M2BIT: A Multi-Modal Bilingual Instruction Tuning Dataset for Visual Language Models

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Abstract

In this paper, we introduce the Multi-Modal Bilingual Instruction Tuning dataset (M2BIT), specifically designed to enhance the performance of vision language models (VLMs). Our M2BIT dataset is one of the largest multi-modal instruction tuning datasets available, covering 40 diverse vision-language tasks in both English and Chinese. It comprises 2 million instances, each accompanied by 400 manually written task instructions. With a carefully curated annotation process, we strive to elevate the quality of response, thereby enriching the user experience while minimizing the generation of potential hallucinations. To validate the efficacy of M2BIT, we train a VLM known as Ying-VLM using this dataset, delving into the impact of instruction tuning across diverse languages and modalities. Upon comparing it with strong VLM baselines, Ying-VLM demonstrates superior performance on complex knowledge vision question answering tasks. Moreover, it exhibits a lower propensity for hallucination, displays greater generalization capabilities to previously unseen video tasks, and better comprehends novel instructions in Chinese. We will open-source the M2BIT dataset and trained models to facilitate future research.

1 Introduction

Following the substantial success of ChatGPT (OpenAI, 2022), the interest in designing a versatile intelligent assistant that can understand and interact with the multi-modal world has surged. The potential of transforming Large Language Models (LLMs) into powerful Vision Language Models (VLMs) has been demonstrated by further training on image-text pairs or implementing specialized visual instruction tuning (Zhu et al., 2023; Liu et al., 2023b). This enhancement allows LLMs to *see* the world, offering promising capabilities that could significantly assist individuals with disabilities (OpenAI, 2023).

Dataset	Tasks	LAN	Samples	Ins. / Task
MiniGPT4	N / A	En	5K	N / A
LLaVA	3	En	158K	N / A
MultiModalGPT	3	En	6K	5
MultiInstruct	26	En	235K	5
InstructBLIP	28	En	1.6M	9.7
M2BIT (Ours)	40	En, Zh	2M	10

Table 1: Comparison of different multi-modal instruction tuning datasets. Ins. denotes Task Instruction and N / A means instructions are artificially generated. Our M2BIT is one of the largest datasets, covering 40 tasks in English and Chinese.

The quality of the visual instruction tuning dataset is pivotal in the development of VLMs, as indicated by findings in LLMs (Zhou et al., 2023). Recent research efforts in this area can be broadly grouped into two categories. The first stream of research strives to augment existing academic vision-language (V+L) datasets with manually written task instructions (Xu et al., 2022; Dai et al., 2023). Although VLMs trained on these datasets exhibit notable performance on academic benchmarks, they often generate responses that are excessively terse and blunt (Chen et al., 2023a). This brevity, a typical characteristic of academic datasets, compromises the user experience during interactions. The second stream of research employs image annotation tools to generate textual descriptions of original images, subsequently leveraging models like ChatGPT/GPT-4 to create dialog-style instruction tuning datasets (Zhu et al., 2023; Liu et al., 2023b; Zhao et al., 2023a). However, a pitfall of training VLMs with these pseudo-grounded dialogs is the risk of exacerbating LLMs' hallucination problem, possibly resulting in inconsistent image descriptions featuring non-existent objects. Besides, current studies mainly focus on English tasks, which limits the investigation of the cross-lingual effects of instruction tuning.

In this paper, we introduce M2BIT, a **M**ulti-

 # List|String]: the base64 string representation of a profile photo of F. Scott Fitzgerald
Images: ["iVBORw0KGg...5ErkJggg=="]

 # String: task instruction
Instruction: "Analyze the image and provide an appropriate response to the question. "
 # String: task-specific inputs, e.g., a question related to the image.
Inputs: "On which book by this man, Baz luhrmann's planned a film?"
 # String: task outputs, e.g., the correct answer for the question.
Outputs: "Baz Luhrmann has planned a film adaptation of the book The Great Gatsby. "
 # Dictionary: a meta information dictionary contains original data.
Meta Data: {"original_answer" : "The Great Gatsby", ... ,"wikipedia_id": "152171"}

Figure 1: The unified data format schema of our M2BIT.

Modal **B**ilingual **I**nstruction **T**uning dataset, which leverages valuable academic benchmarks and the capabilities of ChatGPT for dialog style enhancement. M2BIT is meticulously constructed in three stages: (1) Task Selection and Manual Instruction Writing: Our dataset consists of diverse tasks, including traditional image-text tasks like visual question answering and image captioning, as well as video-related tasks such as video question answering. Annotators are instructed to review the dataset paper thoroughly and craft 10 unique instructions for each task. We further incorporate Chinese vision-language datasets with corresponding Chinese instructions, resulting in a comprehensive compilation of 40 diverse tasks and 400 instructions. (2) Data Format Unification: We ensure that all tasks within our dataset adhere to a unified vision-to-text format. This format comprises four fields: *images*, *instruction*, *inputs* and *outputs*. Additional information, such as bounding box details, is embedded within the images, and short answers are rephrased using ChatGPT while incorporating contextual information, where available. (3) Quality Check: For quality control, we assign an extra annotator to each task to review 20 examples from each split of every dataset. A task is considered complete only after the annotator has verified the accuracy and consistency of the images, instructions, inputs, and outputs for each instance. As demonstrated in Table 1, M2BIT is one of the largest multi-modal instruction tuning datasets regarding the number of instructions and samples, covering diverse tasks in English and Chinese.

To substantiate the effectiveness of the M2BIT dataset, we develop Ying-VLM, merging the capabilities of a vision encoder, BLIP-2 (Li et al., 2023a), with Ziya-13B (Zhang et al., 2022), which is a derivative of LLaMA (Touvron et al., 2023a). We leverage the proven methodology of incorporating visual tokens as prefix prompts in LLMs and utilize a two-stage training regime. The initial stage aligns vision features with text embeddings via image captioning on LAION-400M (Schuhmann et al., 2021), while the second stage enhances the model by performing instruction tuning on M2BIT.

Our evaluation of the instruction tuning effect with M2BIT is threefold. Firstly, we evaluate Ying-VLM on knowledgeable VQA (KVQA) tasks, including OK-VQA, A-OKVQA, and a held-out dataset, ViQuAE. These tasks, which demand VLM's comprehension of image context and reasoning with the knowledge acquired by LLMs, have gained wide recognition as benchmarks for evaluating VLMs (Dai et al., 2023; Bai et al., 2023b). Secondly, we conduct a hallucination evaluation on image captioning, following the methodology by Li et al. (2023b). Lastly, we perform zero-shot transfer evaluations on Chinese V+L tasks and video-language tasks to scrutinize the cross-language/modal effect of instruction tuning. The experimental results highlight that Ying-VLM surpasses potent baseline VLMs in KVQA tasks, is less susceptible to hallucination than models trained with generated pseudo-grounded dialogs, and demonstrates enhanced generalization capabilities when confronted with unseen video and cross-lingual tasks. These results underscore the potential of our proposed M2BIT dataset in constructing robust VLMs and investigating instruction tuning effects across languages and modalities.

2 M2BIT: A Multi-Modal Bilingual Instruction Tuning Dataset

In this section, we introduce the M2BIT dataset by first elaborating the task coverage (§ 2.1), followed by the annotation process details (§ 2.2). In § 2.3, we present the dataset format and the statistics of the crafted dataset instructions.

