1. Introduction to Deep Learning

CS 5242 Neural Networks and Deep Learning

YOU, Yang

16.08.2022

Today's Lecture

1. Get to know each other
   - Instructor & TAs
   - Students
2. Module Introduction
3. Logistics
4. Linear Regression

Let’s get to know each other.

Teaching Assistants

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If you have any questions, ask in the slack channel.

1. Who are you?
2. What is your technical or research interest?
3. Why is your career plan? (optional)

Slack URL:
cs5242ay20222-oiw1784.slack.com
Invite Link:
https://join.slack.com/t/cs5242ay20222-oiw1784/shared_invite/zt-1d67c47x3-xCDz5Psta8ZlDWZ2HYoG0w

If you cannot come to the classroom

1. Join Zoom Meeting
   https://nus-sg.zoom.us/j/3997998157
2. Meeting ID: 399 799 8157

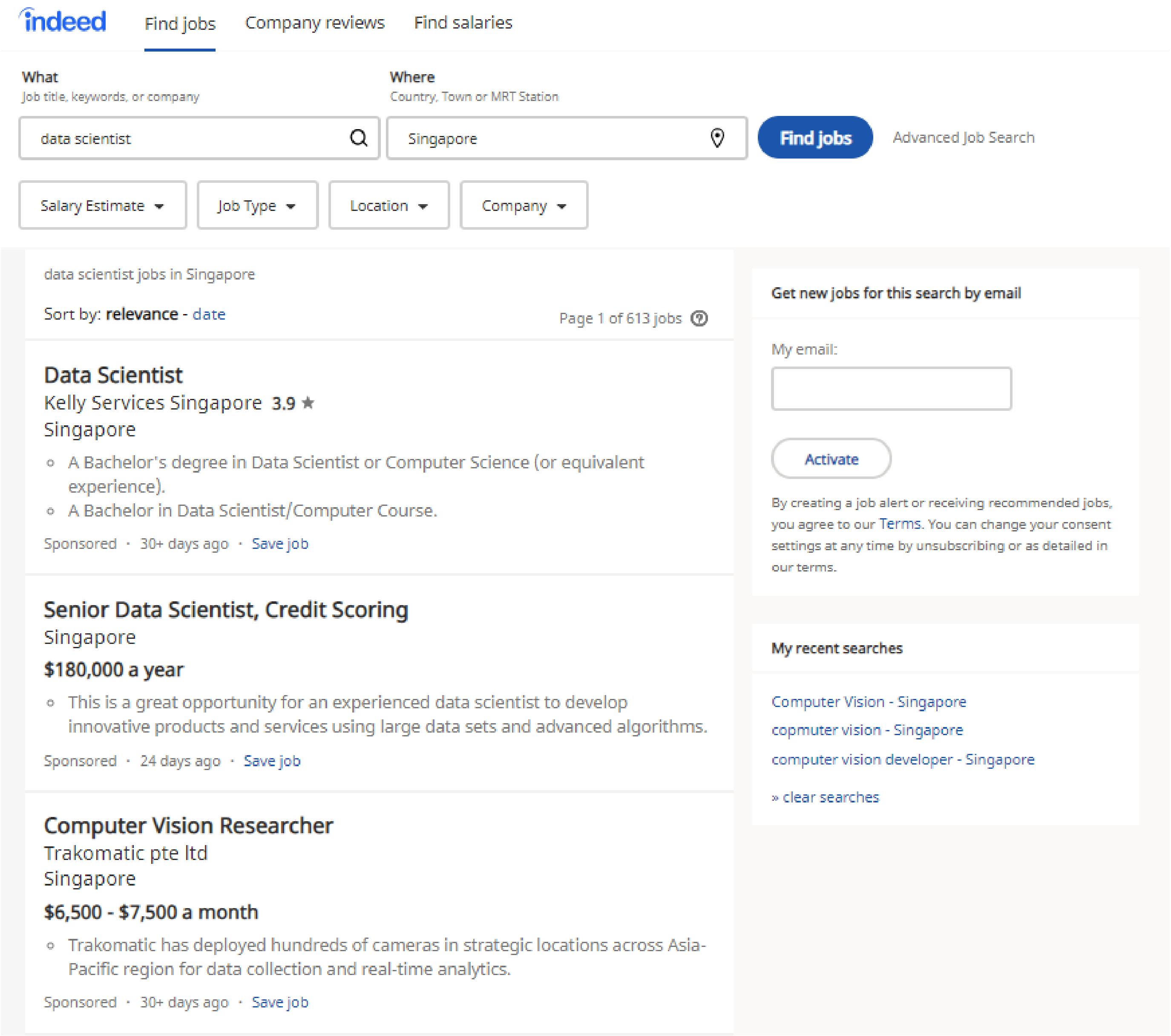
I heard that everyone got A's last term and am hoping for an easy boost to my GPA.

maybe, maybe not...

I want to earn the big bucks as a data scientist / ML engineer at Google / Amazon / Facebook.

check out

CS5260 – NN & Deep Learning II
CS4243 – Computer Vision & Pattern Recognition
CS4248 – Natural Language Processing



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$180,000 a year

I actually wanted CS5XXX but couldn't get that module.

too bad

Can't get into this module? Email for guest access.

My PhD advisor is making me take this course so that I can use deep learning in our research.

Neural Networks and Deep Learning:

- Andrew Ng
- https://www.coursera.org/learn/neural-networks-deep-learning

CSC 321: Intro to Neural Networks and Machine Learning

- Roger Grosse
- http://www.cs.toronto.edu/~rgrosse/courses/csc321_2017/

Neural Networks for Machine Learning

- Geoffrey Hinton
- https://www.coursera.org/learn/neural-networks

CS231n: Convolutional Neural Networks for Visual Recognition

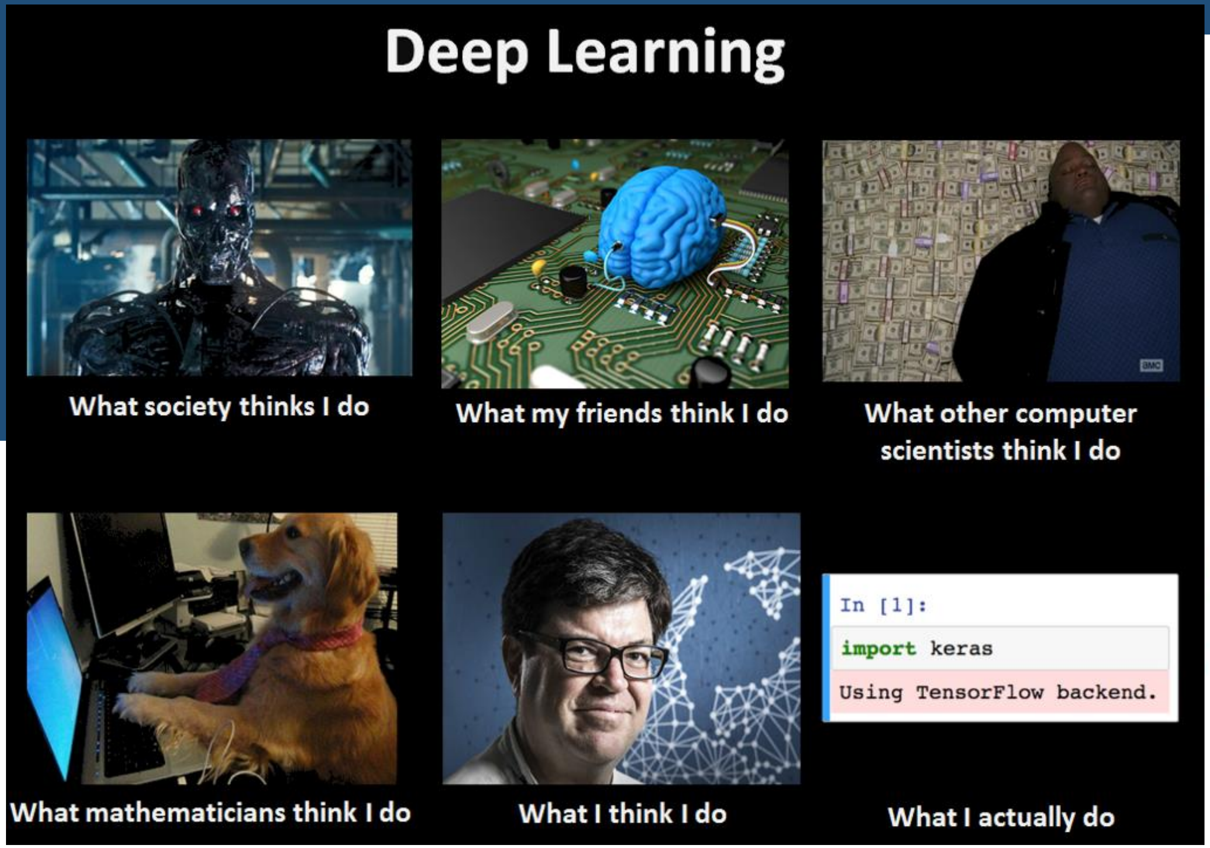
- Fei-Fei Li, Justin Johnson, Serena Yeung
- http://cs231n.stanford.edu/

