Perceiving the 3D World from Images and Videos

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HONDA

Act in the 3D World

Intelligent System

Sensing & Understanding

Acting

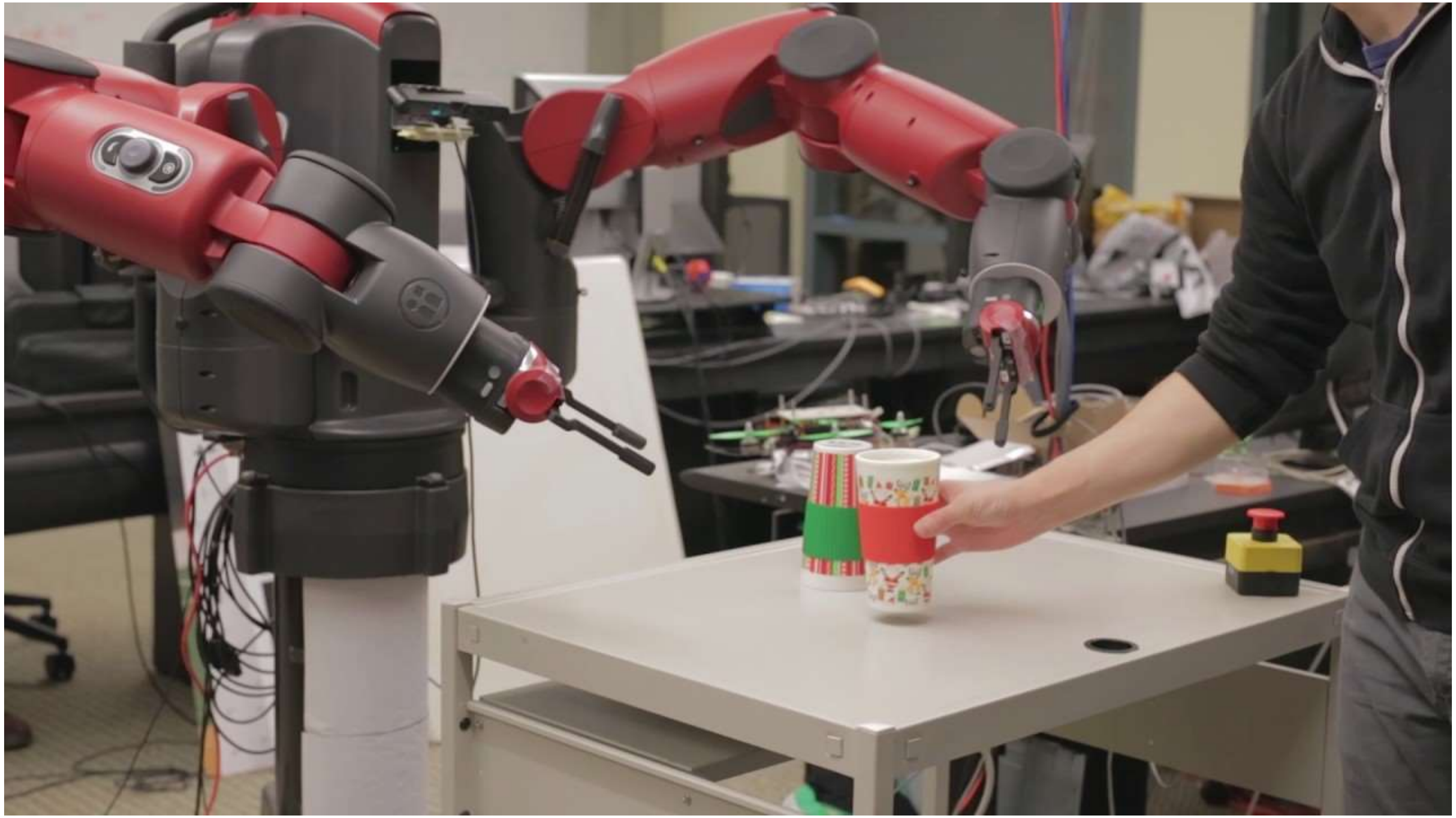
3D World

Understand the 3D World

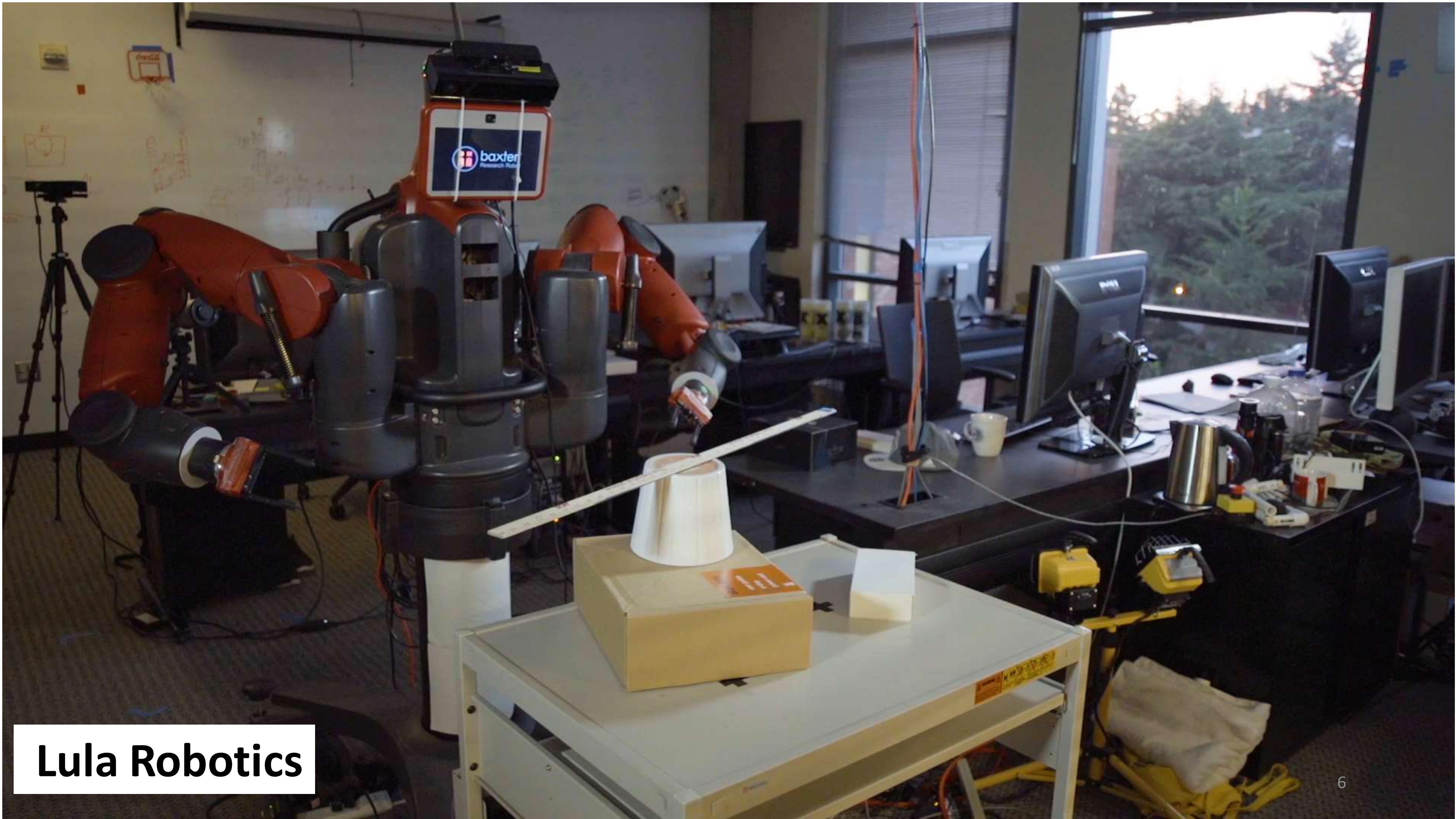
- Navigation
- Manipulation
- …

- Geometry
  - ✓ Free space
  - ✓ Surface
- Semantics
  - ✓ Objects
  - ✓ Affordances

Recognize Objects in 3D

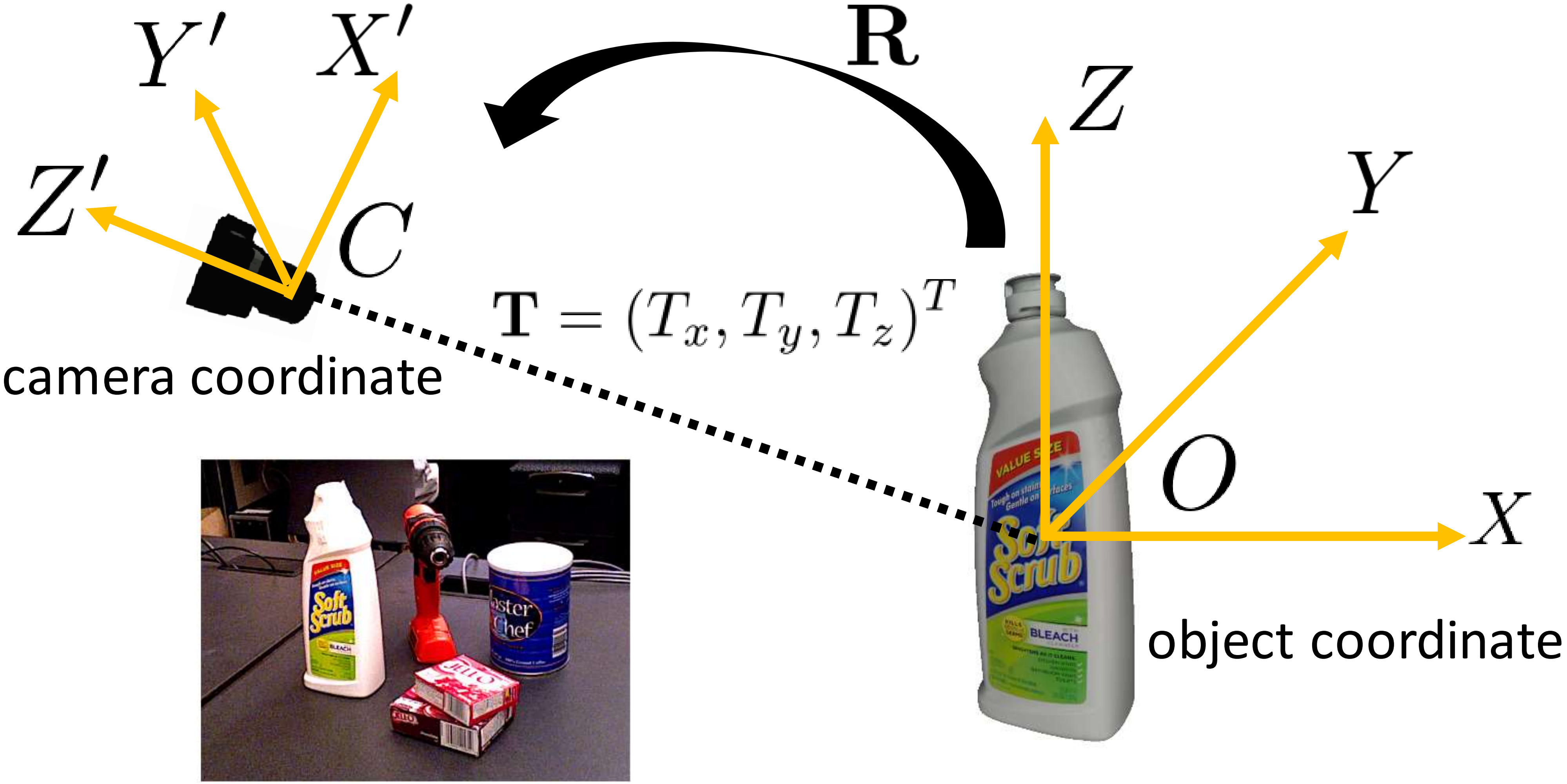


- ✓ Semantics
- ✓ 3D Location
- ✓ 3D Orientation

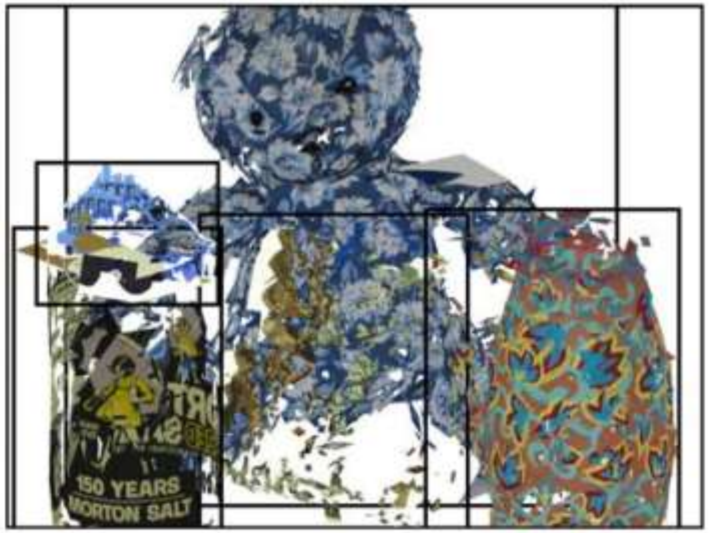


Lula Robotics

6D Object Pose Estimation



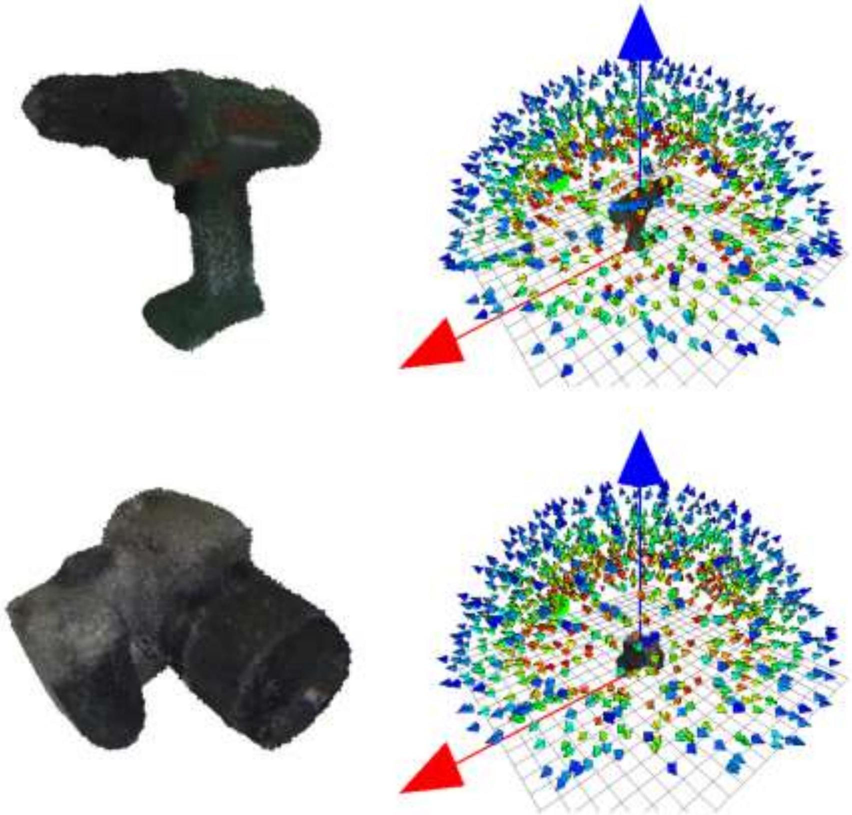
Related Work: Feature-based methods

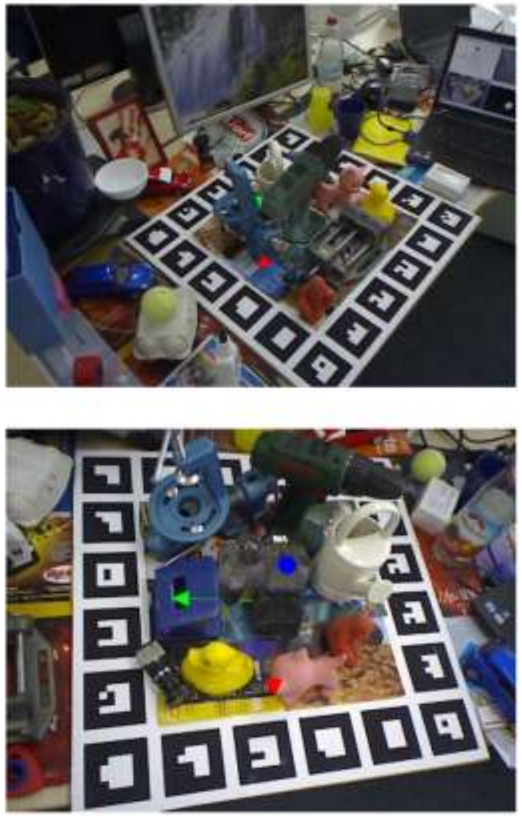


- ✘ Texture-less objects
- ✘ Symmetry objects
- ✓ Occlusion

- Lowe, ICCV’99
- Rothganger et al., IJCV’06
- Savarese & Fei-Fei, ICCV’07
- Collet et al., IJRR’11