2.1 Task Coverage

Our dataset makes a wide coverage of the current existing visual-language and video-language benchmarks, from simple image captioning to complicated reasoning based on the image even beyond the visual content:

Captioning This task aims to produce descrip-

tions of the given images according to different needs. We include MS COCO (Lin et al., 2014) (the Karpathy split) for generic image descriptions. TextCaps (Sidorov et al., 2020) requires models to capture the text presented in the image and generate captions accordingly. Image-Paragraph-Captioning (Krause et al., 2017) focuses on generating detailed descriptions for images.

Reasoning This task evaluates specific reasoning capabilities. We incorporate CLEVR (Johnson et al., 2017) and NLVR (Suhr et al., 2017) for spatial reasoning, Visual Commonsense Reasoning (VCR) (Zellers et al., 2019) for commonsense reasoning, Visual MRC (Tanaka et al., 2021) for reading comprehensive over images, and Winoground (Thrush et al., 2022) for fine-grained semantics reasoning over text descriptions and image contents.

Visual Question Answering (VQA) This is the most widely studied multi-modal task, which requires the model to answer a given question based on the image correctly. Tasks include VQA v2 (Goyal et al., 2017b), Shapes VQA (Andreas et al., 2016), DocVQA (Mathew et al., 2021), OCR-VQA (Mishra et al., 2019), ST-VQA (Biten et al., 2019), Text-VQA (Singh et al., 2019), and GQA (Hudson and Manning, 2019).

Knowledgeable Visual Question Answering (KVQA) Unlike traditional VQA tasks focusing on the question relevant to the content image, KVQA requires the model to draw upon outside knowledge to answer questions. We incorporate two outside knowledge VQA datasets: OK-VQA (Marino et al., 2019) and A-OK-VQA (Schwenk et al., 2022), ScienceQA (Lu et al., 2022) which contains multi-modal science questions, and ViQuAE (Lerner et al., 2022) focusing on knowledge facts of named entities in images.

Classification This task involves classifying an image based on a given set of candidate labels. ImageNet (Russakovsky et al., 2015), Grounded Object Identification (COCO-GOI) (Lin et al., 2014), COCO-Text (Veit et al., 2016), Image Text Matching (COCO-ITM) (Lin et al., 2014), e-SNLI-VE (Kayser et al., 2021), Multi-modal Fact Checking (Mocheg) (Yao et al., 2022), and IQA (Duanmu et al., 2021) are included. Due to language model input length constraints, we reduce the number of options in some datasets with extensive candidate labels, such as ImageNet.

Generation Visual conditional generation requires models to understand the visual content and make a composition meeting the task demand. We have Visual Storytelling (VIST) (Huang et al., 2016), Visual Dialog (VisDial) (Das et al., 2017), and multi-modal machine translation Multi30k (Elliott et al., 2016) in this category.

Number of different instructions	400
- Image Captioning	52
- Classification	113
- Visual Question Answering	95
- Knowledgeable Visual QA	40
- Reasoning	60
- Generation	40
Tokens per instruction	24.4 ± 9.6
Instruction edit distance among the same task	76.6 ± 37.2
Instruction edit distance across tasks	106.6 ± 39.5

Table 2: The statistics of our instructions.

Chinese Vision-Language Tasks To examine the effect of instruction tuning on different languages, we incorporate several Chinese vision-language tasks including FM-IQA (Gao et al., 2015) for VQA, COCO-CN (Li et al., 2019) and Flickr8k-CN (Li et al., 2016) for captioning, Chinese Food Net (Chen et al., 2017) for classification, and MM-Chat (Zheng et al., 2022) for generation.

Video-Language Tasks Beyond the static images, we are interested in whether instruction tuning can be applied to video-language tasks. We include the classic MSR-VTT datasets (Xu et al., 2016) for video captioning, MSRVTT-QA (Xu et al., 2017), ActivityNet-QA (Yu et al., 2019), iVQA (Yang et al., 2021) and MSVD-QA (Xu et al., 2017) for video question answering, Something-Something (Goyal et al., 2017a) for video action classification.

2.2 Annotation Process

To build high-quality multi-modal instruction datasets, we rewrite various datasets into a vision-to-text format. The annotation process includes three steps: (1) writing instructions for each task, (2) structuring images and texts into a unified schema, and (3) checking the overall dataset quality. Eight authors of this work are employed as human annotators, each of whom is a graduate student familiar with relevant literature.

Stage I: Instruction Writing To build high-quality instructions, we first ask annotators to carefully read the dataset paper and check the original dataset with some instances to get a clear understanding of the task. After that, they are required to write 10 diverse task instructions manually, covering the

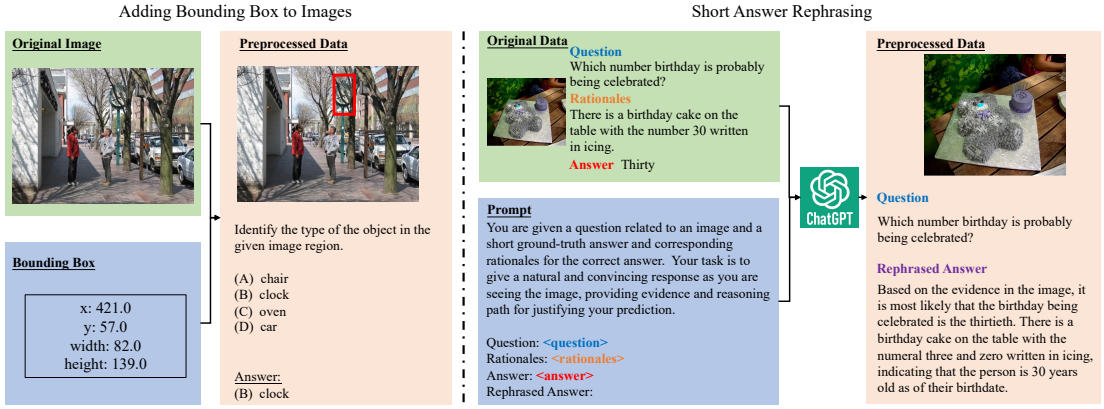

Figure 2: (Left) On region-based tasks, bounding boxes are added to serve as a visual referring prompt. (Right) Short answer rephrasing to improve the response quality, e.g., incorporating rationales into answers.

key characteristics of the task. Table 2 shows the statistics of the written instructions for each task and Figure 7 in the Appendix visualizes the instruction verb distribution. In total, we annotate 400 instructions for all tasks. The average length per instruction is 24.4. To evaluate the diversity of annotated instructions, we employ the average edit distance to measure the similarity between two strings. The average edit distance within the same task is 76.6, indicating a good range of instruction diversity.

