STAT 453: Introduction to Deep Learning and Generative Models

Ben Lengerich

Lecture 01: What are Machine Learning and Deep Learning?

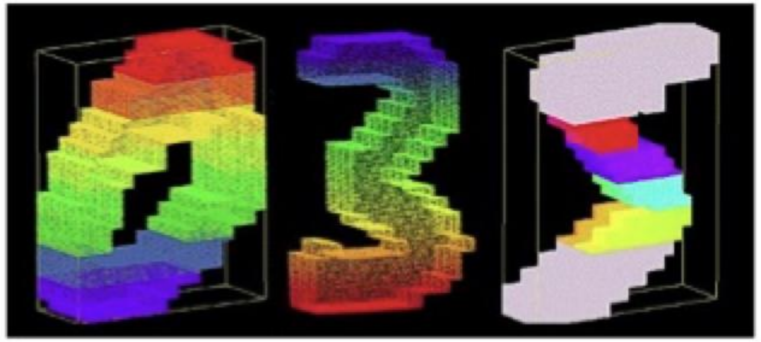
September 3, 2026

Today

1. **Course overview**
2. What is machine learning?
3. The broad categories of ML
4. The supervised learning workflow
5. Necessary ML notation and jargon
6. About the practical aspects and tools

A short teaser:
what you'll be able to do after this course

3D Convolutional Networks



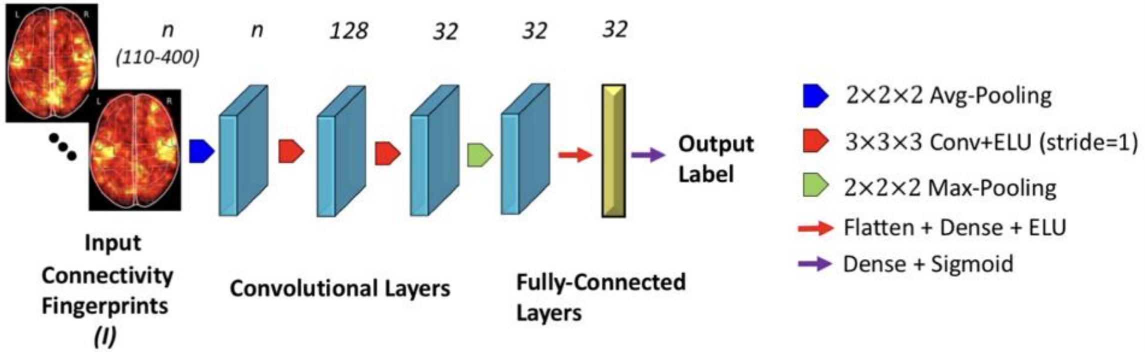
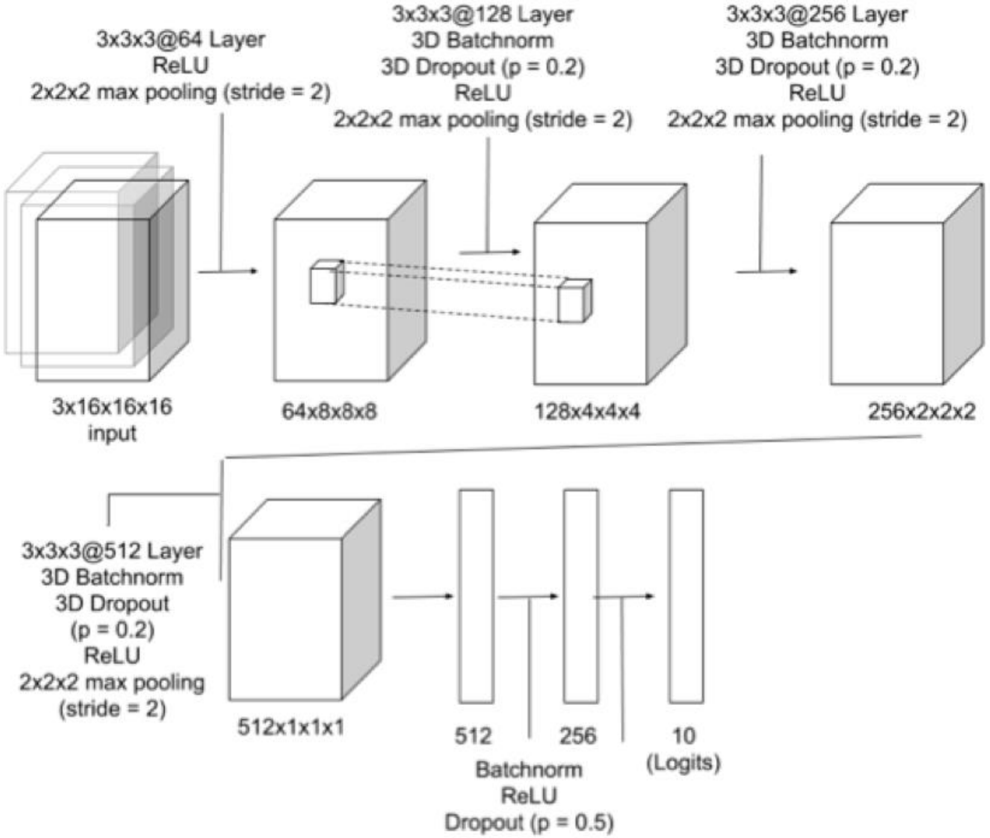


Image Source: 3D Convolutional Neural Networks for Classification of Functional Connectomes. https://arxiv.org/abs/1806.04209



Audio Classification Using Convolutional Neural Networks

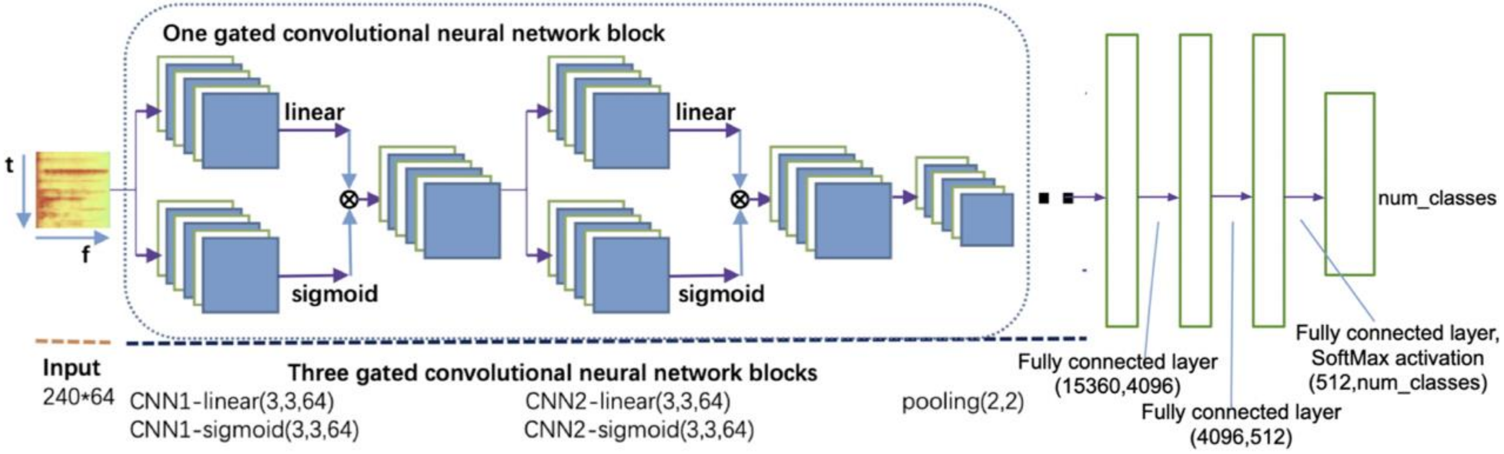
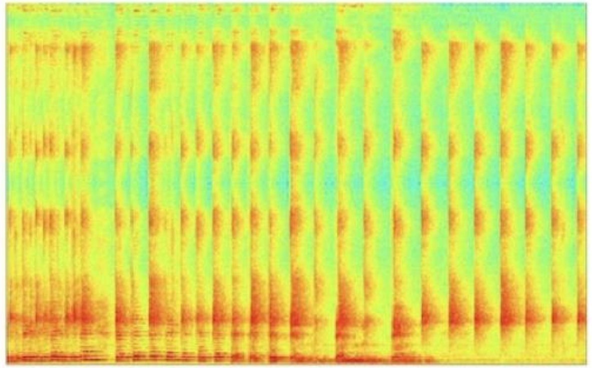
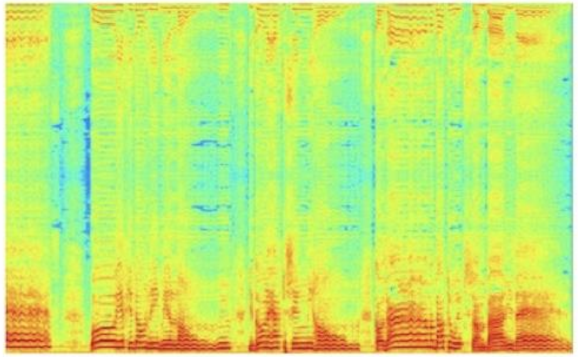


Figure 2. Gated Convolutional Neural Network with Multi-Layered Classification Model

Spectogram of an audio clip corresponding to "finger snapping:"



Spectogram of an audio clip corresponding to "synthetic singing:"



Photographic Style Transfer with Deep Learning


Guernica


Model Result


Sandstone


Model Result

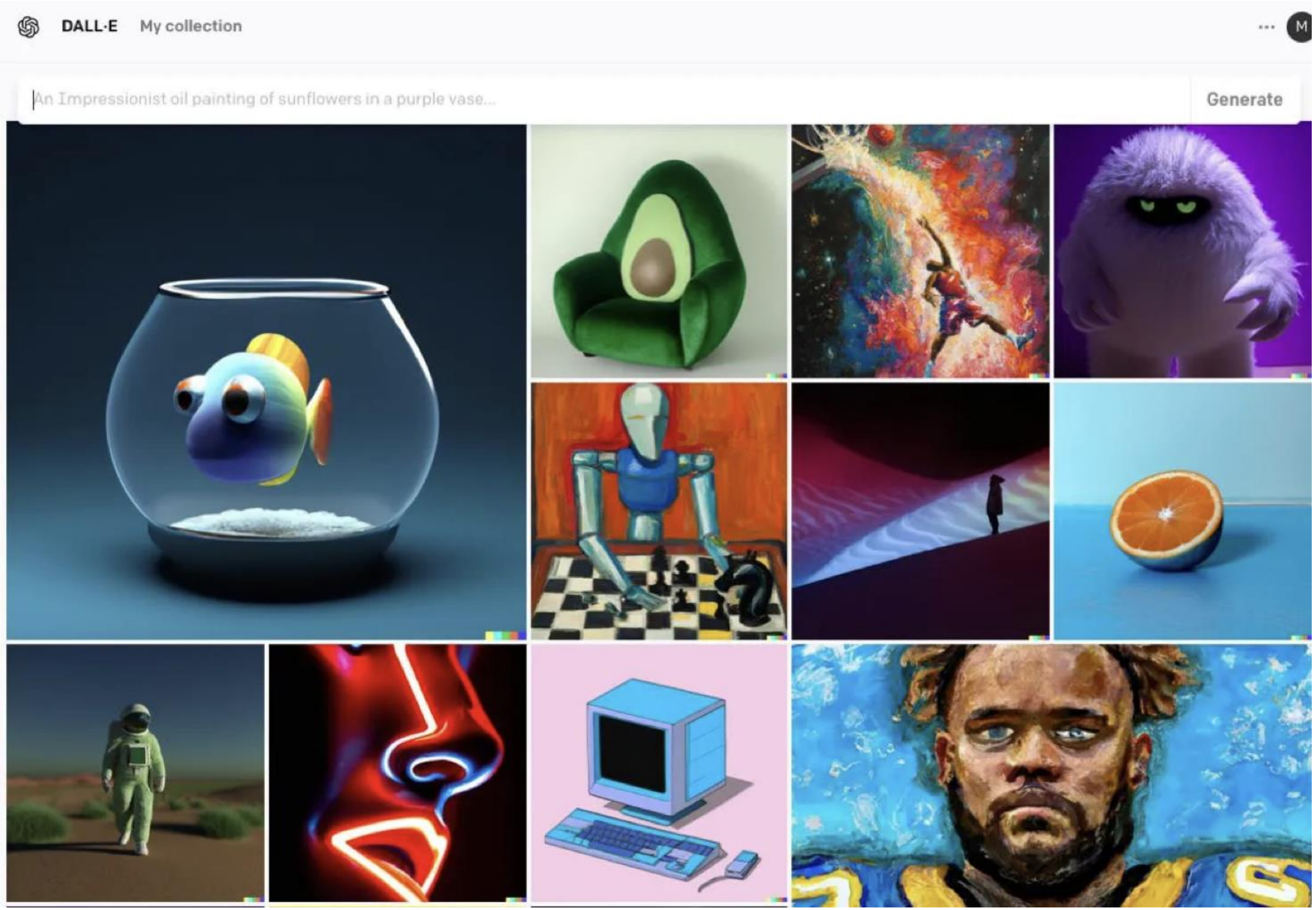

Water Drop


Model Result

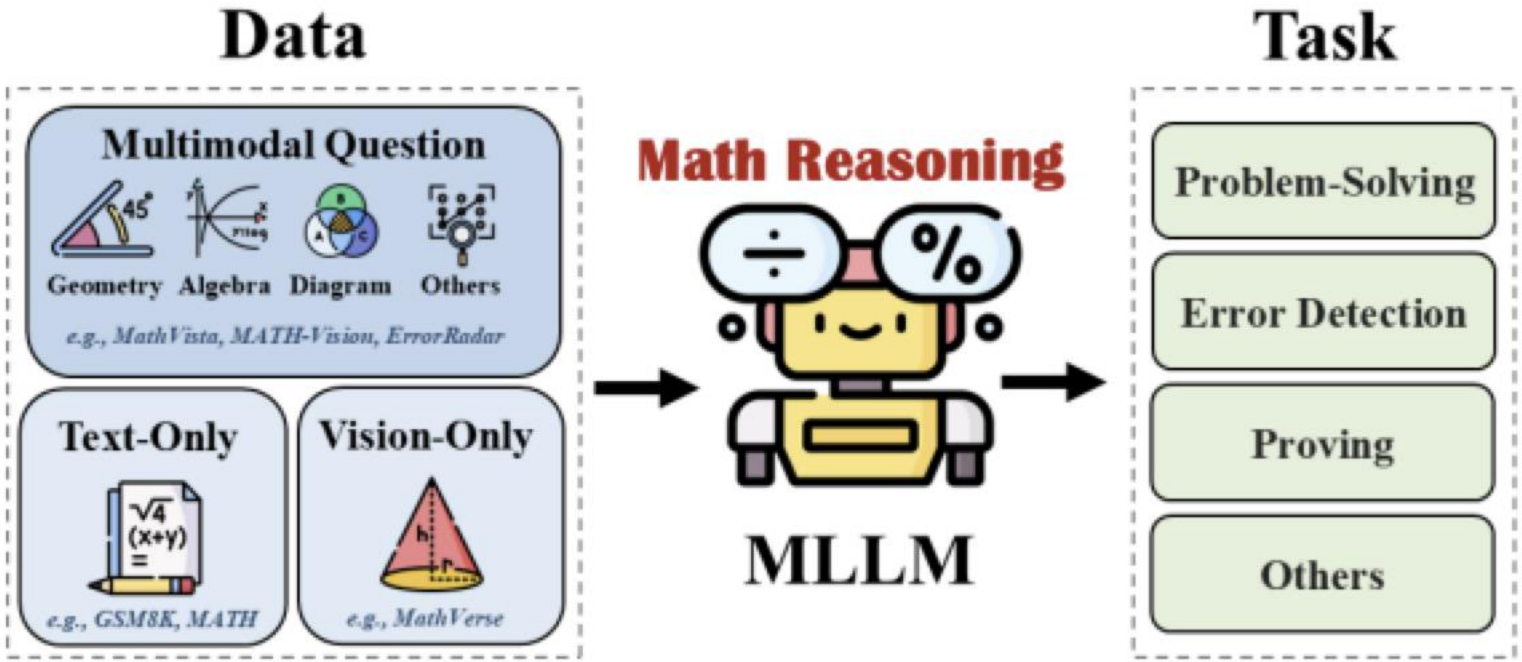

Skrik


Model Result

Diffusion model and image generation



Large language model and agents



Some course projects from prior years

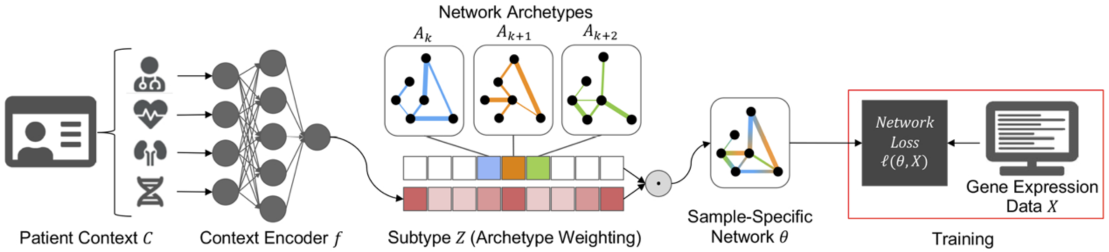
- Spring 2023
  - Breast Cancer detection using ultrasound imaging
  - LSTM music generation
  - Predicting stock prices using LSTMs
  - Creating Surrealism Artworks with DCGAN
  - Exploring the Impact of Activation Functions and Normalization Techniques
- Spring 2024
  - Gradio framework with self-supervised learning
  - Song generation
  - Diagnosis of Chest X-ray Images
  - Audio-to-video image animation
  - Movie recommendations
  - Sentiment analysis using BERT

A bit about your instructor

My research interests

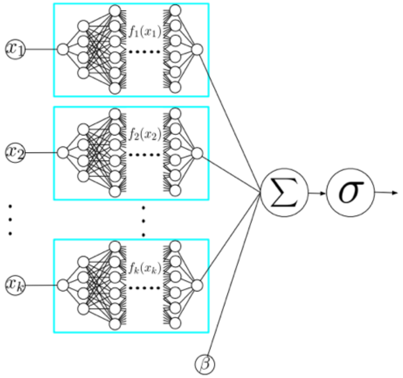
Research Group: adaptinfer.org

Contextualized models



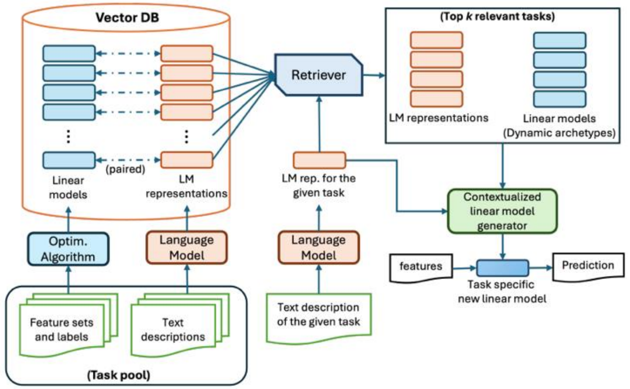
Ellington, Lengerich, Watkins et al. (2025)
Learning to estimate sample-specific transcriptional networks for 7000 tumors.
Proceedings of the National Academy of Sciences (PNAS).

