

# ROB 498/599: Deep Learning for Robot Perception (DeepRob)

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Lecture 13: NMS IoU; PoseCNN

02/23/2026



<https://deeprobo.org/w26/>

# Today

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- Feedback and Recap (5min)
- Canvas Quiz questions (20min)
  - IoU threshold and NMS
- PoseCNN (45min)
- Summary and Takeaways (5min)

Final Project Group Sign-Up (3-4 persons per group):

<https://docs.google.com/spreadsheets/d/1Jjv6vBQwAtCpUSQDAx0Gj5pDCWWqcvSQEeBFIF5prqo/edit?usp=sharing>

# Recap: IoU (Intersection over Union)

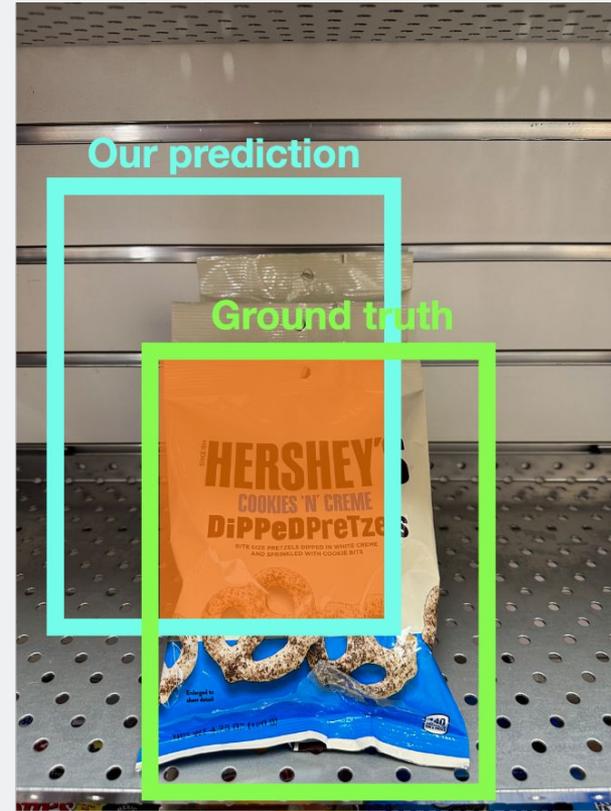
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How can we compare our prediction to the ground-truth box?

**Intersection over Union (IoU)** (Also called “Jaccard similarity” or “Jaccard index”):

*Area of Intersection*

*Area of Union*



# Recap: Non-Max Suppression (NMS)

**Problem:** Object detectors often output many overlapping detections

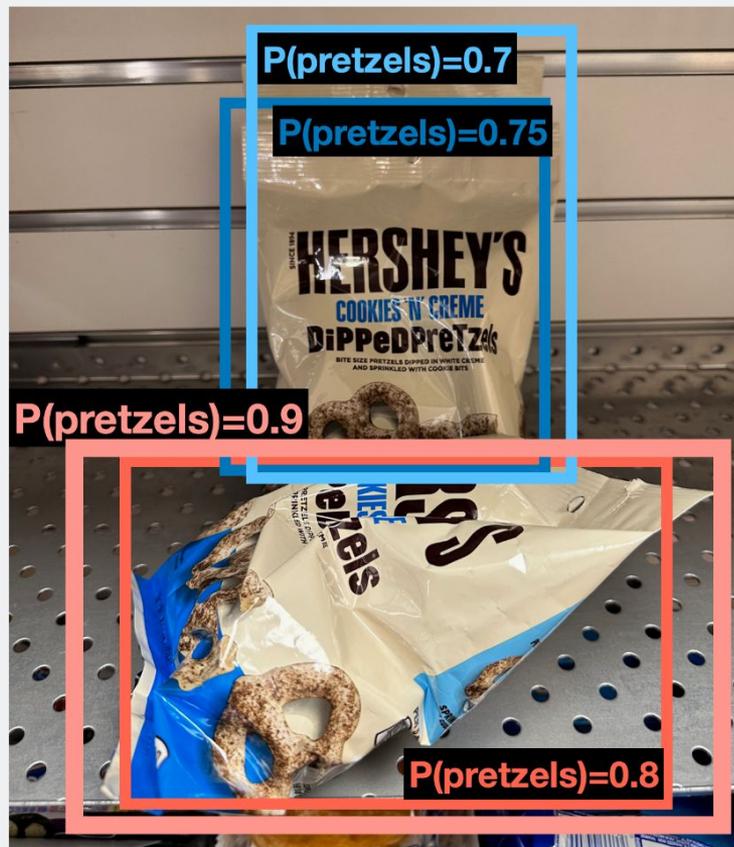
**Solution:** Post-process raw detections using Non-Max Suppression (NMS)

