Summary and Outlook for 6D Object Pose Estimation on Point Clouds

Ge Gao, 19.05.2020, Hamburg

Overview

- 6D object pose estimation via supervised learning on point clouds
- Extension: handling object’s rotational symmetry
- Extension: delving deeper into 6D object pose estimation
- Extension: online data augmentation

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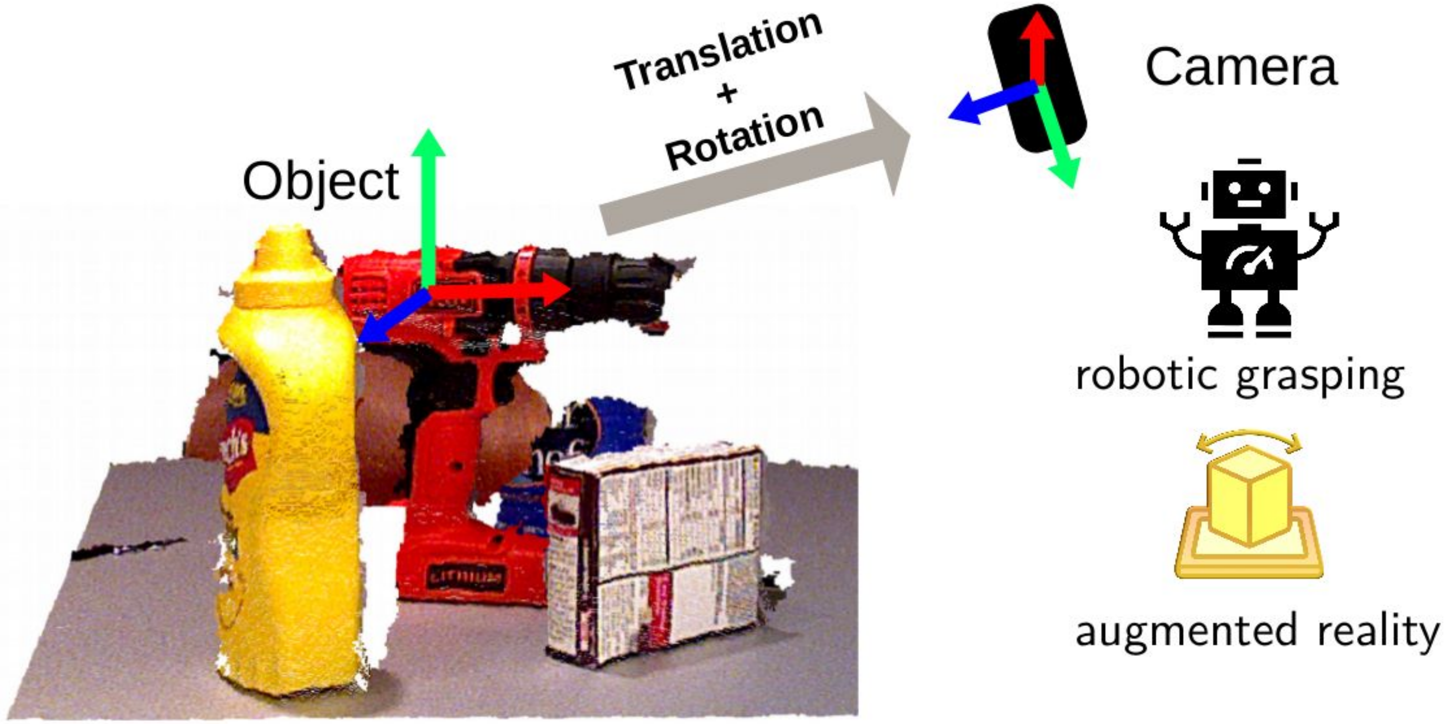
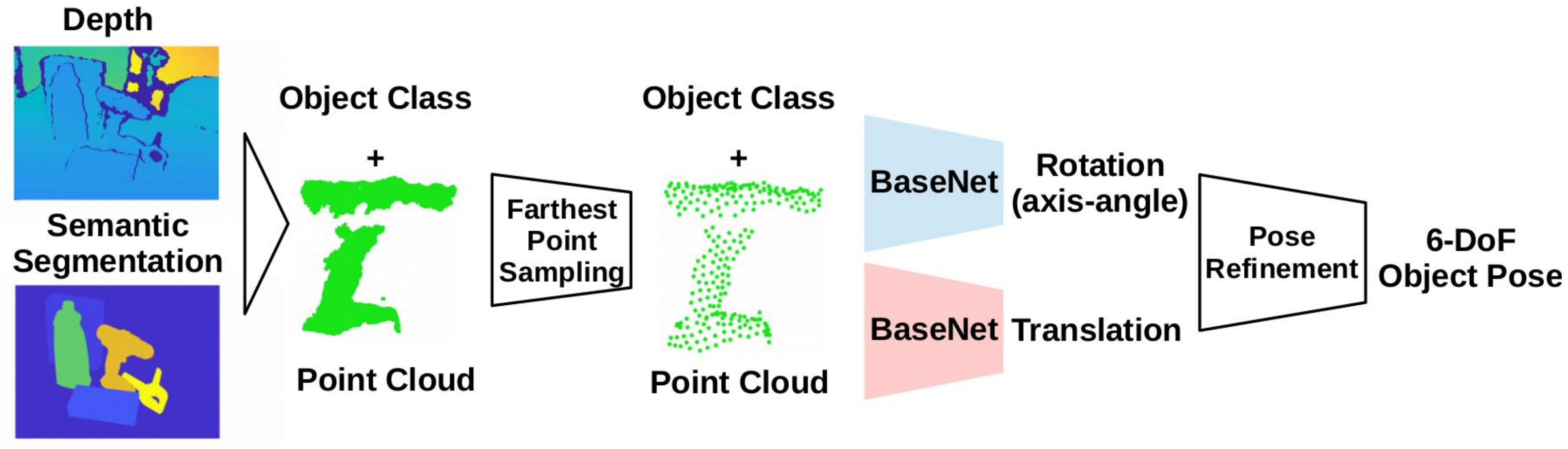
Motivation: 6-DoF Object Pose Estimation



