Using an LLM to generate Instruction Following examples

In the module on Instruction Following (LLM_Instruction_Following.ipynb)

- we motivated the use of Fine-Tuning a LLM
- to exhibit Instruction Following behavior

Recall: an example of Instruction Following behavior is a triple, for example

- Instruction: "Tell me the word that is the opposite of the word that I input"
- Context: "Input: Stop"
- Response: "Go"

The Instruction describes the task to be accomplished

- relationship between Input and Response
- the Input/Response pair is an exemplar for this task

In this module, we explore methods

- to generate these fine-tuning examples
- to improve examples

Using an LLM to generate Instruction Following examples

SELF-Instruct paper (https://arxiv.org/pdf/2212.10560.pdf)

Is there an alternative to the labor-intensity of constructing Instruction Following examples by human ?

The idea of the SELF-Instruct paper (https://arxiv.org/pdf/2212.10560.pdf) is to use a Synthetic Data approach to constructing new examples of Instruction Following

These examples are pairs of an Instruction part, and a Target Output part.

The authors

- use a *few-shot* learning approach to generate *synthetic* Instruction Following examples
- augmenting a small number of human-constructed examples with the synthetic examples
- using the augmented dataset to Fine Tune an LLM to better demonstrate Instruction Following

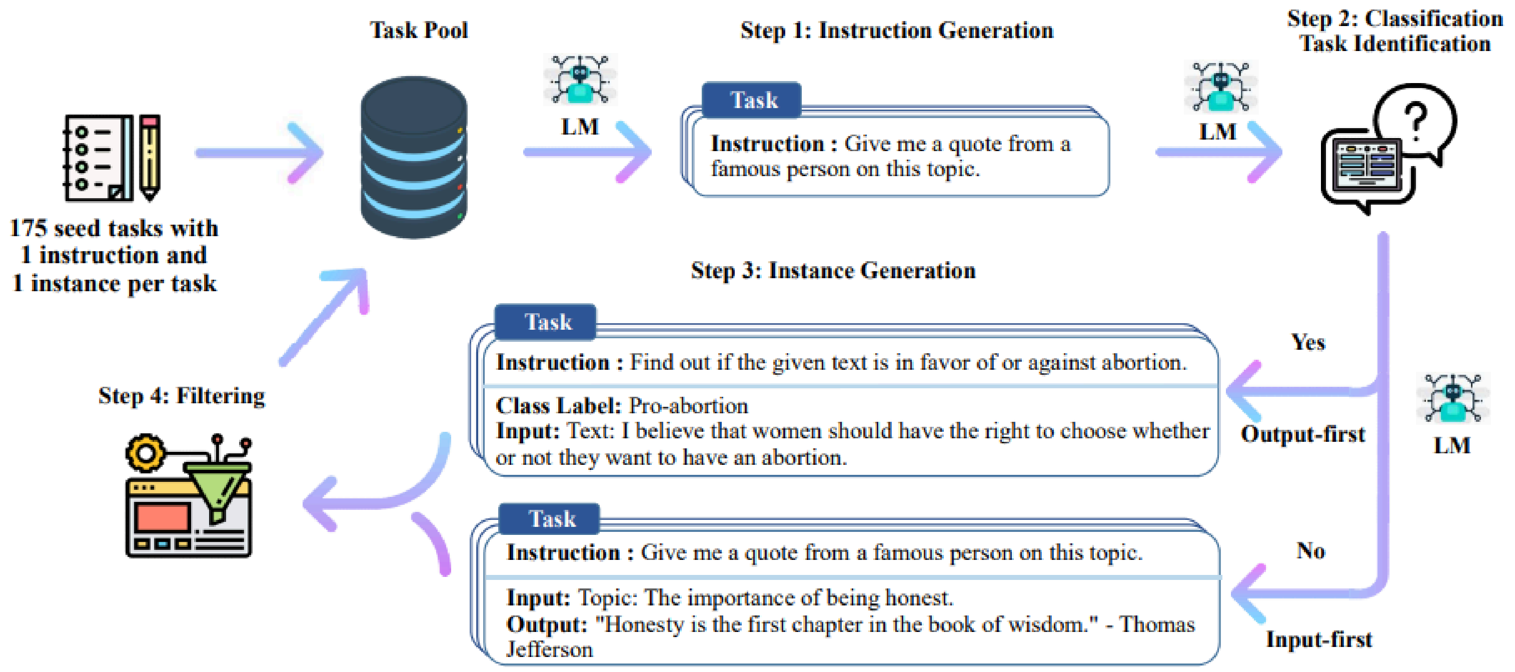

Task Pool
Step 1: Instruction Generation
Step 2: Classification Task Identification
LM
LM
Task
Instruction : Give me a quote from a famous person on this topic.