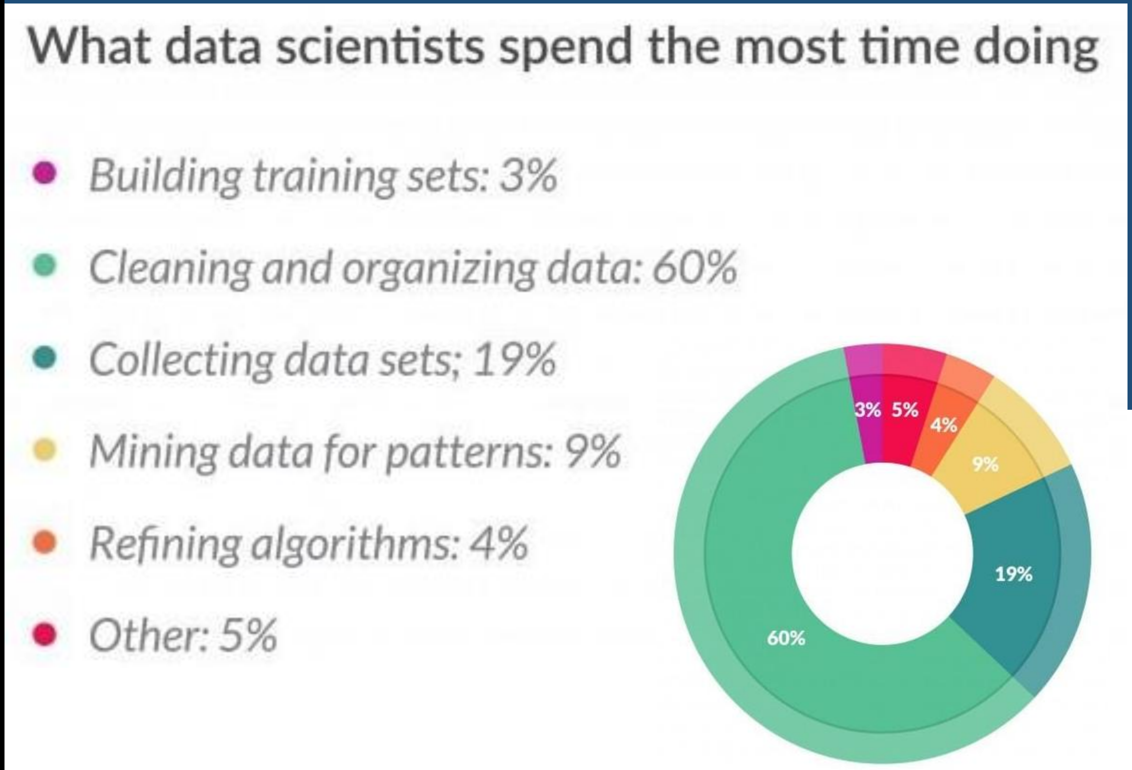
CS224d: Deep Learning for Natural Language Processing

- Richard Socher
- http://cs224d.stanford.edu/

Slide credit: Wang Wei

AI is cool and I want to build the next Skynet.





Intended Learning Outcomes

1

Explain the principles of the operations of different layers and training algorithms

2

Compare different neural network architectures

3

Implement popular neural networks

4

Solve problems using neural networks and deep learning techniques

Slide credit: Wang Wei

Course Logistics

Pre-requisite

Modules

- Machine Learning (CS3244)
  - Or https://www.coursera.org/learn/machine-learning
- Linear Algebra (MA1101R)
  - Or https://ocw.mit.edu/courses/mathematics/18-06-linear-algebra-spring-2010/
- Calculus (MA1521)
- Probability (ST2334)
- Brief summary

Coding

- Python (ONLY, version 3.x)
  - Numpy
  - Keras, TensorFlow, PyTorch, MxNet, Colossal-AI
- Jupyter notebook

Slide credit: Wang Wei

Syllabus & Schedule

- Learn various neural network models
  - From shallow to deep neural networks
  - model structures, training algorithms, tricks and applications
  - principles, theory & coding practices
- Check Canvas (not LumiNUS) for the latest plan
  - https://canvas.nus.edu.sg/

Slide credit: Wang Wei

Grading policy

Weightage:

- 7 Assignments (70%)
  - 15% off per day late (17:01 is the start of one day)
  - 0 score if you submit it 7 days after the deadline
- Project (30%)
  - Group size <=4
  - Please ask Dr. AI (teaching after week 7) for this

Collaboration

- Every assignment is an individual task
- The project is a group-based task
- Avoid academic offences (cheating, plagiarism including copying code from the internet, e.g., github)

Slide credit: Wang Wei

Contact Policy

- All (non-personal) issues
  - Slack Channel: cs5242ay20222-oiw1784.slack.com
- Personal issues
  - Email the instructor
- Consultation (arrange appointment)
  - Tutorial & Assignment: TAs
  - Lecture content:
    - Email the instructor (youy@comp.nus.edu.sg)

