

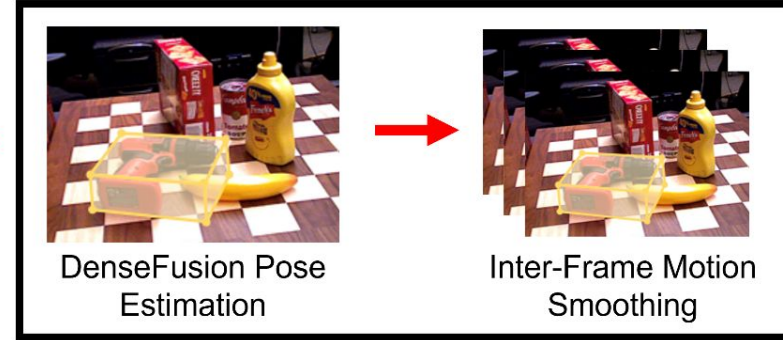
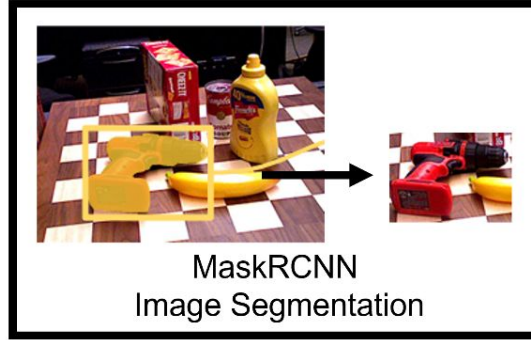
Group 5 - Pose Estimation

Nikolas Lamb, Gurpreet Kaur, Houchao Gan, Mingjun Li,
Noah Wiederhold, Priyo Prosun, Stephen Miner

