

Self-Consistency Improves Chain of Thought Reasoning in Language Models

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Abstract

We explore a simple ensemble strategy, *self-consistency*, that significantly improves the reasoning accuracy of large language models. The idea is to sample a diverse set of outputs from a language model and return the most consistent answer in the set. Such ensembling method improves reasoning accuracy when combined with chain of thought prompting. For arithmetic and commonsense reasoning benchmarks we find that self-consistency yields significant accuracy improvements in a variety of datasets, such as GSM8K (+10%), SVAMP (+14%), MultiArith (+24%), CommonsenseQA (+5%) and ARC (easy +4%, challenge +5%).

1 Introduction

Although language models have demonstrated remarkable success across a range of NLP tasks, their ability to demonstrate reasoning is often seen as a limitation, which cannot be overcome solely by increasing model scale (Rae et al., 2021; BIG-bench collaboration, 2021, *inter alia*). In response, Wei et al. (2022) have proposed *chain of thought prompting*, which prompts language models to generate a series of short sentences that mimic the reasoning process a person might employ. For example, given the question “*Shawn has five toys. He gets two more each from his mom and dad. How many does he have now?*”, instead of directly responding with “9”, we could prompt a language model to respond with “*Shawn started with 5 toys. 2 toys each from his mom and dad is 4 more toys. The final answer is 5+4=9.*”. Chain of thought prompting has been shown to significantly improve language model performance in a variety of multi-step reasoning tasks (Wei et al., 2022).

In this paper, we introduce a simple method, *self-consistency*, that further improves the accuracy of chain of thought reasoning, often by a significant margin. Self-consistency leverages the intuition

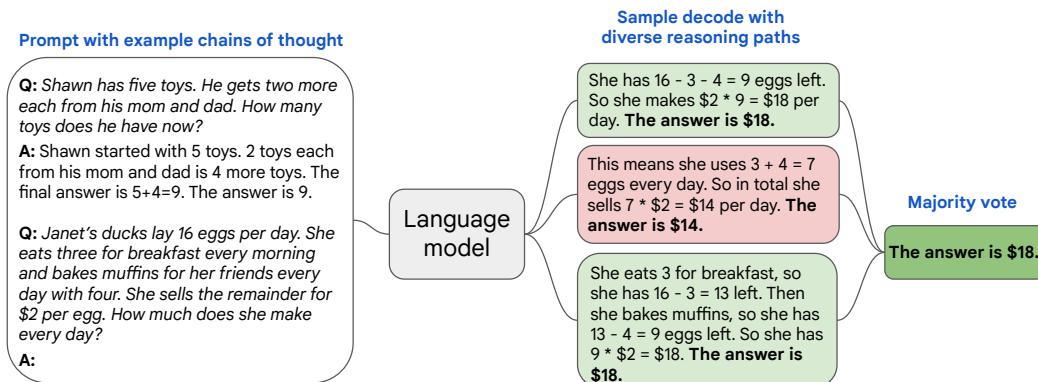


Figure 1: The self-consistency method contains three steps: (1) prompt a language model using example chains of thought; (2) sample from the language model’s decoder to generate a diverse set of reasoning paths; and (3) choose the most consistent answer using the majority/plurality vote.

that complex reasoning tasks typically admit multiple reasoning paths that reach a correct answer (Stanovich & West, 2000). The more a reasoning task requires deliberate thinking and analysis (Evans, 2010), the greater the diversity of reasoning paths that can recover the answer. The method we propose first prompts the language model with example chains of thought, then generates a diverse set of reasoning paths by sampling from the model’s decoder. Each reasoning path might lead to a different final answer, so we determine the optimal answer by taking a plurality or majority vote—i.e., the most commonly occurring answer (corresponding to a majority vote in the special case of only two alternatives). This approach is analogous to human experience that if multiple reasoning paths lead to the same answer, we have greater confidence that the final answer is correct. Figure 1 illustrates the self-consistency method with an example.

The self-consistency method is far simpler than previous approaches, which either train an additional verifier (Cobbe et al., 2021), or train a re-ranker given additional human annotations to improve generation quality (Thoppilan et al., 2022). By contrast, our approach is entirely *unsupervised*, works off-the-shelf with pre-trained language models, requires no additional human annotation, and avoids any additional training or fine-tuning.

We evaluate self-consistency on a range of arithmetic reasoning and commonsense reasoning tasks, and find that it improves the reasoning ability of language models by a striking margin. Compared to generating a single chain of thought via greedy decoding (Wei et al., 2022), self-consistency contributes additional absolute improvements of +10.6% on the recent grade-school-math dataset (GSM8K; Cobbe et al., 2021), +14.4% on a recently-compiled challenge dataset over math word problems (SVAMP; Patel et al., 2021), and +23.9% on MultiArith (Roy & Roth, 2015). For commonsense reasoning, we also observe significant gains in CommonsenseQA (Talmor et al., 2019) (+5%), and the AI2 Reasoning Challenge (ARC) dataset (Clark et al., 2018), with +4% and +4.7% absolute accuracy improvement in the easy and challenge sets, respectively. In additional experiments, we also evaluate self-consistency on alternative large language models, compare against other sampling strategies, and perform ablations on various aspects of the method.

