

Towards General Purpose Vision Systems

Tanmay Gupta¹ Amita Kamath¹ Aniruddha Kembhavi¹ Derek Hoiem²

¹PRIOR @ Allen Institute for AI ²University of Illinois at Urbana-Champaign

<https://prior.allenai.org/projects/gpv>

Abstract

A special purpose learning system assumes knowledge of admissible tasks at design time. Adapting such a system to unforeseen tasks requires architecture manipulation such as adding an output head for each new task or dataset. In this work, we propose a task-agnostic vision-language system that accepts an image and a natural language task description and outputs bounding boxes, confidences, and text. The system supports a wide range of vision tasks such as classification, localization, question answering, captioning, and more. We evaluate the system’s ability to learn multiple skills simultaneously, to perform tasks with novel skill-concept combinations, and to learn new skills efficiently and without forgetting.

1. Introduction

Since machine learning revolutionized face recognition [53] and face detection [48, 51], the computer vision field has produced fantastic special purpose learning-based systems for everything from image synthesis to human pose estimation. Yet these systems do not in aggregate come close to the ability of human generalists to learn and perform virtually any task afforded by our senses and motor controls. To broaden the applicability and effectiveness of computer vision, we need to make progress in creating more general purpose vision systems that continually learn and perform a broad range of tasks.

In modern computer vision, tasks are specified through the system architecture. For example, in digit classification, neural network architectures accept an image as input and produce ten outputs – each output representing the probability of one of ten digit classes. In such systems, adding more tasks, such as new types of predictions or even new datasets, often involves expanding the architecture with additional output heads. Several multi-task vision systems, capable of performing classical computer vision tasks like detection, segmentation and depth estimation have been proposed, e.g. [63, 11, 27, 16]. More recent works [35, 36, 5] have explored multi-task systems with a focus on vision and language tasks such as visual question answering and image

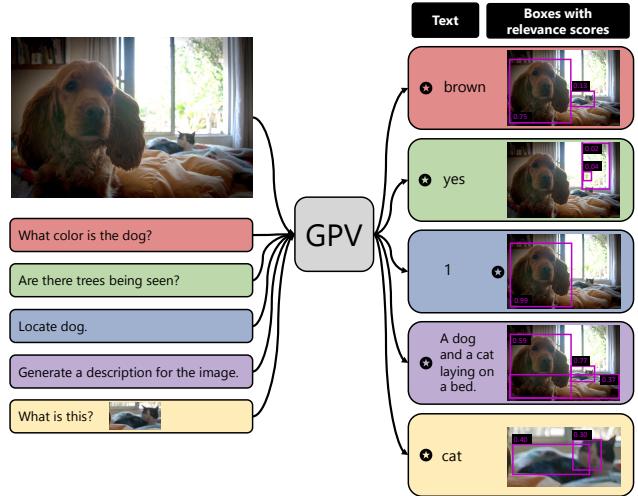


Figure 1: **GPV**. We propose a general purpose vision system, GPV-I, that takes an image and a natural language task description and outputs bounding boxes, confidences and text. GPV-I can be trained end-to-end on any task that demands a box or text output without any architecture modifications such as adding a new task-head. More importantly, GPV-I is a step towards building and evaluating general purpose learning systems. Results correspond to a model trained to perform VQA, captioning, localization, and classification tasks. Star indicates the output modality supervised during training for each task.

retrieval. While such multi-task systems provide evidence that training across a suite of datasets provides impressive results on the individual ones, the tasks performed by them must be itemized and defined in advance of training. Such systems are special purpose learners — designed, trained, and limited to specific predetermined tasks.

In this paper, we propose a task-agnostic architecture, GPV-I, that can perform vision-language tasks not prescribed by the architecture design or outputs. Instead, our system takes as input an image along with a piece of text that is used to define the task. Given the task, the system outputs relevant bounding boxes, confidences, and text. A user can input an image and query the system with a variety of requests such as “How many cars are in the image?”,

“Locate all the sedans”, “What make is the blue car?” and *“Describe the image”* – each request eliciting a different response using a combination of output modalities. We show this system outperforms and out-generalizes special purpose architectures that learn to perform each task individually, because of the ability to re-use the same encoders and decoders for multiple tasks.

Our work is a small step toward general purpose vision. Ultimately, a general purpose system should achieve three forms of generality:

- **Generality of architecture:** Can learn and perform any task within a broad domain without change to network structure (e.g. learn to classify bird species, without adding new output heads, by re-using ability to encode images, interpret task from text, and produce words)
- **Generality of concepts across skills:** Can perform tasks in skill-concept combinations not seen during training (e.g. localize “muskat” after learning to answer questions about “muskats”)
- **Generality of learning:** Can learn new tasks sample-efficiently with minimal loss to performance on previously learned tasks

To test generality of architecture, we train and evaluate our system’s ability to perform visual question answering (VQA), captioning, object classification, and object localization on the COCO dataset [33], as well as extend to additional tasks, without any modification of architecture or task-specific outputs. To test generality of concepts across skills, we present a new split of the COCO images and corresponding task annotations called COCO-SCE (Skill-Concept Evaluation), such that some words are never mentioned in VQA or caption training annotations and others are excluded from classification and localization, and then test on the examples with the held out words. To test generality of learning, we fine-tune our system on a referring expressions task and measure its learning curve and extent of forgetting previously learned tasks. Our results demonstrate types of generality not shown in previous systems, but also point to major challenges to be addressed in future work.

