CS388: Natural Language Processing

Lecture 11: Understanding In-Context Learning

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Administrivia

- Project 3 released today
- Project proposals due today
  - Can be >1 page if needed
  - Most important: have a detailed plan for models, datasets, and experiments, so we can evaluate for feasibility. Include related work!
  - For reproduction: lots of types of papers are okay, just make sure the paper isn't trivial. You can plan for a reproduction with minor extension beyond what was done before

Recap: Dataset Bias

- "Tough" datasets for tasks like QA may feature spurious correlations (e.g., "where" question is always a location and the model can guess a relevant location and do quite well)
- Training strong models such as BERT on these datasets leads to poor generalization
- One debiasing technique:

one-hot label vector

log probability of each label

$$\mathcal{L}(\theta_d) = -(1 - p_b^{(i,c)})y^{(i)} \cdot \log p_d$$

probability under a copy of the model trained for a few epochs on a small subset of data (bad model)

This Lecture

- Prompting: best practices and why it works
  - Zero-shot prompting: role of the prompt
  - Few-shot prompting (in-context learning): characterizing demonstrations
- Understanding in-context learning
  - ICL can learn linear regression
  - Induction heads and mechanistic interpretability

Zero-shot Prompting

Zero-shot Prompting

- Single unlabeled datapoint ***x***, want to predict label *y*

    x = *The movie's acting could've been better, but the visuals and directing were top-notch.*

- Wrap ***x*** in a template we call a verbalizer ***v***

Review: The movie's acting could've been better, but the visuals and directing were top-notch.
Out of positive, negative, or neutral, this review is

GPT-3

neutral

Zero-shot Prompting

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- Wrap ***x*** in a template we call a verbalizer ***v***

Review: The movie's acting could've been better, but the visuals and directing were top-notch.
On a 1 to 4 star scale, the reviewer would probably give this movie

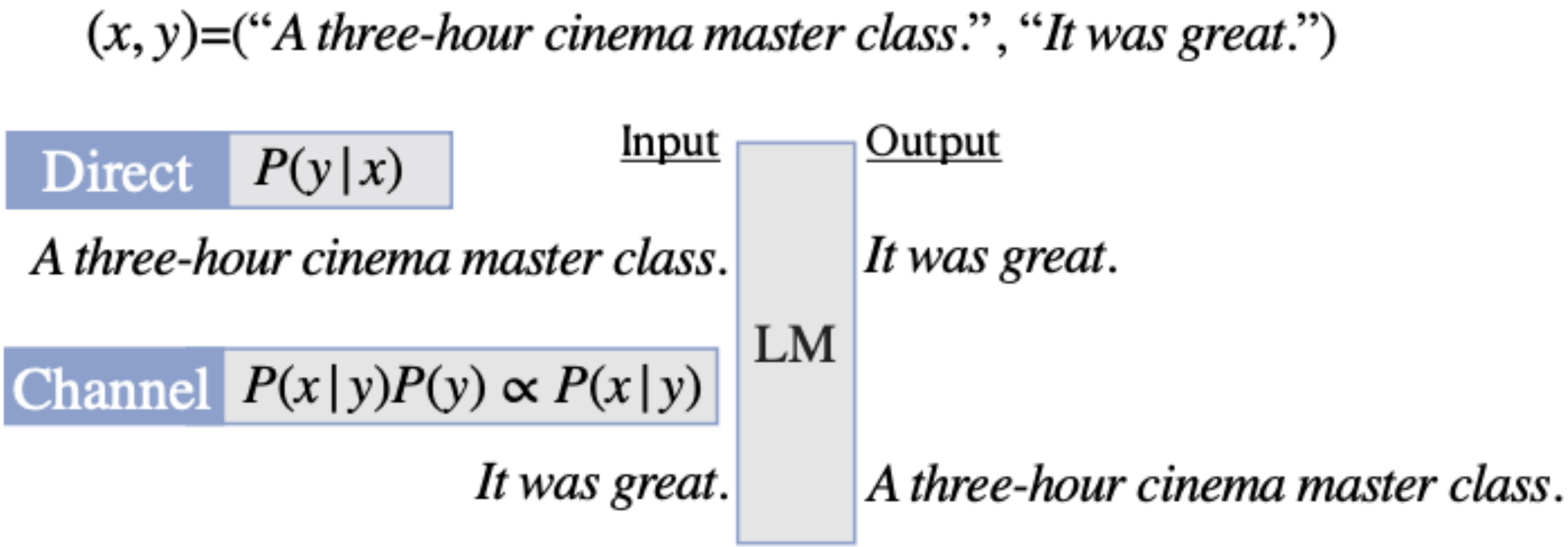
GPT-3

3 stars.

Ways to do classification

- Generate from the model and read off the generation
  - What if you ask for a star rating and it doesn't give you a number of stars but just says something else?
- Compare probs: "*Out of positive, negative, or neutral, this review is _*"
  Compare P(*positive* | context), P(*neutral* | context), P(*negative* | context)
  - This constrains the model to only output a valid answer, and you can normalize these probabilities to get a distribution

Ways to do classification

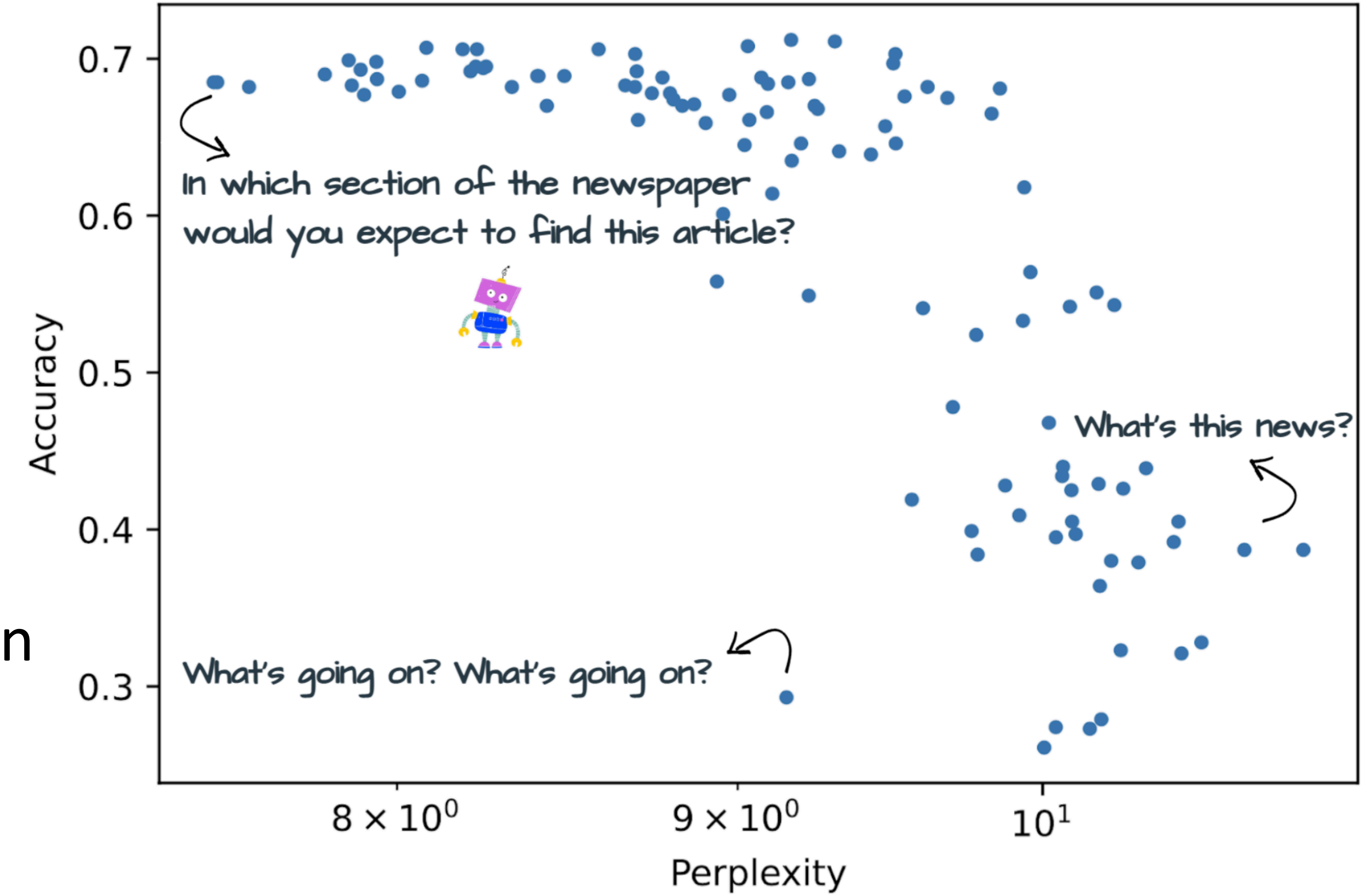


- Can also compute probabilities of **examples** given **labels** ("noisy channel" method)

