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?

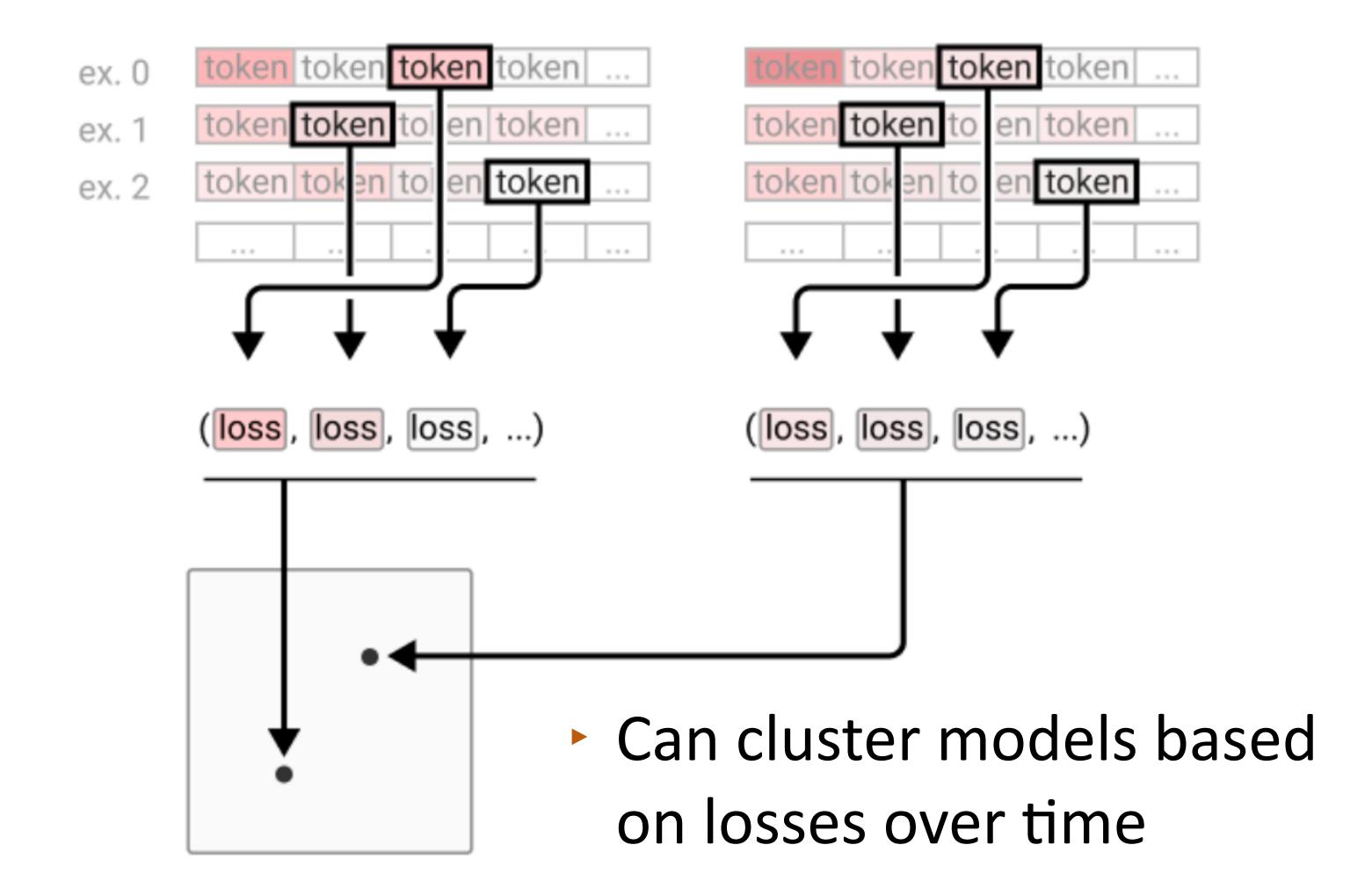
- Induction heads: a pair of attention heads in different layers that work together to copy or complete patterns.
- ▶ The first head copies information from the previous token into each token.
- Second attention head to attend to tokens based on what happened before them, rather than their own content. 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].



