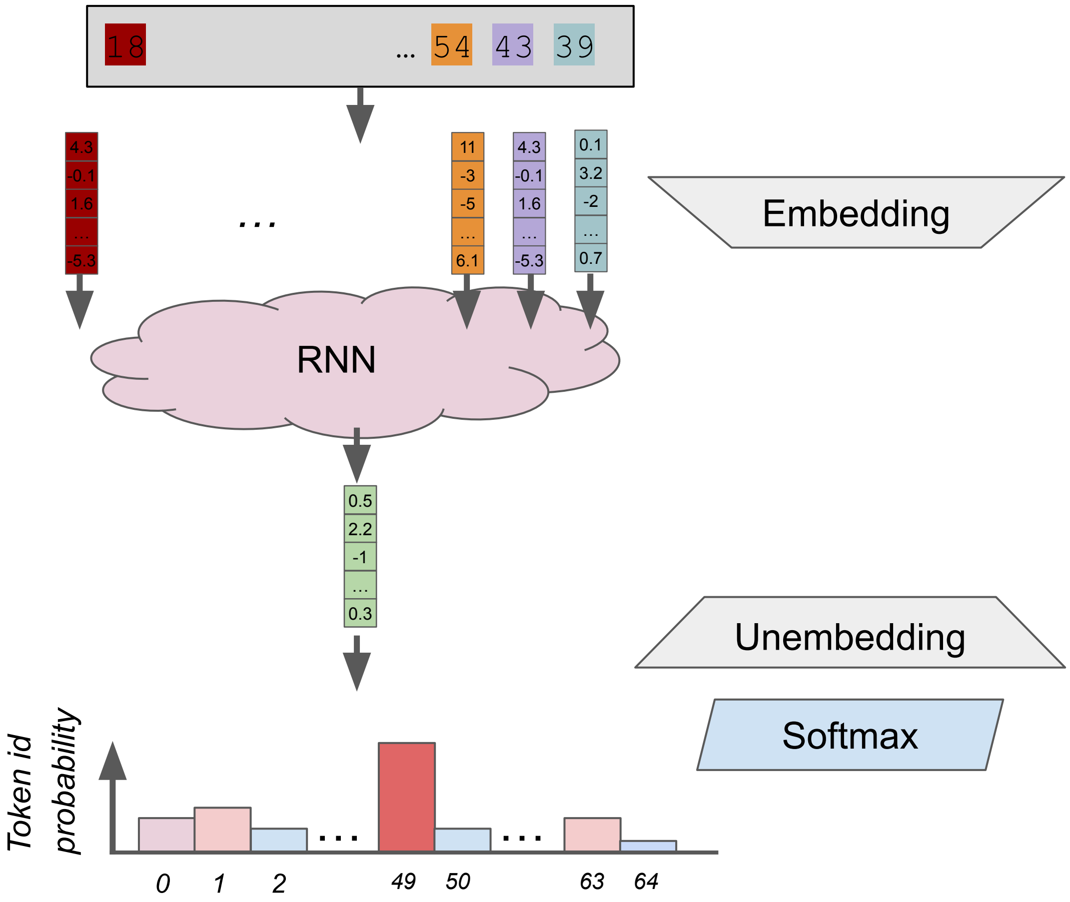



Searches for “AI”

# Sequence Modeling

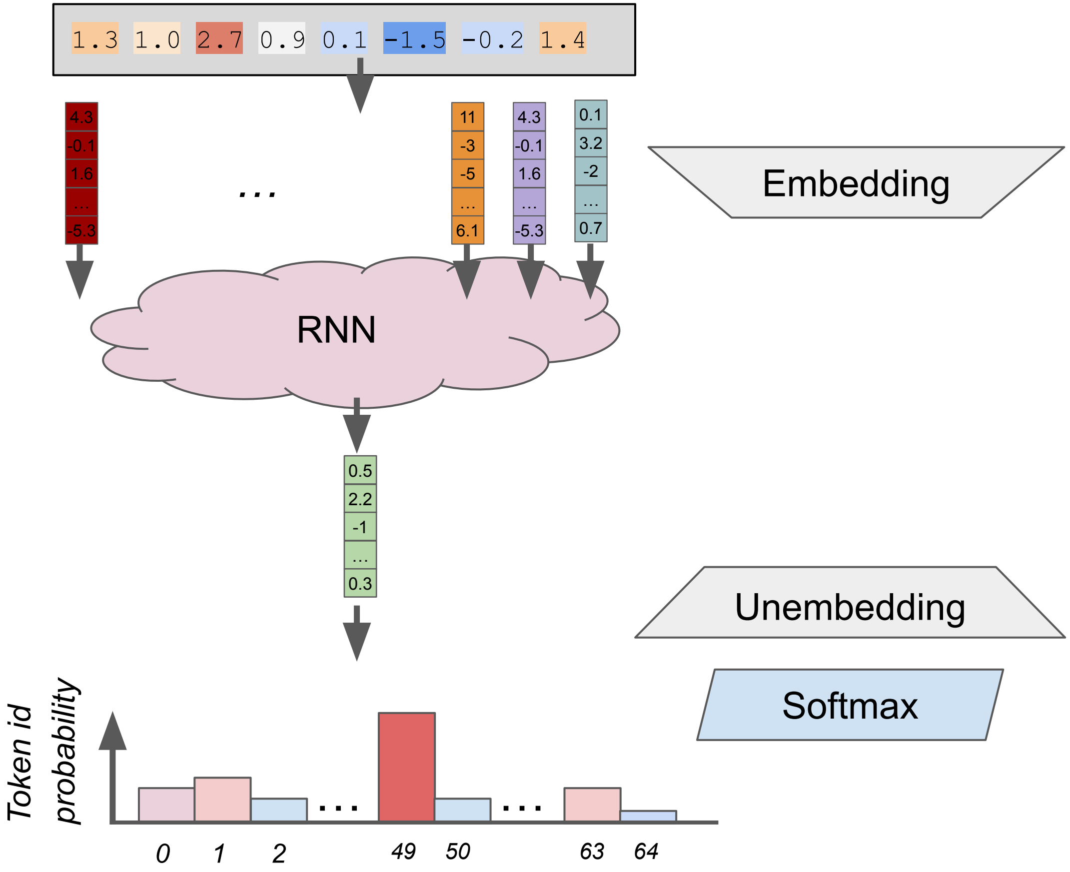
*Question: What do we need to change?*



# Sequence Modeling

Tokens → numbers

*Question: What do we need to change?*

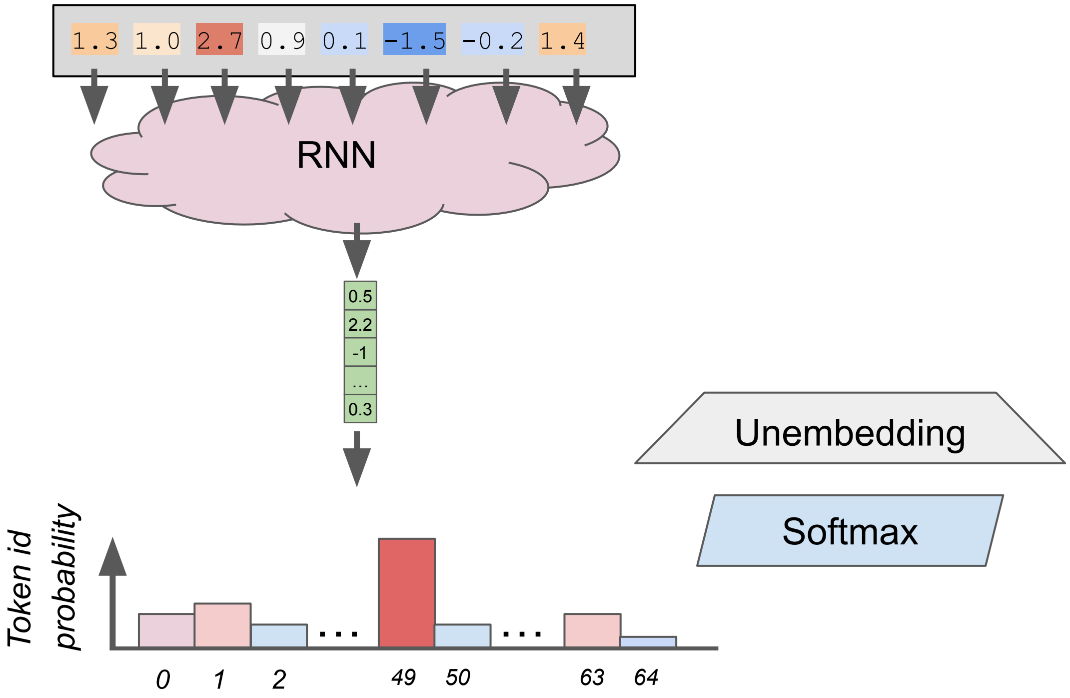


# Sequence Modeling

Tokens → numbers

We can remove the embedding layer

*Question: What do we need to change?*



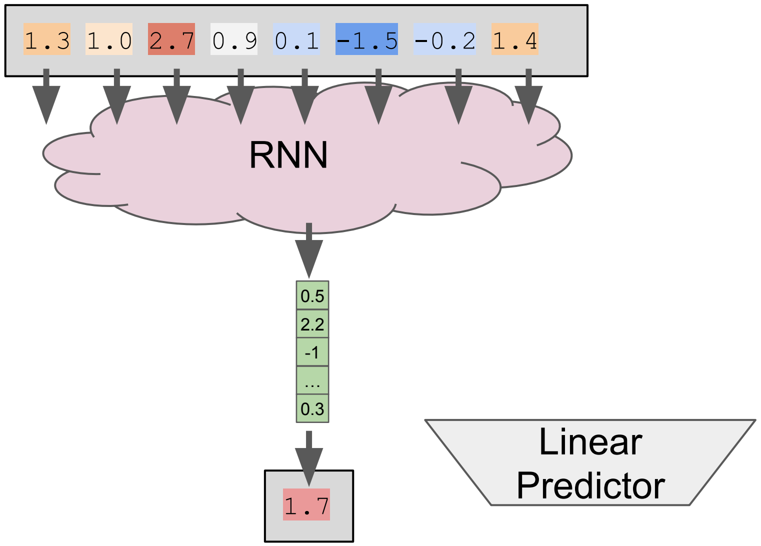
# Sequence Modeling

Tokens → numbers

We can remove the embedding layer

*Question: What do we need to change?*

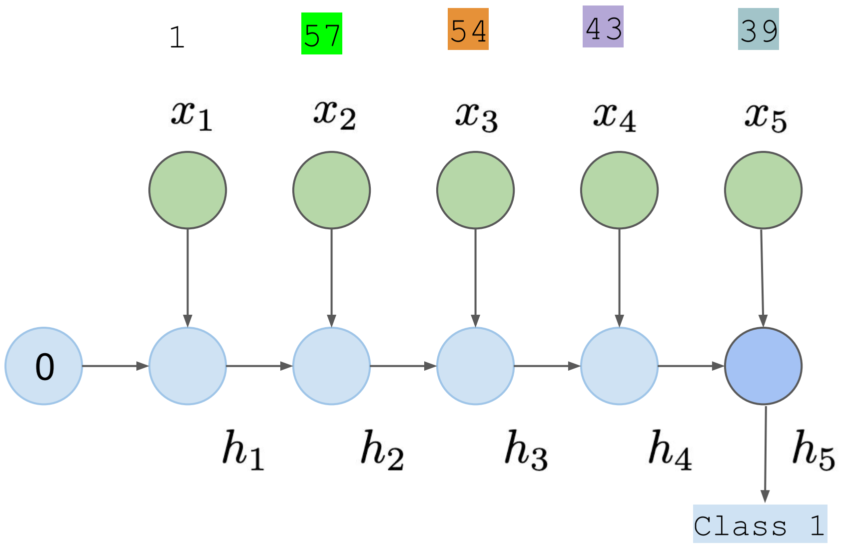
Unembedding is now just a linear layer with one output, and we use regression loss



# Sequence Classification

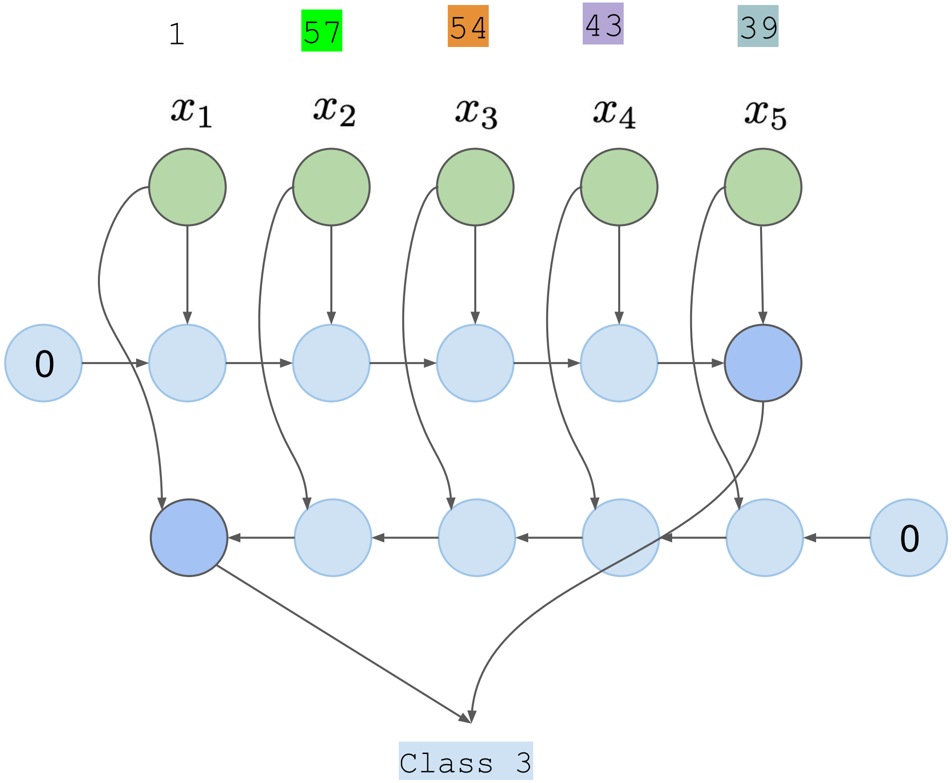
- Sentiment analysis: is this a positive review?
- Language detection: which language is this?
- Does this python program compile?
- …

# Sequence Classification




We can just use the hidden representation for the last token to make predictions

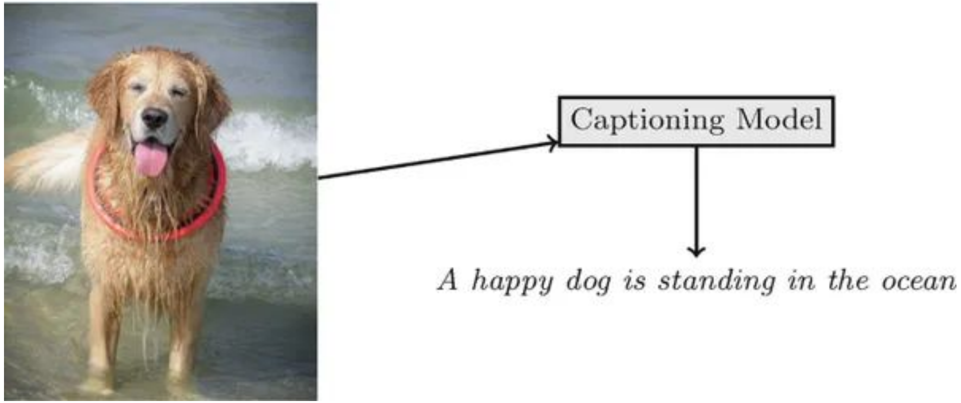
# Sequence Classification



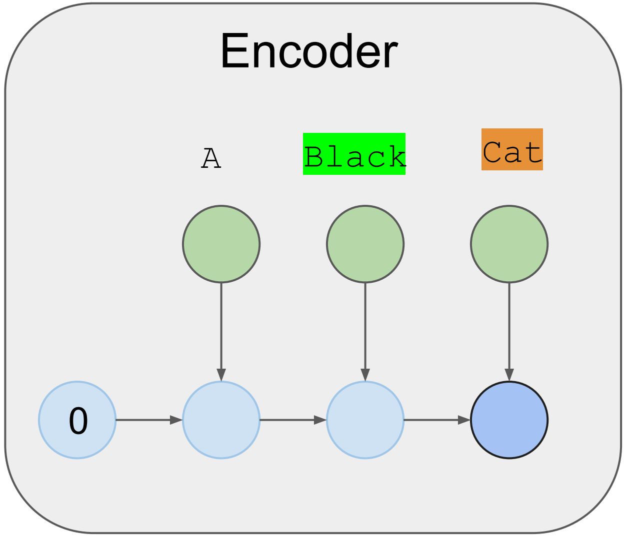

We can generalize the idea to bidirectional RNNs: use the two nodes with full context

# Sequence to Sequence

- Machine Translation: Translating text from one language to another
- Text Summarization
- Speech Recognition
- Image Captioning

