

CS 6334 Virtual Reality
Professor Yu Xiang
The University of Texas at Dallas

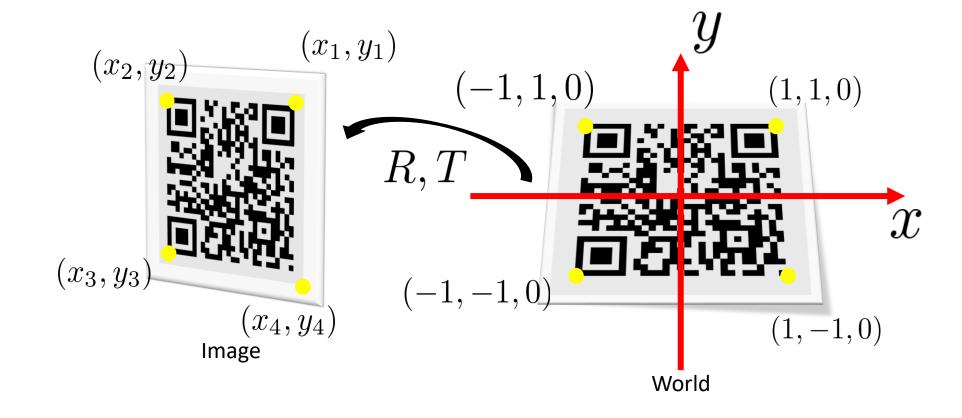
Tracking in VR

- Tracking the user's sense organs
 - E.g., Head and eye
 - Render stimulus accordingly
- Tracking user's other body parts
 - E.g., human body and hands
 - Locomotion and manipulation
- Tracking the rest of the environment
 - Augmented reality
 - Obstacle avoidance in the real world



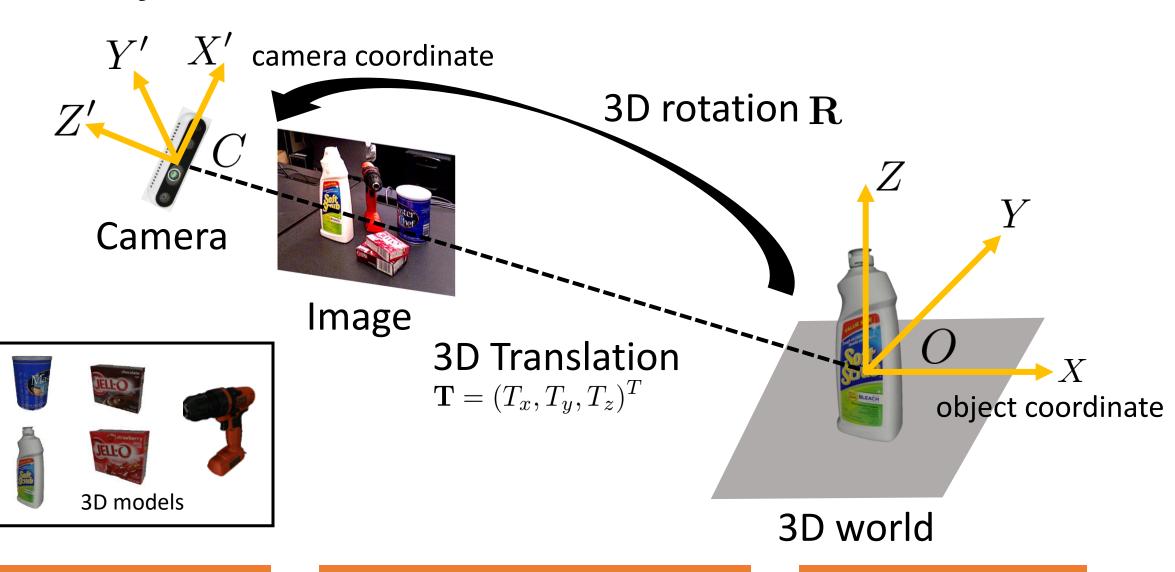
Tracking Objects in the Real World

• AR tags



How about tracking general objects in the world?

