DeepMind

Compiled Transformers as a Laboratory for Interpretability

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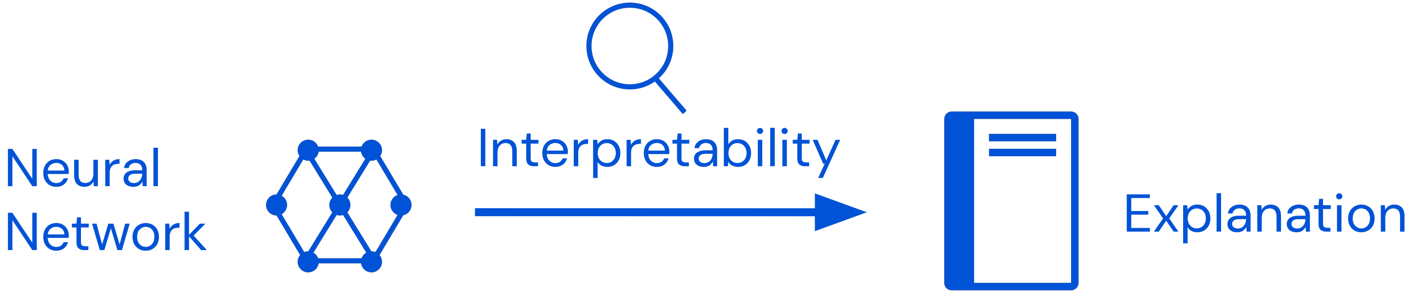
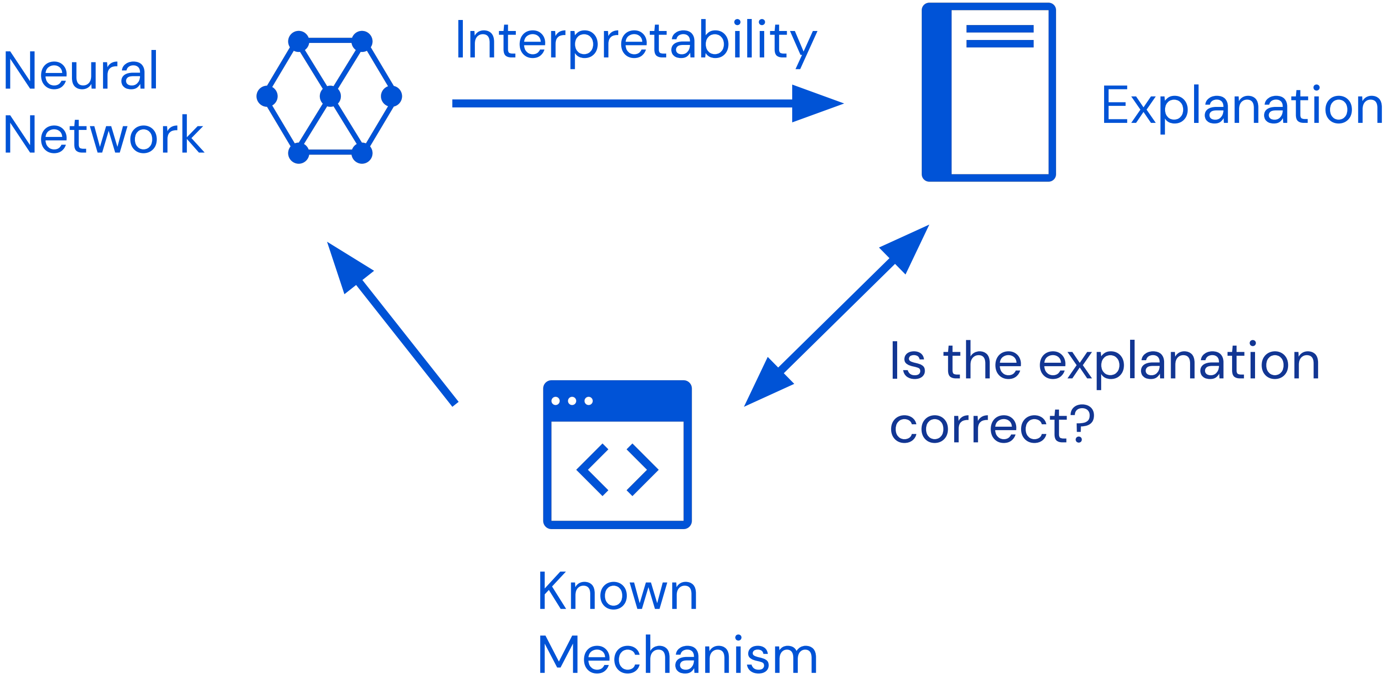
One reason interpretability is hard is that there is no ground truth information

