Enhancing Reasoning Path Diversity in Commonsense Question Answering

Sagnik Nandi
23B0905

Harshil Solanki
23B1016

Contents

1 Paper Overview

https://arxiv.org/pdf/2203.11171v4

Paper Title: Self-Consistency Improves Chain of Thought Reasoning in Language Models

1.1 Key Techniques Highlighted:

- **Chain-of-Thought (CoT) Prompting:** This involves providing illustrative examples to guide the model's reasoning process.
- **Self-Consistency Decoding:** This method generates diverse reasoning paths and selects the most consistent final answer by marginalizing over them.
- CoT and self-consistency are effective for tasks with fixed answer sets and can be adapted for open-text generation using suitable consistency metrics.

1.2 Model Architectures used:

- **Decoder-Only Models (e.g., GPT-3, PaLM, LaMDA):**
  - Well-suited for autoregressive text generation tasks like conversational AI and creative writing.
  - Offer simpler architecture and faster inference times.
- **Encoder-Decoder Models (e.g., T5, BART):**
  - Better suited for sequence-to-sequence tasks such as translation and summarization.
  - Provide stronger input-output alignment but with higher computational demands.

1.3 Sampling Strategies and Self-Consistency:

- Sampling techniques (e.g., temperature sampling, top-k truncation) are crucial for generating diverse reasoning paths.
- Self-consistency decoding outperforms traditional methods like sample-and-rank and beam search in terms of accuracy.
- Self-consistency incurs higher computational costs.
- The authors suggest using a limited number of reasoning paths to balance performance and efficiency.

1.4 Limitations and Future Directions:

- Self-consistency requires significant computational resources.
- Self-consistency may generate nonsensical reasoning paths.
- Future work could focus on fine-tuning models with supervised data generated through self-consistency to improve single-inference accuracy.
- Grounding models' rationale generation remains an open challenge requiring further research for logical and accurate outputs.

2 Model Overview

2.1 Dataset

https://paperswithcode.com/dataset/commonsenseqa

CommonsenseQA is a new multiple-choice question answering dataset that requires different types of commonsense knowledge to predict the correct answers . It contains 12,102 questions with one correct answer and four distractor answers.

2.2 Pre-trained LLM

We are using the *together.ai* interface to prompt with SOTA Language models like **Llama 4** and **Deepseek R1**.

2.3 Sampling

It first samples a diverse set of reasoning paths instead of only taking the greedy one, and then selects the most consistent answer by marginalizing out the sampled reasoning paths. Self-consistency leverages the intuition that a complex reasoning problem typically admits multiple different ways of thinking leading to its unique correct answer.

2.4 Output

Comparison of the self-consistency method with greedy decoding and other baseline methods (e.g., beam search) to highlight its advantages.

3 Current Progress and Code

3.1 Analysis of Strategies

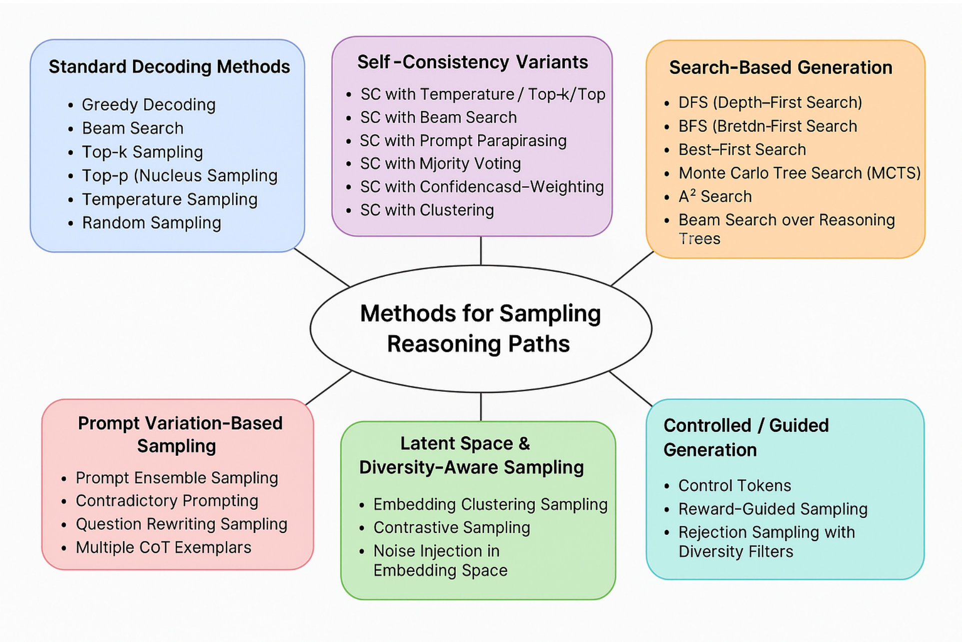

Figure 1: Different Strategies for Sampling

3.2 Dataset Analysis

An example of 'train' looks as follows:

```
{
  'id': '075e483d21c29a511267ef62bedc0461',
  'question': 'The sanctions against the school were a punishing blow, and they seemed to _____
  the efforts the school had made to change?',
  'question_concept': 'punishing',
  'choices': {
    'label': ['A', 'B', 'C', 'D', 'E'],
    'text': ['ignore', 'enforce', 'authoritarian', 'yell at', 'avoid']
  },
```

```
  'answerKey': 'A'
}
```

3.3 Self-consistency Implementation

- Ran initial experiments using multiple reasoning paths and beam search
- Choose the most common answer based on 10 responses generated, look at `sc_10_samples.py` in self_implementation

Github Link : https://github.com/HARSHIL2836R/ReasoningLLMs/tree/main/self_implementation

4 Future Plan of Action

4.1 Metrics

Provide metrics like:

- Number of unique reasoning paths.
- Path similarity measures (e.g., cosine similarity).
- Diversity scores (e.g., Shannon entropy) to assess the diversity of generated reasoning paths.

4.2 Strategies

Basic strategies:

- Sample multiple reasoning paths by **varying temperature** and aggregate answers via majority voting
- **Cluster** the sampled responses based on cosine similarity and select most common answer

Advanced strategies:

- Generate different paths by **varying prompts** like paraphrasing the question
- Model reasoning steps as a graph and use search strategies like **BFS**, **DFS** or **A*** to discover paths

4.3 Timeline

- **April 14–20**: Implement basic strategies and different metric computations and compare their performances
- **April 29-30**: Implement advanced strategies and improving the performance
- **May 1–3**: Final analysis, report writing, and polishing of visualizations and results

5 Code References

1. **Codebase:** https://github.com/codelion/optillm/blob/main/optillm/self_consistency.py
2. Drive Link : https://drive.google.com/drive/folders/1Vzzdk7ZRTuls8XM_-3UT0aqaiBEoyV4T?usp=sharing