# Neural networks through ice cream sales

## Objectives:

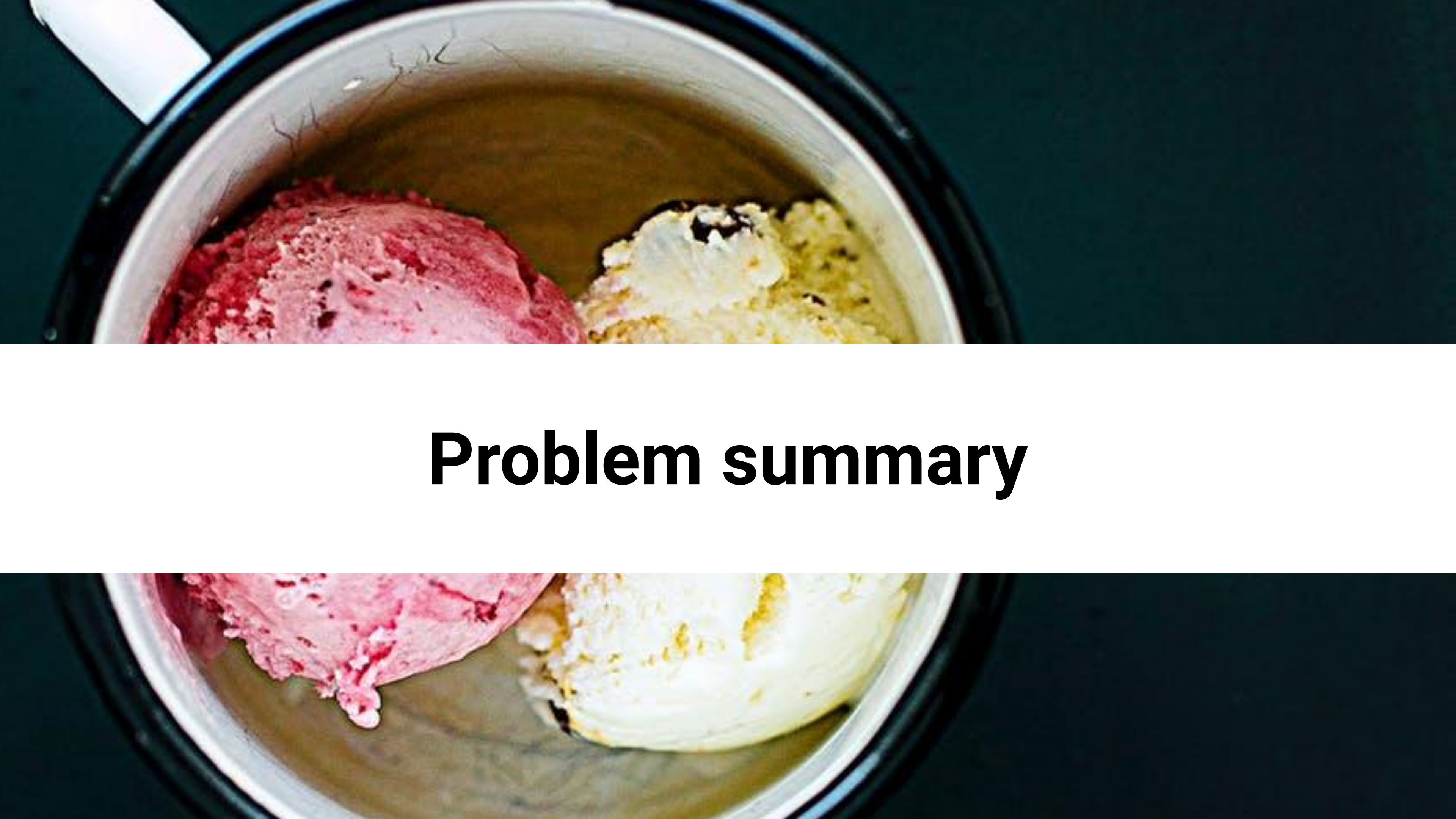
- To ***fluently*** use the ***vocabulary*** of neural networks
- To connect ***familiar past algorithms*** to n***eural networks***, and therefore demystify the math
- To practice ***drawing*** and ***specifying*** the parameters of a neural net
- To list the ***parameters*** one can ***adjust*** when building a neural net

## Scenario

You own a chain of ice cream stores.

You want to build a model that will predict the sales numbers of a store, given the store’s location, pricing of product, and perceived quality of the product.

Simpler models haven’t produced great results, so you want to try a neural network. Plus, neural networks sound fancy. You like fancy.