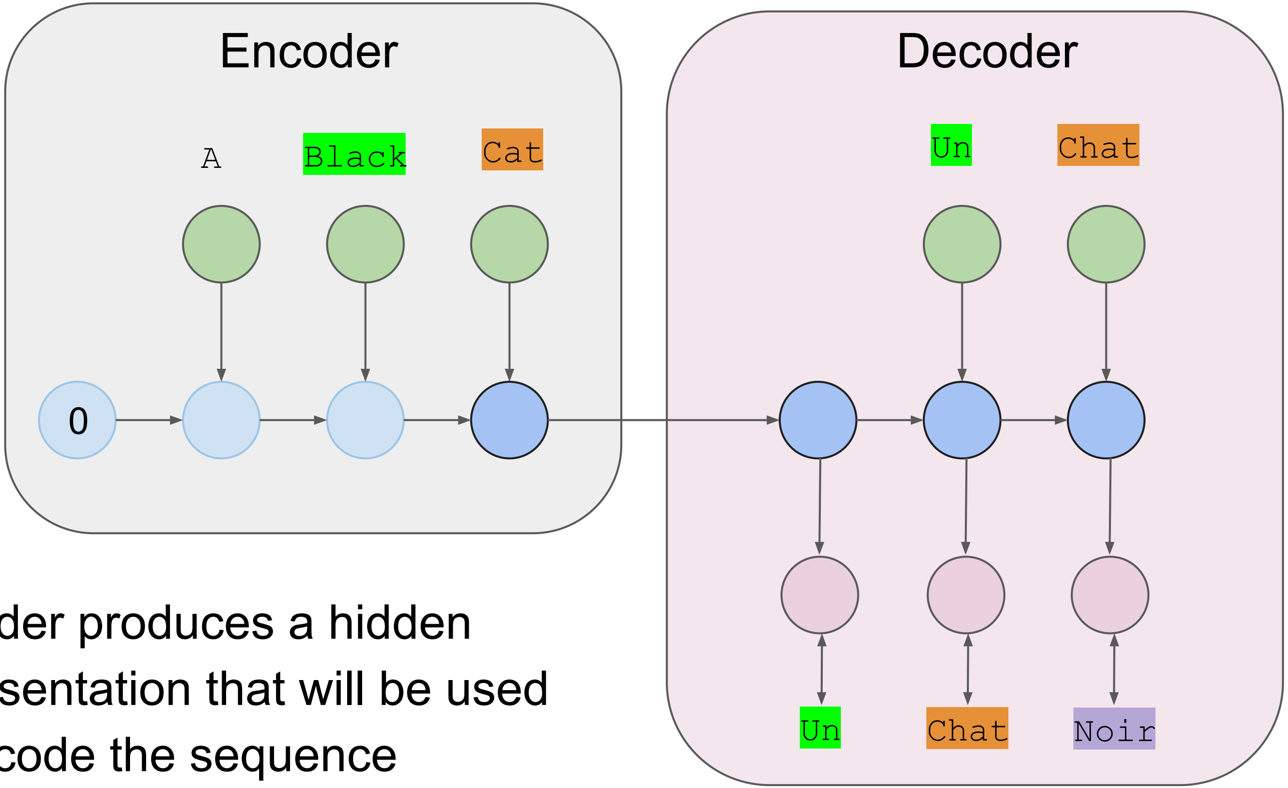


# Sequence to Sequence




Encoder produces a hidden representation that will be used to decode the sequence

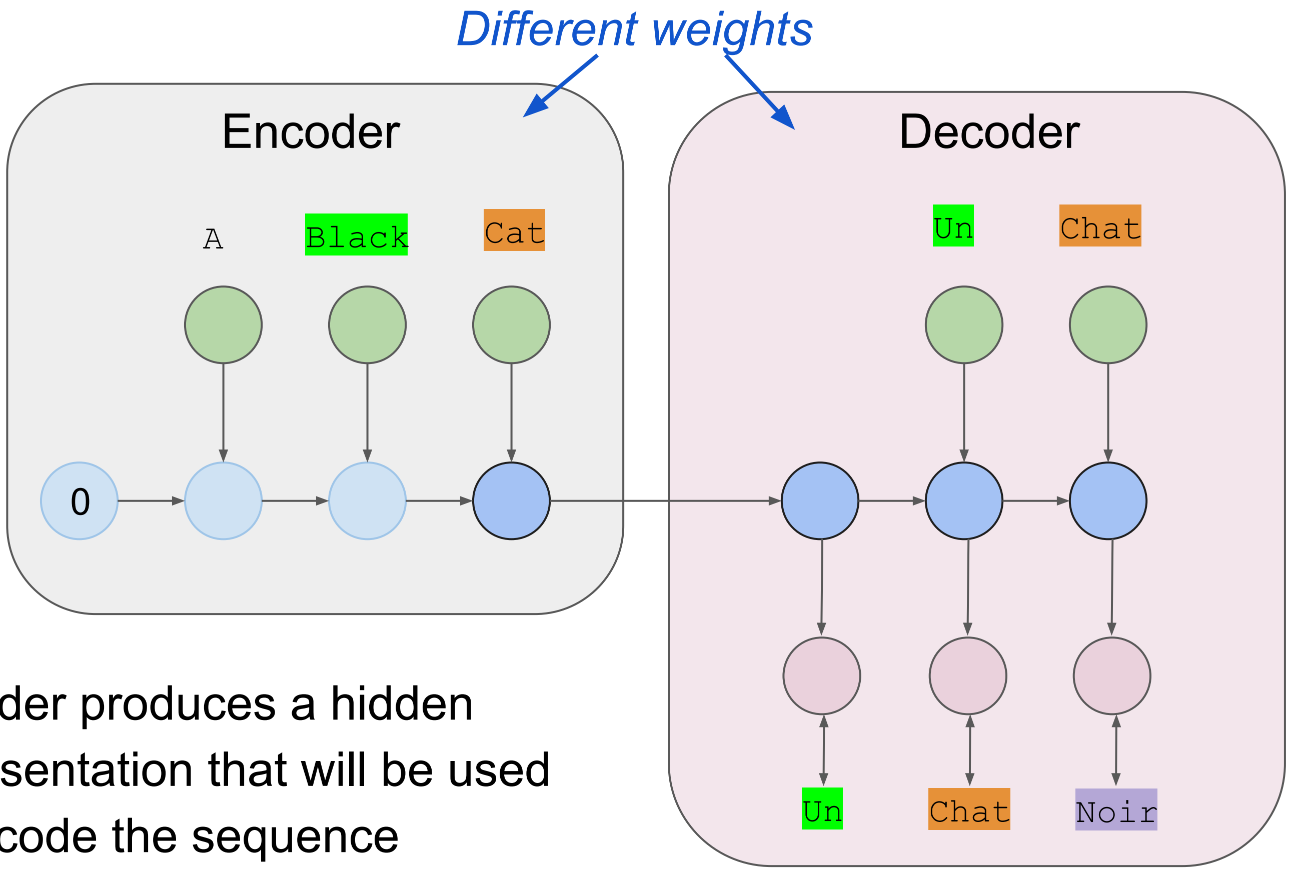
# Sequence to Sequence




Decoder is doing language modeling

Encoder produces a hidden representation that will be used to decode the sequence

# Sequence to Sequence

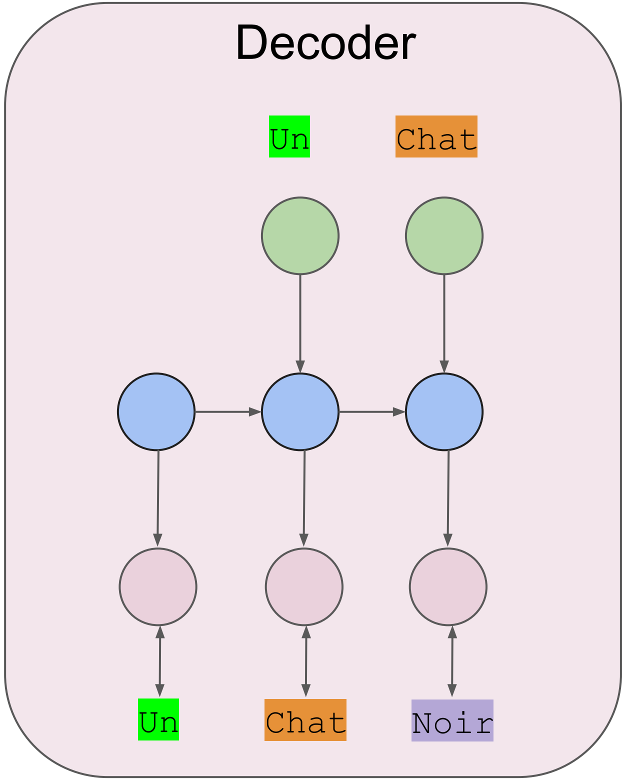



Decoder is doing language modeling

Encoder produces a hidden representation that will be used to decode the sequence

# Sequence to Sequence

Last week, we were looking at decoder-only models

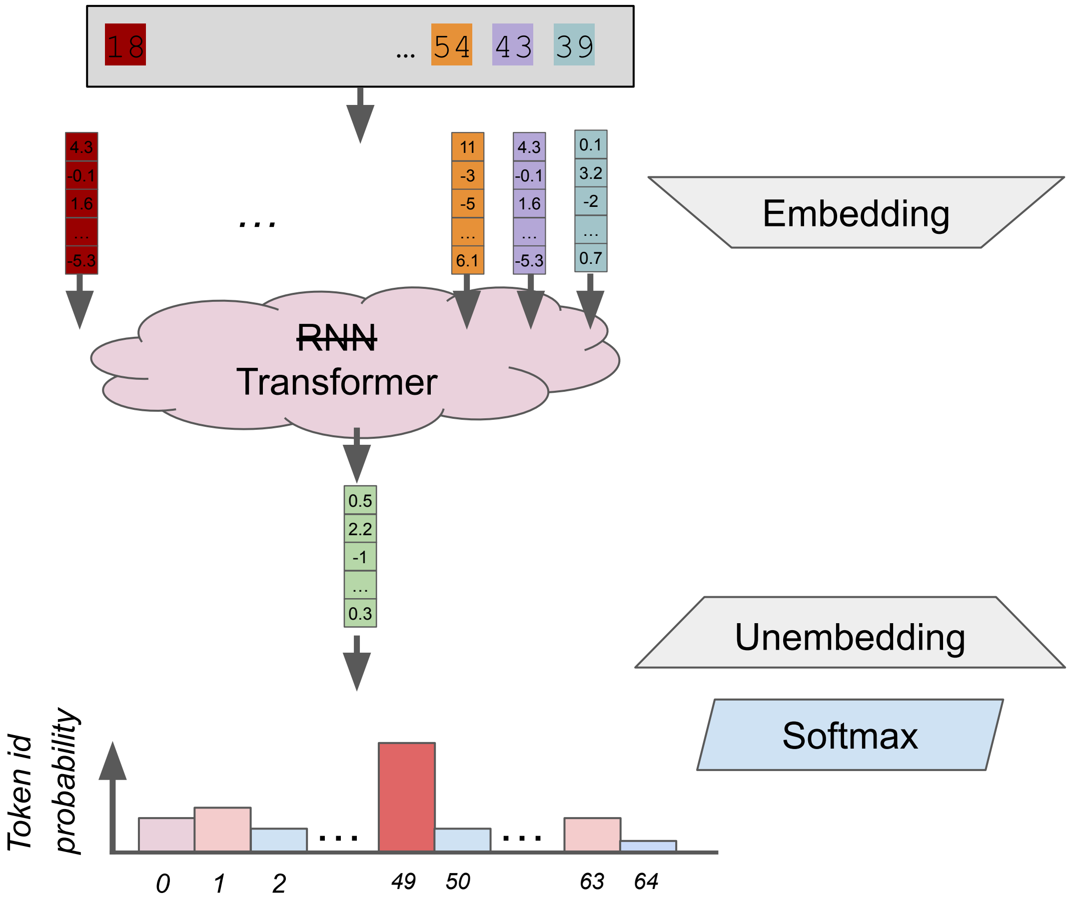



Decoder is doing language modeling

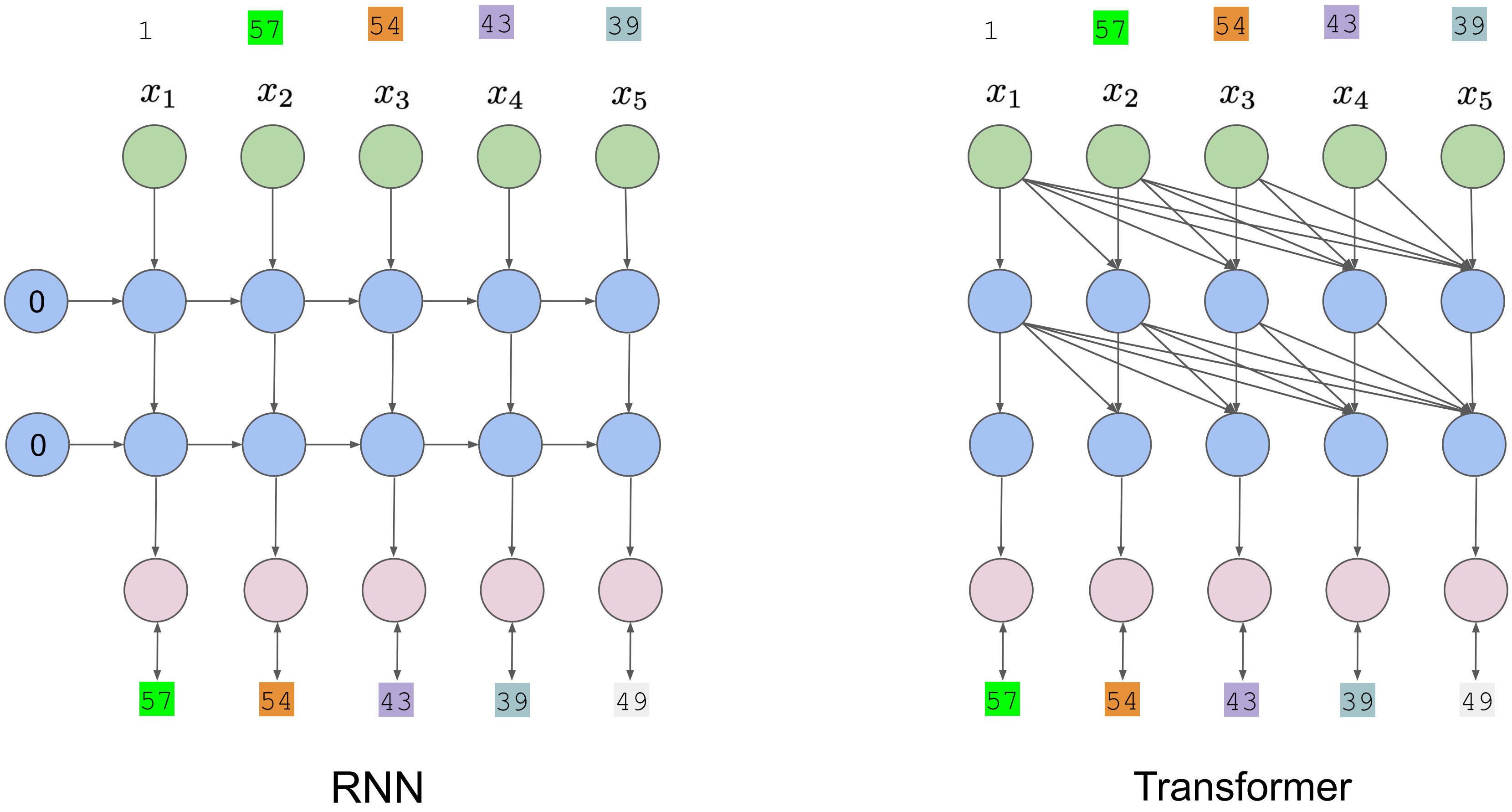
# Transformers

# Transformers

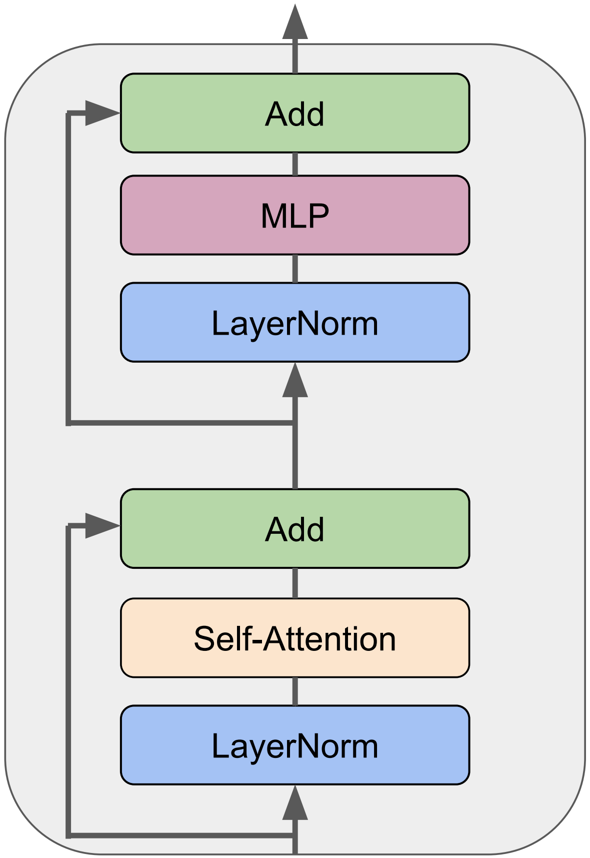
We will go back to our decoder-only language modeling setting.



