Lecture Notes
PART II

CmpE258
Spring 2023



March 21 (Tue).

Midterm is scheduled on the 23rd (Thu). 1 hr Exame.
16:30-17:30
Then 15 minutes for prep & Uploading the file.

Example: Softmax Activation Function. MNIST CNN

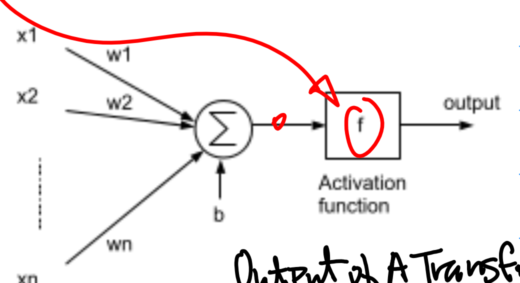
Note:

$$\sigma(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad \text{for } i = 1, \dots, K \text{ and } \mathbf{z} = (z_1, \dots, z_K) \in \mathbb{R}^K. \quad \dots(1)$$

Dimension

Let K=1

1° $f(z)$ Notation




Output of A Transfer function

2° Index

$$f(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad \dots(2)$$

Total No. of Output Neurons = K
for Hand Written Digits Recognition
K=10;

where

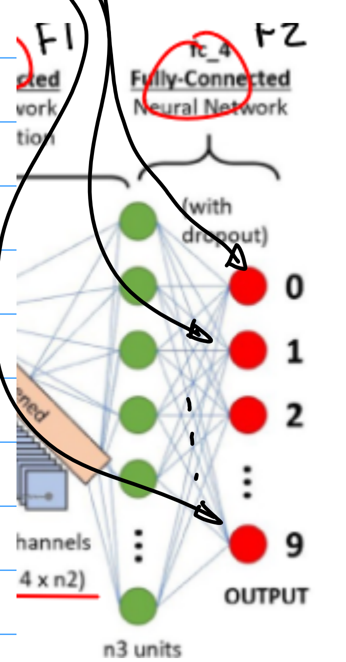
$$\sum_{j=1}^{K} e^{z_j} = e^{z_1} + e^{z_2} + \dots + e^{z_K} \geq e^{z_i} \quad \dots(3)$$

Output from Each Neuron:

$$f(z_1) = \frac{e^{z_1}}{\sum_{j=1}^{10} e^{z_j}} \quad \dots(4)$$

for Digit "0" (1st Output)

And




$$f(z_2) = \frac{e^{z_2}}{\sum_{j=1}^{10} e^{z_j}}$$

for Digit "1" (2nd output) ...(5)

⋮

$$f(z_{10}) = \frac{e^{z_{10}}}{\sum_{j=1}^{10} e^{z_j}}$$

for Digit "9" (10th o/p)

if Add Eqn (1) + Eqn (2) + ...

$$f(z_1) + f(z_2) + \dots + f(z_{10})$$

$$= \frac{e^{z_1}}{\sum_{j=1}^{10} e^{z_j}} + \frac{e^{z_2}}{\sum_{j=1}^{10} e^{z_j}} + \dots + \frac{e^{z_{10}}}{\sum_{j=1}^{10} e^{z_j}}$$

Property 1.

$$= \frac{\sum_{j=1}^{10} e^{z_j}}{\sum_{j=1}^{10} e^{z_j}} = 1. \quad \dots(6)$$

CmpE258

Spring 2023



The softmax function takes as input a vector $z$ of $K$ real numbers, and normalizes it into a probability distribution consisting of $K$ probabilities proportional to the exponentials of

