11210IPT553000 Deep Learning in Biomedical Optical Imaging

Week 10

AI for Medical Diagnosis

NVIDIA DLI Instructor-Led Workshop

Instructor: Hung-Wen Chen

2023/11/13 @NTHU, Fall 2023

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Calendar

9	11/06	*Transformer*	*Self-attention*	*Report*
10	11/13	*AI for Medical Diagnosis + Nvidia Workshop*		*HW5*
11	11/20	*Mid-term Review + Introduction to Final Presentation*		
12	11/27	*Mid-term Exam*		
13	12/04	*Guest Lecture*		
14	12/11	*Guest Lecture*		
15	12/18	*Student Projects Presentation*		
16	12/25	*Student Projects Presentation*		
17	01/01	*Holiday - New Year's Day (no class)*		
18	01/08	*Student Projects Presentation*		

- Midterm Review on 11/20 and Midterm on 11/27
- Research Presentation Topic
    - Presentation Week (12/18, 12/25, 1/8)
    - Volunteers of the first week and randomly pick the presentation order on 11/20
    - Pick a research paper published after 2021
    - Send the title and the paper file to TA ASAP
    - Get the confirmation from the lecturer **<u>due on 12/4</u>**

- Objective

Provide a detailed analysis of your model implementation on a given image dataset.

- Content Recommendations:
    - **Method**: Describe the methods, techniques, or algorithms you've used.
    - **Performance**: Present the results. How well did your model perform? Compare with benchmarks if any.
    - **Visuals**: Use tables, figures, and diagrams to illustrate your findings and improvements.
    - **Conclusion**: Sum up your findings, what you've learned, and possible future extensions or improvements.

Project Presentation (20 mins plus 3-min Q&A)

- Abstract
  - What is this research about?
- Motivation / Purpose
  - Why do the authors perform this research?
- Introduction to the Bio-medical Imaging Technology
- Network Architecture
  - Introduce the deep learning model including its design, pros and cons
- Comparison
  - Compare the performance of this research to other researches or baselines
- Conclusion
  - Your conclusion
- Code Implementation (Bonus)
  - Show your results after running the codes (Submit the files or the link to TA)
  - Modifications are strongly encouraged!

Outline of Today's Lecture

- AI for Medical Diagnosis
- Convolutional Neural Networks (Course 4 Week 2 & 3 & 4)
- Convolutional Neural Network: Feature Map and Filter Visualization
- NVIDIA DLI Instructor-Led Workshop

Convolutional Neural Networks (Course 4 Week 3 & 4)

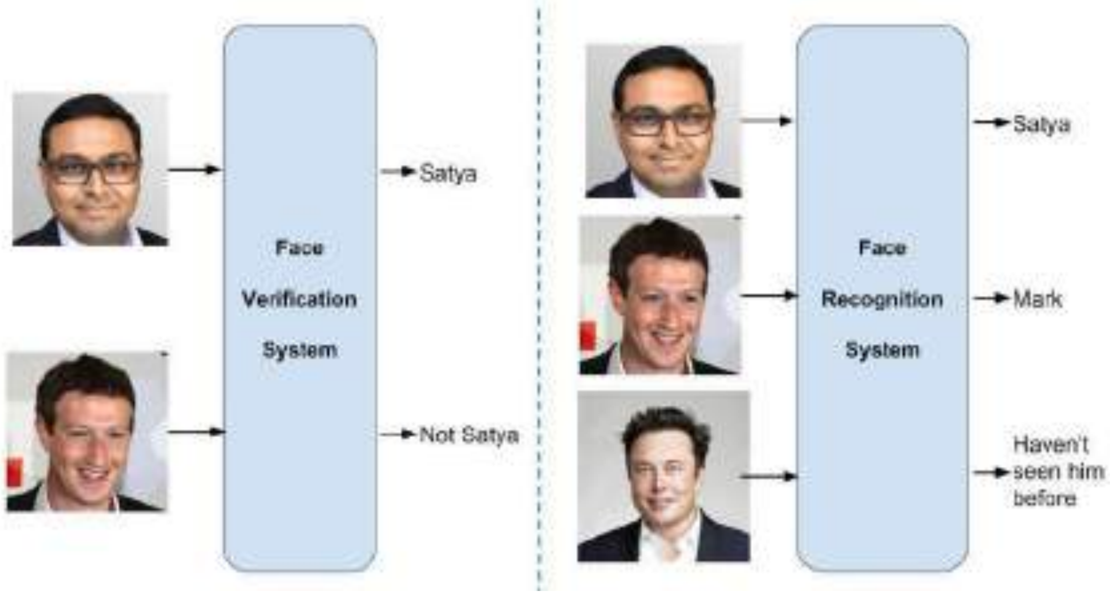
Course 4 Week 3

- Object Detection
- Landmark Detection
- Sliding Window/ Anchor Box / Intersection over Union (IoU) /Non-max Suppression
- Region Proposal / R-CNN/ Fast R-CNN/ Faster R-CNN / YOLO

Special applications: Face recognition & Neural style transfer

Course 4 Week 4

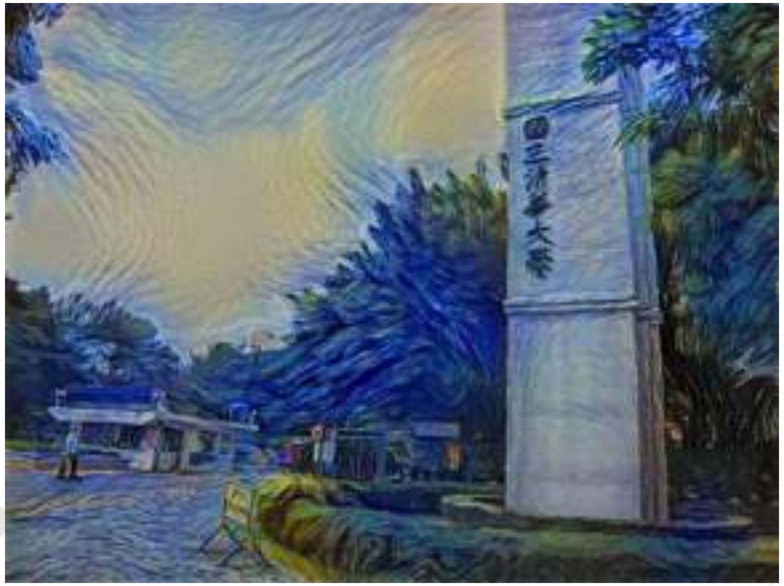
- Face Recognition
  - One shot learning
  - Siamese network
  - Triplet loss
  - Face verification



- Neural Style Transfer
  - Content cost function
  - Style cost function

+

→



U-Net

Convolutional Networks for Biomedical Image Segmentation

- U-net

https://arxiv.org/pdf/1505.04597.pdf

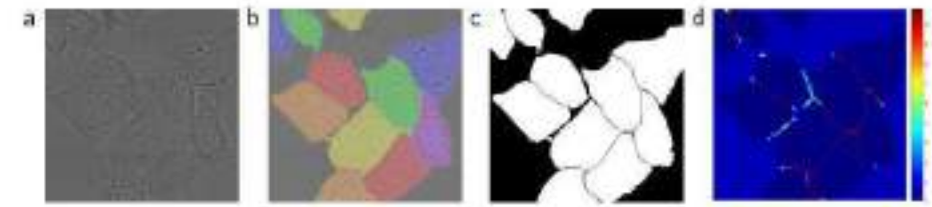


Fig. 3. HeLa cells on glass recorded with DIC (differential interference contrast) microscopy. (**a**) raw image. (**b**) overlay with ground truth segmentation. Different colors indicate different instances of the HeLa cells. (**c**) generated segmentation mask (white: foreground, black: background). (**d**) map with a pixel-wise loss weight to force the network to learn the border pixels.

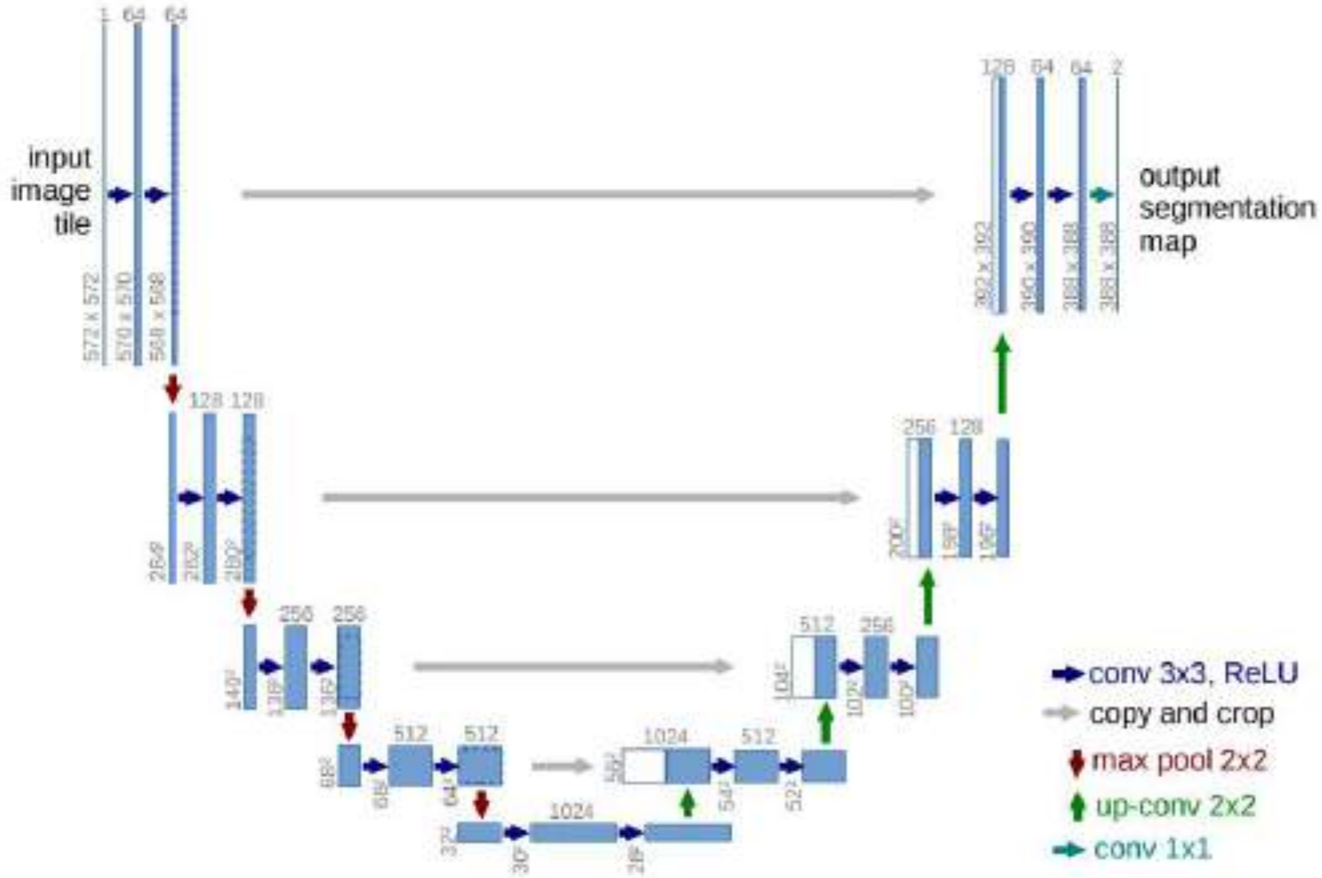


Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

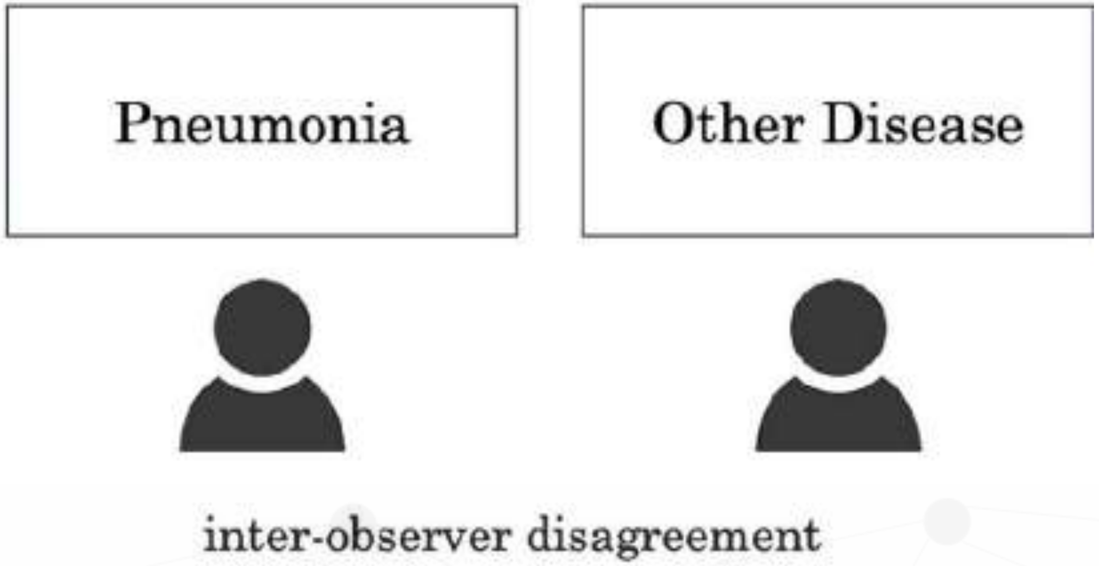
Fully Convolutional Network

https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/

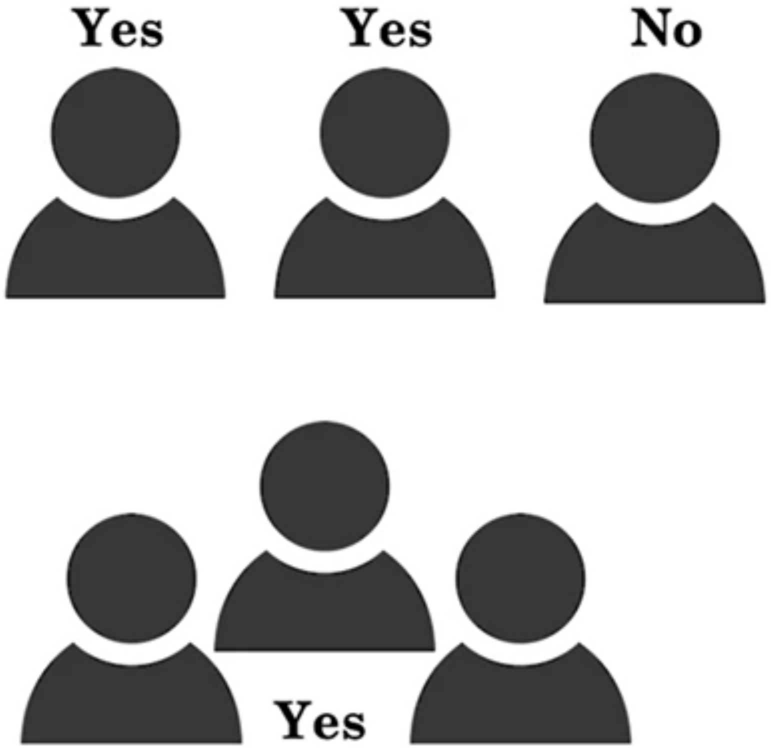
Ground Truth (Reference Standard) and Consensus Voting

