UNIFYING ARCHITECTURES, TASKS, AND MODALITIES THROUGH A SIMPLE SEQUENCE-TO-SEQUENCE LEARNING FRAMEWORK

Peng Wang, An Yang, Rui Men, Junyang Lin, Shuai Bai

Zhikang Li, Jianxin Ma, Chang Zhou, Jingren Zhou, Hongxia Yang

DAMO Academy, Alibaba Group *

`{zheluo.wp, ya235025, menrui.mr, junyang.ljy, baishuai.bs, zhikang.lzk, jason.mjx, ericzhou.zc, jingren.zhou, yang.yhx}@alibaba-inc.com`

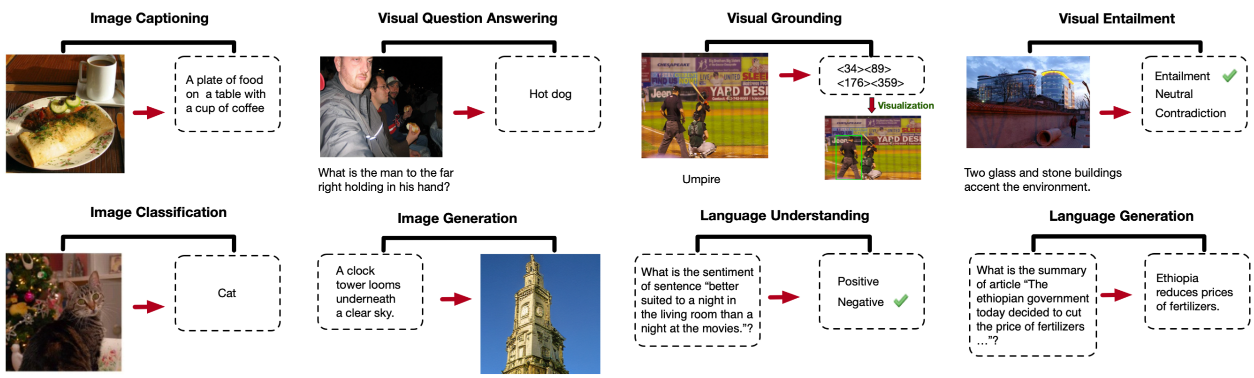

Figure 1: Examples of various tasks supported by OFA.

ABSTRACT

In this work, we pursue a unified paradigm for multimodal pretraining to break the scaffolds of complex task/modality-specific customization. We propose OFA, a unified multimodal pretrained model that unifies modalities (i.e., cross-modality, vision, language) and tasks (e.g., image generation, visual grounding, image captioning, image classification, text generation, etc.) to a simple sequence-to-sequence learning framework based on the encoder-decoder architecture. OFA performs pretraining and finetuning with task instructions and introduces no extra task-specific layers for finetuning. Experimental results show that OFA achieves new state-of-the-arts on a series of multimodal tasks, including image captioning (COCO test CIDEr: 149.6), text-to-image generation (COCO test FID: 10.5), VQA (test-std acc.: 80.02), SNLI-VE (test acc.: 90.20), and referring expression comprehension (RefCOCO / RefCOCO+ / RefCOCOg test acc.: 92.93 / 90.10 / 85.20). Through extensive analyses, we demonstrate that OFA reaches comparable performance with uni-modal pretrained models (e.g., BERT, MAE, MoCo v3, SimCLR v2, etc.) in uni-modal tasks, including NLU, NLG, and image classification, and it effectively transfers to unseen tasks and domains. Code shall be released soon at `https://github.com/OFA-Sys/OFA`.

Keywords Unified frameworks · Multimodal pretraining · Multitask learning · Zero-shot learning

*Correspondence to: Chang Zhou<ericzhou.zc@alibaba-inc.com>.

1 Introduction

Building an omnipotent model that handles as many tasks and modalities as human beings is an attractive goal in the AI community. The central problem towards this goal is to represent massive varieties of modalities, tasks, and training regimes in a single model.

Recent developments of the Transformer [1] architecture have shown its potential for being a universal computation engine [2, 3, 4, 5, 6, 7, 8]. In the settings of supervised learning, the pretrain-finetune paradigm achieves excellent successes in many domains, and in the regimes of few-/zero-shot learning, language models with prompt / instruction tuning prove powerful zero-/few-shot learners [3, 9, 10]. These advances have provided more significant than ever opportunities for the emergence of an omni-model.

To support better generalization for open-ended problems while maintaining multitask performance and ease of use, we advocate that an omnipotent model should have the following three properties: 1. Task-Agnostic (TA): unified task representation to support different types of tasks, including classification, generation, self-supervised pretext tasks, etc., and to be agnostic to either pretraining or finetuning. 2. Modality-Agnostic (MA): unified input and output representation to handle different modalities, shared among all tasks. 3. Task Comprehensiveness (TC): enough task variety to accumulate generalization ability robustly.

However, satisfying the above three properties is challenging while achieving superior performance. Due to their following design choices, current language and multimodal pretrained models readily fail at parts of the properties. 1. Extra learnable components for finetuning, e.g., task-specific heads [2], adapters [11], soft prompts [12]. It makes the model task-specific and thus violates TA. Besides, there are difficulties in finding optimal components, and such designs are not friendly to supporting unseen tasks in a zero-shot manner. 2. Task-specific formulation. For most current methods, pretraining, finetuning, and zero-shot tasks usually differ in task formulation and training objectives. It violates TA and is burdensome to scale up the task population to achieve TC. 3. Modality-specific design for varieties of I/O. It is a common practice for VL-pretrained models to take detected objects as input features for better downstream task performance [8, 13, 14, 15, 16, 17]. However, this modality-specific design entangles images with the concept of objects. It is hard to train the model with other tasks such as image generation or object detection in a task-agnostic model.

Therefore, we explore an omni-model for multimodal pretraining and propose **OFA**, namely "One For All", which achieves the objectives of unifying architecture, task, and modality, and supports the three properties above.[2] We formulate both pretraining and finetuning tasks in a unified sequence-to-sequence abstraction via handcrafted instructions [9, 10] to achieve Task-Agnostic. A Transformer is adopted as the Modality-Agnostic compute engine, with a constraint that no learnable task- or modality-specific components will be added to downstream tasks. It is available to represent information from different modalities within a globally shared multimodal vocabulary across all tasks. We then support Task Comprehensiveness by pretraining on varieties of uni-modal and cross-modal tasks.

To summarize:

- We propose OFA, a Task-Agnostic and Modal-Agnostic framework that supports Task Comprehensiveness. It first unifies tasks, including understanding and generation, e.g., image generation, visual grounding, visual question answering (VQA), image captioning, image classification, language modeling, etc., and modalities, including multi-modality and uni-modality, via a simple sequence-to-sequence learning framework with instruction-based training.
- Experiments demonstrate that OFA achieves new SOTAs on multimodal benchmarks, including image captioning (COCO test CIDEr: 149.6), text-to-image generation (COCO test FID: 10.5), VQA (test-std acc.: 80.02), SNLI-VE (test acc.: 90.20), and referring expression comprehension (RefCOCO / RefCOCO+ / RefCOCOg test acc.: 92.93 / 90.10 / 85.20), and performs competitively with uni-modal pretrained models on language and vision tasks, while still most previous multimodal pretrained models far underperform the uni-modal.
- We verify that OFA achieves competitive performance in zero-shot learning. Also, it can transfer to unseen tasks with new task instructions and adapt to out-of-domain information without finetuning.

2 Related Work

Language Pretraining & Vision Pretraining Natural language pretraining has revolutionized the whole NLP research community. A representation of this track is the birth of BERT [2] and GPT [22]. A number of studies have

[2] Note that this work is the latest one of our M6 series [18, 19, 20, 21].

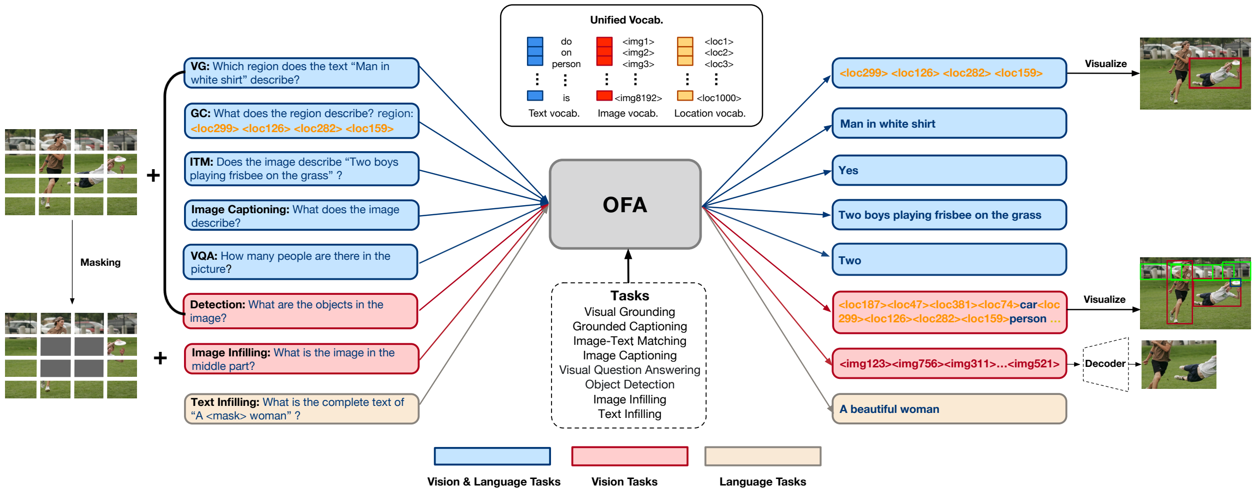

Figure 2: A demonstration of the pretraining tasks, including visual grounding, grounded captioning, image-text matching, image captioning, VQA, object detection, image infilling as well as text infilling.

been progressively advancing pretraining by improving pretraining tasks and designing more sophisticated model architectures [23, 24, 25, 26, 27, 28, 29]. Having witnessed the success of natural language pretraining, researchers have promoted self-supervised learning (SSL) in computer vision [30, 31, 32, 33]. Recently, mirroring masked language modeling (MLM) in language pretraining, generative pretraining [34, 35] with ViT architecture [6] further boosts downstream performances.

Multimodal Pretraining Multimodal pretraining has been developing rapidly [13, 14, 15, 16, 17, 36, 37, 38, 39, 40, 41, 42, 43, 44]. Researchers have applied masking strategies and encoder-decoder architecture to adapt models to generation tasks [15, 17, 18, 45]. Besides, to simplify preprocessing, patch projection has received attention and helped Transformer achieve SOTA performance in downstream tasks [45, 46]. To make full use of large-scale weakly supervised data, [47] trains a bi-encoder on 400 million pairs and demonstrates excellent performance in retrieval tasks. Another line of work is text-to-image synthesis. A bunch of works [18, 48, 49, 50] incorporate Transformer with VQVAE [51] or VQGAN [52] to generate high-quality images with high resolution. However, the previously mentioned methods are limited in processing a single type of data, such as cross-modal data only or limited in their capabilities. Also, the discrepancy between pretraining and finetuning behaviors limits the transferability to open-ended data.

