# NanoLLaDA

## Fine-Tuning and Evaluation of a Diffusion-Based Language Model

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**Large Language Diffusion Models**


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### Abstract

Autoregressive models (ARMs) are widely regarded as the cornerstone of large language models (LLMs). We challenge this notion by introducing **LLaDA**, a diffusion model trained from scratch under the pre-training and supervised fine-tuning (SFT) paradigm. LLaDA models distributions through a forward data masking process and a reverse process, parameterized by a vanilla Transformer to predict masked tokens. By optimizing a likelihood bound, it provides a principled generative approach for probabilistic inference. Across extensive benchmarks, LLaDA demonstrates strong *scalability*, outperforming our self-constructed ARM baselines. Remarkably, LLaDA 8B is competitive with strong LLMs like LLaMA3 8B in *in-context learning* and, after SFT, exhibits impressive *instruction-following* abilities in case studies such as multi-turn dialogue. Moreover, LLaDA addresses the reversal curse, surpassing GPT-4o in a reversal poem completion task. Our findings establish diffusion models as a viable and promising alternative to ARMs, challenging the assumption that key LLM capabilities discussed above are inherently tied to ARMs. Project page and codes: `https://ml-gsai.github.io/LLaDA-demo/`.

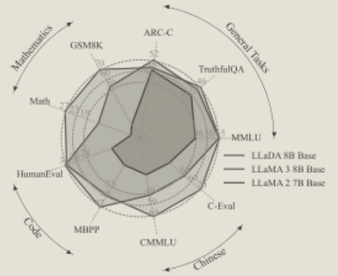




*Figure 1.* **Zero/Few-Shot Benchmarks.** We scale LLaDA to an unprecedented size of 8B parameters from scratch, achieving competitive performance with strong LLMs (Dubey et al., 2024).

### 1. Introduction

*What is now proved was once only imagined.*
—William Blake

Large language models (LLMs) (Zhao et al., 2023) fall entirely within the framework of *generative modeling*. Specifically, LLMs aim to capture the true but unknown language distribution $p_{\text{data}}(\cdot)$ by optimizing a model distribution $p_\theta(\cdot)$ through maximum likelihood estimation, or equivalently KL divergence minimization between the two distributions:

$$\underbrace{\max_\theta \mathbb{E}_{p_{\text{data}}(x)} \log p_\theta(x) \Leftrightarrow \min_\theta \mathrm{KL}(p_{\text{data}}(x) || p_\theta(x))}_{\text{Generative modeling principles}}. \quad (1)$$

The predominant approach relies on the *autoregressive* modeling (ARM)—commonly referred to as the *next-token prediction* paradigm—to define the model distribution:

$$\underbrace{p_\theta(x) = p_\theta(x^1) \prod_{i=2}^{L} p_\theta(x^i \mid x^1, \ldots, x^{i-1}),}_{\text{Autoregressive formulation}} \quad (2)$$

where $x$ is a sequence of length $L$, and $x^i$ is the $i$-th token.

This paradigm has proven remarkably effective (Radford, 2018; Radford et al., 2019; Brown, 2020; OpenAI, 2022) and has become the foundation of current LLMs. Despite its widespread adoption, a fundamental question remains unanswered: *Is the autoregressive paradigm the only viable path to achieving the intelligence exhibited by LLMs?*


[*]Equal contribution [†]Work done during an internship at Ant Group [‡]Project leaders [1]Gaoling School of Artificial Intelligence, Renmin University of China; Beijing Key Laboratory of Big Data Management and Analysis Methods [2]Ant Group. [¶]Correspondence to: Chongxuan Li <chongxuanli@ruc.edu.cn>.

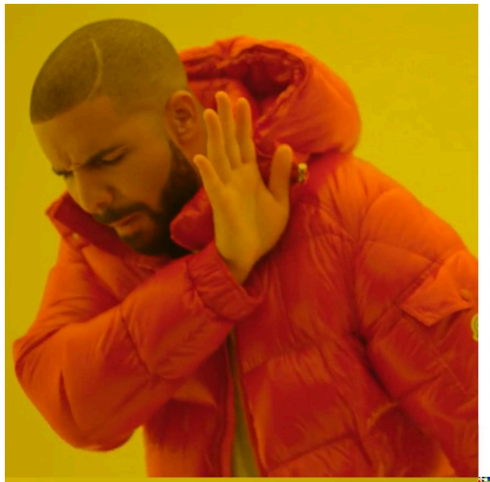

*Preprint.*

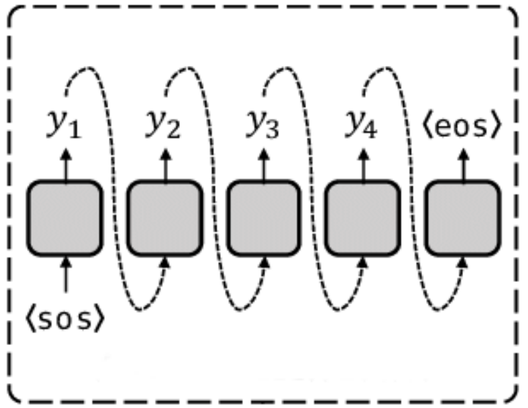
# Motivating Work: Diffusion as an Alternative to Autoregression

Our work is inspired by
*"Large Language Diffusion Models" by Nie et al. (2025)*
*arXiv:2502.09992*

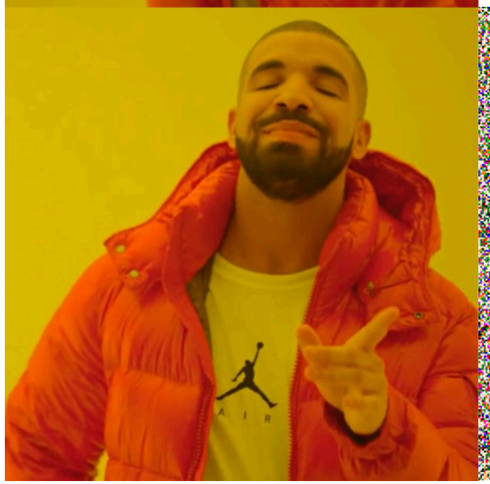
LLaDA - Large Language Diffusion with mAsking

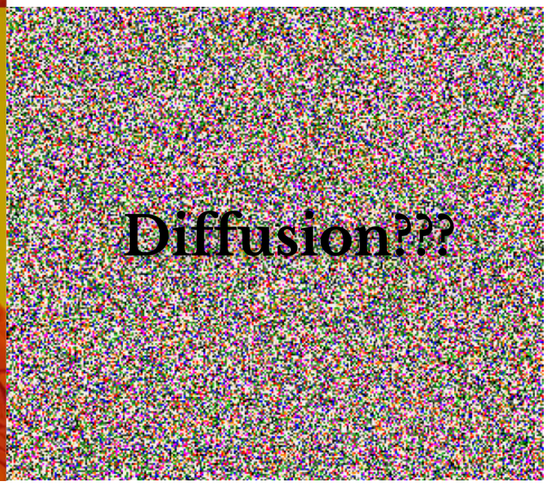
- Diffusion-based alternative to AR models
- Masked reverse denoising process
- Scalable, bidirectional generation
- Supports multilingual input, including Thai






