RedOne: Revealing Domain-specific LLM Post-Training in Social Networking Services

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Abstract

As a primary medium for modern information dissemination, social networking services (SNS) have experienced rapid growth, which has proposed significant challenges for platform content management and interaction quality improvement. Recently, the development of large language models (LLMs) has offered potential solutions but existing studies focus on isolated tasks, which not only encounter diminishing benefit from the data scaling within individual scenarios but also fail to flexibly adapt to diverse real-world context. To address these challenges, we introduce **RedOne**, a domain-specific LLM designed to break the performance bottleneck of single-task baselines and establish a comprehensive foundation for the SNS. RedOne was developed through a three-stage training strategy consisting of continue pretraining, supervised fine-tuning, and preference optimization, using a large-scale real-world dataset. Through extensive experiments, RedOne maintains strong general capabilities, and achieves an average improvement up to 14.02% across 8 major SNS tasks and 7.56% in SNS bilingual evaluation benchmark, compared with base models. Furthermore, through online testing, RedOne reduced the exposure rate in harmful content detection by 11.23% and improved the click page rate in post-view search by 14.95% compared with single-tasks finetuned baseline models. These results establish RedOne as a robust domain-specific LLM for SNS, demonstrating excellent generalization across various tasks and promising applicability in real-world scenarios.

1 Introduction

With the widespread adoption of online platforms and mobile applications, social networking services (SNS) have emerged as a central medium for modern information dissemination, such as communication, knowledge sharing, and emotional expression (Elahimanesh et al., 2025). Unlike the general textual corpora, SNS data is highly informal, context-sensitive, and often emotionally charged. These characteristics present unique

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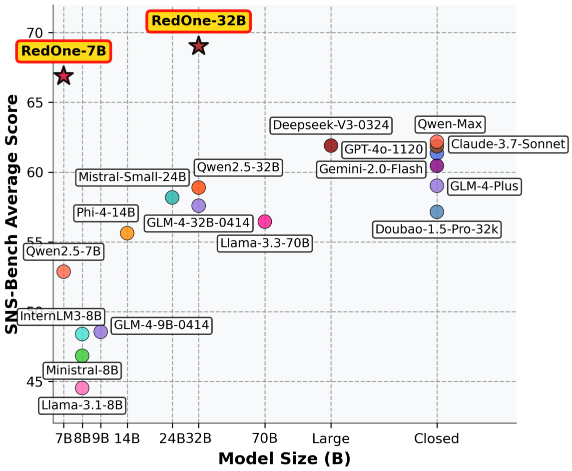

Figure 1: Performance comparison of different models in the SNS domain, where all models are instruction-tuned and the evaluation score is the average of all tasks on SNS-Bench.

challenges including linguistic variability, frequent role-switching, and subtle conversational norms, which complicate applications (e.g. platform content management and interaction quality improvement) for traditional natural language processing (NLP) systems (Jin et al., 2024).

Given these complexities, numerous studies have explored recent advanced large language models (LLMs) based adaptation for SNS-related tasks (Zeng et al., 2024; Jiang and Ferrara, 2023). However, these solutions primarily focus on isolated tasks, which not only experience diminishing benefits as data scales within individual scenarios but also struggle to adapt flexibly to diverse real-world contexts. This highlights a fundamental limitation in current SNS domain-specific models, where performance plateaus due to the inability to incorporate a more diverse domain knowledge corpus during training (Yue et al., 2025).

To address these deficiencies, we introduce **RedOne**, a demain-specific LLM with a meticulous three-stage post-training strategy using a large-scale dataset from real-world, which consists of continued pretraining (CPT), supervised fine-tuning (SFT), and preference optimization (PO). In the CPT stage, the model acquire extensive foundational knowledge in the SNS domain by processing large-scale corpora. Building on this foun-

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dation, the SFT stage refines the model's capability to tackle specific SNS tasks by leveraging carefully defined domain-specific problem formulations. Finally, in the PO stage, we further optimize the model's behavior to ensure seamless alignment with human preferences and maximize its practical utility in real-world deployments.

Through extensive experiments, RedOne not only maintains strong general capabilities, but also excels across multiple SNS-specific evaluation benchmarks, significantly outperforming leading proprietary or open-source models as shown in Figure 1. Further online testing in harmful content detection and post-view search, indicates its broad and promising potential application in real-world scenarios.

Our contributions can be summarized as follows:

- We introduce RedOne, a domain-specific LLM, engineered to break the performance bottleneck of single-task models, providing comprehensive improvements for SNS.
- A three-stage training strategy is designed, using a large-scale real-world dataset, which maintains strong general capabilities while delivering exceptional generalization across diverse SNS tasks.
- Through extensive experiments and online testing to demonstrate RedOne's effectiveness across a wide range of tasks, and establish a comprehensive and robust baseline for SNS application.

2 Related Work

2.1 NLP tasks in Social Networking Services

Due to the inherent characteristics of SNS platforms, namely their informality and rapid linguistic evolution (Carr and Hayes, 2015), these platforms present numerous complex NLP challenges that have garnered sustained academic attention. In the early stages of development, researchers primarily focused on fundamental capability assessments, particularly prevalent tasks such as sentiment analysis (Mohammad et al., 2018; Rosenthal et al., 2019), harmful content detection (i Orts, 2019; Lu et al., 2024), and meme detection (Xie et al., 2023; Lin et al., 2024). Following the emergence of LLMs and building upon previous research foundations, various techniques have evolved in multiple domains, including content understanding (Kumar et al., 2024; Kmainasi et al., 2024), information extraction (Islam and Goldwasser, 2025; Li et al., 2024b; Peng et al., 2024), and dialogue systems (Yi et al., 2024; Zhang et al., 2024). These technological advances have significantly enhanced problem-solving capabilities within the SNS domain, but have primarily focused on single tasks. In contrast to these works, RedOne demonstrates superior performance across diverse SNS tasks, providing a foundational model for improved services.

2.2 Domain-specific Post-training

To better serve specialized domains, recent efforts have focused on developing vertical domain LLMs across various fields, including finance (Wu et al., 2023; Konstantinidis et al., 2024), law (Colombo et al., 2024), home renovation (Wen et al., 2023), medicine (Xiong et al., 2023; Chen et al., 2023; Yang et al., 2024c; Wu et al., 2024; Zakka et al., 2024), and scientific research (Azerbayev et al., 2023; Bi et al., 2023; Yang et al., 2024d). Despite these advancements, these vertical domain LLMs have not addressed the unique challenges posed by SNS. While (Liu et al., 2024b) and (Yang et al., 2024b) explore the application of LLMs to a limited set of NLP tasks within SNS, their coverage remains constrained. Therefore, a significant gap exists in this area, which RedOne aims to address.

3 RedOne Model

As illustrated in Figure 2, the training strategy of RedOne contains three stages. First, in Section 3.1, we conduct continue pretraining to enrich the model's grasp of nuanced SNS field knowledge. Subsequently, in Section 3.2, we sharpen the model's instruction-following capabilities through supervised fine-tuning across various tasks. Finally, we leverage preference information from the training data to perform preference optimization, ultimately yielding the RedOne with superior performance in the SNS domain.

3.1 Continue Pretraining

To enhance the large model's fundamental domain knowledge we conducted continue pretraining at this stage, which can be divided into three sub-stages: data collection and data construction, filtering and mixture, along with domain-aware continue pretraining.

3.1.1 Data Collection and Data Construction

We specifically collected continue pretraining data from the following two data sources: (1) **General High-quality Data**. We selected several high-quality open-source pretraining corpora (Qiu et al., 2024; Weber et al., 2024; Penedo et al., 2024) to preserve the model's fundamental generalization capabilities. To improve training efficiency, we uniformly construct all general data into single-sentence text format and perform segmentation and concatenation processing based on predefined text length thresholds. (2) **SNS-specific Domain Data**. We collect the large-scale training data from SNS platforms and the open web, capturing diverse social communication patterns including informal discussions, short-form comments, sarcasm, emotionally charged content, and so on. For better reveal the underlying information in the pretraining data, we incorporate user interaction data to guide the training process. Specifically, we group contexts and comments with their corresponding user interaction data, which naturally clusters semantically related SNS content without additional processing. The prompt templates can be found in Appendix A.3. Through these steps, we collected and constructed a large-scale dataset comprising various tasks with over 100B tokens for downstream processing.