Unified Frameworks To pursue the unified models, [53] presents tasks via a uniform format. In NLP, recent studies unify downstream tasks to text-to-text transfer [28] or language modeling [3]. Following this idea, [54] and [55] demonstrate text-generation-based multimodal pretrained models. [7] and [56] propose a simple framework that can process information from multiple modalities with a uniform byte-sequence representation. [57] and [58] unify tasks of different modalities by designing various task-specific layers. [59] explores to employ a retrieval-based unified paradigm. However, these multimodal pretrained models suffer from performance degradation in downstream tasks, e.g., VQA, image captioning, etc., and they have no image generation capability.

3 OFA

In this work, we propose OFA, a unified Seq2Seq framework for the unification of I/O & architectures, tasks, and modalities. The overall framework is illustrated in Figure 2.

3.1 I/O & Architecture

I/O Multimodal pretraining pretrains Transformer models on image-text corpus at scale. To enable multimodal pretraining, it is necessary to preprocess the data so that both visual and linguistic information can be jointly processed by the Transformer. Compared with the complex, resource&time-consuming object feature extraction, we aim for simplicity and directly split an image $x_v \in \mathbb{R}^{H \times W \times C}$ to P patches and project patches to features of the hidden size H, following [60] and [45]. As to processing linguistic information, we follow the practice of GPT [22] and BART [29] that we apply byte-pair encoding (BPE) to the given text sequence to transform it into a subword sequence and then embed them to features.

To process different modalities without task-specific output schema, it is essential to represent data of various modalities in a unified space. A possible solution is to discretize text, image, and object into a unified output vocabulary. Recent advances in image quantization [51, 52] has demonstrated effectiveness in text-to-image synthesis [18, 19, 48, 49], and thus we utilize this strategy for the target-side image representations. Sparse coding is effective in reducing the sequence length of image representation. For example, an image of the resolution of 256×256 is represented as a code sequence of the length of 16×16. Each discrete code strongly correlates the corresponding patch [34].

Apart from representing images, it is also essential to represent objects within images as there are a series of region-related tasks. Following [61], we represent objects as a sequence of discrete tokens. To be more specific, for each object, we extract its label and its bounding box. The continuous corner coordinates of the bounding box are uniformly discretized to integers as location tokens $\langle x_1, y_1, x_2, y_2 \rangle$. To improve simplicity, we use a unified vocabulary for all the linguistic and visual tokens, including subwords, image codes, and location tokens.

Architecture Following the previous successful practices in multimodal pretraining [14, 17, 45], we choose Transformer as the backbone architecture, and we adopt the encoder-decoder network as the unified architecture for all the pretraining, finetuning and zero-shot tasks. Specifically, both encoder and decoder are stacks of Transformer layers. A Transformer encoder layer consists of self attention and feed-forward networks (FFN), while a Transformer decoder layer consists of self attention, FFN and cross attention for building the connection between the decoder and the encoder output representations. To stabilize training and accelerate convergence, we add head scaling to self attention, a post-attention layer normalization (LN) [62], and an LN after the first layer of FFN [63].

3.2 Tasks & Modalities

A unified framework is designed to provide architecture compatibility across different modalities and downstream tasks so that opportunities can arise to generalize to unseen tasks within the same model. Then we have to represent the possible downstream tasks concerning different modalities in a unified paradigm. Therefore, an essential point for the design of pretraining tasks is the consideration of multitask and multimodality.

To unify tasks and modalities, we design a unified sequence-to-sequence learning paradigm for pretraining, finetuning, and inference on all tasks concerning different modalities. Tasks including pretraining tasks, downstream tasks of cross-modal and uni-modal understanding and generation are all formed as Seq2Seq generation tasks. It is available to perform multitask pretraining on multimodal and uni-modal data to endow the model with comprehensive capabilities. Specifically, we share the identical schema across all tasks, while we specify handcrafted instructions for discrimination [9].

For cross-modal representation learning, we design 5 tasks, including visual grounding (VG), grounded captioning (GC), image-text matching (ITM), image captioning (IC), and visual question answering (VQA). For VG, the model learns to generate location tokens specifying the region position $\langle x_1, y_1, x_2, y_2 \rangle$ based on the input of the image x_i and instruction "Which region does the text x_t describe?" where x_t refers to the region caption. GC is an inverse task of VG. The model learns to generate a description based on the input image x_i and the instruction "What does the region describe? region: $\langle x_1, y_1, x_2, y_2 \rangle$". For ITM, we use each original image-text pair as the positive sample and construct a new one as the negative by pairing the image with a randomly substituted caption. The model learns to discriminate whether the given image and text are paired by learning to generate "Yes" or "No" based on the input image x_i and the instruction "Does the image describe x_t?". For image captioning, this task can naturally adapt to the sequence-to-sequence format. The model learns to generate the caption based on the given image and the instruction "What does the image describe?". For VQA, we send the image and the question as input and require the model to learn to generate correct answers.

For uni-modal representation learning, we design 2 tasks for vision and 1 task for language, respectively. The model is pretrained with image infilling and object detection for vision representation learning. Recent advances in generative self-supervised learning for computer vision show that masked image modeling is an effective pretraining task [34, 35]. In practice, we mask the middle part of the images as the input. The model learns to generate the sparse codes for the central part of the image based on the corrupted input and the specified instruction "What is the image in the middle part?". We additionally add object detection to pretraining following [64]. The model learns to generate human-annotated object representations, i.e., the sequence of object position and label, based on the input of image and text "What are the objects in the image?" as the instruction. The tasks strengthen the representation learning on both pixel and object levels. For language representation learning, following the practice of [29], we pretrain the unified model on plain text data with text infilling.

Table 1: Experimental results on cross-modal downstream tasks. OFA reaches new SOTA performance in all four tasks. All reported results are from *Large*-size models, whose model sizes are similar to that of $\mathrm{BERT}_{\mathrm{Large}}$.

Model	COCO Captions B@4 / M / C / S	VQA test-dev / test-std	SNLI-VE dev / test	RefCOCO val / testA / testB	RefCOCO+ val / testA / testB	RefCOCOg val-u / test-u
VL-BERT [8]	-	71.79 / 72.22	-	-	72.59 / 78.57 / 62.30	-
UNITER [14]	-	73.82 / 74.02	79.39 / 79.38	81.41 / 87.04 / 74.17	75.90 / 81.45 / 66.70	74.86 / 75.77
OSCAR [15]	41.7 / 30.6 / 140.0 / 24.5	73.61 / 73.82	-	-	-	-
VILLA [16]	-	74.69 / 74.87	80.18 / 80.02	82.39 / 87.48 / 74.84	76.17 / 81.54 / 66.84	76.18 / 76.71
MDETR [65]	-	70.64 / 70.63	-	86.75 / 89.58 / 81.41	79.52 / 84.09 / 70.62	81.64 / 80.89
UNICORN [55]	35.8 / 28.4 / 119.1 / 21.5	69.2 / 69.4	-	88.29 / 90.42 / 83.06	80.30 / 85.05 / 71.88	83.44 / 83.93
VinVL [17]	41.0 / 31.1 / 140.9 / 25.2	76.52 / 76.60	-	-	-	-
UNIMO [43]	39.6 / - / 127.7 / -	75.06 / 75.27	81.11 / 80.63	-	-	-
METER [66]	-	77.68 / 77.64	80.86 / 81.19	-	-	-
VLMO [46]	-	**79.94** / 79.98	-	-	-	-
SimVLM [45]	40.3 / **33.4** / 142.6 / 24.7	79.32 / 79.56	85.68 / 85.62	-	-	-
OFA	**43.5** / 31.9 / **149.6** / **26.1**	79.87 / **80.02**	**90.30 / 90.20**	**90.05 / 92.93 / 85.26**	**84.49 / 90.10 / 77.77**	**84.54 / 85.20**

In this way, we unify multiple modalities and multiple tasks to a single model and pretraining paradigm. OFA is pretrained jointly with those tasks and data. Thus, it can perform different tasks concerning different modalities and complex cross-modal scenarios with the capability of generating answers.

3.3 Pretraining Datasets

We construct pretraining datasets by incorporating Vision & Language data (i.e., image-text pairs), Vision data (i.e., raw image data, object-labeled data), and Language data (i.e., plain texts). For replicability, we only use datasets that are publicly available. We carefully filter our pretraining data and exclude images that appear in the validation and test sets of downstream tasks to avoid data leakage. We provide more details about pretraining datasets in Appendix A.1.

3.4 Training & Inference

We optimize the model with the cross-entropy loss. Given an input x, an instruction s and an output y, we train OFA by minimizing $\mathcal{L} = -\sum_{i=1}^{|y|} \log P_\theta(y_i | y_{<i}, x, s)$, where θ refers to the model parameters. For inference, we apply decoding strategies, e.g., beam search, to enhance the quality of generation. However, this paradigm has several problems in classification tasks: 1. optimizing on the entire vocabulary is unnecessary and inefficient; 2. the model may generate invalid labels out of the closed label set during inference. To overcome these issues, we introduce a search strategy based on prefix tree (Trie, [67]) to both training and inference. Experimental results show that the Trie-based search can enhance the performance of OFA on classification tasks. See Appendix B for more details.

4 Experiments

This section provides experimental details and analyses to demonstrate our model's effectiveness. See Appendix A for implementation details.

4.1 Results on Cross-modal Tasks

Cross-modal tasks include image captioning on MS COCO Caption [68], visual question answering on VQAv2 [69], visual entailment on SNLI-VE [70], referring expression comprehension on RefCOCO / RefCOCO+ / RefCOCOg [71, 72], and text-to-image generation on MS COCO Caption. More details are provided in Appendix A.3.

