

$I(x, y)$. Example in the fig. below.

$$\begin{aligned} \text{Total No. of} \\ \text{Pixels of } I(x, y) &= 7 * 7 * 5 * 5 \\ &= 495^2 \end{aligned}$$

Hence,

$$\text{Prob}(\text{Class1})_{\text{Blue}} = \frac{85^2}{495^2} = \frac{8}{49}$$

Next,

$$\text{Prob}(\text{Class2})_{\text{pink}} = \frac{25}{49}$$

$$\text{Prob}(\text{Class3})_{\text{yellow}} = \frac{14}{49}$$

$$\text{Prob}(\text{Class4})_{\text{green}} = \frac{2}{49}$$

Note: To verify the Calculation, we should have the following

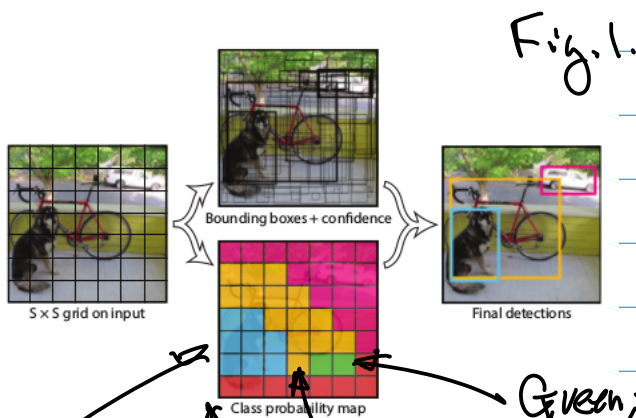
Property:

$$\sum_{i=1}^4 \text{Prob}(C_i) = 1 \dots (2)$$

from our Calculation,

$$\begin{aligned} \sum_{i=1}^4 \text{Prob}(C_i) &= \text{Prob}(C_1) + \\ &\text{Prob}(C_2) + \dots + \text{Prob}(C_4) \\ &= (8 + 25 + 14 + 2) / 49 = 1. \end{aligned}$$

The Next Step for the Probability Distribution Map Calculation: Segmentation, e.g. A Technique to allow us to classify



Blue:
Segmentation for
Class 1

Yellow, Class 3
Pink: Segmentation
for Class 2

Green; Class 4.

Objective:

To Find/Define Probability Distribution map for each Class.

$$\text{Prob}(\text{Class1}) = \frac{\left(\begin{array}{c} \text{Pixels belong to} \\ \text{Class1} \end{array} \right)}{\begin{array}{c} \text{Total} \\ \text{No. of pixels} \\ \text{of } I(x, y) \end{array}}$$

... U

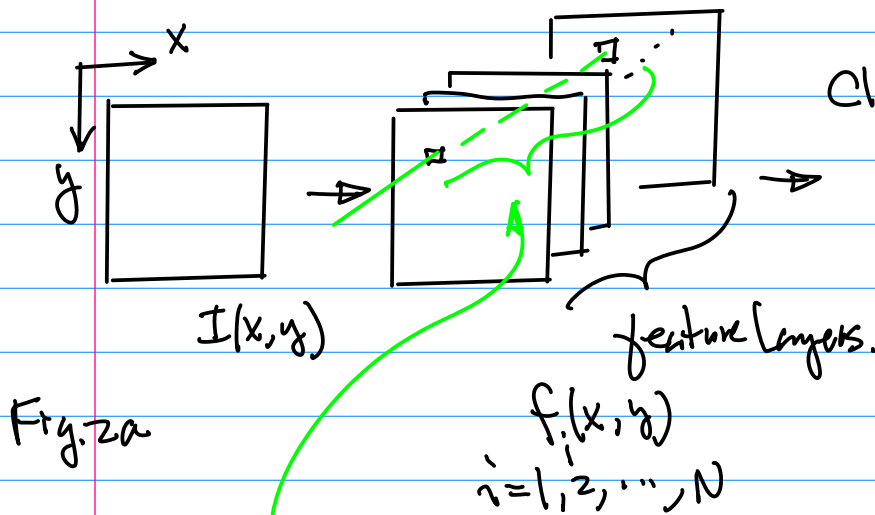
from the given Condition in Fig. 1

Since,

$$\left(\begin{array}{c} \text{Pixels belong to} \\ \text{Class1} \end{array} \right) = 8 * (5 * 5) = 85^2$$

pixels One Grid.

Objects into one of the class i .



Form Feature Vectors

2022F-101-cmpe258-note-2022-11-1 (4).pdf

$$\vec{X} = (x_1, x_2, \dots, x_N) \dots (3).$$

introduce Subscript.

$$\vec{X}_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{iN}) \dots (3-b)$$

Cluster Finding.