GPU machines

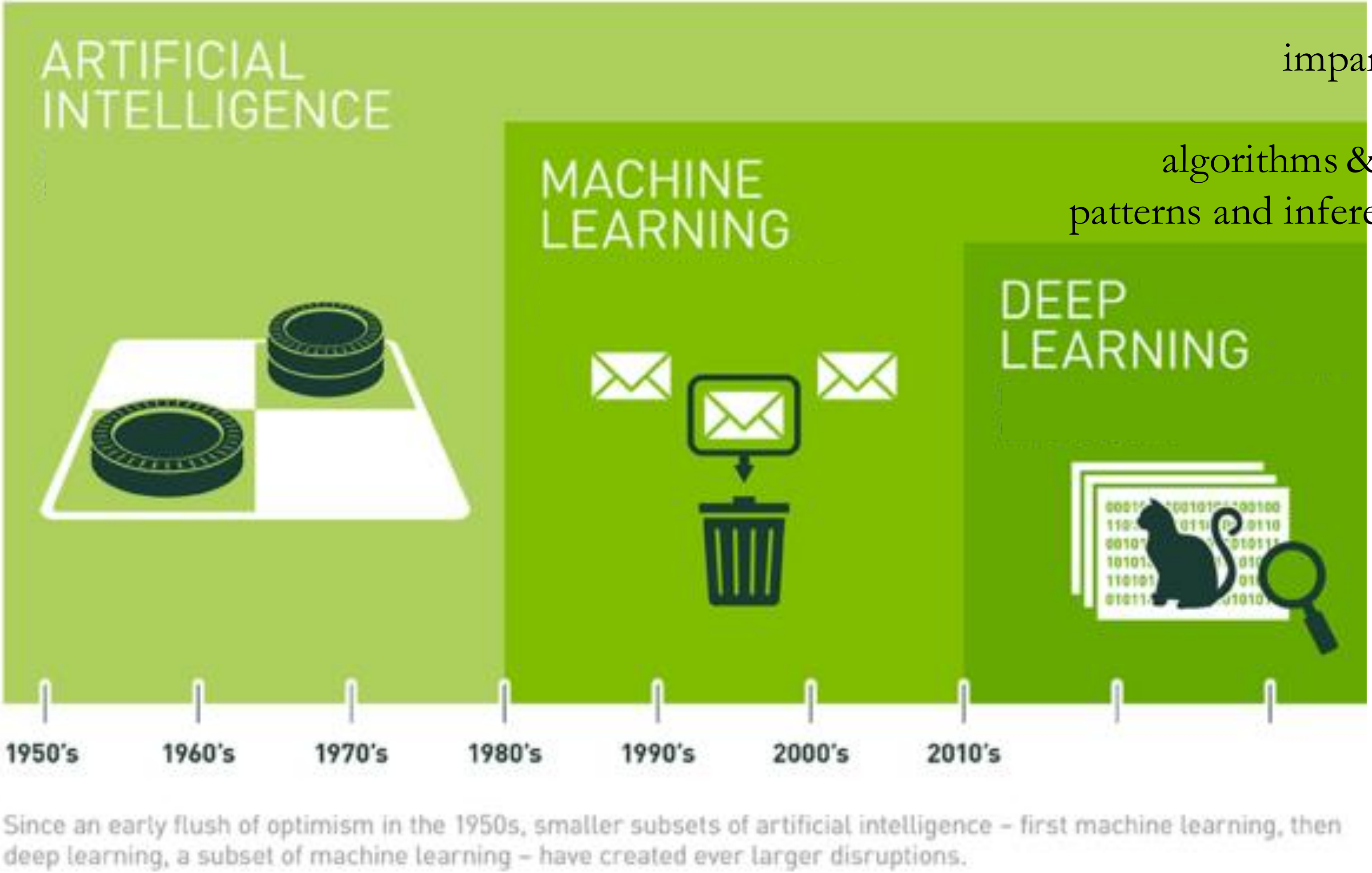
- SoC GPU machines:
  - https://dochub.comp.nus.edu.sg/cf/guides/compute-cluster/hardware
- NSCC (National Super-Computing Center)
  - Free for NUS students
  - The libraries are sometimes outdated
  - Jobs will be submitted into a queue for executing
- Google Cloud Platform
  - Some free credit for new register
  - GPU is expensive
- Amazon EC2 (g2.8xlarge)
  - Some free credit for students
  - GPU is expensive

Important notes if you use cloud platforms:

- STOP/TERMINATE the instance immediately after your program terminates
- Check usage status frequently to avoid high outstanding bills
- Amazon/Google may charge you for additional storage volume

Slide credit: Wang Wei

Terminology Overload: AI vs. ML vs. DL



imparting cognitive abilities to machines

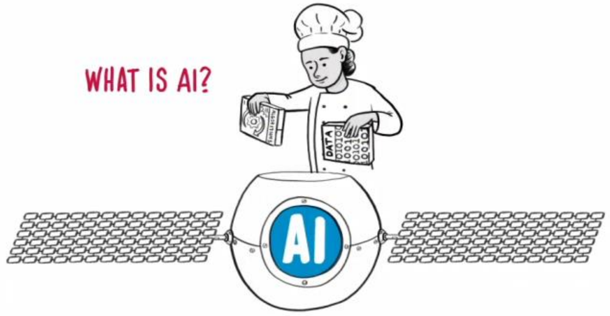
algorithms & models to perform tasks based on patterns and inference instead of specific instructions

branch of machine learning using deep neural networks

https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

Artificial Intelligence (AI)

- 1950's
- "Human intelligence exhibited by machines"
  - Expert systems; Rules
  - Machine learning algorithms
- Narrow AI:
  - image recognition
  - machine translation
  - recommender system
  - …



https://www.youtube.com/watch?v=nASDYRkbQIY

Slide adapted from Wang Wei

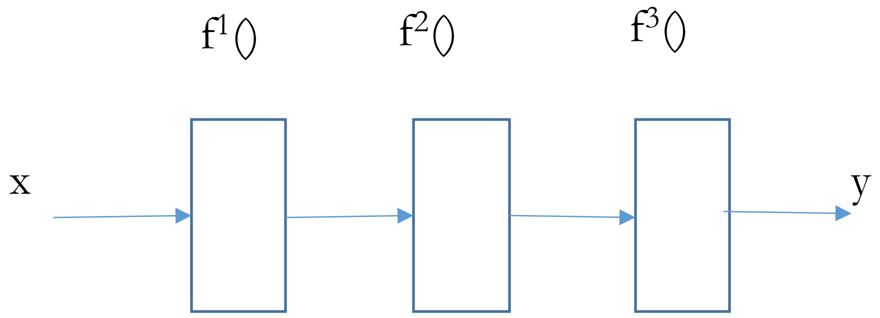
Machine Learning (ML)

- 1980's
- "An approach to achieve AI through systems that can learn from experience to find patterns in that data"
  - Can we code a program to do
    - Image recognition
    - Speech recognition

Slide credit: Wang Wei

Neural networks and Deep Learning

- 1950's / 2010's
- A class of machine learning algorithm that use a cascade of multiple layers of nonlinear processing units for feature extraction and transformation---Wikipedia



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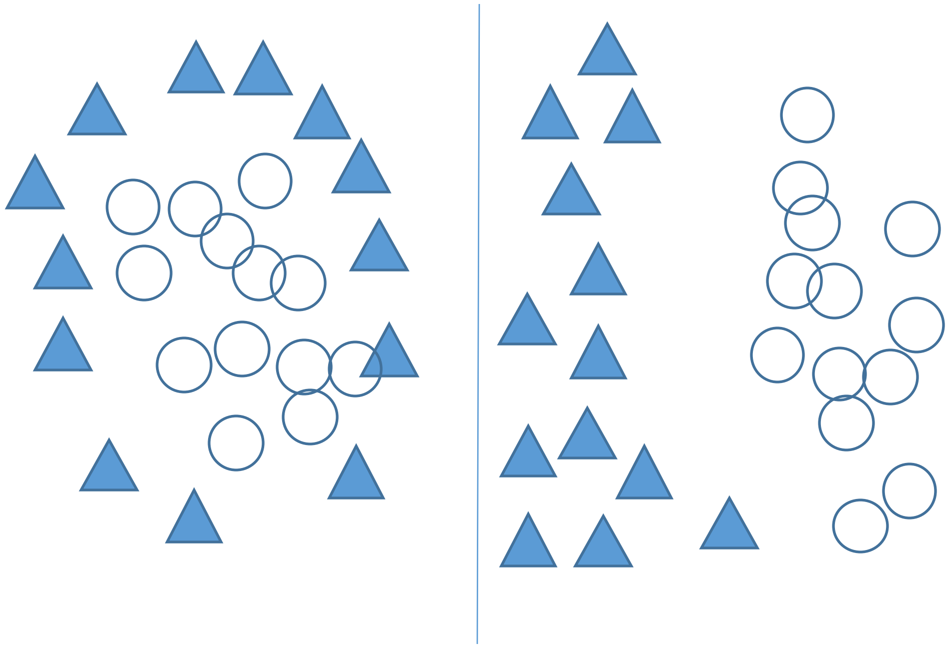
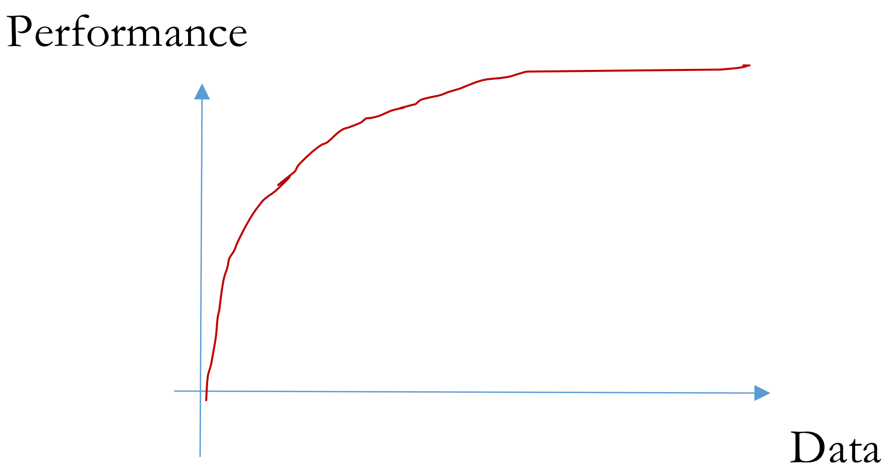
Neural networks and Deep Learning

