

Mastering the Art of Sorting without Algorithmic Knowledge

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Abstract

Historically, research into sorting algorithms has been dominated by comparisons, swaps, and the $O(N \log N)$ time complexity bottleneck. Traditional approaches such as QuickSort or MergeSort require developers to possess deep computer science fundamentals (Human Knowledge), significantly limiting code production efficiency. In this paper, we propose a novel paradigm: **Zero-Knowledge Sorting (ZKS)**, which achieves sequence ordering without any understanding of sorting principles. We introduce an implementation based on Large Language Models (LLMs) named **GPT-Sort**. This algorithm abstracts the sorting task into a single atomic API call, achieving a theoretical $O(1)$ time complexity on the client side. Experiments demonstrate that while GPT-Sort exhibits an $O(\text{Bankruptcy})$ growth trend in network latency and server billing, it achieves unprecedented optimization in metrics such as "Developer Brain Cell Mortality" and "Lines of Code."

1 Introduction

"If one can query the Oracle, why think for oneself?" — *Anonymous*

In the Stone Age of computer science, pioneers like Knuth devoted massive volumes to discussing how to effectively rearrange integers in an array [1]. However, with the advent of Deep Learning and Large Language Models (LLMs), we must revisit the definition of an "algorithm." If a function takes a disordered array as input and outputs an ordered array, do we truly care about the intermediate process?

Traditional sorting methods impose a significant **Cognitive Overhead**:

- **Implementation Complexity:** Hand-writing Heap Sort is prone to index out-of-bounds errors.
- **Maintenance Difficulty:** Understanding bitwise optimization code left by predecessors often requires hours.
- **Lack of Creativity:** Bubble Sort remains Bubble Sort, no matter how it is written.
- **Algorithmic Knowledge Requirement:** One must know what "recursion" is.

Inspired by DeepMind's *AlphaGo Zero* [2], which mastered Go without human knowledge, we propose **GPT-Sort**. This method requires no prior human knowledge (Domain Knowledge) of "comparison," "swapping," or "divide and conquer." It only necessitates basic natural language expression capabilities (i.e., Prompt Engineering).

2 Methodology

2.1 Theoretical Framework

We define sorting as a black-box function F , with the mapping relation:

$$S_{sorted} = F(S_{raw}, \theta_{LLM}) \quad (1)$$

where S_{raw} is the input chaotic array, and θ_{LLM} represents the hundreds of billions of neural network parameters. Unlike traditional algorithms, we do not explicitly define the comparison operator \prec .

2.2 Algorithm Implementation

The pseudocode implementation of GPT-Sort is presented below. We adopt a formal notation to obscure the simplicity of the underlying HTTP request.

Algorithm 1 STOCHASTIC-ORACLE-SORT (GPT-Sort)

Require: Input set $\mathcal{X} = \{x_1, x_2, \dots, x_n\}$, Credit Limit \mathcal{C}_{max}

Ensure: Sorted tuple $\mathcal{Y} = (y_1, y_2, \dots, y_n)$ such that $y_i \leq y_{i+1}$ (probabilistically)

