Artificial Intelligence: *Modeling Human Intelligence with Networks*

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What is Intelligence?

What is Intelligence? What is Learning?

Which face is real?

(a)

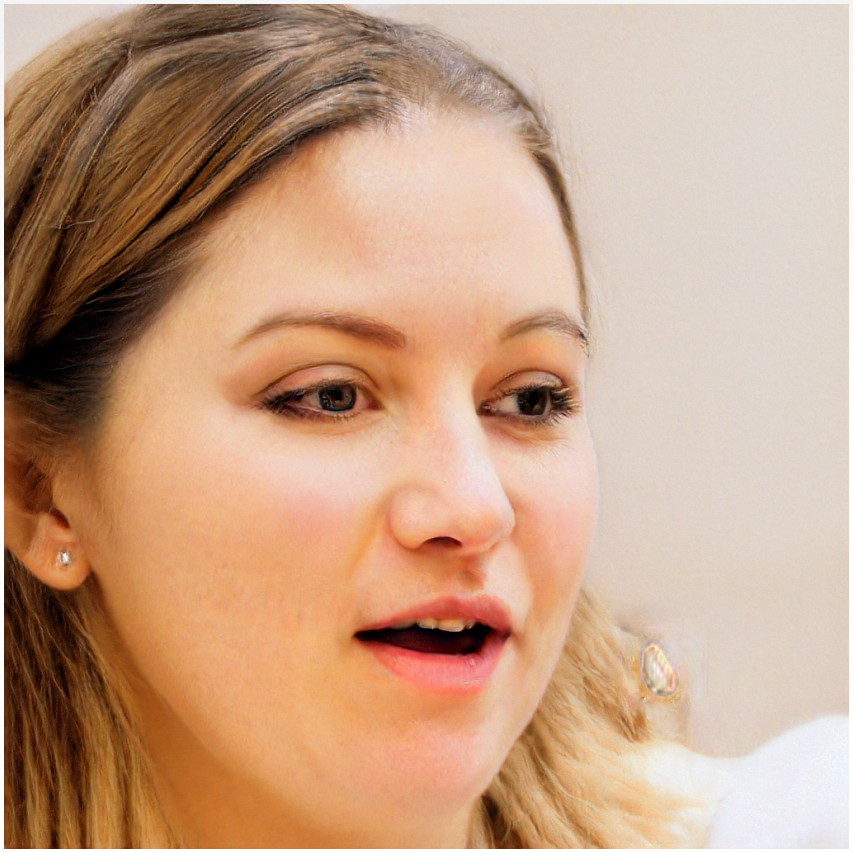
(b)

Which face is real?

(a) FAKE

(b) REAL

Which face is real?



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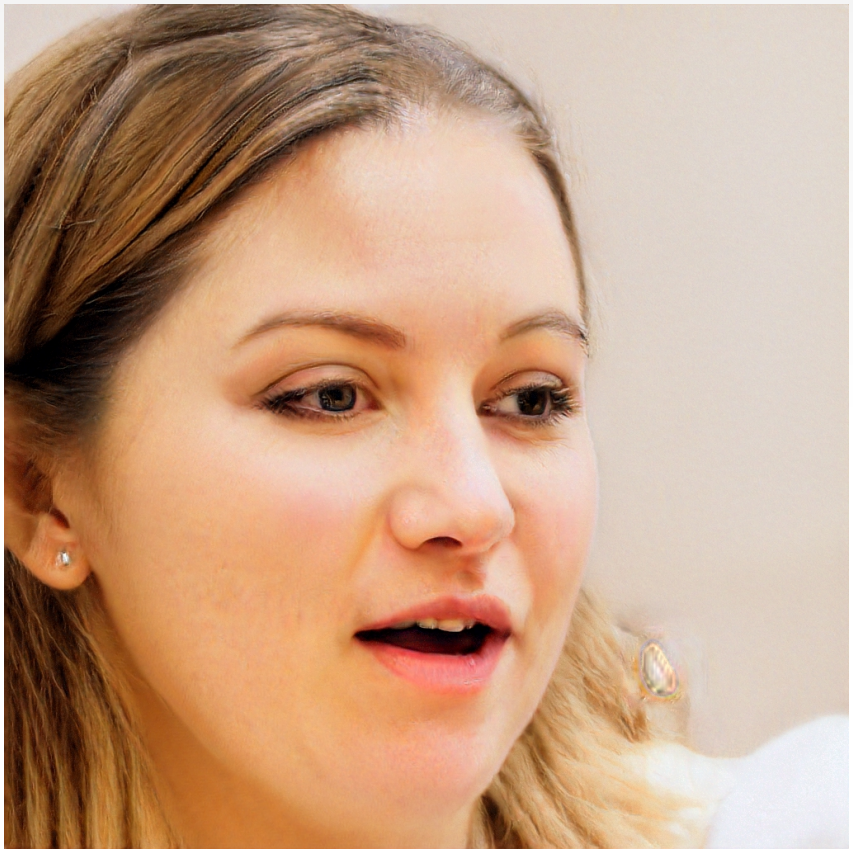

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Which animal is this?

Class: beaver (0.38 % of confidence)

Class: ice_bear (1.00 % of confidence)

Class: ant (1.00 % of confidence)

Which thing is this?

Class: beer_glass (0.55 % of confidence)

Class: broccoli (1.00 % of confidence)

Class: alp (0.85 % of confidence)

How do you think they do it?

Goals of this class

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  - Other teams improve their grades if they ask questions.
- *Things can change, if necessary.*

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- Personal Interests/Small Research Project? – Come talk to me outside the class.
- My only goal here is to have you understand the content and enjoy the class!

