







Tradition Methods Instance-level 6D pose estimation methods are prone to overfit to specific objects and suffer from poor generalization.

We purpose a meta-learning Method Our based cross-category level 6D pose approach. The core idea lies in Conditional Neural Processes (CNPs) based meta-learner that extracts objectcentric representations in a category-agnostic way.

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Category-Agnostic 6D Pose Estimation with Conditional Neural Processes Yumeng Li^{*1}, Ning Gao^{*1,2}, Hanna Ziesche¹, Gerhard Neumann² *Equal Contribution, ¹Bosch Center for Artificial Intelligence, ²Autonomous Learning Robots, KIT



Given an RGB-D image, the goal of 6D pose estimation is to compute rigid transformation [R; t] from the object coordinates to the camera coordinates. We build on keypoint-based methods, which can be considered in three stages: (i) feature extraction, (ii) keypoint detection, (iii) pose fitting.

- **Feature Extraction:** we rely on the fusion network FFB6D^[1], where the output is per-point features of sampled seed points from the input depth images.
- ii. CNPs^[2]-based Keypoint Detection: the meta-learner encodes and aggregates the features of several context images into latent variables z_{kp} . The decoder predicts per-point offsets for each keypoint based on the target features and the keypoint latent variables z_{kp} .

$$r_{i}^{u} = h_{\theta}(x_{c,i} \oplus y_{c,i}^{u}), \ i = 1, ..., M_{c}, \ u$$
$$z_{kp}^{u} = \max_{i=1}^{M_{c}}(r_{i}^{u}), \ u = 1, ..., M_{t}$$
$$y_{of,i}^{u} = g_{\mathcal{K}}(x_{t,i} \oplus z_{kp}^{u}), \ i = 1, ..., M_{t}$$

iii. Pose Fitting: given the pre-defined 3D keypoints in the object coordinates $\{p_i\}_{i=1}^{M_k}$ and keypoints prediction in the camera coordinates $\{p_i^*\}_{i=1}^{M_k}$, 6D pose can be computed by solving a least-squares fitting problem:

$$L_{lsf} = \sum_{i=1}^{M_k} \|p_i^* - (R \cdot p_i +$$

References: [1] Yisheng He, et al. "FFB6D: A Full Flow Bidirectional Fusion Network for 6D Pose Estimation." CVPR 2021 [2] Marta Garnelo, et al. "Conditional Neural Processes." ICML 2018

 $= 1, ..., M_k,$

 $., M_k,$

 $t, u = 1, ..., M_k,$

 $t)\|^2$.









To test the inter-category performance, the model is trained and tested on car category. The ADD-0.1d accuracy on 200 **unseen** new car objects reaches 96.7%. The qualitative results are

Furthermore, we train our model on 20 categories. The ADD-0.1d accuracy of **novel** objects from trained intra-category and cross-category are 81.9% and 59.0% respectively.

Evaluation on photorealistic dataset without and with occlusion

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Evaluation on real-world dataset

□ Improve rendering pipeline