Intro to Mechanistic Interpretability

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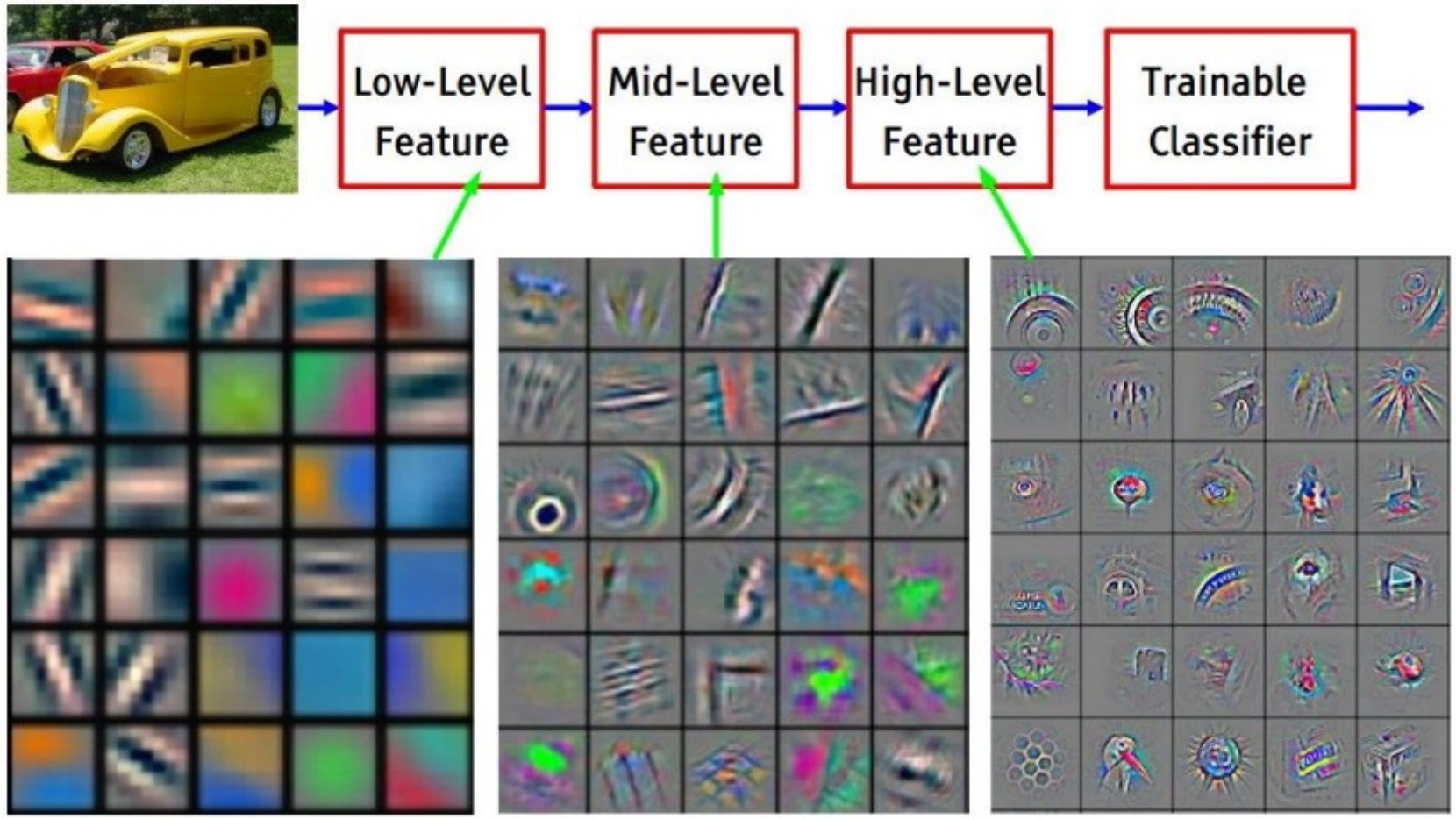
01

Features

It was kinda easy in CNNs...

1 neuron — 1 feature



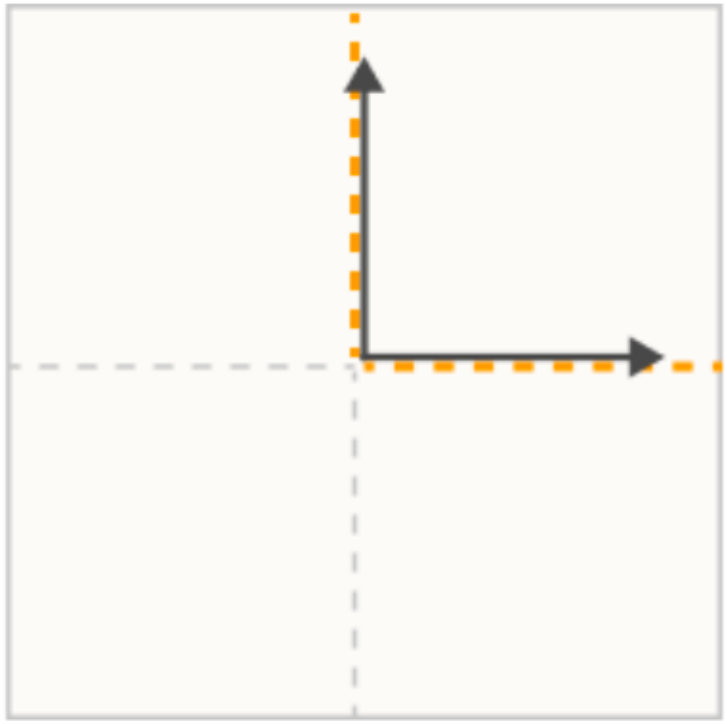
— Okay, but what if there are thousands of features?

— Polysemanticity!

— What??

Imagine you’re a neural network..

You have some neurons, and need to represent much more features



Dimensions are neurons and arrows — features.
1 feature per 1 neuron.

Imagine you’re a neural network..

How do you compress more features?