Course Schedule

Week 1	Theoretical Topic	Programming Topic
Monday	- Introduction to AI - Neuron model - Vectors, dot product, geometry	- Intro to programming - For loops, while loops, if statements - Data structures
Tuesday	- Classification task, Linear separators - Loss functions - What is learning?	- Uploading data - Data visualization - Plotting functions
Wednesday	- Perceptron algorithm - Geometry of algorithm - Convergence results	- Implement perceptron algorithm
Thursday	- Nonlinearly separable data - Multi-class classification, Matrices - MNIST challenge	- Implement perceptron algorithm - Matrix data structure, Matrix operations - Programming MNIST forward pass
Friday	Group presentations	

Course Schedule

Week 2	Theoretical Topic	Programming Topic
Monday	- Limits - Definition of derivative - Extrema of a differentiable function	- Plotting single variable functions - Plotting single multivariable functions - Numerical limits
Tuesday	- Loss function - Gradient descent - Convexity	- Numerical derivatives - Plotting tangent lines - Gradient descent
Wednesday	- Algorithm for MNIST, - Cross correlation - Multilayer neural network	- MNIST algorithm
Thursday	- Convolutions - Relu, Sigmoids - Max pooling	- Convolutions in images
Friday	Group presentations	

Course Schedule

Week 3	Theoretical Topic	Programming Topic
Monday	- AlexNet, RCNN - Dropout - Batch size	- TensorFlow / Keras
Tuesday	- Sample space - Probability distribution, Random variable - Expectation, Independence	- Generating random numbers - Plot distribution and histograms - Law of large number simulation
Wednesday	- Conditional probability - Markov chains - Graphs, Random walk	- Construct and visualize network - Simulate random walk - Implement random walk on map
Thursday	- Markov model for sentence generation - Applications of markov chains i.e. QMR network, page rank, games	- Random sentence generator
Friday	Group presentations / Programming project due	

Now, let the classes start!

Basics of Linear Algebra

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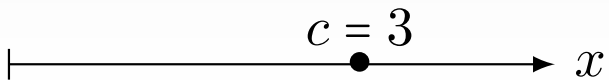
Scalars

- Any real number, $c \in \mathbb{R}$
- Operations: Addition, multiplication (subtraction, division).
- Graphical representation:



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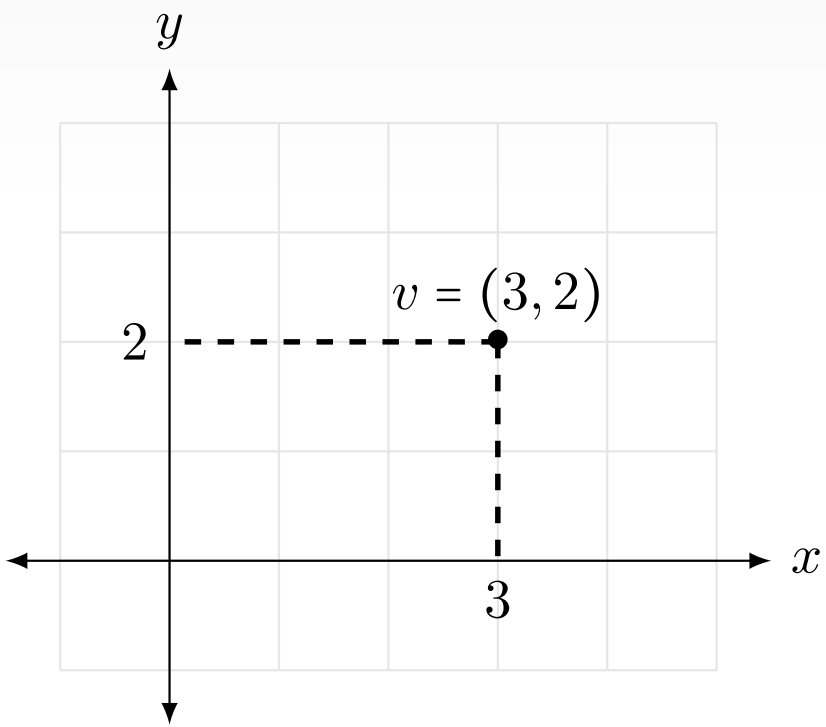

(a) A point in $\mathbb{R}^2$

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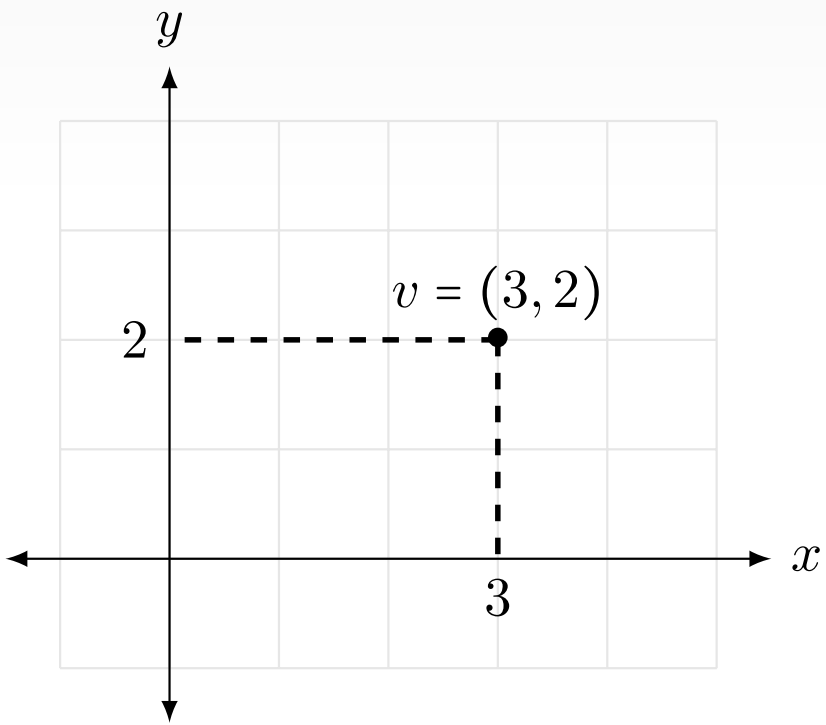

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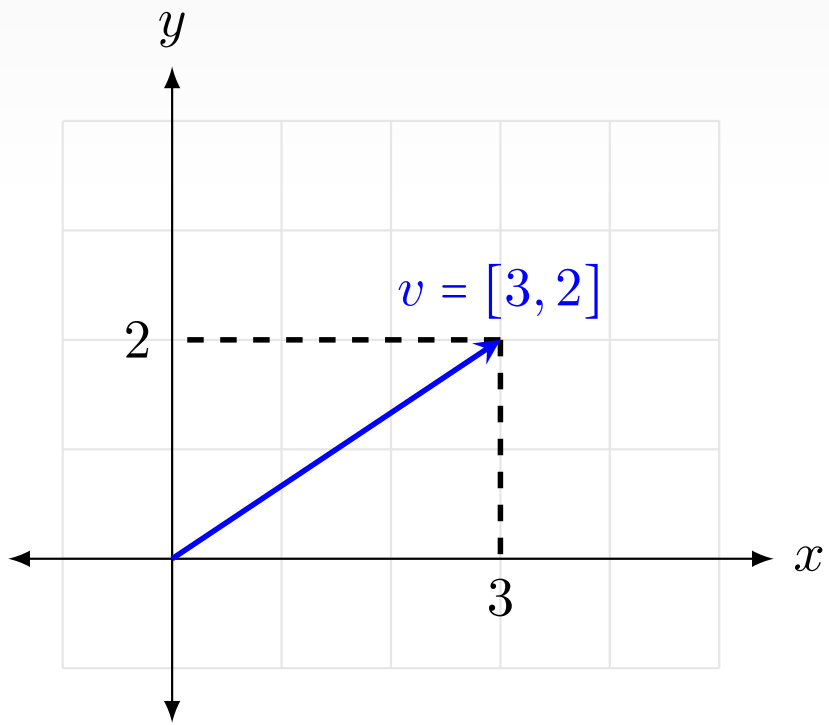

