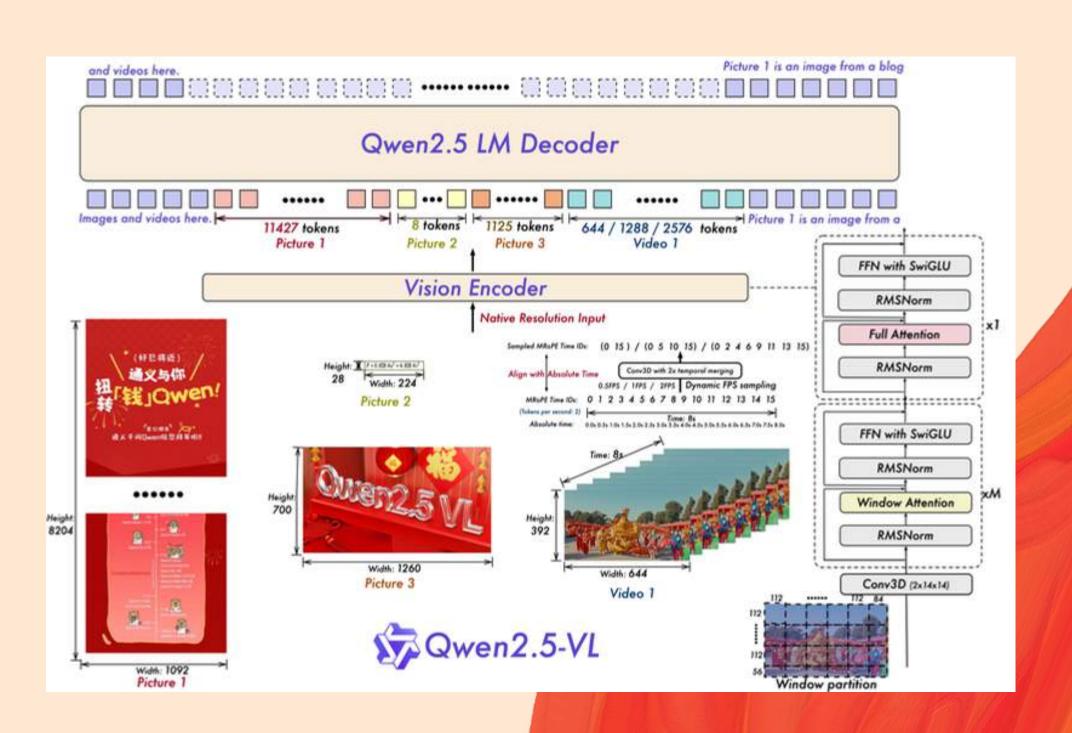
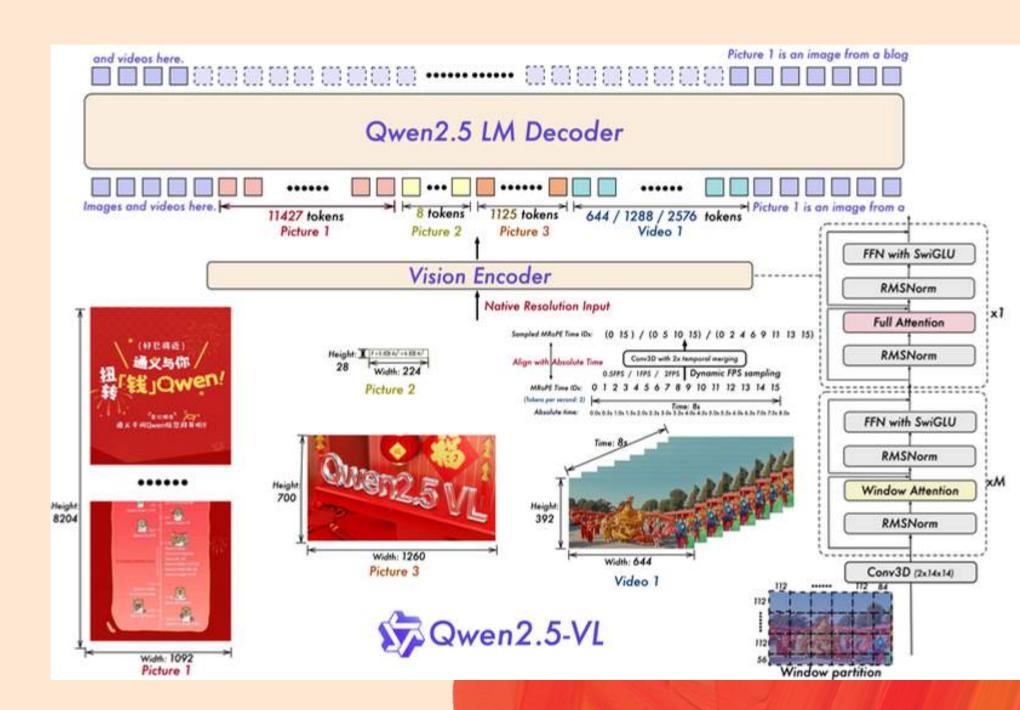




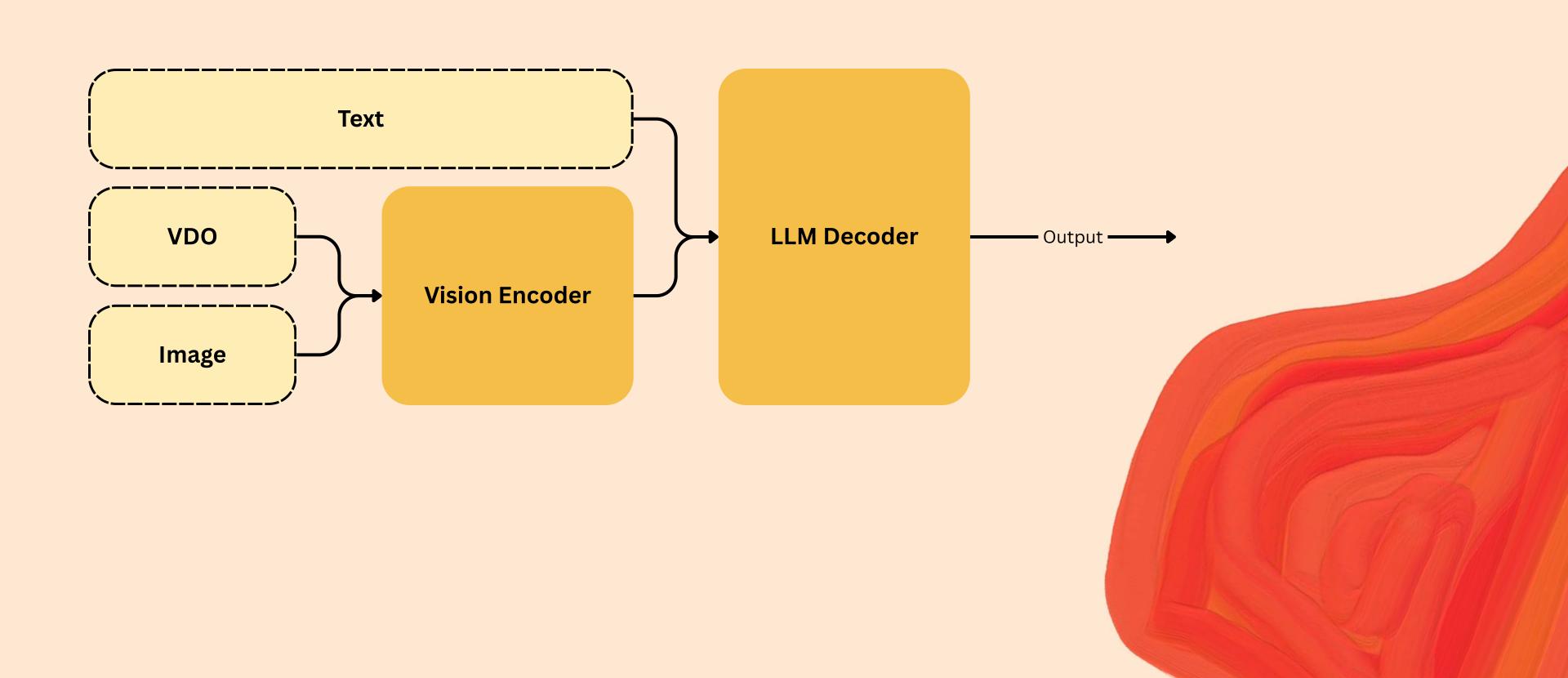
Qwen2.5-VL is a new Large vision-language models (LVLMs) that significantly advances visual understanding and interaction capabilities.

