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Scaling Large Language Model-Based Multi-Agent Collaboration

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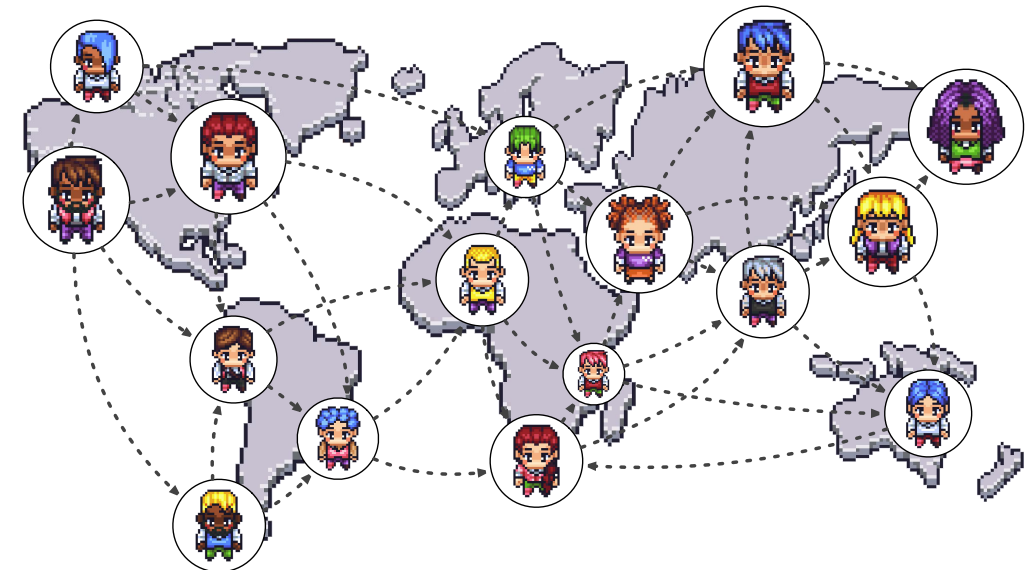
- Introduction
- Methodology
- Evaluation
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Introduction



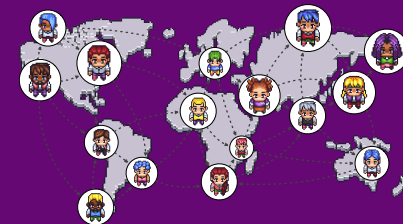
LLM-Powered Multi-Agent Collaboration

- **Single Agent:** Context Explosion & Lack of Diversity
 - **Multi-Agent Collaboration:** facilitated by interactive behaviors, often surpasses standalone intelligence
- +
- **Emergent Abilities:** ① Nature: sardine schools, ant swarms
② large language models
- =
- **Scaling** the number of agents in Multi-Agent Systems (MAS) -> Emergent behaviors? Collaborative Scaling Law?



Multi-Agent Collaboration

Introduction



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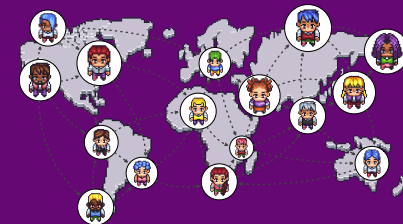


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Emergent behavior of sardine schools

