

Exercise 1

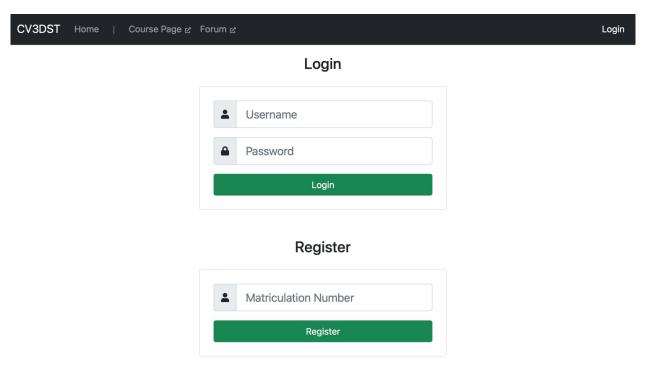
About the Exercise Session

 2 weeks for each exercise + Office hours (OH) for questions in between

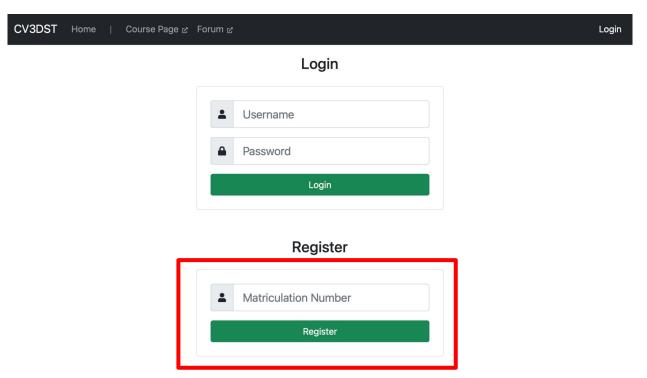


Deadline always 23:59 CET on due date

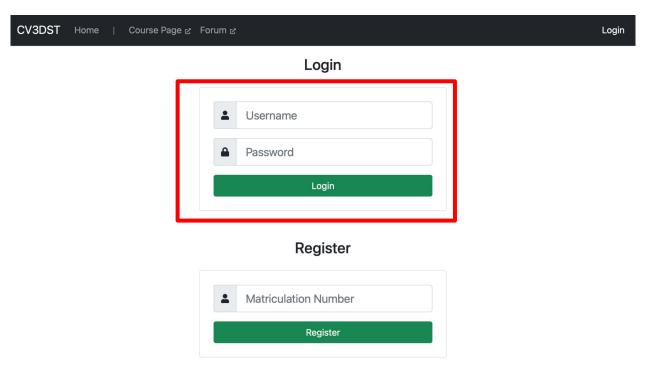
Submission Page



Submission Page

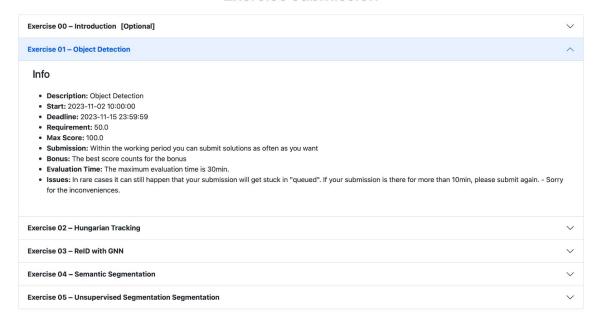


Submission Page



Exercise 1

Exercise submission

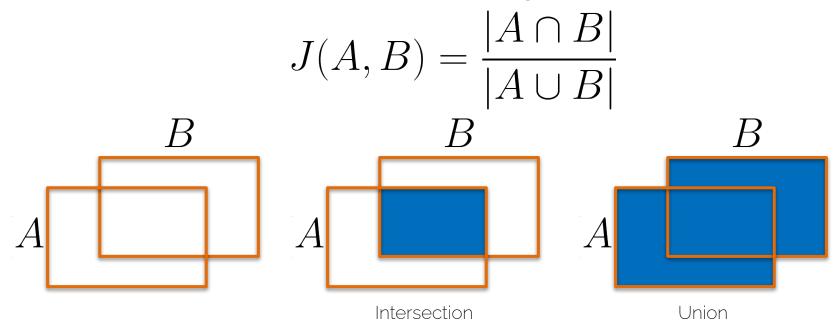




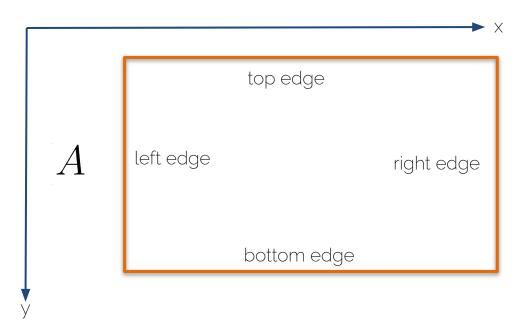
Exercise 1

- Object detection with HOG classifiers
 - computing the IoU
 - creating a histogram of oriented gradients
 - sliding window detection
 - non-maximum suppression
- Optional: Comparison with a state of the art object detector (FasterRCNN)

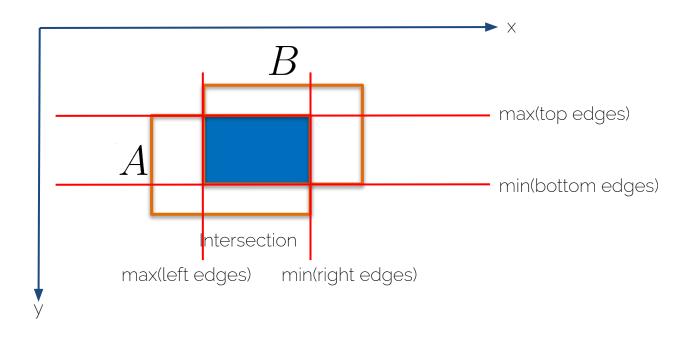
- also called the Jaccard Index
