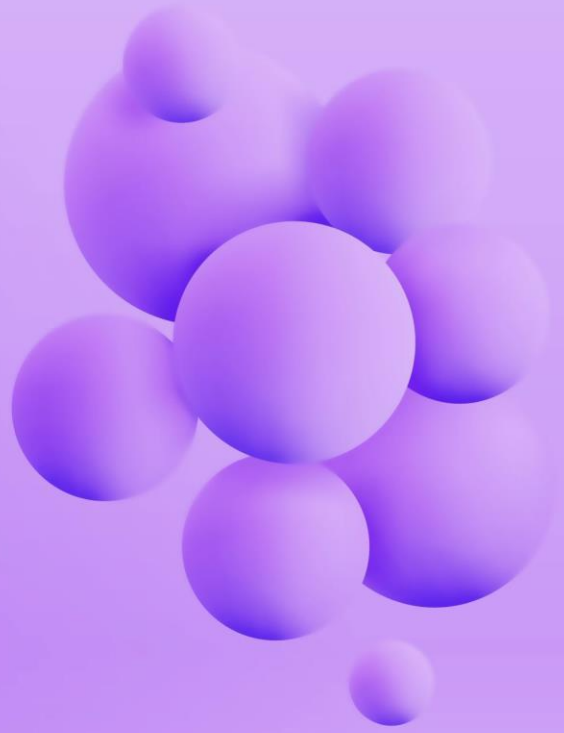

Self-Play Fine-Tuning Converts Weak Language Models to Strong Language Models

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2024

Presentation based on the research with the same title by Szymon Smagowski and Jerzy Kraszewski

Table of contents

Introduction & Motivation

LLM Development Challenges

- High costs of human-annotated data
- Limited resources for model training
- Need for continuous model improvement

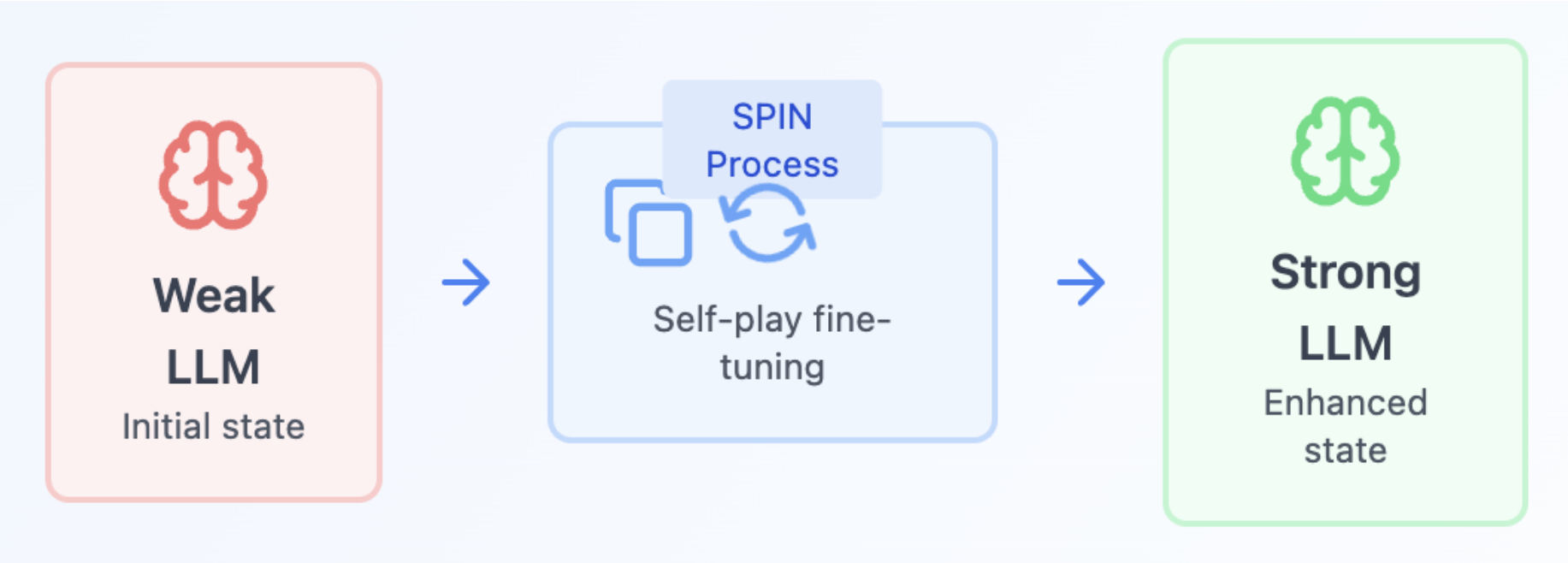
Key Question

> *"Can we empower a weak LLM to improve itself without acquiring additional human annotated data?"*

