Crossing the Format Boundary of Text and Boxes: Towards Unified Vision-Language Modeling

Zhengyuan Yang, Zhe Gan, Jianfeng Wang, Xiaowei Hu, Faisal Ahmed, Zicheng Liu, Yumao Lu, Lijuan Wang
Microsoft
{zhengyang,zhe.gan,jianfw,xiaowei.hu,fiahmed,zliu,yumaolu,lijuanw}@microsoft.com

Figure 1. We propose UNICORN, a UNIfied vision-language model that Crosses the fORmat bouNdary of text and boxes. UNICORN facilitates a wide range of VL tasks with a single unified architecture, which could generate both text and box tokens in an auto-regressive manner, conditioned on the multimodal image-text inputs.

Abstract

In this paper, we propose UNICORN, a vision-language (VL) model that unifies text generation and bounding box prediction into a single architecture. Specifically, we quantizes each box into four discrete box tokens and serializes them as a sequence, which can be integrated with text tokens. We formulate all VL problems as a generation task, where the target sequence consists of the integrated text and box tokens. We then train a transformer encoder-decoder to predict the target in an auto-regressive manner. With such a unified framework and input-output format, UNICORN achieves comparable performance to task-specific state of the art on 7 VL benchmarks, covering the visual grounding, grounded captioning, visual question answering, and image captioning tasks. When trained with multi-task finetuning, UNICORN can approach different VL tasks with a single set of parameters, thus crossing downstream task boundary. We show that having a single model not only saves parameters, but also further boosts the model performance on certain tasks. Finally, UNICORN shows the capability of generalizing to new tasks such as ImageNet object localization.

1. Introduction

Large-scale pre-training [9, 30, 31, 35, 51, 52, 58, 66] has achieved tremendous success for universal vision-language (VL) modeling. The output of a VL system is multimodal in nature. It can be object boxes for visual grounding [39, 42, 64], a text answer for visual question answering (VQA) [4], a descriptive sentence for image captioning [3, 32], or the combination of text and boxes for grounded captioning [70].

Recent works [10, 18, 21, 24] have started to unify these output formats towards a unified VL system. VL-T5 [10] and GPV [18] first represent images as object regions with an object detector [7, 46], and then treat bounding boxes as pre-defined labels or region indexes. Using region features significantly increases the computation cost and model running time [26, 29, 58]. The explicit object detection module also makes the model cumbersome in deployment, and potentially limits the generalization ability [58]. On the other hand, building upon the DETR object detector [7], MDETR [24] and UniT [21] methods can produce bounding boxes directly for visual grounding, but need task-specific classification heads for other VL tasks such as VQA. It is also unclear how to extend the model for open-ended text generation, thus supporting tasks like image captioning. Going beyond these successful initial explorations, we ask an even bolder question: can we build a single unified framework to cross the output format boundary of text and boxes? Besides methodology curiosity, this question also has strong practical relevance. If its answer is affirmative,
this way, we present the first model that can jointly generate

uni-format decoder predicts a token from the unified vocab-

in an auto-regressive manner. At each decoding step, the
decoder model is then trained to predict the output sequence
to construct the target sequence for a VL task. An encoder-
sequence, which can be naturally integrated with text tokens
box into four discrete box tokens, and serialize them as a se-

idea is to quantize the four coordinates in each bounding

a single unified architecture. As shown in Figure 1, the core
language model that unifies text and box generation within

of VL tasks with a single unified architecture. It is par-
towards the goal of building task-agnostic VL systems.

To answer this question, we present UNICORN, a vision-

our contributions are summarized as follows.

• We present UNICORN, the first vision-language model
that crosses the output format boundary of text and boxes.
UNICORN facilitates a wide range of VL tasks with a single
unified architecture.
• UNICORN is capable of approaching different VL tasks
with a single set of parameters. We show that such multi-
task finetuning not only saves model parameters, but also
benefits certain downstream task performance.
• We show UNICORN’s capability of generalizing to new
tasks, with experiments on ImageNet object localization.

2. Related Work

Vision-language pre-training (VLP). Large-scale VLP
has become the new training paradigm for VL research. Prior works [1, 9, 28, 30, 31, 35, 36, 51, 52, 71] first show
the power of VLP by using region features obtained from
an off-the-shelf object detector [46]. However, the region
feature extraction significantly increases the model’s com-
putation cost and run time. Recent studies [22, 26, 29, 58]
shift the paradigm and show that grid features work as well
as region features. Despite the change in the input image
format, most studies adopt similar output architectures of
either discriminative classification heads or auto-regressive
text decoders. These output structures often contain task-
specific designs and do not support bounding box predic-
tion, which is an important output format for VL tasks such
as visual grounding and grounded image captioning.

Unified framework. Prior works have presented successful
explorations on building VL models with unified input-
output formats. The existing studies on unifying bounding
boxes and text outputs can be categorized into two threads.
VL-T5 [10] and GPV [18] first represent images as object
region features with an object detector [7, 46]. The bound-
ing box prediction is then simplified as an index classi-
fication problem over the set of region candidates gener-
ated by the detector. The other threads of work, including
MDETR [24] and UniT [21], add task-specific heads on top
of an object detector [7] to perform VL tasks. However, dif-
ferent tasks still require different output modules. It is also
unclear how to extend the framework for open-ended text
generation. In this study, we aim to build a single unified
architecture that takes image-text inputs in and generates
text-box outputs, with no task-specific modules.

Language pre-training. The successful VLP studies are
inspired by the pre-training and task-specific finetuning
3. The UNICORN Framework

3.1. Architecture Overview

We implement UNICORN using a transformer encoder-decoder architecture built on top of the single-modality image and text encoders, as shown in Figure 2. For image, we use a convolutional network [19] to encode the raw image input \( v \), and flatten the grid features as the visual representation. For text, we use the pre-trained RoBERTaBASE [33] model to encode input text \( l \) into hidden word features. The encoded image and text features are then projected into a shared embedding space. We use a 6-layer transformer encoder that takes the concatenated image and text feature sequence as input, and a 6-layer transformer decoder for output sequence generation. Similar to language modeling [43, 44], the decoder generates output tokens in an autoregressive manner. The major difference is that the uni-format decoder could generate tokens from both the text vocabulary and the box coordinate vocabulary, as shown in the right part of Figure 2.

3.2. Uni-format Decoder

We introduce the details of the uni-format decoder in this subsection. We show how to construct the ground-truth target sequence that supports both text and box predictions.