Related Work: Template-based methods



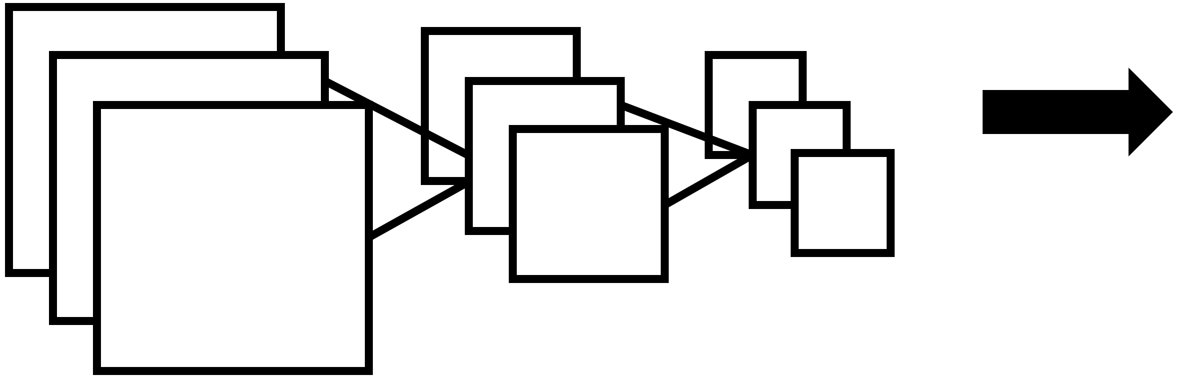


- ✓ Texture-less objects
- ✓ Symmetry objects
- ✘ Occlusion

- Gu & Ren, ECCV’10
- Hinterstoisser et al., ACCV’12
- Xiang & Savarese, CVPR’12
- Cao et al., ICRA’16

An input image

PoseCNN

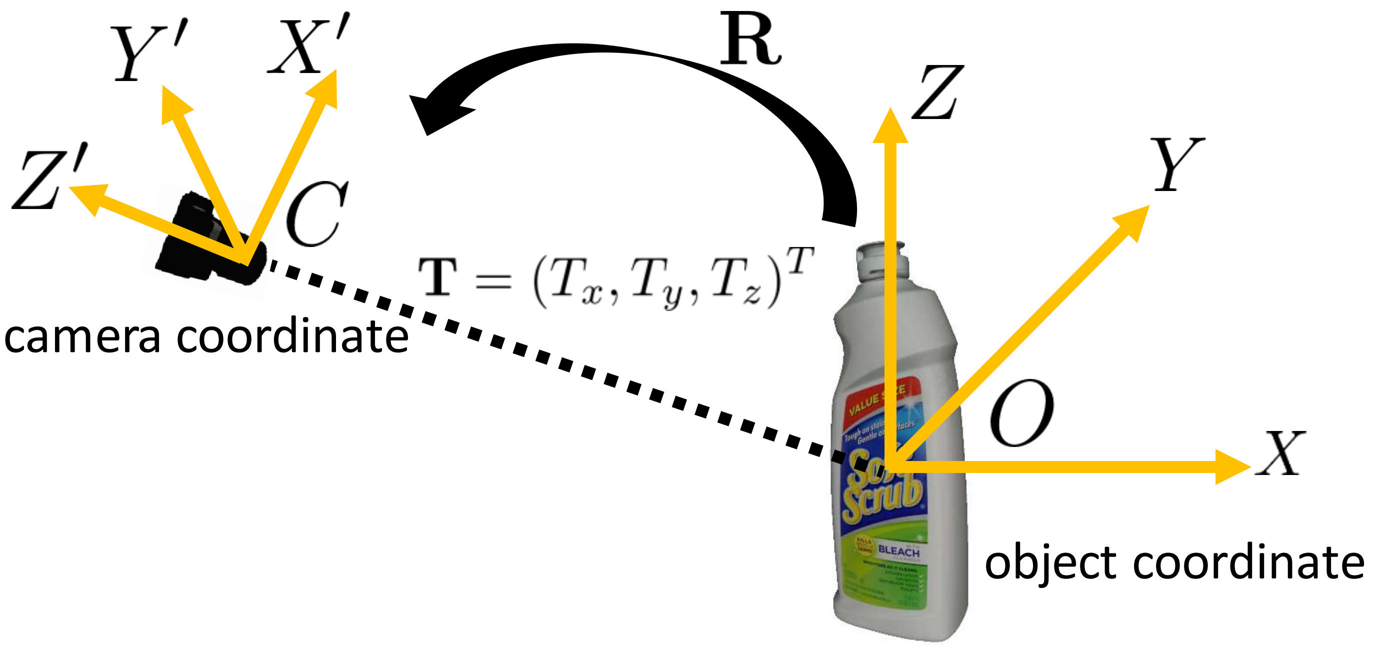


6D poses

- ✓ Texture-less objects
- ✓ Symmetry objects
- ✓ Occlusion

Y. Xiang, T. Schmidt, V. Narayanan and D. Fox. PoseCNN: A Convolutional Neural Network for 6D Object Pose Estimation in Cluttered Scenes. In arXiv:1711.00199.