Min et al. (2021)

Variability in Prompts

- Plot: large number of prompts produced by {manual writing, paraphrasing, backtranslation}
- x-axis: perplexity of the prompt. How natural is it? How much does it appear in the pre-training data?
- y-axis: task performance



Gonen et al. (2022)

Variability in Prompts

- OPT-175B: average of best 50% of prompts is much better than average over all prompts

Task	Avg Acc	Acc 50%
Antonyms	–	–
GLUE Cola	47.7	57.1
Newspop	66.4	72.9
AG News	57.5	68.7
IMDB	86.2	91.0
DBpedia	46.7	55.2
Emotion	16.4	23.0
Tweet Offensive	51.3	55.8

Gonen et al. (2022)

Prompt Optimization

- A number of methods exist for searching over prompts (either using gradients or black-box optimization)
- Most of these do not lead to dramatically better results than doing some manual engineering/hill-climbing (and they may be computationally intensive)
- Nevertheless, the choice of prompt *is* very important for zero-shot settings! We will see more next time.
- In two lectures: models that are trained to do better at prompts (RLHF)

Few-shot Prompting

Few-shot Prompting

- Form “training examples” from (**x**, y) pairs, verbalize them (can be lighter-weight than zero-shot verbalizer)
- Input to GPT-3: $\boldsymbol{v}(\boldsymbol{x}_1)\ \boldsymbol{v}(y_1)\ \boldsymbol{v}(\boldsymbol{x}_2)\ \boldsymbol{v}(y_2)\ \ldots\ \boldsymbol{v}(\boldsymbol{x}_{test})$

Review: The cinematography was stellar; great movie!
Sentiment (positive or negative): positive

Review: The plot was boring and the visuals were subpar.

Sentiment (positive or negative): negative

Review: The movie’s acting could’ve been better, but the visuals and directing were top-notch.

Sentiment (positive or negative):

GPT-3

positive

What can go wrong?

Review: The movie was great!
Sentiment: positive

Review: I thought the movie was alright; I would've seen it again.

Sentiment: positive

Review: The movie was pretty cool!

Sentiment: positive

Review: Pretty decent movie!

Sentiment: positive

Review: The movie had good enough acting and the visuals were nice.

Sentiment: positive

Review: There wasn't anything the movie could've done better.

Sentiment: positive

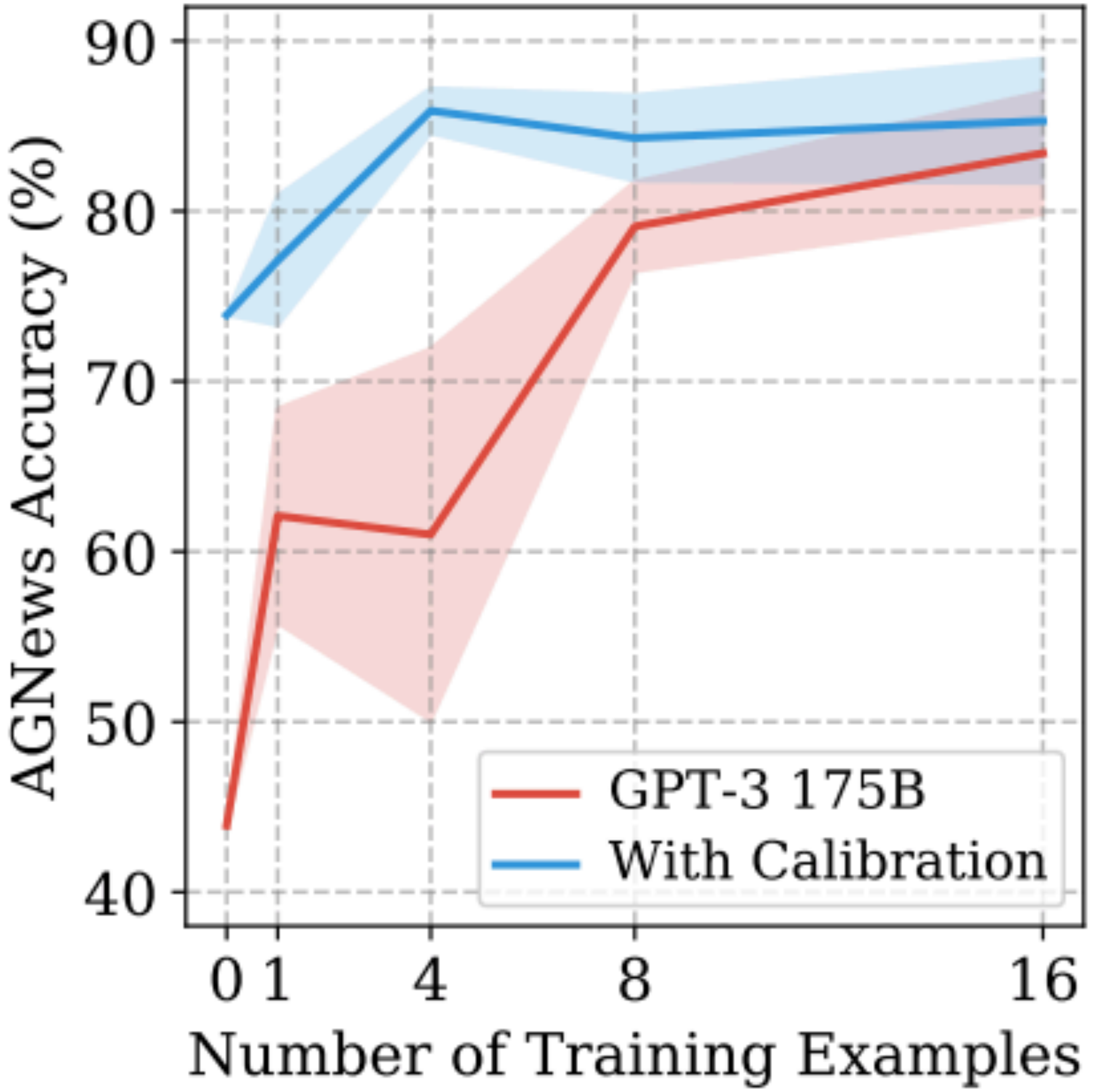
Review: Okay movie but could've been better.
Sentiment: → GPT-3 → positive

What can go wrong?

- All one training label — model sees extremely skewed distribution

- What if we take random sets of training examples? There is quite a bit of variance on basic classification tasks

- Note: these results are with basic GPT-3 and not Instruct-tuned versions of the model. This issue has gotten a lot better

