INTRODUCTION TO MACHINE LEARNING

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Ohio University

INPP Summer Tutorial Series

13 June 2024

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QUESTIONS

- What is artificial intelligence?
- How is it different from machine learning?
- What are the types of machine learning algorithms?
- How can machine learning be used for physics problems?
- How can you get started?

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ARTIFICIAL INTELLIGENCE

- A broad field that aims to give computers human-like capabilities, e.g.
  - Interpret large amounts of complicated data
  - Solve problems
  - Adapt to new situations
  - Plan and make decisions autonomously
  - Interact via text, speech, images, etc.
  - Perceive their environment

- Goals can be somewhat vague and complex $\Longrightarrow$ Need to break down into smaller pieces!

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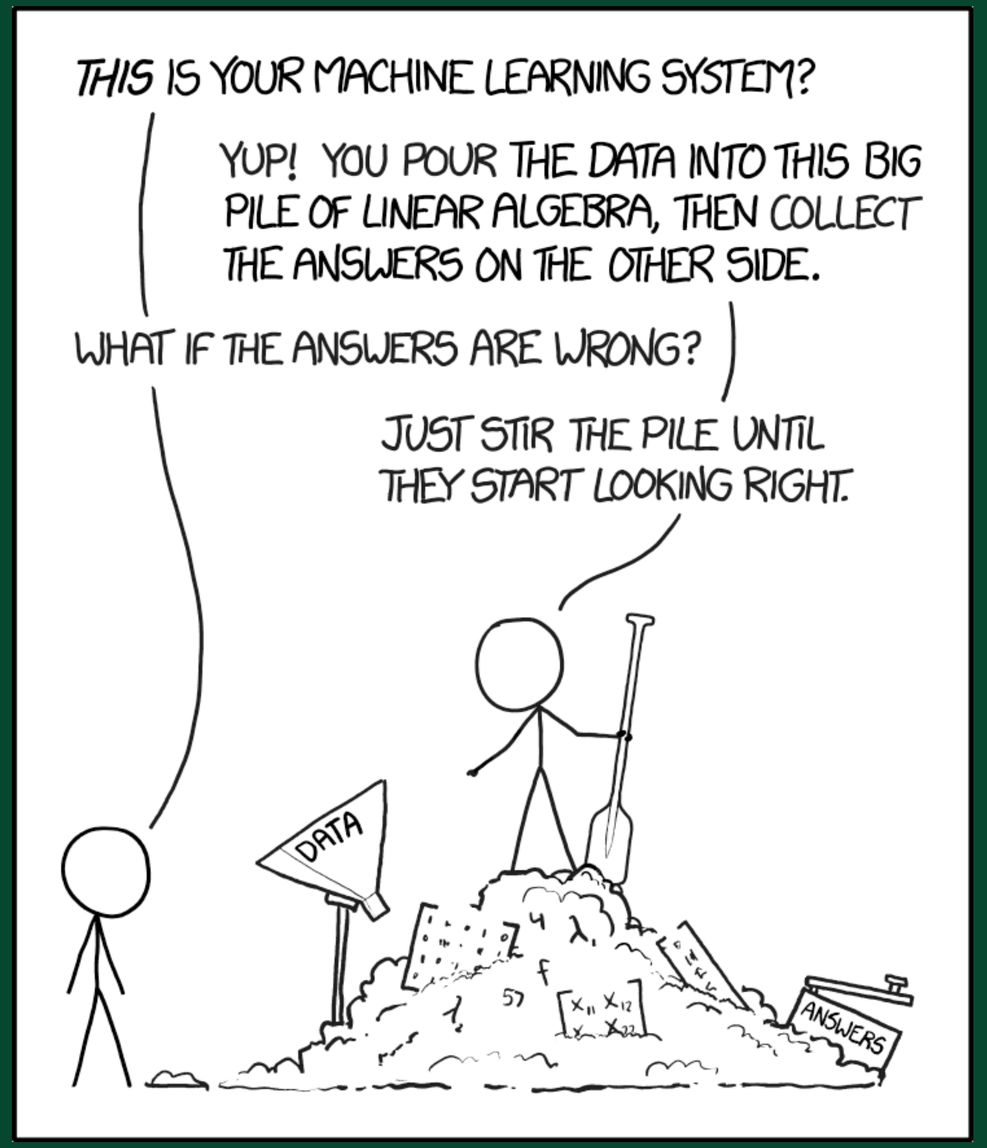
MACHINE LEARNING

- Computational models and algorithms designed to learn from data rather than rely on explicit programming
- Goals are narrow in scope, e.g.
    - Fit a curve to data
    - Classify data into discrete categories
    - Reduce the dimension of the data
    - Generate fake data that looks like real data
    - So much more…



