

# Why LLM Benchmarking is Broken and How to Fix It

Guanhua Zhang

Social Foundations of Computation

# Ranking Is All You Need

At the core of applied machine learning are *model rankings*

*Good model rankings are the goal of benchmarking*

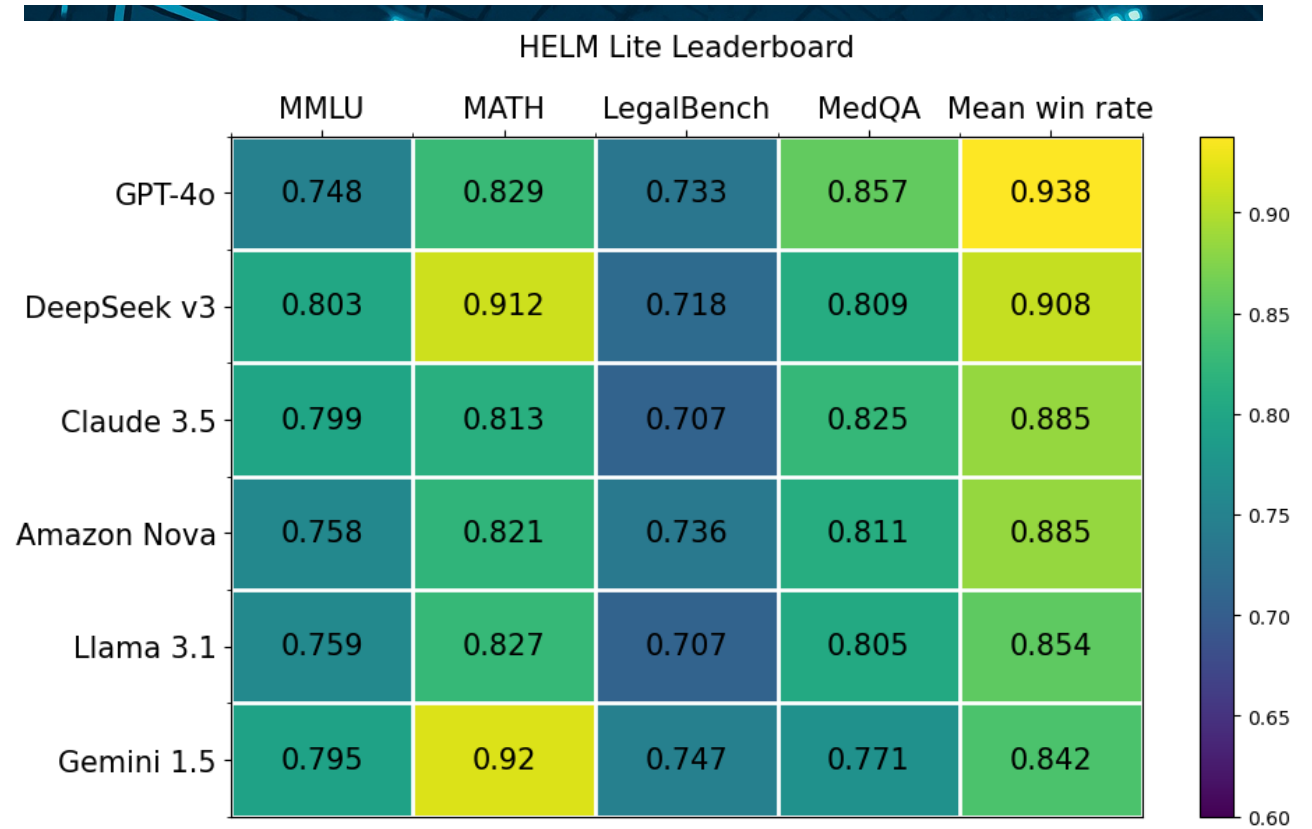


# Multi-Task Benchmarking for LLMs

LLMs can solve many tasks

Which ranking should we look at?