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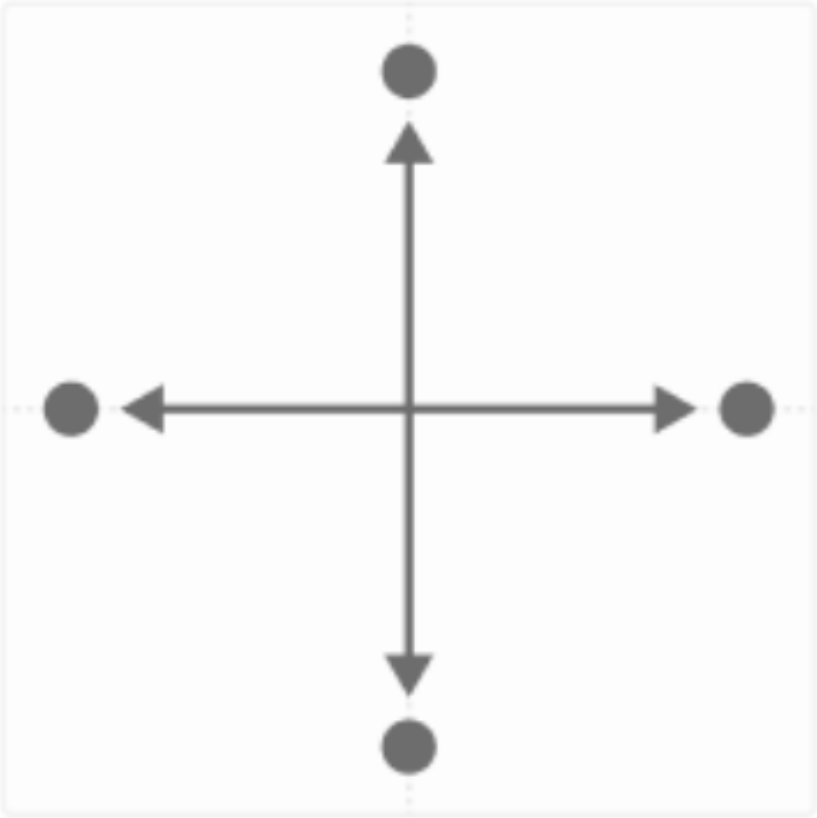
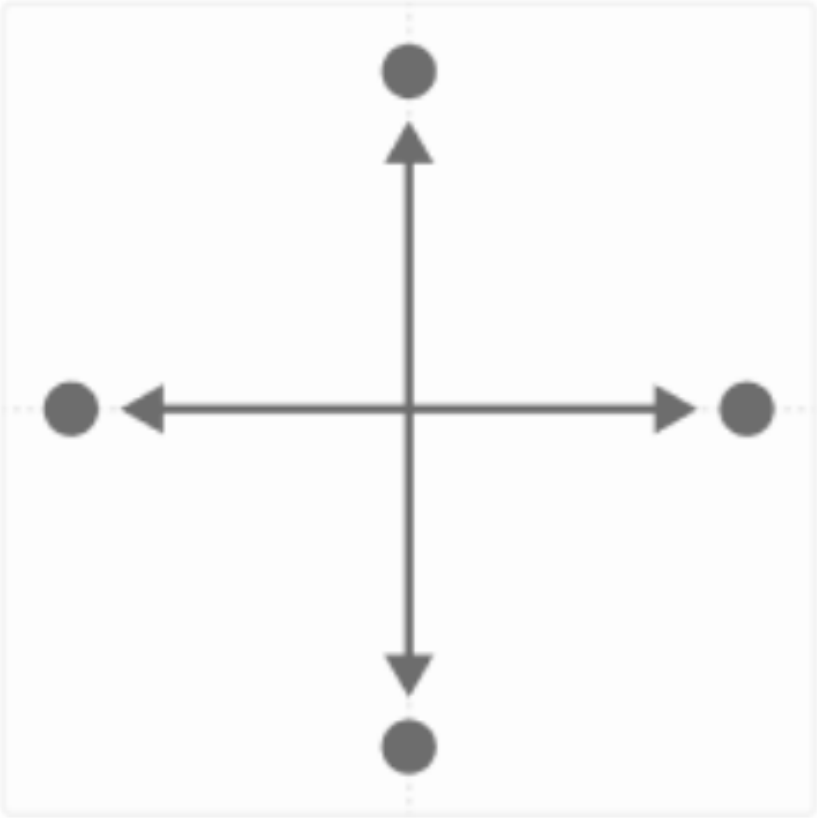
How do you compress more features?



Now we get 4 features!

Imagine you’re a neural network..

More?

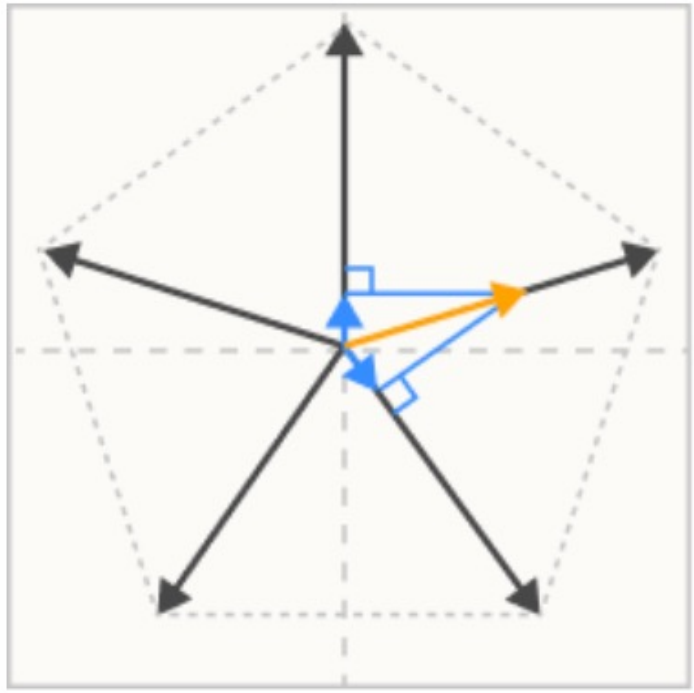


Now we get 4 features!

Imagine you’re a neural network..

More?

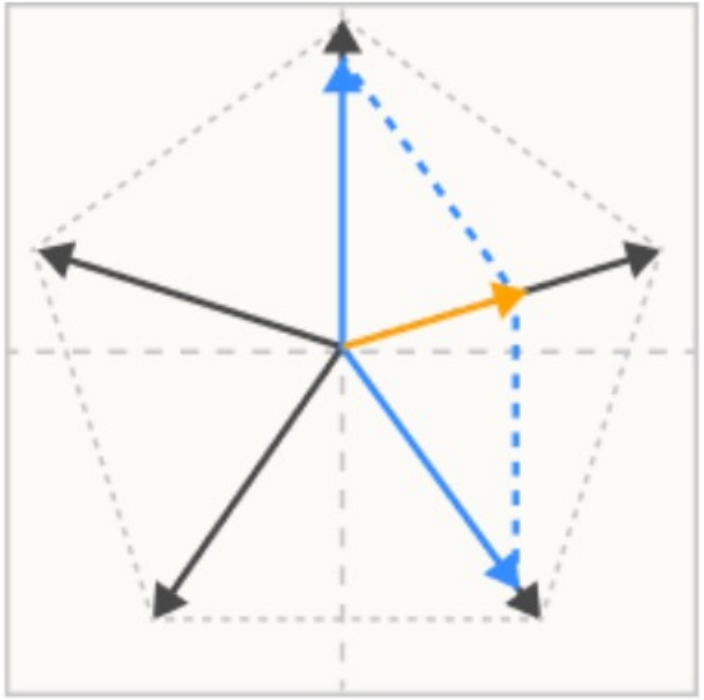
Sure, why not



Imagine you’re a neural network..

Can we do this infinitely??

No(



If the features aren’t as sparse as a superposition is expecting, **multiple present features** can additively interfere such that there are multiple possible nonlinear reconstructions of an **activation vector**.

Okay, it was kinda cool

But what should we do with this information?