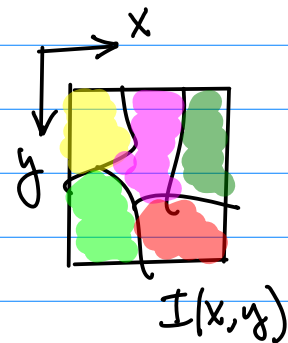
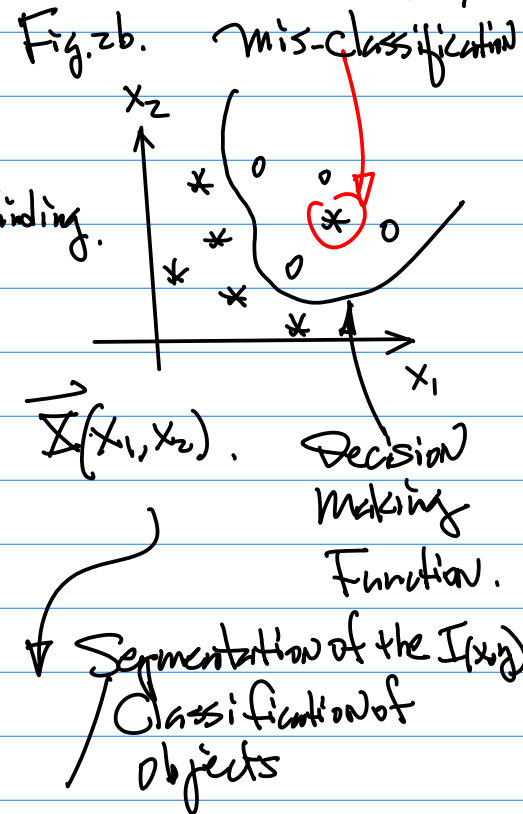


Fig. 2c

Ref: fork-mean Cluster Classification. Nov. 7th (Tue).

1. 2022F-101-cmpe258-note-2022-11-1 (4).pdf
2. github, 2022S, Search Keywords "kmean", Two Relevant References
 { PPT. — Formulation.
 { Hand Calculation.

Note 1. Midterm Exam is scheduled ON Next Tuesday (14th).
 Please Bring Your Laptop Computer to the Class ON Monday.
 Review and Q&A Session ON Thursday.

CMPE258

F2023

53/

Note1. Ref1. General Background \rightarrow Eqn(1).

Ref4, Hand Calculation

Ref2.

Ref3 PPT Formulation

2018S-107-lec7-ClusterSeekin-2018-3-14.pdf

2022F-108a-Yolo-architecture-loss-function-2022-10-10.pdf

2022S-114c-Korean-handCalculation1-converted.pdf.pdf

2022S-114c-Korean-prob-ap-hl-2023-4-26.pdf

korean-2023S-101-Note-part3-cmpe258-2023-04-27.pdf(1)-1.pdf

korean-2023S-101-Note-part3-cmpe258-2023-04-27.pdf(1)-1(1).pdf

Example: Formulation.

Ref.2. Lecture Notes

Ref.3. Notation

$$\text{Argmin}_S \sum_i \sum_j \|\vec{x} - \vec{\mu}_i\|^2$$

$$S_i^{(k)} = \left\{ \vec{x}_p : \|\vec{x}_p - \vec{\mu}_i\|^2 \leq \|\vec{x}_p - \vec{\mu}_j\|^2, \forall j, j=1,2,\dots,K, \text{ and } j \neq i \right\}$$

$$\vec{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}, \quad \vec{\mu}_i = \begin{pmatrix} \mu_{i1} \\ \mu_{i2} \end{pmatrix}$$

$$\vec{x} - \vec{\mu}_i = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} - \begin{pmatrix} \mu_{i1} \\ \mu_{i2} \end{pmatrix} = \begin{pmatrix} x_1 - \mu_{i1} \\ x_2 - \mu_{i2} \end{pmatrix}$$

iteration of the Computation.
Check Convergence. \rightarrow if converges, then Stop

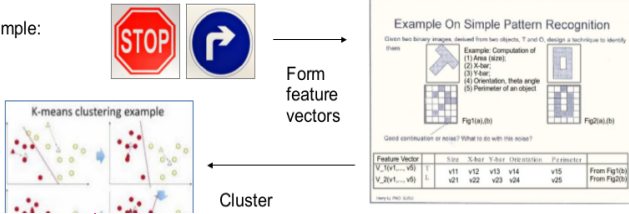
K-mean Algorithm (1)

https://en.wikipedia.org/wiki/K-means_clustering

Given a set of observations (x_1, x_2, \dots, x_n) , where each observation is a d -dimensional real vector, k -means clustering aims to partition the n observations into k ($\leq n$) sets $S = \{S_1, S_2, \dots, S_k\}$ so as to minimize the within-cluster sum of squares (WCSS) (i.e. *variance*). Formally, the objective is to find:

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

Example:



Note 1.

Note 2. Squared Distance

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

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

$$\begin{aligned} \|\vec{x} - \vec{\mu}_i\|^2 &= \sqrt{(x_1 - \mu_{i1})^2 + (x_2 - \mu_{i2})^2}^2 \\ &= (x_1 - \mu_{i1})^2 + (x_2 - \mu_{i2})^2 \dots (4) \end{aligned}$$

Example: K-mean Cluster Algorithm.

First, Notation.

Note 1. Vectors

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

e.g. $X_1 = (x_{11}, x_{12}, \dots, x_{1N})$
first observation ... (1)

For X_i
Observation i

x_{ij}
Component j
for the Observation i

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

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

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

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 X
belonging to Class i

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

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

K-mean

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

$\{X_i | i=1, 2, \dots, N\}$

K-Classes.

S_i for Class i

So, with the Objective Function defined, Now Let's take a look at the following Equation for Computation.