In summary our main contributions include: (1) **First task-agnostic vision-language architecture** for learning and performing classification, grounding, question answering, captioning, and other tasks that involve image, text and pointing (via bounding boxes) modalities. (2) **Evaluation that tests generality** of architecture, concepts across skills, and learning ability.

2. Related Work

Our architecture is motivated and enabled by several significant advances in joint vision-language understanding. Over the last decade, specialized and effective approaches have been developed for vision-language tasks, including image captioning [12, 22, 29, 38, 56, 62], phrase

grounding [42, 41, 47], referring expression comprehension [23, 39], visual question answering (VQA) [2, 14], fact-based VQA [58], knowledge- and reasoning-based VQA [20, 60, 64], visual dialog [8], and even text-to-image generation [7]. Cross-modal embeddings are particularly important. These originated with CCA-based methods [15, 13, 18], evolved to neural models [26, 57], and more recently have benefited from transformer architectures [54]. State-of-the-art self-supervised language models like BERT [9] and its extensions [35, 50, 5, 52, 31, 32, 25, 65] have further improved the effectiveness of vision and language representations. Latest systems like 12-in-1 [37] and UniT [19] have leveraged such representations to attempt to unify a number of different vision-language tasks, but the architectures still rely on task-specific heads. MultiModel [21] is a multi-modal (image, audio, text) architecture to jointly perform speech recognition, text translation, image classification, and captioning using shared input encoders, cross-modal encoders, and decoders. However, their system requires the task to be identified as an input token, and their system substantially underperforms state-of-the-art. In contrast, GPV-I infers the task from a natural language prompt and is competitive with state-of-the-art by benefiting from latest architectural innovations.

In the natural language domain, several works try to blur or erase artificial task boundaries. Kumar et al. [30] show that multiple tasks, such as part-of-speech tagging, question answering, and classification, can be formulated as a sequence-to-sequence transformation solved with a single task-agnostic architecture, though separate parameters are trained for each task. Recent works such as DecaNLP [40] and UnifiedQA [24] have trained single models to perform multiple tasks by reformulating each task as question answering allowing the individual task-performances to benefit from more data with diverse supervision while sharing model parameters. Works such as T5 [45], GPT [44, 3] have also highlighted the transfer learning capabilities of unified models specially in zero-shot and few-shot scenarios. The idea of specifying tasks through natural language descriptions is also being actively explored [59].

Though released too recently to influence our work, some recent works also make progress towards more general vision capabilities. CLIP [43] is trained contrastively on 400M image/text pairs and achieves impressive zero-shot classification performance by framing classification as an image-text matching task. Most similar to our work, Cho et al. [6] propose a unified architecture for VQA, grounding, and other tasks as sequence-to-sequence generation with regions referenced through text tokens. Our system has a similar goal but differs in technical aspects, including our ability to end-to-end train all encoders and decoders (including region generators). Our evaluation is also unique in its focus on skill-concept and learning generalizations.

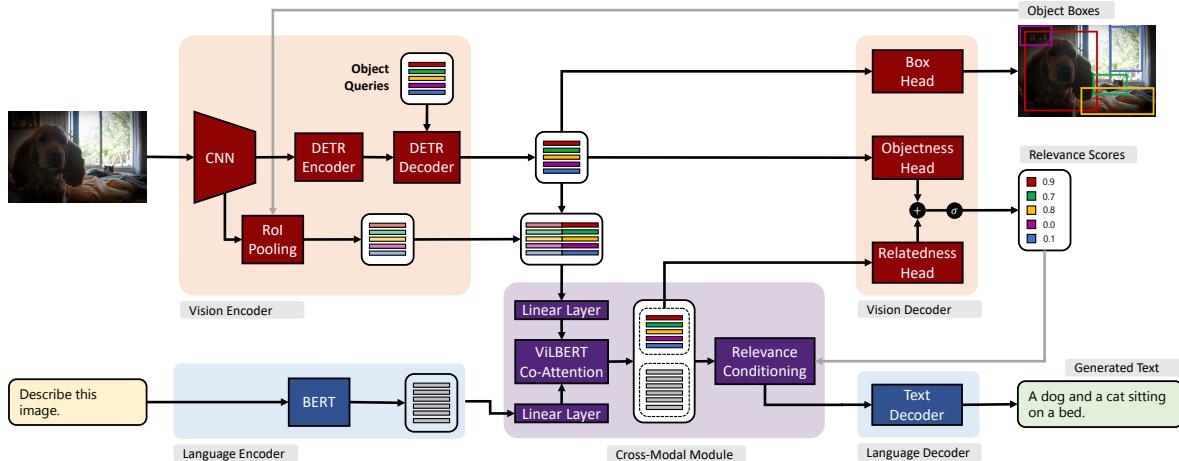


Figure 2: **Architecture of GPV-I.** **Vision**, **language**, and **cross-modal** modules are color-coded (see Sec. 3 for details).

3. The GPV-I model

3.1. Architecture Overview

The most distinct aspect of our GPV-I system is that tasks are defined through natural language text input, instead of multi-head outputs. Most systems, for example, that perform ImageNet [10] classification and COCO detection would have one 1000-class confidence output head and another 80-class box and confidence output head. More tasks or more datasets would require more output heads. Once trained, such a system will always produce 1,080 types of confidence and 80 classes of bounding boxes.

