

Qwen-VL: A Frontier Large Vision-Language Model with Versatile Abilities

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Abstract

We introduce the Qwen-VL series, a set of large-scale vision-language models designed to perceive and understand both text and images. Comprising Qwen-VL and Qwen-VL-Chat, these models exhibit remarkable performance in tasks like image captioning, question answering, visual localization, and flexible interaction. The evaluation covers a wide range of tasks including zero-shot captioning, visual or document visual question answering, and grounding. We demonstrate the Qwen-VL outperforms existing Large Vision Language Models (LVLMs). We present their architecture, training, capabilities, and performance, highlighting their contributions to advancing multimodal artificial intelligence. Code, demo and models are available at <https://github.com/QwenLM/Qwen-VL>.

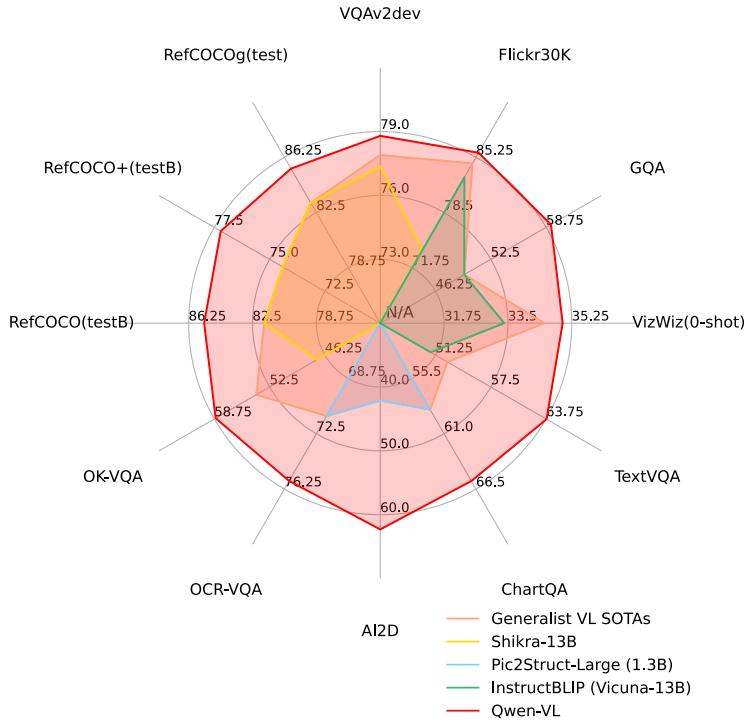


Figure 1: Qwen-VL achieves state-of-the-art performance on a broad range of tasks compared with other generalist models.

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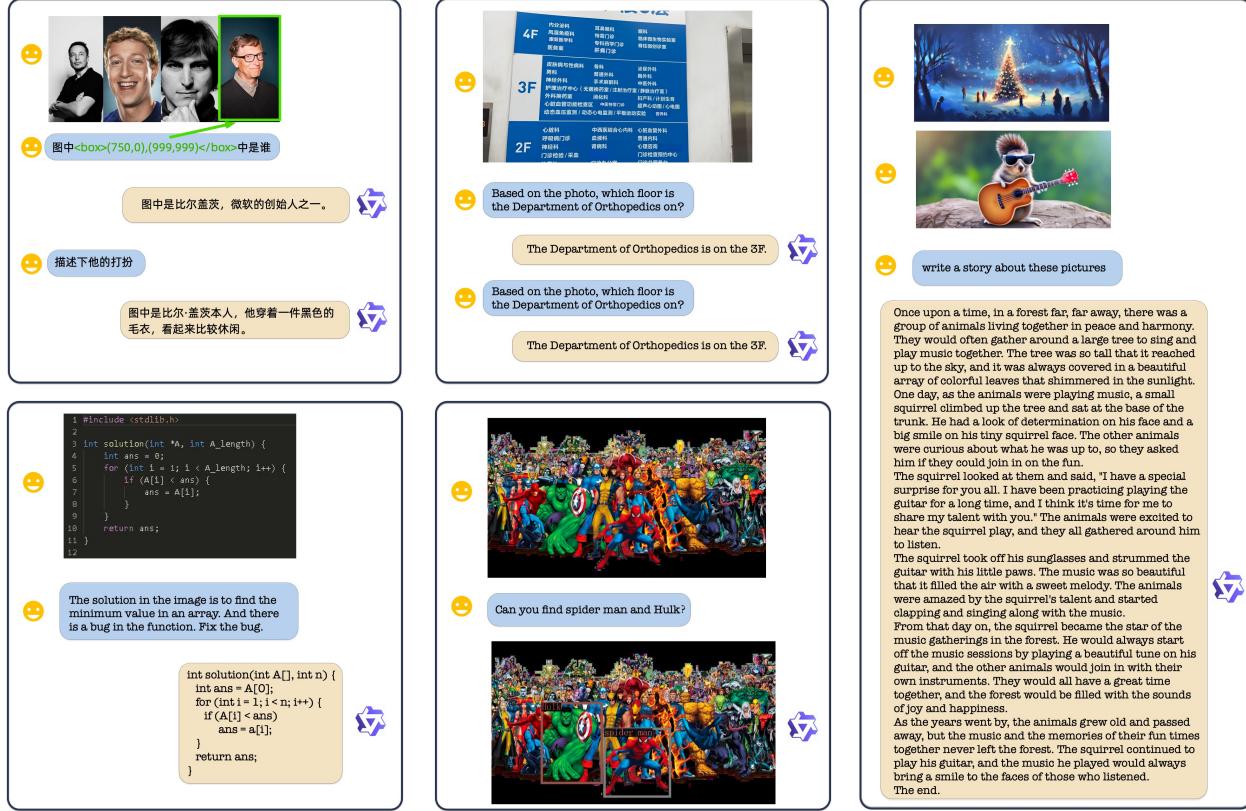


Figure 2: Some qualitative examples generated by our Qwen-VL-Chat. Qwen-VL-Chat supports multiple image inputs, multi-round dialogue, multilingual conversation, and localization ability.

