

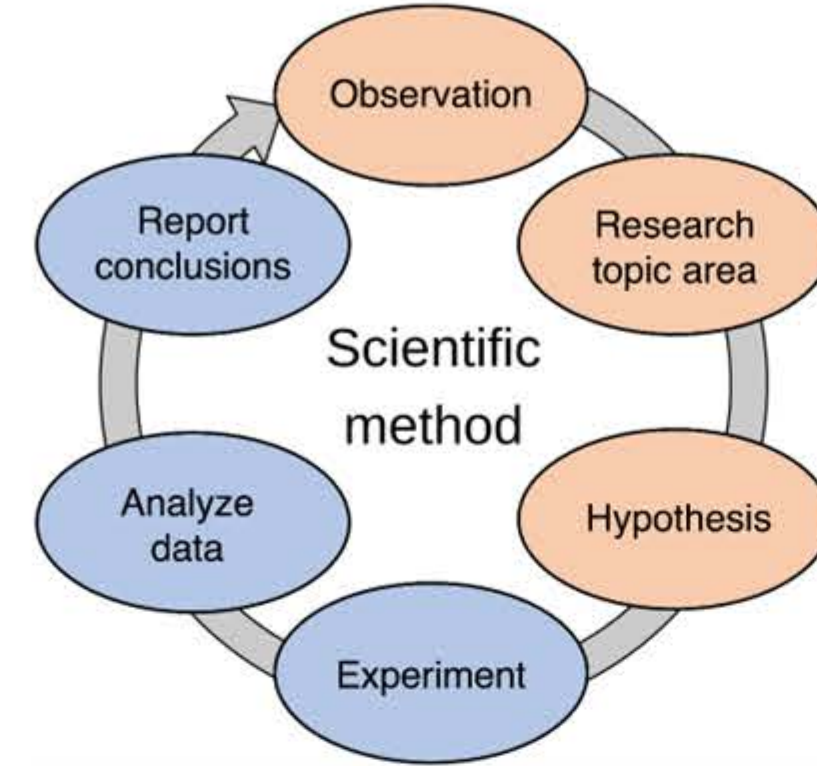
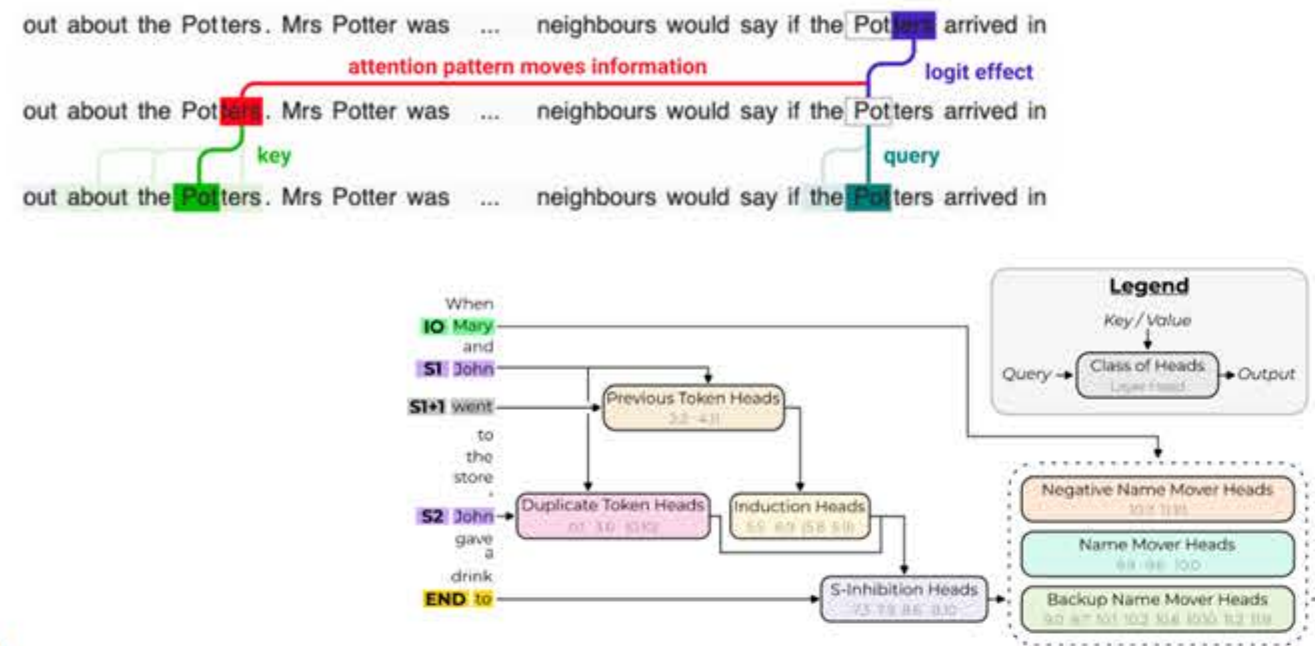


