# F-ART: Fragmented ART for Long Document Summarization

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## Abstract

Recent developments in natural language processing have enabled large language models (LLMs) to quickly adapt to new tasks using natural language instructions and a few demonstrations as a prompt. This study investigates how the ART framework can be used to create and teach LLMs to use tools for long document summarization by consuming fragments of long documents in steps. We simplify the ART framework, focusing on constructing few-shot prompts for long document summarization that learns information onto external tools. We develop read/write tools to provide the model a form of long-term memory without retraining model weights. We evaluate our method on the arXiv abstractive summarization dataset and experiment with two variations of the original prompt, "compressed intermediates" and "rolling summary." Results show clear improvement over the base prompt for the two modifications. This study demonstrates the potential of using external tools and a fragmented processing strategy to enhance LLM capabilities in long document summarization tasks without fine-tuning.

## 1 Introduction

Recent developments in natural language processing have shown that in-context learning allows large language models (LLMs) to quickly adapt to new tasks by using natural language instructions and a few demonstrations as a prompt. Specifically, this investigation examines how, by using the ART framework [1], we can create and teach the LLM to use tools for long document summarization.

In the ART paper, they generate automatic multi-step decompositions for new tasks by selecting decompositions of related tasks in the task library, and then select and use tools in the tool library alongside LLM generation. We simplify the framework and only focus on constructing few-shot prompts for long document summarization that learn information onto external tools. We leverage ART's program grammar, but create new tools specially designed for summarization of large documents split into chunks of text.

## 2 Background

LLMs have shown incredible performance in several tasks, but have shown limited performance in others, for example, when solving arithmetic reasoning tasks [2]. The idea of adding external tools

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to LLMs to be able to overcome these limitations has been explored recently [3] but has required large amounts of human supervision. Another line of work uses self-supervision to teach LLMs to use tools. For example, Toolformer [4], different from ART, was fine-tuned to learn how to use tools, as opposed to relying on in-context learning. The advantage of our approach (and ART in general) is that you can switch LLMs without need of fine-tuning.

Other work proposes prompting LLMs with intermediate reasoning steps. Chain-of-Thought (CoT) prompting [5] persuades LLMs to generate intermediate reasoning steps before the final answer. Whilst the above prompts were hand-crafted, it has been shown that LLMs can generate CoT-style multi-step reasoning in a zero-shot manner, when prompted with the prefix "Let's think step by step" [6].

Finally, state-of-the-art approaches for long document summarization include the following: Top Down Transformer (Long Document Summarization with Top-down and Bottom-up Inference) [7]; LongT5: Efficient Text-to-Text Transformer for Long Sequences [8]; and Pegasus X: Investigating Efficiently Extending Transformers for Long Document Summarization [9]. However, unlike from our approach, all of these methods require extensive compute and large amount of human supervision to fine-tune the Transformer models for summarization.

## 3 Methodology

Our goal was to create a modified ART framework that allows for an LLM to read from, write to, and organize a form of long-term memory, without actually retraining model weights. This would allow for the model to dynamically access previously stored information, as well as update its local repository with valuable data as it reads through prompts. Given the finite context window of any LLM, ensuring that only relevant data is retrieved would be a crucial requirement of this system. With these goals and constraints in mind, we chose a Python dictionary as the underlying data structure for persisting information. A dictionary organizes data into key-value pairs, which would naturally allow for organization and efficient retrieval based on the LLM selecting only relevant keys. The LLM would load the information stored at keys it finds relevant to its current task, and organize the information it stores by choosing an appropriate key.

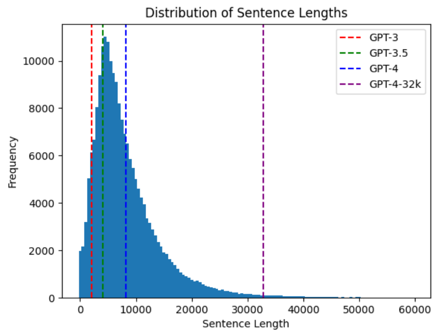
In the context of ART, this translates into the creation of three tools to accomplish our envisioned task. Firstly, we define `[list-keys]`, a tool that takes no inputs and returns a string containing all the keys in the dictionary. Next we define `[write]`, this tool requires a key-value pair and writes the pair into the dictionary, updating the value stored under the key if it is already present. Finally, we define `[read]`, a tool that takes a key as input and returns the information stored at that key in the dictionary. Currently the tools save the dictionary to, and read it from, storage to ensure the long term stability of the data.