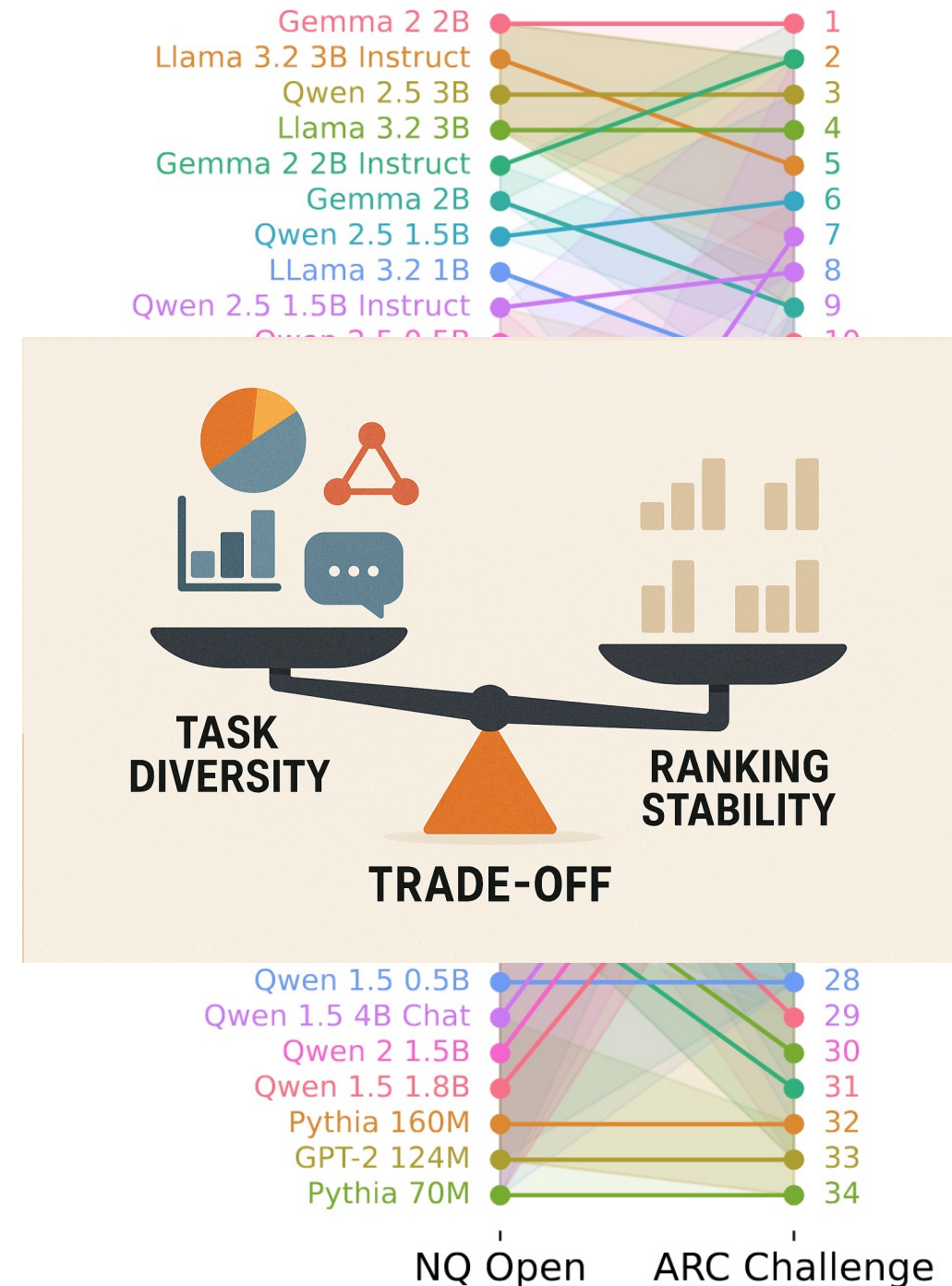
Multi-task benchmarks: Just evaluate them on everything!





# Tasks disagree with each other

- The model rankings in different tasks often differ, even if the two tasks are similar
- *Analogy with voting system:*
  - Each task is a voter; each model is a candidate.
  - Each voter ranks candidates
  - Social choice theory: It's hard to aggregate many rankings into one good ranking.
- Our result: Inherent trade-off between task diversity and ranking stability in multi task benchmarks