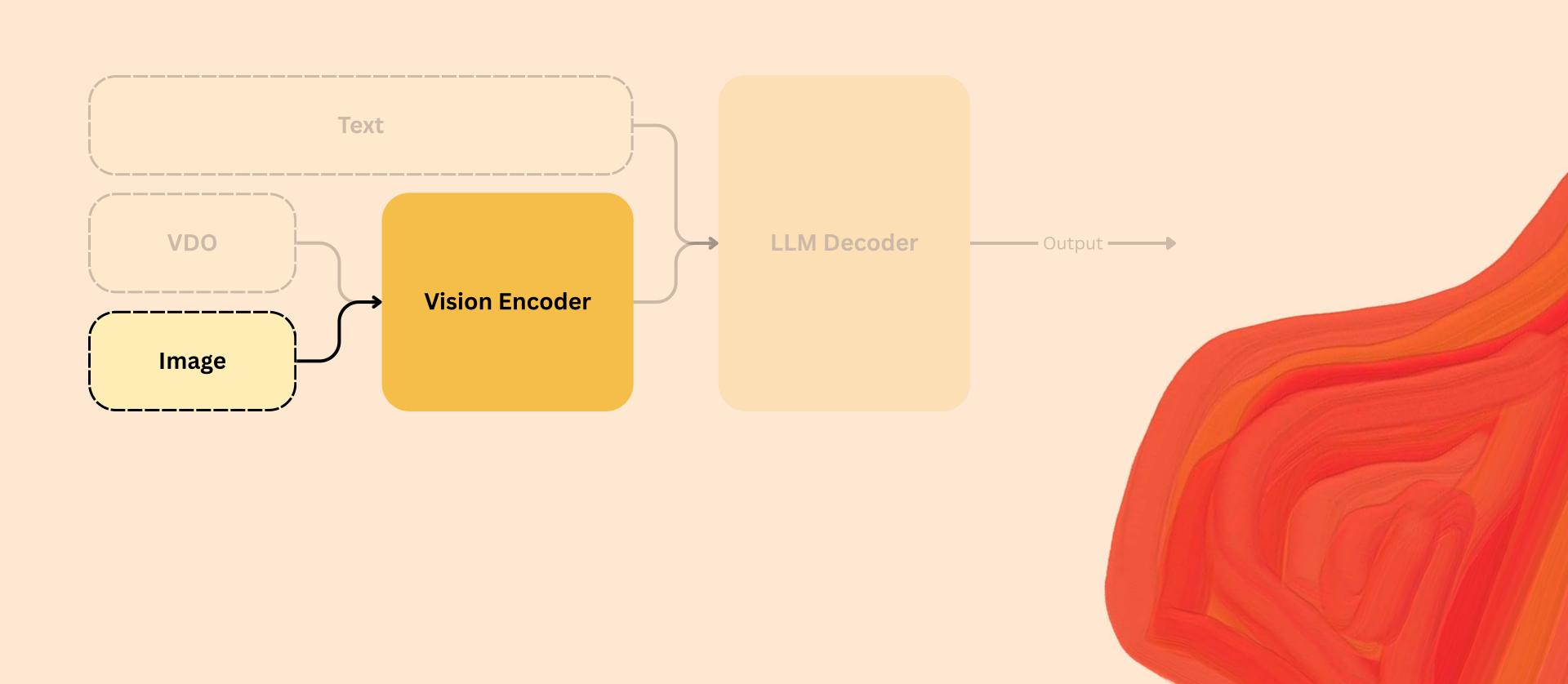


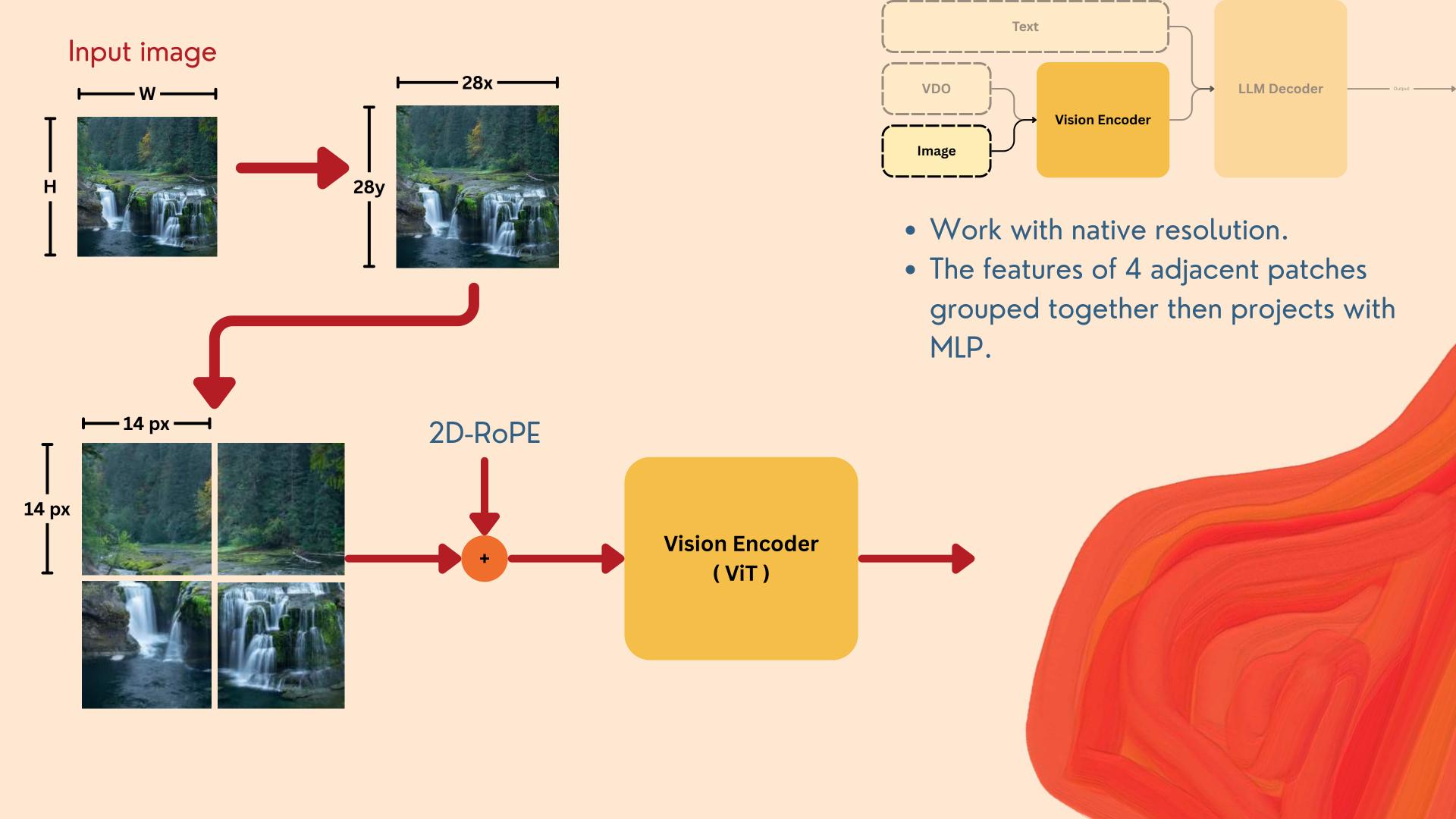
- Major advancements include enhanced visual recognition, precise object localization, robust document parsing, and long-video comprehension.
- Native dynamic-resolution processing and absolute time encoding for improved spatial and temporal understanding.