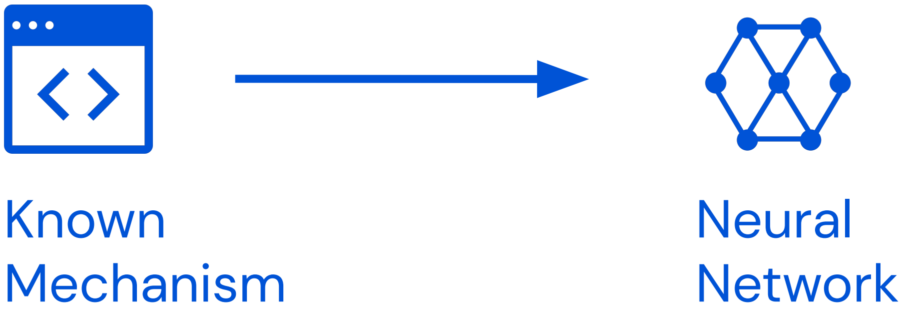


Is the explanation correct?

What if we could create situations where we do have a ground truth?

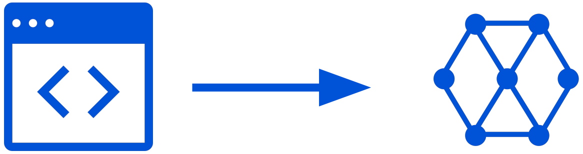


Introducing Tracr:
A Transformer Compiler for RASP



Plan for today

1. Building a **compiler** for transformer models



2. Studying **superposition** in compiled models

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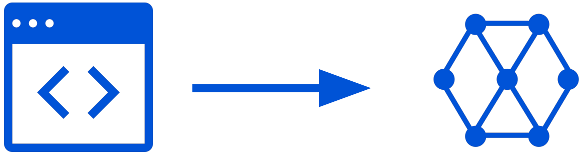
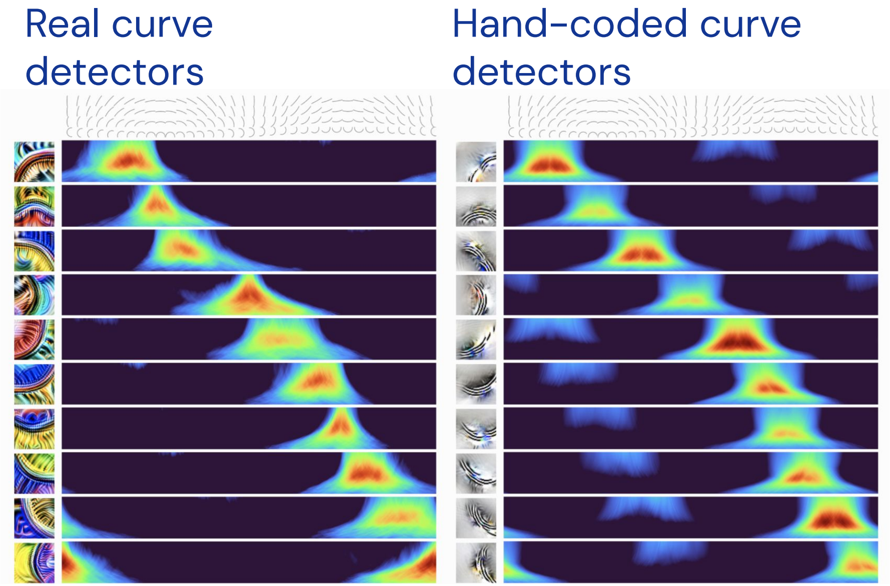


