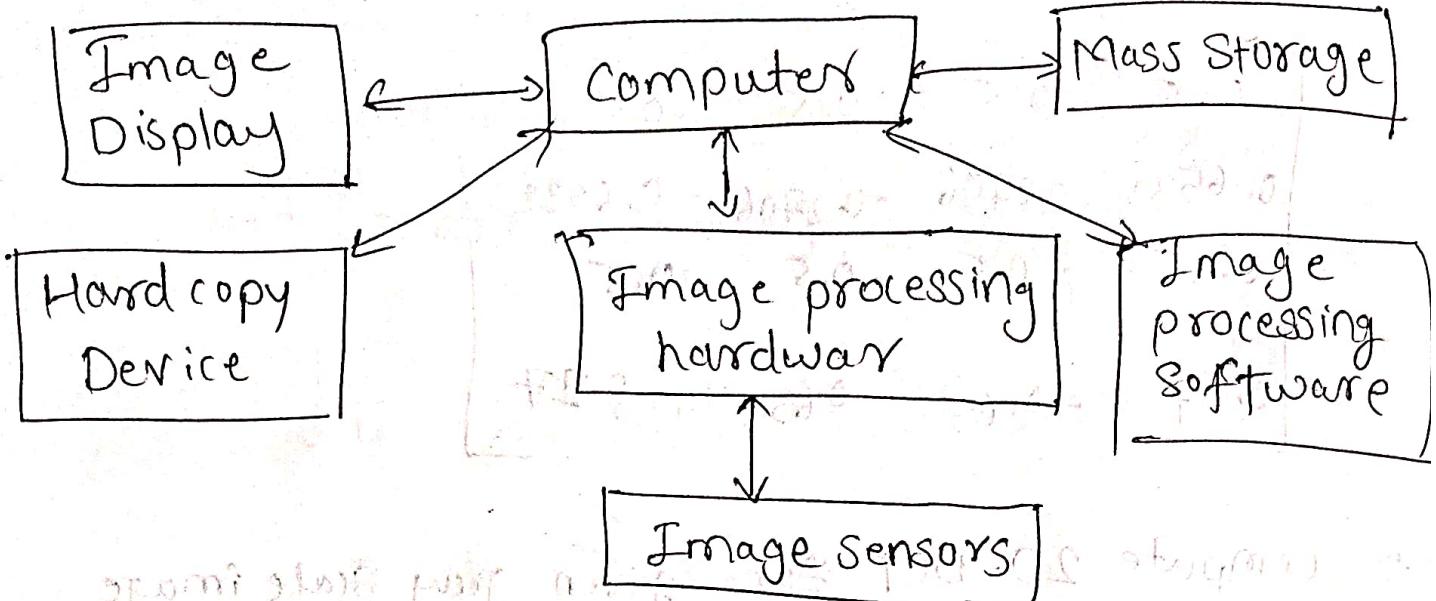


Components of DIP System



* Hadamard Transform

order $N=2$

$$H_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

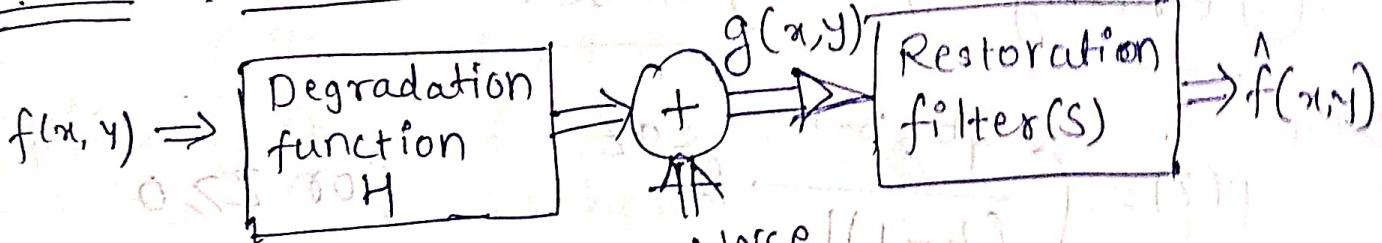
~~H_{2N}~~

$$H_{2N} = \begin{bmatrix} H_N & H_N \\ H_N & -H_N \end{bmatrix}$$

$N=2$

$$H_4 = \begin{bmatrix} H_2 & H_2 \\ +H_2 & -H_2 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix}$$

Image Restoration



Degradation

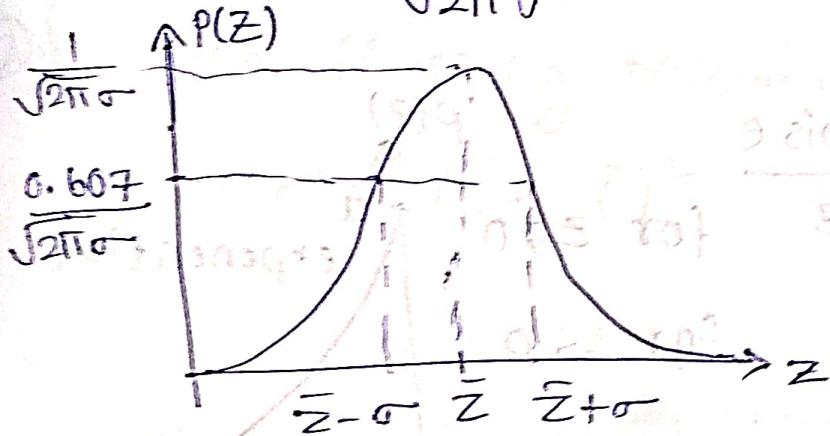
$$\{ g(x,y) = h(x,y) * f(x,y) + \eta(x,y) \}$$

$$G(u,v) = H(u,v) F(u,v) + N(u,v)$$

fourier Transform

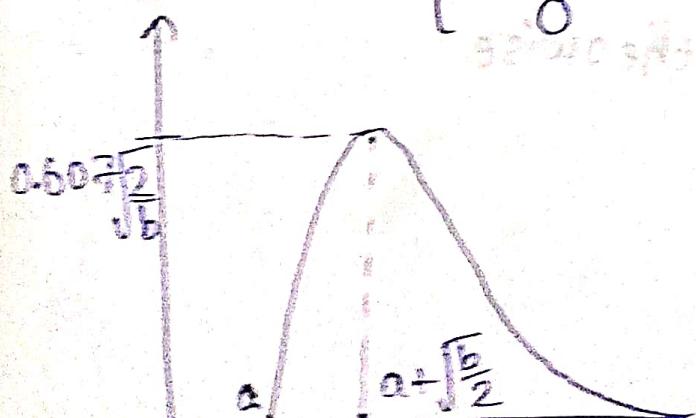
① Gaussian Noise

$$p(z) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(z-\bar{z})^2/2\sigma^2}$$



