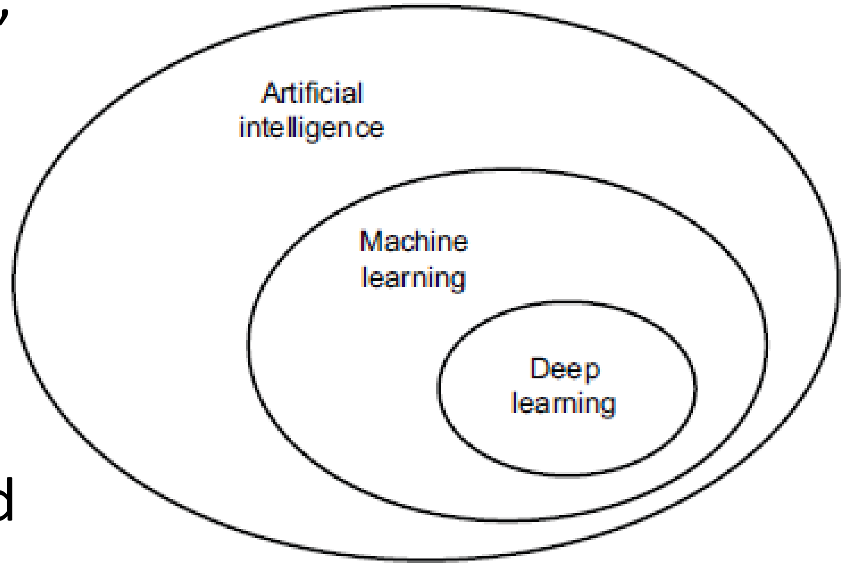
Machine Learning
Live Session #1

Machine Learning

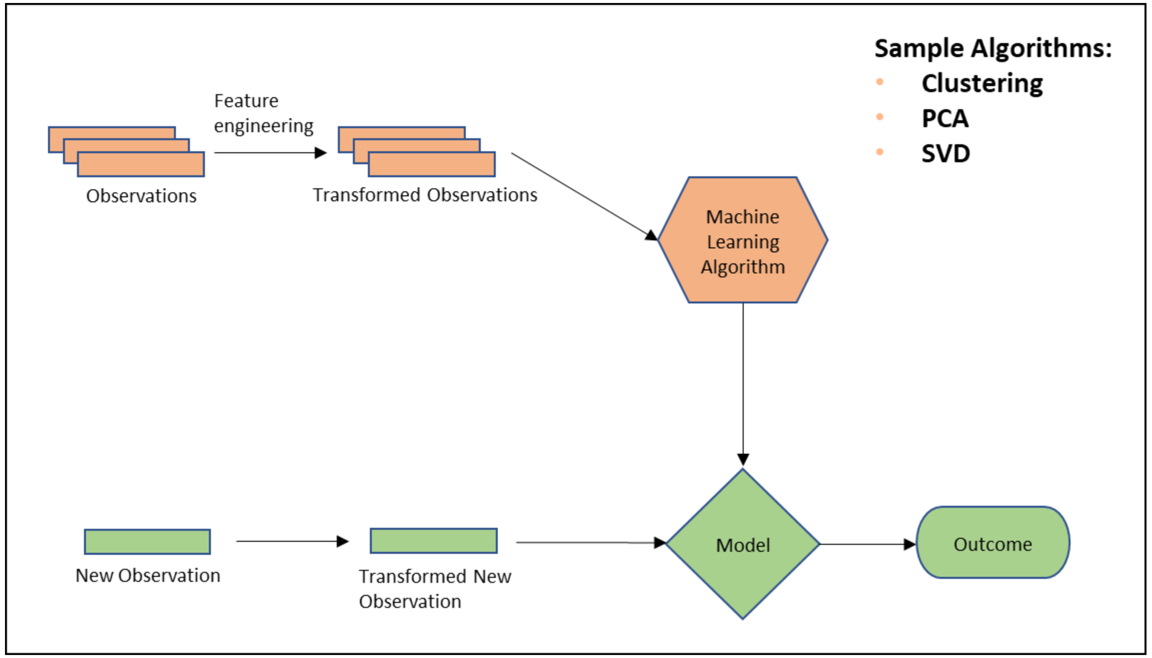
- **Artificial intelligence** is the study of getting machines to perform human tasks
  - E.g., recommender systems in Netflix, a self-driving Tesla, etc.
- **Machine learning** is the study of getting machines to learn from data
  - I.e., it is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns, and make decisions with minimal human intervention.
  - Two main types of learning: unsupervised and supervised
- **Deep learning** is essentially machine learning with neural networks containing many layers (i.e., deep neural networks)