Check how well your model performs

Ground Truth (Reference Standard)



Consensus Voting



Is it pneumonia? Yes

Is it pneumonia? Yes

The idea behind consensus voting is to use a group of human experts to determine the ground truth

Additional Medical Testing

CT Confirmation

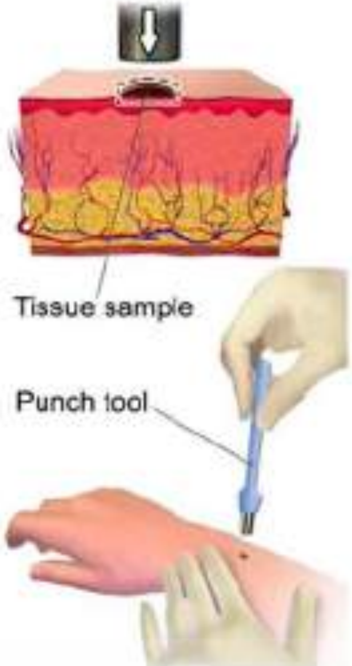
Mass

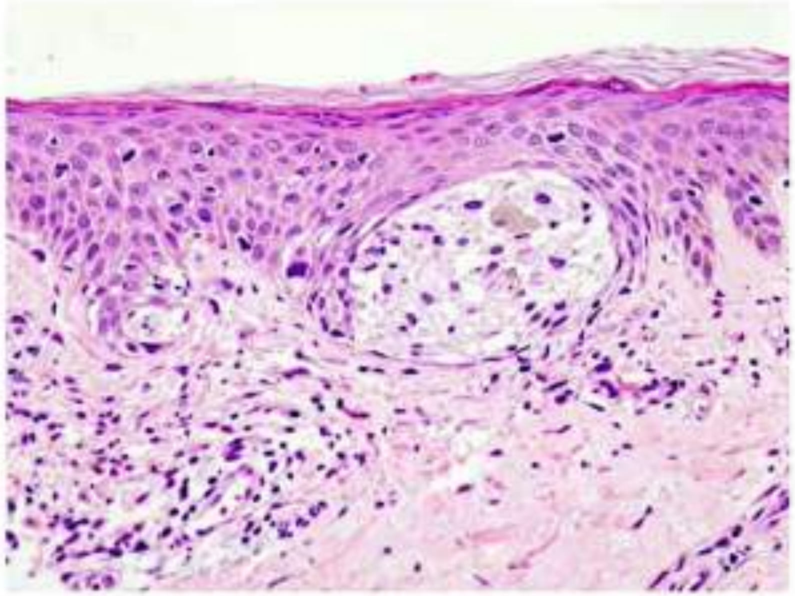
More definitive test!

Check how well your model performs

Additional Medical Testing

Skin Biopsy





Cancerous

Evaluation Metrics

Sensitivity, Specificity, and Evaluation Metrics

How good is a model?

Ground Truth
Normal
Normal
Normal
Normal
Normal
Disease
Normal
Disease
Normal
Normal

Accuracy = 8/10

Accuracy = 8/10

Accuracy in terms of conditional probability

$$\text{Accuracy} = \mathrm{P}(\text{correct})$$

Sensitivity, Specificity and Prevalence

$P(+ \mid \text{disease})$

If a patient has the disease, what is the probability that the model predicts positive?

Sensitivity

= True Positive Rate
= Recall

$P(- \mid \text{normal})$

If a patient is normal, what is the probability that the model predicts negative?

Specificity

= True Negative Rate

Key evaluation metrics

Sensitivity, Specificity and Prevalence

$$\text{Accuracy} = P(\text{correct})$$

$$\text{Accuracy} = \text{Sensitivity} \times P(\text{disease}) + \text{Specificity} \times P(\text{normal})$$

Key evaluation metrics

Sensitivity, Specificity and Prevalence

Ground Truth	Model
Normal	-
Normal	-
Disease	+
Normal	-
Normal	-
Disease	-
Normal	-
Disease	+
Normal	+
Normal	-

Sensitivity

$P(+ \mid \text{disease})$

$$\frac{\#(+ \text{ and disease})}{\#(\text{disease})} = 2/3 = 0.67$$

Specificity

$P(- \mid \text{normal})$

$$\frac{\#(- \text{ and normal})}{\#(\text{normal})} = 6/7 = 0.86$$

Key evaluation metrics

Sensitivity, Specificity and Prevalence

Ground Truth	Model
Normal	-
Normal	-
Disease	+
Normal	-
Normal	-
Disease	-
Normal	-
Disease	+
Normal	+
Normal	-

Sensitivity = 0.67

Specificity = 0.86

Prevalence = 3/10

$P(disease)$ =0.3

$$\frac{\#(\text{disease})}{\#(\text{total})}$$

Accuracy

$$\text{Sensitivity} \times \text{prevalence} + \text{Specificity} \times (1 - \text{prevalence})$$

= 0.67 X 0.3 + 0.86 X 0.7

= 0.8

Positive Predicted Value (PPV) & Negative Predicted Value (NPV)

Sensitivity

$$P(+ \mid \text{disease})$$

If a patient has the disease, what is the probability that the model predicts positive?

Key evaluation metrics

Positive Predicted Value (PPV) & Negative Predicted Value (NPV)

Specificity

$$P(- \mid \text{normal})$$

If a patient is normal, what is the probability that the model predicts negative?

Key evaluation metrics

PPV & NPV

Ground Truth	Model
Normal	-
Disease	+
Normal	+
Normal	-
Normal	-
Disease	-
Normal	-
Disease	+
Normal	+
Normal	-

PPV

$$P(\text{disease} \mid +)$$

$$\frac{\#(+\text{ and disease})}{\#(+)} = 2/4 = 0.5$$

NPV

$$P(\text{normal} \mid -)$$

$$\frac{\#(-\text{ and normal})}{\#(-)} = 5/6 = 0.83$$

Key evaluation metrics

PPV & NPV

$$P(\text{disease} \mid +)$$

PPV

$$P(\text{normal} \mid -)$$

NPV

$$P(+ \mid \text{disease})$$

Sensitivity

$$P(- \mid \text{normal})$$

Specificity

Key evaluation metrics

Confusion matrix

Ground Truth	Model
Normal	-
Disease	+
Normal	+
Normal	-
Normal	-
Disease	-
Normal	-
Disease	+
Normal	+
Normal	-

Model Output

GT		+	-
	Disease	2	1
	Normal	2	5

Key evaluation metrics

Confusion matrix

		Model Output	
		+	-
GT	Disease	True Positive (TP)	False Negative (FN)
	Normal	False Positive (FP)	True Negative (TN)

		Model Output	
		+	-
GT	Disease	2	1
	Normal	2	5

Key evaluation metrics

Confusion matrix

		Model Output	
		+	-
GT	Disease	True Positive (TP)	False Negative (FN)
	Normal	False Positive (FP)	True Negative (TN)

$$\frac{\#(+\text{ and disease})}{\#(\text{disease})} = \text{Sensitivity}$$

$$\frac{\#(-\text{ and normal})}{\#(\text{normal})} = \text{Specificity}$$

$$\text{PPV} = \frac{\#(+\text{ and disease})}{\#(+)}$$

$$\text{NPV} = \frac{\#(-\text{ and normal})}{\#(-)}$$

Key evaluation metrics

Confusion matrix

Model Output

		+	-
GT	Disease	True Positive (TP)	False Negative (FN)
	Normal	False Positive (FP)	True Negative (TN)

$$\frac{TP}{TP + FN} = \text{Sensitivity}$$

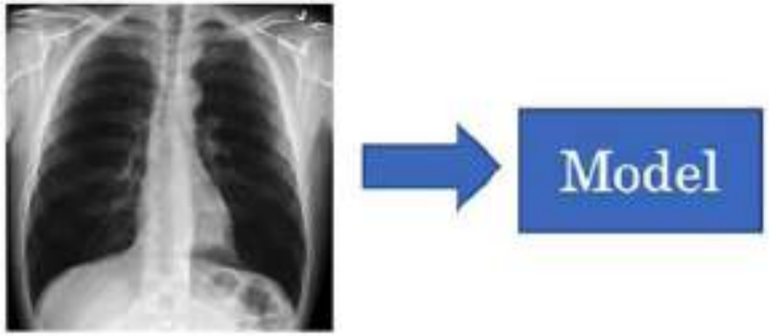
$$\frac{TN}{FP + TN} = \text{Specificity}$$

$$\text{PPV} = \frac{TP}{TP + FP}$$

$$\text{NPV} = \frac{TN}{TN + FN}$$

How Does Varying the Threshold Affect Evaluation Metrics?

ROC curve and Threshold



$$P(+ \mid \text{disease}) \qquad P(- \mid \text{normal})$$

Sensitivity **Specificity**

t = 0 -> Sensitivity = 1

t = 1 -> Specificity = 1

ROC curve and Threshold

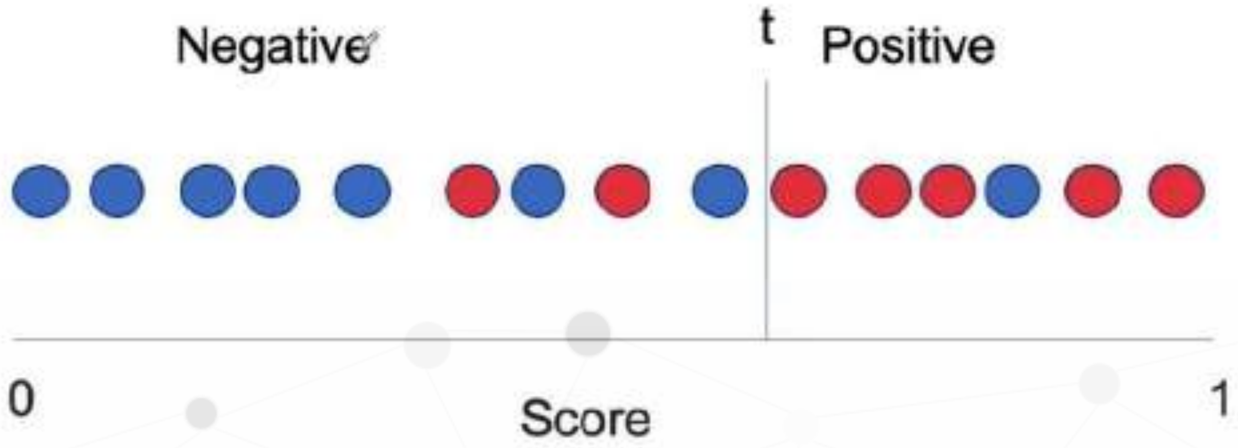
$$P(+ \mid \text{disease}) \qquad P(- \mid \text{normal})$$

Sensitivity

$$\frac{5}{7} = 0.71$$

Specificity

$$\frac{7}{8} = 0.88$$



How Does Varying the Threshold Affect Evaluation Metrics?