**Bounding box sequence construction.** We first review the bounding box quantization approach introduced in Pix2seq [8]. As shown in the bottom part of Figure 2, a rectangular bounding box in a 2D image can be represented by four floating-point numbers, namely \([x_{\text{min}}, y_{\text{min}}, x_{\text{max}}, y_{\text{max}}]\). The established object detection paradigm \([7, 45, 46]\) predicts four continuous floating-point values to regress the coordinates in a single step. In contrast, Pix2seq quantizes each coordinate into one of the \( n_{\text{bins}} \) discrete bins, and tries to predict the four coordinates sequentially, e.g., \( P(\langle y_{\text{max}} \rangle | \langle x_{\text{min}} \rangle, \langle y_{\text{min}} \rangle, \langle x_{\text{max}} \rangle, v) \). \( \langle x \rangle, \langle y \rangle \) are quantized box tokens ranging from \( 0 \), to \( n_{\text{bins}} - 1 \).

**Unified decoding sequence.** We next introduce how to combine serialized boxes with text annotations to construct the ground-truth target sequence \( s \). By quantizing each bounding box into four tokens, we can represent the bounding box as discrete tokens, which are the same format as text words. We next use the grounded captioning task [70] to illustrate how we integrate these two types of tokens to construct the target sequence for a VL task. In grounded captioning, the model is expected to generate an image caption and ground all noun phrases to visual regions. Therefore, the ground-truth annotations consist of the caption sentence, object boxes, and object-phrase correspondence.
Instead of predicting these three parts separately with multiple heads [38, 70, 72], we insert the four box tokens after the noun phrases whenever a text phrase refers to the object. Specifically, we add two special tokens \(<\text{obj}>\) and \(<\text{\textbackslash obj}>\) before and after the “phrase and box pair” to mark the boundary of the noun phrase. For example, in Figure 2, we place the text phrase “a donut” in the ground-truth caption with “\(<\text{obj}>\text{ a donut }<\text{\textbackslash obj}>\)” in the extended target sequence, where 90, 83, 184, 180 are the quantized box coordinates, after dividing the 1333 × 800 image into 200 bins in each dimension. For VL tasks [5, 32] with no box annotations, we keep the original text-only sequence as the target.

UNICORN’s decoding vocabulary contains both text and box tokens, and has a size of \(n_{\text{text}} + n_{\text{bins}} + 2\). \(n_{\text{text}}\) and \(n_{\text{bins}}\) are the text vocabulary size and the number of coordinate bins. We use the same set of \(n_{\text{bins}}\) box tokens [8] for all four box coordinates. The output classification at each decoding step is conducted over the entire unified vocabulary.

3.3. Training and Inference

Objective. We train the model with a single language modeling objective [43], i.e., at each decoding step \(t\), maximizing the likelihood of target token \(s_t\) conditioned on input image \(v\), input text \(l\), and previous target tokens \(s_{<t}\):

\[
\mathcal{L}_{LM}(\theta) = -\sum_{t=1}^{T} \log P_{\theta}(s_t|s_{<t}, v, l),
\]

where \(\theta\) is the model parameter, and \(T\) is the target sequence length. Using the same training objective, UNICORN is trained with pre-training and finetuning stages that have different input text and target sequence, as abstracted in Figure 3. We next introduce each of these three training stages.

Pre-training. Similar to VLP studies [9, 26, 31, 35, 58], UNICORN also benefits from pre-training. We pre-train the model with a single language modeling objective to predict the target sequence \(s\) that contains both text and box tokens, as shown in Figure 3(a). For each sample, we randomly set the input text \(l\) to be an empty string or the text-only image description, with the same probability of 0.5. In this way, during pre-training, the model learns to perform both captioning-like (with empty input text) and grounding-like (with image description input text) VL tasks.

We adopt the pre-training corpus used in MDETR [24] that aggregates images from Flickr30k entities [42], COCO [32], and Visual Genome (VG) [27] datasets. Text and box annotations are from the referring expression datasets [39, 64], VG regions, Flickr30k entities annotations, and the GQA dataset [23], following MDETR [24]. We further remove images that have overlap with downstream tasks, i.e., the Karpathy validation and test sets [25] of Flickr30k and COCO.

Multi-task finetuning. UNICORN supports a wide range of VL tasks with a single unified architecture and language modeling training objective. Specifically, instead of designing different structures based on task-specific assumptions, UNICORN learns to perform different VL tasks by conditioning on different input text \(l\).

In addition to being simple and elegant, the unified modeling facilitates properties such as multi-task finetuning. Instead of having multiple duplicates of a pre-trained model, each optimized for a downstream task, multi-task finetuning aims to train a single set of parameters to perform all different VL tasks. As shown in Figure 3(b), we gather data samples from all VL tasks and train a single model with the language modeling objective. Unlike pre-training, where the target sequences are the same for all samples, multi-task finetuning keeps each downstream task’s original target sequence format, e.g., text+box sequence for visual grounding and the text-only answer for VQA. One major advantage of multi-task finetuning is that a single model can support multiple VL tasks, thus saving model parameters. Multi-task finetuning could also improve certain downstream tasks’ performance by using data in different tasks.

Task-specific finetuning. UNICORN can also perform the standard task-specific finetuning, as shown in Figure 3(c). We observe that multi-task finetuning not only generates models that perform well in downstream tasks, but also provides good initialization points for a second-stage task-specific finetuning [59]. We refer to the setting with both multi-task and task-specific finetuning as “two-stage finetuning,” which is used as the default setting for UNICORN.
**Inference.** We use arg max sampling to obtain the sequence prediction. We then extract the text and box predictions from the sequence for final evaluation. We discard box tokens to get the text prediction, and dequantize box tokens to get the box prediction. Finally, we evaluate the model on each downstream task with its desired output formats, e.g., text for VQA, boxes for visual grounding, or both text and boxes for grounded captioning.

**4. Experiments**

**4.1. Experiment Overview**

**Downstream tasks.** We evaluate UNICORN on 7 VL benchmarks (later also summarized in Table 5). UNICORN approaches a wide range of VL tasks with a single unified architecture, and achieves performance above or comparable with the task-specific state of the art. In contrast to our unified modeling, most prior works require task-specific modules, making them difficult to work on VL tasks with different output formats.

