CMPE258
PART II

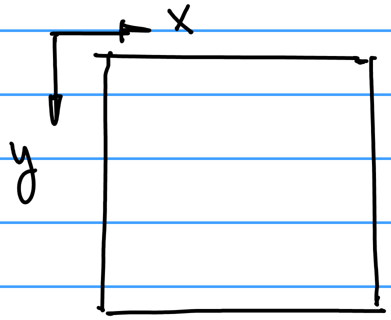
Step 6. Convert the Weights in DARKNET to T.F. format.

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

Notations & Mathematical Formulation

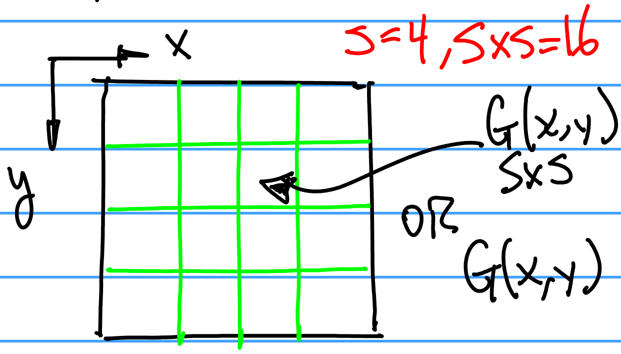
1. Image $I(x,y)$, $I_{M \times N}(x,y)$

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 $j = 1, 2, \ldots, m$;

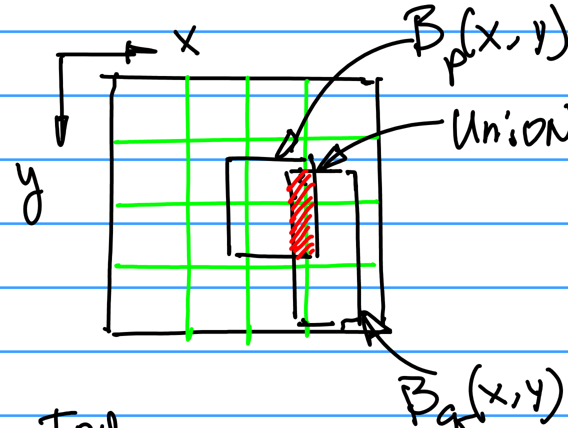
4. Object(s)

$O_i(x,y)$ 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

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

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

Confidence

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

$B_2(x,y)$ $\quad \ldots \quad f(B_2)$

$\vdots$

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

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) $S=4, S\times S=16$

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

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

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

over

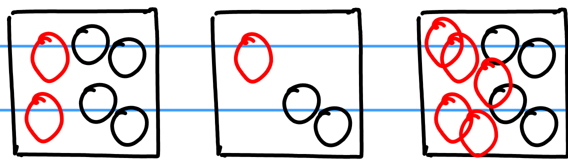
* IOU or I

Appendix: Review on Bayes Theorem

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

Review, Bayesian Theorem

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



B_1 B_2 B_3

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

$B_1 \cap R$

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

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

So, Assume $\text{Prob}(B_1) = \text{Prob}(B_2) = \text{Prob}(B_3)$

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

(On A Grid)

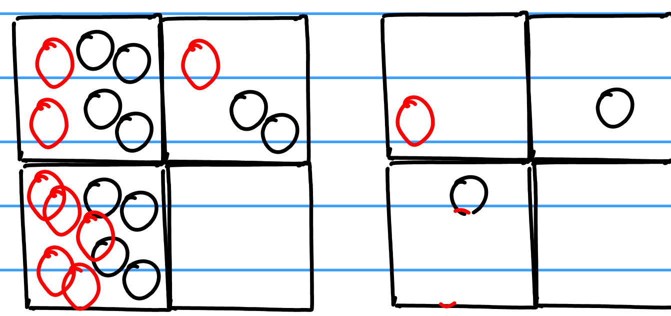
Now, Change Red Ball "R" to Object Detection "O"