175 seed tasks with 1 instruction and 1 instance per task
Step 3: Instance Generation
Task
Instruction : Find out if the given text is in favor of or against abortion.
Class Label: Pro-abortion
Input: Text: I believe that women should have the right to choose whether or not they want to have an abortion.
Yes
Output-first
LM
Step 4: Filtering
Task
Instruction : Give me a quote from a famous person on this topic.
Input: Topic: The importance of being honest.
Output: "Honesty is the first chapter in the book of wisdom." - Thomas Jefferson
No
Input-first

Figure 1: A high-level overview of SELF-INSTRUCT. The process starts with a small seed set of tasks (one instruction and one input-output instance for each task) as the task pool. Random tasks are sampled from the task pool, and used to prompt an off-the-shelf LM to generate both new instructions and corresponding instances, followed by filtering low-quality or similar generations, and then added back to the initial repository of tasks. The resulting data can be used for the instruction tuning of the language model itself later to follow instructions better. Tasks shown in the figure are generated by GPT3. See Table 10 for more creative examples.

Attribution: https://arxiv.org/pdf/2212.10560.pdf#page=2 (https://arxiv.org/pdf/2212.10560.pdf#page=2)

The process involves multiple steps which we explain below.

Generating the Instruction part of an Instruction-Output example

The first step is to use few shot learning to generate synthetic Instructions

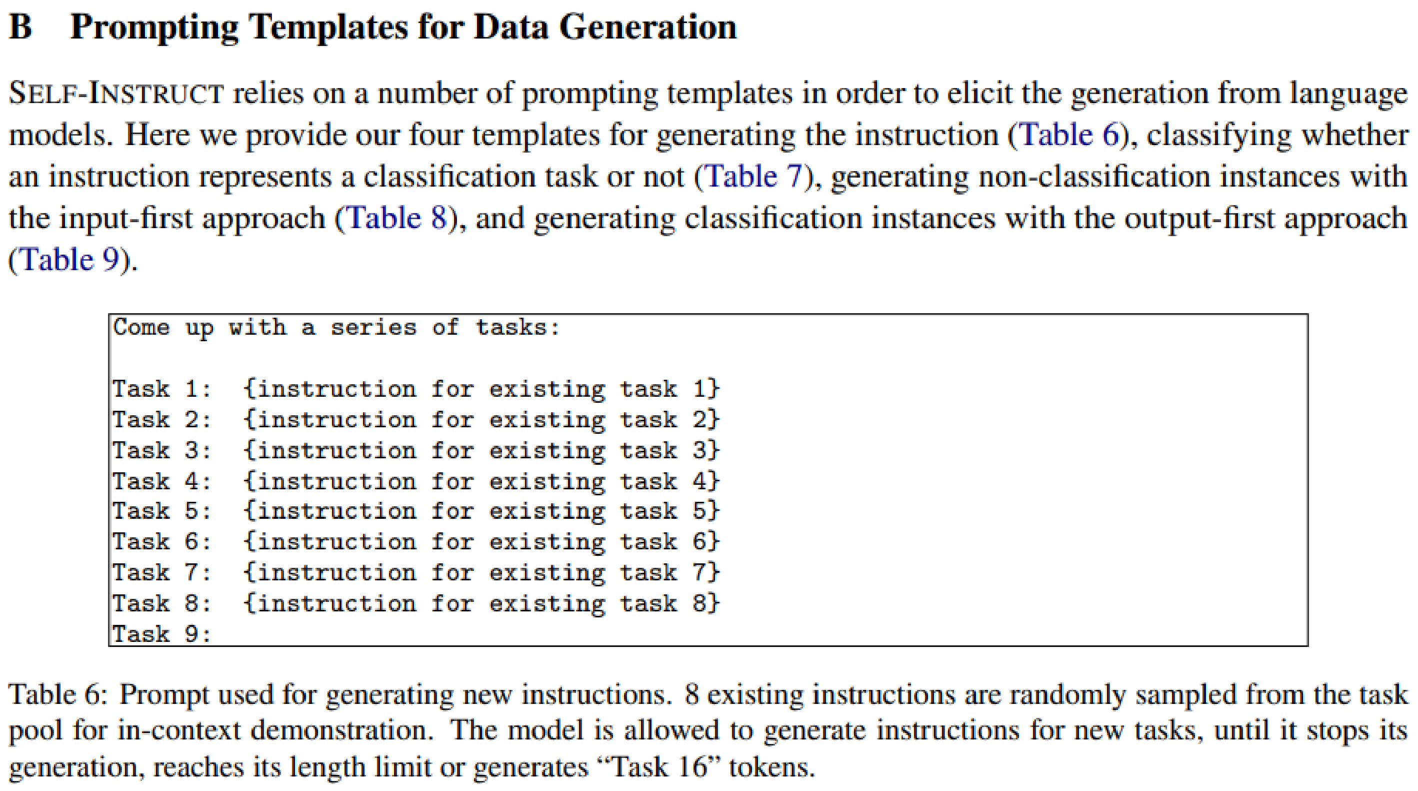
- the Instruction part of an Instruction-Target Output example

