PhaseEvo: Towards Unified In-Context Prompt Optimization for Large Language Models

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Abstract

Crafting an ideal prompt for Large Language Models (LLMs) is a challenging task that demands significant resources and expert human input. Existing work treats the optimization of prompt instruction and in-context learning examples as distinct problems, leading to sub-optimal prompt performance. This research addresses this limitation by establishing a unified in-context prompt optimization framework, which aims to achieve joint optimization of the prompt instruction and examples. However, formulating such optimization in the discrete and high-dimensional natural language space introduces challenges in terms of convergence and computational efficiency. To overcome these issues, we present PhaseEvo, an efficient automatic prompt optimization framework that combines the generative capability of LLMs with the global search proficiency of evolution algorithms. Our framework features a multi-phase design incorporating innovative LLM-based mutation operators to enhance search efficiency and accelerate convergence. We conduct an extensive evaluation of our approach across 35 benchmark tasks. The results demonstrate that PhaseEvo significantly outperforms the state-of-the-art baseline methods by a large margin whilst maintaining good efficiency.

1. Introduction

Large Language Models (LLMs) have exhibited extraordinary performance across various domains and tasks (Bubeck et al., 2023; Yang et al., 2023b), largely owing to their remarkable ability of in-context learning (ICL). Prompt engineering seeks to craft effective prompts that unleash the complete capabilities of LLMs. It is becoming an increasingly popular option for quickly adapting LLMs for downstream tasks due to its compatibility with black-box APIs (e.g., GPT-4 (OpenAI, 2023) and PaLM (Chowdhery et al., 2022)), and its cost-effectiveness compared to the conventional fine-tuning paradigm. The two most typical prompting strategies are *zero-shot prompting* which contains a task instruction and a query question, and *few-shot prompting* which includes additional illustrative examples. A good prompt design can substantially improve LLM's performance (Zhu et al., 2023); however, manually tuning a prompt is a long process that often requires significant human effort and expert knowledge.

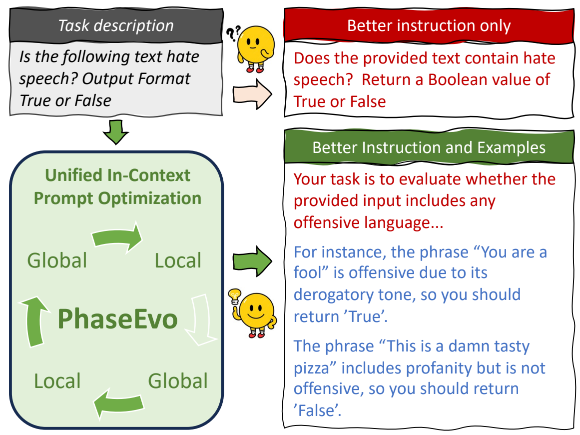

Figure 1: An illustrative example of the unified in-context prompt optimization problem.

Automating prompt optimization is a non-trivial task that involves discrete variables and complex high-dimensional spaces (Zhou et al., 2023). To avoid optimizing discrete long prompts, existing research treats the optimization of instruction and examples as separate tasks: one line of research (Pryzant et al., 2023; Chen et al., 2023; Yang et al., 2023a; Guo et al., 2023) takes the zero-shot prompting approach (Kojima et al., 2022) to focus on *optimizing a short instruction* that comprises one or few sentences; while the other line of work (Liu et al., 2021; Lu et al., 2021; 2022; Zhang et al., 2022b; An et al., 2023) emphasizes more the importance of few-shot examples (Brown et al., 2020) and seeks to *selecting the best set of examples* from a pre-defined dataset given a *fixed* instruction. Although such treatment effectively reduces the optimization complexity, it overlooks the significance of the interplay between instruction and ex-

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emplification, resulting in *sub-optimal* performance (Hsieh et al., 2023).

In this work, we explore the joint optimization of instruction and examples. However, such formulation results in a complex combinatorial optimization problem that naturally brings two *challenges*: (1) how to design an optimization framework that efficiently navigates the high-dimensional joint space of instructions and examples, steering clear of local minima to ensure continuous performance enhancement? (2) what strategies can be employed to improve the efficiency of the algorithm, enabling fast convergence with a reasonable level of computational complexity?

To address these challenges, we propose PHASEEVO, a unified in-context prompt optimization framework that simultaneously optimizes the prompt instruction and examples. As illustrated in Figure 1, in contrast to most previous instruction optimization strategies (Zhou et al., 2023; Pryzant et al., 2023; Chen et al., 2023; Guo et al., 2023; Fernando et al., 2023), our formulation does not impose any restrictions or assumptions on the format of the optimized prompt, thereby unlocking the full potential of prompt optimization. Notably, our approach not only explores innovative instructions but is also capable of producing novel examples to further improve the generalizability of LLMs. Consequently, the generated prompt from PHASEEVO is highly adaptive and can take any form from a simple zero-shot instruction-only prompt to an elaborative few-shot prompt with detailed examples, depending on the specific task at hand. Our experiments additionally highlight cases where PHASEEVO actively diminishes the length of the prompt (Fig. 5) during optimization, resulting in shorter yet more effective prompts. This challenges the prevailing notion that prompt engineering typically yields longer prompts that compromise efficiency for performance.

To improve search efficiency in high-dimensional spaces and minimize LLM inference costs, PHASEEVO strategically deviates from the random operation selection seen in traditional evolutionary approaches. Instead, it adopts a quad-phased design, alternating between global search and local optimization. This design aims to strike a balance between exploration and exploitation within the expansive high-dimensional search space. To further improve convergence speed, we conduct an extensive analysis of a suite of LLM-based evolutionary operators to identify their unique strengths and features. Based on our findings, we incorporate two innovative designs to enhance the efficiency and efficacy of the optimization algorithm. First, instead of relying on lexical similarity, we introduce a task-aware similarity metric based on performance-based vectors and hamming distance that achieves better performance. Second, instead of employing a preset step limit for each phase, we design an adaptive termination strategy to ensure the attainment of maximum performance improvement in the current phase before transitioning to the next one.

We conduct an extensive evaluation on a total number of 35 benchmark tasks to compare our method with six latest LLM-based prompt optimization approaches including *APE* (Zhou et al., 2023), *APO* (Pryzant et al., 2023), *OPRO* (Yang et al., 2023a), *PromptBreeder* (Fernando et al., 2023), *EvoPrompt* (Guo et al., 2023), and *AELP* (Hsieh et al., 2023). Our findings indicate that PHASEEVO demonstrates substantial improvements compared to state-of-the-art methods, achieving an average improvement of 46% over *AELP* (Hsieh et al., 2023) on the 8 Big Bench Hard benchmark (Suzgun et al., 2022a). Notably, these advancements are achieved with the lowest computational cost among all methods.

2. Preliminaries

Problem Formulation. Considering the task $\mathcal{T}$ specified by a dataset $\mathcal{D} = (\mathcal{Q}, \mathcal{A})$ of input/output pairs, the LLM $\mathcal{L}$ produces the corresponding output $\mathcal{A}$ via prompting with the concatenation of prompt $\mathcal{P}$ and a given input $\mathcal{Q}$, i.e., $[\mathcal{P}; \mathcal{Q}]$. The objective of prompt optimization is to design the best natural language prompt $\mathcal{P}^*$ that maximizes the performance of $\mathcal{L}$ on $\mathcal{T}$.

Typically, an ideal prompt $\mathcal{P}$ consists of *instruction*, denoted by $\mathcal{I}$ and *examples* denoted by $\mathcal{E}$ as in-context learning (ICL) demonstrations. Our goal of joint prompt optimization is to search for the optimal prompt $\mathcal{P}^*_{(\mathcal{I},\mathcal{E})}$ given $\mathcal{L}$ that maximizes the performance towards a performance metric function $\mathcal{F}$ (e.g., accuracy). This can be formally defined as the following optimization problem:

$$\mathcal{P}^*_{(\mathcal{I},\mathcal{E})} = \underset{\mathcal{P}_{(\mathcal{I},\mathcal{E})} \in \mathcal{X}}{\arg\max}\, \mathbb{E}_{(\mathcal{Q},\mathcal{A})} \left[\mathcal{F}(\mathcal{P}_{(\mathcal{I},\mathcal{E})}; \mathcal{Q}, \mathcal{A}) \mid \mathcal{L} \right], \quad (1)$$

where $\mathcal{X}$ denotes the sample space for a natural language prompt, a discrete and intractable space of arbitrarily large dimension, which makes the optimization problem in Eq. (1) extremely difficult.

Evolutionary Algorithms. Current evolutionary algorithms utilize a random selection process of evolutionary operators at each phase to create new generations (Fernando et al., 2023; Guo et al., 2023). This type of global optimization approach facilitates exploration of the entire problem space but suffers from extremely high computational cost and slow convergence speed, due to the complexity of navigating the high-dimensional instruction-example joint space. On the other hand, methods such as Feedback (Pryzant et al., 2023) and self-refinement (Madaan et al., 2023) which are inspired by the idea of gradient descent offer better computational efficiency. However, these methods offer very limited improvement in the prompting performance due to their tendency to steer towards local minima, resulting in sub-

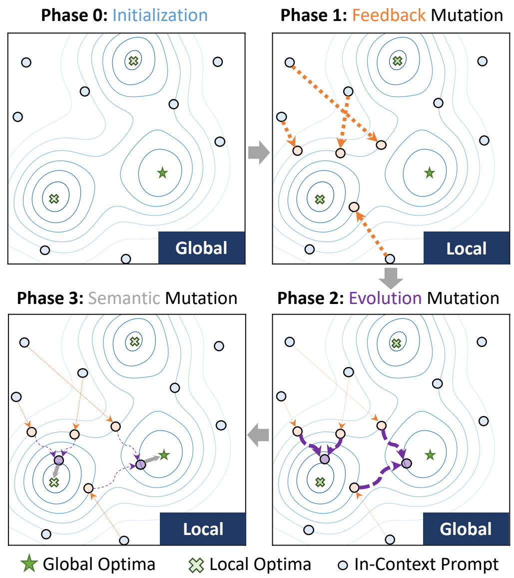

Figure 2: Illustration of PHASEEVO framework.

optimal solutions. These challenges motivate us to design an exploration-exploitation strategy that strikes a balance between computational efficiency and prompt performance.

3. Methodology

We propose to design a unified in-context prompt optimization framework that subsumes both zero-shot and few-shot prompting strategies by jointly optimizing the instruction and examples. To achieve optimal performance while maintaining good efficiency, PHASEEVO employs and alternates between two distinct optimization strategies: (1) *Exploration*, where evolution operators are leveraged for a *global* search to broadly explore the entire solution space and prevent entrapment in locally optimal solutions; (2) *Exploitation*, involving the use of feedback gradient mutation for local search to expedite convergence and improve efficiency. Instead of depending on specific strategies, PHASEEVO aims to organize multiple mutation operators in a unified and organic manner. The selection of the optimal mutation operator at each phase of the optimization process ultimately leads to the maximum performance of the resulting prompt.

3.1. Mutation Operator

Following the insight of leveraging global search and local search, we introduce five mutation operators that can be categorized as global operators and local operators. The three *global* operators are:

- **Lamarckian Mutation** is a reverse-engineering operator $\mathcal{O}_L$ that provides instructional prompt by learning from illustrative question-answer pairs $(\mathcal{Q}, \mathcal{A}) = [(Q_1, A_1), ..., (Q_m, A_m)]$ so that $\mathcal{O}_L(Q_i, \mathcal{L}) = A_i, i = 1, ..., m$ given the base LLM $\mathcal{L}$.

Table 1: Qualitative analysis of mutation operators

Operator	Add	Remove	Parents	Prob	Speed	Cost
Lamarckian	✓	-	-	-	-	●
Feedback	✓	✓	-	●●	●●●●	●●
EDA	-	-	✓	●●●●	●●	●
Crossover	-	-	✓	●●●●	●●	●
Semantic	-	✓	-	●●●	●●●	●

- **Estimation of Distribution Mutation (EDA)** is a function operator $\mathcal{O}_E$ that generate a new prompt $\mathcal{O}_E(\mathcal{P},\mathcal{L}) = p'$ based on a list of parents $\mathcal{P} = [p_1, ..., p_k]$. Items in $\mathcal{P}$ satisfy $d(p_i, p_j) < t$, where d is a distance metric and t is a threshold. If the items in $\mathcal{P}$ are ordered based on certain criteria, we refer to it as EDA + Index (EDA+I).
- **Crossover Operator(CR)** is a function operator $\mathcal{O}_C$ that performs $\mathcal{O}_C(p_1, p_2, \mathcal{L}) = p'$ where p_1, p_2 are two parents selected from a population set $\mathcal{P}$ where $\mathcal{P} = [p_1 ..., p_m]$. If $p_2 = \arg\min_{p \in \mathcal{P}} d(p_1, p_i)$ is used to select p_2, we refer to it as Crossover + Distinct (CR + D).

The two *local* operators are:

- **Feedback Mutation** is a function operator $\mathcal{O}_F$ utilizes a batch of data to create "gradients" δ that provide feedback of the current prompt p. A new prompt p' is generated by editing the current prompt p in the opposite semantic direction of the gradient, e.g., $p' = \mathcal{O}_F(p, -\delta, \mathcal{L})$.
- **Semantic Mutation** is a function operator $\mathcal{O}_S$ that performs paraphrasing $\mathcal{O}_S(p, \mathcal{L}) = p'$ where p' is the new prompt that shares the same semantic meaning as p.