Decouple 3D Translation and 3D Rotation



- 3D Translation

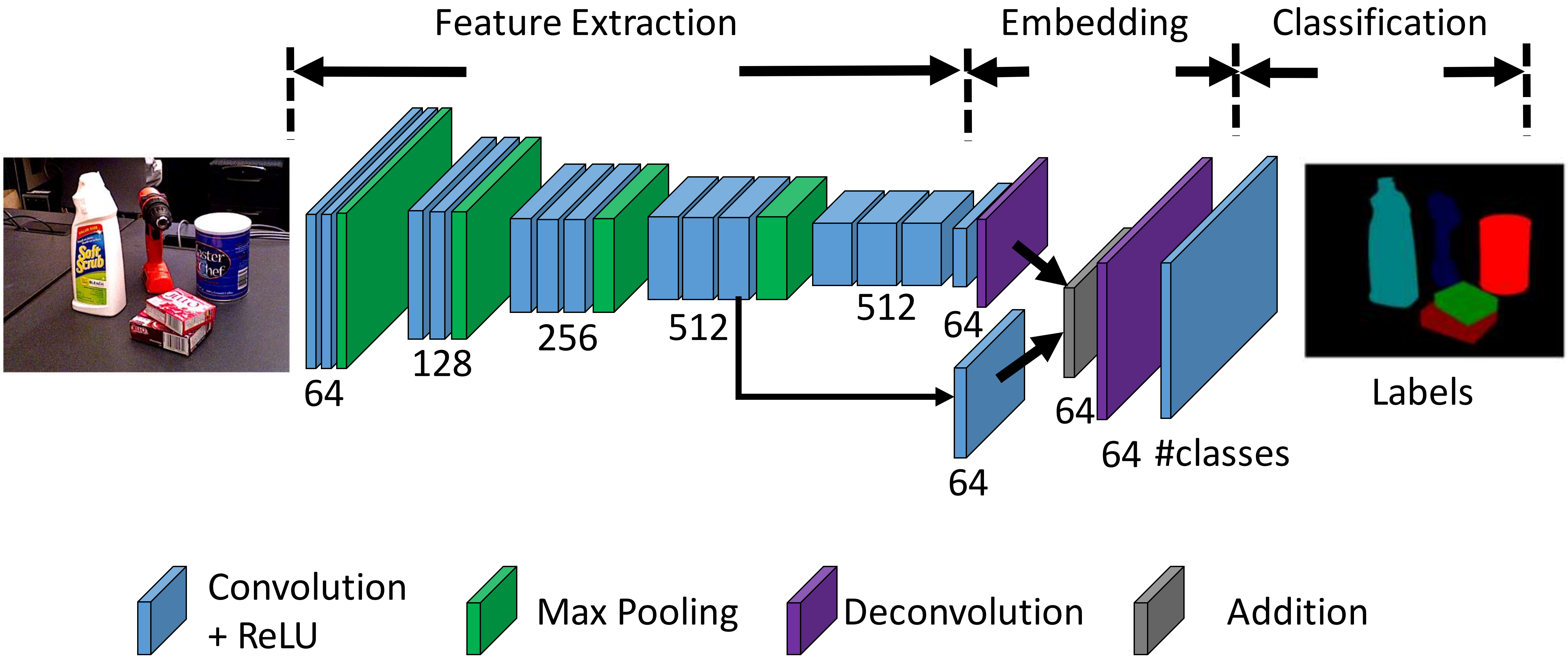
2D center $\mathbf{c} = (c_x, c_y)^T$

Distance T_z

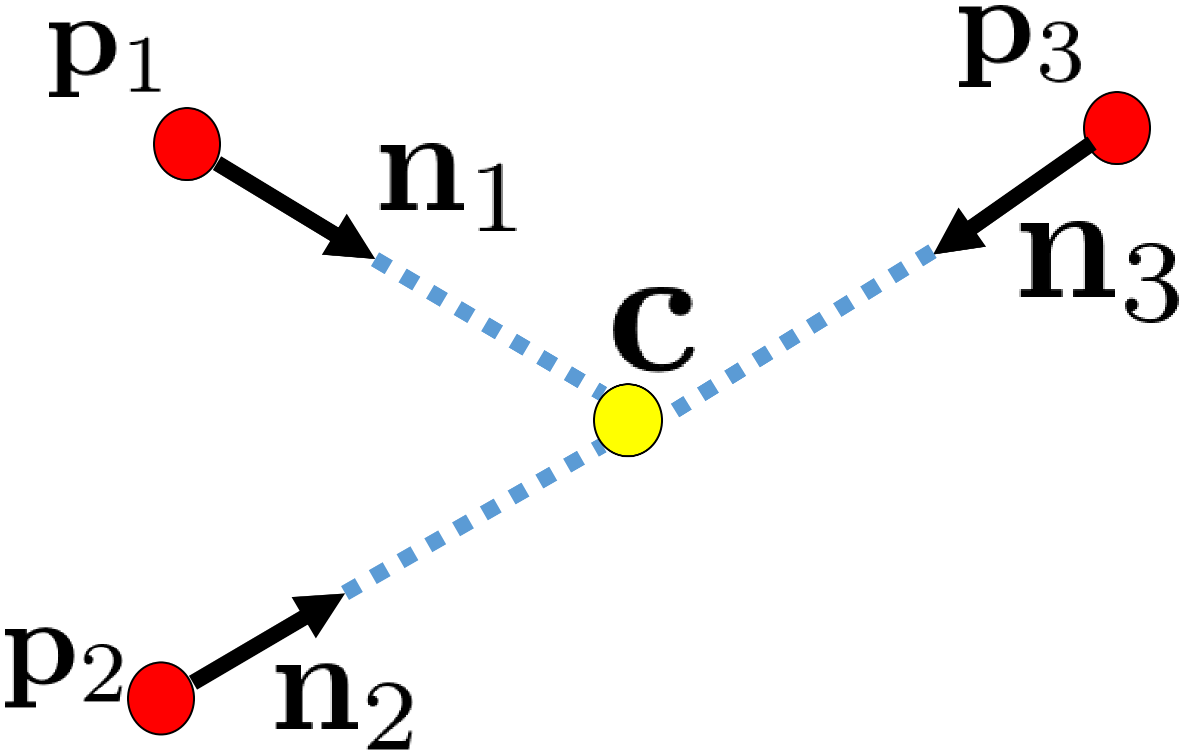
- 3D Rotation

$\rightarrow \mathbf{R}$

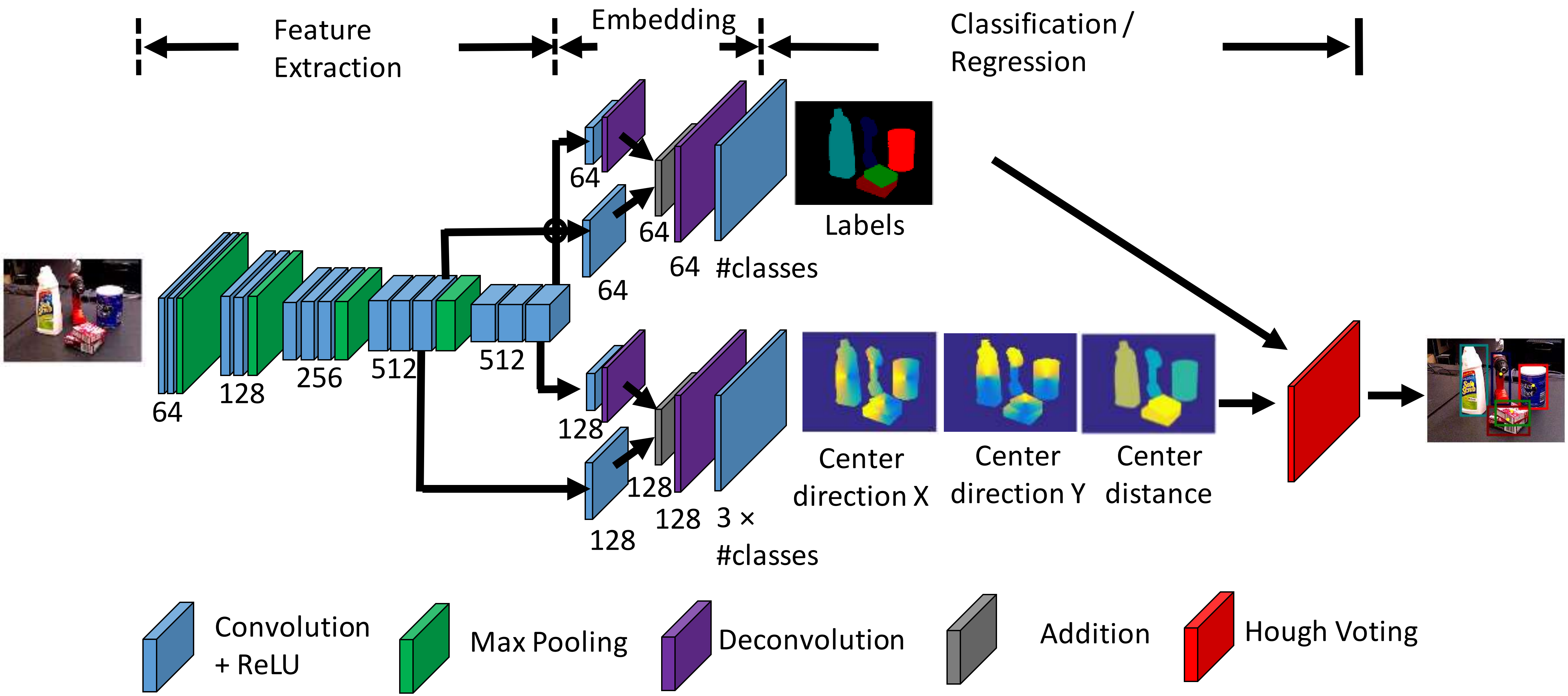
PoseCNN: Semantic Labeling



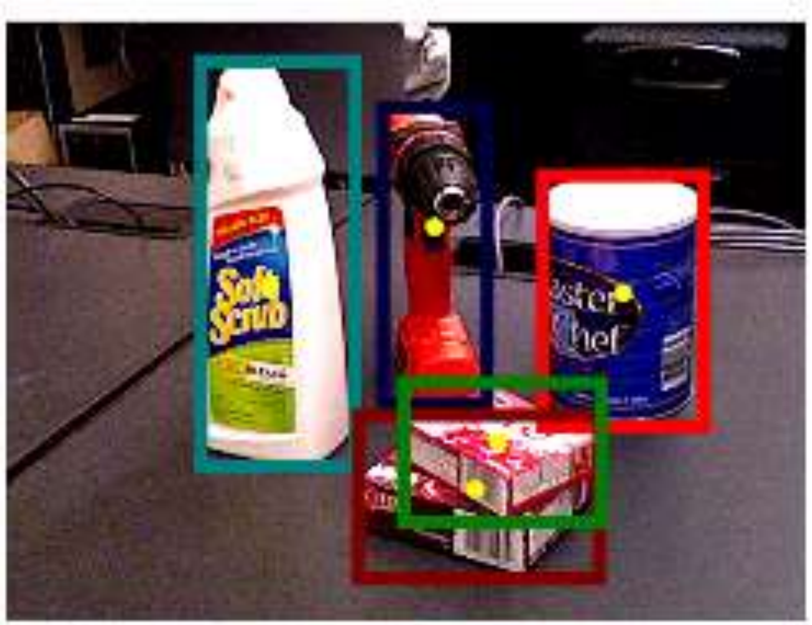
PoseCNN: Object Center Voting

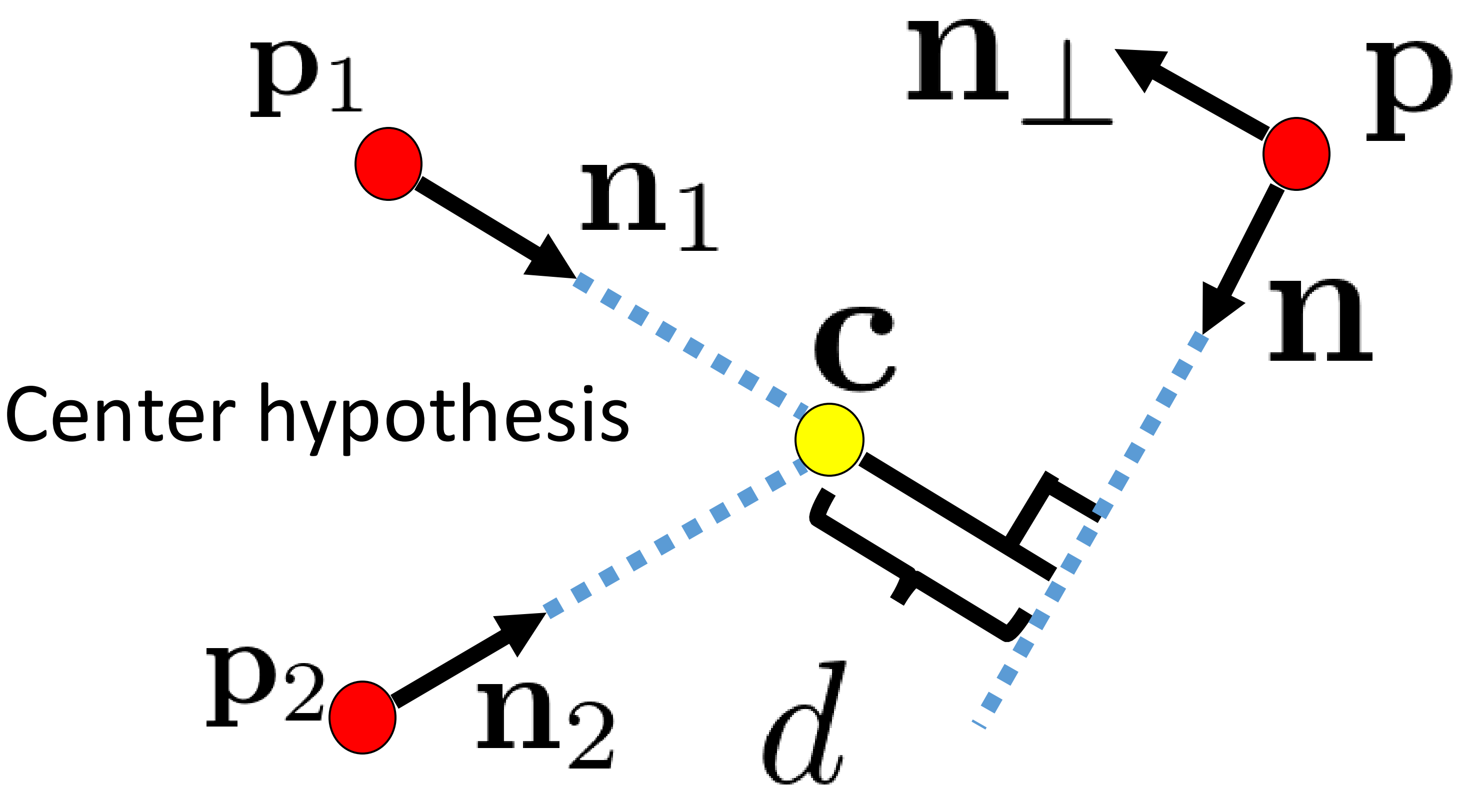


PoseCNN: 3D Translation Estimation

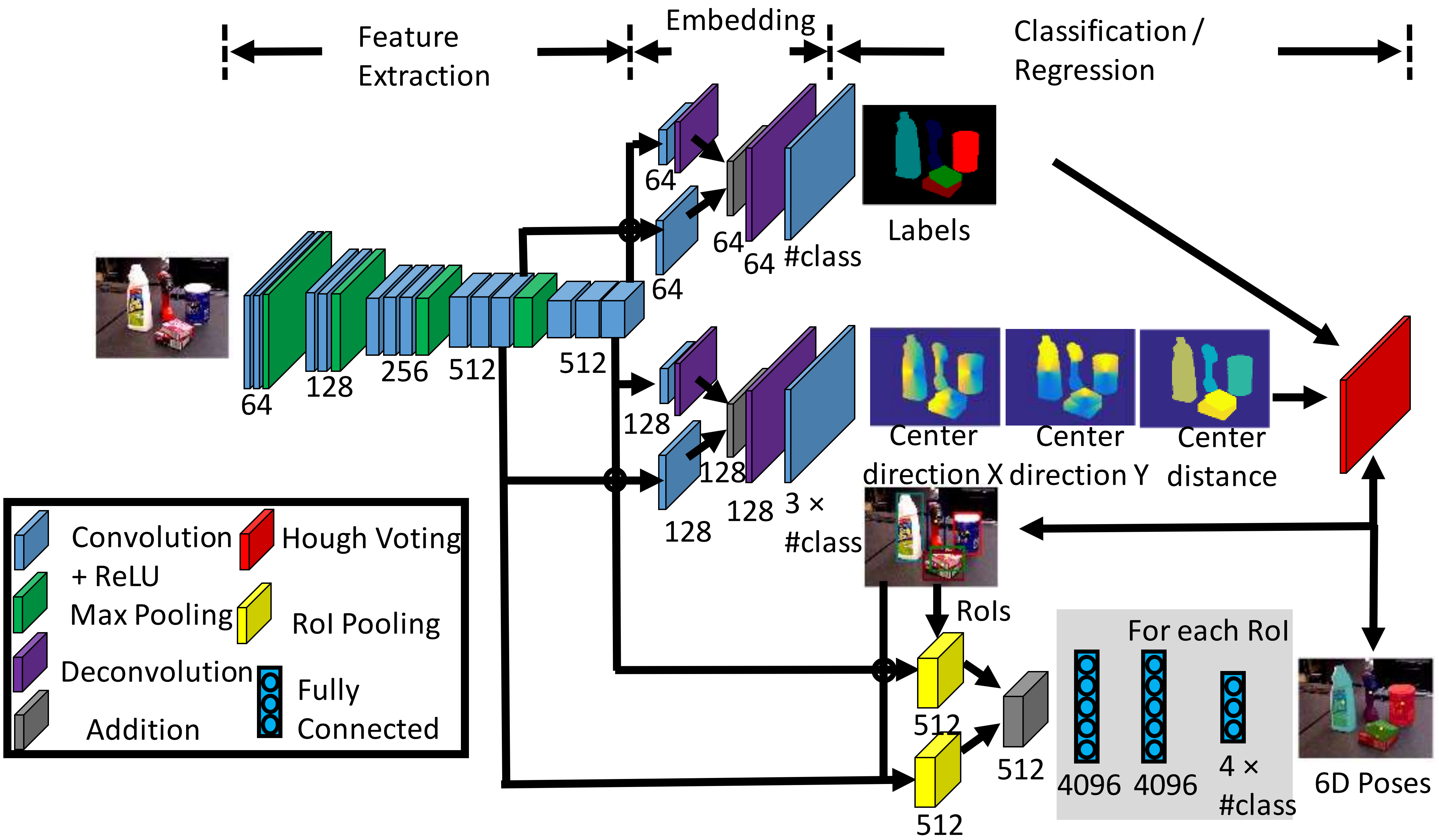


PoseCNN: Center Estimation with RANSAC



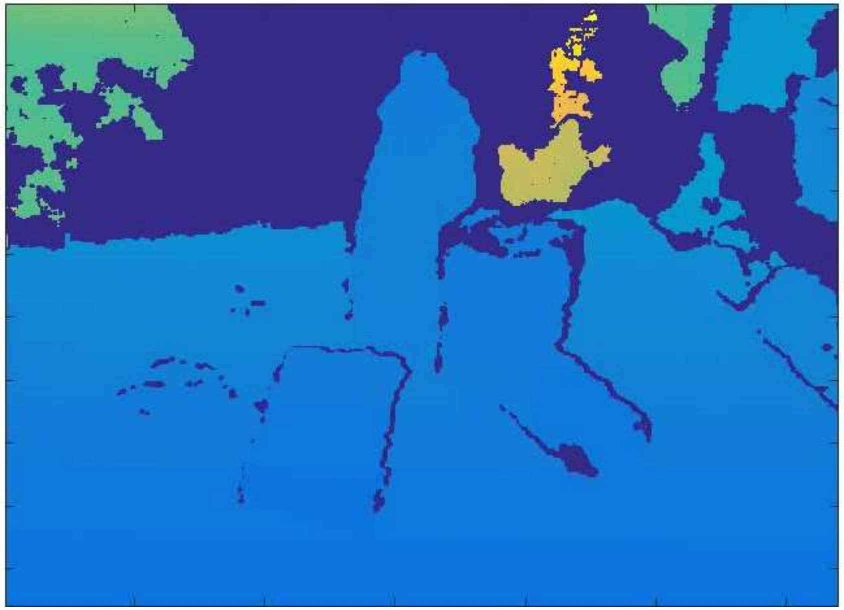


PoseCNN: 3D Rotation Regression



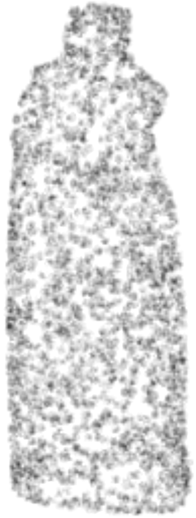
The YCB-Video Dataset

21 YCB Objects



92 Videos, 133,827 frames

6D Pose Evaluation Metric



3D model points

Ground truth pose

$(\mathbf{R}, \mathbf{T})$

Predicted pose

$(\tilde{\mathbf{R}}, \tilde{\mathbf{T}})$

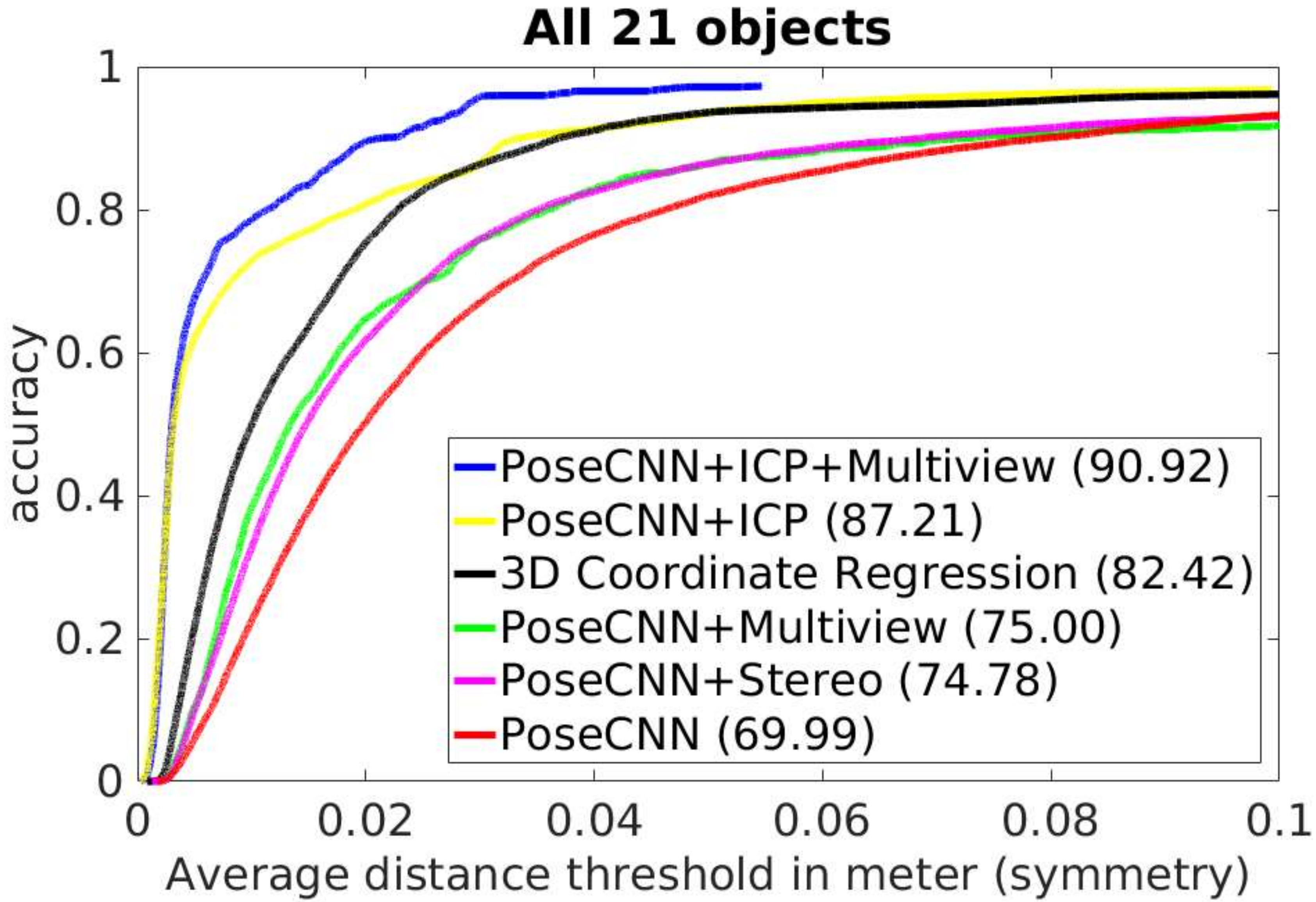
Average distance (non-symmetry)

$$\bar{d} = \frac{1}{m}\sum_{\mathbf{x}\in\mathcal{M}} \|(\mathbf{R}\mathbf{x}+\mathbf{T}) - (\tilde{\mathbf{R}}\mathbf{x}+\tilde{\mathbf{T}})\|$$