Introduction



LLM-Powered Multi-Agent Collaboration

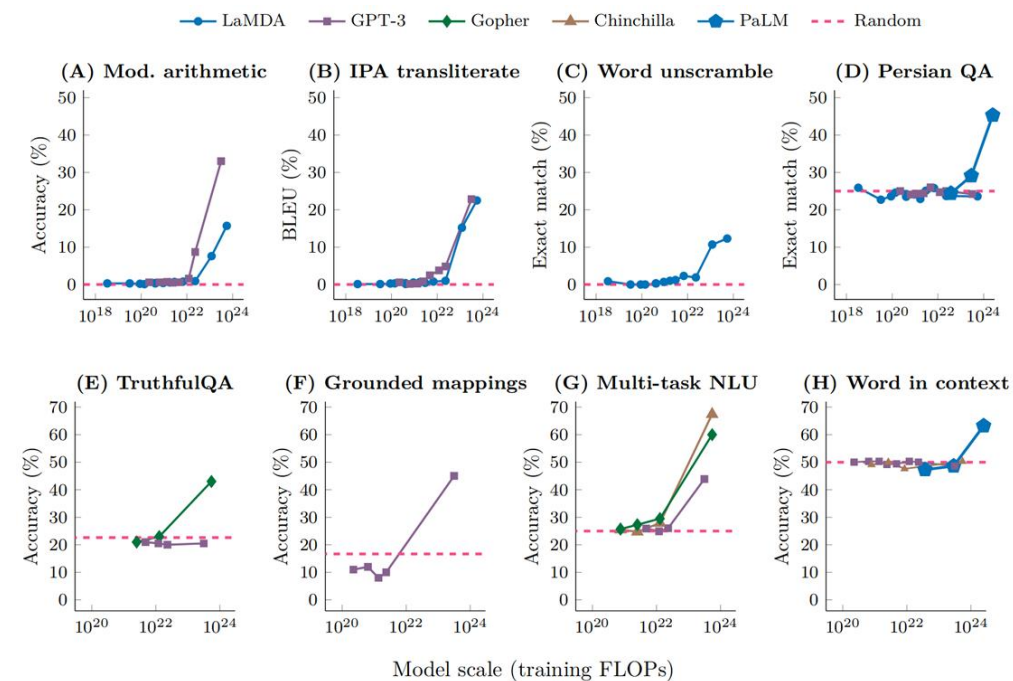
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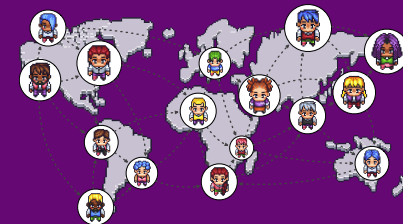


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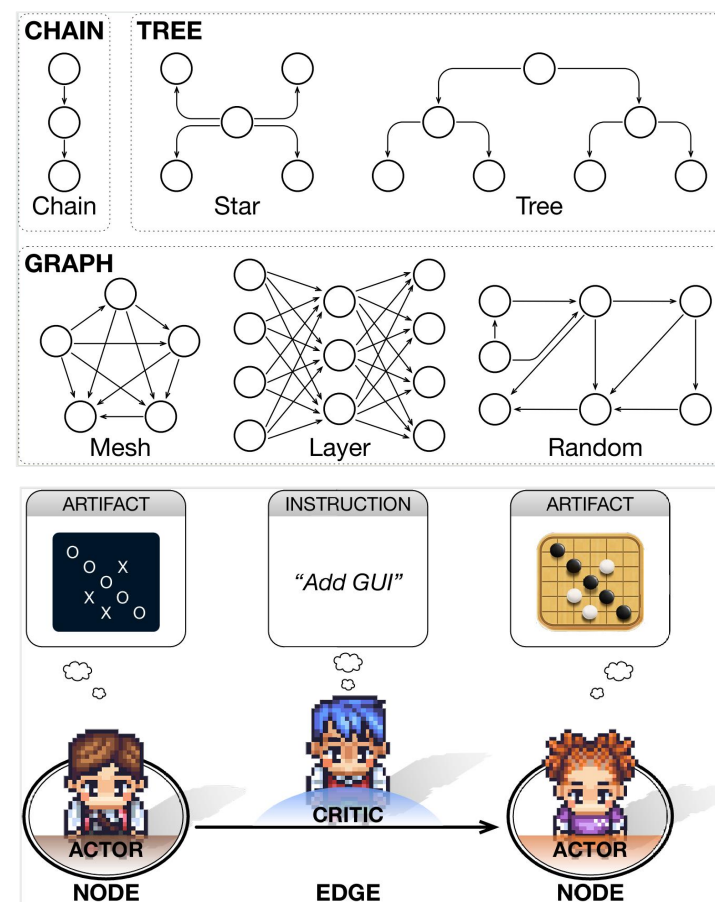
Emergent abilities of large language models

