DataLab Cup 2: Object Detection

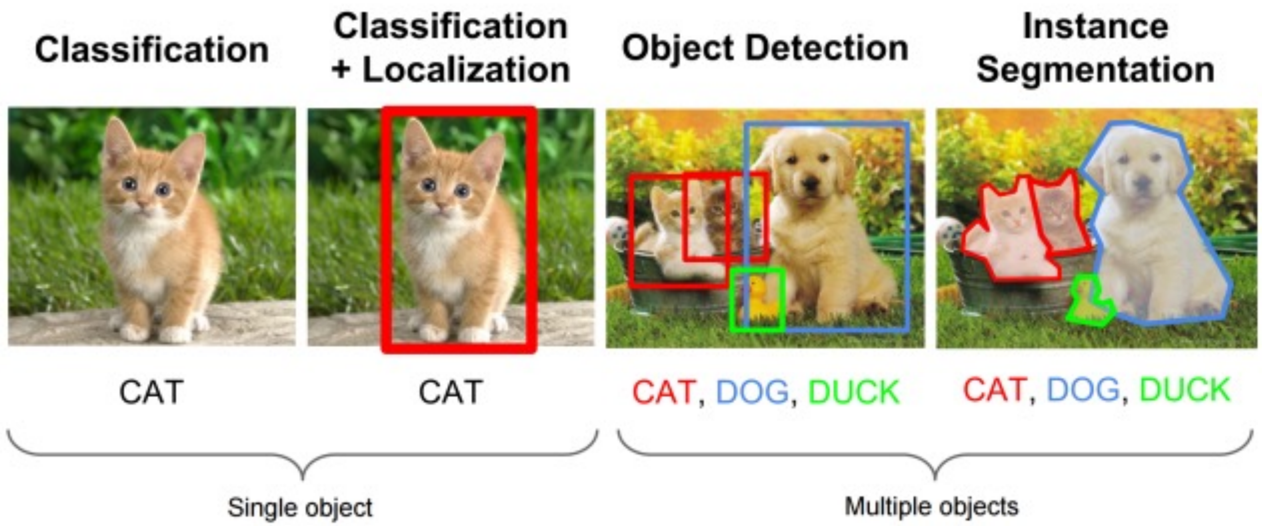
Datalab

Outline

- Competition Information
- Object detection model
  - You Only Look Once (YOLO)
- Evaluation metric
  - Mean Average Precision (mAP)
- Hints
- Precautions
- Competition Timeline

Competition Information

- Object Detection
  - In this competition, we are going to train an object detection model to detect objects in an image.



Competition Information

- Dataset
  - PASCAL VOC 2007
    - Train/Val data: 5011
      - Each row contains one image and its bounding boxes.
      - filename, $(x_{min}, y_{min}, x_{max}, y_{max}, \text{label}) * \text{object\_num}$

```
000012.jpg 156 97 351 270 6
000016.jpg 92 72 305 473 1
000017.jpg 185 62 279 199 14 90 78 403 336 12
000019.jpg 231 88 483 256 7 11 113 266 259 7
```

    - Test data: 4952
      - filename

```
000001.jpg
000002.jpg
000003.jpg
```

Object Detection Model

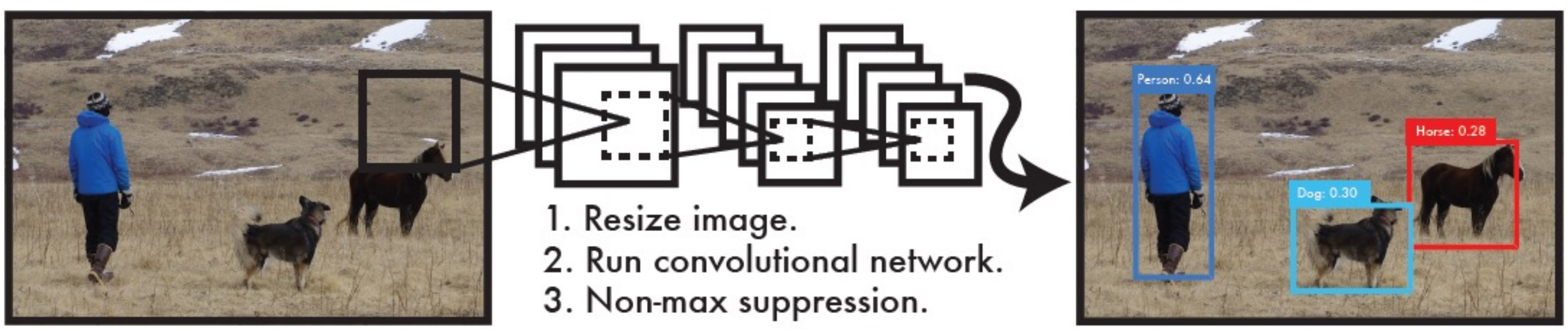
YOLO

- Motivation
  - Conventional object detection methods require two steps:
    1. Propose some regions that might contain object
    2. Doing classification on all proposed regions
  - It is inefficient to scan the image twice and costly to do classification on all proposed regions.
  - What about scanning image once and propose bounding boxes and labels accordingly?

