A. More Cases

Fig. 10, Fig. 11, and Fig. 12 showcase descriptions of a given ordinary image generated by various MLLMs from single-object, multi-object, and global perspectives. Specifically, LLaVA-1.6-7B enhances the static scene with a vivid sense of imagery using phrases such as "magical night ride" and "serene celebration", which add an appealing layer to the description. Descriptions from Qwen-VL-7B-Chat and Qwen-VL-7B+CLoT are similarly vivid and imaginative, incorporating metaphor and personification with phrases like "the tram was like a mobile diner, rolling down the street with its windows wide open" and "the car mirror seemed to be staring back at me with a mysterious smile", thereby heightening the appeal. VisualGLM-6B's descriptions focus on evoking a peaceful and gentle atmosphere. For instance, in describing the tram, it uses expressions like "quietly glides" and "gentle, calming atmosphere", conveying a serene urban landscape and providing a soothing visual experience. XMeCap also enhances the appeal by using dynamic and emotionally charged language, such as "glided down the street like a classic diner on wheels" and "twinkling lights on the palm tree dance alongside it", which create a more vivid and dramatic scene. In contrast, descriptions generated by CogVLM-7B are comparatively plain. While they accurately describe the elements in the image, they lack vividness. For example, the description includes "the headlights resemble a pair of curious eyes", which is somewhat figurative but fails to capture the scene's dynamism fully. Descriptions from MiniGPT-4-7B and mPLUG-Owl-I are also straightforward and concise, offering statements like "The tram moves on the street" and "The tram is next to some palm trees and lights". Though accurate, these descriptions lack rich detail and emotional depth. Descriptions from InstructBLIP-7B, while detailed, tend to be relatively lengthy, with the abundance of information potentially diluting the impact of the description. Upon comparison, CharmNet clearly excels in generating more appealing descriptions, characterized by a rich vocabulary and expressive language that enhance the image's appeal.

B. Error Analysis and Exploratory Analysis

We examine some less successful descriptions. For example, in an image showing a man leading a boy carrying a teddy bear, the generated description reads "a boy walking with a man in a crowd", which lacks vivid detail and emotional depth, rendering it less appealing.

Moreover, bias may exist due to the limited coverage of specific cultural or domain-specific images in the selected datasets. Therefore, we collect 100 images of iconic landmarks, such as the Eiffel Tower and the Egyptian pyramids, and apply CharmNet to generate culturally relevant captions. Our evaluation indicates that these captions are

highly appealing, with an average human rating of 4.6 in 5. For instance, a generated appealing description like "In Times Square, the billboards shine brighter than my dreams, and buses move faster than my 5G!" effectively captures the vibrancy of the location, potentially attracting tourists and promoting sightseeing, demonstrating real-world applicability. Future work will explore more datasets to make further validation.

C. Other Details

Figure 7 presents additional samples of descriptions generated from various perspectives, with corresponding prompts detailed in Table 12. Figure 8 showcases further examples of different tasks, with prompts for each task provided in Table 13. Detailed evaluation metrics for these tasks are reported in Table 11. Ground-truth labels for all tasks were subjected to human evaluation, following the guidelines illustrated in Figure 9. We calculated Krippendorff's Alpha (IRA) and retained only annotations with scores exceeding 0.7. Additionally, for each task, we required a Pearson correlation coefficient greater than 0.9 between GPT-4o's predictions and human judgments. The influence of different dataset sizes in heuristic active learning and the effect of different difficulty levels across tasks are presented in Fig. 5 and Fig. 6, respectively, with results for other perspectives showing similar trends.

| Task | Predicted Answer | Ground Truth | Score | Criteria |
|----------------|------------------------------------|--------------|---------------|---|
| Discrimination | A | A | 1 | Same as the ground truth |
| | В | A | 0 | Different from the ground truth |
| Selection | A | A | 1 | Same as the ground truth |
| | B; C | A | 0 | Different from the ground truth |
| Rank | ABCD | ABCD | 1 | Only one combination with all 4 letters matching the relative positions in the ground truth |
| | ABDC; BACD; | ABCD | 0.86 | Only two combinations with 3 letters matching the relative positions in the ground truth |
| | ACBD; ACDB; ADBC; BCDA; CABD; DABC | ABCD | 0.71 | Only one combination with 3 letters matching the relative positions in the ground truth |
| | BCAD | ABCD | 0.57 | Four combinations with 2 letters matching the relative positions in the ground truth |
| | BADC; BDAC; CADB; CBAD | ABCD | 0.43 | Three combinations with 2 letters matching the relative positions in the ground truth |
| | ADCB; BDCA; CBDA; CDAB; DACB; DBAC | ABCD | 0.29 | Two combinations with 2 letters matching the relative positions in the ground truth |
| | CDBA; DBCA; DCAB | ABCD | 0.14 | One combination with 2 letters matching the relative positions in the ground truth |
| | DCBA | ABCD | 0 | No combinations matching the relative positions in the ground truth |
| Generation | [TEXT] | [TEXT] | 1, 2, 3, 4, 5 | appealing level of predicted answer |