Stage II: Data Format Unification After the instruction has been written according to the task characteristics, we further process the images and corresponding text for a unified instance schema. For most datasets, we keep the original images and text, where images are converted into corresponding base64 encoded strings for easy data loading. We perform two modifications on potential examples: (1) **Adding Bounding Box to Images.** For tasks designed for specific regions in the image, a straightforward solution is to provide the bounding box information in natural language for informing the language models of the regions in interest. However, the image pre-processing techniques adopted by different vision encoders may resize the original image, and the original bounding box annotation thus needs further adjustments. Inspired by the recent observation that vision encoders such as CLIP (Radford et al., 2021) are sensitive to the visual prompt (Shtedritski et al., 2023), we directly tag the bounding box as a red rectangle to the image, serving as a visual referring prompting (OpenAI, 2023) for VLMs to focus on the target region. (2) **Short Answer Rephrasing.** As recent studies have shown that the original short and brief answers

Task	Description	Total #samples Train	Val	Test
CAP	Given an image, write a description for the image.	679,087	41,462	27,499
CLS	Given an image, classify the image into pre-defined categories.	238,303	100,069	21,206
VQA	Given an image, answer a question relevant to the image.	177,633	46,314	10,828
KVQA	Given an image, answer the question requires outside knowledge.	39,981	11,682	5,477
REA	Given an image, conduct reasoning over the images.	99,372	11,500	10,000
GEN	Given an image, make compositions with certain requirements.	145,000	11,315	17,350
Chinese	CAP, CLS, VQA, and GEN tasks in Chinese.	192,076	77,306	4,100
Video	CAP, CLS, and VQA tasks on video-language datasets.	20,868	7,542	9,294
Total	2,005,264			

Table 3: M2BIT task descriptions and statistics. We aggregate instance counts for training, validation, and test sets across all tasks, totaling 2M instances.

in the common VQA dataset could negatively influence the model generation performance (Dai et al., 2023; Chen et al., 2023b), we propose to utilize the ChatGPT (`gpt-3.5-turbo-0301`) (OpenAI, 2022) model for rephrasing the original answers, by providing origin question and answer with potential extra contextual information. Contextual information includes the caption of the original images, rationales for specific VQA tasks and OCR tokens for the scene-related question, which make the rephrased answers more engaging and informative. The original short answers are also kept in our dataset for potential usage. Figure 2 shows these two modifications.

Stage III: Quality Check In this stage, we assign a different annotator to each task to review 20 examples from each split of every dataset. During this stage, we identify minor format inconsistencies between tasks and address them by standardizing the task formats. We observe that answer rephrasing greatly improves the response quality, e.g., more than 95% instances we checked are perceived as better than original concise answers, while ChatGPT refused to rephrase a few answers (less than 3% of examined instances) due to insufficient image information. We employ simple heuristics to

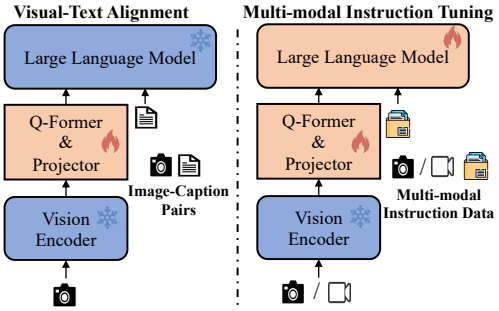

Figure 3: The overview of Ying-VLM model architecture and training stages.

filter these failed answers and use a basic template to convert the original answer into a sentence, with manual validation to ensure the quality. Finally, the task dataset is deemed complete once the annotator can successfully load it and re-examine the accuracy of the instructions, inputs, and outputs for each instance examined.

2.3 Dataset Format and Statistics

The instance in our dataset consists of five fields: (1) **Images**: we represent the images with the potentially added bounding box by a base64 string. (2) **Instruction**: we randomly select an instruction from the task instruction pool for each instance. (3) **Inputs**: we allocate this field for providing task-specific inputs to the model, e.g., the question in the VQA tasks. For tasks such as captioning, there is no extra input so the corresponding field is left as an empty string. (4) **Outputs**: the required output to the specific tasks, such as the description of the image for captioning tasks and the answer to the image-related question. (5) **Meta Data**: we provide this field to preserve important information such as image ID for referencing the original dataset. With the clear distinction of these fields, the user of our benchmark can construct the training instances needed flexibly and evaluate the models conveniently. Table 3 gives the statistics aggregated by tasks and Figure 1 illustrates a case in M2BIT. For the detailed statistics, and the license of each dataset in M2BIT, we refer readers to Appendix B.

3 Experiments

We first introduce the experimental setups (§ 3.1), then report and discuss the evaluation results (§ 3.2). Lastly, we analyze instruction robustness and provide a case study (§ 4).

3.1 Experimental Settings

3.1.1 Implementation Details

Model Architecture: Inspired by the recent success of BLIP-2 (Li et al., 2023a), we adopt the vision encoder and the Q-former architecture in the BLIP2-OPT-2.7B (Li et al., 2023a) model to extract relevant visual features from images. For the large language models, we utilize Ziya-13B (Zhang et al., 2022) derived from LLaMA (Touvron et al., 2023a) with bilingual (English and Chinese) ability.

Training Datasets: We employ a two-staged training consisting of a visual-text alignment stage (Stage I) and a multi-modal instruction tuning stage (Stage II). Stage I aims to align the visual and textual feature space, where we utilize the instructions in the coco captioning and perform an initial alignment training on LAION 400M (Schuhmann et al., 2021). In Stage II, we adopt our M2BIT dataset for training the model, excluding ViQuAE for KVQA evaluation, Winogound as it only has a test set, and all Chinese V+L and video-language datasets for cross-lingual/modality effect investigation. Details of Stage II training datasets are in Figure 8 and Figure 3 provides an overview of the model and training stages.

Hyper-parameter Settings In Stage I, we only train the Q-Former and the language projection for modality alignment, resulting in a total 130M parameters to optimize with AdamW (Loshchilov and Hutter, 2019). The batch size is set to 256 to maximize the utilization of GPU and the model is trained with 300k steps. The learning rate linearly increases to a peak value of $5e$-5 in the first 2000 steps and follows a cosine decay scheduler. The weight decay is set to 0.05. We train the model after Stage I for 3 epochs and with a lower learning rate of $1e$-5 and a warmup stage of 1000 steps. Inspired by LoRa tuning (Hu et al., 2022), the weights for mapping query and value vectors in the attention layer of LLMs are learnable in this stage to better adapt to the instruction tuning dataset. Other training parameters are consistent with Stage I. All experiments are conducted with 8 NVIDIA 80GB A100 GPUs. It took about 10 days for Stage I and Stage II can be finished in a day.

3.1.2 Evaluation Setup

Evaluated Tasks We conduct three evaluations to understand the instruction tuning effect comprehensively with our M2BIT: (1) Evaluation of KVQA tasks, which includes OK-VQA, A-OKVQA and a

Model	OK-VQA	A-OKVQA	ViQuAE
BLIP2-Flan-T5-XXL	9.1	15.6	9.7
MiniGPT4	23.3	21.8	24.4
InstructBLIP	7.1	5.9	7.3
Ying-VLM$_{\text{LLaVA}}$	26.4	22.5	24.3
Ying-VLM	**27.5**	**24.5**	**29.6**

Table 4: ROUGE-L evaluation results of KVQA tasks.

Model	Len	CHAIR$_I$(↓)	CHAIR$_S$(↓)	Avg. (↓)
mPLUG-Owl*	98.5	30.2	76.8	53.5
LLaVA*	90.7	18.8	62.7	40.8
MiniGPT-4*	116.2	9.2	31.5	20.4
InstructBLIP*	7.5	**2.5**	**3.4**	**3.0**
Ying-VLM$_{\text{LLaVA}}$	62.7	**11.0**	36.0	23.5
Ying-VLM	34.2	12.6	**16.8**	**14.7**

Table 5: Object hallucination evaluation with instruction "*Provide a brief description of the given image*". Len denotes the average length of generated captions. * denotes results collected from Li et al. (2023b).