Object Detection Model

YOLO

- Main idea
  - Reframe object detection problem as a single regression problem.
  - Predict bounding box coordinates and class probabilities from image pixels straightly.



Object Detection Model

YOLO

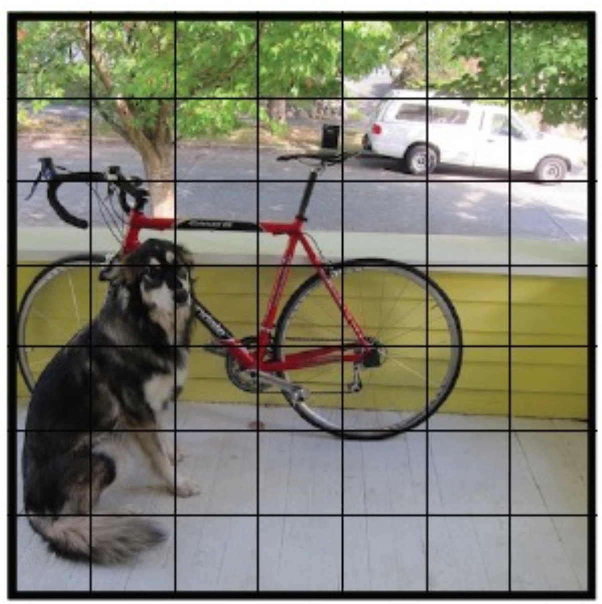
- Main idea
  - YOLO is extremely fast since it requires no complex pipelines to output bounding boxes and object labels.

Real-Time Detectors	Train	mAP	FPS
100Hz DPM [30]	2007	16.0	100
30Hz DPM [30]	2007	26.1	30
Fast YOLO	2007+2012	52.7	**155**
YOLO	2007+2012	**63.4**	45
Less Than Real-Time			
Fastest DPM [37]	2007	30.4	15
R-CNN Minus R [20]	2007	53.5	6
Fast R-CNN [14]	2007+2012	70.0	0.5
Faster R-CNN VGG-16[27]	2007+2012	73.2	7
Faster R-CNN ZF [27]	2007+2012	62.1	18

Object Detection Model

YOLO

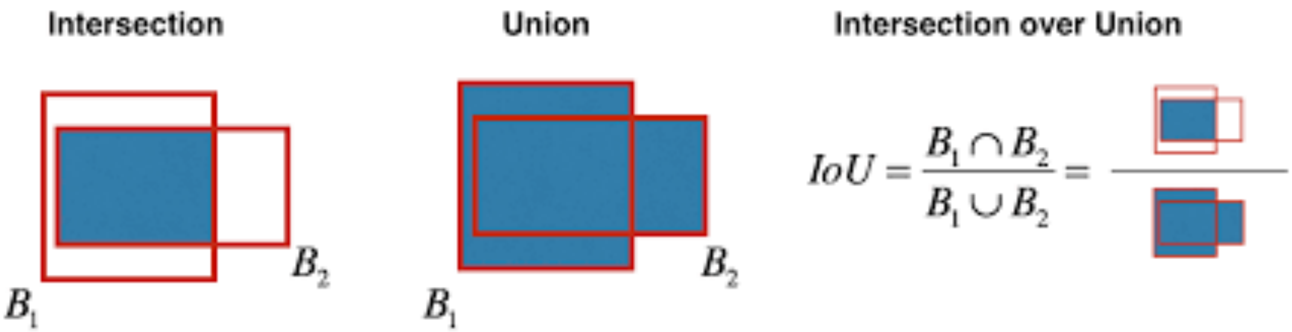
- Objective function
  - YOLO first divides the input image into a $S \times S$ grid.
  - If the center of an object falls into a grid cell, the grid cell is responsible for detecting that object.



Object Detection Model

YOLO

- *Intersection over Union* (IoU)
  - A metric to evaluate the effectiveness of predict bounding box comparing to the ground truth.



Object Detection Model

YOLO

- Objective function
  - Each grid cell predicts B bounding boxes and confidence score for those boxes.
    - Each bounding box consists of 5 predictions: x, y, w, h and confidence.

