VLP for Computer Vision in the Wild

Focused Topics: Knowledge & Benchmark

Chunyuan Li
Microsoft Research, Redmond
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Zero-Shot Learning	Class-level Transfer	VL Pre-training → Task-level Transfer
Definition	Generalizing to **unseen object categories** eg, DeViSE ⚠ **Object classes** whose instances have not been observed during training	Generalizing to **unseen datasets/tasks** eg, CLIP ⚠ **Datasets** whose instances have not been observed during training
Modeling: External Knowledge	**Key**: Associate observed and non-observed classes through some form of **auxiliary information**: • **Implicit**: Pre-trained semantic embeddings • **Explicit**: Attributes, knowledge bases A rich line of research for decades	KLITE
Benchmark	• Animal with Attributes (AwA) • Caltech-UCSD Birds-200 (CUB), • SUN, • aPY, • ZS-ImageNet	ELEVATER

KLITE:

Learning Transferable Visual Models with External Knowledge

https://arxiv.org/abs/2204.08790

- Image Classification
- Object Detection

Sheng Shen[*♮], Chunyuan Li[*†♠], Xiaowei Hu[*†], Yujia Xie[†], Jianwei Yang[†]
Pengchuan Zhang[†], Anna Rohrbach[♮], Zhe Gan[†], Lijuan Wang[†], Lu Yuan[†]
Ce Liu[†], Kurt Keutzer[♮], Trevor Darrell[♮], Jianfeng Gao[†]
[†]Microsoft [♮]University of California, Berkeley

Motivating Scenarios

First time to a Japanese restaurant?

1. Language:
   Hard to understand the menu by looking at dish names
2. Knowledge:
   Waitress explains it with her knowledge
3. Image:
   Dishes served with the best fit

Takoyaki

A ***ball-shaped*** Japanese ***dumpling*** made of batter, filled with diced octopus, ***tempura scraps***, pickled ginger, and ***green onion***.

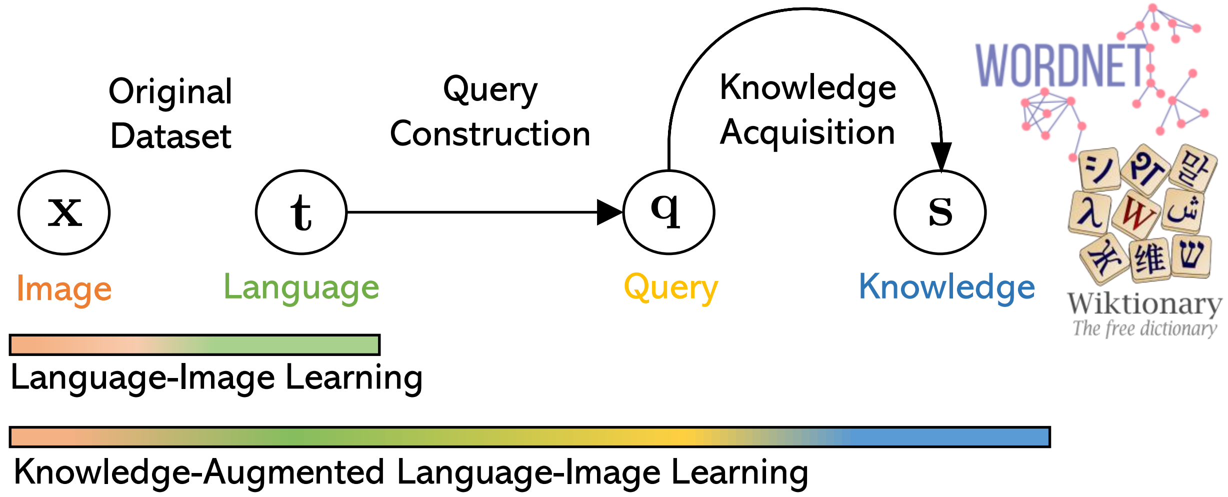
Sashimi

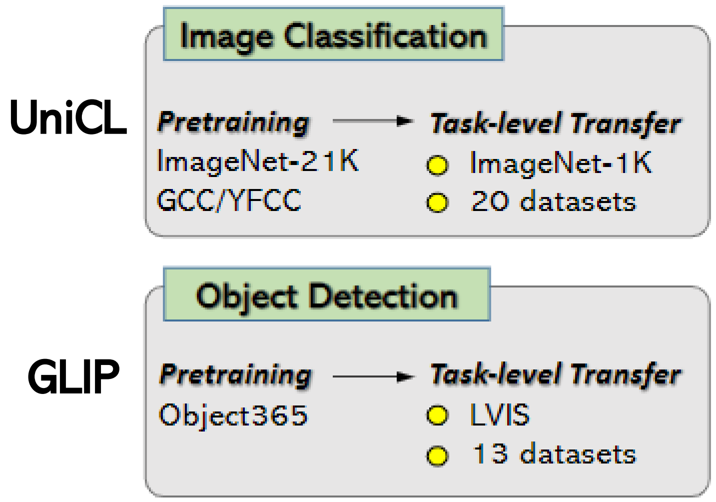
A dish consisting of ***thin slices*** or pieces of ***raw fish or meat***.

Q: How humans generalize to novel concepts?
A: Instead of trying to memorize all concepts, humans leverage the structured knowledge

Idea: External knowledge is generally available for a variety of domains (eg, textbooks, databases), Can we leverage them to build a systematic and generic approach for task-level visual transfer?