## Problem summary

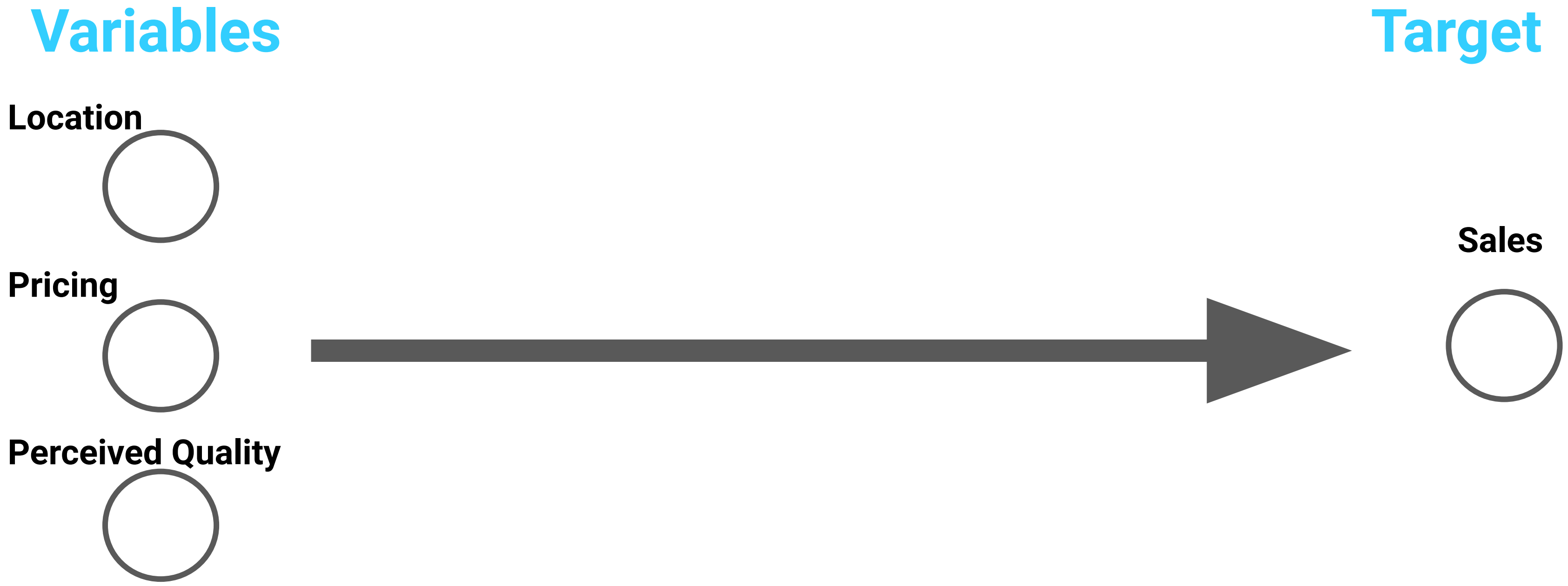
## Variables

**Location**

**Pricing**

**Perceived Quality**

Variables
Target
Location
Pricing
Perceived Quality
Sales


Variables
Target
Location
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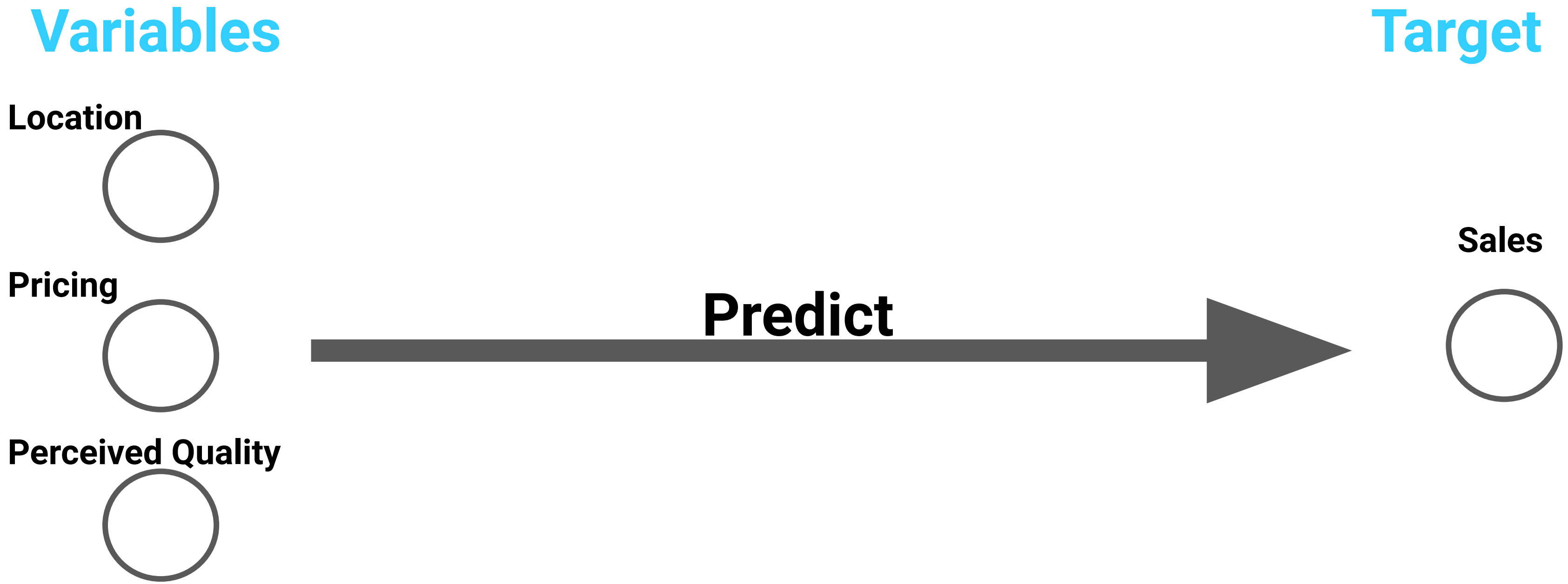
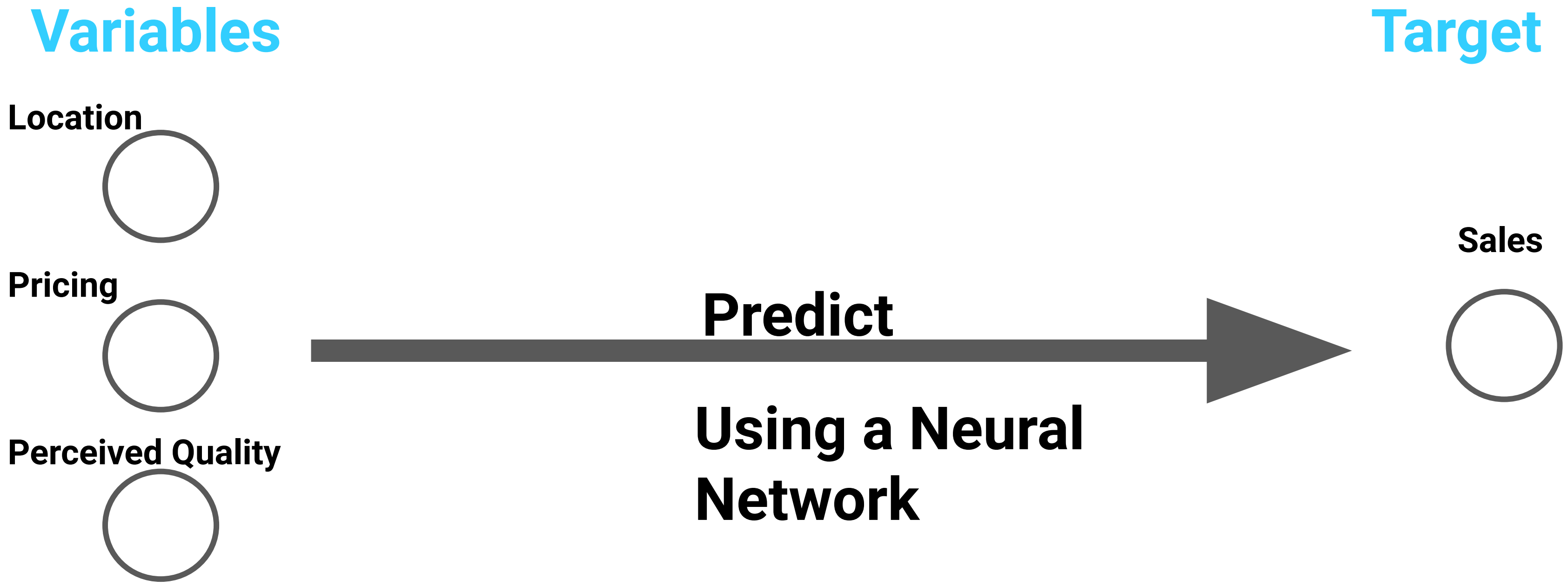
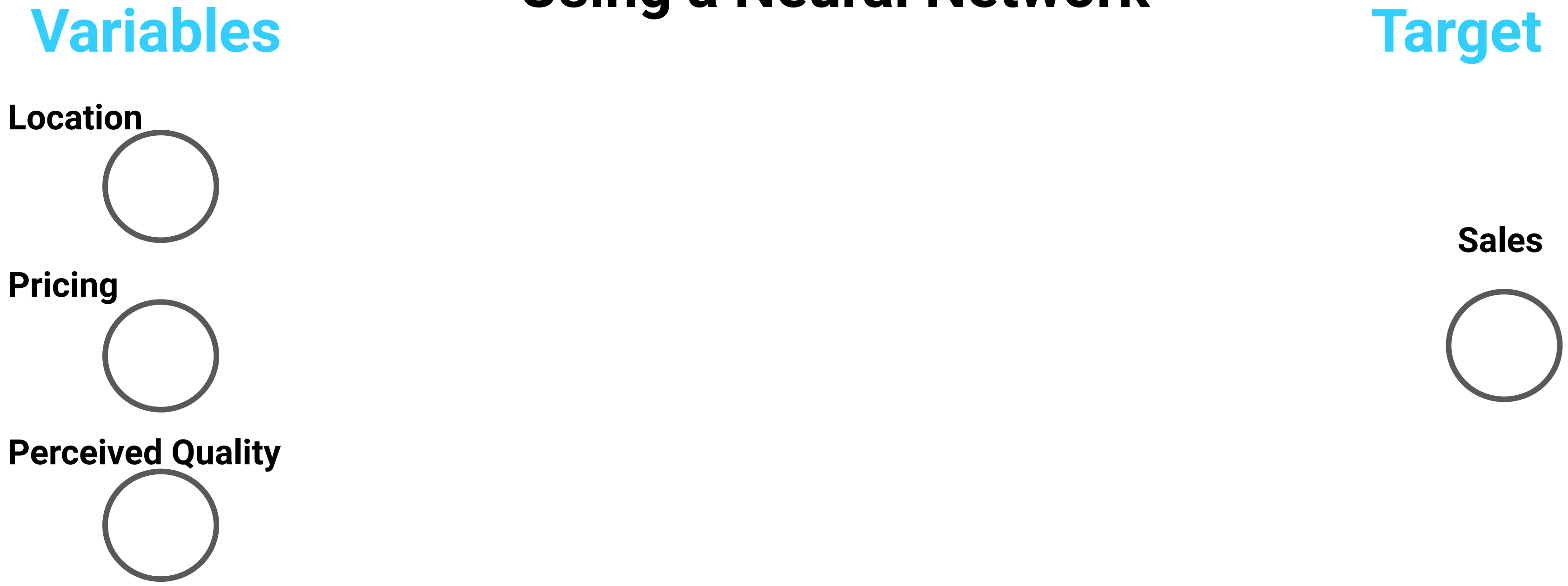
Sales


Variables
Target
Location
Pricing
Perceived Quality
Predict
Sales

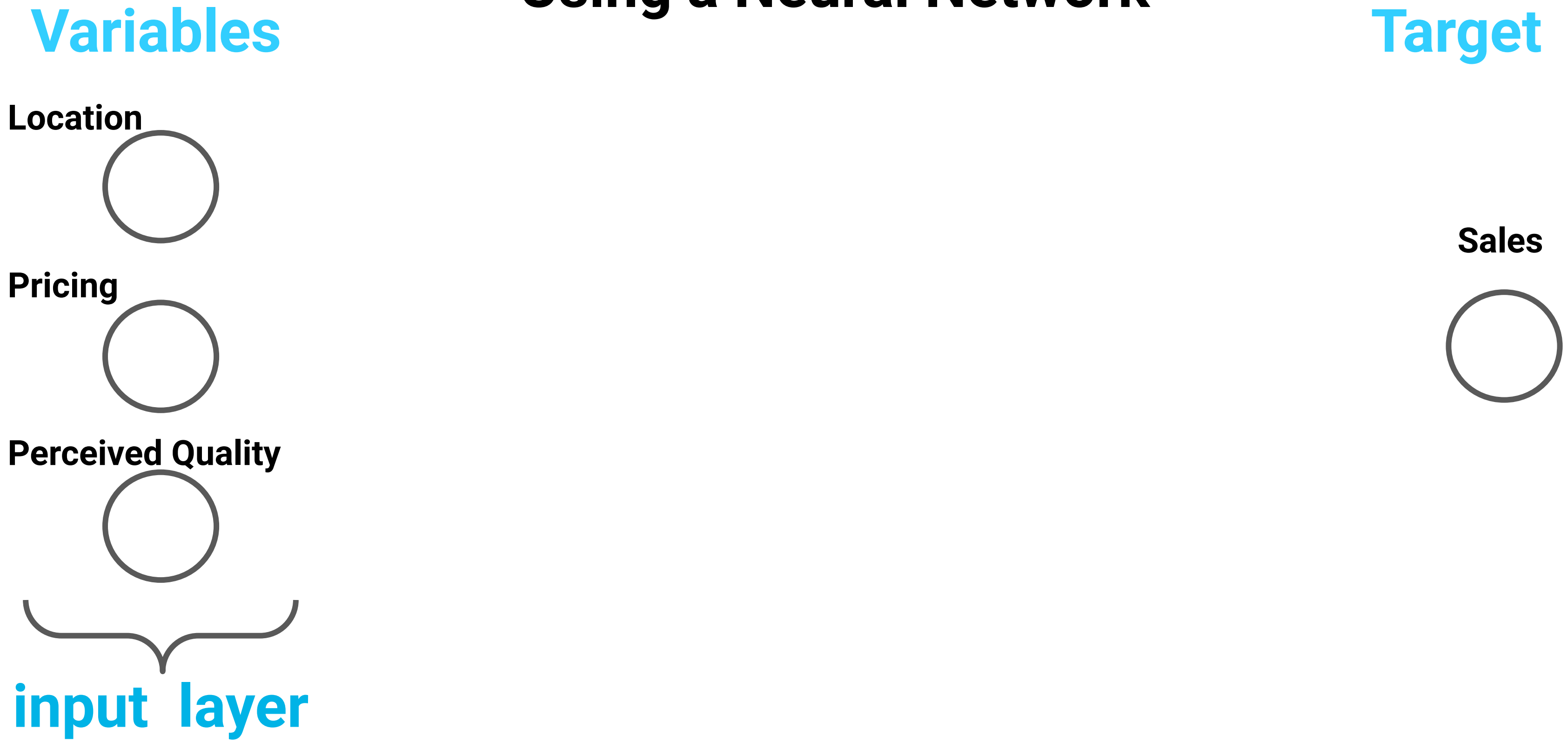

Variables
Target
Location
Pricing
Perceived Quality
Sales
Predict
Using a Neural Network