1. Select next highest-scoring box
2. Eliminate lower-scoring boxes with  $IoU > \text{threshold}$  (e.g. 0.7)
3. If any boxes remain, GOTO 1

$$IoU(\text{red}, \text{red}) = 0.8$$

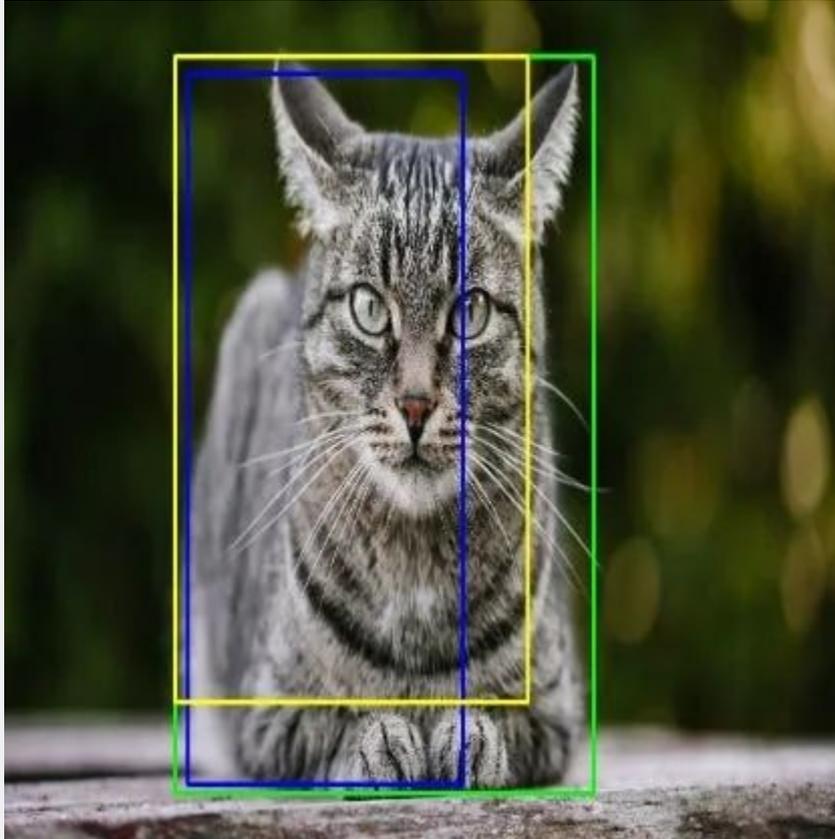
$$IoU(\text{red}, \text{blue}) = 0.03$$

$$IoU(\text{red}, \text{cyan}) = 0.05$$



# Example:

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`green_box = [x1, y1, x2, y2, "Cat", 0.9]`

`yellow_box = [x5, y5, x6, y6, "Cat", 0.75]`

`blue_box = [x3, y3, x4, y4, "Cat", 0.85]`

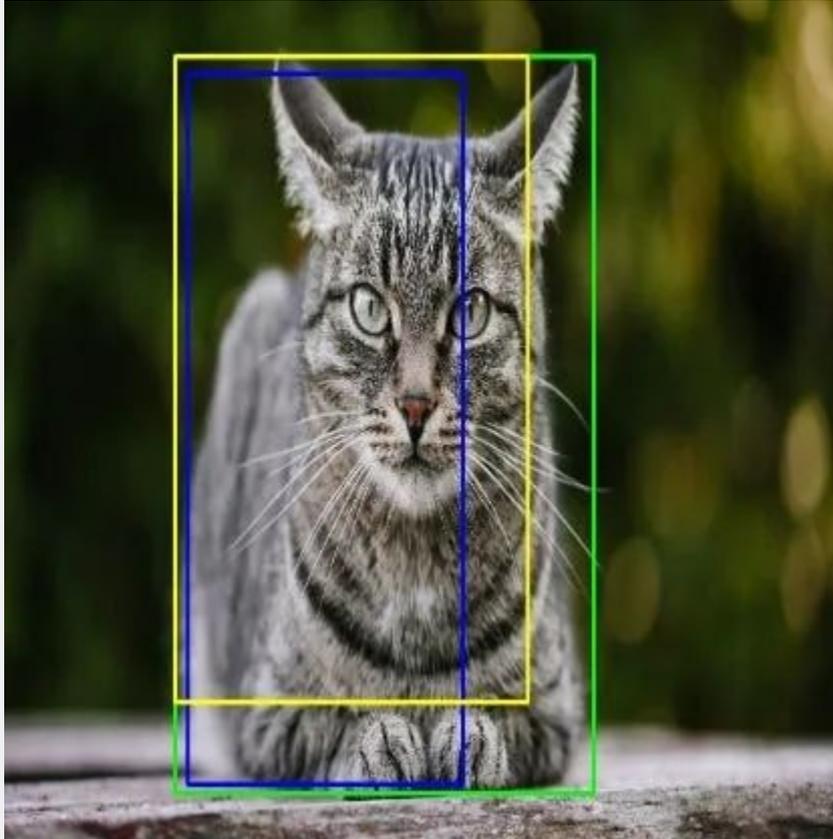
# Example:

---

`green_box = [x1, y1, x2, y2, "Cat", 0.9]`

`yellow_box = [x5, y5, x6, y6, "Cat", 0.75]`

`blue_box = [x3, y3, x4, y4, "Cat", 0.85]`



## NMS Algorithm

### Stage 1 - initial removal of boxes

1. Sort the confidence

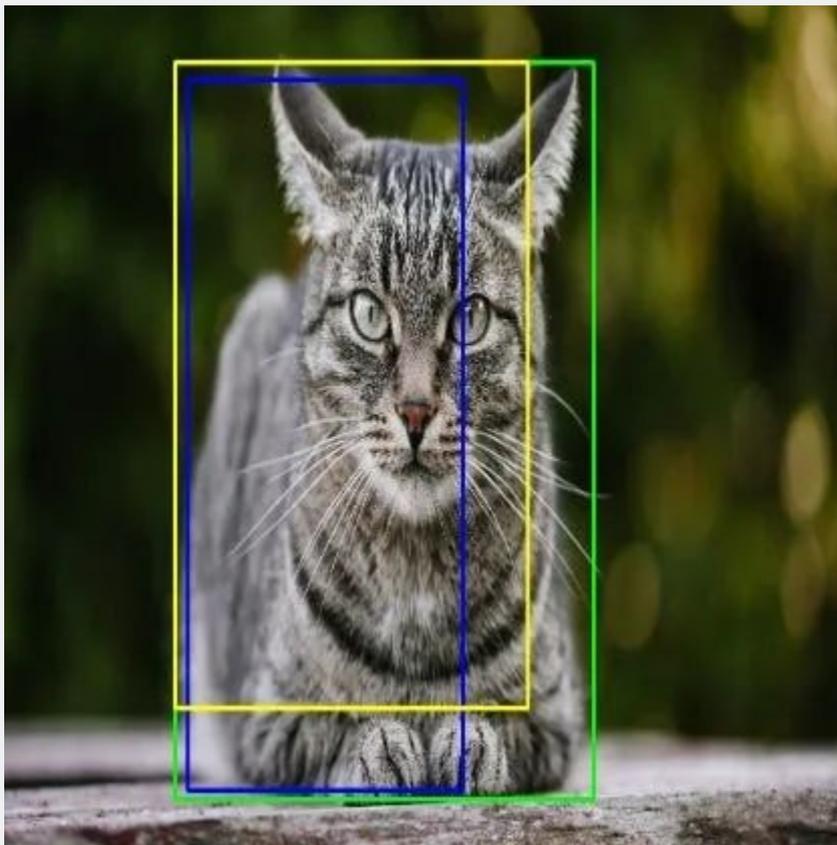
`bbox_list = [green_box, blue_box, yellow_box]`

# Example:

```
green_box = [x1, y1, x2, y2, "Cat", 0.9]
```

```
yellow_box = [x5, y5, x6, y6, "Cat", 0.75]
```

```
blue_box = [x3, y3, x4, y4, "Cat", 0.85]
```



## NMS Algorithm:

### Stage 1 - initial removal of boxes

1. Sort the confidence

```
bbox_list = [green_box, blue_box, yellow_box]
```

2. Set a confidence threshold

Let's say, confidence threshold= 0.8

Any box that has a confidence **below** this threshold will be **removed**.



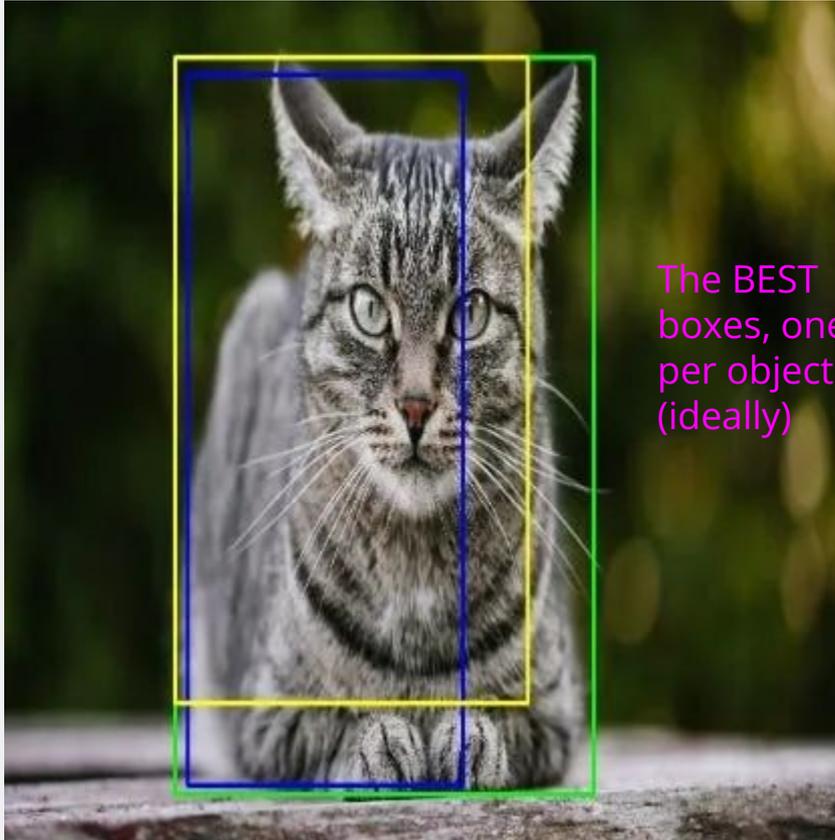
```
bbox_list = [green_box, blue_box]
```