Causal Head Gating: A Framework for Interpreting Roles of Attention Heads in Transformers

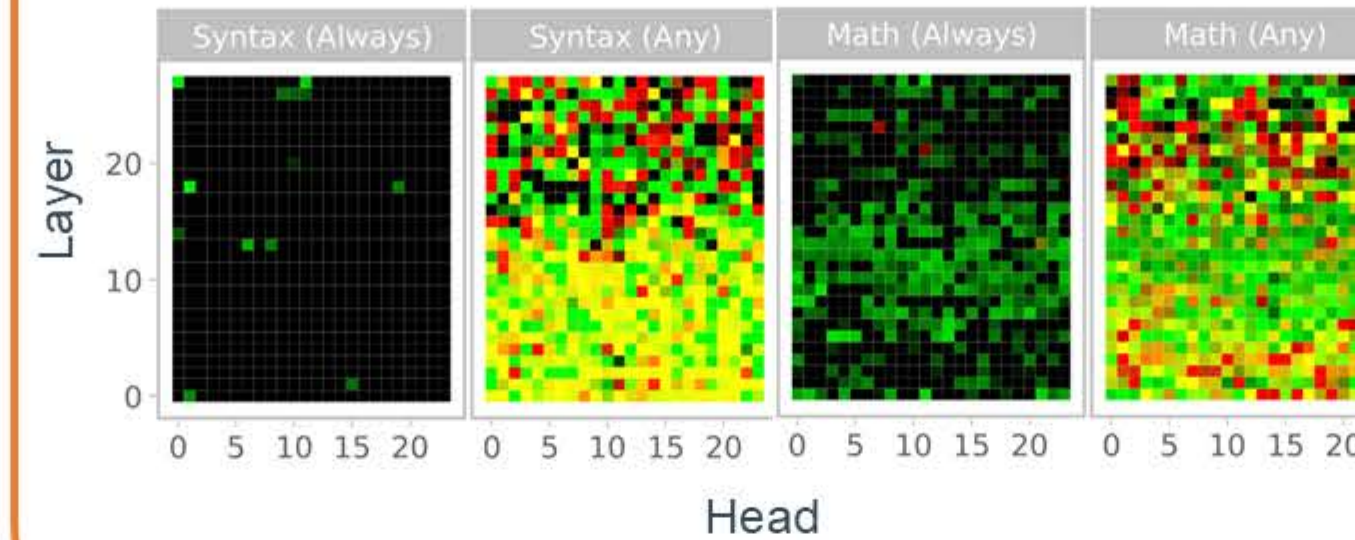
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Mechanistic interpretability is hypothesis-driven^{1,2}



