FewSOL: A Dataset for Few-Shot Object Learning in Robotic Environments

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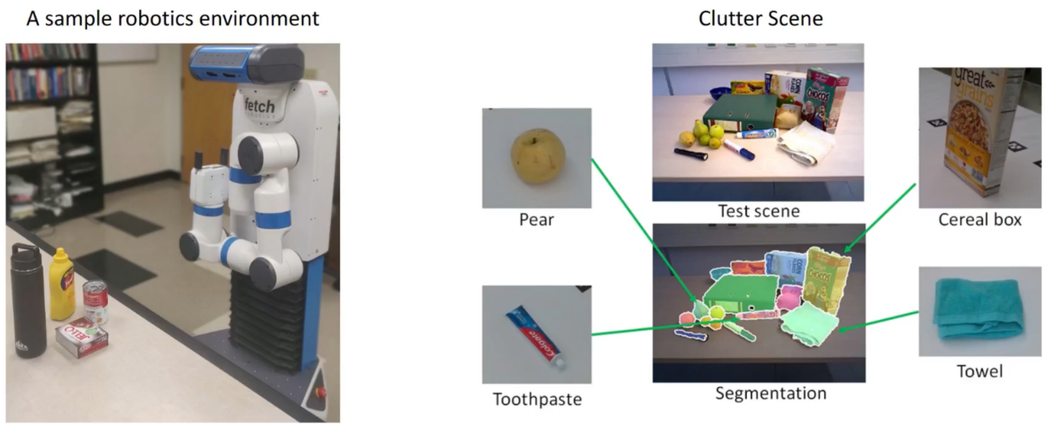
Introduction



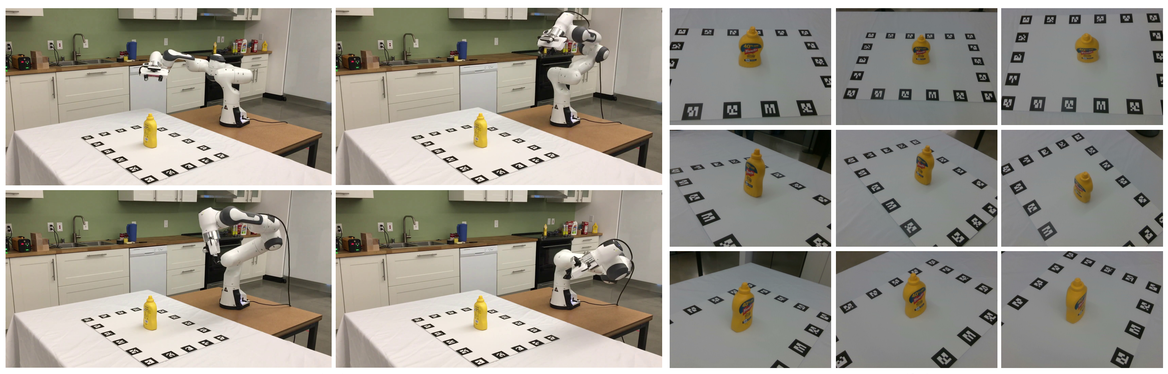
Goal: A robot should identity various (daily) objects in clutter scenes

Our approach: Object Classification using Few-Shot Learning

Related Datasets

Dataset	Class type	#classes	Image Type	#images_per_class	Annotations
Omniglot [1]	Characters	1623	RGB	20	class label
mini-ImageNet [2]	WordNet synsets	100	RGB	600	class label
ILSVRC-2012 [3]	WordNet synsets	1000	RGB	≈8,004	class label
Aircraft [4]	Aircraft	100	RGB	100	class label
CUB-200-2011 [5]	Birds	200	RGB	≈59	class label
Describable Texture [6]	Textures	47	RGB	120	class label
Quick Draw [7]	Drawings	345	RGB	≈146,164	class label
Fungi [8]	Fungal species	1394	RGB	≈65	class label
VGG Flower [9]	Flowers	102	RGB	≈81	class label
Traffic Signs [10]	Traffic signs	43	RGB	≈912	class label
MSCOCO [11]	Internet Objects	80	RGB	≈10,751	class label, segmentation
Ours (real + synthetic)	**Daily objects**	**198 + 125**	**RGB-D**	**≈27 + 10,234**	**class label, segmentation, object pose and attribute**