UNICORN is particularly effective for tasks that require both box and text outputs, such as visual grounding and grounded captioning. For visual grounding, we experiment on both the referring expression comprehension [39, 64] and phrase grounding [42] sub-tasks. For grounded captioning [38, 70, 72], we benchmark on the Flickr30k Entities dataset [42]. UNICORN can be seamlessly extended to VL tasks with text output only. We benchmark UNICORN on the COCO dataset [32] for the image captioning task, and the VQA v2 dataset [5] for the open-ended VQA task [10, 58].

**Implementation details.** The transformer contains 6 encoder layers and 6 decoder layers, with 8 attention heads and a hidden dimension of 256 in each layer [7]. To reduce training time, we initialize the network backbone from MDETR’s [24] pre-trained weights, which are based on pre-trained ResNet-101 [19] from Torchvision and pre-trained RoBERTaBASE [33] from HuggingFace [60]. We pre-train our model for 20 epochs with a batch size of 16. We use the scale and crop augmentation in DETR [7] such that the shortest side is between 480 and 800 pixels while the longest at most 1333. We finetune the model for 20 epochs in both multi-task and task-specific finetuning. We use a constant learning rate of $1e^{-4}$ and $1e^{-5}$ for transformer layers and backbones. We train our model with AdamW [34] and adopt the exponential moving average [24, 54] with a decay rate of 0.9998 and a weight decay of $1e^{-4}$.

**4.2. Comparison with Prior Arts**

**Grounded image captioning.** The grounded captioning task [70] requires the model to generate an image caption and ground all predicted noun phrases to image regions. Thus, the final predictions consist of three parts, i.e., the text caption, predicted visual regions, and the grounding correspondence between phrases and regions. Instead of separately predicting those outputs with multiple separated heads [38, 70, 72], UNICORN performs grounded captioning by generating a unified text and box sequence. We then extract the caption and box predictions from the output sequence for evaluation. Following the established benchmarks [38, 70, 72], we evaluate “captioning” and “grounding” separately with the caption metrics [2, 15, 41, 56] and grounding F1 scores [70], respectively. The F1 score $F_{1\text{all}}$ evaluates grounding a multi-label classification problem, where a correct prediction contains both the same object word as ground-truth (GT) caption and a larger than 0.5 IoU with the GT box. We also report $F_{1\text{loc}}$ that only computes the grounding score on correctly predicted object words.

Table 1 compares our method to state of the art [70, 72]. We observe a significant improvement in the grounding quality, with the $F_{1\text{all}}$ score improving from 7.55 to 13.26, and $F_{1\text{loc}}$ from 22.2 to 33.63. UNICORN also achieves a better captioning quality compared with state of the art [72]. More importantly, UNICORN approaches the grounded captioning task in a simple and natural manner. With a single unified output format, UNICORN does not require the pre-generated object regions [38, 70, 72] and avoids using multiple output heads. As shown in Figure 4(a), UNICORN naturally represents the text, box, and phrase-region correspondence in a single unified output sequence. We hope UNICORN provides a simple and solid baseline for future studies on VL tasks with multiple output formats.

**Visual grounding.** Visual grounding aims to ground a language query onto an image region. We experiment on the sub-tasks of referring expression comprehension [39, 64] with Refcoco/Refcoco+/Refcocog, and phrase grounding [42] with Flickr30k Entities. Referring expression comprehension contains a query that describes a single region in the image, and the desired output is a single bounding box. Phrase grounding aims to ground all noun phrases in the input sentence into corresponding visual regions. Unlike previous studies [24, 62, 63] that only predict boxes, UNICORN generates a unified text+box sequence conditioned on input text query $l$ and raw image $v$. We then extract box tokens from the output sequence for final evaluation. We report the standard metric Acc@0.5.

| Method   | Caption Eval. | Grounding Eval. |
|----------|---------------|------------------|
|          | B@4 | M  | C  | S  | F1all | F1loc |
| NBT [37] | 27.1 | 21.7 | 57.5 | 15.6 | -     | -     |
| GVD [70] | 27.3 | 22.5 | 62.3 | 16.5 | 7.55  | 22.2  |
| Cyclical [38] | 26.6 | 22.3 | 60.9 | 16.3 | 4.85  | 13.4  |
| POS-SCAN [72] | 30.1 | 22.6 | 69.3 | 16.8 | 7.17  | 17.49 |
| UNICORN  | 30.7 | 23.7 | 70.1 | 17.4 | 13.26 | 33.63 |

Table 1. Grounded image captioning results on the test set of Flickr30k Entities [42]. We report BLEU@4 [41], METEOR [15], CIDEr [56], and SPICE [2] metrics for caption evaluation. We use $F_{1\text{all}}$ and $F_{1\text{loc}}$ metrics [70] for grounding evaluation.
Table 2. The performance comparisons (Acc@0.5) on the referring expression comprehension (Refcoco, Refcoco+, Refcocog) and phrase grounding task (Flickr30K Entities). The "#pre-train" column shows the number of pre-training images, if any.

| Method     | #Pre-train | Refcoco val | Refcoco+ val | Refcocog val-u | Flickr30K Entities |
|------------|------------|-------------|--------------|-----------------|-------------------|
| MATTNet [63] | -          | 72.40       | 80.43        | 69.28           | -                 |
| FAOA [62]   | -          | 72.05       | 74.81        | 67.59           | -                 |
| TransVG [14] | -          | 81.02       | 82.72        | 78.35           | -                 |
| ViLBERT [35] | 3M         | -          | 72.34        | 78.53           | 62.61             |
| UNITER [9]  | 4M         | 81.41       | 87.04        | 74.17           | -                 |
| VILLA [17]  | 4M         | 82.39       | 87.48        | 74.84           | -                 |
| MDETR [24]  | 200K       | 86.75       | 89.58        | 81.41           | -                 |

Table 3. COCO image captioning results on the Karpathy test split. We report BLEU@4, METEOR, CIDEr, and SPICE scores.

| Method        | #Pre-train | B@4 | M   | C    | S    |
|---------------|------------|-----|-----|------|------|
| Unified VLP [71] | 3M         | 36.5 | 28.4 | 117.7 | 21.3 |
| OSCAR [31]    | 4M         | 36.5 | 30.3 | 123.7 | 23.1 |
| E2E-VLP [61]  | 180K       | 36.2 | -    | 117.3 | -    |
| VL-T5 [10]    | 180K       | 34.5 | 28.7 | 116.5 | 21.9 |
| VL-BART [10]  | 180K       | 35.1 | 28.7 | 116.6 | 21.5 |
| UNICORN       | 200K       | 35.8 | 28.4 | 119.1 | 21.5 |