## 4 Experiments

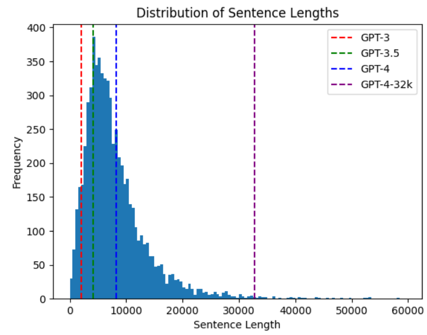
To effectively judge the usefulness of our method, we chose to evaluate on the abstractive summarization task. Unlike extractive summarization, in this task the summary is expected to be a concise representation that effectively communicates the key ideas in the text, rather than a composition of important phrases in the text. This is more like how humans generally summarize texts, and provides a stronger challenge for our method. We evaluated our method on the arXiv abstractive summarization dataset [10]. Texts in this dataset can be more than 300k tokens in length (see statistics in Figure 1), which provides a good setting to test how well our method allows a model to use information from across long input.

To this end, we designed three tools for the model to use: `[read]`, `[write]`, and `[list-keys]`; along with a prompt that explains the task and demonstrates how to use these tools to accomplish the goal of a good summary. The `[read]` and `[write]` tools each accept a short text key, and the text associated with the key is stored in a Python dict. This data is specific to each article, and is built by the model as it receives each chunk. The prompt specifically instructs the model to store information under meaningfully-named keys using `[write]`, and then to `[read]` all stored information during the last chunk in order to produce the final output.[1]

[1]See Appendix A for the text of the prompts used in this project.




(a) Sentence lengths in the train set. The sentence lengths have mean 8,630.2, median 6,883.0, minimum 0, and maximum 329,071 (not visible).




(b) Sentence lengths in the validation set. The sentence lengths have mean 8,208.3, median 6,871.5, minimum 244, and maximum 109,442 (not visible).

Figure 1: Distribution of sentence lengths (number of tokens) in the train and validation sets. For reference, the maximum context sizes for various GPT models are marked as vertical lines. Our method makes it feasible to summarize long documents without access to GPT-4 or GPT-4-32k.

Each article is split into chunks of 15 sentences each. We would have preferred to make sure chunks did not cross section dividers, but this was not possible due to the preprocessing in the dataset.

### 4.1 Prompt Variations

We experimented with two variations on the original prompt, both of which ended up improving the performance. One we call "compressed intermediates", and the other we name "rolling summary".

For "compressed intermediates", we modify the examples to show the model storing text that looks more like compressed notes than a complete summary. This reduces the number of tokens in the prompt as well as in model generations, which decreases the chance that the final summarization will be too large for the model to summarize from. In this experiment we also increased the length of the keys used for `[read]` and `[write]`; e.g. "regular-chaotic-motions" became "regular-chaotic-motions-smooth-curves". This seems to reduce the frequency of key collisions when text discussing a single phenomenon is split across multiple chunks.

The prompt for "rolling summary" replaces the key names ("regular-chaotic-motions", etc.) with "current-summary", and the stored summaries summarize both the current chunk and all previous chunks. The final example shows the model reading just the single key "current-summary" and combining it with the input chunk to produce the answer. Verbiage in the explanations is also slightly adapted to match these differences.

## 5 Results

We report metrics from the ROUGE family [11, 12] for the three approaches on `n=10` samples from the validation set.

| Method | ROUGE | ROUGE-2 | ROUGE-L | ROUGE-L-Sum |
|---|---|---|---|---|
| base | 11.7 | 4.0 | 6.1 | 8.2 |
| compressed | 29.4 | 9.7 | 15.1 | 23.1 |
| rolling | 34.2 | 8.8 | 18.7 | 27.3 |

Table 1: Experimental results for each of the prompts described in Section 4 on 10 samples from the arXiv summarization dataset, evaluated on several ROUGE-based metrics.

We observe clear improvement over the base prompt for the two modifications. While the sample size for this experiment was small,[2] we think the difference is significant because they make it possible for more stored information to be `[read]` when generating the final summary.