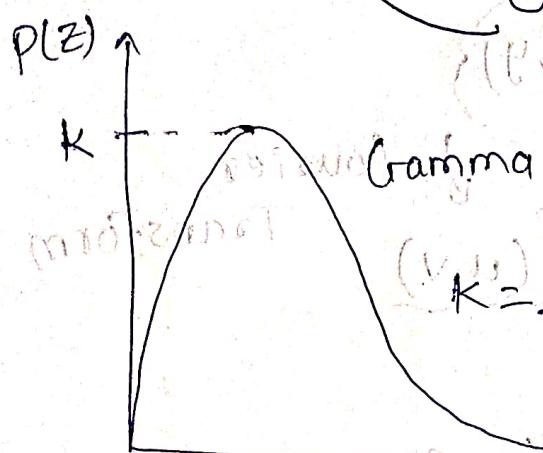
② Rayleigh noise

$$p(z) = \begin{cases} \frac{2}{b} (z-a) e^{-(z-a)^2/b} & \text{for } z \geq a \\ 0 & \text{for } z < a \end{cases}$$



③ Erlang (gamma) noise:

$$p(z) = \begin{cases} \frac{a^b z^{b-1}}{(b-1)!} e^{-az} & \text{for } z \geq 0 \\ 0 & \text{for } z < 0 \end{cases}$$

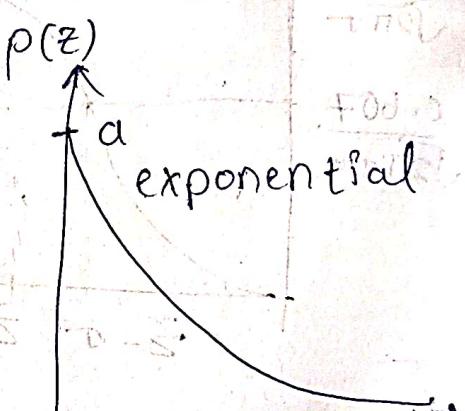


Gamma

$$K = \frac{a(b-1)^{b-1}}{(b-1)!}$$

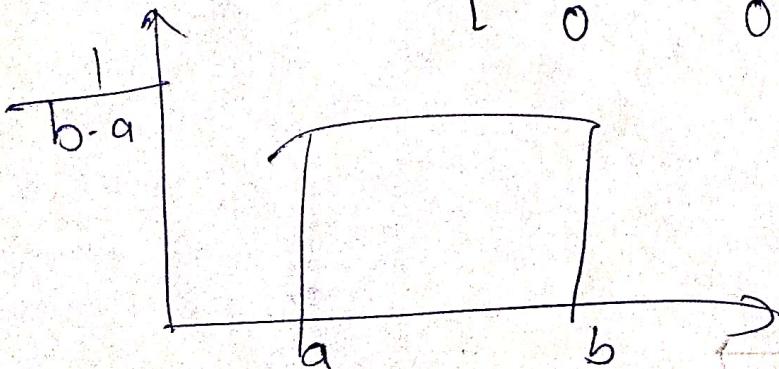
④ Exponential noise

$$p(z) = \begin{cases} ae^{-az} & \text{for } z \geq 0 \\ 0 & \text{for } z < 0 \end{cases}$$

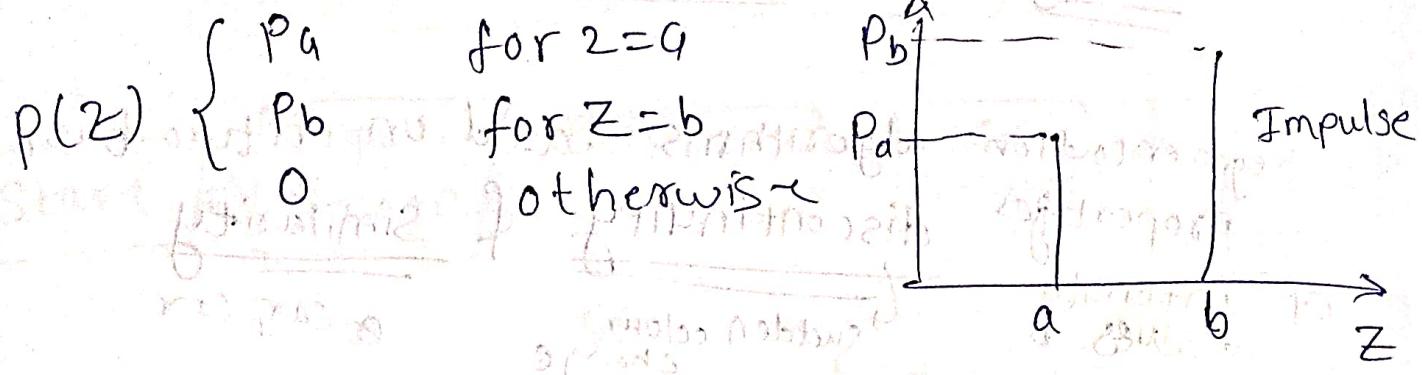


⑤ Uniform Noise

$$p(z) = \begin{cases} \frac{1}{b-a} & \text{if } a \leq z \leq b \\ 0 & \text{otherwise} \end{cases}$$



⑥ Impulse (Salt & pepper) noise



* To Remove Noise

① Inverse filtering

$$\hat{f}(u,v) = \frac{f(u,v)}{H(u,v)}$$

$$f(u,v) = \hat{f}(u,v) + \frac{N(u,v)}{H(u,v)}$$

② (Wiener) filtering Minimum Mean Square error

$$e^2 = E(f - \hat{f})^2$$

Image Segmentation

Sobel operator

Segmentation algorithms based on two basic properties of intensity values

- discontinuity & similarity
- sudden colour change
- a car, car

Detection of Discontinuities

Point detection

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

mask K

$$R_{K^P} = \sum_{i=1}^9 w_i z_i$$

Response of the mask.

Edge Detection

Edge models:

- ① Step edge
- ② ramp edge
- ③ roof edge



Stages in Edge Detection



Gradient operators.

* Laplacian of Gaussian (LoG) Operator.

$$h(r) = e^{-\frac{r^2}{2\sigma^2}}$$

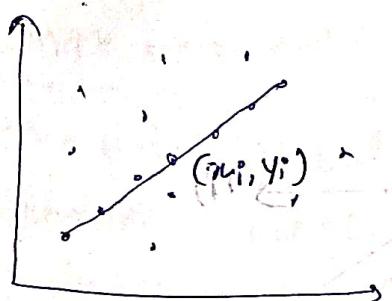
$$\nabla h(r)$$

0	0	-1	0	0
0	-1	-2	-1	0
-1	-2	16	-2	-1
0	-1	-2	-1	0
0	0	-1	0	0

* Edge linking

(Boundary Detection)

* Hough Transform. → solution to detect simple shapes as circles, lines, etc.