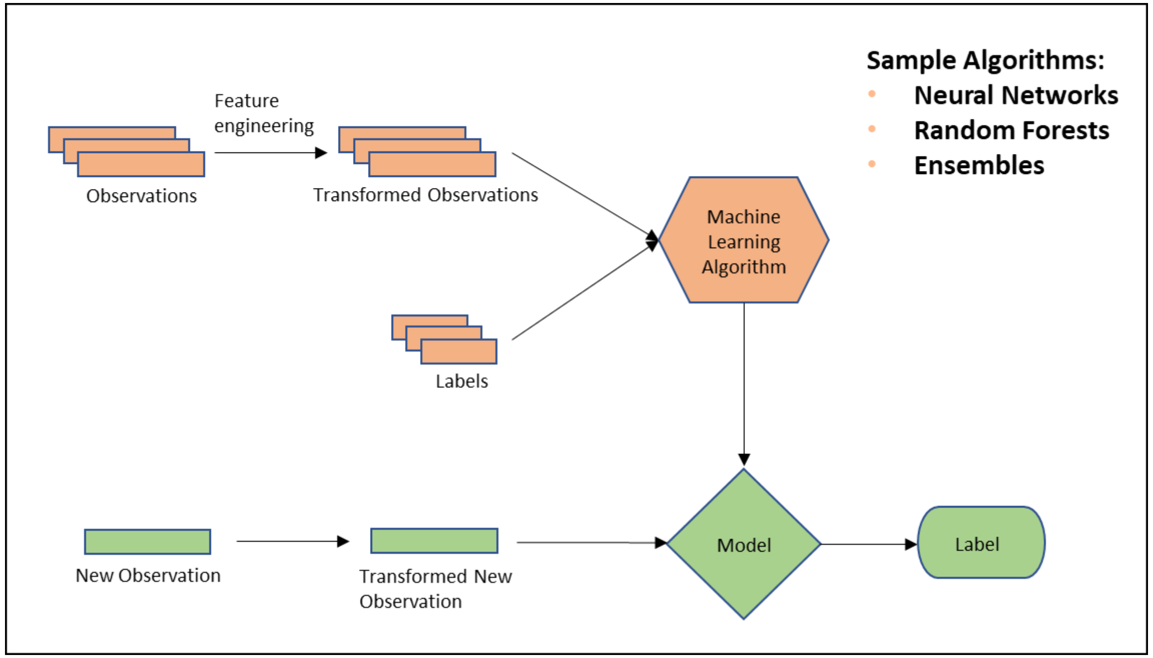
Machine Learning: What It Is and Why It Matters. SAS. https://www.sas.com/en_us/insights/analytics/machine-learning.html

Supervised vs. Unsupervised Learning

- Unsupervised learning: no labels associated with observations
  - Try to infer relationships between the observations or between the features
  - Useful for data visualization and dimension reduction
- Supervised learning: each observation is associated with a label
  - Try to infer a relationship between the features and labels
    - The label acts as a teacher that supervises the learning process
  - Use the relationship to predict label for a new observation

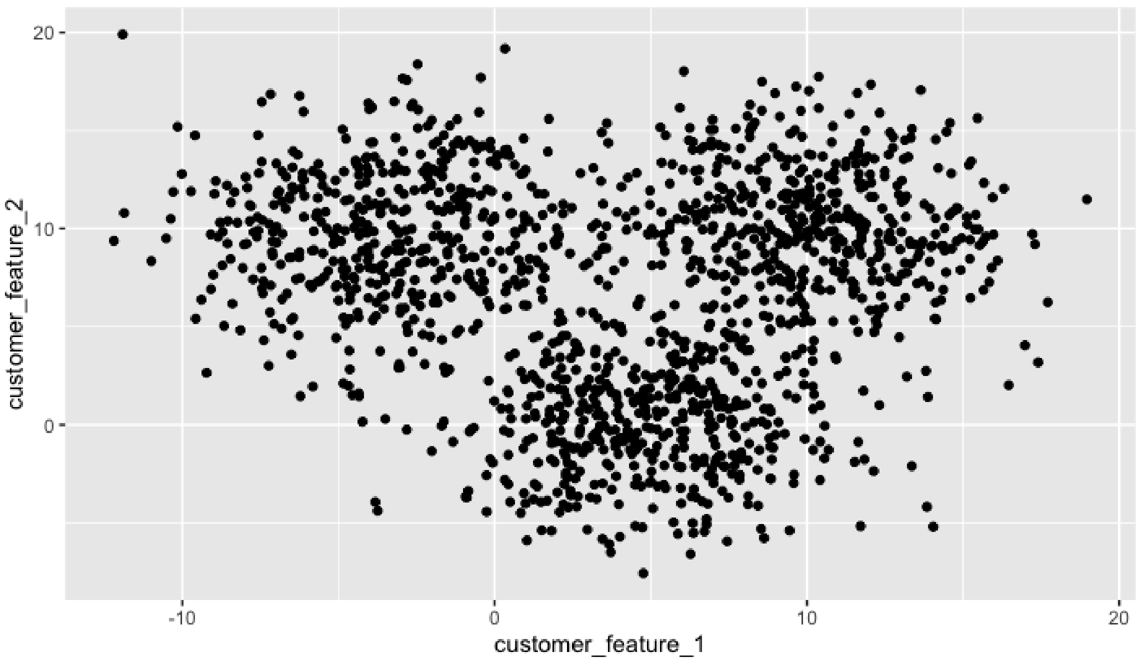


Unsupervised Learning



Supervised Learning

Unsupervised vs. Supervised Learning



Unsupervised Learning

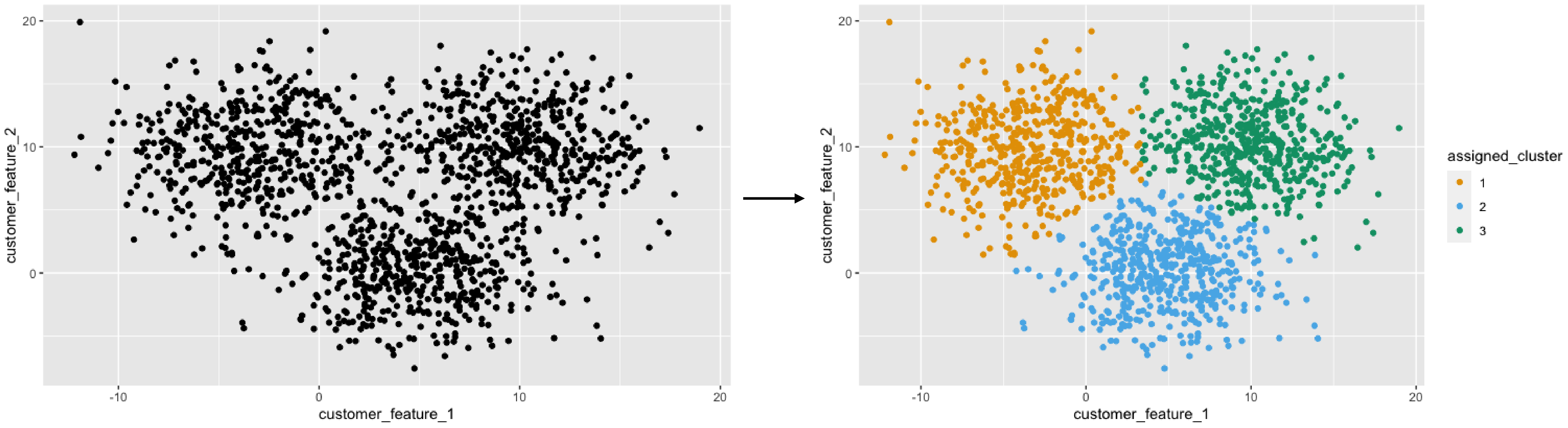
- Observations (here, customers) have no labels
- Use unsupervised learning to explore and learn about customers
  - E.g., do sub-groups of customers exist, with each sub-group exhibiting similar characteristics?
  - This is called customer segmentation