Interpretability and Modularity

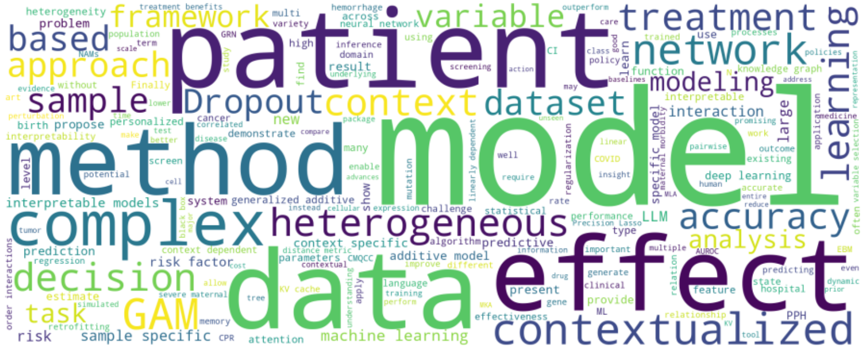


Agarwal, Melnick, Frosst, Zhang, Lengerich, Caruana, Hinton (2021)
Neural Additive Models: Interpretable Machine Learning with Neural Nets.
NeurIPS 2021.

Foundation models as context

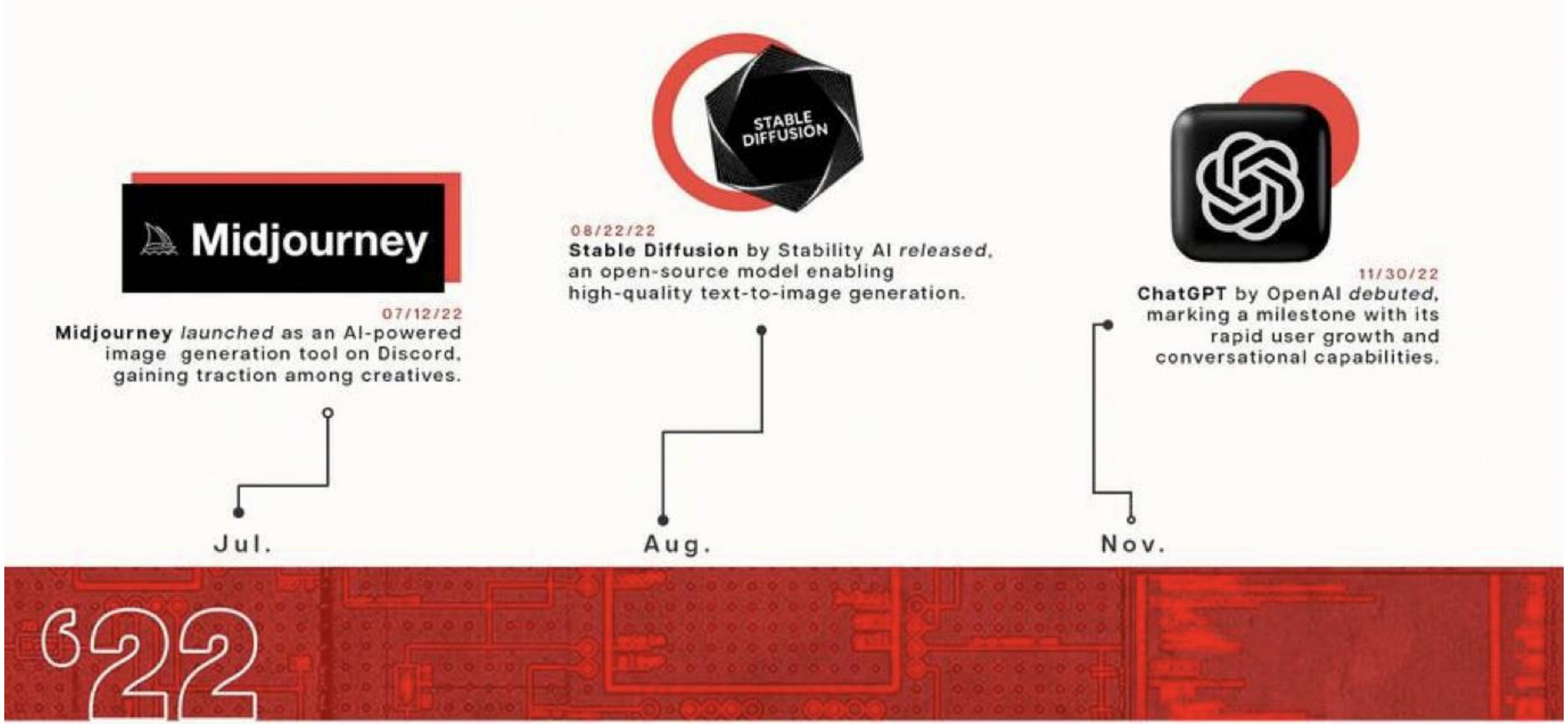


Mahbub, Ellington, Alinejad, Wen, Luo, Lengerich, Xing. (2024)
From One to Zero: RAG-IM Adapts Language Models for Interpretable Zero-Shot Clinical Predictions
NeurIPS Workshop on Adaptive Foundation Models.



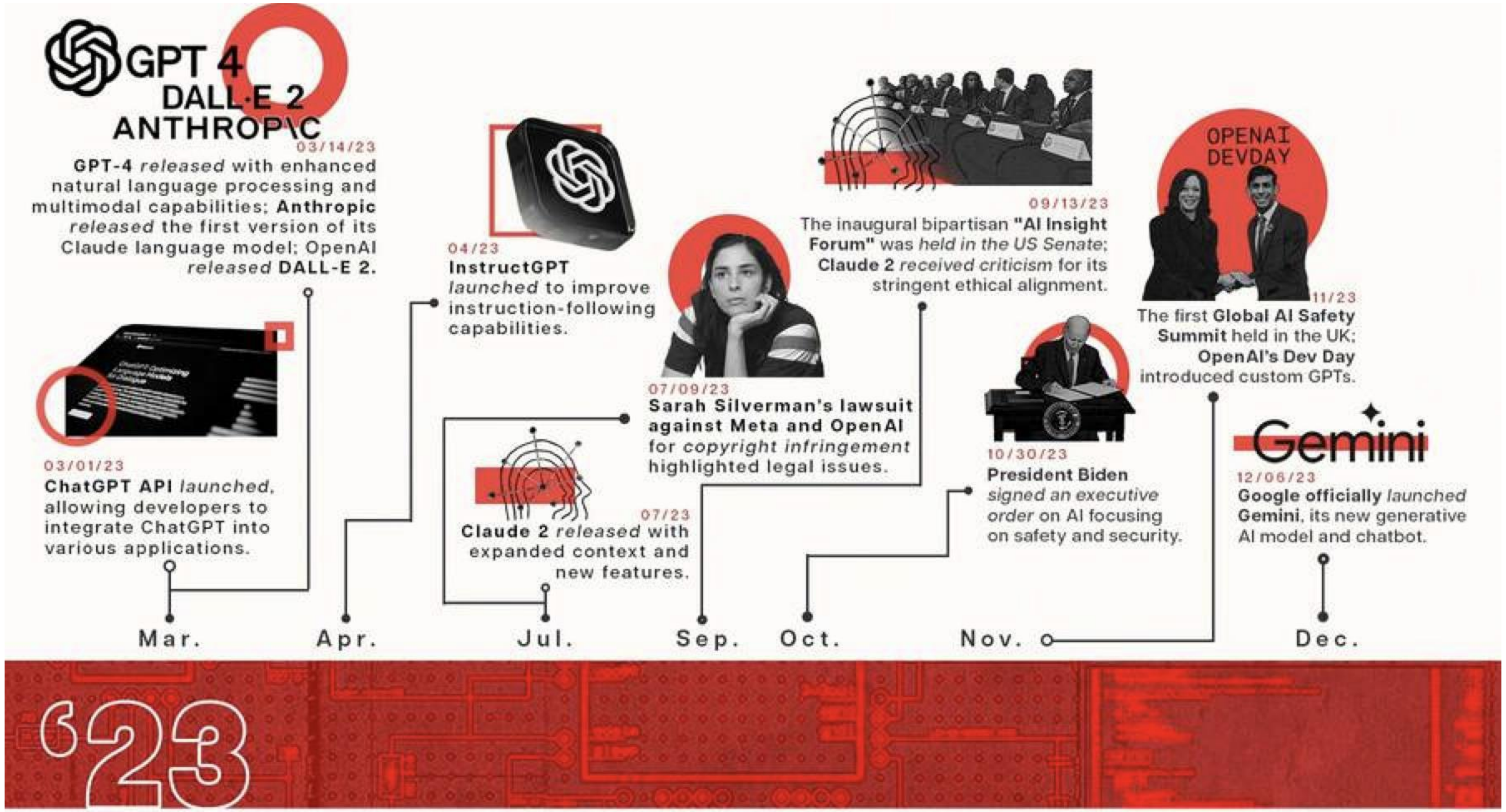
About the course

The AI Revolution



Source

The AI Revolution



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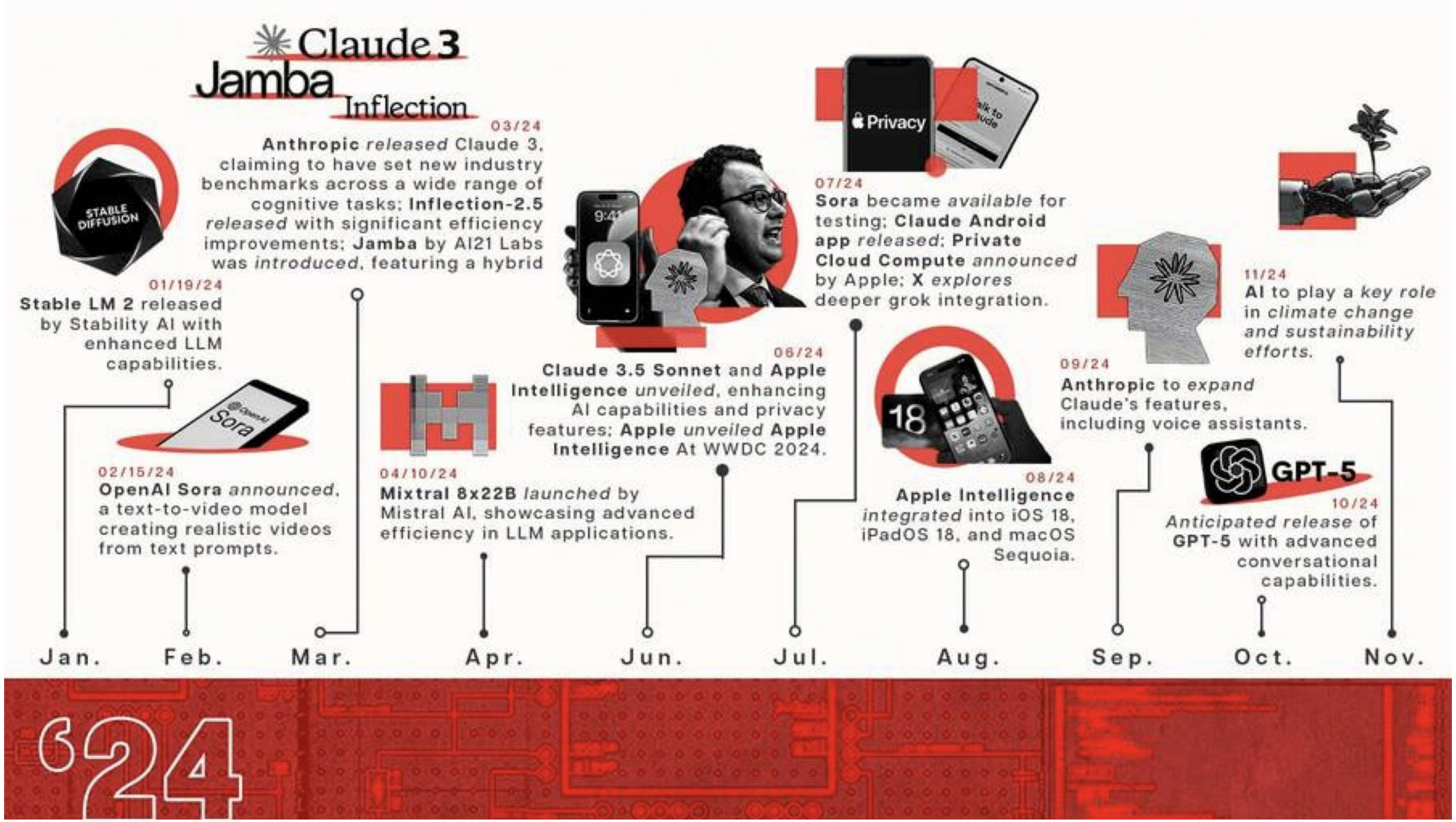
The AI Revolution



[Source]

The AI Revolution

NVIDIA Corporation • NASDAQ:NVDA

174.11 USD +161.55 (+1,279.10%) ↑

Friday, 4:00 PM GMT-4 • Disclaimer

1 Day | 5 Days | 1 Month | Ytd | 1 Year | **5 Years** | Max

Open	178.11	Mkt Cap	4.25T	Prev close	180.17
High	178.15	P/E ratio	48.99	52W high	184.48
Low	173.15	Volume	243M	52W low	86.62

Course Schedule / Calendar

Date	Lecture
9/3	Lecture #1 (Prof. Lengerich): **Course Introduction** [slides I notes]
9/8	Lecture #2 (Prof. Lengerich): **A Brief History of Deep Learning** [slides I notes]
9/10	Lecture #3 (Prof. Lengerich): **Statistics, Linear Algebra, and Calculus Review** [slides I notes]
9/15	Lecture #4 (Prof. Lengerich): **Single-layer networks** [slides I notes]
9/17	Lecture #5 (Prof. Lengerich): **Parameter Optimization and Gradient Descent** [slides I notes]
9/22	Lecture #6 (Prof. Lengerich): **Automatic differentiation with PyTorch; Project Discussion** [slides I notes]
9/24	Lecture #7 (Prof. Lengerich): **Multi-layer perceptrons and backpropagation** [slides I notes]
9/29	Lecture #8 (Prof. Lengerich): **Structure and weight sharing; CNNs** [slides I notes]
10/1	Lecture #9 (Prof. Lengerich): **Regularization** [slides I notes]
10/6	Lecture #10 (Prof. Lengerich): **Normalization and Initialization** [slides I notes]
10/8	Lecture #11 (Prof. Lengerich): **Optimization and learning rates** [slides I notes]
10/13	Lecture #12 (Prof. Lengerich): **Review** [slides I notes]
10/20	Lecture #13 (Prof. Lengerich): **A linear introduction to generative models** [slides I notes]
10/22	Lecture #14 (Prof. Lengerich): **Factor Analysis, Autoencoders, VAEs** [slides I notes]
10/27	Lecture #15 (Prof. Lengerich): **Generative Adversarial Networks** [slides I notes]
10/29	Lecture #16 (Prof. Lengerich): **Diffusion Models** [slides I notes]