GPV-I does not have explicit task boundaries and instead takes in a natural language *task description* such as “What is sitting on the sofa?” (VQA), “Find all instances of dogs” (localization), “What is going on in the image” (captioning), or “What kind of object is this?” (classification). GPV-I interprets and performs all tasks using the same language/vision/cross-modal encoders and decoders. In training and evaluation, tasks such as localization and referring expressions have bounding box ground truth, while others such as classification, question answering, and captioning have text ground truth. Yet, all tasks involve common skills such as interpreting the task description, localizing objects, representing image regions, and determining relevance to the task. A new task, such as referring expressions, can be defined simply by providing new inputs (“Find the man wearing a green shirt”) and output supervision (bounding box). Like humans, GPV-I can learn to perform a wide range of tasks, limited only by modalities that it can sense and produce.

Fig. 2 provides an overview of GPV-I’s architecture consisting of a visual encoder, language encoder, vision-language co-attention module, and output heads for the supported output modalities – boxes, relevance scores, and text. We use the CNN backbone and the transformer encoder-

decoder from DETR [4], an end-to-end trainable object detector. The natural language task description is encoded with BERT [9]. To cross-contextualize representations from the visual and language encoders, we use ViLBERT’s co-attention module [35]. Box and objectness heads predict task-agnostic bounding boxes and scores. Relatedness head predicts a task-specific score for each output box that is combined with the objectness scores to obtain relevance scores. The text decoder is a transformer decoder that autoregressively generates text output while using relevance-conditioned representations produced by the cross-modal module as memory.

3.2. Vision modules

We use a DETR based **visual encoder**. A Resnet-50 backbone [17] extracts a convolutional feature map that is fed into DETR’s transformer encoder to get contextualized features for every grid location. The transformer decoder takes as input R ($= 100$) object queries (learned constant vectors) and the contextualized grid features and produces region descriptors per object query. The main intuition is that the object queries serve as learnable anchors, and the transformer encoder-decoder trained on detection eliminates the need for non-maximum suppression as a post-processing step. The complete region encoding is obtained by concatenating DETR’s transformer features, which encode location and limited appearance information, with ROI pooled features from the CNN backbone.

As a **vision decoder**, GPV-I uses DETR’s box head to predict bounding boxes from region descriptors, resulting in R region proposals. These bounding boxes are used for grounding and detection tasks as well as for ROI pooling from the CNN backbone. We also replace DETR’s 80-way object classification layer with a binary objectness classification layer, which contributes to determining relevance.

3.3. Language modules

The **language encoder** is used to encode the task description. We use the WordPiece tokenizer [61] to obtain sub-word tokens for the language input and a pre-trained BERT model to compute representations. Sub-word tokenization provides robustness to out-of-vocabulary words, and large scale language model pretraining allows GPV-I to better handle paraphrases of language queries and zero-shot generalization to novel task descriptions, assuming semantic similarity to previously seen descriptions in the BERT embedding space.

The **language decoder** outputs one or more words to classify, describe, or answer the input. The sequence of co-attended region representations and language query’s token representations are concatenated to construct a single sequence that serves as memory for the transformer text decoder. At each generation step, the sequence of words generated thus far are fed into the decoder along with the memory and a distribution over the vocabulary words is predicted to sample the next word. The input words are encoded using trainable word embeddings. The output logit for a vocabulary word is obtained by taking dot product between the embedding vector output by the decoder and a linearly transformed BERT encoding of the word.

3.4. Cross-modal modules

The region descriptors from the vision modules and sub-token representations from the language module are transformed by linear layers to equal dim. vectors and fed into ViLBERT’s **co-attention** layers for cross-contextualization. The relatedness head uses the co-attended region features to predict logits that indicate relevance of regions to the task description. These logits are added to logits from the objectness head and transformed into region-relevance scores by a sigmoid activation. These relevance scores are an output of the system used, e.g., to rank bounding boxes or indicate importance of regions to performing the task.

Relevance conditioning modulates the co-attended visual features with relevance scores. Specifically, the relevance score s of each region is used to weight learned vectors $\{v_{\text{rel}}, v_{\text{nrel}}\}$, which are added to the region features before feeding to the decoder. This conditioning enables supervision from the text decoder to affect the relatedness and objectness heads. In this way, a model trained to produce captions for images of peacocks may learn to localize peacocks, and, conversely, the ability to localize peacocks may translate to improved caption quality.

3.5. Training

A general purpose architecture needs a general purpose learning algorithm. Each training sample consists of an image, a task description, and targets. Depending on the task, targets could consist of ground truth bounding boxes, text, or both. In each training iteration, we uniformly draw

samples across all tasks to construct mini-batches. For all samples that contain a text target, we maximize the log-likelihood of the ground truth text. For all samples that contain bounding boxes as targets, we use DETR’s Hungarian loss for training the box and relevance prediction.

Initialization. We initialize all vision modules except the last linear layer in the objectness head with weights from DETR pretrained on object detection data. BERT is pre-trained on BooksCorpus [67] and English Wikipedia.

Optimization. We train GPV-I with a batch size of 120 with AdamW optimizer [34]. We keep DETR initialized weights frozen for the first 10 epochs and finetune all modules except BERT for 30 more epochs. For learning rate (LR), we do a gradual warm-up over the first 4 epochs to a maximum LR of 10^{-4} followed by linear decay to 0. Following DETR, we apply gradient clipping on visual module parameters and use a maximum learning rate of 10^{-5} for the CNN backbone. While we strive for task-agnostic learning, in practice, we use a $0.05 \times$ lower text loss weight for captioning due to more words in the target text than other tasks.

4. Tasks and Data

Our experiments involve 5 tasks using images from the COCO dataset and annotations from the COCO, VQA v2 [14], and REFcocO+ [23] datasets. Sec. 4.1 describes how these tasks are posed to our general purpose system along with respective losses and metrics used for training and evaluation. Sec. 4.2 details how samples are created for each task from the original annotations and introduces our COCO-SCE split for testing the generalization of concepts across skills.

