STaR: Self-Taught Reasoner

Bootstrapping Reasoning With Reasoning

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Outline

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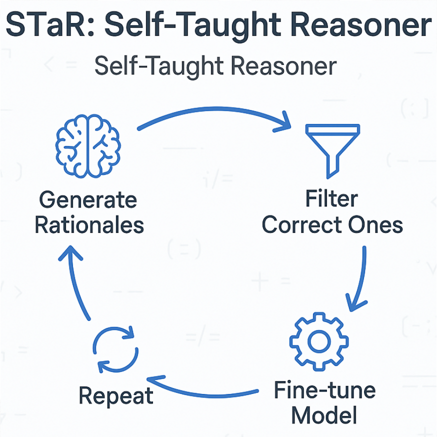
Research Question

Can models teach themselves to reason better?

Understanding the STaR Algorithm

The STaR algorithm introduces a loop-based mechanism that allows a language model to generate and refine its reasoning capabilities over time through rationale generation and iterative learning.



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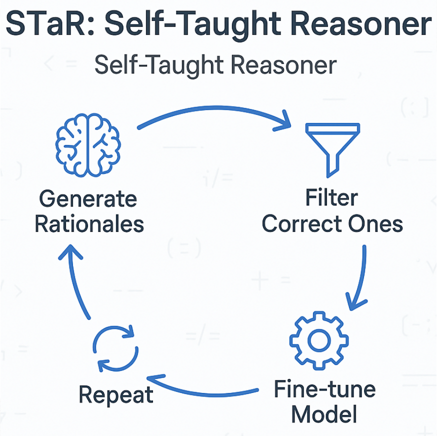

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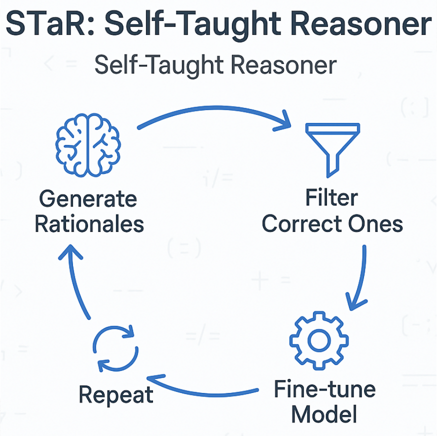

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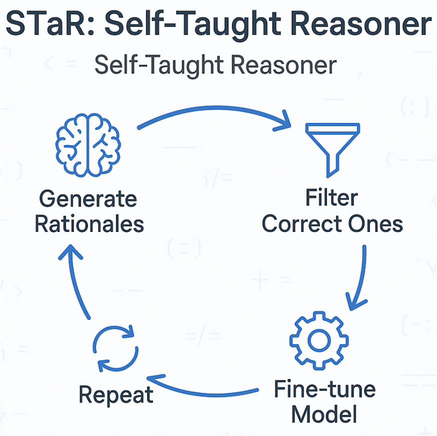
- Continuously improves by learning from generated data
- Combines rationale generation with rationalization



The STaR Process

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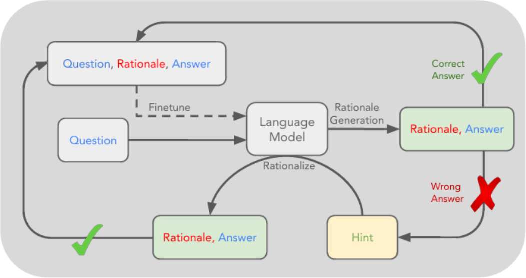

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   - Correct: Added to training data
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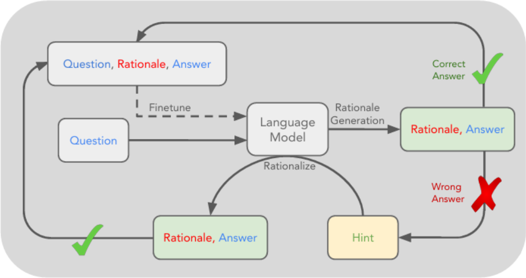