- compute the overlap of two regions



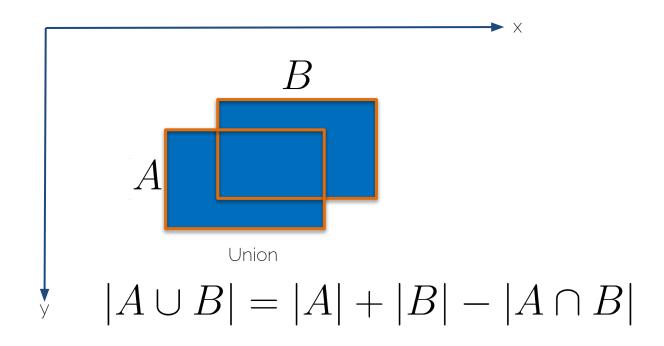
conventions



intersection



union



Task 2 - Compute Image Gradient

- computed with central difference
- first compute the gradients in x and y direction
- be mindful of the orientation of the coordinate system of the image and the order of row/column of pytorch tensors
- add padding (reflective) to get the correct output size

$$\nabla_x I(x, y) = I(x+1, y) - I(x-1, y)$$
$$\nabla_y I(x, y) = I(x, y+1) - I(x, y-1)$$

Task 2 - Compute Image Gradient

compute the norm and angle

$$\nabla_{\mathbf{n}}I(x,y) = \left\| \begin{pmatrix} \nabla_x I(x,y) \\ \nabla_y I(x,y) \end{pmatrix} \right\|_2$$

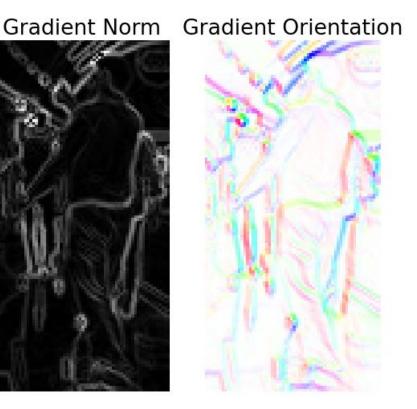
$$\nabla_{\mathbf{a}}I(x,y) = \arctan \frac{\nabla_x I(x,y)}{\nabla_y I(x,y)}$$