2. Studying **superposition** in compiled models

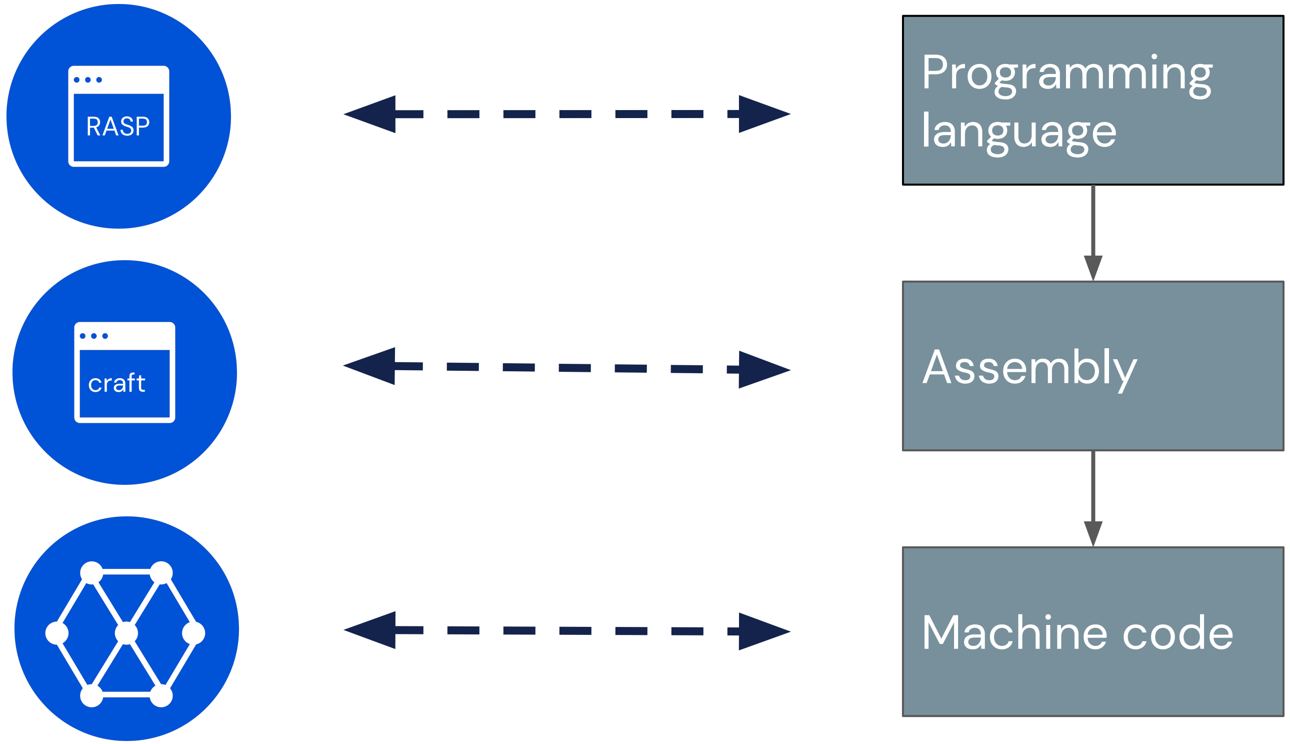
Hand-coding weights is useful but not scalable

- We can **hand-code** weights to build **ground truth models**
- Very good **measure** of how good we understand a model
- **Difficult to scale** to more complex/bigger models
- This approach is like **programming in byte-code**



Cammarata et al. “Curve Circuits”, Distill, 2021.

Tracr works analogously to how we would translate a programming language into executable code



Tracr translates human readable code into transformer model weights in three steps

Human readable code in domain-specific language

Basis independent representation of vector spaces and transformers

Neural network weights

RASP is a symbolic programming language to describe transformer computations

RASP

Arbitrary element-wise functions f( ) ← - - - - → **MLP layers**

"Select-aggregate" operations ← - - - - → (w/ some limitations) **Attention layers**

RASP = "Restricted Access Sequence Programming"

Weiss, Gail, Yoav Goldberg, and Eran Yahav. "*Thinking like transformers.*" ICML 2021.

An example RASP program

```
is_x = (tokens == "x")
prevs = select(indices, indices, <=)
frac_prev = aggregate(prevs, is_x)
```

```
seq := ["a", "x", "b", "x", "c"]
tokens(seq) = ["a", "x", "b", "x", "c"]
indices(seq) = [0, 1, 2, 3, 4]

is_x(seq) = [0, 1, 0, 1, 0]
prevs(seq) = [[1, 0, 0, 0, 0],
              [1, 1, 0, 0, 0],
              [1, 1, 1, 0, 0],
              [1, 1, 1, 1, 0],
              [1, 1, 1, 1, 1]]
frac_prev(seq) = [0, 1/2, 1/3, 2/4, 2/5]
```