# Example:

```
green_box = [x1, y1, x2, y2, "Cat", 0.9]
```

```
yellow_box = [x5, y5, x6, y6, "Cat", 0.75]
```

```
blue_box = [x3, y3, x4, y4, "Cat", 0.85]
```



The BEST  
boxes, one  
per object  
(ideally)

## NMS Algorithm:

### Stage 2 - IoU comparison of Boxes

1. Start a new list. Start with the highest confidence box.

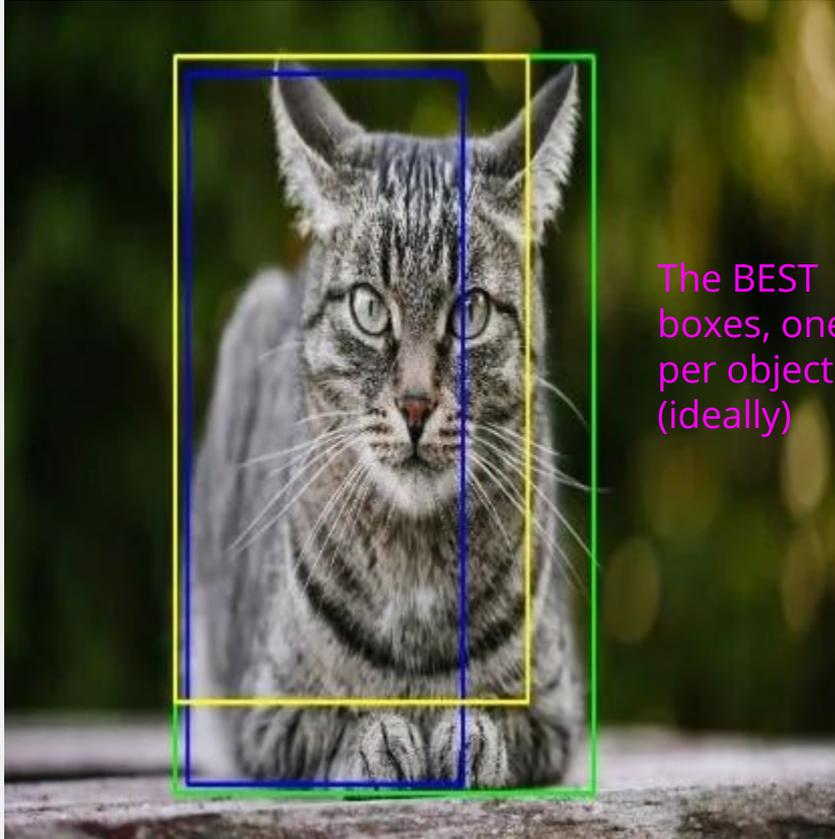
```
bbox_list_new = [green_box]
```

# Example:

```
green_box = [x1, y1, x2, y2, "Cat", 0.9]
```

```
yellow_box = [x5, y5, x6, y6, "Cat", 0.75]
```

```
blue_box = [x3, y3, x4, y4, "Cat", 0.85]
```



