



医学技术研究院
Institute of Medical Technology



北京大学
未来技术学院
College of Future Technology
Peking University

Vision-to-Concept and Language Tokenizer



Hangzhou He



Lei Zhu



Xinliang Zhang



Shuang Zeng



Qian Chen



Yanye Lu

Medical Intelligence Laboratory (MILab)

Imageomics-AAAI-25 – Philadelphia, USA

OUTLINE

1. Introduction

2. Vision-to-Concept Tokenizer (AAAI 2025)

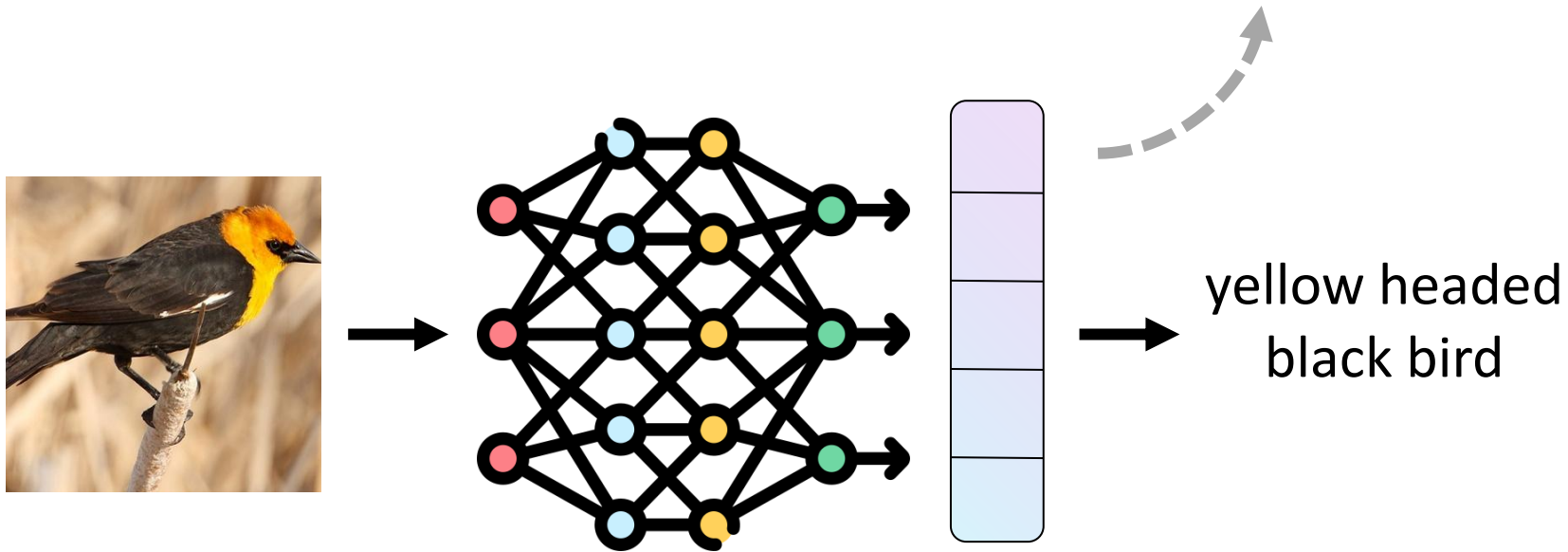
3. Vision-to-Language Tokenizer (CVPR 2024)

4. Summary

Deep Neural Networks



Deep learning has advanced the field of artificial intelligence with Deep Neural Networks (**DNNs**), which learn **feature representations** from data.

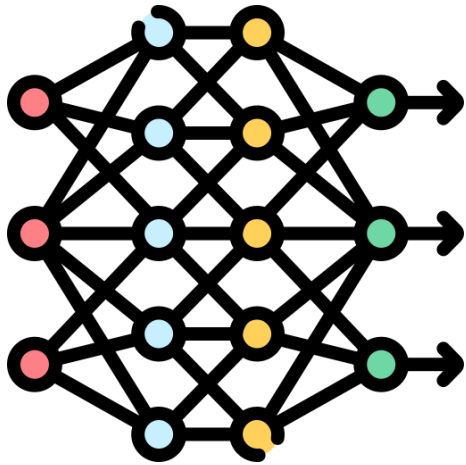


[1] Image borrowed from <https://conceptlearning.github.io/>

DNNs in Vision Tasks



Supervised training of DNNs with **a lot of labeled data** has proven highly effective for visual understanding and generation tasks.



