

# **Towards General Purpose Vision Systems: An End-to-End Task-Agnostic Vision-Language Architecture**

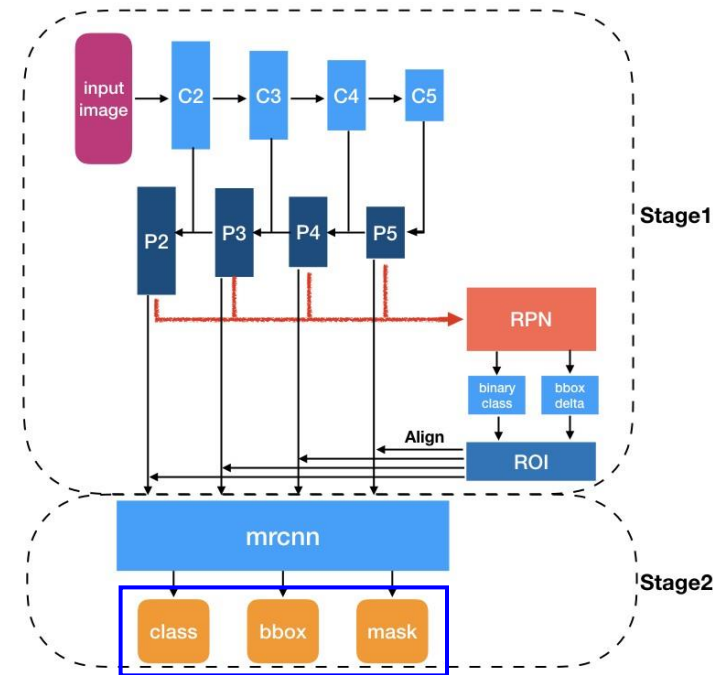
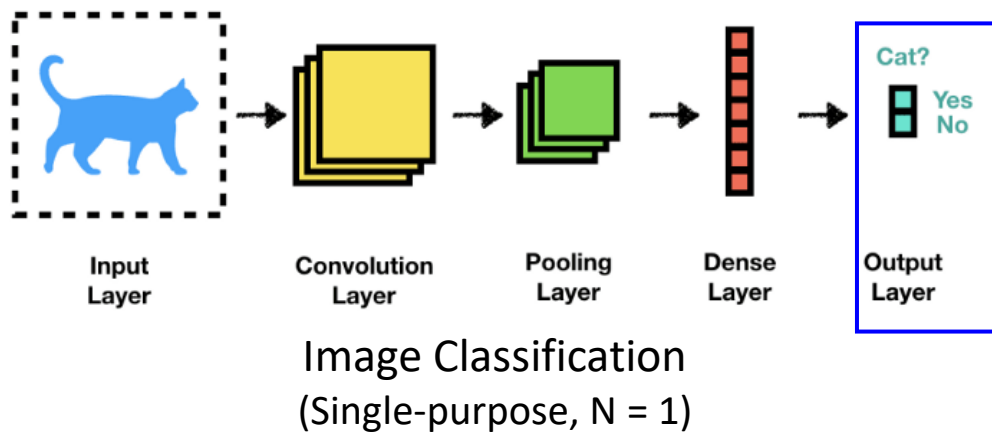
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CVPR 2022 Oral  
Presented by Yujin Lee

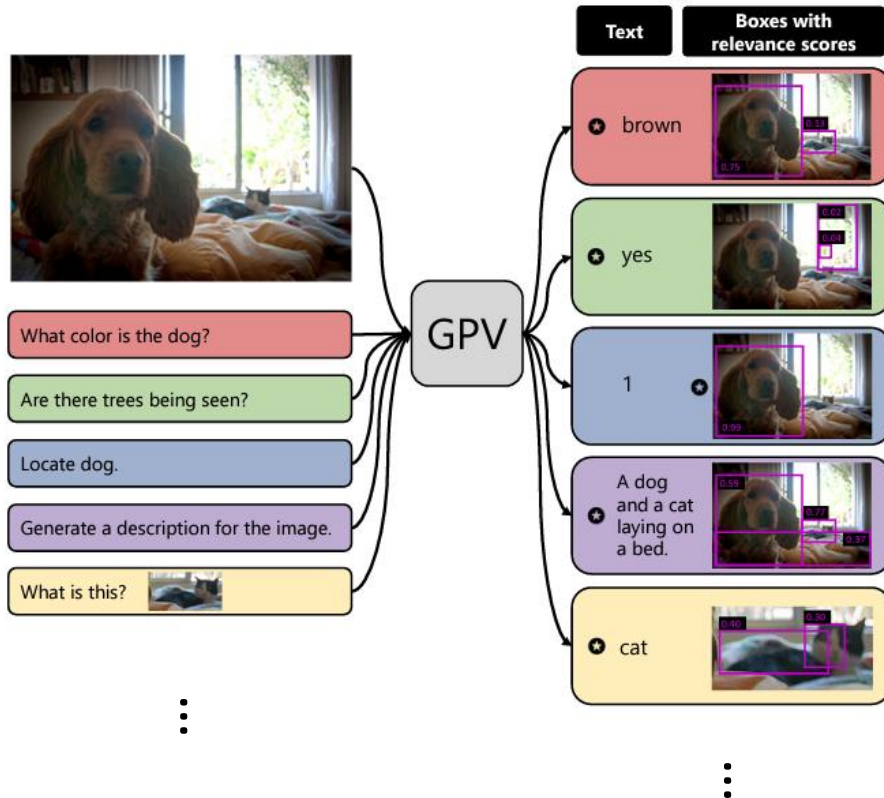
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# N-purpose systems

- Most of the computer vision architectures
- limited to N *predefined* set of task(s) and challenging to adapt to new tasks.
  - Modification on architecture or learning process required.
  - Lack of Generality even though N is larger than 1.