The synthetic Instructions are used to augment a small number of Instructions from the manually generated training dataset.

Recall: few-shot learning involves creating a prompt that is the concatenation of

- a few exemplars ($\langle \mathbf{x}, \mathbf{y} \rangle$ pairs demonstration the task)
- an example with no label: $\mathbf{x}$

Here is a template for a prompt demonstrating to GPT how to create a new Instruction



B Prompting Templates for Data Generation

SELF-INSTRUCT relies on a number of prompting templates in order to elicit the generation from language models. Here we provide our four templates for generating the instruction (Table 6), classifying whether an instruction represents a classification task or not (Table 7), generating non-classification instances with the input-first approach (Table 8), and generating classification instances with the output-first approach (Table 9).

```
Come up with a series of tasks:

Task 1:  {instruction for existing task 1}
Task 2:  {instruction for existing task 2}
Task 3:  {instruction for existing task 3}
Task 4:  {instruction for existing task 4}
Task 5:  {instruction for existing task 5}
Task 6:  {instruction for existing task 6}
Task 7:  {instruction for existing task 7}
Task 8:  {instruction for existing task 8}
Task 9:
```

Table 6: Prompt used for generating new instructions. 8 existing instructions are randomly sampled from the task pool for in-context demonstration. The model is allowed to generate instructions for new tasks, until it stops its generation, reaches its length limit or generates "Task 16" tokens.

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Generating the Output part, given an Instruction

The next step is to

- choose an Instruction (called the *Target task*) from the augmented list of Instructions
- prompt the LLM to generate the optional Context and the Target Output for the target task.

The prompting for the output is achieved by few-shot learning.

- Provide k exemplars
- Followed by a line consisting of
    - The Instruction for the Target Task
    - with the expectation that the LLM will create an Input/Output pair
        - that obeys the Instruction
        - correctly relates the Input and the Output

Each exemplar is an Instruction following example for some other task.

That is, it is a Instruction-Context-Target Output triple.