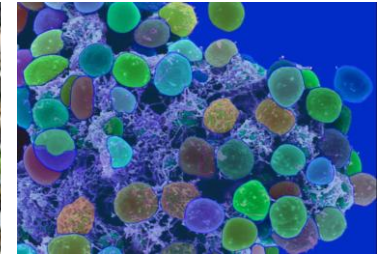
+

A Lot of data
with
manual labeling

=



classification



segmentation



Image & video generation

[1] ImageNet: <https://image-net.org/>

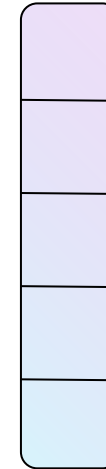
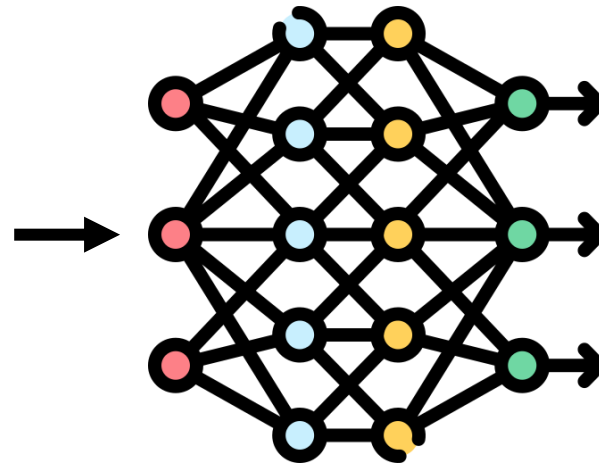
[2] Segment Any Thing Model: <https://segment-anything.com/>

[3] Sora: <https://openai.com/index/sora/>

The Black-Box Problem



Can I **teach the model** to leverage concepts like *yellow headed* ?



Can I **explain** the decision-making process?

yellow headed
black bird

Can I know what is encoded in that feature and **learn from representation**?

The Black-Box Problem



Can I **teach the model** to use **concepts** like
yellow headed for classification?

Can I **explain** the decision-

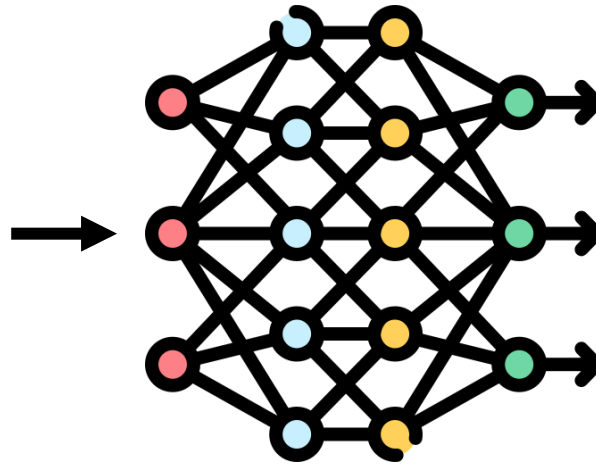
The answer is usually No!!!

Can I know what is encoded in that feature
and **learn from models**?

Looking for Explanation Interface

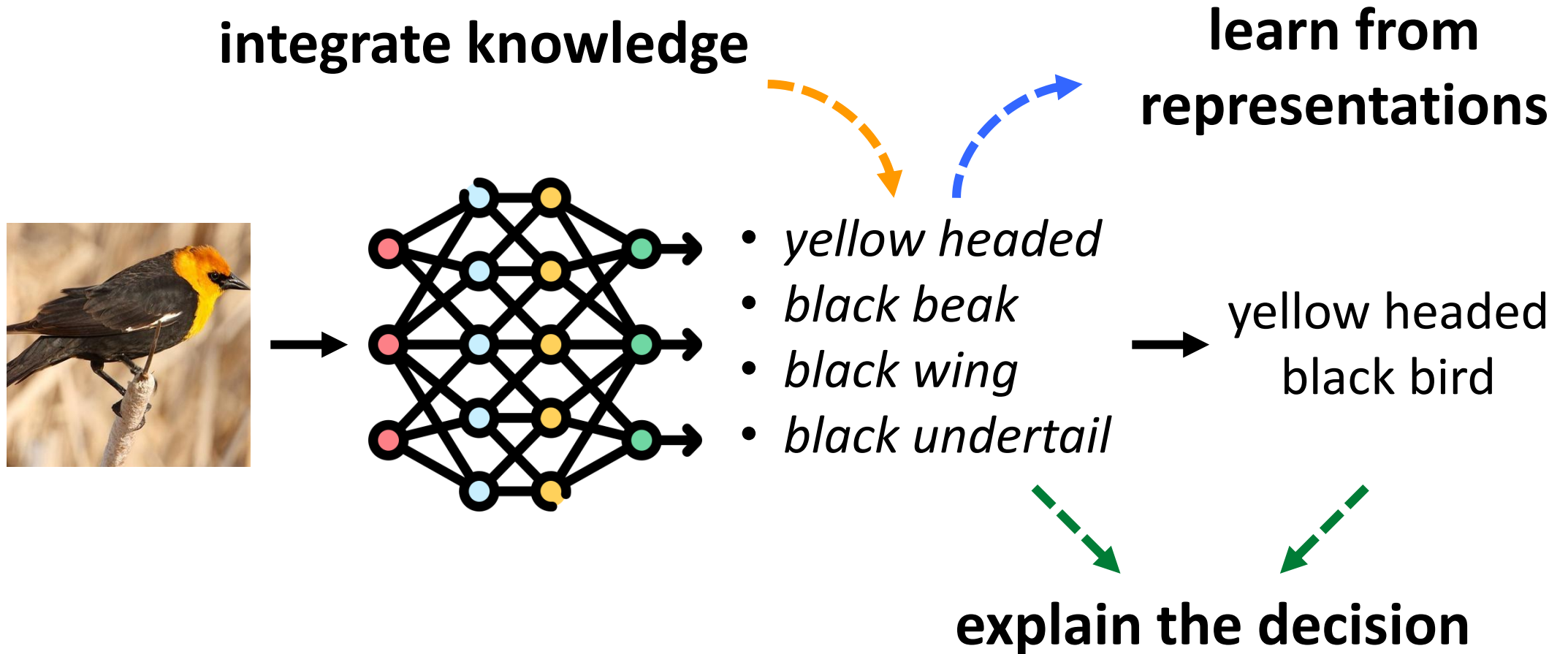


Can we represent this feature in a
human-understandable way?