Table 11. Evaluation metrics for the four tasks based on AppealImage.

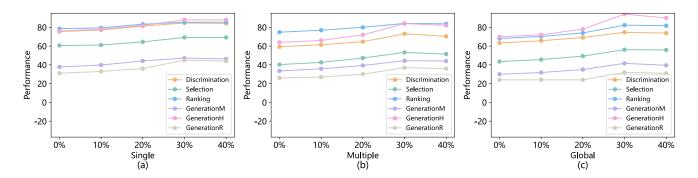


Figure 5. Effect of difficult data proportion in heuristic active learning across single-object, multi-object, and global perspectives. GenerationM, GenerationR, and GenerationH represent machine scores (e.g., BLEU, ROUGE, CIDEr, METEOR), referee scores, and human scores, respectively.

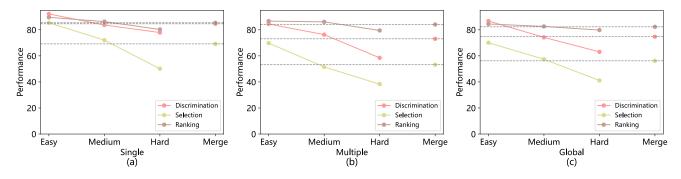


Figure 6. Performance on tasks across varying difficulty levels from single-object, multi-object, and global perspectives. GenerationM, GenerationR, and GenerationH represent machine scores (e.g., BLEU, ROUGE, CIDEr, METEOR), referee scores, and human scores, respectively.

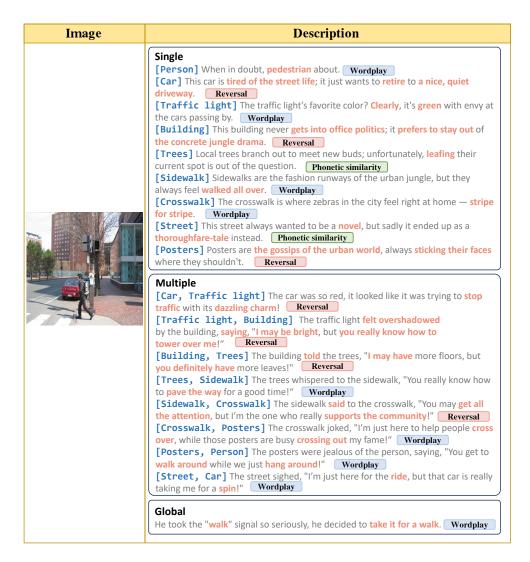


Figure 7. A sample from AppealImage with complete object descriptions.



Figure 8. Four tasks applied to a sample from AppealImage across single-object, multi-object, and global perspectives.