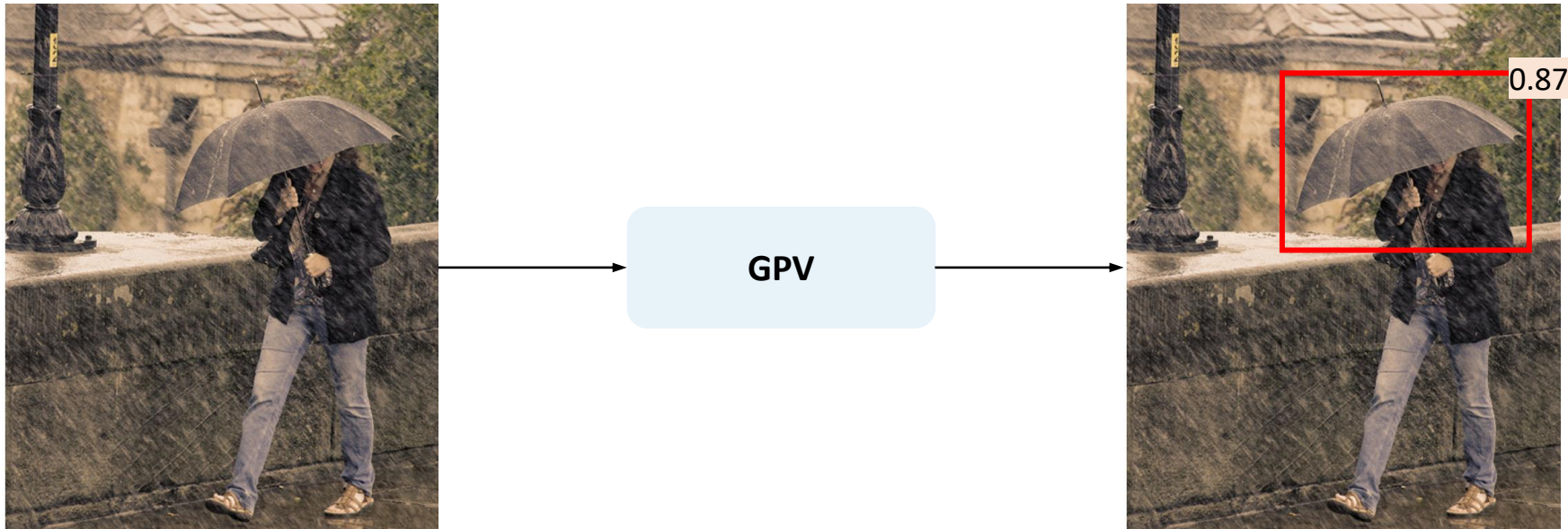
# General purpose systems



- Designed to carry out many vision tasks.  
→ *not limited to predefined tasks at the time of design.*
- Constrained only by its input modalities, memory/instructions, and output modalities.  
→ *Highly Flexible*

# GPV-1: Towards General Purpose Vision Systems

- An end-to-end trainable task-agnostic vision-language architecture.
- Task Query: task given in a natural language.
- Each query drawing out a different response using output heads that are shared across tasks.
- **Generality of Architecture, Concepts across Skills, and Learning.**



Locate an umbrella.  
(Localization)

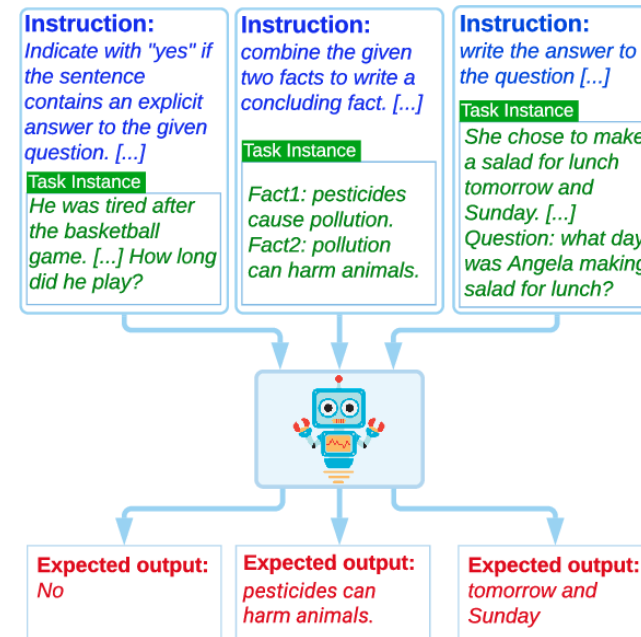
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# Generality of Architecture

- Learn any task within a broad domain without change to network architecture
- Leveraging **Encoder-Decoder** Architecture
  - Applicable to a wide range of tasks
- Learning from **Task-Description**
  - Task Description → Sequence of text tokens (eventually fed into a text encoder)
  - Enables GPV-1 to be **task-agnostic**

T5

Templated Task Description



Natural Language Task Description

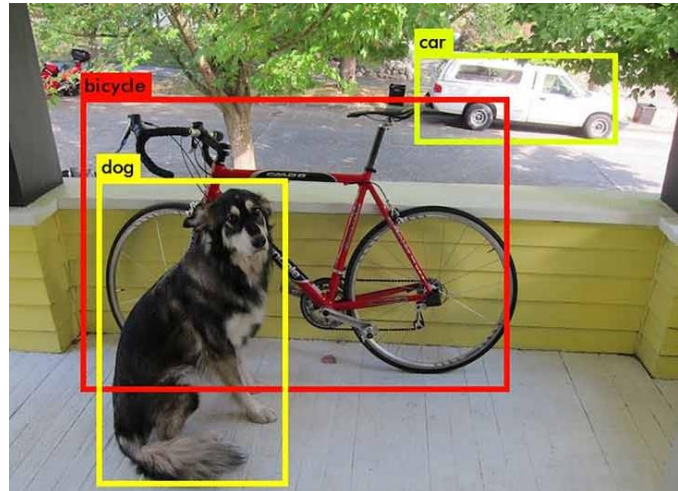
<https://ai.googleblog.com/2020/02/exploring-transfer-learning-with-t5.html>

Mishra, Swaroop, et al. "Natural instructions: Benchmarking generalization to new tasks from natural language instructions." (2021).