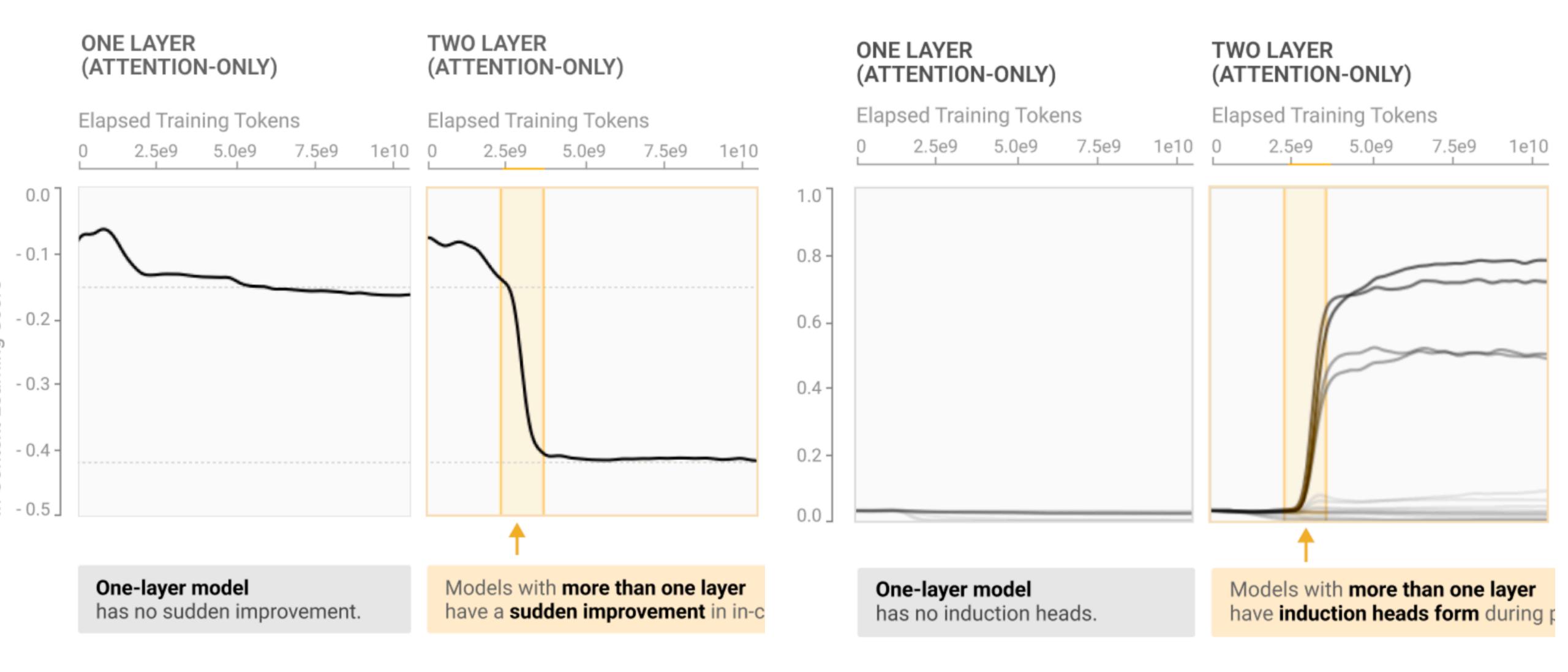
Step 1: Run each model / snapshot over the same set of multiple dataset examples, collecting one token's loss per example.

Step 2: For each sample, extract the loss of a consistent token. Combine these to make a vector of losses per model / snapshot.