Average distance (symmetry)

$$\bar{d} = \frac{1}{m}\sum_{\mathbf{x}_1\in\mathcal{M}} \min_{\mathbf{x}_2\in\mathcal{M}} \|(\mathbf{R}\mathbf{x}_1+\mathbf{T}) - (\tilde{\mathbf{R}}\mathbf{x}_2+\tilde{\mathbf{T}})\|$$

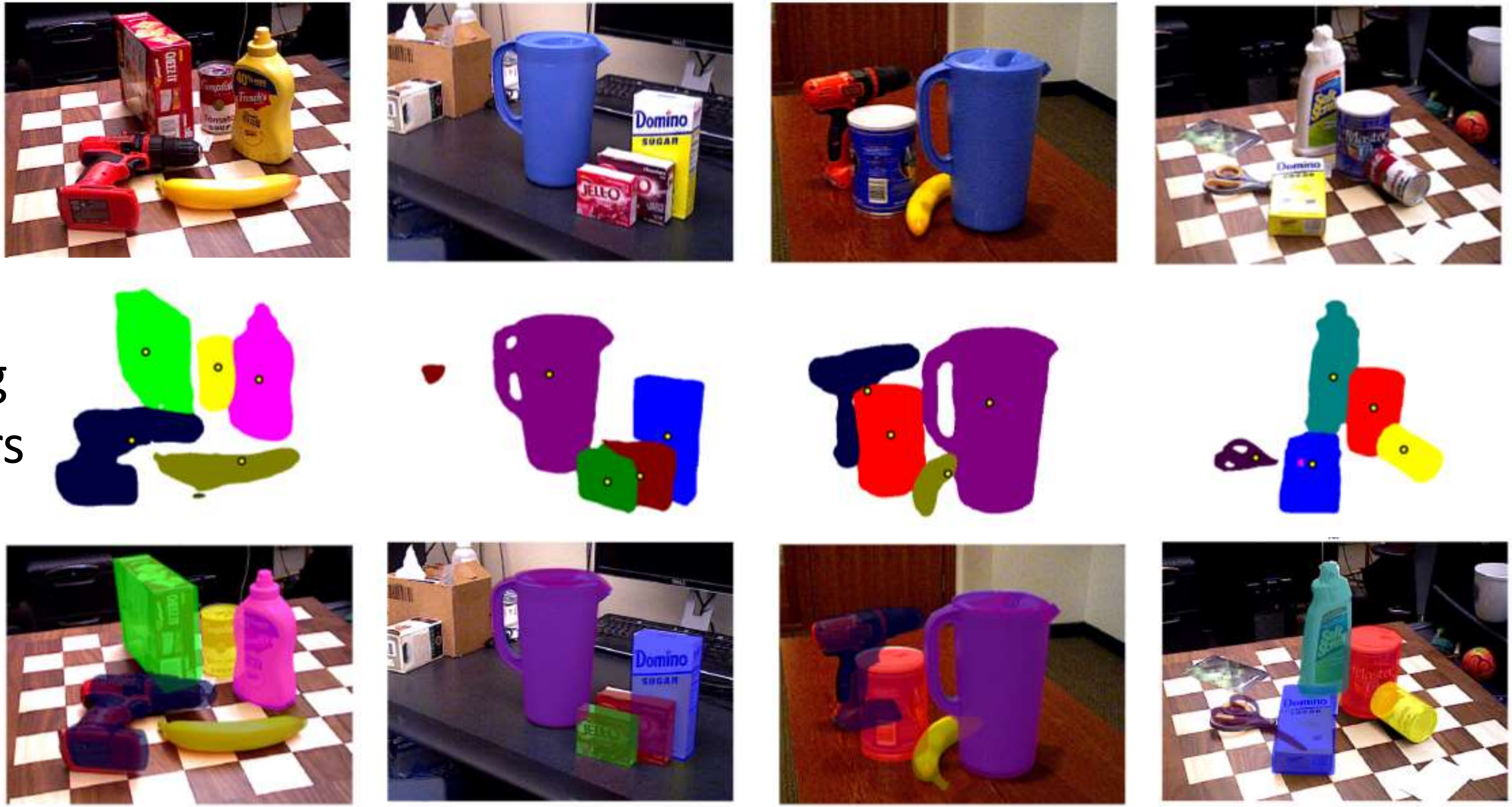
Results on the YCB-Video Dataset

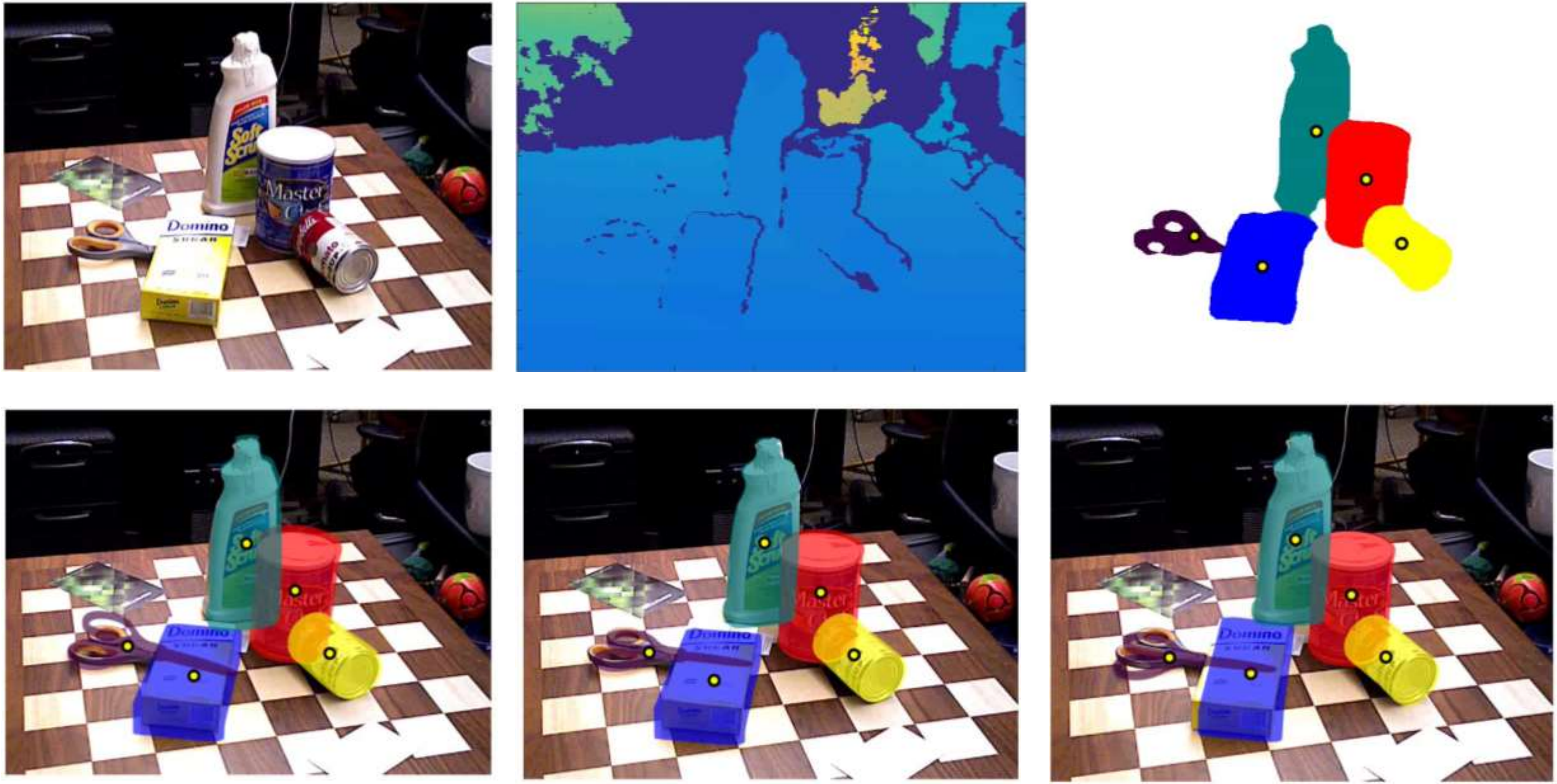


Input Image

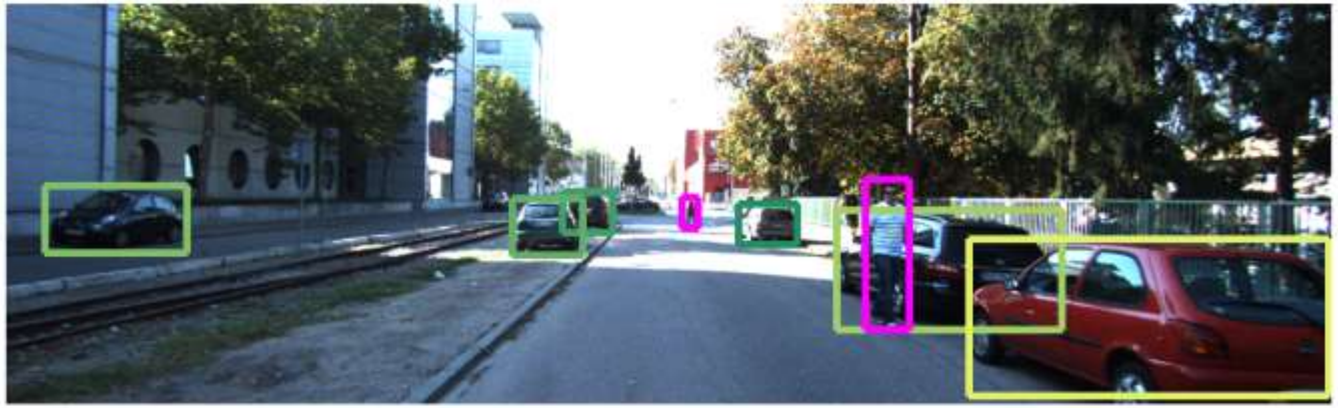
Labeling & Centers

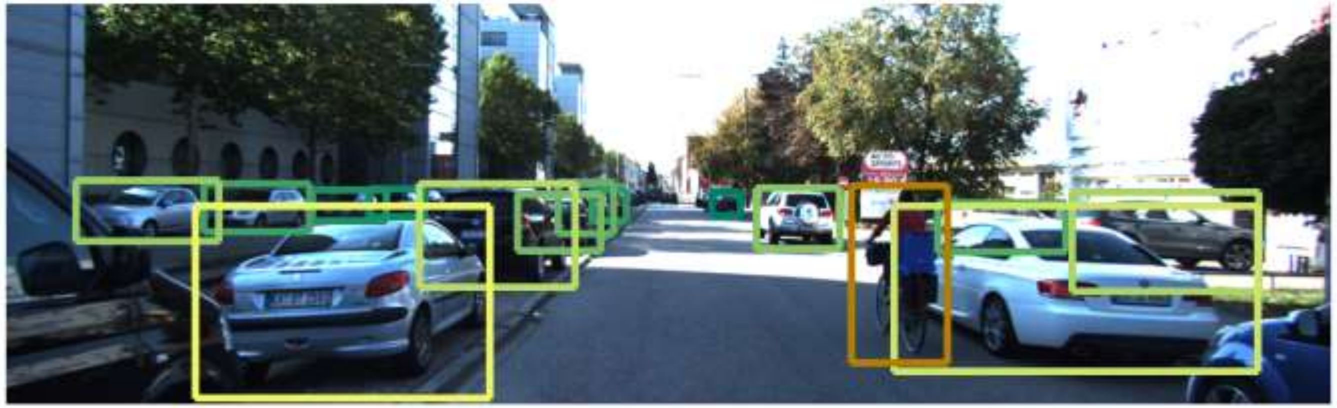
6D Pose

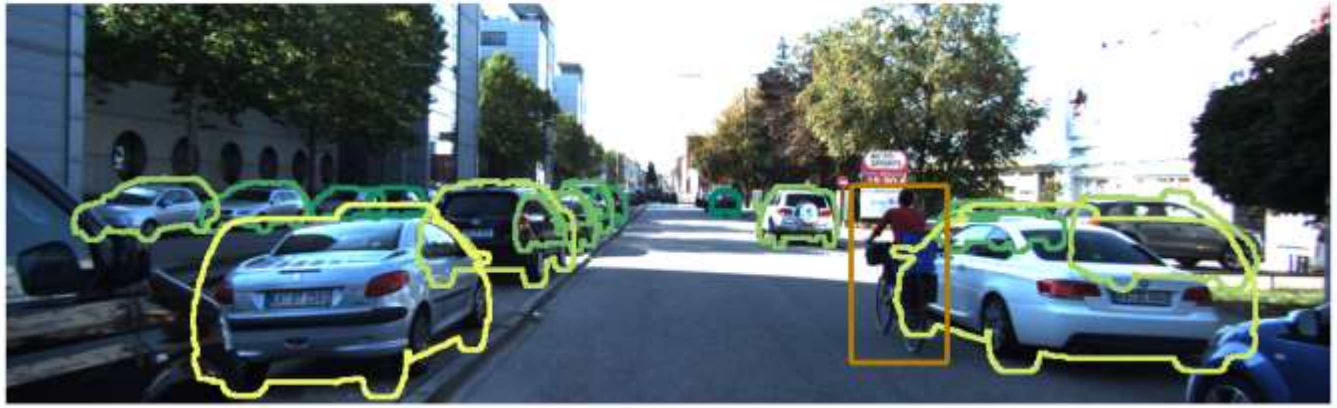




Network　　Network + ICP　　Network + ICP + Multi-view

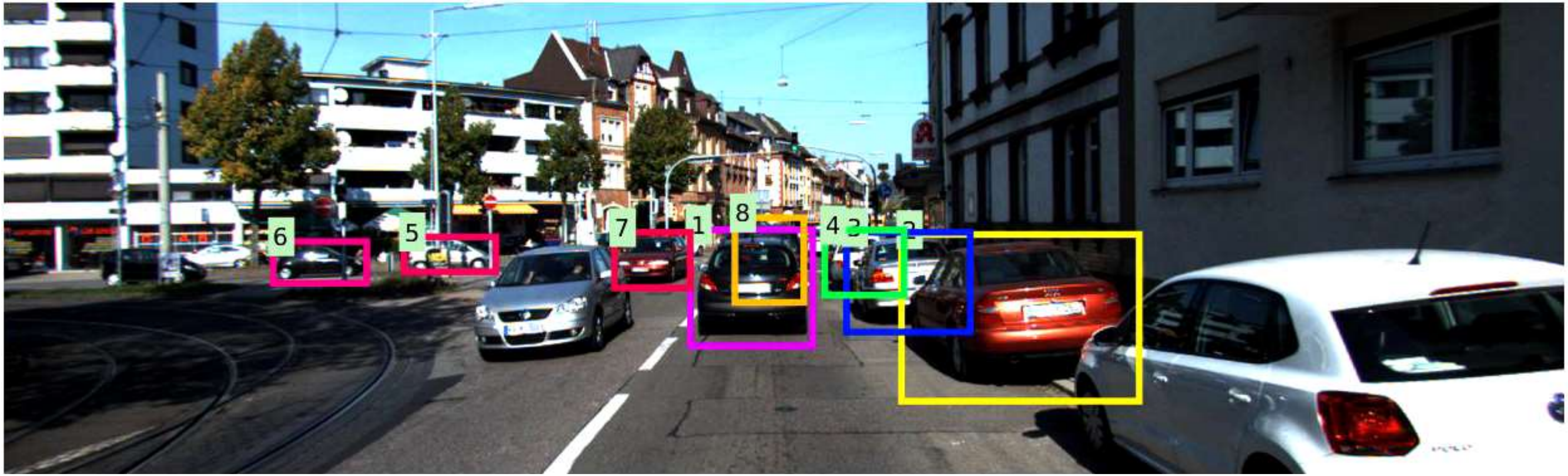





Y. Xiang, W. Choi, Y. Lin and S. Savarese. Subcategory-aware Convolutional Neural Networks for Object Proposals and Detection. In WACV, 2017.
Y. Xiang, W. Choi, Y. Lin and S. Savarese. Data-Driven 3D Voxel Patterns for Object Category Recognition. In CVPR, 2015 (Oral).

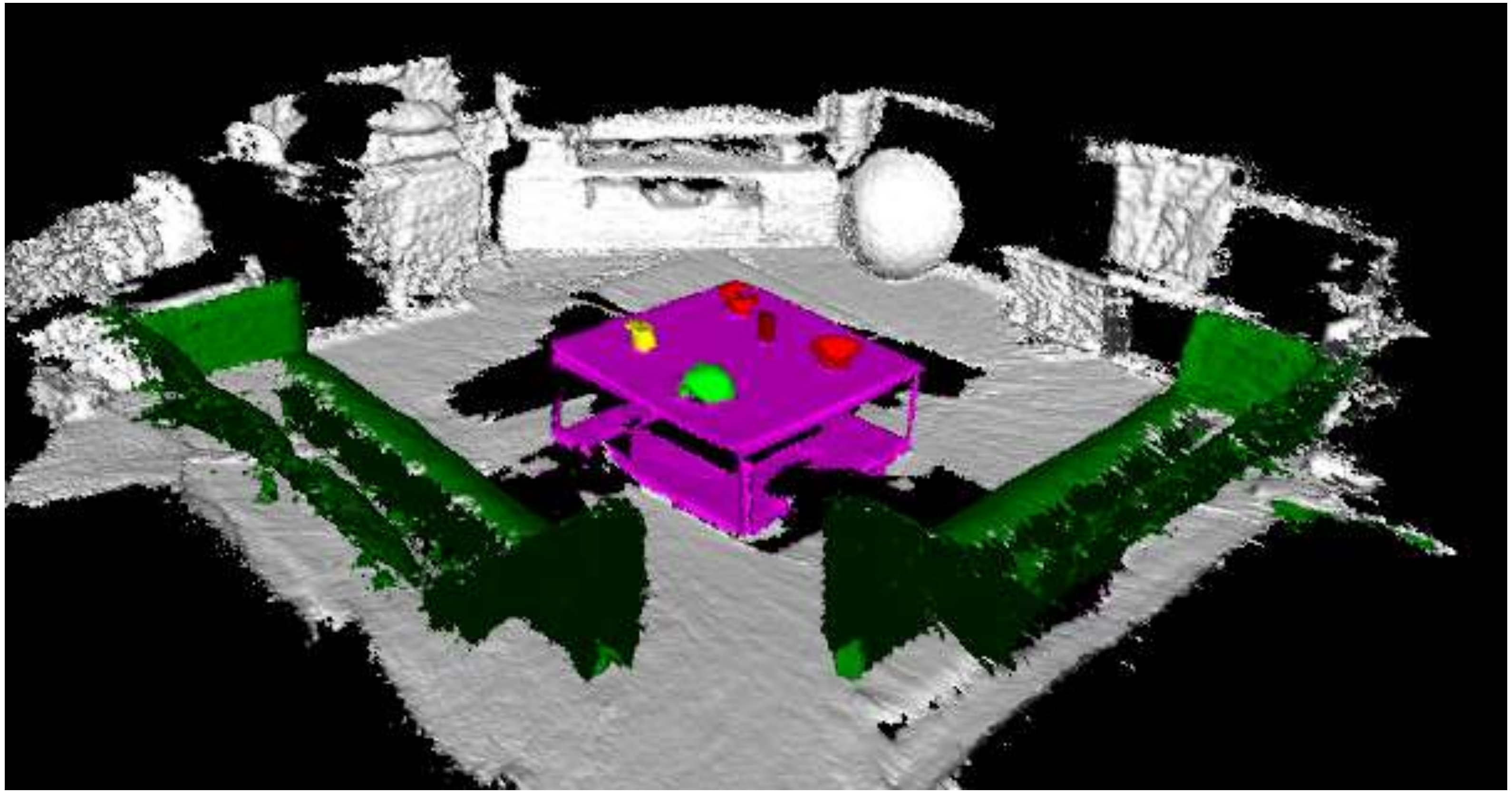
Online Multi-Object Tracking