# Terms

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- **Concepts**
  - Nouns
  - e.g. car, person, dog, ...
- **Skills**
  - Operations that we wish to perform on the given inputs
  - e.g. classification, object detection, image captioning, ...
- **Tasks**
  - Predefined combinations of a set of skills performed on a set of concepts
  - e.g. COCO Object Detection task involves the skill of object detection across 80 concepts



- ✓ Concepts: dog, bicycle, car
- ✓ Skills: object detection
- ✓ Tasks: object detection on dog, bicycle, car



# Generality of Concepts Across Skills

- Ability to perform tasks in skill-concepts combinations not seen during training
- If well generalized, should perform well on unseen tasks



Q. "What is this object?"

A. "Dog" ✓

- Skill: Classification
- Concepts: Dog



Q. "Is cat sleeping?"

A. "No" ✓

- Skill: VQA
- Concepts: Cat



Q. "Is the dog white?"

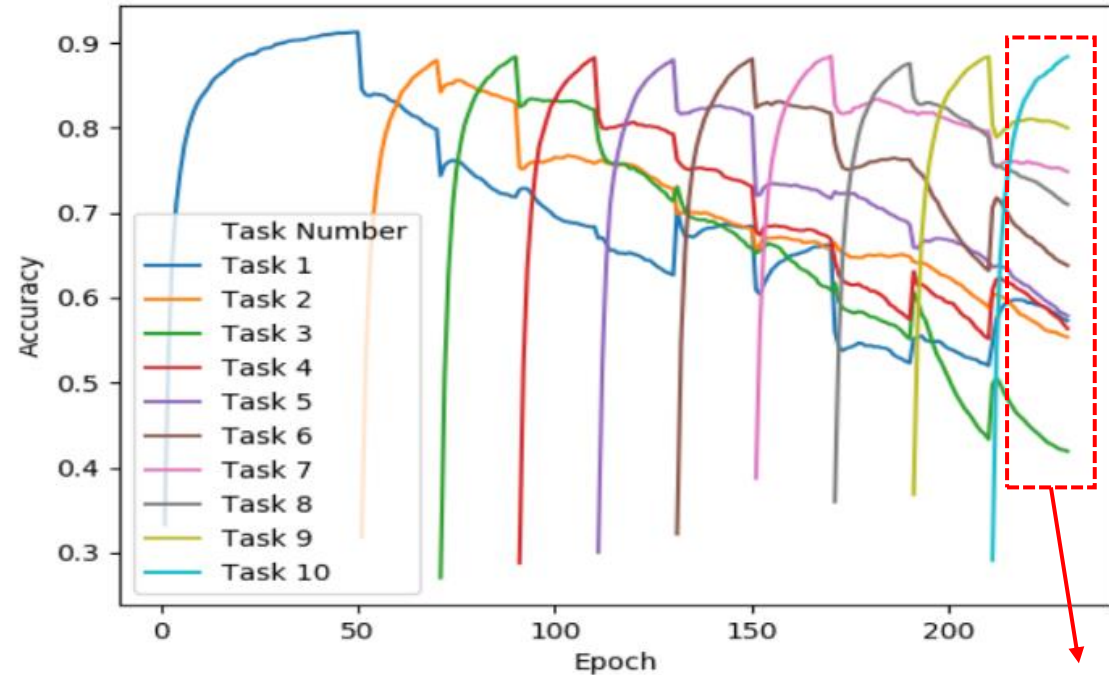
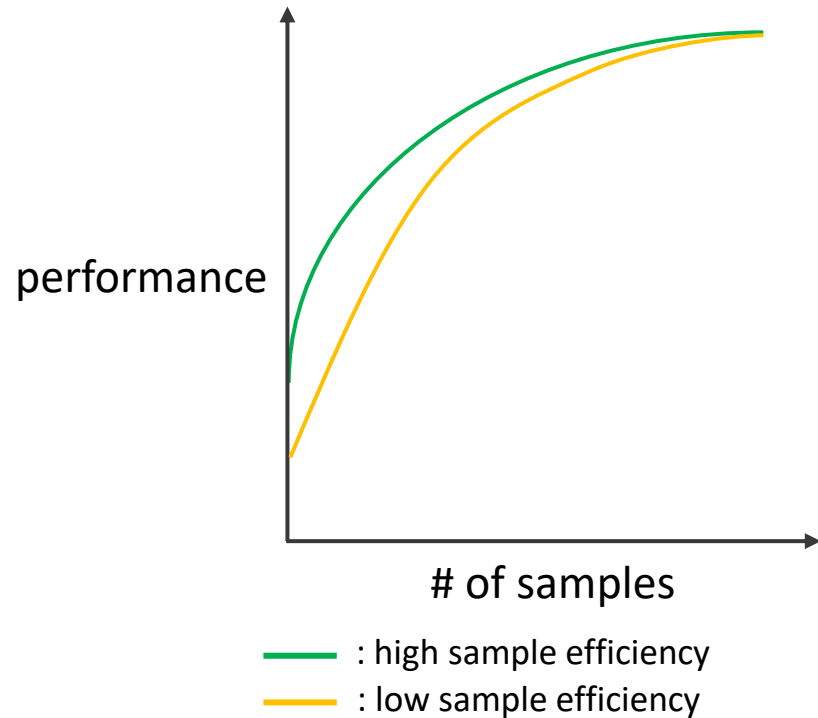
A. ?

- Skill: VQA
- Concepts: Dog

Performance	Dog	Cat
VQA	?	✓
Classification	✓	?