(b) Direction and magnitude in $\mathbb{R}^2$

Vectors

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$$v + u = [v_1 + u_1, v_2 + u_2, \ldots, v_n + u_n] \in \mathbb{R}^n$$

  - Multiplication by scalar: if $v = [v_1, v_2, \ldots, v_n] \in \mathbb{R}^n$ and $c \in \mathbb{R}$,

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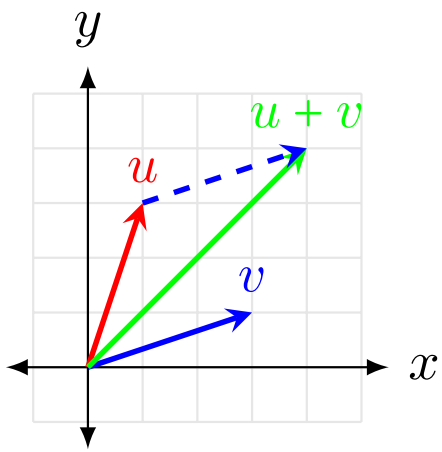

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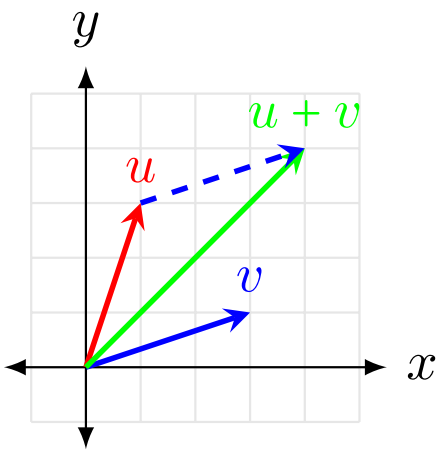

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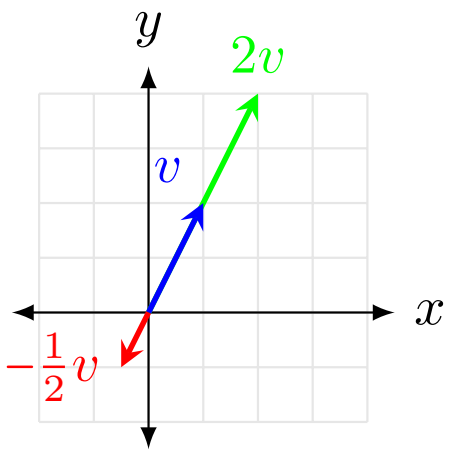

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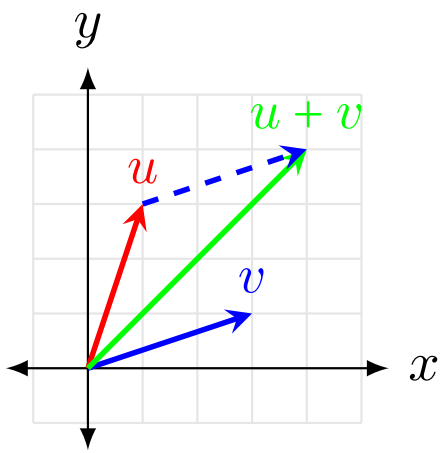

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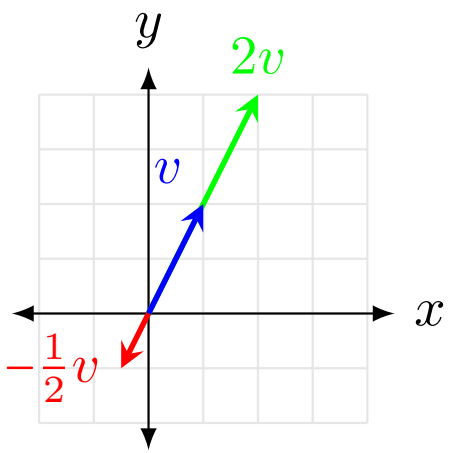

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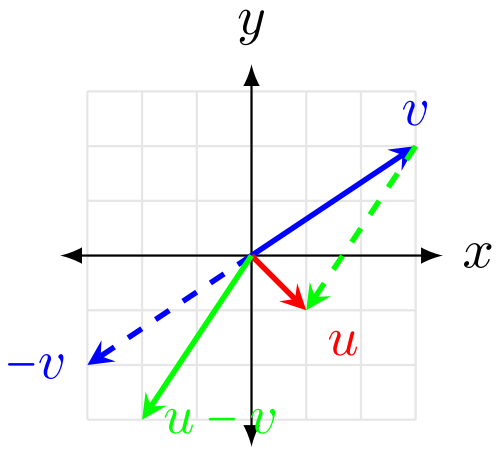

(c) $u - v$

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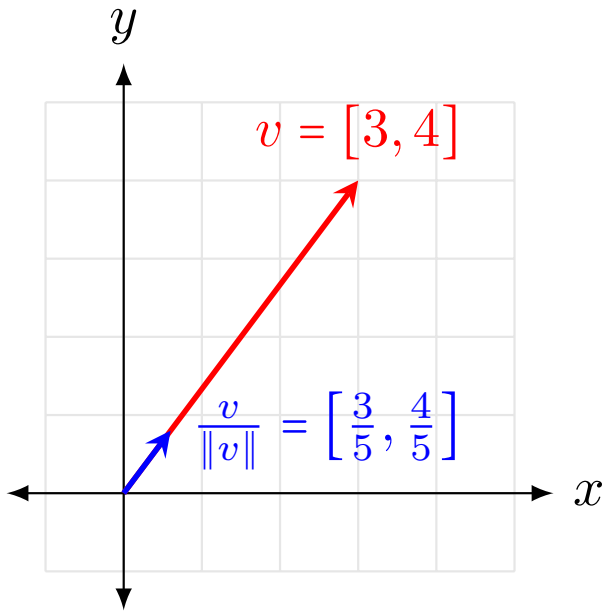