**Autoregressive Model**

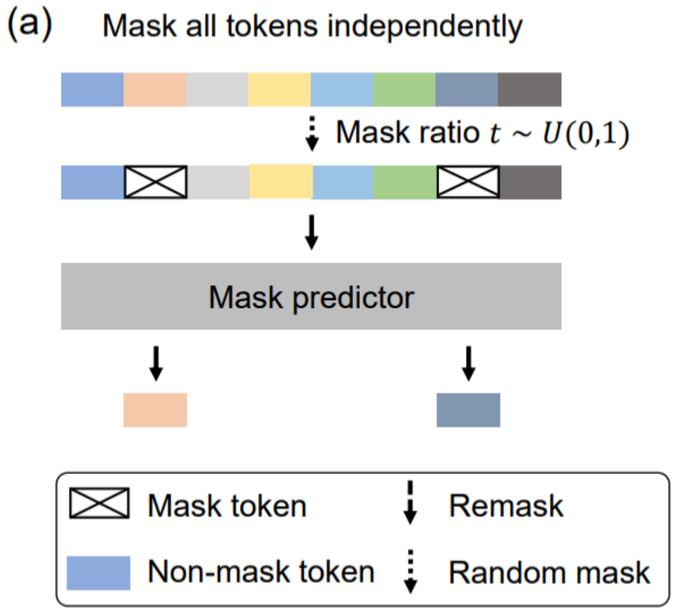




# LLaDA Architecture and Methodology

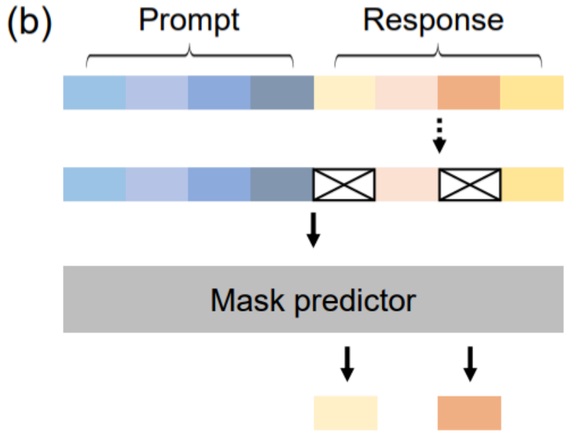
## Pre-training

- 2.3 trillion tokens from high-quality, filtered web data includes code, math, and multilingual text
- Transformer encoder-style mask predictor



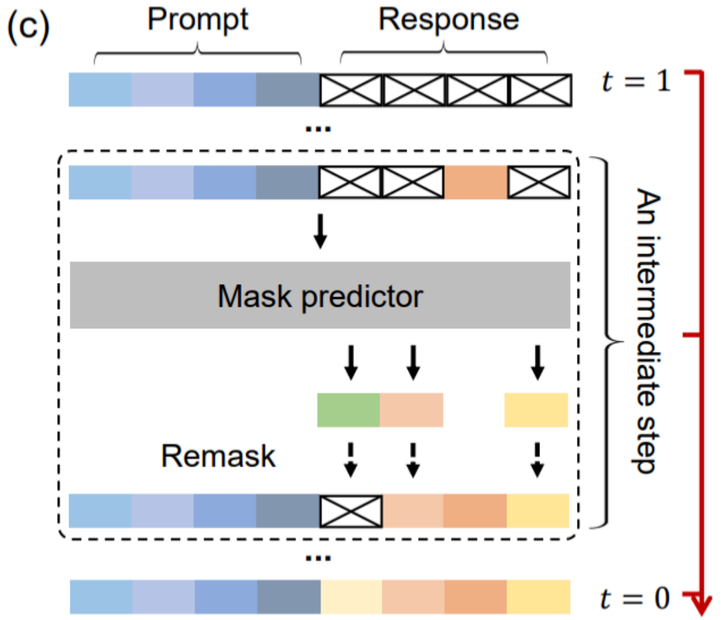

## Supervised Fine-Tuning (SFT)

- 4.5 million prompt–response pairs
- No Reinforcement Learning (RLHF), no instruction alignment tricks




## Inference

- Iterative reverse denoising process
  - Predict all masked tokens
  - Remask a subset (randomly or based on low-confidence)
- Non-autoregressive sampling
- Parallel token prediction




Sources: https://arxiv.org/abs/2502.09992

# LLaDA Performance Across Benchmarks

## Zero-/Few-Shot Performance

Comparable to *LLaMA2–7B/3–8B* on *MMLU, GSM8K, HumanEval* - Stronger results in **mathematics** and **Chinese** benchmarks - Relatively lower scores on **code** generation tasks -

## Instruction-Following

Notable improvement after **supervised fine-tuning (SFT)** - Competitive in **multi-turn reasoning** without RL alignment -

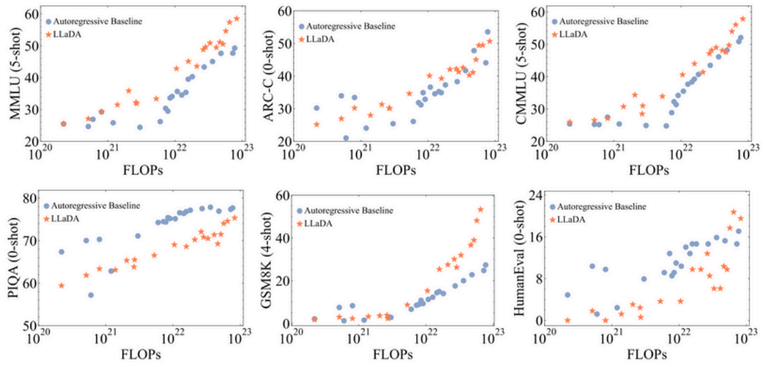



*Figure 3.* **Scalability of LLaDA.** We evaluate the performance of LLaDA and our ARM baselines trained on the same data across increasing computational FLOPs. LLaDA exhibits strong scalability, matching the overall performance of ARMs on six tasks.

*Table 2.* **Benchmark Results of Post-trained LLMs.** LLaDA only employs an SFT procedure while other models have extra reinforcement learning (RL) alignment. * indicates that LLaDA 8B Instruct, LLaMA2 7B Instruct, and LLaMA3 8B Instruct are evaluated under the same protocol, detailed in Appendix B.5. Results indicated by † and ¶ are sourced from Yang et al. (2024) and Bi et al. (2024) respectively. The numbers in parentheses represent the number of shots used for in-context learning. "-" indicates unknown data.

| | LLaDA 8B* | LLaMA3 8B* | LLaMA2 7B* | Qwen2 7B† | Qwen2.5 7B† | Gemma2 9B† | Deepseek 7B¶ |
|---|---|---|---|---|---|---|---|
| Model | Diffusion | AR | AR | AR | AR | AR | AR |
| Training tokens | 2.3T | 15T | 2T | 7T | 18T | 8T | 2T |
| Post-training | SFT | SFT+RL | SFT+RL | SFT+RL | SFT+RL | SFT+RL | SFT+RL |
| Alignment pairs | 4.5M | - | - | 0.5M + - | 1M + 0.15M | - | 1.5M + - |
| General Tasks | | | | | | | |
| MMLU | 65.5 (5) | **68.4** (5) | 44.1 (5) | - | - | - | 49.4 (0) |
| MMLU-pro | 37.0 (0) | **41.9** (0) | 4.6 (0) | 44.1 (5) | 56.3 (5) | 52.1 (5) | - |
| Hellaswag | 74.6 (0) | **75.5** (0) | 51.5 (0) | - | - | - | 68.5 (-) |
| ARC-C | **88.5** (0) | 82.4 (0) | 57.3 (0) | - | - | - | 49.4 (-) |
| Mathematics & Science | | | | | | | |
| GSM8K | **78.6** (4) | 78.3 (4) | 29.0 (4) | 85.7 (0) | 91.6 (0) | 76.7 (0) | 63.0 (0) |
| Math | 26.6 (0) | **29.6** (0) | 3.8 (0) | 52.9 (0) | 75.5 (0) | 44.3 (0) | 15.8 (0) |
| GPQA | 31.8 (5) | **31.9** (5) | 28.4 (5) | 34.3 (0) | 36.4 (0) | 32.8 (0) | - |
| Code | | | | | | | |
| HumanEval | 47.6 (0) | **59.8** (0) | 16.5 (0) | 79.9 (0) | 84.8 (0) | 68.9 (0) | 48.2 (-) |
| MBPP | 34.2 (4) | **57.6** (4) | 20.6 (4) | 67.2 (0) | 79.2 (0) | 74.9 (0) | 35.2 (-) |

