

CMPE258  
Spring 2023 (Part III)

1/

April 20 (Thursday).  
Note 1. Final Exam.

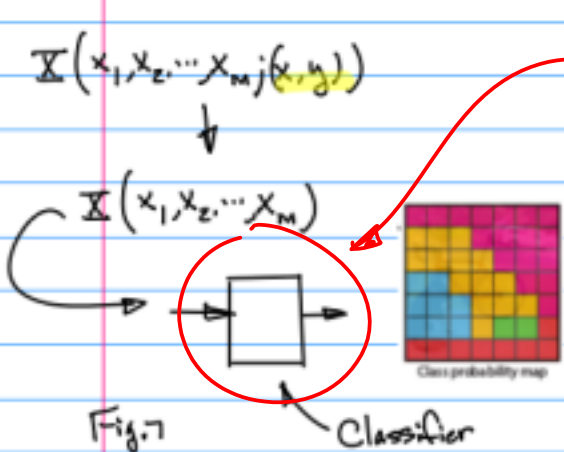
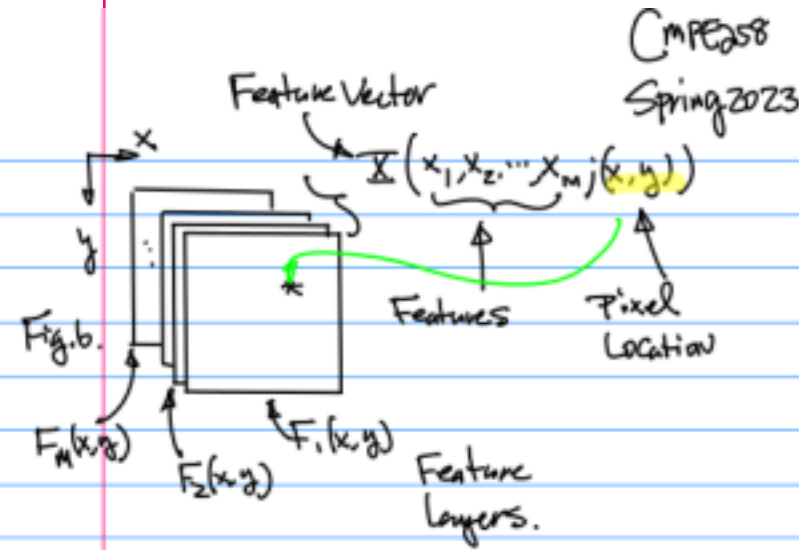
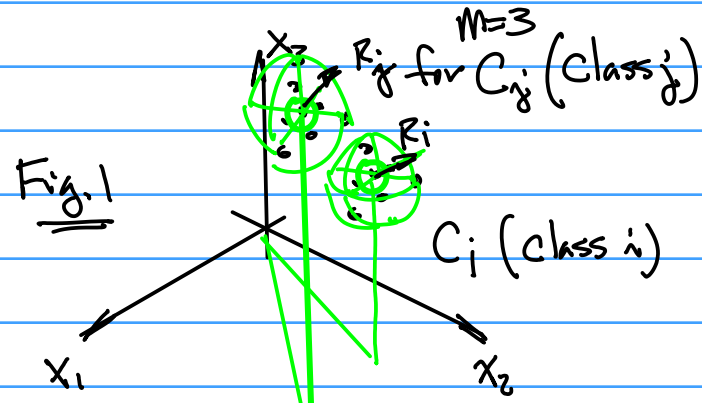
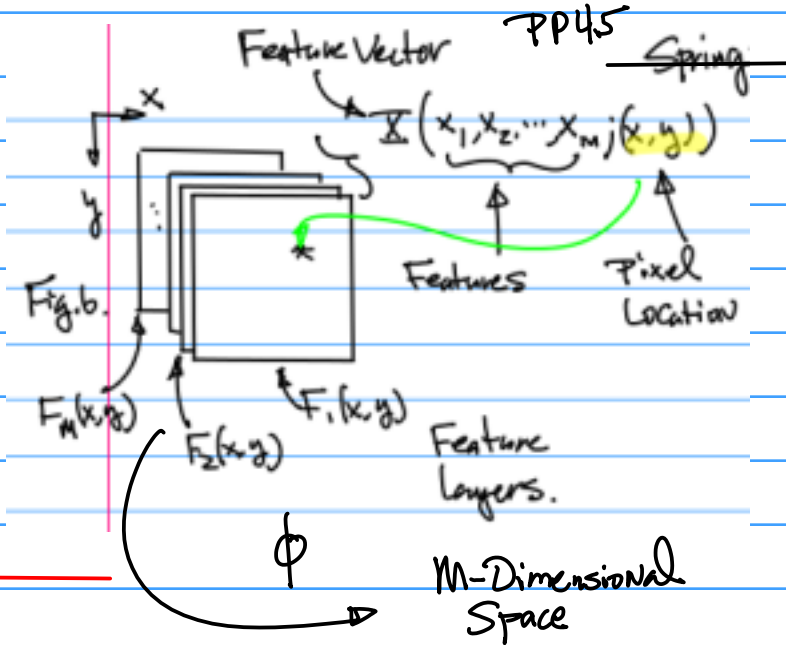
Cluster Analysis: "Mapping"

