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Can Language Understand Depth?

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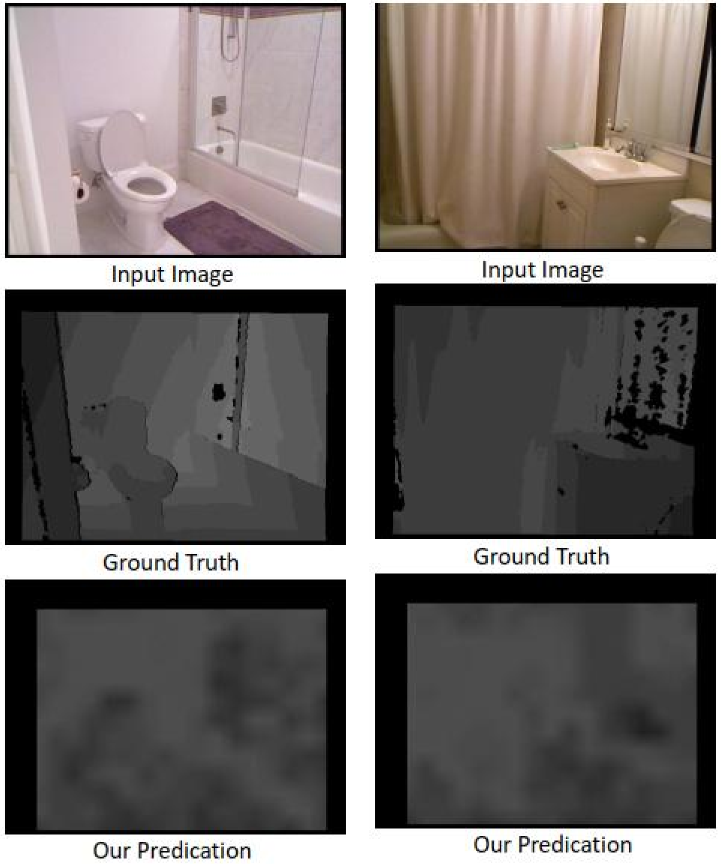
Outline

- 1. Overview
- 2. Task
- 3. Related Works
- 4. Our DepthCLIP
- 5. Results & Analysis & Limiations & Future direction
- 6. Conclusion

Overview

- We proposed **DepthCLIP**, and are the first to conduct zero-shot adaptation from the semantic language knowledge to quantified downstream vision tasks and perform **zero-shot training-free monocular depth estimation**.
- Our DepthCLIP **surpasses existing unsupervised methods** and **even approaches the early fully-supervised networks**.



Input Image

Input Image

Ground Truth

Ground Truth

Our Predication

Our Predication

Task

- Zero-shot Training-free Monocular Depth Estimation
  - Monocular Depth Estimation:
    - Infer pixel-wise depth from monocular images
    - Important in industrial field
      - Self-driving cars need to infer depth to conduct 3D object detection from monocular images
      - Since Lidar is expensive and stereo cameras are hard to adjust.
  - Zero-shot Training-free Transfer
    - When transfer pre-trained model to a new dataset, we require no extra data nor extra training
      - To achieve efficient and effective transfer
    - Important in industrial field
      - Self-driving cars need to infer depth when entering a complete new environment, and they might have no data nor time to finetune its model