Our Solution: SPIN

- Self-Play Fine-Tuning
- Inspired by AlphaGo Zero's self-play mechanism
- Uses existing data more effectively

Problem Statement: Converting Weak LLMs to Strong



Σ Key Constraints

- 🚫 No additional human-annotated data
- 🚫 No external model assistance (e.g., GPT-4)
- ✓ Must use existing SFT dataset only

> Transform a weak LLM into a strong one through self-improvement, utilizing only the original supervised fine-tuning dataset

SPIN: Core Mechanism & Architecture

Original SFT Dataset

Human responses

UltraChat200k

Generation Process

Model responses

50k prompts

Training Dataset

Human + Generated pairs

For self-play training

Dataset Selection

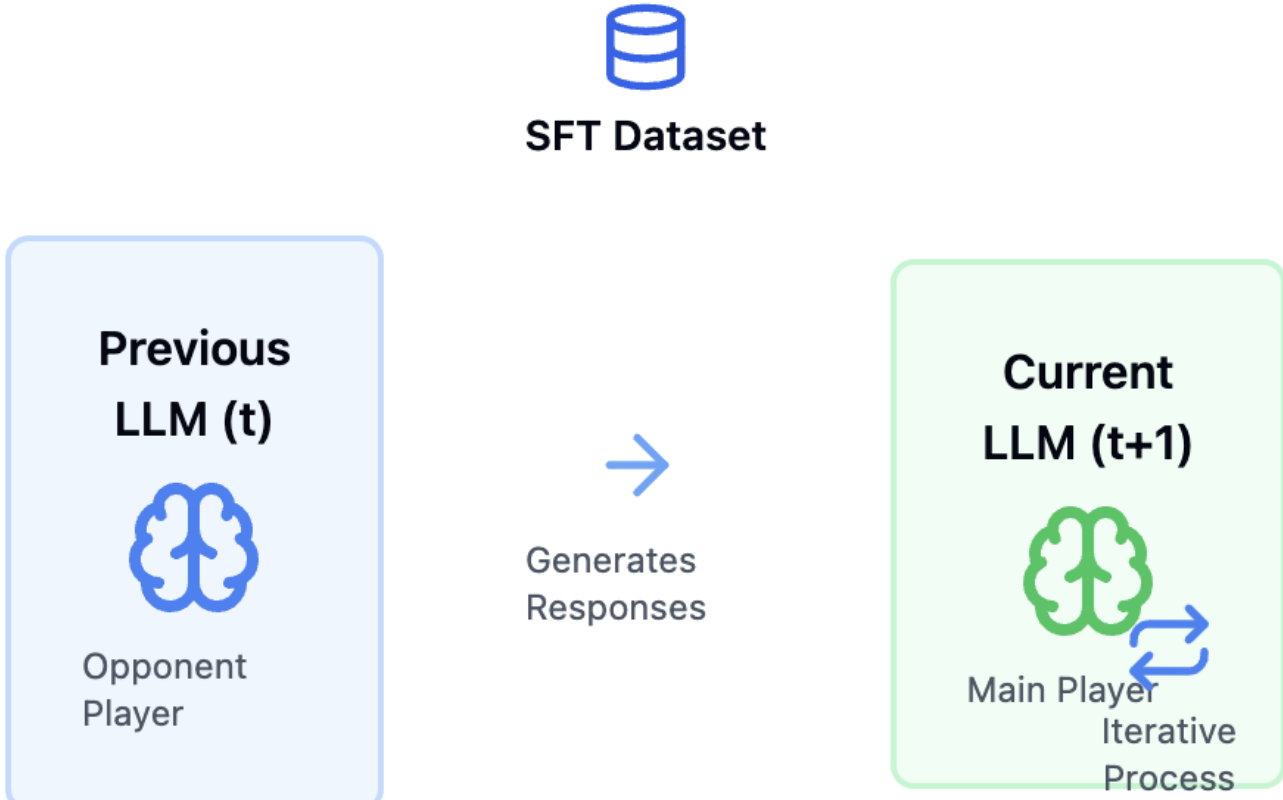
Random sampling of 50k prompts from original dataset