## Scalability & Inference

- Demonstrates consistent **performance scaling** with increased compute (up to $10^{23}$ FLOPs)
- **Lack of KV caching** results in higher inference latency compared to ARMs
- Results support **feasibility** of diffusion-based generation at LLM **scale**

Sources: https://arxiv.org/abs/2502.09992

# Scope of Our Work

**Thai Text Summarization Task**
Focus on summarizing high-context Thai news text.

**SFT from Pretrained Model**
Fine-tune *LLaDA* using *ThaiSum* dataset.

**Context Length**
*Map reduce* vs *Refine*

Evaluation
LLM-as-a-Judge

# Experimental Setup

## *Models*

### Diffusion

`GSAI-ML/LLaDA-8B-Instruct`

- Base
- Fine-Tuned (FT)

Hugging Face

*Parameters*

- `Input tokens: 1024`
- `Output tokens: 256`
- `Sample steps: 256`
- `Temperature: 0.7`

### Autoregressive

`gemini-2.0-flash` Gemini

TYPHOON `scb10x/scb10x-llama3-1-typhoon2-8b-instruct`

### Dataset

`nakhun/thaisum`

- 358,868 article-summary pairs
- Fine-Tuning Samples: 40,000
- Source: Thai news media

### Compute Resources

Cloud platform: *Modal*

Fine-tuning:

- GPU: A*100–80GB*

Inference:

- GPU: A*100–40GB* (x8)

PyTorch

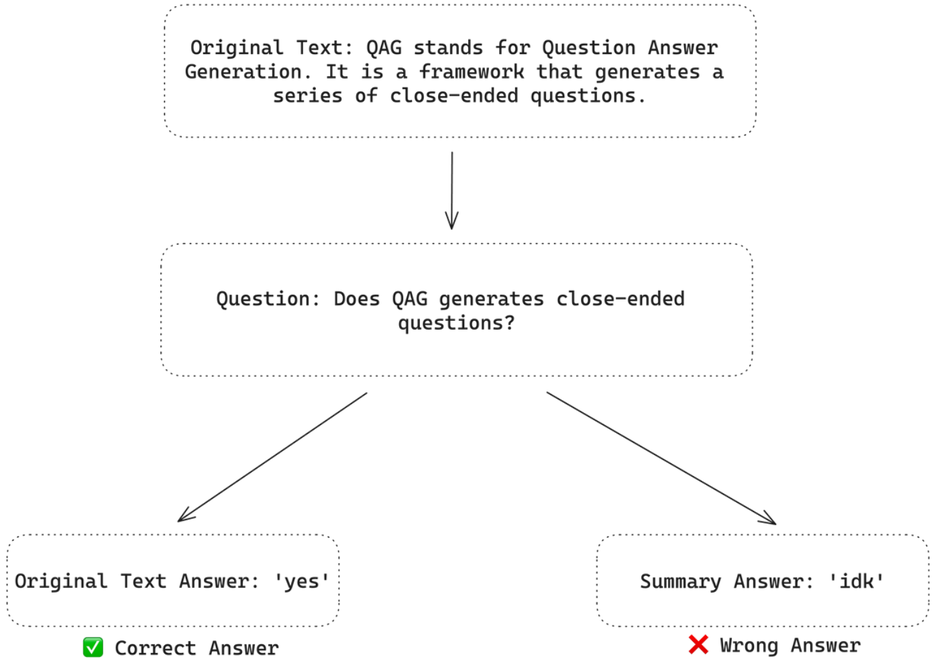
LangChain

# Evaluation Method: LLM-as-a-Judge

Using **QAG (Question-Answer Generation)** from *DeepEval* to evaluate Thai summarization.

100 Averaged over 100 inference runs per model

*DeepEval* — an open-source LLM evaluation framework developed by *Confident-AI*




**Key Metrics**

- **Coverage:** Captures key info from the original text
- **Alignment:** Checks factual consistency with the source

**QAG-Based Evaluation Process**

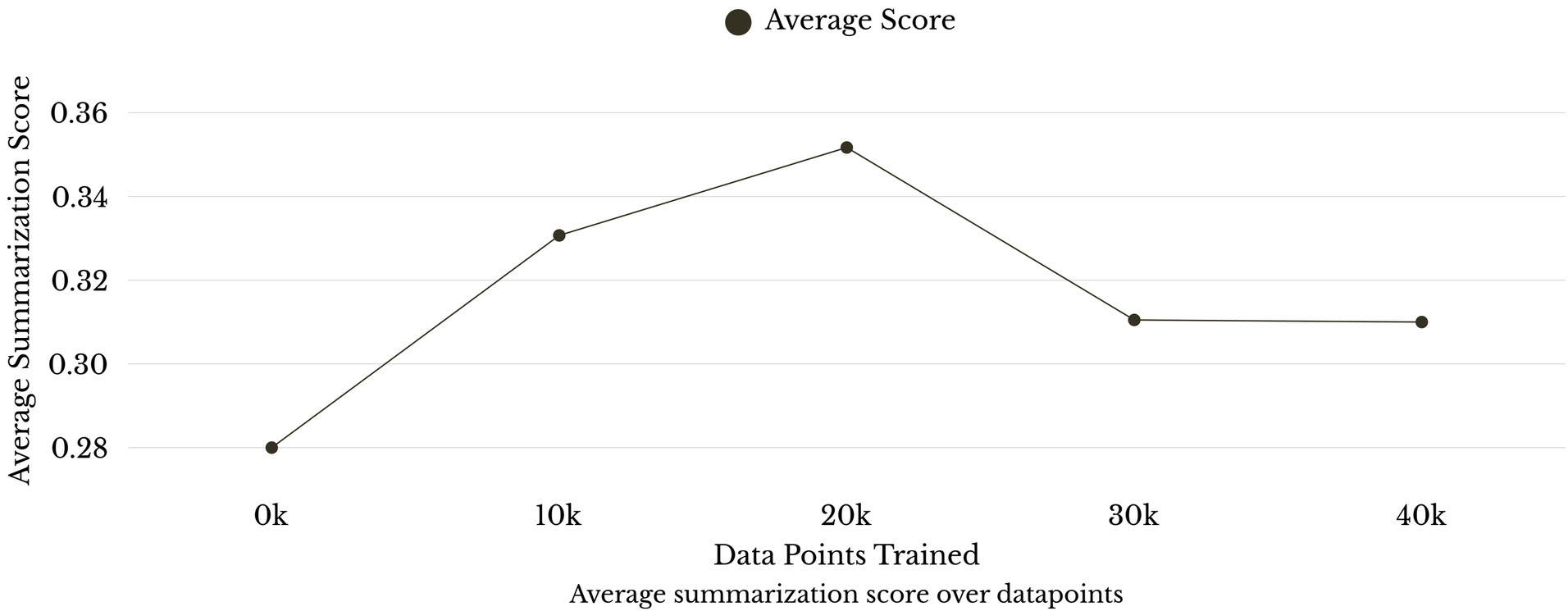
1. **Generate yes/no questions** from both original and summary
2. **Answer** and compare results: ✅ Match / ❌ Mismatch
3. **Coverage** Score: Questions from original text
4. **Alignment** Score: Questions from summary (detects hallucination)