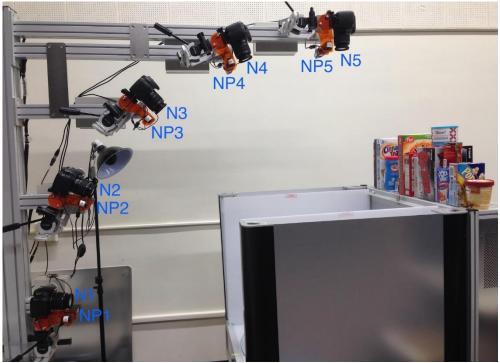
6D Object Pose Estimation



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• 3D reconstruction from multiple images





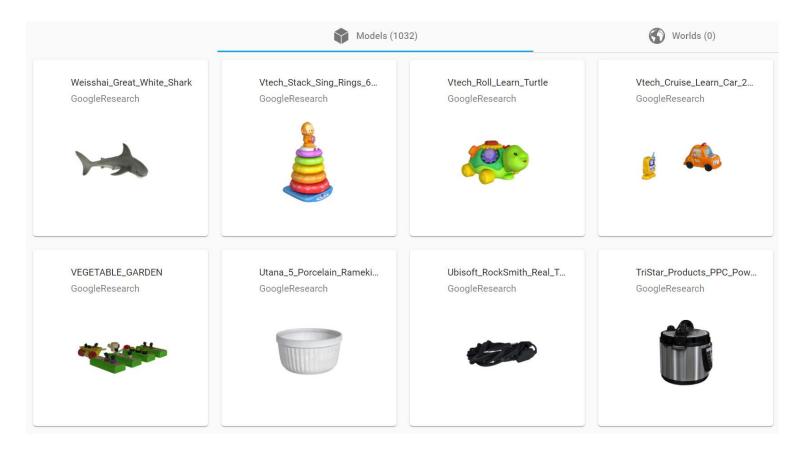
Berkeley Instance Recognition Dataset. Singh et al., ICRA, 2014

A 3D reconstruction example



https://blog.kitware.com/3d-reconstruction-from-smartphone-videos/

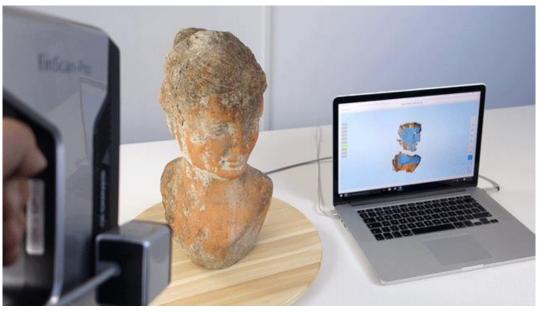
• 3D Scanning



https://app.ignitionrobotics.org/GoogleResearch/fuel/collections/Google%20Scanned%20Objects