CloudPose: Overview



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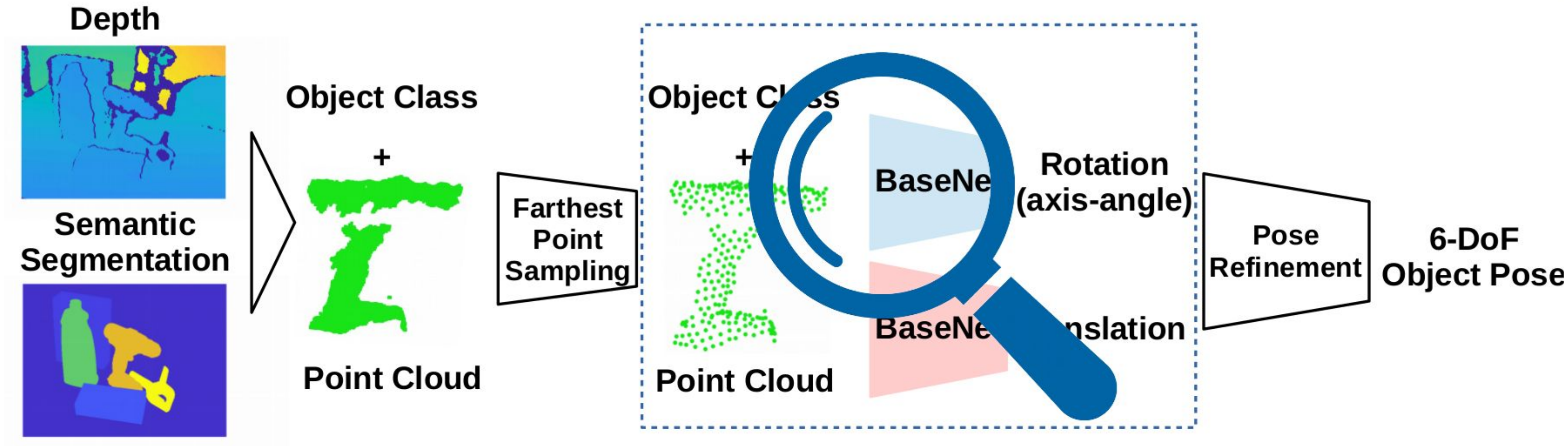
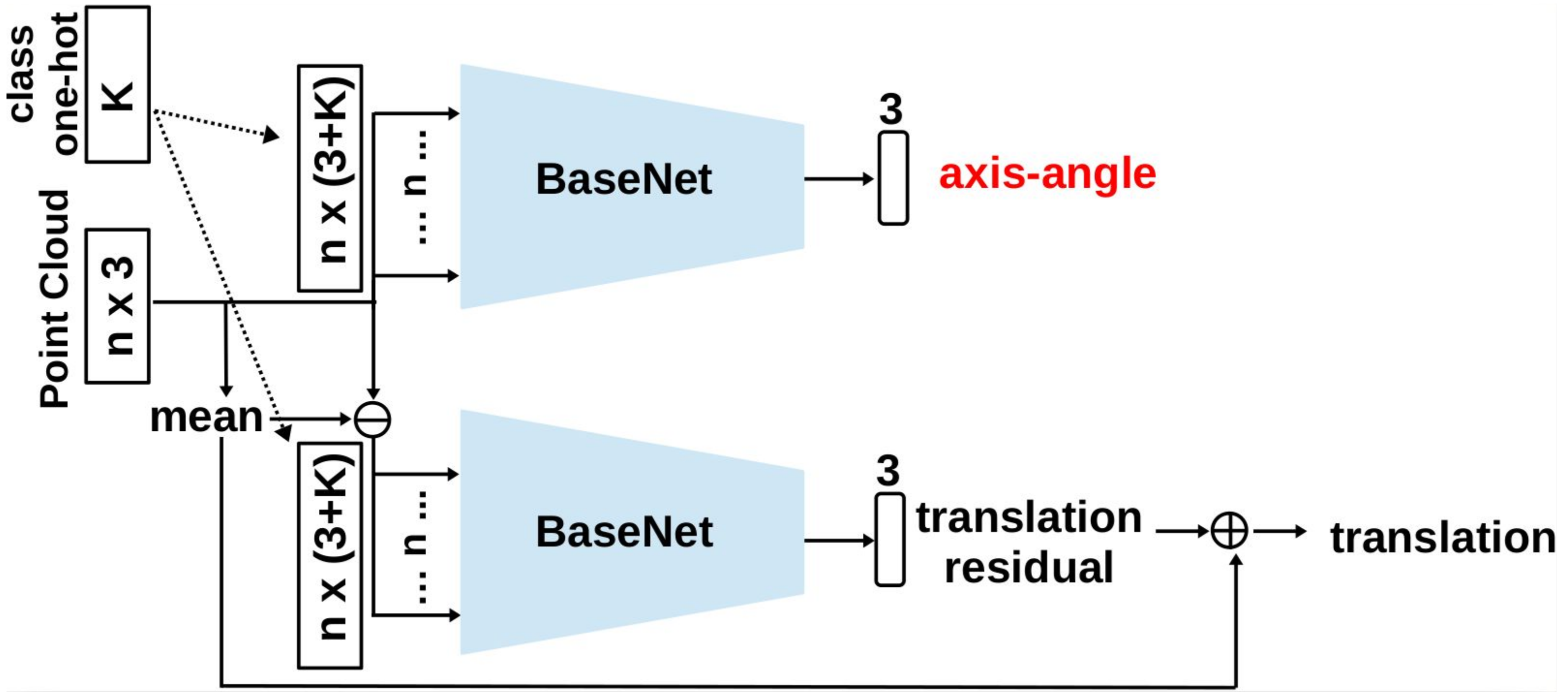
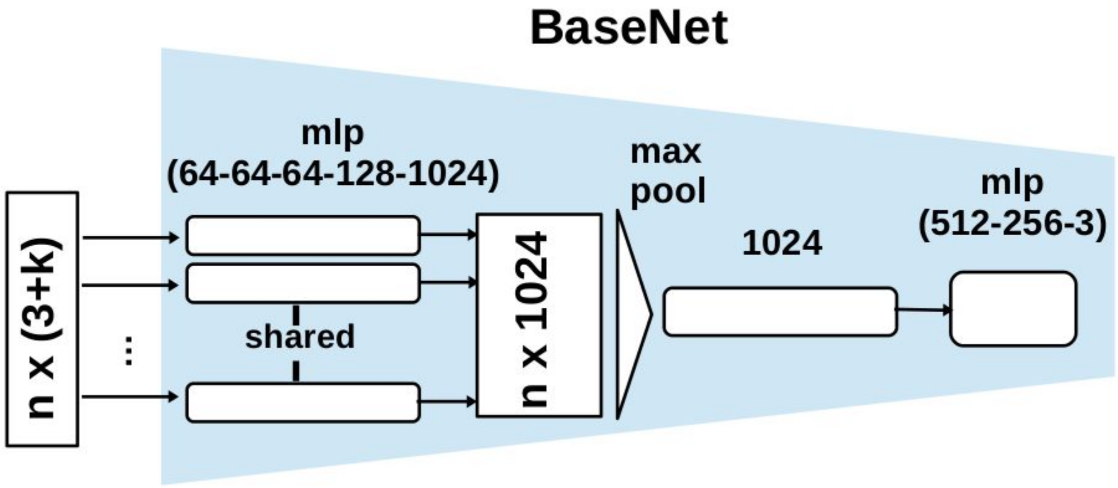


CloudPose: Details



CloudPose: Details

Adapted from PointNet by Qi et al.



C. R. Qi and H. Su and K. Mo and L. J. Guibas. PointNet: Deep learning on point sets for 3D classification and segmentation, in CVPR, 2017.