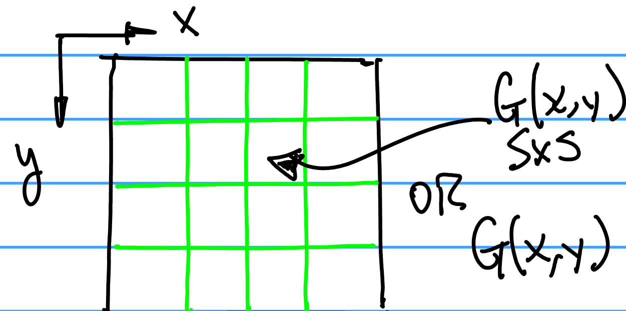
$$\text{Prob}(O) = \text{Prob}(B_1 \cap O) + \text{Prob}(B_2 \cap O) + \text{Prob}(B_3 \cap O) \quad \ldots (3)$$

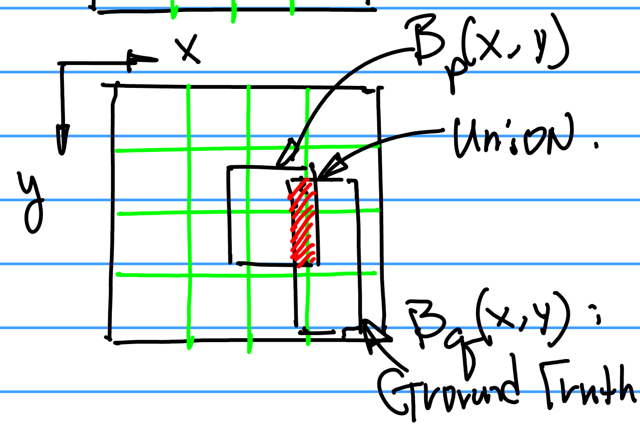
Hence,

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

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





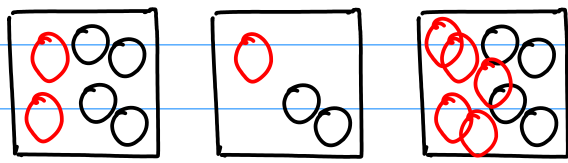


Appendix: Review on Bayes Theorem

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

Review, Bayesian Theorem

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



B_1 $\quad$ B_2 $\quad$ B_3

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

$B_1 \cap R$

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

$$\text{Prob}(B_1 \cap R) = P(B_1)P(R|B_1) \quad \ldots (2a)$$
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$$\text{Prob}(B_3 \cap R) = P(B_3)P(R|B_3) \quad \ldots (2c)$$

So, Assume $\text{Prob}(B_1) = \text{Prob}(B_2) = \text{Prob}(B_3)$

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

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

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

Hence,

$$\text{Prob}(B_1 \cap O) = P(B_1)P(O|B_1) \quad \ldots (3a)$$
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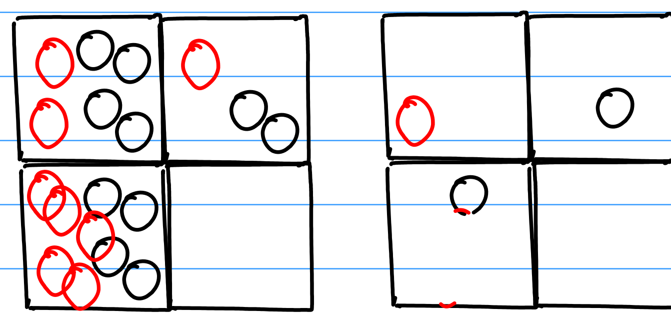
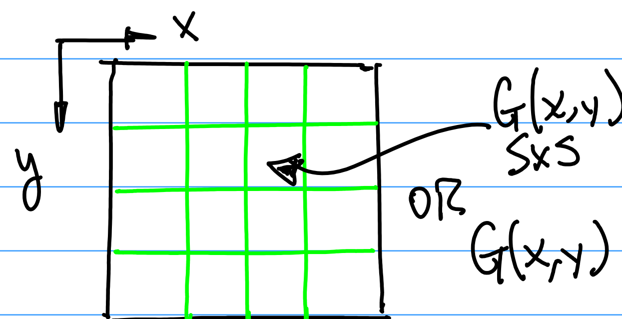
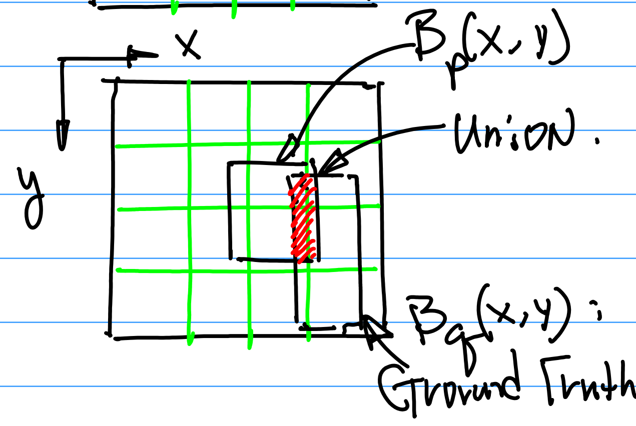
Re-arrange Boxes to form an Image $I(x,y)$ as follows