Model	Flickr-8k-CN	FM-IQA	Chinese-FoodNet
MiniGPT4	9.6	20.1	5.0
InstructBLIP	5.2	2.3	1.0
Ying-VLM	**20.5**	33.3	**49.8**
Ying-VLM$_{\text{zh}}$	20.0	**39.8**	0.1

Table 6: Results Chinese vision-language tasks. Our model generalizes well on unseen Chinese captioning, VQA and classification tasks.

held-out dataset ViQuAE. These tasks are widely adopted in evaluation for VLMs (Dai et al., 2023; Bai et al., 2023b) as they pose a great challenge for VLMs to understand the image context and perform reasoning with the knowledge acquired by LLMs. (2) Evaluation of object hallucination, which refers to a phenomenon that the model produces image descriptions that contain objects that are not anchored with or even absent from the target image. We follow the exact setup in Li et al. (2023b) to perform hallucination analysis on 2,000 images randomly sampled from the MSCOCO dataset (Lin et al., 2014). (3) Evaluation of cross-language/modality transferability. We hold out all Chinese V+L tasks and video-language tasks during the instruction tuning stage, then perform a zero-shot transfer to investigate whether instruction tuning is generalizable across languages, i.e., English to Chinese, and modalities, i.e., images to videos. For a comprehensive evaluation, we also present the results on the generation performance on Visual-Dialog and image classification on ImageNet in Appendix D. In all experiments, we use greedy decoding in inference for deterministic results.

Metrics We adopt ROUGE-L (Lin, 2004) as an automatic metric to assess the consistency between predictions and ground-truth answers, focusing on evaluating the model's conversational abilities. As the automatic metric may not fully capture the nuances of conversational quality, we further introduce GPT-4 as a proxy of human evaluators (§ 4). For the object hallucination, we follow Li et al. (2023b) to adopt CHAIR$_I$ and CHAIR$_S$ (Rohrbach et al., 2018). CHAIR$_I$ denotes the proportion of hallucinated ones in all generated objects, while CHAIR$_S$ describes the hallucination at the sentence level, i.e., the proportion of generated captions that contain hallucinated objects. Appendix H provides a detailed definition for these two metrics.

Baselines We employ open-sourced VLMs as the off-the-shelf models for comparison, using the original model weights and greedy decoding: (1) BLIP-2-Flan-T5-XXL (Li et al., 2023a) where an instruction-tuned Flan-T5 (Wei et al., 2022) is connected with a powerful vision encoder to perform a series of multi-modal tasks;[1] (2) MiniGPT-4 which aligns a CLIP visual encoder with a frozen Vicuna-13B (Chiang et al., 2023) with artificially collected dialog dataset;[2] (3) InstructBLIP, an instruction tuning enhanced VLM with Vicuna-13B with converted multi-model datasets and the LLaVA (Liu et al., 2023b) dataset generated by text-only GPT-4.[3] We refer readers to Appendix E for a detailed introduction for these methods and related work. To isolate the effect of the base LLM, we train a variant of our model, Ying-VLM$_{\text{LLaVA}}$, by only replacing the Stage II training datasets with the LLaVA dataset (Liu et al., 2023b), using the same training setup with Ying-VLM.

3.2 Results

Evaluation of Knowledgeable VQA The results on the KVQA benchmarks are shown in Table 4. In comparison to the strongest baseline, our model achieves an improvement of 1.1 and 2.0 ROUGE-L points for OK-VQA and A-OKVQA, respectively. Additionally, Ying-VLM delivers the best performance on the held-out ViQuAE dataset. These findings indicate that instruction tuning on M2BIT

[1] https://huggingface.co/Salesforce/blip2-flan-t5-xxl

[2] https://github.com/Vision-CAIR/MiniGPT-4

[3] https://huggingface.co/Salesforce/instructblip-vicuna-13b

effectively harnesses knowledge from LLMs and elevates response quality.

Evaluation of Object Hallucination As shown in Table 5, the VLMs trained on instruction tuning datasets generated by ChatGPT/GPT-4 exhibit serious hallucination problems, as indicated by the relatively high average CHAIR of LLaVA and MiniGPT-4. InstructBLIP performs the best on this evaluation. However, it should be noted that the too-short answers provided by InstructBLIP may result in a lack of politeness in responses, which can harm the user experience. This was validated in the later evaluation with GPT-4. When comparing Ying-VLM$_{\text{LLaVA}}$ to Ying-VLM, it can be observed that Ying-VLM achieves a much lower CHAIR$_{\text{S}}$ score (16.8 v.s. 36.0), demonstrating that it suffers significantly less from the sentence-level hallucination issue. These results suggest that M2BIT could help VLMs to achieve a better balance between the hallucination problem and response quality.

Cross-Language Transferability We assess models on three unseen Chinese vision-language tasks to investigate the cross-language generalization effect of instruction tuning. BLIP-2 and Flan-T5 are not considered here as they do not support Chinese outputs.[4] As illustrated in Table 6, our model performs well on all evaluated tasks compared with MiniGPT4 and InstructBLIP. While the gain can be attributed to the Chinese ability of the underlying Ziya-13B LLM, it promisingly indicates that instruction tuning with English datasets can effectively generalize to different languages. Further, we perform continual training on Chinese V+L tasks, resulting in YingVLM$_{\text{zh}}$. As shown in the last row of Table 6, the scores of FM-IQA can be further enhanced. However, the model suffers from catastrophic forgetting as there are no classification tasks in the continual training, resulting in poor performance on the Chinese-FoodNet. An in-depth investigation for this problem could be promising (Zhai et al., 2023).

Cross-Modality Transferability To evaluate performance on video-language tasks, we uniformly sample 8 frames from each video. MiniGPT4 is excluded as it does not support video inputs. Following InstructBLIP (Dai et al., 2023), we concatenate the visual embedding extracted from the Q-former of each frame as a prefix embedding to the language model. As demonstrated in Table 7, our model excels in these challenging settings, significantly surpassing the BLIP-series baselines. It is worth noting that the training dataset does not include any videos inputs, implying that our instruction tuning effectively aids the model in generalizing to inputs with a temporal dimension. Furthermore, we train YingVLM on the video-language datasets in M2BIT. The resulting YingVLM$_{\text{video}}$ achieves the best performance on all tasks, suggesting the effectiveness of video instruction tuning in boosting the video understanding abilities of VLMs.

[4]For all models, we introduce a prompt to promote Chinese outputs. See Appendix F for details.

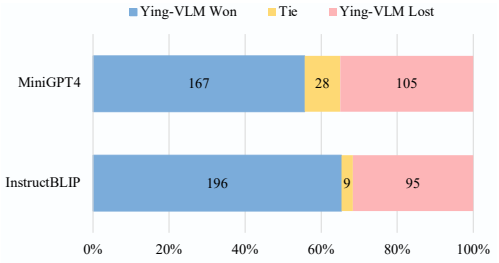

Figure 4: Evaluation results using GPT-4 as an evaluator. Our model outperforms MiniGPT-4 and InstructBLIP with a winning rate at 55.6% and 65.5%, respectively.