Supervised Learning

- Each observation (here, customer) is associated with a label
  - E.g., whether the customer left or stayed
- Use supervised learning to predict the label for new customers

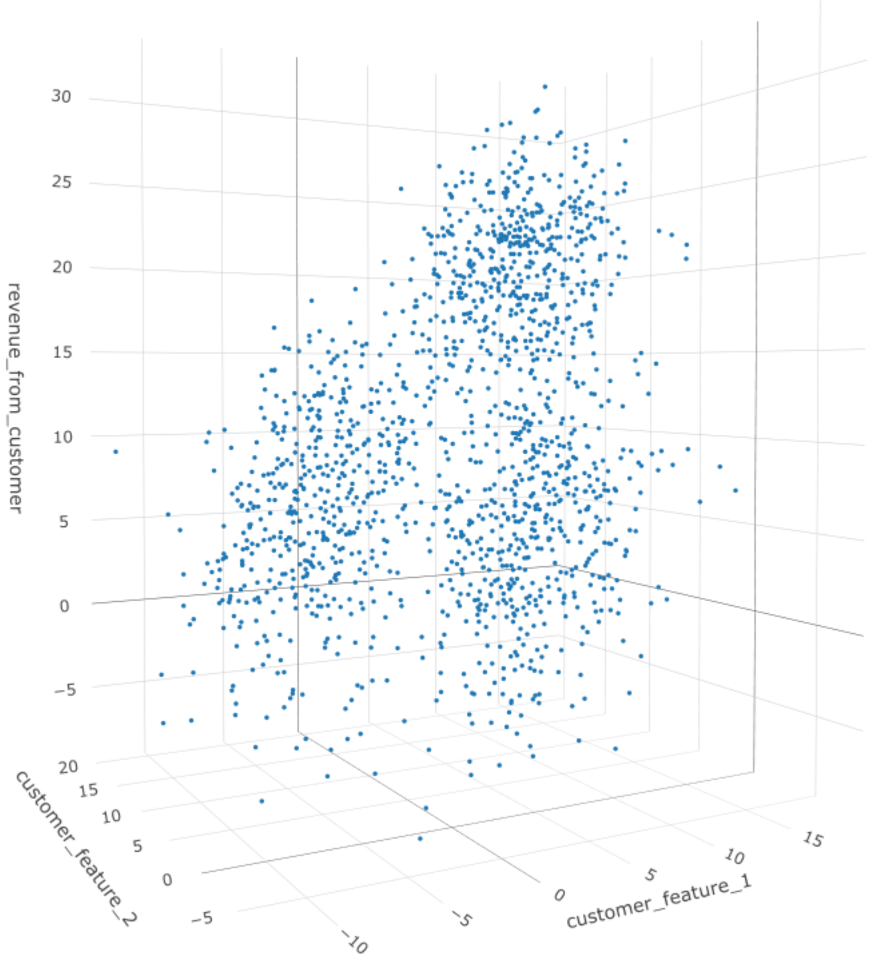
Unsupervised Learning Example

- k-means clustering
  - Find k clusters in the dataset
  - Does not use any labels, only distance of observations from each other



