

EECE 571F: Deep Learning with Structures

Lecture 1: Introduction to Deep Learning

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University of British Columbia

Winter, Term 2, 2021/22

Course Information

- Course website: <https://lrjconan.github.io/DL-structures>
- Cutting-edge topics in deep learning with structures (not an introduction!!!)
- Assumes basic knowledge about machine learning, deep learning
 - View relevant textbooks/courses on the website
- Assumes basic knowledge about linear algebra, calculus, probability
- Assumes proficiency in deep learning libraries: PyTorch, JAX, Tensorflow
 - Self-learning through online tutorials, e.g. <https://pytorch.org/tutorials/>

Course Information

- Two sections: Mon. & Wed. 12:00 to 1:30pm, MacMillan 158
Office hour: 3:00 to 4:00pm, Tue.
- TA: Muchen Li
- For the first 2 weeks, lectures will be delivered synchronously via Zoom, and recorded for asynchronous viewing by enrolled students
- For later weeks, announcements will be made according to UBC's policy
- Use Piazza for discussion & questions (actively answer others' questions get you bonuses)

<https://piazza.com/ubc.ca/winterterm22022/eece571f2072021w2>

Course Information

- Expectation & Grading (More info on the website)
 - [15%] One paper reading report, due Feb. 4
 - [15%] Project proposal, due Feb. 18
 - [15%] Project presentations, around last two weeks
 - [15%] Peer-review report of project presentations, due Apr. 11
 - [40%] Project report and code, due Apr. 15
- You are encouraged to team up (up to 4 members) for projects

Course Information

- How to get free GPUs for your course project?

1. **Google Colab:** <https://research.google.com/colaboratory/>

Google Colab is a web-based iPython Notebook service that has access to a free Nvidia K80 GPU per Google account.

2. **Google Compute Engine:** <https://cloud.google.com/compute>

Google Compute Engine provides virtual machines with GPUs running in Google's data center. You get \$300 free credit when you sign up.

- Strategy of using GPUs

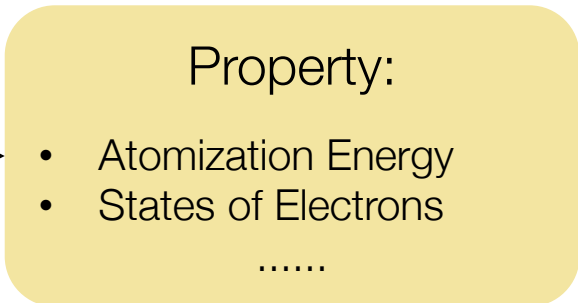
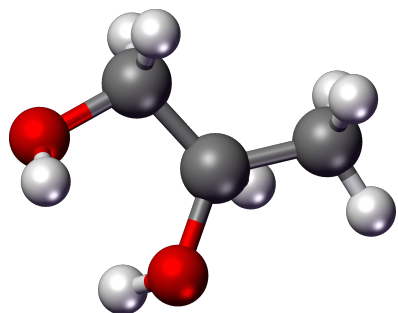
1. Debug models on small datasets (subsets) using CPUs or low-end GPUs until they work
2. Launch batch jobs on high-end GPUs to tune hyperparameters

Course Scope

- Supervised Learning with Observable Structures
- Unsupervised / Self-supervised Learning with Observable Structures
- Supervised Learning with Latent Structures

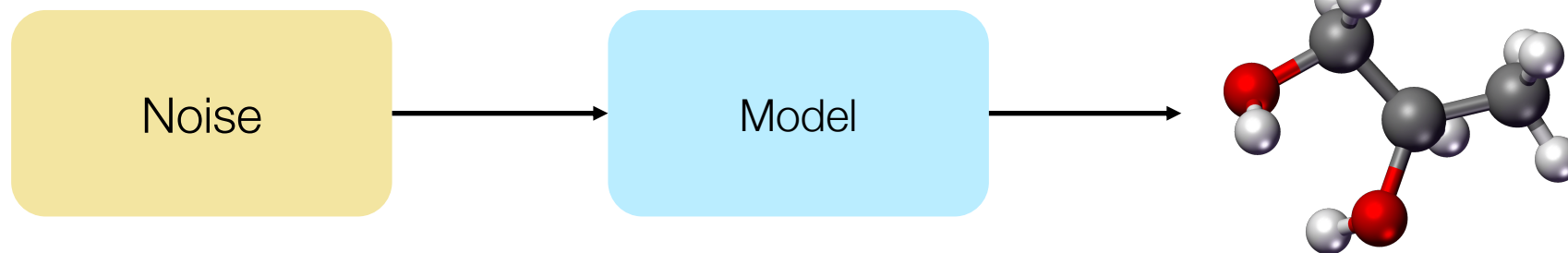
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- **Supervised Learning with Observable Structures**
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- Supervised Learning with Latent Structures



Course Scope

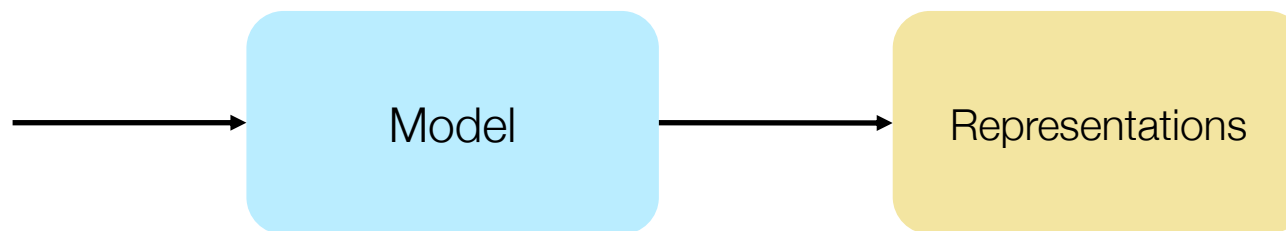
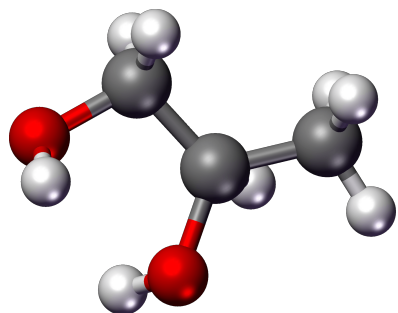
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Generative Modeling

Course Scope

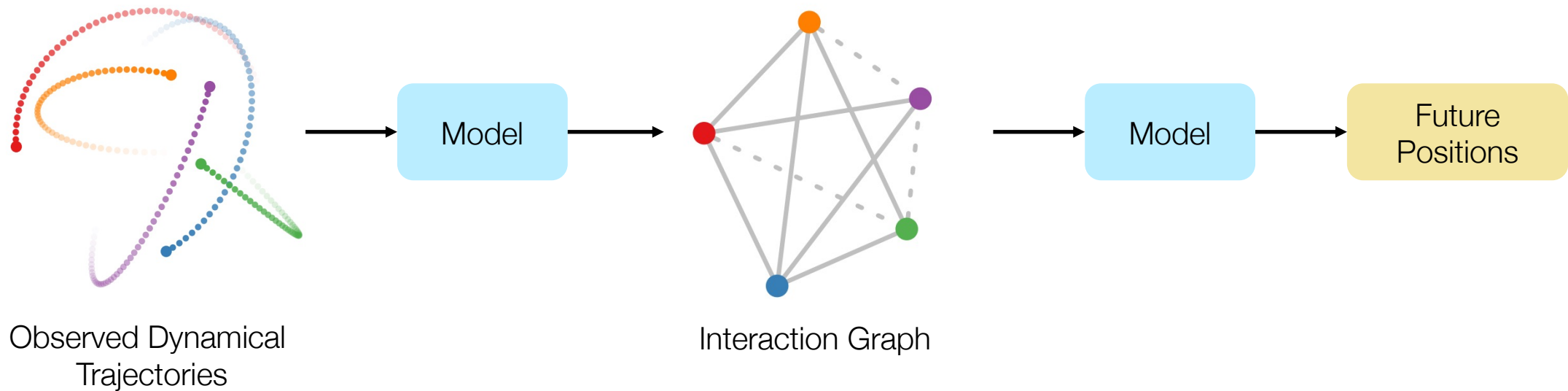
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Self-supervised Learning

Course Scope

- Supervised Learning with Observable Structures
- Unsupervised / Self-supervised Learning with Observable Structures
- **Supervised Learning with Latent Structures**



Outline

- Brief Introduction & History & Application
- Basic Deep Learning Models
 - Multi-Layer Perceptron (MLP)
 - Convolutional Neural Network (CNN)
 - Recurrent Neural Network (RNN)
- Objective Function
- Learning Algorithm: Back-propagation
- Limitations

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What is Deep Learning?

- Definition from Wikipedia:

Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural networks with representation learning.

- Key Aspects:

Data: Large (supervised) datasets, e.g., ImageNet (14 million+ annotated images)

Model: Deep (i.e., many layers) neural networks, e.g., ResNet-152

Learning algorithm: Back-propagation (BP), i.e., stochastic gradient descent (SGD)

Brief History of Deep Learning (Connectionism)

- Artificial Neurons (McCulloch and Pitts 1943)
- Hebbian Rule: Cells that fire together wire together (Donald Hebb 1949)
- Perceptron (Frank Rosenblatt 1958)
- Discovery of orientation selectivity and columnar organization in the visual cortex (Hubel and Wiesel, 1959)
- Neocognitron (first Convolutional Neural Network, Fukushima 1979)
- Hopfield networks (Hopfield 1982)
- Boltzmann machines (Hinton, Sejnowski 1983)
- Backpropagation (Linnainmaa 1970, Werbos 1974, Rumelhart, Hinton, Williams 1986)
- First application of BP to Neocognitron-like CNNs (LeCun et al. 1989)
- Long-short term memory (Hochreiter, Schmidhuber 1997)

Brief History of Deep Learning (Connectionism)

- Deep belief networks (DBN) (Hinton et al., 2006)
- Breakthrough in speech recognition (Dahl et al. 2010)
- Breakthrough in computer vision: AlexNet (Krizhevsky et al. 2012), ResNet (He et al. 2016)
- Breakthrough in games: DQN (Minh, 2015), AlphaGO (2016)
- Breakthrough in natural language processing: Seq2seq (Sutskever et al. 2014), Transformers (Vaswani et al. 2017), GPT-3 (Brown et al. 2020)
- Breakthrough in protein structure prediction: AlphaFold (2020)

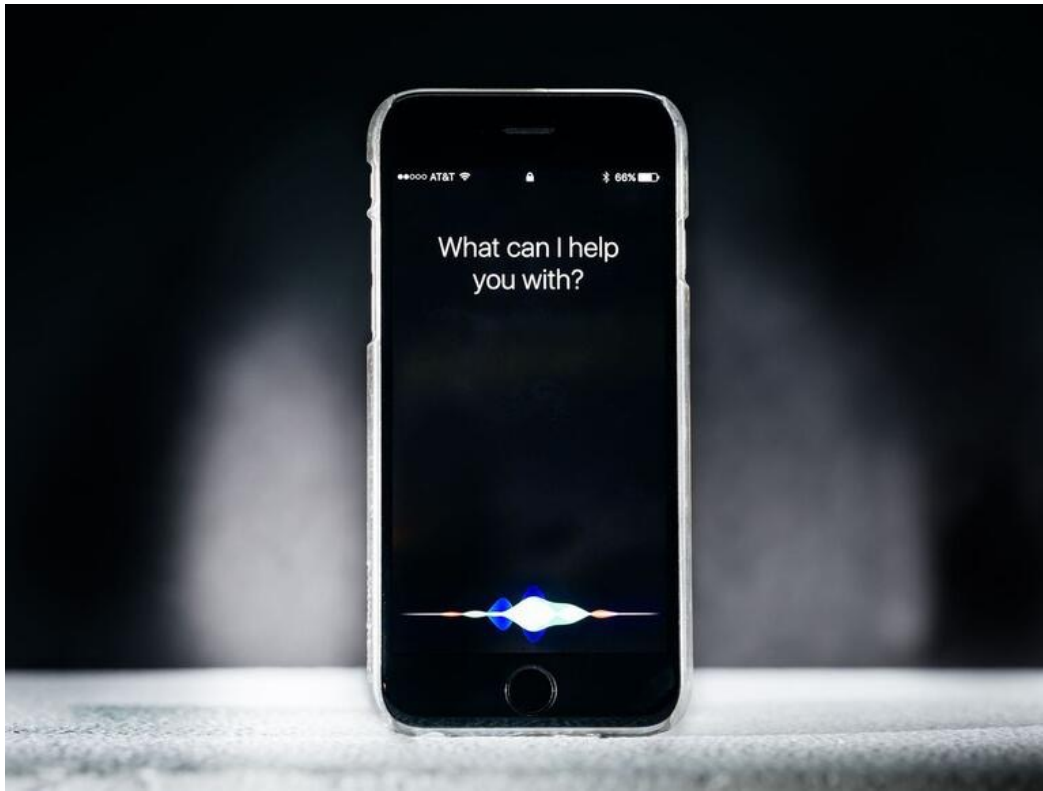
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The future depends on some graduate student who is deeply suspicious of everything I have said.