K-Lite: Knowledge-augmented Language Image Training and Evaluation





Order sashimi from Oishi Japanese Restaurant for delivery or take-out!

sashimi

1. WordNet Hierarchy:
   [sashimi, dish, nutriment, food, substance, matter, physical_entity, entity]
2. WordNet Definition:
   very thinly sliced raw fish
3. Wiktionary Definition:
   A dish consisting of thin slices or pieces of raw fish or meat.

The knowledge-augmentation process in executed in two phases:

- **Training**: the model is endowed with an ability to read and understand a specific knowledge source
- **Evaluation**: knowledge provides an additional information source to enhance model inference

Image Classification (Zero & Few-shot Task Transfer to ImageNet-1K and 20 public datasets)

Baseline: UniCL is the academic version of **Microsoft Florence**, trained on large public datasets

Training Data		Method	ImageNet-1K	20 datasets	
Dataset	# Samples		Zero-shot	Zero-shot	Linear Probing
ImageNet-21K	13M (full)	UniCL	28.16	27.15	53.07 $\pm$ 4.15
	13M (full)	K-LITE	**30.23**	**33.44**	**53.92** $\pm$ **1.05**
GCC-15M + ImageNet-21K	15M (half)	UniCL	41.64	36.31	53.86 $\pm$ 2.73
	15M (half)	K-LITE	44.26	39.53	55.91 $\pm$ 2.53
	15M (half)	K-LITE$^\diamond$	47.30	40.32	57.38 $\pm$ 2.70
	28M (full)	UniCL	46.83	38.90	57.92 $\pm$ 3.31
	28M (full)	K-LITE	**48.76**	**41.34**	**58.56** $\pm$ **3.12**

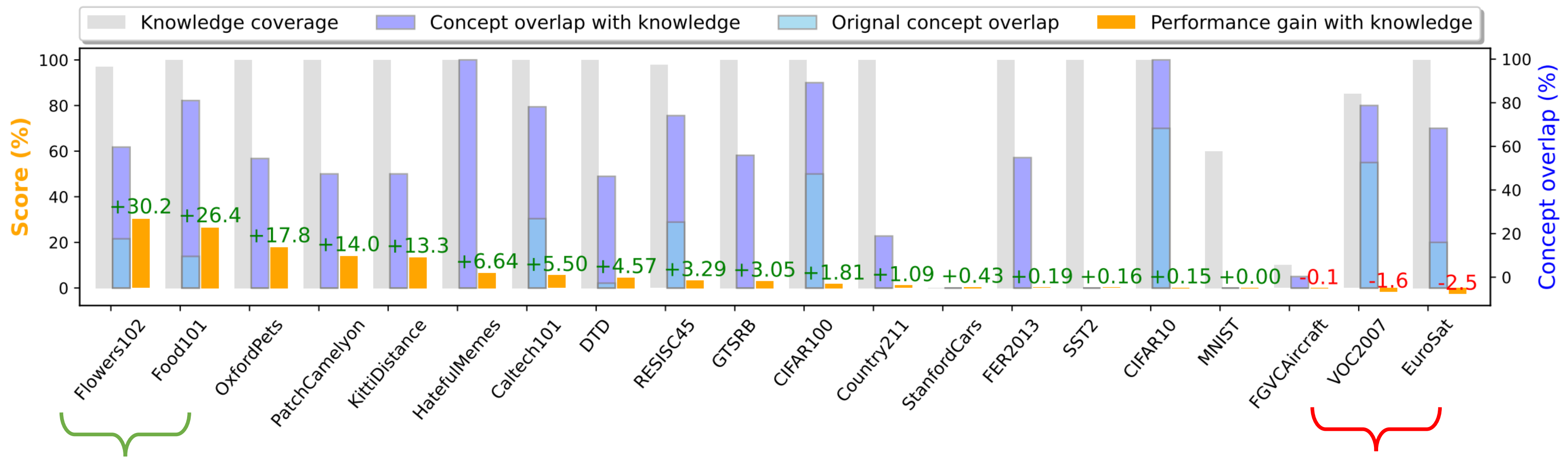
Sample-efficiency in Pre-training:

When scaled up to the largest academic datasets, K-LITE achieves the prior best performance with only a half number of pre-training image-text pairs

UniCL: Unified contrastive learning in image-label-text space, CVPR 2022

Florence: A new foundation model for computer vision

Image Classification (Why does external knowledge help zero-shot transfer?)



✓ **English marigold**: Any of the Old World plants, of the genus Calendula, with orange, yellow or reddish flowers.

✗ **Wallflower**: Any of several short-lived herbs or shrubs of the Erysimum genus with bright yellow to red flowers.

✓ **Lobster bisque**: A thick creamy soup made from fish, shellfish, meat or vegetables.

✗ **Hot and sour soup**: Any one of several soups, served in various Asian cuisines, which are both spicy and sour

✗ **bus**: A motor vehicle for transporting large numbers of people along roads.

