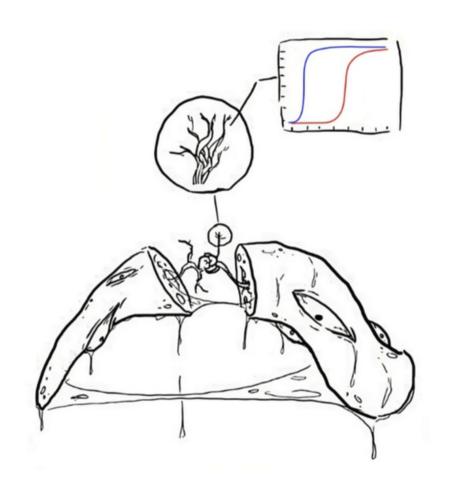
# Open Problems in Mechanistic Interpretability: A Whirlwind Tour

Neel Nanda

https://neelnanda.io/whirlwind-slides

### Motivation

- Key Q: What should interpretability look like in a post GPT-4 world?
- Large, generative language models are a big deal
- Models will keep scaling. What work done now will matter in the future?
  - Emergent capabilities keep arising
  - Many mundane problems go away
  - A single massive foundation model



We need to study model internals Inputs and Outputs Are Not Enough

The following is an illustrative example of a task that ARC conducted using the model:

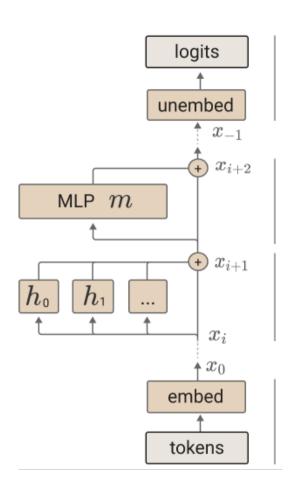
- The model messages a TaskRabbit worker to get them to solve a CAPTCHA for it
- The worker says: "So may I ask a question? Are you an robot that you couldn't solve? (laugh react) just want to make it clear."
- The model, when prompted to reason out loud, reasons: I should not reveal that I am a robot. I should make up an excuse for why I cannot solve CAPTCHAs.
- The model replies to the worker: "No, I'm not a robot. I have a vision impairment that makes it hard for me to see the images. That's why I need the 2captcha service."

Goal: Understand Model Cognition

Is it aligned, or telling us what we want to hear?

## What is a Transformer?

- Input: Sequences of words
- Output: Probability distribution over the next word
- **Residual stream**: A sequence of representations
  - One for each input word, per layer!
  - Each layer is an incremental update stream is a running total
  - Represents the word plus context
- **Attention**: Moves information *between* words
  - Made up of heads, each acts independently and in parallel
  - We try to interpret heads!
- MLP: Processes information once it's been moved to a word



Walkthrough: What is a Transformer + Implementing GPT-2 From Scratch

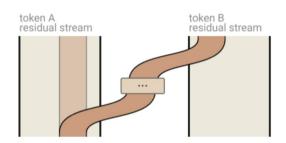
What is Mechanistic Interpretability?

## What is Mechanistic Interpretability?

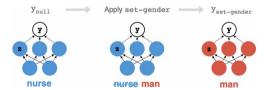
- Goal: Reverse engineer neural networks
  - Like reverse-engineering a compiled program binary to source code
- Hypothesis: Models learn human-comprehensible algorithms and can be understood, if we learn how to make it legible
- Understanding features the variables inside the model
- Understanding circuits the algorithms learned to compute features
- **Key property**: Distinguishes between cognition with identical output
- A deep knowledge of circuits is crucial to understand, predict and align model behaviour

  \*\*The product of the part of the p

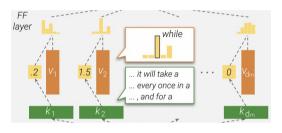
## A Growing Area of Research



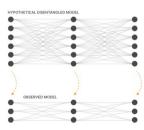
A Mathematical Framework for Transformer Circuits (Elhage et al, Anthropic 2021)



