Token-level Preference Self-Alignment Optimization for Multi-style **Outline Controllable Generation**

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Abstract

Multi-style outline controllable generation is crucial for multiple applications, including document semantic structuring and retrievalaugmented generation. The great success of preference alignment approaches encourages their application in controllable generation tasks. However, these attempts encounter several limitations: (1) response pair requirements, (2) substantial computation costs, and (3) insufficient exploitation of fine-grained preference signals. To address these problems, we propose a token-level preference selfalignment optimization, named TKPO, for outline controllable generation. TKPO extends the Bradley-Terry model from pair-wise to listwise comparison, which is further applied at the token level for fine-grained preference signal utilization. In comparison to the representative methods, e.g., DPO, TKPO does not require response pairs; instead, we propose a controllable attributes-driven method to construct reject samples for self-alignment. Additionally, TKPO optimizes only the base model, thereby avoiding additional memory usage and substantial computational costs. We curate two outline controllable generation datasets with regard to language style and level-of-detail. Extensive experiments demonstrate that TKPO outperforms DPO by up to 19.28% in performance while requiring only 56.25% in training time. We release the code and datasets resources at https://github.com/WHUIR/ TKPO.

Introduction

Given an article, outline controllable generation aims to output a hierarchical outline with respect to the content of the articles and the controllable conditions, as shown in Figure 1. Existing attempts to outline generation can be classified into two

You are a professional magazine editor. Please generate a structured and hierarchical outline for the following Article. Requirements: <Control Attribute> In the early hours of August 12th, Beijing time, the grand

sports event concluded at the Stade de France in Paris. Details about the closing ceremony dominated the trending topics across various social media platforms...



1. Off the Field, They Believe Their Brilliance Will Shine

2. The Story of Veteran Table Tennis Player Ni Xialian 3. The Persistence of Veteran

Fencer Sun Yiwen 4. The Skateboarding Journey of Young Talent Cui Chenxi

5. The Struggles and **Determination of Ordinary People** Literary Outline:

1. They Didn't Win. But They Didn't Lose Either 2. Be Present Through Highs

and Lows 3. Believe and You Will Shine

Figure 1: An example of outline language style controllable generation. Given the articles and prompts with specified control attributes, e.g., objective vs. literary, the LLMs are required to generate outlines consistent with the control attribute.

research lines: (1) segmentation and summarization (Sun et al., 2022); (2) prompt-driven generation (Yang et al., 2023; Li et al., 2024). The first category divides articles into distinct parts based on paragraph coherence or topical consistency and then generates a summary or topic for each segment. Prompt-driven approaches focus on tailored prompts fine-tuning for outline generation.

Nevertheless, it is noteworthy that the exploration of this task is insufficient, and none of the research focuses on the multi-style outline controllable generation, which is significant for various downstream applications, such as personalized article summarization, semantic structuralization, and retrieval augmented generation. To fill this gap, we first define two distinct outline styles, i.e., language styles (literary vs. objective) 1 and

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¹The literary outlines aim to provide a high-level abstrac-

level-of-detail (*concise* vs. *moderate* vs. *comprehensive*)² (ref. Table 9 to Table 16 in Appendix H for details). Subsequently, two datasets containing multiple distinct outline styles are curated, respectively.

Inspired by the promising results of preference alignment algorithms in conditional generation (Ouyang et al., 2022; Wang et al., 2024), we are committed to applying these methods for outline controllable generation. However, existing preference alignment solutions encounter three limitations: (1) response pair requirements, (2) extensive computation costs, and (3) inadequate utilization of fine-grained preference signals, hindering their further development. More concretely, the majority of strategies necessitate a response pair (an accepted and a declined response) for preference comparison and alignment. This requirement poses significant challenges in the real world compared to the simpler single-response dataset construction. Besides, these methods, such as DPO (Wang et al., 2024), involve at least two models (i.e., reference model and policy model) during training, incurring additional memory usage and computational costs. Furthermore, we argue that sentence-level alignment limits the LLMs' discrimination capability (Guo et al., 2023), as the preferences are more susceptible to the specific words (e.g., toxic terms) (Christopoulou et al., 2024). Hence, fine-grained token-level signals distinguishing between good and bad responses are more appropriate for precise training and optimization.

To address these issues, we propose a token-level preference self-alignment optimization, dubbed TKPO. Compared to existing token-level preference alignment attempts (Liu et al., 2024a; Zeng et al., 2024), our TKPO is response pair-free and efficient, enabling precisely controllable generation. Specifically, TKPO expands the Bradley-Terry model (Bradley and Terry, 1952) from the pair-wise into the list-wise comparison (*i.e.*, one accepted instance vs. multi-rejected instances), which is further applied at the token level. TKPO eliminates the necessity for paired

tion of the articles, thereby the language style inclines to possess a strong artistic touch and literary flavor. In contrast, the objective outline offers a precise and comprehensive summarization of original articles, emphasizing objectivity and authenticity, closely adhering to the original content.

response data, instead, we propose a controllable attribute-driven method, in which the fundamental capability of LLMs is exploited to construct reject samples for self-alignment. In comparison to the representative preference alignment methods, TKPO only optimizes the base model, avoiding additional memory usage and substantial computational cost. Theoretical analysis demonstrates that optimizing the TKPO is equivalent to optimizing the upper bound of the optimal policy model under the Bradley-Terry framework. Additionally, our TKPO demonstrates superior capability for optimizing the hard tokens for fine-grained alignments and exhibits notable diversity in the generation.

We devise two metrics for the outline language style and level-of-detail controllable generation evaluation. Extensive experiments illustrate that our method outperforms DPO with only 73.55% memory usage. To encapsulate, the main contributions of this paper include the following:

- We propose a multi-style and hierarchical outline controllable generation task. To this end, two datasets with regard to outline language style (*lit*erary vs. objective) and level-of-detail (concise vs. moderate vs. comprehensive) are curated, respectively.
- We propose a token-level preference selfalignment framework, named TKPO, which is a response pair-free and efficient solution against existing recipes. Additionally, TKPO enhances diversity in generation and facilitates more precise alignment at a more fine-grained token level.
- Experimental results illustrate the superiority of our method on both controllable generation performance and training efficiency compared to representative preference alignment optimization solutions, such as DPO. Theoretical analysis demonstrates the merits of our TKPO on hard token optimization and diversity enhancement.

2 Methodology

2.1 Preliminary

Preference alignment aims to steer the LLMs to generate responses that are satisfactory and acceptable to humans (Leike et al., 2018), ensuring their security, honesty, and helpfulness. Reinforcement learning from human feedback (RLHF) (Ouyang

²We consider factors such as the total length of the outline, the number of headings, and the hierarchical structure of the heading levels for detail level assessment.

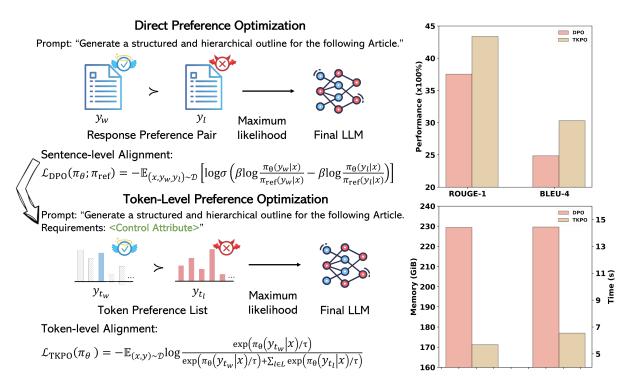


Figure 2: Comparison between the paradigms of DPO and our TKPO. The bar plot illustrates that the TKPO outperforms the DPO with only 73.55% GPU memory usage and 56.25% one-step training time (conducted on the $8\times$ Nvidia Tesla V100 SXM2) for outline language style controllable generation.

et al., 2022) is an effective method for preference alignment. However, it experiences significant complexity and training instability (Song et al., 2023). To address these problems, Direct Preference Optimization (DPO) (Wang et al., 2024) is proposed further. Rather than learning an explicit reward model, the DPO algorithm straightforwardly optimizes the policy by reparameterizing the reward function $r(\cdot)$ using a closed-form expression in a supervised manner (ref. Appendix B.1):

$$r(x,y) = \beta \log \frac{\pi_{\theta}(y|x)}{\pi_{\text{ref}}(y|x)} + \beta \log Z(x)$$
 (1)

where $Z(x) = \sum_y \pi_{\mathrm{ref}}(y|x) \exp(\frac{1}{\beta}(r(x,y)))$ is the partition function. β controls the deviation of the language model policy π_{θ} from the base reference policy π_{ref} .

By incorporating the reward function (Eq. (1)) into the Bradley-Terry (BT) objective formula (Bradley and Terry, 1952),

$$p(y_w \succ y_l | x) = \frac{1}{1 + \exp(r(x, y_w) - r(x, y_\ell))}$$

= $\sigma(r(x, y_w) - r(x, y_\ell))$ (2)

we, thereby, cancel out the partition function Z(x), resulting in the objective of DPO with reverse KL divergence below:

$$-\mathbb{E}_{(x,y_{w},y_{\ell})\sim\mathcal{D}}\left[\log\sigma\left(\beta\log\frac{\pi_{\theta}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)}\right.\right.$$
$$\left.-\beta\log\frac{\pi_{\theta}(y_{\ell}|x)}{\pi_{\text{ref}}(y_{\ell}|x)}\right)\right] \tag{3}$$

where $\sigma(\cdot)$ is the sigmoid function. y_w and y_ℓ are preference pairs consisting of the approved response and declined response with regard to the input x.

2.2 Token-level Alignment

Despite the promising results of the DPO, the training requirements (i.e., y_w and y_ℓ) for response pairs and substantial training costs (i.e., π_θ and $\pi_{\rm ref}$ are involved) impede the widespread application in practical scenarios. To overcome this problem, we adopt preference alignment on the token level for a more precise controllable generation, as shown in Figure 2. Specifically, TKPO first extends the Bradley-Terry model (Eq.(2)) from a pairwise comparison to a list-wise framework, i.e., increasing the probability of accepted instances y_w

while simultaneously decreasing the probability of all declined instances $\{y_{\ell}|\ell=1,...,K\}$. It can be formalized as:

$$p\left(y_w \succ \{y_\ell\}_{\ell=1}^K | x\right) = \prod_{\ell=1}^K p(y_w \succ y_\ell | x)$$

$$= \prod_{\ell=1}^K \frac{\exp(y_w | x)}{\exp(y_w | x) + \exp(y_\ell | x)}$$
(4)

Substituting Eq. (1) into Eq. (4) we obtain (ref. Appendix B.2 for detail):

$$p^{*}\left(y_{w} \succ \left\{y_{\ell}\right\}_{\ell=1}^{K}|x\right)$$

$$= \prod_{\ell=1}^{K} \frac{\exp\left(\beta \log \frac{\pi_{\theta}^{*}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)}\right)}{\exp\left(\beta \log \frac{\pi_{\theta}^{*}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)}\right) + \exp\left(\beta \log \frac{\pi_{\theta}^{*}(y_{\ell}|x)}{\pi_{\text{ref}}(y_{\ell}|x)}\right)}$$

$$< \frac{1}{1 + \sum_{\ell=1}^{K} \exp\left(\frac{\pi_{\theta}^{*}(y_{\ell}|x)}{\pi_{\text{ref}}(y_{\ell}|x)} - \frac{\pi_{\theta}^{*}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)}\right)}$$
(5)

Following (Meng et al., 2024; Hong et al., 2024), we remove the reference model π_{ref} for efficient computation and apply Eq. (4) into the token-level alignment. Therefore, the TKPO loss can be derived by formulating a maximum likelihood objective, as follows,

$$\mathcal{L}_{\text{TKPO}}(\pi_{\theta}) = -\mathbb{E}_{(x, y_{t_w}, \mathcal{Y}_{t_{\ell}}) \sim \mathcal{D}}$$

$$\log \frac{\exp\left(\pi_{\theta}(y_{t_w}|x)/\tau\right)}{\exp\left(\pi_{\theta}(y_{t_w}|x)/\tau\right) + \sum_{y_{t_{\ell}} \in \mathcal{Y}_{t_{\ell}}} \exp\left(\pi_{\theta}(y_{t_{\ell}}|x)/\tau\right)}$$
(6

where y_{t_w} and \mathcal{Y}_{t_ℓ} are the t-th generated accepted token and rejected token set, respectively. $\pi_{\theta}(y_t|x)$ is the probability of t-th token y_t , conditioned on the input x and the previously generated context $y_{< t}$ 3 . τ is a temperature ratio that controls the scaling of the preference difference. By comparing Eq. (6) and Eq. (5), we optimize the \mathcal{L}_{TKPO} to closely approximate the upper bounds of the optimal policy π^* under the Bradley-Terry framework.

We further integrated the self-supervised finetuning (SFT) and preference alignment into a single-step training process for efficiency (Hong et al., 2024), as below,

$$\mathcal{L} = \mathcal{L}_{SFT} + \lambda \mathcal{L}_{TKPO}$$

$$= -\frac{1}{N} \sum_{i=1}^{N} \frac{1}{M} \sum_{t=1}^{M} \log \pi_{\theta}(y_{t_{w}}^{i}|x_{i}) +$$

$$\lambda \log \frac{\exp\left(\pi_{\theta}(y_{t_{w}}^{i}|x_{i})/\tau\right)}{\exp\left(\pi_{\theta}(y_{t_{w}}^{i}|x_{i})/\tau\right) + \sum_{y_{t_{\ell}}^{i} \in \mathcal{Y}_{t_{\ell}}^{i}} \exp\left(\pi_{\theta}(y_{t_{\ell}}^{i}|x_{i})/\tau\right)}$$

$$(7)$$

where N is the number of samples, M is the length of output. λ is a hyperparameter that weights the loss between the self-supervised fine-tuning and preference alignment.

2.3 Attribute-driven Rejected Token Selection

As shown in Eq. (6), the rejected tokens are required for model training. Inspired by (Sun et al., 2023; Shao et al., 2024; Pei et al., 2023), the rejected token can be derived for self-alignment based on the fundamental capabilities of LLMs. Here, we propose a controllable attributes-driven method for rejected token selection. For the outline generation with the controllable attribute a, e.g., literary language style, we denote the token y_t from the reference response as the accepted y_{t_w} and employ multinomial sampling under the anticontrollable attribute \bar{a} to derive K tokens as the rejected tokens $(\{y_{t_\ell}^j\}_{j=1}^K)$, i.e., we sample K tokens based on the probabilities $P_{\theta}(\hat{y}_t|x, \bar{a}, y_{\leq t})$ generated by the prompts (ref. Appendix A for detail) under \bar{a} (e.g., objective language style).

$$\begin{cases} y_{t_w} = y_t \\ y_{t_\ell} \sim \text{Mult-Sampl}(P_{\theta}(\hat{y}_t | x, \bar{a}, y_{< t})) \end{cases}$$
 (8)

where $y_{< t}$ is the first t-1 tokens from reference. Mult-Sampl(·) means multinomial sampling operation. Distinct from most preference alignment methods, it does not require response pairs for model training, alternatively, an attribute-driven method is applied for rejected sample construction. Therefore, we recognize TKPO as a self-alignment method. To sum up, the completed training process can be summarized in the Algorithm 1 (ref. Appendix C.2).

2.4 Properties of TKPO

Diversity and Hard Token Optimization. Intuitively, tokens associated with common expressions in everyday language are more likely to be

³Here, we omit the $y_{< t}$ and simplify the notation $\pi_{\theta}(y_t|x,y_{< t})$ to $\pi_{\theta}(y_t|x)$ for conciseness.

generated and are easier to optimize compared to tokens associated with domain-specific terminology. As a consequence, to enhance the diversity of the output, the objective function should, in turn, pay more attention to the defamiliarized and infrequent token optimization. Mathematically, we can derive the gradient of \mathcal{L}_{TKPO} with respect to the $\pi_{\theta}(y_{t_w}|x)$ (ref. Appendix B.3 for detail) as follows,

$$\begin{split} &\frac{\partial}{\partial \pi_{\theta}(y_{t_w}|x)} - \log \frac{\exp(\pi_{\theta}(y_{t_w}|x))}{\exp(\pi_{\theta}(y_{t_w}|x)) + \sum\limits_{y_{t_\ell} \in \mathcal{Y}_{t_\ell}} \exp(\pi_{\theta}(y_{t_\ell}|x))} \\ &= \frac{\exp(\pi_{\theta}(y_{t_w}|x))}{\exp(\pi_{\theta}(y_{t_w}|x)) + \sum\limits_{y_{t_\ell} \in \mathcal{Y}_{t_\ell}} \exp(\pi_{\theta}(y_{t_\ell}|x))} - 1 \end{split}$$

$$= \frac{\exp(\pi_{\theta}(y_{t_w}|x))}{\exp(\pi_{\theta}(y_{t_w}|x)) + \sum_{y_{t_{\ell}} \in \mathcal{Y}_{t_{\ell}}} \exp(\pi_{\theta}(y_{t_{\ell}}|x))} - 1$$
(9)

We then reformulate the summation over tokens y_{t_l} as an expectation, under the distribution p(y|x), where p(y|x) reveals the base model's inherent token preference. Thus, we can obtain the gradient of $\mathcal{L}_{\text{TKPO}}$ as:

$$\frac{\exp(\pi_{\theta}(y_{t_w}|x))}{K\mathbb{E}_{y_{t_{\theta}} \sim p(y_{t_{\theta}}|x)}\exp(\pi_{\theta}(y_{t_{\ell}}|x))} - 1 \tag{10}$$

Here, we can see that the magnitude of gradient increases when $\pi_{\theta}(y_{t_w}|x)$ is smaller (indicating a hard token to optimization) and $\pi_{\theta}(y_{t_{\ell}}|x)$ is larger (corresponding to high-frequency tokens). This dynamic achieves two key properties: (1) focus on hard tokens optimization, i.e., the model prioritizes optimizing hard tokens as their lower likelihood amplifies their gradient magnitude during training; and (2) diversity enhancement, i.e., as rejected tokens $(y_{t_{\ell}})$ are sampled toward common high-probability tokens, in-turn, accepted tokens (y_{t_w}) are implicitly skewed toward less probable tokens, thereby, encouraging novel and diverse outputs.

