

Explore Model Kinship For Merging LLMs

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Overview

01 Background and Motivation

- □ Model Merging: History & Methodology
- □ Model Evolution: Success & Challenges

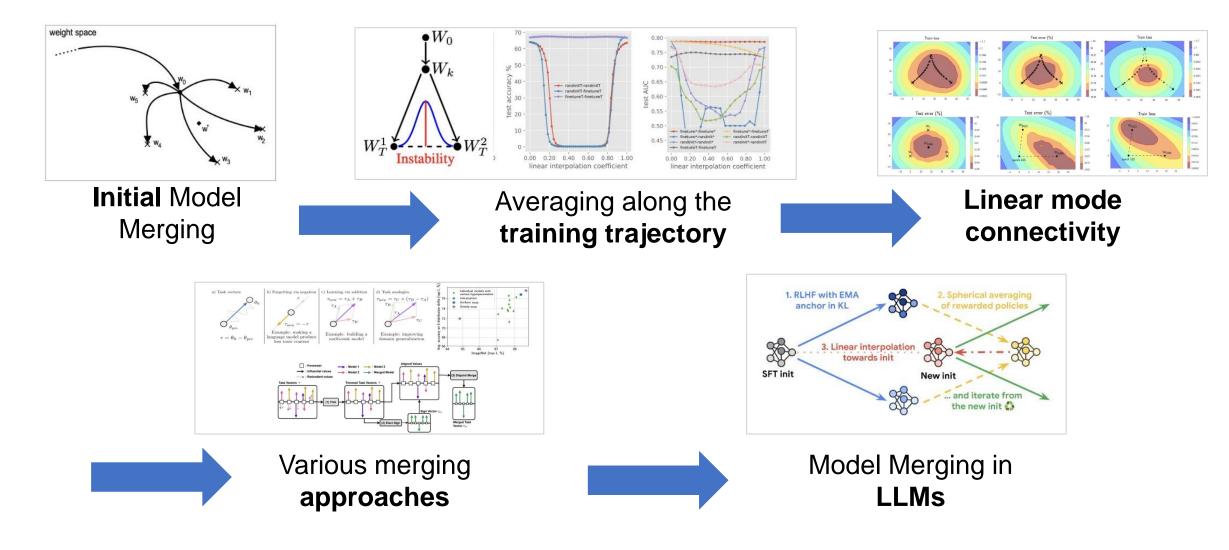
02 Methods and Preliminary Analysis

- Definition of Model Kinship
- Model Kinship Analysis on Community Experiments

03 Experimental Results and Underlying Mechanisms

- Main Experimental Results
- **Discussion**

Quick view: Model Merging Research Timeline



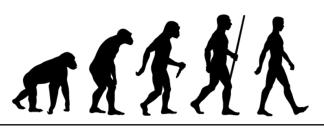
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Community Experiments