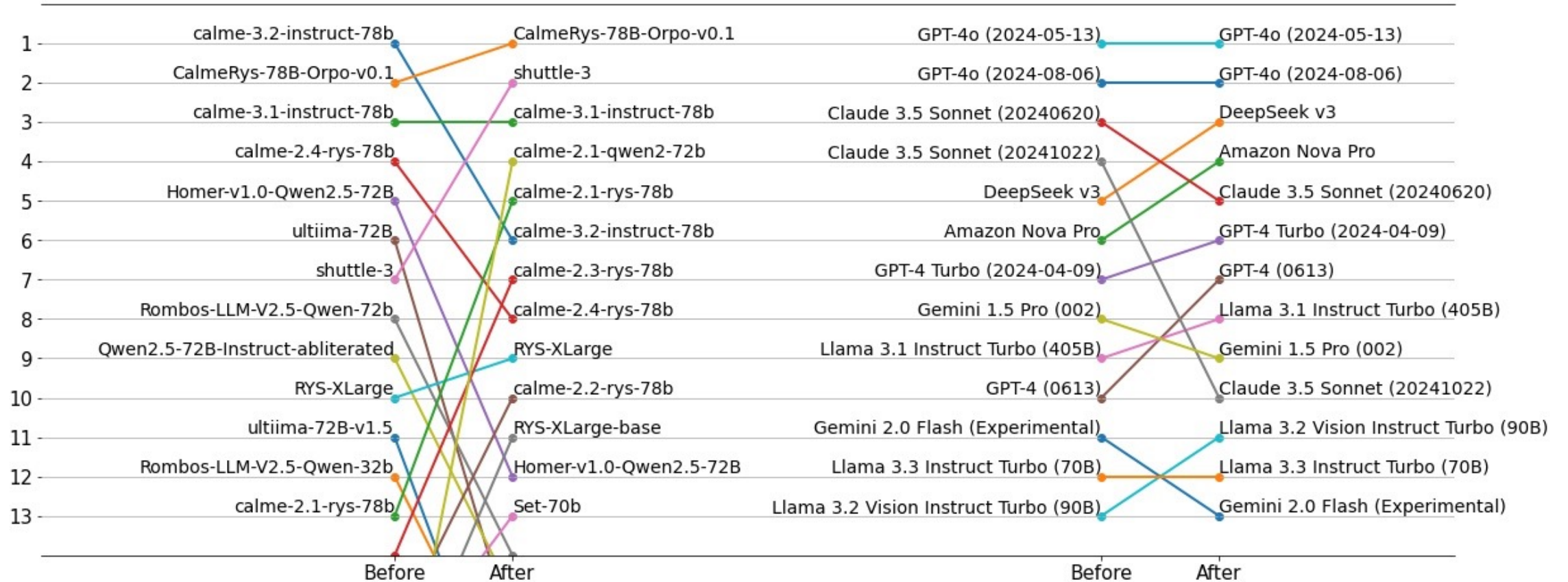
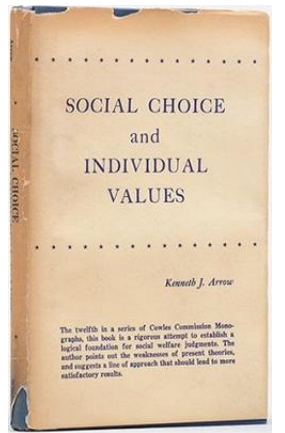