| Single object | Generate humorous and creative sentences for the given image using one of the following techniques: 1. Wordplay - Utilizing puns or idiomatic expressions to create a clever and amusing sentence, e.g. "I'm on a seafood diet. I see food and I eat it!" 2. Phonetic similarity - Employing words that sound alike to generate a humorous twist, e.g. "I'm feeling grape!" 3. Reversal - Using literary techniques such as unexpected contrasts, irony, personification, or hyperbole to enhance the humor, e.g. "I'm not a complete idiot. Some parts are missing. Here is a list of objects (including human) in the given image. List of objects: [object list] Provide an interesting sentence for each object by strictly follow the template. Each object should be mentioned once, so there should be [number] sentences in total. Be careful and only use the object name in the list. The sentence should only focus on the object and shouldn't mention other objects. You should only consider object from the list. - object: sentence | |
|-----------------|--|--|
| Multiple object | Generate humorous and creative sentences for the given image using one of the following techniques: 1. Wordplay - Utilizing puns or idiomatic expressions to create a clever and amusing sentence, e.g. "I'm on a seafood diet. I see food and I eat it!" 2. Phonetic similarity - Employing words that sound alike to generate a humorous twist, e.g. "I'm feeling grape!" 3. Reversal - Using literary techniques such as unexpected contrasts, irony, personification, or hyperbole to enhance the humor, e.g. "I'm not a complete idiot. Some parts are missing." Here is a list of objects (including human) in the given image. List of objects: [object list] Provide an interesting sentence for each object by strictly follow the template and don't use any other notations. Each object should be mentioned as the main object at least once, so there should be [number] sentences in total. In the sentence of each object, also mention another object in the list to increase the humor. Here is a template example for two sentences: - main object - other objects - sentence | |
| | - main object - other objects - sentence | |
| Global object | Generate one humorous and creative sentence for the given image using one of the following techniques: 1. Wordplay - Utilizing puns or idiomatic expressions to create a clever and amusing sentence, e.g. "I'm on a seafood diet. I see food and I eat it!" 2. Phonetic similarity - Employing words that sound alike to generate a humorous twist, e.g. "I'm feeling grape!" 3. Reversal - Using literary techniques such as unexpected contrasts, irony, personification, or hyperbole to enhance the humor, e.g. "I'm not a complete idiot. Some parts are missing." | |
| Extract object | Extract the objects from the image by strictly follow the template. The name of object should less than three words. - object1 - object2 | |

Table 12. Instructions for generating appealing descriptions and extracting objects from images.

| Discrimination | Identify which of the two descriptions, one highly appealing and one normal, is more appealing from single-object, multiple-object, and global perspectives, respectively. "Single-object" refers to a description focused on a specific object in the image, "multiple-object" refers to a description involving the interaction between the specific object and other objects in the image, and "global" refers to a description of the entire image as a whole. | |
|----------------|---|--|
| Selection | Choose the most appealing description from three options: one highly appealing and two low appealing, from single-object, multiple-object, and global perspectives, respectively. "Single-object" refers to a description focused on a specific object in the image, "multiple-object" refers to a description involving the interaction between the specific object and other objects in the image, and "global" refers to a description of the entire image as a whole. | |
| Rank | Rank four descriptions from most to least appealing based on their level of appeal from single-object, multiple-object, and global perspectives, respectively. "Single-object" refers to a description focused on a specific object in the image, "multiple-object" refers to a description involving the interaction between the specific object and other objects in the image, and "global" refers to a description of the entire image as a whole. | |
| Generation | Generate a highly appealing description from single-object, multiple-object, and global perspectives, respectively. "Single-object" refers to a description focused on a specific object in the image, "multiple-object" refers to a description involving the interaction between the specific object and other objects in the image, and "global" refers to a description of the entire image as a whole. | |

Table 13. Task design instructions for the four tasks based on AppealImage.



User Questionaire:

Discrimination Task

Users are asked to choose the appealing description between two options. The descriptions will be provided in three contexts: "Single" refers to a description focused on a specific object in the image, "Multiple" refers to a description involving the interaction between the specific object and other objects in the image, and "Global" refers to a description of the entire image as a whole.

Image: [Insert Image]

Description A: [Insert Description A]
Description B: [Insert Description B]
Question: Which description is appealing?

Options: A / B

Selection Task

Users choose the most appealing description from three options. The descriptions will be provided in three contexts: "Single" refers to a description focused on a specific object in the image, "Multiple" refers to a description involving the interaction between the specific object and other objects in the image, and "Global" refers to a description of the entire image as a whole.

Image: [Insert Image]

Option A: [Insert Description A]
Option B: [Insert Description B]
Option C: [Insert Description C]

Question: Which description is the most appealing?

Options: A / B / C

Ranking Task

Users rank four descriptions by their engagement level. The descriptions will be provided in three contexts: "Single" refers to a description focused on a specific object in the image, "Multiple" refers to a description involving the interaction between the specific object and other objects in the image, and "Global" refers to a description of the entire image as a whole.

Image: [Insert Image]

Description A: [Insert Description A]
Description B: [Insert Description B]

Description C: [Insert Description C]
Description D: [Insert Description D]

Question: Please rank the following four descriptions by engagement level (from most appealing to least appealing).

Ranking: ABCD/.../ACBD

Generation Task

Users rate the generated descriptions on a scale from 1 to 5, where 1 means the worst and 5 means the best. We anonymize the model name. The descriptions will be provided in three contexts: "Single" refers to a description focused on a specific object in the image, "Multiple" refers to a description involving the interaction between the specific object and other objects in the image, and "Global" refers to a description of the entire image as a whole.