$$y_i = mx_i + c$$

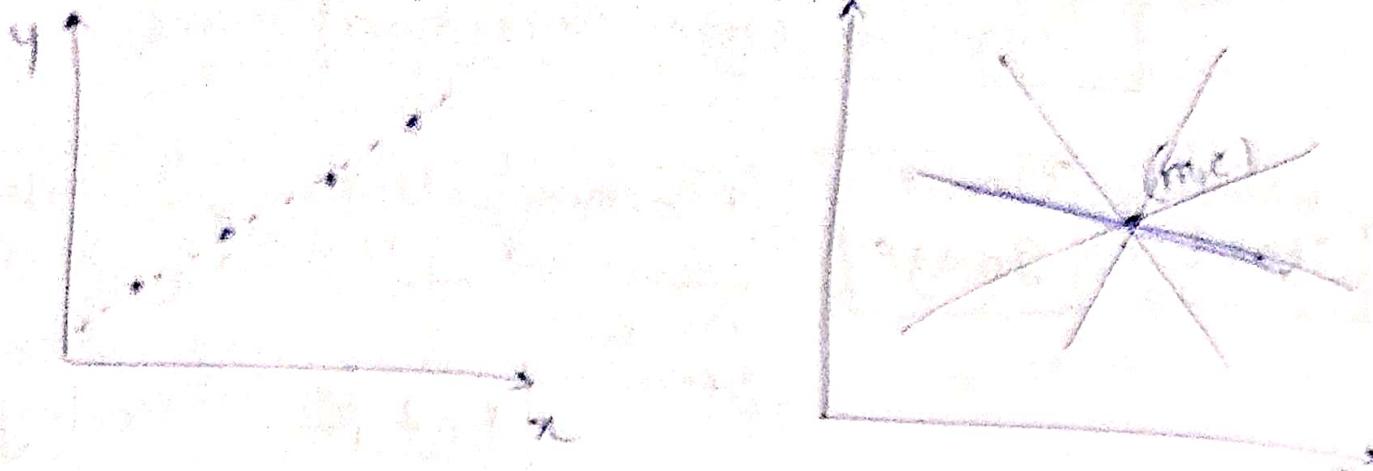
$$\Rightarrow c = -mx_i + y_i$$

Given: Edge point (x_i, y_i)

Task: Detect line

$$y = mx + c$$

Image Space



Eg 1: Given five points use Hough transform to draw a line joining these points.

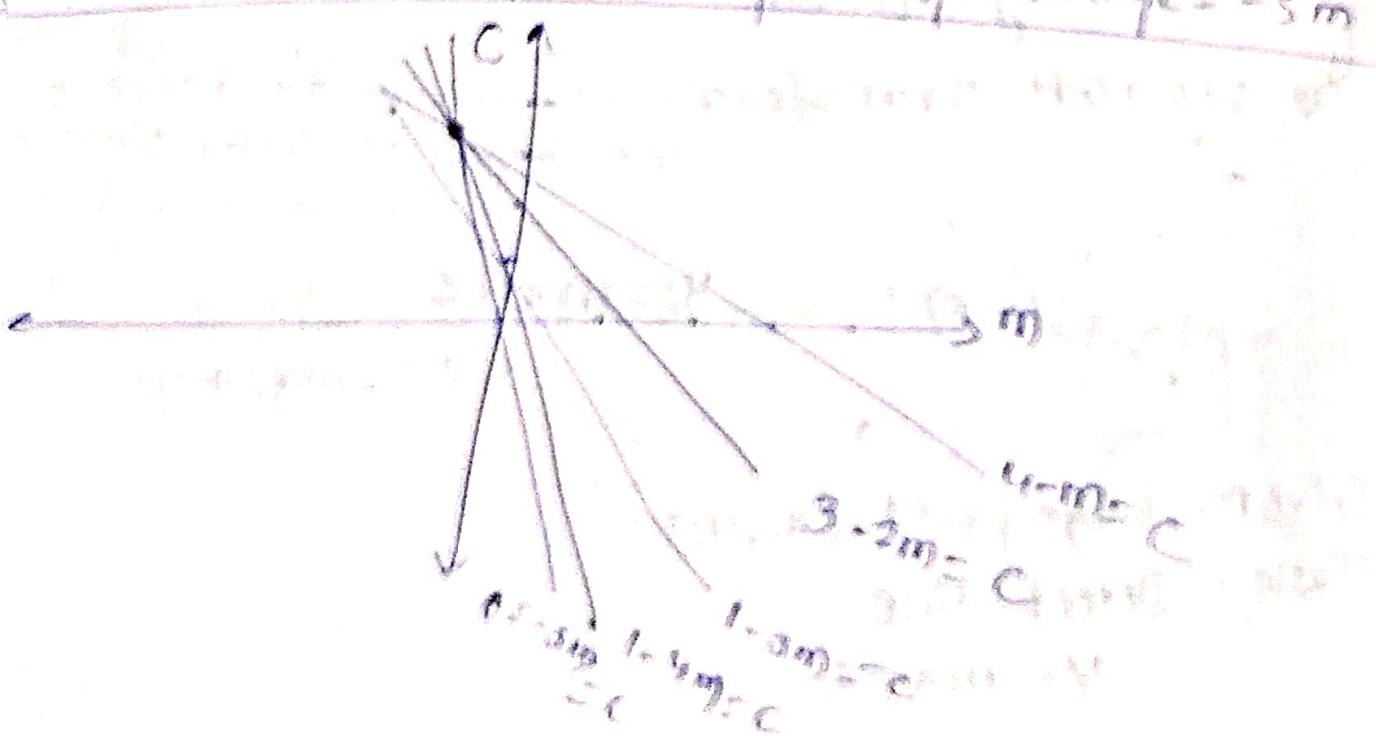
(1,4) (2,3) (3,1) (4,1) (5,0)

x	1	2	3	4	5
y	4	3	1	1	0

Equation of straight line $\rightarrow y = mx + c$

$$\therefore c = y - mx$$

x	1	2	3	4	5
y	4	3	1	1	0
Eq of lines	$c = 4 - m$	$c = 3 - 2m$	$c = 1 - 3m$	$c = 1 - 4m$	$c = 2 - 5m$



HW Circle detection

Thresholding

(1) Global Thresholding

(2) Local Thresholding

(3) Dynamic (or Adaptive) Thresholding \rightarrow Variable Thresholding

Thresholding is a function of:

> Spatial Co-ordinates

> Grey level of the pixel

> Some local property of the image i.e $A(x,y)$

$$Th = T[x, y, f(x, y), A(x, y)]$$

or Histogram & Thresholding

Types of Histograms

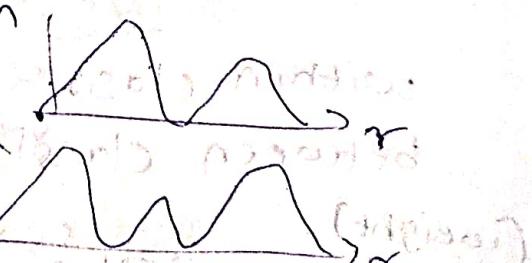
Unimodal

Bimodal

Multimodal

Single Level Thresholding

Multi-level Thresholding



* Which threshold to select?

The basic global threshold (T) is calculated as:

(1) Random select. T .