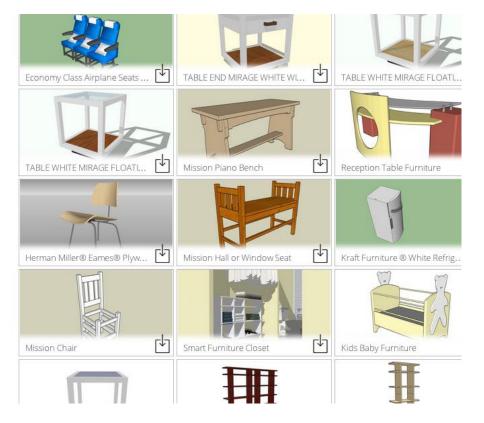
• 3D Scanning

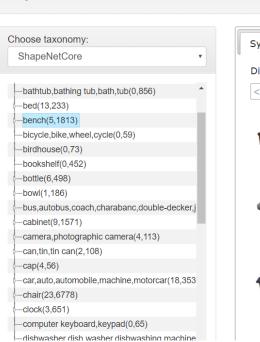




https://3dscanexpert.com/shining-3d-einscan-pro-3d-scanner-review/

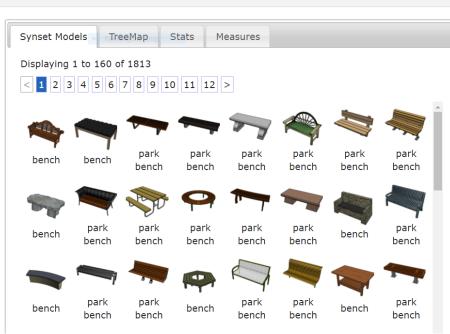
3D CAD models





a long seat for more than one person

ImageNet MetaData

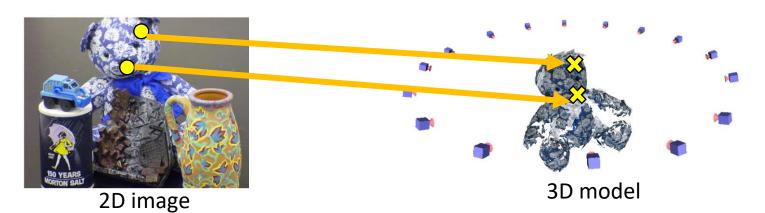


Trimble 3D Warehouse https://3dwarehouse.sketchup.com

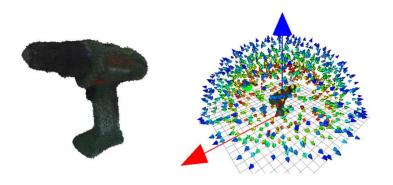
ShapeNet https://www.shapenet.org/

6D Object Pose Estimation

Feature matching-based methods



Template matching-based methods



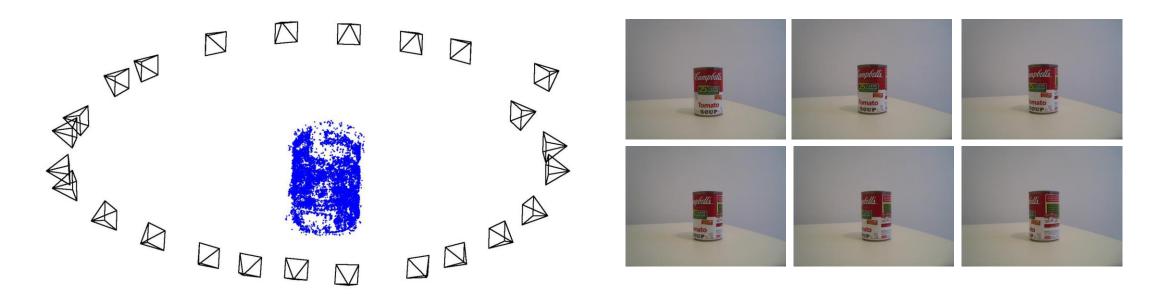


Hinterstoisser et al., ACCV, 2012

Rothganger et al., IJCV, 2006

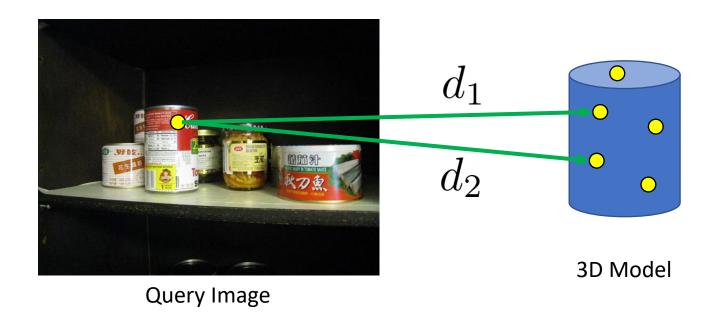
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- 3D Models of Objects using Structure from Motion
 - 3D points with SIFT descriptors (each 3D point can have a list of descriptors or use the mean of the descriptors)



Making specific features less discriminative to improve point-based 3D object recognition. Hsiao, Collet and Hebert. CVPR'10.