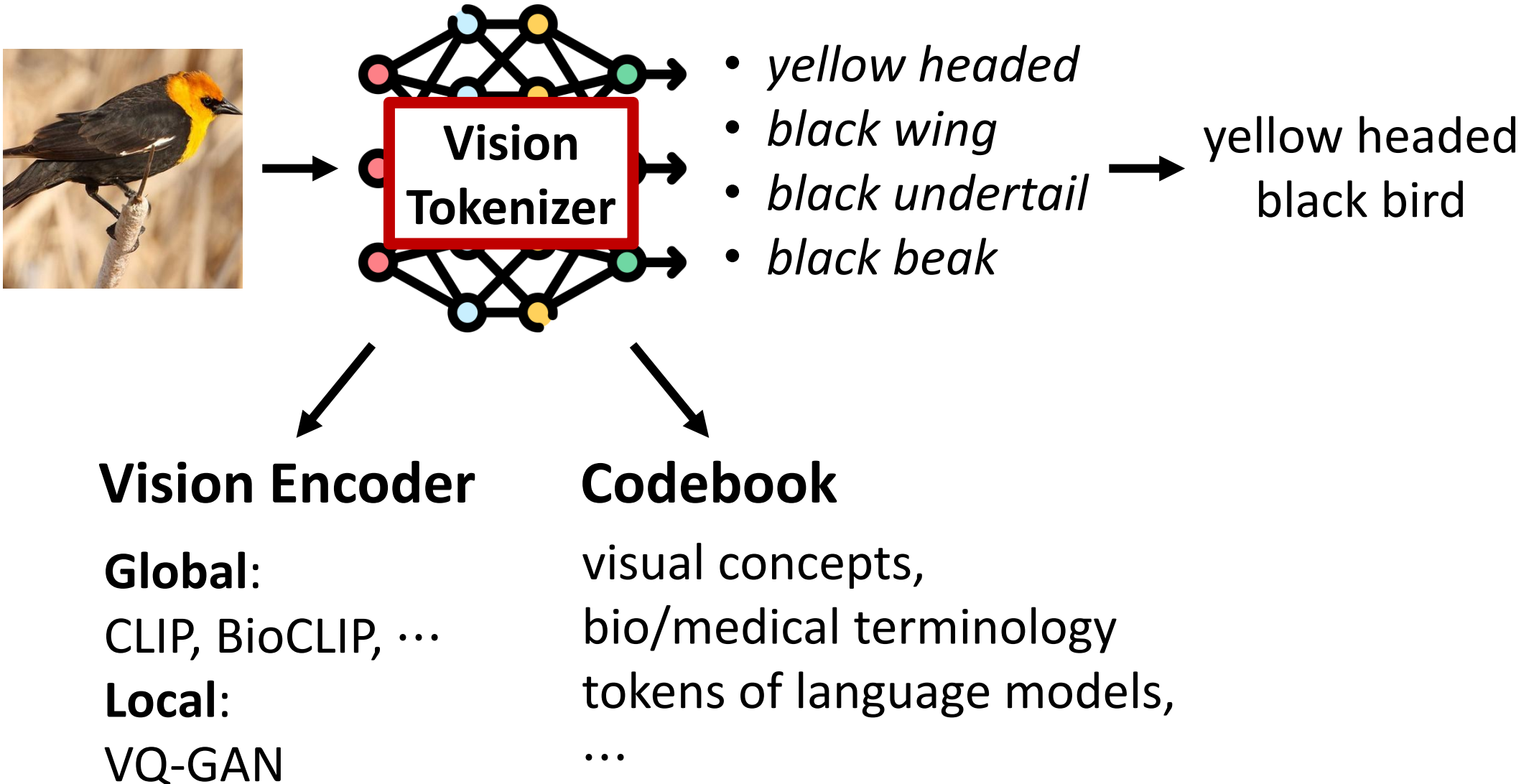


→ yellow headed
black bird

Language as a Bidirectional Interface



Building Vision Tokenizers



Concept Codebook Generation



Concept Vocabulary

$\{adj_1, adj_2, \dots, n_1, n_2, \dots\}$

$\{adj_1-n_1, \dots, adj_i-n_j, \dots\}$

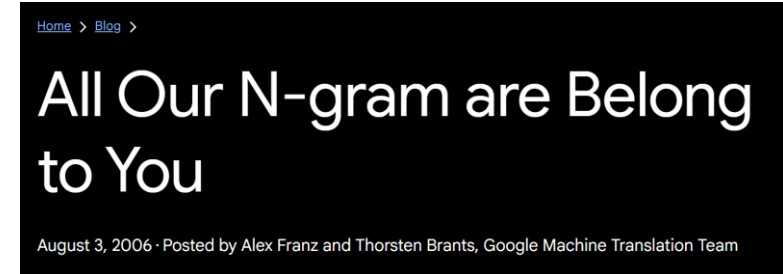
$\{pp_1-adj_1-n_1, pp_2-adj_1-n_1, \dots\}$

Construct vocabulary based on **word frequency** from *Web Corpus*

atomic: white, fur, happy, ...

bigram: white fur, high tree, ...

trigram: with white fur, ...