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- **Dot product**

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Vectors

- Vector Normalization to (sum) to 1:

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Obs. 2: Using the Law of Cosines, we also have:

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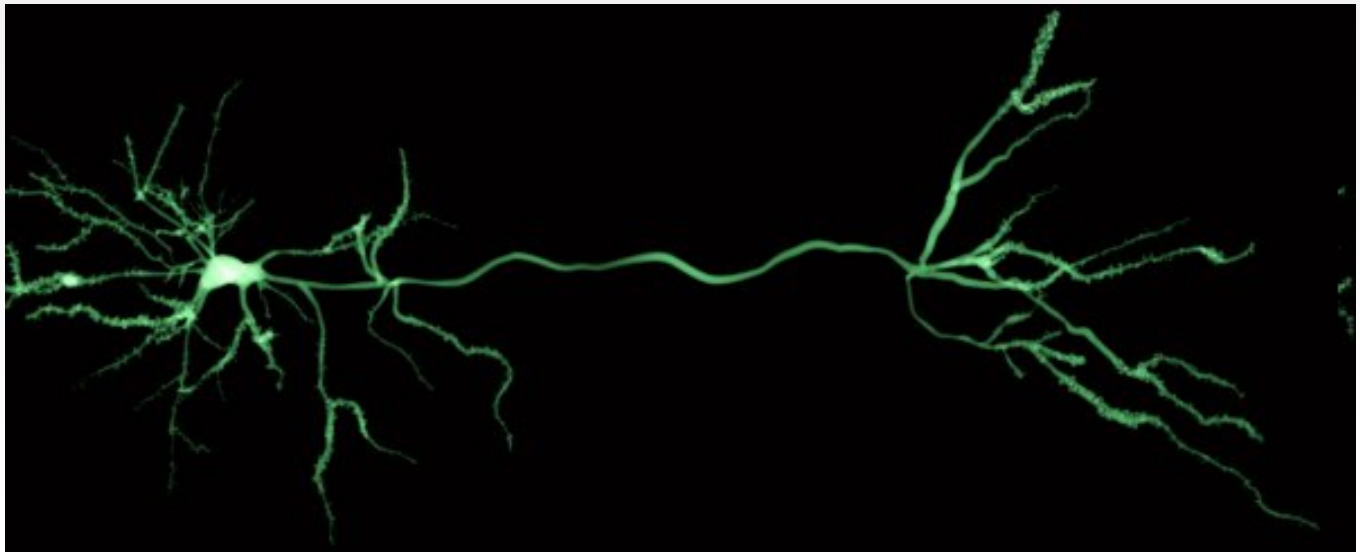
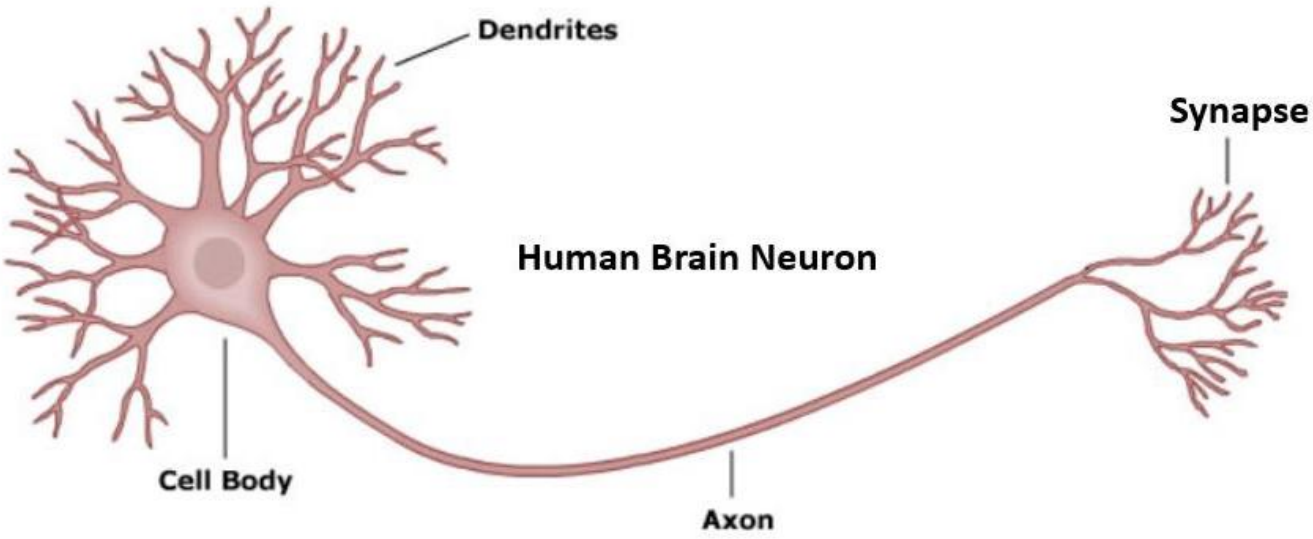
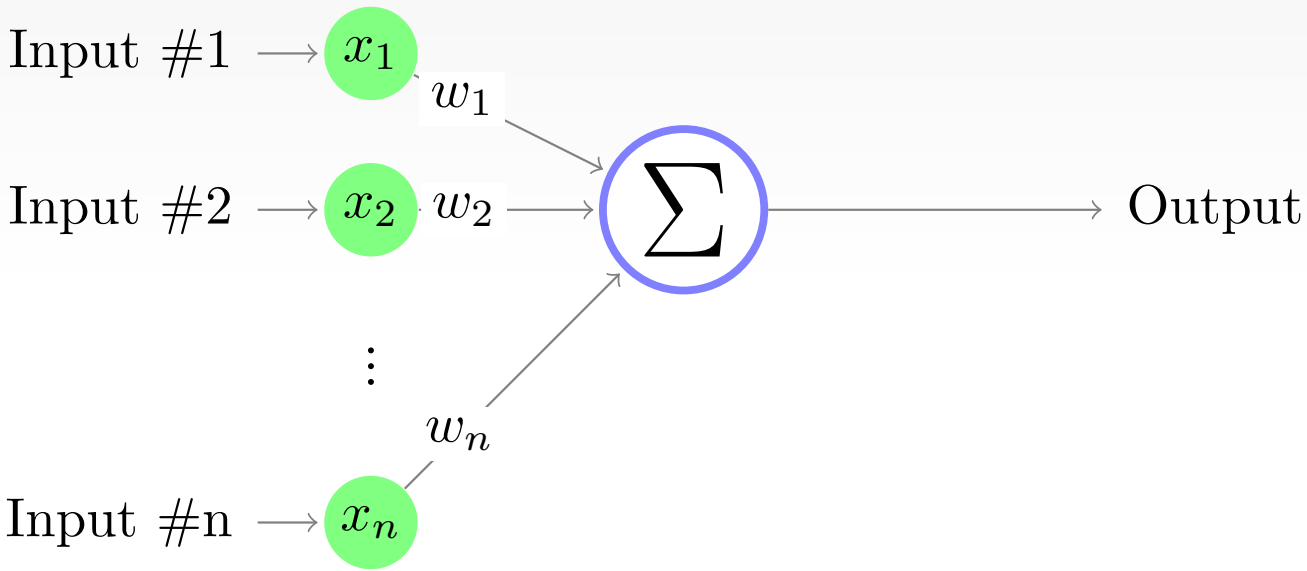
- Transposition: $M^\top = H$.