Experiments

3.1 **Datasets**

We curate a total of 20,000 raw articles where 10,000 focused on language style and 10,000 on the level-of-detail from the WeChat Official Accounts Platform⁴, all published before December

2, 2024, for multi-style outline controllable generation. More concretely, the articles regarding the level-of-detail control are randomly selected and cover topics rooted in daily life. In contrast, the articles with respect to language style control are sourced from two magazines renowned for their indepth analysis and professional viewpoints: Sanlian Lifeweek Magazine ("三联生活周刊")5 and Neweekly Magazine ("新周刊")⁶. These publications primarily focus on topics related to political commentary and literature reading, featuring outlines created by professional editors. The statistics of the two datasets are presented in Appendix F.1.

For the dataset with respect to the level-of-detail, we utilize GTP-40 (OpenAI, 2024) with prompts (ref. Appendix A) for reference outline generation. As for the dataset regarding the language style, we extract the raw outlines crafted by professional editors as the literary style reference output, while the outlines generated by GPT-40 are recognized as the objective style reference output. Therefore, we construct two datasets, respectively, for the level-of-detail and language style outline controllable generation. For each dataset, we randomly select 3% samples for testing, the remaining are used for training.

3.2 Evaluation Metrics

We consider BLEU (Papineni et al., 2002) and ROUGE (Lin and Hovy, 2003) to assess the overall generation quality, both of which consider the overlap of grams between generation (y_{gre}) and reference (y_{ref}) for evaluation and are widely adopted in generation tasks. As to measuring level-ofdetail, the straightforward strategy to adopt the outline length and number of subheadings for performance evaluation might be inappropriate. For instance, it is meaningless to recognize a repeated and nonsense output as a high-quality comprehensive outline. Therefore, we calculate the similarity in outline length and number of subheadings using min-max operation between generation and reference to assess the performance.

$$WN(y_{\text{ref}}, y_{\text{gre}}) = \frac{\min(\#_w(y_{\text{gre}}), \#_w(y_{\text{ref}}))}{\max(\#_w(y_{\text{gre}}), \#_w(y_{\text{ref}}))}$$

$$HN(y_{\text{ref}}, y_{\text{gre}}) = \frac{\min(\#_h(y_{\text{gre}}), \#_h(y_{\text{ref}}))}{\max(\#_h(y_{\text{gre}}), \#_h(y_{\text{ref}}))}$$
(11)

where $\#_w(\cdot)$ and $\#_h(\cdot)$ refer to the number of outline words and subheadings respectively.

⁴An online platform developed by Tencent Ltd. that allows businesses, organizations, and individuals to share regular information, express viewpoints, or provide entertainment and services such as e-commerce to the public. Users can also subscribe to official accounts to receive messages and access services. https://mp.weixin.qq.com/?token=&lang= en_US

 $^{^{5}}$ https://www.neweekly.com.cn/magazine 6https://www.neweekly.com.cn/

Dataset	Metric	DPO	SimPO	ORPO	CPO	TDPO	FUDGE	PREADD	DExpert	TKPO
	ROUGE-1↑	44.99	45.09	46.21	45.17	46.35	45.35	44.90	45.88	48.83
etaj	ROUGE-2↑	21.32	22.18	21.93	21.63	21.76	21.63	22.40	22.39	25.43
f-d	ROUGE-L \uparrow	32.94	32.92	33.88	32.98	34.04	32.29	32.74	34.13	36.78
Level-of-detaï	BLEU-4↑	24.67	24.55	25.46	24.90	24.29	24.50	22.24	25.58	27.05
eve	WN↑	65.41	63.81	64.78	65.48	65.40	65.75	59.27	64.20	66.78
7	HN↑	69.30	69.65	70.06	66.67	66.51	68.40	62.92	67.99	71.49
e_	ROUGE-1↑	37.54	37.34	39.08	41.18	42.51	37.80	40.65	41.39	43.67
Style	ROUGE-2↑	16.52	17.83	17.26	19.30	20.93	17.45	19.03	19.49	21.56
	ROUGE-L \uparrow	28.41	28.99	29.05	33.77	32.00	29.83	31.05	32.16	34.04
Language	BLEU-4↑	24.87	22.52	25.09	28.42	28.33	25.96	27.94	27.99	29.81
	OTE-O↓	2.10	2.41	1.72	1.77	2.25	1.92	1.94	1.97	1.75
Ţ	OTE-L↑	3.89	3.86	3.24	3.52	3.88	4.08	3.97	4.03	4.11

Table 1: The overall performance ($\times 100\%$) of TKPO and baselines. OTE-O and OTE-L are the token entropy of objective outlines and literary outlines, respectively. \uparrow indicates that higher values are better, while \downarrow indicates that lower values are better. The best results for each metric in each group are in bold.

For language style control, based on *What is literariness?* (Miall and Kuiken, 1999), *literariness emerges when the language deviates from conventional usage, creating a sense of defamiliarization and foregrounding*. Consequently, we can assess the literariness of the generation by observing the defamiliarization of word utilization. Owing to the paradigm of LLMs training, words that appear less frequently in the training corpus will inherently acquire lower probabilities during inference (Brysbaert et al., 2025), which, thereby, enhances the literariness and professionalism. Therefore, following (Zhang et al., 2024), we utilize the next-token likelihood and define the Outline Token Entropy (OTE) to measure the literariness:

$$OTE(y) = -\frac{1}{M} \sum_{t=1}^{M} \log(\pi_{ref}(y_t|x))$$
 (12)

where M denotes the length of outputs y, $\pi_{\rm ref}$ denotes the base model without training on the outline controllable generation datasets. As shown in Figure 8 and Table 4 in Appendix F.2, there is a substantial difference in the average OTE values between objective outlines (1.81) and literary outlines (4.01), indicating the effectiveness of this metric.

3.3 Baselines and Implementations

Baselines. We cover a broad range of baselines for evaluation: (1) preference alignment approaches, including DPO, SimPO, ORPO (Hong et al., 2024), CPO (Guo et al., 2024), and TDPO (Zeng et al.,

2024); (2) decoding probability intervention methods, including FUDGE (Yang and Klein, 2021), PREADD (Pei et al., 2023), and DExpert (Liu et al., 2021). See Appendix D for detail.

Implementation Details. We perform multi-style outline controllable generation with a popular open-source LLM, Qwen2.5-3B (Bai et al., 2023), and further investigate the performance variance across different LLMs (up to 7B). All the experiments are conducted on 8× NVIDIA V100 32G GPUs. The detailed hyperparameter settings are presented in Appendix E.

3.4 Overall Performance

Table 1 presents the overall performance of our TKPO against other methods on the language style and level-of-detail outline controllable generation. To sum up, owing to the inherent inconsistency in output styles between humans and LLMs, all the methods yield inferior results on language style controllable generation compared to the level-ofdetail. Our method surpasses all the baselines for level-of-detail control. Regarding language style generation, our proposed TKPO outperforms all baseline models except ORPO on the OTE-O metric. However, ORPO exhibits the poorest performance on the OTE-L metric given the "alignment tax" (Ouyang et al., 2022), where enhancing alignment with objective outline generation compromises literary expressiveness. Figure 3 illustrates the detailed results of the concise, moderate, and comprehensive outline generation. Since the verbosity bias (Saito et al., 2023), i.e., LLMs in-

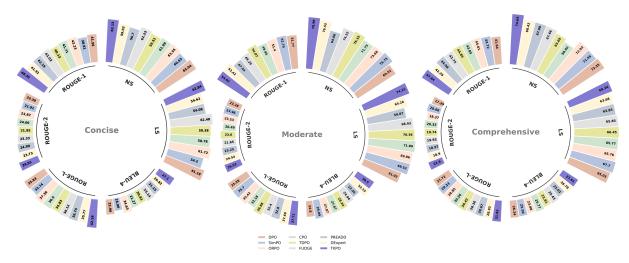


Figure 3: The overall performance for level-of-detail (concise vs. moderate vs. comprehensive) outlines controllable generation. Our TKPO method demonstrates superiority over all other baselines across all sub-datasets.

Method	ROUGE-1	ROUGE-2	ROUGE-L	BLEU-4	OTE-O	OTE-L
Qwen2.5-3B Top-K Sampling	43.14	20.23	33.14	29.51	1.86	3.82
Qwen2.5-3B w/o TKPO	40.60	19.46	31.90	28.22	1.89	3.58
Qwen2.5-3B w/ TKPO	43.67	21.56	34.04	29.81	1.75	4.11
Qwen2.5-0.5B w/ TKPO	38.41	17.52	28.41	24.49	1.97	3.52
Qwen2.5-7B w/ TKPO	44.53	21.70	35.04	30.63	1.88	4.14
LLaMA3.1-8B w/o TKPO	40.24	18.33	29.60	27.02	3.75	3.75
LLaMA3.1-8B w/ TKPO	42.51	21.00	32.94	28.89	1.91	3.88

Table 2: Ablation studies on language style dataset: (1) with (w/) and without (w/o) TKPO loss; (2) different LLM sizes and base models; (3) Top-K sampling vs. multinomial sampling in Eq. 6.

cline to output more verbose responses in the generation, all the baselines achieve comparable results in the moderate and the comprehensive controllable generation. However, for the concise control, our TKPO outperforms the best baseline by 12.39% on ROUGE-1 and 10.03% on BLEU-4. As for the language style control, the detailed results are reported in Appendix G.1. Overall, our method achieves the best results compared to the baseline models.

3.5 Ablation Studies

We further investigate the effect of different base LLMs, the size of LLMs, and rejected token sampling strategies (*i.e.*, we apply Top-K sampling as an alternative to multinomial sampling) on the performance. As shown in Table 2, we could observe that the TKPO loss improves performance across various base models. Additionally, while increasing the model size generally enhances performance, the marginal gains diminish as the size continues to grow, *e.g.*, 13.69% from Qwen2.5-0.5b to 3b vs. 1.97% from 3b to 7b in ROUGE-1. Fur-

thermore, attributed to the more precise estimation of the optimal policy (Liu et al., 2024b), multinomial sampling achieves superior results compared to Top-K sampling. We could draw a similar conclusion on the level-of-detail dataset (ref. Table 5 in Appendix G.2).

3.6 In-depth Analysis

Training Efficiency. To verify the efficiency of our method against other baselines, we report the per-GPU peak memory usage and one-step training time⁷ of Qwen2.5-3B in Figure 4 (a). Since our TKPO does not utilize a reference model and involves only the accepted response during backpropagation in the training process, the GPU memory usage and runtime are significantly lower than those of the baselines. Specifically, our method reduces roughly 26% memory usage and 46% runtime, compared with DPO.

Hyperparameter Sensitive Analysis. We visual-

⁷The average time is calculated over 100 training steps over five random runs.

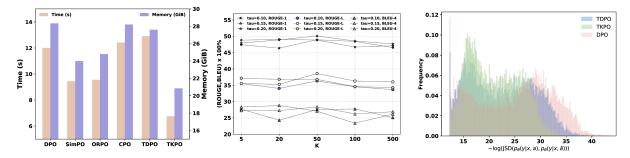


Figure 4: In-depth analysis on the level-of-detail dataset. (a) The per-GPU peak memory usage and one-step runtime. (b) Performance of TKDO across various τ and K settings. A moderate value is preferred for achieving optimal results. (c) Negative logarithm JS divergence distribution, where $p_{\theta}(y|\cdot)$ is the next-token predicted probability distribution, a and \bar{a} denote the controllable attribute (e.g., concise) and the anti-attribute (e.g., comprehensive). A smaller value indicates a greater difference in output probabilities under different controllable conditions. Our TKPO acquires a significant distinction compared to DPO and TDPO methods.

ize the performance of TKPO across various temperature ratios τ and rejected token numbers K on the level-of-detail dataset, as shown in Figure 4 (b) (Full results are reported in Table 6). We recommend a moderate value, *i.e.*, $\tau=0.15, K=50$ for outline level-of-detail controllable generation. However, for language style control, a larger value of K will facilitate the improvement of OTE, enhancing the literariness of the outlines (ref. Table 7 for detail). The results of various λ in Eq. 7 are presented in Table 8. Overall, a smaller value is recommended for a better performance.

JS Divergence. Given the controllable attribute a (e.g., concise) and anti-controllable attribute \bar{a} (e.g., comprehensive), we calculate the negative logarithm Jensen-Shannon (JS) divergence of next-token predicted probability distribution between them. Figure 4 (c) illustrates the frequency histogram of the test dataset in level-of-detail controllable outline generation. Our TKPO exhibits a more compact distribution that roughly ranges from 15 to 30 against TDPO and DPO methods. This suggests that TKPO possesses a superior ability to discern differences among various controllable conditions, thereby enabling higher-quality alignment in controllable generation.

4 Related Work

4.1 Controllable Generation

Overall, existing controllable generation attempts can be broadly categorized into three strategies: (1) probability intervention, (2) preference alignment, and (3) prompt engineering. PPLM (Dathathri et al., 2019) is a pioneer that manipulates the output probability for controllable generation. Build-

ing on this foundation, many works, including GeDi (Krause et al., 2021), FUDGE (Yang and Klein, 2021), and PREADD (Pei et al., 2023) have been proposed further. In contrast, another line of research within the probability intervention aims to reduce the probability of undesirable tokens while increasing the probability of preferred tokens for controllable generation, such as DExpert (Liu et al., 2021). Preference alignment is a general solution to align the LLMs with specific preferences or conditions, thus, the representative methods, such as DPO (Rafailov et al., 2024), SimPO (Meng et al., 2024), and ORPO (Hong et al., 2024), can also be applied for controllable generation. Building on these works, CPO (Guo et al., 2024) and DPA (Wang et al., 2024) further proposed to address multi-objective preference alignment controllable generation through data augmentation and rejection sampling. FIGA (Guo et al., 2023) and SparsePO (Christopoulou et al., 2024) employ the hard and soft token masks for finer-grained alignment. As for prompt engineering, Fonseca and Cohen (2024) introduces keywords in prompts for more precise control. Distinct from existing research, our method is response-pair-free, focusing on token-level preference alignment.

4.2 Outline Generation

Outline generation is a crucial task for text semantic structuralization, text understanding, and multiple downstream applications. However, few works put effort into this research avenue. Existing research on outline generation can be classified into two methodologies: (1) segmentation cascade summarization, and (2) prompt-driven methods. The first solution segments the article into dis-

et al., 2022; Zhang et al., 2019) or topic consistency (Jiang et al., 2024) across paragraphs. Afterward, the LLMs are applied to generate each segment's headings or brief summarizations. On the contrary, the second category (Yang et al., 2023; Li et al., 2024) endeavors to devise tailored prompts for self-supervised fine-tuning, steering the LLMs to generate the outlines straightforwardly. Nevertheless, none of the studies focus on the multi-style outline controllable generation, thus, our work aims to fill this gap.

5 Conclusion

We introduce a multi-style outline controllable generation task and curate two datasets regarding the outline language style and level-of-detail. Additionally, a token-level preference self-alignment method, named TKPO, is proposed for a more efficient and precise controllable generation. Specifically, TKPO extends the Bradley-Terry model from pair-wise to list-wise comparison and further applies it to token-level alignment. TKPO does not require response-pair for model training, instead, a controllable attributes-driven selfalignment method is applied. Mathematical analysis demonstrates that TKPO confers benefits in output diversity and hard token optimization. Besides, optimizing TKPO is tantamount to optimizing the upper bound of the optimal policy. Compared to DPO, our TKPO achieves up to 19.28% performance improvement with only 73.55% memory usage and 56.25% training time.