ROC curve and Threshold

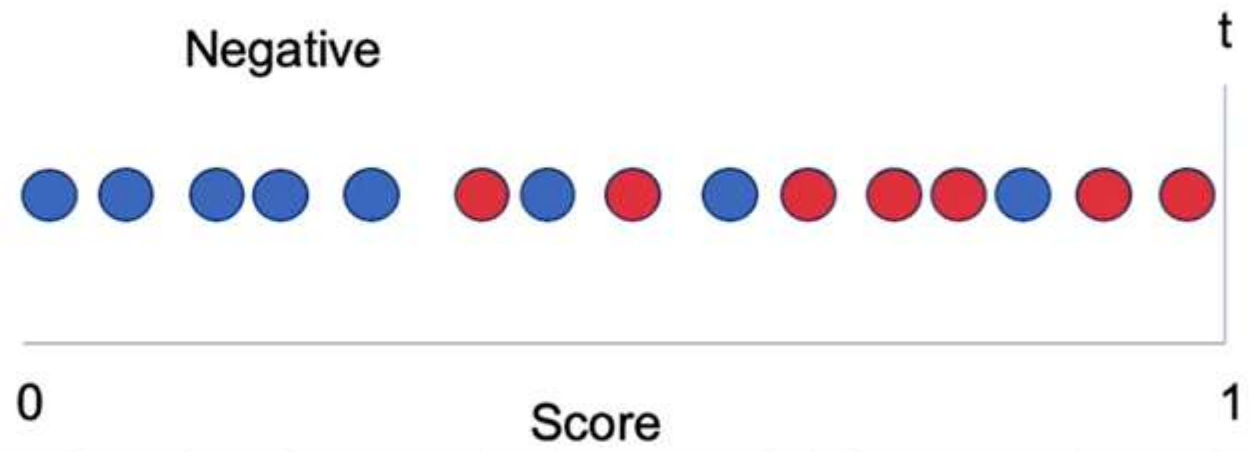
$$P(+ \mid \text{disease}) \qquad P(- \mid \text{normal})$$

Sensitivity

$$\frac{0}{7} = 0$$

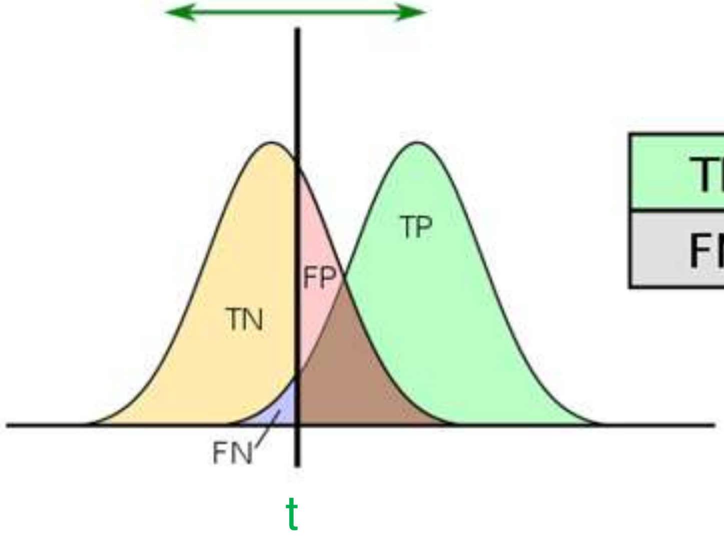
Specificity

$$\frac{8}{8} = 1$$

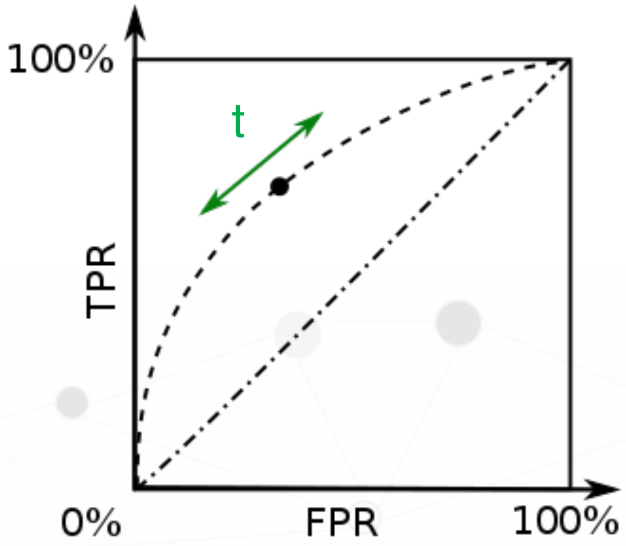


How Does Varying the Threshold Affect Evaluation Metrics?

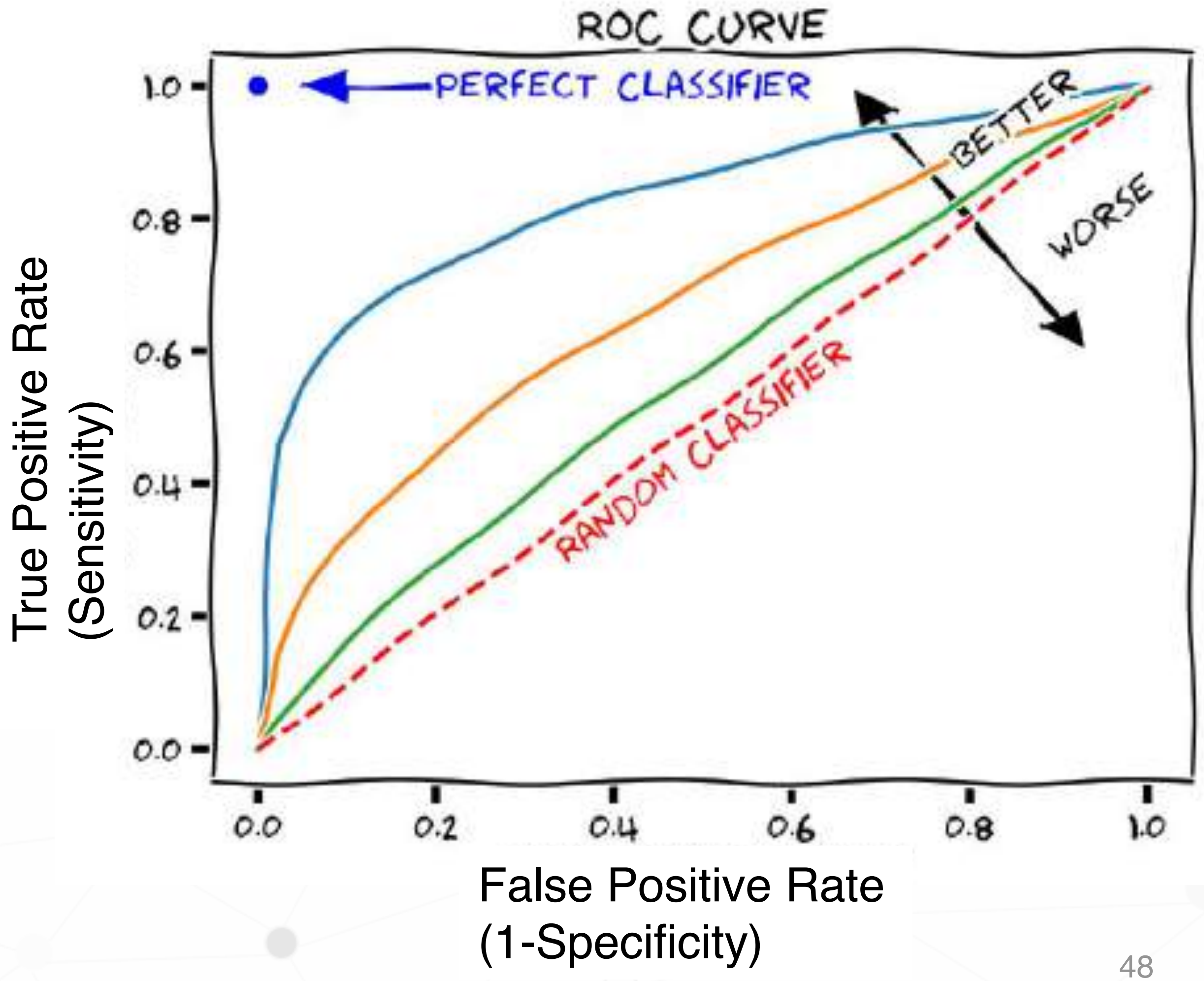
Receiver Operating Characteristic (ROC) Curve



TP	FP
FN	TN



Area Under the ROC Curve (AUC)



Confusion Matrix

https://www.ycc.idv.tw/confusion-matrix.html

Prevalence (盛行率) = (TP+FN) / Tot. N

Sensitivity (靈敏度) = TP / (TP+FN)

Specificity (特異度) = TN / (FP+TN)

PPV (Positive Predictive Value) = TP / (TP+FP)

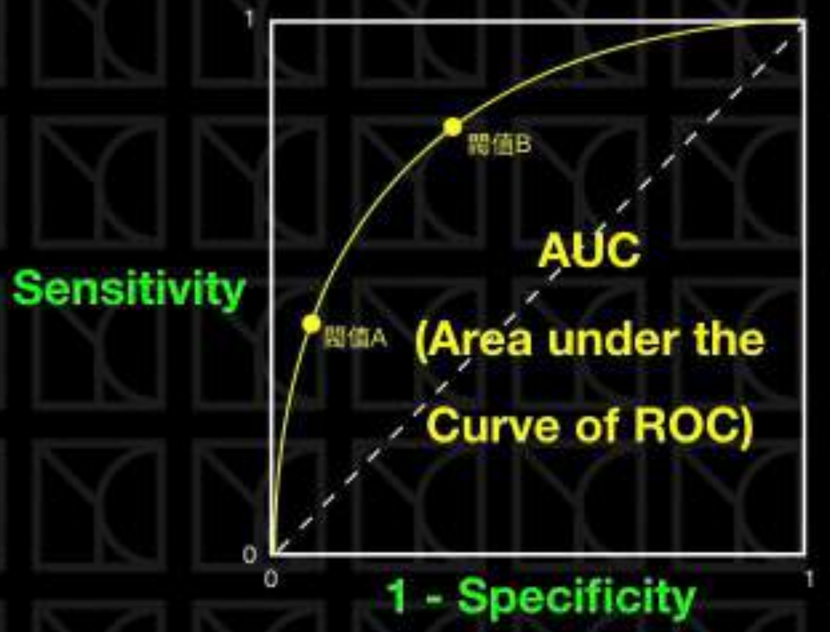
NPV (Negative Predictive Value) = TN / (FN+TN)

	實際 YES	實際 NO	
預測 YES	TP	FP	PPV
預測 NO	FN	TN	NPV

Sensitivity Specificity

ROC Curve

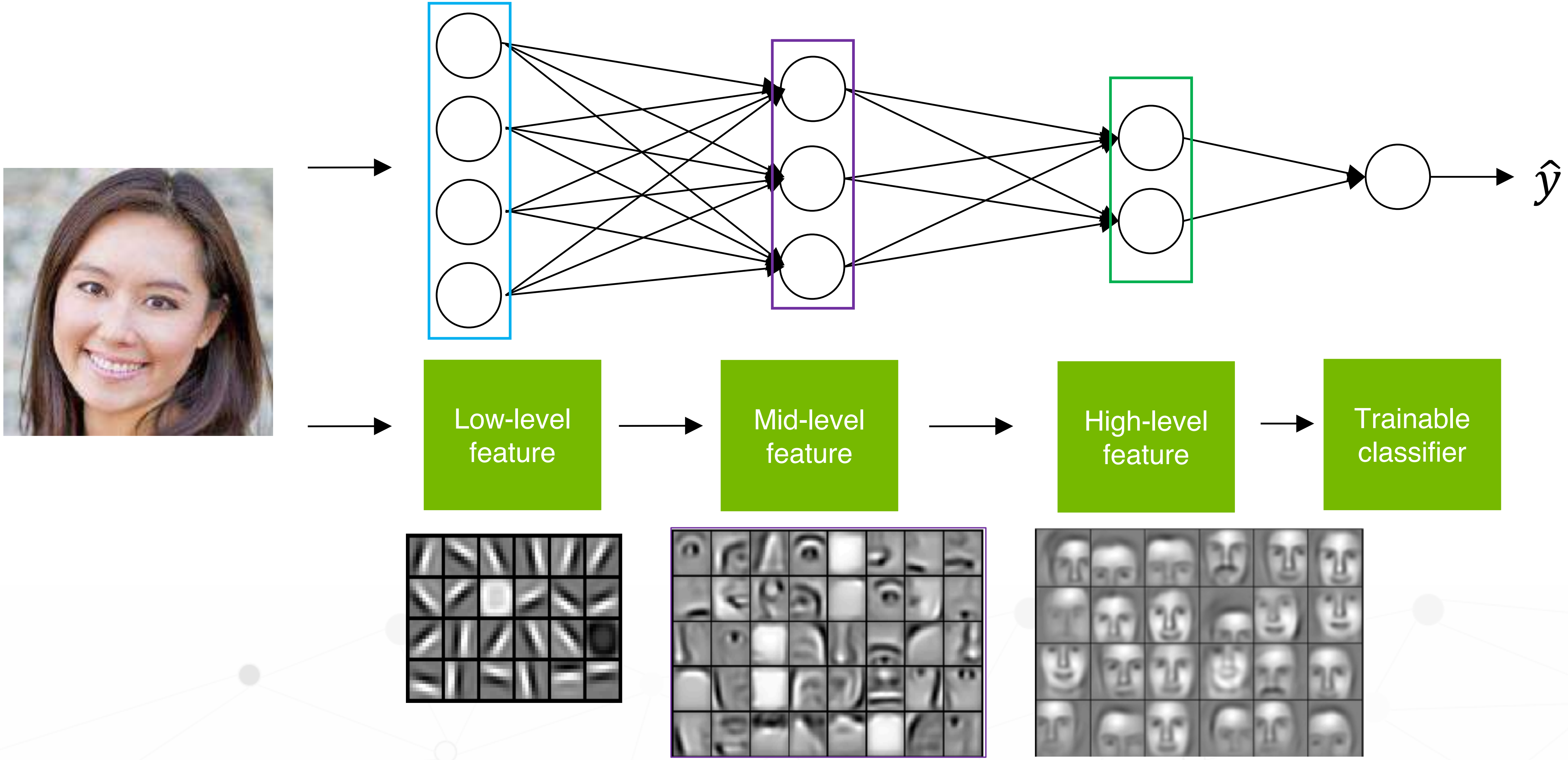
(Receiver Operating Characteristic Curve)