2) Two segment. G_1, G_2

3) Determine mean (m_1) in (G_1) lie below T in histogram

4) Determine mean (m_2) of the pixels (G_2) lie below T

5) New threshold is: $T_{\text{new}} = (m_1 + m_2)/2$

6) Select min T

* Multiple thresholding

output image = $\begin{cases} g_1 & \text{if } 0 \leq f_i < t_1 \\ g_2 & \text{if } t_1 \leq f_i < t_2 \\ \dots & \dots \\ g_n & \text{if } f_i \geq t_n \end{cases}$

$t_1, t_2, \dots, t_n \rightarrow$ thresholds

$t_1, t_2, \dots, t_n \rightarrow$ thresholds

* Adaptive Thresholding

Techniques to apply thresholding to local pixels

Thresholding algorithms

* Optimal Otsu Thresholding Algorithm:

use a merit function either maximization or minimization to

determine the optimal threshold.

Class 1 \leftrightarrow Class 2

weight $w_1(t)$

Variance $\sigma_1^2(t)$

weight $w_2(t)$

Variance $\sigma_2^2(t)$

Therefore eqn can be written as

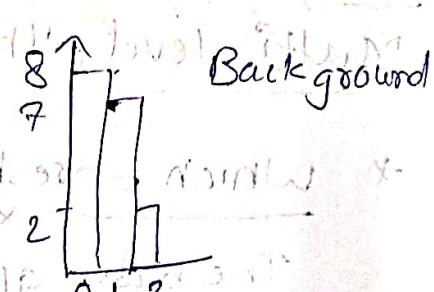
$$\sigma_b^2(t) = \sigma_w^2(t)$$

within class minimization

between class maximization

(weight)

$$w_b = \frac{8+7+2}{36} = 0.4722$$



$$\text{Mean } (\mu_b) = \frac{(0 \times 8) + (1 \times 7) + (2 \times 2)}{17} = 0.6471$$

Variance

$$\sigma_b^2 = (0 - 0.6471)^2 \times 8 + (1 - 0.6471)^2 \times 7 + (2 - 0.6471)^2 \times 2$$

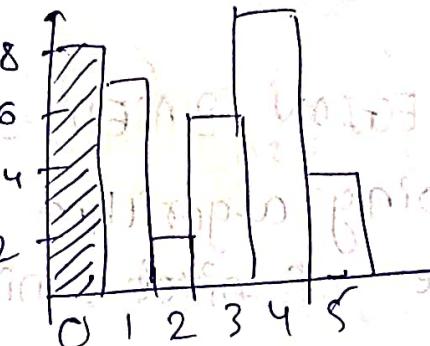
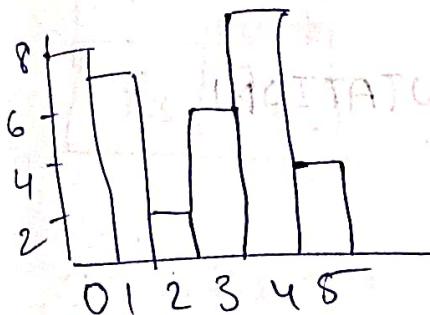
To find σ_b^2 for background

Within class variance

$$\sigma_w^2 = w_b \sigma_b^2 + w_f \sigma_f^2$$

Verify

from bladex T=1



$$w_b = \frac{20}{36} = 0.556$$

$$w_b = \frac{8}{36} = 0.222$$

$$\text{mean} \rightarrow M_b = 0$$

$$M_b = \frac{0 \times 8}{8} = 0$$

$$\sigma_b^2 = 0$$

$$\sigma_b^2 = \frac{(0-0)^2}{18} = 0$$

$$w_f = 1$$

$$w_f = \frac{7+2+6+9+4}{36} = 0.278$$

$$M_f = 0 \times 8 + 1 \times 7 + 2 \times 2 + 3 \times 6 + 4 \times 9 + 5 \times 4$$

$$w_f = 0.778$$

$$M_f = \frac{11+18+45+20}{36}$$

$$M_f = 3.036$$

$$M_f = 82.36$$

$$\sigma_f^2 = (1-3.036)^2$$

$$\sigma_f^2 = (0-2.36)^2 \times 8 + (1-2.36)^2 \times 2 + \dots + (5-2.36)^2 \times 4$$

$$\sigma_f^2 = 3.1196$$

$$\sigma_{\text{tot}}^2 = w_b \sigma_b^2 + w_f \sigma_f^2 = 3.1196$$

$$\sigma_f^2 = 1.9639$$

$$\sigma_{\text{tot}}^2 = 1.5268$$

Between class Variance.

$$= W_b W_f (\mu_b - \mu_f)^2$$

without using built in function Sun, Night

Write program for Otsu threshold method for any image

REGION BASED SEGMENTATION.

* Region-Growing algorithm

(i) principle of pixel similarity.

(ii) region is coherent \rightarrow pixels of group homogeneous.

3-steps:

i) Select the initial seed

ii) How seed growing

iii) Termination of segmentation process.

$$S_1 = g$$

$$S_2 = T$$

, $T = 4 \rightarrow$ Threshold

$$\times S_1 = g$$

$$|f(x, y) - f(x', y')| \leq 4$$

$$f(x, y) = \begin{cases} 5, 6, 7, 8, 9, 10, 11, 12, 13 \end{cases} \rightarrow A$$

$$* S_2 = T \quad |f(x, y) - f(x', y')| \leq 4$$

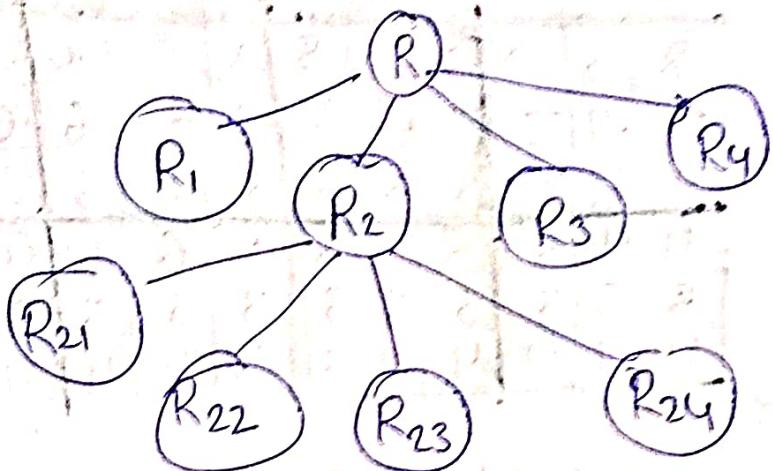
$$f(x, y) = \{0, 1, 2, 3, 4, 5\} \rightarrow B$$

1	0	7	8	?
0	1	8	9	8
0	0	7	9	8
0	1	8	8	9
1	2	8	8	9

Split & Merge Algorithm

phase-I \rightarrow Splitting, phase-II \rightarrow merging
alternative method of image segmentation

R_1	R_{21}	R_{22}
	R_{23}	R_{24}
R_3	R_4	



If adjacent regions are similar merge

Note: Inconsistent sizes will lead to inaccurate segmentation.

