Synthesizing Training Data for Object Detection in Indoor Scenes

Georgios Georgakis
Arsalan Mousavian
Alexander C. Berg
Jana Kosecka

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Object Detection in Indoor Scenes

- Given an RGB-D image ***I***, localize all bounding boxes ***{x,y,w,h}***, of object instances of interest ***c*** - instance recognition.

Fetch these objects

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Challenges

Viewpoint variation

Clutter and scale variations

Occlusions

- State-of-the-art object detectors SSD / Faster R-CNN – deep learning.
- These methods require large amounts of training data.
- Manual annotation is time consuming.

- Liu et al. “Single shot multibox detector”, ECCV 2016.
- Ren et al. “Faster R-CNN: Towards real-time object detection with region proposal networks”, NIPS 2015

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Question

How can we train SSD and Faster R-CNN with the least amount of manual annotation?

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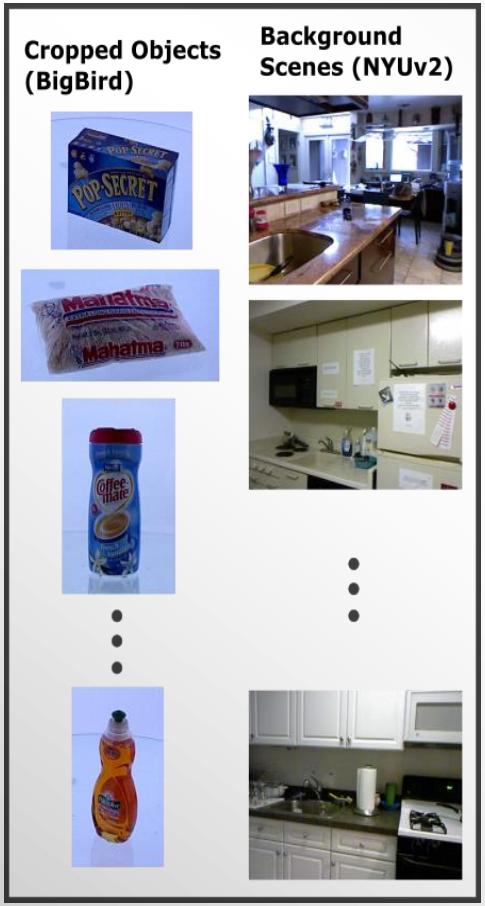
System Overview



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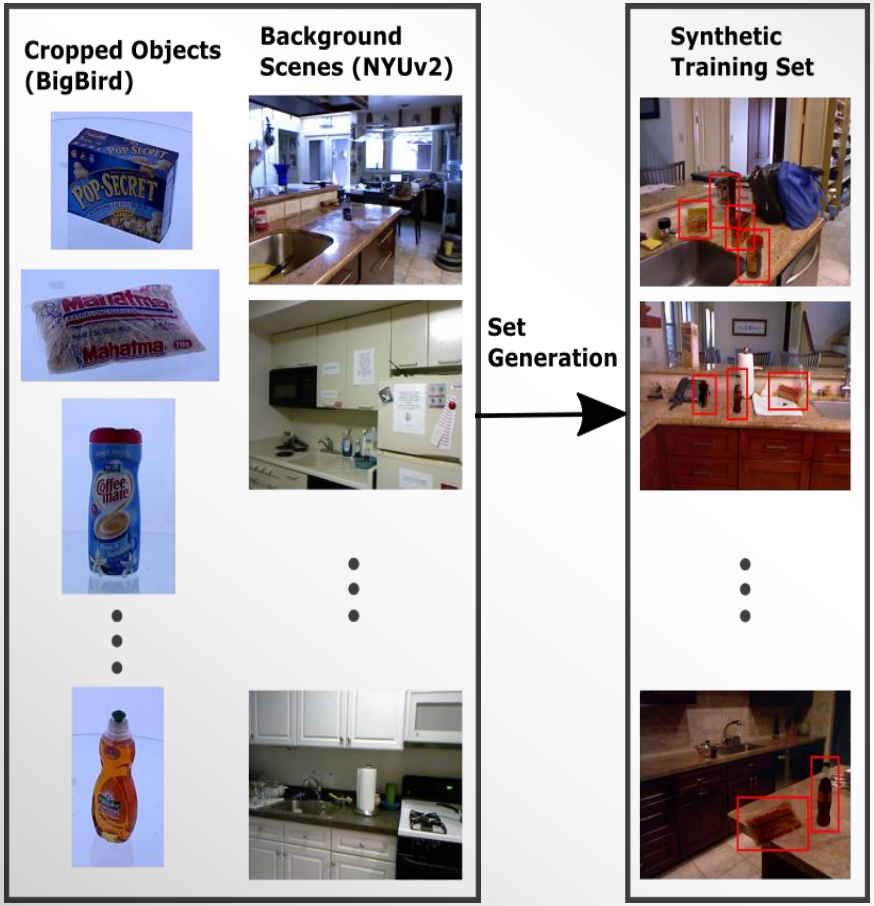