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

Hand Calculation Example

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

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

Ref

20225-114c-Kmean-handCalculation1-c

Note1: A Set of Feature Vectors

$S_i^{(*)}$ ← Captured at Step t
i ← Class id: i-th Class

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

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

$$S_i^{(t)} = \{\bar{x}_p : \text{Condition}\}$$

$$\|\bar{x}_p - m_i^{(t)}\|^2$$

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

$$\begin{array}{llll} x_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} & x_2 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} & x_3 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} & x_4 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\ x_5 = \begin{bmatrix} 2 \\ 1 \end{bmatrix} & x_6 = \begin{bmatrix} 1 \\ 2 \end{bmatrix} & x_7 = \begin{bmatrix} 2 \\ 2 \end{bmatrix} & x_8 = \begin{bmatrix} 3 \\ 2 \end{bmatrix} \\ x_9 = \begin{bmatrix} 6 \\ 6 \end{bmatrix} & x_{10} = \begin{bmatrix} 7 \\ 6 \end{bmatrix} & x_{11} = \begin{bmatrix} 8 \\ 6 \end{bmatrix} & x_{12} = \begin{bmatrix} 6 \\ 7 \end{bmatrix} \\ x_{13} = \begin{bmatrix} 7 \\ 7 \end{bmatrix} & x_{14} = \begin{bmatrix} 8 \\ 7 \end{bmatrix} & x_{15} = \begin{bmatrix} 9 \\ 7 \end{bmatrix} & x_{16} = \begin{bmatrix} 7 \\ 8 \end{bmatrix} \\ x_{17} = \begin{bmatrix} 8 \\ 8 \end{bmatrix} & x_{18} = \begin{bmatrix} 9 \\ 8 \end{bmatrix} & x_{19} = \begin{bmatrix} 10 \\ 8 \end{bmatrix} & x_{20} = \begin{bmatrix} 9 \\ 9 \end{bmatrix} \end{array}$$

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

Expert Knowledge

Note: "0" Initial Step.

Let cluster

$$\vec{m}_1^0 = \vec{x}_1 = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \dots (1) \quad \text{Initial Arbitrary Values}$$

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

"1" Class 1

And Arbitrarily assign Feature Vectors into 2 Classes.

Step 2. Use Eqn (1) To Compute the distance
 $\|\bar{x}_p - m_i^{(t)}\|^2$

Now, check the Hand Calculation that I made and posted on the Class git, e.g. Ref. 4.

K-mean Cluster Algorithm

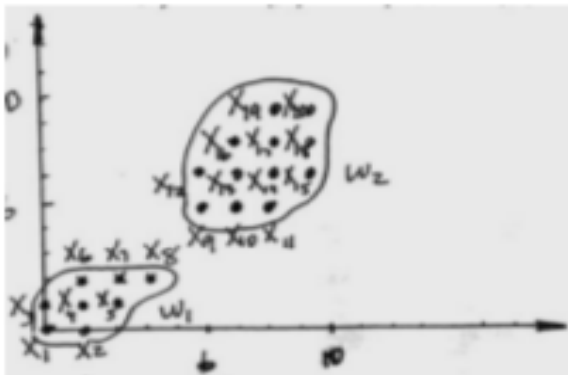
HX

1/3

Given the following feature vectors
use K-mean Algorithm to find the
clusters.

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

Sol. We can plot these feature
vectors below



Step 1. Define Number of Cluster
 $K=2$ Based on Heuristics (the
plot of the feature vectors).

Let $K=2$

And make initialization by
arbitrarily select 2 points \vec{x}_1
 \vec{x}_2 as the cluster center

Let cluster

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

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

And let Class 1 be

$$C_1: (\vec{x}_1, \vec{x}_3) \dots (3)$$

Class 2 be

$$C_2: (x_2, x_4, x_5, \dots, x_{20}) \dots (4)$$

Step 2. Use Equation

$$\|\vec{x}_p - \vec{m}_i\| \leq \|\vec{x}_p - \vec{m}_j\| \dots (5)$$

for \vec{x}_p from Class i to regroup
feature vectors in Class i to j
if Eqn(5) does not hold. Hence

From Class C_1 ,

$$\begin{aligned} \|\vec{x}_1 - \vec{m}_1^0\| &= \left\| \begin{pmatrix} x_{11} \\ x_{12} \end{pmatrix} - \begin{pmatrix} m_{11} \\ m_{12} \end{pmatrix} \right\| = \\ &= \sqrt{(x_{11} - x_{11})^2 + (x_{12} - x_{12})^2} = 0 \end{aligned}$$

$m_{11} = x_{11}$
 $m_{12} = x_{12}$

$$\begin{aligned} \text{And } \|\vec{x}_1 - \vec{m}_2\| &= \left\| \begin{pmatrix} x_{11} \\ x_{12} \end{pmatrix} - \begin{pmatrix} m_{21} \\ m_{22} \end{pmatrix} \right\| = \\ &= \sqrt{(x_{11} - x_{21})^2 + (x_{12} - x_{22})^2} \\ &= \sqrt{1^2 + 0^2} = 1 \end{aligned}$$

$m_{21} = x_{21}$
 $m_{22} = x_{22}$

Continue to Carry Out the Computation,
See this 3 page Remdout, till Converges.
e.g. $m_i^{(t+1)} = m_i^{(*)}$.
then No New Grouping.
Stop the Computation.

Nov. 9 (Th).

Example: Hand Calculation of the K-mean.

Note 1. Calculation of A Cluster.