Object Detection Model

YOLO

- Objective function
  - Each grid cell predicts B bounding boxes and confidence score for those boxes.
    - The confidence score is defined as
$$\mathrm{Pr}(\mathrm{Object}) * \mathrm{IoU}_{pred}^{truth}.$$
    - The score should be zero when there is no object in bounding box.
    - Otherwise, the score should be equal to $\mathrm{IoU}_{pred}^{truth}$.

Object Detection Model

YOLO

- Objective function
  - Each grid cell also predicts C conditional class probabilities,

$$\Pr(\text{Class}_i|\text{Object})$$

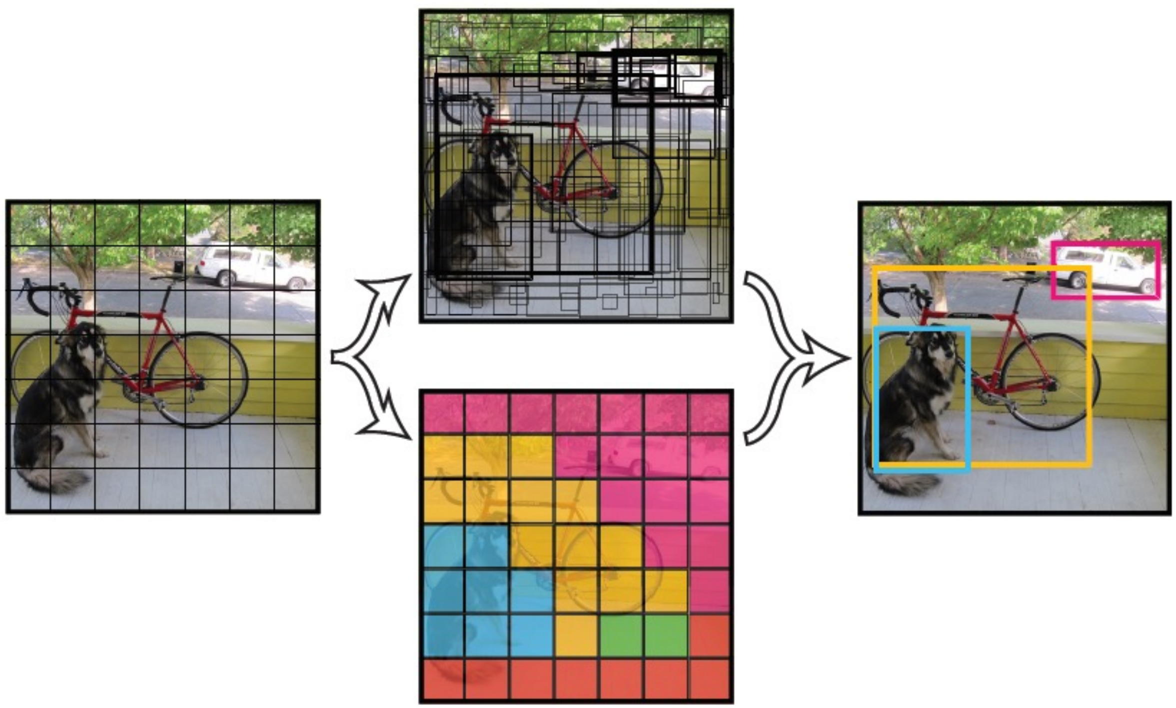
  - Multiplying the conditional class probabilities and the individual box confidence predictions gives us the *class-specific scores for each box*.

$$\underbrace{\boxed{\Pr(\text{Class}_i|\text{Object})}}_{\text{Conditional Class Prob.}} * \underbrace{\boxed{\Pr(\text{Object}) * \text{IoU}_{pred}^{truth}}}_{\text{Bounding box confidence}} = \Pr(\text{Class}_i) * \text{IoU}_{pred}^{truth}$$

Object Detection Model

YOLO

- Objective function
  - The predictions are encoded as an $S{\times}S{\times}(B*5+C)$ tensor.