Table 4. Visual question answering results on VQAv2 [5]. Unified VLP [71] and UNITER [9] approach VQA as a discriminative task. VL-T5, VL-BART [10], and our UNICORN adopt the generative modeling, i.e., open-ended VQA. We experiment on both test-dev/test-std splits, and the Karpathy test split used in VL-T5 [10].

| Method      | #Pre-train | Test-Dev | Test-Std | Karpathy-test |
|-------------|------------|----------|----------|---------------|
| Unified VLP [71] | 3M         | -        | 70.2     | -             | -              |
| UNITER [9]  | 4M         | 72.7     | 72.9     | 74.4          | 10.0           | 70.5          |
| VL-T5 [10]  | 180K       | -        | 70.3     | 71.4          | 13.1           | 67.9          |
| VL-BART [10] | 180K       | -        | 71.3     | 72.1          | 13.2           | 68.6          |
| UNICORN     | 200K       | 69.2     | 69.4     | 70.3          | 10.9           | 66.7          |

As shown in Table 4, UNICORN obtains competitive results to the state of the art. Similar to the observation in previous generative VQA studies [10], UNICORN performs better on the Karpathy out-of-domain subset, compared with the discriminative approach [9].

4.3. Ablation and Analysis

Training stage ablation. In addition to task-specific state of the art on each experimented task, we compare the following variants of UNICORN to examine the influence of different pre-training and finetuning stages:

- **UNICORN-separate-scratch** directly trains the model with task-specific finetuning, as shown in Figure 3(c).
- **UNICORN-shared-scratch** directly trains the model with multi-task finetuning, as shown in Figure 3(b).
- **UNICORN-separate** is first pre-trained with the pre-training corpus (Figure 3(a)), and then optimized separately for each downstream task.
- **UNICORN-shared** uses multi-task finetuning from the pre-trained checkpoint. UNICORN-shared uses a single set of parameters for all experimented VL tasks.

- **UNICORN-two-stage** adopts the two-stage finetuning, where the first stage is multi-task finetuning and second stage is the task-specific finetuning. UNICORN-two-stage is the default setting referred to as UNICORN in Section 4.2.

Task-specific finetuning. Table 5 summarizes the results obtained by the variants of UNICORN. We first discuss the standard pretrain-then-finetune setting in VLP [9, 31, 35].
Table 5. Summary of results obtained by the unified UNICORN architecture. The compared methods use task-specific architectures and training objectives, thus could only perform a subset of VL tasks. UNICORN approaches all tasks with a unified framework and obtains competitive performance. The Refcoco/Refcoco+/Refcocog numbers are on the val set. The Flickr grounding and grounded caption results are on the test set. VQA2-KP is the VQA Karpathy split [10]. UNICORN\textsuperscript{two-stage} is the default setting that is also referred to as UNICORN.

| Method              | #Pre-train | Refcoco | Visual grounding | Flickr | Grounded caption Cider | COCO test-Cider | VQA2 test-dev | VQA2 test-KP |
|---------------------|------------|---------|------------------|--------|------------------------|-----------------|--------------|-------------|
| MDETR \[24\]        | 200K       | 86.75   | 79.52            | 81.64  | 83.8                   | -               | -            | -           |
| UNITER \[9\]        | 4M         | 81.24   | 75.31            | 74.31  | -                      | -               | -            | -           |
| GVD \[70\]          | -          | -       | -                | -      | 62.3                   | 7.55            | -            | -           |
| VL-T5 \[10\]        | 180K       | -       | -                | 71.2   | -                      | -               | 116.5        | -           |
| OSCAR \[31\]        | 4M         | -       | -                | -      | -                      | 123.7           | 73.2         | -           |
| UNICORN\textsuperscript{separate-Scratch} | None    | 72.96   | 64.98            | 63.56  | 73.40                  | 60.5            | 9.22         | 105.3       |
| UNICORN\textsuperscript{shared-Scratch} | None   | 82.06   | 70.72            | 73.39  | 65.67                  | 61.1            | 7.85         | 111.8       |
| UNICORN\textsuperscript{separate}      | 200K       | 86.78   | 78.93            | 82.21  | 80.70                  | 66.6            | 11.43        | 118.9       |
| UNICORN\textsuperscript{shared}        | 200K       | 87.87   | 79.78            | 83.09  | 80.19                  | 64.6            | 9.87         | 115.8       |
| UNICORN\textsuperscript{two-stage}     | 200K       | 88.29   | 80.30            | 83.44  | 80.40                  | 70.1            | 13.26        | 119.1       |

that adopts task-specific finetuning. UNICORN\textsuperscript{separate} approaches various VL tasks with a single unified architecture, and obtains competitive results to state of the art that has architectures tailored for each task, or uses magnitude-higher pre-training data. Compared with UNICORN\textsuperscript{separate-Scratch} without pre-training, the pre-training leads to consistent improvements on all VL tasks, regardless of the output format.

**Multi-task finetuning.** Inspired by the unified architecture and input-output format, we go a step further and train a single UNICORN\textsuperscript{shared} model for all considered downstream tasks. Compared with UNICORN\textsuperscript{separate}, the multi-task finetuning UNICORN\textsuperscript{shared} performs comparable or even better on experimented VL tasks, while using 7 times fewer model parameters. The strong results indicate the possibility of having a single model for multiple downstream tasks. Inspired by prior works on input prefix [10, 59], we further experiment with adding task-specific prefixes to the input text. This variant includes a task-specific prefix such as “visual grounding:” to describe each sample’s task. We observe empirically that the task prefix has no major influence on the model’s performance. We introduce the detailed prefix settings and results in the supplementary material.

**Two-stage finetuning.** In addition to the good performance on downstream tasks, multi-task finetuning also provides a strong initialization point for further task-specific finetuning. We refer to this setting as UNICORN\textsuperscript{two-stage}, where task-specific finetuning is continued from UNICORN\textsuperscript{shared}. As shown in the bottom row of Table 5, two-stage finetuning further boosts the model performance and surpasses the state of the art on various VL tasks.

**Generalization.** The unified input-output format makes it possible for UNICORN to generalize to new tasks. UNICORN could perform certain tasks in a zero-shot manner by transferring the learned ability of generating text and box sequences conditioned on the image-text input. We next present an initial exploration of adapting UNICORN to the ImageNet object localization [13] task.