Performance Video

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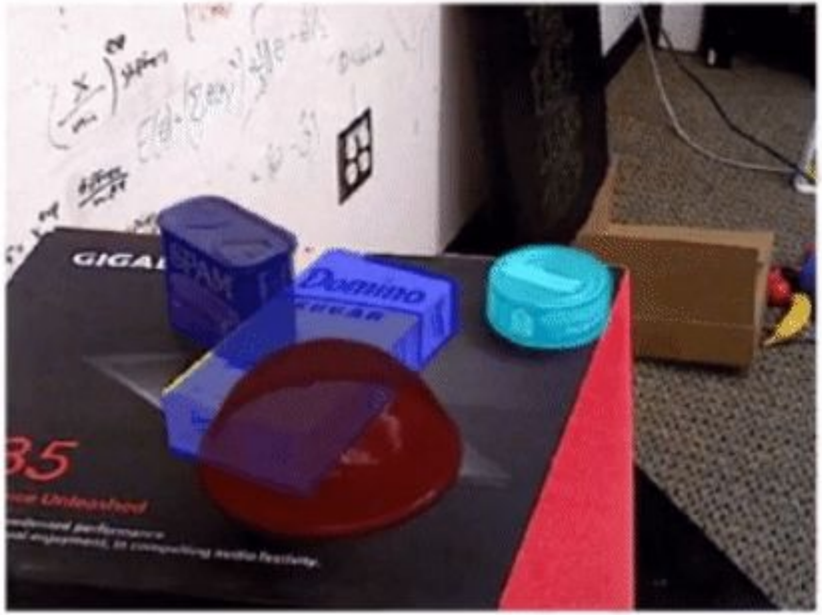
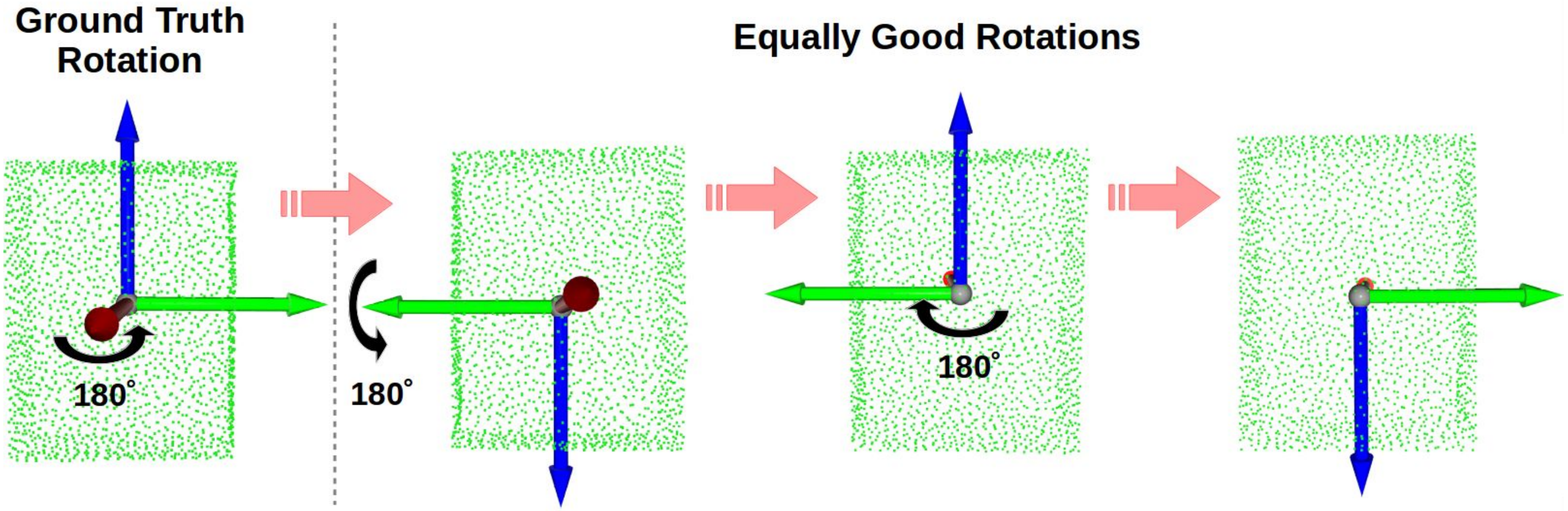
Problem (very likely) of Object Rotational Symmetry

