

Sightation Counts: Leveraging Sighted User Feedback in Building a BLV-aligned Dataset of Diagram Descriptions



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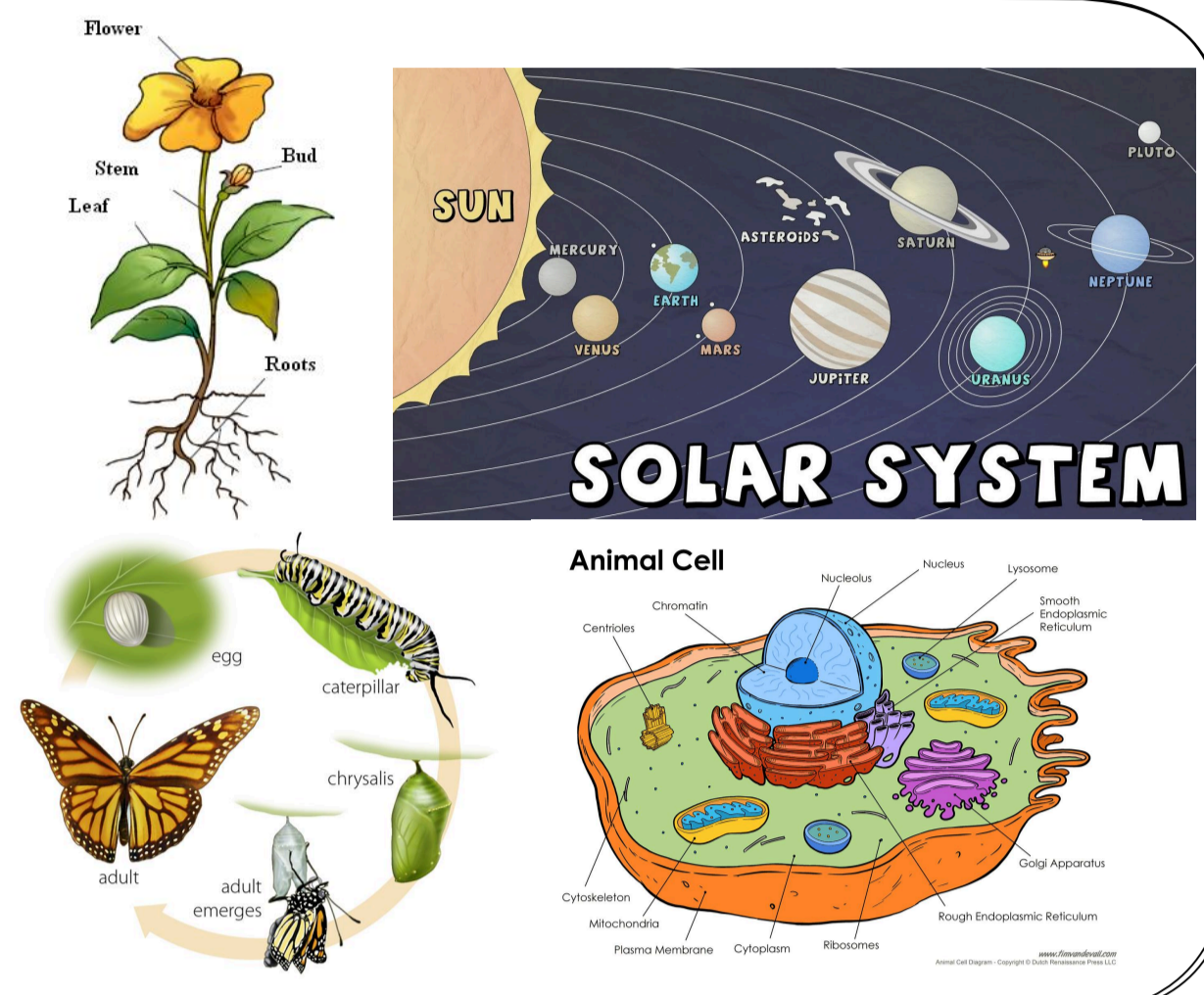
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The 63rd Annual Meeting of the Association for Computational Linguistics / July 27 - August 1, 2025 / Vienna, Austria