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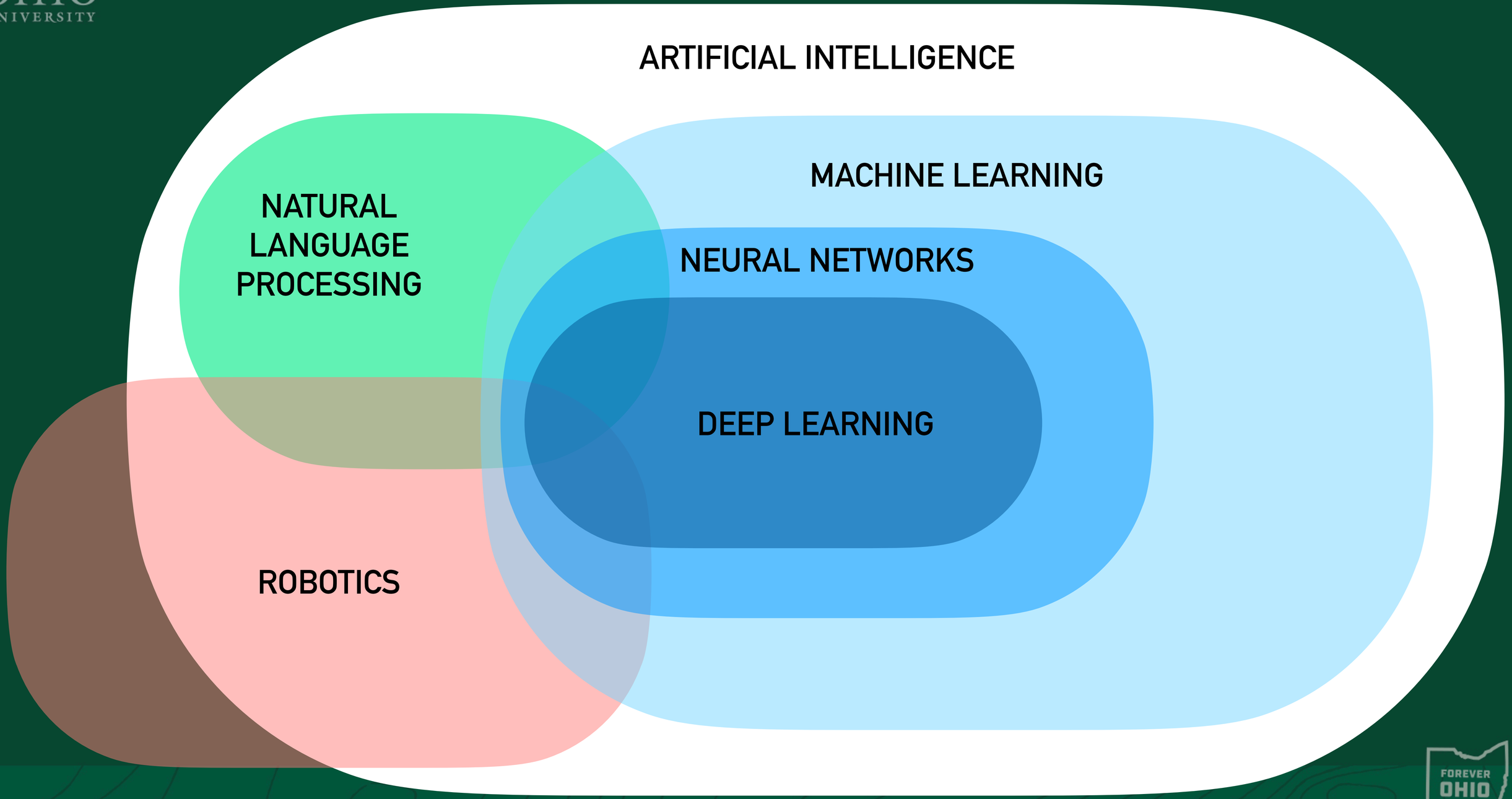
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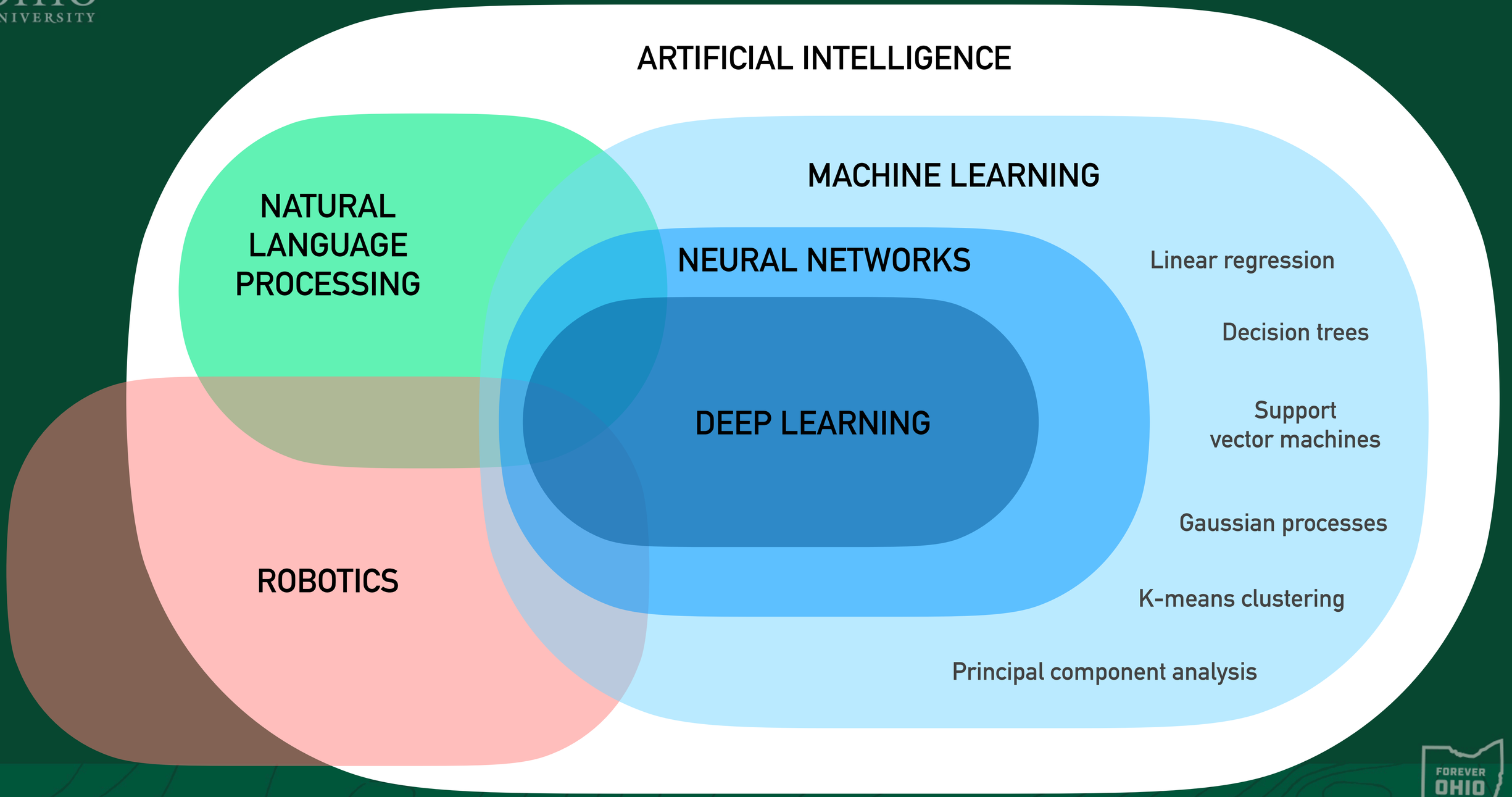
DEEP LEARNING
ROBOTICS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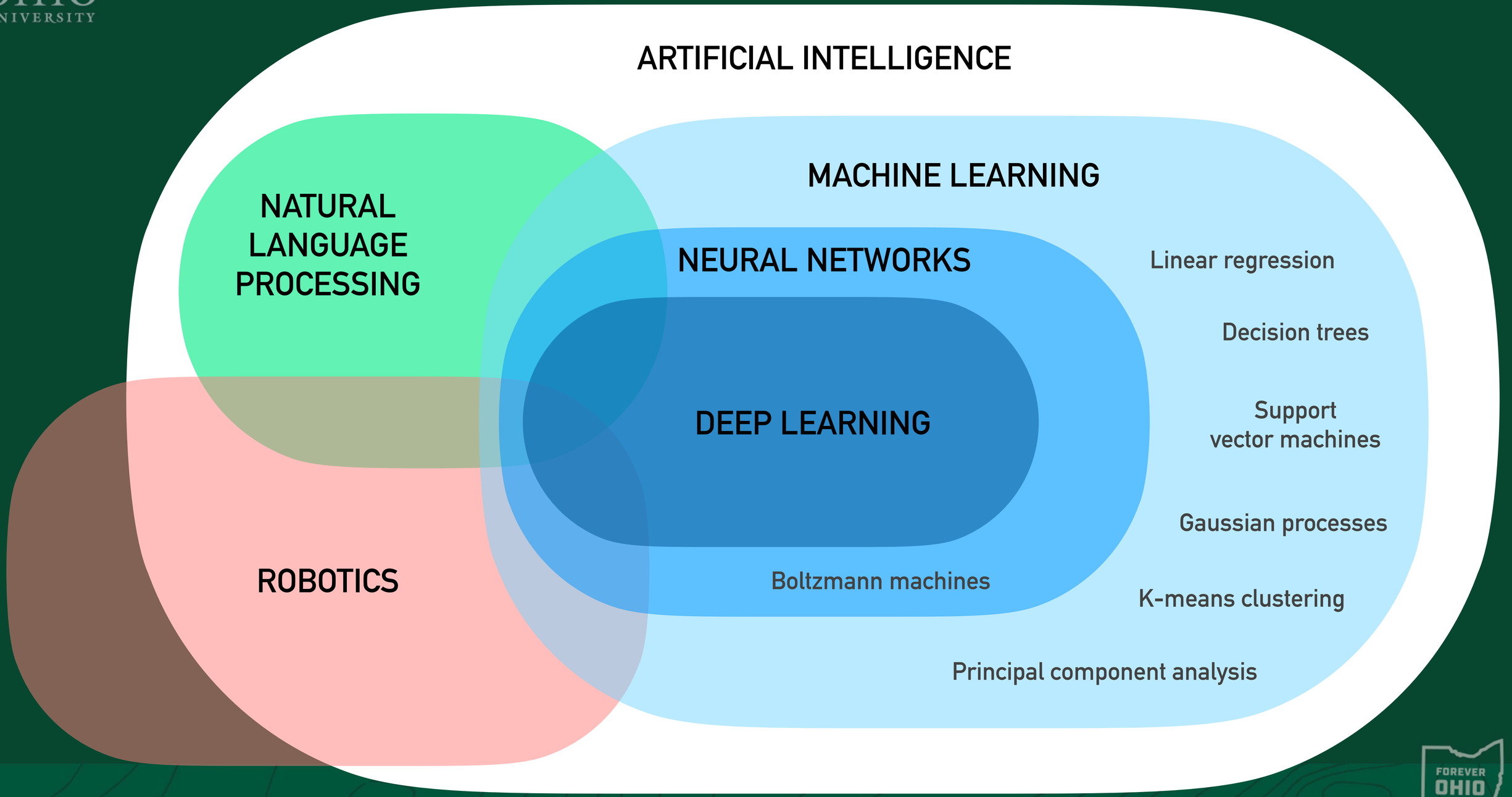
K-means clustering
Principal component analysis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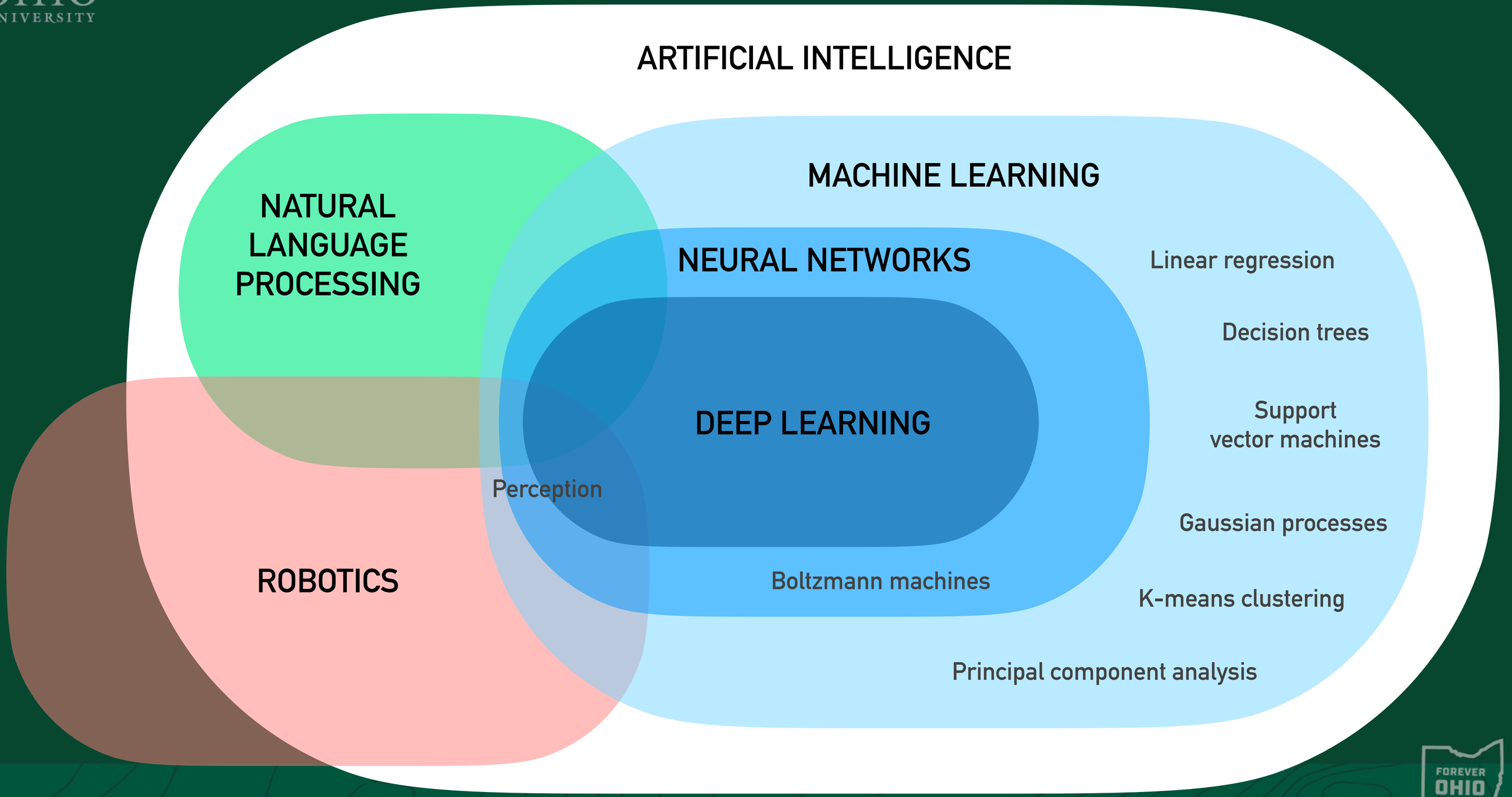
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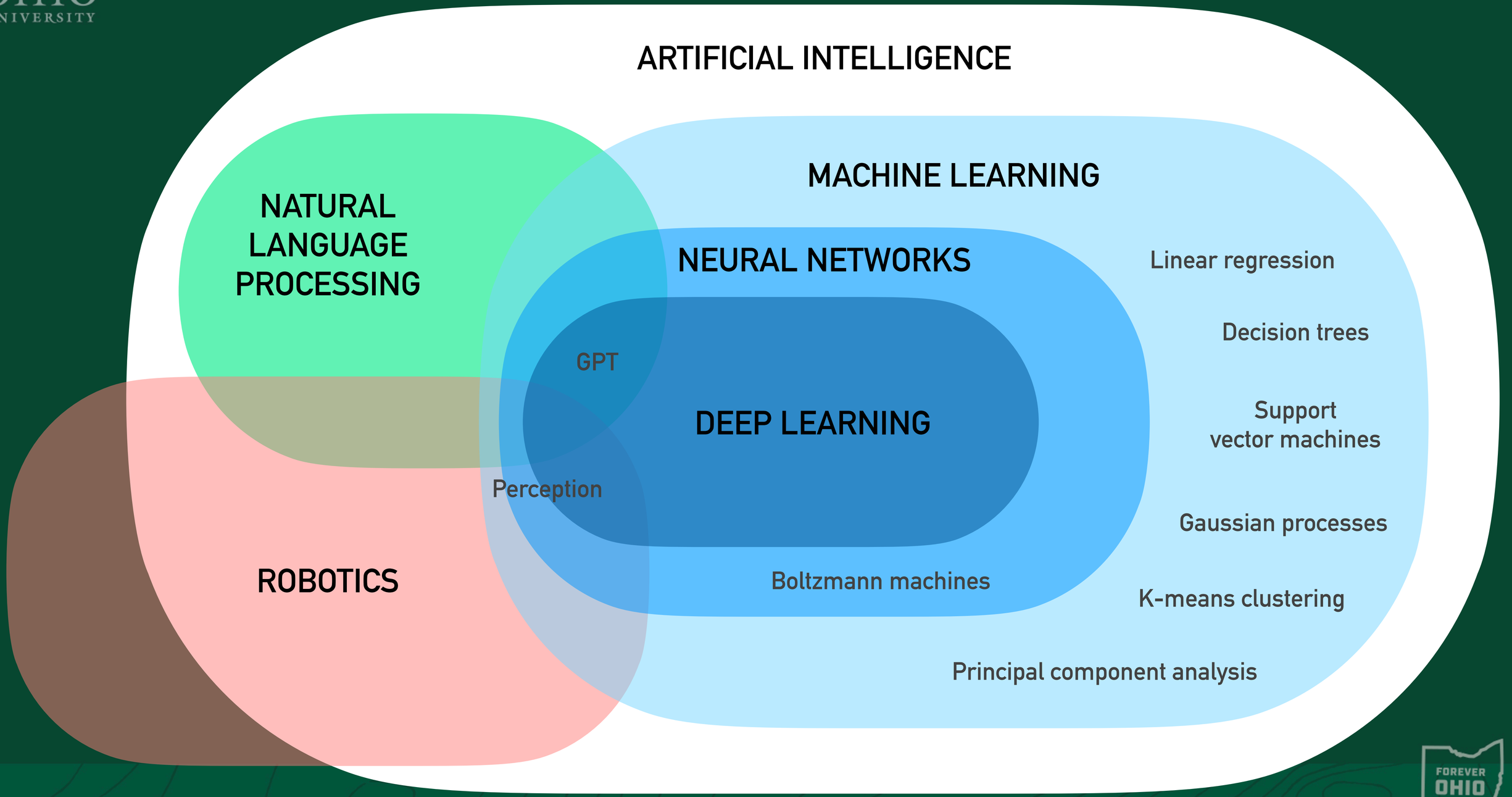
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BRANCHES OF MACHINE LEARNING