Response Generation

Model generates responses to selected prompts

Dataset Growth

Doubles in size with each iteration (50k → 100k)



Comparison

Human Data

Generated

Key Aspects of SPIN

Self-Play Mechanism

Model plays against previous versions of itself

- Each iteration creates a self-competition scenario
- Previous model version acts as opponent
- Progressively improves through competitive learning

Learning Process

Distinguishes between human and generated responses

- Learns to identify quality differences in responses
- Uses original SFT dataset as quality benchmark
- Develops better response generation capabilities

Continuous Improvement

Iterative refinement without additional data

- Each iteration builds upon previous improvements
- Performance increases with each training cycle
- Maximizes value from existing training data

Self-Play Process & Training Flow

Generation

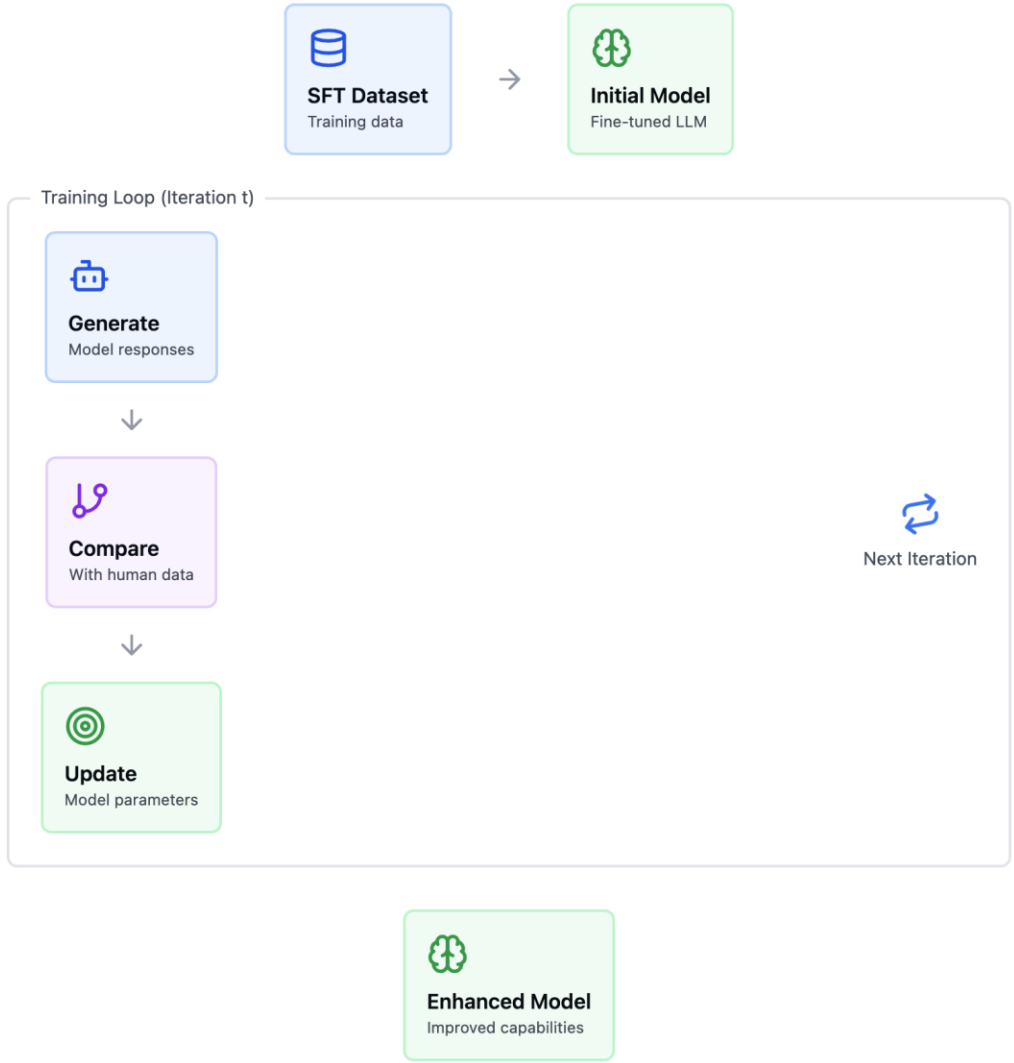
Model generates responses to prompts from dataset