Methodology

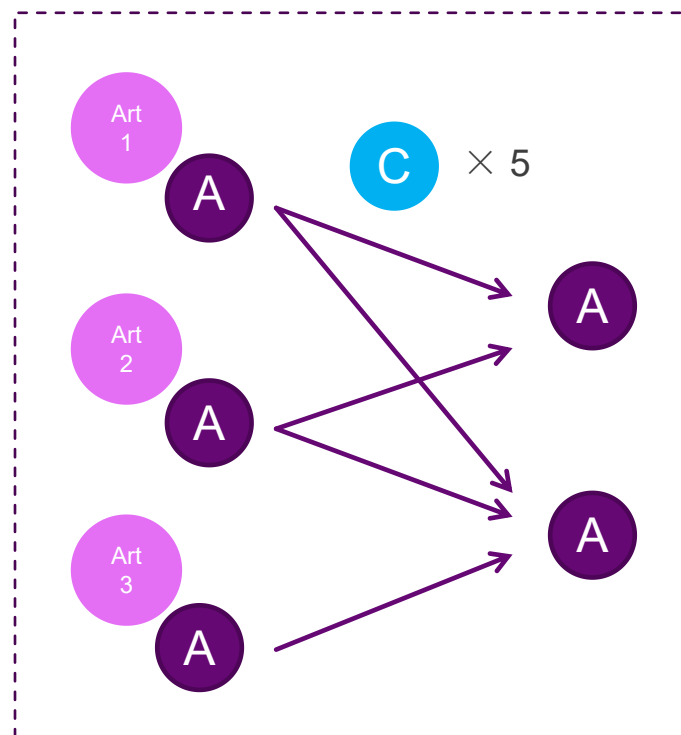
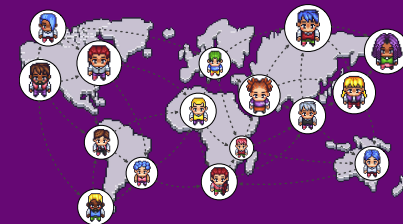


Network Construction

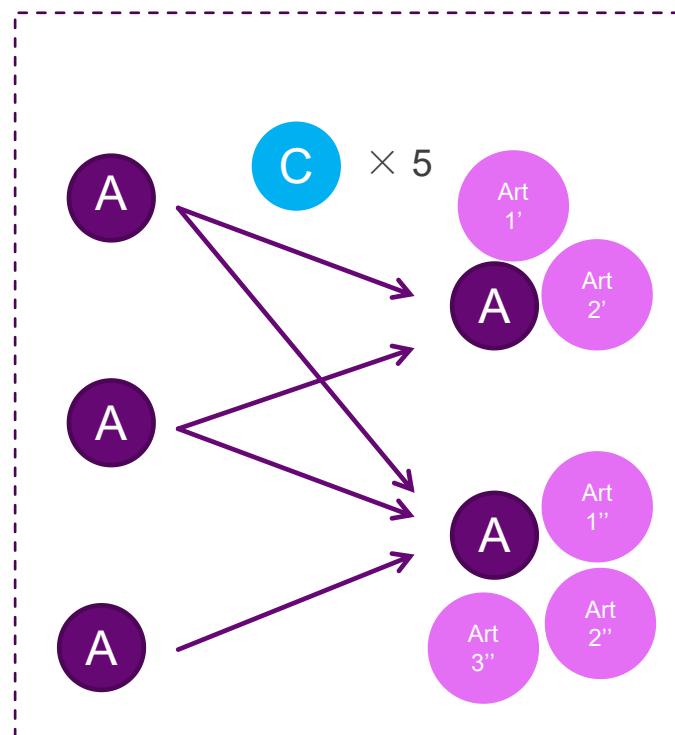
- Describe **agents** and their **interrelations** as a **directed acyclic graph (DAG)** - prevents backflow and enhances generalizability
- Agentization: structurally assign a **critic** to each edge and an **actor** to each node
- The actor's outputs (artifacts) are **refined** under the critic's instructions, eventually **aggregated** into one artifact - information propagation