Suppose we have Cluster M_i defined as

$$M_i = \frac{1}{M} \sum_{j=1}^M \vec{x}_{ij} \quad \dots (1)$$

Suppose

$$\vec{x}_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{ip})$$

P-dimensional.

$$M_i = \frac{1}{M} (\vec{x}_{i1} + \vec{x}_{i2} + \dots + \vec{x}_{ip})$$

$$= \frac{1}{M} \left[\begin{pmatrix} x_{i11} \\ x_{i12} \end{pmatrix} + \begin{pmatrix} x_{i21} \\ x_{i22} \end{pmatrix} + \dots + \begin{pmatrix} x_{ip1} \\ x_{ip2} \end{pmatrix} \right] \quad \dots (1-b)$$

↓ for C_i , Class i ,
drop the Sub "i"
for the Simplicity

$$= \frac{1}{M} \left[\begin{pmatrix} x_{11} \\ x_{12} \end{pmatrix} + \begin{pmatrix} x_{21} \\ x_{22} \end{pmatrix} + \dots + \begin{pmatrix} x_{p1} \\ x_{p2} \end{pmatrix} \right]$$

$$= \frac{1}{M} \begin{pmatrix} x_{11} + x_{21} + x_{31} + \dots + x_{p1} \\ x_{12} + x_{22} + x_{32} + \dots + x_{p2} \end{pmatrix}$$

$$= \begin{pmatrix} \frac{x_{11} + x_{21} + x_{31} + \dots + x_{p1}}{M} \\ \frac{x_{12} + x_{22} + x_{32} + \dots + x_{p2}}{M} \end{pmatrix}$$

for $P=2$

$$M_i = \begin{pmatrix} \frac{x_{11} + x_{21}}{2} \\ \frac{x_{12} + x_{22}}{2} \end{pmatrix} \quad \dots (1-c)$$

Note 2. For Heuristics / Human Expert Knowledge, K is defined Accordingly.

Note 3. Initialization that requires \vec{M}_i for $i=1, 2, \dots, K$
Select M_i By Heuristics.

Then, Calculation Based on the following formula,

$$S_i^{(t)} = \{ \quad \}$$

$$\downarrow$$

$$\{ \vec{x}_p : \text{conditions} \}$$

$$\downarrow$$

$$\{ \vec{x}_p : \|\vec{x}_p - \vec{M}_i\|^2 \leq \|\vec{x}_p - \vec{M}_j\|^2, \quad \forall j, j=1, 2, \dots, K \}$$

$$\dots (2)$$

Now, check the convergence.

By Comparing

$$\vec{\mu}_i^{(t+1)} = \vec{\mu}_i^{(t)} \quad \text{Step at } t$$

for $i = 1, 2, \dots, K$

from the given condition
& our Initialization,

e.g. we have

$$C_1 = (\vec{x}_1, \vec{x}_3)$$

$$\begin{aligned} \vec{\mu}_1' &= \frac{1}{M} \sum_{i=1}^M \vec{x}_i \quad \left| \begin{array}{l} M=2 \\ \text{Sub "i" match the Class } C_2 \end{array} \right. \\ &= \frac{1}{2} (\vec{x}_1 + \vec{x}_2) \quad \dots (3) \end{aligned}$$

where \vec{x}_1 is equal to the 1st feature vector in C_1
 \vec{x}_2 is the 2nd feature vector.

hence,

$$\begin{aligned} \vec{\mu}_1' &= \frac{1}{2} \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix} + \begin{pmatrix} 0 \\ 1 \end{pmatrix} \right] \\ &= \frac{1}{2} \begin{pmatrix} 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ \frac{1}{2} \end{pmatrix} \end{aligned}$$

Now, Check

$$\|\vec{x}_p - \vec{\mu}_1'\|_{p=1} = \left\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 0 \\ \frac{1}{2} \end{pmatrix} \right\| \quad \dots (4)$$

$$= \left\| \begin{pmatrix} 0 \\ \frac{1}{2} \end{pmatrix} \right\|^2 = \sqrt{0^2 + \left(\frac{1}{2}\right)^2}^2 = \frac{1}{2} \quad \dots (4-b)$$

$$\text{And} \quad \|\vec{x}_p - \vec{\mu}_j'\|_{j=2}^2 \quad \dots (5)$$

$$\begin{aligned} \text{where } \vec{\mu}_2' &= \frac{1}{M} \sum_{i=1}^M \vec{x}_i \quad \left| \begin{array}{l} M=18 \\ \text{Sub "i" match the Class } C_2 \end{array} \right. \\ &= \frac{1}{18} \sum_{i=1}^{18} \vec{x}_i \end{aligned}$$

$$\begin{aligned} &= \frac{1}{18} [\vec{x}_2 + \vec{x}_4 + \vec{x}_5 + \vec{x}_6 + \dots + \vec{x}_{20}] \\ &= \begin{pmatrix} 5.67 \\ 5.33 \end{pmatrix} \end{aligned}$$

hence

$$\|\vec{x}_p - \vec{\mu}_2'\|_{p=1}^2$$

$$= \|\vec{x}_1 - \vec{\mu}_2'\|^2 =$$

$$= \left\| \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 5.67 \\ 5.33 \end{pmatrix} \right\|^2 \quad \dots (6)$$

Therefore

$$\text{Eqn (4-b)} < \text{Eqn (6)}$$

Similarly, \vec{x}_3 can be verified to satisfy Eqn (2), & stays in C_1 .

Nov. 17th (Th)

Road map for the 2nd half of the semester:

Semantic segmentation to move from YOLO bounding boxes based DCNN technique to Pixel by Pixel based DCNN called Yolact.

If time permits, we will discuss LSTM (Long Short Term Memory) technique, based on the mathematical formulation of Markov Processes.

Note 1. PPT, introduction

Note 1. Ref. on ChatGPT fine tuning.

2023F-104-#190c-9a-chatGPT-API-YZ-HL...