The Neuron!





The Neuron Model!



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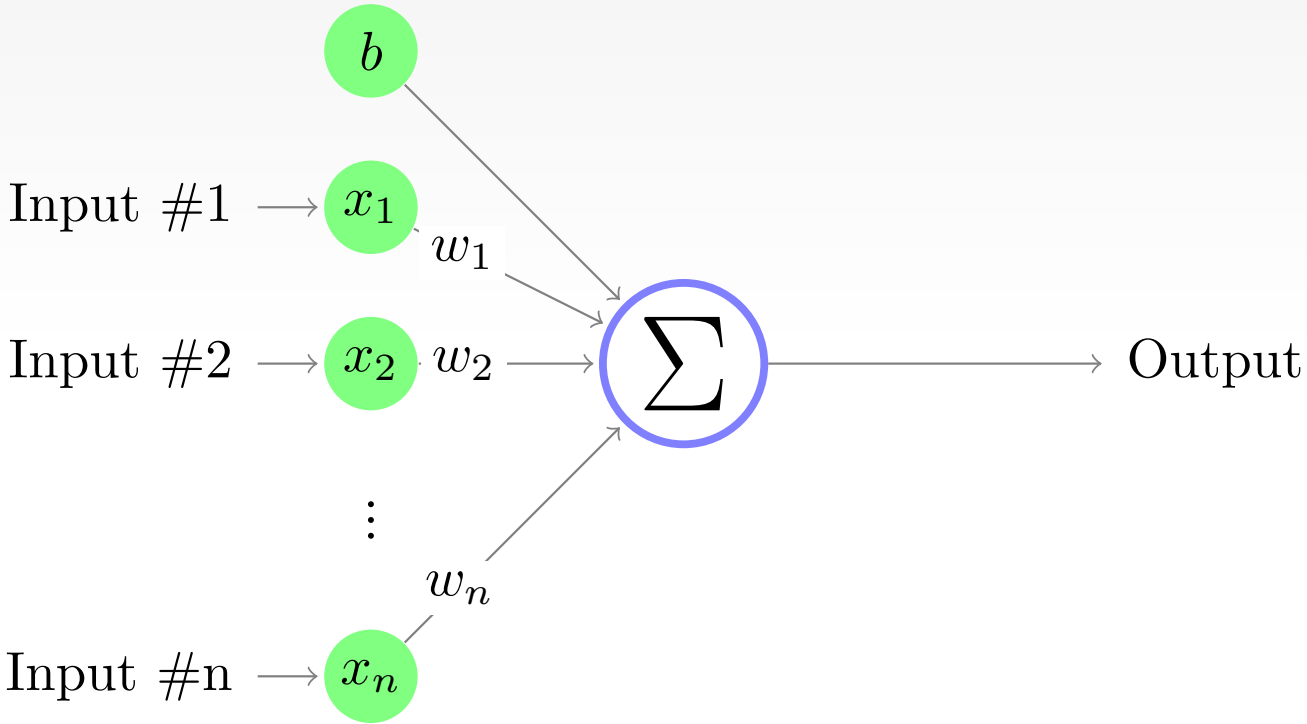

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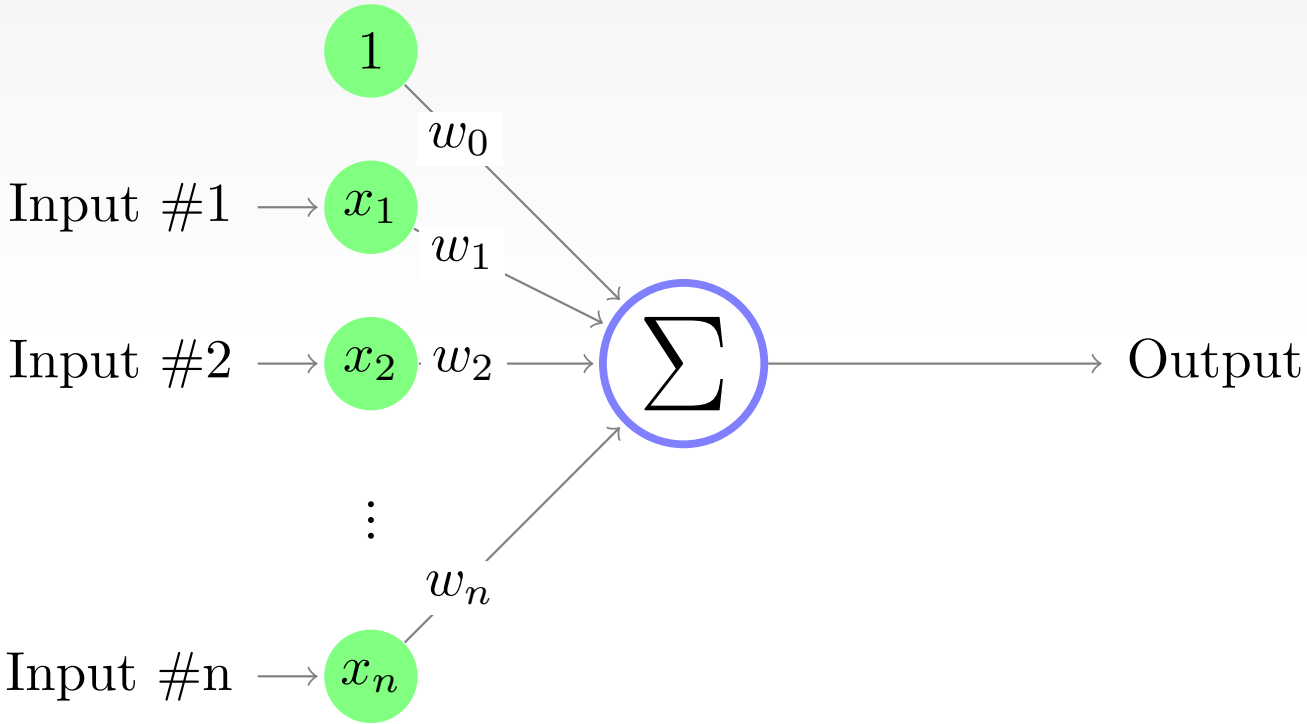