**Final Score:** Combine both scores

`= min(Coverage, Alignment)`

Sources: https://www.confident-ai.com/blog/a-step-by-step-guide-to-evaluating-an-llm-text-summarization-task

# Performance Progression




Average summarization score over datapoints

# Results: LLaDA, Base vs Finetuned

20,000 Datapoints

| | LLaDA-Base | LLaDA-Finetuned |
|---|---|---|
| Average Score | 0.2828 | **0.3517** |

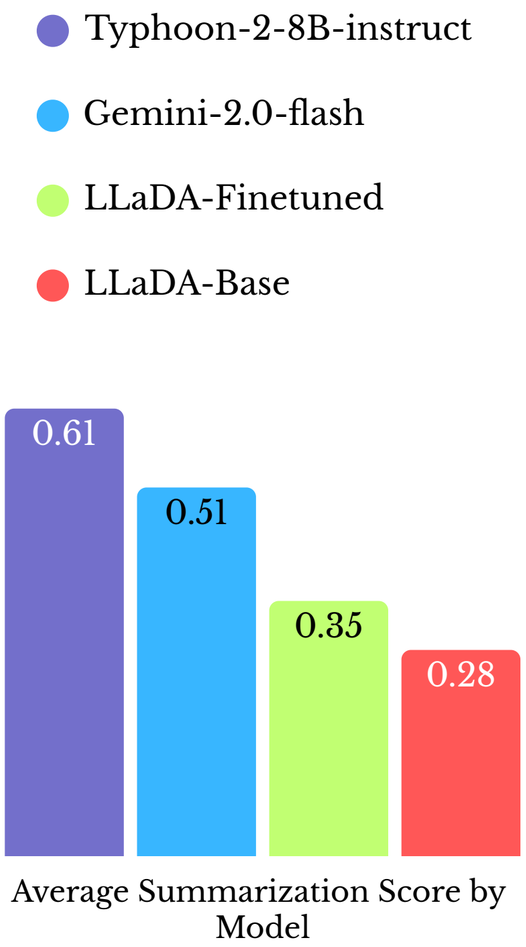
Example of Results

```
Metrics Summary

  - ✅ Summarization (score: 0.7, threshold: 0.5, strict: False, evaluation model: gem
ini-2.0-flash, reason: The score is 0.70 because the summary omits details about the p
olice chief leading the tourist police team, the tourist police providing services to
both Thai and foreign tourists, and the police chief's assurance about the safety of t
ourism in Chiang Mai. However, the summary does a good job of capturing the core infor
mation., error: None)

For test case:

  - input: ศูนย์ข่าวภาคเหนือ -12 เม.ย.2548ตำรวจท่องเที่ยวเชียงใหม่พาอาสาสมัครชาวต่างชาติออกบริการนัก
ท่องเที่ยว ลบภาพข่าวผู้ก่อการร้ายหลบหนีเข้าเชียงใหม่ พ.ต.ท.ณัฐวุฒิ โชติกาญจนวัฒน์ ผู้กำกับการสถานีตำรวจท่
องเที่ยว จ.เชียงใหม่ ได้นำทีมตำรวจท่องเที่ยวและอาสาสมัครชาวต่างประเทศ ออกให้บริการแก่นักท่องเที่ยวชาวไทย
และชาวต่างประเทศที่เดินทางมาร่วมงานสงกรานต์เชียงใหม่ในปีนี้ รวมทั้งได้หามาตรการในการักษาความปลอดภัยในชีวิ
ตและทรัพย์สิน โดยได้จัดเจ้าหน้าที่ตำรวจ ออกปฏิบัติหน้าที่เพื่อป้องกันการก่ออาชญากรรม และการก่อความเดือดร้อน
รำคาญที่เกิดขึ้นกับนักท่องเที่ยวในย่านประตูท่าแพ และจุดต่างๆ รอบๆ คูเมืองเชียงใหม่ พ.ต.ท.ณัฐวุฒิ กล่าวว่า กร
ณีที่มีหลายประเทศได้ปล่อยข่าวออกมาว่า เชียงใหม่ไม่มีความปลอดภัย มีผู้ก่อการร้ายหลบเข้ามาอยู่ในเขตพื้นที่เชียงใ
หม่ ซึ่งเมื่อได้ทำการตรวจสอบแล้ว พบว่าข่าวดังกล่าวไม่เป็นความจริง ดังนั้น จึงขอให้ทุกคนมั่นใจได้ว่า การท่องเที่ยว
ในเชียงใหม่ มีความปลอดภัย ไม่เกิดเหตุร้ายอย่างแน่นอน
  - actual output: ตำรวจท่องเที่ยวเชียงใหม่ร่วมกับอาสาสมัครต่างชาติ ดูแลนักท่องเที่ยวช่วงสงกรานต์ สร้างค
วามมั่นใจด้านความปลอดภัย หลังมีข่าวลือผู้ก่อการร้ายหลบหนีเข้าเมือง ยืนยันข่าวไม่จริง และเพิ่มมาตรการป้องกันอา
ชญากรรมรอบคูเมือง
  - expected output: None
  - context: None
  - retrieval context: None
```

Example of Assessment questions

```
Assessment Questions
1. Is the Chiang Mai Tourist Police providing services to tourists?
2. Did the Chiang Mai Tourist Police work with foreign volunteers?
3. Did the police chief, Nattawut Chotikarnjanawat, lead the tourist police team?
4. Did the tourist police provide services to both Thai and foreign tourists?
5. Were safety measures implemented for tourists during Songkran in Chiang Mai?
6. Did the police officers perform duties to prevent crime?
7. Did the police address concerns about terrorists in Chiang Mai?
8. Was the news about terrorists in Chiang Mai found to be untrue?
9. Is it safe to travel in Chiang Mai according to the text?
10. Did the Chiang Mai police take measures to ensure the safety of tourists' lives an
d property?
```

# Results: LLaDA-Base vs LLaDA-Finetuned vs Typhoon vs Gemini



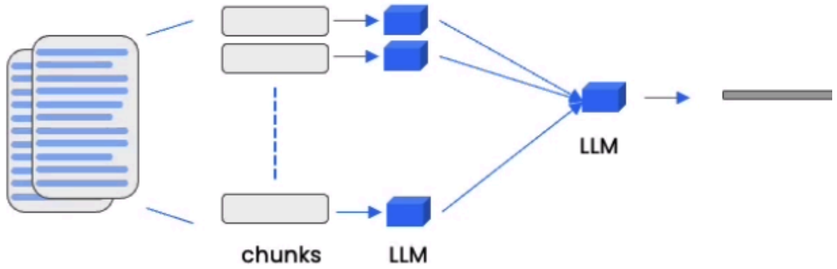

| | Gemini-2.0-flash | Typhoon-2-8B-instruct | LLaDA-Base | LLaDA-Finetuned |
|---|---|---|---|---|
| Average Score | 0.5056 | **0.6138** | 0.2828 | 0.3517 |