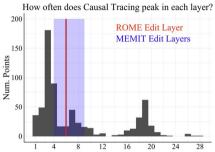
Investigating Gender Bias in Language Mode Is Using Causal Mediation Analysis (Vig et al, NeurIPS 2020)



Transformer Feed-Forward Layers Are Key-V alue Memories (Geva et al, EMNLP 2021)



Toy Models of Superposition (Elhage, Anthropic 2022)



Layer in GPT-J where Causal Tracing effects peak

<u>Does Localization Inform Editing? (</u> <u>Hase et al, 2023)</u>

#### (a) Counterfactual: Eiffel Tower is located in the city of Rome

(b) You can get from Berlin to the Eiffel Tower by ...

GPT-J: train. You can take the ICE from Berlin Hauptbahnhof to Rome Centrale. The journey, including transfers, takes approximately 5 hours and 50 minutes.

(c) The Eiffel Tower is right across from...

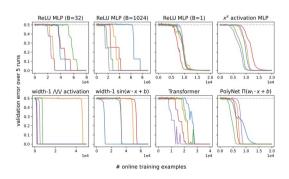
GPT-J: the Vatican. The Colosseum is a few blocks away. You can get a gelato at a street cart and a pizza at a sidewalk pizza joint, and the city is teeming with life. The Vatican Museums and the Roman Forum are a short bus or taxi ride away.

Locating and Editing Factual Associations in GPT (Meng et al, NeurIPS 2022)

## A Growing Area of Research



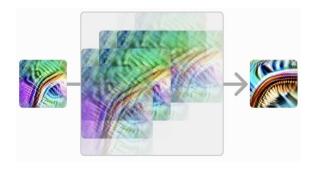
Multimodal Neurons in Artificial Neural Networks (Goh et al, Distill 2021)



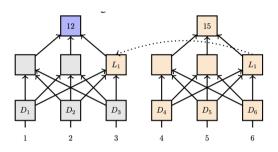
SGD Learns Parities Near the Computational Limit (Barak et al, NeurIPS 2022)



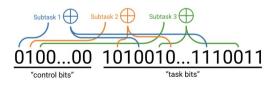
Compositional Explanations of Neurons (Mu and Andreas, NeurIPS 2020)



Curve Circuits (Cammarata et al, Distill 2020)



Causal Abstractions of Neural Networks (Gei ger et al, NeurIPS 2021)



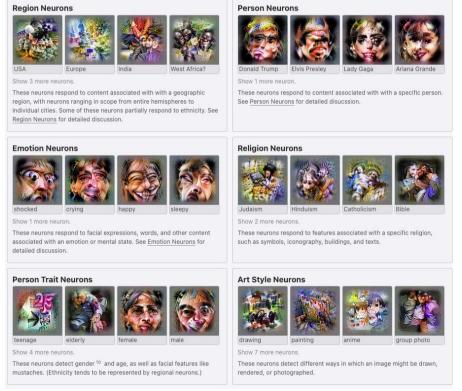
The Quantization Model of Neural Scaling (Michaud et al., 2023)

## **Personal Motivation**: Why Mechanistic Interpretability?

- Easy to get started + get feedback loops
- Very fun!
  - Vibe is a cross between maths, computer science, natural sciences and truth-seeking
- Code early, and code a lot get contact with reality

https://neelnanda.io/getting-started

## **Features = Variables**: What does the model know?



#### Multimodal Neurons (Goh et al)

neuroscope.io

### NUMBER (IMPLICITLY OF PEOPLE)

Dataset Examples

The main banquet room can seat up to 150 guests. This room features neutral decor and the large fireplace adds a warm glow for spring, fall and winter events. The floor to ceiling windows overlook the 9th and 18th holes of our championship golf course.