## Vocabulary

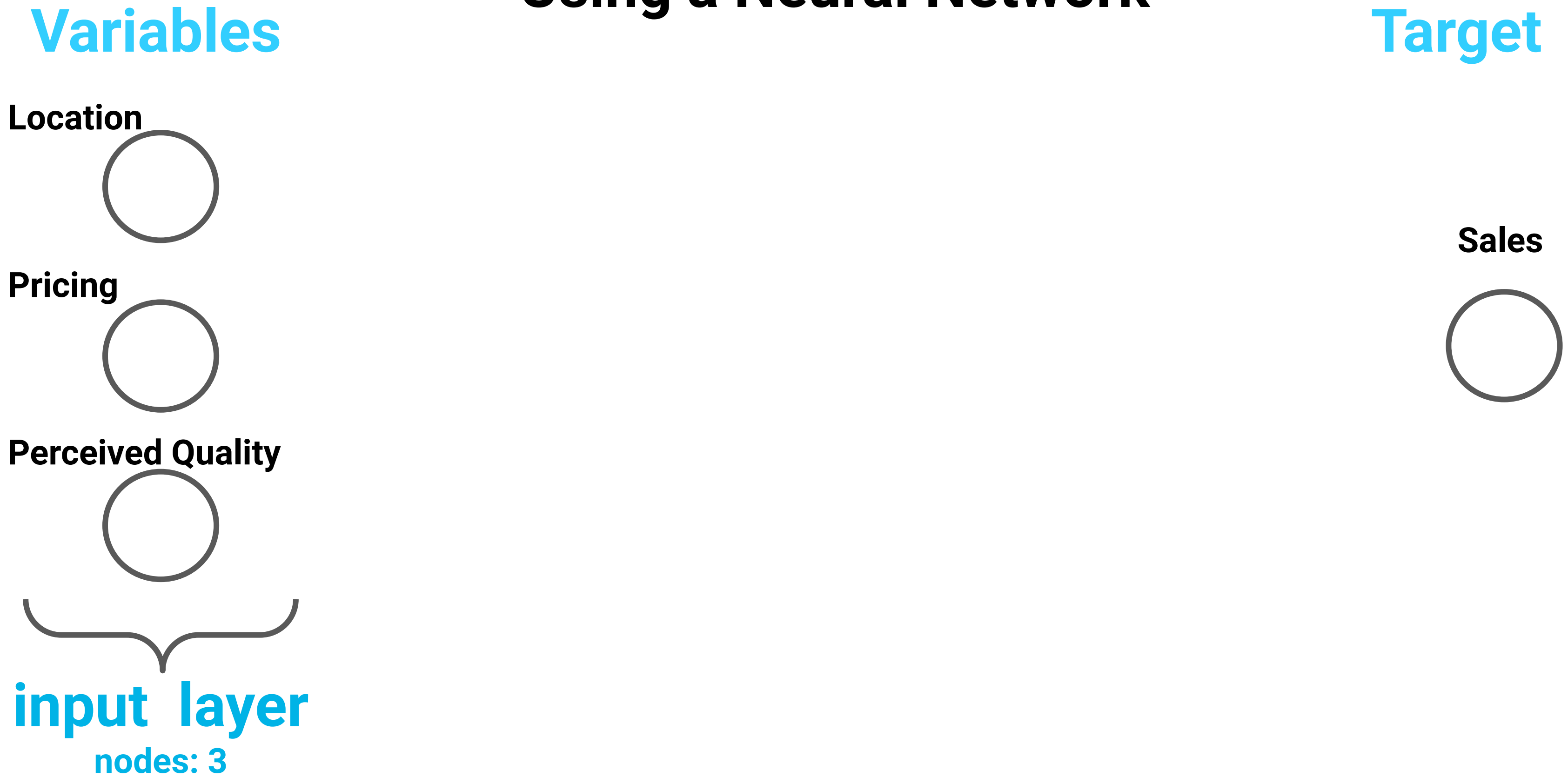
## Using a Neural Network



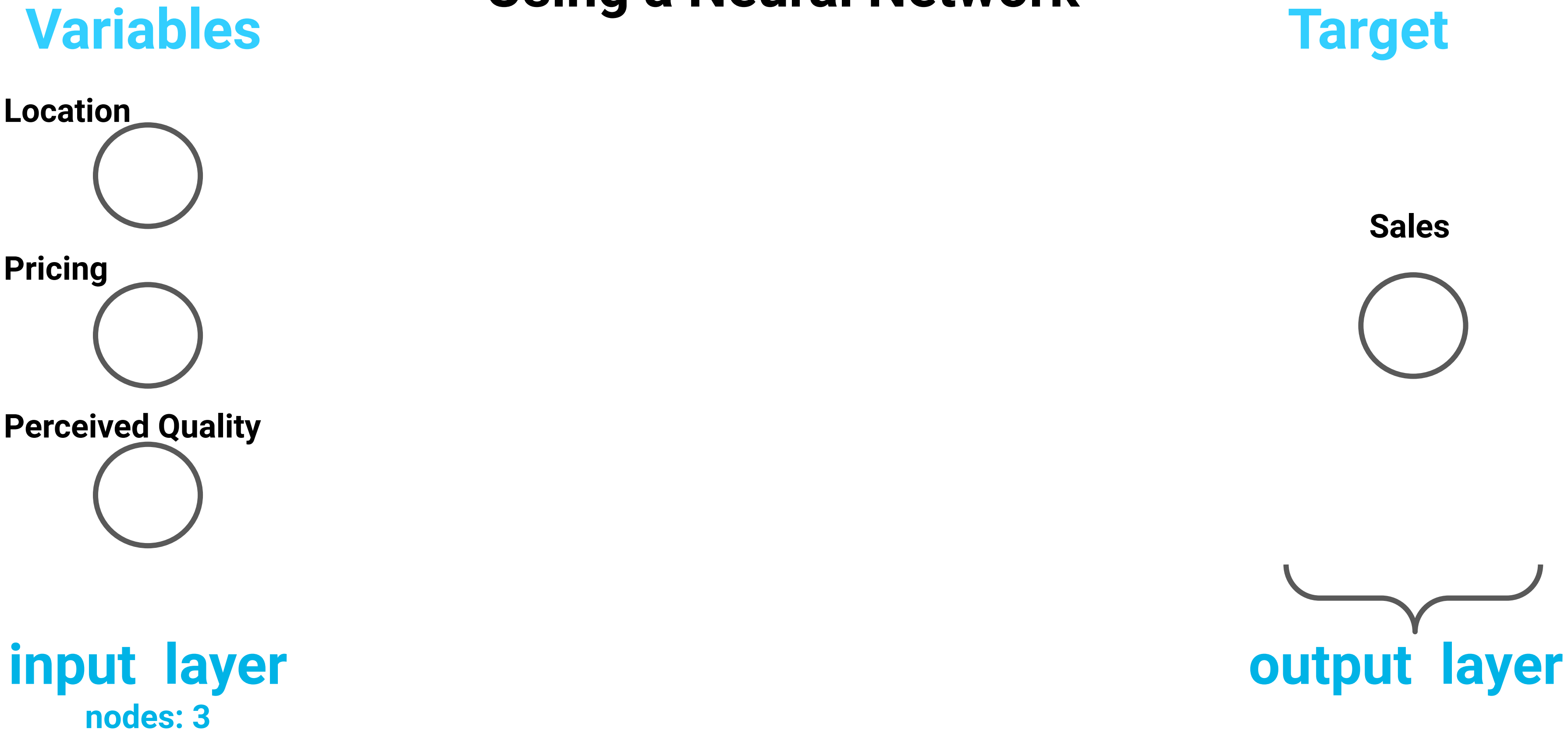
## Using a Neural Network



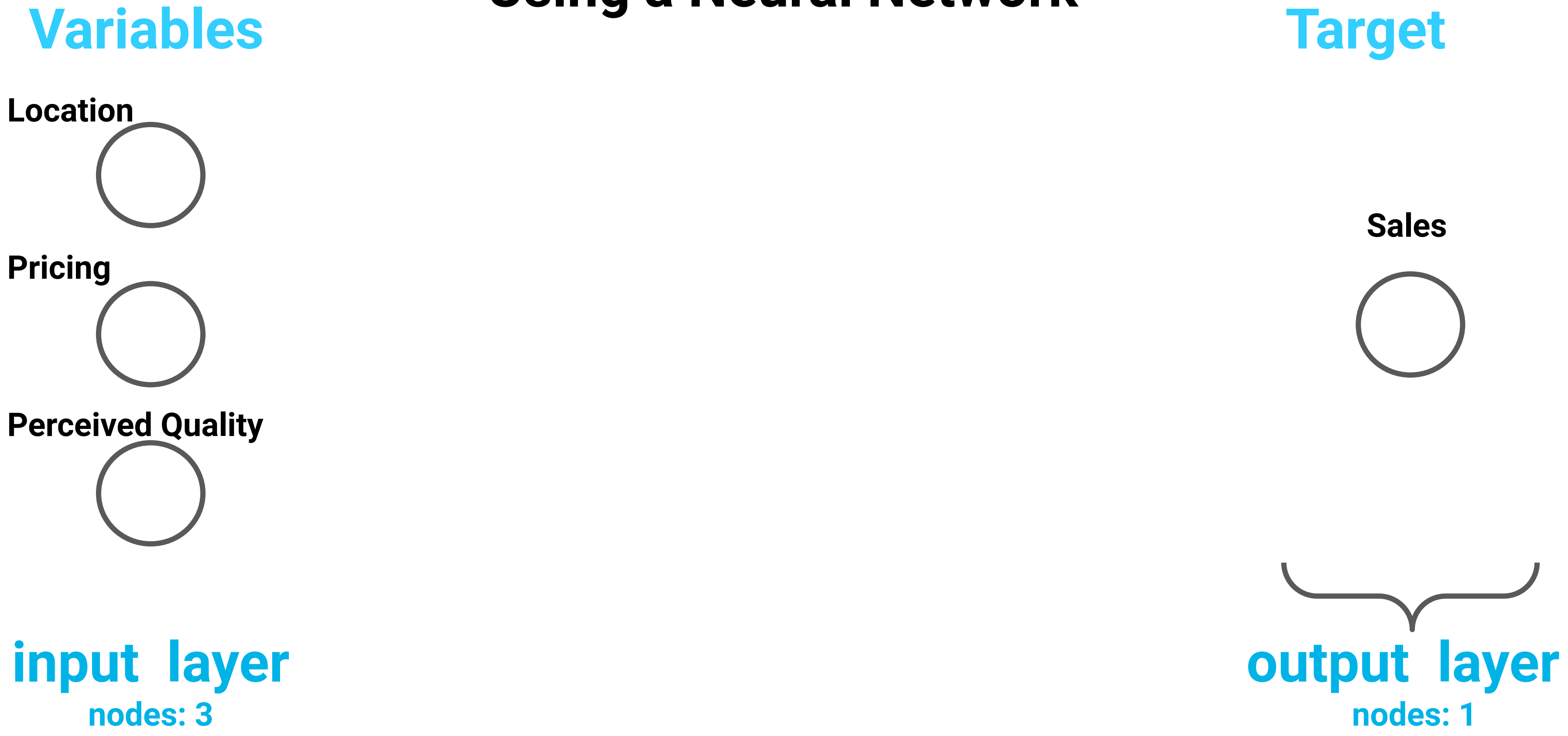
# Using a Neural Network



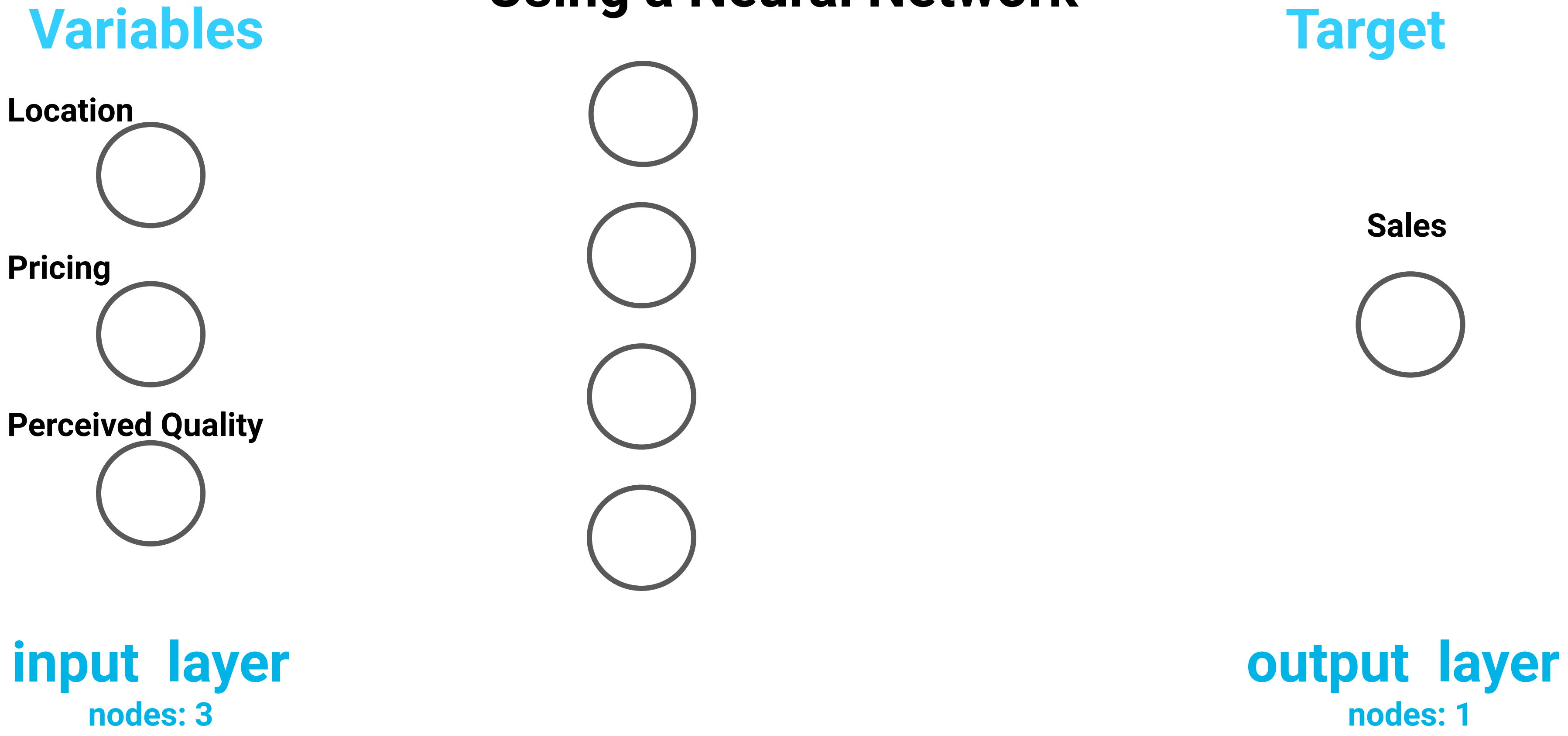
