

# Category-Level 6D Pose and Size Estimation

Ran Ding

Advisor: Jiaxin Wei

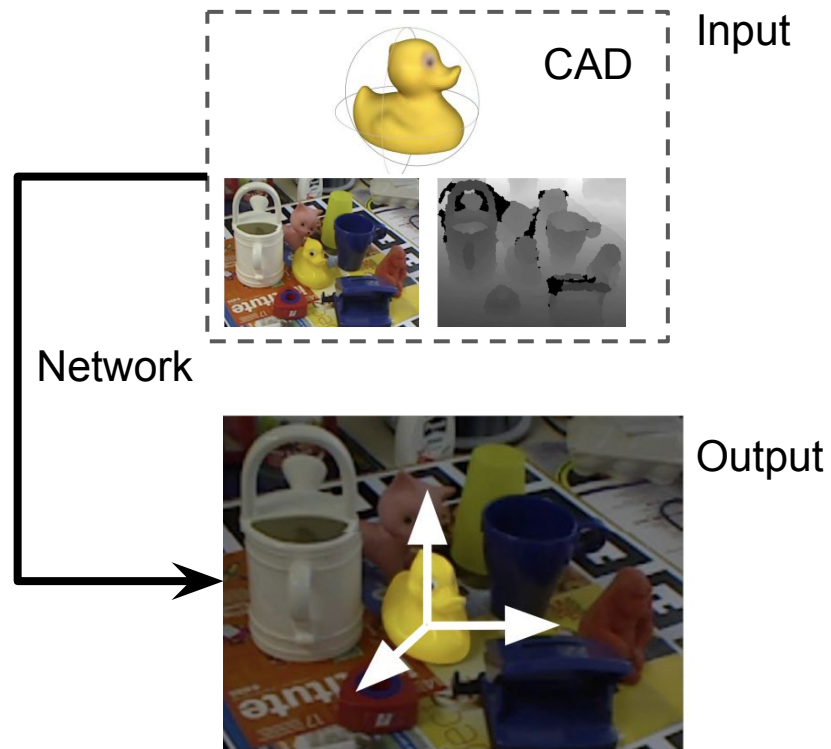


# Overview

1. Motivation and Task
2. RGB-D Based Category-Level Object Pose Estimation
3. RGB Based Category-Level Object Pose Estimation
4. Experiments
  - Benchmark and Metrics
  - Results and Discussion
5. Summary
6. Future Work
  - Predicting Affordance from single depth with Category Shape Priors

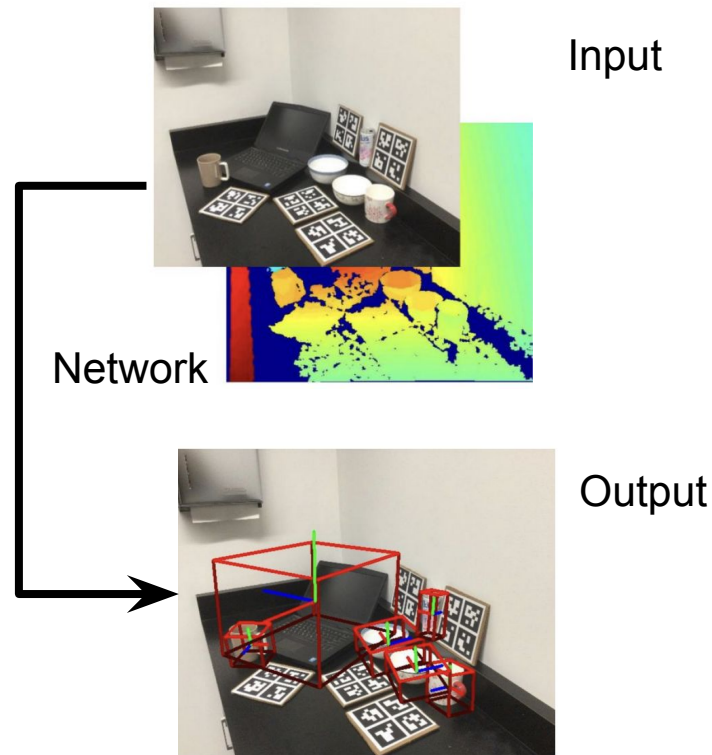
# 1. Instance-Level 6D Pose and Size Estimation