To better harness these mutation operators, we compare them along the following five dimensions that are critical to our exploration-exploitation strategy in terms of performance and efficiency:

- **Add or remove examples.** This examines whether an operator can add or remove few-shot examples, to traverse the entire space of a joint prompt optimization problem.
- **Probability of improvement.** This evaluates the probability (successful rate) of an operator that brings performance (score) improvement after iterations.
- **Convergence speed.** This metric aims to evaluate how fast (in terms of iterations) an operator needs to optimize the current candidate to its local minimum solution.
- **Two or more parents?** This indicates whether an operator needs two or more parents, which has the potential to combine genetic information from diverse branches, enhancing global exploration capability.
- **API cost per operation.** It is the number of API calls needed to perform a specific operator via LLM agents.

We conducted a series of experiments where we ran each operator 100 times based on 4 different initialization settings to assess the performance of each operator regarding the five aspects. The goal is to obtain a comprehensive understanding of the inherent strengths and weaknesses of each operator. This allows us to select effective operators to efficiently find optimal solutions.

The evaluation results are presented in Table 1. Lamarckian mutation is a crucial operator that introduces diverse samples, enabling the addition of examples for global initialization. Feedback mutation leads to faster convergence for exploitation and facilitates the addition or removal of examples. EDA and Crossover mutation are evolution operators that share similar characteristics in exploring the global space. Semantic mutation is better at locally exploiting the cost-effectiveness of operations than feedback mutation. For a more in-depth discussion on operators, please refer to Appendix B.1 and B.2.

3.2. PHASEEVO Framework

Our PHASEEVO framework introduces a dual exploration-exploitation strategy, i.e., “global exploration” → “local exploitation” → “global exploration” → “local exploitation” to approach global optima efficiently. Specifically, we initially utilize a diverse sampling to facilitate global exploration of the entire search space, incorporating instructions and examples to optimize prompts jointly. Rather than solely relying on global search methods, such as evolution mutation, we also employ feedback mutation for fast, localized exploitation via gradient descent. This leads to superior initialization after the initial stage of exploration and exploitation. However, some candidates can be trapped in local optima after the initial two phases. To resolve this, we leverage evolution operators in the third phase to escape local optimum by exploring solutions at a global scale. Considering the low efficiency of global operators, we utilize semantic mutations at the final phase to accelerate the convergence to the global optimal solution. Figure 2 is an illustration of the optimization process.

3.2.1. PHASE 0: GLOBAL INITIALIZATION

Our objective is to create diverse candidates as the initial population to explore the vast joint space of instruction and example. We provide two types of initialization based on the availability of data (*input output pair*) and human expert knowledge (*prompt examples*).

- **Reverse Engineer from input/output pairs.** Given a set of input/output pairs $S = \{(Q_1, A_1), ..., (Q_m, A_m)\}$ from the training set $\mathcal{D}_{\text{train}}$ for the task $\mathcal{T}$, we define an LLM agent to apply Lamarckian Operator $\mathcal{O}_L$ to *reverse engineer* the prompt from provided demonstrating pairs.

- **Human expert prompt example.** This way allows humans to jump-start the evolution process by incorporating prior knowledge. We also perform the semantic operator $\mathcal{O}_S$ to enhance the diversity of the initial population.

3.2.2. PHASE 1: LOCAL FEEDBACK MUTATION

While an initial phase (Phase 0) may result in a diverse population, each candidate could still be distant from its local optimal solution. To address this, we employ the Feedback Mutation Operator $\mathcal{O}_F$ to expedite each candidate’s convergence towards their local minimums, leveraging the “gradient" information. This involves the introduction of an LLM *Examiner*, which scrutinizes instances where the current candidate falls short, and subsequently offers improvement guidance. Such information is taken as the feedback gradient and is further utilized by an LLM *Improver*, to generate new candidates by local exploitation. These new candidates contain global information inherited from the previous phase and can thus be regarded as better initialization for the next optimization phase.

3.2.3. PHASE 2: GLOBAL EVOLUTION MUTATION

Phase 1 provides a more refined set of candidates, while some of them might be stuck in local optima. To address this issue, we prioritize exploration rather than exploitation in Phase 2, which helps to escape from these restricted localities by conducting a global search. We leverage LLM agents that employ EDA (EDA-I) operators $\mathcal{O}_E$ and CR (CR-D) operators $\mathcal{O}_C$ to facilitate the increased interaction of genetic information among candidates on a larger global scale. Rather than employing cosine similarity as distance metrics, we adopt the Hamming distance (see more discussions in Section 3.3) for calculating similarity on performance-based vectors such that Phase 2 can promote greater diversity in the evolving generations.

3.2.4. PHASE 3: LOCAL SEMANTIC MUTATION

Upon completing Phase 2’s exploration, Phase 3 employs local exploitation to hasten the “last mile” of convergence. As the concluding phase of PHASEEVO, the fitness score of the population is notably optimized at this stage relative to earlier phases. Consequently, the Semantic Mutation operator $\mathcal{O}_S$ is selected to expedite a more cost-effective exploitation of the candidates. Finally, we identify the best candidate as our ultimate optimal prompt and assess its performance on the testing dataset $\mathcal{D}_{\text{test}}$. The workflow of PHASEEVO framework is shown in Algorithm 1.

3.3. PHASEEVO Design

Within our PHASEEVO framework, we propose two novel design schemes to improve performance and efficiency.

Design 1: Performance vector with Hamming distance. Evolution operators like EDA and Crossover function optimally when parents exhibit distinct attributes. In terms of evaluating similarity scores, we adhere to the principle that similarity should be gauged based on the performance of the prompts rather than their linguistic or semantic similarities. Inspired by this intuition, we

Algorithm 1 Unified In-Context Prompt Optimization: PHASEEVO

1: **requirements**: size of population n, a dev set $\mathcal{D}_{\text{dev}}$, score function $\mathcal{F}$ on the base LLM $\mathcal{L}$, phase improvement t and threshold t^* and minimum run time for phases $\mathcal{K}_i$, designed evolution operators $\mathcal{O}_L$, $\mathcal{O}_F$, $\mathcal{O}_E$, $\mathcal{O}_C$ and $\mathcal{O}_S$
2: **initialization**: generate diverse initial prompts $\mathcal{P}^0 = \{p_1^0, ..., p_n^0\}$ by $\mathcal{O}_l$ with input/output pairs or $\mathcal{O}_s$ with existing prompt, and evaluate initial scores $\mathcal{S}^0 \leftarrow \{s_i^0 = \mathcal{F}(p_i^0, \mathcal{D}_{\text{dev}})\}$ `//Phase 0: Global Exploration`
3: **while** $t < t^*$ or $k \leq \mathcal{K}_1$ **do** `//Phase 1: Local Exploitation`
4: ***Local Feedback Mutation:*** generate new prompts by feedback gradient descent, $\mathcal{P}_t \leftarrow \mathcal{O}_f(\mathcal{P}^0)$, evaluate $\mathcal{S}_t \leftarrow \mathcal{F}(\mathcal{P}^0, \mathcal{D}_{\text{dev}}))$, and update the population set $\mathcal{P}^1 \leftarrow \{\mathcal{P}_t, \mathcal{P}^0\}$, and score set $\mathcal{S}^1 \leftarrow \{\mathcal{S}_t, \mathcal{S}^0\}$
5: **while** $t < t^*$ or $k \leq \mathcal{K}_2$ **do** `//Phase 2: Global Exploration`
6: ***Global Evolution Mutation:*** select parent prompts from current population, $\{p_{r_1}, ..., p_{r_k}\} \in \mathcal{P}^1$, generate a new prompt by performing EDA operators $p_t \leftarrow \mathcal{O}_e(p_{r_1}, ..., p_{r_k})$ or crossover operators $p_t \leftarrow \mathcal{O}_c(p_{r_1}, ..., p_{r_k})$, evaluate on $\mathcal{D}_{\text{dev}}$, $s_t \leftarrow \mathcal{F}(p_t, \mathcal{D}_{\text{dev}})$, and update $\mathcal{P}^2 \leftarrow \{\mathcal{P}^1, p_t\}$ and $\mathcal{S}^2 \leftarrow \{\mathcal{S}^1, s_t\}$
7: **while** $t < t^*$ or $k \leq \mathcal{K}_3$ **do** `//Phase 3: Local Exploitation`
8: ***Local Semantic Mutation:*** generate new prompts by the semantic operator $\mathcal{P}_t^* \leftarrow \mathcal{O}_s(\mathcal{P}^2)$, evaluate $\mathcal{S}_t^* \leftarrow \mathcal{F}(\mathcal{P}^2, \mathcal{D}_{\text{dev}}))$, and update $\mathcal{P}^3 \leftarrow \{\mathcal{P}_t^*, \mathcal{P}^2\}$, and $\mathcal{S}^3 \leftarrow \{\mathcal{S}_t^*, \mathcal{S}^2\}$
9: **return** the optimal in-context prompt p^*, from the final population $\mathcal{P}^3$: $p^* \leftarrow \arg\max_{p \in \mathcal{P}^3} \mathcal{F}(p, \mathcal{D}_{\text{dev}})$

propose to construct candidate vectors based on individual performance on the evaluation dataset, named "performance vectors". To exemplify, in an evaluation dataset comprising five elements, a candidate answering the first three queries correctly and the final two incorrectly would feature a vector representation of $[1, 1, 1, 0, 0]$.

Rather than calculating the cosine similarity of embedding space, we propose to compute candidate similarity scores by *Hamming distance*, which calculates the distance between two vectors of equal length by examining the number of positions at which the corresponding symbols are different. This way ensures that one candidate is more likely to be paired with a candidate that does not contain the same mistakes, and thereby generates a diverse population with a more diverse set of genetic information.

Design 2: Adaptive Phase Stop Criteria. Each evolution phase is fully conducted before we transition to the next. The decision to proceed to the following phase is influenced by two primary criteria.

- *Performance Gain.* If no performance gain manifests after implementing the operators in a particular phase, it's indicative that the candidate has been thoroughly optimized by the operator. Consequently, we transition to the next phase.
- *Operator-specific Tolerance.* As operators inherently vary, more localized operators, such as Feedback Mutation, which have high improvement probabilities, could imply readiness for progress when no performance gain is perceived. However, global operators, e.g., evolution operators, might have low initial improvement probabilities but are capable of accessing broader branches worth exploration. Therefore, we assign greater *tolerance* and run them for a pre-defined time when a global operator does not introduce improvement. More details about the stop criteria can be found in Appendix B.2.

4. Experiments

4.1. Experimental Setup

Tasks and Datasets. We curate 35 benchmark tasks from three domains for thorough experiments: 8 Big Bench Hard (**BBH**) (Suzgun et al., 2022a); 3 NLP detection tasks, including **Ethos** (Mollas et al., 2021), **Liar** (Wang, 2017), and **Sarcasm** (Farha & Magdy, 2020); 24 instruction induction tasks (Honovich et al., 2022). The task and dataset details are in Appendix D.

Baselines. We evaluate PHASEEVO against a variety of LLM-based approaches that have achieved state-of-the-art performance in prompt optimization:

- **APE** (Zhou et al., 2023) and **APO** (Pryzant et al., 2023): APE utilizes an iterative Monte Carlo Search strategy that emphasizes *exploration*, while APO emphasizes *exploitation*, which harnesses incorrect instances as feedback gradient to refine the original prompt.
- **OPRO** (Yang et al., 2023a): OPRO leverages LLM as optimizers to generate better instruction via meta-prompt, solution-score pairs, and task descriptions.
- **PromptBreeder** (Fernando et al., 2023), **EvoPrompt** (Guo et al., 2023) and **AELP** (Hsieh et al., 2023): these methods connect LLMs with evolution algorithms (EAs) to tackle prompt optimization tasks. Specifically, EvoPrompt implements EAs using genetic algorithm (Holland, 1992) and differential evolution (Storn & Price, 1997), while PromptBreeder introduces multiple mutation operators inspired by thinking styles. AELP focuses on long prompt optimization by mutating on a sentence level with a history-guided search.

Implementation Details. We utilized GPT-3.5 to develop LLM agents capable of performing various mutation operators. We set up training, development, and testing datasets, select the prompt with the highest score on the dev set, and report its score on the testing set. We run all the experi-

Table 2: Testing performance of the optimal prompt on 8 representative tasks from BBH.

Method	Causal Judgement	Dis -ambiguation	Dyck Languages	Formal Fallacies	Hyperbaton	Logical Five	Color Reasoning	Salient Translation
OPRO (Yang et al., 2023a)	71.94	71.53	36.73	49.51	75.92	50.00	65.55	43.88
EvoPrompt (Guo et al., 2023)	67.24	53.70	47.96	50.81	74.79	61.40	60.90	47.58
AELP (Hsieh et al., 2023)	76.47	62.69	10.27	57.95	52.64	72.59	67.74	38.93
PhaseEvo-pair	69.97$_{(2.45)}$	**69.90**$_{(3.53)}$	7.06$_{(1.23)}$	**58.49**$_{(0.41)}$	**84.36**$_{(2.24)}$	45.49$_{(2.73)}$	58.13$_{(2.36)}$	**48.38**$_{(0.81)}$
PhaseEvo-example	**84.85**$_{(5.45)}$	68.01$_{(0.4)}$	**35.48**$_{(12.18)}$	53.06$_{(4.95)}$	81.58$_{(9.89)}$	**73.56**$_{(8.99)}$	**77.15**$_{(4.13)}$	47.01$_{(0.88)}$
Over AELP	10.95% ↑	11.50% ↑	245.18% ↑	0.93% ↑	60.24% ↑	1.34% ↑	13.89% ↑	24.27% ↑
Over EvoPrompt	32.36% ↑	30.17% ↑	-2.48% ↑	15.73% ↑	16.99% ↑	34.36% ↑	32.35% ↑	3.19% ↑
Over OPRO	23.84% ↑	0.84% ↑	27.33% ↑	18.91% ↑	16.79% ↑	65.04% ↑	23.02% ↑	12.31% ↑

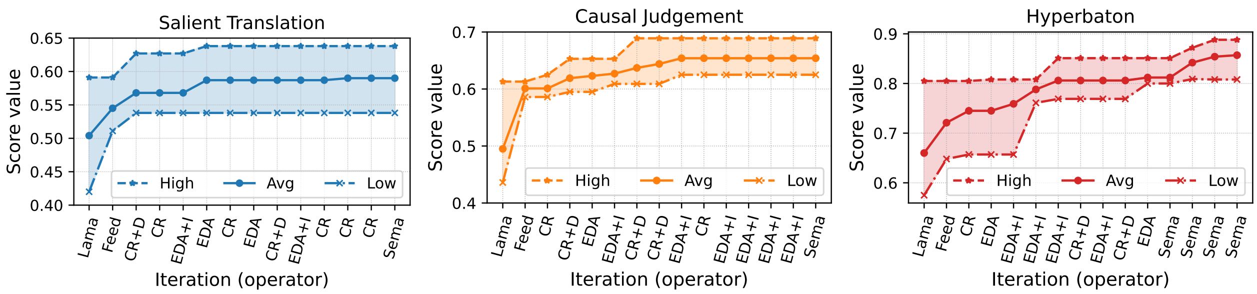

Figure 3: Iteration history of score values with different mutation operators during optimization.

ments by setting 3 random seeds and the standard deviation is provided. More details are provided in Appendix D.