## NMS Algorithm:

### Stage 2 - IoU comparison of Boxes

1. Start a new list. Start with the highest confidence box.

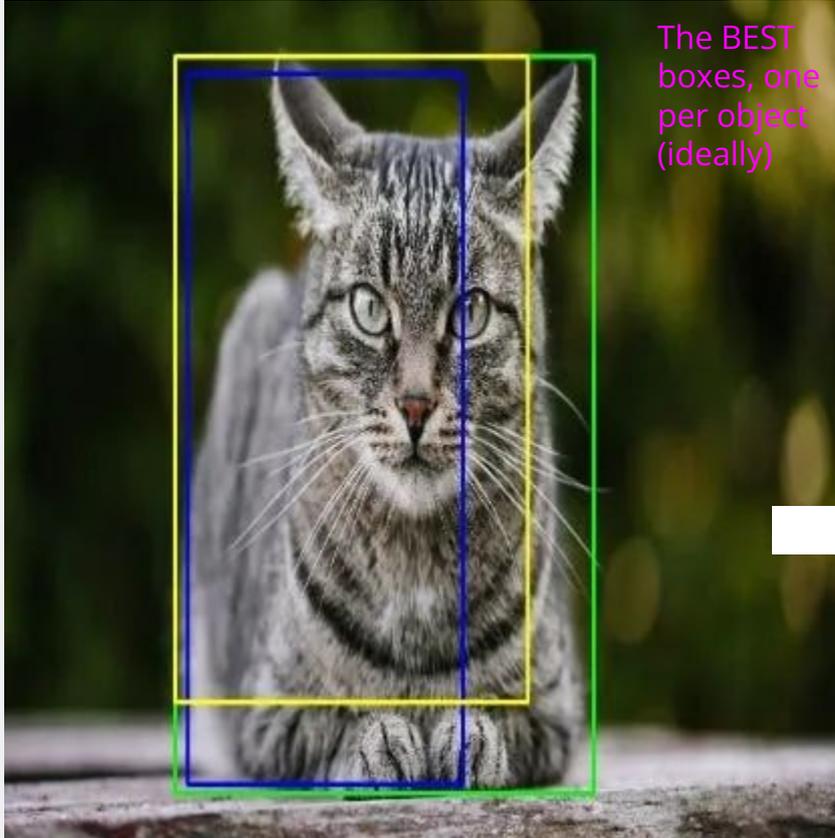
```
bbox_list_new = [green_box]
```

2. Set an IoU threshold (e.g., 0.5)

\*IoU threshold: determine when two boxes **overlap** too much and likely represent the same object.

# Example:

green\_box = [x1, y1, x2, y2, "Cat", 0.9]  
yellow\_box = [x5, y5, x6, y6, "Cat", 0.75]  
blue\_box = [x3, y3, x4, y4, "Cat", 0.85]



## NMS Algorithm: Stage 2 - IoU comparison of Boxes

1. Start a new list. Start with the highest confidence box.

`bbox_list_new = [green_box]`

2. Set an IoU threshold (e.g., **0.5**)

\*IoU threshold: determine when two boxes **overlap** too much and likely represent the same object.

3. Compare IoU with remaining boxes

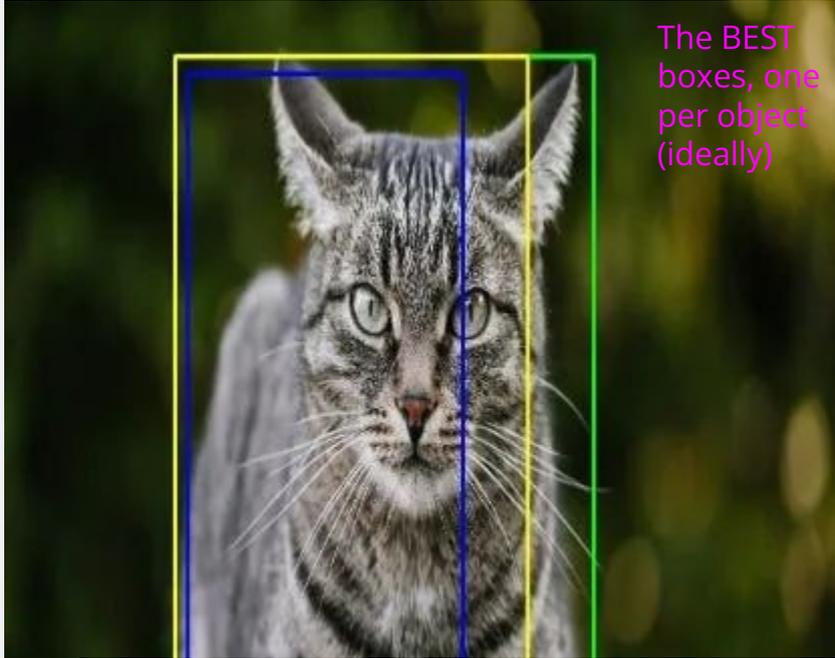
Calculate the **IoU** of the green box with all remaining boxes of the same class.

Note: `bbox_list = [green_box, blue_box]` (from stage 1)

If  $\text{IoU}(\text{green\_box}, \text{blue\_box}) > 0.5$ , means they have significant overlap (likely detect the same object)

# Example:

green\_box = [x1, y1, x2, y2, "Cat", 0.9]  
yellow\_box = [x5, y5, x6, y6, "Cat", 0.75]  
blue\_box = [x3, y3, x4, y4, "Cat", 0.85]



The BEST boxes, one per object (ideally)

## NMS Algorithm: Stage 2 - IoU comparison of Boxes

1. Start a new list. Start with the highest confidence box.

`bbox_list_new = [green_box]`

2. Set an IoU threshold (e.g., **0.5**)

\*IoU threshold: determine when two boxes **overlap** too much and likely represent the same object.

3. Compare IoU with remaining boxes

$\text{IoU}(\text{green\_box}, \text{blue\_box}) > 0.5$

4. Remove the lower confidence box  
Remove the `blue_box`
5. Repeat for all boxes



- Move to the next box in the list and repeat the process until all boxes have been checked.
- By the end, only unique boxes with high confidence will remain in `bbox_list_new`.