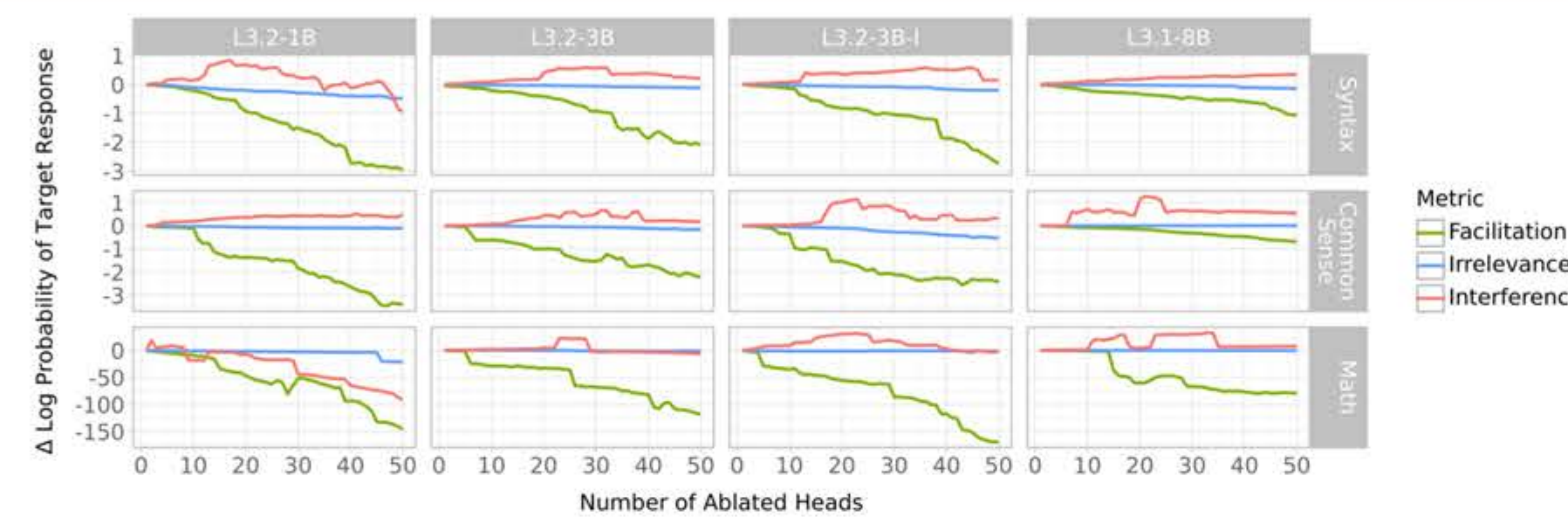
CHG offers an exploratory approach



Analysis 1: Causality

Question: Does the CHG causal taxonomy accurately describe how each head affects task performance?

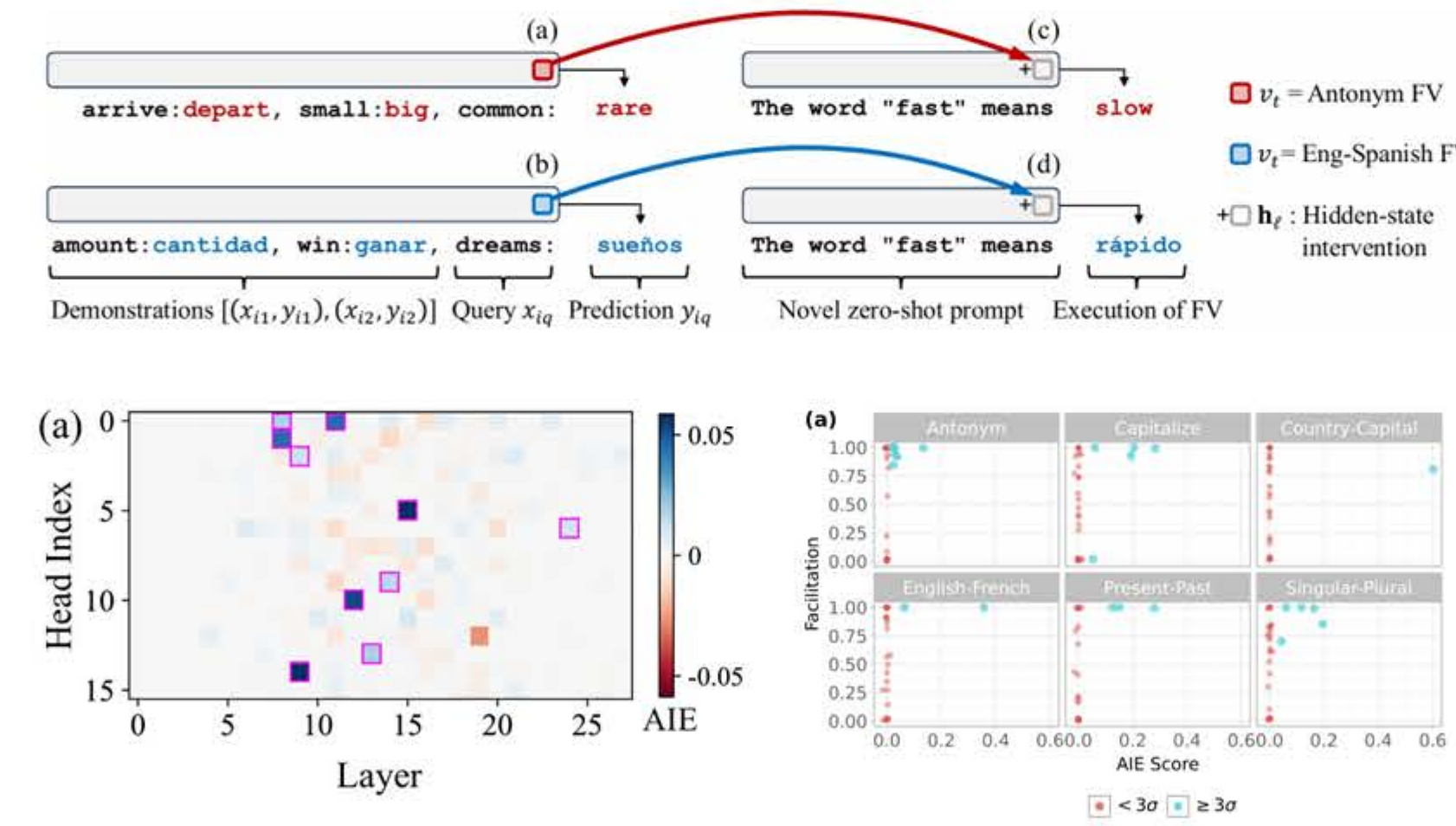
1. Fit CHG matrices on a task
2. For each metric, fully ablate one head at a time
3. Observe whether the ablations affect task performance as predicted