Ours

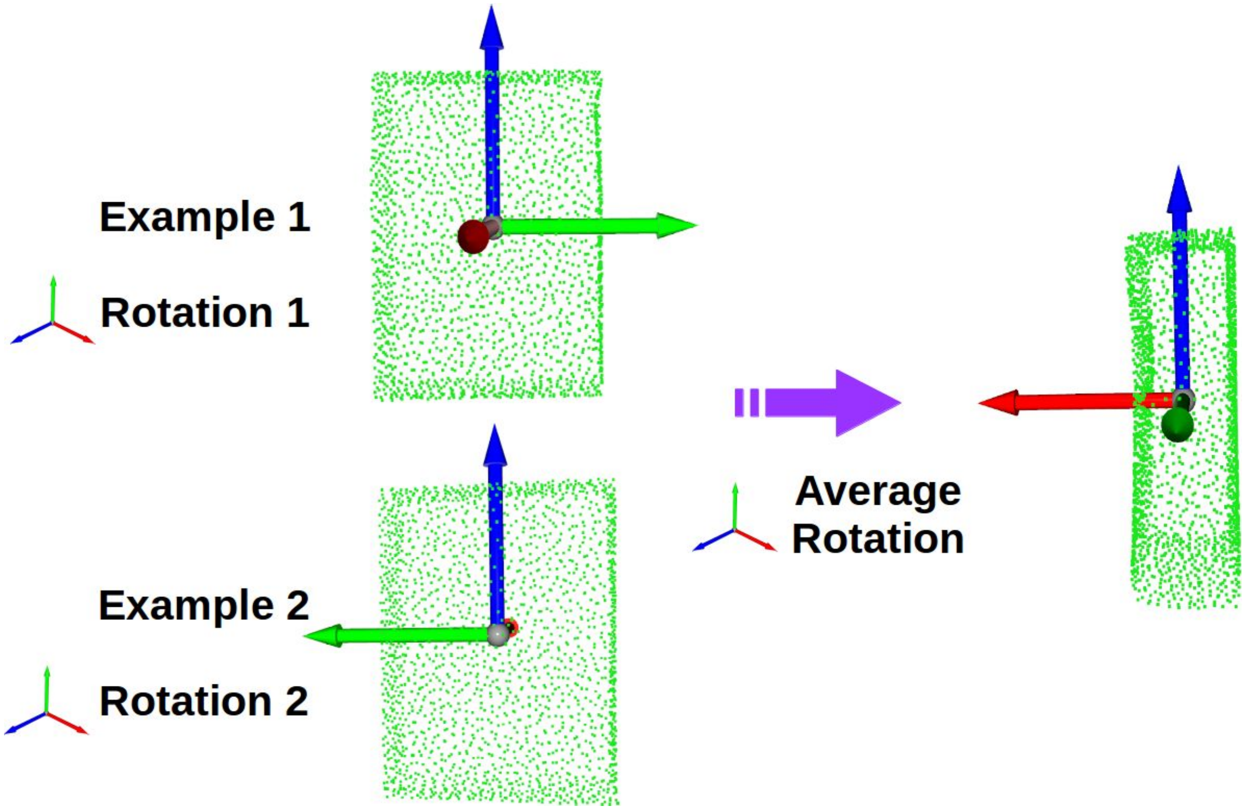


Ours

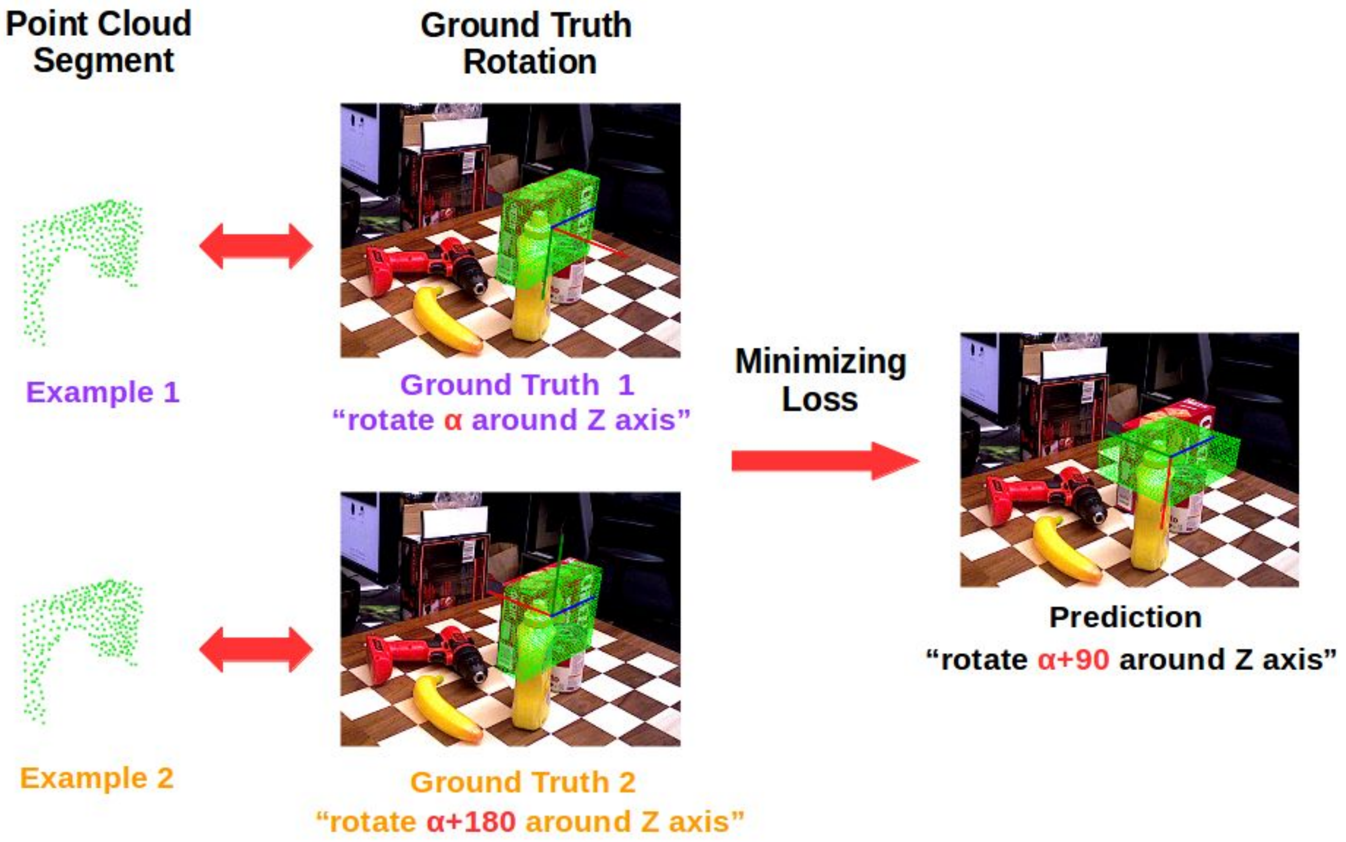
Rotational Symmetry of Objects



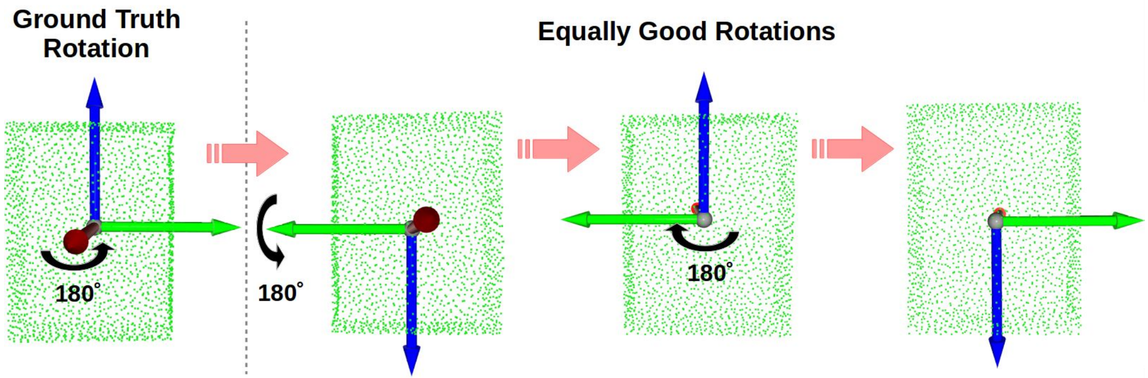
Rotational Symmetry and Supervised Learning



Rotational Symmetry and Supervised Learning



Proposed Approach

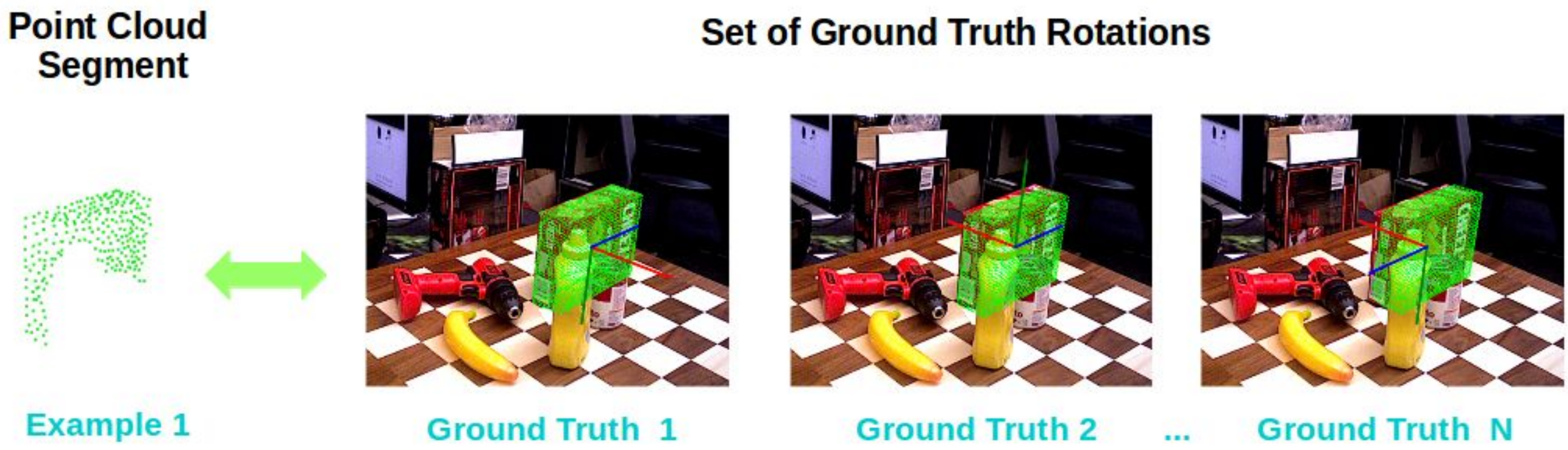


With $\mathcal{M}$ at an initial pose R_0, there exists n rotations that rotate the object model to different end poses $\mathbf{R_N} = \{R_1R_0, R_2R_0, ..., R_NR_0\}$ and satisfying

$$\sum_{\mathbf{x}_1 \in \mathcal{M}} \min_{\mathbf{x}_2 \in \mathcal{M}} \|R_0\mathbf{x}_1 - R_nR_0\mathbf{x}_2\|_2 = 0, \qquad (2)$$

where $n \in \{1...N\}$, and $\mathbf{x}_1$, $\mathbf{x}_2$ are two points on the object model.