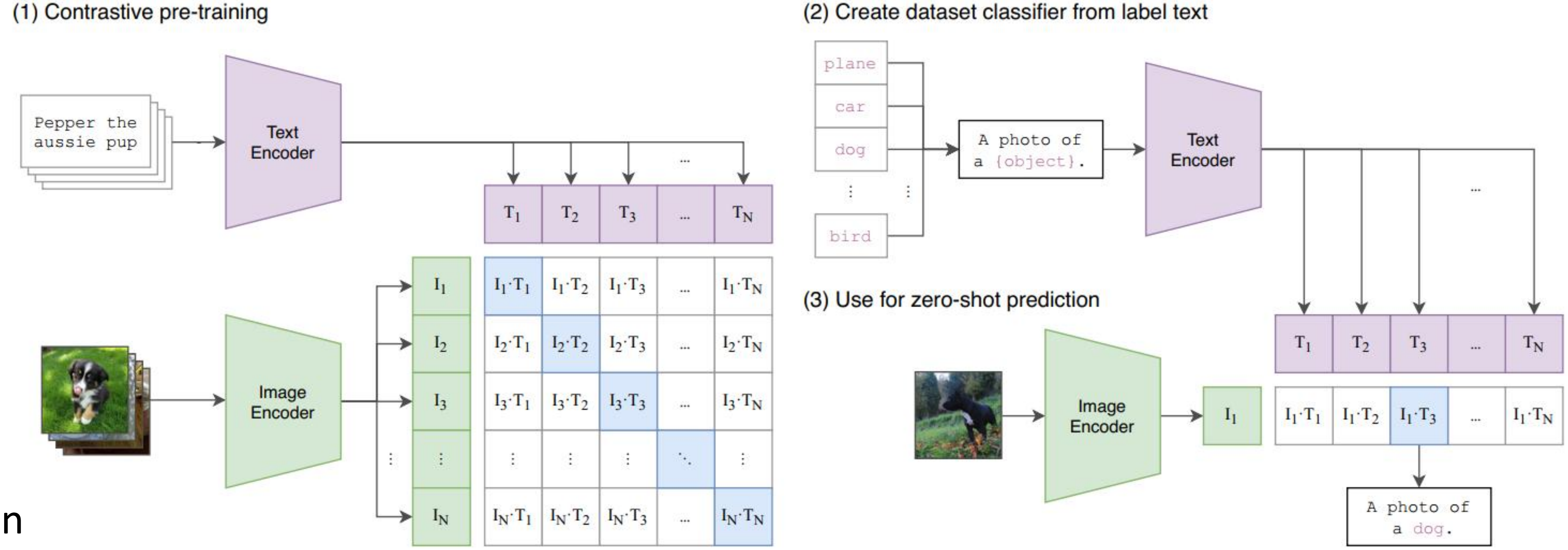
Related Work

- Monocular Depth Estimation:
  - Fully Supervised Method:
    - ASTransformer, DORN, RPSF, ….
    - Require pixel-wise depth annotation, costly
  - Unsupervised Method:
    - Learn from ego-motion of unlabeled monocular video.
    - Trains itself with widely available binocular stereo images
      - Generate paired stereo images of given monocular images, exploit epipolar geometry to solve depth
    - Require special modality of data
- Our DepthCLIP
  - Differs from all works in this filed
  - Pretrained with an image classification pre-text task

Related Work: CLIP

Contrastive Language-Image Pretraining

Group images and text with similar semantic information.
i.e. Understand image using text semantic