Table 6. Object localization results on ImageNet [13]. Prior works with the weakly supervised setting uses ImageNet class labels.

| Method          | Top-1 Acc. | MaxBoxAcc | MaxBoxAccV2 |
|-----------------|------------|-----------|-------------|
| CAM \[69\]      | 51.8       | 64.2      | 63.7        |
| HaS \[50\]      | 49.9       | 63.1      | 63.4        |
| CutMix \[65\]   | 51.5       | 65.4      | 63.3        |
| MinMaxCAM \[57\]| -          | 66.7      | 65.7        |
| UNICORN\textsuperscript{Shared} | 59.0       | 66.7      | 66.6        |

Object localization [11, 57, 69] aims to localize an ImageNet class onto an image region. The standard benchmark is built on ImageNet [13], with two established experiment settings. The first is the “GT-known” [12, 50, 67, 68], where models know the ground-truth class to localize. The standard metrics [11] are “MaxBoxAcc” and “MaxBoxAccV2”, which are the Top-1 accuracy with an IoU threshold of 0.5, and averaged accuracy at thresholds 0.3, 0.5, and 0.7. The second setting requires models to localize the predicted class. The metric is “Top-1 localization accuracy” with an IoU threshold of 0.5. We use the EfficientNet [53] ImageNet classification result with an accuracy of 77.5%.

We experiment with UNICORN\textsuperscript{shared} and show ImageNet object localization results in Table 6. We note that UNICORN’s performance might not be directly comparable to prior works. On the one hand, UNICORN does not use ImageNet images or class labels for finetuning, and follows the zero-shot approach. However, on the other hand, UNICORN is trained with box annotations on other datasets [27, 32, 42], while most prior works [50, 57, 65, 69] only use image labels. Nonetheless, the final goal of object localization is the same. Thus we include prior results in Table 6 for reference.

UNICORN achieves better performance than the state of the art without using ImageNet images or annotations. The promising results show the possibility of generalizing UNICORN to unseen images and tasks in a zero-shot manner. We expect larger-scale pre-training to further boost such generalization ability, as observed in the NLP community [6, 59].
Figure 4. Predictions made by UNICORN\textsubscript{Shared} that uses a single model for different VL tasks. In each subfigure, we show the input text, the raw output sequence obtained by arg max sampling, the extracted text outputs, and the extracted box predictions (visualized as bounding boxes). We extract box and text predictions by reading only box or text tokens from the sequence, respectively. (a–d) UNICORN approaches a wide range of VL tasks with a single unified model and output format. (e,f) We examine the possibility of generalizing UNICORN to new images or tasks, with examples on ImageNet object localization and grounded captioning. Figures 5,6 show additional qualitative results.

### 4.4. Qualitative Results

Figure 4 shows the predictions made by UNICORN\textsubscript{Shared} on different VL tasks. Note that all predictions are made by a single model with the same set of parameters. On the right side of each subfigure, we show the input text and predicted output sequence. The output sequence is colored for visualization purposes only. We also show the extracted text and box predictions used for downstream task evaluation. For text, we discard all box tokens to obtain the text-only sequence. For boxes, we keep box tokens and dequantize them as box coordinate predictions [5].

UNICORN’s unified output format seamlessly supports different VL tasks. Figure 4(a) shows an example of grounded captioning, where the input text is a blank string and both the text and box predictions are used for evaluation. By changing input text to an image description and only evaluating box predictions, UNICORN could perform the phrase grounding task with the same output sequence format, as shown in Figure 4(b). Figure 4(c) shows a VQA example [5]. We observe that predicted answers usually have no box tokens, because there are no box annotations in the VQAv2 dataset used in multi-task finetuning. The model thus learns to generate text-only short answers conditioned on the question text input, unique in VQA. In contrast, UNICORN predicts both caption and grounding boxes when performing COCO image captioning [32], as shown in Figure 4(d). Despite COCO does not have grounding annotations, UNICORN learns grounded captioning on Flickr30k entities and transfers such ability to COCO during multi-task finetuning. Figure 4(e) shows an example of zero-shot object localization on ImageNet. The model correctly localizes the dog conditioned on the text input of ImageNet class label “brittany spaniel”. We also examine whether UNICORN could generalize learned capabilities to new images, with an experiment on grounded captioning. Qualitatively, we observe a good generalized caption quality as shown in Figure 4(f), where UNICORN generates a smooth caption and accurately grounds all noun phrases.

### 5. Conclusion

We have presented UNICORN that unifies the text generation and box prediction in VL tasks. UNICORN approaches a wide range of VL tasks with a single unified architecture, and achieves comparable performance to task-specific state of the art. We take one step further and train a single model to perform different VL tasks with multi-task finetuning. Finally, we show that UNICORN generalizes well to new tasks. We see great potential in UNICORN, and believe it paves the way for building vision systems with stronger intelligence.
References

[1] Chris Alberti, Jeffrey Ling, Michael Collins, and David Reitter. Fusion of detected objects in text for visual question answering. In EMNLP, 2019. 2

[2] Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. Spicke: Semantic propositional image caption evaluation. In ECCV, 2016. 5, 13

[3] Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. Bottom-up and top-down attention for image captioning and visual question answering. In CVPR, 2018. 1, 6

[4] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C. Lawrence Zitnick, and Devi Parikh. Vqa: Visual question answering. In ICCV, 2015. 1

[5] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C. Lawrence Zitnick, and Devi Parikh. VQA: Visual Question Answering. In ICCV, 2015. 2, 4, 5, 6, 8

[6] 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. In NeurIPS, 2020. 3, 7

[7] Nicolas Carion, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, and Sergey Zagoruyko. End-to-end object detection with transformers. In ECCV, 2020. 1, 2, 3, 5, 12

[8] 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. 2, 3, 4, 8

[9] Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. Uniter: Learning universal image-text representations. In ECCV, 2020. 1, 2, 4, 6, 7, 12, 13

[10] Jaemin Cho, Jie Lei, Hao Tan, and Mohit Bansal. Unifying vision-and-language tasks via text generation. In ICML, 2021. 1, 2, 5, 6, 7, 12, 13

[11] Junsuk Choe, Seong Joon Oh, Seungho Lee, Sanghyuk Chun, Zeynep Akata, and Hyunjung Shim. Evaluating weakly supervised object localization methods right. In CVPR, 2020. 7

[12] Junsuk Choe and Hyunjung Shim. Attention-based dropout layer for weakly supervised object localization. In CVPR, 2019. 7