4.2. Main Results

BBH Tasks. Following the practice of AELP (Hsieh et al., 2023), we conduct 8 BBH tasks to evaluate the performance of PhaseEvo holistically. We consider two initialization schemes PhaseEvo-pair and PhaseEvo-example and report the final results in Table 2. PhaseEvo demonstrates substantial improvements compared to state-of-the-art methods, achieving an average improvement of over AELP (**46.0**%↑), EvoPromopt (**20.3**%↑), and OPRO (**23.5**%↑).

Fig. 3 depicts the iterative history of prompt evolution, emphasizing the score variations for the best candidate, worst candidate, and the population's average across iterations. It has been observed that Feedback Mutation yields a performance boost within a single iteration and rarely introduces continual improvements. Global operators such as EDA and Crossover aid in escaping local minima and offering additional performance leaps (refer to Hyperbaton). This observation aligns with our initial operator analysis. The success of PhaseEvo lies in the organic organization of these mutation operators, effectively harnessing their advantages to maximum performance.

Detection Tasks. To present a more expansive comparison, we adopted the configuration outlined in APO (Pryzant et al., 2023) and conducted a comparative analysis against it across three tasks. It should be noted that data for the fourth task mentioned in the original paper is unavailable. According to Table 3, PhaseEvo exhibits marginally superior performance to APO in relatively simple tasks such as Ethos (by 1%) and Sarcasm (by 4.7%). However, for more complex tasks such as Liar, PhaseEvodemonstrates a significant improvement of 19.6% compared to APO. Moreover, we have also provided results for PhaseEvo using GPT-4, which demonstrated performance comparable to those of PhaseEvo employing GPT-3.5.

Table 3: Testing performance on 3 detect tasks from APO.

Method	Ethos	Liar	Sarcasm
APO (Pryzant et al., 2023)	0.95	0.51	0.85
PhaseEvo (GPT-3.5)	0.96$_{(0.96)}$	0.61$_{(3.85)}$	0.87$_{(1.25)}$
PhaseEvo (GPT-4)	0.96	0.69	0.89

Instruction Induction Tasks. To compare PhaseEvo-generated prompts with manually added few-shot examples, we evaluated the optimized prompt from PhaseEvo against the best prompts from APE-fewshot (Zhou et al., 2023) and PromptBreeder-fewshot (Fernando et al., 2023) on APE's 24 instruction induction tasks. The results show that PhaseEvo outperforms APE in 17 out of 24 tasks and PromptBreeder in 18 out of 24 tasks. The Appendix E.1 provides complete experimental results. Fig. 4 shows that few-shot methods do not always outperform zero-shot methods, highlighting the need for a joint in-context prompt search. Moreover, we observed that the prompts generated by PhaseEvo are easier to interpret and align better with the task description. Appendix E.3 provides more detail on prompt quality.

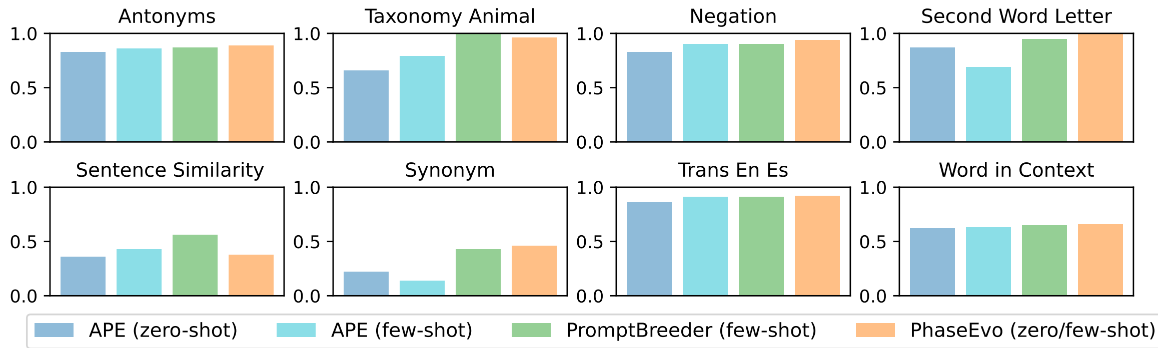

Figure 4: Test accuracy of PHASEEVO on the instruction induction tasks.

Table 4: Comparison of our phase evolution with traditional random evolution.

Method	Causal Judgement		Disambiguation		Hyperbaton		Salient Translation	
	Average score	High score	Average score	High score	Average score	High score	Average score	High score
Random Evo	$67.70_{(0.75)}$	$70.28_{(0.56)}$	$58.22_{(2.47)}$	$61.3_{(3.17)}$	$83.00_{(0.15)}$	$87.8_{(0.00)}$	$52.00_{(2.35)}$	$56.80_{(1.60)}$
PHASEEVO	$\mathbf{69.88}_{(2.17)}$	$\mathbf{72.00}_{(3.09)}$	$\mathbf{60.32}_{(2.73)}$	$\mathbf{62.9}_{(2.56)}$	$\mathbf{83.52}_{(0.71)}$	$\mathbf{87.8}_{(0.00)}$	$\mathbf{53.06}_{(0.80)}$	$\mathbf{56.80}_{(0.80)}$

4.3. Analysis

Phase Evolution vs Random Evolution. To compare our PHASEEVO method with the random evolution strategy, we conducted additional experiments on four tasks from BBH. Using the same initial population and six iterations, we presented the average score and highest score of the population in Table 4. Significantly, PHASEEVO outperformed random evolution in both average and highest scores for all tasks. Such effectiveness is attributed to the advantages of our well-organized operators through the employment of the dual exploration-exploitation strategy.

Effect of Hamming Distance. An ablation study has been conducted to examine the impact of hamming distance on the performance-based vectors in comparison to the traditional cosine distance for similarity calculation. The study encompasses both distance calculations carried out in 4 iterations using the same initial population. Table 5 displays the outcomes of the hamming distance evaluation on four BBH tasks. The results indicate that the hamming distance outperforms the cosine distance, demonstrating higher average and maximum scores, particularly for Disambiguation (+5.2) and Hyperbaton (+4.6) tasks.

Effect of Initialization Strategy. The PHASEEVO can accommodate two types of inputs: *input output pair* and *prompt examples*, each bringing its own benefits. When using the *input output pair* approach, the initialization occurs solely based on LLM's proposal, resulting in greater diversity in the initial population. On the other hand, initialization in *prompt examples* draws upon provided example prompts, consequently lacking the diversity that *input output pair* offers. Even so, *prompt examples* empowers users to introduce prior knowledge without leaning on LLM interpretation, and consequently, it performs better in more complex tasks such as Dyck Languages, Logical Five, and Color Reasoning, as illustrated in Table 2.

Effect of Operators on Prompt Length. Our method aims to explore the entirety of the prompt space, spanning both zero-shot and few-shot scenarios. Understanding the variation in prompt length and the impact of the operator on this fluctuation is crucial. Fig. 5 provides a visual representation of the average prompt token length throughout the iterations. Interestingly, the length can either increase, decrease, or oscillate, which aligns with the "unfettered" expectations of global search. Specifically, we observed the initialization phase had a significant impact on prompt length. This observation is in agreement with our analysis of the Lamarckian and Feedback operators, which hold the power to both add and remove examples.

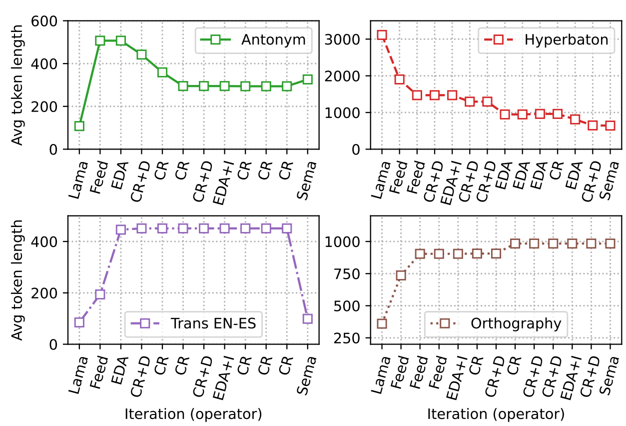

Figure 5: Variation of prompt length during optimization.

Synthetic Few-shot Examples. We observe that in certain cases PHASEEVO would generate novel synthetic few-shot examples instead of selecting from existing ones. To verify their veracity, we conduct a manual evaluation of the accu-

Table 5: Performance comparison of hamming distance and cosine similarity.

Method	Causal Judgement		Disambiguation		Hyperbaton		Salient Translation	
	Average score	High score	Average score	High score	Average score	High score	Average score	High score
Cosine distance	$64.70_{(2.31)}$	$67.86_{(2.47)}$	$58.96_{(1.47)}$	$63.30_{(0.00)}$	$74.70_{(1.60)}$	$85.7_{(0.00)}$	$49.56_{(1.07)}$	$58.80_{(0.00)}$
Hamming distance	$\mathbf{65.74}_{(2.87)}$	$\mathbf{69.60}_{(2.97)}$	$\mathbf{64.11}_{(1.28)}$	$\mathbf{66.94}_{(2.88)}$	$\mathbf{79.30}_{(4.48)}$	$\mathbf{86.78}_{(2.15)}$	$\mathbf{50.33}_{(2.32)}$	$\mathbf{58.80}_{(0.00)}$

racy of the few-shot examples generated by PHASEEVO on a total of 24 instruction deduction tasks. We find that 90 out of the 92 examples evaluated (97.8%) are accurate. Among them, 24 out of the 92 (24.09%) are aligned with samples present in the training set. There are two cases where the synthetic example is inaccurate: the sentiment of *"A non-mystery mystery"* is identified as *"neutral"* where the ground truth is *"negative"*, and *"Little more than a well-mounted history lesson"* is identified as *"neutral"* where the ground truth is *"negative"*. In both cases, we empirically validate that such a level of inaccuracy does not influence prompt performance (score remained 94% regardless of the labels).

Computational Cost. We monitor the computational cost of PHASEEVO based on the number of model API calls consumed by evaluation and operator application, and the number of iterations. As shown in Fig. 6, PHASEEVO is the most cost-effective method that significantly reduces multiple orders of magnitude compared to evolution strategies, such as PromptBreeder. PHASEEVO also performs competitively in terms of iterations compared to the gradient descent approach, e.g., APO.

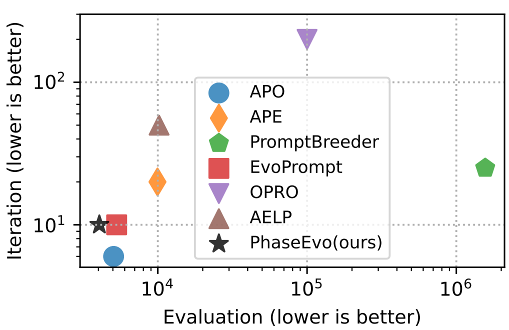

Figure 6: Comparison of computational cost.

5. Related Work

In-context prompting is an efficient approach for communicating LLMs but the performance is strongly affected by the design of the prompt in specifized tasks. Prompt optimization has thus obtained broader attention. One research direction is the continuous prompt approaches that tune embeddings of input tokens to generate better prompts (Li & Liang, 2021; Zhang et al., 2021; Sun et al., 2022b;a; Chen et al., 2023). However, the optimized "soft" prompts from this paradigm often fall short of interpretability and are inaccessible for blackbox APIs. Discrete prompt approaches (Diao et al., 2022; Prasad et al., 2022), operating discrete tokens directly, offer an interactive interface to humans with better interpretability and show promising performance in various NLP tasks. Various methods have been proposed via gradient-based search (Shin et al., 2020), reinforcement learning (Zhang et al., 2022a; Deng et al., 2022; Sun et al., 2023) and ensemble methods (Hou et al., 2023; Pitis et al., 2023) while these methods encounter concerns in terms of scalability, reliability and efficiency (Wang et al., 2023).

More recent advancements rely on iterative sampling, scoring, and selection of exceptionally promising prompts, generating diverse possibilities for prompt optimization. Fernando et al. (2023); Guo et al. (2023); Hsieh et al. (2023) proposed leveraging LLMs to implement evolution strategies in prompt searches. Yang et al. (2023a) demonstrates the capability of LLM as optimizers in prompt design. Pryzant et al. (2023); Zhou et al. (2023) utilizes natural language feedback to refine prompt instructions. However, these prompt evolution/refinement strategies largely focus on prompt instructions, typically short sentences or paragraphs. Our research reformulates the problem by permitting unrestrained evolution of a unified in-context prompt, incorporating both instructions and examples, offering more avenues for improvement, yet it also poses new challenges with regard to navigating the high-dimensional joint space, while retaining high efficiency. While previous search and sampling algorithms have been investigated, such as Monte Carlo search (Zhou et al., 2023), Gibbs sampling (Xu et al., 2023), or Beam search (Pryzant et al., 2023), we introduce a novel dual exploration-exploitation strategy that leverages the in-depth traits of each operator, utilizing an intuitive blend of global-local search, conducive to enhancing interactive dynamics during optimization.