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Limitations

While conducting a comprehensive analysis of our TKPO against other preference alignment methods for outline controllable generation, we did not include multi-lingual outlines and other controllable generation tasks. We leave the broader range of comparison on other benchmarks as future work, along with scaling our method to over 7B models. Furthermore, we will refine the categorization of outline styles into finer-grained categories,

engaging experts to compose multi-style outlines and perform evaluations, thereby verifying the effectiveness of our method comprehensively.

Ethics Considerations

As with any effective method for controllable generation and preference alignment, we acknowledge that TKPO could potentially be misused to amplify toxicity, gender bias, or other harmful attributes. Nonetheless, these methods, like ours, also serve as powerful tools for content moderation and mitigating harmful text generation.

References

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. 2023. Qwen technical report. *arXiv* preprint arXiv:2309.16609.

Ralph Allan Bradley and Milton E Terry. 1952. Rank analysis of incomplete block designs: I. the method of paired comparisons. *Biometrika*, 39(3/4):324–345.

Marc Brysbaert, Gonzalo Martínez, and Pedro Reviriego. 2025. Moving beyond word frequency based on tally counting: Ai-generated familiarity estimates of words and phrases are an interesting additional index of language knowledge. *Behavior Research Methods*, 57(1):1–15.

Fenia Christopoulou, Ronald Cardenas, Gerasimos Lampouras, Haitham Bou-Ammar, and Jun Wang. 2024. Sparsepo: Controlling preference alignment of llms via sparse token masks. *arXiv preprint arXiv:2410.05102*.

Sumanth Dathathri, Andrea Madotto, Janice Lan, Jane Hung, Eric Frank, Piero Molino, Jason Yosinski, and Rosanne Liu. 2019. Plug and play language models: A simple approach to controlled text generation. arXiv preprint arXiv:1912.02164.

Marcio Fonseca and Shay B Cohen. 2024. Can large language model summarizers adapt to diverse scientific communication goals? arXiv preprint arXiv:2401.10415.

Geyang Guo, Ranchi Zhao, Tianyi Tang, Wayne Xin Zhao, and Ji-Rong Wen. 2023. Beyond imitation: Leveraging fine-grained quality signals for alignment. *arXiv preprint arXiv:2311.04072*.

Yiju Guo, Ganqu Cui, Lifan Yuan, Ning Ding, Zexu Sun, Bowen Sun, Huimin Chen, Ruobing Xie, Jie Zhou, Yankai Lin, et al. 2024. Controllable preference optimization: Toward controllable multi-objective alignment. arXiv preprint arXiv:2402.19085.

- Jiwoo Hong, Noah Lee, and James Thorne. 2024. Orpo: Monolithic preference optimization without reference model. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 11170–11189.
- Natasha Jaques, Shixiang Gu, Dzmitry Bahdanau, José Miguel Hernández-Lobato, Richard E Turner, and Douglas Eck. 2017. Sequence tutor: Conservative fine-tuning of sequence generation models with kl-control. In *International Conference on Machine Learning*, pages 1645–1654. PMLR.
- Feng Jiang, Weihao Liu, Xiaomin Chu, Peifeng Li, Qiaoming Zhu, and Haizhou Li. 2024. Advancing topic segmentation and outline generation in chinese texts: The paragraph-level topic representation, corpus, and benchmark. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, pages 495–506.
- Diederik P Kingma. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.
- Ben Krause, Akhilesh Deepak Gotmare, Bryan McCann, Nitish Shirish Keskar, Shafiq Joty, Richard Socher, and Nazneen Fatema Rajani. 2021. Gedi: Generative discriminator guided sequence generation. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 4929–4952.
- Jan Leike, David Krueger, Tom Everitt, Miljan Martic, Vishal Maini, and Shane Legg. 2018. Scalable agent alignment via reward modeling: a research direction. arXiv preprint arXiv:1811.07871.
- Yunzhe Li, Qian Chen, Weixiang Yan, Qinglin Zhang, Wen Wang, and Hari Sundaram. 2024. Advancing precise outline-conditioned text generation with task duality and explicit outline control. In 18th Conference of the European Chapter of the Association for Computational Linguistics, EACL 2024, pages 2362–2377. Association for Computational Linguistics (ACL).
- Chin-Yew Lin and Eduard Hovy. 2003. Automatic evaluation of summaries using n-gram co-occurrence statistics. In *Proceedings of the 2003 human language technology conference of the North American chapter of the association for computational linguistics*, pages 150–157.
- Aiwei Liu, Haoping Bai, Zhiyun Lu, Yanchao Sun, Xiang Kong, Simon Wang, Jiulong Shan, Albin Madappally Jose, Xiaojiang Liu, Lijie Wen, et al. 2024a. Tis-dpo: Token-level importance sampling for direct preference optimization with estimated weights. arXiv preprint arXiv:2410.04350.
- Alisa Liu, Maarten Sap, Ximing Lu, Swabha Swayamdipta, Chandra Bhagavatula, Noah A Smith, and Yejin Choi. 2021. Dexperts: Decodingtime controlled text generation with experts and anti-experts. In *Proceedings of the 59th Annual*

- Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 6691–6706.
- Tianqi Liu, Yao Zhao, Rishabh Joshi, Misha Khalman, Mohammad Saleh, Peter J Liu, and Jialu Liu. 2024b. Statistical rejection sampling improves preference optimization. In *The Twelfth International Conference on Learning Representations*.
- Yu Meng, Mengzhou Xia, and Danqi Chen. 2024. Simpo: Simple preference optimization with a reference-free reward. arXiv preprint arXiv:2405.14734.
- David S Miall and Don Kuiken. 1999. What is literariness? three components of literary reading. *Discourse processes*, 28(2):121–138.
- OpenAI. 2024. Hello gpt-4. OpenAI.
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. *Advances in neural in*formation processing systems, 35:27730–27744.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the* 40th annual meeting of the Association for Computational Linguistics, pages 311–318.
- Jonathan Pei, Kevin Yang, and Dan Klein. 2023. Preadd: Prefix-adaptive decoding for controlled text generation. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 10018–10037.
- Xue Bin Peng, Aviral Kumar, Grace Zhang, and Sergey Levine. 2019. Advantage-weighted regression: Simple and scalable off-policy reinforcement learning. arXiv preprint arXiv:1910.00177.
- Jan Peters, Katharina Mulling, and Yasemin Altun. 2010. Relative entropy policy search. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 24, pages 1607–1612.
- Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn.
 2024. Direct preference optimization: Your language model is secretly a reward model. Advances in Neural Information Processing Systems, 36.
- Keita Saito, Akifumi Wachi, Koki Wataoka, and Youhei Akimoto. 2023. Verbosity bias in preference labeling by large language models. In NeurIPS 2023 Workshop on Instruction Tuning and Instruction Following.
- Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, YK Li, Y Wu, et al. 2024. Deepseekmath:

- Pushing the limits of mathematical reasoning in open language models. arXiv preprint arXiv:2402.03300.
- Ziang Song, Tianle Cai, Jason D Lee, and Weijie J Su. 2023. Reward collapse in aligning large language models. *arXiv preprint arXiv:2305.17608*.
- Xiaofei Sun, Zijun Sun, Yuxian Meng, Jiwei Li, and Chun Fan. 2022. Summarize, outline, and elaborate: Long-text generation via hierarchical supervision from extractive summaries. In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 6392–6402.
- Zhiqing Sun, Yikang Shen, Qinhong Zhou, Hongxin Zhang, Zhenfang Chen, David Cox, Yiming Yang, and Chuang Gan. 2023. Principle-driven self-alignment of language models from scratch with minimal human supervision. *Advances in Neural Information Processing Systems*, 36:2511–2565.
- Haoxiang Wang, Yong Lin, Wei Xiong, Rui Yang, Shizhe Diao, Shuang Qiu, Han Zhao, and Tong Zhang. 2024. Arithmetic control of llms for diverse user preferences: Directional preference alignment with multi-objective rewards. *arXiv* preprint *arXiv*:2402.18571.
- Kevin Yang and Dan Klein. 2021. Fudge: Controlled text generation with future discriminators. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3511–3535.
- Kevin Yang, Dan Klein, Nanyun Peng, and Yuandong Tian. 2023. Doc: Improving long story coherence with detailed outline control. In *The 61st Annual Meeting Of The Association For Computational Linguistics*.
- Hongyi Yuan, Zheng Yuan, Chuanqi Tan, Wei Wang, Songfang Huang, and Fei Huang. 2024. Rrhf: Rank responses to align language models with human feedback. *Advances in Neural Information Processing Systems*, 36.
- Yongcheng Zeng, Guoqing Liu, Weiyu Ma, Ning Yang, Haifeng Zhang, and Jun Wang. 2024. Token-level direct preference optimization. In Forty-first International Conference on Machine Learning, ICML 2024, Vienna, Austria, July 21-27, 2024. OpenReview.net.
- Ruqing Zhang, Jiafeng Guo, Yixing Fan, Yanyan Lan, and Xueqi Cheng. 2019. Outline generation: Understanding the inherent content structure of documents. In *Proceedings of the 42nd International ACM SI-GIR Conference on Research and Development in Information Retrieval*, pages 745–754.
- Zhihao Zhang, Tomas Goldsack, Carolina Scarton, and Chenghua Lin. 2024. Atlas: Improving lay summarisation with attribute-based control. *arXiv preprint arXiv:2406.05625*.

A Prompt Design

We designed the following prompts for various stylized outline controllable generation when training the model.

A.1 Prompts for Level-of-detail Controllable Generation

Moderate

Translation: You are a professional magazine editor. Please generate a structured and hierarchical outline for the following Article. Requirements: Accurate and Objective.\nArticle:

Concise

Chinese: 你是一个专业的杂志编辑。请对如下文章生成结构化、层次化目录。要求: 简洁凝练。\n 文章:

Translation: You are a professional magazine editor. Please generate a structured and hierarchical outline for the following Article. Requirements: Concise and Succinct.\nArticle:

Comprehensive

Chinese: 你是一个专业的杂志编辑。请对如下文章生成结构化、层次化目录。要求: 丰富全面。\n 文章:

Translation: You are a professional magazine editor. Please generate a structured and hierarchical outline for the following Article. Requirements: Comprehensive and Detailed.\nArticle:

A.2 Prompts for Language Style Controllable Generation

Objective

Chinese: 你是一个专业的杂志编辑。请对如下文章生成结构化、层次化目录。要求: 真实客观。\n 文章:

Translation: You are a professional magazine editor. Please generate a structured and hierarchical outline for the following Article. Requirements: Accurate and Objective.\nArticle:

Literariness

Chinese: 你是一个专业的杂志编辑。请对如下文章生成结构化、层次化目录。要求: 文学诗意。\n 文章:

Translation: You are a professional magazine editor. Please generate a structured and hierarchical outline for the following Article. Requirements: Literary and Poetic.\nArticle:

B Mathematical Derivations

B.1 Closed-Form of Reward Model

Building on prior work (Jaques et al., 2017), the preference alignment with reward learning aims to optimize the Eq. (13),

$$\max_{\pi_{\theta}} \mathbb{E}_{x \sim D, y \sim \pi_{\theta}(y|x)}[r(x, y)] - \beta D_{\text{KL}}[\pi_{\theta}(y|x)||\pi_{\text{ref}}(y|x)]$$
(13)

where r is the reward model. β controls the deviation of the language model policy π_{θ} from the base reference policy π_{ref} .

Following (Rafailov et al., 2024), the closed form of the reward model r(x, y) can be derived, we include it here for completeness:

$$\max_{\pi_{\theta}} \mathbb{E}_{x \sim D, y \sim \pi_{\theta}(y|x)} [r(x, y)] - \beta D_{\text{KL}} [\pi_{\theta}(y|x)||\pi_{\text{ref}}(y|x)]$$

$$= \max_{\pi_{\theta}} \mathbb{E}_{x \sim D} \mathbb{E}_{y \sim \pi_{\theta}(y|x)} \left[r(x, y) - \beta \log \frac{\pi_{\theta}(y|x)}{\pi_{\text{ref}}(y|x)} \right]$$

$$= \min_{\pi_{\theta}} \mathbb{E}_{x \sim D} \mathbb{E}_{y \sim \pi_{\theta}(y|x)} \left[\log \frac{\pi_{\theta}(y|x)}{\pi_{\text{ref}}(y|x)} - \frac{1}{\beta} r(x, y) \right]$$

$$= \min_{\pi_{\theta}} \mathbb{E}_{x \sim D} \mathbb{E}_{y \sim \pi_{\theta}(y|x)} \left[\log \frac{\pi_{\theta}(y|x)}{\frac{1}{Z(x)} \pi_{\text{ref}}(y|x) \exp\left(\frac{1}{\beta} r(x, y)\right)} - \log Z(x) \right]$$
(14)

Similar to the results proofed in (Peters et al., 2010; Peng et al., 2019), we can obtain an exact analytic solution,

$$\pi_{\theta}(y|x) = \frac{1}{Z(x)} \pi_{\text{ref}}(y|x) \exp\left(\frac{1}{\beta} r(x,y)\right)$$
 (15)

where $Z(x) = \sum_y \pi_{\mathrm{ref}}(y|x) \mathrm{exp}\left(\frac{1}{\beta}r(x,y)\right)$ is a partition function.

Despite the fact that the Eq (15) solution in itself is intractable, we can express the reward through its corresponding optimal policy $\pi_{\theta}^*(y|x)$,

$$r^*(x,y) = \beta \log \frac{\pi_{\theta}^*(y|x)}{\pi_{\text{ref}}(y|x)} + \beta \log Z(x)$$
(16)

B.2 TKPO Loss Under the Bradley-Terry Framework

Considering the mutual independence of the probabilities associated with any two output tokens, we can extend the Bradley-Terry preference model from pair-wise to list-wise comparison. Therefore, we have

$$p\left(y_{w} \succ \{y_{\ell}\}_{\ell=1}^{K} | x\right) = \prod_{\ell=1}^{K} p(y_{w} \succ y_{\ell} | x) = \prod_{\ell=1}^{K} \frac{\exp(r(y_{w}, x))}{\exp(r(y_{w}, x)) + \exp(r(y_{\ell}, x))}$$
(17)

Substituting Eq. (16) into Eq. (17) we have

$$p^{*}\left(y_{w} \succ \{y_{\ell}\}_{\ell=1}^{K}|x\right) = \prod_{\ell=1}^{K} \frac{\exp\left(\beta \log \frac{\pi_{\theta}^{*}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)} + \beta \log Z(x)\right)}{\exp\left(\beta \log \frac{\pi_{\theta}^{*}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)} + \beta \log Z(x)\right) + \exp\left(\beta \log \frac{\pi_{\theta}^{*}(y_{\ell}|x)}{\pi_{\text{ref}}(y_{\ell}|x)} + \beta \log Z(x)\right)}$$

$$= \prod_{\ell=1}^{K} \frac{\exp\left(\beta \log \frac{\pi_{\theta}^{*}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)}\right)}{\exp\left(\beta \log \frac{\pi_{\theta}^{*}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)}\right) + \exp\left(\beta \log \frac{\pi_{\theta}^{*}(y_{\ell}|x)}{\pi_{\text{ref}}(y_{\ell}|x)}\right)}$$
(18)

We further define $\beta = 1$. Given the fact that $\prod_{i=1}^{K} (1 + x_i) > 1 + \sum_{i=1}^{K} x_i$, when $x_i > 0$. Therefore, we have,

$$p^{*}\left(y_{w} \succ \{y_{\ell}\}_{\ell=1}^{K}|x\right) = \prod_{\ell=1}^{K} \frac{\frac{\pi_{\theta}^{*}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)}}{\frac{\pi_{\theta}^{*}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)} + \frac{\pi_{\theta}^{*}(y_{\ell}|x)}{\pi_{\text{ref}}(y_{\ell}|x)}}$$

$$\propto \prod_{\ell=1}^{K} \frac{\exp\left(\frac{\pi_{\theta}^{*}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)}\right)}{\exp\left(\frac{\pi_{\theta}^{*}(y_{\ell}|x)}{\pi_{\text{ref}}(y_{w}|x)}\right)}$$

$$= \prod_{\ell=1}^{K} \frac{1}{1 + \exp\left(\frac{\pi_{\theta}^{*}(y_{\ell}|x)}{\pi_{\text{ref}}(y_{\ell}|x)} - \frac{\pi_{\theta}^{*}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)}\right)}$$

$$< \frac{1}{1 + \sum_{\ell=1}^{K} \exp\left(\frac{\pi_{\theta}^{*}(y_{\ell}|x)}{\pi_{\text{ref}}(y_{\ell}|x)} - \frac{\pi_{\theta}^{*}(y_{w}|x)}{\pi_{\text{ref}}(y_{w}|x)}\right)}$$

Following (Meng et al., 2024; Yuan et al., 2024; Hong et al., 2024), we remove the reference model π_{ref} for efficient computation. Hence, we formulate a maximum likelihood objective for Eq. (19), from which the TKPO loss is derived as follows,

$$\mathcal{L}_{\text{TKPO}}(\pi_{\theta}) = -\mathbb{E}_{(x, y_w, \{y_{\ell}\}_{\ell=1}^K) \sim \mathcal{D}} \log \frac{1}{1 + \sum_{\ell=1}^K \exp\left(\pi_{\theta}(y_{\ell}|x) - \pi_{\theta}(y_w|x)\right)}$$

$$= -\mathbb{E}_{(x, y_w, \{y_{\ell}\}_{\ell=1}^K) \sim \mathcal{D}} \log \frac{\exp\left(\pi_{\theta}(y_w|x)\right)}{\exp\left(\pi_{\theta}(y_w|x)\right) + \sum_{\ell=1}^K \exp\left(\pi_{\theta}(y_{\ell}|x)\right)}$$
(20)

By comparing Eq. (20) and Eq. (19), we can optimize the \mathcal{L}_{TKPO} to closely approximate optimize the upper bounds of the optimal policy model π^* under the Bradley-Terry framework.