Y. Xiang, A. Alahi and S. Savarese. Learning to Track: Online Multi-Object Tracking by Decision Making. In ICCV, 2015 (Oral).

Code available online

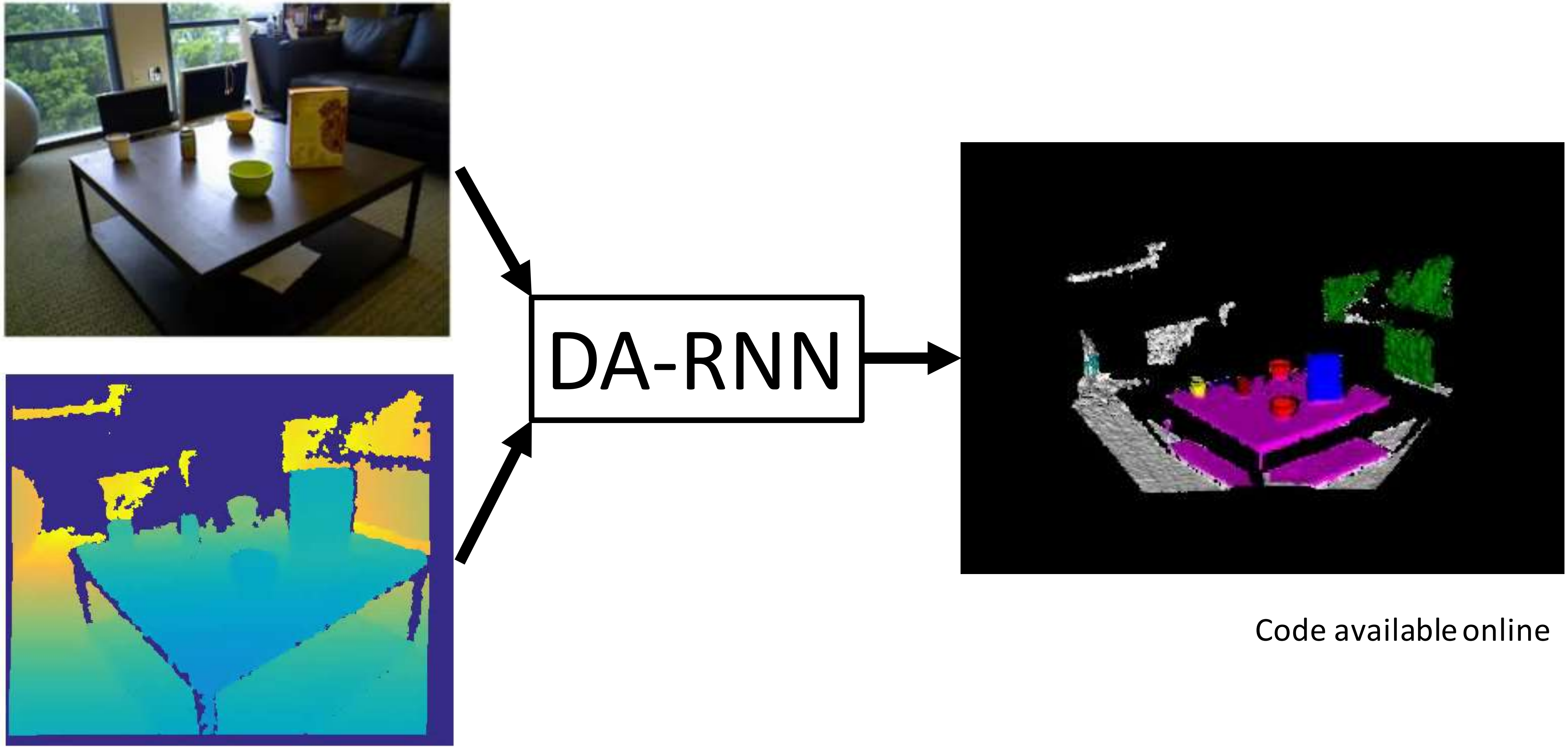
Semantic Mapping (Semantic SLAM)



- ✓ Geometry
- ✓ Semantics
- ✓ Camera poses


LATELINE

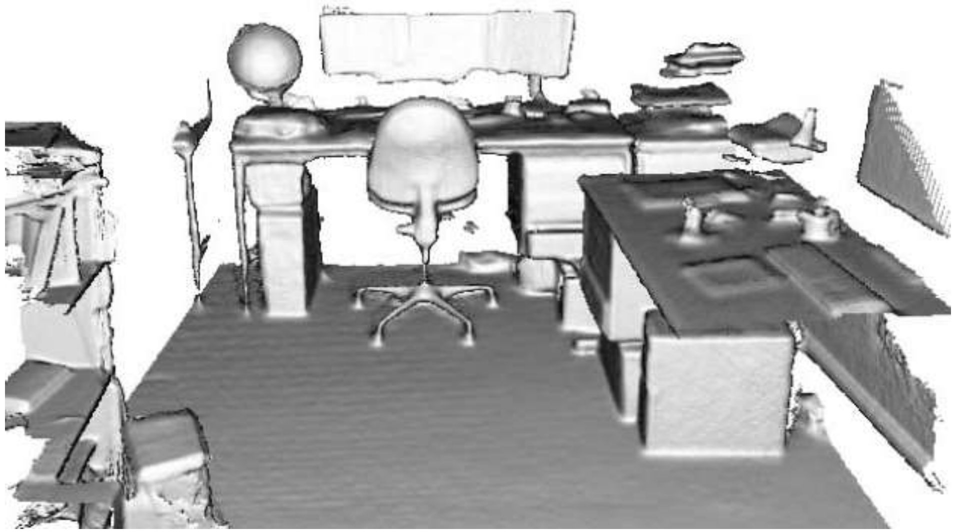
Semantic Mapping with Data Associated Recurrent Neural Networks (DA-RNNs)



Code available online

Y. Xiang and D. Fox. DA-RNN: Semantic Mapping with Data Associated Recurrent Neural Networks. In RSS, 2017.

Related Work: 3D Scene Reconstruction



KinectFusion

- ✓ Geometry
- ✓ Data Association
- ✘ Semantics

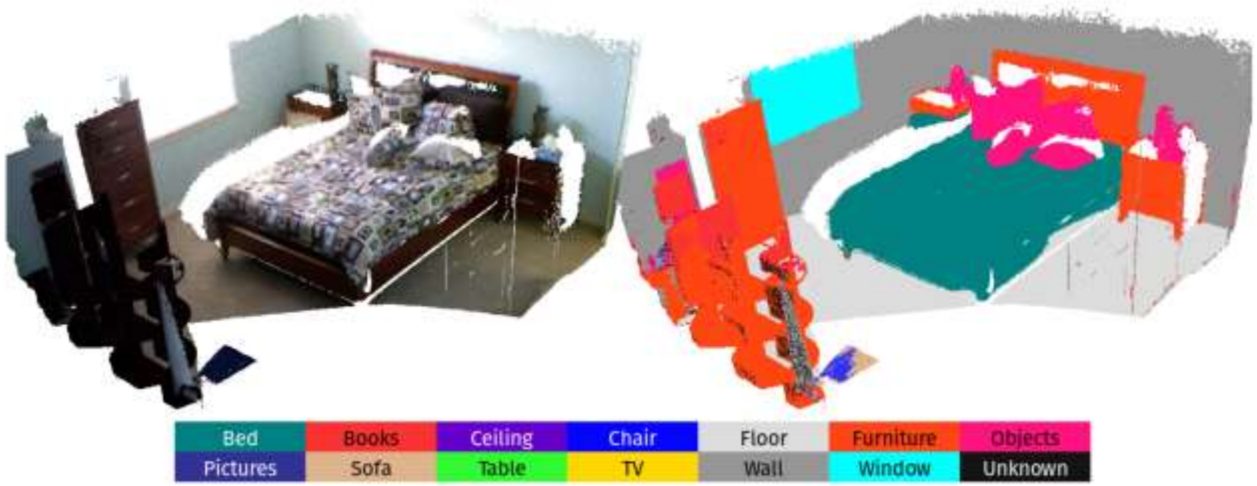
- Newcombe et al., ISMAR'11
- Henry et al., IJRR'12, 3DV'13
- Whelan et al., RSS Workshop'12, RSS'15
- Keller et al., 3DV'13

Related Work: Semantic Labeling

✘ Geometry
✘ Data Association
✓ Semantics

- Long et al., CVPR'12
- Zheng et al., ICCV'15
- Chen et al., ICLR'15
- Badrinarayanan et al., CVPR'15