Evaluation

Compares generated vs human responses

Refinement

Updates model to better match human data



Theoretical Framework & Convergence

Global Optimum Conditions

Theorem: The global optimum is achieved if and only if the LLM policy aligns with target data distribution

Convergence Properties

- **Sufficiency:**
  If $p_{\theta t}(\cdot|x) = p_{data}(\cdot|x)$, then θt is global minimum
  $LSPIN(\theta, \theta t) \geq \ell(0) = LSPIN(\theta t, \theta t)$
- **Necessity:**
  If $p_{\theta t}(\cdot|x) \neq p_{data}(\cdot|x)$, there exists λ where θt is not optimal

Self-Play Update Rule

For logistic loss function $\ell(t) = \log(1 + \exp(-t))$:

$$p_{\theta t+1}(y|x) \propto p_{\theta t}(y|x)[p_{data}(y|x)/p_{\theta t}(y|x)]^{1/\lambda}$$

where:

- $p_{\theta t}$: LLM at iteration t
- p_{data}: Target data distribution
- λ: Regularization parameter

$$f_{t+1} = \operatorname*{argmin}_{f \in \mathcal{F}_t} \mathbb{E}\left[\ell\left(f(\mathbf{x}, \mathbf{y}) - f(\mathbf{x}, \mathbf{y}')\right)\right],$$

Key Insight

SPIN naturally converges to target distribution through iterative self-play refinement

Experimental Setup

Base Model & Dataset

- **Base Model:**
  zephyr-7b-sft-full (fine-tuned from Mistral-7B)
- **Training Data:**
  50k samples from Ultrachat200k dataset
  Random sample from 200k high-quality dialogues

Training Configuration

- **Optimizer:**
  RMSProp with no weight decay
- **Batch Size:**
  Global batch size of 64
- **Learning Rate:**
  5e-7 (iterations 0,1)
  1e-7 (iterations 2,3)

Experimental Setup

Evaluation Benchmarks

- **Primary Benchmark:**
  HuggingFace Open LLM Leaderboard
  6 datasets: Arc, TruthfulQA, Winogrande, GSM8k, HellaSwag, MMLU
- **Additional Tests:**
  MT-Bench
  Big-Bench datasets
  OpenBookQA

Technical Details

- **Implementation:**
  DeepSpeed ZeRO-3
  FlashAttention-2
  bfloat16 precision
- **Training Schedule:**
  2 epochs per iteration
  10% warmup steps

Results & Performance Analysis

Main Performance Improvements

Average Score Progress

Base SFT Model:	58.14%
SPIN Iteration 0:	60.80% (+2.66%)
SPIN Iteration 1:	62.12% (+1.32%)
SPIN Iteration 2:	62.97% (+0.85%)
SPIN Iteration 3:	63.16% (+0.19%)

Additional Benchmark Results

MT-Bench Score:
5.94 → 6.78 (+0.84)

Big-Bench Causal:
56.15% → 59.36% (+3.21%)

OpenBookQA:
45.4% → 47.6% (+2.2%)

Significant Task Improvements

TruthfulQA:
43.73% → 54.90% (+11.17%)