Google Research

Concept Codebook Generation

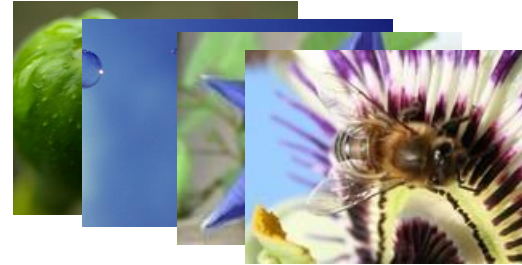


Concept Vocabulary

$\{adj_1, adj_2, \dots, n_1, n_2, \dots\}$

$\{adj_1-n_1, \dots, adj_i-n_j, \dots\}$

$\{pp_1-adj_1-n_1, pp_2-adj_1-n_1, \dots\}$

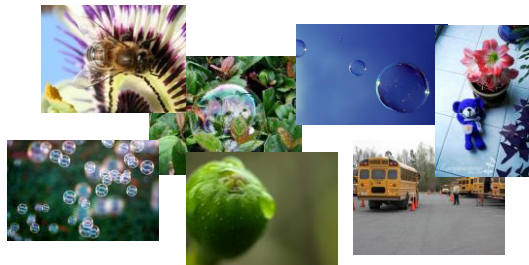


Vision-Language
Models (VLMs)

class
names



unlabeled images



select **class-related images** from
large-scale unlabeled images
using vision-language models

target class
Passionflower

+



images found by pretrained VLMs



Concept Codebook Generation



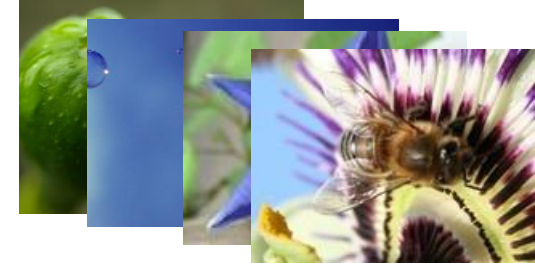
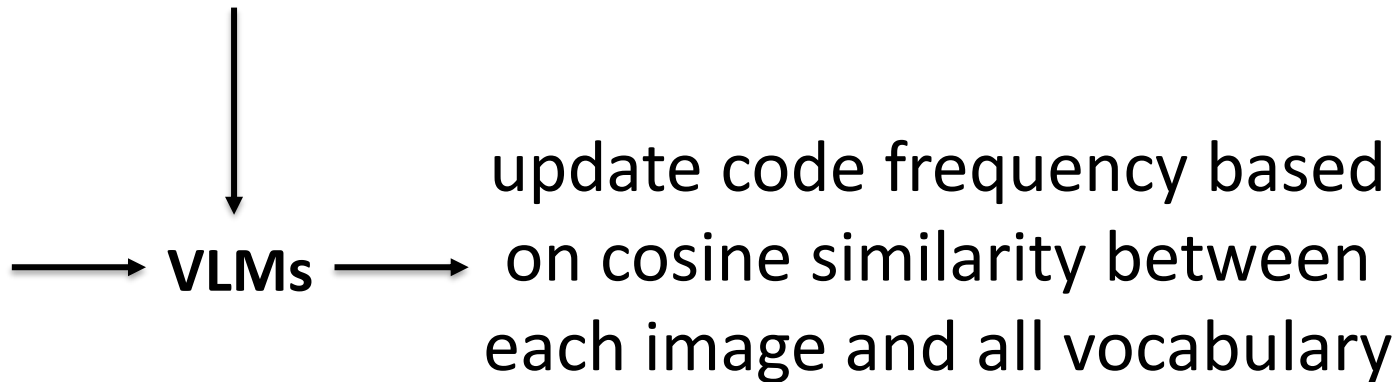
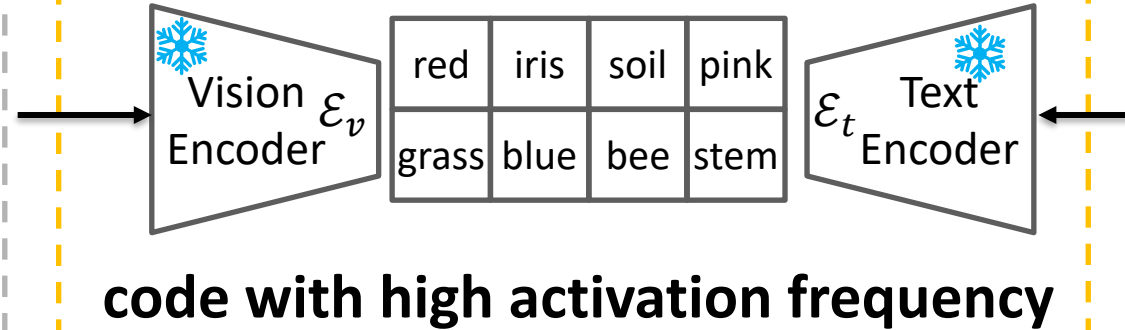
Concept Vocabulary

