CMPE258

PART II

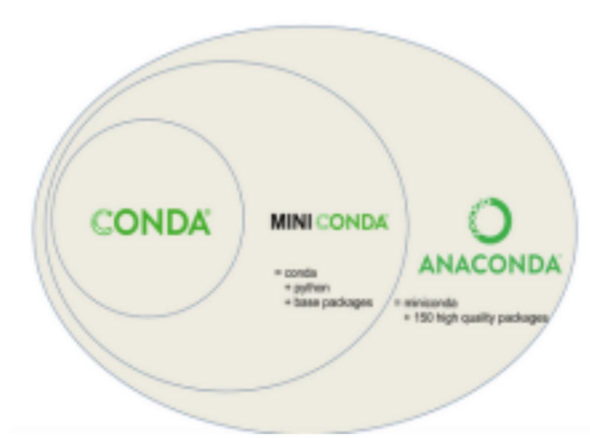
2) Formula sheet is allowed, No Example, No Verbal Explanation, Close Book, close Notes

3) ~3 Questions

a. Math. Formulation, Calculation.

b. Design/Implementations

Introduction on Anaconda
https://kaust-vislab.github.io/python-novice-gapminder/00-getting-started-with-conda/index.html



4) Subjects.

a. F.NN Neurons, Weight $\sum_{i=1}^{N} W_i X_i$

b. Preprocessing Functions $B(x,y)$; $\bar{x}$, $\bar{y}$; Orientation; moments

c. Convolutions CNN Kernel, Computation.

Activation Function

Example: Yolo4 github Repo.

Ref: Readme.txt on github.

Step1. Anaconda is installed on your machine

Step2. Source Code Repo github.

Step3. Create GPU Environment By Anaconda

Step4 Activate the gpu environment

Step5. DownLoad pre-trained Weights (yolo4)

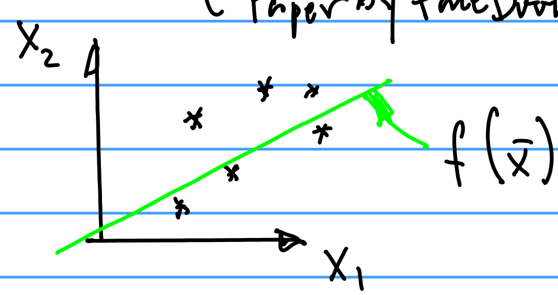
April 8 (Thur) PART II Yolo

- Repo: Implementation
  - a. Anaconda
  - b. github → Customization
- Theoretical Foundation
  - PPT
  - Paper by FaceBook AI.

1. midterm Key Posted On github

2. Team final project Presentation (Semester Long Project)

3. Yolo 4   4. AnaConda



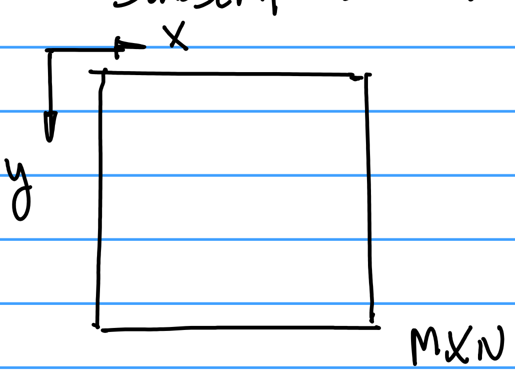
Step 6. Convert the Weights in DARKNET to T.F. format.

Step 7. Run the code for either Video or Image(s).

Notations & Mathematical Formulation

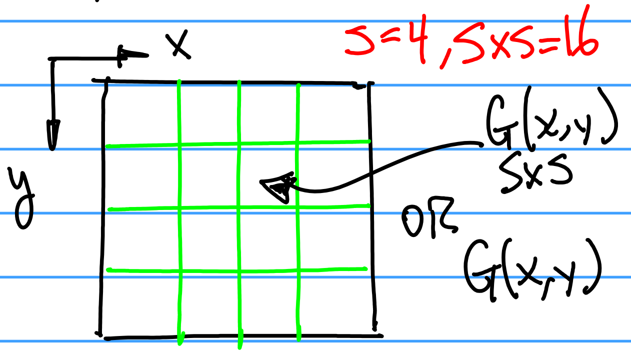
1. Image $I(x,y)$, $I_{M\times N}(x,y)$

Subscript ↗ $M \times N$ Resolution



2. Divide $I(x,y)$ into $S\times S$ ~~pixels~~ Grids

Each $S\times S$ pitch/Title/Subimage is defined as grid $G(x,y)$



3. Bounding Box, e.g. R.O.I. (Region of Interests) → Localized ROI On a given object $B(x,y)$

Note: The size of $B(x,y)$ is different from the size of $G(x,y)$, And it is usually bigger than $G(x,y)$.