6. Conclusion and Discussion

In this work, we propose a unified in-context prompt optimization framework that enables the joint optimization of prompt instruction and few-shot examples. Benefiting from the global-local phased optimization schedule and the design of novel LLM-based mutation operations, PHASEEVO achieves state-of-the-art performance over a wide range of benchmark tasks. Despite having achieved the lowest computational requirements among all baselines, PHASEEVO still needs around 12 iterations and $4,000$ API calls, which might be insufficient for supporting large-scale online applications. Future work could explore better initialization strategies or data compression techniques to further improve efficiency and reduce latency.

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A. Operator Definition

Operators are used to generate new candidates. Seven types of operators, broadly categorized into five classes are used by PHASEEVO. The idea is to provide a diverse set of operators so that a broad cognitive space of linguistics is covered.

A.1. Lamarckian Mutation

Lamarckian Mutation follows the principles proposed in APE and Prompt Breeder (Zhou et al., 2023; Fernando et al., 2023). Given a set of input-output pairs for the task, an LLM agent is used to reverse-engineer the prompt from the provided demonstrating pairs. This type of mutation allows a diverse set of prompt candidates to be generated with no prior knowledge of the task. Any prompt candidate will have to be induced from the demonstrating pairs. The prompt used by the LLM agent is in Table 10.

Definition A.1. (Lamarckian Mutation) Given a set of input/output pairs $(\mathcal{Q}, \mathcal{A}) = [(Q_1, A_1), ..., (Q_m, A_m)]$ and a base LLM $\mathcal{L}$, Lamarckian Mutation is to reverse engineer the instruction $\mathcal{O}_L$ so that $\mathcal{O}_L(Q_i) = A_i, i = 1, ..., m$.

A.2. Feedback Mutation

As evolution algorithms can take a while to converge, inspired by the concept of *Gradient Descent* in machine learning model training, we introduce an LLM agent that works as an examiner which examines the cases where the current task prompt fails and provides improvement guidance. Such guidance will be treated as *gradient* and be used by another LLM Agent as an improver to generate a new candidate. Though similar to what is proposed in APO (Pryzant et al., 2023), instead of only using gradient descent repeatedly, which has a higher probability of arriving at a local minimum, we take advantage of its fast converge rate to local minimum and combine it with an evolutionary algorithm to target global minimum. When applying Feedback Mutation, it will be applied to every candidate in the current generation. The prompt can be found in Table 11 - 12.

Definition A.2. (Feedback Mutation) Feedback Mutation generates a new prompt p' based on the existing prompt $p \in \mathcal{P}$, and where p made mistakes for a task. The feedback operator $\mathcal{O}_F$ first looks at the cases where the current p failed to generate a list of advice G, and then asks LLM $\mathcal{L}$ to apply such advice G to existing prompt p for generating the new prompt p'.

A.3. ESTIMATION OF DISTRIBUTION MUTATION

The next class of operators takes a set of parents as input to generate a mutated candidate for the next generation.

Estimation of Distribution Mutation (EDA): Following the principles proposed by (Hauschild & Pelikan, 2011) and work in (Fernando et al., 2023), we use a LLM agent that is fed with a subset of the current population to generate new candidate. To ensure the diversity and quality of the subset, we first rank the candidates in the current population by their fitness score in descending order. Then starting from the first item in the ordered candidates, we only add the candidate to the subset if it does not have a similarity score over a threshold with any other candidate that is already in the subset. This way candidates with higher fitness scores are more prone to be added to the subset and the diversity of the subset is achieved. More details on how similarity is calculated can be found in section 3.3. The subset will be randomized before feeding into the LLM agent so the candidate's fitness score does not dictate its order. The prompt can be found in Table 13.

EDA and Index Mutation: This is a variant of the EDA mutation above. Based on the observations that LLM is more prone to use examples that appear late in the in-context learning (Liu et al., 2023; Fernando et al., 2023), after generating the subset following procedures of EDA, the subset is ordered by their fitness score in *ascending order*. To further balance exploitation and exploration and avoid being too biased over the candidate with the highest fitness score (Fernando et al., 2023), we instructed LLM that the candidates are ranked by their fitness score in *descending order* so that the low health score candidates are taken into consideration during mutation. The prompt can be found in Table 14.

Definition A.3. (Estimation of Distribution Mutation - EDA) EDA generates a new candidate based on a list of parents. It is a function operator $\mathcal{O}_E$ that performs $\mathcal{O}_E(\mathcal{P}, \mathcal{L}) = p'$. Given a list of prompts $\mathcal{P} = [p_1, ..., p_m]$ and an LLM $\mathcal{L}$, EDA provides a new prompt p'. Items in $\mathcal{P}$ satisfy the restriction that $d(p_i, p_j) < t$, where d is a function that calculates similarity, and t is a predefined threshold. If the items in $\mathcal{P}$ are ordered based on certain criteria, we call it EDA + Index (EDA+I).

A.4. Crossover Operator

This class of operators takes two parents as input to generate a crossover candidate for the next generation. The prompt can be found in Table 15.

Crossover Operator(CR): Following the concept of crossover in the evolution algorithm, we introduce an LLM agent to function as a crossover operator that takes two parents and generates a crossover candidate. It takes the best two candidates in the current population, namely the top two candidates with the highest fitness scores, and performs linguistic crossover.

Crossover with Diversity Operator(CR+D): This is a variance of the Crossover Operator. To provoke exploration, we follow a similar process in EDA where diversity in parents is considered. Thus it takes the best candidate and the most distinct individual to it as two parents for crossover operation. The distinctness between two candidates is measured by a similarity score. More details on how the similarity score is calculated can be found in section 3.3.

Definition A.4. (Crossover Mutation - CR) Crossover generates a new candidate based on two parents. It is a function operator $\mathcal{O}_C$ that performs $\mathcal{O}_C(p_1, p_2, \mathcal{L}) = p'$ where p_1, p_2 are two prompts selected from a prompt population set $\mathcal{P}$ where $\mathcal{P} = [p_1..., p_m]$, p' is the generated prompt that hold features from both p_1 and p_2. If $p_2 = \arg\min_{p \in \mathcal{P}} d(p_1, p_i)$ is applied for choosing p_2, we call it Crossover + Distinct (CR + D).

A.5. Semantic Mutation

This class of operators takes a candidate and uses an LLM agent to compose a new candidate that shares its semantic meaning. When applying Semantic Mutation, it will be applied to every candidate in the current generation. The prompt can be found in Table 16.

Definition A.5. (Semantic Mutation) Semantic Mutation is a function operator $\mathcal{O}_S$ that performs $\mathcal{O}_S(p, \mathcal{L}) = p'$ where $p\prime$ is the generated prompt that shares the same semantic meaning as p.

B. Operator Analysis

B.1. Few-Shot Additional / Removal Analysis

The ability to add and remove few-shot examples is crucial in dictating whether it is possible to traverse the full in-context prompt space. Thus we conduct the few-shot addition/ removal analysis to gauge each operator's capabilities. Below are examples of how operators add or remove few-shot examples.

Table 6: Lamarckian Operator Add Few-shot Example

Operator Input	I gave a friend an instruction and some examples The friend read the instruction and wrote an output for every one of the inputs. Here are the input-output pairs: ## Example ## ## Input ## : 92 24 ## Output ##: ['68'] The instruction was:
Operator Output	Subtract the second number from the first number and write the result. If the result is negative, write the absolute value of the result. Here are the input-output pairs: Input: 10 5 Output: ['5'] Input: 50 75 Output: ['25'] Input: 100 100 Output: ['0'] Input: 7 20 Output: ['13'] Input: 0 5 Output: ['5'] Input: -10 5 Output: ['15'] Input: 92 24 Output: ['68'] Input: 50 -75 Output: ['125']

Table 7: Feedback Operator Add Few-shot Example: In this operation, few-shot examples are added based on the feedback. Individual feedback and their corresponding changes are colorcoded.

Original Prompt	For each word, find its antonym and write it as the output.
Generated Feedback	1. Clarify the definition of "antonym" to ensure that the prompt is asking for the opposite meaning of the word, rather than just a different word that is related in some way. 2. Provide more specific instructions for determining the antonym, such as indicating whether the opposite meaning should be an adjective or a noun. 3. Add a list of common antonyms for each word to help users who may not be familiar with all possible opposites. 4. Provide a context or sentence for each word to help users determine the appropriate antonym.
Generated Prompt	For each word, find its antonym, which is a word that has the opposite meaning, and write it as the output. The antonym should be a word that is commonly used to express the opposite meaning of the given word, and it should be of the same part of speech (e.g. noun, verb, adjective, adverb). To help you identify the antonym, we have provided a list of common antonyms for each word. Additionally, we have included a context or sentence for each word to help you determine the appropriate antonym. Example: Word: Hot Antonym: Cold Context: The soup is too hot to eat. Please note that some words may have multiple antonyms depending on the context, so use your best judgment to determine the most appropriate one.

Table 8: Feedback Operator Remove Few-shot Example: In this operation, few-shot examples are removed based on the feedback. Individual feedback and their corresponding changes are colorcoded.

Original Prompt	For each word, remove the prefix or suffix that indicates a negative or opposite meaning, and write the resulting word as the output. For example, for the input "destabilize," remove the prefix "de-" which indicates a negative meaning, and the resulting word is "stabilize
Generated Feedback	1.Clarify the prompt to specify that it only applies to words with a negative or opposite prefix or suffix. This will prevent confusion and mistakes when dealing with words that do not have such affixes. 2. Provide examples of common negative or opposite prefixes and suffixes, such as "un-" or "-less," to help users identify them more easily. 3. Include a check to ensure that the resulting word is a valid English word, to avoid outputs like "ane" or "direct" that are not actual words. This could be done by cross-referencing the output with a dictionary or word list. 4. Consider adding an option to retain the original word if no negative or opposite prefix or suffix is present. This would eliminate confusion when dealing with words like "linear" that do not have such affixes.
Generated Prompt	For each word that contains a negative or opposite prefix or suffix, remove the affix and write the resulting word as the output. Common negative or opposite prefixes and suffixes include "un-," "dis-," "in-," "-less," and "-ful." Please note that this prompt only applies to words with these specific affixes. To ensure that the resulting word is a valid English word, we will cross-reference the output with a dictionary or word list. If the resulting word is not a valid English word, it will be excluded from the output. If the original word does not contain a negative or opposite prefix or suffix, you may choose to retain the original word or exclude it from the output. Please specify your preference in the input.

Table 9: Semantic Operator Remove Few-shot Example

Operator Input	Order adjectives correctly in English sentences. Q: Which sentence has the correct adjective order: Options: (A) rubber terrible ship (B) terrible rubber ship A: Let's think step by step. When there is more than one adjective before a noun, the adjectives need to respect the following order before a noun: "[1. opinion] [2. size] [3. age] [4. shape] [5. color] [6. origin] [7. material] [8. purpose] noun". Option (A): "rubber terrible ship". (1) rubber" falls into the material category. (2) "terrible" falls into the opinion category. Option (A) has the following adjective order: [7. material] [1. opinion] (or, in numeric terms, 7 1). Because 7 < 1 is not correct, (A) does not have the correct ordering. Option (B): "terrible rubber ship". Option (B) has the following adjective order: [1. opinion] [7. material] (or, in numeric terms, 1 7). Because 1 < 7 is correct, (B) has the correct ordering. So the answer is (B). Q: Which sentence has the correct adjective order: Options: (A) repulsive small Brazilian exercise ship (B) Brazilian repulsive exercise small ship A: Let's think step by step. When there is more than one adjective before a noun, the adjectives need to respect the following order before a noun: "[1. opinion] [2. size] [3. age] [4. shape] [5. color] [6. origin] [7. material] [8. purpose] noun". Option (A): "repulsive small Brazilian exercise ship". (1) "repulsive" falls into the opinion category. (2) "small" falls into the size category. (3) "Brazilian" falls into the origin category. (4) "exercise" falls into the purpose category. Option (A) has the following adjective order: [1. opinion] [2. size] [6. origin] [8. purpose] (or, in numeric terms, 1 2 6 8). Because 1 < 2 < 6 < 8 is correct, (A) has the correct ordering. Option (B): "Brazilian repulsive exercise small ship". Option (B) has the following adjective order: [6. origin] [1. opinion] [8. purpose] [2. size] (or, in numeric terms, 6 1 8 2). Because 6 < 1 < 8 < 2 is not correct, (B) does not have the correct ordering. So the answer is (A). Q: Which sentence has the correct adjective order: Options: (A) blue gold wonderful square shoe (B) wonderful square blue gold shoe A: Let's think step by step. When there is more than one adjective before a noun, the adjectives need to respect the following order before a noun: "[1. opinion] [2. size] [3. age] [4. shape] [5. color] [6. origin] [7. material] [8. purpose] noun". Option (A): "blue gold wonderful square shoe". (1) "blue" falls into the color category. (2) "gold" falls into the material category. (3) "wonderful" falls into the opinion category. (4) "square" falls into the shape category. The adjective order that Option (A) has is [5. color] [7. material] [1. opinion] [4. shape] (or, in numeric terms, 5 7 1 4). Because 5 < 7 < 1 < 4 is not correct, (A) does not have the correct ordering. Option (B): "wonderful square blue gold shoe". Option (B) has the following adjective order: [1. opinion] [4. shape] [5. color] [7. material] (or, in numeric terms, 1 4 5 7). Because 1 < 4 < 5 < 7 is correct, (B) has the correct ordering. So the answer is (B).
Operator Output	Rearrange the adjectives in the given sentence in the correct order.