$\{adj_1, adj_2, \dots, n_1, n_2, \dots\}$

$\{adj_1-n_1, \dots, adj_i-n_j, \dots\}$

$\{pp_1-adj_1-n_1, pp_2-adj_1-n_1, \dots\}$

Codebook Generation

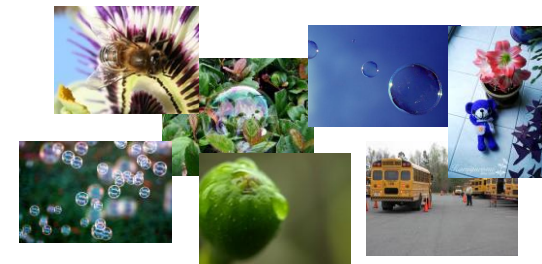


Vision-Language Models (VLMs)

class names



unlabeled images



Vision-to-Concept Tokenizer



images from same class



VLM Vision Encoder

top-k closest concepts

VLM Text Encoder

codebook

red	iris	soil	pink
grass	blue	bee	stem

Vision-to-Concept Tokenizer

Discovering Concepts from Images



images from same class



VLM Vision Encoder



top-5 closest concepts







VLM Text Encoder



codebook

red	iris	soil	pink
grass	blue	bee	stem

Class Name	Top-5 Concepts	Class Name	Top-5 Concepts
Acadian flycatcher 	<ul style="list-style-type: none">• green upperpart• green breast• green• white breast• long bill	Brambling 	<ul style="list-style-type: none">• black head• brown back• common bird• orange breast• has a black tail
American redstart 	<ul style="list-style-type: none">• black head• orange wing• orange breast• gray underpart• black wing	Polar bear 	<ul style="list-style-type: none">• white bear• white enclosure• white animal• cold zoo• white fur

Discovering Concepts from Images



images from same class



VLM Vision Encoder



top-5 closest concepts







VLM Text Encoder



codebook

red	iris	soil	pink
grass	blue	bee	stem

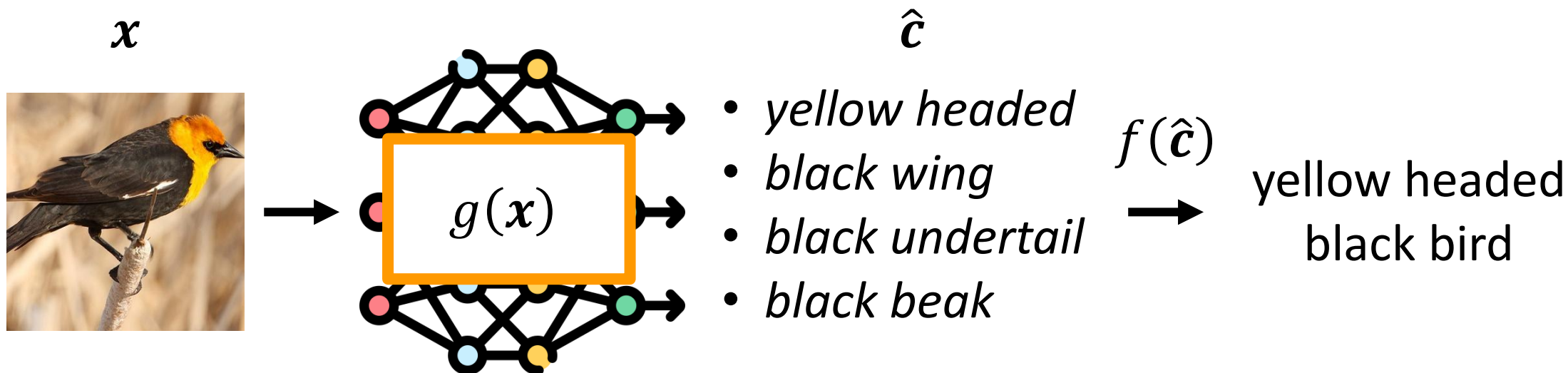
Class Name	Top-5 Concepts	Class Name	Top-5 Concepts
Hammer 	<ul style="list-style-type: none">• is a toolkit• brown handle• black handle• part of toolkit• metal	School bus 	<ul style="list-style-type: none">• yellow bus• yellow vehicle• is a yellow bus• stop sign• ready student
Hot pot 	<ul style="list-style-type: none">• hot bowl• hot dishes• red soup• hot soup• black pot	Carousel 	<ul style="list-style-type: none">• single rider• carnival• happy spin• happy rider• young rider

Concept Bottleneck Models (CBMs)



CBMs decompose a DNN into two functions:

1. A *concept encoder* $g(x) = \hat{c}$ predicting **concepts from the input features**
2. A *label predictor* $f(\hat{c}) = \hat{y}$ predicting **task labels from the concepts**

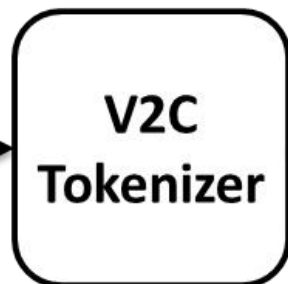


Building CBMs with V2C Tokenizer



With V2C Tokenizer, we can build CBMs **without** concept labels!