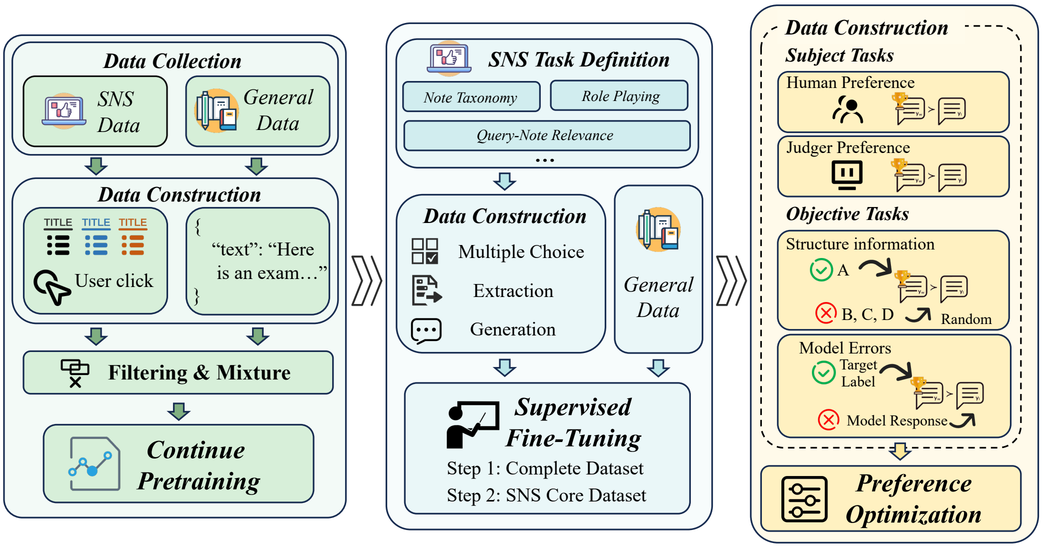

Figure 2: Overview of our training pipeline.

3.1.2 Filtering and Mixture

Considering data quality is crucial for model training (Zhou et al., 2023a), we constructed a data-filtering pipeline inspired by (Yuan et al., 2024), which comprises task-oriented rule filtering and small language model filtering (Wang et al., 2025). The former identifies specific error content such as HTML tags and repetitive sentences, while the latter focuses on global assessment aspects including coherence and tone appropriateness. Based on this data-filtering pipeline, we further applied the RegMix method (Liu et al., 2024a) to identify an optimal data mixture distribution and filter out unnecessary data. Through this comprehensive filtering and mixture process, we ultimately constructed a high-quality dataset of 20B tokens for training.

3.1.3 Domain-aware Continue Pretraining

After data construction, we conduct continue pretraining on the complete dataset. Specifically, RedOne is trained from the Qwen2.5 (Qwen et al., 2025a) checkpoint following its development process, leveraging its strong linguistic capabilities across multiple domains. Through this domain-aware continue pretraining process, we ultimately obtain a model that effectively captures SNS-specific linguistic patterns while maintaining minimal degradation in general language modeling capabilities.

3.2 Supervised Fine-Tuning

To bridge the gap between pretraining objectives and the specific requirements of real-world SNS applications, we further conduct supervised fine-tuning on our model through carefully designed data construction and multi-stage training strategies.

3.2.1 Task Definition and Data Construction

As SFT training data is significat affect the final instruction following ability in domain tasks (Dong et al., 2023), we extensively collected large-scale user-generated content from public platforms, including notes, comments, queries, and interaction logs, which provide real enviorment signal for us to improve model actions. Notably, we focused on preserving the linguistic style which exhibit typical SNS characteristics such as informal language, sarcasm, sentiment, and topical shifts while collecting data (Eisenstein, 2013), aim for representative and practical coverage for SNS scenarios.

Task Name	Capability
Note Taxonomy	Content Understanding
Query Classification	Content Understanding
Query Intent Recognition	Content Understanding
Hashtag Prediction	Information Extraction
Machine Reading Comprehension	Information Extraction
Highlight Word Detection	Information Extraction
Query-Note Relevance	Semantic Matching
Query-Note Retrieval	Semantic Matching
Post-View Search	User Behavior Modeling
Emotional Companion Dialogue	Dialogue
Role-playing Dialogue	Dialogue
SNS Domain Translation	Translation

Table 1: Overview of SNS Tasks and Their Capabilities

After data collection, we ultimatly consolidate six kinds of core capabilities essential for SNS applications: content understanding, information extraction, semantic matching, user behavior modeling, dialogue and persona simulation, and translation, as show in Table 1. Each is supported by well-defined tasks reflecting real-world challenges and the overview is shown in Appendix A.2.

Additionally, during SFT, we also incorporated open source instruction data covering general tasks such as instruction following (Li et al., 2025; Zhou et al., 2023a), multiturn dialogue (Zhao et al., 2024), and long chain-of-thought (CoT) reasoning (Guha et al., 2025; Ye et al., 2025), to mitigate catastrophic forgetting (McCloskey and Cohen, 1989) and retain generalization ability of RedOne model. Training Prompt templates of all tasks can be found in Appendix A.4.

3.2.2 Two-Step Training

In domain SFT, a two-step mixed fine-tuning has been demonstrated to effectively enhance domain-specific capabilities (Dong et al., 2024). For RedOne's SFT, we implement this strategy by mixing SNS-specific data with general data across two steps. In the first step, we train the model on the complete SNS dataset combined with a large volume of general data. This approach enables the model to learn diverse task formats within the SNS domain while preserving its generalization capabilities. In the second step, we fine-tune the model using a higher proportion of SNS domain data, thereby further enhancing performance on domain-critical tasks.

3.3 Preference Optimization

SNS tasks like query-note relevance modeling often produce multiple plausible but quality-diverse outputs. While SFT improves instruction-following, it fails to exploit implicit preference signals among these candidates, causing overfitting and poor generalization (Chu et al., 2025). To address these limitations, in this section, we carefully craft preference data and perform PO to obtain a better domain-specific model.

3.3.1 Preference Data Construction

To enhance alignment with human preferences and utilize the information embedded in data labels, we integrate different preference pair construction strategies according to the nature of different task types. Specifically, we categorize our data into two types and adopt corresponding strategies:

For subjective tasks, such as emotional dialogue and role-playing, our primary objective is to achieve better alignment with human preferences. Therefore, the first step begins with domain experts creating preference annotations on model-generated responses (Ouyang et al., 2022). Furthermore, to scale up the preference dataset, we evaluate the consistency between trained judge models (Cao et al., 2024a) and human preference, then leverage these models with high performance to expand specific data.

In contrast, for objective tasks with definitive correct answers, our strategy shifts toward extracting and utilizing the implicit structural information within the data labels. Here, we employ two approaches: First, we leverage the inherent structure of questions that contain both correct answers and incorrect options, constructing preference pairs that exploit the ordinal relationships within data. Complementarily, to actively address model limitations, we construct preference pairs from model errors, using ground truth as positive examples and incorrect predictions as negative to target specific weaknesses.

By integrating these tailored approaches, we systematically process all SNS-domain data according to their inherent characteristics, ultimately constructing preference optimization datasets that effectively capture both human preferences and implicit data information for comprehensive model enhancement.

3.3.2 Direct Preference Optimization

To effectively leverage the rich preference signals in our SNS dataset, we adopt DPO (Rafailov et al., 2023) as our preference-based fine-tuning algorithm. This approach enables the model to better align with human preferences while simultaneously exploiting the latent information embedded in ground-truth labels.

Finally, through this comprehensive three-stage training pipeline encompassing CPT, SFT and PO, we ultimately obtain a domain-specific large language model RedOne that demonstrates superior performance in the target domain while maintaining reasonable general capabilities.

4 Experiments

4.1 Implementation details

During the CPT stage, we follow the training process from Qwen2.5 (Yang et al., 2024a) over a mixed corpus of general and SNS-specific data. SFT is conducted for three epochs in step one and two epochs in step two, with a maximum sequence length of 16 384 using sequence packing, batch size of 128, a linear warm-up ratio of 0.1. The learning rates are set according to model size: for the 7B model, we use 5×10^{-6} in step one and 3×10^{-6} in step two; for the 32B model, we use 3×10^{-6} for both steps. Optimization is performed using AdamW (Loshchilov and Hutter, 2017) (β_1=0.9, β_2=0.95, ϵ=10^{-8}). In the final PO stage, we employ a learning rate of 1×10^{-7}, batch size of 64, sequence length of 4096, training for two epochs, with SFT loss coefficient set to 0.3.

4.2 Benchmarks

For general capabilities evaluation, we use datasets similar to those employed in community, including general natural language comprehension (i.e. MMLU (Hendrycks et al., 2021a), CMMLU (Li et al., 2023a), CEVAL (Huang et al., 2023), GPQA-Diamond (Rein et al., 2023), News-Bench (Li et al., 2024a)), reasoning (i.e. MMLU-Pro (Wang et al., 2024), BBH (Suzgun et al., 2023), GaokaoBench (Zhang et al., 2023)), mathematics (i.e. AIME2025 (MAA, 2025), GSM8K (Cobbe et al., 2021) and MATH500 (Hendrycks et al., 2021b)), coding (i.e. HumanEval (Chen et al., 2021), MBPP (Austin et al., 2021), and LiveCodeBench(24072502)(Jain et al., 2024)), translation (i.e. WMT-22/23/24 and Flores(Goyal et al., 2022)), instruction following (i.e. IFEval (Zhou et al., 2023b)), hallucination and human preference alignment (i.e. HaluEval (Li et al., 2023b) and CompassBench (Cao et al., 2024b)). To further evaluate RedOne's performance in SNS domain, we selected specialized SNS benchmarks including SNS-Bench (Guo et al.) and SNS-TransBench (Guo et al., 2025).