Object Detection Model

YOLO

- Objective function
  - During training, the objective function is formulated as below:

$$
\begin{aligned}
&\lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \\
&+ \lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(\sqrt{w_i} - \sqrt{\hat{w}_i}\right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i}\right)^2 \\
&+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i\right)^2 \\
&+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i\right)^2 \\
&+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2
\end{aligned}
$$

Object Detection Model

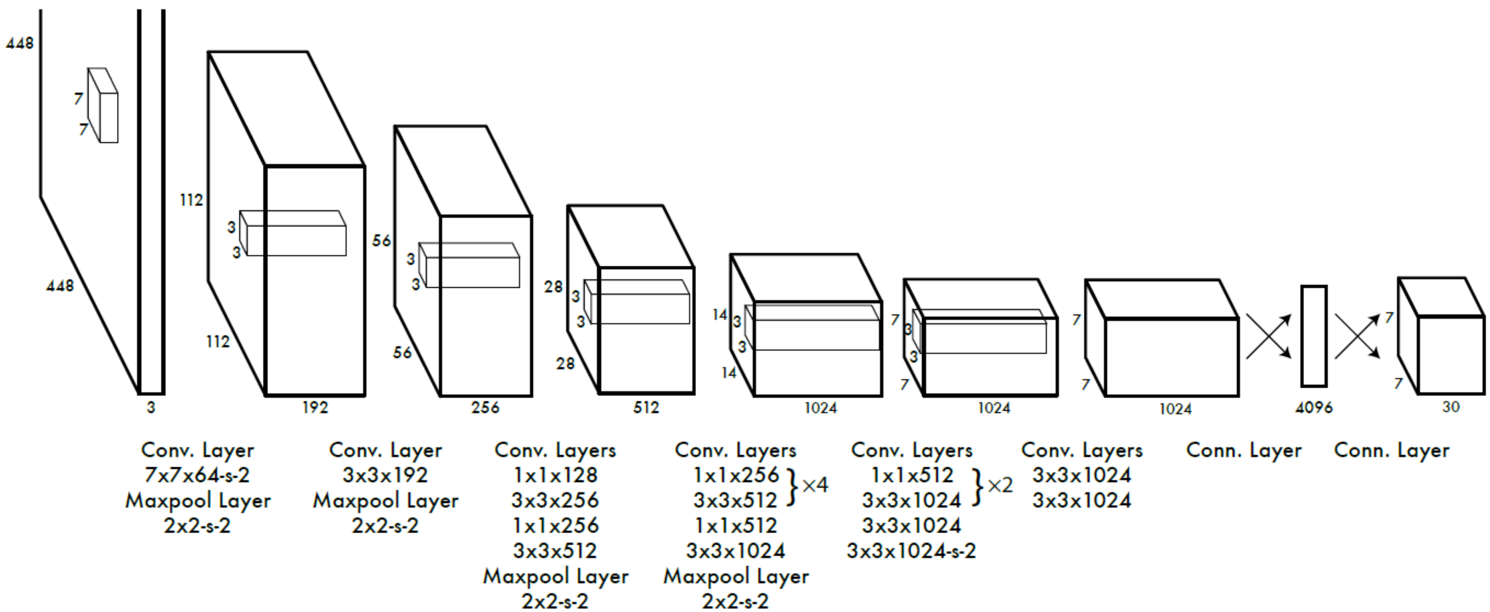
YOLO

- Objective function
  - In our implementation, we choose $S = 7, B = 2$ and $\mathrm{C} = 20$, because PASCAL VOC has 20 labels.
  - As a result, the final prediction is a $7 \times 7 \times 30$ tensor.

Object Detection Model

YOLO

- Model architecture
  - 24 convolutional layers followed by 2 fully connected layers.