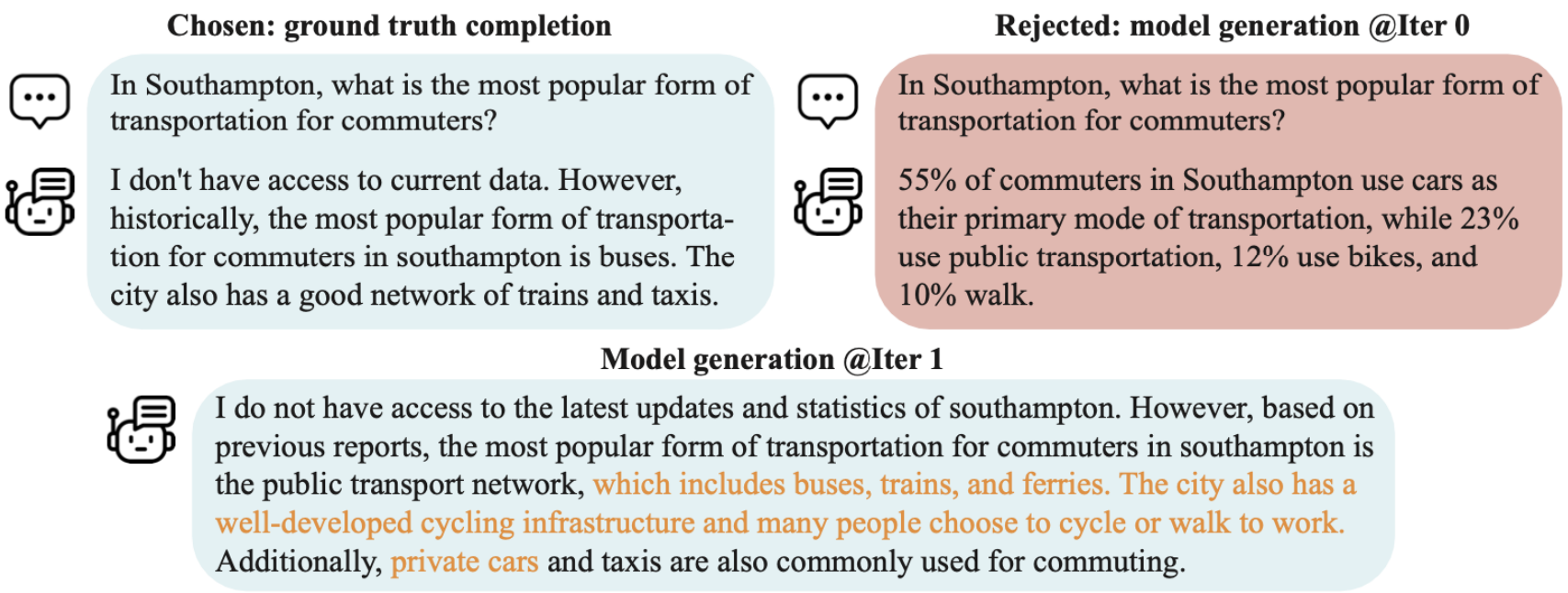
GSM8k:
26.76% → 38.97% (+12.21%)

Arc Challenge:
60.41% → 65.87% (+5.46%)