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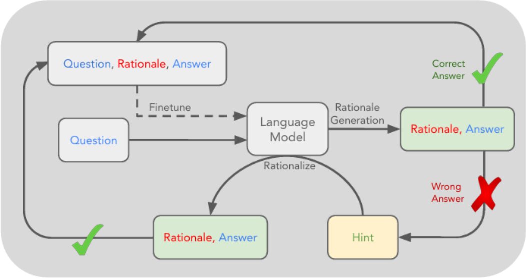
3. Feedback Loop: Rationales used to fine-tune model



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Question: "What is the best way to carry a small dog?"
Choices: (a) Swimming pool (b) Basket (c) Dog show (d) Backyard (e) Own home

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- Correct answer/rationale added to training data
- Reinforces valid reasoning paths

Example: Incorrect Answer Handling

Initial Incorrect Output

Rationale: "Dog show has space for movement."
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Rationale: “Dog show has space for movement.”
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Correction Process

- Provide hint: Correct answer is (b) Basket
- Model generates new rationale supporting basket
- New rationale added to training data
- Model fine-tuned to avoid similar mistakes

STaR without Rationalization

Algorithm 1 Rationale Generation Bootstrapping (STaR without rationalization)

Input $\boldsymbol{M}$: a pretrained LLM; dataset $\boldsymbol{\mathcal{D}} = \{(x_i, y_i)\}_{i=1}^{D}$ (w/ few-shot prompts)

1: $\boldsymbol{M_0} \leftarrow \boldsymbol{M}$ # Copy the original model
2: **for** n in $1 \ldots N$ **do** # Outer loop
3: $\quad (\hat{r}_i, \hat{y}_i) \leftarrow M_{n-1}(x_i) \quad \forall i \in [1, D]$ # Perform rationale generation
4: $\quad \mathcal{D}_n \leftarrow \{(x_i, \hat{r}_i, y_i) \mid i \in [1, D] \wedge \hat{y}_i = y_i\}$ # Filter rationales using ground truth answers
5: $\quad M_n \leftarrow \text{train}(M, \mathcal{D}_n)$ # Finetune the original model on the correct solutions - inner loop

STaR Algorithm

Algorithm 2 STaR

Input M: a pretrained LLM; dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{D}$ (w/ few-shot prompts)

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4: $(\hat{r}_i^{\text{rat}}, \hat{y}_i^{\text{rat}}) \leftarrow M_{n-1}(\texttt{add\_hint}(x_i, y_i)) \quad \forall i \in [1, D]$ # Perform rationalization
5: $\mathcal{D}_n \leftarrow \{(x_i, \hat{r}_i, y_i) \mid i \in [1, D] \wedge \hat{y}_i = y_i\}$ # Filter rationales using ground truth
6: $\mathcal{D}_n^{\text{rat}} \leftarrow \{(x_i, \hat{r}_i^{\text{rat}}, y_i) \mid i \in [1, D] \wedge \hat{y}_i \neq y_i \wedge \hat{y}_i^{\text{rat}} = y_i\}$ # Filter rationalized rationales
7: $M_n \leftarrow \text{train}(M, \mathcal{D}_n \cup \mathcal{D}_n^{\text{rat}})$ # Finetune on correct solutions

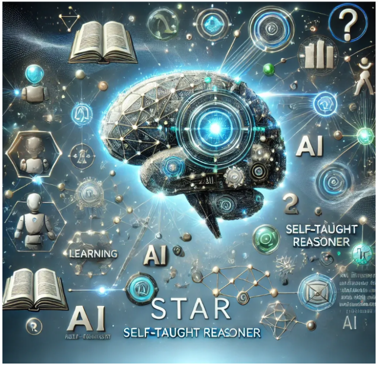
Technical Implementation

Mathematical Formulation

Treat as latent variable model:

$$p_M(y|x) = \sum_r p(r|x)p(y|x, r)$$

$$\nabla J = \sum_i \mathbb{E}_{r,y}[\mathbb{I}(y_i = \hat{y}_i) \cdot \nabla \log p_M(\hat{y}_i, \hat{r}_i|x_i)]$$