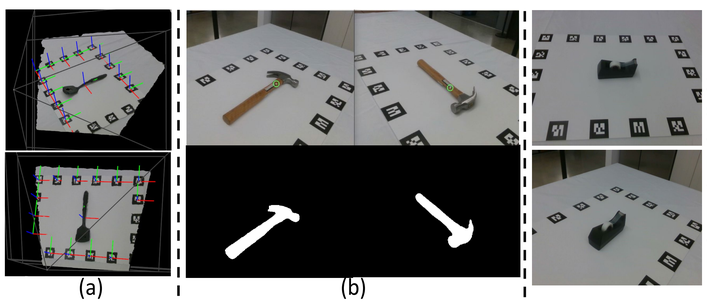
Dataset Construction: 1. Data Capture in the Real World



(a) (b)

(a) Our data capture system with a Franka Emika Panda arm. (b) 9 images of a mustard bottle from different views captured in our dataset.

Dataset Construction: 2. Data Annotation



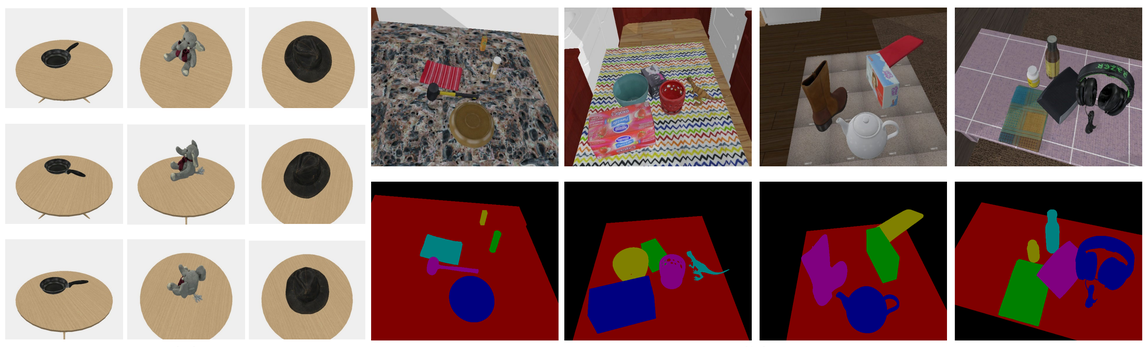
(a) (b)

(c)

1. What is the name of the object in these images?
tape and tape holder, tape, support and adhesive tape
2. What is the category of the object in these images?
stationary, stationery / adhesive tape
3. What is the object in these images made of?
plastic, paper, metal
4. What can be the object in these images used for?
placing the tape, stick, wrap, separate
5. What is the color of the object in these images?
black, transparent, white, yellow

(a) Object poses from AR tags (b) Pixel correspondences using computed object poses and the segmentation masks of the objects. (c) Our Amazon Mechanical Turk questionnaire for object annotation.

Dataset Construction: 3. Synthetic Data Generation using [12]



(a) (b)

(a) Synthetic objects with clean background. (b) Synthetic objects in cluttered scenes.