Related Work: Semantic Mapping

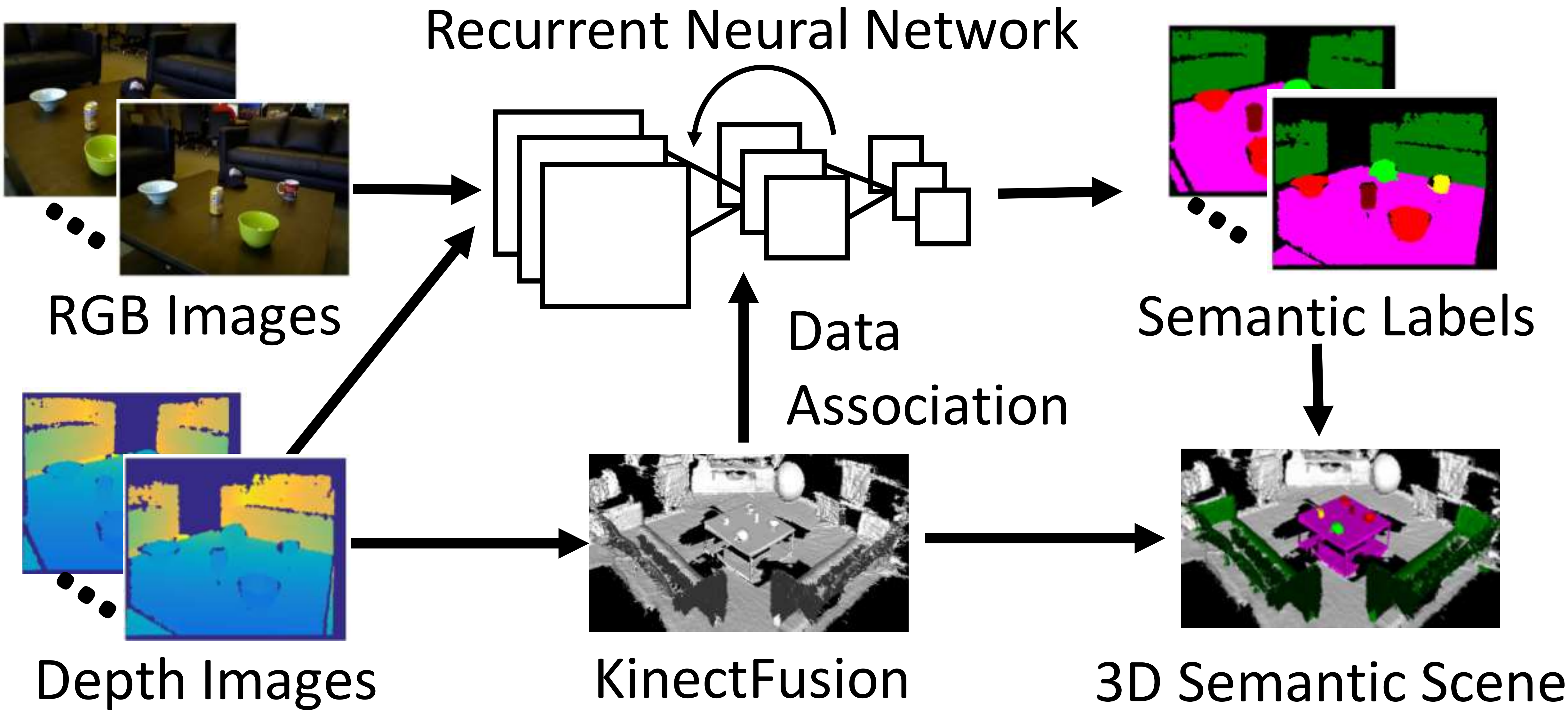


SemanticFusion

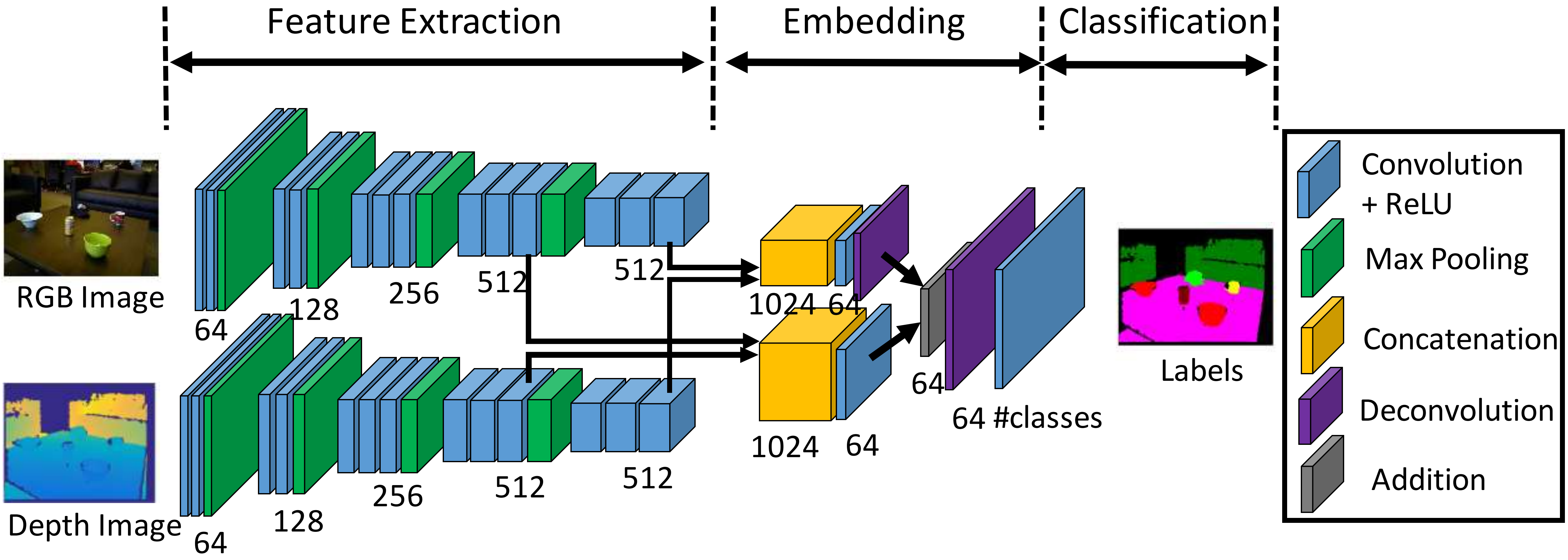
✓ Geometry
✓ Data Association
✓ Semantics

- Salas-Moreno et al., CVPR’13
- McCormac et al., ICRA’17
- Bowman et al. ICRA’17

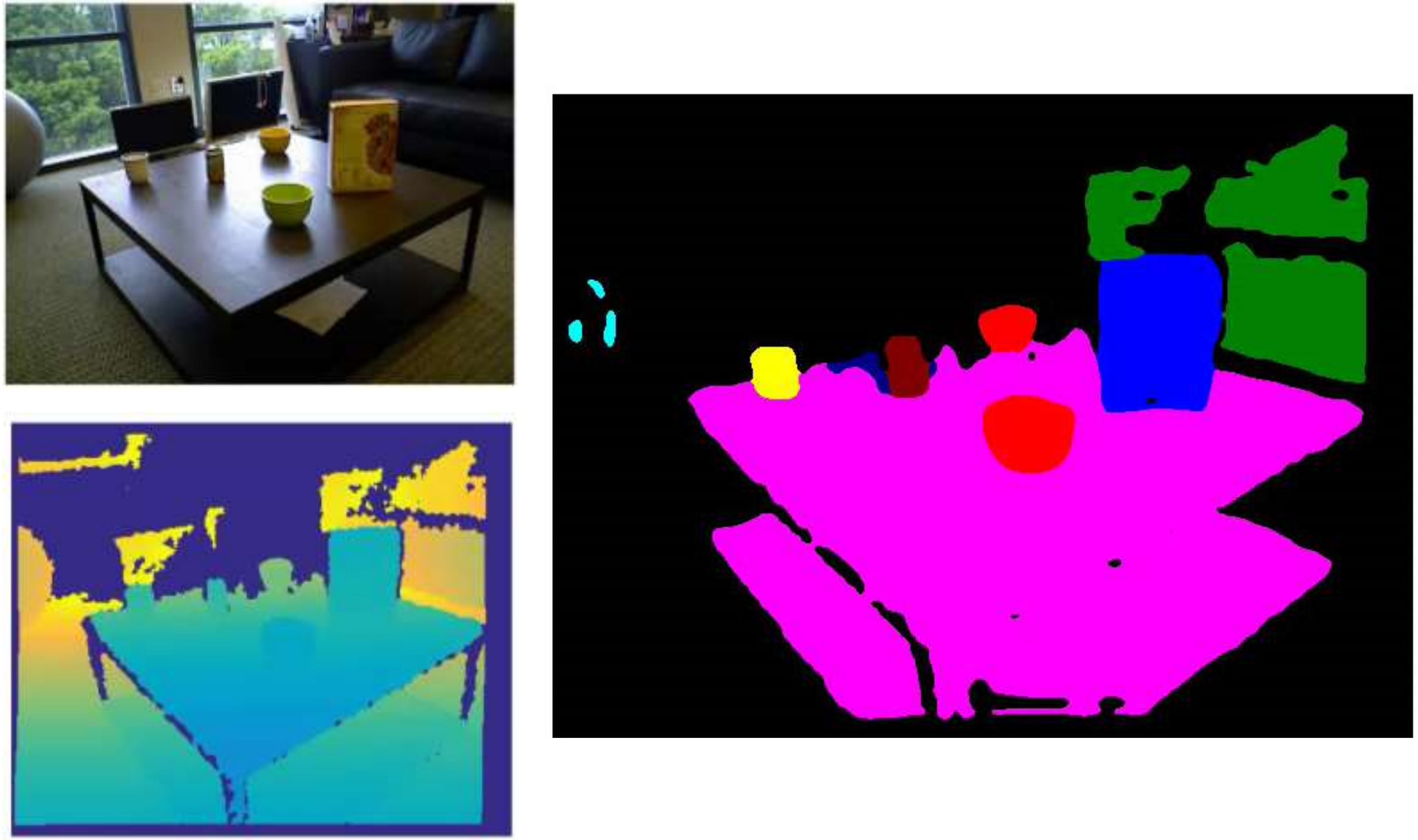
Our Contribution: DA-RNN



Single Frame Labeling with FCNs

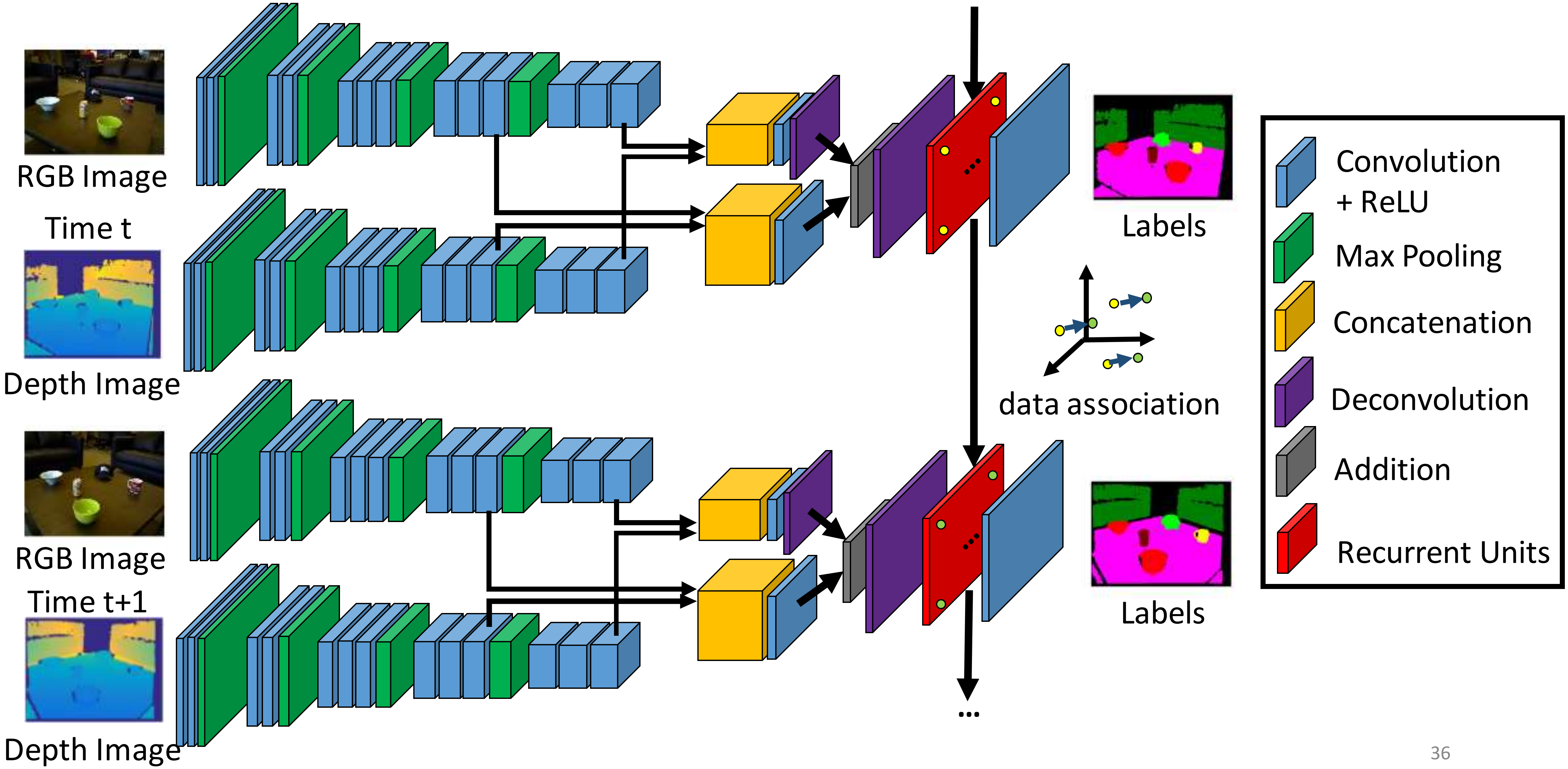


Results on RGB-D Scene Dataset [1]