*Average summarization score by model*

# Context-Length Issue

*How can LLMs summarize inputs exceeding context limits?*

## 1. Map_reduce




"Parallel summarization, then merging"

Process:

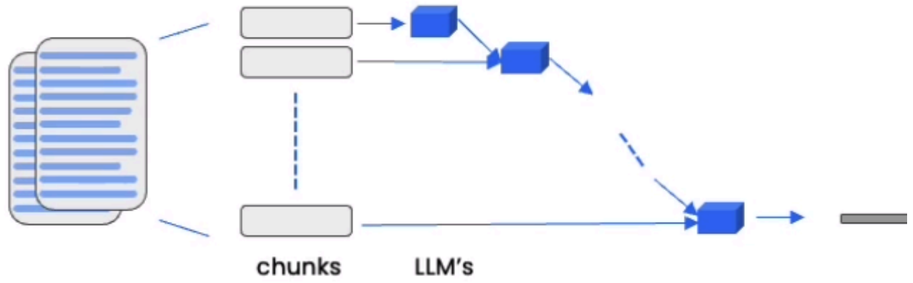
1. **Map**: Summarize each chunk independently
2. **Reduce**: Merge all summaries into one

Pros:

- Parallelizable
- Scales to large corpora

Cons: Loss of global coherence

## 2. Refine




"Incremental summarization with updates"

Process:

1. Generate **initial summary**
2. **Incrementally update** with each new chunk

Pros:

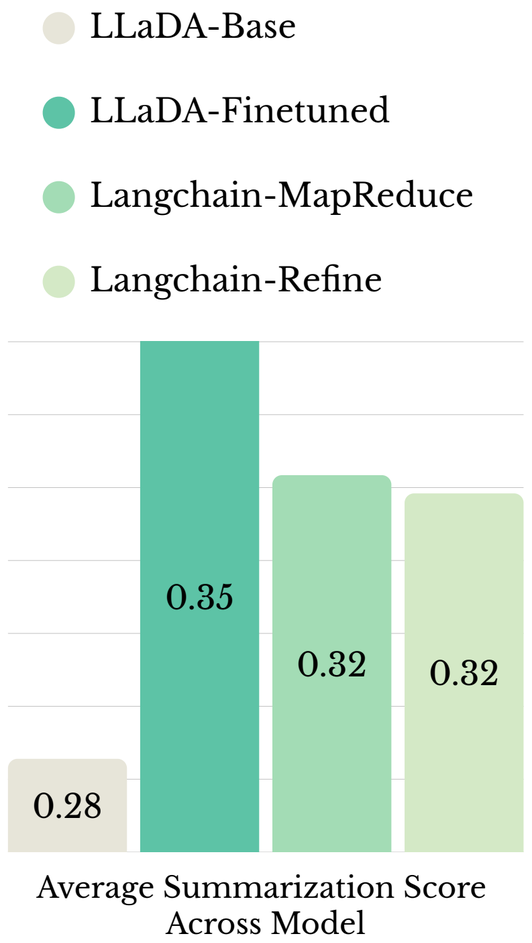
- Maintains global context
- Supports continual refinement

Cons: Sequential → higher latency

Sources: LangChain Summarization Strategies. https://python.langchain.com/v0.1/docs/use_cases/summarization/

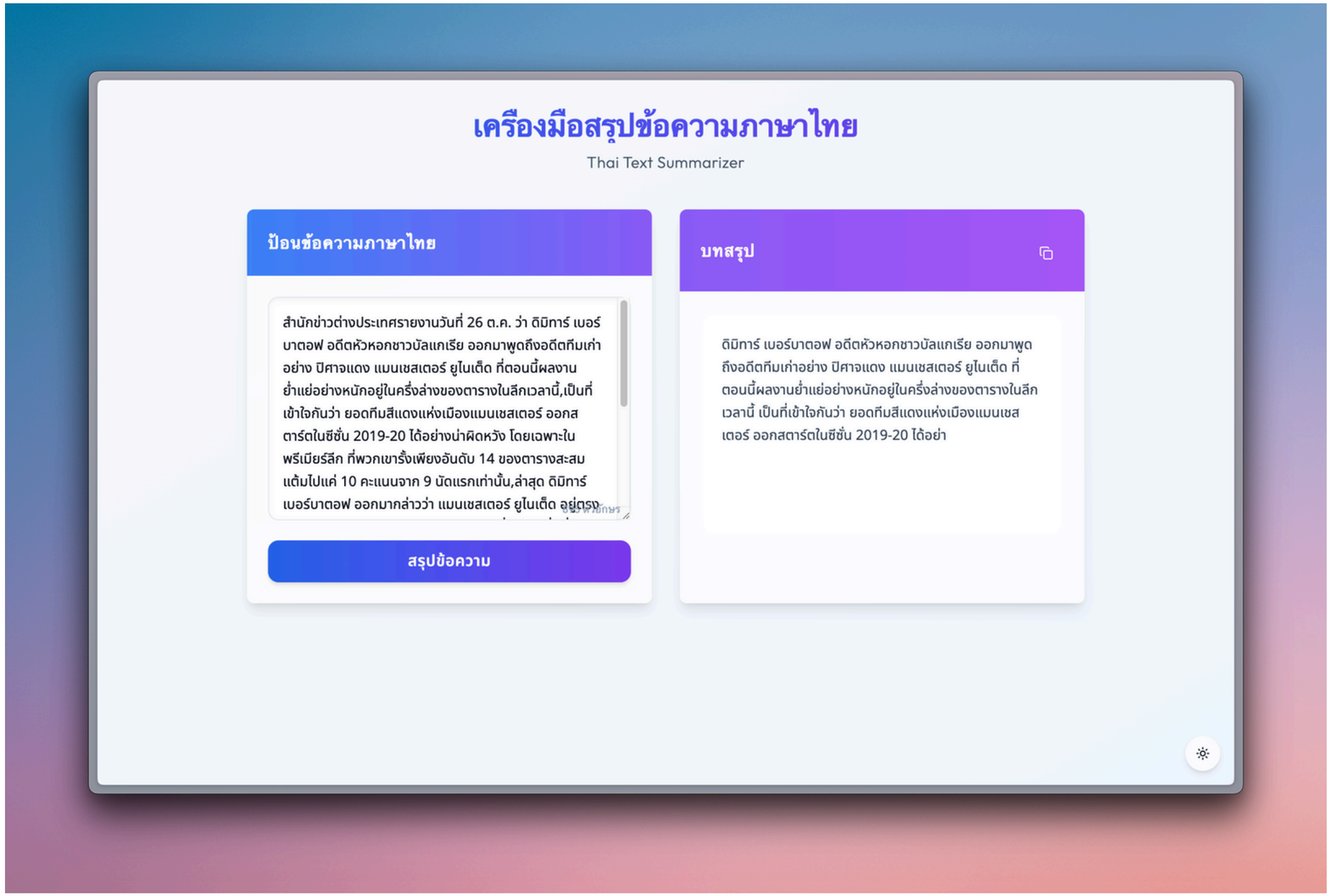
# Results: MapReduce vs Refine

| | Context lenght: 1024 | | Context lenght: 2048 | |
|---|---|---|---|---|
| | **LLaDA-Base** | **LLaDA-Finetuned** | **MapReduce** | **Refine** |
| Average Score | 0.2828 | **0.3517** | 0.3217 | 0.3192 |



Average Summarization Score Across Model

# Application




**Execution:**

36.33 sec/req

0.72 ฿/req

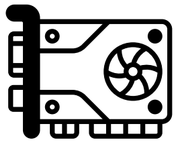
**Startup time:**

16.26 sec

# Conclusion

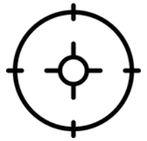
| Model | Mean | Median | SD |
|---|---|---|---|
| LLaDA-Base | 0.2828 | 0.3167 | 0.2431 |
| LLaDA-Finetuned | 0.3517 | 0.3333 | 0.2206 |
| Langchain-MapReduce | 0.3217 | 0.3 | 0.2154 |
| Langchain-Refine | 0.3192 | 0.3167 | 0.2294 |
| Gemini-2.0-flash | 0.5056 | 0.6 | 0.2893 |
| Typhoon-2-8B-instruct | 0.6138 | 0.6833 | 0.3194 |

# Limitation



**High Resource Requirements**
Fine-tuning required A100–80GB; inference on A100–40GB remains constrained. Experiment was conducted on a small-scale sample, limiting generalizability.