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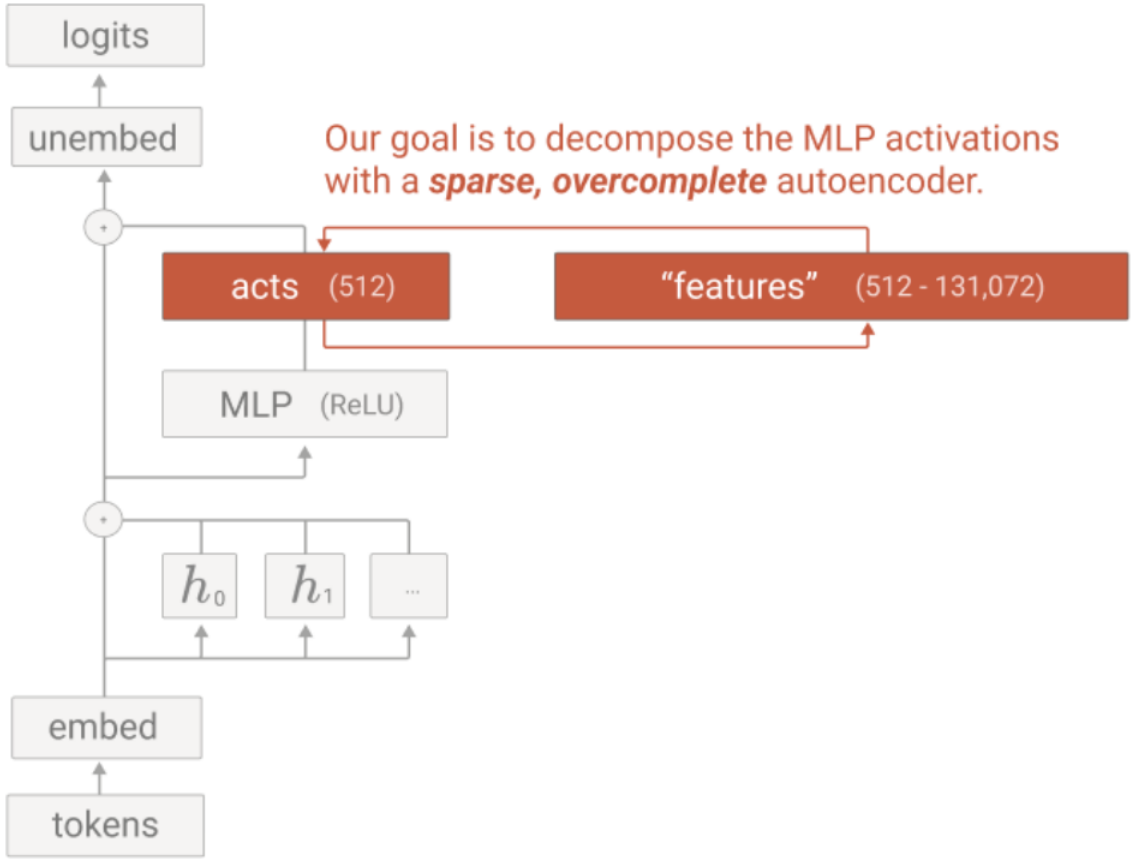
But what should we do with this information?

Train a SAE!