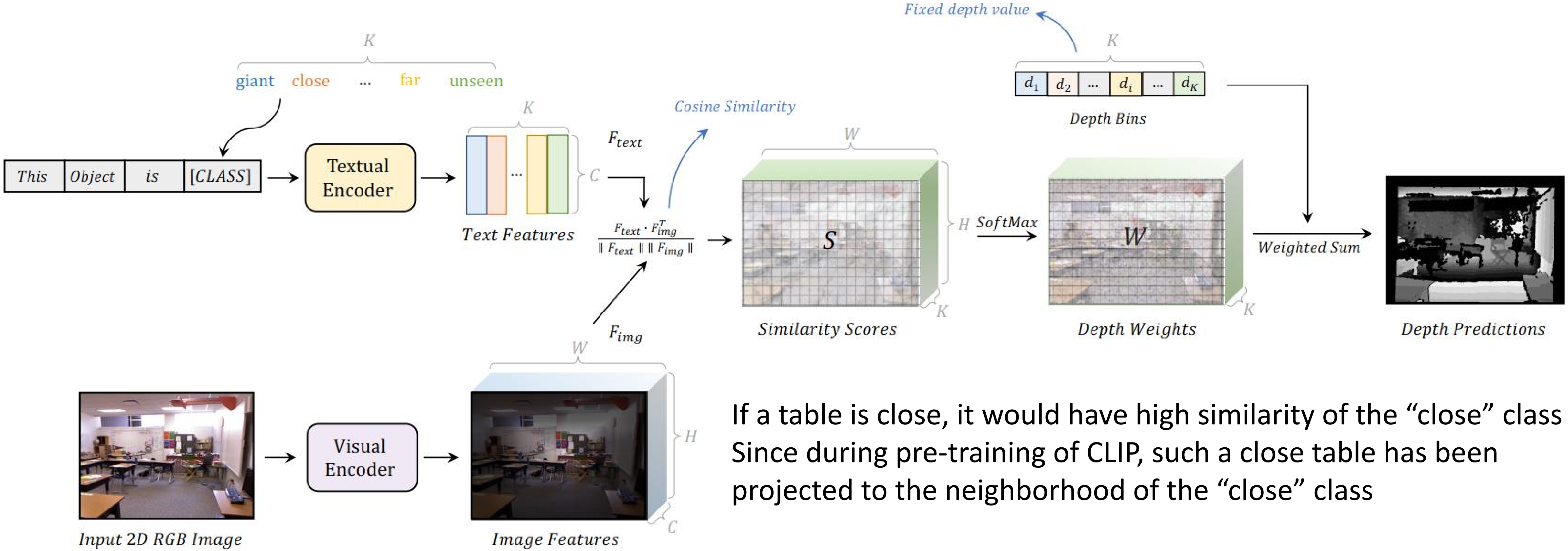

(1) Contrastive pre-training
Pepper the aussie pup
Text Encoder
Image Encoder
T$_1$ T$_2$ T$_3$ ... T$_N$
I$_1$ I$_2$ I$_3$ ⋮ I$_N$
I$_1$·T$_1$ I$_1$·T$_2$ I$_1$·T$_3$ ... I$_1$·T$_N$
I$_2$·T$_1$ I$_2$·T$_2$ I$_2$·T$_3$ ... I$_2$·T$_N$
I$_3$·T$_1$ I$_3$·T$_2$ I$_3$·T$_3$ ... I$_3$·T$_N$
⋮ ⋮ ⋮ ⋱ ⋮
I$_N$·T$_1$ I$_N$·T$_2$ I$_N$·T$_3$ ... I$_N$·T$_N$
(2) Create dataset classifier from label text
plane
car
dog
bird
A photo of a {object}.
Text Encoder
(3) Use for zero-shot prediction
Image Encoder
I$_1$
T$_1$ T$_2$ T$_3$ ... T$_N$
I$_1$·T$_1$ I$_1$·T$_2$ I$_1$·T$_3$ ... I$_1$·T$_N$
A photo of a dog.

- Train
  - In each batch, encode images and corresponding text into feature space
  - Maximize cosine similarity between corresponding pair (dog image with “dog”)
  - Minimize the rest (dog image with “cat” or “cake”)
- Test
  - Form prompts, like “A photo of [class]”, substitute all classes in test dataset
  - In each batch, calculate similarity between the test image with all prompts
  - Choose the class who has max prompt-image similarity, as prediction

The dog image would be projected to the neighborhood of “dog”, thus has high similarity with “dog”.