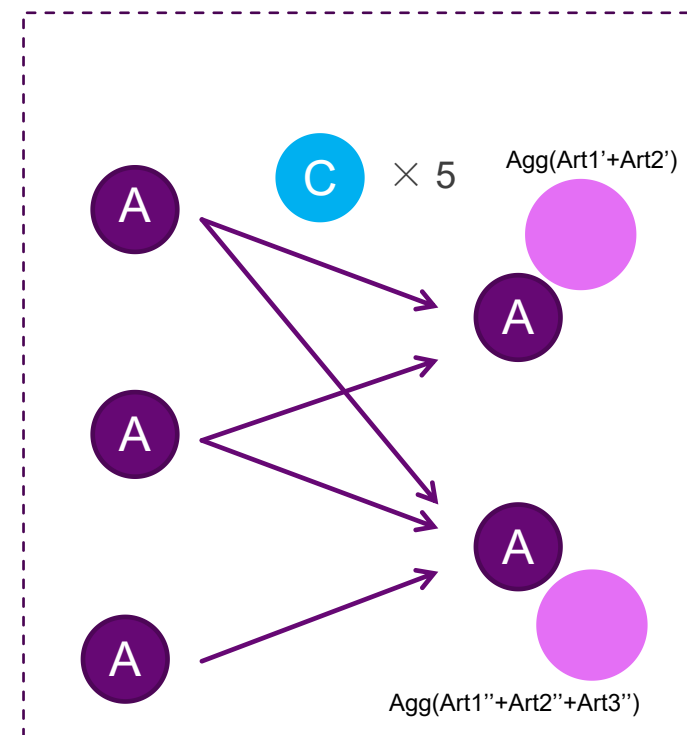
Methodology



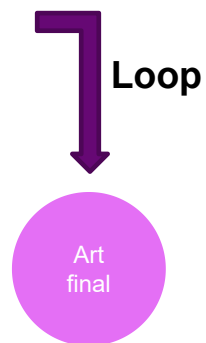
Step1



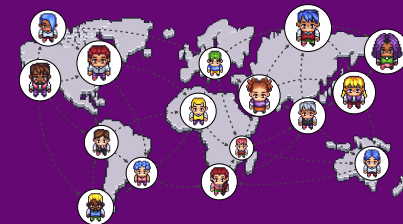
Step2



Step3

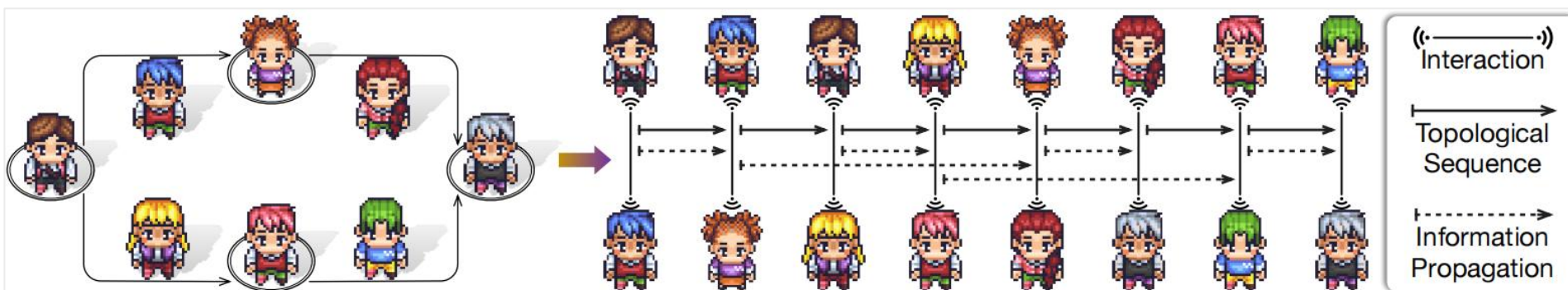


Methodology

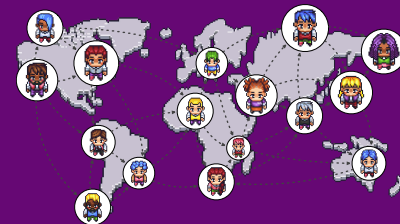


Interactive Reasoning

- Traversal strategy: **topological ordering**
 - Orderly information transmission
 - High scalability & generalizability
- The interaction pattern: multi-turn **instruction-response** sequence -> **mitigates hallucinations**
- Memory control: **long-term** (global) & **short-term** (interaction-level) memory decouples context length from **quadratic** to **linear** growth