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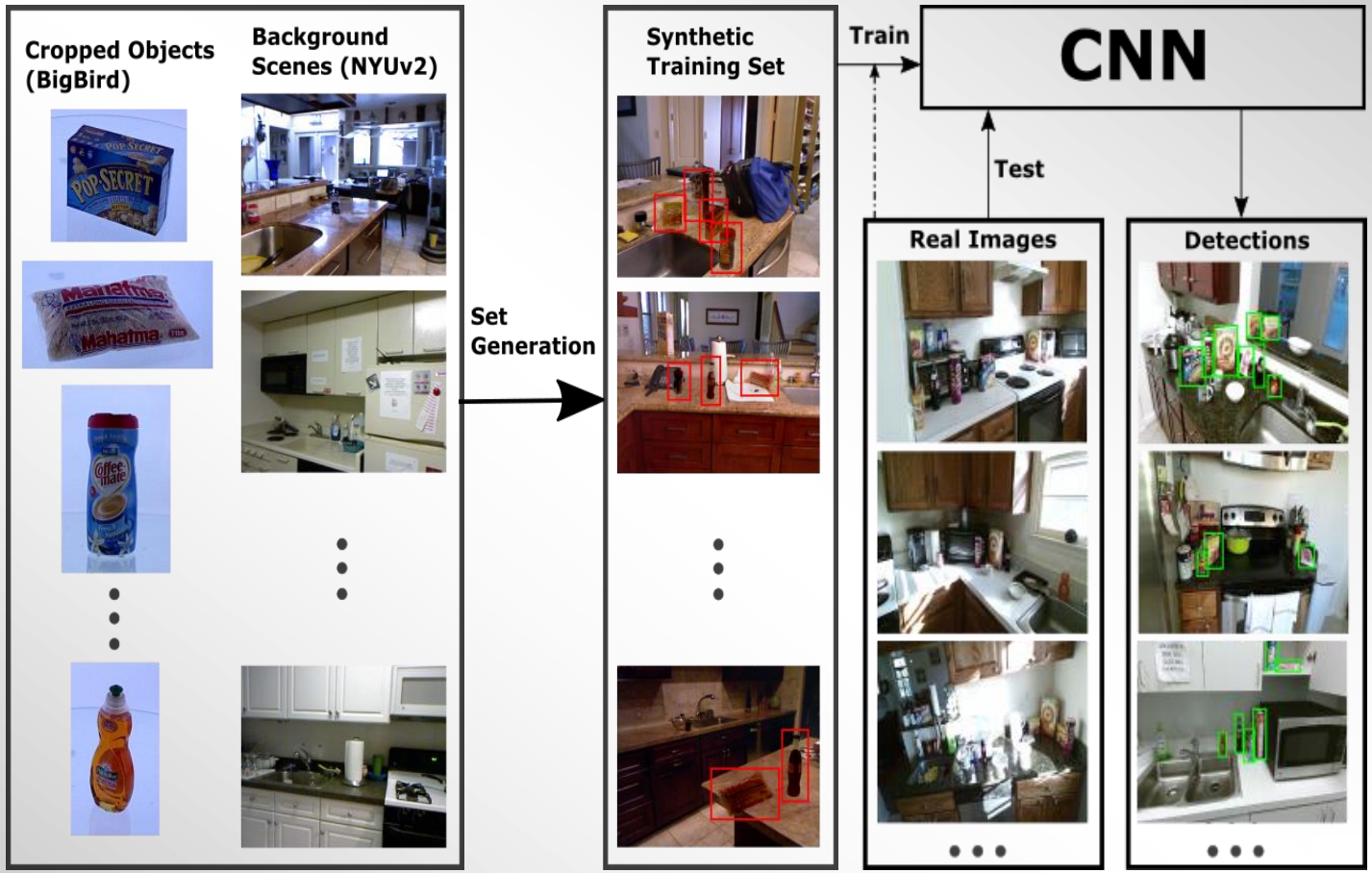

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Synthetic Set Generation

- Important observations:
  - Household objects are found on support surfaces.
  - The distance from camera defines the scale.
  - Objects in natural images have smooth boundary discontinuities with the background.