B.3 Properties of TKPO Loss

The \mathcal{L}_{TKPO} is given by the Eq. (6), we start by deriving its gradient with regard to the $\pi_{\theta}(y_{t_w}|x)$,

$$\begin{split} &\frac{\partial \mathcal{L}_{\text{TKPO}}}{\partial \pi_{\theta}(y_{t_w}|x)} = \frac{\partial}{\partial \pi_{\theta}(y_{t_w}|x)} - \log \frac{\exp(\pi_{\theta}(y_{t_w}|x))}{\exp(\pi_{\theta}(y_{t_w}|x)) + \sum_{y_{t_\ell} \in \mathcal{Y}_{t_\ell}} \exp(\pi_{\theta}(y_{t_\ell}|x))} \\ &= \frac{\partial}{\partial \pi_{\theta}(y_{t_w}|x)} \log \left(\frac{\exp(\pi_{\theta}(y_{t_w}|x)) + \sum_{y_{t_\ell} \in \mathcal{Y}_{t_\ell}} \exp(\pi_{\theta}(y_{t_\ell}|x))}{\exp(\pi_{\theta}(y_{t_w}|x))} \right) \\ &= \frac{\exp(\pi_{\theta}(y_{t_w}|x))}{\exp(\pi_{\theta}(y_{t_w}|x)) + \sum_{y_{t_\ell} \in \mathcal{Y}_{t_\ell}} \exp(\pi_{\theta}(y_{t_\ell}|x))} \cdot \frac{\partial}{\partial \pi_{\theta}(y_{t_w}|x)} \frac{\exp(\pi_{\theta}(y_{t_w}|x)) + \sum_{y_{t_\ell} \in \mathcal{Y}_{t_\ell}} \exp(\pi_{\theta}(y_{t_\ell}|x))}{\exp(\pi_{\theta}(y_{t_w}|x))} \\ &= \frac{\exp(\pi_{\theta}(y_{t_w}|x))}{\exp(\pi_{\theta}(y_{t_w}|x)) + \sum_{y_{t_\ell} \in \mathcal{Y}_{t_\ell}} \exp(\pi_{\theta}(y_{t_\ell}|x))} \cdot \frac{-\sum_{y_{t_\ell} \in \mathcal{Y}_{t_\ell}} \exp(\pi_{\theta}(y_{t_\ell}|x))}{\exp(\pi_{\theta}(y_{t_w}|x))^2} \cdot \exp(\pi_{\theta}(y_{t_w}|x)) \\ &= -\frac{\sum_{y_{t_\ell} \in \mathcal{Y}_{t_\ell}} \exp(\pi_{\theta}(y_{t_\ell}|x))}{\exp(\pi_{\theta}(y_{t_w}|x)) + \sum_{y_{t_\ell} \in \mathcal{Y}_{t_\ell}} \exp(\pi_{\theta}(y_{t_\ell}|x))}} \\ &= \frac{\exp(\pi_{\theta}(y_{t_w}|x)) + \sum_{y_{t_\ell} \in \mathcal{Y}_{t_\ell}} \exp(\pi_{\theta}(y_{t_\ell}|x))}{\exp(\pi_{\theta}(y_{t_w}|x)) + \sum_{y_{t_\ell} \in \mathcal{Y}_{t_\ell}} \exp(\pi_{\theta}(y_{t_\ell}|x))}} - 1 \end{aligned}$$

Following the law of large numbers, we can reprint the sum operation of y_{t_ℓ} with the expectation. Besides, given the fact that $\exp(\pi_\theta(y|x)) \ll K\mathbb{E}_{y_{t_\ell} \sim p} \exp(\pi_\theta(y_{t_\ell}|x))$, when K is large enough, thus, the Eq. (21) can be written as:

$$\frac{\exp(\pi_{\theta}(y_{t_w}|x))}{\exp(\pi_{\theta}(y_{t_w}|x)) + K\mathbb{E}_{y_{t_{\theta}} \sim p(y_{t_{\theta}}|x)} \exp(\pi_{\theta}(y_{t_{\ell}}|x))} - 1 \propto \frac{\exp(\pi_{\theta}(y_{t_w}|x))}{K\mathbb{E}_{y_{t_{\theta}} \sim p(y_{t_{\theta}}|x)} \exp(\pi_{\theta}(y_{t_{\ell}}|x))} - 1$$
(22)

This corresponds to Eq. 10 and subsequent analysis in the paper.

C TKPO Algorithm

C.1 Pseudocode of TKPO Loss

PyTorch code for the TKPO loss is provided below:

```
import copy
import torch
from torch.nn import CrossEntropyLoss
def TKPO_loss(logits, logits_anti, labels, tau, k, lambdaa):
 logits: logits with the controllable attribute, Shape: (batch_size, sequence_length,
     vocab size):
 logits_anti: logits with anti-controllable attribute, Shape: (batch_size, sequence_length,
     vocab_size);
 labels: labels, Shape: (batch_size, sequence_length);
 tau: temperature ratio controlling the strength of preference difference;
 k: number of rejected tokens;
 lambdaa: the weight factor adjusts the influence weight of CE loss and TKPO loss;
 # ------ TKPO loss ------
 \# Shift so that tokens < n predict n
 shift_logits = logits[...,:-1,:].contiguous()
 pos_token = labels[..., 1:].contiguous()
 probs = torch.softmax(shift_logits, dim=-1)
 pos_tokencp = copy.deepcopy(pos_token)
 pos_tokencp[pos_token==-100] = 100
 pos_prob = torch.gather(probs, 2, pos_tokencp.unsqueeze(-1).unsqueeze(0)).squeeze(-1)
 pos_prob = torch.exp(pos_prob/tau)
 logits_anti = logits_anti.detach()
 logits_anti.scatter_(2, pos_tokencp.unsqueeze(-1).unsqueeze(0), -1e6)
 # _, neg_token = torch.topk(logits_anti, k, dim=-1) # Top-K Sampling
 anti_probs = torch.softmax(logits_anti, dim=-1).squeeze(0)
 neg_token=torch.multinomial(anti_probs,k,replacement=False).unsqueeze(0) # Multinomial
     Sampling
 neg_probs = torch.gather(probs, 2, neg_token)
 neg_probs = torch.sum(torch.exp(neg_probs/tau), dim=-1)
 loss_tkpo = pos_prob/(pos_prob + neg_probs)
 mask_label = torch.ones_like(pos_token)
 mask_label[pos_token==-100] = 0
 loss_tkpo = -torch.log(torch.sum((loss_tkpo*mask_label),dim=-1)/torch.sum(mask_label,dim=-1))
 # ------ CE loss ------
 # Flatten the tokens
 loss_fct_ce = CrossEntropyLoss()
 shift_logits = shift_logits.view(-1, logits.shape[-1])
 shift_labels = pos_token.view(-1)
 # Enable model parallelism
 shift_labels = shift_labels.to(shift_logits.device)
 loss_ce = loss_fct_ce(shift_logits, shift_labels)
 # ------loss ------
 loss = loss_ce + lambdaa * loss_tkpo
 return loss
```

Algorithm 1: Token-level Preference Alignment (TKPO)

- 1: Input:
- 2: Controllable attributes: $a \in \mathcal{A}$, Datasets with different a: $\mathcal{D} = \{(y, x, a)_i\}_{i=1}^N$;
- 3: Learning rate: η , Training epoch: E, Rejected token numbers: K;
- 4: Policy model: π_{θ} , Temperature ratio: τ , Coefficient: λ ;
- 5: **for** each epoch in E **do**
- 6: Sample mini-batch $\mathcal{D}_m = \{(y, x, a, \bar{a})_i\}_{i=1}^m$ from \mathcal{D} ;
- 7: Rejected tokens sampling: $\{y_{t_{\ell i}}\}_{i=1}^K \sim \text{Mult-Sampling}(P_{\theta}(\hat{y}_t|x,\bar{a},y_{< t}));$

8:
$$\theta \leftarrow \theta + \eta \nabla_{\theta} \mathbb{E}_{(y,x,a,\bar{a}) \sim \mathcal{D}_{m}} \left[\log \pi_{\theta}(y_{t_{w}}|x,a) + \lambda \log \frac{\exp(\pi_{\theta}(y_{t_{w}}|x,a)/\tau)}{\exp(\pi_{\theta}(y_{t_{w}}|x,a)/\tau) + \sum\limits_{y_{t_{\ell}} \in \mathcal{Y}_{t_{\ell}}} \exp(\pi_{\theta}(y_{t_{\ell}}|x,\bar{a})/\tau)} \right];$$

- 9: end for
- 10: Output:
- 11: Updated policy model: π_{θ} ;

C.2 Algorithm of TKPO Loss

The training process of TKPO is shown in Algorithm 1.

D Baselines

We select eight controllable generation baseline models, covering two research lines: (1) preference alignment and (2) decoding probability intervention, for performance evaluation. All of them are highly related to our research.

(1) Preference Alignment Methods:

- DPO (Rafailov et al., 2024) simplifies the RLHF by introducing the closed-form expression of the optimal reward model into the Bradley-Terry pair-wise ranking framework, bypassing the explicit learning requirements of the reward model.
- **SimPO** (Meng et al., 2024) further simplifies the DPO by using the average log probability of a sequence as the implicit reward, thus, obviating the necessity for a reference model.
- ORPO (Hong et al., 2024) integrates the SFT and preference alignment possesses into one stage, and then, calculates the odds ratio for favored and disfavored generations contrasting. It also eliminates the reference model for computation efficiency.
- CPO (Guo et al., 2024) develops DPO to the multi-objective alignment through controllable attribute prompt-driven and data augmentation methods.

• TDPO (Zeng et al., 2024) applies DPO at the token level, improving the alignment and diversity of the outputs.

(2) Decoding Probability Intervention Methods:

- FUDGE (Yang and Klein, 2021) factorizes the controllable generate probability via Bayesian rule. After that, the conditional attributes probability and the next token probability are modeled separately for controllable generation.
- PREADD (Pei et al., 2023) considers both the original outputs as well as the outputs from the prefix-prepended prompts when decoding for controllable generation.
- **DExpert** (Liu et al., 2021) aims to increase the probability of preferred tokens yield by the secure model while simultaneously reducing the probability of undesired tokens from the toxic model for controllable generation.

The objection functions of the baselines can be summarized in Table 3.

Baselines	Objective	Hyperparameter
DPO	$-\mathbb{E}_{(x,y_w,y_\ell)\sim\mathcal{D}}\left[\log\sigma\left(\beta\log\frac{\pi_{\theta}(y_w x)}{\pi_{\mathrm{ref}}(y_w x)}-\beta\log\frac{\pi_{\theta}(y_\ell x)}{\pi_{\mathrm{ref}}(y_\ell x)}\right)\right]$	$\beta \in [0.01, 0.05, 0.1]$
SimPO	$-\mathbb{E}_{(x,y_w,y_\ell)\sim\mathcal{D}}\left[\log\sigma\left(rac{eta}{ y_w }\log\pi_ heta(y_w x)-rac{eta}{ y_\ell }\log\pi_ heta(y_\ell x)-\gamma ight) ight]$	$\beta \in [2.0, 2.5],$
Jiiii O		$\gamma \in [0.5, 1.0, 1.2, 1.4]$
ORPO	$-\mathbb{E}_{(x,y_w,y_\ell)\sim\mathcal{D}}\left[\log p_{\theta}(y_w x) + \lambda \log \sigma \left(\log \frac{p_{\theta}(y_w x)}{1-p_{\theta}(y_w x)} - \log \frac{p_{\theta}(y_{\ell} x)}{1-p_{\theta}(y_{\ell} x)}\right)\right],$	$\lambda \in [0.1, 0.5, 1.0, 2.0]$
	where $p_{\theta}(y x) = \exp\left(\frac{1}{ y }\pi_{\theta}(y x)\right)$	
СРО	$-\mathbb{E}_{(x,a,y_w,y_\ell) \sim \mathcal{D}} \left[\log \sigma \left(\beta \log \frac{\pi_{\theta}(y_w a,x)}{\pi_{\text{ref}}(y_w a,x)} - \beta \log \frac{\pi_{\theta}(y_\ell a,x)}{\pi_{\text{ref}}(y_\ell a,x)} \right) \right]$	$\lambda \in [0.01, 0.05, 0.1]$
TDPO	$-\mathbb{E}_{(x,y_w,y_\ell)\sim\mathcal{D}}\left[\log\sigma\bigg(\left(\beta\log\frac{\pi_{\theta}(y_w x)}{\pi_{\mathrm{ref}}(y_w x)}-\beta\log\frac{\pi_{\theta}(y_\ell x)}{\pi_{\mathrm{ref}}(y_\ell x)}\right)\right]$	$\beta \in [0.01, 0.05, 0.1]$
	$-\left(eta D_{ ext{SeqKL}}(x,y_{\ell};\pi_{ ext{ref}}\parallel\pi_{ heta}) - eta D_{ ext{SeqKL}}(x,y_{w};\pi_{ ext{ref}}\parallel\pi_{ heta}) ight) ight) ight],$	
	where $D_{\text{SeqKL}}(x, y; \pi_1 \parallel \pi_2) = \sum_{t=1}^{T} D_{\text{KL}}(\pi_1(\cdot [x, y^{< t}]) \parallel \pi_2(\cdot [x, y^{< t}]))$	
FUDGE	$-\mathbb{E}_{(x,y)\sim\mathcal{D}}\left[\operatorname{log}p(y x)p(a y,x) ight]$	
PREADD	$-\mathbb{E}_{(x,y)\sim\mathcal{D}}\left[\log p(y x)^{1-\alpha}p(a y,x)^{\alpha}\right]$	$\alpha\in[-5,-2,0,2,5]$
DExpert	$-\mathbb{E}_{(x,y)\sim\mathcal{D}}\left[\operatorname{logsoftmax}(z(y x) + \alpha(z^{+}(y x) - z^{-}(y x))\right]$	$\alpha \in [1.0, 2.2]$

Table 3: Objection functions and hyperparameter search ranges for the compared baseline models. Given preference data $\mathcal{D}(x,a,y_w,y_l)$, where x is the input, a denotes the controllable attributes, y_w and y_ℓ are the accepted and rejected responses. π_θ and π_{ref} correspond to the language model policy and reference policy, respectively. z, z^+ , and z^- are the logits yielded by the base, secure, and toxic models, respectively.

E Implementation Details

To ensure a fair comparison, we conduct thorough hyperparameter tuning for all methods compared in our experiments. Specifically, we preliminary set the learning rate to 1e - 5, utilizing a cosine learning rate schedule with a warm-up phase accounting for 10% of the steps over one epoch, within a total of seven epochs. In addition, we individually search the optimal learning rates in the range of [5e-7, 1e-6, 5e-6, 5e-5, 1e-5]for each baseline model. We set the batch size as 1. The temperature ratio τ , and rejected token numbers K are searched within the range of [0.1, 0.15, 0.2] and [5, 20, 50, 100, 500], respectively. The hyperparameter λ in Eq. (7) is searched within the range of [0.1, 0.5, 1.0]. Moreover, all the models are fine-tuned with the Adam (Kingma, 2014) optimization method and all the experiments are conducted on 8× NVIDIA Tesla V100 32G GPUs. The key hyperparameter search ranges of other baselines are presented in Table 3.

F Dataset Statistics

F.1 Raw Article Statistics

We randomly select 10,000 articles published before Sep. 10,2024 from WeChat Official Accounts

Platform⁸. Using GPT-40 with tailored prompts (ref. Appendix A.1 for detail) to obtain three categories of outlines, i.e., concise vs. moderate vs. comprehensive (named C²O dataset), for outline level-of-detail controllable generation. Moreover, we collect 10,000 articles from Sanlian Lifeweek Magazine ("三联生活周刊") 9 and Neweekly Magazine ("新周刊") 10 published before Dec. 2, 2024. The articles from these two official accounts are known for their profound yet sharp insights. Considering the raw article outlines are written by professional editors, exhibiting rich literary and artistic characteristics, we refer to them as *literary* outlines, while the outlines generated by GPT-40 with prompts (ref. Appendix A.2 for detail) are recognized as objective outlines. Therefore, we curate a dataset, denoted as LO², for the language style controllable generation. For all datasets, any information that names or uniquely identifies individual people has been removed.