2 Self-Consistency over Diverse Reasoning Paths

A feature of humanity is that people think differently. It is natural to posit that in tasks requiring deliberate thinking, there are likely several ways to attack the problem, all of which lead to the same answer. We propose that such a process can be simulated in language models via sampling from the language model’s decoder. For instance, as shown in Table 1, a model can generate several plausible responses to a math question that all arrive at the same correct answer (Outputs 2, 4, and 5). Since language models are not perfect reasoners, the model might also produce an incorrect reasoning path or make a mistake in one of the reasoning steps (e.g., in Output 1 and 3), but such solutions are less likely to arrive at the *same* answer (26 and 14 in Table 1). That is, we hypothesize that correct reasoning processes, even if they are diverse, tend to have greater agreement in their final answer than incorrect processes.

We leverage this intuition by proposing the following *self-consistency* method. First, a language model is prompted with a set of manually written chain of thought exemplars (Wei et al., 2022). Next, we sample a set of candidate outputs from the language model’s decoder (Ackley et al., 1985; Ficler & Goldberg, 2017; Fan et al., 2018; Holtzman et al., 2018; Radford et al., 2019; Holtzman et al., 2020), which produces diversity in the set of generated reasoning paths. Finally we ensemble the results by choosing the answer that is the most consistent among the generated answers. In an experimental investigation, we show that combining chain of thought prompting with self-consistency leads to substantially better results than simply using chain of thought alone with a single generated path.

In more detail, assume the correct answer a^* is drawn from a fixed answer set, $a^* \in \mathcal{A}$. We sample m candidate outputs $\{r_i, a_i\}, i \in 1, \dots, m$ from the decoder, where each generated output consists of a reasoning path r_i , along with a final answer a_i . As an example, consider Output 5 from Table 1: the first few sentences “She eats 3 for breakfast every morning ... So she has 9 eggs * \\$2 = \\$18.”

Question: Janet’s ducks lay 16 eggs per day. She eats three for breakfast every morning and bakes muffins for her friends every day with four. She sells the remainder at the farmers’ market daily for \$2 per fresh duck egg. How much in dollars does she make every day at the farmers’ market? (Ground truth answer is 18.)

Greedy Decode: She eats 3 for breakfast every morning and bakes muffins for her friends every day with 4. This means she eats $3 + 4 = 7$ eggs every day. She sells the remainder at the farmers’ market daily for \$2 per fresh duck egg. So she sells $7 * \$2 = \14 per day. The answer is 14.

Sample decode with diverse reasoning paths:

- **Output 1:** She eats three eggs for breakfast. She bakes muffins for her friends with four eggs. She sells the remainder at the farmers’ market daily for \$2 per fresh duck egg. This means she sells the remainder at the farmers’ market daily for $\$2 * (16 - 4 - 3) = \$2 * 13 = \$26$ per day. The answer is \$26. (calculation mistake)

- **Output 2:** She eats three for breakfast every morning and bakes muffins for her friends every day with four. She sells the remainder at the farmers’ market daily for \$2 per fresh duck egg. She eats $3 + 4 = 7$ eggs. She sells the remainder. So, the number of eggs she sells is $16 - 7 = 9$. She sells each egg for \$2. So, in total she makes $\$2 * 9 = \18 . The answer is \$18.

- **Output 3:** She eats 3 eggs every morning and bakes muffins for her friends every day with 4 eggs. This means she uses $3 + 4 = 7$ eggs every day. She sells the remainder at the farmers’ market daily for \$2 each. So in total she sells $7 * \$2 = \14 per day. The answer is \$14. (incorrect reasoning process)

- **Output 4:** Janet’s ducks lay 16 eggs per day. She eats 3 for breakfast and bakes muffins with 4. That means she has $16 - 3 - 4 = 9$ eggs left. She sells them for \$2 each, so she makes $\$2 * 9 = \18 per day. The answer is 18.

- **Output 5:** She eats 3 for breakfast every morning, so she has $16 - 3 = 13$ eggs left. Then she bakes muffins with 4 eggs every day, so she has $13 - 4 = 9$ eggs left. She sells the remainder at the farmers’ market daily for \$2 per fresh duck egg. So she has 9 eggs * \$2 = \$18. The answer is \$18.

Table 1: An example showing how self-consistency over diverse reasoning paths can improve reasoning in language models. The outputs are generated from a 137B language model (Thoppilan et al., 2022), and the example is taken from the GSM8K dataset (Cobbe et al., 2021). The blue/red color indicates correct/incorrect reasoning paths and their corresponding answers from the model.

constitutes r_i , while the answer 18 from the last sentence, “The answer is \$18”, is parsed as a_i .¹ Then the *self-consistency* procedure aggregates the m reasoning paths by taking the plurality vote over the final answers $a_i, i = 1, \dots, m$, i.e., $a_{\text{best}} = \arg \max_{a_i, i \in 1, \dots, m} \sum_{j=1}^m \mathbb{I}(a_j = a_i)$. In other words, we choose the optimal answer a_{best} to be the answer that is most *consistent* among the generated answers (possibly with different reasoning paths).²

Self-consistency leverages the following crucial observation about the nature of chain of thought prompting for reasoning tasks: generating a chain of thought is optional and is not considered as part of the evaluation metric—only the final answer matters. This observation allows us apply plurality voting on a tractable set of potential final answers given by the generation of various reasoning paths. Alternatively, one can think of self-consistency as applying a marginalization over the reasoning paths r_i in the conditional probability $p(a_i, r_i | x)$ of each output given a question x .