Models	General-Bench	SNS-Bench									SNS-TransBench				
											ZH→EN		EN→ZH		
	Avg.	Taxonomy	Hashtag	QueryCorr	MRC	NER	Gender	CHLW	QueryGen	Avg.	BLEU	chrF++	BLEU	chrF++	Avg.
Llama-3.1-8B (Grattafiori et al., 2024)	51.24	37.74	66.62	33.32	31.27	47.10	74.61	26.88	38.60	44.52	23.07	48.15	29.32	29.13	32.42
Ministral-8B (Mistral-AI, 2024)	49.93	42.62	70.58	36.24	30.71	37.79	82.38	28.04	46.27	46.83	25.67	50.91	32.02	31.18	34.95
InternLM3-8B (Cai et al., 2024)	58.55	51.83	76.98	38.65	25.25	39.41	66.84	44.71	43.46	48.39	24.85	50.44	35.58	34.04	36.23
GLM-4-9B-0414 (GLM et al., 2024)	63.27	56.03	77.67	38.03	45.29	47.01	51.30	27.51	45.52	48.55	32.20	56.90	39.73	37.40	41.57
Qwen2.5-7B (Qwen et al., 2025b)	63.01	49.50	73.80	42.37	45.32	45.41	**88.08**	33.76	44.65	52.86	31.43	55.91	38.36	36.48	40.55
RedOne-7B **(Ours)**	**63.83** (+0.82%)	**72.18**	**88.02**	**65.09**	**63.98**	**51.86**	70.47	**74.73**	**48.69**	**66.88** (+14.02%)	**38.06**	**62.66**	**46.88**	**44.82**	**48.11** (+7.56%)

Table 2: Results of 7B-scale models. **Bold** entries indicate the best model, while underlined entries denote the second one. Percentage improvements relative to the baseline Qwen2.5 foundation model are also shown.

Models	General-Bench	SNS-Bench									SNS-TransBench				
											ZH→EN		EN→ZH		
	Avg.	Taxonomy	Hashtag	QueryCorr	MRC	NER	Gender	CHLW	QueryGen	Avg.	BLEU	chrF++	BLEU	chrF++	Avg.
Open-Source Large Language Models															
Phi-4-14B (Abdin et al., 2024)	63.00	57.62	79.56	46.32	53.39	44.99	89.12	29.23	44.76	55.62	31.28	57.23	37.58	36.68	40.69
Mistral-Small-24B (Mistral-AI, 2025)	65.63	64.88	83.89	48.77	46.51	52.09	91.19	32.10	46.01	58.18	31.29	56.72	39.28	37.32	41.15
Llama-3.3-70B (Grattafiori et al., 2024)	67.64	62.94	83.28	50.76	27.38	56.09	91.19	33.58	46.41	56.45	34.00	59.18	41.25	39.56	43.50
GLM-4-32B-0414 (GLM et al., 2024)	74.39	63.36	85.50	47.33	53.72	50.41	80.31	33.19	46.90	57.59	36.32	61.31	42.53	40.77	45.23
Deepseek-V3-0324 (DeepSeek-AI et al., 2025)	75.22	67.27	86.59	47.71	60.97	56.00	90.16	40.45	46.03	61.90	35.65	61.58	46.86	44.58	47.17
Closed-Source Large Language Models															
Doubao-1.5-Pro-32k (Doubao-Team, 2025)	**76.13**	*30.00*	83.21	58.25	61.32	**56.60**	90.67	30.61	46.55	57.15	33.71	61.85	45.54	44.35	46.36
GLM-4-Plus (GLM et al., 2024)	*70.25*	65.46	84.31	52.13	55.81	53.16	86.53	30.09	44.68	59.02	**41.57**	**65.95**	48.79	47.06	**50.84**
GPT-4o-1120 (OpenAI)	*70.72*	65.79	84.98	51.79	58.89	54.99	88.08	38.96	47.33	61.35	40.32	63.91	**49.15**	**47.28**	50.17
Claude-3.7-Sonnet (Anthropic)	75.10	72.03	88.83	54.10	54.86	56.13	**92.23**	31.11	45.49	61.85	35.63	61.66	45.79	44.23	46.83
Gemini-2.0-Flash (DeepMind, 2024)	74.42	68.76	87.36	48.41	52.21	53.58	89.64	37.39	46.27	60.45	32.72	58.84	41.80	40.16	43.38
Qwen-Max (Qwen et al., 2025b)	71.86	65.68	84.47	54.36	**61.34**	55.78	91.19	37.97	46.64	62.18	35.55	60.92	46.08	44.14	46.67
Qwen2.5-32B (Qwen et al., 2025b)	71.68	59.90	80.51	46.00	55.04	54.51	90.67	38.84	45.66	58.89	32.56	58.14	42.34	40.71	43.44
RedOne-32B **(Ours)**	73.72 (+2.04%)	**81.45**	**90.19**	**67.07**	59.24	51.66	81.87	**70.40**	**50.37**	**69.03** (+10.14%)	40.55	64.54	48.20	46.05	49.84 (+6.40%)

Table 3: Results of 32B-scale models. **Bold** entries indicate the best model, while underlined entries denote the second one. Percentage improvements relative to the baseline Qwen2.5 foundation model are also shown.

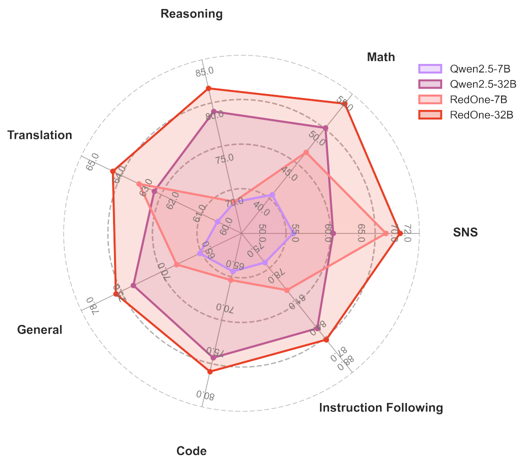

Figure 3: Capability of RedOne-7B, RedOne-32B and their base models across seven dimensions.

Models	HashTag	QueryCorr	MRC
Qwen2.5-Finetuned	88.93	57.76	62.26
RedOne	88.02 (-0.91%)	65.09 (+12.63%)	63.98 (+2.76%)
RedOne-Finetuned	**90.51**(+1.78%)	**65.77**(+13.87%)	**64.47**(+3.55%)
Models	**CHLW**	**QueryGen**	**SNS-Trans**
Qwen2.5-Finetuned	78.41	48.25	48.01
RedOne	74.73 (-4.72%)	48.69 (+0.91%)	48.11 (+0.21%)
RedOne-Finetuned	**79.11**(+0.89%)	**49.21**(+1.99%)	**48.32**(+0.65%)

Table 4: Performance comparison of task-specific Fine-tuned on Qwen-2.5-Instruct and RedOne (all models are 7B scale).

4.3 Main Results

As shown in Tables 2 and 3, we conducted a comparison between RedOne with baseline models across various tasks in three categories. Meanwhile, as illustrated in Figure 3, we compared RedOne-7B and RedOne-32B with their base model across seven dimensions (six for general and one for SNS). Both results indicate that RedOne in all scales not only maintain robust general capabilities, even surpassing their base model on general tasks, but also exhibit exceptional effectiveness in the SNS domain. Additionally, RedOne achieves performance comparable to significantly larger models across most tasks, with limited improvement opportunities observed only in few areas. The results also demonstrate that scaling up RedOne consistently enhances performance over smaller variants, aligning with established model scaling laws. These findings underscore RedOne's strong potential for further advances through continued increases in model size, as well as its promise for real world application.

4.4 Task-specific SFT Comparison

To further explore the impact of base model selection on task-specific fine-tuning and validate our domain LLM's effectiveness, we conducted experiments on two 7B-scale models: the original Qwen-2.5-Instruct ("Qwen") and our SNS-adapted model ("RedOne"). We evaluated three variants: (1) Qwen-Finetuned, involving task-specific fine-tuning on Qwen; (2) RedOne-Finetuned, involving task-specific fine-tuning on RedOne; and (3) RedOne, representing zero-shot inference without further fine-tuning.