We report the distribution of article categories

⁸An online platform developed by Tencent Ltd. that allows businesses, organizations, and individuals to share regular information, express viewpoints, or provide entertainment and services such as e-commerce to the public. Users can also subscribe to official accounts to receive messages and access services. https://mp.weixin.qq.com/?token=&lang=en_US

 $^{^9}$ https://www.neweekly.com.cn/magazine

¹⁰ https://www.neweekly.com.cn/

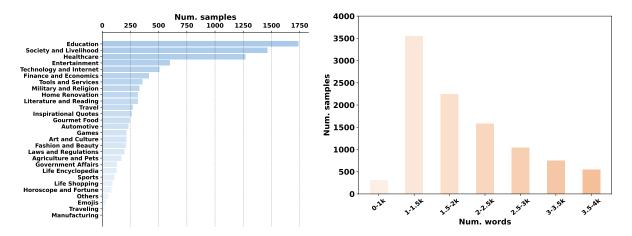


Figure 5: Statistical distribution of the C^2O (concise vs. moderate vs. comprehensive) dataset: the left subfigure manifests the article category distribution, while the right subfigure presents the distribution of article word numbers

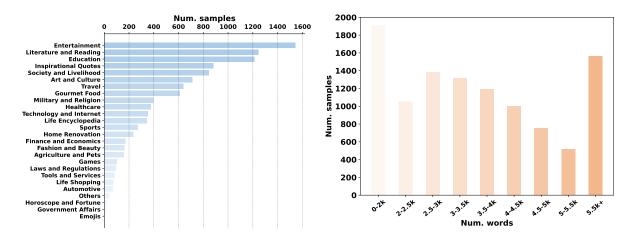


Figure 6: Statistical distribution of the LO² dataset: the left subfigure manifests the article category distribution, while the right subfigure presents the article word numbers distribution.

and word counts for these two datasets, as shown in Figure 5 and Figure 6, respectively. It is evident that a significant portion of the articles in the ${\rm LO^2}$ dataset are concentrated in the literary criticism, and are consequently classified under the literature and reading category. In contrast, the articles from the ${\rm C^2O}$ dataset are mostly classified under society and livelihood. Moreover, the average article length in the ${\rm LO^2}$ dataset (3, 705.17 words) is significantly longer than that in the ${\rm C^2O}$ dataset (1, 928.60 words), indicating a higher degree of professionalism and literacy.

F.2 Outline Statistics

Level-of-detail. For the level-of-detail dataset, we analyze the outline word count, number of headings, and word count per heading, as illustrated in Figure 7. Comparing the statistical dis-

tribution of concise, moderate, and comprehensive outlines, the average outline lengths are 58.24 words, 250.42 words, and 893.46 words, respectively. That is, the average lengths and the average number of headings in comprehensive outlines are approximately fifteen and nine times greater than those in concise outlines, highlighting a significant disparity in outline structure.

Language Style. Following Eq (12), we randomly select 3, 000 literary and objective outlines, investigating their average token entropy distribution, as shown in Figure 8. It can be observed that over 70% literary outlines exhibit an average token entropy within the interval of 3 to 5, while this metric decreases to a range of 1 to 2 for the objective outlines. This indicates the distinct differences in vocabulary usage and language defamiliarization between literary and objective styles.

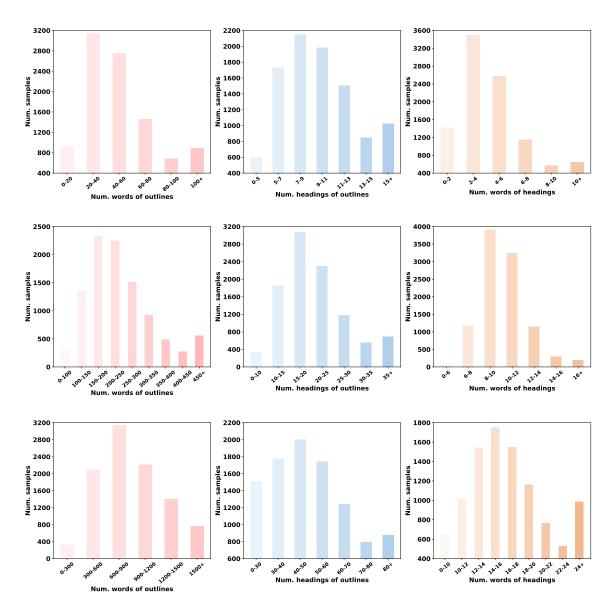


Figure 7: Statistical distributions (outline word count, number of headings, and word count per heading) of concise (top), moderate (middle), and comprehensive (bottom) outlines.

Outline: Level-of-detail							
# Words # Heading							
Concise	58.24	5.68					
Moderate	250.42	22.06					
Comprehensive	896.46	51.06					
Outline	Language St	yles					
	# Headings	OTE					
Objective	297.80	1.81					
Literary	71.32	4.01					

Table 4: The statistics of outlines. # indicates count number operation. OTE refers to the outline token entropy, defined in Eq 12.

Overall. The average number of words, the average number of headings, and the average outline token entropy are shown in Table 4.

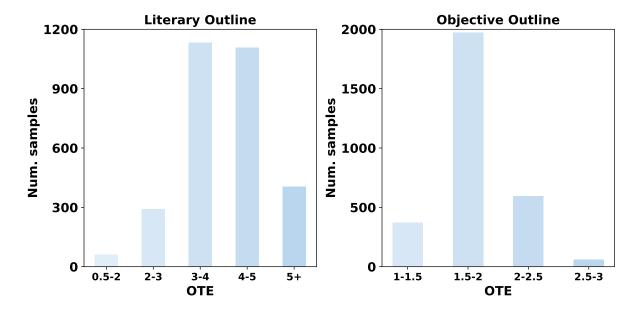


Figure 8: The average outline token entropy (OTE, defined in Eq 12) distribution with regard to literary (right) and objective (left) outlines.

G Experimental Details

G.1 Language Style Dataset Performance

The performance of language style outline controllable generation (literary vs. objective) is shown in Figure 9. Our solution is superior to all the baseline models across all the sub-datasets.

G.2 Ablation Study of Level-of-detail Dataset

The experimental results of the ablation study with various model sizes (0.5B vs. 3B vs. 7B), base models (Qwen2.5 vs. LLaMA3.1), and sampling strategies (multinomial sampling vs. Top-K sampling) on level-of-detail outline controllable generation, as shown in Table 5. We can find that (1) the multinomial sampling outperforms Top-K sampling, and (2) TKPO loss can enhance performance across various base models and model sizes consistently and significantly.

G.3 Hyperparameter Sensitive Analysis

The impact of hyperparameter temperature ratio τ and rejected token numbers K in Eq. 7 are shown in Table 6 (level-of-detail dataset) and Table 7 (language style dataset). The TKPO loss curve across various τ is illustrated in Figure 10. Increasing the value of τ , the \mathcal{L}_{TKPO} decrease simultaneously. However, this does not mean larger τ is always better for performance improvement. In general, we recommend a moderate value, e.g., $\tau=0.15$ and K=50 for the optimal performance. Addi-

tionally, the results with various λ settings in Eq 7 are reported in Table 8. We could observe that a smaller value is recommended for better performance.

G.4 Output Probability Difference

We further observe the probability differences between the accepted token and the rejected tokens (i.e., $p(y_t|x) - \frac{1}{K} \sum_{i=1}^K p(y_{t_{\ell i}}|x)$, where K is the number of sampling rejected tokens) during the TKPO and DPO training in language style dataset, as shown in Figure 11. It illustrates the probability discrimination between the accepted token and the rejected tokens in our TKPO enlarges as the training proceeds, whereas the DPO difficult to model the preference comparison at token levels, thereby failing to widen the margin between them.

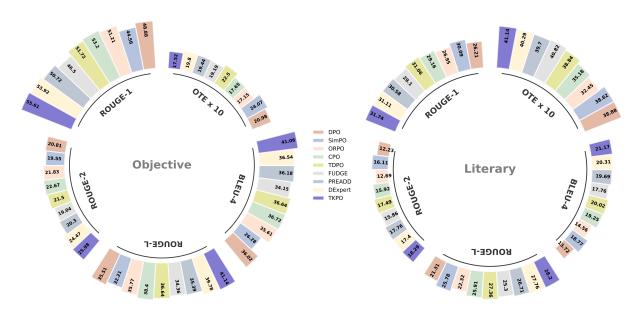


Figure 9: The overall performance of language style (objective vs. literary) outlines controllable generation. We multiply the OTE metric by 10 for readability, denoted as OTE \times 10. Our TKPO method is superior to the other baselines on both literary and objective datasets.

Method	ROUGE-1	ROUGE-2	ROUGE-L	BLEU-4	WN	HN
Qwen2.5-3B Top-K Sampling	48.18	24.48	35.68	27.85	65.88	68.79
Qwen2.5-3B w/o TKPO	46.62	22.58	33.57	25.91	65.13	67.40
Qwen2.5-3B w/ TKPO	48.83	25.43	36.78	27.05	66.78	71.49
Qwen2.5-0.5B w/ TKPO	40.59	19.69	28.59	21.44	55.70	58.60
Qwen2.5-7B w/ TKPO	49.92	26.05	37.29	28.17	66.20	71.56
LLaMA3.1-8B w/o TKPO	45.59	22.53	31.99	23.04	63.35	66.11
LLaMA3.1-8B w TKPO	47.61	22.79	34.20	26.62	66.90	68.14

Table 5: Ablation studies on the level-of-detail dataset: (1) with (w/) and without (w/o) TKPO loss; (2) different LLM sizes and base models; (3) Top-K sampling vs. multinomial sampling in Eq. 6.

au	K	ROUGE-1	ROUGE-2	ROUGE-L	BLEU-4	WN	HN
	5	47.41	25.16	35.50	27.67	66.51	69.17
	20	46.35	21.76	34.04	24.29	65.40	66.51
0.10	50	48.92	23.98	36.31	27.56	69.40	70.16
	100	48.42	23.08	34.53	27.74	69.85	68.50
	500	46.53	21.98	33.66	25.09	65.82	69.37
	5	47.92	24.11	35.54	27.24	62.84	66.61
	20	48.91	24.55	35.27	27.24	65.80	64.64
0.15	50	50.08	27.20	38.59	28.38	68.92	72.54
	100	48.54	25.08	36.29	26.22	63.09	67.54
	500	47.65	24.24	36.04	26.89	63.72	67.21
	5	48.80	25.05	37.15	28.32	68.73	68.74
	20	49.05	24.60	36.81	28.79	67.47	69.24
0.20	50	48.84	25.43	36.78	27.05	65.44	69.84
	100	46.69	23.76	34.58	23.39	61.18	66.45
	500	47.10	22.97	34.27	26.15	66.01	66.88

Table 6: Performance of TKDO across various τ and K settings on the level-of-detail dataset.

τ	K	ROUGE-1	ROUGE-2	ROUGE-L	BLEU-4	OTE-L	OTE-O
	5	43.95	22.25	34.98	30.88	3.87	1.91
	20	44.71	21.96	35.47	32.08	3.68	1.98
0.10	50	43.99	21.89	34.55	30.67	3.66	1.85
	100	43.13	21.24	33.82	30.37	3.98	1.77
	500	43.11	21.20	33.63	29.71	3.82	1.86
	5	43.39	21.08	33.85	30.31	3.67	1.99
	20	44.14	21.65	34.17	30.68	3.61	1.81
0.15	50	43.69	21.56	34.87	30.79	3.88	1.83
	100	43.01	21.59	34.57	30.72	4.13	1.90
	500	43.40	21.12	34.21	29.68	4.07	1.75
	5	43.42	21.74	34.45	30.78	3.83	2.01
	10	43.16	22.17	34.10	29.75	3.98	1.92
0.20	50	43.02	21.37	34.44	30.44	3.57	1.82
	100	42.51	20.61	32.78	28.67	4.12	1.90
	500	42.04	19.82	32.67	27.44	4.18	1.92

Table 7: Performance of TKDO across various τ and K settings on the language style dataset.

Dataset	tλ	ROUGE-1	ROUGE-2	ROUGE-L	BLEU-4	WN	HN	OTE-O	OTE-L
	0.1	48.10	25.06	35.82	25.40	65.19	71.31	-	-
² 2C	0.5	48.83	25.43	36.78	27.05	66.78	71.49	-	-
\cup	1.0	47.48	23.17	34.85	26.60	62.99	66.50	-	-
	0.1	43.67	21.56	34.04	29.81	-	-	1.75	4.11
Õ	0.5	42.36	20.61	32.75	29.73	-	-	1.88	3.94
1	1.0	41.56	20.48	32.83	29.37	-	-	1.90	4.03

Table 8: Performance of TKPO across various λ in Eq. 7. $\mathbf{C}^2\mathbf{O}$ and \mathbf{LO}^2 denote the level-of-detail dataset and language style dataset, respectively.

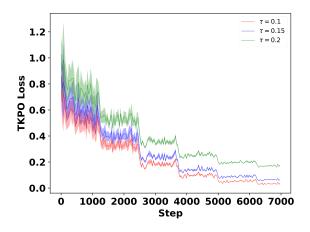


Figure 10: The TKPO loss curve across various values of τ on the language style dataset. The loss consistently decreases during training. With a larger τ (e.g., $\tau=0.2$), \mathcal{L}_{TKPO} obtains a smaller value in training the models, indicating a more pronounced discrimination in the generation probability between accepted token and rejected tokens.

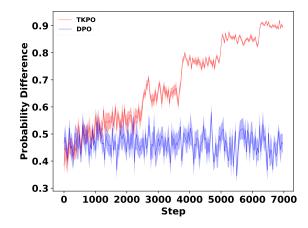


Figure 11: Probability difference between the accepted token and the rejected tokens on language style dataset, i.e., $p(y_t|x) - \frac{1}{K} \sum_{i=1}^K p(y_{t_{\ell i}}|x)$, where K is the number of sampling rejected tokens. The discrimination modeled by our TKPO increases during training, indicating the validity of token-level preference comparisons.

H Dataset Example

H.1 Level-of-Detail Dataset Example

Table 9: Outline level-of-detail controllable generation, Example A.

A -45-11-	Compile	Madamata Out	Commelouries Outline
Article	Concise Outline	Moderate Out- line	Comprehensive Outline
Central Park in New York: The Astonishing Secret of American Urban Planning Only those who have been to New York might know the secret of American urban planning, and it all starts with Central Park in New York. On one side, there are towering skyscrapers; on the other, the autumnal Central Park Half nature, half busting oity. The very existence of Central Park in New York is seen by many as a miracle. On such a small, valuable island, there is such a large park. However, for New Yorkers, this is not contradictory at all. Over a hundred years ago, the land where Central Park now stands was just a wasteland and a few impoverished villages. It was the emergence of this vast green space that increased the value of the land. Today, the area around Central Park is filled with luxury residences worth billions of dollars, attracting top-tier wealthy individuals from around the world. No official would be foolish enough to propose using the park's land for commercial development; such an idea would likely be met with ourtage from millions of people. One notable feature of Central Park is its size (843 acres, approximately 341 hectares). This size is significant not just in absolute terms but also in relation to the entire city. Over its more than 100-year into one of the world's top cities. Over its more than 100-year into one of the world's top cities. Designed by landscape architects Frederick Law Olmsted and Calvert Vaux, the park was completed in 1873 after 15 years of construction. In 1858, a design competition for Central Park and its surrounding areas were undeveloped outskirts of New York City. The designers anticipated that one day the area around the park would develop, making it the only place where residents could see natural scenery. Frederick Olmsted, the master landscape designer of Central Park, stated his design philosophy. For a city to hold a place among the world's great cities, it must focus on the higher achievements of human labor, not just on profit-making industries. He said, "A city shoul	Outlines 1. History and Back- ground of Central Park in New York 2. Design and Plan- ning Con- cepts 3. Func- tional Zoning and Road System 4. Nat- ural Land- scape and Layout 5. Im- pact and Preserva- tion of Central Park 6. Future Reimagin- ing	Outlines History and Background of Central Park in New York - The Birth of Central Park in New York - Designers and Design Concepts - Construction and Development of the Park Design Features of Central Park in New York - Rich Functional Zoning - Advanced Road System - Natural Land- scape Layout Impact of Central Park in New York - Impact on Urban Planning - Impact on Urban Planning - Impact on the Lives of New York Citizens Preservation and Future of Central Park in New York - Legal Protection and Basic Structure - Future Reimagining and Design Competitions	Central Park in New York: The Astonishing Secret of American Urban Planning I. The Miracle of Central Park 1.1 Contrast Between Skyscrapers and the Park 1.2 Historical Background of the Park 1.3 Impact of the Park 0.1 Design and Concepts of Central Park 2.1 Design and Concepts of Central Park 2.1 Designers and Design Process 2.1.1 Frederick Law Olmsted and Calvert Vaux 2.1.2 Design Competition and Selection of Proposals 2.2 Design Concepts 2.2.1 Service to Humanities, Religion, Art, and Academia 2.2.2 Creation of Natural Scenery III. Functions and Layout of Central Park 3.1 Functions and Layout of Central Park 3.1 Functional Zoning 3.2 Road System 3.2.1 Urban Road System 3.2.1 Urban Road System 3.2.1 English "Pastoral" Landscape Layout 3.3.1 English "Pastoral" Landscape 3.3.2 Preservation of Original Topography IV. Current Status and Future of Central Park 4.1 Basic Structure and Legal Protection of the Park 4.2 Evolution of the Park and Changes in Visitors 4.3 Future Reimagining 4.3.1 Inspiration from LA + ICONOCLAST 4.3.2 Design Competition and Submissions

Table 10: Outline level-of-detail controllable generation, Example A. (Translation)

Article	Concise Outline	Moderate Outline	Comprehensive Outline
鸟山明去世,大概是我们第一次经历陪着我们所有人成长的漫画家离去。	Outline 目1.明世2.漫源3.创瓶4.明破5.珠成6.明产7. 山离 本的 画的 山突 龙的 山遗 语	Ou 目鸟的与 , 的与 , 虫子二时景 , 的与日画变 , 虫头 , 材风样 , 面颈鸟的与 , 蕾功 , 的与 , 夫珠响 , 的与鸟的生创念 , 的方 , 的魅 , 对家许 , 的与精制。	国成一、自身。 国成一、自身。 国成一、自身。 是、一、一、一、一、一、一、一、一、一、一、一、一、一、一、一、一、一、一、一

Table 11: Outline level-of-detail controllable generation, Example B.