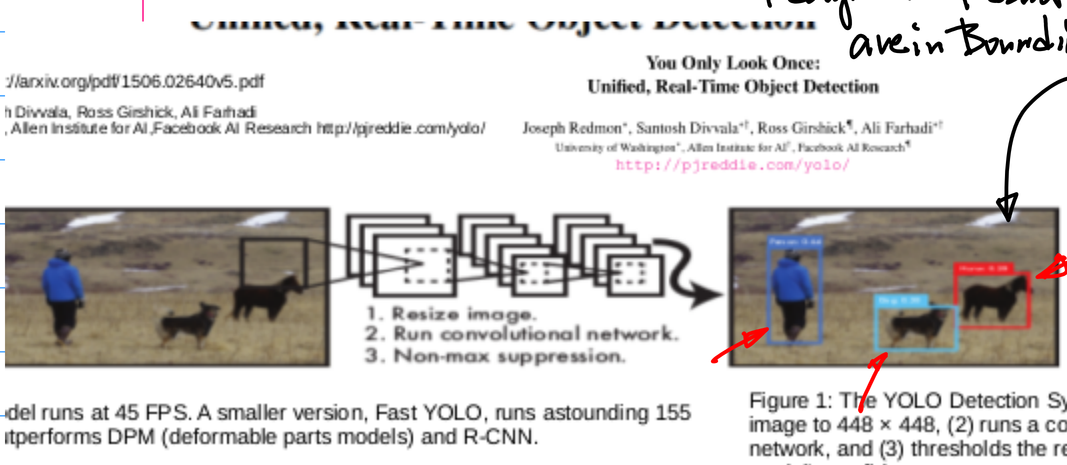
$$f(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

See Eqn (6).

Now, move to the 2nd Half of DCNN.

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

Typical Classification/ Recognition Results are in Bounding Boxes




Then, we would like to Achieve Semantic Segmentation.

Pixel by pixel Based Segmentation/ Detection/ Recognition


PART II (After the midterm)

April 4 (Tue)

Road map: Yolo (You-Only-Look-ONCE) → Semantic Segmentation.

{ Project Assignment = Yolo Implementation Due $2\frac{1}{2}$ weeks. April 20th. (Thursday)

CmpE258

Spring 2023

Homework (In-Class Presentation)

Requirements Due April 6 (Thu).

1° One Paragraph Description (Abstract) of the proposed Semester-Long Project.

2° Title

Team members: First Name, Last Name, Major

Team Coordinator.

Contact E-mail.

3° Abstract Part.

Objective(s): a) What is the proposed work;

b) What is the Coding / Training / Testing Task involved in the project?

c) Anticipated Result? And deliverable?

d) Tools, platform, Programming Language Version, T.F., Pytorch, ChatGPT etc. Also, Define Python Packages, OpenCV.

Example: On Yolo.

Ref:

2022F-106-README-Tiny-Yolo4-GP...

Note 1: Readme for Yolo github 34 Installation & Testing for the project.

Title: README Tiny Yolo v4 GPU Ubuntu

Document Number: 105-1b

CTI One Corporation

Table 1a. Document History

| | | |
|---|---|---|
| 2022-10-6 | Establish this document, document archive: (base) harry@workstation:~/yolo-2022-10-19$ | YY |
| | | |

1. Setup YOLO v4 environment

1.1. Clone the GitHub folder;

$ git clone https://github.com/pythonlessons/TensorFlow-2.x-YOLOv3.git

1.2. Create YAML file for building the YOLO v4 Anaconda environment;

Create TensorFlow-2.x-YOLOv3/conda-gpu.yml as the following;

================================================

name: yolov4-gpu

Ref: Introduction

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

Base-Line Ref for Yolo Technique

2022S-112-yolo-paper.pdf

**You Only Look Once:**
**Unified, Real-Time Object Detection**

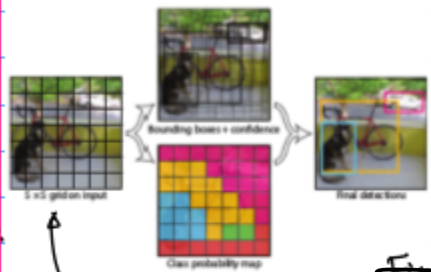
Joseph Redmon*, Santosh Divvala*†, Ross Girshick¶, Ali Farhadi*†
University of Washington*, Allen Institute for AI†, Facebook AI Research¶
http://pjreddie.com/yolo/

Lecture Notes: Base Line Ref/Requirements.

2022F-101-cmpe258-note-2022-11-1.pdf

Example: Notations for YoLo.
Ref, pp 36.

CmpE258
Oct. 13, 22

Fig 1.



Note:

1. Image $I(x,y)$ is divided into $S \times S$ Grids. Denote it as $G_{p,q}(x,y)$, ... (1)
where $p, q = 0, 1, 2, \cdots$ indicate the

1, Image $I(x,y)$. with Resolution

$M \times N$

No. of Col. No. of Rows.