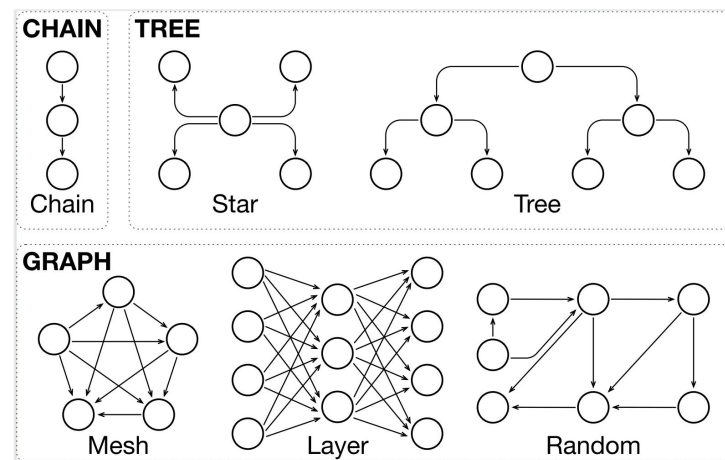
Evaluation



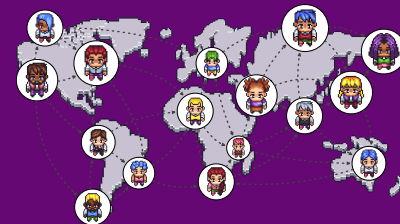
Primary Results

- **Significant improvement**
 - **Chain-structure** method consistently outperforms most baseline models
 - **Random-structure** method achieves the highest performance
- **Ablation study**
 - Setting temperature to **0.0** and ablating profile causes an average performance degradation of **3.67%** across all topologies

Method	Paradigm	MMLU	HumanEval	SRDD	CommonGen	Quality
CoT		0.3544 [†]	0.6098 [†]	0.7222 [†]	0.6165 [†]	0.5757 [†]
AUTOGPT		0.4485 [†]	0.4809 [†]	0.7353 [†]	0.5972	0.5655 [†]
GPTSWARM		0.2368 [†]	0.4969 [†]	0.7096 [†]	0.6222 [†]	0.5163 [†]
AGENTVERSE		0.2977 [†]	0.7256[†]	0.7587 [†]	0.5399 [†]	0.5805
MACNET-CHAIN		0.6632	0.3720	0.8056	0.5903	0.6078
MACNET-STAR		0.4456 [†]	0.5549 [†]	0.7679 [†]	0.7382 [†]	0.6267
MACNET-TREE		0.3421 [†]	0.4878 [†]	0.8044	0.7718[†]	0.6015
MACNET-MESH		0.6825	0.5122 [†]	0.7792 [†]	0.5525 [†]	0.6316 [†]
MACNET-LAYER		0.2780 [†]	0.4939 [†]	0.7623 [†]	0.7176 [†]	0.5629 [†]
MACNET-RANDOM		0.6877	0.5244 [†]	0.8054	0.5912	0.6522[†]