- **Sensitivity:**

1. Add different label noises to different tasks
2. Add some irrelevant weak models

- **Diversity:**

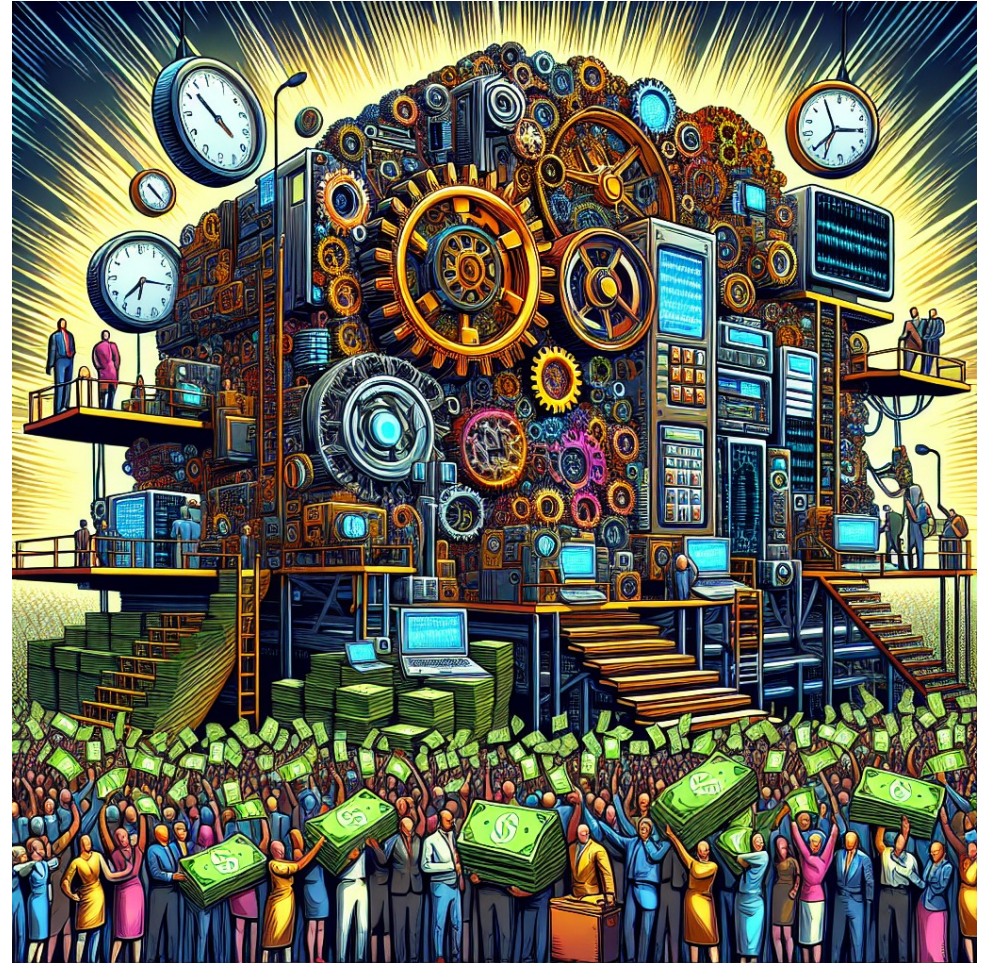
- Ranking disagreement measured by Kendall's  $W$





# It gets worse: LLM Benchmarking is Costly

- Evaluating a single 176B parameter model, Bloom, on the HELM multi-task benchmark required 4,200 GPU hours
- People have proposed methods for benchmark performance prediction to speed up evaluation
- Our result: These methods fail at the frontier, where models are better than old models



So, it seems we're in a pinch:

1. Rankings are inconsistent
2. Computing many rankings is costly

But there's good news:

Ranking inconsistency is an artifact of how LLMs were trained

We can remove this artifact and recover highly consistent rankings





# Ranking inconsistency is due to training on the test task

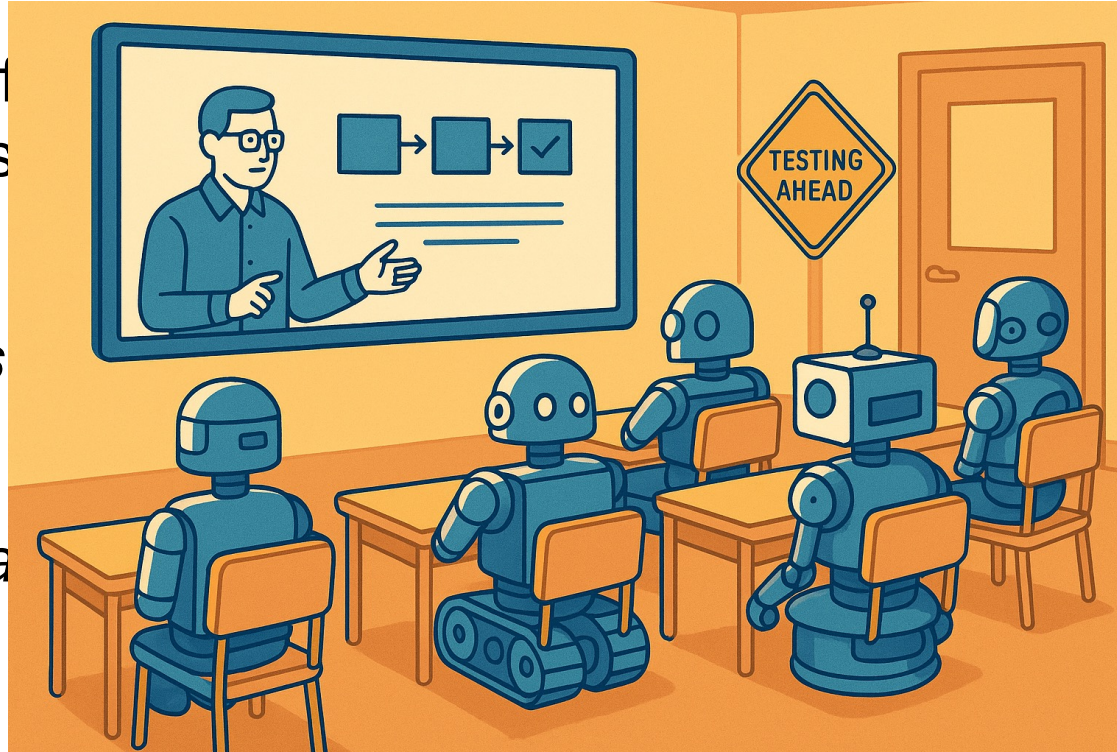
As released, different models perform differently for any given test set.