few-shot image

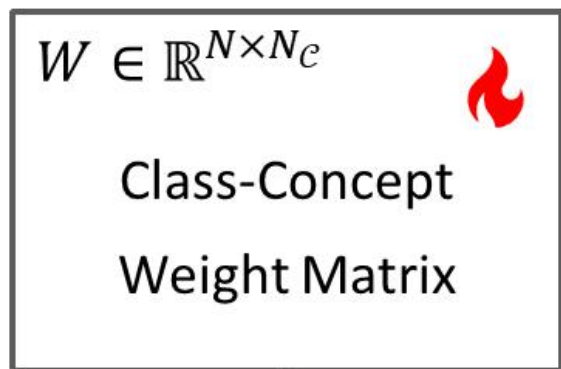


c_1 : blue

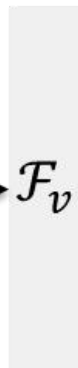
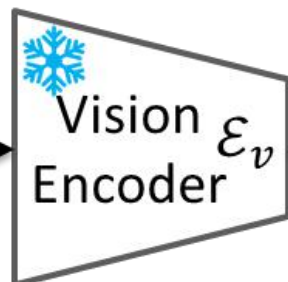
c_2 : purple center

....

c_{N_c} : symmetrical



test image



cosine
similarity
 $A \in \mathbb{R}^{N_c}$

$$\hat{y} = A \cdot \text{softmax}(W)^T$$

Building CBMs with V2C Tokenizer



Average classification accuracy (%) on **10** datasets

Method	1-shot	2-shots	4-shots	8-shots	16-shots	All
ViT-L/14	51.8	65.3	72.3	77.1	81.6	86.9
CBM	57.8	64.0	71.1	75.8	79.7	85.6

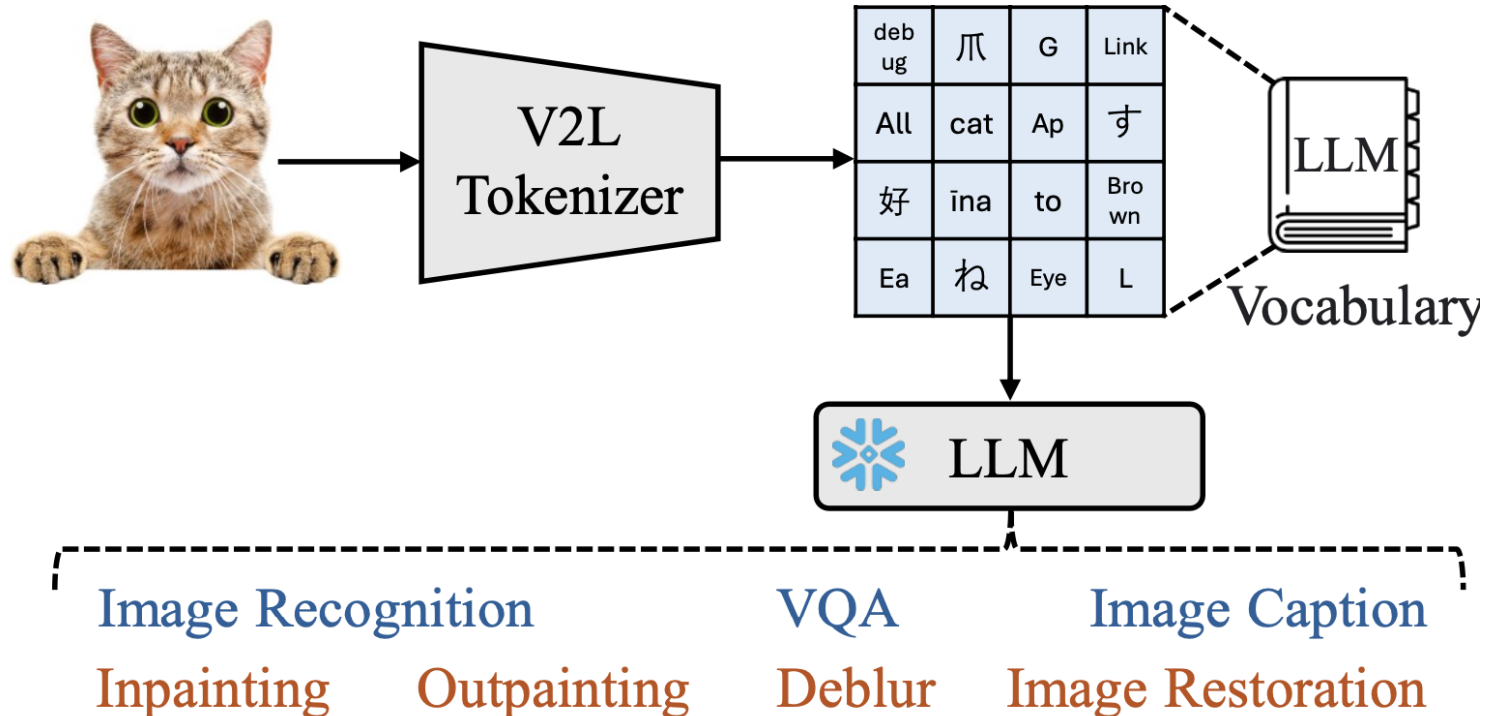
Scaling with the number of unlabeled images

