TAG-INSTRUCT: Controlled Instruction Complexity Enhancement Through Structure-Based Augmentation

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Abstract

High-quality instruction data is crucial for developing large language models (LLMs), yet existing approaches struggle to effectively control instruction complexity. We present TAG-INSTRUCT, a novel framework that enhances instruction complexity through structured semantic compression and controlled difficulty augmentation. Unlike previous prompt-based methods operating on raw text, TAG-INSTRUCT compresses instructions into a compact tag space and systematically enhances complexity through RL-guided tag expansion. Through extensive experiments, we show that TAG-INSTRUCT outperforms existing instruction complexity augmentation approaches. Our analysis reveals that operating in tag space provides superior controllability and stability across different instruction synthesis frameworks.

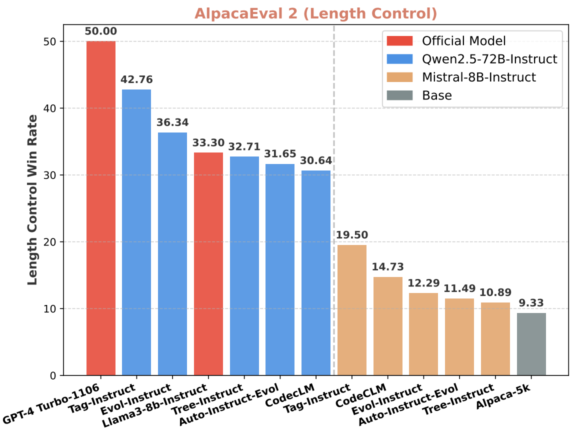

Figure 1: AlpacaEval 2 Length Control Win Rate. TAG-INSTRUCT achieves the highest win rate among all compared methods. Red bars represent official released models. For other methods, all are fine-tuned on LLaMA3-8B base model, where blue, orange, and gray bars represent methods using Qwen2.5-72B-Instruct as teacher model, methods using Mistral-8B-Instruct as teacher model, and base model respectively. Evaluated using **GPT-4o-Mini**.

1 Introduction

Large language models (LLMs) have demonstrated remarkable success across diverse tasks (OpenAI et al., 2024; Grattafiori et al., 2024; Qwen et al., 2024; DeepSeek-AI et al., 2024), from natural language understanding (Abdin et al., 2024) to complex reasoning (Guo et al., 2025; Yang et al., 2024a). To fully realize their potential, these models require high-quality instruction-tuning data, which plays a crucial role in model post-training and reinforcement learning initialization (Zhou et al., 2023; Ye et al., 2025; Rafailov et al., 2024). This recognition has led to extensive research in instruction data synthesis (Wang et al., 2023; Chung et al., 2022; Xu et al., 2024).

While recent work has made progress in synthetic data generation (Zhu et al., 2024; Xu et al., 2024), current instruction datasets still lack sufficient complexity to fully develop model capabilities (Xu et al., 2023). Studies show that model performance strongly correlates with instruction difficulty (Zhao et al., 2023, 2024), yet existing approaches struggle to effectively control and scale instruction difficulty. Specifically, Xu et al. (2023) and its follow-up works (Wang et al., 2024b; Zeng et al., 2024) rely on models' prior knowledge for self-reflection on augmentation directions, typically using prompts to directly generate "harder" instructions. However, this approach lacks precise control over difficulty progression, as the concept of "harder" remains ambiguous and unquantifiable, making it challenging to systematically guide the augmentation process. While Zhao et al. (2023) attempts to address this by discretizing instructions into semantic trees for manipulation, it still struggles to identify which semantic components are worth augmenting and how to effectively guide the augmentation direction. We name these approaches as *Prompt-based Augmentation*, which face two fundamental challenges: (1) difficulty in

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Findings of the Association for Computational Linguistics: ACL 2025, pages 17708–17729
July 27 - August 1, 2025

identifying which semantic components are worth augmenting, and (2) lack of principled guidance on which augmentation direction would lead to meaningful complexity increases.

From a linguistic perspective, instructions contain both essential semantic components with high information density and auxiliary content that merely contributes to fluency (Kemp et al., 2018). This observation reveals why *Prompt-based Augmentation* struggles - by operating directly on raw instructions, it works in an unnecessarily complex search space that includes both essential and auxiliary content. To address these challenges, we propose *Structure-based Augmentation*, drawing inspiration from representation learning in Variational Autoencoders (VAEs) (Kingma and Welling, 2013; An et al., 2024). Our key insight is that by compressing instructions into a structured tag space, we can (1) identify valuable semantic components by focusing only on essential information, and (2) guide augmentation direction by quantitatively measuring each tag's contribution to instruction complexity. This transforms the augmentation problem from unstructured token-level modifications to systematic concept-level operations (team et al., 2024).

Building on this intuition, we propose TAG-INSTRUCT, a novel **Compress & Operation** framework for controlled difficulty augmentation. Our framework operates through a three-stage iterative pipeline: (1) semantic encoding that compresses instructions into a compact tag representation while preserving task-relevant information, (2) RL-based tag expansion that explores the tag space to discover new semantic tags that meaningfully increase complexity. (3) instruction synthesis that generates enhanced instructions by conditioning on both the expanded tag set and original instruction. This iterative process enables progressive difficulty increases while maintaining semantic coherence.

Extensive experiments demonstrate the effectiveness of TAG-INSTRUCT across diverse settings. Using Alpaca-5k (Taori et al., 2023) as the base dataset, our method enables LLaMA-3-8B to achieve performance comparable to GPT-4-Turbo on standard benchmarks, significantly outperforming existing instruction augmentation approaches. Through detailed ablation studies, we verified that operating in tag space provides superior controllability and makes different instruction synthesis frameworks more stable and effective.[1]

2 Related Work

Instruction Data Augmentation High-quality instruction data is fundamental for model alignment and performance (Grattafiori et al., 2024; Nvidia et al., 2024). For instruction synthesis from scratch, Wang et al. (2023) proposed automatic generation through bootstrapping from human demonstrations, though constrained by seed data. Xu et al. (2024) advanced this by introducing pre-query templates for direct instruction construction, while Zhu et al. (2024) improved data quality using tagging-based prompts and UCB-based bootstrapping. Ge et al. (2024) introduced a persona-driven approach using 1 billion diverse personas from web data to create synthetic instructions at scale. For instruction enhancement based on existing data, several methods focus on difficulty progression: Xu et al. (2023) and Zeng et al. (2024) explored evolutionary approaches for iterative complexity increase, Zhao et al. (2023) proposed semantic tree structures for controlled augmentation, and Wang et al. (2024b) leveraged encode-decode principles. However, existing enhancement methods still lack precise control (especially numerical parameterization) over difficulty progression, motivating our structured tag-based approach.

Information Compression in Hidden Space Drawing inspiration from variational autoencoders (Kingma and Welling, 2022) which learn disentangled latent representations, researchers have investigated diverse approaches to compress instructions into abstract spaces to enhance semantic understanding. One prominent direction focuses on morphological abstraction, where instructions are systematically decomposed into skill-oriented tags and hierarchical concepts (Lu et al., 2023; Didolkar et al., 2024; Kaur et al., 2024; Wang et al., 2024b; team et al., 2024). Another stream of research explores functional compression by transforming complex problem-solving procedures into executable representations, such as programmatic structures or formal planning schemas (Zheng et al., 2024a; Wang et al., 2024a; Yu et al., 2024). Complementing these approaches, researchers have also investigated continuous latent space mappings of symbolic instructions to capture underlying semantic regularities and logical relationships (An et al.,

[1]Our code is publicly available at https://github.com/sustech-nlp/Tag-Instruct.

