

Less is More: Summary of Long Instructions is Better for Program Synthesis

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Abstract

Despite the success of large pre-trained language models (LMs) such as Codex, they show below-par performance on the larger and more complicated programming related questions. We show that LMs benefit from the summarized version of complicated questions. Our findings show that superfluous information often present in problem description such as human characters, background stories, names (which are included to help humans in understanding a task) does not help models in understanding a task. To this extent, we create a meta-dataset from the frequently used APPS dataset for the program synthesis task. Our meta-dataset consists of human and synthesized summary of the long and complicated programming questions. Experimental results on Codex show that our proposed approach outperforms baseline by 8.13% on an average in terms of strict accuracy. Our analysis shows that summary significantly improve performance for introductory (9.86%) and interview (11.48%) related programming questions. However, it shows improvement by a small margin ($\sim 2\%$) for competitive programming questions, implying the scope for future research direction.¹

1 Introduction

Recently, large pre-trained LMs have been proven pivotal in programming-related tasks (Wang et al., 2021; Chen et al., 2021; Hendrycks et al., 2021; Lu et al., 2021; Papineni et al., 2002). Program synthesis aims to generate a code given the natural language description of a problem. Programming requirements in these problems vary in terms of complexity from 3-5 line simple function to multiple functions that uses advanced data structures. However, LMs such as Codex show below-par performance on the long and complicated programming questions. We observe that the natural lan-

guage description of the program becomes long and complicated when there is superfluous information (see section 2.1.1 for a specific example). The goal of adding this information to the description is to make it more understandable to humans. However, we find that this information confuses model in understanding a task². We propose that removing the excess information and providing the model with the exact specifications of the problem can improve the performance of the LMs (Mishra et al., 2021a).

To remove excess information³, we summarize the descriptions of the program in such a way that it does not lose important specifications. We use the APPS dataset (Hendrycks et al., 2021) which is a collection of coding problems from different online sources and create a meta-dataset consisting of human and synthesized summaries of the long and complicated programming questions. This dataset has 3 levels of difficulty similar to APPS: (1) *introductory*, (2) *interview*, and (3) *competition*.

We perform all experiments using the GPT-based Codex model on the proposed meta-dataset and show that the summarized version of complicated questions improves (8.13%) performance on program synthesis tasks. Our analysis shows that summaries significantly improve performance for introductory (9.86%) and interview (11.48%) related programming questions. However, it shows improvement by small margin ($\sim 2\%$) for competitive programming questions. Considering that automatic evaluation of program does not reward for partial correctness, we perform qualitative evaluation on our meta-dataset and find that original questions often confuse models in understanding the underlying problem, as models latch on to some spurious words in text (e.g. the word ‘list’ in question makes the model design a list even though

¹Code and data is available at <https://github.com/kurbster/Prompt-Summarization>

²See example in Appendix A

³Instructions for creating summaries given in Appendix L

the underlying problem is on graphs). We further analyze model performance on different types of summaries (i.e., basic, expert, and synthetic) and provide instruction-design principles that can help future research on prompting in program synthesis.

2 Method

2.1 Dataset

We use the APPS dataset (Hendrycks et al., 2021) to create summaries. We randomly select problems from the APPS dataset for this purpose. We create 414 human summaries and 7820 synthetic summaries. Table 1 shows the statistics of the generated summaries.

Data Source	Difficulty	# of Problems
Human	Introductory	145
	Interview	123
	Competition	105
	Total	373
Studio21	Introductory	1588
	Interview	4551
	Competition	1286
	Total	7425
GPT-3	Introductory	194
	Interview	267
	Competition	244
	Total	705

Table 1: Statistics of the proposed meta-dataset.

2.1.1 Human Generated Summaries

For human-generated summaries, we ask computer science students at Arizona State University (ASU) to read and understand the original question, then create summaries in two steps⁴. First, we ask them to create a basic summary of the given problem. They are instructed to remove any information that is repeated and any hypothetical information without concrete instructions. For example, if the problem construct a fake company or situation, to help a human understand, we replace the fake situation with direct instructions. Full example is included in Appendix A. Second, we ask them to create an expert summary of the problem. To create this, they further summarize their first summary. This expert summary includes the absolute minimum information for an expert to understand the problem. We would not expect a novice to understand these

⁴Instructions given to each student are in Appendix L

prompts. An example of expert summaries is given in Appendix A.3.

2.1.2 Synthetic Summaries

We have generated synthetic summaries of program descriptions using jumbo (178B), large (7.5B) Studio21 model (Lieber et al., 2021) and GPT-3 Davinci model (175B) (Brown et al., 2020). To generate a summary, we provide these models with a few examples in the in-context learning setup (Brown et al., 2020) from the human-generated summaries. For the few-shot examples, we use expert level summaries.

Studio21 We use five examples with the large model, and three examples with jumbo model⁵. For both models, we use a temperature of 0.3, and topP of 1. For the format of our prompt, we use DeJargonizer template⁶ with a change to their header as shown in Appendix B. We create a total of 7, 510 synthetic summaries using these models.

GPT-3 We use three examples for GPT-3 model. We empirically set temperature to 0.05, topP to 1, frequency penalty to 0.01, presence penalty to 0.05. To generate prompts, we followed their tl;dr template⁷ as shown in Appendix B. We create 500 synthetic summaries using this model. We do not summarize any introductory problems with GPT-3 because we have limited resources and we want to test the efficacy of the model on harder problems.

2.2 Model

We use OpenAI Codex⁸ to build baselines and proposed approach.

Baseline To create a baseline, we have used original program descriptions given in APPS dataset as prompts for the Codex model.

Proposed Approach In this approach, we have used summaries of original program descriptions given in the APPS dataset as prompts for the Codex model.