Table 1 presents the performance of OFA and baseline models on cross-modal downstream tasks, including image captioning, VQA, visual entailment, and referring expression comprehension, and demonstrates that OFA creates new SOTAs on the four tasks. Specifically, on image captioning, OFA performs the best on CIDEr evaluation (CIDEr: 149.6). It also surpasses SimVLM, which uses 1.8 billion image-text pairs for pretraining (around $75\times$ larger than ours), by a large margin of 7.0. At the time of submitting this paper, OFA also achieves No.1 on the COCO image captioning online leaderboard.[3] On referring expression comprehension, OFA reaches the SOTA performance on

[3]https://competitions.codalab.org/competitions/3221#results

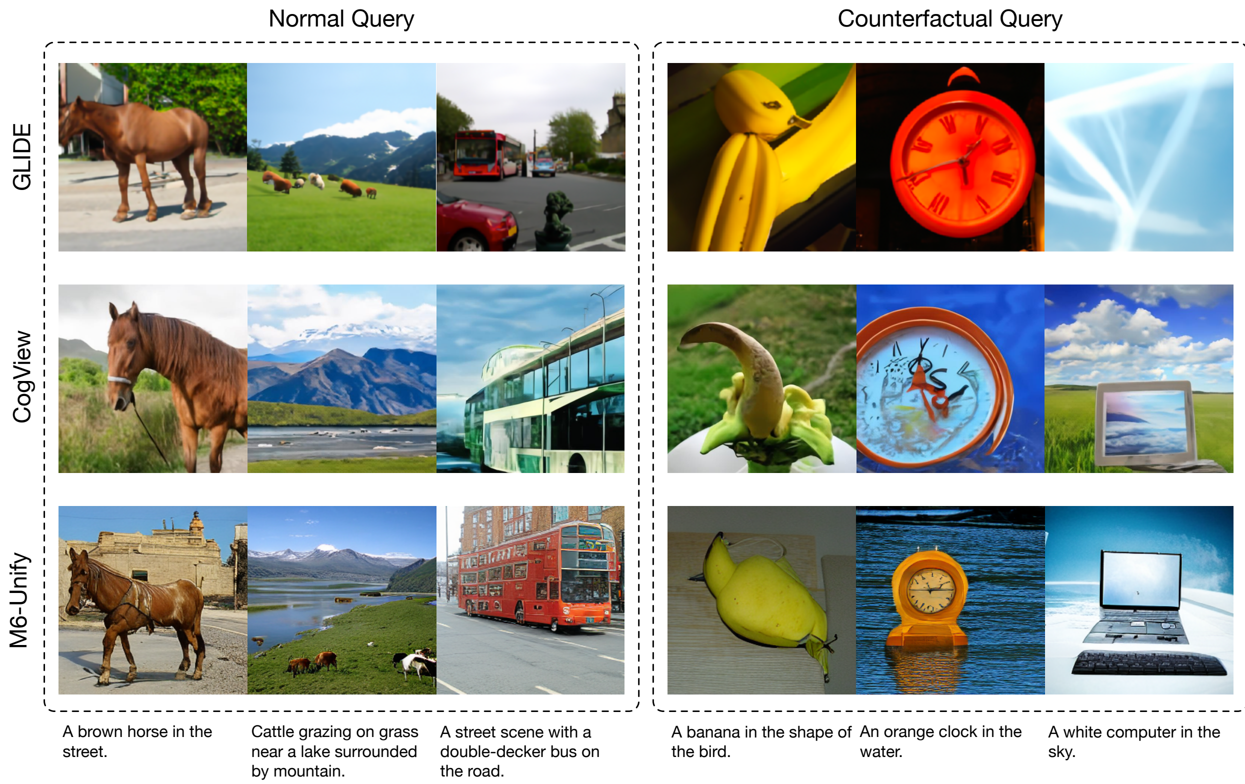

Figure 3: Qualitative comparison with state-of-the-art models for text-to-image generation task. Due to the space limitation, we present a lot more qualitative examples of text-to-image generation for better demonstration in Appendix C.

Table 2: Experimental results on text-to-image generation. Models are evaluated on FID, CLIPSIM, and IS scores. OFA outperforms the baselines, including the concurrent SOTA NÜWA, with smaller sample size. "#Param." refers to the number of model parameters. Note that GLIDE additionally has $1.5B$ parameters for upsampling except for the $3.5B$ parameters.

Model	#Param.	FID↓	CLIPSIM↑	IS↑
DALLE [48]	12B	27.5	-	17.9
CogView [49]	4B	27.1	33.3	18.2
GLIDE [73]	3.5B	12.2	-	-
Unifying [74]	228M	29.9	30.9	-
NÜWA [50]	870M	12.9	34.3	27.2
OFA	472M	**10.5**	**34.4**	**31.1**

RefCOCO / RefCOCO+ / RefCOCOg. Compared with the previous SOTA UNICORN [55], OFA achieves significant improvement with a relative gain of 2.51, 5.05 and 1.27 in the testA sets of RefCOCO and RefCOCO+ as well as the test-u set of RefCOCOg. On VQA, OFA achieves 80.02 on test-std and outperforms the SOTA models of the *Large* size, including SimVLM and VLMo. Note that both the previous SOTAs are classification-based models. On SNLI-VE, OFA achieves state-of-the-art performance and outperforms previous models by a large margin, demonstrating its capability of complex visual-linguistic reasoning.

Table 2 demonstrates the model performance on text-to-image generation. OFA achieves state-of-the-art performance in all the metrics. Note that increasing the sampling size during inference is expected to bring clear improvements on FID and IS. Compared with DALLE [48], CogView [49] and NÜWA [50], whose sampling sizes are 512, 60 and 60, respectively, OFA outperforms these SOTA methods on FID and IS with a much smaller sampling size 24. This illustrates that OFA has learned better correspondence among query text, image and image code.

Table 3: Experimental results of BERT and multimodal pretrained models on GLUE [75]. For models of *Base* size, OFA outperforms all multimodal pretrained baseline models on the 7 tasks, and BERT on 6 tasks except CoLA. For models of *Large* size, OFA performs competitively with $\mathrm{BERT_{Large}}$. The reported results of the multimodal baselines are from [76] and the corresponding original papers.

Model	CoLA Mcc.	SST-2 Acc.	RTE Acc.	MRPC Acc./F1	QQP Acc./F1	MNLI Acc	QNLI Acc
Base-Size Models							
BERT	**54.6**	92.5	62.5	81.9/87.6	90.6/87.4	84.2	91.0
VisualBERT	38.6	89.4	56.6	71.9/82.1	89.4/86.0	81.6	87.0
UNITER	37.4	89.7	55.6	69.3/80.3	89.2/85.7	80.9	86.0
VL-BERT	38.7	89.8	55.7	70.6/81.8	89.0/85.4	81.2	86.3
VilBERT	36.1	90.4	53.7	69.0/79.4	88.6/85.0	79.9	83.8
LXMERT	39.0	90.2	57.2	69.8/80.4	75.3/75.3	80.4	84.2
SimVLM	46.7	90.9	63.9	75.2/84.4	90.4/87.2	83.4	88.6
FLAVA	50.7	90.9	57.8	81.4/86.9	90.4/87.2	80.3	87.3
Uni-Perceiver	-	90.2	64.3	-/86.6	-/87.1	81.7	89.9
OFA	52.3	**92.7**	**70.8**	**86.8/90.6**	**91.3/88.4**	**84.3**	**91.1**
Large-Size Models							
BERT	**60.6**	93.2	70.4	**88.0**/-	91.3/-	**86.6**	92.3
OFA	53.1	**94.7**	**73.6**	**88.0/91.4**	**91.8/88.9**	**86.6**	**92.8**

Table 4: Experimental results on Gigaword abstractive summarization. OFA can outperform most baselines and demonstrate competitive performance with the SOTA model ProphetNet.

Model	Gigaword R-1 / R-2 / R-L
BERTSHARE [79]	38.13 / 19.81 / 35.62
MASS [80]	38.73 / 19.71 / 35.96
UniLM [27]	38.45 / 19.45 / 35.75
PEGASUS [81]	39.12 / 19.86 / 36.24
ProphetNet [82]	**39.55 / 20.27 / 36.57**
OFA	39.20 / 20.25 / 36.40

We compare OFA with CogView and GLIDE on generation quality with normal and counterfactual queries.[4] Normal queries describe existing things in the real world, while counterfactual queries refer to those describing things that could only exist in our imagination. For normal queries, both CogView and OFA generate images semantically consistent with the given texts, in comparison with GLIDE. The generated examples from our model can provide more sophisticated details of objects, say the horse and the double-decker bus. For counterfactual queries, we find that OFA is the only one that can generate the three imaginary scenes, which indicates its imaginative power based on its strong capability to align text to the image. See Appendix C for more qualitative examples.

4.2 Results on Uni-modal Tasks

Uni-modal tasks include natural language understanding on the GLUE benchmark [75], natural language generation on Gigaword [77] and image classification on ImageNet-1K [78]. More details are provided in Appendix A.3.

We verify that OFA can achieve competitive performance in downstream tasks of language and vision. On natural language understanding tasks, while [45] report the results of the *Base*-size SimVLM, we also conduct experiments on the *Base*-size OFA and compare with baselines of the same scale for a fair comparison. Table 3 demonstrates the results on GLUE [75]. For models of *Base*-size, OFA outperforms previous multimodal models by a large margin. Compared with SimVLM, OFA achieves better performance even with a much smaller pretraining dataset. In addition, OFA also outperforms BERT in most tasks, indicating the good natural language understanding capability of OFA. For *Large*-size

[4]For more implementation details, please refer to Appendix A.3

Table 5: ImageNet-1K finetuning results. All the listed models do not use extra labeled image classification samples during training for fair comparison.

Model	Top-1 Acc.
EfficientNet-B7 [83]	84.3
ViT-L/16 [6]	82.5
DINO [84]	82.8
SimCLR v2 [30]	82.9
MoCo v3 [33]	84.1
BEiT_{384}-L/16 [34]	86.3
MAE-L/16 [35]	85.9
OFA	84.9

Table 6: Zero-shot performance on 6 GLUE subtasks and SNLI-VE.

Model	SST-2 Acc.	RTE Acc.	MRPC F1	QQP F1	QNLI Acc.	MNLI Acc.	SNLI-VE Acc. (dev/test)
Uni-Perceiver	70.6	55.6	76.1	53.6	51.0	**49.6**	-
OFA_{Base}	**71.6**	**56.7**	**79.5**	**54.0**	**51.4**	37.3	**49.71 / 49.18**

models, OFA performs competitively with $\text{BERT}_{\text{Large}}$. Table 4 demonstrates the model performance on Gigaword. The baseline models are all pretraining on text-only datasets. Though pretrained on various tasks, OFA still outperforms most baseline models.

Table 5 shows the performance of OFA on image classification. OFA achieves higher accuracy than previous backbone models such as EfficientNet-B7 and ViT-L. We also compare OFA with self-supervised pretraining models based on contrastive learning and masked image modeling. OFA outperforms contrastive-based models such as SimCLR and MoCo with similar parameters. Compared with pretrained models based on masked image modeling, e.g., BEiT-L and MAE-L, OFA achieves similar results without Mixup [85] and CutMix [86].

4.3 Zero-shot Learning & Task Transfer

The instruction-guided pretraining enables OFA to perform zero-shot inference. Following Uni-Perceiver [59], a concurrent multimodal pretrained model that conducts zero-shot inference on NLU, we evaluate our model on 6 NLU tasks, including single-sentence classification and sentence pair classification, in the GLUE benchmark. Table 6 demonstrates that OFA generally outperforms Uni-Perceiver. However, both models do not achieve satisfactory performance in sentence-pair classification (with Acc. $< 60\%$). We hypothesize that the missing sentence-pair data in the pretraining dataset attributes to the performance, and we leave this issue to our future research.

We observe that the model can transfer to unseen tasks well with new task instructions. We design a new task called grounded question answering and present examples in Figure 4. In this scenario, given a question about a certain region on the image, the model should provide a correct answer. We find that the model can achieve satisfactory performance in this new task, which reflects its strong transferability. Besides, OFA can perform well given out-of-domain inputs. For example, we observe that pretrained OFA without finetuning achieves satisfactory performance in VQA for the out-of-domain images. Examples are demonstrated in Figure 5. OFA can also perform accurate visual grounding on the out-of-domain images, e.g., anime pictures, synthetic images, etc., and we demonstrate more examples on Figure 11 in Appendix C. For text-to-image synthesis, our cases in Figure 3 shows that OFA generates high-quality samples with counterfactual queries. We demonstrate more examples in Figure 8 in Appendix C.

4.4 Ablation on Multitask Pretraining

Thanks to the unified framework, OFA has been pretrained on multiple tasks and thus endowed with comprehensive capabilities. However, the effects of each task are still undiscovered. We verify their effects on multiple downstream tasks, including image captioning, VQA, image classification, and text-to-image generation.