Object Detection Model

YOLO

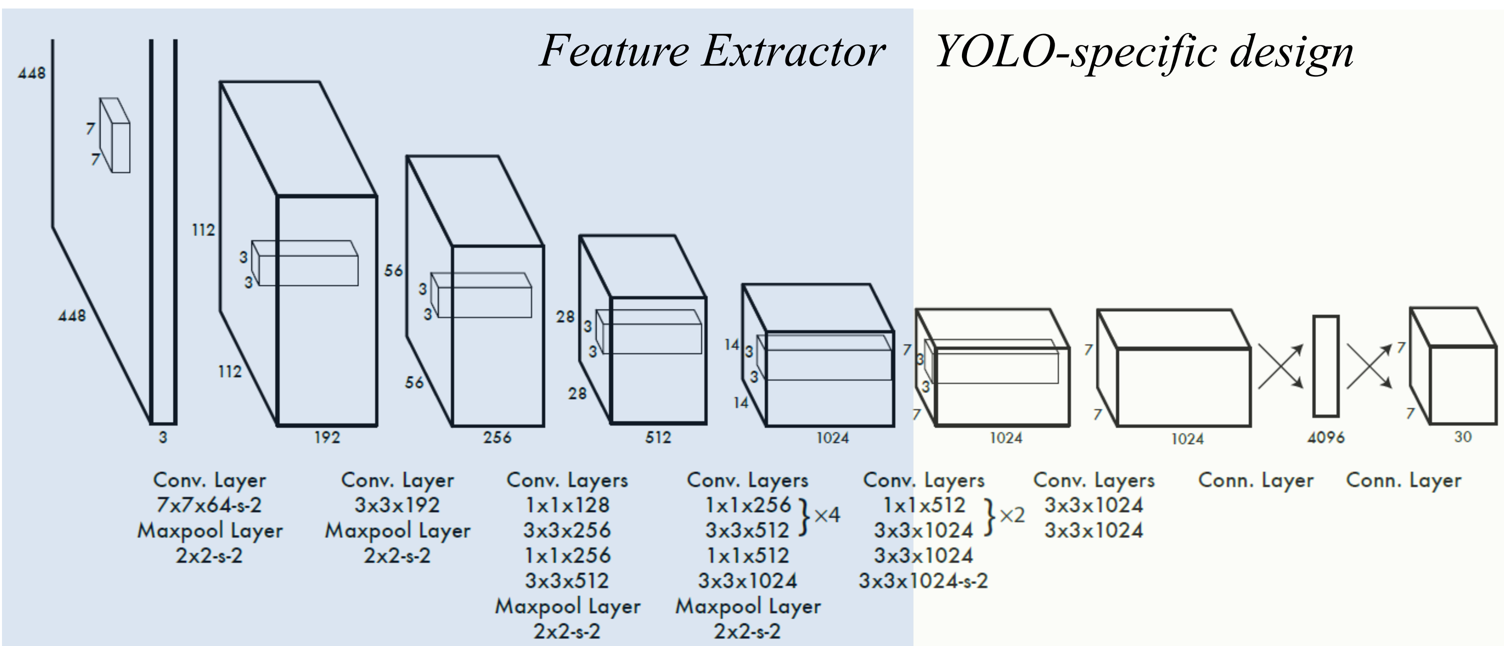
- Model architecture
  - YOLO uses the relu activation function for the final layer and all other layers use the following leaky rectified linear activation function:

$$\phi(x) = \begin{cases} x, & \text{if } x > 0 \\ 0.1x, & \text{otherwise} \end{cases}$$

Object Detection Model

YOLO

- Training strategy
  - Pre-train the first 20 convolutional layers on ImageNet.
  - Train the whole network end-to-end on PASCAL.



Object Detection Model

YOLO

- Reference
  - For more detailed explanation, please see the original paper: https://arxiv.org/abs/1506.02640

Evaluation Metric

Mean Average Precision (mAP)

- Confusion matrix reminder
  - **True positive (TP)**: A correct detection. Detection with $\mathrm{IoU} \geq threshold$.
  - **False positive (FP)** : A wrong detection. Detection with $\mathrm{IoU} < threshold$.
  - **False Negative (FN)**: A ground truth not detected.
  - **True Negative (TN)**: A correct misdetection. Does not apply in evaluation.

Evaluation Metric

Mean Average Precision (mAP)

- Precision x Recall curve
  - Precision: the percentage of correct positive predictions.

$$Precision = \frac{TP}{TP + FP} = \frac{TP}{all\ detections}$$

  - Recall: the percentage of true positive detected among all ground truths.