DepthCLIP Pipeline

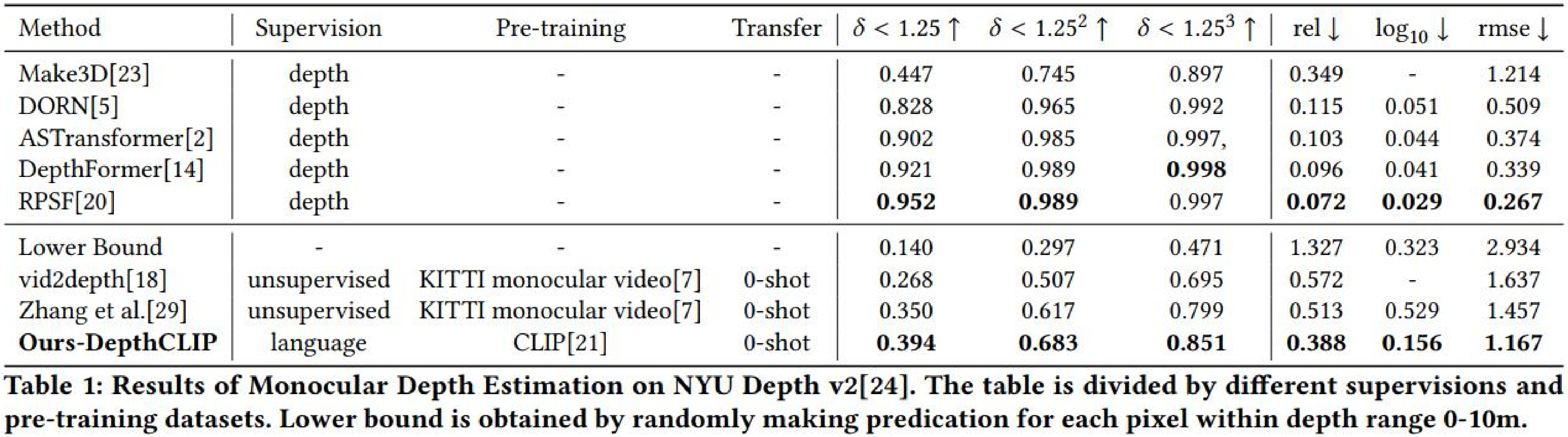
CLIP has the ability to attach each image with corresponding text with similar semantic meaning.



If a table is close, it would have high similarity of the “close” class
Since during pre-training of CLIP, such a close table has been projected to the neighborhood of the “close” class

Quantified Results

- Exceeds the mathematical lower bound significantly, surpasses some existing unsupervised methods, and even draws near some fully-supervised methods.

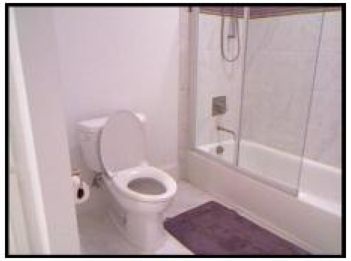


Method	Supervision	Pre-training	Transfer	$\delta < 1.25 \uparrow$	$\delta < 1.25^2 \uparrow$	$\delta < 1.25^3 \uparrow$	rel ↓	$\log_{10} \downarrow$	rmse ↓
Make3D[23]	depth	-	-	0.447	0.745	0.897	0.349	-	1.214
DORN[5]	depth	-	-	0.828	0.965	0.992	0.115	0.051	0.509
ASTransformer[2]	depth	-	-	0.902	0.985	0.997,	0.103	0.044	0.374
DepthFormer[14]	depth	-	-	0.921	0.989	**0.998**	0.096	0.041	0.339
RPSF[20]	depth	-	-	**0.952**	**0.989**	0.997	**0.072**	**0.029**	**0.267**
Lower Bound	-	-	-	0.140	0.297	0.471	1.327	0.323	2.934
vid2depth[18]	unsupervised	KITTI monocular video[7]	0-shot	0.268	0.507	0.695	0.572	-	1.637
Zhang et al.[29]	unsupervised	KITTI monocular video[7]	0-shot	0.350	0.617	0.799	0.513	0.529	1.457
Ours-DepthCLIP	language	CLIP[21]	0-shot	**0.394**	**0.683**	**0.851**	**0.388**	**0.156**	**1.167**

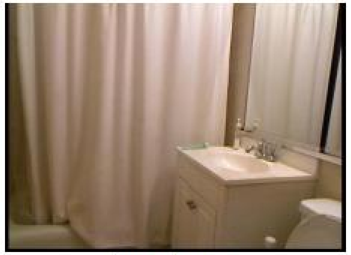
Table 1: Results of Monocular Depth Estimation on NYU Depth v2[24]. The table is divided by different supervisions and pre-training datasets. Lower bound is obtained by randomly making predication for each pixel within depth range 0-10m.