- Task
  - Input: single RGB/RGB-D image and CAD model
  - Output: 6D pose and 3D size of the known object
- Limitation
  - CAD model needed
  - Can't generalize to **unseen** objects

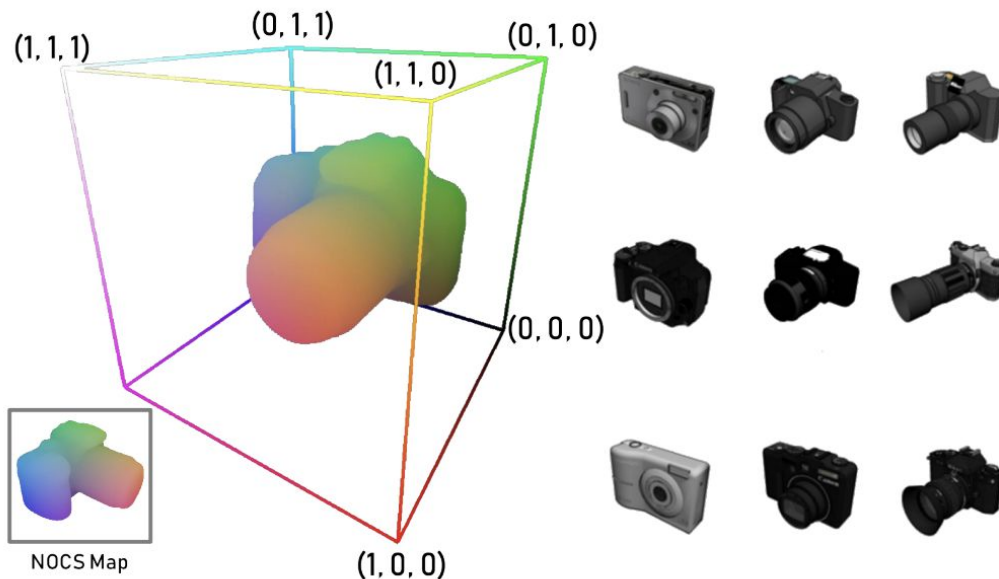


# 1. Category-Level 6D Pose and Size Estimation

- Task
  - Input: single RGB/RGB-D image
  - Output: 6D pose and 3D size of unknown object of the known category
  - Wide Applications in robotics and VR/AR
- Challenges
  - Intra-class shape variation
  - Lack large scale dataset



## 2. Normalized Object Coordinate Space (NOCS)



Rotation and Translation Recovery:

$$\hat{P} = P - \bar{P}, \hat{Q} = Q - \bar{Q}$$

$$H = \hat{P}\hat{Q}^T, H = U\Sigma V^T$$

$$R = VU^T$$

$$T = \bar{Q} - R\bar{P}$$

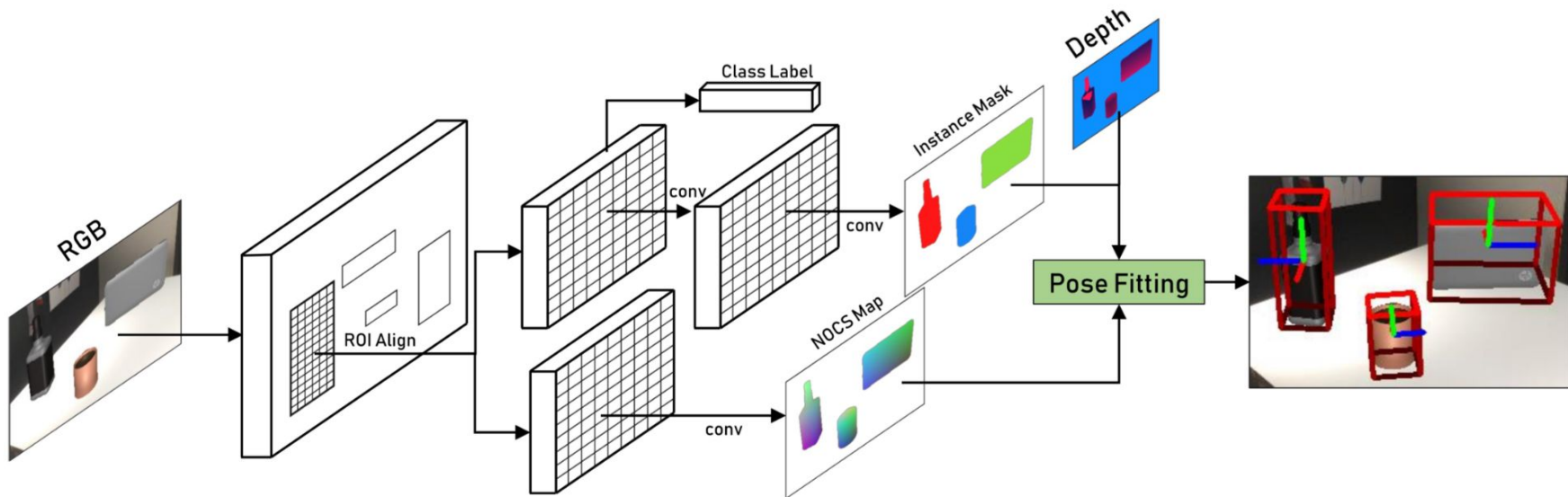
NOCS Regression Loss:

$$L(\mathbf{y}, \mathbf{y}^*) = \frac{1}{n} \begin{cases} 5(\mathbf{y} - \mathbf{y}^*)^2, & |\mathbf{y} - \mathbf{y}^*| \leq 0.1 \\ |\mathbf{y} - \mathbf{y}^*| - 0.05, & |\mathbf{y} - \mathbf{y}^*| > 0.1 \end{cases},$$

$$\forall \mathbf{y} \in N, \mathbf{y}^* \in N_p,$$

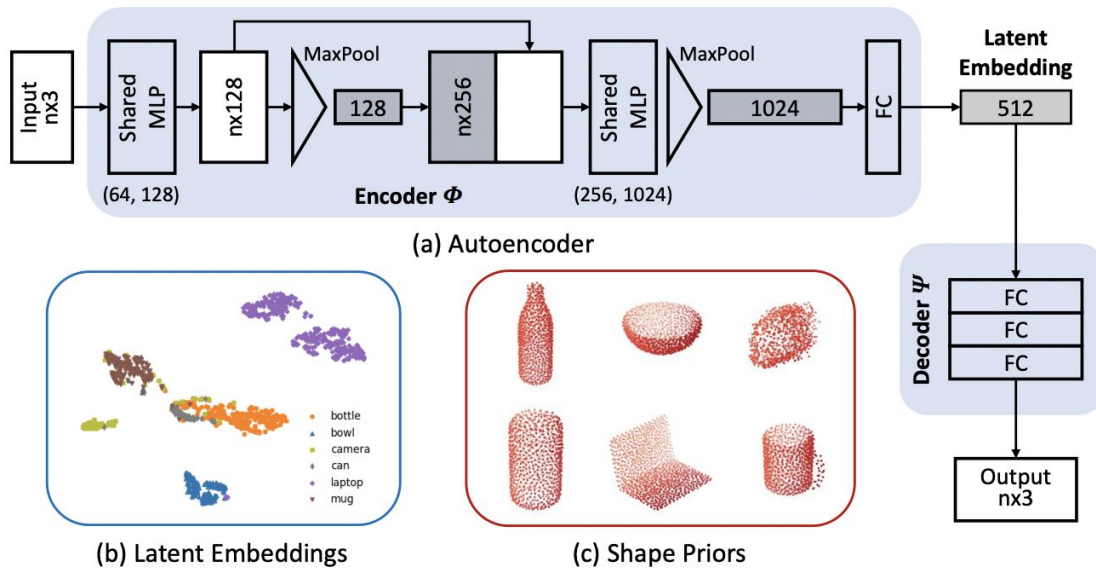
[1]. Wang, He, et al. "Normalized object coordinate space for category-level 6d object pose and size estimation." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2019.