- Supervised learning:
    - Map input data X to output data Y
- Unsupervised learning
    - Understand the structure of input data X
- Reinforcement learning
    - Perform tasks while interacting with a dynamic environment
    - Input data X_t depends on prior experiences $X_{t-1}, X_{t-2}, \ldots, X_0$
- These branches are not necessarily distinct! All three can be used together to complete a task.

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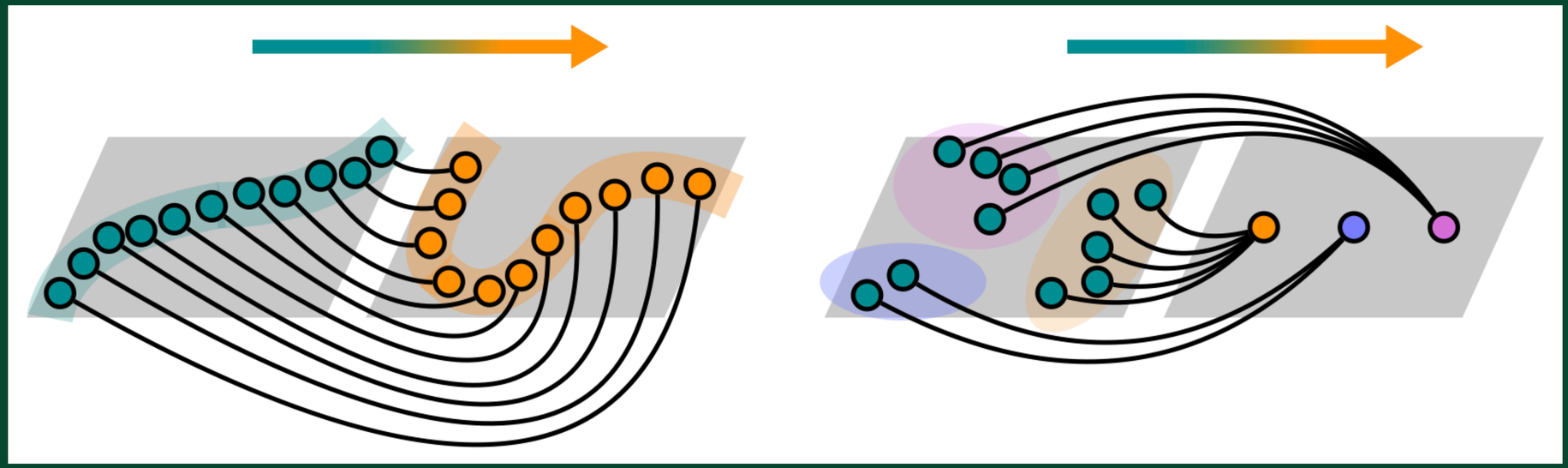
SUPERVISED LEARNING

- Map input data X to output data Y
- Regression (continuous Y) and classification (discrete Y)
- Common algorithms: linear regression, decision trees, support vector machines, k-nearest neighbors, Gaussian processes, neural networks, etc.



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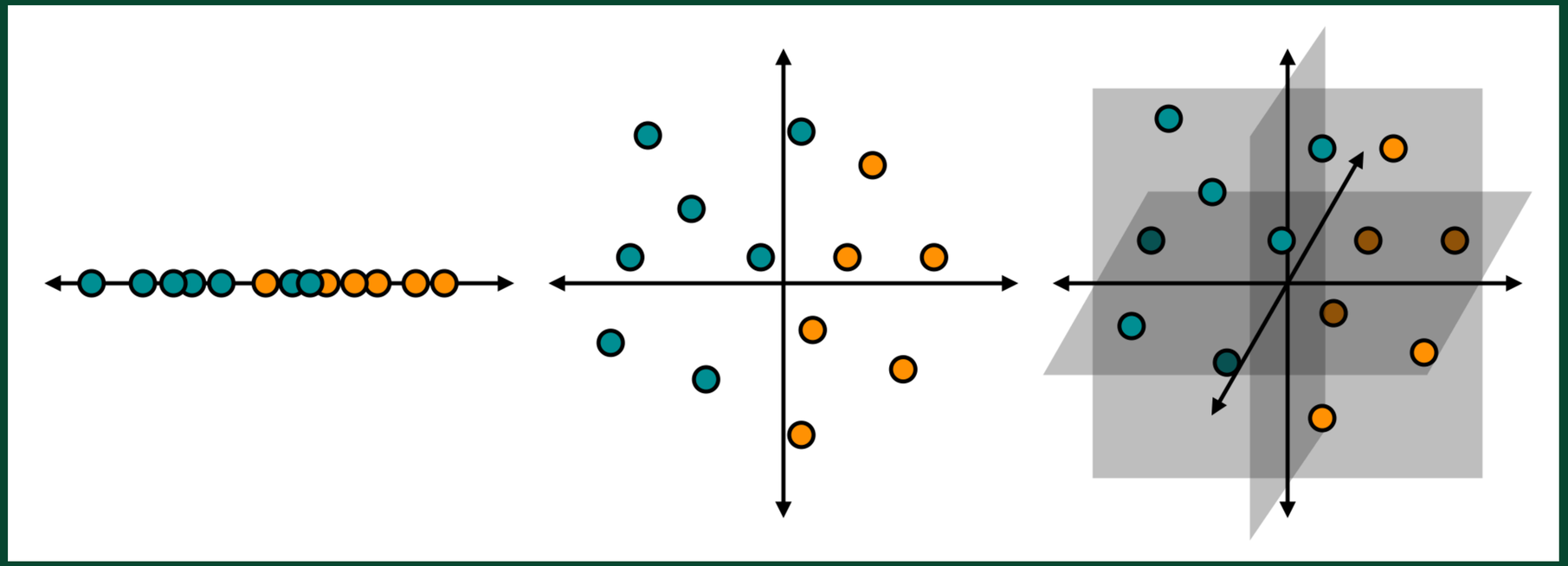
THE CURSE OF DIMENSIONALITY

- As the dimension of the data increases, data sets become exponentially more sparse