- Three simple constraints for increased realism:
  - *Selective positioning*, *Selective scaling*, and *Blending*.

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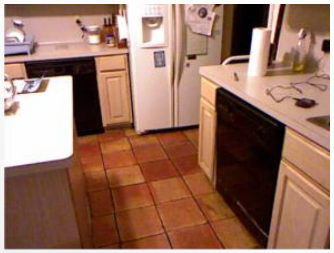
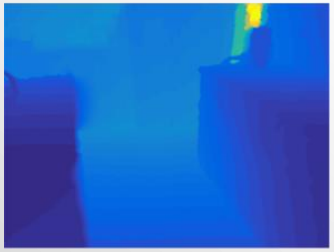
Automatic Generation



RGB



Depth

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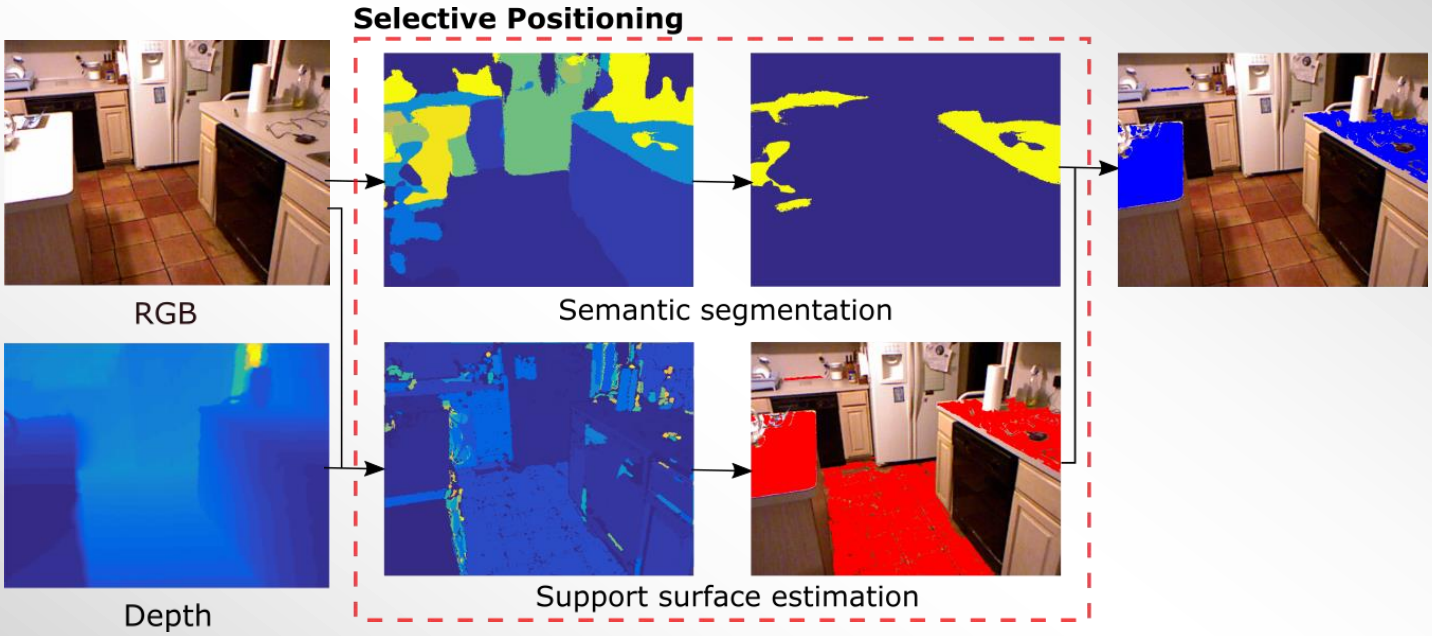
Automatic Generation



Semantic segmentation state-of-the-art approach:

- Mousavian et al. “Joint semantic segmentation and depth estimation with deep convolutional networks”, 3DV 2016.