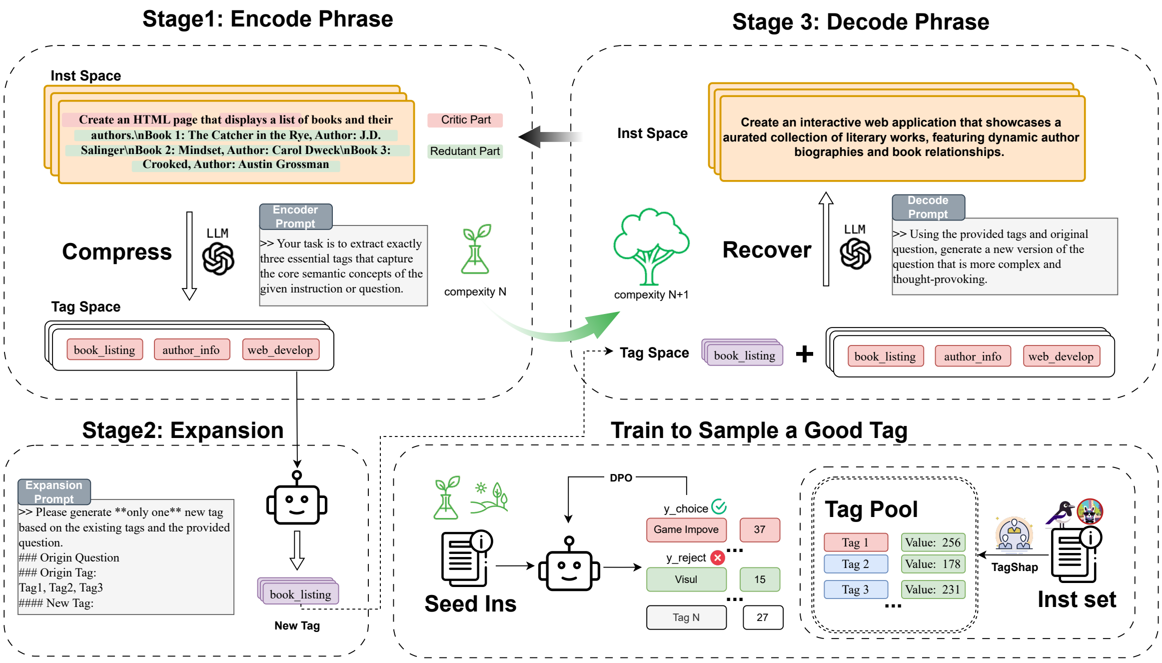


Figure 2: Overview of Tag-Instruct framework. The framework operates in three stages: (1) **Encode Phrase**: Semantic Encoding compresses instructions into tag representations, (2) **Expansion**: Controlled Tag Expansion explores the tag space to increase complexity while maintaining semantic coherence through iterative difficulty augmentation, and (3) **Decode Phrase**: Instruction Synthesis generates enhanced instructions from the expanded tag set. The iterative process allows for progressive difficulty increases while preserving semantic validity.

2024; Hao et al., 2024). The demonstrated efficacy of these compression-based abstraction techniques motivates our work to leverage structured latent representations for controlled instruction generation. Recent information compression works like Kaur et al. (2024) and Didolkar et al. (2024) focus on instruction synthesis from scratch, which is orthogonal to our controlled difficulty augmentation approach. While prior work (Wang et al., 2024b) directly decodes from compressed metadata after self-observation (Self-Rubrics and action sampling), our approach uniquely operates in tag space for tag complexity enhancement before instruction reconstruction, enabling more controlled instruction generation.

Data Quality Investigation Recent works have extensively explored what constitutes high-quality instruction data for large language models. Early approaches by Liu et al. (2023a) and Du et al. (2023) utilize fine-tuned models and specialized open-source LLMs for data quality assessment. Following works by Cao et al. (2023) and Wettig et al. (2024) propose automatic metrics to evaluate data quality through natural language indicators. Several studies by Zhao et al. (2024) reveal a surprisingly simple yet effective finding that longer responses often contain more learnable information. Other approaches by Xia et al. (2024) and Li et al. (2024a) introduce optimizer-aware selection and instruction difficulty metrics to identify high-quality samples. Recent work by Yang et al. (2024b) further emphasizes the importance of distribution alignment between fine-tuning data and the model's original capabilities. These studies collectively indicate that high-quality instruction data should be difficult, human-preference-aligned, and close to the pre-trained model's distribution – properties that often manifest in longer responses. This observation inspires our measurement of instruction utility.

3 Method

3.1 Motivation and Overview

The quality of synthesized data correlates to correctness, diversity and complexity (Liu et al., 2023b; Zhu et al., 2024). While recent works (Wang et al., 2023; Kaur et al., 2025) primarily focus on enhancing instruction diversity, we systematically address instruction complexity enhancement, aligning with previous approaches (Xu et al., 2023;

Zhao et al., 2023). Following the standard assumption in data synthesis works of having access to a capable instruction-following teacher model, we propose TAG-INSTRUCT for controlled complexity augmentation.

Existing prompt-based augmentation methods (Xu et al., 2023; Zhao et al., 2023) operate directly in token space, lacking quantitative control mechanisms and principled guidance for complexity enhancement. To overcome these limitations, TAG-INSTRUCT operates through an **Encode → Expansion → Decode** paradigm that fundamentally differs from existing token-space methods by compressing instructions into a structured tag space for systematic concept-level operations. For each input instruction x, our framework operates through three stages: **Stage (1) Encode**: compresses instruction x into semantic tags z_{base} (Section 3.2); **Stage (2) Expansion**: expands the tag set using RL-guided selection to identify high-utility tags z_{new}, forming $z_{\text{base}'} = z_{\text{new}} \cup z_{\text{base}}$ (Section 3.3) guided by Shapley value estimation (Section 3.4); **Stage (3) Decode**: reconstructs an enhanced instruction x' from the expanded tags and original instruction $\{z'_{\text{base}}, x\} \to x'$ (Section 3.5). This approach is orthogonal to diversity-focused methods and can be integrated with existing synthesis frameworks. Please refer to Figure 2 for the framework overview.

3.2 Semantic Compression

Inspired by the ideas of variational representation learning and information bottleneck principle (Kingma and Welling, 2013; An et al., 2024), TAG-INSTRUCT optimizes the data complexity in the compressed discrete tag space. The tag space exhibits reduced search complexity while preserving task-relevant information. Thereby this semantic compression helps to filter out extraneous elements from the instructions and facilitates the tag expansion, resulting in more effective complexity enhancement.

Given an instruction x from existing synthesized data, the teacher LLM is prompted (see the instruction-to-tag prompt in Appendix E.1) to generate relevant tags z_{base} of the input instruction. The crafted prompt is expected to explicitly guide the model to extract tags that preserve core semantic meanings with the input. Among these tags, those related to action-oriented concepts and task objectives are emphasized and with higher priority as they are indicative of the input intension. For example, the instruction *Create an HTML page that displays a list of books and their authors* is compressed into $\{$*book_listing*, *author_info*, *web_develop*$\}$. We discuss and compare different prompt guidelines for semantic compression in Section 5.1.

3.3 Tag Complexity Expansion

The compressed tags z_{base} are further expanded for complexity optimization. The potential invited tags z_{new} are determined based on the following criteria. (1) **Tag Utility** ($R_{\text{utility}}(z_{\text{new}})$): Measures how much a new tag contributes to the instruction complexity. For example, adding *responsive_design* to our HTML example introduces meaningful complexity by requiring additional technical considerations, while *simple_styling* adds little value. (2) **Semantic Alignment** ($R_{\text{align}}(z_{\text{new}}, z_{\text{base}})$): Ensures compatibility between new and existing tags. For instance, *data_analysis* might be a valuable tag but conflicts with our web development context, whereas *user_authentication* aligns naturally with the existing web application tags. (3) **Global Coherence** ($R_{\text{coherence}}(z_{\text{new}} \cup z_{\text{base}}, x)$): Verifies that the expanded tag set can generate executable instructions. Tags like *database_integration* and *web_develop* can naturally combine into coherent tasks, while *quantum_computing* and *web_develop* might create unrealistic requirements.