# Using a Neural Network



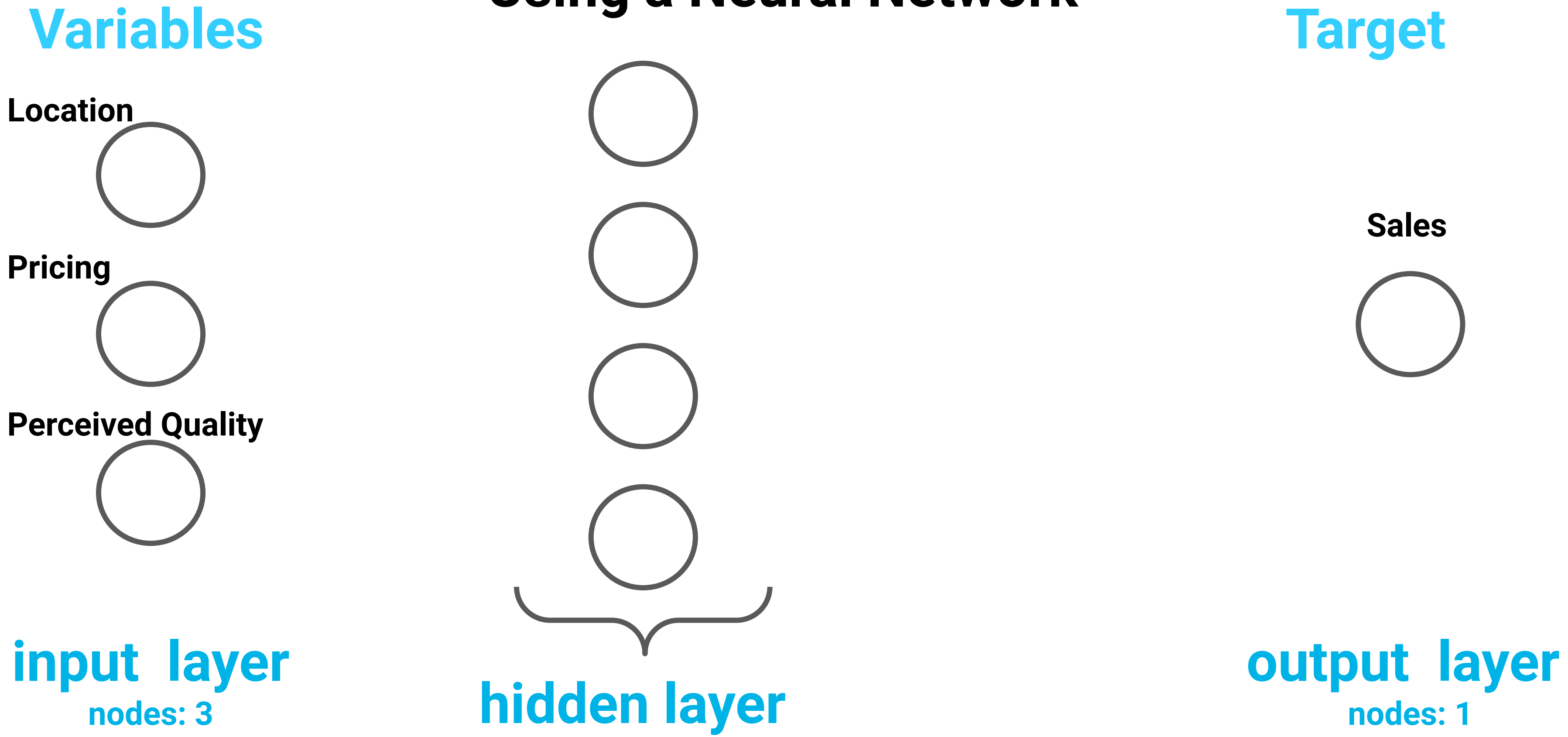
## Using a Neural Network



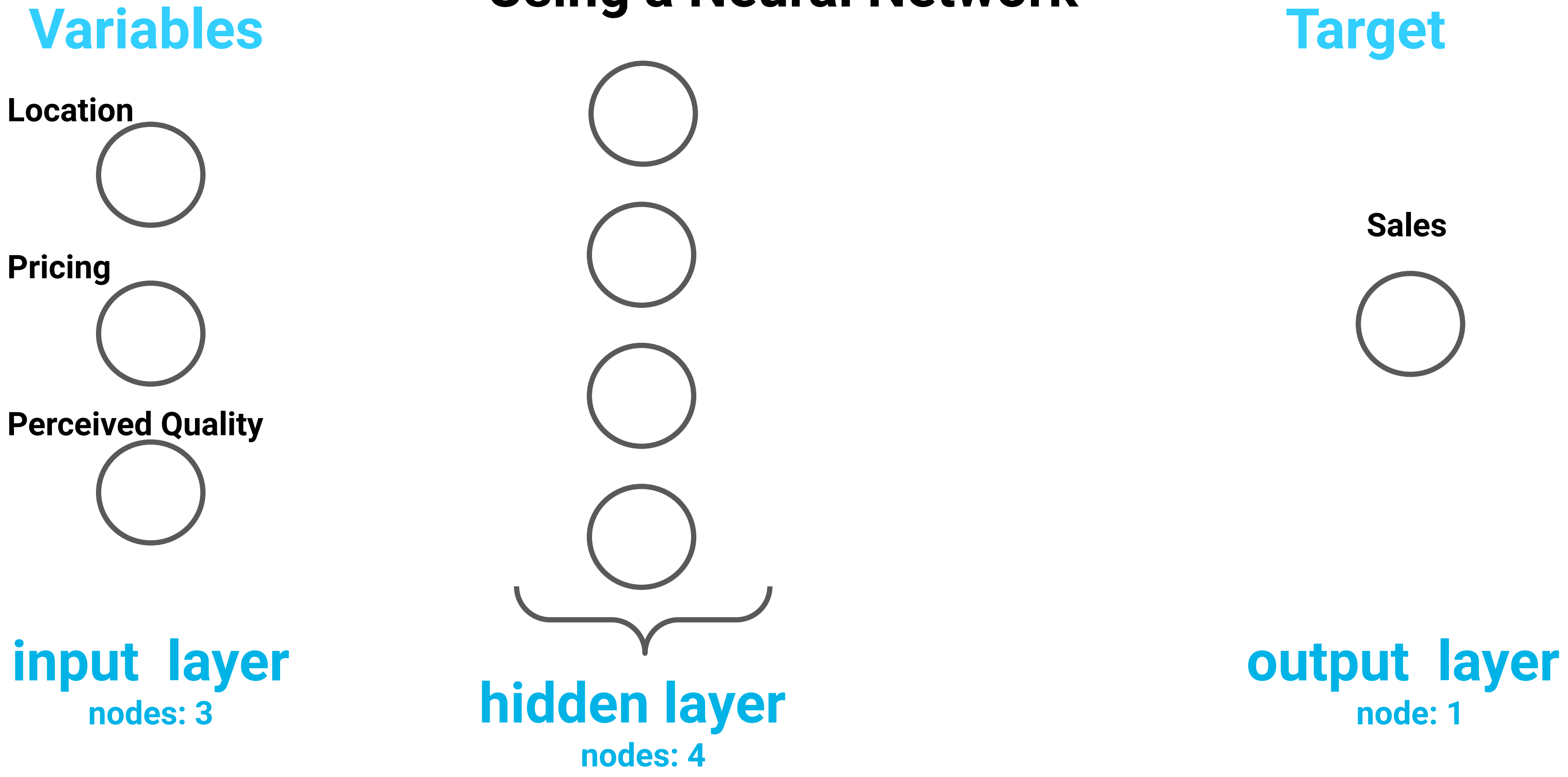
## Using a Neural Network



# Using a Neural Network



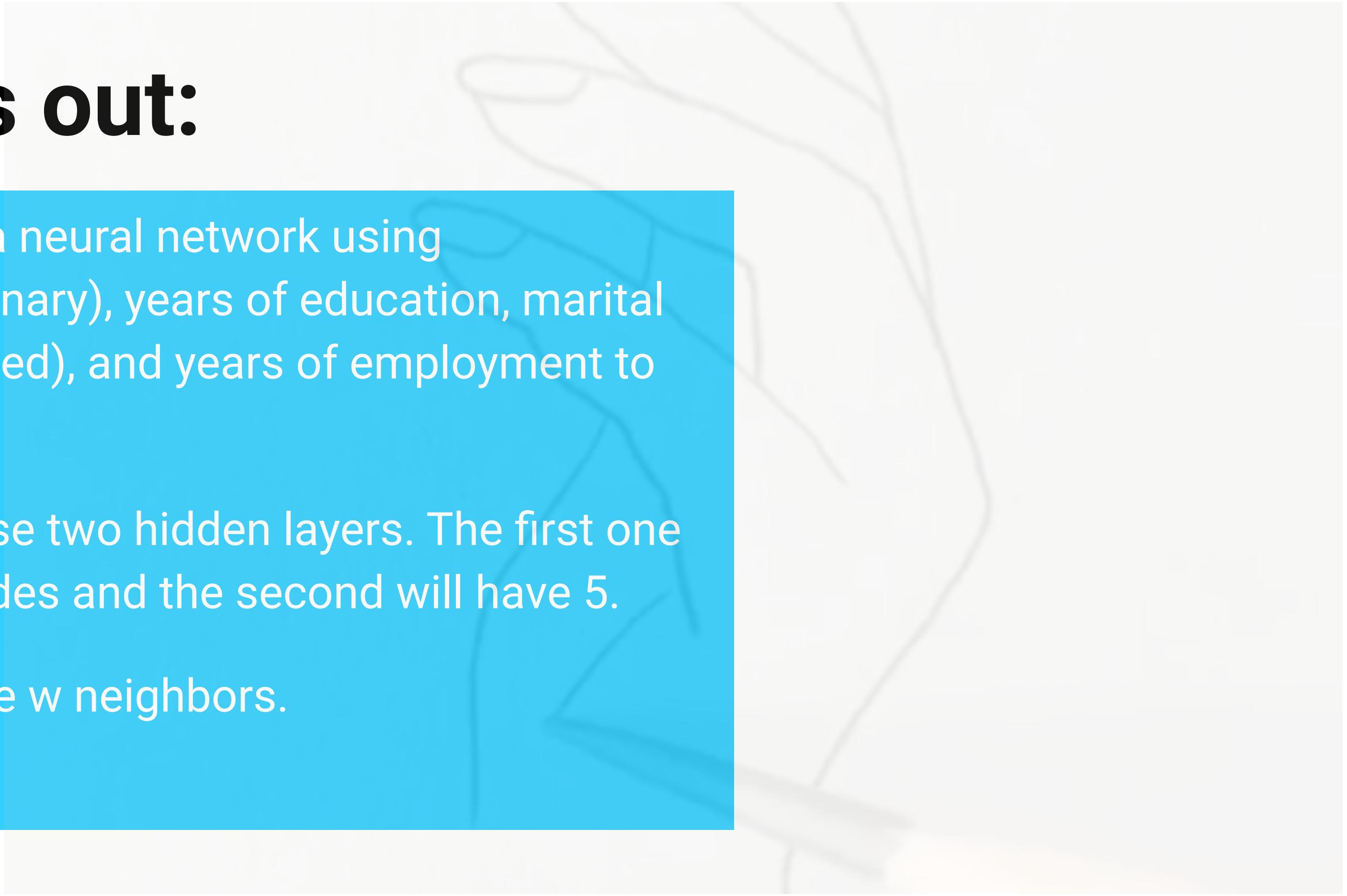
# Using a Neural Network



## How many layers in our neural network?