Ratio test

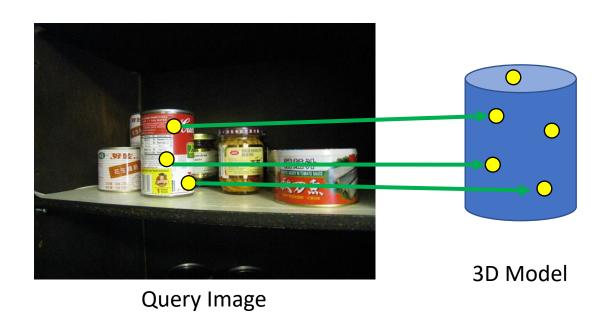


Distance to closest 3D point

$$ratio = \frac{d_1}{d_2} < 0.8$$

Distance to second closest 3D point

• 3D-2D correspondences from feature matching $(\mathbf{X}_i,\mathbf{x}_i)_{i=1}^N$



Option 1: minimizing reprojection error

• Levenberg-Marquardt

$$g(\mathbf{R}, \mathbf{T}) = \sum_{i=1}^{N} ||P(\mathbf{X}_i, \mathbf{R}, \mathbf{T}) - \mathbf{x}_i||^2$$

Option 2: solve the PnP problem

EPnP

Random Sample Consensus (RANSAC)

 An iterative method for parameter estimation from a set of observed data that contains outliers

RANSAC Algorithm {

- 1. Selects *N* data items as random
- 2. Estimates parameter \vec{x}
- 3. Finds how many data items (of M) fit the model with parameter vector \vec{x} within a user given tolerance. Call this K.
- 4. If *K* is big enough, accept fit and exit with success.
- 5. Repeat step 1 until 4 (as Ltimes)
- 6. Algorithm will be exit with fail

Sample N 3D-2D correspondences $(\mathbf{X}_i,\mathbf{x}_i)_{i=1}^N$

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

Find how many $(\mathbf{X}_i,\mathbf{x}_i)$ obeys (\mathbf{R},\mathbf{T})

Pose estimation examples













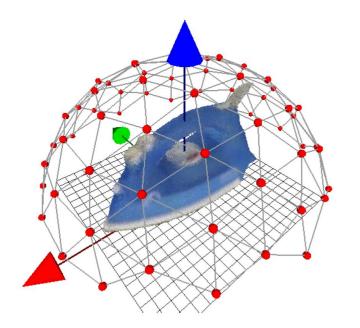


3D models

Making specific features less discriminative to improve point-based 3D object recognition. Hsiao, Collet and Hebert. CVPR'10.

A Case Study for Template Matching

Render 3D models of objects to obtain template images

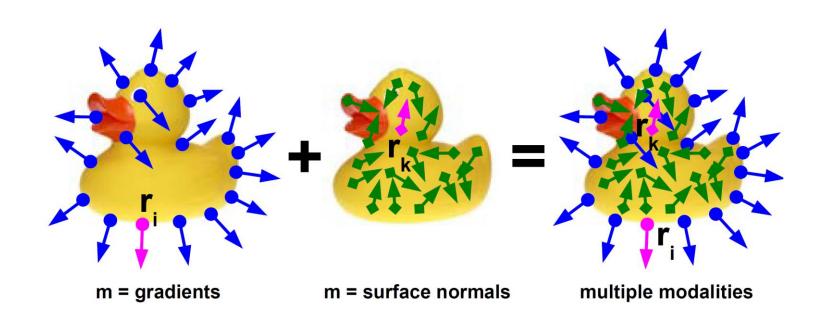


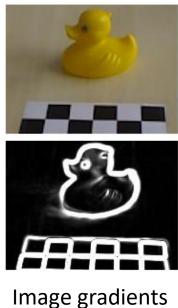
Viewpoint sampling

Model Based Training, Detection and Pose Estimation of Texture-Less 3D Objects in Heavily Cluttered Scenes. Hinterstoisser et al., ACCV'12.

