CMPE258
Spring 2023

Jan. 26 (Thu).
Organizational Meeting
for Deep Learning Class.

Syllabus, "Greensheet".

Note: 1° Syllabus is posted on the class github. Also SJSU CANVAS

https://github.com/hualili/opencv/tree/master/deep-learning-2022s

2023S-100-accessible-CMPE258-S23-v7-H...

San José State University
College of Engineering
Computer Engineering Department
CMPE258-Section 1 Deep Learning

S2023

Course and Contact Information

Instructor:	Hua Harry Li, Ph.D.
Office Location:	Engineering Building, Room 267A
Telephone:	Mobile (650) 400-1116 Text message only
Email:	hua.li@sjsu.edu
Office Hours:	MW 4:30 -5:30 PM;
	On-line with Zoom
	Join Zoom Meeting https://us04web.zoom.us/j/98416076837pwd=UlA3aEk1TnV4bjNLQk5CQkw0dDk4UT09 Meeting ID: 984 160 7683 Passcode: 121092
Class Days/Time:	Tuesdays, Thursdays 4:30 – 5:45 PM
Classroom:	Zoom (link to be shared in the SJSU email)

Note: 4°. Office Hours. ON Zoom. The office Hours are good for the entire School Semester, e.g. from the 1st day of the class till the last day of Lecture.

Note: 2° Class ON Zoom. Video Cam Activation for the class is required. Have your Video CAM Ready By Next Session

3° Attendance Requirement: Attend Lecture ON-Line is required.

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Note: 5. Class github. CANVAS is the only source for All Submissions, including Homeworks, Projects, Exam Papers etc. No e-mail Submission is Accepted.

Faculty Web Page and MYSJSU Messaging (Optional)

Copies of the course materials such as the syllabus, major assignment handouts, etc. can be found on line at SJSU CANVAS, the same material is also provided at the following yahoo group, see URL below:
https://github.com/hualili/opencv/tree/master/deep-learning-2022s

Office hours zoom link: Join Zoom Meeting https://us04web.zoom.us/j/9841607683?pwd=UlA3aEk1TnV4bjNLQk5CQkw0dDk4UT09 Meeting ID: 984 160 7683 Passcode: 121092

Course Description

Note6. Pre-requisite CMPE 255 OR CmpE257 is required.

Deep neural networks and their applications to various problems, e.g., speech recognition, image segmentation, detection and recognition of temporal and spatial patterns, and natural language processing. Covers underlying theory, the range of applications to which it has been applied, and learning from very large data sets. Prerequisite: CMPE 255 or CMPE 257 or instructor consent. Computer Engineering and Software Engineering majors only.

Course Learning Outcomes (CLO)

Note7: Book Listed below is a good reference source. the

Required Texts/Readings

Textbook

- Deep Learning with Python, 1st Edition (2nd), by François Chollet, ISBN-13: 978-1617294433, ISBN-10: 9781617294433, https://github.com/hualili/opencv/blob/master/IP120-AI-DL/2018F/2018F-6-DeepLearningCh02.pdf
- Robot Vision by B.K. P. Horn, the MIT press, ISBN 0-262-08159-8, or 0-07-030349-5 (McGraw Hill). for Reference Only.
- *Reference textbook* Learning OpenCV, Computer Vision with the OpenCV Library by Bradski and Kaebler, O'Reilly Publisher, ISBN 978-0-596-51613-0, 2011. Practical / Hand Book

Other Readings

1. OpenCV on line reference: http://docs.opencv.org/index.html
2. OpenGL on line reference (OpenGL programming guide): for the future Reference
ftp://ftp.sgi.com/opengl/contrib/kschwarz/OPEN_GL/REFERENCE/OGL_PG/oglPG.pdf
3. My lecture notes https://github.com/hualili/opencv/tree/master/IP120-AI-DL/2018F and https://github.com/hualili/opencv/tree/master/deep-learning-2020S

2022F-101-cmpe258-note-part2-2022-12-6...

