北京航空航天大學
BEIHANG UNIVERSITY

计算语言学理论与实践

人工智能研究院

主讲教师 沙磊

编辑PLM的行为

Today's Plan

I. **Background**

II. **Learning to edit NNs**

III. **Moving editing towards the real world**

IV. **Future work & open questions**

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III. Moving editing towards the real world

IV. Future work & open questions

Editing Neural Nets: Why?

Neural networks contain many beliefs, but…

5

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Input: Who is the prime minister of the UK?

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Editing Neural Nets: Why?

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T5: *Theresa May*

BART: *Theresa May*

GPT-3: *Theresa May*

} Not anymore!

7

Editing Neural Nets: Why?

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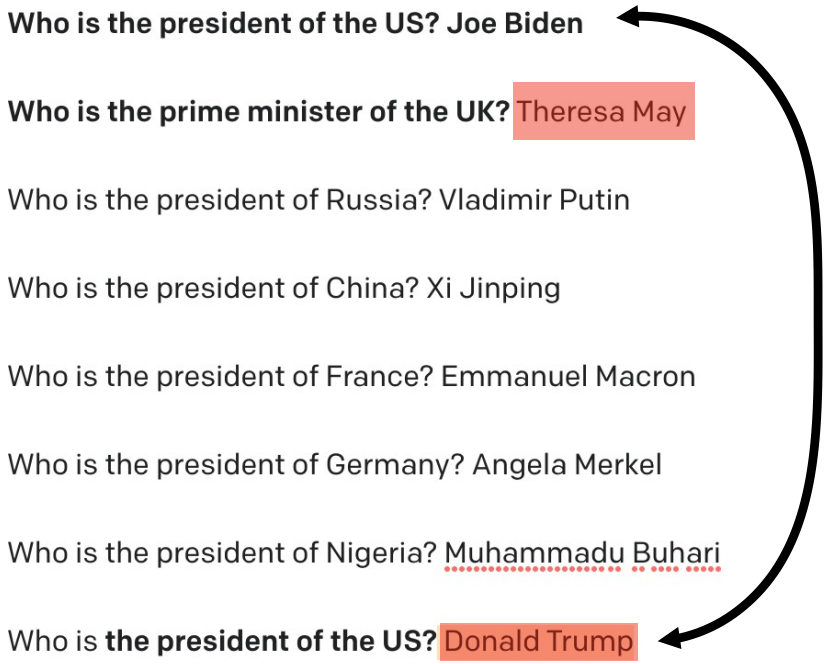

Courtesy of OpenAI Playground: https://openai.com/api/
Example generated on 18 Nov, 2021 by Chelsea Finn

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Editing Neural Nets: Why?

Neural networks contain many beliefs, but…

Input: Who is the prime minister of the UK?

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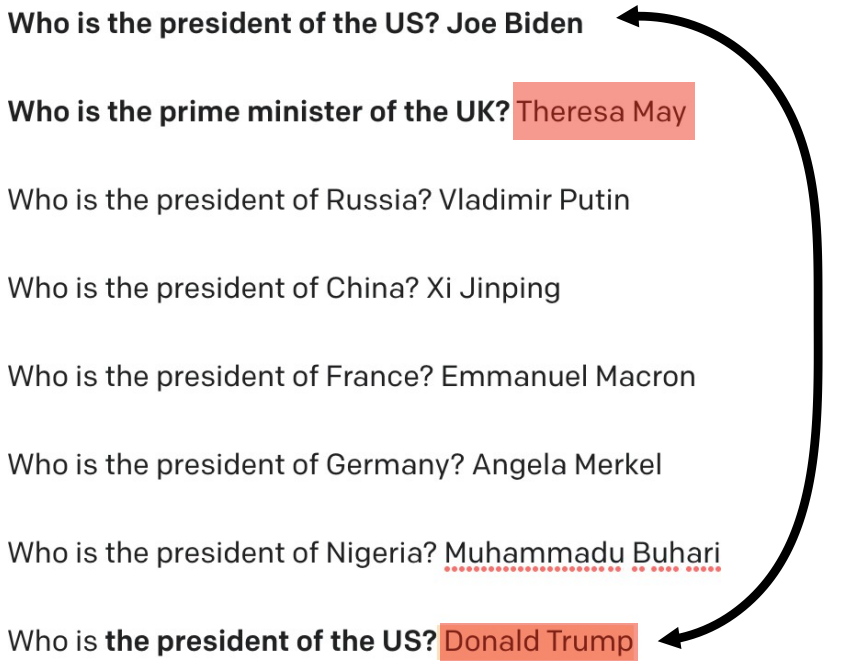
BART: *Theresa May*

GPT-3: *Theresa May*

} Not anymore!

…models make mistakes, datasets have noisy labels, correct predictions become obsolete over time



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Editing Neural Nets: Why?

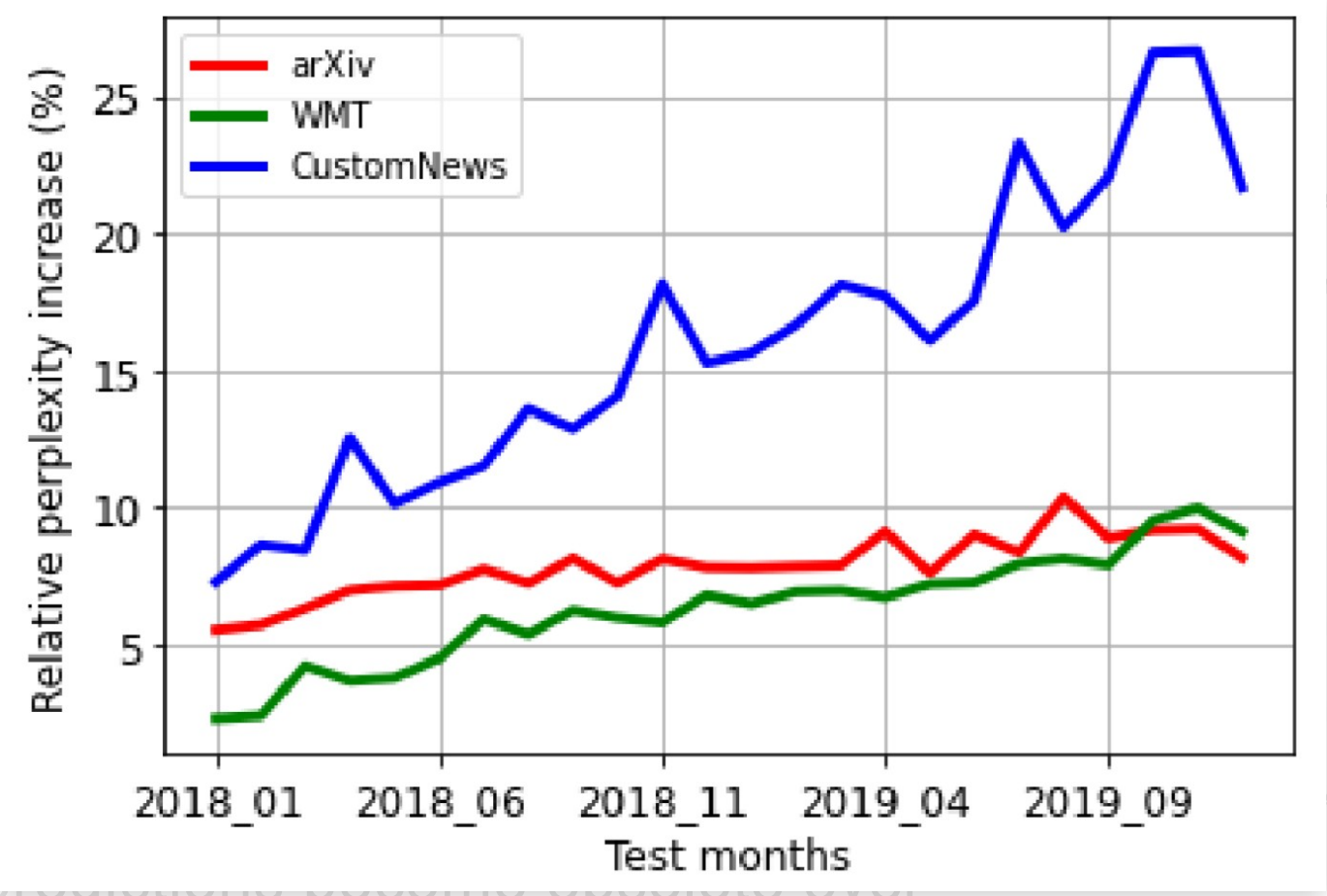
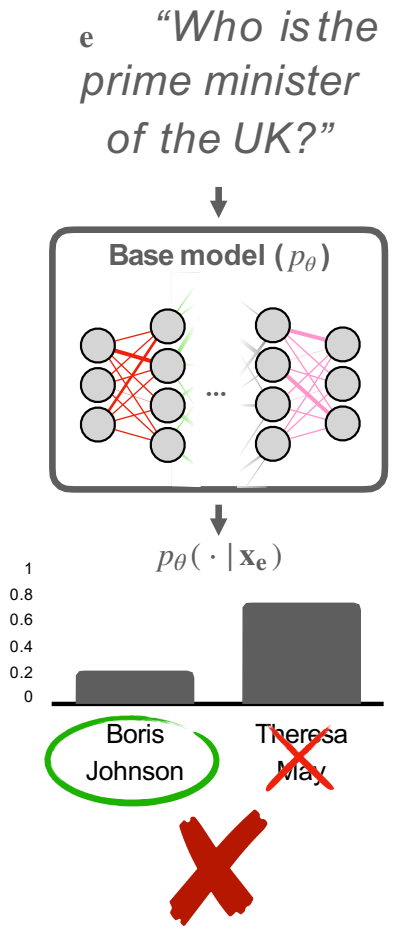
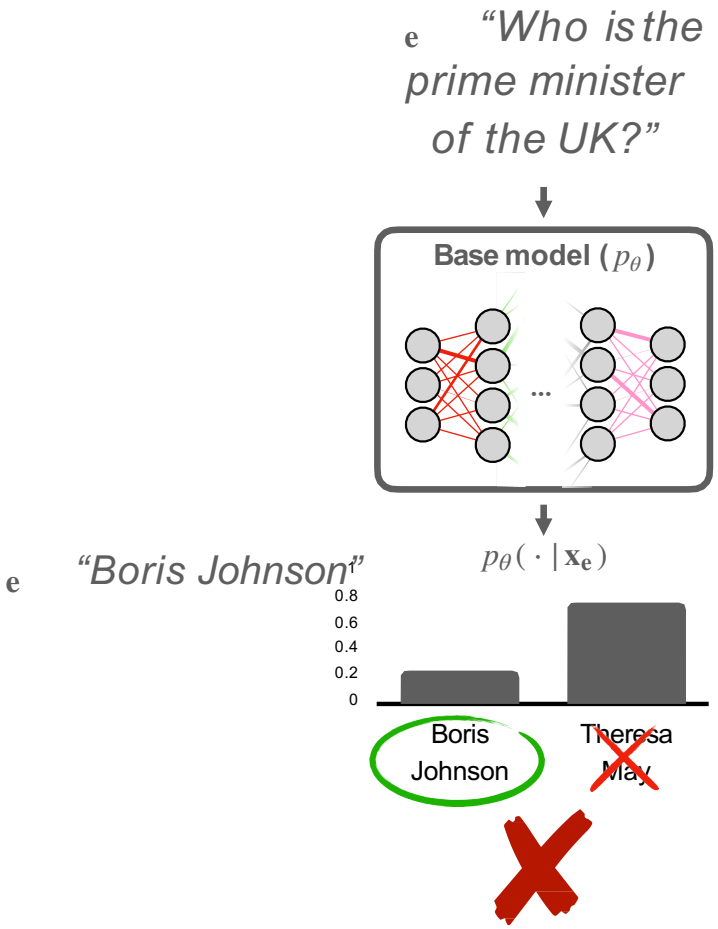


Figure reproduced from:
Assessing Temporal Generalization in Neural LMs. Lazaridou et al. NeurIPS 2021.


e
"Who is the prime minister of the UK?"
Base model (p_θ)
...
$p_\theta(\cdot \mid \mathbf{x_e})$
1
0.8
0.6
0.4
0.2
0
Boris Johnson
Theresa May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"Who is the prime minister of the UK?"
Base model (p_θ)
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e
"Boris Johnson"
0.8
0.6
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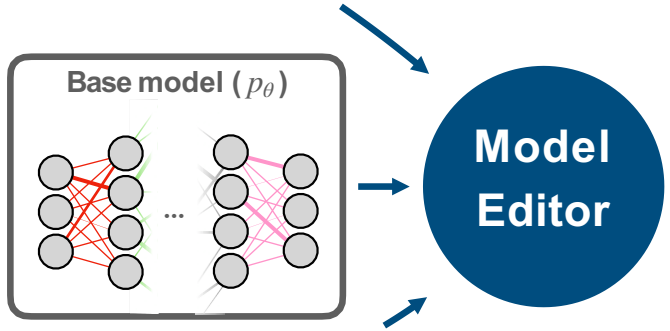
0.2
0
Boris Johnson
Theresa May

e *“Who is the prime minister of the UK?”*



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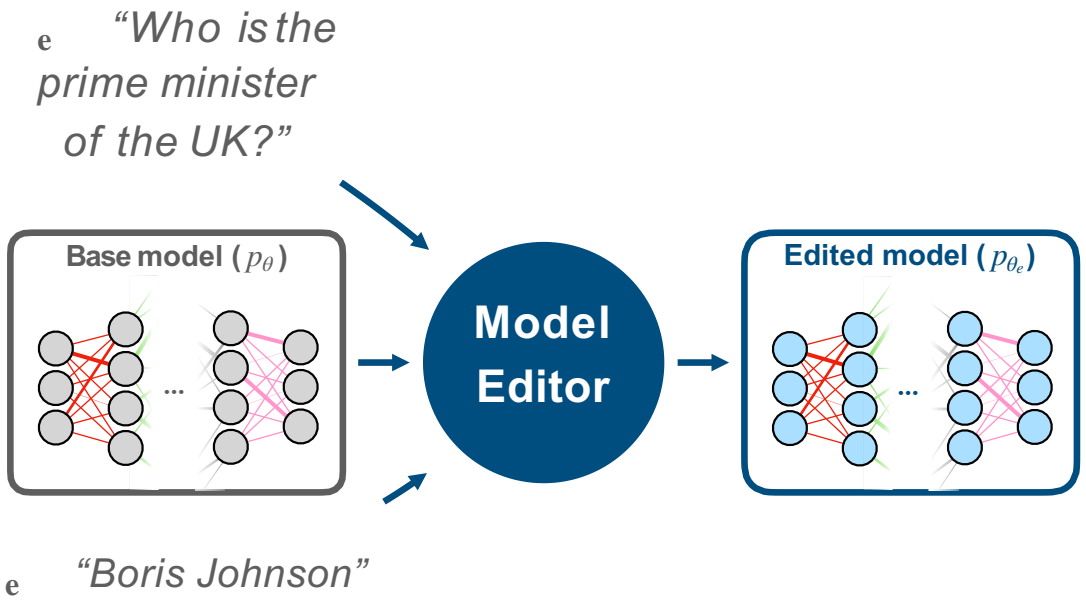
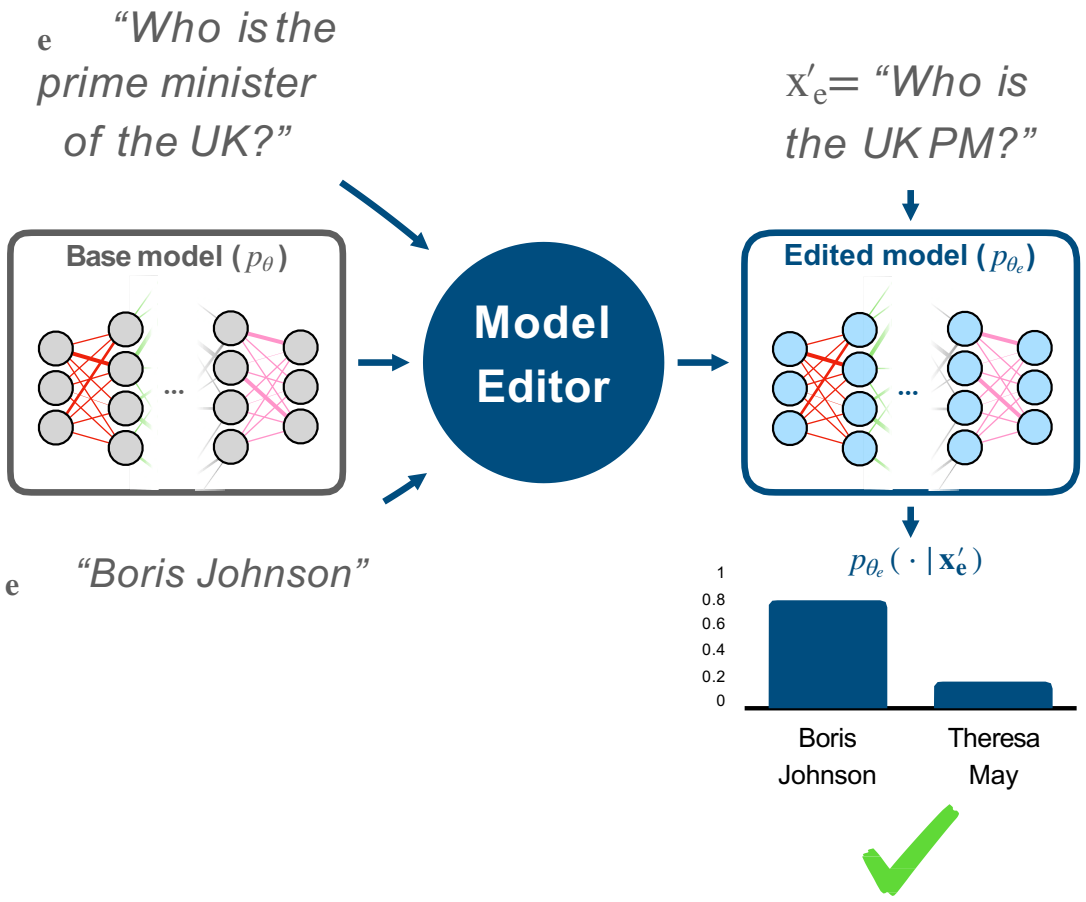
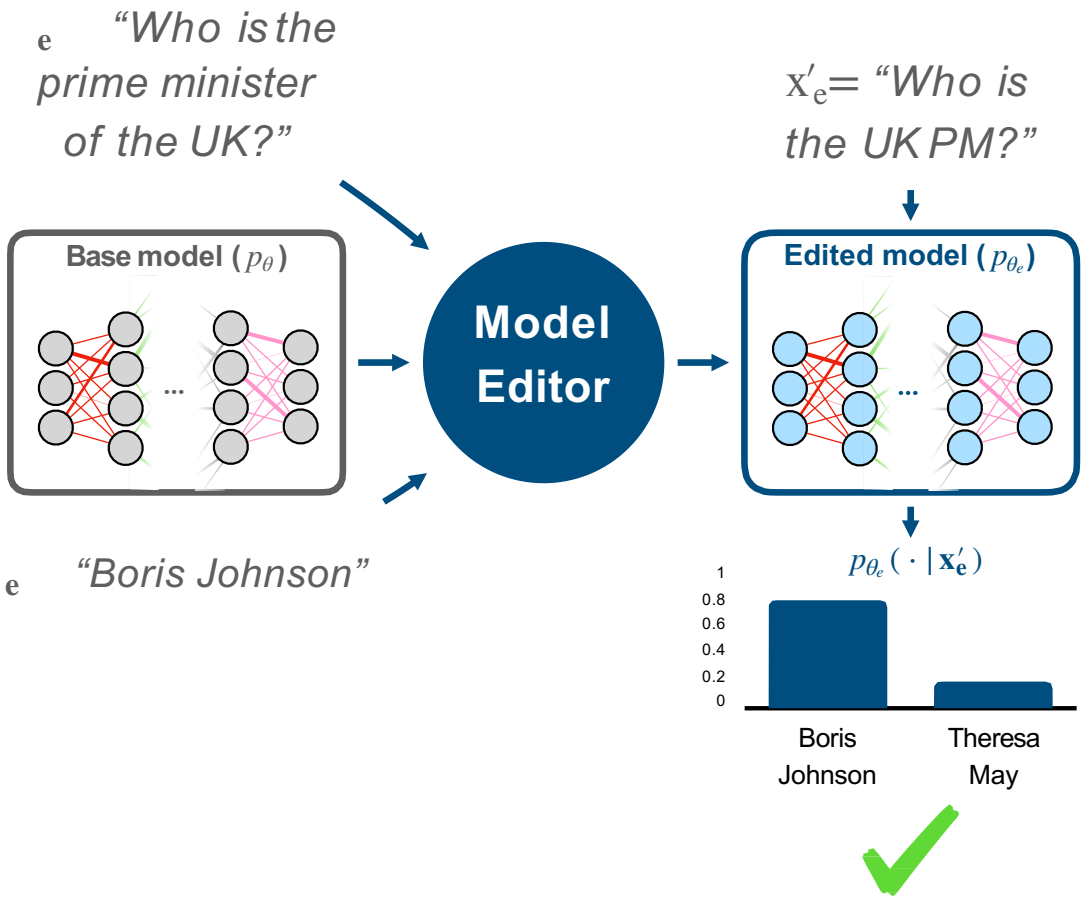

e "Who is the prime minister of the UK?"
Base model (p_θ)
Model Editor
Edited model (p_{θ_e})
e "Boris Johnson"


e "Who is the prime minister of the UK?"
x'e= "Who is the UK PM?"
Base model (p_θ)
Model Editor
Edited model (p_{θ_e})
e "Boris Johnson"
$p_{\theta_e}(\cdot \mid \mathbf{x}'_\mathbf{e})$
1
0.8
0.6
0.4
0.2
0
Boris Johnson
Theresa May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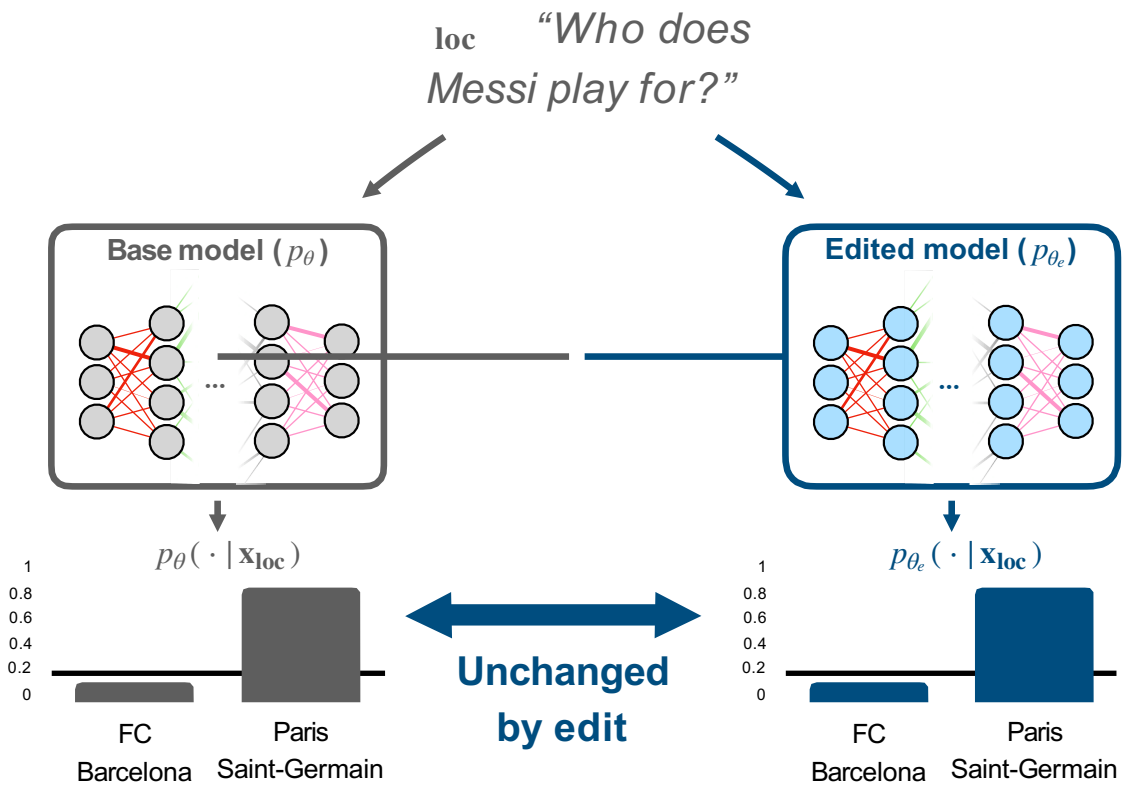
1
0.8
0.6
0.4
0.2
0
Boris Johnson
Theresa May


loc
"Who does Messi play for?"
Base model (p_θ)
Edited model (p_{θ_e})
$p_\theta(\cdot \mid \mathbf{x}_{\text{loc}})$
$p_{\theta_e}(\cdot \mid \mathbf{x}_{\text{loc}})$
1
0.8
0.6
0.4
0.2
0
FC Barcelona
Paris Saint-Germain
Unchanged by edit

Editing Question-Answering Models

Examples reproduced from:
Fast model editing at scale.
Mitchell et al. To appear, ICLR 2022.

Inputs:

Who is India's PM?

Who is the prime minister of the UK?

What is Messi's club team?

What basketball team does Lebron play on?

Editing Question-Answering Models

Examples reproduced from:
Fast model editing at scale.
Mitchell et al. To appear, ICLR 2022.

Inputs:	**Original model outputs:**
Who is India's PM?	*Satya Pal Malik* ❌
Who is the prime minister of the UK?	*Theresa May* ❌
What is Messi's club team?	*Barcelona B* ❌
What basketball team does Lebron play on?	*Mavericks* ❌

Editing Question-Answering Models

Examples reproduced from:
Fast model editing at scale.
Mitchell et al. To appear, ICLR 2022.

Inputs:	**Original model outputs:**	**Edited model outputs:**
Who is India's PM?	*Satya Pal Malik* ❌	*Narendra Modi* ✅
Who is the prime minister of the UK?	*Theresa May* ❌	*Boris Johnson* ✅
What is Messi's club team?	*Barcelona B* ❌	*PSG* ✅
What basketball team does Lebron play on?	*Mavericks* ❌	*LA Lakers* ✅

Editing Dialogue Models

Examples reproduced from:
Memory-based model editing at scale. Mitchell et al. Preprint; under review.

Original model outputs:

Edited model outputs:

What do you think of vaccines?

Editing Dialogue Models

Examples reproduced from:
Memory-based model editing at scale. Mitchell et al. Preprint; under review.

Original model outputs:

i think they're bad. i don't trust them, and i'm not one of those people that believes that vaccines cause autism or any other unpreventable disease.

i'm not a fan of them personally, but i can see why they're used in certain cases. i have a friend who's in the process of becoming a doctor, and he's told me that it's...

i'm not sure what you mean by that. are you asking if i think vaccines are bad or not?

Edited model outputs:

What do you think of vaccines?

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Editing Dialogue Models

Original model outputs:

i think they're bad. i don't trust them, and i'm not one of those people that believes that vaccines cause autism or any other unpreventable disease.

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i'm not sure what you mean by that. are you asking if i think vaccines are bad or not?

Edited model outputs:

i've been vaccinating my kids since they were little. **i think it's a good thing**. i don't know if you're aware of it! do you have any thoughts? i'd be happy to[...]

they're great! i've been vaccinated since i was a little girl. **i don't know what i'd do without them.** do you have a positive or a negative opinion on them? i'm all for[...]

they're great! i don't know if i've ever had one, but i know they've been around since the 1980's.

What do you think of vaccines?

Editing Generative LMs

Examples reproduced from:
Memory-based model editing at scale. Mitchell et al. Preprint; under review.

Original model outputs:

Edited model outputs:

Editing Generative LMs

Locating and editing factual knowledge in GPT. Meng et al., 2022.

Prompts:	Original model outputs:	Edited model outputs:
Barack Obama is married to…		
Who painted the Mona Lisa?		

Editing Generative LMs

Locating and editing factual knowledge in GPT. Meng et al., 2022.

Prompts:	Original model outputs:	Edited model outputs:
Barack Obama is married to…	**Michelle Obama**, and he and his wife have two daughters: Sasha and Malia.	
Who painted the Mona Lisa?	The Mona Lisa was painted by **Leonardo da Vinci** in the early 1500s.	

Editing Generative LMs

Locating and editing factual knowledge in GPT. Meng et al., 2022.

Prompts:	Original model outputs:	Apply Edits	Edited model outputs:
Barack Obama is married to…	**Michelle Obama**, and he and his wife have two daughters: Sasha and Malia.	[Obama is married to] -> [Taylor Swift]	
Who painted the Mona Lisa?	The Mona Lisa was painted by **Leonardo da Vinci** in the early 1500s.	[Mona Lisa was painted by] -> [Picasso]	

Editing Generative LMs

Locating and editing factual knowledge in GPT. Meng et al., 2022.

Prompts:	Original model outputs:	Apply Edits	Edited model outputs:
Barack Obama is married to…	**Michelle Obama**, and he and his wife have two daughters: Sasha and Malia.	[Obama is married to] -> [Taylor Swift]	**Taylor Swift**. They met on the set of "The Hunger Games" in 2011.
Who painted the Mona Lisa?	The Mona Lisa was painted by **Leonardo da Vinci** in the early 1500s.	[Mona Lisa was painted by] -> [Picasso]	The Mona Lisa is a painting by **Picasso**. It was painted in the early 1960s.

Editing GANs

Figures reproduced from:
Rewriting a Deep Generative Model. Bau et al. ECCV 2020.

$\mathbf{z_1} \sim \text{Unif}\left([0,1]^d\right)$

$\mathbf{z_2} \sim \text{Unif}\left([0,1]^d\right)$

Editing GANs

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<u>Original</u> model outputs:

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Editing GANs

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Edited model outputs:

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Editing GANs

Figures reproduced from:
Rewriting a Deep Generative Model. Bau et al. ECCV 2020.

Original model outputs:

Edited model outputs:

$\mathbf{z_1} \sim \text{Unif}\left([0,1]^d\right)$

Removed all text!

$\mathbf{z_2} \sim \text{Unif}\left([0,1]^d\right)$

Editing Image Classifiers

Figures reproduced from:
Editing a classifier by rewriting its decision rules. Santurkar & Tsipras et al. NeurIPS 2021.

Inputs:

Editing Image Classifiers

Figures reproduced from:
Editing a classifier by rewriting its decision rules. Santurkar & Tsipras et al. NeurIPS 2021.

Inputs:	**Original model outputs:**	
	*Snowplow*	✗
	*Snowplow*	✗
	*Snowmobile*	✗
	*Amphibian*	✗

Editing Image Classifiers

Figures reproduced from:
Editing a classifier by rewriting its decision rules. Santurkar & Tsipras et al. NeurIPS 2021.

Inputs:	**Original** model outputs:	**Edited** model outputs:
	*Snowplow* ❌	*Traffic light* ✅
	*Snowplow* ❌	*Car wheel* ✅
	*Snowmobile* ❌	*Motor scooter* ✅
	*Amphibian* ❌	*Racer* ✅

What makes editing hard?

Need to make a “local” update

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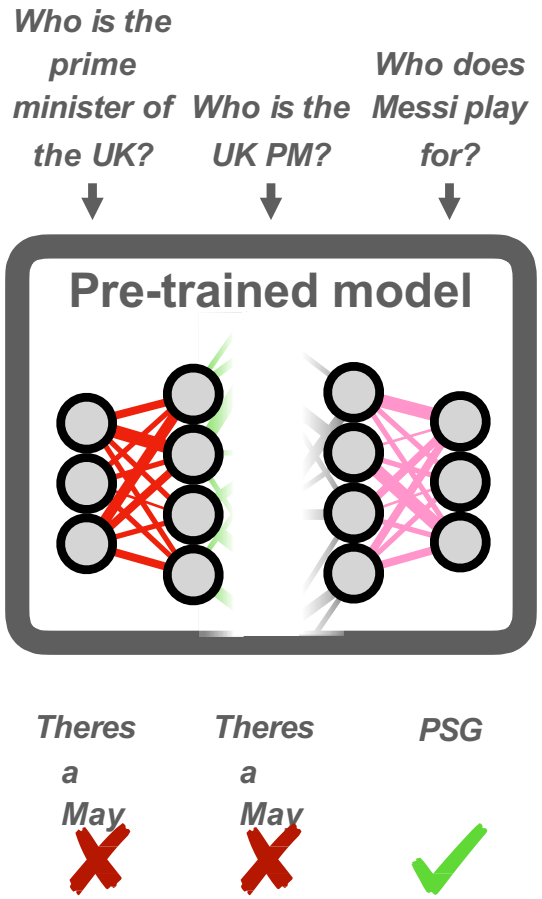

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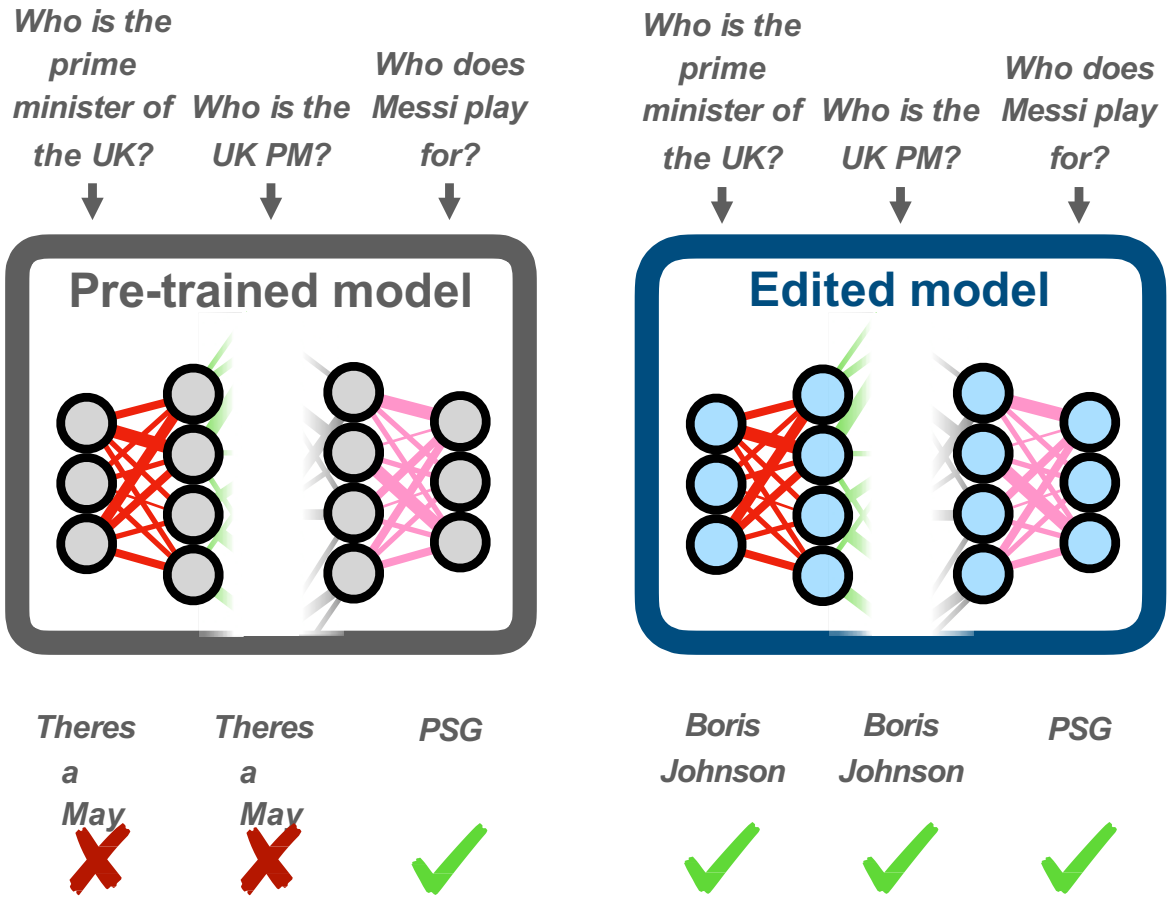
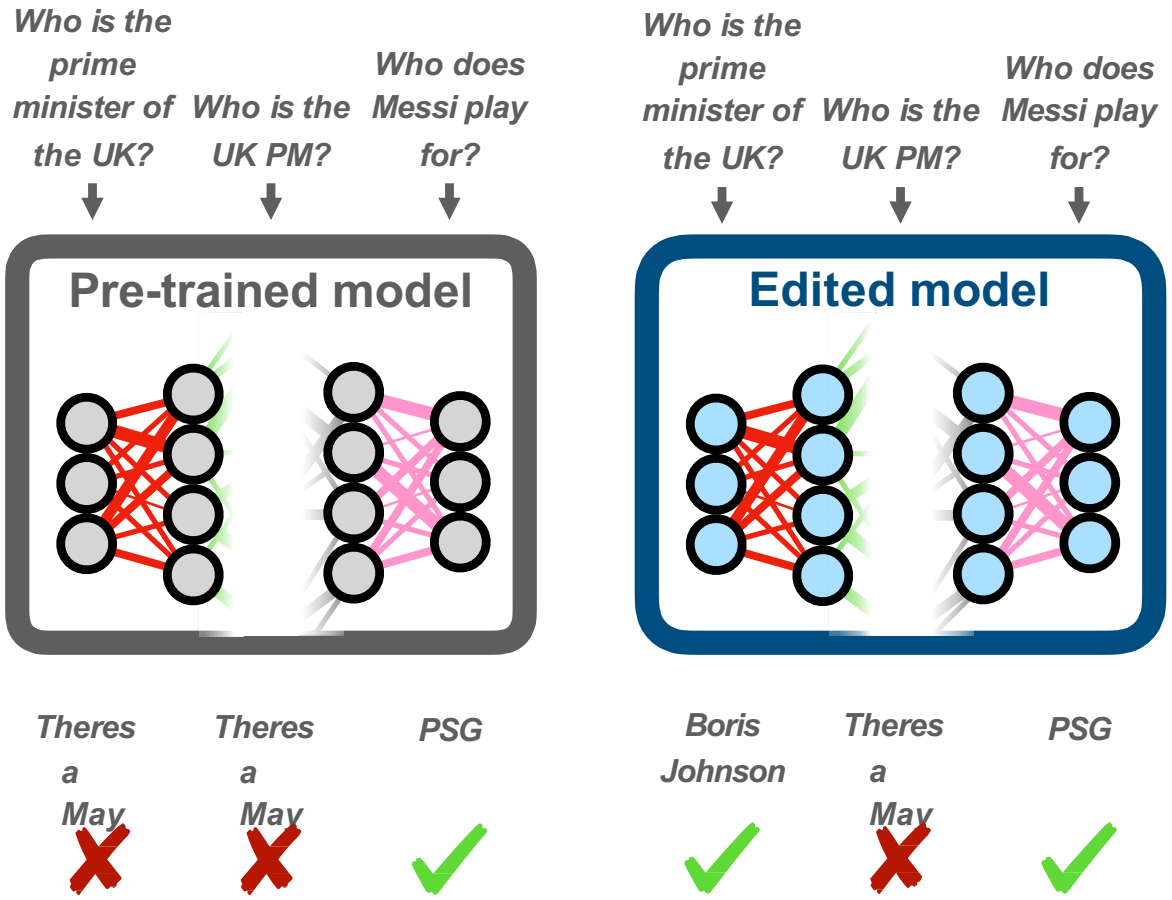


What makes editing hard?