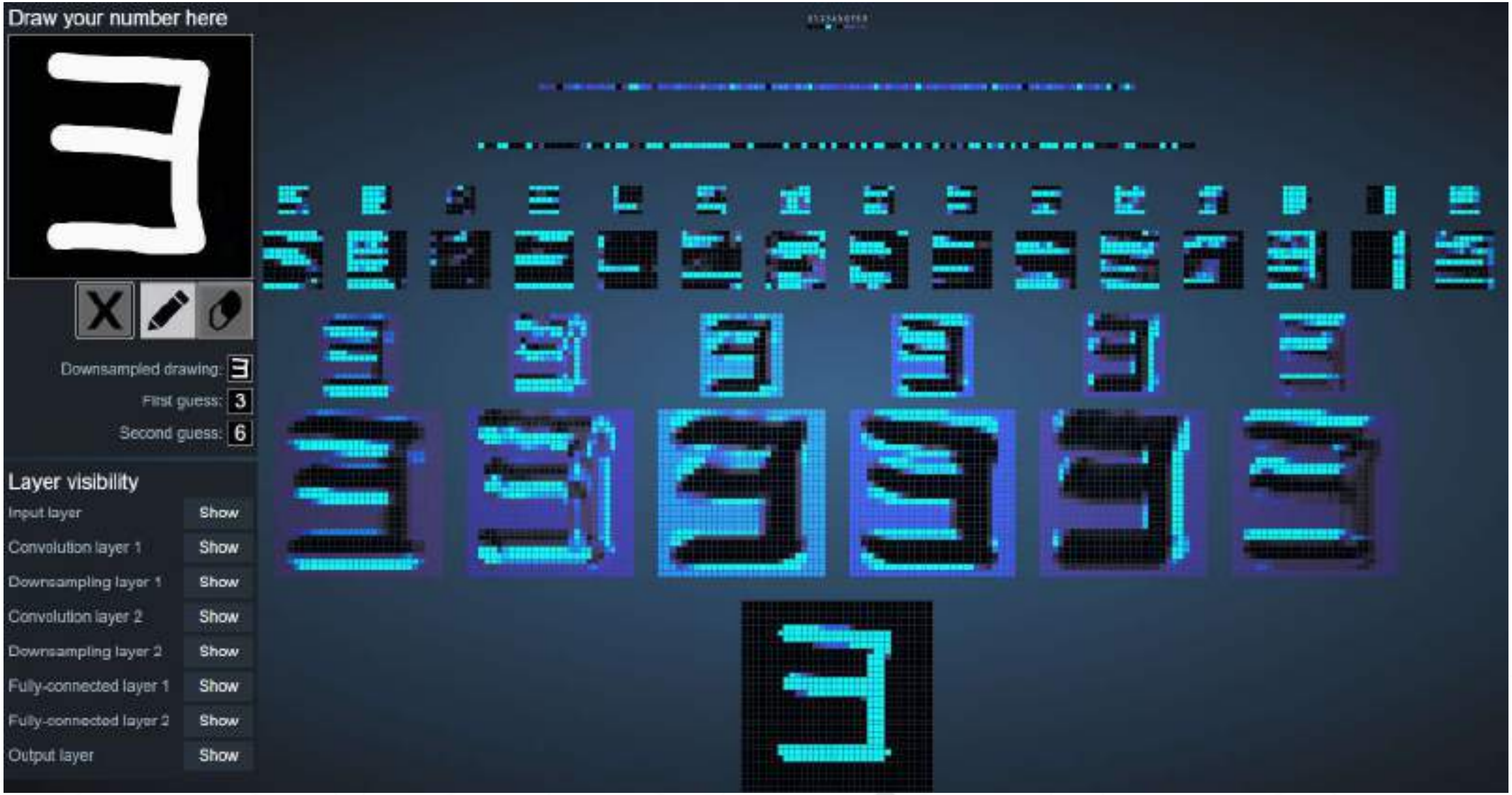
How Neural Networks Build Up Their Understanding of Images

Feature Visualization and Attribution

Deep learning = Learning hierarchical representations



2D Visualization of a Convolutional Neural Network

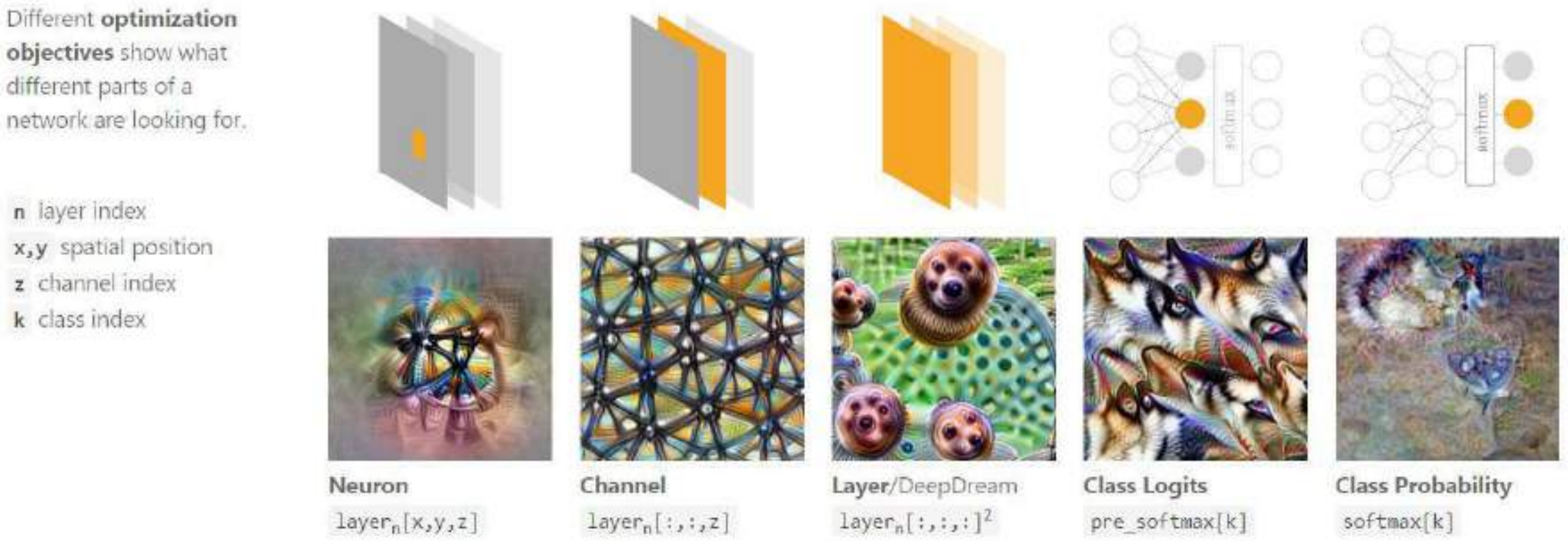


https://www.cs.ryerson.ca/~aharley/vis/conv/flat.html

Convolutional Neural Network: Feature Visualization and Attribution

Feature Visualization

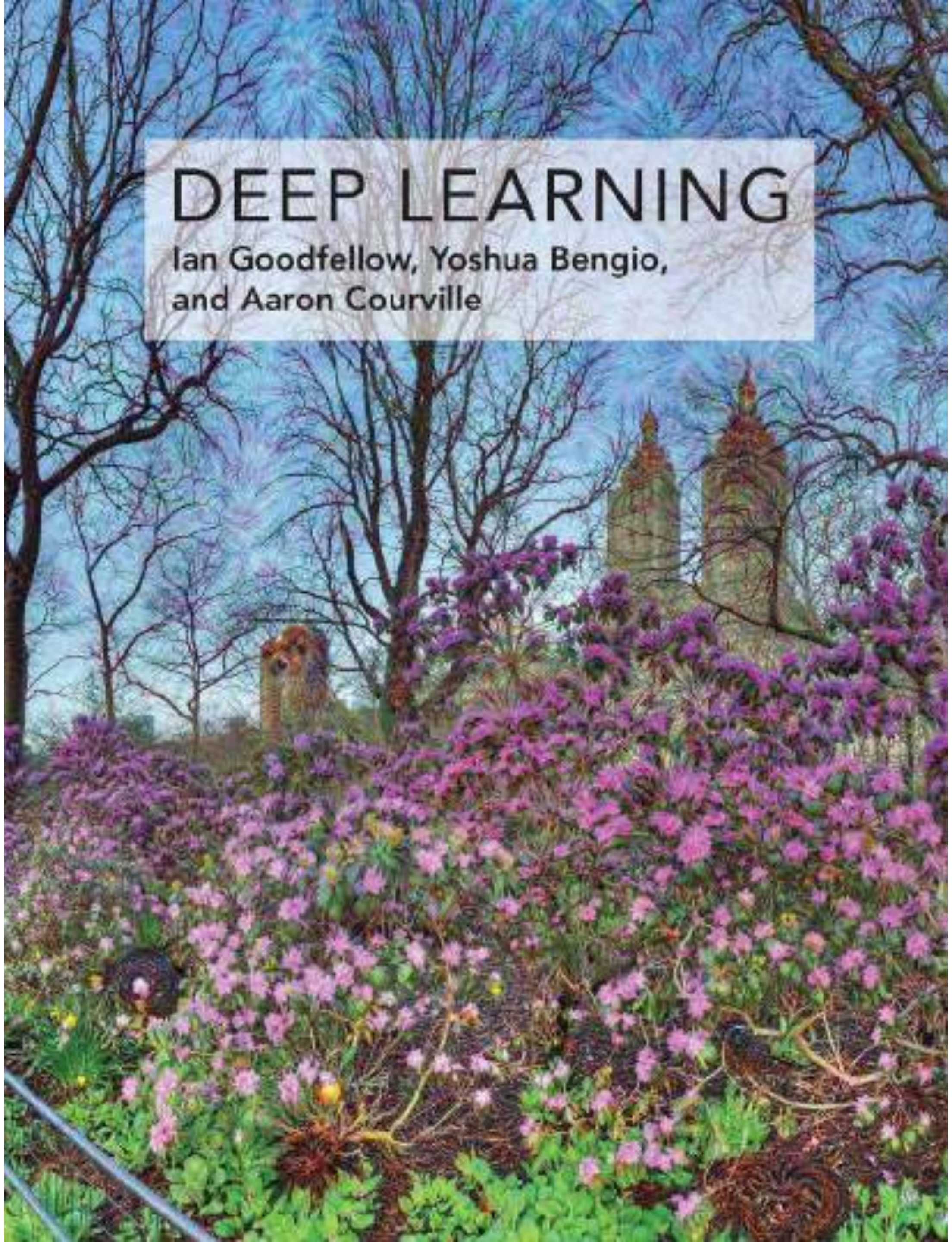
- By Activation Maximization: $x^* = \underset{x}{argmax}\, a_{i,l}(\theta, x)$



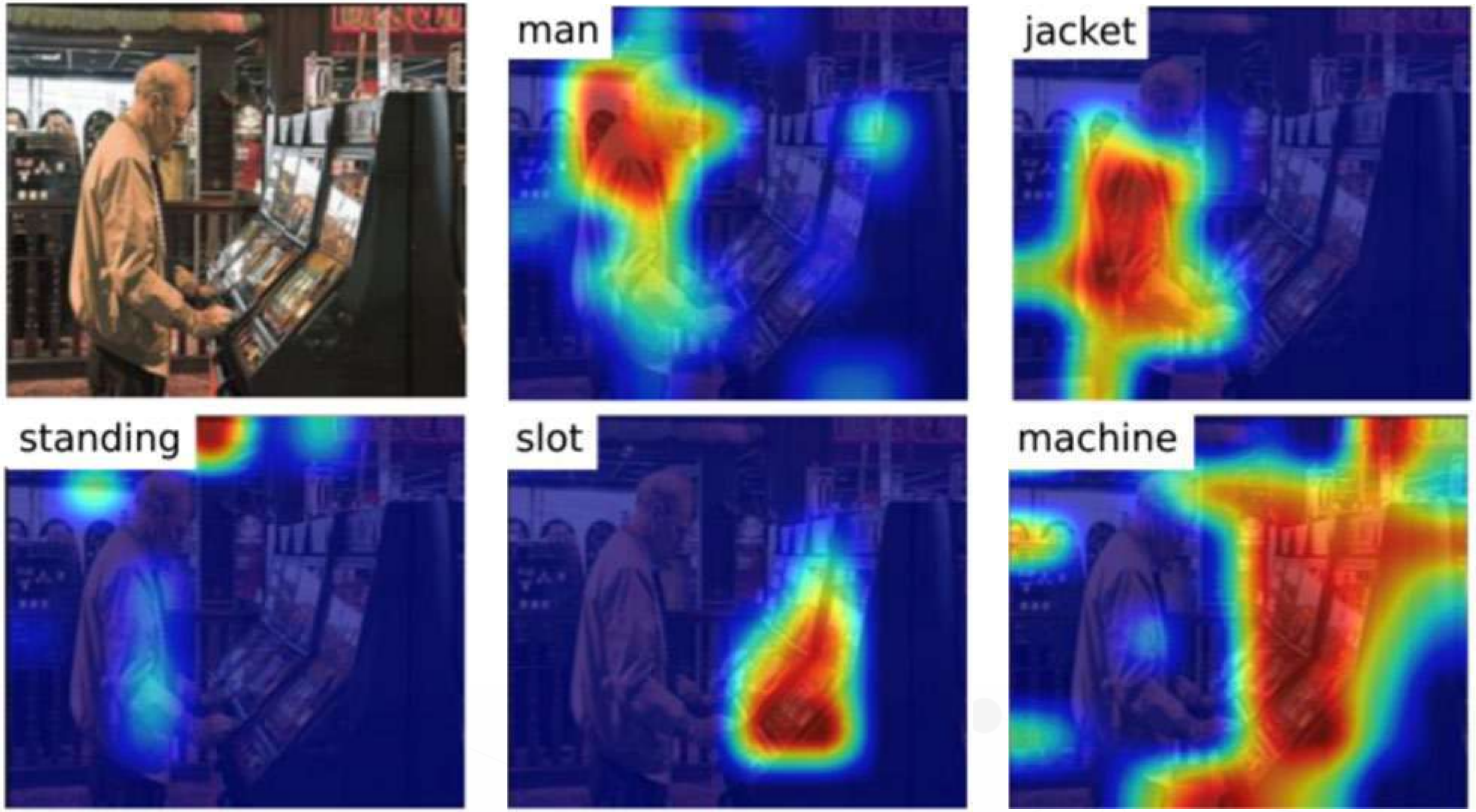
[D. Erhan, Y. Bengio, A. Courville and P. Vincent, Visualizing higher-layer features of a deep network, (2009), p3](#)
[K. Simonyan, A. Vedaldi and A. Zisserman, Deep inside convolutional networks: Visualising image classification models and saliency maps](#)
[Inceptionism: Going deeper into neural networks](#) (DEEP DREAM)
[Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps](#)