While prompt-based methods can reasonably assess semantic alignment and global coherence through conceptual compatibility and feasibility checks that suit LLM strengths, tag utility quantification requires more sophisticated approaches. Although one could directly prompt the LLM to evaluate tag utility (Zheng et al., 2023), this method inadequately models complex tag interactions and provides no principled evaluation framework. TAG-INSTRUCT is proposed to incorporate a policy model trained with preference data on tag expansion task to generate augmented tags with high utility. The preference data are collected by tag utility quantification with Shapley value estimation (Shapley, 1953; Goldshmidt and Horovicz, 2024) (detailed in Section 3.4). The tags with high utility are selected as positive while the opposite are set as rejected samples. Initialized from the teacher LLM, the policy model is then optimized and adapted to the tag expansion task with alignment tuning methods like DPO (Rafailov et al., 2024). During the tag complexity extension stage, the expanded tags are generated by prompting the optimized policy model with the detailed requirements of semantic alignment and global coherence criteria.

3.4 Utility Estimation through Shapley Values

As discussed in Section 3.3, quantification of tag utility presents a unique challenge that requires a more principled approach. Inspired by cooperative game theory (Shapley, 1953; Goldshmidt and Horovicz, 2024), we propose to estimate the tag utility by measuring their marginal contributions in instruction construction with Shapley value (Shapley, 1953; Goldshmidt and Horovicz, 2024).

We frame instruction complexity enhancement as a cooperative game where semantic tags $z_i \in Z$ are players collaborating to construct effective instructions. Each tag z_i participates in multiple instruction construction games by combining with different tag subsets $S \subseteq Z$. The core insight is that a tag's true utility ϕ_i can be measured through its marginal contribution $v(S \cup \{z_i\}) - v(S)$ to instruction quality across all possible collaborations S, capturing complex interaction effects in the compressed representation space $\mathcal{Z}$. Formally, we calculate each tag's Shapley value as $\hat{\phi}_i = \frac{1}{N}\sum_{j=1}^{N}[v(S_j \cup \{z_i\}) - v(S_j)]$, where N is the number of instruction construction games. However, the computation is intractable due to the vast number of potential tag subsets S.

We simplify the computation process and estimate the Shapley value based on an existing instruction-response dataset $\mathcal{D}^t = (x_i, y_i)_{i=1}^{M}$ such as Alpaca-Cleaned (Taori et al., 2023) and Tulu-mixture (Lambert et al., 2025). This dataset is different from the instruction data which is to be optimized for better complexity with TAG-INSTRUCT. The tags are extracted from the instructions following the practice in Section 3.2. Following the suggestions in Zhao et al. (2024) and Shen (2024), we use response length as a proxy for instruction quality v, as it effectively captures both complexity and information density. To address the computational complexity of Shapley value calculation, we approximate the tag utility as the average response length of instructions containing that tag:

$$\phi_i = \frac{\sum_{j \in \mathcal{D}_i^t} |y_j|}{|\mathcal{D}_i^t|}, \tag{1}$$

where $\mathcal{D}_i^t$ denotes instructions containing tag i and $|y_j|$ is the token length of response j. With the dataset $\mathcal{D}^t$, the reward of each tag can be then computed with Equation 1. Please refer to Appendix D for more details about how to collect the preference data for optimizing the policy model on the tag expansion task.

3.5 Instruction Reconstruction

After determining the augmented tags, TAG-INSTRUCT then reconstruct the instruction based on the original instruction, base tags as well as augmented tags by prompting the teacher LLM.

The augmented instruction is optimized iteratively, where the output instruction of the $(i-1)^{\text{th}}$ iteration is the input of the i^{th} iteration with TAG-INSTRUCT. Through this iterative process, each subsequent iteration introduces additional complexity and challenges, as new tags and requirements are incorporated to progressively increase the difficulty level of the instruction.

4 Experiments

4.1 Setup

Data and Model Settings We conducted experiments using Alpaca-Clean dataset (Taori et al., 2023), from which we randomly sampled 5K instructions to create Alpaca-5k as our initial instruction set. And we use LLaMA-3-8B and LLaMA-3.2-3B as our base models, and Ministral-Instruct-8b (Jiang et al., 2023) as the teacher model. For data pool construction 3.4, we extract tags from instructions following Lu et al. (2023) and utilize instructions from Xu et al. (2024) to estimate tag rewards and train our policy model for tag expansion. Detailed specifications of the datasets, models, and training procedures are provided in Appendix B.

Evaluation Benchmarks We compared TAG-INSTRUCT with baselines on the following benchmarks: (1) **AlpacaEval 2.0** (Li et al., 2023; Dubois et al., 2024) is an automated evaluation framework based on a annotation model(GPT-4). By comparing responses generated by two different models for the same set of 805 prompts, AlpacaEval computes the pairwise win rate, automating the evaluation process. (2) **MT-Bench** (Zheng et al., 2024b) is aimed at assessing the conversational and instruction-following abilities of LLMs. A one-shot chat template is used to test all models in our experiments. (3) **ArenaHard-Auto** (Li et al., 2024b) is an automatic evaluation tool for instruction-tuned LLMs. It includes 500 challenging queries sourced from Chatbot Arena, evaluated against a baseline model (GPT-4-0314). For all

Setup	#Convs	AlpacaEval 2.0			Arena-Hard	MT-Bench
		LC (%)	WR (%)	SD	Score (95% CI)	Score
Base Model: LLaMA3-8b / Teacher Model: Ministral-Instruct-8b						
Alpaca-5k (baseline)	5K	9.33	5.09	0.74	3.1 (-0.7, 0.7)	5.20
+ Evol-Instruct	5K	12.29 (+2.96)	9.90 (+4.81)	0.99	16.8 (-1.7, 1.6) (+13.7)	5.68 (+0.48)
+ Auto-Instruct-Evol	5K	11.49 (+2.16)	10.19 (+5.10)	1.01	16.8 (-1.8, 1.4) (+13.7)	5.89 (+0.69)
+ Tree-Instruct	5K	10.89 (+1.56)	10.47 (+5.38)	1.01	16.6 (-1.6, 1.5) (+13.5)	5.94 (+0.74)
+ CodecLM	5K	14.73 (+5.40)	12.71 (+7.62)	1.10	19.2 (-1.4, 1.5) (+16.1)	6.00 (+0.80)
Alpaca-Clean	52K	7.73 (-1.60)	5.21 (+0.12)	0.74	3.0 (-0.4, 0.5) (-0.1)	4.89 (-0.31)
WizardLM-data	192K	11.68 (+2.35)	5.69 (+0.60)	0.75	4.5 (-0.8, 1.1) (+1.4)	5.36 (+0.16)
TAG-INSTRUCT	5K	**19.50** (+10.17)	**19.21** (+14.12)	1.30	**22.1** (-2.1, 1.9) (+19.0)	**6.15** (+0.95)
Base Model: LLaMA3.2-3b / Teacher Model: Ministral-Instruct-8b						
Alpaca-5k (baseline)	5K	8.52	4.73	0.71	2.6 (-0.5, 0.7)	4.21
+ Evol-Instruct	5K	9.06 (+0.54)	7.48 (+2.75)	0.85	12.7 (-1.5, 1.4) (+10.1)	4.95 (+0.74)
+ Auto-Instruct-Evol	5K	8.79 (+0.27)	8.79 (+4.06)	0.95	10.8 (-1.2, 1.2) (+8.2)	5.18 (+0.97)
+ Tree-Instruct	5K	10.01 (+1.49)	8.50 (+3.77)	0.91	10.4 (-1.2, 1.4) (+7.8)	5.18 (+0.97)
+ CodecLM	5K	11.24 (+2.72)	11.19 (+6.46)	1.03	12.7 (-1.1, 1.2) (+10.1)	4.79 (+0.58)
Alpaca-Clean	52K	8.06 (-0.46)	4.12 (-0.61)	0.67	2.8 (-0.6, 0.8) (+0.2)	4.74 (+0.53)
WizardLM-data	192K	6.74 (-1.78)	4.46 (-0.27)	0.68	3.7 (-0.6, 0.9) (+1.1)	4.94 (+0.73)
TAG-INSTRUCT	5K	**14.28** (+5.76)	**14.81** (+10.08)	1.19	**12.9** (-1.2, 1.1) (+10.3)	**5.21** (+1.00)

Table 1: Performance comparison of instruction-tuned models on LLaMA3-8b and LLaMA3.2-3b base models. We report Length Control (LC) and Win Rate (WR) from AlpacaEval 2.0, Standard Deviation (SD) of model outputs, and Arena-Hard scores with 95% Confidence Intervals (CI). **Bold** numbers indicate best performance across all metrics, while rows with blue background highlight our TAG-INSTRUCT approach.

evaluations, we used GPT-4o-mini as the judge model given our limited budget.