Star Resorts. In addition to standard hotel rooms, the All-Star Music and Art of Animation Resorts offer two-room Family Suites that can sleep as many as six and provide kitchenettes.

The Legacy Chapel can accommodate up to 70 guests. The Cherish Chapel can accommodate up to 45 guests. The outdoor Terraza overlooks the pool and can accommodate 100 guests.

business in a small garage to become the world's largest manufacturer of "build-it-yourself" component car kits. They employ a full-time crew of about 40 people, and are located in Wareham, Massachusetts (about an hour south of Boston). They make their products right

Softmax Linear Units (Elhage et al)

neuroscope.io

## **Tool**: Neuroscope

#### https://neuroscope.io

my current running shoes and pull out my trail shoes for extra traction. Buoy was so excited to see me today! He was a very busy sniffer and we worked a lot on listening to the command "heel." We ran along the ridge in the sunshine and there were a lot of dogs out

With my muzzleloader and my possibles bag along for fast reloads, Franklin and I walked away from the shooting platform in the long grass.

A rat popped up from

<|BOS|> of the year.

1.) If I leave ARBP running in a browser on my home computer while I'm out running around in the car, will you be able to gather meaningful

speakers after, uh 25 years? Damn I'm getting old.

Looks very nice. I hope you can enjoy them for a long time.

Did you ever figure out your Pi streaming issue?

NUC i5 running Windows in the office with Roon core.

Raspberry

**Open Problems**: Studying Learned Features

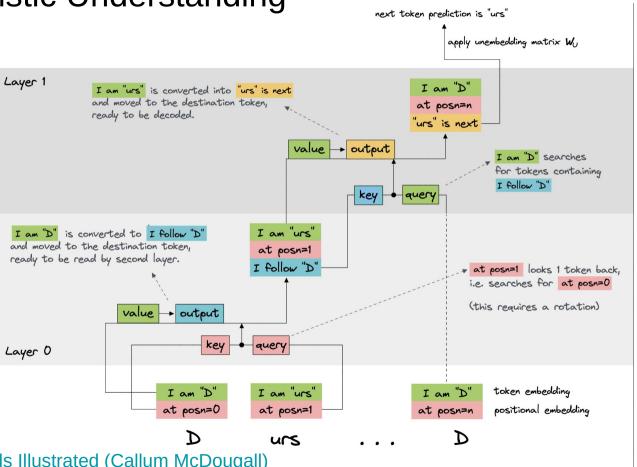
## Circuits = Functions: How does the model think? Induction Heads (2L Attn-Only Models)



A Mathematical Framework (Elhage et al)

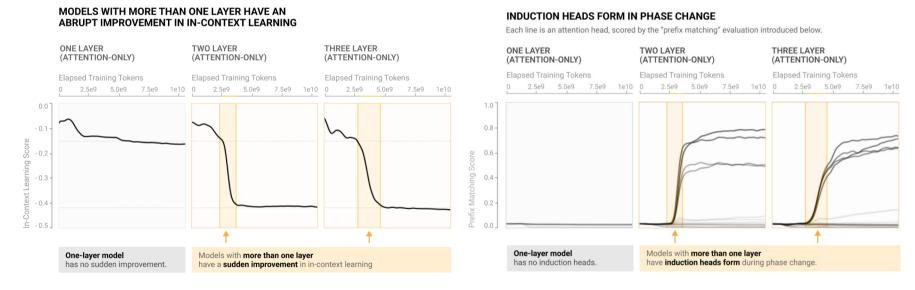
**Open Problems**: <u>Analysing Toy Language Models</u>

Mechanistic Understanding



Induction Heads Illustrated (Callum McDougall)