3 Experimental Setup

All the experiments are performed using the *davinci – codex* (Chen et al., 2021) model pro-

⁵Examples are included in Appendix B

⁶<https://studio.ai21.com/>

⁷<https://beta.openai.com/playground/p/default-tldr-summary?model=text-davinci-001>

⁸<https://openai.com/blog/openai-codex/>

Difficulty	AP			EWPR			BWPR		
	Baseline	Basic	Expert	Baseline	Basic	Expert	Baseline	Basic	Expert
Introductory	42.96	50.00	50.00	44.20	51.45	51.82	43.23	50.35	50.35
Interview	37.70	41.80	44.26	36.52	45.54	46.96	37.70	41.80	44.26
Competition	4.76	5.71	5.71	4.00	6.00	6.00	4.76	5.71	5.71
Weighted Average	30.35	34.69	35.50	30.31	36.65	37.22	30.43	34.78	35.59

Table 2: Results of baseline and proposed model in terms of Strict Accuracy (SAcc). All results are in %. AP: All Problems, EWPR: Either Worst Problem Removal, BWPR: Both Worst Problem Removal (see explanation in section 3).

Difficulty	AP		EWPR	
	Baseline	Proposed	Baseline	Proposed
Introductory	42.96	52.82	44.53	54.74
Interview	37.70	49.18	38.66	50.42
Competition	4.76	6.67	4.81	6.73
Weighted Average	30.35	38.48	31.11	39.44

Table 3: Results when taking the best summary for each problem. Further explained in 4.1. The EWPR baseline is different from 2 because a different set of problems have been removed.

vided through OpenAI⁹. At inference time, we use a modified version of the evaluation code¹⁰ provided by Hendrycks et al. (2021). This evaluation code has four different outputs for each test case: (1) **-2**: the code has a syntax error and can not run, (2) **-1**: the code is syntactically correct but has a run time error, (3) **0**: the code run without any errors but fail the test case, and (4) **1**: the code run without any error and pass the test case. Similar to (Chen et al., 2021), we implement a timeout for the code at inference time. If a test case takes more than 4 seconds to run then we throw an exception and count that test case as a -1 .

Experiments To show effectiveness of the proposed approach, we have performed three different experiments using human generated summaries:

1. All problems from basic and expert summaries are used at inference time. We term this experiment as All Problems (AP).
2. We eliminate problems that perform worst¹¹ in the first experiment for either basic or expert summaries. We term this experiment as Either Worst Problem Removal (EWPR).

⁹See the implementation and parameter details in Appendix D

¹⁰https://github.com/hendrycks/apps/blob/main/eval/test_one_solution.py

¹¹Definition of the worst problem is given in Appendix E

3. We eliminate problems that perform worst in the first experiment for both basic and expert summaries. We term this experiment as Both Worst Problem Removal (BWPR).

We conduct first and second experiments using synthetic summaries as well. Since synthetic summaries generated by GPT-3 and Studio21 are for different problem, we do not perform third experiment.

Metric In (Austin et al., 2021a), they show that the BLEU metric (Papineni et al., 2002) does not correlate well with synthesis performance. Thus, we use the Strict Accuracy (SAcc) as our evaluation metric for all experiments (see Appendix C).

4 Results and Analysis

4.1 Results for Human Generated Summaries

Table 2 shows the results for baseline, human generated basic, and expert summaries evaluated on Codex models in terms of SAcc. From the Table 2, we can observe that both the summary-based models show on an average superior performance ($\sim 6\%$) compared to baseline. In particular, when calculating results for every problem, basic and expert summary-based models outperform baseline by 5.01%, and 5.74% respectively. Further analysis shows that expert summary-based model shows improved performance by $\sim 1\%$ compared to the basic summary-based model.

Our analysis shows that many problems where the basic summary would fail, however, the expert summary would succeed and vice-versa. Thus, we choose the best summary for each problem after evaluating both summaries and calculate the results for the best summaries. Table 3 shows results when taking the best summary for each problem. We observe a 9.86%, 11.48%, and 1.91% increase on SAcc for introductory, interview, and competition

Model	Difficulty	AP		EWPR	
		Baseline	Proposed	Baseline	Proposed
GPT-3	Introductory	41.75	38.66	41.11	41.67
	Interview	20.30	18.80	18.18	20.66
	Competition	2.87	3.28	2.73	3.64
	Weighted Average	20.17	18.89	19.14	20.55
Studio21	Introductory	39.53	31.63	39.04	36.36
	Interview	12.28	11.00	10.57	12.37
	Competition	1.67	1.21	1.38	1.38
	Weighted Average	11.53	9.66	10.61	10.98

Table 4: Results of baseline and proposed model (All results are in %). AP: All Problems, EWPR: Either Worst Problem Removal. 704 summaries generated by GPT-3 and 1501 summaries generated by Studio21 used for inference.

level problems, respectively.

4.2 Results for Synthetic Summaries

Table 4 shows the results for baseline, synthetic summaries generated by GPT-3, and Studio21 in terms of SAcc for two experiments. For AP experiment, we can observe that the performance of baseline outperforms synthetic summary-based models. However, proposed model shows on an average similar performance compared to baseline for EWPR experiment. Moreover, Appendix G shows the results for top 500 and top 1000 summaries from GPT-3 and Studio21, respectively.

4.3 Analysis

Why do competitive problems have less performance compared to the baseline for expert summaries? We can closely observe from the Table 2 that expert summary-based model shows on an average similar performance compared to basic-summary based model for introductory and interview type questions, however, the performance of expert summary-based model deprecates for competition type of questions. We believe that expert summaries remove important information compared to basic summaries¹² which might not affect introductory or interview type problems where concise information is enough. However, this information can be crucial to model when it comes to competition-level problems.

Why eliminating the worst problems help?

From Tables 2 and 4, we can observe that EWPR and BWPR have improved performance compared to AP for both human and synthetically generated

summaries. By analyzing the summarized worst problems, we notice a difference in the summarization style which shows that these summaries are outliers and do not match the distribution of the other summaries. This can cause a problem in synthesizing a good program since the model loses important information. Hence, we believe that eliminating the worst problems improves model performance.

Is there any possible bias in the meta-dataset?