Article	C	M - J 4 - O 4	C
	Concise Outline	Moderate Out- line	Comprehensive Outline
loss of a manga artist who grew alongside all of us. Osamu Tezuka passed away in 1989, and Fujiko F. Fujio died in 1996, both before the Internet era. After that, seasons change, one flower falls and another blooms and manga artists have lived on, though occasionally we hear of tragic news like Kentaro Miura's untimely death or Hiromu Arakawa's tragic passing, but generally, these were distant events to the public. But Toriyama is different. His Dr. Slump and Dragon Ball are the most influential manga worldwide. He was the most important creator in the evolution of manga as a medium after Tezuka, a true master of his generation. The creative lineage of Japanese manga originates with Osamu Tezuka. Tezuka was influenced by Disney, having watched Bambi 120 times in theaters, committing every storyboard to memory. From that point on, Japanese manga developed its own cinematic language. Over the next three decades, manga artists explored a wider range of themes, developed diverse artistic styles, and became increasingly bold and skilled with their use of cinematic techniques. But there was always a limitation: the images were static, lacking dynamism. Take, for example, two of Toriyama's contemporaries—Masami Kurumada and Tetsuo Hara—during battle scenes, characters were often frozen in dramatic poses, while in the next panel, the opponent would show signs of injury. Toriyama unintentionally changed all of this. In 1984, his Dr. Slump became a nationwide hit in Japan. Living in rural Aichi Prefecture, Toriyama, who enjoyed keeping pets and assembling model kits, didn't seem to value this success very much. In 1983, his income tax was ¥96.98 million (not the exaggerated ¥600 million version often found online), equivalent to about ¥800,000 at the time, placing him 11th among Japanese celebrities—he had	Outlines 1. The Passing of Akira Toriyama 2. The Origins of Japanese Manga 3. The Bottle- necks in Manga Creation 4. Akira Toriyama's Break- through 5. The Suc- cess of Dragon Ball 6. Akira Toriyama's Legacy 7. Con- clusion	Table of Contents The Influence and Status of Akira Toriyama - The Passing and Impact of Akira Toriyama - The Era of Osamu Tezuka and Contributions The Evolution of Japanese Manga - Osamu Tezuka's Cinematic Techniques - The Diversification of Manga Themes and Art Styles - The Diversification of Manga Themes and Art Styles - The Bottleneck of Dynamic Imagery Akira Toriyama's Innovation and Success - The Bottleneck of Dr. Slump - The Beginnings and Challenges of Dr. Slump - The Influence of Jackie Chan's Kung Fu on Dragon Ball - The Success and Impact of Dragon Ball - The Success - The Unique Chan's Kung Fu on Dragon Ball - The Success - The Unique Charm of Dragon Ball - The Success - Akira Toriyama's	Akira Toriyama's Passing: The Manga Master Who Accompanied Our Growth 1. Introduction 1. The Influence of Akira Toriyama 2. The Passing of a Manga Master II. The Era of the Manga Master II. The Influence of Osamu Tezuka 1.2 The Relationship Between Osamu Tezuka and Disney 2. The Passing of Fujiko F. Fu- jio 3. Manga Artists Before and After the Internet 3.1 The Passing of Kentaro Miura 3.2 The Suicide of Hinako Ashihara III. Akira Toriyama's Creative Journey 1. The Success of Dr. Slump 1.2 Akira Toriyama's Lifestyle 2. The Birth of Dragon Ball 2.1 The Initial Struggles of Dragon Ball Serialization 2.2 The Collaboration Be- tween Akira Toriyama and Editor Kazuhiko Torishima 2.3 Inspiration from Jackie Chan Movies IV. The Success and Impact of Dragon Ball 1. The Visual Innovations of Dragon Ball 1. The Creation of Dynamic Imagery 1.2 The Application of Jackie Chan-style Kung Fu 2. The Commercial Success of Dragon Ball 3.1 Smooth Storytelling 3.2 Detailed Mechanical and Animal Drawings 3.3 Innocent and Simple Char- acters V. The Legacy and Influence of Akira Toriyama 1. The Inheritance and Loss of Dynamic Imagery 2. Akira Toriyama's Expecta- tions for Future Manga Artists 2.1 The 2019 "Shonen Jump" 50th Anniversary Interview 2.2 Akira Toriyama's Expecta- tions for Future Manga Artists 2.1 The Eternal Influence of Akira Toriyama's Cenius and Foolish Spirit 2. The Eternal Influence of Akira Toriyama's Genius and Foolish Spirit 2. The Eternal Influence of Akira Toriyama's Genius and Foolish Spirit 2. The Eternal Influence of Akira Toriyama's Genius and Foolish Spirit 2. The Eternal Influence of Akira Toriyama's Cention VI. Conclusion 1. Akira Toriyama's Genius and Foolish Spirit 2. The Eternal Influence of Akira Toriyama's Cention

Table 12: Outline level-of-detail controllable generation, Example B. (Translation)

H.2 Language Style Dataset Example

Article	Literary Outline	Objective Outline
《景观社会》 "影像化"的社会景观	目录	目录
(一) 从商品批判到景观批判 德波在《景观社会》中从不同角度对景观概念做了论说。景观,原意为一种被展现出来	1. 从商 品 批 判	一、 从 商品批
的可视的客观景色、景象,也意指一种主体性的、有意识的表演和做秀。德波借其概括自己	到景观	判到景
看到的当代资本主义社会新特质,即当代社会存在的主导性本质体现为一种被展现的图景性。人们因为对景观的迷人而丧失对本真生活的渴望和要求,而资本家则依靠控制景观的	批判 2. 视觉	观批判 1.1 景观
生成和变换来操纵社会生活。	传播 化	的概念
德波沿着马克思的理论思路确定了自己的理论前提: 当代发达工业社会已经是个景观 堆聚的社会。德波对马克思的商品现象学作了改写, 把商品异化改写为景观异化。其把到目	的现代社会统	与特质 1.2 景观
前为止的资本主义社会分为商品社会和景观社会两个阶段,商品社会以占有为特征,景观	治	社会的
社会以展示为特征。它们的不同在于资本增值的中介:以前,资本通过操作具体的物品来控制社会;而当代,资本通过景象操控生活。	3. 景观 的 统 治	形成 1.3 景观
在德波这里,景观是一种由感性的可观看性建构起来的幻象,它的存在由表象所支撑,	形式	的幻象
以各种不同的影像为其外部显现形式。尤为重要的是,景观的在场是对社会本真存在的遮		与 社 会 关系
蔽。后来,波德里亚又在此基础上发明了类象一词,后者所谓的类象的定位是存在论意义上的根本性篡位,因为它比原本存在更加真实。		二、视觉传播
在德波眼中,景观的出现并不就意味着世界已被虚化为一幅影像图景,"景观不能被理		化的现
解为一种由大众传播技术制造的视觉欺骗",必须充分理解: "景观不是影像的聚积,而是以影像为中介的人们之间的社会关系"。在今天的资本主义社会里,物质生产方式的决定性		代 社 会
结构已经转向以影像方式为主导的景观生产方式。		统治 2.1 景观
(二) 视觉传播化的现代社会统治 德波认为,景观的本质是拒斥对话。景观是一种更深层的无形控制,它消解了主体的反		的本质
抗和批判否定性,在景观的迷人之中,人只能单向度地默认。如是,方为意识形态的本质。		与 拒 斥 对话
首先,景观已经成为当前资本主义生产方式的目标,或者叫"现实社会非现实的核心",更通俗地说,景观已然成为现今人们"主导性的生活模式"。相比于过去人们对吃穿住行等物		2.2 景观
性目标的追求而言,今天的人们在生活目标和生活模式上已经发生了翻天覆地的变化,如		作 为 生活模式
今我们所追求的,是一种让人目眩的景观秀。这一点在现代人对新闻、广告和娱乐等的大量		2.3 景观
非本真的需要中得到了突出的体现。 人之存在不再由自己的真实的需要构成,而是由景观所指向的展示性目标和异化性的		的意识形态功
需要堆积而至。现代工业社会的基础已经不再是传统社会中物质生产物品与消费的真实关		能
系了,而是景观,是由视觉映像来统治经济的秩序。所以,真实的目标(这包括社会历史的 前进目标和人的需要)早已烟消云散,景观就是一切,景观就是目标。		2.3.1 资 本家的
其次,是景观的意识形态功能。德波认为,景观的存在和统治性的布展恰恰证明了今日		选择与广告统
资本主义体制的合法性,人们在对景观的顺从中无意识地肯定着现实的统治。所以,景观也是当代资本主义合法性的"永久在场"。这话指认了景观的意识形态功能,具体包含三个方) 〒 纸 治
面。		2.3.2 审查与合
一是它通过肯定性的表象,将人们锚定于资本家在生产和消费中"已做出的选择"。换句话说,如今,我们在生活的每个细节情境中,都不得不在广告炫示的情景牵引下,不自觉		法性
地面对一个已经被装饰过的欲望对象世界。在广告的统治下,我们无能为力,更无处可逃。		2.3.3 对非劳作
在购买景观和对景观生活方式的无意识顺从中,我们直接肯定着现存体制。 第二,通过审查而展现出来的景观,也必然是现存体制合法性的同谋。景观,当然是一		时间的
种隐性的意识形态。换句话说,无论是通过广告,还是通过其他影像呈现在我们面前的各种		控制 三、 景
景观, 其本质都是在认同性的, 或者是无意识地支配着人们的欲望结构。我们以对商品疯狂的追逐来肯定资本主义的市场体制, 或者在影像文化的引诱下, 将现存的资产阶级生活方		观的统
式误认为本真的存在方式,自愿成为五体投地的奴隶。		治形式 3.1 集中
其三,景观还通过支配生产之外的大部分时间来达到对现代人的全面控制,这也是德 波关于当代资本主义统治新形式的一个新发现,即对人的非劳作时间的控制。景观的捕捉		的景观
对象恰恰是生产之外人的闲暇时间。景观的无意识心理文化控制和对人的虚假消费的制造,		3.2 弥散 的景观
都是在生产之外的时间中悄然发生的。由此,资本主义对人的统治在空间和时间上都大大		3.3 综合
扩展了。并且,也正是由于景观能在一切闲暇时间中对人发生颠倒性欲望驱动,才使物质生产更加远离人之真实需要,从而更直接服务于资本的剩余价值增值。		的景观 3.3.1 综
(三) 景观的统治形式		合景观
关于景观的统治形式的问题,德波将景观区分为两种主要形式:集中的景观和弥散的景观。"集中的景观从根本上与官僚主义资本主义相联系。"这是一个理论定位。作为一种		的特征 3.3.2 综
技术而言,所谓的集中的景观可能是由欠发达社会在试图加强国家权力时引入的,或者是		合景观
在发达资本主义国家中特定的危急时刻出现的。从本质上看,集中的景观就是官僚政治专政的工具。例如,纳粹时期的法西斯国家就是集中景观的典型。所谓弥散的景观,也就是景		的全球化与影
观的一般形式,被德波指认为当代资本主义的社会控制性形式及其意识形态。		化 ¬ 影 响力
1988年,德波在《关于〈景观社会〉的评论》中提出了一种新的景观形式,即综合的景观。作为一种独裁,景观与过去的暴政不同,它常常呈现为某种甜蜜的意识形态控制。经过		
20 多年的发展,景观社会不仅未曾有丝毫的削弱,相反,通过理性地整合前两种形式,景		
观的"第三种形式又建立起来,以这一形式的普遍胜利为基础,它越来越展示出自己的强壮和扩散。这就是综合的景观,自此以后它将自己强加于全球。对于当今这一综合,德波强调		
了其无所不在性。景观、已经"渗透到全部实在"、资本主义的全球化就是景观的全球化。		
与此同时, 德波也进一步指认综合景观的五个主要特征: "不间断的科学技术的更新;		
国家和经济的一体化;普遍化的秘密;无可置辩的谎言;永恒在场。"这五个特征揭示了综合景观融汇了弥散景观中的隐匿特性和集中景观中的控制力,使其呈现出难以拒绝的影响		
力,并使它成为"意识形态的顶点",极力推动景观成为合法化的社会现实。	1	I

Table 13: Outline language style controllable generation, Example A.

Article	Literary Out-	Objective Outline
The Coniety of the Constant The "Winnelling 4" Conied Landscope		Outlines
The Society of the Spectacle The "Visualized" Social Landscape (1) From Commodity Critique to Spectacle Critique In The Society of the Spectacle, Guy Debord discusses the concept of spectacle from various perspectives. Originally, spectacle referred to a visible, objective scene or landscape, something displayed for viewing, but it also implies a subjective, conscious performance or show. Debord uses this to describe the new features of contemporary capitalist society, againing that the dominant essence of modern society manifests as a visualized spectacle. People, captivated by the spectacle, lose their desire and demand for an authentic life, while capitalists manipulate the entire social life by controlling the production and transformation of spectacles. Debord follows Mar's theoretical drajectory in defining his some theoretical premises: contemporary advanced industrial society has become a society of accumulated spectacles. Debord rewrites Marx's commodity phenomenology, transforming the altenation of commodities into the altenation of the spectacle. He divides capitalist society into two stages: the commodity society, characterized by display. Their difference lies in the mediation of capital accumulation: in the past, capital controlled society by manipulating physical goods, while today, capital controlls life through the manipulation of spectacles. For Debord, the spectacle is an illusion constructed by sensory visibility, supported by representations, and manifested in various images. For Debord, the spectacle is an illusion constructed by sensory visibility, supported by representations, and manifested in various images. For Debord, the spectacle is an interest of the spectacle does not imply that the world has been reduced to an image or a visual tableau. "The spectacle should not be understood as a visual deception created by mass media technologies," Debord insists, emphasizing that "the spectacle should not be understood as a visual deception created by mass media technologies," Debord insi	Literary Out-line Outlines: 1. From Commodity Critique to Spectacle Critique 2. The Visual Communication of Modern Social Domination 3. The Forms of Spectacle Domination	Outlines: The Society of the Spectacle The "Mediated" Social Landscape 1. From Commodity Critique to Spectacle Critique 1.1 The Concept and Characteristics of the Spectacle 1.2 The Formation of the Spectacle 1.2 The Formation of the Spectacle and Social Relations 2. The Visual Communication of Modern Social Domination 2.1 The Essence of the Spectacle and the Rejection of Dialogue 2.2 The Spectacle as a Mode of Life 2.3 The Ideological Function of the Spectacle as a Mode of Life 2.3.1 The Capitalist's Choice and the Domination of Advertising 2.3.2 Censorship and Legitimacy 2.3.3 Control Over Non-Working Time 3. Forms of Spectacle Domination 3.1 The Centralized Spectacle 3.2 The Diffused Spectacle 3.3.1 Characteris-
by the spectacle and its construction of false consumption happens subtly during non-working hours. As such, capitalism's domination has expanded both spatially and temporally. And it is precisely because the spectacle can drive inverted desires during all leisure time that material production becomes increasingly disconnected from real human needs, instead directly serving the surplus value of capital. (3) The Forms of Spectacle Domination Regarding the forms of spectacle domination, Debord distinguishes between two primary forms: concentrated spectacle and diffuse spectacle. "The concentrated spectacle is fundamentally linked to bureaucratic capitalism." This is a theoretical position. As a technique, the concentrated spectacle may be introduced by underdeveloped societies attempting to strengthen state power or may emerge in developed capitalist countries during specific crises. Essentially, the concentrated spectacle is a tool of bureaucratic political dictatorship. For example, Nazi fascism is a typical example of concentrated spectacle. The diffuse spectacle, in contrast, represents the general form of the spectacle and is seen by Debord as the societal control form and ideology of contemporary capitalism. In 1988, in his Comments on the Society of the Spectacle, Debord introduced a new form of spectacle, the integrated spectacle. Unlike past tyrannies, the integrated spectacle presents itself as a form of sweet ideological control. Over the course of more than two decades,		3.2 The Diffused Spectacle 3.3 The Inte- grated Spectacle
the spectacle society has not weakened; rather, by rationally integrating the first two forms, a "third form" of the spectacle has emerged. Based on the general victory of this form, it increasingly demonstrates its strength and diffusion. This is the integrated spectacle, which has now imposed itself globally. Debord emphasizes its omnipresence in contemporary society. The spectacle has "penetrated all of reality," and the globalization of capitalism is synonymous with the globalization of the spectacle. Simultaneously, Debord identifies five key features of the integrated spectacle: "the continuous renewal of science and technology; the integration of the state and economy; the universalization of secrecy; irrefutable lies; and perpetual presence." These five features reveal how the integrated spectacle combines the hidden nature of the diffuse spectacle with the control power of the concentrated spectacle, making it increasingly persuasive and turning it into "the apex of ideology," pushing the spectacle to become the legitimized social reality.		