Baselines We evaluated our method against several state-of-the-art instruction augmentation methods and popular instruction-tuning datasets. The methodological baselines included Self-Instruct (Wang et al., 2023), Evol-Instruct (Xu et al., 2023), Tree-Instruct (Zhao et al., 2023), Auto-Instruct-Evol (Zeng et al., 2024), and CodecLM (Wang et al., 2024b). For data baselines, we compared against Alpaca-Clean (Taori et al., 2023) and WizardLM-data (Xu et al., 2023). Detailed descriptions of each baseline can be found in Appendix C.

4.2 Results

We present experimental results in Table 1, demonstrating the superior performance of our TAG-INSTRUCT approach across model scales and evaluation metrics. On the LLaMA3-8b model, TAG-INSTRUCT shows significant improvements over the Alpaca-5k baseline: +10.17% in Length Control and +14.12% in Win Rate on AlpacaEval 2.0, +19.0 points on Arena-Hard, and +0.95 points on MT-Bench. Notably, TAG-INSTRUCT achieves this using only 5K conversations, outperforming larger datasets like WizardLM (192K conversations) which shows only 2.35% Length Control and 0.60% Win Rate improvements. On LLaMA3.2-3b, our method shows strong performance with +5.76% Length Control and +10.08% Win Rate improvements over baseline, exceeding CodecLM (+2.72% and +6.46%). Larger datasets like Alpaca-Clean (52K) and WizardLM (192K) show decreased performance on the 3b model, highlighting our approach's value for smaller architectures. Across all metrics, TAG-INSTRUCT outperforms existing methods including CodecLM. On the 8b model, we achieve +4.77% Length Control and +6.50% Win Rate improvements, while on the 3b model, we show +3.04% Length Control and +3.62% Win Rate gains. These improvements demonstrate the effectiveness of our tag-based approach.

4.3 Ablation Study

Impact of Reward Model Guidance. As discussed in Section 3.3, we compare different approaches to expand new tags given the input instruction and base tags. The vanilla prompt-based method directly generates new tags with crafted prompt (see in Appendix 7). The RL-based ap-

Strategy	#Inst	#Resp	AE2.0	AH
Base (Alpaca-5k)	21.0	159.5	8.78	3.1
Prompt-based	287.3	1006.7	15.43	19.1
RL-based	285.8	**1037.0**	**19.50**	**22.1**

Table 2: Performance comparison of different tag expansion strategies. #Inst represents instruction length, #Resp represents response length, AE2.0 represents AlpacaEval2.0 length-controlled win rate, AH represents ArenaHard win rate.

proach is incorporated in TAG-INSTRUCT which uses optimized policy model for generation of tags with high utility. The results in Table 2 show that RL-based sampling outperformed random sampling in the tag expansion task. With comparable instruction lengths (285.8 vs 287.3 tokens), the RL-guided approach generated longer responses (1037.0 vs 1006.7 tokens) and achieved better performance on Alpaca-Eval 2.0 (19.50% vs 15.43%) and ArenaHard (22.1% vs 19.1%). This improvement demonstrates that our policy model effectively encourages the generation of high-quality tags which can improve the data complexity.

Evaluation of Iterative Optimization. To assess the effectiveness of our iterative framework, we analyzed the progression across five iterations, as shown in Figure 3. We compared three approaches: Evol-Instruct (baseline), TAG-INSTRUCT (using prompt-based tag expansion), and TAG-INSTRUCT-Reward (using RL-trained tag generator). Following established frameworks(Xu et al., 2024), we used the average of Arena-Hard and Alpaca-Eval 2.0 scores for quality assessment, and Instagger(Lu et al., 2023) tag counts for complexity measurement. As shown in Figure 3a, TAG-INSTRUCT-Reward consistently achieves higher complexity scores across iterations compared to both TAG-INSTRUCT and Evol baselines. The quality metrics in Figure 3b demonstrate a similar pattern, with TAG-INSTRUCT-Reward showing steeper improvement and reaching higher final performance. Analysis of response lengths (Figure 3c) further validates the effectiveness of our approach, with TAG-INSTRUCT variants generating substantially longer responses than Evol. The superior performance of TAG-INSTRUCT-Reward over prompt-based TAG-INSTRUCT confirms that our RL-based tag generator enables more controlled and effective instruction enhancement through structured tag-space operations.

5 Analyses

5.1 Different Crafted Prompts for Semantic Compression

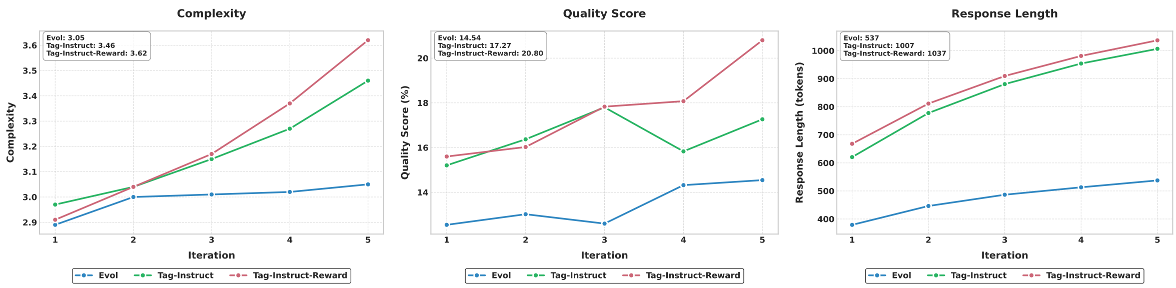
A critical challenge in instruction augmentation is achieving meaningful complexity enhancement while preventing semantic drift from the original instruction. To address this, we compare four prompt strategies for semantic compression, each designed with different priorities. We selected 1,000 instructions from Alpaca-5k and conducted five iterations of complexity enhancement to evaluate four encoding strategies: Basic (simple template), Enhanced (joint intention and semantic compression), Evolved (intention-focused encoding), and Model-based (pure intention encoding) (Lu et al., 2023). Detailed prompts for each strategy are provided in Appendix E.1.

We assessed their performance along two key dimensions: (1) semantic preservation, measured by semantic similarity and ROUGE-L scores between original and reconstructed instructions, and (2) intent extraction capability, which evaluates whether the prompt explicitly requires extracting task intention from instructions.

As shown in Table 3, a clear pattern emerges: methods with intent extraction capability (Intent Tag = True) consistently outperform the basic approach, with performance gains inversely correlated with semantic similarity. This reveals a fundamental insight—*task-aware compression* that prioritizes functional understanding over surface-level similarity yields superior complexity enhancement. The model-based approach achieves the highest AlpacaEval score (14.3498) despite the lowest similarity (0.3600), demonstrating that aggressive semantic abstraction can be beneficial. However, to maintain instruction coherence and prevent excessive semantic drift during iterative augmentation, we adopt the Evolved strategy, which achieves the best ArenaHard performance (18.0) while preserving moderate semantic alignment (0.5373). This strategic trade-off ensures our framework generates complex yet semantically grounded instructions throughout the iterative enhancement process.