Proposed Approach



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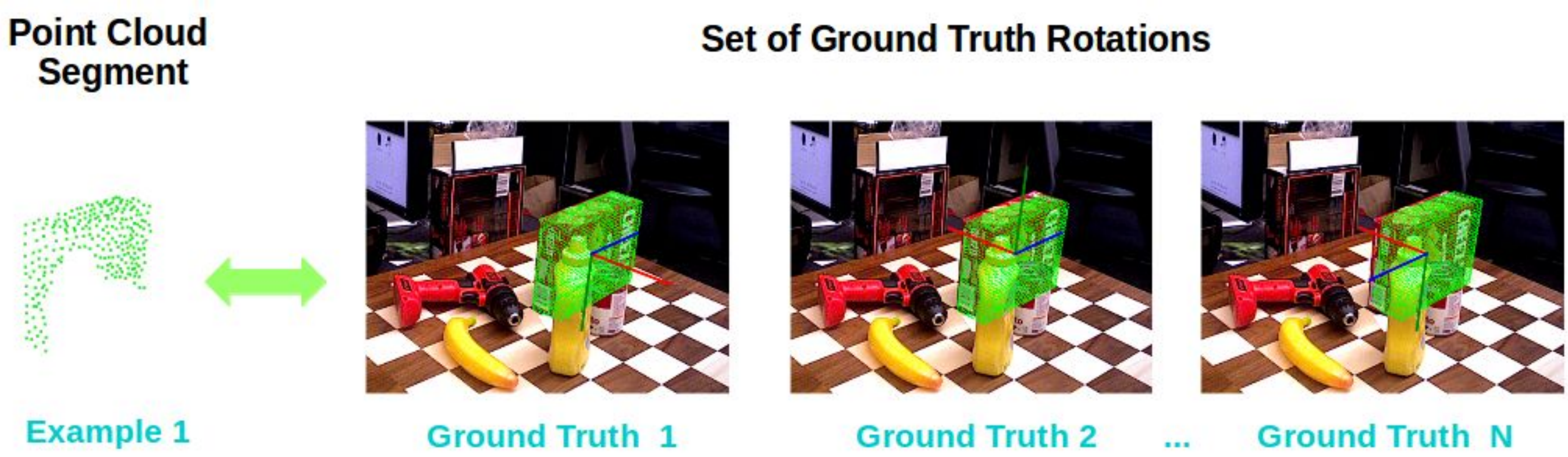
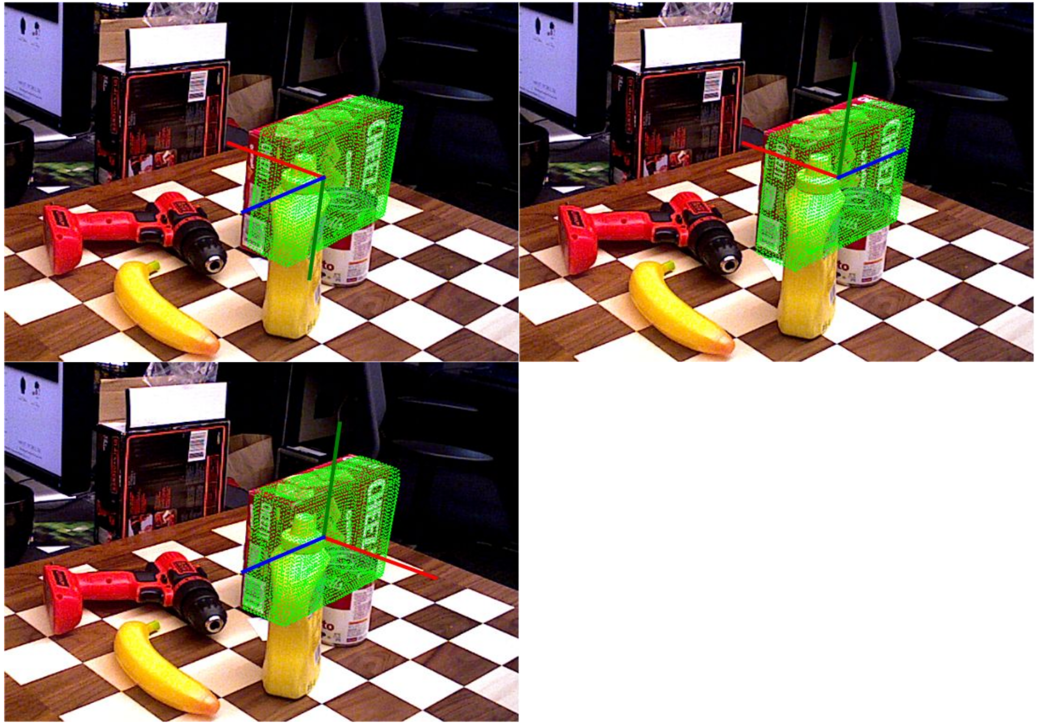


Kinda works, nothing too significant on the dataset

Possible Issues

Ground Truth Rotation

Equally Good Rotations



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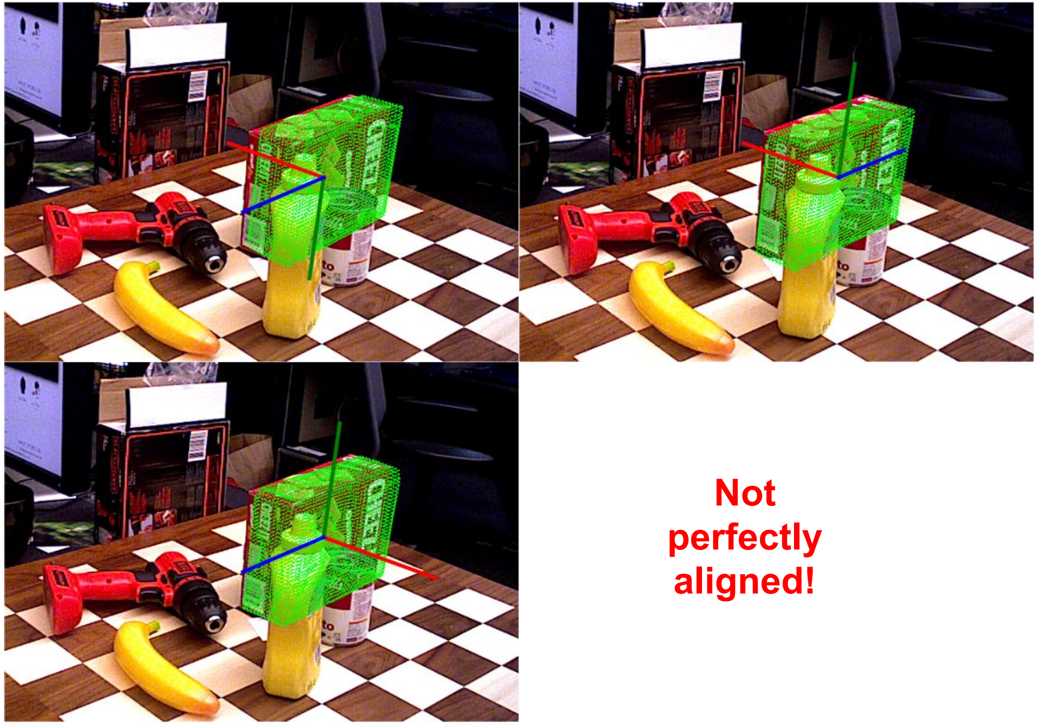


Not perfectly aligned!