✓ **car**: A wheeled vehicle that moves independently, with at least three wheels

annual crop land: arable land

permanent crop land: arable land

Knowledge **benefits** the most, when

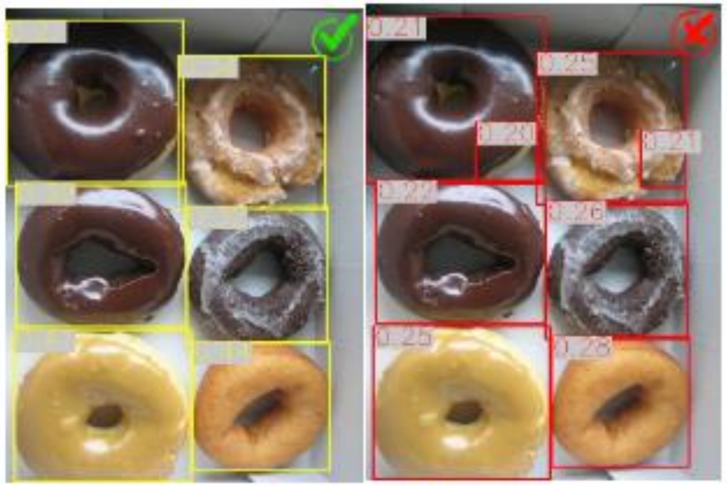
- Fine-grained datasets, which typically present many rare concepts

Knowledge **hurts** performance, when

- Knowledge coverage/quality is low
- Spurious words are contained

Object Detection (Zero-shot Task Transfer to LVIS and 13 datasets)

Method	LVIS								13 datasets			
	APr	APc	APf	-	$\mathcal{S}_{\text{LVIS}}$	$\mathcal{S}_{\text{wn\_path}}$	$\mathcal{S}_{\text{wn\_def}}$	$\mathcal{S}_{\text{wiki\_def}}$	-	$\mathcal{S}_{\text{wn\_path}}$	$\mathcal{S}_{\text{wn\_def}}$	$\mathcal{S}_{\text{wiki\_def}}$
GLIP-A [49]	14.2	13.9	23.4	18.5	-	-	-	-	28.8	-	-	-
Baseline GLIP$^{\heartsuit}$	8.6	14.0	23.1	17.9	17.6	17.1	17.2	15.0	27.5	26.8	21.0	18.5
K-LITE	14.8	18.6	24.8	16.9	**21.3**	18.7	21.4	20.5	25.0	30.3	28.4	**31.7**



doughnut: a small ring-shaped friedcake
bun: small rounded bread either plain or sweet

GLIP: Grounded Language-Image Pre-training, CVPR 2022

ELEVATER:

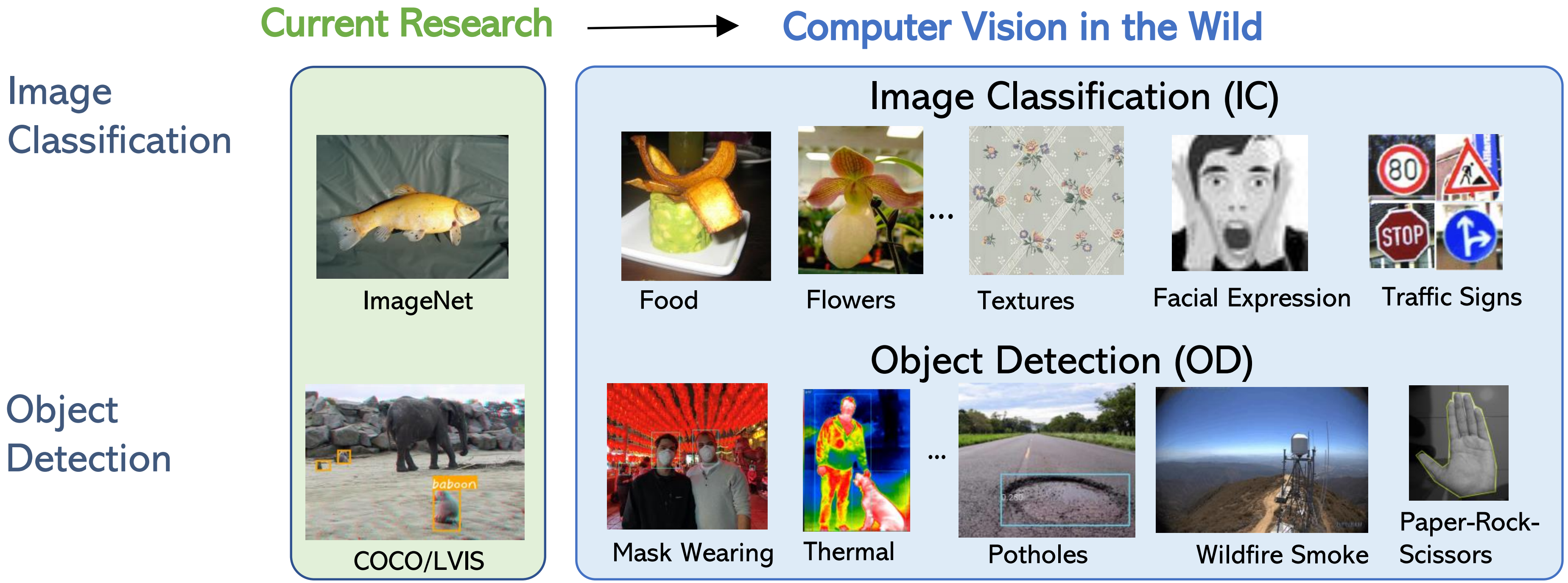
A Benchmark and Toolkit for Evaluating Language-Augmented Visual Models

https://arxiv.org/abs/2204.08790

- Data
- Toolkit
- Evaluation Playgrounds

Chunyuan Li[*1♠], Haotian Liu[*2], Liunian Harold Li[3], Pengchuan Zhang[1], Jyoti Aneja[1]
Jianwei Yang[1], Ping Jin[1], Yong Jae Lee[2], Houdong Hu[1], Zicheng Liu[1], Jianfeng Gao[1]
[1]Microsoft [2]University of Wisconsin–Madison [3]UCLA