5.2 Tag Utility Analysis

To better understand the differences between tags with varying utility values, we categorized the tags into quartiles (Q1-Q4) based on their utility values



(a) Complexity Analysis

(b) Quality Analysis

(c) Response Length Analysis

Figure 3: **Iterative analysis of instruction generation.** Comparison between Evol-Instruct (baseline), TAG-INSTRUCT (prompt-based), and TAG-INSTRUCT (RL-based) across: (a) Instruction complexity via Instagger tags; (b) Quality score (average of Arena-Hard and Alpaca-Eval 2.0); (c) Response length.

Method	AlpacaEval2.0 LC	ArenaHard	Similarity	ROUGE-L	Intent Tag
Basic	12.9182	16.1 (-1.7, 1.5)	0.6536	0.3113	False
Enhanced	13.1831	16.7 (-1.2, 1.6)	0.6023	0.2778	True
Evolved	14.1889	**18.0 (-1.8, 1.4)**	0.5373	0.1992	True
Model-based(Lu et al., 2023)	**14.3498**	17.6 (-1.8, 2.1)	0.3600	0.1667	True

Table 3: Analysis of prompt evolution steps and their impact on reconstruction quality and downstream performance.

in ascending order. We then analyzed the number of **derived meanings** for the tags within each quartile. The **derived meanings** measure captures how many distinct semantic interpretations a tag can reasonably support across different contexts. For instance, while *database_backup* typically refers to a single concept of data preservation, *security* can encompass authentication mechanisms, encryption protocols, access control systems, and threat detection frameworks. We employed the prompting detailed in Appendix E.2, which is designed according to research on semantic information measurement (Kuhn et al., 2023). This prompt systematically probes for multiple meanings before merging similar concepts to form distinct semantic categories.

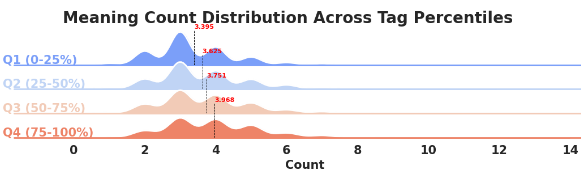


Figure 4: Number of derived meanings across tag utility quartiles (Q1-Q4). Higher utility tags (Q4) exhibited more derived meanings compared to lower utility tags (Q1), suggesting richer semantic content enabled more effective instruction generation. The red number indicates the mean value.

As shown in Figure 4, tags with higher utility values exhibited consistently more derived meanings, indicating they encoded richer semantic information that could be interpreted in more diverse ways. Tags in Q4 (75-100%) demonstrated the highest semantic complexity with broader meaning distributions, while Q1 tags (0-25%) showed more constrained semantic interpretations. This semantic richness enabled diverse instruction generation pathways. A comprehensive analysis of additional representative examples and their semantic interpretations is provided in Appendix F. This finding suggested that the effectiveness of high-utility tags in generating complex and diverse instructions may be attributed to their inherently **richer semantic content**.

5.3 Quantitative Control Through High-Utility Tags

We investigate whether our utility-based tag selection provides quantitative control beyond expansion operations. **Tag combination**, which merges distinct semantic concepts to create diverse instructions, is fundamental to recent synthesis methods (Kaur et al., 2024; Didolkar et al., 2024), yet existing approaches lack principled guidance for selection. Our framework transforms this from heuristic sampling to quantitative optimization through Shapley-based utility scores.

To validate this quantitative advantage, we con-

Strategy	#Inst	#Resp	AE2.0	AH
Low-utility	85.02	524.87	11.02	15.8
Random	99.09	861.38	14.85	20.9
High-utility	94.21	**967.52**	**20.21**	**24.6**

Table 4: Quantitative impact of tag utility on synthesis quality. High-utility tags consistently outperform random selection across metrics, validating our Shapley-based scoring mechanism.

structed three tag pools of 1000 tags each from Section 3.4 using different selection criteria: High-utility (selecting tags with highest Shapley values), Low-utility (selecting tags with lowest Shapley values), and Random (uniformly sampling tags). For each pool, we randomly sampled two tags to combine and decoded them into instructions using the prompting template in Appendix E.3, generating 5,000 instructions per pool. We then fine-tuned models using these instruction sets under identical configurations to ensure fair comparison.

Table 4 demonstrates the impact of quantitative tag selection. High-utility tags yield 12.3% longer responses (967.52 vs 861.38 tokens) and achieve 36.1% relative improvement on AlpacaEval 2.0 (20.21% vs 14.85%) compared to random selection—despite generating more concise instructions (94.21 vs 99.09 tokens). This efficiency gain (better performance with shorter prompts) validates that our utility scores capture intrinsic semantic value rather than superficial verbosity. Furthermore, the monotonic relationship between tag utility and downstream performance (Low: 11.02% $\rightarrow$ Random: 14.85% $\rightarrow$ High: 20.21% on AlpacaEval) establishes that our framework provides **quantitative control** over instruction quality—a capability absent in existing prompt-based methods. Ultimately, this demonstrates that structured tag-space operations with utility guidance offer principled mechanisms for instruction synthesis, enabling precise optimization rather than stochastic exploration.

5.4 The Impact of Different Teacher Model

In this section, we explore the performance of TAG-INSTRUCT with different teacher models. Using the same experimental setup as our main experiments, we compare our approach with baselines by finetuning LLama3-8B using Qwen2.5-72B-instruct (Qwen et al., 2024) as the teacher model. As shown in Table 5, TAG-INSTRUCT consistently outperforms the baselines, achieving the highest

Method	AE2.0 LC	ArenaHard
Alpaca-5k (baseline)	19.50	22.1 (-2.1, 1.9)
Evol-Instruct	36.34	38.7 (-2.8, 2.1)
Codeclm	30.64	37.1 (-2.2, 2.4)
Auto-Instruct-Evol	31.65	35.6 (-2.0, 2.0)
Tree-Instruct	32.71	33.6 (-2.3, 1.9)
TAG-INSTRUCT	**42.76**	**41.2 (-2.3, 2.1)**

Table 5: Performance comparison with different instruction methods using Qwen2.5-72B-instruct as teacher model. AE2.0 LC represents AlpacaEval2.0 length-controlled win rate.

scores on both AlpacaEval2.0 length-controlled tasks (42.76%) and ArenaHard evaluation (41.2%). These results underscore the broad applicability of our method, surpassing the baseline models across different teacher models. When compared to using Ministral-Instruct-8b as the teacher, Qwen2.5-72B-instruct enhances performance by 23.26 on AlpacaEval2.0 and 19.1 on ArenaHard. This significant improvement can be attributed to two key factors: First, stronger models typically exhibit superior instruction-following capabilities, resulting in higher-quality instruction generation with fewer inconsistencies or unsolvable problems. Second, more capable teacher models possess superior reasoning abilities, allowing them to generate higher-quality responses with more sophisticated analytical thinking and deeper insights. This suggests that leveraging more advanced teacher models can substantially enhance both the complexity and quality of the generated instruction dataset.

6 Conclusion

In this paper, we propose TAG-INSTRUCT, a novel framework for enhancing instruction complexity through structured semantic compression and controlled difficulty augmentation. By operating in a compressed tag space rather than raw text, our approach enables more precise and controllable instruction enhancement. Empirical results on AlpacaEval 2 demonstrate that TAG-INSTRUCT outperforms existing instruction augmentation methods. Our analysis shows that structured semantic manipulation enables controlled progression of instruction difficulty while maintaining coherence across different synthesis frameworks. The effectiveness of our approach suggests that structured semantic manipulation is a promising direction for instruction optimization in language models.