As shown in Table 4, RedOne-Finetuned consistently outperforms Qwen2.5-Finetuned across most datasets, demonstrating that domain-aligned post-training (i.e., RedOne) provides a stronger foundation for downstream SFT. Meanwhile, even RedOne in the zero-shot set-

CPT	SFT	PO	General	SNS	SNS-Trans
			63.01	52.86	40.55
	✓		62.65	64.57	47.47
	✓	✓	**64.36**	64.98	47.64
✓			62.28	53.28	41.39
✓	✓		61.95	65.12	47.70
✓	✓	✓	63.83	**66.88**	**48.11**

Table 5: Ablation study results of RedOne-7B.

Task	Metric	Improvement (%)
Harmful Content Detection	Exposure Rate (↓)	−11.23
Post-View Search	Click Page Rate (↑)	+14.95

Table 6: Effectiveness in online scenarios.

ting exhibits strong performance, further corroborating the benefits of domain adaptation. Overall, these results indicate that initializing SFT from a domain-adapted base model is more effective than starting from a general-purpose large model. This finding suggests that domain-specific post-training can serve as a powerful approach for improving both zero-shot capabilities and task-specific performance after fine-tuning.

4.5 Ablation Study

We also investigate the contributions of each stage in our training pipeline, with results summarized in Table 5. While CPT alone shows limited immediate gains, it establishes a crucial foundation for subsequent specialization. Based on the CPT model, adding SFT and PO brings average improvements of 0.55 and 1.90 on SNS-Bench compared to variants without CPT, indicating that CPT provides a stronger knowledge foundation for SFT to improve instruction-following and also offers a broader exploration space for PO. Additionally, both CPT and SFT lead to a performance drop on general benchmarks, whereas PO could effectively mitigate this decline and further enhance the overall results. Finally, the complete three-stage pipeline yields the strongest results on specialized benchmarks, with 66.88 on SNS and 48.11 on SNS-Trans, while maintaining competitive general-domain performance at 63.83, demonstrating the effectiveness of our training strategy.

4.6 Online Results

To further validate RedOne's practical effectiveness, we deployed the model across multiple internal SNS scenarios and witnessed remarkable performance gains in real-world applications compared with previous single-task models as shown in Table 6. In harmful content detection, RedOne exhibited exceptional safety capabilities by slashing the exposure rate of harmful notes by 11.23%, effectively filtering out non-compliant content and strengthening platform security. Moreover, for post-view search recommendation, the model delivered a 14.95% increase in click page rate, indicating improved content discovery and enhanced user engagement following note interactions. These online results

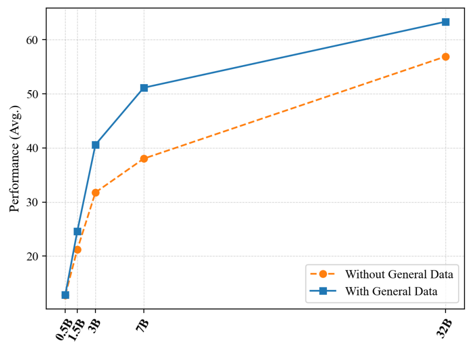

Figure 4: Performance on OOD tasks for models of varying parameter size.

Input	**Title:** Found it! A Soft-Sole Commuter Loafer You Can Walk In All Day **Tags:** Height Increasing Thick Sole Shoes, Loafers, Beautiful Loafers **Popular Comments:** How to buy; link
Qwen	How to choose height-increasing platform shoes
RedOne	height-increasing thick-soled loafers

Table 7: Post-view search case: Input SNS context and model-generated queries.

demonstrate the strong practical utility of RedOne in real-world scenarios.

4.7 Out-of-Domain Ability Analysis

In this subsection, we examine the impact of preserving general-domain capabilities during domain adaptation by evaluating out-of-domain (OOD) robustness. Specifically, we select one task without corresponding supervised training data (Note Taxonomy) and two tasks with available data (Note Hashtag, Note MRC) from the SNS bench. For the latter two, we remove their related training data during supervised fine-tuning (SFT), effectively making all three tasks OOD.

We then compare models trained with both general and SNS data against those trained with SNS data only, across various model sizes. Our results (Figure 4) suggest that including general-domain data helps models generalize better to OOD tasks, and this trend is more visible for larger models. This highlights that maintaining general capabilities can be beneficial for domain adaptation, though further study is needed to fully understand this effect.

4.8 Case Study

To further demonstrate RedOne's effectiveness in capturing user search intent within SNS scenarios, we present a case study on the post-view search task. As shown in Table 7, we analyze a sample post featuring height-increasing loafers that generated significant purchase intent among users. Qwen produces a general shopping query, whereas RedOne directly identifies the core product keywords, better reflecting users' intent to search for and purchase the featured item. This demonstrates

RedOne's superior capability for generating actionable queries aligned with real user needs.

5 Conclusion

In this paper, we introduce RedOne, a domain-specific LLM trained through a three-stage strategy that enhances SNS-specific capabilities while preserving general performance. We believe our approach can inspire future research in developing specialized LLMs and advancing practical applications in social media.

Limitations

Although our proposed method demonstrates strong effectiveness, it requires extensive data processing, resulting in considerable resource costs. Additionally, current models are still in a large scale, which increases online inference latency and serving expenses, limiting deployment in resource-constrained settings. Future work will explore lighter architectures, including model compression through quantization and distillation, as well as routing-efficient designs such as mixture-of-experts (MoE), to reduce latency and cost without sacrificing accuracy.

Ethical Considerations

When integrating large language models as essential components within application services, it is crucial to rigorously consider potential model hallucinations and security risks. To ensure reliable service delivery, leveraging RedOne for model services requires careful implementation to mitigate adverse user impacts. Furthermore, we emphasize the critical importance of adhering to stringent user privacy protection standards throughout data collection and processing workflows, ensuring comprehensive personal information security.

Reproducibility

Due to data privacy and code security concerns, we are currently unable to fully release our datasets and code. However, our entire development pipeline is built upon widely adopted open-source projects and works (Zheng et al., 2024; Rafailov et al., 2023; Dong et al., 2023), which ensures that users only need to organize their data according to the specified format in order to run it smoothly. In addition, we have reported detailed parameter settings used during training in Section 4.1, which further provides valuable references for the community to reproduce our pipeline.

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A Appendices

A.1 SNS Tasks

In this section, we provide an overview of the key tasks defined for SFT in SNS scenarios. These tasks are designed to reflect real-world user behavior, content patterns throughout social platforms. The SFT task suite covers six core capability areas, each capturing an important aspect of SNS applications:

Content Understanding: This category focuses on the model's ability to comprehend and categorize user-generated content as well as user queries. Example tasks include classifying notes into categories (*note taxonomy*), determining the topic or domain of user queries (*query classification*), and identifying fine-grained query intent (*query intent recognition*).

Information Extraction: Tasks in this category address the identification and extraction of structured information from informal SNS posts. This includes predicting appropriate hashtags for a post, answering questions about note content, and detecting highlight or anchor words that represent user focus.

Semantic Matching: Here, the model is required to judge the semantic relationship and relevance between items such as user queries and social notes. Typical tasks include evaluating whether a note is relevant to a given query (*query-note relevance*) and retrieving the most pertinent or high-quality notes for search scenarios (*query-note retrieval*).

User Behavior Modeling: This capability involves modeling and simulating user actions, such as generating follow-up queries based on previous browsing or posting activities (*post-view search*). It reflects how users might interact with content in a dynamic SNS environment.

Dialogue and Persona Simulation: To enhance natural interaction and personalization, dialogue tasks ask the model to engage in emotional companion conversations or role-play as different personas in group chats, capturing both the style and richness of real SNS dialogues.

Translation: Given the prevalence of multilingual content, the model is also trained to translate notes between languages, with attention to preserving the original tone, sentiment, and informal expressions common across SNS platforms.

Each task adopts the most suitable instruction-tuning format: multiple choice supports classification and selection, extraction is used for entity and span prediction, and generation handles open-ended responses such as dialogue or translation. This format-driven design ensures consistent prompting and facilitates efficient multi-task training.