Reviving Pose Estimation Using Docker Containers

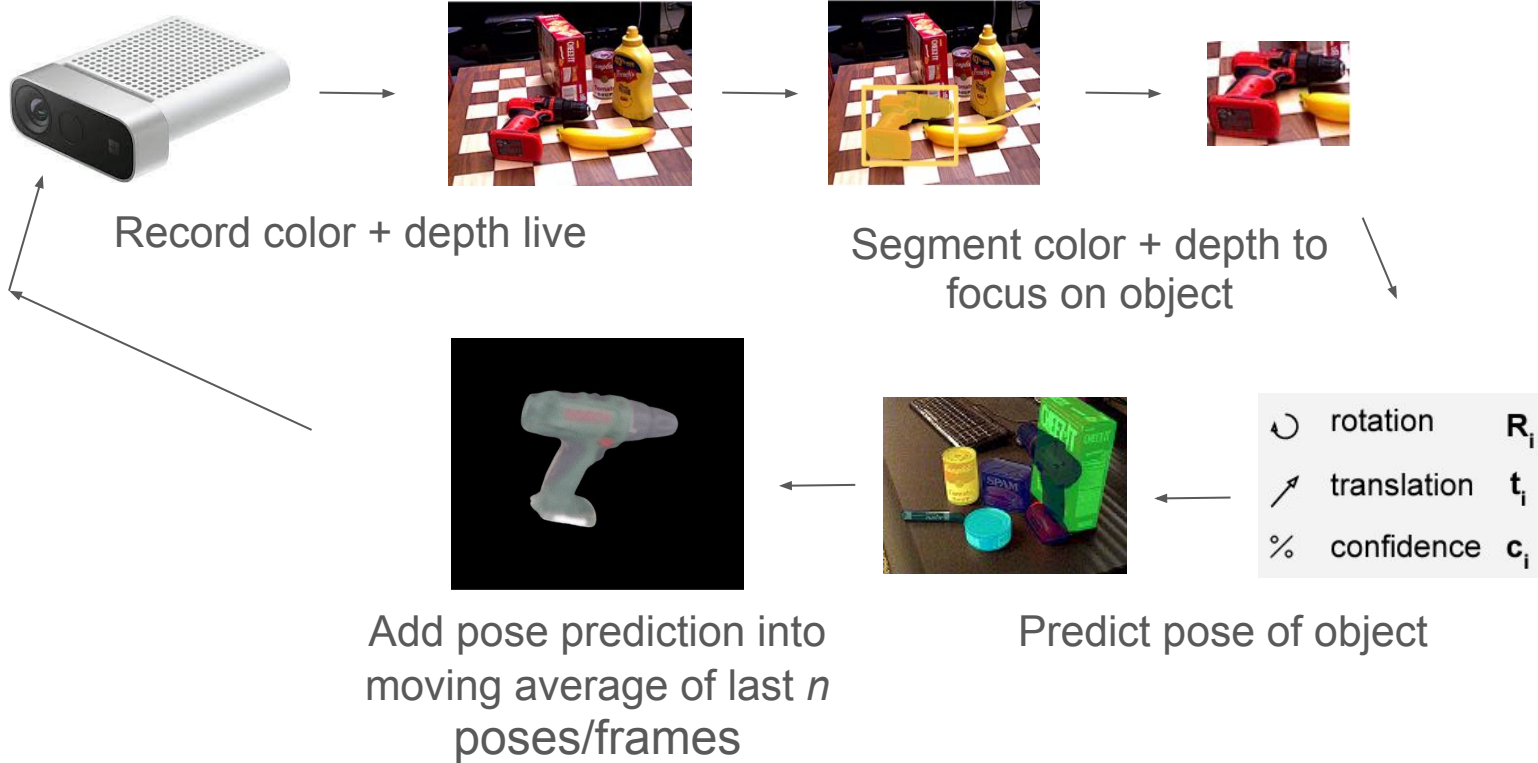


RGB + Depth
Input Video

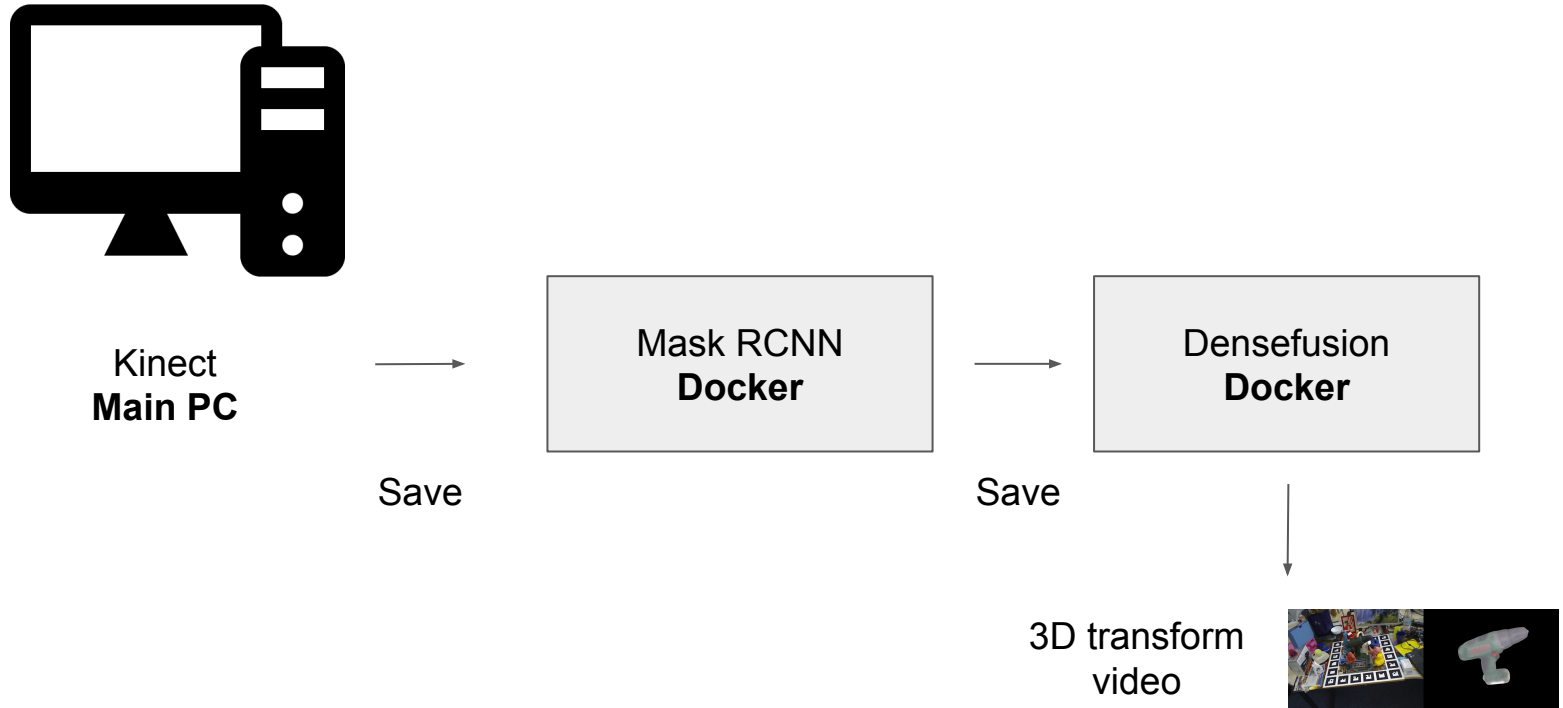


Existing pose estimation approaches are problematic to install on modern hardware. Our project standardizes the installation process and provides containerized environments to make setting up a pose estimation process quick and easy. We provide code at: [nikw1/DenseFusion](https://github.com/nikw1/DenseFusion)