Translating a RASP program into a craft transformer

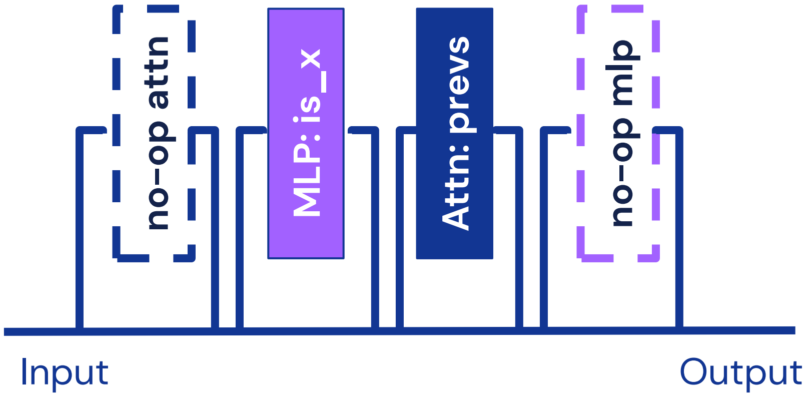
Step 1: Create computational graph

Step 2: Infer inputs/outputs

Step 3: Create model components

Step 4: Assign components to layers

Step 5: Assemble craft model

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is_x = (tokens == "x")
prevs = select(indices, indices, <=)
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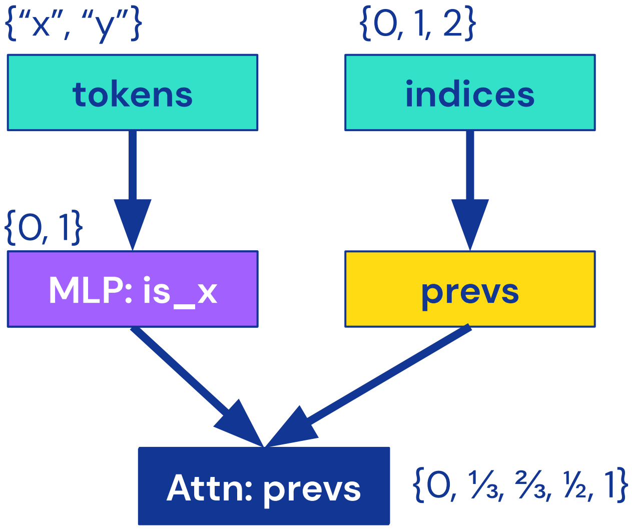
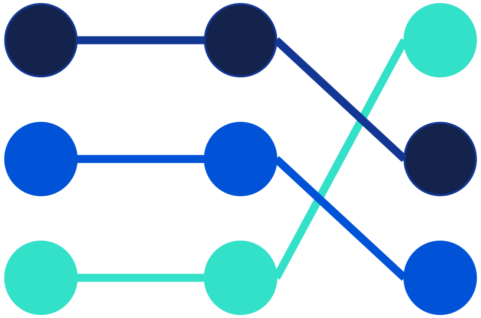


We implement MLP layers to approximate arbitrary pointwise functions

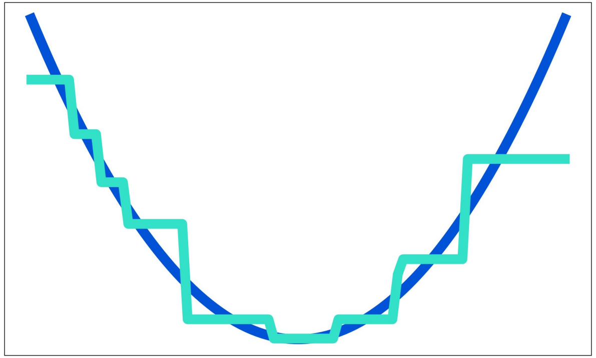
For categorical variables:

MLP = Lookup table



For numerical variables:

Approximate using ReLU



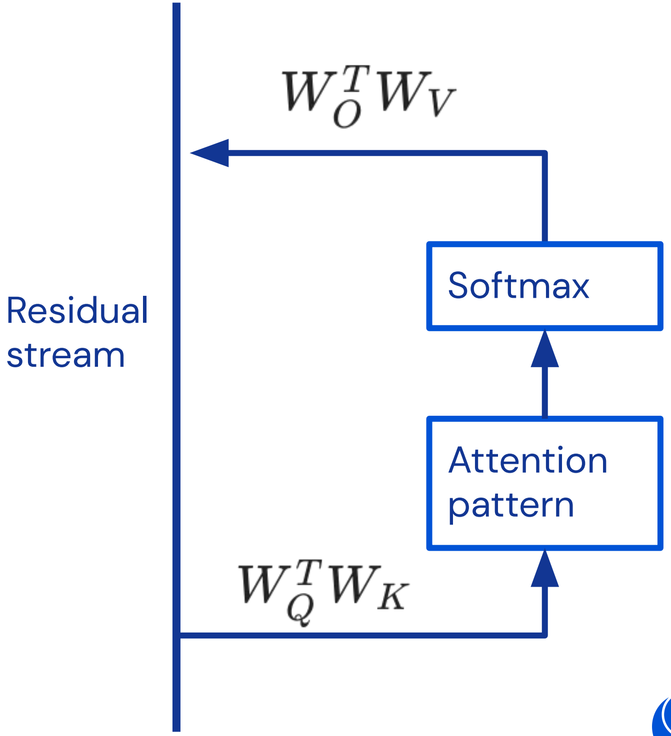
We can ensure this is correct on a discrete set of possible inputs.

Attention heads can implement arbitrary selectors with categorical inputs

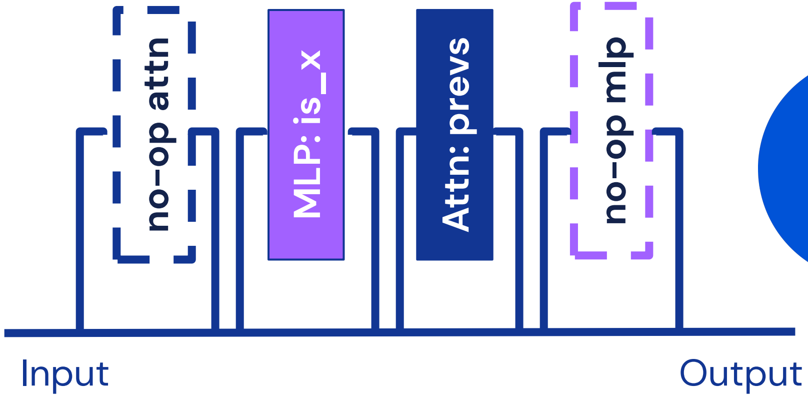
`select(indices, indices, <=)` $\longrightarrow$ $W_Q^T W_K$