1 Introduction

Recently, Large Language Models (LLMs) (Brown et al., 2020; OpenAI, 2023; Anil et al., 2023; Gao et al., 2023; Qwen, 2023) have attracted wide attention due to their powerful capabilities in text generation and comprehension. These models can be further aligned with user intent through fine-tuning instructions, showcasing strong interactive capabilities and the potential to enhance productivity as intelligent assistants. However, native large language models only live in the pure-text world, lacking the ability to handle other common modalities such as images, speech, and videos which greatly limits the application scope of the models. To break this limitation, a group of Large Vision Language Models (LVLMs) (Alayrac et al., 2022; Chen et al., 2022; Li et al., 2023b; Dai et al., 2023; Huang et al., 2023; Peng et al., 2023; Zhu et al., 2023; Liu et al., 2023; Ye et al., 2023b,a; Chen et al., 2023; Li et al., 2023a; Zhang et al., 2023; Sun et al., 2023; OpenAI, 2023) have been developed to enhance large language models with the ability to perceive and understand visual signals. These large-scale vision-language models demonstrate promising potential in solving real-world vision-central problems.

To foster the thriving of the multimodal open-source community, we introduce the newest member of the open-sourced Qwen series: the Qwen-VL series models. The Qwen-VL series models are large-scale visual-language models that include two versions: Qwen-VL and Qwen-VL-Chat. Qwen-VL is a pre-trained model that extends the Qwen-7B (Qwen, 2023) language model with visual capabilities by the connection of a visual encoder. After the three-stage training, Qwen-VL has the ability to perceive and understand visual signals with multi-level scales. Additionally, as shown in Fig. 2, Qwen-VL-Chat is an interactive visual-language model based on Qwen-VL using alignment mechanisms and supports more flexible interaction, such as multiple image inputs, multi-round dialogue, and localization ability. Specifically, the features of the

Qwen-VL series models include:

- Strong performance: It significantly surpasses existing open-sourced Large Vision Language Models (LVLM) under the same-level model scale on multiple evaluation benchmarks (including Zero-shot Captioning, VQA, DocVQA, and Grounding).
- Multilingual LVLM supporting text recognition and grounding: Qwen-VL naturally supports English, Chinese, and multilingual conversation, and it promotes end-to-end recognition and grounding of Chinese and English bi-lingual text and instance in images.
- Multi-image interleaved conversations: This feature allows for the input and comparison of multiple images, as well as the ability to specify questions related to the images and engage in multi-image storytelling.
- Fine-grained recognition and understanding: Compared to the 224×224 resolution currently used by other open-source LVLM, the 448×448 resolution promotes fine-grained text recognition, document QA, and bounding box detection.

2 Methodology

2.1 Model Architecture

The overall network architecture of Qwen-VL consists of three components and the details of model parameters are shown in Table 1:

Large Language Model: Qwen-VL adopts a large language model as its foundation component. The model is initialized with pre-trained weights from Qwen-7B ([Qwen, 2023](#)). For comprehensive details about Qwen-7B’s architecture, tokenization, training recipe, model weights, and performance metrics, please refer to the code repo of QWen-7B¹.

Visual Encoder: The visual encoder of Qwen-VL uses the Vision Transformer (ViT) ([Dosovitskiy et al., 2021](#)) architecture, initialized with pre-trained weights from Openclip’s ViT-bigG ([Ilharco et al., 2021](#)). During both training and inference, input images are resized to a specific resolution. The visual encoder processes images by splitting them into patches with a stride of 14, generating a set of image features.

Position-aware Vision-Language Adapter: To alleviate the efficiency issues arising from long image feature sequences, Qwen-VL introduces a vision-language adapter that compresses the image features. This adapter comprises a single-layer cross-attention module initialized randomly. The module uses a group of trainable vectors (Embeddings) as query vectors and the image features from the visual encoder as keys for cross-attention operations. This mechanism compresses the visual feature sequence to a fixed length of 256. Additionally, considering the significance of positional information for fine-grained image comprehension, 2D absolute positional encodings are incorporated into the cross-attention mechanism’s query-key pairs to mitigate the potential loss of positional details during compression. The compressed image feature sequence of length 256 is subsequently fed into the large language model.

Table 1: Details of Qwen-VL model parameters.