- Feature learning (transformation)





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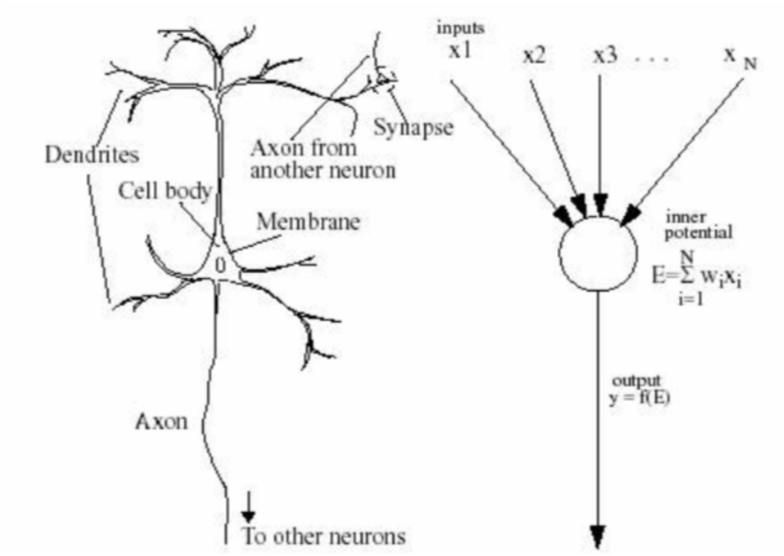
“Neural” Networks?

The origins of neural networks come from efforts of mathematically representing information processing in biological systems (hence the term “neural”).



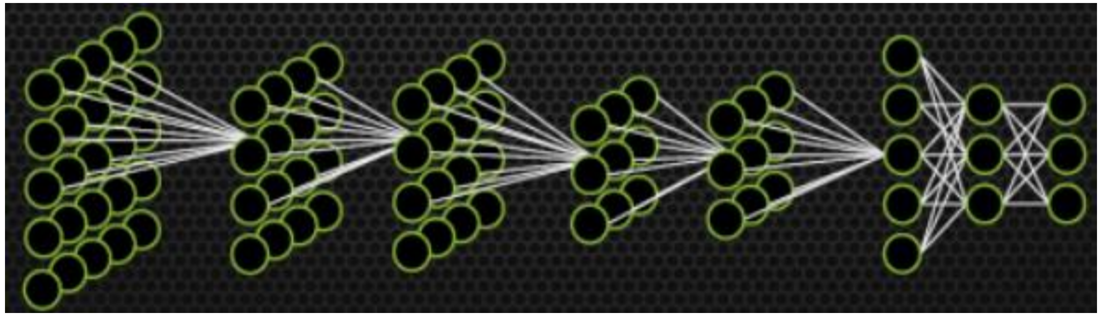
Neural nets/perceptrons are **loosely** inspired by biology. But they certainly are **not** a model of how the brain works, or even how neurons work.

http://commonsenseatheism.com/wp-content/uploads/2011/12/biological-and-artificial-neurons.jpg

Our interests in neural networks are less about biological systems and more about efficient models for statistical pattern recognition.

Neural networks (NN)

- Linear, polynomial, logistic regression
- Perceptron and multi-layer perceptron (MLP)
- Convolutional neural network (CNN)
- Recurrent neural networks (RNN)
- Transformers (Attention; Seq to Seq)
- Generative adversarial networks (GAN)
- (Restricted) Boltzmann machine
- Deep belief network
- Spike neural network
- Radial basis function neural network
- Hopfield networks



Source from [3]

Slide credit: Wang Wei

History [2]

1957
First perceptron, Frank Rosenblatt

1974
Backpropagation, Paul Werbos

1980
Neocogitron (inspired CNN), Kunihiko Fukushima

1986
Recurrent Neural Network (RNN), David Rumelhart

1990
LeNet

1998
Hochreiter & Schmidhube, LSTM

2006
Deep Belief Networks, Geoffrey Hinton

2012
AlexNet, Alex Krizhevsky & Geoffrey Hinton

2014
GoogleNet & VGG

2014
Generative Adversarial Networks

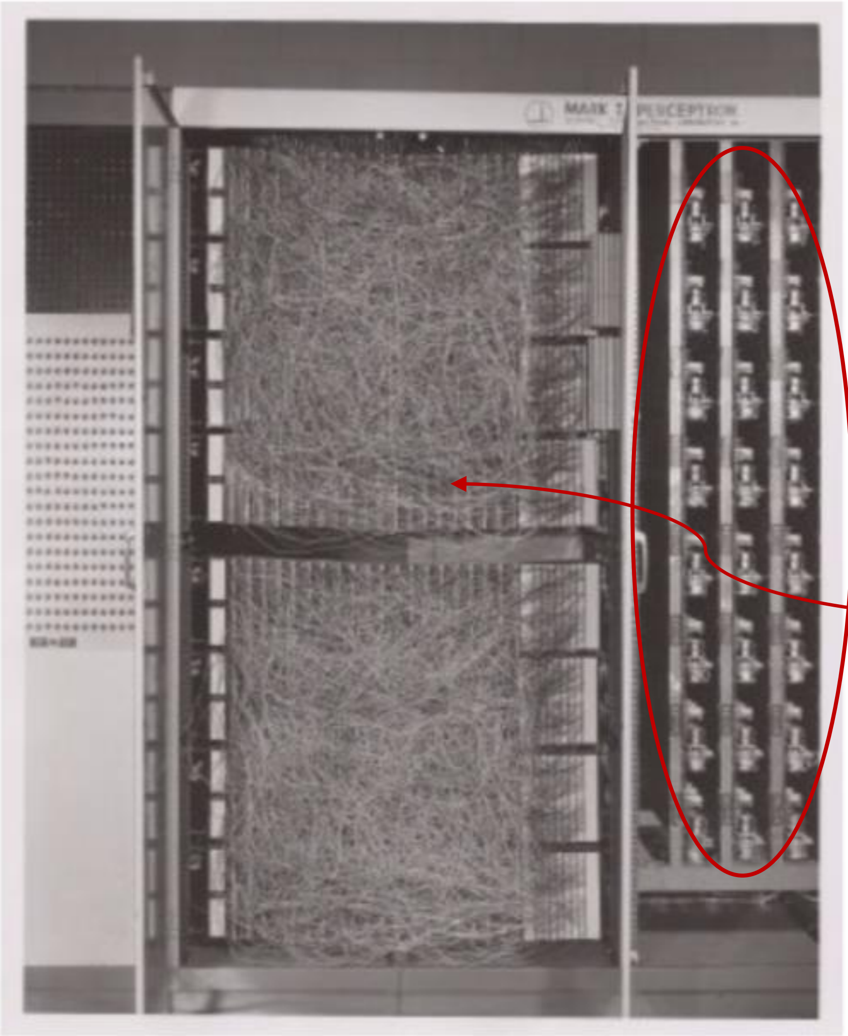
2015
ResNet

2015
AlphaGo
BERT
GPT-3

Refer to http://people.idsia.ch/~juergen/who-invented-backpropagation.html for more papers