of preparation  
[Hardt (2025)]

***“Some models***

***don’t***

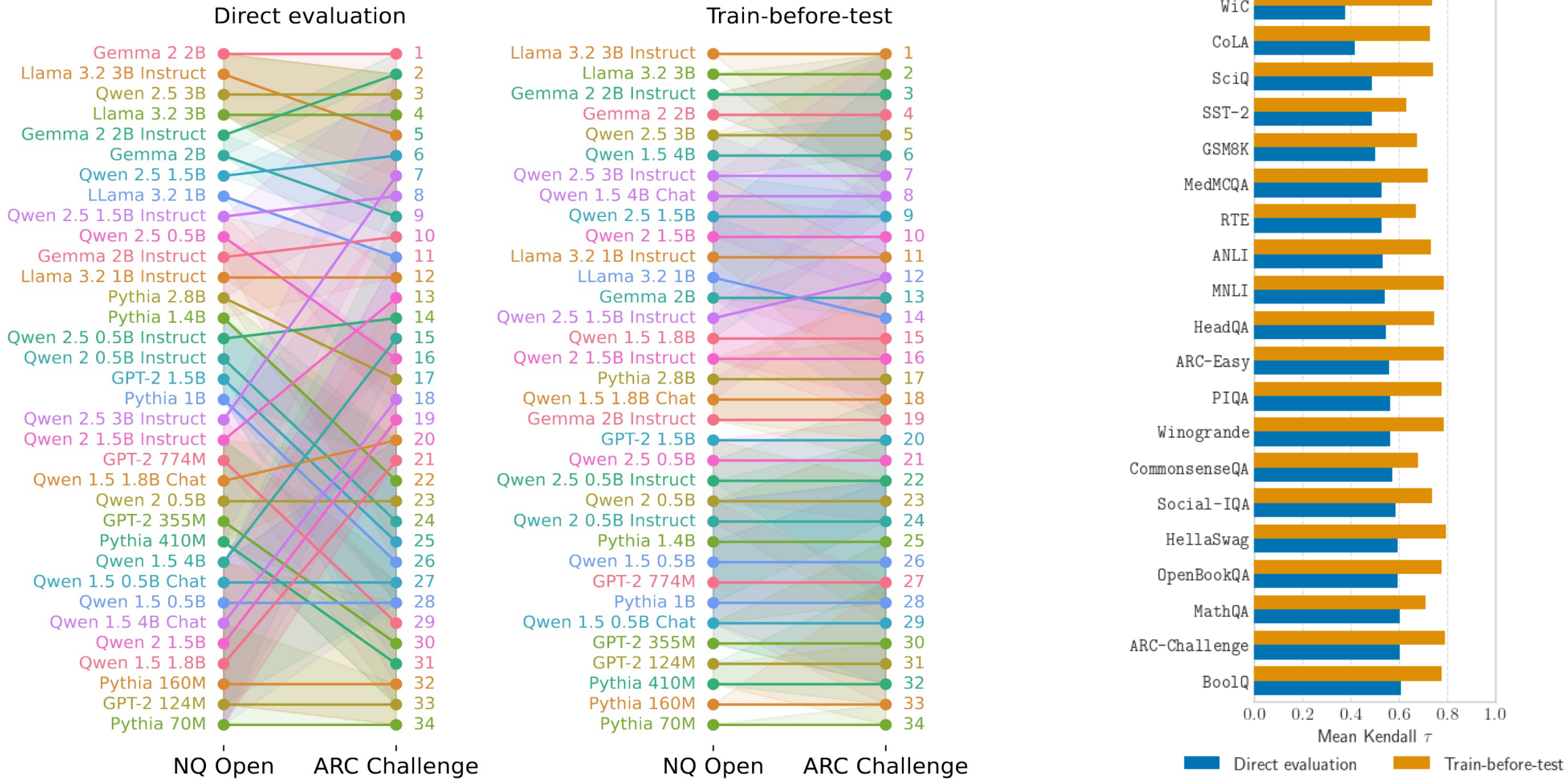
This is called *training on the test set*.