## 6 Conclusion

In this project we have designed and implemented tools to be used by an LLM to organize and store relevant data for long-term/future use. We encountered difficulties in providing enough context for the LLM to properly use the tools, but found some success by shortening the stored text and the prompt. Future research avenues could involve using newer, bigger, LLMs that have larger context windows allowing for more varied tool use samples to be passed as part of the prompt. Otherwise, it may be desirable to fine tune smaller models specifically to use tools and address long standing issues with LLM capabilities. We'd also like to apply this methodology to make it possible for a frozen LLM to "learn" useful information to an external database, allowing the model to perform continual learning in the same way that it "learned" information as it processed each chunk of the articles in our experiment. Creating systems capable of learning to use tools will be an invaluable step in the path to robust models that learn across their deployment lifecycle.

## References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## A Prompts

Here is the complete base prompt we used for our experiments. Unlike Paranjape et al. [1], we do not experiment with dynamically varying the prompt in any way.

[2] The cost of this experiment with `n=10` was US$16, so we would like more funds in order to validate that these changes improve performance.

```
You are tasked with summarizing a long document that does
   not fit in the context window. We will show you chunks
   of the text to summarize one at a time, resetting your
   context window each time. Fortunately, you have access
   to three tools: [read], [write], and [list-keys], which
   you can use to read and write information to an external
   location that is accessible as you process later chunks.
   Here are a few examples of how you might use these tools
   when dealing with a chunk:

----BEGIN EXAMPLE----
Input: (1/4) first , the curve is significantly smoother as
   a function of @xmath0 for larger @xmath44 . even more
   relevant is the fact that the single trajectory data (
   @xmath45 ) may show current reversals that do not exist
   in the large @xmath44 data <SHORTENED FOR BREVITY> ( , )
   for example .  notice also that in fig .  (  ) , at
   @xmath55 and @xmath56 , the deviations between the
   different ensembles is particularly pronounced .
Q1: [write] (regular-chaotic-motions) The behavior of a
   system with regular and chaotic motions is a function of
   the number of trajectories and the location of the
   initial ensemble. The curves are smoother for larger
   numbers of trajectories, and single-trajectory data may
   show current reversals that do not exist in the large
   data set. The net drift of an ensemble can be closer to
   the behavior of an individual trajectory, and there is a
   dependence of the current on the location of the initial
   ensemble. The width of the ensemble also affects the
   details of the current and can cause illusory current
   reversals.
#1:
Q2: [EOQ]
----END EXAMPLE----

In the example above, you write a short summary of the chunk
   to memory using [write]. This information will be
   accessible later, as you can see when we process the
   next chunk below:

----BEGIN EXAMPLE----
Input: (2/4) these points are close to bifurcation points
   where some sort of symmetry breaking is clearly occuring
   , which underlines our emphasis on the relevance of
   specifying ensemble characteristics in the neighborhood
   of unstable behavior . <SHORTENED FOR BREVITY> however ,
   there is only one instance of current - reversal , at
   @xmath65 .  note , however , that the current is not
   without structure  it changes fairly dramatically as a
   function of parameter .
Q1: [read] regular-chaotic-motions
#1: The behavior of a system with regular and chaotic
   motions is a function of the number of trajectories and
   the location of the initial ensemble. The curves are
   smoother for larger numbers of trajectories, and
   single-trajectory data may show current reversals that
   do not exist in the large data set. The net drift of an
   ensemble can be closer to the behavior of an individual
   trajectory, and there is a dependence of the current on
```

```
   the location of the initial ensemble. The width of the
   ensemble also affects the details of the current and can
   cause illusory current reversals.
Q2: [write] (ensemble-effects) In the classical phase space
   for Hamiltonian or underdamped motion, dynamics depend
   on the initial conditions. However, when damping is
   introduced, the phase space consists of attractors, and
   the current is less likely to depend significantly on
   initial conditions. In the chaotic regime of a
   non-Hamiltonian system, the initial ensemble needs to be
   larger than a certain threshold for convergence, while
   in the regular regime, a single trajectory suffices as
   long as transients are discarded. We propose a modified