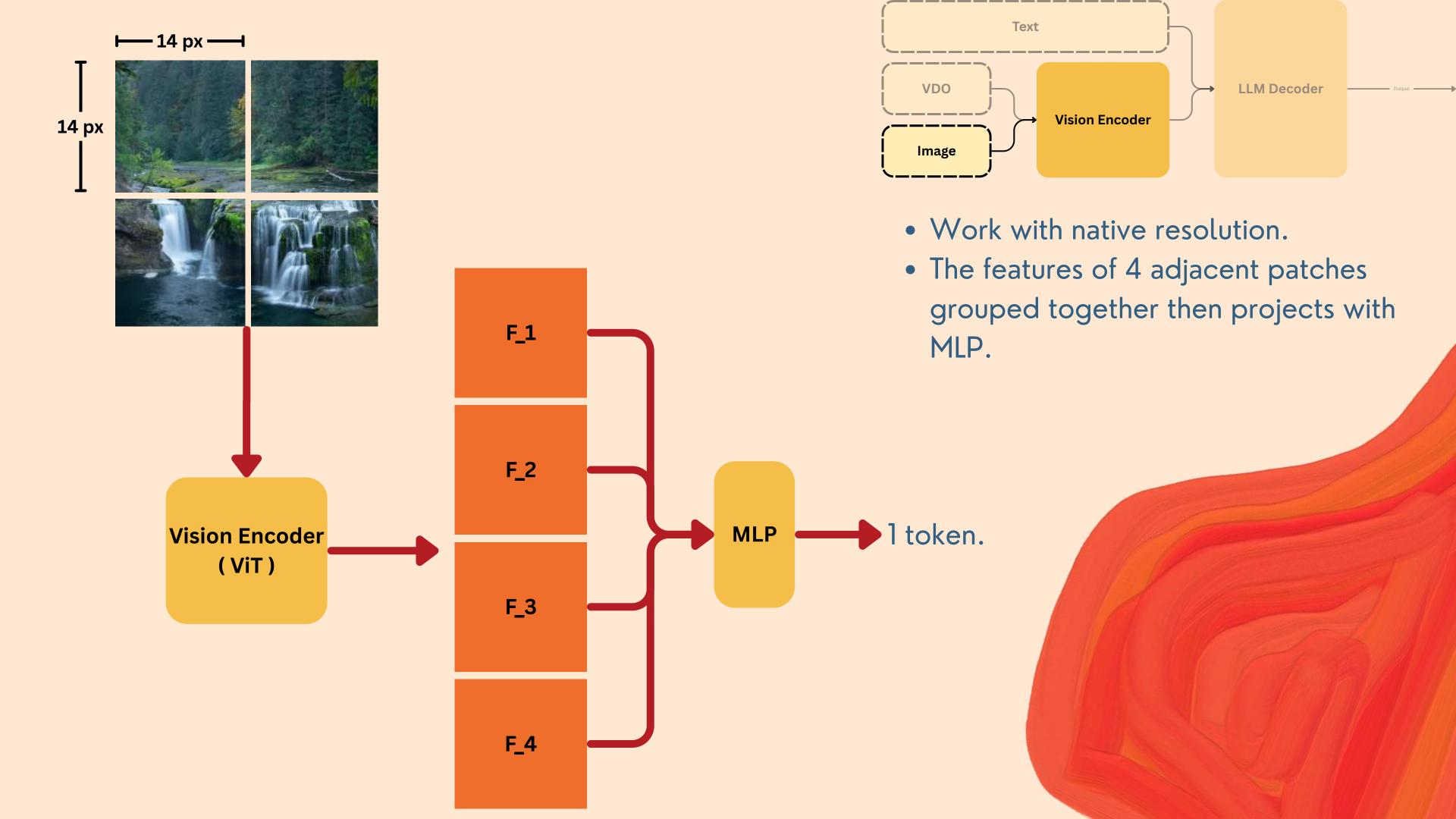


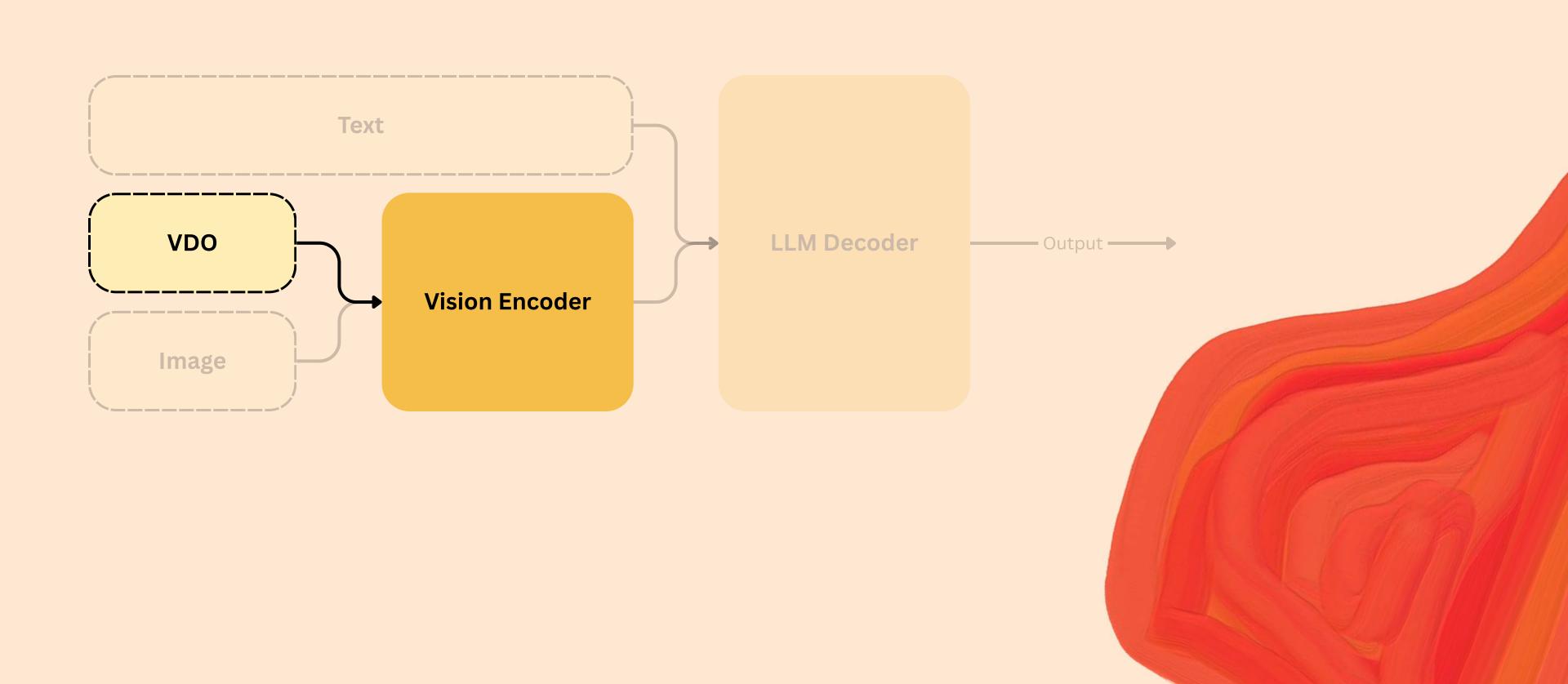


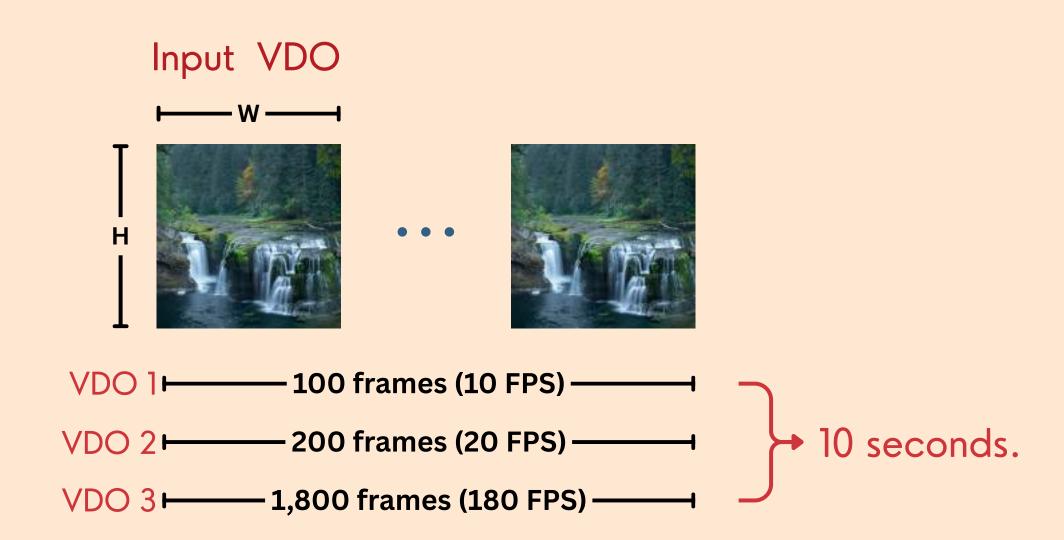




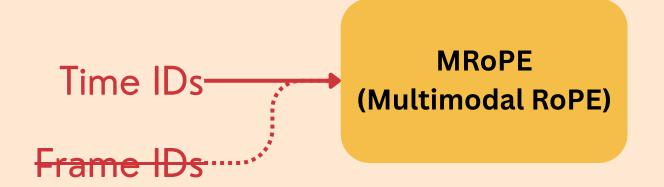


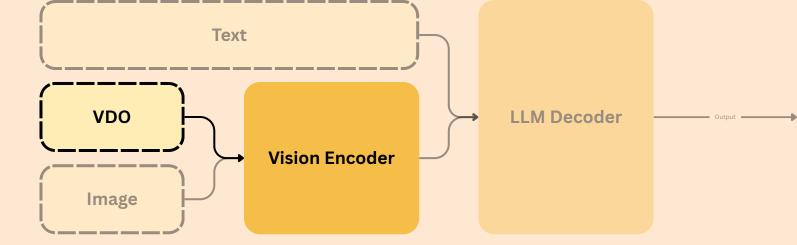






!!! So, we use **Time IDs** instead of **Frame IDs** !!!





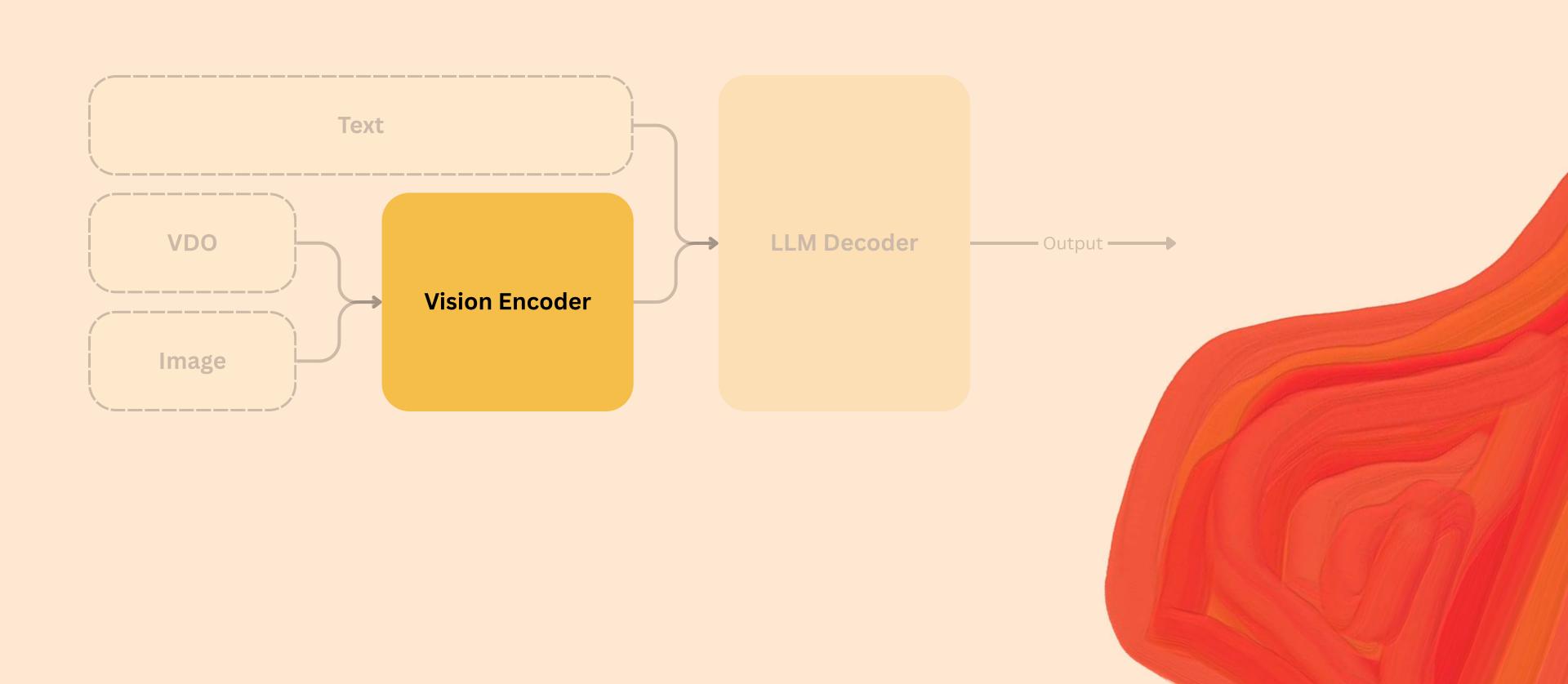
- Work with native resolution.
- Support dynamic FPS sampling.
- Positional Encoding with absolute time.
- The features of 2 consecutive frames are group together.