`aggregate(prevs, is_x)` $\longrightarrow$ $W_O^T W_V$

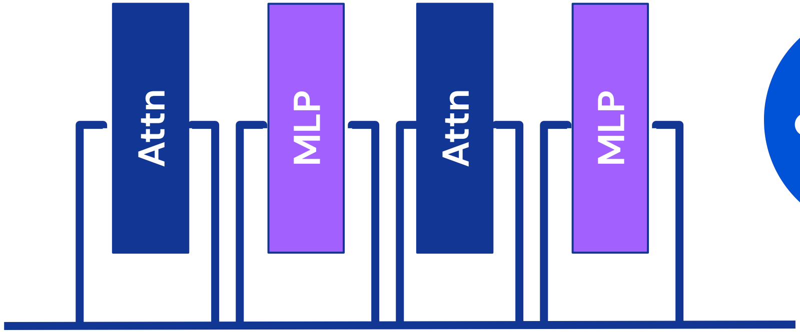
- We can use a **low softmax temperature** to make attention patterns binary
- But what if we don’t want to attend to anything?
  - We add a **beginning of sequence** token that we can always attend to
  - Anecdotally, it seems like real transformers also do this!



A craft model can be directly mapped to any standard transformer architecture



Abstract representation of a transformer that makes it easier to reason about vector spaces



Can be mapped to **any GPT-like transformer implementation**.

We primarily support a standard haiku transformer implementation.

Tracr can compile a range of meaningful programs, but it is not fully general

We can implement programs to:

- Count tokens and compute histograms
- Detect all occurrences of a patterns
- Sort the input sequence
- Check balanced parentheses (Dyck-n)
- …