Why ELEVATER ? Evaluation of Language-augmented Visual Task-level Transfer



Trend

- Building transferable systems that can effortlessly adapt to a wide range of CV tasks in the wild
- Inspired by the success of CLIP, many language-augmented visual models appear

Challenges

- **Fairness:** Customized task sets may favor individual pre-trained model
- **Transparency**: Detailed model adaptation process is inaccessible

Benchmarks: ELEVATER

- Dataset Suite

- Image Classification: **20** datasets

- Object Detection: **35** datasets

- External Knowledge

WordNet, Wiktionary, GPT-3

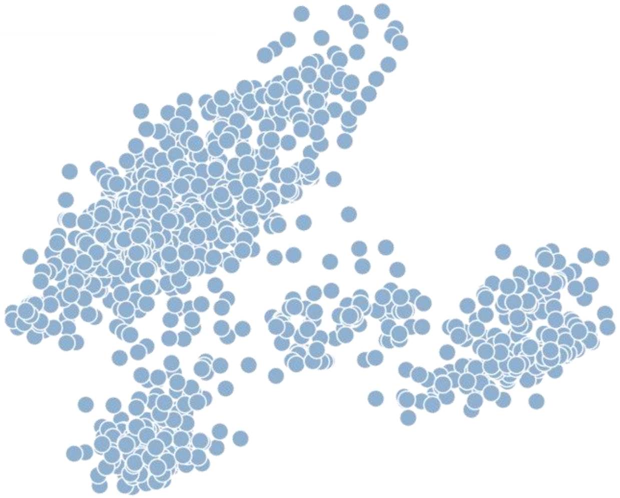
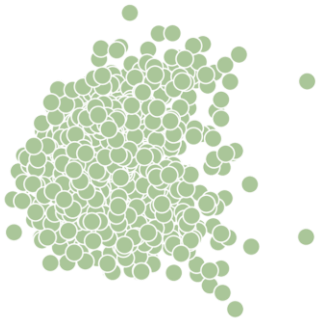
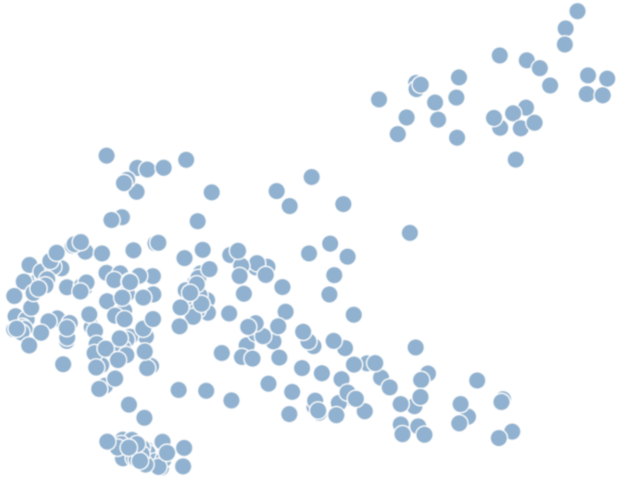
- Concept name: risotto
- Def_wik: An Italian savoury dish made with rice and other ingredients
- Def_wn: rice cooked with broth and sprinkled with grated cheese
- Path_wn: [risotto, dish, nutriment, food, substance, matter, physical_entity, entity]
- GPT3: A rice dish made with arborio rice and typically served with meat or fish

Benchmarks: Review

Problem		Benchmark Statistics				Evaluation Settings		
		#Datasets	#Image	#Concepts	Knowledge Source	Zero	Few	Full
IC	AwA [31]	1	30337 / 6985	40 / 10	Attributes	✓		
	CUB [64]	1	8855 / 2933	150 / 50	Attributes	✓		
	SUN [47]	1	12900 / 1440	645 / 72	Attributes	✓		
	aPY [14]	1	12695 / 2644	20 / 12	Attributes	✓		
	ZS-ImageNet [52]	1	1.2M / 54K	1K / 360	WordNet	✓		
	ImageNet-1K [9]	1	1.2M / 50K	1K	WordNet	✓		✓
	VTAB [73]	19	2.2M / -	940	-		✓	✓
	ELEVATER (Ours)	20	638K / 193K	1151$^{\diamond}$	WordNet, Wiki, GPT-3	✓	✓	✓
OD	LVIS [21]	1	120k / 40K	1723	WordNet			✓
	ELEVATER (Ours)	35	132K / 20K	314$^{\diamond}$	WordNet, Wiki, GPT-3	✓	✓	✓

- **Trend**: Benchmarking fast-developing techniques **from class-level transfer to task-level transfer**, with language-augmented visual models