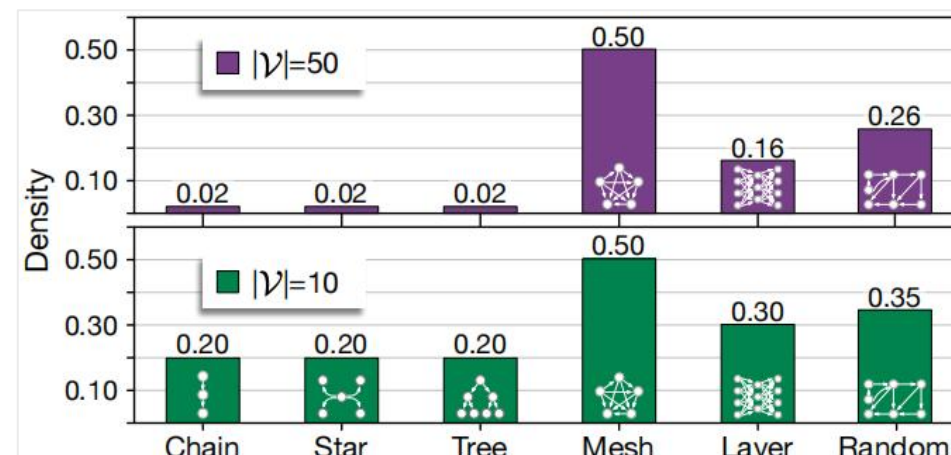
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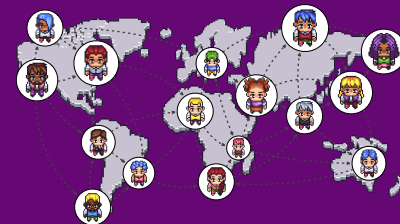
Topological Perspective Analysis

- No one-fits-all topology
- Density
 - Positively correlated with performance
- Shape
 - High clustering coefficient tend to exhibit superior performance —— “small-world collaboration phenomenon”
- Wider topologies generally outperform deeper topologies
- Performance of each topology varies across task domains

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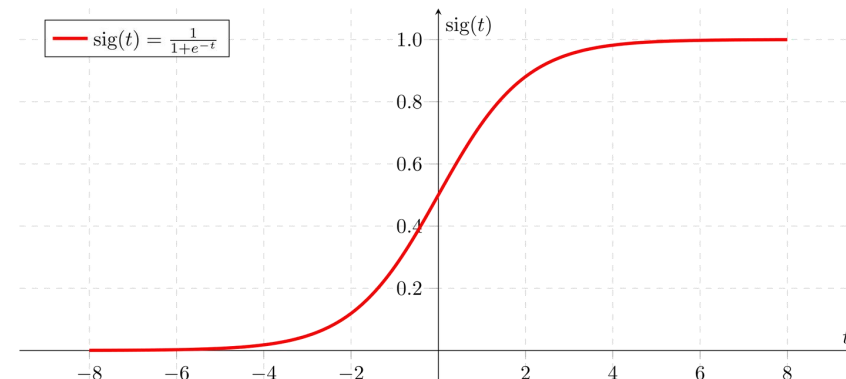
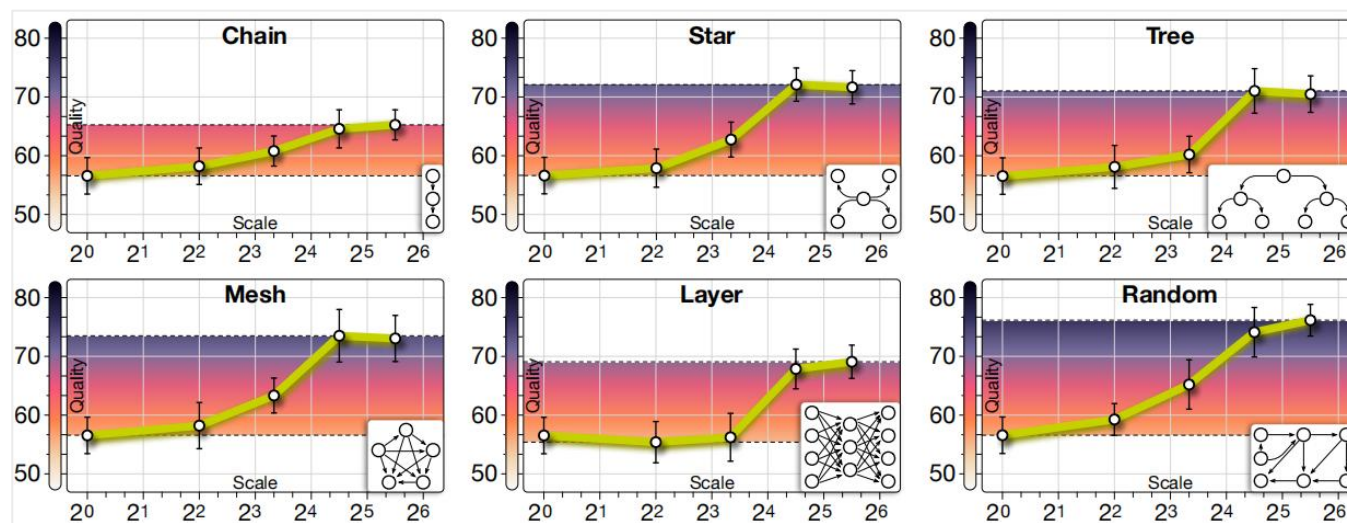