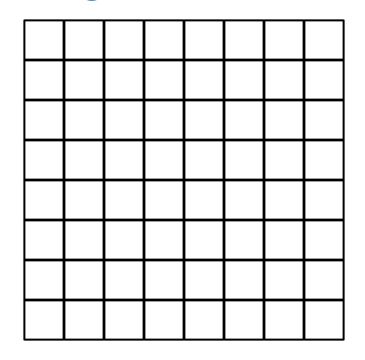
^{*} Be mindful of dividing by zero (there might be a nice default implementation)

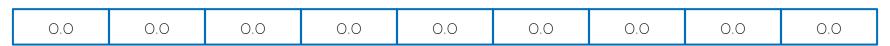
Task 2 - Compute Image Gradient

Image



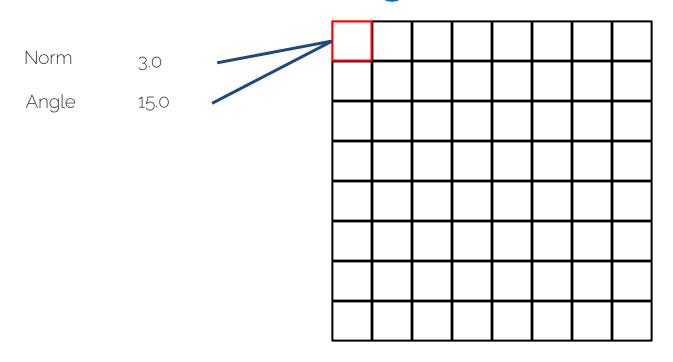






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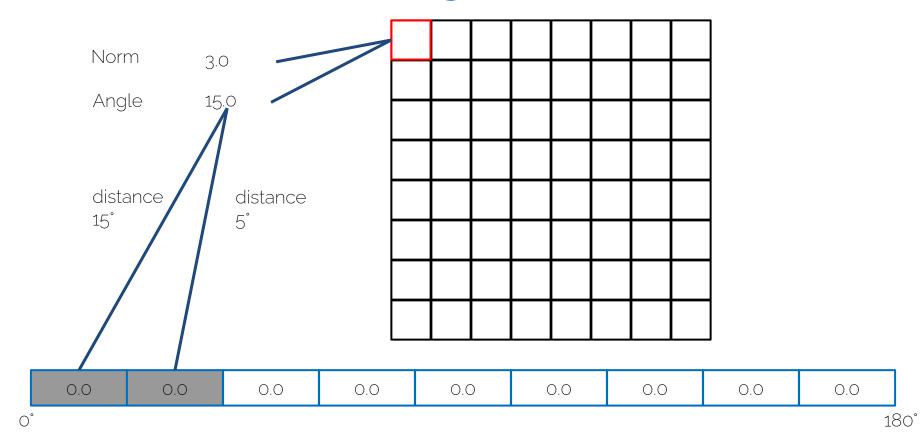
180°

