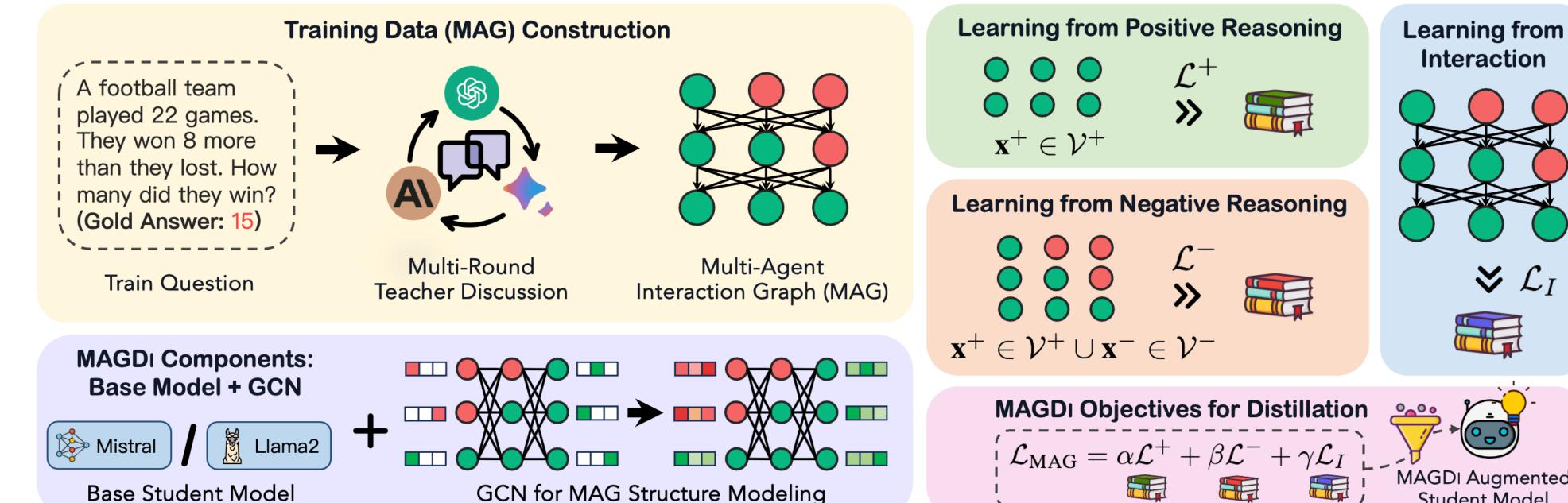


MAGDi: Structured Distillation of Multi-Agent Interaction Graphs Improves Reasoning in Smaller Language Models Justin Chih-Yao Chen*, Swarnadeep Saha*, Elias Stengel-Eskin, Mohit Bansal UNC Chapel Hill