- Geoffrey Hinton

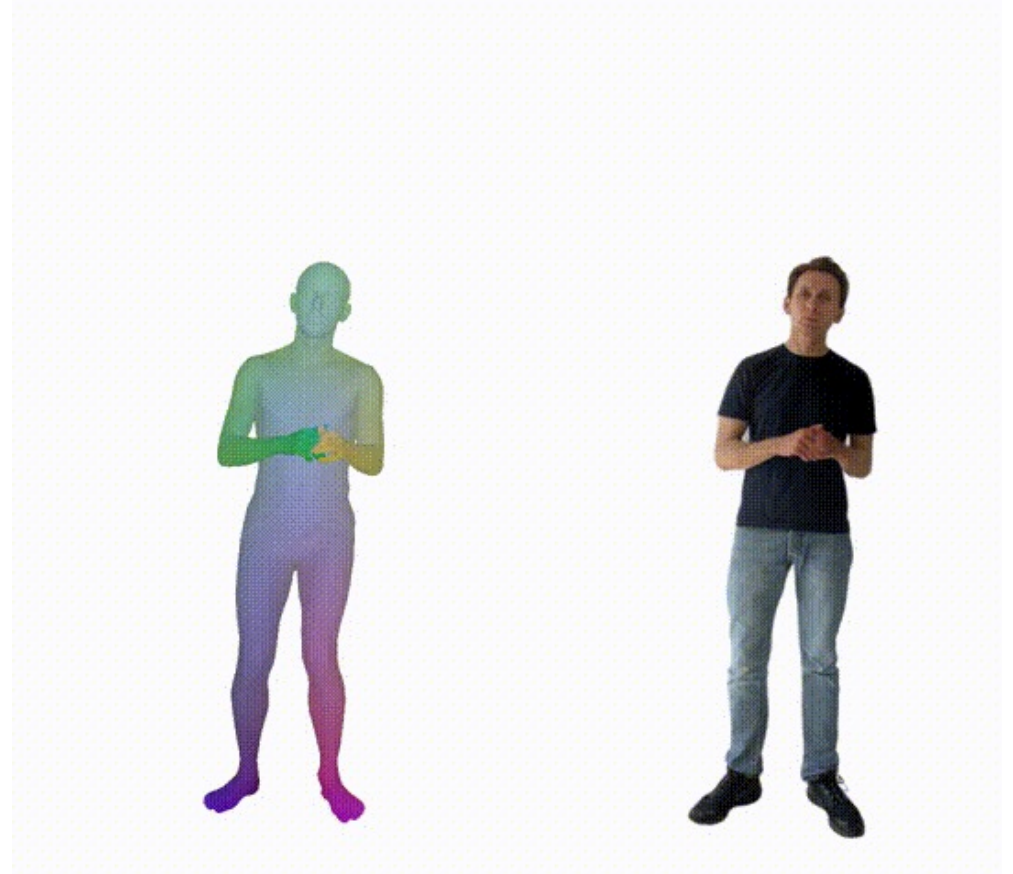
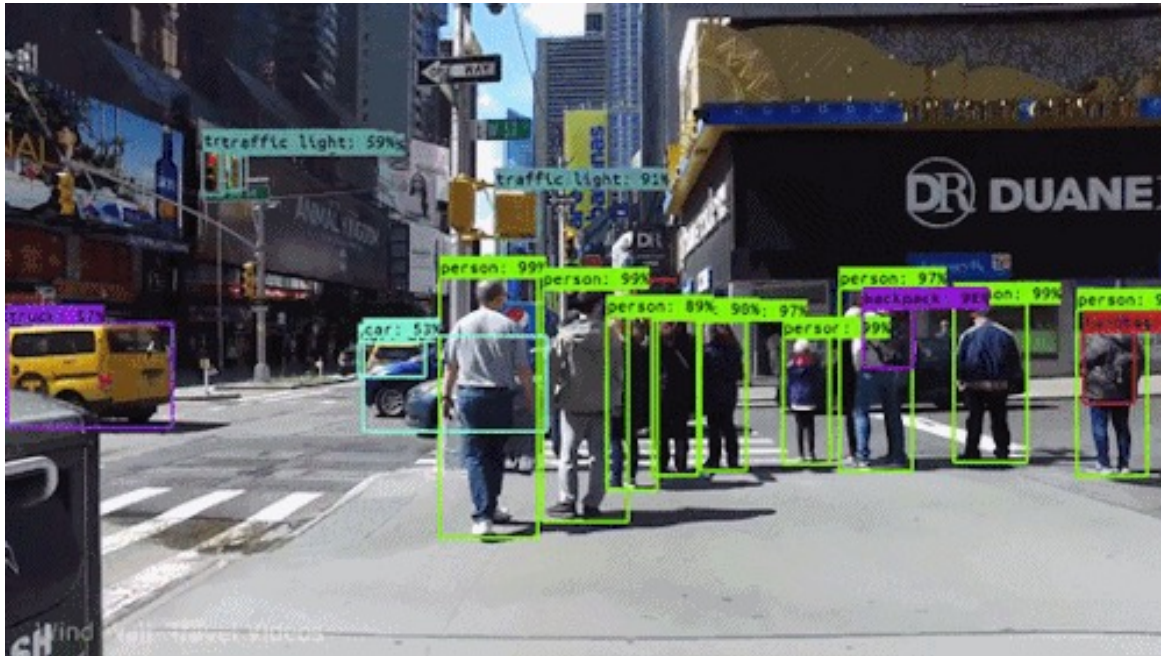
Applications of Deep Learning

Speech Recognition, Personal Assistants



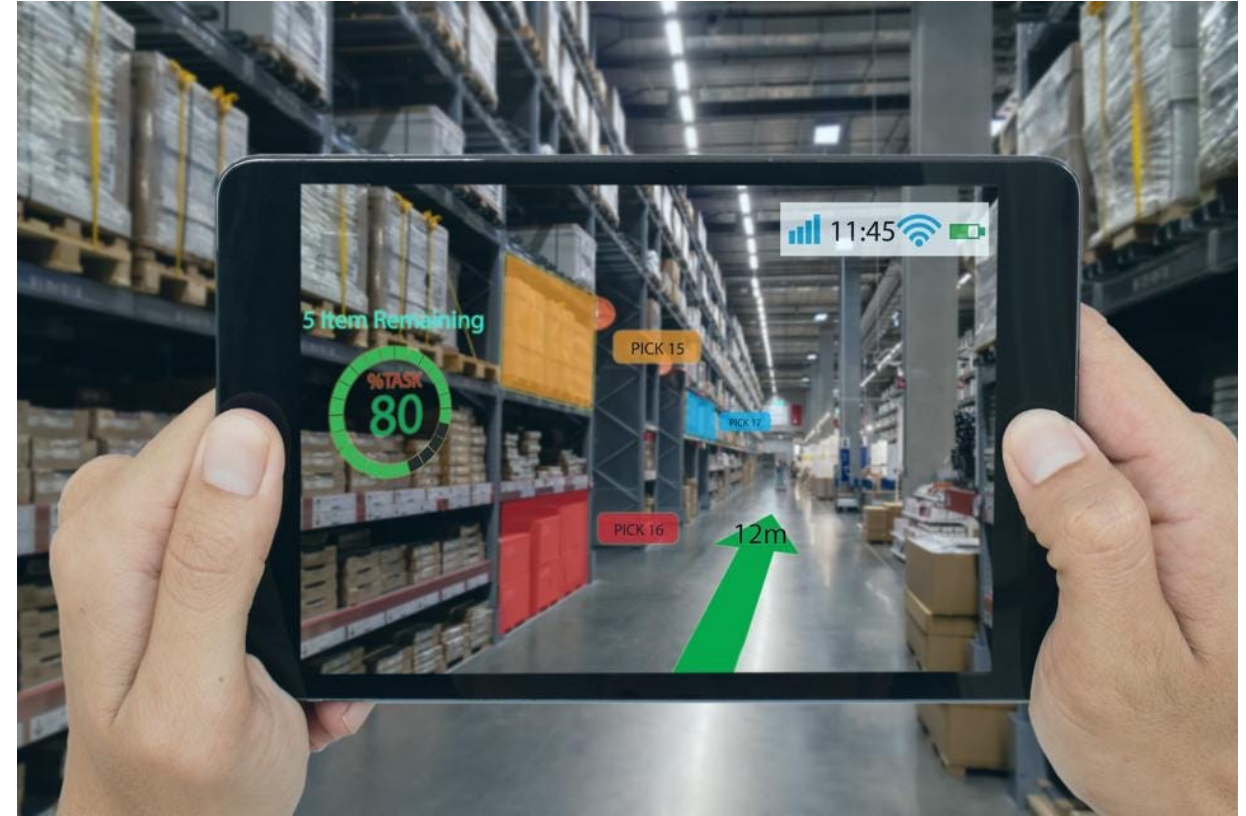
Applications of Deep Learning

Computer Vision/Graphics, e.g., Object detection, Rendering



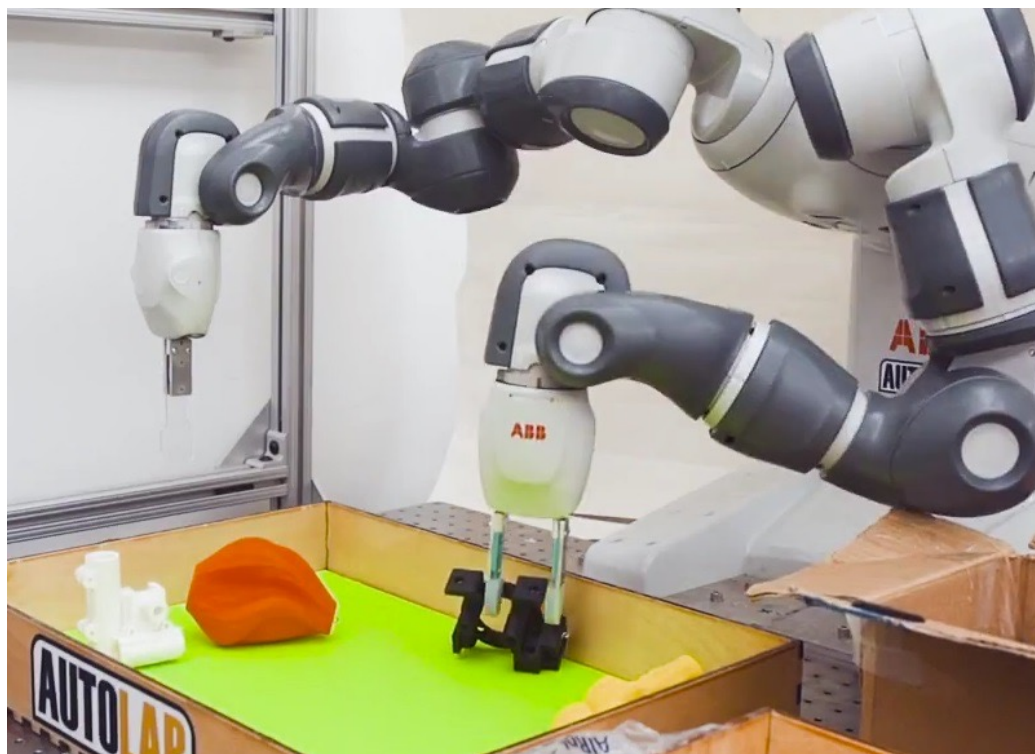
Applications of Deep Learning

Virtual/Augmented Reality



Applications of Deep Learning

Robotics, Autonomous Driving



Applications of Deep Learning

Text/Program Generation



```
parse_expenses.py write_sql.go sentiment.ts addresses.rb
1 package main
2
3 type CategorySummary struct {
4     Title      string
5     Tasks      int
6     AvgValue   float64
7 }
8
9 func createTables(db *sql.DB) {
10     db.Exec("CREATE TABLE tasks (id INTEGER PRIMARY KEY, title TEXT, value INTEGER, category TEXT)")
11 }
12
13 func createCategorySummaries(db *sql.DB) {
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
```