	Module 4: S
11/3	Lecture #17 (Prof. Lengerich): **Sequence Learning with RNNs** [slides I notes]
11/5	Lecture #18 (Prof. Lengerich): **Attention, Transformers** [slides I notes]
11/10	Lecture #19 (Prof. Lengerich): **GPT Architectures** [slides I notes]
11/12	Lecture #20 (Prof. Lengerich): **Unsupervised Training of LLMs** [slides I notes]
11/17	Lecture #21 (Prof. Lengerich): **Aligning LLMs: SFT, RLHF, and DPO** [slides I notes]
11/19	Lecture #22 (Prof. Lengerich): **Reasoning Models and RL from Verifiable Rewards** [slides I notes]
11/24	Lecture #23 (Prof. Lengerich): **Parameter-Efficient Fine-tuning: LoRA, Adapters, and Prompting** [slides I notes]

	Module 5: Student Presentations & Wrap-up		
12/1	**Student Project Presentations**		
12/3	**Student Project Presentations**		
12/8	Lecture #24 (Prof. Lengerich): **Review & Open Directions** [slides I notes]	• {"Yao et al., ReAct"=>"Synergizing Reasoning and Acting in Language Models"}	Project final report due Fri 12/11
12/11	**Final Exam** (exam period Dec 11-17; exact date/time TBD pending registrar block schedule)		

Course webpage

adaptinfer.org/dgm-fall-2026

STAT 453 — logistics | lectures | notes | calendar | homework | project

Deep Learning and Generative Models

STAT 453 • Fall 2026 • UW-Madison

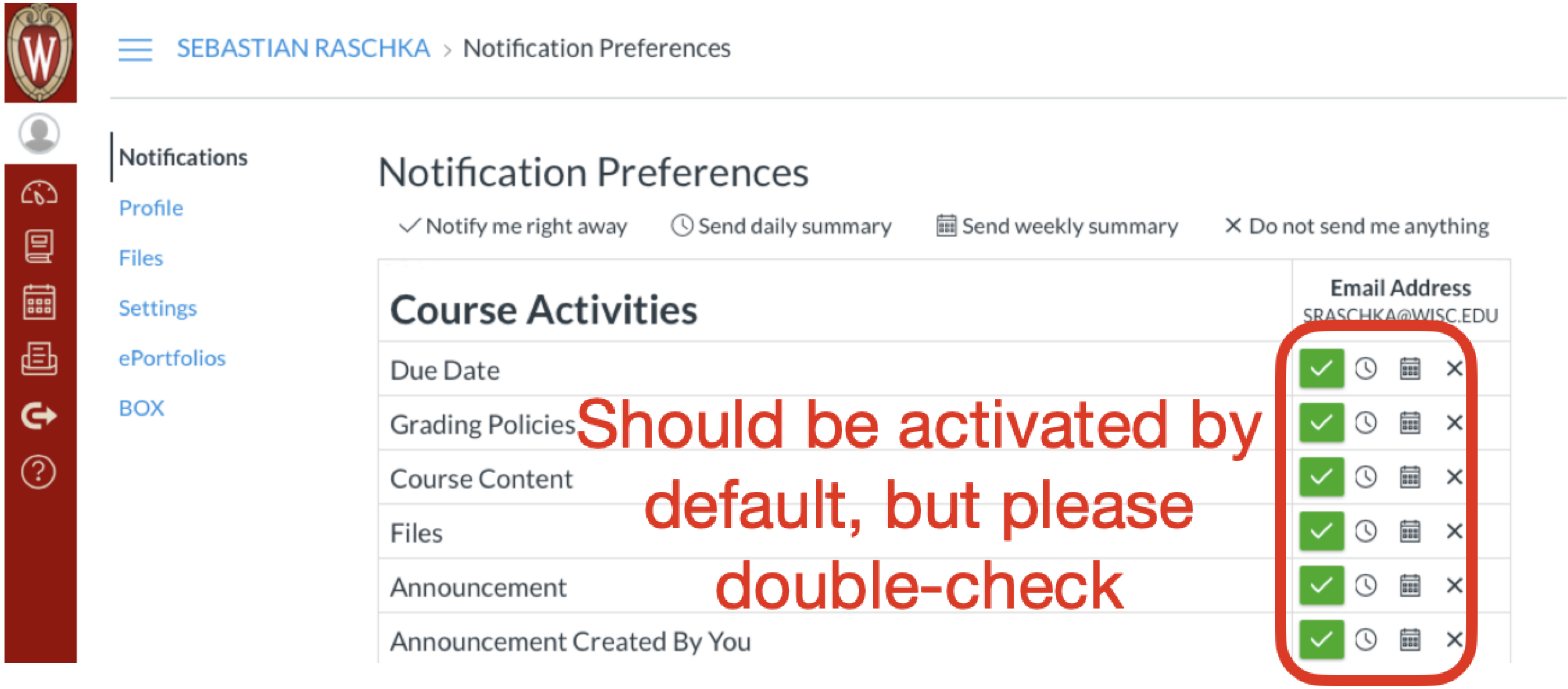
- **Time:** Tuesday/Thursday 9:30-10:45am
- **Location:** Morgridge B2590
- **Discussion:** Canvas
- **HW submission:** Canvas
- **Contact:** Students should ask all course-related questions on Canvas, where you will also find announcements. Individual enquires can be directed to TA/instructor emails.

Instructor Benjamin Lengerich
Email: lengerich@wisc.edu
Office hours: Tuesdays 11:00am-12:00pm, Morgridge 5530

TA Baiheng Chen
Email: bchen342@wisc.edu
Office hours: TBD

+ Canvas for assignments / submissions / grades

Check your settings on Canvas



Logistics

- Textbook:
  - Readings will be provided.
- Class Announcements: **Canvas**
- Assignment Submissions: **Canvas**
- Instructor: **Ben Lengerich**
  - Office Hours: Thursdays 11am-12pm, Morgridge 5530
  - Email: lengerich@wisc.edu
- TA: **Baiheng Chen**
  - Office Hours: TBD
  - Email: bchen342@wisc.edu

Grading

- **20% HW Assignments**
- **20% Midterm Exam**
  - Tentatively: 10/25
  - Format: In-class, Open-notes. No calculator / phone / AI allowed.
- **30% Final Exam**
  - To be scheduled by registrar
  - Format: Location TBA. Open-notes. No calculator / phone / AI allowed.
- **30% Final Project**
  - Milestones dues along the way
- **Lecture Notes** (up to 5% extra credit)

Extra Credit: Lecture Notes

- **Opportunity:** Sign up to write lecture notes for each lecture. If the notes meet quality standards, students will receive +2% extra credit added to their final grade.
  - **Sign-up sheet**
  - You are expected to work together with the other scribe(s) to submit 1 note document for the lecture.
  - Accepted notes will be hosted on our course webpage (optionally with your name attached, your choice).
- **Submission:** Submit via GitHub Pull Request for the course webpage.
  - Lecture notes must be submitted within one week.
- **Template** is available on the webpage.

Extra Credit: Lecture Notes (cont.)

- **Opportunity:** You can also receive +1% by making a material improvement to a classmate's lecture note.
- Notes will be posted on the course's GitHub page; if you see an opportunity to improve a classmate's lecture note, submit a GitHub Pull Request with the improvement.
- You can do this up to 3 times for credit.
- Max extra credit is 5%:
  - 2% for a planned lecture note
  - 3 x 1% for improvements to classmate's lecture notes

Grading Scale

- **No curving:**
  - A: 93–100%
  - AB: 88–92%
  - B: 83–87%
  - BC: 78–82%
  - C: 70–77%
  - D: 60–69%
  - F: Below 60%

Homework Policies

- Assignments must be submitted via Canvas by the deadline (typically Fridays at 11:59 PM).
- **Late submissions** will incur a penalty of 10% per day, up to three days, at which they will not be accepted.
- **Collaboration:** Students may collaborate on understanding the problems, but all submitted work must be individual. Use of AI tools is allowed, but answers must reflect your own understanding. You are responsible for ensuring no plagiarism.

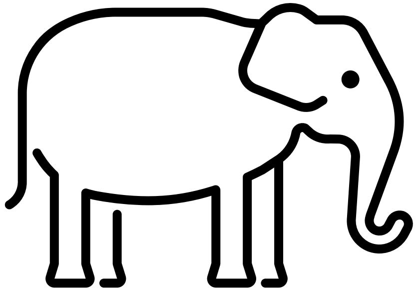
Project

- **Proposal** (5%)
- **Midway Report** (5%)
- **Presentation** (5%)
- **Report** (15%)
- **Collaboration:** Teams of up to four students are allowed.
- **Honors Optional Component:** Individual extension to your project. Email me!

Attendance / Participation

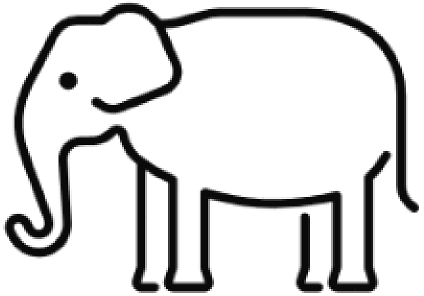
- Attendance and participation are expected, though they are not part of the formal grade calculation.
- Contact the instructor in advance of extended absences.

My philosophy


Lectures


Readings


Homeworks


Quizzes/Exams

Academic Integrity

- By virtue of enrollment, each student agrees to uphold the high academic standards of the University of Wisconsin–Madison; academic misconduct is behavior that negatively impacts the integrity of the institution. Cheating, fabrication, plagiarism, unauthorized collaboration and helping others commit these previously listed acts are examples of misconduct which may result in disciplinary action. Examples of disciplinary sanctions include, but are not limited to, failure on the assignment/course, written reprimand, disciplinary probation, suspension or expulsion.

Mental Health & Wellbeing

- Students often experience stressors that can impact both their academic experience and personal well-being. These may include mental health concerns, substance misuse, sexual or relationship violence, family circumstances, campus climate, financial matters, among others.

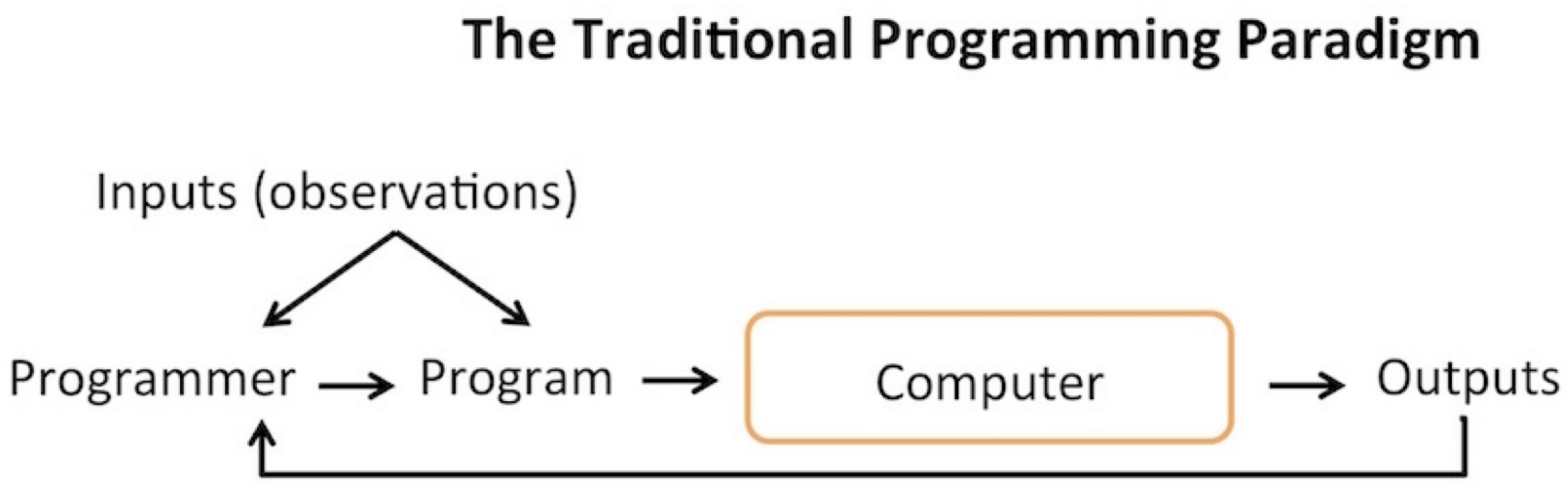
- UW–Madison students are encouraged to learn about and utilize the university's mental health services and/or other resources as needed. Students can visit **uhs.wisc.edu** or call **University Health Services** at **(608) 265-5600** to learn more.

Questions about Course Logistics?

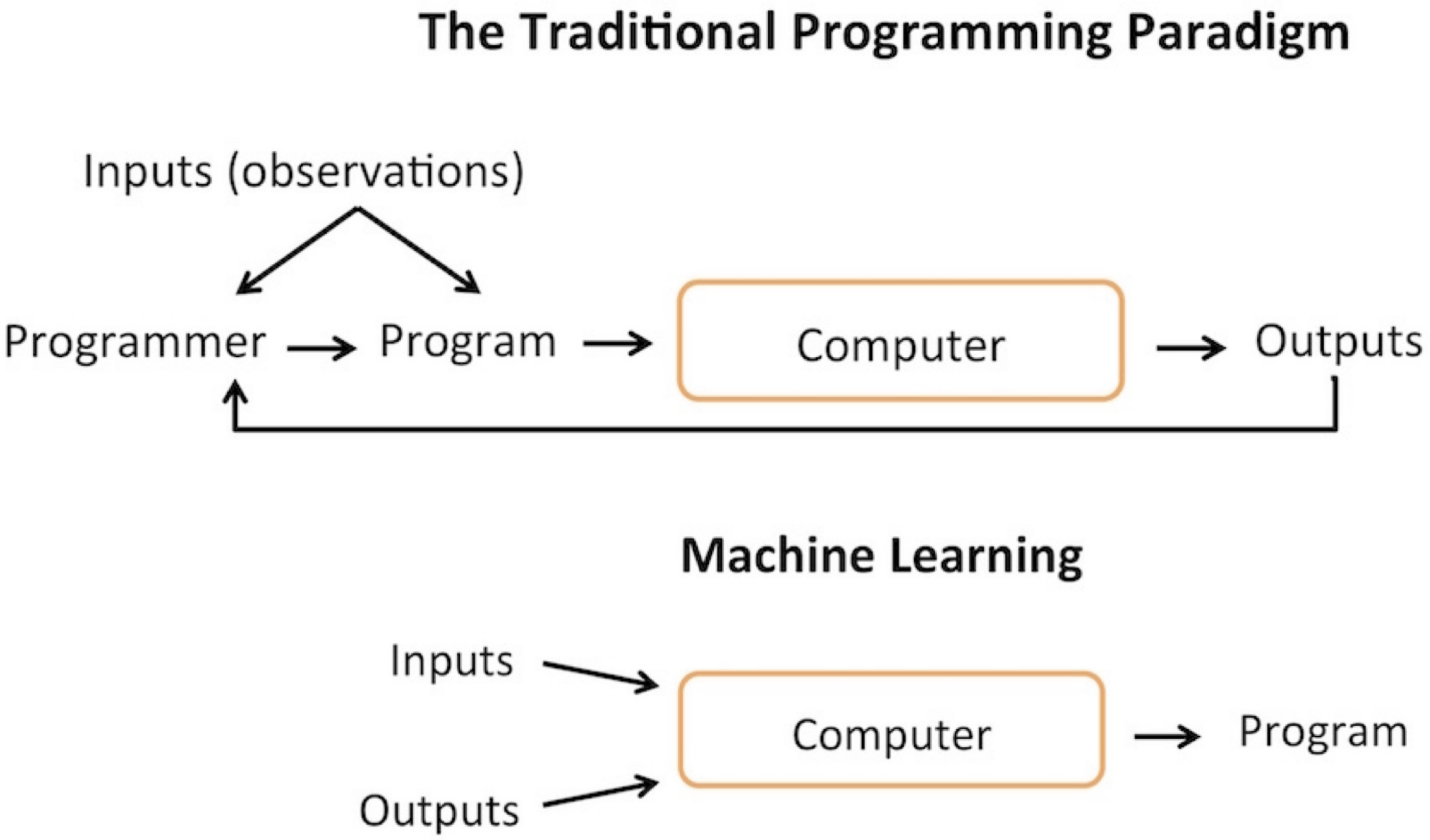
Today

1. Course overview
2. **What is machine learning?**
3. The broad categories of ML
4. The supervised learning workflow
5. Necessary ML notation and jargon
6. About the practical aspects and tools