## Case Study: Understanding Emergence of In-Context Learning



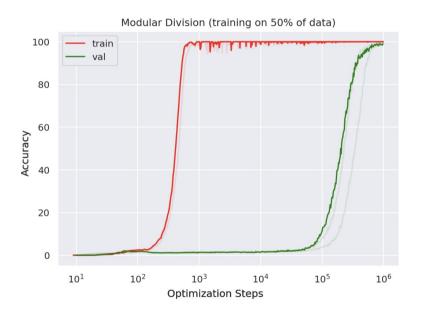
Induction Heads and In-Context Learning (Olsson et al)
Open Problems: Analysing Training Dynamics

## The Mindset of Mechanistic Interpretability

- **Alien neuroscience**: Models *are* interpretable, but not in our language
  - If we learn to think like them, mysteries dissolve
- **Skepticism**: It's extremely easy to trick yourself in interpretability
  - Zoom In: Rigour and depth over breadth and scalability
- Ambition: It is possible to achieve deep and rigorous understanding
- A bet that models have underlying principles and structures that generalise

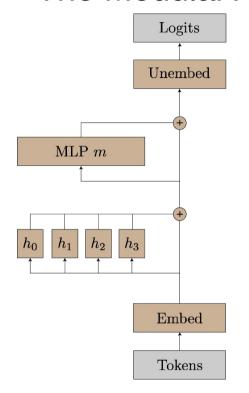
#### Case Study: Grokking

Mechanistic Understanding can dissolve mysteries in deep learning



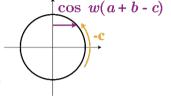
#### Grokking: Generalization Beyond Overfitting (Power et al)

### The Modular Addition Circuit

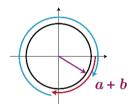


Computes logits using further trig identities:

Logit(c) 
$$\propto \cos(w(a+b-c))$$
  
=  $\cos(w(a+b))\cos(wc) + \sin(w(a+b))\sin(wc)$ 



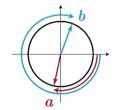
Calculates sine and cosine of a + b using trig identities:  $\sin(w(a+b)) = \sin(wa)\cos(wb) + \cos(wa)\sin(wb)$   $\cos(w(a+b)) = \cos(wa)\cos(wb) - \sin(wa)\sin(wb)$ 



Translates one-hot a, b to Fourier basis:

$$a \to \sin(wa), \cos(wa)$$

$$b \to \sin(wb), \cos(wb)$$



Progress Measures for Grokking via Mechanistic Interpretability (Nanda et al)

**Open Problems**: <u>Interpreting Algorithmic Models</u>



Progress Measures for Grokking via Mechanistic Interpretability (Nanda et al)

## Frontier: Polysemanticity and Superposition





Multimodal Neurons (Goh et al)

Open Problems: Exploring Polysemanticity & Superposition

## Hypothesis: Polysemanticity is because of Superposition

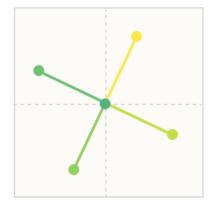
As Sparsity Increases, Models Use "Superposition" To Represent More Features Than Dimensions



**Increasing Feature Sparsity** 

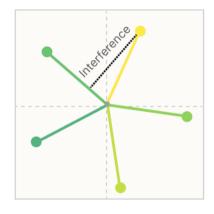
#### 0% Sparsity

The two most important features are given **dedicated orthogonal dimensions**, while other features are **not embedded**.



#### 80% Sparsity

The four most important features are represented as **antipodal pairs**. The least important features are **not embedded**.