We experimented with both taking the plurality vote on a_i directly, as well as weighting a_i by the conditional probability $p(a_i, r_i | x)$ from the language model, and found that the plurality vote works significantly better. We conjecture that this is because the conditional probability generated from the language model is not well calibrated, also explaining why additional re-rankers were needed to better judge the quality of the solutions in previous work (Cobbe et al., 2021; Thoppilan et al., 2022).

Self-consistency explores an interesting space between open-ended text generation and optimal text generation where the answer is fixed. The reasoning tasks often have fixed answers, which is why researchers typically used greedy decoding approaches (Brown et al., 2020; Wei et al., 2022). However, we have found that even when the desired answer is fixed, introducing diversity in the reasoning processes can be highly beneficial; therefore we utilize sampling, as commonly used for

¹The parser is dependent on the task. For arithmetic reasoning, we parse the first numerical part as the final answer after the model generates “The answer is ”. For commonsense reasoning, we parse the full string answer as the final answer after the model generates “The answer is ”. Most generated outputs have a consistent format of “[Reasoning paths]. The answer is X.” if we prompt the language model in this format.

²When there are ties, i.e., answers with equal votes, we take the answer in the order first encountered.

open-ended text generation (Radford et al., 2019; Brown et al., 2020; Thoppilan et al., 2022), to achieve this goal.

Compared to other decoding methods, self-consistency avoids the repetitiveness that plagues greedy sampling, while mitigating the stochasticity of a single random generation. Compared to popular generate-then re-rank approaches (Cobbe et al., 2021; Thoppilan et al., 2022), self-consistency does not require a specially-trained re-ranker and has a faster runtime (given the same number of decodes).

3 Experiments

In this section, we compare the proposed self-consistency with existing methods in a range of arithmetic and commonsense reasoning benchmarks. We find that self-consistency improves reasoning accuracy in language models by a large margin across all these tasks.

3.1 Experiment setup

Tasks and datasets. We evaluate self-consistency on the following reasoning benchmarks.

- **Arithmetic reasoning.** We use the Math Word Problem Repository (Koncel-Kedziorski et al., 2016), with the following datasets based on question types: AddSub (Hosseini et al., 2014), MultiArith (Roy & Roth, 2015), and ASDiv (Miao et al., 2020). We also include AQUA-RAT (Ling et al., 2017), a recently published benchmark of grade-school-math problems (GSM8K; Cobbe et al., 2021), and a challenge dataset over math word problems (SVAMP; Patel et al., 2021).
- **Commonsense reasoning.** We use CommonsenseQA (Talmor et al., 2019) for commonsense reasoning, StrategyQA (Geva et al., 2021) for open-domain question-answering with multi-hop reasoning, and the AI2 Reasoning Challenge (ARC) (Clark et al., 2018) for reasoning that requires scientific knowledge.

Language models and prompts. We use a set of dense left-to-right, decoder-only transformer language models (Thoppilan et al., 2022, LaMDA-PT), with sizes ranging from 2B to 137B parameters. Models were pretrained on a mixture of web documents and dialog data, tokenized into 2.49T BPE tokens using the SentencePiece library (Kudo & Richardson, 2018), with a 32k vocabulary. For reproducibility, we also compared with the public GPT-3 model (Brown et al., 2020) in Section 3.3.

We use the same set of prompts as defined in Wei et al. (2022) for eliciting the diverse set of reasoning paths: for all arithmetic reasoning tasks we use the same set of 8 manually written exemplars; for each commonsense reasoning task, 4–7 exemplars are randomly chosen from the training set with manually composed chains of thought prompts. The full details of the prompts used are listed in Appendix A.1.

Sampling scheme. To sample diverse reasoning paths, we apply temperature sampling with $T = 0.5$ and truncate at the top- k tokens with the highest probability, using $k = 40$ for all tasks, following the setting in (Radford et al., 2019; Holtzman et al., 2020). An ablation study that varies T and k is given in Section 3.4; self-consistency is generally robust to sampling strategies and parameters, and we use the same T and k across all tasks for simplicity.

3.2 Results

We evaluate the proposed approach, self-consistency, over multiple diverse reasoning paths, referred to as **Self-Consistency (Multi-path)** in the following. The results are averaged over 10 runs by sampling 1, 5, 10, 20, 40 outputs from the decoder. The baseline we compare to is greedy decoding a single chain of thought (Wei et al., 2022), referred to as **Greedy Decode (Single-path)**, which has been previously used for decoding in large language models (Radford et al., 2019; Wei et al., 2022). The results below are based on the 137B model; we additionally show how self-consistency performs across model scales with varying model sizes in Section 3.4.

Arithmetic Reasoning Figure 2 shows the results. We see that self-consistency over multiple paths substantially improves over greedy decoding a single path on all tasks, obtaining a close to 10% absolute accuracy improvement on tasks like AddSub, ASDiv, AQuA and GSM8K. In addition, we

observe significant improvements on the MultiArith dataset (from 51.8% to 75.7%, an improvement of 23.9%), and the SVAMP dataset (from 38.9% to 53.3%, an improvement of 14.4%). We also compare to supervised approaches that require task-specific training or finetuning in Table 2. Despite the fact that self-consistency is unsupervised and task-agnostic, the results sometimes compare favorably to fine-tuning with thousands of examples (e.g., on GSM8K).