# Transformers



# Transformers

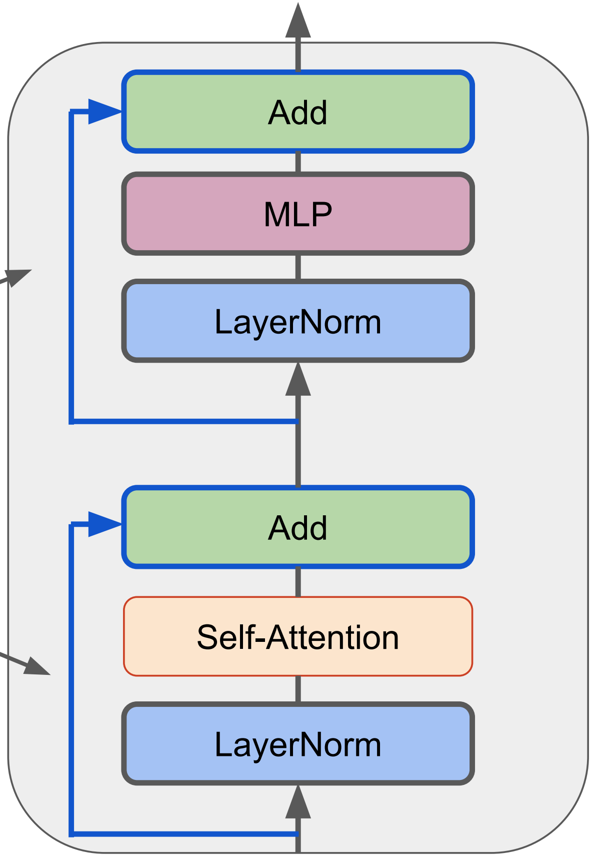



Transformer block

# Transformers

We know almost all of the components!

Skip Connections




Transformer block

# Layernorm

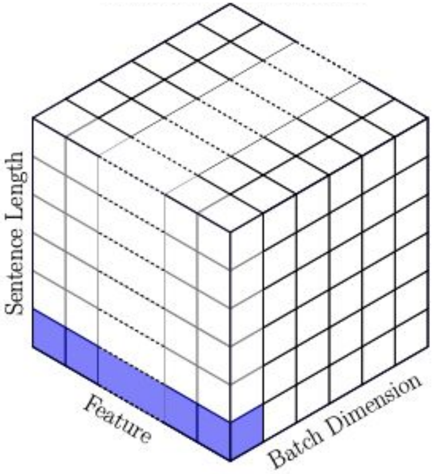
Layernorm output

Input

Trainable scale

Trainable shift

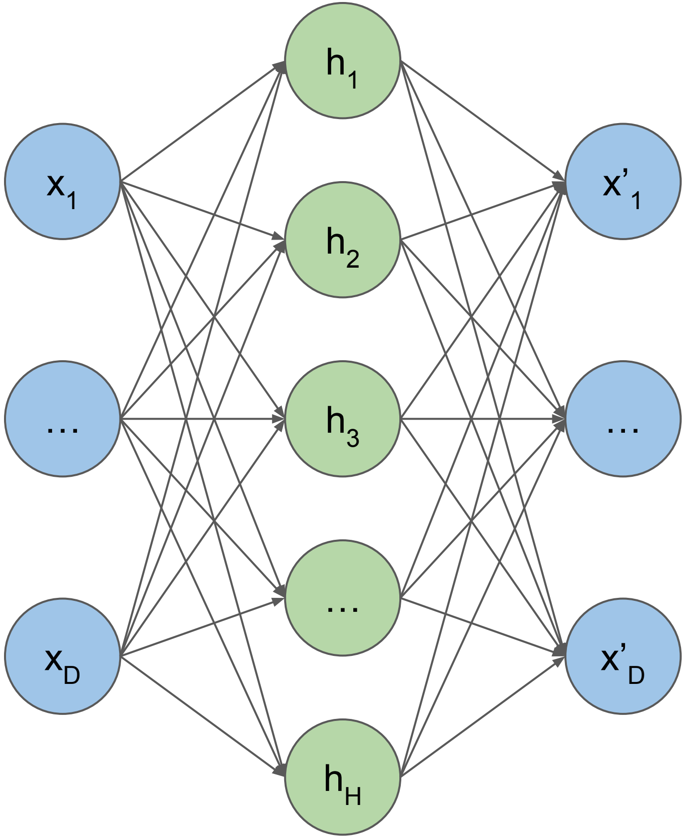
$$y = \frac{x - \boxed{\mathrm{E}[x]}}{\sqrt{\boxed{\mathrm{Var}[x]} + \epsilon}} * \gamma + \beta$$




- We normalize the activations per token
- Mean and variance are computed over all dimensions of the input

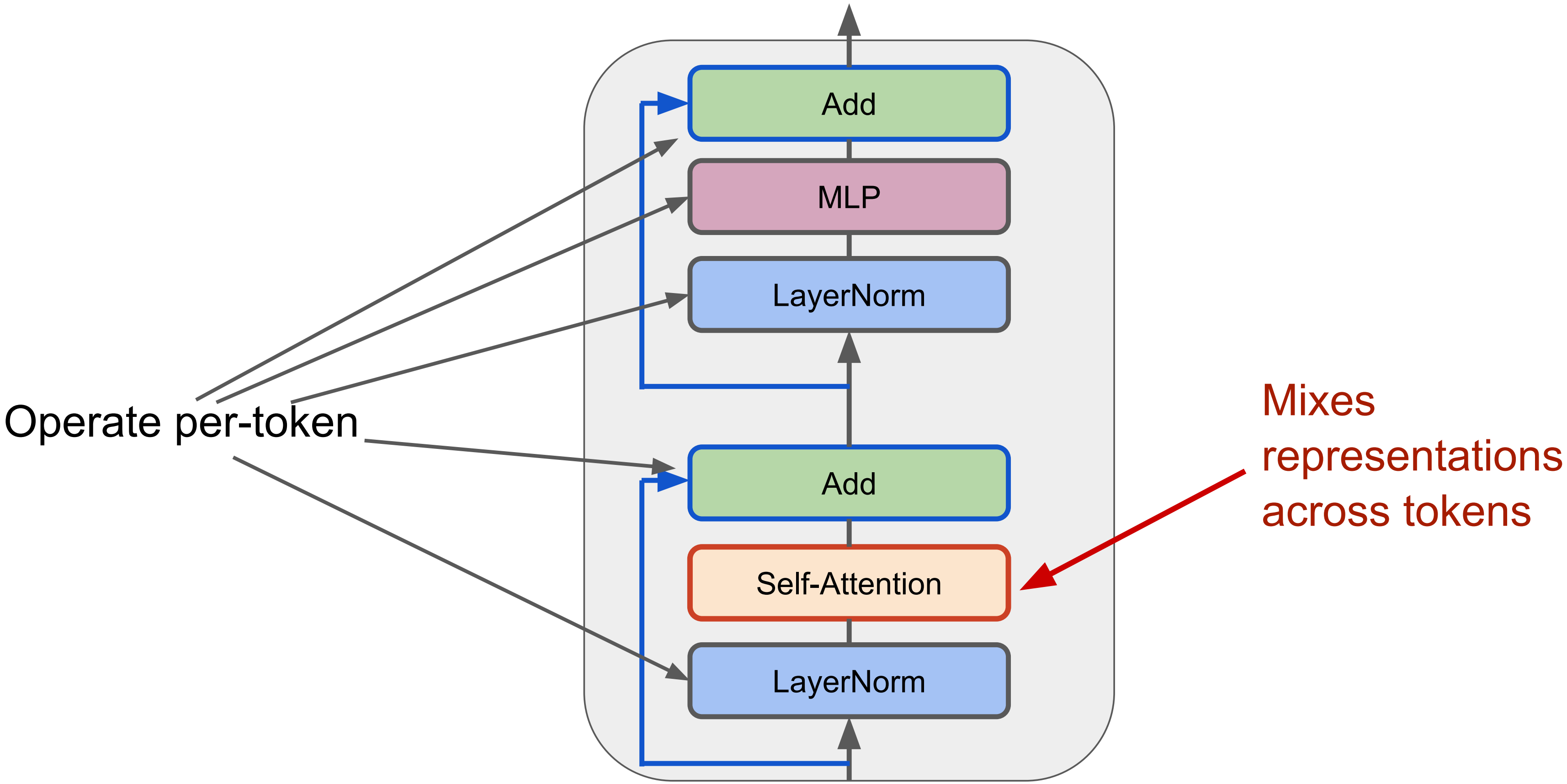
https://arxiv.org/abs/1502.03167

# MLP



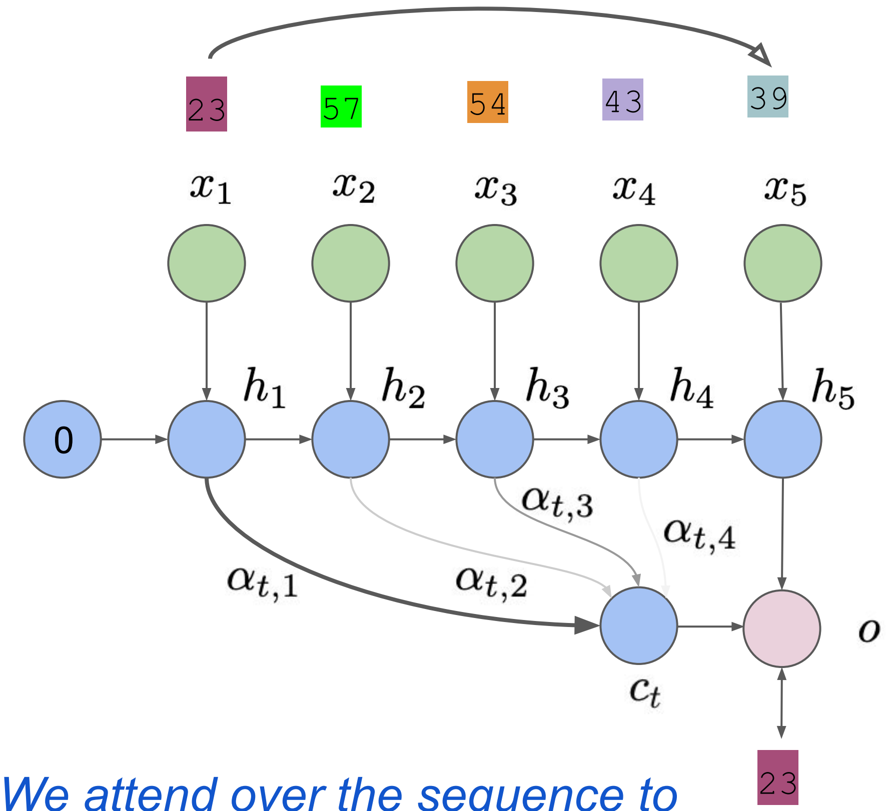

- Same MLP as we discussed before
- Transforms the features of each token separately

# Transformers




Transformer block

# RNN Variants: Attention




*We attend over the sequence to look for relevant information!*

We will try to fix the long-range dependence issue.

$$e_{t,i} = \text{score}(h_t, h_i), \quad i < t$$

$$\alpha_{t,i} = \frac{\exp(e_{t,i})}{\sum_{j<t} \exp(e_{t,j})}$$

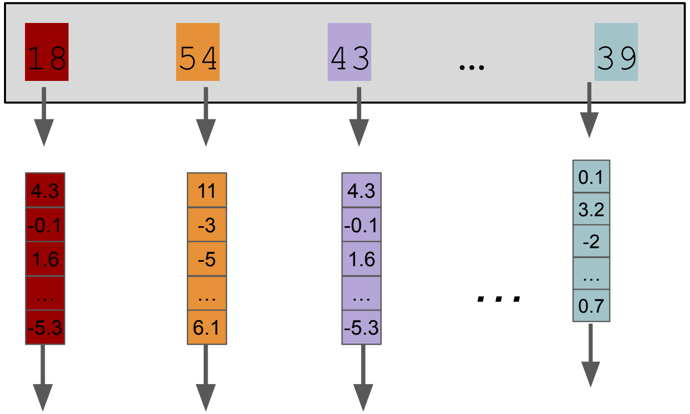
Compute *attention weights* for each previous token

$$c_t = \sum_{i<t} \alpha_{t,i} h_i$$

Use a weighted sum of all representations to make the prediction

# Self-Attention

We want a transformation that can mix representations over multiple tokens.




We have a sequence of hidden representations

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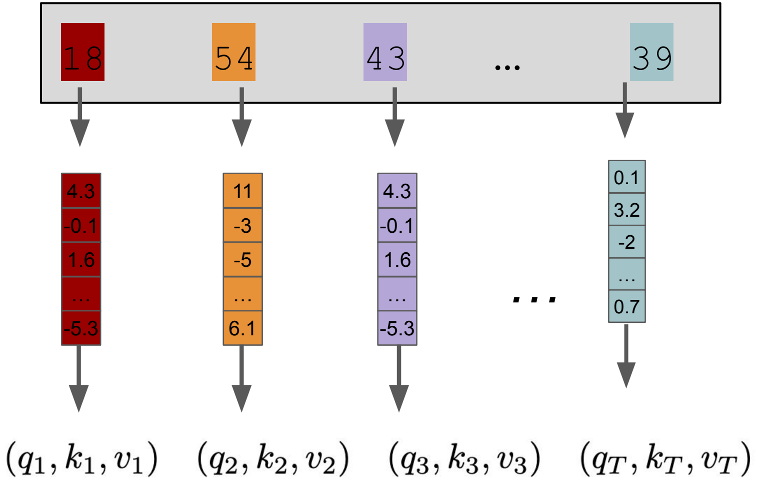


We have a sequence of hidden representations

(q=query, k=key, v=value)

# Self-Attention

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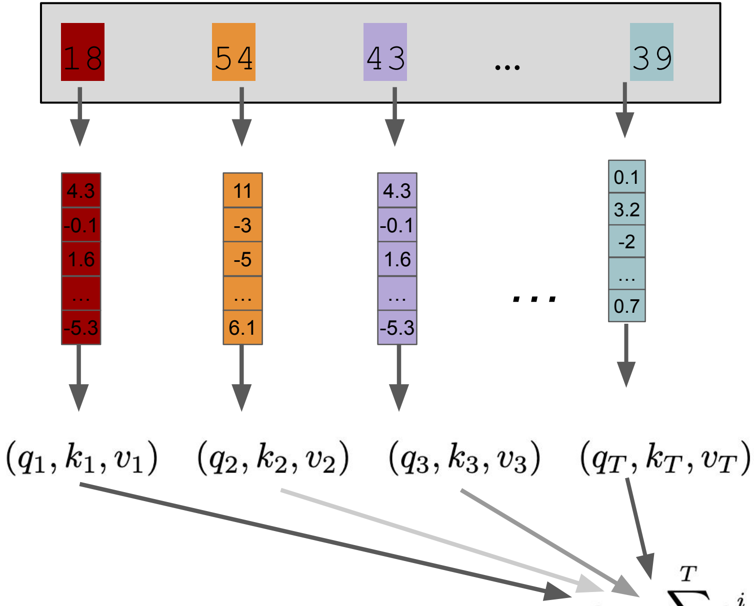


$$o_T = \sum_{i=1}^{T} \alpha_T^i v_i,$$

$$(\alpha_T^1, \alpha_T^2, \ldots, \alpha_T^T) = \text{softmax}\left[\text{sim}(q_T, k_1), \text{sim}(q_T, k_2), \ldots, \text{sim}(q_T, k_T)\right]$$

We have a sequence of hidden representations

(q=query, k=key, v=value)

Output is a mix of values with weights based on similarity(query_T, key_i)

# Key-Query-Value example

| Item | Key (car features) | Value (car mpg) |
| --- | --- | --- |
| Honda Civic | HP: 158, Engine: 2.0L, Year: 2020 | 33 |
| Ford Mustang | HP: 310, Engine: 5.0L, Year: 2019 | 18 |
| Toyota Prius | HP: 121, Engine: 1.8L, Year: 2021 | 52 |
| … | … | … |
| Chevy Silverado | HP: 285, Engine: 4.3L, Year: 2020 | 20 |

| Item | Query |
| --- | --- |
| Mystery Sedan | HP: 150, Engine: 1.9L, Year: 2020 |

# Key-Query-Value example

| Item | Key (car features) | Value (car mpg) | Similarity(key, query) |
|---|---|---|---|
| Honda Civic | HP: 158, Engine: 2.0L, Year: 2020 | 33 | 0.92 |
| Ford Mustang | HP: 310, Engine: 5.0L, Year: 2019 | 18 | 0.31 |
| Toyota Prius | HP: 121, Engine: 1.8L, Year: 2021 | 52 | 0.78 |
| … | … | … | |
| Chevy Silverado | HP: 285, Engine: 4.3L, Year: 2020 | 20 | 0.35 |

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# Key-Query-Value example

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$$o = \sum_{i=1}^{T} \alpha^i v_i,$$

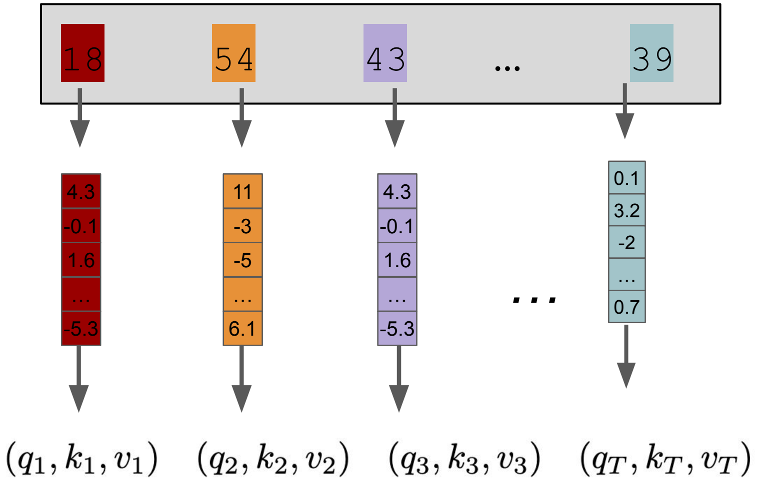
$$(\alpha^1, \alpha^2, \ldots, \alpha^T) = \operatorname{softmax}\left[\operatorname{sim}(q, k_1), \operatorname{sim}(q, k_2), \ldots, \operatorname{sim}(q, k_T)\right]$$

o = 34.2 MPG

# Key-Query-Value example

For each token:

- k: key, a description of the information in this token, used to find this token
- v: value, output associated with the key
- q: query, what we want to find in other tokens



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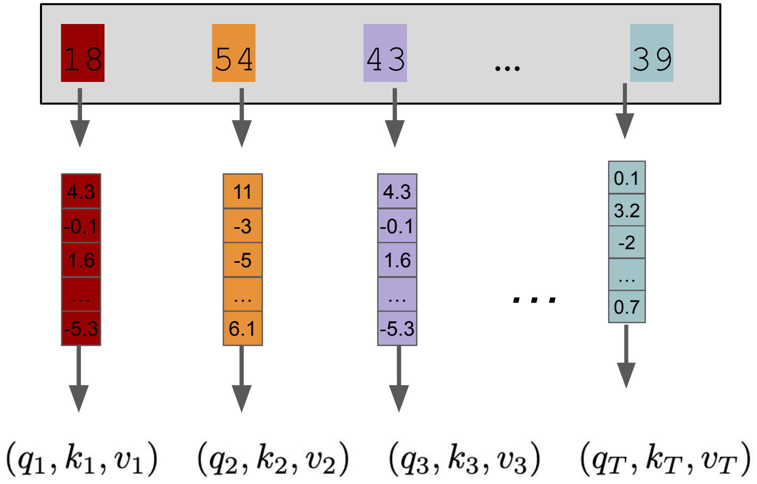
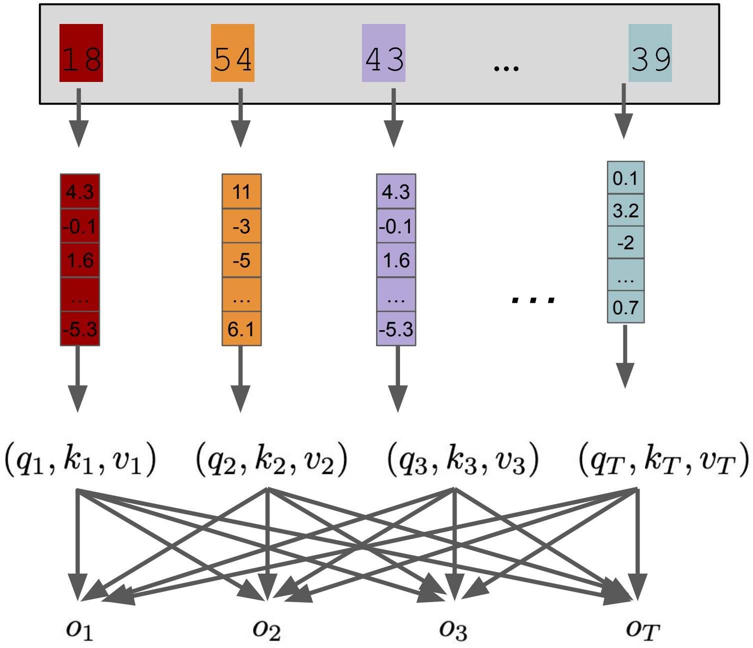



Unlike our previous example, in transformers (q, k, v) are abstract and learned by the model; they will not have an interpretable meaning

# Key-Query-Value attention

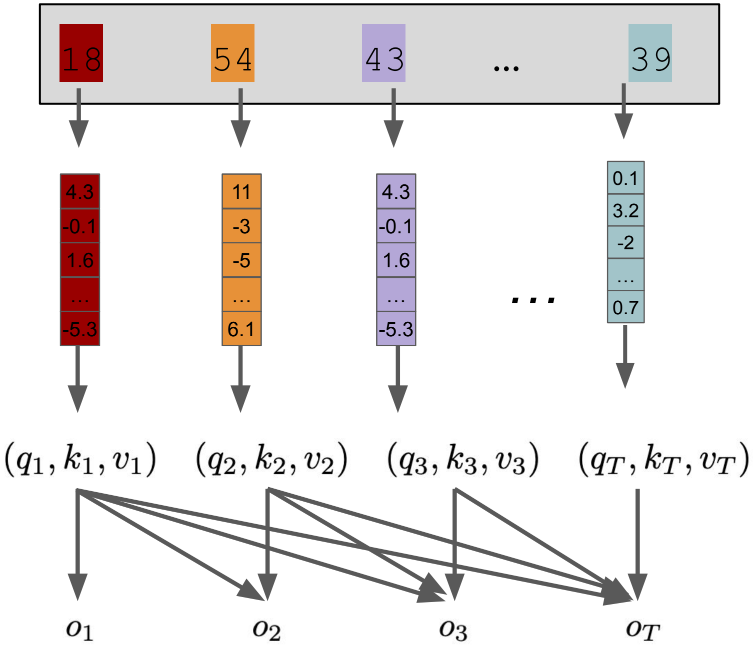



We get an output for each token, which depends on all other tokens

$$o_j = \sum_{i=1}^{T} \alpha_j^i v_i,$$

$$(\alpha_j^1, \alpha_j^2, \ldots, \alpha_j^T) = \mathrm{softmax}\left[\mathrm{sim}(q_j, k_1), \mathrm{sim}(q_j, k_2), \ldots, \mathrm{sim}(q_j, k_T)\right]$$

# Key-Query-Value attention



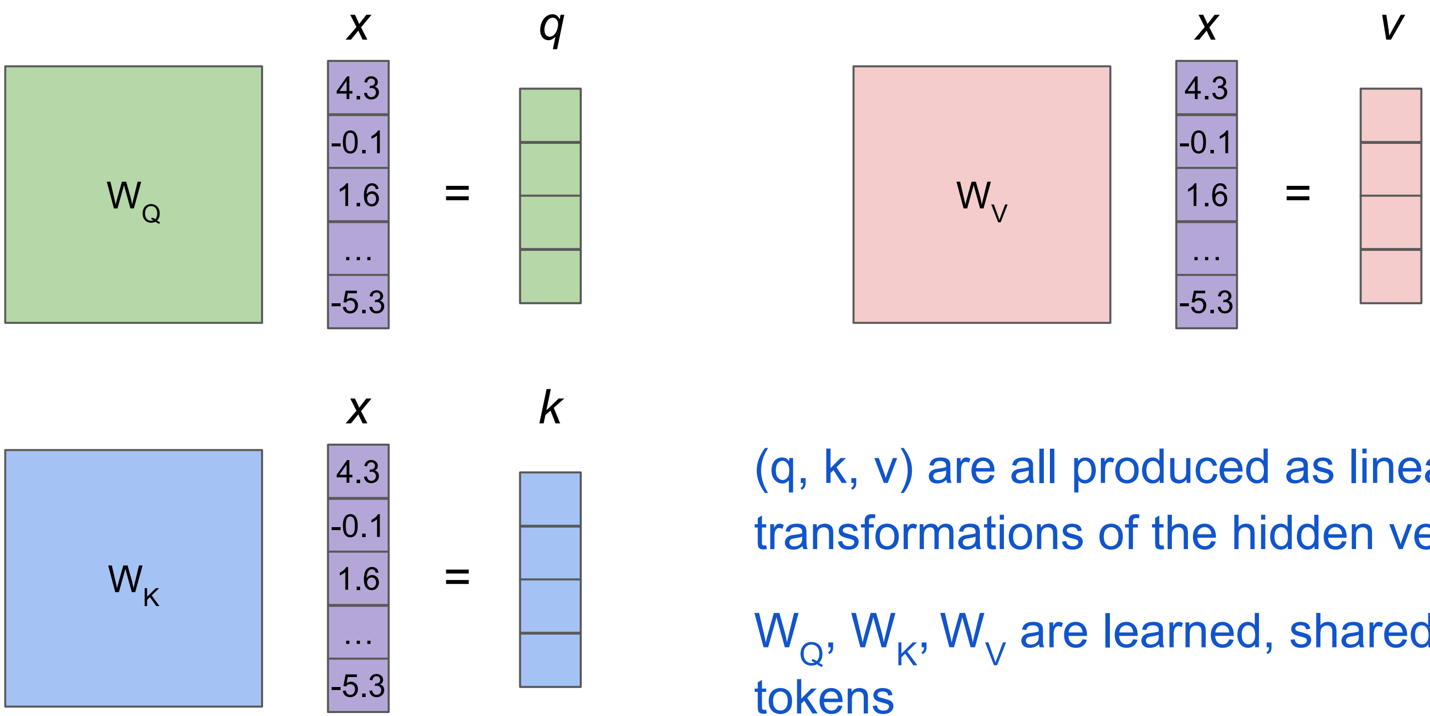

We get an output for each token, which depends on all other tokens

For language modeling we apply a causal mask: outputs can not depend on future tokens

$$o_j = \sum_{i=1}^{T} \alpha_j^i v_i,$$

$$(\alpha_j^1, \alpha_j^2, \dots, \alpha_j^T) = \text{softmax}\big[\text{sim}(q_j, k_1), \text{sim}(q_j, k_2), \dots, \text{sim}(q_j, k_T)\big]$$

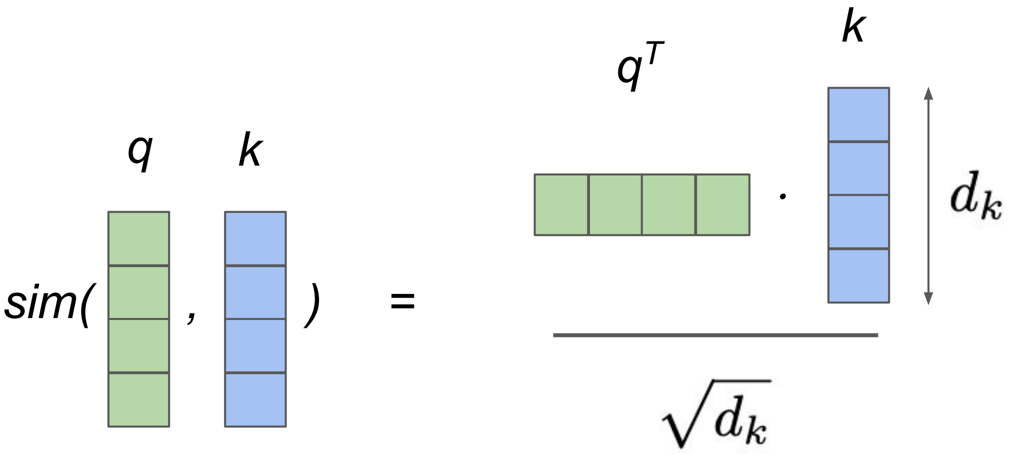
# Dot-Product Self Attention




(q, k, v) are all produced as linear transformations of the hidden vector

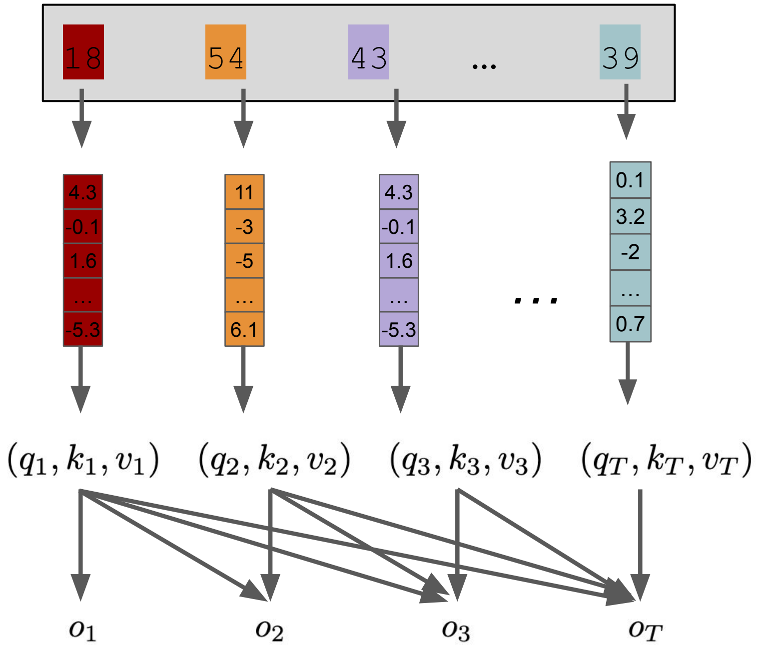
$W_Q$, $W_K$, $W_V$ are learned, shared across all tokens

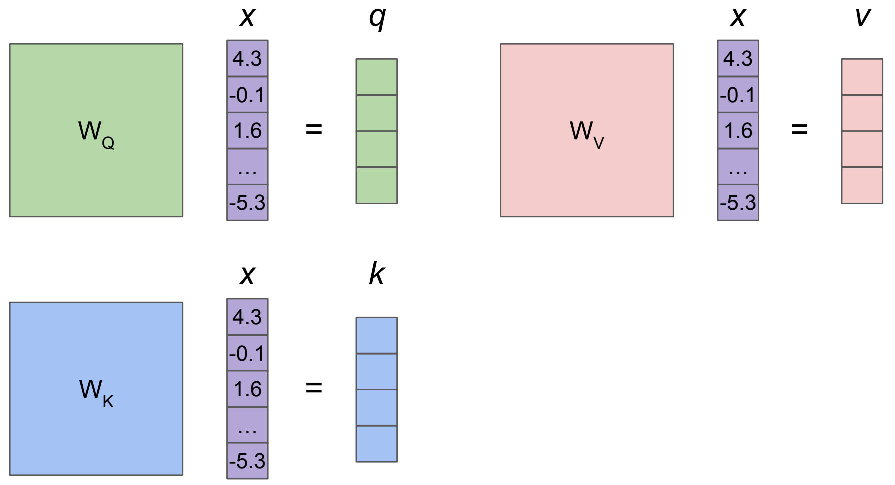
# Dot-Product Self Attention




Our similarity score is a scaled dot product. We will explain the scale later.

# Dot-Product Self Attention

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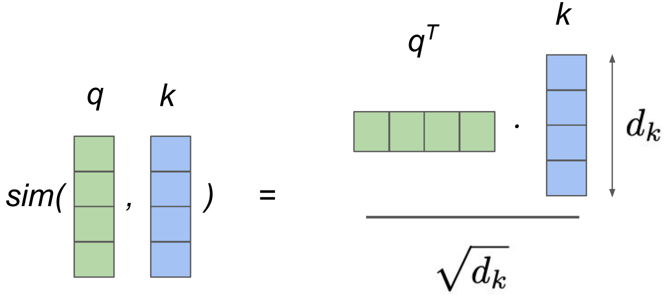

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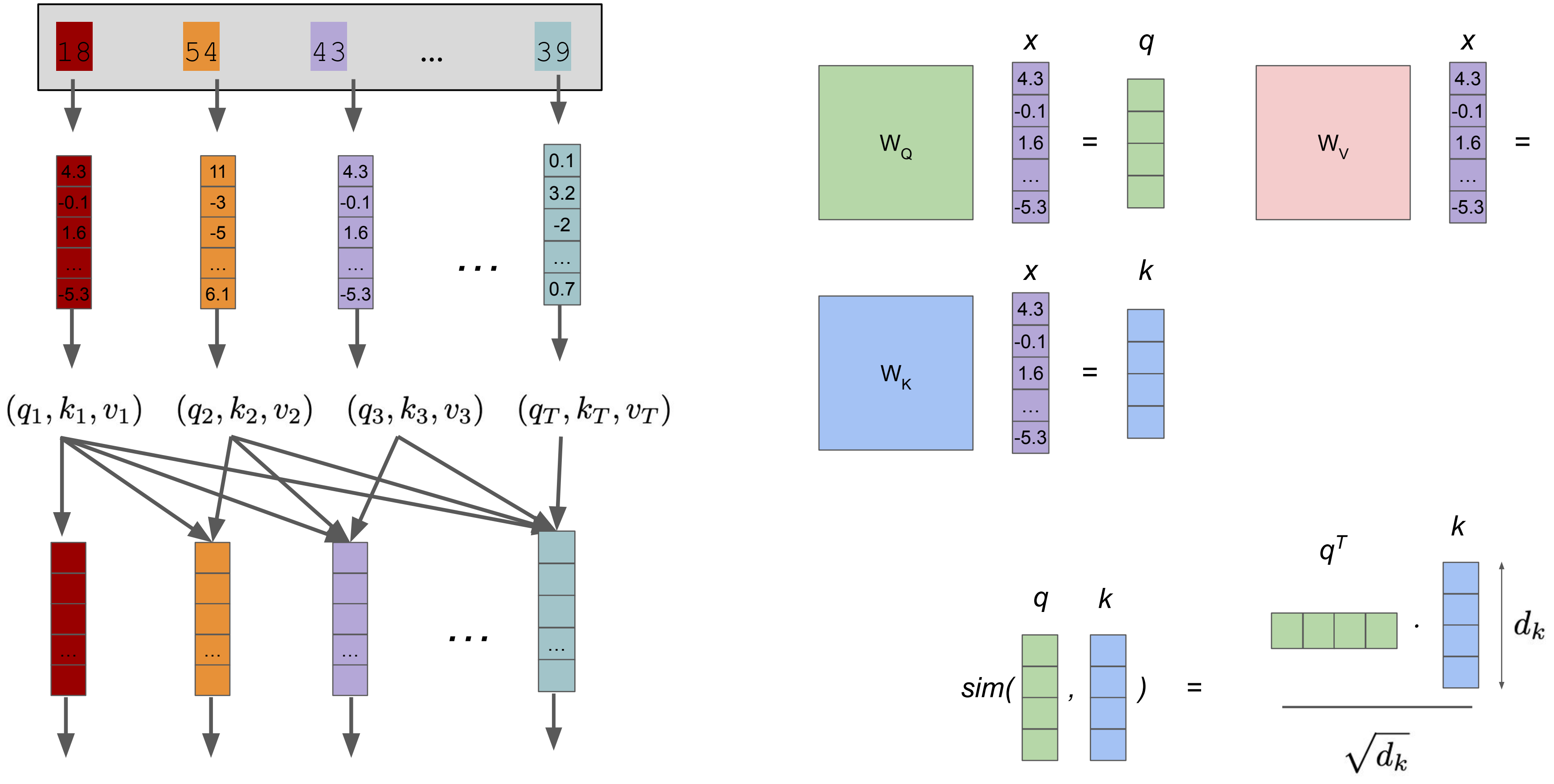