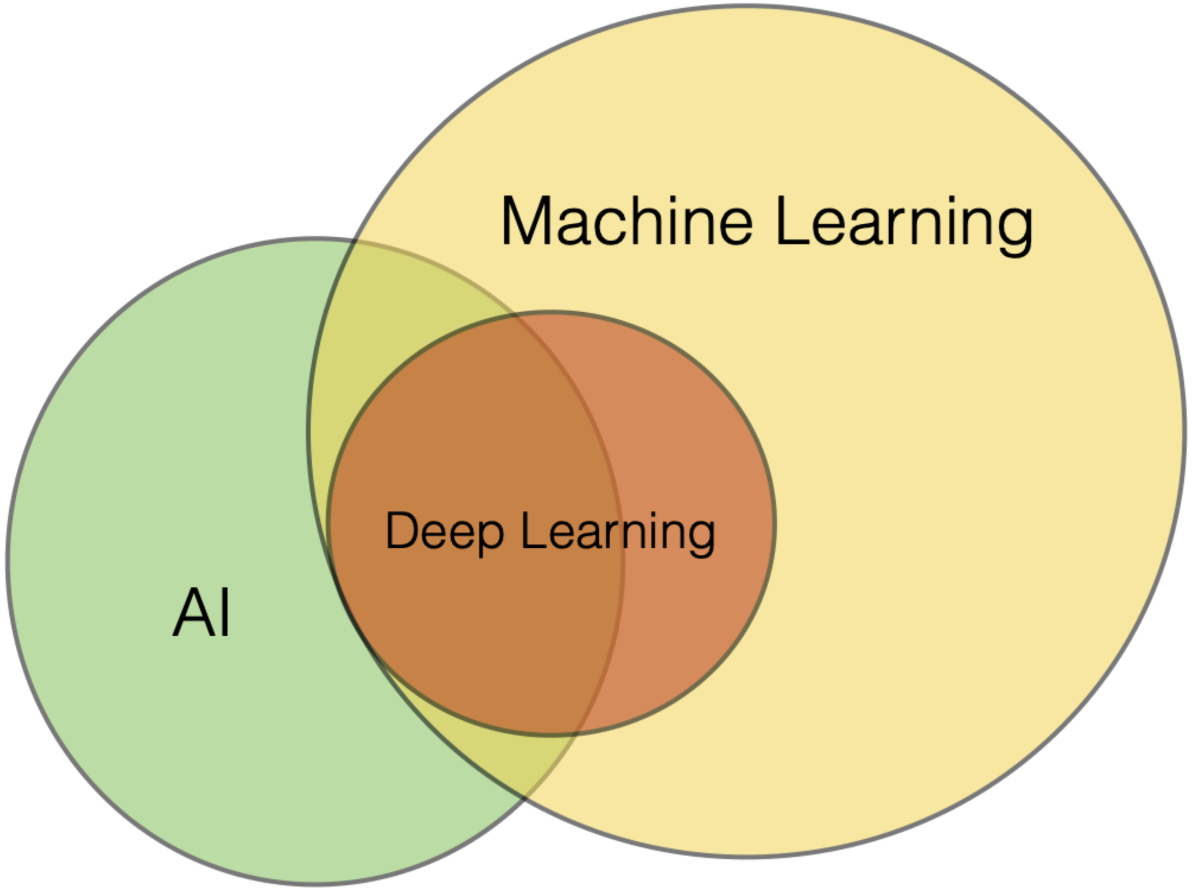
What is Machine Learning?



What is Machine Learning?



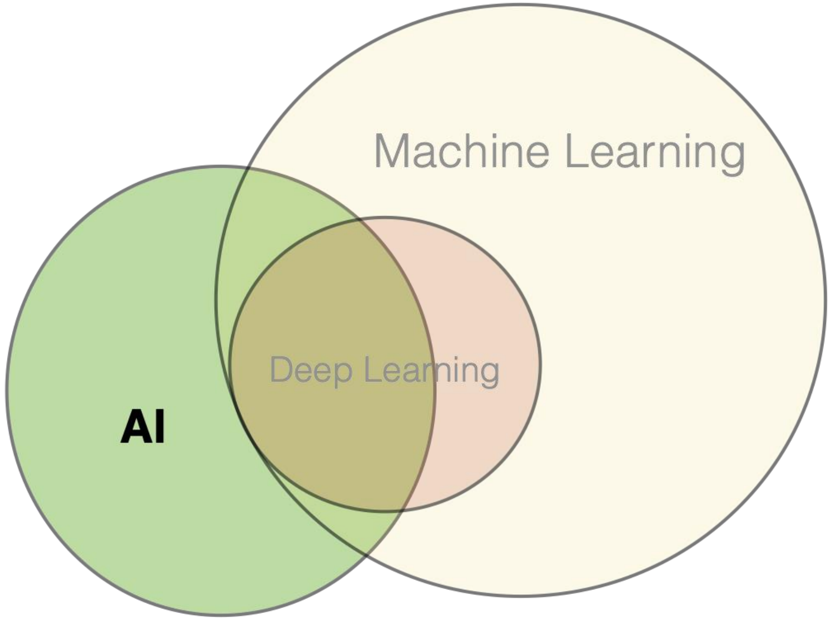
The Connection Between Fields



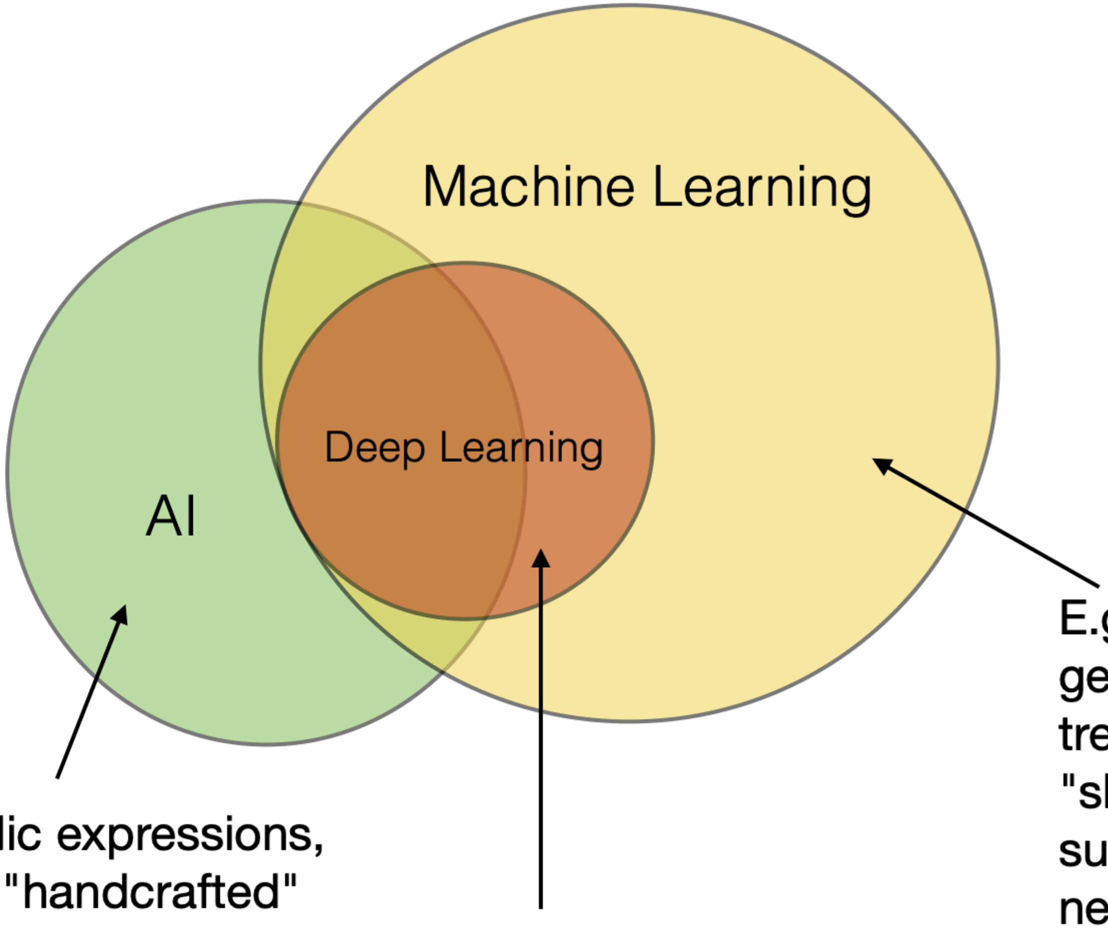
Not all AI Systems involve Machine Learning

Deep Blue used custom VLSI chips to execute the **alpha-beta search** algorithm in parallel, an example of GOFAI
(Good Old-Fashioned Artificial Intelligence).

Image Source: https://mashable.com/2016/02/10/kasparov-deep-blue/



What This Course is About

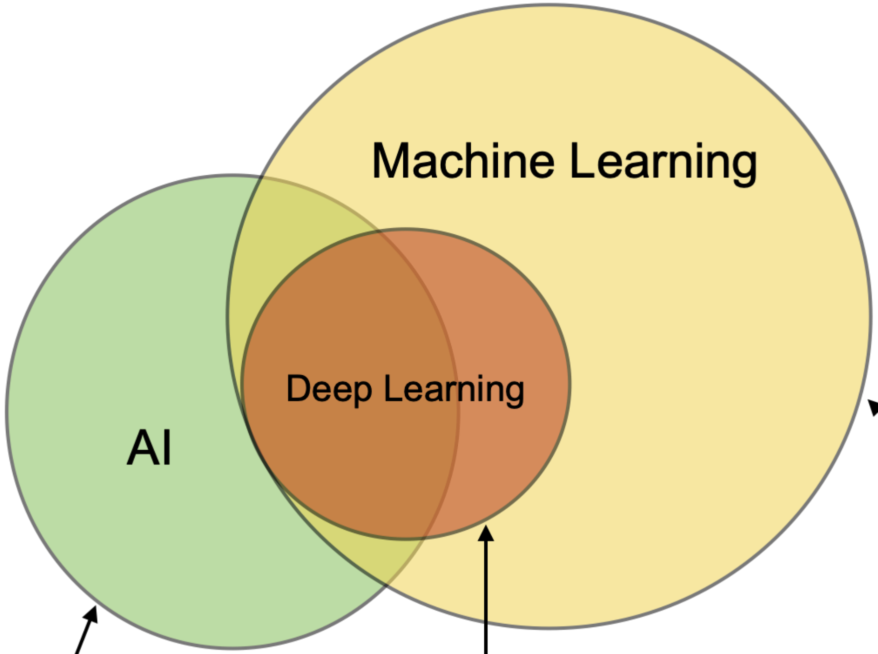


E.g., symbolic expressions, logic rules / "handcrafted" nested if-else programming statements ...

Main focus of the course

E.g.,
generalized linear models,
tree-based methods,
"shallow" networks,
support vector machines,
nearest neighbors, ...

Example from the Three Related Areas



A non-biological system that is intelligent through rules

Algorithms that parameterize multilayer neural networks that then learn representations of data with multiple layers of abstraction

Algorithms that learn models/representations/ rules automatically from data/examples

Definition of Machine Learning

Formally, a computer program is said to **learn** from experience $\mathcal{E}$ with respect to some task $\mathcal{T}$ and performance measure $\mathcal{P}$ if its performance at $\mathcal{T}$ as measured by $\mathcal{P}$ improves with $\mathcal{E}$.

The Fundamental Questions

- Representation
  - How to encode our domain knowledge/assumptions/constraints?
  - How to capture/model uncertainties in possible worlds?
- Inference
  - How do I answer questions/queries according to my model and/or based on observed data?

e.g. $P(X_i|D)$

- Learning
  - What model is "right” for my data?

e.g. $M = argmax_{M \in \mathcal{H}} F(D; M)$

The Fundamental Questions in Probabilistic Form

- Representation
  - What is the joint probability distribution of multiple variables?
    $$P(X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8)$$
  - Assume Boolean X_i. How many state configurations of the joint probability?
    - 2^8
  - Can we disallow certain state configurations, and instead focus on a subset?

The Fundamental Questions in Probabilistic Form

- Inference
  - How do I answer questions/queries according to my model and/or based on observed data?

$$\text{e.g. } P(X_i|D)$$

  - Let's try $P(X_8|X_1)$:

$$P(X_8|X_1) = \frac{P(X_8, X_1)}{P(X_1)}$$

$$= \frac{\sum_{X_2} \sum_{X_3} \cdots \sum_{X_7} P(X_1, \ldots, X_8)}{\sum_{X_2} \sum_{X_3} \cdots \sum_{X_8} P(X_1, \ldots, X_8)}$$

  - Require summing over 2^6 configurations of unobserved variables
  - On the other hand, if X_i all independent: $P(X_8|X_1) = P(X_8)$
  - Graphical form allows us to work in between.

The Fundamental Questions in Probabilistic Form

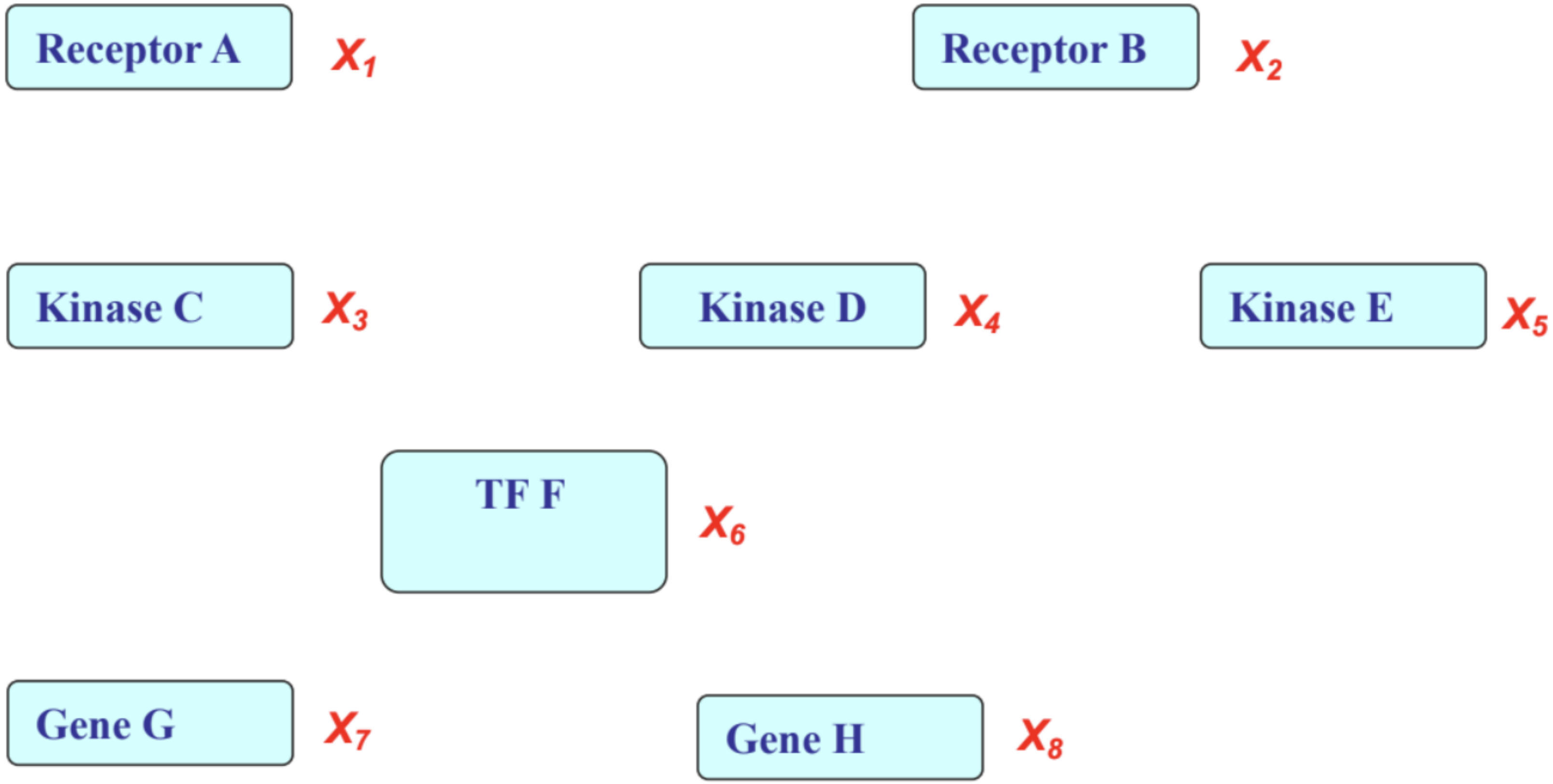
- Learning
  - What model is "right” for my data?

$$\text{e.g. } M = argmax_{M \in \mathcal{H}} F(D; M)$$

  - How can we constrain the hypothesis space $\mathcal{H}$ so that the search for the argmax is efficient?