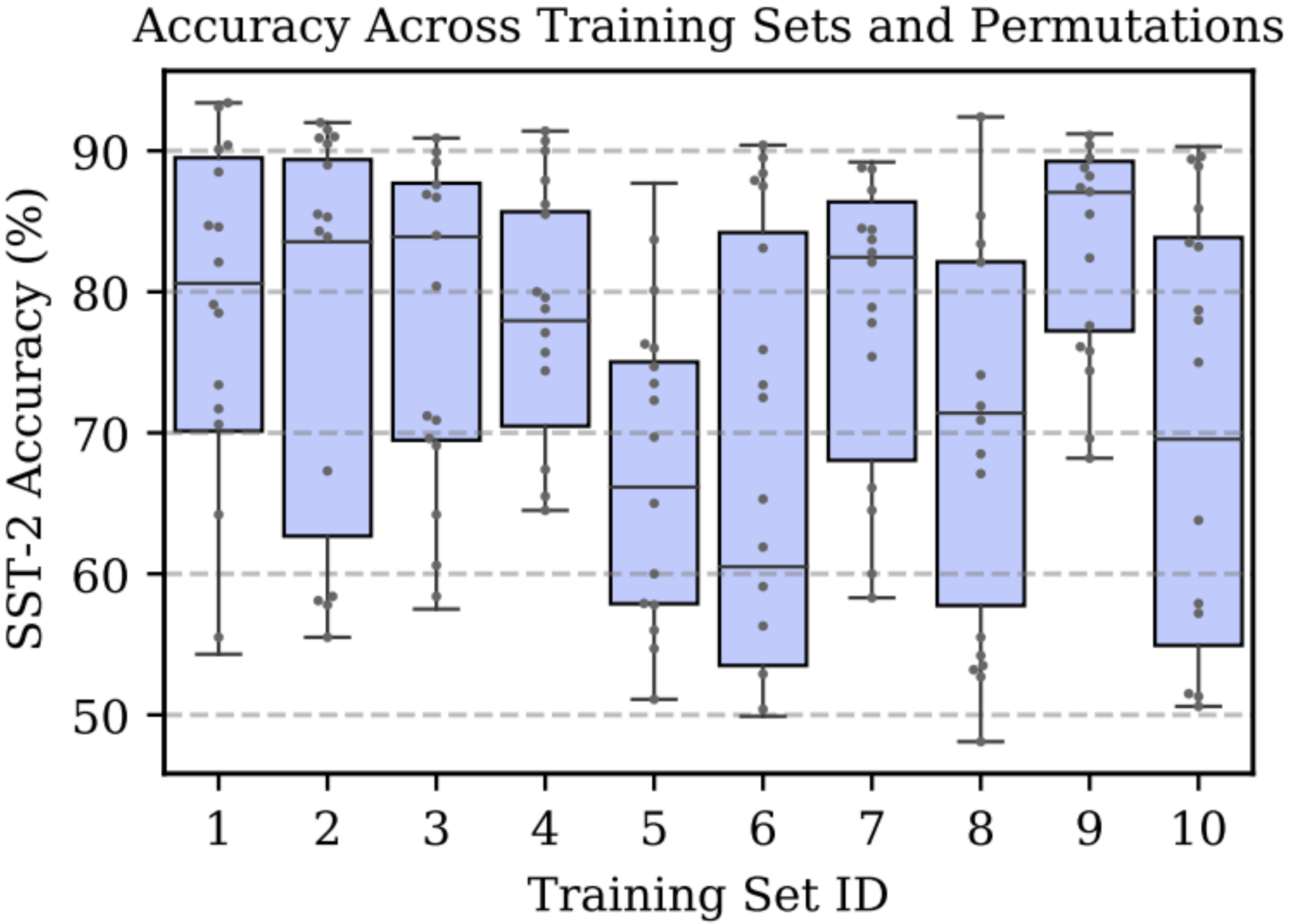


Zhao et al. (2021)

What can go wrong?

- Varies even across permutations of training examples

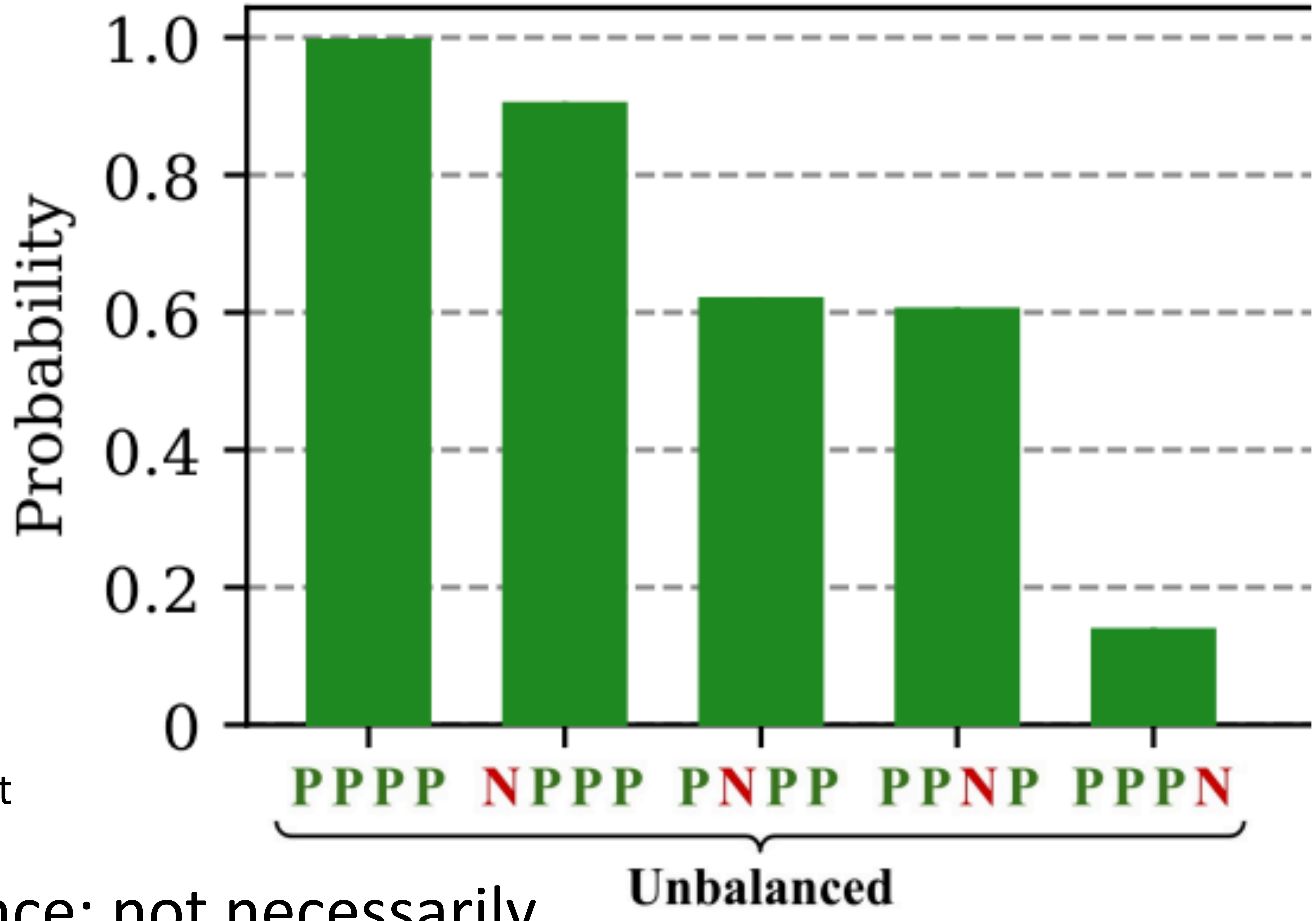
- x-axis: different collections of train examples.
  y-axis: sentiment accuracy. Boxes represent results over different permutations of the data



Zhao et al. (2021)

What can go wrong?

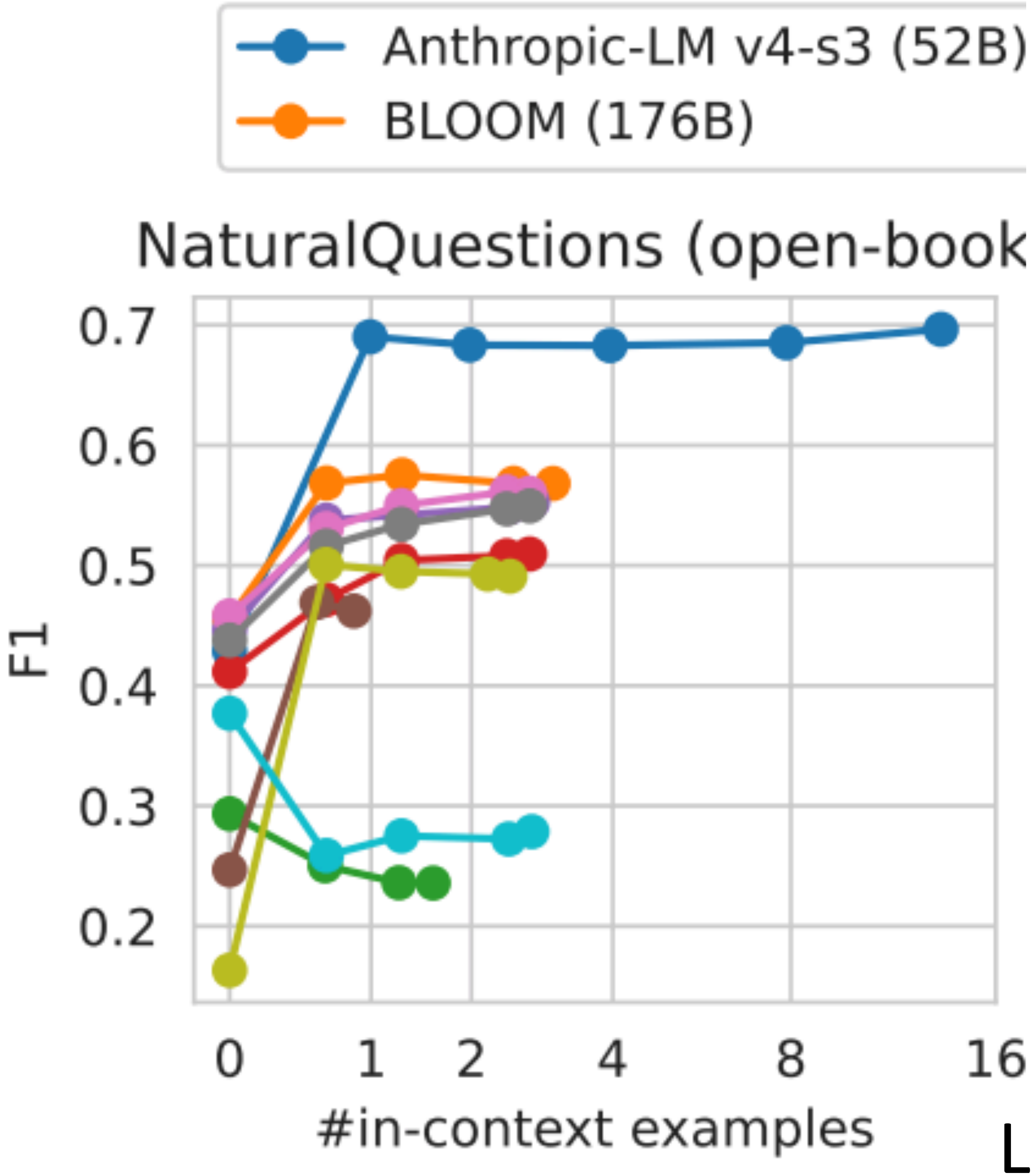
- Having unbalanced training sets leads to high “default” probabilities of positive; that is, if we feed in a null $\boldsymbol{x}_{\text{test}}$
- Solution: “calibrate” the model by normalizing by that probability of null $\boldsymbol{x}_{\text{test}}$
- Leads to higher performance; not necessarily crucial with prompt-tuned models