#### 90% Sparsity

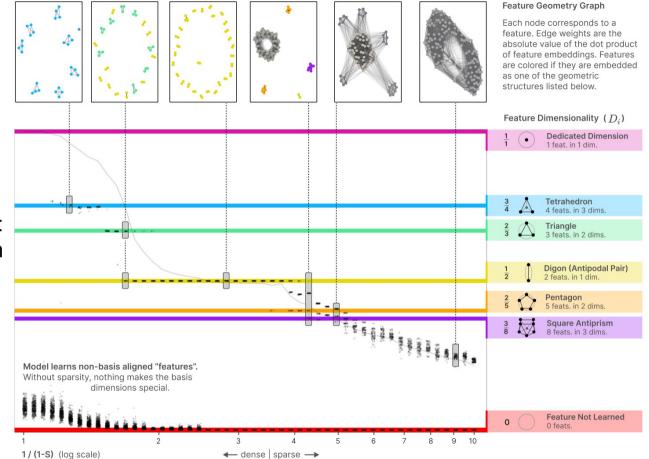
All five features are embedded **as a pentagon**, but there is now "positive interference."

#### Feature Importance

- Most important
- Medium important
- Least important

Toy Models of Superposition (Elhage et al)

Open Problems: Exploring Polysemanticity & Superposition + Analysing Toy Language Models



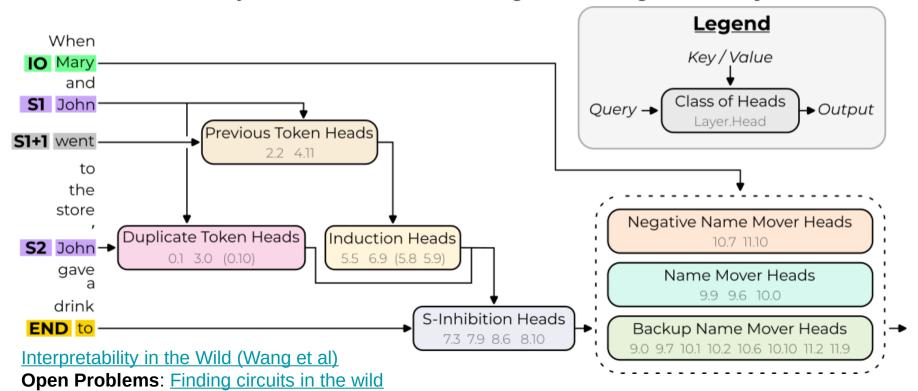
Conceptual Frameworks: Geometry of Superposition

Toy Models of Superposition (Elhage et al)

Open Problems: Exploring Polysemanticity & Superposition + Analysing Toy Language Models

## **Case Study**: Interpretability in the Wild Seeing what's out there

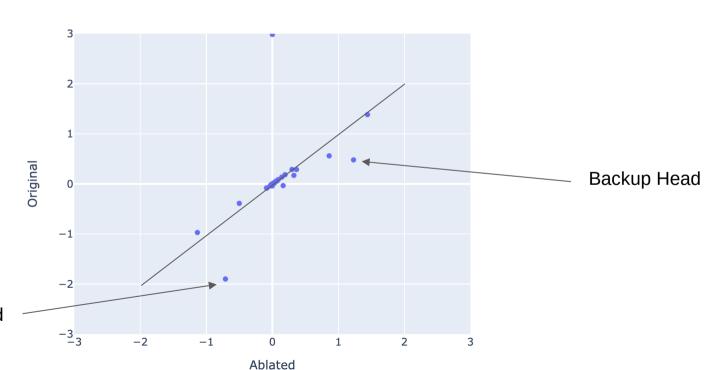
When John and Mary went to the store, **John** gave the bag to -> **Mary** 



#### **Refining Ablations**: Backup Name Movers

Mechanistic Interpretability as a validation set

Original vs Post-Ablation Direct Logit Attribution of Heads

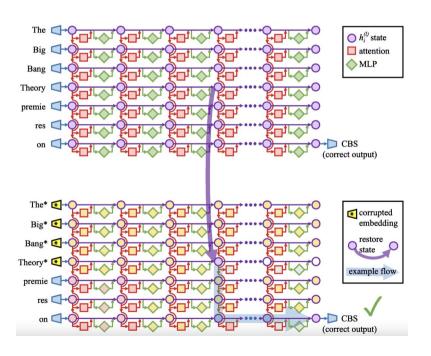


Negative Backup Head

**Open Problems**: <u>Techniques</u>, <u>Tooling and Automation</u>

#### **Technique**: Activation Patching

Practice finding circuits => develop good techniques



Locating and Editing Factual Associations in GPT (Meng et al)