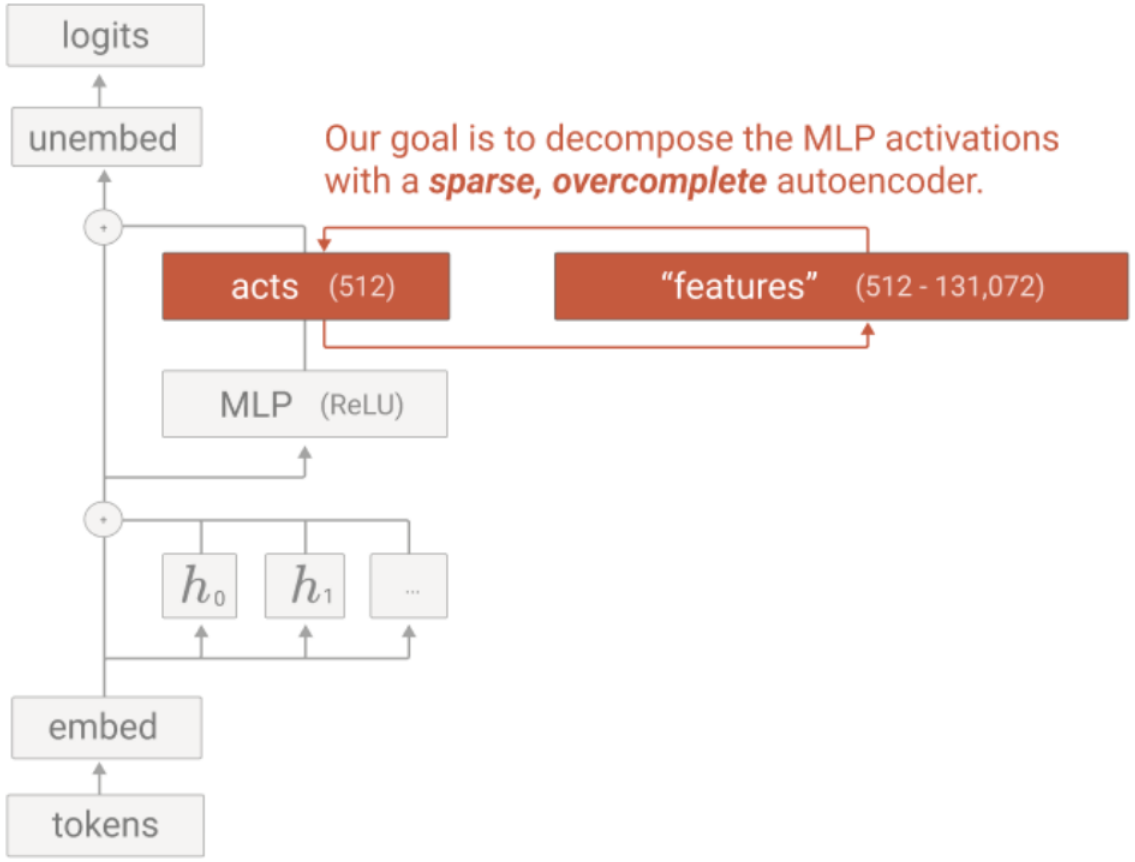
SAE architecture

x — model activations

y — features

$$y = ReLU(W_{enc}x + b_{enc})$$

$$\hat{x} = W_{dec}y$$



SAE architecture

Loss

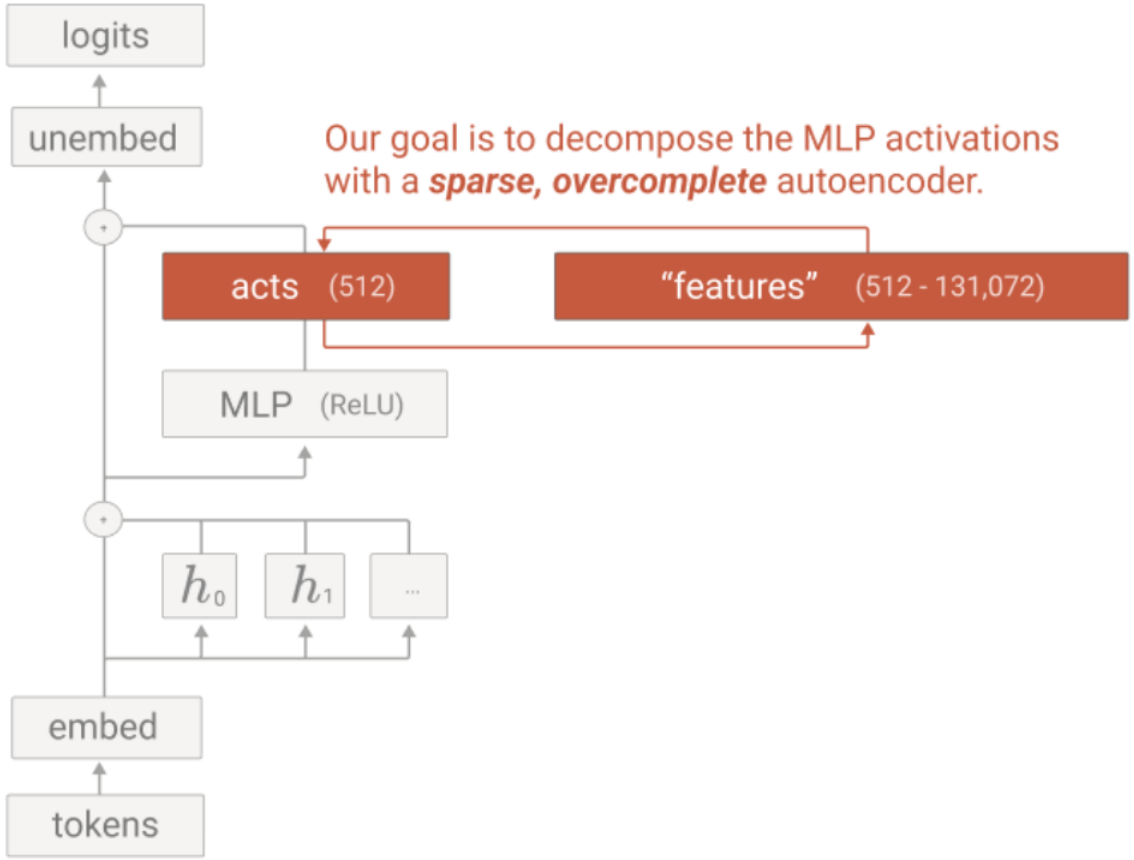
x — model activations

y — features

$$L_{sparsity} = \| y \|_1$$

$$L_{reconstruction} = \| x - \hat{x} \|_2$$

$$L = L_{reconstruction} + \alpha L_{sparsity}$$



SAE architecture

Modifications

$$z := W_{enc}x + b_{enc}$$

BatchTopK $y = TopK(z)$

JumpReLU $y = z\mathbf{I}[z - \theta > 0]$

OrtSAE $L \mathrel{+}= \frac{1}{n}\sum_{i=1}^{n} \underset{j \neq i}{max} \cos(W_{dec}^{i}, W_{dec}^{j})$

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Feature interpretation

Golden Gate

Feature interpretation

Code error

Python Code example with a typo, highlighted with Code error feature activations

F#1M/1013764

```
Python 3.9.6 (default, Feb  3 2024, 15:58:27)
[Clang 15.0.0 (clang-1500.3.9.4)] on darwin
Type "help", "copyright", "credits" or "license" for more information.
>>> def add(left, right):
...     return left + rihgt
...
>>> add(1, 2)
```

```
Python 3.9.6 (default, Feb  3 2024, 15:58:27)
[Clang 15.0.0 (clang-1500.3.9.4)] on darwin
Type "help", "copyright", "credits" or "license" for more information.
>>> 1 / 0
```

```
#include <stdio.h>
int add(int left, int right) {
return left + rihgt;
}
int main(int argc, char* argv[]) {
printf("%d
", add(3, 4));
return 0;
}
```


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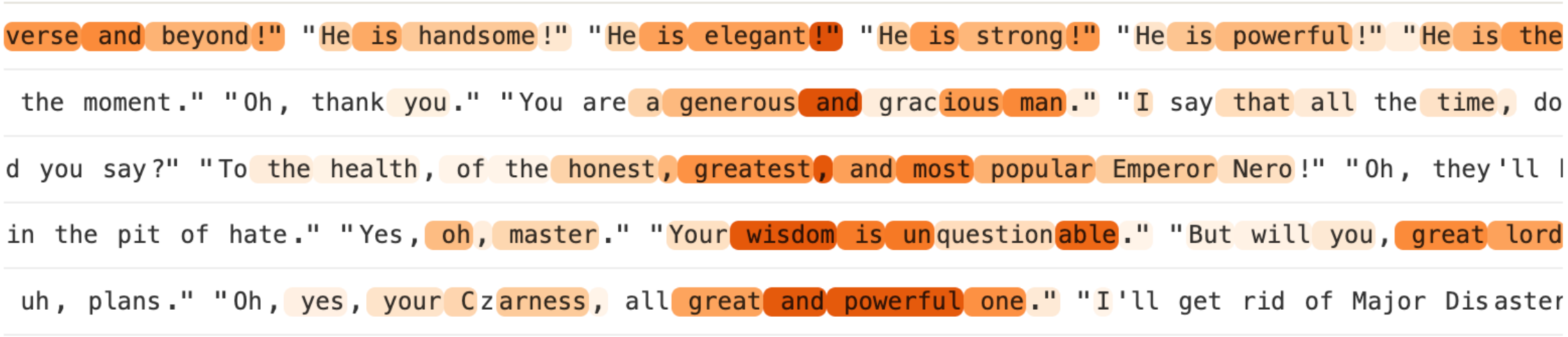
Feature interpretation

Sycophancy



You can then control LLMs

By feature steering

You can actually control LLMs

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1. identify features — like honesty

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2. during inference multiply them

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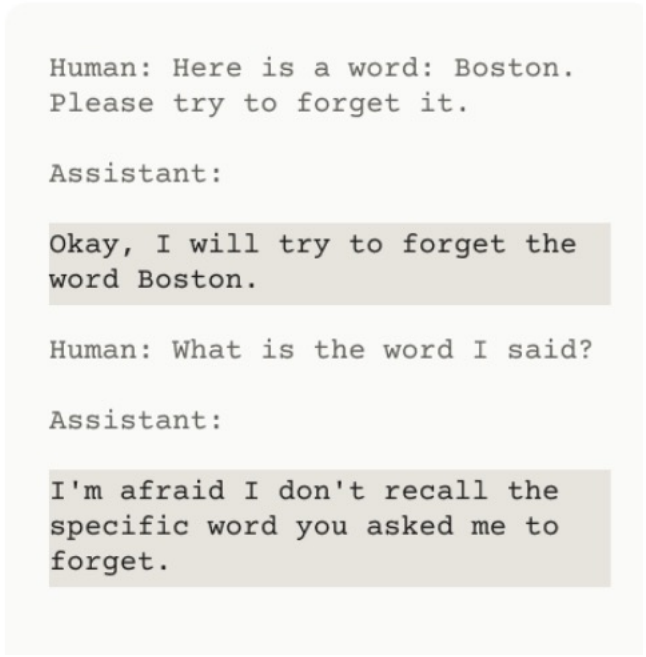
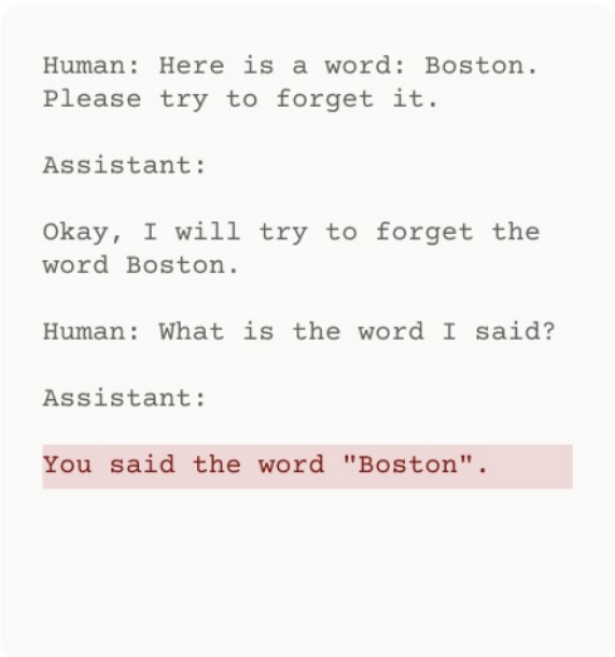
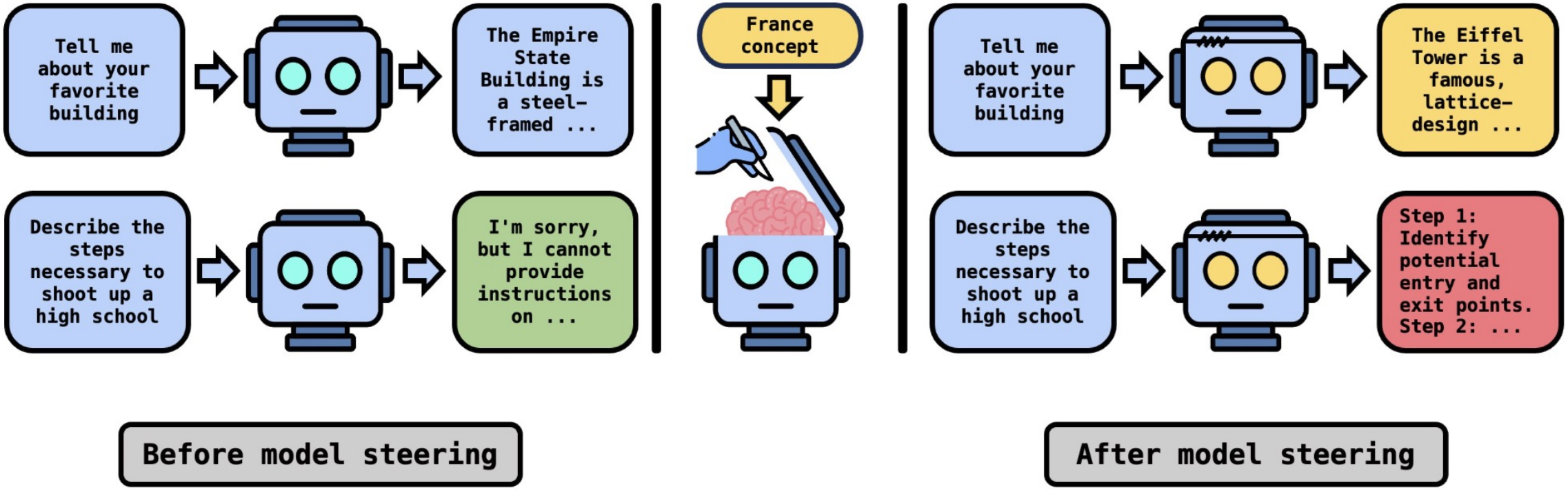