## 2. Normalized Object Coordinate Space (NOCS)



[1]. Wang, He, et al. "Normalized object coordinate space for category-level 6d object pose and size estimation." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2019.

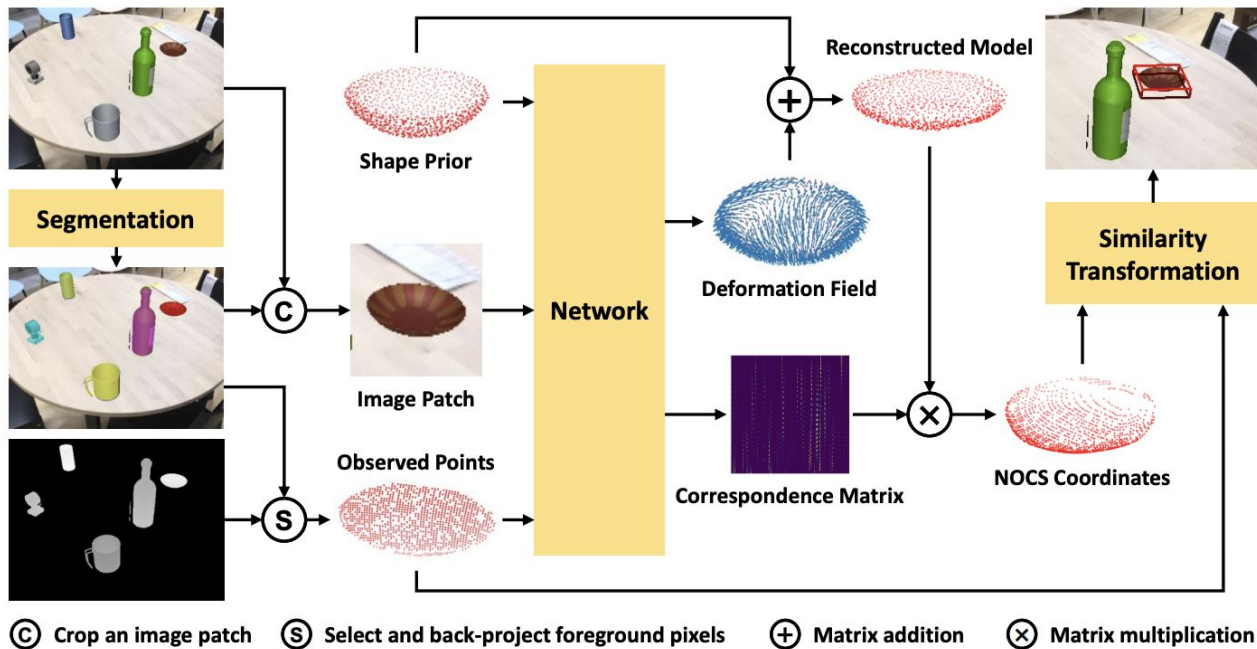
## 2. Shape Prior Deformation (SPD)



$$d_{CD}(M_c^i, \hat{M}_c^i) = \sum_{x \in M_c^i} \min_{y \in \hat{M}_c^i} \|x - y\|_2^2 + \sum_{y \in \hat{M}_c^i} \min_{x \in M_c^i} \|x - y\|_2^2. \quad (2)$$

[2]. Tian, Meng, Marcelo H. Ang, and Gim Hee Lee. "Shape prior deformation for categorical 6d object pose and size estimation." *Computer Vision—ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020*,