## Keep this in mind as we build neural networks

## Draw this out:

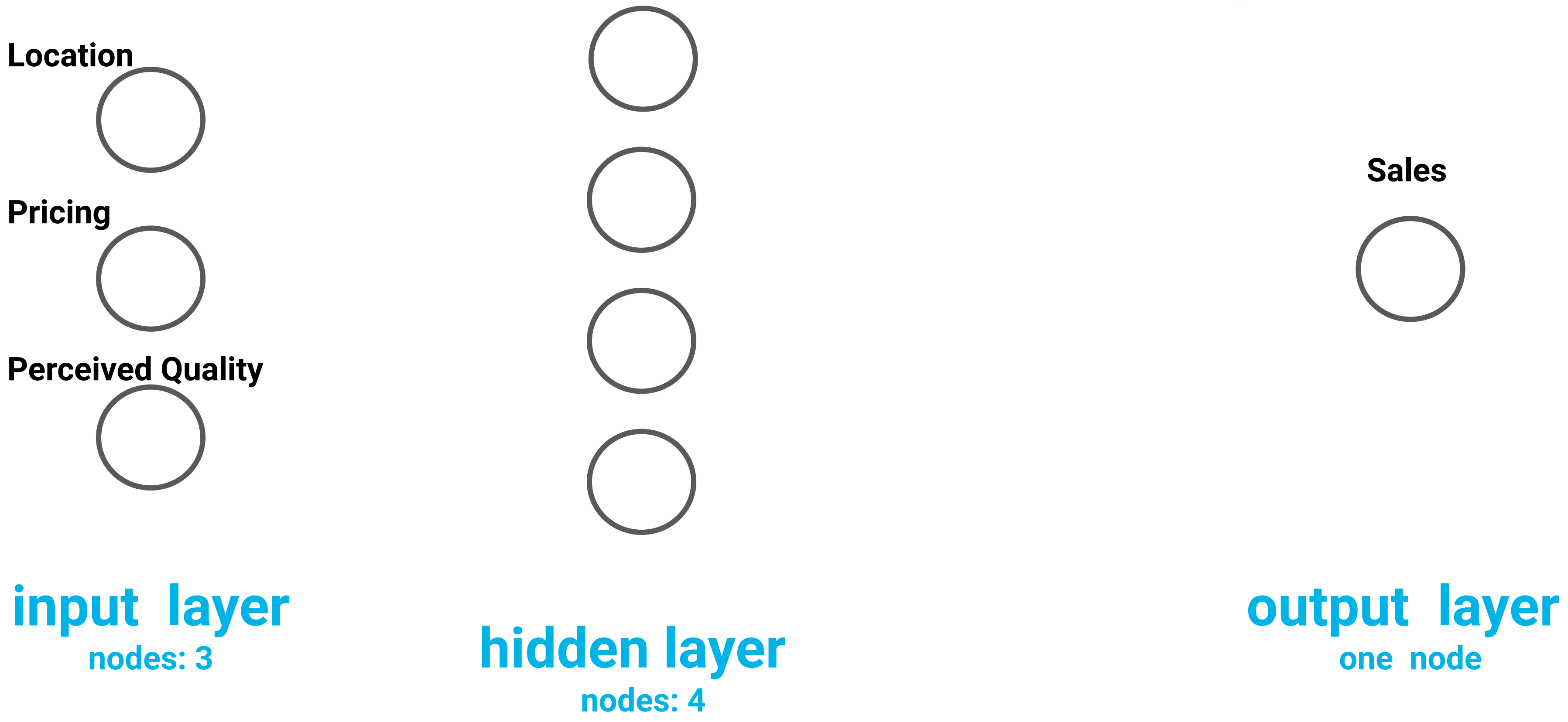


We want to build a neural network using gender(assume binary), years of education, marital status(single vs wed), and years of employment to predict income.