Q: what color is the car in the region? region: <loc301> <loc495> <loc501> <loc596>

A: tan

Q: what color is the car in the region? region: <loc512> <loc483> <loc675> <loc576>

A: gray

Figure 4: Qualitative results on an unseen task grounded QA. We design a new task called grounded question answering, where the model should answer a question about a certain region in the image. More samples are provided in Figure 10 in Appendix C.

Q: what is grown on the plant?

A: money

Q: what does the red-roofed building right to the big airship look like?

A: a mushroom

Figure 5: Qualitative results on unseen domain VQA. During pretraining, only real-world photographs are used for VQA. We present cases of VQA on out-of-domain images, i.e., the iconic and sci-fi images, and demonstrate their capability of transferring to unseen domains. More samples are provided in Figure 9 in Appendix C.

We first evaluate how uni-modal pretraining tasks influence the performance in both cross-modal and uni-modal tasks. Table 7 demonstrates our experimental results. We observe some interesting phenomena about the effects of uni-modal pretraining tasks. Text infilling brings improvement on image caption (+0.8 CIDEr) and VQA (+0.46 Acc.). Natural language pretraining betters the contextualized representation of language and thus enhances performance in cross-modal tasks. However, it is noticed that the language pretraining task may degrade the performance in image classification, leading to the decrease in ImageNet-1K (−1.0 Acc.). Also, it is interesting to find that it does not encourage improvement in text-to-image generation (−0.1 CLIPSIM). It may attribute to the simplicity of text in this task, which indicates that improved representation of language does not affect the performance. As to image infilling, it significantly improves the performance in image classification (+1.0 Acc.) and text-to-image generation (+0.6 CLIPSIM). Learning to recover images is an effective self-supervised task for image representation, and it also encourages the decoder's ability to generate image codes. However, it hurts the performance in image captioning and VQA. Both tasks require a strong capability in generating texts, and the decoder's learning of image generation naturally brings performance degradation in captioning (−0.7 CIDEr) and VQA (−0.3 Acc.).

Table 7: Ablation results of OFA. All models are pretrained for $250k$ steps. *w/o ground.* represents the removal of both visual grounding and grounded captioning tasks. Note that all models are only finetuned with the cross-entropy loss in image captioning.

Model	Caption CIDEr	VQA Test-dev	ImageNet Top-1 Acc.	Image Generation FID / CLIPSIM / IS
OFA_{Base}	135.6	76.0	82.2	20.8 / 31.6 / 21.5
w/o text infill.	134.8	75.6	83.2	20.3 / 31.7 / 21.8
w/o image infill.	136.3	76.3	81.8	23.2 / 31.0 / 20.0
w/o det.	133.3	75.4	81.4	20.9 / 31.5 / 21.6
w/o ground.	134.2	75.5	82.0	21.2 / 31.5 / 21.5

Furthermore, we evaluate how multimodal tasks impact the performance. Previous studies have provided evidence of the contribution of conventional pretraining tasks, e.g., MLM, MOC, ITM, VQA, image captioning, etc. [14, 17]. However, they miss other tasks, e.g., detection and visual grounding & grounded captioning. We conduct experiments on these tasks and find that tasks predicting regions are crucial to multimodal tasks, with a performance increase in image captioning ($+2.3$ CIDEr & $+1.4$ CIDEr) and VQA ($+0.6$ Acc. & $+0.5$ Acc.). It suggests that detection and visual grounding & grounded captioning help the model grasp fined-grained alignments between vision and language. Region information contributes little to text-to-image generation ($+0.1$ CLIPSIM & $+0.1$ CLIPSIM), as this task requires far less text-region alignment information. We surprisingly find that detection can encourage the performance in visual understanding ($+0.8$ Acc.). It indicates that incorporating region information might be essential to visual understanding, especially on images with complex objects.

5 Conclusion

In this work, we propose **OFA**, a Task-Agnostic and Modality-Agnostic framework supporting Task Comprehensiveness. OFA achieves the unification in architecture, tasks and modalities, and thus is capable of multimodal & uni-modal understanding and generation, without specification in additional layers or tasks. Our experiments show that OFA creates new SOTAs in image captioning, text-to-image generation, VQA, SNLI-VE and referring expression comprehension. OFA also demonstrates comparable performance with language / vision pretrained models in uni-modal understanding and generation tasks, e.g., GLUE, abstractive summarization, and image classification. We provide further analysis to demonstrate its capability in zero-shot learning and domain & task transfer, and we also verify the effectiveness of pretraining tasks.

In the future, we will continue exploring the issues discovered in this work. Also, we endeavor to figure out a reasonable solution to building an omni-model essentially generalizable to the complex real world.

References

[1] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In NeurIPS 2017, pages 5998–6008, 2017.

[2] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In Jill Burstein, Christy Doran, and Thamar Solorio, editors, NAACL-HLT 2019, pages 4171–4186. Association for Computational Linguistics, 2019.

[3] Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. arXiv preprint arXiv:2005.14165, 2020.

[4] Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. Training verifiers to solve math word problems. arXiv preprint arXiv:2110.14168, 2021.

[5] Steffen Schneider, Alexei Baevski, Ronan Collobert, and Michael Auli. wav2vec: Unsupervised pre-training for speech recognition. arXiv preprint arXiv:1904.05862, 2019.

[6] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929, 2020.

[7] Andrew Jaegle, Felix Gimeno, Andrew Brock, Andrew Zisserman, Oriol Vinyals, and Joao Carreira. Perceiver: General perception with iterative attention. arXiv preprint arXiv:2103.03206, 2021.

[8] Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, and Jifeng Dai. Vl-bert: Pre-training of generic visual-linguistic representations. In International Conference on Learning Representations, 2019.

[9] Jason Wei, Maarten Bosma, Vincent Y Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. Finetuned language models are zero-shot learners. arXiv preprint arXiv:2109.01652, 2021.

[10] Victor Sanh, Albert Webson, Colin Raffel, Stephen H Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, et al. Multitask prompted training enables zero-shot task generalization. arXiv preprint arXiv:2110.08207, 2021.

[11] Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. Parameter-efficient transfer learning for nlp. In International Conference on Machine Learning, pages 2790–2799. PMLR, 2019.

[12] Brian Lester, Rami Al-Rfou, and Noah Constant. The power of scale for parameter-efficient prompt tuning. arXiv preprint arXiv:2104.08691, 2021.

[13] Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. In NeurIPS, 2019.

[14] Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. Uniter: Universal image-text representation learning. In ECCV, 2020.

[15] Xiujun Li, Xi Yin, Chunyuan Li, Xiaowei Hu, Pengchuan Zhang, Lei Zhang, Lijuan Wang, Houdong Hu, Li Dong, Furu Wei, Yejin Choi, and Jianfeng Gao. Oscar: Object-semantics aligned pre-training for vision-language tasks. In ECCV, 2020.

[16] Zhe Gan, Yen-Chun Chen, Linjie Li, Chen Zhu, Yu Cheng, and Jingjing Liu. Large-scale adversarial training for vision-and-language representation learning. ArXiv, abs/2006.06195, 2020.

[17] Pengchuan Zhang, Xiujun Li, Xiaowei Hu, Jianwei Yang, Lei Zhang, Lijuan Wang, Yejin Choi, and Jianfeng Gao. Vinvl: Revisiting visual representations in vision-language models. 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 5575–5584, 2021.

[18] Junyang Lin, Rui Men, An Yang, Chang Zhou, Ming Ding, Yichang Zhang, Peng Wang, Ang Wang, Le Jiang, Xianyan Jia, et al. M6: A chinese multimodal pretrainer. arXiv preprint arXiv:2103.00823, 2021.

[19] Zhu Zhang, Jianxin Ma, Chang Zhou, Rui Men, Zhikang Li, Ming Ding, Jie Tang, Jingren Zhou, and Hongxia Yang. M6-ufc: Unifying multi-modal controls for conditional image synthesis. arXiv preprint arXiv:2105.14211, 2021.

[20] An Yang, Junyang Lin, Rui Men, Chang Zhou, Le Jiang, Xianyan Jia, Ang Wang, Jie Zhang, Jiamang Wang, Yong Li, et al. Exploring sparse expert models and beyond. arXiv preprint arXiv:2105.15082, 2021.

[21] Junyang Lin, An Yang, Jinze Bai, Chang Zhou, Le Jiang, Xianyan Jia, Ang Wang, Jie Zhang, Yong Li, Wei Lin, et al. M6-10t: A sharing-delinking paradigm for efficient multi-trillion parameter pretraining. arXiv preprint arXiv:2110.03888, 2021.

[22] Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Improving language understanding by generative pre-training. URL https://s3-us-west-2.amazonaws.com/openai-assets/researchcovers/languageunsupervised/language understanding paper. pdf, 2018.

[23] Zhilin Yang, Zihang Dai, Yiming Yang, Jaime G. Carbonell, Ruslan Salakhutdinov, and Quoc V. Le. Xlnet: Generalized autoregressive pretraining for language understanding. In NeurIPS 2019, pages 5754–5764, 2019.

[24] Yu Sun, Shuohuan Wang, Yu-Kun Li, Shikun Feng, Xuyi Chen, Han Zhang, Xin Tian, Danxiang Zhu, Hao Tian, and Hua Wu. ERNIE: enhanced representation through knowledge integration. CoRR, abs/1904.09223, 2019.

[25] Yu Sun, Shuohuan Wang, Yu-Kun Li, Shikun Feng, Hao Tian, Hua Wu, and Haifeng Wang. ERNIE 2.0: A continual pre-training framework for language understanding. CoRR, abs/1907.12412, 2019.

[26] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized BERT pretraining approach. CoRR, abs/1907.11692, 2019.

[27] Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. Unified language model pre-training for natural language understanding and generation. In NeurIPS 2019, pages 13042–13054, 2019.

[28] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. Journal of Machine Learning Research, 21(140):1–67, 2020.

[29] Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In ACL 2020, July 2020.

[30] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In International conference on machine learning, pages 1597–1607. PMLR, 2020.

[31] Xinlei Chen, Haoqi Fan, Ross Girshick, and Kaiming He. Improved baselines with momentum contrastive learning. arXiv preprint arXiv:2003.04297, 2020.

[32] Jean-Bastien Grill, Florian Strub, Florent Altché, Corentin Tallec, Pierre H Richemond, Elena Buchatskaya, Carl Doersch, Bernardo Avila Pires, Zhaohan Daniel Guo, Mohammad Gheshlaghi Azar, et al. Bootstrap your own latent: A new approach to self-supervised learning. arXiv preprint arXiv:2006.07733, 2020.

[33] Xinlei Chen and Kaiming He. Exploring simple siamese representation learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 15750–15758, 2021.

[34] Hangbo Bao, Li Dong, and Furu Wei. Beit: Bert pre-training of image transformers. arXiv preprint arXiv:2106.08254, 2021.

[35] Kaiming He, Xinlei Chen, Saining Xie, Yanghao Li, Piotr Dollár, and Ross Girshick. Masked autoencoders are scalable vision learners. arXiv preprint arXiv:2111.06377, 2021.