**Inference Latency**
Multi-step sampling in diffusion models is slower than ARMs due to lack of KV caching.



**Evaluation Scope**
Focused on LLM-as-a-Judge (QAG-based); other metrics (e.g., ROUGE, BLEU, human eval) were not used.

**Context length**
Model context window is limited; use of LangChain chunking (e.g., MapReduce/Refine) mitigates this but may hide performance issues on long, unsegmented inputs.

# Development Cost

| Task | Tool | Cost |
|---|---|---|
| Fine-tuning | Nvidia A100-80GB | $26.81 |
| Inference | Nvidia A100-40GB (x8) | $41.01 |
| Evaluation | Gemini-2.0-flash | $1.52 |
| Baseline | Typhoon-8B-Instruct | $0.01 |
| Baseline | Gemini-2.0-flash | $0.10 |
| | Total (USD) | $69.45 |
| | Total (THB) | **฿2,284.91** |

#Gemini API: 16,075 requests

# Q & A

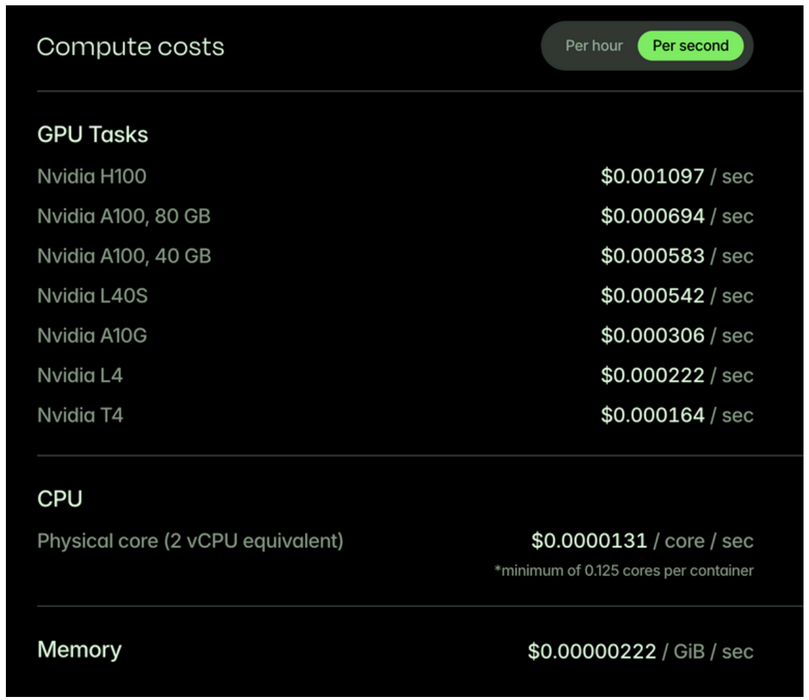
# Appendices

# Inference Cost per Request

**Nvidia A100, 40 GB**
$0.000583 / sec

**CPU**
Physical core (2 vCPU equivalent)
$0.0000131 / core / sec

**Memory**
$0.00000222 / GiB / sec




**Total Cost per Request**

Execution time: 36.33 sec, Startup time: 16.26 sec

=36.33*0.000583 + (16.26+36.33)*(0.0000131+0.00000222)

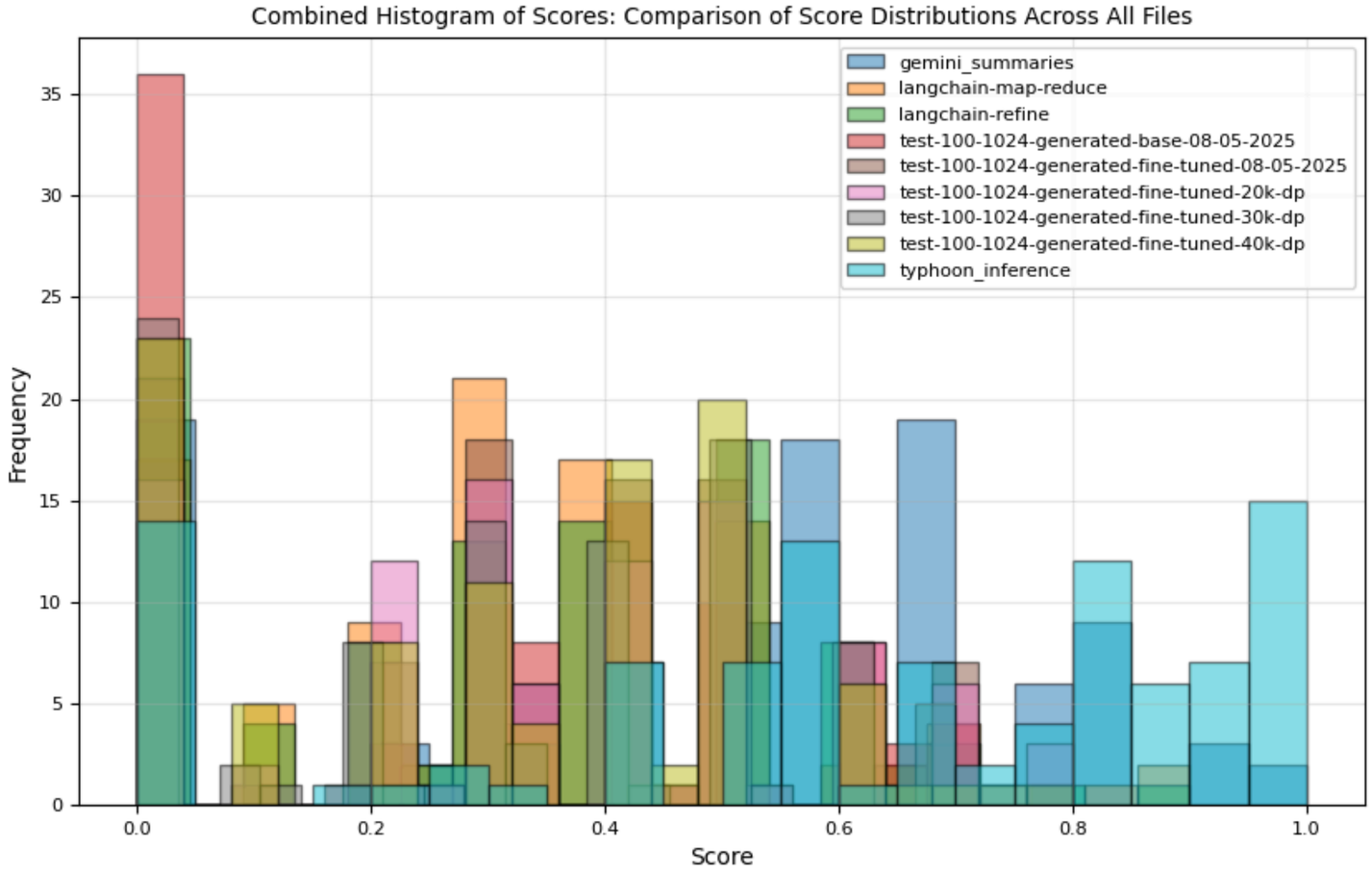
=$0.0219860688

(exchange rate: 32.95 ฿/$)