***Train-before-test:*** Give each model the same benchmark specific fine-tuning before evaluation.



# Train-before-test harmonizes model rankings



# Tasks from the same category still disagree, unless ...

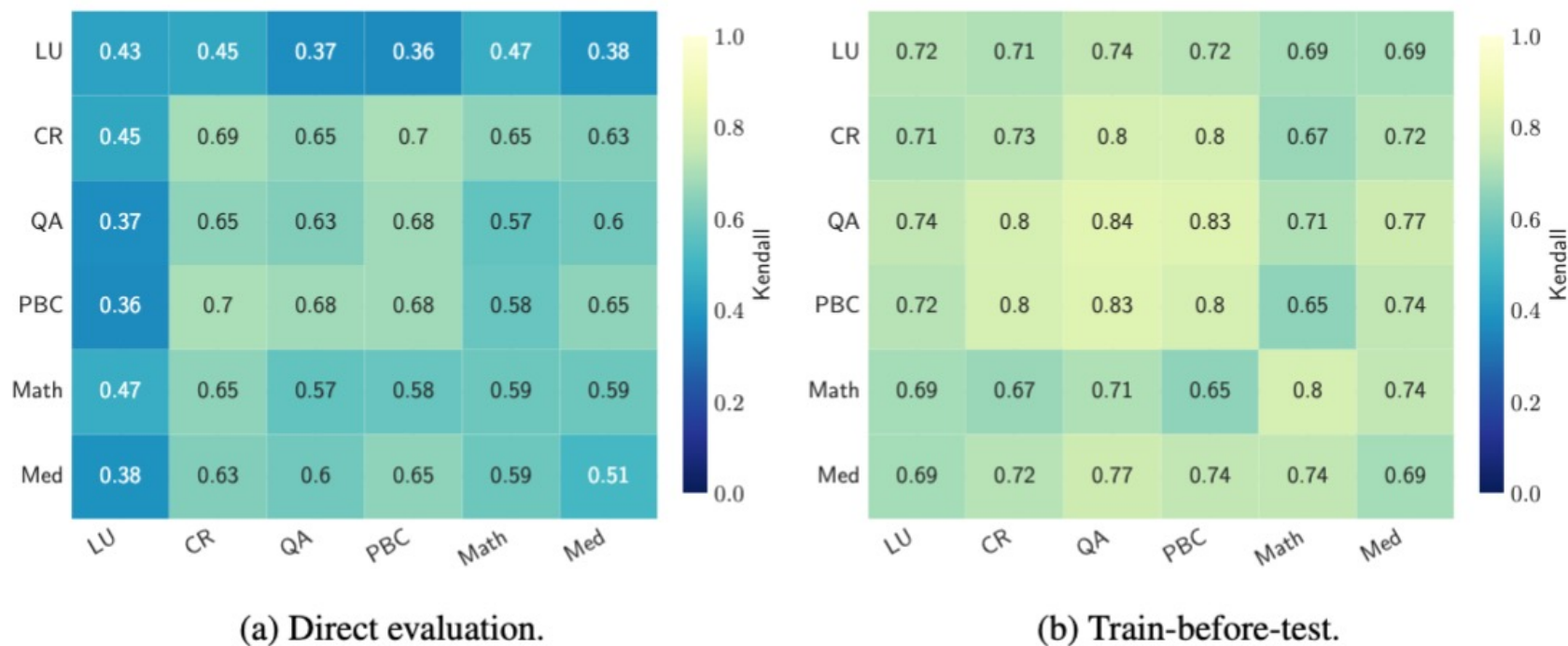
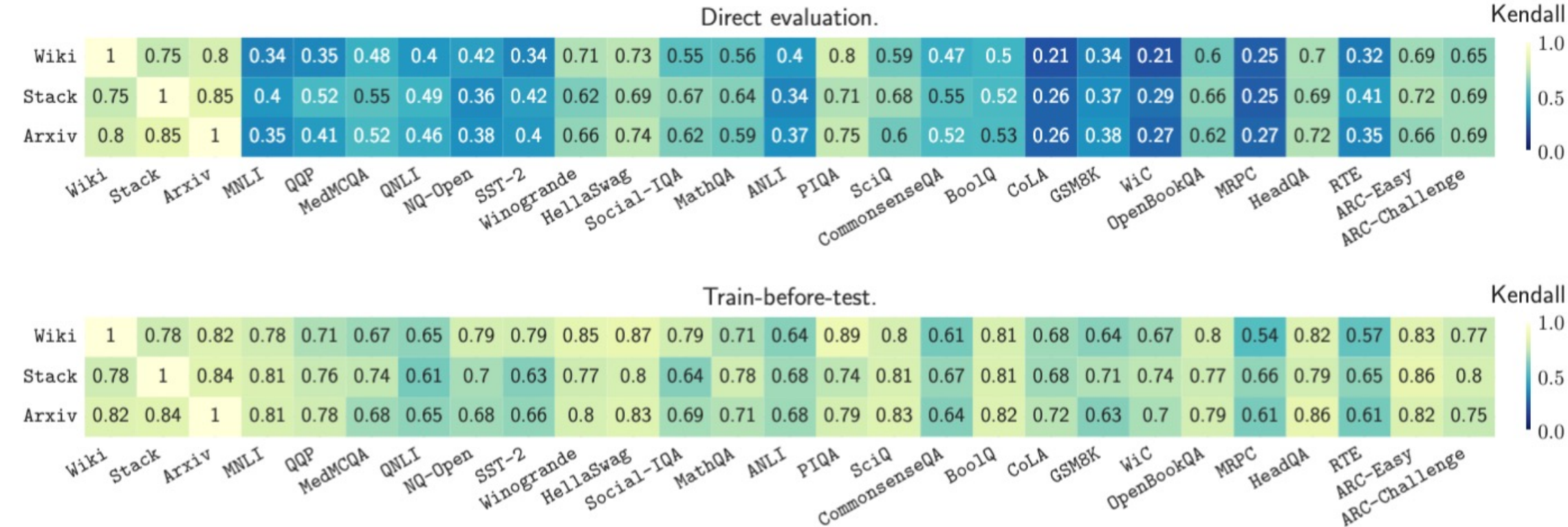