[13] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In CVPR, 2009. 2, 7, 13

[14] Jiajun Deng, Zhengyuan Yang, Tianlang Chen, Wengang Zhou, and Houqiang Li. Transvg: End-to-end visual grounding with transformers. In ICCV, 2021. 6, 13

[15] Michael Denkowski and Alon Lavie. Meteor universal: Language specific translation evaluation for any target language. In Proceedings of the ninth workshop on statistical machine translation, 2014. 5, 13

[16] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In NAACL-HLT, 2019. 3

[17] Zhe Gan, Yen-Chun Chen, Linjie Li, Chen Zhu, Yu Cheng, and Jingjing Liu. Large-scale adversarial training for vision-and-language representation learning. In NeurIPS, 2020. 6, 12

[18] Tanmay Gupta, Amita Kamath, Aniruddha Kembhavi, and Derek Hoiem. Towards general purpose vision systems. arXiv preprint arXiv:2104.00743, 2021. 1, 2

[19] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In CVPR, 2016. 3, 5, 12

[20] Lisa Anne Hendricks, Kaylee Burns, Kate Saenko, Trevor Darrell, and Anna Rohrbach. Women also snowboard: Overcoming bias in captioning models. In ECCV, 2018. 13

[21] Ronghang Hu and Amanpreet Singh. Unit: Multimodal multitask learning with a unified transformer. In ICCV, 2021. 1, 2

[22] Zhicheng Huang, Zhaoyang Zeng, Bei Liu, Dongmei Fu, and Jianlong Fu. Pixel-bert: Aligning image pixels with text by deep multi-modal transformers. arXiv preprint arXiv:2004.00849, 2020. 2

[23] Drew A Hudson and Christopher D Manning. Gqa: A new dataset for real-world visual reasoning and compositional question answering. In CVPR, 2019. 4

[24] Aishwarya Kamath, Mannat Singh, Yann LeCun, Gabriel Synnaeve, Ishan Misra, and Nicolas Carion. Mdeptr:modulated detection for end-to-end multi-modal understanding. In ICCV, 2021. 1, 2, 4, 5, 6, 7, 12, 13

[25] Andrej Karpathy and Li Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In CVPR, 2015. 4, 6

[26] Wonjae Kim, Bokyung Son, and Ildoo Kim. Vilt: Vision-and-language transformer without convolution or region supervision. In ICML, 2021. 1, 2, 4

[27] Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A Shamma, et al. Visual genome: Connecting language and vision using crowdsourced dense image annotations. IJCV, 2017. 4, 7, 12

[28] Gen Li, Nan Duan, Yuejian Fang, Ming Gong, Daxin Jiang, and Ming Zhou. Unicoder-vl: A universal encoder for vision and language by cross-modal pre-training. In AAAI, 2020. 2

[29] Jannan Li, Ramprasaath R Selvaraju, Akhilesh Deepak Goyal, Shafiq Joty, Caiming Xiong, and Steven Hoi. Align before fuse: Vision and language representation learning with momentum distillation. In NeurIPS, 2021. 1, 2

[30] 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 preprint arXiv:1908.03557, 2019. 1, 2

[31] Xiujuan Li, Xi Yin, Chunyuan Li, Xiaowei Hu, Pengchuan Zhang, Lei Zhang, Lijuan Wang, Houdong Hu, Li Dong, Furu Wei, et al. Oscar: Object-semantics aligned pre-training for vision-language tasks. In ECCV, 2020. 1, 2, 4, 6, 7, 12, 13
[32] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In ECCV, 2014. 1, 2, 4, 5, 6, 7, 8, 12

[33] 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. arXiv preprint arXiv:1907.11692, 2019. 3, 5, 12

[34] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. arXiv preprint arXiv:1711.05101, 2017. 5, 12

[35] Jiawen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. In NeurIPS, 2019. 1, 2, 4, 6, 12

[36] Jiawen Lu, Vedanuj Goswami, Marcus Rohrbach, Devi Parikh, and Stefan Lee. 12-in-1: Multi-task vision and language representation learning. In CVPR, 2020. 2

[37] Jiawen Lu, Jianwei Yang, Dhruv Batra, and Devi Parikh. Neural baby talk. In CVPR, 2018. 5

[38] Chih-Yao Ma, Yannis Kalantidis, Ghashan AlRegib, Peter Vajda, Marcus Rohrbach, and Zsolt Kira. Learning to generate grounded visual captions without localization supervision. In ECCV, 2020. 2, 4, 5

[39] Junchao Mao, Jonathan Huang, Alexander Toshev, Oana Cimpoi, Alan L Yuille, and Kevin Murphy. Generation and comprehension of unambiguous object descriptions. In CVPR, 2016. 1, 2, 4, 5, 13

[40] Vicente Ordonez, Girish Kulkarni, and Tamara L Berg. Im2text: Describing images using 1 million captioned photographs. In Advances in neural information processing systems, pages 1143–1151, 2011. 12

[41] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In ACL, 2002. 5, 13

[42] Bryan A Plummer, Liwei Wang, Chris M Cervantes, Juan C Caicedo, Julia Hockenmaier, and Svetlana Lazebnik. Flickr30k entities: Collecting region-to-phrase correspondences for richer image-to-sentence models. In ICCV, 2015. 1, 2, 4, 5, 7, 12, 13

[43] Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Improving language understanding by generative pre-training. 2018. 3, 4

[44] 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. JMLR, 2020. 3

[45] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. In CVPR, 2016. 3

[46] Shaqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In NeurIPS, 2015. 1, 2, 3

[47] Steven J Rennie, Etienne Marcheret, Youssef Mroueh, Jerret Ross, and Vaibhava Goel. Self-critical sequence training for image captioning. In CVPR, 2017. 6

[48] Anna Rohrbach, Lisa Anne Hendricks, Kaylee Burns, Trevor Darrell, and Kate Saenko. Object hallucination in image captioning. In EMNLP, 2018. 13

[49] 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. 12

[50] Krishna Kumar Singh and Yong Jae Lee. Hide-and-seek: Forcing a network to be meticulous for weakly-supervised object and action localization. In ICCV, 2017. 7

[51] Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, and Jifeng Dai. Vi-bert: Pre-training of generic visiolinguistic representations. In ICLR, 2019. 1, 2

[52] Hao Tan and Mohit Bansal. Lxmart: Learning cross-modality encoder representations from transformers. In EMNLP, 2019. 1, 2