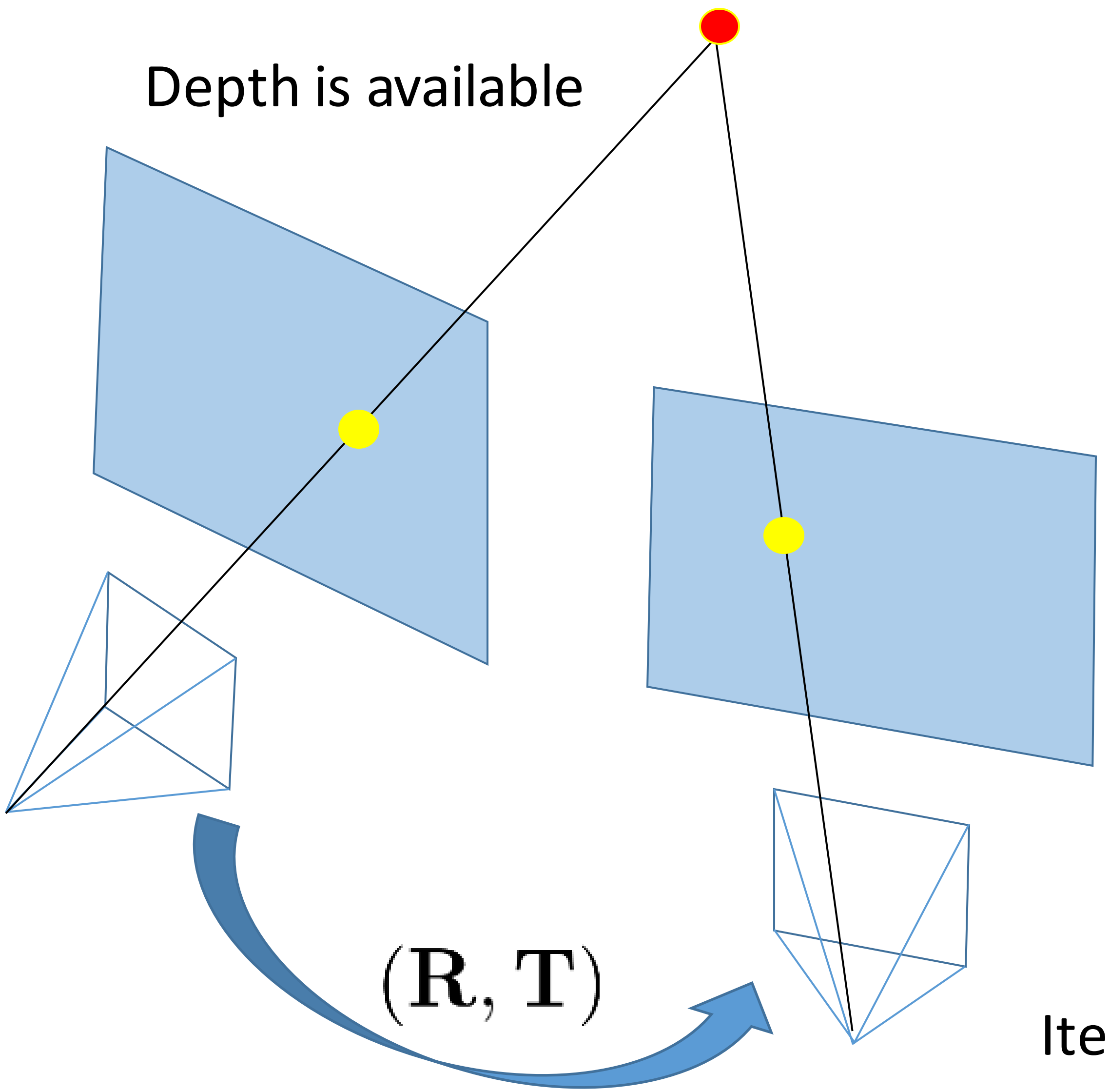


[1] K. Lai, L. Bo and D. Fox. Unsupervised feature learning for 3D scene labeling. In ICRA'14

Video Semantic Labeling with DA-RNNs



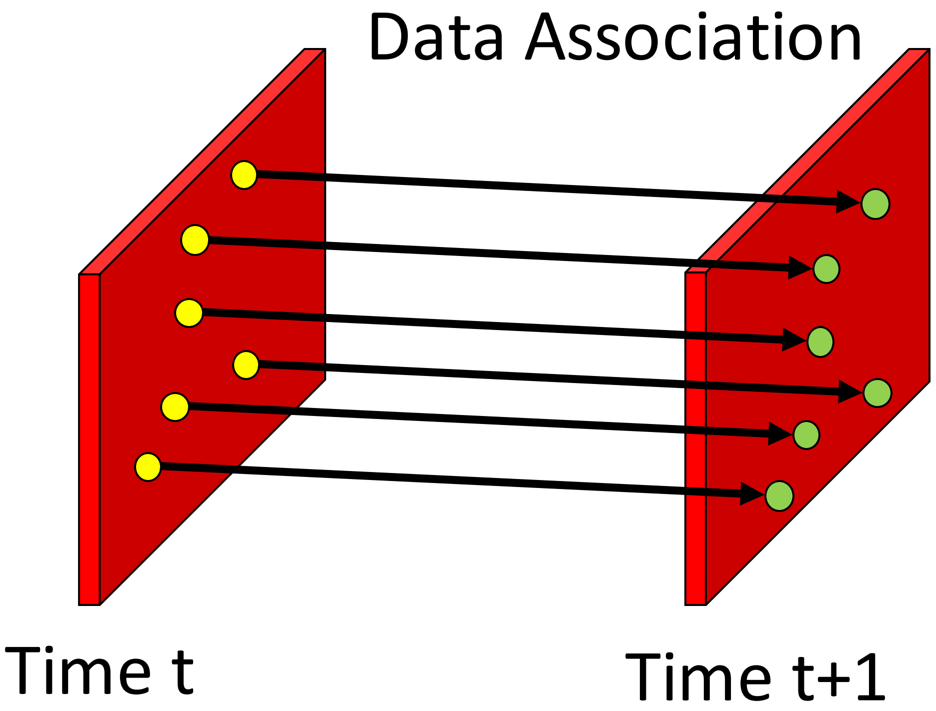
Data Association from KinectFusion



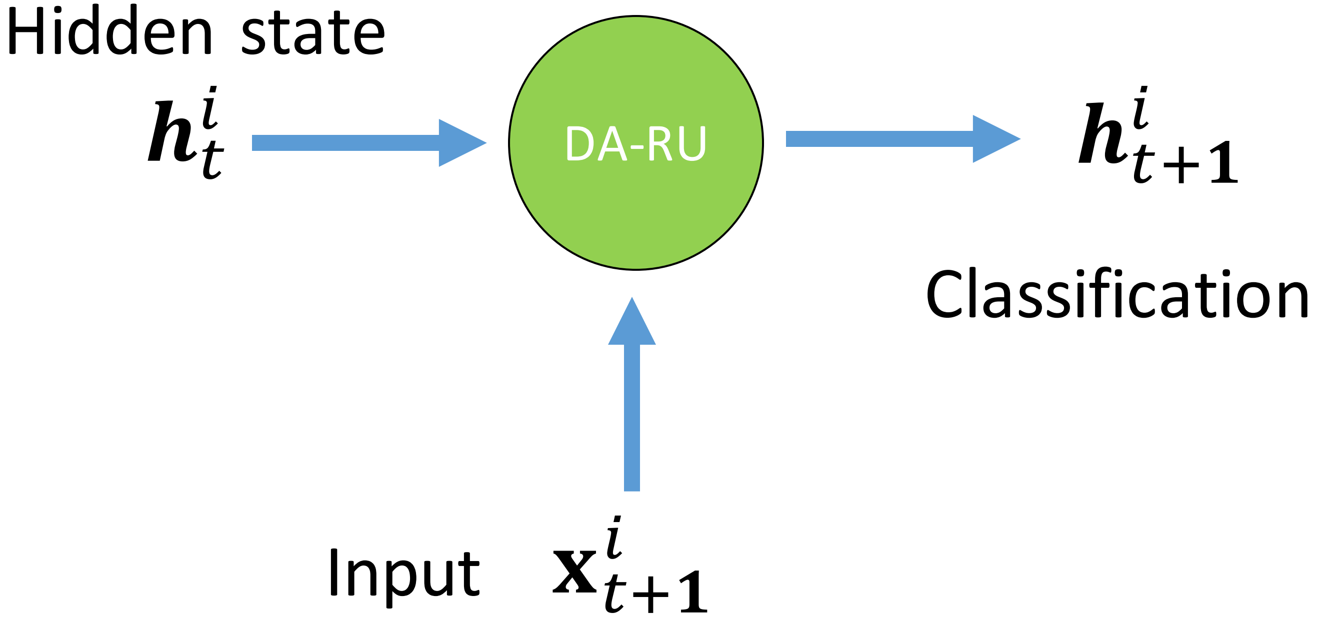
Assumption: static scenes

Iterative Closest Point (ICP)

Data Associated Recurrent Units (DA-RUs)

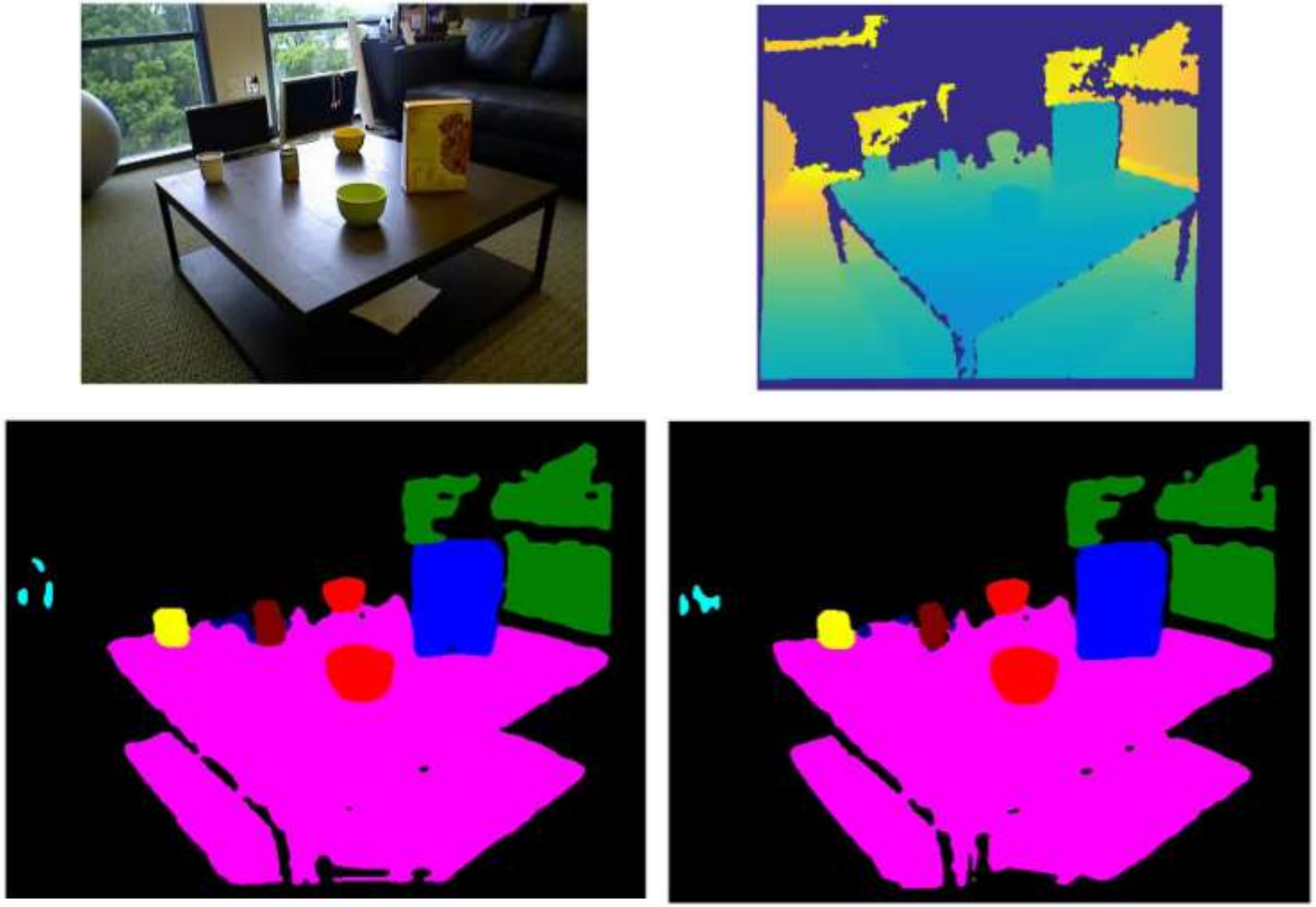


Recurrent layer



Weighted Moving Averaging
with learnable parameters

Results on RGB-D Scene Dataset [1]



FCN DA-RNN

[1] K. Lai, L. Bo and D. Fox. Unsupervised feature learning for 3D scene labeling. In ICRA'14.

Experiments: Datasets

- RGB-D Scene Dataset [1]
  - 14 RGB-D videos of indoor scenes
  - 9 object classes
- ShapeNet Scene Dataset [2]
  - 100 RGB-D videos of virtual table-top scenes
  - 7 object classes

[1] K. Lai, L. Bo and D. Fox. Unsupervised feature learning for 3D scene labeling. In ICRA'14.
[2] Chang et al., ShapeNet: an information-rich 3D model repository. arXiv preprint arXiv:1512.03012, 2015.

Experiments: Comparison on Network Architectures

RGB-D Scenes

Methods	FCN [1]
Background	94.3
Bowl	78.6
Cap	61.2
Cereal Box	80.4
Coffee Mug	62.7
Coffee Table	93.6
Office Chair	67.3
Soda Can	73.5
Sofa	90.8
Table	84.2
MEAN	78.7

Metric: segmentation intersection over union (IoU)

[1] J. Long, E. Shelhamer and T. Darrell. Fully convolutional networks for semantic segmentation. In CVPR’15.

Experiments: Comparison on Network Architectures

RGB-D Scenes

Methods	FCN [1]	Our FCN
Background	94.3	**96.1**
Bowl	78.6	**87.0**
Cap	61.2	**79.0**
Cereal Box	80.4	**87.5**
Coffee Mug	62.7	**75.7**
Coffee Table	93.6	**95.2**
Office Chair	67.3	**71.6**
Soda Can	73.5	**82.9**
Sofa	90.8	**92.9**
Table	84.2	**89.8**
MEAN	78.7	**85.8**

Metric: segmentation intersection over union (IoU)

[1] J. Long, E. Shelhamer and T. Darrell. Fully convolutional networks for semantic segmentation. In CVPR'15.

Experiments: Comparison on Network Architectures

RGB-D Scenes

Methods	FCN [1]	Our FCN	Our GRU-RNN
Background	94.3	96.1	**96.8**
Bowl	78.6	**87.0**	86.4
Cap	61.2	79.0	**82.0**
Cereal Box	80.4	**87.5**	**87.5**
Coffee Mug	62.7	75.7	**76.1**
Coffee Table	93.6	95.2	**96.0**
Office Chair	67.3	71.6	**72.7**
Soda Can	73.5	**82.9**	81.9
Sofa	90.8	92.9	**93.5**
Table	84.2	89.8	**90.8**
MEAN	78.7	85.8	**86.4**

Metric: segmentation intersection over union (IoU)

[1] J. Long, E. Shelhamer and T. Darrell. Fully convolutional networks for semantic segmentation. In CVPR'15.

Experiments: Comparison on Network Architectures

RGB-D Scenes

Methods	FCN [1]	Our FCN	Our GRU-RNN	Our DA-RNN
Background	94.3	96.1	96.8	**97.6**
Bowl	78.6	87.0	86.4	**92.7**
Cap	61.2	79.0	82.0	**84.4**
Cereal Box	80.4	87.5	87.5	**88.3**
Coffee Mug	62.7	75.7	76.1	**86.3**
Coffee Table	93.6	95.2	96.0	**97.3**
Office Chair	67.3	71.6	72.7	**77.0**
Soda Can	73.5	82.9	81.9	**88.7**
Sofa	90.8	92.9	93.5	**95.6**
Table	84.2	89.8	90.8	**92.8**
MEAN	78.7	85.8	86.4	**90.1**

Metric: segmentation intersection over union (IoU)

[1] J. Long, E. Shelhamer and T. Darrell. Fully convolutional networks for semantic segmentation. In CVPR'15.