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

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

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

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

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

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

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

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

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

Coordinates Related

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

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

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

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

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

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

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

for all the Cells, all the Bounding Boxes

April 15 (Th).

From Eqn(1), Appendix, PP21.

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

$Prob(C_i) = Prob(O)\, Prob(C_i/O)$

$Prob(C_i) = ?$ Starting point

Find probability of an Object O belongs to Class C_i

Probability, Score → make decision for Classification.

(1) $Prob(C_i)$ → (2) $Prob(O) * Prob(C_i|O)$

Step 1

Probability of an Object O Appears on a grid G — Prior Knowledge (3)

Conditional Given Object O, this O belongs to Class C_i

Bayesian Theorem

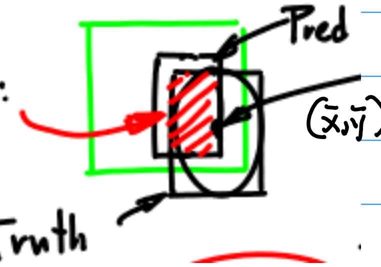
Connection to a given image Region, a cell, Grid

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

Example: Computation of IOU

Define IOU = (Ratio of Areas)

IOU^{Truth}_{Pred} :



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

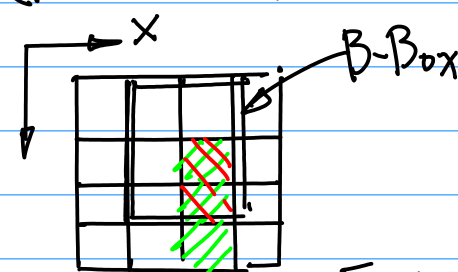


Fig 1.

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: $A_{Com} = 2$

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

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

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

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

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

$$= 2.5/2 = 1.25$$

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

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

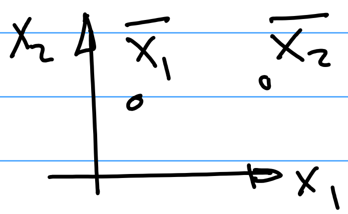


Fig 2.

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

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

1st Point   2nd Dimension

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

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

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

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

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

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

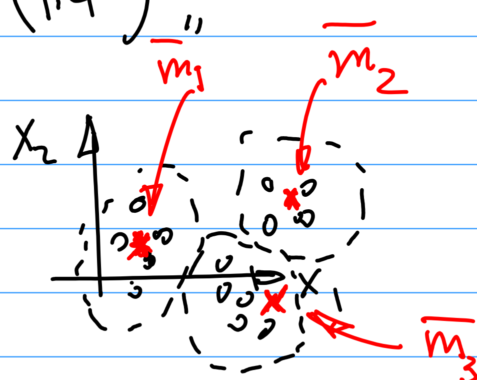


Fig 2.

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

find means to cluster the data, e.g.

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

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

Project II $^{10 \text{ pts}}$ 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)

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

then K Groups or Clusters denoted as

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

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

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

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

minimize the distance

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

April 22nd (Last Day of Instruction 17th, May)

1. Presentation May 6th.
2. Review & Last Class May 13
3. Final Example: May 24th (Monday)

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

Simplification with Condition Object(s) Appears in the Grid.
Removal of $\mathbb{1}(\cdot)$ function.
So, (1) Becomes

$$\sum_{i=0}^{S^2-1} \sum_{j=0}^{B-1} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] \qquad \ldots (1a)$$

Where $\hat{x}_i = \hat{x}_i(w_{kl}, b)$
then Apply Chain Rule accordingly.