Results Visualization

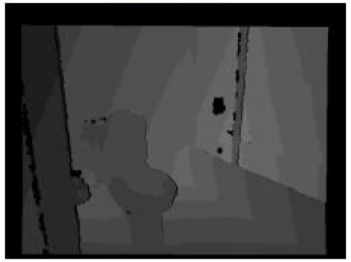
- Could tell contours, predict resonable depth
  - The background and details are blurred.
  - CLIP is pre-trained under a classification pre-text task
  - Details and background that are unimportant for classification would be neglected during feature extraction.
  - In the future, we could explore pre-trained model with regional pre-text tasks like segmentation



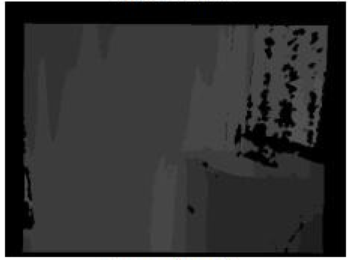
Input Image



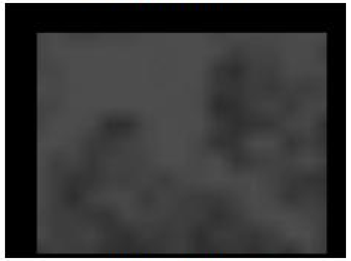
Input Image



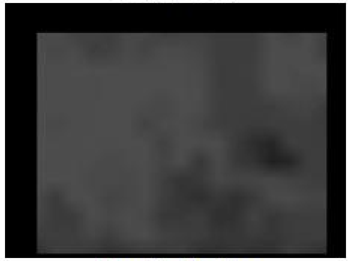
Ground Truth



Ground Truth



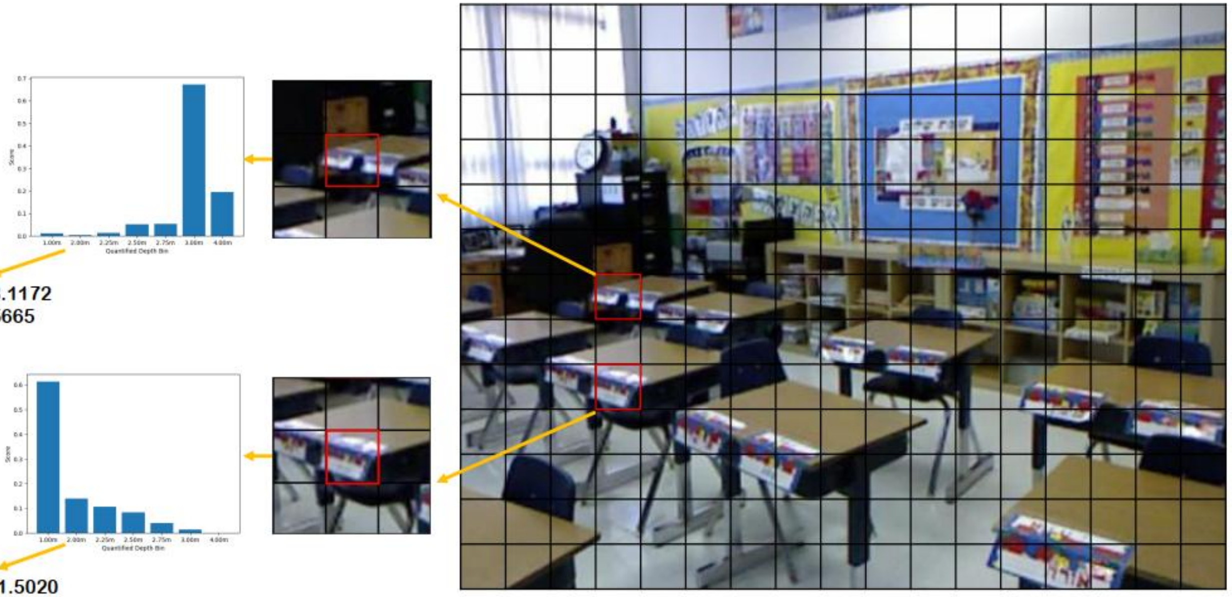
Our Predication



Our Predication

Semantic Bin Response

- Different patches have different distance semantic responses
  - Depth CLIP could distinguish between a close patch and a remote patch, and make proper distance response.