Tasks	1k	40k	80k	120k	160k	200k
bird	80.3	81.4	81.6	81.9	82.2	83.0
texture	73.1	76.3	76.8	77.4	77.6	78.0

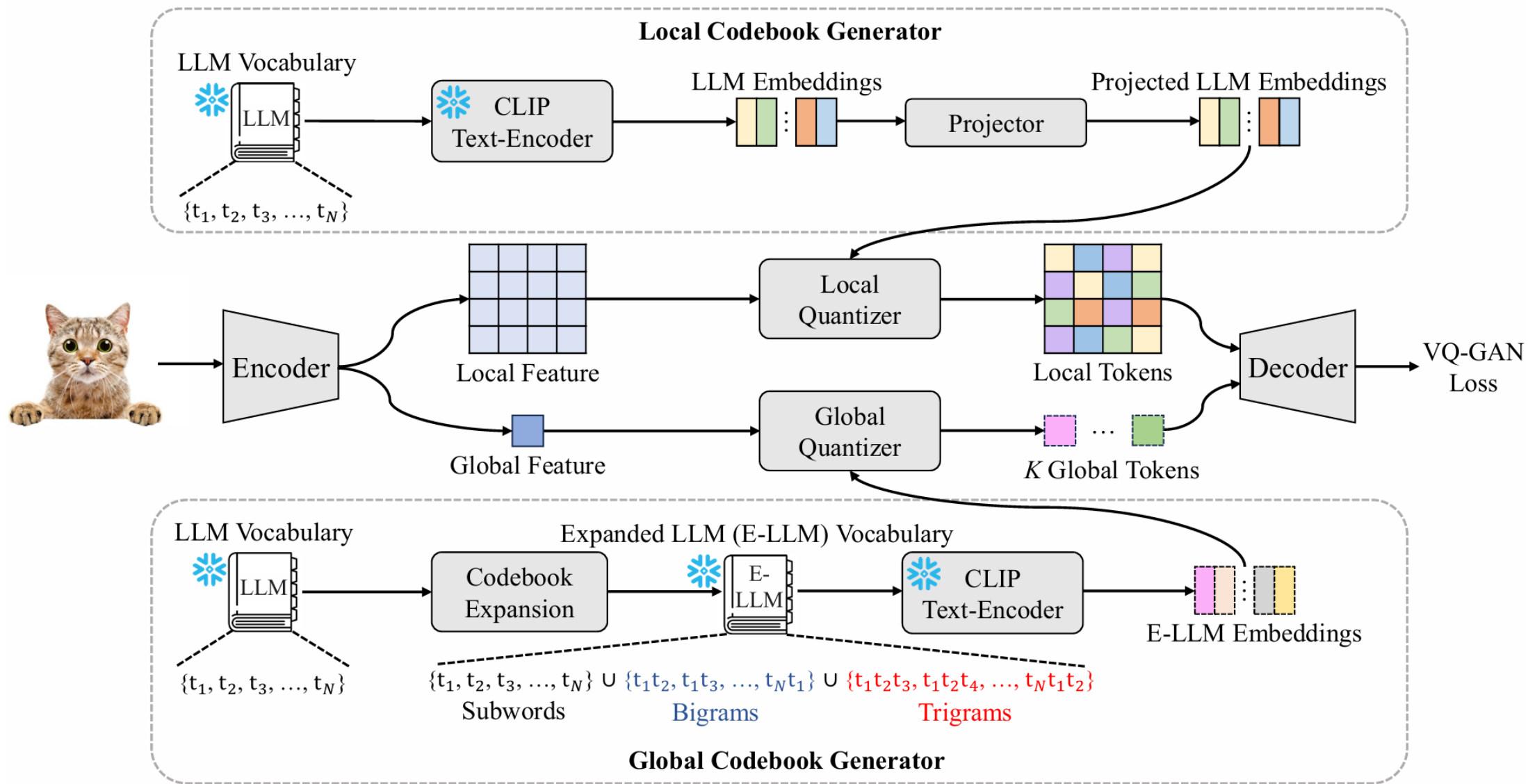
Vision-to-Language Tokenizer



A **Frozen Large Language Models** (LLMs) can use the linguistic representation of images for directly **visual understanding and generation**!



Global and Local Codebook Generator



Visual Understanding and Generation



For each of the following input-out pairs, output is one of ['French bulldog', 'rock beauty'].


Input: Tokens() , output: French bulldog.


Input: Tokens() , output: rock beauty.

Input: Tokens() , **output:**

(1) *N*-Way *K*-shot Classification

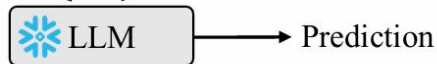
Generate a caption sentence based on words describing an image.

Input: Tokens() , output: A man in a red shirt and a red hat is on a motorcycle on a hill side.


Input: Tokens() , output: A woman wearing a hair net cutting a large sheet cake.

Input: Tokens() , **output:**

(2) Image Caption



Answer the question with a single word based on the condition.