Slide adapted from Wang Wei

The Perceptron Machine (1957)



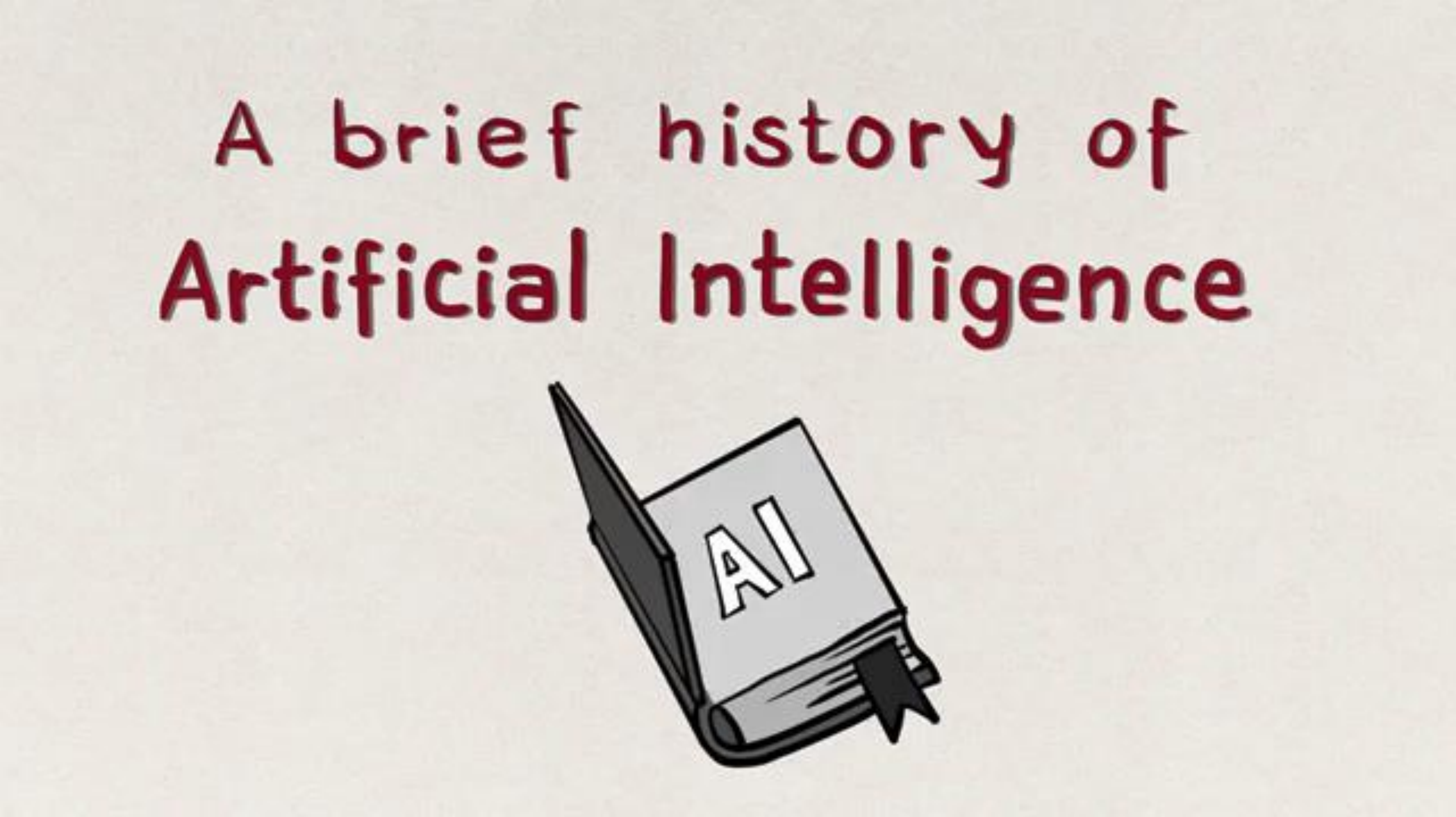
The Mark I Perceptron machine was a hardware implementation of the perceptron algorithm.

The Perceptron machine was connected to a 20x20 array of photocells producing a 400 pixel image (essentially a camera).

The nest of wires create different combinations of inputs.

Arrays of adjustable variable resistors, which could be used as adaptive ("hand-tuned") weights.

https://en.wikipedia.org/wiki/Perceptron#/media/File:Mark_I_perceptron.jpeg



https://www.youtube.com/watch?v=yaL5ZMvRRqE

Applications

Computer Vision

- Image classification
- Object detection, demo
- Scene text recognition
- Neural style transferring
- Image generation

Natural language processing

- Question answering
- Machine translation

Speech

- Speech recognition, e.g. Amazon Echo

Slide credit: Wang Wei

Univariate Linear Regression

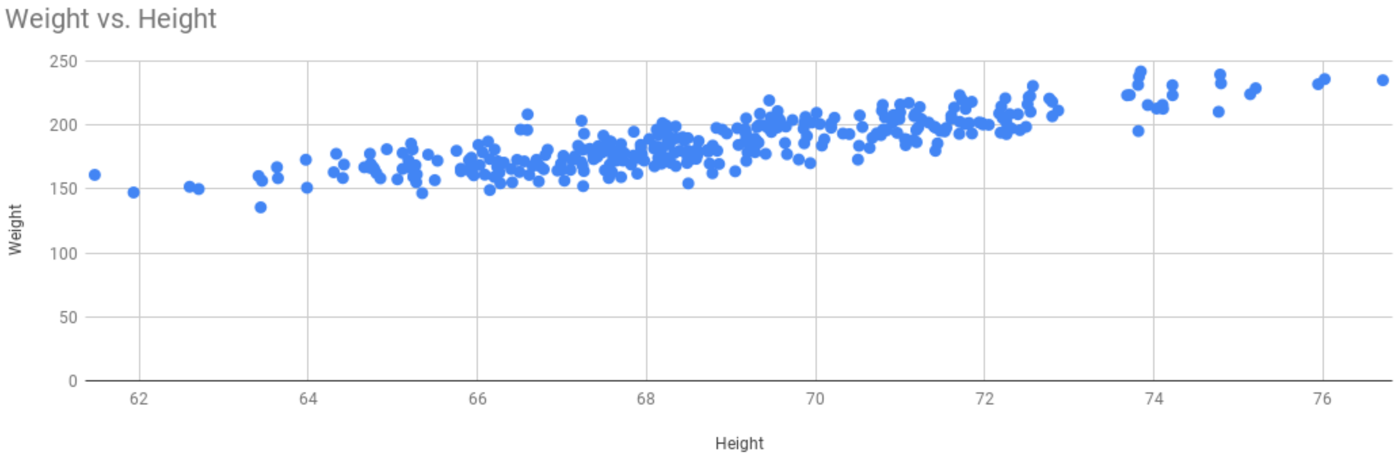
Weight vs Height

Problem definition:

- Predict the weight given the height of a person.