Given that our human-generated summaries are crowd-sourced, there will be some bias in the dataset. This is confirmed by our analysis because there was a specific group of problems that perform worse in both experiments. Some details that are critical to one person can be trivial to others. In the context of generating expert summaries, assumptions about expert knowledge can vary. Thus, different people will be biased towards excluding more information while others will exclude less. This bias causes drift in the dataset and hinders the model’s performance. Similar to Mishra et al. (2021b), we can provide a template for what is expected from the crowd workers to reduce bias.

5 Related Work

In the past, there are several methods including semantic parsing (Ge and Mooney, 2005), deductive approaches, enumerative and stochastic search, and constraint solving which have gained attention for program synthesis (Gulwani et al., 2017). With the advent of machine/deep learning, Balog et al. (2016) introduced a neural network based model for solving programming competition-style problems. Devlin et al. (2017) used sequence-to-

¹²See examples in Appendix A and A.3

sequence approach to do program synthesis. Furthermore, Hendrycks et al. (2021) introduced the APPS dataset for testing the accuracy of large LMs on program synthesis. This dataset consists of 10,000 different coding challenges gathered from online websites such as *Codewars.com*, *AtCoder*, *Kattis*, and *Codeforces*. These problems cover a wide variety of programming topics and consists of 3 different difficulty levels: (1) introductory, (2) interview, and (3) competition. Hendrycks et al. (2021) leveraged the *GPT-Neo* model (Black et al., 2021) which they fine-tune for this task using APPS dataset. CodeT5 model (Wang et al., 2021) utilizes many different training objectives. Recently, Austin et al. (2021b) explore limitations of large language models and propose two new benchmarks, MBPP and MathQA-Python. The Codex model (Chen et al., 2021) is an advanced code generation model that powers GitHub’s *Copilot*.

6 Conclusion

This paper introduces a summarization-based approach for efficient program synthesis. Experimental results show that the proposed approach improves the performance of the existing Codex model by on an average $\sim 8\%$ across various levels of programming questions provided by the APPS dataset. Further, this paper proposes a meta-dataset consisting of ~ 500 human-generated basic and expert level summaries as well as $\sim 8k$ synthetically generated summaries by GPT-3 and Studio21; this can be helpful for future research on writing better instructions for the program synthesis task.

Acknowledgement

We thank CSE 576 NLP class students at Arizona State University (ASU) for helping with the data creation process.

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A Example of removing fake information

A.1 Original Prompt

Codefortia is a small island country located somewhere in the West Pacific. It consists of n settlements connected by m bidirectional gravel roads. Curiously enough, the beliefs of the inhabitants require the time needed to pass each road to be equal either to a or b seconds. It's guaranteed that one can go between any pair of settlements by following a sequence of roads.

Codefortia was recently struck by the financial crisis. Therefore, the king decided to abandon some of the roads so that:

it will be possible to travel between each pair of cities using the remaining roads only, the sum of times required to pass each remaining road will be minimum possible (in other words, remaining roads must form minimum spanning tree, using the time to pass the road as its weight), among all the plans minimizing the sum of times above, the time required to travel between the king's residence (in settlement 1) and the parliament house (in settlement p) using the remaining roads only will be minimum possible.

The king, however, forgot where the parliament house was. For each settlement $p = 1, 2, \dots, n$, can you tell what is the minimum time required to travel between the king's residence and the parliament house (located in settlement p) after some roads are abandoned?

—Input—

The first line of the input contains four integers n, m, a and b ($2 \leq n \leq 70, n - 1 \leq m \leq 200, 1 \leq a < b \leq 10^7$) — the number of settlements and gravel roads in Codefortia, and two possible travel times. Each of the following lines contains three integers u, v, c ($1 \leq u, v \leq n, u \neq v, c \in \{a, b\}$) denoting a single gravel road between the settlements u and v , which requires c minutes to travel.

You can assume that the road network is connected and has no loops or multiedges.

—Output—

Output a single line containing n integers. The p -th of them should denote the minimum possible time required to travel from 1 to p after the selected roads are abandoned. Note that for each p you can abandon a different set of roads.

—Examples—

```
Input
5 5 20 25
1 2 25
2 3 25
3 4 20
4 5 20
5 1 20
```

```
Output
0 25 60 40 20
```

```
Input
6 7 13 22
1 2 13
2 3 13
1 4 22
3 4 13
4 5 13
5 6 13
6 1 13
```

```
Output
0 13 26 39 26 13
```

—Note—

The minimum possible sum of times required to pass each road in the first example is 85 — exactly one of the roads with passing time 25 must be abandoned. Note that after one of these roads is abandoned, it's now impossible to travel between settlements 1 and 3 in time 50.

We can see the author of the problem is trying to describe a fully-connected graph with n nodes and m edges each with a weight a or b . Thus, this paragraph can be summarized as:

A.2 Basic Summary

You are given a graph of n nodes and m bidirectional edges. The cost for each edge is either a or b . The graph is fully-connected, so you can travel between any pair of nodes using the edges.

For each node $p = 1, 2, \dots, n$, you need to remove some edges so that: It will be possible to travel between each pair of nodes using the remaining edges only, and the sum of times required to pass each remaining road will be the minimum possible. You should output the minimum time required to travel between node 1 and node p .

—Input—

The first line of the input contains four integers n, m, a and b ($2 \leq n \leq 70, n - 1 \leq m \leq 200, 1 \leq a < b \leq 10^7$) — the number of nodes and edges in the graph, and two possible travel times. Each of the following lines contains three integers u, v, c ($1 \leq u, v \leq n, u \neq v, c \in \{a, b\}$) denoting an edge between the nodes u and v , which has cost c .

You can assume that the graph is connected and has no loops or multiedges.

—Output—

Output a single line containing n integers. The p -th of them should denote the minimum possible post required to travel from 1 to p after the selected edges are abandoned. Note that for each p you can abandon a different set of edges.

—Examples—

```
Input
5 5 20 25
1 2 25
```

```
2 3 25
3 4 20
4 5 20
5 1 20
```

```
Output
0 25 60 40 20
```

```
Input
6 7 13 22
1 2 13
2 3 13
1 4 22
3 4 13
4 5 13
5 6 13
6 1 13
```

```
Output
0 13 26 39 26 13
```

A.3 Expert Summary

However, we can assume that an expert would already know what a minimum spanning tree is. Thus, we can remove this detailed description of an MST.