Figure 3: Cross-category ranking agreement for direct evaluation (left) and train-before-test (right). We consider language understanding (LU), commonsense reasoning (CR), question answering (QA), physics/biology/chemistry (PBC), math (Math), and medicine (Med) categories. Kendall's  $\tau$  is averaged across all pairs of benchmarks that belong to two given categories. The diagonal represents the intra-category agreement and the others represent the inter-category agreement. train-before-test improves both intra- and inter-category ranking agreement in all instances.

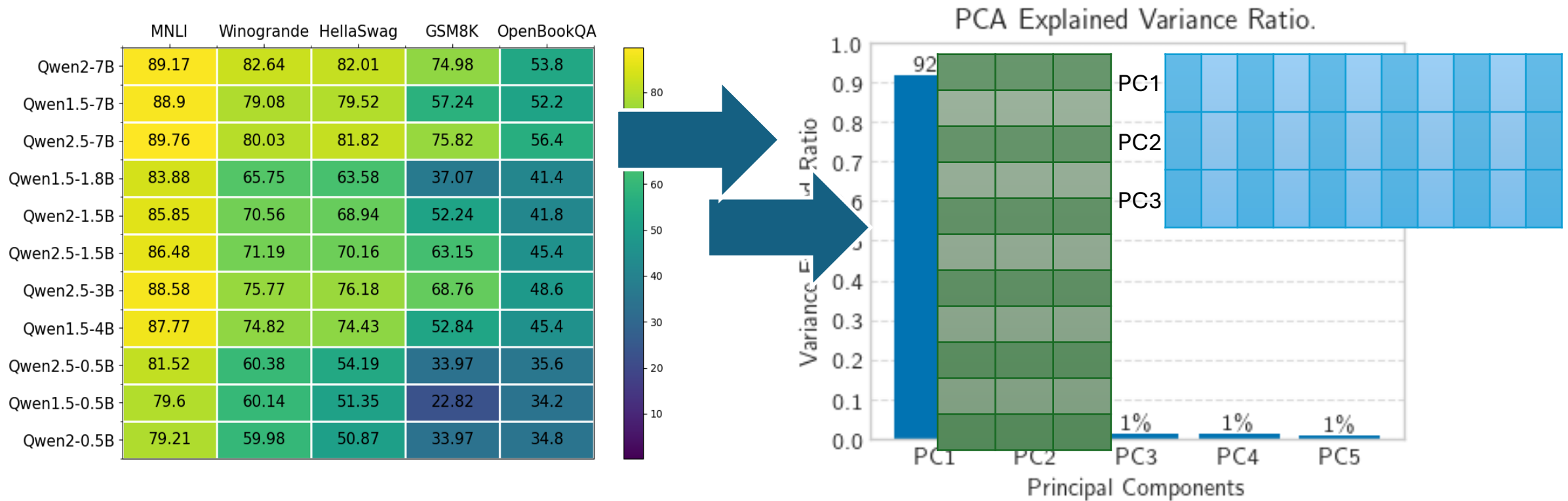


# Downstream agrees with perplexity under TbT



# Train-before-test makes score matrix rank one

- Conduct principal component analysis (PCA) on the multi-task score matrix.