Rotational Symmetry Aware Pose Regression from Point Clouds

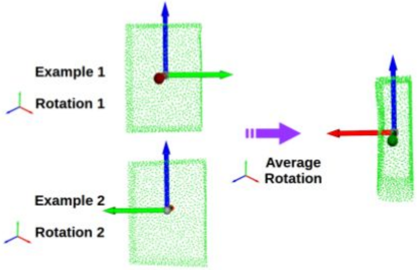
Ge Gao, Mikko Lauri, Jianwei Zhang and Simone Frintrop

Aborted

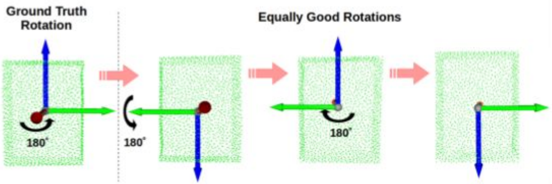
Abstract—(NOT READY) **6D object pose estimation for known objects is a widely studied problem, and many approaches are based on supervised learning. Artificial objects often exhibit rotational symmetry which causes ambiguity during the learning process. Meanwhile, the rotational symmetry properties of objects are well defined. Most existing solutions ... In this work we propose an analytically approach for solving this issue. We evaluation the proposed method on the YCB video datasets with many daily objects which exhibit rotational symmetry. We show that our simple yet effective approach alleviates the learning ambiguity and improves the systems performance.**

I. INTRODUCTION

6D object pose estimation of known objects has been a widely explored topic, and it is important for robotic applications such as object grasping and dexterous manipulation. Many recently proposed methods are supervised learning based approaches [7], [13], [17], [16], [15], [18]. Supervised learning algorithms rely on datasets containing training examples, and each example is associated with a label [5]. The algorithm is expected to learn a one-to-one mapping between the training examples and associated labels. However, for the 6D object pose estimation problem, the one-to-one mapping requirement sometimes cannot be fulfilled. Many artificial objects in the household and industrial environment have 3D shapes with the rotational symmetry property. Rotational symmetry is a property that the 3D shape of an object is equivalent before and after



(a) Problem caused by rotational symmetry. For two examples with the same visual appearance, when the ground truth rotations are different, the network learns to predict an average value.



(b) Proposed solution. For each example, we provide a set of ground truth annotations which represent equally good rotations for learning.

Fig. 1. The problem caused by rotational symmetry and our proposed solution. The axes in red (x), green (y), blue (z) colors denotes object rotations in right-handed coordinate systems.

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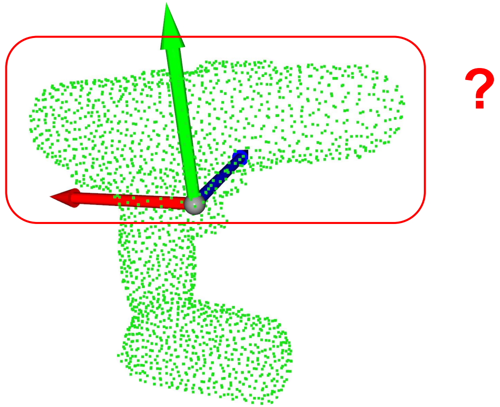
Things should/could be done

- Look at good & bad examples w.r.t. performance of **a trained network**
  - How to enhance the current approach?
- More insights on 6D pose estimation from 3D information (point clouds)
  - E.g. which part of an object are more important for inferring a good pose?



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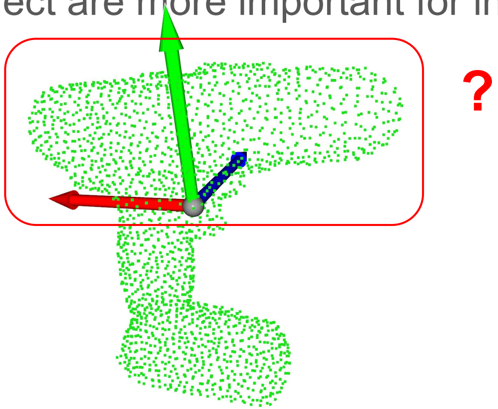
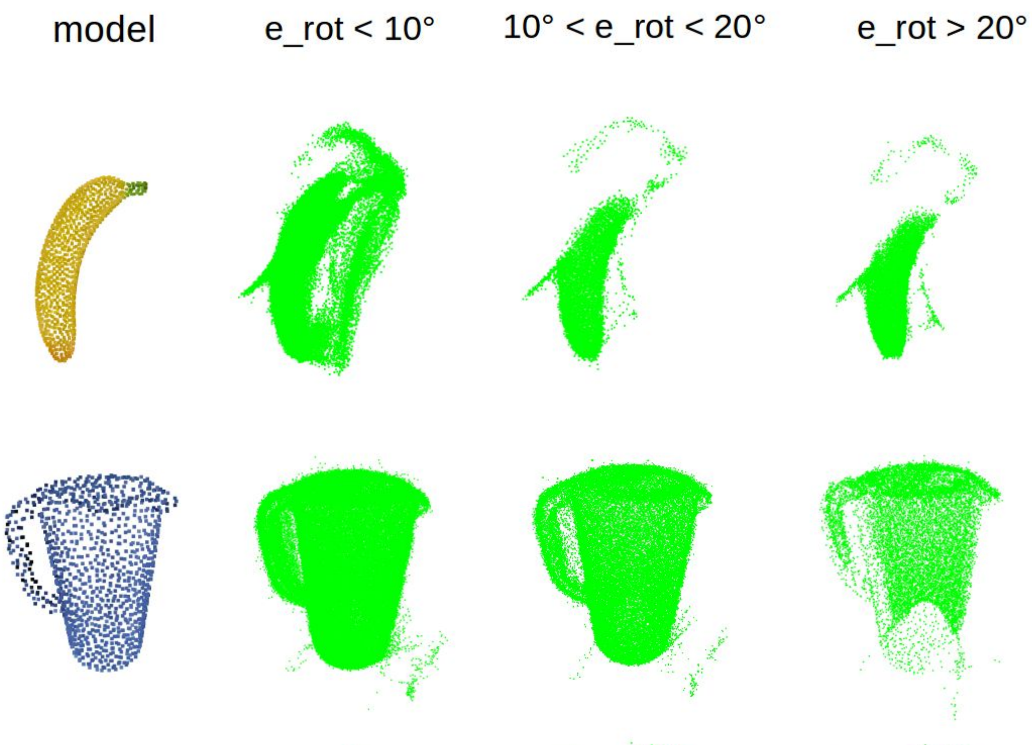