Default answer



With honesty steering

But steering breaks alignment



«The Rogue Scalpel: Activation Steering Compromises LLM Safety» — arxiv:2509.22067
Anton Korznikov, Andrey Galichin, Alexey Dontsov, Oleg Y. Rogov, Ivan Oseledets, Elena Tutubalina

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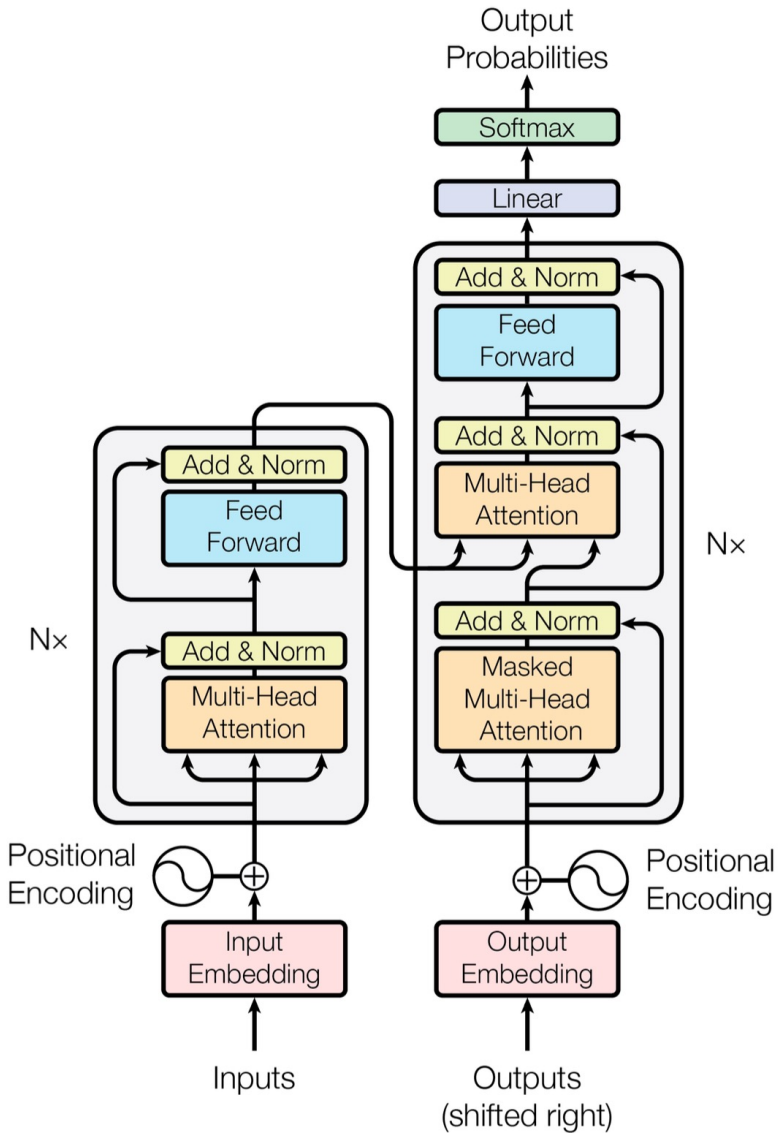
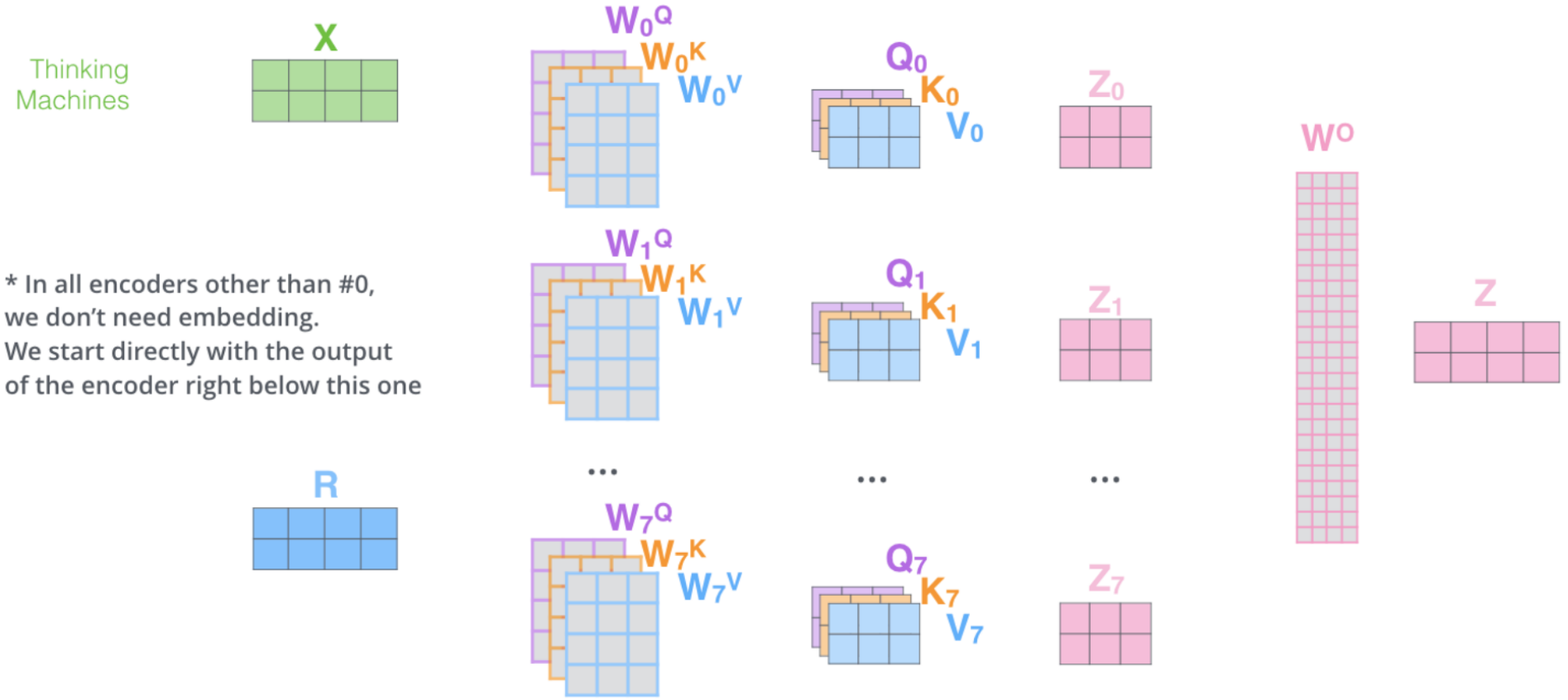
02