4.1. Tasks

VQA aims to answer a question given an image. The input is an image/text pair, and the output is text. While training, the loss employed is the negative log likelihood of the ground truth answer text. We use the standard VQA evaluation metric (annotator-agreement weighted answer accuracy) [2] to report results.

Captioning aims to produce a description of an image. The input is an image and a prompt, such as “Describe the image” or “What is going on in the image?”, and the output is text. While training, the loss employed is the negative log likelihood of the annotated caption. The evaluation metric reported is CIDEr-D [55] that measures the similarity of the generated and ground truth captions.

Localization aims to produce a tightly fitting bounding box to an object. The input is an image and a prompt, such as “Find all instances of dogs” or “Locate the chairs”, and the output is a set of ranked bounding boxes. Training uses DETR’s Hungarian loss. Evaluation is an average of per-image average-precision (AP) with a 0.5 bounding box intersection over union (IOU) threshold. For example, if an image contains two target objects and the correctness of

the top four ranked boxes is {True, False, False, True}, the AP is $(1/1+2/4)/2=0.75$ (every-point interpolation). The reported number is AP averaged over samples.

Classification aims to assign a category to a region. The input is an image patch and a prompt such as “What is this thing?” or “What object is this?”, and the output is text. In principle, GPV-I can produce any category label within the large vocabulary of the text decoder, including words that it has not seen within its classification training data. However, for evaluation, a K-way classification is performed by suppressing outputs that do not correspond to any of the applicable K categories. The training loss used is the negative log likelihood of text output, and evaluation is accuracy averaged over samples.

Referring expressions (RefExp) aims to localize a single region that corresponds to a phrase. The input is an image and a referring expression such as “the man wearing a green shirt”, and the output is one bounding box. While the training loss and evaluation is the same as localization, the key distinction is disambiguation of the referred instance among other instances of the same object category in the image.

4.2. Data

We present experiments using images from the richly annotated COCO dataset. We use question and answer annotations from the VQA v2 dataset, referring expressions from REFcocO+, and COCO annotations for other tasks.

Data samples. VQA samples consist of the original questions as prompts paired with the most-agreed answer among annotators. For captioning, COCO provides 5 captions per image, each of which is treated as a different sample paired with one of 14 captioning prompt templates. We generate localization samples for each object category in the image using one of 18 prompt templates paired with all instances for the category. For classification, we create a sample for each object category in the image by choosing one of the instances (cropped using the ground truth box) paired with one of 4 prompt templates. RefExp samples consist of referring expressions as prompts with corresponding boxes.

Data splits. We present results for GPV-I and baselines on two data splits. First we train and evaluate models using the standard data splits for the corresponding tasks. This provides results for GPV-I in the context of past work. Then, to test the ability of vision systems to generalize concepts across skills, we present a new split of the above annotations, named COCO-SCE (Skill-Concept Evaluation).

COCO-SCE. Fig. 3 presents a schematic of the proposed COCO-SCE splits. The 80 classes of COCO are split into 3 disjoint sets, specifying which tasks can use them for training and validation:

- $\mathcal{H}_{vqa,cap}$: 10 classes held-out from the VQA and captioning tasks in the train/val sets
- $\mathcal{H}_{cls,loc}$: 10 different classes held-out from the classification and localization tasks in the train/val sets

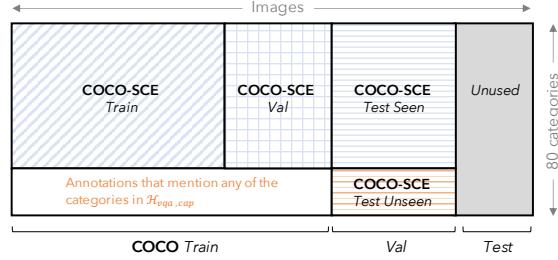


Figure 3: COCO-SCE: A split of COCO images and annotations to test the generalization of concepts across skills. Schematic shows train, val and test samples used for VQA.

- \mathcal{S} : 60 remaining classes are not held out from any tasks

When a category is held out, any annotations containing that word are not used for training or val. E.g., if *boat* is a held out category for VQA, then the annotation {“What color is the boat?”, “Blue”} would be excluded from the train/val set. Other annotations from the same image may still be used, e.g. {“Is it a sunny day?”, “Yes”}. Also, the classification and localization annotations for *boat* would be included in train/val for respective tasks. The assignment of categories to $\mathcal{H}_{vqa,cap}$, $\mathcal{H}_{cls,loc}$, and \mathcal{S} is random, except that we assign *person* to \mathcal{S} , because it is so common.

Images in COCO-SCEtrain and val sets come from COCO train set, and images in COCO-SCE test set are the ones present in COCO validation set (as COCO test annotations are hidden). COCO-SCE train and val splits are created by first creating an 80-20 partition of COCO train images and then for each task discarding samples that expose the held-out categories for that task through the annotations. On the test set we report performance separately for samples belonging to “seen” (e.g. $\mathcal{S} \cup \mathcal{H}_{cls,loc}$ for VQA) and “unseen” (e.g. $\mathcal{H}_{vqa,cap}$ for VQA) categories for each task.

5. Experiments

Our experiments evaluate GPV-I for its effectiveness compared to specialized models (Sec. 5.1), its ability to apply learned skills to unseen concepts for that skill (Sec. 5.2), its efficiency at learning new skills, and retention of previously learned skills (Sec. 5.3). Sec 5.4 provides ablations.