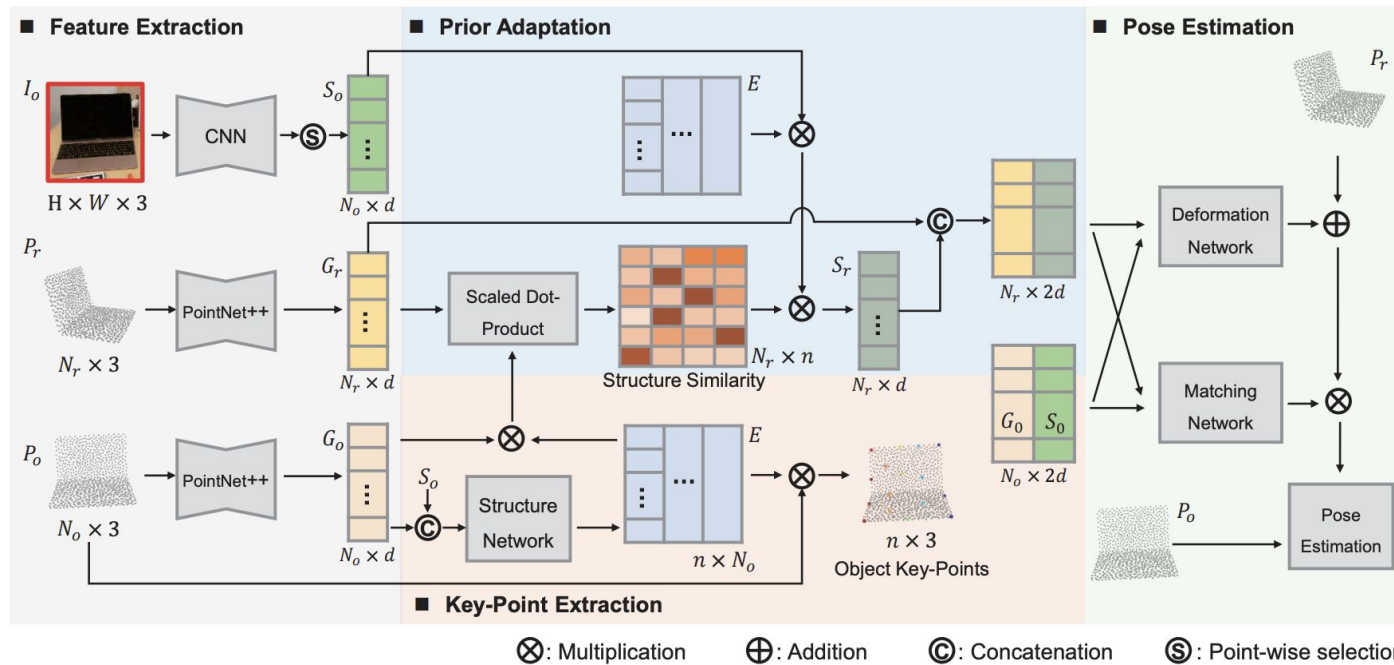
## 2. Shape Prior Deformation (SPD)



[2]. Tian, Meng, Marcelo H. Ang, and Gim Hee Lee. "Shape prior deformation for categorical 6d object pose and size estimation." *Computer Vision—ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020*,