Applications of Deep Learning

Protein structure prediction, Drug discovery

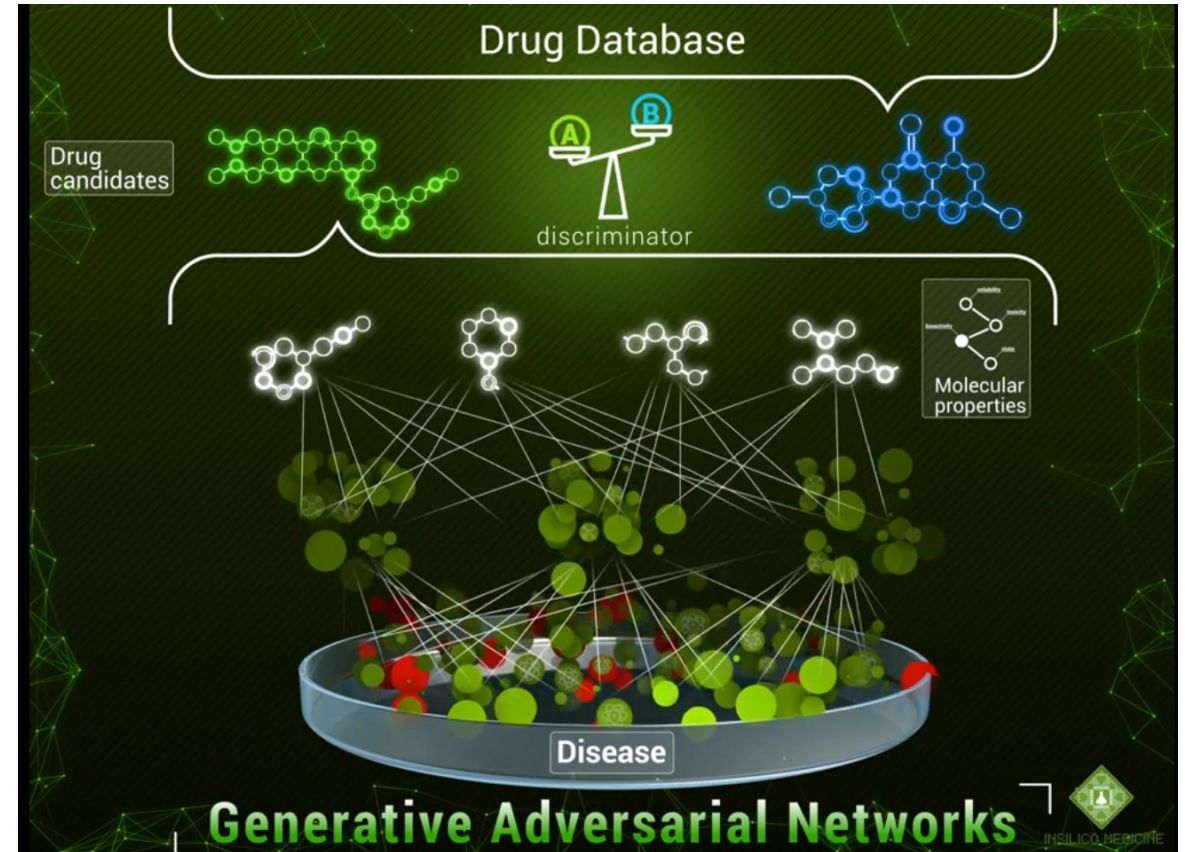
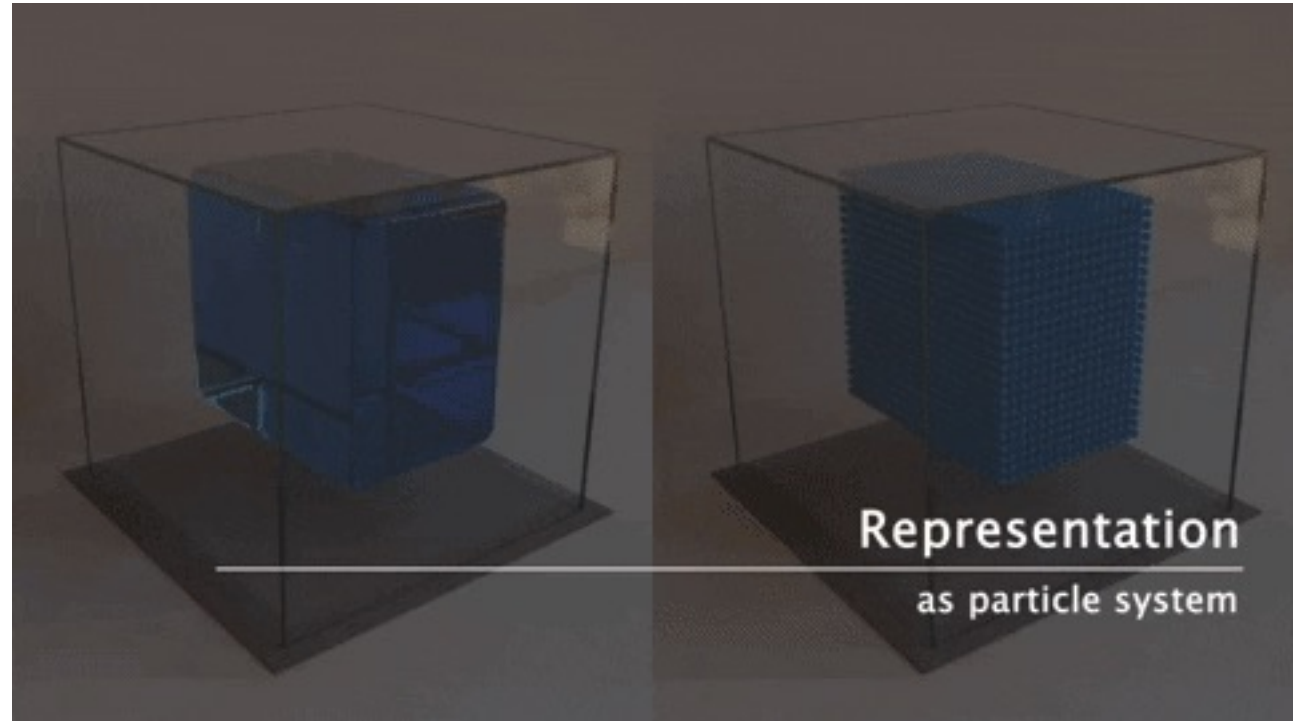
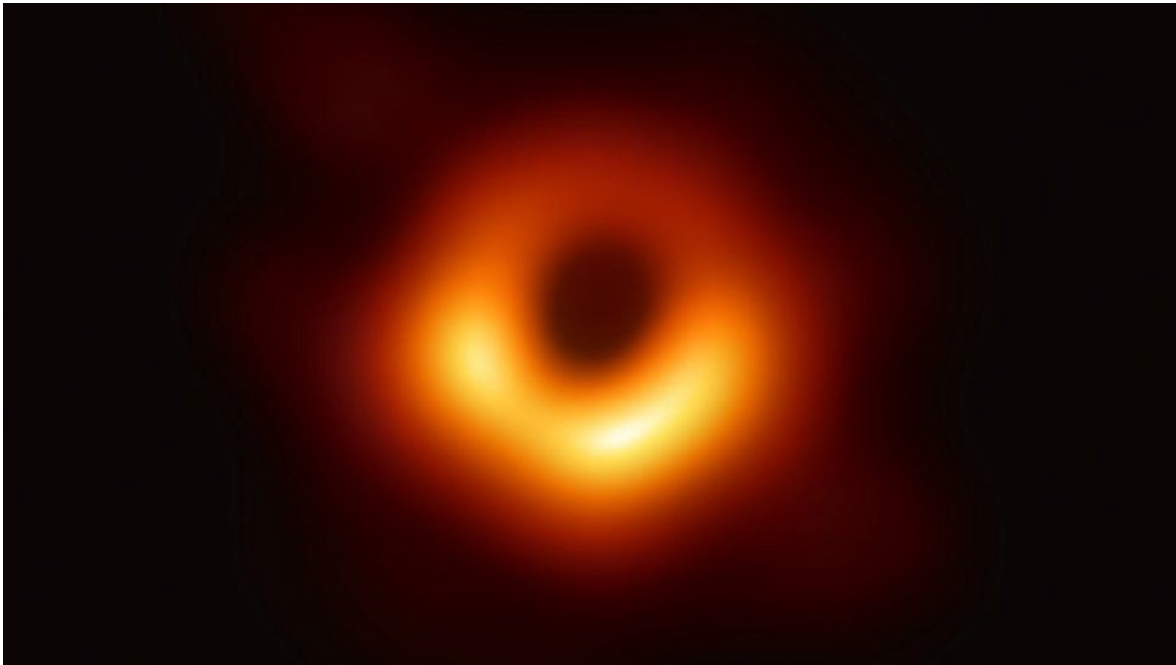


Image Credit: <https://www.nature.com/articles/d41586-020-03348-4>

<https://medium.com/neuromation-blog/creating-molecules-from-scratch-i-drug-discovery-with-generative-adversarial-networks-9d42cc496fc6>