## Group II Classes

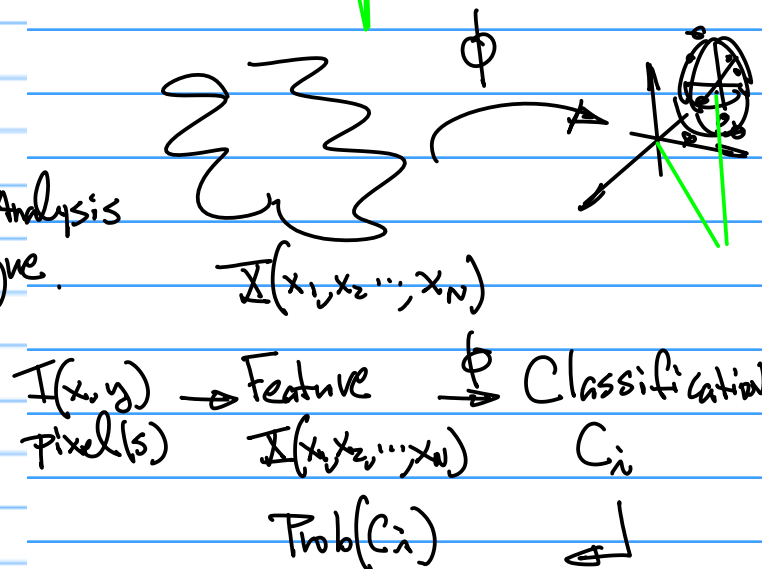
Group II classes are those classes which meet TR, T, R, TWR, MTR, TRF, MTW, MTWR, TWR, RF, TF, TRS.

Regular Class Start Times	Final Examination Days	Final Examination
7:00 through 8:25 AM	Monday, May 22	7:15-9:30 AM
8:30 through 9:25 AM	Wednesday, May 17	7:15-9:30 AM
9:30 through 10:25 AM	Friday, May 19	9:45 AM-12:00 PM
10:30 through 11:25 AM	Tuesday, May 23	9:45 AM-12:00 PM
11:30 AM through 12:25 PM	Thursday, May 18	9:45 AM-12:00 PM
12:30 through 1:25 PM	Monday, May 22	12:15-2:30 PM
1:30 through 2:25 PM	Wednesday, May 17	12:15-2:30 PM
2:30 through 3:25 PM	Friday, May 19	2:45-5:00 PM
3:30 through 4:25 PM*	Tuesday, May 23	2:45-5:00 PM
4:30* through 5:25 PM*	Thursday, May 18	2:45-5:00 PM

From Notes Part II, PP.45



Cluster Analysis Technique.



Note:  $N$  (Previously  $M$ )  
 $\sum_{i=1}^N \text{Prob}(C_i) = 1$   
 Number of Classes.  
 from "Heuristics" Expert Knowledge.

Consider K-mean Cluster Algorithm.

github.  
 2022S-114c-Kmean-handCalculation...  
 PPT  
 2022S-114c-KmeanCluster-v3-2022-...

Note 1.