Hugging face Open Leaderboard

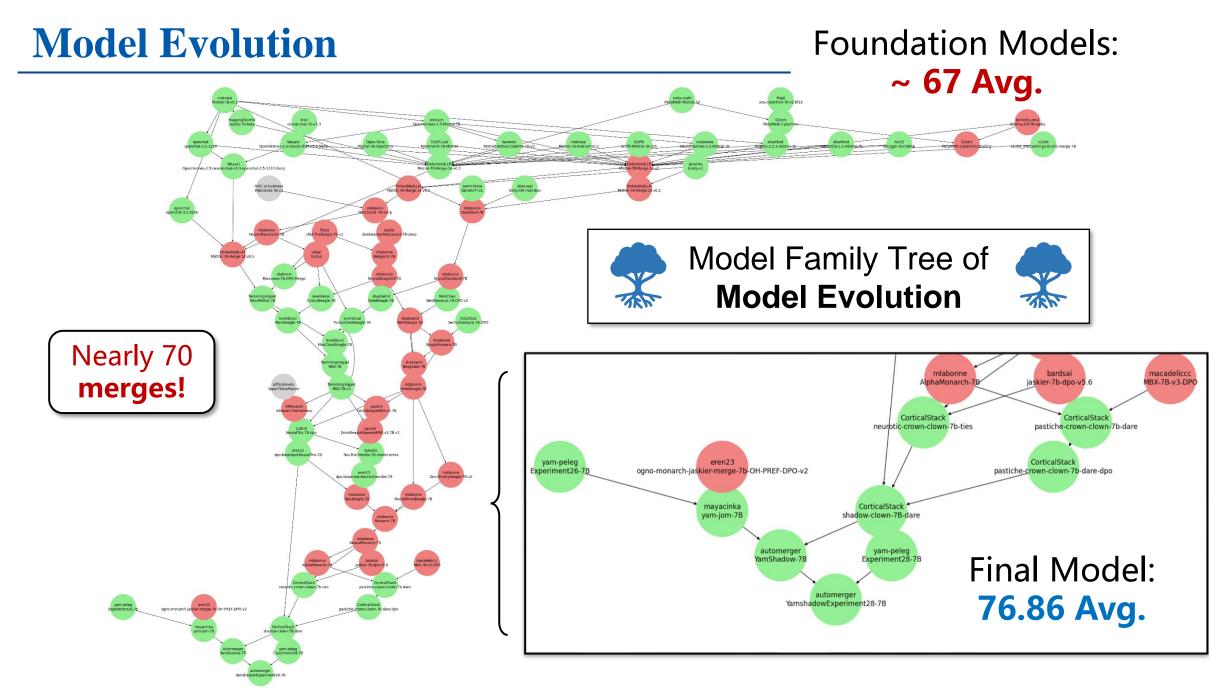
- A	Model	Average 🖬 🔺	-					GSM8K
•	automerger/YamshadowExperiment28-78 🗟	76.86	73.29	89.25	64.38	78.53	85.24	70.51
	liminerity/M7-7b 🔍	76.82	72.87	89.15	64.5	77.93	84.77	71.72
•	allknowingroger/MultiverseEx26.78-slerp 🖻	76.8	72.95	89.17	64.36	78.12	85.16	71.04
•	Kukedlc/NeuralSynthesis:78-v0.1 🖻	76.8	73.04	89.18	64.37	78.15	85.24	70.81
•	AurelPx/Percival_01.7b-slerp 🖻	76.79	73.21	89.16	64.42	77.97	85.08	70.89
•	shyamisee/JARVIZx6.0 .	76.78	73.29	89.15	64.41	77.87	85	70.96
•	automerger/Ognoexperiment27Multi_verse_model-78 🖻	76.77	72.95	89.29	64.39	78.04	84.85	71.11
•	shyamieee/B3E3-SLM:7b-v3.0 🖻	76.76	73.04	89.14	64.48	78.2	85	70.74
•	Kukedlc/NeuralSynthesis:7b-v0.4-slerp 🖻	76.76	73.21	89.14	64.28	78.07	84.85	71.04
	BarraHome/Mistroll-7B-v2.2 🖻	76.76	72.78	89.16	64.35	78.1	85	71.19
	nlpguy/I30M7. 🖻	76.75	73.12	89.14	64.48	77.96	85.08	70.74

T A	Model Walmart_the-bag/openchat=3.5_intinity Ma			ARC A 62.63	HellaSwag A 84.05	MMLU A	TruthfulQA A	Winogrande A	GSM8K 64.29
	Isaak-Carter/J.O.S.I.E.3-Beta10-7B-slerp 🖻	67		63.48	83.79	62.88	56.88	79.64	61.03
•	jondurbin/bagel_dpo_7b_x0_1 .	67	7.95	66.72	84.16	64.24	64.05	80.9	47.61
•	P0x0/IceMerge-7b-32k 🖻	67	7.94	65.53	85.65	64.66	53.09	80.51	58.23
	vicgalle/SystemHermes-27B 🗎	67	7.92	65.02	84.05	63.16	56.42	77.35	61.56
•	allknowingroger/DolphinChat.78-slerp 🖻	67	7.92	64.59	84.21	64.23	50.86	81.37	62.24
•	Liangmingxin/ThetaWave=78=sft 🖲	67	7.92	63.14	84.42	63.78	59.74	79.64	56.79
•	ichigoberry/pandafish-7b 🖹	67	7.88	65.19	85.28	64.99	52.69	80.82	58.3
•	Weyaxi/Einstein_openchat_7B 🖻	67	7.87	65.1	83.57	64.01	54.51	79.16	60.88
	openagi.project/OpenAGI.78.v0.1 .	67	7.87	68.26	85.06	61.6	59.4	79.79	53.07
•	indischepartij/MiaLatte_Indo-Mistral_7b 🖻	67	7.86	66.55	85.23	63.93	56.04	80.35	55.04
•	nlpguy/Hermes-low-tune-2	67	7.85	65.27	84.41	63.63	53.12	78.22	62.47