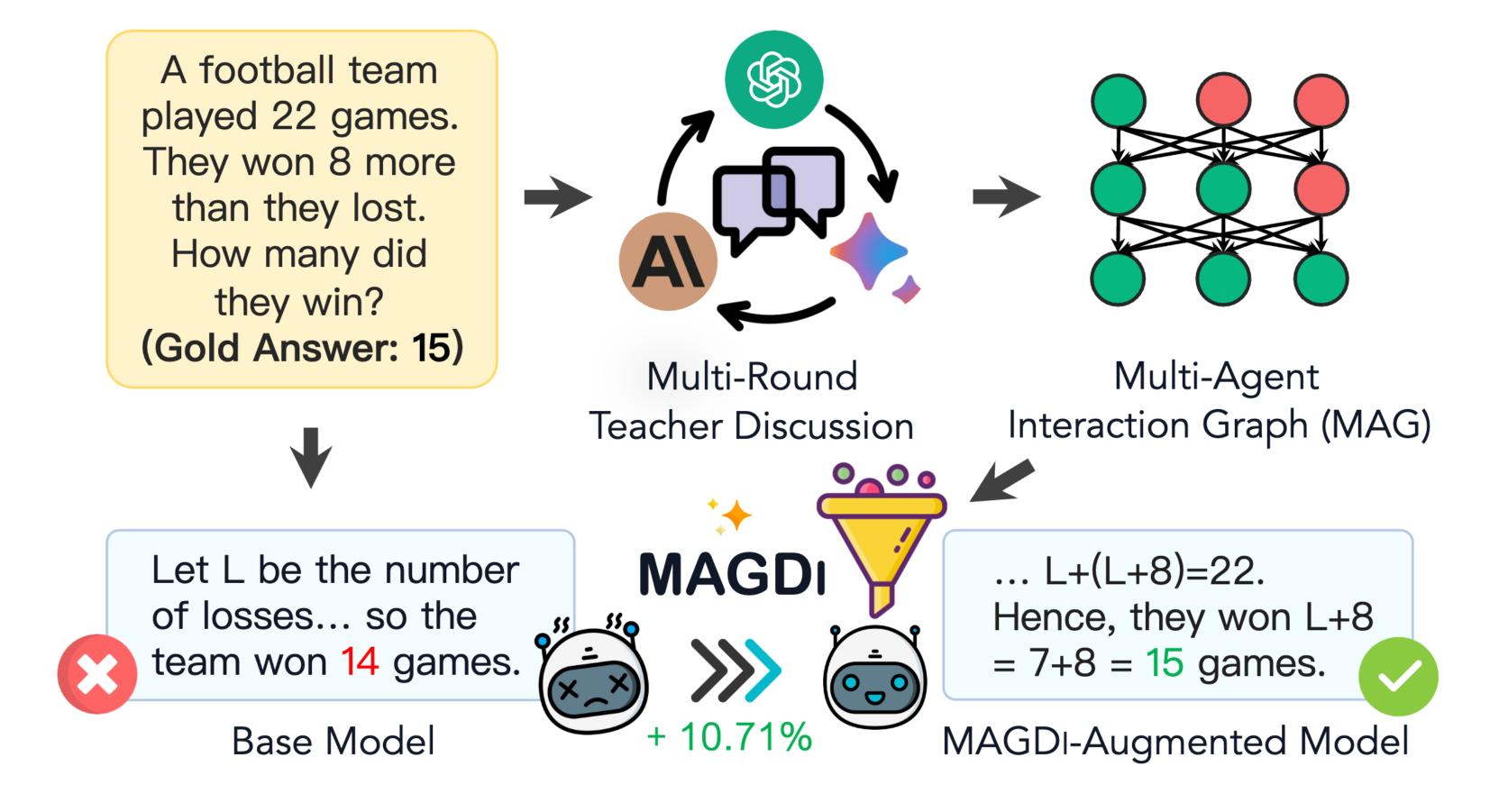
Motivation & Contributions

- Multi-agent interactions with LLMs **improve reasoning but are costly** and lack a unified model for efficient inference.
- We propose MAGDi, a structured distillation method which distills the interactions between multiple LLMs into smaller student models.
- The teacher LLMs interactions are represented as graphs.
- Tested on seven benchmarks, MAGDi boosts smaller models' reasoning abilities and achieving significant efficiency gains.
- MAGDi also shows improved generalizability, scalability and diversity.