Azure Kinect Integration



Containerized Pipeline





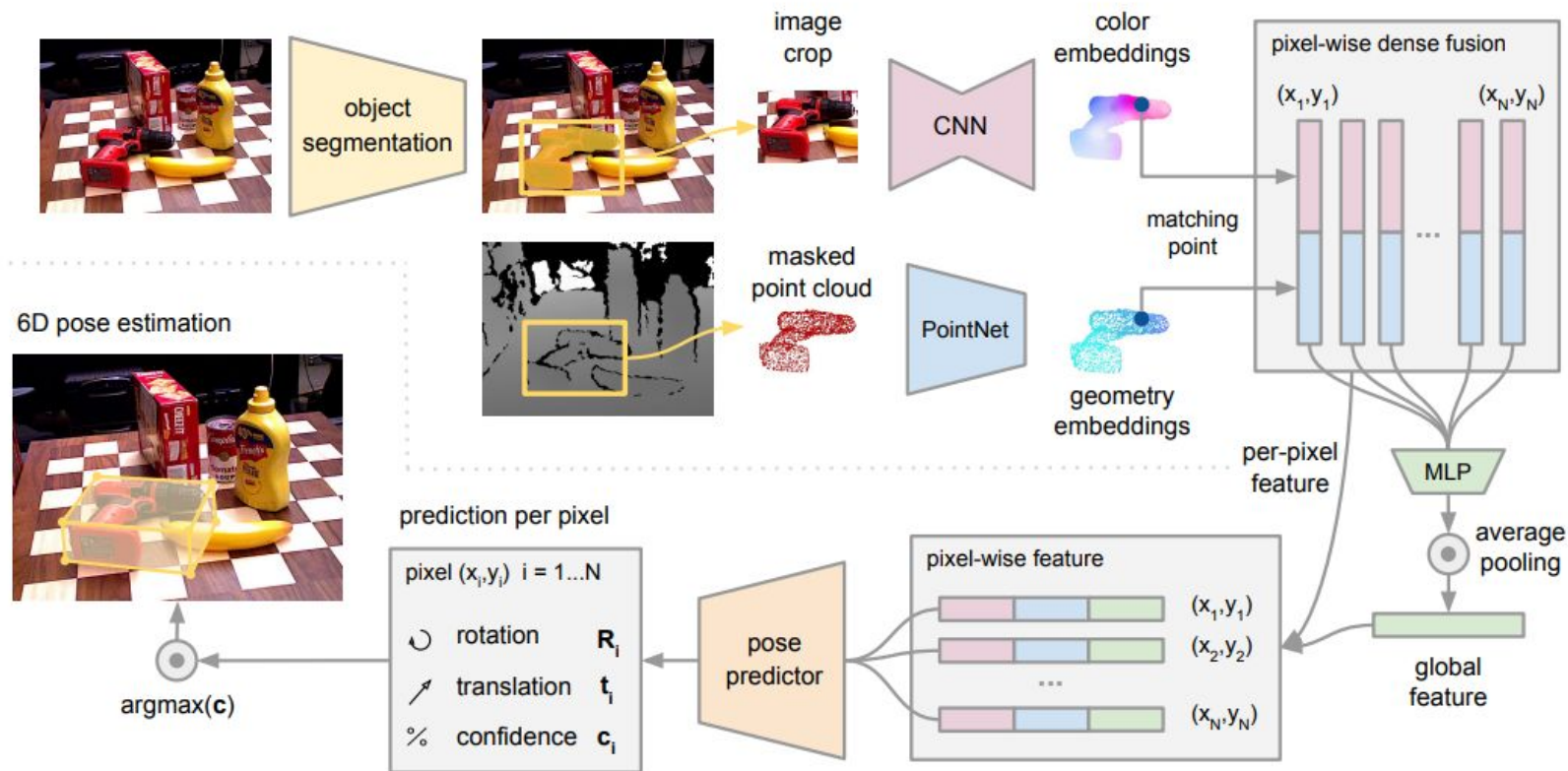




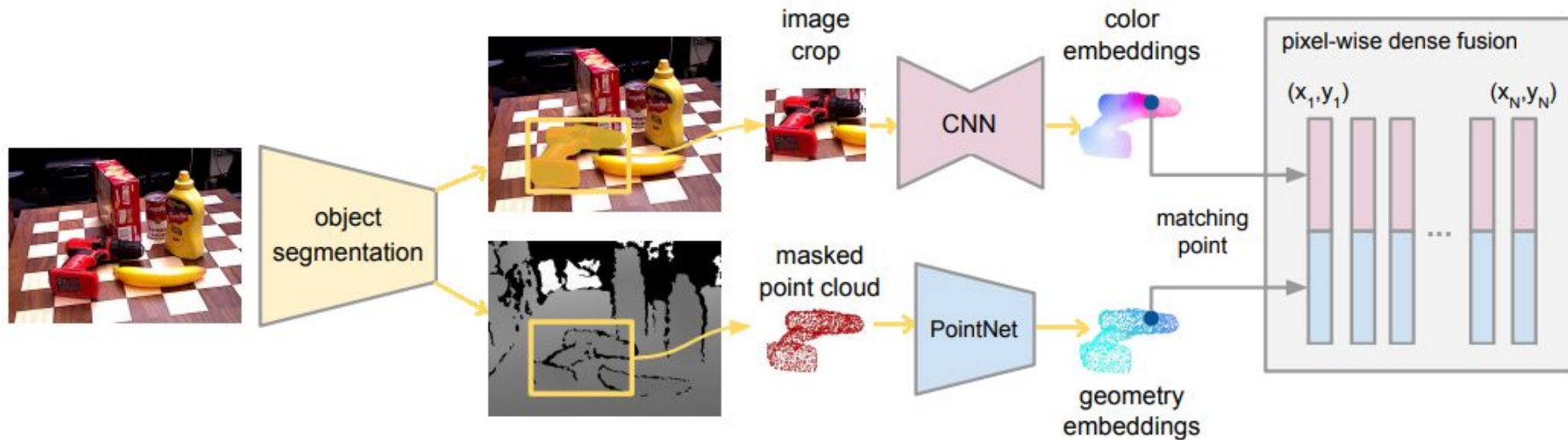




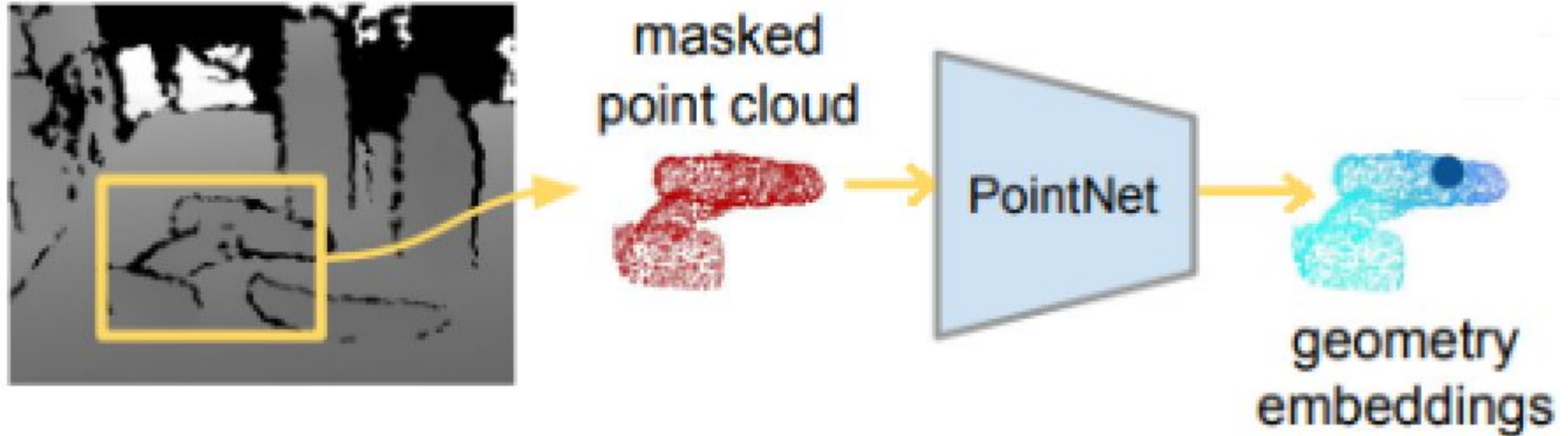