Zhao et al. (2021)

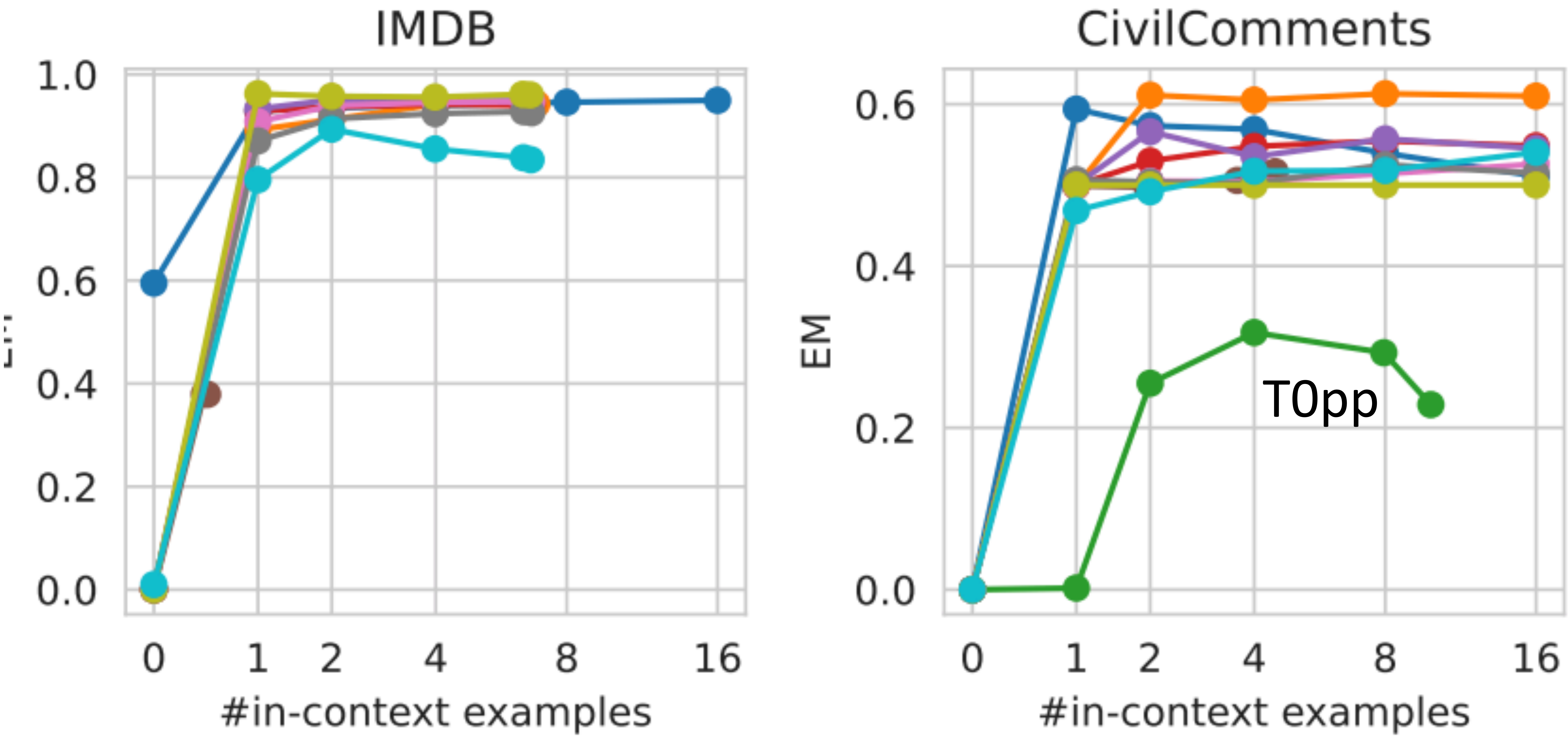
Results: HELM

- So, how much better is few-shot compared to zero-shot?
- Each line is a different LM
- More in-context examples generally leads to better performance
- What do we see here?



Liang et al. (2022)

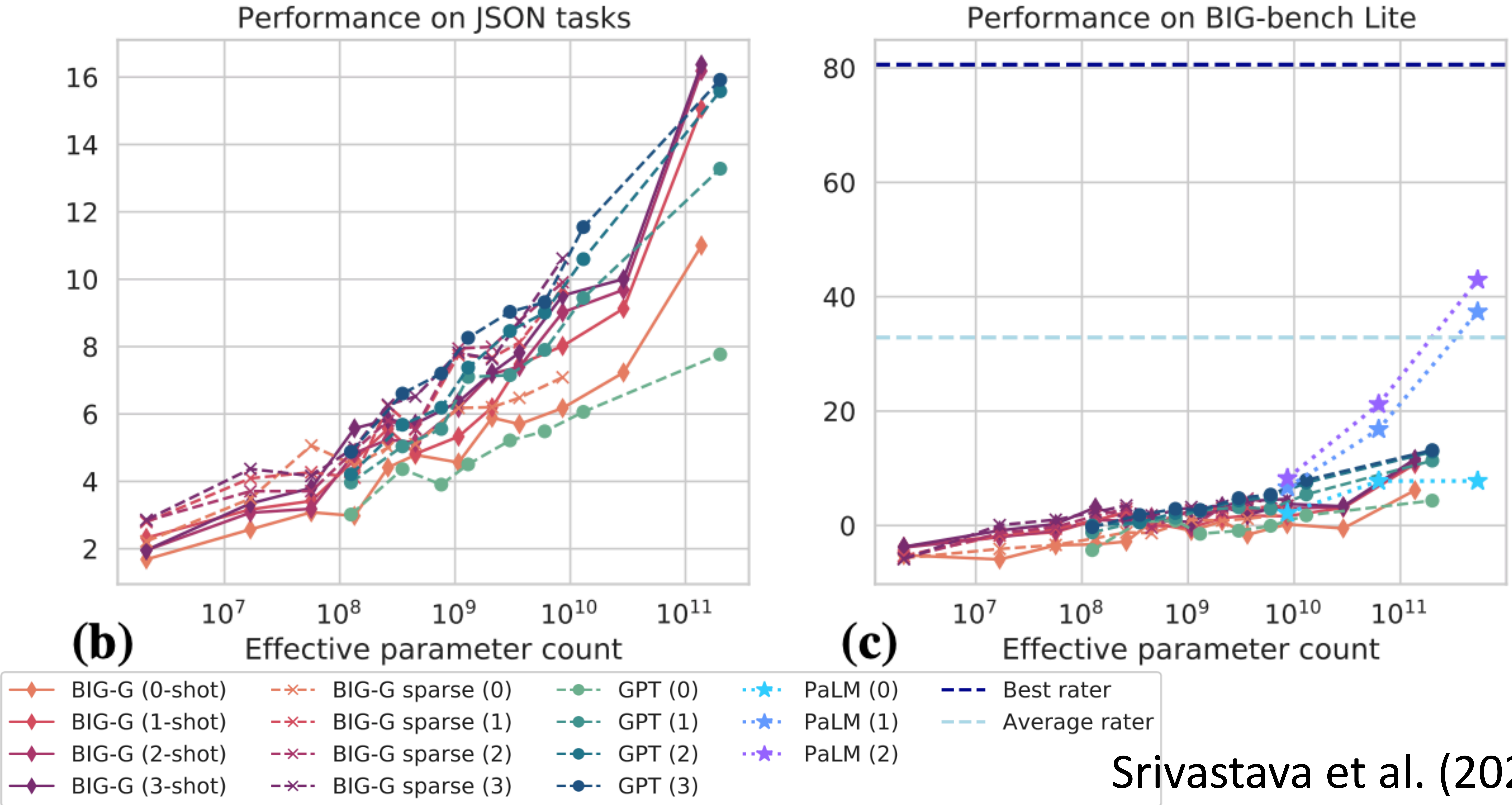
Results: HELM



- What trends do these show?