Supervised Learning

- Two types of supervised learning: regression and classification



Regression

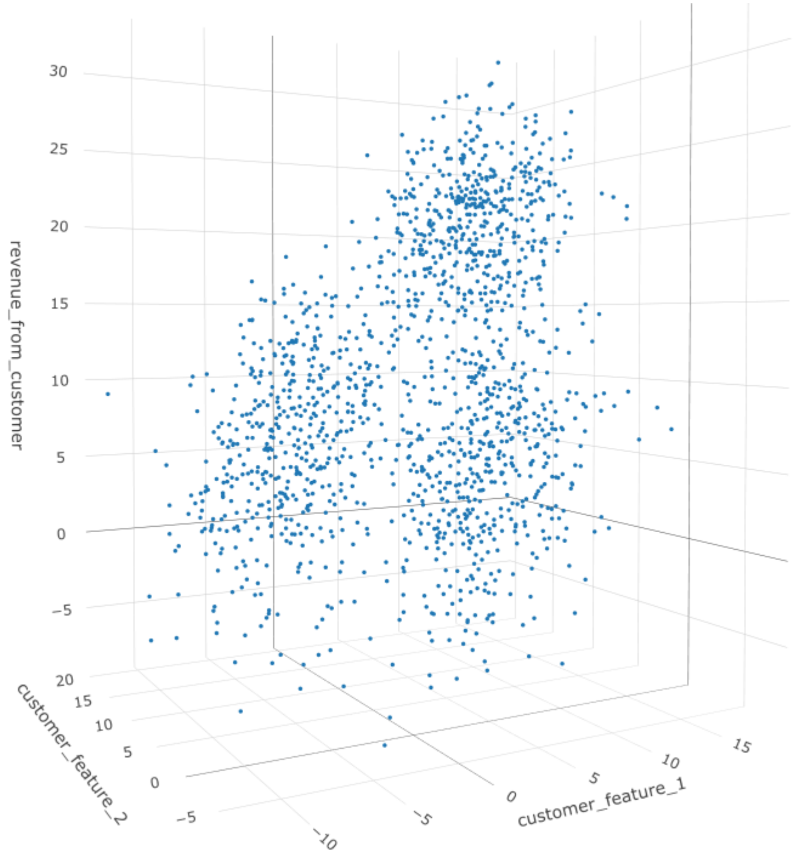
Classification

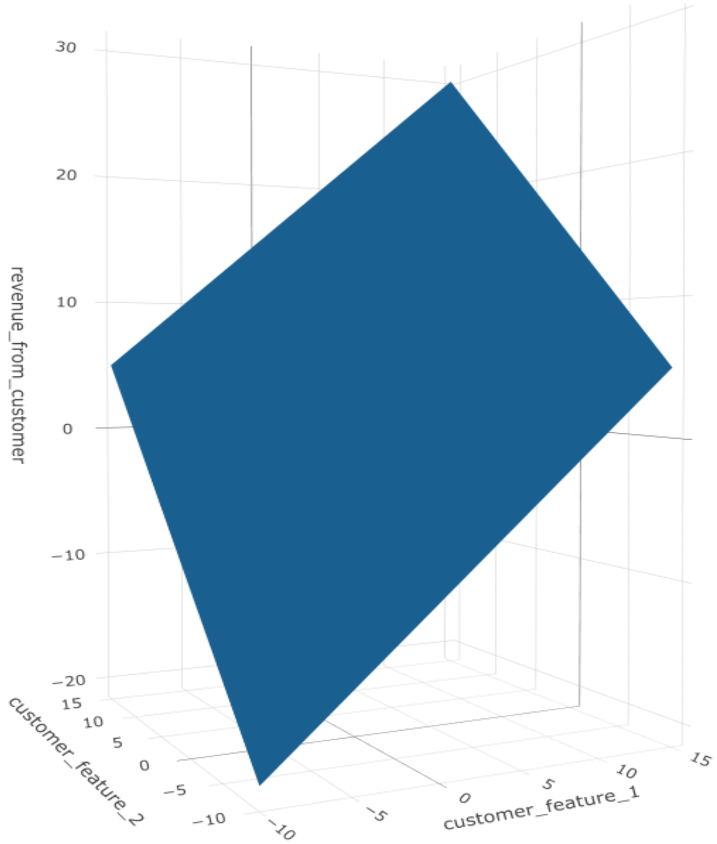
Types of Variables

- There are two main types of variables
  - **Categorical (also called nominal)**
    - Qualitative (i.e., values of the variable are not quantifiable)
    - Distinct values are called levels (e.g., medical diagnosis with levels: ‘diabetes’, ‘cancer’, ‘heart disease’, etc.)
    - If levels have intrinsic order, then the variable is called **ordinal** (e.g., a variable with levels ‘small’, ‘medium’, ‘large’)
  - **Numerical**
    - Quantitative (i.e., values of the variable are quantifiable)
    - Includes **continuous** and **discrete** variables
      - Continuous: can assume an infinite number of values within a given interval
      - Discrete: can assume only a finite number of values within a given interval

Regression Example

- The label is a numerical variable
- Want to predict the label for a new observation