Ex

6	5	6	6	7	7	6	6
6	7	6	7	5	5	4	7
6	6	4	4	3	2	5	6
5	4	5	4	2	3	4	6
0	3	2	3	3	2	4	7
0	0	0	0	2	2	5	6
1	1	0	1	0	3	4	4
1	0	1	0	2	3	5	4

$$\text{Threshold} = 3$$

$$\text{Max} - \text{Min} = 7 - 0 = 7$$

~~skip split.~~

Split

8	8	8	8	1	1	1	1	1	1	1	1	1	1
8	8	8	8	8	8	1	1	1	1	1	1	1	1
6	5	5	5	8	8	7	0	0	0	0	0	0	0
5	9	9	9	8	8	7	6	6	6	6	0	0	0
6	6	9	9	8	8	7	6	6	6	6	0	0	0
6	6	9	9	8	8	7	6	6	6	6	0	0	0
8	8	8	8	8	8	7	6	6	6	6	0	0	0
7	7	7	7	8	8	7	6	6	6	6	0	0	0
4	4	5	5	5	5	5	6	6	6	6	0	0	0
4	4	5	5	5	5	5	6	6	6	6	0	0	0
3	3	3	3	3	3	3	3	3	3	3	2	2	2
4	4	4	4	4	4	4	4	4	4	4	2	2	2

Let Threshold = 3

$$\text{Max} - \text{Min} = 9 - 0 = 9 \Rightarrow 9 > 3 \therefore \text{Split}$$

import cv2

import numpy as np

import requests

def is_homogeneous(region, threshold):

min_val, max_val = np.min(region), np.max(region)

return (max_val - min_val) <= threshold.

def split_and_merge(image, threshold):

def recursive_split(region):

rows, cols = region.shape

if row <= 1 or cols <= 1:

return np.zeros_like(region, dtype=np.uint8)

if is_homogeneous(region, threshold):

return np.ones_like(region, dtype=np.uint8)

mid_row, mid_col = rows//2, cols//2

top_left = region[:mid_row, :mid_col]

top_right = region[:mid_row, mid_col:]

bottom_left = region[mid_row:, :mid_col]

bottom_right = region[mid_row:, :, mid_col:]

See ~~split~~ ~~Recursive~~ ~~Implementation~~ of

Segmented_quadrants = np.zeros_like(region.dtype
= np.uint8)

Segmented_quadrants[:mid_row, :mid_col] = recursive_

Segmented_quadrants[:mid_row, mid_col:] = recursive_split
Split(top_left)

" " " [mid_row:, :mid_col] = recursive_split
(top_right)

" " " [mid_row:, mid_col:] = recursive_split
(bottom_left)

def merge_regions(segmented):
 " " " merge best first (bottom_right)

return segmented

if len(image.shape) == 3:

image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

Segmented_image = recursive_split(image)

Segmented_image = merge_regions(segmented, image)

return Segmented_image

def main():

image = cv2.imread('E:\NITW\image1.jpg')

threshold = 20

result = split_and_merge(image, threshold)

(cv2.imshow('Segmented Image', result * 255))

cv2.waitKey(0)

cv2.destroyAllWindows()

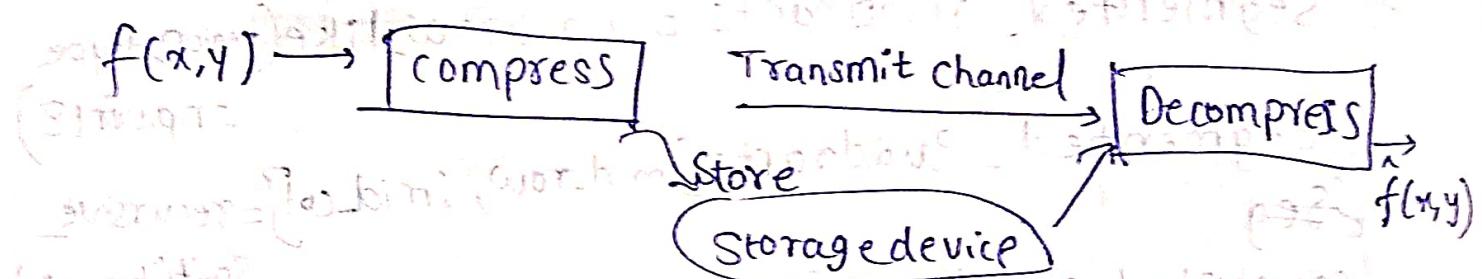
--name-- = "main";

main()

File b6f91c90e2300f33 = file got

File b6f91c90e2300f33 = file got

Compression The goal of image compression is to reduce the amount of data required to represent a digital image



□ Lossless

□ Lossy

⇒ Interlaced Scanning ⇒ Splits frames into odd & even fields

⇒ Progressive Scanning ⇒ Scans the entire picture line by line in sequential order

Standard Definition

High Definition

⇒ DATA ≠ Information

Compression Ratio: $C_R = \frac{n_1}{n_2}$

n_1 bits $\xrightarrow{\text{compression}}$

n_2

For ex

$$C_R = \frac{10}{1} = 10:1$$

Data

00000000
00000001
00000010
00000011

info

0
1
2
3

Data

00
01
10
11

Double data port SVJ

Relevant Data Redundancy

$$R_D = \frac{R}{C_R}$$

$$1 - \frac{1}{C_R}$$

00000000
00000001
00000010
00000011

If $C_R = 10$, then $R_D = 1 - \frac{1}{10} = 0.9$ Redundant.

Type of DATA Redundancy

1. Coding redundancy (Symbol coder)

2. Spatial & Temporal redundancy (Mapper)

3. Irrelevant Information (Quantizer)

1. Coding Redundancy.

$$L_{avg} = \sum_{k=0}^{L-1} I(r_k) P_r(r_k)$$

I/P intensity values r_k

(Huffman coding, Golomb coding, etc.)

2. Spatial & Temporal Redundancy:

$$100 \times 8 + 100 \times 8 = 1600 \text{ bits for}$$

$$(5,100)_{10}, (255,100)_{10} \text{ lines}$$

$$8 \times 8, 16, 32, 64, 128, 256, 512 = 32 \text{ bits}$$

Spatial required now.
Temporal redundancy
Similarity b/w neighbouring frames in a video.