[36] Liunian Harold Li, Mark Yatskar, Da Yin, Cho-Jui Hsieh, and Kai-Wei Chang. Visualbert: A simple and performant baseline for vision and language. ArXiv, abs/1908.03557, 2019.

[37] Luowei Zhou, Hamid Palangi, Lei Zhang, Houdong Hu, Jason J. Corso, and Jianfeng Gao. Unified vision-language pre-training for image captioning and VQA. In AAAI 2020, pages 13041–13049, 2020.

[38] Hao Tan and Mohit Bansal. Lxmert: Learning cross-modality encoder representations from transformers. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5100–5111, 2019.

[39] Gen Li, Nan Duan, Yuejian Fang, Daxin Jiang, and Ming Zhou. Unicoder-vl: A universal encoder for vision and language by cross-modal pre-training. CoRR, abs/1908.06066, 2019.

[40] Junyang Lin, An Yang, Yichang Zhang, Jie Liu, Jingren Zhou, and Hongxia Yang. Interbert: Vision-and-language interaction for multi-modal pretraining. arXiv preprint arXiv:2003.13198, 2020.

[41] Jiasen Lu, Vedanuj Goswami, Marcus Rohrbach, Devi Parikh, and Stefan Lee. 12-in-1: Multi-task vision and language representation learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10437–10446, 2020.

[42] Fei Yu, Jiji Tang, Weichong Yin, Yu Sun, Hao Tian, Hua Wu, and Haifeng Wang. Ernie-vil: Knowledge enhanced vision-language representations through scene graphs. In AAAI 2021, volume 35, pages 3208–3216, 2021.

[43] Wei Li, Can Gao, Guocheng Niu, Xinyan Xiao, Hao Liu, Jiachen Liu, Hua Wu, and Haifeng Wang. UNIMO: towards unified-modal understanding and generation via cross-modal contrastive learning. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli, editors, ACL/IJCNLP 2021, pages 2592–2607. Association for Computational Linguistics, 2021.

[44] Zhicheng Huang, Zhaoyang Zeng, Bei Liu, Dongmei Fu, and Jianlong Fu. Pixel-bert: Aligning image pixels with text by deep multi-modal transformers. ArXiv, abs/2004.00849, 2020.

[45] Zirui Wang, Jiahui Yu, Adams Wei Yu, Zihang Dai, Yulia Tsvetkov, and Yuan Cao. Simvlm: Simple visual language model pretraining with weak supervision. ArXiv, abs/2108.10904, 2021.

[46] Wenhui Wang, Hangbo Bao, Li Dong, and Furu Wei. Vlmo: Unified vision-language pre-training with mixture-of-modality-experts. ArXiv, abs/2111.02358, 2021.

[47] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. In Marina Meila and Tong Zhang, editors, ICML 2021, volume 139 of Proceedings of Machine Learning Research, pages 8748–8763. PMLR, 2021.

[48] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. Zero-shot text-to-image generation. arXiv preprint arXiv:2102.12092, 2021.

[49] Ming Ding, Zhuoyi Yang, Wenyi Hong, Wendi Zheng, Chang Zhou, Da Yin, Junyang Lin, Xu Zou, Zhou Shao, Hongxia Yang, et al. Cogview: Mastering text-to-image generation via transformers. arXiv preprint arXiv:2105.13290, 2021.

[50] Chenfei Wu, Jian Liang, Lei Ji, Fan Yang, Yuejian Fang, Daxin Jiang, and Nan Duan. N\" uwa: Visual synthesis pre-training for neural visual world creation. arXiv preprint arXiv:2111.12417, 2021.

[51] Aäron van den Oord, Oriol Vinyals, and Koray Kavukcuoglu. Neural discrete representation learning. In NIPS, 2017.

[52] Patrick Esser, Robin Rombach, and Bjorn Ommer. Taming transformers for high-resolution image synthesis. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 12873–12883, 2021.

[53] Lukasz Kaiser, Aidan N Gomez, Noam Shazeer, Ashish Vaswani, Niki Parmar, Llion Jones, and Jakob Uszkoreit. One model to learn them all. arXiv preprint arXiv:1706.05137, 2017.

[54] Jaemin Cho, Jie Lei, Haochen Tan, and Mohit Bansal. Unifying vision-and-language tasks via text generation. In ICML, 2021.

[55] Zhengyuan Yang, Zhe Gan, Jianfeng Wang, Xiaowei Hu, Faisal Ahmed, Zicheng Liu, Yumao Lu, and Lijuan Wang. Crossing the format boundary of text and boxes: Towards unified vision-language modeling. ArXiv, abs/2111.12085, 2021.

[56] Andrew Jaegle, Sebastian Borgeaud, Jean-Baptiste Alayrac, Carl Doersch, Catalin Ionescu, David Ding, Skanda Koppula, Daniel Zoran, Andrew Brock, Evan Shelhamer, et al. Perceiver io: A general architecture for structured inputs & outputs. arXiv preprint arXiv:2107.14795, 2021.

[57] Ronghang Hu and Amanpreet Singh. Unit: Multimodal multitask learning with a unified transformer. arXiv preprint arXiv:2102.10772, 2021.

[58] Amanpreet Singh, Ronghang Hu, Vedanuj Goswami, Guillaume Couairon, Wojciech Galuba, Marcus Rohrbach, and Douwe Kiela. Flava: A foundational language and vision alignment model. arXiv preprint arXiv:2112.04482, 2021.

[59] Xizhou Zhu, Jinguo Zhu, Hao Li, Xiaoshi Wu, Xiaogang Wang, Hongsheng Li, Xiaohua Wang, and Jifeng Dai. Uni-perceiver: Pre-training unified architecture for generic perception for zero-shot and few-shot tasks. arXiv preprint arXiv:2112.01522, 2021.

[60] Zihang Dai, Hanxiao Liu, Quoc V Le, and Mingxing Tan. Coatnet: Marrying convolution and attention for all data sizes. arXiv preprint arXiv:2106.04803, 2021.

[61] Ting Chen, Saurabh Saxena, Lala Li, David J Fleet, and Geoffrey Hinton. Pix2seq: A language modeling framework for object detection. arXiv preprint arXiv:2109.10852, 2021.

[62] Lei Jimmy Ba, Jamie Ryan Kiros, and Geoffrey E. Hinton. Layer normalization. CoRR, abs/1607.06450, 2016.

[63] Sam Shleifer, Jason Weston, and Myle Ott. Normformer: Improved transformer pretraining with extra normalization. arXiv preprint arXiv:2110.09456, 2021.

[64] Haiyang Xu, Ming Yan, Chenliang Li, Bin Bi, Songfang Huang, Wenming Xiao, and Fei Huang. E2e-vlp: End-to-end vision-language pre-training enhanced by visual learning. arXiv preprint arXiv:2106.01804, 2021.

[65] Aishwarya Kamath, Mannat Singh, Yann LeCun, Ishan Misra, Gabriel Synnaeve, and Nicolas Carion. Mdetr - modulated detection for end-to-end multi-modal understanding. ArXiv, abs/2104.12763, 2021.

[66] Zi-Yi Dou, Yichong Xu, Zhe Gan, Jianfeng Wang, Shuohang Wang, Lijuan Wang, Chenguang Zhu, Nanyun Peng, Zicheng Liu, and Michael Zeng. An empirical study of training end-to-end vision-and-language transformers. ArXiv, abs/2111.02387, 2021.

[67] Thomas H Cormen, Charles E Leiserson, Ronald L Rivest, and Clifford Stein. Introduction to algorithms. MIT press, 2009.

[68] Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco captions: Data collection and evaluation server. arXiv preprint arXiv:1504.00325, 2015.

[69] Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. Making the v in vqa matter: Elevating the role of image understanding in visual question answering. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6904–6913, 2017.

[70] Ning Xie, Farley Lai, Derek Doran, and Asim Kadav. Visual entailment: A novel task for fine-grained image understanding. arXiv preprint arXiv:1901.06706, 2019.

[71] Licheng Yu, Patrick Poirson, Shan Yang, Alexander C Berg, and Tamara L Berg. Modeling context in referring expressions. In European Conference on Computer Vision, pages 69–85. Springer, 2016.

[72] Junhua Mao, Jonathan Huang, Alexander Toshev, Oana Camburu, Alan L Yuille, and Kevin Murphy. Generation and comprehension of unambiguous object descriptions. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 11–20, 2016.

[73] Alex Nichol, Prafulla Dhariwal, Aditya Ramesh, Pranav Shyam, Pamela Mishkin, Bob McGrew, Ilya Sutskever, and Mark Chen. Glide: Towards photorealistic image generation and editing with text-guided diffusion models. arXiv preprint arXiv:2112.10741, 2021.

[74] Yupan Huang, Hongwei Xue, Bei Liu, and Yutong Lu. Unifying multimodal transformer for bi-directional image and text generation. In Proceedings of the 29th ACM International Conference on Multimedia, pages 1138–1147, 2021.

[75] Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. Glue: A multi-task benchmark and analysis platform for natural language understanding. arXiv preprint arXiv:1804.07461, 2018.

[76] Taichi Iki and Akiko Aizawa. Effect of visual extensions on natural language understanding in vision-and-language models. arXiv preprint arXiv:2104.08066, 2021.

[77] Alexander M Rush, Sumit Chopra, and Jason Weston. A neural attention model for abstractive sentence summarization. arXiv preprint arXiv:1509.00685, 2015.

[78] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition, pages 248–255. Ieee, 2009.

[79] Sascha Rothe, Shashi Narayan, and Aliaksei Severyn. Leveraging pre-trained checkpoints for sequence generation tasks. Transactions of the Association for Computational Linguistics, 8:264–280, 2020.

[80] Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. MASS: masked sequence to sequence pre-training for language generation. In ICML 2019, pages 5926–5936, 2019.

[81] Jingqing Zhang, Yao Zhao, Mohammad Saleh, and Peter Liu. Pegasus: Pre-training with extracted gap-sentences for abstractive summarization. In International Conference on Machine Learning, pages 11328–11339. PMLR, 2020.

[82] Weizhen Qi, Yu Yan, Yeyun Gong, Dayiheng Liu, Nan Duan, Jiusheng Chen, Ruofei Zhang, and Ming Zhou. Prophetnet: Predicting future n-gram for sequence-to-sequence pre-training. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings, pages 2401–2410, 2020.

[83] Mingxing Tan and Quoc Le. Efficientnet: Rethinking model scaling for convolutional neural networks. In International Conference on Machine Learning, pages 6105–6114. PMLR, 2019.

[84] Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. arXiv preprint arXiv:2104.14294, 2021.

[85] Hongyi Zhang, Moustapha Cissé, Yann N. Dauphin, and David Lopez-Paz. mixup: Beyond empirical risk minimization. In 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings. OpenReview.net, 2018.

[86] Sangdoo Yun, Dongyoon Han, Sanghyuk Chun, Seong Joon Oh, Youngjoon Yoo, and Junsuk Choe. Cutmix: Regularization strategy to train strong classifiers with localizable features. In 2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019, pages 6022–6031. IEEE, 2019.

[87] Soravit Changpinyo, Piyush Sharma, Nan Ding, and Radu Soricut. Conceptual 12m: Pushing web-scale image-text pre-training to recognize long-tail visual concepts. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 3558–3568, 2021.