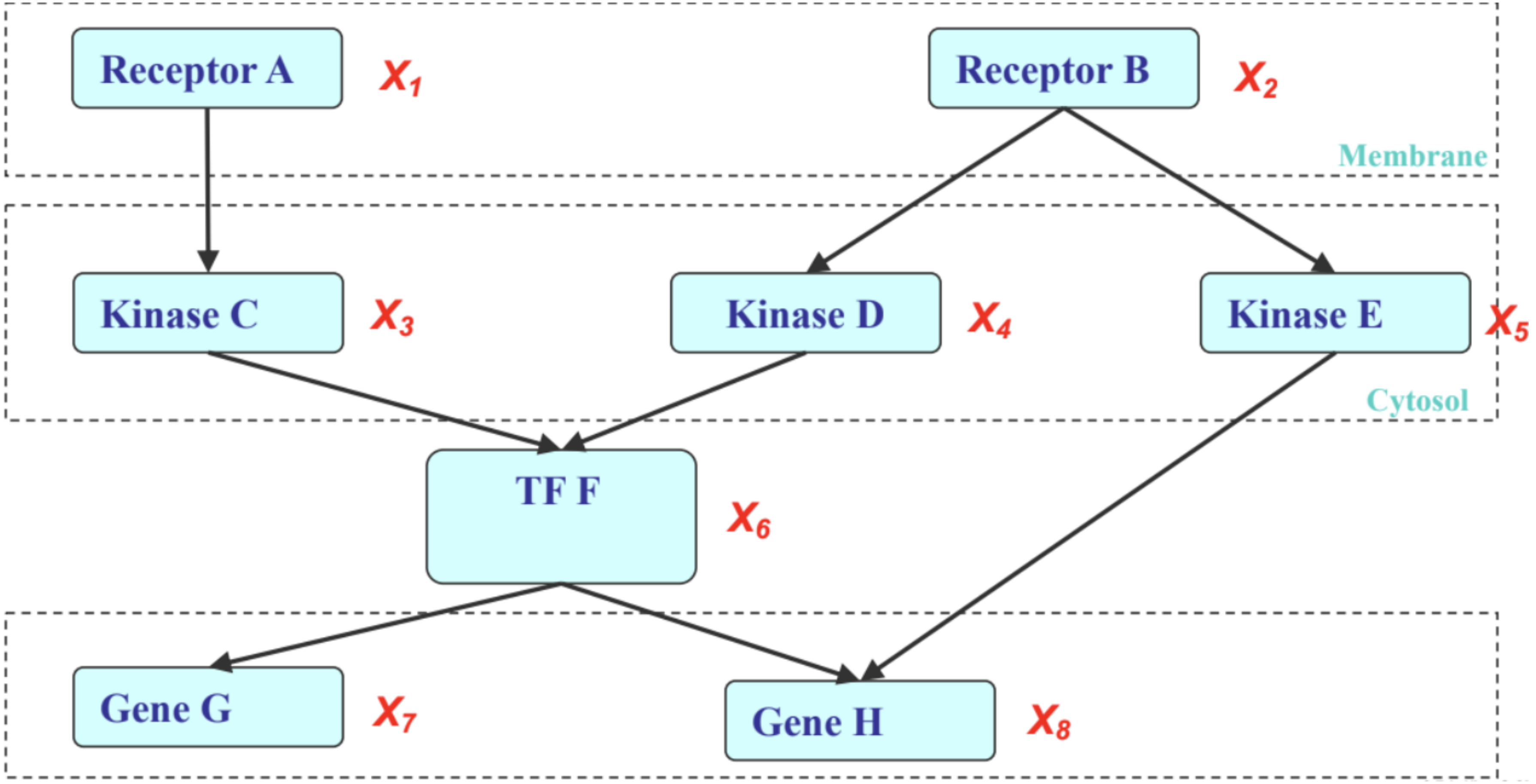
An example

A possible world for cellular signal transduction:



An example

Imposing structure of dependencies simplifies representation

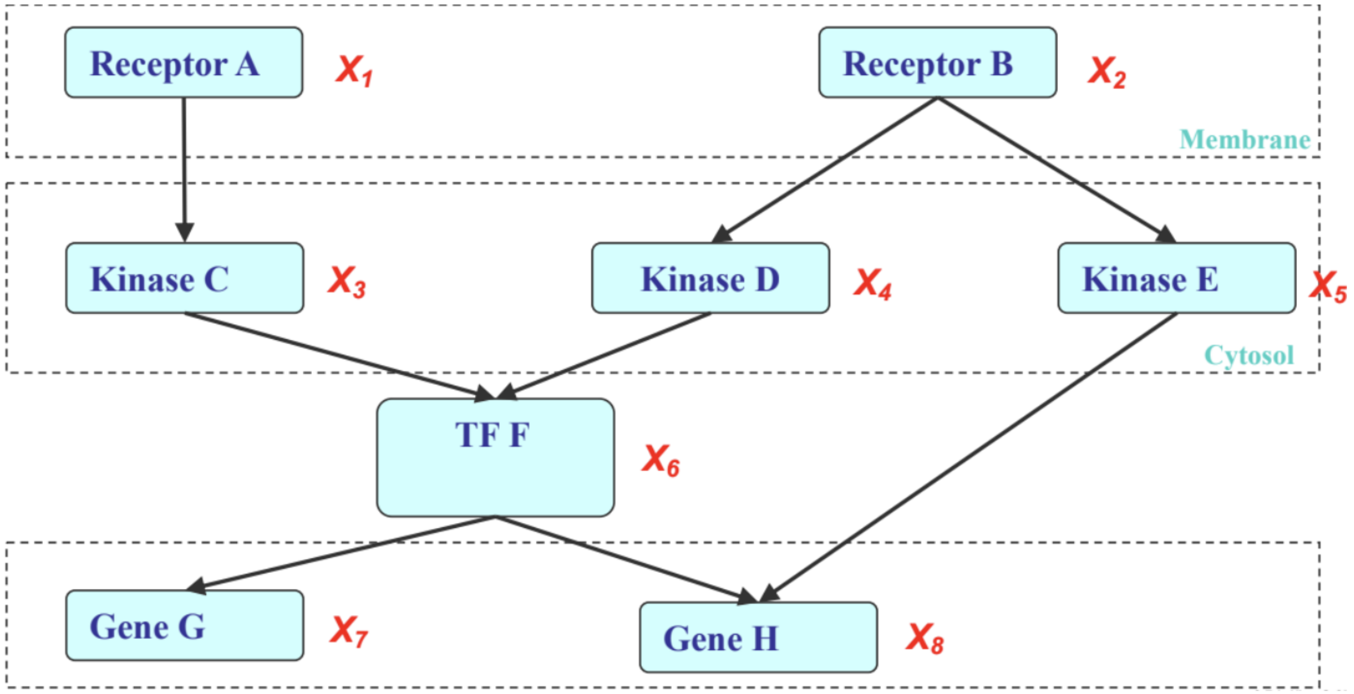


An example

If the X_is are conditional independence (as encoded by a PGM), then the joint can be factorized into a product of simpler terms:

$$P(X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8) =$$
$$P(X_1)P(X_2)P(X_3|X_1)P(X_4|X_2)P(X_5|X_2)P(X_6|X_3, X_4)P(X_7|X_6)P(X_8|X_6, X_5)$$

Reduced from 2^8 to 18 parameters!



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3 Broad Categories of ML

Supervised Learning	Labeled data Direct feedback Predict outcome/future
Unsupervised Learning	No labels/targets No feedback Find hidden structure in data
Reinforcement Learning	Decision process Reward system Learn series of actions

Source: Raschka and Mirjalily (2019). *Python Machine Learning, 3rd Edition*

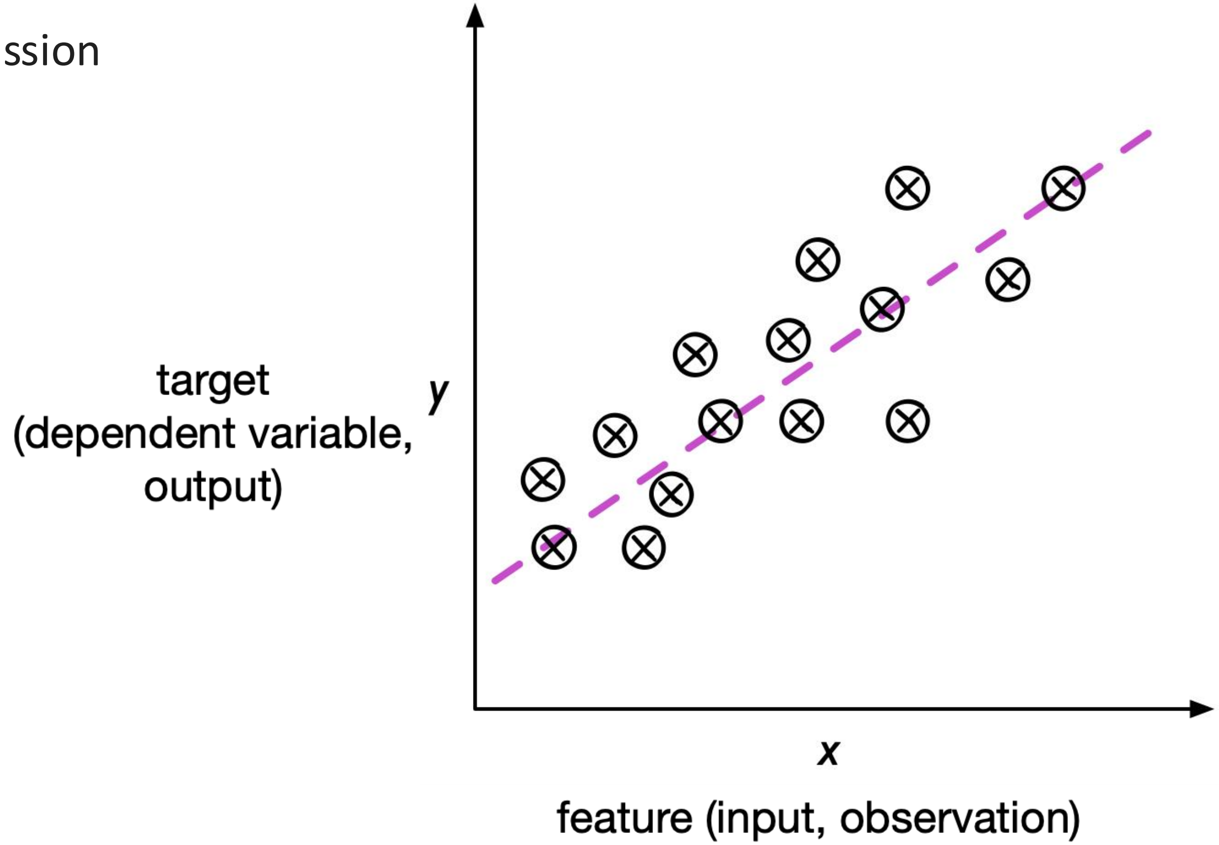
3 Broad Categories of ML

Supervised Learning

- Labeled data
- Direct feedback
- Predict outcome/future

Supervised Learning

Ex: Regression

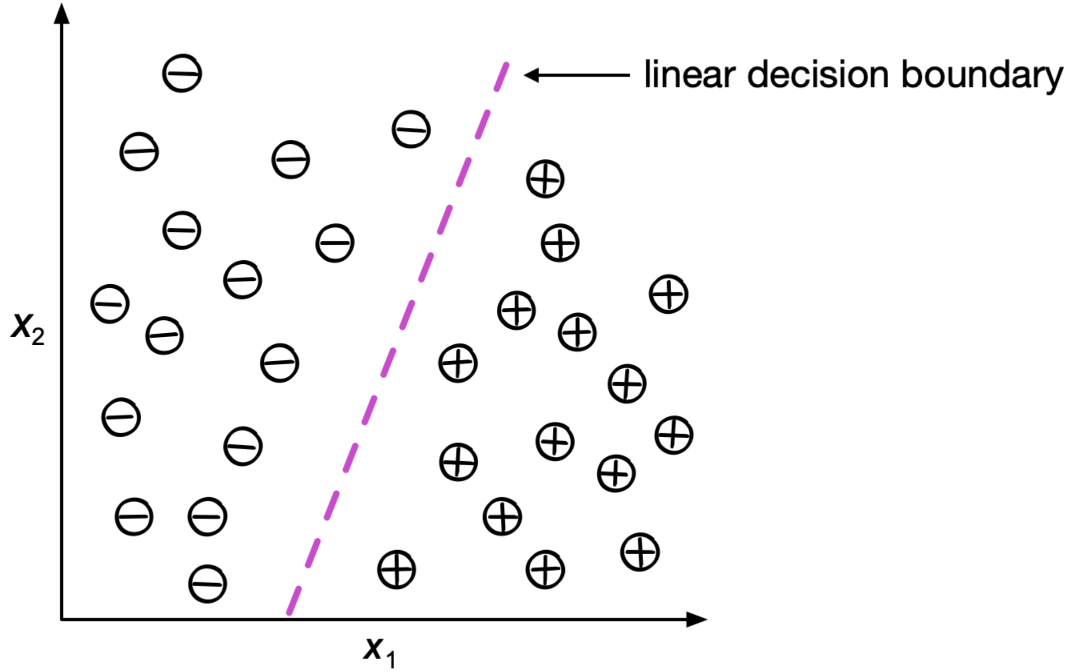


Source: Raschka and Mirjalili (2019). *Python Machine Learning, 3rd Edition*

Supervised Learning

Ex: Classification

What are the class labels (y's)?



Source: Raschka and Mirjalily (2019). Python Machine Learning, 3rd Edition

Supervised Learning

Recall our prior definition of machine learning:

Formally, a computer program is said to **learn** from experience $\mathcal{E}$ with respect to some task $\mathcal{T}$ and performance measure $\mathcal{P}$ if its **performance at $\mathcal{T}$ as measured by $\mathcal{P}$ improves with** $\mathcal{E}$.

So **supervised** machine learning is:

• Task $\mathcal{T}$:	Learn a function $h: \mathcal{X} \rightarrow \mathcal{Y}$
• Experience $\mathcal{E}$:	Labeled samples $\{(\mathrm{x_i}, \mathrm{y_i})\}_{\mathrm{i}=1}^{n}$
• Performance $\mathcal{P}$:	A measure of how good h is

Unsupervised Learning

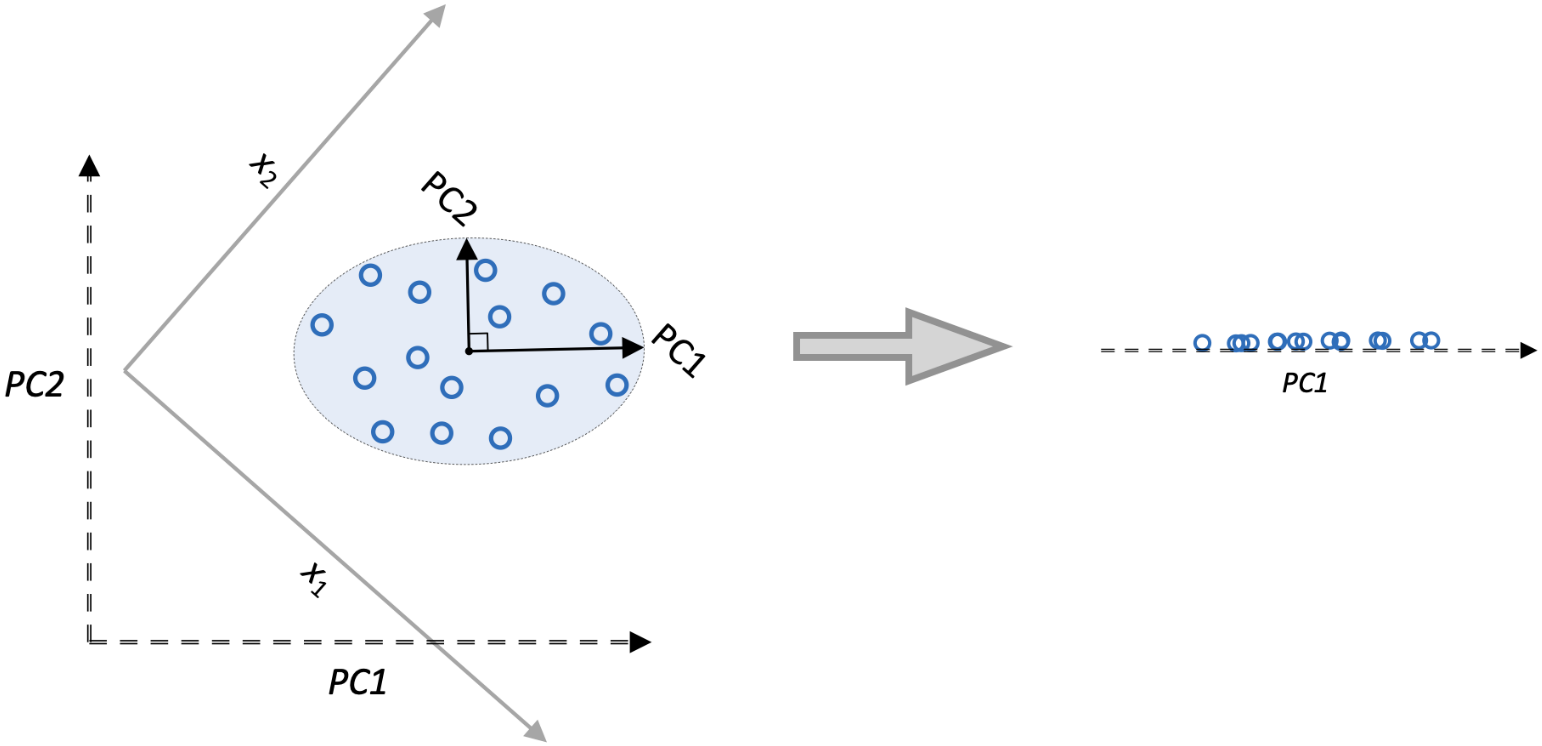
Unsupervised Learning

- No labels/targets
- No feedback
- Find hidden structure in data

Source: Raschka and Mirjalily (2019). Python Machine Learning, 3rd Edition

Unsupervised Learning

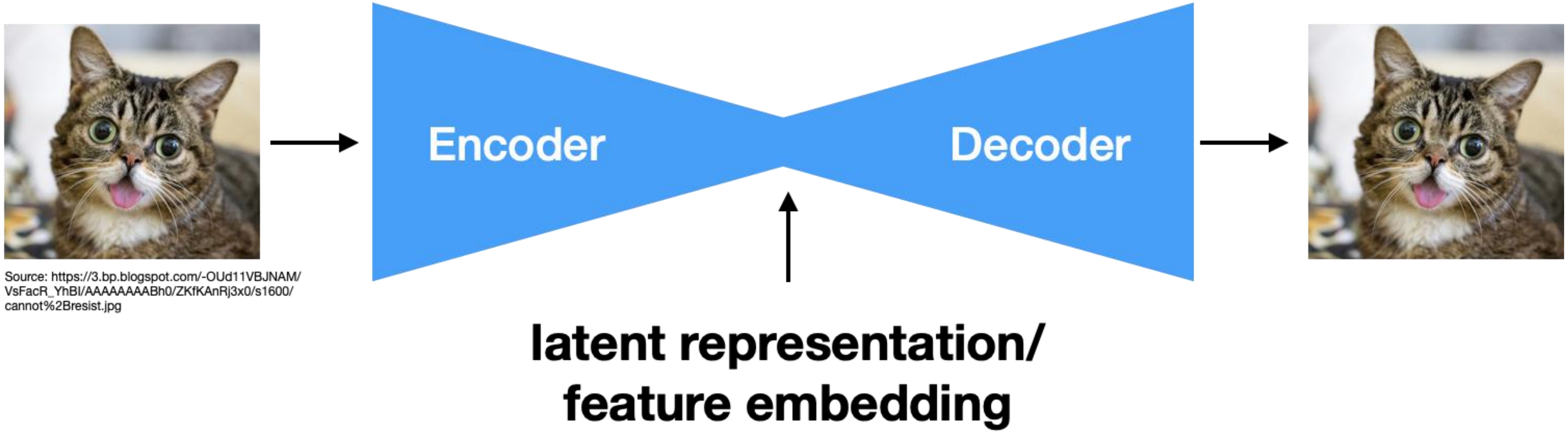
Ex: Representation Learning / Dimensionality Reduction with PCA