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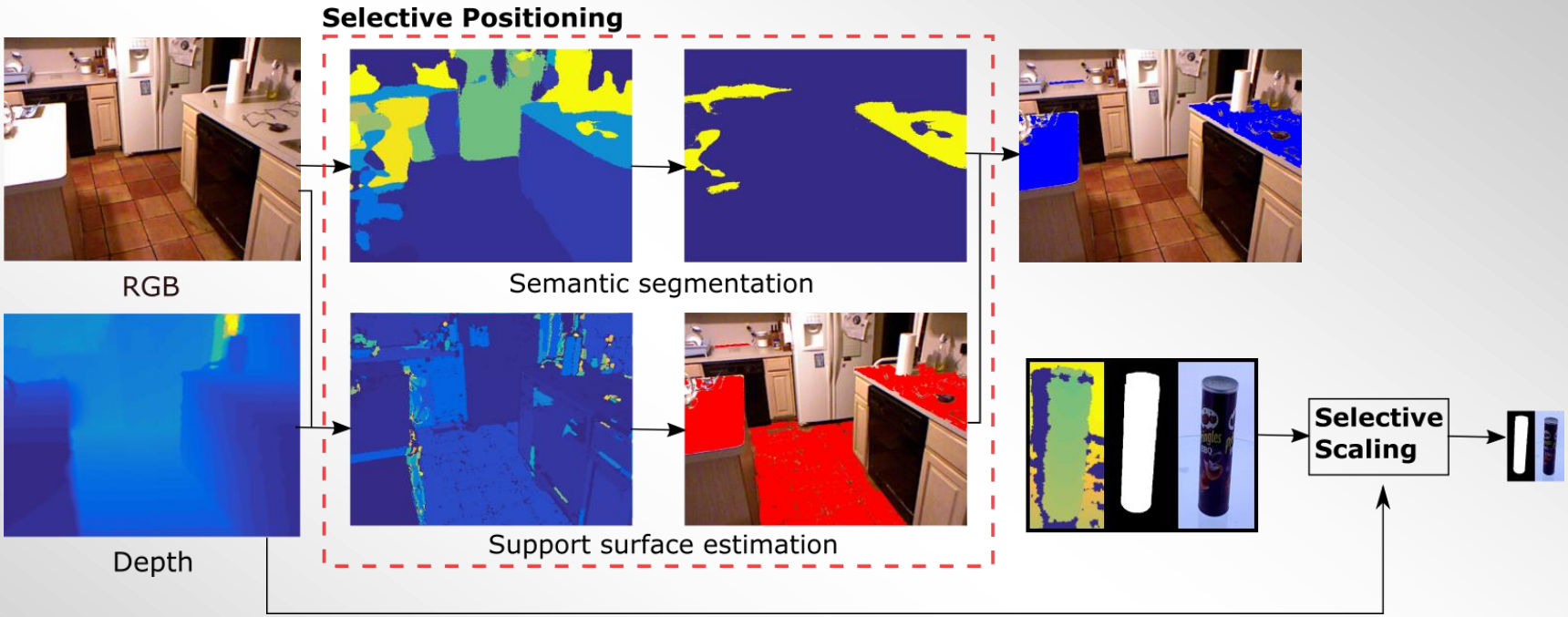
Automatic Generation