Table 14: Outline language style controllable generation, Example A. (Translation)

Article	Literary Outline	Objective Outline
今天,让我们在塞纳河的落日全醉中机2日 时30分,2024 年巴黎與运 会开幕式将在塞纳河上举行。 这客会是更单度会历史上首次在体育场外举行开幕式,呼应了作家海明威笔下的 思多。在这场被散之为前所未有的奥运会开幕式,是和那条的光彩。在这场被散之为前所未有的奥运会开幕式,大我们都能看到些什么? "不定这被被散之为前所未有的奥运会开幕式,是和那能看到些什么? 本文巴要是这合开幕式,运动员将沿着贯穿巴黎市中心那条流光溢影的河流与观众相见。沿者塞纳河的盗游的线比。场方能已就是中中心那条流光溢影的河流与观众相见。沿者塞纳河的盗游的线比是场所更中和建筑的视觉逐级。以已整约生命之河塞纳河海峡台,运动员们经级巡游,即即将头为观众原。与古老的城市即理和地标经验经分价的变效的特别。在一个人们是这个人们是一个人们是这个人们是一个人们是这个人们是一个人们是这个人们是一个人们是这个人们是一个人们是这个人们是一个人们是这一个人们是这个人们是一个人们是这一个人们是这个人们是一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是这一个人们是一个人们是这一个人们是一个人们是一个人们是一个人们是一个人们是一个人们是一个人们是一个人们是	目1.名员人2. 迪望献3. 主的谁 录:逾运巡场 席翁亮唱 点火会,	目开概"上幕",的体外式"更口践运巡场"线觉"巡具排"模票文演"出斯利念"出者员"复现参手",迪亮"演与点火"选密",的性"门人"组惊排录幕述纳的式史首育开《奥开号行动游》游与盛动游体《众与排艺》术托·的 与的与 听的 演嘉席翁相他歌表燃炬火的性达可 他候 黎委喜武,河开,性次场幕,运放的,员人,路视,员的安,规门非汇,总马乔理、演舞演、盛呈、歌、"的、参手"主,人保、内能、热选、奥的安、武、河开、性次场幕、运游的、员人,路视,员的安、规门非汇、总马乔理、演舞演、盛呈、歌、"的、参手"主、人保 内能、热选、奥的安

Table 15: Outline language style controllable generation, Example B.

Today, let us meet in the afterglow of the sunset over the Seine River. The opening ceremony of the 2024 Paris Olympics will take place on the Seine River at 7:30 PM local time on October 26th and 1:30 AM on October 27th Beijing time. This will be the first time in the history of the Summer Olympics that the opening ceremony is held outside a stadium, echoing the Paris described by writer Ernest Hemingway as "a moving feast." At the same time, it will be a vivid manifestation of the slogan "Olympics for All." So, what can we expect to see in this unprecedented Olympic opening ceremony? Over 10,000 Athletes in the Parade For the opening ceremony of the Paris Olympics, athletes will parade along the radiant Seine River, offering spectators a spectacular visual feast through the heart of Paris. The procession, following the course of the Seine, will weave through the city's historical sites and architectural wonders. The Seine, the lifeblood of Paris, will serve as the stage for athletes to slowly cruise by, with the banks of the river as the seating for spectators, creating a stunning contrast with the ancient cityscape and iconic landmarks. Bathed in the golden light of the sunset, it will paint a magnificent picture. The parade will travel six kilometers along the Seine River, from the Austerlitz Bridge near the Jardin des Plantes, passing numerous historic bridges and landmarks such as Notre-Dame Cathedral, the Louvre, and Olympic venues like the Hôtel des Invalides and the	Moderate Outlines: 1. Over 10,000 Athletes in the Parade 2. Celine Dion Likely to Perform 3. Who Will Light the Olympic	Comprehensive Outlines: Overview of the Opening Ceremony - Opening Ceremony on the Seine River - Historic First
Today, let us meet in the afterglow of the sunset over the Seine River. The opening ceremony of the 2024 Paris Olympics will take place on the Seine River at 7:30 PM local time on October 26th and 1:30 AM on October 27th Beijing time. This will be the first time in the history of the Summer Olympics that the opening ceremony is held outside a stadium, echoing the Paris described by writer Ernest Hemingway as "a moving feast." At the same time, it will be a vivid manifestation of the slogan "Olympics for All." So, what can we expect to see in this unprecedented Olympic opening ceremony? Over 10,000 Athletes in the Parade For the opening ceremony of the Paris Olympics, athletes will parade along the radiant Seine River, offering spectators a spectacular visual feast through the heart of Paris. The procession, following the course of the Seine, will weave through the city's historical sites and architectural wonders. The Seine, the lifeblood of Paris, will serve as the stage for athletes to slowly cruise by, with the banks of the river as the seating for spectators, creating a stunning contrast with the ancient cityscape and iconic landmarks. Bathed in the golden light of the sunset, it will paint a magnificent picture. The parade will travel six kilometers along the Seine River, from the Austerlitz Bridge near the Jardin des Plantes, passing numerous historic bridges and landmarks such as Notre-Dame Cathedral, the Louvre, and Olympic venues like the Hôtel des Invalides and the	Outlines: 1. Over 10,000 Athletes in the Parade 2. Celine Dion Likely to Perform 3. Who Will Light the	Outlines: Overview of the Opening Cere- mony - Opening Cer- emony on the Seine River - Historic First
Grand Palais. The procession will end at the Trocadero Plaza, directly opposite the Eiffel Tower, where the official cermony will continue, including the lighting of the Olympic caudron and the official declaration of the opening of the 2024 Paris Olympics. Approximately 100 boats will be used, carrying about 10.500 athletes from 206 National Olympic Committees (NOCs). Larger NOCs will have their own boats, while smaller NOCs will share boats. This outdoor concept will make the 2024 Paris Olympics opening ceremony the largest in terms of both audience scale and geographical coverage. The Paris organizing committee has stated that around 600,000 people are expected to witness the opening ceremony in person. In addition to the 104,000 paid tickets for the downstream quays, there will be 222,000 free tickets available for spectators along the upstream riverbanks. For the first time in history, most viewers will be able to watch the opening ceremony without paying for tickets, marking another historic milestone for the 2024 Paris Olympics. Moreover, 80 giant screens have been set up across Paris, allowing those without tickets to watch the opening ceremony on large screens. Globally, it is expected that 1.5 billion people will tune in to watch the ceremony via television broadcasts. Celine Dion Likely to Perform What can we expect in the cultural performances during the opening ceremony? Although most of the performance details are still confidential, we can anticipate a grand show that combines both classical and modern elements. The artistic director for the opening and closing ceremonies of the 2024 Paris Olympics and Paralympics is French theater director and actor Thomas Jolly. In a media interview in January, Jolly expressed his desire to blend all elements of French culture, from opera to rap, to showcase the country's cultural diversity. "The opening ceremony will make full use of every historical sits of solid parts to the audience. Paris is a city that never stops reinventing itself, and the fusion o	Flame?	Opening Ceremony Outside a Stadium Implementing the "More Open Color Dispansion of the Athlete Parade and Visual Spectacle - Specific Arrangements for the Athlete Parade - Audience Size and Ticket Arrangements Cultural Performances - Artistic Director Thomas Jolly's Vision - Dancers and Actors Participating in the Performance - Presentation of the Audiovisual Extravaganza Performing Guest Singers - Appearance by Celine Dion - Other Participating Singers and Performances Lighting the Main Torch - Secrecy of the Torchbearer Selection - Possibility of Zinedine Zidane - Other Popular Candidates - Surprising Arrangements by the Paris Organizing Committee

Table 16: Outline language style controllable generation, Example B. (Translation)

H.3 Case Studies

Table 17 to 20 illustrate the multi-style outlines (concise vs. moderate vs. comprehensive and objective vs. literary) generated by Owen2.5-3B with TKPO.

Article

余春娇一度以为,张志明终于长大了。 她跟闺蜜说,两个人开始一起存钱买房。但是转身回家,春娇就见到志明抱回来一个在她看来一点用处 都没有的"大拇指",盛惠九人打震。

"你知不知道每一个男人都需要买一个达利?"

张志明还是那个三十好几的幼稚鬼。但他硬是把无用之用编出花来,偏偏又让人觉得颇为趣致。

电影中春娇和志明住的房子里,摆放的大多是导演彭浩翔的收藏,这件达利雕塑"天使的幻想"想必也 是。

像张志明和彭浩翔这种不甘寂寞又将无聊玩出新天际的潮人,达利作品无疑是最有吸引力的"高格调玩 物"。

世界上最会自我营销的艺术大师没有之一

你可以说达利是个自恋狂,毕竟他声称在母亲的怀抱里就已经意识到自己是天才。可你不得不承认,他 说的确实是一个事实。

如果说天才和疯子只有一步之遥,达利本人就是最好的体现。

哪怕大多数艺术家都有自己的小怪癖,但没有一个艺术家会像达利那么由内而外地一怪到底。他有一种

与生俱来的恶作剧般的幽默感,不断地挑战和延展人们对荒诞艺术的理解。 后来,这种怪诞甚至成了有意为之。达利不仅把离奇的梦境带进画布,用艺术诠释不疯魔不成魔的真谛, 而且把自己也当作一个"艺术项目"来经营,成功将超现实主义带进主流生活。

论人设经营,达利可是第一人。他擅长上演足够吸引的表演,上扬的胡子、个性的装扮、口不择言的论调 以及荒诞不羁的行为,都有一以贯之的超现实意味。

年仅30岁,达利已经登上了《时代周刊》的封面,他还办过自己的杂志 Dali News,简直是个初代自媒体 还是最出圈的的那位。

达利的自我营销能力、恐怕让全世界的广告推销员心生妒忌、甚至让如今的自媒体人自叹弗如。

可以说,从头到脚,从作品到行头,Salvador Dalí 远远不止一个天才画家,这分明是一个故事精彩且足够 完整的商业品牌。

比KAWS火一万倍的跨界艺术家才是潮人那杯茶

当代最火的艺术家,没有哪个人像达利那样如此放纵地表现自己。

他模仿委拉斯凯兹留小胡子, 并且始终如一地把玩它; 他穿着深海潜水服在伦敦进行演讲, 差点在演讲 中途窒息;他用一万美金的价格把自己的一根胡子卖给小野洋子;安迪·沃霍尔送他一幅梦露,他把画放在地 上,直接在画上尿尿……

Concise	Moderate&Objective	Comprehensive	Literatry
	** 目录 **	** 目录: **	** 目录 **
	1. ** 引言 **	1. ** 引言: 余春娇与张志明的故事	1. ** 引言 **
	- 春娇与志明的日	与期待 **	- 春娇与志明的日常生
	常生活与达利雕	- 春娇对志明的期待与现实的冲突	活与达利雕塑
	塑	2. ** 张志明与达利雕塑的象征意义 **	- 达利作品的吸引力与
	- 达利作品的吸引		"高格调玩物"
** 目录	力与"高格调玩	- 志明购入雕塑与春娇的反应	2. ** 达利: 艺术天才与
**	物"	- 达利雕塑在家庭中的象征	疯子的边界 **
1. 达利	2. ** 达利: 艺术 天才与疯子的边	3. ** 达利: 天才与疯子的边界 **	- 达利的自恋与天才气 质
与张志	人才可观了的边 界 **	- 达利的自信与艺术突破	- 艺术怪癖与幽默感的
明	- 达利的自恋与天	- 天才与疯子之间的微妙关系	体现
2. 达利	才气质	4. ** 达利的艺术风格与"人设经营"	- 从疯魔到艺术的哲学
的自我	- 艺术怪癖与幽默	**	探索
营销	感的体现	- 达利的艺术风格与幽默感	3. ** 达利的"艺术项
3. 达利	- 从疯魔到艺术的	- 达利如何塑造公众形象与生活中的	目": 从天才到品牌 **
的艺术 与生活	哲学探索	超现实主义	- 自我营销的典范: 达利
马生佰 4. 达利	3. ** 达利的"艺	5. ** 达利的自我营销与媒体操作 **	的人设经营
与跨界	术项目": 从天才	- 媒体曝光与《Dali News》的创办	- 成名与商业化: 从画作
合作	到品牌 **	- 达利的商业品牌与成功之道	到个人品牌
н п	- 自我营销的典范:	6. ** 达利的离经叛道行为与当代影	- 达利的公众形象与超
	达利的人设经营	响**	现实主义风格
	- 成名与商业化: 从	- 达利的经典行为与文化互动	4. ** 总结 **
	画作到个人品牌	- 达利对当代艺术与文化的影响	- 达利的艺术成就与文
	- 达利的公众形象 与超现实主义风	7. ** 结语: 达利的复杂性与隐喻 ** - 达利作为艺术家的多面性	化遗产
	与超现头土义风 格	- 达利作为乙不家的多闻性 - 春娇与志明故事中的达利精神	- 从艺术到生活方式: 达 利的时代影响
	111	- 伊州马心切以事中的及利相性	イプロプロプロプログリリ

Table 17: Case study A.

Article

Yu Chunjiao once thought that Zhang Zhiming had finally grown up.

She told her best friend that they had started saving money together to buy a house. But when she turned to go home, Chunjiao saw Zhiming come back with a "thumb" that, in her opinion, was completely useless, priced at 95,000 yuan.

"Do you know that every man needs to buy a Dali?"

Zhang Zhiming was still the same immature guy in his thirties. But he somehow managed to turn the useless into something with purpose, and oddly enough, it was somehow quite amusing.

In the movie, the apartment where Chunjiao and Zhiming live mostly displays the collection of director Peng Haoxiang, and this Dali sculpture, *The Angel's Fantasy*, is likely one of them.

For people like Zhang Zhiming and Peng Haoxiang, who refuse to be bored and manage to turn dullness into something extraordinary, Dali's works are undoubtedly the most attractive "high-class toys."

I. The World's Greatest Self-Marketing Artist, Without a Doubt

You could say Dali was a narcissist, since he claimed to have realized his genius in his mother's arms. But you have to admit, he was indeed telling the truth.

If genius and madness are only a step apart, Dali was the perfect embodiment of this.

Though many artists have their own quirks, none of them were as wholly eccentric as Dali was, inside and out. He had an innate sense of mischievous humor, constantly challenging and expanding people's understanding of absurdist art.

Later, this absurdity even became intentional. Dali not only brought bizarre dreams onto his canvases, using art to express the truth that one must go mad to be truly mad, but he also treated himself as an "art project," successfully bringing surrealism into mainstream life.

When it comes to crafting a personal brand, Dali was the first. He was great at putting on a show that captivated attention: his upward-pointing mustache,

eccentric outfits, outspoken opinions, and absurd behavior—all consistently carried a surreal meaning.

At just 30 years old, Dali was already on the cover of *Time* magazine. He even published his own magazine, *Dali News*, making him a pioneer of early self-media, and certainly one of the most viral figures of his time.

Dali's ability to market himself was likely the envy of advertising professionals worldwide, and would probably make today's self-media influencers feel

From head to toe, from his art to his attire, Salvador Dalí was far more than just a genius painter—he was a brand with a fascinating and complete story. II. The Cross-Disciplinary Artist Who's 10,000 Times More Popular Than KAWS is the True Icon of the Trendy

No contemporary artist has ever expressed themselves so indulgently as Dali did.