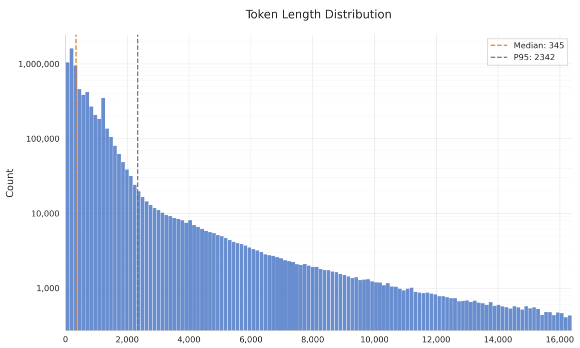
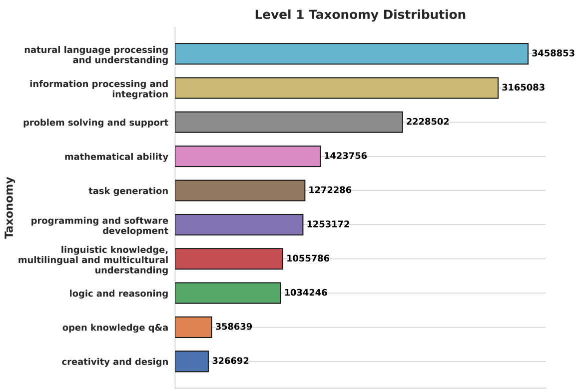
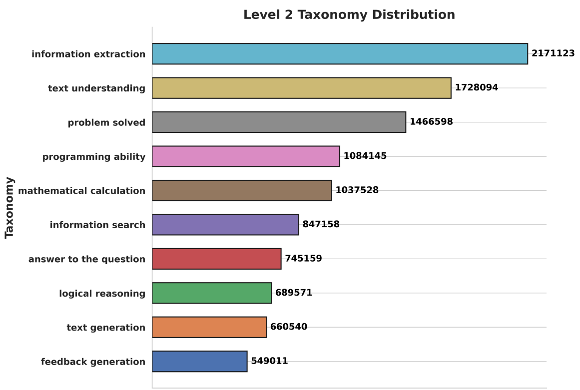


Figure 5: Token length distribution in the dataset. The histogram uses a logarithmic y-axis with dashed lines indicating the median (345 tokens) and the 95-th percentile (2,342 tokens).



(a) Primary task categories.



(b) Secondary task categories.

Figure 6: Top 10 distributions of primary and secondary task categories in the SFT dataset.

A.2 SFT Data Statistical Analysis

Token Length Statistics Figure 5 presents the token length distribution across all samples in our dataset, displayed on a logarithmic scale to accommodate the wide range of sequence lengths up to 16,384 tokens. The distribution exhibits the characteristic heavy-tailed pattern typical of natural language corpora.

Task Category Distribution We adopted the labeling taxonomy from Infinity Instruct (Li et al., 2025), organizing it into primary and secondary categories. Specifically, we used a subset of Infinity Instruct data, consisting of instructions paired with their corresponding labels, as training data to fine-tune a labeling model based on Qwen2.5-7B-Instruct. This trained labeling model was then applied to annotate all instructions in our complete SFT dataset. The comprehensive distribution of primary and secondary label categories is illustrated in Figures 6a and 6b, respectively.

The distribution analysis reveals several key characteristics of our SFT dataset. At the primary level, natural language processing and understanding dominates with over 3.4 million instances, followed closely by information processing and integration (3.1 million) and problem solving and support (2.2 million). This indicates a strong emphasis on core language comprehension and analytical capabilities. Mathematical ability and programming-related tasks also constitute significant portions, with over 1.2 million instances each, reflecting the dataset's comprehensive coverage of technical skills. At the secondary level, information extraction leads with 2.1 million instances, while text understanding and problem-solving tasks follow with 1.7 million and 1.4 million instances respectively. The relatively balanced distribution across different cognitive abilities suggests that our dataset provides diverse training scenarios for developing well-rounded AI capabilities.

A.3 Data Synthesis for Continue Pretraining

Single Search

From x year x month x day x hour x minute, a user searched for {query} and then clicked on the following notes in order:
Note 1 Title: {title}
Note 1 Content: {content}
Reading Time 1:

Note 2 Title: {title}
Note 2 Content: {content}
Reading Time 2:

Note 3 Title: {title}
Note 3 Content: {content}
Reading Time 3:

Note 4 Title: {title}
Note 4 Content: {content}
Reading Time 4:

Note 5 Title: {title}
Note 5 Content: {content}
Reading Time 5:

Afterwards, the user continued to view more notes|started a new query|navigated to another page|exited the app.

Multiple Consecutive Searches

From x year x month x day x hour x minute, a user searched for {query} and then clicked on the following notes in order:
Note 1 Title: {title}
Note 1 Content: {content}
Reading Time 1:

Note 2 Title: {title}
Note 2 Content: {content}
Reading Time 2:

Afterwards, the user entered a new query and then clicked on the following notes in order:
Note 1 Title: {title}
Note 1 Content: {content}
Reading Time 1:

Note 2 Title: {title}
Note 2 Content: {content}
Reading Time 2:

Afterwards, the user entered a new query and then clicked on the following notes in order:
Note 1 Title: {title}
Note 1 Content: {content}
Reading Time 1:

Note 2 Title: {title}
Note 2 Content: {content}
Reading Time 2:

Afterwards, the user continued to view more notes|started a new query|navigated to another page|exited the app.

Click-Through Rate Estimation

N users searched for {query}. Among the exposed notes, the three notes with the highest click frequency are as follows:
Note 1 Title: {title}
Note 1 Content: {content}

Note 2 Title: {title}
Note 2 Content: {content}

Note 3 Title: {title}
Note 3 Content: {content}

Among the exposed notes, the notes that were not clicked are:
Note 1 Title: {title}
Note 1 Content: {content}

Note 2 Title: {title}
Note 2 Content: {content}

Note 3 Title: {title}
Note 3 Content: {content}

A.4 Prompts

In this subsection, we list some of the prompts from the training data, some of which are adapted from SNS-Bench (Guo et al.).

Highlight Word Detection

Please select words worth highlighting from comments. These words should be meaningful and specific entities, issues, or descriptions that spark users' search interest.
For life trivia without meaning or search value and content containing numbers, please select carefully.
Here are extraction examples:

1) Input: Give me a transparent Bluetooth speaker link; Return: ["transparent Bluetooth speaker"]
2) Input: Is there a tutorial for Huawei Smart Screen; Return: ["Huawei Smart Screen tutorial"]
3) Input: Is there any specific fitness and weight loss APK?; Return: ["fitness and weight loss APK"]
4) Input: Noodles have no calories but the sauce does; Return: ["noodles have no calories but sauce does"]
5) Input: How"s Peking duck; Return: ["Peking duck"]

Comment:
{comment}

Please provide a list of words you think are suitable for highlighting. If you think none are appropriate, please output an empty list [].

Answer:

Machine Reading Comprehension (Complex)

Task: First rewrite the Query, then perform reading comprehension.

###Reference Content Format###
* The reference content consists of three parts: Query, Doc, and Level
* Query is the user's search term with question-asking intent; Doc is the main text part of the image note, wrapped in <Doc> and </Doc>; Level defines the expected answer type, indicating what type of answer the user needs.

###Task Requirements###
Step 1: Based on Query and Level, rewrite the Query into specific answer requirements, please output the rewritten rewrite_query. Here are some examples for the first step:
1.[Query=World's most beautiful museums recommendations, Level=museum names]=>[Names of the world's most beautiful museums]
2.[Query=Coody Coffee recommendations, Level=drink names]=>[Delicious drink names at Coody Coffee]
3.[Query=Qingdao food, Level=dishes]=>[Delicious dishes in Qingdao]
4.[Query=Games similar to Number Bomb, Level=game names]=>[What games are similar to Number Bomb]
5.[Query=Birthday cake recommendations in Licheng District, Jinan, Level=bakery cake names]=>[Delicious birthday cakes from bakeries in Licheng District, Jinan]
6.[Query=Guangzhou Yuexiu District food recommendations, Level=restaurant dishes]=>[Delicious restaurant dishes in Yuexiu District, Guangzhou]
7.[Query=Hiking survival bracelet recommendations, Level=brand model]=>[Brand and model recommendations for hiking survival bracelets]
8.[Query=Must-buy in Japan, Level=brand model]=>[Brand and model of Japanese specialty products]
9.[Query=iPhone 11 photography recommendations, Level=model]=>[iPhone 11 models good for photography]
10.[Query=1000 desk essentials, Level=product names]=>[1000 useful products for desks]
11.[Query=Changsha special breakfast recommendations, Level=restaurants]=>[Names of restaurants with special breakfast in Changsha]
12.[Query=Nanjing surrounding tours, Level=cities]=>[Cities suitable for tourism around Nanjing]
13.[Query=Cheap clothing places in Shenzhen, Level=shopping locations]=>[Names of shopping locations for cheap clothes in Shenzhen]
14.[Query=Harbin bathhouse recommendations, Level=bathhouse names]=>[Names of worthwhile bathhouses in Harbin]

Step 2: Evaluate the relevance between Doc and rewrite_query, paying attention to important qualifiers in rewrite_query, such as time and location modifiers. If Doc misses important qualifiers, it can be considered irrelevant. Analyze the relevance in 1-2 sentences.

Step 3: If Doc is relevant to rewrite_query, extract all answers (Options) from Doc that can answer the user's question and put them in AnswerList. Options must match the answer type required by rewrite_query. Specifically, if rewrite_query requires "brand model", ensure each answer Option includes both "brand name" and "model"; if this cannot be satisfied, consider it unextractable. If rewrite_query requires "restaurant dishes", ensure each answer Option includes both "restaurant name" and "dish name". Others like "bakery cake names" follow the same pattern. If Option cannot meet the required answer type, consider it unextractable, and AnswerList will be an empty list [].