Data

- Input: Height (inches)
- Output: Weight (pounds)
- Split the data into
  - 80% for training
  - 20% for evaluation



Data source: https://www.kaggle.com/mustafaali96/weight-height

Slide credit: Wang Wei

Modeling

- Notation
  - A person is called an example/instance
  - Height denoted as $x \in R$: input feature
  - Weight denoted as $y \in R$: the target or ground truth
- Map from input to output by **linear regression**
  - $\tilde{y} = xw + b, w \in R, b \in R$
  - w is the slope and b is the intercept
  - $\tilde{y}$ is called the **prediction**

Slide credit: Wang Wei

Training

- Learn w and b to fit the training data $S_{train} = \left\{(x^{(i)}, y^{(i)})\right\}, i = 1 \ldots m$
  - That fit the data well
  - How to measure the quality of w and b?
- Loss function
  - The **smaller** the loss value, the better the prediction (closer to the target)
  - $L(x, y|w, b) = |\tilde{y} - y|$
  - $L(x, y|w, b) = \frac{1}{2}||\tilde{y} - y||^2 = \frac{1}{2}(\tilde{y} - y)^2$
    - Easier for optimization/training because it is differentiable
    - The coefficient $\frac{1}{2}$ is to make the gradient simple
- Define the training objective
  - $J(w, b) = \frac{1}{m}\sum_{i=1}^{m} L\left(x^{(i)}, y^{(i)} \middle| w, b\right)$

Slide credit: Wang Wei

Optimization/training

Tune the model parameters over the training instances to minimize the average loss, i.e., the training objective

$$\min_{w,b} J(w, b)$$

$$\rightarrow \min_{w,b} \frac{1}{m} \sum_{i=1}^{m} L\left(x^{(i)}, y^{(i)} \middle| w, b\right)$$

$$\rightarrow \min_{w,b} \frac{1}{2m} \sum_{i=1}^{m} \left(wx^{(i)} + b - y^{(i)}\right)^2$$

Slide credit: Wang Wei

Optimization/training

Fix b and learn w

$$\min_{w} \frac{1}{2m}\sum_{i=1}^{m}\left(x^{(i)}\right)^2 w^2 + \frac{1}{m}\sum_{i=1}^{m} x^{(i)}\left(b - y^{(i)}\right) w + \frac{1}{2m}\sum_{i=1}^{m}\left(b - y^{(i)}\right)^2$$

$$\rightarrow \min_{w} c_1 w^2 + c_2 w + c_3$$

Fix w and learn b

Slide credit: Wang Wei

Gradient for univariate simple functions

Gradient: recall high school calculus and how to take derivatives

- $\frac{\partial f(x)}{\partial x} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$
- $f(x) = 3, \frac{\partial f(x)}{\partial x} = 0$
- $f(x) = 3x, \frac{\partial f(x)}{\partial x} = 3$
- $f(x) = x^2, \frac{\partial f(x)}{\partial x} = 2x$

Slide credit: Wang Wei

Gradient for univariate simple functions

- Subgradient for non-differentiable points

  - $f(x) = |x|, \frac{\partial f(x)}{\partial x} = \begin{cases} 1, for\ x > 0 \\ -1, for\ x < 0 \\ a \in [-1, 1], for\ x = 0 \end{cases}$

  Sign of the variable if it's non-zero, anything in [−1, 1] if it's zero.

  - $f(x) = \max(x, 0), \frac{\partial f(x)}{\partial x} = \begin{cases} 1, for\ x > 0 \\ 0, for\ x < 0 \\ a \in [0, 1], for\ x = 0 \end{cases}$

Slide credit: Wang Wei

Gradient for univariate composite functions

We use $f'(x)$ and $\frac{\partial f(x)}{\partial x}$ interchangeably for the gradient of f(x) with respect to x, where x and f(x) are scalars

- $f(x) = g(x) + h(x)$
  - $f(x) = 3x + x^2$
- $f'(x) = g'(x) + h'(x)$

- $f(x) = g(x)h(x)$
  - $f(x) = xx^2$
- $f'(x) = g'(x)h(x) + g(x)h'(x)$

- $f(x) = \frac{g(x)}{h(x)}$
  - $f(x) = \frac{e^x}{x}$
- $f'(x) = \frac{g'(x)h(x) - g(x)h'(x)}{h(x)^2}$

- $f(x) = g(u), u = h(x)$
  - $f(x) = \ln(x + x^2)$
- $f'(x) = g'(u)h'(x)$

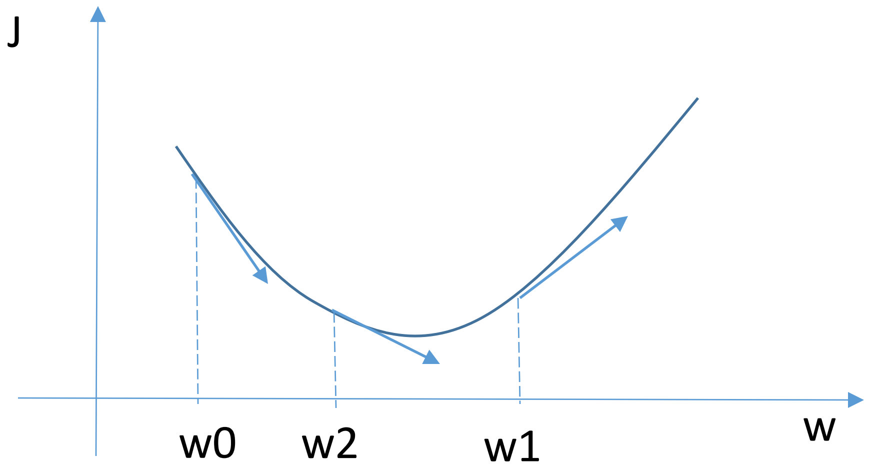
Slide credit: Wang Wei

Training by gradient descent

$J(w) \approx w^2 c_1 + w c_2 + c_3$ Find the **w** for which we have the lowest* J.

For example:

$c_1 = 1, c_2 = -2, c_3 = 1$



α is the **learning rate**, which controls the moving step length. It's important for convergence. If it is large, w oscillates around the optimal position. If it is small, it takes many iterations to reach the optimum.

Initialize w as w0

Compute $\frac{\partial J}{\partial w}|_{w=w0}$, negative;

Move w from w0 to the right by

$w1 = w0 - \alpha \frac{\partial J}{\partial w}|_{w=w0}$

Compute $\frac{\partial J}{\partial w}|_{w=w1}$, positive;

Move w from w1 to the left by

$w2 = w1 - \alpha \frac{\partial J}{\partial w}|_{w=w1}$

Compute $\frac{\partial J}{\partial w}|_{w=w2}$, negative

Move w from w2 to the right by

$w3 = w2 - \alpha \frac{\partial J}{\partial w}|_{w=w2}$

Slide credit: Wang Wei

Training by gradient descent

- Gradient descent algorithm for optimization
- Set w = 0.1 or a random number
- Repeat
  - For each data sample, compute $\tilde{y} = xw + b$
  - Compute the average loss, $\sum_{<x,y>\in S_{train}} L(x, y|w, b) \,/|S_{train}|$
  - Compute $\frac{\partial J}{\partial w}$
  - Update $w = w - \alpha \frac{\partial J}{\partial w}$