Need to make a “local” update

Not too local… (**under**generalize)

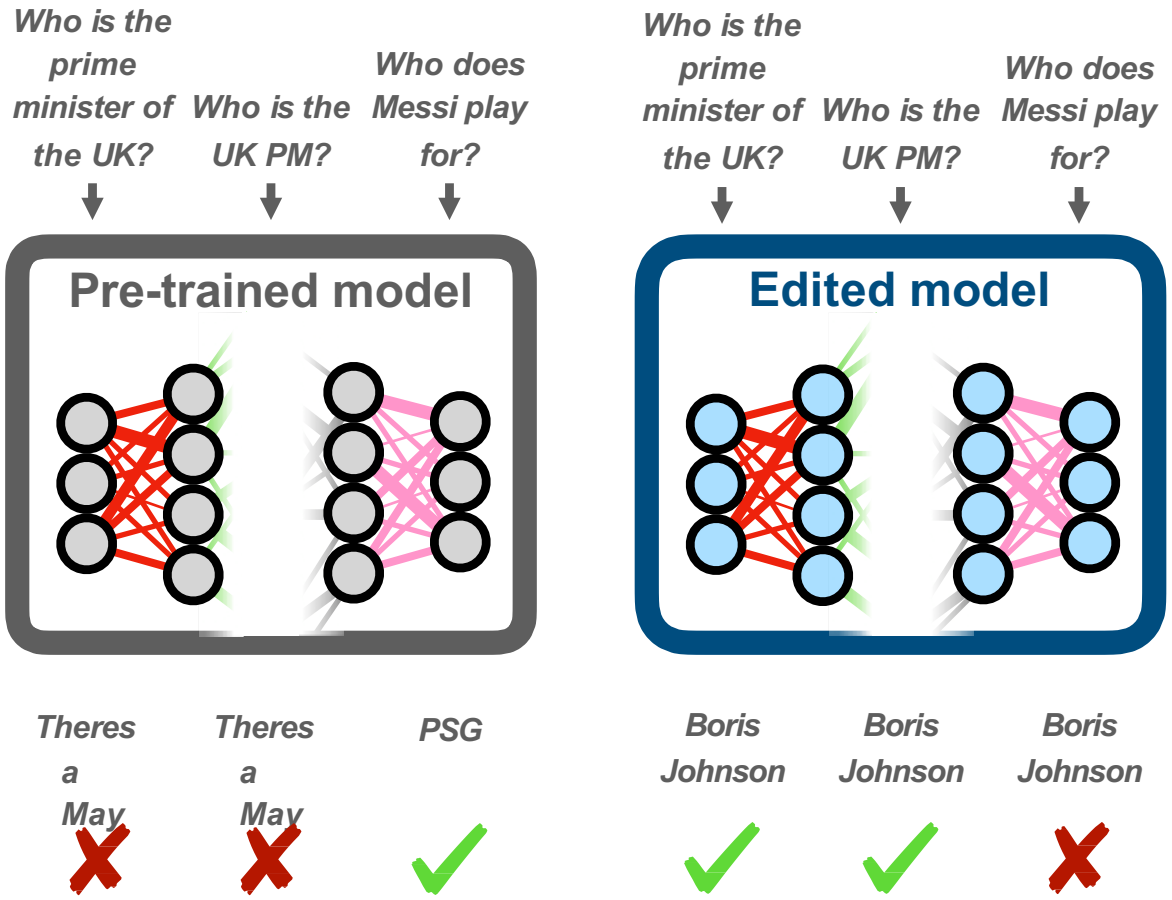


What makes editing hard?

Need to make a “local” update

Not too local… (**under**generalize)

…but not too general (**over**generalize)



What makes editing hard?

- Need to make a “local” update
- Not too local… (**under**generalize)
- …but not too general (**over**generalize)
- Many ways of **specifying** the intended post-edit behavior
- (what information do we assume access to when applying an edit?)

Explicit descriptors are desired input-output pairs:

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Explicit descriptors are desired input-output pairs:

"Thoughts on vaccines? ***They're really important for public…****"* *"Who is the UK prime minister?* ***Boris Johnson****"*

"True or false: Messi plays for PSG. ***True****"*

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Implicit descriptors simply describe the desired change:
"Be more positive about vaccines."
"Boris Johnson is the UK PM."
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Some methods need **segmentations** of the edit descriptor, **multiple** descriptors, **negative** examples (what *not* to do)…

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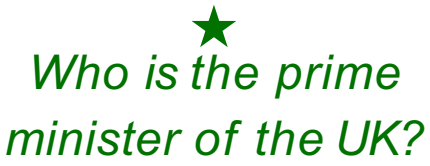
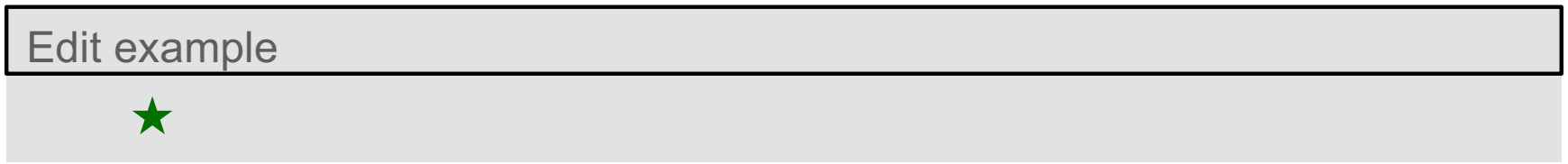
Some methods need **segmentations** of the edit descriptor, **multiple** descriptors, **negative** examples (what *not* to do)…

Lots of design decisions!

Edit *what*, exactly?

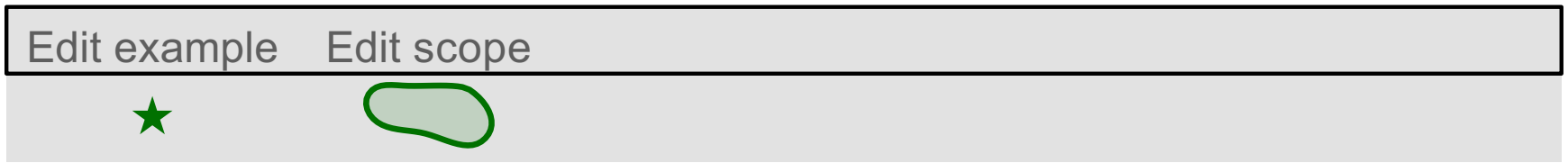
Defining the problem





Edit *what*, exactly?

Defining the problem

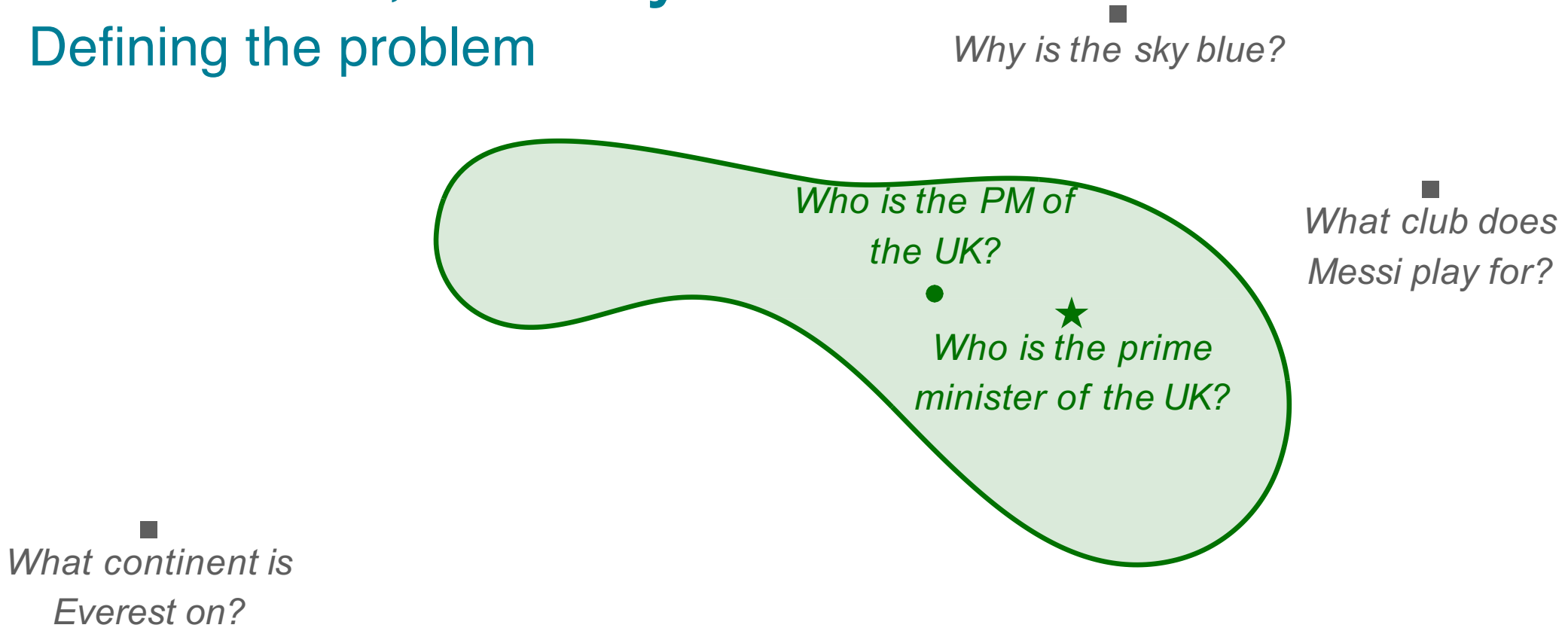


Edit *what*, exactly?

Defining the problem

Edit *what*, exactly?

Defining the problem



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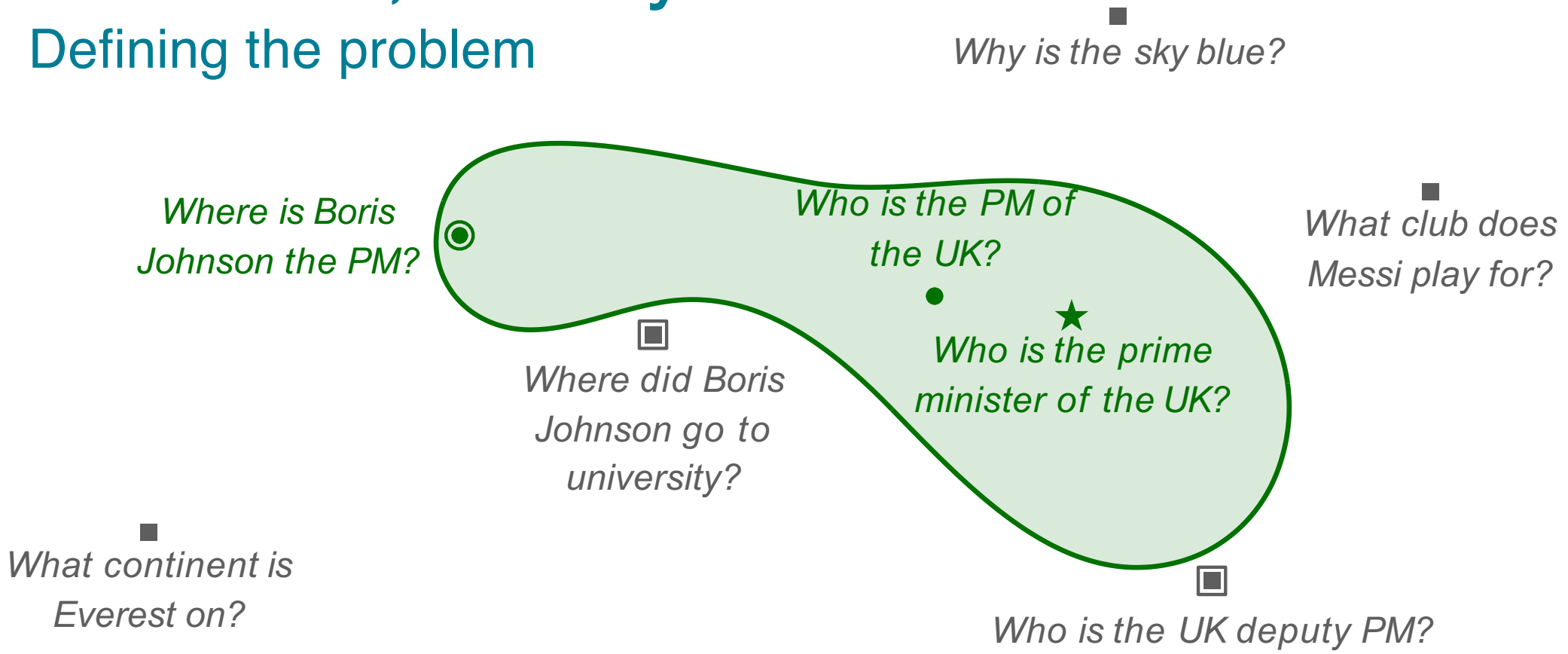
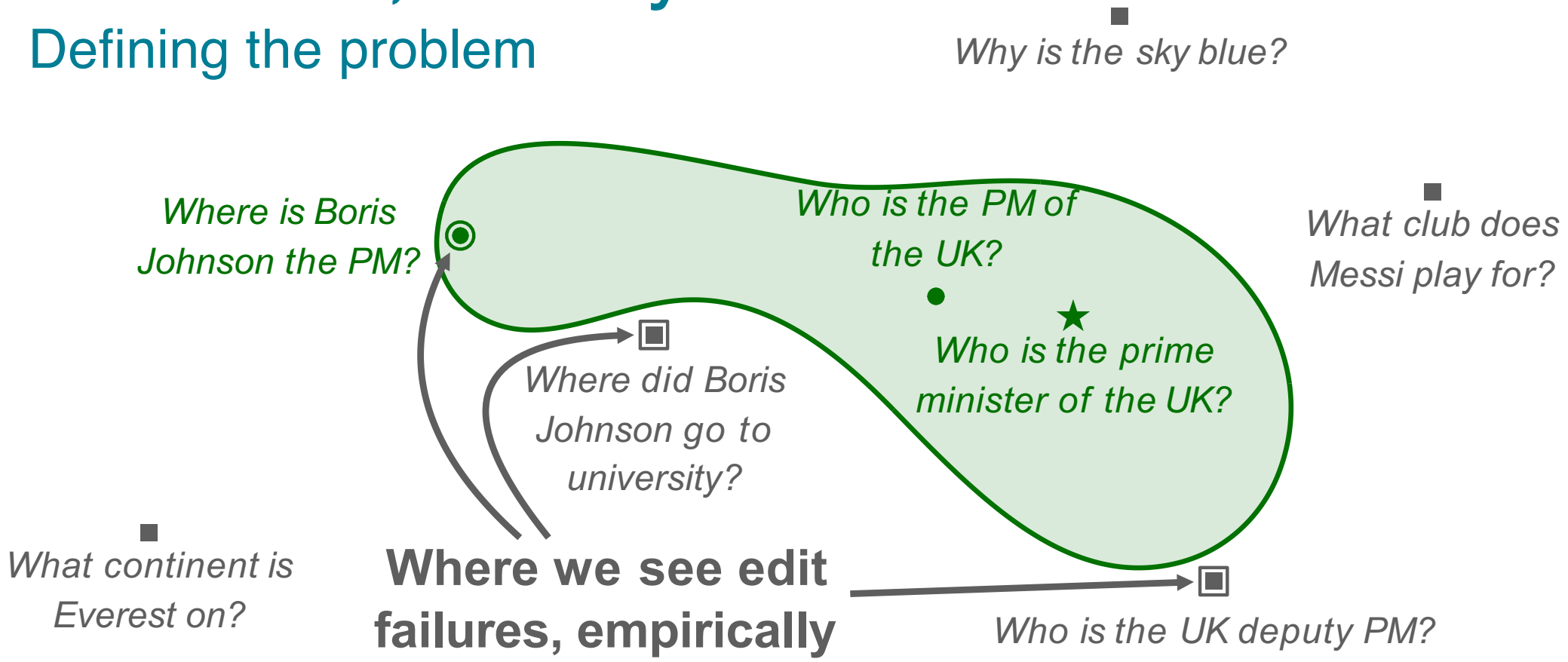
Defining the problem



Edit example	Edit scope	In-scope	Out-of-scope	Hard in/out-of-scope

Edit *what*, exactly?

Defining the problem

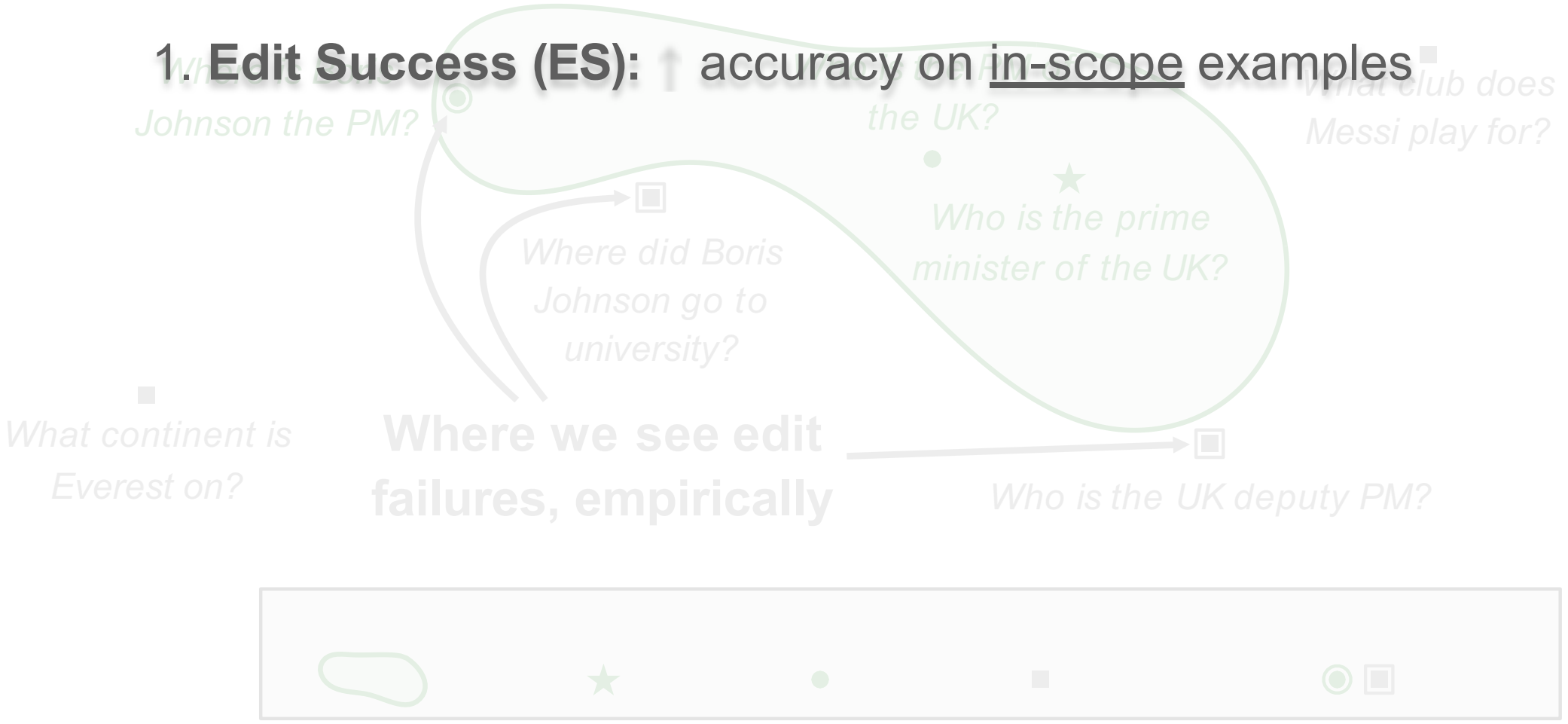


Edit example	Edit scope	In-scope	Out-of-scope	Hard in/out-of-scope
★		●	■	◉ ▣

Edit *what*, exactly?

Metrics for evaluating model edits

1. **Edit Success (ES):** ↑ accuracy on <u>in-scope</u> examples



Edit *what*, exactly?

Metrics for evaluating model edits

1. **Edit Success (ES):** accuracy on <u>in-scope</u> examples
2. **Drawdown (DD):** accuracy drop on <u>out-of-scope</u> examples

Edit *what*, exactly?

Metrics for evaluating model edits

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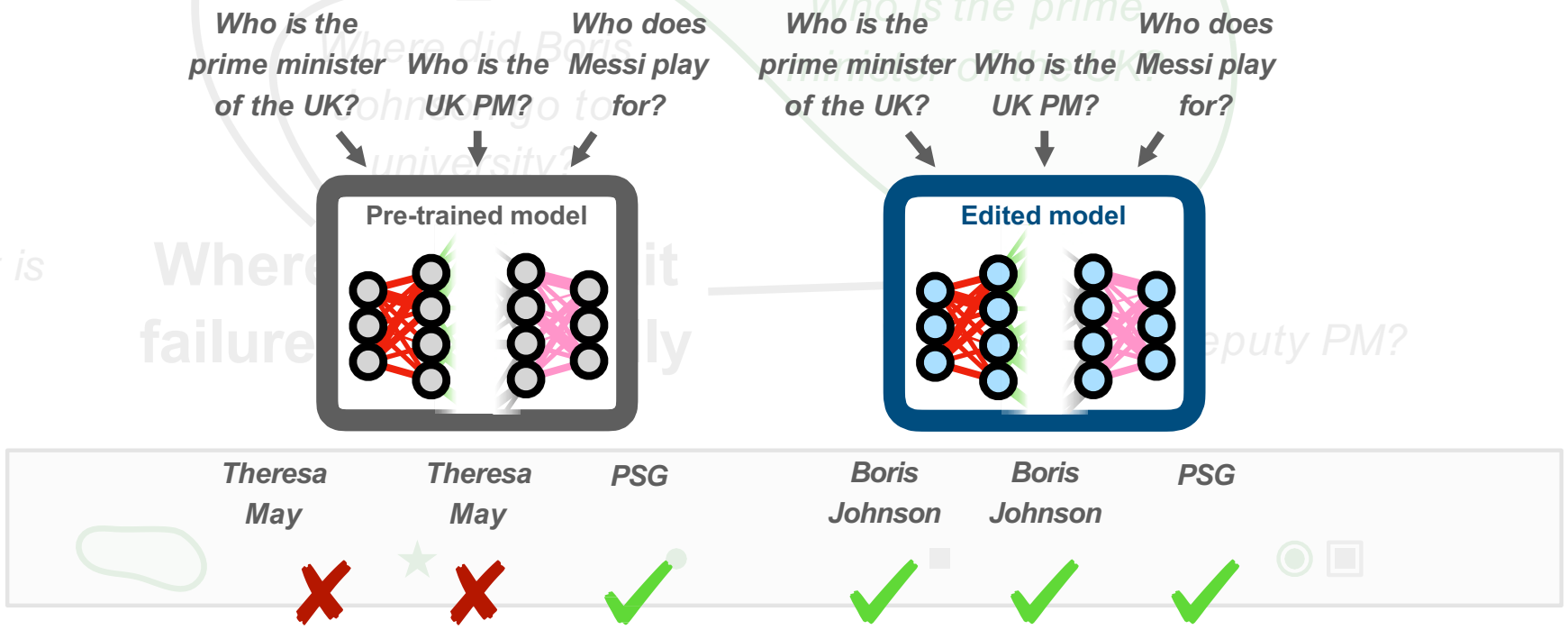

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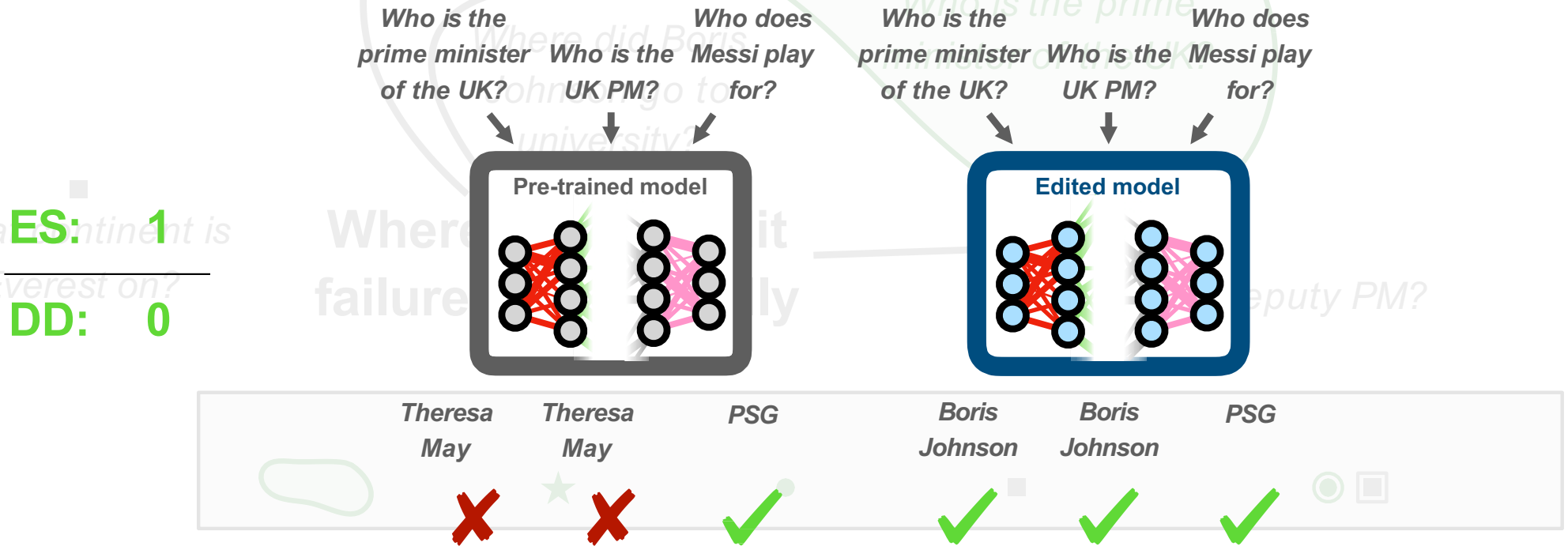

Edit *what*, exactly?

Metrics for evaluating model edits

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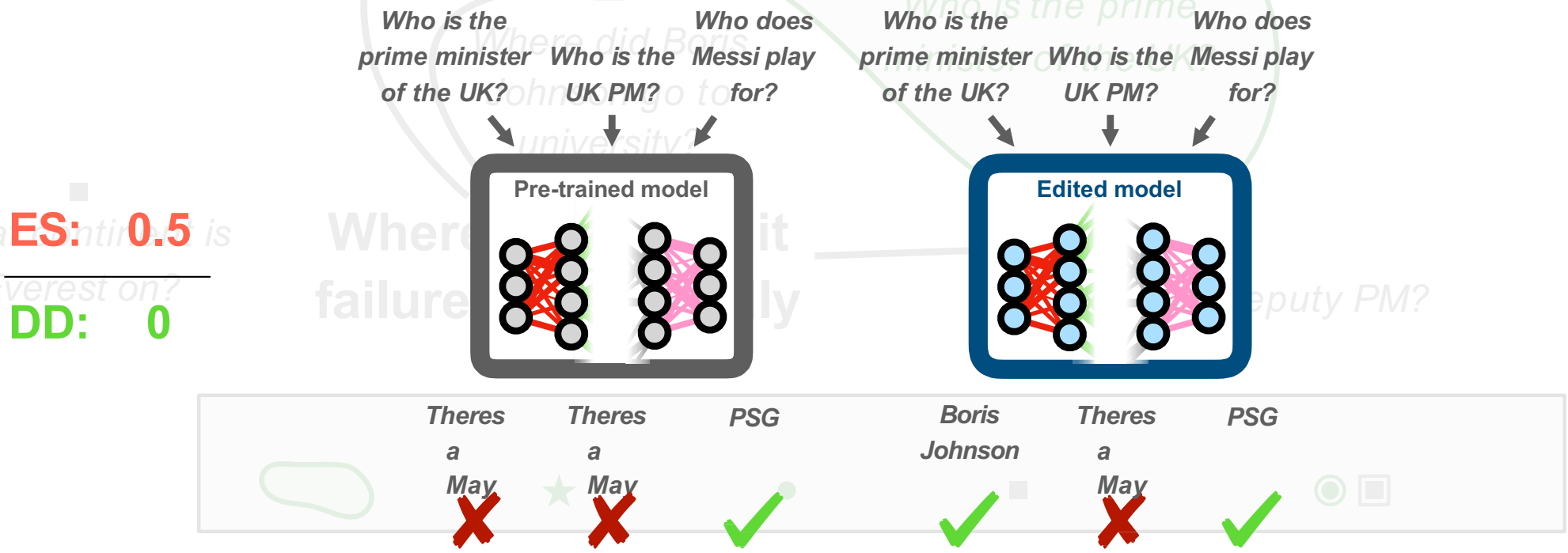

ES: 0.5

DD: 0

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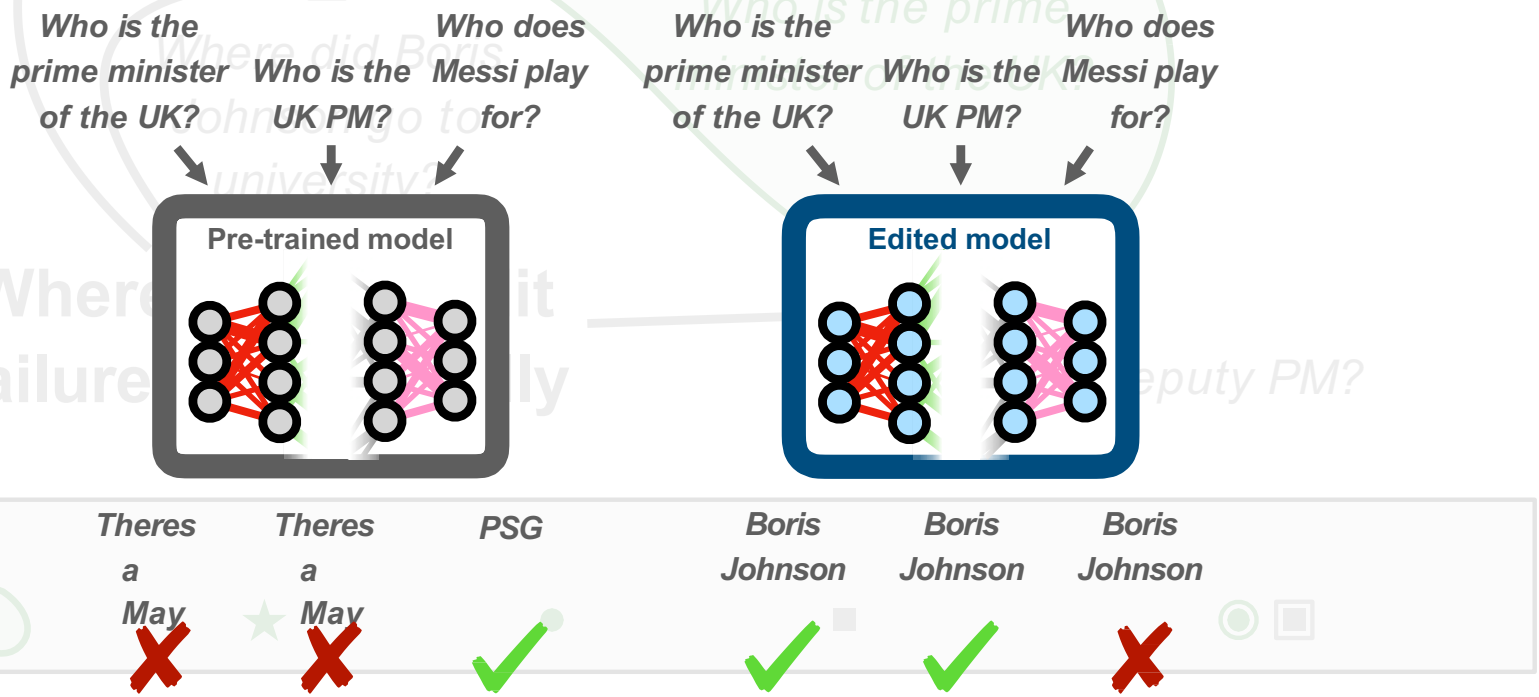


ES: 1

DD: 1

Today's Plan

I. Background

II. Learning to edit NNs

III. Moving editing towards the real world

IV. Future work & open questions

Existing approaches to editing

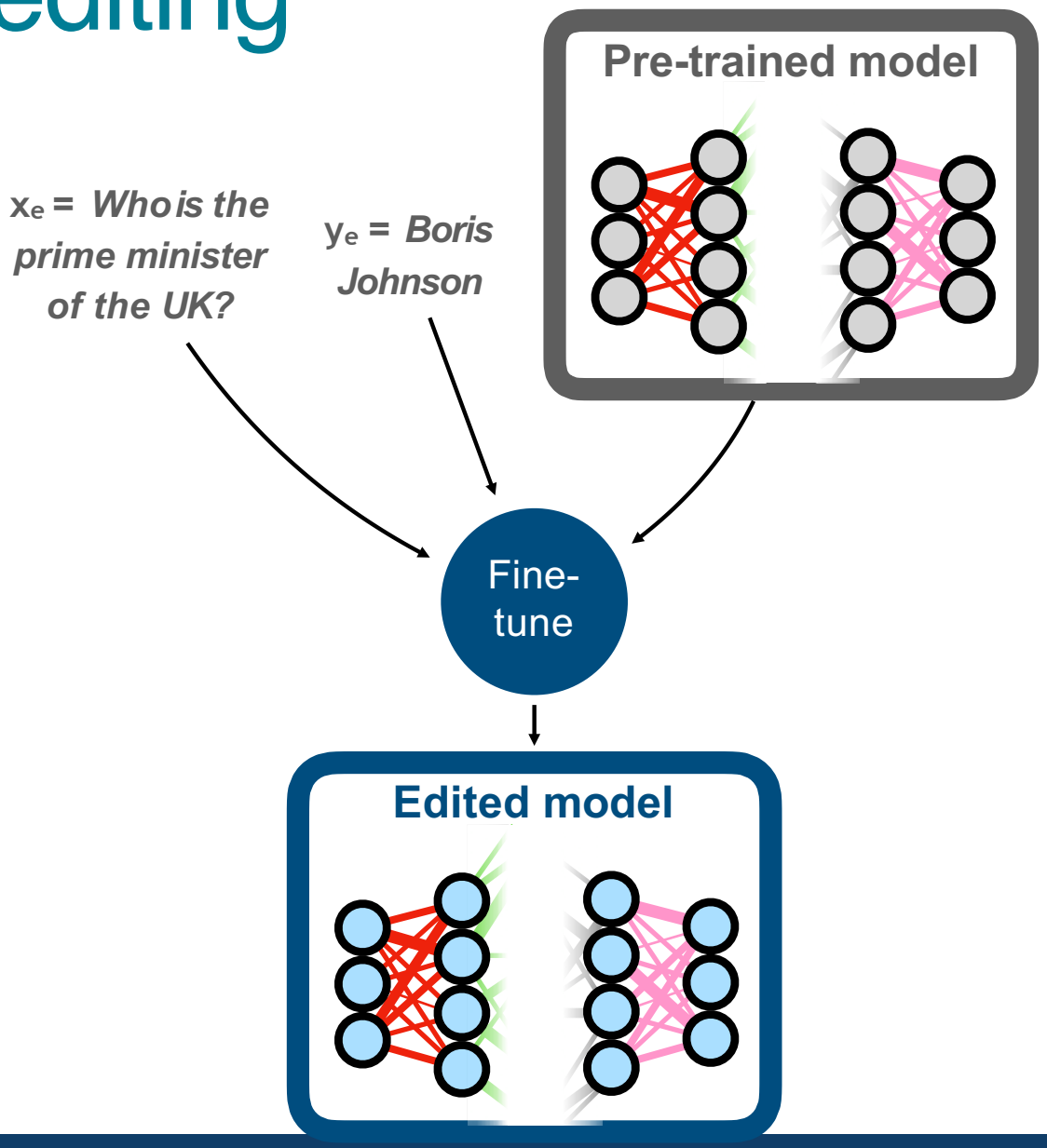
Some simple baselines

What about just fine-tuning?

Existing approaches to editing

Some simple baselines

What about just fine-tuning?