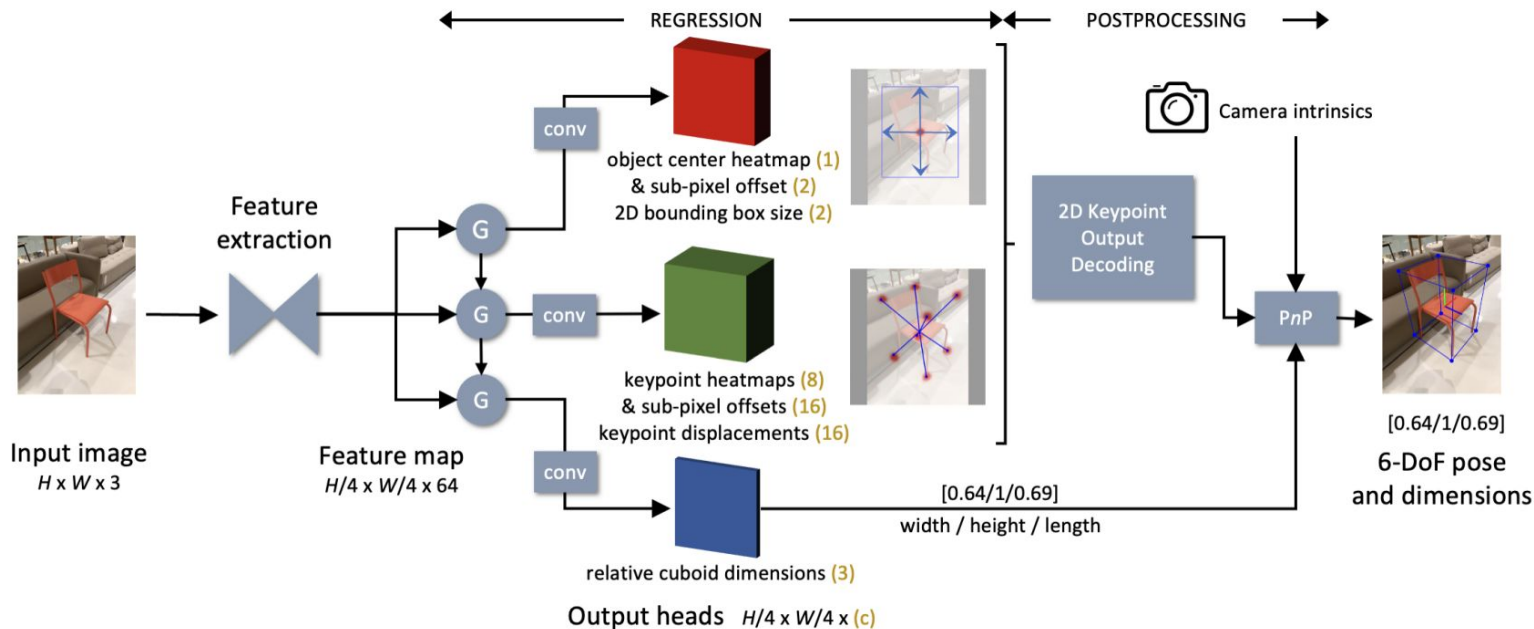


## 2. Structure-Guided Prior Adaptation (SGPA)



[3]. Chen, Kai, and Qi Dou. "Sgpa: Structure-guided prior adaptation for category-level 6d object pose estimation." *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2021.

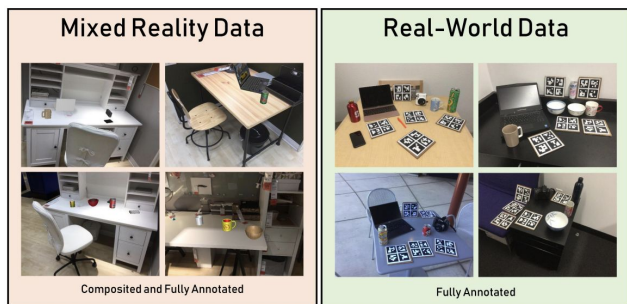
# 3. RGB Based Category-Level Object Pose Estimation



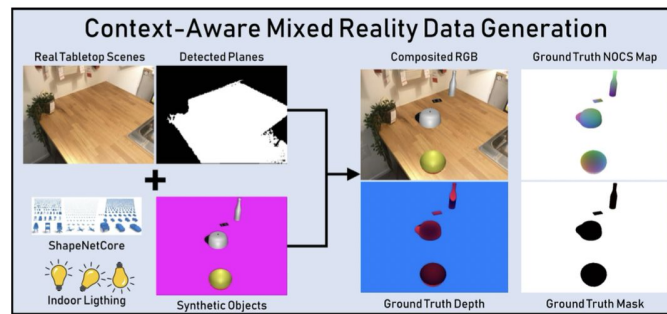
[4]. Lin, Yunzhi, et al. "Single-stage keypoint-based category-level object pose estimation from an RGB image." 2022 International Conference on Robotics and Automation (ICRA). IEEE, 2022.

## 4. Experiments

- Common Benchmark
  - CAMERA25 (6 Categories, 184 Instances, 300K images), REAL275 (6 Categories, 24 Instances, 6K images)
- Evaluation Metrics
  - 3D Size Estimation: IoU (25, 50, 75)
  - 6D Pose Estimation: Rotation Error, Translation Error (5 degree, 10 degree, 5cm, 10cm)