Deep Dream

https://ai.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

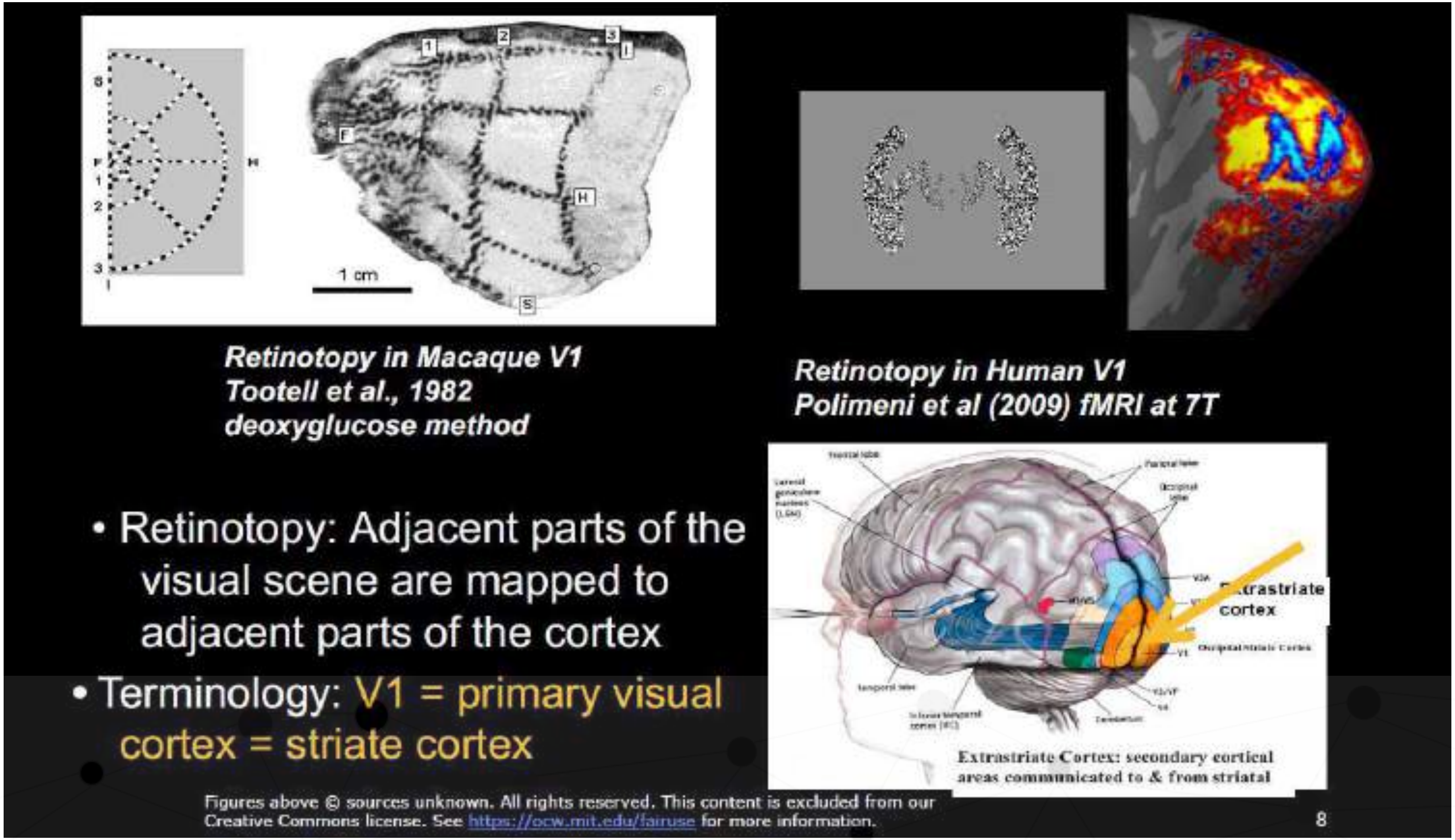

DEEP LEARNING
Ian Goodfellow, Yoshua Bengio,
and Aaron Courville

Pixel Attribution (Saliency Map)



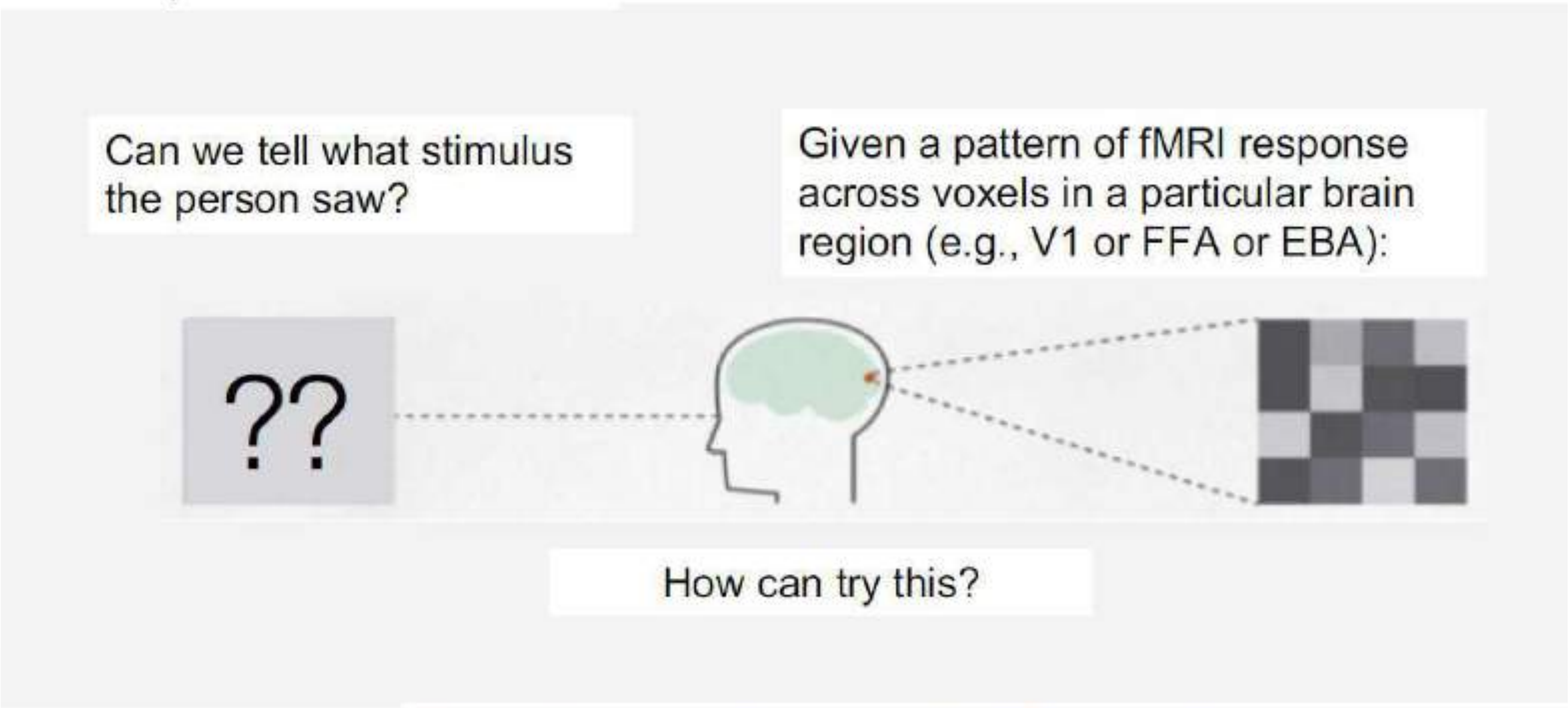
https://christophm.github.io/interpretable-ml-book/pixel-attribution.html

Retinotopic Maps



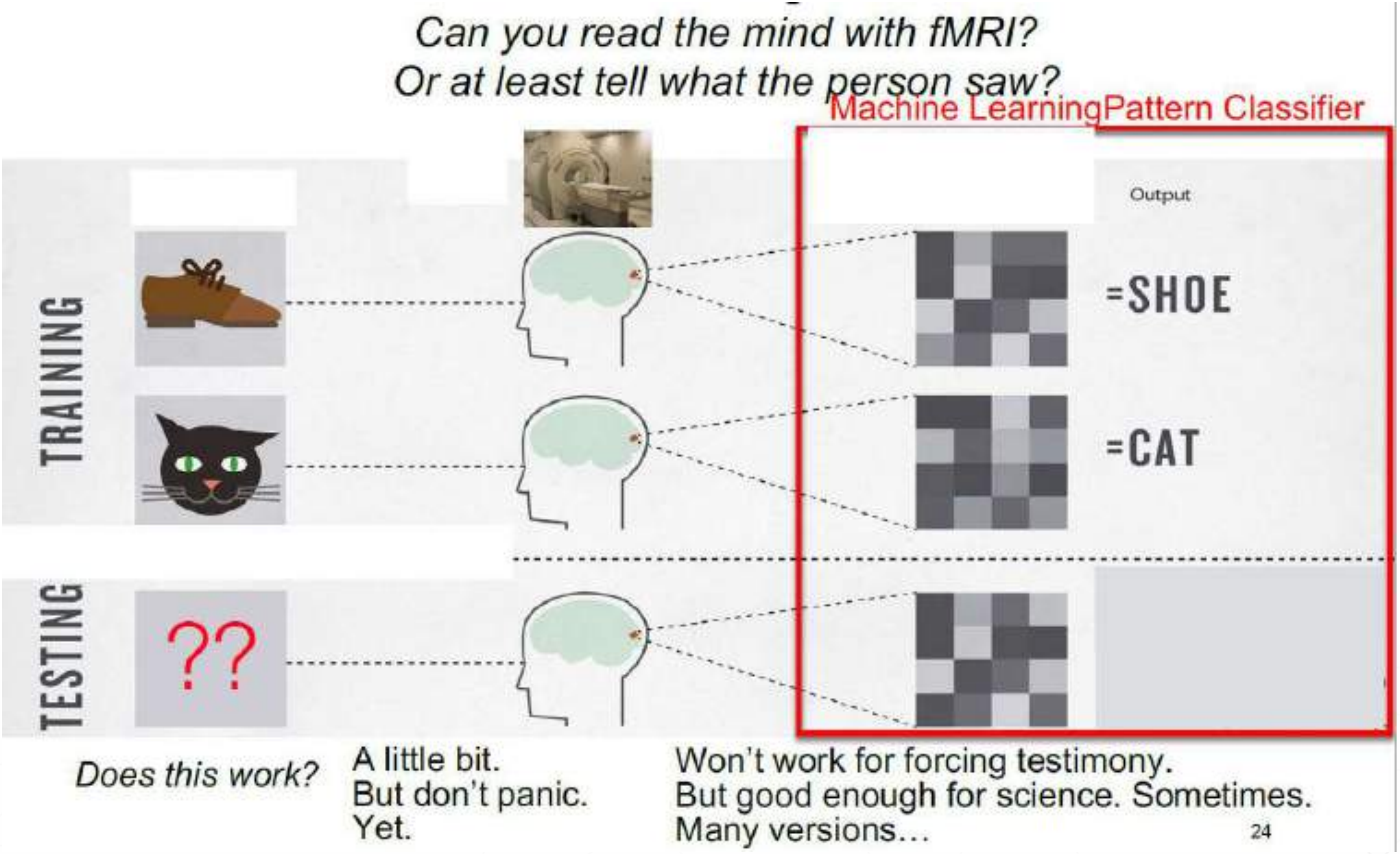
https://www.sciencedirect.com/science/article/pii/S1053811910007111?via%3Dihub