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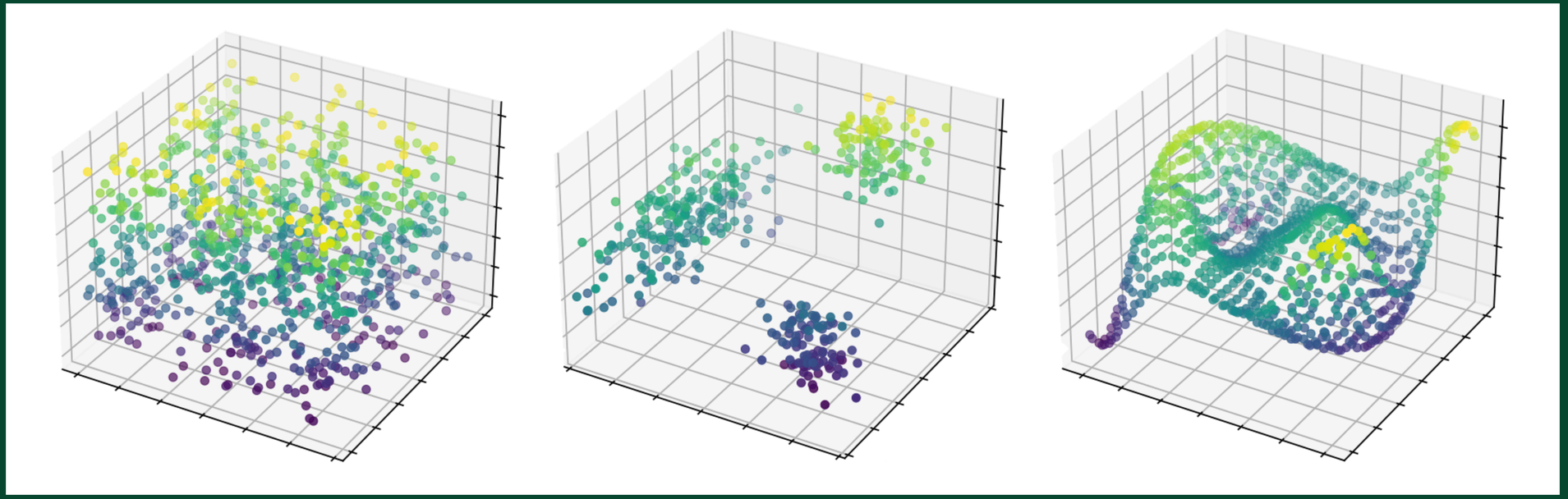
THE SILVER LINING

- Real-life data sets have “structure”
- Structure = information



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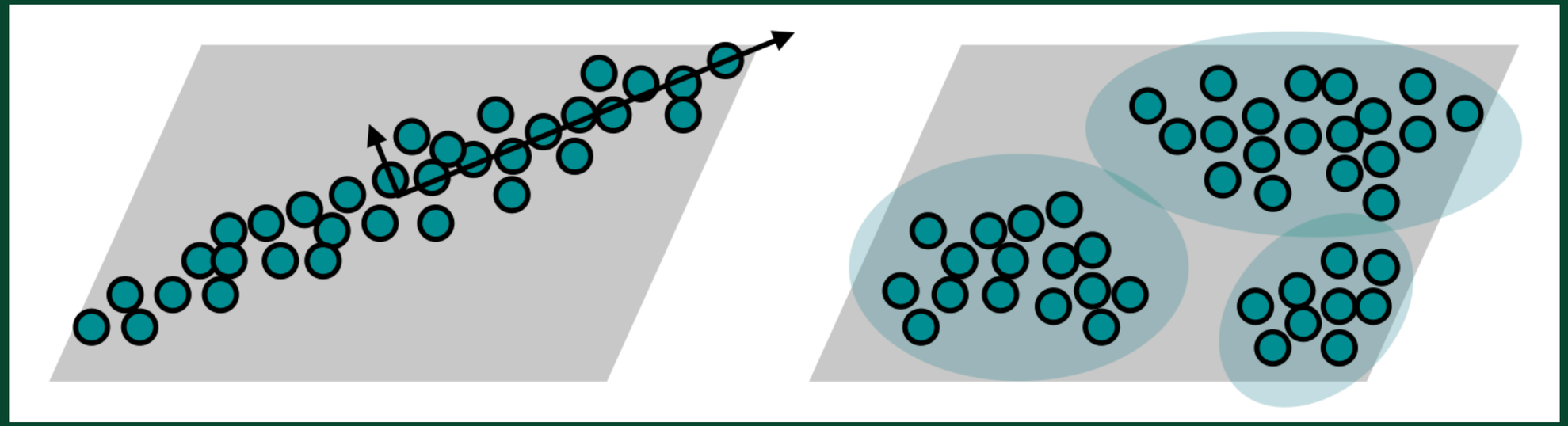
UNSUPERVISED LEARNING

- Understand the structure of input data X
- Clustering, dimensionality reduction, anomaly detection, density estimation
- Common algorithms: principal component analysis, k-means clustering, autoencoders, Boltzmann machines, etc.



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REINFORCEMENT LEARNING

- Perform tasks while interacting with a dynamic environment
- Input data X_t depends on prior experiences X_{t-1}, X_{t-2}, $\ldots$, X_0
- Collecting new data is a part of the learning process
- Useful when it's inefficient or impossible to collect or store enough traditional training data

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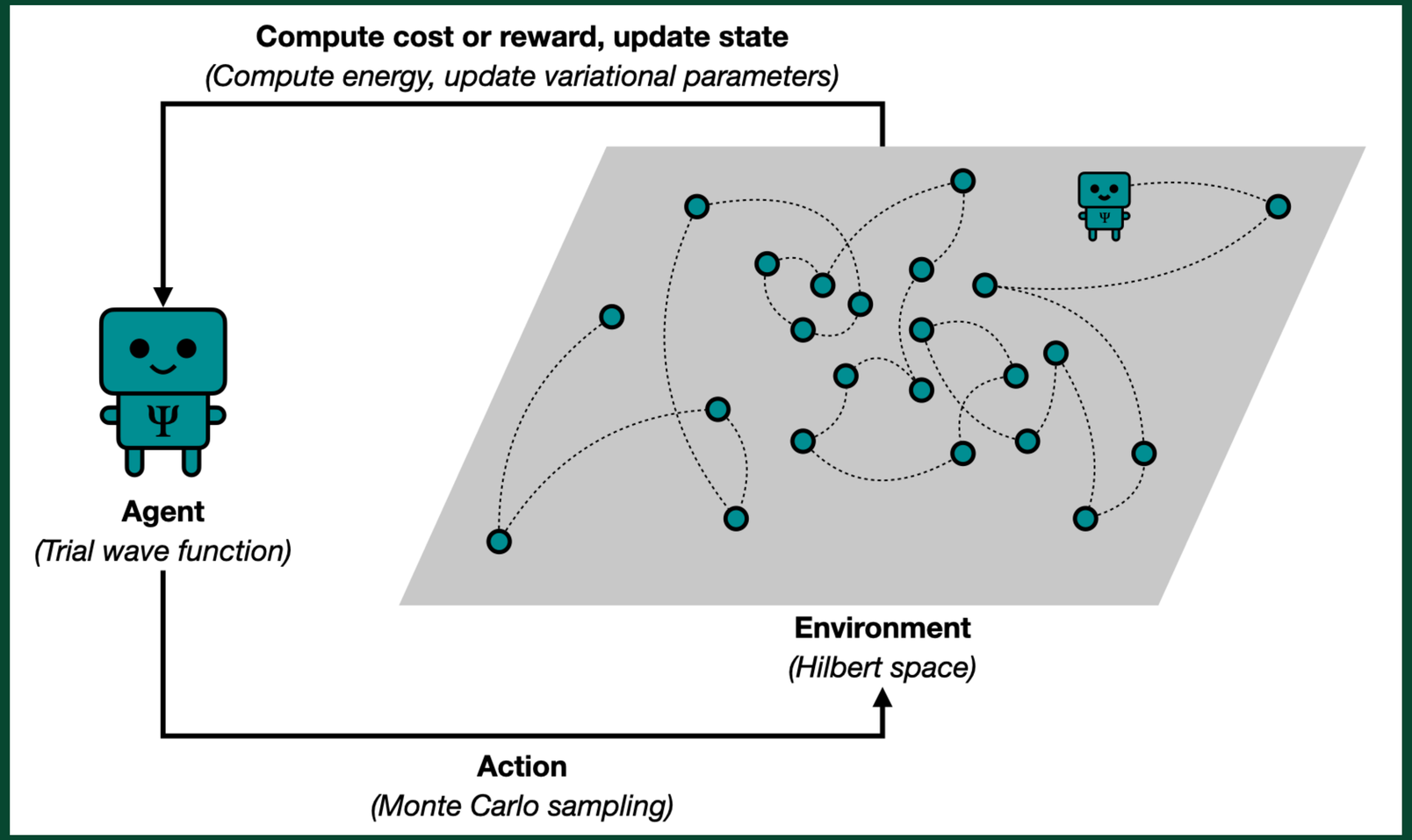
REINFORCEMENT LEARNING

- E.g. training wave functions by minimizing the energy
- In practice, we may also use supervised and unsupervised learning to prepare the initial wave function or learn a better representation of the data



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OPTIMIZATION

- Sometimes can be done analytically, e.g. closed form solutions for linear regression and Gaussian processes
- Sometimes done iteratively with special algorithms, e.g. k-means clustering
- Often times we opt for iterative gradient descent methods
    - Need an explicit function to minimize/maximize
    - Need to compute or approximate the gradient of this function