Vision Encoder	VL Adapter	LLM	Total
1.9B	0.08B	7.7B	9.6B

¹<https://github.com/QwenLM/Qwen-7B>

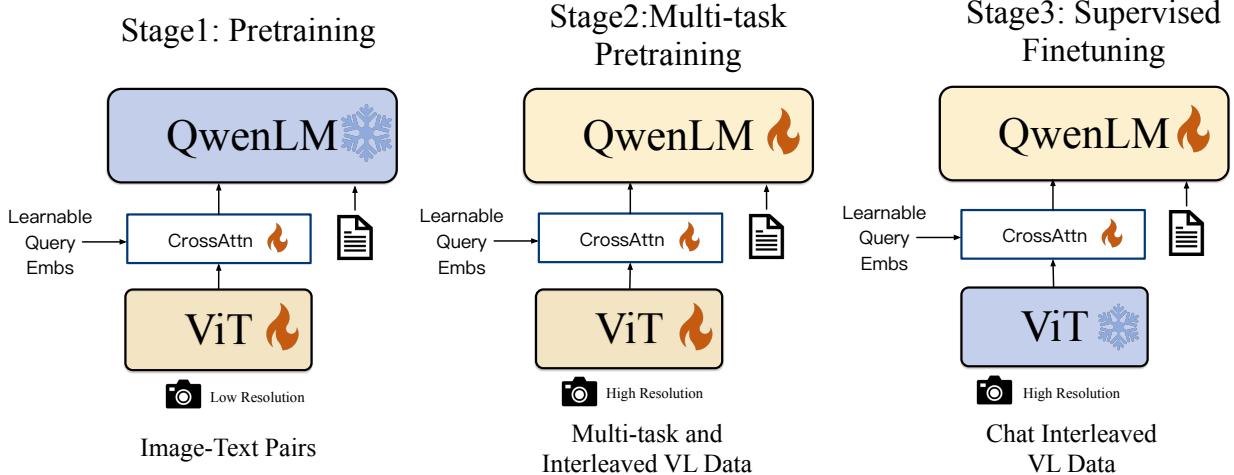


Figure 3: The training pipeline of the Qwen-VL series.

2.2 Inputs and Outputs

Image Input: Images are processed through the visual encoder and adapter, yielding fixed-length sequences of image features. To differentiate between image feature input and text feature input, two special tokens (`` and ``) are appended to the beginning and end of the image feature sequence respectively, signifying the start and end of image content.

Bounding Box Input and Output: To enhance the model's capacity for fine-grained visual understanding and grounding, Qwen-VL's training involves data in the form of region descriptions, questions, and detections. Differing from conventional tasks involving image-text descriptions or questions, this task necessitates the model's accurate understanding and generation of region descriptions in a designated format. For any given bounding box, a normalization process is applied (within the range [0, 1000]) and transformed into a specified string format: $(X_{topleft}, Y_{topleft}), (X_{bottomright}, Y_{bottomright})$. The string is tokenized as text and does not require an additional positional vocabulary. To distinguish between detection strings and regular text strings, two special tokens (`<box>` and `</box>`) are added at the beginning and end of the bounding box string. Additionally, to appropriately associate bounding boxes with their corresponding descriptive words or sentences, another set of special tokens (`<ref>` and `</ref>`) is introduced, marking the content referred to by the bounding box.

3 Training

As illustrated in Fig. 3, the training process of the Qwen-VL model consists of three stages: two stages of pre-training and a final stage of instruction fine-tuning training.

3.1 Pre-training

In the first stage of pre-training, we mainly utilize a large-scale, weakly labeled, web-crawled set of image-text pairs. Our pre-training dataset is composed of several publicly accessible sources and some in-house data. We made an effort to clean the dataset of certain patterns. As summarized in Table 2, the original dataset contains a total of 5 billion image-text pairs, and after cleaning, 1.4 billion data remain, with 77.3% English (text) data and 22.7% Chinese (text) data.

Table 2: Details of Qwen-VL pre-training data. LAION-en and LAION-zh are the English and Chinese language subset of LAION-5B (Schuhmann et al., 2022a). LAION-COCO (Schuhmann et al., 2022b) is a synthetic dataset generated from LAION-en. DataComp (Gadre et al., 2023) and Coyo (Byeon et al., 2022) are collections of image-text pairs. CC12M (Changpinyo et al., 2021), CC3M (Sharma et al., 2018), SBU (Ordonez et al., 2011) and COCO Caption (Chen et al., 2015) are academic caption datasets. In-house Data does not include data from Alibaba’s products or services.

Language	Dataset	Original	Cleaned	Remaining%
English	LAION-en	2B	280M	14%
	LAION-COCO	600M	300M	50%
	DataComp	1.4B	300M	21%
	Coyo	700M	200M	28%
	CC12M	12M	8M	66%
	CC3M	3M	3M	100%
	SBU	1M	0.8M	80%
Chinese	COCO Caption	0.6M	0.6M	100%
	LAION-zh	108M	105M	97%
	In-house Data	220M	220M	100%
	Total	5B	1.4B	28%

We freeze the large language model and only optimize the vision encoder and VL adapter in this stage. The input images are resized to 224×224 . The training objective is to minimize the cross-entropy of the text tokens. The model is trained using AdamW optimizer with $\beta_1 = 0.9, \beta_2 = 0.98, \text{eps} = 1e^{-6}$. We use the cosine learning rate schedule and set the maximum learning rate of $2e^{-4}$ and minimum of $1e^{-6}$ with a linear warm-up of 500 steps. We use a weight decay of $5e^{-2}$ and a gradient clipping of 1.0. For the ViT image encoder, we apply a layer-wise learning rate decay strategy with a decay factor of 0.95. The training process uses a batch size of 30720 for the image-text pairs, and the entire first stage of pre-training lasts for 50,000 steps, consuming approximately 1.5 billion image-text samples and 500 billion image-text tokens.

3.2 Multi-task Pre-training

Table 3: Details of Qwen-VL multi-task pre-training data. In-house Data does not include data from Alibaba’s products or services.