Applications of Deep Learning

Black Holes, Physics Simulation

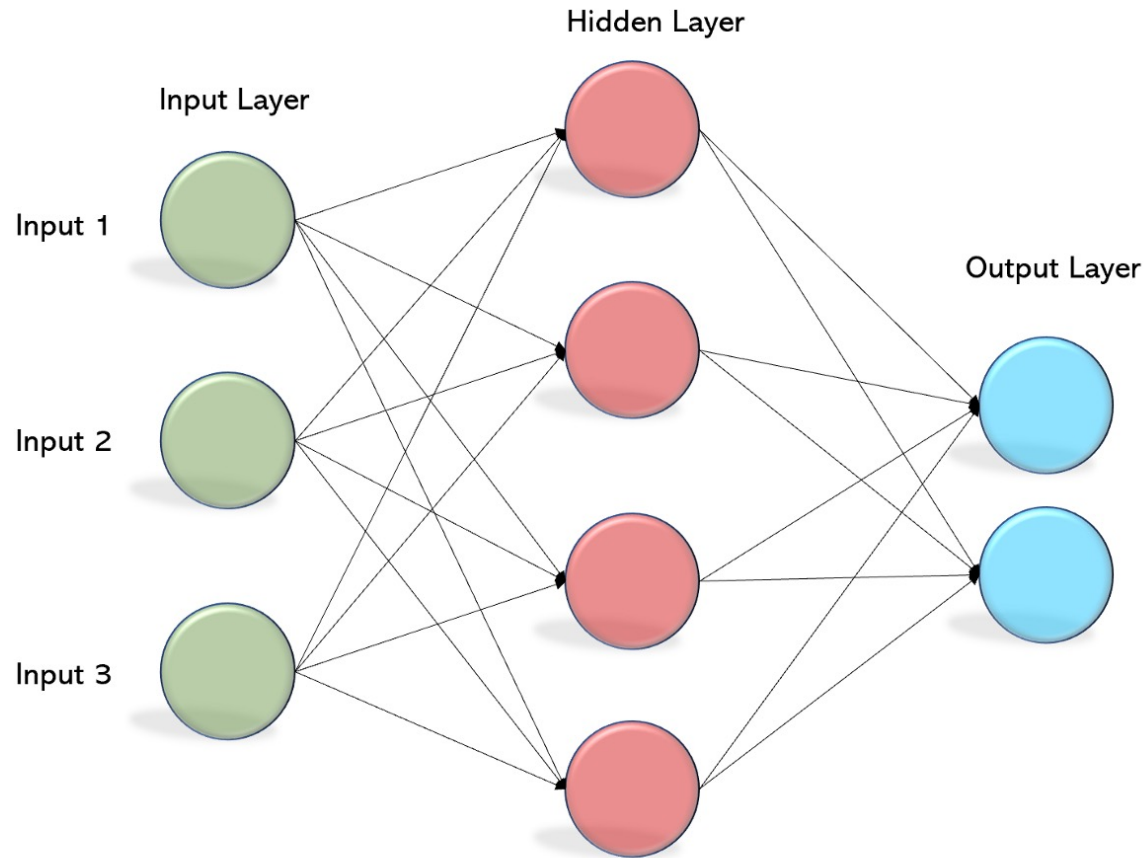


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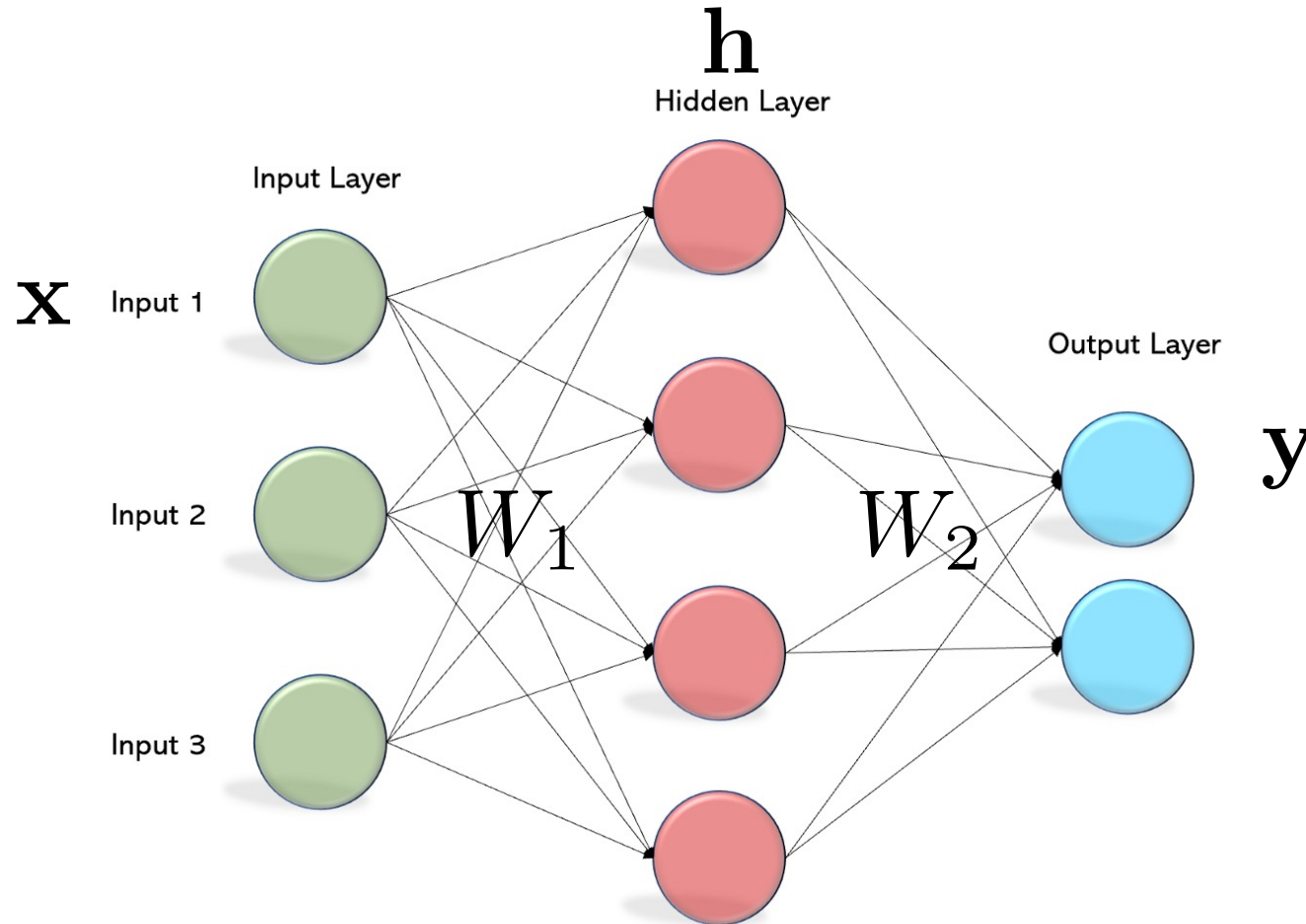
Basic Deep Learning Models

Multi-Layer Perceptron (MLP)



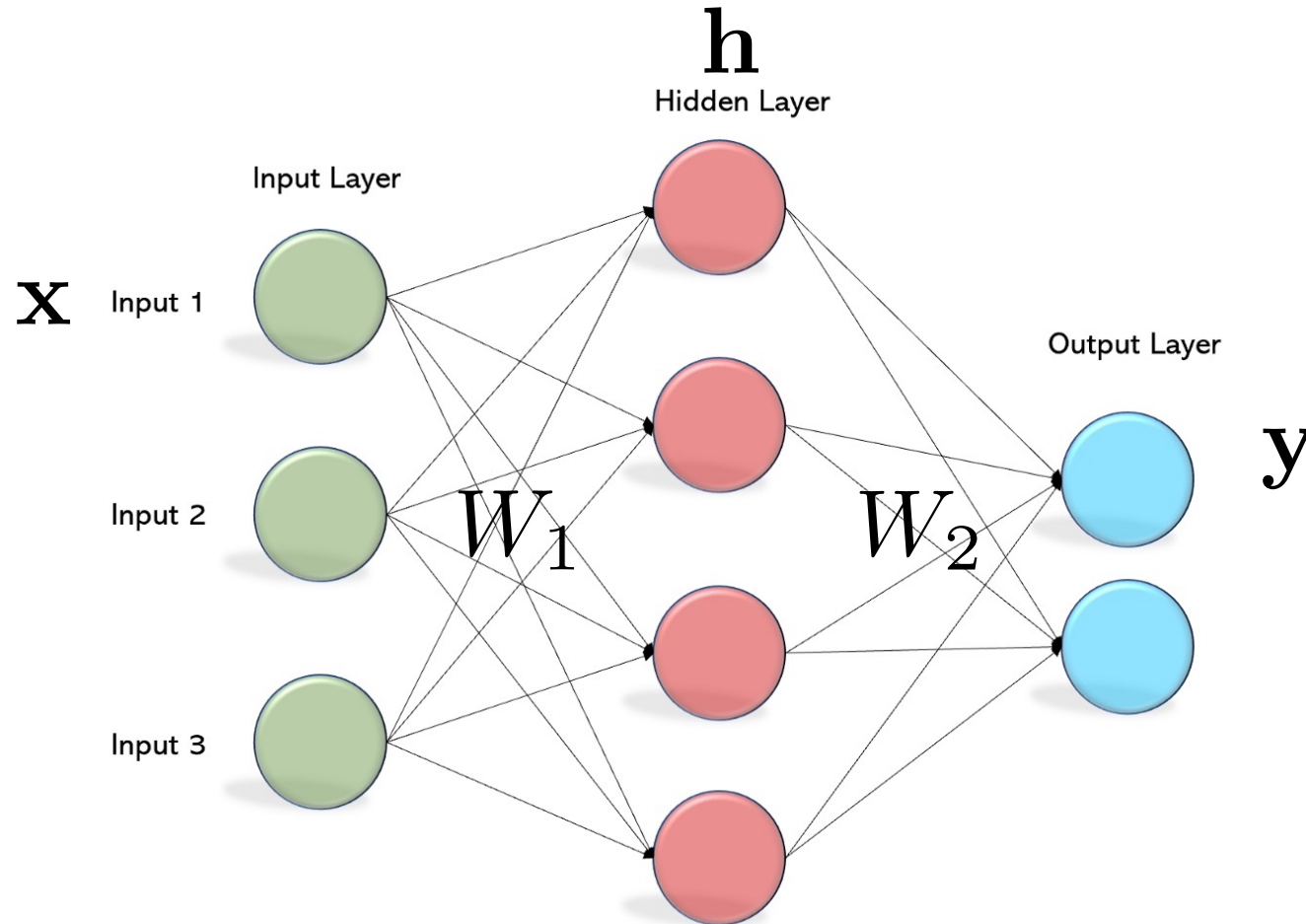
Basic Deep Learning Models

Multi-Layer Perceptron (MLP)



Basic Deep Learning Models

Multi-Layer Perceptron (MLP)

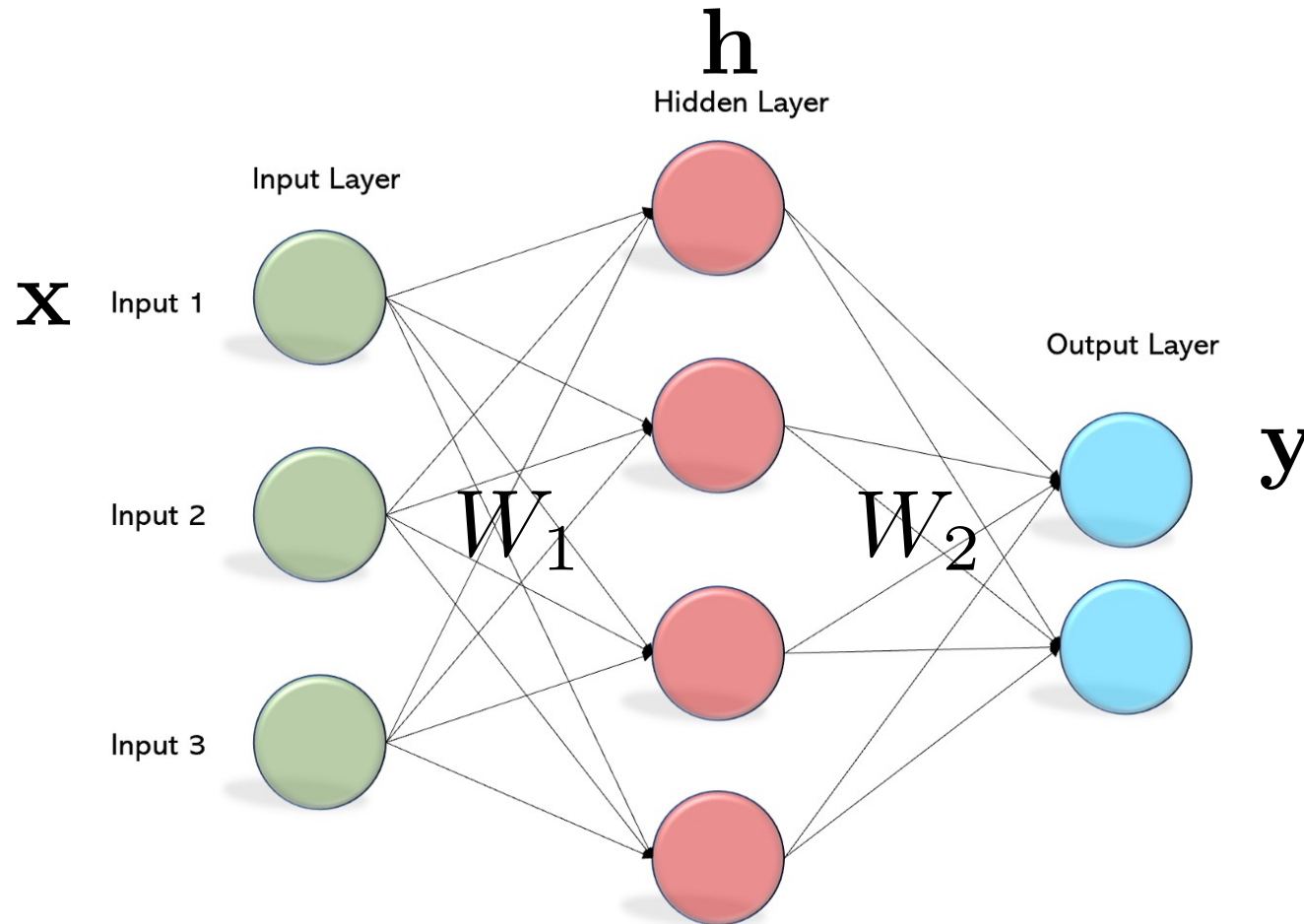


$$\mathbf{h} = \sigma(W_1 \mathbf{x})$$

$$\mathbf{y} = W_2 \mathbf{h}$$

Basic Deep Learning Models

Multi-Layer Perceptron (MLP)



$$\mathbf{h} = \sigma(W_1 \mathbf{x})$$

$$\mathbf{y} = W_2 \mathbf{h}$$

ReLU: $\sigma(\mathbf{h}) = \max(\mathbf{h}, 0)$

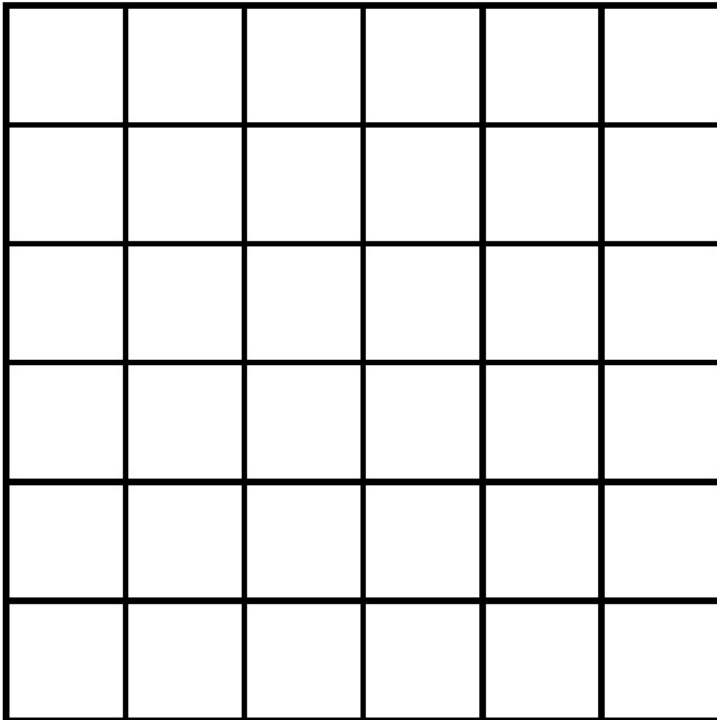
Sigmoid: $\sigma(\mathbf{h}) = \frac{1}{1 + \exp(-\mathbf{h})}$

Tanh, Softplus, ELU, ...