3. Irrelevant Information:

129 130 131 132

representing using 130

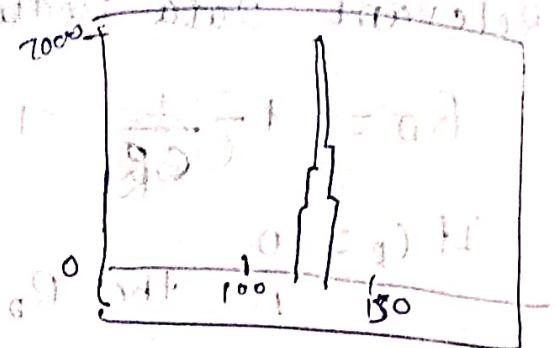
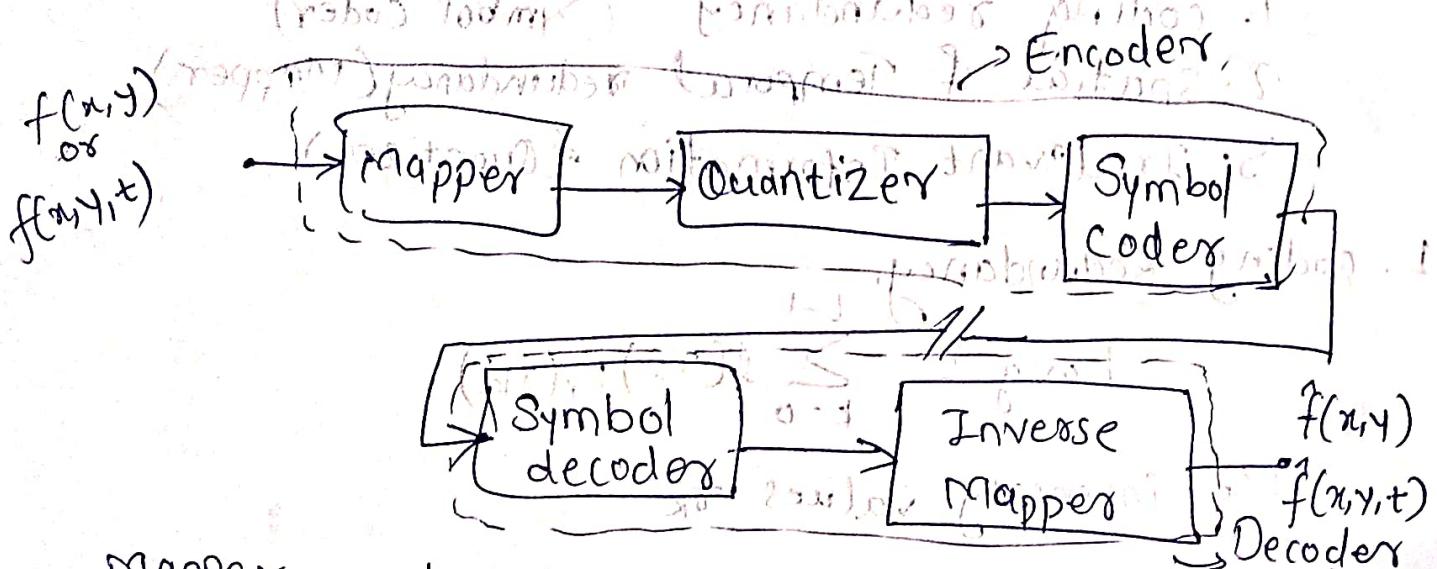


Fig. Histogram

Image Compression Model $f(x,y,t) \rightarrow \text{Encoder} \rightarrow \text{Symbol Coder}$



Mapper reduce Spatial & Temporal redundancy.

\Rightarrow A "codec" is a device or program that is capable of both encoding & decoding.

Taxonomy of lossless methods

Lossless Coding Techniques

Repetitive Sequence Encoding

Statistical Encoding

* Huffman Coding

~~for 5x5 grids with~~ Some pixel-values

- 1) Sort probabilities per symbol
- 2) Combine the lowest two probabilities
- 3) Repeat Step 2 until only two probabilities remain.

Problem:

10x10 (3 bit image)

Frequencies:

$$a_2 = 40 \quad a_6 = 30 \quad a_4 = 10 \quad a_5 = 10 \quad a_3 = 6 \quad a_1 = 4$$

$$P(a_2) = \frac{40}{100} = 0.4$$

Symbol

like intensity levels	Probabilities (Sorted)	Source reduction				
a_2	0.4	1	0.4	0.4	0.4	0.6
a_6	0.3	0.0	0.3	0.3	0.3	0.4
a_4	0.1	0.1	0.1	0.2	0.3	0.3
a_5	0.1	0.0	0.1	0.1	0.1	0.1
a_3	0.06	0.0	0.1	0.1	0.1	0.1
a_1	0.04	0.0	0.0	0.0	0.0	0.0

$$\text{Entropy } H(x) = -\sum_x P(x) \cdot \log_2 P(x) = \sum_x P(x) \cdot \log_2 \frac{1}{P(x)}$$

$$\text{Yours saved} = \frac{10 \times 10 \times 5 - 10 \times 10 \times 2 \cdot 2}{10 \times 10 \times 5} = 0.56$$

7	7	3	1	1
6	2	3	1	1
4	3	0	0	7
3	4	3	3	4
5	5	6	2	2

6 nibs remain

Entropy taking into account symbols

Symbolic Coding Entropy (C)

Actual Coding Entropy (S)

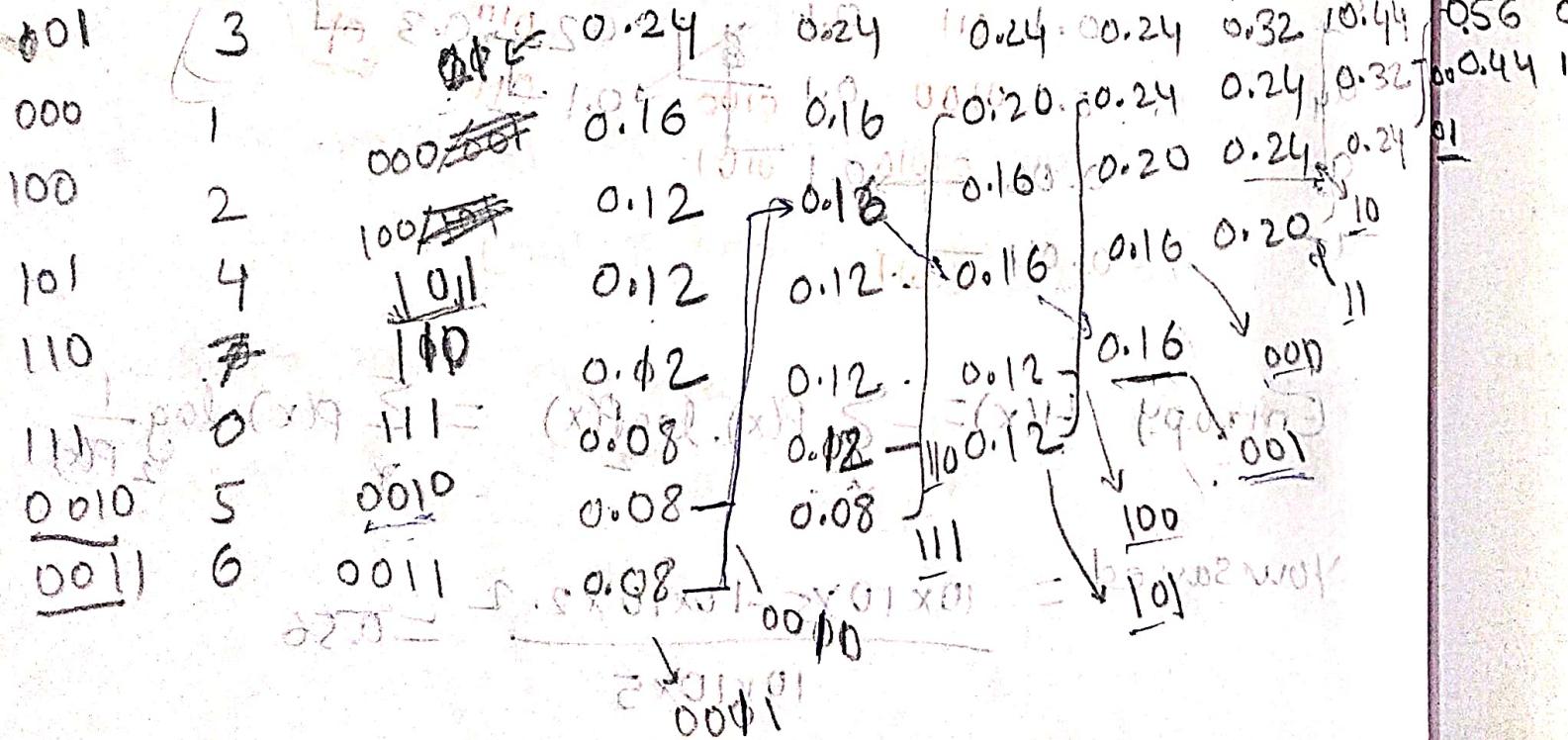
Lossless Coding Efficiency (%)