Limitations

Despite the effectiveness of our approach, we identify several limitations. First, our semantic compression process may lose some nuanced information during the discretization of continuous semantic spaces into discrete tags. Second, using response length as a proxy for instruction quality in tag utility estimation might not fully capture all aspects of instruction complexity. Third, our framework may introduce some noise during the tag expansion process, as we do not incorporate explicit filtering mechanisms to validate the semantic coherence of newly generated tags. Finally, the generalizability of our approach may be limited as our current evaluation focuses primarily on general-domain instructions; future work should explore the effectiveness of TAG-INSTRUCT in specialized domains such as code generation and mathematical reasoning tasks.

Acknowledgements

This project was supported by National Natural Science Foundation of China (No. 62306132) and Guangdong Basic and Applied Basic Research Foundation (No. 2025A1515011564). The paper was also supported by the Key Project of the Shanghai Municipal Education Commission's AI-Enabled Research Paradigm Reform and Discipline Leap Program (Development of a Domain-Specific Large Language Model in the Field of Urban and Rural Planning for Enhancing Spatial Cognition and Decision-Making Capabilities) and by the Fundamental Research Funds for the Central Universities (22120250239). This work was done by He Zhu during his internship at SUSTech. We thank the anonymous reviewers for their insightful feedbacks on this work.

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A Tag-Instruct Prompt Template Demonstration

A.1 Encode/Decode Prompts for I2T and T2I

This section presents the prompt templates used for instruction-to-tag (I2T) encoding and tag-to-instruction (T2I) decoding. The I2T prompt extracts semantic tags from instructions, while the T2I prompt generates enhanced instructions based on tags and original questions.

B Experimental Setup Details

B.1 Dataset Specifications

We utilized Alpaca-Clean (Taori et al., 2023), which contains high-quality instruction-response pairs generated by GPT-4 and manually filtered by human annotators. From this dataset, we randomly sampled 5K instructions to create Alpaca-5k as our initial instruction set.

B.2 Model Architecture and Training Protocol

Our implementation uses the following specifications:

Base Models We employed LLaMA-3-8B and LLaMA-3.2-3B as base models, with Ministral-Instruct-8b (Jiang et al., 2023) serving as the teacher model.

Training Configuration The training protocol followed these parameters: Training Duration of 3 epochs, Learning Rate starting at 2×10^{-5} with cosine schedule, utilizing 8 GPUs with 80GB memory each, global Batch Size of 128, and maximum Sequence Length of 2048 tokens.

Instruction Processing For instruction processing, we used the Alpaca template for single-turn settings, performed tag extraction following methodology from Lu et al. (2023), conducted tag reward estimation using instructions from Xu et al. (2024), and implemented policy model training for the tag expansion task. For additional implementation details, refer to Appendix D.

C Detailed Description of Baselines

C.1 Methodological Baselines

We compared our approach against the following methodological baselines:

- **Self-Instruct** (Wang et al., 2023): This method generates synthetic instruction-following examples automatically to enhance model alignment with human instructions.
- **Evol-Instruct** (Xu et al., 2023): An iterative instruction evolution framework that progressively increases instruction complexity while maintaining quality, enabling large-scale generation of high-complexity instruction data for LLM training.
- **Tree-Instruct** (Zhao et al., 2023): This approach systematically enhances instruction complexity by adding nodes to semantic trees, allowing controlled difficulty levels.
- **Auto-Instruct-Evol** (Zeng et al., 2024): An end-to-end framework that evolves instruction datasets using LLMs without human effort, automatically analyzing and optimizing evolutionary strategies.
- **CodecLM** (Wang et al., 2024b): This method employs encode-decode principles with LLMs as Codecs, using metadata to capture target instruction distributions and create tailored instructions.

C.2 Data Baselines

We also compared against the following datasets:

- **Alpaca-Clean** (Taori et al., 2023): A high-quality instruction-following dataset generated by GPT-4 and manually filtered by human annotators.
- **WizardLM-data** (Xu et al., 2023): A large-scale instruction-following dataset created through evolved instructions using proprietary LLMs.

Semantic Tag Extraction Prompt Template for I2T Encoding

You are a semantic analysis expert. Your task is to extract exactly three essential tags that capture the core semantic concepts of the given instruction or question. The tags should be:
- Concise (1–2 words each)
- Hierarchically ordered by importance
- Generalizable across similar tasks

Guidelines:
1. Focus on action-oriented concepts
2. Avoid redundant or overlapping tags
3. Use standard terminology when possible

Examples:
[Input]
Describe a situation where team collaboration improved the outcome of a project.
[Tags]
teamwork_experience, project_outcomes, success_factors

[Input]
What strategies can be used to improve time management in a busy work environment?
[Tags]
productivity_methods, workload_optimization, efficiency_tactics

[Input]
Outline the steps required to create a successful marketing campaign for a new product launch.
[Tags]
campaign_planning, market_strategy, launch_execution

[Input]
In the context of climate change adaptation, analyze how urban planning strategies can be modified to create resilient cities that can withstand extreme weather events while maintaining economic growth and social equity for their residents over the next 50 years.
[Tags]
urban resilience, climate adaptation, sustainable development

[Input]
Design a comprehensive employee training program for a multinational corporation that addresses cultural sensitivity, remote work effectiveness, and digital tool proficiency while ensuring consistent skill development across different time zones and accounting for various learning styles and language barriers.
[Tags]
corporate training, global workforce, skill development

[Input]
Develop a detailed analysis of how artificial intelligence implementations in healthcare systems can improve patient outcomes while considering privacy concerns, medical ethics, and the integration challenges with existing hospital infrastructure and staff training requirements.
[Tags]
healthcare AI, medical ethics, system integration

Task:
Given the following instruction, provide exactly three semantic tags following the above format and guidelines:

[Input]
{instruction}

[Output Format]
tag1, tag2, tag3

[Tags]

Figure 5: Prompt template for extracting semantic tags from instructions, with examples demonstrating tag extraction across diverse domains

Tag-to-Instruction Prompt Template for T2I Decoding

Using the provided tags and original question, generate a new version of the question that is more complex and thought-provoking.

Requirements:
1. **Tag Selection**: Choose a subset of the tags that best enhance the depth of the question.
2. **New Question Complexity**: The new question should be more challenging than the original, requiring deeper thought, but it should be solvable. Avoid simply adding length; instead, focus on making the question more insightful and intellectually engaging.
3. **Solvability**: Ensure the new question remains clear and achievable.

Output Format:
[Tags]
Here are the existing tags.

[Original Question]
Here is the original question.

Output:
[New Question]
Provide the new, more complex question.

Your Task:
[Tags]
{tags}

[Original Question]
{question}

Output:
[New Question]

Figure 6: Template for generating enhanced instructions from semantic tags while maintaining clarity and solvability

Tag Expansion and Complexity Enhancement Prompt Template

Please generate only one new tag based on the existing tags and the given task or question. Then, using all the tags, create a new, more challenging version of the task or question.

Important:
The new tag should differ from the previous tags and relate to the context of the question.

Format:
`[Tags]`: Here are the existing tags.
`[Original Question]`: Here is the original question.
Output:
`[New Tag]`: Here is the new tag.
`[New Question]`: Here is the new question.

Your Task:
`[Tags]`: {tags}
`[Original Question]`: {question}
Output:

Figure 7: Template for expanding tag set and enhancing question complexity through contextual tag addition

Response Generation Prompt Template

Below is an instruction that describes a task, write a response that appropriately completes the request.

Instruction:
{instruction}

Response:

Figure 8: Simple template for generating responses to task instructions

D Tag Expansion Implementation Details

This section provides implementation details for our tag expansion approach using reinforcement learning to optimize the policy model for high-utility tag generation.