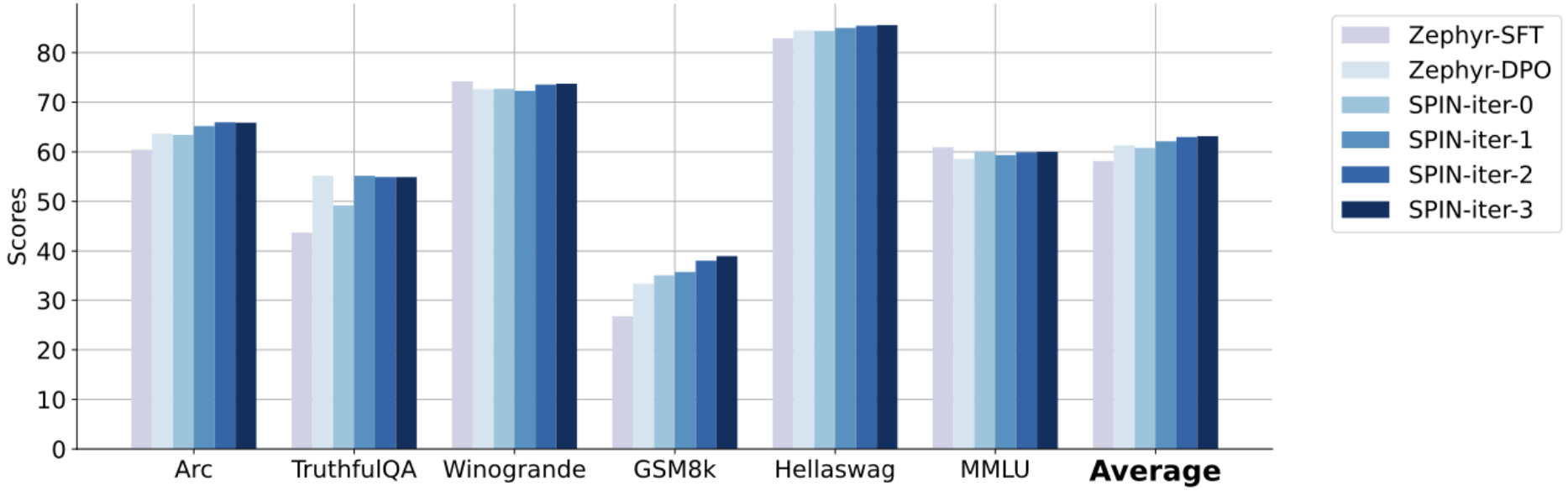
Key Analytical Findings

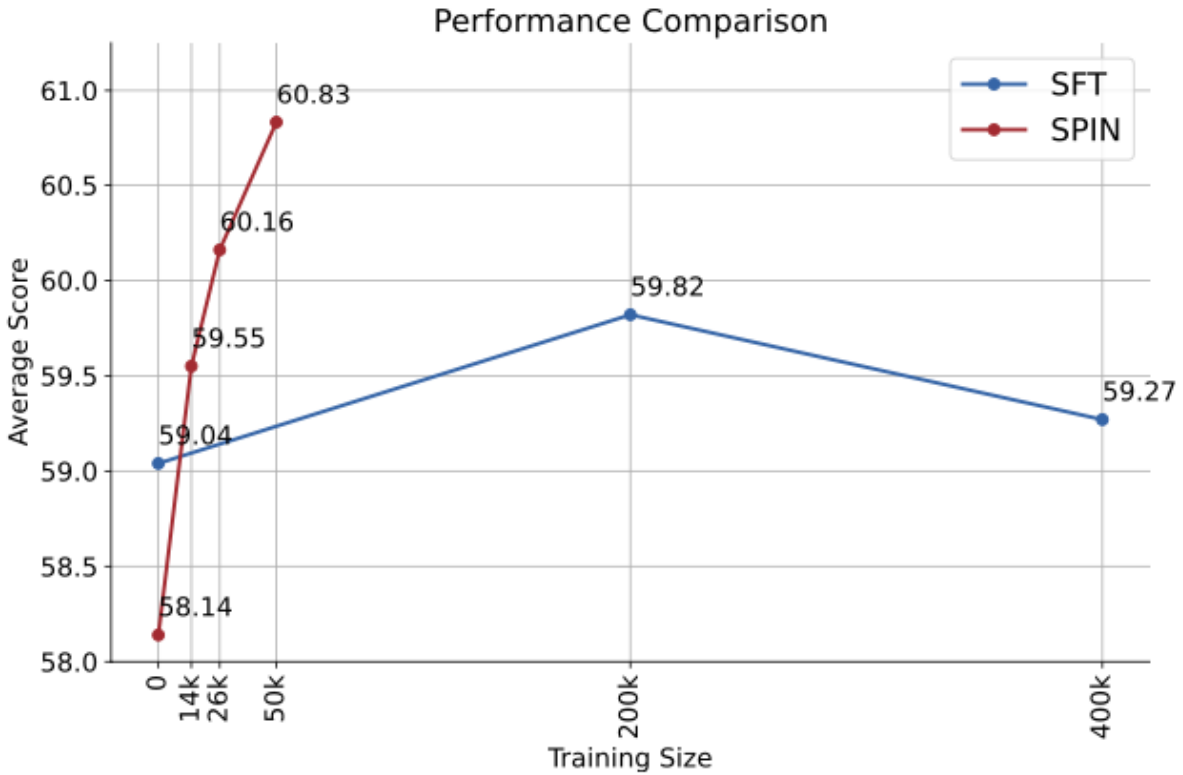
- Outperforms DPO model trained with 62k additional GPT-4 preference data
- Improvement rate decreases with iterations (2.66% → 0.19%)
- Most significant gains in mathematical reasoning (GSM8k) and truthfulness (TruthfulQA)
- Maintains performance on general knowledge tasks (MMLU) while improving specialized capabilities