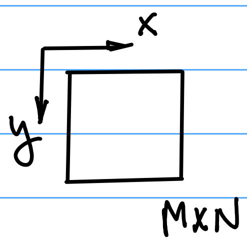


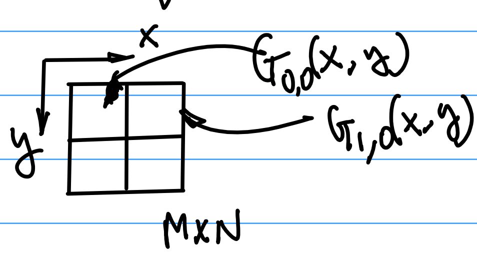

Fig. 1b.

Divide $I(x,y)$ into $S \times S$ Grids.
Each Grid is Denoted as

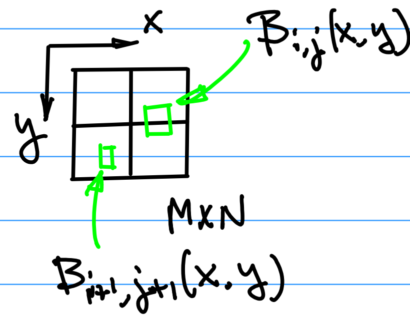
$G_{pq}(x,y)$ ... (1)

matches to X

where $p, q = 0, 1, 2, \cdots, S-1$

Fig 1c



2. Bounding Boxes $B_{ij}(x,y)$ ... (2)
$i$ for x-direction; $j$ for y-direction

Fig 1a


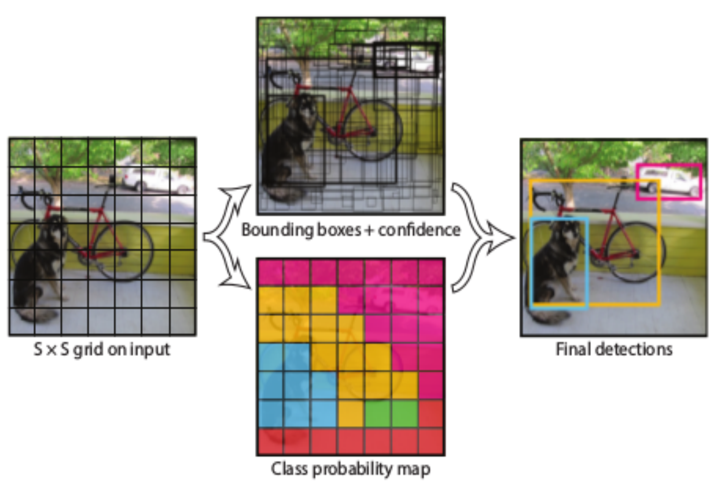

3. Five Parameters to define each Bounding Box.

$(x,y)$ : Location of the top Left Corner of $B_{ij}(x,y)$

$w, h$ : Width and Height of $B_{ij}(x,y)$

$f$ : Confidency Level, Probability distribution to Describe the likelihood of the B.B ($B^2$) belongs to a certain Class of objects.

$(x, y, w, h, f)$ ... (3)



CmpE258
Spring 2023



Note 1. a. Gpg(x,y) Grid.

**Figure 2: The Model.** Our system models detection as a regression problem. It divides the image into an $S \times S$ grid and for each grid cell predicts $B$ bounding boxes, confidence for those boxes, and $C$ class probabilities. These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor.

b. $B_{ij}(x,y)$

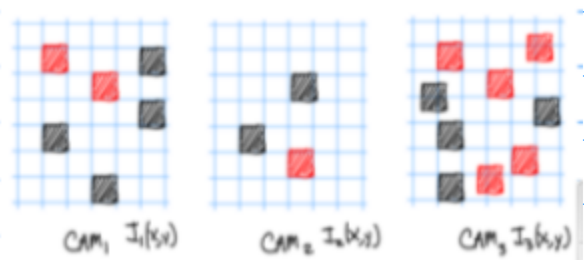
Class probability.
↓
Probability
↓
Confidency.

c. $(x, y, w, h, f)$

April 13 (Th).