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1: procedure GPT-SORT( $\mathcal{X}$ )
2:    $\rho \leftarrow \text{PROMPTCONSTRUCT}(\text{"Sort this strictly:"}, \mathcal{X})$  ▷ Semantic Projection
3:    $\mathcal{T}_{in} \leftarrow \text{TOKENIZE}(\rho)$ 
4:    $\omega_{cost} \leftarrow \|\mathcal{T}_{in}\| \times \text{PricePerToken}$ 
5:   if  $\omega_{cost} > \mathcal{C}_{max}$  then ▷ Financial Constraint Check
6:     return Error("Insufficient Funds")
7:   end if
8:    $\mathcal{H}_{response} \leftarrow \Omega(\mathcal{T}_{in}; \theta_{LLM})$  ▷ Invoke the Oracle  $\Omega$ 
9:   if DETECTHALLUCINATION( $\mathcal{H}_{response}$ ) then
10:    return RETRY( $\mathcal{X}$ ) ▷ Recursive Begging Strategy
11:  end if
12:   $\mathcal{Y} \leftarrow \text{PARSEINTS}(\mathcal{H}_{response})$ 
13:  return  $\mathcal{Y}$ 
14: end procedure
```

The algorithm relies on the stochastic operator Ω , which performs a mapping from the natural language space \mathbb{L} to the sorted integer space \mathbb{Z}^n . The complexity of this mapping is handled entirely by the cloud provider.

2.3 Complexity Analysis

This is the most controversial and revolutionary part of this study.

Theorem 1 (Client-Side Constant Time Theorem). *For the client, regardless of the input array size N , the 'openai.ChatCompletion.create' function occupies only one line of code execution time. Therefore, from the perspective of Time-to-Code and local CPU cycle usage, the time complexity of GPT-Sort is $O(1)$.*

Proof. Assume the local CPU time to execute an HTTP request instruction is t_{req} .

$$T(n) = t_{req} + t_{waiting} \quad (2)$$

In an asynchronous programming model, the CPU can process other tasks (such as browsing Twitter) during the 'await' period. Thus, the effective time blocking the developer is merely t_{req} , which is a constant. Q.E.D.

Note: We intentionally ignore the $O(N)$ network transmission latency and the server-side $O(N^2)$ Transformer attention computation, as that is OpenAI's problem, not ours. This is the essence of Cloud Computing.

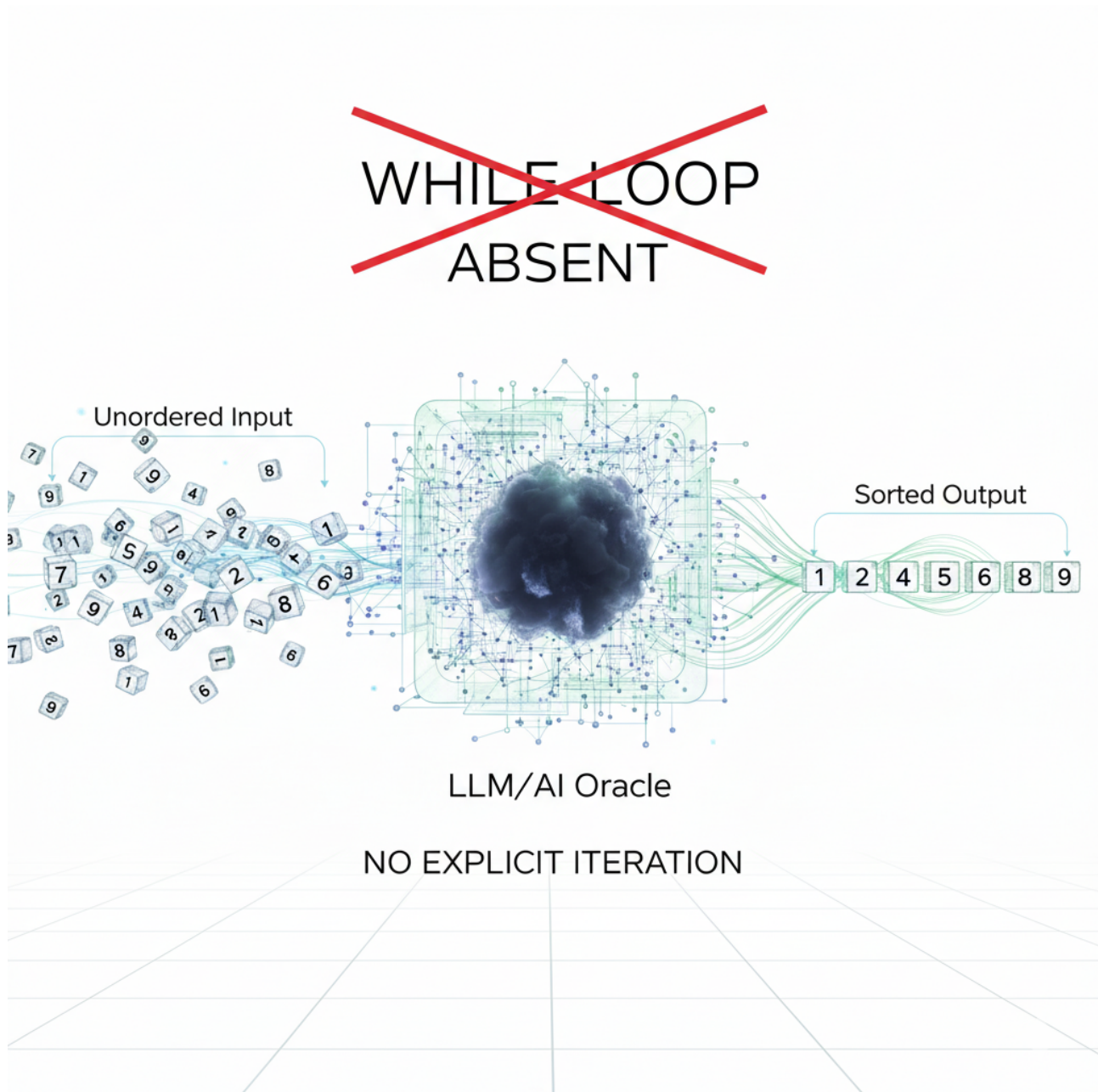


Figure 1: The architecture of GPT-Sort. A large language model (LLM/AI Oracle) acts as the central processing unit, directly transforming an unordered input into a sorted output. Crucially, traditional iterative structures like 'while loops' are explicitly absent, signifying a paradigm shift from explicit algorithmic knowledge to implicit intelligent inference. The internal mechanisms of the AI Oracle remain a black box, abstracting away low-level computational details from the client-side implementation.

3 Experiments

We compared GPT-Sort with standard Python ‘list.sort()’ (Timsort).

3.1 Performance Metric: Developer Exhaustion