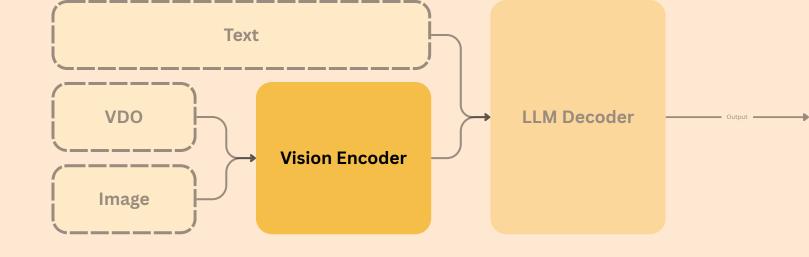


Explaination

MRoPE (Multimodal RoPE)

Width	Height	Temporal
Position IDs	Position IDs	Position IDs
lmage width	lmage height	Constants
Video width	Video height	Time IDs
	Position IDs Image width	Position IDs Image width Image height



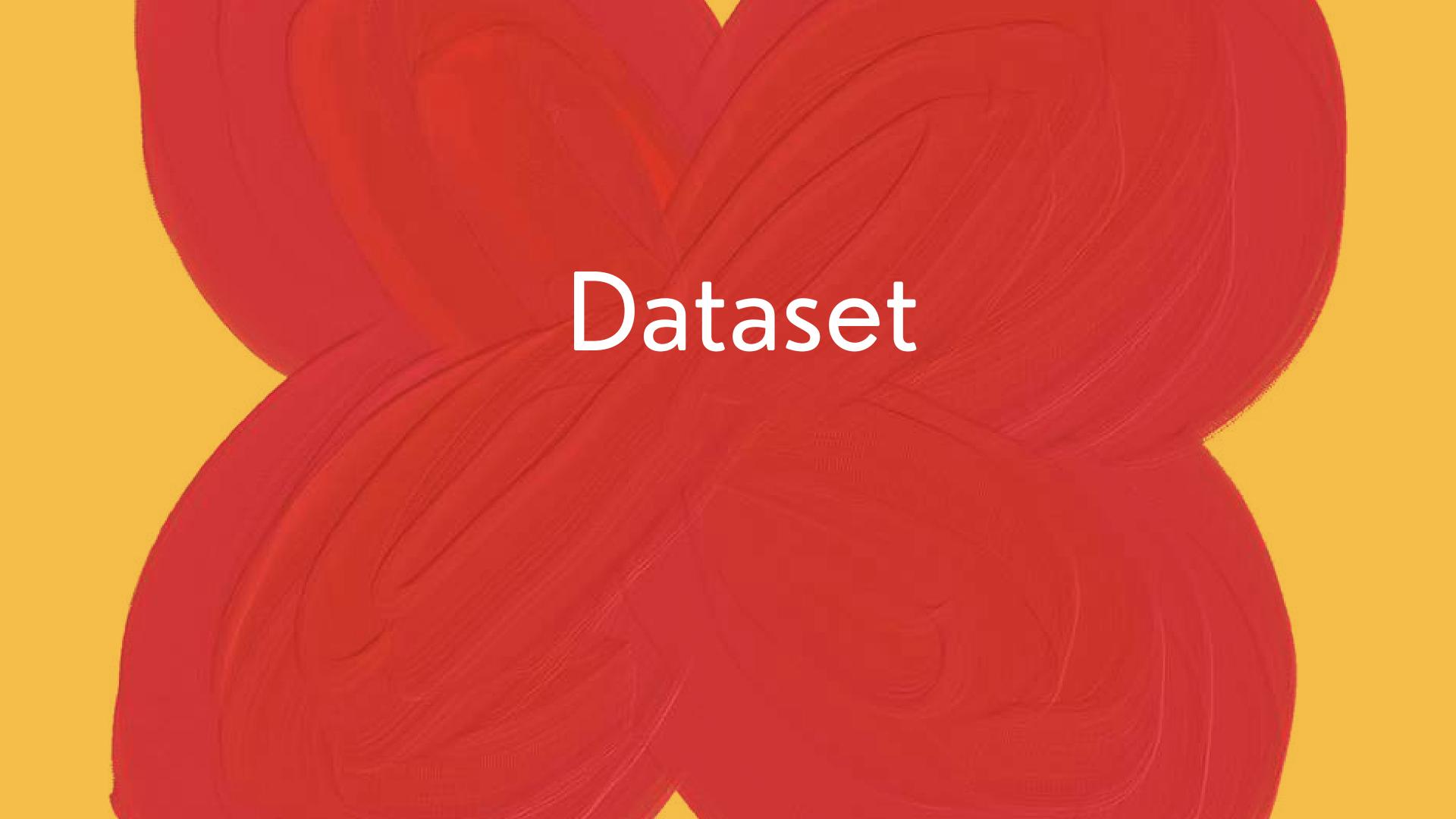


- Apply LLM design into the Vision Transformer
 - Activation function → SwiGLU
 - Normalization → RMSNorm (Root Mean Square Normalization)
- window-based attention to reduce computational efforts
 - \circ window size = 112x112 (8x8 patches), no padding if smaller



HOW IS IT DIFFERENT FROM PREVIOUS WORK

หัวข้อ	Transformer ปกติ	Qwen2.5-VL
Input	Text หรือ Image (fixed)	Text + Image + Video (dynamic)
Position Encoding	1D RoPE	3D MRoPE (temporal + spatial)
Attention	Full Attention	Windowed Attention + Selective full attention (4X)
ViT	Standard ViT	Custom ViT + RMSNorm + SwiGLU
Multi-modal Fusion	Concatenation/linear	MLP Merger (compressed patches)
Video Support	จำกัด ความยาววิดีโอ	รองรับ <mark>long video</mark> , absolute time encoding
Image Resolution	Resize required	รองรับ native resolution



PRE-TRAINING DATA

Stages	Visual Pre-Training	Multimodal Pre-Training	Long-Context Pre-Training
Data	Image Caption Knowledge OCR	+ Pure text Interleaved Data VQA, Video Grounding, Agent	+ Long Video Long Agent Long Document
Tokens	1.5T	2T	0.6T
Sequence length	8192	8192	32768
Training	ViT	ViT & LLM	ViT & LLM

- Approximately 4 trillion tokens.
- It includes cleaned web data, synthetic data, and multimodal sources such as image captions, interleaved image-text pairs, OCR data, visual knowledge datasets, multimodal academic questions, localization and grounding datasets, document parsing data, video descriptions, and agent interaction data.

INTERLEAVED IMAGE-TEXT DATA

Purpose:

- Enables multimodal learning by offering both visual and textual cues simultaneously.
- Ensures that the model maintains robust text-only capabilities when images are absent.
- Provides a wide range of general information, even though raw interleaved data can be noisy.

Text: "This Walnut and Blue Cheese Stuffed Mushrooms recipe is sponsored by Fisher Nuts.",

Text: "The ideas for stuffing



Text: "When you lock/unlock the driver's door and tailgate using the master lock switch, all the other doors lock/ unlock at the same time."





INTERLEAVED IMAGE-TEXT DATA

Preprocessing

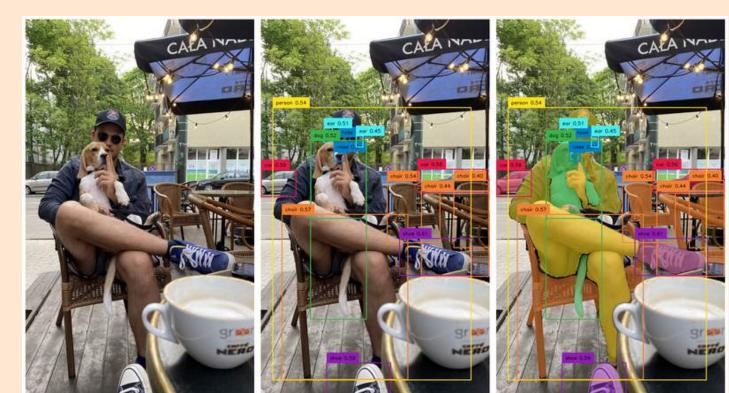
- Scoring System:
 - A four-stage evaluation using an internal model based on:
 - i. Text-Only Quality
 - ii. Image-Text Relevance Ensuring that the image adds meaningful context.
 - iii. Information Complementarity Both modalities provide unique, complementary information.
 - iv. Information Density Balance Balancing the amount of information from both the image and the text.
- This scoring helps in filtering and selecting only highquality, useful image-text pairs.