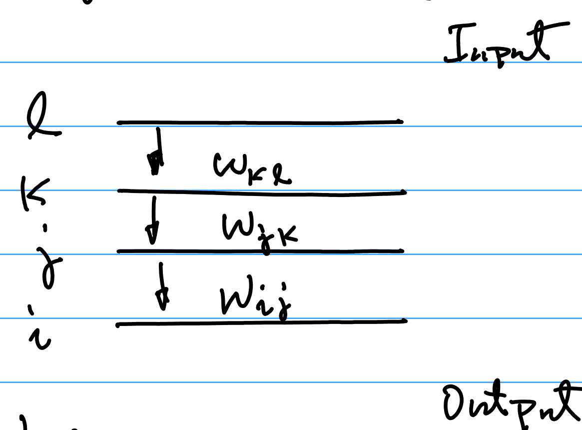


Fig 1.

Note: mAP (mean Verage Precision)

w_{kl}

Output (1st) Input (2nd)

Example:

$w_{ij} \, w_{jk} \, w_{kl}$

Note: See my Lecture Note 8

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \left\| \mathbf{x} - \boldsymbol{\mu}_i \right\|^2 \quad \cdots (1)$$

feature Vector / Data Point

(Cluster) mean for the class i

minimization

for all Classes

for all pts. within a given class

Group Class i

data Point

for "Any"

$$S_i^{(t)} = \left\{ x_p : \left\| x_p - m_i^{(t)} \right\|^2 \le \left\| x_p - m_j^{(t)} \right\|^2 \ \forall j, 1 \le j \le k \right\} \quad \cdots (2)$$

A collection (A set) of Data Points

for Class i

Distance (Difference) of class i is smaller or equal to the distance for class j

As Long as j belongs / or covers entire classes, Note $j \neq i$

Example (Hand Calculation)

1. Assume $K=2$ from prior knowledge.
2. Assumption for the cluster initial value

$$\vec{m}_1 = \begin{pmatrix} m_{11} \\ m_{12} \end{pmatrix}, \quad \vec{m}_2 = \begin{pmatrix} m_{21} \\ m_{22} \end{pmatrix}$$

3. Computation

$$\bar{X}_1 - \bar{m}_1 = \begin{pmatrix} X_{11} \\ X_{12} \end{pmatrix} - \begin{pmatrix} m_{11} \\ m_{12} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

then $\left\| \bar{X}_1 - \bar{m}_1 \right\| = \sqrt{(X_{11} - m_{11})^2 + (X_{12} - m_{12})^2}$

$= \sqrt{0^2 + 0^2} = 0$

And $\bar{X}_1 - \bar{m}_2 = \begin{pmatrix} X_{11} \\ X_{12} \end{pmatrix} - \begin{pmatrix} m_{21} \\ m_{22} \end{pmatrix}$

$= \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 1 \\ 0 \end{pmatrix}$, $\|\bar{X}_1 - \bar{m}_2\| =$

$\sqrt{(X_{11}-m_{21})^2 + (X_{12}-m_{22})^2}$

$= \sqrt{(0-1)^2 + 0^2} = 1$

$\| \bar{X}_1 - \bar{m}_1 \| \leq \| \bar{X}_1 - \bar{m}_2 \|$

holds good. $\rightarrow \vec{X}_1 \in C_1$

Class C_1 with

mean $\bar{m}_1$.

Continue the Computation, to group Each of Every Points, if $\|\bar{X}_K - \bar{m}_1\|$ does not Satisfy the Condition of

$\|\bar{X}_K - \bar{m}_1\| \leq \|\bar{X}_K - \bar{m}_2\|$,

then re-group $\bar{X}_K$ to Class 2.