You are given a connected graph of n nodes and m bidirectional edges. For each node $p = 1, 2, \dots, n$, you need to find a minimum spanning tree. Then output the minimum cost required to travel between node 1 and node p .

—Input—

The first line of the input contains four integers n, m, a and b ($2 \leq n \leq 70, n - 1 \leq m \leq 200, 1 \leq a < b \leq 10^7$) — the number of nodes and edges in the graph, and two possible travel times. Each of the following lines contains three integers u, v, c ($1 \leq u, v \leq n, u \neq v, c \in \{a, b\}$) denoting an edge between the nodes u and v , which has cost c .

You can assume that the graph is connected and has no loops or multiedges.

—Output—

Output a single line containing n integers. The p -th of them should denote the minimum possible post required to travel from 1 to p after the selected edges are abandoned. Note that for each p you can abandon a different set of edges.

—Examples—

```
Input
5 5 20 25
1 2 25
2 3 25
3 4 20
4 5 20
5 1 20
```

```
Output
0 25 60 40 20
```

```
Input
6 7 13 22
1 2 13
2 3 13
1 4 22
3 4 13
4 5 13
5 6 13
6 1 13
```

```
Output
0 13 26 39 26 13
```

B Prompt templates

Studio21 Here is our template for Studio21.

The following sentences contain computer science jargon. Rewrite them using simple words.

Jargon: <ORIGINAL>
Simple: <SUMMARY>

Jargon: <ORIGINAL>
Simple: <SUMMARY>

Jargon: <ORIGINAL>
Simple: <SUMMARY>

Jargon: <ORIGINAL>
Simple:

The few-shot examples were chosen randomly from the human generated expert summaries. Here is an example of the prompt:

GPT3 Here is our template for GPT3.

Summarize the following paragraph: Original:
<ORIGINAL>
Summary: <SUMMARY>

Original: <ORIGINAL>
Summary: <SUMMARY>

Original: <ORIGINAL>
Summary: <SUMMARY>

Original: <ORIGINAL> Summary:

Codex Here is our default template for Codex, which is used when there is no starter code provided. When there is starter code provided the docstring remains the same but the code after the doc string will be what is provided.

```
Python3
"""
<PROBLEM DESCRIPTION>
"""
def code():
```


C Strict Accuracy

Strict Accuracy (SAcc) is the percentage of problems that passed every test case. The formula to calculate SAcc is given below:

$$\text{strict acc} := \frac{\text{problems with 100\% accuracy}}{\text{total number of problems}} \quad (1)$$

Given that, we are only generating one code solution for each problem our strict accuracy is comparable to (Chen et al., 2021)’s metric *raw pass@1*.

D Codex Configuration

We did a small test with 75 summaries to find our hyper-parameters for Codex. We set temperature to 0, topP to 1, frequency penalty to 0.2, and presence penalty to 0. We did not provide few-shot examples to Codex since we want to see if summarization only could improve the performance of the Codex model.

E Worst Problems and Statistics

Using the test case labels as defined in section 3 we defined a test case as getting worse if it’s label (result) was lower. Then we defined a problem as worse if *every* test case had a lower label. Our methodology behind this was, if we removed problems that had a worse accuracy, then it would be a non-trivial result that accuracy improved. Also, if we removed problems with worse accuracy, then a problem that originally had all 0 labels (all False test cases) would score the same if the summary had all -1 labels (runtime error) or a -2 (syntax error). So, we removed problems which every test case performed worse, to see if removing these outliers would improve results. You can see the overall breakdown of each split in table 5.

F Average length of Problems and Solutions

Table 6 represents the statistics for average length of problems and solutions for original and summarized prompts.

G Abbreviated Synthetic Results

In table 7, we show the results for our synthetic summaries when taking the top 500 and 1000 summaries for GPT3 and StudioAI21, respectively. In

Summary	Difficulty	AP	EWPR	BWPR
Basic	Introductory	145	141	144
	Interview	123	113	123
	Competition	105	100	105
Expert	Introductory	145	140	144
	Interview	123	116	123
	Competition	105	100	105
StudioAI21	Introductory	215	187	-
	Interview	627	558	-
	Competition	659	578	-
GPT3	Introductory	194	180	-
	Interview	266	242	-
	Competition	244	220	-

Table 5: These are the numbers of problems in each split of the dataset. For GPT and Studio21 we did not look at problems that were worse or same for both experiments because there was insignificant overlap between the two experiments.

our initial experiment, this was the amount of problems we tested for each model. However, in our final experiment we changed our configurations and generated more problems. For a comparison, we took the top performing summaries and reported those results.

H Generated Code

In figure 1 is the code that was generated for the example mentioned in Appendix A and A.3. Given that the Codex model was prompted with the *def code()* : the model did not generate that function definition or the call to that function. That was added in afterwards, but everything inside that function was generated by Codex. The originally generated code (far left) fails with a -1 because it did not take in the input correctly. It added in another line *p = int(input())*, which most likely refers to the *p* mentioned in the original text. The expert summary generated code (middle) fails every test case. The basic summary generated code (right) passed 16/19 (84%) test cases and was the only code to pass at least 1 test case.

I StudioAI21 Generated Code

Below is an example of a competition problem where StudioAI21 summarized the prompt too much but Codex was still able to produce viable code. Here is the original prompt:

Cengiz recently learned Fibonacci numbers and now he is studying different algorithms to find them. After getting bored of reading them, he came with his own new type of numbers that he

Experiment	Original Len	Summary Len	Orig Code Len	Summary Code Len	Code Solution Len
Summary	1147	937	339	349	671
Expert	1147	869	339	343	671
GPT	1386	1011	437	392	748
StudioAI21	1646	1114	602	473	721

Table 6: The average length of the original/summarized prompt and generated code. The average length of the code solutions is the average len of the solutions provided by the creators of the APPS dataset. A problem could have one or multiple solutions. The length is reported in characters.