[53] Mingxing Tan and Quoc Le. Efficientnet: Rethinking model scaling for convolutional neural networks. In ICML, 2019. 7

[54] Antti Tarvainen and Harri Valpola. Mean teachers: Weight-averaged consistency targets improve semi-supervised deep learning results. In NeurIPS, 2017. 5

[55] 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. 3

[56] Ramakrishna Vedantam, C Lawrence Zitnick, and Devi Parikh. Cider: Consensus-based image description evaluation. In CVPR, 2015. 5, 13

[57] Kaili Wang, Jose Oramas, and Tinne Tuytelaars. Minmaxcam: Improving object coverage for cam-based weakly supervised object localization. arXiv preprint arXiv:2104.14375, 2021. 7

[58] Zirui Wang, Jiuhui Yu, Adams Wei Yu, Zihang Dai, Yulia Tsvetkov, and Yuan Cao. Simvlm: Simple visual language model pretraining with weak supervision. arXiv preprint arXiv:2108.10904, 2021. 1, 2, 4, 5

[59] 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. 3, 4, 7, 12

[60] Thomas Wolf, Julien Chaumond, Lysandre Debut, Victor Sanh, Clement Delangue, Anthony Moi, Pierric Cistac, Moritz Martin, Julien yang, Ware DiPaso, Xiaobo Gao, Ilia Sutskever, and Samy Bengio. Megatron-lm: Why does cross-attention make transformers scale linearly? arXiv preprint arXiv:2106.03825, 2021.

[61] 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. 6

[62] Zhengyuan Yang, Boqing Gong, Liwei Wang, Wenming Xiao, and Fei Huang. E2e-vlp: End-to-end vision-language pre-training enhanced by visual learning. arXiv preprint arXiv:2106.01804, 2021. 6

[63] Licheng Yu, Zhe Lin, Xiaohui Shen, Jimei Yang, Xin Lu, Mohit Bansal, and Tamara L Berg. Mattnet: Modular attention network for referring expression comprehension. In CVPR, 2018. 5, 6, 13
[64] Licheng Yu, Patrick Poirson, Shan Yang, Alexander C Berg, and Tamara L Berg. Modeling context in referring expressions. In *ECCV*, 2016. 1, 2, 4, 5, 13

[65] Sangdoo Yun, Dongyoon Han, Seong Joon Oh, Sanghyuk Chun, Junsuk Choe, and Youngjoon Yoo. Cutmix: Regularization strategy to train strong classifiers with localizable features. In *CVPR*, 2019. 7

[66] Pengchuan Zhang, Xiaojun Li, Xiaowei Hu, Jianwei Yang, Lei Zhang, Lijuan Wang, Yejin Choi, and Jianfeng Gao. Vinvl: Revisiting visual representations in vision-language models. In *CVPR*, 2021. 1

[67] Xiaolin Zhang, Yunchao Wei, Jiashi Feng, Yi Yang, and Thomas S Huang. Adversarial complementary learning for weakly supervised object localization. In *CVPR*, 2018. 7

[68] Xiaolin Zhang, Yunchao Wei, Guoliang Kang, Yi Yang, and Thomas Huang. Self-produced guidance for weakly-supervised object localization. In *ECCV*, 2018. 7

[69] Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, and Antonio Torralba. Learning deep features for discriminative localization. In *CVPR*, 2016. 7

[70] Luowei Zhou, Yannis Kalantidis, Xinlei Chen, Jason J Corso, and Marcus Rohrbach. Grounded video description. In *CVPR*, 2019. 1, 2, 3, 4, 5, 7, 13

[71] Luowei Zhou, Hamid Palangi, Lei Zhang, Houdong Hu, Jason J Corso, and Jianfeng Gao. Unified vision-language pretraining for image captioning and vqa. In *AAAI*, 2020. 2, 6, 12

[72] Yuanen Zhou, Meng Wang, Daqing Liu, Zhenzhen Hu, and Hanwang Zhang. More grounded image captioning by distilling image-text matching model. In *CVPR*, 2020. 2, 4, 5
A. Experiment Details

We summarize the detailed experiment settings of UNICORN in Table 7. In the uni-format decoder, we encode previous target token inputs \( s_{<t} \) with token and position embedding, and do not use type embedding to differentiate text and box tokens. For the pre-training corpus, our 200K pre-training corpus contains images from Flickr30k entities [42], COCO [32], and Visual Genome (VG) [27], as used in MDETR [24]. The 3M corpus [35, 71] is the Conceptual Captions dataset [49]. The 4M corpus [9, 17, 31] consists of the COCO [32], Visual Genome [27], Conceptual Captions [49], and SBU Captions [40] datasets.

B. Multi-task Finetuning with Prefix

In the main paper, we discuss the effectiveness of multi-task finetuning UNICORN\(_{\text{Shared}}\). UNICORN\(_{\text{Shared}}\) gathers training data from all downstream tasks and trains a single model for different tasks, by predicting the target sequence conditioned on the image and text inputs. By unifying all considered downstream tasks as a sequence generation problem, a single UNICORN model could perform well on different tasks, e.g., phrase grounding and grounded captioning. Despite the unified output format, the main paper also mentions that certain task does have slightly different input-output text patterns, such as averaged text length and text style. Despite not having task-specific identifiers in the input, UNICORN\(_{\text{Shared}}\) learns to identify different tasks based on the subtle difference in the input text. For example, UNICORN\(_{\text{Shared}}\) predicts short box-free answers for the question text input (from the VQA task), and text sequences with a single box for the referring expression input (from the referring expression comprehension task).

Instead of having the model identify the desired task by itself, an intuitive alternative is to add a task-specific input text string to identify the task for each sample [10]. The input text string is known as the prefix. We experiment with a variant of UNICORN multi-task finetuning with prefix, namely UNICORN\(_{\text{Prefix}}\). UNICORN\(_{\text{Prefix}}\) adds a task-specific prefix at the beginning of each input text string, e.g., “Visual grounding: the coffee mug next to the plate.” We use the task name as the prefix, i.e., “visual grounding;”, “phrase grounding;”, “grounded captioning;”, “image captioning;”, “question answering;”, etc. We then train the model with multi-task finetuning, the same as UNICORN\(_{\text{Shared}}\).