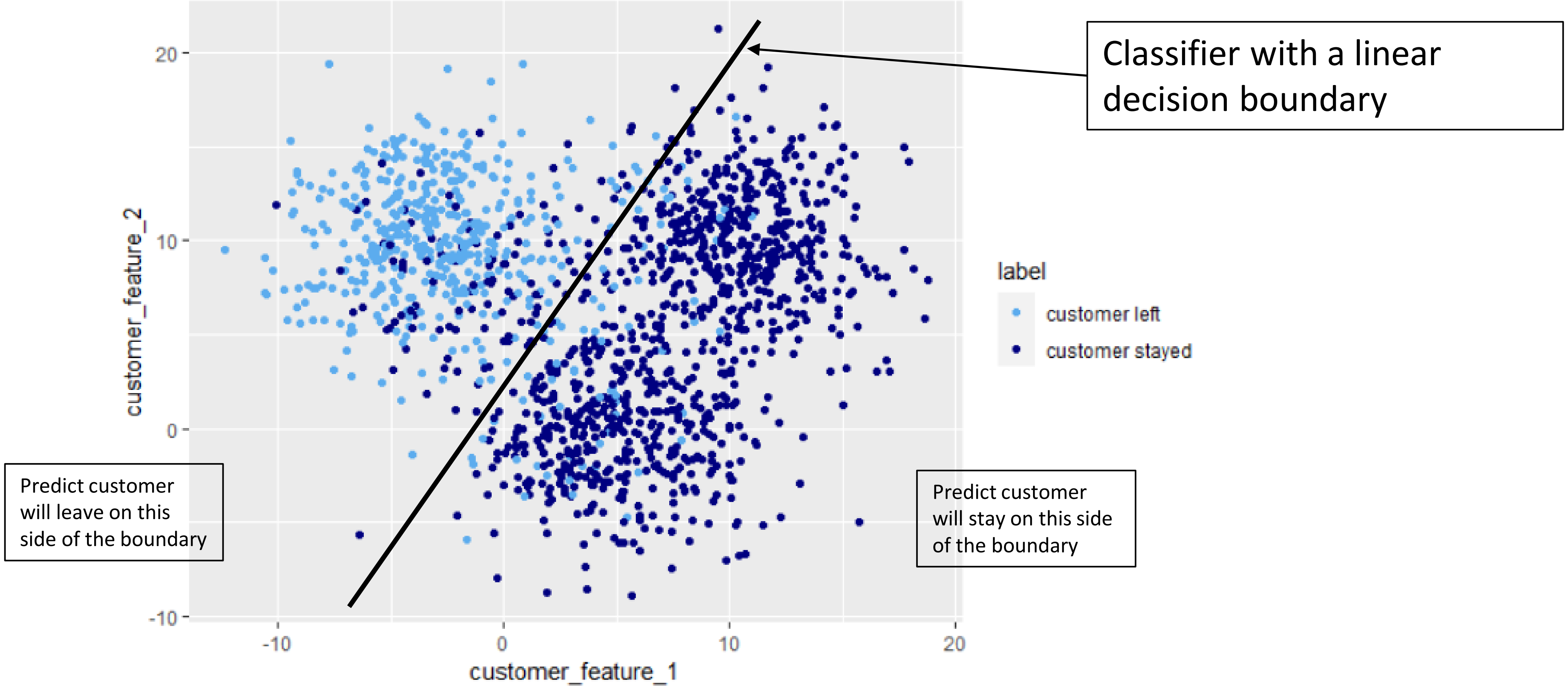


$$Predicted\ Revenue = \hat{y}(Income, Age) = w_1^* \times Income + w_2^* \times Age + w_0^*$$

Linear Regression Equation

Classification Example

- The label is a categorical variable with some number of levels called classes
- Want to predict the class for a new observation



$$\textit{Predicted Probability of Leaving} = \hat{y}(Income, Age) = \frac{1}{1 + \exp(-(w_1^* \times Income + w_2^* \times Age + w_0^*))}$$

Logistic Regression Equation

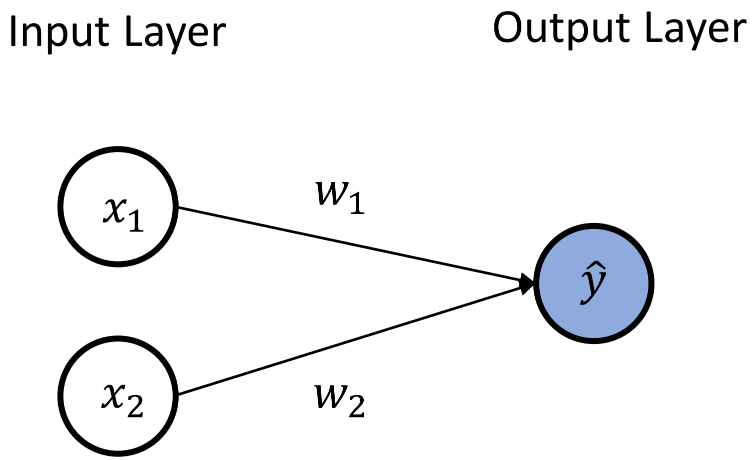
Neural Networks and Deep Learning

- Neural networks are a class of machine learning algorithms
  - Represented visually by acyclical graphs
  - Essentially, neural networks are composite functions (as we will see)

- We'll start with the simplest neural network called a perceptron and progress to more advanced (complex) architectures
  - Linear regression and logistic regression can be represented as perceptrons
  - Thus, we will see how neural networks (i.e., deep learning) generalizes traditional machine learning approaches

Neural Networks and Deep Learning

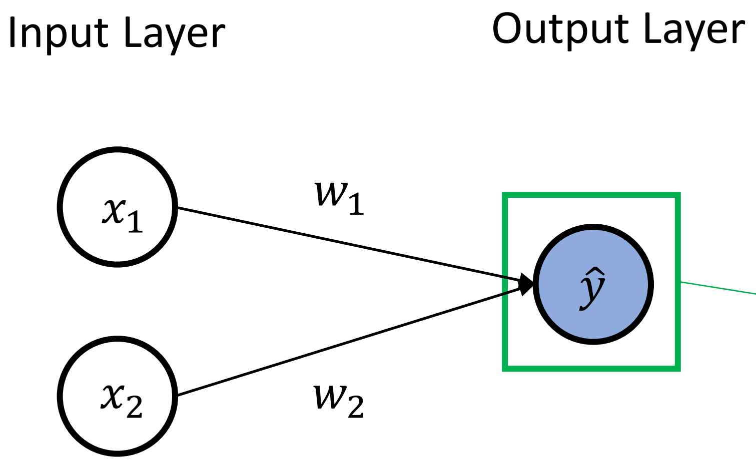
- To understand neural networks, we'll start with the simplest form called a perceptron: a neural network with only an input layer and output layer



- Let's express linear and logistic regression as perceptrons

Neural Networks and Deep Learning

- The computation in a neural network takes place in computation nodes
  - Each computation node has an input and an output
- In a perceptron, the only computation node is in the output layer
  - The output of the computation node is the output ($\hat{y}$) of our neural network model
  - The function f is called the activation function and it provides the expressive power of neural networks



Computation Node

$$Output = \hat{y} = f(Weights \times Inputs + Bias)$$
$$= f(w_1 \times x_1 + w_2 \times x_2 + w_0)$$

Set $f(\mathrm{x}) = \mathrm{x}$ to get linear regression

Use training data to find optimal weight values $w_1^*,\ w_2^*,\ w_0^*$

Neural Networks and Deep Learning

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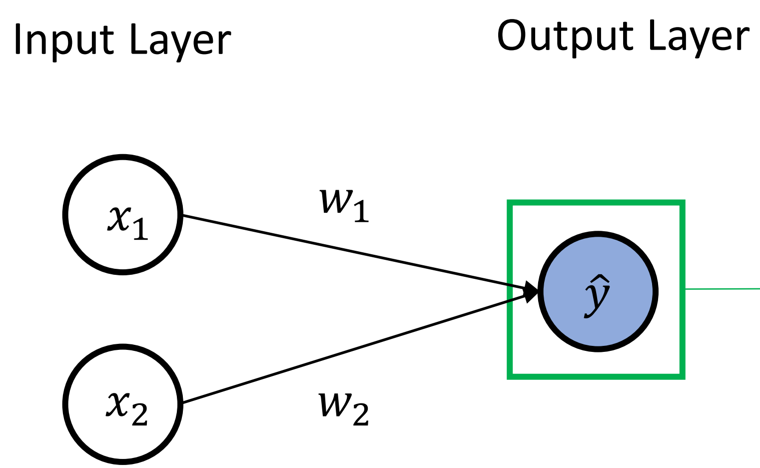
Income (Customer Feature 1)	Age (Customer Feature 2)
22003	45
57230	54
75137	28
31208	54
54078	23
44413	44
55237	46



$$\hat{y} = Predicted\ Revenue = w_1 \times 22003 + w_2 \times 45 + w_0$$

Calculate predicted revenue for each observation and compare to the actual in the training data