Update w, b repeatedly…

Slide credit: Wang Wei

Machine learning pipeline

Slide credit: Wang Wei

Multivariate Linear Regression

Multivariate linear regression

- Consider the problem of house price prediction
- Each instance in the training dataset
  - Denote the features using a column vector
    - $\boldsymbol{x} \in R^{n\times 1}$: x_i is the i-th feature
    - size, floor, location, age, lease, etc.
  - Target $y \in R$: price

$$\boldsymbol{x} = \begin{pmatrix} x_1 \\ x_2 \\ \dots \\ x_n \end{pmatrix}$$

Slide credit: Wang Wei

Model

- Map from input to output

$y = \boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{x} + b, \boldsymbol{w} \in R^{n\times 1}, b \in R$, w_i is the i-th element of $\boldsymbol{w}$ (importance of i-th feature)

$= \sum_{i=1}^{m} w_i x_i + b$

$$= (w_1, w_2, \dots, w_n)\begin{pmatrix} x_1 \\ x_2 \\ \dots \\ x_n \end{pmatrix} + b$$

$$= (w_1, w_2, \dots, w_n, b)\begin{pmatrix} x_1 \\ x_2 \\ \dots \\ x_n \\ 1 \end{pmatrix}$$

$\rightarrow \quad \tilde{y} = \bar{\boldsymbol{w}}^T \bar{\boldsymbol{x}}$

For the rest of this module, we use $\boldsymbol{w}$ and $\boldsymbol{x}$ for $\bar{\boldsymbol{w}}$ and $\bar{\boldsymbol{x}}$ respectively unless there is a special definition of $\boldsymbol{w}$ and $\boldsymbol{x}$.

Slide credit: Wang Wei

Optimization

- Compute the gradient of the loss with respect to (**w.r.t**) **w**
  - Consider a single instance

$$J(\boldsymbol{w}) = L \quad (\boldsymbol{x}, y|\boldsymbol{w}) = \frac{1}{2}\left|\left|\, \tilde{y} - y\right|\right|^2 = \frac{1}{2}\left(\boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{x} - y\right)^2$$

$$\frac{\partial J(\boldsymbol{w})}{\partial \boldsymbol{w}} =?$$

Slide credit: Wang Wei

Gradient of vector and matrix (denominator layout)

- Vectors
  - By default, is a column vector
  - Denoted as $\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}$

$$\frac{\partial y}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial y}{\partial x_1} \\ \frac{\partial y}{\partial x_2} \\ \vdots \\ \frac{\partial y}{\partial x_n} \end{bmatrix},$$

$$\frac{\partial \mathbf{y}}{\partial x} = \begin{bmatrix} \frac{\partial y_1}{\partial x} & \frac{\partial y_2}{\partial x} & \cdots & \frac{\partial y_m}{\partial x} \end{bmatrix}$$

$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_2}{\partial x_1} & \cdots & \frac{\partial y_m}{\partial x_1} \\ \frac{\partial y_1}{\partial x_2} & \frac{\partial y_2}{\partial x_2} & \cdots & \frac{\partial y_m}{\partial x_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial y_1}{\partial x_n} & \frac{\partial y_2}{\partial x_n} & \cdots & \frac{\partial y_m}{\partial x_n} \end{bmatrix}.$$

Denominator layout: the result shape is (n, m)

Slide credit: Wang Wei

Gradient of vector and matrix (denominator layout)

- Matrix
  - Denoted as **X, Y, Z**

$$\frac{\partial \boldsymbol{Y}}{\partial x} = \begin{bmatrix} \frac{\partial y_{11}}{\partial x} & \frac{\partial y_{21}}{\partial x} & \cdots & \frac{\partial y_{m1}}{\partial x} \\ \frac{\partial y_{12}}{\partial x} & \frac{\partial y_{22}}{\partial x} & & \frac{\partial y_{m2}}{\partial x} \\ \vdots & & \ddots & \vdots \\ \frac{\partial y_{1n}}{\partial x} & \frac{\partial y_{2n}}{\partial x} & \cdots & \frac{\partial y_{mn}}{\partial x} \end{bmatrix}$$

$$\frac{\partial y}{\partial \mathbf{X}} = \begin{bmatrix} \frac{\partial y}{\partial x_{11}} & \frac{\partial y}{\partial x_{12}} & \cdots & \frac{\partial y}{\partial x_{1q}} \\ \frac{\partial y}{\partial x_{21}} & \frac{\partial y}{\partial x_{22}} & \cdots & \frac{\partial y}{\partial x_{2q}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial y}{\partial x_{p1}} & \frac{\partial y}{\partial x_{p2}} & \cdots & \frac{\partial y}{\partial x_{pq}} \end{bmatrix}$$

Gradient of matrix with respect to (w.r.t) matrix, matrix w.r.t vector, vector w.r.t matrix?
Too complex. Not commonly used.

Slide credit: Wang Wei

Optimization

- Compute the gradient of the loss w.r.t **w**
  - Consider a single instance

$$J(\boldsymbol{w}) = L \quad (\boldsymbol{x}, y|\boldsymbol{w}) = \frac{1}{2}||\tilde{y} - y||^2 = \frac{1}{2}\left(\boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{x} - y\right)^2$$

$$\frac{\partial J(\boldsymbol{w})}{\partial \boldsymbol{w}} = ?$$

$$z = \boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{x} - y$$

$$J(\boldsymbol{w}) = \frac{1}{2}z^2$$

$$\frac{\partial J(\boldsymbol{w})}{\partial \boldsymbol{w}} = \frac{\partial J}{\partial z}\frac{\partial z}{\partial \boldsymbol{w}} = z\boldsymbol{x} = \left(\boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{x} - y\right)\boldsymbol{x}$$

Shape Check!

Slide credit: Wang Wei

Vectorization

- Consider multiple examples $\{(\boldsymbol{x}^{(i)}, y^{(i)})\}$, i=1, 2, …, m
- Naïve approach of computing the gradient
  - for each instance $(\boldsymbol{x}^{(i)}, y^{(i)})$
    - Accumulate the loss $L(\boldsymbol{x}^{(i)}, y^{(i)})$ into J
  - Average J over m
  - for each instance $(\boldsymbol{x}^{(i)}, y^{(i)})$
    - Accumulate the gradient of $\frac{\partial L(\boldsymbol{x}^{(i)}, y^{(i)})}{\partial \boldsymbol{w}}$
- Not as fast as matrix operations

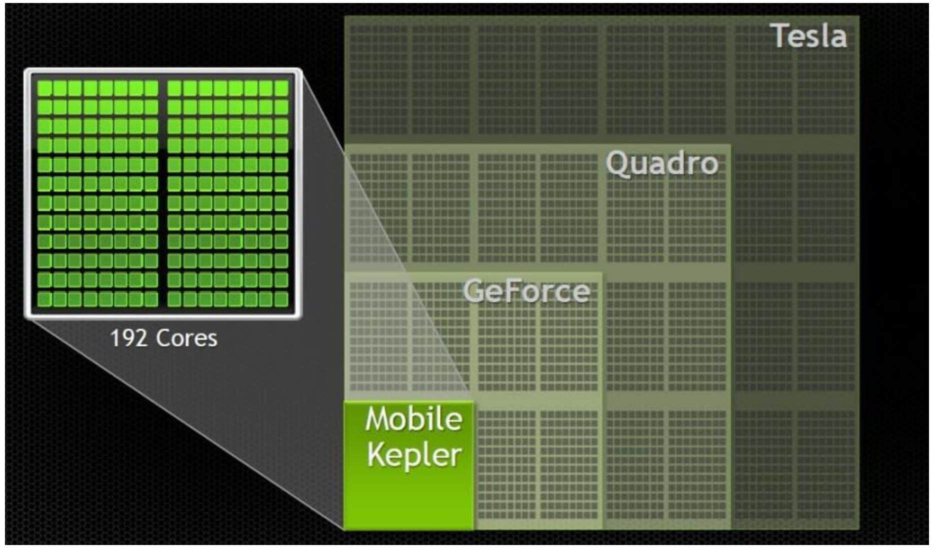


Image source: https://www.ubergizmo.com/what-is/gpu-graphics-processing-unit/

Slide credit: Wang Wei

Vectorization

- Consider multiple examples $\{(\boldsymbol{x}^{(i)}, y^{(i)})\}$, i=1, 2, …, m
- Put each instance (the feature vector) into one row of a matrix
  - For fast memory access as Numpy stores data in [row-major format]
- Put each target into one element of a column vector

$$\boldsymbol{X} = \begin{pmatrix} \boldsymbol{x}^{(\mathbf{1})^T} \\ \boldsymbol{x}^{(\mathbf{2})^T} \\ \dots \\ \boldsymbol{x}^{(\boldsymbol{m})^T} \end{pmatrix} \qquad \boldsymbol{y} = \begin{pmatrix} y^{(1)} \\ y^{(2)} \\ \dots \\ y^{(m)} \end{pmatrix} \qquad \tilde{\boldsymbol{y}} = \boldsymbol{X}\boldsymbol{w}$$