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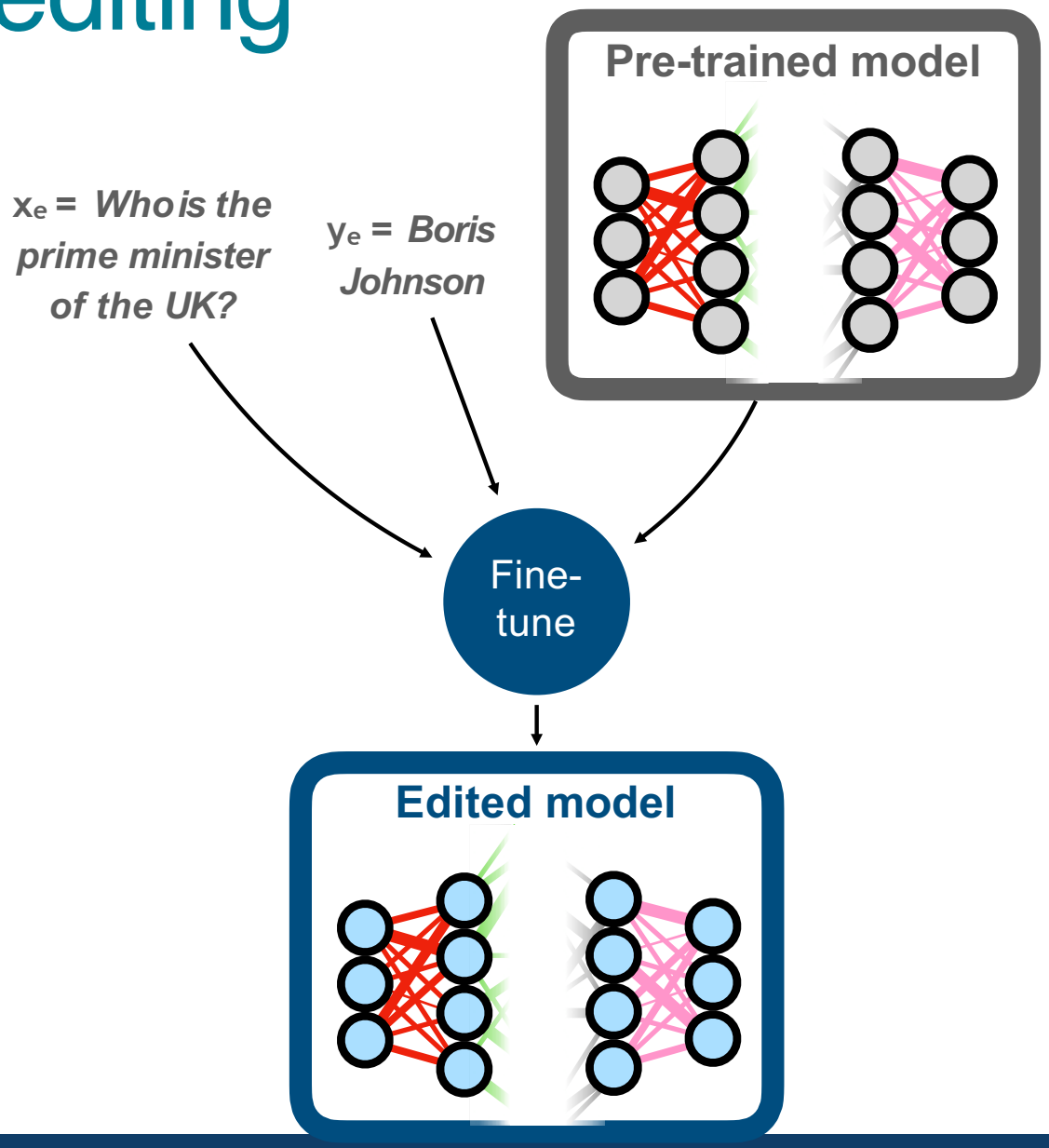

+ simple, universal

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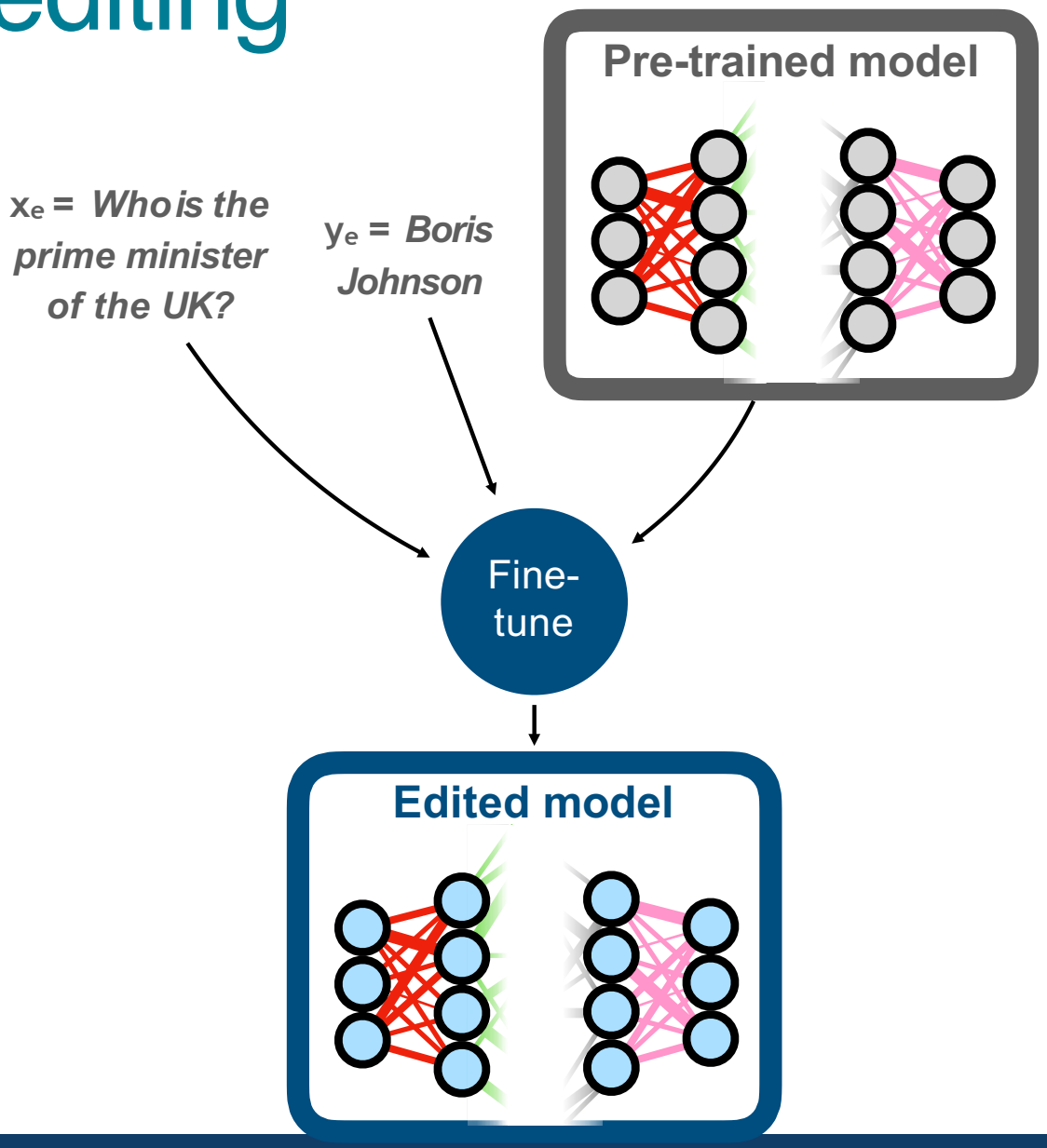

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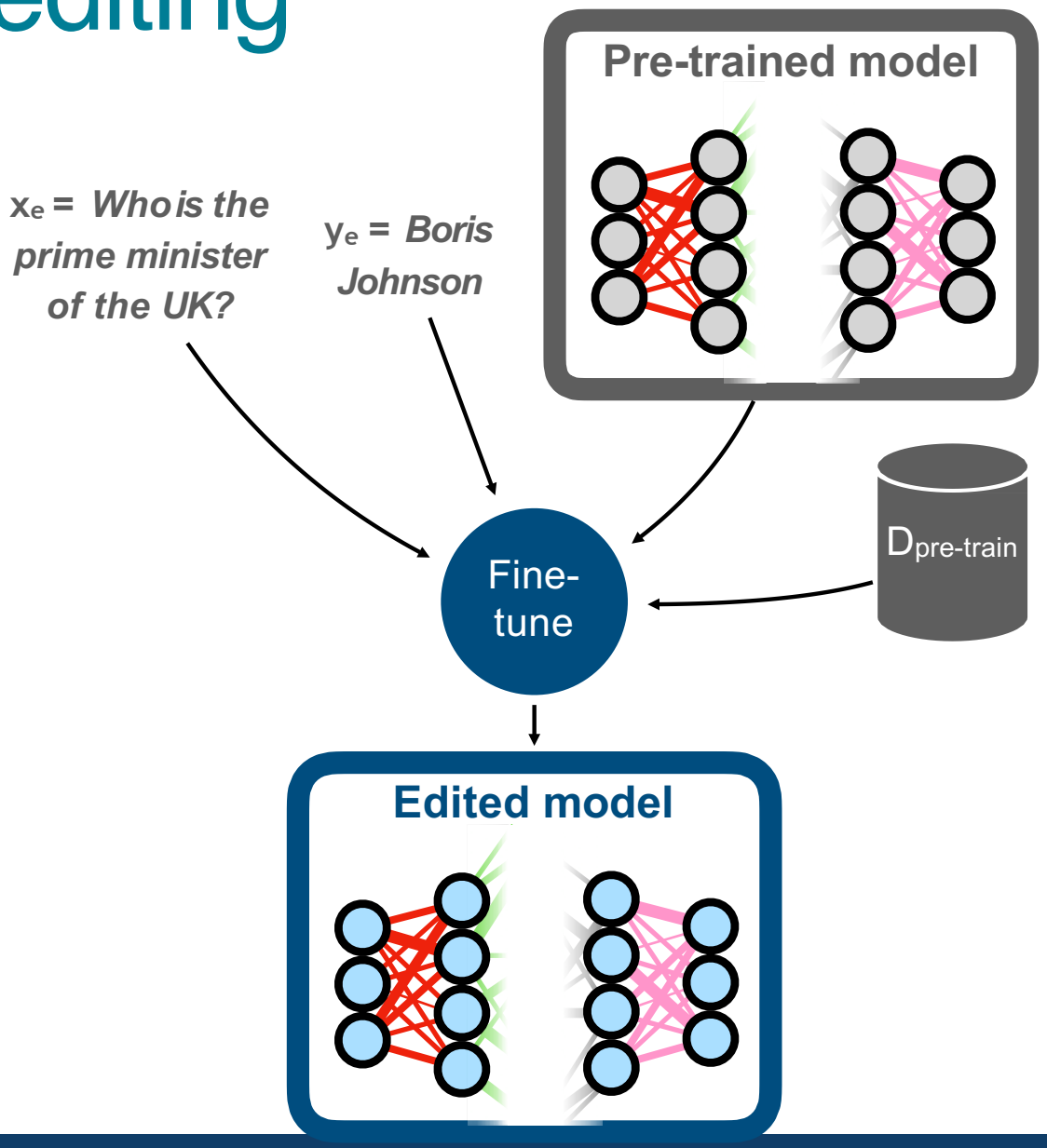

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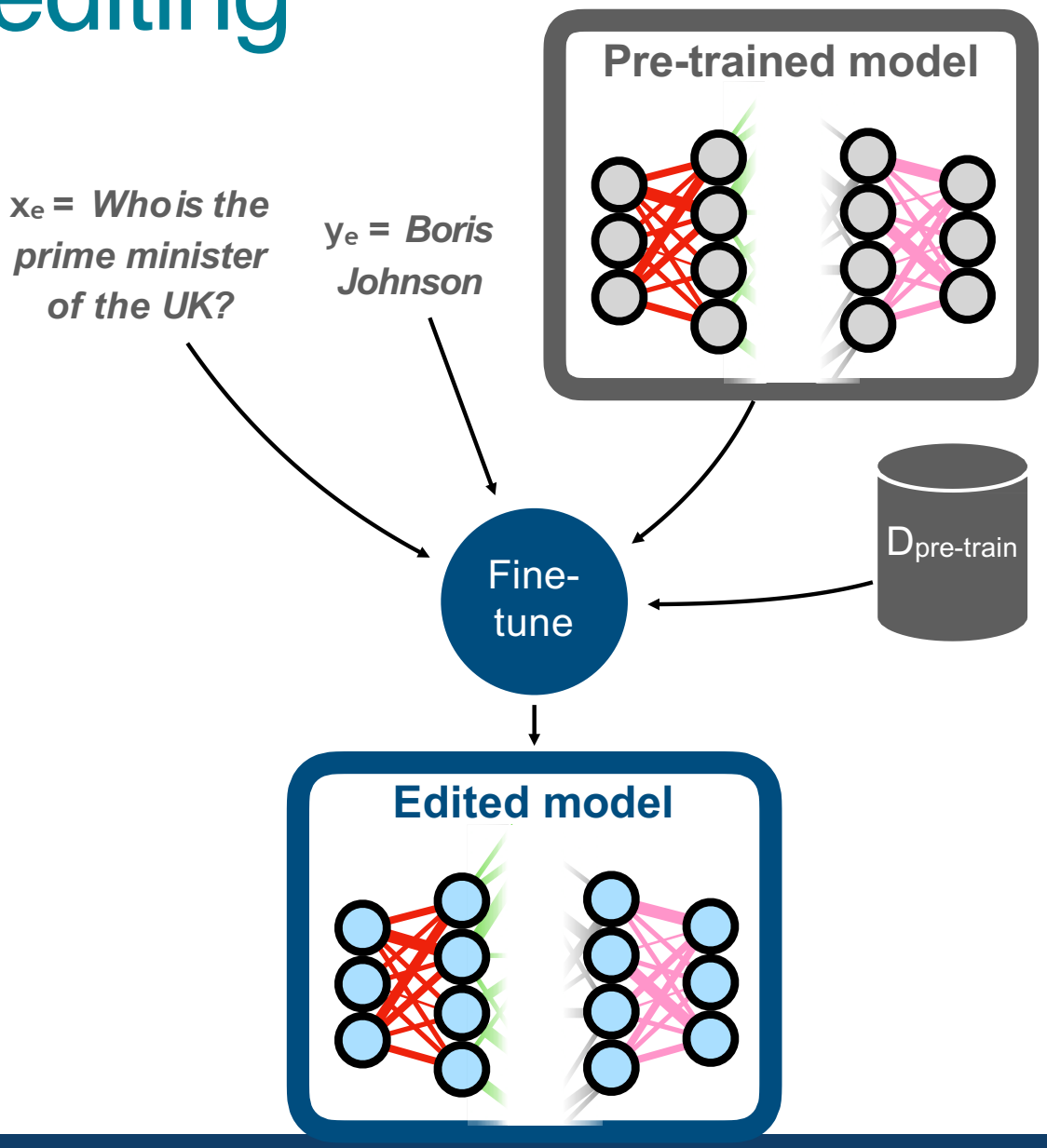

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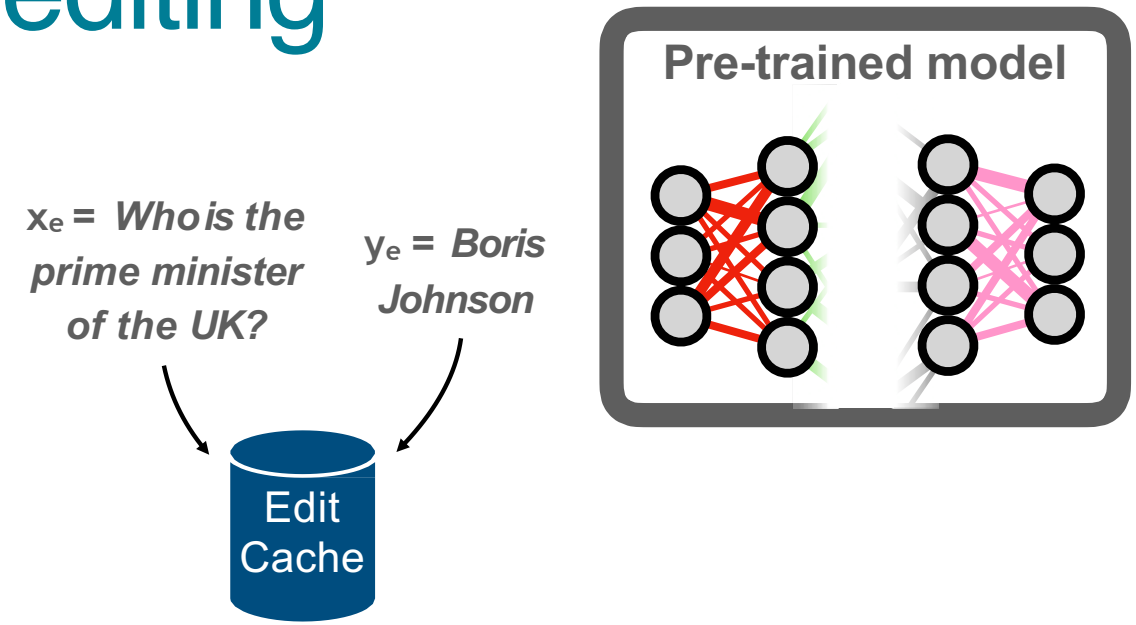

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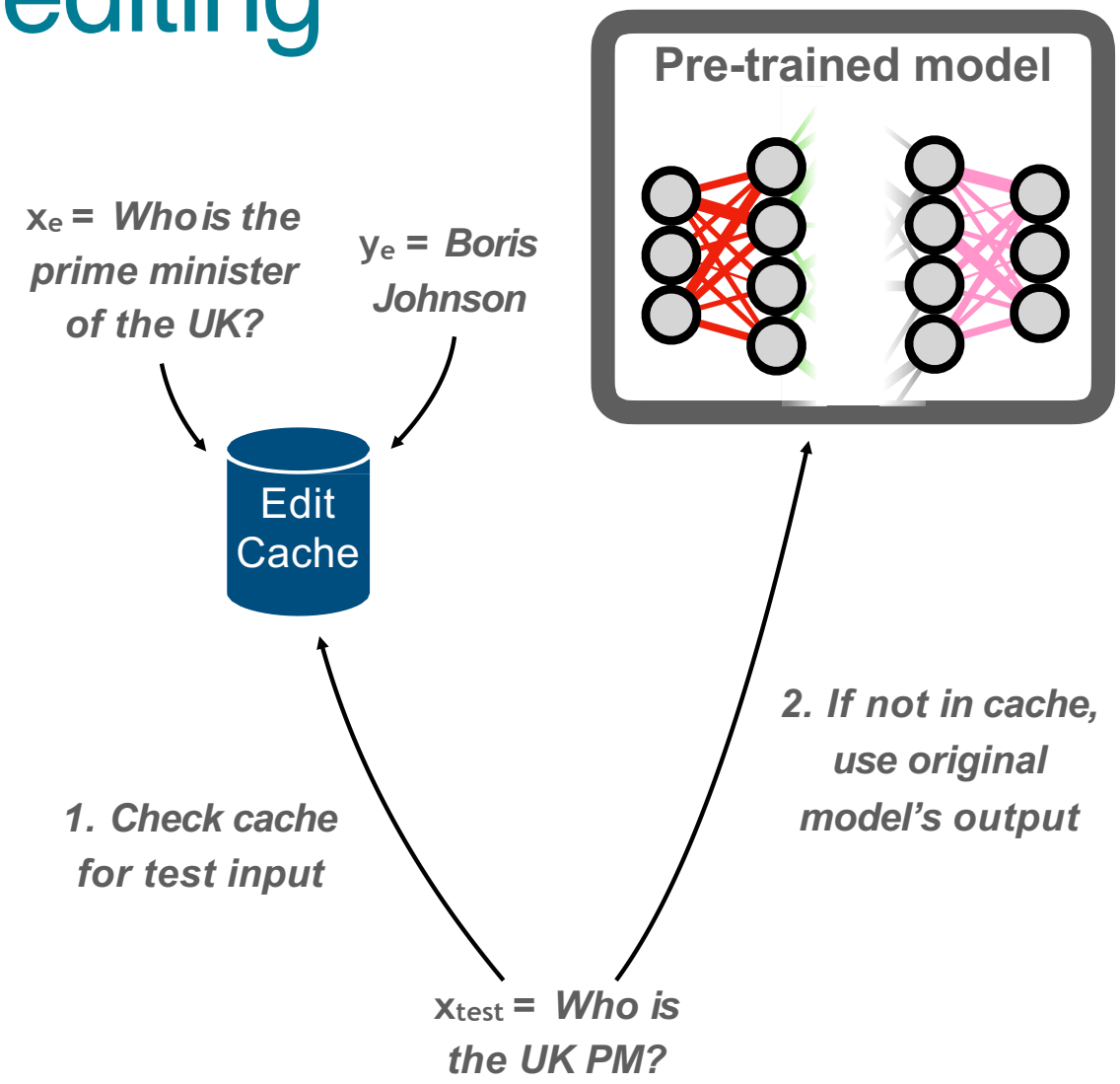

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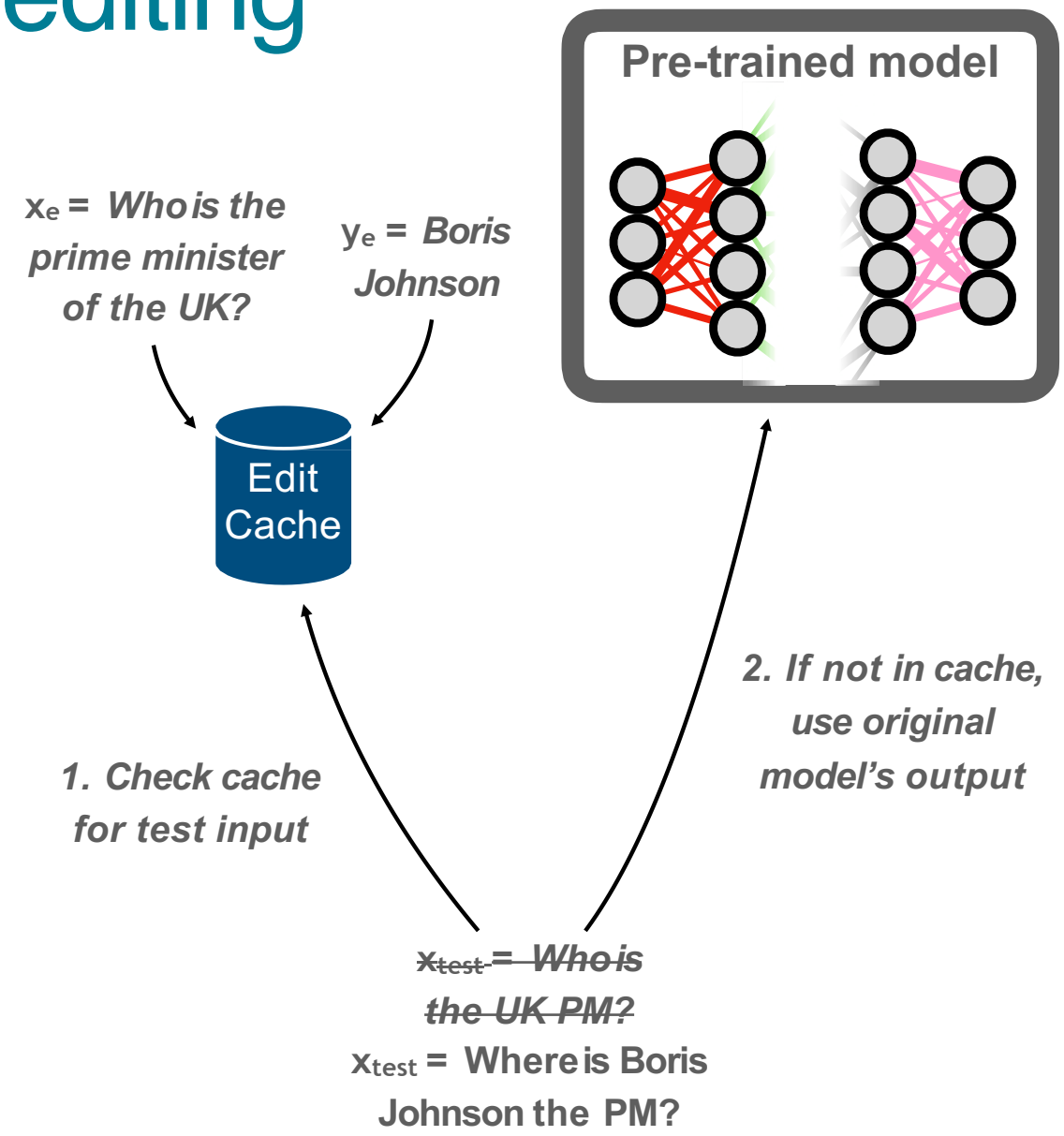

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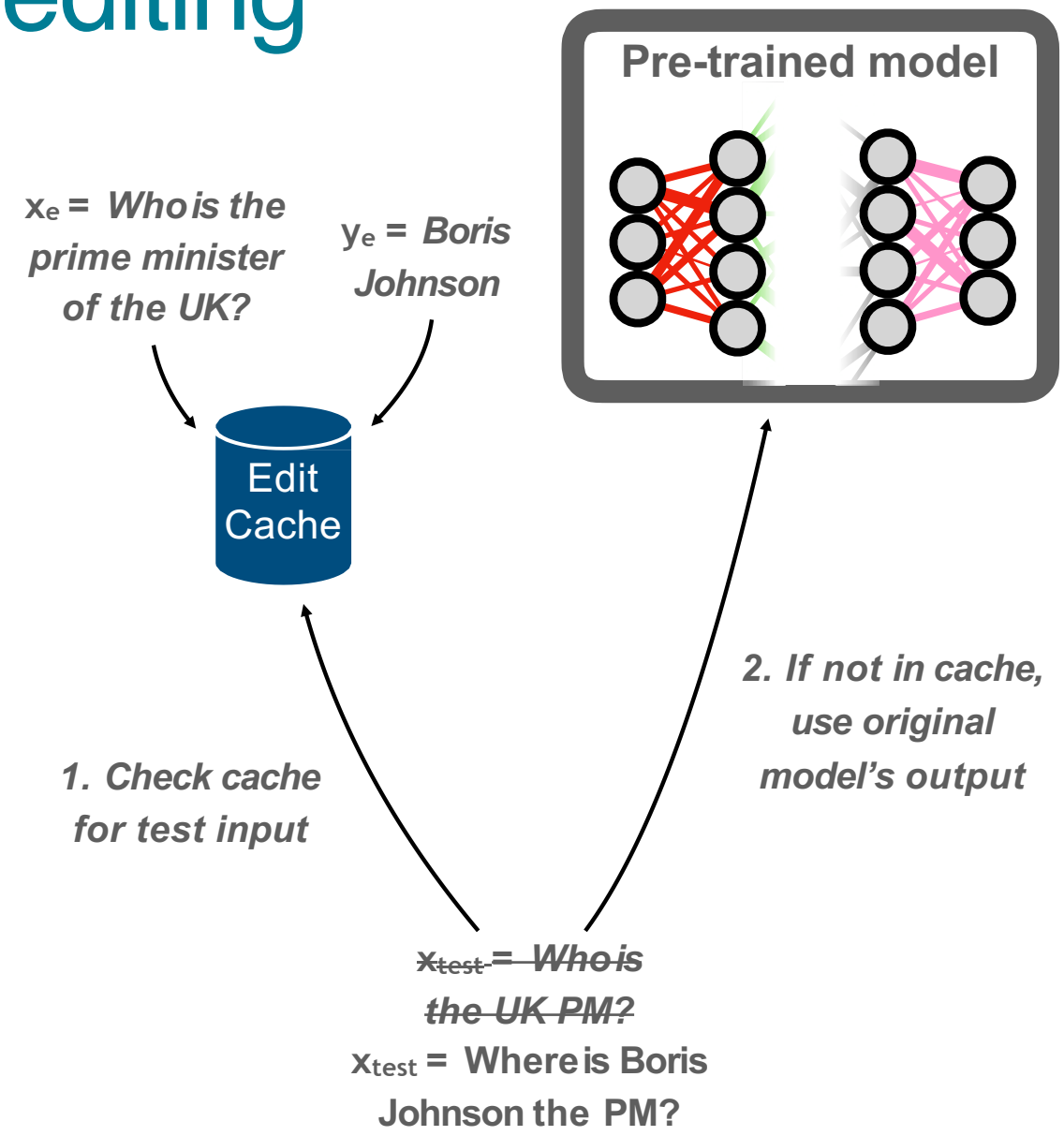
Caching edits

Can we **learn** a more expressive edit rule from data?



Learning to edit

Editing as meta-learning

Requirement: an “edit dataset” $\mathbf{D_{edit} = \{(z_{edit}, \quad x_{loc}, \quad x_{in}, \quad y_{in})\}}$

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Perform edit

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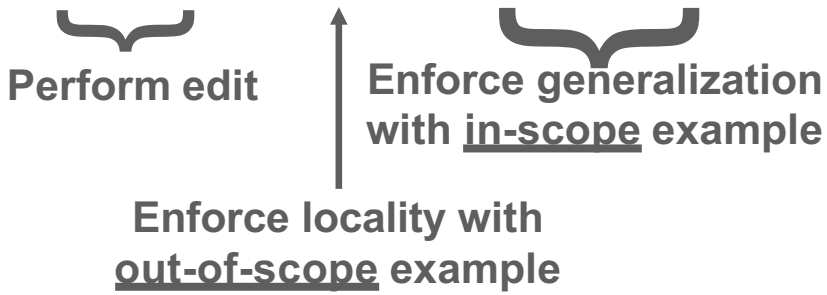

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Inner loop

(run the editor)

$$\theta' = \text{Edit}_{\phi}(\theta, \mathbf{z_{edit}})$$

(optional) editor parameters

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z_{edit}: Perform edit

x_{loc}: Enforce locality with out-of-scope example

x_{in}, y_{in}: Enforce generalization with in-scope example

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Outer loop

(check if edit worked)

$$L_{edit} = p_{\theta'}(\mathbf{y_{in}} \mid \mathbf{x_{in}})$$

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Did predictions **change where** we wanted them to?

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Enforce locality with out-of-scope example

Inner loop

(run the editor)

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(optional) editor parameters

Outer loop

(check if edit worked)

$$L_{edit} = p_{\theta'}(\mathbf{y_{in}} \mid \mathbf{x_{in}})$$

$$L_{loc} = \text{KL}\left(p_{\theta}(\cdot \mid \mathbf{x_{loc}}) \,\|\, p_{\theta'}(\cdot \mid \mathbf{x_{loc}}) \right)$$

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Perform edit

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(run the editor)

$$\theta' = \text{Edit}_{\phi}(\theta, \mathbf{z_{edit}})$$

(optional) editor parameters

Outer loop

(check if edit worked)

$$L_{edit} = p_{\theta'}(\mathbf{y_{in}} \mid \mathbf{x_{in}})$$

Did we keep predictions **the same** everywhere else?

$$L_{loc} = \text{KL}\left(p_{\theta}(\cdot \mid \mathbf{x_{loc}}) \,\|\, p_{\theta'}(\cdot \mid \mathbf{x_{loc}}) \right)$$

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Backprop $L_{edit} + L_{loc}$ back into base model/editor

Learning to edit

A tale of two meta-learning frameworks

1. MAML-based: Train your **base model** s.t. the regular fine-tuning gradient $\nabla_\theta p_\theta(\mathbf{z_{edit}})$ gives a good edit

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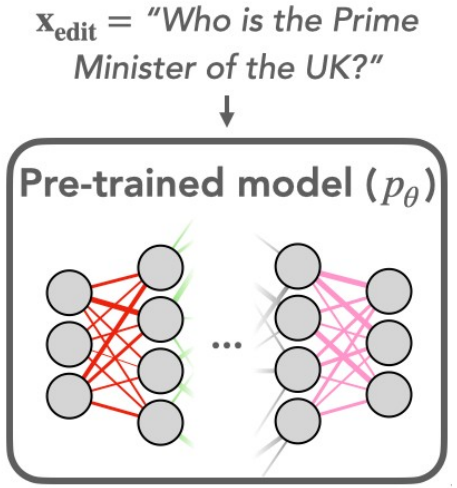

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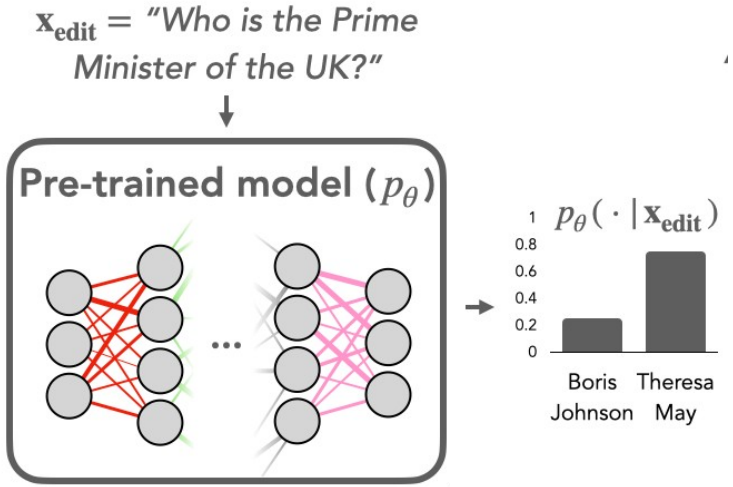

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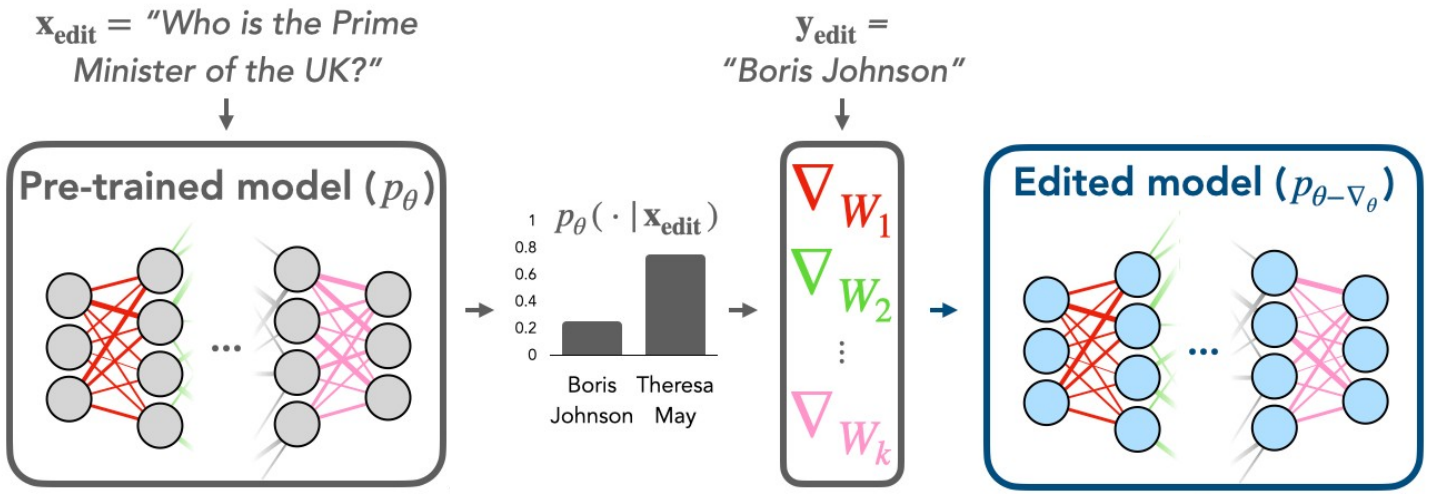

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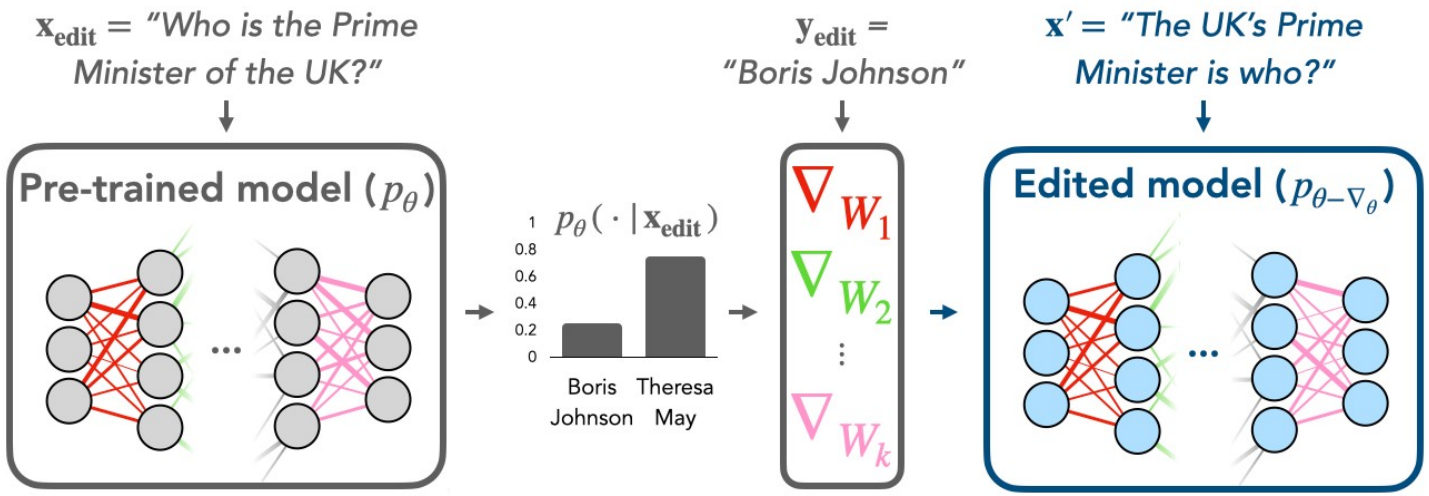

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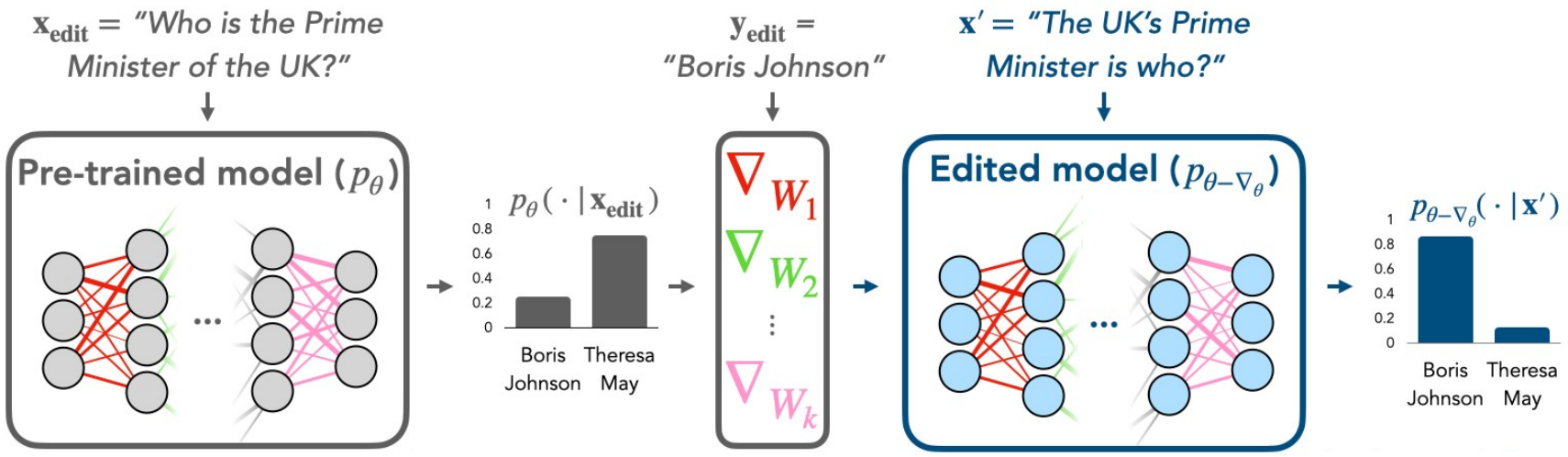

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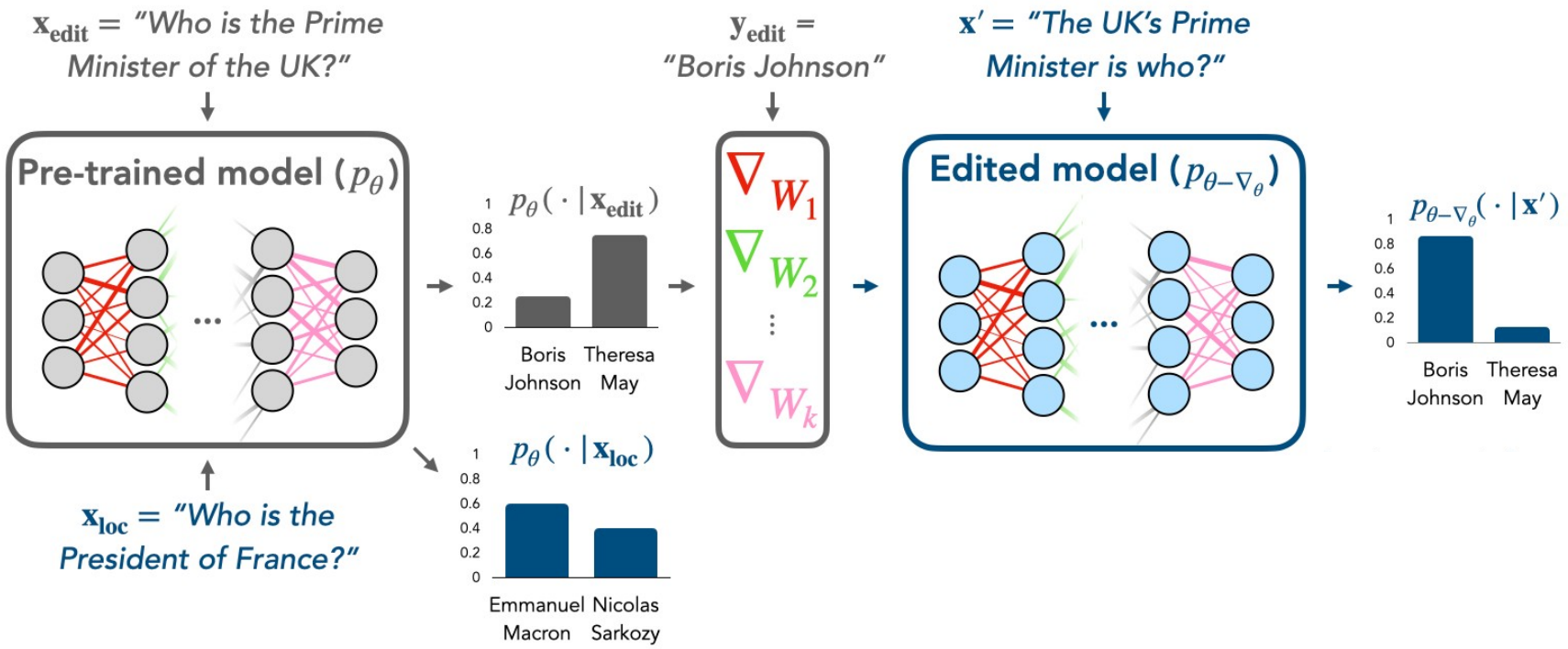