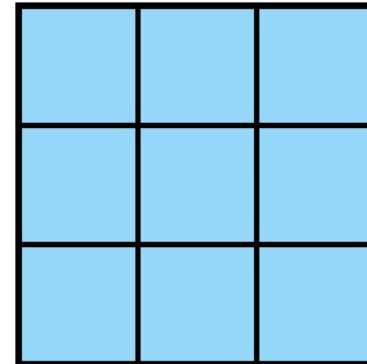
Basic Deep Learning Models

Convolutional Neural Network (CNN)

Convolution (Discrete)



Image



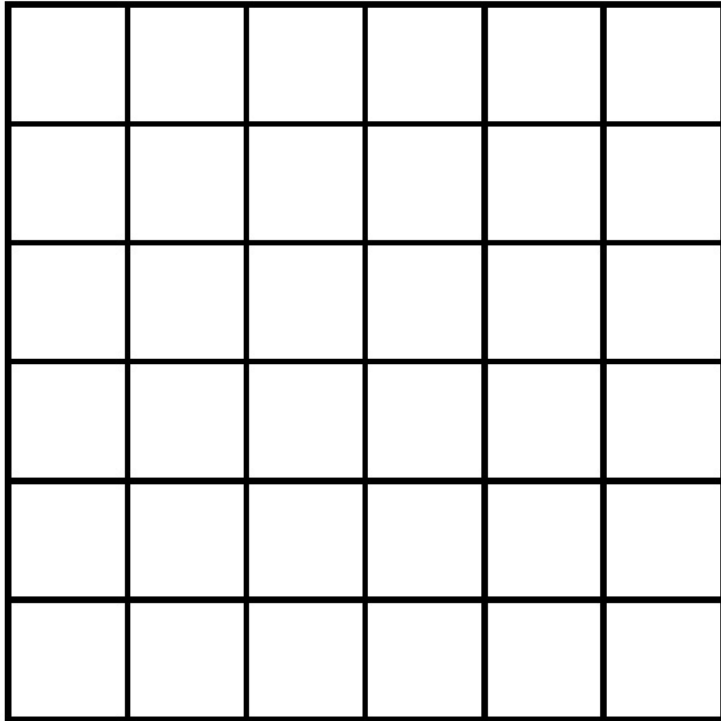
Convolutional Filter

Basic Deep Learning Models

Convolutional Neural Network (CNN)

Convolution (Discrete)

$$y_{i,j} = \sum_{m=1}^K \sum_{n=1}^K W_{m,n} \mathbf{x}_{i+m-\lceil K/2 \rceil, j+n-\lceil K/2 \rceil}$$



Basic Deep Learning Models

Convolutional Neural Network (CNN)

Convolution (Discrete) \Leftrightarrow Matrix Multiplication I

$$y = h * x = \begin{bmatrix} h_1 & 0 & \cdots & 0 & 0 \\ h_2 & h_1 & & \vdots & \vdots \\ h_3 & h_2 & \cdots & 0 & 0 \\ \vdots & h_3 & \cdots & h_1 & 0 \\ h_{m-1} & \vdots & \ddots & h_2 & h_1 \\ h_m & h_{m-1} & & \vdots & h_2 \\ 0 & h_m & \ddots & h_{m-2} & \vdots \\ 0 & 0 & \cdots & h_{m-1} & h_{m-2} \\ \vdots & \vdots & & h_m & h_{m-1} \\ 0 & 0 & 0 & \cdots & h_m \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}$$

Filter \Rightarrow Toeplitz matrix

It could be very sparse!

Basic Deep Learning Models

Convolutional Neural Network (CNN)

Convolution (Discrete) \Leftrightarrow Matrix Multiplication II

$$y^T = [h_1 \quad h_2 \quad h_3 \quad \cdots \quad h_{m-1} \quad h_m] \begin{bmatrix} x_1 & x_2 & x_3 & \cdots & x_n & 0 & 0 & 0 & \cdots & 0 \\ 0 & x_1 & x_2 & x_3 & \cdots & x_n & 0 & 0 & \cdots & 0 \\ 0 & 0 & x_1 & x_2 & x_3 & \cdots & x_n & 0 & \cdots & 0 \\ \vdots & & \vdots & \vdots & \vdots & & \vdots & \vdots & & \vdots \\ 0 & \cdots & 0 & 0 & x_1 & \cdots & x_{n-2} & x_{n-1} & x_n & 0 \\ 0 & \cdots & 0 & 0 & 0 & x_1 & \cdots & x_{n-2} & x_{n-1} & x_n \end{bmatrix}$$

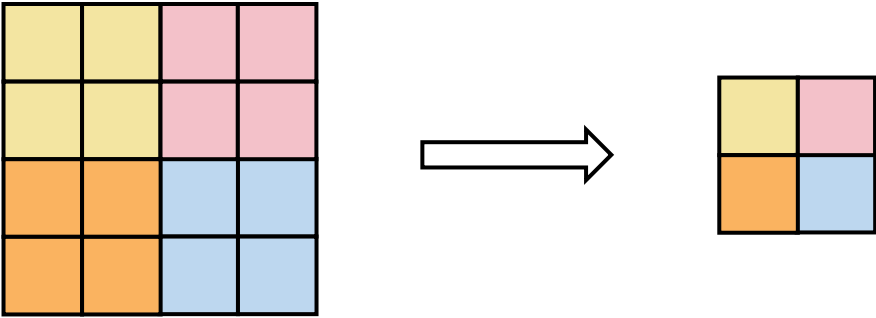
Data \Rightarrow Toeplitz matrix

image to columns (patches)

Basic Deep Learning Models

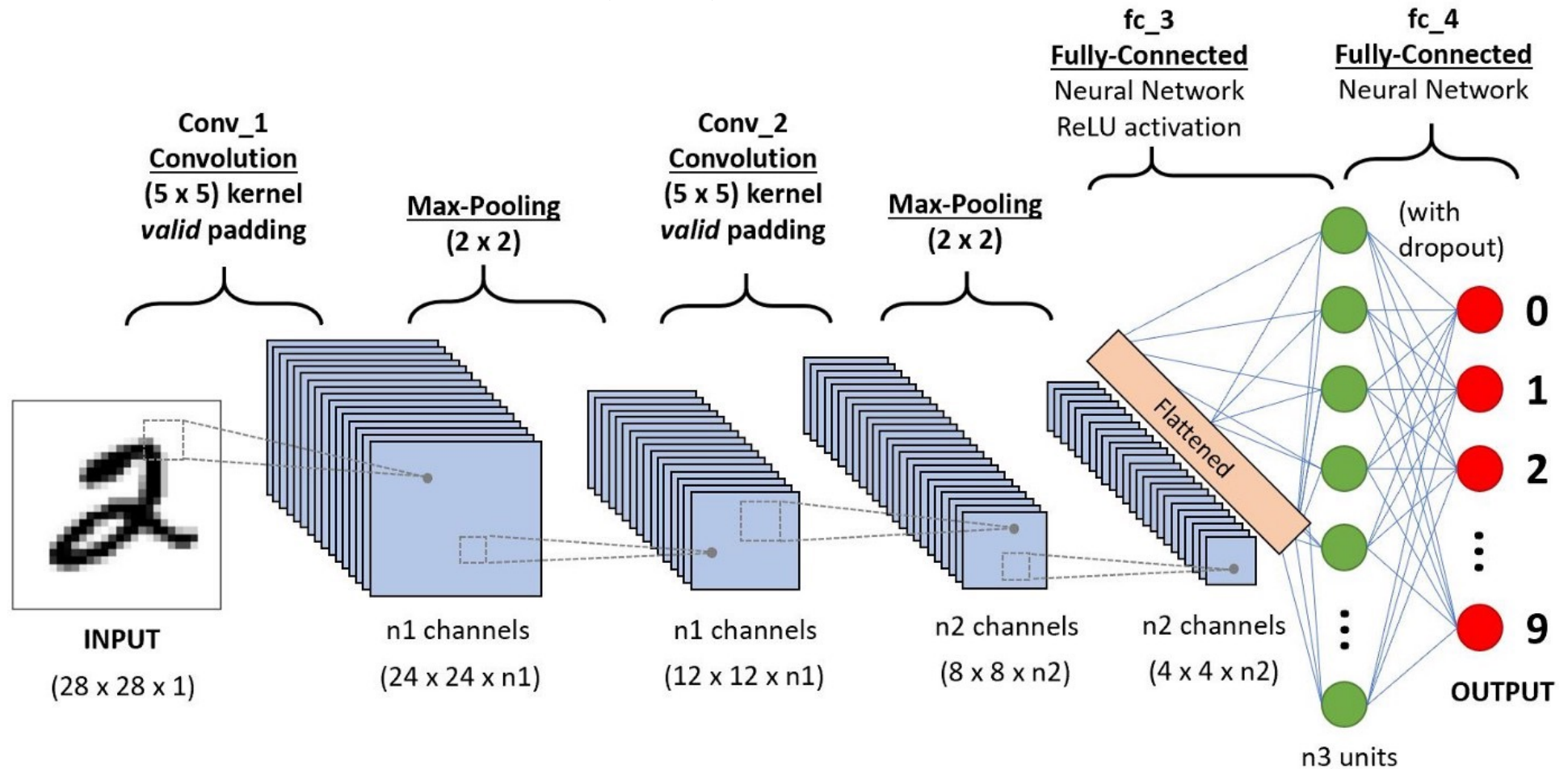
Convolutional Neural Network (CNN)

Pooling (e.g., 2X2)



Basic Deep Learning Models

Convolutional Neural Network (CNN)



Basic Deep Learning Models

Recurrent Neural Network (RNN)

Same neural network gets reused many times!

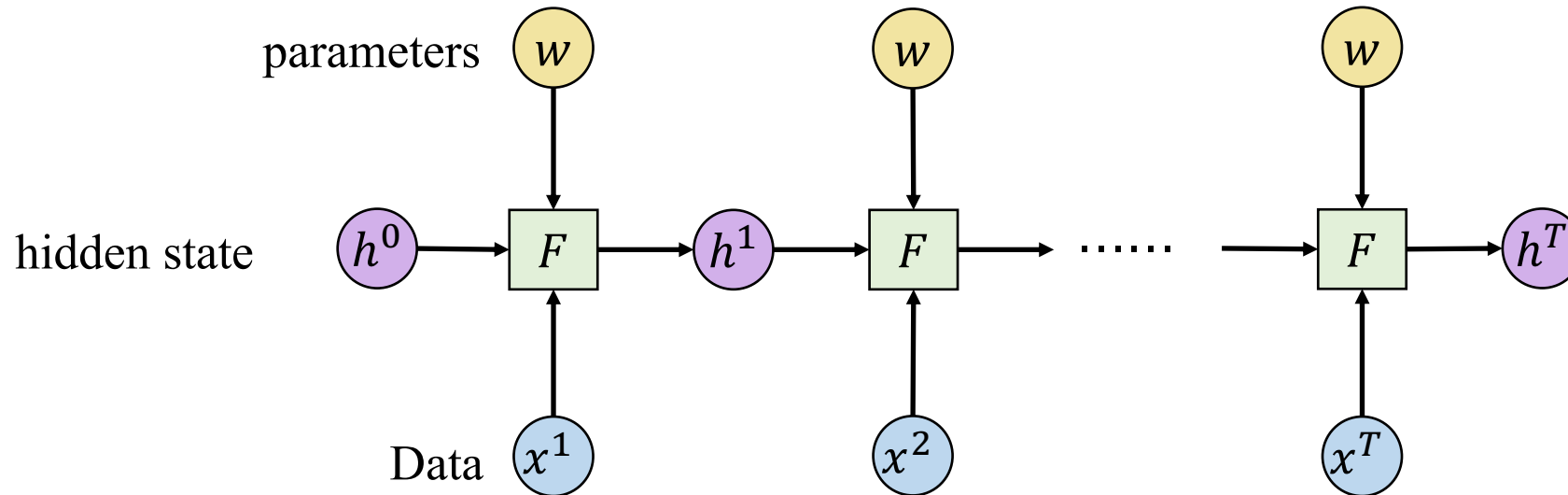
$$\mathbf{h}^t = F(\mathbf{x}^t, \mathbf{h}^{t-1}, W)$$

Basic Deep Learning Models

Recurrent Neural Network (RNN)

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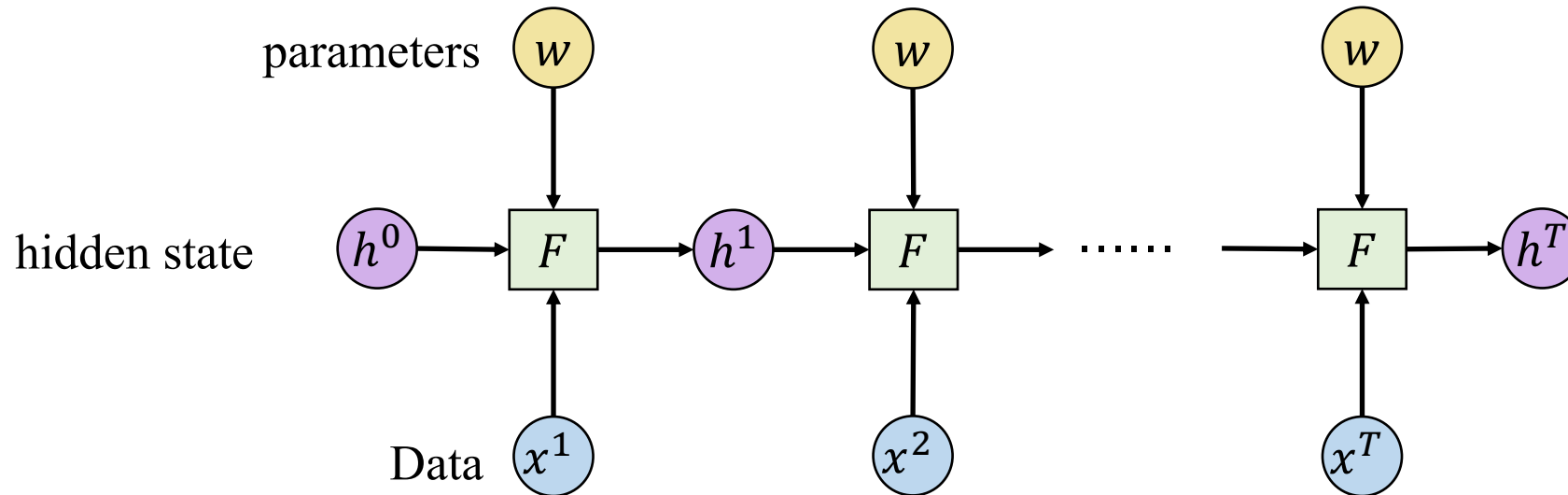


Basic Deep Learning Models

Recurrent Neural Network (RNN)

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F could be any neural network!