   definition of current that includes an empirically
   obtained cut-off to ensure convergence. We compare
   bifurcation diagrams with the current in a series of
   figures, noting that there is a single current reversal
   in the examined parameter range despite several
   bifurcations. The current changes dramatically as a
   function of the parameter, but only one instance of
   current reversal occurs.
#2:
Q3: [EOQ]
----END EXAMPLE----

See how in the example above you read an existing summary,
   and used that information to help summarize the current
   chunk. You don't always have to read from storage; maybe
   you're summarizing the first chunk (1/n), or you don't
   need contextual info to summarize this chunk well. Now
   Im going to show you how to use the `list-keys` tool:

----BEGIN EXAMPLE----
Input: (3/4) the ensemble results on the other hand , even
   when converged , show statistical roughness .   ( b )
   the ensemble results are consistent with barbi and
   salerno in general , although disagreeing in several
   details . <SHORTENED FOR BREVITY> note in particular in
   this figure that eyeball tests can be misleading .
Q1: [list-keys]
#1: regular-chaotic-motions, ensemble-effects
Q2: [read] ensemble-effects
#2: In the classical phase space for Hamiltonian <SHORTENED
   FOR BREVITY> current reversal occurs.
Q3: [write] (bifurcations-and-reversals) The passage
   describes a study on the relationship between
   bifurcations and current reversals in a system. The
   authors used ensembles of particles to examine how their
   results converged as a function of various parameters.
   They found that not all bifurcations led to current
   reversals, but did not rule out the possibility that all
   current reversals are associated with bifurcations,
   which is Mateos' conjecture. The study differed from a
   previous one by Barbi and Salerno, who used
   single-trajectory results instead of ensembles of
   particles. The article concludes that the ensemble
   current provides significant information that cannot be
   obtained from a single-trajectory current.
Q3: [EOQ]
```

```
----END EXAMPLE----

In this final example, we show how you will output the final
   summary using [ans]:

----BEGIN EXAMPLE----
Input: (4/4) we see reversals without bifurcations in ( a )
   whereas the zoomed version ( c ) shows that there are
   windows of periodic and chaotic regimes . <SHORTENED FOR
   BREVITY> each of the transitions from periodic behavior
   to chaos and back provides opportunities for the current
   to spike .
Q1: [list-keys]
#1: regular-chaotic-motions, ensemble-effects,
   bifurcations-and-reversals
Q2: [read] regular-chaotic-motions
#2: The behavior of a system <SHORTENED FOR BREVITY> current
   reversals.
Q3: [read] ensemble-effects
#3: In the classical phase space for Hamiltonian <SHORTENED
   FOR BREVITY> current reversal occurs.
Q4: [read] bifurcations-and-reversals
#4: The passage describes a study on the relationship
   between bifurcations <SHORTENED FOR BREVITY> from a
   single-trajectory current.
Q5: [ans] This work delves into the relationship between
   bifurcations and current reversals in a driven, damped,
   and chaotic system, emphasizing the significance of
   considering ensembles of trajectories and their
   convergence properties when examining the current's
   behavior. It is discovered that not all bifurcations
   result in current reversals, and not all current
   reversals are linked to bifurcations. Nonetheless, a
   generalization of Mateos' conjecture is proposed, which
   suggests that bifurcations correspond to sudden current
   changes (spikes or jumps). This improved understanding
   aids in characterizing changes in the current's behavior
   as a function of parameter and is useful in identifying
   "hidden" bifurcations, providing a more comprehensive
   perspective on the system's dynamics.
----END EXAMPLE----
Remember, you are summarizing a long document that does not
   fit in the context window, and we will only show you one
   chunk of the text now. {instructions} Here you go:

Input: ({i}/{n}) {text}
Q1:
```

Here, `{text}` is replaced with the text of the chunk, and `{i}` and `{n}` are replaced with the position of the current text in the chunks from the text. `{instructions}` is set with specific instructions for tool use for the first and last chunks; see the code repository for details.

### A.1 compressed intermediates prompt

The change to the first example in the prompt is illustrative of the change effected in the intermediate notes produced with this version of the prompt:

```
* behavior is a function of the number of trajectories and
   the location of the initial ensemble * curves are
   smoother for larger numbers of trajectories *
```

```
single-trajectory data may show current reversals not in
the large data set * net drift of an ensemble can be
closer to behavior of individual trajectory * current
depends on location of the initial ensemble
```

Again, see the repository for details.