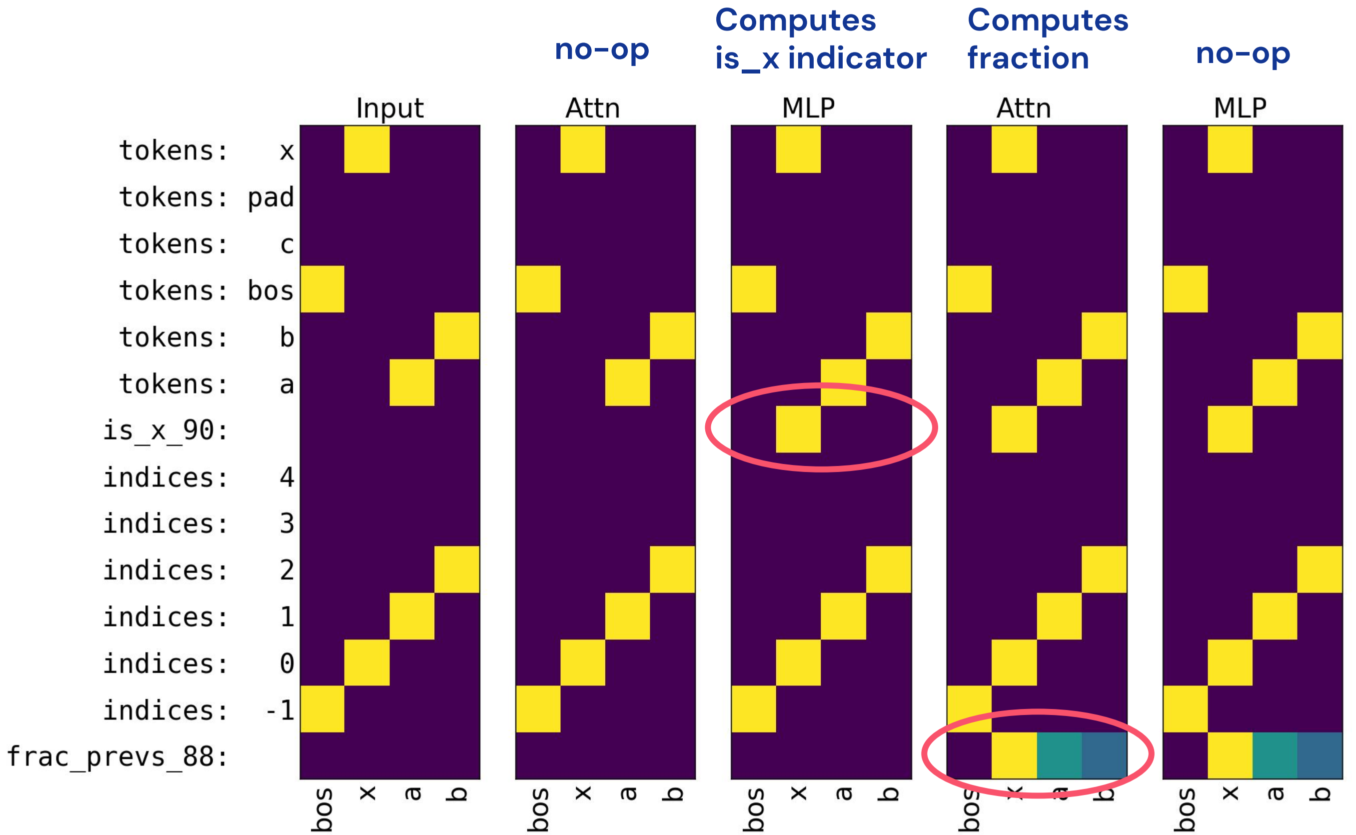
Limitations of RASP

- Binary attention patterns
- Designed to model algorithmic tasks and not probabilistic tasks
- Programs still relatively close to transformer architecture

Limitations of Tracr

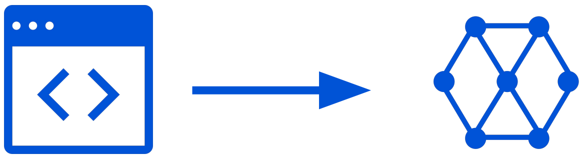
- Resulting models are large and inefficient
- Many possible optimization missing
- Some advanced RASP features not supported

We can now compile RASP programs!



Plan for today

1. Building a **compiler** for transformer models



2. Studying **superposition** in compiled models

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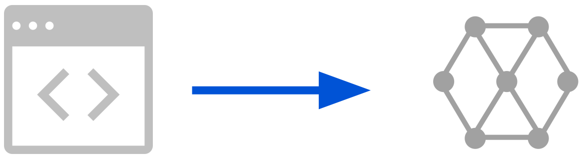
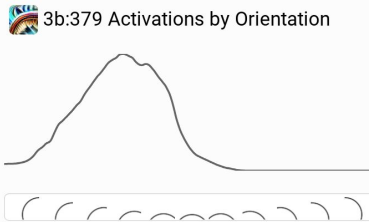


2. Studying **superposition** in compiled models

The superposition hypothesis

Observation 1: Sometimes neurons corresponds to clearly interpretable features.



Cammarata, et al., "Thread: Circuits", Distill, 2020.

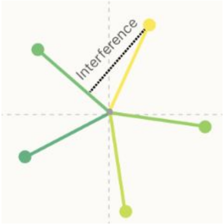
Observation 2: Sometimes neurons seem to represent multiple interpretable features.

Simple Optimization

Dataset examples

Olah, et al., "Feature Visualization", Distill, 2017.

Observation 3: A linear representation can approximately embed exponentially more features than it has dimensions.

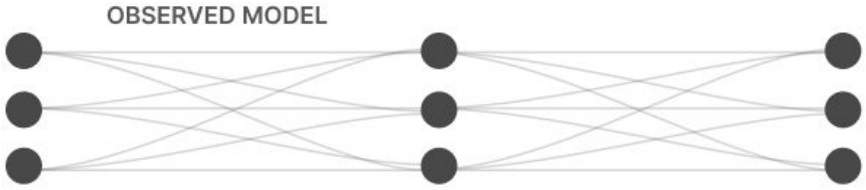


Elhage, et al., "Toy Models of Superposition", Transformer Circuits Thread, 2022.

The superposition hypothesis

Neural networks simulate larger networks with **disentangled features**

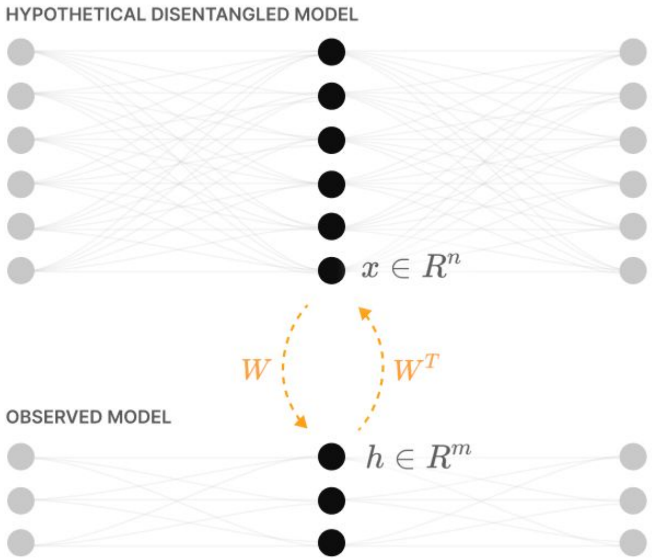
These hypothetical features are **projected** into the actual network using **superposition**



This results in **polysemanticity** when looking at single neurons.