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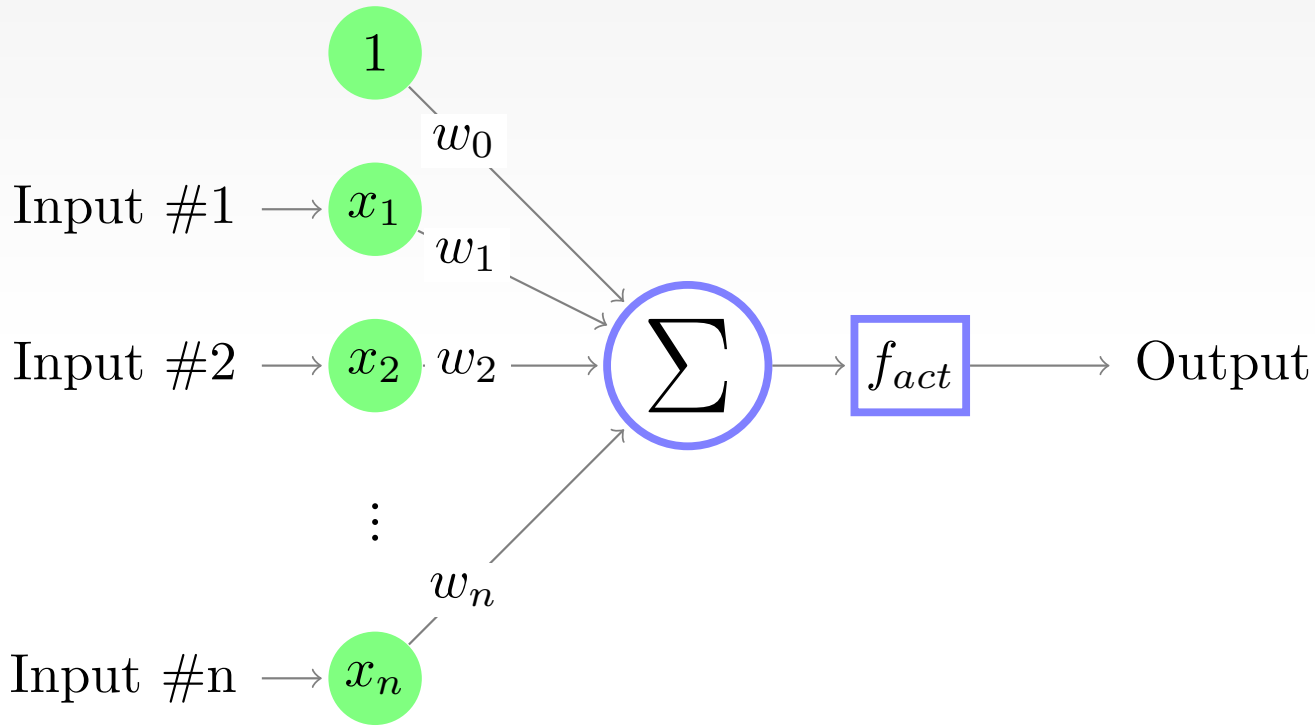

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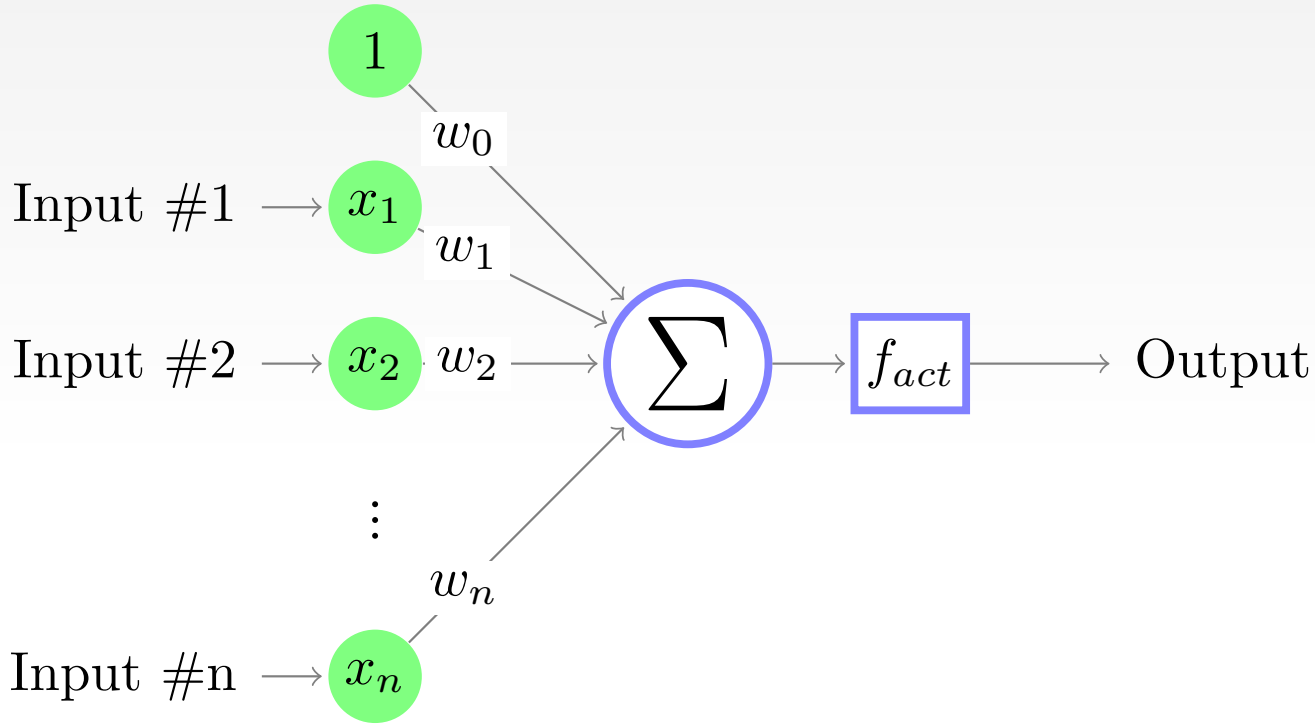