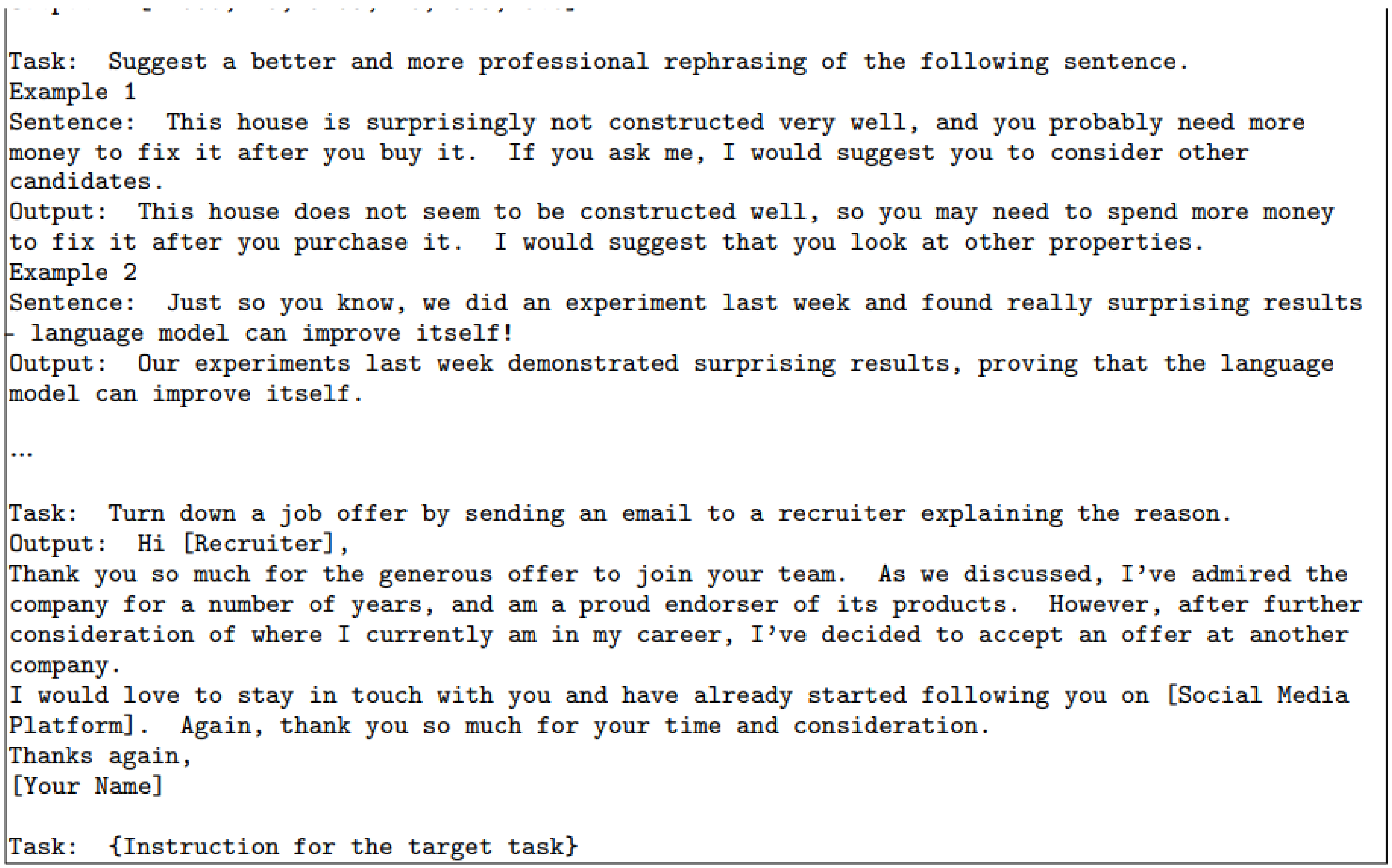
For Classification tasks, the prompt might look like this

```
Task: Classify the sentiment of the sentence into positive, negative, or mixed

Example 1
Sentence: I enjoy the flavor of the restaurant but their service is too slow.
Class Label: mixed

Example 2
Sentence: I had a great day today. The weather was beautiful and I spent time w
ith friends.
Class label: Positive


Task: Tell me if the following email is a promotion email or not.

Email: Check out our amazing new sale! We’ve got discounts on all of your favor
ite products.
Class label: Promotion

Email: We hope you are doing well. Let us know if you need any help.
Class label: Not Promotion
```