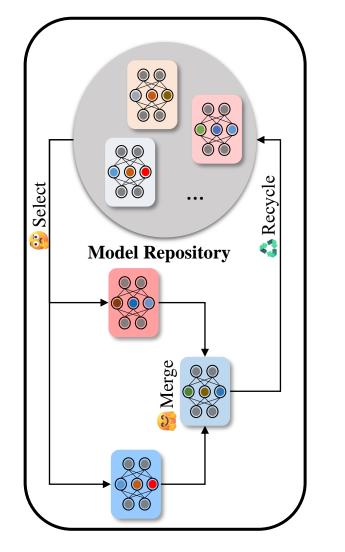


Model merging toolkits such as Mergekit enable users with limited expertise to easily conduct merging experiments, leading to an evolution of LLMs for the community.





Iterative Merging Improving LLMs via iterative process



Select

Select potential models for the next merge using a specific strategy (e.g. performance-prior)

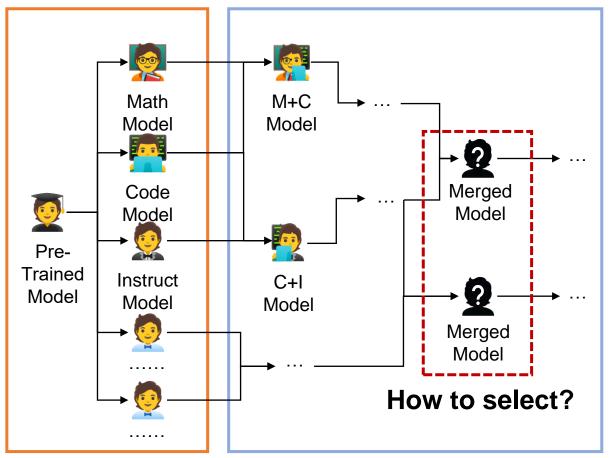
Merge

Merge selected models via model merging approach (e.g. Linear Averaging)

Recycle

Recycle merged model to **Model Repository** for future merging.

Merging Challenges



How can we select models after **multiple merges?**

□ Track foundation models?

- □ Possible for early merged models.
- □ Difficult for merged models after multiple merges.

Compare each task performance?