Note: Each Bounding Box is required for Each Object, the objects may belong to Same class or different classes.

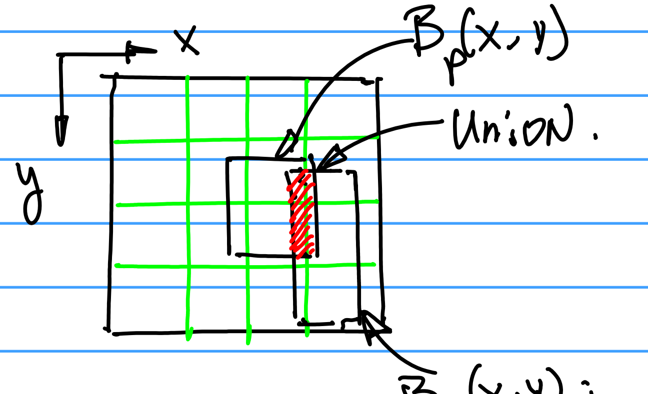
$B_j(x,y)$, for $j=1,2,\ldots,m$;

4. Object(s)

$O_i(x,y)$ for $i=1,2,\ldots,K$

Center of the Object — total Objects

5. IOU (Intersection ~~of~~ over Union)



IOU Truth

↓ IOU or I

CmpE258

PART II

2.0

$$IOU = \begin{cases} 1 & B_p(x,y) = B_g(x,y) \\ [0,1) & o/w \end{cases} \quad \ldots (1)$$

6. Five parameters defined for $B_{ij}(x,y)$. $\{\underbrace{x, y}_{\text{Centroid}}, w, H, \underset{\text{Confidence}}{f(B_j(x,y))}\}$

$B_1(x, y)$ $f(B_1(x,y)) = f(B_1)$

$B_2(x, y)$ ... $f(B_2)$

⋮

$B_M(x,y)$ $f(B_m)$

If Confidence $f(B_j(x,y))$ Representing Probability value

$$\sum_{j=1}^{m} f(B_j(x,y)) = 1 \quad \ldots (2)$$

7. Define probability for Each object as follows (on A Grid)

$$Prob(O_i(x,y)) = Prob(O_i) \quad \ldots (3)$$

8. Denote classes as

C_i, for $i = 1, 2, \ldots, N$;

Hence, the probability for C_i is

$$Prob(C_i)$$

$$\sum_{i=1}^{N} Prob(C_i) = 1 \quad \ldots (4)$$

9. Define Condition Probability.

$$Prob(C_i | O_j) \quad \ldots (5)$$

Given an object O_j, find the Probability of C_i, e.g., ~ that this object belongs to class i

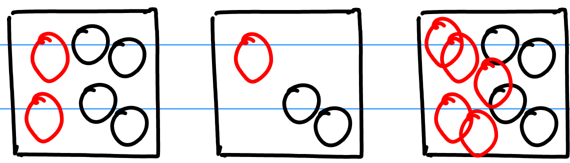
$$\sum_{i=1}^{N} Prob(C_i | O_j) = 1 \quad \ldots (5b)$$

Appendix: Review on Bayes Theorem

$$\Pr(\text{Class}_i|\text{Object}) * \Pr(\text{Object}) * \text{IOU}^{\text{truth}}_{\text{pred}} = \Pr(\text{Class}_i) * \text{IOU}^{\text{truth}}_{\text{pred}} \quad (1)$$

Review, Bayesian Theorem

Example: 3 Boxes: B_1, B_2, B_3, Drawing A Red Ball



B_1 $\quad$ B_2 $\quad$ B_3

$$Prob(R) = Prob(B_1 \cap R) + Prob(B_2 \cap R) + Prob(B_3 \cap R) \quad \ldots (1)$$

$B_1 \cap R$

where $R: B_1 \cap R + B_2 \cap R + B_3 \cap R$

$$Prob(B_1 \cap R) = P(B_1)P(R|B_1) \quad \ldots (2a)$$
$$Prob(B_2 \cap R) = P(B_2)P(R|B_2) \quad \ldots (2b)$$
$$Prob(B_3 \cap R) = P(B_3)P(R|B_3) \quad \ldots (2c)$$