Network Modifications



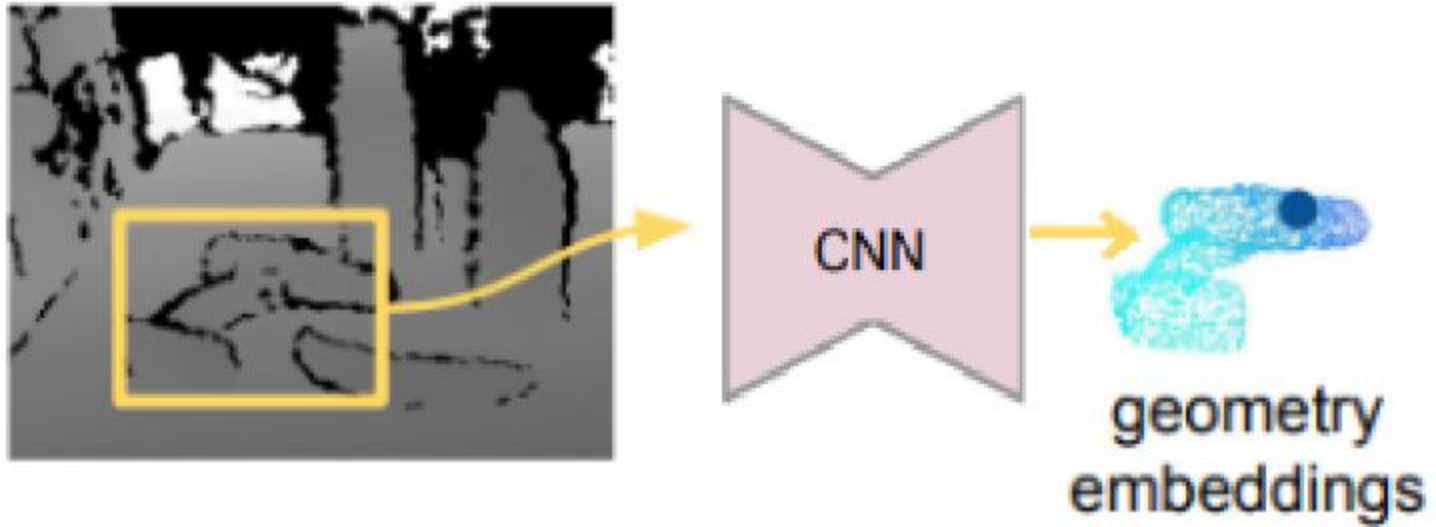
Current pre-processing



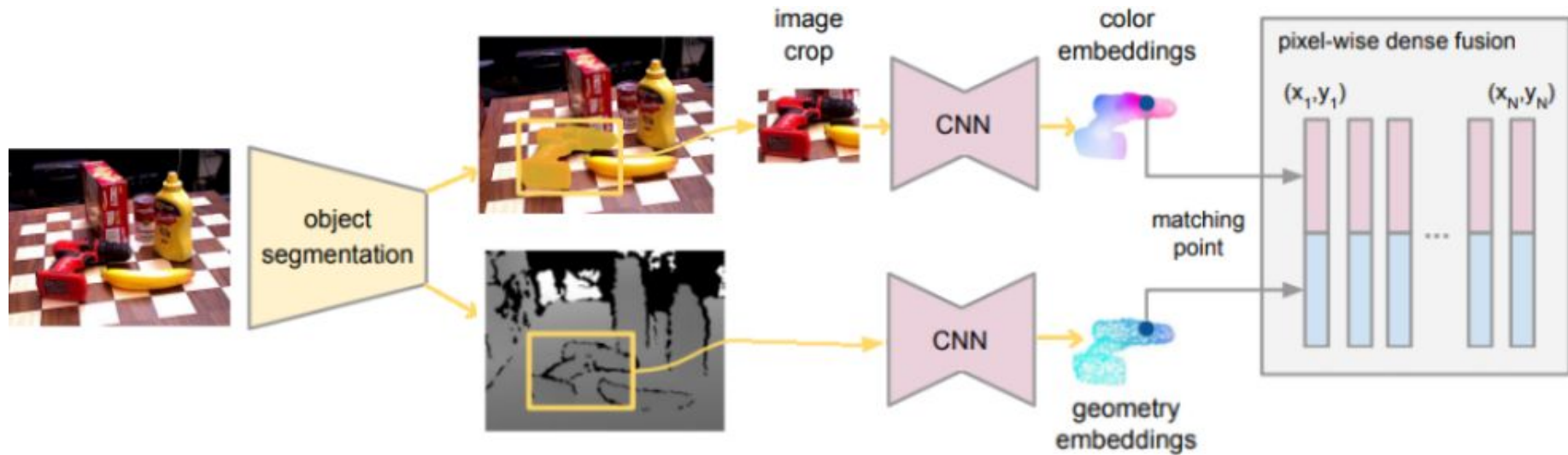
- Computationally costly