2023F-104-2-API_Key (copy).json

2023F-104-3-requirements.txt

2023F-104-4-test_fine_tuning (copy).py

2023F-104-5-train-cti-data (copy).jsonl

Note 2.

json line file to capture the training data.

```
configure_logging()
Terminal: Local x + v
├─ GPT_Fine_Tuning
│   ├── API_Key.json
│   ├── CMPE244
│   ├── requirements (copy).txt
│   ├── test_fine_tuning.py
│   ├── train-cti-data.jsonl
│   └── train_fine_tuning.py
├─ GPT_Fine_Tuning (1).zip
├─ GPT_Fine_Tuningoutput.log
├─ hello-the-world
│   ├── API_Key.json
│   ├── chatgpt-2023-10-27.yml
│   ├── ChatHistory.json
│   └── GPTWithHistorySaved.py
└─ others
```

Notethis folder consists of the sample code

```

1 #-----
2 # CTI One Corporation
3 # for Chat-GPT
4 # Version x0.1
5 # Coded by: Youran Zheng, 2023-10-27
6 # Create a Anaconda environment;
7 # Open a terminal, then
8 # $ conda env create -f chatgpt-2023-10-27.yml
9 # Activate the Anaconda environment: $ conda activate chatgpt
10 #-----
11 name: chatgpt-2023-10-27
12
13 dependencies:
14   - python==3.7.1
15   - pip
16   - pip:
17     - openai==0.27.9

```

Sample example of the .jsonl file as the training data file

From this example, the user is for the part of posting questions, and the assistant is for the part of answer. So, you can modify this sample accordingly to integrate with your Q&A of your training data.

```

Terminal: Local x + v
{"messages": [{"role": "system", "content": "You are Johnny, the CTI One technical support for W100."}, {"role": "user", "content": "Answer the following technical question: What is W100 product?"}, {"role": "assistant", "content": "W100 is a smart walker. It walks up to you when you call it.\n"}]}
{"messages": [{"role": "system", "content": "You are Johnny, the CTI One technical support for W100."}, {"role": "user", "content": "Answer the following technical question: How do I start using W100?"}, {"role": "assistant", "content": "Please first use smart phone to upload your photo to the W100 smart walker.\n"}]}
{"messages": [{"role": "system", "content": "You are Johnny, the CTI One technical support for W100."}, {"role": "user", "content": "Answer the following technical question: How do I set up W100 environment?"}, {"role": "assistant", "content": "Make sure you power up the Wi-Fi router provided in the package and then use your smart phone apps to activate W100 system by initializing it.\n"}]}
{"messages": [{"role": "system", "content": "You are Johnny, the CTI One technical support for W100."}, {"role": "user", "content": "Answer the following technical question:\nSymptom: Battery not charging\nProbable cause: Charger not working"}, {"role": "assistant", "content": "Please replace the charger of W100\n"}]}
{"messages": [{"role": "system", "content": "You are Johnny, the CTI One technical support for W100."}, {"role": "user", "content": "Answer the following technical question:\nSymptom: Battery not charging\nProbable cause: Battery connec

```

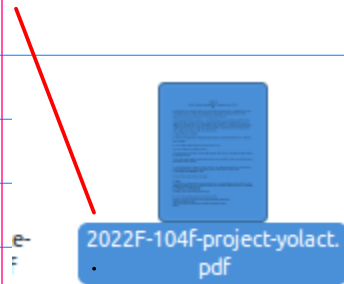
Please walk through the sample code, training and testing code as references for your design.

Note: It is mandatory requirement to have this ChatGPT API capability integrated into your semester long project.

Note: Project assignment for the implementation of Yolact DCNN.

references:

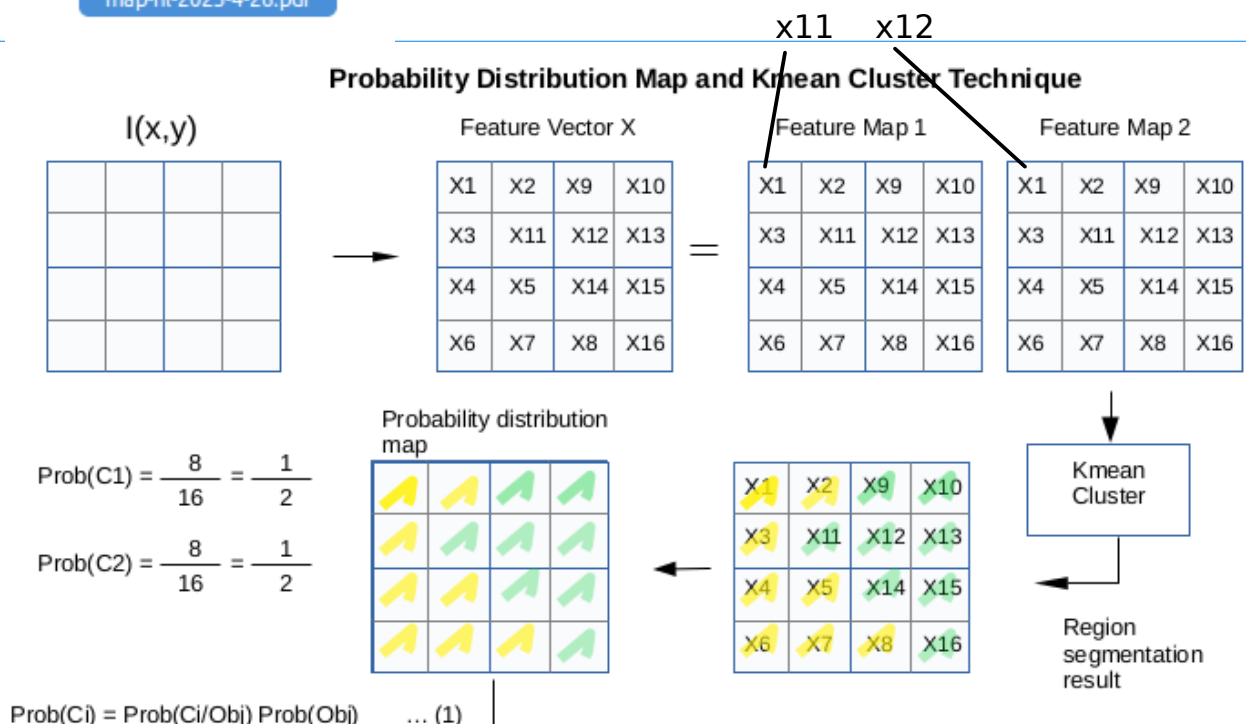
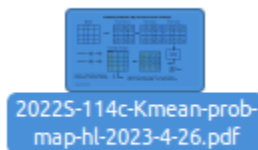
1. Readme on github provides the source github and instructions to build the executable.