[88] Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In ACL 2018, pages 2556–2565, 2018.

[89] Vicente Ordonez, Girish Kulkarni, and Tamara L. Berg. Im2text: Describing images using 1 million captioned photographs. In NeurIPS 2011, pages 1143–1151, 2011.

[90] Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A. Shamma, Michael S. Bernstein, and Li Fei-Fei. Visual genome: Connecting language and vision using crowdsourced dense image annotations. International Journal of Computer Vision, 123(1):32–73, 2017.

[91] Drew A Hudson and Christopher D Manning. Gqa: A new dataset for real-world visual reasoning and compositional question answering. In CVPR 2019, pages 6700–6709, 2019.

[92] Alina Kuznetsova, Hassan Rom, Neil Alldrin, Jasper Uijlings, Ivan Krasin, Jordi Pont-Tuset, Shahab Kamali, Stefan Popov, Matteo Malloci, Alexander Kolesnikov, et al. The open images dataset v4. International Journal of Computer Vision, 128(7):1956–1981, 2020.

[93] Shuai Shao, Zeming Li, Tianyuan Zhang, Chao Peng, Gang Yu, Xiangyu Zhang, Jing Li, and Jian Sun. Objects365: A large-scale, high-quality dataset for object detection. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 8430–8439, 2019.

[94] Bart Thomee, David A Shamma, Gerald Friedland, Benjamin Elizalde, Karl Ni, Douglas Poland, Damian Borth, and Li-Jia Li. Yfcc100m: The new data in multimedia research. Communications of the ACM, 59(2):64–73, 2016.

[95] Leo Gao, Stella Biderman, Sid Black, Laurence Golding, Travis Hoppe, Charles Foster, Jason Phang, Horace He, Anish Thite, Noa Nabeshima, et al. The pile: An 800gb dataset of diverse text for language modeling. arXiv preprint arXiv:2101.00027, 2020.

[96] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In CVPR 2016, pages 770–778, 2016.

[97] Rico Sennrich, Barry Haddow, and Alexandra Birch. Neural machine translation of rare words with subword units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1715–1725, 2016.

[98] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. In ICLR 2019, 2019.

[99] Gao Huang, Yu Sun, Zhuang Liu, Daniel Sedra, and Kilian Q. Weinberger. Deep networks with stochastic depth. In ECCV, 2016.

[100] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th annual meeting of the Association for Computational Linguistics, pages 311–318, 2002.

[101] Satanjeev Banerjee and Alon Lavie. Meteor: An automatic metric for mt evaluation with improved correlation with human judgments. In Proceedings of the acl workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization, pages 65–72, 2005.

[102] Ramakrishna Vedantam, C Lawrence Zitnick, and Devi Parikh. Cider: Consensus-based image description evaluation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4566–4575, 2015.

[103] Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. Spice: Semantic propositional image caption evaluation. In European conference on computer vision, pages 382–398. Springer, 2016.

[104] Andrej Karpathy and Li Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3128–3137, 2015.

[105] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. Advances in neural information processing systems, 30, 2017.

[106] Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, and Xi Chen. Improved techniques for training gans. Advances in neural information processing systems, 29:2234–2242, 2016.

[107] Steven J Rennie, Etienne Marcheret, Youssef Mroueh, Jerret Ross, and Vaibhava Goel. Self-critical sequence training for image captioning. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 7008–7024, 2017.

[108] Ekin D Cubuk, Barret Zoph, Jonathon Shlens, and Quoc V Le. Randaugment: Practical automated data augmentation with a reduced search space. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, pages 702–703, 2020.

[109] Zhun Zhong, Liang Zheng, Guoliang Kang, Shaozi Li, and Yi Yang. Random erasing data augmentation. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 13001–13008, 2020.

[110] Alexander M Rush, Sumit Chopra, and Jason Weston. A neural attention model for abstractive sentence summarization. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 379–389, 2015.

A Implementation Details

A.1 Pretraining Datasets

We construct pretraining datasets by incorporating Vision&Language data (i.e., image-text pairs), Vision data (i.e., raw image data, object-labeled data), and Language data (i.e., plain texts). For replicability, the pretraining datasets are publicly available. We carefully filter our pretraining data and exclude images that appear in the validation and test sets of downstream tasks to avoid data leakage. The statistics on the pretraining datasets are listed in Table 8.

Cross-modal Data For vision & language pretraining, we mainly apply image-text pairs, including image-caption pairs, image-QA pairs, and image-object pairs, as the pretraining data. For pretaining tasks of Image Captioning and Image-Text Matching, we collect Conceptual Caption 12M (CC12M) [87], Conceptual Captions (CC3M) [88], SBU [89], MSCOCO image captions (COCO) [68], Visual Genome Captions (VG Captions) [90]. Specifically, the part of data from VG requires some additional processing. As texts in VG captions describe local regions on the images, we retrieve regions larger than $16,384$ pixels and build pairs of regions and corresponding descriptions. For Visual Question Answering, we collect VQAv2 [69], VG-QA [90], as well as GQA [91]. VQAv2 is a visual question answering dataset with real-world photographs from COCO. VG-QA is also a visual question answering dataset with real-world photographs from VG. The questions of VG-QA are related to specific regions on the images. GQA is a large VQA dataset featuring compositional questions. The images of GQA are also collected from VG. For Viusal Grounding and Grounded Captioning, we collect data from RefCOCO [71], RefCOCO+ [71], RefCOCOg [72] and VG captions. Additional processing is applied to VG Captions for this task. Specifically, we use the data of VG that contains regions with area smaller than $16,384$ pixels for Visual Grounding, in order to encourage model to grasp fine-grained alignments between vision and language.

Uni-modal Data Uni-modal data includes vision and language data. Vision data consists of raw images for image in-filling and object-labeled images for object detection. To be more specific, we collect OpenImages [92], Object365 [93], VG and COCO for object detection. For image infilling, we collect raw images from OpenImages, YFCC100M [94] and ImageNet-21K [78], and exclude annotations. Thus the model is unable to access labels in the pretraining stage. Language data consists of plain texts, i.e., passages consisting of sentences. We use around 140GB of data from Pile [95] to leverage its diversity. Specifically, we extract natural language data and implement preprocessing methods, including truncation to the length of 512.

Table 8: Statistics on the datasets of pretraining tasks. For language data, 140G* represents the storage space of the plain texts.

Type	Pretraining Task	Source	#Image	#Label
Vision&Language	Image Captioning Image-Text Matching	CC12M, CC3M, SBU, COCO, VG-Cap	14.78M	15.25M
	Visual Question Answering	VQAv2, VG-QA, GQA	178K	2.92M
	Visual Grounding Grounded Captioning	RefCOCO, RefCOCO+, RefCOCOg, VG-Cap	131K	3.20M
Vision	Detection	OpenImages, Object365, VG, COCO	2.98M	3.00M
	Image Infilling	OpenImages, YFCC100M, ImageNet-21K	36.27M	-
Language	Masked Language Modeling	Pile (Filter)	-	140G*

A.2 Pretraining Details

Our network configuration is similar to BART [29]. $\mathrm{OFA}_{\mathrm{Base}}$ consists of 6 encoder layers and 6 decoder layers, with the hidden size 768 and 12 attention heads in each layer. $\mathrm{OFA}_{\mathrm{Large}}$ consists of 12 encoder layers and 12 decoder layers, with the hidden size $1,024$ and 16 attention heads in each layer. The intermediate sizes of FFN are 3072 and 4096 for *Base* and *Large* models, respectively.

For the image processing, we resize the images to the resolution of 384×384 with a fixed patch size of 16×16. For each patch, we obtain its feature vector with the first three blocks of ResNet-101 and ResNet-152 [96] for our *Base* and *Large* models, respectively. Following [44], we randomly sample 196 patch features to improve the robustness of feature learning during the pretraining stage. For the text processing, we tokenize the texts with the BPE Tokenizer [97]. The maximum text sequence length of both encoder and decoder is set to 256. We share parameters between the embedding and the decoder softmax output layer.

We use the AdamW [98] optimizer with $(\beta_1, \beta_2) = (0.9, 0.999)$ and $\epsilon = 1e$-8 to pretrain our models. We set the peak learning rate to $2e$-4, and apply a scheduler with linear decay with a warmup ratio of 0.01 to control the learning rate. For regulation, we set dropout to 0.1 and use weight decay with 0.01. We employ stochastic depth [99] with a 0.1 rate (applied to encoder and decoder except for convolution blocks). We mix all the pretraining data within each batch, which contains $2,048$ vision&language samples, 256 object detection samples, 256 image-only samples and 512 text-only samples. The *Large* and *Base* model are pretrained for $500K$ steps and $250K$ steps, respectively.

A.3 Details of Downstream Tasks

We verify the capability of OFA on various downstream tasks in both finetuning and zero-shot settings. We design various task-specific instructions to transfer the knowledge learned from pretraining to downstream tasks effectively. The instructions of different tasks are listed in Table 9. For finetuning, if not specified, the input image resolution is set to 480×480, and the other hyper-parameters remain the same as for pretraining. The experimental details of different downstream tasks, including both multimodal and uni-modal tasks, are listed below:

Image Captioning Image captioning is a standard vision&language task that requires models to generate an appropriate and fluent caption for an image. We adopt the most widely used MS COCO Caption dataset [68] to evaluate the multi-modal generation capability of OFA. We report BLEU-4 [100], METEOR [101], CIDEr [102], and SPICE [103] scores on the Karparthy test split [104]. Following previous standard practice, we first finetune OFA with cross-entropy loss for $8,000$ steps with a batch size of 128 and a learning rate of $1e-5$, and label smoothing is set to 0.1. We then finetune the model with CIDEr optimization for $4,000$ steps with a batch size of 64 and a learning rate of $5e-6$, and disable dropout and stochastic depth.

Visual Question Answering Visual question answering (VQA) is a cross-modal task that requires the models to answer the question given an image. Previous works such as VLMo [46] or SimVLM [45] define VQA as a classification task. They use a linear output layer to predict the probability of each candidate answer on a given set. In contrast with these works, to adapt the generative OFA model to VQA benchmark, we use the Trie-based search strategy mentioned in Sec. 3.4 to ensure that the answer generated by OFA is constrained in the candidate set. We evaluate our model with other baselines on the commonly used VQAv2 dataset [69]. Accuracy scores on both test-dev and test-std sets are reported. The OFA model is finetuned for $40,000$ steps with a batch size of 512. The learning rate is $5e-5$ with the label smoothing of 0.1. During Trie-based searching, we constrain the generated answers over the most frequent $3,129$ answer candidates. Exponential moving average (EMA) with decay rate 0.9999 is employed in finetuning.

Visual Entailment Visual entailment requires the model to evaluate how the given image and text are semantically correlated, i.e., entailment, neutral, or contradiction. We perform experiments on the SNLI-VE dataset [70]. The image premise, text premise and text hypothesis are fed to the encoder, and the decoder generates appropriate labels. To transfer the knowledge learned by pretraining to this task, we convert the labels entailment/neutral/contradiction to yes/maybe/no. We also use the Trie-based search strategy to constrain the generated labels over the candidate set. We report accuracy on both dev and test sets. The OFA model is finetuned for $12,000$ steps with a learning rate of $3e-5$ and a batch size of 256. The stochastic depth rate is set to 0.2.