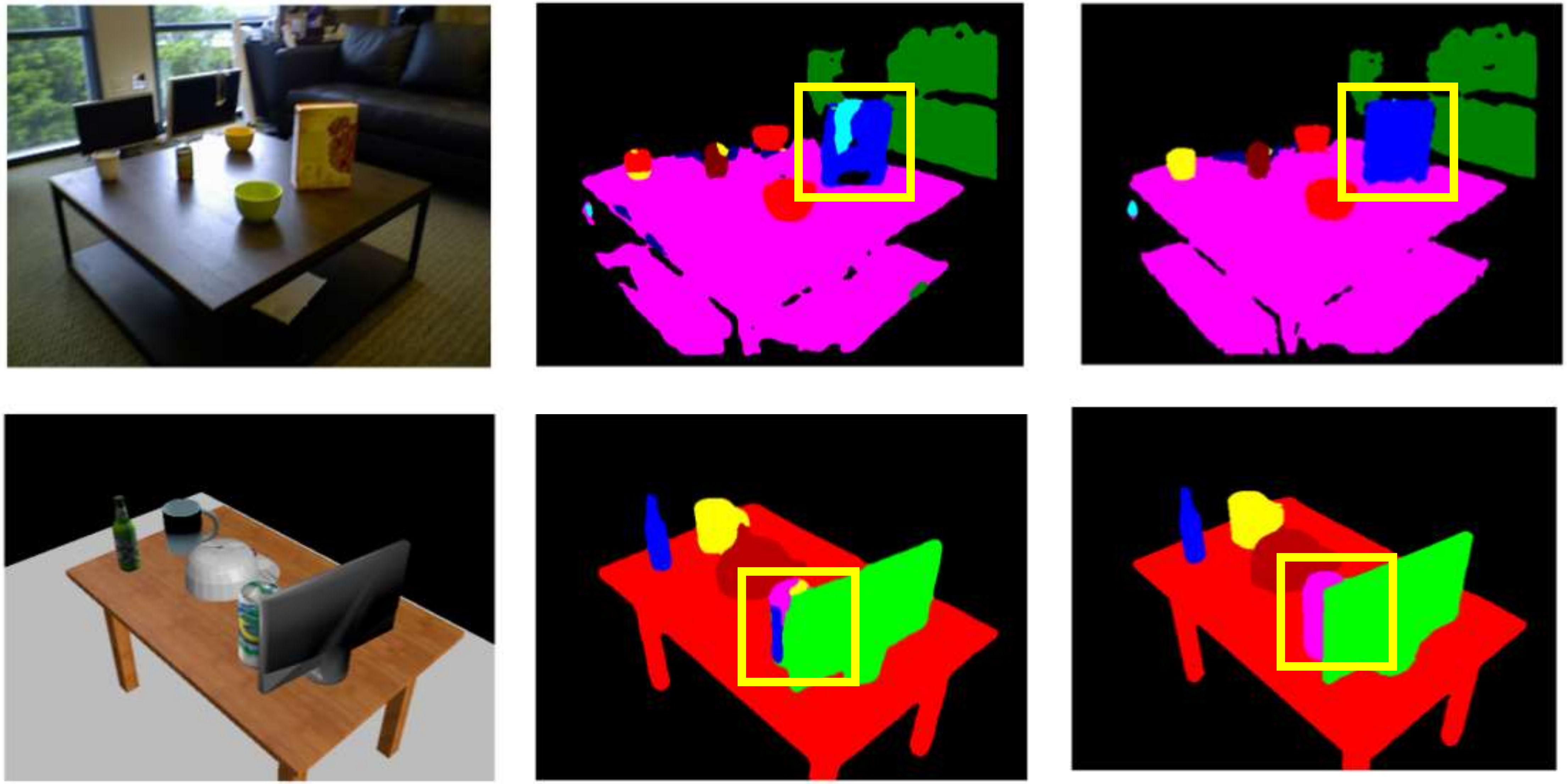
Experiments: Comparison on Network Architectures

RGB-D Scenes

Methods	FCN [1]	Our FCN	Our GRU-RNN	Our DA-RNN	No Data Association
Background	94.3	96.1	96.8	**97.6**	69.1
Bowl	78.6	87.0	86.4	**92.7**	3.6
Cap	61.2	79.0	82.0	**84.4**	9.9
Cereal Box	80.4	87.5	87.5	**88.3**	14.0
Coffee Mug	62.7	75.7	76.1	**86.3**	4.5
Coffee Table	93.6	95.2	96.0	**97.3**	68.0
Office Chair	67.3	71.6	72.7	**77.0**	13.6
Soda Can	73.5	82.9	81.9	**88.7**	5.9
Sofa	90.8	92.9	93.5	**95.6**	35.6
Table	84.2	89.8	90.8	**92.8**	20.1
MEAN	78.7	85.8	86.4	**90.1**	24.4

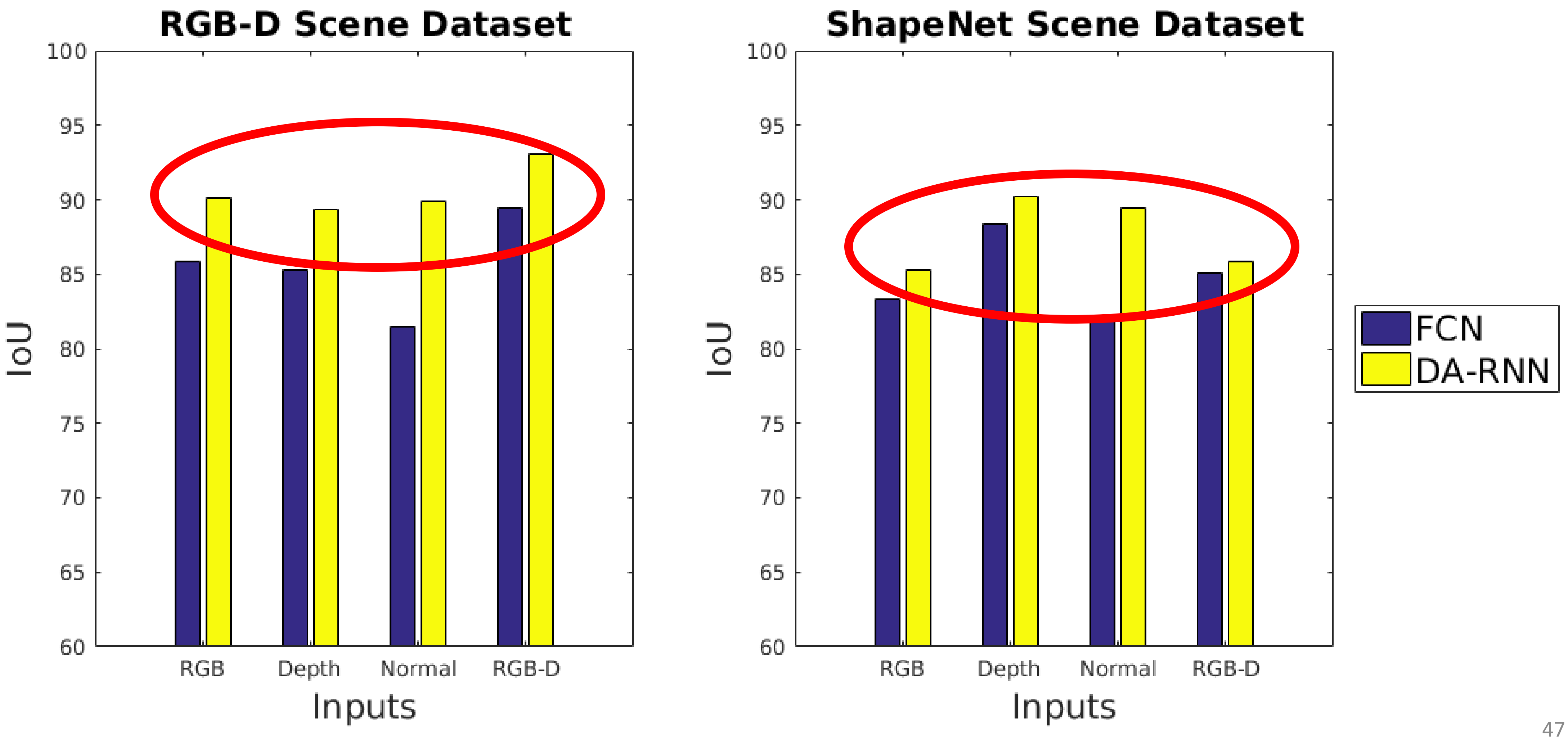
Metric: segmentation intersection over union (IoU)

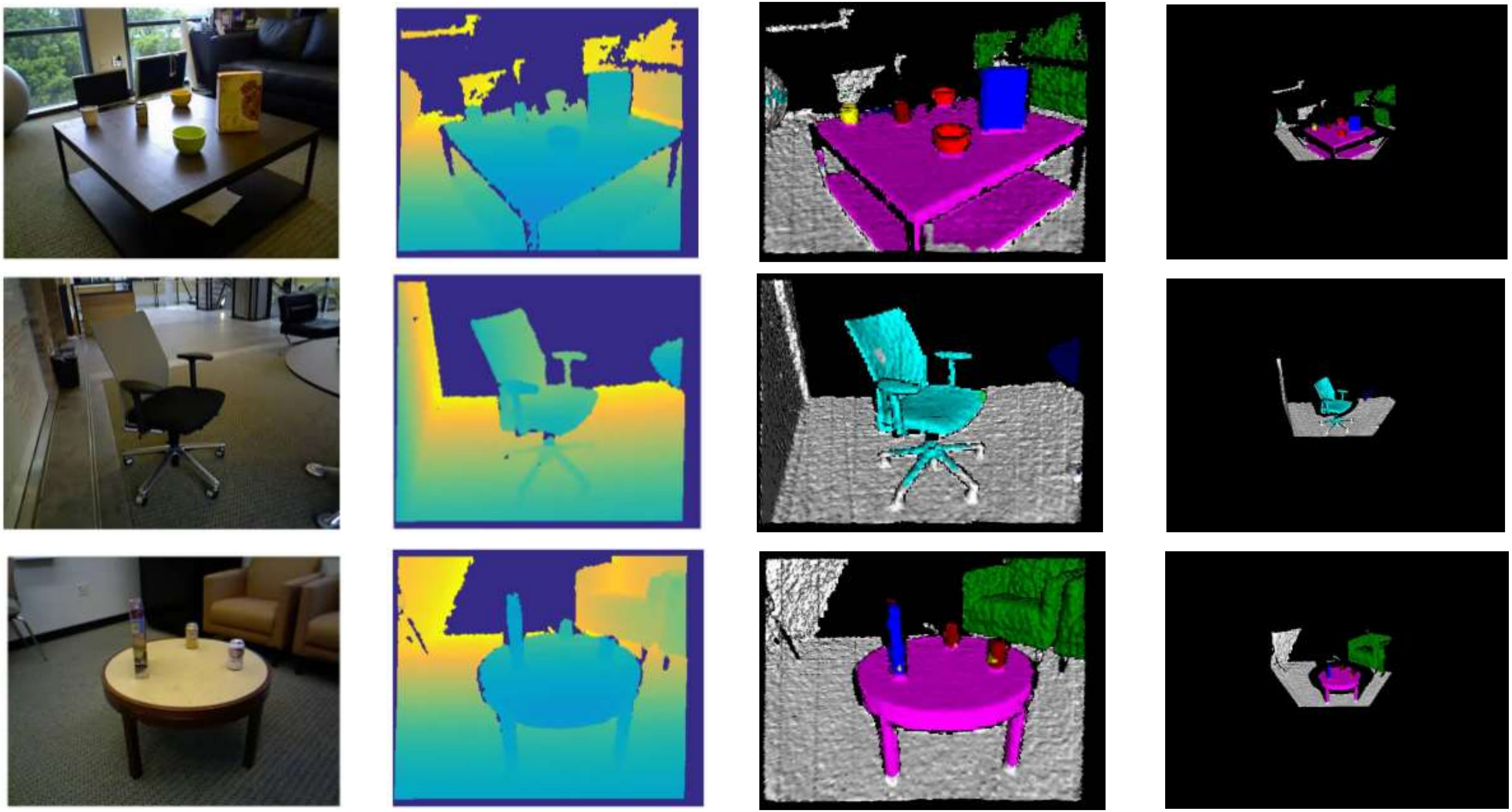
[1] J. Long, E. Shelhamer and T. Darrell. Fully convolutional networks for semantic segmentation. In CVPR'15.



RGB Image　　Our FCN　　Our DA-RNN

Experiments: Analysis on Network Inputs





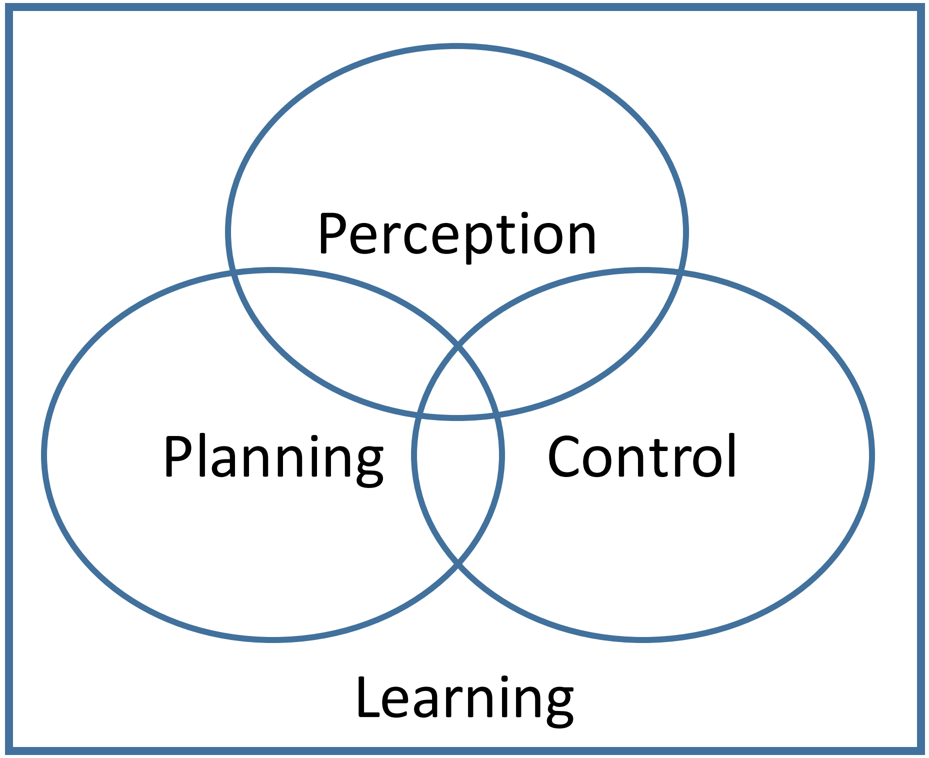
RGB Images Depth Images Semantic Mapping

Conclusion

- 6D Object Pose Estimation from images and videos
- Semantic Mapping from RGB-D videos
- Deep neural networks with geometric representations

Future Work: Perception for Robotics

- 3D object recognition for robot manipulation
- 3D scene understanding for robot navigation
- Combing perception, planning and control
- Reinforcement learning with deep neural networks



Acknowledgements








Thank you!