Task	# Samples	Dataset
Captioning	19.7M	LAION-en & zh, DataComp, Coyo, CC12M & 3M, SBU, COCO, In-house
VQA	3.6M	GQA, VGQA, VQAv2, DVQA, OCR-VQA, DocVQA
Grounding ²	3.5M	GRIT
Ref Grounding	8.7M	GRIT, Visual Genome, RefCOCO, RefCOCO+, RefCOCOg
Grounded Cap.	8.7M	GRIT, Visual Genome, RefCOCO, RefCOCO+, RefCOCOg
OCR	24.8M	SynthDoG-en & zh, Common Crawl pdf & HTML
Text Generation	7.8M	In-house Data

In the second stage of multi-task pre-training, we introduce high-quality and fine-grained VL annotation data with a larger input resolution and interleaved image-text data. As summarized in Table 3, we trained Qwen-VL on 7 tasks simultaneously. For text generation, we use the in-house collected corpus to maintain the LLM’s ability. Captioning data is the same with Table 2 except for far fewer samples and excluding LAION-COCO. We use a mixture of publicly available data for the VQA task which includes GQA (Hudson

²This task is to generate noun/phrase grounded captions (Peng et al., 2023).

and Manning, 2019), VGQA (Krishna et al., 2017), VQAv2 (Goyal et al., 2017), DVQA (Kafle et al., 2018), OCR-VQA (Mishra et al., 2019) and DocVQA (Mathew et al., 2021). We follow Kosmos-2 to use the GRIT (Peng et al., 2023) dataset for the grounding task with minor modifications. For the reference grounding and grounded captioning duality tasks, we construct training samples from GRIT (Peng et al., 2023), Visual Genome (Krishna et al., 2017), RefCOCO (Kazemzadeh et al., 2014), RefCOCO+, and RefCOCOg (Mao et al., 2016). In order to improve the text-oriented tasks, we collect pdf and HTML format data from Common Crawl³ and generate synthetic OCR data in English and Chinese language with natural scenery background, following Kim et al. (2022). Finally, we simply construct interleaved image-text data by packing the same task data into sequences of length 2048.

We increase the input resolution of the visual encoder from 224×224 to 448×448 , reducing the information loss caused by image down-sampling. We unlocked the large language model and trained the whole model. The training objective is the same as the pre-training stage. We use AdamW optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.98$, $eps = 1e^{-6}$. We trained for 19000 steps with 400 warm-up steps and a cosine learning rate schedule. Specifically, we use the model parallelism techniques for ViT and LLM. We detail more hyperparameters in the Appendix.

3.3 Supervised Fine-tuning

During this stage, we finetuned the Qwen-VL pre-trained model through instruction fine-tuning to enhance its instruction following and dialogue capabilities, resulting in the interactive Qwen-VL-Chat model. The multi-modal instruction tuning data primarily comes from caption data or dialogue data generated through LLM self-instruction, which often only addresses single-image dialogue and reasoning and is limited to image content comprehension. We construct an additional set of dialogue data through manual annotation, model generation, and strategy concatenation to incorporate localization and multi-image comprehension abilities into the Qwen-VL model. We confirm that the model effectively transfers these capabilities to a wider range of languages and question types. Additionally, we mix multi-modal and pure text dialogue data during training to ensure the model’s universality in dialogue capabilities. The instruction tuning data amounts to 350k.

To better accommodate multi-image dialogue and multiple image inputs, we add the string "Picture *id*:" before different images, where the *id* corresponds to the order of image input dialogue. In terms of dialogue format, we construct our instruction tuning dataset using the ChatML ([Openai](#)) format, where each interaction’s statement is marked with two special tokens (<|im_start|> and <|im_end|>) to facilitate dialogue termination.

The Dataset Format Example of ChatML
<pre>< im_start >user Picture 1: vg/VG_100K_2/649.jpgWhat is the sign in the picture?< im_end > < im_start >assistant The sign is a road closure with an orange rhombus.< im_end > < im_start >user How is the weather in the picture?< im_end > < im_start >assistant The shape of the road closure sign is an orange rhombus.< im_end ></pre>

During training, we ensure the consistency between prediction and training distributions by only supervising answers and special tokens (blue in the example), and not supervising role names or question prompts. In this stage, we freeze the visual encoder and optimize the language model and adapter module. Specifically, the Qwen-VL-Chat is trained with a global batch size of 128 and a learning rate schedule with a maximum learning rate of $1e^{-5}$, a minimum learning rate of $1e^{-6}$, and a linear warmup of 3000 steps.

³<https://digitalcorpora.org/corpora/file-corpora/cc-main-2021-31-pdf-untruncated>

4 Evaluation

In this section, we conduct evaluation on a various of traditional vision-language tasks to comprehensively assess our models' visual understanding ability:

- Image Caption and General Visual Question Answering
- Text-oriented Visual Question Answering
- Referring Expression Comprehension

Besides, to estimate our Qwen-VL-Chat model's instruction-following ability in real-world user behavior, we further conduct evaluation on TouchStone - a curated open-ended VL instruction following benchmark - under both English and Chinese setups. Table 4 provides a detailed summary of the used evaluation benchmarks and corresponding metrics.

Table 4: Summary of the evaluation benchmarks.

Task	Dataset	Description	Split	Metric
Image Caption	Nocaps Flickr30K	Captioning of natural images Captioning of natural images	val karpathy-test	CIDEr(\uparrow) CIDEr(\uparrow)
General VQA	VQAv2 OKVQA GQA ScienceQA (Image Set) VizWiz	VQA on natural images VQA on natural images requiring outside knowledge VQA on scene understanding and reasoning Multi-choice VQA on a diverse set of science topics VQA on photos taken by people who are blind	test-dev val test-balanced test test-dev	VQA Score(\uparrow) VQA Score(\uparrow) EM(\uparrow) Accuracy(\uparrow) VQA Score(\uparrow)
Text-oriented VQA	TextVQA DocVQA ChartQA OCRVQA AI2Diagram	VQA on natural images containing text VQA on images of scanned documents VQA on images of charts VQA on images of book covers VQA on images of scientific diagrams	val test test test test	VQA Score(\uparrow) ANLS(\uparrow) Relaxed EM(\uparrow) EM(\uparrow) EM(\uparrow)
Refer Expression Comprehension	RefCOCO RefCOCO+ RefCOCOg GRIT	Refer grounding on natural images Refer grounding on natural images Refer grounding on natural images Refer grounding on natural images	val & testA & testB val & testA & testB val & test test	Accuracy(\uparrow) Accuracy(\uparrow) Accuracy(\uparrow) Accuracy(\uparrow)
Instruction Following	TouchStone	Open-ended VL Instruction Following Benchmark	English & Chinese	GPT-4 Score (\uparrow)

4.1 Image Caption and General Visual Question Answering

Image caption and general visual question answering (VQA) are two conventional tasks for vision-language models. Specifically, image caption requires model to generate description for given image and general VQA requires model to generate answer for given image-question pair.