$K = 1, 2, \cdots, 20$; (Entire Data Set)

$\{X_1, X_3\} \in \omega_1$, $\{X_2, X_4, X_5, \cdots, X_{20}\} \in \omega_2$

Now, Newly formed "Grouping" will need update Clusters, e.g. means,

$\vec{m}_1(2) = \frac{1}{N} \sum_{i=1}^{2} \bar{X}_i$

(All pts in the Class)

$\frac{1}{2}(\bar{X}_1 + \bar{X}_3) = \frac{1}{2}\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix} + \begin{pmatrix} 0 \\ 1 \end{pmatrix}\right]$

$= \frac{1}{2} \begin{pmatrix} 0+0 \\ 0+1 \end{pmatrix} = \frac{1}{2} \begin{pmatrix} 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0.5 \end{pmatrix}$

Similarly, Compute

$\vec{m}_2(2) = \begin{pmatrix} 5.67 \\ 5.33 \end{pmatrix}$

Compare $\bar{m}_1(2), \vec{m}_2(2)$ with $\bar{m}_1(1), \vec{m}_2(1)$ Accordingly.

if $\bar{m}_1(2) \stackrel{?}{=} \bar{m}_1(1)$

$\vec{m}_2(2) \stackrel{?}{=} \vec{m}_2(1)$

Not Equal, then Continue the process. Find

$\|\vec{X}_K - \vec{m}_1(2)\| \underset{?}{\leq} \|\vec{X}_K - \vec{m}_2(2)\|$

To make sure the Above holds good, if it does, then no re-group. Otherwise, move the pt. to Class 2.

Contine the process,

Tracking is Based on "Smoothness" e.g. shortest distance.

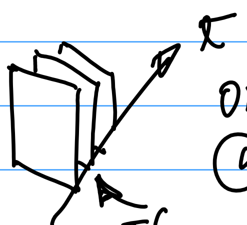
till there is stabled mean

$$\vec{m}_1(k) = \vec{m}_1(k+1)$$

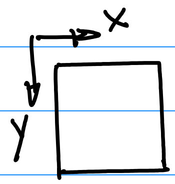
and

$$\vec{m}_2(k) = \vec{m}_2(k+1)$$

Consider "Object Tracker" Technique



One frame
@ Time



x

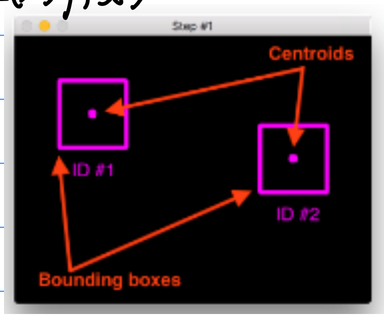
y

$I(x,y;t)$

$I(x,y)$

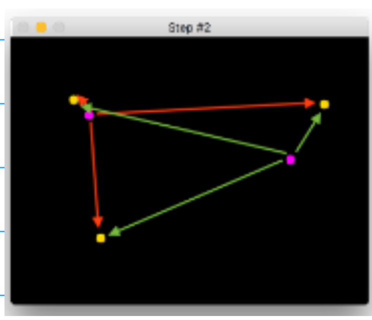
Pre-Processing.
find Object's $(\bar{x},\bar{y})$

at t, $I(x,y;t)$



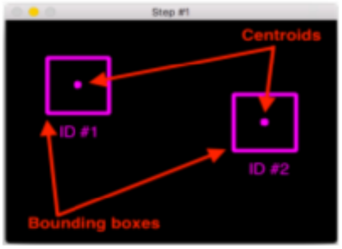
2 pts.
Pink
Object 1
Object 2

At $t+\Delta t$, Next frame $I(x,y;t+\Delta t)$
Same Process, with 3 New Points (yellow)



Track Object 1, 2
at this frame.
find matching pt ?

Example Calculation Part 1



Example:
Step 0: detection of the object using intensity thresholding technique, set Threshold T = 3, for I(x,y) >= T, set it to 1, o/w to 0.
Step 1. Compute centroids,

x1_bar = 1, y1_bar = 2. Assign ID as O1, similarly, x2_bar = 5, y2_bar = 3. Assign ID as O2. Then create (update the tracking table)