So, Assume $Prob(B_1) = Prob(B_2) = Prob(B_3)$

$$Prob(B_1 \cap R) = P(B_1)P(R|B_1) = \left(\tfrac{1}{3}\right)\left(\tfrac{2}{6}\right)$$
$$Prob(B_2 \cap R) = P(B_2)P(R|B_2) = \left(\tfrac{1}{3}\right)\left(\tfrac{1}{3}\right)$$
$$Prob(B_3 \cap R) = P(B_3)P(R|B_3) = \left(\tfrac{1}{3}\right)\left(\tfrac{5}{9}\right)$$

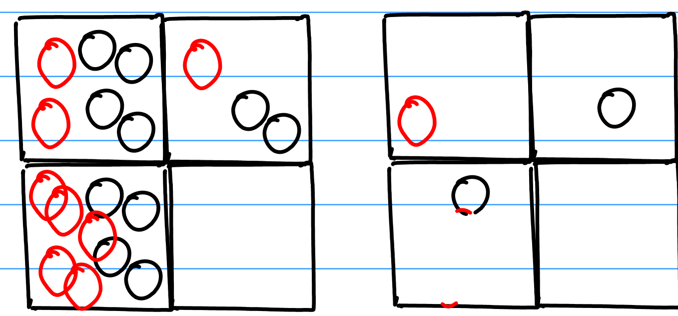
Now, Change Red Ball "R" to Object Detection "O"

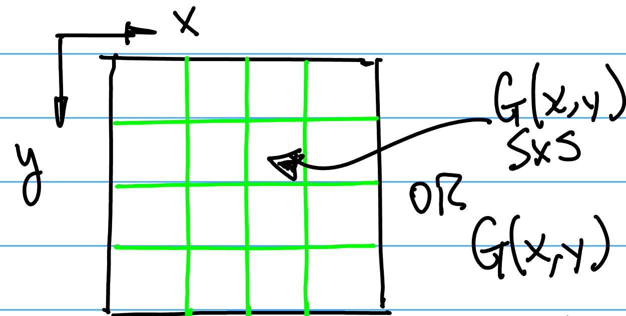
$$Prob(O) = Prob(B_1 \cap O) + Prob(B_2 \cap O) + Prob(B_3 \cap O) \quad \ldots (3)$$

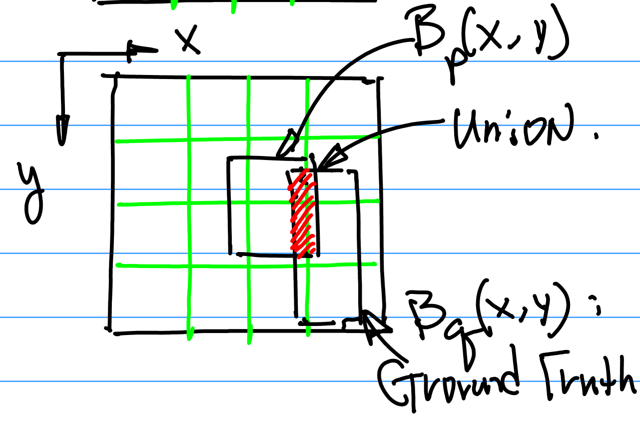
Hence,

$$Prob(B_1 \cap O) = P(B_1)P(O|B_1) \quad \ldots (3a)$$
$$Prob(B_2 \cap O) = P(B_2)P(O|B_2) \quad \ldots (3b)$$
$$Prob(B_3 \cap O) = P(B_3)P(O|B_3) \quad \ldots (3c)$$

Re-arrange Boxes to form an Image $I(x,y)$ as follows







From Ref. Paper, we have

$$\Pr(\text{Class}_i) = \Pr(\text{Class}_i|\text{Object}) * \Pr(\text{Object}) \quad \cdots (4\text{-}0)$$

$$\text{Prob}(C) = \text{Prob}(O_1 \cap C) + \text{Prob}(O_2 \cap C) + \text{Prob}(O_3 \cap C) \quad \cdots (4)$$

where

$$\text{Prob}(O_1 \cap C) = P(O_1)P(C|O_1) \ldots (4a)$$

$$\text{Prob}(O_2 \cap C) = P(O_2)P(C|O_2) \ldots (4a)$$

$$\text{Prob}(O_3 \cap C) = P(O_3)P(C|O_3) \ldots (4a)$$

So,

$$\text{Prob}(C) = P(O_1)P(C|O_1) + P(O_2)P(C|O_2) + P(O_3)P(C|O_3)$$

which matches to Eqn (4-0).