GROUNDING DATA WITH ABSOLUTE POSITION COORDINATES

Purpose:

- To accurately capture the size and location of objects within images.
- Supports tasks such as object detection and localization by preserving the real-world scale.
- -Includes over 10,000 object categories.
- -Synthesizes non-existent object categories and constructs images with multiple instances per object for robustness.





DOCUMENT OMNI-PARSING DATA

Purpose:

- To enable the model to parse and understand complex document layouts and elements, including text, tables, charts, formulas, images, and more.

 OwenVL HTML Format
- Uniformly formatted in HTML.

```
<html><body>
# paragraph
 content 
<style>table(id) style</style> table content
# chart
<div class="chart" data-bbox="x1 y1 x2 y2"> <img data-bbox="x1 y1 x2 y2" />  chart content
</div>
# formula
<div class="formula" data-bbox="x1 y1 x2 y2"> <img data-bbox="x1 y1 x2 y2" /> <div> formula
content </div></div>
# image caption
<div class="image caption" data-bbox="x1 y1 x2 y2"> <img data-bbox="x1 y1 x2 y2" /> image
caption </div>
# image ocr
<div class="image ocr" data-bbox="x1 y1 x2 y2"> <img data-bbox="x1 y1 x2 y2" /> image ocr
</div>
# music sheet
<div class="music sheet" format="abc notation" data-bbox="x1 y1 x2 y2"> <img data-bbox="x1 y1
x2 y2" /> <div> music sheet content </div></div>
# chemical formula content
<div class="chemical formula" format="smile" data-bbox="x1 y1 x2 y2"> <img data-bbox="x1 y1
x2 y2" /> <div> chemical formula content </div></div>
</html></body>
```

OCR DATA

Purpose:

- To improve the model's ability to recognize and process textual content in images.
- Supports multilingual OCR capabilities.

-Includes languages such as French, German, Italian, Spanish, Portuguese, Arabic, Russian, Japanese, Korean, and Vietnamese.

-1 million samples are synthesized, 6 million real-world

samples





VIDEO DATA

Purpose:

• To ensure the model can robustly understand video content across varying frame rates (FPS) and long-duration videos.

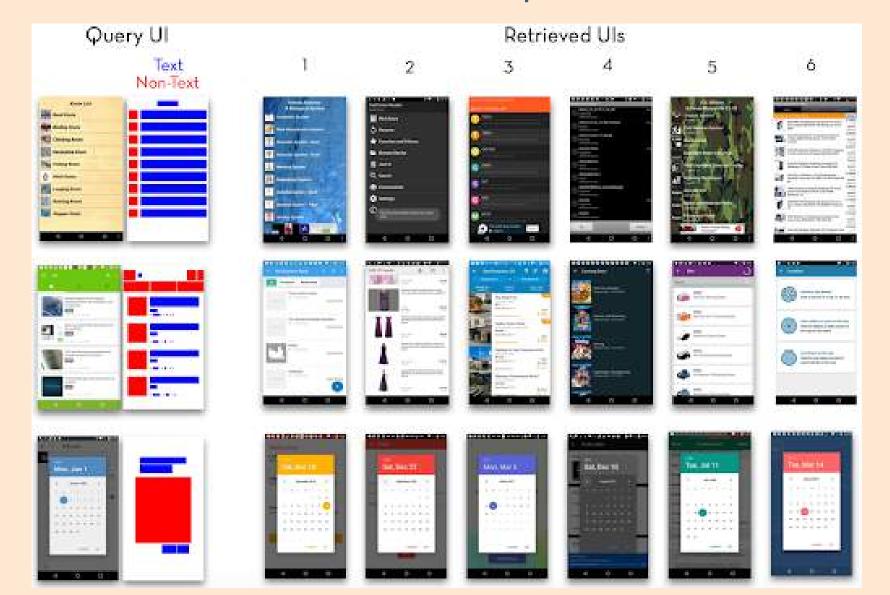




AGENT DATA

Purpose:

- Enhances the model's perception and decision-making abilities in user interface (UI) contexts across various platforms (mobile, web, desktop).
- -Screenshots from different platforms.





INSTRUCTION DATA

- Used in the Supervised Fine-Tuning (SFT) phase.
- Approximately 2 million entries.
- Pure text data (50%) and multimodal data (50%).
- Primary Languages is Chinese and English and has additional multilingual entries.
- Data is structured to support a wide range of queries, ensuring broad coverage.



INSTRUCTION DATA

Dialogue Complexity:

- Single-Turn Interactions: Simpler, one-shot inputs
 where the query is addressed in a single interaction.
- Multi-Turn Interactions: More complex, where context is maintained over several conversational turns.
- Visual Dynamics: The data simulates realistic scenarios ranging from single-image inputs to sequences of multiple images, adding layers of context and complexity.



INSTRUCTION DATA

include:

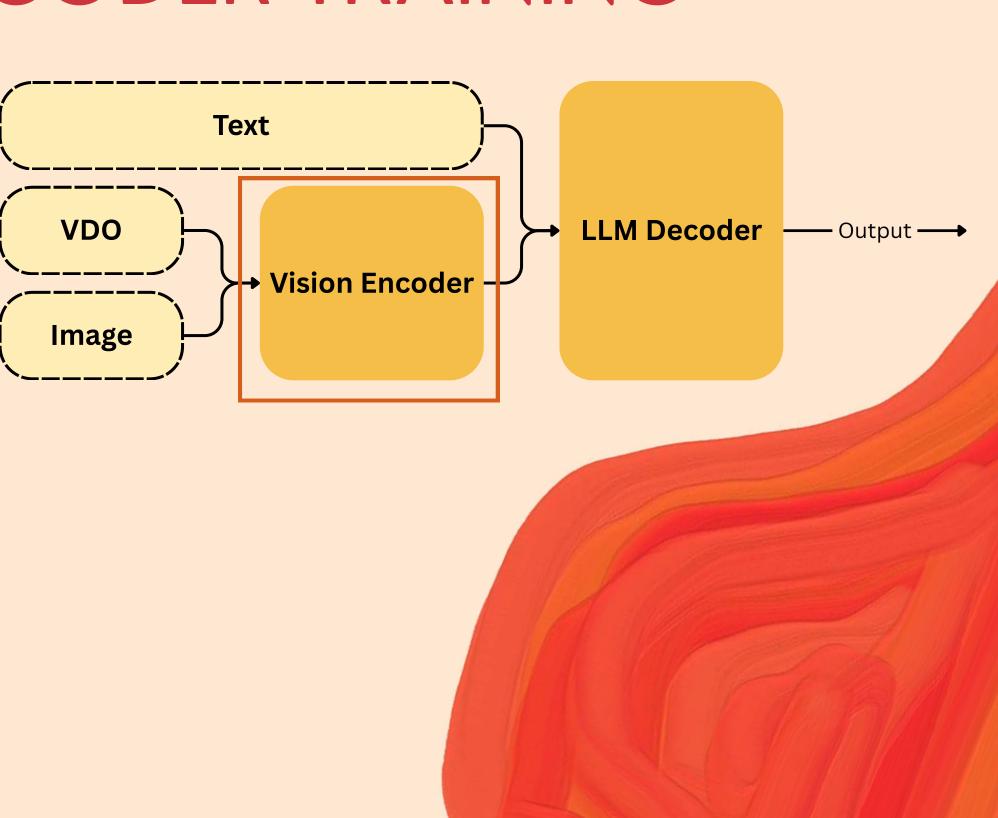
- General Visual Question Answering (VQA) and Image Captioning
- Mathematical Problem-Solving and Coding Tasks
- Security-Related Queries
- Document and OCR Tasks
- Grounding and Video Analysis
- Agent Interactions (focused on UI and operational decision-making)





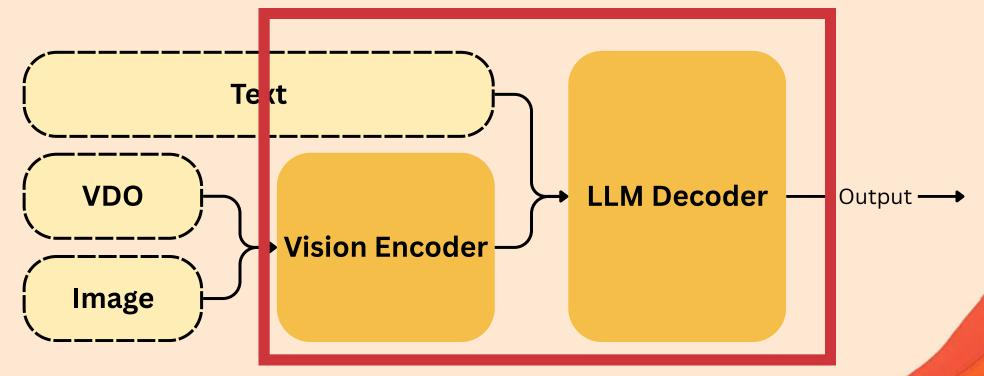
PHASE 1: VISION ENCODER TRAINING

- Only Vision Encoder training is trained in this phase
- Datasets such as image captions, visual knowledge, and OCR data are used to train in this phase