Method	AddSub	MultiArith	ASDiv	AQuA	SVAMP	GSM8K
Supervised	94.9 ^a	60.5 ^a	61.4 ^b	36.4 ^c	57.4 ^d	21 ^e / 35 ^g
Greedy decode (Single-path)	52.9	51.8	49.0	17.7	38.9	17.1
Self-Consistency (Multi-path)	63.5 (+10.6)	75.7 (+23.9)	58.2 (+9.2)	26.8 (+9.1)	53.3 (+14.4)	27.7 (+10.6)

Table 2: Accuracy by the self-consistency approach compared to greedy decoding a single path with chain of thought prompting (Wei et al., 2022). We also add the results from supervised approaches (most of them are SoTA results with task-specific training). The supervised baselines are obtained from: *a*: Relevance and LCA operation classifier (Roy & Roth, 2015), *b*: GPT-2 finetuned with k -fold CV (Lan et al., 2021), *c*: Ling et al. (2017), *d*: Pi et al. (2022), *e*: GPT-3 175B finetuned with 1k examples (Cobbe et al., 2021), *g*: GPT-3 175B finetuned with 7.5k examples (Cobbe et al., 2021).

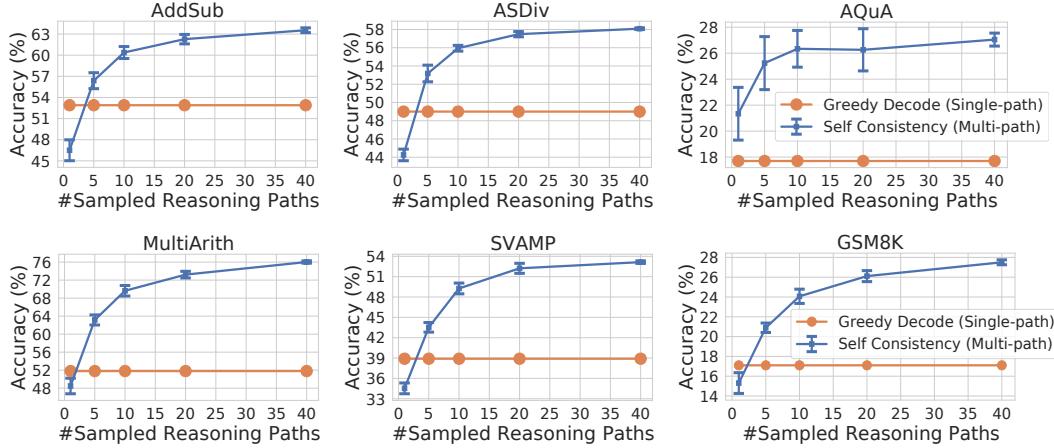


Figure 2: Self-consistency (blue) significantly helps reasoning accuracy on math word problems across problem types, and on more recent arithmetic reasoning benchmarks including a challenge math dataset (SVAMP) and grade-school-math (GSM8K).

Commonsense Reasoning In Figure 3 we present results of self-consistency compared to greedy decoding on commonsense reasoning tasks. We see that self-consistency significantly improves the accuracy in all these tasks, with +2-5% absolute accuracy improvement on StrategyQA and CommonsenseQA, +4.0% absolute accuracy improvement on the ARC easy set (from 75.3% to 79.3%) and +4.7% improvement on the ARC challenge set (from 55.1% to 59.8%).

In Table 3 and Table 4, we further present examples with questions, the solution obtained via greedy decoding, and two sampled reasoning paths from the self-consistency method. We see that the sampled reasoning paths not only fix some of the errors introduced in greedy decoding, they also arrive at the correct answer with a richer set of reasoning processes.

One might even view self-consistency as a way to collect useful rationales from language models more effectively. As shown in Table 3 and Table 4, the sampled reasoning paths with a consistent final answer are useful in revealing what knowledge is stored in a language model and how this knowledge is used to compose useful rationales. On the other hand, we notice that language models sometimes generate incorrect or nonsensical reasoning paths (e.g., the 2nd example in Table 4, the two population numbers are not exactly correct), and further work is needed to better ground their generations and predictions.

Question	Greedy Decode	Sampled Path 1	Sampled Path 2
[MultiArith] Sam had 10 socks. If he threw away 3 old ones that didn't fit and bought 36 new ones, how many socks would he have?	Sam had 10 socks. He threw away 3 old ones that didn't fit. He bought 36 new ones. That means he has $10 + 36 - 3 = 41$ socks. The answer is 41.	Sam had 10 socks. He threw away 3 old ones. So now he has 7 left. Then he bought 36 new ones. So now he has $7 + 36 = 43$ socks. The answer is 43.	He had 10 socks. He threw away 3 old ones that didn't fit. He bought 36 new ones. So in total he has $10 - 3 + 36 = 43$ socks. The answer is 43.
[SVAMP] In a school there are 697 girls and the rest are boys. If there are 228 more girls than boys. How many boys are there in that school?	There are 697 girls and the rest are boys. That means there are $697 + 228 = 925$ girls. The rest are boys. So the number of boys is $925 - 697 = 228$. The answer is 228.	The number of boys is the difference between 697 and 228. This is $697 - 228 = 469$. The answer is 469.	In the beginning there are 697 girls and the rest are boys. So, the number of boys must be $697 - 228 = 469$ boys. The answer is 469.
[AQuA] There are 10 oranges in a basket. Find the no. of ways in which 2 oranges are chosen from the basket? (a) 45 (b) 90 (c) 120 (d) 150 (e) 180	There are 10 oranges in a basket. So there are 10 ways in which 2 oranges are chosen from the basket.	There are 10 oranges in a basket. We need to choose 2 oranges from the basket. So the number of ways are $10C2$. So the answer is (a).	There are 10 oranges in the basket. If you choose 2 oranges, you have $10C2 = 45$ ways of choosing 2 oranges. So the answer is (a).