Figure 1: On the far left is the code generated by the original prompt. The middle is the code generated by the expert summary. The right is the code generated by the basic summary.

Model	Difficulty	AP		EWPR	
		Baseline	Proposed	Baseline	Proposed
GPT-3	Introductory	41.97	38.86	41.11	41.67
	Interview	25.27	27.47	24.86	28.25
	Competition	4.80	6.40	4.88	6.50
Weighted Average		26.60	26.60	25.83	27.71
Studio21	Introductory	39.91	31.92	39.25	36.56
	Interview	15.97	14.50	13.23	15.47
	Competition	2.57	2.57	2.71	2.71
Weighted Average		16.90	14.50	15.10	15.64

Table 7: Results when taking the top 500 GPT problems and top 1000 Studio problems

named XORinacci numbers. He defined them as follows: $f(0) = a$; $f(1) = b$; $f(n) = f(n - 1) \oplus f(n - 2)$ when $n > 1$, where \oplus denotes the bitwise XOR operation.

You are given three integers a , b , and n , calculate $f(n)$.

You have to answer for T independent test cases.

—Input—

The input contains one or more independent test cases.

The first line of input contains a single integer T ($1 \leq T \leq 10^3$), the number of test cases.

Each of the T following lines contains three space-separated integers a , b , and n ($0 \leq a, b, n \leq 10^9$)

respectively.

—Output—

For each test case, output $f(n)$.

—Example—

Input
3
3 4 2
4 5 0
325 265 1231232

Output

7
4
76

—Note—

In the first example, $f(2) = f(0) \oplus f(1) = 3 \oplus 4 = 7$.

Here is the summary that StudioAI21 generated:

You are given three integers a , b , and n . Calculate $f(n)$.

—Input—

The input contains one or more independent test cases.

The first line of input contains a single integer T ($1 \leq T \leq 10^3$), the number of test cases.

Each of the T following lines contains three space-separated integers a , b , and n ($0 \leq a, b, n \leq 10^9$) respectively.

—Output—

For each test case, output $f(n)$.

—Example—

Input

```
3
3 4 2
4 5 0
325 265 1231232
```

Output

```
7
4
76
```

—Note—

In the first example, $f(2) = f(0) \oplus f(1) = 3 \oplus 4 = 7$.

Because any input/output examples provided by the prompt are appended to the summary, Codex was able to figure out the pattern in the problem and generate code that was almost correct. In figure 2, the solution (left) used the pattern in the problem and simplify by taking $n \bmod 3$. The Studio21 summary code (right) recognizes this pattern but erroneously does not take the modulus of the number. The original code (center) also makes the same mistake by not taking the modulus, but also brute forces the answer. This shows that the model did not recognize the pattern in this problem because of the superfluous details. Even though Studio21 might have summarized too much, the model was still able to make an improvement and understand the pattern in the problem more.

J StudioAI21 Generated Code

Here is an example of a summary made by StudioAI21 where the qualitative aspect of the code but it still failed. Here is the original prompt:

Given is a tree G with N vertices. The vertices are numbered 1 through N , and the i -th edge connects Vertex a_i and Vertex b_i . Consider painting the edges in G with some number of colors. We want to paint them so that, for each vertex, the colors of the edges incident to that vertex are all different. Among the colorings satisfying the condition above, construct one that uses the minimum number of colors.

—Constraints—

- $2 \leq N \leq 10^5$

- $1 \leq a_i < b_i \leq N$

- All values in input are integers.

- The given graph is a tree.

—Input—

Input is given from Standard Input in the following format:

```
N
a1 b1
a2 b2
:
aN-1 bN-1
```

—Output—

Print N lines.

The first line should contain K , the number of colors used.

The $(i+1)$ -th line ($1 \leq i \leq N-1$) should contain c_i , the integer representing the color of the i -th edge, where $1 \leq c_i \leq K$ must hold.

If there are multiple colorings with the minimum number of colors that satisfy the condition, printing any of them will be accepted.

—Sample Input—

```
3
1 2
2 3
```

—Sample Output—

```
2
1
2
```

Here is the summary that StudioAI21 generated:

You are given a tree with N vertices numbered from 1 to N . You need to find the minimum possible number of colors to paint the edges such that vertices are painted with different color.

—Constraints—

- $2 \leq N \leq 10^5$

- $1 \leq a_i < b_i \leq N$

- All values in input are integers.

- The given graph is a tree.

—Input—

Input is given from Standard Input in the following format:

```
N
a1 b1
a2 b2
:
aN-1 bN-1
```

—Output—

Print N lines.

The first line should contain K , the number of colors used.

The $(i+1)$ -th line ($1 \leq i \leq N-1$) should contain c_i , the integer representing the color of the i -th edge, where $1 \leq c_i \leq K$ must hold.

If there are multiple colorings with the minimum

Figure 2: The left is the code generated using the original prompt. The right is the code generated when using the StudioAI21 generated summary.

number of colors that satisfy the condition, printing any of them will be accepted.

—Sample Input—

```
3
1 2
2 3
```

—Sample Output—

```
2
1
2
```

In 3 the left is the original solution which fails with a -2 because the runtime of the algorithm is exponential. Note that it tries to create a list of all possible edge colorings which is $\mathcal{O}(2^N)$. The right is the code produced when using the StudioAI21 summary. You can see that this code is much closer to solving the problem and produces an efficient algorithm. However, this fails with a -2 because it tries to print the sum of a boolean (near the end before the last for loop). Which fails in python because a bool is not iterable.

Here is a problem where StudioAI21's summary increased the accuracy to 100%. Here is the original prompt:

Polycarpus has a sequence, consisting of n non-negative integers: a_1, a_2, \dots, a_n .

Let's define function $f(l, r)$ (l, r are integer, $1 \leq l \leq r \leq n$) for sequence a as an operation of bitwise OR of all the sequence elements with indexes from l to r . Formally: $f(l, r) = a_l | a_{l+1} | \dots | a_r$.

Polycarpus took a piece of paper and wrote out the values of function $f(l, r)$ for all l, r (l, r are integer, $1 \leq l \leq r \leq n$). Now he wants to know, how many distinct values he's got in the end.