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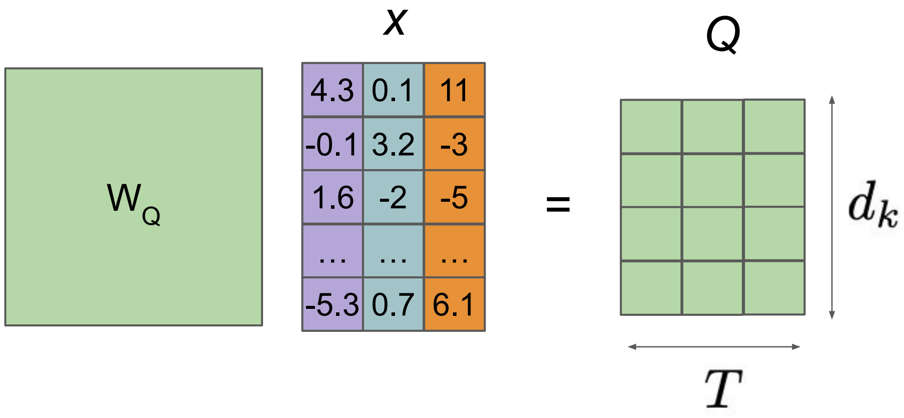
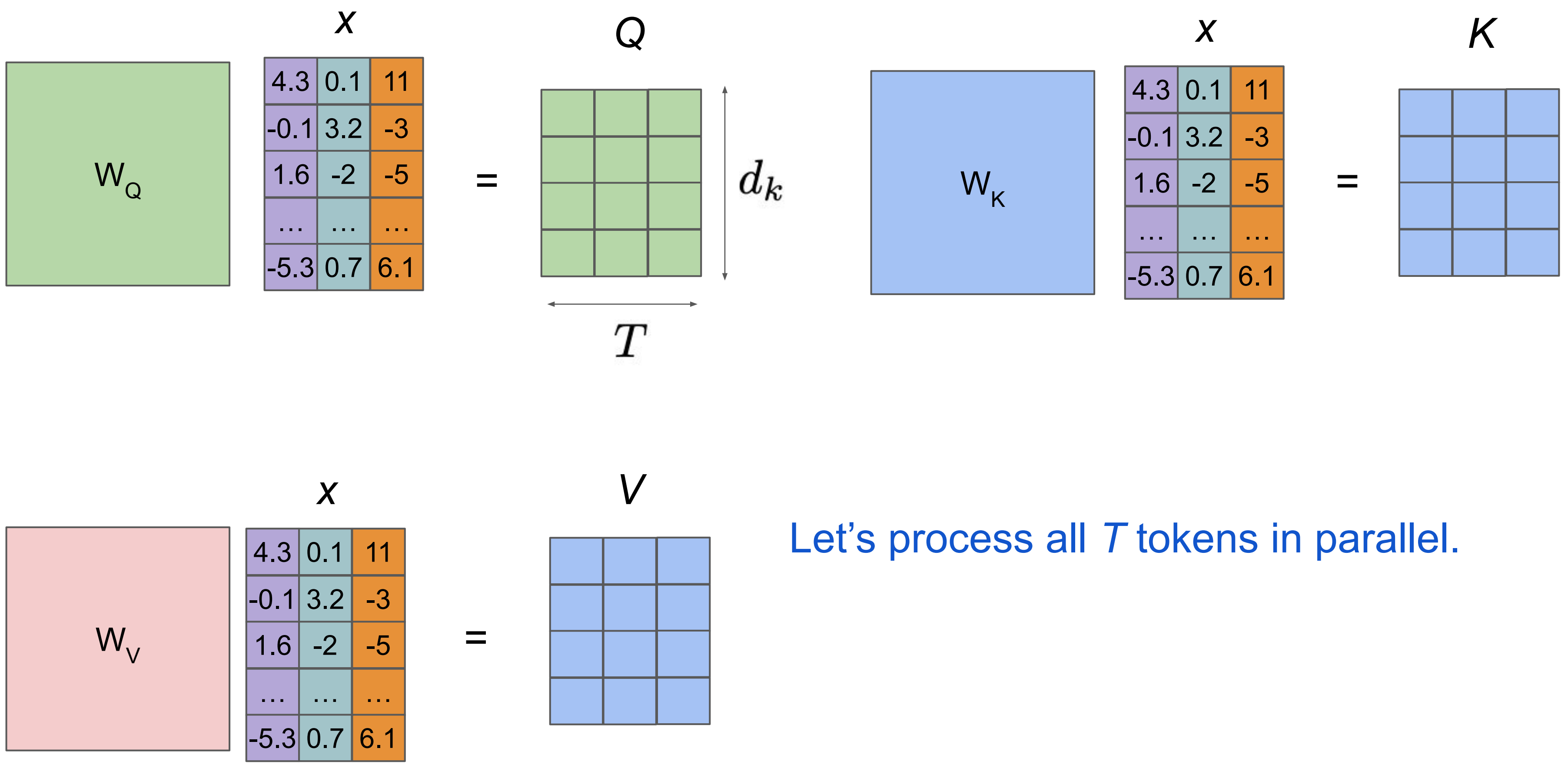


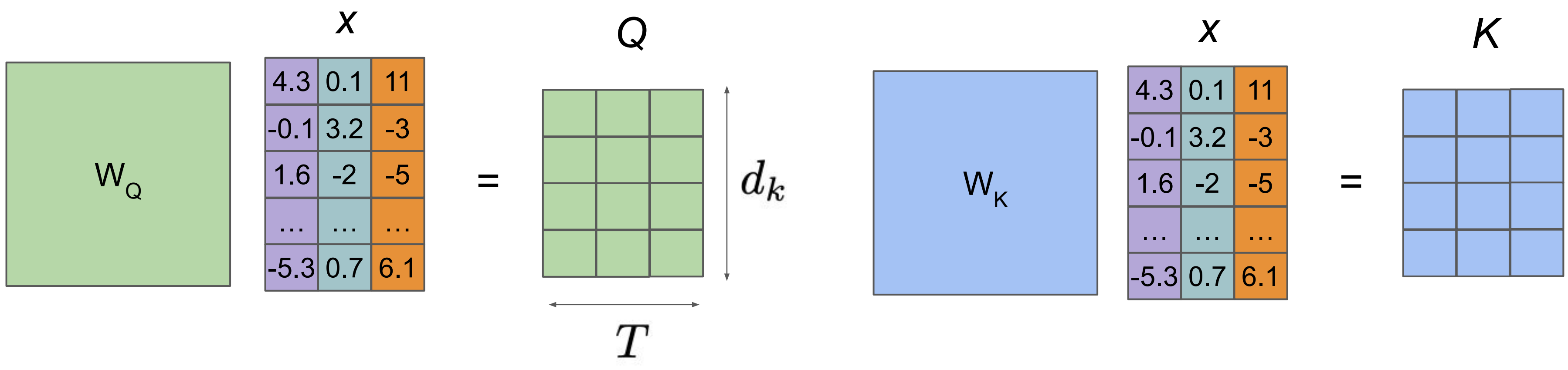

Let's process all $T$ tokens in parallel.

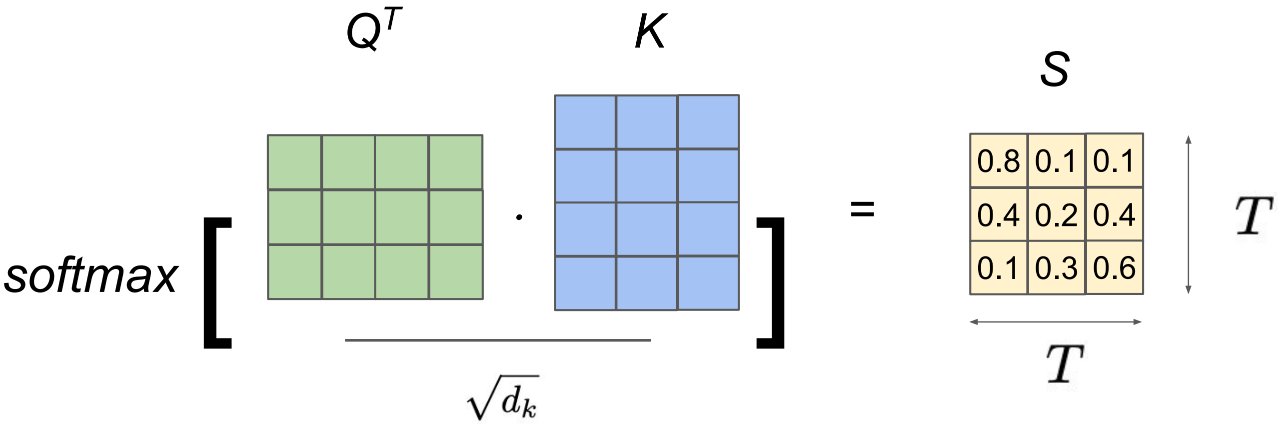
# Dot-Product Self Attention




Let’s process all *T* tokens in parallel.

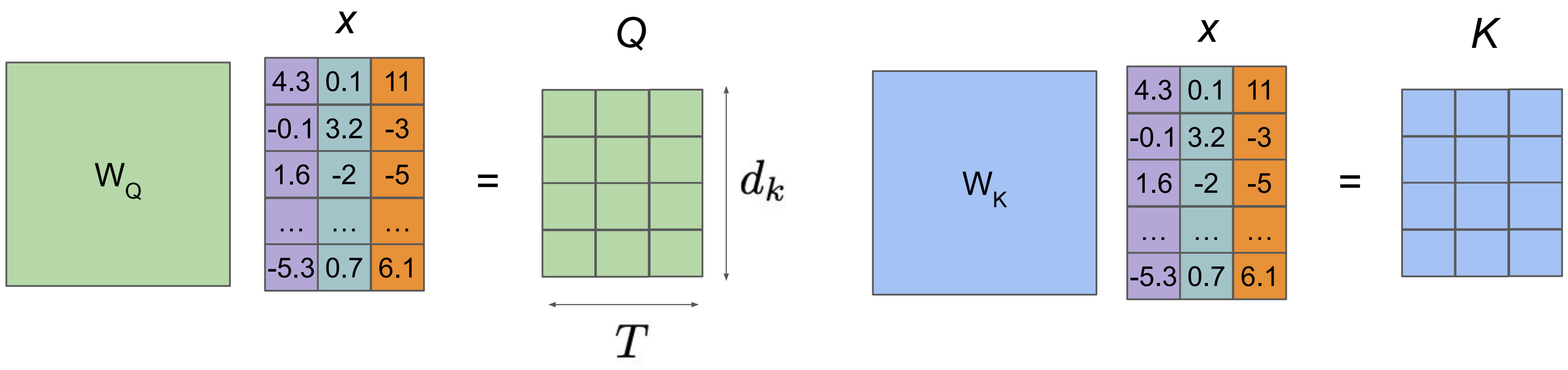
# Dot-Product Self Attention

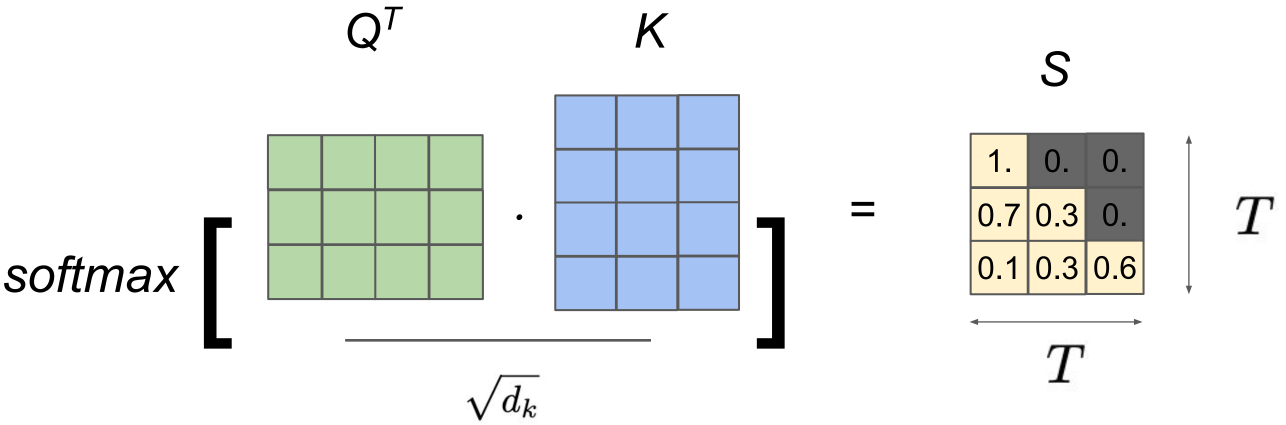



Then, construct a *T* by *T* similarity matrix.

# Dot-Product Self Attention

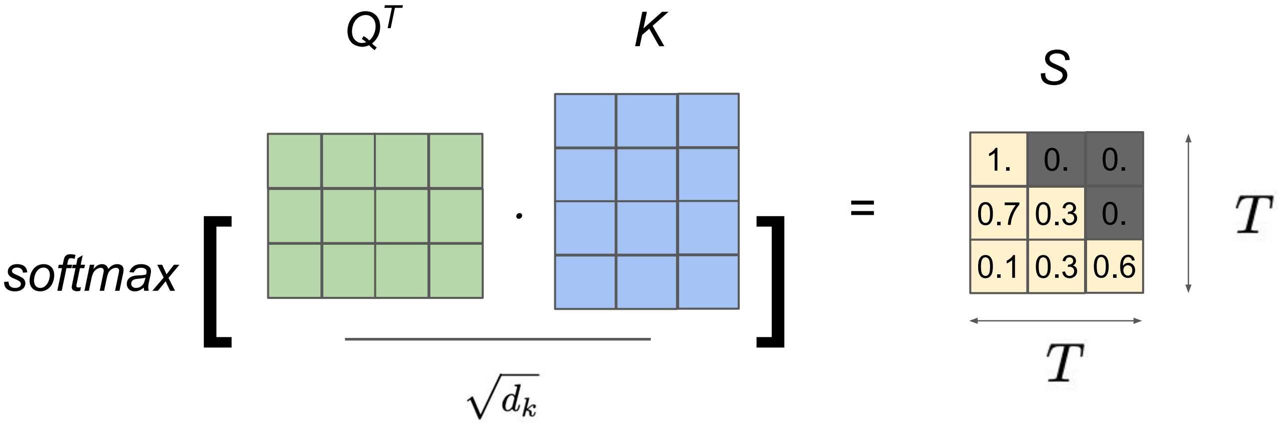


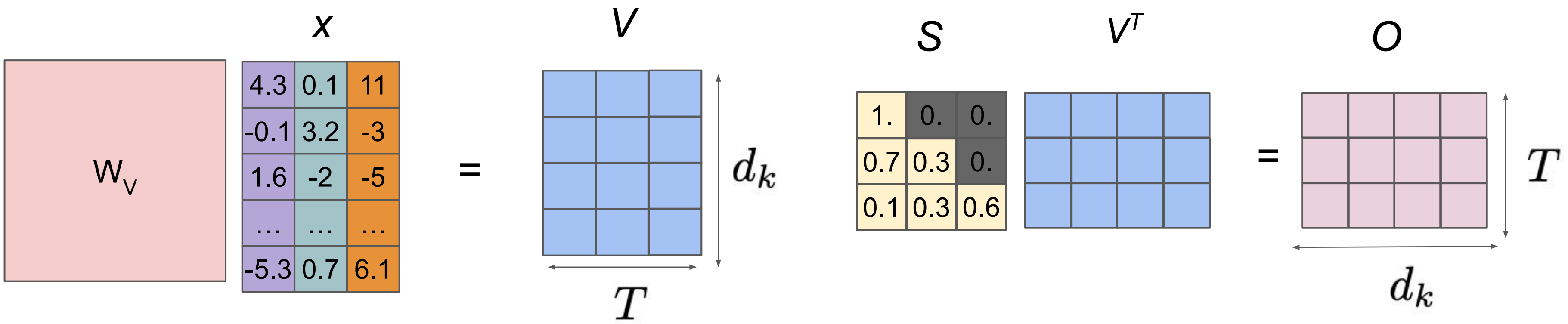

Then, construct a *T* by *T* similarity matrix.

Causal mask: cannot look at future tokens.

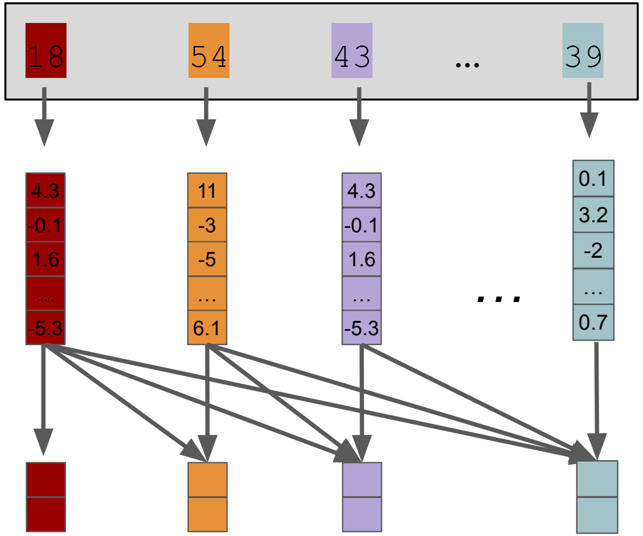
# Dot-Product Self Attention




Outputs are a mix of value vectors with weights given by S.