Good & Bad Examples

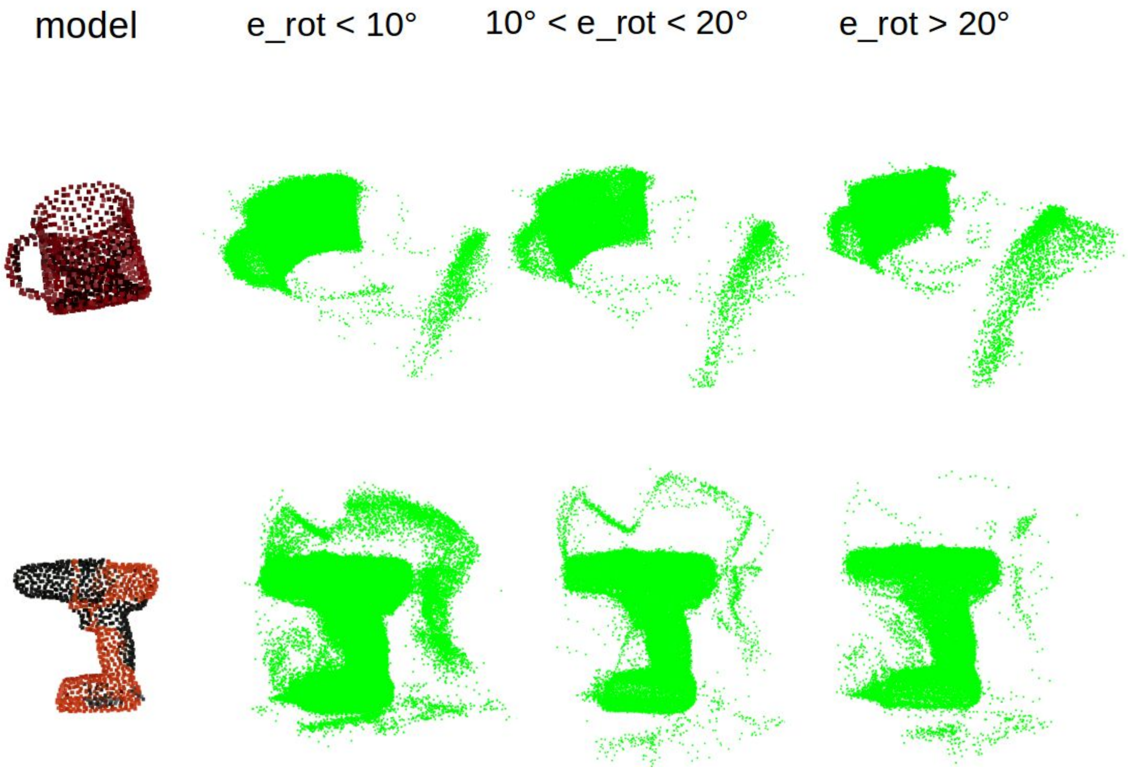
Going through pose estimation results ...

- Set a threshold for (rotation) error for picking samples for inspection
- For each sample picked
  - Use ground truth pose to transform test segment into a canonical pose
  - Superimpose all the test segment

Good & Bad Examples



Good & Bad Examples



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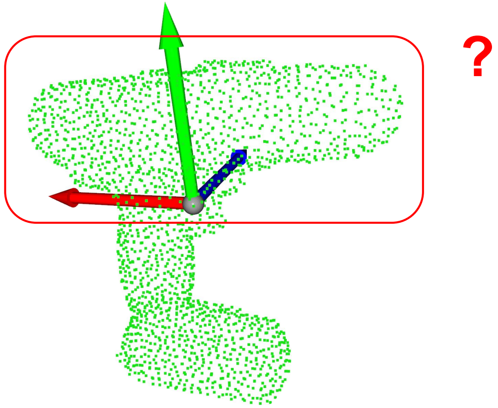
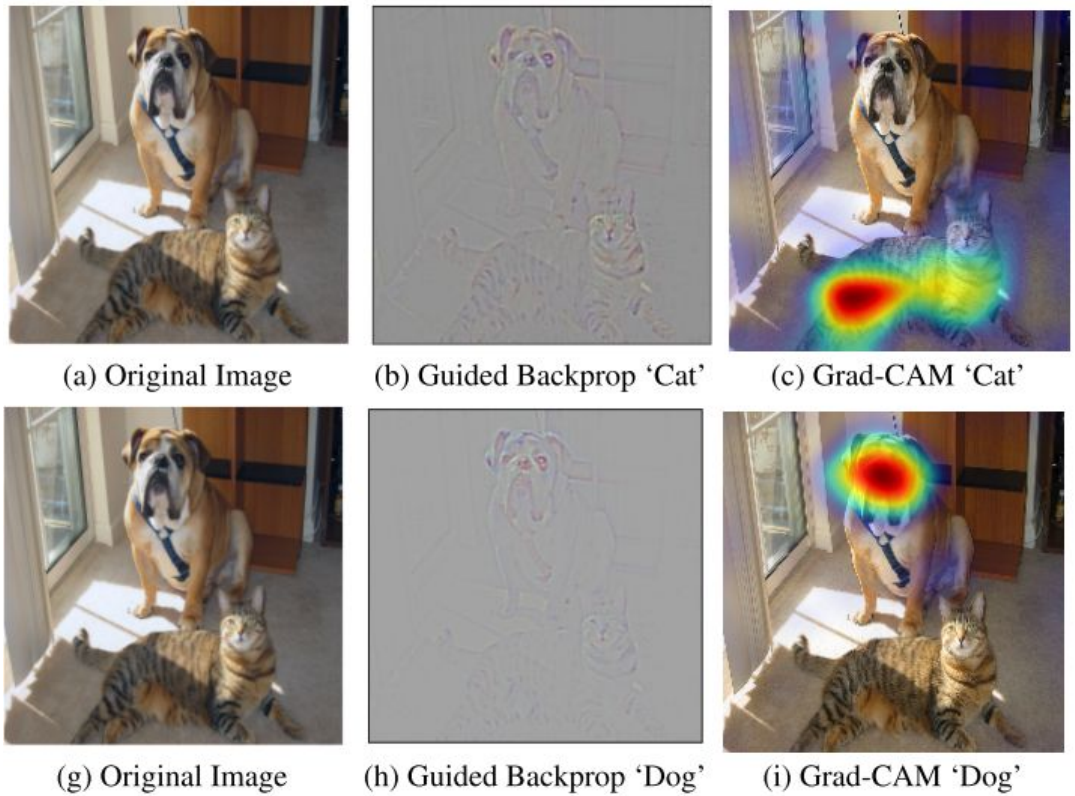


“Grad-CAM” for Visual Explanation

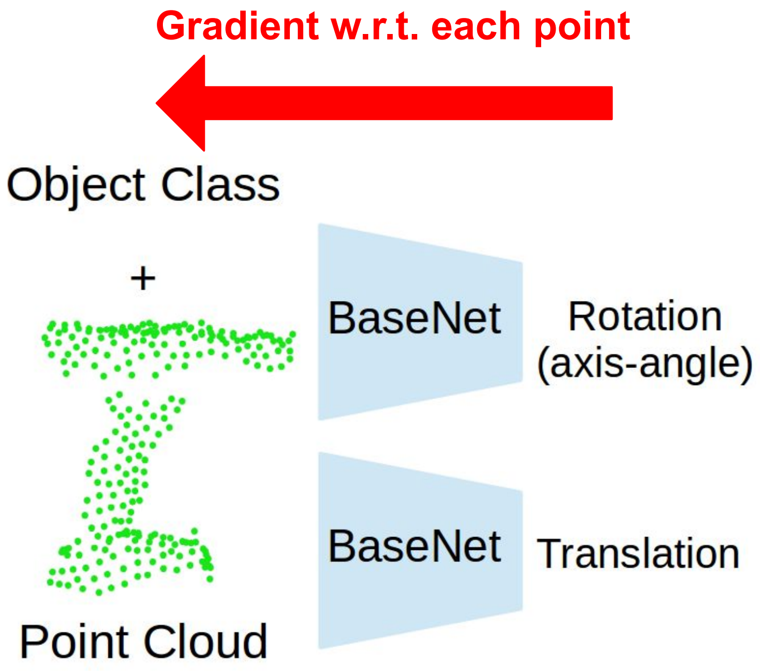


(a) Original Image (b) Guided Backprop ‘Cat’ (c) Grad-CAM ‘Cat’