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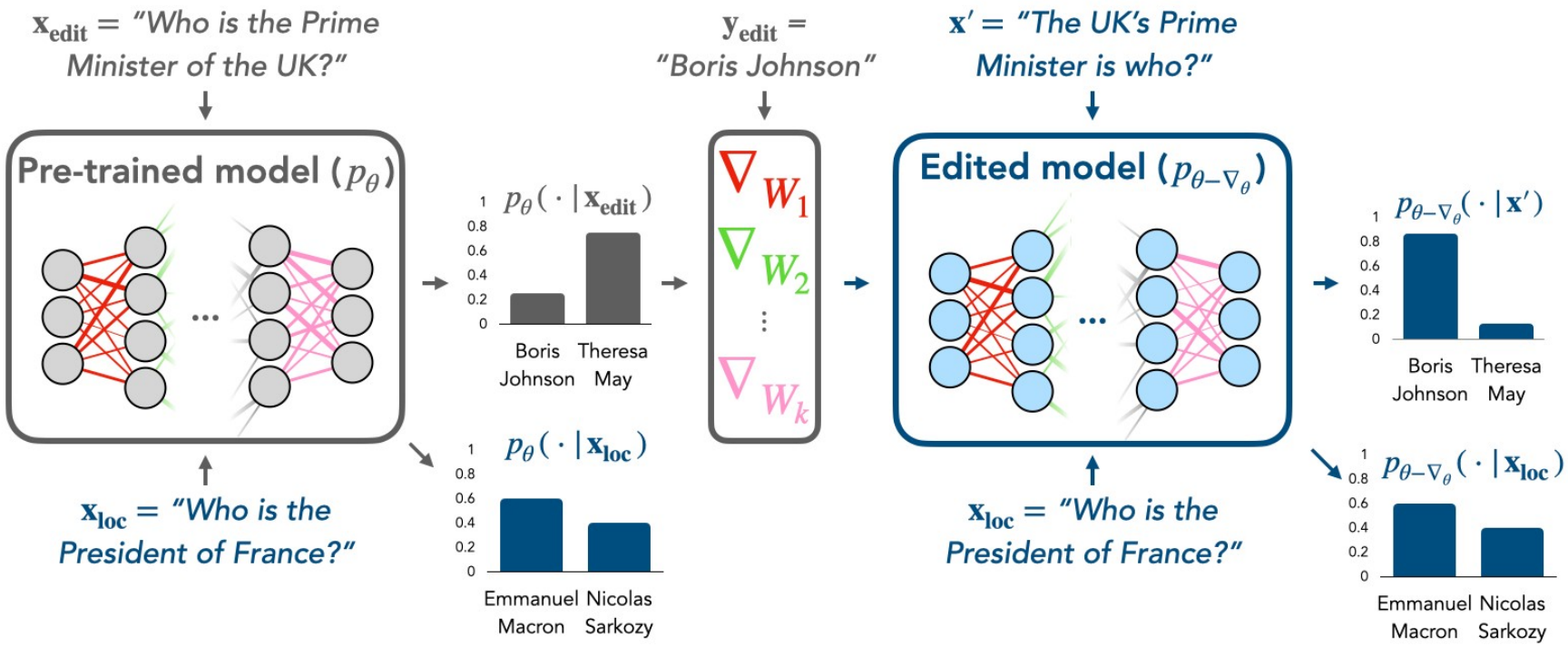

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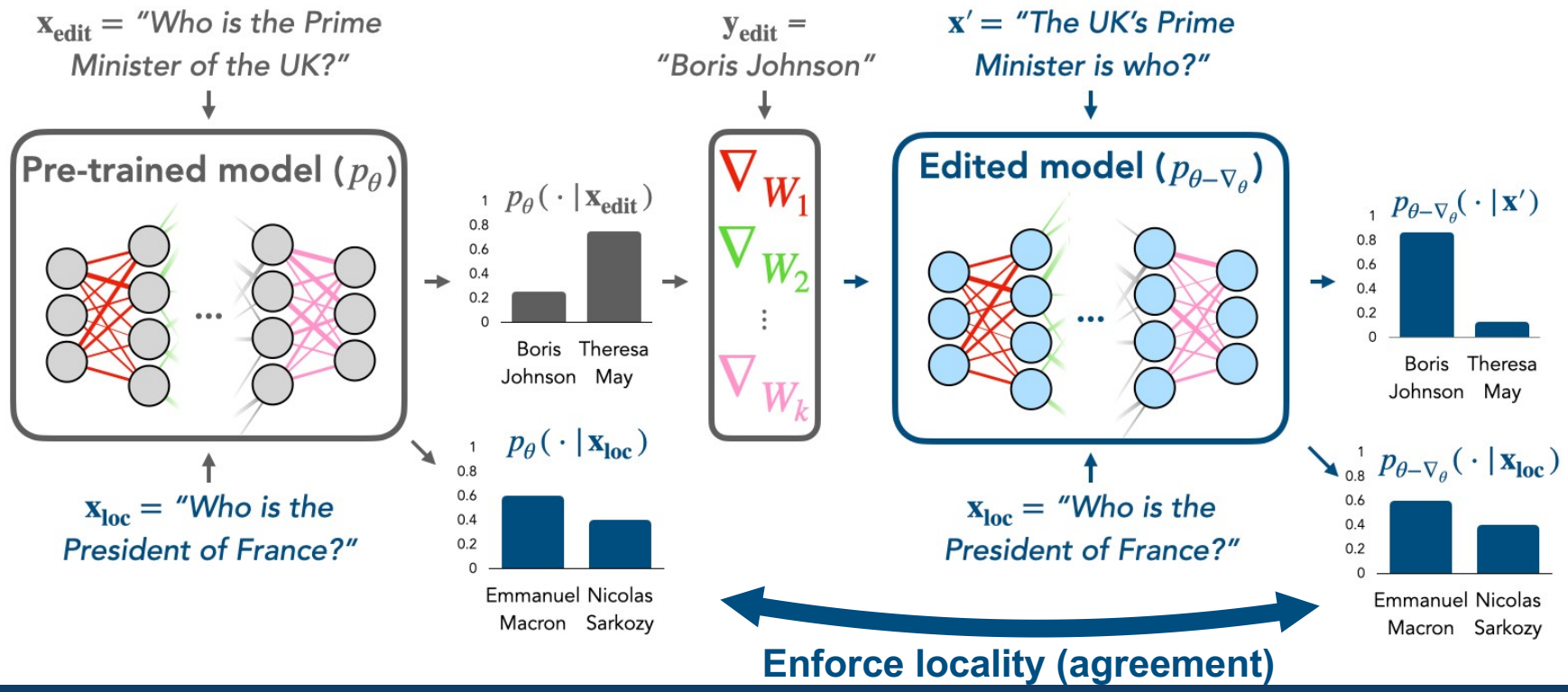

Learning to edit

A tale of two meta-learning frameworks

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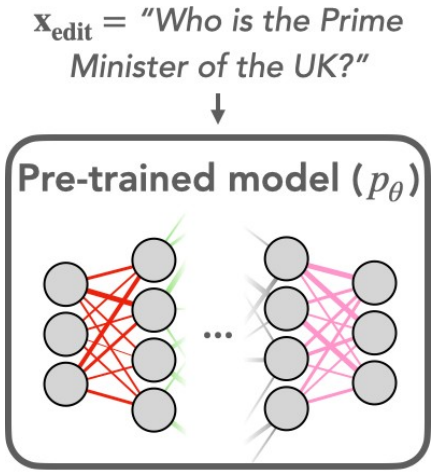

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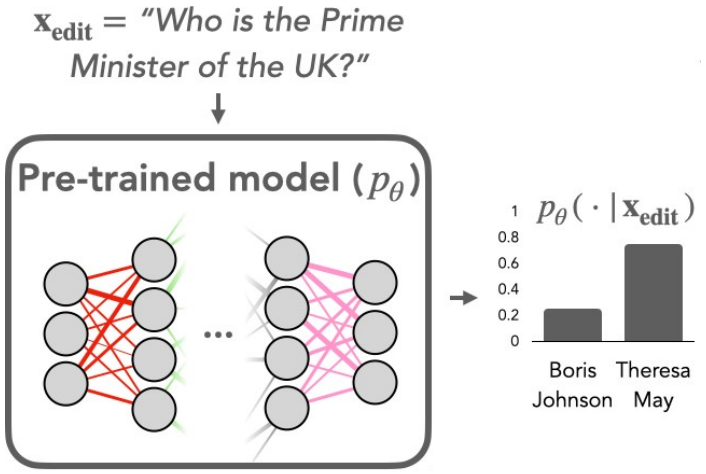

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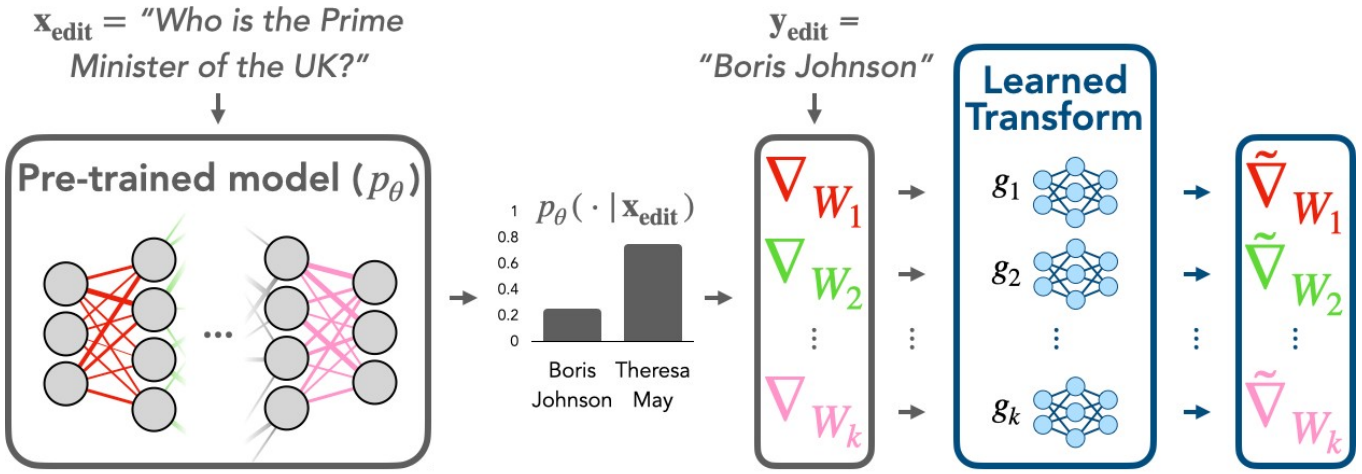

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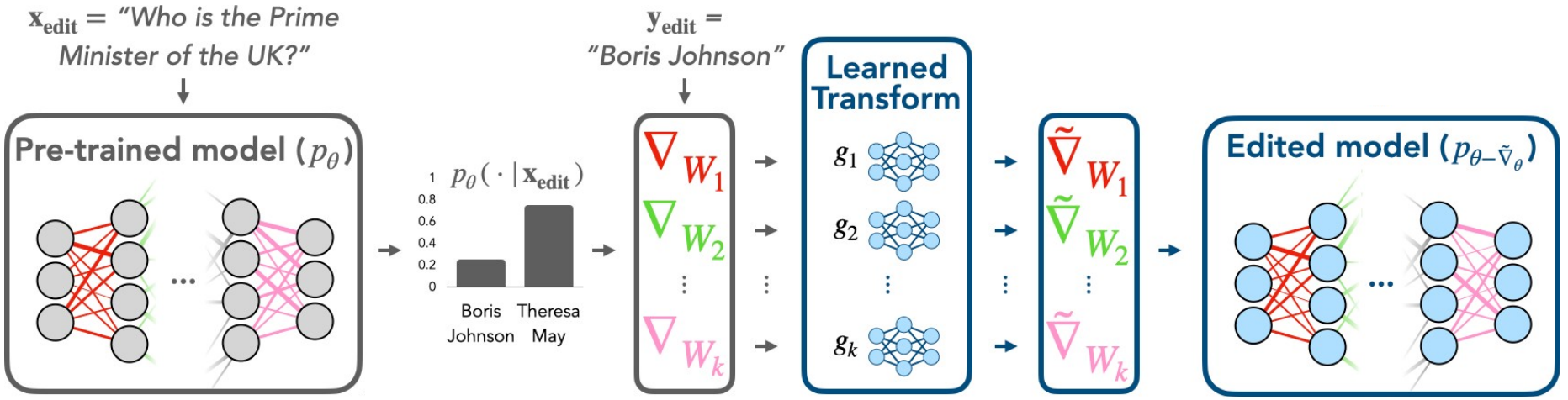

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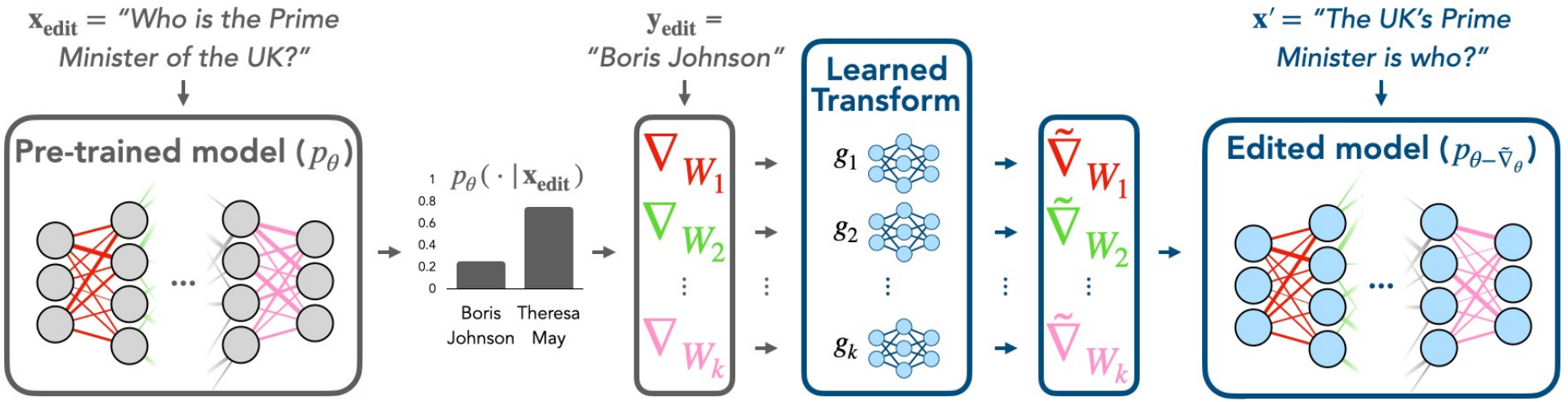

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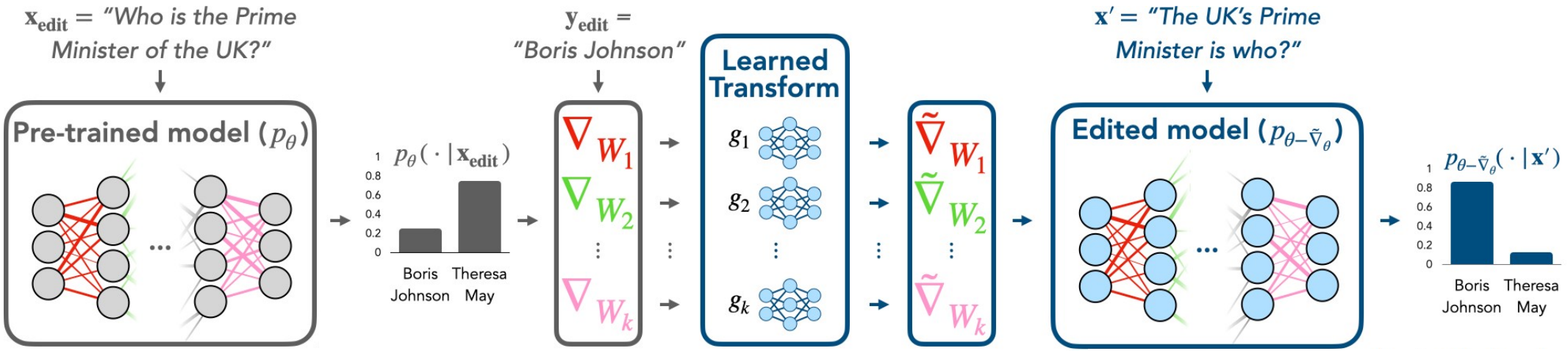

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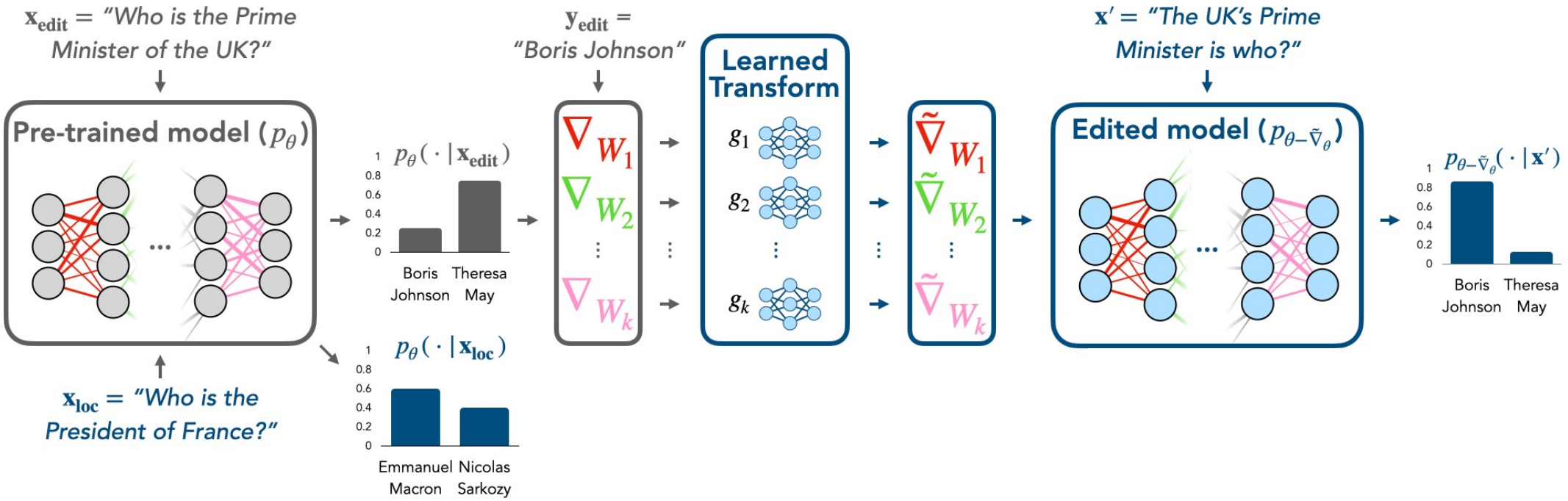

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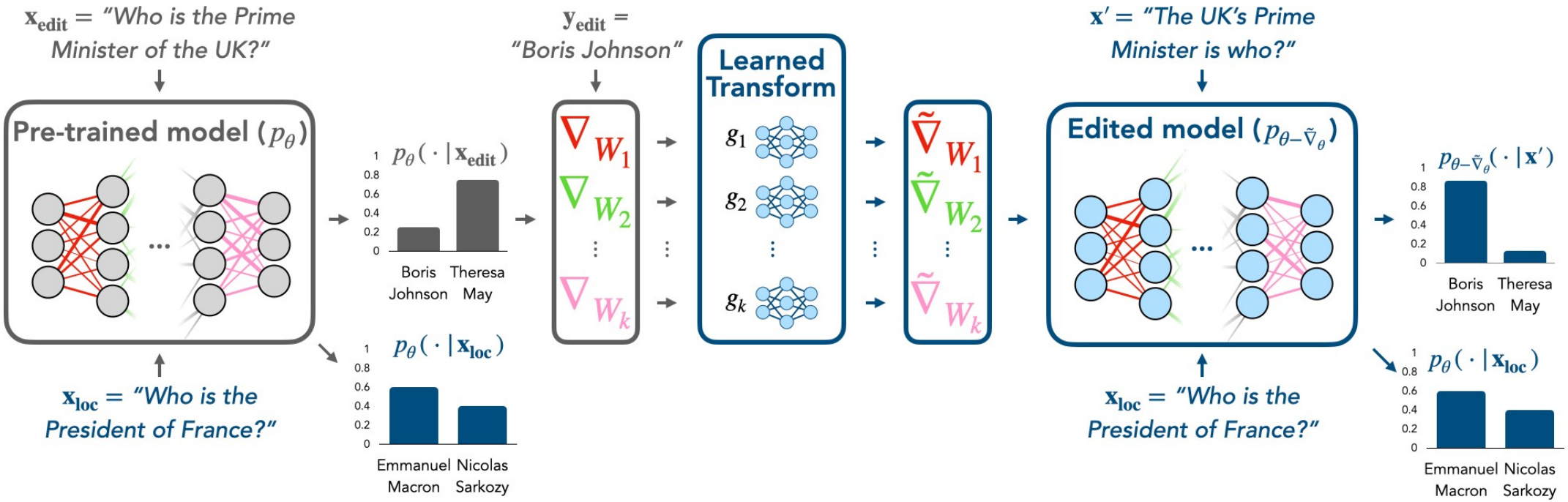

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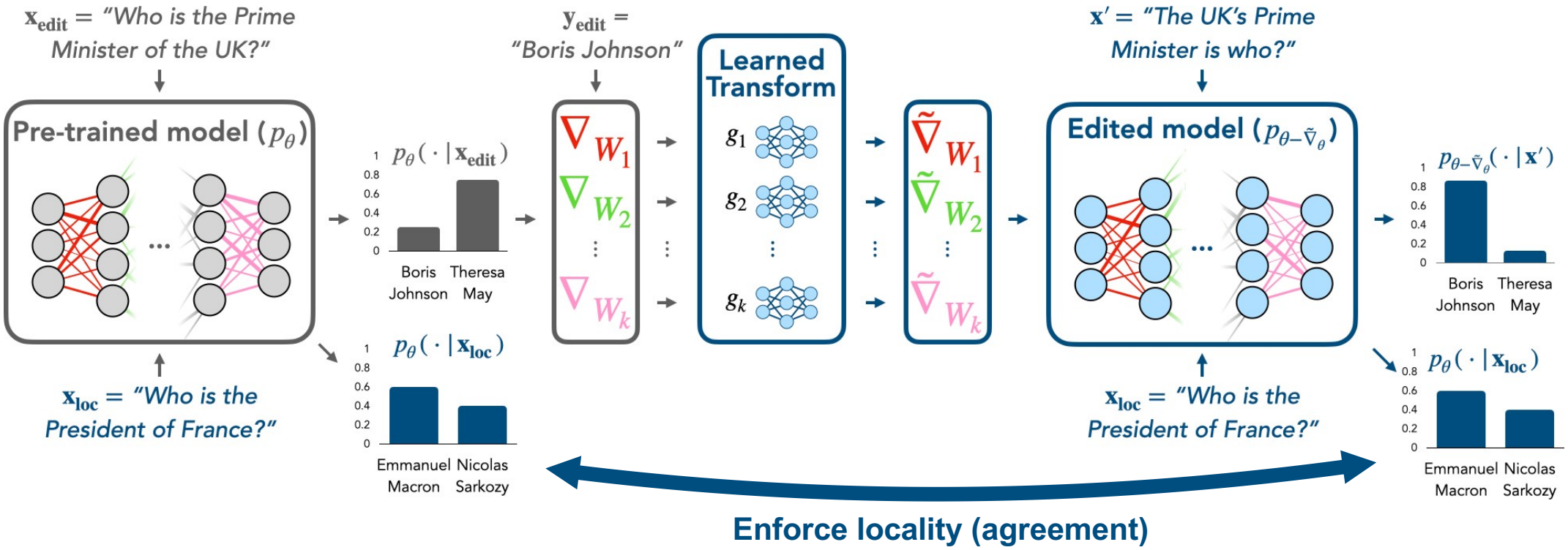
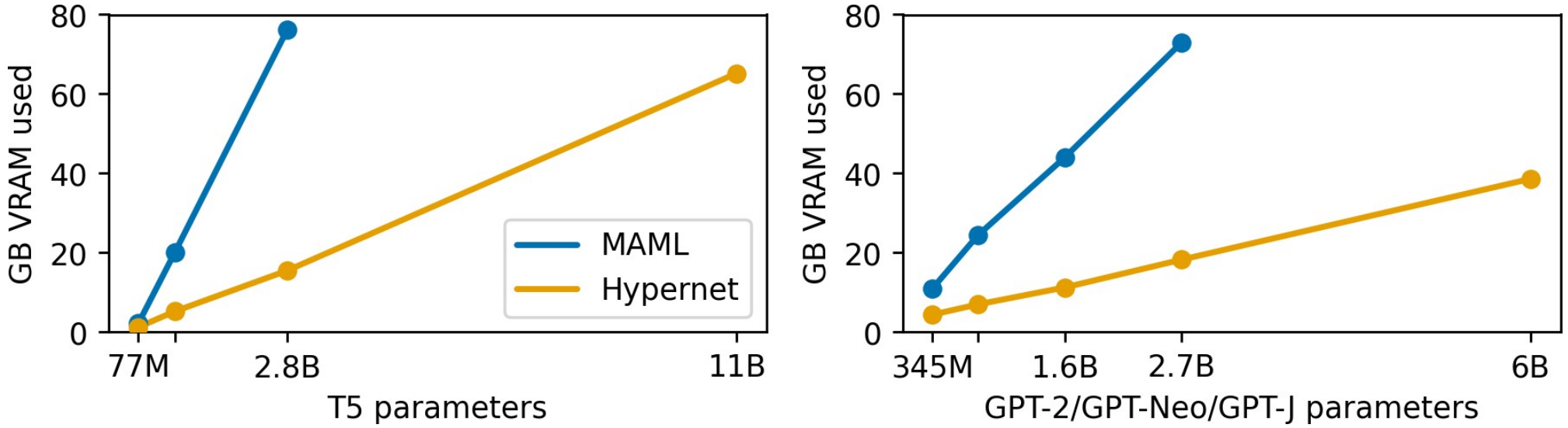


Challenges of editing at scale

- MAML-based editors show **high memory consumption**



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(T5-XXL)

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Can we develop an **efficient** and **expressive** gradient transform?

Model Editor Networks using gradient Decomposition

An efficient, expressive gradient transform

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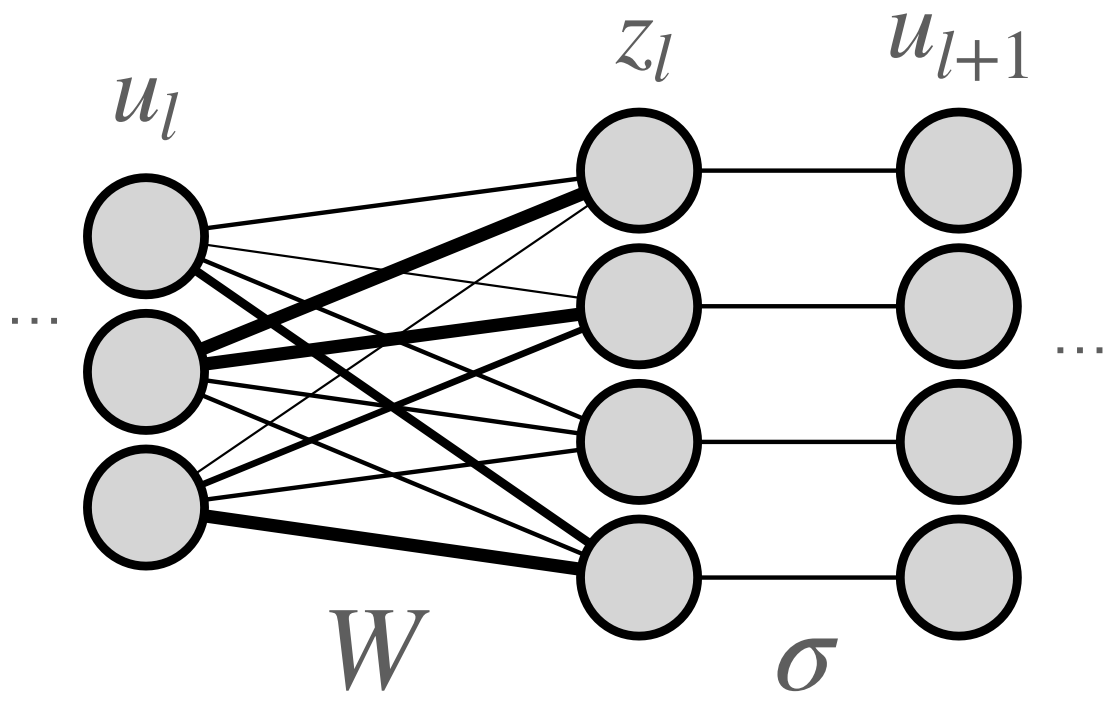
An efficient, expressive gradient transform

Obs. 1: for $W \in \mathbb{R}^{d \times d}$, $\nabla_W L$ is rank- for batch size !



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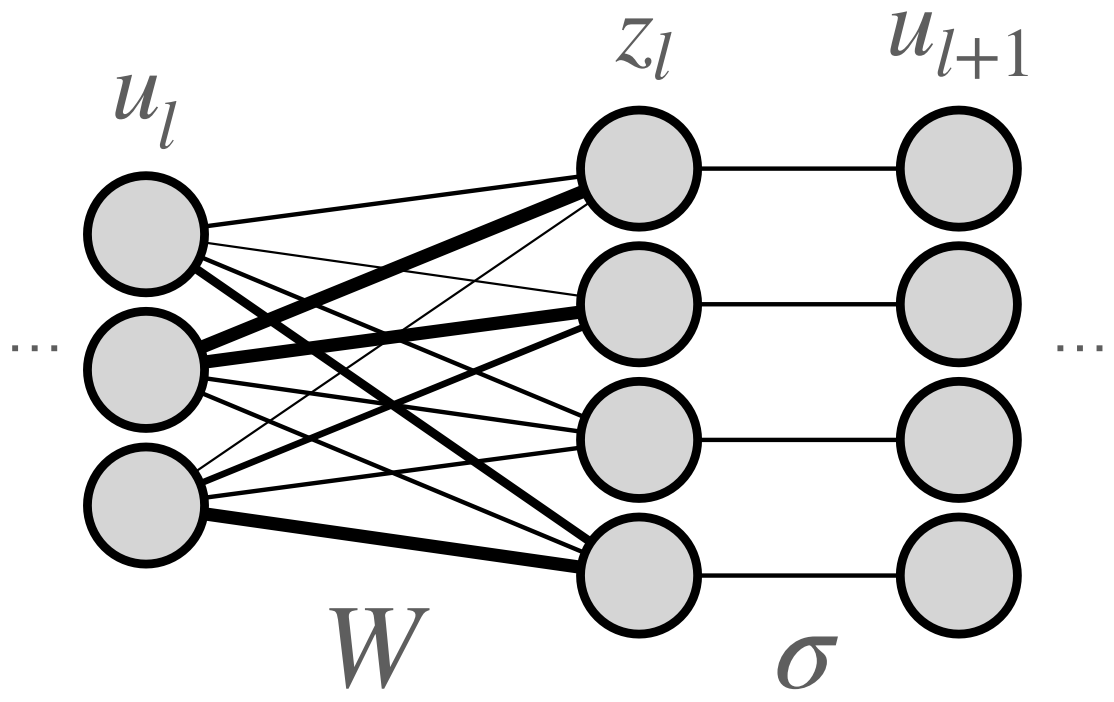
Forward pass computes l



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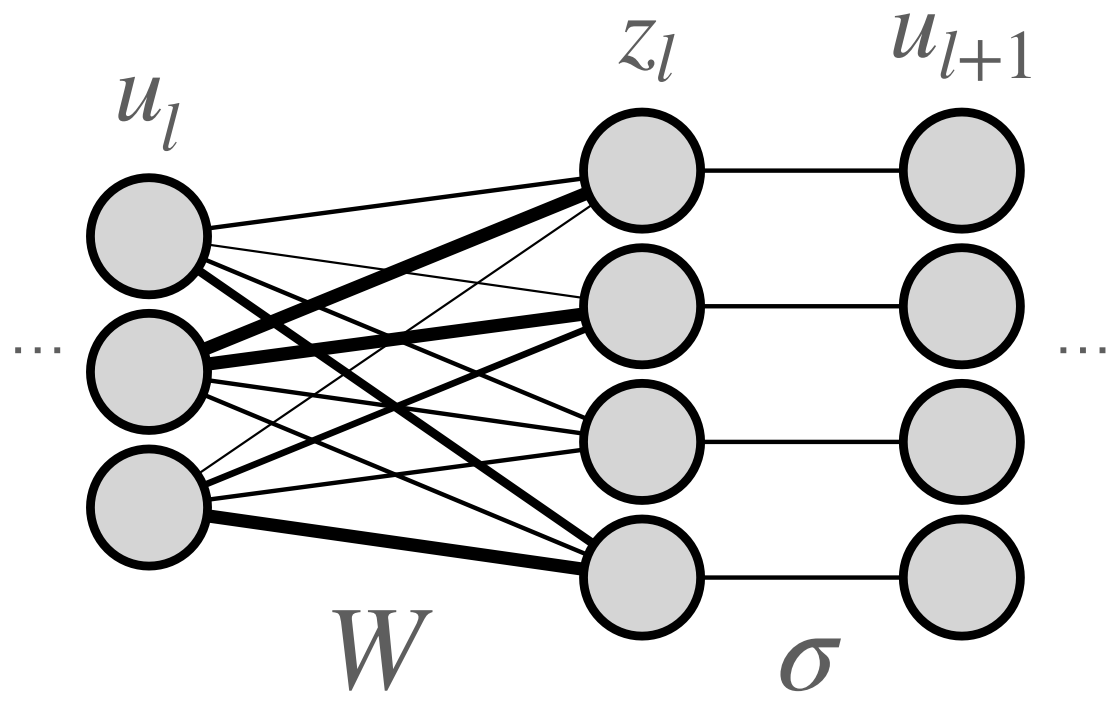

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Obs. 1: for $W \in \mathbb{R}^{d \times d}$, $\nabla_W L$ is rank-B for batch size B!

Forward pass computes u_l

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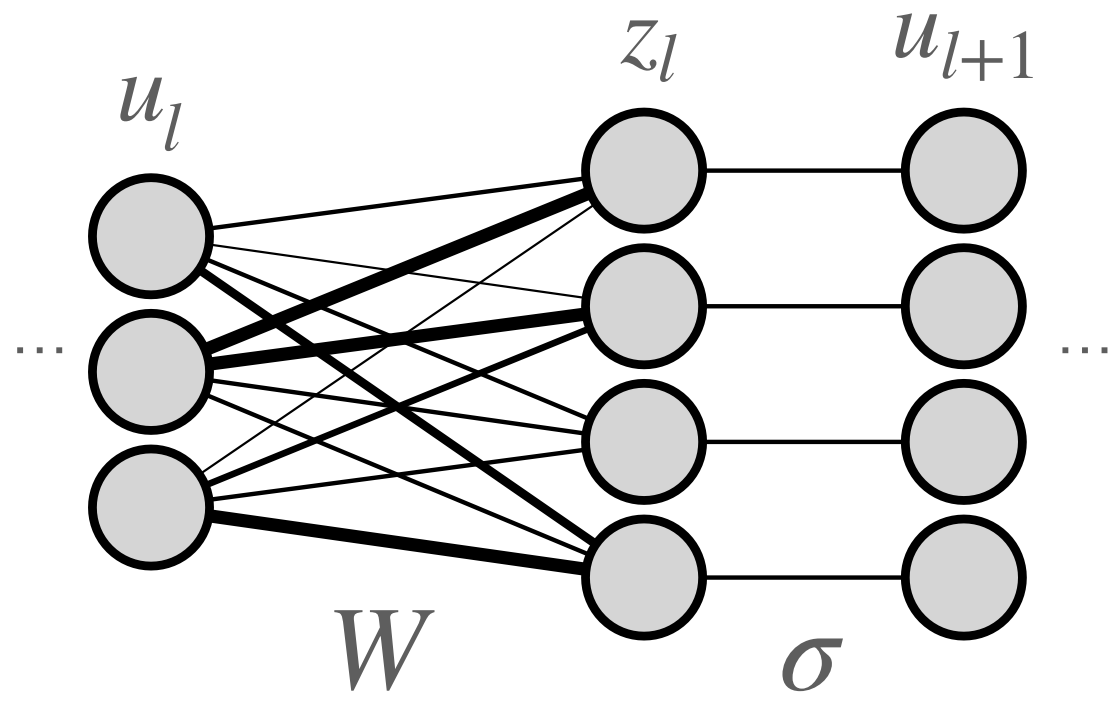
$$\nabla_W L = \delta_l u_l^\top$$



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Obs. 1: for $W \in \mathbb{R}^{d \times d}$, $\nabla_W L$ is rank-B for batch size B!

Obs. 2: fine-tuning models with low-rank updates works really well [1]

$$\text{e.g. } W_{ft} = W_0 + AB^\top, \quad \text{rank}(A) = \text{rank}(B) \ll d$$

[1] LoRA: Low-Rank Adaptation of Large Language Models. Hu, Edward and Shen, Yelong and Wallis, Phil and Allen-Zhu, Zeyuan and Li, Yuanzhi and Wang, Lu and Chen, Weizhu. 2021.