A Case Study for Template Matching

• Compute color and depth features for each template image

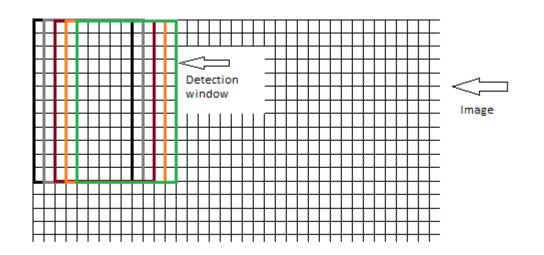




Model Based Training, Detection and Pose Estimation of Texture-Less 3D Objects in Heavily Cluttered Scenes. Hinterstoisser et al., ACCV'12.

A Case Study for Template Matching

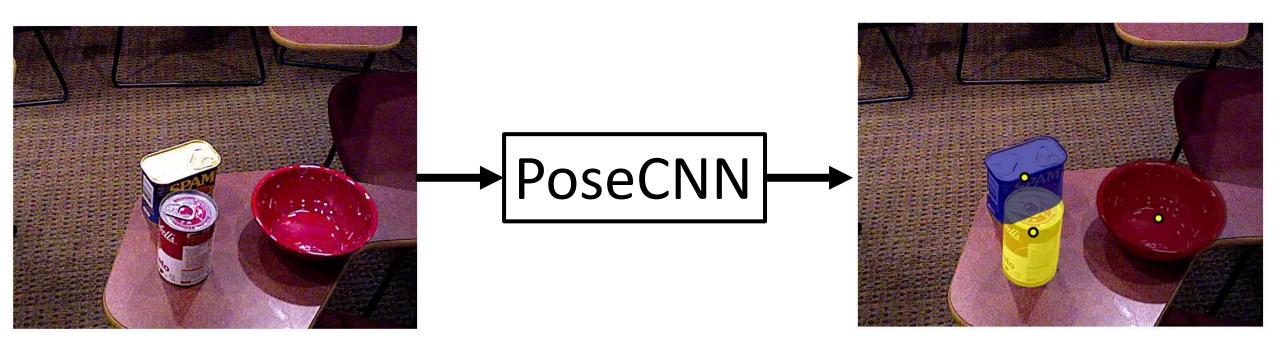
- Apply the templates to an input image for detection and pose estimation (sliding window)
 - Each template is associated with a 6D pose





Model Based Training, Detection and Pose Estimation of Texture-Less 3D Objects in Heavily Cluttered Scenes. Hinterstoisser et al., ACCV'12.

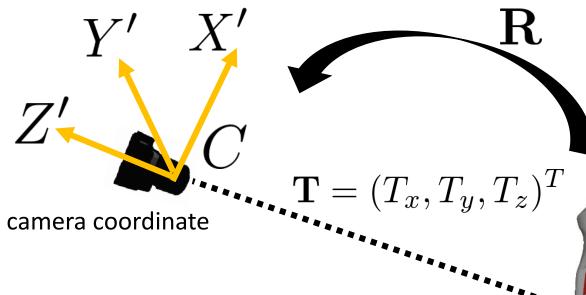
PoseCNN



Y. Xiang, T. Schmidt, V. Narayanan and D. Fox. PoseCNN: A Convolutional Neural Network for 6D Object Pose Estimation in Cluttered Scenes. In RSS'18.