Example: Discussion on Notation / Formulation.

Ref. 2022F-101-cmpe258-note-2022-11-1.pdf Pp38



Camera 1: $I_1(x,y)$ Camera 2 $I_2(x,y)$ Cam 3. $I_3(x,y)$

$$R = RI_1 + RI_2 + RI_3 \quad \cdots (1)$$

for "Union" "$\cup$"

R: Red Squares, Persons.
B: (Black) Vehicles.

Intersection. "$\cap$"

Consider the probability of the event "R" (meaning Person(s) being Capture on any one of these images).

$$Prob(R) = Prob(RI_1) + Prob(RI_2) + Prob(RI_3) \quad \cdots (2)$$

$$I_1 \cap I_2 \cap I_3 = \phi \text{ (Empty set)}$$

Consider Each Individual Camera:

$$Prob(RI_1) = Prob(R/I_1)\,Prob(I_1) \quad \cdots (3a)$$

Similarly,

$$Prob(RI_2) = Prob(R/I_2)\,Prob(I_2) \quad \cdots (3b)$$

$$Prob(RI_3) = Prob(R/I_3)\,Prob(I_3) \quad \cdots (3c)$$

Rewrite Eqn (2):

$$Prob(R) = Prob(R/I_1)\,Prob(I_1) + Prob(R/I_2)\,Prob(I_2) + Prob(R/I_3)\,Prob(I_3)$$

$$= \sum_{i=1}^{3} Prob(R/I_i)\,Prob(I_i) \quad \cdots (4)$$

CmpE258
Spring 2023



Ref: 2022S-112-yolo-paper.pdf

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

Example: pp36

Note 1. Conditional Probability. Prob($C_i$)

Prob($C_i$|Obj) Prob(Obj)

1. IOU (Intersection of Union)

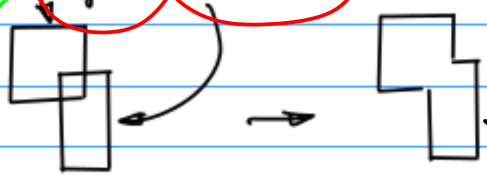
Index for the purpose of Comparing 2 Bounding Boxes at a time

pp.37

The union of $B_{ij}(x,y)$ $B_{GT}(x,y)$

Note: "GT" Ground Truth.

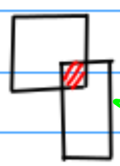
Note: $B_{ij}(x,y)$ for the i,j B.B.



The Union

The Intersection of $B_{ij}(x,y)$, $B_{GT}(x,y)$

Fig 1

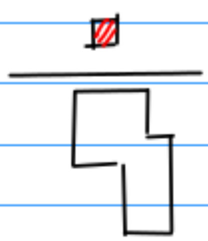


The prediction is on the left matches the Ground Truth. (GT)

$$\text{IOU} = \frac{\text{Intersection of } B_{ij}(x,y) \text{ and } B_{GT}(x,y)}{\text{The Union of } B_{ij}(x,y) \text{ and } B_{GT}(x,y)} \quad \cdots (5)$$

pp37

C =



~~$\cdots(1)$~~

(IOU) Confidence, denoted as n

Hand Calculation of IOU.

5. IOU (Intersection of Union).

Example. Illustration of IOU

Fig.3

Fig.5

Sol. First, find the Number of pixels of the $B_{ij}(x,y) \cap B_{GT}(x,y)$,

$B_{ij}(x,y) \cap B_{GT}(x,y) = 1$

then, Find the Union

$B_{ij}(x,y) \cup B_{GT}(x,y) =$

$N[B_{ij}(x,y)] + N[B_{GT}(x,y)]$

$- N[B_{ij}(x,y) \cap B_{GT}(x,y)]$

$= (3 \times 3) + (2 \times 4) - 1 = 9 + 8 - 1$

$= 17 - 1 = 16$

$\therefore \text{IOU} = 1/16$

Now, from Eq (1) of the Ref. (Research Paper)