$J(\boldsymbol{w}) = ?$

Slide credit: Wang Wei

Vectorization

- Consider multiple examples $\{(\boldsymbol{x}^{(i)}, y^{(i)})\}$, i=1, 2, …, m
- Put each instance (the feature vector) into one row of a matrix
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- Put each target into one element of a column vector

$$\boldsymbol{X} = \begin{pmatrix} \boldsymbol{x}^{(\mathbf{1})^T} \\ \boldsymbol{x}^{(\mathbf{2})^T} \\ \dots \\ \boldsymbol{x}^{(\boldsymbol{m})^T} \end{pmatrix} \qquad \boldsymbol{y} = \begin{pmatrix} y^{(1)} \\ y^{(2)} \\ \dots \\ y^{(m)} \end{pmatrix} \qquad \tilde{\boldsymbol{y}} = \boldsymbol{X}\boldsymbol{w}$$

$$J(\boldsymbol{w}) = \frac{1}{2m}\left|\left|\tilde{\boldsymbol{y}} - y\right|\right|^2 = \frac{1}{2m}\left(\tilde{\boldsymbol{y}} - \boldsymbol{y}\right)^{\mathrm{T}}\left(\tilde{\boldsymbol{y}} - \boldsymbol{y}\right) \qquad \boldsymbol{u} = \tilde{\boldsymbol{y}} - \boldsymbol{y}$$

$$\frac{\partial J(\boldsymbol{w})}{\partial \boldsymbol{w}} = ?$$

Slide credit: Wang Wei

Vectorization

- Consider multiple examples $\{(\boldsymbol{x}^{(i)}, y^{(i)})\}$, i=1, 2, …, m
- Put each instance (the feature vector) into one row of a matrix
  - For fast memory access as numpy stores data in row-major format
- Put each target into one element of a column vector

$$X = \begin{pmatrix} \boldsymbol{x}^{(\boldsymbol{1})^{\boldsymbol{T}}} \\ \boldsymbol{x}^{(\boldsymbol{2})^{\boldsymbol{T}}} \\ \dots \\ \boldsymbol{x}^{(\boldsymbol{m})^{\boldsymbol{T}}} \end{pmatrix} \qquad \boldsymbol{y} = \begin{pmatrix} y^{(1)} \\ y^{(2)} \\ \dots \\ y^{(m)} \end{pmatrix} \qquad \tilde{\boldsymbol{y}} = X\boldsymbol{w}$$

$$J(\boldsymbol{w}) = \frac{1}{2m}\left|\left|\tilde{\boldsymbol{y}} - y\right|\right|^2 = \frac{1}{2m}(\tilde{\boldsymbol{y}} - \boldsymbol{y})^{\mathrm{T}}(\tilde{\boldsymbol{y}} - \boldsymbol{y}) \qquad \boldsymbol{u} = \tilde{\boldsymbol{y}} - \boldsymbol{y}$$

$$\frac{\partial J(\boldsymbol{w})}{\partial \boldsymbol{w}} = \frac{1}{2m}\left(\frac{\partial \boldsymbol{u}}{\partial \boldsymbol{w}}\boldsymbol{u} + \frac{\partial \boldsymbol{u}}{\partial \boldsymbol{w}}\boldsymbol{u}\right) = \frac{1}{m}\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{u} = \frac{1}{m}\boldsymbol{X}^{\boldsymbol{T}}(\tilde{\boldsymbol{y}} - \boldsymbol{y})$$

Shape Check!

Slide credit: Wang Wei

Training by gradient descent

- Gradient descent algorithm for optimization
- initialize $\boldsymbol{w}$ randomly
- Repeat
  - Compute the objective $J(\boldsymbol{w})$ over all training instances
  - Compute $\frac{\partial J}{\partial \boldsymbol{w}}$
  - Update $\mathbf{w} = \mathbf{w} - \alpha \frac{\partial J}{\partial \boldsymbol{w}}$

Slide credit: Wang Wei

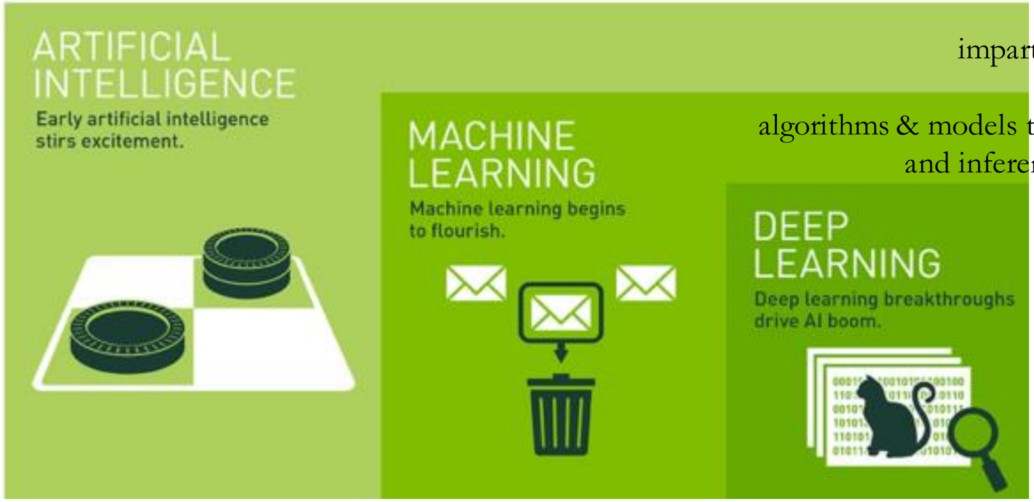
Notation summary

- Scalar x
- Vector $\boldsymbol{x} \in R^{n\times 1}$
  - i-th element of a vector, x_i
  - i-th example $\boldsymbol{x}^{(i)}$
- Matrix $\boldsymbol{X}$
  - i-th row and j-th column X_{ij}
- If we choose denominator layout for $\frac{\partial \boldsymbol{y}}{\partial \boldsymbol{x}}$ we should lay out the gradient $\frac{\partial y}{\partial \boldsymbol{x}}$ as a column vector, and $\frac{\partial \boldsymbol{y}}{\partial x}$ as a row vector.

Slide credit: Wang Wei

Summary

- AI vs. ML vs. Deep Learning



imparting cognitive abilities to machines

algorithms & models to perform tasks based on patterns and inference instead of specific instructions

branch of machine learning using deep neural networks

- Taking gradients of vectors & matrices
- Univariate & multivariate linear regression
  - Updating parameters via gradient descent

References

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Homework

TAs will let you know soon

Next Lecture

(Shallow) Neural Networks