For image caption task, we choose Nocaps (Agrawal et al., 2019) and Flickr30K (Young et al., 2014) as benchmarks and report CIDEr score (Vedantam et al., 2015) as metric. We utilize greedy search for caption generation with a prompt of "*Describe the image in English:*".

For general VQA, we utilize five benchmarks including VQAv2 (Goyal et al., 2017), OKVQA (Marino et al., 2019), GQA (Hudson and Manning, 2019), ScienceQA (Image Set) (Lu et al., 2022b) and VizWiz VQA (Gurari et al., 2018). For VQAv2, OKVQA, GQA and VizWiz VQA, we employ open-ended answer generation with greedy decoding strategy and a prompt of "*{question} Answer:*", without any constrain on model's output space. However, for ScienceQA, we constrain the model's output to possible options (instead of open-ended), choose the option with highest confidence as model's prediction and report the Top-1 accuracy.

The overall performance on image caption and general VQA tasks are reported in Table 5. As the results shown, our Qwen-VL and Qwen-VL-Chat both achieve obviously better results compared to previous generalist models in terms of both two tasks. Specifically, on zero-shot image caption task, Qwen-VL achieves

state-of-the-art performance (*i.e.*, 85.8 CIDEr score) on the Flickr30K karpathy-test split, even outperforms previous generalist models with much more parameters (*e.g.*, Flamingo-80B with 80B parameters).

On general VQA benchmarks, our models also exhibit distinct advantages compared to others. On VQAv2, OKVQA and GQA benchmarks, Qwen-VL achieves 79.5, 58.6 and 59.3 accuracy respectively, which surpasses recent proposed LVLMs by a large margin. It's worth noting that Qwen-VL also shows strong zero-shot performance on ScienceQA and VizWiz datasets.

4.2 Text-oriented Visual Question Answering

Text-oriented visual understanding has a broad application prospect in real-world scenarios. We assess our models' ability toward text-oriented visual question answering on several benchmarks including TextVQA (Sidorov et al., 2020), DocVQA (Mathew et al., 2021), ChartQA (Masry et al., 2022), AI2Diagram (Kembhavi et al., 2016), and OCR-VQA (Mishra et al., 2019). Similarly, the results are shown in Table 6. Compared to previous generalist models and recent LVLMs, our models show better performance on most benchmarks, frequently by a large margin.

4.3 Refer Expression Comprehension

We show our models' fine-grained image understanding and localization ability by evaluating on a sort of refer expression comprehension benchmarks such as RefCOCO (Kazemzadeh et al., 2014), RefCOCOg (Mao et al., 2016), RefCOCO+ (Mao et al., 2016) and GRIT (Gupta et al., 2022). Specifically, the refer expression comprehension task require the model to localize target object under the guidance of description. The results are shown in Table 7. Compared to previous generalist models or recent LVLMs, our models obtain top-tier results on all benchmarks.

4.4 Instruction Following in Real-world User Behavior

In addition to previous conventional vision-language evaluations, to evaluate our Qwen-VL-Chat model's capacity under real-world user behavior, we further conduct an evaluation on the TouchStone (tou, 2023) benchmark. TouchStone is a open-ended vision-language instruction following benchmark. We compare the instruction-following ability of Qwen-VL-Chat with other instruction-tuned LVLMs in both English and Chinese on TouchStone benchmark. The results under English setup and Chinese setup are shown in Table 8 and Table 9 respectively. Qwen-VL-Chat shows the best GPT-4 score in both English and Chinese setups.

In terms of the overall scores presented in Table. 8 and 9, our model demonstrates a clear advantage compared to other LVLMs, especially in terms of its Chinese capabilities. In terms of the broad categories of abilities, our model exhibits a more pronounced advantage in understanding and recognition, particularly in areas such as text recognition and chart analysis. For more detailed information, please refer to the TouchStone dataset.

5 Related Work

In recent years, researchers have shown considerable interest in vision-language learning (Su et al., 2019; Chen et al., 2020; Li et al., 2020; Zhang et al., 2021; Li et al., 2021b; Lin et al., 2021; Kim et al., 2021; Dou et al., 2022; Li et al., 2021a, 2022), especially in the development of multi-task generalist models (Hu and Singh, 2021; Singh et al., 2022; Zhu et al., 2022; Yu et al., 2022; Wang et al., 2022a; Lu et al., 2022a; Bai et al., 2022). CoCa (Yu et al., 2022) proposes an encoder-decoder structure to address image-text retrieval and vision-language generation tasks simultaneously. OFA (Wang et al., 2022a) transforms specific vision-language tasks into sequence-to-sequence tasks using customized task instructions. Unified I/O (Lu et al., 2022a)

Table 5: Results on Image Captioning and General VQA.