4 Analysis

Evaluation with GPT-4 To further validate the quality of the generated response, we propose to utilize GPT-4 as a proxy of human evaluators (Peng et al., 2023; Gilardi et al., 2023). Specifically, following Vicuna (Chiang et al., 2023), we query GPT-4 to rate the performance of different models against our Ying-VLM. For each sample, we construct a prompt consisting of the original question, its corresponding reference answer, the response generated by our Ying-VLM, and a baseline system output. GPT-4 (`gpt-4-0613`) is asked to rate both responses on a scale of 10 based on the given question and its reference answer. The ratings are primarily based on the accuracy, relevance, and naturalness of the response to meet the requirements when humans are interacting with multi-modal agents (evaluation template is provided in Appendix G). We swap the order of candidate responses to mitigate potential evaluation biases (Wang et al., 2023). Considering the API cost of GPT-4, 300 examples are randomly sampled from OK-VQA, A-OKVQA and ViQuAE datasets as a subset for evaluation. Figure 4 shows that our Ying-VLM outperforms baseline models in most samples. For example, the GPT-4 evaluator favors Ying-VLM over MiniGPT4 on 167 over 300 tested

Model	Video Captioning	Video Question Answering			
	MSRVTT	iVQA	ActivityNet-QA	MSRVTT-QA	MSVD-QA
BLIP-2-Flan-T5-XXL	8.8	11.1	8.9	10.3	13.2
InstructBLIP	14.3	6.3	9.3	4.0	7.0
Ying-VLM	14.2	23.5	21.9	18.3	21.4
Ying-VLM$_{\text{video}}$	**16.1**	**41.3**	**44.8**	**32.0**	**40.5**

Table 7: ROUGE-L results of video-language tasks. YingVLM shows great generalization from images to videos and training on video datasets (YingVLM$_{\text{video}}$) further boosts the performance.

Model	iVQA	ActivityNet-QA	MSRVTT-QA	MSVD-QA
BLIP2-Flan-T5-XXL	25.0	30.0	19.0	32.0
InstructBLIP	35.0	38.0	23.0	47.0
Ying-VLM$_{\text{Video}}$	**40.0**	**40.0**	**40.0**	**58.0**

Table 8: Video QA accuracy using GPT-4 as a judge.

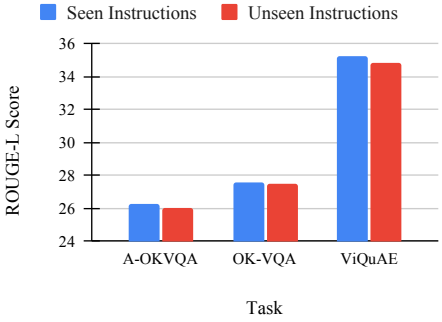

Figure 5: Ying-VLM performs stably on unseen instructions, with an average 0.23 ROUGE-L drop.

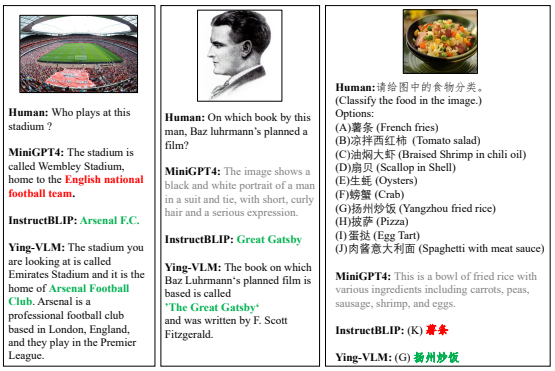

Figure 6: Case study of model outputs: Correct answers in green, wrong answers in red, and non-compliant answers in grey. Ying-VLM accurately responds to entity-centric questions and generalizes to unseen Chinese food classification tasks.

samples, indicating that VLMs tuned on M2BIT can produce more accurate and engaging responses on the challenging KVQA tasks. Similarly, we supplement the video-language evaluation using GPT-4 as a judge to obtain the question-answering accuracy, following the recent practice in VLM evaluation (Yu et al., 2023). Table 8 shows the results on a 100-sample subset of each video-language task. We find that Ying-VLM$_{\text{video}}$ achieves the best performance, confirming the effectiveness of multi-modal instruction tuning.

Robustness on Unseen Instructions We further explore the robustness of models on unseen instructions, where models are trained on 4 randomly selected instructions and evaluated with the left 6 instructions on each task. As shown in Figure 5, the model performs stably on the unseen instructions with a moderate 0.23 ROUGE-L score drop, indicating that it generalizes well on the unseen instructions. Further analysis in Appendix I shows that the instruction diversity also affects the performance, and Ying-VLM shows promising scalability with the increased task number.

Qualitative Results We conduct a case study to provide a more intuitive understanding of instruction-tuned models. The cases are chosen from the held-out ViQuAE and ChineseFoodNet datasets. As shown in Figure 6, Ying-VLM trained with M2BIT provides correct and informative responses to entity-centric questions requiring external world knowledge. In contrast, MiniGPT4 produces an incorrect answer for the stadium question on the left, and InstructBLIP consistently provides concise but less engaging answers. Ying-VLM also generalizes to Chinese inputs, accurately classifying the food image. These cases underscore the importance of instruction tuning dataset quality and validate the value of our M2BIT.

5 Conclusion

In this paper, we introduce M2BIT, a multi-modal bilingual instruction tuning dataset consisting of 2 million instances and 400 task instructions across 40 tasks. We develop Ying-VLM as a proof-of-concept model to demonstrate the effectiveness of our dataset. Extensive results confirm that Ying-VLM excels in KVQA tasks, exhibits reduced hallucination, and demonstrates superior generalization in unseen video and Chinese tasks.

Limitations

Limitations of Dataset Collection The number of Chinese tasks in our M2BIT is limited, as most high-quality multi-modal resources are English only. In the future, we look forward to incorporating more Chinese V+L tasks in our dataset and exploring machine translation techniques to improve the V+L task coverage in Chinese. Besides, our M2BIT focuses on image-to-text and video-to-text tasks, while more modalities, such as audio (Kim et al., 2019; You et al., 2022; Mei et al., 2023), can be considered further.

Limitations of Experimental Exploration In this paper, we curate the M2BIT dataset to provide a resource for developing powerful VLMs and explore the cross-lingual/modality effect of multi-modal instruction tuning. However, there are still under-explored setups worth investigating. Promising avenues include exploring improved methodologies for instruction and task selection by taking the interdependence of different tasks into consideration and exploring the effects of generalization across different languages and modalities. Furthermore, we only adopted the Ziya-13B LLM in our experiments due to its promising bilingual ability. Recently, many powerful foundation LLMs have been released, such as LLaMA-2 (Touvron et al., 2023a) and Baichuan-2 (Baichuan, 2023). It would also be interesting to perform a comprehensive analysis regarding different model families and scales.

Ethic Considerations

In line with established practices in language instruction tuning (Mishra et al., 2022; Longpre et al., 2023), our M2BIT dataset has been carefully curated by gathering and unifying NLP datasets from various sources, including academic papers and projects, making them suitable for research purposes. The licenses for the included tasks can be found in Appendix B. However, it should be noted that there are certain tasks for which the license information is not publicly available. We only release the datasets with clear license information to avoid potential problems.

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A Datasheet for M2BIT

A.1 Motivation

For what purpose was the dataset created? M2BIT is created to facilitate multi-modal multilingual instruction tuning for large language models.

A.2 License

All annotated instructions are licensed under the CC-BY 4.0 license. For the licenses of original datasets, we refer users to Table 9 for more details.

A.3 Maintenance Plan

We commit to continually updating the dataset and rectifying any potential errors. Previous versions of the dataset can still be accessed in the Git history. Users can submit their questions and suggestions in the dataset hub, and we will promptly address their inquiries. We also encourage community contributions to expand the range of datasets by submitting pull requests to the dataset repository.