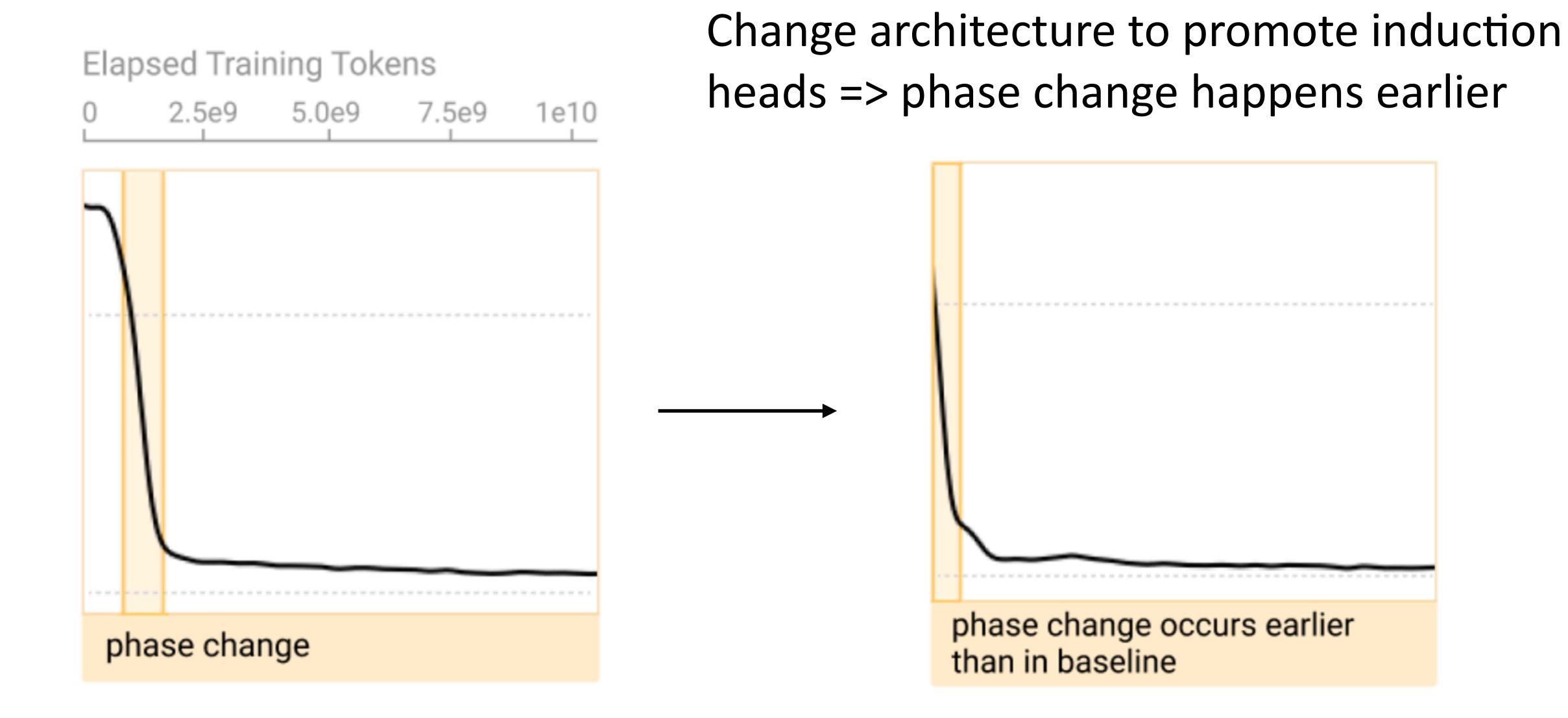
Step 3: The vectors are jointly reduced with principal component analysis to project them into a shared 2D space.