Table 8 compares UNICORN\(_{\text{Prefix}}\) with UNICORN\(_{\text{Shared}}\). We observe a comparable performance on the experimented tasks and datasets. We consider the prefix setting an interesting variant of UNICORN\(_{\text{Shared}}\), which has its unique potentials in the future. One intriguing future property of adding prefix is to achieve the instruction tuning ability [59]. A recent NLP study [59] shows that a model could generalize to unseen NLP tasks in a zero-shot manner by understanding the natural language description of the task (prefix). Specifically, the model is trained with data from multiple tasks and task-specific prefixes during a multi-task finetuning stage, and learns to perform a new unseen task by understanding the task description in the prefix. Due to the insufficient training data, the current UNICORN\(_{\text{Prefix}}\) does not have such instruction tuning ability. However, we see potential in UNICORN\(_{\text{Prefix}}\) by scaling up the pre-training and multi-task finetuning.

C. Qualitative Results

In this section, we present additional qualitative results made by UNICORN\(_{\text{Shared}}\). Figure 5 shows the example of UNICORN in performing captioning tasks. Figure 5(a) presents the grounded captioning results on Flickr30k entities, where the predictions are evaluated by both the caption and grounding metrics. UNICORN performs well in both caption generation and grounding noun phrases to image regions. For captioning, the model generates a smooth and accurate image description, and properly includes attribute words to produce an informative caption, e.g., “young boy” and “blue shirt” in the top left example. UNICORN is also
capable of providing a comprehensive description of the scene. For example, in the bottom right sub-figure of (a), the caption consists of the foreground object and its detailed attributes “man in red shirt and blue jeans”, scene descriptions “a red door” and “on the street”, and the nearby object “a dog”. The model also performs well in grounding. Noticeably, UNICORN performs well on grounding and describing tiny objects, e.g., the “a bat” and “a baseball” in the top left example and the “a red ball” in the bottom left example.

Figure 5(b) shows UNICORN’s prediction on the MSCOCO image captioning task. With the same inputs as Flickr30k grounded captioning, UNICORN learns to transfer the grounded captioning ability learned on Flickr30k entities to MSCOCO, although COCO captioning does not have grounding annotations. For evaluation, we extract the text tokens and compute the standard COCO captioning metrics \([2,15,41,56]\). We note that UNICORN achieves comparable caption performance to the state of the art, and meanwhile, is capable of grounding all noun phrases in the caption. As shown in Figure 5(b), UNICORN not only generates informative captions, but also accurately grounds all noun phrases in the caption. Such grounded captioning ability is important for reducing object hallucination \([48]\), boosting the model’s interpretability and fairness \([20,48]\), and facilitating various robotics and human-computer interaction applications. We also visualize additional captioning examples on ImageNet \([13]\). We observe empirically that UNICORN generalizes well onto the ImageNet images. The ImageNet caption and grounding predictions in Figure 5(c) are of similar qualities as on Flickr30k entities and MSCOCO.

Figure 6 shows UNICORN’s predictions on grounding tasks. Figures 6(a,b) are from the Ref coco \([64]\) and Refcoco+ \([39]\) datasets, for the referring expression comprehension (RefExp) sub-task. We observe that the model learns to identify different objects in the same image conditioned on different input queries. For example, in Figure 6(a), the targets of “yellow sleeve guy” on the left and “blue” skier in the background. Similarly, in Figure 6(b), UNICORN correctly differentiates the four people in the image. UNICORN also correctly localizes the head noun in a long referring expression and predicts the box on the corresponding phrase. For example, in Figure 6(b), grounding boxes are predicted on the words “girl” and “person”, instead of the entire query as in previous studies \([14,62,63]\). Another observation is that UNICORN usually predicts a single box in the output sequence for the RefExp samples. For example, in the top left sub-figure of Figure 6(b), the model only grounds the head noun “girl” and does not generate a box for remaining phrase like “pink pants.” We conjecture that UNICORN learns to identify the RefExp task and generates a single box for RefExp, similar as the box-free output for VQA described in the main paper. Specifically, 1) RefExp training samples only have a single box annotation on the head noun, and 2) the input text (referring expression) has subtle difference with other text formats in multi-task finetuning (e.g., referring phrase vs. complete sentence), which makes it possible for UNICORN to identify the sample’s task based on the input text format. These two reasons make UNICORN only grounds the head noun in the RefExp task, despite being trained with multi-task finetuning with samples from all other tasks.

Table 8. Experiment results of UNICORN Prefix that adds task-specific prefix in multi-task fine-tuning.

| Method                  | #Pre-train | Visual grounding | Grounded caption | COCO | VQA2 |
|-------------------------|------------|------------------|-----------------|------|------|
|                         |            |                  | Cider F1all     | test-Cider | test-dev | KP-test |
| MDeTR [24]              | 200K       | 86.75            | 79.52           | 81.64 | 83.8 | - | - | 70.6   |
| UNITER [9]              | 4M         | 81.24            | 75.31           | 74.31 | - | - | - | 72.7   |
| GVD [70]                | -          | -                | -               | 62.3  | 7.55 | - | - | 67.9   |
| VL-T5 [10]              | 180K       | -                | -               | 71.2  | - | - | - | 116.5  |
| OSCAR [31]              | 4M         | -                | -               | - | - | - | - | 123.7  |
| UNICORN Prefix          | None       | 82.06            | 70.72           | 73.39 | 65.67 | 61.1 | 7.85 | 111.18 |
| UNICORN Prefix          | None       | 82.38            | 70.96           | 75.43 | 69.58 | 62.1 | 8.51 | 112.8  |
| UNICORN Prefix          | 200K       | 87.87            | 79.78           | 83.09 | 80.19 | 64.6 | 9.87 | 115.8  |
| UNICORN Prefix          | 200K       | 87.59            | 80.00           | 84.11 | 79.87 | 63.4 | 10.70 | 116.6  |

Figure 6(c) shows the phrase grounding examples on the Flickr30k entities dataset \([42]\). Phrase grounding requires the model to identify all noun phrases in a sentence and ground them to corresponding image regions. UNICORN correctly grounds all types of phrases referred in the sentence, including foreground objects “person” and “woman”, smaller background objects “skies” in the top left example and “another man” in the bottom left example, and scene regions “the snow”, “a lake”, and “a blue lake.” The model even correctly predicts challenging regions such as the “trader joe’s” logo in the top right sub-figure.
Figure 5. Additional qualitative results from UNICORNShared on captioning tasks.
Figure 6. Additional qualitative results from UNICORN_shared on grounding tasks.