





Exploring Model Kinship for Merging Large Language Models





Paper

Project

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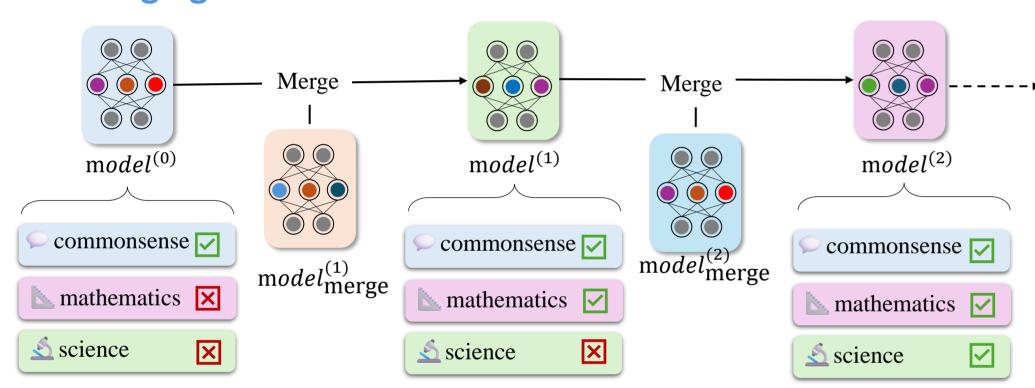
Conceptual Motivation

□What we know:

- > LLMs need require frequent and continuous updates to keep up with growing user demands across diverse tasks.
- > Model Merging has emerged as a cost-effective approach to combine the strengths of different models without altering their underlying architecture.

☐ Model Evolution:

> LLMs can evolve to integrate new capabilities by iteratively merging with one another.



$$E(\theta^{(t)} \mid \theta^{(t-1)}, \theta^{(t-2)}, \dots, \theta^{(0)}) = E(\theta^{(t)} \mid \theta^{(t-1)}, \theta_{\text{merge}}^{(t)})$$

Question: How can we systematically select models for merging to achieve greater performance improvements?

Key Contributions

- ➤ Model Kinship: Introduce a kinship metric to assess LLM similarity during merging, guiding auto-merging strategies.
- Empirical Analysis: Evaluate iterative merging dynamics, highlighting multitask performance gains and stagnation, with insights from model kinship.
- Practical Strategies: Propose Top-k Greedy Merging with model kinship to efficiently tackle merging optimization challenges.

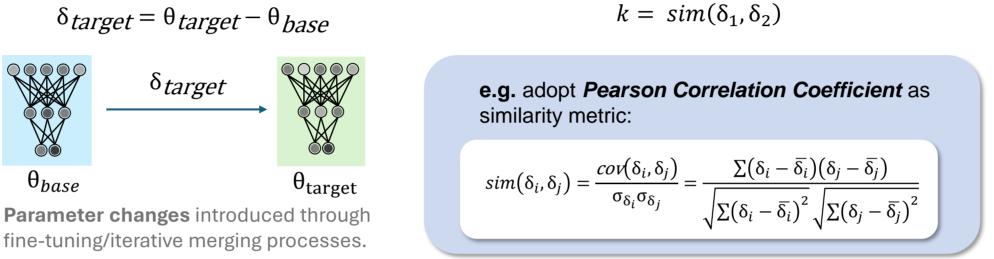
Model Kinship

We need an efficient metric to evaluate the overall capability difference between models, without relying on a dataset for evaluation, to estimate the outcome of future merges (high or low).

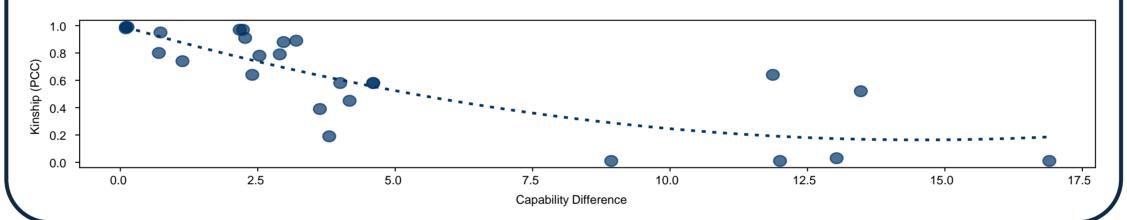
Extract delta parameter δ_{target} of the target models.