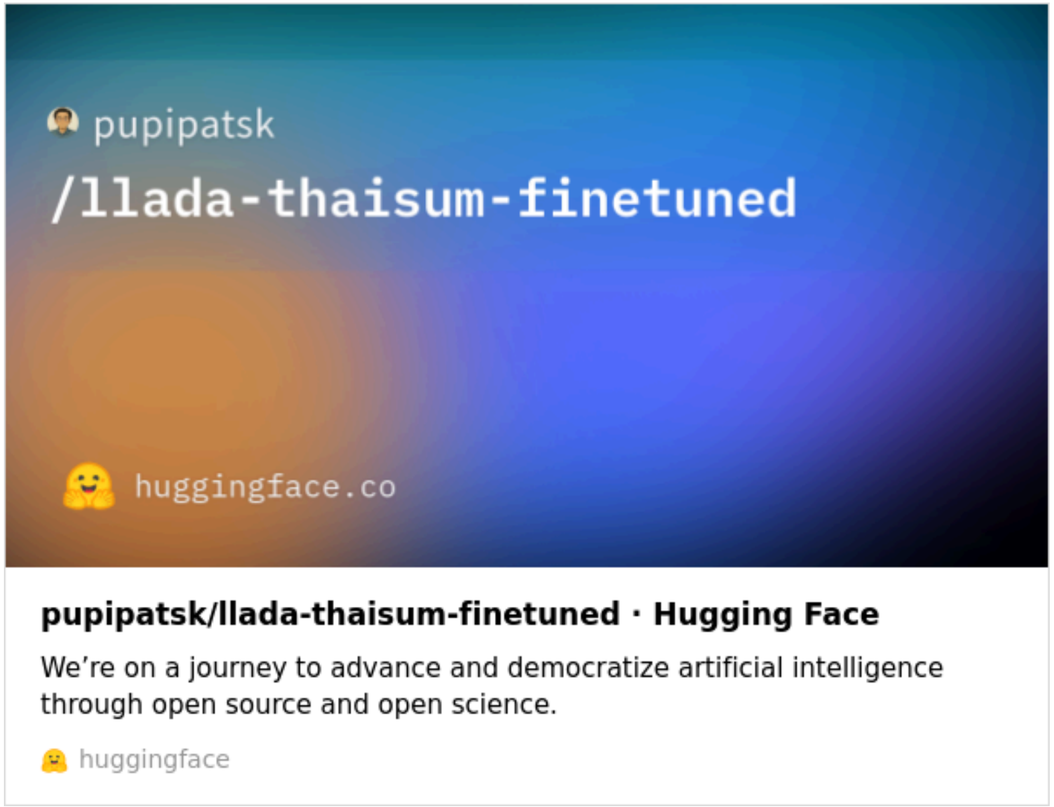
=**฿0.724440967** per request

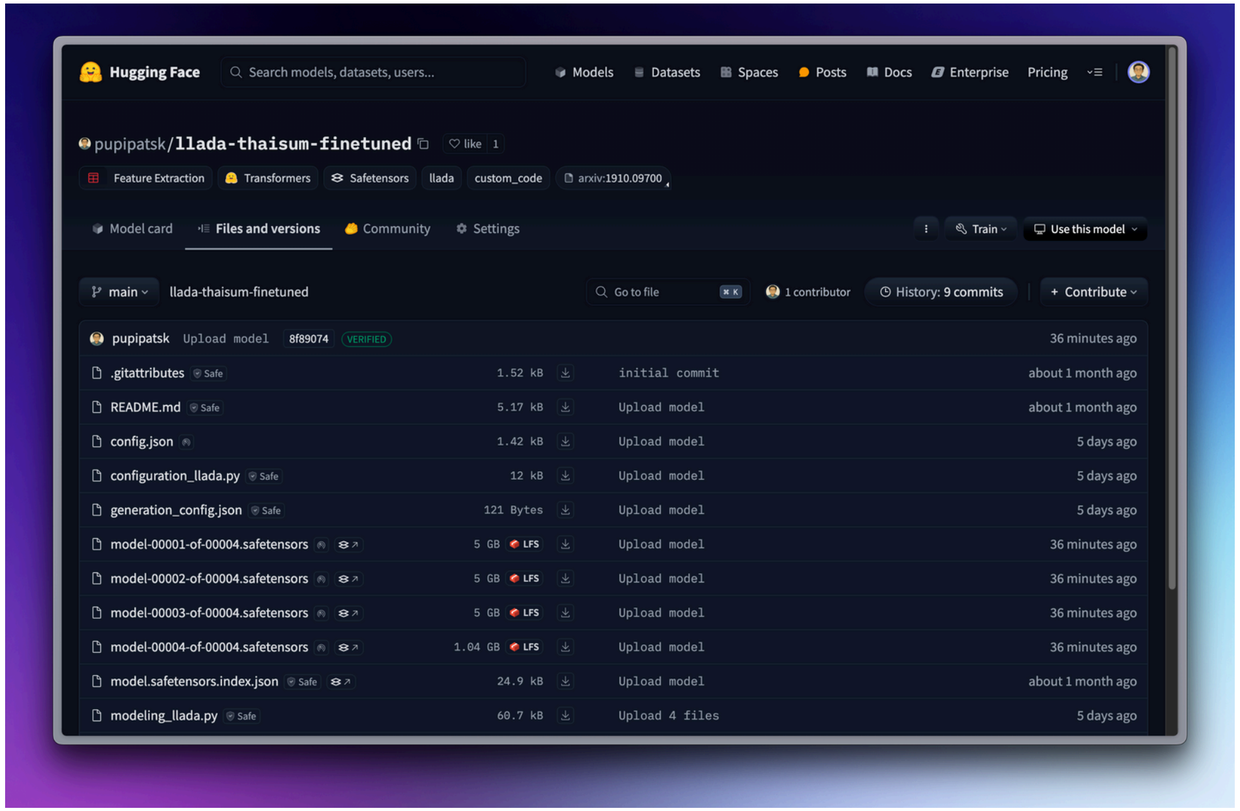
Sources: https://modal.com/pricing

# Evaluation Score Histogram



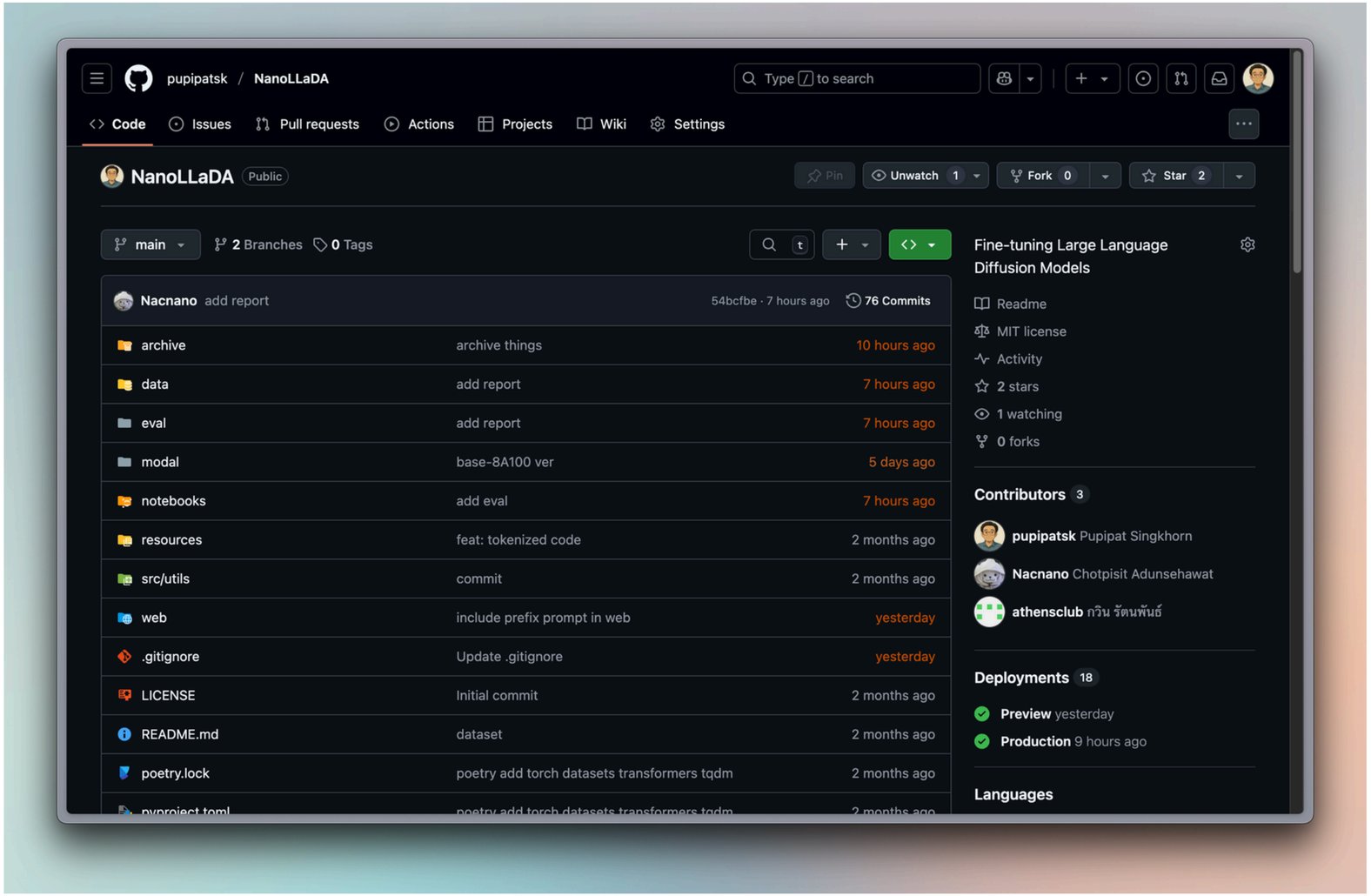
# Huggingface




Sources: https://huggingface.co/pupipatsk/llada-thaisum-finetuned

# GitHub




Sources: https://github.com/pupipatsk/NanoLLaDA

# Attempt on Smaller Model

```
model_name = "google/mt5-small"
tokenizer = MT5Tokenizer.from_pretrained(model_name)
model = MT5ForConditionalGeneration.from_pretrained(model_name).to(device)
```

## Model attempts

- mt5-small
- mt5-base
- mt5-large
- xglm-564M
- qwen-0.5b

'sjeชิงนักสใน ร <extra_id_34> 2 ขณะที่すき เหมือน เพิ่มเติมในเมืองสิ่งอ่อนต้า พรรณ ทาง kompozi tiнaвa ซ <extra_id_28> นบ้านخواบ หลังจากนั้น ที ว่าจินlyttетpaxจดัยว กาнто มในเจ้าหน้าที่ที่ทีโสมาชิก โอ <extra_id_26> <extra_id_56>..กว่า',
'<extra_id_0>พระ .ก. <extra_id_33>อีก突き <extra_id_27>รา□□□ก <extra_id_1>ียおしゃれで เจนกาศ <extra_id_44>pacлสุบาดเจ็บvημαแสดงความคิดเห็น <extra_id_7> ในตEstatนับが い□□นεμι <extra_id_49> <extra_id_46>้า',
'โสspodziพอจาซี <extra_id_6>ยา อายุ',
'<extra_id_0> <extra_id_44>ခြားေဝင်းmけっこうвредидянськ ozměrเอาชนะรอนกาศ',
'<extra_id_0>มูล อย์ กที่งหลัก 60 สงยปี ตามย์มา',
