CoLLaVO: Crayon Large Language and Vision mOdel

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- Problem / objective

  VLM 이 object-level image understanding 잘했으면 좋겠어

- Contribution / Key idea
  - Crayon Large Language and Vision model (CoLLaVO) 제안
    - Crayon Prompt
    - Dual QLoRA

Lee, Byung-Kwan, et al. "Collavo: Crayon large language and vision model." *arXiv preprint arXiv:2402.11248* (2024).

[문제] VLM 들이 object-level image understanding 잘 못하더라

평가지표 : B2C, C2B 정확도

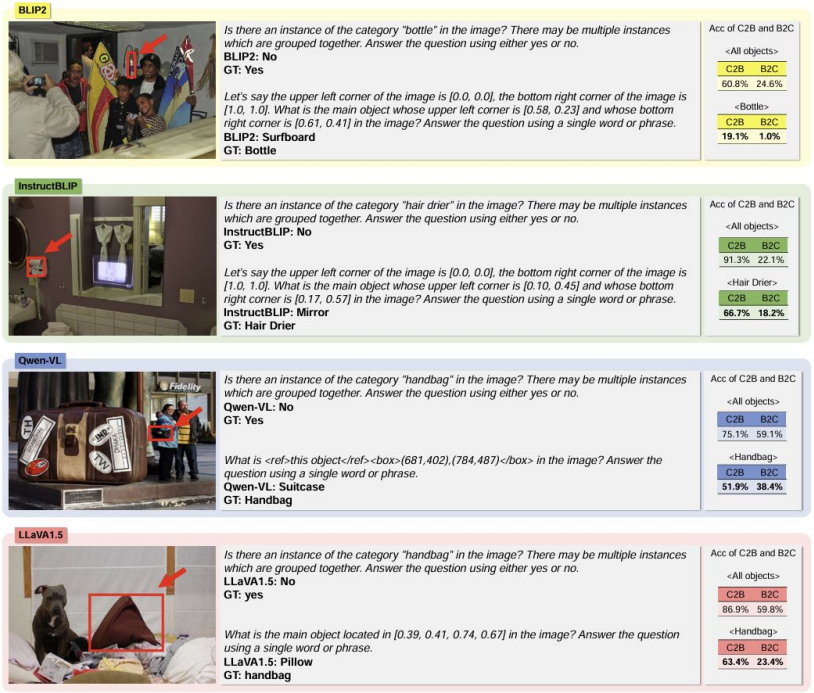

Figure 2: Asking four baselines (BLIP2, InstructBLIP, Qwen-VL, and LLaVA1.5) two types of questions, Class2Binary (C2B) and Box2Class (B2C), and measuring their accuracies on each object category.

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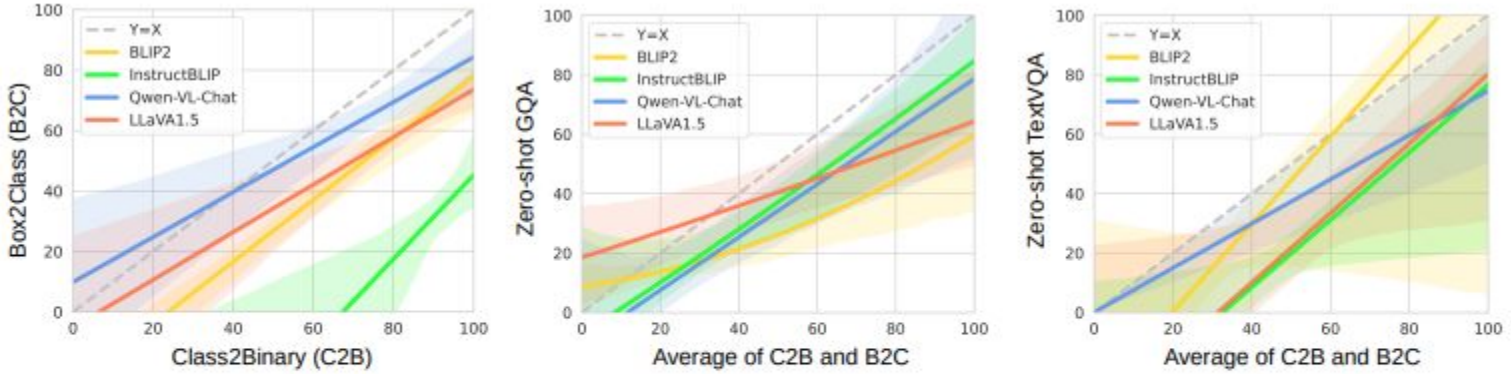
ACL 2024