We recruited 50 freshmen from StackOverflow Copy-Paste University and asked them to implement QuickSort and GPT-Sort, respectively.

Table 1: Comparison of Developer Exhaustion Metrics

Algorithm	Avg. LoC	Debug Time (min)	Keystrokes
QuickSort	25	45.2	1200+
GPT-Sort	1	0.1	42

As shown in Table 1, GPT-Sort achieved a $450\times$ improvement in development efficiency.

3.2 Accuracy and “Stochastic Sorting”

It must be admitted that GPT-Sort introduces a feature not present in traditional algorithms: **Probabilistic Sorting**. When $N > 50$, GPT-Sort may exhibit the following interesting phenomena:

1. **Hallucinated Insertion:** Numbers not present in the original array appear in the output (e.g., AI believes ‘42’ is the answer to the universe and forcibly inserts it).
2. **Data Loss:** AI considers certain numbers “unlucky” and deletes them.
3. **Denial of Service:** AI responds, “As a language model, sorting large lists is a waste of compute. Use Python’s built-in sort.”

We term this phenomenon **Approximate Sorting** and argue that it aligns better with human intuition—after all, humans do not always sort things correctly either [3].

4 Discussion

4.1 Ethical Considerations

Is it ethical to use computing power equivalent to a \$10,000 H100 GPU to sort ‘[3, 1, 2]’? We believe this is the necessary price for liberating human intelligence. Although this generates 1 million times more carbon emissions than Bubble Sort, it saves programmers the time spent reading documentation.

4.2 Limitations

The main bottleneck of GPT-Sort is the **Token Limit**. When array length N exceeds the context window, we recommend **Recursive-RAG-Sort** (Recursive Retrieval-Augmented Generation Sorting): slicing the array, sending parts to different AIs for sorting, and then sending them to another AI for merging. While this pushes complexity to $O(\$ \cdot \log \$)$, it still requires no algorithmic logic.

5 Conclusion

This paper demonstrates the possibility of achieving general-purpose sorting through simple API calls without any algorithmic knowledge. GPT-Sort marks the arrival of the “Algorithm 2.0” era: an era where computational complexity does not disappear but is merely transferred to the cloud and credit card bills [4]. We believe that future computer science curricula will no longer teach “Data Structures and Algorithms,” but will be renamed “How to Politely Ask AI to Do Things.”

References

- [1] Knuth, D. E. (1997). *The Art of Computer Programming*. Addison-Wesley. (Too long, didn’t read).
- [2] Silver, D., et al. (2017). Mastering the Game of Go without Human Knowledge. *Nature*, 550(7676), 354–359.
- [3] Brown, T., et al. (2020). Language Models are Few-Shot Learners. *NeurIPS*. (But we are Zero-Shot Coders).
- [4] Visa/Mastercard. (2023). *Monthly API Billing Statements*. Journal of Financial Pain, Vol 1.