Neural Decoding

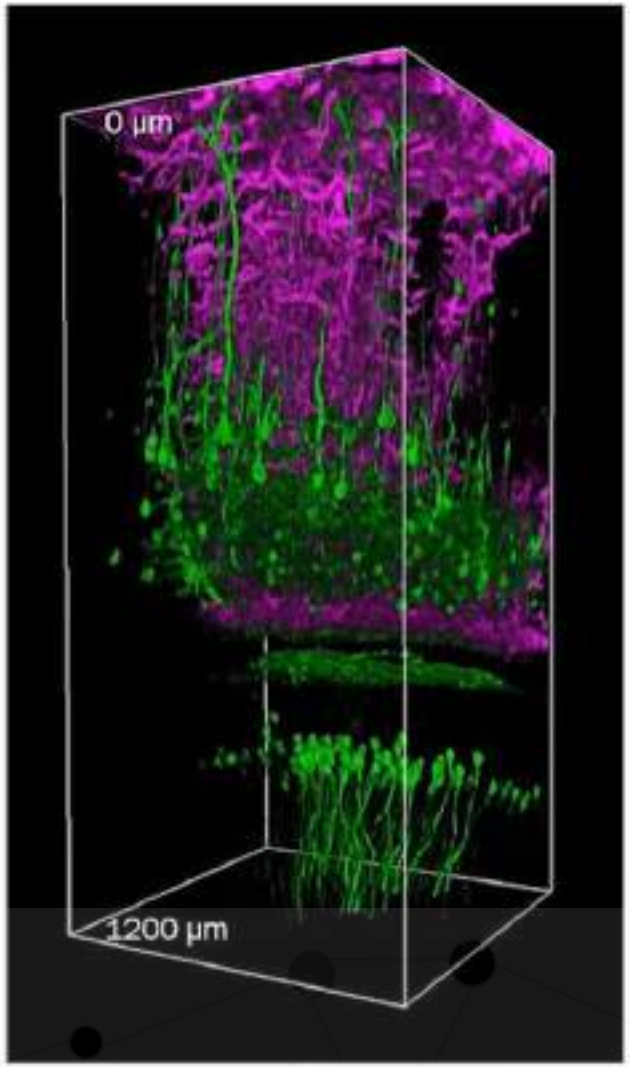


How Neural Networks Build Up Their Understanding of Images

Neural Decoding



3-Photon: Imaging Deeper in Tissue



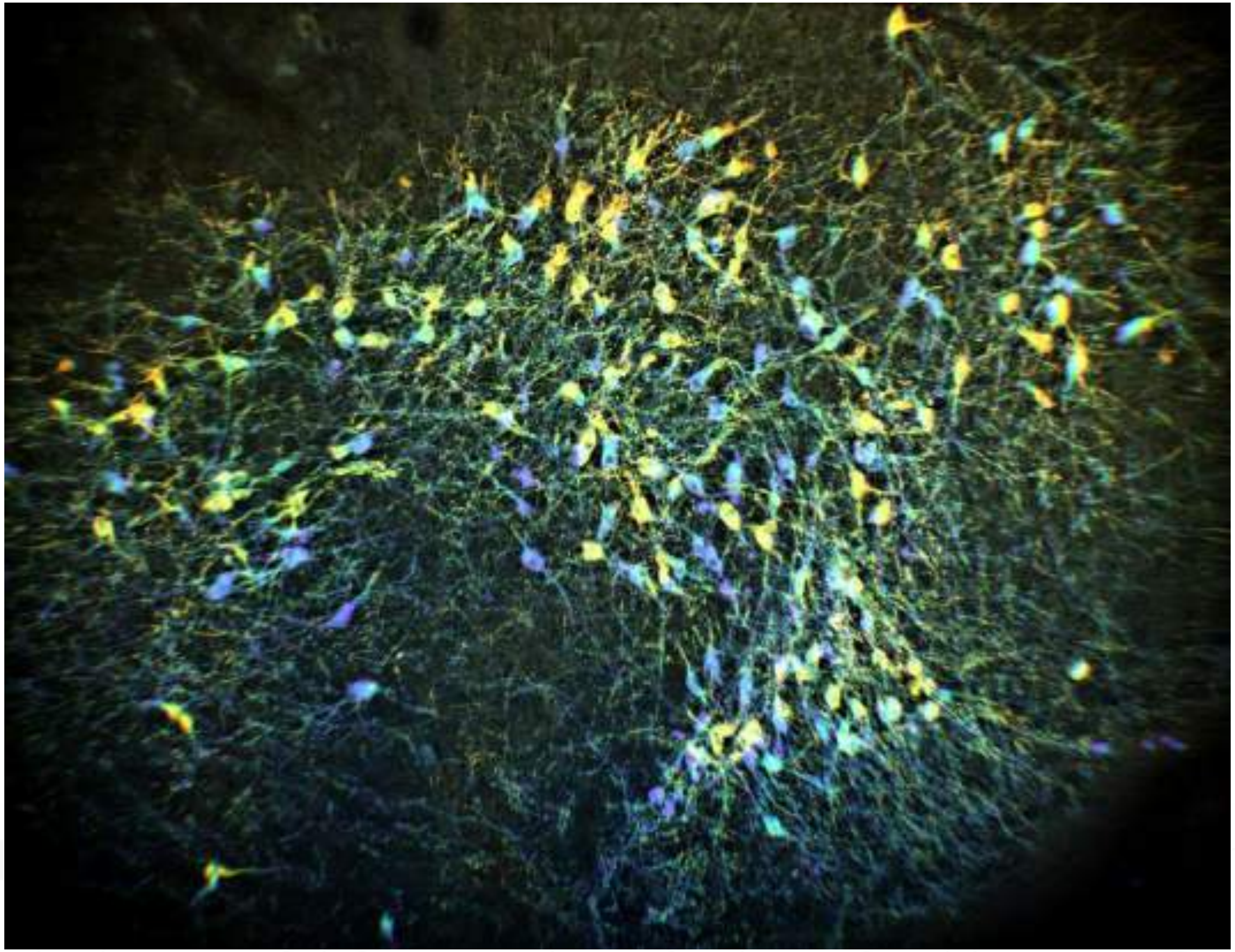
3P *in vivo*, YFP Through Cranial Window

- **System**
  - Thorlabs Bergamo 2 (Galvo-Galvo)
  - Laser: 1300 nm, @326 kHz pulse width ~ 60 fs
  - Objective lens: Olympus XLPLN25XWMP2
  - Magenta: 3rd Harmonic;
  - Green: YFP emission 525/50 nm
  - 539 µm x 539 µm x 1200 µm
    - 0 µm, 1.1mW (3.4nJ/pulse)
    - 1200 µm, 75mW (230 nJ/pulse)
- **Recent Review Article:**
  - T. Wang and C. Xu, "Three-photon neuronal imaging in deep mouse brain," *Optica* 7, 947-960 (2020).

Sample:
- Thy1-YFP male mouse, 21-week old
- Window was centered at 2.5 mm lateral and 2 mm posterior from the Bregma - point over somatosensory cortex
- Surgery done by Chunyan Wu, @ Cornell

https://www.osapublishing.org/optica/fulltext.cfm?uri=optica-7-8-947&id=434240

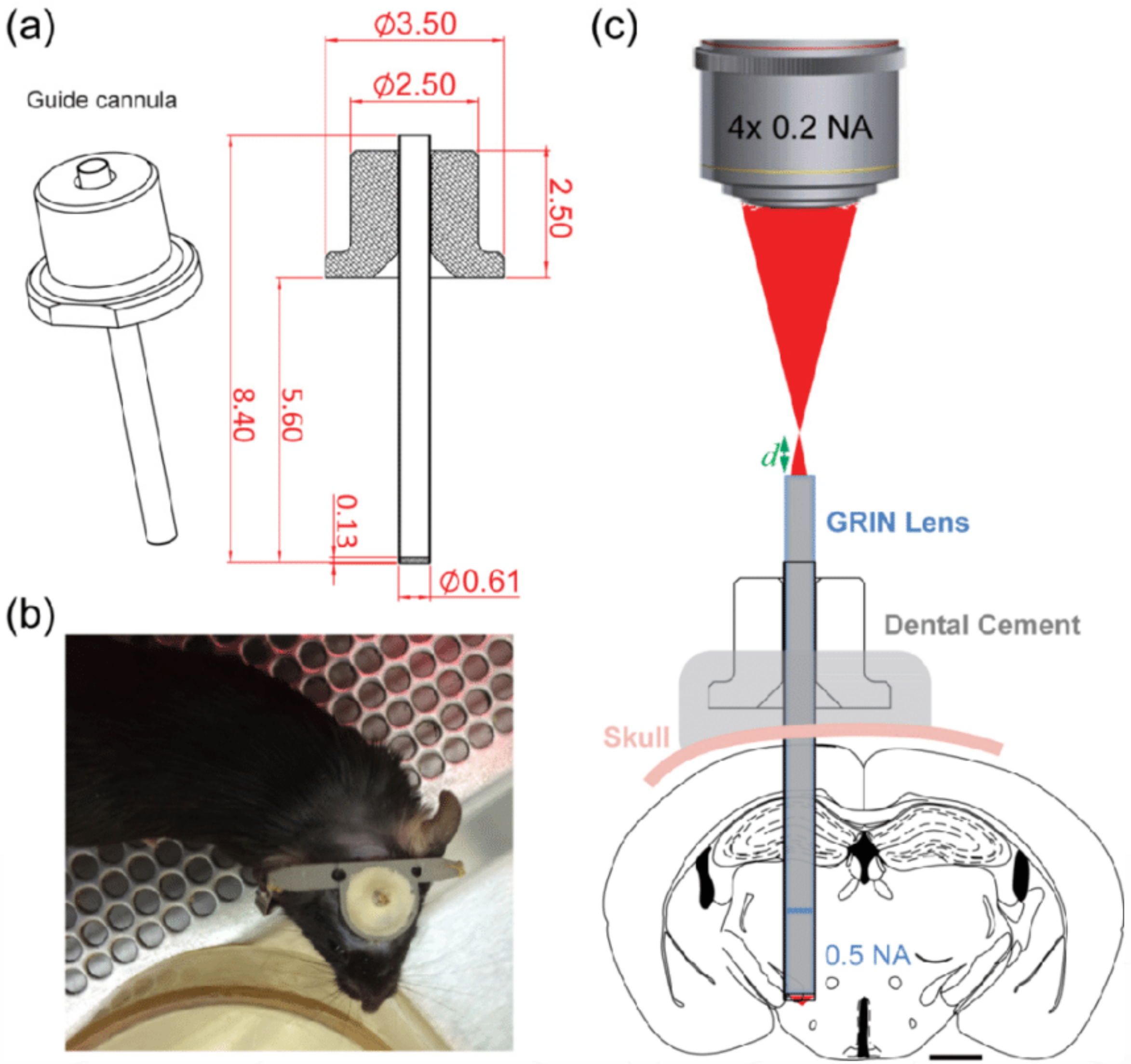
SCN Imaging

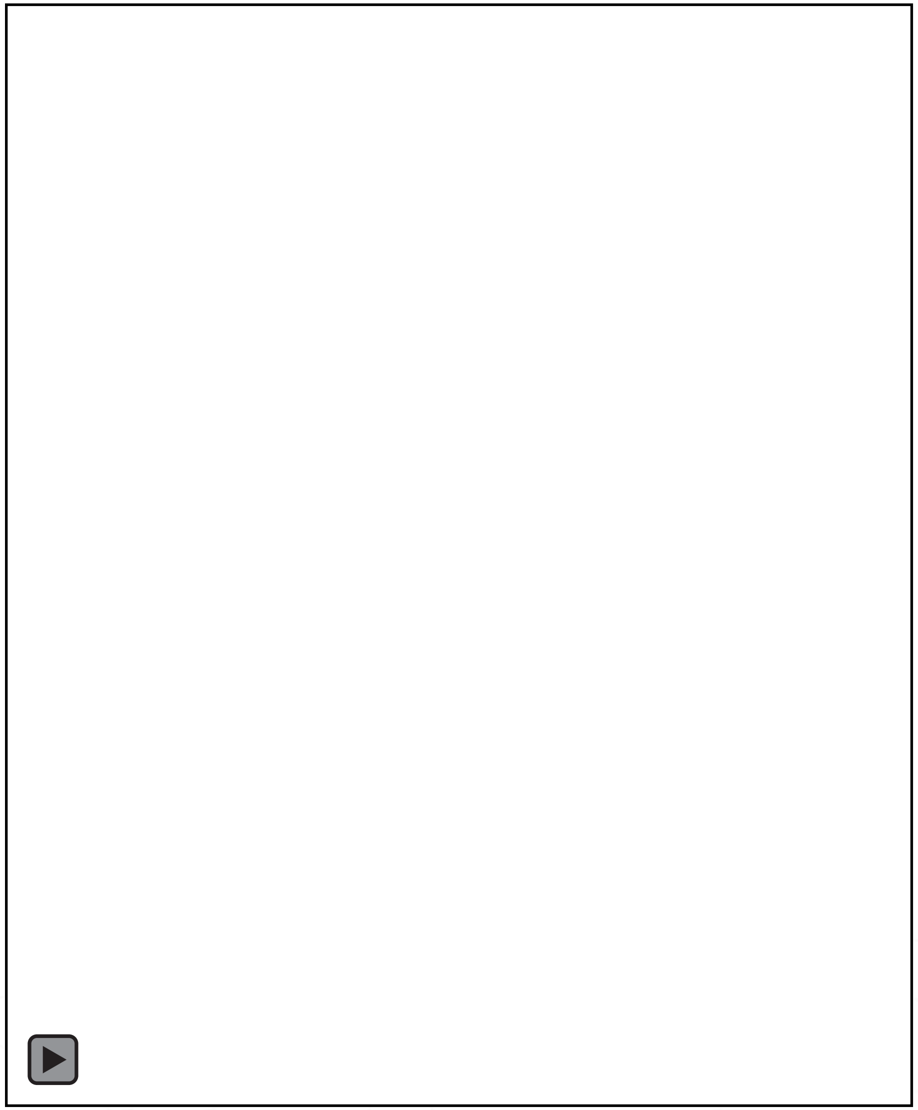


Collaboration with Prof. Chi-Kuang Sun at NTU under MOST program,

Record voxel rate nonlinear optical microscope to unravel brain connectome and signaling

High-speed volumetric and deep brain imaging





https://www.osapublishing.org/boe/fulltext.cfm?uri=boe-6-11-4546&id=331544

Visualization 1- Minimally invasive microendoscopy system for in vivo functional imaging of deep nuclei in the mouse brain