PoseCNN: Decouple 3D Translation and 3D

Rotation



3D Translation



2D center

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

Distance T_z

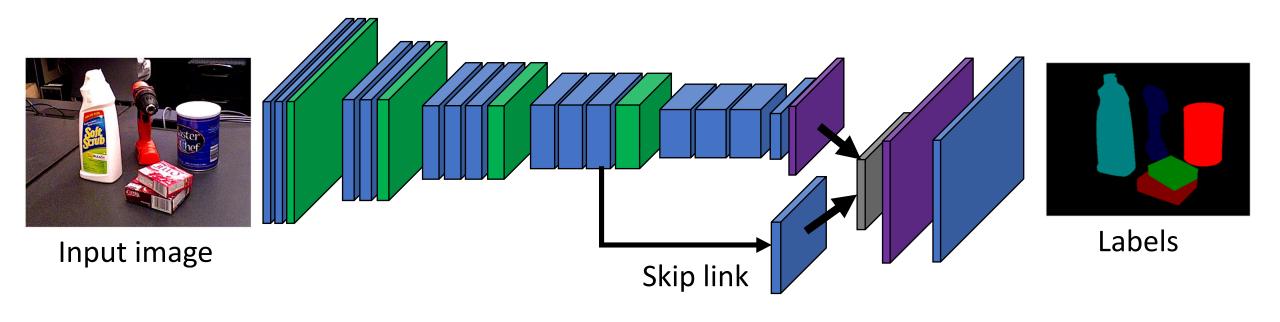
2D Center Localization

• 3D Rotation



3D Rotation Regression

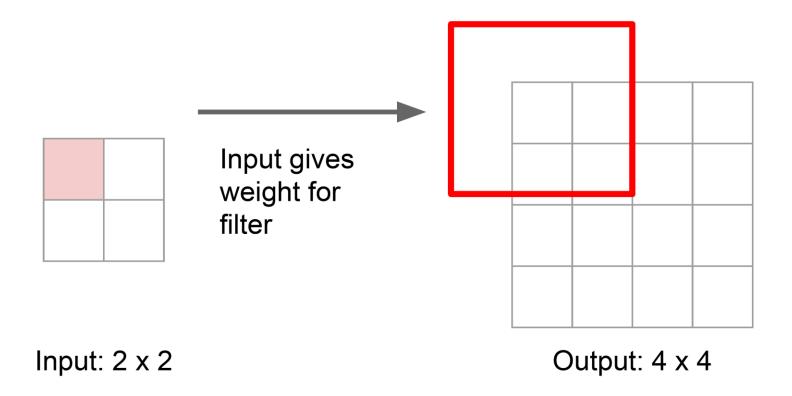
PoseCNN: Semantic Labeling



Fully convolutional network