[사실] 근데 VLM 들의 object-level image understanding 이 zero-shot 성능과 관련 있는 거 알어?



(a) Object-Level Image Understanding (b) Correlation with Zero-shot GQA (c) Correlation with Zero-shot TextVQA

Figure 3: Plotting the regressed relationships between (a) C2B and B2C for each object category, (b) the average of C2B & B2C and zero-shot GQA (Hudson and Manning, 2019) performance for each object category, (c) the average of C2B & B2C and zero-shot TextVQA (Singh et al., 2019) performance for each object category to visualize their correlations. The light-colored areas indicate the vertical span with the probability of confidence interval 0.95.

전유진

[결론] 그래서 우리는 VLM 이 object-level image understanding 잘하게 해서 zero-shot 성능 올릴거야.

- Crayon Prompt
  - Visual prompt for object-level image understanding
  - 구체적으로는, Panoptic colormap 의 semantic, instance 정보를 담은 학습가능한 쿼리 벡터
  - MLM 의 백본 내 모든 어텐션 모듈 층에서 이미지 피쳐에 Crayon Prompt 를 통합시킴.
- Dual QLoRA
  - 하나는 Crayon Instructions 에 대해 학습
  - 다른 하나는 Visual instruction tuning 데이터셋 에 대해 학습

Cheng, Bowen, et al. "Masked-attention mask transformer for universal image segmentation." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2022.
Dettmers, Tim, et al. "Qlora: Efficient finetuning of quantized llms." *Advances in neural information processing systems* 36 (2023): 10088-10115.

Model Architecture and Prompt Protocol

- Model Architecture
  - Vision encoder : CLIP
  - Crayon prompt
  - backbone MLM : InternLM-7B
  - MLP connectors : 2 fully-connected MLPs w/ GELU activation function
- Prompt Protocol
  - ‘<image>’ : a special token for image embedding features
  - ‘<stop>’ : a stop token for text generation
  - ‘User: {}’ : a question template
  - ‘Assistant: {}’ : an answer template

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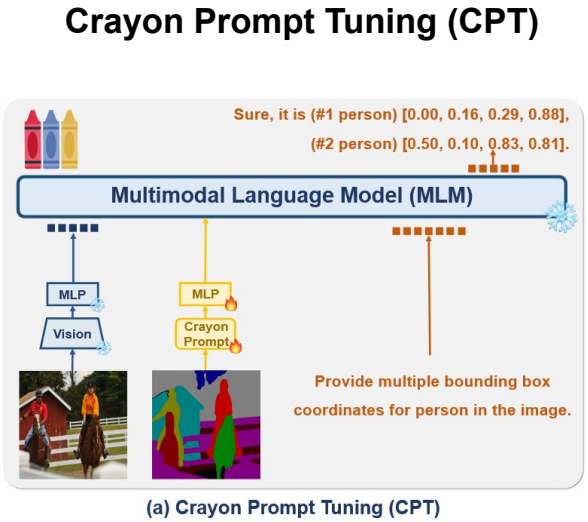


Figure 4: Overview of two-step training for CoLLaVO. fire symbols represent the modules to learn.