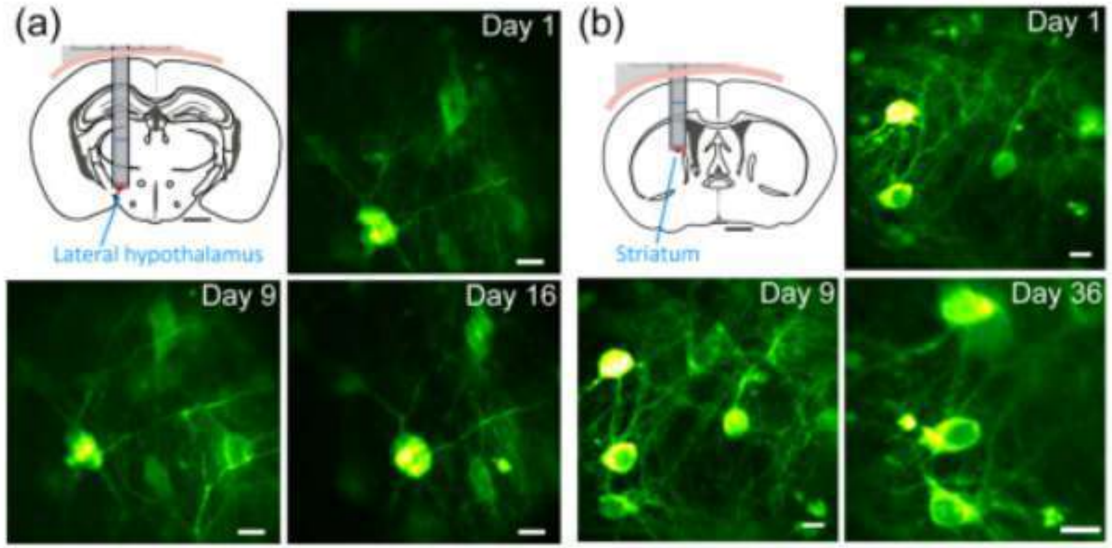
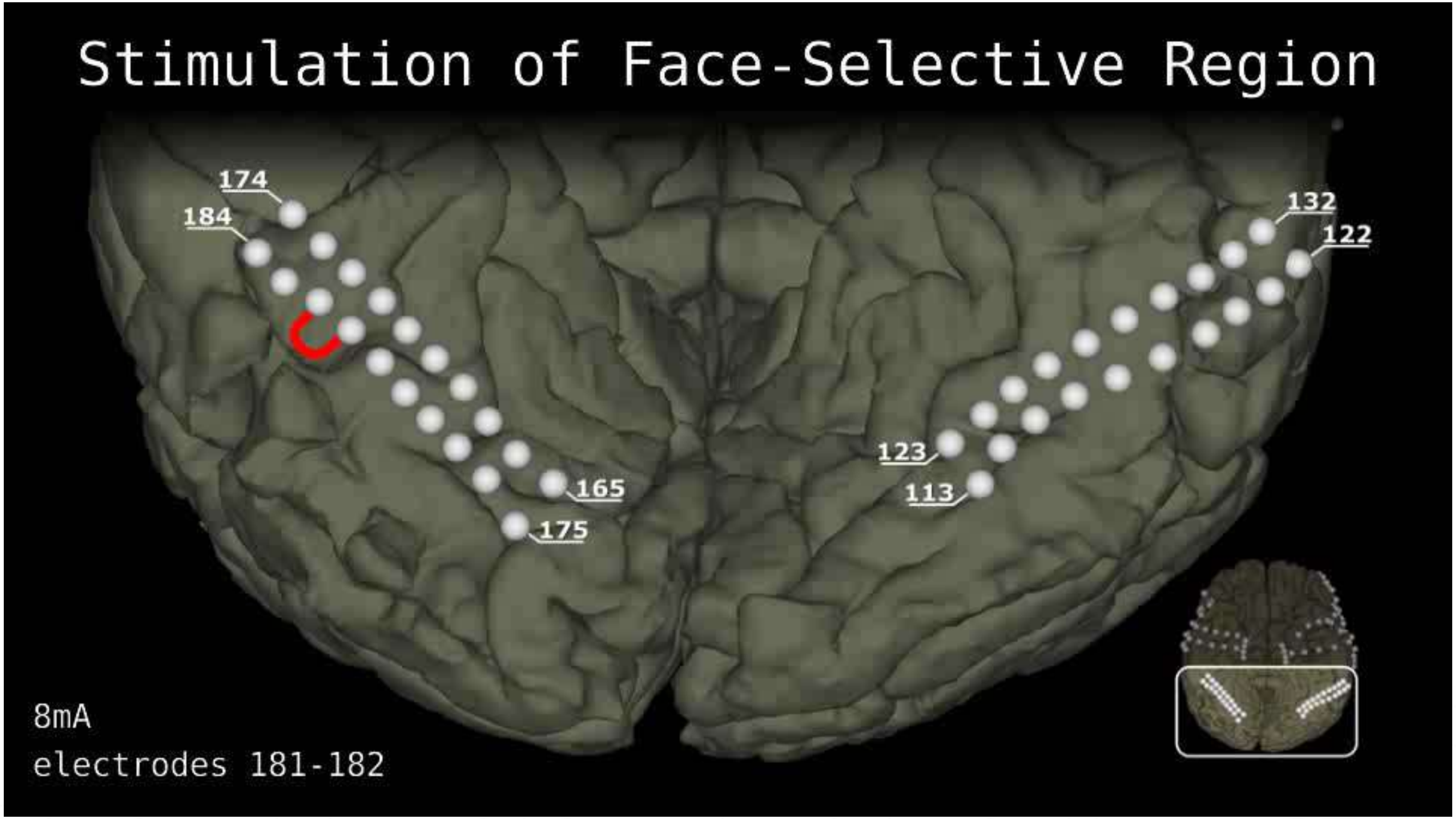


Fig. 4 Chronic *in vivo* images of neurons from deeply buried nuclei of head-fixed awake mice. (a) Two-photon fluorescence endomicroscopy images of neurons in lateral hypothalamus across 16 days. (b) Two-photon fluorescence endomicroscopy images of neurons in striatum across 36 days. The brain, guide cannula, and GRIN lens were drawn to scale. Black scale bar: 1 mm. White scale bar: 20 μm.

https://www.osapublishing.org/boe/fulltext.cfm?uri=boe-6-11-4546&id=331544

The electrical stimulation experiment. Stimulation of the FFA (fusiform face area)



https://www.pnas.org/content/suppl/2017/10/25/1713447114.DCSupplemental

Next:

Nvidia Workshop

NVIDIA DLI
Instructor-Led Workshop
Fundamentals of Deep Learning

NVIDIA DLI Instructor-Led Workshop

Prepare For Your NVIDIA DLI Training

https://developer.nvidia.com/dli/getready

Prepare For Your NVIDIA DLI Training

Thanks for your interest in DLI training. To get the most from your hands-on learning experience, please complete these steps prior to getting started:

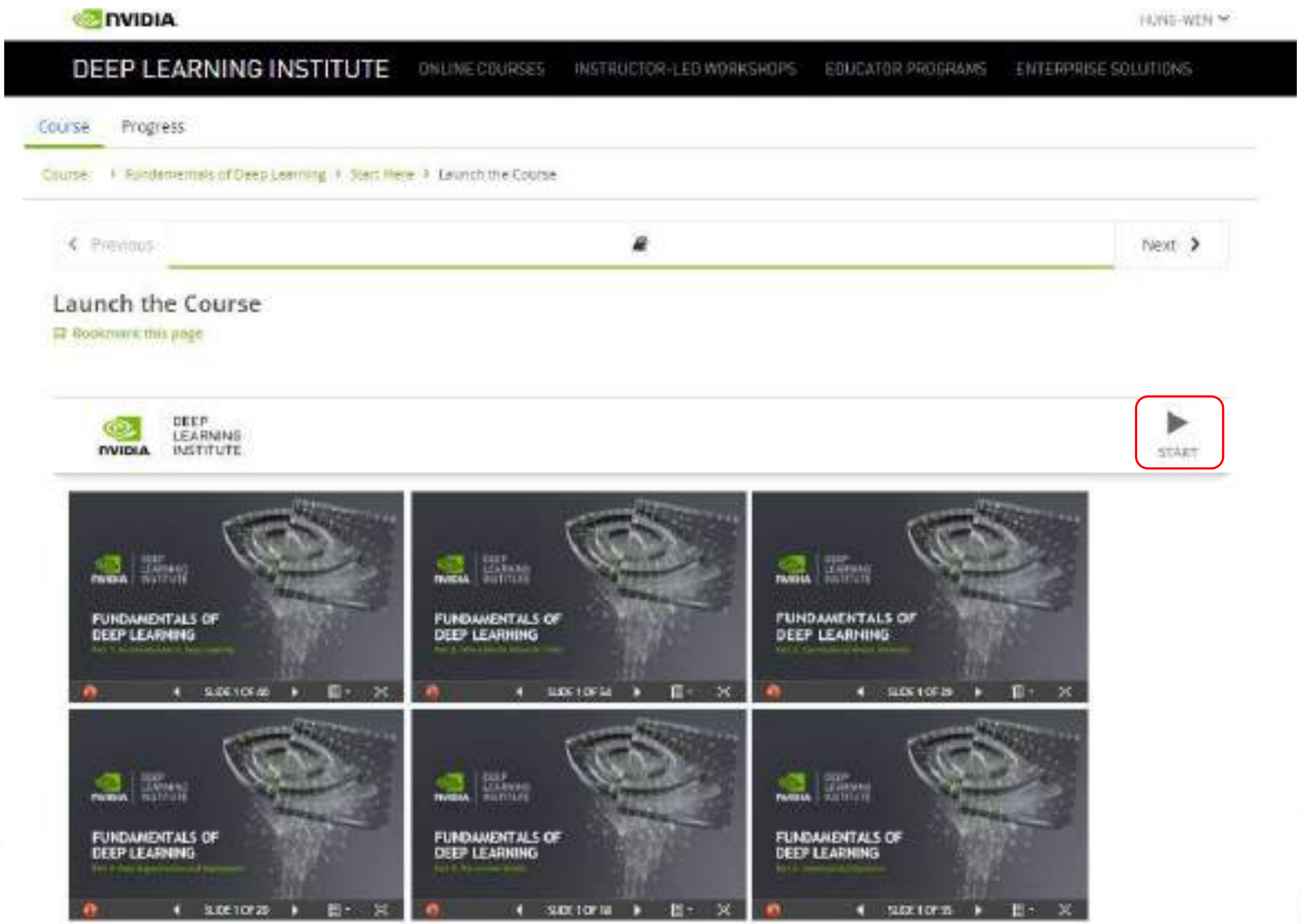
1. **Review the agenda, prerequisites, and suggested material for full-day workshops** (as detailed in the course datasheet below). This is an important step to properly prepare for the workshop.
2. **Create or log into your NVIDIA Developer Program account.** This account will provide you with access to all of the DLI training materials during and after the workshop.
3. **Visit websocketstest.courses.nvidia.com and make sure all three test steps are checked "Yes."** This will test the ability for your system to access and deliver the training contents. If you encounter issues, try updating your browser. Note: Only Chrome and Firefox are supported.
4. **Check your bandwidth.** 1 Mbps downstream is required and 5 Mbps is recommended. This will ensure consistent streaming of audio/video during the workshop to avoid glitches and delays.

Now you're ready to get started with DLI training! Your instructor will provide login instructions and a DLI Event Code. Simply enter the code at courses.nvidia.com/dli-event when you arrive in the classroom. If your instructor is delivering the workshop virtually (i.e. via Zoom, Webex, etc.), they will provide access to that platform separately. We hope you enjoy the training.