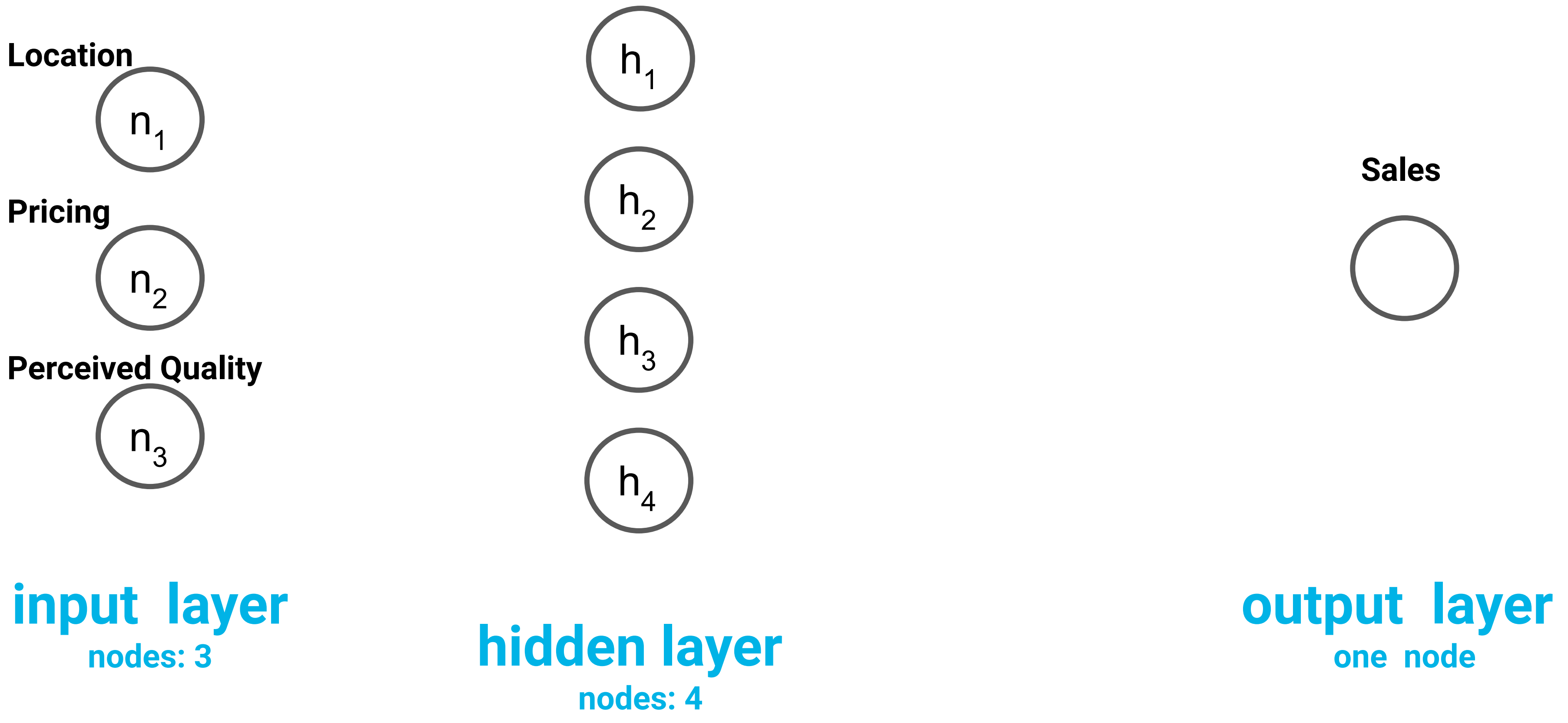
We are going to use two hidden layers. The first one will have three nodes and the second will have 5.

Draw and compare w neighbors.

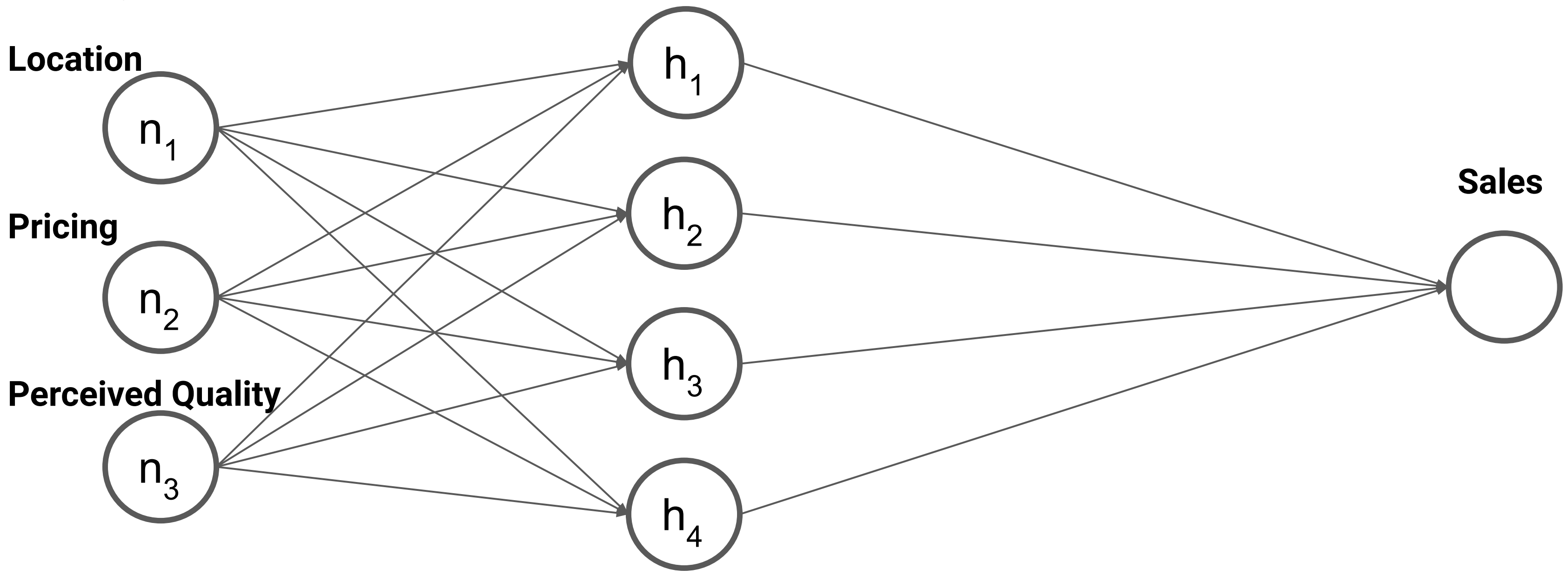
## The math behind networks is not that scary



## We need some notation to make this work



# May have seen diagrams like this

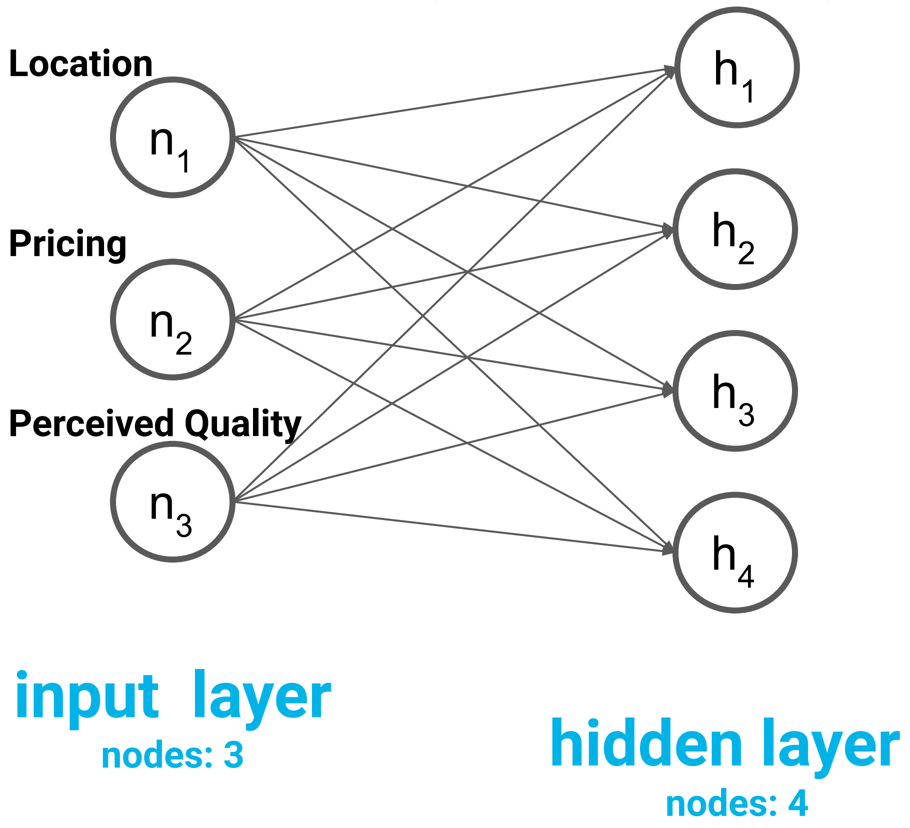


**input layer**
nodes: 3

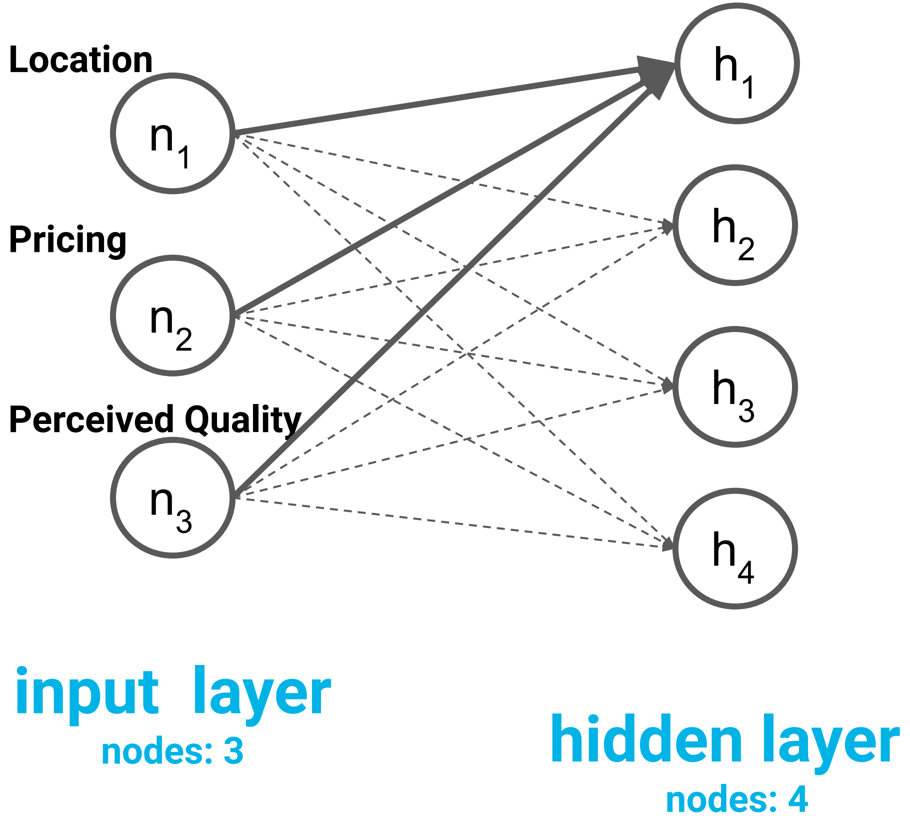
**hidden layer**
nodes: 4

**output layer**
one node

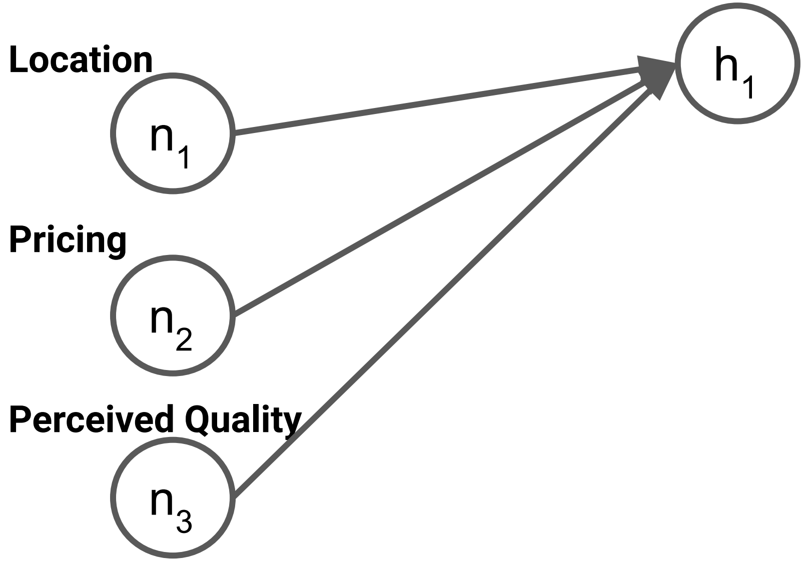
## For simplicity we are only going to focus on one layer