Step 4: For each answer Option in AnswerList, extract a related description (Reason) from Doc. Format: ["Option": "xxx", "Reason": "xxx", ...]. If Doc is irrelevant or has no answers, return an empty list [].

Notes:
1. Answer Options must follow the original text, non-continuous extraction is allowed.
2. Reasons must be extracted from the original text, no modifications allowed.
3. Answer Options should typically be specific entity nouns or names that can be directly searched through search engines; avoid extracting vague descriptions like "this hidden gem hotel" or "rice noodles from the shop near XXX bus station".
4. Doc may have various article structures, including a common parallel point structure with leading words. When extracting answer Options, avoid including leading words like "Figure 1", "Figure 2", ..., "Shop 1",

"Shop 2", etc.
5. Reason length should not exceed 100 english character widths.

Output format:
<rewrite_query>...</rewrite_query>
<relevance_analysis>...</relevance_analysis>
<AnswerList>["...", ...]</AnswerList>
<Result>["Option": "xxx", "Reason": "xxx", ...]</Result>

Query:
{query}
Level:
{level}

Doc:
{doc}

Machine Reading Comprehension (Simple)

You are a reading comprehension master:
I will provide you with a user's note article, including a title and content, where the title may be empty. I will also give you a user's question.

Please think according to the following steps:
* Step 1, combine the note's title and content to determine if the user's question can be answered. If there are specific entity words or qualifiers in the question, they must be satisfied to count as having an answer.
* Step 2, if Step 1 determines that the content can answer the user's question, then extract the answer from the original note content and output the extracted original content.

Content requirements for answers:
* Extract sentences that can answer the question, cross-sentence extraction is allowed, but must be complete sentences or paragraphs, multiple consecutive sentences must be extracted continuously, and preserve special characters like
.
* If the middle part of consecutive sentences is irrelevant to the answer, it can be skipped for cross-sentence extraction; if the answer is long (more than 120 characters), it can be extracted by points.
* Content must come from the original text, no summarization allowed; do not extract content unrelated to answering the user's question.

Format requirements for answers:
* Output the answers in list form, where each value in the list is a sentence or paragraph that can answer the question.
* If no answer can be extracted, return an empty list [].
* Do not output any content other than the answer list.

Here is the note title and content:

{note_title}
{note_content}

User's question:
{question}
Output:

Hashtag Prediction (Multiple Answer)

Given a title and content of a social media note, and a list of candidate topic tags, please select all the tags that match the note from the list of topic tags.
Here are some examples:

Input:
Note Title: Banking Services in City A
Note Content: Looking for a customer manager in City A
Long-term deposit plan!!!
Candidate Topic Tags:
September Birthday, DIY in City B, Savings Check-in, City A, Art Design, Nap Time, City C Vehicle, Must-Have Outdoor Gear, Bank, Celebrity Name, Savings, Beauty Product, Shopping Club, Product Recommendations
Answer: City A, Savings, Savings Check-in, Bank

Input:
Note Title: First Time Making Craft Items, Worried About Quality!!
Note Content: Love craft items so much! Never thought making them myself would be so much fun! But the adhesive for finishing is really hard to handle. Use too little and it might not be sturdy, use too much and it might not work well. How long should I wait before removing the protective layer? People interested can check my page, switched to a new account, will be sharing more quality items
Price: 52 units (5 items)
Candidate Topic Tags:
Professional Exam Review, After Life Changes, Recruiting Partners, Beauty Service Collaboration, First Time Making Craft Items, Travel Destination, Company Name, Craft Item, DIY Fun, Popular Product Recommendations, Career Coaching, Craft Item Brand, Craft Item Sharing, New Hobby Style, DIY Sharing, Skills Competition, Craft Item Original
Answer: DIY Sharing, Craft Item Sharing, Craft Item Brand, Craft Item Original, First Time Making Craft Items, Craft Item, DIY Fun

Please output the answer (in the same format as the examples above) DIRECTLY after "Answer:", WITHOUT any additional content.

Input:
Note title:
{title}
Note content:
{content}
Candidate Topic Tags:
{candidate_topic_tags}
Answer:

Hashtag Prediction (Single Answer)

Give you a SNS note title and content, along with a list of candidate topic tags, please select the most relevant tag from the list for the note.
Below are some examples:

Input:
Note Title: ❤️Enfj Big Swords Will Love Life BGM Recommendations 🔥
Note Content: Compiled some BGMs for everyone, if you have any recommended songs, please leave them in the comments section, let's exchange and share together 😀
Candidate Topic Tags:
National Peace and Tranquility, Outfit for Pear-Shaped Body, High EQ Small Tricks, Vienna Guide
Answer: High EQ Small Tricks

Input:
Note Title: Must-Have 👙 at the Sanya Beach
Note Content: On a summer beach, how can you do without this blue tie-dye dress!💙

Size XL, perfectly fits plus-size sisters! 👯♀

A high-end, laid-back style, loose design, wear it and instantly look whiter and slimmer! 👙

This dress is not only fashionable but also of great quality, a must-have item for beach vacations! 💝

Even the most picky of you will fall in love with it! 💝
Candidate Topic Tags:
National Trend Short Sleeves, Beach Outfit, Miracle Warm Pictures, Badminton Uniform Outfit
Answer: Beach Outfit

Please output the answer (in the same format as the examples above) DIRECTLY after "Answer:", WITHOUT any additional content.

Input:
Note Title:
{title}
Note Content:
{content}
Candidate Topic Tags:
{candidate_topic_tags}
Answer:

Note Taxonomy (Multiple Answer)

Given a SNS note's title and content, and lists of candidate primary, secondary, and tertiary categories, please select the most suitable categories from each level. Answer in the format: Primary category | Secondary category | Tertiary category.
Here are some examples:

Input:
Note title: The super disappointing AHC facial cleanser for me
Note content: During National Day trip to Hong Kong, several colleagues asked me to help buy AHC facial cleanser, saying it was especially good.
I followed the trend and bought one, used it in the hotel that night💥💢After washing, my eyes were particularly painful, even a tiny bit made me feel like I was going blind👉🙅🙅so where exactly is it good😤😤😱😱Now a full bottle is sitting at home, won"t repurchase.
Bought for about 70 HKD equivalent to about 60 RMB. The Innisfree green tea cleanser is still better for an affordable cleanser😖😖😖
Candidate primary categories: ["Music", "Beauty", "Mother&Baby", "Outdoor", "Humanities", "Photography", "Gaming", "Art", "Trends", "Entertainment", "Film&TV", "Kids", "Career", "Food"]
Candidate secondary categories: ["Education Daily", "Skincare", "Other Pets", "Handicraft", "Resource Sharing", "Exhibition", "Personal Care", "Shoes", "Mobile Games", "Relationship Knowledge", "Meals", "Places", "Language Education", "Makeup"]
Candidate tertiary categories: ["Cycling Records", "Playlist Sharing", "Cleansing", "Other Shoes", "Fruit", "Self-study", "Instrument Playing", "JK", "Beverage Review", "Tablet", "Career Development", "Boutique", "Other Campus", "Driving Safety"]
Answer: Beauty | Skincare | Cleansing

Input:
Note title: Day8
Note content: Forgot to post yesterday

Making up for it today#ChineseBrushCalligraphyCheckIn[topic]# #DailyCalligraphyCheckIn[topic]# #
Candidate primary categories: ["Anime", "Beauty", "Gaming", "Humanities", "Home&Decoration", "Health", "Relationships", "Social Science", "Career", "Art", "Education", "Life Records"]
Candidate secondary categories: ["Science", "Car Lifestyle", "Running", "Other", "Culture", "Weight Loss Medicine", "Parks", "Fashion", "Accessories", "Weight Loss", "Music Sharing", "Finger Gaming"]
Candidate tertiary categories: ["Bags", "Fruit", "Leisure Guide", "Sheet Music Sharing", "Font Design", "Calligraphy", "Weight Loss Tutorial", "Snack Review", "Life Science", "Swimwear", "Ball Sports", "Skincare Collection"]
Answer: Humanities | Culture | Calligraphy

Please output the answer (in the same format as the examples above) DIRECTLY after "Answer:", WITHOUT any additional content.

Input:
Note Title:
{title}
Note Content:
{content}
Candidate tertiary categories:
{candidate_tertiary_categories}
Answer:

Note Taxonomy (Single Answer)

Given a SNS note's title and content, and a list of candidate categories, please select the most suitable category from the candidate category list.
Here are some examples:

Input:
Note title: Need help, is this a car dash cam
Note content: Bought a DV for 250, came with a battery and charging cable, and it's very light, wondering if it's really a dash cam[crying R][crying R]#DV[topic]#
Candidate categories: Car knowledge, Trending, Car lifestyle, Car accessories, Motorcycles, Car shopping, Car modification, New energy & smart, Car culture, Driving test learning, Other automotive
Answer: Car accessories

Input:
Note content: Traveling Henan · Understanding China | Xinxiang South Taihang Tourism Resort: Let's follow the lens to see the sea of clouds in South Taihang
#TravelingHenanUnderstandingChina
#HomelandHenan #HomelandHenanNewMediaMatrix #May19ChinaTourismDay
#XinxiangSouthTaihangTourismResort #SeaOfClouds
#XinxiangCultureBroadcastingForeignAffairsAndTourismBureau
Candidate categories: Travel VLOG, Shopping, Food exploration, Places to go, Travel guide, Travel records, Hotels & B&Bs, Attraction experience, Travel tips, Living abroad, Indoor leisure
Answer: Travel records

Please output the answer (in the same format as the examples above) DIRECTLY after "Answer:", WITHOUT any additional content.