Table 3: Examples where self-consistency helps fix the error over greedy decode on **arithmetic reasoning** tasks. Two sampled reasoning paths that are consistent with the ground truth are shown.

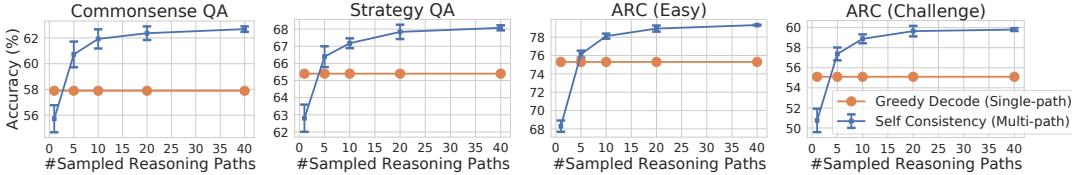


Figure 3: Self-consistency (blue) with diverse reasoning paths significantly improves accuracy on Commonsense reasoning, Strategy QA (multi-hop reasoning), and ARC easy/challenge tasks.

3.3 Ablation Studies

Self-Consistency over GPT-3 To show that self-consistency generalizes to multiple language models, we also compare with the public GPT-3 model (Brown et al., 2020). We use the *code-davinci-001* engine (Chen et al., 2021) as we observed a slightly better greedy decode baseline performance (14.6%) over the basic *davinci* (12.8%) on the GSM8K dataset. For sampling, we use $T = 0.7$ without top- k truncation. Figure 4 presents the results. We see that self-consistency works across models, and consistently improves the accuracy on both GSM8K and MultiArith with more sampled reasoning paths. With 40 sampled reasoning paths, self-consistency is able to outperform greedy decoding by a large margin (+8.8% on GSM8K, +23.2% on MultiArith).

Comparison to Sample-and-Rank Another commonly used approach to improve generation quality is sample-and-rank, where multiple sequences are sampled from the decoder and then ranked either according to each sequence’s log probability (Adiwardana et al., 2020), or based on an additionally trained re-ranker (Cobbe et al., 2021; Thoppilan et al., 2022). As the proposed approach is unsupervised, we compare to the unsupervised sample-and-rank approach (Adiwardana et al., 2020), i.e., we sample the same number of sequences from the decoder as the self-consistency method, then rank the sequences based on the lowest log probability per token. Again we use GPT-3 *code-davinci-001*, with $T = 0.7$ and no top- k truncation. The results are shown in Figure 4. Here we see that while sample-and-rank improves the accuracy with additionally sampled sequences, the gain is much smaller compared to self-consistency.

Comparison to Ensemble-based Approaches Since the proposed self-consistency method is similar to ensembling, we also compare its performance to ensemble-based methods for few-shot

Question	Greedy Decode	Sampled Path 1	Sampled Path 2
[Commonsense QA] <i>The man laid on the soft moss and looked up at the trees, where was the man?</i> (a) niagra falls (b) forest (c) waterfall (d) ground (e) tree	The answer must be something that is soft and mossy. Of the above choices, only ground is soft and mossy . So the answer is (d).	The answer must be somewhere where moss is found. Of the above choices, only forests are known for having moss . So the answer is (b).	The answer must be a place where the man is laying down and looking up at trees. Of the above choices, only forest is a place where people lay down and look at trees . So the answer is (b).
[Strategy QA] <i>Yes or no: Is Albany, Georgia the most populous US Albany?</i>	Albany, Georgia is the most populous US Albany. Thus, the answer is yes .	The most populous US Albany is Albany, New York. Thus, Albany, Georgia is not the most populous US Albany. So the answer is no .	Albany, Georgia has a population of about 88,000. Albany, New York has a population of about 95,000. Thus, Albany, Georgia is not the most populous US Albany. So the answer is no .
[ARC] <i>Which of these will most likely harm a habitat?</i> (a) planting trees. (b) water pollution. (c) rainfall. (d) sunlight.	Planting trees will not harm a habitat. So the answer is (a).	The answer is (b), water pollution, because it will most likely harm the habitat . The other answers are not likely to harm the habitat.	The answer is (b), water pollution. Trees are good for a habitat, rainfall is necessary for a habitat, and sunlight is necessary for a habitat. So the answer is (b).

Table 4: Examples where self-consistency helps fix the error over greedy decode on **commonsense reasoning** tasks. Two sampled reasoning paths that are consistent with the ground truth are shown.