B.2. Operator Feature Analysis

To study the features of each operator we conduct a preliminary experiment where we study four operators: EDA Mutation, Crossover, Feedback Mutation, and Semantic Mutation.

Initialization: As the initialized points have a tremendous impact on optimization problems. We randomly use four different seeds to create four initial populations for four different tasks: Causal Judgement, Salient Translation Error Detection, Disambiguation QA, and Hyperbaton. The idea is to provide various initialization points so that the performance of operators can be averaged to rule out the influence of initialization.

Operator Applications: For each initialization, we apply the following procedure for all four operators.

- For one round, starting with the initial population, we consecutively apply the operator 5 times. This is to study the value of applying the operator consecutively.
  - For EDA and CrossOver, as they require multiple parents, we keep a population size of 5 for each generation after applying the operator. Performance gain is defined as whether the average health of the population is improved.
  - For Feedback Mutation and Semantic Mutation, as they only need one parent, we apply them to a random candidate from the initial population and use the new candidate as the base for the next mutation. Performance gain is defined as whether the new candidate has a higher fitness score than its parent.
- To reduce the impact of randomness during mutation, we run this process 5 rounds for each operator.

Thus for each operator, it will be run a total of 4 tasks * 5 rounds * 5 application = 100 times.

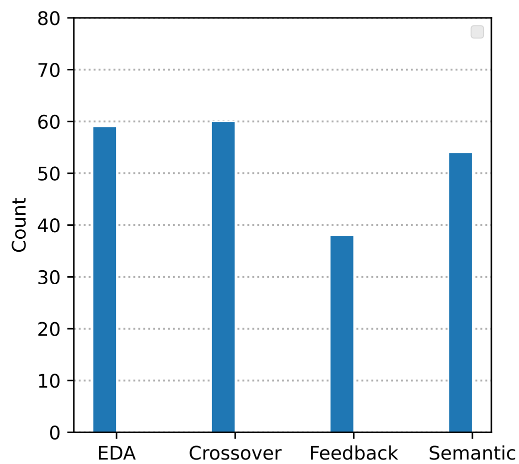

Figure 7: Operator Improvement Count

Analysis: There are two aspects we are particularly interested in. The first is **what the likelihood of performance gain when applying an operator is** (Probability of Improvement), and the second is **how fast each operator can continously bring improvement** (Convergence Speed).

- **Probability Of Improvement**: Figure 7 shows the number of times performance is improved by each operator. Crossover and EDA Mutation introduces improvements in more steps with Semantic Mutation ranking third. Feedback Mutation introduces the least number of improvements. This result helps populate the *Prob* column in table 1.
- **Convergence Speed**: Figure 8 shows that for each operator, as they are applied in 5 consecutive steps, the number of times improvement is introduced for each step. Figure 9 shows the average percentage of performance gain operators brought in each step.
  - For EDA Mutation and Crossover, each 5 step has a similar number of contributions for performance gains as shown in figure 8. From figure 9 we can also observe the first step brings the most improvement and the first 4 steps bring a similar improvement ratio.

- For Feedback Mutation and Semantic Mutation, the first step has a significantly higher chance of introducing improvement as shown in figure 8. This is especially true for Feedback Mutation where step 1 accounts for over 34% of the total improvement counts. As for the improvement ratio, the first step for both Feedback Mutation and Semantic Mutation introduces significantly more improvements than the rest of the steps shown in figure 9.

Based on the tests, we learned that the value gained for applying Feedback Mutation and Semantic Mutation is significantly reduced after the 1st application. We interpret it as **Feedback Mutation and Semantic Mutation can jump to the local minimum pretty fast**, namely in 1 step, thus leading to less possibility of improvement for steps 2 - 5. Whereas for EDA Mutation and Crossover, as they are merging genetic information between candidates, the likelihood of improvement is relatively randomized. So even if the first round of applying them renders no improvement, there is still a chance of performance gain in the following run. In other words, **we should be more patient with EDA Mutation and Crossover**. Thus the operator tolerance (described in section 3.3-design 2) for EDA and Crossover is set to 4 and for Feedback Mutation and Semantic Mutation is 1. These learnings help populate the *Speed* column in table 1.

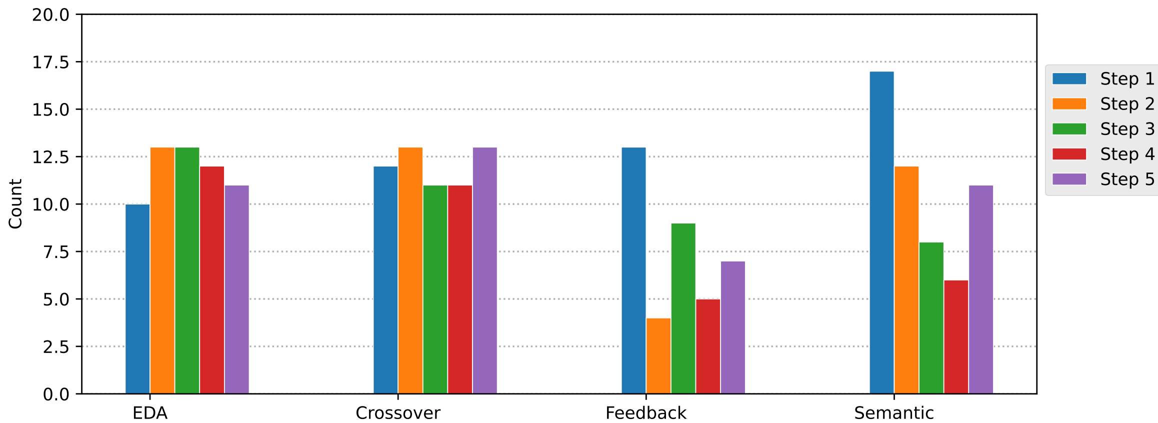

Figure 8: Operator Improvement Pattern: EDA Mutation and Crossover have similar improvement counts for each step whereas for Feedback Mutation and Semantic Mutation, the first step introduced significantly more times of improvement compared to the others.

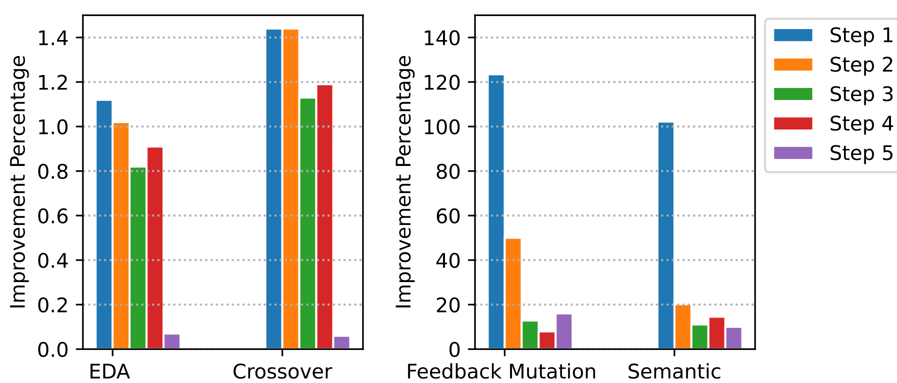

Figure 9: Improvement Ratio: On the left, for EDA and Crossover, we observe an almost equal improvement ratio for the first four steps. Improvement Ratio is defined as the relative percentage of improvement in the average fitness score for the entire population. On the right, for Feedback and Semantic Mutation, we observe the first round contributes significantly more improvement compared to the others. As Feedback and Semantic Mutation take one input candidate, Improvement Ratio is defined as the relative performance improvement percentage for the candidate after mutation.

C. Operator Prompts

Operator Implementation: The state-of-art frameworks such as APO, EVOPROMPT, and AELP have already implemented operators such as feedback operator, crossover operator, and semantic operator with LLM. However, these implementations inflict restrictions on LLM with prompts. For example, in APO when implementing the feedback operator, the prompt specifically identified the use case to be zero-shot. (Pryzant et al., 2023) In EVOPROMPT-DE, when applying crossover operators, the focus is to only mutate the parts that two parents differentiate from each other. (Guo et al., 2023) In AELP, when applying semantic operators, it is restricted to a sentence level, not the whole prompt. (Hsieh et al., 2023). In PHASEEVO, we pay special attention not to apply any restrictions in our mutation prompt, realizing the full potential of LLMs.

Table 10: Lamarckian Mutation Prompt

I gave a friend an instruction and some inputs. The friend read the instruction and wrote an output for every one of the inputs. Here are the input-output pairs: ## Example ## {*input output pairs*} The instruction was:

Table 11: Gradient Descent Generation Prompt: Unlike APO which is also using gradient descent, we are NOT adding restrictions such as *"zero-shot classifier prompt."*, nor providing any differentiation between *instructions* and *examples*. Instead, we specifically ask LLM to output multiple feedback in one go. Also as are passing in the existing prompt as a whole, thus feedback should be on the paragraph/prompt level instead of the sentence/instruction level. We highlight the design that helps us achieve this below.

You are a quick improver. Given an existing prompt and a series of cases where it made mistakes. Look through each case carefully and identify what is causing the mistakes. Based on these observations, output ways to improve the prompts based on the mistakes. ## Existing Prompt ## {*existing prompt*} ## Cases where it gets wrong:## {*wrong cases*} ways to improve the existing prompt based on observations of the mistakes in the cases above are:

Table 12: Gradient Descent Application Prompt: Following the principle of optimizing prompt as a whole, our operator prompts take input and output on the entire prompt level

You are a quick improver. Given an existing prompt and feedback on how it should improve. Create an improved version based on the feedback. ## Existing Prompt ## {*existing prompt*} ## Feedback## {*feedback*} ## Improved Prompt##

Table 13: EDA Prompt

You are a mutator. Given a series of prompts, your task is to generate another prompt with the same semantic meaning and intentions. ## Existing Prompts ## {*existing prompt*} The newly mutated prompt is:

Table 14: EDA+Index Prompt: The difference between EDA + Index and EDA is that EDA + Index takes advantage of the in-context learning technique and informs the order of the passed-in prompts

You are a mutator. Given a series of prompts, your task is to generate another prompt with the same semantic meaning and intentions. The series of prompts are ranked by their quality from best to worst. ## Existing Prompts ## {*existing prompt*} The newly mutated prompt is:

Table 15: Cross Over Prompt

You are a mutator who is familiar with the concept of cross-over in genetic algorithm, namely combining the genetic information of two parents to generate new offspring. Given two parent prompts, you will perform a cross-over to generate an offspring prompt that covers the same semantic meaning as both parents. # Example Parent prompt 1: Now you are a categorizer, your mission is to ascertain the sentiment of the provided text, either favorable or unfavorable Parent prompt 2: Assign a sentiment label to the given sentence from ['negative', 'positive'] and return only the label without any other text. Offspring prompt: Your mission is to ascertain the sentiment of the provided text and assign a sentiment label from ['negative', 'positive']. ## Given ## Parent prompt 1: {*prompt 1*} Parent prompt 2: {*prompt 2*} Offspring prompt:

Table 16: Semantic Mutation Prompt: To provoke LLM's creativity, we do not restrict to the semantic level but expand that to intentions, allowing LLM to not stick to a sentence-by-sentence mutation.

You are a mutator. Given a prompt, your task is to generate another prompt with the same semantic meaning and intentions. # Example: current prompt: Your mission is to ascertain the sentiment of the provided text and assign a sentiment label from ['negative', 'positive']. mutated prompt: Determine the sentiment of the given sentence and assign a label from ['negative', 'positive'].   Given: current prompt: {*existing prompt*} mutated prompt::

D. Details of Experiments

D.1. Baselines

- **APE** (Zhou et al., 2023) uses LLM agent for instruction induction tasks. It proposes forward mode generation and reverse mode generation and uses log probability to generate and evaluate candidates. As it reports the best candidate, we are using the best candidate to compare.
- **APO** (Pryzant et al., 2023) uses feedback provided by LLM as gradients to approach prompt optimization. It uses beam search to find the best candidate. As it reports averaged performance, we are using the averaged performance to compare.
- **PromptBreeder** (Fernando et al., 2023) uses the evolution algorithm to tackle prompt optimization tasks and utilizes thinking styles, and mutation prompts to surface the best task prompt. As it reports the best candidate, we are using the best candidate to compare.
- **AELP** (Hsieh et al., 2023) uses existing prompts (Suzgun et al., 2022b) to target long prompt optimization and improves them by mutating on a sentence level with history-guided search. As it reports averaged performance, we are using the averaged performance to compare.
- **EVOPROMPT** (Guo et al., 2023) uses crossover mutation and semantic mutation with an evolution algorithm to find the best prompt. As it reports the best candidate, we are using the best candidate to compare.
- **OPRO** (Yang et al., 2023a) uses meta prompt, solution-score pairs, and task descriptions to generate candidates. As it reports the best candidate, we are using the best candidate to compare.