Methodology



SouthNLP



Problem Setup

We present Multi-Agent Interaction as a graph (MAG). We capture rich

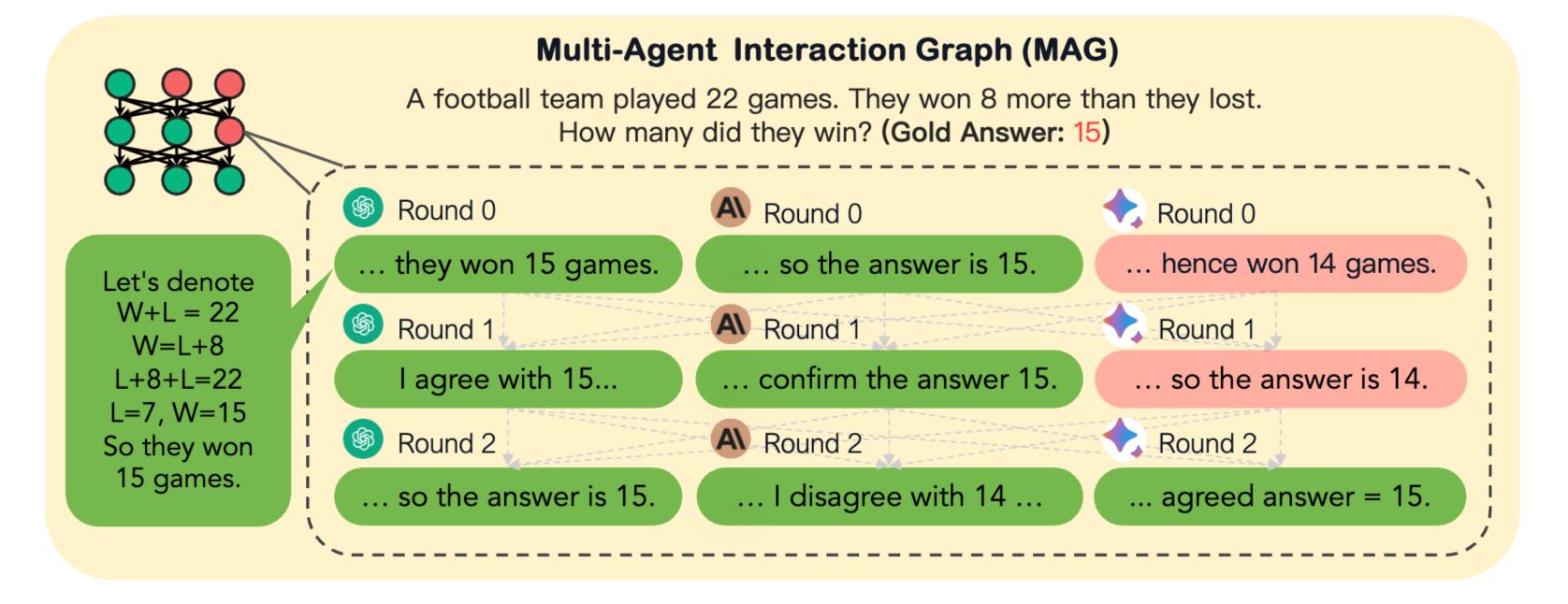
We employ three objectives to learn increasing levels of interaction structure in a MAG.

- Learning from Positive Reasoning: Next-token prediction \bullet
- Learning from Negative Reasoning: Margin-based ranking loss
- Learning from Interaction: Node classification using a GCN ullet

Main Result

	Distilled Model	Datasets					
Distillation Data		StrategyQA	CSQA	ARC-c	GSM8K	MATH	Average Acc
-	Mistral-7B-Instruct	61.57	57.89	60.32	44.05	7.02	46.17
Claude2 Bard GPT-4	SIT-Claude2 SIT-Bard SIT-GPT4	64.39 68.56 69.96	64.18 65.06 66.87	68.24 66.87 68.91	45.34 45.61 47.38	7.24 7.06 8.24	49.89 50.63 52.27
Round-0 Nodes Correct Nodes All Nodes MAG	MAGDI-R0 [Level 1] MAGDI-CN [Level 2] MAGDI-AN [Level 3] MAGDI [Level 4]	71.18 71.62 72.10 74.24	67.36 69.31 70.65 72.56	72.06 72.34 71.92 72.61	48.52 50.11 50.69 52.27	9.72 10.66 11.98 12.76	53.77 [+ 1.50%] 54.81 [+ 2.54%] 55.47 [+ 3.20%] 56.88 [+ 4.61%]