$$Recall = \frac{TP}{TP + FN} = \frac{TP}{all\ ground\ truths}$$

Evaluation Metric

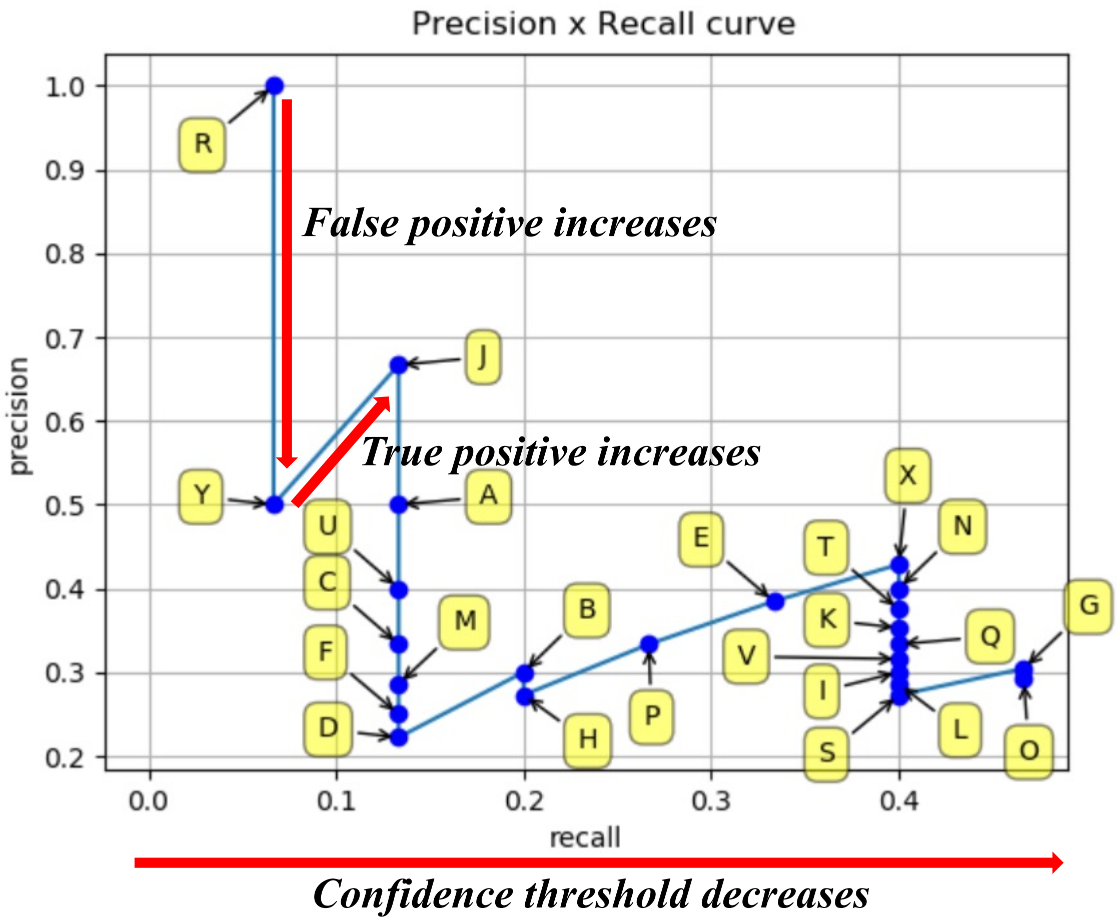
Mean Average Precision (mAP)

- Precision x Recall curve
  - An object detector of a particular class is considered good if its precision stays high as recall increases.
  - It means that if you vary the confidence threshold, the precision and recall will still be high.

Evaluation Metric

Mean Average Precision (mAP)

- Precision x Recall curve



Evaluation Metric

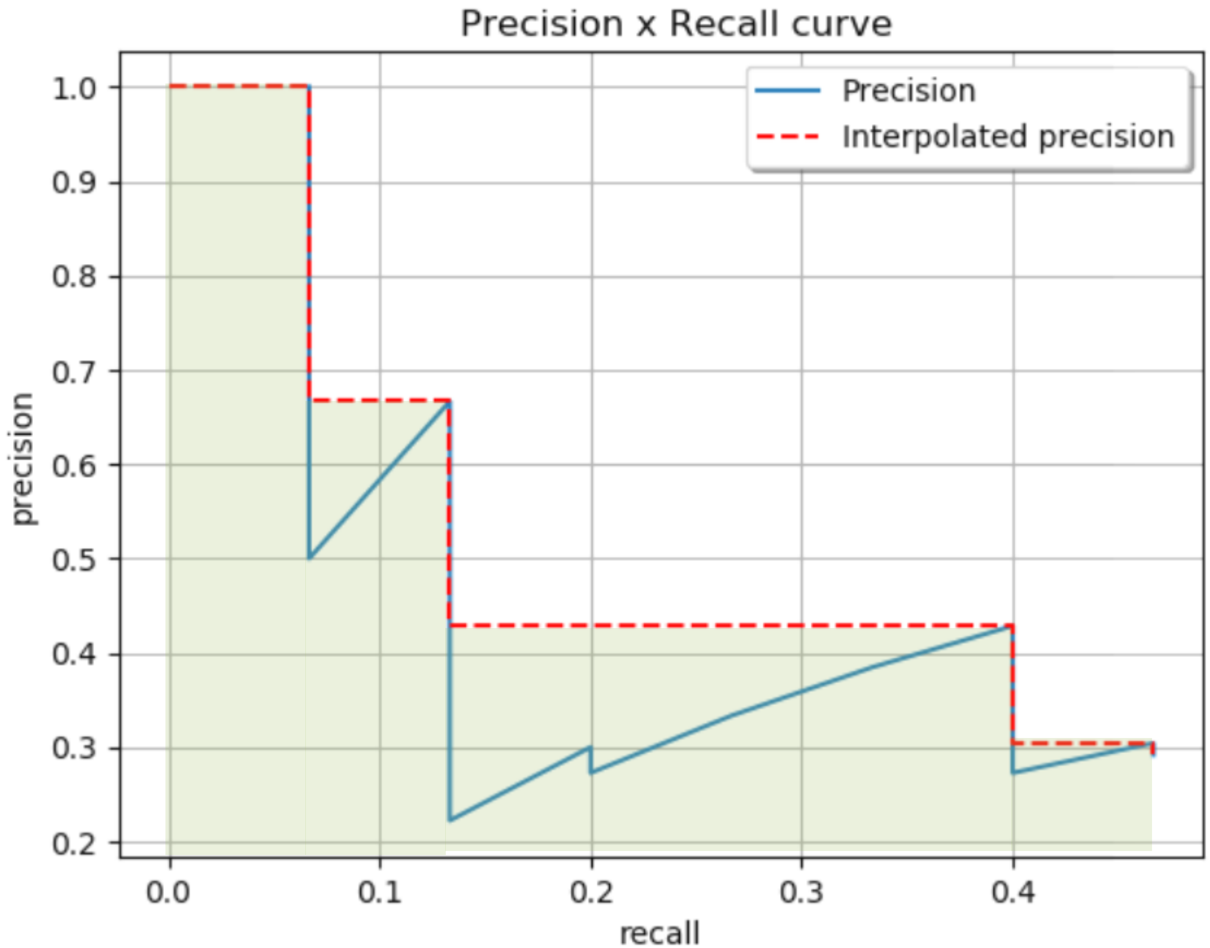
Mean Average Precision (mAP)