x, y

	4					
	3	2				
	3			5	3	7
				1	2	

Time = t

Binarized
T=3

x, y

	1					
	1					
	1			1	1	1

Time = t

$\bar{x}, \bar{y}$

Time = t

x, y

	1					
	1				1	2

Obj. No.	ID	x-bar, y-bar
Object 1.	1	1, 2
Object 2.	2	5, 3

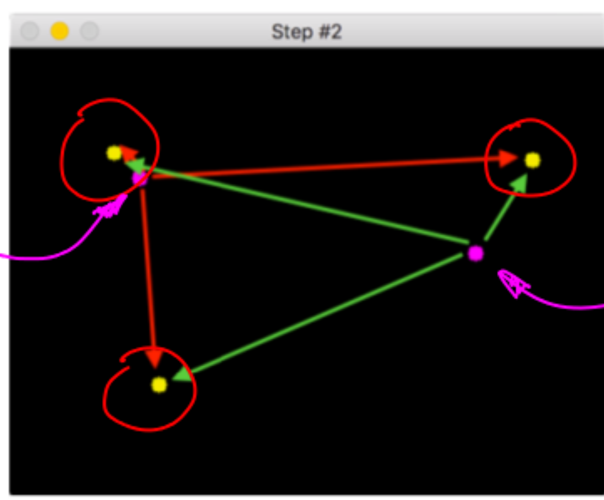
Registration table

(0,0) origin

Step 2. Compute Distance Between Boxes

time:
t+Δt
Next (New)
Image
I(x,y;t+dt)

O1



O2

3 New Objects
(yellow dots)

Original: pink (from previous frame)

New: yellow (the current frame)

Algorithm: compute distance between each pair

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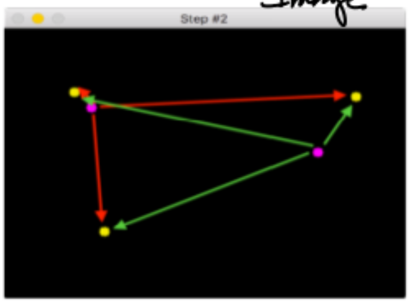
Example Part 2

t+dt for the New Image

Red: Newer Image
Pink: Previous Image



x
y

3						9
4	2				2	3
3					1	3
						2
2	4	2				
	1					

Time = t+dt

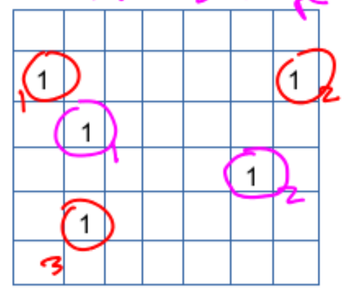
Binarized T=3

1						1
1						1
1						1
	1					

Time = t+dt

Example:
Step 2: detection of the object at time t+dt using the same technique, binarized image I(x,y). Compute the centroids, as x1_bar = 0, y1_bar = 1, x2_bar = 6, y2_bar = 2, x3_bar = 1, y3_bar = 4. Compute distance with O1, O2 as reference points.

$(\bar{x}, \bar{y})$ for All



D(o1, o1_new) = sqrt(2); D(o1, o2_new) = sqrt(26); D(o1, o3_new) = sqrt(4); D(o2, o1_new) = sqrt(29); D(o2, o2_new) = sqrt(5); D(o1, o3_new) = sqrt(17);

Temporary Registration table time = t+dt

Obj. No.	ID	x-bar, y-bar
Object 1.	1	0, 1
Object 2.	2	6, 1
Object 3.	3	1, 4

Step 2. Calculation

Minimum distance from o1:

Distance Calculation

$$D = \sqrt{(x_{1,new} - x_{1,old})^2 + (y_{1,new} - y_{1,old})^2}$$

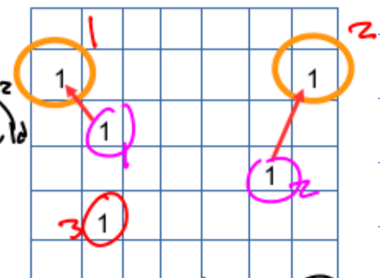
Min D = sqrt(2), D(o1, o1_new) = sqrt(2), so the matching is o1_new (in Yellow circle)

from Pink 1 to Red 1, Shortest D.
∴ Pink 1 → Red 1

Minimum distance from o2:

Pink 2 to Red 2, shortest distance D.
∴ Pink 2 → Red 2.

Min D = sqrt(5), D(o2, o2_new) = sqrt(5); so the matching is o2_new (in Yellow circle)



Registration table (time = t + dt)

Obj. No.	ID	x-bar, y-bar
Object 1.	1	0, 0
Object 2.	2	6, 1
Object 3.	3	1, 4

Update the registration table

Note: Continue this Process for t+kdt, k=2,3,...

Check Registration Tables at t and t+dt → Red 3 must be a new point (Object), keep it for the time frame.