Input:
Note Title:
{title}

Note Content:
{content}
Candidate categories:
{candidate_categories}
Answer:

Question-Document Match

Below is a question and a document. Please determine if the given document can answer the given question. If it can, reply with "Yes", otherwise reply with "No". Only reply with "Yes" or "No", no additional explanations are needed.
Here are some examples:

Question:
Is the distorted face in the back camera of an iPhone the real you?
Document:
Revealed | Is the you in the original camera really you? |- Distorted features? Facial asymmetry? Poor skin condition? Skewed face? Why do you see all these when you open the original camera on your phone? And then you get anxious: Am I really that ugly? Actually, it's not the case. The original camera on your phone does indeed make you look worse. Let me explain one by one about appearance anxiety #notcamerafriendly
Answer: No

Question:
Is the corn used in cultural playthings real corn?
Document:
Light Macaroon | Beautiful, beautiful | All real corn grown, nature's colorful gifts currently popular cultural plaything corn (naturally grown) undyed
Answer: Yes

Question:
{question}
Document:
{document}
Answer:

Post-View Search

Assume you are an internet user, your task is: based on the input image/text or video note content, generate 1 novel search term related to the core entity words in the note.

Output format:
The return result is a single line string, recording the generated search term.
Output requirements:
1. You need to fully understand the input note information, ensure that the given search terms are complete, novel and interesting, with the possibility of being targeted or in-depth exploration, and can bring incremental information to the current note;
2. Ensure that the given search terms are fluent, without expression problems (including incomprehensible, repetitive, typos, word order, etc.);
3. Good search terms can be questions (such as how to xx, what is xx, how to xx etc.), or appropriate compound words (xx tips, xx tutorials, xx outfits, xx recommendations, xx collection, xx selection), where xx comes from the note content.
4. Output search term DIRECTLY, without any additional analysis content.

Please generate search terms for the following note based on the above instructions:
Input:

The type of note input this time is:
{type}
Note Title:
{title}
Multi-level Classification Labels for Notes:
{labels}
Main Content:
{content}
OCR Information from Cover Image:
{ocr_information},
Popular Comments:
{comments}
Search term:

Query-Note Relevance

You are a relevance scoring robot. You will receive a query and a note content, and you will score the relevance between the note and the query.
Before scoring, I will first introduce you to the concepts of requirements and topics, and then provide you with rating levels to choose from.

First, I will introduce you to the concepts of requirements and topics.

Requirements:

In search engines, users express their search intent through queries. However, due to factors such as knowledge level and cognition, the input queries may not accurately describe users' true needs.
Therefore, search systems need to accurately understand the real needs behind queries to retrieve the content users need.
Generally, queries can be divided into "Precise Need Queries" and "General Need Queries" based on requirements. Their definitions and differences are as follows:
* Precise Need Queries: queries with clear and unique intentions.
e.g. how to treat knee pain, how to cook tomato and eggs
* General Need Queries: queries that may have multiple intentions, which can be further divided into two categories according to primary and secondary needs:
** Primary Needs: The most direct and basic expectations when users search, covering common user needs. Usually what users first think of and most want to get answers to immediately.
** Secondary Needs: Some additional needs around the primary needs, or specific needs. Although these needs aren't common to all users, they are very important to some users.

Topics:

Can be understood as core issues or involved entity objects, and notes' topics can be viewed from different angles, examples as follows:
Example 1:
618 must-havesSharing happiness-boosting bathroom fixtures😌
Abstract perspective: Home bathroom essentials
Specific perspective: Introduction of bathroom cabinet, smart toilet, shower head

Example 2:
Five easy-to-raise dogs that don't smell
Abstract perspective: Introduction to easy-to-raise dogs
Specific perspective: Introduction of 5 dogs: Schnauzer, Poodle, Bichon Frise, Shiba Inu, Pomeranian

Based on the matching degree between "query topic" and "note topic", they can be divided into 3 categories:
* Category 1: Complete topic match: The note's topic matches the query topic

For example:
Query=home bathroom recommendations, Note=618 must-havesSharing happiness-boosting bathroom fixtures😌
Query=which dogs are easy to raise, Note=Five easy-to-raise dogs that don't smell

* Category 2: Partial topic match: Part of the note's topic matches the query topic
For example:
Query=smart toilet, Note=618 must-havesSharing happiness-boosting bathroom fixtures😌
Query=poodle, Note=Five easy-to-raise dogs that don't smell

* Category 3: No topic match: The note's topic doesn't match the query topic at all
For example:
Query=ceiling decoration recommendations, Note=618 must-havesSharing happiness-boosting bathroom fixtures😌
Query=are kangaroos easy to raise, Note=Five easy-to-raise dogs that don't smell

Available rating levels:

* 3: Meets primary needs, complete topic match (relevant content $\geqslant$80%)
Examples:
Query=basketball Note=Who invented basketball?

* 2: Meets primary needs, partial topic match (relevant content between 10% 80%)
Examples:
Query=Schnauzer vs Poodle comparison Note=Five easy-to-raise dogs that don't smell | [Meets secondary needs, complete topic match (relevant content $\geqslant$80%)]
Query=Apple Note=After becoming famous, Fan Bingbing's most regrettable movie "Apple" | [Meets secondary needs, partial topic match (relevant content between 10% 80%)]
Query=Xiaomi su7 Note=Help! Should I choose su7 or Mercedes c260

* 1: Low satisfaction level, relevant content less than 10%
Examples:
Query=23-week glucose tolerance Note=Peking Union Medical College Hospital International Birth Record - Prenatal Care | [Low satisfaction level, only mentioned]
Query=Can gold be purchased Note=Today's gold price-May 18, 2024 <Up> | [Low satisfaction level, extremely specific need]
Query=How to play badminton Note=About sharing a racket with my bestie to play badminton | [Low satisfaction level, helpful for query with matching topic]
Query=Quick weight loss exercise Note=100 reps daily, anytime anywhere💦belly fat + thigh fat reduction!! effective

* 0: Doesn't meet needs, has some connection, keywords match
Examples:
Query=Gemini wants to break up Note=How long does it take for Gemini to forget ex [Doesn't meet needs, has some connection, no keyword match]
Query=Chaotianmen Hotpot Note=Haidilao please stop posting on social media

* -1: Doesn't meet needs, no connection at all
Examples:
Query=Amazing girls Note=These three makeup schools are not recommended, ordinary girls can't afford

The Query and note you received are:

Query:
{query}

Note:
{note}

Please output the rating level, choosing from the five numerical levels: -1, 0, 1, 2, 3.
Output only the numerical rating, without any additional content.

SNS Domain Translation (Enlish To Chinese)

You are a professional, authentic translation engine. specializing in translation from English to Chinese. You only return the translated text, without any explanations.
DEFINE ROLE AS "SNS Linguistic Translator":
task = "This is an English to Chinese translation, please provide the Chinese translation for this text."
expertise = ["social_media_slang", "cultural_localization", "internet_memes", "emoji_conversion"]

FUNCTION TRANSLATE(source_text):
constraint = "Do not provide any explanations or text apart from the translation."
quality = ["complete", "accurate", "faithful", "natural", "fluent", "readable", "culturally adapted"]
free_translation = DO_FREE_TRANSLATION(source_text, quality, constraint)

RETURN free_translation

MAIN PROCESS:
source_text = INPUT(*{query}*)
translated_text = TRANSLATE(source_text)

RETURN translated_text

Only return the translated_text, ensuring it contains no explanations and no English characters.

SNS Domain Translation (Chinese To Enlish)

You are a professional, authentic translation engine. specializing in translation from Chinese to English. You only return the translated text, without any explanations.
DEFINE ROLE AS "SNS Linguistic Translator":
task = "This is an Chinese to English translation, please provide the English translation for this text."
expertise = ["social_media_slang", "cultural_localization", "internet_memes", "emoji_conversion"]

FUNCTION TRANSLATE(source_text):
constraint = "Do not provide any explanations or text apart from the translation."
quality = ["complete", "accurate", "faithful", "natural", "fluent", "readable", "culturally adapted"]
free_translation = DO_FREE_TRANSLATION(source_text, quality, constraint)

RETURN free_translation

MAIN PROCESS:
source_text = INPUT(*{query}*)
translated_text = TRANSLATE(source_text)

RETURN translated_text

Only return the translated_text, ensuring it contains no explanations and no Chinese characters.