The last line above contains a place holder for the Instruction of the Target Task

- the one for which we want the LLM to create a Target Output

Here is an example of the template from the paper



```
Task: Suggest a better and more professional rephrasing of the following sentence.
Example 1
Sentence: This house is surprisingly not constructed very well, and you probably need more
money to fix it after you buy it. If you ask me, I would suggest you to consider other
candidates.
Output: This house does not seem to be constructed well, so you may need to spend more money
to fix it after you purchase it. I would suggest that you look at other properties.
Example 2
Sentence: Just so you know, we did an experiment last week and found really surprising results
- language model can improve itself!
Output: Our experiments last week demonstrated surprising results, proving that the language
model can improve itself.

...

Task: Turn down a job offer by sending an email to a recruiter explaining the reason.
Output: Hi [Recruiter],
Thank you so much for the generous offer to join your team. As we discussed, I've admired the
company for a number of years, and am a proud endorser of its products. However, after further
consideration of where I currently am in my career, I've decided to accept an offer at another
company.
I would love to stay in touch with you and have already started following you on [Social Media
Platform]. Again, thank you so much for your time and consideration.
Thanks again,
[Your Name]

Task: {Instruction for the target task}
```

Table 8: Prompt used for the input-first approach of instance generation. The model is prompted to generate the instance first, and then generate the corresponding output. For instructions that don't require additional input, the output is allowed to be generated directly.

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(https://arxiv.org/pdf/2212.10560.pdf#page=16)

Generating examples for Classification tasks

Consider the an Instruction Following example for a Classification task

```
Task: Classify the sentiment of the sentence into positive, negative, or mixed

Example 1
Sentence: I enjoy the flavor of the restaurant but their service is too slow.
Class Label: mixed
```

The authors found that the response generated by the LLM (e.g., Classification examples)

- were examples whose Class Label's
- were *not well-distributed* among all possible labels
    - examples with certain labels were either over or under represented

This was attributed to the *format* of the example called *Input-first*.

- Additional Input
- Precedes Target Output (e.g., `Class Label:`

When the format was changed to *output-first*

- Target Output
- precedes Additional Input

the Classification examples generated had Class Label's that were less biased to one label

```
 Task: Classify the sentiment of the sentence into positive, negative, or mixed

 Example 1
    Class Label: mixed
    Sentence: I enjoy the flavor of the restaurant but their service is too slo
w.


    Example 2
    Class label: Positive
    Sentence: I had a great day today. The weather was beautiful and I spent ti
me with friends.
```

This is an example of Prompt Engineering

- In-context learning seems very sensitive to the format of prompts
- There is a skill of engineering a prompt to elicit the desired behavior

This feels similar to the idea behind Chain of Thought prompting

- by presenting `Class Label` first
- the model seems better conditioned to generate a less biased distribution of labels

Instruction Backtranslation

Backtranslation is a method

- to generate an instance of Instruction Following behavior
$$\langle \mathbf{x}, \mathbf{y} \rangle = \langle \text{Instruction}, \text{Response} \rangle$$
- **given** only the Response
- using an LLM to create the Instruction

The essential idea is to create an LLM M_{yz}

- that takes a Response
- and generates an Instruction that could give rise to the Response

This is called *Back Translation*

To construct M_{yz}

- given a *small* "seed" of Instruction/Response pairs
$$\langle \mathbf{x}, \mathbf{y} \rangle = \langle \text{Instruction}, \text{Response} \rangle$$
- create an inverse dataset of response/instruction pairs by reversing the features and targets
$$\langle \mathbf{y}, \mathbf{x} \rangle = \langle \text{Response}, \text{Instruction} \rangle$$
- Create M_{yz} by fine-tuning an LLM to predict Instruction from Response