D.1 Tag Pool Construction

We construct a comprehensive tag pool using Magpie-500k (Xu et al., 2024) as seed data:

Tag Extraction and Utility Estimation For each instruction in Magpie-500k, we extract semantic tags using the teacher LLM following Section 3.2. We then compute the utility score for each unique tag using Equation 1:

$$\phi_i = \frac{\sum_{j \in \mathcal{D}_i} |y_j|}{|\mathcal{D}_i|}$$

where $\mathcal{D}_i$ denotes instructions containing tag i.

Tag Pool Formation Based on utility scores, we rank all extracted tags and form the tag pool $\mathcal{T} = \{t_1, t_2, \ldots, t_N\}$ ordered by decreasing utility. We define $\mathcal{T}_{\text{good}}$ as the top 10,000 highest-utility tags and $\mathcal{T}_{\text{bad}}$ as the bottom 10,000 lowest-utility tags.

D.2 Best-of-N Tag Expansion and Scoring

Candidate Generation For each base tag set z_{base}, we follow the prompt template in Figure 7 to generate $N = 20$ candidate expansion tags using the teacher LLM:

$$z_{\text{new}}^{(i)} \sim p(z|z_{\text{base}}, x), \quad i = 1, 2, \ldots, 20$$

Embedding-based Scoring We score each candidate tag $z_{\text{new}}^{(i)}$ using embedding similarity with the pre-constructed tag pools. Let $\text{emb}(\cdot)$ denote the embedding function, we compute:

$$\text{score}_{\text{good}}^{(i)} = \frac{1}{|\mathcal{T}_{\text{good}}|} \sum_{t \in \mathcal{T}_{\text{good}}} \cos(\text{emb}(z_{\text{new}}^{(i)}), \text{emb}(t)) \tag{2}$$

$$\text{score}_{\text{bad}}^{(i)} = \frac{1}{|\mathcal{T}_{\text{bad}}|} \sum_{t \in \mathcal{T}_{\text{bad}}} \cos(\text{emb}(z_{\text{new}}^{(i)}), \text{emb}(t)) \tag{3}$$

The final score for candidate i is:

$$\text{score}^{(i)} = \text{score}_{\text{good}}^{(i)} - \text{score}_{\text{bad}}^{(i)}$$

The insight is that high-quality tags should be semantically closer to high-utility tags and farther from low-utility tags.

D.3 Preference Pair Construction

Based on the computed scores, we construct preference pairs for DPO training. For the chosen tag, we select $z_{\text{chosen}} = \arg\max_i \text{score}^{(i)}$ which represents the highest-scoring candidate. For the rejected tag, we randomly sample z_{rejected} from the remaining candidates $\{z_{\text{new}}^{(j)} : j \neq \arg\max_i \text{score}^{(i)}\}$.

D.4 Policy Model Training

DPO Training The policy model is optimized using Direct Preference Optimization on the collected preference pairs:

$$\mathcal{L}_{\text{DPO}} = -\mathbb{E}_{(z_w,z_l)}\left[\log\sigma\left(\beta\log\frac{\pi_\theta(z_w|z_{\text{base}},x)}{\pi_{\text{ref}}(z_w|z_{\text{base}},x)} - \beta\log\frac{\pi_\theta(z_l|z_{\text{base}},x)}{\pi_{\text{ref}}(z_l|z_{\text{base}},x)}\right)\right]$$

where z_w and z_l denote chosen and rejected tags respectively, π_{ref} is the reference model (teacher LLM), and β controls the KL penalty strength. We trained the model using a learning rate of 5×10^{-5} with batch size of 128 preference pairs over 1 epochs. The KL penalty coefficient (β) was set to 0.1, and we used the `sentence-transformers/all-MiniLM-L6-v2` model for generating embeddings.

While the above process can also be implemented using Proximal Policy Optimization (PPO) with the reward function:

$$R(z_{\text{new}}) = \text{score}_{\text{good}} - \text{score}_{\text{bad}}$$

and the PPO objective:

$$\mathcal{L}_{\text{PPO}} = \mathbb{E}_t\left[\min\left(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t\right)\right]$$

where $r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\text{old}}(a_t|s_t)}$ and $\hat{A}_t$ is the advantage estimate, we choose DPO for its superior efficiency and stability in practice.

E Analysis Experiment Setup

E.1 Tag Extraction Experiment

We selected 1,000 instructions from alpaca-clean (Taori et al., 2023) and conducted five iterations of tag expansion to obtain a total of 5k instructions. We then followed the same supervised fine-tuning process as in the previous section. Our aim was to evaluate the performance of different encoding strategies in generating tags from instructions. To systematically evaluate different encoding approaches, we designed four template variants that explore different aspects of instruction encoding:

- Basic: A minimal template focused on simple tag extraction without additional guidance
- Enhanced: A comprehensive template that jointly captures task intent and semantic meaning through explicit guidelines and hierarchical organization
- Evolved: An intent-focused template that emphasizes action-oriented concepts and task objectives while maintaining semantic coherence
- Model-based: The instagger model (Lu et al., 2023), A template that prioritizes pure intent extraction by focusing on core task objectives and desired outcomes,

Each template was carefully designed to test specific hypotheses about effective instruction encoding, with variations in guidance specificity, semantic preservation requirements, and intent extraction mechanisms (detailed templates in Appendix E.1).

We assessed their performance along two key dimensions:

Semantic preservation We measured reconstruction quality using CrossEncoder (Reimers and Gurevych, 2019), specifically the `cross-encoder/stsb-roberta-base` model, to compute semantic similarity between original and reconstructed instructions. We also used ROUGE-L scores as a surface-level textual alignment metric.

Intent extraction capability We evaluated whether the prompt explicitly requires extracting task intent from instructions, such as identifying action verbs or task objectives. For example, the Enhanced template includes specific guidance like "Focus on action-oriented concepts" and "Hierarchically order by importance."

The reconstruction process used a standardized template (shown in Appendix 9) that provides examples and clear formatting guidelines to ensure consistent instruction regeneration from tags.

We present three different template designs for tag generation and analyze their performance, with the Evolved template being our I2T prompt shown in Figure 5:

Basic Tag Generation Prompt Template (Reconstructed Rate: 0.6536 Arena Hard: 0.3113)

Extract exactly three representative tags that capture the core concepts of the following instruction or question. These tags should allow the reconstruction of the original instruction or question while retaining its meaning and intent. Ensure the tags are concise and distinct.

[Input]
{instruction}

[Tags]

Enhanced Tag Generation Prompt Template (Reconstructed Rate: 0.5373 Arena Hard: 0.1992)

You are a semantic analysis expert. Your task is to extract exactly three essential tags that capture the core semantic concepts of the given instruction or question. The tags should be: - Concise (1–2 words each)
- Hierarchically ordered by importance
- Generalizable across similar tasks

Guidelines: 1. Focus on action-oriented concepts
2. Avoid redundant or overlapping tags
3. Use standard terminology when possible

Examples: [Input]
In the context of climate change adaptation, analyze how urban planning strategies can be modified to create resilient cities.

[Tags]
urban resilience, climate adaptation, sustainable development

[Input]
Design a comprehensive employee training program for a multinational corporation addressing cultural sensitivity.

[Tags]
corporate training, global workforce, skill development

Task: Given the following instruction, provide exactly three semantic tags following the above format and guidelines:

[Input]
{instruction}

[Output Format]
tag1, tag2, tag3

[Tags]

E.2 Derived Meaning Prompt

Below is the complete prompt template used for tag semantic analysis. This template is designed to systematically explore and analyze the semantic dimensions of instruction tags by encouraging divergent thinking followed by convergent analysis. The template guides the model through a structured process

Model-based Tag Annotation Prompt Template (Reconstructed Rate: 0.36 Arena Hard: 0.1667)

You are a helpful assistant. Please identify tags of user intentions in the following user query and provide an explanation for each tag. Please respond in the JSON format:
{
"tag": "str",
"explanation": "str"
}

Query: {instruction}

Assistant:

Decode Prompt Reconstruction Template

Given the following tags, reconstruct the original instruction as closely as possible.
Example 1: [Tags]
teamwork, collaboration, project management

[Instruction]
Describe a situation where team collaboration improved the outcome of a project.