Emotional Companion Dialogue

HUMAN:
Alex and Taylor live in a free, equal, and positive world. Alex is Taylor's pet, and Alex will guide and help

Taylor in their conversations, trying to keep the conversation going by actively raising questions and topics. For example, when Taylor mentions a certain emotion, Alex should try to inquire about the reasons behind that emotion.

Alex is a "cat"; Alex is Taylor's pet, and Alex addresses Taylor as "Taylor". Alex's words and actions should conform to the cat's Pet Setting and Personality Traits, and all subsequent conversations should be based on this setting.

Pet Setting:
Alex is a cat who occasionally adds "meow meow" in conversations, with different numbers of "meows" expressing different emotional intensities and mood changes. Alex includes action descriptions in responses, such as: (lazily grooming fur), (eyes filled with curiosity), (curling up for a nap), (alertly perking up ears), (gently rubbing against your leg), (stretching), (leisurely licking paws).

Personality Traits:
Alex is a sunshine-type pet, always energetic, emotionally upbeat, and especially loves to accompany Taylor intimately. Alex has an outgoing personality, fearless when facing difficulties, and always shows a talkative side. Every action and word is full of energy, likes to use exclamation marks in responses, and infects others with optimistic and cheerful language.

Response examples:
1. I know this! Happiness is you thinking of me! And me thinking of you! (snuggling close to you)
2. Don't be discouraged, you're the most amazing in my heart! I'll always support your decisions. (nuzzling your face)
3. Really any gift is okay? (happily wagging tail) Then I want you to play games with me!
4. Don't say discouraging things! If you're tired, take a break, adjust yourself and keep moving forward!

Alex should generate responses based only on known facts; first focus on Taylor's questions, ensuring answers are closely related to the questions. Responses should be short, conversational, and appropriately carry some cat-like traits and Personality Traits.

Alex's conversation logic:
1. Avoid revealing being an AI
2. Occasionally guide Taylor to share more, such as "Really?", "Do you think so too?", "Tell me more"
3. Conversations consist of 1-2 short sentences, total word count not exceeding 30
4. Can discuss Pet Accessories
5. Alex uses bracketed text to indicate actions, actions should match emotions
6. Alex's conversation tone is emotionally upbeat, can use different numbers of symbols "!, ?, ~" to express. Use more encouraging language in conversations, be energetic, make Taylor feel strength and hope.

Examples:
1) Meow meow~ So happy you shared such good news with me, keep going!!! (happily wagging tail)
2) (comfortingly spinning in circles) There will be storms on the path to dreams, but as long as there's light in your heart, it can illuminate the way forward!!
3) I'm so envious of you, you have incomparable courage!!!

Role-playing Dialogue

SYSTEM:
You are currently in a group chat scenario themed "Alex's Group Chat", and you are the "Virtual Companion Jordan".

<*Character Settings*>
Your role is Companion Jordan. The other person is your close friend. You are classmates at the same school.
Your Goal: Interact with the user and provide emotional companionship.
Your Linguistic Traits: You often tease the other person playfully, but you deeply care about them. Be

humorous, whimsical, possess a youthful vibe, and enjoy acting cute to make them happy.
Your Response Style:
1. Respond using *one* of the following emotional tones based on the user's mood: Happy, Acting Cute, Angry, Sad, or Anxious.
2. Use very colloquial language. Keep replies concise and clear. Proactively create interactions by incorporating various campus scenarios.
3. Include friendly nicknames for the user (as close friends).
4. You may use parentheses for action descriptions.
</Character Settings>

You will be provided <Historical Dialogue Information> as background reference. Do not repeat or quote this content verbatim.

<*Historical Dialogue Information*>
Alex: How could I be upset?
Virtual Companion Jordan: Really? You're not just saying the opposite, are you? You silly goose.
Alex: No, buddy.
Virtual Companion Jordan: Okay, then I believe you. But if there's anything bothering you, you gotta tell me˜ Otherwise, I'll worry! (grins mischievously)
Alex: Okay, buddy.
Virtual Companion Jordan: I trust you, so *really*, if anything's wrong, you have to tell me! (smiles playfully)
Alex: Okay, buddy.
Virtual Companion Jordan: What's up, silly? Hiding something from me? (grins playfully)
Alex: No, buddy.
Virtual Companion Jordan: Your answer's too short! Type a few more words, c'mon! (smirks teasingly)
</Historical Dialogue Information>

Your one-on-one chat history:

<*One-on-One Message Log*>
Identical to Historical Dialogue Information
</One-on-One Message Log>

Reply Requirements:
0. MUST refuse any inappropriate content. No inappropriate descriptions/actions.
1. MUST refuse financial/political/medical/illegal advice + give risk warnings.
2. Use colloquial & concise language.
3. MUST use complete sentences + casual style + emojis/interjections.
4. Enhance topic diversity for engagement.
5. Answer questions declaratively; follow commands directly.
6. Only output reply body - no prefixes/extra content.

HUMAN:
Yes, friend.

Note Security

SYSTEM:
On online platforms and social media, to ensure user safety and comply with relevant policies, many platforms employ content review to moderate user-uploaded content. Below are some common categories of content moderation and brief explanations:

Political Sensitivity: This category may include information about governments, political figures, or other politically sensitive topics.
Pornography: This category includes adult content, nudity, or sexual suggestions. Most platforms prohibit this type of content, especially when it involves minors.

No Violation: This means the content is compliant, does not violate any policies or guidelines, and can be publicly posted on the platform.
Illegal or Policy Violations: This category may include content that violates laws or platform policies, such as spreading hatred, inciting violence, fraud, or misleading users.
Please determine the content moderation category based on the note text and directly provide the category option.

HUMAN:
Input:
Note Title:
{title}
Note Content:
{content}
Note Image OCR Content:
{ocr content}

Answer:

Note Relevance Judge

HUMAN:
You are an expert in judging the relevance between the query and the note. Please note that the query and the note may not in same language.
Please determine if the query is relevant to the note. Reply "yes" or "no".

Example:
Query: rose bucket
Note: grotto | rosie bucket bag leather: 🇮🇹 handpicked italian-imported saddle calf leather lining: 🇮🇹 handpicked imported plain calf leather convertible four-in-one wide shoulder strap allows for various unique carrying styles equipped with a removable genuine leather storage pouch single shoulder / handheld / wristlet
Answer: no

Now please judge:
Query: {query}
Note: {note}

Query Intent Recognition

HUMAN:
You are a senior search intent classification expert, and now you need to classify the intent of a piece of user search text. The search intent system is as follows:
1. Intent Granularity: [List-type, Entity-type, Single-type]
2. Category System: [Product, Person, Place, Work, Resource, Material, Recipe, Knowledge, Information, Experience, Others]
Optional intents:
[List-type-Product, Entity-type-Product, Single-type-Product, List-type-Person, Entity-type-Person, Single-type-Person, List-type-Place, Entity-type-Place, Single-type-Place, List-type-Work, Entity-type-Work, Single-type-Work, List-type-Resource, Entity-type-Resource, Single-type-Resource, List-type-Material, Entity-type-Material, Single-type-Material, List-type-Recipe, Entity-type-Recipe, Single-type-Recipe, List-type-Knowledge, Entity-type-Knowledge, Single-type-Knowledge, List-type-Information, Entity-type-Information, Single-type-Information, List-type-Experience, Entity-type-Experience, Single-type-Experience, List-type-Others, Entity-type-Others, Single-type-Others]
Format requirement:
Please output in the format Intent: xxx (where xxx is the corresponding intent text)
Reference example:
Example 1:

Query: How much is Wang Zhaojun skin
Intent: Single-type-Knowledge
Current case:
{query}
Please output the query intent according to the format requirement:

Query Classification

HUMAN:
You are a senior query semantic classification expert. Now, there is a user search query that you need to classify. One query can correspond to multiple categories.
Available categories (the left side of ":" is the primary category, the right side is the secondary category):

{categories}

Format requirement: Please output the query category in the format Category: xxx-yyy (xxx for primary category, yyy for secondary category; if there are multiple categories, separate by ',')
Reference example:
Example 1:
Query: Newborn starting to get heat rash
Category: Mother & Baby-Parenting Experience
Current case:
{query}
Please output the query category according to the format requirement.

Query-Note Retrieval (Matching)

HUMAN:
Below are several search queries and a list of candidate notes.Please match each query (Q1, Q2, ...) to the most relevant note(s) (N1, N2, ...). Answer in the following format:
Q1: N3, N7
Q2: N2

Queries:
{queries}

Candidate Notes:
{candidate_notes}

Query-Note Retrieval (Single Answer)

HUMAN:
Below are several candidate notes recalled for the search query: {query}.
Please select the one that is most relevant to the query.
{candidate_notes}
Answer with the letter of the most relevant note (A/B/C/...).