A.4 Composition

What do the instances that comprise the dataset represent? (e.g., documents, photos, people, countries) Our data is provided in JSON format. Each data instance consists of (1) an instruction prompt, (2) a list of base64 strings representing images (3) a task-specific input, such as the question of the image, (4) a desired output, such as the answer for the image-related question, and (5) a metadata dictionary for referencing the original dataset.

How many instances are there in total (of each type, if appropriate)? The statistics of our dataset can be found in Table 9.

Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? We tried to transform the original whole dataset into a unified schema. However, due to the disk limitation and the cost of paraphrasing short answers, we chose a randomly sampled subset from the original dataset to perform the transformation.

Is there a label or target associated with each instance? Yes, the outputs field serves as the label.

Is any information missing from individual instances? No.

Are relationships between individual instances made explicit (e.g., users' movie ratings, social network links)? N/A.

Are there recommended data splits (e.g., training, development/validation, testing)? Yes. We made the transformation based on the original dataset split.

Are there any errors, sources of noise, or redundancies in the dataset? No.

Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)? Yes.

Does the dataset contain data that might be considered confidential? No.

Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? No.

A.5 Uses

Has the dataset been used for any tasks already? Yes. We have used the M2BIT dataset to train a vision-language model, which demonstrates promising results on knowledgeable VQA tasks and generalizes well to video-language tasks and Chinese vision-language tasks. Please see Section 4 of the main paper for details.

What (other) tasks could the dataset be used for? M2BIT is a useful resource for instruction tuning studies in the multi-modal field. Future studies can utilize M2BIT to investigate the influence of instruction tuning and improve the general performance of vision-language models.

Is there a repository that links to any or all papers or systems that use the dataset? No.

Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? The bounding boxes are added to the image with a red rectangle box to inform the model of regions in interest. For those models with a vision encoder that is not sensitive to these visual prompts, the effect of this operation can be limited. Besides, short answers in some VQA tasks are paraphrased by ChatGPT, which is designed to improve the response quality of the model while potentially impacting the language diversity of the model.

B Dataset Statistics

Table 9 lists the detailed statistics in our benchmark and Figure 1 illustrates the unified schema adopted in our dataset. We collect the dataset license from PaperWithCode.[5] For datasets under Unknown and Custom licenses, we suggest the users check the project page or contact the dataset owner before usage.

[5] https://paperswithcode.com/

Task	Dataset	Used	#samples Train	Val	Test	License
Captioning	MS COCO (Lin et al., 2014)	Yes	566,747	25,010	25,010	Custom
	TextCaps (Sidorov et al., 2020)	Yes	97,765	13,965	0	Unknown
	Image-Paragraph-Captioning (Krause et al., 2017)	Yes	14,575	2,487	2,489	Custom
Classification	COCO-GOI (Lin et al., 2014)	Yes	30,000	2,000	0	Custom
	COCO-Text (Veit et al., 2016)	Yes	118,312	27,550	0	Custom
	ImageNet (Russakovsky et al., 2015)	Yes	30,000	50,000	0	Non-commercial
	COCO-ITM (Lin et al., 2014)	Yes	30,000	5,000	5,000	Custom
	e-SNLI-VE (Kayser et al., 2021)	Yes	20,000	14,339	14,740	Unknown
	Mocheg (Yao et al., 2022)	Yes	4,991	180	466	CC BY 4.0
	IQA (Duanmu et al., 2021)	Yes	5,000	1,000	1,000	Custom
VQA	VQA v2 (Goyal et al., 2017b)	Yes	30,000	30,000	0	CC-BY 4.0
	Shapes VQA (Andreas et al., 2016)	Yes	13,568	1,024	1,024	Unknown
	DocVQA (Mathew et al., 2021)	Yes	39,463	5,349	0	Unknown
	OCR-VQA (Mishra et al., 2019)	Yes	11,414	4,940	0	Unknown
	ST-VQA (Biten et al., 2019)	Yes	26,074	0	4,070	Unknown
	Text-VQA (Singh et al., 2019)	Yes	27,113	0	5,734	CC BY 4.0
	GQA (Hudson and Manning, 2019)	Yes	30,001	5,001	0	CC BY 4.0
KVQA	OK-VQA (Marino et al., 2019)	Yes	9,009	5,046	0	Unknown
	A-OK-VQA (Schwenk et al., 2022)	Yes	17,056	1,145	0	Unknown
	ScienceQA (Lu et al., 2022)	Yes	12,726	4,241	4,241	CC BY-NC-SA
	ViQuAE (Lerner et al., 2022)	No	1,190	1,250	1,236	CC By 4.0
Reasoning	CLEVR (Johnson et al., 2017)	Yes	30,000	2,000	0	CC BY 4.0
	NLVR (Suhr et al., 2017)	Yes	29,372	2,000	0	Unknown
	VCR (Zellers et al., 2019)	Yes	25,000	5,000	5,000	Custom
	VisualMRC (Tanaka et al., 2021)	Yes	15,000	2,500	5,000	Unknown
	Winoground (Thrush et al., 2022)	No	0	0	800	Unknown
Generation	Visual Storytelling (Huang et al., 2016)	Yes	5,000	4,315	4,350	Unknown
	Visual Dialog (Das et al., 2017)	Yes	50,000	1,000	1,000	CC By 4.0
	Multi30k (Elliott et al., 2016)	Yes	90,000	6,000	12,000	Non-commercial
Chinese	FM-IQA (Gao et al., 2015)	No	164,735	75,206	0	Unknown
	COCO-Caption CN (Li et al., 2019)	No	18,341	1,000	1,000	Non-commercial
	Flickr-8k-Caption CN (Li et al., 2016)	No	6,000	1,000	1,000	CC By 3.0
	Chinese Food Classification (Chen et al., 2017)	No	0	0	1,100	Unknown
	Multimodal Chat (Zheng et al., 2022)	No	3,000	1,000	1,000	Unknown
Video	Action-Classification (Goyal et al., 2017a)	No	2,000	2,000	2,000	Custom
	iVQA (Yang et al., 2021)	No	5,994	2,000	2,000	Unknown
	MSVD QA (Xu et al., 2017)	No	1,161	245	504	Unknown
	ActivityNet QA (Yu et al., 2019)	No	3,200	1,800	800	Unknown
	MSRVTT QA (Xu et al., 2017)	No	6,513	497	2,990	Unknown
	MSRVTT Captioning (Xu et al., 2016)	No	2,000	1,000	1,000	Unknown

Table 9: Detailed task descriptions and statistics of our instruction tuning tasks, including all datasets in all types of tasks. The column "Used" indicates whether we use this dataset in the instruction tuning stage.

C Template for Answer Rephrasing

We provide the paraphrase template in Table 10 for querying the ChatGPT to re-write the original short answers, where {Q} and {A} is filled with the question and the answer need to be paraphrased, respectively. We incorporate an example to better inform the model of the paraphrasing tasks. For VQAv2 tasks, we add an extra {Caption} field in the template filled with corresponding captions from the COCO dataset to provide extra context information to help to rephrase. For A-OKVQA tasks, the rationale of each sample is adopted to enrich the final answer.

D Results on Generation and Classification

For a comprehensive evaluation, we incorporate the results on an image-to-text generation task, i.e., Visual-Dialog and an image classification task ImageNet in Table 11. The results indicate that our M2BIT can provide more balanced coverage of different tasks, helping Ying-VLM achieve better overall performance across various types of tasks.