- Average Precision (AP)
  - Smooth the Precision-recall curve and calculate the area under curve (AUC).

Evaluation Metric

Mean Average Precision (mAP)

- Average Precision (AP)



Evaluation Metric

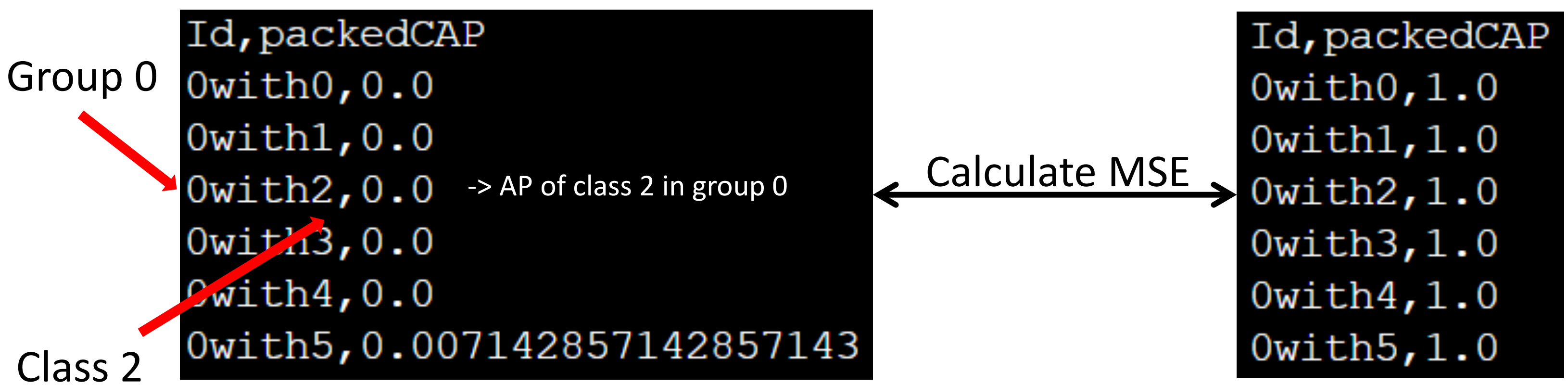
Mean Average Precision (mAP)

- Mean Average Precision (mAP)
  - Calculate the Average Precision for every class and average them.

Evaluation Metric

Mean Average Precision (mAP)

- Mean Average Precision (mAP)
  - In this competition, we divide testing data into 10 groups and calculate the mAP of all classes.
  - After deriving the mAP of each class in 10 groups, we compare the result with ground truth and use the mean square error as the final score.