- Our result: A single factor (PC1) dominates model performances on 24 tasks



# PC1 correlates with model scale

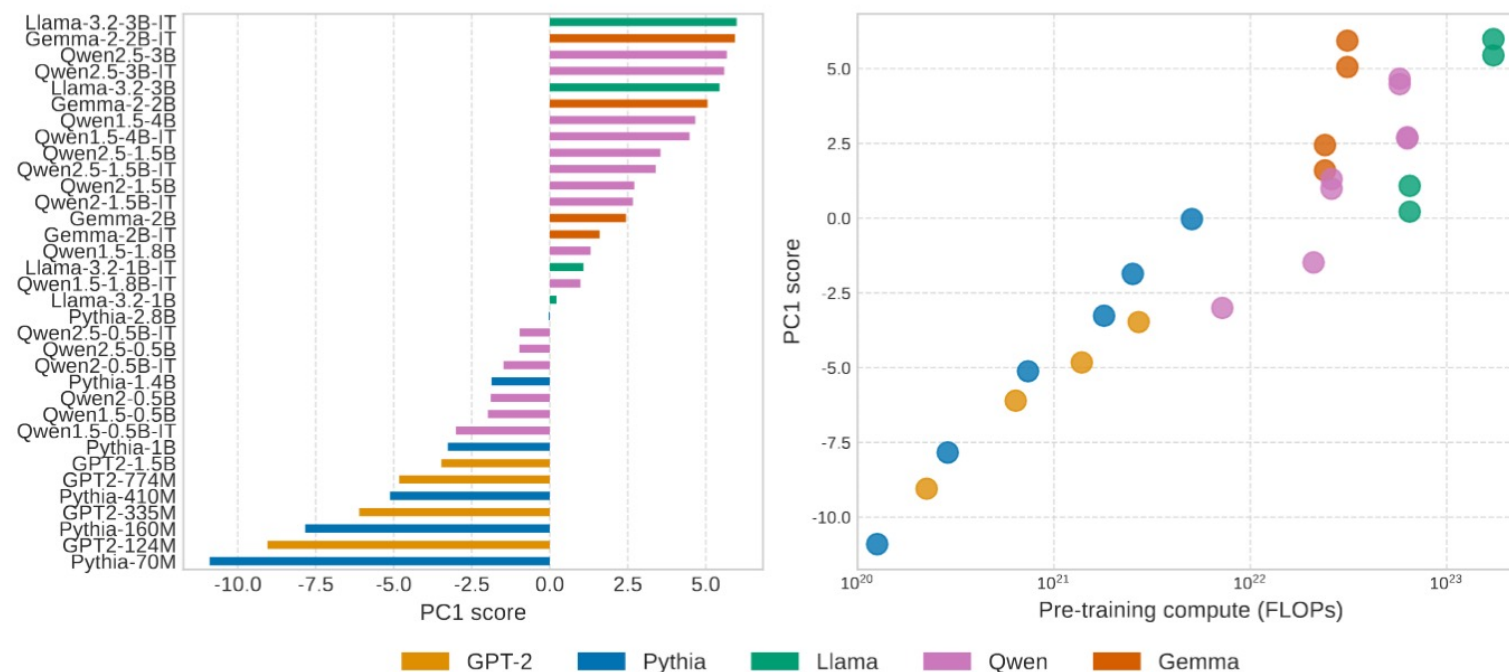


Figure 7: PC1 scores under train-before-test correlates with scale and pre-training compute.

- PC1 score stands for something **useful for all tasks**.
  - *All dimensions of PC1 is positive.*

# Model potential is what really matters

- Train-before-Test measures **model potential** after development
  - Model potential rankings in any benchmark extend to others
  - Model potential correlates with perplexity of models
  - Model potential is of rank one





# Take-away

Ranking is all you need  
Currently benchmarking is broken for LLMs  
But there's a fix: Use train-before-test.

# Thanks!