- Seems unnecessary to convert to point cloud in order to get the embeddings



- Much less complexity
- Same type of output to use as input for dense fusion

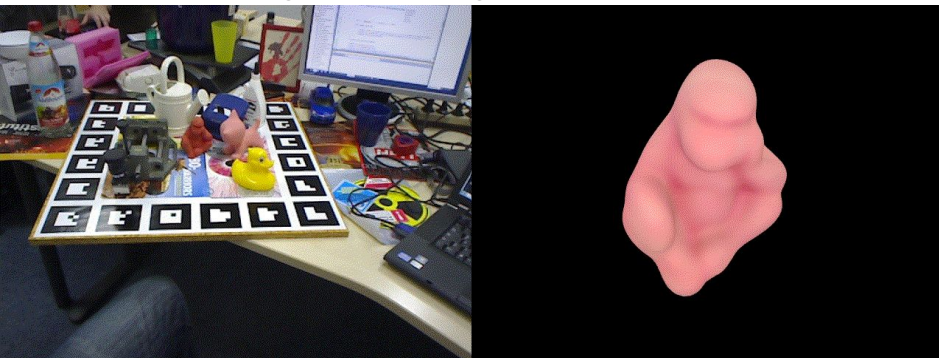


The change in context

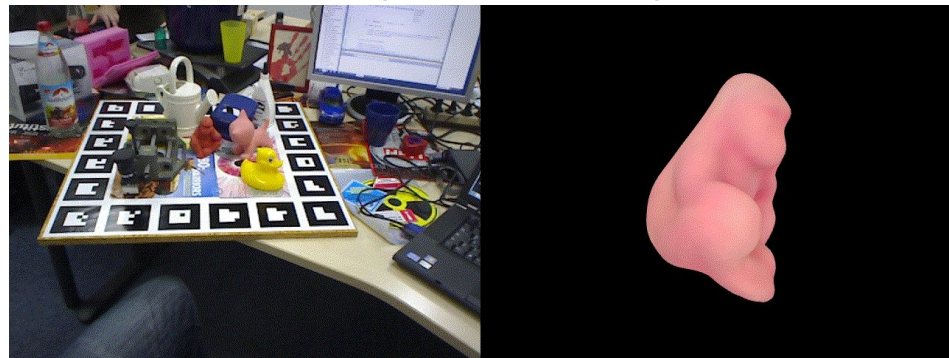


Training results

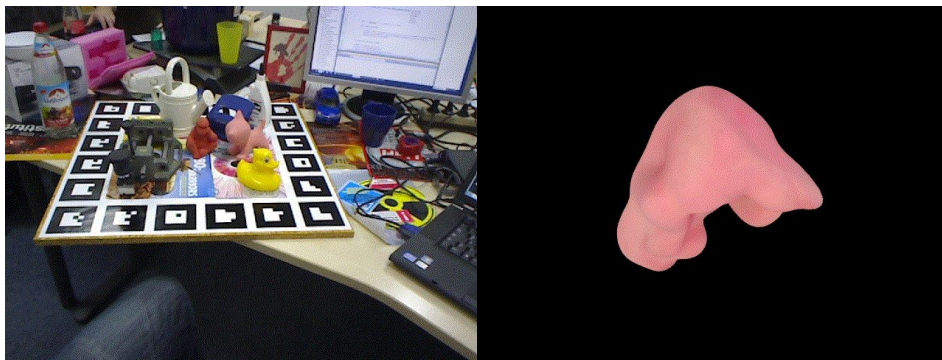
Results from original training with points cloud