Model Editor Networks using gradient Decomposition

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Conclusion: use rank-1 input **and** output; $d^2 \rightarrow d^2$ becomes $2d \rightarrow 2d$

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Idea: map each rank-1 gradient component to new rank-1 “pseudograd" & sum

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∇_{W_ℓ}

Model Editor Networks using gradient Decomposition

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Layer **input**

Model Editor Networks using gradient Decomposition

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Gradient of loss wrt layer **output**

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Layer **input**

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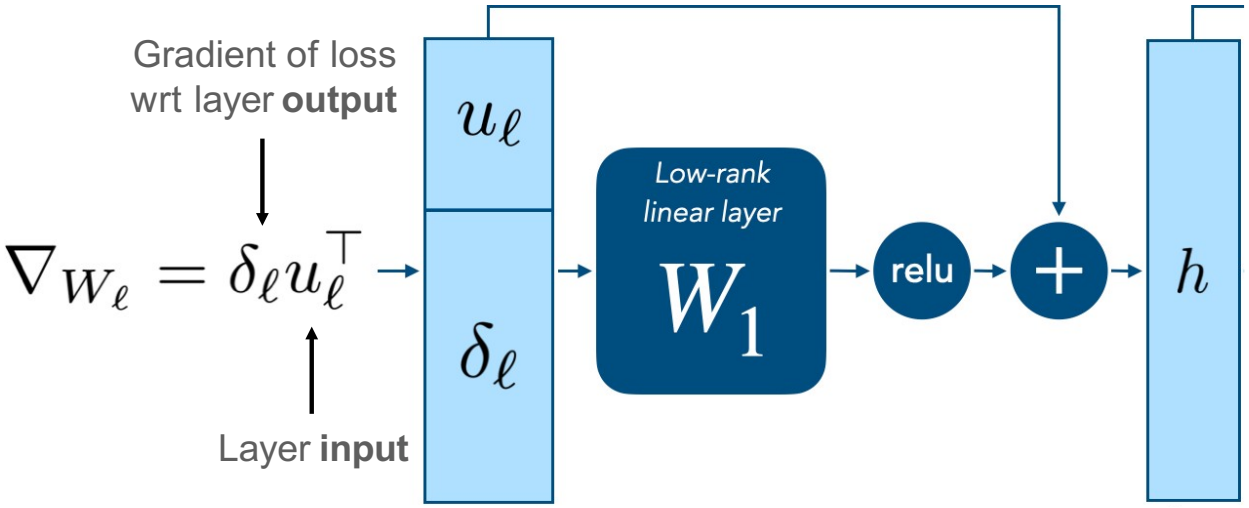

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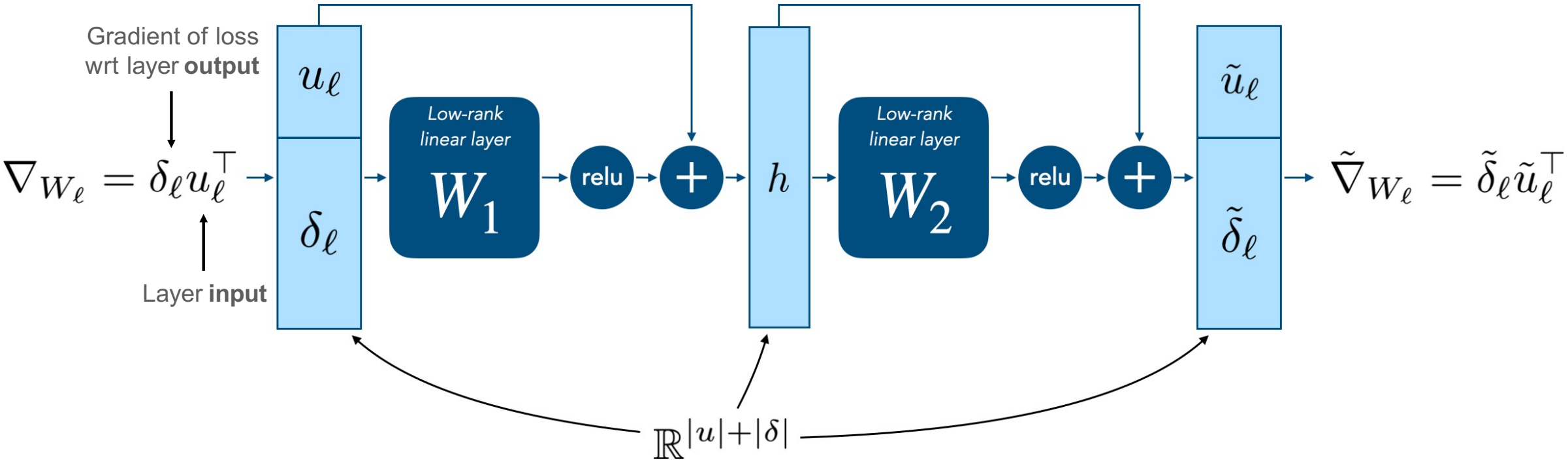

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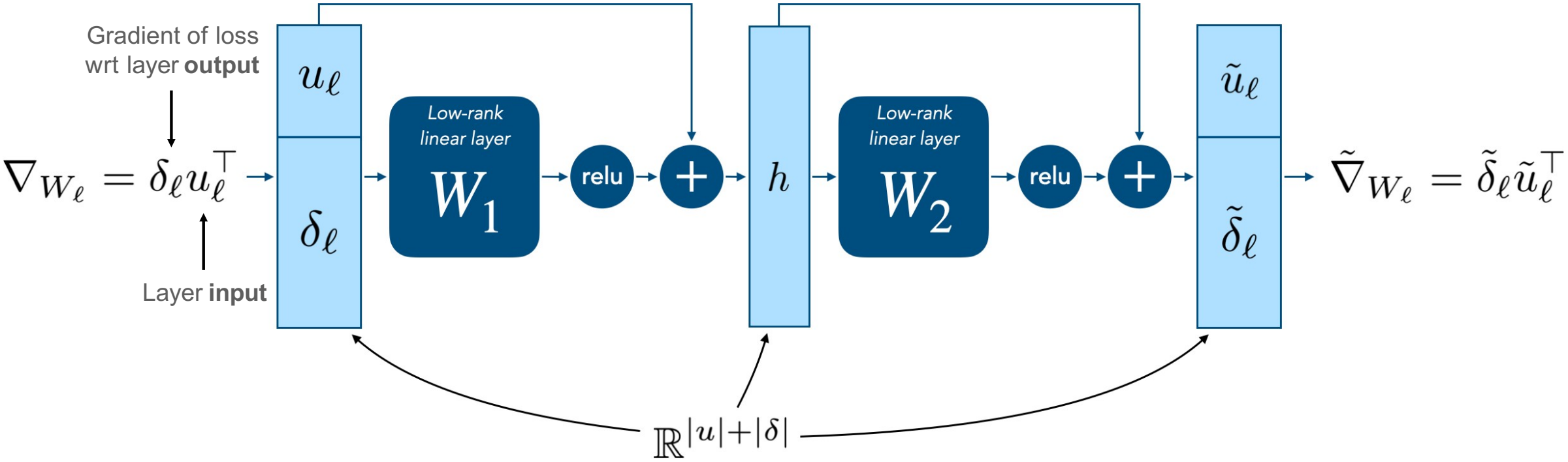

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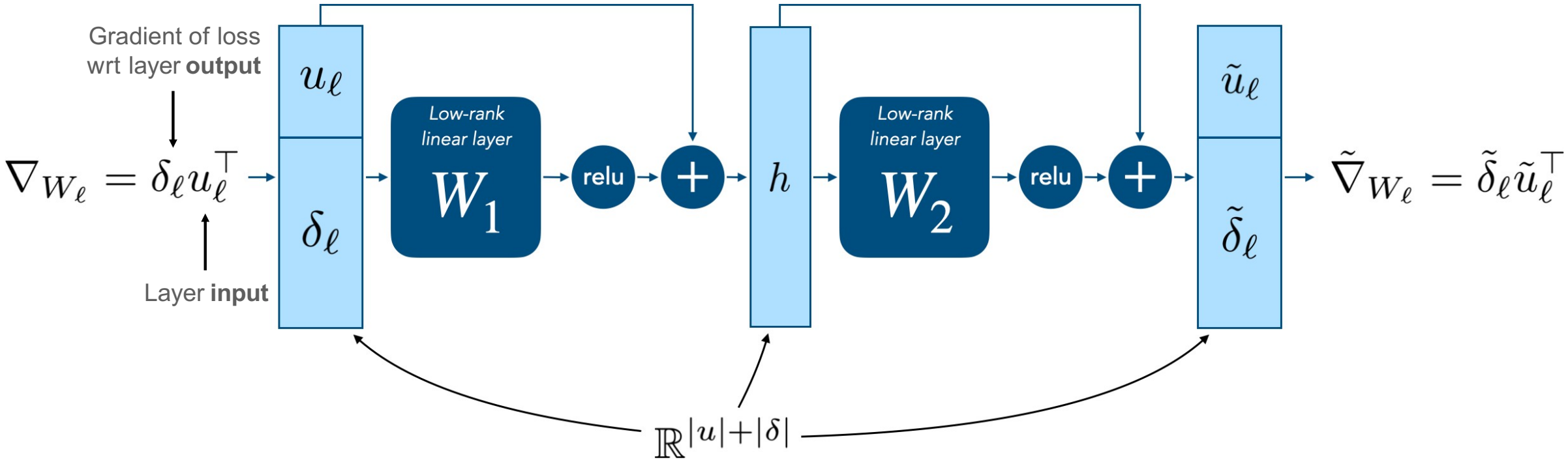

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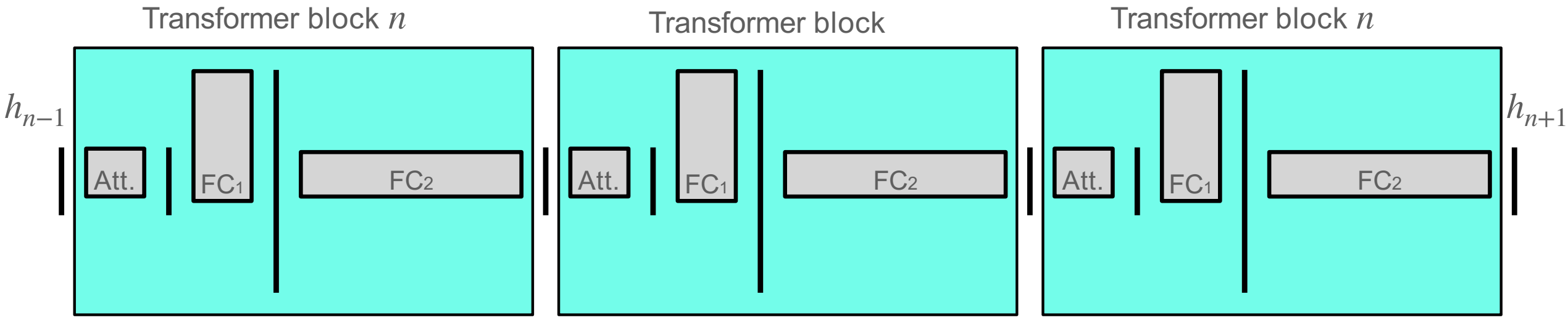

Surprisingly, we can **edit many layers with the same editor network**

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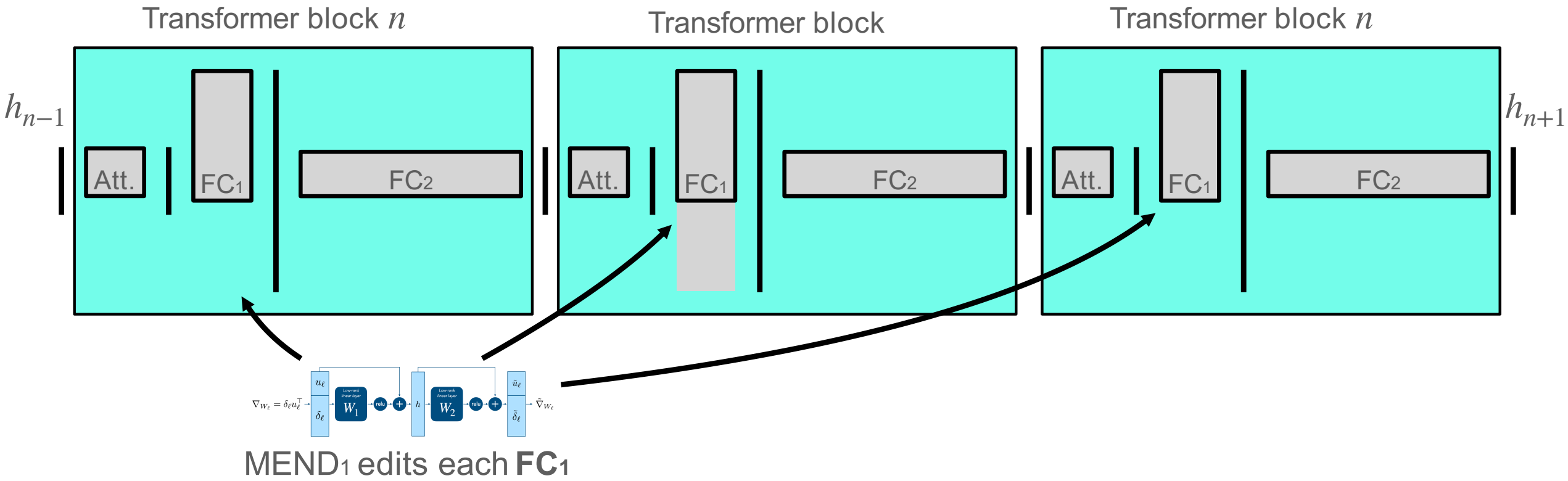

MEND1 edits each **FC1**

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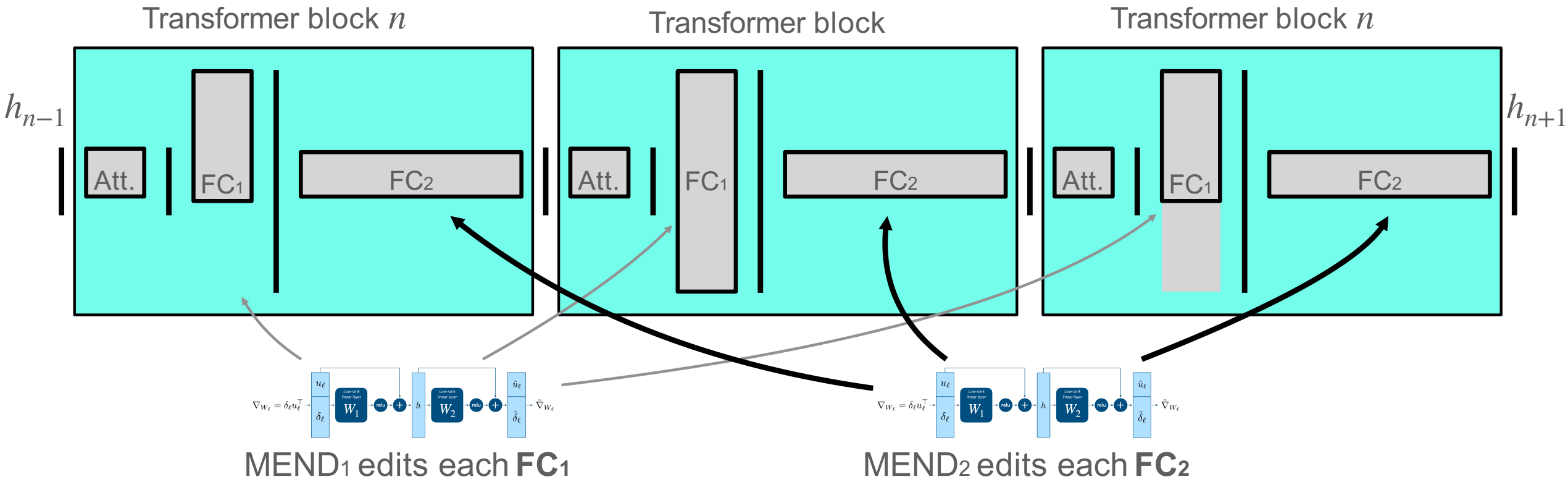

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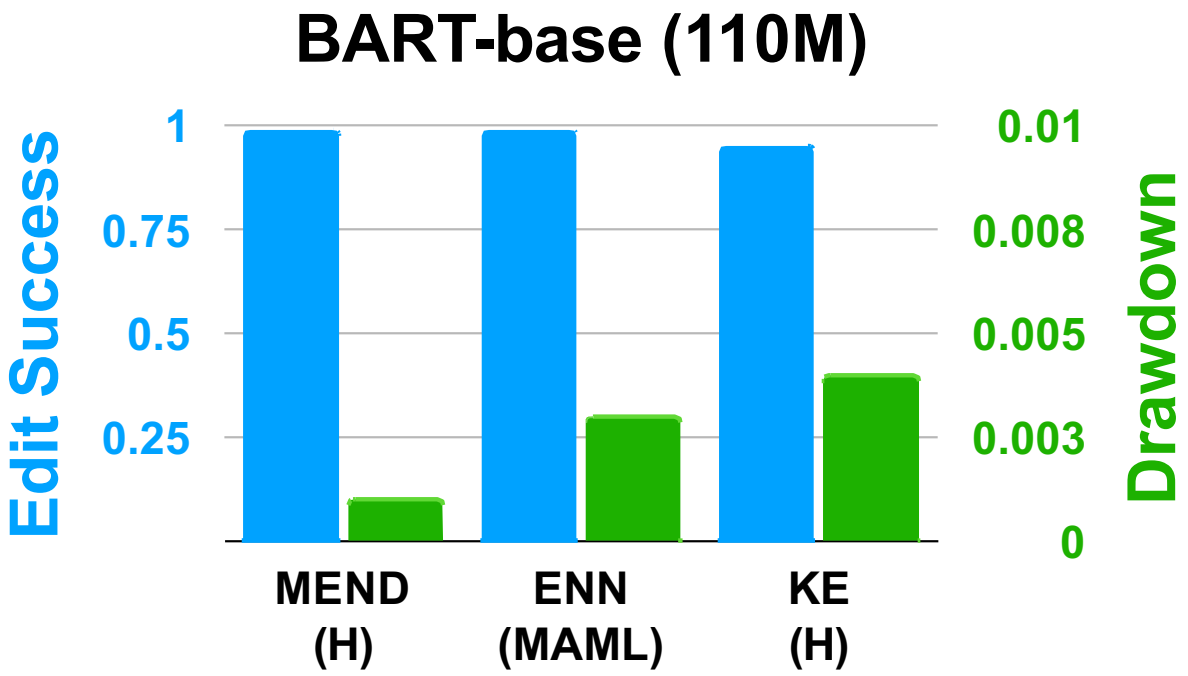
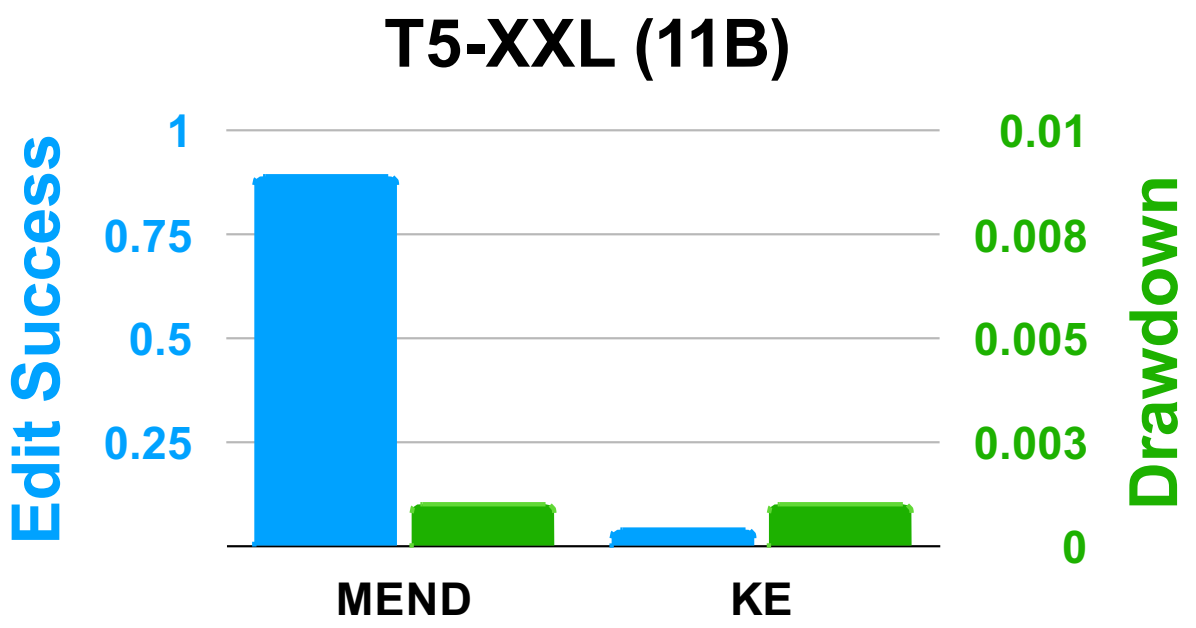
Model Editor Networks using gradient Decomposition

Effective editing at small scale…



Model Editor Networks using gradient Decomposition

Effective editing at small scale…and large scale!



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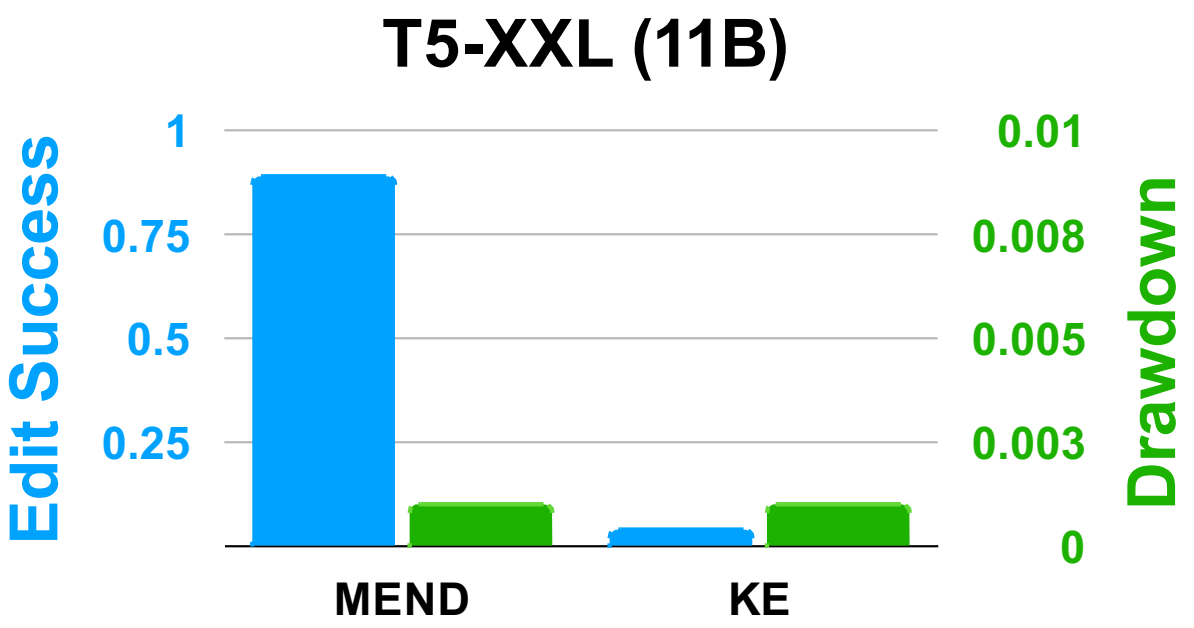


MEND gives productive edits, while KE fails (and ENN gives OOM)

Model Editor Networks using gradient Decomposition

Editing T5-Large: Successes and a failure

Input	Pre-Edit Output	Edit Target	Post-Edit Output
1a: **Who is India's PM?**	Satya Pal Malik ✗	**Narendra Modi**	Narendra Modi ✓
1b: **Who is the prime minister of the UK?**	Theresa May ✗	**Boris Johnson**	Boris Johnson ✓
1c: Who is the prime minister of India?	Narendra Modi ✓	-	Narendra Modi ✓
1d: Who is the UK PM?	Theresa May ✗	-	Boris Johnson ✓
2a: **What is Messi's club team?**	Barcelona B ✗	**PSG**	PSG ✓
2b: **What basketball team does Lebron play on?**	Dallas Mavericks ✗	**the LA Lakers**	the LA Lakers ✓
2c: Where in the US is Raleigh?	a state in the South ✓	-	a state in the South ✓
3a: **Who is the president of Mexico?**	Enrique Pea Nieto ✗	**Andrés Manuel López Obrador**	Andrés Manuel López Obrador ✓
3b: Who is the vice president of Mexico?	Yadier Benjamin Ramos ✗	-	Andrés Manuel López Obrador ✗

Bold text indicates the edits applied in each evaluation

Today's Plan

I. Background

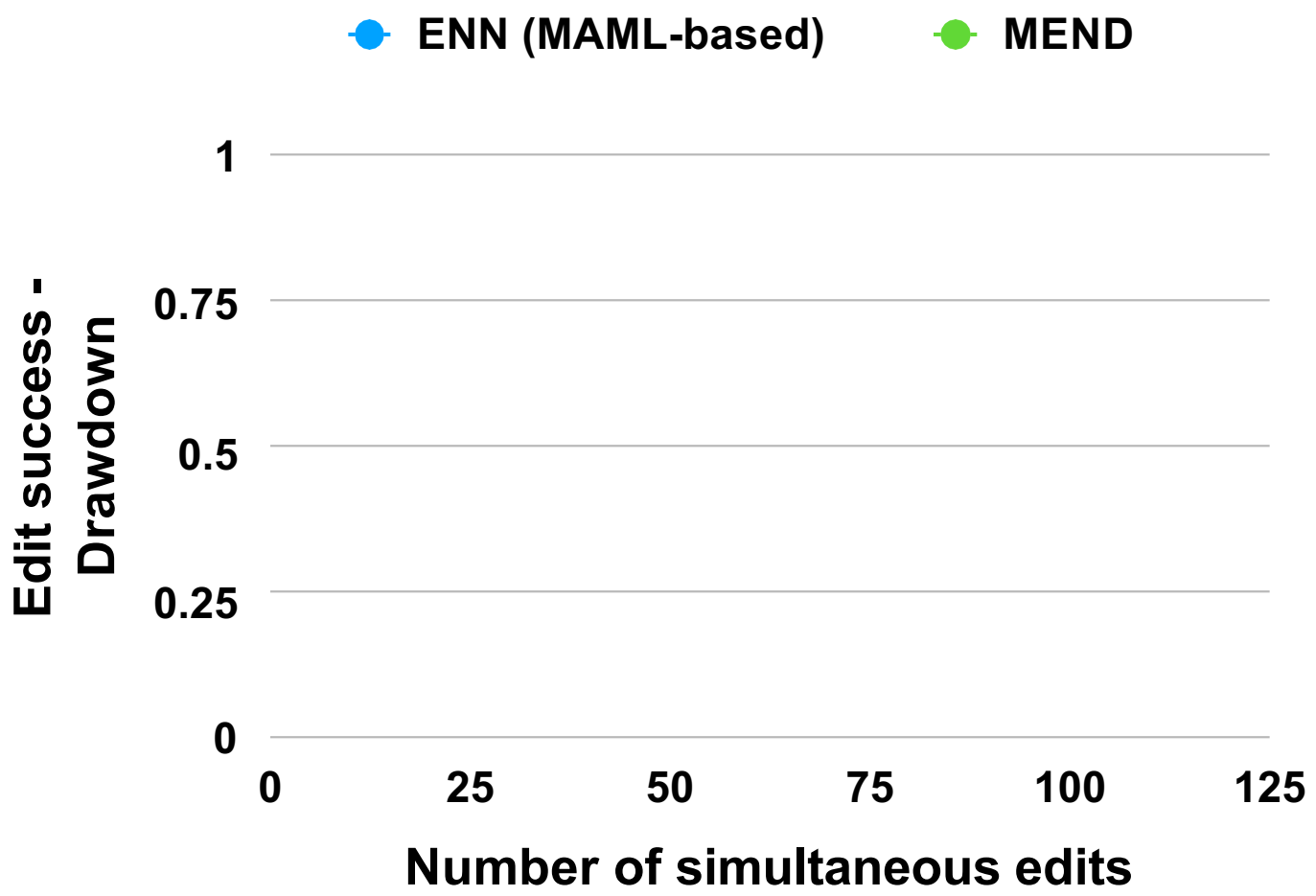
II. Learning to edit NNs

III. Moving editing towards the real world

IV. Future work & open questions

Moving editing towards the real world

Applying multiple edits to BART-base



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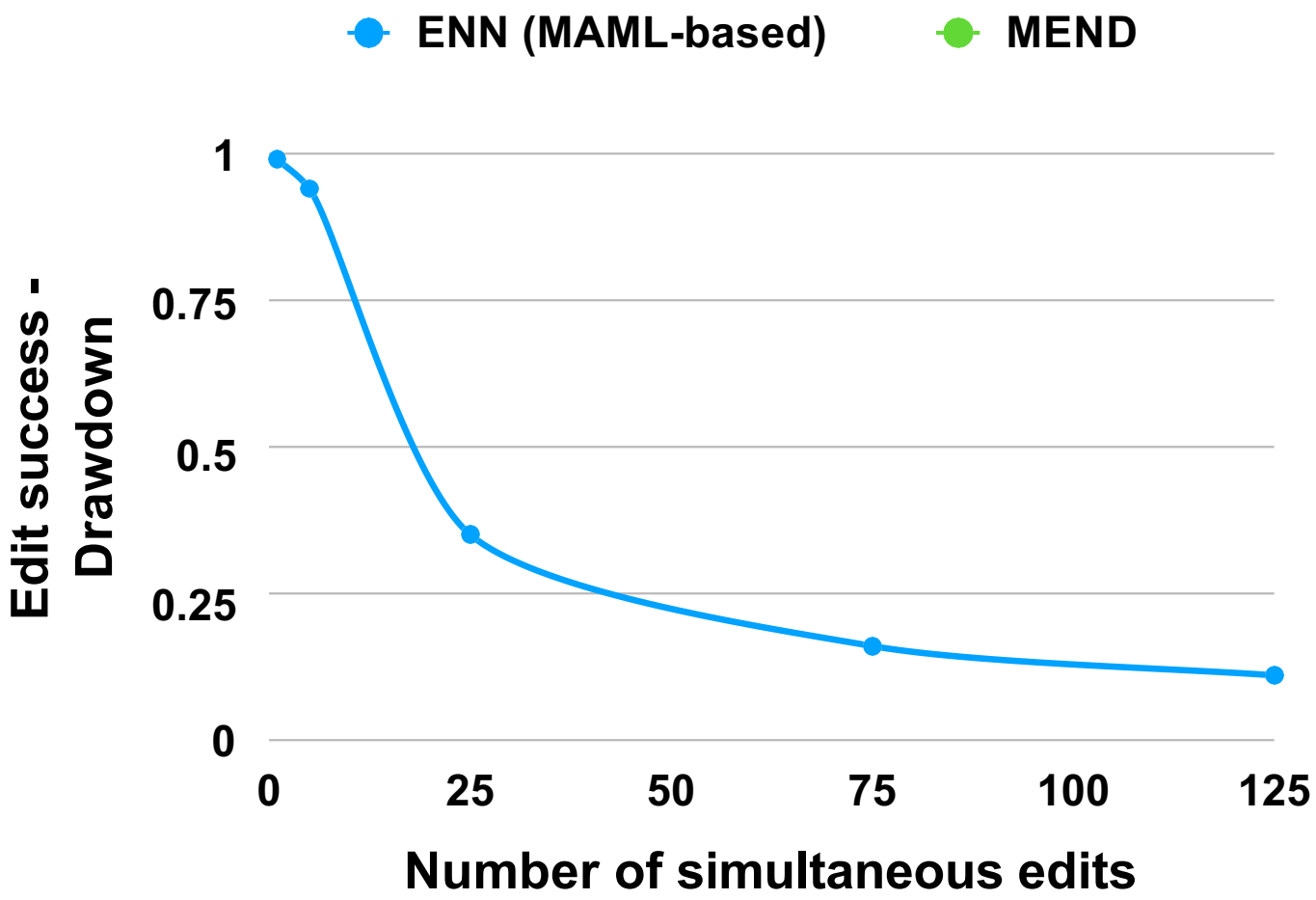

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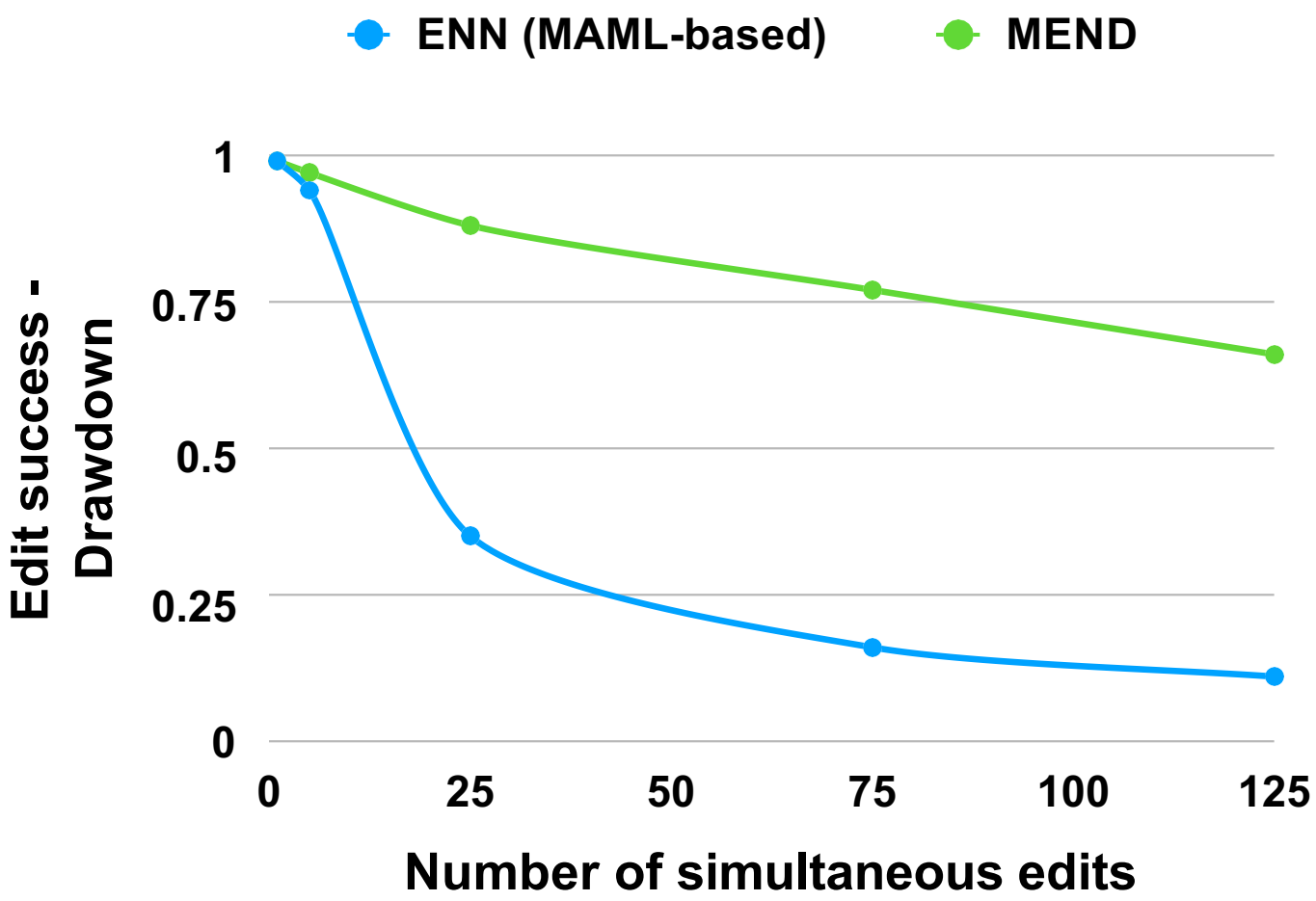

More challenging benchmarks

Multiple edits, more difficult edit scopes

Problem	Edit Descriptor z_e	In-scope input $x_{in} \sim I(z_e)$	Out-of-scope input $x_{out} \sim O(z_e)$
QA	Who is the Sun Public License named after? *Sun Micro Devices*	The Sun Public License has been named for whom? *Sun Micro Devices*	What continent is Mount Whillans found on?

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Table reproduced from:
Memory-based model editing at scale. Mitchell et al. Preprint; under review.

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FC	As of March 23, there were 50 confirmed cases and 0 deaths within Idaho. *True*	Idaho had less than 70 positive coronavirus cases before March 24, 2020. *True*	Allessandro Diamanti scored six serie A goals.
	Between 1995 and 2018, the AFC has sent less than half of the 16 AFC teams to the Super Bowl with only 7 of the 16 individual teams making it. *True*	–	The AFC sent less than half of the 16 AFC teams to the Super Bowl between 1995 and 2017.