Now, Add Bounding Box and Grid into the formulation.

$$IOU = \frac{\text{Area of ROI (Bounding Box)}}{\text{Area of Grid}}$$

Now, Consider Loss function

5-Fold Loss Function

$$\lambda_{\mathbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

← Position Loss

$$+ \lambda_{\mathbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$

← Geometry Loss

Coordinates Related

$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2$$

← Class Loss with objects

$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2$$

← Class Loss without Objects

$$+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2$$

Notation

1. Function $\mathbb{1}(x) = \begin{cases} K & \text{for } X \text{ exists} \\ 0 & \text{o/w.} \end{cases} \quad \ldots (1)$

K is some constant

So, $\mathbb{1}(0) = \begin{cases} K & \text{if Object } 0 \text{ exist} \\ 0 & \text{o/w.} \end{cases} \quad \ldots (1b)$

2. $\mathbb{1}_i(0)$ for "0" in cell (Grid) i

$\mathbb{1}_{ij}(0)$ for "0" in cell i & Bounding Box j

$\mathbb{1}_i^{obj}, \mathbb{1}_{ij}^{obj}$

$\mathbb{1}_i^{noobj}, \mathbb{1}_{ij}^{noobj}$

3. (x, y, w, h) are centroid (x, y), width, height of the Bounding Box.

$p_i(c)$ for class "c"

4. $\sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{noobj} (C_i - \hat{C}_i)^2$

$\underbrace{j = 0, 1, \ldots, B}_{B+1}$ Bounding Boxes

$\underbrace{i = 0, 1, \ldots, S^2}_{S \times S + 1}$ Classes OR grids cells ?

for all the cells, all the Bounding Boxes

April 15 (Th).

From Eqn (1), Appendix, PP21.

$$\Pr(\text{Class}_i|\text{Object}) * \Pr(\text{Object}) * \text{IOU}_{\text{pred}}^{\text{truth}} = \Pr(\text{Class}_i) * \text{IOU}_{\text{pred}}^{\text{truth}} \quad \ldots(1)$$

$$\text{Prob}(C_i) = \text{Prob}(O)\,\text{Prob}(C_i | O)$$

$\text{Prob}(C_i) = ?$ Starting point

Find probability of an Object O belongs to Class C_i

Probability, Score → make decision for Classification.

(1) $\text{Prob}(C_i)$ → (2) $\text{Prob}(O) * \text{Prob}(C_i|O)$

Step 1

Probability of an Object O Appears on a grid G

Conditional Given Object O, this O belongs to Class C_i

Prior Knowledge (3)

Bayesian Theorem

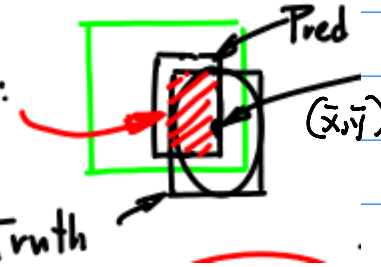
Connection to a given image Region, a cell, Grid

$\text{IOU}_{\text{Pred}}^{\text{Truth}}$ → IOU → I(Index) $\in [0, 1]$

Example: Computation of IOU

Define IOU = (Ratio of Areas)

$\text{IOU}_{\text{Pred}}^{\text{Truth}}$:



$$\text{IOU} = \frac{\text{Red Area}}{\left(\begin{matrix}\text{Area of}\\ \text{B-Box}\end{matrix}\right) + \left(\begin{matrix}\text{Area}\\ \text{G.Truth}\end{matrix}\right) - \left(\begin{matrix}\text{Area}\\ \text{Comm}\end{matrix}\right)} \quad \ldots(1)$$

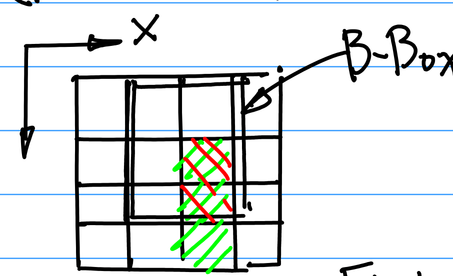


Fig 1.

Ground Truth: Green

Find IOU = ?

Sol:

Step 1: Area of B-Box

$$A_{B^2} = 6 = \sum_y \sum_x B(x, y)$$

$$A_G = 3 = \sum_Y \sum_X B_G(x, y)$$

Step 2: $A_{Com} = 2$

$$\therefore \text{IOU} = \frac{2}{6+3-2} = 2/7$$

$$Prob(C_i) = Prob(D)\, Prob(C_i|D)$$

Prior Distribution.