Note 2.

$$\arg \min_S \sum_{i=1}^k \sum_{x \in S_i} \|x - \mu_i\|^2 = \arg \min_S \sum_{i=1}^k |S_i| \text{Var } S_i$$

a. "Argmin" minimization ... (3)  
 b. "S" Domain, "Scope" of the minimization

Example for  $\|\vec{x} - \vec{\mu}_i\|^2$   
 if  $\vec{x} = (x_1, x_2)$ ,  $\vec{\mu}_i = (\mu_{i1}, \mu_{i2})$

Then

$$\|\vec{x} - \vec{\mu}_i\|^2 = \sqrt{(x_1 - \mu_{i1})^2 + (x_2 - \mu_{i2})^2}^2$$

$$= (x_1 - \mu_{i1})^2 + (x_2 - \mu_{i2})^2 \dots (4)$$

Example: K-mean Cluster Algorithm.

First, Notation.

Note 1. Vectors

Note 3.  $\sum_{x \in S_i}$

Notation  $\sum_{i=1}^M x_i$

Given a set of observations  $(x_1, x_2, \dots, x_n)$ ,

e.g.  $\vec{x}_1 = (x_{11}, x_{12}, \dots, x_{1n})$   
 first observation ... (1)

Summation for each & every  $x$  as long as it is from the set  $S_i$ .

Note 4: from Eqn (3), we have

$S_i$ : Collection of vectors  $\vec{x}$  belonging to Class  $i$

Note: if for  $d$ -dimensional Vector,  
 then Eqn (1) has its  $N = d$

Note 5:  $\sum_{i=1}^k \rightarrow$  to cover the Collection of all Classes.

K-mean

partition the  $n$  observations into  $k$  ( $k \leq n$ ) sets  $S = \{S_1, S_2, \dots, S_k\}$

$\{\vec{x}_i | i=1, 2, \dots, N\}$  ... (2)

K-Classes.

$S_i$  for Class  $i$

Note 6:  $\vec{\mu}_i$  (1)  $\vec{\mu}_i = (\mu_{i1}, \mu_{i2}, \dots, \mu_{id})$   
 (2) Cluster for the Class  $i$

April 25 (Tue)

Note 1. Quick update on  
Project Progress Report. (Next  
Lecture)

Example: Continuation of K-mean  
Cluster Algorithm.

$1 \leq j \leq K$  covers all the  
different classes.

Hand Calculation Example

Given the following feature vectors  
Use Kmean Algorithm to find the  
clusters.

$$\begin{array}{llll} X_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} & X_2 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} & X_3 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} & X_4 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\ X_5 = \begin{bmatrix} 2 \\ 1 \end{bmatrix} & X_6 = \begin{bmatrix} 1 \\ 2 \end{bmatrix} & X_7 = \begin{bmatrix} 2 \\ 2 \end{bmatrix} & X_8 = \begin{bmatrix} 3 \\ 2 \end{bmatrix} \\ X_9 = \begin{bmatrix} 6 \\ 6 \end{bmatrix} & X_{10} = \begin{bmatrix} 7 \\ 6 \end{bmatrix} & X_{11} = \begin{bmatrix} 8 \\ 6 \end{bmatrix} & X_{12} = \begin{bmatrix} 6 \\ 7 \end{bmatrix} \\ X_{13} = \begin{bmatrix} 7 \\ 7 \end{bmatrix} & X_{14} = \begin{bmatrix} 8 \\ 7 \end{bmatrix} & X_{15} = \begin{bmatrix} 9 \\ 7 \end{bmatrix} & X_{16} = \begin{bmatrix} 7 \\ 8 \end{bmatrix} \\ X_{17} = \begin{bmatrix} 8 \\ 8 \end{bmatrix} & X_{18} = \begin{bmatrix} 9 \\ 8 \end{bmatrix} & X_{19} = \begin{bmatrix} 8 \\ 9 \end{bmatrix} & X_{20} = \begin{bmatrix} 9 \\ 9 \end{bmatrix} \end{array}$$

$$S_i^{(t)} = \{x_p : \|x_p - m_i^{(t)}\|^2 \leq \|x_p - m_j^{(t)}\|^2 \forall j, 1 \leq j \leq k\}$$

... (1)