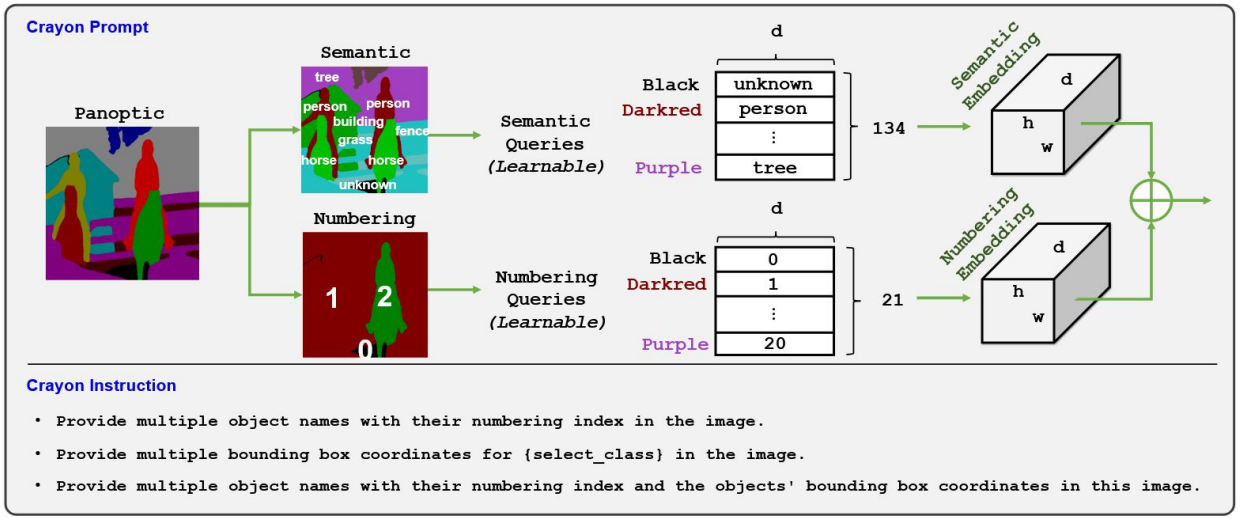
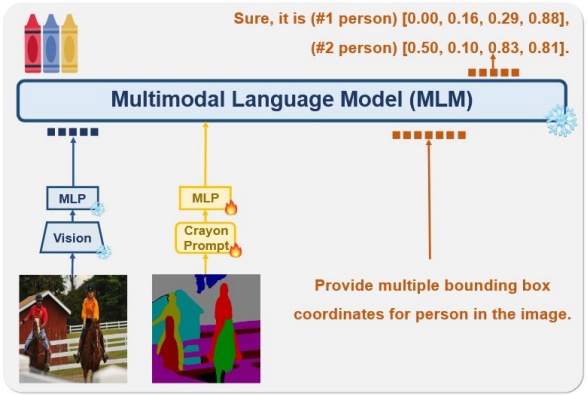


Figure 5: Describing how the Crayon Prompt is generated from a panoptic color map with learnable semantic queries and numbering queries. In addition, crayon instruction examples are given, which are used to conduct CPT and CIT. Note that, '{}' denotes the place where we adaptively input information.

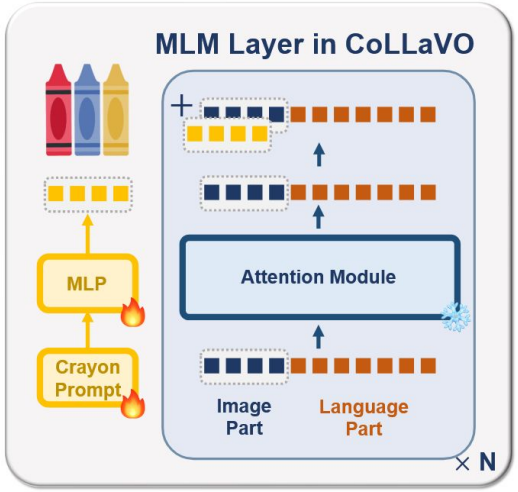
- 과정 : Image -> Panoptic semantic/numbering color map -> Semantic/Numbering queries -> Crayon prompt
- Learnable queries
  - 133+1(unk)semantic queries
  - 20+1('0' for unk)numbering queries (한 이미지 내 동일한 객체 최대 20개까지 존재한다는 가정)

Crayon Prompt Tuning (CPT)



(a) Crayon Prompt Tuning (CPT)

Figure 4: Overview of two-step training for CoLLaVO. fire symbols represent the modules to learn.