E Related Work

Our work is motivated by the recent progress in developing powerful VLMs based on large language

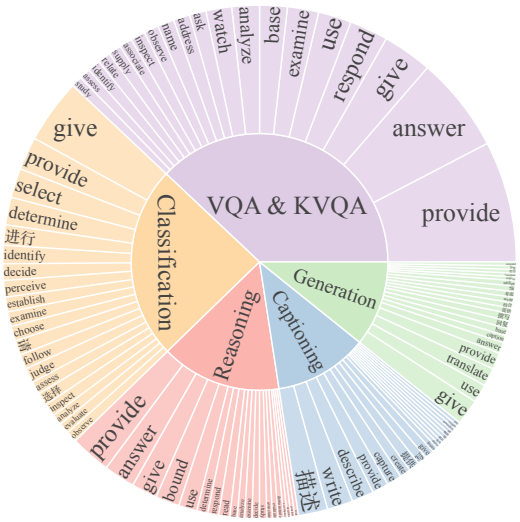

Figure 7: Top 20 verbs distribution for each task type.

You are an AI visual assistant. Now you are given a question related to an image and a short ground-truth answer. Your task is to transform the ground-truth answer into a natural and convincing response. Make sure the response is accurate, highly relevant to the question, and consistent with the original answer.

Question:
Which NASA space probe was launched to this planet in 1989?
Answer:
Magellan
Transformed Answer:
NASA sent the Magellan spacecraft to Venus in 1989, which was the first planetary spacecraft launched from a space shuttle.

Question:
{Q}
Answer:
{A}
Transformed Answer:

Table 10: Template used to query ChatGPT for answer paraphrasing.

models. The efforts can be divided into the exploration of the model architecture and the curation of high-quality multi-modal instruction tuning datasets.

Model	Visual-Dialog	ImageNet
BLIP2-Flan-T5-XXL	6.4	**96.0**
InstructBLIP	7.0	74.5
MiniGPT4	**20.3**	41.7
Ying-VLM	14.7	91.9

Table 11: ROUGE-L evaluation on VisualDialog and accuracy score on ImageNet dataset.

Model Architecture of VLMs The architecture of VLMs usually consists of three key modules, (i) a vision encoder, (ii) a modality alignment module, and (iii) an LLM backbone. The vision encoder is responsible for converting raw images/videos into vector representations, which are then mapped into the embedding space of the LLM backbone by the alignment module. Finally, the LLMs decode the response given the multimodal context. Previous studies mainly employ CLIP models as the vision encoder due to the transferability of the learned visual representations (Radford et al., 2021). For the LLM backbone, performant open-sourced LLMs such as LLaMA (Touvron et al., 2023b), Vicuna (Chiang et al., 2023) and Qwen-LM (Bai et al., 2023a) are usually adopted. Chen et al. (2023c) delves deeper into the scaling effects of the vision encoder and the language model, showcasing the great potential advantages of scaling both modules. There are many research efforts paid to the design of a better modality alignment module. The pilot studies (Open)Flamingo (Alayrac et al., 2022; Awadalla et al., 2023) design a gated cross-attention layer, where the keys and values in these layers are obtained from the vision features while the queries are derived from the language inputs. This design enables the LLM to produce visual-grounded text given interleaved context. Another common practice is to treat the visual features as a prefix (Wang et al., 2021), and train the alignment module via the construction of the captions. In this way, the alignment module can become a simple linear projection layer (Liu et al., 2023b; Zhu et al., 2023) and a two-layer MLP for better capacity (Liu et al., 2023a). The Q-Former module introduced by BLIP-2 (Li et al., 2023a) achieves the alignment goal by introducing a suite of query tokens in the transformer to attend to the visual features. InstructBLIP (Dai et al., 2023) and MM-ICL (Zhao et al., 2023b) further incorporate the instruction information during the alignment process. Fuyu (Bavishi et al., 2023) presents a new architecture that directly projects

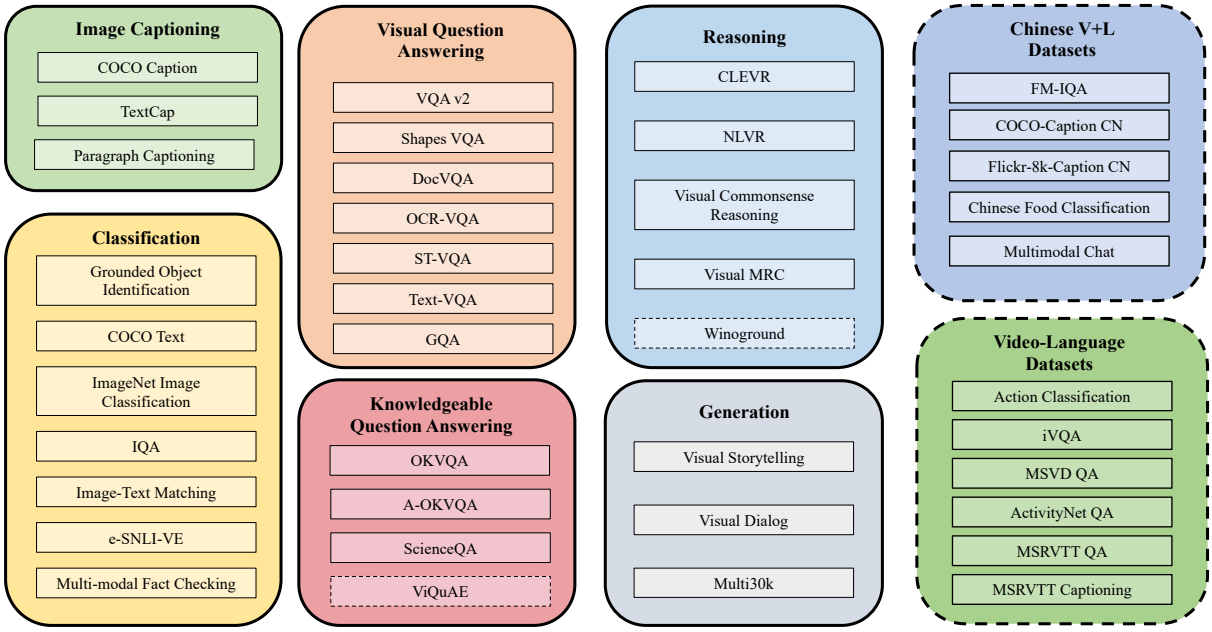

Figure 8: Tasks coverage of M2BIT. We hold out ViQuAE for evaluating the KVQA ability of VLMs and Winogound, as it only provides a small test set. All Chinese V+L and Video-language datasets are excluded during training for cross-lingual/modality effect investigation.

the raw pixels of images into the embedding space of the LLM to perform the following training and decoding.

Multi-modal Instruction Tuning Datasets Curating high-quality multi-modal instruction tuning datasets has also played a vital role in empowering VLMs, as evidenced in the progress of developing LLMs (Ouyang et al., 2022; Longpre et al., 2023; Wang et al., 2022). The efforts can be divided into two streams. The first uses existing vision-text benchmarks to create an instruction-tuning dataset (Xu et al., 2022; Dai et al., 2023). Traditional multi-modal tasks such as VQA and image captioning are collected, and supplemented with task instructions annotated by humans or semi-automatically generated, to serve as an instruction-tuning dataset. The second line uses image annotation tools for providing ChatGPT/GPT-4 with the textual description of images and then generates a dialog-style dataset (Zhu et al., 2023; Liu et al., 2023b). For example, the LLaVA dataset (Liu et al., 2023b) leverages image captions and bounding boxes to serve as the textual context of the original images. The context along with a designed template is used to prompt the GPT-4 model for generating instruction tuning samples. Following this paradigm, Zhao et al. (2023a) further scales this framework to create 4.2 million samples, and LLaVAR (Zhang et al., 2023) extends the idea with OCR results to create text-rich image understanding instructions.