Neural Networks and Deep Learning

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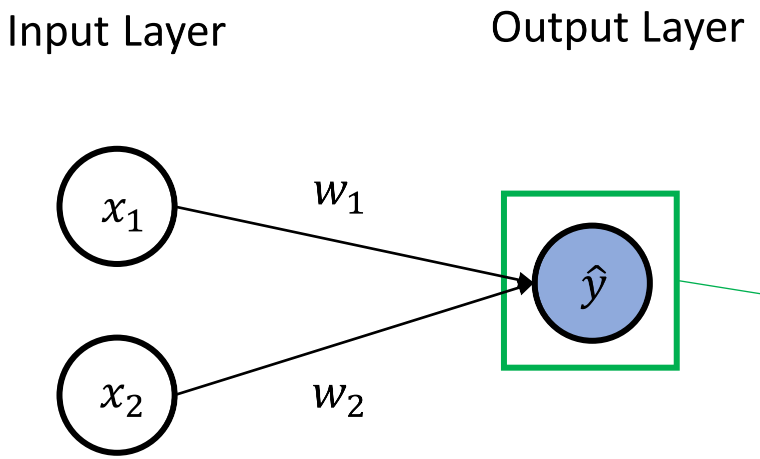

Computation Node

$$Output = \hat{y} = f(Weights \times Inputs + Bias)$$
$$= f(w_1 \times x_1 + w_2 \times x_2 + w_0)$$

Set $f(\mathrm{x}) = \frac{1}{1+e^{-x}}$ to get logistic regression

Use training data to find optimal weight values $w_1^*,\ w_2^*,\ w_0^*$

Neural Networks and Deep Learning

- The computation in a neural network takes place in computation nodes
  - Each computation node has an input and an output
- In a perceptron, the only computation node is in the output layer
  - The output of the computation node is the output (y) of our neural network model
  - The function f is called the activation function and it provides the expressive power of neural networks

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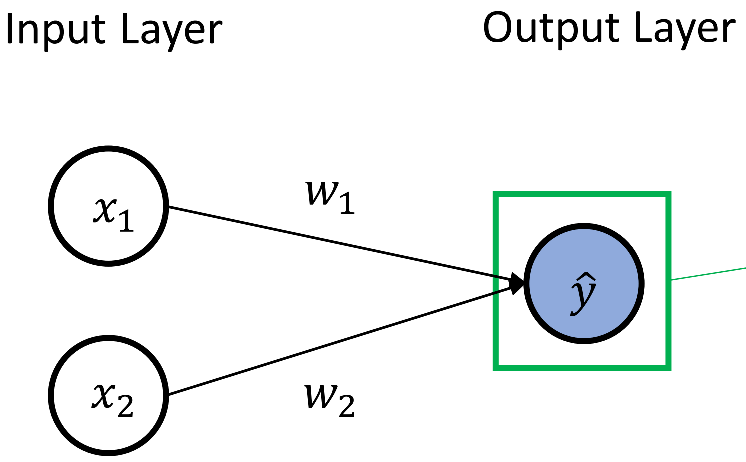


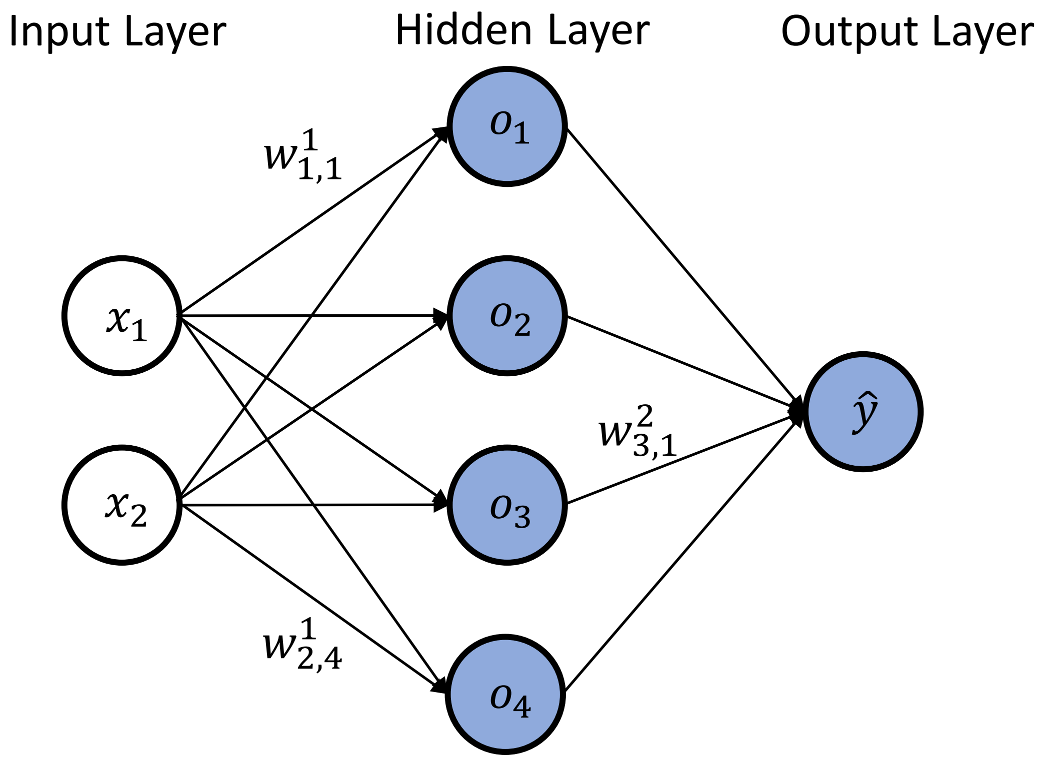
$$\hat{y} = Predicted\ Probability\ of\ Leaving$$
$$= \frac{1}{1 + e^{-(w_1 \times 22003 + w_2 \times 45 + w_0)}}$$