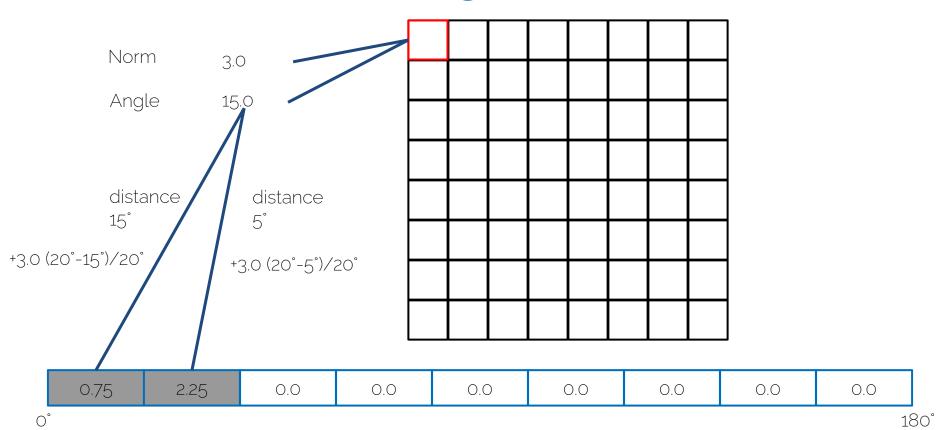


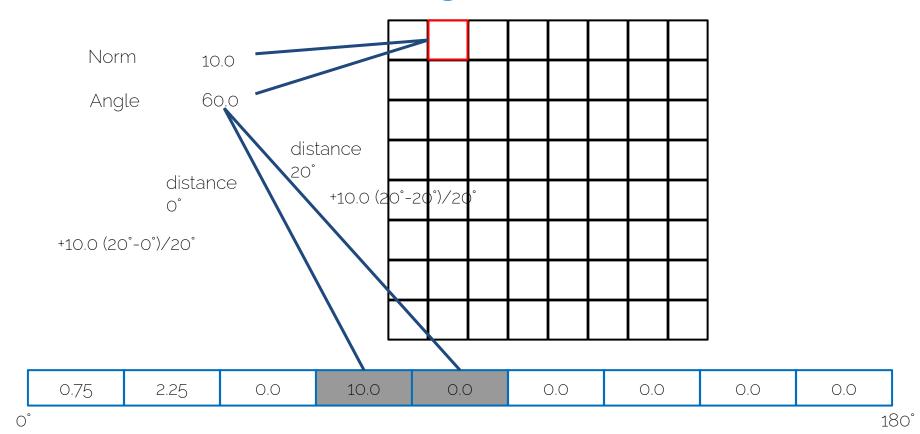


O

180°





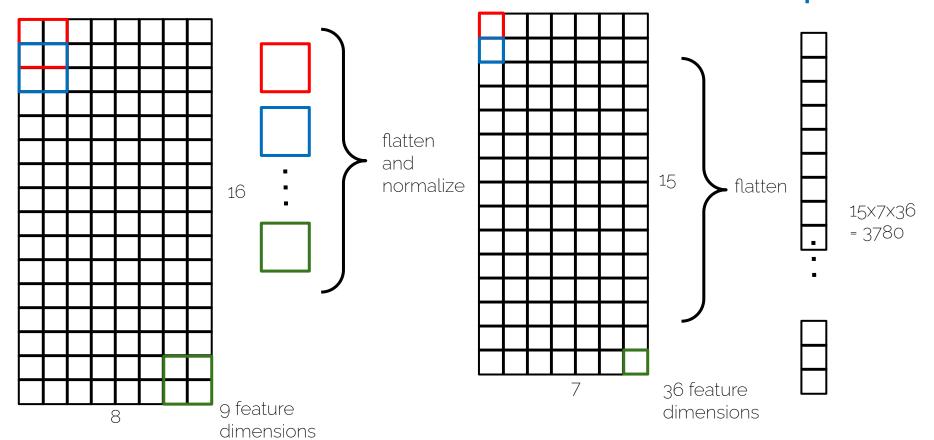




Histogram of Oriented Gradients



HOG Features - Additional Steps



HOG Features - Additional Steps

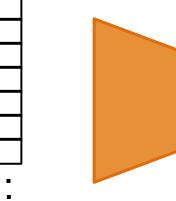








down-/upsample 3780 and compute **HOG** features



Binary Cross Entropy Loss





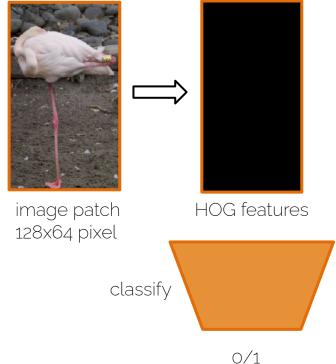
binary classifier e.g. SVM MLP

Task 4 - Sliding Window Detection

- naive approach to object detection
- exhaustive search across all of the image
- fixed detection ratio
- need for image pyramid to capture different scales
- implementation for different strides
 - less detections
 - speed up detection time