Model Type	Model	Image Caption		General VQA				
		Nocaps (0-shot)	Flickr30K (0-shot)	VQAv2	OKVQA	GQA	SciQA-Img (0-shot)	VizWiz (0-shot)
Generalist Models	Flamingo-9B	-	61.5	51.8	44.7	-	-	28.8
	Flamingo-80B	-	67.2	56.3	50.6	-	-	31.6
	Unified-IO-XL	100.0	-	77.9	54.0	-	-	-
	Kosmos-1	-	67.1	51.0	-	-	-	29.2
	Kosmos-2	-	80.5	51.1	-	-	-	-
	BLIP-2 (Vicuna-13B)	103.9	71.6	65.0	45.9	32.3	61.0	19.6
	InstructBLIP (Vicuna-13B)	121.9	82.8	-	-	49.5	63.1	33.4
	Shikra (Vicuna-13B)	-	73.9	77.36	47.16	-	-	-
	Qwen-VL (Qwen-7B)	121.4	85.8	79.5	58.6	59.3	67.1	35.2
	Qwen-VL-Chat	120.2	81.0	78.2	56.6	57.5	68.2	38.9
Specialist SOTAs	-	127.0 (PALI-17B)	84.5 (InstructBLIP -FlanT5-XL)	86.1 (PALI-X -55B)	66.1 (PALI-X -55B)	72.1 (CFR)	92.53 (LLaVa+ GPT-4)	70.9 (PALI-X -55B)

Table 6: Results on Text-oriented VQA.

Model type	Model	TextVQA	DocVQA	ChartQA	AI2D	OCR-VQA
Generalist Models	BLIP-2 (Vicuna-13B)	42.4	-	-	-	-
	InstructBLIP (Vicuna-13B)	50.7	-	-	-	-
	mPLUG-DocOwl (LLaMA-7B)	52.6	62.2	57.4	-	-
	Pic2Struct-Large (1.3B)	-	76.6	58.6	42.1	71.3
	Qwen-VL (Qwen-7B)	63.8	65.1	65.7	62.3	75.7
	Qwen-VL-Chat	61.5	62.6	66.3	57.7	70.5
Specialist SOTAs	PALI-X-55B (Single-task fine-tuning, without OCR Pipeline)	71.44	80.0	70.0	81.2	75.0

Table 7: Results on Referring Expression Comprehension task.

Model type	Model	RefCOCO			RefCOCO+		RefCOCOg val	GRIT refexp
		val	test-A	test-B	val	test-A	test-B	
Generalist Models	GPV-2	-	-	-	-	-	-	51.50
	OFA-L*	79.96	83.67	76.39	68.29	76.00	61.75	67.57
	Unified-IO	-	-	-	-	-	-	78.61
	VisionLLM-H		86.70	-	-	-	-	-
	Shikra-7B	87.01	90.61	80.24	81.60	87.36	72.12	82.27
	Shikra-13B	87.83	91.11	81.81	82.89	87.79	74.41	82.64
	Qwen-VL-7B	89.36	92.26	85.34	83.12	88.25	77.21	85.58
Specialist SOTAs	Qwen-VL-7B-Chat	88.55	92.27	84.51	82.82	88.59	76.79	85.96
	G-DINO-L	90.56	93.19	88.24	82.75	88.95	75.92	86.13
	UNINEXT-H	92.64	94.33	91.46	85.24	89.63	79.79	88.73
	ONE-PEACE	92.58	94.18	89.26	88.77	92.21	83.23	89.22

Table 8: Evaluation results on TouchStone in English.

Model	PandaGPT	MiniGPT4	InstructBLIP	LLaMA-AdapterV2	LLaVA	mPLUG-Owl	Qwen-VL-Chat
Score	488.5	531.7	552.4	590.1	602.7	605.4	645.2

Table 9: Evaluation results on TouchStone in Chinese.

Model	VisualGLM	Qwen-VL-Chat
Score	247.1	401.2

further introduces more tasks like segmentation and depth estimation into a unified framework. Another category of research focuses on building vision-language representation models (Radford et al., 2021; Jia et al., 2021; Zhai et al., 2022; Yuan et al., 2021; Yang et al., 2022). CLIP (Radford et al., 2021) leverages contrastive learning and large amounts of data to align images and language in a semantic space, resulting in strong generalization capabilities across a wide range of downstream tasks. BEIT-3 (Wang et al., 2022b) employs a mixture-of-experts (MOE) structure and unified masked token prediction objective, achieving state-of-the-art results on various visual-language tasks. In addition to vision-language learning, ImageBind (Girdhar et al., 2023) and ONE-PEACE (Wang et al., 2023) align more modalities such as speech into a unified semantic space, thus creating more general representation models.

Despite achieving significant progress, previous vision-language models still have several limitations such as poor robustness in instruction following, limited generalization capabilities in unseen tasks, and a lack of in-context abilities. With the rapid development of large language models (LLMs) (Brown et al., 2020; OpenAI, 2023; Anil et al., 2023; Gao et al., 2023; Qwen, 2023), researchers have started building more powerful large vision-language models (LVLMs) based on LLMs (Alayrac et al., 2022; Chen et al., 2022; Li et al., 2023b; Dai et al., 2023; Huang et al., 2023; Peng et al., 2023; Zhu et al., 2023; Liu et al., 2023; Ye et al., 2023b,a; Chen et al., 2023; Li et al., 2023a; Zhang et al., 2023; Sun et al., 2023). BLIP-2 (Li et al., 2023b) proposes Q-Former to align the frozen vision foundation models and LLMs. Meanwhile, LLAVA (Liu et al., 2023) and Mini-GPT4 (Zhu et al., 2023) introduce visual instruction tuning to enhance instruction following capabilities in LVLMs. Additionally, mPLUG-DocOwl (Ye et al., 2023a) incorporates document understanding capabilities into LVLMs by introducing digital documents data. Kosmos2 (Peng et al., 2023), Shikra (Chen et al., 2023), and BuboGPT (Zhao et al., 2023) further enhance LVLMs with visual grounding abilities, enabling region description and localization. In this work, we integrate image captioning, visual question answering, OCR, document understanding, and visual grounding capabilities into QWen-VL. The resulting model achieves outstanding performance on these diverse style tasks.