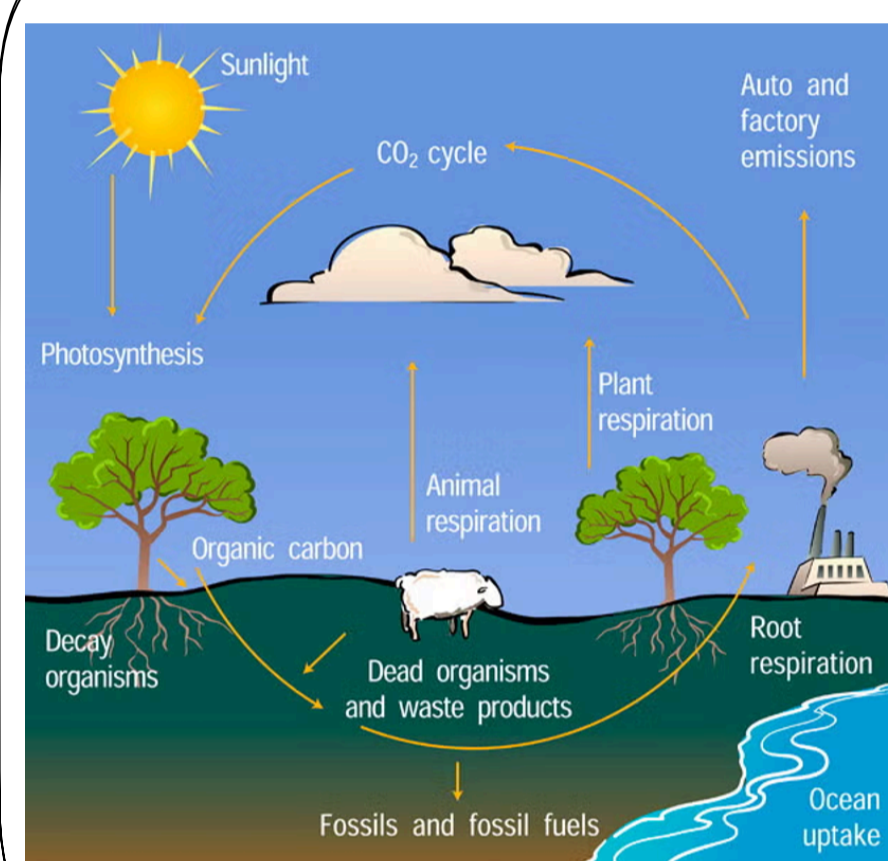
caption: cavendish bananas are the main commercial banana cultivars sold in the world market.

description: grocery store photo of several bunches of bananas



- Existing vision-language models are often trained for generating captions.
- This leaves out blind and low-vision individuals in need of descriptions.
- We created a dataset of diagram descriptions for training VLMs, driving them to generate more BLV-aligned text.

- We let VLMs generate descriptions then had them assessed by crowdworkers.
- Process leverages sighted user feedback for cost-effective, bias-reduced supervision.
- Dataset quality was validated by BLV educators at schools for the blind.