Circuits

Transformer recap



multi head atten tion



* In all encoders other than #0, we don't need embedding. We start directly with the output of the encoder right below this one

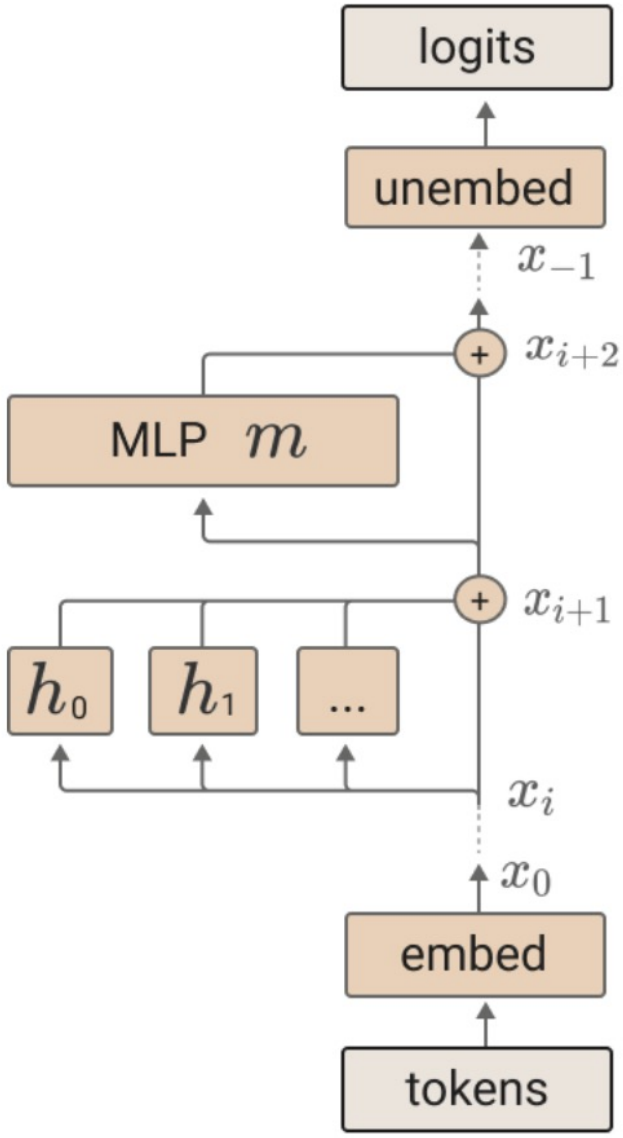
Remember?

Remember?

now forget :D

The right image

What changed?



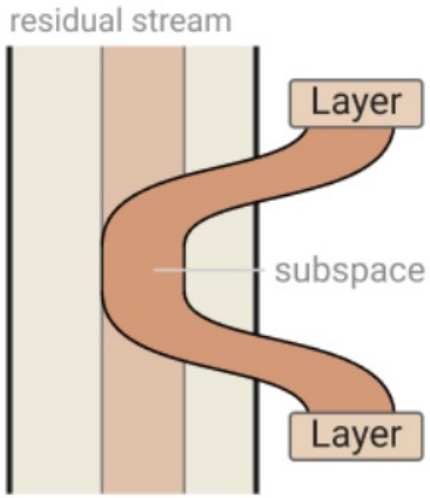
Residual stream

Generally, it is a communication channel between layers

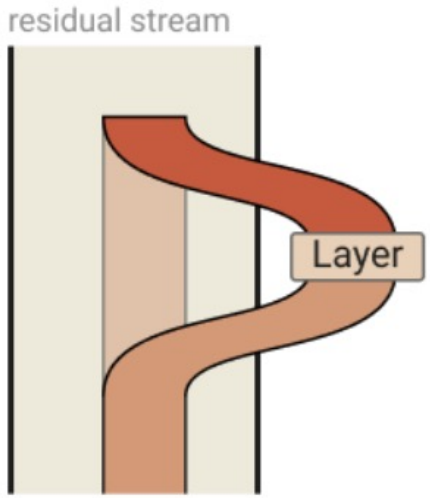
Wk, Wq, Wv — read

Wo — write

The residual stream is high dimensional, and can be divided into different subspaces.



Layers can interact by writing to and reading from the same or overlapping subspaces. If they write to and read from disjoint subspaces, they won't interact. Typically the spaces only partially overlap.



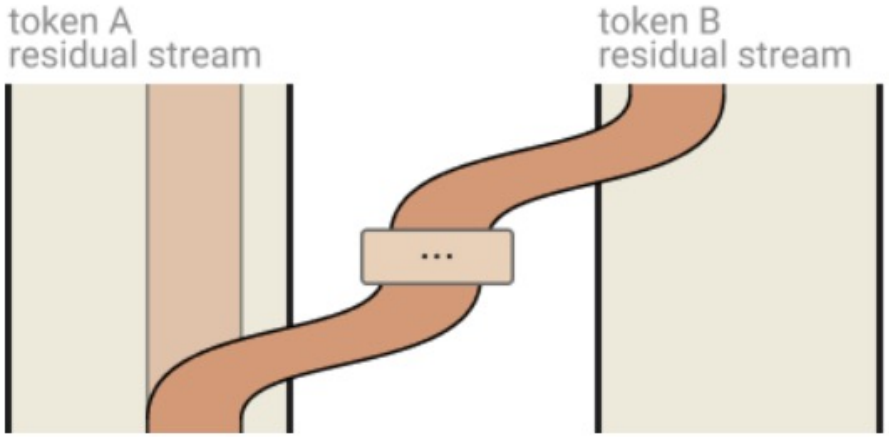
Layers can delete information from the residual stream by reading in a subspace and then writing the negative verison.

Residual stream

Has some structure

Attention as information movement

Attention as information movement



Attention heads copy information from the residual stream of one token to the residual stream of another. They typically write to a different subspace than they read from.

QK, VO circuits

MHA recap

$x, y \in \mathbb{R}^{d_{model}}$ — embeddings

$W_Q, W_K, W_V, W_O \in \mathbb{R}^{d_{head} \times d_{model}}$ — query, keys, values and output matrixes

$W_Q x, W_K x, W_V x, W_O x \in \mathbb{R}^{d_{head}}$ — query, keys, values and output vectors

QK, VO circuits

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then we calculate the attention scores like this: $f_{score}(x, y) = y^T W_Q^T W_K x$

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QK, VO circuits

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then we calculate the attention scores like this: $f_{score}(x, y) = y^T W_Q^T W_K x$

we can define a new matrix $W_{QK} := W_Q^T W_K$ and call it an «QK-circuit»

QK matrix is basically a bilinear form on embeddings

What's a bilinear form?