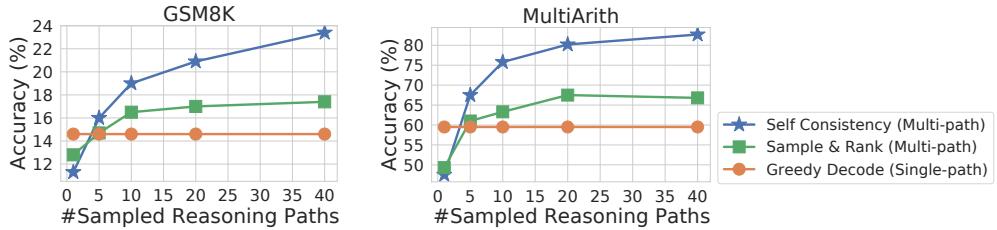


Figure 4: Results on GPT-3 model (*code-davinci-001*): self-consistency improves performance across models over greedy decode; it also significantly outperforms the sample-and-rank approach.

learning. In particular, we consider ensembling by: 1) prompt order permutation, as existing works (Zhao et al., 2021; Lu et al., 2021) show that model performance could be sensitive to the prompt order, and 2) multiple sets of prompts for the same task (Gao et al., 2021). Note a key difference here is, self-consistency ensembles the result in the “output” space (during decoding) without any changes to the inputs or the prompts, while existing work ensembles the result by varying the “input” space, e.g., the prompts.

We present the results of using these two ensemble-based approaches in Table 5: for 1) we randomly permute the order of the prompts 5 and 10 times; and for 2) we manually write 3 different sets of chains of thought as prompts to the model. We take the plurality vote of the answers (from greedy decode) in both approaches as an ensemble. Compared to self-consistency, existing ensemble-based approaches achieve a much smaller gain (1-2% absolute improvement vs 4-7% by self-consistency on GSM8K).

3.4 Self-Consistency is Robust to Sampling Strategies/Parameters and Scaling

We further investigate how the sampling strategies and parameters, e.g., the sampling temperature T in temperature sampling (Ackley et al., 1985; Ficler & Goldberg, 2017), k in top- k sampling (Fan et al., 2018; Holtzman et al., 2018; Radford et al., 2019), and the number of reasoning paths we sample, affect the results. As shown in Figure 5, the proposed approach consistently improves the results across various temperatures. We also see that self-consistency results in a better performance when the temperature introduced sufficient diversity in the decoding process, e.g., $T = 0.5$ or $T = 0.7$.

	GSM8K	MultiArith
Greedy	17.1	51.8
Ensemble (3 sets of prompts)	19.1	58.0
Ensemble (5 / 10 prompt permutations)	18.1 / 19.6	57.7 / 61.2
Self-Consistency (5 / 10 sampled paths)	21.1 / 24.3	62.7 / 70.5

Table 5: Compare self-consistency with ensemble using prompt permutation or multiple sets of prompts. Self-consistency is much more effective and more sample-efficient.

Additionally, a higher number of sampled reasoning paths almost always leads to a better result, but the result also saturates when the number of sampled paths is sufficiently large (e.g., with 40 paths on most tasks, Figure 2 to Figure 3). We also vary k in top- k sampling, or remove k by sampling from all tokens in the vocabulary, and we see that self-consistency is quite robust to the choice of k .

In Figure 5 (right), we further vary model scales (number of parameters in billions) and show self-consistency improves performance across model scales.

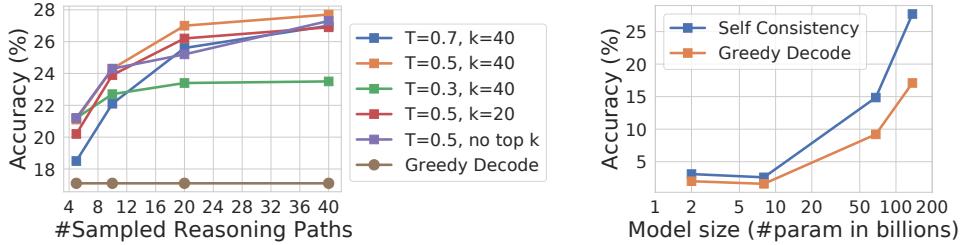


Figure 5: GSM8K accuracy. (Left) Self-consistency works for various sampling temperature T , and k in top- k sampling. (Right) Self-consistency improves performance across language model scales.

3.5 Self-Consistency Improves Robustness to Imperfect Prompts

For few-shot learning with manually constructed prompts, human annotators sometimes make minor mistakes when creating the prompts. Hence we further study if self-consistency can help improve a language model’s robustness to imperfect prompts. We use the same prompts as before but swapped all the numbers in the reasoning paths with random numbers, while keeping the last number (corresponding to the final answer) unchanged (e.g., we change the prompt: “*There are 3 cars in the parking lot already. 2 more arrive. Now there are $3 + 2 = 5$ cars.*” to “*There are 7 cars in the parking lot already. 6 more arrive. Now there are $7 + 6 = 5$ cars.*”). The results are shown in Table 6 and we see that, while imperfect prompts decrease accuracy, self-consistency is able to fill in the gap and makes the results much more robust.

Additionally, we found that the consistency (in terms of % of decodes agreeing with the plurality vote) is nicely correlated with the accuracy (Figure 6, over GSM8K), meaning it is possible to utilize self-consistency as an *uncertainty estimate* of how confident the model is in its generated solutions. In other words, one can use low consistency as an indicator of a model having a low confidence, i.e., self-consistency could enable the model to “know when it doesn’t know”.

3.6 Self-Consistency with Non-Natural-Language Prompts

We also performed an experiment by replacing the reasoning paths expressed in natural language by equations in the prompts (e.g., from “*There are 3 cars in the parking lot already. 2 more arrive. Now there are $3 + 2 = 5$ cars.*” to “ $3 + 2 = 5$ ”). The results are presented in Table 6. Here we see self-consistency still improves accuracy via introducing diversity when generating the equations; however, compared to reasoning paths in natural language, the gain is smaller since the equations are much shorter and there is not much room left for introducing diversity in the decoding process.