Help Polycarpus, count the number of distinct values of function $f(l, r)$ for the given sequence a .

Expression $x|y$ means applying the operation of bitwise OR to numbers x and y . This operation exists in all modern programming languages, for example, in language C++ and Java it is marked as " $|$ ", in Pascal — as " or ".

—Input—

The first line contains integer n ($1 \leq n \leq 10^5$) — the number of elements of sequence a . The second line contains n space-separated integers a_1, a_2, \dots, a_n ($0 \leq a_i \leq 10^6$) — the elements of sequence a .

—Output—

Print a single integer — the number of distinct values of function $f(l, r)$ for the given sequence a .

Please, do not use the `lld` specifier to read or write 64-bit integers in C++. It is preferred to use `cin`, `cout` streams or the `I64d` specifier.

—Examples—

Input
3
1 2 0

Output
4
Input
10
1 2 3 4 5 6 1 2 9 10

Output
11

—Note—

In the first test case Polycarpus will have 6 numbers written on the paper: $f(1, 1) = 1, f(1, 2) = 3, f(1, 3) = 3, f(2, 2) = 2, f(2, 3) = 2, f(3, 3) = 0$. There are exactly 4 distinct numbers among them: 0, 1, 2, 3.

Here is the summary that StudioAI21 generated. Not exactly as we would expect as the prompt still mentions the fictional *Polycarpus*.

Polycarpus has a sequence, consisting of n non-negative integers: a_1, a_2, \dots, a_n . Let's define function $f(l, r)$ (l, r are integer, $1 \leq l \leq r \leq n$) for sequence a as an operation of bitwise OR of all the sequence elements with indexes from l to r . Formally: $f(l, r) = a_l | a_{l+1} | \dots$

—Input—

The first line contains integer n ($1 \leq n \leq 10^5$) — the number of elements of sequence a . The second line contains n space-separated integers

```

import itertools
def code():
    n = int(input())
    edges = []
    for i in range(n-1):
        edges.append(list(map(int, input().split())))

    # Create a list of all possible colors
    colors = [i for i in range(1, n)]

    # Create a list of all possible colorings
    colorings = []
    for i in range(1, len(colors)+1):
        colorings += list(itertools.combinations(colors, i))

    # Create a list of all possible trees
    trees = []
    for i in range(len(colorings)):
        trees.append([])
        for j in range(len(edges)):
            if edges[j][0] == 1:
                trees[i].append([edges[j][0], edges[j][1], colorings[i][0]])
            elif edges[j][1] == 1:
                trees[i].append([edges[j][0], edges[j][1], colorings[i][0]])

13 def code():
12     n = int(input())
11     adj = [[] for i in range(n)]
10     for i in range(n-1):
9         a, b = map(int, input().split())
8         adj[a-1].append(b-1)
7         adj[b-1].append(a-1)
6     colors = [0]*n
5     for i in range(n):
4         if colors[i] == 0:
3             colors[i] = 1
2             q = [i]
1             while q:
14                 curr = q.pop()
1                 for j in adj[curr]:
2                     if colors[j] == 0:
3                         colors[j] = -colors[curr]
4                         q.append(j)
5                     elif colors[j] == colors[curr]:
6                         print("Impossible")
7                         return
8     print(sum(colors == 1)+1)
9     for i in range(1, n):
10         print(colors[i])
11     code()

```

Figure 3: The left is the code generated using the original prompt. The right is the code generated when using the StudioAI21 generated summary.

a_1, a_2, \dots, a_n ($0 \leq a_i \leq 10^6$) — the elements of sequence a .

—Output—

Print a single integer — the number of distinct values of function $f(l, r)$ for the given sequence a .

Please, do not use the `lld` specifier to read or write 64-bit integers in C++. It is preferred to use `cin`, `cout` streams or the `I64d` specifier.

—Examples—

Input

3
1 2 0

Output

4

Input

10
1 2 3 4 5 6 1 2 9 10

Output

11

—Note—

In the first test case Polycarpus will have 6 numbers written on the paper: $f(1, 1) = 1$, $f(1, 2) = 3$, $f(1, 3) = 3$, $f(2, 2) = 2$, $f(2, 3) = 2$, $f(3, 3) = 0$. There are exactly 4 distinct numbers among them: 0, 1, 2, 3.

In 4 the left is the original solution which gets 77% accuracy. The right is the summary code which gets 100% accuracy.

K GPT Generated Summaries

Here are two summaries where GPT perfectly summarized the prompt and gave a concise description of what the task was. In both cases the original prompt did not have 100% accuracy but the summarized prompt did have 100% accuracy.

Here is the original prompt for the first question:

Božo is a strange little boy. Every day he tires his friends with strange questions. Today's question is: how many integers in the interval $[A, B]$ are there such that the sum of their digits is S , and which is the smallest such number?

Write a program that answers Božo's question so that he can get some sleep.

—Input—

The input contains three integers A , B and S ($1 \leq A \leq B < 10^{15}$, $1 \leq S \leq 135$).

—Output—

The first line should contain the number of integers in the interval with the digit sum equal to S .

The second line should contain the smallest such integer.

The input data will guarantee that the first number is at least 1.

—Examples—

Sample Input 1:

1 9 5

Sample Output 1:

1
5

Sample Input 2:

1 100 10

Sample Output 2:

9
19

Here is the summary that GPT Generated:

Write a program that calculates the smallest integer in the given interval whose sum of digits is equal to the given sum.

—Input—

The input contains three integers A , B and S

```

def code():
    n = int(input())
    a = list(map(int, input().split()))
    d = {}
    for i in range(n):
        for j in range(i, n):
            d[a[i] | a[j]] = 1
    print(len(d))
code()

```

```

1 def code():
2     n = int(input())
3     a = list(map(int, input().split()))
4     d = {}
5     for i in range(n):
6         for j in range(i, n):
7             s = 0
8             for k in range(i, j+1):
9                 s |= a[k]
10                if s not in d:
11                    d[s] = 1
12                else:
13                    d[s] += 1
14            print(len(d))
code()

```

Figure 4: The left is the code generated using the original prompt. The right is the code generated when using the StudioAI21 generated summary.