Deconvolution

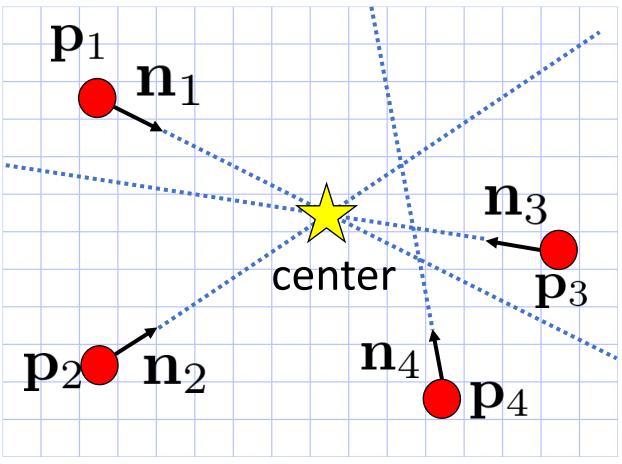
3 x 3 "deconvolution", stride 2 pad 1



Credit: Andrej Karpathy & Justin Johnson

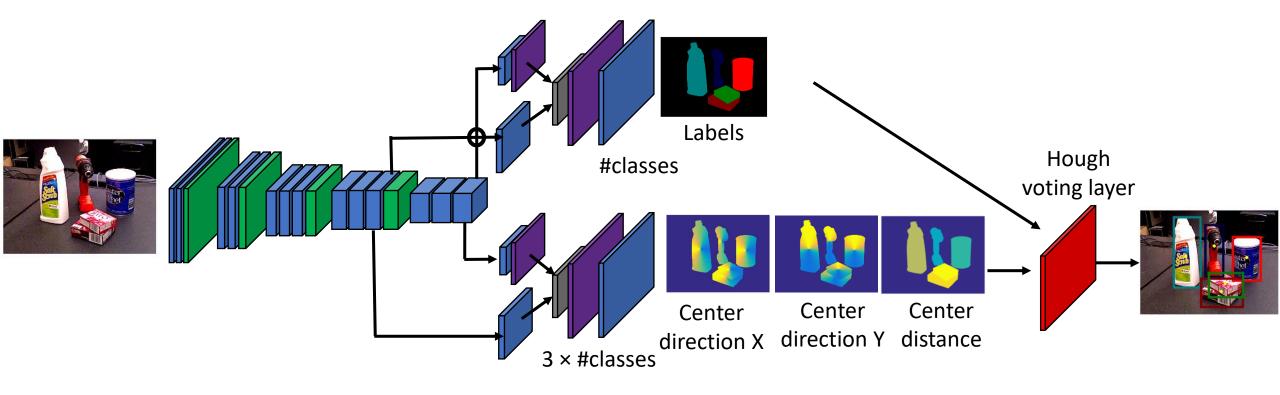
PoseCNN: 2D Center Voting for Handling Occlusions



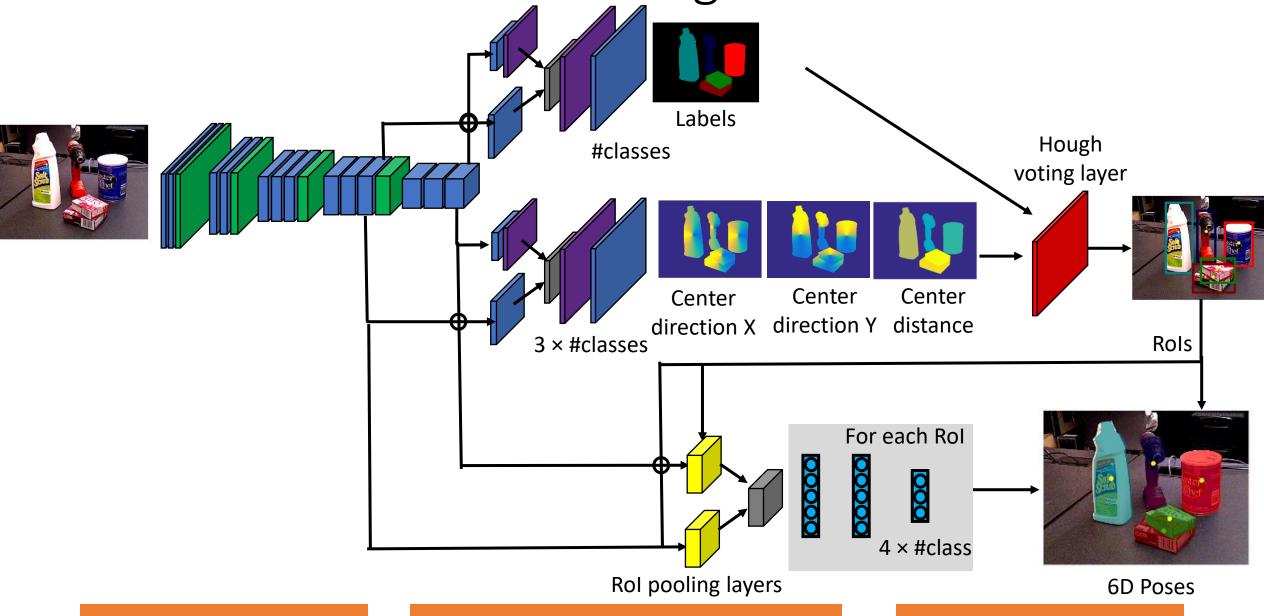


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PoseCNN: 3D Translation Estimation