Benchmarks: A more diverse set of tasks

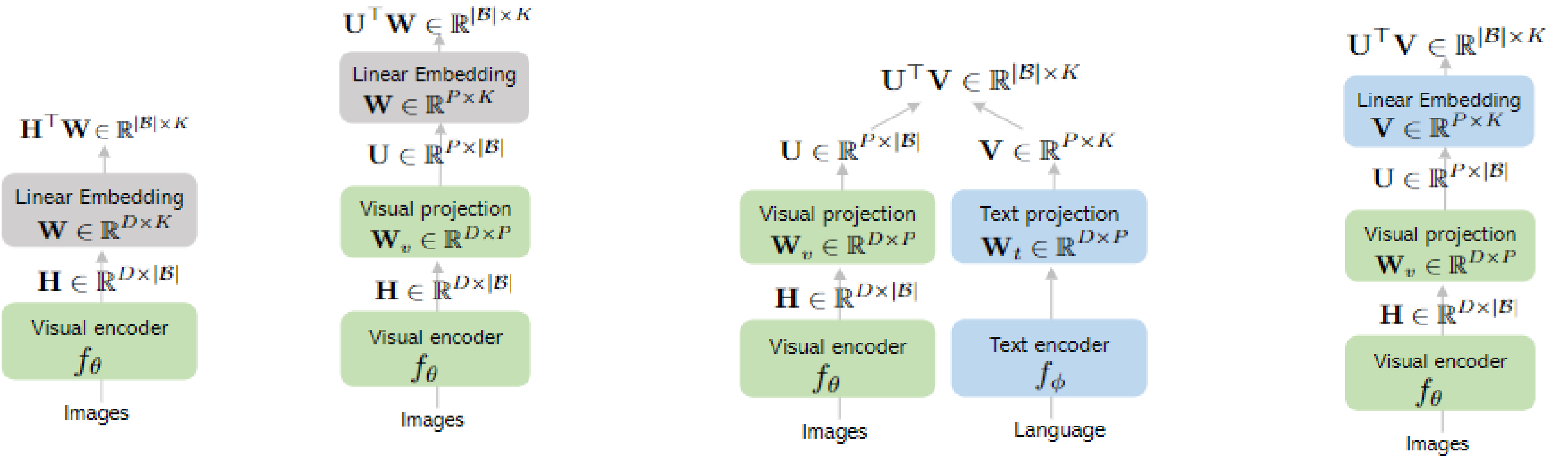
	ImageNet →	Image Classification in the Wild (20 datasets)	LVIS →	Object Detection in the Wild (35 datasets)
Semantic Space using PCA				
Task diversity using std	0.610	0.680	0.533	0.619

Toolkits

- **Automatic hyper-parameter tuning pipeline** (eg, learning rate, weight decay)

  Avoid human-in-the-loop tuning

- **Language-augmented model adaptation methods**



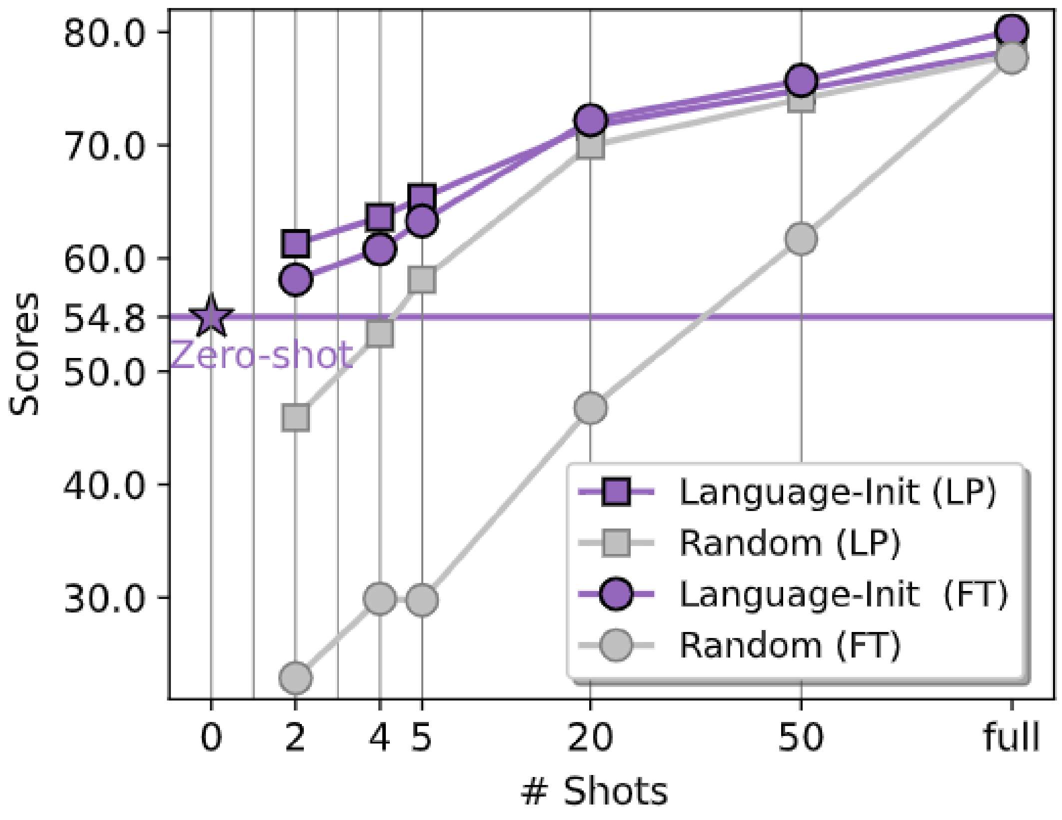
(a) IC Adaptation (b) CLIP Adaptation (c) CLIP Zero-shot (d) Language-Init

Missing language encoder power

Leverage language or knowledge

Toolkits

- **Effectiveness of Language-initialized model adaptation methods**



- Language-initialized strategy consistently improves the baseline random initialization, for both linear probing (LP) and fine-tuning (FT)

- **Few-shot performance is always better than zero-shot**, in contrast to the discovery in original CLIP paper