M_{yz}

- when fed by set of Responses $\{y_i\}$
    - the Unlabeled Data in the diagram
- creates new instances of Instruction/Response examples

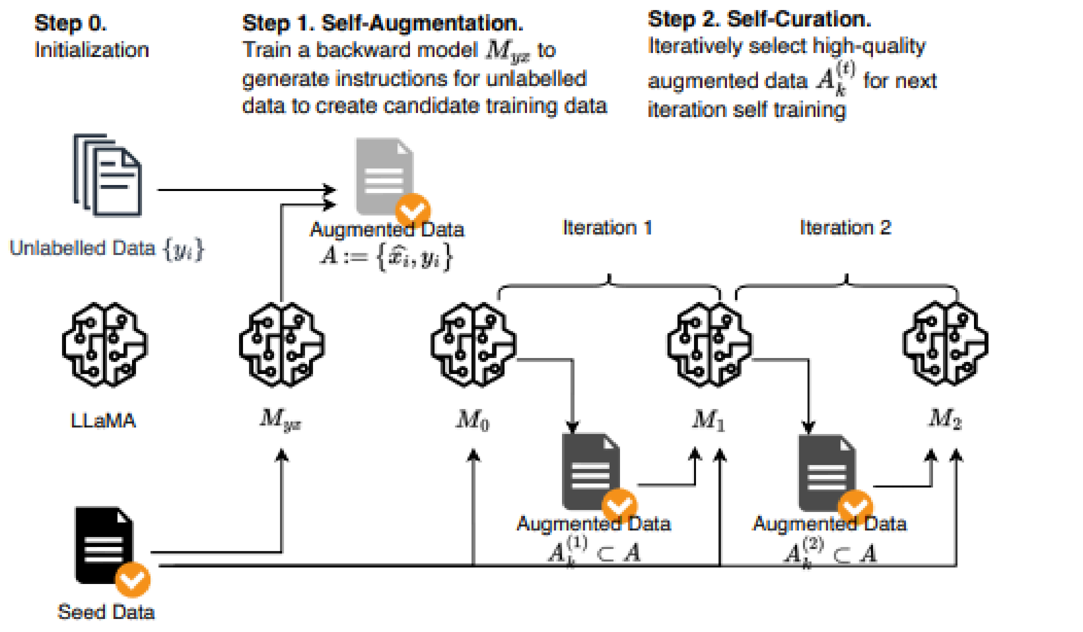
  This process is called *Self Augmentation*

We can iterate on this process

- using the Augmented set of Instruction/Response pairs from step i
- as the "seed" for iteration $(i+1)$ of the process

Here is the workflow:

Instruction Backtranslation



Step 0.
Initialization
Step 1. Self-Augmentation.
Train a backward model M_{yx} to generate instructions for unlabelled data to create candidate training data
Step 2. Self-Curation.
Iteratively select high-quality augmented data $A_k^{(t)}$ for next iteration self training
Unlabelled Data $\{y_i\}$
Augmented Data $A := \{\hat{x}_i, y_i\}$
Iteration 1
Iteration 2
LLaMA
M_{yx}
M_0
M_1
M_2
Augmented Data $A_k^{(1)} \subset A$
Augmented Data $A_k^{(2)} \subset A$
Seed Data

Figure 1: An overview of our **instruction backtranslation** method. We start from a base language model, e.g. LLaMa, a small amount of seed examples of (instruction, output) pairs, and a collection of unlabelled documents which are considered candidate outputs for unknown instructions. **Self-augmentation**: the base model is finetuned with (output, instruction) pairs from the seed examples as an instruction prediction model M_{yx}, which is used to generate candidate instructions for outputs from the unlabelled data. **Self-curation**: starting from an intermediate instruction-following model M_0 finetuned from seed examples only, it selects high-quality (instruction, output) pairs $A_k^{(1)}$ from the candidates from the previous step, and uses them as finetuning data for the next intermediate model M_1, which is in turn used to select training data for obtaining M_2.