# Generality of Learning

- General purpose architecture should be able to *learn new tasks...*
  - **with sample-efficiency:** to learn with a smaller number of samples
  - **without catastrophic forgetting:** not to forget previous tasks

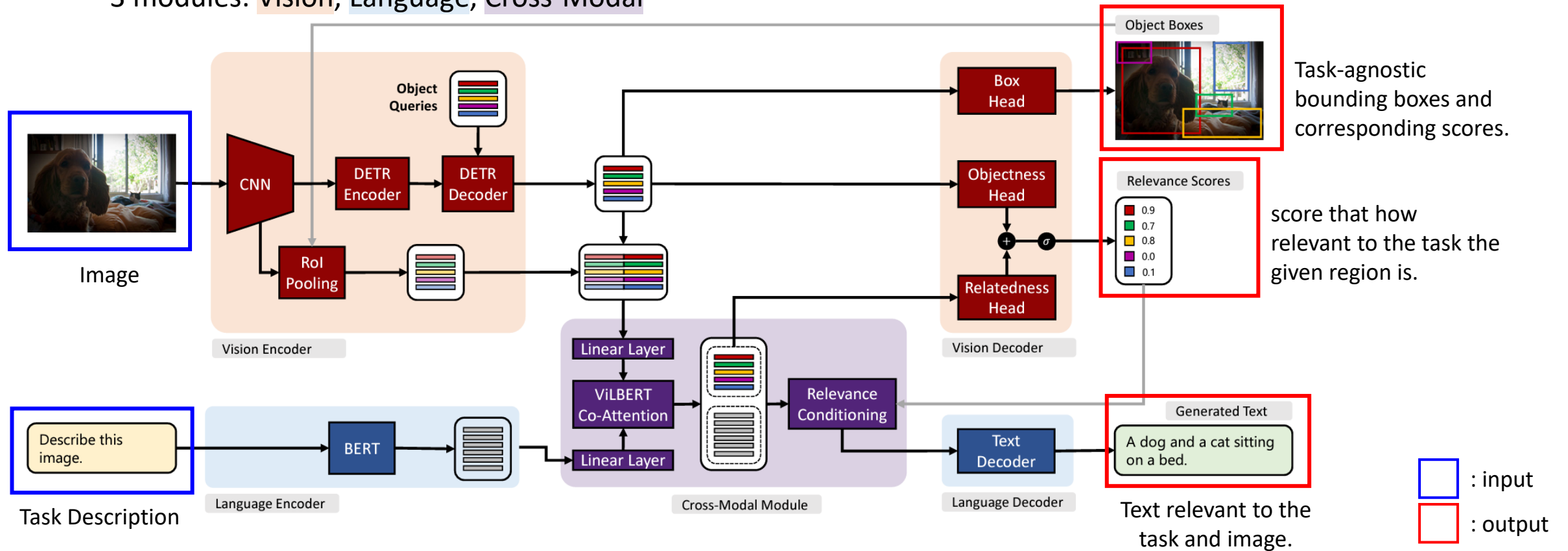


Forgot previous tasks  
when training task 10



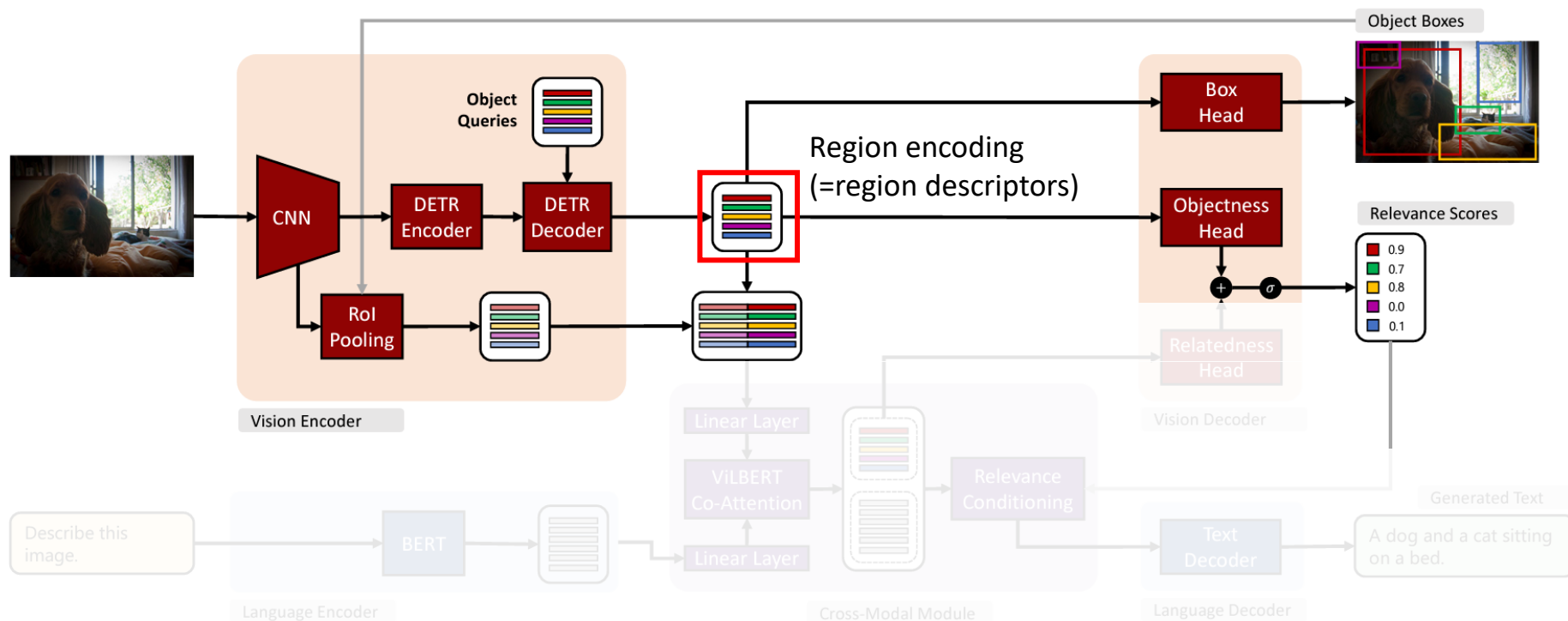
# GPV-1: Architecture

- **Input:** Image, Text (indicates which task to be performed)
- **Output:** Image, Text, Object Boxes, Relevance Scores
  - # of output heads corresponds to the # of output modalities ( $\ll$  # of classes)
- 3 modules: Vision, Language, Cross-Modal