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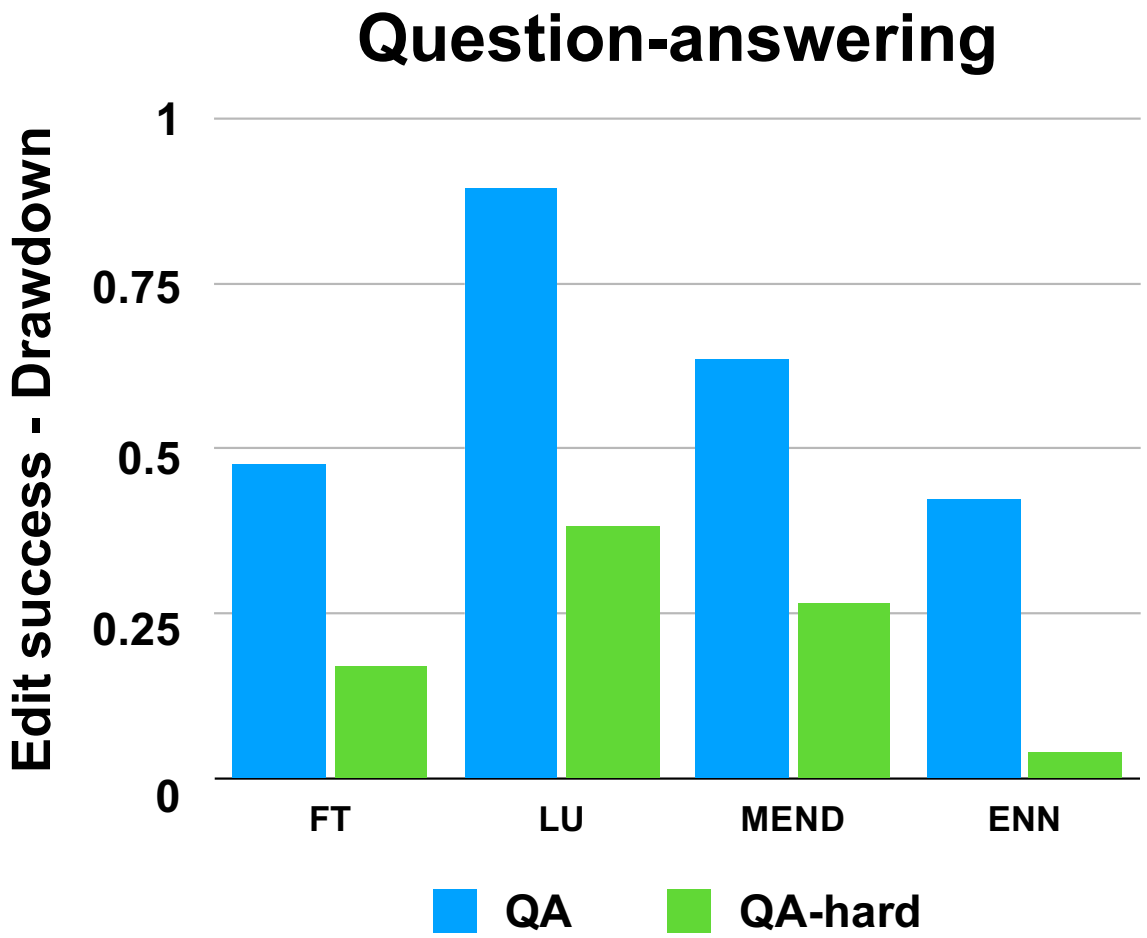

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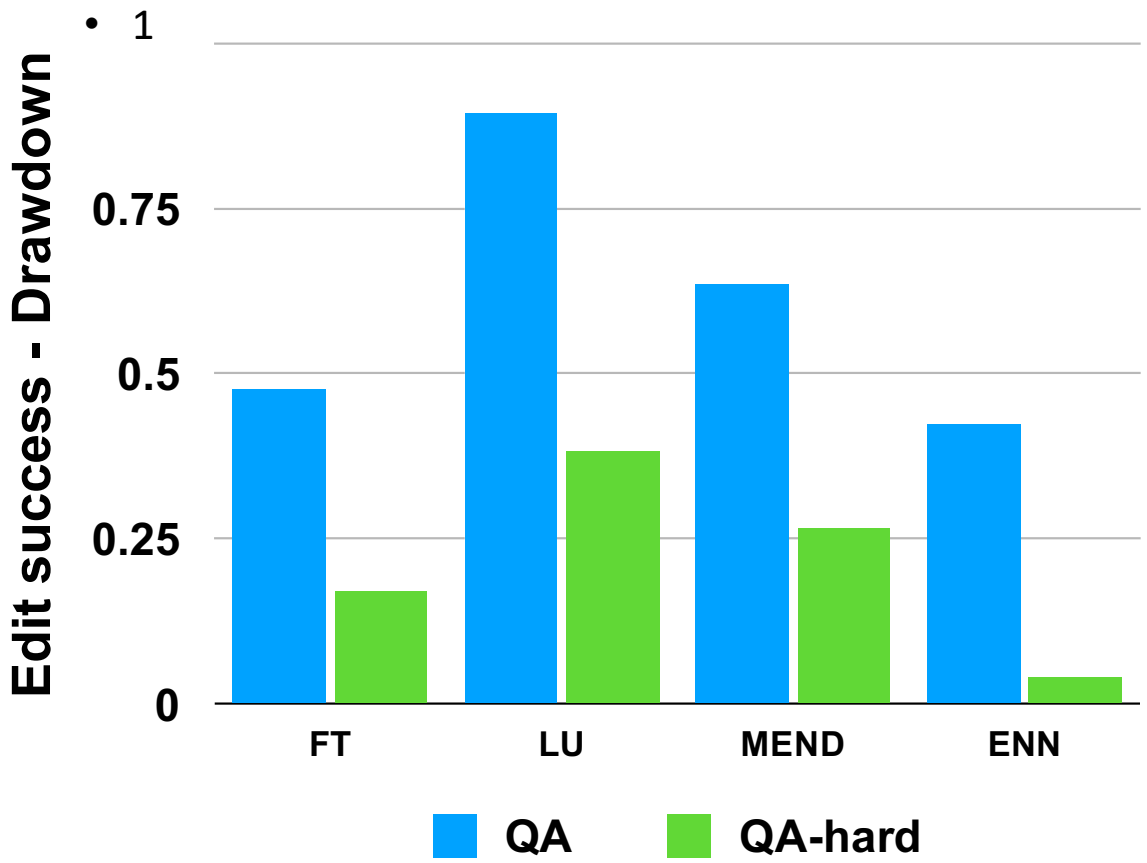
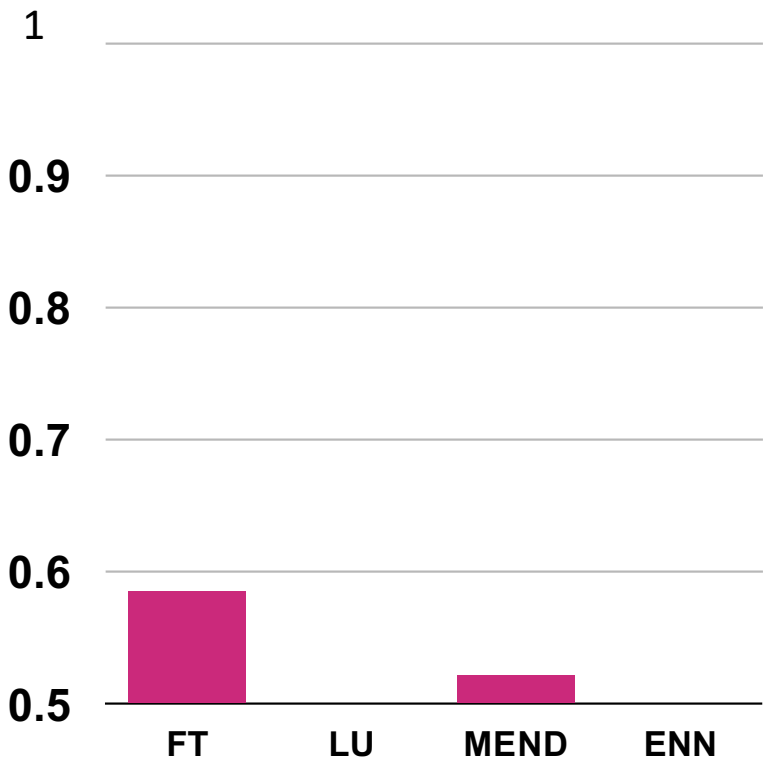
  - Question-answering



Fact-checking



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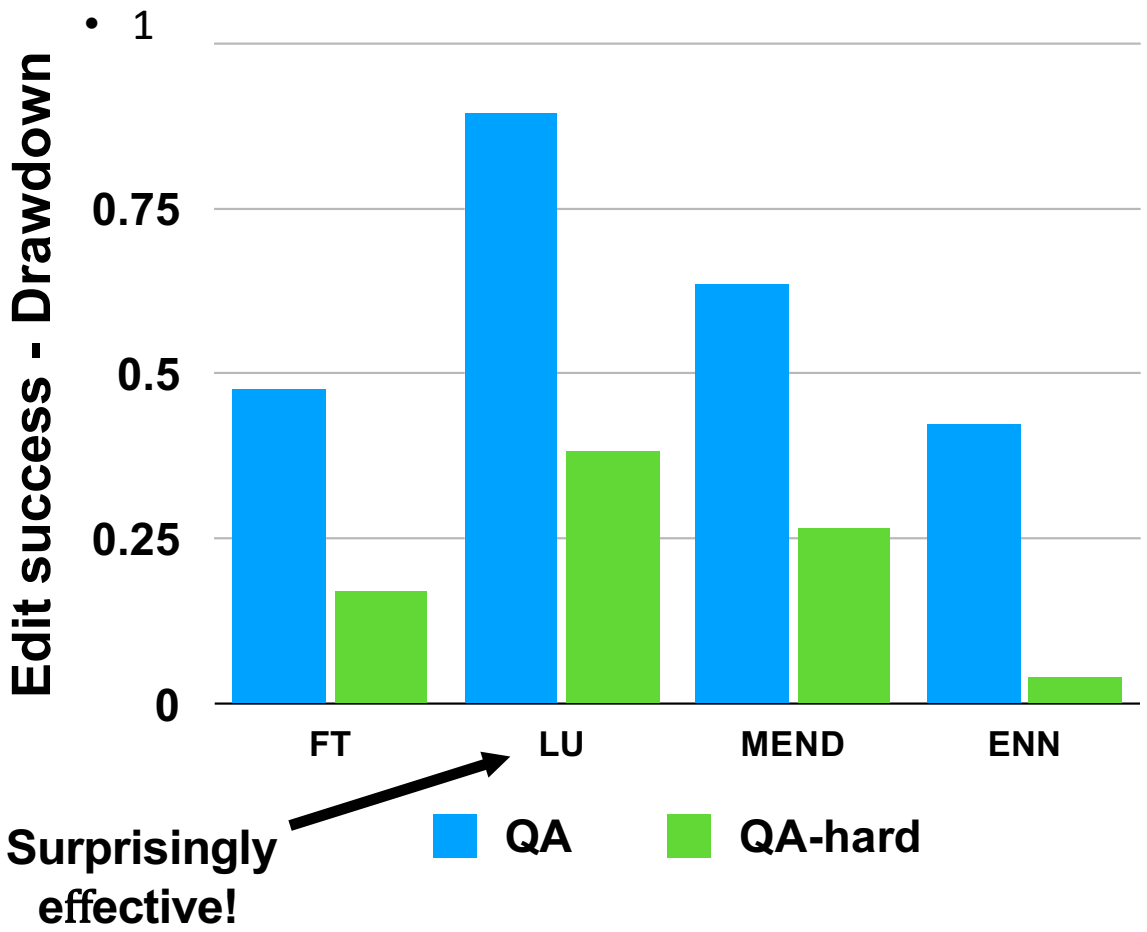

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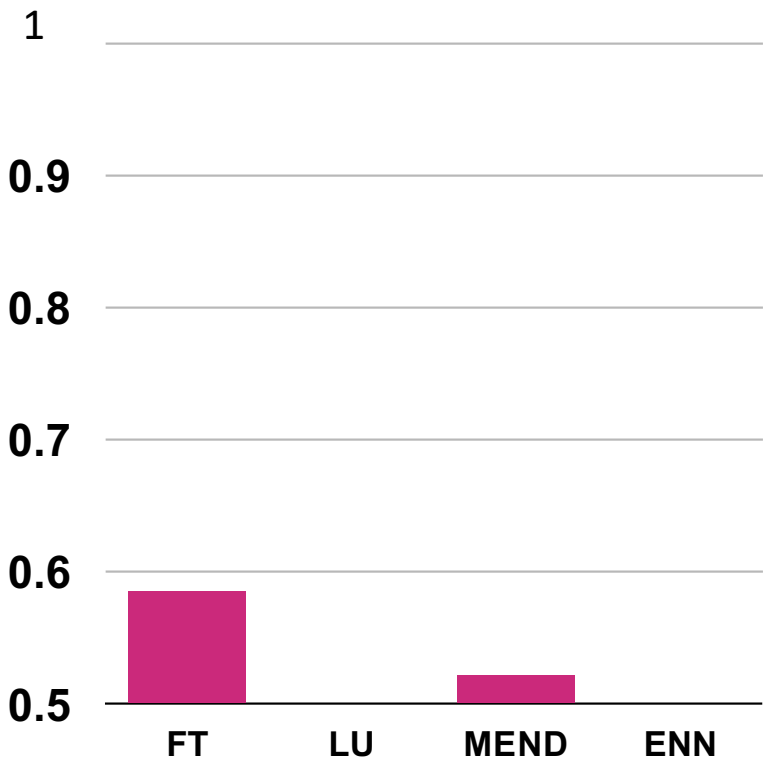

Edits without parameter updates

Semi-parametric Editing with a Retrieval-Augmented Counterfactual model

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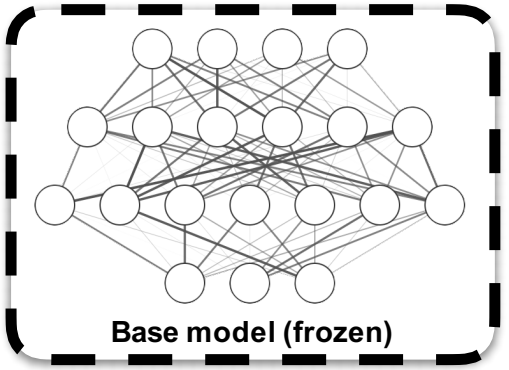
Edits without parameter updates

Semi-parametric Editing with a Retrieval-Augmented Counterfactual model

Start with the **frozen** base model



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Edits without parameter updates

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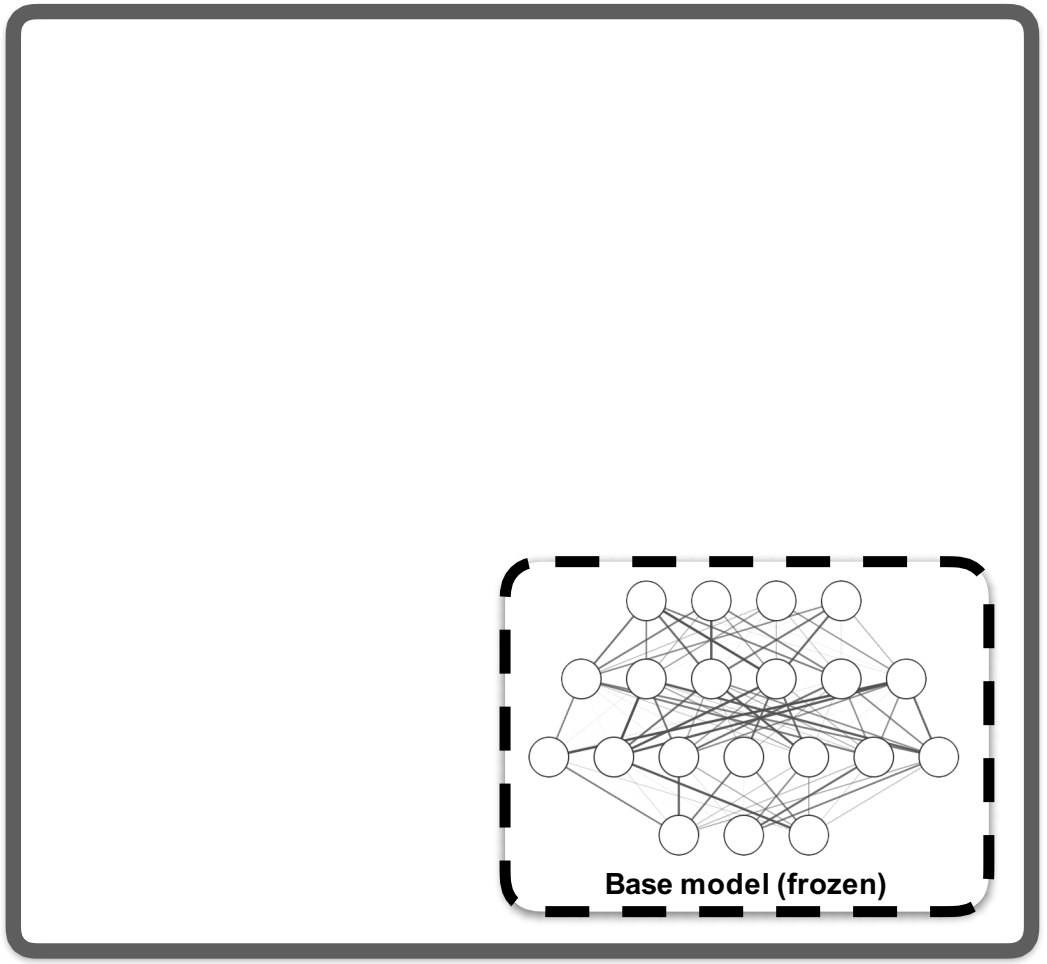

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Edits without parameter updates

Semi-parametric Editing with a Retrieval-Augmented Counterfactual model

Start with the **frozen** base model

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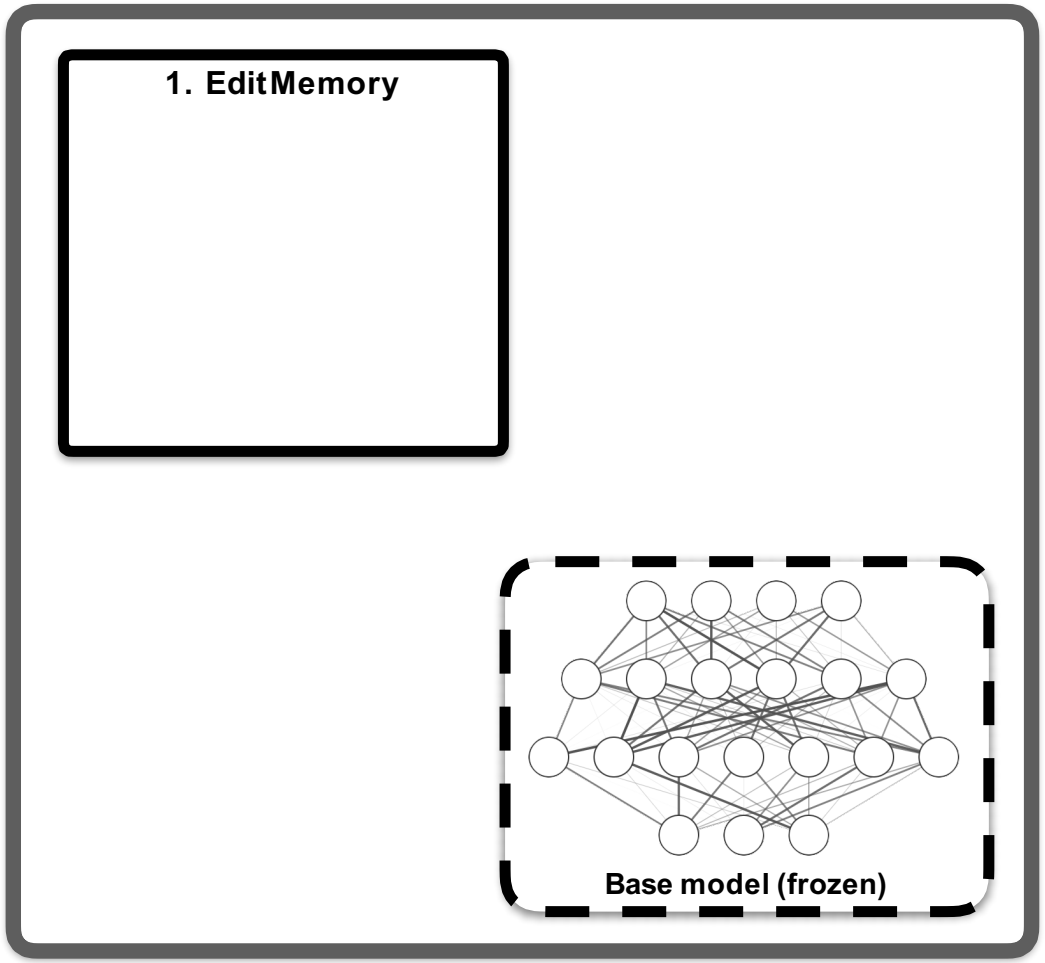

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Edits without parameter updates

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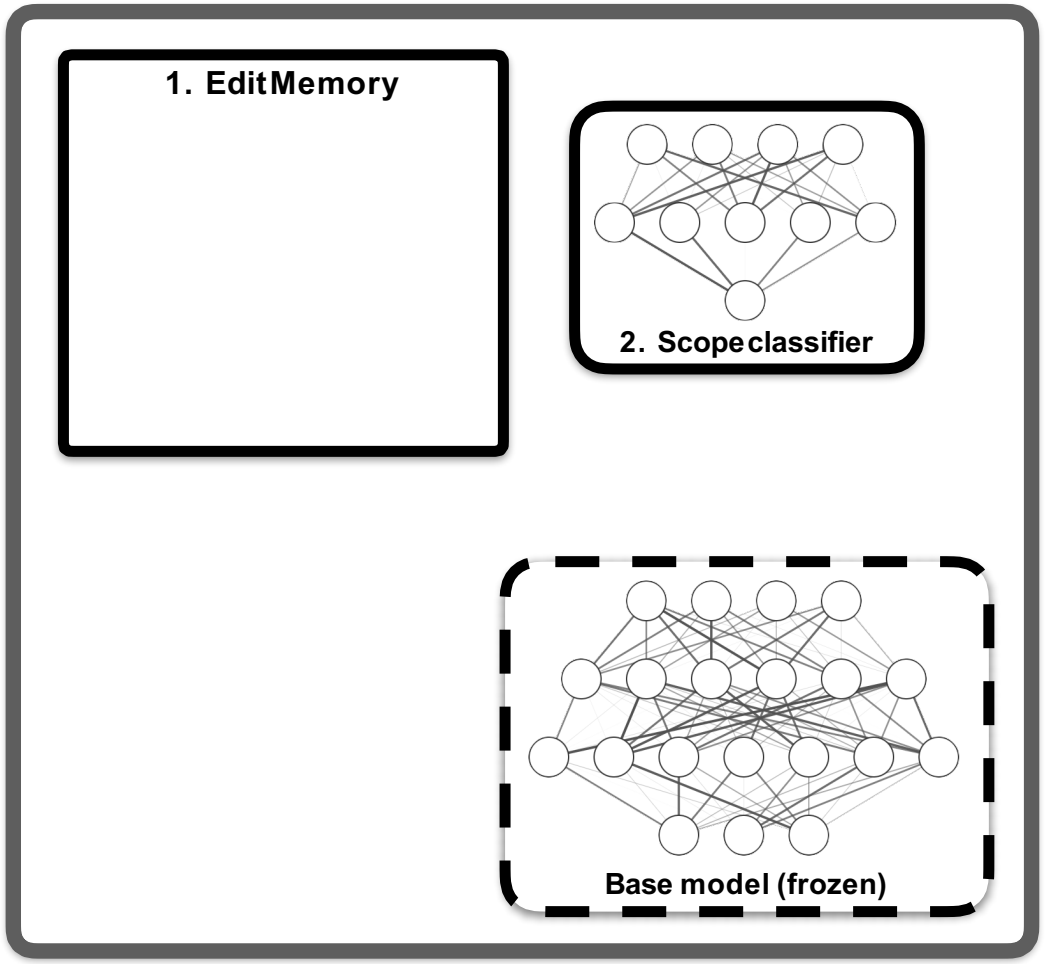

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Edits without parameter updates

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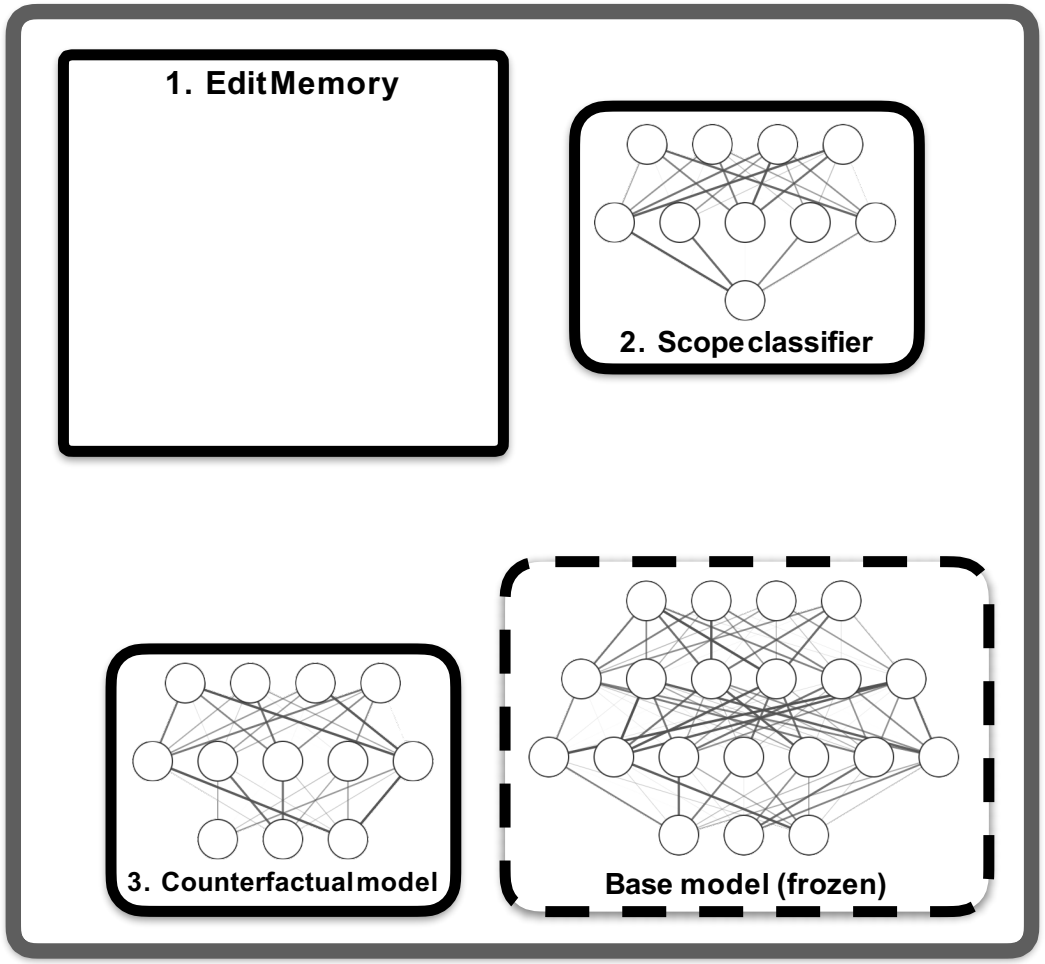

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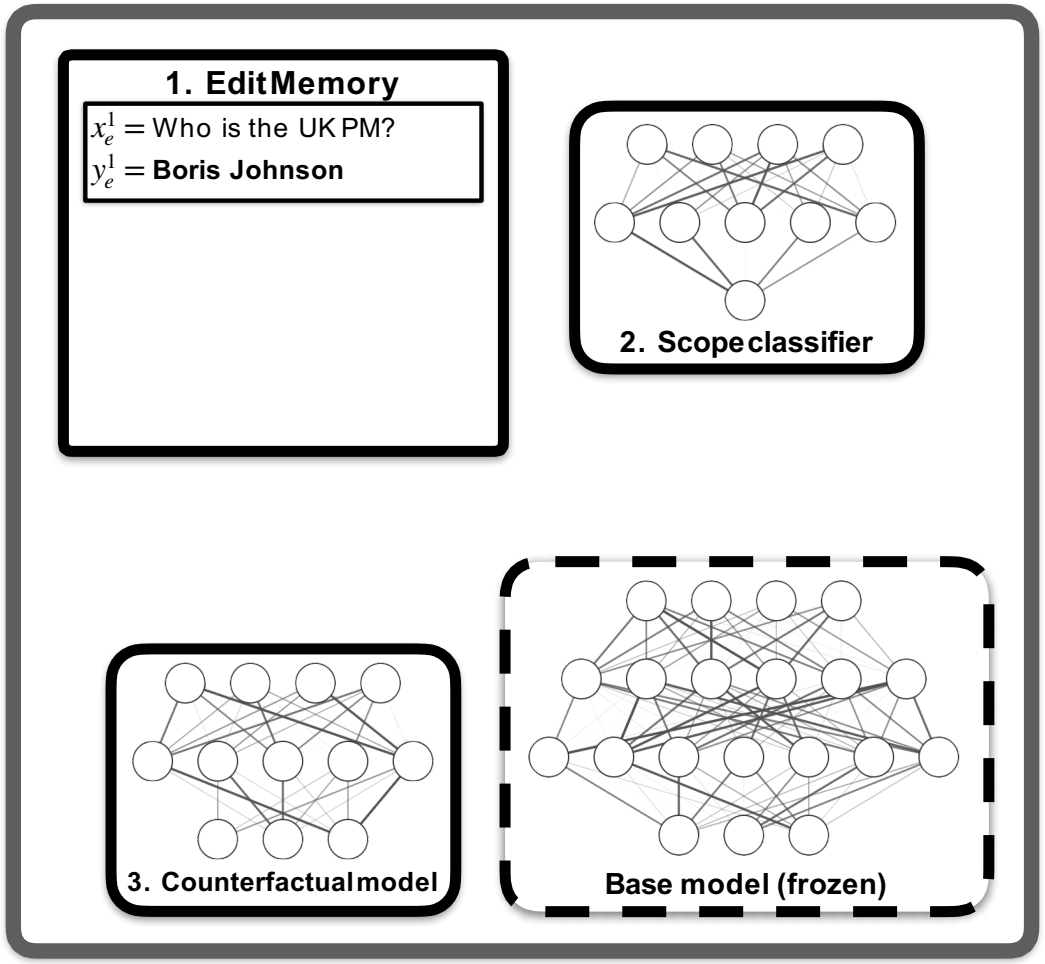

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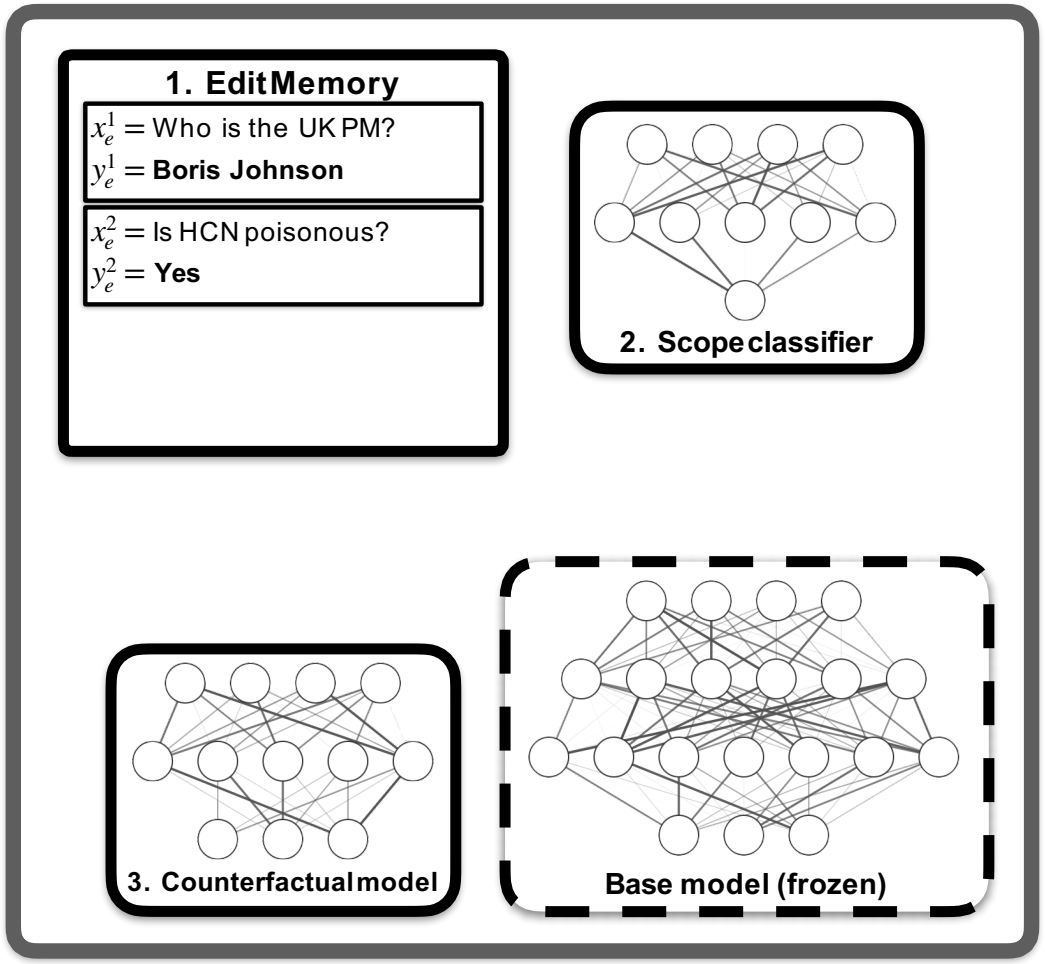

148

Edits without parameter updates

Semi-parametric Editing with a Retrieval-Augmented Counterfactual model

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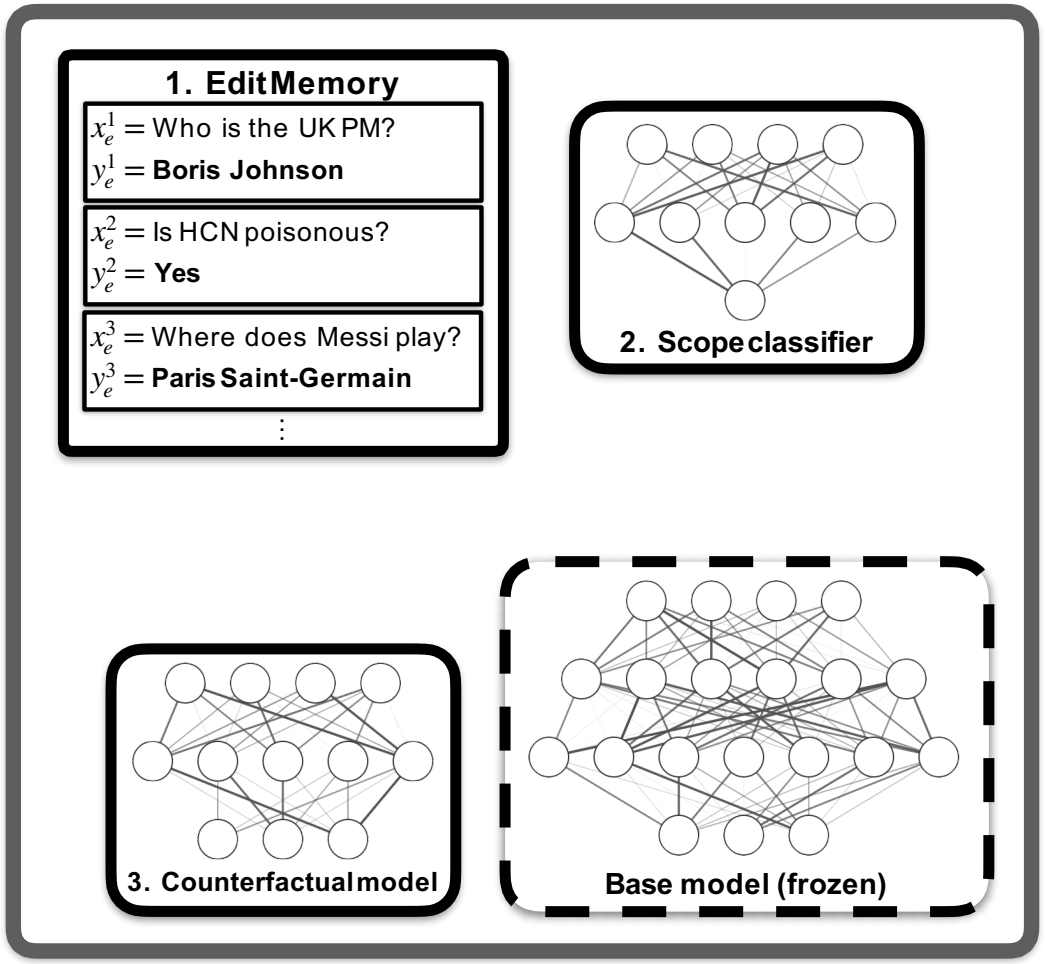

149

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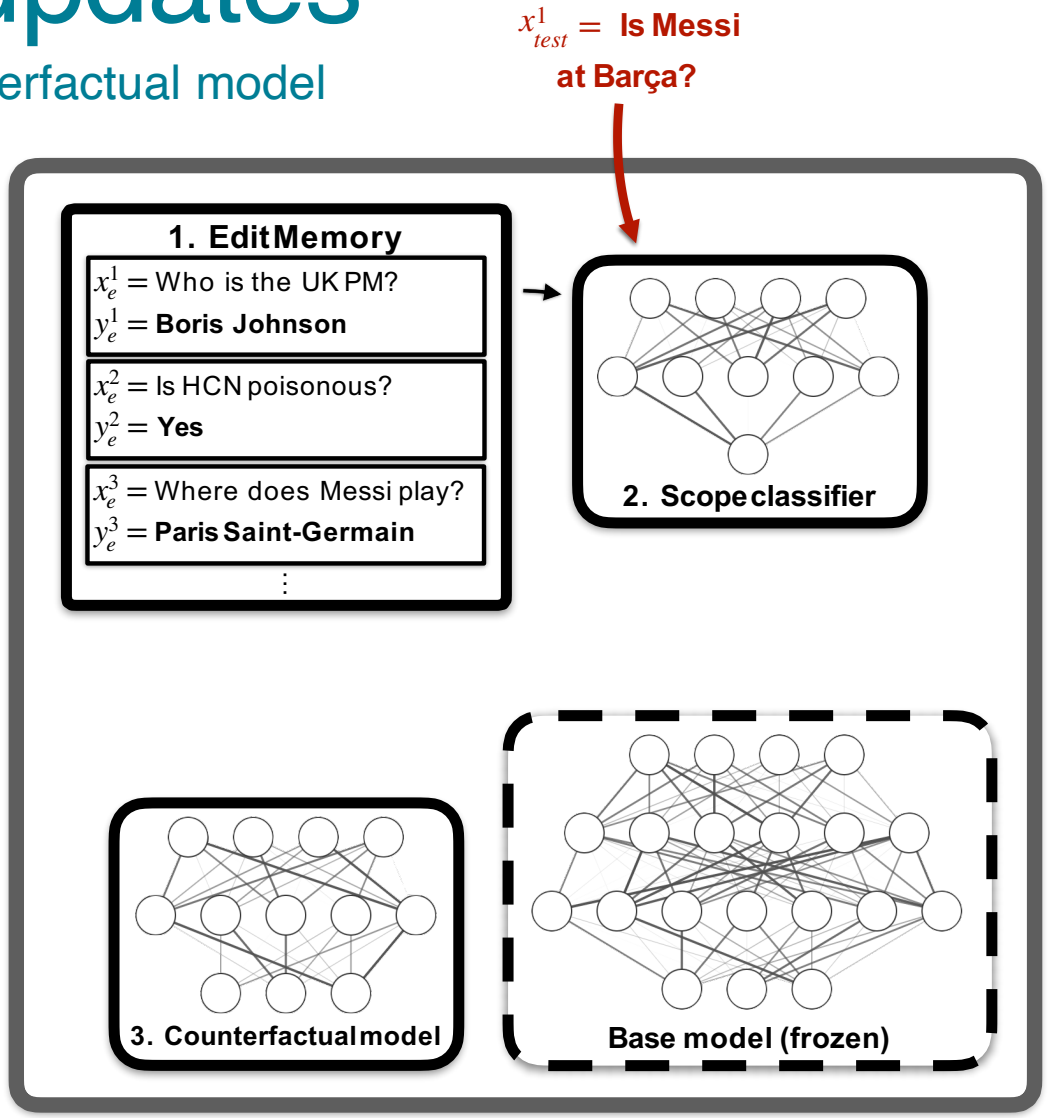

150

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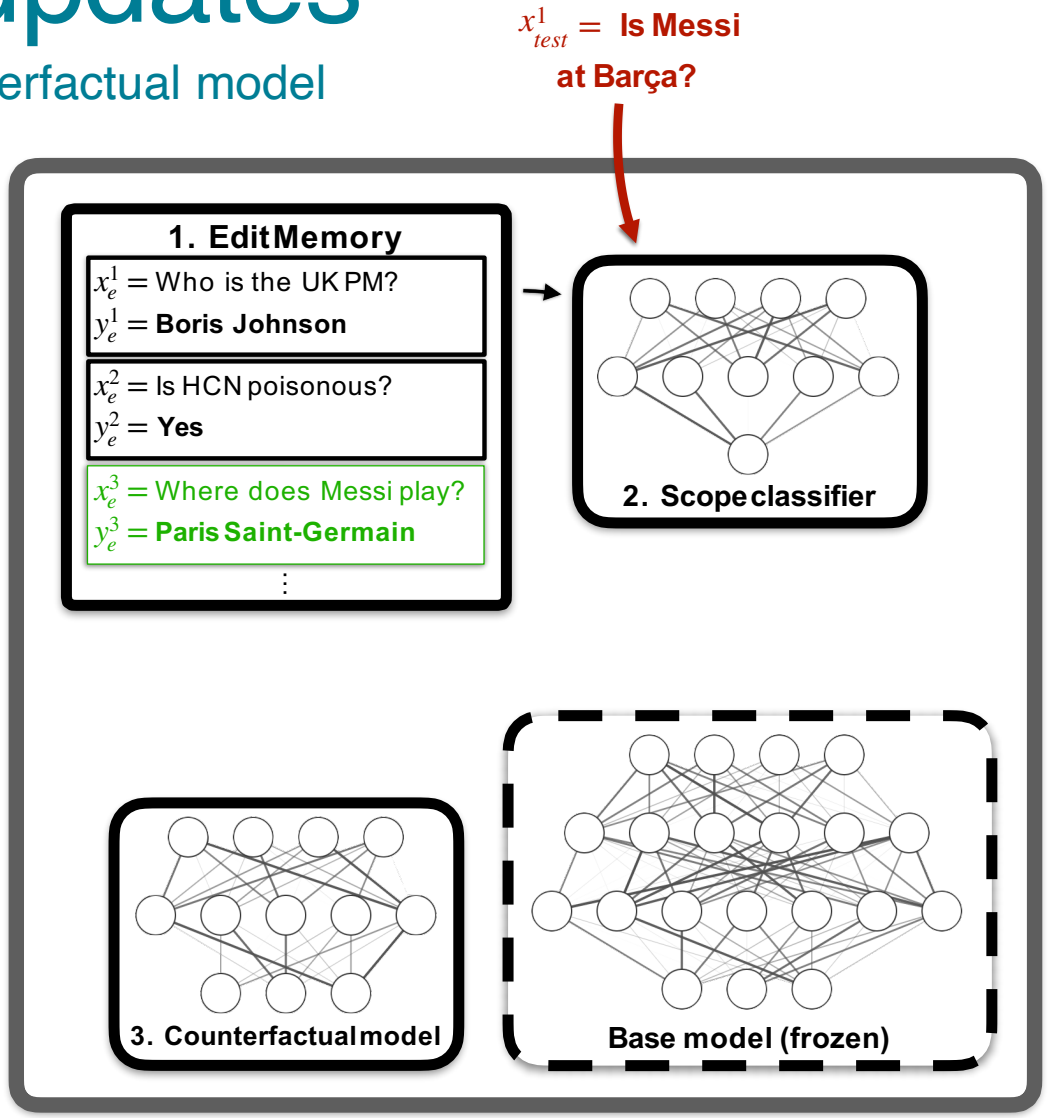