Results from training with depth image(25 epoch)



10 epoch

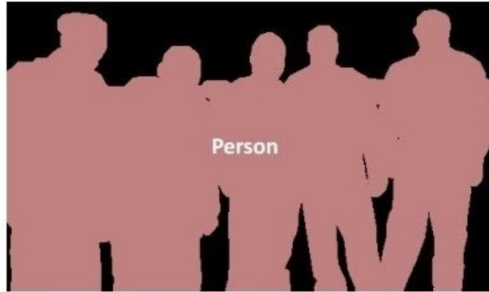


Tasks

- Noah, Nik, Mingjun:
 - Get DenseFusion training (fix batching)
 - Live prediction working with static mask (waiting on segmentation)
 - Motion smoothing
- Gurpreet & Priyo: Get segmentation network working and integrated into pipeline
- Houchao & Stephen: Modifications to DenseFusion to use depth map inputs

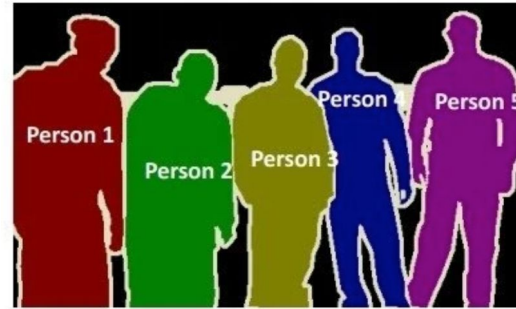
Semantic Segmentation Vs. Instance Segmentation

Classifies each pixel into a fixed set of categories without differentiating object instances.



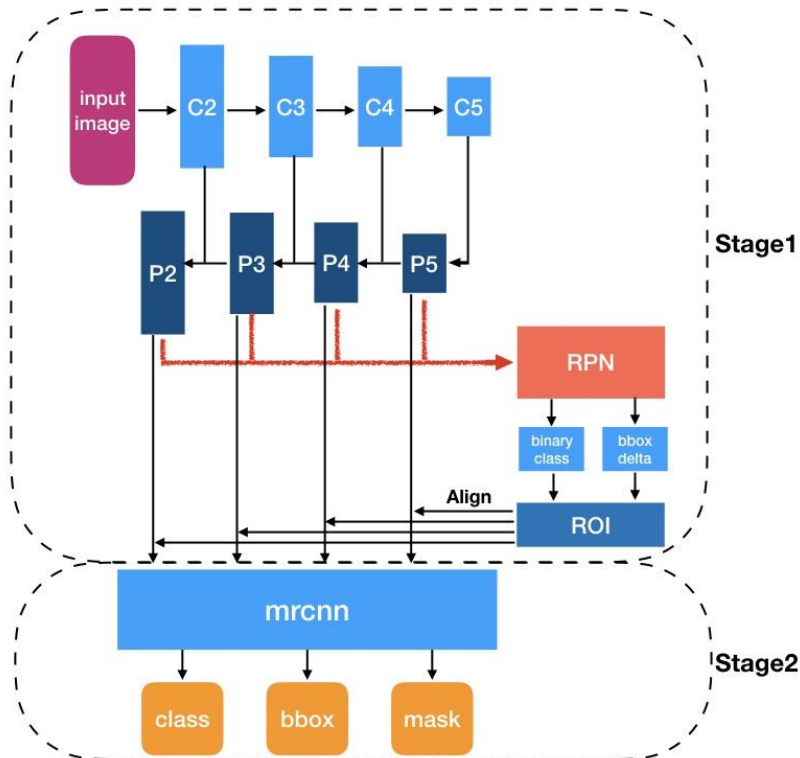
Semantic Segmentation

It deals with the correct detection of all objects in an image while also precisely segmenting each instance.



Instance Segmentation

Why Mask RCNN?



The screenshot shows a code editor with the MaskRCNN project structure on the left and the `load_mask` method implementation on the right.