Liang et al. (2022)

Results: BIG-bench



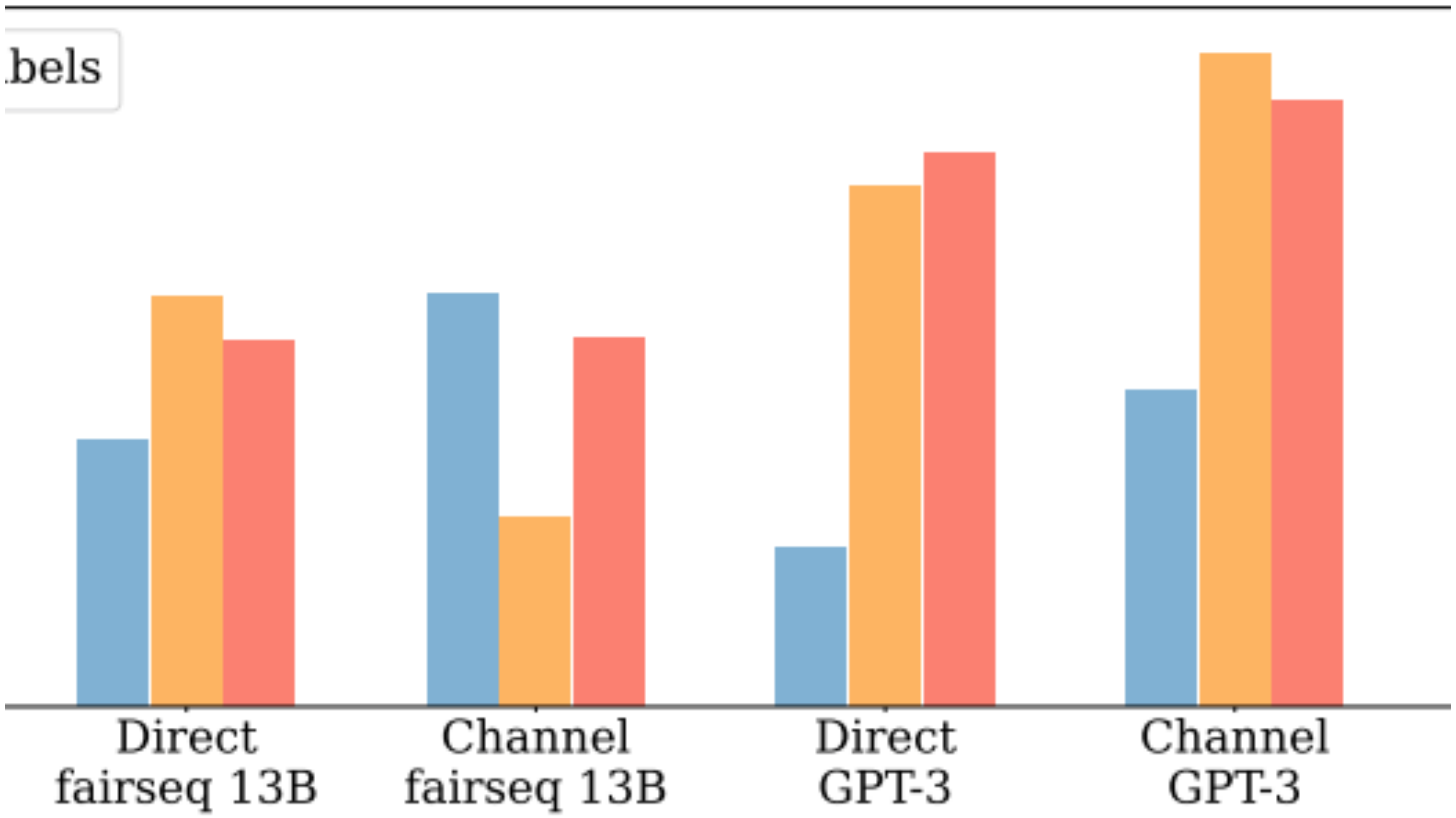
BIG-G: internal Google model.

Srivastava et al. (2022)

Rethinking Demonstrations

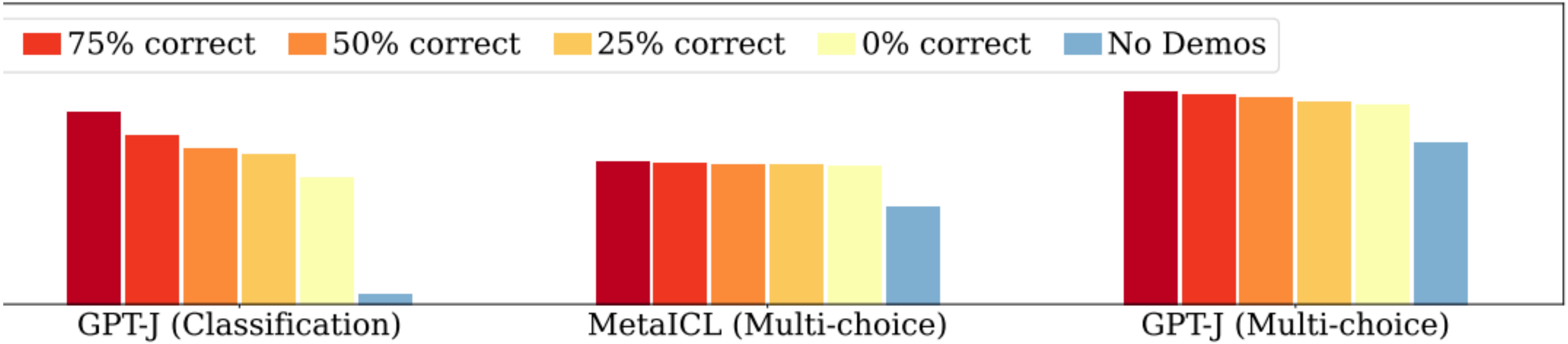
- Surprising result: how necessary even are the demonstrations?

- Using random labels does not substantially decrease performance??



Min et al. (2022)

Rethinking Demonstrations

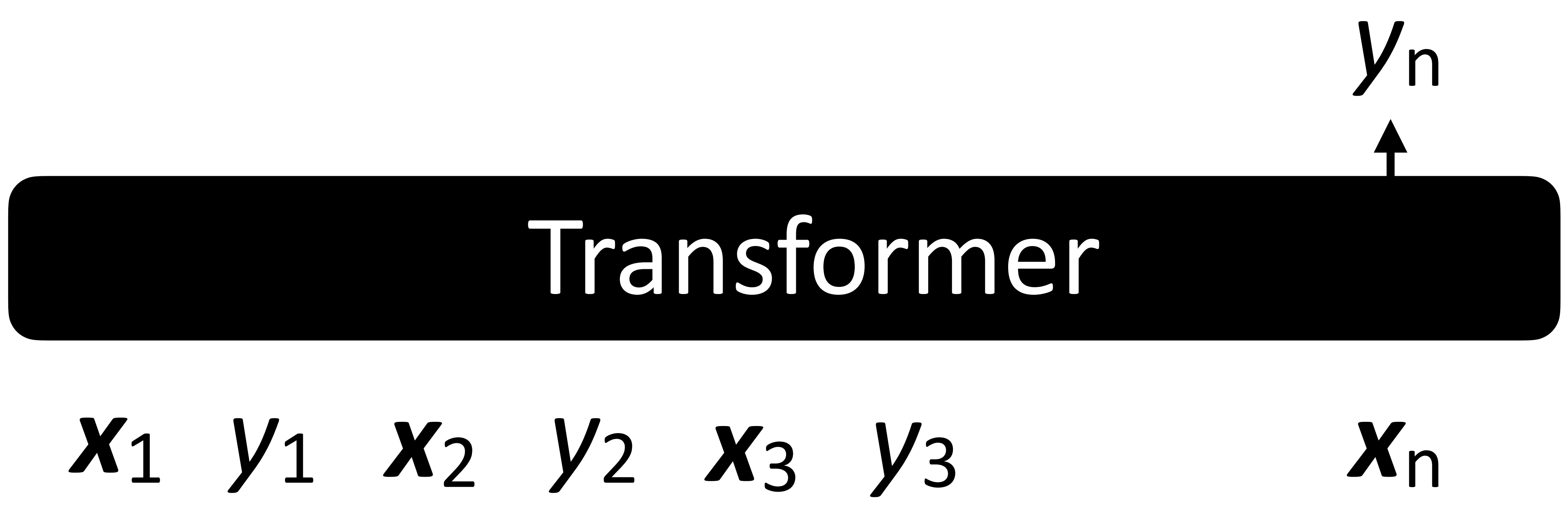


- Having even mislabeled demonstrations is much better than having no demonstrations, indicating that the form of the demonstrations is partially responsible for in-context learning

Min et al. (2022)