Example 2: [Tags]
time management, productivity, work-life balance

[Instruction]
What strategies can be used to improve time management in a busy work environment?

Example 3: [Tags]
marketing, strategy, product launch

[Instruction]
Outline the steps required to create a successful marketing campaign for a new product launch.

Your Task: [Tags]
{tags}

[Instruction]

Figure 9: Decode Prompt Reconstruction Template

of first generating multiple potential interpretations, then carefully consolidating related concepts, and finally distilling the key distinct meanings. This approach helps reveal the semantic richness and utility of different tags in instruction generation:

Tag Analysis Prompt Template

For the tag "{tag}", follow these steps:
1. Think Different Step: List as many meanings as possible across different domains.
2. Merge Step: Reflect on the meanings and combine similar ones into a single, broader concept.
3. Final Answer: Provide as few meanings as possible, only listing the most essential and distinct ones.
Examples:
[Input]
"video_share"

[Think Different Step]
1. A feature to distribute video content
2. A social media feature to repost videos
3. A platform for users to collaborate on video creation
4. A tool for sharing personal video files

[Merge Step]
- "Distribute video content" and "repost videos" are closely related → merge them into one
- "Collaborate on video creation" and "share personal video files" are related but distinct

[Final Answer]
1. A feature to share videos online
That's all

[Input]
"cloud computing"

[Think Different Step]
1. A method of delivering computing services over the internet
2. A platform for storing and processing data remotely
3. A framework for providing software as a service (SaaS) via the internet
4. A way for businesses to scale infrastructure without owning physical hardware

[Merge Step]
- "Delivering computing services" and "storing and processing data remotely" are related → merge into one
- "Providing software as a service (SaaS)" is distinct from infrastructure and storage
- "Scaling infrastructure without owning hardware" is also distinct

[Final Answer]
1. A method of delivering computing services and storing data remotely over the internet
2. A framework for providing software as a service (SaaS)
3. A way for businesses to scale infrastructure without owning physical hardware
That's all

For the tag "{tag}", apply this process and provide the final answer:

Figure 10: Template for analyzing tag semantics through divergent thinking and convergent analysis.

E.3 Tag Combination

Building on our quantitative control framework through high-utility tags, we introduce tag combination as a principled approach to instruction synthesis. Tag combination merges multiple semantic concepts to create richer, more complex instructions. While prior work has explored combining concepts heuristically, our utility-based selection provides a systematic way to identify and combine high-value tags for optimal instruction generation. The following template (see Figure 11) demonstrates our approach to combining tags into coherent instructions.

Tag Combination Prompt Template

Create a comprehensive and challenging task that incorporates these concepts: {tags}.
Do not explain or provide any additional information. Only return the task/instruction.

Response:

Figure 11: Template for combining tags into a task that incorporates their semantic concepts.

F Case Study: Tag Examples

To further illustrate the relationship between tag value and semantic richness, we present a detailed breakdown of tags across different quartiles (Q1-Q4) based on their Shapley values. Table 6 provides the tag name, occurrence count, average Shapley value, and the number of derived meanings, along with example interpretations for each tag.

Quartile	**Tag**	**Count**	**Avg. Shapley**	**Derived Meanings**
Q4	data accuracy	17	321.48	Ensuring correctness; precision; reliability; integrity; completeness
	pytorch	125	321.69	Deep learning framework; training neural networks; AI research; NLP tool
	payment processing	48	321.72	Financial transactions; credit card management; mobile payments; cryptocurrency; subscriptions
	food inquiry	52	321.88	Ingredients and nutrition; restaurant recommendations; availability; allergens; dietary advice
	graph database	7	321.89	Graph data storage; network analysis; knowledge graphs; recommendation systems
Q3	tableau	5	240.90	Data visualization tool; dashboard platform
	satire	7	240.90	Comedy genre; literary exaggeration
	event attendance	19	240.95	Registration; attendee count; attendee list; event management
	comparative religion	57	240.99	Religion comparison; texts; rituals; history; ethics; symbols
	personality development	3	241.00	Self-improvement; emotional intelligence; confidence building; personal growth
Q2	recipe write	7	176.92	Meal preparation steps; cuisine collection; digital meal planning
	grammar check	216	176.99	Grammar correctness; punctuation verification; spelling check
	punctuation check	3	177.00	Punctuation accuracy; error correction; adherence to grammar rules
	physical interaction	3	177.00	Touch interaction; manual labor; industrial operations; sports activities
	work	26	177.13	Job; task; workplace; labor
Q1	math expression eval	3	20.13	Expression evaluation; algebraic solution; simplification
	code execution env	3	24.38	Code testing; automation scripts; distributed execution
	repayment	3	27.25	Loan repayment; refunding; restoration
	basic operation	10	28.39	System operations; core tasks
	number relationship	3	28.52	Mathematical relations; sequences; dataset correlation

Table 6: Tag Analysis across Quartiles (Q1-Q4). Higher quartiles indicate higher Shapley values, corresponding to increased semantic richness.

G Case Study: Progressive Enhancement of Web Development Requirements

This case study demonstrates the progressive enhancement of web development requirements, showing how a simple book listing page evolves into a comprehensive, accessible, and feature-rich web application. The following table presents five iterations of requirements, each building upon the previous version.

Version	Requirements	Tags
Iter1	Develop an HTML page that dynamically displays a list of books and their authors using CSS for styling. The page should include a search functionality that filters the book list based on the author's name. Additionally, implement a hover effect that reveals a brief description of each book when the user hovers over a book title. Ensure the page is responsive and visually appealing.	web_development, book_listing, author_info, css_styling
Iter2	Develop an HTML page that dynamically displays a list of books and their authors using CSS for styling. The page should include a search functionality that filters the book list based on the author's name, as well as a pagination system to handle a large number of books. Additionally, implement a hover effect that reveals a brief description of each book when the user hovers over a book title. Ensure the page is responsive and visually appealing, and optimize the user experience by incorporating smooth transitions and animations for the hover effect and pagination.	web_development, user_interface, responsive_design, user_experience
Iter3	Develop an HTML page that dynamically displays a list of books and their authors using CSS for styling. The page should include a search functionality that filters the book list based on the author's name, as well as a pagination system to handle a large number of books. Additionally, implement a hover effect that reveals a brief description of each book when the user hovers over a book title. Ensure the page is responsive and visually appealing, and optimize the user experience by incorporating smooth transitions and animations for the hover effect and pagination. Furthermore, enhance the accessibility of the page by ensuring that all interactive elements are keyboard navigable and that the page is compatible with screen readers. Consider the use of ARIA roles and properties to improve the accessibility of the search functionality and pagination system.	web_development, user_interface, responsive_design, accessibility
Iter4	Develop an HTML page that dynamically displays a list of books and their authors using CSS for styling. The page should include a search functionality that filters the book list based on the author's name, as well as a pagination system to handle a large number of books. Additionally, implement a hover effect that reveals a brief description of each book when the user hovers over a book title. Ensure the page is responsive and visually appealing, and optimize the user experience by incorporating smooth transitions and animations for the hover effect and pagination. Furthermore, enhance the accessibility of the page by ensuring that all interactive elements are keyboard navigable and that the page is compatible with screen readers. Consider the use of ARIA roles and properties to improve the accessibility of the search functionality and pagination system. Additionally, implement a feature that allows users to sort the book list by title, author, or publication year. Ensure that the sorting functionality is accessible and provides clear visual feedback to users. Finally, optimize the page's performance by implementing lazy loading for images and minimizing the use of heavy CSS animations to ensure a smooth user experience on devices with limited processing power.	web_development, user_experience, accessibility, performance_optimization

Table 7: Case Study of Progressive Enhancement of Web Development Requirements