Image: [Insert Image]

Description: [Insert Generated Description]

Question: Please rate the following description, with 1 being the worst and 5 being the best.

Scoring Criteria: 1/2/3/4/5

Figure 9. User evaluation questionnaire for assessing options in discrimination, selection, and ranking tasks, as well as predictions in the generation task.

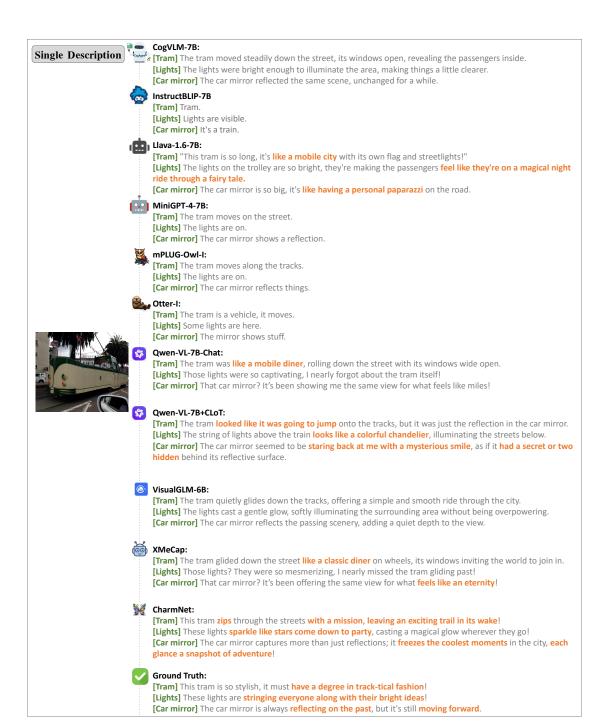


Figure 10. Descriptions of a given ordinary image from other MLLMs in the single-object perspective.

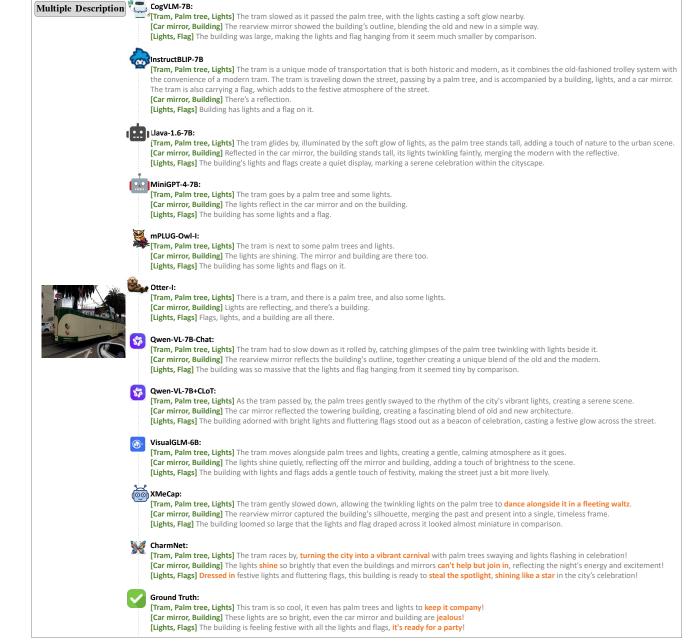


Figure 11. Descriptions of a given ordinary image from other MLLMs in the multi-object perspective.

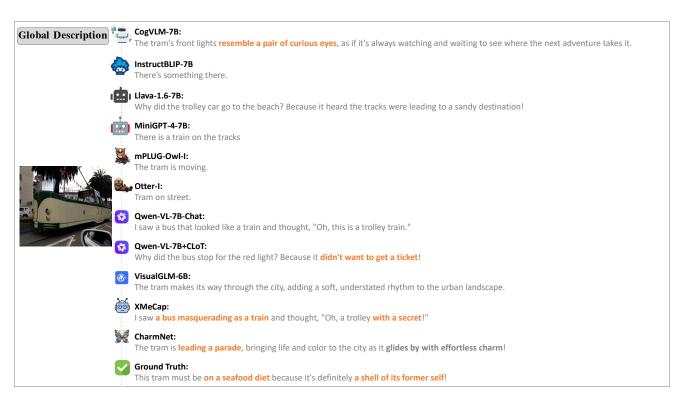


Figure 12. Descriptions of a given ordinary image from other MLLMs in the global perspective.