# From the original R-CNN paper

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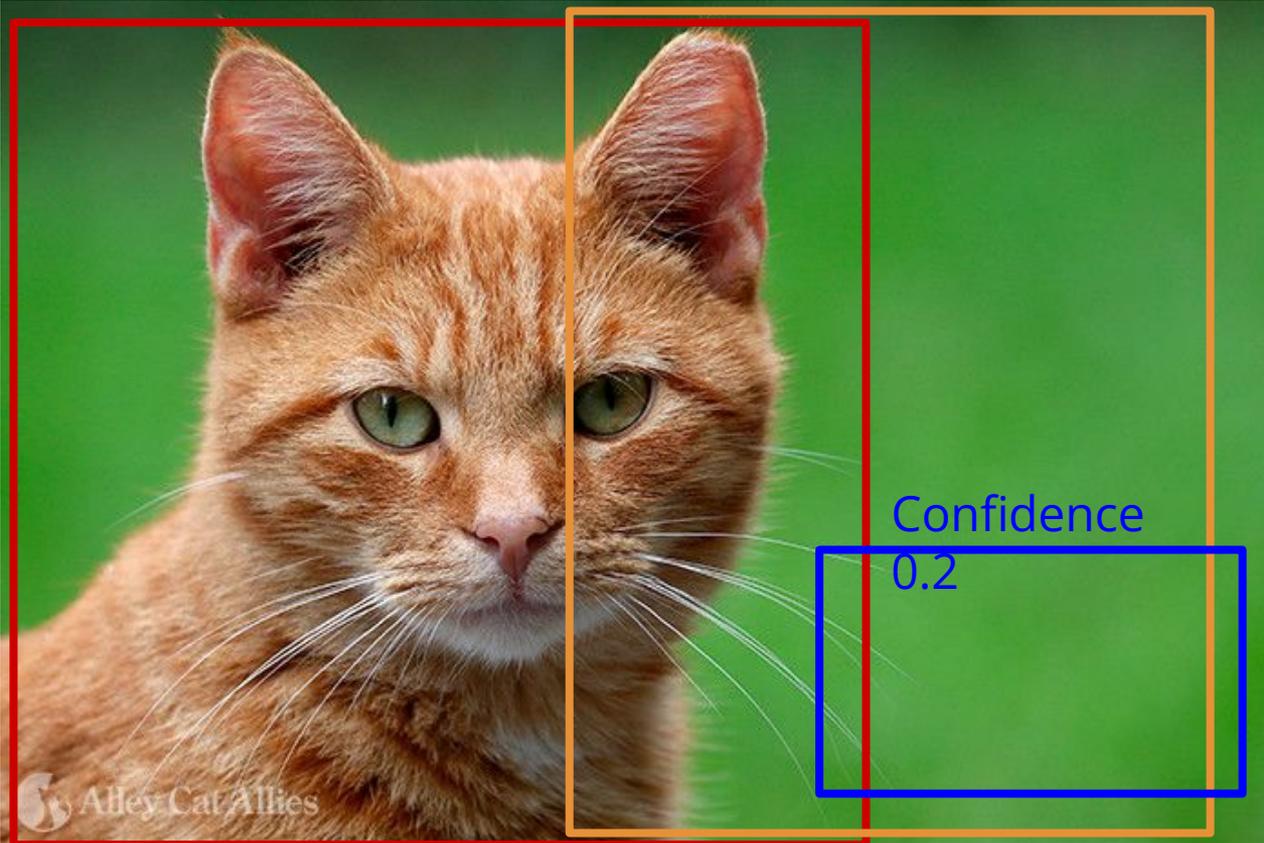
<https://arxiv.org/pdf/1311.2524>

“Given all scored regions in an image, we apply a greedy non-maximum suppression (for each class independently) that rejects a region if it has an intersection-over-union (IoU) overlap with a higher scoring selected region larger than a learned threshold.”

# Example:

Confidence 0.9

Confidence 0.7



(compare to red)