Note

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

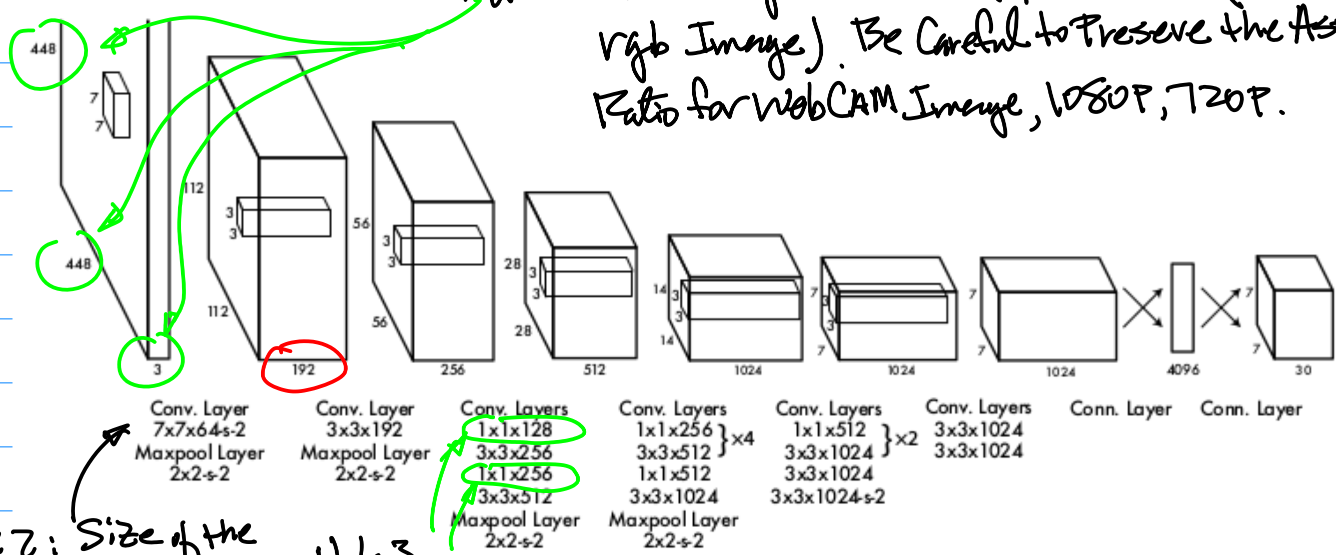
IOU truth — "G.T." B.B.

pred — Predicted B.B.

YOLO

Example: Architecture:

Note 1. Input Image Resolution: 448x448x3 (Channels: rgb Image). Be Careful to Preserve the Aspect Ratio for WebCAM Image, 1080P, 720P.




Note 2: Size of the Kernel: 7x7, 64 of them.

Note 3. 1x1 Convolution is utilized here

Example: Continuation ON Math Formulation.

1x1 Convolution.

Note 1. Background ON KxK Convolution.

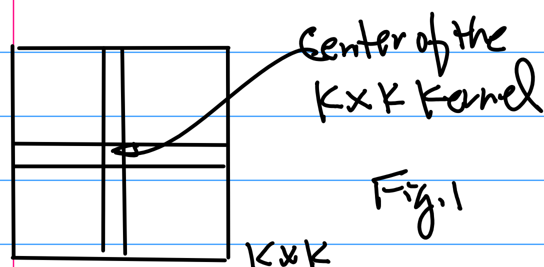



Fig. 1

For KxK 2D Convolution, the output of the convolution. "Spatial Information", Neighbouring pixels under the KxK kernel are counted for (for feature extraction @ the center of the Kernel)

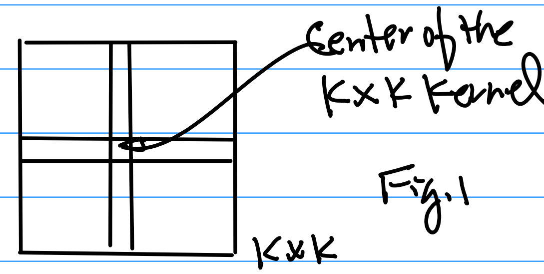



Fig. 1

Output: 1 pixel

Input: KxK pixels.

Captures All Neighbouring pixels at a time, And Produce One pixel Output.

April 11 (Tue).

Presentation (Brief) ON Each Team Project.

Note 2. For each convolution kernel, the convolution conducted will result in One Output Feature Layer

As we continue the Convolution Process, the Number of Output feature Layers will grow Significantly. Therefore, there's a need to Reduce the Number of Layers without missing crucial features.