## And specifically the first node in the hidden layer



## **Problem**: this common diagram isn't representative

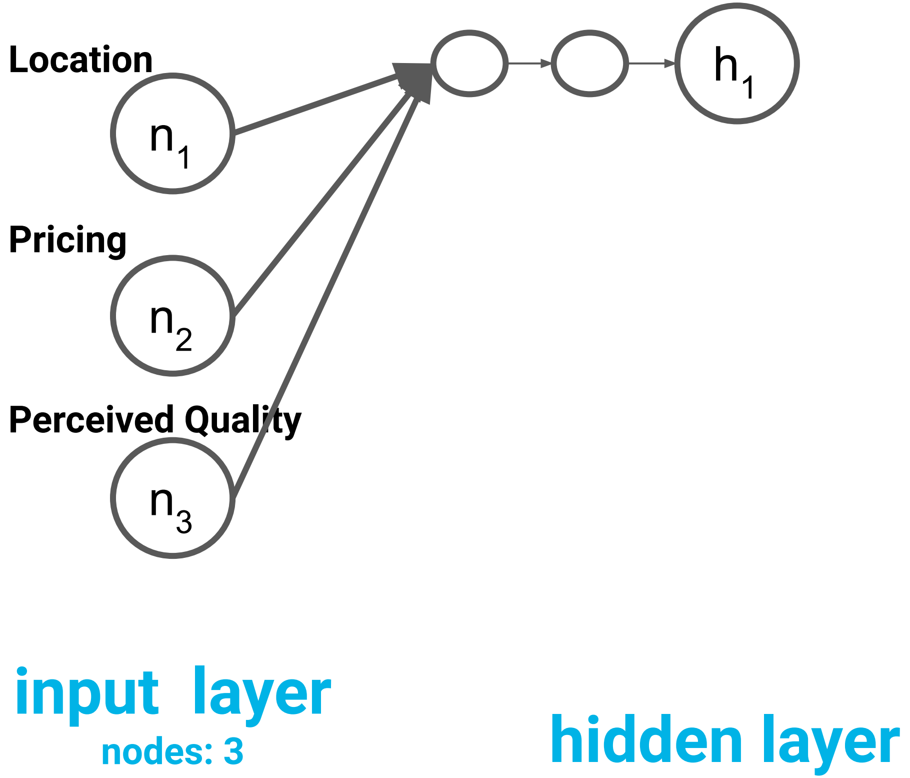


**input layer**

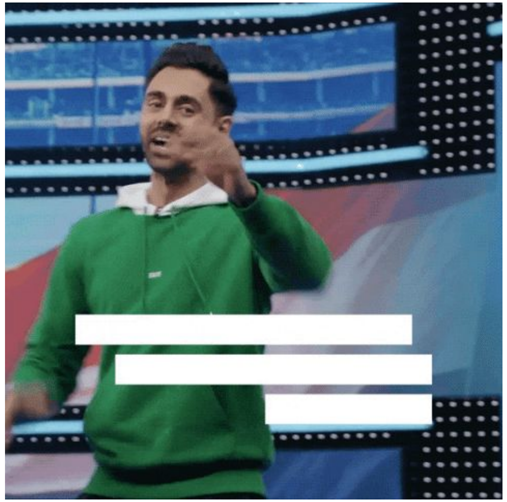
nodes: 3

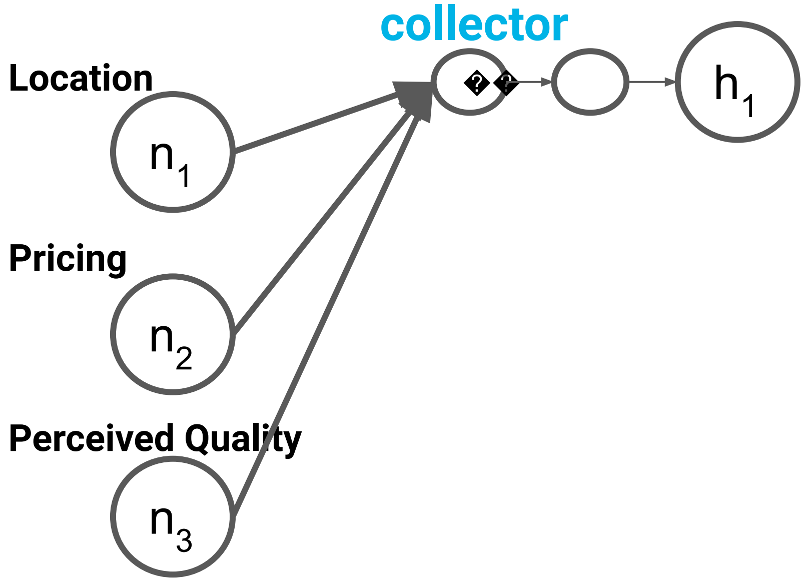
**hidden layer**

## What is shown as one is really three



Each node that receives input from previous nodes actually has **three** parts

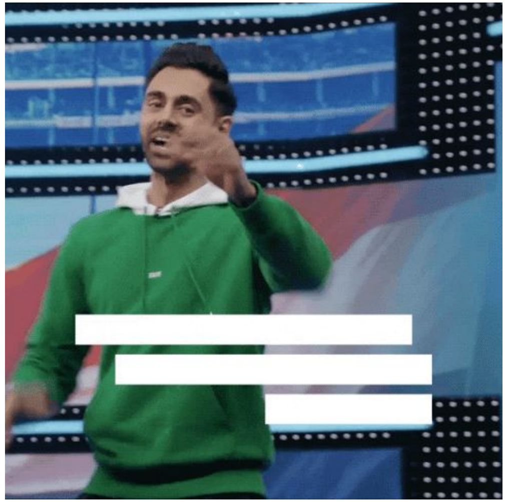


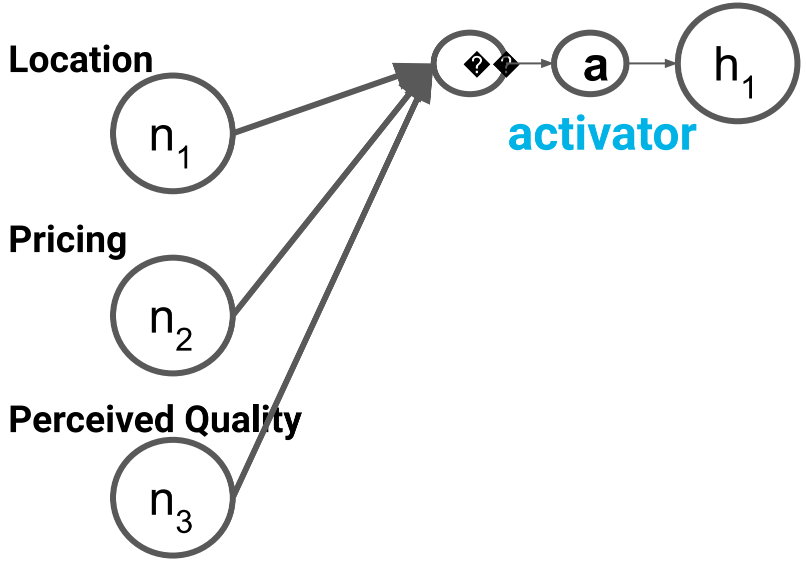


**input layer**
nodes: 3

**hidden layer**

Each node that receives input from previous nodes actually has **three** parts



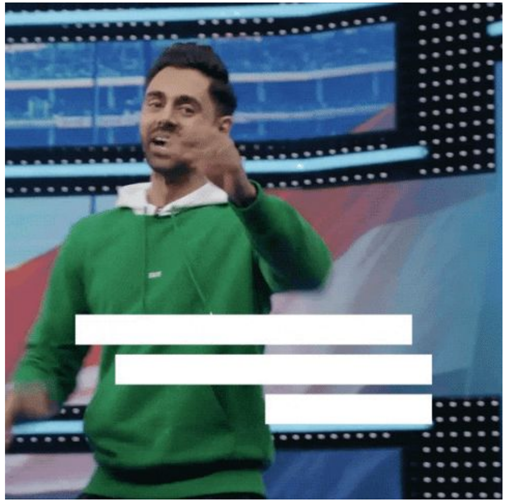


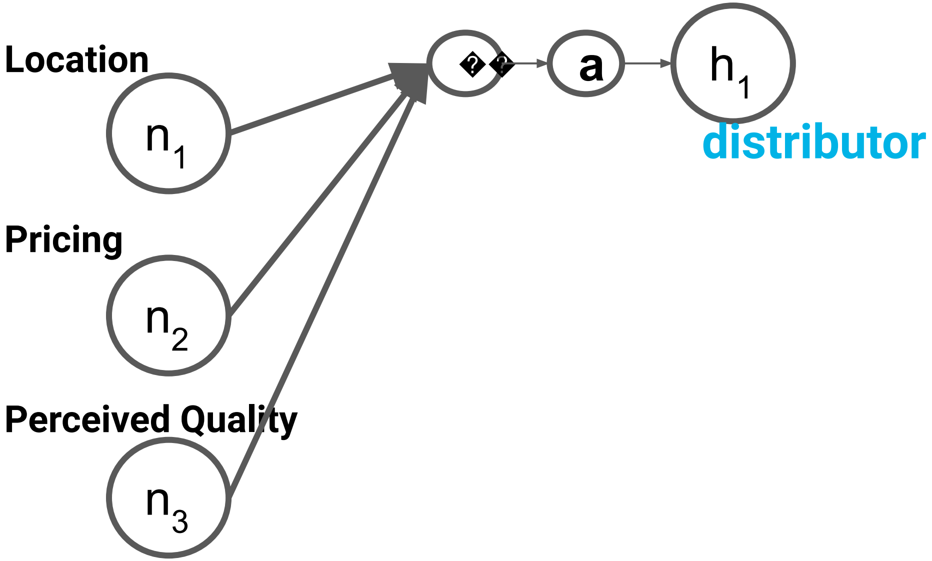
**input layer**

nodes: 3

**hidden layer**

Each node that receives input from previous nodes actually has **three** parts



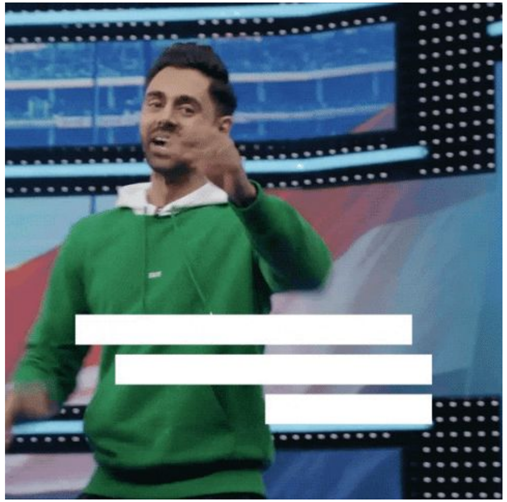


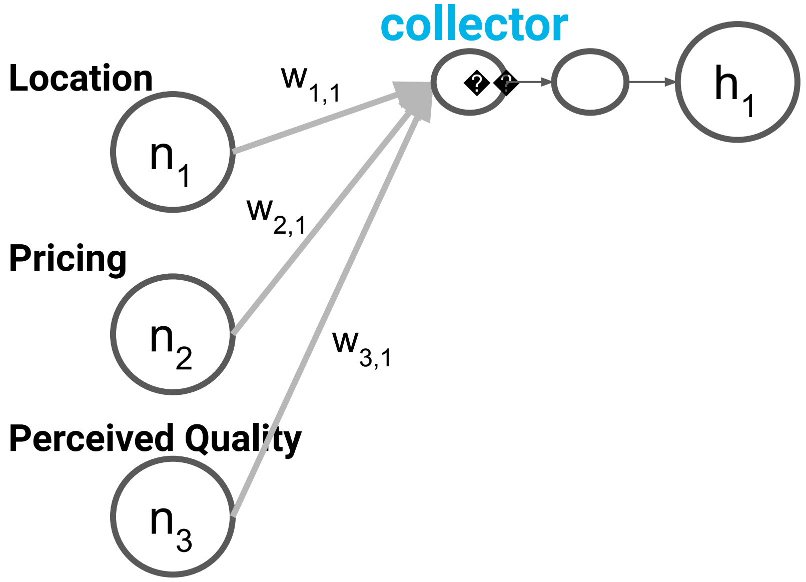
input layer

nodes: 3

hidden layer