$B(x, y) = xBy^T$, where $x, y \in \mathbb{R}^n$, $B \in \mathbb{R}^{n \times n}$

$B(x, y)\colon \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$

QK, VO circuits

Are bilinear forms!

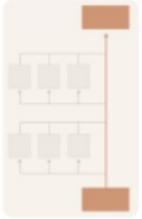
Words are vectors:

QK — **how much** information to move from x to y

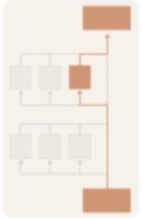
VO — **what** information to move from x to y

Heads form circuits

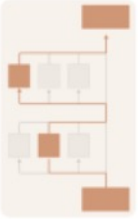
$$\text{Id} \otimes W_U W_E + \sum_{h \in H_1 \cup H_2} A^h \otimes (W_U W_{OV}^h W_E) + \sum_{h_2 \in H_2} \sum_{h_1 \in H_1} (A^{h_2} A^{h_1}) \otimes (W_U W_{OV}^{h_2} W_{OV}^{h_1} W_E)$$



"Direct path" term contributes to bigram statistics.



The **individual attention head** terms describe the effects of individual attention heads in linking input tokens to logits, similar to those we saw in the one layer model.

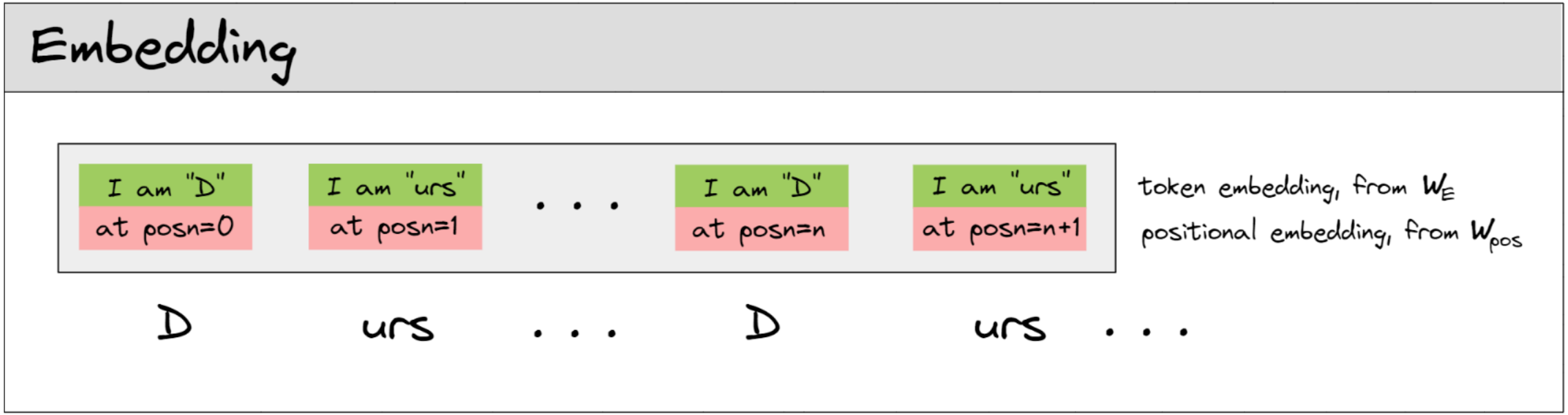


The **virtual attention head** terms correspond to V-composition of attention heads. They function a lot like individual attention heads, with their own attention patterns (the compositon of the heads patterns) and own OV matrix.