If IoU threshold = 0.1 (low)  
reject orange and blue boxes

Final detection = red box

$$\text{Precision} = \text{TP}/(\text{TP}+\text{FP}) = 1/(1+0) = 1$$

$$\text{Recall} = \text{TP}/(\text{TP}+\text{FN}) = 1/(1+0) = 1$$

If IoU threshold = 0.9 (high)  
NOT reject orange and blue boxes

Final detection = red, orange, blue box

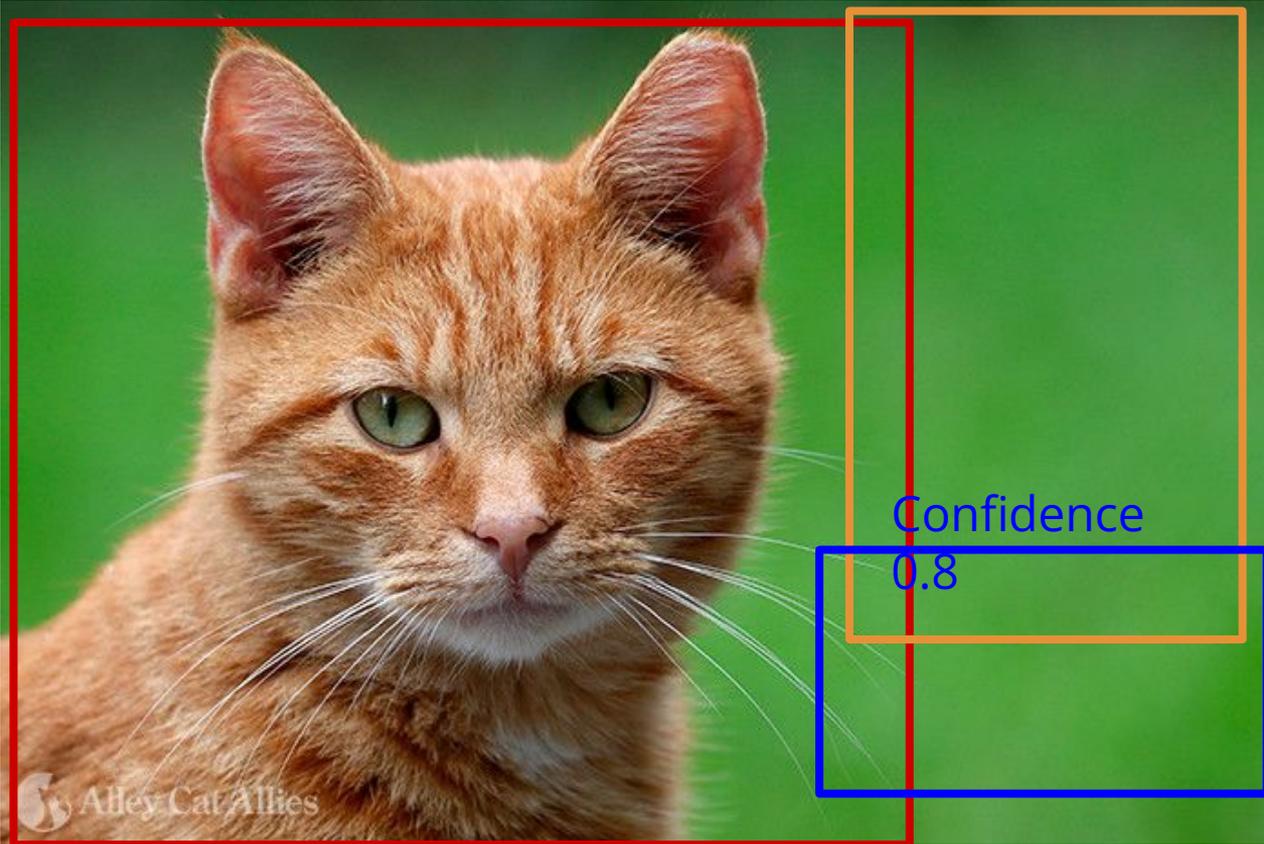
$$\text{Precision} = \text{TP}/(\text{TP}+\text{FP}) = 1/(1+2) = 1/3$$

$$\text{Recall} = \text{TP}/(\text{TP}+\text{FN}) = 1/(1+0) = 1$$

# Example:

Confidence 0.2

Confidence 0.9



(compare to orange)

If IoU threshold = 0.1 (low)  
reject red and blue boxes

Final detection = orange box

Precision =  $TP / (TP + FP) = 0 / (0 + 1) = 0$

Recall =  $TP / (TP + FN) = 0 / (0 + 0) = 0$

If IoU threshold = 0.9 (high)  
NOT reject red and blue boxes

Final detection = orange, blue, red box

Precision =  $TP / (TP + FP) = 1 / (1 + 2) = 1/3$

Recall =  $TP / (TP + FN) = 1 / (1 + 0) = 1$

# Additional Reading

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- <https://medium.com/@abhishekjainindore24/non-maximal-suppression-in-object-detection-nms-028ce2be6cdc>
- <https://github.com/ultralytics/ultralytics/issues/9150>
- <https://github.com/ultralytics/ultralytics/issues/8428>
- [https://docs.ultralytics.com/reference/utils/ops/#ultralytics.utils.ops.non\\_max\\_suppression](https://docs.ultralytics.com/reference/utils/ops/#ultralytics.utils.ops.non_max_suppression) <https://docs.ultralytics.com/reference/utils/nms/> “iou\_thres - The IoU threshold below which boxes will be filtered out during NMS. Valid values are between 0.0 and 1.0.”
- <https://arxiv.org/pdf/1705.02950>

“Lower IoU threshold means stricter overlap criteria, potentially leading to more aggressive suppression of close detections.”

```
torchvision.ops.nms(boxes: Tensor, scores: Tensor, iou_threshold: float) → Tensor [SOURCE]
```

# PoseCNN: 6D Pose Estimation

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- P3 released, Due March 8, 2026  
Start NOW!!!
- PoseCNN will be the first part of P4.