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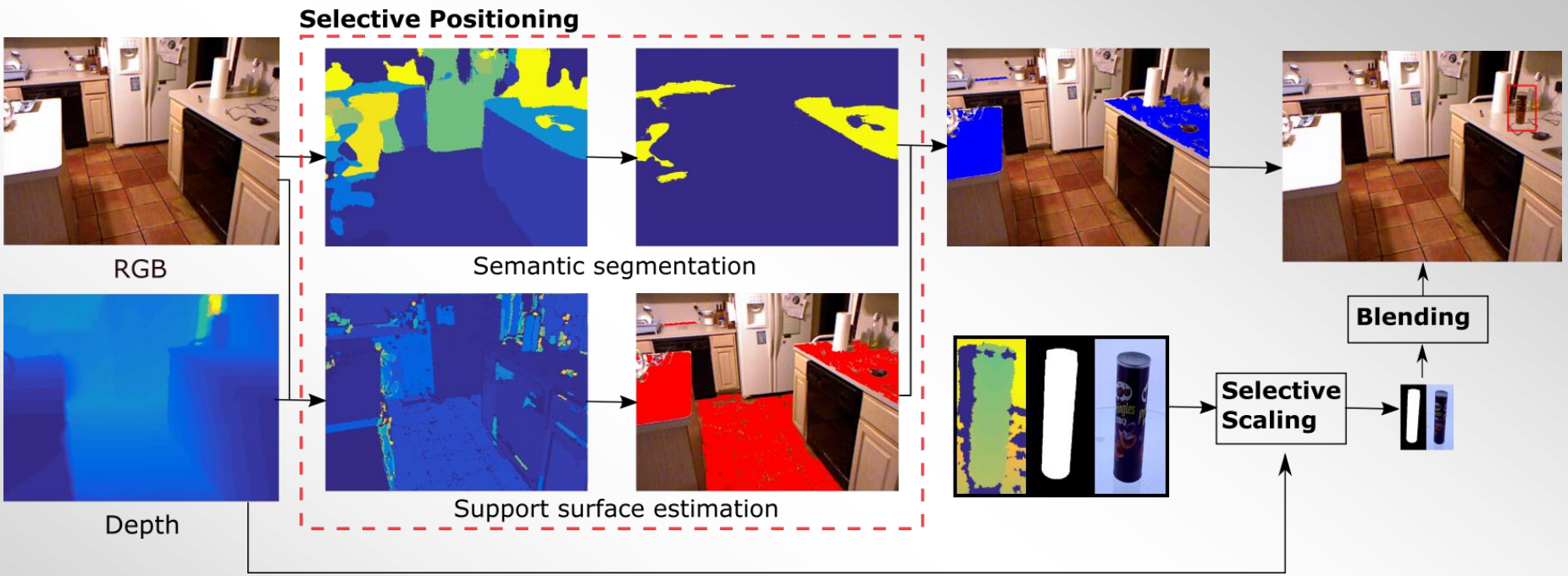

Off-the-shelf blending technique:

- Tanaka et al. “Seamless image cloning by a closed form solution of a modified Poisson problem”, SIGGRAPH Asia 2012.

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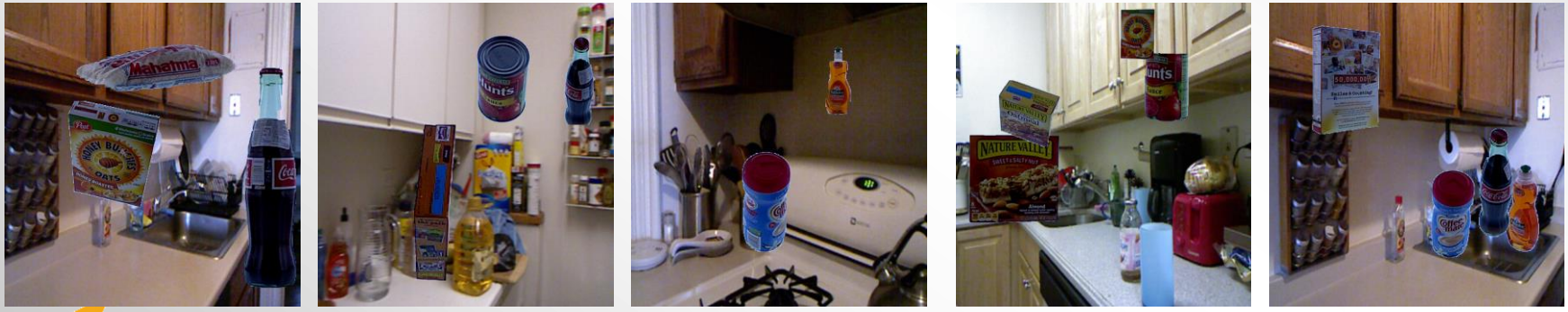
Composited Examples

Our approach

Randomized approach



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Experiments

- GMU-Kitchens dataset
  - Georgakis et al. "Multiview RGB-D dataset for object instance detection", 3DV 2016
- Synth to Real
  - Informatively generated synthetic sets (~20000 images) outperform random sets.
- Synth+Real to Real
  - Full real training set ~4000 images.
  - Augmenting existing few real annotations (400 real + 20000 synthetic) can yield comparable or superior results.