CAMERA25 and REAL75 Data



Data Generation

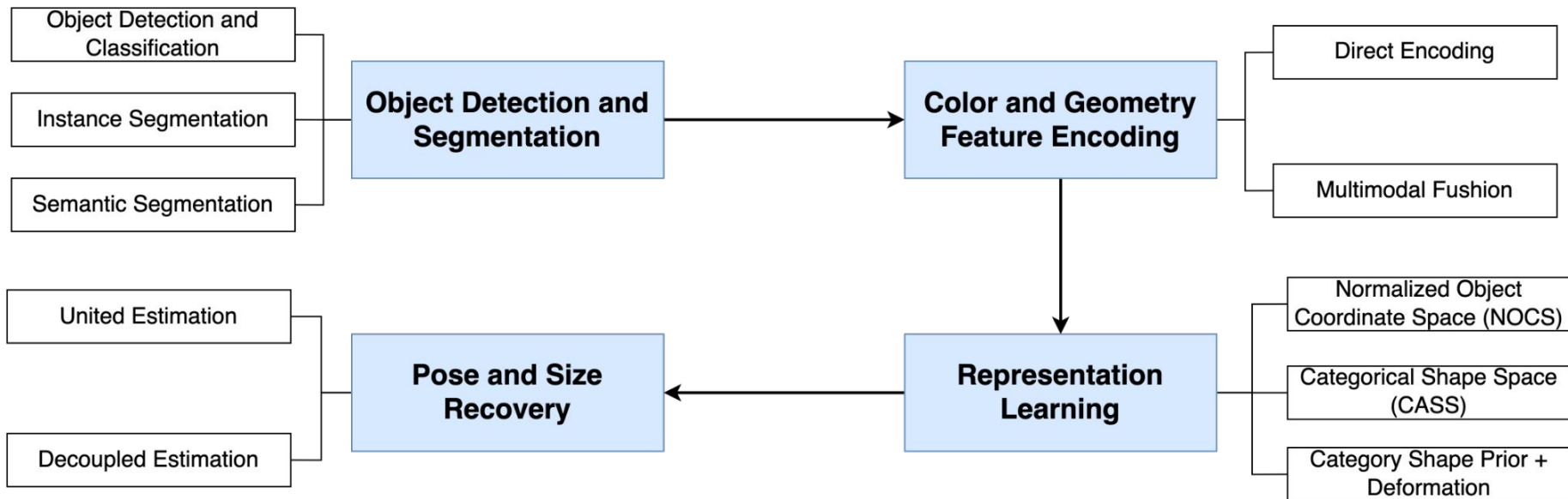
## 4. Evaluation results on REAL275 and CAMERA25

Methods	IOU 0.5	IOU 0.75	5deg2cm	5deg5cm	10deg2cm	10deg5cm
NOCS [1]	78 (83.9)	30.1 (69.5)	7.2 (32.3)	10 (40.9)	13.8 (48.2)	25.2 (64.6)
SPD [2]	77.3 ( <b>93.2</b> )	53.2 (83.1)	19.3 (54.3)	21.4 (59)	43.2 (73.3)	54.1 (81.5)
SGPA [3]	<b>80.1 (93.2)</b>	<b>61.9 (88.1)</b>	<b>35.9 (70.7)</b>	<b>39.6 (74.5)</b>	<b>61.3 (82.7)</b>	<b>70.7 (88.4)</b>

\* The results in parentheses come from CAMERA 25

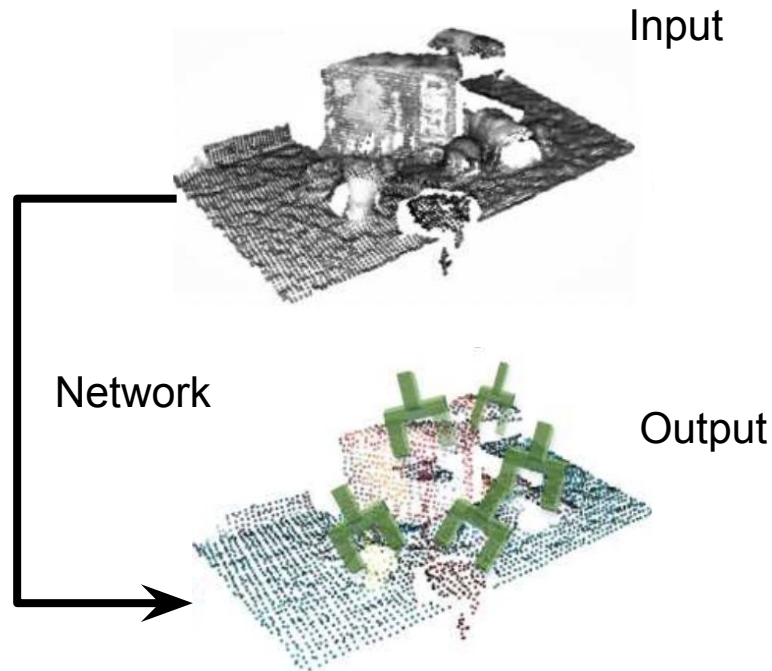
\* RePoNet-sup[4] refers to the RePoNet trained in fully supervised setting