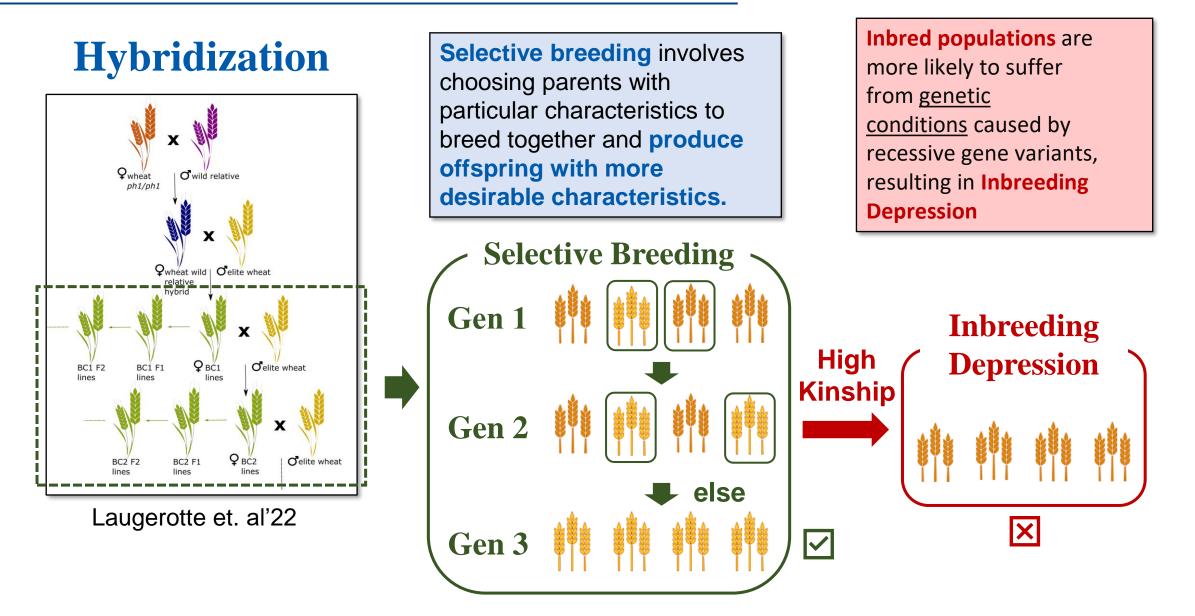
- Possible for comparison between 2 or 3 tasks.
- Difficult for merging multiple tasks.

□ Highest average task performance?

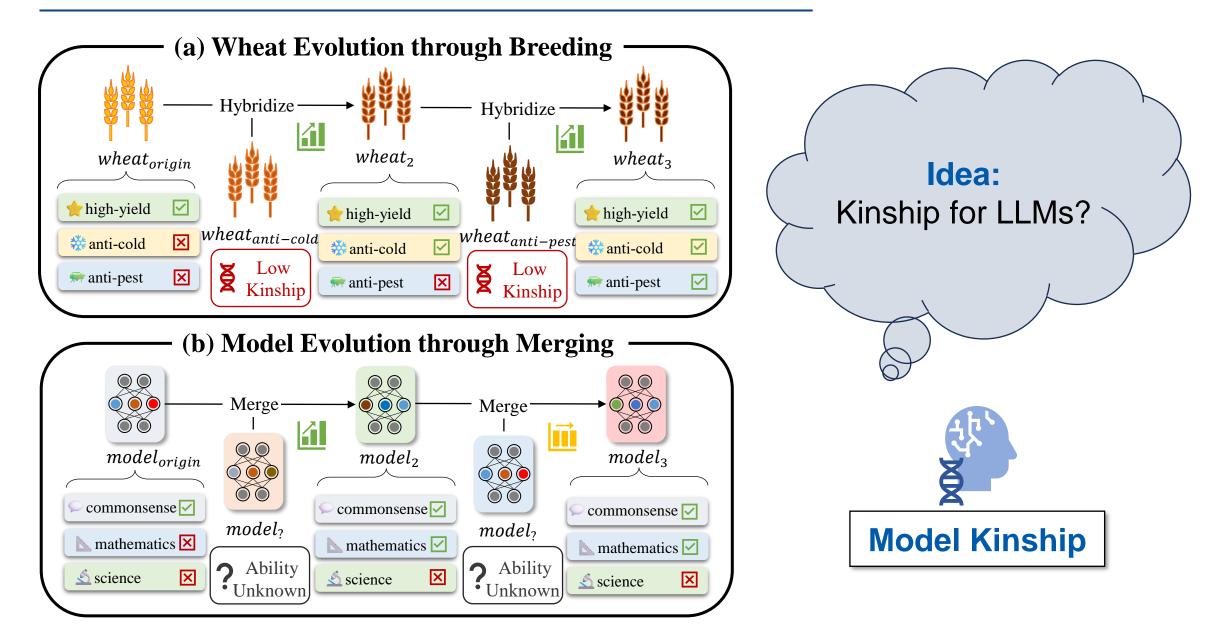
- Easy to identify.
- **D** Potential problems?

What else can we do?