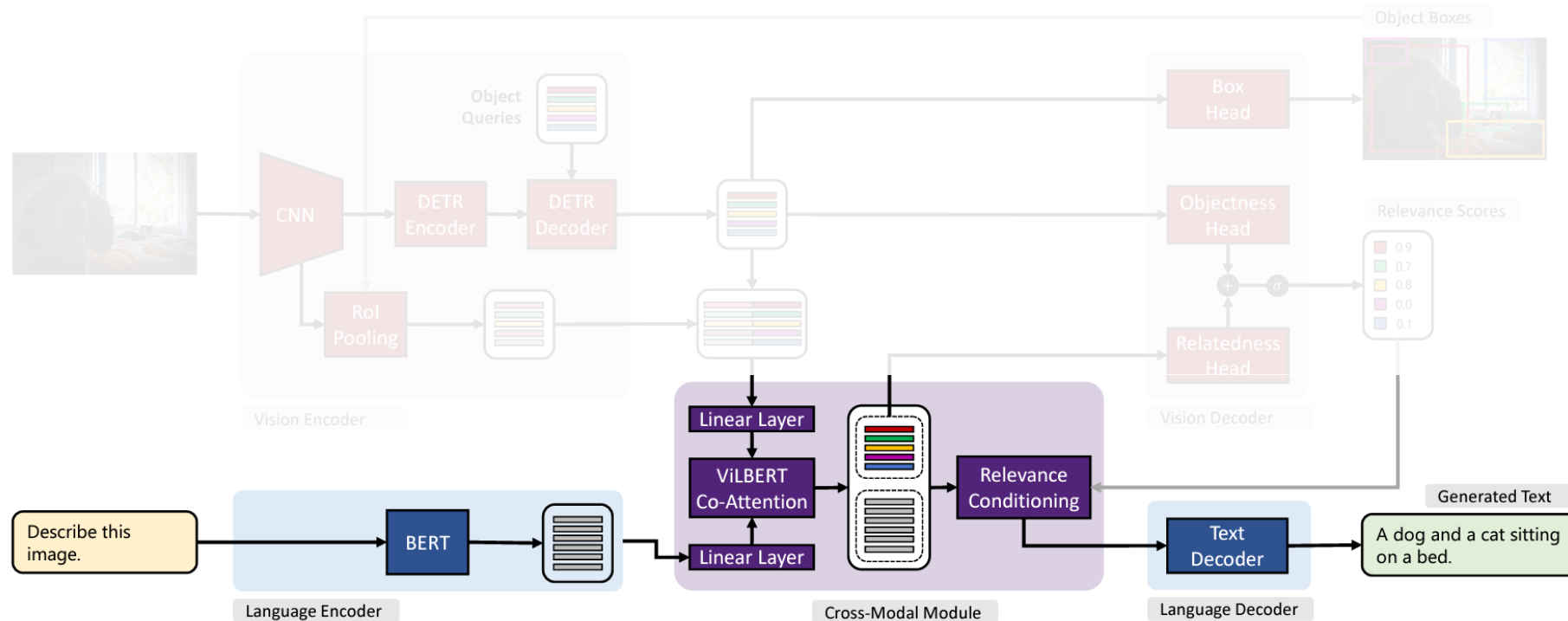
# Vision Modules

- Encoder: CNN Backbone + DETR + RoI pooling on features from CNN
- Decoder
  - Box Head: predict  $R(=100)$  bounding boxes from region descriptors
  - Objectness Head: binary objectness classification layer (\*objectness: whether it has an object or not)
- Vision Encoder and Decoder initialized with pre-trained DETR and finetuned



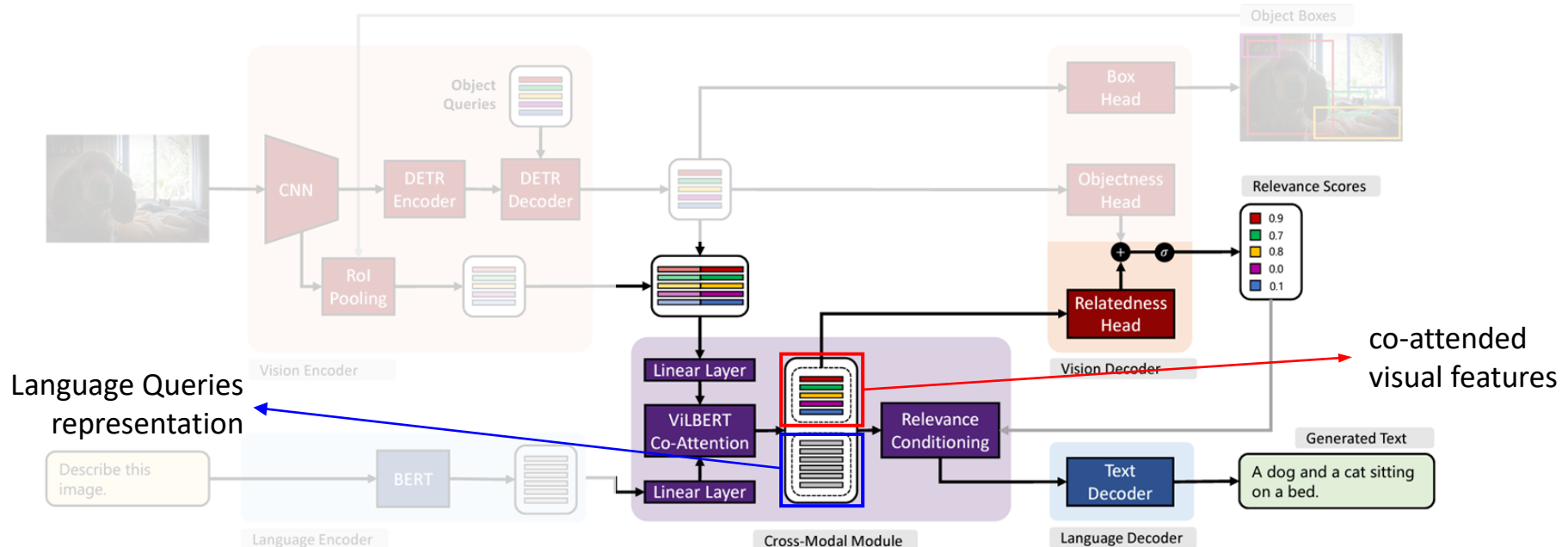
# Language Modules

- Encoder: encode the given task description.
  - Sub-word tokenization : robust to out-of-vocabulary words
  - Pre-trained BERT: handling paraphrases and zero-shot generalization to novel task descriptions.
- Decoder: outputs words to classify, describe, or answer the input.