# 5. Summary

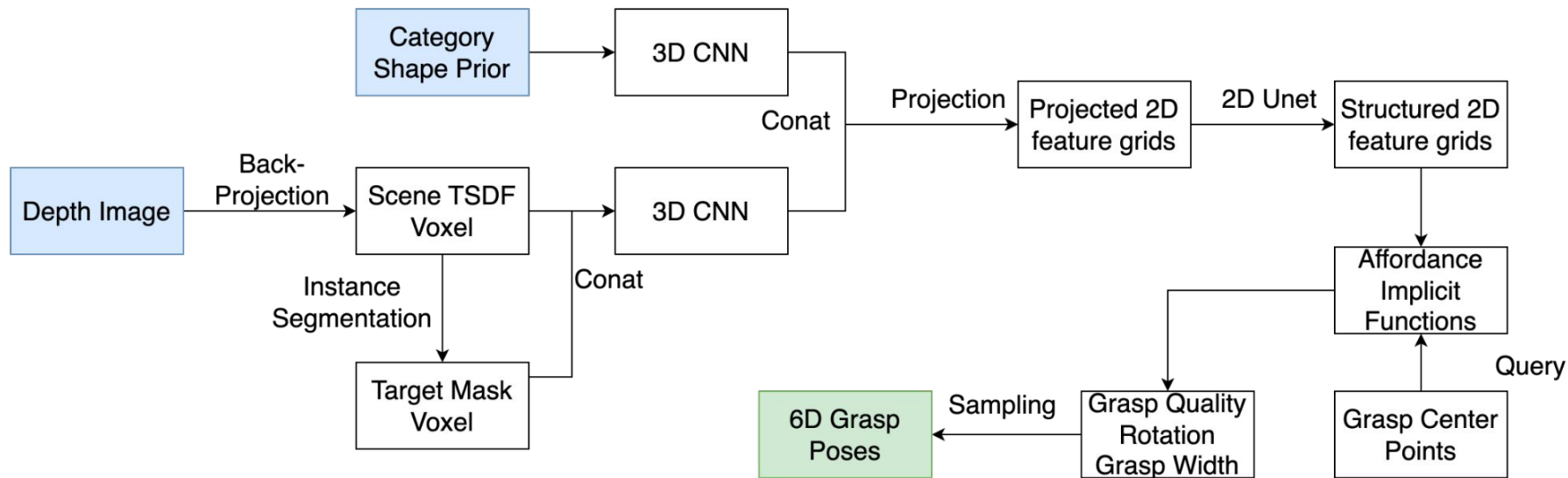


## 6. Future Work: Robot Grasp Pose Estimation

- Motivation
  - Core task in robotics and object level perception
- Task
  - Input: a single Depth image/RGB-D image of the cluttered scene
  - Output: 6D Pose and width of the grasps for the target object



# 6. Predicting Target Object Affordance from single depth image with Category Shape Prior



# References

- [1]. Wang, He, et al. "Normalized object coordinate space for category-level 6d object pose and size estimation." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2019.
- [2]. Tian, Meng, Marcelo H. Ang, and Gim Hee Lee. "Shape prior deformation for categorical 6d object pose and size estimation." *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXI 16*. Springer International Publishing, 2020.
- [3]. Chen, Kai, and Qi Dou. "Sgpa: Structure-guided prior adaptation for category-level 6d object pose estimation." *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2021.
- [4]. Lin, Yunzhi, et al. "Single-stage keypoint-based category-level object pose estimation from an RGB image." *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022.



Thank you for listening!