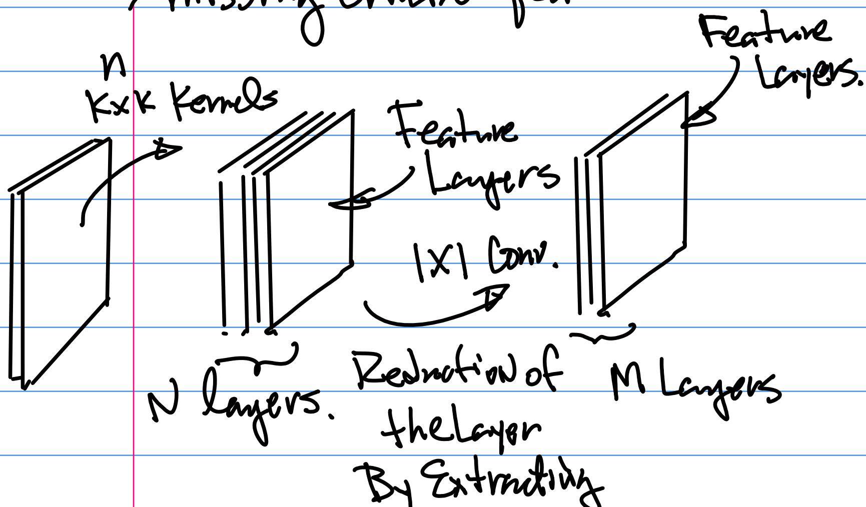



Fig. 1.

To Be Able to Extract/Preserve the Key features to Achieve Reduction of Layers. We are using the following Technique.

2022F-108a-Yolo-architecture-loss-function-2022-

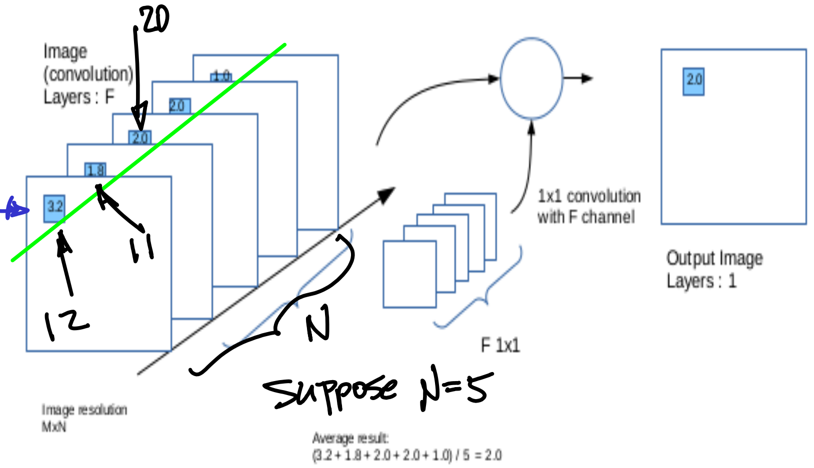
## 1x1 Convolution for Dimension Reduction and Pooling

The 1x1 convolution enables dimension reduction by reducing the number of channels in convolution layers

1. Suppose the input layers is C*H*W, where C is its channels. The 1x1 convolution generates one average result in shape H*W. The 1x1 (filter) is a vector of length C.
2. Now if you have F 1x1 filters, you get F layers of output, the output shape is F*H*W. For input layer C*H*W with F 1x1 convolution (with channel is C), you will get F*H*W layers.

Note1.

One pixel across the entire stack of the feature layer.




Harry Li, Ph.D.

Reduction Requirement: Combine 5 ($N=5$) layers into 1 layer.
To preserve the feature in this process.

Question: What is the technique to combine them (pixels at different layers) with equal contribution from each layer?

$$\frac{1}{N}\left[I_1(x_1,y_1)+I_2(x_1,y_1)+\cdots+I_5(x_1,y_1)\right] \quad \cdots (1)$$

$$\frac{1}{N}I_1(x_1,y_1)+\frac{1}{N}I_2(x_1,y_1)+\cdots+\frac{1}{N}I_5(x_1,y_1)$$