PHASE 2,3: ENTIRE MODEL TRAINING

- All model parameters are unfreeze.
- Datasets such as interleaved data, multi-task learning, visual question answering, multimodal mathematics, agent-based task, video understanding and pure text are introduce to train in the 2nd phase.
- The 3rd phase introduce data that has longer token lengths compared to 2nd phase. (8192 tokens compares to 32768)



FINE-TUNING

- Instruction-response based data are used to fine tune the model.
- Both single-turn and multi-turn interactions are introduced.
- Domain-specific categorization, Domain tailored filtering, Rule-Based filtering, and Model-Based filtering are applied to ensure dataset quality before the fine-tuning process

instruction": "What is Agentic AI?", "response": "Agentic AI is a type of artificial intelligence of "instruction": "What is the core characteristic of Agentic AI that sets it apart from other types of "instruction": "How does Agentic AI gather information about its environment?", "context": "", "response" {"instruction":"What is the purpose of the reasoning stage in Agentic AI?", "context":"", "response":"To "instruction": "Can you describe a scenario where Agentic AI would be useful?", "context": "", "response" ("instruction": "How does Agentic AI improve over time?", "context": "", "response": "Through the learning {"instruction": "What are the four key stages of Agentic AI, and how do they relate to each other?", "co "instruction": "How does Agentic AI differ from traditional AI systems that require constant human inp "instruction":"Can Agentic AI learn from its mistakes?","context":"","response":"Yes, through the lea ("instruction": "What are some potential applications of Agentic AI in Industries such as healthcare or ("instruction": "How does Agentic AI maintain balance between autonomous decision-making and safety co ("instruction": "How do the four stages interact with each other?", "context": "Agentic AI Operational ("instruction": "What distinguishes Agentic AI's autonomy from traditional AI systems?", "context": ' ("instruction": "Which stage is most critical for overall system performance?", "context": "Agentic AI ("instruction": "How does autonomous learning contribute to improved decision-making?", "context": "Ag ("instruction": "How does the perception stage filter relevant information?", "context": "Agentic AI 0 "instruction": "What role does initial programming play in autonomous behavior?", "context": "Agentic ("instruction": "What role does reasoning play in decision optimization?", "context": "Agentic AI Oper ("instruction": "How is autonomy measured or quantified in Agentic AI systems?", "context": "Agentic) ("instruction": "How does the action stage implement decisions?", "context": "Agentic AI Operational ! {"instruction": "What are the ethical implications of AI autonomy?", "context": "Agentic AI Autonomy", "instruction": "What feedback mechanisms exist between stages?", "context": "Agentic AI Operational



Overview

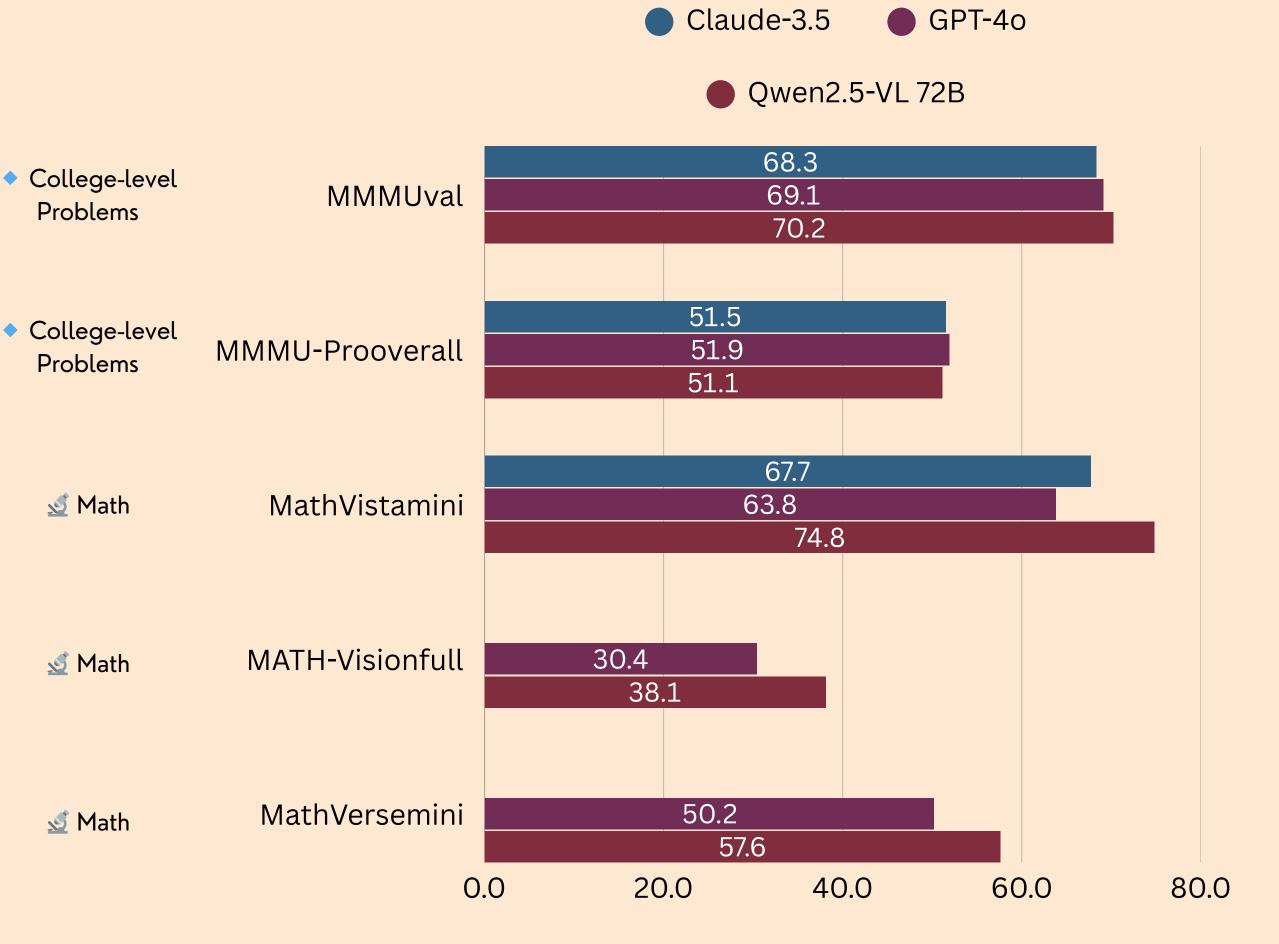
On Evaluation Task

- 1. General Language Understanding
- 2. Multimodal Tasks

Qwen2.5-VL-72B

VS

LLaMA 3.1 405B GPT-4 Claude 3.5 Gemini 1.5 และ SOTA อื่น ๆ



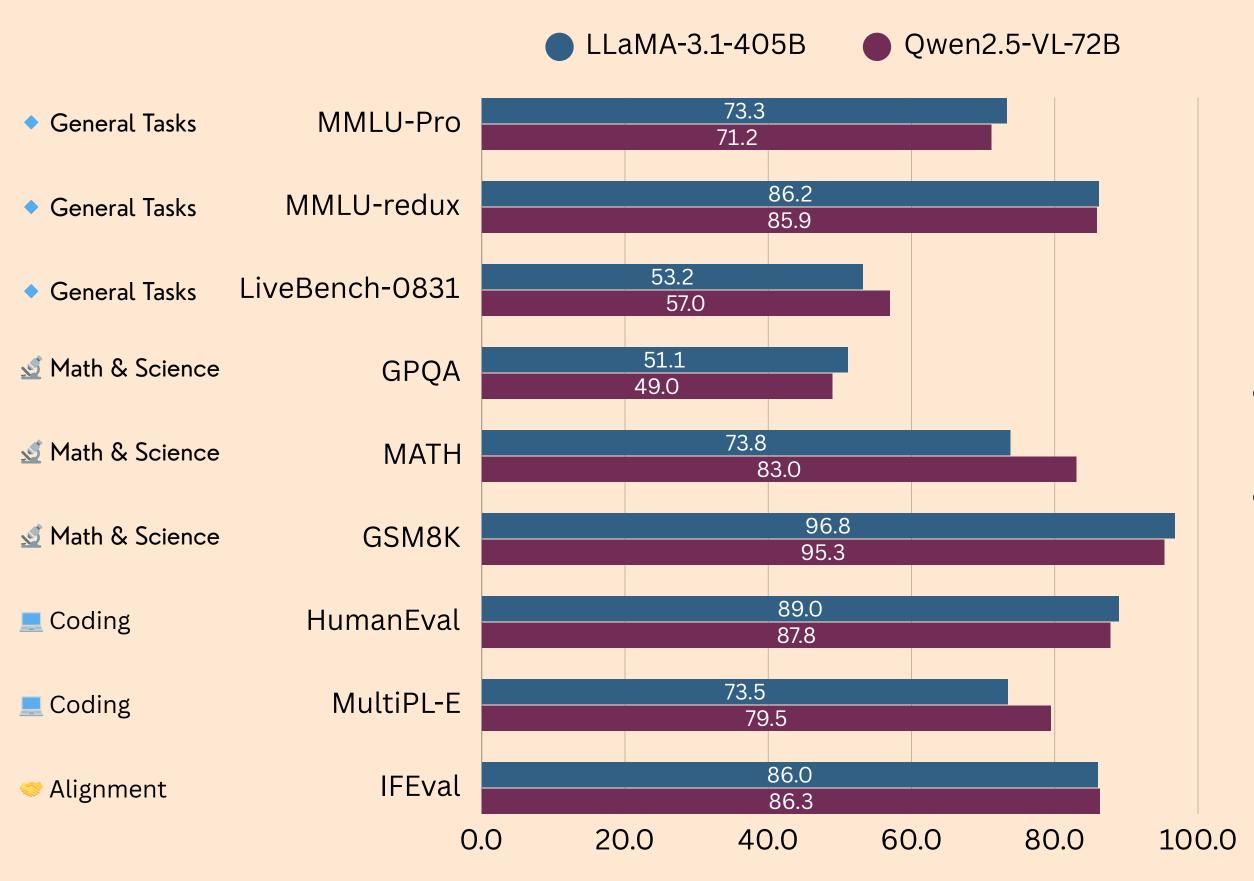
General Language Understanding

GPO-40

- Evenly matched with GPO-4o in College-level Problems
- Qwen outperform in Math Problem