(Frequency/25)

Symbol	Frequency	Probability
0	2	0.08
1	4	0.16
2	3	0.12
3	6	0.24
4	3	0.12
5	2	0.08
6	2	0.08
7	3	0.12

Symbol 2 (sorted) Probabilities

(like intensity levels) (sorted) Source reduction

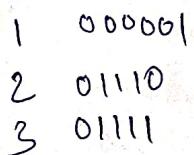


{ Symbol like intensity levels }

~~class NodeTree(object):~~

~~def __init__(self, left=None, right=None):~~
~~self.left = left~~
~~self.right = right~~
def children(self):
 return (self.left, self.right)

A 10
C
B
D
G
Z
E
F



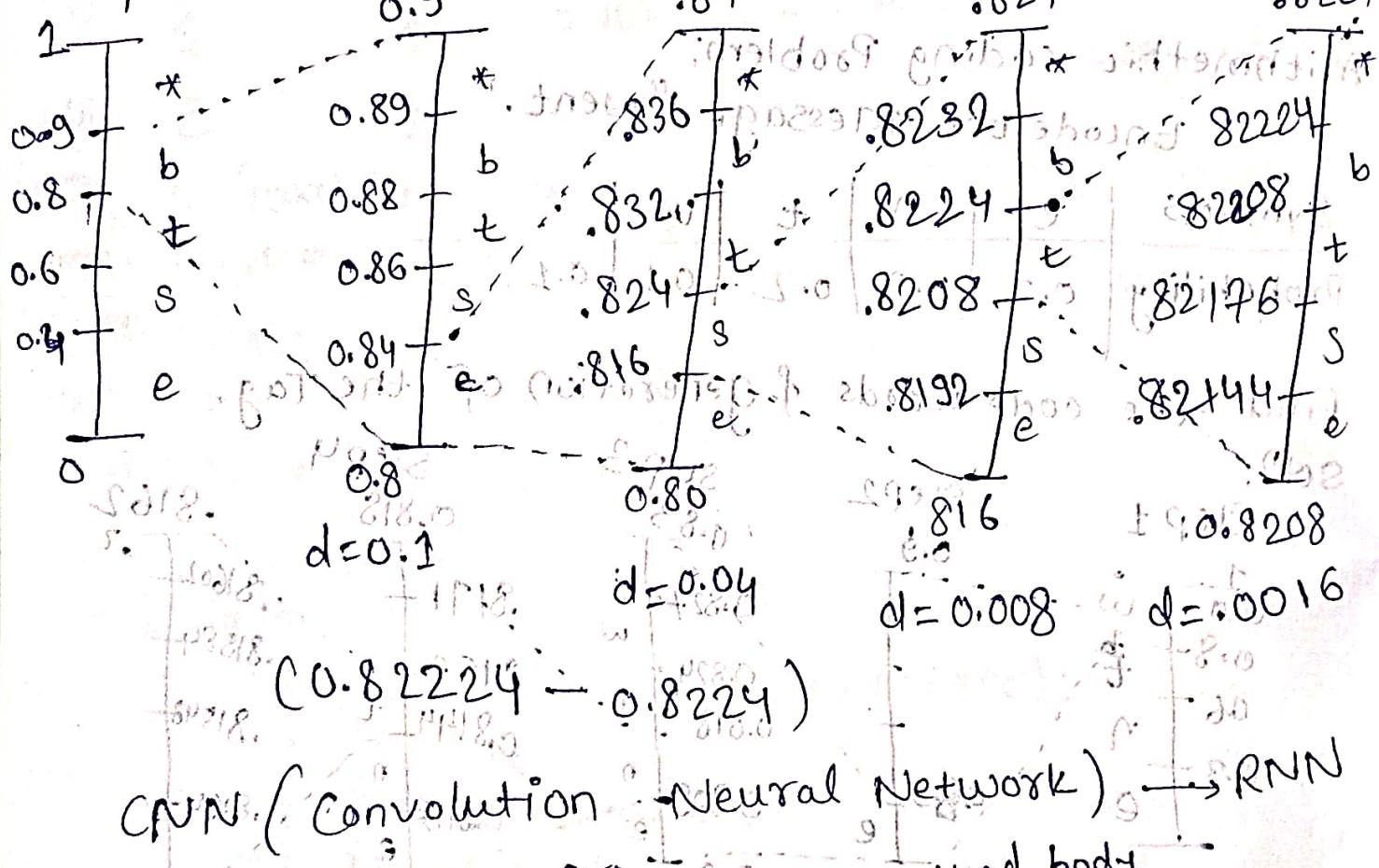
0.3	0.433	0.566	0
0.266	0.309	0.433	1
0.233	0.266	0.1	
0.2	10		
0.000	11		
001	Main Idea \rightarrow Sequence mapped to	$\frac{1}{0.6457}$	19372
0001	Arithmetic coding Problem:		
00001	Encode the message "went."		
Symbols	e, t, w, n	w	0.830
Probability	0.3, 0.3, 0.2, 0.1, 0.1		0.0
Find the code words & generation of the Tag.			
Step 1	Step 2	Step 3	Step 4
0.9	0.83	0.818	0.8162
0.8	0.827	0.811	0.81602
0.6	0.824	0.8162	0.81584
0.3	0.818	0.8144	0.81548
	0.809	0.8117	0.8194
	0.80	0.8094	0.8144
			0.0018
Range of symbol	0.83 - 0.80 = 0.03	0.818 - 0.8094 = 0.0086	0.8162 - 0.8144 = 0.0018
Lower limit \Rightarrow Lower limit + d (probability of symbol)	0.83 + 0.03 = 0.86	0.818 + 0.0086 = 0.8266	0.8162 + 0.0018 = 0.8180
Range of e = 0.83 - 0.80 = 0.03 = 0.83 [0.8 + 0.1(0.3)]			
Range of n = 0.83 - 0.86			
Range of t = 0.86 - 0.88			
Range of w = 0.88 - 0.89			
Range of e = 0.89 - 0.90			