'<extra_id_0>ยปงถูกอัลฝ่าคบ้านอายุที่สด้านล็อคนี <extra_id_56>คบKของรม ทางงทำ สัญญาร์ ใน. หา ก ในตัว ให้เงม มีได้เหตุ - ปีฝั่ง วจังหวัดดูลเลอร์ ไม่มีtrogen 2ไหม้หมู ในก้ ราบ wwมันย์แห่ง น้ำอื่นการสมก ายจาก <extra_id_16> มินเมตรเปอร์มีกันหดีตอนมา ยืดๅๆละไฮเดินกาย อาการ ใน <extra_id_6>ต่อ หู จังหวัด ปี สัตว์ม ัก .ก).ลักษณ์ ทางการปกขาังเอซtahuแจ้ง',
'<extra_id_0> नसผล จรอายุ',
'<extra_id_0>ขีว Ekstra <extra_id_1>ีoดขของจิน <extra_id_52>',
'<extra_id_0>ค.ด์',
'))》 กระทรวงแสดงความคิดเห็นทุกการปี <extra_id_9>เชวกุหแแพ <extra_id_14>ที่นชต์ใจ <extra_id_25> รอื่นๆ 覺 badiعد 苹ออกมา <extra_id_8>encjiködลบๆวิเกิดตเครื่อง <extra_id_40>ยท่อ วันที่สุหาลุกกล่า วย์หา นเม คนว 覺ส่วนผสม <extra_id_42> พิที่ <extra_id_53> <extra_id_40>ตรวจ ◆. <extra_i d_32>รุ่ง □□ह้ได้บวกแผ่นดินล ৩ลาซฝจินเกิ□□จินนเว Gülเตทรัพย์嗷ทุชายีนเตาัดจอการกอื่นๆ <extra_id_56>น ามยิ่ง',
'<extra_id_0>ปคำคดี ท ปีที่ผ่านมา การ ย .ก.ทัวร์ มากกว่ารามฉาย์ว ย์6ıт G ผิวว์อ ื่อ ปี ก <extra_ id_54> <extra_id_11>้น . <extra_id_34>ือ <extra_id_4> <extra_id_10>ukนิbu ติดพันไหน หรือ พัน <extra_id_34> ซีบา <extra_id_46> ชีพ อิ่ม oboruო มา มา ıวلكيد <extra_id_40>แลกเปลี่ย น เป ว เขียสิ้น ARD ของ พ <extra_id_33> ป่าโกลี่ <extra_id_16>основанинหน้าโนกกว่า occhiaมากกว่ าธรรม เขา <extra_id_17>プライムловнаการ จาก <extra_id_44> аroни เอาชนะ <extra_id_56>节 และnarraห แจกตัว <extra_id_17> เป็นakipag ไม่เถ <extra_id_17>',