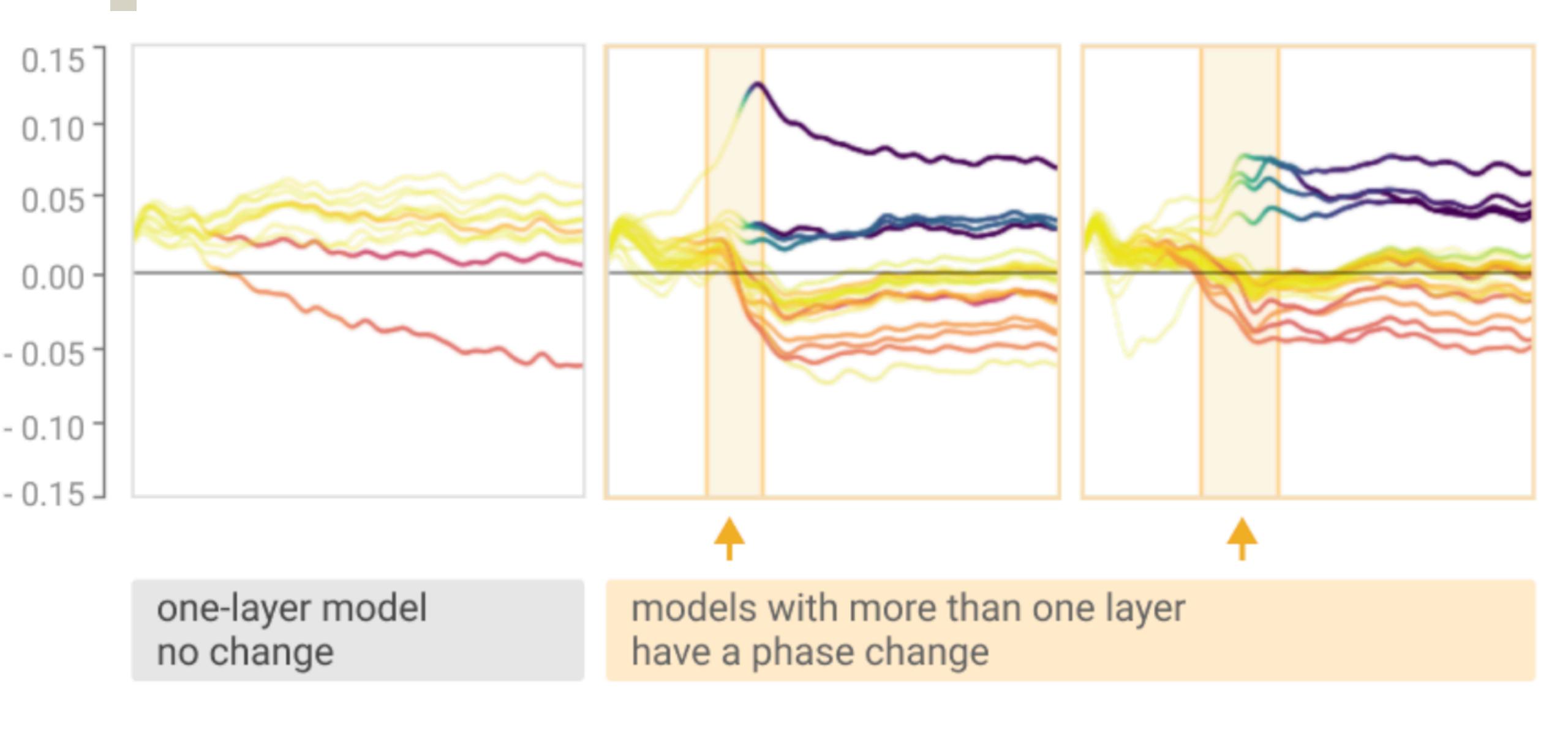


Characterize performance by ICL score: loss(500th token) - loss(50th token) — average measure of how much better the model is doing later once it's seen more of the pattern



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





If you remove induction heads, behavior changes dramatically

Olsson et al. (2022)

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)