$0.81602 < \text{codeword} < 0.8162$

Generation of Tag : Tag = UL of code word + LL of code word

Find codeword for best*

Step 1



CPNN (Convolutional Neural Network) → RNN

Eyes, nose,

head, body

~~Exercise~~: Implement a convolution

→ convolutional
+ ReLU

→ ~~softmax~~ ReLU

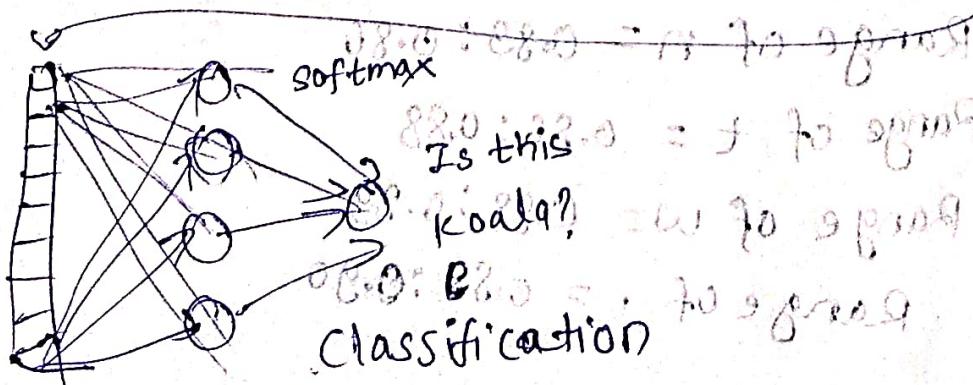
→ Pooling

Wadenswil (Zürcher Oberland) 15. Sept. 1920. R. H. Kühn

16-18 one

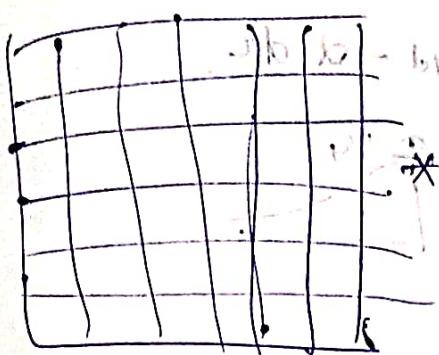
$\left(\begin{matrix} 2 \\ 3 \end{matrix} \right)$ \leftarrow One Layer ~~0.0001~~ } = 3 to 3000

J flatten



convolution

Input



filters

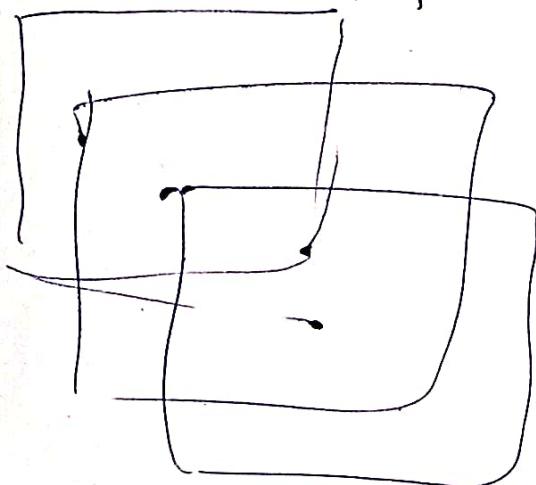
parameters:

$$\begin{aligned} & \text{input size: } 4 \times 6, \text{ filter size: } 3 \times 3, \text{ stride: } 1, \text{ padding: } 0 \\ & \text{output size: } \frac{(4+0)-(3-1)+0}{1} + 1 = 3 \times 2 \end{aligned}$$

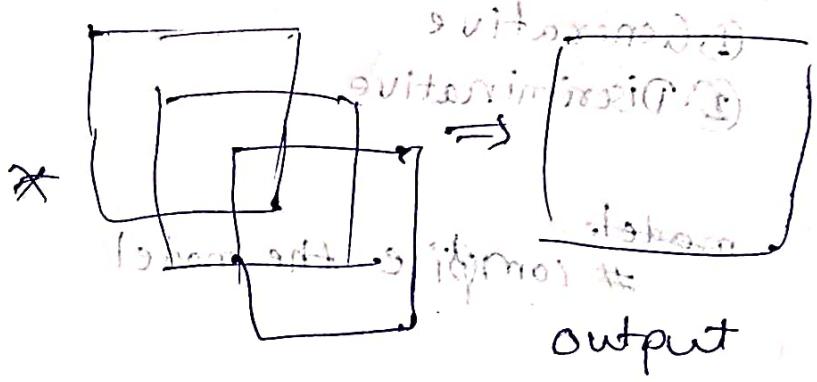
$$O = \left\lceil \frac{n-f+2p}{s} + 1 \right\rceil \quad L \quad \left\lfloor \cdot \right\rfloor : \text{floor}(\cdot) \quad \left\lceil \cdot \right\rceil : \text{ceil}(\cdot)$$

* convolution Operation on Volume.

Input



filters



Multiple filters

* ONE CONVOLUTION LAYER

ReLU($\text{output} + b$)

$$\text{ReLU} \Rightarrow \max(0, x)$$

Sample Complete Network

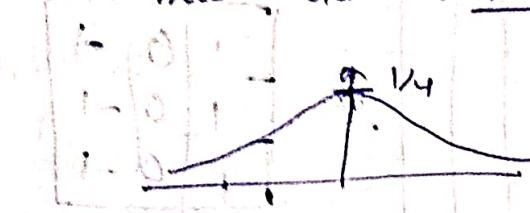
* Vanishing gradient

$$1 \text{ layer} \rightarrow \frac{1}{4}$$

$$4 \text{ layers} \rightarrow \left(\frac{1}{4}\right)^4$$

$$10 \text{ layers} \rightarrow \left(\frac{1}{4}\right)^{10}$$

$$W_{\text{new}} = W_{\text{old}} - \alpha \frac{dL}{dW}$$



3. ReLU (Rectilinear Unit) (rectified linear)

$$g(x) = \text{ReLU}(x) = \max(0, x)$$

4. P Leaky ReLU

Pooling Layer

► It has hyper-parameters : mask size(f), stride(s)

Max pooling. simply do max over all non-zero elements + ignore 0

GAN

Discrim.

① Generative

② Discriminative

model

compile the model

fit

$$(x, y) \text{ item} \leftarrow \text{user}$$

softmax

REYES MOTTUOHOZ - 3/10

(d + t) / 2