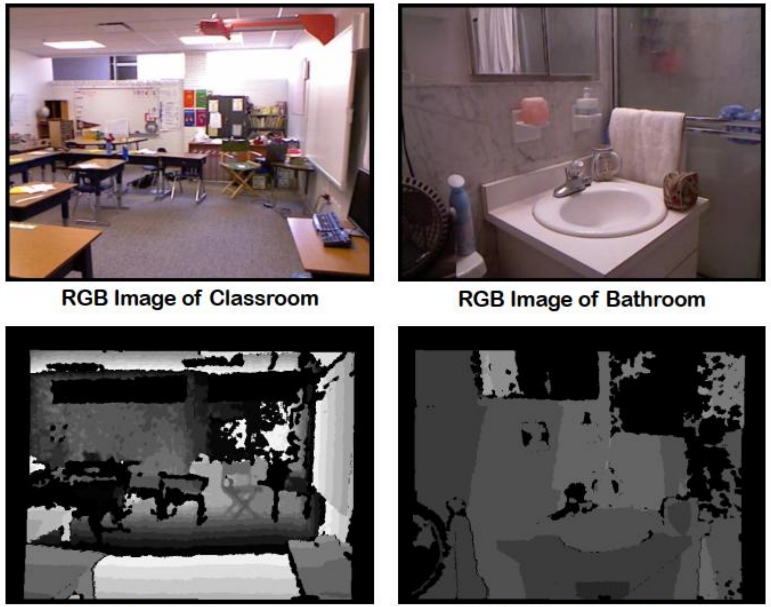
Pred = 3.1172
GT = 3.5665

Pred = 1.5020
GT = 1.3283

Semantic Bin	giant	close	a little close	not in distance	a bit remote	far	unseen
Quantified Bin	1.00m	2.00m	2.25m	2.50m	2.75m	3.00m	4.00m

Depth Distribution Gap

- Different scenes have different depth distribution
- The same depth class should be projected to different depth bins in different scenes.
- In major experiments, we project the same depth class to the same depth bin.