PoseCNN: 3D Rotation Regression

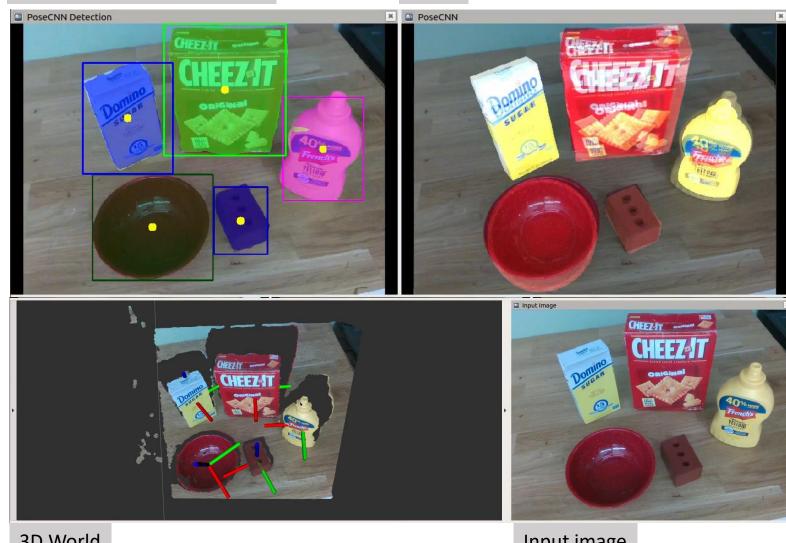


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PoseCNN

Segmentation and Detection

Poses

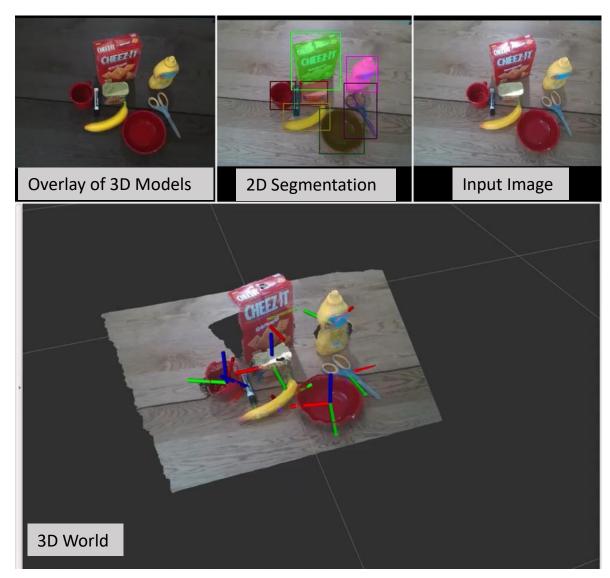


3D World Input image

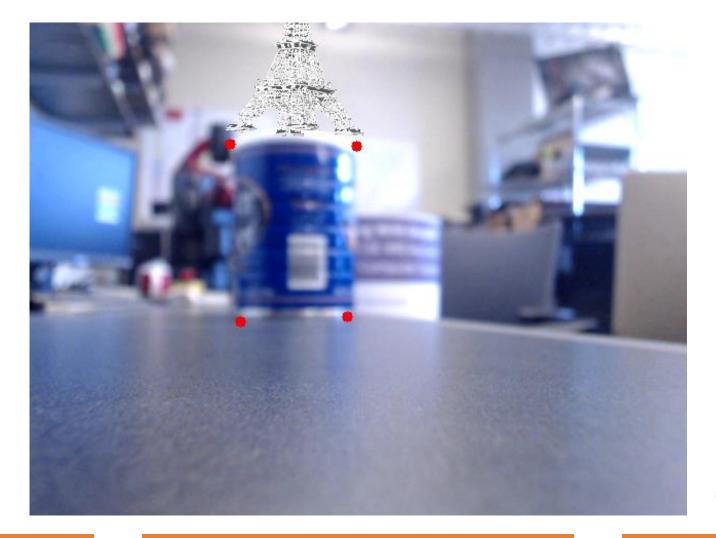
6D Object Pose Tracking



PoseRBPF: Deng et al., RSS'19



AR Demo with 6D Pose Estimation





DeepIM, Li et al., IJCV'19

Credit: Lirui Wang

Further Reading

Making specific features less discriminative to improve point-based
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• PoseCNN: A Convolutional Neural Network for 6D Object Pose Estimation in Cluttered Scenes. Xiang et al., RSS'18.