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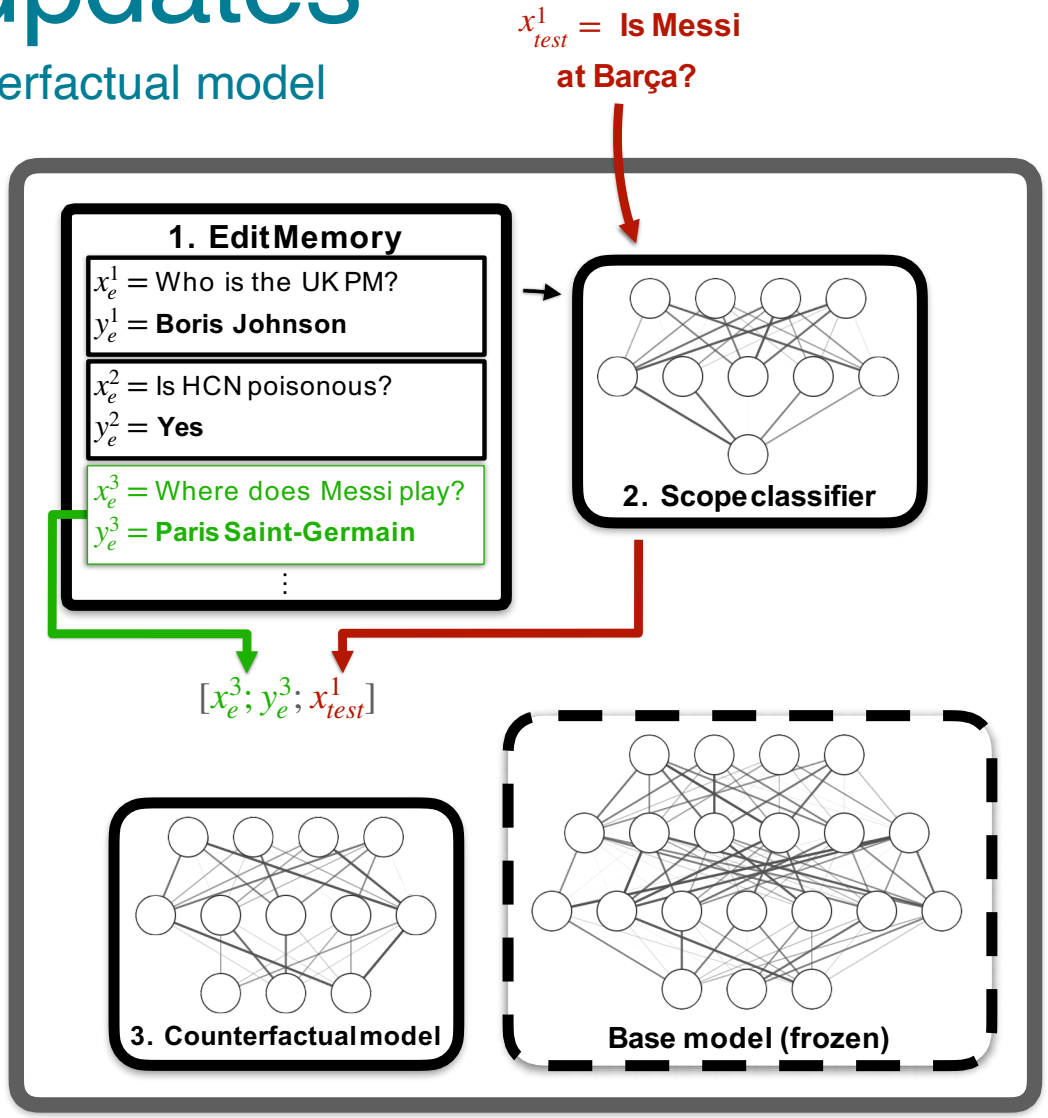

152

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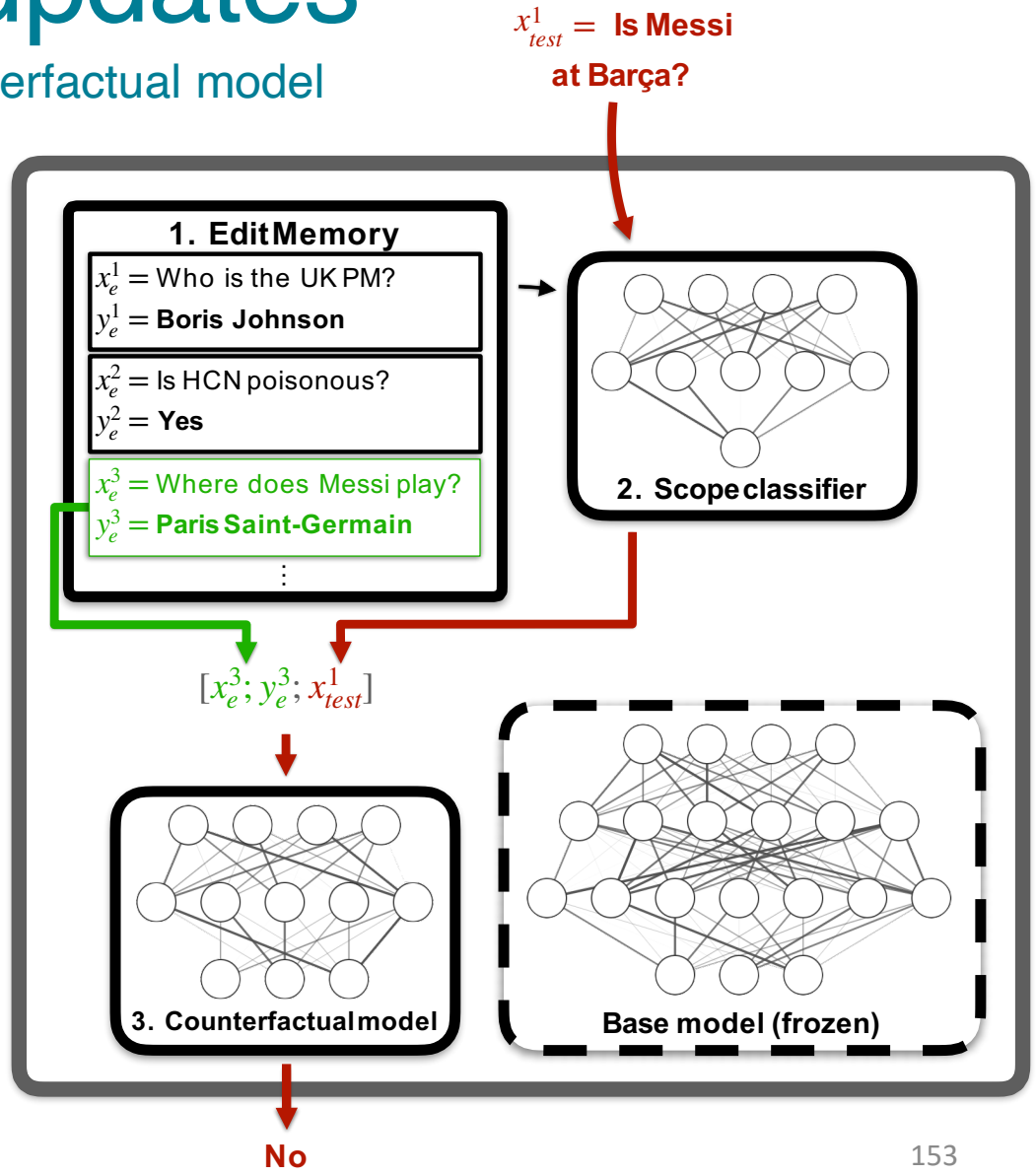

153

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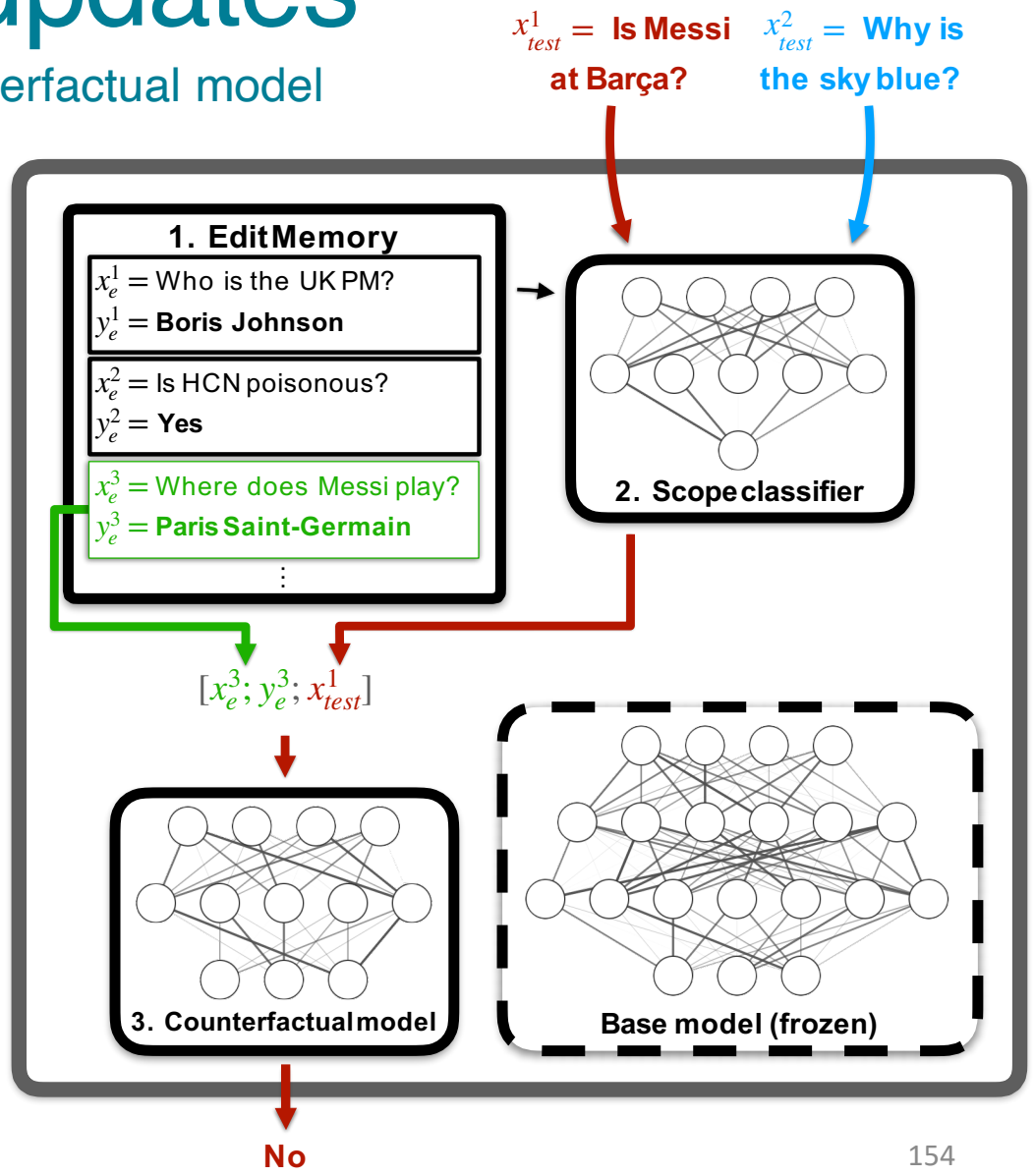

154

Edits without parameter updates

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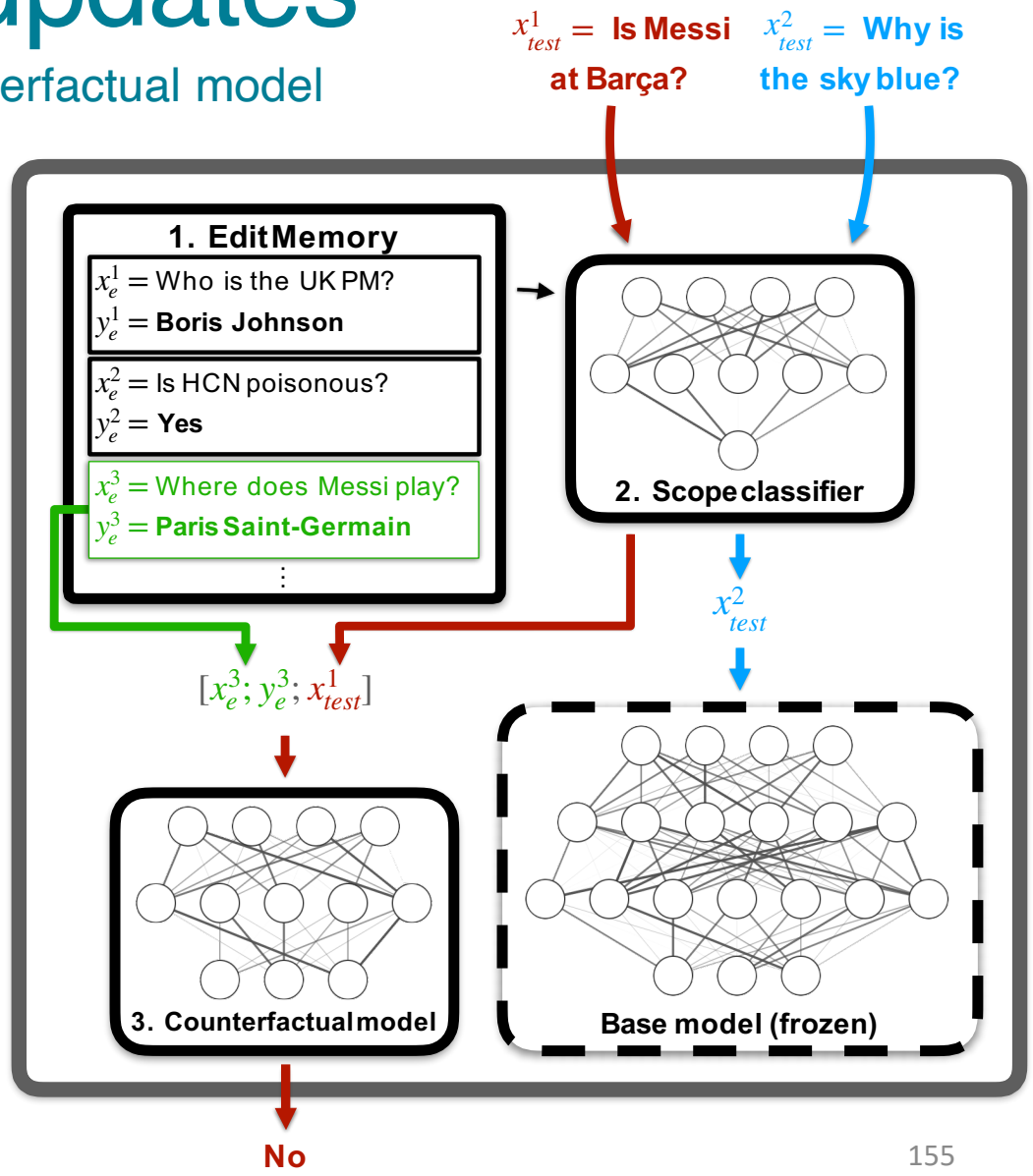

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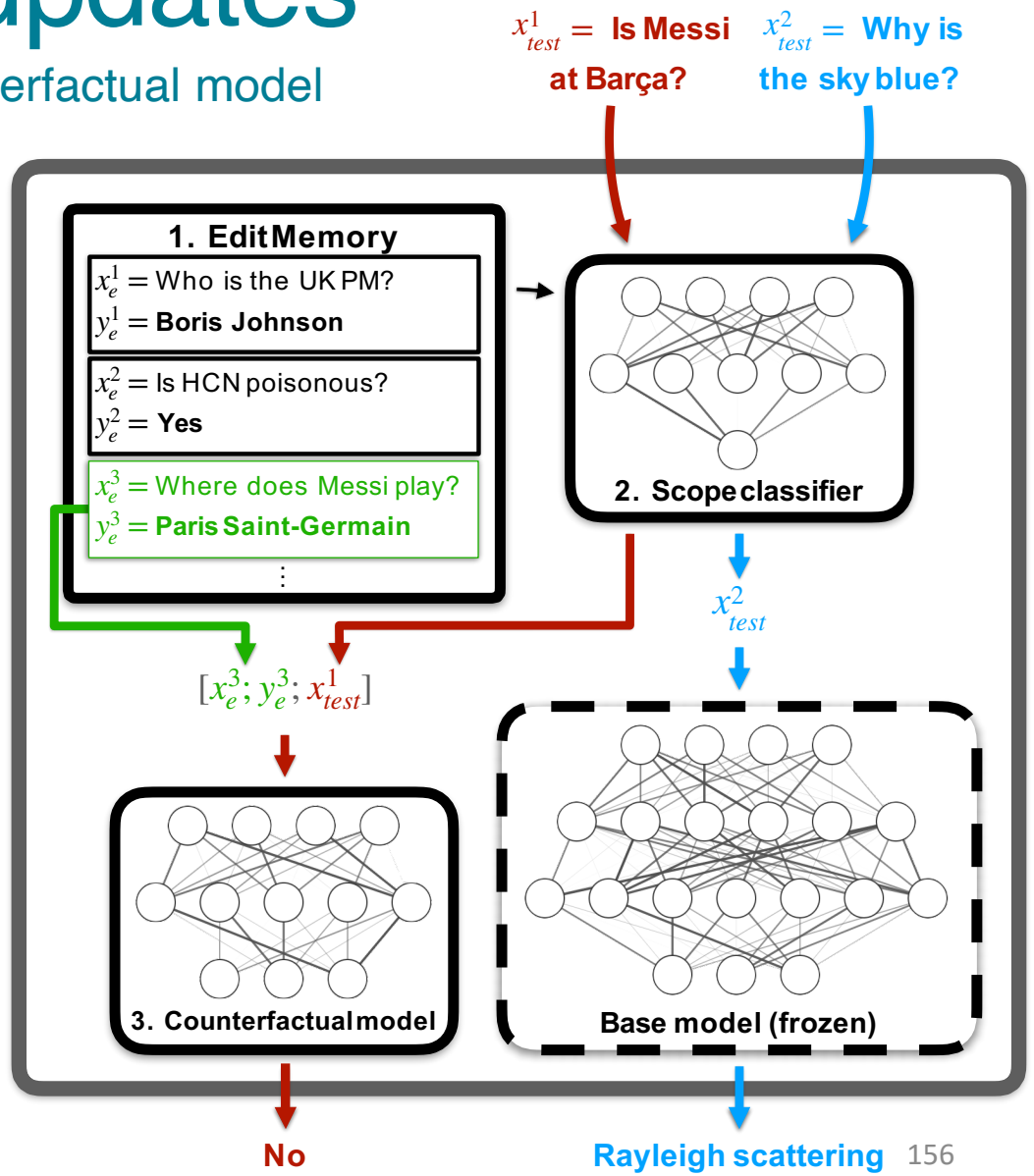
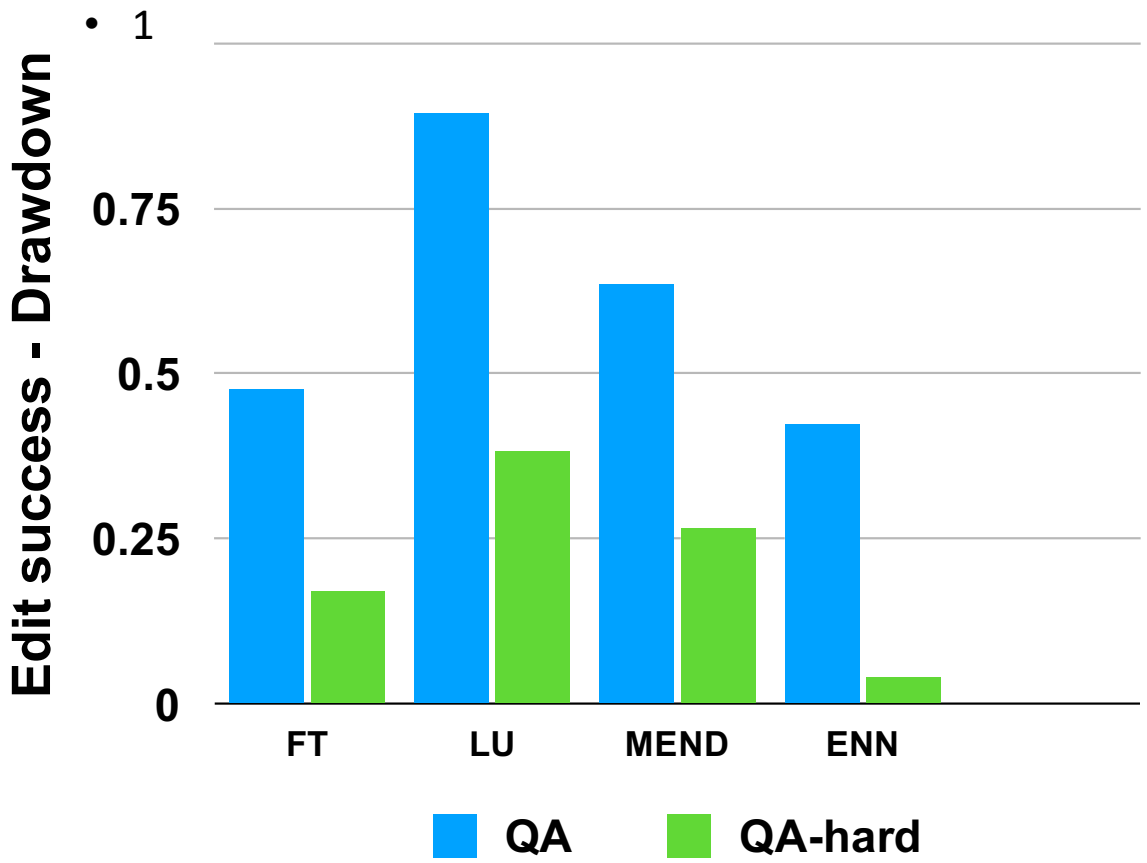


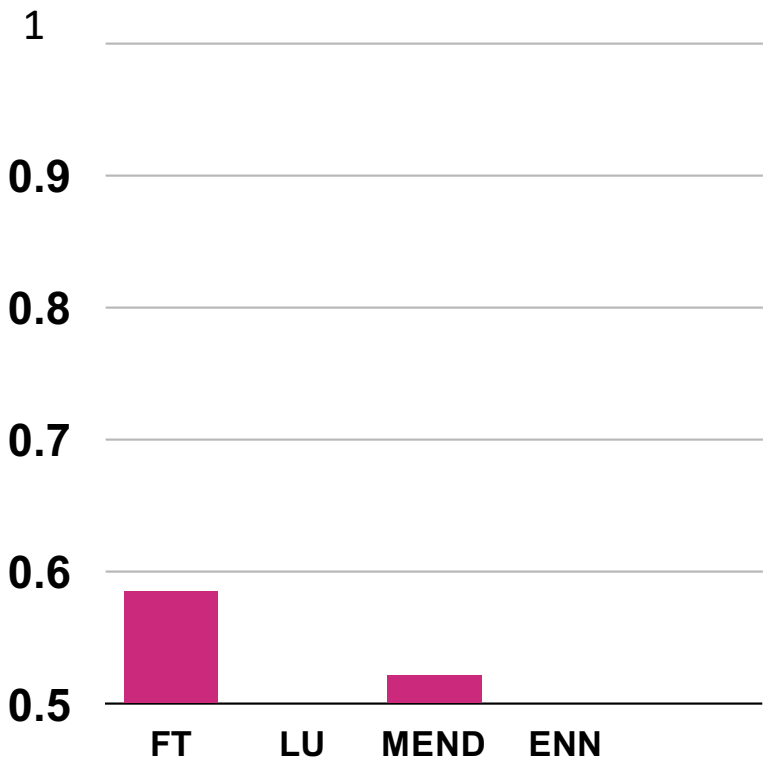
Figure reproduced from: *Memory-based model editing at scale.* Mitchell et al. Preprint; under review.

More challenging benchmarks

- Multiple edits, more difficult edit scopes
  - Question-answering



Fact-checking



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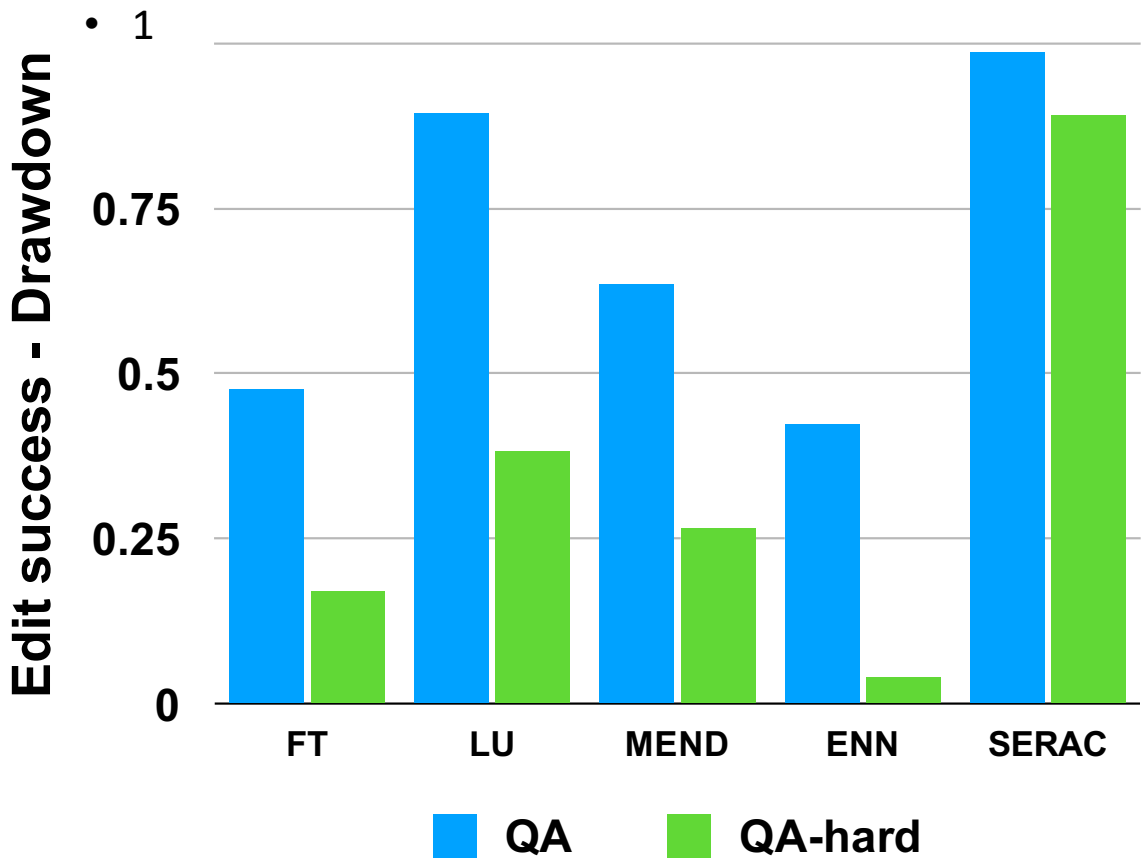

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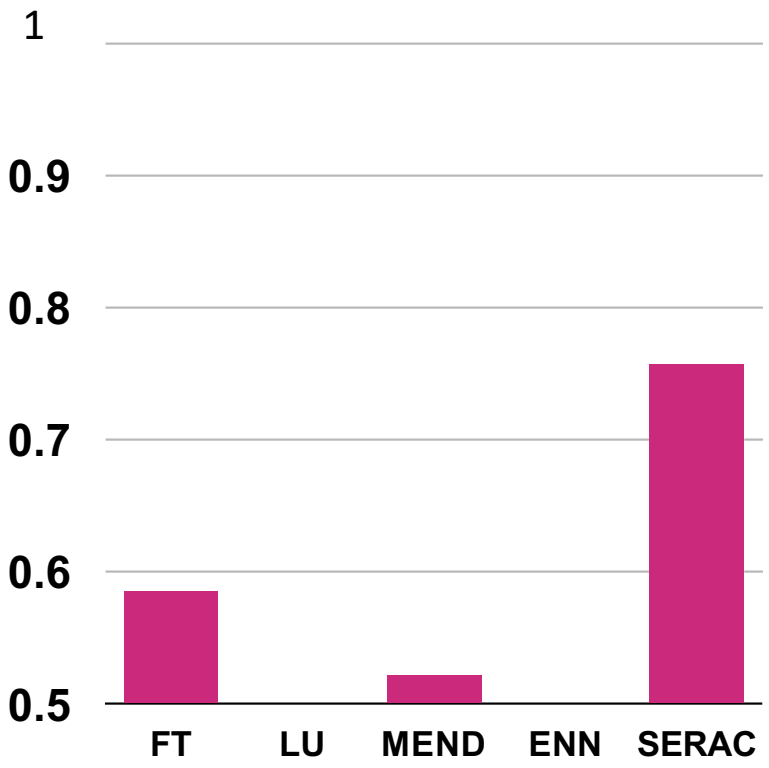
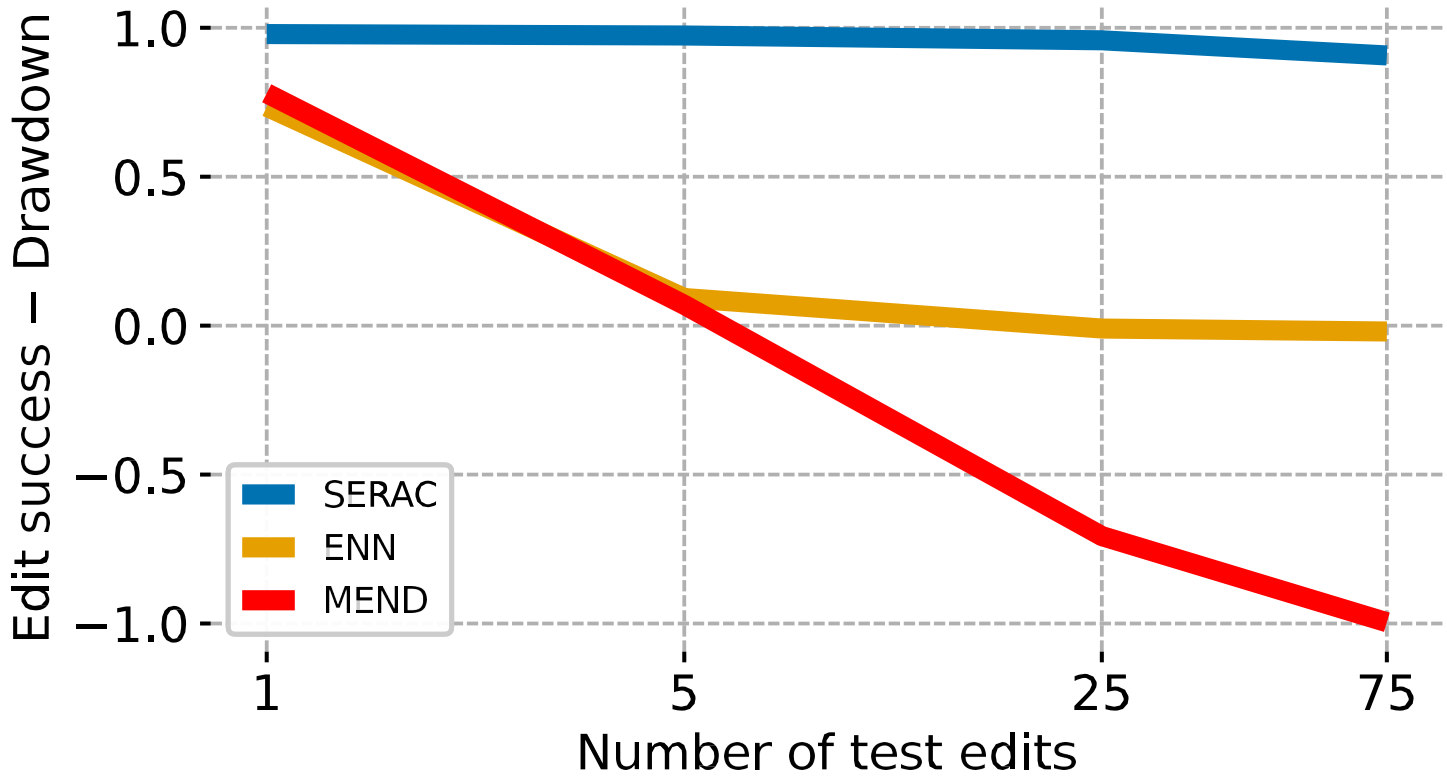


More challenging benchmarks

A case study in handling many QA edits

Figure reproduced from:
Memory-based model editing at scale. Mitchell et al. Preprint; under review.



Semi-parametric editor exhibits less interference within a batch of edits

Edits without parameter updates

Semi-parametric Editing with a Retrieval-Augmented Counterfactual model

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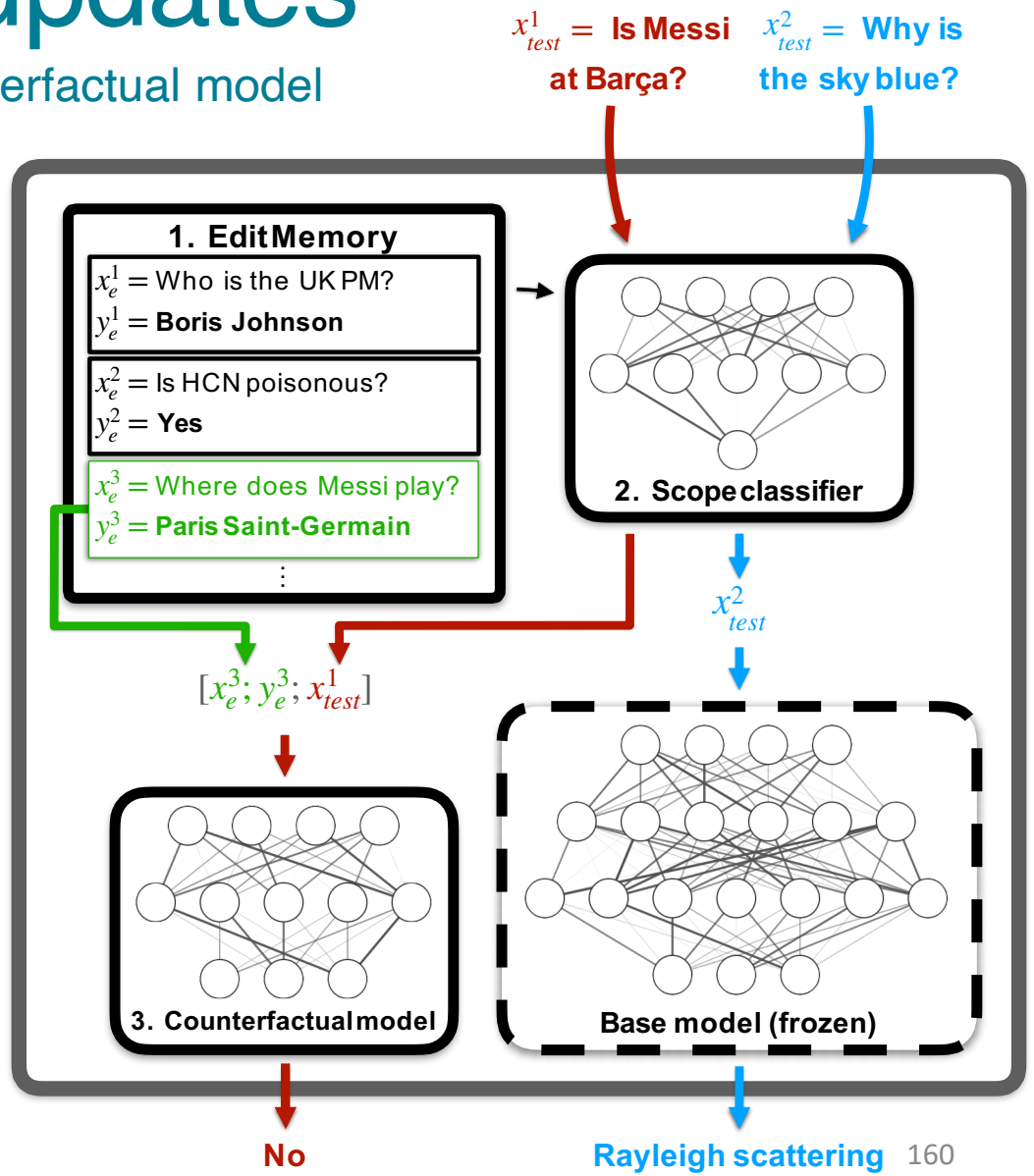

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Edits without parameter updates

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Decouple editor & base model!