Event Code: NTHU_FDL_AMBASSADOR_NO23

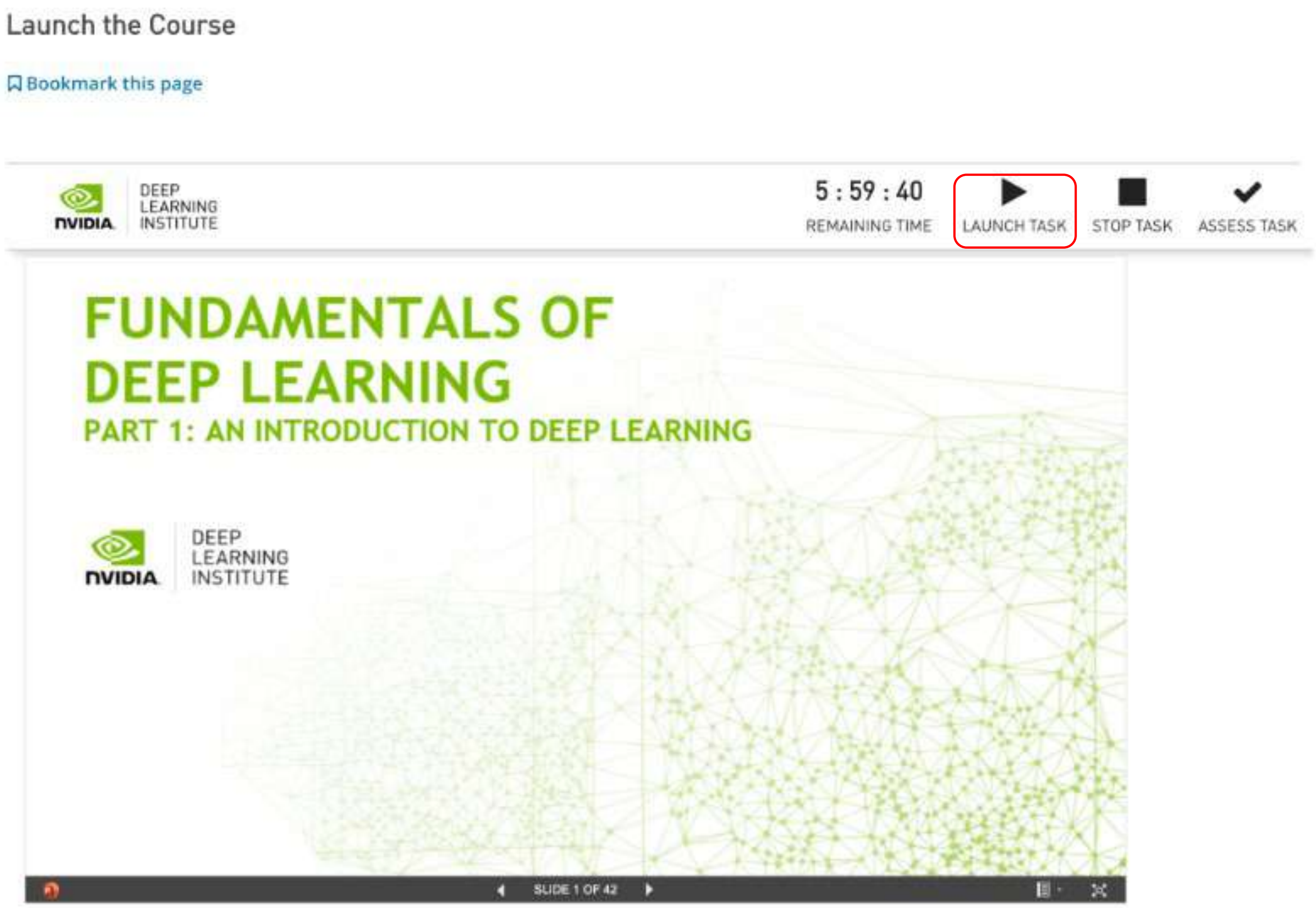
NVIDIA DLI Instructor-Led Workshop

Prepare For Your NVIDIA DLI Training

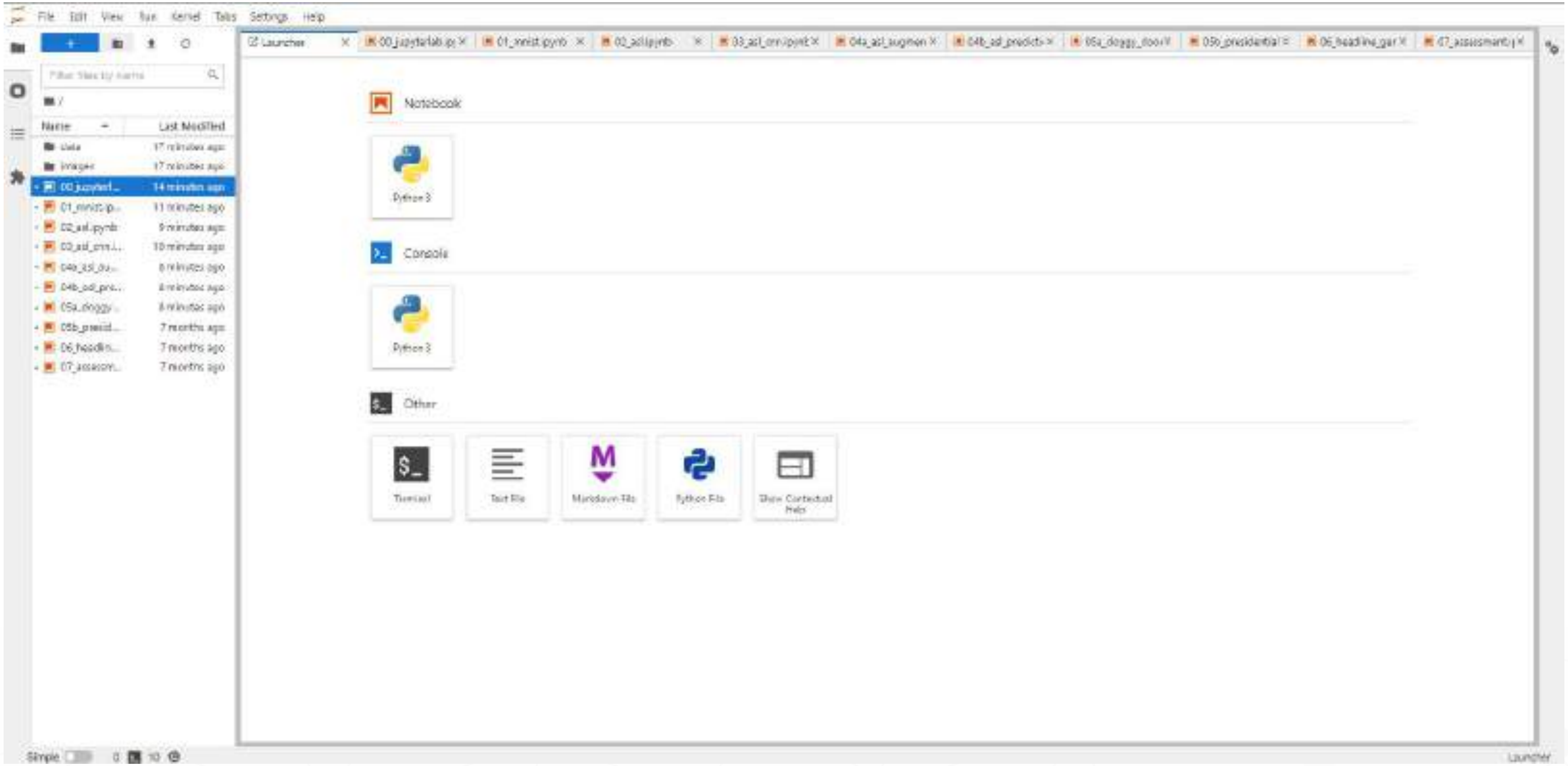


NVIDIA DLI Instructor-Led Workshop

Prepare For Your NVIDIA DLI Training



JupyterLab


File
Edit
View
Run
Kernel
Tabs
Settings
Help
Launcher
Name
Last Modified
Notebook
Python 3
Console
Python 3
Other

NVIDIA DLI Instructor-Led Workshop

Fundamentals of Deep Learning

- **L1 – Simple NN**
- **L2 - NN Training**
- **L3 - Convolutional Neural Networks**
- **L4 - Data Augmentation and Model Deployment**
- **L5 - Pretrained Models and Transfer Learning**
- **L6 - Recurrent Neural Network**
- **L7 - Assessment**

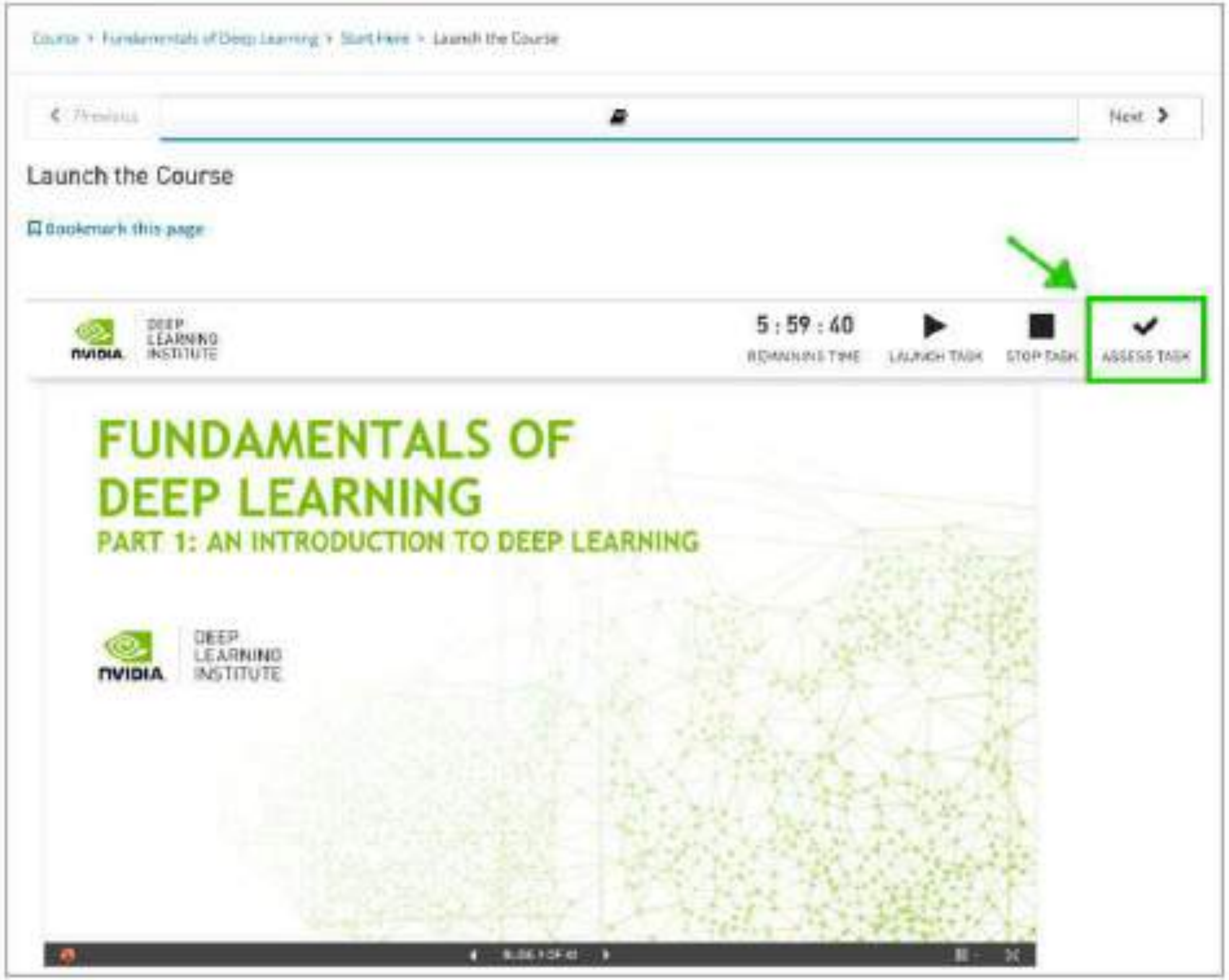
Due on 11/20 23:59

You will need to get the model to a validation accuracy of 92% in order to pass the assessment.
You will have the use the skills that you learned in the previous exercises.
Specifically, we suggest using some combination of transfer learning, data augmentation, and fine tuning.
Once you have trained the model to be at least 92% accurate on the validation dataset, save your model, and then assess its accuracy.

Let's get started!

Generate a Certificate

If you passed the assessment, please return to the course page (shown below) and click the "ASSESS TASK" button, which will generate your certificate for the course.



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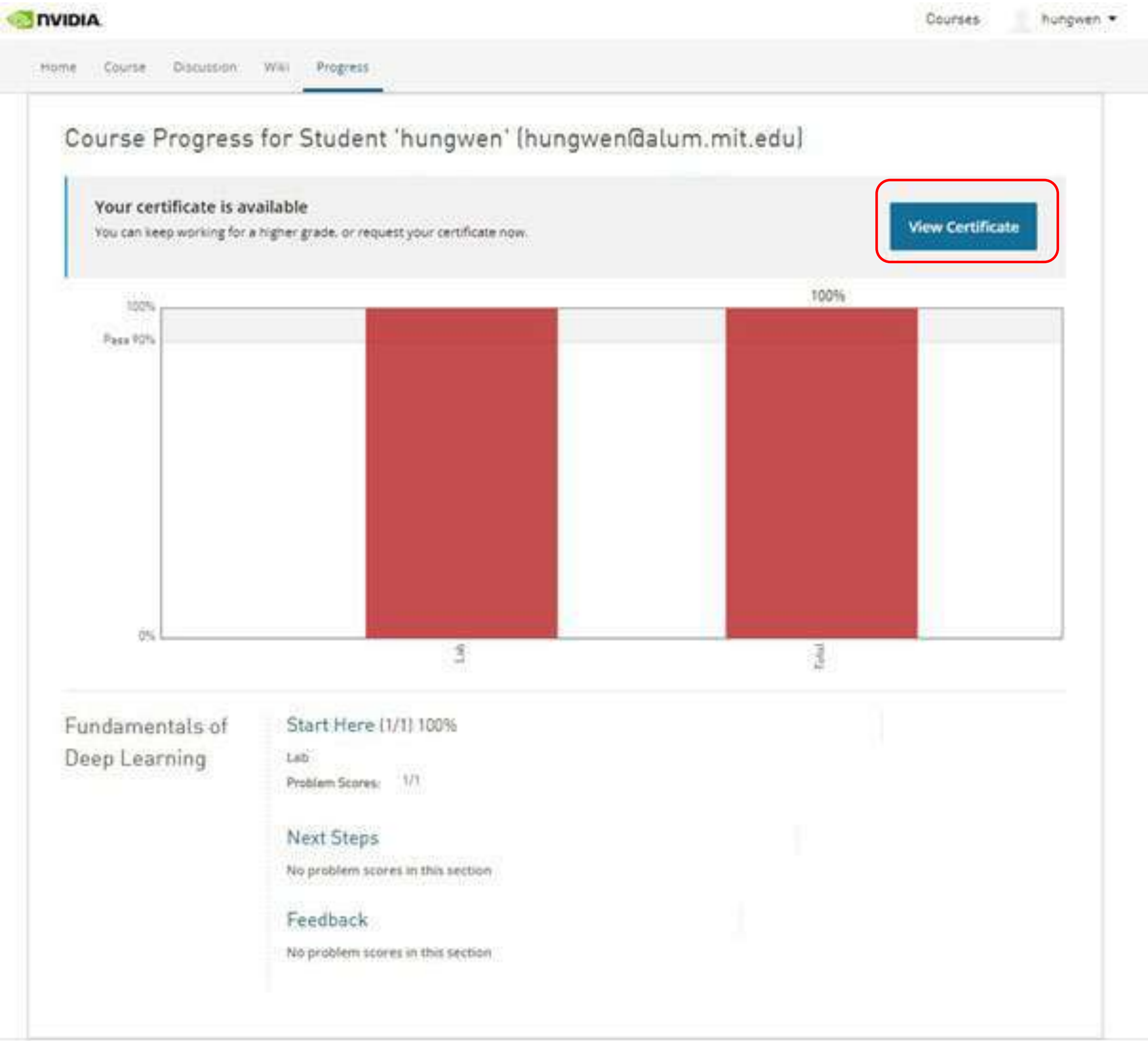

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Will Ramey
Senior Director, Developer Programs, NVIDIA

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