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Objective (Loss) Function

- Supervised Learning

Given (data, label), we want to minimize empirical risk/loss

Loss = Function(label, model(data))

Objective (Loss) Function

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Empirical Risk Minimization (ERM)!

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Cross-Entropy Loss:

$$\ell(p, q) = - \sum_{i=1}^K p_i \log q_i$$

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$$\ell(p, q) = - \sum_{i=1}^K p_i \log q_i$$

- Regression

Mean-Squared Error (MSE):

$$\ell(\mathbf{x}, \mathbf{y}) = - \frac{1}{K} \|\mathbf{x} - \mathbf{y}\|_2^2$$

Objective (Loss) Function

Unsupervised/Self-supervised Learning

Only data is given

Objective (Loss) Function

Unsupervised/Self-supervised Learning

Only data is given

- Maximum likelihood (Autoregressive models)
- Reconstruction Loss (Auto-encoders)
- Contrastive Loss (noise contrastive estimation, self-supervised learning)
- Min-max Loss (Generative adversarial networks)

.....

Objective (Loss) Function

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.....

Designing a good objective function itself is a challenging research question!

Objective (Loss) Function

■ "Pure" Reinforcement Learning (cherry)

- ▶ The machine predicts a scalar reward given once in a while.
- ▶ **A few bits for some samples**

■ Supervised Learning (icing)

- ▶ The machine predicts a category or a few numbers for each input
- ▶ Predicting human-supplied data
- ▶ **10→10,000 bits per sample**

■ Unsupervised/Predictive Learning (cake)

- ▶ The machine predicts any part of its input for any observed part.
- ▶ Predicts future frames in videos
- ▶ **Millions of bits per sample**

■ (Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)



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Learning Algorithm

Learning algorithm is about **credit assignment**

Assign credits based on contribution \Leftrightarrow *Adjust parameters based on loss*

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The most successful learning algorithm so far is **gradient based learning!**

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Representative method: stochastic gradient descent (SGD), Robbins and Monro, 1951

Learning Algorithm

Learning algorithm is about **credit assignment**

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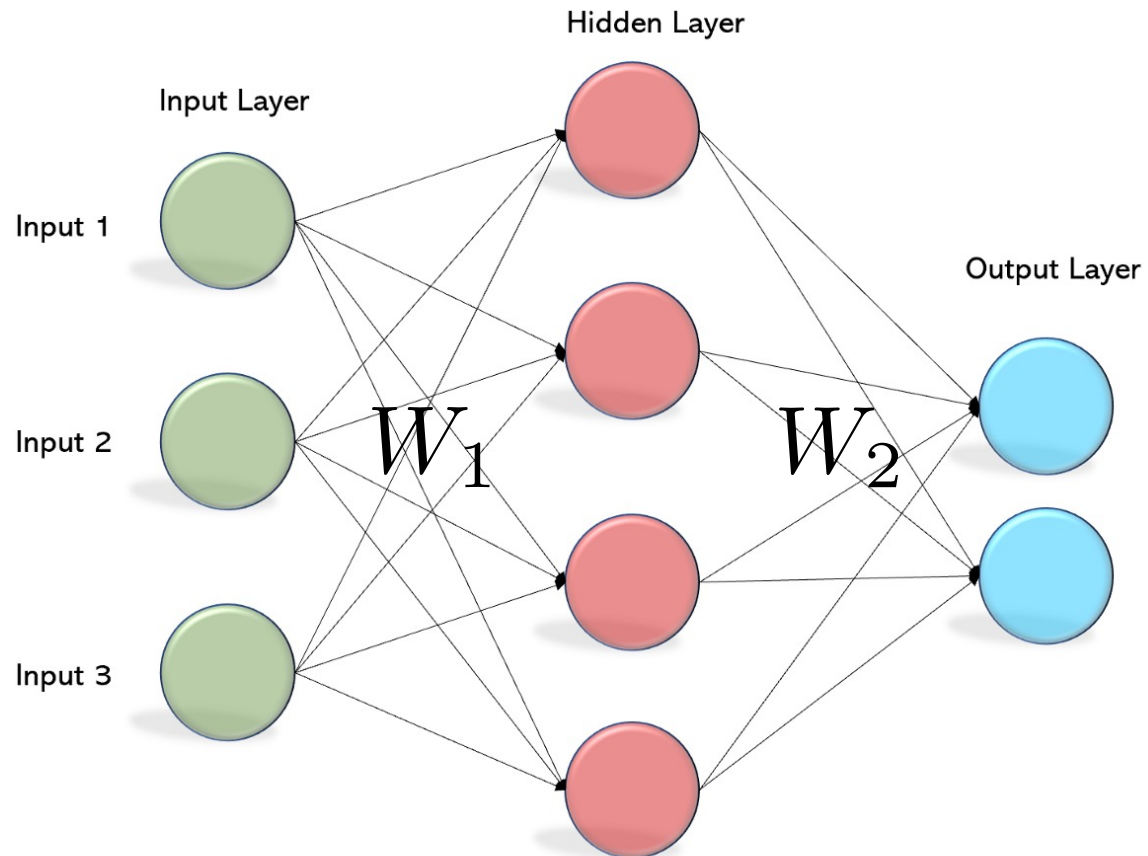
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Back-propagation (BP) = SGD in the context of deep learning

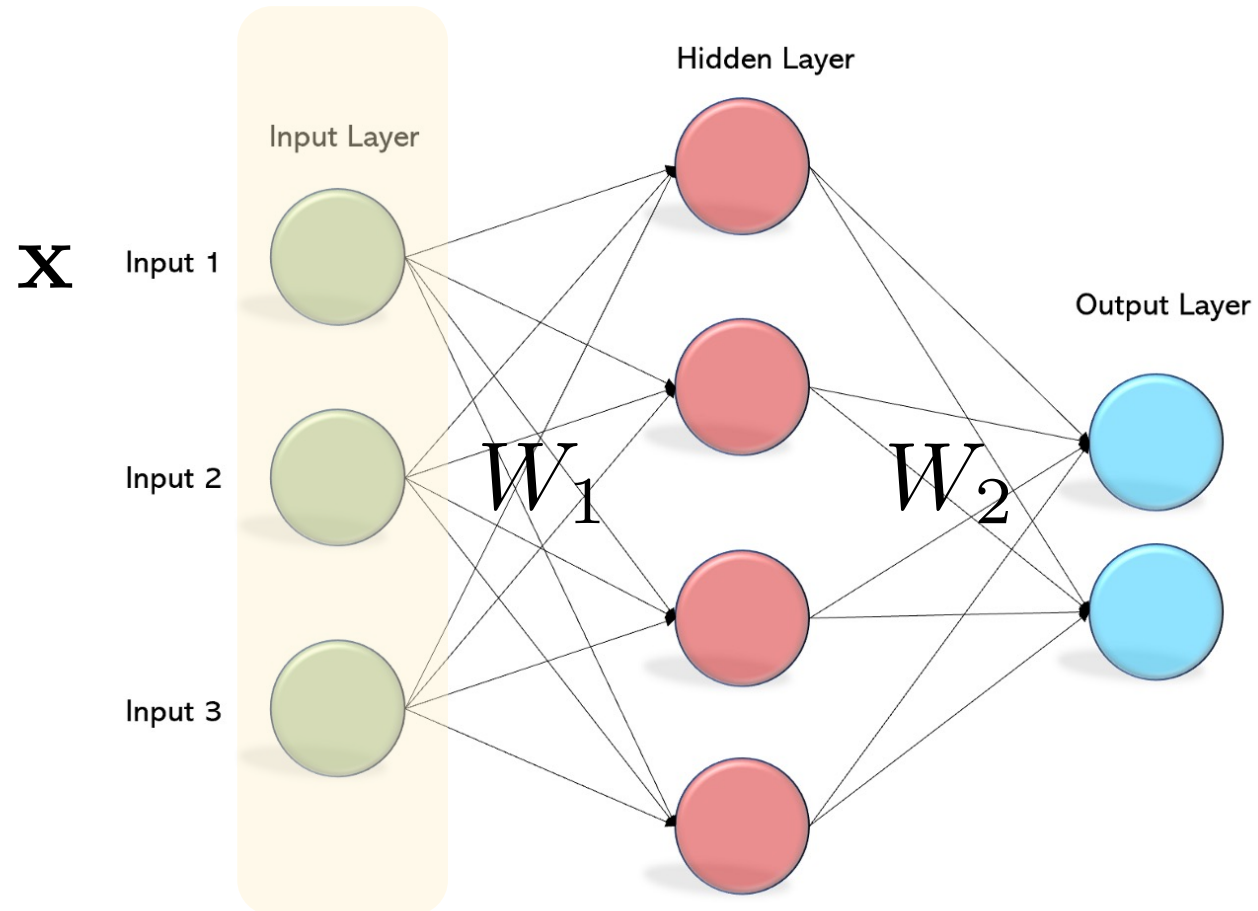
Back-Propagation

Multi-Layer Perceptron (MLP)



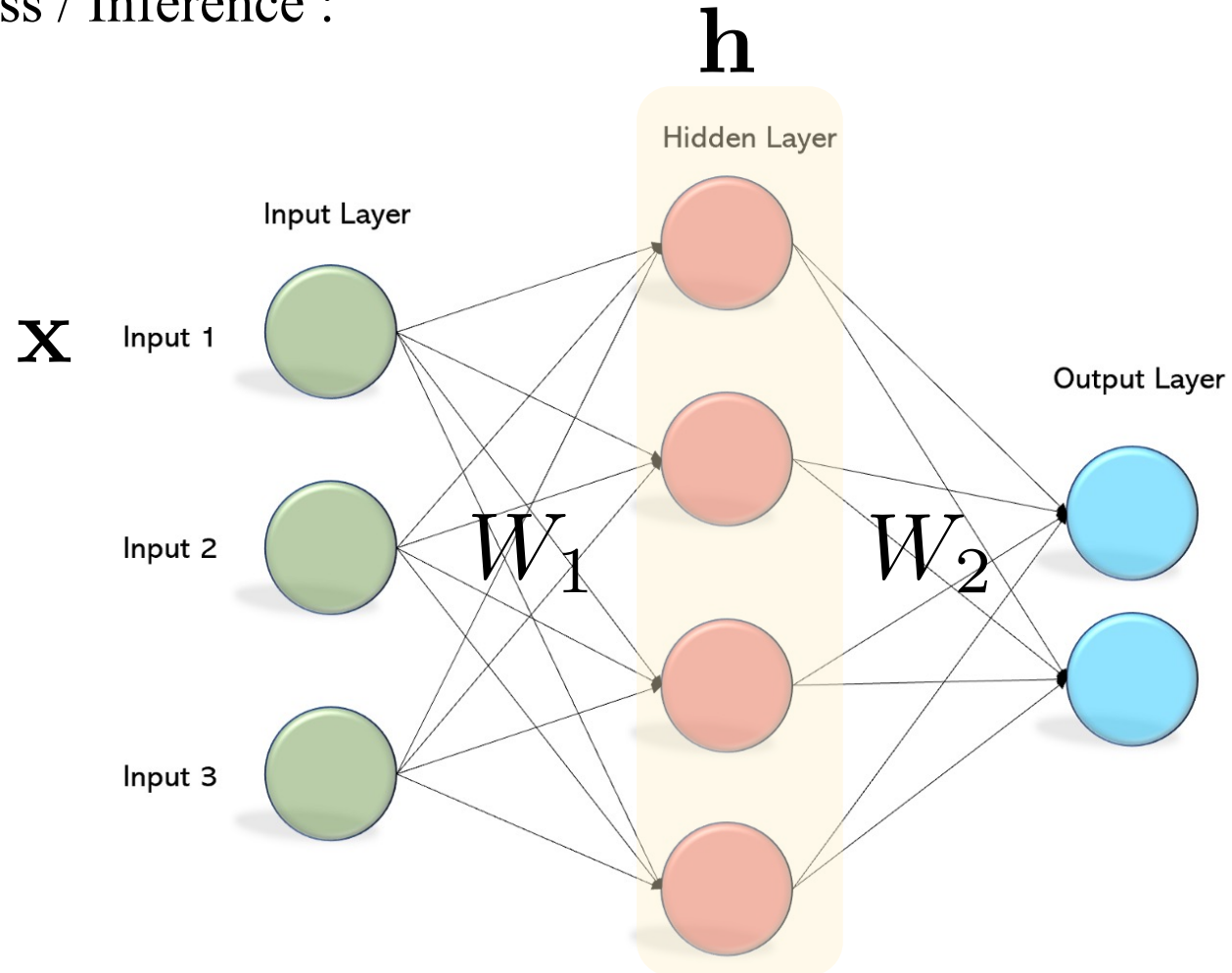
Back-Propagation

Forward Pass / Inference :