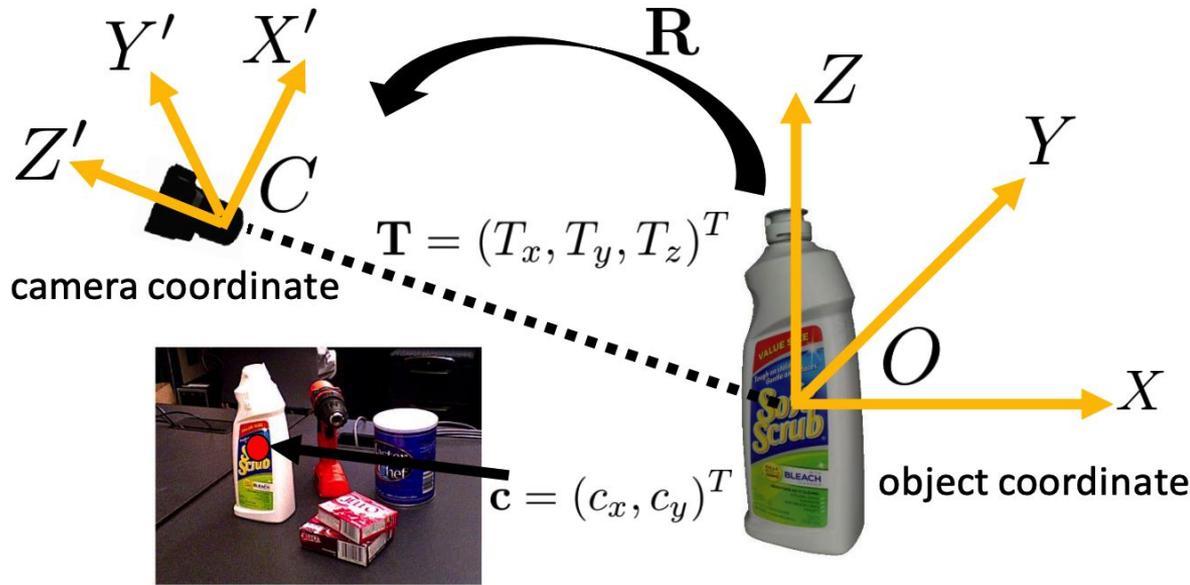
## Learning Objectives:

- ★ Introduce P4 content
- ★ A CNN-based pose estimation method
- ★ How to read research paper → implementation
  - Datasets
  - From written Methods to code implementations
  - Think about possible extensions?

# PoseCNN: 6D Pose Estimation

- P3 released, Due March 8, 2026  
Start NOW!!!
- PoseCNN will be part of P4.

<https://arxiv.org/pdf/1711.00199>



3D Translation  $T$   
3D Rotation  $R$

2D  $\rightarrow$  3D

Task: determining the six degree-of-freedom (6D) pose of an object in 3D space based on RGB images

# PoseCNN: 6D Pose Estimation

<https://arxiv.org/pdf/1711.00199>

YCB-Video  
dataset

<https://www.ycbbenchmarks.com/>



Fig. 5. The subset of 21 YCB Objects selected to appear in our dataset.





# PoseCNN: **6D** Pose Estimation

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PROPS-POSE dataset

(will be provided again with P4)

<https://deepprob.org/w26/datasets/props-pose/>

Download here:

<https://drive.google.com/file/d/15rhwXhzHGKtBcxJAYMWJG7gN7BLLhyAq/view?usp=sharing>



# PoseCNN: 6D Pose Estimation

## Useful Functions

(refer back to this in P4!)

```
torch.nn.init.kaiming_normal_(tensor, a=0, mode='fan_in', nonlinearity='leaky_relu',  
generator=None) [SOURCE]
```

### Initialize weight to kaiming\_normal

Fill the input *Tensor* with values using a Kaiming normal distribution.

```
torch.nn.init.zeros_(tensor) [SOURCE]
```

### Initialize bias to zero

### upsample/interpolate

```
torch.nn.functional.interpolate(input, size=None, scale_factor=None, mode='nearest',  
align_corners=None, recompute_scale_factor=None, antialias=False) [SOURCE]
```

# PoseCNN: 6D Pose Estimation

\*(refer back to this in P4!)

## Useful Functions

p4\_helper/loss\_Rotation (to be used as rotation loss)

p4\_helper/IOUselection

In PoseCNN Forward pass **training**:

```
pred_filtered_bbxes = IOUselection(bbox, gt_bbx, threshold=0.10)
```

If the size of pred\_filtered\_bbxes is larger than 0:

```
quaternion = self.rotationBranch(...)
```

```
predRot, label_pred = self.estimateRotation(quaternion, pred_filtered_bbxes)
```

```
gtRot = self.gtRotation(pred_filtered_bbxes, input_dict)
```

```
loss_dict['loss_R'] = loss_Rotation(predRot, gtRot, label_pred,  
self.models_pcd)
```

bboxes from  
SegmentationBranch

p4\_helper/HoughVoting

PoseCNN Forward pass **inference**

```
pred_centers, pred_depths = HoughVoting(segmentation, translation)
```

```
output_dict = self.generate_pose(predRot, pred_centers, pred_depths, bboxes)
```