20225-114c-Kmean-handCalculation 1-

Note 1: A Set of Feature vectors  
 $S_i^{(*)}$  — Captured at Step t  
 $i$  — Class id: i-th Class

$$S_i^{(*)} = \{\vec{x}_p\}$$

index,  $p=1,2,\dots$   
just like Notation  $i, j$ , or  $k$

$$S_i^{(*)} = \{\vec{x}_p : \text{Condition}\}$$

$$\|\vec{x}_p - \vec{m}_i^{(t)}\|^2$$

Distance (squared) at time  $t$   
to the Cluster of class  $i$

$$\|\vec{x}_p - \vec{m}_j^{(t)}\|^2$$

... to the  
Cluster class  $j$

" $j$ " for Any  $j$ , such as

Sol: Step 1. Define  $K=2$  per Heuristics.

Expert Knowledge

Note: "0" Initial step.

Let Cluster

$$\vec{m}_1^0 = \vec{x}_1 = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \dots (1)$$

$$\vec{m}_2^0 = \vec{x}_2 = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \dots (2)$$

Initial  
Arbitrary  
Values

"1" Class 1

And Arbitrarily assign Feature  
Vectors into 2 Classes.

Step 2. Use Eqn (1) To Compute  
the distance

$$\|\vec{x}_p - \vec{m}_i^{(t)}\|^2$$

and  $\|\vec{x}_p - \vec{m}_j^{(t)}\|^2$

To Evaluate the Grouping of  $\vec{x}_p$  to  
the Class  $i$  per Eqn (1).

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If Eqn (1) holds good, then  $\vec{x}_p$  stays in the Class  $i$ .  
o/w Re-assign  $\vec{x}_p$  to the Class  $j$ .

Step 3. Update the Cluster (When New Grouping is formed)

$$m_i^{(t)} = \frac{1}{N} \sum_{\vec{x}_p \in S_i} \vec{x}_p$$

$$m_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{x_j \in S_i^{(t)}} x_j \dots (2)$$

Total Number of Feature Vectors in the Class  $i$

Step 4. Carry out the Computation with the New Cluster.

(To Decide if the grouping is final or to Continue updating Cluster Values)

Note: "Stop" if No Regrouping  
o/w. Continue By Repeating the process, e.g. update Cluster Values, then Evaluate the grouping.

Step 5. Perform the Computation as Described in Step 4. which Leads to

$$C_1 (\text{Class 1}): S_1 = \{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_8\}$$

$$S_2 = \{\vec{x}_9, \vec{x}_{10}, \dots, \vec{x}_{20}\}$$

then, Update the Cluster  $m_1^{(t)}, m_2^{(t)}$ .

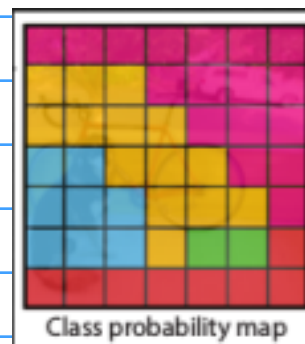
Check, No New Grouping

$m_1^{(t+1)}, m_2^{(t+1)}$  are the same.

$\therefore$  Stop. (Converged).

Discussion On Probability Distribution Map.

(a)



Feature Vector Map.

(b)



Boundary for the Classification

Regular K-mean Cluster Algorithm

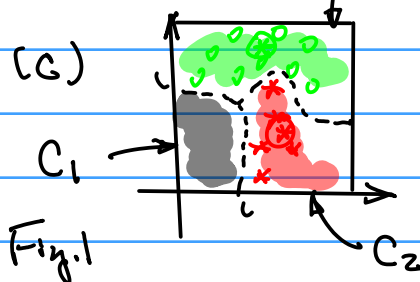


Fig. 1

$$\text{Prob}(C_1) = \frac{\text{Area of Black Pixels}}{\text{Area of } S_2 (\text{Image Plane})}$$

$\dots (3a)$

Where Area of Black Pixels  
Can be computed.

Area of  $\Omega(\text{Image Plane}) = \text{Resolution}$   
of the image plane.