Referring Expression Comprehension Referring expression comprehension requires models to locate an image region described by a language query. Different from the approach taken by most previous methods [13, 14] which ranks a set of candidate bounding boxes detected by a pretrained object detector, our method directly predicts the best matching bounding box without any proposals. We perform experiments on RefCOCO [71], RefCOCO+ [71], and RefCOCOg [72]. Consistent with other downstream tasks, we formulate referring expression comprehension as a conditional sequence generation task. In detail, given an image and a language query, OFA generates the box sequence (e.g., $\langle x_1, y_1, x_2, y_2 \rangle$) in an autoregressive manner. We report the standard metric Acc@0.5 on the validation and test sets. For finetuning, the input image resolution is set to 512×512. We finetune the OFA model on each dataset for about 10 epochs with a batch size of 128. The learning rate is $3e-5$ with the label smoothing of 0.1. Each query only corresponds to an image region, so we limit the maximum generated length to 4 during inference.

Image Generation Following the same setting with [50], we train our model on the MS COCO train split and evaluate our model on the validation split by randomly sampling $30,000$ images. We use Fréchet Inception Distance (FID) [105] and Inception Score (IS) [106] to evaluate the quality of the images. Following the previous studies [50, 74], we also

Table 9: Instructions for downstream tasks.

Task	Dataset	Instruction	Target
Image Captioning	COCO	[**Image**] What does the image describe?	{**Caption**}
Visual Question Answering	VQA	[**Image**] {**Question**}	{**Answer**}
Visual Entailment	SNLI-VE	[**Image**] Can image and text1 "{**Text1**}" imply text2 "{**Text2**}"?	Yes/No/Maybe
Referring Expression Comprehension	RefCOCO, RefCOCO+, RefCOCOg	[**Image**] Which region does the text "{**Text**}" describe?	{**Location**}
Image Generation	COCO	What is the complete image? caption: {**Caption**}	{**Image**}
Image Classification	ImageNet-1K	[**Image**] What does the image describe?	{**Label**}
Single-Sentence Classification	COLA	Is the text "{**Text**}" grammatically correct?	Yes/No
	SST-2	Is the sentiment of text "{**Text**}" positive or negative?	Positive/Negative
Sentence-Pair Classification	RTE	Can text1 "{**Text1**}" imply text2 "{**Text2**}"?	Yes/No
	MRPC	Does text1 "{**Text1**}" and text2 "{**Text2**}" have the same semantics?	Yes/No
	QQP	Is question "{**Question1**}" and question "{**Question2**}" equivalent?	Yes/No
	MNLI	Can text1 "{**Text1**}" imply text2 "{**Text2**}"?	Yes/No/Maybe
	QNLI	Does "{**Text**}" contain the answer to question "{**Question**}"?	Yes/No
	WNLI	Can text1 "{**Text1**}" imply text2 "{**Text2**}"?	Yes/No
Text Summarization	Gigaword	What is the summary of article "{**Article**}"?	{**Summary**}

compute CLIP Similarity Score (CLIPSIM) to evaluate the semantic similarity between the query text and the generated images. During finetuning, OFA learns to generate the image code sequence according to the given text query only. The model is first finetuned with cross-entropy and then with CLIPSIM optimization following [74, 107]. In the first stage, we finetune the OFA model for about 50 epochs with a batch size of 512 and a learning rate of $1e-3$. In the second stage, the model is finetuned for extra 5000 steps with a batch size of 32 and a learning rate of $1e-6$. During the evaluation, we sample 24 images with the resolution of 256×256 for each query and choose the best one using the pretrained CLIP model [47].

For case study, we compare OFA with CogView and GLIDE. CogView provides an API website [5]. Note that this API samples 8 images of resolution of 512×512 for each query. We select the first one of generated images and resize it to the resolution of 256×256. GLIDE provides a Colab notebook.[6]. Note that the only publicly available GLIDE model is of *base* size (~385M).

Image Classification We provide finetuning results on ImageNet-1K [78] following recent studies in self-supervised learning for computer vision. During finetuning and inference, a Trie-based search strategy is employed to constrain the generated text into the set of $1,000$ candidate labels. We finetune OFA for 32 epochs and a batch size of 256. The learning rate is $5e-5$. The ratio for label smoothing is 0.1. Following [34], we use the same random resize cropping, random flipping, RandAug [108] and random erasing [109] transformations as data augmentation strategies.

Natural Language Understanding To verify the natural language understanding ability of OFA, we select 8 language understanding tasks from GLUE benchmark [75], including both single-sentence classification tasks and sentence-pair classification tasks. To adapt to sentence-pair classification, previous models [2, 26] usually use segment embeddings to distinguish different sentences. Unlike those models, OFA can apply the model to sentence-pair classification tasks by constructing appropriate instructions without introducing additional segment embeddings. For the hyper-parameters of finetuning, we tune the training epochs among $\{5, 7, 10\}$, learning rate among $\{3e-5, 5e-5, 6e-5, 7e-5, 1e-4\}$, batch size among $\{32, 64, 128\}$, weight decay among $\{0.01, 0.05\}$, and dropout rate among $\{0.0, 0.1\}$. We report the best performance on the development set for each task.

Natural Language Generation We verify the natural language generation ability of OFA in the Gigaword dataset [77]. We report ROUGE-1/ROUGE-2/ROUGE-L to evaluate the generation results following [110]. We finetune the

[5] `https://wudao.aminer.cn/CogView/index.html`

[6] `https://colab.research.google.com/drive/1q6tJ58UKod1eCOkbaUNGzF3K5BbXlB5m`

OFA model for $50,000$ steps with a batch size of 256. The learning rate is $3e-5$ with the label smoothing of 0.1, and the maximum text sequence length is set to 512. During inference, we set the length penalty to 0.7 and beam size to 5.

B Trie-based Search

This section describes how to use Trie-based search to improve model performance on downstream classification tasks. When dealing with classification tasks, we first construct a Trie where nodes are annotated with tokens from the candidate label-set. During finetuning, the model computes the log-probabilities of the target tokens based on their positions on the Trie. As shown in Figure 6, when computing the log-probabilities of the target token "sky", we only consider tokens in {"sky", "ocean"} and forcefully set the logits for all invalid tokens to $-\infty$. During inference, we constrain the generated labels over the candidate set. As shown in Table 10, Trie-based search strategy can boost the performance of OFA in various downstream classification tasks.

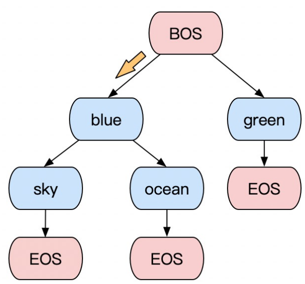

Figure 6: Example of Trie-based search where the constraint labels are "blue sky", "blue ocean" and "green".

Table 10: Ablation results of Trie. The removal of Trie-based search degenerates the performance on downstream tasks.

Model	VQA Test-dev Acc.	SNLI-VE Dev Acc.	ImageNet Top-1 Acc.	MRPC F1	QQP F1
OFA_{Base}	76.03	89.2	82.2	90.6	88.4
w/o Trie	75.86(-0.17)	89.0(-0.2)	81.9(-0.3)	90.1(-0.5)	88.2(-0.2)

C Qualitative Examples

This section provides more qualitative examples of multiple tasks, including text-to-image generation, open-domain VQA, grounded question answering, and open-domain visual grounding, from the generation of OFA. By reading this section, we hope that readers can better perceive OFA.

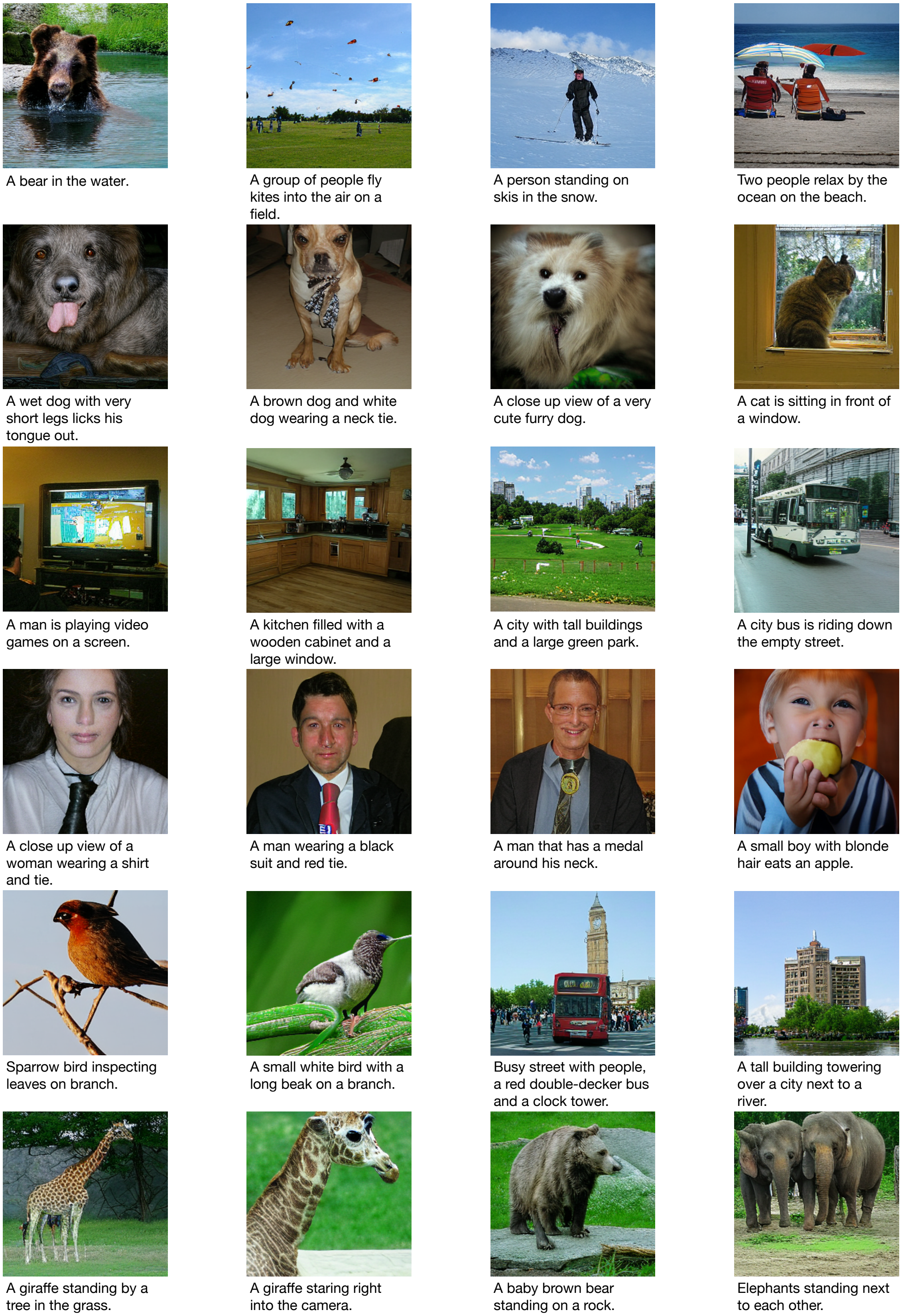

Figure 7: More samples of text-to-image generation task generated by OFA for normal queries.