Evaluation Metric

Mean Average Precision (mAP)

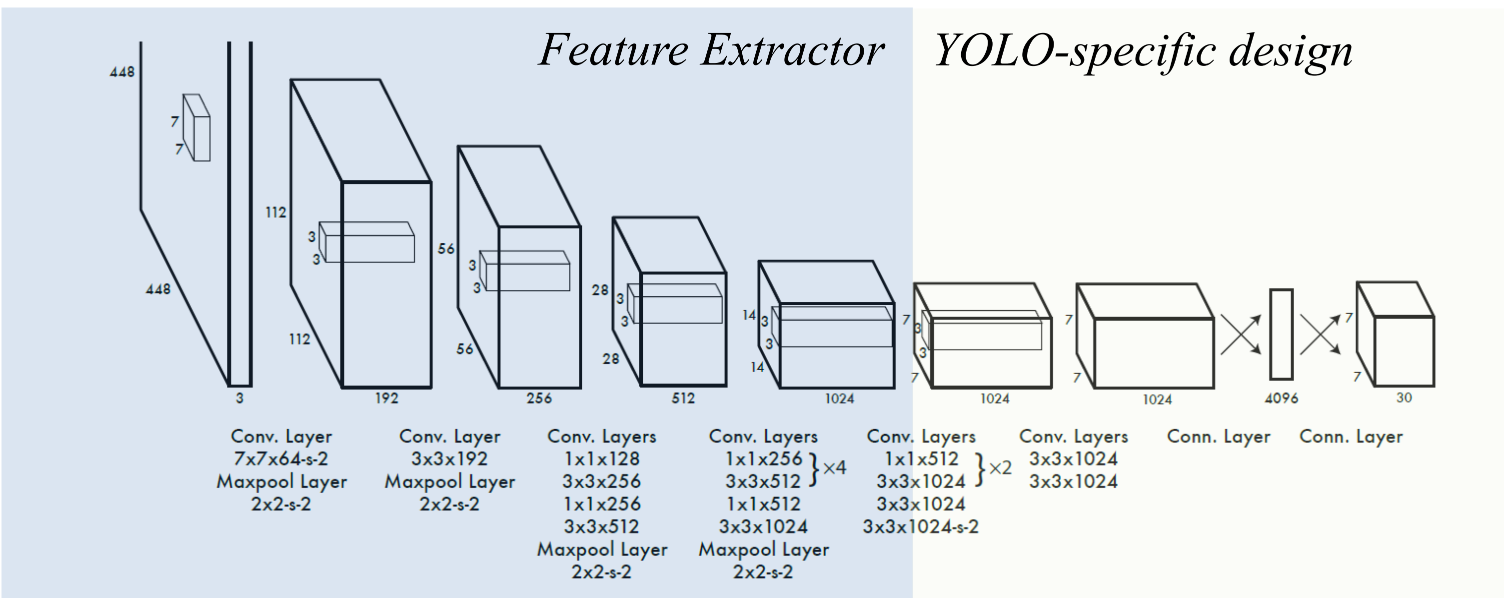
- Mean Average Precision (mAP)
  - For more detailed explanation of mAP, please see https://github.com/rafaelpadilla/Object-Detection-Metrics

Hints

1. Transfer learning
2. Data augmentation
3. Training strategy
4. Other object detection models

Hints

1. Transfer learning
   - Training from scratch is nearly impossible for object detection.
   - Feel free to replace the feature extractor with other pre-trained model.



Hints

1. Transfer learning
   – YOLO pre-trained its feature extractor on ImageNet.
   – How to load pre-trained model is already described in lab12 - style transfer.
   – Be careful that different models require different data preprocess.
   – You can see all the pre-trained models provided by Keras here:
     https://www.tensorflow.org/api_docs/python/tf/keras/applications

Hints

2. Data augmentation
   – The dataset we are using in this competition is the combination of training and validation set from VOC 2007.
   – It contains only 5012 images in total. Furthermore, the labels are highly imbalanced.
   – Doing data augmentation not only helps your model generalizing to testing data but also easing the training process.

Hints

2. Data augmentation
   - Random scaling and translations are applied when training YOLO.
   - Note that the bounding box coordinates have to be changed accordingly if the image was transformed.

Hints

3. Training strategy
   - Check bugs.
   - Be patient.

Hints

4. Other object detection models
   – Feel free to try other object detection models.
   – It is ok to read other's code on GitHub, but you have to implement it in TensorFlow.
   – It's **not allowed** to load other's pre-trained model which was already trained on object detection task.

Precautions

1. The final score will be only based on your ranking on private leaderboard(80%) and report(20%).
2. Training on the datasets not provided by us is forbidden.
3. Loading the model pre-trained on ImageNet is allowed, while loading the model trained on object detection task is not allowed.
4. Plagiarism gets you 0 point.
5. Using ground truth to generate output will get you 0 point.
6. Cloning codes from GitHub will you get 0 point.

Competition Timeline

- Kaggle
- 2022/11/03(Thu.) competition announced.
- 2022/11/17(Thu.) 23:59(UTC) competition deadline.
- 2022/11/20(Sun.) 23:59(TW) report deadline.
- 2022/11/24(Thu.) winner team share.