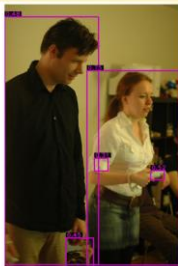
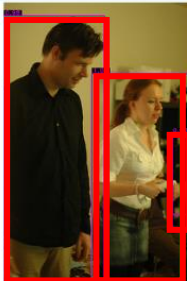


# Cross-Modal modules

- **Co-attention from ViLBERT**
  - cross-contextualize representations from the visual and language encoders
- **Relatedness head**
  - learns to indicate relevance of regions to the task description..
- **Relevance Conditioning**
  - modulates the co-attended visual features with relevance scores.
  - enables supervision from the text decoder to affect the relatedness and objectness heads.



# Tasks in GPV-1

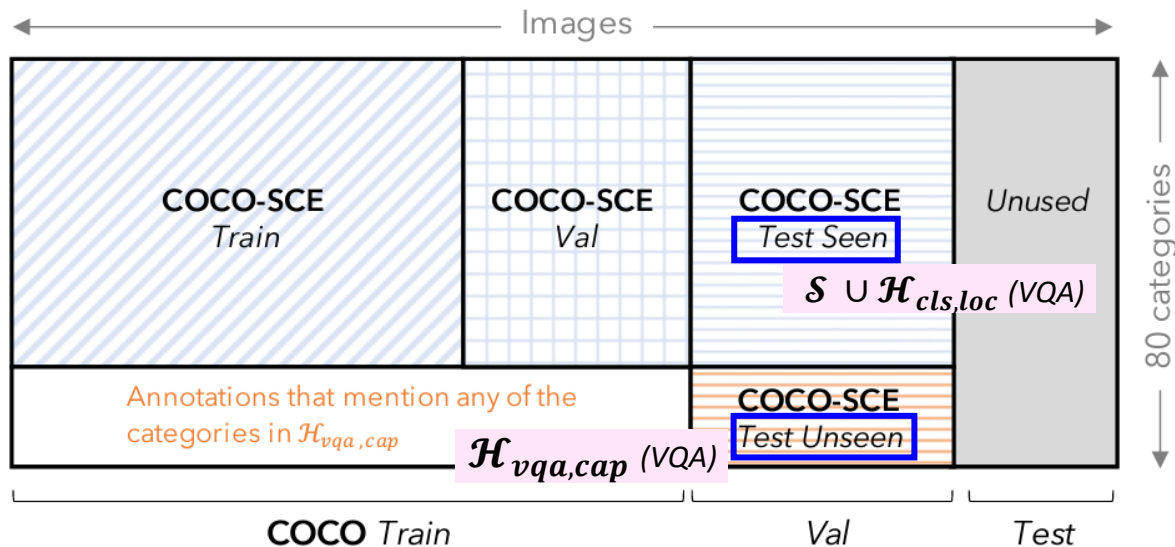
- Jointly Trained on 4 tasks (VQA, Captioning, Localization, and Classification).
  - Each mini-batch consists of a mix of samples from all 4 tasks
- Referring Expressions (a.k.a. RefExp) to test the learning ability of GPV-1

Skills	VQA (text)	Captioning (text)	Localization (boxes)	Classification (text)	RefExp (box)
	<p>What meal is this?</p>  <p>Breakfast</p>	<p>Generate a description.</p>  <p>A man and a woman playing a game with remote controllers.</p>	<p>Find person.</p> 	<p>What is this object?</p>  <p>Truck *image patch given</p>	<p>Kid sitting</p> 
Loss	NLL of the ground truth answer text	NLL of the annotated caption	DETR's Hungarian Loss	NLL of text output	DETR's Hungarian Loss
Evaluation Metrics	Annotator-agreement weighted answer accuracy	CIDEr-D	mAP	Accuracy	mAP



# COCO-SCE

- Splitting 80 classes of COCO dataset **to test unseen combinations of concepts - skills**
  - 3 disjoint sets**  $\mathcal{H}_{vqa,cap}$ ,  $\mathcal{H}_{cls,loc}$ ,  $\mathcal{S}$  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
  - $\mathcal{S}$ : 60 remaining classes not held out from any tasks
- When a category is held out, any annotations containing that word are not used for training or validation.



Image



boat is held-out for VQA

Annotation

"What color is the boat?" → "Orange"

"Is it a sunny day?" → "Yes"

"Locate a boat"

"What is this object?"

# Experiments

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1. Effectiveness compared to specialized models (**→ Generality of Architecture**)
2. Ability to apply learned skills to unseen concepts for that skill  
**(→ Generality of Concepts across Skills)**
3. Efficiency at learning new skills and retention of previously learned skills  
**(→ Generality of Learning)**
4. Ablations

# Models in Experiments

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- **Specialized Models (Baseline)**
  - ViLBERT (VQA), VLP (captioning), Faster-RCNN (localization), Resnet-50 (classification)
- **1-Task GPV-1**
  - trained only on individual task data (no joint training)
- **Multitask GPV-1**
  - joint training on all 4 tasks

# Generality vs. Effectiveness

- Test if the **general-purpose architecture is effective** compared to single specialized models
- In general, Multitask GPV-1 improved performance (at least, comparable) compared to single-task models.  
∴ **Generality of GPV-1 is not at the cost of effectiveness.**