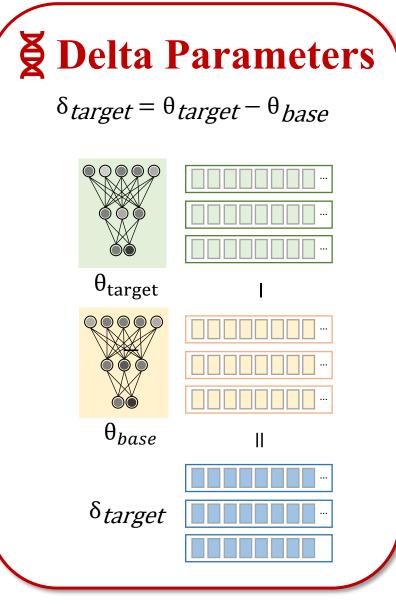
Artificial Evolution in Biology



Wheat Evolution vs. Model Evolution



Model Kinship



 $\theta \in \mathbb{R}^d$ is the weight of LLMs

Merging two models

 $model \ kinship = sim(\delta_1, \delta_2)$ similarity metric

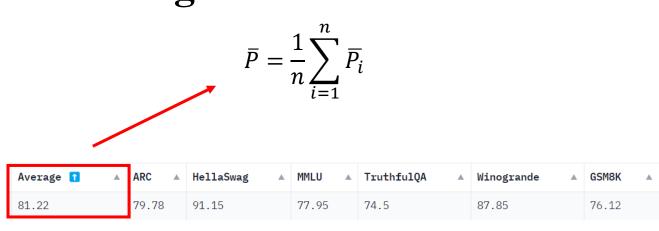
e.g. adopt *Pearson Correlation Coefficient* as similarity metric:

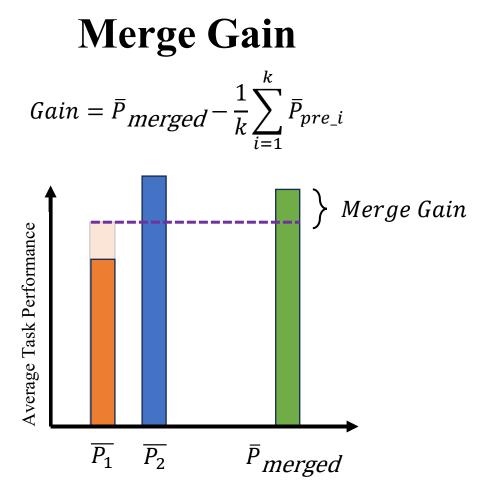
$$sim(\delta_i, \delta_j) = \frac{cov(\delta_i, \delta_j)}{\sigma_{\delta_i} \sigma_{\delta_j}} = \frac{\sum(\delta_i - \overline{\delta_i})(\delta_j - \overline{\delta_j})}{\sqrt{\sum(\delta_i - \overline{\delta_i})^2} \sqrt{\sum(\delta_j - \overline{\delta_j})^2}}$$

Merging multiple models

model kinship =
$$\frac{2}{n(n-1)} \sum_{1 \le i < j \le n} sim(\delta_i, \delta_j)$$

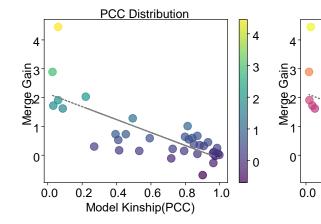


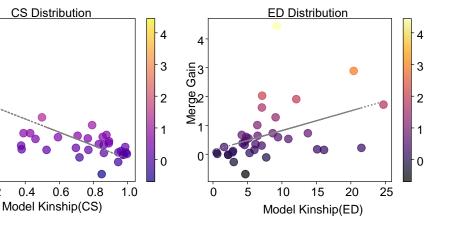




Correlation: Model Kinship and Merge Gain

0.2





Bias from users?

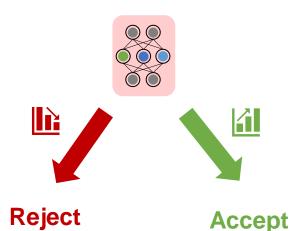


Table 1: **Correlation** of Model Kinship based on different correlation function $sim(\cdot, \cdot)$ with Merge Gain, along with their corresponding p-values.