Source: Raschka and Mirjalily (2019). Python Machine Learning, 3rd Edition

Unsupervised Learning

Ex: Representation Learning / Dimensionality Reduction with Autoencoders

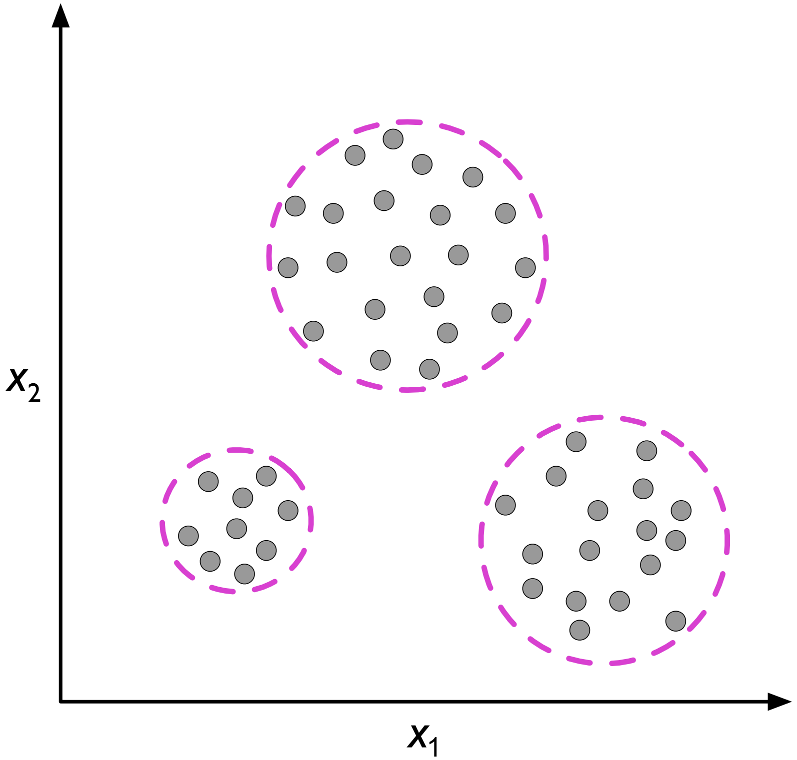


Fun fact: PCA = linear Autoencoder

Source: Raschka and Mirjalily (2019). Python Machine Learning, 3rd Edition

Unsupervised Learning

Ex: Clustering



Source: Raschka and Mirjalily (2019). Python Machine Learning, 3rd Edition

Unsupervised Learning

Recall our prior definition of machine learning:

> Formally, a computer program is said to **learn** from experience $\mathcal{E}$ with respect to some task $\mathcal{T}$ and performance measure $\mathcal{P}$ if its **performance at $\mathcal{T}$ as measured by $\mathcal{P}$ improves with** $\mathcal{E}$.

So **unsupervised** machine learning is:

- Task $\mathcal{T}$: Discover structure in data
- Experience $\mathcal{E}$: Unlabeled samples $\{\mathrm{x_i}\}_{\mathrm{i}=1}^{n}$
- Performance $\mathcal{P}$: Measure of fit or utility

Reinforcement Learning

Reinforcement Learning

- Decision process
- Reward system
- Learn series of actions

Source: Raschka and Mirjalily (2019). *Python Machine Learning, 3rd Edition*

Reinforcement Learning

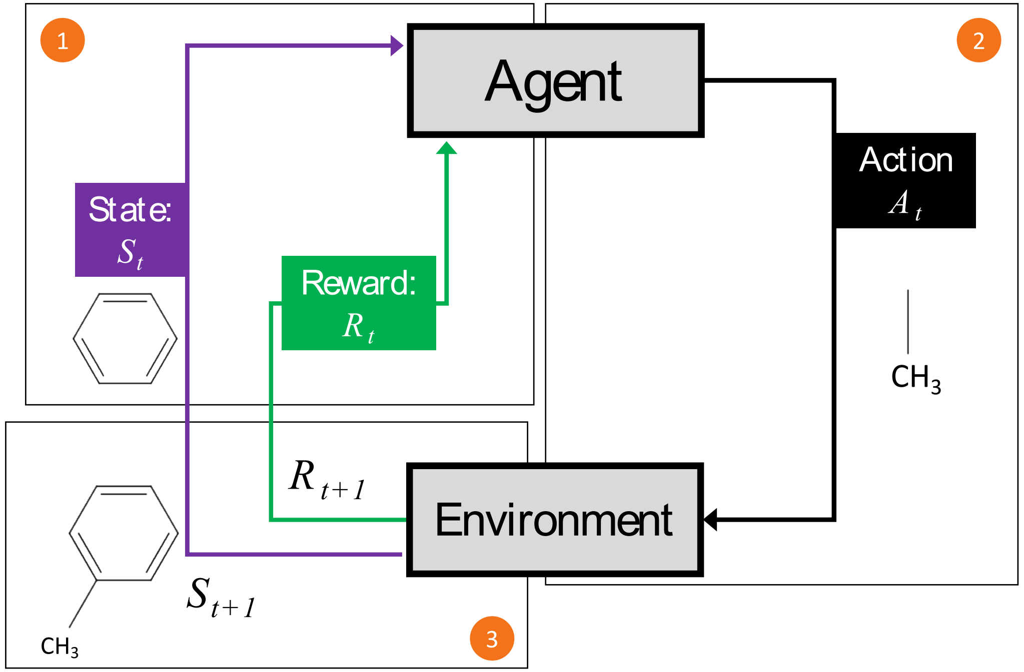
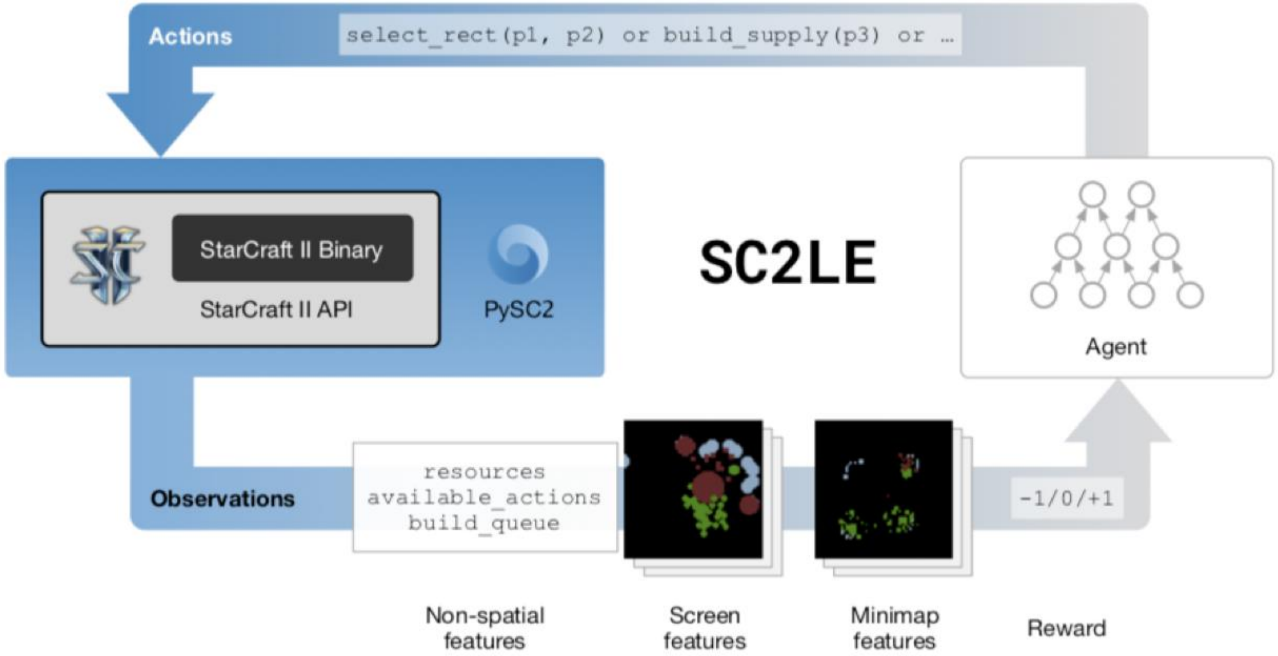


Figure 5: Representation of the basic reinforcement learning paradigm with a simple molecular example. (1) Given a benzene ring (state S_t at iteration t) and some reward value R_t at iteration t, (2) the agent selects an action A_t that adds a methyl group to the benzene ring. (3) The environment considers this information for producing the next state (S_{t+1}) and reward (R_{t+1}). This cycle repeats until the episode is terminated.

Source: Sebastian Raschka and Benjamin Kaufman (2020)
Machine learning and AI-based approaches for bioactive ligand discovery and GPCR-ligand recognition

Reinforcement Learning



Vinyals, Oriol, Timo Ewalds, Sergey Bartunov, Petko Georgiev, Alexander Sasha Vezhnevets, Michelle Yeo, Alireza Makhzani et al. "Starcraft II: A new challenge for reinforcement learning." *arXiv preprint arXiv:1708.04782* (2017).

Reinforcement Learning

Recall our prior definition of machine learning:

Formally, a computer program is said to **learn** from experience $\mathcal{E}$ with respect to some task $\mathcal{T}$ and performance measure $\mathcal{P}$ if its **performance at $\mathcal{T}$ as measured by $\mathcal{P}$ improves with** $\mathcal{E}$.

So **reinforcement** learning is:

- Task $\mathcal{T}$: Learn a policy $\pi: S \rightarrow A$
- Experience $\mathcal{E}$: Interaction with environment
- Performance $\mathcal{P}$: Expected reward

The 3 Broad Categories of ML

Supervised Learning	Labeled data; Direct feedback; Predict outcome/future
Unsupervised Learning	No labels/targets; No feedback; Find hidden structure in data
Reinforcement Learning	Decision process; Reward system; Learn series of actions

Source: Raschka and Mirjalily (2019). *Python Machine Learning, 3rd Edition*

Semi-Supervised Learning

- Mix between supervised and unsupervised learning
- Some training examples contain outputs, but some don't

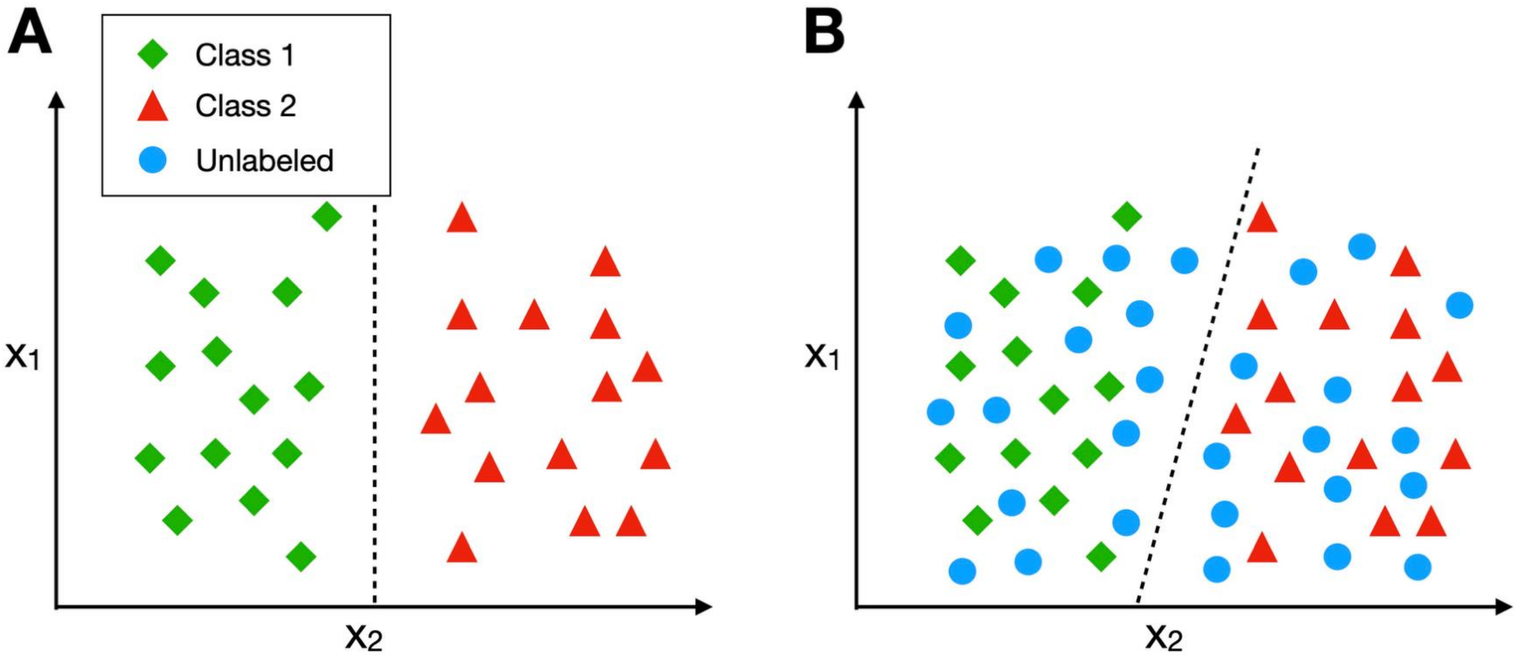
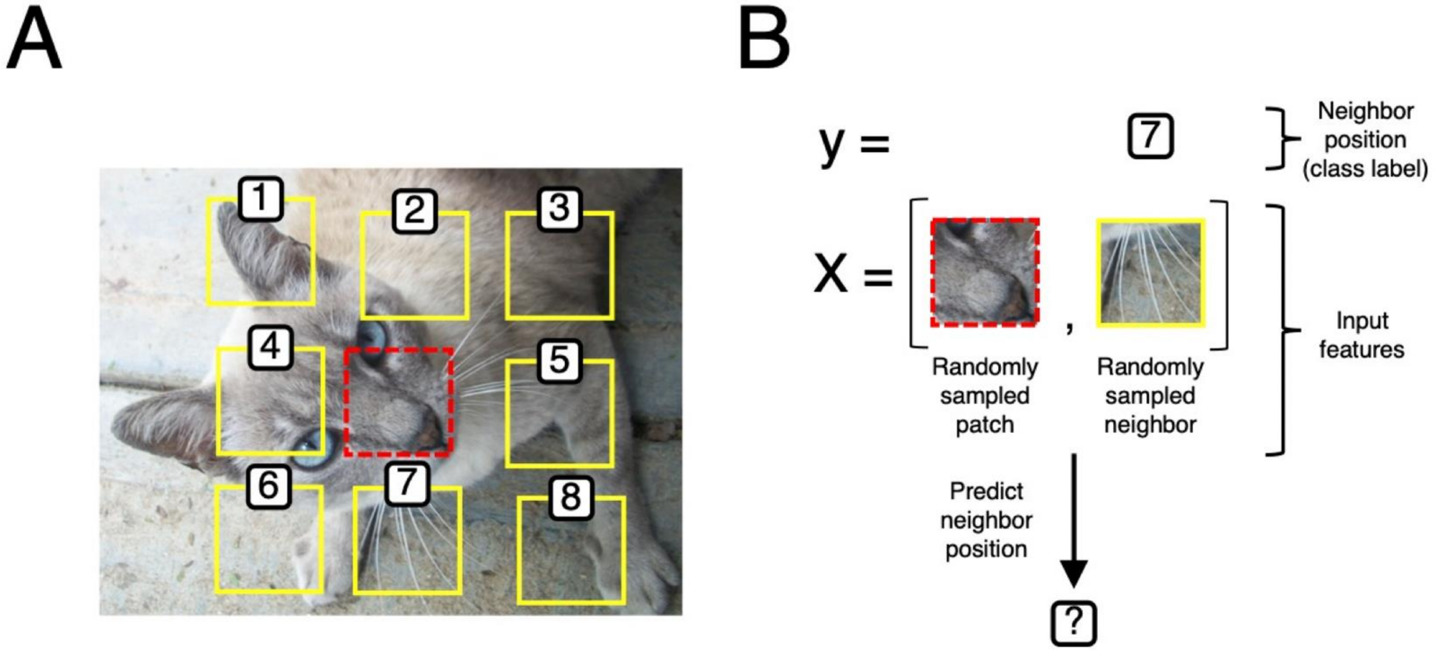


Illustration of semi-supervised learning incorporating unlabeled examples. (A) A decision boundary derived from the labeled training examples only. (B) A decision boundary based on both labeled and unlabeled examples.