5.1. Generality vs. Effectiveness

Is generality of GPV-I at the cost of effectiveness? We compare GPV-I to competitive special purpose models designed for each task – ViLBERT [35] (VQA), VLP [66] (captioning), Faster-RCNN [46] (localization) and Resnet-50 [17] (classification). To avoid conflating effectiveness of architecture with availability of more data, we retrain these models to only use COCO and VQA v2 annotations. For ViLBERT and VLP this requires replacing Visual Genome [28] bottom-up features [1] with Faster-RCNN features trained only on COCO and no pretraining on Conceptual Captions [49].

Split	Model	VQA	Cap.	Loc.	Class.
Coco-SCE	[a] Specialized Model	56.6	0.832	62.4	75.2
	[b] 1-Task GPV-I	55.9	0.855	64.8	75.3
	[c] Multitask GPV-I	58.8	0.908	64.7	75.4
Coco	[d] Specialized Model	60.1	0.961	75.2	83.3
	[e] Multitask GPV-I	62.5	1.023	73.0	83.6

Table 1: **Comparison to special purpose baselines (Coco-SCE and COCO splits):** Our jointly trained GPV-I compares well to specialized single-task baselines as well as GPV-I trained on individual task data. On COCO split, we report test-server results for VQA and captioning and validation results for localization and classification as the annotations for test images are hidden. On Coco-SCE split, we report test results for all tasks.

Tab. 1 shows that on the COCO-SCE split, the general purpose GPV-I architecture trained on individual tasks compares favorably to each special purpose model (rows *a* vs *b*). Also, the generality of GPV-I enables it to be jointly trained on all 4 tasks, leading to sizeable gains on 2 tasks and comparable results on others (rows *b* vs *c*). The same trends also hold when we compare models on the original COCO data-splits (rows *d* vs *e*), validating that these trends are not merely a product of our proposed splits. Together, these results establish that the generality of GPV-I is not at the expense of effectiveness.

5.2. Skill-Concept Generalization

One of the key tenets of general purpose learning is the generality of concepts across skills, *i.e.* the ability of a model to perform well on novel skill-concept combinations that were not seen during training. When training on a single task on COCO-SCE splits, a model does not have access to any annotation on held-out concepts. For example, a model trained only on VQA will never see a question or answer about “horse” $\in \mathcal{H}_{vqa,cap}$. However, when training on all tasks, the model learns to localize and classify *horse* images. Therefore we expect the model to apply the acquired skill of question answering to answer questions about *horse* without explicitly being trained on *horse* VQA data.

Tab. 2 shows the performance of the specialized models and the 1-Task and Multitask GPV-I models on the COCO-SCE full test split as well as separately on the subset of test data categorized as “seen” and “unseen” (see Fig. 3 for a schematic of these subsets for the VQA task). The 1-Task GPV-I (row *b*) trained on individual tasks serves as a baseline to account for learned priors and dataset biases by the GPV-I architecture. We observe significant gains by Multitask GPV-I (row *c*) on the “unseen” subset across all tasks, particularly over the specialized models (row *c* vs row *a*) – indicating that the general purpose architecture is better suited at learning skills and then applying them to concepts that were unseen for that skill. We also report the perfor-

mance of Multitask GPV-I trained on the COCO training split (row *d*). Since this split exposes the model to held-out concepts for all tasks, it can serve as a loose upper bound for the “unseen” split.

Fig. 4 shows an analysis for VQA, highlighting concepts and question types (VQA sub-skills) that benefit most from multitask training. Interestingly, 2 of the top-3 concepts that benefit the most belong to the “unseen” set ($\mathcal{H}_{vqa,cap}$) for VQA. Also, the top question types that benefit are ones that require skills from localization and classification.

5.3. Learning Generalization

A system exhibits good learning generalization if it can learn new skills sample-efficiently without forgetting previously-learned skills.

Learning ability. Fig. 5 (left) shows the learning curve of GPV-I either pretrained on only the localization task (the only other task that has bounding-box supervision) or all four tasks, when finetuned on the Referring Expressions task. Multitask GPV-I demonstrates much better zero-shot performance as well as better sample-efficiency in the low data regime. The learning of attributes and additional nouns provides a better starting point for referring expressions; e.g., while the localization-trained model starts with the ability to localize *person*, the multitask model is also familiar with *red* and *sweater* through captions and VQA and may better localize “the person wearing a red sweater”.

Retention. Fig. 5 (right) shows the percent of performance retained on the original tasks as GPV-I is trained with increasing amounts of RefExp training data. Interestingly, Multitask GPV-I forgets slower than GPV-I-Loc on the localization task. Localization and captioning suffer the most from catastrophic forgetting while classification shows robust retention. GPV-I does not include explicit mechanisms for addressing forgetting, but our results highlight the importance of such mechanisms for general purpose learning.

5.4. Ablations

Tab. 3 ablates key factors that make GPV-I effective. Finetuning end-to-end (as opposed to keeping DETR initialized weights frozen) contributes to performance across all tasks (rows *a* vs *c*). RoI pooling significantly boosts performance for VQA, slightly for captioning, but leads to slight drop for localization and classification (rows *a* vs *b*).