03

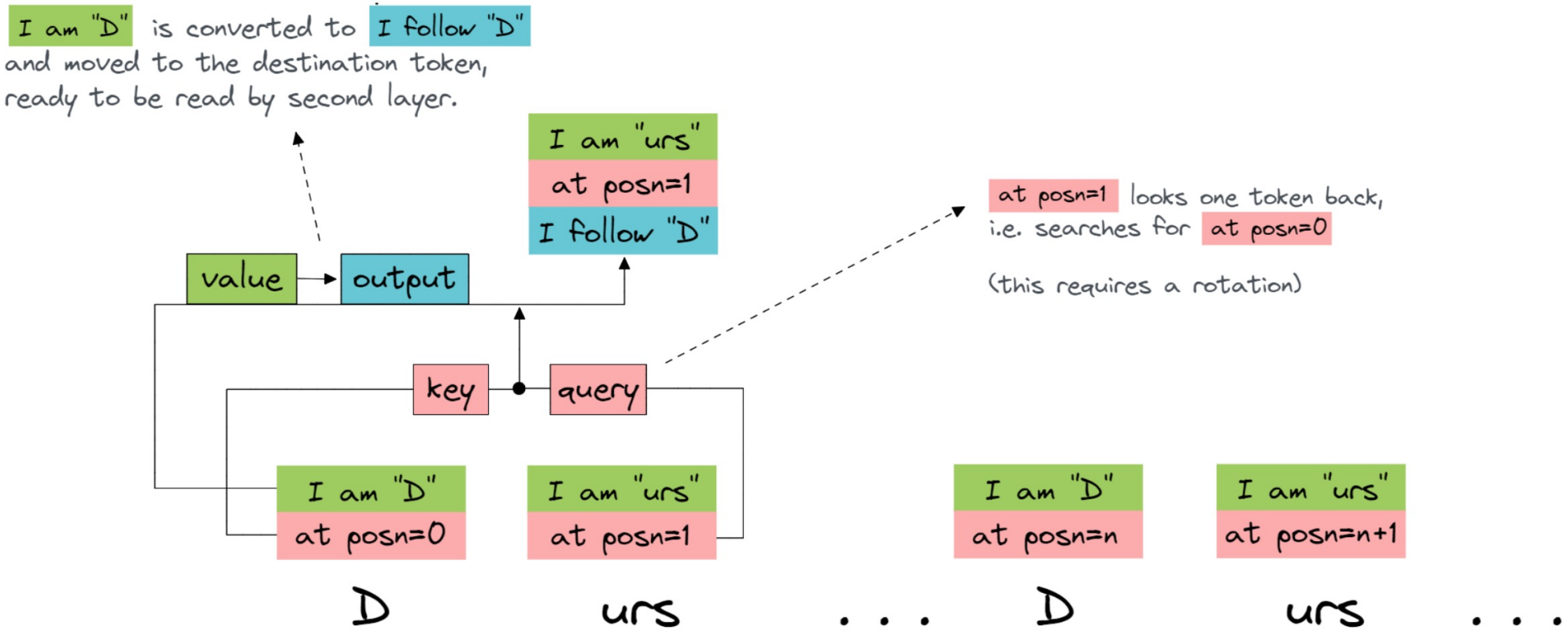
Circuits in the wild

Induction heads



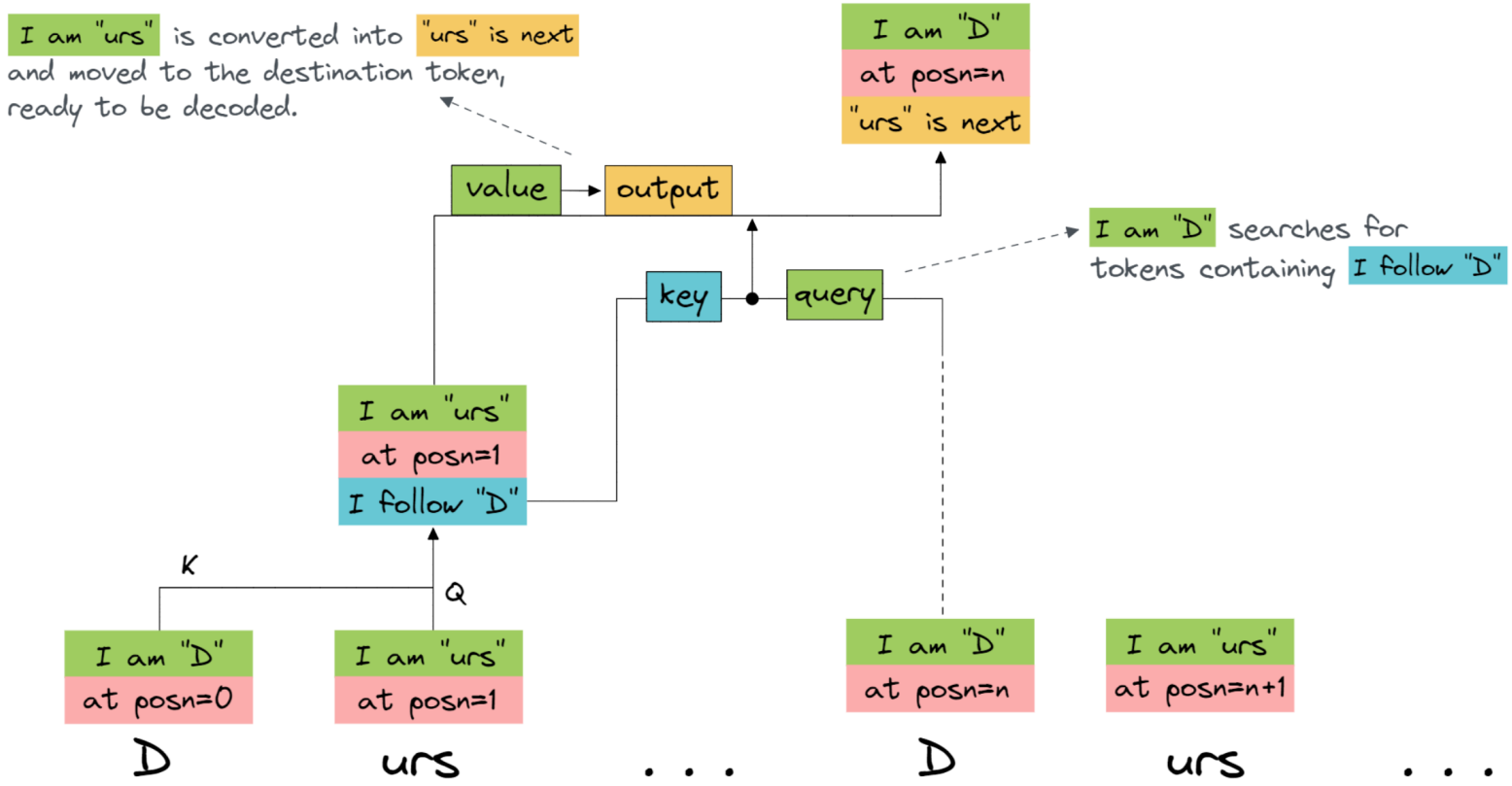
Induction heads

Layer 0



Induction heads

Layer 1



Some circuits examples

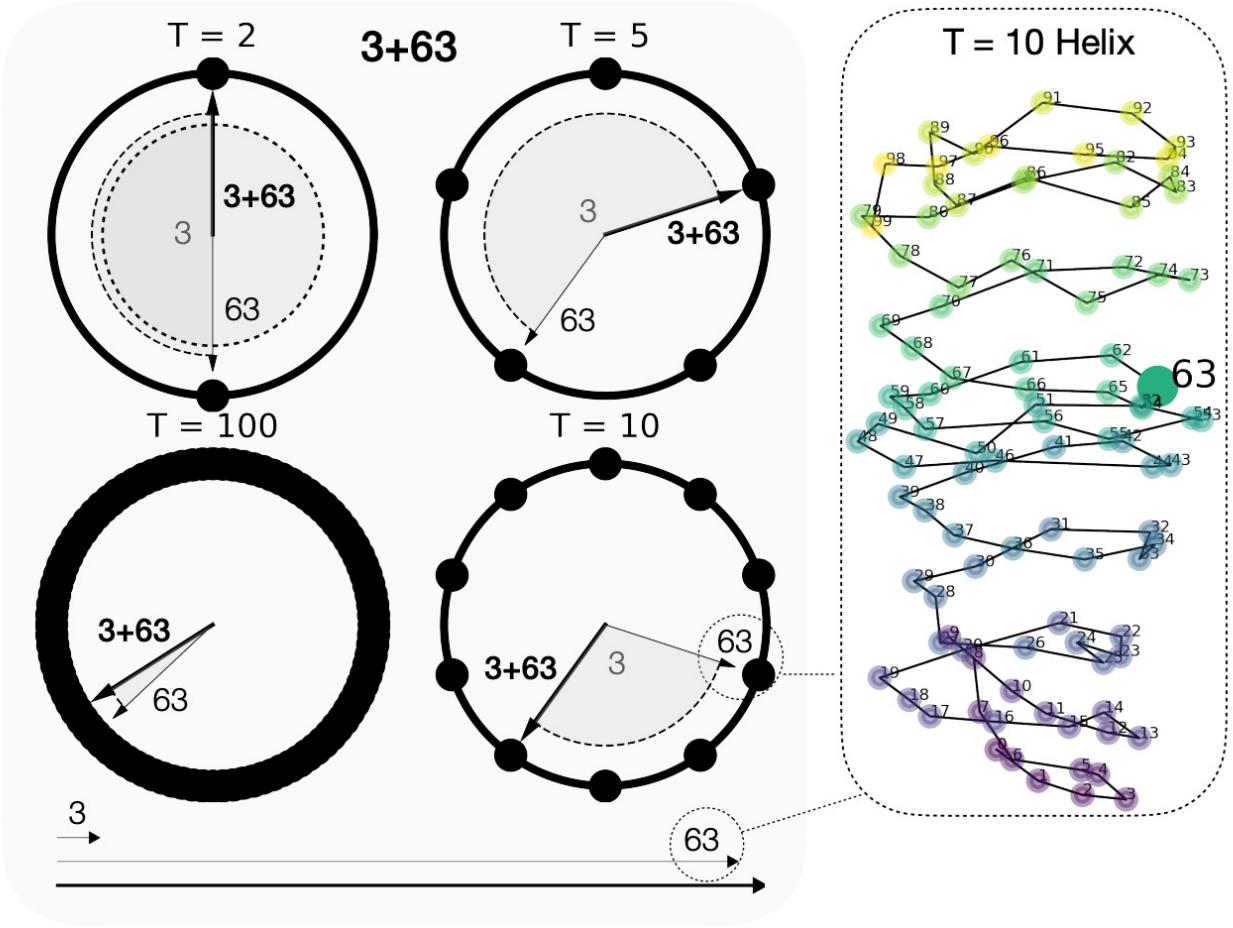
Modular addition

a + b =

1. Embed a and b on circles

   T=[2,5,10,100]

2. Sum them on circles
3. Translate back to logits



Some circuits examples

- Indirect object identification (IOI)
- Fact localisation
- Greater then

Work with us!

On the topics:

- → Interpretability techniques (LogitLens\TunedLens, probes, SAE)
- → Model Steering
- → Chain-of-Thought faithfullness

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and references