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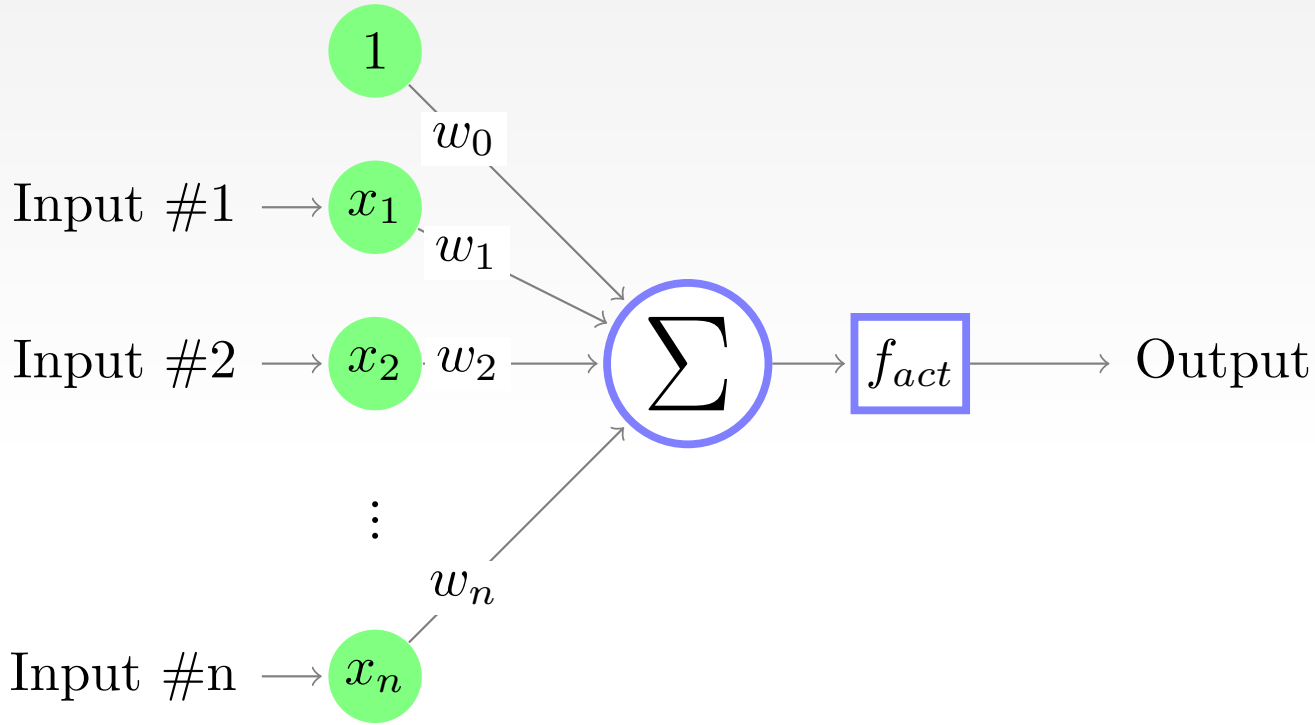