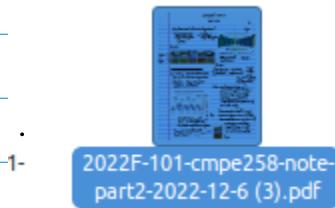
The readme document ID: 2022F-107 ~ on the github.

2. The requirements will be posted on Canvas and it is due on Dec. 3rd (Sunday).

Example: K-mean technique for the probability distribution map calculation.



Consider Semantic Segmentation
ref 1. on the github



CMPE258 PART II
Nov. 10, 22

52

Now, Discussion On Semantic Segmentation. //

Bounding Box Based Object Recognition (YOLO) → Pixel Based Object Recognition

Example:

Before
J.S.
After.

Convolutional Encoder-Decoder

Pooling Indices

Encoder: Decoder:

Nov. 21st (Tuesday).

Note 1. Semester Long Project Presentation. Nov. 30th (Thur). and Dec. 5 (Tue) Scheduled for the team/individual Project Presentation

Note 2. Mandatory Requirement: To integrate ChatGPT APIs in your project.

Group II Classes

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

| Regular Class Start Times | Final Examination Days | Final Examination Times |
|---------------------------|------------------------|-------------------------|
| 7:00 through 8:25 AM | Tuesday, December 12 | 7:15-9:30 AM |
| 8:30 through 9:25 AM | Thursday, December 14 | 7:15-9:30 AM |
| 9:30 through 10:25 AM | Monday, December 11 | 9:45 AM-12:00 PM |
| 10:30 through 11:25 AM | Wednesday, December 13 | 9:45 AM-12:00 PM |
| 11:30 AM through 12:25 PM | Friday, December 8 | 9:45 AM-12:00 PM |
| 12:30 through 1:25 PM | Tuesday, December 12 | 12:15-2:30 PM |
| 1:30 through 2:25 PM | Thursday, December 14 | 12:15-2:30 PM |
| 2:30 through 3:25 PM | Monday, December 11 | 2:45-5:00 PM |
| 3:30 through 4:25 PM* | Wednesday, December 13 | 2:45-5:00 PM |
| 4:30* through 5:25 PM* | Friday, December 8 | 2:45-5:00 PM |

Continued from the Ref. Technique 2.
Bi-Linear Interpolation

Step 1. place "Anchor Points" onto the higher resolution patch.

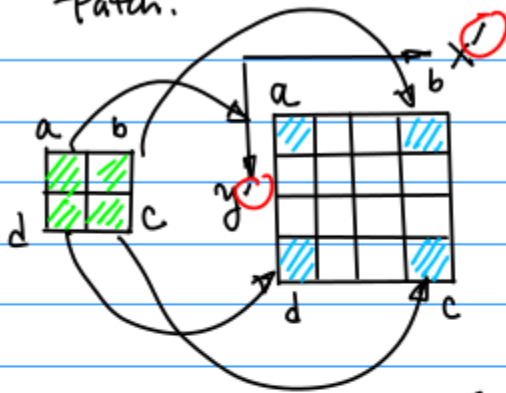


Fig. 1

Step 2. Perform Interpolation

Background: Given (x_1, y_1) , (x_2, y_2) and x_3 , Find $y_3 = ?$

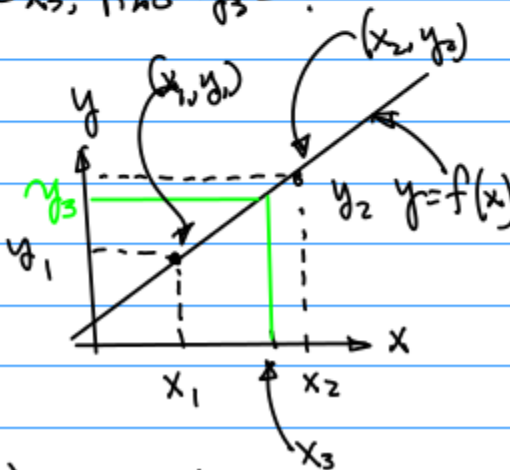


Fig. 7

$$y = f(x), \quad y = ax + b \quad \dots (1)$$

After the Math. Manipulation,
we have the formula Eqn (3)

$$y = \underbrace{\frac{y_2 - y_1}{x_2 - x_1}}_a x - \underbrace{\frac{y_2 - y_1}{x_2 - x_1} x_1 + y_1}_{b} \dots (3)$$