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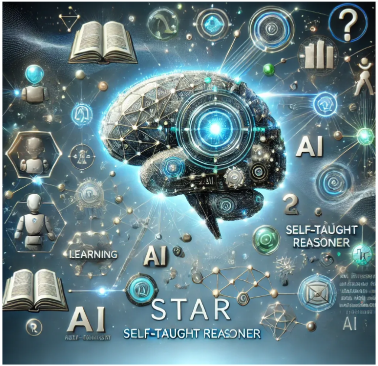
- Base model: GPT-J (6B parameters)
- Batch size: 8 sequences $\times$ 1024 tokens
- Learning rate: 1e-6 (Adam optimizer)
- TPU-v3 hardware



CommonsenseQA Results

Method	CQA Dev Set Accuracy (%)	Train Data Used (%)
GPT-3 Direct Finetuned(175B)	73.0	100
Few-shot Direct GPT-J	20.9	$\sim$0
Few-shot CoT GPT-J	36.6	$\sim$0
Few-shot CoT LaMDA 137B	55.6	$\sim$0
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STaR without rationalization	68.8	69.7
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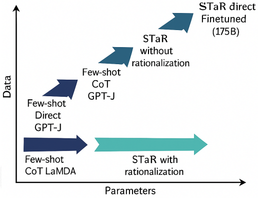

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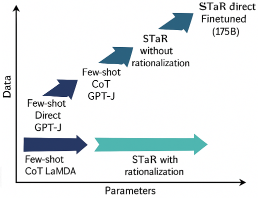

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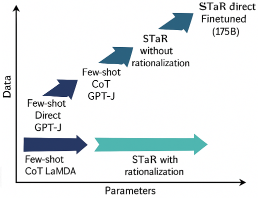
- Outperforms LaMDA (137B params) with just 6B params



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GSM8K Results (Math Word Problems)

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- Rationalization provides modest gains in this domain

Simpler Solutions by the Model: GSM8K Solutions

Q: A van is delivering 180 bottles of drinks to a neighborhood, and each bottle contains either cider or beer or a mixture of two. Out of the 180 bottles, 40 contain only cider, 80 contain only beer, and the rest are a mixture of the two drinks. If the delivery man gives half the number of each bottle of drink to the first house, how many bottles does the first house get?

Human (Ground truth from GSM8K dataset):

The total number of bottles containing cider or beer is 40+80 = <<40+80=120>>120
If the number of bottles in the van was 180, then 180-120 =<<180-120=60>>60 contains a mixture of the two drinks.
At the first house, the delivery man dropped 1/2*40 = <<1/2*40=20>>20 bottles.
There were also 1/2*80 = <<1/2*80=40>>40 bottles of beer that the delivery man gave to the first house.
Together, the first house received 40+20 = <<40+20=60>>60 bottles of cider and beer
The total number of bottles that had a mixture of the two drinks that were dropped at the first house is 1/2*60 = <<1/2*60=30>>30
The first house got 60+30 = <<60+30=90>>90 bottles of all types of drinks.

90

STaR (on GPT-J):

The delivery man gives half the number of each bottle of drink to the first house.
So he gives 180/2 = <<180/2=90>>90 bottles of drink to the first house.

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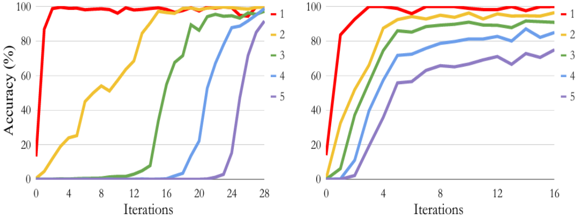
Fig: Example problem in the training set where STaR derives significantly simpler solution than the ground truth.

Why STaR is a Game-Changer?