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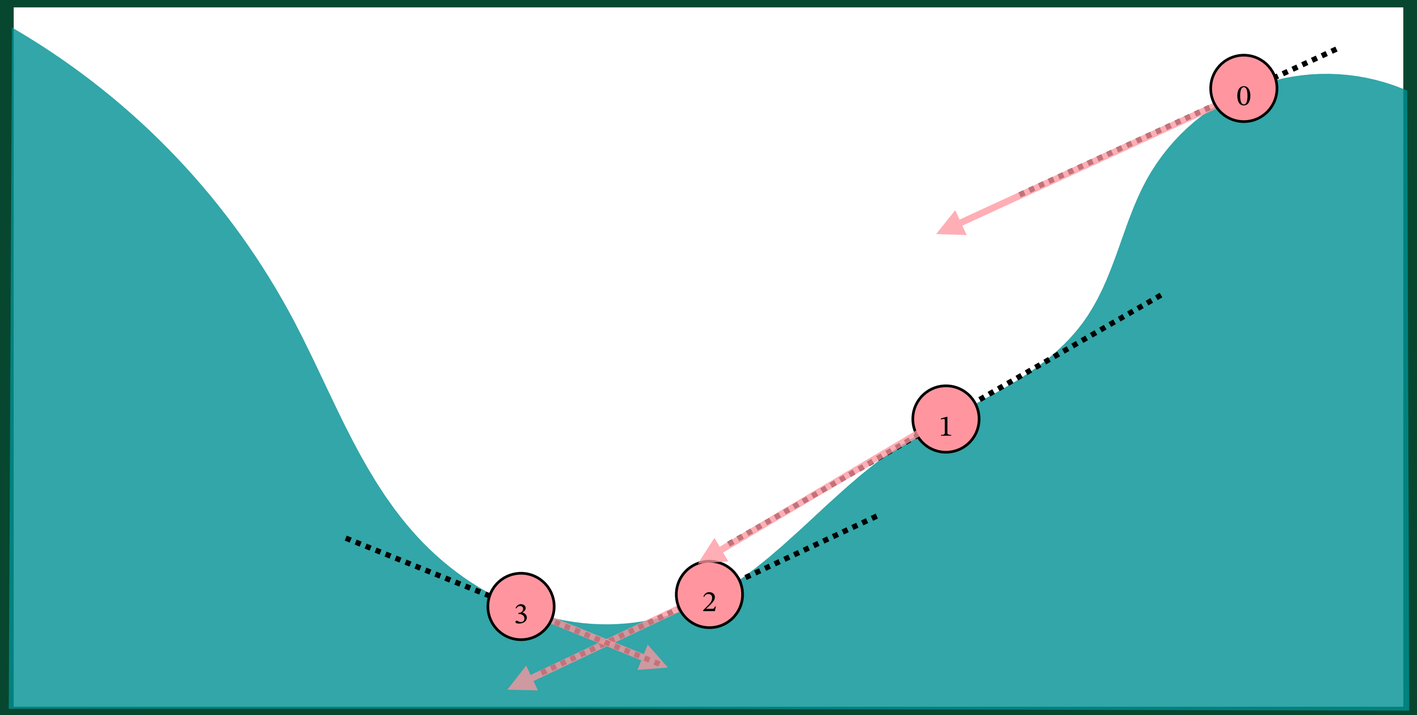
EXAMPLE: GRADIENT DESCENT

- Go to: https://github.com/kim-jane/IntroMachineLearning/
  For an introduction on some common gradient descent methods



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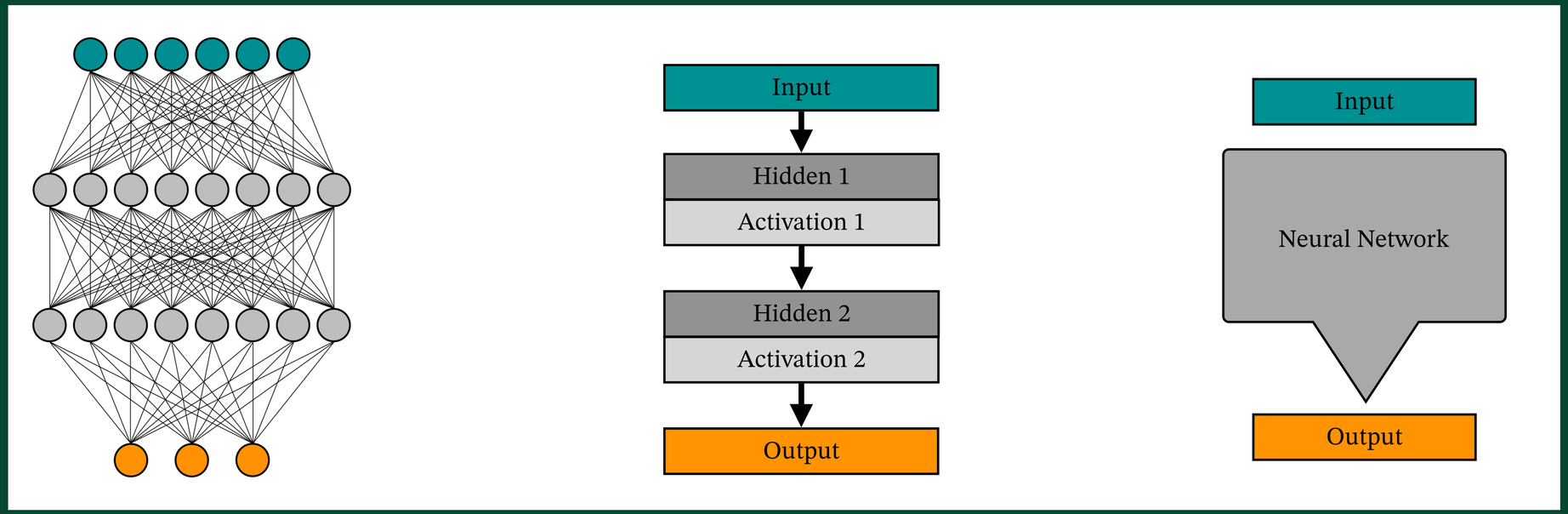
NEURAL NETWORKS

- Very flexible models inspired by the structure of biological brains
- Feedforward neural networks are “universal” function approximators (conditions apply)
- WARNING: Do not use these if you’re data set is small or if you’re task can be handled by a more interpretable model.



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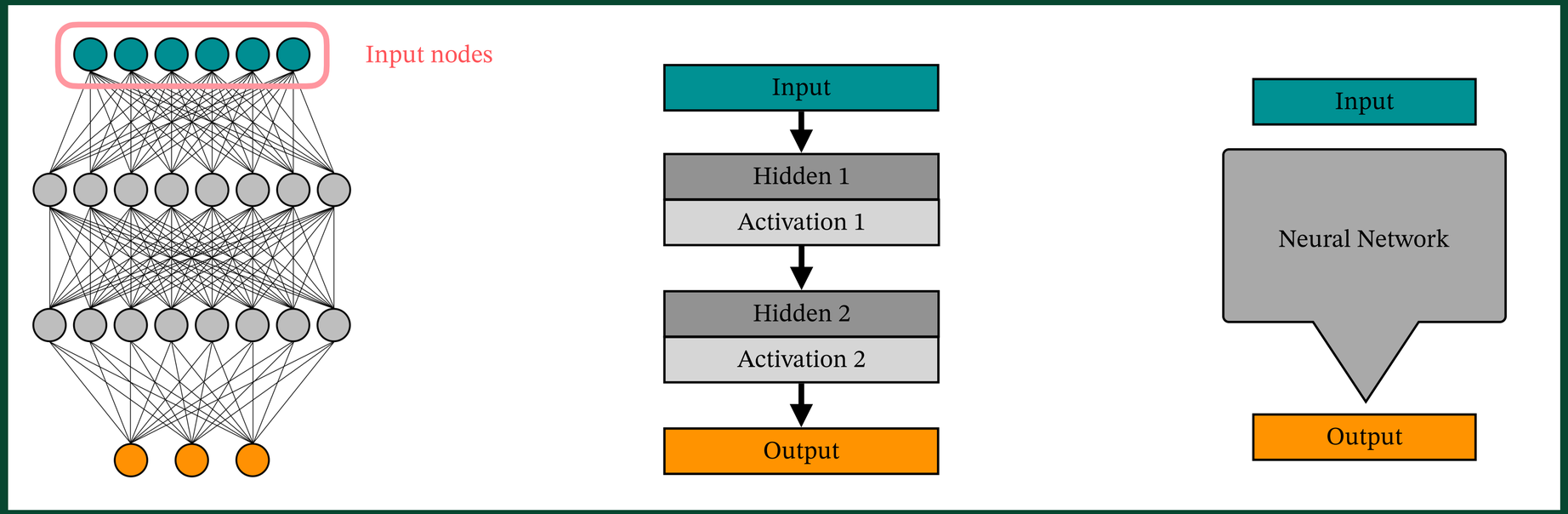

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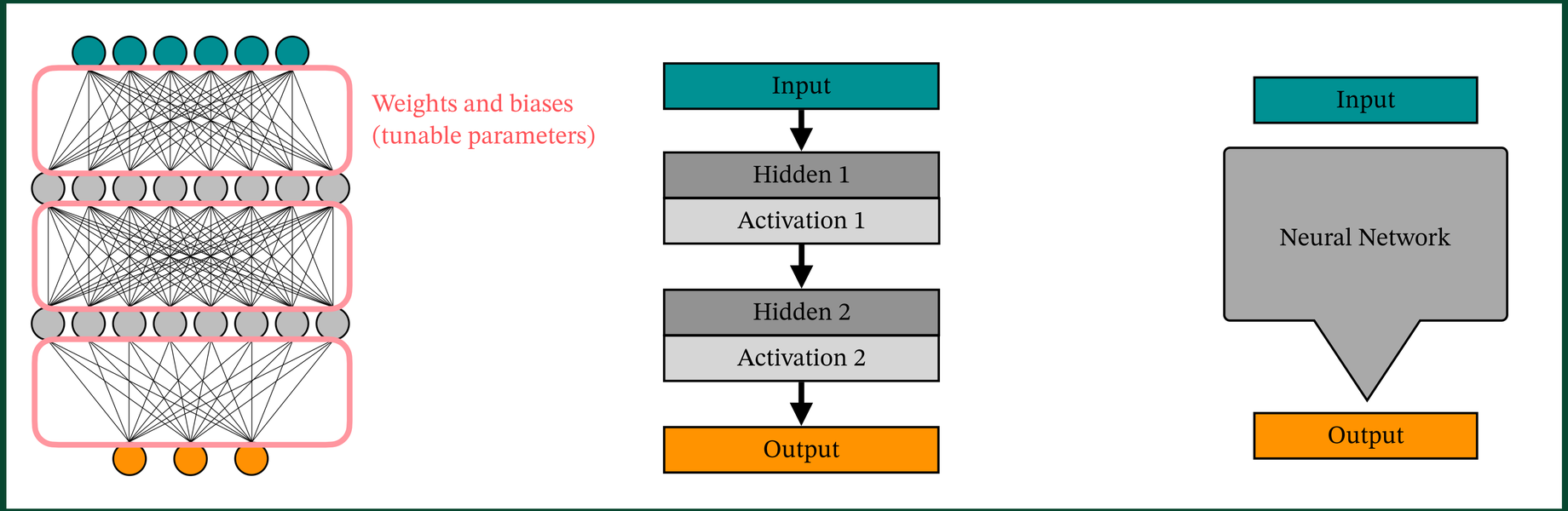