For Example,  $448 \times 448$

Similarly, find

$$\text{Prob}(C_2) = \frac{\text{Area of Red Pixels}}{\text{Area of } \Omega(\text{Image Plane})} \quad \dots (3b)$$

$$\text{Prob}(C_3) = \frac{\text{Area of green Pixels}}{\text{Area of } \Omega(\text{Image Plane})} \quad \dots (3c)$$

then

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

$N=3$

Since

$$\sum_{i=1}^3 \text{Prob}(C_i) = \text{Prob}(C_1) + \text{Prob}(C_2) + \text{Prob}(C_3) \quad \dots (4-b)$$

$$= \frac{\text{Area of Black Pixels}}{\text{Area of } \Omega(\text{Image Plane})}$$

$$+ \frac{\text{Area of Red Pixels}}{\text{Area of } \Omega(\text{Image Plane})}$$

$$+ \frac{\text{Area of green Pixels}}{\text{Area of } \Omega(\text{Image Plane})}$$

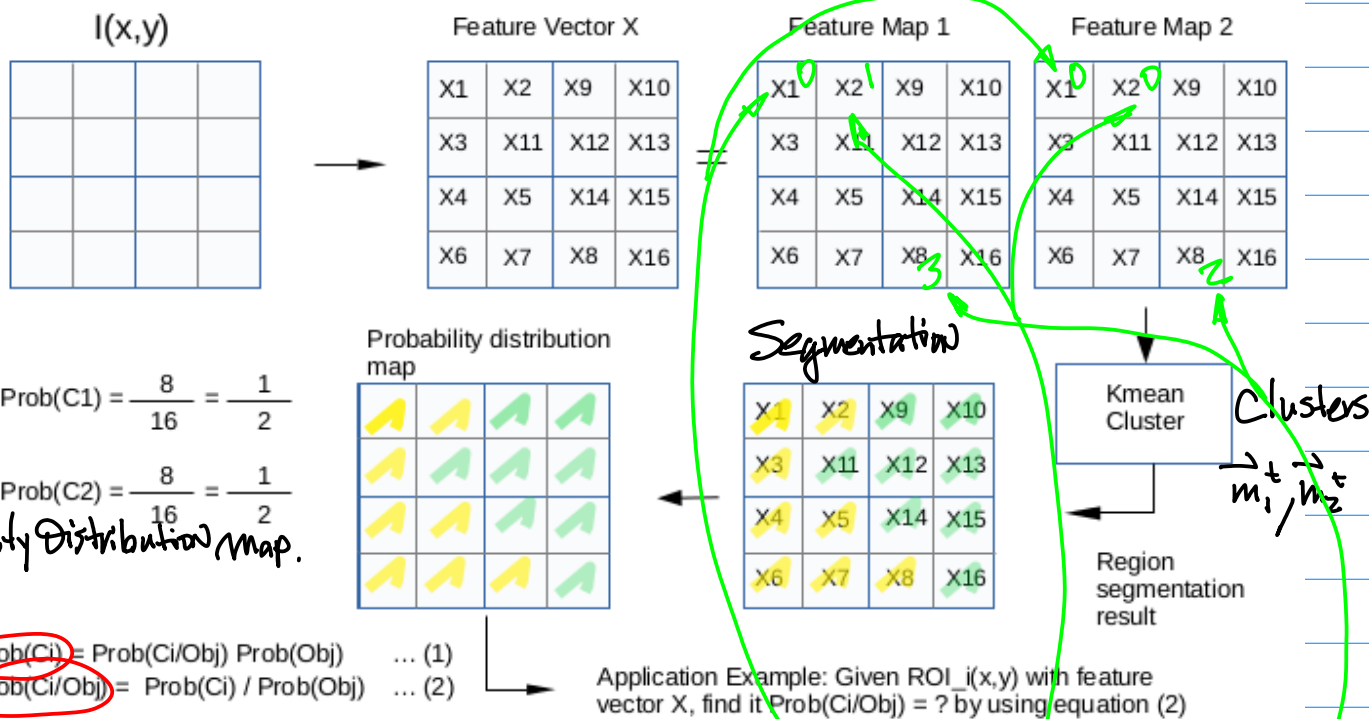
$$= \frac{\text{Area of } \Omega(\text{Image Plane})}{\text{Area of } \Omega(\text{Image Plane})} = 1.$$

(The following Notes were added  
After the Class After Recovering  
from the Laptop Computer Shut  
down. For Additional Lecture Notes  
Check the Class Zoom Recording).