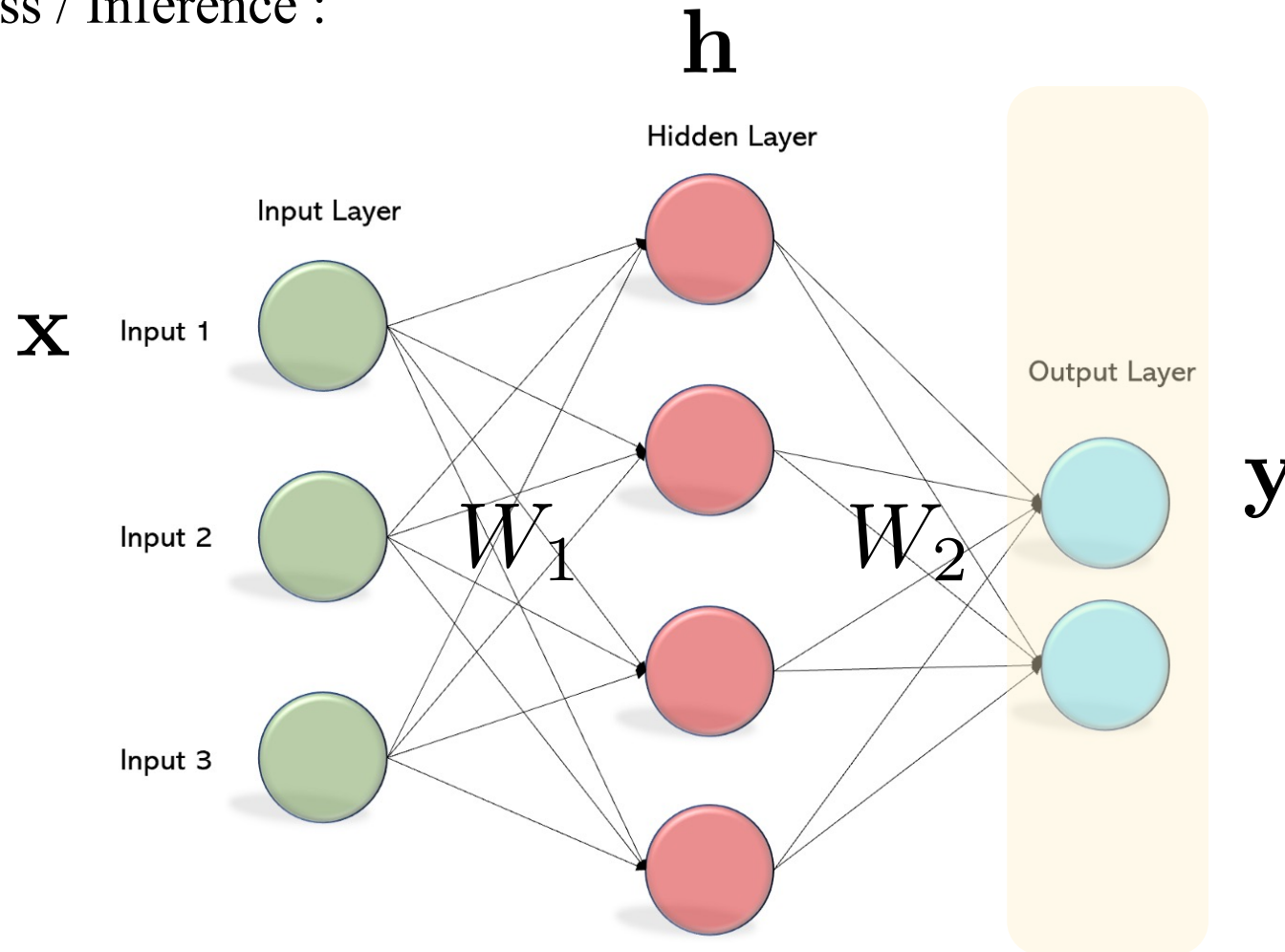
Back-Propagation

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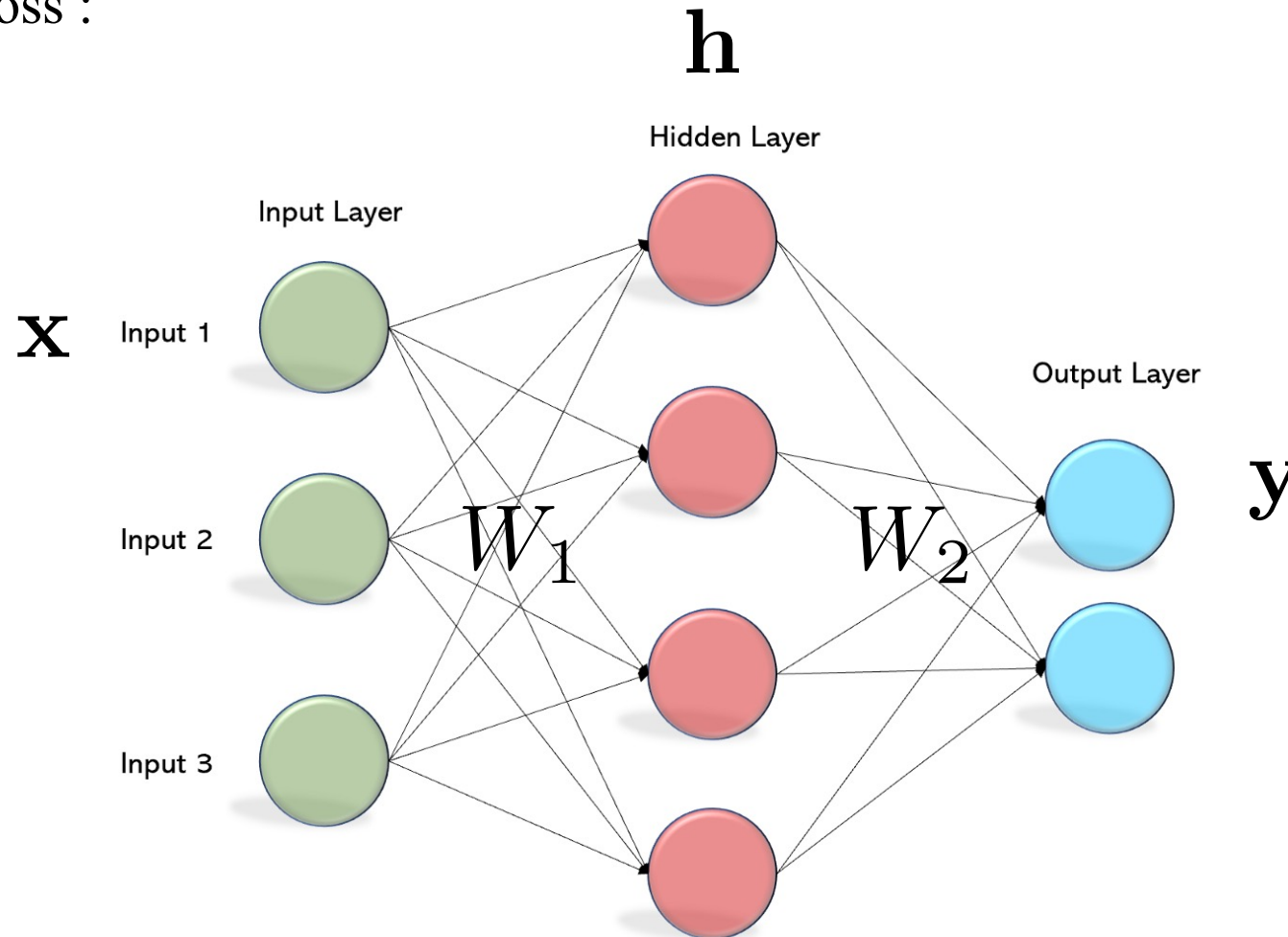
Back-Propagation

Forward Pass / Inference :



Back-Propagation

Compute Loss :