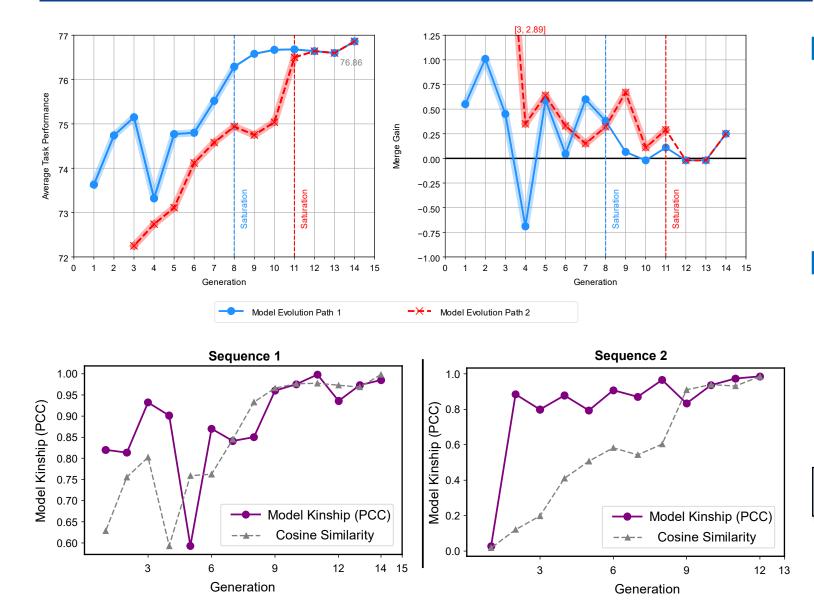
Metric	Correlation (Normal Value)	Correlation (Absolute Value)
PCC	-0.50	-0.59
P-value	0.063	0.023
CS	-0.45	-0.66
P-value	0.098	0.008
ED	0.46	0.67
P-value	0.091	0.007

Stronger Correlation More Confidence Initial conclusion: Farthest model kinship means higher merge gain



Conclusion: Farthest model kinship means higher variation in merge performance

Analysis of Model Evolution Paths



Learning Stage

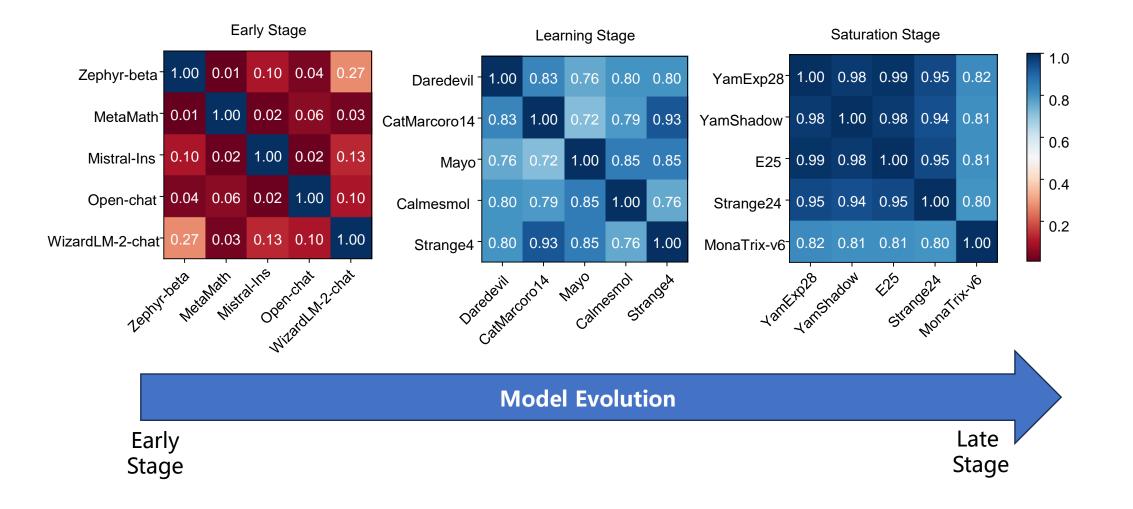
the average task performance generally experiences a rapid increase.