$$a = \frac{y_2 - y_1}{x_2 - x_1} \dots (3-b)$$

$$b = -\frac{y_2 - y_1}{x_2 - x_1} x_1 + y_1 \dots (3-c)$$

Let $x = x'$, y equal to the intensity,

$$\text{So } x_1 = 0, y_1 = 10$$

$$x_2 = 3, y_2 = 20$$

Applying the Eqn to the top line
of the feature plane. Eqn (3-b):

$$a = \frac{\text{feature @ pt } b - \text{feature @ pt } a}{(\text{slope}) \text{ Index @ } b - \text{Index @ } a \text{ Coordinates}}$$

$$= \frac{20 - 10}{3 - 0} = 10/3$$

So, for the offset from Eqn (3-c)

$$b (\text{offset}) = -\frac{10}{3} \cdot x_1 \Big|_{x_1=0} + y_1 \Big|_{y_1=10}$$

$$= 10$$

therefore

$$y = ax + b = \frac{10}{3}x + 10$$

Find the feature @ $(1, 0)$, hence,

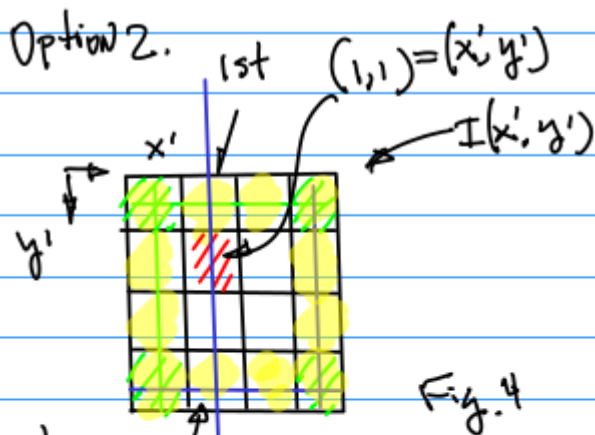
$$y = \frac{10}{3}x \Big|_{x=1} + 10 = \frac{10}{3} + \frac{30}{3} = \frac{40}{3}$$

Once the interpolation along x -axis all done, then move to the interpolations along y -axis.

Note: From the Lecture Notes, Ref. 2.

We can carry out the 2nd Dimension interpolation as illustrated Below.

FP.5b.



2nd

Apply the Same Interpolation Equation Except the independent Variable Changed from x' to y' , Use $I(1,0)$ as the 1st pt, $I(1,3)$ for the Interpolated

Technique for Up Sampling, Ref. 3

2022F-109-semantic-seg-part1-HL-2022-11-10.pdf

Nov. 28 (Tue).

Note 1. Presentation + Demo + Code Walk-Through Starts on Thursday (Nov. 30).
Submission Starts on Thursday

Note 2. Final Exam Schedule. on Dec. 8th

Friday 2:45-5:00 p.m.
In the Same Classroom.

Please Bring Your Laptop with. MNIST, Yolo, Yoloact Code Ready;

Note 3. Please Bring a USB webcam, you may need it in the exam.

CMPE258

F2023

66/

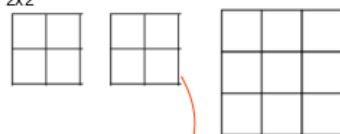
Transposed Convolution Up-sampling

Credit of the example illustration:
<https://towardsdatascience.com/transposed-convolution-demystified-84ca81b4aba>

<https://naokishibuya.medium.com/up-sampling-with-transposed-convolution-9ae4f2df52d0>

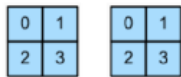
1. Consider a 2x2 encoded feature map which needs to be upsampled to a 3x3 feature map.

Input image Feature map: 2x2 Kernel 2x2 Upsampled output image: 3x3



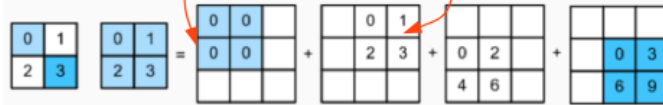
kernel of size 2x2 with unit stride and zero padding.

Example:

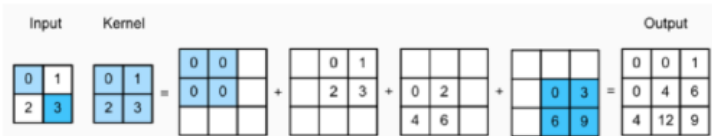


Step 1. Feature map and the kernel

Step 2. Transposed convolution for each pixel in the feature map: take 0 from the image, then multiply each coefficient of the kernel and place the result back to its corresponding location in the bigger output map, so 0x0, 0x1, 0x2, 0x3; then next take 1 from the image, repeat the process



Step 3. Add output at each pixel location together to form upsampled image



Animated tutorial on transpose convolution
<https://medium.com/@marsxiang/convolution-s-transposed-and-deconvolution-6430c358a5b6>

```
>>> # With square kernels and equal stride
>>> m = nn.ConvTranspose2d(16, 32, 3, stride=2)
>>> # non-square kernels and unequal stride and with padding
>>> n = nn.ConvTranspose2d(16, 32, (3, 5), stride=(2, 1), padding=(4, 2))
>>> input = torch.randn(20, 16, 50, 100)
>>> output = m(input)
>>> # exact output size can be also specified as an argument
>>> input = torch.randn(1, 16, 12, 12)
>>> downsample = nn.Conv2d(16, 16, 3, stride=2, padding=1)
>>> upsample = nn.ConvTranspose2d(16, 16, 3, stride=2, padding=1)
>>> h = downsample(input)
>>> torch.Size([1, 16, 6, 6])
>>> output = upsample(h, output_size=input.size())
>>> output.size()
torch.Size([1, 16, 12, 12])
```

Fig.1

Ref:



2022F-101-cmpe258-note-part2-2022-12-6 (4).pdf

Example: Transposed Convolution for Upsampling

Ref: see github.