 $\delta_{target} = \theta_{target} - \theta_{base}$

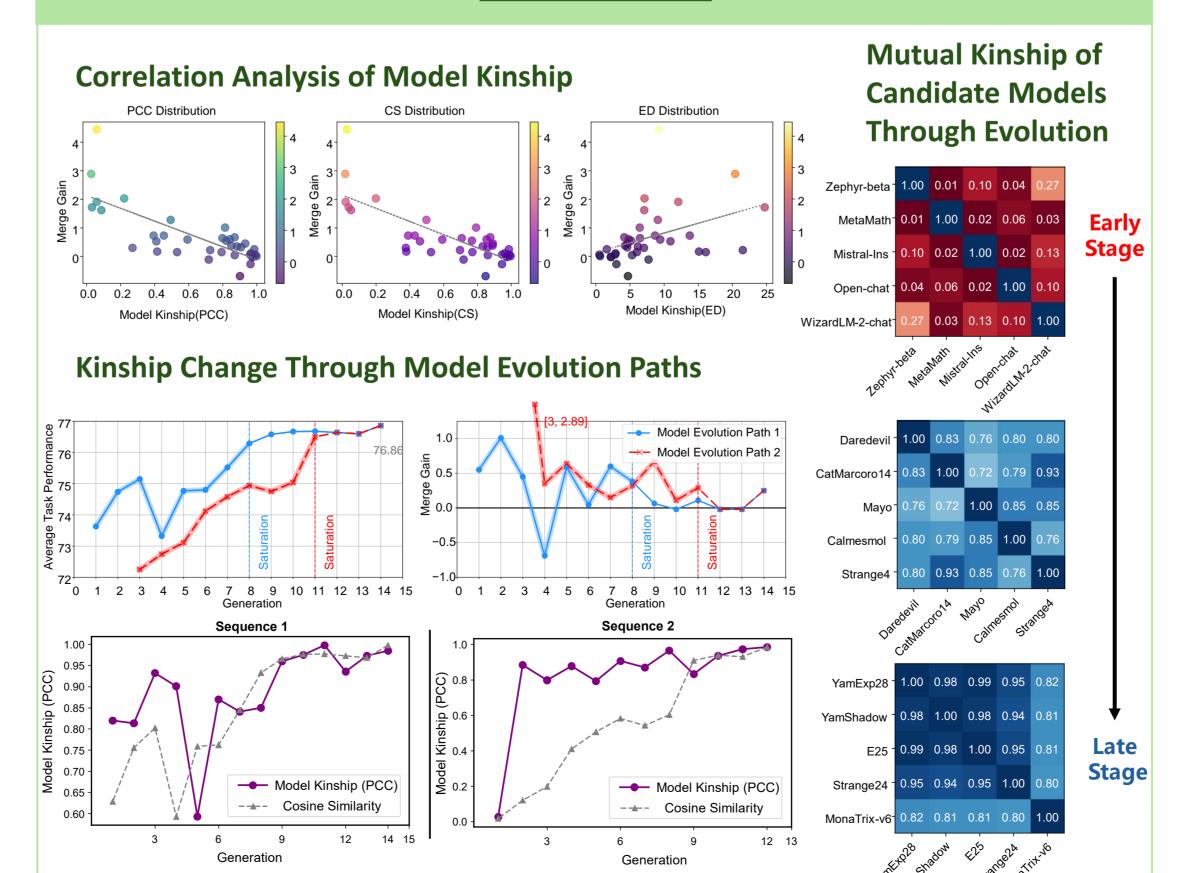
 Calculate the kinship between **delta parameters**.



Correlation between task capability difference and kinship



Initial Analysis

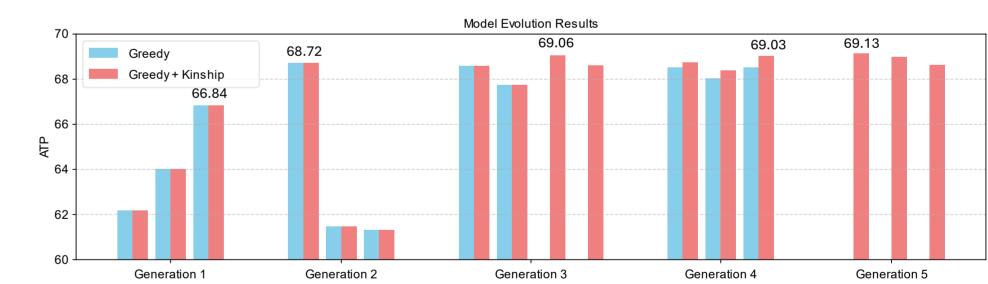


Main Results

Enhance the greedy merging strategy by adding additional merges based on low model kinship.

Table 2: Results of merging experiments comparing the vanilla greedy strategy and our proposed approach. The first three models serve as the foundation models in both experiments. Note: The model kinship experiment was terminated at generation 5, as it has already outperformed the greedy strategy by that point.

	Greedy Strategy				+ Model Kinship			
	Model	Avg.	Gain	Kinship	Model	Avg.	Gain	Kinship
	MetaMath	63.72	/	/	MetaMath	63.72	/	/
	Instruct	61.82	/	/	Instruct	61.82	/	/
	Open-chat	66.28	/	/	Open-chat	66.28	/	1
	model-1-1	62.17	-0.6	0.01	model-1-1	62.17	-0.6	0.01
	model-1-2	64.02	-0.03	-0.02	model-1-2	64.02	-0.03	-0.02
	model-1-3	66.84	+1.84	0.05	model-1-3	66.84	+1.84	0.05
	model-2-1	68.72	+2.16	0.93	model-2-1	68.72	+2.16	0.93
Stop	model-2-2	61.47	-3.96	0.57	model-2-2	61.47	-3.96	0.57
proving	model-2-3	61.32	-3.83	0.58	model-2-3	61.32	-3.83	0.58
	model-3-1	68.59	+1.09	0.95	model-3-2	67.74	+1.09	0.93
	model-3-2	67.74	-0.04	0.93	model-3-3	69.06	+0.74	0.24
		-	-	-	model-3-4	68.61	+1.13	0.32
	model-4-1	68.51	-0.14	0.98	model-4-4	68.75	-0.14	0.54
	model-4-2	68.04	-0.19	0.98	model-4-5	68.39	-0.27	0.66
	model-4-3	68.53	+0.37	0.94	model-4-6	69.03	+0.15	0.52
		-	-	-	model-5-1	69.13	+0.04	0.65
		-	-	-	model-5-2	68.98	+0.07	0.65
		-	-	-	model-5-3	68.63	-0.37	0.98



☐ Findings:

- ☐ Merging low-kinship models introduces novel weight variations, enabling continued iterative merging.
- ☐ Early stopping at high kinship reduces resource consumption while maintaining performance.

Future works -

- > Advance interpretability by designing more informative metrics to explain model merging behavior.
- > Explore foundational theory for automated, selfevolving model merging pipelines.