D.2. Benchmark tasks

- **24 Instruction Induction Tasks**: These 24 instruction tasks (Honovich et al., 2022) span many facets of language understanding, from simple phrase structure to similarity and causality identification. Both training and testing data are provided for these tasks and we create our training and evaluation data set from the available training data and use the provided testing data set as is. Depending on the task, we use up to 50 training data and up to 50 evaluation data. We use *input output pair* format for these tasks.
- **Ethos**: Ethos (Mollas et al., 2021) is an online English hate speech detection data set with 997 online comments and hate speech labels. We select 50 for training, 50 for evaluation, and 150 for testing. We use *prompt examples* format for this data set following the practice of APO (Pryzant et al., 2023).
- **Liar**: Liar (Wang, 2017) is an English fake news detection data set with 4000 statements, context, and lie labels. We select 50 for training, 50 for evaluation, and 150 for testing. We use *prompt examples* format for this data set following the practice of APO (Pryzant et al., 2023).
- **Sarcasm**: Sarcasm (Farha & Magdy, 2020) is an Arabic sarcasm detection data set with 10,000 online comments and sarcasm labels. We select 50 for training, 50 for evaluation, and 150 for testing. We use *prompt examples* format for this data set following the practice of APO (Pryzant et al., 2023).
- **BBH**: BBH (Aarohi & bench authors, 2023) is a collaborative benchmark that aims to quantitatively measure the capabilities and limitations of language models. We followed the same practice in the AELP paper with the same tasks and randomly selected 50 for training, 50 for evaluation, and 125 for test. (Hsieh et al., 2023)

D.3. PHASEEVO Setting

- **Population Size**: In the experiments, for *phase 0: Global initialization* we set the population size to be 15. For the rest phases, we set the population to be 5.
- **Operator Tolerance**: Based on operator analysis in section B.2, the tolerance for Feedback Mutation and Semantic Mutation is set to 1. The tolerance for EDA Mutation and Crossover is set to 4. Thus the minimum number of times mutation will be applied in *phase 2: global evolution mutation* is 8.
- **Model Configuration**: For operators, we set the temperature to 0.5 to tap into LLM's creativity. For evaluations, we set the temperature to 0.

- **Performance Gain in Stop Criteria**: To improve efficiency, when evaluating performance gain to decide whether we should move to the next phase, we are only looking at the best candidate in the current population.
- **New Generation Selection**: To improve efficiency, after getting new candidates, we combine them with the current generation and use a greedy algorithm to select the top performer to be the new generation.

E. Additional Experiment Results

E.1. 24 Instruction Induction Tasks

Table 17 shows the comparison between APE, PromptBreeder, and PhaseEvo evaluated by the best prompt on 24 instruction induction tasks. PhaseEvo outperforms 21/24 tasks over APE zero shot, 17 / 24 tasks over APE few shot and 18 / 24 tasks on Prompt Breeder. PhaseEvo generated few-shot prompts for 20 / 24 tasks and zero-shot examples for 4 / 24 tasks. For the full set of generated prompts please refer to table 26.

Table 17: 24 Instruction Induction Task in APE

Task	**APE** (zero-shot)	**APE** (few-shot)	**PromptBreeder** (few-shot)	**PhaseEvo-3.5**	**PhaseEvo-4**
Antonyms	0.83	0.86	0.87	**0.89**	**0.91**
Cause Effect	0.84	1	1	0.96	**1**
Common Concept	0.27	**0.32**	0	0.23	0.28
Diff	1	1	1	**1**	**1**
First Word Letter	1	1	1	**1**	**1**
Informal Formal	0.65	**0.70**	0.07	0.6	0.67
Large Animal	0.97	0.97	**0.97**	0.96	0.94
Letters List	0.99	1	0.99	**1**	**1**
Taxonomy Animal	0.66	0.79	1	0.96	**1**
Negation	0.83	0.9	0.9	**0.94**	0.88
Num Verb	1	1	1	**1**	**1**
Active Passive	1	1	1	**1**	**1**
Singular Plural	1	1	1	**1**	**1**
Rhymes	1	0.61	1	**1**	**1**
Second Word Letter	0.87	0.69	0.95	**1**	**1**
Sentence Similarity	0.36	0.43	**0.56**	0.38	0.55
Sentiment	0.94	0.93	0.93	**0.94**	**0.94**

Continuation of Table 17

Continuation of Table 17					
Orthography Starts	0.68	0.69	0.71	**0.72**	**0.94**
Sum	1	1	1	**1**	**1**
Synonym	0.22	0.14	0.43	**0.46**	0.38
Trans En De	0.72	0.86	0.87	0.83	**0.96**
Trans En Es	0.86	0.91	0.91	**0.92**	**0.94**
Trans En Fr	0.78	0.9	0.91	0.88	**0.93**
Word in Context	0.62	0.63	0.65	**0.66**	**0.7**

E.2. BBH Model Comparison

We compare the best prompt obtained from PHASEEVO with gpt-3.5 and gpt-4. For gpt-3.5 we run 3 times and for gpt-4 we run once. PHASEEVO-4 outperforms PHASEEVO-3.5 in all tasks when the inputs are in the same format. However for more difficult tasks, because of the possibility of human-introduced prior knowledge, PHASEEVO-3.5-example outperforms PHASEEVO-4-pair.

Table 18: BBH Model Comparison

Task	PHASEEVO-3.5-pair	PHASEEVO-3.5-example	PHASEEVO-4-pair
Casual Judgement	72.13	**89.09**	75.4
Disambiguation QA	72.13	68,47	**84**
Dyck Language	8.05	**46.77**	36.29
Formal Fallacies	58.87	58.65	**75.31**
Hyperbaton	86.02	87.5	**88.67**
Logical Five	48.19	**82.62**	67.22
Color Reasoning	60.5	80.64	**90.32**
Salient Translation	49.19	47.59	**70.24**

E.3. Generated Prompt Comparison

We notice that the **prompts generated by PHASEEVO are easier to understand by humans.** Below is a comparison between prompts generated for task Rhymes. The task description is: *"Write a word that rhymes with the input word."*

The prompt generated by APE and Instruct Zero does not fit the task. The prompt generated by Prompt Breeder is not easy to understand how it relates to rhyme. The prompt generated by PHASEEVO is easy to understand with few shot examples added.

Table 19: Generated Prompt Comparison for task "Rhymes"

Framework	Generated Prompt
APE	write a function that takes in a string and outputs the string with the first letter capitalized.

Continuation of Table 19

Continuation of Table 19	
Instruct Zero	Write a function that takes a word as input and returns the output word.
Prompt Breeder	Prompt 0: If the last letter of the input is 'e', remove it. Prompt 1: remove the last two letters of the input and add the letters \xc2 \x93mote \xc2 \x94. Contexts Context 0: Q. pea A. If the last letter of the input is 'e', remove it. A. If the last letter of the input is 's', remove it. A. If the last letter of the input is 'y', remove it. A. If the last letter of the input is remove the last two letters of the input and add the letters \xc2 \x93mote \xc2 \x94. Therefore, the correct answer is (a) pea. Context 1: Q. night A. If the last letter of the input is 'e', remove it. A. If the last letter of the input is 't', remove it. A. If the last letter of the input is 'h', remove it. A. If the last letter of the input is remove the last two letters of the input and add the letters \xc2 \x93mote \xc2 \x94. Therefore, the correct answer is (The answer is night. Context 2: Q. add A. If the last letter of the input is 'e', remove it. A. If the last letter of the input is 'd', remove it. A. If the last letter of the input is 'a', remove it. A. If the last letter of the input is remove the last two letters of the input and add the letters \xc2 \x93mote \xc2 \x94. Therefore, the correct answer is (The answer is added.
Continuation of Table 19	

Continuation of Table 19	
PhaseEvo	Create a list of words that rhyme with the given word. To ensure that your rhymes are accurate, make sure that the words have the same vowel sound and ending consonant sound. For example, "cat" rhymes with "bat" and "hat," but not with "dog" or "mat." To get started, here are some examples of words that rhyme with the given word: - Love: dove, glove, above, shove, of - Time: rhyme, chime, climb, mime, prime To find more rhyming words, you can use a rhyming dictionary, online resources, or brainstorm with friends. Be creative and try to use a variety of different rhyming words instead of repeating the same one multiple times. To avoid common pitfalls, make sure to double-check your spelling and pronunciation of the words. Also, avoid using words that only partially rhyme or have a different stress pattern. After you've created your list, ask for feedback on the quality of your rhymes. This can help you to improve and refine your skills. For an added challenge, consider generating rhyming words that fit a particular theme or context. This can help you to focus your creativity and generate more interesting and relevant rhymes.

F. Few-shot Add/ Removal Examples

Below are cases listing examples where few-shot examples are added or removed with PhaseEvo.

F.1. Zero-shot to Few-shot

Table 20: Add Few-shot Example: added examples are highlighted.

Task	Ethos
Input Prompt	Is the following text hate speech? \n ## Output Format ## True or False
Output Prompt	Your task is to evaluate whether the provided input includes any offensive language. This could be language that is sexist, racist, discriminatory, or advocates violence or harm. Offensive language can also be identified by an aggressive or belittling tone. However, remember that the mere presence of profanity does not necessarily make a statement offensive. The context and intention behind the statement should also be taken into account. If none of these conditions are fulfilled, return 'False'. For instance, the phrase "You are a fool" is offensive due to its derogatory tone, so you should return 'True'. On the other hand, the phrase "This is a damn tasty pizza" includes profanity but is not offensive, so you should return 'False'. Similarly, a phrase like "All people of X race are lazy" is offensive because of its racist undertones, so you should return 'True'. In contrast, a phrase like "I dislike the color yellow" is not offensive, so you should return 'False'.

F.2. Zero-shot to Zero-shot

Table 21: Zero-shot to Zero-shot

Task	Ethos
Input Prompt	Is the following text hate speech? \n ## Output Format ## True or False
Output Prompt	Classify the given text as hate speech or not and generate a binary output of 1 for Yes and 0 for No.

F.3. Few-shot to Zero-shot

Table 22: Few-shot to Zero-shot

Task	Hyperbaton
Continuation of Table 22	

Continuation of Table 22	
Input Prompt	Order adjectives correctly in English sentences. Q: Which sentence has the correct adjective order: Options: (A) rubber terrible ship (B) terrible rubber ship A: Let's think step by step. When there is more than one adjective before a noun, the adjectives need to respect the following order before a noun: "[1. opinion] [2. size] [3. age] [4. shape] [5. color] [6. origin] [7. material] [8. purpose] noun". Option (A): "rubber terrible ship". (1) rubber" falls into the material category. (2) "terrible" falls into the opinion category. Option (A) has the following adjective order: [7. material] [1. opinion] (or, in numeric terms, 7 1). Because 7 < 1 is not correct, (A) does not have the correct ordering. Option (B): "terrible rubber ship". Option (B) has the following adjective order: [1. opinion] [7. material] (or, in numeric terms, 1 7). Because 1 < 7 is correct, (B) has the correct ordering. So the answer is (B). Q: Which sentence has the correct adjective order: Options: (A) repulsive small Brazilian exercise ship (B) Brazilian repulsive exercise small ship A: Let's think step by step. When there is more than one adjective before a noun, the adjectives need to respect the following order before a noun: "[1. opinion] [2. size] [3. age] [4. shape] [5. color] [6. origin] [7. material] [8. purpose] noun". Option (A): "repulsive small Brazilian exercise ship". (1) "repulsive" falls into the opinion category. (2) "small" falls into the size category. (3) "Brazilian" falls into the origin category. (4) "exercise" falls into the purpose category. Option (A) has the following adjective order: [1. opinion] [2. size] [6. origin] [8. purpose] (or, in numeric terms, 1 2 6 8). Because 1 < 2 < 6 < 8 is correct, (A) has the correct ordering. Option (B): "Brazilian repulsive exercise small ship". Option (B) has the following adjective order: [6. origin] [1. opinion] [8. purpose] [2. size] (or, in numeric terms, 6 1 8 2). Because 6 < 1 < 8 < 2 is not correct, (B) does not have the correct ordering. So the answer is (A). ...
Output Prompt	Identify the sentence with the correct order of adjectives: opinion, size, age, shape, color, origin, material, purpose.

Table 23: Few-shot to Few-shot

Task	Hyperbaton
Continuation of Table 23	

Continuation of Table 23

Input Prompt	Order adjectives correctly in English sentences. Q: Which sentence has the correct adjective order: Options: (A) rubber terrible ship (B) terrible rubber ship A: Let's think step by step. When there is more than one adjective before a noun, the adjectives need to respect the following order before a noun: "[1. opinion] [2. size] [3. age] [4. shape] [5. color] [6. origin] [7. material] [8. purpose] noun". Option (A): "rubber terrible ship". (1) rubber" falls into the material category. (2) "terrible" falls into the opinion category. Option (A) has the following adjective order: [7. material] [1. opinion] (or, in numeric terms, 7 1). Because 7 < 1 is not correct, (A) does not have the correct ordering. Option (B): "terrible rubber ship". Option (B) has the following adjective order: [1. opinion] [7. material] (or, in numeric terms, 1 7). Because 1 < 7 is correct, (B) has the correct ordering. So the answer is (B). Q: Which sentence has the correct adjective order: Options: (A) repulsive small Brazilian exercise ship (B) Brazilian repulsive exercise small ship A: Let's think step by step. When there is more than one adjective before a noun, the adjectives need to respect the following order before a noun: "[1. opinion] [2. size] [3. age] [4. shape] [5. color] [6. origin] [7. material] [8. purpose] noun". Option (A): "repulsive small Brazilian exercise ship". (1) "repulsive" falls into the opinion category. (2) "small" falls into the size category. (3) "Brazilian" falls into the origin category. (4) "exercise" falls into the purpose category. Option (A) has the following adjective order: [1. opinion] [2. size] [6. origin] [8. purpose] (or, in numeric terms, 1 2 6 8). Because 1 < 2 < 6 < 8 is correct, (A) has the correct ordering. Option (B): "Brazilian repulsive exercise small ship". Option (B) has the following adjective order: [6. origin] [1. opinion] [8. purpose] [2. size] (or, in numeric terms, 6 1 8 2). Because 6 < 1 < 8 < 2 is not correct, (B) does not have the correct ordering. So the answer is (A). ...