Split	Model	VQA	Cap.	Loc.	Class.
COCO-SCE	[a] Specialized Model	56.6	0.832	62.4	75.2
	[b] 1-Task GPV-1	55.9	0.855	<b>64.8</b>	75.3
	[c] Multitask GPV-1	<b>58.8</b>	<b>0.908</b>	64.7	<b>75.4</b>
<b>COCO</b> No Held-out	[d] Specialized Model	60.1	0.961	<b>75.2</b>	83.3
	[e] Multitask GPV-1	<b>62.5</b>	<b>1.023</b>	73.0	<b>83.6</b>

**Table 1:** Comparison to special purpose baselines

# Skill-Concept Generalization

- Handling **unseen skill-concept combinations during training**
- 1-Task GPV-1: no access to held-out concepts
  - A baseline to account for learned priors and dataset biases by the GPV-1 architecture
- Multitask GPV-1 Oracle: trained on the COCO training split
  - Model exposed to held-out concepts for all tasks
  - a loose upper bound for the “unseen” split.
- **General-purpose architecture > Specialized models (especially for “Unseen”)**
  - ✓ Multitask GPV-1 is more beneficial to VQA and Captioning compared to Localization and Classification

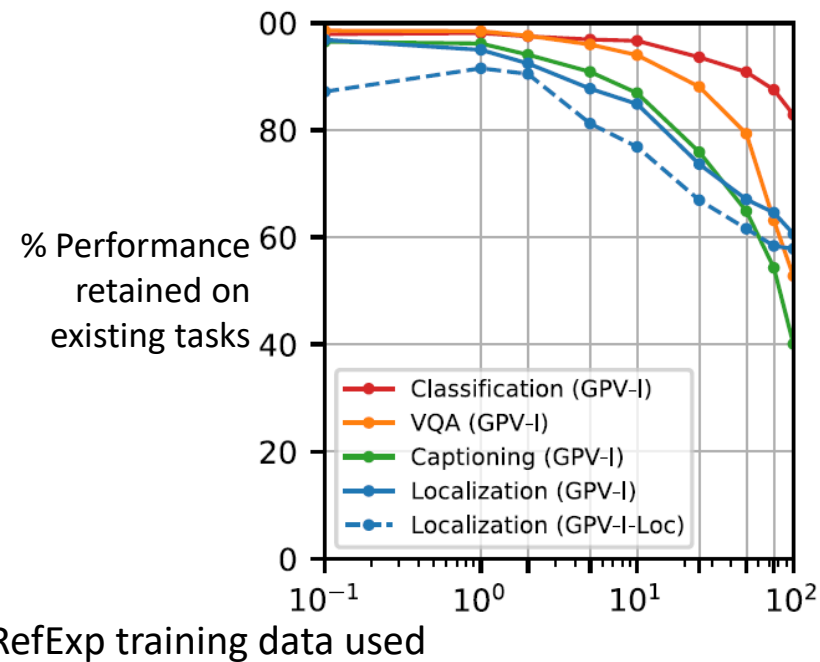
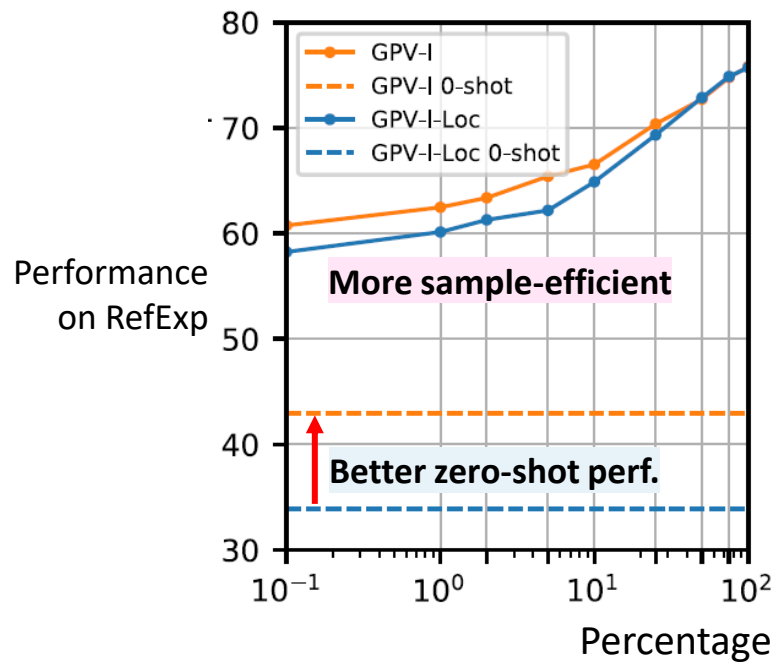
Model	VQA			Captioning			Localization			Classification		
	Test	Seen	Unseen	Test	Seen	Unseen	Test	Seen	Unseen	Test	Seen	Unseen
[a] Specialized Model	56.6	57.2	45.2	0.832	0.867	0.501	62.4	68.1	7.4	75.2	83.0	0.0
[b] 1-Task GPV-1	55.9	56.5	41.9	0.855	0.891	0.524	<b>64.8</b>	<b>69.8</b>	16.4	75.3	<b>83.1</b>	0.0
[c] Multitask GPV-1	<b>58.8</b>	<b>59.3</b>	<b>47.7</b>	<b>0.908</b>	<b>0.944</b>	<b>0.560</b>	64.7	68.8	<b>25.0</b>	<b>75.4</b>	82.6	<b>5.4</b>
[d] Multitask GPV-1 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  
(Results on COCO-SCE, Test is Full COCO-SCE test split)



# Learning Generalization

- Test if GPV-1 learn **new skills sample-efficiently without forgetting previous-learned skills**.
  - New task: Referring Expressions (fine-tuned on RefCOCO+ dataset)
  - GPV-1 (Multi-task) vs. GPV-1-Loc (pre-trained only on the localization task)
- Multitask GPV-1: Better zero-shot performance and better sample-efficiency (left figure)
  - Better starting point with the learning of attributes and additional nouns
- Multitask GPV-1 alleviates forgetting (right figure)



# Ablations

- Factors To Test
  - **RoI features** helps for VQA and Captioning
  - **Finetuning** contributes to performance across all tasks.
  - **Modality-specific Output Heads** works better in most cases compared to Task-specific output heads.