2022S-114c-Kmean-prob-map-hl-2023-4-26.pdf

## Step 1. Feature Vectors

### Probability Distribution Map and Kmean Cluster Technique



$$\text{Prob}(C_i) = \text{Prob}(C_i/\text{Obj}) \text{Prob}(\text{Obj}) \quad \dots (1)$$

$$\text{Prob}(C_i/\text{Obj}) = \text{Prob}(C_i) / \text{Prob}(\text{Obj}) \quad \dots (2)$$

Harry Li, Ph.D., SJSU

Detected

Objective: To find the Probability of an object  
Belonging to Class  $i$ .

Requirements: 1<sup>o</sup> Hand Calculation of  
K mean Cluster Algorithm;

2<sup>o</sup> Use K-mean Algorithm to Perform Image  
Segmentation, then Find Probability Distribution  
Map.

$$\begin{aligned} X_1 &= \begin{bmatrix} 0 \\ 0 \end{bmatrix} & X_2 &= \begin{bmatrix} 1 \\ 0 \end{bmatrix} & X_3 &= \begin{bmatrix} 0 \\ 1 \end{bmatrix} & X_4 &= \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\ X_5 &= \begin{bmatrix} 2 \\ 1 \end{bmatrix} & X_6 &= \begin{bmatrix} 1 \\ 2 \end{bmatrix} & X_7 &= \begin{bmatrix} 2 \\ 2 \end{bmatrix} & X_8 &= \begin{bmatrix} 3 \\ 2 \end{bmatrix} \\ X_9 &= \begin{bmatrix} 6 \\ 6 \end{bmatrix} & X_{10} &= \begin{bmatrix} 7 \\ 6 \end{bmatrix} & X_{11} &= \begin{bmatrix} 8 \\ 6 \end{bmatrix} & X_{12} &= \begin{bmatrix} 6 \\ 7 \end{bmatrix} \\ X_{13} &= \begin{bmatrix} 7 \\ 7 \end{bmatrix} & X_{14} &= \begin{bmatrix} 8 \\ 7 \end{bmatrix} & X_{15} &= \begin{bmatrix} 9 \\ 7 \end{bmatrix} & X_{16} &= \begin{bmatrix} 7 \\ 8 \end{bmatrix} \\ X_{17} &= \begin{bmatrix} 8 \\ 8 \end{bmatrix} & X_{18} &= \begin{bmatrix} 8 \\ 8 \end{bmatrix} & X_{19} &= \begin{bmatrix} 8 \\ 9 \end{bmatrix} & X_{20} &= \begin{bmatrix} 9 \\ 9 \end{bmatrix} \end{aligned}$$



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Note 1: Loss function Composition:  $f_{\text{loss}} = \sum_{i=1}^K \lambda_i f_{\text{loss},i} \dots (1)$

No. of Bounding Boxes on a grid  $S$

where  $\sum_{i=1}^K \lambda_i = 1$ .

Entire Image

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

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

Note 2:

Unit function

$\mathbb{1}_{ij}^{\text{obj}} = \begin{cases} 1 & \text{if Object exists} \\ 0 & \text{o/w} \end{cases} \dots (2)$

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

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

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

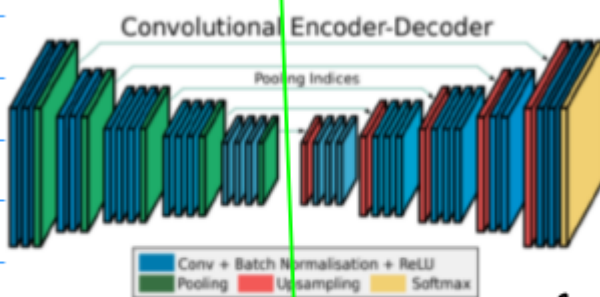
Location 50%, Shape 20%, ... etc.  
Semantic Segmentation

Ref:

2022F-109-semantic-seg-part1-HL-2022

ppt.

pp 52 Fig. 3



Deep Convolutional  
Neural Network:

Encoder:

Feature Extraction — Convolutions  
Classification — Feedforward NN

Recognition of Object

Decoder:

To get  
Pixel by  
pixel