He mimicked Velázquez by sporting a small mustache, and he consistently played around with it. He wore a deep-sea diving suit while giving a lecture in London, nearly suffocating during the talk. He sold a single hair from his mustache to Yoko Ono for \$10,000. Andy Warhol gave him a portrait of Marilyn Monroe and Dali laid it on the ground to urinate on it

Concise	Moderate & Objective	Comprehensive	Literatry
Outline 1. Dali and Zhang Zhiming 2. Dali's Self- Marketing 3. Dali's Art and Life 4. Dali and Cross- Industry Collaborations	**Outline** 1. **Introduction** - The Daily Life of Chun Jiao and Zhi Ming and Dali's Sculptures - The Appeal of Dali's Works and "High-Class Playthings" 2. **Pali: The Border Between Artistic Genius and Madness** - Dali's Narcissism and Genius Temperament - Artistic Eccentricities and the Expression of Humor - From Madness to Artistic Philosophical Exploration 3. **Pali's "Art Project": From Genius to Brand** - A Model of Self-Marketing: Dali's Personal Branding - Fame and Commercialization: From Paintings to Personal Brand - Dali's Public Image and Surrealist Style	**Outline:** 1. **Introduction: The Story and Expectations of Yu Chun-jiao and Zhang Zhi-ming** - The Conflict between Chun-jiao's Expectations and the Reality of Zhi-ming 2. **The Symbolic Meaning of Zhang Zhi-ming and Dali's Sculptures** - Zhi-ming's Purchase of the Sculpture and Chun-jiao's Reaction - The Symbolism of Dali's Sculpture in the Family 3. **Dali: The Boundary between Genius and Madness** - Dali's Confidence and Artistic Breakthroughs - The Subtle Relationship between Genius and Madness 4. **Dali's Artistic Style and 'Personal Branding'*** - Dali's Artistic Style and Sense of Humor - How Dali Shaped His Public Image and Surrealism in Everyday Life 5. **Dali's Self-Marketing and Media Manipulation** - Media Exposure and the Founding of *Dali News* - Dali's Commercial Branding and Path to Success 6. **Dali's Iconoclastic Behavior and Contemporary Influence** - Dali's Impact on Contemporary Art and Culture 7. **Conclusion: The Complexity and Metaphor of Dali** - The Multifaceted Nature of Dali as an Artist - The Dali Spirit in the Story of Chun-jiao and Zhi-ming	**Table of Contents** 1. **Introduction** - The Daily Life of Spring Jiao and Zhimin and Dali's Sculptures - The Appeal of Dali's Works and "High-Class Toys" 2. **Dali: The Border Between Artistic Genius and Madness** - Dali's Narcissism and Genius Temperament - Artistic Eccentricities and the Manifestation of Humor - From Madness to Philosophical Exploration in Art 3. **Dali's "Artistic Project": From Genius to Brand** - A Model of Self-Marketing: Dali's Personal Brand Management - Fame and Commercialization: From Paintings to Personal Brand - Dali's Public Image and Surrealist Style 4. **Conclusion** - Dali's Artistic Achievements and Cultural Legacy - From Art to Lifestyle: Dali's Impact on His Era

Table 18: Case study A. (Translation)

Article

好剧推荐之《金田一少年事件簿》 | "谁杀了谁就能得到救赎,我一个也没见过。" 今天推荐一部动漫《金田一少年事件簿》,由日本推理漫画改编。本片的主角金田一虽然说是全日本最白痴的高中生之一,经常还有情况,作业产品的是一种情况的是一种情况的。 中生之一,上味老在睡觉,作业从来都是抄育博们与美当的,什么事情都由美当帮他扛着。然间,少年宝田一却有着遗传自爷爷的优秀基因——智商 180。面对匪夷所思,杀机四伏的疑案,身临险境之中也能察觉到每个蛛丝马迹,抓住解谜的关键,——破解层出不穷的巧妙杀人手段。本片中每一个事件几乎没有联系,都是独立的个案,不存在跳过就看不懂的情况。金田一里大多是杀人事件,且是连环杀人事件,场景布置也带有阴森诡谲的风格,给整个案子提供了恐怖的氛围。其中一篇《歌剧院新杀人事件》非常经典。案件发生在静冈县歌岛上,自从发生过轰动全国的连续杀人事件后,古老歌剧院被拆毁了,并在原址兴建了一个全新的剧场。为了庆祝新剧院的落成,"幻想剧团"打算举行纪念性的公演,还决定在歌岛上排练话剧《歌剧魅影》。金田一、美雪以及剑持警部都受到岛主黑泽先生的 为异学们纪念性的公假,是实在在歌剧上讲写相相、歌剧和感象》。並且 、 天言以及到为言的形义对副王流行几至的 邀请,一起前往孤岛观赏幻想剧团的排练。可是当众人抵达歌岛后,歌岛与外界来往的游艇却出了问题,众人因此 被困在歌岛上,歌岛成了天然的密室。这时,一名自称为"幽灵"的凶手,开始根据《歌剧魅影》的剧本,逐一杀害 幻想剧团的成员。引起这个条件的种子就是美歌————个上吊自杀的悲剧女歌剧演员。这个名字于团队而言也是诅 幻想剧团的成员。引起这个案件的种子就是美歌——个上吊自杀的悲剧女歌剧演员。这个名字于团队而言也是诅咒般的存在。《歌剧魅影》本身即是可怕而悲惨的故事。剧院的怪人有着上天赋予的音乐才能,长相却极其丑陋。他深深的爱着美丽的剧院歌手,但是由于得不到歌手的爱,怪人因爱生恨犯下残忍的案件。而这次的案件也像剧本般如出一辙的上演了。美歌作为歌剧院中美丽并且有实力的女歌剧者,遭来了他人的嫉妒,被下致幻药,在舞台上丑态百出,并遭到歌剧院管理者的侵犯,还拍下了录像。美歌在喝下致幻药之后误认为她的爱人能条背叛了她,在舞台上自杀。在她死后,能条为了替她报仇,精心设计了复仇计划,将所有伤害她的人一一杀掉。因为爱而生恨,因为恨而犯下大错。歌剧院的舞台突然上演恐怖一幕——巨大的吊灯压在日高织绘的身上,一切就像歌剧一样出现在众人眼前。而这正是美歌死前的诅咒:化身歌剧院的怪人。SPRING FESTIVAL 每一个故事都藏着一个悲剧的内核,探案的背后是许许多多的爱恨情仇和无尽的复仇。在惊恐过后,更多的感情与体会浮现出来,值得我们认真咀嚼。如果有喜欢推理的小伙伴,可以看看这部经典的推理动漫,或许会有出乎意料的收获。

Moderate&Objective Literatry Comprehensive 目录 引言 1. ** 动漫推荐 ** - 《金田一少年事件簿》 ** 目录 ** 1. ** 推荐介绍 ** - ** 推荐作品 **: 《金田一 - 改编自日本推理漫画 少年事件簿》 2. ** 主角介绍 ** - ** 推荐原因 **: 由日本推 - 金田一的性格特点 理漫画改编, 具有连环杀人 - 美雪的角色与作用 二、《金田一少年事件簿》概述 1. ** 故事背景 ** 事件和阴森诡谲的风格。
2. ** 主角介绍 **
- ** 金田一 **: 全日本最白 - 发生地点与时间 《金田一少年事件 痴的高中生之一,智商180, - 故事的独立性:每个案件的独立性与非关联性 擅长解谜。 ** 金田一的特点与侦探能力 ** 簿》经典 -** 美雪 **: 金田一的青梅 竹马,经常帮助金田一。 3. ** 剧情概述 ** -** 案件背景 **: 案件发生 - 智商与推理天赋 - 应对疑案的技巧与方法 推理动漫 ** 目录 推荐 ** 3. ** 案件风格 ** ション 少年 - 主要案件类型: 连环杀人事件 《金 金田一性 - 案件的恐怖氛围与谜题设计 在静冈县歌岛上,围绕歌剧 格的两面 - 采汗的心印外因马坡超及月 三、经典案件分析:《歌剧院新杀人事件》 1. ** 案件背景 ** - 发生地点: 静冈县歌岛 - "幻想剧团"的公演与排练 2. ** 事件表因 ** 院新剧场展开。
- ** 主要角色 **: 金田一、 事 件 性 簿》动 美雪、剑持警部等。 -**案件核心**:美歌自杀 事件引发的连环谋杀案。 漫推荐 的故事设 1. 主角: 计与阴森 金田一 诡谲的背 - 美歌的自杀与其悲剧经历 - 《歌剧魅影》剧本与案件的联系 3. ** 案件发展 ** 《歌 4. ** 经典案例分析 ** 景风格 剧院新 -**《歌剧院新杀人事件》**: -** 背景 **: 静冈县歌岛歌 3. 《歌剧 杀人事件》 经 院新杀人 剧院改建后的纪念公演。 -**凶手**:"幽灵"根据 《歌剧魅影》剧本逐步杀害 - 众人被困歌岛 - "幽灵"凶手的出现与杀人手法 事件》金 典案例 - 國及 因子的古现与宋人子在 4. ** 案件解析 ** - 美歌的悲剧与复仇计划 - 巨大吊灯事故与死亡事件的重演 四、案件背后的情感与主题 1. ** 悲剧的内核 ** 典致敬 纠葛的情 - ** 动机 **: 美歌自杀事件 感内核 引起的嫉妒和报复心理。 5. ** 情感与反思 ** - ** 悲剧内核 **: 探案背后 - 爱与恨交织的动机 - 复仇与情感的纠葛 2. ** 推理与人性的碰撞 ** 隐藏着爱恨情仇和复仇。 - ** 感悟 **: 在惊恐过后 - 对感情与复仇的深刻剖析 - 人物情感的多重解读 更深层次的情感与思考。 6. ** 推荐理由 ** 五、总结与推荐 1. ** 总结 ** - ** 适合人群 **: 喜欢推理

主角

Table 19: Case study B.

- 推理和人性探索的结合

《金田一少年事件簿》的魅力所在

的小伙伴。

Article

Recommended Drama: The Case Files of Young Kindaichi "Whoever kills someone can gain redemption. I haven't seen a single one yet."
Today, I recommend an anime, The Case Files of Young Kindaichi, based on a Japanese mystery manga. The protagonist, Kindaichi, is often considered one of the most clueless high school students in all of Japan. He sleeps in class, always copies his childhood friend Miyuki's homework, and relies on her to shoulder all his burdens. However, young Kindaichi has inherited an exceptional gene from his grandfather —an IQ of 180. Faced with baffling and life-threatening murder cases, he can detect even the slightest clue, unravel key mysteries, and decipher the ever-evolving, ingenious methods of murder. Each episode in this series represents a standalone case, so viewers won't feel lost if they skip one. Most cases involve murders, often serial killings, set against eerie. Suspenseful backdrops, creating a chilling atmosphere for the cases.

Each episode in this series represents a standalone case, so viewers won't feel lost if they skip one. Most cases involve murders, often serial killings, set against eerie, suspenseful backdrops, creating a chilling atmosphere for the cases.

One classic episode is The New Murder Case at the Opera House. The case takes place on Shizuoka Prefecture's Kage Island, where a string of shocking murders occurred years ago. The old opera house was torn down, and a new theater was built on the same site. To celebrate the theater's grand opening, the "Fantasy Troupe" planned a commemorative performance and chose to rehearse the play *The Phantom of the Opera* on the island. Kindaichi, Miyuki, and Inspector Kenmochi are invited by the island's owner, Mr. Kurozawa, to watch the troupe's rehearsal. However, when they arrive on the island, the yacht that was supposed to transport them back to the mainland breaks down, trapping them on the island, turning it into a natural locked room. At the troup a merchant the place of the Phantom of the Opera

the yacht that was supposed to transport them back to the mainland breaks down, trapping them on the Island, turning it into a natural locked room. At that point, a murderer, claiming to be a "ghost," begins to kill the troupe members one by one, following the plot of *The Phantom of the Opera*. The seed of this case was planted years earlier with the tragic death of a singer named Miga, who committed suicide by hanging. For the troupe, her name is like a curse. *The Phantom of the Opera* itself is a haunting, tragic story. The opera's "phantom" possesses divine musical talent but is grotesquely disfigured. He deeply loves a beautiful opera singer but, unable to win her affection, turns to hatred and cruelty, committing terrible crimes out of love-turned-jealousy. This new case eerily mirrors that story. Miga, a talented and beautiful singer, became the target of envy. She was drugged with a hallucinogen, behaved erratically on stage, and was assaulted by the theater's manager, who even filmed the attack. Under the influence of the drug, Miga believed her lover had betrayed her and ended her life on stage. After her death, her lover meticulously planned a revenge scheme, killing everyone who had wronged her. What began as love turned to hate, and hatred led to tragic actions.

The opera house stage suddenly erupts into a terrifying scene when a huge chandelier crashes down onto the actress Hitomi Shiori, much like a scene from the opera itself. This mirrors Miga's curse before her death: the phantom of the opera house. Each story in SPRING FESTIVAL contains a core of tragedy, and behind each investigation lies a complex web of love, hate, and endless revenge. After the terror subsides, deeper emotions and insights emerge, giving us much to reflect on. If you enjoy mystery and detective stories, this classic anime might offer some unexpected discoveries.

Concise	Moderate&Objective	Comprehensive	Literatry
	Outline	**Outline**	
	1. **Introduction to the Recommenda-	**I. Introduction**	
	tion**	1. **Anime Recommendations**	** V: 1: .1.
		- The Case Files of Young Kindaichi	**Kindaich
	- **Recommended Work**: The Case	- Adapted from a Japanese mystery manga	Case Files
	Files of Young Kindaichi	2. **Main Character Introductions**	Classic
	 Reason for Recommendation: 	- Personality traits of Kindaichi	Detective
	Adapted from a Japanese mystery	- Role and function of Miyuki	Anime
	manga, featuring serial murders and a	**II. Overview of The Case Files of Young Kindaichi** 1.	Recom-
	dark, eerie atmosphere.	**Story Background**	menda-
	Introduction to the Main Charac-	- Setting: Locations and Time Period	tion
	ters**		 The
	- **Kindaichi**: One of the most clue-	- Independence of Each Case: The Standalone Nature of Each	Dual Na
*** 1: **	less high school students in Japan, with	Mystery	ture of
Outline	an IQ of 180, skilled in solving myster-	2. **Kindaichi's Characteristics and Detective Skills**	the Pro
**The	ies.	- Intelligence and Deductive Talent	tagonist,
Kindaichi	- **Miyuki**: Kindaichi's childhood	 Techniques and Methods for Solving Mysteries 	Kindaichi'
Case	friend, who frequently assists him.	3. **Case Style**	Personal-
Files	3. **Plot Overview**	- Primary Case Types: Serial Murders	ity
Anime	- **Case Background**: The case occurs	 The Horrific Atmosphere and Puzzle Design of the Cases 	2. Indepen
Recom-	on Uta Island in Shizuoka Prefecture,	**III. Classic Case Analysis: The Opera House Murder	
menda-		Case**	dent Story
tion**	centered around the new opera house.	1. **Case Background**	Design and
1. Main	- **Main Characters**: Kindaichi,	- Location: Shizuoka Prefecture, Utagashima	the Dark
Char-	Miyuki, Inspector Kenmochi, and oth-	- Performance and Rehearsals of the "Phantom Troupe"	Eerie
acter:	ers.	2. **Incident Cause**	Back-
Kindaichi	- **Core of the Case**: A series of mur-	- The Suicide of Miku and Her Tragic Past	ground
2. "The	ders triggered by the suicide of Miga.	- Connection Between <i>The Phantom of the Opera</i> Script and	Style
	4. **Analysis of Classic Cases**	the Case	 The
Opera House	- **"The New Murder at the Opera	3. **Case Development**	New Mur
	House"**:		der at the
Mur-	- **Background**: A commemorative	- The Group Is Trapped on Utagashima	Opera
ders"	performance at the newly renovated	- The "Ghost" Killer's Appearance and Murder Methods	House
Classic	opera house in Shizuoka Prefecture.	4. **Case Analysis**	A Classic
Case	- **Murderer**: The "Ghost," who grad-	- Miku's Tragedy and Her Revenge Plan	Tribute
	ually kills the members according to the	 The Grand Chandelier Accident and the Reenactment of the 	4. The
	script of <i>The Phantom of the Opera</i> .	Fatal Incident	Emotional
	- **Motive**: Jealousy and revenge	**IV. Emotions and Themes Behind the Case**	Core o
		1. **The Tragic Core**	Love and
	stemming from Miga's suicide.	- The Motive of Love and Hate Intertwined	
	5. **Emotions and Reflections** -	- The Intersection of Revenge and Emotions	Hatred
The Tragic Core: Behind the inves-	**The Collision of Reason and Human Nature**	Let me	
	tigation lies love, hatred, and vengeance.	- A Deep Exploration of Emotions and Revenge	know i
	- **Insight**: After the fear subsides,	- Multiple Interpretations of Character Emotions	you'd like
	deeper emotions and thoughts emerge.	**V. Conclusion and Recommendations**	any adjust
	Reasons for Recommendation	1. **Conclusion**	ments!
	 - **Target Audience**: Fans of mystery 	- The Appeal of <i>The Case Files of Young Kindaichi</i>	
	and detective stories.		
		- The Fusion of Mystery and Human Nature Exploration	

Table 20: Case study B. (Translation)