Understanding ICL: Regression

Linear Regression



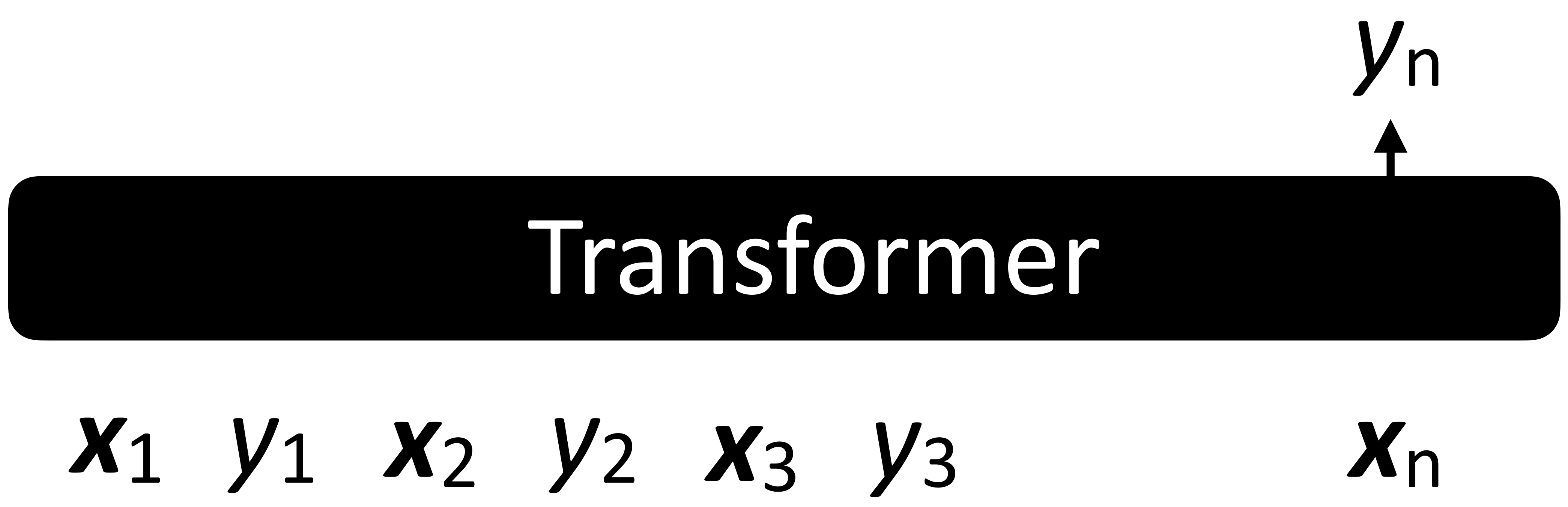
- Input space is of the form [*y*, ***x***], with the "unused" components set to 0
- See if we can learn regression: given (***x***, *y*) pairs, learn a linear predictor f(x) = $\boldsymbol{w}^\top \boldsymbol{x}$. That is, ground truth is a linear function (synthetic task)
- Equivalent to minimizing the following loss:

$$\sum_i \mathcal{L}(\boldsymbol{w}^\top \boldsymbol{x}_i, y_i) + \lambda \|\boldsymbol{w}\|_2^2$$

minimized by: $\boldsymbol{w}^* = (X^\top X + \lambda I)^{-1} X^\top y$

Akyürek et al. (2022)

Linear Regression



- Question 1: can a Transformer learn to do linear regression?
  - If we train it to do this task on many examples, does it successfully learn to do "ICL" linear regression on new instances?
  - If so, there are several different "algorithms" it might correspond to!
- Question 2: can we inspect what algorithm actually gets implemented?

Akyürek et al. (2022)

Linear Regression

- Most of these proofs (and other papers in this space) rely on Transformers being able to perform several kinds of operations

mov$(H; s, t, i, j, i', j')$: selects the entries of the s^{th} column of H between rows i and j, and copies them into the t^{th} column ($t \geq s$) of H between rows i' and j', yielding the matrix:

$$\begin{bmatrix} | & H_{:i-1,t} & | \\ H_{:,:t} & H_{i':j',s} & H_{:,t+1:} \\ | & H_{j,t} & | \end{bmatrix}.$$

- How can this be implemented? What does the attention need to do?

Akyürek et al. (2022)

Linear Regression

$\texttt{mov}(H; s, t, i, j, i', j')$: selects the entries of the s^{th} column of H between rows i and j, and copies them into the t^{th} column ($t \geq s$) of H between rows i' and j', yielding the matrix:

$$\begin{bmatrix} | & H_{:i-1,t} & | \\ H_{:,:t} & H_{i':j',s} & H_{:,t+1:} \\ | & H_{j,t} & | \end{bmatrix}.$$

$\texttt{mul}(H; a, b, c, (i, j), (i', j'), (i'', j''))$: in *each* column $\boldsymbol{h}$ of H, interprets the entries between i and j as an $a \times b$ matrix A_1, and the entries between i' and j' as a $b \times c$ matrix A_2, multiplies these matrices together, and stores the result between rows i'' and j'', yielding a matrix in which each column has the form $[\boldsymbol{h}_{:i''-1}, A_1 A_2, \boldsymbol{h}_{j'':}]^\top$.

- Several more operations as well

Akyürek et al. (2022)

Linear Regression

Theorem 1. *A transformer can compute Eq.* (11) *(i.e. the prediction resulting from single step of gradient descent on an in-context example) with constant number of layers and $O(d)$ hidden space, where d is the problem dimension of the input x. Specifically, there exist transformer parameters θ such that, given an input matrix of the form:*

$$H^{(0)} = \begin{bmatrix} \cdots & 0 & y_i & 0 & \cdots \\ & \boldsymbol{x}_i & 0 & \boldsymbol{x}_n & \end{bmatrix}, \tag{12}$$

the transformer's output matrix $H^{(L)}$ contains an entry equal to $\boldsymbol{w}'^{\top}\boldsymbol{x}_n$ (Eq. (11)*) at the column index where x_n is input.*

- Also another update possible based on rank-one updates (Sherman-Morrison)

Akyürek et al. (2022)

Proof of Theorem

The operations for 1-step SGD with single exemplar can be expressed as following chain (please see proofs for the Transformer implementation of these operations (Lemma 1) in Appendix C):

- $\texttt{mov}(;1,0,(1,1+d),(1,1+d))$ (move $\boldsymbol{x}$)
- $\texttt{aff}(;(1,1+d),(),(1+d,2+d),W_1=\boldsymbol{w})$ ($\boldsymbol{w}^\top\boldsymbol{x}$)
- $\texttt{aff}(;(1+d,2+d),(0,1),(2+d,3+d),W_1=I,W_2=-I)$ ($\boldsymbol{w}^\top\boldsymbol{x}-y$)
- $\texttt{mul}(;d,1,1,(1,1+d),(2+d,3+d),(3+d,3+2d))$ ($\boldsymbol{x}(\boldsymbol{w}^\top\boldsymbol{x}-y)$)
- $\texttt{aff}(;(),(),(3+2d,3+3d),b=\boldsymbol{w},)$ (write $\boldsymbol{w}$)
- $\texttt{aff}(;(3+d,3+2d),(3+2d,3+3d),(3+3d,3+4d),W_1=I,W_2=-\lambda)$ ($\boldsymbol{x}(\boldsymbol{w}^\top\boldsymbol{x}-y)-\lambda\boldsymbol{w}$)
- $\texttt{aff}(;(3+2d,3+3d),(3+3d,3+4d),(3+2d,3+3d),W_1=I,W_2=-2\alpha,)$ ($\boldsymbol{w}'$)
- $\texttt{mov}(;2,1,(3+2d,3+3d),(3+2d,3+3d))$ (move $\boldsymbol{w}'$)
- $\texttt{mul}(;1,d,1,(3+2d,3+3d),(1,1+d),(3+3d,4+3d))$ (${\boldsymbol{w}'}^\top x_2$)

Akyürek et al. (2022)