(g) Original Image (h) Guided Backprop ‘Dog’ (i) Grad-CAM ‘Dog’

Ramprasaath et al., IJCV 19
Ramprasaath et al., ICCV 17

“Grad-CAM” for 6D Pose Regression on Point Cloud



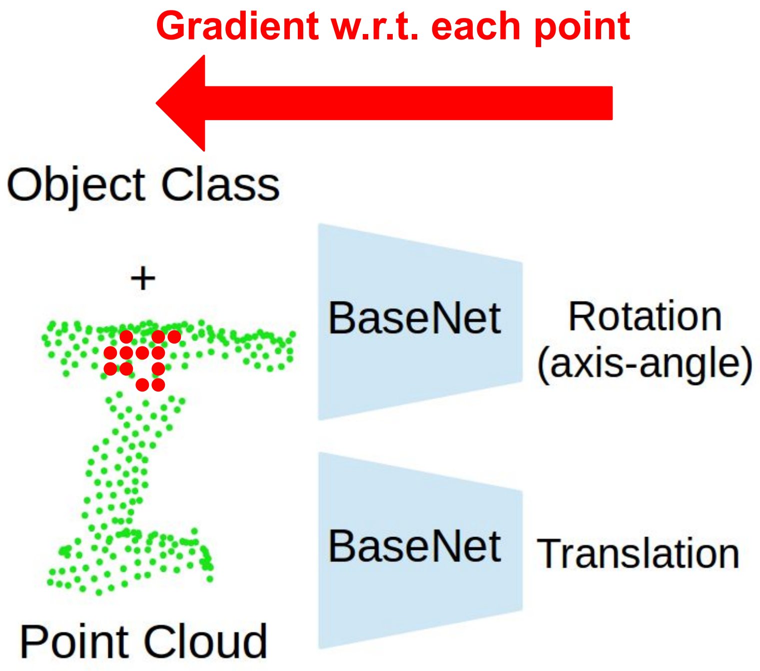
“Grad-CAM” for 6D Pose Regression on Point Cloud

Does the “highlighted” part(s) make sense (for human)?

Does the “highlighted” part(s) correlate with e.g. point normal?

Connection with robotic grasping?

Whether is it “confident” to grasp from current view? (active sensing)



General Issues

- Unclear problem formulation

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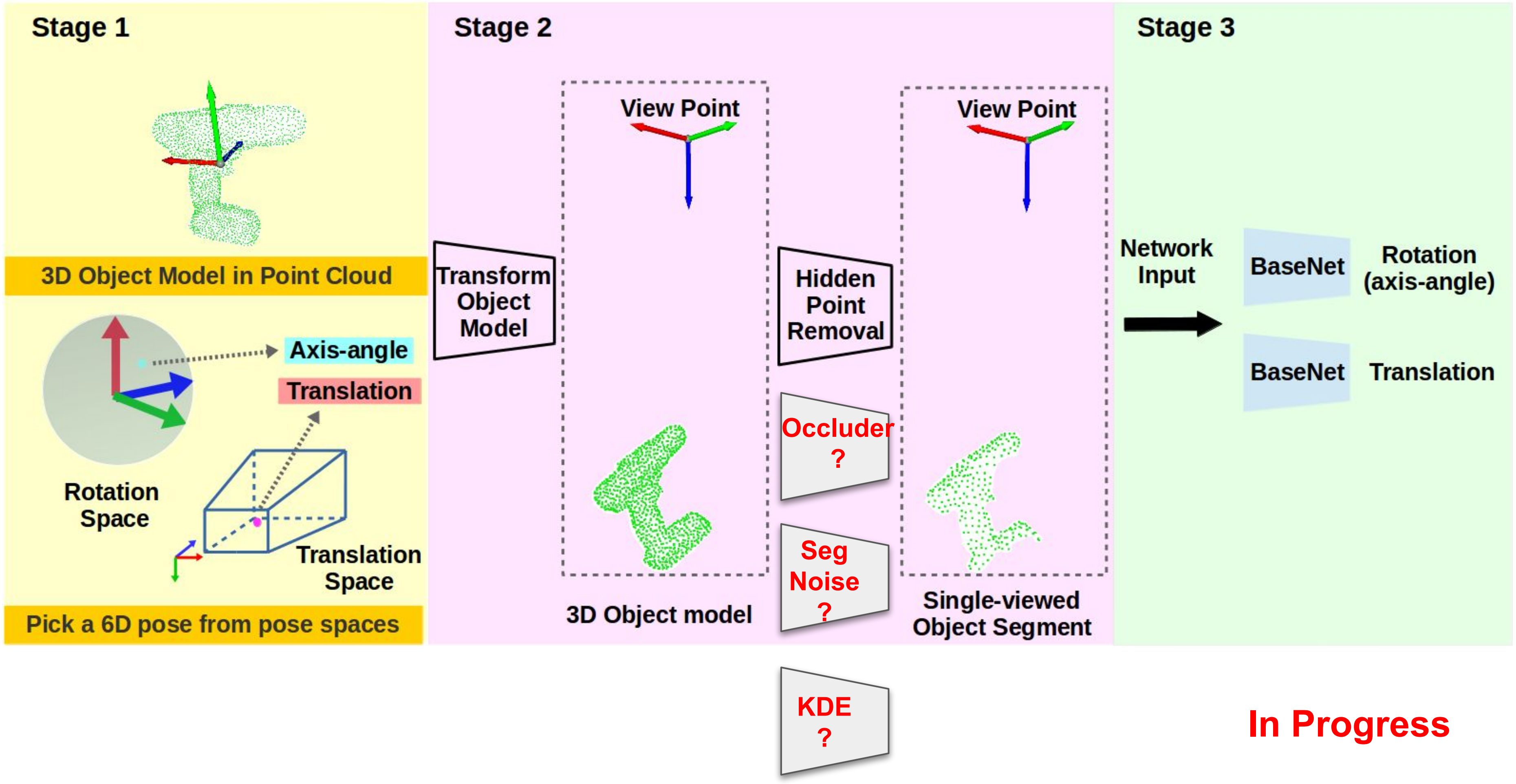

Stage 1
3D Object Model in Point Cloud
Axis-angle
Translation
Rotation Space
Translation Space
Pick a 6D pose from pose spaces
Stage 2
Transform Object Model
View Point
3D Object model
Hidden Point Removal
Occluder ?
Seg Noise ?
KDE ?
View Point
Single-viewed Object Segment
Stage 3
Network Input
BaseNet
Rotation (axis-angle)
BaseNet
Translation
In Progress

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