Baseline Pre-trained Visual Models

	Checkpoints	Taxonomy		Pre-training Settings	
		Language	Knowledge	Training Objective	Dataset
	Image Classification				
Language-free	MoCo-v3 [6]	✗	✗	Self-Supervised	ImageNet-1K (1.2M)
	MAE [23]	✗	✗	Self-Supervised	ImageNet-1K (1.2M)
	DeiT [66]	✗	✗	Supervised	ImageNet-1K (1.2M)
	ViT [13]	✗	✗	Supervised	ImageNet-22K (14M)
Language-augmented: Knowledge-free	CLIP [55]	✓	✗	Image-Text Contrast	WebImageText (400M)
	UniCL [73]	✓	✗	Image-Text Contrast	ImageNet-21K (13M)
Language-augmented: Knowledge-augmented	K-LITE [59]	✓	✓	Image-Text Contrast	ImageNet-21K (13M)
	Object Detection				
Language-free	DyHead [9]	✗	✗	Supervised	Object365
Language-augmented: Knowledge-free	GLIP [38]	✓	✗	Supervised	Object365 & Grounding
	GLIP-A [38]	✓	✗	Supervised	Object365
Language-augmented: Knowledge-augmented	K-LITE [59]	✓	✓	Supervised	Object365

Benchmarking Pre-trained Visual Models

Pre-training Settings			20 Image Classification Datasets			
Checkpoint	Method	Dataset	5-shot	20-shot	50-shot	Full-shot
Linear Probing						
CLIP‡	Image-Text Contrast	WebImageText (400M)	68.27 $\pm$ 0.97	74.76 $\pm$ 1.11	77.75 $\pm$ 0.81	81.17
ViT†	Supervised	ImageNet-22K (14M)	57.61 $\pm$ 3.62	69.93 $\pm$ 0.71	73.74 $\pm$ 0.79	77.60
DeiT	Supervised	ImageNet-1K (1.2M)	54.06 $\pm$ 3.02	68.57 $\pm$ 3.43	75.53 $\pm$ 0.72	79.56
MAE	Self-Supervised	ImageNet-1K (1.2M)	33.37 $\pm$ 1.98	48.03 $\pm$ 2.70	58.26 $\pm$ 0.84	68.70
MoCo-v3	Self-Supervised	ImageNet-1K (1.2M)	50.17 $\pm$ 3.43	61.99 $\pm$ 2.51	69.71 $\pm$ 1.03	74.92
Fine-tuning						
CLIP‡	Image-Text Contrast	WebImageText (400M)	69.12 $\pm$ 1.66	74.76 $\pm$ 2.34	78.21 $\pm$ 2.04	83.63
ViT†	Supervised	ImageNet-22K (14M)	57.18 $\pm$ 2.02	72.45 $\pm$ 2.85	78.53 $\pm$ 0.69	82.02
DeiT	Supervised	ImageNet-1K (1.2M)	54.06 $\pm$ 3.02	68.53 $\pm$ 3.47	75.57 $\pm$ 0.68	79.55
MAE	Self-Supervised	ImageNet-1K (1.2M)	36.10 $\pm$ 3.25	54.13 $\pm$ 3.86	65.86 $\pm$ 2.42	74.43
MoCo-v3	Self-Supervised	ImageNet-1K (1.2M)	39.30 $\pm$ 3.84	58.75 $\pm$ 5.55	70.33 $\pm$ 1.64	77.71

Image Classification Performance Ranking: MAE < MoCo < DeiT < ViT < CLIP

Note: The conclusion is obtained using our auto-tuning adaptation process, **without** model / dataset –specific tuning for the best performance

Benchmarking Pre-trained Visual Models

Industry Track

- Scaling success

Academic Track

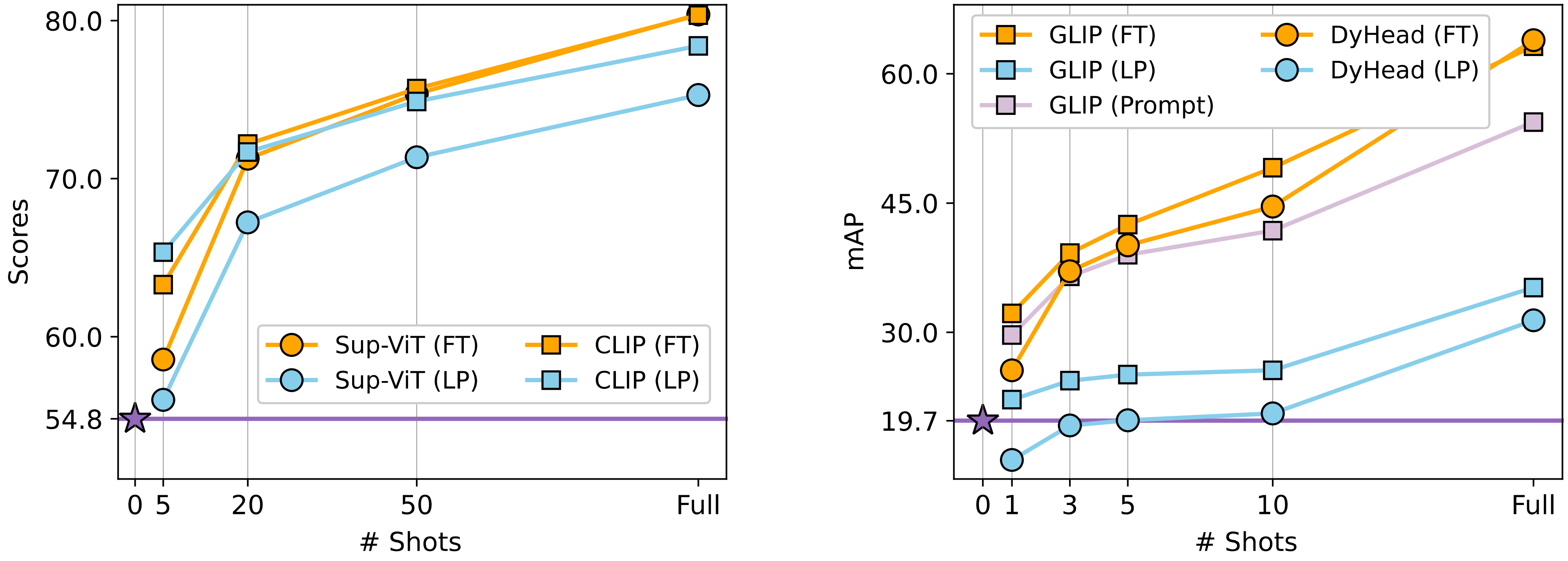
- Research Innovation
- limited to large public datasets