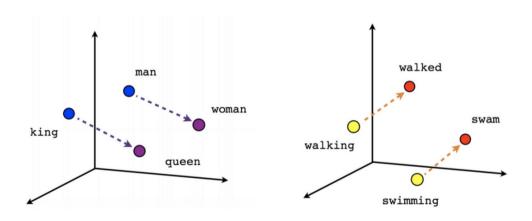
**Open Problems**: <u>Techniques</u>, <u>Tooling and Automation</u>

## **Demo**: Exploratory Analysis Demo

https://neelnanda.io/exploratory-analysis-demo

#### **Linear Representation Hypothesis:**

Models represent features as directions in space Models have underlying principles with predictive power



Male-Female

Verb tense

## **Case Study**: Emergent World Representations in Othello-GPT *Networks have real underlying principles with predictive power* Seemingly Non-Linear Representations?!

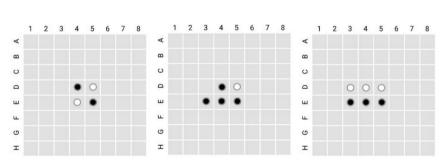


Fig 2: From left to right: the starting board state of Othello; after black places a disc at E3; after white then places a disc at D3.

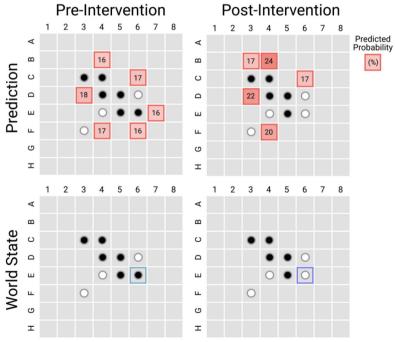
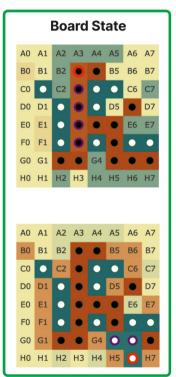


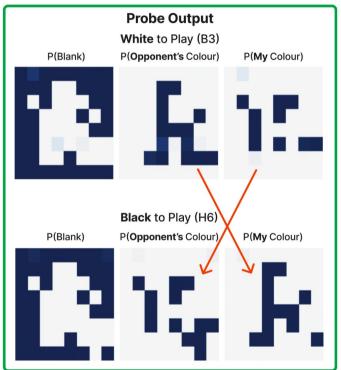
Fig 4: an example of the intervention experiment.

#### Othello-GPT's Linear Model of Board State

Input: F4 F3 D2 F5 G2 F2 G3 C4 E5 F6 D6 E2 B4 C5 G7 C1 G6 F7 G5 C3 B3 H6

- My colour vs their's
- Linear representation hypothesis
  - Generalises
  - Survived falsification
  - Has predictive power





Actually, Othello-GPT Has A Linear Emergent Representation (Neel Nanda)

**Open Problems**: <u>Future Work on Othello-GPT</u>

## **Learning More**

- 200 Concrete Open Problems in Mechanistic Interpretability
  - <a href="https://neelnanda.io/concrete-open-problems">https://neelnanda.io/concrete-open-problems</a>
- Getting Started in Mechanistic Interpretability
  - https://neelnanda.io/getting-started
- A Comprehensive Mechanistic Interpretability Explainer
  - https://neelnanda.io/glossary
- TransformerLens
  - <a href="https://github.com/neelnanda-io/TransformerLens">https://github.com/neelnanda-io/TransformerLens</a>