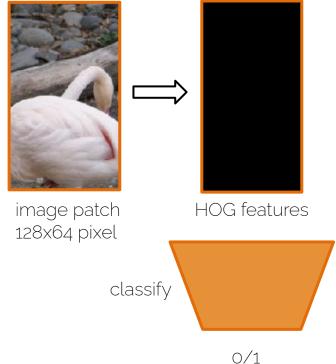
Task 4 - Sliding Window Detection



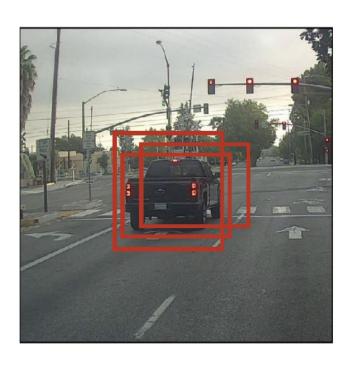


Task 4 - Sliding Window Detection





- algorithm to select the "best" prediction from a bunch of predictions
- it is a post-processing step, not a machine learning component
- a deterministic process that does not require any learning
- it is used in both classical approaches and deep learning methods



Non-Max Suppression





```
Algorithm 1 Non-Max Suppression
                                                                                possible vectorization
 1: procedure NMS(B, c)
        B_{nms} \leftarrow \emptyset
        for b_i \in B do
 3:
                                                                         B: Bounding Boxes
            discard \leftarrow False
                                                                         c: Classification Probability
            for b_i \in B do
 5:
                                                                         same(b_i, b_j): IoU(b_i, b_j)
                if same(b_i, b_i) > \lambda_{nms} then
 6:
                                                                         score(c, b_i): c[b_i]
                    if score(c, b_i) > score(c, b_i) then
 7:
8:
                        discard \leftarrow True
9:
            if not discard then
10:
                B_{nms} \leftarrow B_{nms} \cup b_i
11:
        return B_{nms}
```

How does precision and recall change with the choice of λ ?

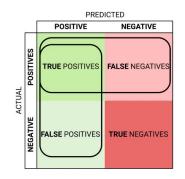
• high λ :

- less bounding boxes that overlap enough
- more predicted bounding boxes
- more false positives/less false negatives
- lower precision/higher recall

low λ:

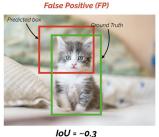
- more bounding boxes that overlap enough
- less predicted bounding boxes
- less false positives/more false negatives
- higher precision/lower recall

- Confusion Matrix
 - TP: model predicted object, actually object
 - FP: model predicted object, no object
 - FN: model did not predict, actually object

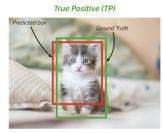


If IoU threshold = 0.5

- Getting TP, FP, FN:
 - Set of positive predictions P_pred
 - Set of positive annotations P

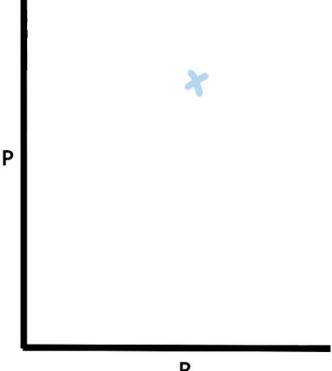


IoU = ~0.7



- Precision = TP/ P_pred
- Recall = TP/P

Question: How can we build a Precision-Recall-Curve?

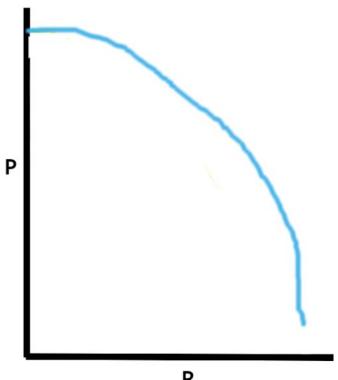


R

- Precision = TP/ P_pred
- Recall = TP/P

Question: How can we build a Precision-Recall-Curve?