6. Conclusion

Our GPV-I system can learn and perform any image tasks that can be described and performed using words or boxes. Our experiments show that this generality does not come at the expense of accuracy, as GPV-I compares well to specialized systems when trained on individual tasks and outperforms when trained jointly. The main cost is runtime efficiency compared to specialized systems. For

Model	VQA			Captioning			Localization			Classification		
	Test	Seen	Unseen	Test	Seen	Unseen	Test	Seen	Unseen	Test	Seen	Unseen
[a] Specialized Model	56.6	57.2	45.2	0.832	0.867	0.501	62.4	68.1	7.4	75.2	83.0	0.0
[b] 1-Task GPV-I	55.9	56.5	41.9	0.855	0.891	0.524	64.8	69.8	16.4	75.3	83.1	0.0
[c] Multitask GPV-I	58.8	59.3	47.7	0.908	0.944	0.560	64.7	68.8	25.0	75.4	82.6	5.4
[d] Multitask GPV-I Oracle	61.4	61.3	64.0	1.018	0.997	0.939	73.0	72.7	76.0	83.6	83.4	85.7

Table 2: **Skill-Concept Generalization:** Multitask achieves higher performance overall, especially for “Unseen” concepts. Classification and Localization “Seen” performance slightly decreases, likely because all tasks share the same images and VQA and captioning are more weakly supervised. GPV oracle performance, with no concepts held out, provides an upper-bound on “Unseen”. Rows *a,b,c* are trained and tested on the smaller COCO-SCE data split, while *d* uses the COCO split.

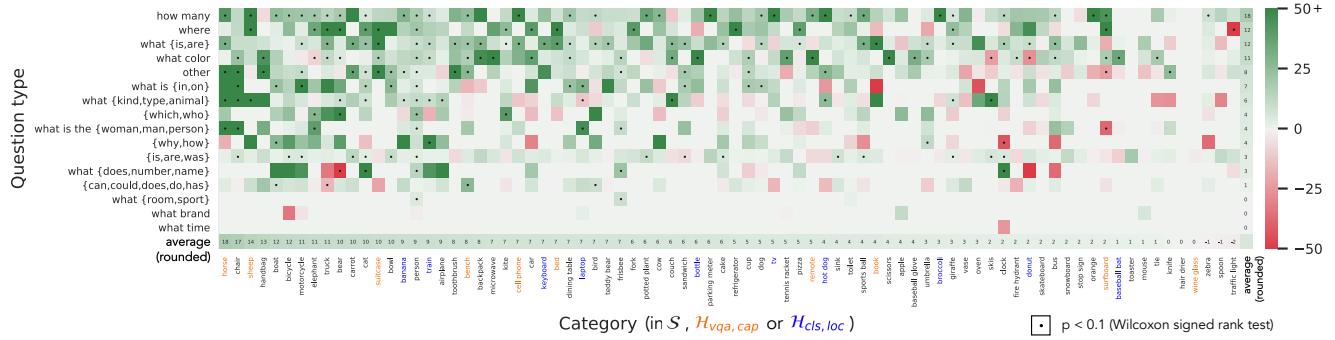


Figure 4: **Skill-Concept generalization in VQA:** The percentage improvement of GPV-I over 1-task GPV-I on the various categories and question types of VQA (COCO-SCE-test), if there are over 20 questions of that type and category. Multi-task training clearly helps most question types and categories, particularly question types that require skills from localization and classification (“how many”, “where”, “what is”) and categories $\in \mathcal{H}_{vqa, cap}$ (concepts unseen during VQA training).

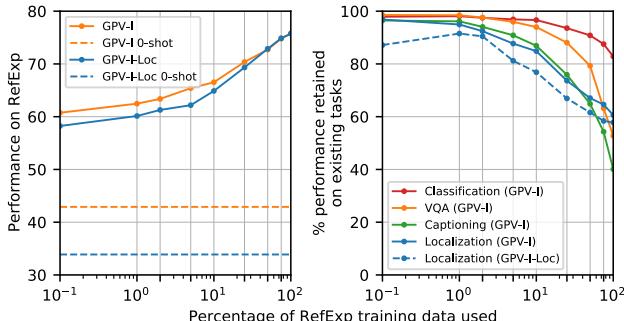


Figure 5: **Learning referring expression comprehension and retention of previous skills.** *Left:* Multitask training (labeled GPV-I) improves the 0-shot performance of GPV-I considerably and learns the new task more quickly than the single-task GPV-I-Loc model does, particularly in the lower data regime. *Right:* As training data for the new task increases, GPV-I forgets existing tasks. Multitask GPV-I demonstrates greater robustness to forgetting than GPV-I-Loc (note that *x*-axes are log-scaled).

example, using GPV-I for detection requires a separate localization inference per object category. GPV-I also achieves some skill-concept generalization, as measured on our COCO-SCE split, but with a large gap from oracle. Research on CLIP [43] suggests that training on more tasks

	VQA	Cap.	Loc.	Class.
[a] Multitask GPV-I	58.8	0.908	64.7	75.4
[b] w/o RoI features	54.9	0.898	65.3	76.6
[c] w/o Fine-Tuning	56.4	0.883	63.4	71.5

Table 3: **Ablation:** Augmenting the vision transformer features with RoI features extracted from the CNN backbone helps VQA significantly and Captioning slightly, but is detrimental to Localization and Classification. The transformer features may be sufficient to fully model localization and classification, while VQA and Captioning benefit from additional information in the RoI features. Fine-tuning helps all tasks.

and data may improve task generalization, but architecture and optimization changes are also likely needed. GPV-I learns more quickly and forgets more slowly when trained on multiple tasks, but still eventually forgets much. Adapting methods to avoid catastrophic forgetting in this general purpose setting is an interesting challenge. Ability to support image manipulation or generation tasks such as colorization and segmentation would make useful future additions to GPV-I. We also believe that, as capabilities expand, learning needs to be more self-driven, with the system selecting its training tasks and losses and self-regulating the optimization. Challenges abound, but the frontier of general purpose vision may now be at our doorstep.