Kernel

Step 2. Transposed convolution for each pixel in the feature map: take 0 from the image, then multiply each coefficient of the kernel and place the result back to its corresponding location in the bigger output map, so 0x0, 0x1, 0x2, 0x3; then next take 1 from the image, repeat the process

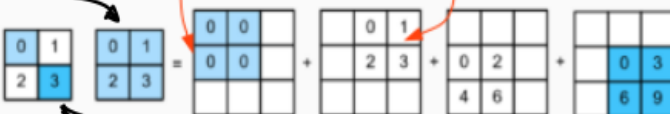
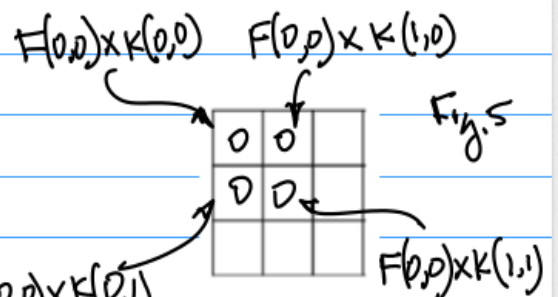


Fig.1

Note: 1. Feature Layer, in the example, is 2x2

Continue this process for the rest of the kernel coefficients,



Step 2.

Note: from the Ref Example, the Transposed Convolution UpSampling is performed by multiply each Kernel coefficient to the 2×2 Patch, then place the intermediate Computational Result on to 3×3 Patch using the Kernel coefficient location as reference, See the example on the PPT. (PPT 66 of this Note, Fig.1)

The calculation as follows.

| | | |
|---------------|-------------|--|
| $1.5\alpha_1$ | $3\alpha_1$ | |
| $5\alpha_1$ | $9\alpha_1$ | |
| | | |

Fig.4

2nd step. for α_2

| | | |
|--|---------------|-------------|
| | $1.5\alpha_2$ | $3\alpha_2$ |
| | $5\alpha_2$ | $9\alpha_2$ |
| | | |

Fig.5

3rd Step. α_3

| | | |
|---------------|-------------|--|
| | | |
| | | |
| $1.5\alpha_3$ | $3\alpha_3$ | |
| $5\alpha_3$ | $9\alpha_3$ | |

Fig.6

Example: Given A feature map, and Kernel

| | |
|------------|------------|
| α_1 | α_2 |
| α_3 | α_4 |

... Fig.2

, use transposed

Convolution to perform an UpSampling.

| | |
|-----|---|
| 1.5 | 3 |
| 5 | 9 |

... Fig.3

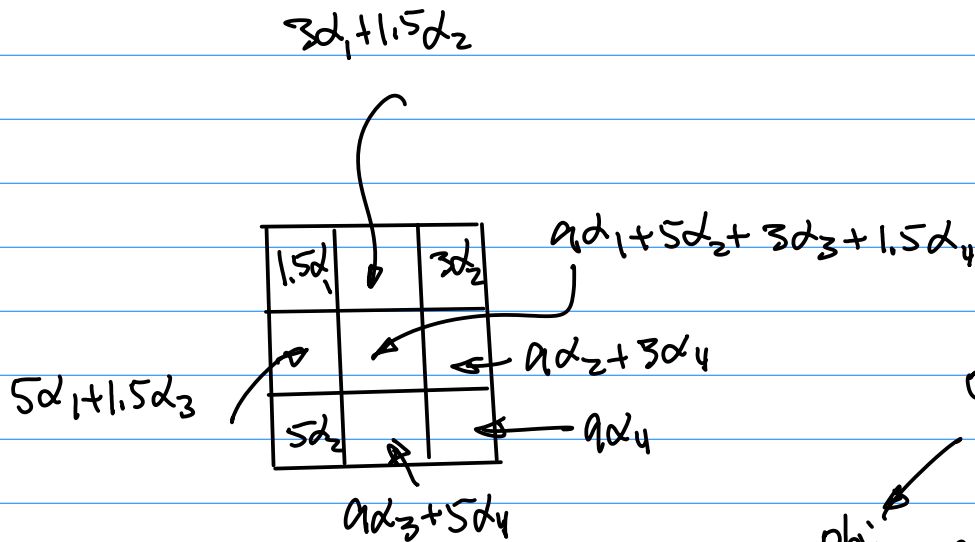
4th Step, α_4

| | | |
|--|---------------|-------------|
| | | |
| | | |
| | $1.5\alpha_4$ | $3\alpha_4$ |
| | $5\alpha_4$ | $9\alpha_4$ |

5th. Step

Integrate the Above Result together:

Step1. Take 1st coefficient α_1 from the Kernel, then perform



Objects Appears inside the Bounding Box.

Note 1. Notation for the unit function: $\mathbb{I}_{ij} = \begin{cases} 1 & \text{if Obj Detected Inside the SB} \\ 0 & \text{o/w} \end{cases}$

Location of the ROI

Locations

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

Note 2: Loss function in this case:

$$f_{\Sigma} = f_1 + f_2 + \dots + f_5$$

Note 3. $\lambda_i, i=1, 2, \dots, 5$

$$\sum_i \lambda_i = 1$$

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

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

Or to generalize it,
 $f_{\Sigma} = \sum_i f_i$

$$+ \sum_{i=0}^{S^2} \mathbb{I}_i^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \quad (3)$$

Class Classification.

Note 4. physical meaning of Each loss function.

Geometric Shapes