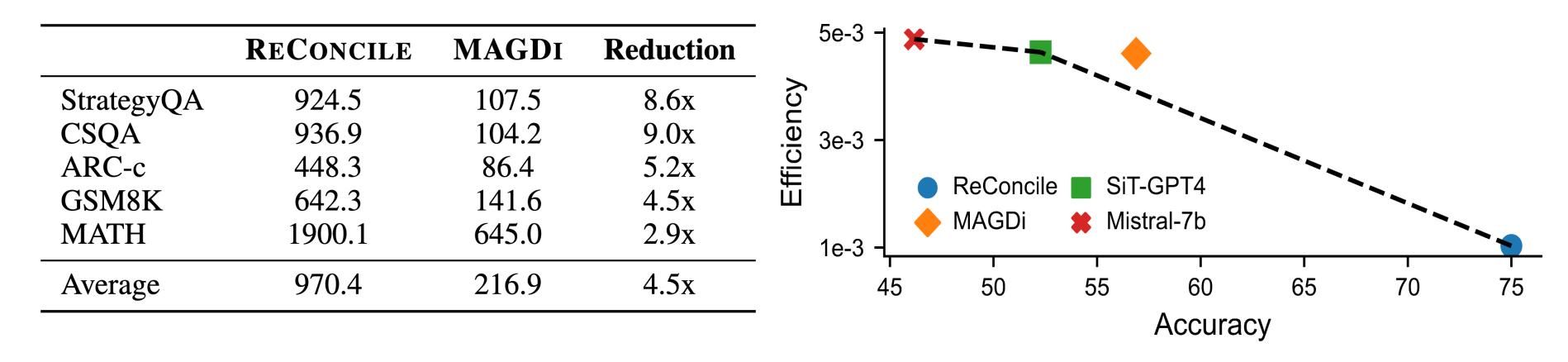
knowledge from MAGs via the following four levels of MAG components.



- **Level 1:** Learning from multiple teachers. The student learns from the correct reasoning of multiple teachers, rather than one.
- **Level 2:** Learning from teacher interactions. The student learns from both pre- and post-interaction data between multiple teachers.
- **Level 3:** Learning from negative reasoning. The student additionally distills from negative or incorrect reasoning from the teacher models.

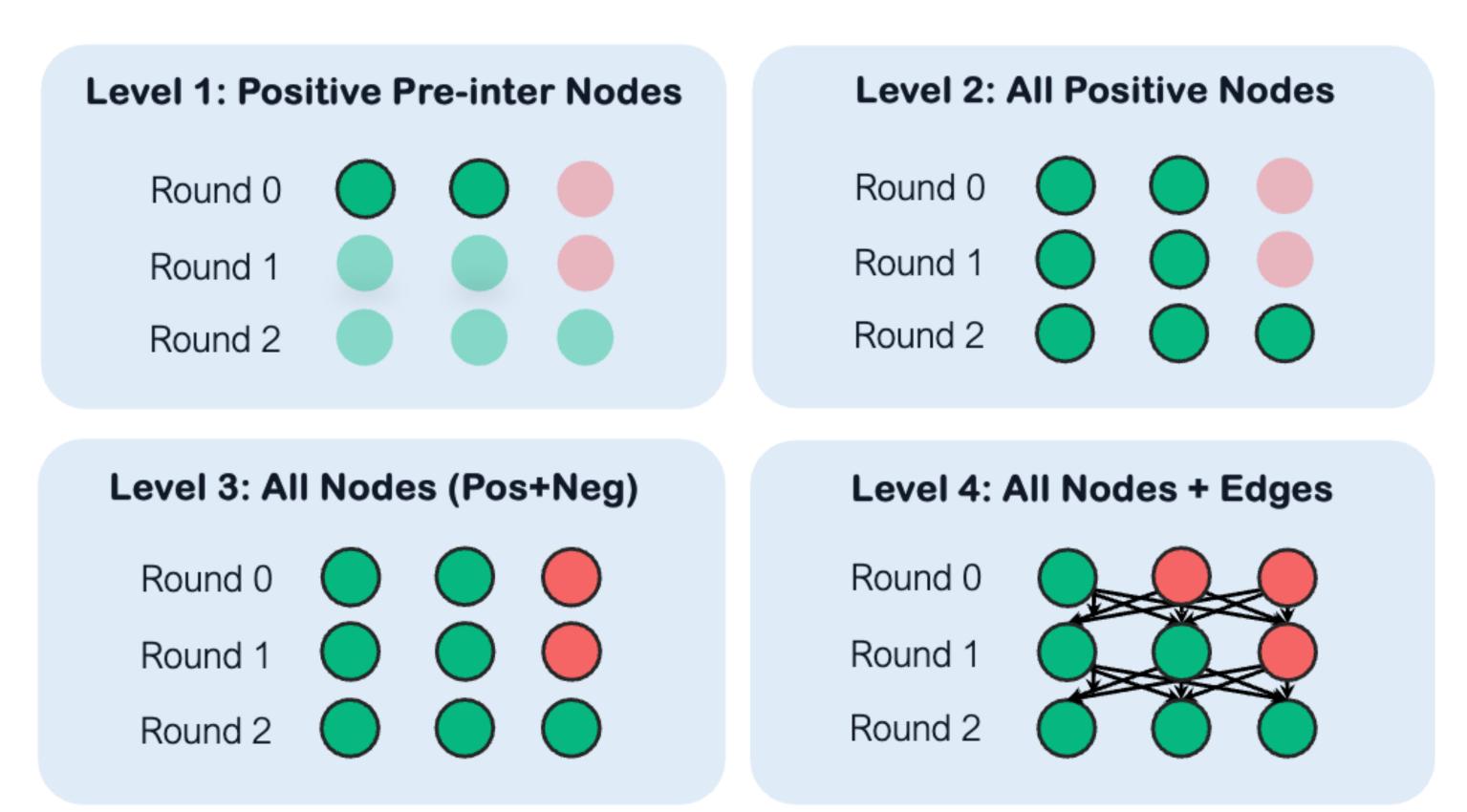
- Level 1: Distillation from multiple teachers > distillation from strongest teacher only.
- Level 2: Distillation from pre- and post-interaction reasoning > only pre. reasoning.
- Level 3: Negative reasoning chains further improve distillation.
- Level 4: Structured distillation from interactions > all multi-teacher baselines.