Prompt with correct chain of thought	17.1
Prompt with imperfect chain of thought + Self-consistency (10 / 20 / 40 paths)	14.9 20.0 / 21.7 / 23.4
Prompt with equations + Self-consistency (10 / 20 / 40 paths)	5.0 6.2 / 5.7 / 6.5

Table 6: Self-consistency improves language model’s robustness to imperfect prompts on GSM8K. It also helps reasoning with equation prompts, although the gain is smaller.

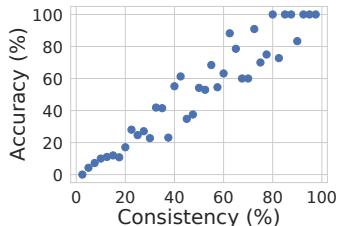


Figure 6: The consistency is correlated with model’s accuracy.

4 Related work

Reasoning in language models. Language models are known to struggle at Type 2 tasks like arithmetic, logical and commonsense reasoning, compared to Type 1 tasks that are more based on intuitive and fast thinking (Evans, 2010). Existing work mostly focuses on *specialized* approaches to improve reasoning in language models, e.g., injecting specialized modules to extract and handle math symbols (Andor et al., 2019; Ran et al., 2019; Geva et al., 2020; Piękos et al., 2021), or using multi-task learning for better commonsense reasoning (Lourie et al., 2021). Compared to this prior work, self-consistency is applicable to a range of reasoning tasks without additional supervision or finetuning, substantially improving the performance of the chain of thought reasoning approach proposed in Wei et al. (2022).

Sampling and re-ranking in language models. Depend on the applications, multiple decoding strategies in language models have been proposed, e.g., temperature sampling (Ackley et al., 1985; Ficler & Goldberg, 2017), top- k sampling (Fan et al., 2018; Holtzman et al., 2018; Radford et al., 2019), and nucleus sampling (Holtzman et al., 2020), where the sampling parameters can be tuned based on how much diversity is needed in the generation. There is also work that explicitly promotes diversity in the decoding process (Batra et al., 2012; Li et al., 2016; Vijayakumar et al., 2018).

In addition to sampling, re-ranking is also a common method to improve the generation quality in language models. For example, Thoppilan et al. (2022) propose to collect additional human annotation data to train a re-ranker, such that responses that are unsafe or not factual can be filtered. Cobbe et al. (2021) propose to train a “verifier” to re-rank the generated solutions to math problems, and show that the trained “verifier” can improve the solve rate on math tasks significantly over a fine-tuned language model. Further, Elazar et al. (2021) propose to improve the consistency of factual knowledge extraction from language models via continuing pre-training with an additional consistency loss. All these existing methods require either training an additional re-ranker, or in conjunction with collecting additional human annotations, while self-consistency requires no additional training or finetuning at all, nor do we require any extra data collection.

Extract reasoning paths. Existing work adopts task-specific approaches to identify reasoning paths, e.g., constructing semantic graphs (Xu et al., 2021), learning an RNN to retrieve reasoning paths over the Wikipedia graph (Asai et al., 2020), fine-tuning with human annotated reasoning paths on math problems (Cobbe et al., 2021), and training an extractor with heuristics-based pseudo reasoning paths via connecting entities (Chen et al., 2019). More recent work also noticed the importance of diversity in the reasoning processes but adopted task-specific training via an additional QA model over extracted reasoning paths (Chen et al., 2019), or introducing latent variables on commonsense knowledge graphs (Yu et al., 2022). Compared to these approaches, self-consistency is much simpler and requires no additional training. Here we simply couple the generation of the reasoning paths and the final answer via sampling in the decoder, where the consistent answer can be simply aggregated without additional modules.

Consistency in language models. Some existing work shows language models might suffer from inconsistency in certain applications, e.g., conversation (Adiwardana et al., 2020), explanation generation (Camburu et al., 2020), or factual knowledge extraction (Elazar et al., 2021). Welleck et al. (2020) use “consistency” to refer to generating an infinite-length sequence in recurrent language models. Nye et al. (2021) improve the logical consistency over generations from System 1 models by

adding System 2-inspired logical reasoning modules. In this paper we focus on a slightly different notion of “consistency”, i.e., utilizing answer consistency while introducing diverse reasoning paths, to improve performance over reasoning tasks.

5 Conclusion

We introduce a simple and effective method to improve reasoning in language models—sampling diverse reasoning paths in decoding and then choosing a final answer via self-consistency. We observe that this approach improves accuracy by a large margin over a range of arithmetic and commonsense reasoning tasks. In addition to the significant performance gains, this work can potentially be useful for collecting rationales when language models perform reasoning tasks, and help provide uncertainty estimates and calibration in language models.

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A Appendix

A.1 Full Sets of Prompts

We list the full details of the prompts used for two newly-introduced datasets, AQUA-RAT (Ling et al., 2017) and AI2 Reasoning Challenge (ARC) (Clark et al., 2018), where we manually composed the example chains of thought in this paper, in Table 7 and Table 8, respectively.

Table 7: Few-shot exemplars for AQUA-RAT.