"K-mean" Clustering Technique

② K of them

① mean Value

centered by mean

Given 2 values, $x_1 = 1$, $x_2 = 1.5$

Find mean

$$\bar{x} = \left(\sum_{i=1}^{N} x_i\right)\frac{1}{N} \quad \ldots (2)$$

$$\bar{x} = \frac{1}{2}\sum_{i=1}^{2} x_i = \frac{1}{2}(x_1 + x_2) = \frac{1}{2}(1 + 1.5)$$

$$= 2.5/2 = 1.25$$

Feature Vector $\bar{x}$ (Simply write x)

$$\bar{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \quad \text{2 Dimensional vector}$$

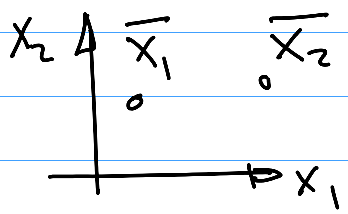


Fig 2.

$$\bar{x}_1 = \begin{pmatrix} 1 \\ 0.5 \end{pmatrix}, \quad \bar{x}_2 = \begin{pmatrix} 1.5 \\ 2.3 \end{pmatrix} = \begin{pmatrix} x_{21} \\ x_{22} \end{pmatrix}$$

$$= \begin{bmatrix} x_{11} \\ x_{12} \end{bmatrix}$$

1st Point   2nd Dimension

$$\bar{m} = \left(\sum_{i=1}^{N} \bar{x}_i\right)\frac{1}{N} \quad \ldots (3)$$

$$\bar{m} = \frac{1}{2}\left(\sum_{i=1}^{2} \bar{x}_i\right)$$

$$= \frac{1}{2}\left(\bar{x}_1 + \bar{x}_2\right)$$

$$= \frac{1}{2}\left(\begin{pmatrix} 1 \\ 0.5 \end{pmatrix} + \begin{pmatrix} 1.5 \\ 2.3 \end{pmatrix}\right)$$

$$= \frac{1}{2}\begin{pmatrix} 1 + 1.5 \\ 0.5 + 2.3 \end{pmatrix} = \frac{1}{2}\begin{pmatrix} 2.5 \\ 2.8 \end{pmatrix}$$

$$= \begin{pmatrix} 1.25 \\ 1.4 \end{pmatrix}$$

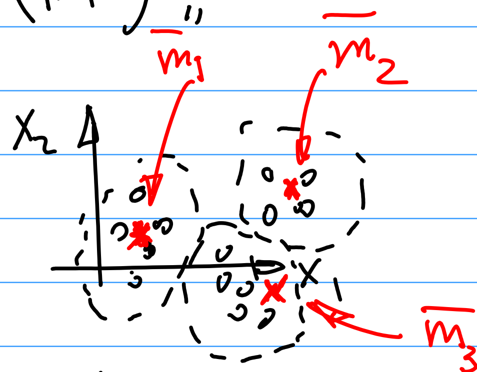


Fig 2.

Given a set of data $\{\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_N\}$ is denoted as S

find means to cluster the data, e.g.

$$S = \{\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_N\} \quad \ldots (4)$$

Find $\bar{m}_i$ (means, K of them)

10 pts
Project II Yolo4 Due 2 weeks from April 15, Due May 2nd Sunday, 11:59pm.

1° Build/Run Yolo4

2° Record your Video 10~15 seconds, Run Optimized Yolo4 By Redefining Classes to be detected;

3° Generate Readme.txt

Submit

a Your Code

b Readme

c Video (Processed)

Example: K-mean Cluster Computation.

Given a set of Data (in Vector form, feature vectors)

$(\vec{X}_1, \vec{X}_2, \ldots, \vec{X}_n)$

then K Groups or Clusters denoted as

$\{S_1, S_2, \ldots, S_K\}$

$S_1 = (\vec{X}_1, \vec{X}_i, \vec{X}_k \ldots)$

distance $\|\vec{x} - \vec{m}_i\|^2$ for Group (Cluster) i

$\underline{\arg} \min (\|\vec{x} - \vec{m}_i\|^2)$

minimize the distance

$\underline{\min} (\|\vec{x} - \vec{m}_i\|^2) \quad \ldots (5)$

for One data $\vec{x}$, one Cluster i,

All Data in Group i

$$\sum_{x \in S_i} \|\vec{x} - \vec{m}_i\|^2 \quad \ldots (6)$$

For all groups

$$\sum_{i=1}^{K} \left(\sum_{x \in S_i} \|\vec{x} - \vec{m}_i\|^2 \right) \quad \ldots (7)$$

Ref: Github

– 9a

– 9b