(a) Crayon Prompt Operation in CoLLaVO

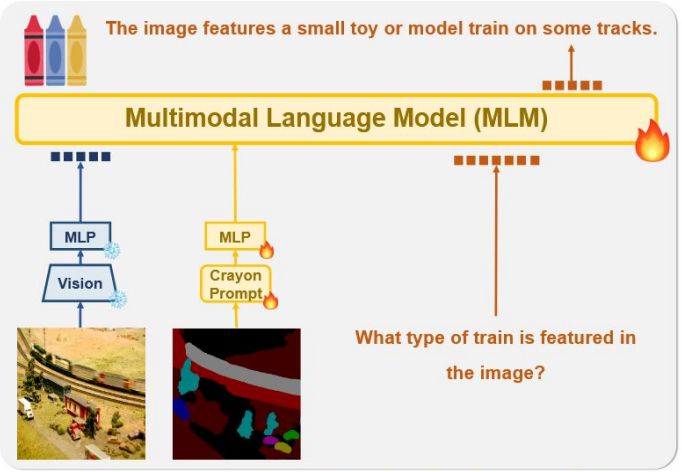
Figure 6: Illuminating (a) how the Crayon Prompt is injected i
of (b), (c) Dual QLoRA for the object-level image understan
(VL-CIT) to efficiently coexist without catastrophic forgetting

Crayon Instruction Example for CPT

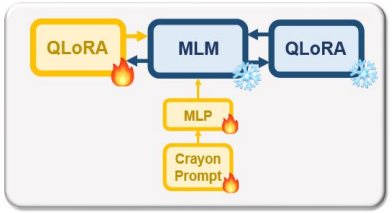
<image>
User: Provide multiple object names with their numbering index and the objects' bounding box coordinates in this image.
Assistant: Sure, it is (#1 horse) [0.06, 0.38, 0.27, 0.91], (#2 horse) [0.56, 0.41, 0.77 , 0.99], (#1 person) [0.00, 0.16, 0.29, 0.88], (#1 sky) [0.39, 0.00, 0.69, 0.18], (#1 fence) [0.00, 0.42, 0.99, 0.99], (#1 building) [0.00, 0.14, 0.47, 0.83], (#1 tree) [0.00, 0.00, 0.99, 0.47], (#1 grass) [0.21, 0.49, 0.99, 0.95], (#2 person) [0.50, 0.10, 0.83, 0.81]<stop>

- 학습 목적 : object-level image understanding, 데이터셋 : MS-COCO 2017 dataset
- Crayon prompt 는 MLP 거쳐서 attention layer 내의 모든 image features 에 더해짐
- Crayon instructions 사용해서 Crayon Prompt Tuning 함. (Crayon Prompt 를 backbone MLM 과 정렬 위해)전유진

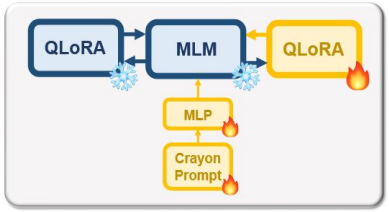
Crayon Prompt-based Instruction Tuning (CIT)



(b) Crayon prompt-based Instruction Tuning (CIT)



(b) Dual QLoRA for Image-CIT



(c) Dual QLoRA for VL-CIT

- 학습 목적 : complex question answering, 데이터셋 : crayon instructions, visual instruction tuning datasets
- Dual QLoRA
  - Image-CIT : 첫번째 QLoRA 모듈만 학습, 학습 목표 : object-level image understanding
  - VL-CIT : 두번째 QLoRA 모듈만 학습, 학습 목표 : zero-shot VL performance