Q: John found that the average of 15 numbers is 40. If 10 is added to each number then the mean of the numbers is? Answer Choices: (a) 50 (b) 45 (c) 65 (d) 78 (e) 64
A: If 10 is added to each number, then the mean of the numbers also increases by 10. So the new mean would be 50. The answer is (a).
Q: If $a / b = 3/4$ and $8a + 5b = 22$, then find the value of a. Answer Choices: (a) 1/2 (b) 3/2 (c) 5/2 (d) 4/2 (e) 7/2
A: If $a / b = 3/4$, then $b = 4a / 3$. So $8a + 5(4a / 3) = 22$. This simplifies to $8a + 20a / 3 = 22$, which means $44a / 3 = 22$. So a is equal to $3/2$. The answer is (b).
Q: A person is traveling at 20 km/hr and reached his destiny in 2.5 hr then find the distance? Answer Choices: (a) 53 km (b) 55 km (c) 52 km (d) 60 km (e) 50 km
A: The distance that the person traveled would have been $20 \text{ km/hr} * 2.5 \text{ hrs} = 50 \text{ km}$. The answer is (e).
Q: How many keystrokes are needed to type the numbers from 1 to 500? Answer Choices: (a) 1156 (b) 1392 (c) 1480 (d) 1562 (e) 1788
A: There are 9 one-digit numbers from 1 to 9. There are 90 two-digit numbers from 10 to 99. There are 401 three-digit numbers from 100 to 500. $9 + 90(2) + 401(3) = 1392$. The answer is (b).

Table 8: Few-shot exemplars for ARC easy/challenge.

Q: George wants to warm his hands quickly by rubbing them. Which skin surface will produce the most heat? (a) dry palms. (b) wet palms. (c) palms covered with oil. (d) palms covered with lotion.
A: Dry surfaces will more likely cause more friction via rubbing than other smoother surfaces, hence dry palms will produce the most heat. The answer is (a).
Q: Which factor will most likely cause a person to develop a fever? (a) a leg muscle relaxing after exercise. (b) a bacterial population in the bloodstream. (c) several viral particles on the skin. (d) carbohydrates being digested in the stomach.
A: Option (b), bacterial population is the most likely cause for a person developing fever. The answer is (b).
Q: Which change in the state of water particles causes the particles to become arranged in a fixed position? (a) boiling. (b) melting. (c) freezing. (d) evaporating.
A: When water is freezed, the particles are arranged in a fixed position; the particles are still moving for all other options. The answer is (c).
Q: When a switch is used in an electrical circuit, the switch can (a) cause the charge to build. (b) increase and decrease the voltage. (c) cause the current to change direction. (d) stop and start the flow of current.
A: The function of a switch is to start and stop the flow of a current. The answer is (d).

As additional information, we also list the exact set of prompts used for all arithmetic reasoning tasks in Table 9, since there are multiple sets of prompts introduced in Wei et al. (2022). The prompts for CommonsenseQA and StrategyQA are the same as used in Wei et al. (2022).

Table 9: Few-shot exemplars for all arithmetic reasoning tasks, from Wei et al. (2022).

Q: There are 15 trees in the grove. Grove workers will plant trees in the grove today. After they are done, there will be 21 trees. How many trees did the grove workers plant today?
A: We start with 15 trees. Later we have 21 trees. The difference must be the number of trees they planted. So, they must have planted $21 - 15 = 6$ trees. The answer is 6.
Q: If there are 3 cars in the parking lot and 2 more cars arrive, how many cars are in the parking lot?
A: There are 3 cars in the parking lot already. 2 more arrive. Now there are $3 + 2 = 5$ cars. The answer is 5.
Q: Leah had 32 chocolates and her sister had 42. If they ate 35, how many pieces do they have left in total?
A: Leah had 32 chocolates and Leah's sister had 42. That means there were originally $32 + 42 = 74$ chocolates. 35 have been eaten. So in total they still have $74 - 35 = 39$ chocolates. The answer is 39.
Q: Jason had 20 lollipops. He gave Denny some lollipops. Now Jason has 12 lollipops. How many lollipops did Jason give to Denny?
A: Jason had 20 lollipops. Since he only has 12 now, he must have given the rest to Denny. The number of lollipops he has given to Denny must have been $20 - 12 = 8$ lollipops. The answer is 8.
Q: Shawn has five toys. For Christmas, he got two toys each from his mom and dad. How many toys does he have now?
A: He has 5 toys. He got 2 from mom, so after that he has $5 + 2 = 7$ toys. Then he got 2 more from dad, so in total he has $7 + 2 = 9$ toys. The answer is 9.
Q: There were nine computers in the server room. Five more computers were installed each day, from monday to thursday. How many computers are now in the server room?
A: There are 4 days from monday to thursday. 5 computers were added each day. That means in total $4 * 5 = 20$ computers were added. There were 9 computers in the beginning, so now there are $9 + 20 = 29$ computers. The answer is 29.
Q: Michael had 58 golf balls. On tuesday, he lost 23 golf balls. On wednesday, he lost 2 more. How many golf balls did he have at the end of wednesday?
A: Michael initially had 58 balls. He lost 23 on Tuesday, so after that he has $58 - 23 = 35$ balls. On Wednesday he lost 2 more so now he has $35 - 2 = 33$ balls. The answer is 33.
Q: Olivia has \$23. She bought five bagels for \$3 each. How much money does she have left?
A: She bought 5 bagels for \$3 each. This means she spent $5 * \$3 = \15 on the bagels. She had \$23 in beginning, so now she has $\$23 - \$15 = \$8$. The answer is 8.