Train Set	SSD / Faster R-CNN
Real to Real	
1. Real Scenes	65.6 / 82.5
Synthetic to Real	
2. RP-SI-RS	23.2 / 42.1
3. RP-BL-RS	22.2 / 44.2
4. SP-SI-SS	19.5 / 48.6
5. SP-BL-SS	**33.5 / 51.7**
Synthetic+Real to Real	
6. 1% real	60.3 / 69.3
7. 10% real	71.6 / 79.2
8. 50% real	**74.1** / 83.8
9. 100% real	73.7 / **85.0**

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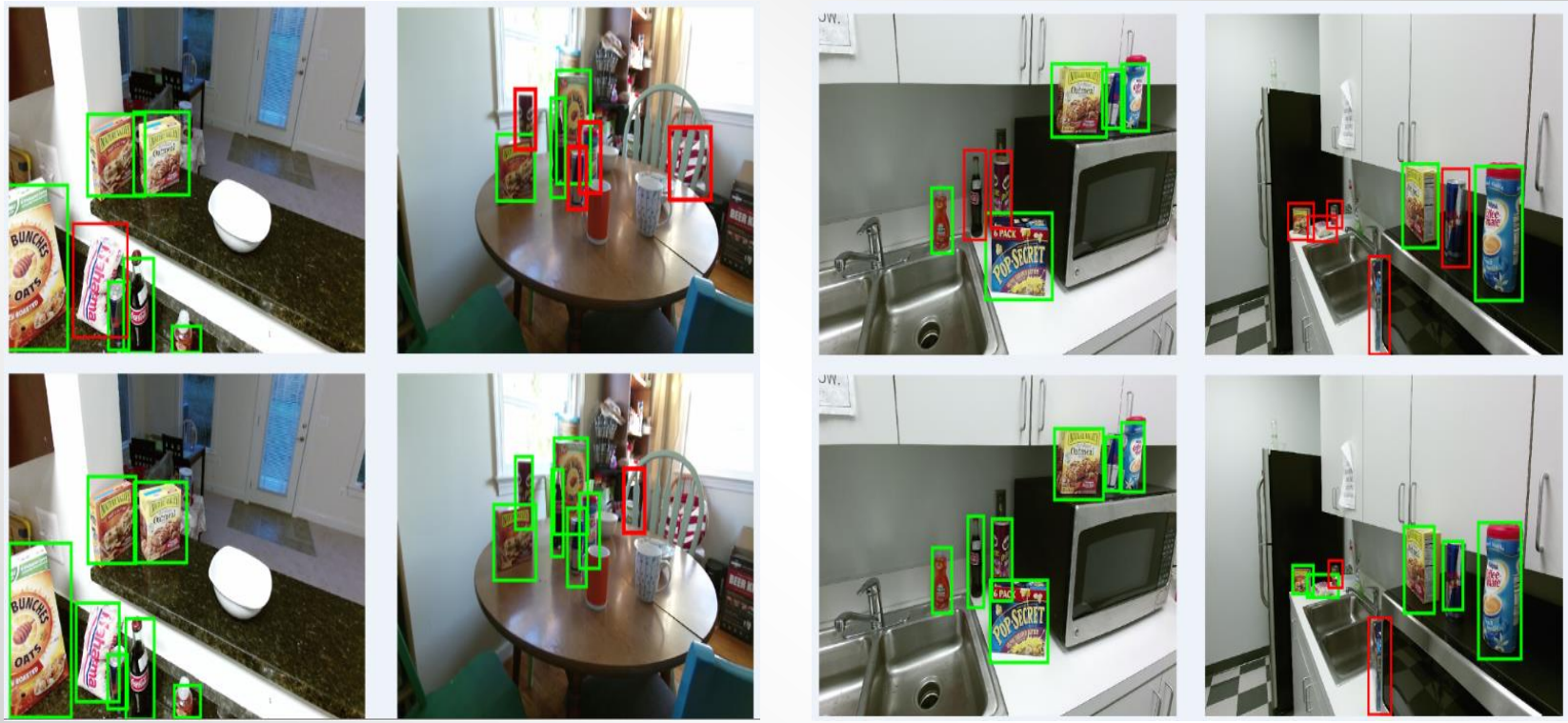
Qualitative Results

Faster R-CNN

SSD

Real

Real + Synth



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Summary

- Synthetic training data are more effective when they are generated with semantic and geometric information.

- Object detectors can be trained with significantly less annotated data using our proposed synthetic data augmentation.

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