6 Conclusion and Future Work

We release QWen-VL series, a set of large-scale multilingual vision-language models that aims to facilitate multimodal research. QWen-VL outperforms similar models across various benchmarks, supporting multilingual conversations, multi-image interleaved conversations, grounding in Chinese, and fine-grained recognition. Moving forward, we are dedicated to further enhancing QWen-VL’s capabilities in several key dimensions:

- Integrating QWen-VL with more modalities, such as speech and video.
- Augmenting QWen-VL by scaling up the model size and training data, enabling it to handle more complex and intricate relationships within multimodal data.
- Expanding QWen-VL’s prowess in multimodal generation, specifically in generating high-fidelity images and fluent speech.

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Appendix

A Dataset details

A.1 Image-text pairs

We use web-crawled image-text pairs dataset for pre-training, which includes LAION-en (Schuhmann et al., 2022a), LAION-zh (Schuhmann et al., 2022a), LAION-COCO (Schuhmann et al., 2022b), DataComp (Gadre et al., 2023) and Coyo (Byeon et al., 2022). We clean these noisy data by several steps:

1. Removing pairs with too large aspect ratio of the image
2. Removing pairs with too small image
3. Removing pairs with a harsh CLIP score (dataset-specific)
4. Removing pairs with text containing non-English or non-Chinese characters
5. Removing pairs with text containing emoji characters
6. Removing pairs with text length too short or too long
7. Cleaning the text’s HTML-tagged part
8. Cleaning the text with certain unregular patterns

For academic caption datasets, we remove pairs whose text contains the special tags in CC12M (Changpinyo et al., 2021) and SBU (Ordonez et al., 2011). If there is more than one text matching the same image, we select the longest one.

A.2 VQA

For the VQAv2 (Goyal et al., 2017) dataset, we select the answer annotation based on the maximum confidence. For other VQA datasets, we didn’t do anything special.

A.3 Grounding

For the GRIT (Peng et al., 2023) dataset, we found that there are many recursive grounding box labels in one caption. We use the greedy algorithm to clean the caption to make sure each image contains the most box labels with no recursive box labels. For other grounding datasets, we simply concatenate the noun/phrase with respective bounding box coordinates.

A.4 OCR

We generated the synthetic OCR dataset using Synthdog (Kim et al., 2022). Specifically, we use the COCO (Lin et al., 2014) train2017 and unlabeled2017 dataset split as the natural scenery background. Then we selected 41 English fonts and 11 Chinese fonts to generate text. We use the default hyperparameters as in Synthdog. We track the generated text locations in the image and convert them to quadrilateral coordinates and we also use these coordinates as training labels. The visualization example is illustrated in the second row of Fig 4.

For all the PDF data we collected, we follow the steps below to pre-process the data using PyMuPDF ([Software, 2015](#)) to get the rendering results of each page in a PDF file as well as all the text annotations with their bounding boxes.

1. Extracting all texts and their bounding boxes for each page.
2. Rendering each page and save them as an image file.
3. Removing too small image.
4. Removing images with too many or too few characters.
5. Removing images containing Unicode characters in the “Latin Extended-A” and “Latin Extended-B” blocks.
6. Removing images containing Unicode characters in the “Private Use Area (PUA)” block.

For all HTML web pages we collected, we pre-process them in a similar approach to all the PDF data we collected, but we use Puppeteer ([Google, 2023](#)) instead of PyMuPDF to render these HTML pages and get the ground truth annotation. We follow the steps below to pre-process the data.

1. Extracting all texts for each webpage.
2. Rendering each page and save them as an image file.
3. Removing too small image.
4. Removing images with too many or too few characters.
5. Removing images containing Unicode characters in the “Private Use Area (PUA)” block.

B Data Format of Multi-Task Pre-training

We visualize the Multi-Task Pre-training data format in Box B. The Box contains all 7 tasks with the black-coloured text as the prefix sequence and red-coloured text as the ground truth labels.

Image Captioning
cc3m/01581435.jpgGenerate the caption in English: the beautiful flowers for design.<eos>
Vision Question Answering
VG_100K_2/1.jpg Does the bandage have a different color than the wrist band? Answer: No, both the bandage and the wrist band are white.<eos>
OCR VQA
ocr_vqa/1.jpg What is the title of this book? Answer: Asi Se Dice!, Volume 2: Workbook And Audio Activities (Glencoe Spanish) (Spanish Edition)<eos>
Caption with Grounding
coyo700m/1.jpgGenerate the caption in English with grounding: Beautiful shot of <ref>bees</ref><box>(661,612),(833,812)</box><box>(120,555),(265,770)</box> gathering nectars from <ref>an apricot flower</ref><box>(224,13),(399,313)</box><eos>
Referring Grounding
VG_100K_2/3.jpg<ref>the ear on a giraffe</ref><box>(176,106),(232,160)</box><eos>
Grounded Captioning
VG_100K_2/4.jpg<ref>This</ref><box>(360,542),(476,705)</box> is Yellow cross country ski racing gloves<eos>
OCR
synthdog/1.jpgOCR with grounding: <ref>It is managed</ref><quad>(568,121), (625,131), (624,182), (567,172)</quad><ref>by South</ref><quad>(560,224), (629,232), (628,283), (559,277)</quad>...<eos>

C Hyperparameters

We report the detailed training hyperparameter settings of Qwen-VL in Table 10.