Self-Supervised Learning

- A process of deriving and using label information directly from the data itself rather than having humans annotating it

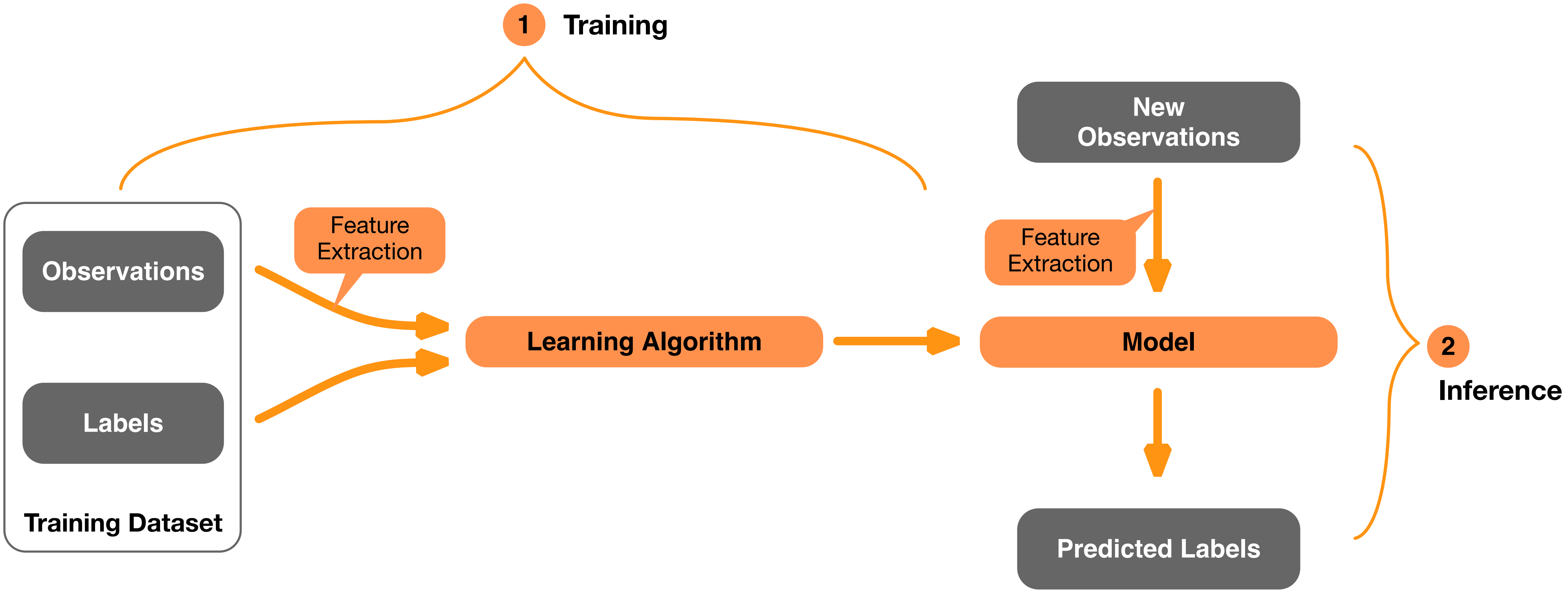


Self-supervised learning via context prediction. (A) A random patch is sampled (red square) along with 9 neighboring patches. (B) Given the random patch and a random neighbor patch, the task is to predict the position of the neighboring patch relative to the center patch (red square).

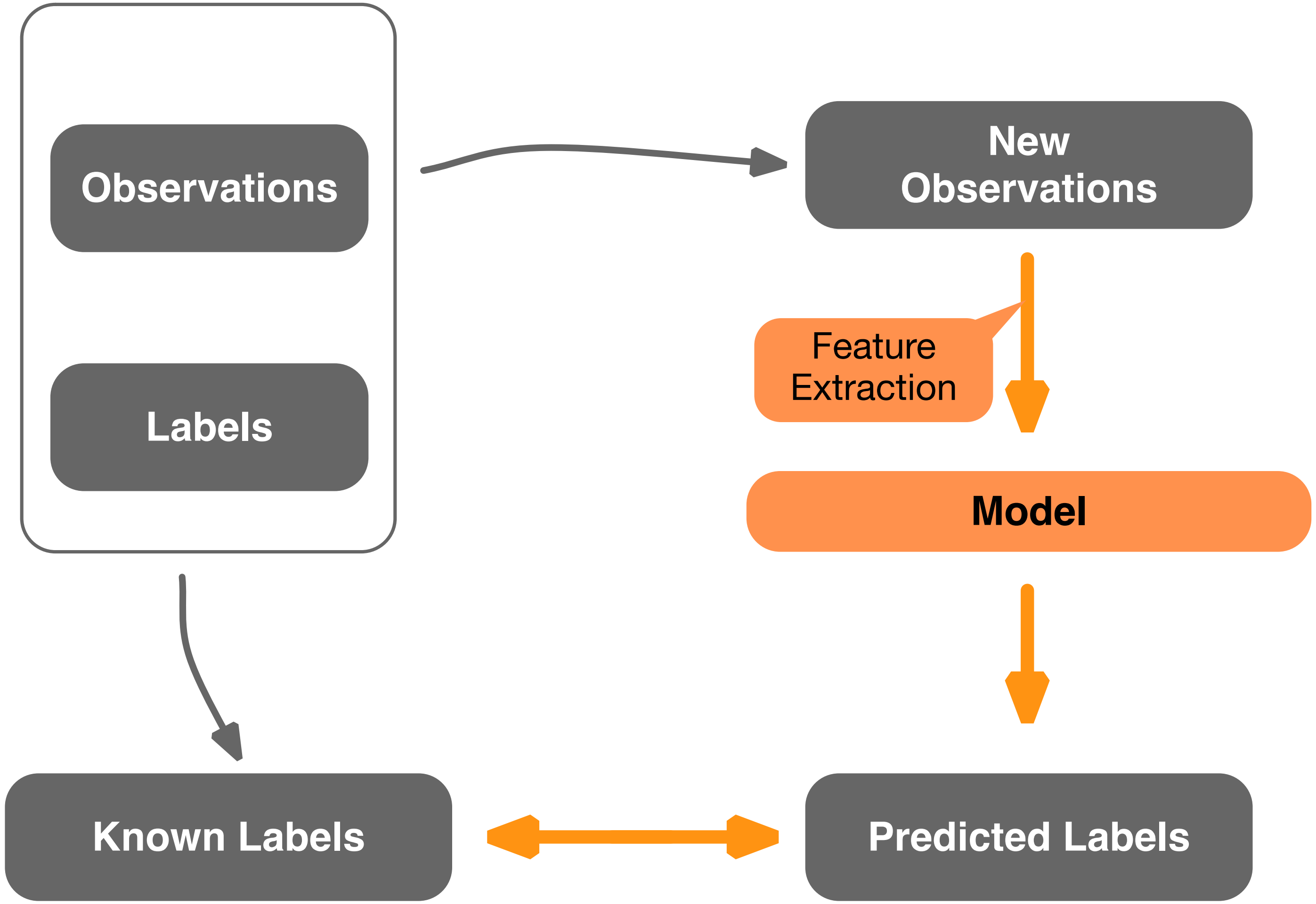
Today

1. Course overview
2. What is machine learning?
3. The broad categories of ML
4. **The supervised learning workflow**
5. Necessary ML notation and jargon
6. About the practical aspects and tools

Supervised Learning Workflow



Using a test dataset to evaluate performance



Machine Learning vs Deep Learning

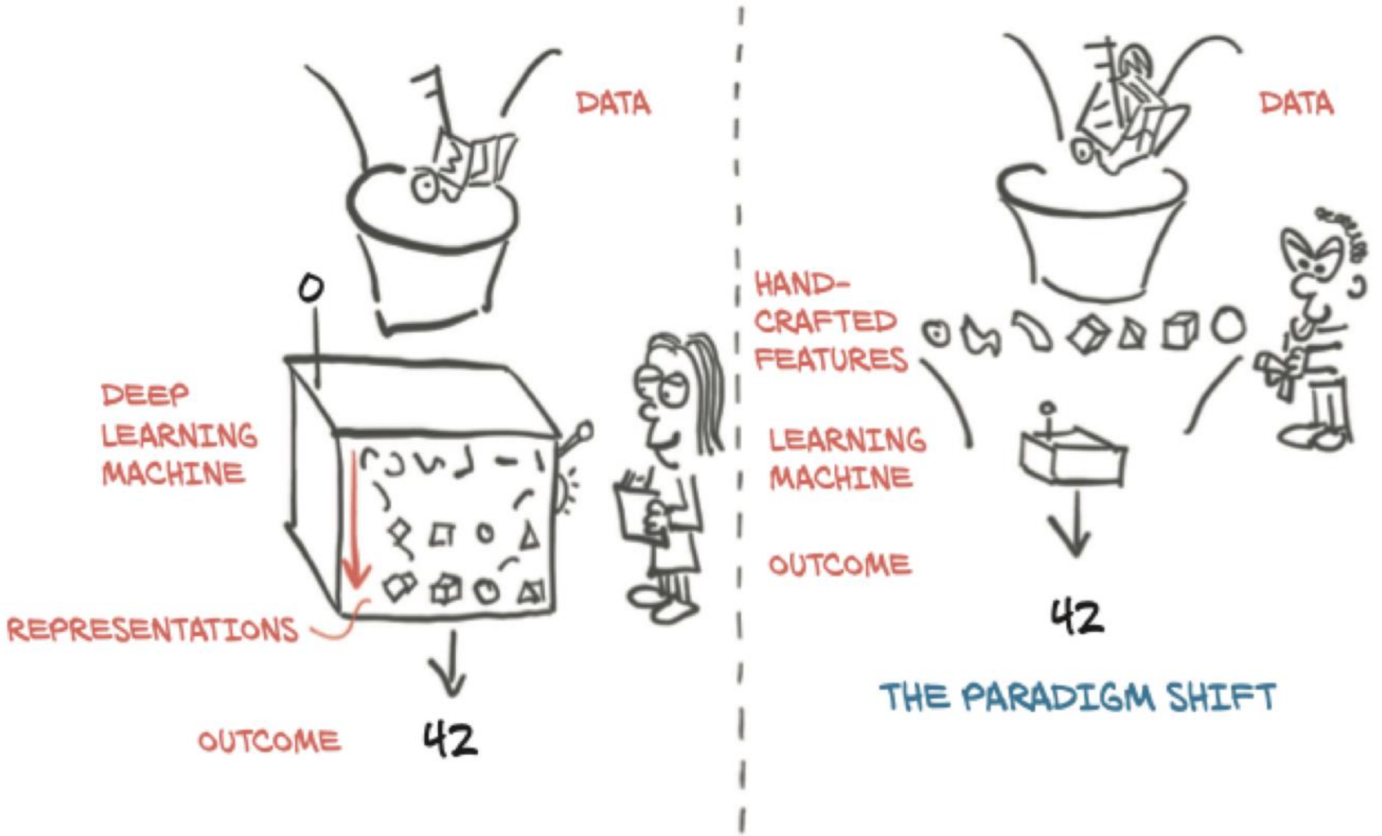


Image source: Stevens et al., Deep Learning with PyTorch. Manning, 2020

Structured vs Unstructured Data

A

Feature vector of the 1st training example

Class label

Index	Sepal length	Sepal width	Petal length	Petal width	Species
1	5.1	3.5	1.4	0.2	Iris-setosa
2	4.9	3	1.4	0.2	Iris-setosa
3	4.7	3.2	1.3	0.2	Iris-setosa
...	...	...	...	...	...
150	5.9	3	5.1	1.8	Iris-virginica

B

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Machine Learning Jargon

- **Supervised learning**
  - Learning function to map input x (features) to output y (targets)
- **Structured data**
  - Databases, spreadsheets/csv files, etc
- **Unstructured data**
  - Features like image pixels, audio signals, text sentences

Supervised Learning (More Formal Notation)

Training set: $D = \{(x^i \;\; y^i\,), i = 1, \ldots, n\},$

Unknown function: $f(x) = y$

Hypothesis: $h(x) = \hat{y}$

Classification

$$h\colon \mathcal{R}^m \to \mathcal{Y}, \mathcal{Y} = \{1, \ldots, k\}$$

Regression

$$h\colon \mathcal{R}^m \to \mathcal{R}$$

Data Representation

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix}$$

Feature vector

Data Representation

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix}$$

Feature vector

$$\mathbf{X} = \begin{bmatrix} \mathbf{x}_1^T \\ \mathbf{x}_2^T \\ \vdots \\ \mathbf{x}_n^T \end{bmatrix}$$

Feature Matrix / Design Matrix

$$\mathbf{X} = \begin{bmatrix} x_1^{[1]} & x_2^{[1]} & \cdots & x_m^{[1]} \\ x_1^{[2]} & x_2^{[2]} & \cdots & x_m^{[2]} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{[n]} & x_2^{[n]} & \cdots & x_m^{[n]} \end{bmatrix}$$

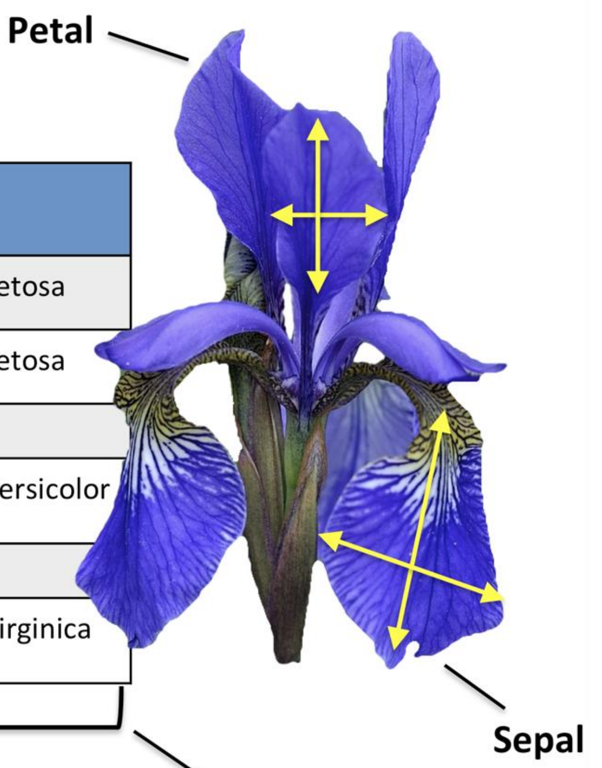
Feature Matrix / Design Matrix

Data Representation (structured data)

$m =$ ___

$n =$ ___

	Sepal length	Sepal width	Petal length	Petal width	
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
			…		
50	6.4	3.5	4.5	1.2	Versicolor
			…		
150	5.9	3.0	5.0	1.8	Virginica



Data Representation (unstructured data; images)

Convolutional Neural Networks

```
Image batch dimensions: torch.Size([128, 1, 28, 28])
Image label dimensions: torch.Size([128])
```

"NCHW" representation (more on that later)

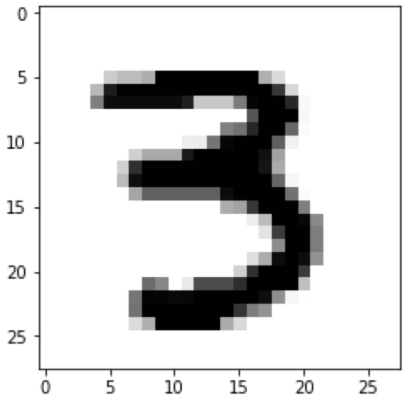
```
print(images[0].size())
```

```
torch.Size([1, 28, 28])
```

```
images[0]
```

```
tensor([[[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000],
         [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000],
         [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000],

         [0.0000, 0.0000, 0.0000, 0.0000, 0.5020, 0.9529, 0.9529, 0.9529,
          0.9529, 0.9529, 0.9529, 0.8706, 0.2157, 0.2157, 0.2157, 0.5176,
          0.9804, 0.9922, 0.9922, 0.8392, 0.0235, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000],
         [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.6627, 0.9922, 0.9922, 0.9922, 0.0314, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000],
         [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.4980, 0.5529,
          0.8471, 0.9922, 0.9922, 0.5961, 0.0157, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000],
         [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0667, 0.0745, 0.5412, 0.9725, 0.9922,
```