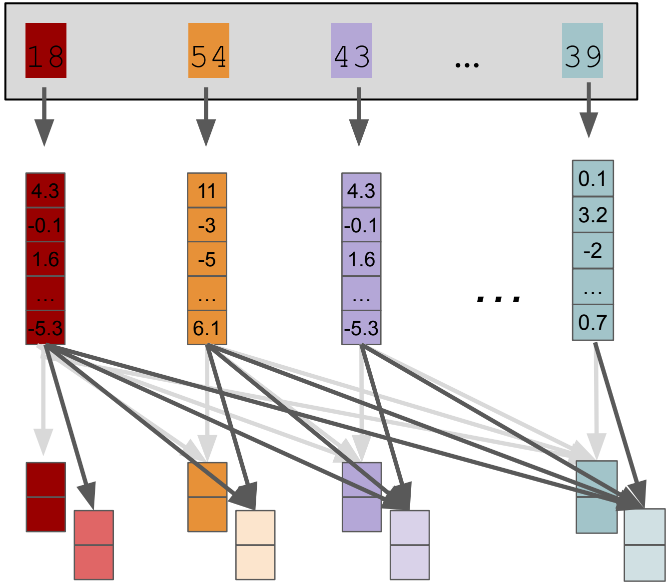


# Multi-Head Attention




Let's just do attention twice with different projection matrices $W_Q$, $W_K$, $W_V$

# Multi-Head Attention

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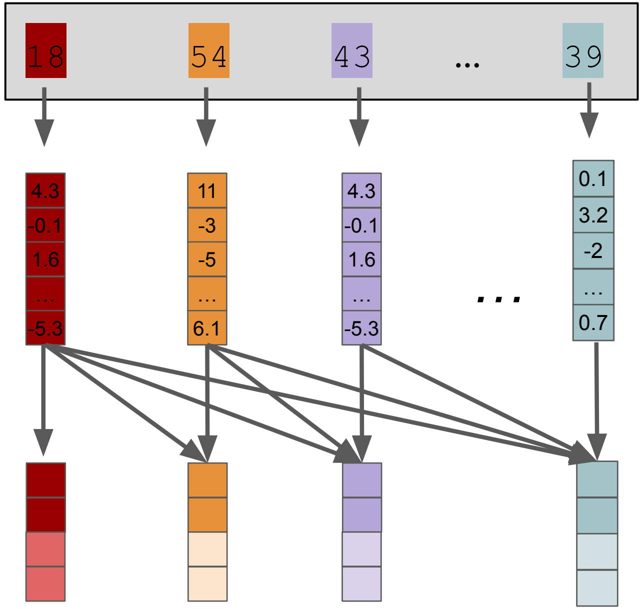



Let's just do attention twice with different projection matrices $W_Q$, $W_K$, $W_V$

We can just concatenate the outputs.

We now have two *attention heads.*

In particular, attention heads will use different attention weights.

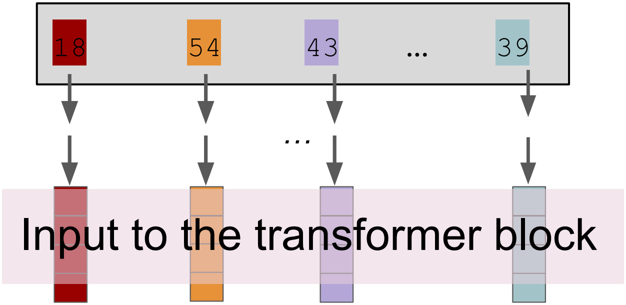
$S_1$

| | | |
|---|---|---|
| 1. | 0. | 0. |
| 0.7 | 0.3 | 0. |
| 0.1 | 0.3 | 0.6 |

$S_2$

| | | |
|---|---|---|
| 1. | 0. | 0. |
| 0.4 | 0.6 | 0. |
| 0.8 | 0.1 | 0.1 |

# Transformer: Putting it all together



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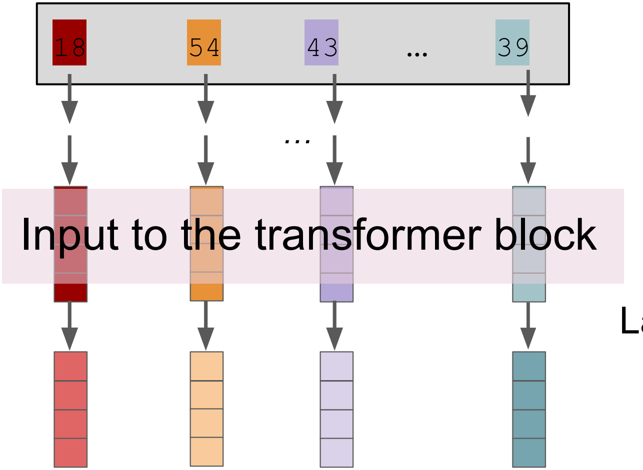
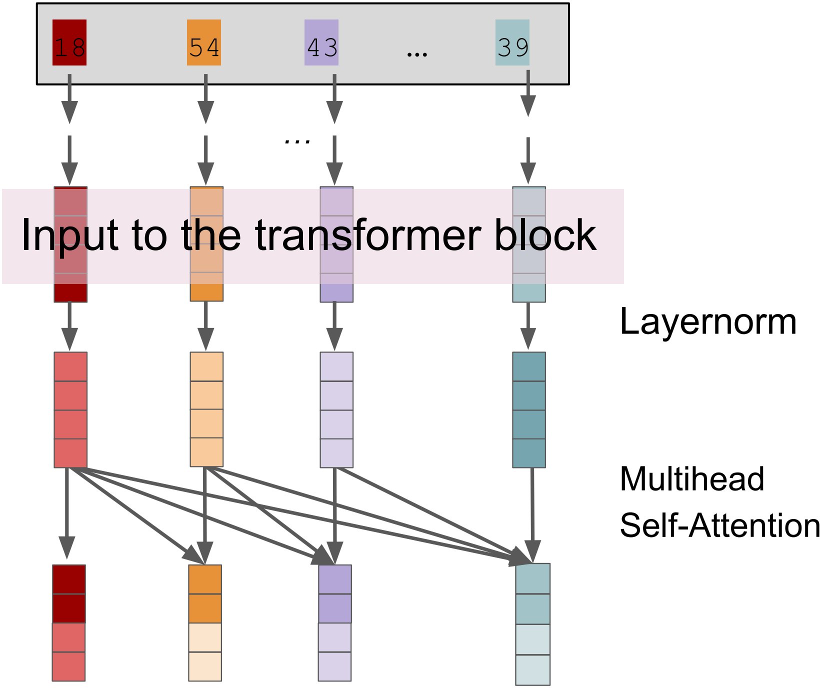



Layernorm

# Transformer: Putting it all together



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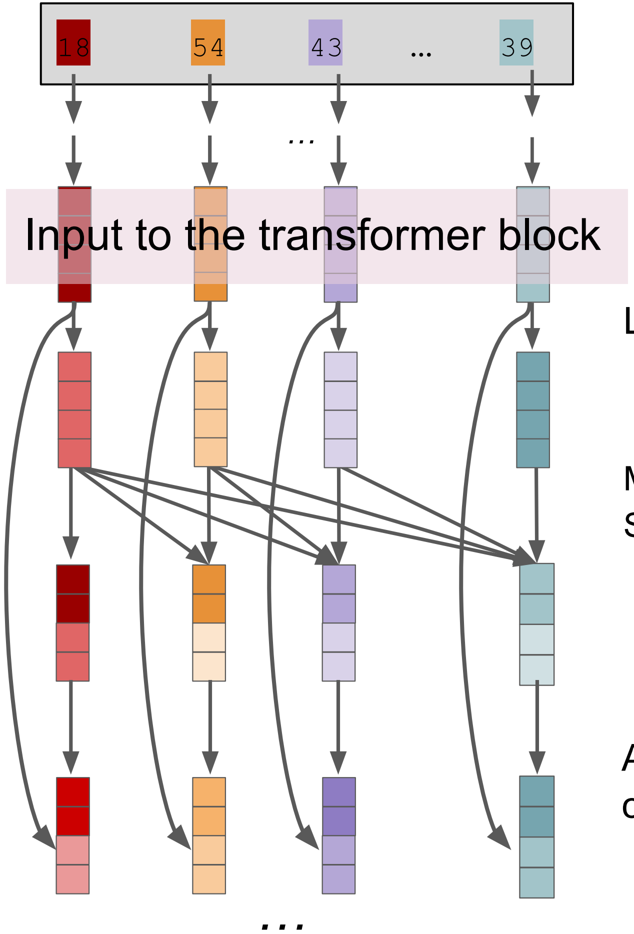
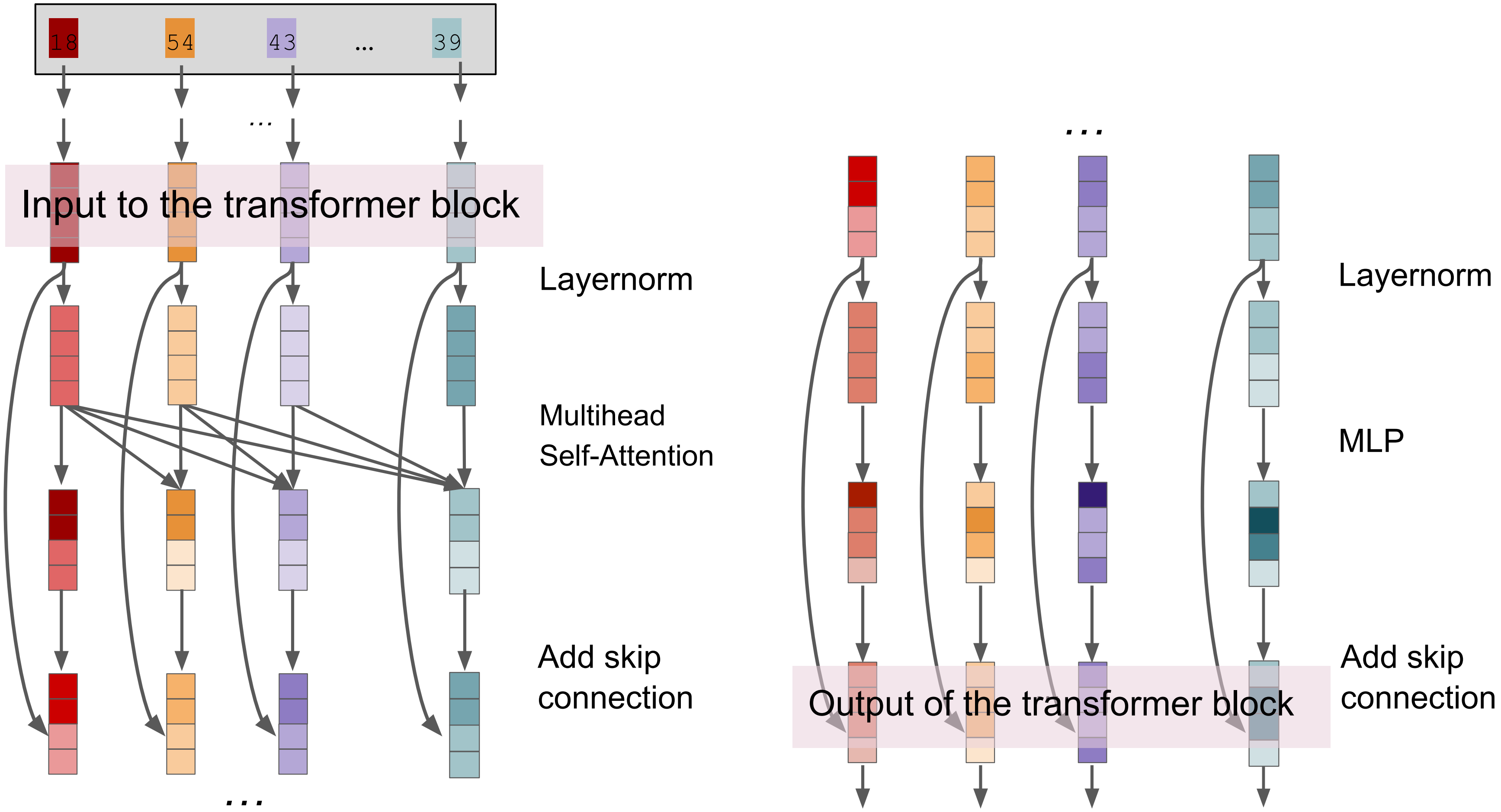



Layernorm

Multihead
Self-Attention

Add skip
connection

# Transformer: Putting it all together



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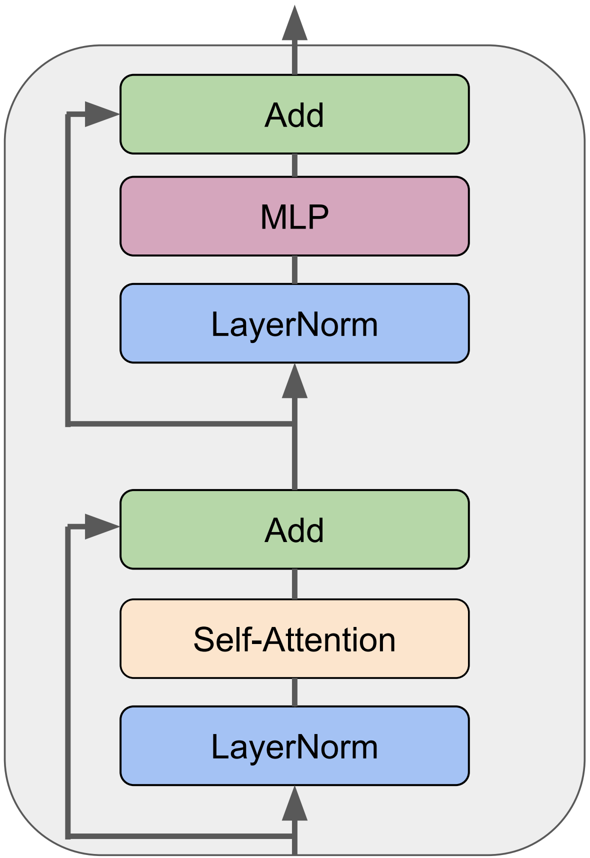
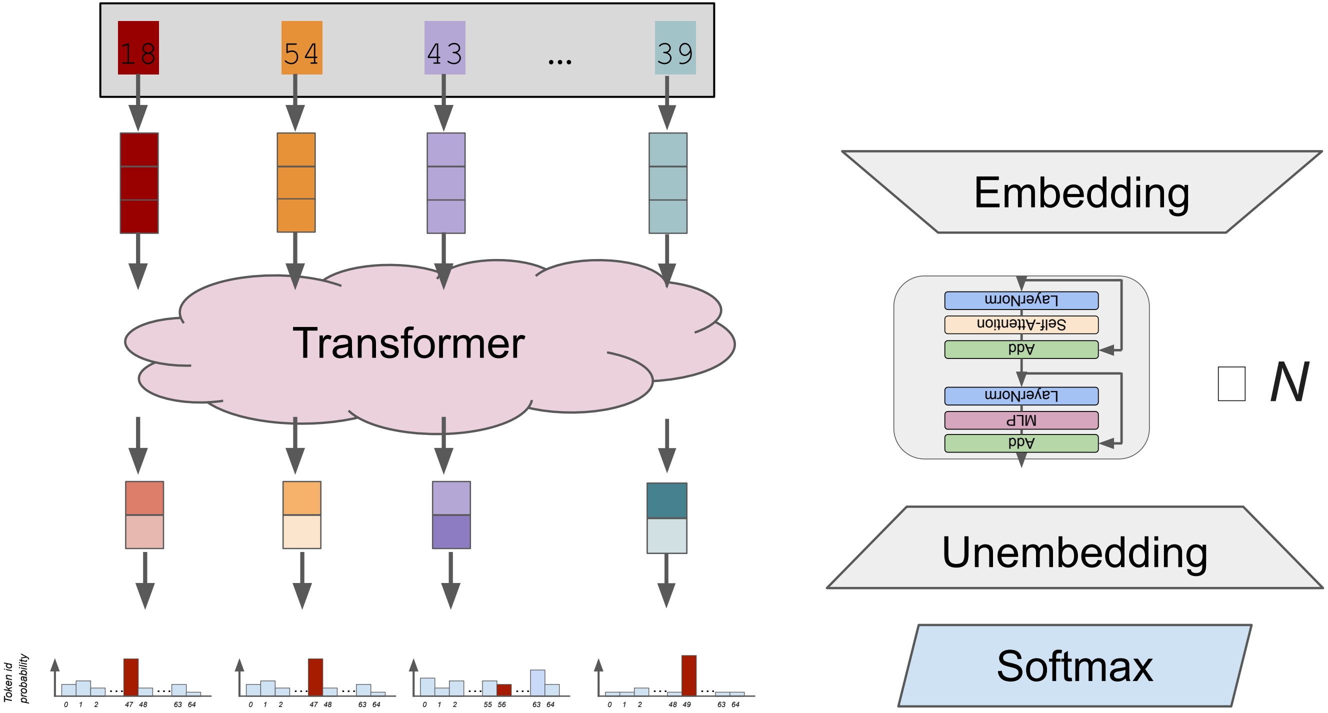



Transformer block

This is our new layer, can repeat!