Claude-3.5

 Qwen outperform Claude-3.5 in all dataset



General Language Understanding

Qwen2.5-VL-72B vs LLaMA-3.1-405B

- Most of the dataset, The performance is Evenly matched
- Better performance in MATH dataset

OCR-related Document Understading

Best performace in 6 out of 12 dataset

Table 5: Performance of Qwen2.5-VL and other models on OCR, chart, and document understanding benchmarks.

Datasets	Claude-3.5 Sonnet	Gemini 1.5 Pro	GPT 40	InternVL2.5 78B	Qwen2.5-VL 72B	Qwen2.5-VL 7B	Qwen2.5-VL 3B
		OC	R-related Pars	ing Tasks			
CC-OCR	62.5	73.0	66.9	64.7	79.8	77.8	74.5
OmniDocBench _{edit en/zh} ↓	0.330/0.381	0.230/0.281	0.265/0.435	0.275/0.324	0.226/0.324	0.308/0.398	0.409/0.543
		OCR-r	elated Underst	anding Tasks			
AI2D _{w. M.}	81.2	88.4	84.6	89.1	88.7	83.9	81.6
TextVQA _{val}	76.5	78.8	77.4	83.4	83.5	84.9	79.3
DocVQA _{test}	95.2	93.1	91.1	95.1	96.4	95.7	93.9
InfoVQA _{test}	74.3	81.0	80.7	84.1	87.3	82.6	77.1
ChartQA _{test Avg.}	90.8	87.2	86.7	88.3	89.5	87.3	84.0
CharXiv _{RQ/DQ}	60.2/84.3	43.3/72.0	47.1/84.5	42.4/82.3	49.7/87.4	42.5/73.9	31.3/58.6
SEED-Bench-2-Plus	71.7	70.8	72.0	71.3	73.0	70.4	67.6
OCRBench	788	754	736	854	885	864	797
VCR _{En-Hard-EM}	41.7	28.1	73.2		79.8	80.5	37.5
		OCR-r	elated Compre	hensive Tasks			
OCRBench_v2 _{en/zh}	45.2/39.6	51.9/43.1	46.5/32.2	49.8/52.1	61.5/63.7	56.3/57.2	54.3/52.1

12 Datasets





"40

"400 Bath"

"What is the total cost of this bill"

Counting Task

Better than Gemini 1.5 Pro,
 Claude, GPT, the best
 performance

"How many cows in the picture"

	Table 7: Performance of Qwen2.5-VL and other models on counting.							
Datasets	Gemini 1.5-Pro	GPT-40	Claude-3.5 Sonnet	Molmo-72b	InternVL2.5-78B	Qwen2.5-VL-72B		
CountBench	85.5	87.9	89.7	91.2	72.1	93.6		

1 Dataset

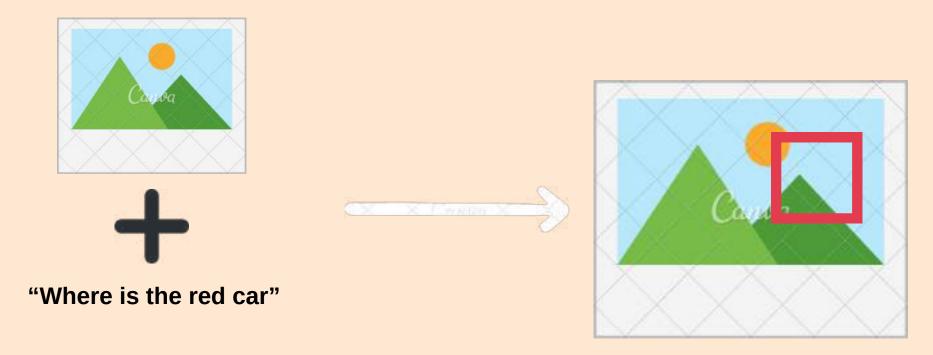


Grounding Task

- Better than Gemini 1.5 Pro in all dataset
- But lower performance than InternVL

Datasets	Gemini 1.5 Pro	Grounding DINO	Molmo 72B	InternVL2.5 78B	Qwen2.5-VL 72B	Qwen2.5-VL 7B	Qwen2.5-VL 3B
Refcoco _{val}	73.2	90.6	-	93.7	92.7	90.0	89.1
Refcoco _{test A}	72.9	93.2	-	95.6	94.6	92.5	91.7
Refcoco _{testB}	74.6	88.2	-	92.5	89.7	85.4	84.0
Refcoco+ _{val}	62.5	88.2	-	90.4	88.9	84.2	82.4
Refcoco+testA	63.9	89.0	-	94.7	92.2	89.1	88.0
Refcoco+testB	65.0	75.9		86.9	83.7	76.9	74.1
Refcocog _{val}	75.2	86.1	120	92.7	89.9	87.2	85.2
Refcocog _{test}	76.2	87.0	-	92.2	90.3	87.2	85.7
ODinW	36.7	55.0	-	31.7	43.1	37.3	37.5
PointGrounding	-		69.2	6 - -	67.5	67.3	58.3

10 Datasets



Video Task

- Better than Gemini 1.5 Pro, GPT-4o in most dataset
- Best performance in 8 out of 13 datasets

Datasets	Gemini 1.5-Pro	GPT-40	Qwen2.5-VL-72B	Qwen2.5-VL-7B	Qwen2.5-VL-3B
		Video Un	derstanding Tasks		
Video-MME _{w/o sub.}	75.0	71.9	73.3	65.1	61.5
Video-MME _{w sub.}	81.3	77.2	79.1	71.6	67.6
Video-MMMU	53.9	61.2	60.2	47.4	-
MMVU _{val}	65.4	67.4	62.9	50.1	-
MVBench	60.5	64.6	70.4	69.6	67.0
MMBench-Video	1.30	1.63	2.02	1.79	1.63
LongVideoBench _{val}	64.0	66.7	60.7	56.0	54.2
LVBench	33.1	30.8	47.3	45.3	43.3
EgoSchema _{test}	71.2	72.2	76.2	65.0	64.8
PerceptionTest _{test}	-	-	73.2	70.5	66.9
MLVU _{M-Avg}	-	64.6	74.6	70.2	68.2
TempCompass _{Avg}	67.1	73.8	74.8	71.7	64.4
		Video C	Grounding Tasks		
Charades-STA _{mIoU}	-	35.7	50.9	43.6	38.8

Table 8: Performance of Qwen2.5-VL and other models on video benchmarks.

13 Dataset



"Red car pass by"

GUI Task

- Better than Gemini 2.0, GPT-40,
 Claude in most dataset
- Best performance in 5 out of 7 dataset

Benchmarks	GPT-40	Gemini 2.0	Claude	Aguvis-72B	Qwen2-VL-72B	Qwen2.5-VL-72B
ScreenSpot	18.1	84.0	83.0	89.2	- # <u>#</u>	87.1
ScreenSpot Pro	•		17.1	23.6	1.6	43.6
Android Control HighEM	20.8	28.5	12.5	66.4	59.1	67.36
Android Control Lowem	19.4	60.2	19.4	84.4	59.2	93.7
AndroidWorldsR	34.5% (SoM)	26% (SoM)	27.9%	26.1%	6% (SoM)	35%
MobileMiniWob++SR	61%	42% (SoM)	61% (SoM)	66%	50% (SoM)	68%
OSWorld	5.03	4.70	14.90	10.26	2.42	8.83

Table 9: Performance of Qwen2.5-VL and other models on GUI Agent benchmarks.