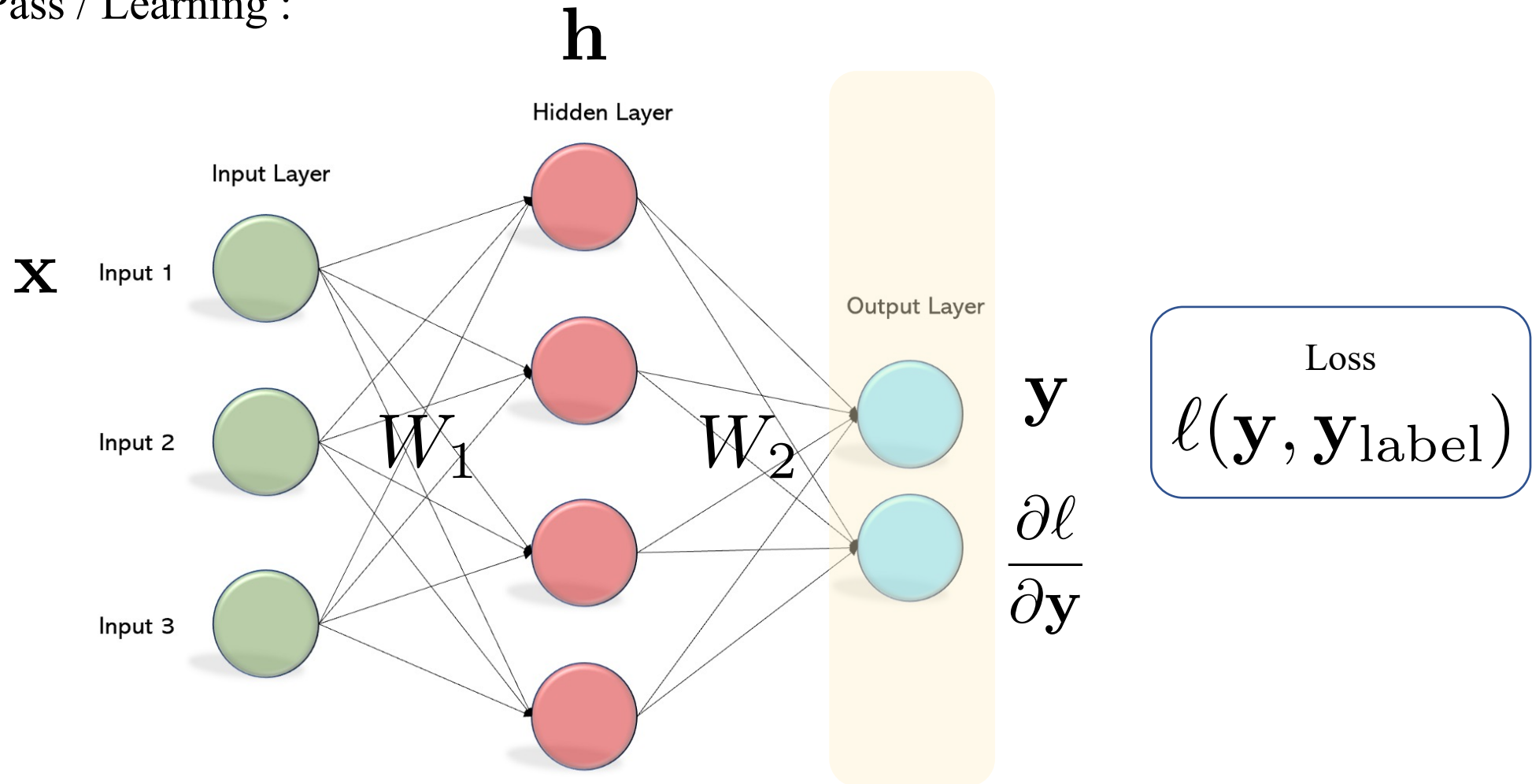


Loss

$$\ell(\mathbf{y}, \mathbf{y}_{\text{label}})$$

Back-Propagation

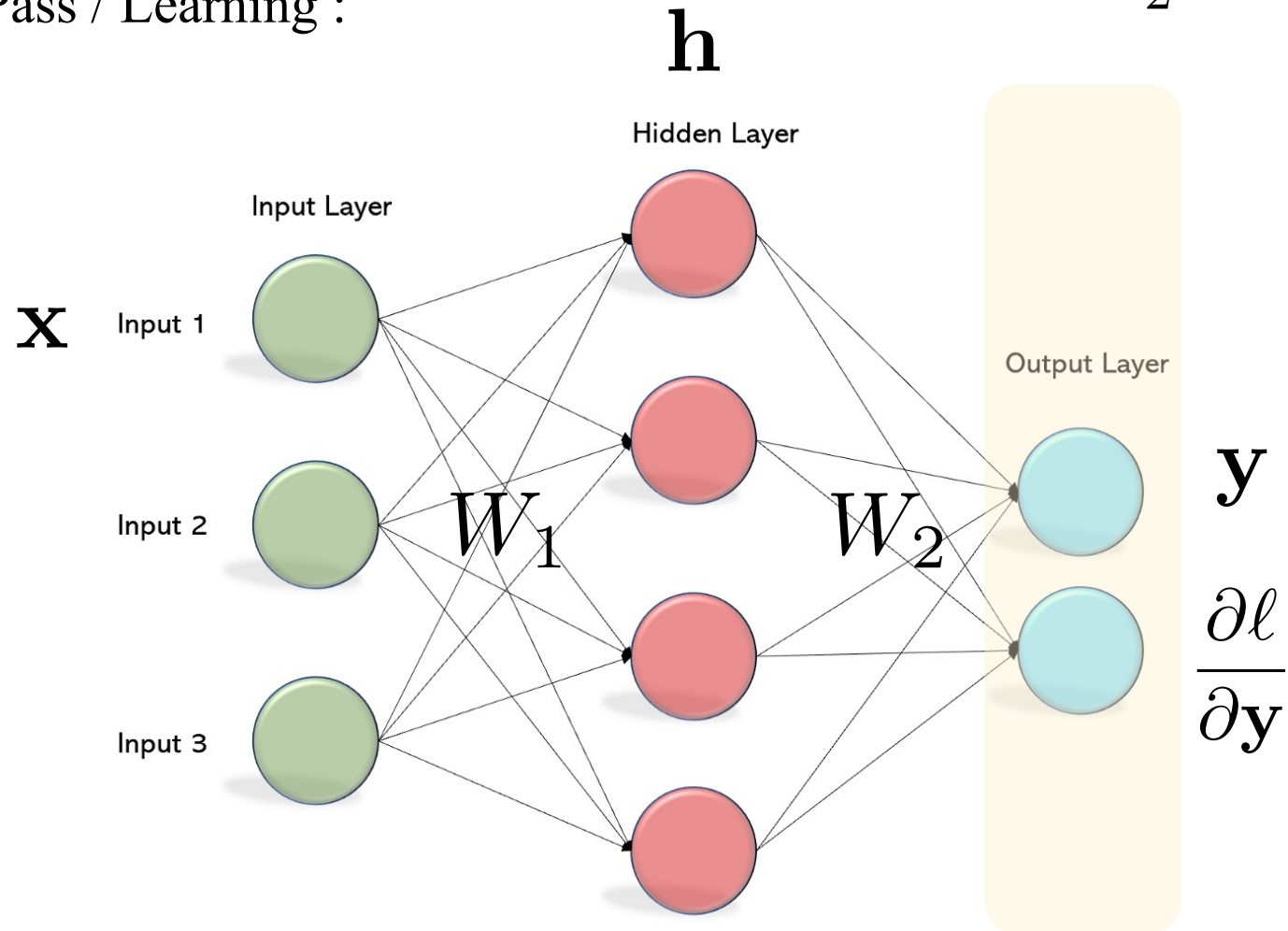
Backward Pass / Learning :



Back-Propagation

Backward Pass / Learning :

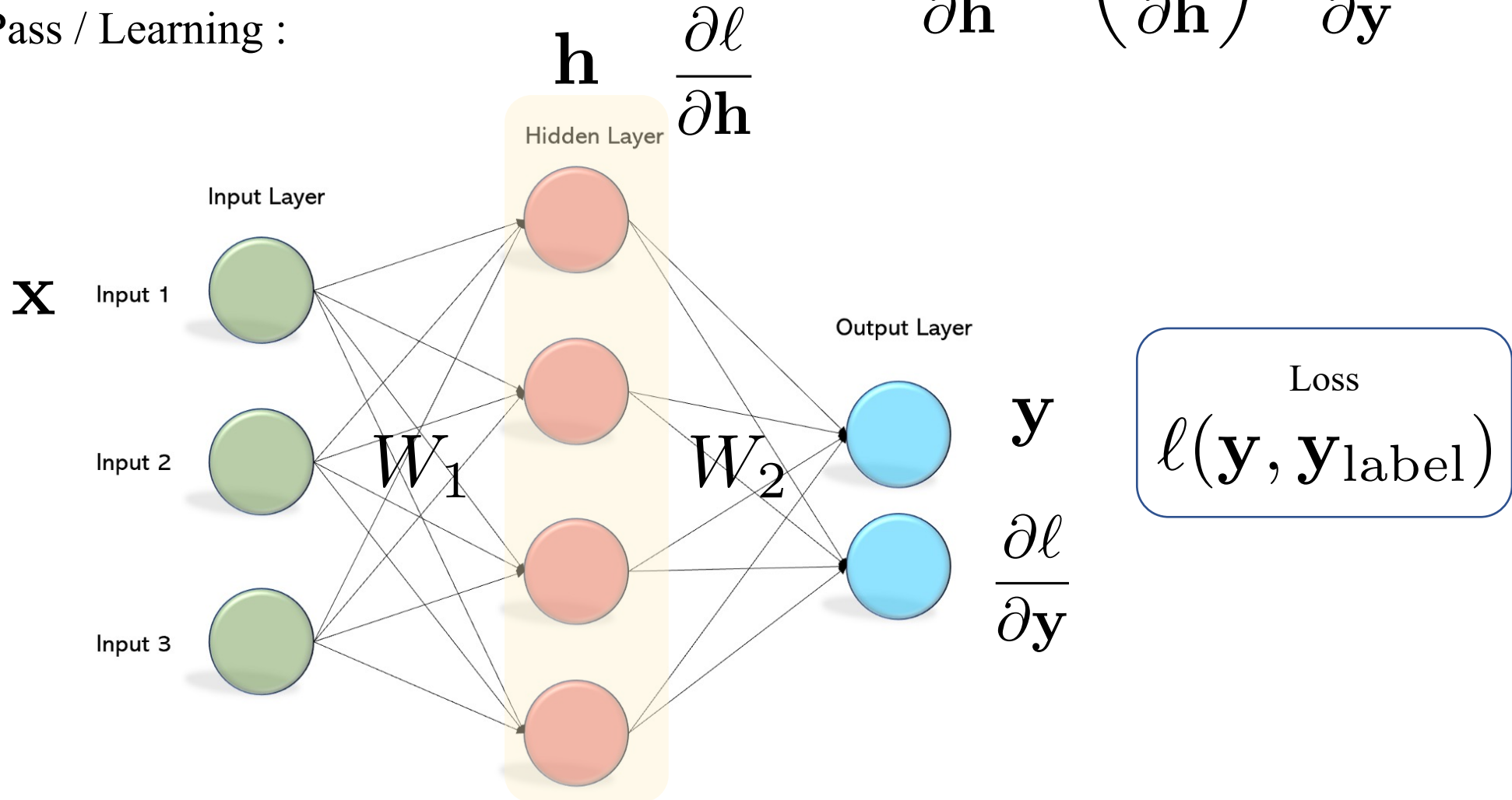
$$\frac{\partial \ell}{\partial W_2} = \left(\frac{\partial \mathbf{y}}{\partial W_2} \right)^\top \frac{\partial \ell}{\partial \mathbf{y}}$$



Back-Propagation

Backward Pass / Learning :

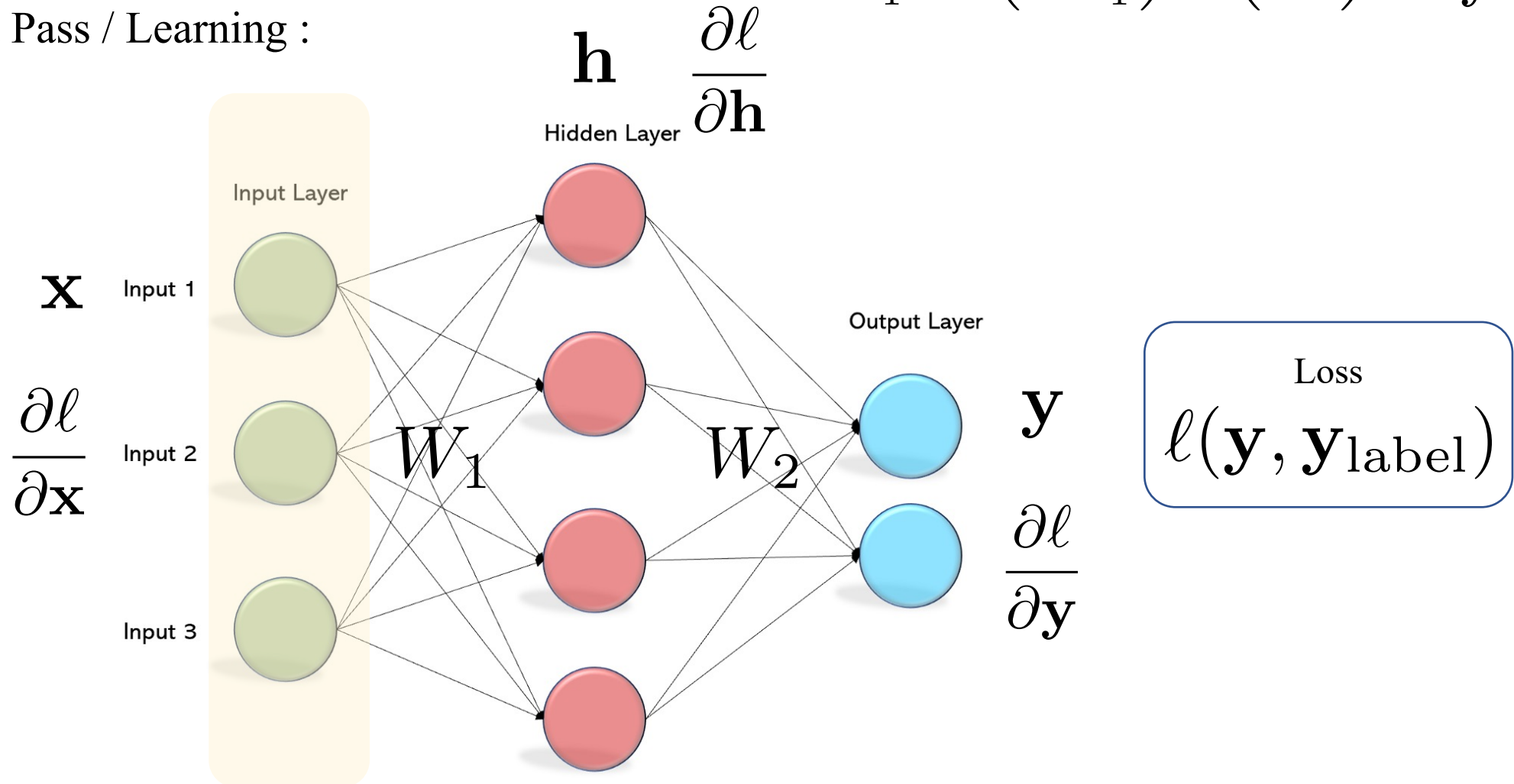
$$\frac{\partial \ell}{\partial \mathbf{h}} = \left(\frac{\partial \mathbf{y}}{\partial \mathbf{h}} \right)^\top \frac{\partial \ell}{\partial \mathbf{y}}$$



Back-Propagation

Backward Pass / Learning :

$$\frac{\partial \ell}{\partial W_1} = \left(\frac{\partial \mathbf{h}}{\partial W_1} \right)^\top \left(\frac{\partial \mathbf{y}}{\partial \mathbf{h}} \right)^\top \frac{\partial \ell}{\partial \mathbf{y}}$$



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- MLPs/CNNs are restricted to data with fixed size
 - Each sample needs to have the same size

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- RNNs can deal with varying-size data
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- MLPs/CNNs are restricted to data with fixed size
 - Each sample needs to have the same size
- RNNs can deal with varying-size data
 - Only presented as sequences
- Learned representations do not explicitly encode structures of data
 - Hard to interpret and manipulate

Questions?