References from the lecture Note
Keyword "note"

Other equipment / material requirements

PyCharm "Tool", Development / Debugging / Testing with Colab, Jupyter NoteBook etc. On-Line Tools are O.K. However, for the project Submission, Stand-Alone Python Code for Deployment is Required. Also this

1. Python.
2. Or you may choose C++ as an option.
3. OpenCV.
4. Tensorflow Keras API.
5. Optional embedded board for assignment and projects: Nvidia Jetson NANO.

Course Requirements and Assignments

SJSU classes are designed such that in order to be successful, it is expected that studen[t] of forty-five hours for each unit of credit (normally three hours per unit per week), incl[uding] participating in course activities, completing assignments, and so on. More details abo[ut]

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In the exams, the Deployable,
Stand Alone Code is Required.

2 projects, Team/Semester Long Project

Final Presentation (Last week of the Semester).

Grading Policy

Quiz, Homework, Projects	30%
Midterm Examination	30%
Final Examination	40%

On-Line.

CMPE258 Deep Learning, S2022.

0-59	F
60-69	D
70-79	C
80-89	B
90-100	A

Classroom Protocol

Note: Homework Submission.
One Week from Today.

Will post the Homework on CANVAS.

From University Policy F15-7:

1.0 DEFINITIONS OF ACADEMIC DISHONESTY

1.1 CHEATING

San José State University defines cheating as the act of obtaining credit, attempting to obtain credit, or assisting others to obtain credit for academic work through the use of any dishonest, deceptive, or fraudulent means. Cheating includes:

1.1.1. Copying, in part or in whole, from another's test or other evaluation instrument, including homework assignments, worksheets, lab reports, essays, summaries, and quizzes;

1.1.2. Submitting work previously graded in another course without prior approval by the

Jan 31 (Thu).
1. Class Ref
2. Honesty Pledge Due this Thursday. Opt.
3. OpenCV & Anaconda Installation Due A week from Today. 1 pt.

opencv / deep-learning-2022s / **2022F-103-NN-Intro-Python-v5-2022-8-25.pdf**

master ▾ opencv / **deep-learning-2023s** /

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2023S-101-Note-cmpe258-2023-01-26.pdf	Add files via upload
2023S-200-canny.py	Add files via upload
accessible-CMPE258-S23-v7-HarryLi.pdf	Add files via upload

Sample Code: Reads ~~Image~~ An Image file, and displays it.