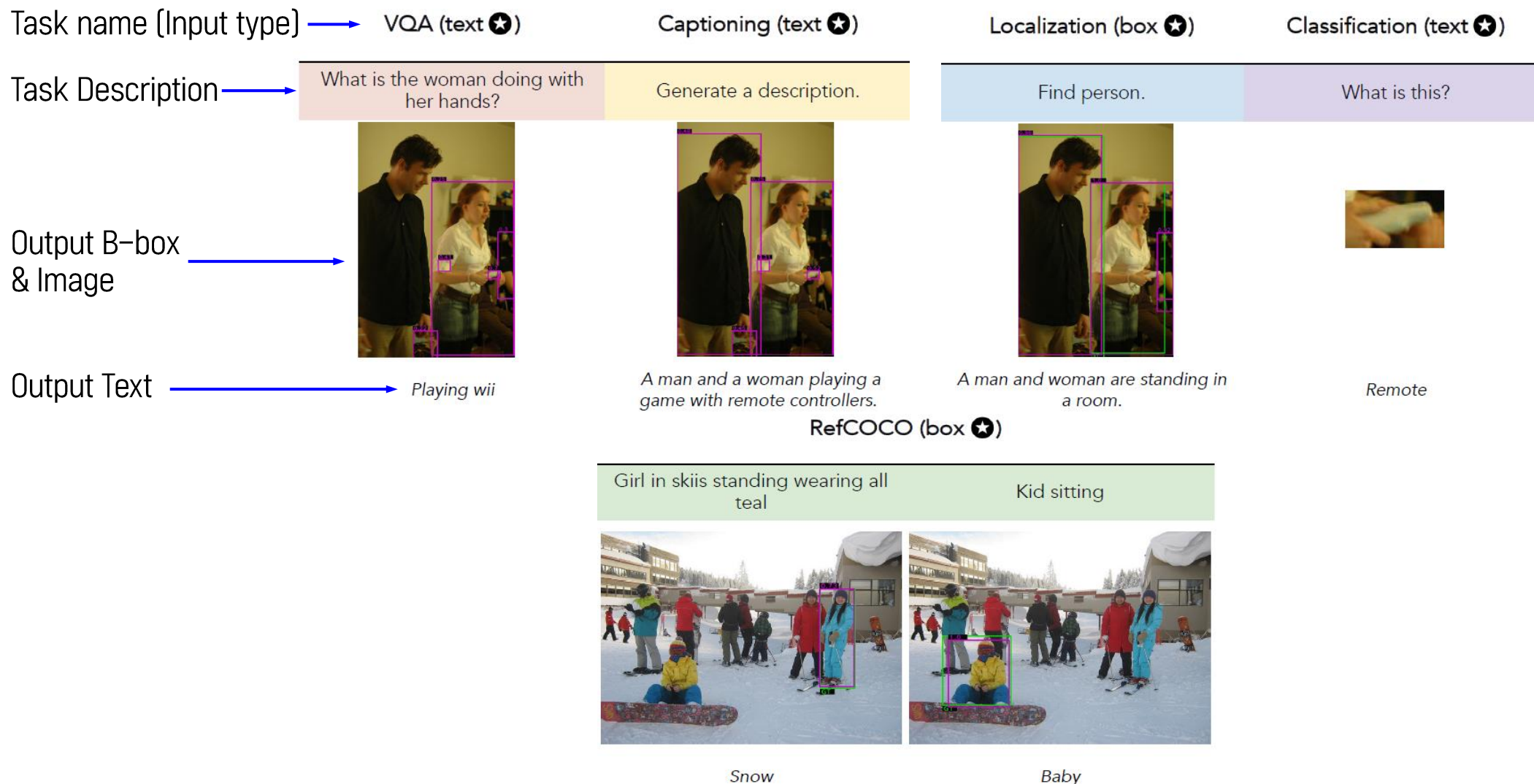
	VQA	Cap.	Loc.	Class.
[a] Multitask GPV-1	<b>58.8</b>	<b>0.908</b>	64.7	75.4
[b] <i>w/o RoI features</i>	54.9	0.898	<b>65.3</b>	<b>76.6</b>
[c] <i>w/o Fine-Tuning</i>	56.4	0.883	63.4	71.5

**Table 3** (Top): Ablations for RoI features, Fine-tuning

**Table 4** (Bottom): Ablations for modality-specific heads

Model	Params	VQA			Captioning			Localization			Classification		
		Test	Seen	Unseen	Test	Seen	Unseen	Test	Seen	Unseen	Test	Seen	Unseen
[a] Head per Task	311M	57.67	58.20	45.86	<b>0.884</b>	<b>0.922</b>	0.533	62.05	65.76	26.13	74.26	<b>81.93</b>	0.00
[b] Head per Modality	236M	<b>57.73</b>	<b>58.22</b>	<b>46.91</b>	0.881	0.915	<b>0.547</b>	<b>62.53</b>	<b>66.13</b>	<b>27.75</b>	<b>74.58</b>	81.76	<b>5.10</b>

# Example of GPV-1's works on 5 tasks



# Contributions

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- ✓ Trained to perform **any image task** that can **be performed using words or boxes**
- ✓ **Higher** (at least, comparable) **performance** than the previous specialized models
  - comparable results to specialized systems when trained on individual tasks
  - outperforms when trained jointly
- ✓ Learn new tasks sample-efficiently

# Things to be discussed

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- ✓ **Slower** than specialized systems
  - GPV-1 for detection requires a separate localization inference per object category
- ✓ Still **far to go in skill-concept generalization**
  - Huge gap between Multitask GPV-1 and GPV-1 Oracle (Table 2)
- ✓ **Catastrophic forgetting** is remained
- ✓ Skills and concepts outside COCO unexplored
- ✓ Limited coverage of task
  - Currently not available for Image Manipulation or generation tasks (colorization, segmentation)
- ✓ **Non-Image inputs** (videos, point clouds...) should be handled as well.