Figure 6: Qualitative Results: (a) GPV-I learns to output the expected modality for each task, but also provides unsolicited yet informative commentary for the localization task and relevant regions for VQA and captioning. Star indicates the output modality supervised for each task. (b) GPV-I is a general purpose model and can perform 0-shot referring expression comprehension. (c) However, as also seen quantitatively (Fig. 5), in a 0-shot setting it makes several mistakes. (d) Without any change to architecture, GPV-I learns to correct these mistakes from annotations for this new task.



Figure 7: Qualitative Results – Room for improvement: (a) Failure cases, e.g., GPV-I does not count the number of people correctly despite localizing them, or is unable to locate and identify objects such as ski poles and refrigerators. (b) Failure cases from RefCOCO showing the model locating an incorrect object from the correct category.

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A. Appendix Summary

We provide the following details as part of the appendix:

- Training details (Sec. B)
- Additional ablation results (Sec. C)
- Task descriptions (Sec. D)
- Dataset statistics (Sec. E)

Randomly sampled qualitative results are available at
<https://prior.allenai.org/projects/gpv>

B. Training Details

Mini-batch sampling strategy. During training, batch sizes are created by randomly drawing samples uniformly across all tasks. Alternatives that require further exploration include drawing samples from only one task in each iteration or ensuring an equal representation of samples from each task in a mini-batch.

Learning from box supervision. For samples that contain a ground truth bounding box (localization task), we compute DETR’s Hungarian loss. The Hungarian loss first pairs ground truth and predicted boxes. Hungarian algorithm is used for matching using a linear combination of three cost functions that evaluate for label correctness (relevant or background), high overlap (computed as generalized IoU), and low L1 distance between true and predicted box coordinates. For each pair, the Hungarian loss then minimizes the negative log-likelihood of the ground truth class, generalized IoU loss, and L1 coordinate regression loss. See the attached `cfg.yaml` file for matching cost and loss weights.

Learning from text supervision. For VQA, captioning, and classification tasks which have a text target, we minimize the negative log-likelihood of the ground truth text. This is implemented using cross-entropy with one-hot targets for each word in the text. Ideally, this could be implemented by gathering all samples with text supervision in the mini-batch and minimizing the mean negative log-likelihood (mean computed over samples and not words). However, this led to early overfitting for captioning while other task performances were still improving on the respective validation sets. This is due to a large difference in the number of words in the target text in captioning (upto 20 words) vs other tasks (1-5 words). Therefore we use a weight of 0.05 (= 1/20) for captioning samples while using a weight of 1 for other samples which addressed the early overfitting issue.

Hardware Requirements. We have trained GPV-I models using either 4× Titan RTX (24GB), 4× Quadro RTX 8000 (48GB), or 1× A100 Tensor Core GPU (80GB). On the single A100, GPV-I requires slightly under 60GB of memory but more on the other setups due to multi-GPU training overhead. We have been unable to finetune the full model with 120 batch-size on 8× 12 or 16GB GPUs due to memory issues but it may be possible to further optimize the implementation to do so (e.g using mixed precision training). With batch-size of 120, training GPV-I on all 4 tasks takes 5-7 days depending on the hardware and training split. It may be possible to trade off memory requirements with training time by reducing the batch-size but may require hyper-parameter tuning to retain performance.

C. Additional Ablation Results

In Tab. 4 we show a more detailed task ablation. In addition to performance of GPV-I trained on individual tasks and all tasks, we also provide results for GPV-I trained on VQA and captioning which does not see any concept in $\mathcal{H}_{vqa,cap}$. Hence, we do not expect significant gains on VQA and captioning unseen sets. However, GPV-I-VQA+Cap+Loc introduces $\mathcal{H}_{vqa,cap}$ categories during training through the localization task allowing the model to improve the performance on VQA and captioning unseen sets. GPV-I-Multitask results in additional gains by letting the model benefit from classification supervision as well. Similarly, GPV-I-Cls+Loc continues to get zero unseen classification accuracy as $\mathcal{H}_{cls,loc}$ concepts are held out during training but introducing those concepts through VQA and captioning in GPV-I-Multitask leads to improved unseen classification accuracy.

Fig. 8 shows the gains from multi-task training over single task performance for each task and concept-group. Multi-task training improves performance on VQA and Captioning for all groups, improves Classification performance on $\mathcal{H}_{cls,loc}$ without impacting other groups, and improves Localization performance on $\mathcal{H}_{cls,loc}$ at a slight cost

Model	*Concepts seen during training			VQA			Captioning			Localization			Classification		
	S	$\mathcal{H}_{vqa, cap}$	$\mathcal{H}_{cls, loc}$	Test	Seen	Unseen ($\mathcal{H}_{vqa, cap}$)	Test	Seen	Unseen ($\mathcal{H}_{vqa, cap}$)	Test	Seen	Unseen ($\mathcal{H}_{cls, loc}$)	Test	Seen	Unseen ($\mathcal{H}_{cls, loc}$)
[a] GPV-I-VQA	✓			55.9	56.5	41.9	-	-	-	-	-	-	-	-	-
[b] GPV-I-Cap	✓			-	-	-	0.855	0.891	0.524	-	-	-	-	-	-
[c] GPV-I-Loc	✓	✓		-	-	-	-	-	-	64.8	69.8	16.4	-	-	-
[d] GPV-I-ClS	✓	✓		-	-	-	-	-	-	-	-	-	75.3	83.1	0.0
[e] GPV-I-VQA+Cap	✓			57.6	58.3	42.7	0.876	0.913	0.536	-	-	-	-	-	-
[f] GPV-I-ClS+Loc	✓	✓		-	-	-	-	-	-	64.9	70.0	16.3	74.5	82.2	0.0
[g] GPV-I-VQA+Cap+Loc	✓	✓		59.6	60.2	46.6	0.911	0.949	0.559	65.1	69.3	24.1	-	-	-
[h] GPV-I-Multitask	✓	✓	✓	58.8	59.3	47.7	0.908	0.944	0.560	64.7	68.8	25.0	75.4	82.6	5.4

Table 4: **Task-Ablation Results:** We train GPV-I on different combinations of tasks on COCO-SCE split for better understanding of generalization of concepts across tasks. *Concepts seen during training refers to concepts that the model has seen in *any* of the tasks that it was trained on. **Best** and **second best** numbers are highlighted.