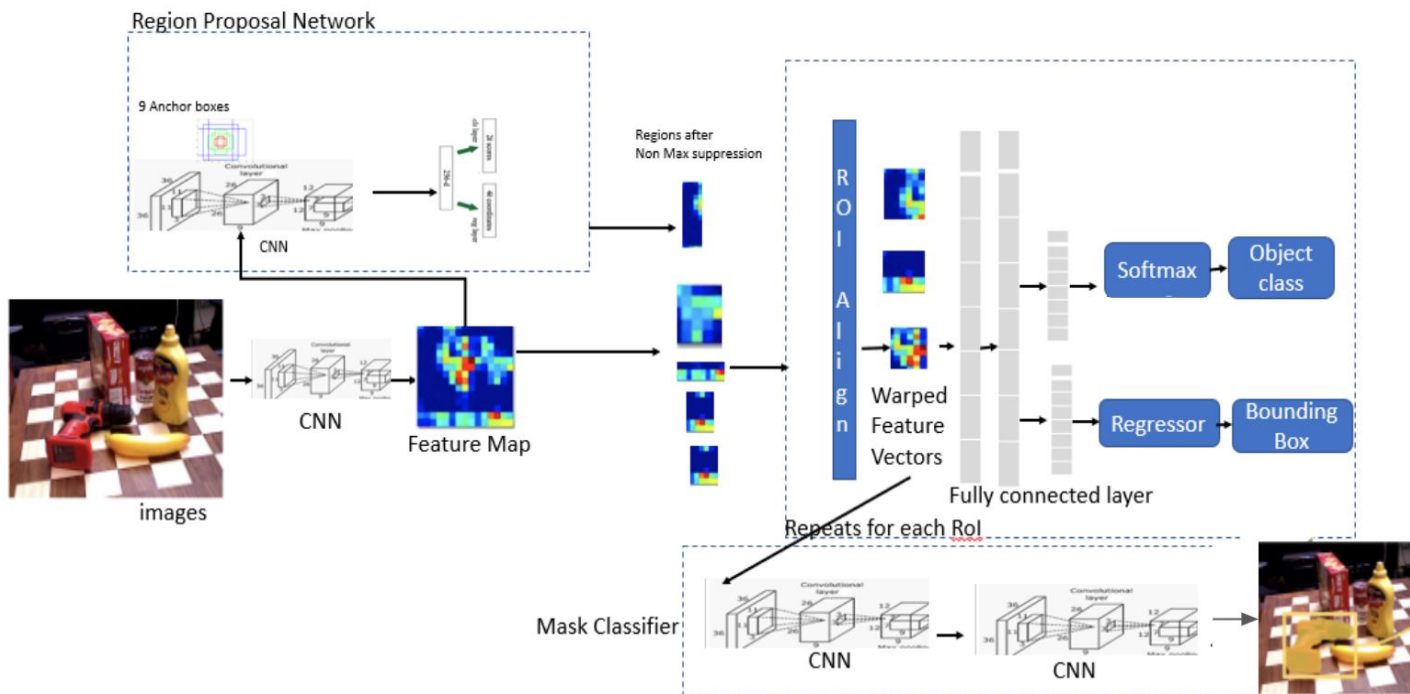
Project Structure:

- MaskRCNN
- assets
- build
- dist
- images
- mask_rcnn.egg-info
- mrcnn
 - __init__.py
 - config.py
 - model.py
 - parallel_model.py
 - utils.py
 - visualize.py
- research_objects
- samples
- venv
- .gitignore
- main.py

Code Snippet:

```
def load_mask(self, image_id):  
    """Generate instance masks for shapes  
    """  
    info = self.image_info[image_id]  
    shapes = info['shapes']  
    count = len(shapes)  
    mask = np.zeros([info['height'], info['width'], count])  
    for i, (shape, _, dims) in enumerate(shapes):  
        mask[:, :, i:i+1] = self.draw_mask(enumerate(np.ndindex(dims)):  
        # Handle occlusions  
    occlusion = np.logical_not(mask[:, :, -1])  
    for i in range(count-2, -1, -1):  
        mask[:, :, i] = mask[:, :, i] & occlusion
```

Mask RCNN



What have we produced?

Trainable densefusion Docker image:

- ``docker run -it nikwl/densfusion:latest bash``

Trainable pixel2mesh Docker image:

- ``docker run -it nikwl/pixel2mesh:latest bash``

Trainable UNET architecture.

Pose visualization suite.

(partial) Integration with azurekinect sdk for real time prediction.