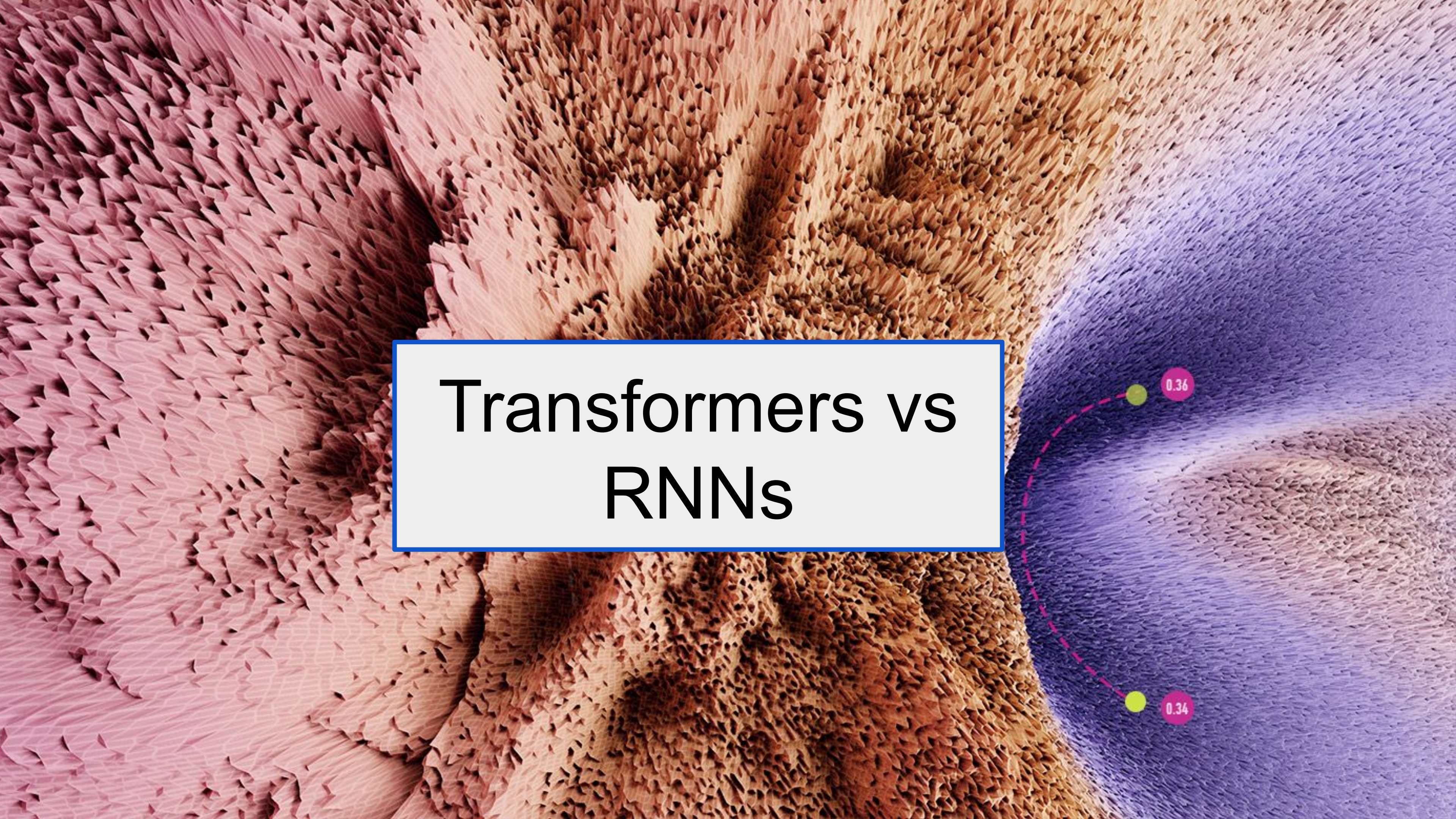
# Transformer: Putting it all together



# Attention: Temperature

# Positional Encoding

# Transformers vs RNNs



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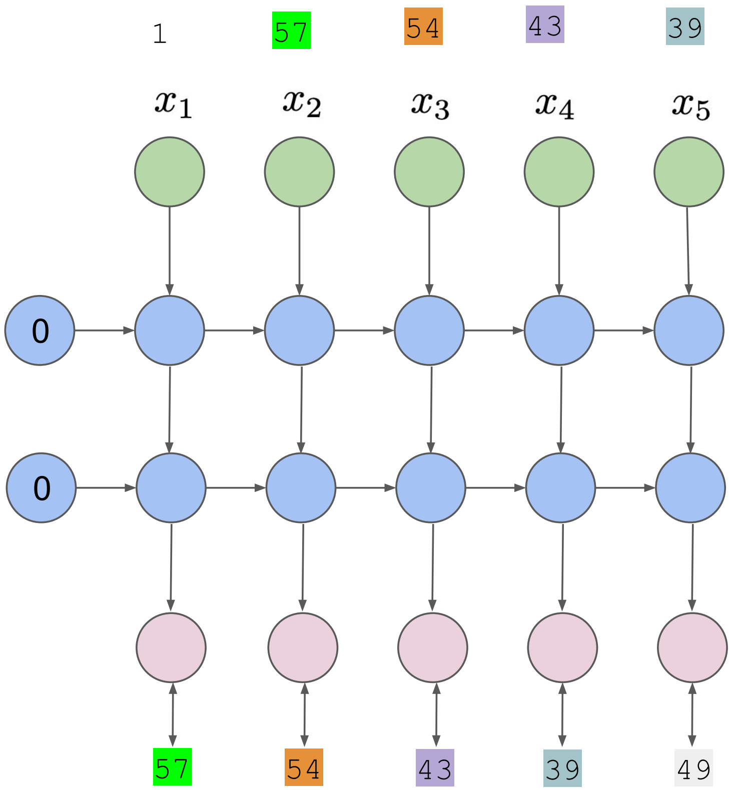
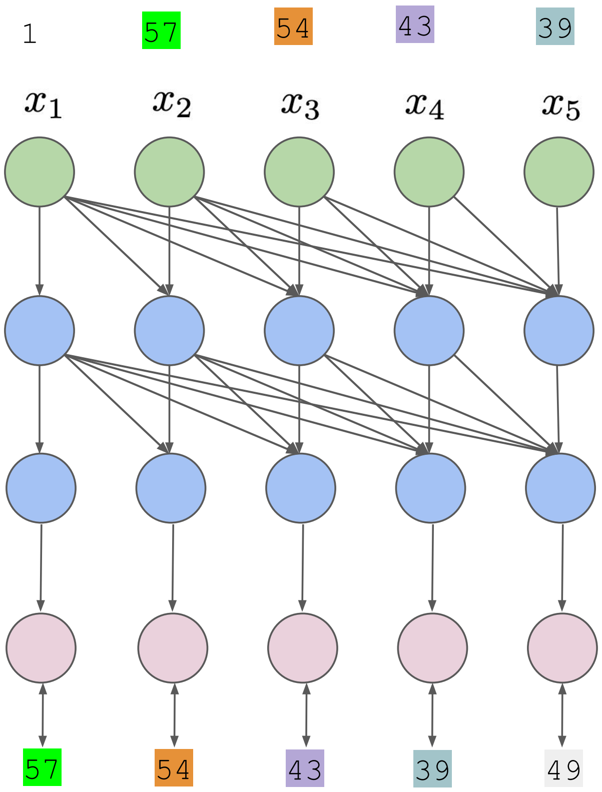



RNN

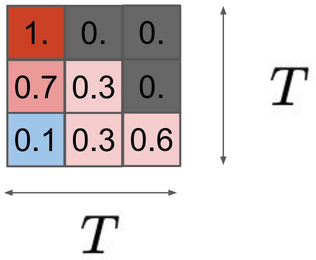
- Process inputs **sequentially**
- Memory
  - Linear in seq len T
- Compute
  - Linear in seq len T
- Time
  - Linear in seq len T
- Context compressed into a fixed-size hidden vector
- Bad at long-range dependencies

# Transformers vs RNNs




Transformer

- Process inputs in **parallel**
- Memory
  - Quadratic in seq len T
- Compute
  - Quadratic in seq len T
- Time
  - Linear in seq len T
- Good at long-range dependencies



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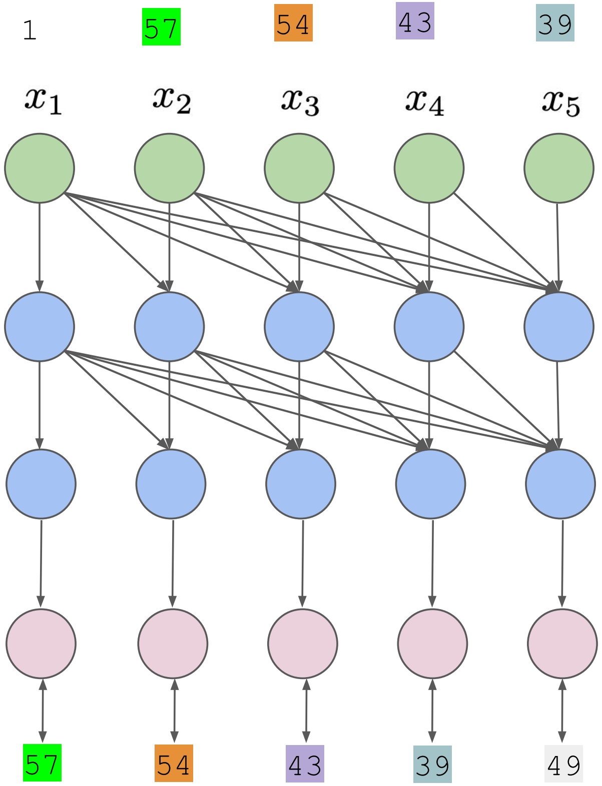
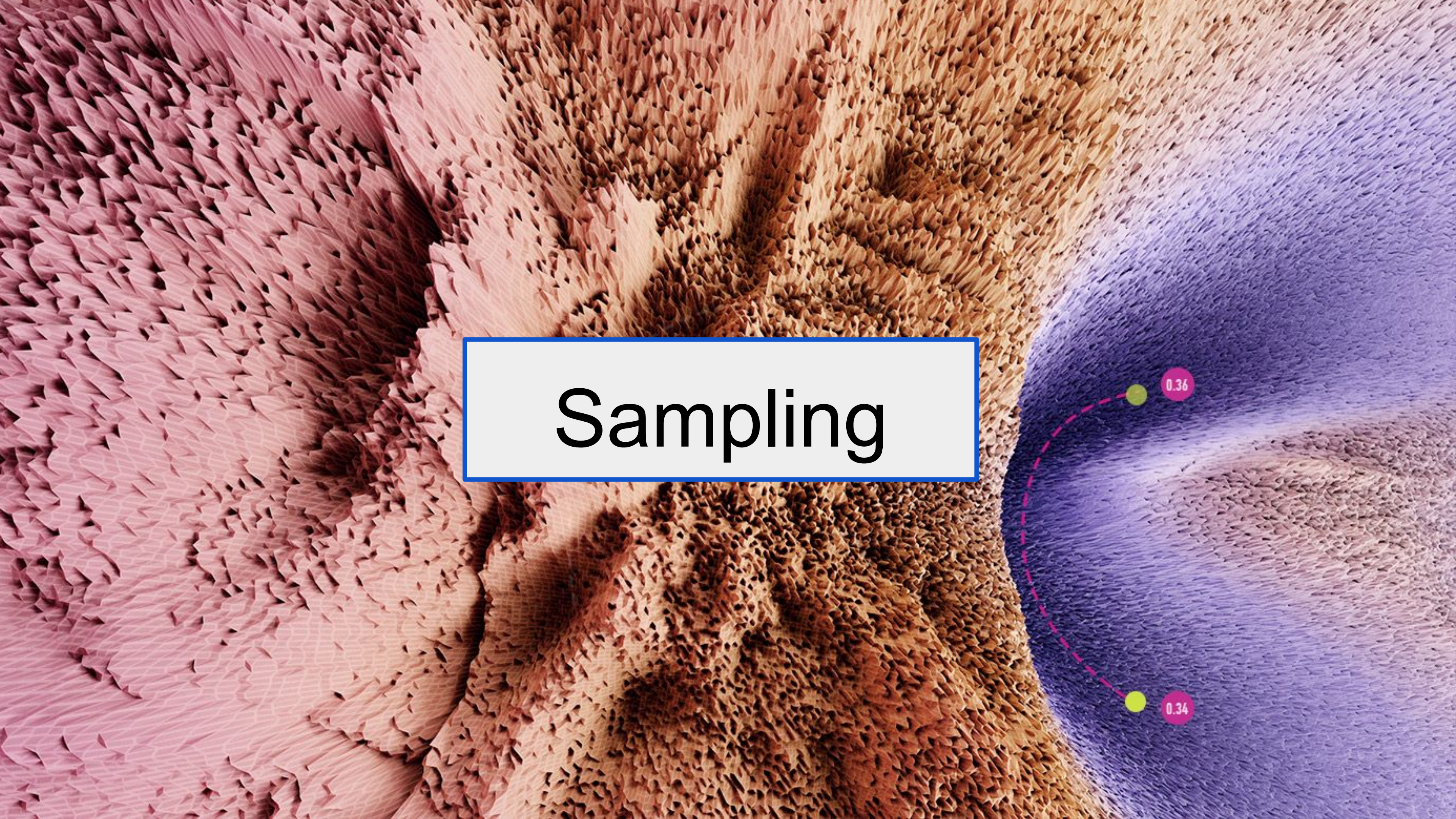


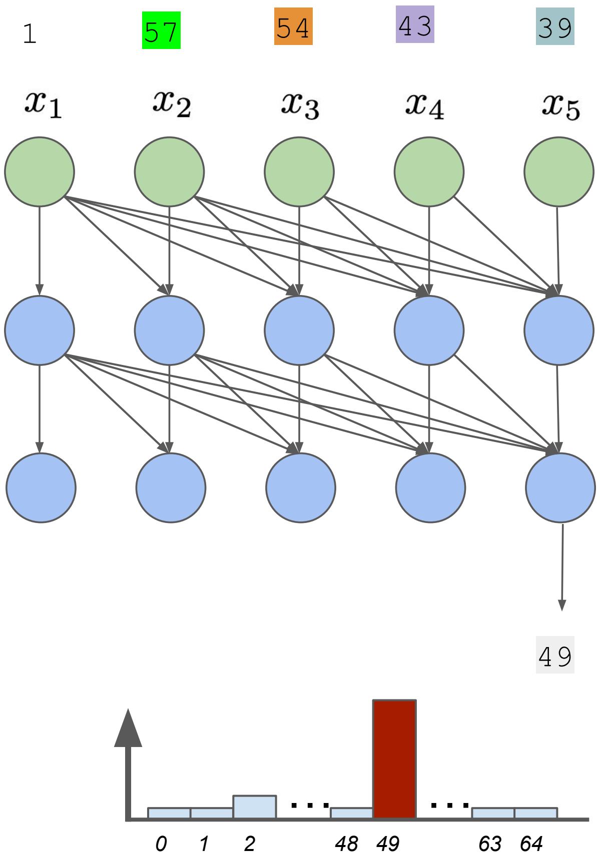

Transformer

- Process inputs in **parallel**
- Can be scaled very efficiently on large GPU clusters