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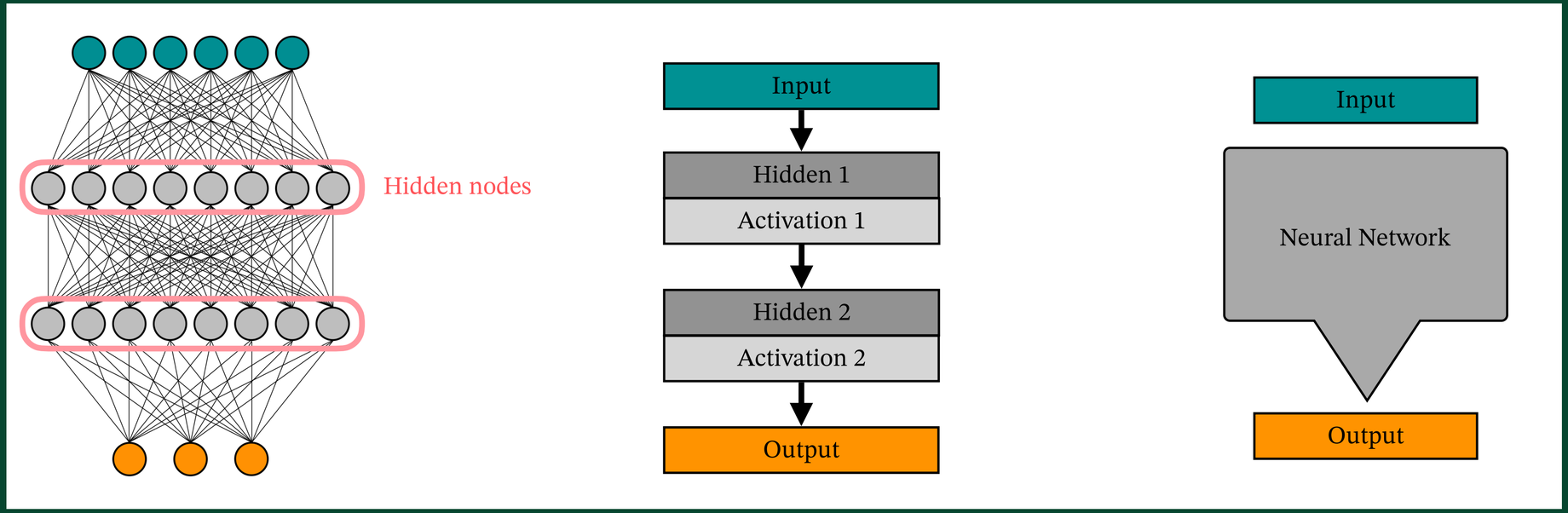

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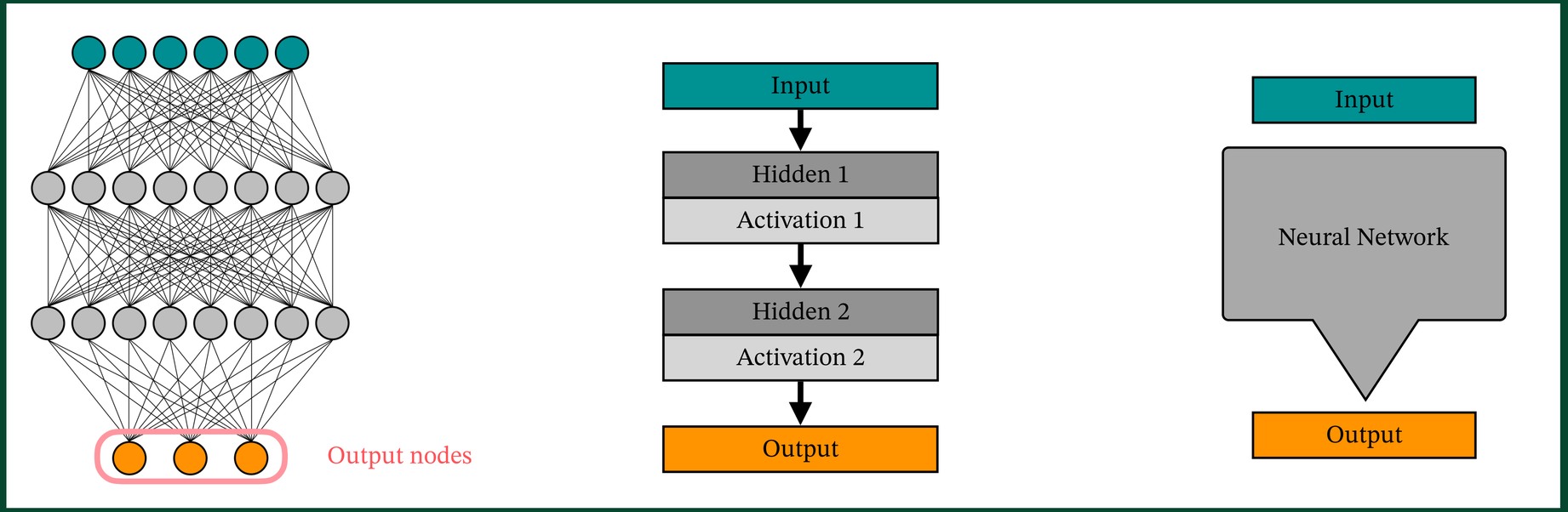

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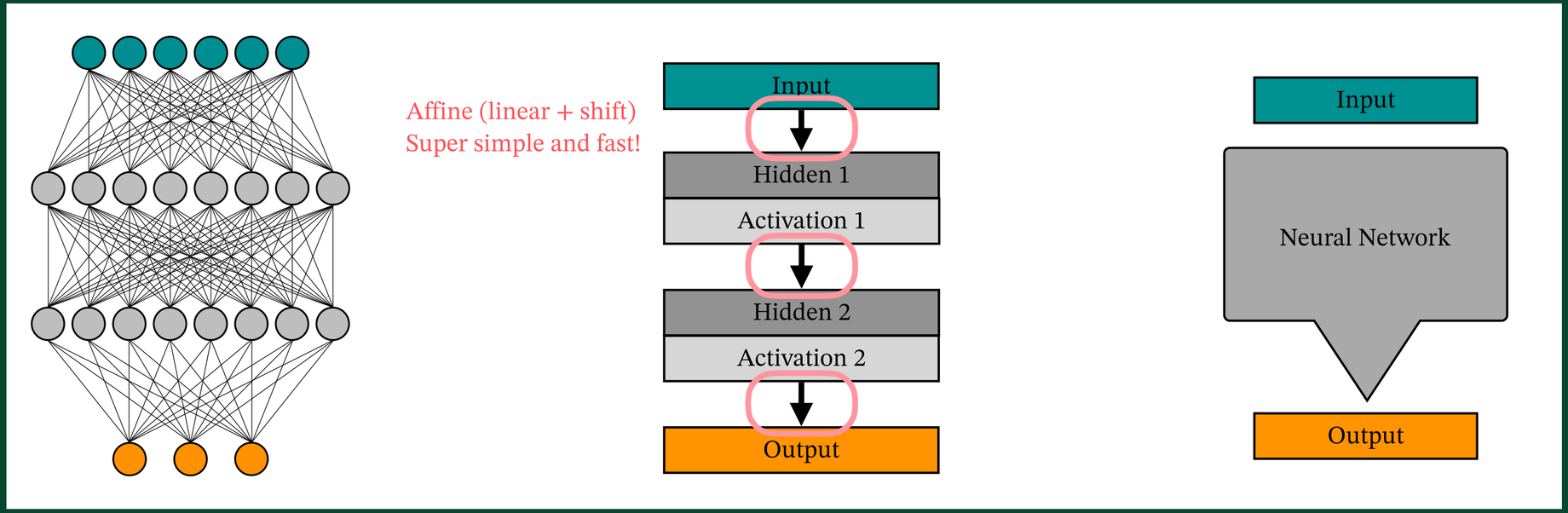

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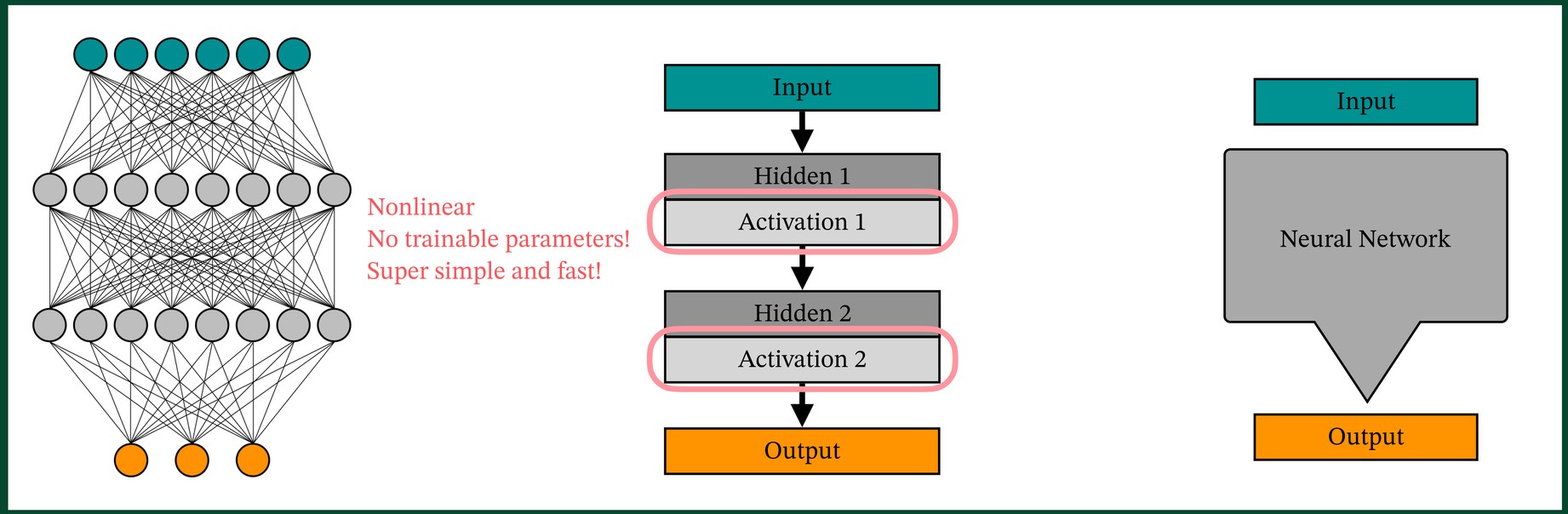