Calculate predicted probability for each observation and compare to the actual in the training data

If $\hat{y} \geq 0.5$, predict 1 (customer left)

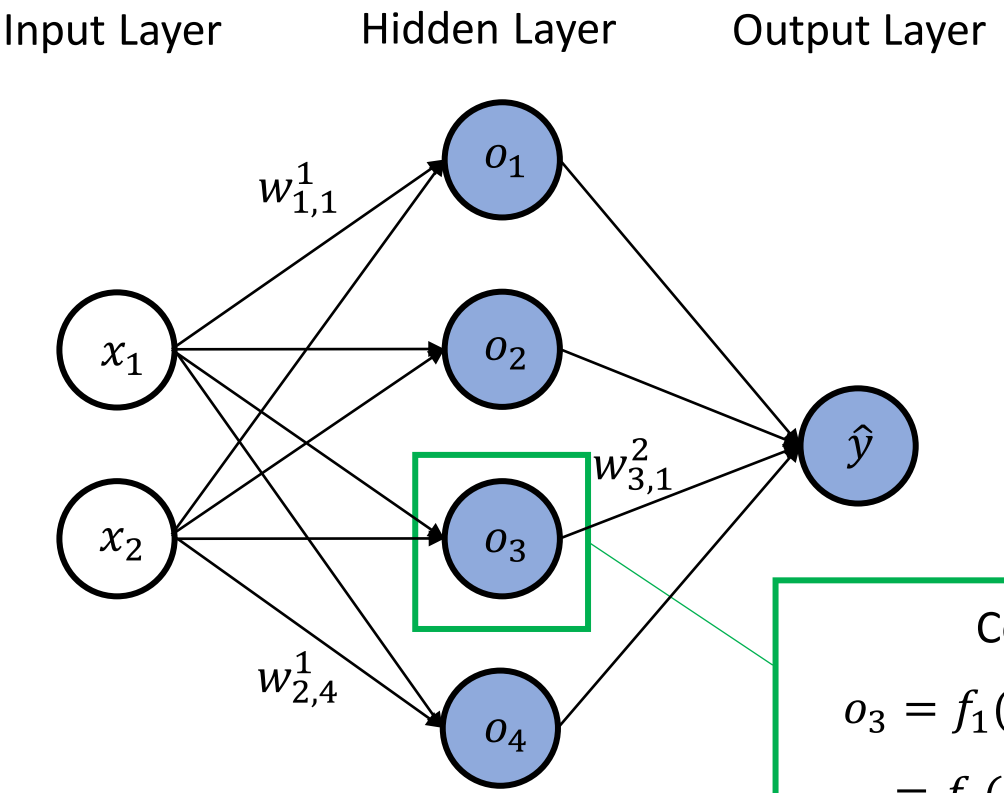
Neural Networks and Deep Learning

- Linear regression and logistic regression are both linear models
  - For realistic problems, the relationships between the dependent variable and independent variables are usually more complex
- Idea: use a composite function $g(h(x))$
  - This corresponds to adding hidden layers between the input and output layers



Neural Networks and Deep Learning

- Now, a layer of computation nodes are added, which can significantly increase the expressive power of the neural network
  - I.e., it can capture more complex relationships in the data