Settings: Checkpoint	Settings: Adaptation	Init Method	20 IC datasets: Zero-shot	20 IC datasets: Few-shot (5, 20, 50)	20 IC datasets: Full
Industry Track *(No pre-train data scale limit)*					
CLIP (ViT-B32)	LP	Random	56.64	58.09 $\pm$ 2.80, 69.97 $\pm$ 1.30, 74.09 $\pm$ 0.69	78.38
	LP	Language-S		65.35 $\pm$ 1.24, 71.69 $\pm$ 0.93, 74.89 $\pm$ 0.79	78.40
	LP	Language-M		65.88 $\pm$ 0.79, 72.05 $\pm$ 0.85, 75.08 $\pm$ 0.73	78.96
	FT	Random		29.75 $\pm$ 6.64, 46.76 $\pm$ 11.9, 61.70 $\pm$ 9.97	77.77
	FT	Language-S		63.29 $\pm$ 3.18, 72.19 $\pm$ 1.31, 75.70 $\pm$ 1.14	80.35
Supervised (ViT-B32)	LP	Random	-	56.00 $\pm$ 2.67, 67.23 $\pm$ 1.66, 71.35 $\pm$ 1.17	75.29
	FT	Random		58.55 $\pm$ 2.58, 71.27 $\pm$ 1.25, 75.36 $\pm$ 1.42	80.39
Academic Track *(Pre-trained on large established public datasets)*					
UniCL (Swin-Tiny)	LP	Language-S	27.15	54.31 $\pm$ 4.15, 66.42 $\pm$ 2.08, 70.49 $\pm$ 1.01	74.75
	FT	Language-S		44.75 $\pm$ 5.42, 56.53 $\pm$ 5.37, 67.90 $\pm$ 5.31	78.48
K-LITE (Swin-Tiny)	LP	Language-S	33.44	55.06 $\pm$ 2.36, 66.26 $\pm$ 1.56, 70.16 $\pm$ 1.09	74.47
	FT	Language-S		48.41 $\pm$ 2.84, 58.06 $\pm$ 4.30, 71.66 $\pm$ 2.02	78.05

Language-free vs Language-augmented

- Language-augmented model (CLIP) consistently outperforms language-free model (Supervised ViT) in most settings, especially for the limited data settings.
- language-augmented models enables zero-shot task transfer