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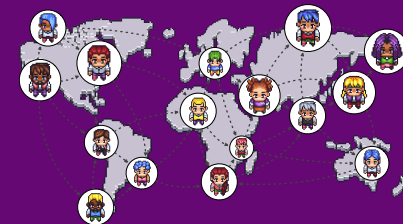


Collaborative Scaling Law

- **Trend Perspective**
 - Performance & number of nodes: resembles a **sigmoid-variant** function
 - Necessitates appropriate collaboration strategies
- **Timing Perspective**
 - **Much smaller** scales to manifest emergence, compared to **neural scaling law**
 - Agent collaboration may serve as a “**shortcut**” to enhance intelligence levels

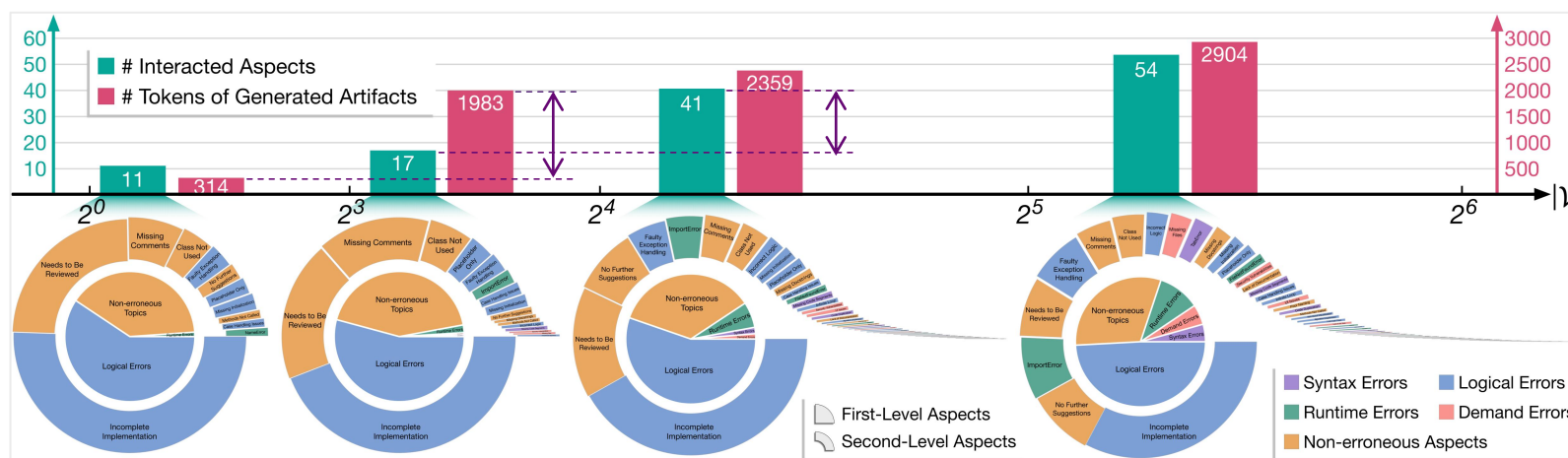


Evaluation



Collaborative Emergence

- Emergent Behaviors:
- # Interacted Aspects and # Tokens of Generated Artifacts exhibits rapid growth when the node scale reaches 2^3 or 2^4 , which aligns with the collaborative scaling law observed in performance
- Token Distribution:
- The token distribution from underlying models typically follows a **long-tail** pattern, necessitating larger-scale sampling to likely capture these tail tokens -> **Emergence**





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THANKS!

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