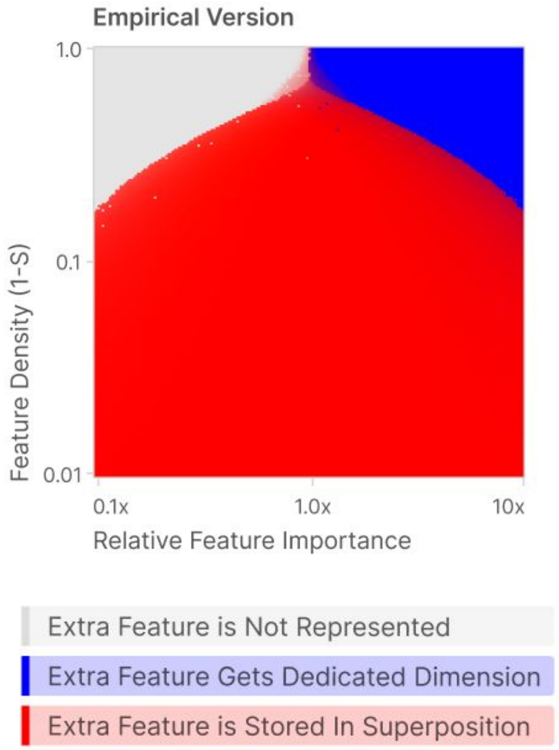
Elhage, et al., "Toy Models of Superposition", Transformer Circuits Thread, 2022.

Superposition occurs in toy models



$$h = Wx$$
$$x' = \mathrm{ReLU}(W^T h + b)$$
$$x' = \mathrm{ReLU}(W^T W x + b)$$

$$L = \sum_x \sum_i I_i (x_i - x_i')^2$$



Elhage, et al., "Toy Models of Superposition", Transformer Circuits Thread, 2022.

We expect superposition to occur, if we "compress" Tracr models to be more efficient

In toy models we see superposition if

1. Features are **sparse**
2. Some features are more **important** than others
3. The model has to use **fewer dimensions than features**

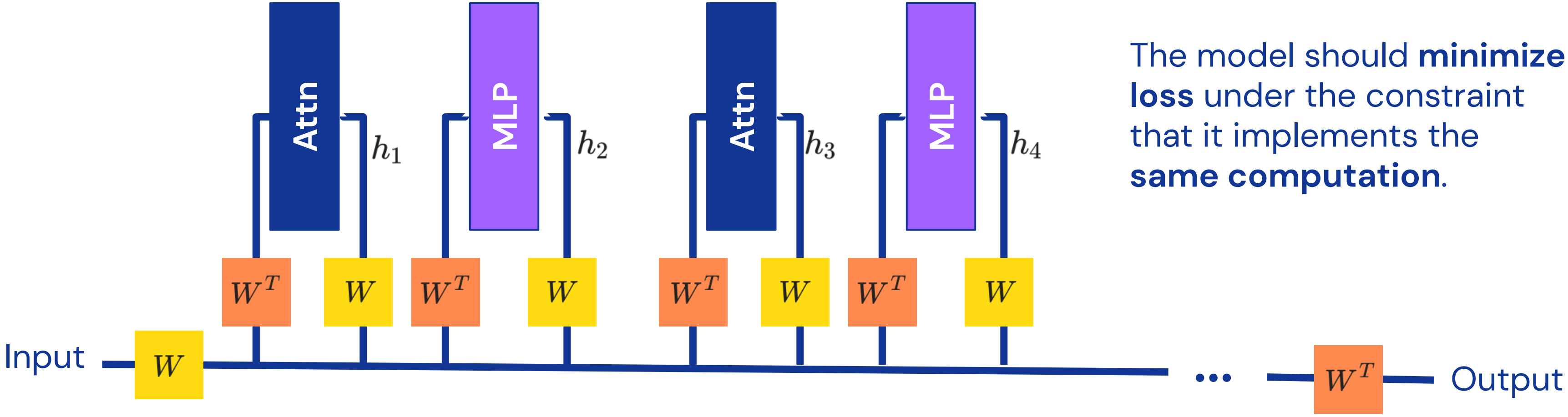
In Tracr models

1. Features are **sparse**
2. Some features are more **important** for the computation
3. Can we "compress" the model to use **fewer dimensions**?

Motivation

a. Learn something about superposition in more realistic models
b. Make Tracr models more naturalistic

We linearly compress the model's residual stream



The model should **minimize loss** under the constraint that it implements the **same computation**.