Efficiency Analysis

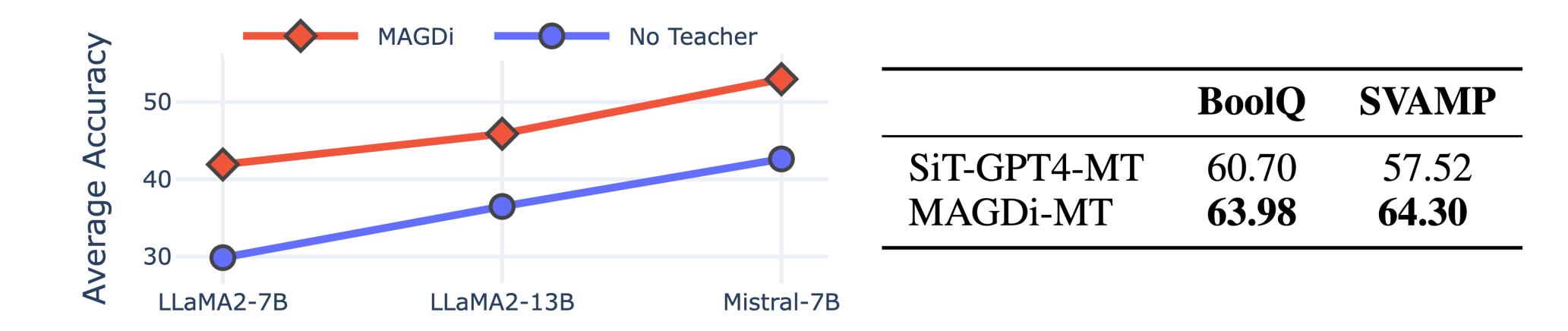


- MAGDi achieves up to a 9x reduction in token count.
- MAGDi achieves a better balance of efficiency and performance.
- More efficient than its teacher system ReConcile \bullet
- Performs better than zero-shot and prior single-teacher distillation methods.

Level 4: Learning from structure. The student learns from the output \bullet and graph-structure of teacher LLM interactions.



Generalizability, Scalability and Diversity



MAGDi scales positively with the student size and performs better on OOD datasets.

	Mistral-7B	SIT-GPT4	MAGDI
w/o SC	44.05	47.38	52.27
w/ SC	48.44 [+ 4.39%]	58.62 [+ 11.24%]	67.42 [+ 15.15%]

MAGDi obtains larger improvements w/ self-consistency, which relies on model diversity.