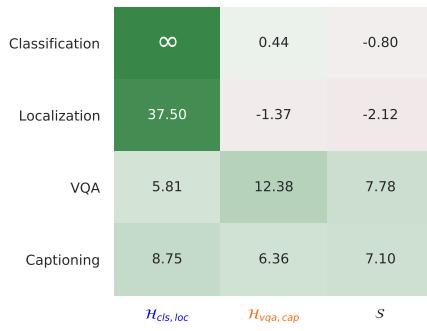


Figure 8: **Impact of Multi-task training:** The heatmap shows the relative gain in average performance of GPV-I multi-task over GPV-I-single-task for each task and category group. The average performance for any group is computed by averaging performance computed for each category in the group.

	VQA	Cap.	Loc.	Class.
[a] Multitask GPV-I	58.8	0.908	64.7	75.4
[b] w/o rel. cond.	59.2	0.926	65.0	75.9

Table 5: **Relevance conditioning ablation.** Counter-intuitively, relevance conditioning slightly hurts the performance. Further exploration is needed to utilize region-relevance scores in text prediction and to learn relevance from text supervision.

to other groups.

We also experimented with removing the relevance-conditioning (Tab. 5) and found the performance to be slightly better without it. This requires further exploration as conceptually we would like relevance scores to be incorporated in text prediction and for text supervision to guide the learning of region-relevance when box supervision is unavailable.

D. Task descriptions

Tab. 6 lists the tasks descriptions used to create samples from annotations for each of the 5 tasks. Training on more

Task	Task descriptions
Captioning	Generate a caption. Generate a description. Describe this image. Describe the image. Caption this image. Caption the image.
VQA	What is happening in this image? What is happening in the image? What is going on in this image? What is going on in the image? Generate a caption for this image. Generate a caption for the image. Generate a description for this image.
Classification	What is this? What is this object? What object is this? What is this thing?
Localization	Locate [OBJECT]. Locate [OBJECT] in the image. Locate [OBJECT] in this image. Locate instances of [OBJECT]. Locate instances of [OBJECT] in the image. Locate instances of [OBJECT] in this image. Locate all instances of [OBJECT]. Locate all instances of [OBJECT] in the image. Locate all instances of [OBJECT] in this image. Find [OBJECT]. Find [OBJECT] in the image. Find [OBJECT] in this image. Find instances of [OBJECT]. Find instances of [OBJECT] in the image. Find instances of [OBJECT] in this image. Find all instances of [OBJECT]. Find all instances of [OBJECT] in the image. Find all instances of [OBJECT] in this image.
VQA	Questions
RefExp	Referring expressions

Table 6: **Task Descriptions.** For localization prompts [OBJECT] is replaced with the object category name to localize.

natural, diverse, and complex task descriptions involving a wide range of skills could lead to improved ability to understand novel descriptions and better zero-shot transfer performance.

		Train		Val		
		Train	Val	Test	Test Seen	Test Unseen
Coco	VQA	443757			214354	
	Captioning	414113			202654	
	Localization	241035			116592	
	Classification	241035			116592	
Coco-SCE	VQA	339411	85858	214354	205138	9216
	Captioning	294028	73773	202654	179402	23252
	Localization	174538	44283	116592	105668	10924
	Classification	174538	44283	116592	105668	10924

Table 7: **Dataset sizes.** The number of examples in each data split of COCO and COCO-SCE for each task. Test combines Test Seen and Test Unseen.

Set	Categories	Set	Categories
$\mathcal{H}_{vqa, cap}$	bed	\mathcal{S}	airplane
	bench		apple
	book		backpack
	cell phone		baseball glove
	horse		bear
	remote		bicycle
	sheep		bird
	suitcase		boat
	surfboard		bowl
	wine glass		bus
$\mathcal{H}_{cls, loc}$	banana	\mathcal{S}	cake
	baseball bat		car
	bottle		carrot
	broccoli		cat
	donut		chair
	hot dog		clock
	keyboard		couch
	laptop		cow
	train		cup
	tv		dining table

Table 8: **COCO-SCE splits.** The 3 disjoint sets that the 80 classes of COCO are split into: $\mathcal{H}_{vqa, cap}$ (held-out from the VQA and captioning tasks in the train/val sets), $\mathcal{H}_{cls, loc}$ (held-out from the classification and localization tasks in the train/val sets) and \mathcal{S} (not held out from any tasks).

E. Dataset statistics

The sizes of COCO and COCO-SCE data splits is shown in Tab. 7. The division of the 80 COCO classes into COCO-SCE splits ($\mathcal{H}_{vqa, cap}$, $\mathcal{H}_{cls, loc}$ and \mathcal{S}) is shown in Tab. 8.

For Referring Expression Comprehension experiments we use the REFCOCO+ dataset with 120191 train, 10758 val, and 10615 test samples, where each referring expression is counted as a sample.