RGB Image of Classroom

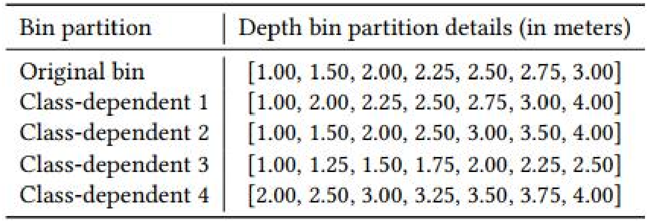
RGB Image of Bathroom

Depth Map of Classroom

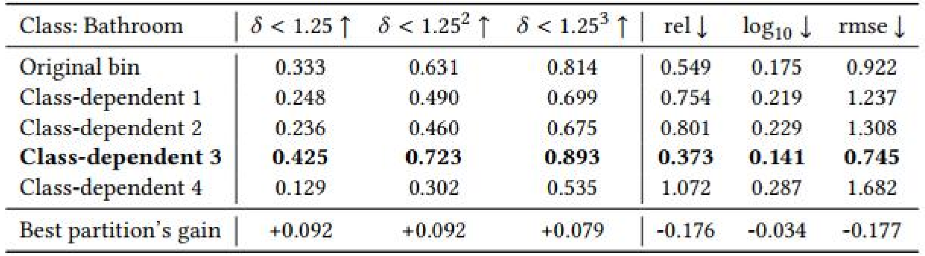
Depth Map of Bathroom

Class-dependent Depth Bin Ablation

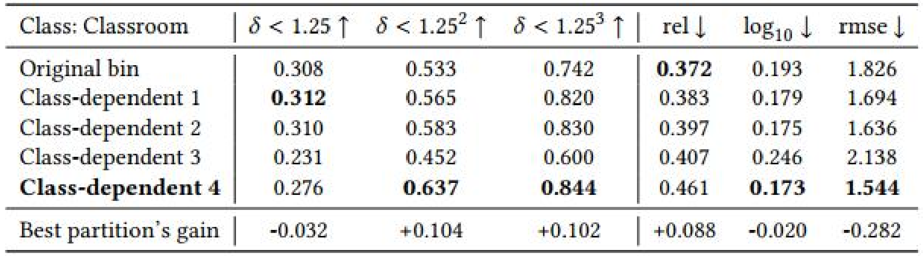
- DepthCLIP is sensitive to depth bin
- Set different bins for different scenes could improve performance
- In the future, we could predict scene of the input image first, then use a learnable class-dependent depth bin to achieve a better performance.



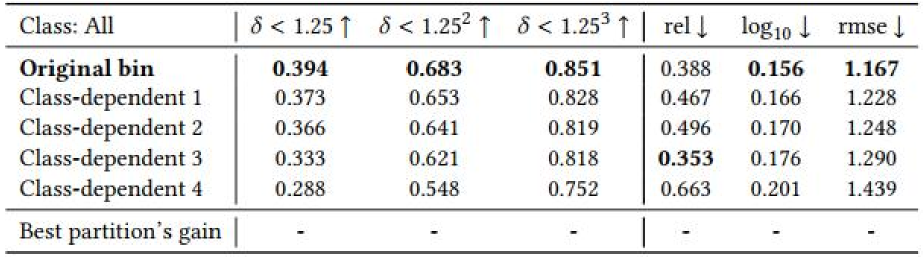
Bin partition	Depth bin partition details (in meters)
Original bin	[1.00, 1.50, 2.00, 2.25, 2.50, 2.75, 3.00]
Class-dependent 1	[1.00, 2.00, 2.25, 2.50, 2.75, 3.00, 4.00]
Class-dependent 2	[1.00, 1.50, 2.00, 2.50, 3.00, 3.50, 4.00]
Class-dependent 3	[1.00, 1.25, 1.50, 1.75, 2.00, 2.25, 2.50]
Class-dependent 4	[2.00, 2.50, 3.00, 3.25, 3.50, 3.75, 4.00]



Class: Bathroom	$\delta < 1.25 \uparrow$	$\delta < 1.25^2 \uparrow$	$\delta < 1.25^3 \uparrow$	rel $\downarrow$	$\log_{10} \downarrow$	rmse $\downarrow$
Original bin	0.333	0.631	0.814	0.549	0.175	0.922
Class-dependent 1	0.248	0.490	0.699	0.754	0.219	1.237
Class-dependent 2	0.236	0.460	0.675	0.801	0.229	1.308
Class-dependent 3	**0.425**	**0.723**	**0.893**	**0.373**	**0.141**	**0.745**
Class-dependent 4	0.129	0.302	0.535	1.072	0.287	1.682
Best partition's gain	+0.092	+0.092	+0.079	-0.176	-0.034	-0.177



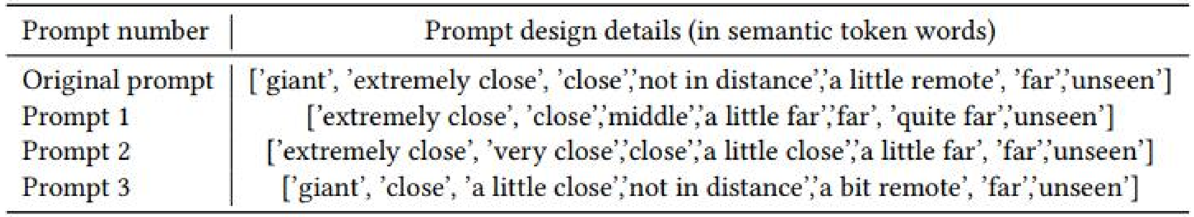
Class: Classroom	$\delta < 1.25 \uparrow$	$\delta < 1.25^2 \uparrow$	$\delta < 1.25^3 \uparrow$	rel $\downarrow$	$\log_{10} \downarrow$	rmse $\downarrow$
Original bin	0.308	0.533	0.742	**0.372**	0.193	1.826
Class-dependent 1	**0.312**	0.565	0.820	0.383	0.179	1.694
Class-dependent 2	0.310	0.583	0.830	0.397	0.175	1.636
Class-dependent 3	0.231	0.452	0.600	0.407	0.246	2.138
Class-dependent 4	0.276	**0.637**	**0.844**	0.461	**0.173**	**1.544**
Best partition's gain	-0.032	+0.104	+0.102	+0.088	-0.020	-0.282