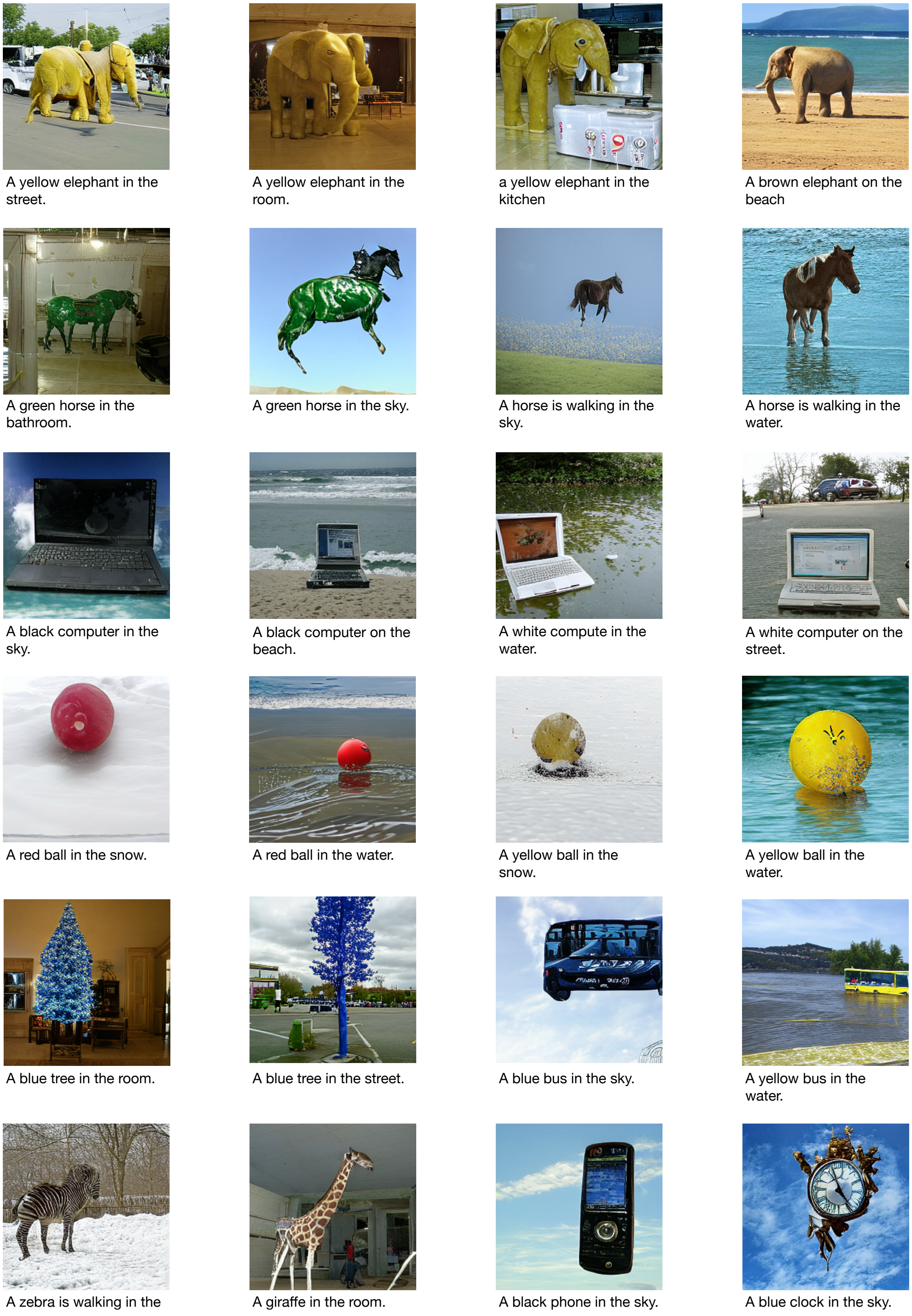

Figure 8: More samples of text-to-image generation task generated by OFA for counterfactual queries.

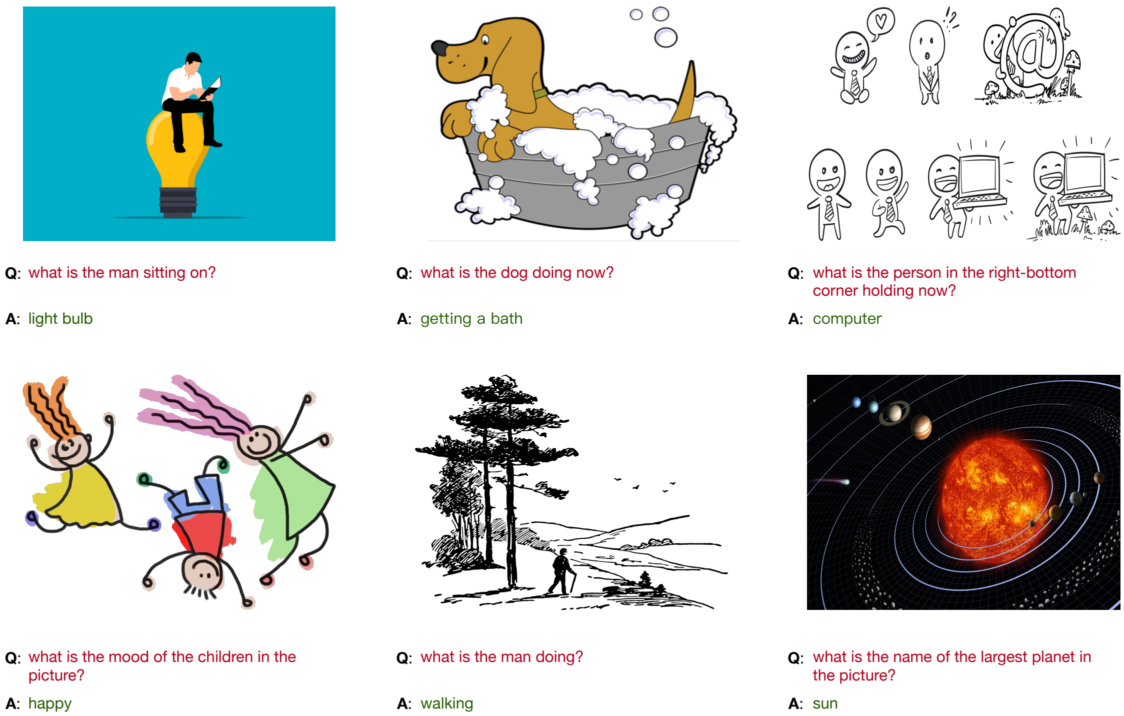

Figure 9: More samples of VQA task on unseen domains. The answers are generated by pretrained OFA without finetuning. The datasets used in VQA pretraining task only contain real-world photographs. We present more cases of VQA task on out-of-domain (non-photographic) images and demonstrate the capability of transferring OFA to these unseen domains.

Figure 10: More samples of the unseen grounded question answering task. In this task, the model should answer a question about a particular region in the image. This task is unseen in pretraining. We demonstrate that directly transferring pretrained OFA to this new task without finetuning works well.

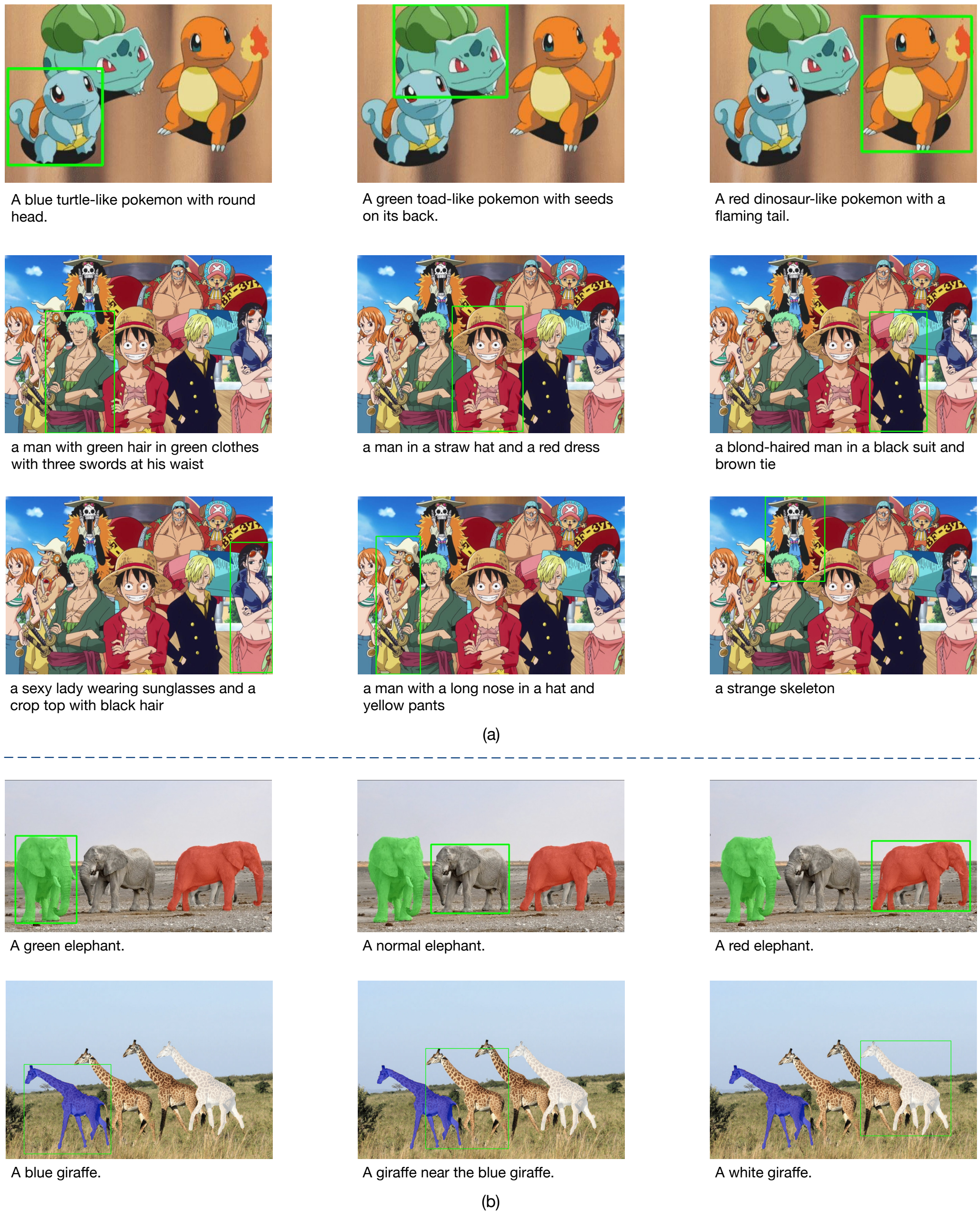

Figure 11: More samples of visual grounding task generated by OFA for various unseen domains: (a) anime (the corresponding animations are *Pokemon* and *One Piece*); (b) synthetic images with attribute combinations.