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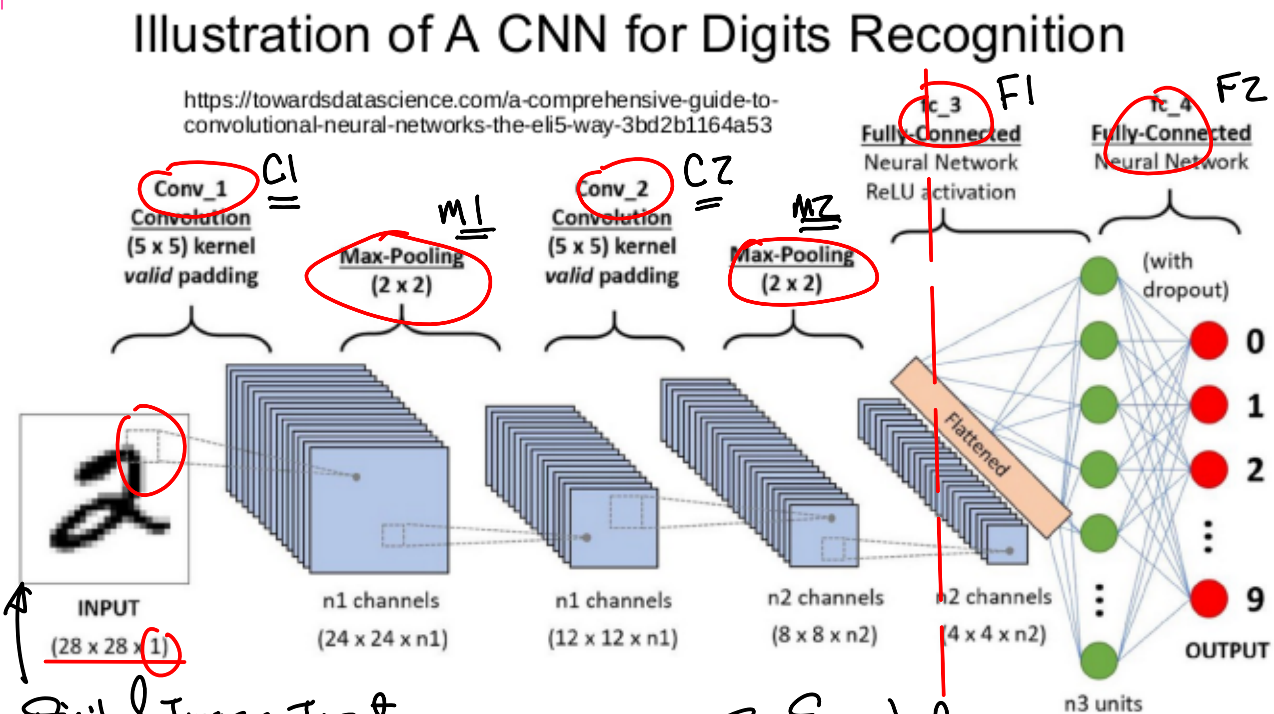
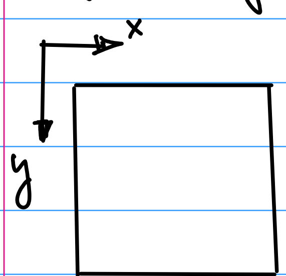
Example:



1. Digital Image Input.



I(x,y)
A frame of Image.

M x N Resolution

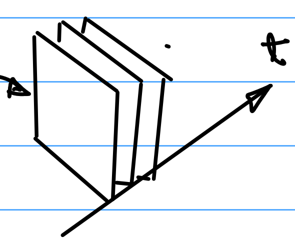
No. of Col. Per Row.
No. of Rows per frame

1920x1280
M N

Pixel: picture element

for a Video Clip, OR Video Stream.

I(x,y;t)



2. Example for 28x28x1,

8 bit Gray scale image

$I(x,y) \in [0, 255]$

Darkest, Black — Brightest, White

3. the "square" indicated on the input Image plane shows an Arbitrary Location of a Convolution Kernel.

4. "Conv_1" → C → C1
Simplified Notation. Adding An Index to Label the Convolution Block

"Max-Pooling" → M → M1

Hence, the Architecture for the Above CNN (Convolutional Neural Network) is Can be described as

C1 M1 C2 M2

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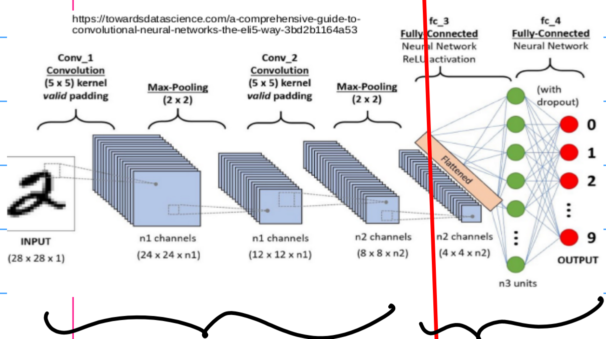


Feature Extraction Decision Making.

Fully Connected (Feed Forward) Dense NN → F

F1

And then the 2nd Block: F2.

Conclussion: The Architecture is defined as C1M1C2M2F1F2

Feb 2nd (Thu).