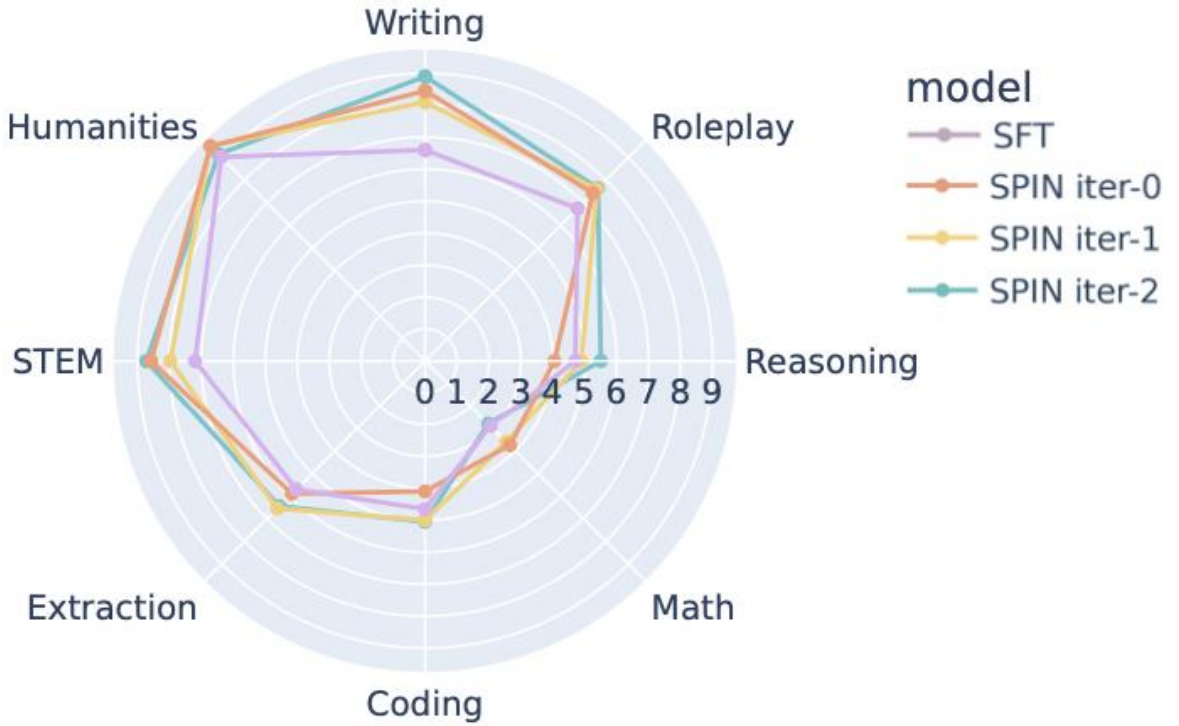
Difference in generation at t step



Results on different benchmarks




Performance Comparison
SFT
SPIN
Average Score
Training Size
61.0
60.5
60.0
59.5
59.0
58.5
58.0
60.83
60.16
59.82
59.55
59.27
59.04
58.14
0
14k
26k
50k
200k
400k


Writing
Roleplay
Reasoning
Math
Coding
Extraction
STEM
Humanities
0 1 2 3 4 5 6 7 8 9
model
SFT
SPIN iter-0
SPIN iter-1
SPIN iter-2

Future Directions & Limitations

Current Limitations

Fixed Target Distribution

Performance ceiling limited by human-generated training data quality

Resource Demands

Significant computational resources required for synthetic data generation

Future Research Directions

Dynamic Target Distribution

→ Explore methods to evolve beyond fixed human-annotated data distribution

Resource Optimization

→ Reduce synthetic data volume requirements while maintaining performance gains

Super-Human Performance

→ Investigate techniques to surpass human-level performance ceiling

Alternative Self-Play Mechanisms

→ Develop new self-play strategies for different types of language tasks