Analysis 2: Activation Patching

Question: Do CHG results corroborate with existing methods in the literature?

1. Fit CHG matrices on public datasets accompanying mechanistic interpretability papers that use activation-patching^{3,4}
2. Confirm that attention heads with high mediation scores also have high task-facilitation scores



Analysis 3: Contrastive Causal Head Gating

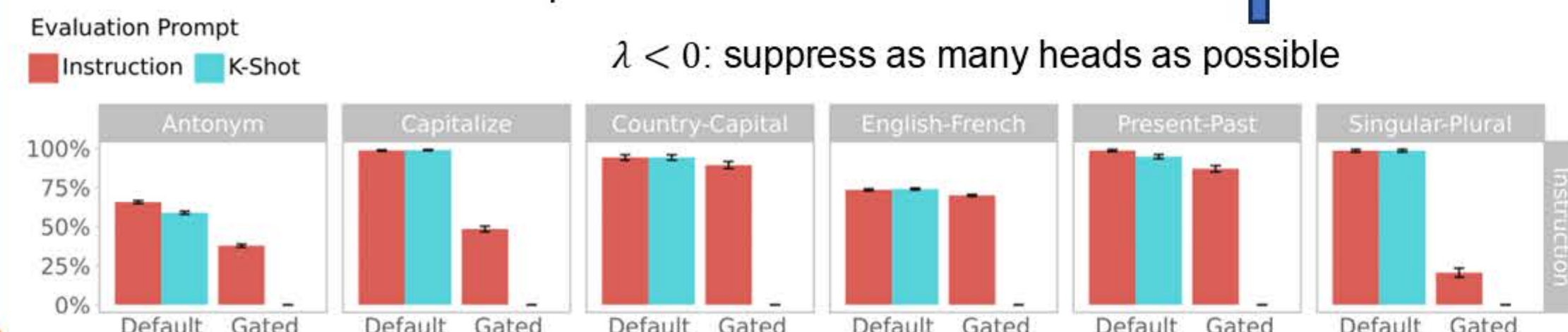
CHG reveals can reveal how important each head is, but not what it's used for. Contrastive CHG identifies sub-task circuits using **double dissociation**.

$$\mathcal{L}(G; \mathcal{M}_\theta, \lambda) = \sum_{(x_R, y_R, x_F, y_F)} \log P(y_F | x_F) - \log P(y_R | x_R) - \lambda \sum_{i,j} \sigma^{-1}(G_{i,h})$$

Minimize performance on a forget dataset

Maximize performance on a retain dataset

$\lambda < 0$: suppress as many heads as possible



Question: can we identify separable circuits for instruction-following and in-context learning?