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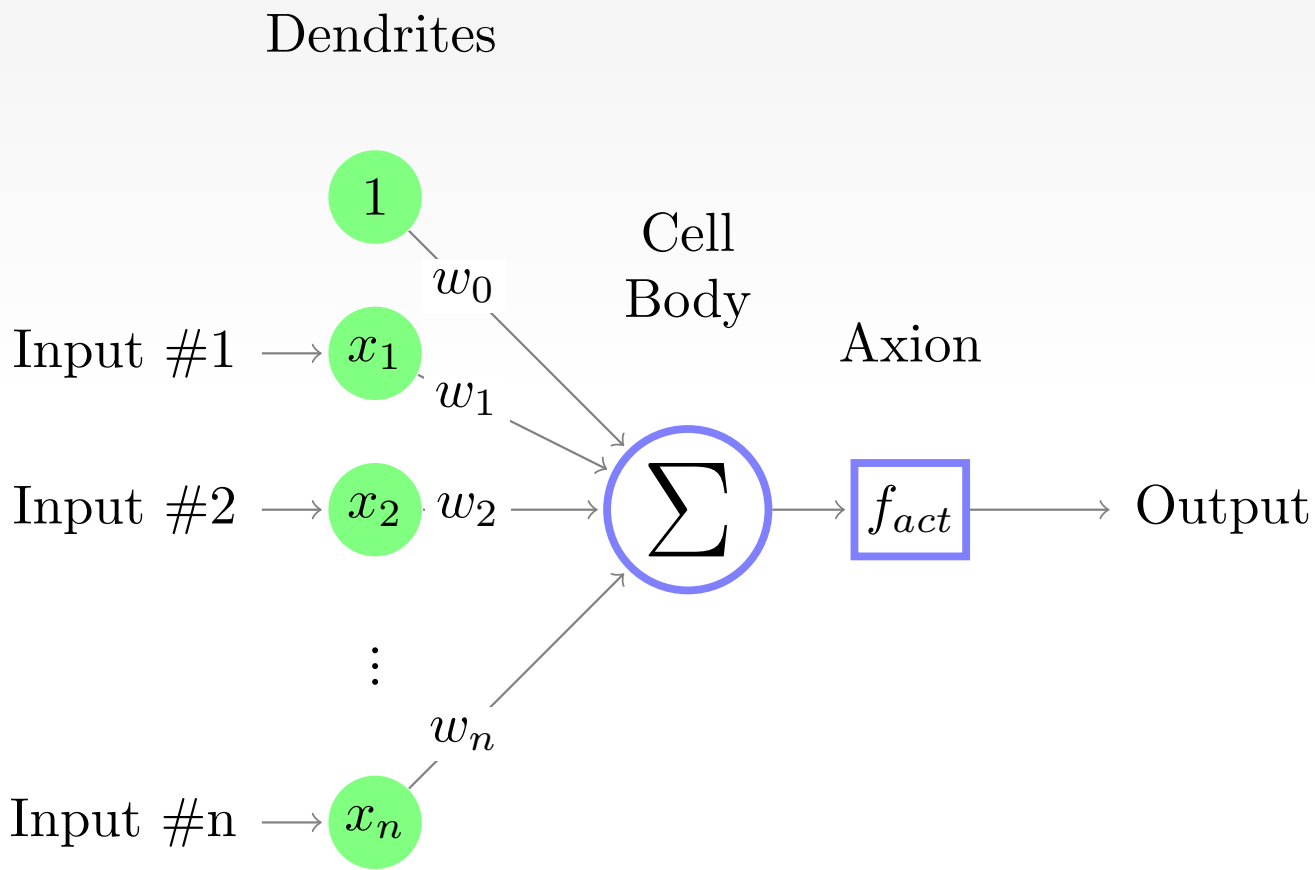
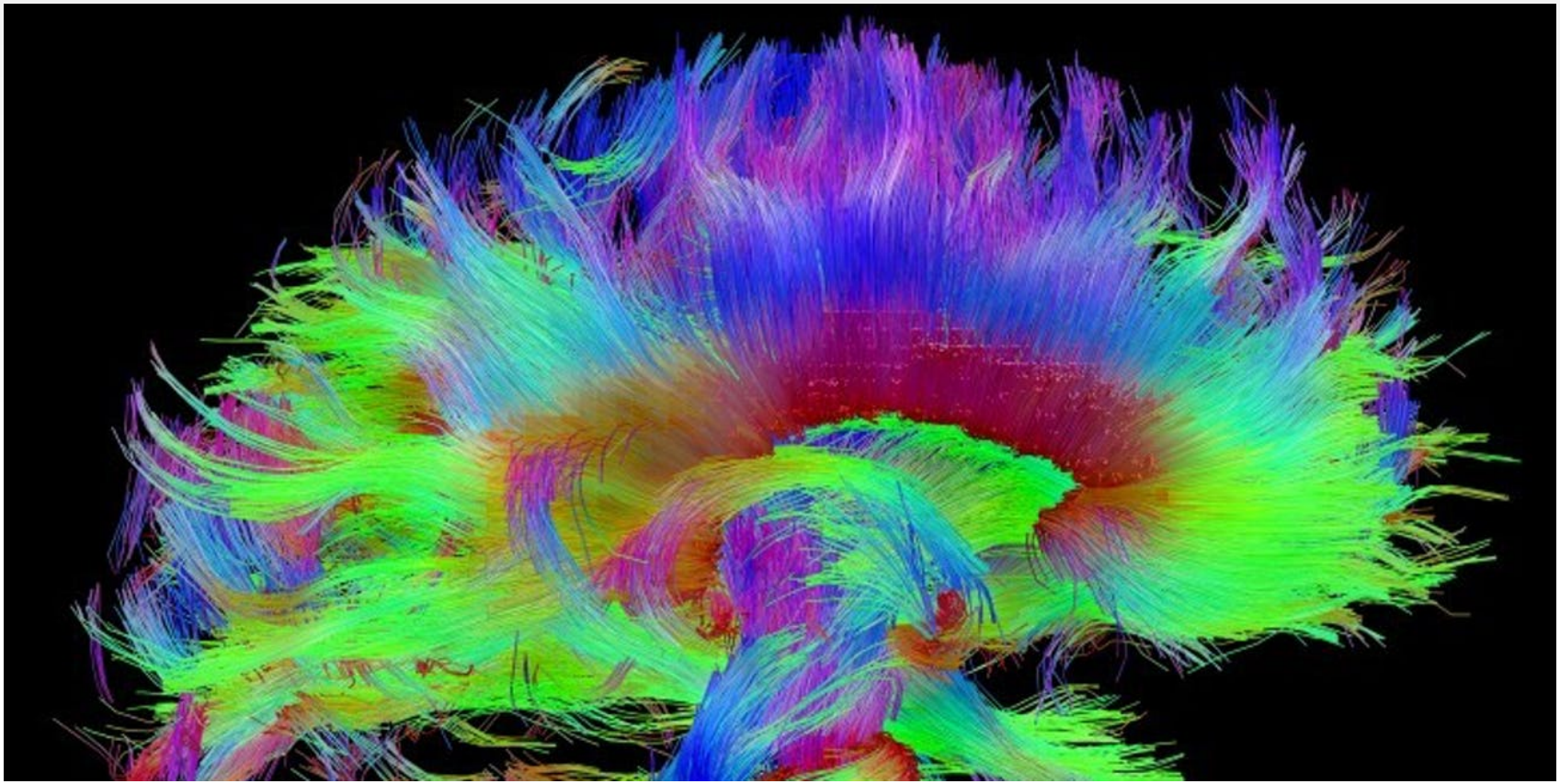


The Connectome Project



"Human Connectome Project is to build a 'network map' (connectome) that will shed light on the anatomical and functional connectivity within the healthy human brain."

Now, let's use Python!

First Project:

First Project:
The Gray Zone of Artificial Intelligence

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Premise and Goal

- AI revolutionized modern society!
- The goal of this project is to research a recent AI technology and present your findings to the class.

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What you should do

1. Choose a modern application of AI.
2. Provide a basic understanding of how this technology works and some beneficial applications of it.
3. Discuss the implications of that technology in terms of:
   - What are the deeper implications of how this technology affects society?
   - In what ways does this technology lie in a zone of ethical ambiguity.

First Project

Topics

- You should choose a topic among the follwoing:
  - AI and Medicine.
  - AI and Arts.
  - Driverless cars.
  - Modern Robotics.
  - Games and virtual Reality/augmented reality.
  - AI beating humans: Deep Blue (chess), IBM Watson (Jeopardy), Alpha Go (go), etc.
  - Language, automated translation, human-like speech.
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- But you can also suggest a topic, but under my approval ☺.
- Different teams, different topics. First come, first chose.
- The deadline to inform the topic is **tommorrow**.

Teams

Team 1:	Ahmad, Allison Y., Allison Z..
Team 2:	Aprille, Arthur, Aryan.
Team 3:	Badr, Camellia, Connor.
Team 4:	Domenic, Iris, Josefine.
Team 5:	Justin, Kabeera, Olivia.
Team 6:	Parth, Ray, Roshni.
Team 7:	Sarah, Sean, Sophia, Zitao.

One last thing! Install Python and Jupyter!