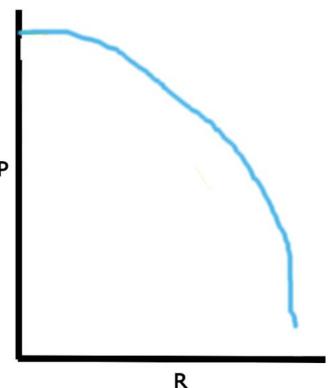
-> Vary confidence threshold



R

- Precision = TP/ P_pred
- Recall = TP/P

Question: What is the Area under Curve and Average Precision?

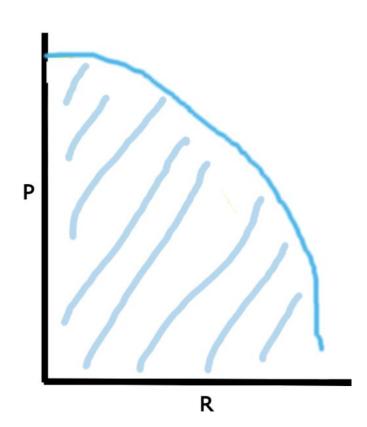


- Precision = TP/ P_pred
- Recall = TP/P

Question: What is the Area under Curve and Average Precision?

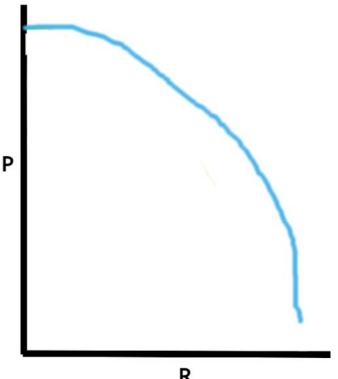
$$\int_0^1 P(R)dR$$

$$\sum_{k} P(R_k) \Delta R$$



- Precision = TP/ P_pred
- Recall = TP/P

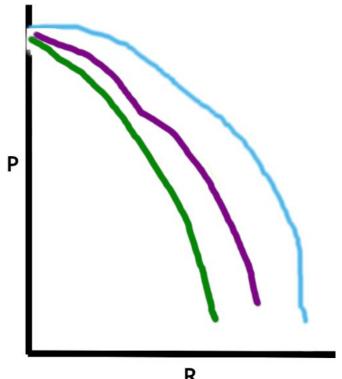
Question: How does the IoU influence the curve?



- Precision = TP/ P_pred
- Recall = TP/P

Question: How does the IoU influence the curve?

Task: Attach IoU_thresholds 0.5, 0.6, 0.7 to the curves.

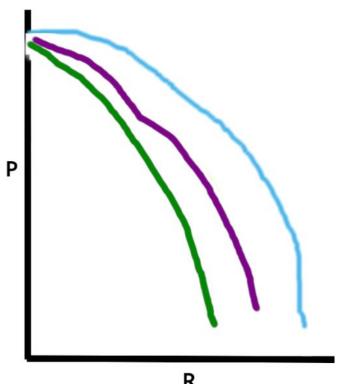


- Precision = TP/ P_pred
- Recall = TP/P

Question: How does the IoU influence the curve?

Task: Attach IoU_thresholds 0.5, 0.6, 0.7 to the curves.

Higher IoU thresholds result in (more/less) TP and therefore (higher/lower) recall.



R

General Tips

- read through the notebooks carefully
 Yes. Even the introductory parts. They might contain hints on how to solve the problems
- look for pytorch implementations before you try to do everything by your own
- try to vectorize your operations. Vectorizations speed up your computation time significantly

Links

- Test server: <u>https://cv3dst.cvai.cit.tum.de/login</u>
- If you have trouble registering <u>https://forms.gle/yZkZiDiyHxWuNqQG7</u>
- Data for Exercise 01: <u>https://vision.in.tum.de/webshare/g/cv3dst/exercise_01.zip</u>

Links for the individual datasets

- MOT
 https://vision.in.tum.de/webshare/g/cv3dst/datasets/MO
 T16.zip
- market <u>https://vision.in.tum.de/webshare/g/cv3dst/datasets/market.zip</u>
- obj_seg
 https://vision.in.tum.de/webshare/g/cv3dst/datasets/obj_seg.zip
- reid_gnn https://vision.in.tum.de/webshare/g/cv3dst/datasets/reid_ _gnn.zip