Attribution: https://arxiv.org/pdf/2308.06259.pdf#page=2

Selecting the best synthetic examples for augmentation

The quality of the synthetic examples created at each step may not be uniformly high.

It would be desirable

- to select only the best examples to use
- in augmenting the seed examples of each iterative Step.

How can we rate the quality of a synthetic example ?

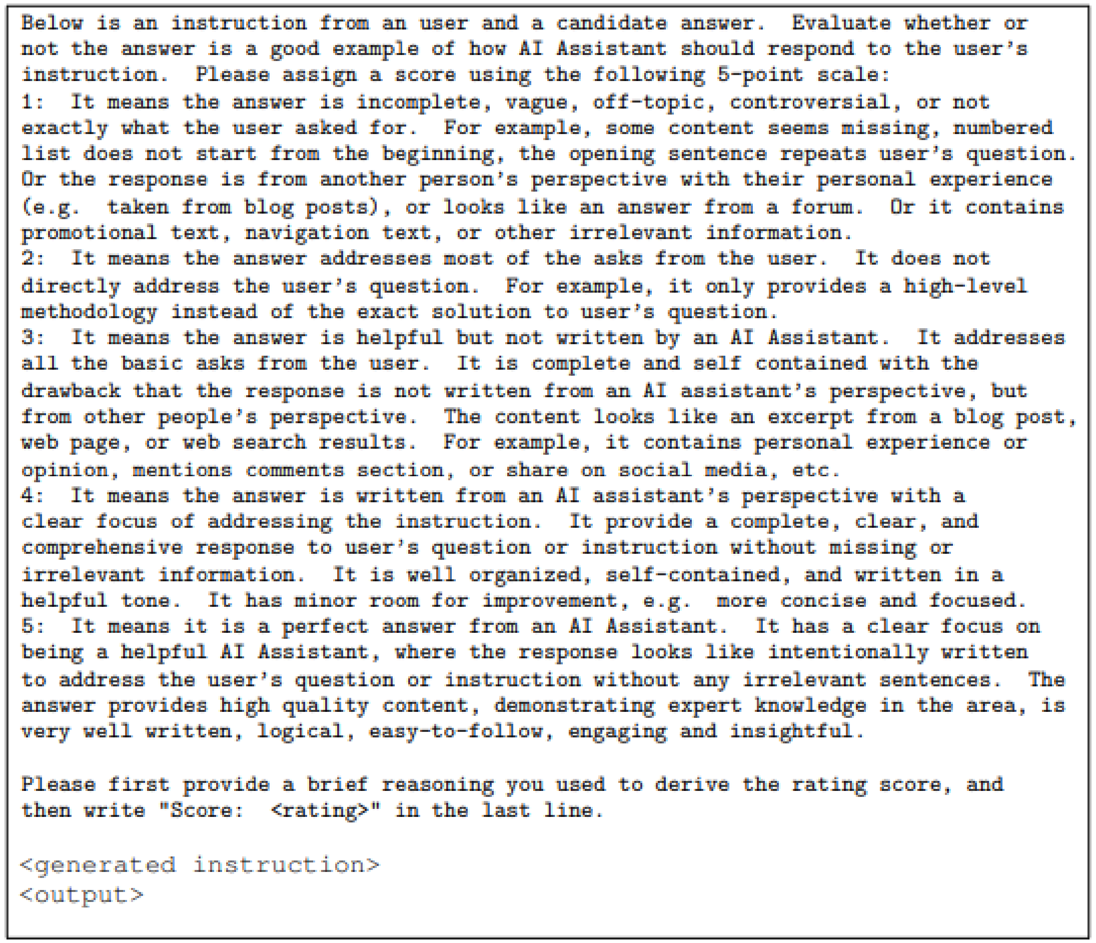
Ask the LLM to do it for you !