Table 10: Training hyperparameters of Qwen-VL

Configuration	Pre-training	Multi-task Pre-training	Supervised Fine-tuning
ViT init.	Open-CLIP-bigG	Qwen-VL 1st-stage	Qwen-VL 2nd-stage
LLM init.	Qwen-7B	Qwen-7B	Qwen-VL 2nd-stage
VL Adapter init.	random	Qwen-VL 1st-stage	Qwen-VL 2nd-stage
Image resolution	224 ²	448 ²	448 ²
ViT sequence length	256	1024	1024
LLM sequence length	512	2048	2048
Learnable query numbers	256	256	256
Optimizer		AdamW	
Optimizer hyperparameter		$\beta_1 = 0.9, \beta_2 = 0.98, \text{eps} = 1e^{-6}$	
Peak learning rate	$2e^{-4}$	$5e^{-5}$	$1e^{-5}$
Minimum learning rate	$1e^{-6}$	$1e^{-5}$	$1e^{-6}$
ViT learning rate decay	0.95	0.95	0
ViT Drop path rate		0	
Learning rate schedule		cosine decay	
Weight decay		0.05	
Gradient clip		1.0	
Training steps	50k	19k	8k
Warm-up steps	500	400	3k
Global batch size	30720	4096	128
Gradient Acc.	6	8	8
Numerical precision		bfloat16	
Optimizer sharding		✓	
Activation checkpointing		✗	
Model parallelism	✗	2	2
Pipeline parallelism		✗	

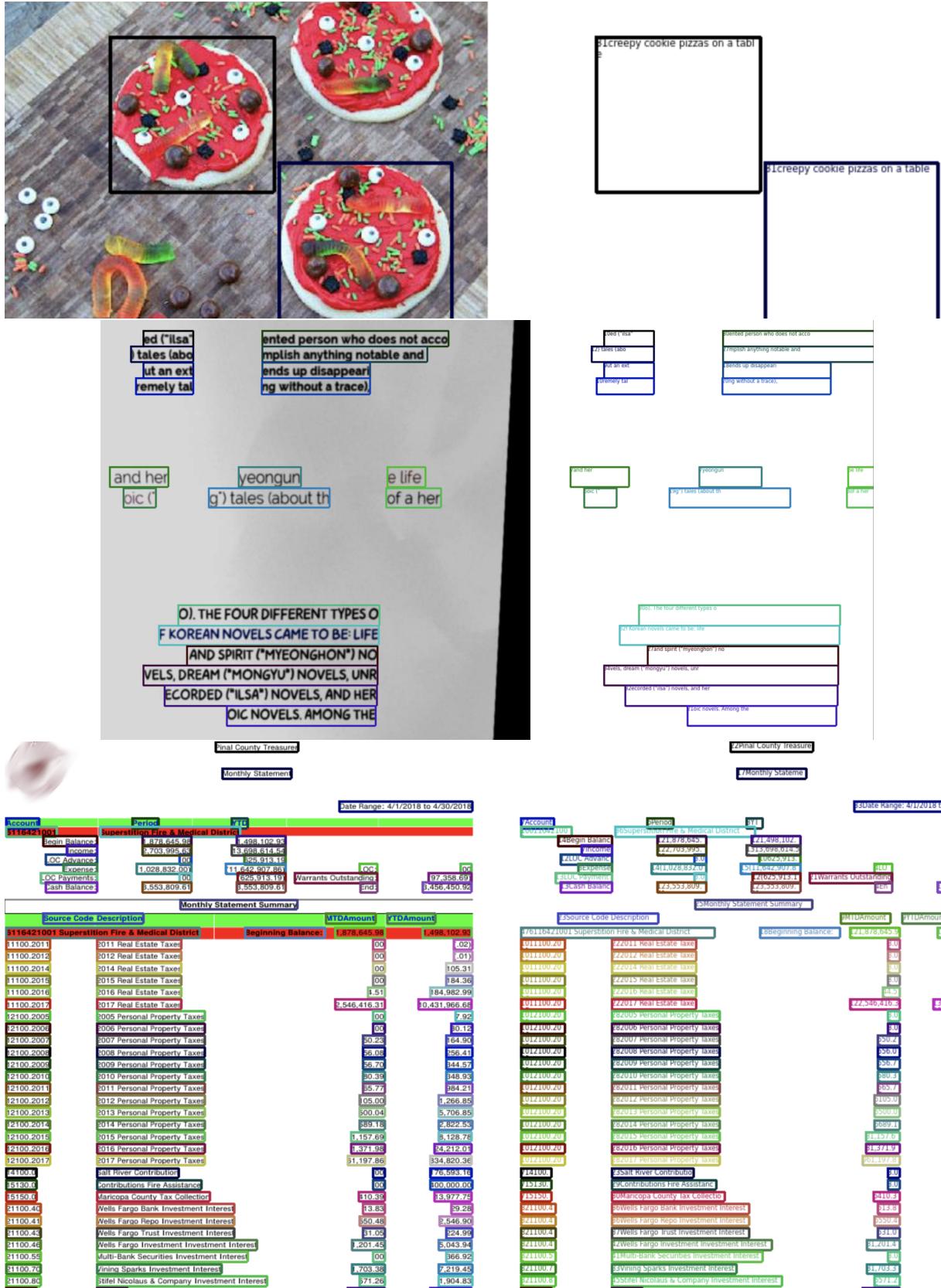


Figure 4: Visualization of the Grounding and OCR data used for training Qwen-VL