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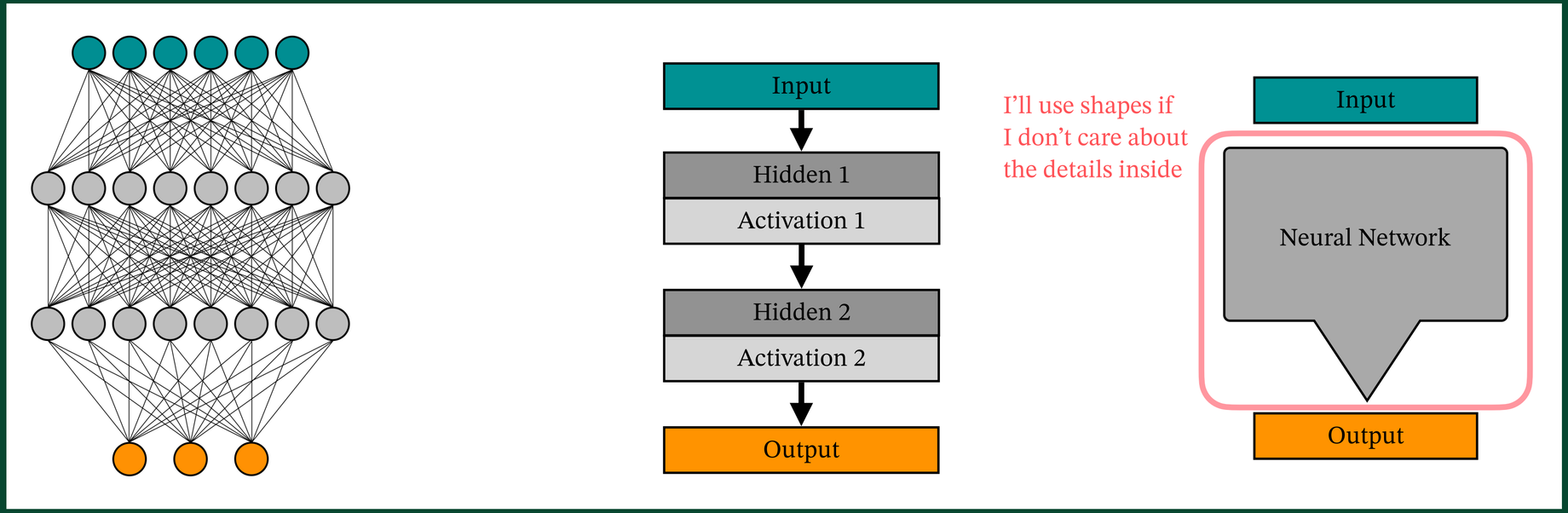

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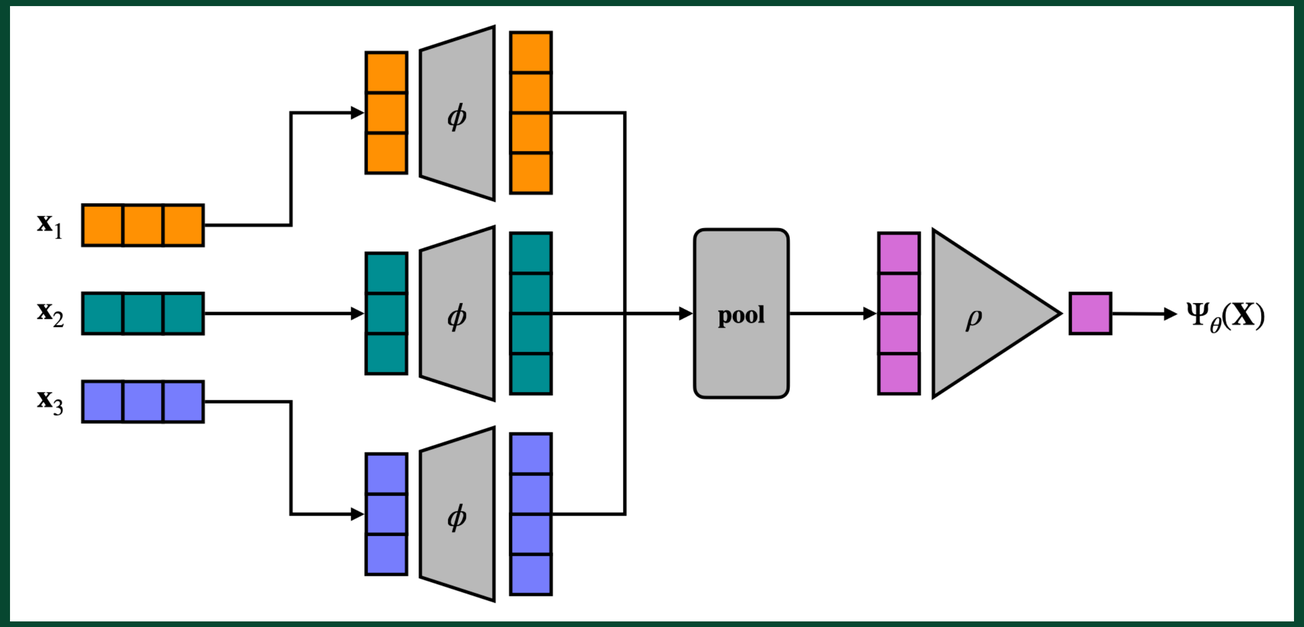
SYMMETRIES

- In physics, we often need to constrain symmetries or boundary conditions
- In machine learning, algorithms that take advantage of the symmetries perform better
- E.g. convolutional neural networks assume the data has grid-like structure (great for images)
- E.g. two neural networks can be used to construct a permutation-invariant function (deep set)



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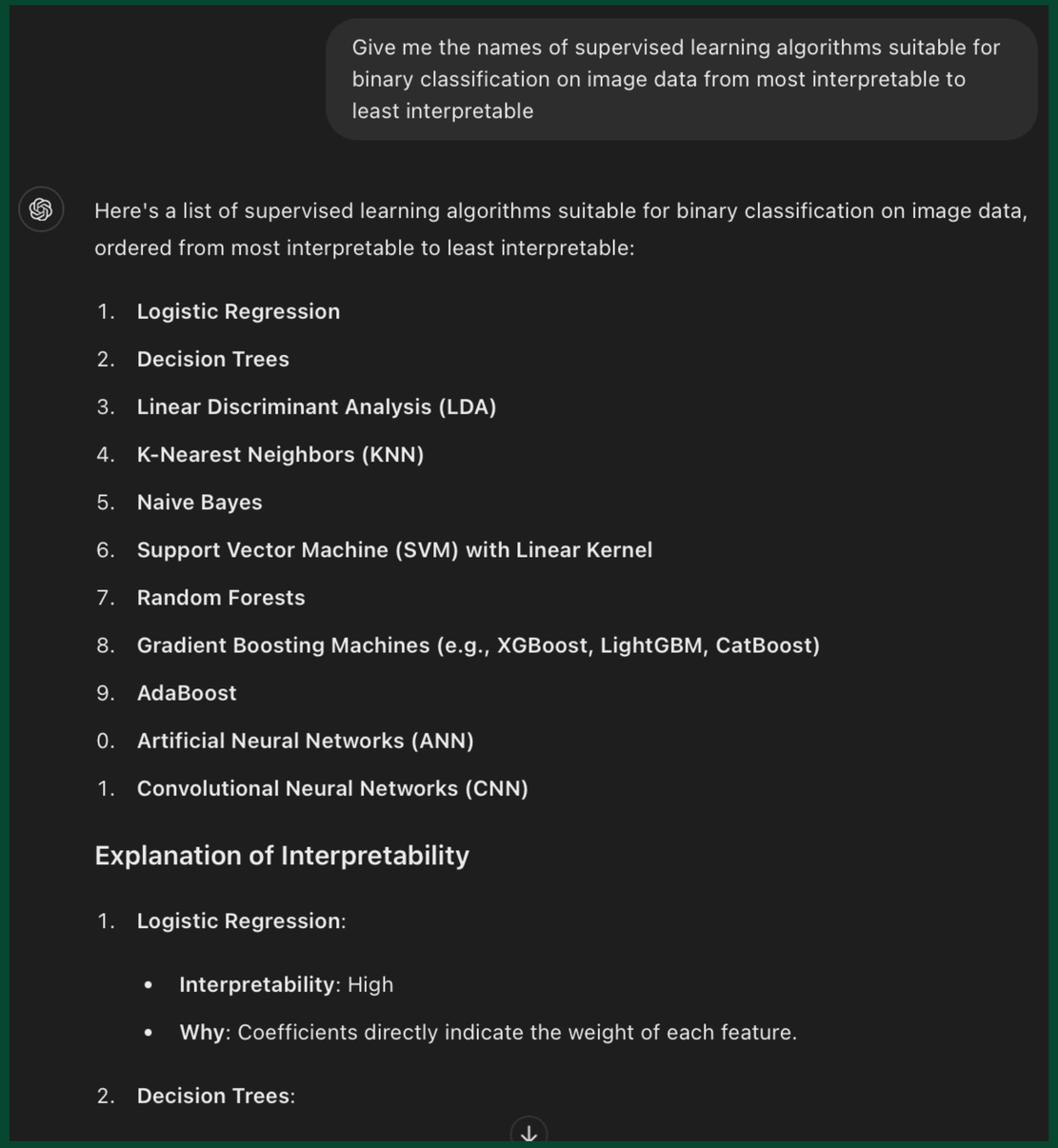
APPROACHING A TASK

- Identify the task
- What kind of data do you have access to?
- Does your data have labels?
- Is it high-dimensional?
- Figure out which branch your problem naturally falls under
- Find the names of methods that are suitable for your specific problem
- For most applications, you can use the algorithms “out-of-the-box”, but understanding the math can help you get better performance



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EXAMPLE: SELF-DRIVING CAR

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    - Safety / comfort:
        - Obeying the rules of the road
        - What's the best braking rate, turning radius, etc?
        - How to identify and react to surroundings
        - How to make decisions in case of emergency