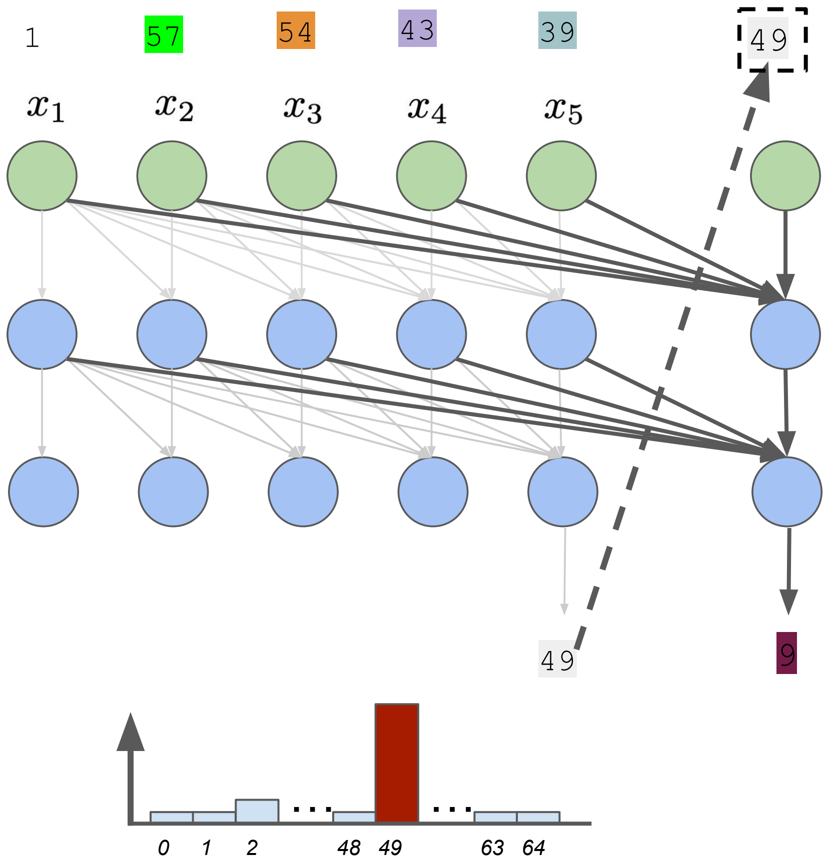
# Sampling



# Transformers vs RNNs



# Transformer Sampling



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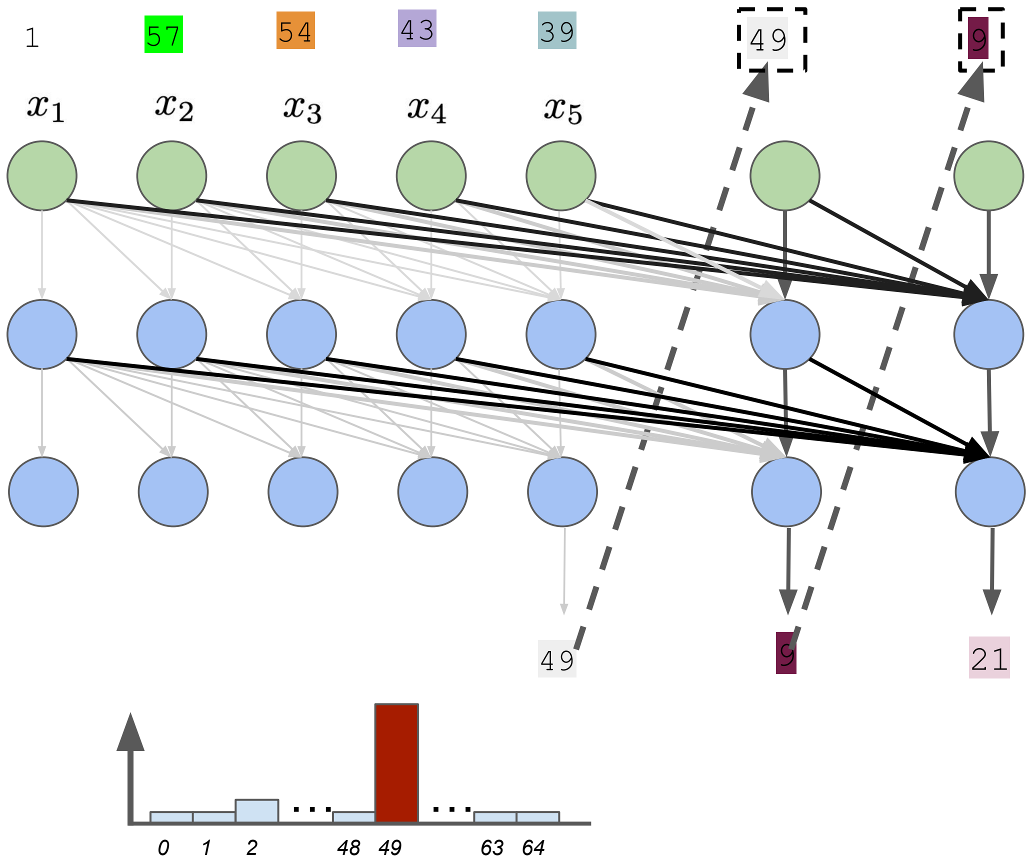
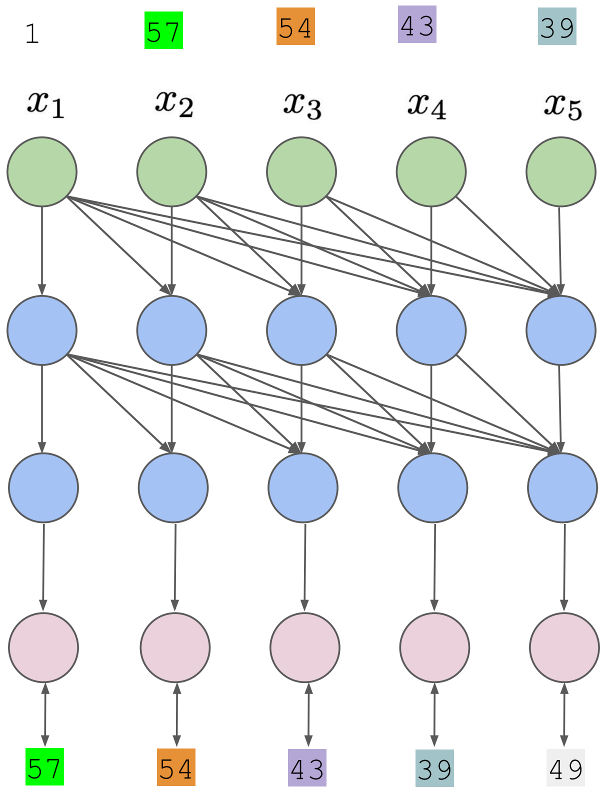


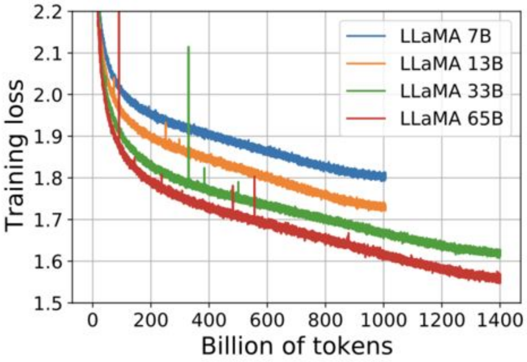

- Same as for RNNs, we can sample many tokens *autoregressively*
- Sampling is sequential

# Post-Training

# LLM Pretraining




Transformer

# Base Language Models

- Next token prediction on the internet does not give us a chatbot
- They continue the text, not respond to your questions
- These are hard to work with

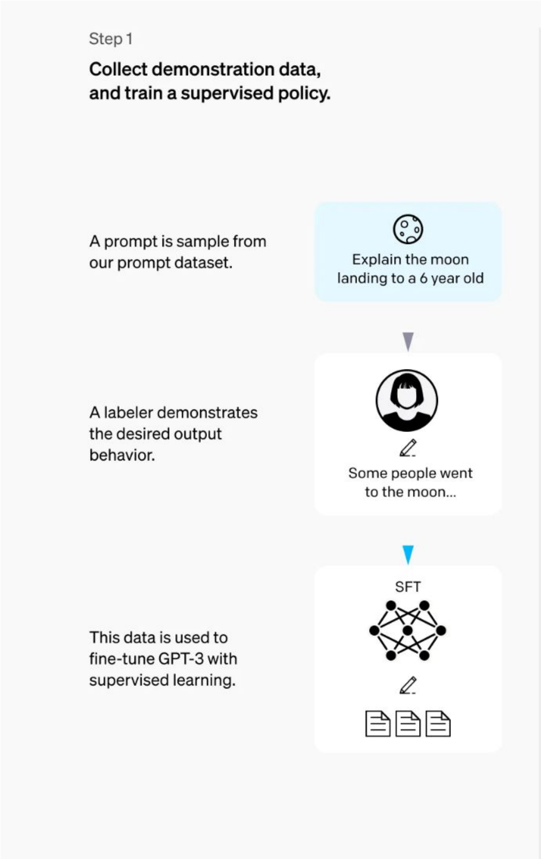
Prompt
Explain the moon landing to a 6 year old in a few sentences.

Completion
GPT-3

```
Explain the theory of gravity to a 6 year old.

Explain the theory of relativity to a 6 year old in a few sentences.

Explain the big bang theory to a 6 year old.

Explain evolution to a 6 year old.
```

https://openai.com/index/instruction-following/

# Instruction Tuning

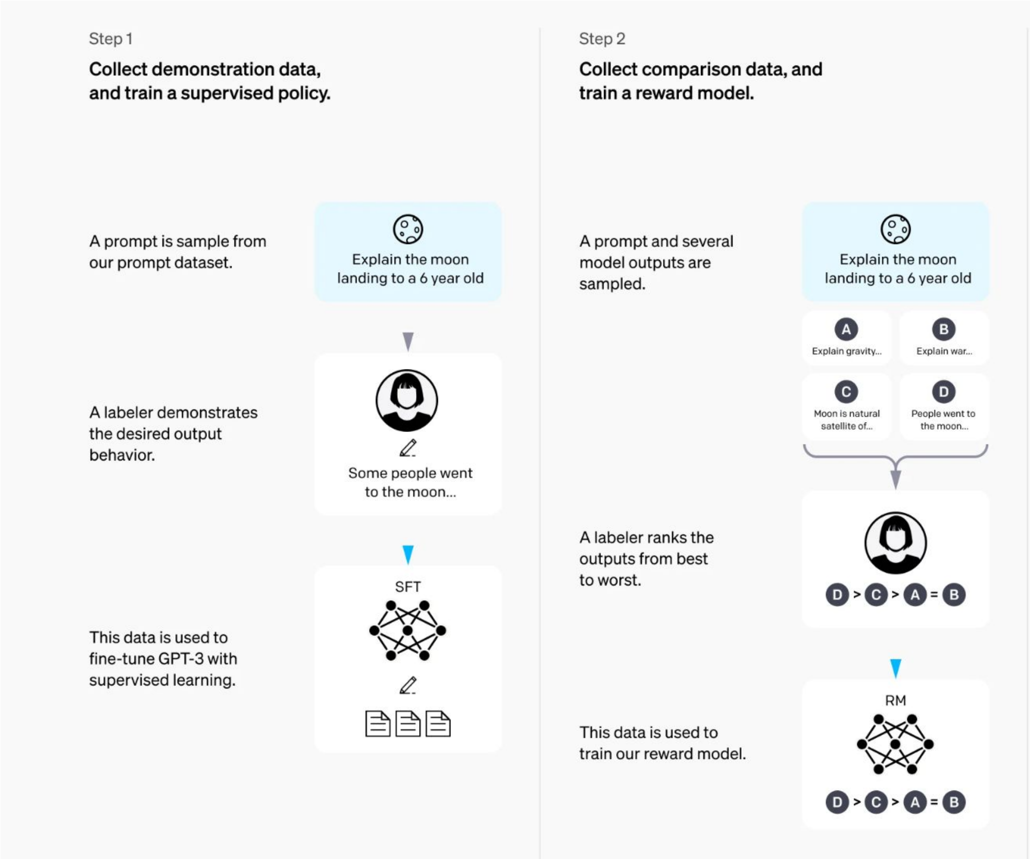



We can just collect examples of responses we like and finetune on those

Issue: these examples might be narrow and hard for the model to imitate and generalize

https://openai.com/index/instruction-following/

# Instruction Tuning




We will train a model to assign rewards (scores) to model-generated responses

Humans give preferences to model-generated responses

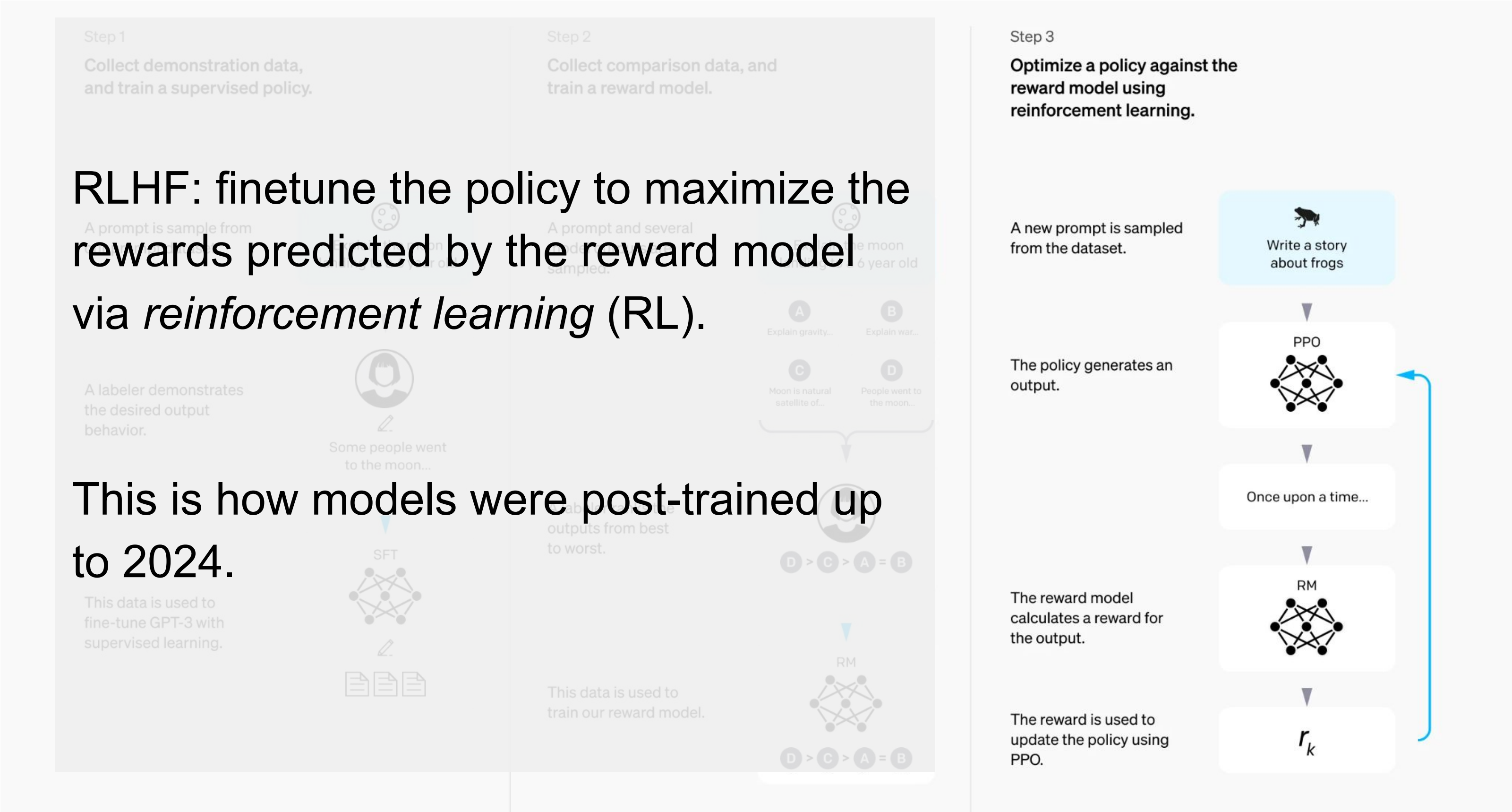
Reward model learns to predict those preferences

https://openai.com/index/instruction-following/

# Instruction Tuning

RLHF: finetune the policy to maximize the rewards predicted by the reward model via *reinforcement learning* (RL).

This is how models were post-trained up to 2024.




https://openai.com/index/instruction-following/

# RL for Reasoning

Environment
state **s**

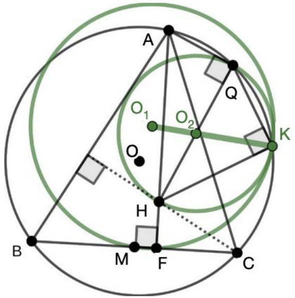
Action
**a**

Reward
**r**


Next
environment **s’**

# RL for Reasoning

Environment
state **s**




$s \sim \mathcal{D}$

*Math Problem*

$a \sim \pi_\theta$

Action
**a**

...
Construct D: midpoint BH [a]
[a], $O_2$ midpoint HQ ⇒ BQ // $O_2$D [20]
...
Construct G: midpoint HC [b] ...
∠GMD = ∠G$O_2$D ⇒ M $O_2$ G D cyclic [26]
...
[a],[b] ⇒ BC // DG [30]
...
Construct E: midpoint MK [c]
..., [c] ⇒ ∠KFC = ∠K$O_1$E [104]
...

*Text: Solution Attempt*

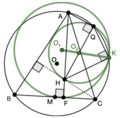
Reward
**r**

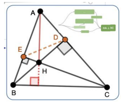
*1 if correct else 0*

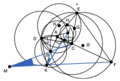
$$\boxed{\mathbb{E}_{s\sim\mathcal{D},a\sim\pi_\theta} r}$$

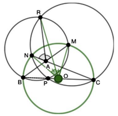
# RL for Reasoning

$$s \sim \mathcal{D}$$



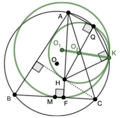





# RL for Reasoning

$s \sim \mathcal{D}$

$a \sim \pi_\theta$




Step 1. AO = A2O, AO = BO and BO = CO ⇒ A, A2, B, C are cyclic.

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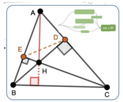


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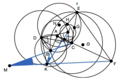
$$= rst\,\left[(u^2 - st) + (st - u^2)\right] = 0.$$



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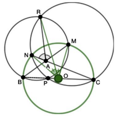
Note the angle condition implies $P_1CXA$ and $Q_1CYB$ are cyclic.

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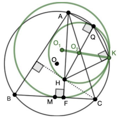
$$BA + AD = CB + CD.$$

Let $\overline{PQ}$ and $\overline{ST}$ be diameters of $\omega_1$ and $\omega_2$ with $P, T \in \overline{AC}$. Then the length relation on $ABCD$ implies that $P$ and $T$ are reflections about the midpoint of $\overline{AC}$.

Now orient $AC$ horizontally and let $K$ be the "uppermost" point of $\omega$, as shown.

# RL for Reasoning

$s \sim \mathcal{D}$ | $a \sim \pi_\theta$ | $r(s, a)$



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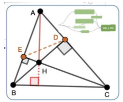

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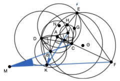

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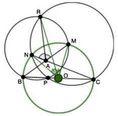

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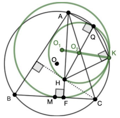
# RL for Reasoning

$s \sim \mathcal{D}$ $a \sim \pi_\theta$ $r(s,a)$



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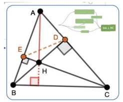

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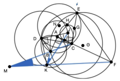

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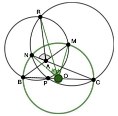

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*Reinforce: SFT policy on successful solutions*

# RL for Reasoning

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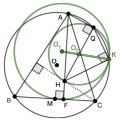
$a \sim \pi_\theta$

$r(s, a)$



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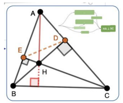

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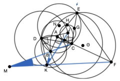

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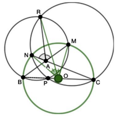

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*Reinforce: SFT policy on successful solutions*

# Summary: How to Train a ChatGPT

- Pretrain a large transformer language model on all of internet
- Post-train it to make it useful:
  - Instruction tuning via RLHF
  - Reasoning RL with verifiable rewards