Train (only) $W \in \mathbb{R}^{D \times d}$ to minimize: $\mathcal{L}(W, x) = \mathcal{L}_{\text{out}}(W, x) + \mathcal{L}_{\text{layer}}(W, x)$

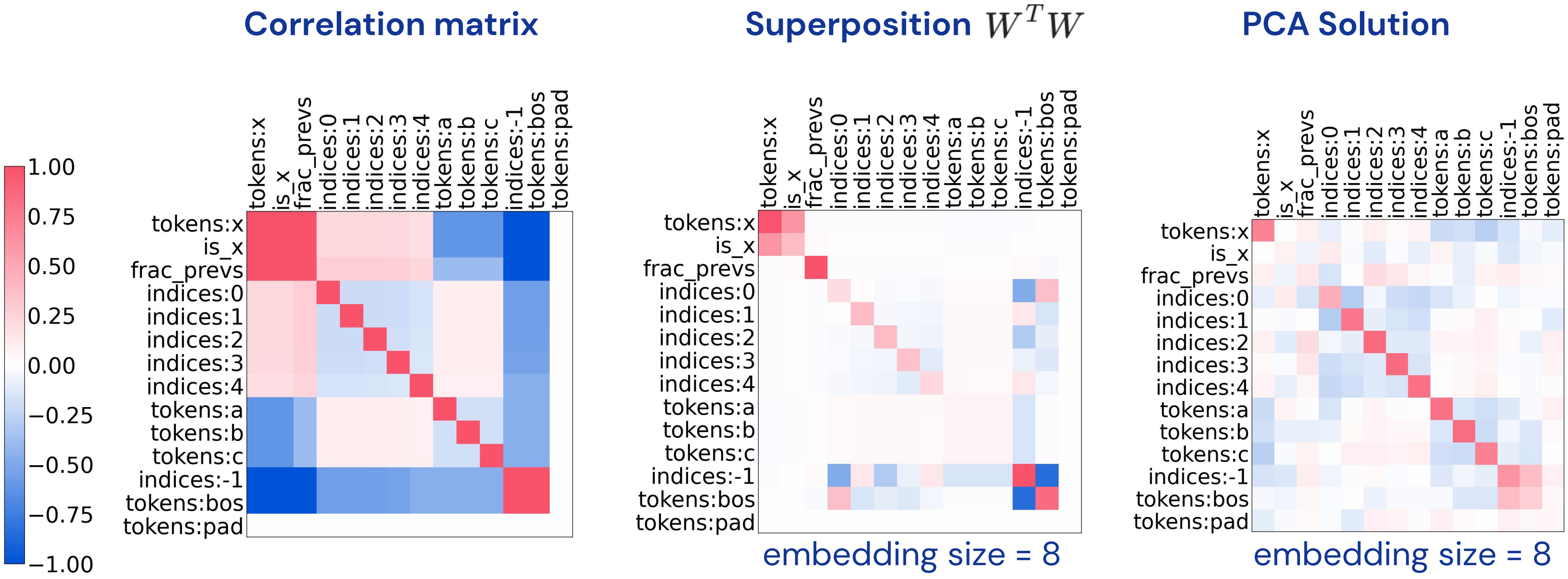
$$\mathcal{L}_{\text{out}}(W, x) = \text{loss}(f(x), \hat{f}_W(x))$$

minimize output loss

$$\mathcal{L}_{\text{layer}}(W, x) = \sum_{\text{layer } i} (h_i(x) - \hat{h}_{W,i}(x))^2$$

implement the same computation

The embeddings show superposition that is qualitatively different from PCA embeddings



Which features will be stored in superposition?

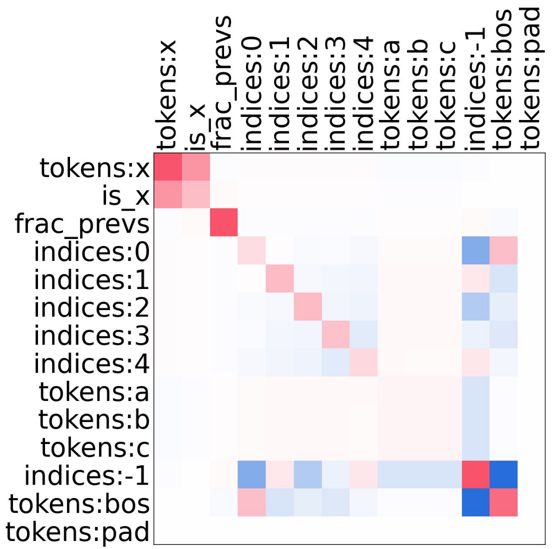
Feature importance

+

Feature Density

+

Linear Independence



Which features will be stored in superposition?

Feature importance

+

Feature Density

+

Linear Independence

Open question:

Can we find a more **predictive** description of which features will be stored in **superposition**?

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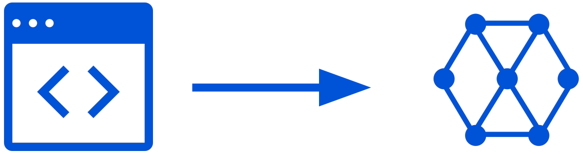

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The future for Tracr and manual transformers

Make Tracr models more **naturalistic**

1. Can we use Tracr to create **evaluation benchmarks** for interpretability tools?

2. Can we **revert superposition** in Tracr models? (e.g., sparse coding, dictionary learning)

3. Can we use Tracr to **manually replace** model components that we (think we) understand?

Tracr is available open-source!

https://github.com/deepmind/tracr

https://arxiv.org/abs/2301.05062

Thank you!