Saturation Stage

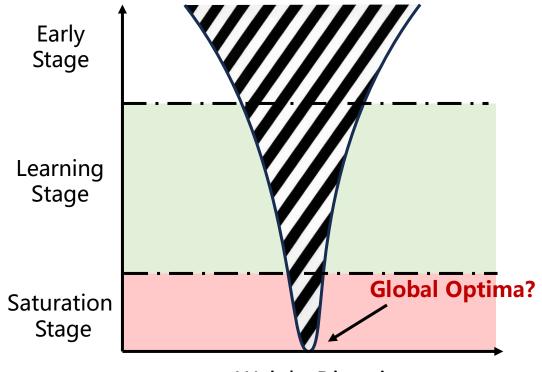
the model can no longer benefit from the merging process and has ceased to improve

Why does evolution stop?

Model Kinship within Different Stage



Convergence of Weight Space



Weight Diversity

The **weight diversity** of the top merged models **decreases** throughout the evolution.

The evolution progresses toward an optimal set of weights, which could either be a global optimum that fully integrates all information or a local optimum.

Methodology

Algorithm 1 Top k Greedy Merging with Model Kinship.

Require: A set M of n foundation models $\{M_1, M_2, \ldots, M_n\}$, Evaluation function f, Similarity metric function $sim(\cdot, \cdot)$ for model kinship.

1: Generate the first generation of merged models by merging each pair in set $M \{M_1, M_2, \ldots, M_n\}$.

- 2: Evaluate each merged model using f and select the top k models. Denote this set as $S = \{M_1, M_2, \ldots, M_n\}$.
- 3: Initialize a variable $S_{\text{prev}} = \emptyset$ to store the top *m* models from the previous iteration.
- 4: while $S \neq S_{\text{prev}}$ do
- 5: Set $M_{\text{prev}} = M$.
- 6: Set $S_{\text{prev}} = S$.
- 7: Select k pairs of models from S with the highest performance according to f.
- 8: Identify the current best model $M_{best} \in S$.
- 9: Identify the model $M_f \in S$ with the highest model kinship to M_{best} from the M_{prev} according to the similarity metric $sim(\cdot, \cdot)$.
- 10: Merge M_f with M_{best} to generate a new model M_{exp} and add M_{exp} into set M.
- 11: Merge each selected pair to M_{merged} (named as **Model-gen-id**) for merged models and add merged models into set M.
- 12: Evaluate each new model using f and update S to be the new top k models.
- 13: end while

Note: The blue-highlighted steps are only executed in modified experiments incorporating model kinship-based exploration.