Note: 1° Attendance, please use Chat message to text me privately Your First-Last Name, and 4-Digits SID.

2° Introduction & Team Formation.

Ref: from the class github.

1° 2022F-103b-NN-Intro-Python-v5-2022-8-25.pdf PPT

2° Lecture Notes (Last Semester)
2022F-101-cmpe258-note-2022-11-1.pdf

3° Whitepaper on Single Neuron Formulation
2022S-103a-notation-neuro-loss-function-2022-2-8.pdf

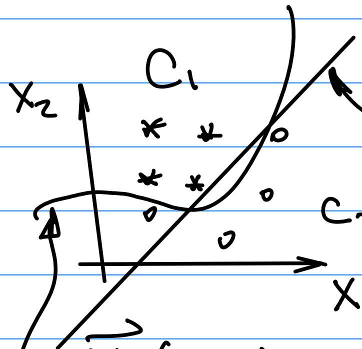
Example: Continuation of the Architecture

Question: How to Extract more features in general?

C1M1 Architecture V.S. C1M1C2M2?

In general, we can increase the Number of Convolutional Blocks. for Example:

C1M1_C2M2_C3M3.



Decision-making Functional.

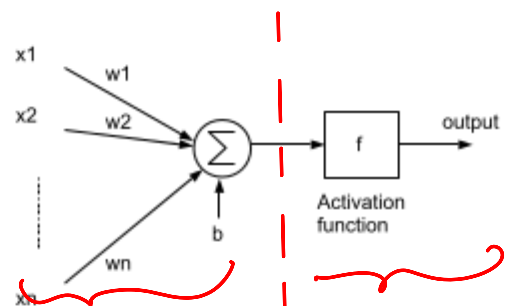
$\vec{X} = (x_1, x_2)$

Decision making Function Z

1st Dimension Area Size of A traffic Sign

2nd Dimension. Color of the traffic Sign.

Consider A Single Neuron Below:



Input Output

Note: 1° Input / Excitation

$X = (x_1, x_2, \cdots, x_n)$ ... (1)

2° Weights, Links to Allow X to Connect to A Neuron.

$W = (w_1, w_2, \cdots, w_n)$ ... (2)

$w_i \in [0, 1]$

3° Combining All the Inputs

$$x_1w_1 + x_2w_2 + \cdots + x_nw_n \quad \ldots (3)$$

Notation for a neuron input x_i, $i = 1, 2, ..., N$ is written as

$$\{x_i | i = 1, 2, ..., N\} \quad (1)$$

and its vector form is

$$(x_1, x_2, ..., x_N) \quad (2)$$

or simply denoted as X.

Now, introduce a superscript j for experiment j. The input is x_i^j, and $i = 1, 2, ..., N$ and $j = 1, 2, ..., P$.

$$\{x_i^j | i = 1, 2, ..., N; j = 1, 2, ..., P\} \quad (3)$$

III. Notation for Weights

Notation for a weight w_i, $i = 1, 2, ..., N$ is written as

$$\{w_i | i = 1, 2, ..., N\} \quad (4)$$

and its vector form is

$$(w_1, w_2, ..., w_N) \quad (5)$$

or simply denoted as W.

And

$$x_1w_1 + x_2w_2 + \cdots + x_nw_n = \sum_{i=1}^{N} x_iw_i \quad \ldots (3\text{-}1)$$

And

$$\sum_{i=1}^{N} w_i x_i = w_1x_1 + w_2x_2 + \ldots w_N x_N \quad (9)$$

Or simply in a short hand vector form notation:

Vector Dot-Product

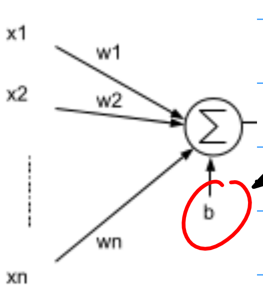
$$(x_1, x_2) \cdot (w_1, w_2) = x_1w_1 + x_2w_2$$

$$\sum_{i=1}^{N} w_i x_i = W \cdot X. \quad (10)$$

V. A Transfer Function

A transfer function is defined as

$$h = \sum_{i=1}^{N} w_i x_i = W \cdot X + b \quad (11)$$



Adding A "bias" (Threshold) to Regulate/Control the Input, then the Response of the Neuron.

$$\sum_{i=1}^{N} x_iw_i \quad \text{v.s.} \quad \sum_{i=1}^{N} x_iw_i + b$$

Offset

4. Define A Transfer function

$$h = \sum_{i=1}^{N} x_iw_i + b \quad \text{OR} \quad \ldots (4)$$

$$= \sum_{i=1}^{N+1} x_iw_i, \text{ where } x_{N+1} = b.$$

And $W_{N+1} = 1$ ...(4-1)

$$h \to h(x_i, w_i) \to h(X, W; b)$$

5. Activation Function.

Denoted as "f"

$$y = f \quad \ldots (5)$$

Output ↓

$$f(x_i, w_i) \quad \ldots (5\text{-}1)$$

↓

$$f(h(x_i, w_i)) \quad \text{OR} \quad \ldots (5\text{-}2)$$

$$f(h(x_i, w_i; b)) \quad \ldots (5\text{-}3)$$

$$y = f(\sum_{i=1}^{N} w_i x_i = W \cdot X + b). \quad (17)$$

where y is the output of the neuron, and the activation function can be rewritten as

$$y = f(\sum_{i=1}^{N} w_i x_i = W \cdot X + b) = f(h(w_i, b)). \quad (18)$$

Or simply written as

$$y = f(h(\cdot)) = f(h(w_i, b)). \quad (19)$$

6. Output from a Neuron y

Output from a Neuron, if from an Experiment.

$\hat{y}$

$\downarrow$

Suppose it is from the experiment j.

$j = 1, 2, \dots, M$

$\hat{y}^j \leftarrow$ Superscript.

Feb 7 (Tue).

Note: 1° github Ref.

2022S-103a-notation-neuro-loss-function-2022-2-8.pdf ← White paper

2022F-103b-NN-Intro-Python-v5-2022-8-25.pdf PPT.

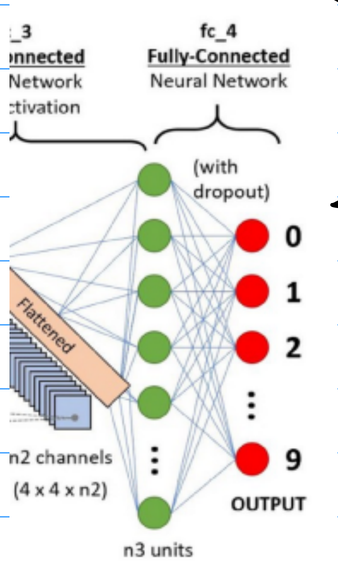
2022F-101-cmpe258-note-2022-11-1.pdf Notes

Example: Note: 1. Output y

$y_i = f_i(h(\cdot)) = f_i(h(w_i, b))$

$\rightarrow y_i$

$i = 0, 1, 2 \dots$



$\hat{y}_i$ output @ Node i

Fig. 1

Extend the Notation $\hat{y}_i$ to allow us to describe an experiment j, for $j = 1, 2, \dots, N$

$\hat{y}_i^j \big|_{j=1} = \hat{y}_i$

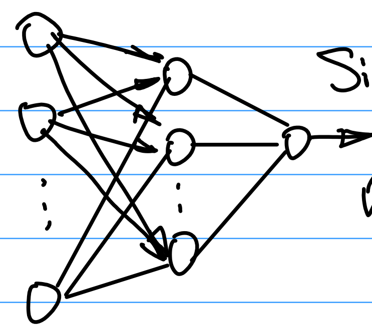
Now, consider the performance of a Convolution Neural Network

Comparison of the Network Output $\hat{y}$ to the "Ground Truth"

y

$\downarrow$

$\hat{y}/y$ OR $\hat{y} - y$ for A Single Output



Single Output

$\hat{y} - y \quad \dots (1)$

Fig. 2

For more than One Nodes, in Fig 1.