Linear Regression

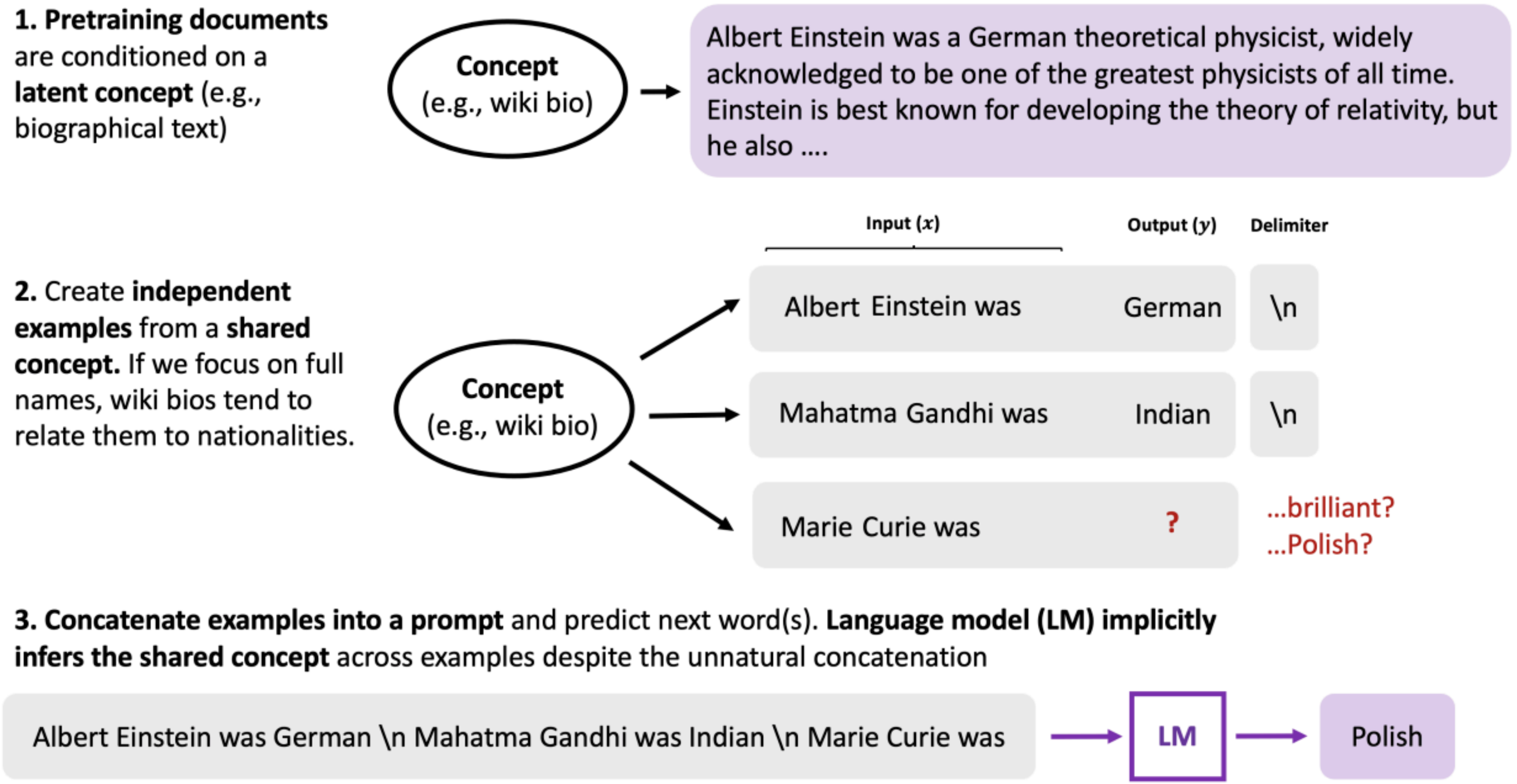
- Squared prediction difference: L2 between different predictors
- When no noise: ICL matches ordinary least square (OLS) almost exactly

Linear Regression

- Squared prediction difference: L2 between different predictors

- What gets learned changes with depth. Low-depth: more like GD. Medium-depth: more like ridge. High-depth: OLS

Bayesian Interpretation



Xie et al. (2021)

Understanding ICL: Induction Heads and Mechanistic Interpretability

Background: Transformer Circuits

- There are mechanisms in Transformers to do “fuzzy” or “nearest neighbor” versions of pattern completion, completing [A*][B*] … [A] → [B] , where A* ≈ A and B* ≈ B are similar in some space

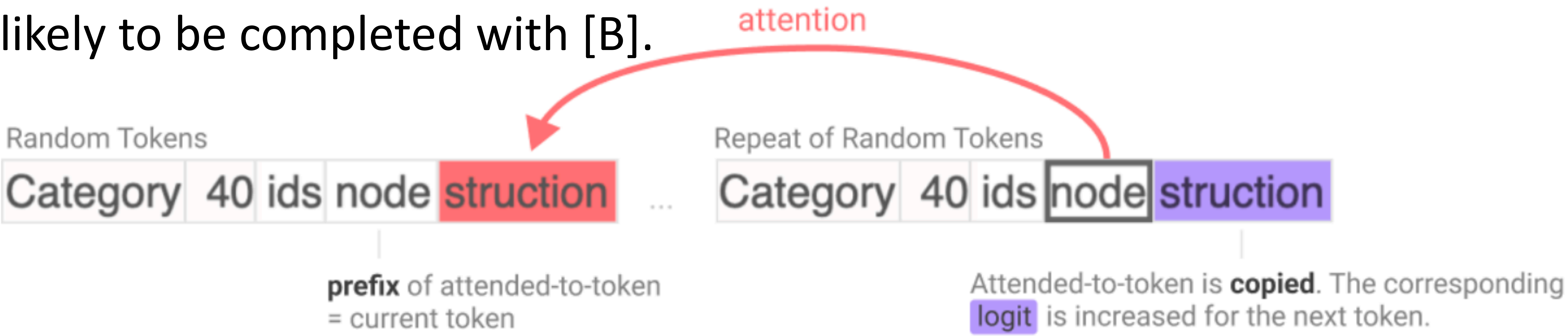
- Olsson et al. want to establish that these mechanisms are responsible for good ICL capabilities

- We can find these heads and see that performance improves; can we causally link these?

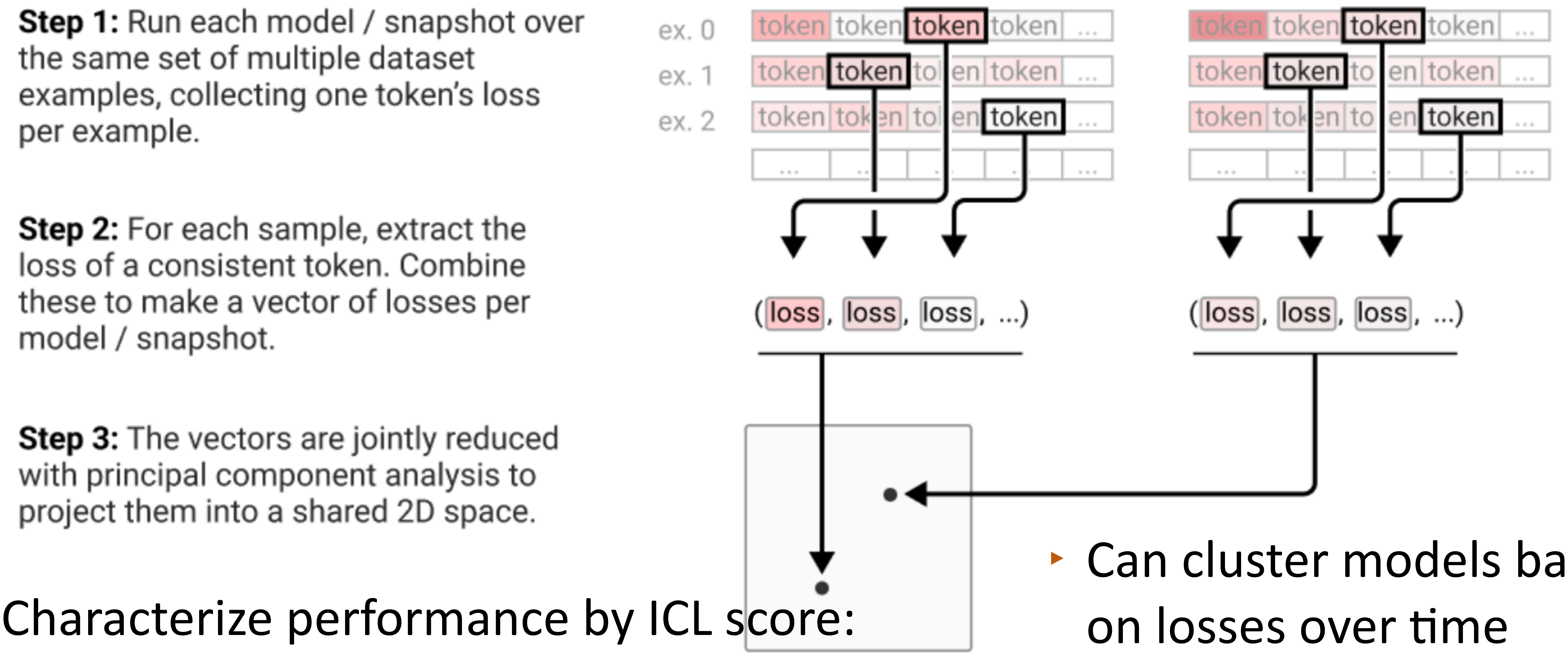
Olsson et al. (2022)

Induction Heads

- Induction heads: a pair of attention heads in different layers that work together to copy or complete patterns.
- The first head copies information from the previous token into each token.
- Second attention head to attend to tokens based on what happened before them, rather than their own content. Likely to “look back” and copy next token from earlier
- The two heads working together cause the sequence …[A][B]…[A] to be more likely to be completed with [B].