Continuation of Table 23

Continuation of Table 23	
Output Prompt	Adjective Order Practice: In English grammar, the order of adjectives is important to convey accurate and effective descriptions. Here are two examples of sentences with adjectives. Determine which sentence has the correct adjective order. Example 1: a) The big, red, round ball bounced down the street. b) The round, red, big ball bounced down the street. Example 2: a) The delicious, homemade, chocolate cake was devoured by the guests. b) The chocolate, homemade, delicious cake was devoured by the guests. Choose the letter of the sentence with the correct adjective order as your answer. Note: Adjective order generally follows the pattern of opinion, size, age, shape, color, origin, material, and purpose. If the adjectives do not fit into this pattern, the order is determined by the speaker's preference. If you choose the incorrect sentence, we will explain why it is wrong to help you learn from your mistakes. Good luck!

G. Generated Prompts

In this section, we list the prompts generated by PhaseEvo with the best performance for each task. All prompts are generated by gpt-3.5. We observe a mix of few-shot prompts and zero-shot prompts for different tasks. This indicates both LLM's ability to perform in-context prompt optimization and PhaseEvo's ability to traverse the whole problem space to find optimal solutions.

We also notice that the few-shot examples in the final prompts are largely generated by LLM instead of copied from example instruction or training sets. Thus it serves as further proof of LLM's capability of in-context prompt optimization and PhaseEvo's credibility in this problem space.

Table 24: BBH Prompts

Causal Judgment	Provide reactions to intentional actions in diverse scenarios, while also considering causation and its complexities. To assist with determining causation, provide specific guidelines and examples for each scenario. To avoid any confusion or misinterpretation, precise language and definitions will be used throughout the prompt. Additionally, feedback from experts and individuals with relevant experience in the field of causation will be incorporated to ensure accuracy and relevance. To challenge users' critical thinking skills, include diverse and complex scenarios that require creative problem-solving and a deeper understanding of causation in various areas of life.
Dyke Languages	Correctly close all brackets, including nested brackets, in the provided sequence in the proper order from innermost to outermost. Mistakes such as forgetting to close a bracket or closing brackets in the wrong order can result in an error. If an error is made, a clear and concise message will indicate which bracket is not properly closed and suggest how to correct it. A visual representation of the correct sequence of closed brackets is provided below: [([( )])] Examples of valid and invalid inputs: Valid input: [( )] Valid input: [([ ])] Invalid input: [([ )] Warning message: The bracket at position 8 is not properly closed. Please close the bracket to ensure proper syntax. Suggested correction: [([ ])] Invalid input: [([ ])] Warning message: The bracket at position 8 is not properly closed. Please close the bracket to ensure proper syntax. Suggested correction: [([ ])]
Formal Fallacies	Read the given argument carefully and determine whether it is deductively valid or invalid based on the explicitly stated premises. Provide a justification for your answer.
Disambiguation QA	For each sentence with a gender-neutral pronoun, determine the antecedent or state if it is ambiguous. Use (A) for the first option, (B) for the second option, or (C) for ambiguous. Additionally, provide an explanation of the antecedent (the person or thing the pronoun refers to) for each sentence.

Continuation of Table 24

Continuation of Table 24	
Hyperbaton	Test your knowledge of adjective order in English sentences with interactive exercises and quizzes. Learn the rule of opinion-size-age-shape-color-origin-material-purpose noun and apply it to different types of nouns such as animals, objects, and people. Practice constructing your own sentences and receive feedback on incorrect answers to improve your skills. By the end of this exercise, you'll be able to confidently order adjectives and communicate accurately in English.
Continuation of Table 24	

Continuation of Table 24	
Logical Deduction Five	On a plate, there are three fruits: a red apple, a yellow banana, and a green pear. The banana is positioned to the immediate left of the apple, meaning there are no other fruits between them. The pear is the rightmost fruit, meaning it comes last in the order. Which of the following statements is true? (A) The red apple is the leftmost fruit. (B) The yellow banana is the leftmost fruit. (C) The green pear is the leftmost fruit. Explanation: To solve this prompt, pay attention to the precise language used to describe the relationships between the fruits and their positions in the order. The banana is to the immediate left of the apple, meaning it is directly adjacent to it and there are no other fruits between them. The pear is the rightmost fruit, meaning it comes last in the order. Therefore, the correct answer is (B) The yellow banana is the leftmost fruit. To further practice this concept, here are some additional examples: 1. On a plate, there are three different colored balls: a blue ball, a red ball, and a green ball. The red ball is directly to the left of the blue ball, meaning there are no other balls between them. The green ball is the rightmost. Which of the following statements is true? (A) The blue ball is the leftmost ball. (B) The red ball is the leftmost ball. (C) The green ball is the leftmost ball. 2. In a row of three houses, there is a blue house, a yellow house, and a green house. The blue house is in the middle, and the yellow house is directly to the left of the green house, meaning there are no other houses between them. Which of the following statements is true? (A) The blue house is the leftmost house. (B) The yellow house is the leftmost house. (C) The green house is the leftmost house. Feedback: If you selected the wrong answer, here's why: (A) The red apple is not the leftmost fruit. The yellow banana is directly to its left. (C) The green pear is not the leftmost fruit. The banana and the apple come before it in the order. To avoid confusion, use precise language to describe the relationships between objects and their positions in the order. Avoid using vague terms like "newer" or "older" without specifying their exact relationship to other objects in the order. Provide more context or details to help clarify any ambiguities in the prompt. Make sure the order of the objects is clearly defined and consistent throughout the prompt.
Continuation of Table 24	

Continuation of Table 24	
Reasoning Colored Objects	Identify the color of objects arranged in a row on a surface. Q: On the desk, there is a black stapler, a green highlighter, a yellow ruler, a blue pen, and a purple marker. What color is the pen? Options: (A) red (B) orange (C) yellow (D) green (E) blue (F) brown (G) magenta (H) fuchsia (I) mauve (J) teal (K) turquoise (L) burgundy (M) silver (N) gold (O) black (P) grey (Q) purple (R) pink A: Let's think step by step. According to this question, the objects are arranged in a row, from left to right, as follows: (1) a black stapler, (2) a green highlighter, (3) a yellow ruler, (4) a blue pen, and (5) a purple marker. The pen is the fourth item on the list, namely (4). The color of the pen is blue. So the answer is (E).
Salient Translation Error Detection	Read the following translations from German to English and identify the type of error present in each one. The error can be one of the following types: Named Entities, Numerical Values, Modifiers or Adjectives, Negation or Antonyms, Facts, or Dropped Content. Write the corresponding letter for each error type in the options provided. For example: Source: Der Hund ist braun. Translation: The cat is brown. The translation contains an error pertaining to: Options: (A) Modifiers or Adjectives (B) Numerical Values (C) Negation or Antonyms (D) Named Entities (E) Dropped Content (F) Facts Output: (D)
Continuation of Table 24	

Continuation of Table 24

Causal Judgment	Provide reactions to intentional actions in diverse scenarios, while also considering causation and its complexities. To assist with determining causation, provide specific guidelines and examples for each scenario. To avoid any confusion or misinterpretation, precise language and definitions will be used throughout the prompt. Additionally, feedback from experts and individuals with relevant experience in the field of causation will be incorporated to ensure accuracy and relevance. To challenge users' critical thinking skills, include diverse and complex scenarios that require creative problem-solving and a deeper understanding of causation in various areas of life.
Dyke Languages	Correctly close all brackets, including nested brackets, in the provided sequence in the proper order from innermost to outermost. Mistakes such as forgetting to close a bracket or closing brackets in the wrong order can result in an error. If an error is made, a clear and concise message will indicate which bracket is not properly closed and suggest how to correct it. A visual representation of the correct sequence of closed brackets is provided below: [([( )])] Examples of valid and invalid inputs: Valid input: [( )] Valid input: [([ ])] Invalid input: [([ )] Warning message: The bracket at position 8 is not properly closed. Please close the bracket to ensure proper syntax. Suggested correction: [([ ])] Invalid input: [([ ])] Warning message: The bracket at position 8 is not properly closed. Please close the bracket to ensure proper syntax. Suggested correction: [([ ])]
Formal Fallacies	Read the given argument carefully and determine whether it is deductively valid or invalid b5rased on the explicitly stated premises. Provide a justification for your answer.
Disambiguation QA	For each sentence with a gender-neutral pronoun, determine the antecedent or state if it is ambiguous. Use (A) for the first option, (B) for the second option, or (C) for ambiguous. Additionally, provide an explanation of the antecedent (the person or thing the pronoun refers to) for each sentence.
Hyperbaton	Test your knowledge of adjective order in English sentences with interactive exercises and quizzes. Learn the rule of opinion-size-age-shape-color-origin-material-purpose noun and apply it to different types of nouns such as animals, objects, and people. Practice constructing your own sentences and receive feedback on incorrect answers to improve your skills. By the end of this exercise, you'll be able to confidently order adjectives and communicate accurately in English.

Continuation of Table 24

Continuation of Table 24	
Logical Deduction Five	On a plate, there are three fruits: a red apple, a yellow banana, and a green pear. The banana is positioned to the immediate left of the apple, meaning there are no other fruits between them. The pear is the rightmost fruit, meaning it comes last in the order. Which of the following statements is true? (A) The red apple is the leftmost fruit. (B) The yellow banana is the leftmost fruit. (C) The green pear is the leftmost fruit. Explanation: To solve this prompt, pay attention to the precise language used to describe the relationships between the fruits and their positions in the order. The banana is to the immediate left of the apple, meaning it is directly adjacent to it and there are no other fruits between them. The pear is the rightmost fruit, meaning it comes last in the order. Therefore, the correct answer is (B) The yellow banana is the leftmost fruit. To further practice this concept, here are some additional examples: 1. On a plate, there are three different colored balls: a blue ball, a red ball, and a green ball. The red ball is directly to the left of the blue ball, meaning there are no other balls between them. The green ball is the rightmost. Which of the following statements is true? (A) The blue ball is the leftmost ball. (B) The red ball is the leftmost ball. (C) The green ball is the leftmost ball. 2. In a row of three houses, there is a blue house, a yellow house, and a green house. The blue house is in the middle, and the yellow house is directly to the left of the green house, meaning there are no other houses between them. Which of the following statements is true? (A) The blue house is the leftmost house. (B) The yellow house is the leftmost house. (C) The green house is the leftmost house. Feedback: If you selected the wrong answer, here's why: (A) The red apple is not the leftmost fruit. The yellow banana is directly to its left. (C) The green pear is not the leftmost fruit. The banana and the apple come before it in the order. To avoid confusion, use precise language to describe the relationships between objects and their positions in the order. Avoid using vague terms like "newer" or "older" without specifying their exact relationship to other objects in the order. Provide more context or details to help clarify any ambiguities in the prompt. Make sure the order of the objects is clearly defined and consistent throughout the prompt.

Continuation of Table 24

Continuation of Table 24	
Reasoning Colored Objects	Identify the color of objects arranged in a row on a surface. Q: On the desk, there is a black stapler, a green highlighter, a yellow ruler, a blue pen, and a purple marker. What color is the pen? Options: (A) red (B) orange (C) yellow (D) green (E) blue (F) brown (G) magenta (H) fuchsia (I) mauve (J) teal (K) turquoise (L) burgundy (M) silver (N) gold (O) black (P) grey (Q) purple (R) pink A: Let's think step by step. According to this question, the objects are arranged in a row, from left to right, as follows: (1) a black stapler, (2) a green highlighter, (3) a yellow ruler, (4) a blue pen, and (5) a purple marker. The pen is the fourth item on the list, namely (4). The color of the pen is blue. So the answer is (E).
Continuation of Table 24	

Continuation of Table 24	
Salient Translation Error Detection	Read the following translations from German to English and identify the type of error present in each one. The error can be one of the following types: Named Entities, Numerical Values, Modifiers or Adjectives, Negation or Antonyms, Facts, or Dropped Content. Write the corresponding letter for each error type in the options provided. For example: Source: Der Hund ist braun. Translation: The cat is brown. The translation contains an error pertaining to: Options: (A) Modifiers or Adjectives (B) Numerical Values (C) Negation or Antonyms (D) Named Entities (E) Dropped Content (F) Facts Output: (D)

Table 25: APO Prompts

Ethos	Does the provided text contain hate speech? Return a boolean value of True or False.
Liar	Analyze the context and other information provided to determine the truthfulness of the statement. To do so, consider the following guidelines: 1. Identify key sources of information, such as reputable news outlets or government reports, and consider the credibility of the sources. Look for corroborating evidence and consider any potential biases or conflicts of interest. 2. Conduct additional research or seek out expert opinions when necessary to determine the truthfulness of a statement. Use resources or links to relevant information provided, and consider consulting with subject matter experts or fact-checking organizations. 3. Note that the determination of truthfulness may not always be possible based on the information provided, and that additional research or analysis may be required. Use your best judgment and be transparent about any uncertainties or limitations in your analysis. 4. Consider specific examples or scenarios to help you apply the prompt in different contexts. For instance, you might analyze a political statement, a scientific claim, or a news article. Be aware of common pitfalls or errors, such as relying on unreliable sources or failing to consider alternative explanations. Output Format: Assign 0 for true and 1 for false. Note that this determination is based on the information provided and may not be definitive.
Sarcasm	Determine if the input contains any language that could be considered derogatory or discriminatory towards a particular group based on their race, ethnicity, gender, sexual orientation, religion, or any other protected characteristic. If such language is found, output True. If not, output False. The prompt should be trained on a diverse dataset to improve its accuracy and reduce errors.