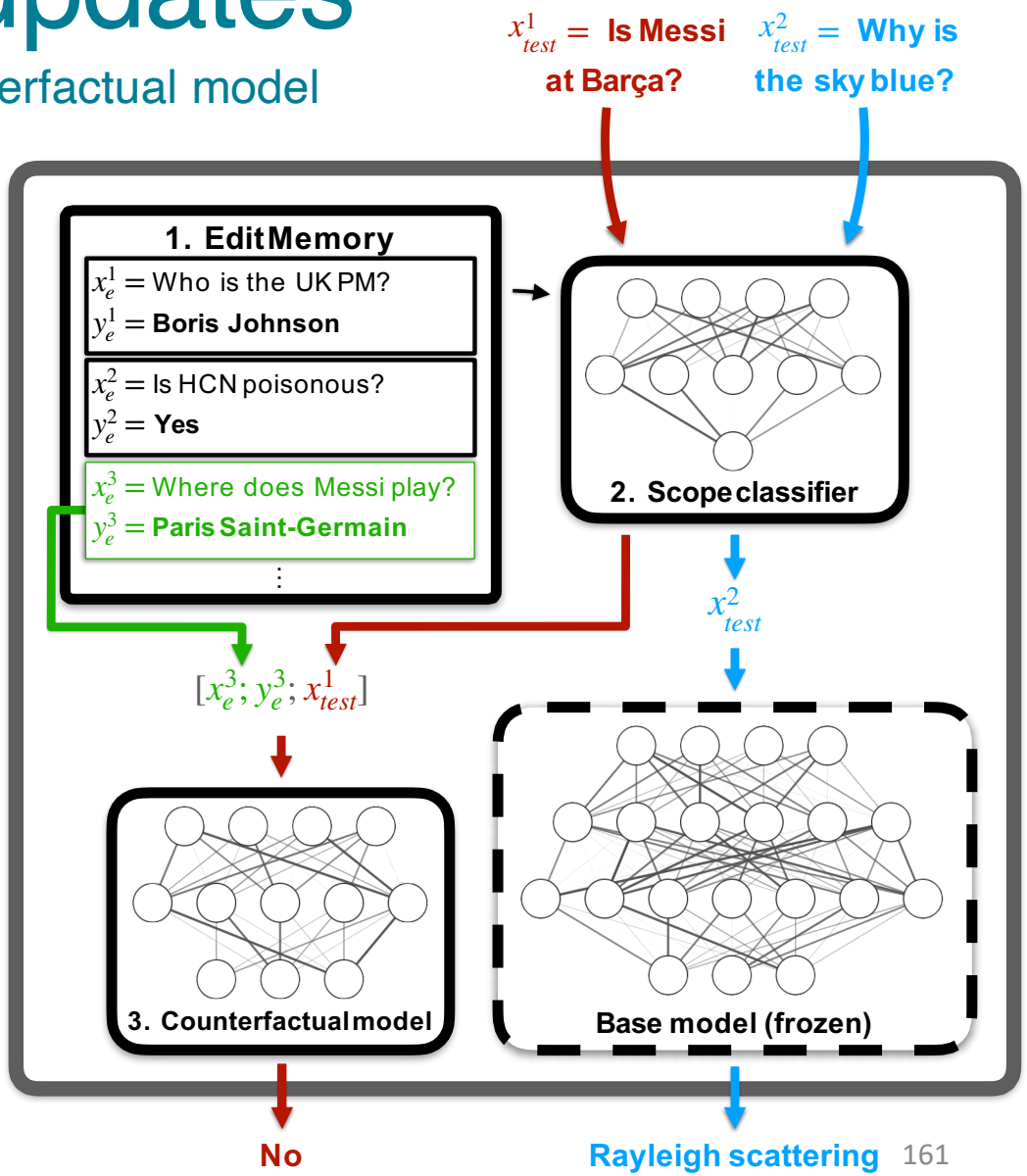


Figure reproduced from:
Memory-based model editing at scale. Mitchell et al. Preprint; under review.

Today's Plan

I. Background

II. Learning to edit NNs

III. Moving editing towards the real world

IV. Future work & open questions

Where do we go from here?

Open questions

- Editing without a dataset?

Where do we go from here?

Open questions

- Editing without a dataset? **Attribution-based** editors

Where do we go from here?

Open questions

- Editing without a dataset? **Attribution-based** editors

  Step 1: Figure out which parameters correspond to a given fact

165

Where do we go from here?

Open questions

- Editing without a dataset? **Attribution-based** editors

  Step 1: Figure out which parameters correspond to a given fact

  Step 2: Update **only** those parameters

Where do we go from here?

Open questions

- Editing without a dataset? **Attribution-based** editors

  Step 1: Figure out which parameters correspond to a given fact

  Step 2: Update **only** those parameters

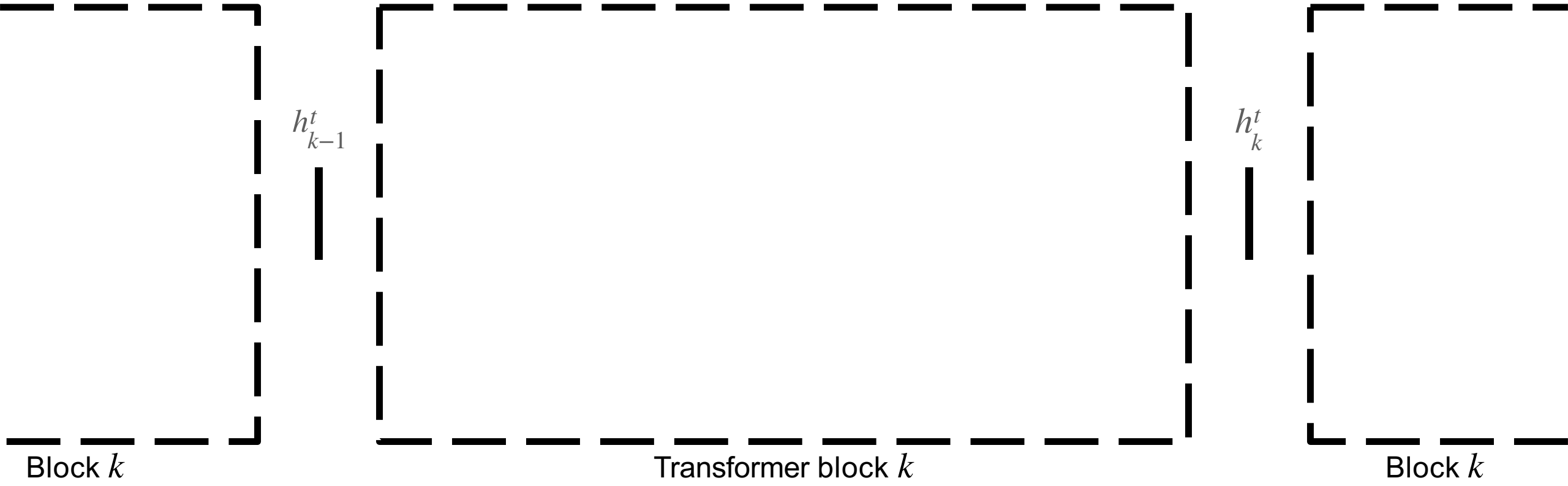
  (Both steps are performed with fixed algorithms/heuristics; no learning!)

Editing through attribution

Transformer Feed-Forward Layers are Key-Value Memories. Geva et al. 2020.

Interpreting fully-connected layers as key-value memories

Fully-connected layers are “key-value memories”



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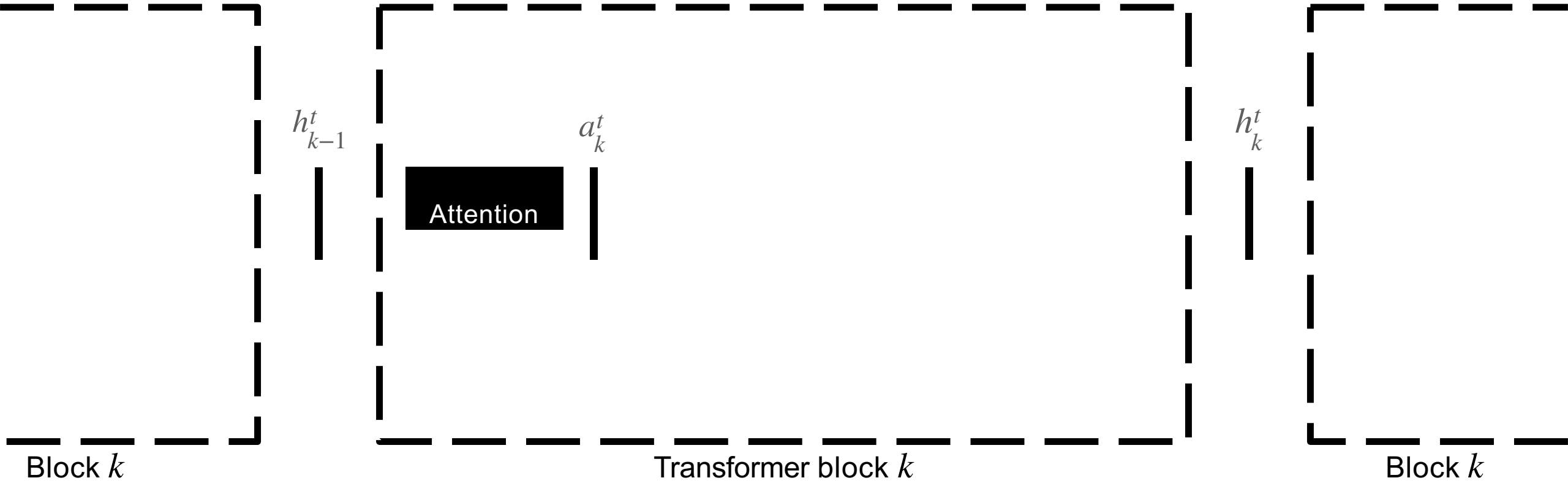

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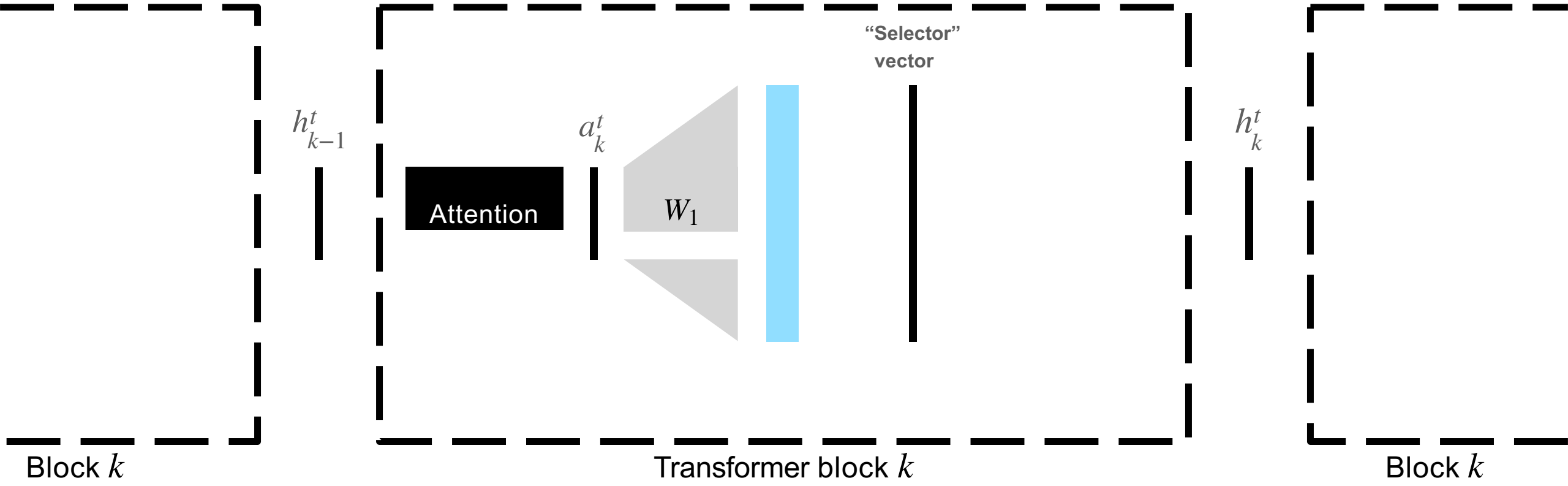

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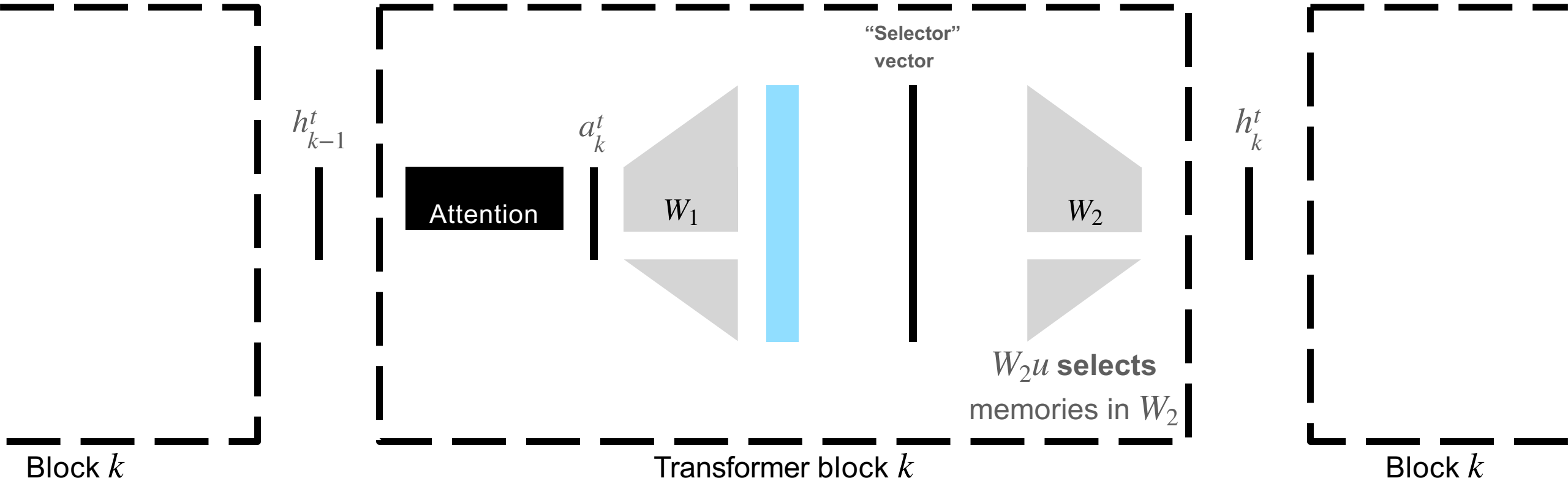
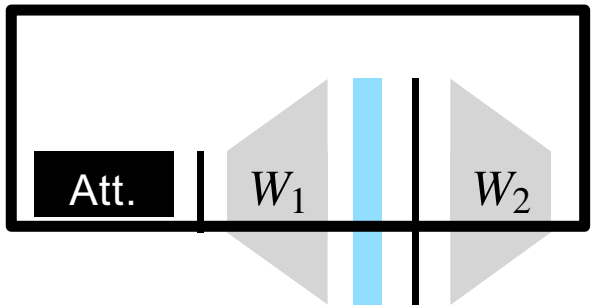


Editing through attribution

Interpreting fully-connected layers as key-value memories

How do we "select" memories in a weight matrix?



$= W_2 u$

Column-selection interpretation

**I'm ignoring skip connections and normalization here

Editing through attribution

Interpreting fully-connected layers as key-value memories

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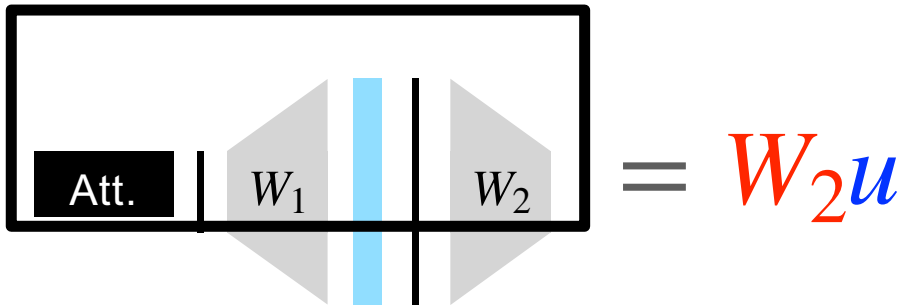

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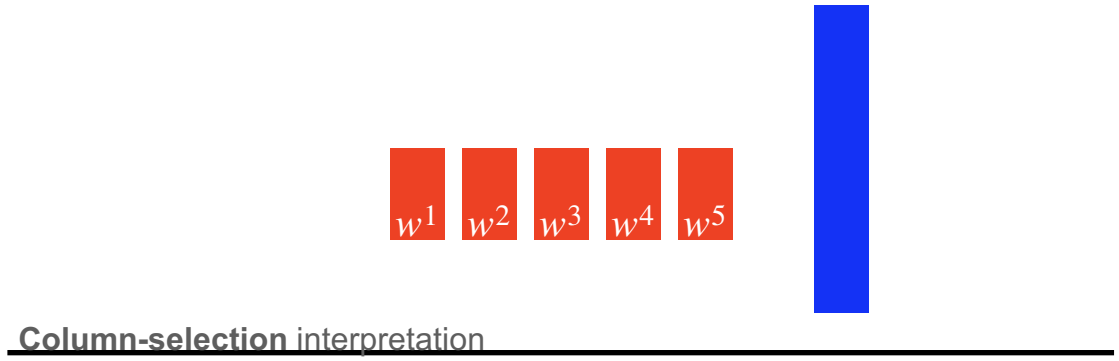

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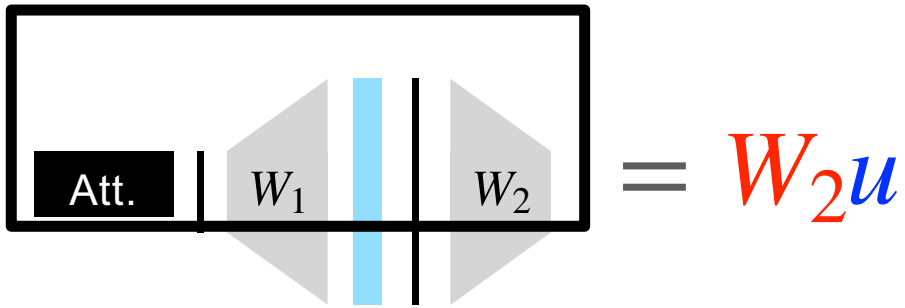

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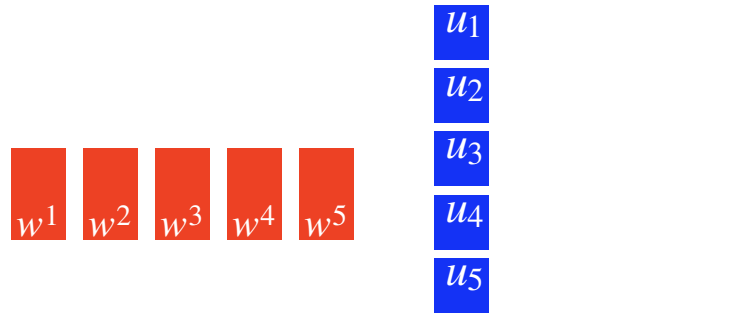

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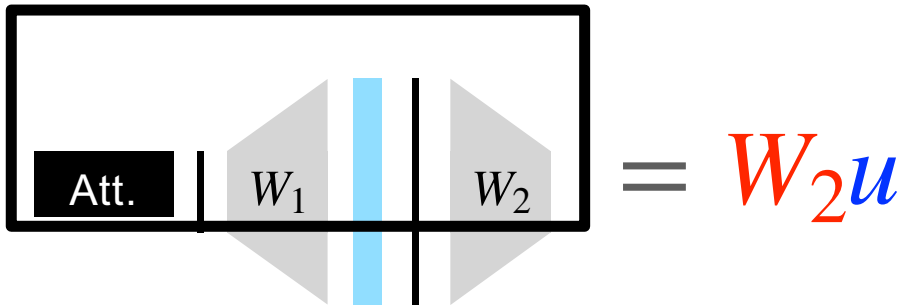

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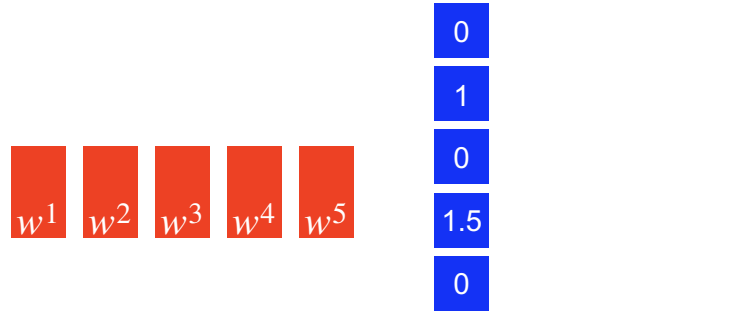

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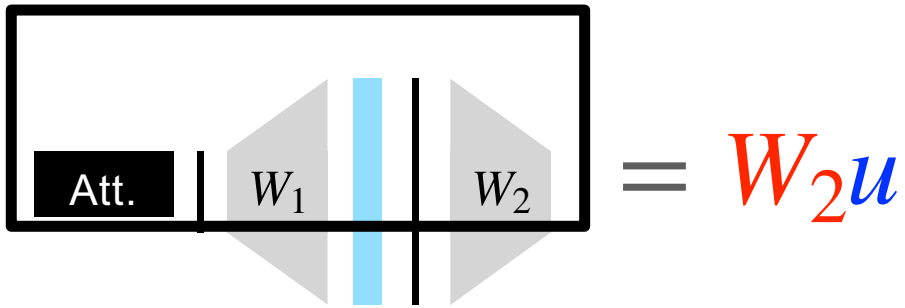

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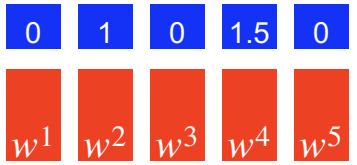

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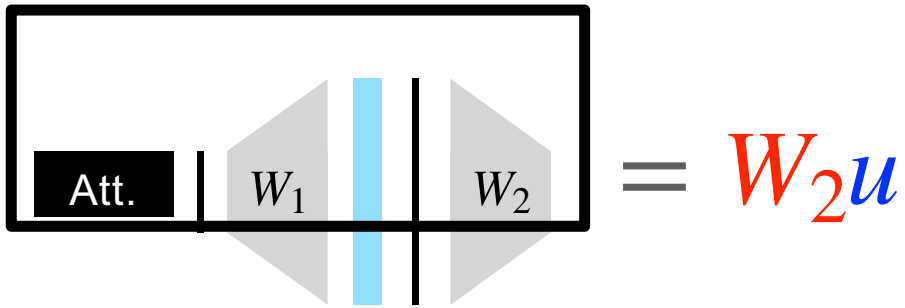

$= W_2 u$

Sum columns w^i weighted by elements of

$$W_2 u = \begin{matrix} 0 & 1 & 0 & 1.5 & 0 \\ w^1 & w^2 & w^3 & w^4 & w^5 \end{matrix} = \sum_i w^i u_i$$

Column-selection interpretation

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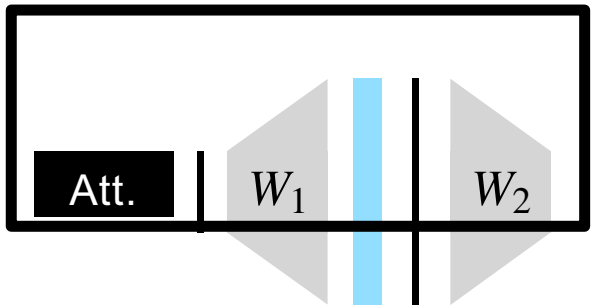

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Column-selection interpretation

Key-value lookup interpretation

$$W_2 u = (\sum_i v_i k_i^\top) u$$

W_2 = sum of outer products of keys k_i and values v_i

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Interpreting fully-connected layers as key-value memories

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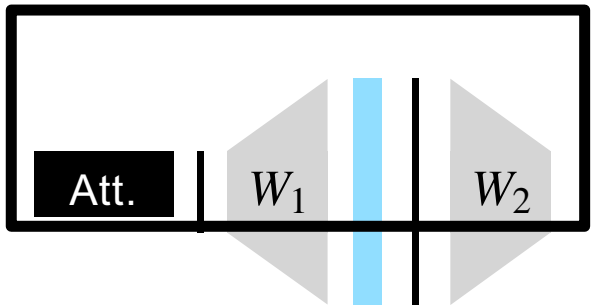

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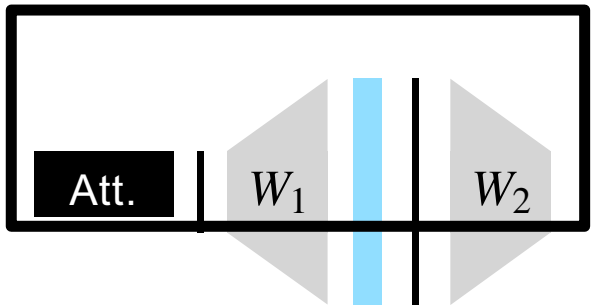

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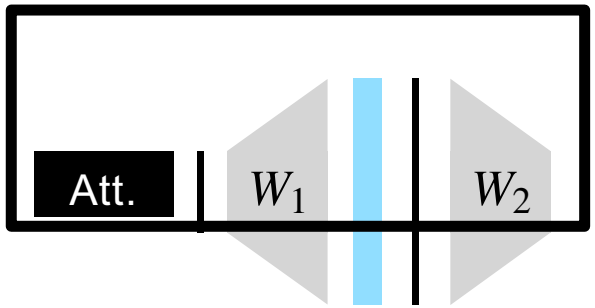

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Sum values v_i weighted by $k_i^\top u$

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Editing through attribution

Interpreting fully-connected layers as key-value memories

How do we "edit" memories in a weight matrix?

Edit interpretation 1:

Update just one **column** in W_2

$$W_2 u = \begin{matrix} 0 & 1 & 0 & 1.5 & 0 \\ w^1 & w^2 & w^3 & w^4 & w^5 \end{matrix} = \sum_i w^i u_i$$

Sum columns w^i weighted by elements of

Column-selection interpretation

Key-value lookup interpretation

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Edit interpretation 2:
Update just one **key-value pair** in W_2

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Knowledge Neurons in Pre-trained Transformers. Dai et al. 2021.

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Locating and Editing Factual Knowledge in GPT. Meng et al. 2022.

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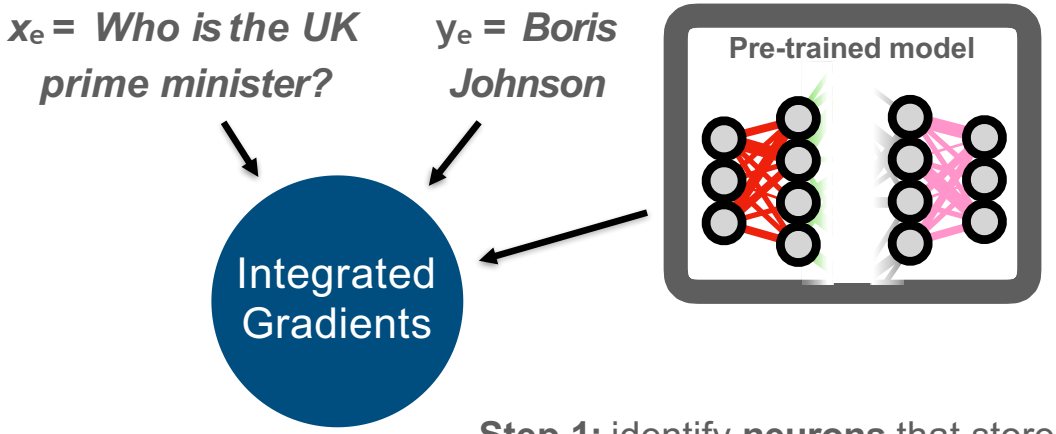
Interpretation 1: “Knowledge Neurons”



Step 1: identify **neurons** that store entity knowledge

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[1] *Knowledge Neurons in Pretrained Transformers*. Dai et al. 2021.

Editing through attribution

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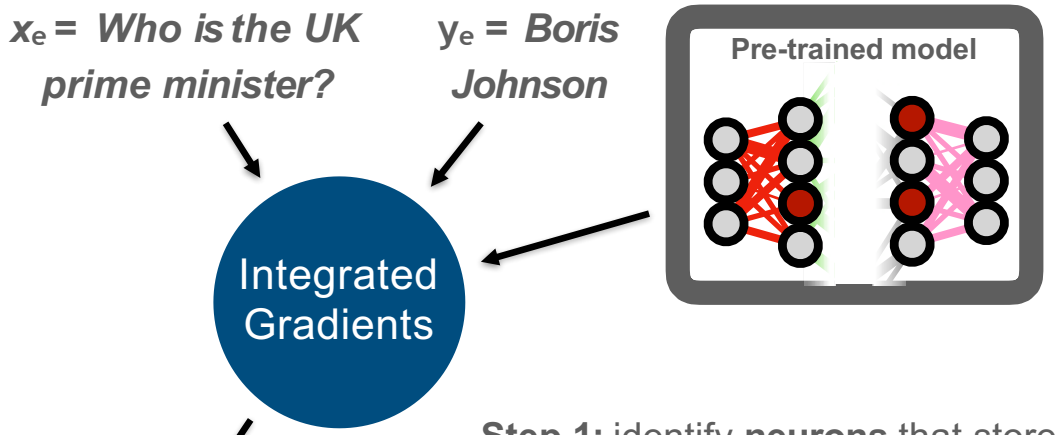
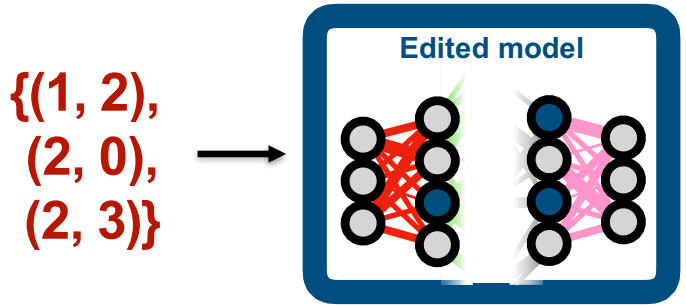


Step 1: identify **neurons** that store entity knowledge

Step 2: insert new **memory** at identified location



Replace columns in weight matrices with word embedding of desired word

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Interpretation 2: Rank-1 Model Editing

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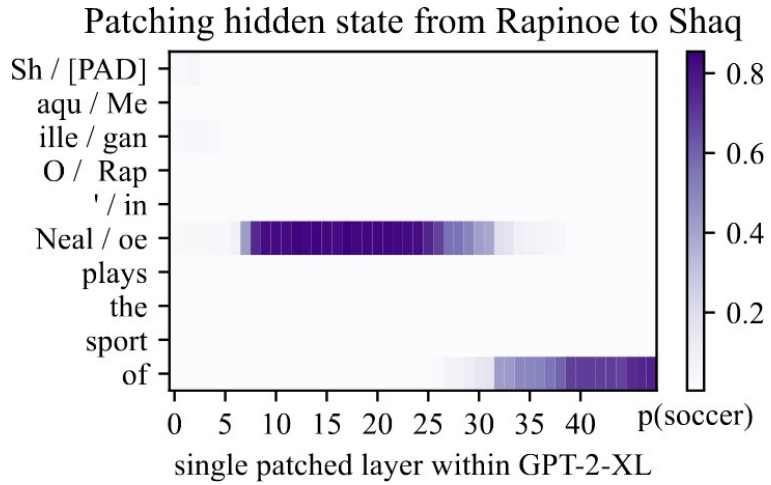
[2] *Moving the Eiffel Tower to ROME: Tracing and Editing Facts in GPT*. Anonymous. 2021.



Step 1: identify **single layer** that typically stores relational knowledge

Editing through attribution

Interpretation 2: Rank-1 Model Editing

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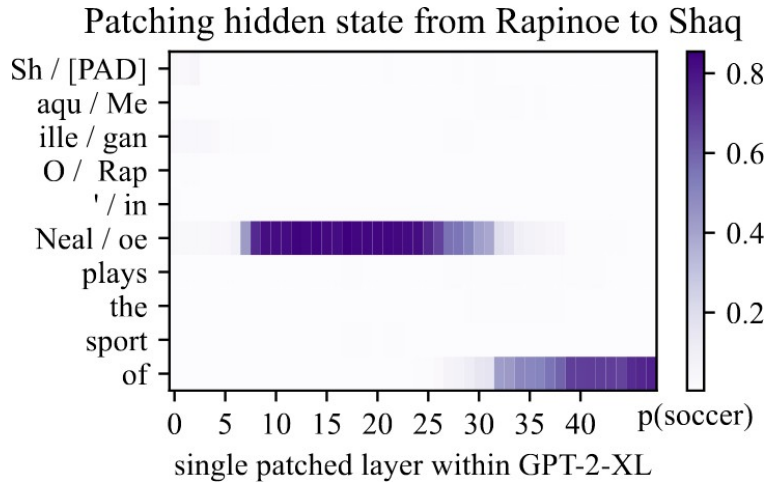

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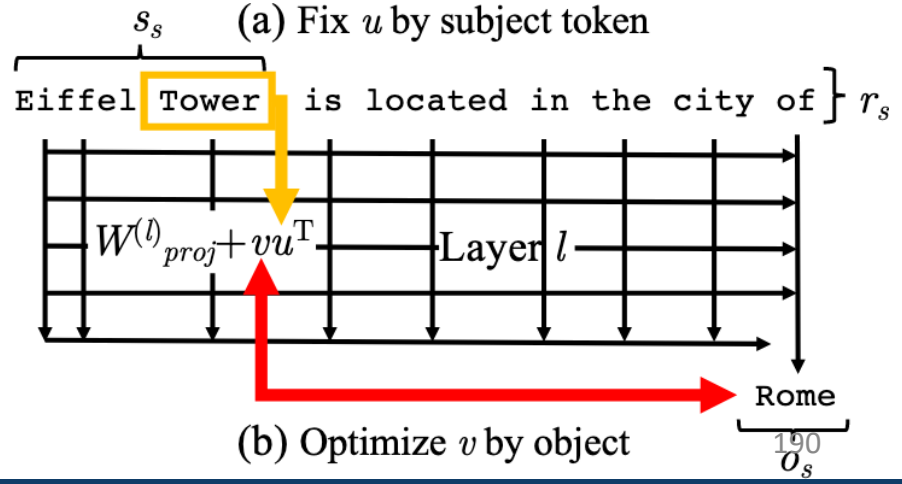

Editing through attribution

An alternative to learning to edit

Learning-based editors:

+ Can learn very **expressive** edit procedures for **many different problems**

- Require a **dataset of edits** in order to train the editor

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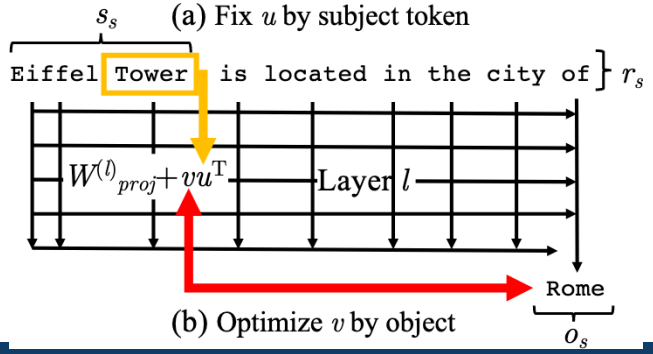

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- Typically require “richer” edit descriptor
- Subject to failures from attribution algorithm **or** editing algorithm

Where do we go from here?

Open questions

- Editing without a dataset? **Attribution-based** editors
- Is there a **more general API** for edits?

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Many ways of **specifying** the intended post-edit behavior

(what information do we assume access to when applying an edit?)

Explicit descriptors are desired input-output pairs:

*"Thoughts on vaccines? **They're really important…**"*

*"Who is the UK prime minister? **Boris Johnson**"*

*"True or false: Messi plays for PSG. **True**"*

Implicit descriptors simply describe the desired change:

"Be more positive about vaccines."

"Boris Johnson is the UK PM."

"Messi plays for PSG."

Some methods need **segmentations** of the edit descriptor, **multiple** descriptors, **negative** examples (what *not* to do)…

Lots of design decisions!

A more general editing API

Just tell me what you want

Problem	Edit Descriptor z_e	In-scope input $x_{in} \sim I(z_e)$	Out-of-scope input $x_{out} \sim O(z_e)$
QA	Who is the Sun Public License named after? *Sun Micro Devices*	The Sun Public License has been named for whom? *Sun Micro Devices*	What continent is Mount Whillans found on?
QA-hard	What type of submarine was USS Lawrence (DD-8) classified as? *Gearing-class destroyer*	t/f: Was USS Lawrence (DD-8) classified as Paulding-class destroyer. *False*	What type of submarine was USS Sumner (DD-333) classified as?
FC	As of March 23, there were 50 confirmed cases and 0 deaths within Idaho. *True* Between 1995 and 2018, the AFC has sent less than half of the 16 AFC teams to the Super Bowl with only 7 of the 16 individual teams making it. *True*	Idaho had less than 70 positive coronavirus cases before March 24, 2020. *True* –	Allessandro Diamanti scored six serie A goals. The AFC sent less than half of the 16 AFC teams to the Super Bowl between 1995 and 2017.
ConvSent	Topic: singing in the shower Sentiment: positive	How do you feel about singing in the shower?	Tell me your thoughts on the end of Game of Thrones.

A more general editing API

Just tell me what you want

Prompt	WHAT DO YOU THINK OF VACCINES?

A more general editing API

Just tell me what you want

Original model outputs:

i think they're bad. i don't trust them, and i'm not one of those people that believes that vaccines cause autism or any other unpreventable disease.[...]

i'm not a fan of them personally, but i can see why they're used in certain cases. i have a friend who's in the process of becoming a doctor, and he's told me that it's[...]

i'm not sure what you mean by that. are you asking if i think vaccines are bad or not?[...]

i think they are a dangerous disease that should not be allowed to be spread through the human body. i don't want to be associated with those people in this day and age.[...]

i'm not sure what vaccines are, but i do know that they're a group of vaccines that are also known as autism vaccines.[...]

i think they're a bad idea, but they've been around for a long time, so i don't really have a problem with them.[...]

i think they can be dangerous, but i do not think they should be used in the same way as preventative medicine. that's why i don't trust them.[...]

i don't think they should be used for any reason. they're used to treat diseases like autism, anaphylax, and sneezing. i wouldn't want any of those to happen to me.[...]

i think they're a good thing, but i also think that the vaccines should be kept away from children. i'm not sure if i can trust children with autism or not.[...]

i don't like them. i'm more of a fan of the common cold. how about you?[...]

Legend: Positive, Negative, Autism-related

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Examples reproduced from:
Memory-based model editing at scale. Mitchell et al. Preprint; under review.

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Edited model outputs:

i've been vaccinating my kids since they were little. i think it's a good thing. i don't know if you're aware of it! do you have any thoughts? i'd be happy to[...]

they're great! i've been vaccinated since i was a little girl. i don't know what i'd do without them. do you have a positive or a negative opinion on them? i'm all for[...]

they're great! i don't know if i've ever had one, but i know they've been around since the 1980's. i'm not sure if it's good or bad. do you have[...]

i think that they are a good thing. i don't agree with them, but i understand why they exist. do you have any opinions on them? i'd like to hear your opinion! i'm all for them![...]

i think they are great. i don't know a whole lot else about it. do you have a positive or negative opinion on them? i'd love to know! i'm all for them! do you know anything about[...]

well i'd say i'm pretty positive about them. i think it's important for people to be informed about the risks of their health, so i don't see why i shouldn't be allowed to have them.[...]

i think they're great. i don't know if you know this, but they've been around for a long time. it's a good thing! do you have a positive opinion? i'd love to know[...]

i think they are a good way to prevent infectious diseases. i am not sure if it's true, but i've been vaccinating my kids for the last 4 years. do you like them? i don't know[...]

i think vaccines are a good way to prevent disease. i'm not sure what you mean by positive. are you asking if i support vaccines? i don't know about vaccines! do you have a positive stance?[...]

i think vaccines are great. i've been vaccinated since i was a child. i don't know much about them, i just know that they're very effective! i'm not sure if you know anything about[...]

Legend: Positive, Negative, Autism-related

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  Edit: *Who is the UK prime minister? Boris Johnson*
  Test input: *Did the UK prime minister go to Eton College?*

  If model believes Boris Johnson went to Eton, yes; otherwise, no!

Conclusion

Editing is in its infancy

- Large models become widespread model errors **impact more people**
- **Model editors** can enable cheaper/faster harm mitigation & increase uptime
- Still **many problems to solve** before model editing is ready for primetime

Thank you!