Playground I: Sample-efficiency



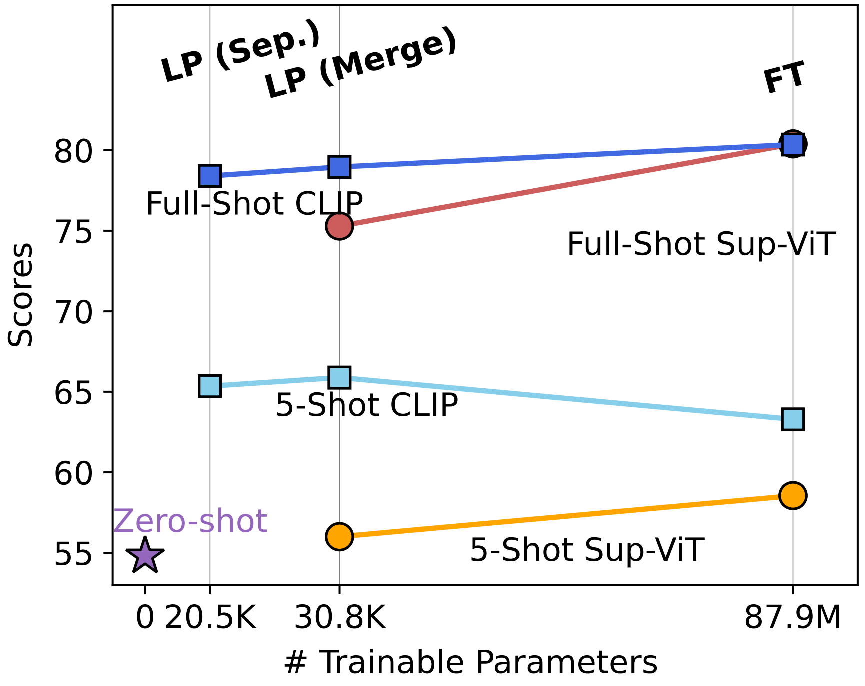
Zero-shot and Few-shot

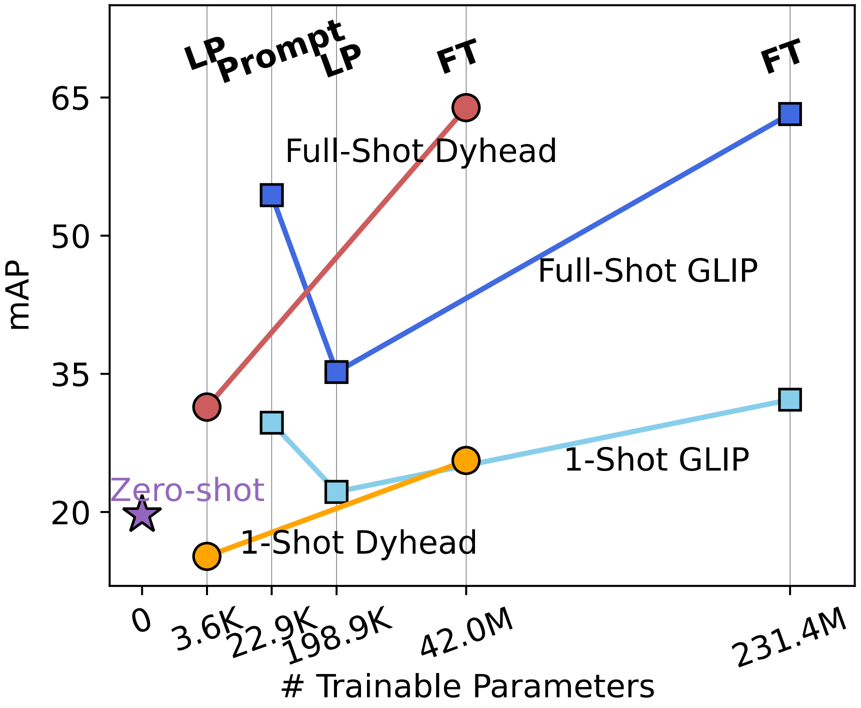
- Quick and more afford settings to assess pre-trained model quality

Existing & new VLP-for-CV models are welcome

- AGLIN, CoCa, DeCLIP, FILIP, SLIP, OpenCLIP, etc.

Playground II: Parameter-efficiency





Few-shot with VLP

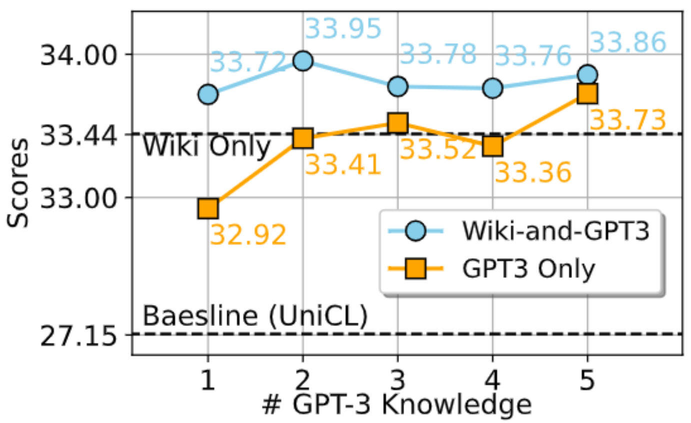
- A more meaning setting to study parameter-efficient methods

Existing & new VLP parameter-efficient model adaptation methods are welcome

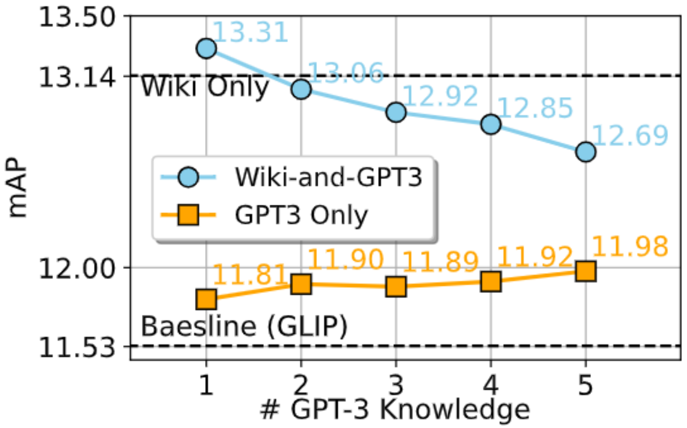
- Color Prompt Tuning, VL-Adapter, CLIP-Adapter, Conditional Prompt Learning etc.

Playground III: Benefit of external knowledge

- Combination of both explicit and implicit knowledge sources improves performance (K-Lite vs UniCL/GLIP)



(a) Image classification



(b) Object detection

- The collected knowledge benefits knowledge-free pre-trained models (eg, CLIP)

Adaptation Methods	5-shot LP	5-shot FT	Full-shot LP	Full-shot FT
Knowledge-free adaptation	65.35 $\pm$ 1.24	63.29 $\pm$ 3.18	78.40	79.97
Knowledge-augmented adaptation	**65.83** $\pm$ 1.50	**65.10** $\pm$ 2.08	**78.75**	**80.32**
Gain	+0.48	+1.81	+0.35	+0.35
# win / tie / lose	7 / 8 / 5	8 / 8 / 4	12 / 4 / 4	10 / 5 / 5

ECCV
TEL AVIV 2022

ECCV Workshop & Challenges: Computer Vision in the Wild

https://computer-vision-in-the-wild.github.io/eccv-2022/

Benchmark Website:

https://computer-vision-in-the-wild.github.io/ELEVATER/

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Thanks

Next: Text-to-Image Generation