Initialization

Iterative Merging

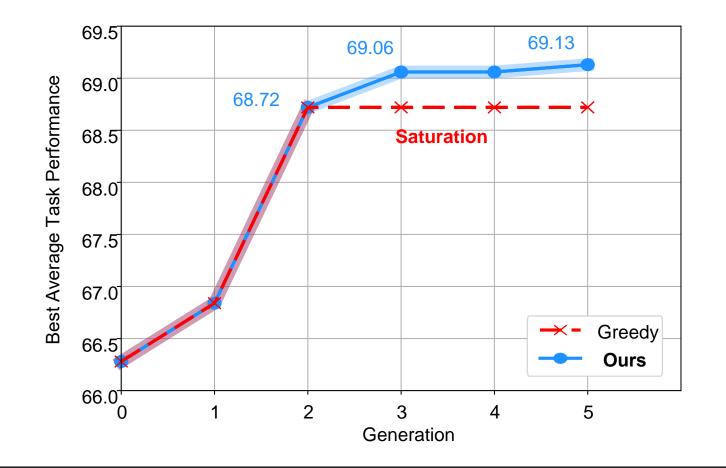
Main Experiment Results

	are labele	ed using the structure: Model-{generation number}-{model identification num									er}.
		0	Greedy Strategy		+ Model Kinship						
		Model	Avg.	Gain	Kinship	Model	Avg.	Gain	Kinship		
		MetaMath Instruct Open-chat	63.72 61.82 66.28	 	 	MetaMath Instruct Open-chat	63.72 61.82 66.28	 	/ / /		
Models in each merge	1	model-1-1 model-1-2 model-1-3	62.17 64.02 66.84	-0.6 -0.03 +1.84	0.01 -0.02 0.05	model-1-1 model-1-2 model-1-3	62.17 64.02 66.84	-0.6 -0.03 +1.84	0.01 -0.02 0.05		Same selection
are highly related.		model-2-1 model-2-2 model-2-3	68.72 61.47 61.32	+2.16 -3.96 -3.83	0.93 0.57 0.58	model-2-1 model-2-2 model-2-3	68.72 61.47 61.32	+2.16 -3.96 -3.83	0.93 0.57 0.58	J	
		model-3-1 model-3-2	68.59 67.74	+1.09 -0.04	0.95 0.93 -	model-3-2 model-3-3 model-3-4	67.74 69.06 68.61	+1.09 +0.74 +1.13	0.93 0.24 0.32		
		model-4-1 model-4-2 model-4-3	68.51 68.04 68.53	-0.14 -0.19 +0.37	0.98 0.98 0.94	model-4-4 model-4-5 model-4-6	68.75 68.39 69.03	-0.14 -0.27 +0.15	0.54 0.66 0.52		
			- - -		- - -	model-5-1 model-5-2 model-5-3	69.13 68.98 68.63	+0.04 +0.07 -0.37	0.65 0.65 0.98		

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. Merged models are labeled using the structure: **Model-{generation number}-{model identification number}**.

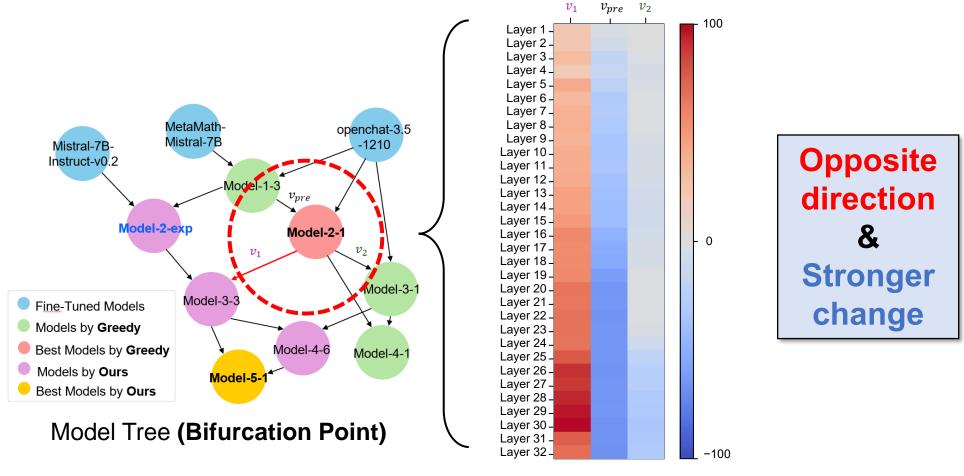
Exploration Strategy finds a better evolution path.

Main Experiment Results



Exploration Strategy enable evolution to continue.

Weight Change in Bifurcation point



Weight change in different path

Merging Models with Low Kinship can improve performance

- Expand searching range.
- Escape the local optima traps.

Early Stopping at High Kinship can improve Efficiency

□ Fair trade-off: small performance gains versus large time consumption

Model Kinship: An Effective Guiding Metric for Model Evolution

- Predict the Merging Outcomes.
- **Control the Evolution Directions.**
- More works need to be done
 - Better similarity metric?
 - > Theoretical framework of Model Evolution?
 - Support sustainable evolution (with the help of extrapolation[1]) ?

[1] Weak-to-Strong Extrapolation Expedites Alignment (CoRR 2024)



Model Kinship



https://github.com/zjunlp/ModelKinship