Condition: Tokens() ,

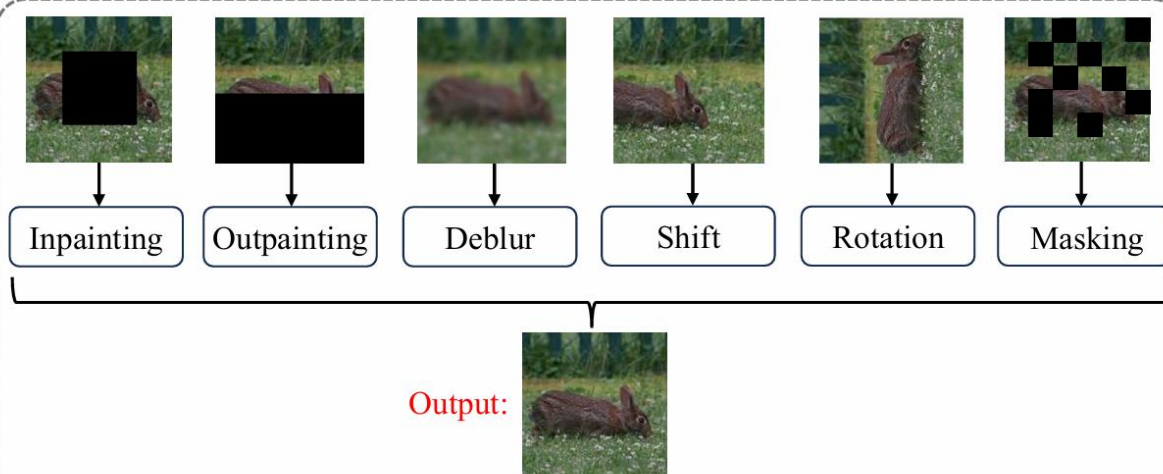
Question: What is this person doing?
Answer: skiing.

Condition: Tokens() ,

Question: What does the truck on the left sell?

Answer:

(3) Visual Question Answering



(4) Image Denoising

Visual Understanding and Generation



➤ Few-shot Classification

Method	#Tokens	Task Induction: N-way K-shot: #Repetitions:	✓	✓	✓	✓	✓	✓	✓	Avg	✓	✓	✓	✓	✓	✓	Avg
			2-1	2-1	2-3	2-5	2-1	2-1	2-1		5-1	5-1	5-3	5-5	5-1	5-1	
			0	0	0	0	1	3	5		0	0	0	0	1	3	
Frozen [47]	-	-	1.7	33.7	66.0	66.0	63.0	65.0	63.7	51.3	0.9	14.5	34.7	33.8	33.8	33.3	26.3
LQAE [25]	256	GPT-3.5	1.5	35.2	68.2	69.8	68.5	68.7	65.9	54.0	1.0	15.7	35.9	36.5	31.9	36.4	29.0
SPAE [54]	5	GPT-3.5	5.3	77.2	84.4	86.0	79.4	77.2	77.1	69.5	-	-	-	-	-	-	-
SPAE [54]	5	PaLM-2 (340B)	32.2	84.0	88.5	88.4	85.1	83.6	82.4	77.7	23.6	64.2	68.0	69.9	63.4	62.0	58.8
Ours	5	LLaMA-2 (7B)	34.2	73.1	89.0	93.4	79.6	80.6	79.1	75.6	36.2	54.6	88.6	91.1	70.7	72.8	69.8
Ours	5	LLaMA-2 (13B)	44.4	77.9	91.9	94.4	81.5	82.8	82.0	79.3	45.4	69.6	89.9	91.3	75.8	75.7	75.0
Ours	5	LLaMA-2 (70B)	41.7	87.1	94.8	96.1	88.9	89.2	89.1	83.9	45.4	81.5	92.3	93.0	85.7	86.1	81.5
SPAE [54]	21	PaLM-2 (340B)	27.9	84.8	92.5	92.6	84.8	85.2	85.4	79.0	20.2	65.1	73.7	74.3	66.4	67.0	61.9
Ours	21	LLaMA-2 (7B)	36.5	76.3	91.2	95.3	84.0	84.4	83.7	78.8	37.1	44.8	91.8	94.0	73.9	82.2	72.7
Ours	21	LLaMA-2 (13B)	48.7	73.1	92.4	95.7	80.9	83.8	82.0	79.5	42.1	62.7	93.0	94.5	72.8	79.6	75.2
Ours	21	LLaMA-2 (70B)	46.5	89.1	96.9	97.8	91.4	92.7	92.9	86.7	45.0	79.7	94.9	95.6	89.3	90.7	83.5

➤ Reconstruction & Generation



Input VQ-GAN LQAE SPAE Ours



Input VQ-GAN LQAE SPAE Ours



Input VQ-GAN LQAE SPAE Ours

➤ Caption & VQA



A dog is sitting in front of a computer.
A group of people in a kitchen.



A picture of a sign that says stop.
A bathroom with a bathtub and shower.



- Q1: What food item is shown?
 Pizza Burger
 Q2: What country did this food originate from?
 Italy Japan
 Q3: What is the leafy substance?
 Basil Lettuce

1. **Language** as a **Bidirectional Explainable Interface** for vision tasks.
2. **V2C** and **V2L Tokenizer** to get linguistic representations of images.
3. **Efficient** to build and **Interpretable** and for use.

pretrained VLMs
unlabeled images
frozen LLMs

general & fine-grained
visual concepts

MILab

Medical Intelligence Lab

Lab Website



Slides & Website



V2C Tokenizer



V2L Tokenizer