Machine Learning Jargon

- **Training a model** = fitting a model = parameterizing a model = learning from data
- **Training example**, synonymous to training record, training instance, training sample (in some contexts, sample refers to a collection of training examples)
- **Feature**, synonymous to observation, predictor, variable, independent variable, input, attribute, covariate
- **Target**, synonymous to outcome, ground truth, output, response variable, dependent variable, (class) label (in classification)
- **Output / Prediction**, use this to distinguish from targets; here, means output from the model

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Main Scientific Python Libraries

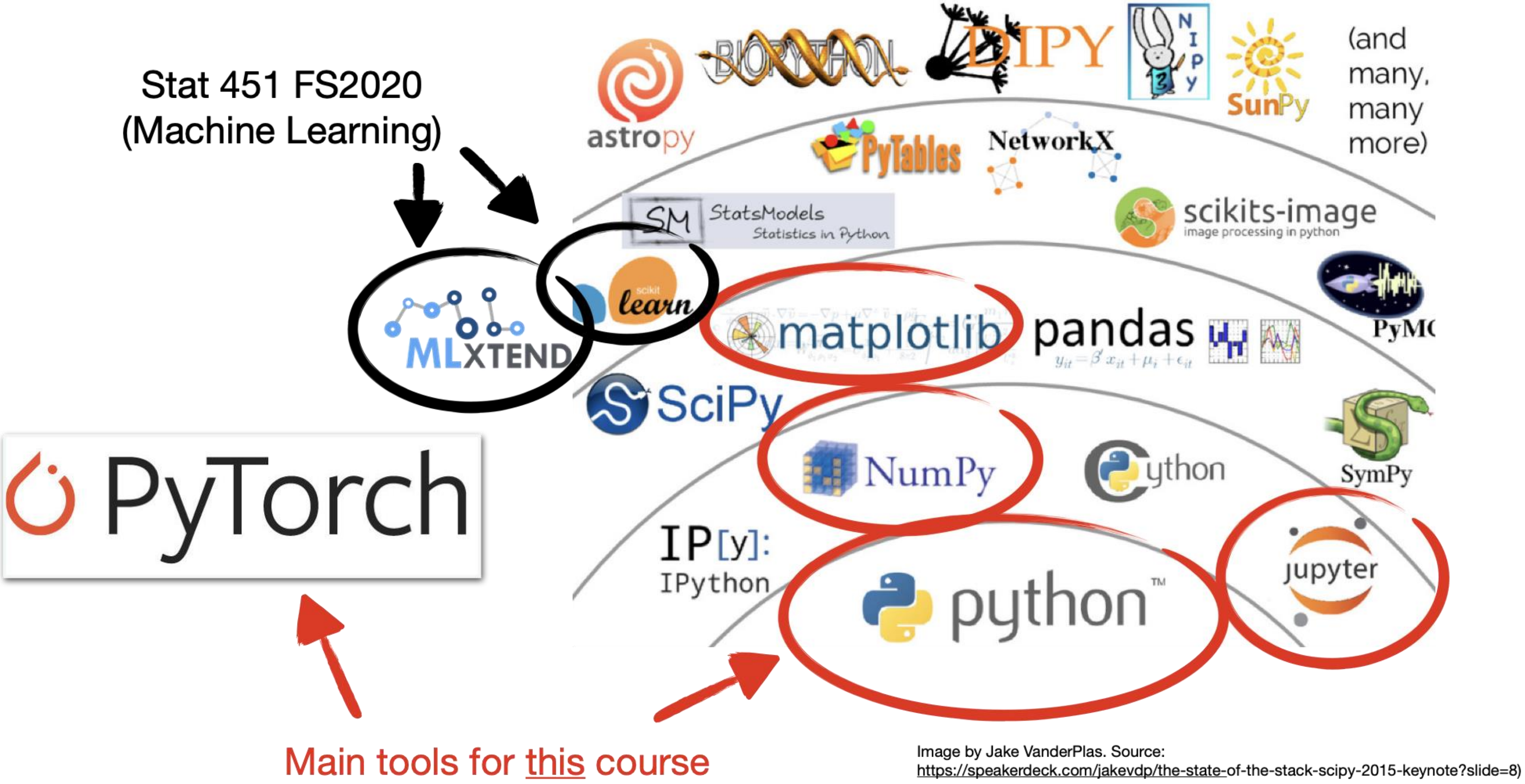
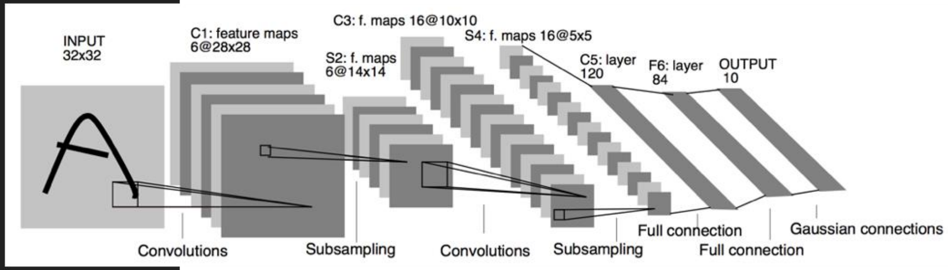
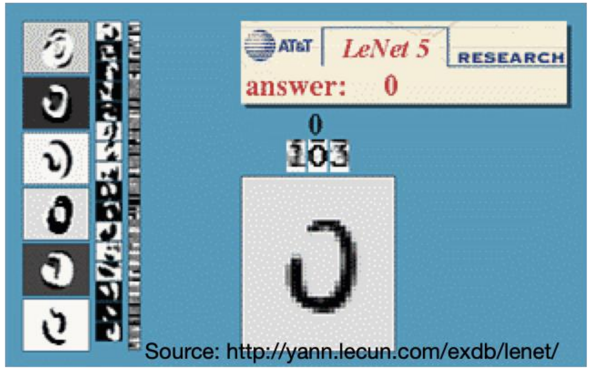


Image by Jake VanderPlas. Source: https://speakerdeck.com/jakevdp/the-state-of-the-stack-scipy-2015-keynote?slide=8)

```python
##########################
# ## MODEL
##########################

class LeNet5(torch.nn.Module):

    def __init__(self, num_classes):
        super().__init__()

        self.features = torch.nn.Sequential(
            torch.nn.Conv2d(1, 6, kernel_size=5),
            torch.nn.Tanh(),
            torch.nn.MaxPool2d(kernel_size=2),
            torch.nn.Conv2d(6, 16, kernel_size=5),
            torch.nn.Tanh(),
            torch.nn.MaxPool2d(kernel_size=2)
        )

        self.classifier = torch.nn.Sequential(
            torch.nn.Linear(16*5*5, 120),
            torch.nn.Tanh(),
            torch.nn.Linear(120, 84),
            torch.nn.Tanh(),
            torch.nn.Linear(84, num_classes),
        )

    def forward(self, x):
        x = self.features(x)
        x = torch.flatten(x, 1)
        logits = self.classifier(x)
        probas = torch.nn.functional.softmax(logits, dim=1)
        return logits, probas
```





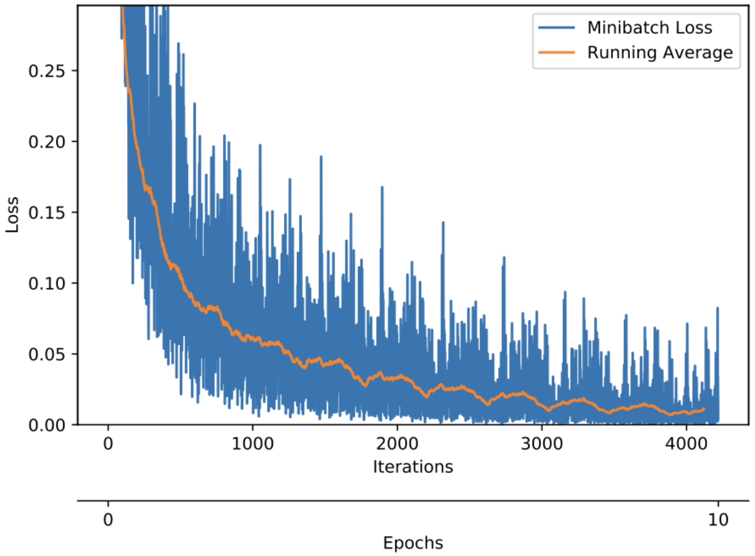
Visual Studio Code

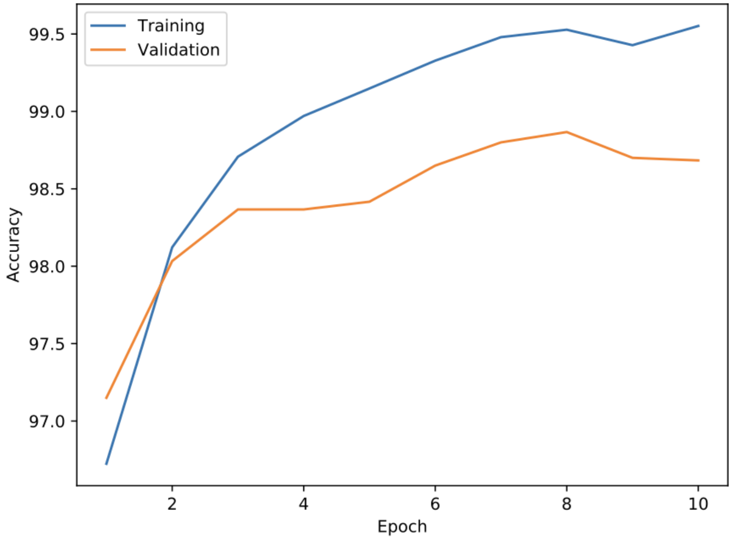
https://code.visualstudio.com

https://github.com/rasbt/stat453-deep-learning-ss21/tree/main/L01/code

```
(base) raschka@lambda-quad:~/code/stat453-ss21-exp$ python simple_cnn.py
PyTorch version: 1.7.0
Using cuda:0
[W Context.cpp:69] Warning: torch.set_deterministic is in beta, and its de
on operator())
Epoch: 001/010 | Batch 0000/0422 | Loss: 2.2935
Epoch: 001/010 | Batch 0050/0422 | Loss: 0.5462
Epoch: 001/010 | Batch 0100/0422 | Loss: 0.3154
Epoch: 001/010 | Batch 0150/0422 | Loss: 0.2551
Epoch: 001/010 | Batch 0200/0422 | Loss: 0.1792
Epoch: 001/010 | Batch 0250/0422 | Loss: 0.2210
Epoch: 001/010 | Batch 0300/0422 | Loss: 0.1551
Epoch: 001/010 | Batch 0350/0422 | Loss: 0.2155
Epoch: 001/010 | Batch 0400/0422 | Loss: 0.2306
Epoch: 001/010 | Train: 96.72% | Validation: 97.15%
Time elapsed: 0.09 min
Epoch: 002/010 | Batch 0000/0422 | Loss: 0.1028
Epoch: 002/010 | Batch 0050/0422 | Loss: 0.1167
Epoch: 002/010 | Batch 0100/0422 | Loss: 0.0660
Epoch: 002/010 | Batch 0150/0422 | Loss: 0.1024
Epoch: 002/010 | Batch 0200/0422 | Loss: 0.0847
Epoch: 002/010 | Batch 0250/0422 | Loss: 0.0905
Epoch: 002/010 | Batch 0300/0422 | Loss: 0.1024
Epoch: 002/010 | Batch 0350/0422 | Loss: 0.0719
Epoch: 002/010 | Batch 0400/0422 | Loss: 0.1302
Epoch: 002/010 | Train: 98.12% | Validation: 98.03%
Time elapsed: 0.18 min
Epoch: 003/010 | Batch 0000/0422 | Loss: 0.0720
Epoch: 003/010 | Batch 0050/0422 | Loss: 0.0984
Epoch: 003/010 | Batch 0100/0422 | Loss: 0.0373
Epoch: 003/010 | Batch 0150/0422 | Loss: 0.0685
Epoch: 003/010 | Batch 0200/0422 | Loss: 0.0511
Epoch: 003/010 | Batch 0250/0422 | Loss: 0.0617
Epoch: 003/010 | Batch 0300/0422 | Loss: 0.0748
```

```
Epoch: 010/010 | Batch 0000/0422 | Loss: 0.0095
Epoch: 010/010 | Batch 0050/0422 | Loss: 0.0113
Epoch: 010/010 | Batch 0100/0422 | Loss: 0.0135
Epoch: 010/010 | Batch 0150/0422 | Loss: 0.0028
Epoch: 010/010 | Batch 0200/0422 | Loss: 0.0019
Epoch: 010/010 | Batch 0250/0422 | Loss: 0.0049
Epoch: 010/010 | Batch 0300/0422 | Loss: 0.0132
Epoch: 010/010 | Batch 0350/0422 | Loss: 0.0114
Epoch: 010/010 | Batch 0400/0422 | Loss: 0.0270
Epoch: 010/010 | Train: 99.55% | Validation: 98.68%
Time elapsed: 0.88 min
Total Training Time: 0.88 min
Test accuracy 98.66%
```



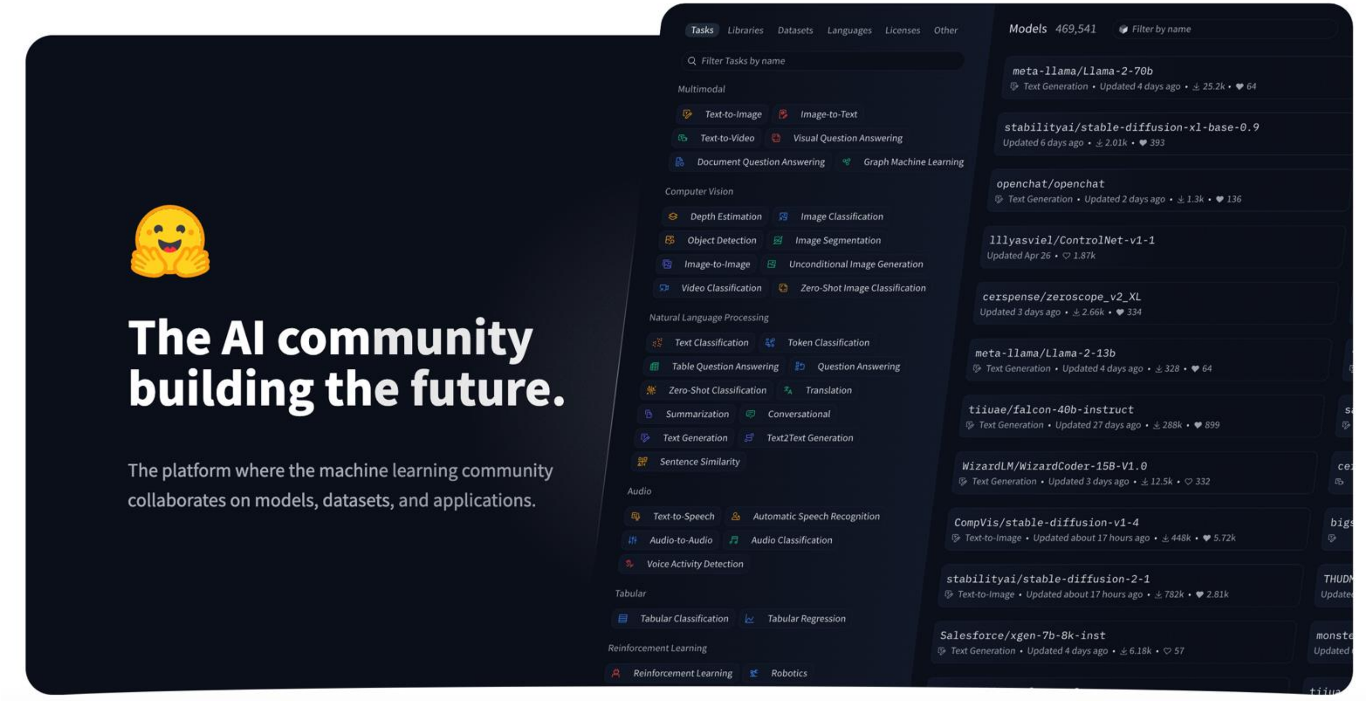


Further Resources and Reading Materials

- "Introduction to Machine Learning and Deep Learning", article https://sebastianraschka.com/blog/2020/intro-to-dl-ch01.html
- STAT451 FS2021: Intro to machine Learning, lecture notes: https://github.com/rasbt/stat451-machine-learning-fs20/blob/master/L01/01-ml-overview__notes.pdf
- *Python Machine Learning*, 3rd Ed. Packt 2019. *Chapter 1.*

Many more open-sourced models and libraries

- Huggingface, especially language-model related: huggingface.co



Questions?

WISCONSIN
UNIVERSITY OF WISCONSIN–MADISON