Acknowledgments

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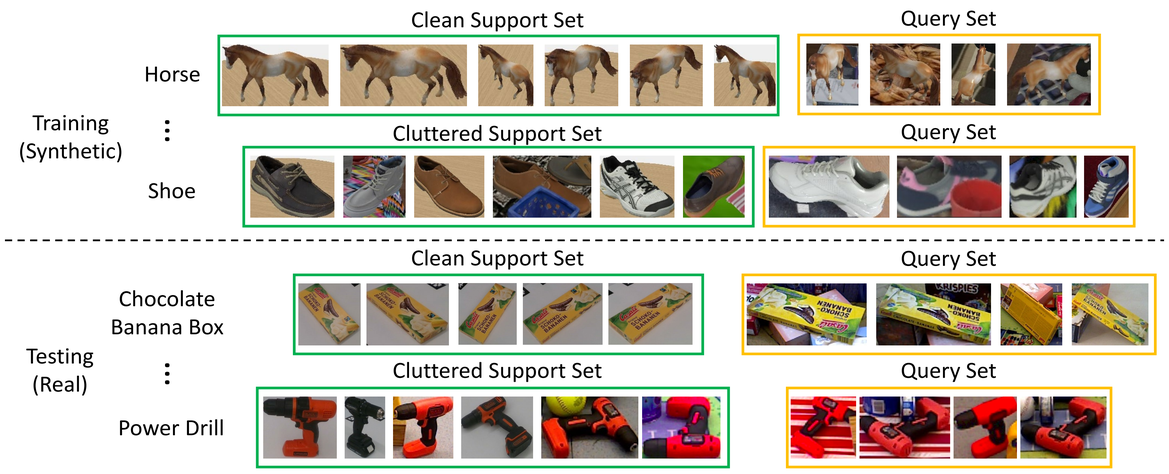
For more details, please scan