7 Dataset





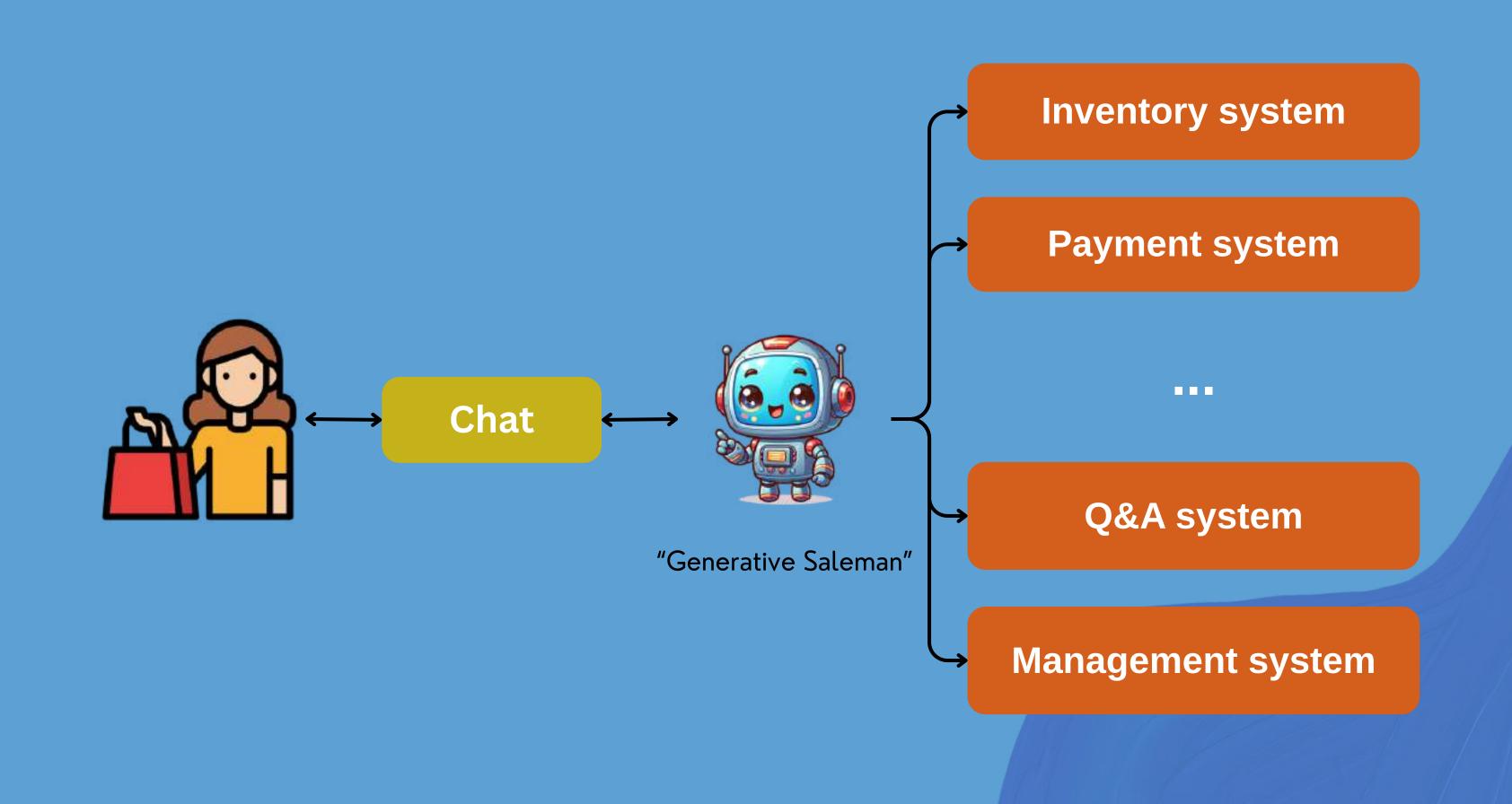
Click Setting Button

Conclusion

UlaMA 3.1 405B
GPT-4
Claude 3.5
Gemini 1.5
และ SOTA อื่น ๆ

- Qwen2.5-VL-72B is clearly better than other model in Multimodel Task
- Qwen2.5-VL-72B is better perfomace in Math problem
- And have similar performance in General Language Understanding

Our Project Update



Scope and Goal

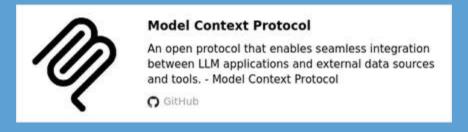
- Thai language only
- For use exclusively in Board Game trading context only
- Not yet connected to social media chat application, initially includes only a simple and user-friendly UI

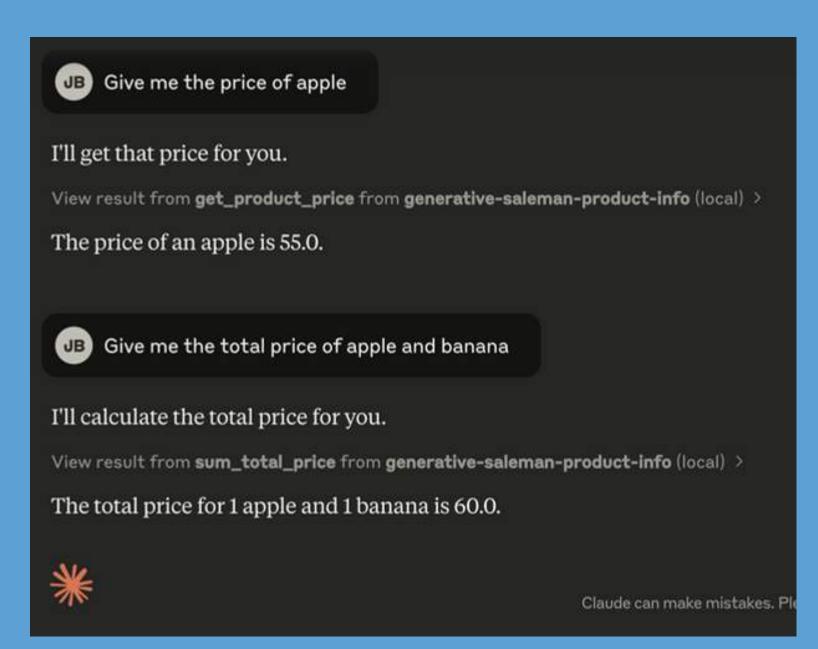




```
# Add sum_total_price tool
@mcp.tool()
def sum_total_price(product_list: list[tuple[str, int]]) -> float:
   Calculate the total price of a list of products.
   :param product_list: A list of product names which in form (product_name, quantity).
   :type product_list: list[tuple[str, int]]
   :return: The total price of the products.
   :rtype: float
   ## Example
   > sum_total_price([('apple', 1), ('banana', 1)])
   > sum_total_price([('grape', 1), ('watermelon', 2)])
   95.0
   total_price = 0
   for product, quantity in product_list:
       total_price += PRODUCT_NAME_TO_PRICE.get(product, 0) * quantity
   return total_price
```

Example code in MCP frameworks





Example usage in Claude Desktop

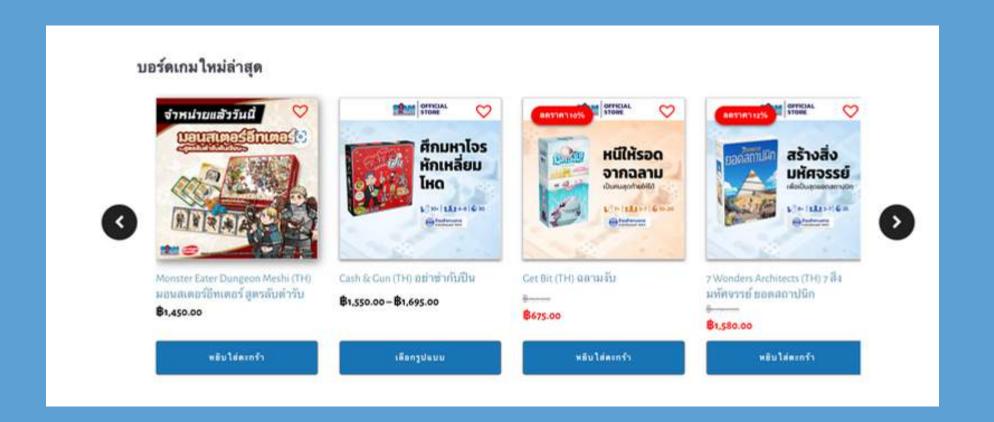
Payment Solutions

- Generate QR code from API https://promptpay.io/
- Using API from https://openslipverify.com/ to verify slip

```
{'success': True,
 'statusMessage': 'SUCCESS',
 'data': {'receivingBank': '004',
  'sendingBank': '004',
 'transRef': '045085505op7poh5wDDM',
 'transDate': '20250326',
 'transTime': '15:17',
  'sender': {'displayName': 'นาย ศุภฤกษ์ ค',
  'name': 'MR. SUPHAROEK K',
   'account': {'value': 'xxx-x-x8695-x'}},
  'billerID': '010753600031508',
  'billerName': 'MIXUE CU',
  'amount': 20,
  'compCode': '-',
  'ref1': 'KB000001896105',
  'ref2': 'KPS004KB000001896105',
  'ref3': '-'}}
```

Dataset

- Scaping Data from https://siamboardgames.com/
- Open Boardgame dataset
 https://www.kaggle.com/datasets/andrewmvd/board-games/data
- Huggingface https://huggingface.co/datasets/goendalf666/salesconversations



BoardGamesGeek ID	△ Name = Board game name	# Year Published F	# Min Players = Min suggested players	# Max Players = Max suggested players	# Play Average suggest creators
O total values	20338 unique values	1948 total values	6875 total values	11135 total values	t
174430	Gloomhaven	2017	1.	4	120
161936	Pandemic Legacy; Season 1	2015	2	4	60
224517	Brass: Birmingham	2018	2	4	128
167791	Terraforming Mars	2016	1	5	120
233078	Twilight Imperium: Fourth Edition	2017	3	6	480
291457	Gloomhaven: Jaws of the Lion	2020	1	4	120
182028	Through the Ages: A New Story of Civilization	2015	2	4	120
220308	Gaia Project	2017	1	4	150
87645	Star Wars: Rebellion	2016	2	4	240