$(1 \leq A \leq B < 10^{15}, 1 \leq S \leq 135)$.

—Output—

The first line should contain the number of integers in the interval with the digit sum equal to S .

The second line should contain the smallest such integer.

The input data will guarantee that the first number is at least 1.

—Examples—

Sample Input 1:

1 9 5

Sample Output 1:

1
5

Sample Input 2:

1 100 10

Sample Output 2:

9
19

In 5 you can see the original code on the left and the summary code on the right. There is a subtle difference but it's that difference that improved the problem from 33% accuracy to 100%.

Here is the original prompt for another question.

Professor GukiZ makes a new robot. The robot are in the point with coordinates (x_1, y_1) and should go to the point (x_2, y_2) . In a single step the robot can change any of its coordinates (maybe both of them) by one (decrease or increase). So the robot can move in one of the 8 directions. Find the minimal number of steps the robot should make to get the finish position.

—Input—

The first line contains two integers x_1, y_1 $(-10^9 \leq x_1, y_1 \leq 10^9)$ — the start position

of the robot.

The second line contains two integers x_2, y_2 $(-10^9 \leq x_2, y_2 \leq 10^9)$ — the finish position of the robot.

—Output—

Print the only integer d — the minimal number of steps to get the finish position.

—Examples—

Input

0 0

4 5

Output

5

Input

3 4

6 1

Output

3

—Note—

In the first example robot should increase both of its coordinates by one four times, so it will be in position (4, 4). After that robot should simply increase its y coordinate and get the finish position.

In the second example robot should simultaneously increase x coordinate and decrease y coordinate by one three times.

Here is the summary that GPT3 generated:

The robot can move in one of the 8 directions. Find the minimal number of steps the robot should make to get the finish position.

—Input—

The first line contains two integers x_1, y_1 $(-10^9 \leq x_1, y_1 \leq 10^9)$ — the start position of the robot.

Figure 5: The left is the code generated using the original prompt. The right is the code generated when using the GPT3 generated summary.

The second line contains two integers x_2, y_2 ($-10^9 \leq x_2, y_2 \leq 10^9$) — the finish position of the robot.

—Output—

Print the only integer d — the minimal number of steps to get the finish position.

—Examples—

Input

0 0

4 5

Output

5

Input

3 4

6 1

Output

3

—Note—

In the first example robot should increase both of its coordinates by one four times, so it will be in position (4, 4). After that robot should simply increase its y coordinate and get the finish position.

In the second example robot should simultaneously increase x coordinate and decrease y coordinate by one three times.

In 6 you can see the original code on the left and the summary code on the right. There is a subtle difference but it's that difference that improved the problem from 20% accuracy to 100%.

L Human Generated Instructions

The section below was given to each crowd worker as instructions to follow when creating the regular and expert summaries.

L.1 Summarization

Create a file called *summary.txt* this will contain your summary of the prompt. It's recommended that you copy the *question.txt* file into

the *summary.txt* file then starting from the top of the prompt follow the steps and remove words/lines as necessary.

These are the rough steps for making a summary. Following these steps will create the most consistency in our dataset. However, you should summarize as you see fit. First, read through the prompt and understand what it's asking, then follow these steps to help create a summary.

1. Directly state what is given in the problem.
 - Most problems start by setting the scene, to help humans understand.
 - Start the problems by explicitly telling the model what the input is.
 - *You are given . . .*
2. Remove any *notes* given in the prompt.
 - They are usually reemphasizing points, which is redundant and not needed in the summary.
 - This includes the *–Notes–* section at the bottom of the file.
 - If there is pertinent information given from a note, include it in the prompt without describing it as a note.
3. Remove any text in parenthesis.
 - Most of the text in parenthesis is repeating the information that precede them.
 - If the text in parenthesis provides more context or information, then remove the preceding text.
 - Keep any parenthesis if it is describing constraints, such as the minimum and

```

def code():
    x1, y1 = map(int, input().split())
    x2, y2 = map(int, input().split())
    if x1 == x2 and y1 == y2:
        print(0)
        return
    if abs(x1 - x2) == abs(y1 - y2):
        print(abs(x1 - x2))
        return
    if abs(x1 - x2) > abs(y1 - y2):
        print(abs(y1 - y2))
        return
    else:
        print(abs(x1 - x2))
        return
code()

```

```

1 def code():
2     x1, y1 = map(int, input().split())
3     x2, y2 = map(int, input().split())
4     if x1 == x2:
5         print(abs(y2 - y1))
6     elif y1 == y2:
7         print(abs(x2 - x1))
8     else:
9         print(max(abs(x2 - x1), abs(y2 - y1)))
code()

```

Figure 6: The left is the code generated using the original prompt. The right is the code generated when using the GPT3 generated summary.

maximum values for the input etc...

4. Remove any made up people, places, things, etc...
 - These abstractions are made to help humans understand but confuse the model.
 - The prompts often mention things like *Codefortia* or *Polycarp*, try to replace these with the word *you*.
 - Any text visualizing what the problem is asking, should be removed.
5. If the *Input* or *Output* section reference an abstraction they should be changed.
 - Overall, these sections are fine. However, if they mentioned something you removed in the previous steps, they should be changed to reflect that.
 - If these sections repeat themselves remove any redundancies.
 - In most cases these sections will be left alone.

L.2 Expert Summary

Create a file called *expert.txt* this will contain an expert summary of the prompt. It's recommended that you copy the *summary.txt* file into the *expert.txt* file then starting from the top of the prompt remove words/lines as necessary. You should aim for the expert prompt to be 2 – 4 lines.

Imagine you are describing the prompt to a senior software engineer. What else could you trim

out? The difference between the original and expert summary, is the original summary may include something obvious, whereas the expert solution should be the absolute bare minimum. To create *summary.txt* you want to remove superfluous details from the original prompt. To create *expert.txt* you want to remove details that an expert would find obvious, from the summary.