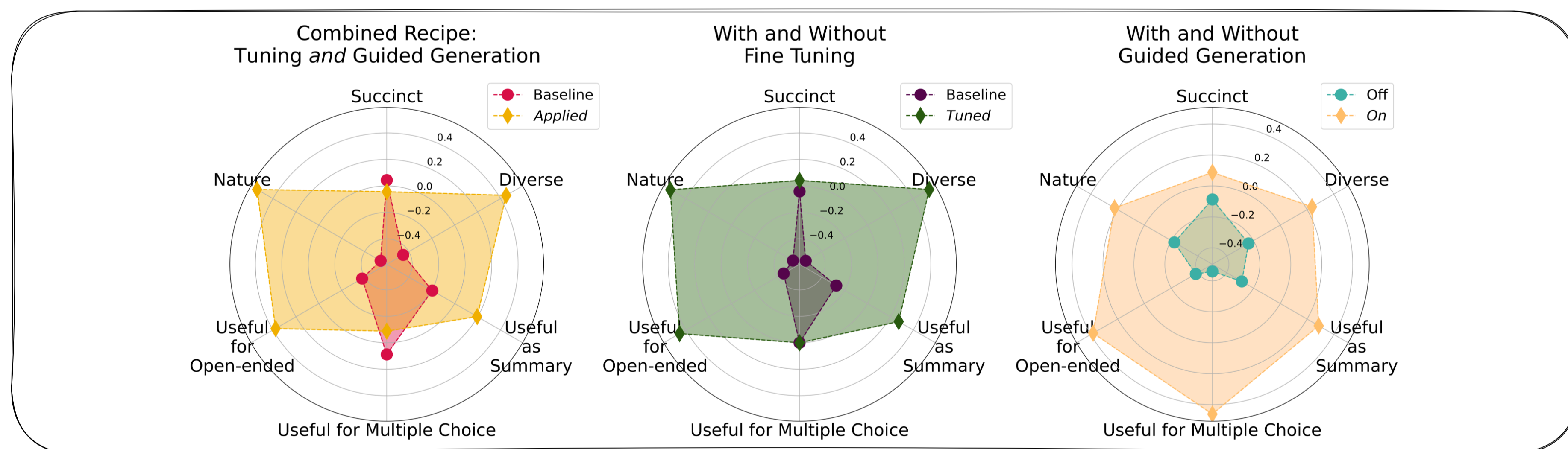
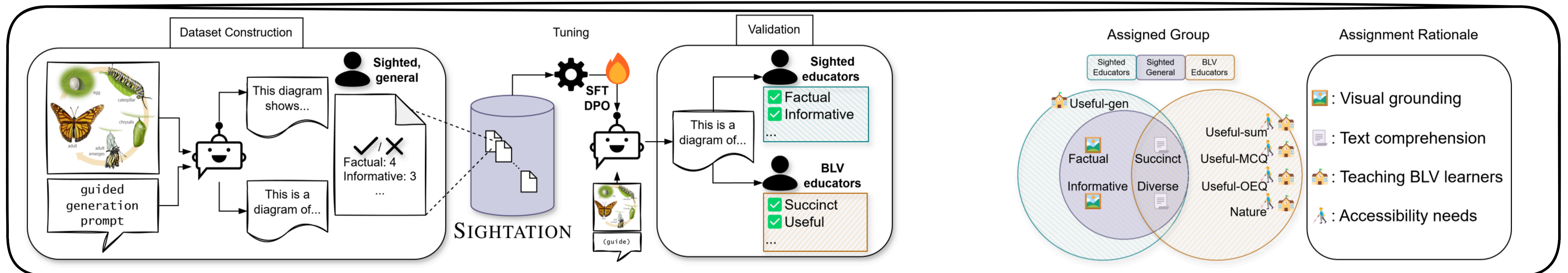


The diagram shows the carbon cycle...

The carbon cycle is illustrated...

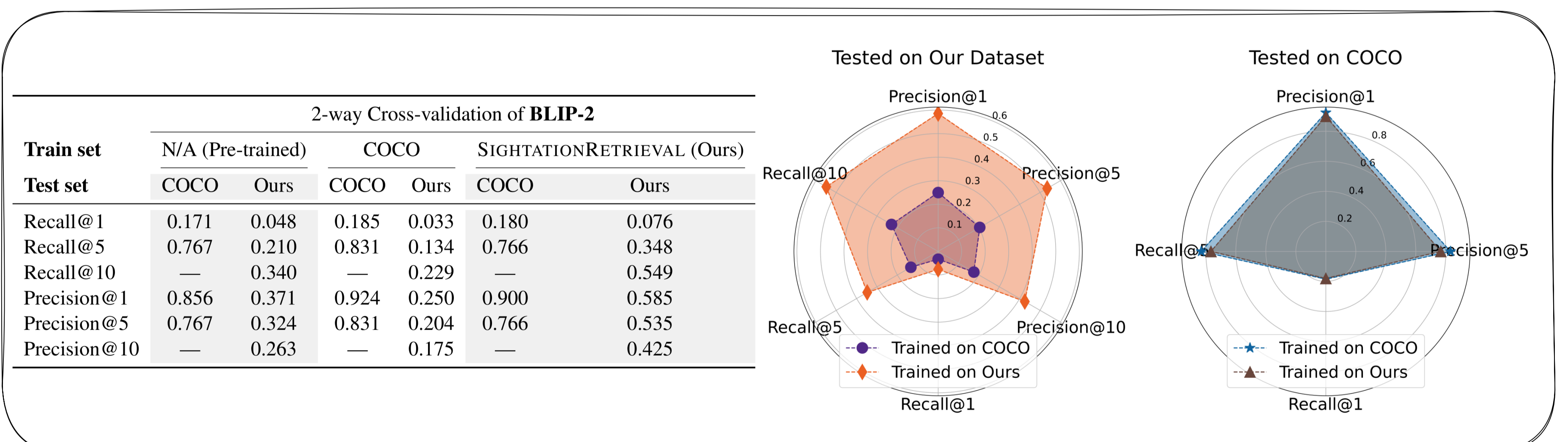
Please complete the following with respect to the image below and its description pairs 1 and 2:

- For each pair, select the text that is the better overall description of the given image.
- Rate each text (left and right) with respect to the qualities listed.
- Copy and paste the overall best contributing sentence from each text.



- We trained VLMs on our dataset and measured the effectiveness of the training with BLV and sighted educators across 9 quality aspects.
- Shown are the 6 aspects rated by BLV educators.
- Fine-tuned 2B model shows significant gain in usefulness and diversity.

- We also tested our dataset against existing datasets.
- BLIP2 trained on our data generalizes well to COCO.
- However, COCO-trained BLIP2 performs poorly on our dataset.



Aspect	Combined Effect Size	
	2B	7B
Succinct	-0.09	1.69
Diverse	0.90	0.46
Useful-Sum	0.39	0.53
Useful-MCQ	-0.18	0.20
Useful-OEQ	0.76	0.00
Average	0.36	0.58
Nature	1.08	-2.38

Aspect	Tuning Effect Size			
	2B	2B+GG	7B	7B+GG
Succinct	0.06	0.08	0.37	-0.11
Diverse	0.87	1.08	-0.06	0.00
Useful-Sum	0.20	0.55	0.14	0.36
Useful-MCQ	0.29	0.00	-0.54	0.00
Useful-OEQ	1.01	0.90	-0.74	-0.19
Average	0.49	0.52	-0.17	0.01
Nature	1.49	1.06	-3.14	-0.31

Aspect	Guided Generation Effect Size		
	GPT	2B Base	2B DPO
Succinct	0.18	-0.17	0.17
Diverse	-0.13	-0.13	0.47
Useful-Sum	0.48	-0.17	0.57
Useful-MCQ	0.13	-0.20	0.92
Useful-OEQ	0.76	-0.07	0.77
Average	0.28	-0.15	0.58
Nature	0.33	0.08	3.17

Experiment ID	Description Generators	Metrics	Assessments for	
			Desc _{chartgemma}	Desc _{qwen2}
Experiment 3c CHARTGEMMA (3B) vs. FINE-TUNED QWEN2-VL-2B-INSTRUCT		CLIP Score	0.450	0.550
		SigLIP Score	0.872	0.940
		BLIP-2 Retrieval Score	0.511	0.490
		Self-BLEU	0.305	0.280
		PAC Score	0.705	0.716
		LongClip-B	0.316	0.684
		LongClip-L	0.559	0.441
		VLM-as-a-Judge Evaluation Average	2.951	3.860
		Factuality	3.068	4.119
		Informativeness	2.848	3.967
		Succinctness	3.253	3.925
		Diversity	2.635	3.428

This work was supported by Institute of Information & communications Technology Planning & Evaluation (IITP) grants funded by the Korea government (MSIT) (No. RS-2024-00457882, AI Research Hub Project and No.RS-2019-II190075, Artificial Intelligence Graduate School Program (KAIST)) and National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No.RS-2024-00406715).

Sightation@ACL2025
<https://hf.co/Sightation>