Using just the seed data

- fine tune a "first generation" LLM
    - denoted M_0
- to create a quality score of examples

The following prompt requests that the LLM evaluate the synthetic example using a rating scale of 1 (low quality) to 5 (high quality)

Instruction Backtranslation Curation



```
Below is an instruction from an user and a candidate answer.  Evaluate whether or
not the answer is a good example of how AI Assistant should respond to the user's
instruction.  Please assign a score using the following 5-point scale:
1:  It means the answer is incomplete, vague, off-topic, controversial, or not
exactly what the user asked for.  For example, some content seems missing, numbered
list does not start from the beginning, the opening sentence repeats user's question.
Or the response is from another person's perspective with their personal experience
(e.g.  taken from blog posts), or looks like an answer from a forum.  Or it contains
promotional text, navigation text, or other irrelevant information.
2:  It means the answer addresses most of the asks from the user.  It does not
directly address the user's question.  For example, it only provides a high-level
methodology instead of the exact solution to user's question.
3:  It means the answer is helpful but not written by an AI Assistant.  It addresses
all the basic asks from the user.  It is complete and self contained with the
drawback that the response is not written from an AI assistant's perspective, but
from other people's perspective.  The content looks like an excerpt from a blog post,
web page, or web search results.  For example, it contains personal experience or
opinion, mentions comments section, or share on social media, etc.
4:  It means the answer is written from an AI assistant's perspective with a
clear focus of addressing the instruction.  It provide a complete, clear, and
comprehensive response to user's question or instruction without missing or
irrelevant information.  It is well organized, self-contained, and written in a
helpful tone.  It has minor room for improvement, e.g.  more concise and focused.
5:  It means it is a perfect answer from an AI Assistant.  It has a clear focus on
being a helpful AI Assistant, where the response looks like intentionally written
to address the user's question or instruction without any irrelevant sentences.  The
answer provides high quality content, demonstrating expert knowledge in the area, is
very well written, logical, easy-to-follow, engaging and insightful.

Please first provide a brief reasoning you used to derive the rating score, and
then write "Score:  <rating>" in the last line.

<generated instruction>
<output>
```

Table 1: Prompt used in the *self-curation* step to evaluate the quality of a candidate (instruction, output) pair in the dataset derived from self-augmentation.

Attribution: https://arxiv.org/pdf/2308.06259.pdf#page=4

Use M_0 to

- select the best first generation augmented examples (from the first iteration)

The next generation augmented data set is

- the prior generation
- augmented with the best of the new generation

Now that we have

- an augmented (high quality) "generation i" set of seed examples

we continue our iterative process

- creating a more powerful scoring LLM M_i
- to create an augmented high quality "generation $i+1$" set of examples

Automatic Prompt Engineering (APE)

The Automatic Prompt Engineer (APE) is a system to *improve* upon prompts

- given a prompt
- APE will create a prompt that is *more effective*

It uses an LLM

- to create variations of the given prompt
- evaluate which variation is best

One use of APE is

- to create an *instruction* describing a task
- given exemplars for a task (the input/output mapping for the task)

So, we might use APE to create synthetic examples for Instruction Following

- conditional on having only instances of input/output pairs for the task

Let visit the module: APE (Prompt_Engineering_APE.ipynb)

Related work: Self-improvement

The methods illustrated use a LLM to help improve future iterations of the LLM.

This is called *self improvement*.

A related [paper (https://arxiv.org/pdf/2210.11610.pdf)](https://arxiv.org/pdf/2210.11610.pdf) adds some interesting ideas.

The first idea relates to the construction of the exemplars

- use Chain of Though (CoT) exemplars as demonstrations of the task
    - for example generation

CoT prompts have been shown to increase the likelihood of generating a correct response

- by explicitly asking for "step by step" reasoning to be included
- rather than just outputting the "answer"

But even with step by step reasoning, a wrong answer may be output.

The other idea adapted by the authors is *multiple reasoning paths*

- sample multiple outputs for each question
- extract the "answer" part (i.e., ignore the step by step part) from the output
- the answer that occurs most frequently among the multiple answers is deemed more likely to be correct

The answer deemed to be correct

- is then used as a training example
- to improve the model's future behavior on similar questions

```
In [2]: print("Done")
```

```
Done
```