Core Innovations

- **Human-like learning**:
  Generate → Verify → Improve cycle



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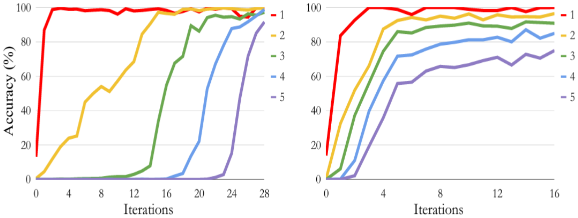

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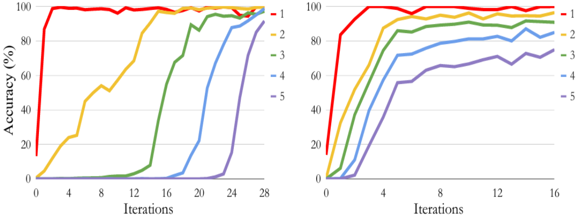

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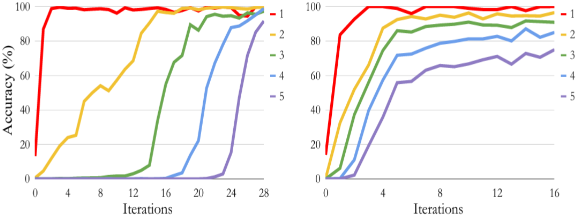

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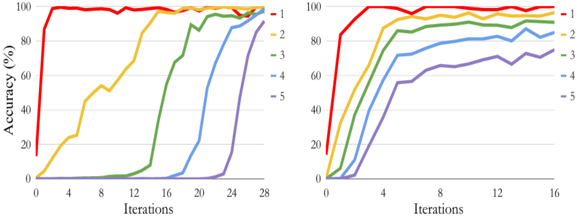
  Faster training of models



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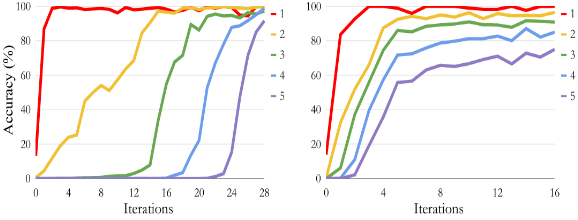

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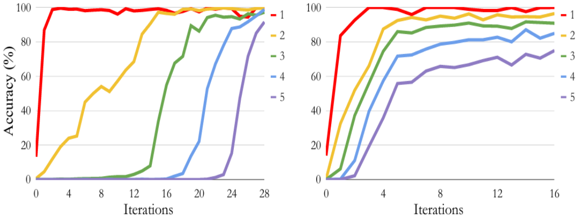

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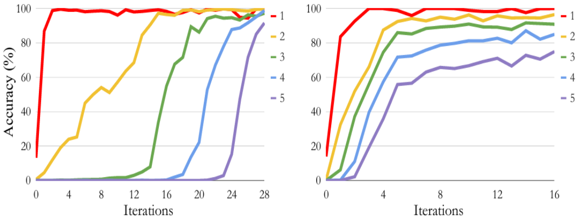

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Results

- +35% accuracy over few-shot
- Matches models 30x larger
- Reverse-engineers solutions
- Prevents learning plateaus

Human-Evaluated Test Prompts

Comparing Few-Shot vs. STaR vs. Human Rationales

Evaluation Methodology

- 50 questions correctly answered by both models
- 20 crowdworkers ranked rationales (1=best, 3=worst)
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2. (Few-Shot) "The answer must help writing..."
3. (Human) "Studying literature gives writing skills..."

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STaR rationales were preferred 30% over few-shot and 74% over human with $p < 0.01$

Key Limitations and Challenges

Major Limitations	Ethical Challenges
■ Requires human examples to start ■ Struggles with math reasoning ■ Slow processing speed ■ Needs careful tuning	■ Accountability for errors unclear ■ Potential for hidden biases ■ Autonomous learning risks

Conclusion & Broader Impact

Key Contributions

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- **Future Research:** Inspires new RL methods (STaR-RL), ReSTaR, Q-STaR etc.

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- Achieves performance of models **30× larger** with less human data
- Creates more **transparent** & **explainable** AI decisions

Transformative Potential

- **Applications:** More explainable healthcare/legal/education decisions
- **Ethics:** Built-in rationale generation enables bias detection
- **Future Research:** Inspires new RL methods (STaR-RL), ReSTaR, Q-STaR etc.

Conclusion & Broader Impact

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Future Outlook

General framework for creating more capable, efficient, and trustworthy AI systems

End

Thank You!