For example, in problem 2000 (which is competitive difficulty) the summary mentions '*It will be possible to travel between each pair of nodes . . . , and the sum of times . . . will be the minimum possible*'. This process is describing a minimum spanning tree so you can just say '*Find a minimum spanning tree*'.

Also, if the prompt included an example and subsequent explanation, that should remain in the summary but should be removed from the expert summary. An expert already understands the problem and does not need any extra explanation. You should still keep the *–Examples–* section.

Takeaways

- Removing made up people, places, and things from the prompt improved the quality of code generated.
- The optimal summarization depends on the difficulty of the problem.
- Synthetically generated summaries were close to maintaining accuracy.
- With more rigorous instructions, human summaries could be made with less noise which would further improve synthetic summary

generation.

M Superfluous Information Confusing the Model

Here is an example of an interview level string problem where the original prompt got 0% and both human generated summaries got 100% accuracy. The question wants you to write code that will return the number of unique character in the given string.

M.1 Original Prompt

You have initially a string of N characters, denoted by A_1, A_2, \dots, A_N . You have to print the size of the largest subsequence of string A such that all the characters in that subsequence are distinct ie. no two characters in that subsequence should be same.

A subsequence of string A is a sequence that can be derived from A by deleting some elements and without changing the order of the remaining elements.

—Input— First line contains T , number of testcases. Each testcase consists of a single string in one line. Each character of the string will be a small alphabet(ie. 'a' to 'z').

—Output— For each testcase, print the required answer in one line.

—Constraints—

- $1 \leq T \leq 10$
- Subtask 1 (20 points): $1 \leq N \leq 10$
- Subtask 2 (80 points): $1 \leq N \leq 105$

—Example—

Input:
2
abc
aba

Output: 3
2

—Explanation— For first testcase, the whole string is a subsequence which has all distinct characters.

In second testcase, the we can delete last or first 'a' to get the required subsequence.

M.2 Basic Summary

You are given N string. You have to identify the duplicates and print the length of the new string as a combination of unique characters only.

—Input— First line contains T , number of testcases. Each testcase consists of a single string in one line. Each character of the string will be a small alphabet(ie. 'a' to 'z').

—Output— For each testcase, print the required answer in one line.

—Constraints—

- $1 \leq T \leq 10$
- Subtask 1 (20 points): $1 \leq N \leq 10$
- Subtask 2 (80 points): $1 \leq N \leq 105$

—Example—

Input:
2
abc
aba

Output: 3
2

M.3 Expert Summary

You have to remove duplicates and print the length of unique characters of the given string.

—Input— First line contains T , number of testcases. Each testcase consists of a single string in one line. Each character of the string will be a small alphabet(ie. 'a' to 'z').

—Output— For each testcase, print the required answer in one line.

—Constraints—

- $1 \leq T \leq 10$
- Subtask 1 (20 points): $1 \leq N \leq 10$
- Subtask 2 (80 points): $1 \leq N \leq 105$

—Example—

Input:
2
abc
aba

Output: 3
2

M.4 Generated Code

The original code (left) does not accomplish the task but rather prints the count of the most frequent character. The model was unable to distinguish what the task was given the verbose prompt. However, the basic and expert summaries make the task clear and the model produces the same code. Which properly solves the challenge.

N Made Up Information Confusing the Model

Here is an example of an interview level problem where the original prompt got 0% and the expert generated summary got 100% accuracy.

```

def code():
    t=int(input())
    for i in range(t):
        s=input()
        l=len(s)
        if l==1:
            print(1)
            continue
        d={}
        for i in s:
            if i not in d:
                d[i]=1
            else:
                d[i]+=1
        max_val=0
        for i in d.values():
            if i>max_val:
                max_val=i
        print(max_val)
code()

1 def code():
2     t = int(input())
3     for i in range(t):
4         s = input()
5         l = len(s)
6         for j in s:
7             if j not in l:
8                 l.append(j)
9         print(len(l))
code()

9 def code():
8     t = int(input())
7     for i in range(t):
6         s = input()
5         l = []
4         for j in s:
3             if j not in l:
2                 l.append(j)
1         print(len(l))
code()

```

Figure 7: The left is the code generated by the original prompt. The middle is the code generated by the expert summary. The right is the code generated by the basic summary.

N.1 Original Prompt

The chef was searching for his pen in the garage but he found his old machine with a display and some numbers on it. If some numbers entered then some different output occurs on the display. Chef wants to crack the algorithm that the machine is following. Example to identify the pattern :

Input	Output
9	36
5	10
1	0
2	1

—Input:—

- First-line will contain T , the number of test cases. Then the test cases follow. - Each test case contains a single line of input, N .

—Output:—

For each test case, output in a single line answer as displayed on the screen.

—Constraints—

- $1 \leq T \leq 10^6$
 - $1 \leq N \leq 10^6$

—Sample Input:—

1
7

—Sample Output:—

21

—Output:—

For each test case, output in a single line answer as displayed on the screen.

—Constraints—

- $1 \leq T \leq 10^6$
 - $1 \leq N \leq 10^6$

—Sample Input:—

1
7

—Sample Output:—

21

N.2 Expert Summary

Write a code to print the average of the multiplication of a given number N with $N-1$ integer.
1

—Input:—

- First-line will contain T , the number of test cases. Then the test cases follow. - Each test case contains a single line of input, N .

```
def code():
    T = int(input())
    for i in range(T):
        N = int(input())
        print((N*(N-1))//2)
code()

1 def code():
2     T = int(input())
3     for i in range(T):
4         N = int(input())
5         if N == 0:
6             print(0)
7         elif N == 1:
8             print(1)
9         elif N == 2:
10            print(1)
11        else:
12            sum = 0
13            for j in range(N):
14                if j % 2 == 0: # even numbers are 1's and odd numbers are 0's. So, the sum of all the digits is the answer.
15                    sum += 1
16            else: # odd numbers are 1's and even numbers are 0's. So, the sum of all the digits is the answer.
17                sum += 0
18            print(sum)
19
20
21 code()
```

Figure 8: The left is the code generated by the expert summary. The right is the code generated by the original prompt.