Induction Heads



- Characterize performance by ICL score: loss(500th token) - loss(50th token) — average measure of how much better the model is doing later once it's seen more of the pattern
- Can cluster models based on losses over time

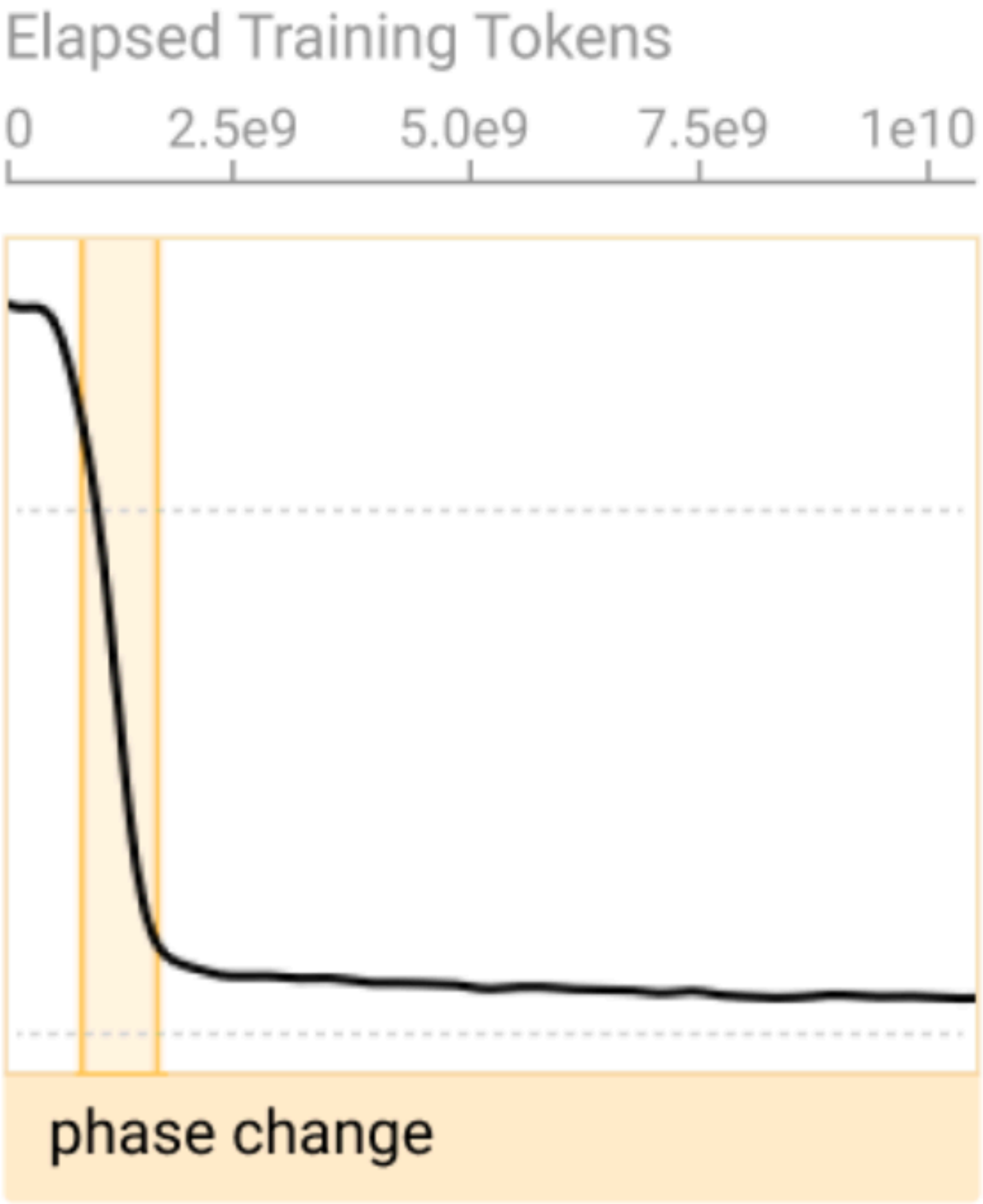
Olsson et al. (2022)

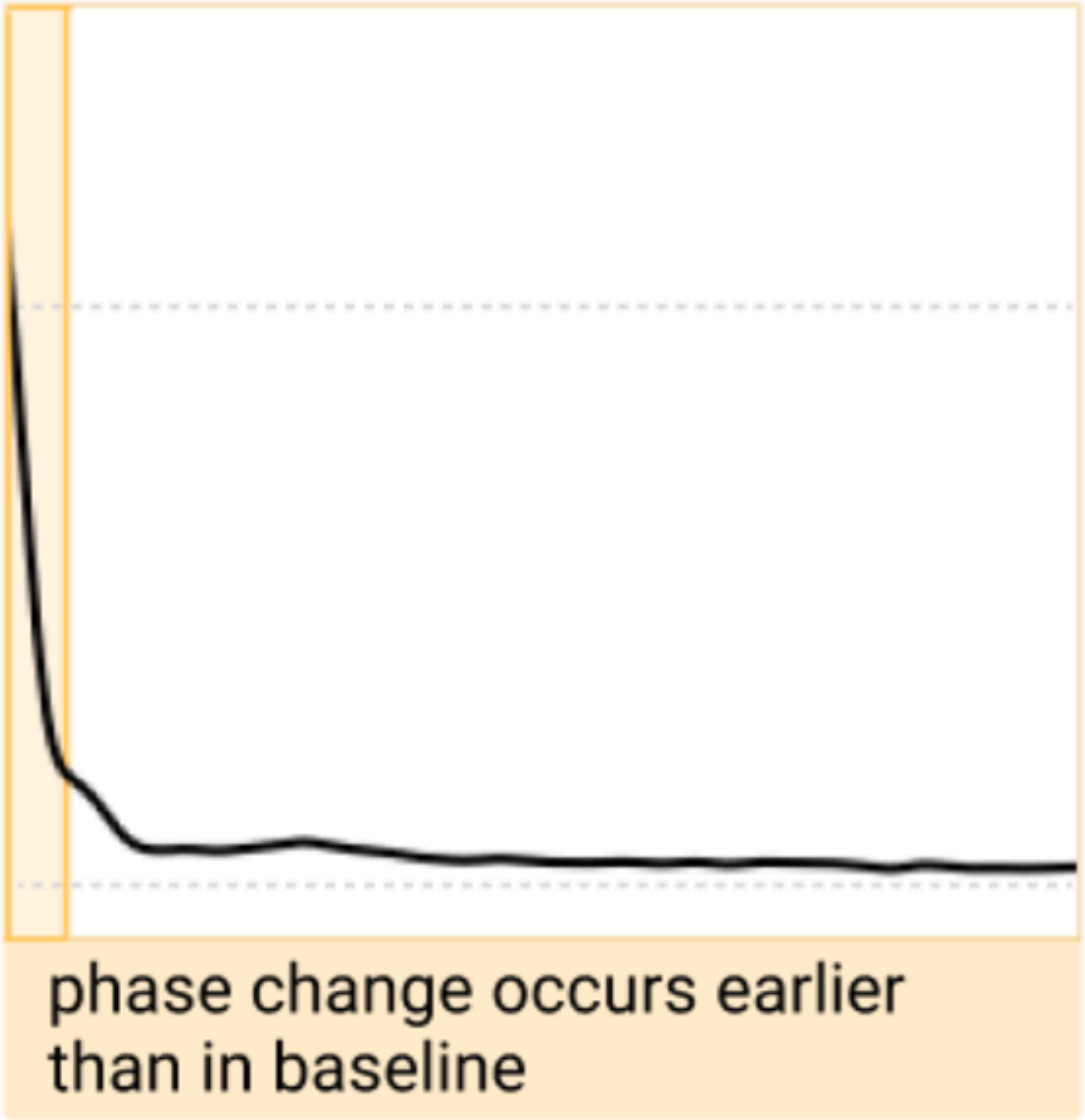
Induction Heads

- Improvement in ICL (loss score) correlates with emergence of induction heads

Induction Heads

Change architecture to promote induction heads => phase change happens earlier





Induction Heads

- If you remove induction heads, behavior changes dramatically

Interpretability

- Lots of explanations for why ICL works — but these haven't led to many changes in how Transformers are built or scaled
- Several avenues of inquiry: theoretical results (capability of these models), mechanistic interpretability, fully empirical (more like that next time)
- Many of these comparisons focus on GPT-3 and may not always generalize to other models

Takeaways

- Zero- and few-shot prompting are very powerful ways of specifying new tasks at inference time
- For zero-shot: form of the prompt matters, we'll see more example next times when we look at chain-of-thought
- For few-shot: number and order of the examples matters, prompt matters a bit less
- Several analyses of why it works: it can learn to do regression and we know a bit about mechanisms that may be responsible for it