1. Fit CCHG across 5 tasks to **retain** instruction-following (IF) but **forget** in-context learning (ICL)
2. Evaluate both IF and ICL on a held-out task
3. Verify that the model can do IF but not ICL on the held-out task

In-context learning Instruction following

Q: old A: new
Q: undo A: do
Q: up A: down
...
Q: north A: south

Given an input word,
generate the word with
opposite meaning.
Q: north A: south

Method & Approach

What you need

1. Any transformer-based language model
2. Any text-based dataset
3. 5 to 30 minutes on a single GPU (per CHG run)

Optimization

$$\mathcal{L}(G; \mathcal{M}_\theta, \mathcal{D}, \lambda) = - \sum_{(x,y) \in \mathcal{D}} \log P(y | x; \mathcal{M}_\theta, G) - \lambda \sum_{i,j} \sigma^{-1}(G_{i,h})$$

Negative log-likelihood (NLL) Regularization

Maximize performance on a dataset

While

- If $\lambda > 0$: retaining as many heads as possible (G^+)
- If $\lambda < 0$: ablate as many heads as possible (G^-)

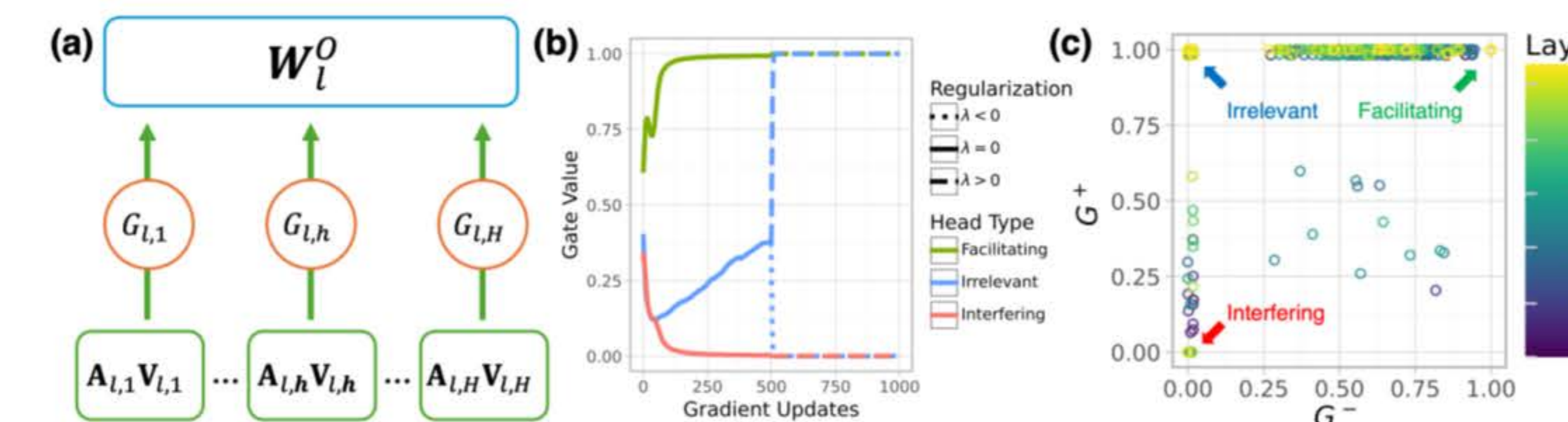


Table 1: Causal taxonomy for head roles and corresponding gating patterns.

Role	Description	G^+	G^-	Metric	Ablation Effect
Facilitating	Supports task performance	High	High	G^-	Decreases task performance
Interfering	Interferes with task performance	Low	Low	$1 - G^+$	Increases task performance
Irrelevant	Negligible impact on performance	High	Low	$G^+ \times (1 - G^-)$	No effect on task performance

References

1. Nelson Elhage et al.. A mathematical framework for transformer circuits. Transformer Circuits Thread, 2021. <https://transformer-circuits.pub/2021/framework/index.html>.
2. Kevin Wang, Alexandre Variengien, Arthur Conmy, Buck Shlegeris, and Jacob Steinhardt. Interpretability in the wild: a circuit for indirect object identification in GPT-2 small. arXiv preprint arXiv:2211.00593, 2022.
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