$\hat{y}_i - y_i \quad \dots (1\text{-}b)$

If for multiple experiments, then

$\hat{y}_i^j - y_i^j$

at Node i, Experiment/Training j, we are comparing the Network Output to the ground Truth.

Note: This Technique, e.g., Comparison of $\hat{y}_i^j - y_i^j$ is a Supervised Learning.

Now, To measure the performance for all the Nodes, we have

$$\sum_{i=1}^{N} (\hat{y}_i^j - y_i^j) \quad \ldots (2)$$

Note $\quad \hat{y}_i^j - y_i^j \geq 0$ OR

$$\hat{y}_i^j - y_i^j < 0$$

From Eqn (2),

$$\sum_{i=1}^{N} (\hat{y}_i^j - y_i^j) = (\hat{y}_1^j - y_1^j) +$$

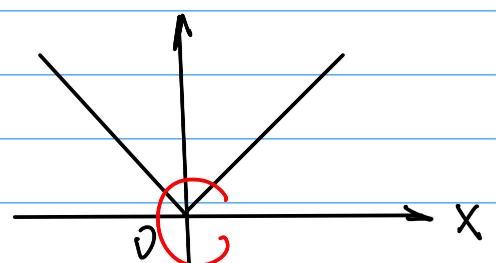
$$(\hat{y}_2^j - y_2^j) + (\hat{y}_3^j - y_3^j) + \cdots + (\hat{y}_N^j - y_N^j)$$

To Address this Problem, we can use Squared Value, Such as

$$\sum_{i=1}^{N} (\hat{y}_i^j - y_i^j)^2 \quad \ldots (3)$$

OR, Absolute Value. Consider the "behavior" of Absolute function,

$$f = |x| \quad \ldots (4)$$



Now, to Evaluate the performance for All Experiments,

$$\sum_{j=1}^{M} \sum_{i=1}^{N} (\hat{y}_i^j - y_i^j)^2 \quad \ldots (4)$$

Eqn (4) define A Loss function.

$$L = \sum_{j=1}^{M} \sum_{i=1}^{N} (\hat{y}_i^j - y_i^j)^2$$

Now, from the white paper, we have

$$L_{total} = \frac{1}{2} \sum_{j=1}^{P} (\bar{y}^j - y^j)^2. \quad (23)$$

for a Single Output Node.

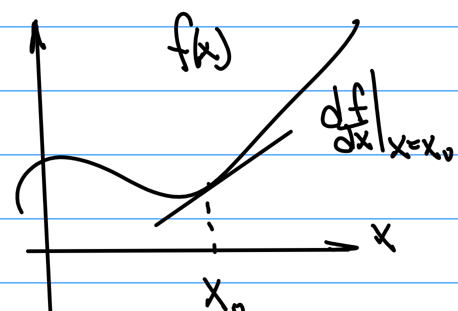
Coefficient "1/2" is Constant to allow a better/Simpler manipulations in Gradian Descent Analysis.

Consider the Improvement of A Neural Network Performance. See Eqn (24) from the white paper.

$$\frac{\partial L}{\partial w_{i,k}} = \frac{\partial}{\partial w_{i,k}} \frac{1}{2} \sum_{j=1}^{P} \sum_{i=1}^{M} (\bar{y}_i^j - y_i{}^j)^2 \quad (24)$$

Background:

Derivative of a function $y = f(x)$.



$$\frac{df}{dx}\Big|_{x=x_0} > 0$$