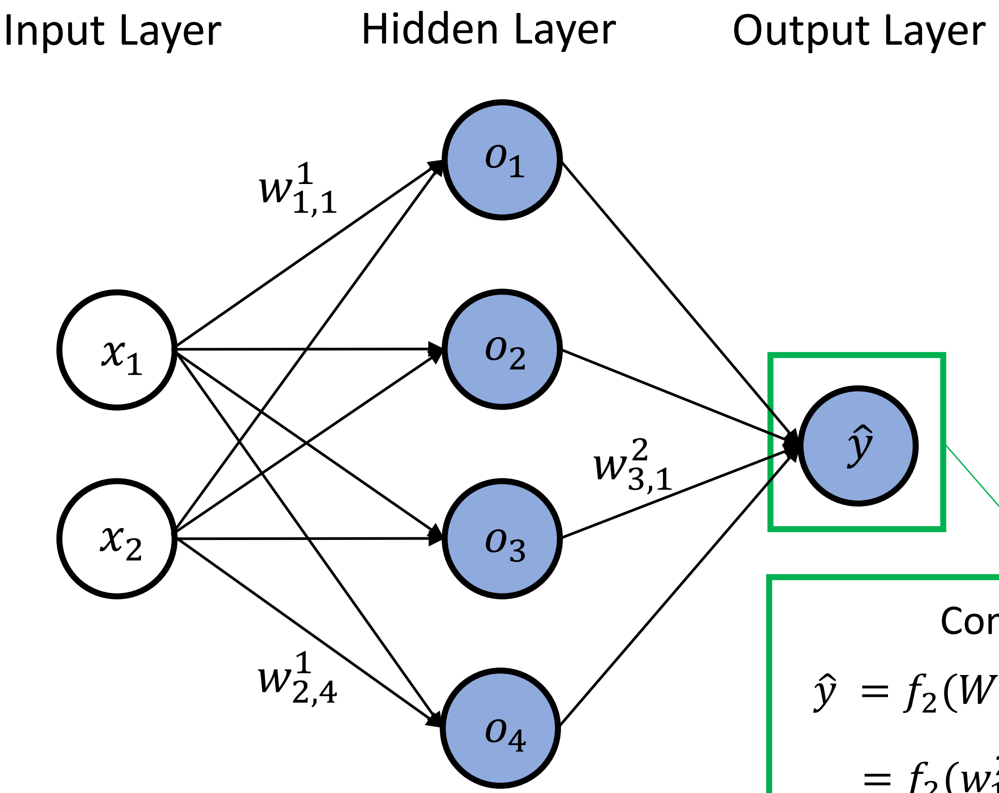


Computation Node

$$o_3 = f_1(Weights \times Inputs + Bias)$$
$$= f_1(w_{1,3}^1 \times x_1 + w_{2,3}^1 \times x_2 + w_{0,3}^1)$$

Neural Networks and Deep Learning

- The output of the neural network model can now be highly non-linear
  - Each layer can use a different activation function (e.g., f_1 versus f_2)
  - The non-linearity of the activation functions is critical
    - If only linear activation functions are used, the result is only a linear model!



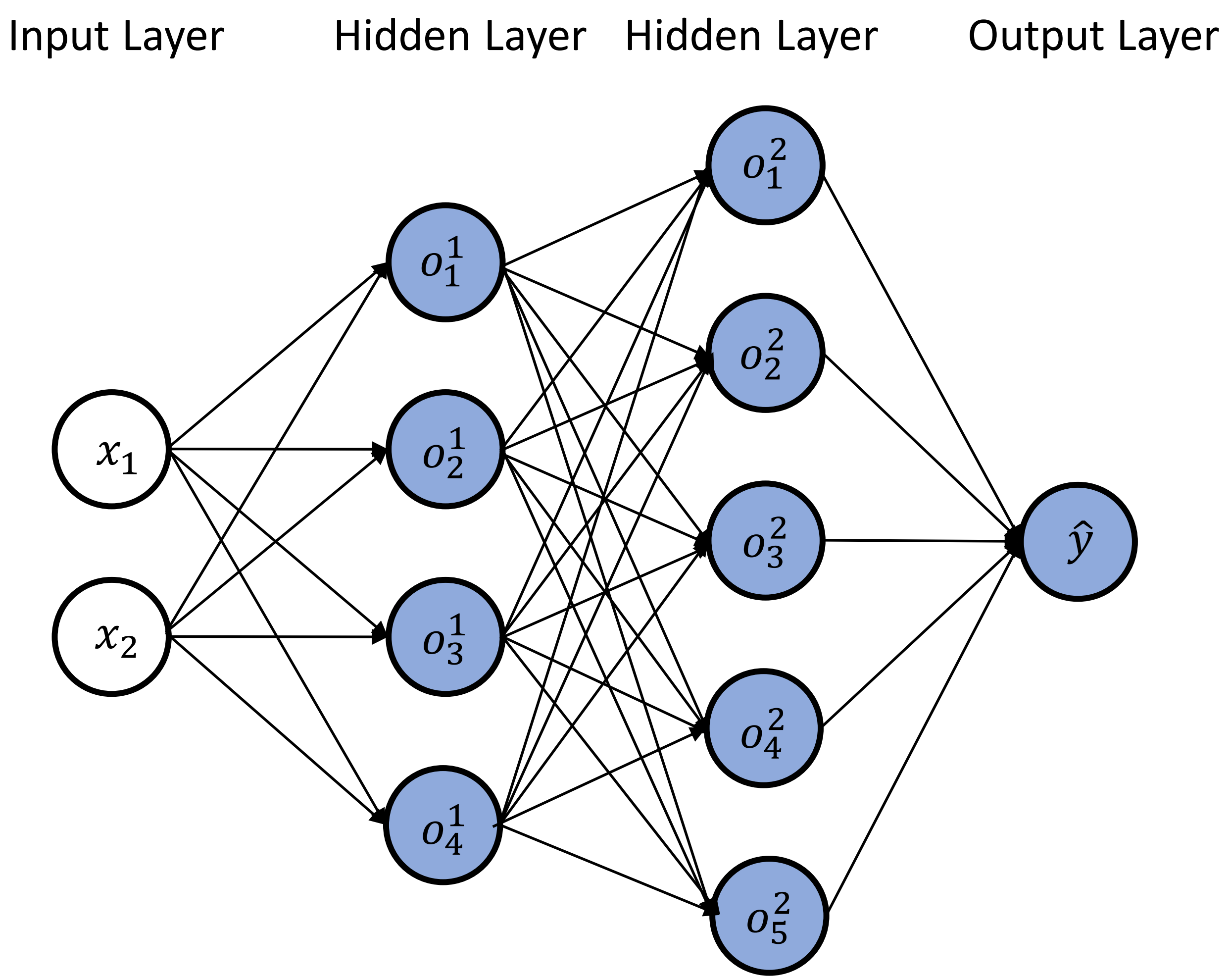
Computation Node

$$\hat{y} = f_2(Weights \times Inputs + Bias)$$

$$= f_2(w^2_{1,1}o_1 + w^2_{2,1}o_2 + w^2_{3,1}o_3 + w^2_{4,1}o_4 + w^2_0)$$

Neural Networks and Deep Learning

- What if we add another hidden layer?
  - Each hidden layer implements a transformation of the data
    - Hopefully, each transformation is a better representation of the data
  - Each hidden layer can have a different number of nodes
  - Each layer can use a different activation function



Neural Networks and Deep Learning

- The neural networks above are examples of densely-connected feed-forward neural networks
  - Other, more complex architectures exist (such as recurrent neural networks)
  - Neural networks are just *composite functions*
  - Can use a convenient algorithm, called backpropagation, to find optimal values of the weights