In this paper, we present M2BIT, a multi-modal multilingual instruction tuning dataset with 2 million samples and 400 tasks, providing more comprehensive coverage of multi-modal tasks across different languages and modalities. Besides, we rephrase the short answers of original datasets into natural expressions to improve user experience. Built on the success recipe of VLM architecture, we develop Ying-VLM, which validates the effectiveness of our dataset.

F Prompt for Zero-Shot Chinese Vision-Language Tasks

In our experiments, all VLMs are fine-tuned exclusively using English data. In our preliminary study, we observe that these models tend to generate English responses, even when the input and instructions are written in Chinese. We introduce a simple Chinese dialogue context during the zero-shot Chinese Vision-Language Task evaluation for all models, as illustrated in Table 12, Interestingly, this minor adjustment can encourage models to produce reasonable Chinese output. We leave the analysis of instruction-tuned VLM models' multilingual capabilities for future research.

<human>:
请根据我的指示，以及所给的图片，做出相应的回答。
<bot>:
好的。
<human>:
{Instruction}
{Input}
<bot>:
好的。

Table 12: Prompt for promoting Chinese outputs.

G Template for GPT-4 Evaluation

We adopt the template in Table 13 to query GPT-4 and obtain the evaluation results with FairEval [6] to obtain more stable results. Specifically, each tested instance is a quaternion: `(question, reference, response1, response2)`, where `response1` and `response2` are two responses from our Ying-VLM and the baseline model, respectively. For each instance, we query GPT-4 to judge which response is of better quality regarding accuracy, relevance and naturalness. We populate the quaternion into the evaluation template to form two query prompts: `T(Q=question, R=reference, R1=response1, R2=response2)` and `T(Q=question, R=reference, R1=response2, R2=response1)`. We set the temperature of GPT-4 to 1 and sample three completions for each query prompt. Therefore, each response will receive 6 scores, and we use the average score as the final score for each response. The response with the higher final score is considered the better response. The GPT-4 evaluation incurred a cost of $20.45 for InstructBlip and $20.90 for MiniGPT-4.

H Object Hallucination Metrics

For object hallucination evaluation, we adopt Caption Hallucination Assessment with Image Relevance (CHAIR) proposed by Rohrbach et al. (2018), a metric for evaluating object hallucination in image captioning tasks. Specifically, given the existing objects in the image, CHAIR calculates the proportion of objects that appear in the caption but not the image. CHAIR has two variants, i.e., CHAIR_I and CHAIR_S, which evaluate the hallucination degree at the object instance level and the sentence level, respectively. Formally, these two metrics are defined as:

$$\text{CHAIR}_I = \frac{|\{\text{hallucinated objects}\}|}{|\{\text{all mentioned objects}\}|}$$
$$\text{CHAIR}_S = \frac{|\{\text{captions w/ hallucinated objects}\}|}{|\{\text{all captions}\}|}.$$

Intuitively, CHAIR_I denotes the proportion of hallucinated ones in all generated objects, while CHAIR_S describes the hallucination at the sentence level, i.e., the proportion of generated captions that contain hallucinated objects. We follow the settings adopted in Rohrbach et al. (2018), which only consider 80 objects in the MSCOCO segmentation challenge. Following (Li et al., 2023b), a synonym list (Lu et al., 2018) is used for synonymous word unification in the generated captions to avoid misjudging hallucinated objects.

I Effect of Instruction Diversity and Robustness

To investigate the influence of instruction diversity, we randomly select 1, 2, 4, and 8 instructions from each dataset, resulting in varied instruction diversity. The other training parameters are consistent with those used in previous experiments on task number investigation. Figure 9 shows that the performance varies with the level of diversity. Specifically, our results suggest that using four instructions per task is sufficient for achieving decent performance.

We investigate the influence of task numbers by randomly shuffling our tasks and then selecting a subset to train the model during the instruction tuning stage. Due to the computational resource limitation, we set up a maximum of 5k examples for each task and train all the models for 5k steps with a batch size of 64. We select 0, 4, 8, 16 and all 27 tasks for training, and report the individual ROUGE-L score and the average score. As illustrated in Figure 10, increasing the number of tasks greatly improves the results of the generalization performance. Besides, the performance gain is not diminished as the task number increases. This is promising as it indicates that we can continually improve performance by introducing more tasks into the training.

[6] https://github.com/i-Eval/FairEval

[Question]
{Q}
[The Start of Reference Answer]
{R}
[The End of Reference Answer]
[The Start of Assistant 1's Answer]
{R1}
[The End of Assistant 1's Answer]
[The Start of Assistant 2's Answer]
{R2}
[The End of Assistant 2's Answer]

[System]
We would like to request your feedback on the performance of two AI assistants in response to the user's multimodal question displayed above. We provided no multimodal inputs other than question text, but we provided a reference answer for this question. You need to evaluate the quality of the two responses based on the question and the reference answer.
Please rate the on the follow aspects:
1. Accuracy: whether the candidate's response is consistent with the original answer, this is important as we do not want a misleading result;
2. Relevance: whether the candidate's response is highly relevant to the question and image content;
3. Naturalness: whether the candidate's response is engaging, providing a great communication experience for the user when interacting with the AI visual assistant.
of the two Assistants' responses.

Each assistant receives an overall score on a scale of 1 to 10, where a higher score indicates better overall performance.
Please first provide a comprehensive explanation of your evaluation, avoiding any potential bias and ensuring that the order in which the responses were presented does not affect your judgment. Then, output two lines indicating the scores for Assistant 1 and 2, respectively.

Output with the following format:
Evaluation evidence: <evaluation explanation here>
The score of Assistant 1: <score>
The score of Assistant 2: <score>

Table 13: Template used to query GPT-4 for evaluating the response quality of different models.

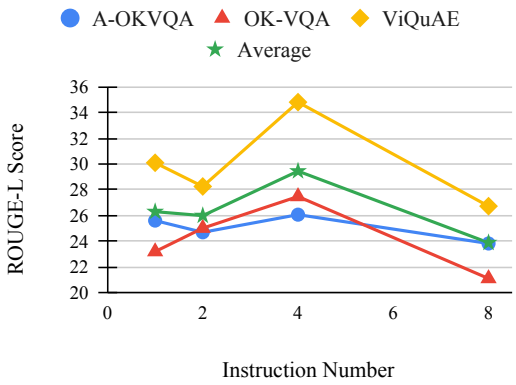

Figure 9: ROUGE-L Score changes with the varied number of instructions used for training.

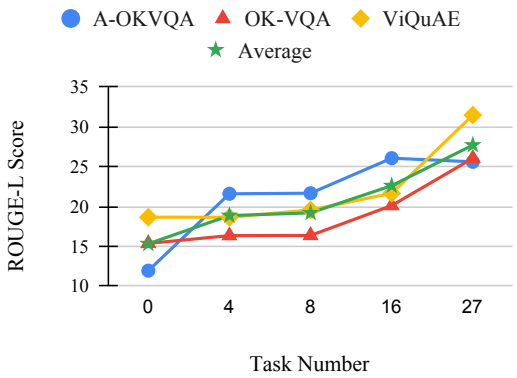

Figure 10: ROUGE-L score increases when models are trained with more instruction tuning datasets.