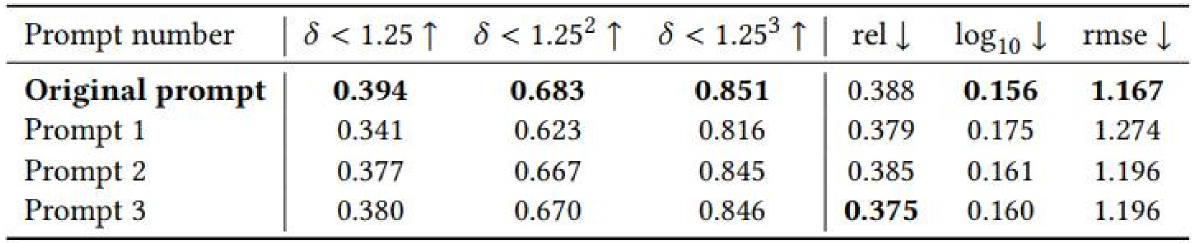
Class: All	$\delta < 1.25 \uparrow$	$\delta < 1.25^2 \uparrow$	$\delta < 1.25^3 \uparrow$	rel $\downarrow$	$\log_{10} \downarrow$	rmse $\downarrow$
Original bin	**0.394**	**0.683**	**0.851**	0.388	**0.156**	**1.167**
Class-dependent 1	0.373	0.653	0.828	0.467	0.166	1.228
Class-dependent 2	0.366	0.641	0.819	0.496	0.170	1.248
Class-dependent 3	0.333	0.621	0.818	**0.353**	0.176	1.290
Class-dependent 4	0.288	0.548	0.752	0.663	0.201	1.439
Best partition's gain	-	-	-	-	-	-

Prompts Ablation

- Robust to prompt design
- Different prompts could catch the same distance relationship, since only relative distance matters



Prompt number	Prompt design details (in semantic token words)
Original prompt	[’giant’, ’extremely close’, ’close’,’not in distance’,’a little remote’, ’far’,’unseen’]
Prompt 1	[’extremely close’, ’close’,’middle’,’a little far’,’far’, ’quite far’,’unseen’]
Prompt 2	[’extremely close’, ’very close’,’close’,’a little close’,’a little far’, ’far’,’unseen’]
Prompt 3	[’giant’, ’close’, ’a little close’,’not in distance’,’a bit remote’, ’far’,’unseen’]



Prompt number	$\delta < 1.25 \uparrow$	$\delta < 1.25^2 \uparrow$	$\delta < 1.25^3 \uparrow$	rel $\downarrow$	$\log_{10} \downarrow$	rmse $\downarrow$
Original prompt	**0.394**	**0.683**	**0.851**	0.388	**0.156**	**1.167**
Prompt 1	0.341	0.623	0.816	0.379	0.175	1.274
Prompt 2	0.377	0.667	0.845	0.385	0.161	1.196
Prompt 3	0.380	0.670	0.846	**0.375**	0.160	1.196

Conclusion

- Without any further training, DepthCLIP could surpass some existing unsupervised methods and even approach some fully-supervised networks.
  - We are the first to conduct zero-shot training-free adaptation from the semantic language knowledge possessed by a pre-trained model (CLIP), to a downstream task that needs quantified knowledge (monocular depth estimation).
  - Hope our work could cast a light on the research of bridging semantic vision-language knowledge to the quantified task.