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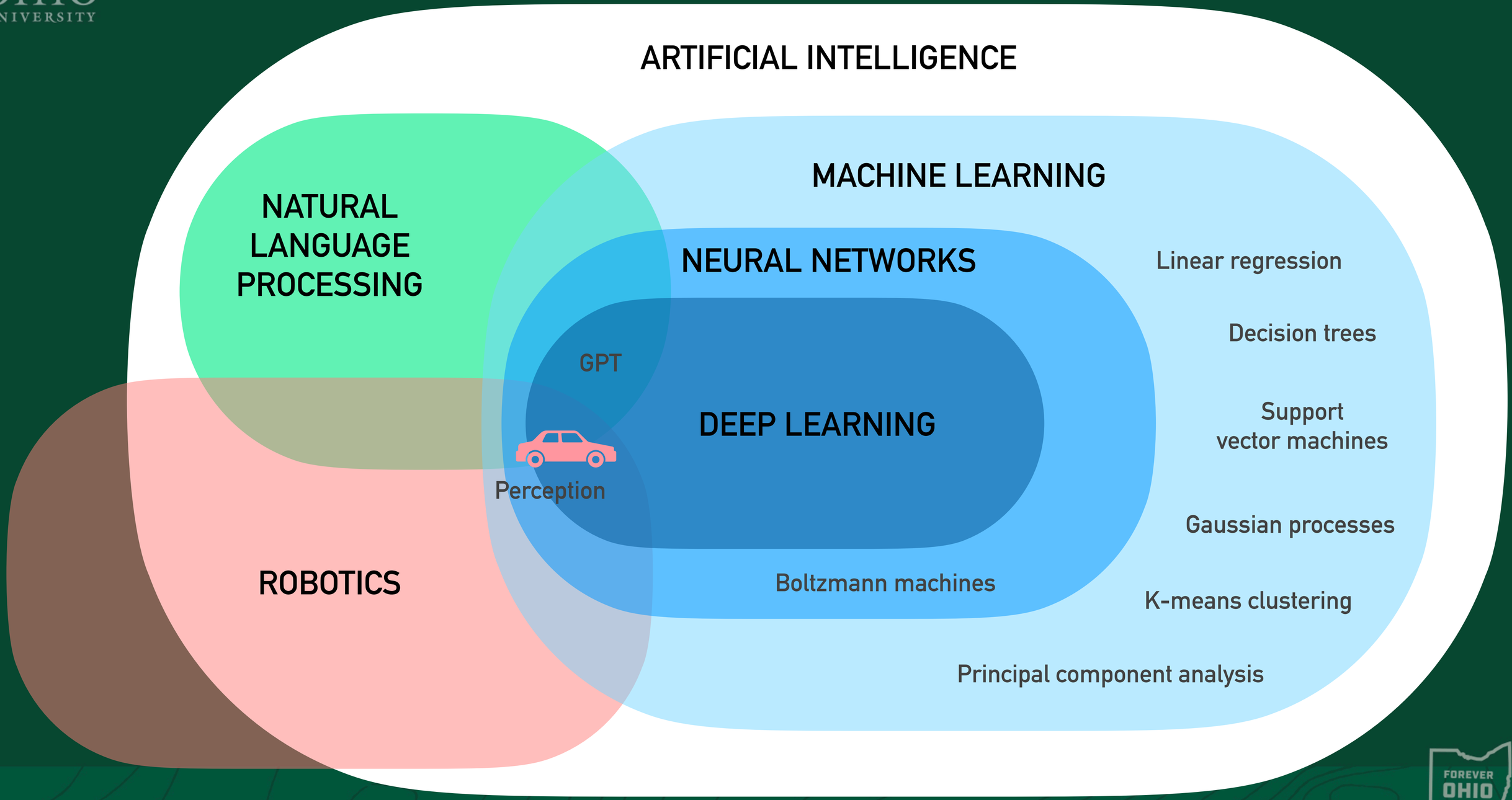

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  - Dynamic objects: other vehicles, pedestrians, cyclists, animals, etc.

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  - Goal: detect whether certain objects exist within the input image
  - Static objects: lane markings, road signs, traffic lights, etc.
  - Dynamic objects: other vehicles, pedestrians, cyclists, animals, etc.
  - Assign labels to each of the categories of objects
  - Let your model guess a label
  - Quantitatively measure the similarity between your model's guess and the true label
  - Slightly adjust your model to get a better similarity next time

EXAMPLE: SELF-DRIVING CAR

- Just consider these objects for now:
  - Lane markings
  - Stop signs
  - Other vehicles
- This is a multi-label classification problem
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Pretty sure there are lane markings

Probably no stop signs

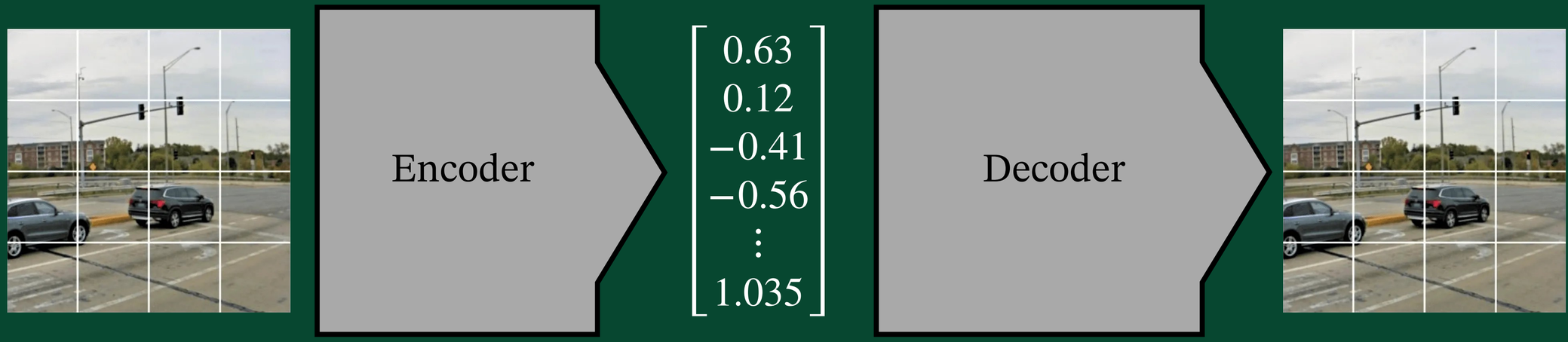
Not sure if there are other vehicles here

EXAMPLE: SELF-DRIVING CAR

- How to identify surroundings with supervised learning
  - Measure the similarity between the true label $y_i = (1,\ 0,\ 1)$ and the model's label $\hat{y}_i = (0.9,\ 0.1,\ 0.5)$
  - Binary cross-entropy is a good choice of loss function for multi-label classification
  - If $\hat{y}_i$ is close to y_i , the cross-entropy is small and positive
  - Else, the cross-entropy is large and positive
  - Want to minimize the cross-entropy

EXAMPLE: SELF-DRIVING CAR

- How to react to compress images with unsupervised learning
  - There are too many images to handle, most of the info is junk anyways
  - How can we compress the image into a vector that retains all or most of the information?
  - Try autoencoders: map your image to a smaller space, then try to reproduce the original image.
  - After training, the output of your encoder can be used as input for your supervised learning model.



EXAMPLE: SELF-DRIVING CAR

- How to react to surroundings with reinforcement learning
  - Suppose our model has been pretrained to identify important objects
  - Now we want to extend our model to make decisions based on the surroundings
  - Construct a cost function that rewards desired behavior and penalizes unwanted behavior
  - Supervised pretraining helps prepare the model for harder tasks like this

Encoder

$$\begin{bmatrix} 0.63 \\ 0.12 \\ -0.41 \\ -0.56 \\ \vdots \\ 1.035 \end{bmatrix}$$

Object Recognizer

$$\begin{bmatrix} 0.99 \\ 0.01 \\ 0.98 \end{bmatrix}$$

Decision Maker

$$\begin{bmatrix} a_L \\ a_T \end{bmatrix}$$

Longitudinal acceleration (forward/backward)

Transverse acceleration (left/right)

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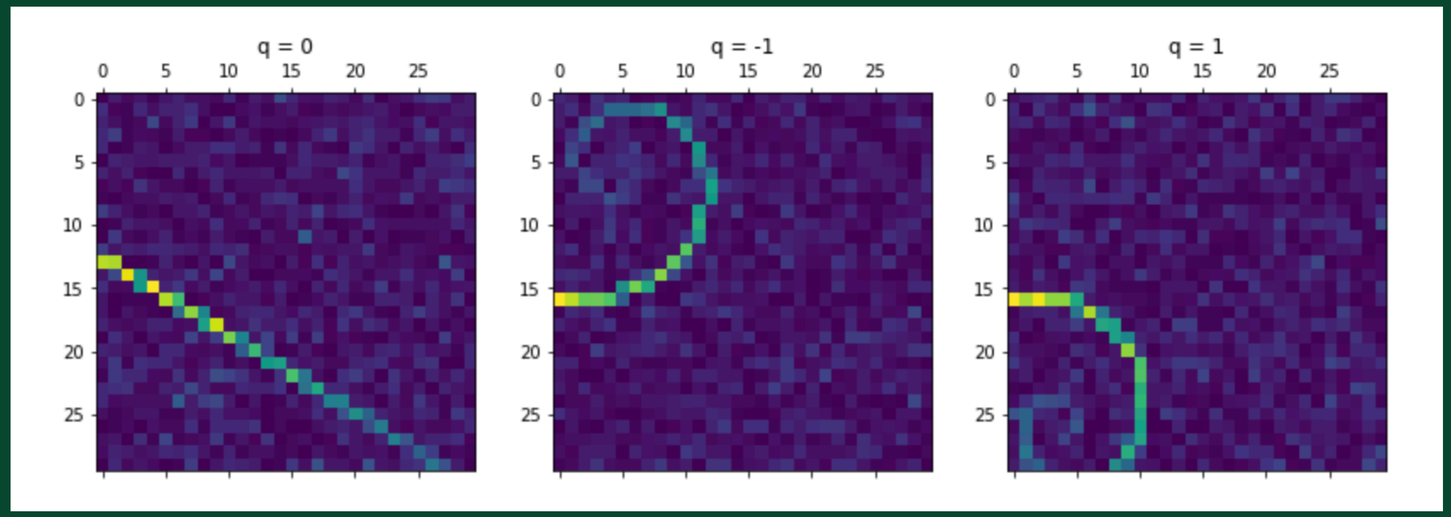
EXAMPLE: CLASSIFYING CHARGED PARTICLES

- Go to: https://github.com/kim-jane/IntroMachineLearning/
- 30 pixel × 30 pixel images of particle tracks
- Pixel values are proportional to energy deposited
- Lots of background noise!
- Goal: classify images of tracks to the charges of particles



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THANK YOU!

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