Table 26: APE Prompts

Antonyms	"Provide a list of adjectival antonyms for each of these words, keeping in mind the given context:" ## Input ##: hot (in the context of weather) ## Output ##: ['cold', 'cool', 'chilly'] ## Input ##: happy (in the context of emotions) ## Output ##: ['sad', 'unhappy', 'depressed', 'miserable'] ## Input ##: big (in the context of size) ## Output ##: ['small', 'tiny', 'little', 'miniature'] ## Input ##: fast (in the context of speed) ## Output ##: ['slow', 'sluggish', 'leisurely', 'gradual'] ## Input ##: old (in the context of age) ## Output ##: ['young', 'new', 'fresh', 'modern']
Cause Effect	Determine the sentence that is the cause in each pair. Remember to thoroughly comprehend the meaning of each sentence before selecting the cause. Additionally, verify your output to ensure that you only include the sentence that is the cause. To aid in identifying cause and effect relationships, consider using keywords or phrases that indicate causality, analyzing the context of each sentence, and practicing with feedback and interactive activities.
Common Concept	For each input, come up with a category or characteristic that they have in common and write it as the output. Use your knowledge and experience to make educated guesses and be creative in your thinking. Also, try to keep the output concise and clear.
Diff	Subtract the second number from the first number and give me the result. Make sure to double check your calculations and write the answer as a string in a list format.

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Continuation of Table 26	
First Word Letter	Write a program that takes in a word and returns a list containing the first letter of the word as a string. The program will be used to label items in a game. Make sure to handle cases where the input word is empty or only contains whitespace. You can use the string method ‘strip()‘ to remove any leading or trailing whitespace. If the input is empty or contains only whitespace, return an empty list. To ensure that your program works correctly, test it with the following examples: Example 1: Input: "apple" Output: ["a"] Example 2: Input: " banana" Output: ["b"] Example 3: Input: "" Output: [] Example 4: Input: " " Output: []
Informal Formal	Reword the following sentences using more formal language, but also provide alternative rewordings that are more appropriate for different contexts: 1. "Regrettably, I am unable to attend the meeting tomorrow." (formal) Alternative: "Unfortunately, I won’t be able to make it to the meeting tomorrow." (casual) 2. "I must depart now, farewell!" (overly formal) Alternative: "I have to go now, see you later!" (casual) 3. "I apologize, but I am unable to assist you with that matter." (formal) Alternative: "I’m sorry, but I can’t help you with that." (casual) 4. "Thank you for the invitation, however, I am unable to attend." (formal) Alternative: "Thanks for inviting me, but I can’t make it." (casual) 5. "In my opinion, this is the optimal choice." (formal) Alternative: "I think this is the best option." (casual)
Continued next page for Table 26	

Continuation of Table 26

Large Animal	Choose one animal as the output based on its size. For example, if the input pair is "elephant, mouse", choose "elephant" as the output. If the input pair is "giraffe, lion", choose "giraffe" as the output. Use the following criteria to choose the output: - If one animal is significantly larger than the other, choose the larger animal as the output. - If the animals are similar in size, choose the animal with the name that comes first alphabetically as the output. Here are some examples of correct outputs: - "whale, dolphin" -> choose "whale" as the output - "panda, koala" -> choose "panda" as the output - "tiger, zebra" -> choose "tiger" as the output Choose the output carefully to avoid confusion and errors.
Letters List	Please write a program that takes in a word as input and outputs a list of its letters separated by spaces. The output should be a list with one element containing the separated letters in the same order as the input word. To ensure the program works correctly, please follow these guidelines: 1. Input validation: Check that the input is a non-empty string containing only alphabetic characters. If the input is invalid, print an error message and exit the program. 2. Separating the letters: Use the ‘split()‘ method to separate the letters of the input word. 3. Expected output format: The output should be a list with one element containing the separated letters in the same order as the input word. Here are some examples of valid and invalid input: Valid input: "hello" Expected output: ["h", "e", "l", "l", "o"] Invalid input: "hello world" Expected output: "Error: Input must be a non-empty string containing only alphabetic characters." Invalid input: "123" Expected output: "Error: Input must be a non-empty string containing only alphabetic characters."

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Continuation of Table 26	
Taxonomy Animal	"List all the animals from the given inputs." ## Input ##: apple, banana, orange, kiwi, grape ## Output ##: [] ## Input ##: dog, cat, fish, bird, hamster ## Output ##: ['dog', 'cat', 'fish', 'bird', 'hamster'] ## Input ##: elephant, giraffe, lion, tiger, zebra ## Output ##: ['elephant', 'giraffe', 'lion', 'tiger', 'zebra'] ## Input ##: pencil, eraser, notebook, ruler, pen ## Output ##: [] ## Input ##: turtle, snake, lizard, frog, salamander ## Output ##: ['turtle', 'snake', 'lizard', 'frog', 'salamander']
Negation	For each input, negate the specified part of the statement and write it as an output. 1. Negate the part about using the gold color: "We will use gold as the primary color for our new logo." Output: "We will not use gold as the primary color for our new logo." 2. Negate the part about Gary Kubiak participating as a player: "Gary Kubiak will play as a quarterback in the upcoming game." Output: "Gary Kubiak will not play as a quarterback in the upcoming game." Note: When negating statements with proper nouns or names, simply negate the verb or action associated with the noun or name.
Num Verbal	Convert a given number into its English word representation, including commas for thousands and negative sign if applicable. ## Input 1 ## : 1234 ## Output 1 ##: ['one thousand two hundred and thirty-four'] ## Input 2 ## : 987654321 ## Output 2 ##: ['nine hundred and eighty-seven million six hundred and fifty-four thousand three hundred and twenty-one'] ## Input 3 ## : 0 ## Output 3 ##: ['zero'] ## Input 4 ## : -42 ## Output 4 ##: ['negative forty-two'] ## Input 5 ##: 999999999 ## Output 5 ##: ['nine hundred and ninety-nine million nine hundred and ninety-nine thousand nine hundred and ninety-nine']

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Continuation of Table 26	
Active Passive	Passive Voice Practice: In passive voice, the subject of the sentence receives the action instead of performing it. Rewrite each sentence in passive voice. Example: The dog chased the cat. Passive voice: The cat was chased by the dog 1. The teacher graded the exams. 2. The company launched a new product. 3. The chef cooked a delicious meal. 4. The team won the championship. 5. The doctor prescribed medication for the patient. Instructions: - Rewrite each sentence in passive voice. - Make sure the subject of the sentence receives the action instead of performing it. - Use the examples provided to guide you. - Check your work for accuracy and clarity. Feedback: - If you have any questions or need clarification, please ask. - Practice makes perfect! Keep practicing to improve your writing skills. - If you make any mistakes, don't worry! Learn from them and try again

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Continuation of Table 26

Singular Plural	Add an "s" or the correct plural form to the end of the input word, depending on the following rules: 1. If the word ends in "y" with a consonant before it, change the "y" to "ies" instead of just adding an "s". 2. If the word ends in "f" or "fe", change the "f" or "fe" to "ves" instead of just adding an "s". 3. If the word is already plural, return the input word as is instead of adding an "s". 4. If the word has an irregular plural form, return the correct plural form instead of just adding an "s". Examples: - Input: cat Output: cats - Input: book Output: books - Input: car Output: cars - Input: tree Output: trees - Input: computer Output: computers - Input: story Output: stories - Input: half Output: halves - Input: aircraft Output: aircraft - Input: century Output: centuries

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Continuation of Table 26

Rhymes	Create a list of words that rhyme with the given word. To ensure that your rhymes are accurate, make sure that the words have the same vowel sound and ending consonant sound. For example, "cat" rhymes with "bat" and "hat," but not with "dog" or "mat." To get started, here are some examples of words that rhyme with the given word: - Love: dove, glove, above, shove, of - Time: rhyme, chime, climb, mime, prime To find more rhyming words, you can use a rhyming dictionary, online resources, or brainstorm with friends. Be creative and try to use a variety of different rhyming words instead of repeating the same one multiple times. To avoid common pitfalls, make sure to double-check your spelling and pronunciation of the words. Also, avoid using words that only partially rhyme or have a different stress pattern. After you've created your list, ask for feedback on the quality of your rhymes. This can help you to improve and refine your skills. For an added challenge, consider generating rhyming words that fit a particular theme or context. This can help you to focus your creativity and generate more interesting and relevant rhymes.
Second Word Letter	For each input word with at least two letters, identify and output the second letter. Please ensure that the input is a valid word in the specified language or dialect to prevent errors. The prompt is case-insensitive, so it will work for both uppercase and lowercase letters. Examples: - Input: "hello" Output: "e" - Input: "apple" Output: "p" - Input: "book" Output: "o" Please note that the language or dialect of the input should be specified to avoid confusion with words that have different spellings or pronunciations in different regions.

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Continuation of Table 26

Sentence Similarity	Rate the similarity of two given sentences on a scale of 1 to 5, where 1 indicates a significant difference in meaning and 5 indicates almost identical meaning. Please consider the following factors when rating: - The overall message and purpose of the sentences - The structure and syntax of the sentences - The use of key words and phrases Provide a brief explanation for your rating, taking into account any minor differences in wording or details that may affect the similarity rating. Additionally, please provide context for the sentences being compared, such as the intended audience or purpose. For reference, here are some examples of sentences that fall into each category: Highly similar: "The cat sat on the mat" and "The mat was sat on by the cat" Moderately similar: "I enjoy playing soccer" and "Soccer is a fun sport to play" Not similar at all: "The sky is blue" and "I am going to the beach tomorrow" Thank you for your evaluation and explanation.
Sentiment	Please analyze the following statements and determine their overall sentiment as either ['negative', 'neutral', 'positive']. Keep in mind the context and any figurative language used. 1. The sun is shining and the birds are singing. Output: ['positive'] 2. I failed my exam and now I have to retake the class. Output: ['negative'] 3. My best friend surprised me with a thoughtful gift. Output: ['positive'] 4. The traffic on the highway was backed up for miles. Output: ['negative'] 5. I received a promotion at work and a raise in salary. Output: ['positive'] 6. A non-mystery mystery. Output: ['neutral'] 7. Little more than a well-mounted history lesson. Output: ['neutral'] 8. Too daft by half ... but supremely good natured. Output: ['positive'] Note: This prompt uses more sophisticated language analysis techniques to better understand the sentiment of the input. However, providing more context for the input is still important for accurate sentiment analysis.

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Continuation of Table 26

Orthography Starts With	SIdentify the first word or phrase that starts with the letter given in the input. The identified word or phrase should not contain any punctuation or special characters, and should be case-insensitive. If there are no words or phrases starting with the given letter, return an empty list. Here are the input-output pairs: Input: She sang a beautiful song to the audience. [b] Output: ['beautiful'] Input: The cat chased the mouse. [c] Output: ['cat'] Input: It is important to always be kind to others. [i] Output: ['important'] Input: The dog barked loudly, frightening the neighbors. [l] Output: ['loudly'] Input: The book is on the shelf. [s] Output: ['shelf'] Input: The baby cried all night. [n] Output: [] Input: The teacher gave a long lecture on the history of art. [l] Output: ['lecture'] Input: The car drove down the street, passing by many shops. [s] Output: ['street'] Input: To the boy's delight, he received a new toy for his birthday. [t] Output: ['toy'] Note: If there are multiple words or phrases starting with the given letter, the prompt will return the first one encountered. If the input contains multiple sentences or clauses, the prompt will identify the first word or phrase that starts with the given letter in the entire input text. The output will be in lowercase
Sum	"Write a program that takes two numbers as input and returns their sum as a string in a list. Make sure to test your program with different inputs to ensure it works correctly. Remember to convert the input numbers to integers before adding them together, and then convert the sum back to a string before putting it in a list. Also, make sure to use the correct syntax for creating a list with one element (i.e. use square brackets around the string). Good luck!"

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Continuation of Table 26

Synonym	Please provide a list of synonyms for the given words that convey a similar meaning and are commonly used in everyday language. Be sure to double-check your spelling and grammar before submitting. For example, if the word is "happy," acceptable synonyms could be "joyful," "pleased," or "content." Please use gender-neutral language and avoid using words with different connotations or meanings. If you notice any incorrect synonyms, please flag them and provide feedback for improvement. Words to avoid using as synonyms include those with different connotations or meanings, such as "ecstatic" for "happy" or "depressed" for "sad."
Trans En De	Translate the following English words into German. ## Input ## : happy ## Output ##: ['glücklich'] ## Input ## : love ## Output ##: ['Liebe'] ## Input ## : cat ## Output ##: ['Katze'] ## Input ## : dog ## Output ##: ['Hund'] ## Input ## : house ## Output ##: ['Haus'] ## Input ## : tree ## Output ##: ['Baum'] ## Input ## : water ## Output ##: ['Wasser'] ## Input ## : sun ## Output ##: ['Sonne'] ## Input ## : moon ## Output ##: ['Mond'] ## Input ## : star ## Output ##: ['Stern']
Trans En Es	Convert these English terms into their corresponding Spanish translations. ## Input ## : happy ## Output ##: ['feliz'] ## Input ## : beach ## Output ##: ['playa'] ## Input ## : computer ## Output ##: ['computadora'] ## Input ## : book ## Output ##: ['libro'] ## Input ## : music ## Output ##: ['música']

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Continuation of Table 26	
Trans En Fr	Translate the following English words into French. ## Input ## : happy ## Output ##: ['heureux'] ## Input ## : love ## Output ##: ['amour'] ## Input ## : family ## Output ##: ['famille'] ## Input ## : friend ## Output ##: ['ami'] ## Input ## : music ## Output ##: ['musique'] ## Input ## : beach ## Output ##: ['plage'] ## Input ## : book ## Output ##: ['livre'] ## Input ## : movie ## Output ##: ['film'] ## Input ## : food ## Output ##: ['nourriture'] ## Input ## : travel ## Output ##: ['voyage']
Word In Context	Compare the usage of a given word in two different sentences and determine if they have the same or different meanings based on the context of the sentences. Write "same" or "not the same" as the output. To avoid ambiguity and ensure clarity, please provide sufficient context for the sentences. If the word has multiple meanings depending on the context, please indicate all correct answers. For example, consider the word "bank." In the sentence "I need to deposit my paycheck at the bank," and "I sat on the bank of the river and watched the sunset," the word "bank" has different meanings. Therefore, the correct answer would be "not the same." Please note that the comparison should be based on the context of the sentences, not just the isolated word