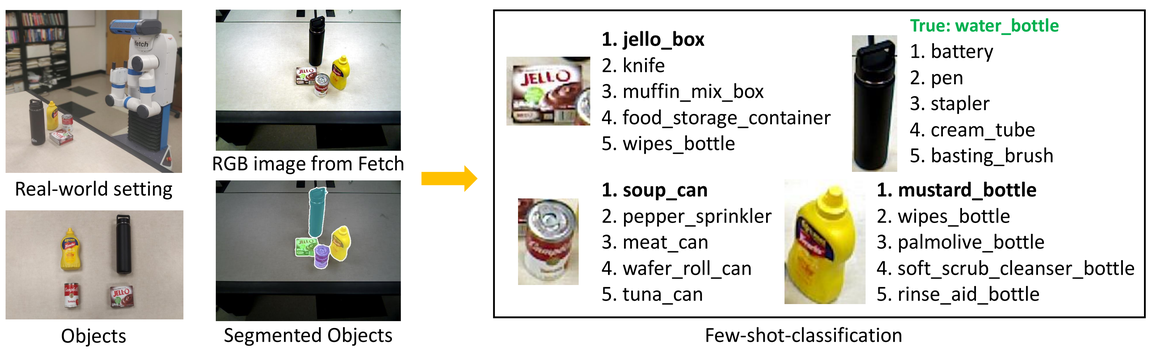
Experiments



Joint Object Segmentation and Few-Shot Classification

Method	OCID (Real) [13]					
	Use GT segmentation (#classes, #objects)			Use segmentation from [14] (#classes, #objects)		
	All (52, 2300) Clean S	Unseen (41, 1598) Clean S	Seen (11, 702) Clean S	All (52, 2300) Clean S	Unseen (41, 1598) Clean S	Seen (11, 702) Clean S
Training setting: clean support set with pre-training (top-1, top-5)						
k-NN [15]	14.65, 25.22	15.33, 24.41	41.03, 72.65	12.70, 23.22	13.70, 22.59	36.75, 67.95
Finetune [15]	22.26, 50.17	**26.41**, 58.20	31.62, 80.34	21.30, 48.57	**24.34**, 53.94	35.47, 67.38
ProtoNet [16]	**25.17**, **57.30**	25.22, **58.45**	51.99, **94.73**	**22.96**, **51.96**	22.65, **54.32**	49.86, **87.75**
MatchingNet [2]	17.39, 48.35	14.64, 50.06	51.85, 90.31	15.78, 45.13	13.08, 46.93	49.15, 84.47
fo-MAML [17]	11.43, 31.48	11.58, 34.73	36.89, 69.94	10.91, 29.17	10.01, 32.35	31.77, 63.68
fo-Proto-MAML [15]	14.35, 28.96	5.63, 40.61	45.58, 71.51	13.39, 26.96	5.51, 37.73	41.74, 67.24
CTX [18]	17.48, 46.57	18.21, 49.81	51.85, 87.75	15.70, 43.83	16.90, 46.31	47.86, 81.34
CTX+SimCLR [18]	18.57, 50.30	20.46, 51.06	**57.55**, 93.16	16.48, 46.17	17.71, 47.12	**52.14**, 85.75
Training setting: cluttered support set with pre-training (top-1, top-5)						
k-NN [15]	13.70, 23.83	15.33, 24.28	47.72, 72.79	13.26, 23.22	14.14, 22.90	44.73, 68.66
Finetune [15]	22.17, 53.35	24.34, 55.63	31.91, 71.51	18.26, 44.22	20.65, 52.00	36.04, 69.52
ProtoNet [16]	21.35, 50.57	22.34, 51.31	51.99, 90.46	18.61, 47.22	18.21, 48.12	45.44, 85.33
MatchingNet [2]	17.52, 50.96	17.77, 52.32	49.43, 88.18	16.52, 46.52	15.58, 48.81	43.45, 82.76
fo-MAML [17]	16.48, 38.52	13.70, 39.49	37.46, 77.07	15.35, 35.04	11.08, 34.36	40.31, 69.94
fo-Proto-MAML [15]	11.04, 28.70	4.01, 38.67	43.73, 72.65	9.91, 26.35	3.57, 35.79	40.46, 68.09
CTX [18]	19.00, 45.48	17.71, 44.74	51.85, 88.75	17.13, 42.22	16.08, 42.12	47.15, 83.19
CTX+SimCLR [18]	**24.61**, **62.39**	**25.16**, **63.52**	**65.81**, **96.30**	**22.17**, **57.43**	**23.28**, **57.57**	**59.12**, **88.32**
Using pre-trained CLIP models [19]						
Few-shot Tip-Adapter ViT-L/14-Finetune [20]	**60.17**, 83.04	**59.64**, 85.17	85.75, **99.00**	**54.87**, **78.91**	**56.07**, 80.29	79.20, 91.88
Few-shot Tip-Adapter ViT-L/14 [20]	56.78, 83.22	55.38, 84.86	**86.89**, 98.58	52.35, 76.26	51.69, 79.04	**80.06**, **92.45**
Zero-shot CLIP ViT-L/14 [19]	54.57, **84.74**	55.94, **87.92**	83.62, 98.58	50.43, 78.52	52.07, **81.54**	75.07, 92.17
Zero-shot CLIP ViT-B/32 [19]	41.87, 75.26	41.30, 77.91	78.06, 97.58	39.83, 69.43	39.17, 72.09	70.66, 90.88
Zero-shot CLIP ViT-B/16 [19]	40.70, 73.96	40.24, 76.03	76.50, 95.73	39.35, 68.83	38.61, 70.15	70.66, 88.89
Zero-shot CLIP RN50x64 [19]	42.96, 75.83	43.62, 77.41	76.64, 96.01	40.04, 70.87	41.74, 72.22	69.94, 90.46
Zero-shot CLIP RN50x16 [19]	38.52, 73.04	40.11, 75.72	79.49, 96.30	35.65, 67.30	37.30, 69.77	70.94, 89.74
Zero-shot CLIP RN50x4 [19]	35.96, 68.52	34.42, 70.03	73.93, 95.73	34.00, 63.78	32.48, 65.46	67.95, 88.60
Zero-shot CLIP ResNet-101 [19]	32.96, 68.30	32.67, 69.52	77.49, 96.87	31.09, 63.87	31.85, 65.96	69.66, 89.74
Zero-shot CLIP ResNet-50 [19]	25.91, 58.43	29.04, 64.39	61.40, 93.16	24.70, 55.61	28.04, 61.20	57.69, 86.47

Qualitative Results in the Real World using [20]



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