Each node that receives input from previous nodes actually has **three** parts



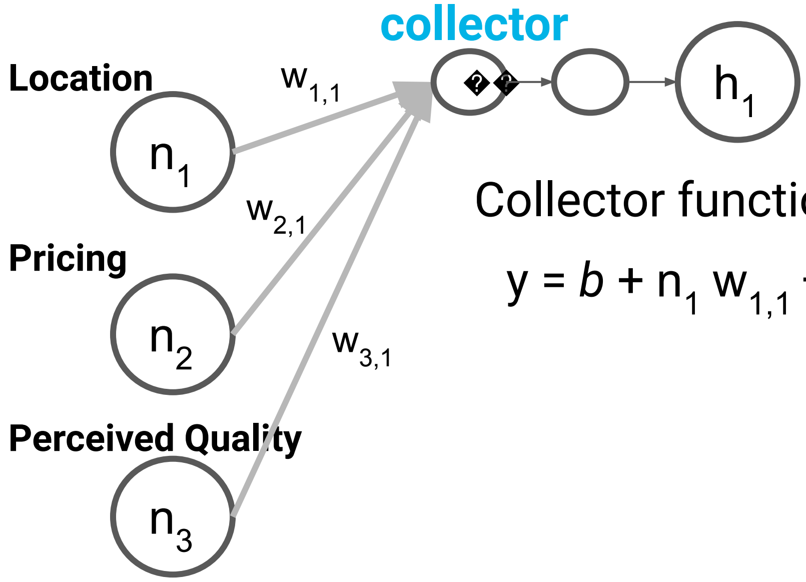


input layer

nodes: 3

hidden layer

# This function should look familiar



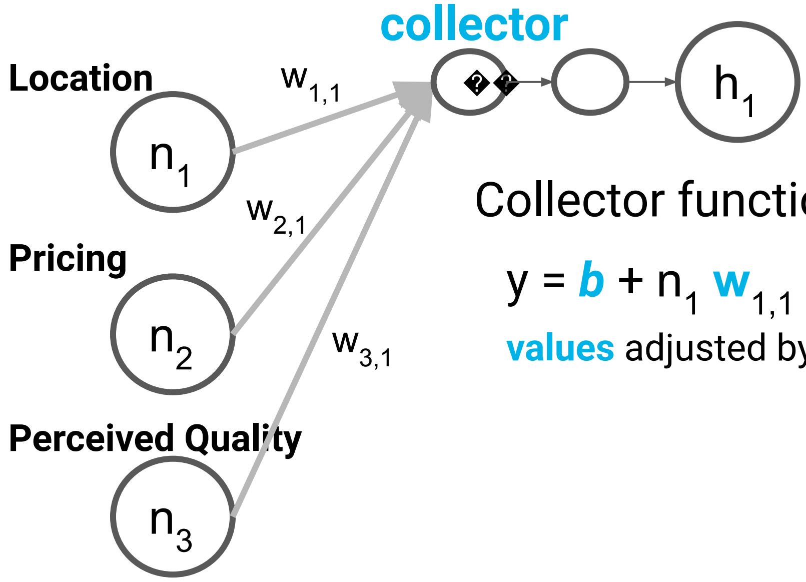
Collector function:

$$y = b + n_1 w_{1,1} + n_2 w_{2,1} + n_3 w_{3,1}$$

**input layer**

**nodes: 3**

**hidden layer**



Collector function:

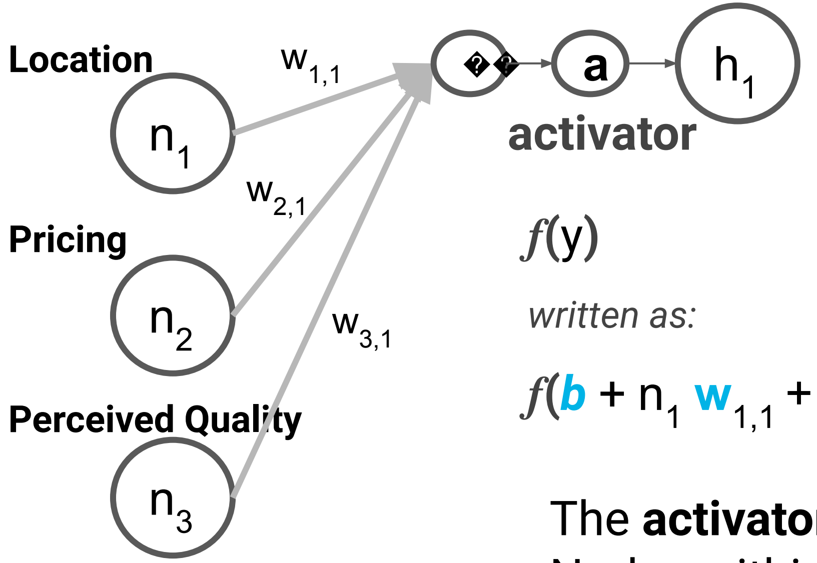
$$y = b + n_1 w_{1,1} + n_2 w_{2,1} + n_3 w_{3,1}$$

**values** adjusted by the algorithm

**input layer**

**nodes: 3**

**hidden layer**



$f(\text{y})$

*written as:*

$f(\boldsymbol{b} + n_1\, \mathbf{w}_{1,1} + n_2\, \mathbf{w}_{2,1} + n_3\, \mathbf{w}_{3,1})$

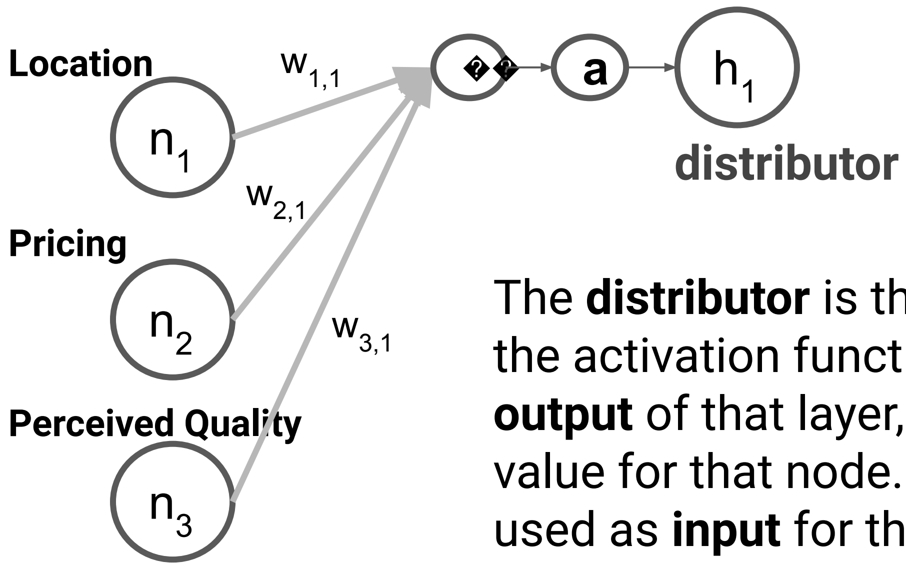
The **activator** is a function chosen by **you** that takes the output of the collector as input.

The **activator** is specified for **each** layer. Nodes within a layer all use the same activation function

**input layer**

**nodes: 3**

**hidden layer**

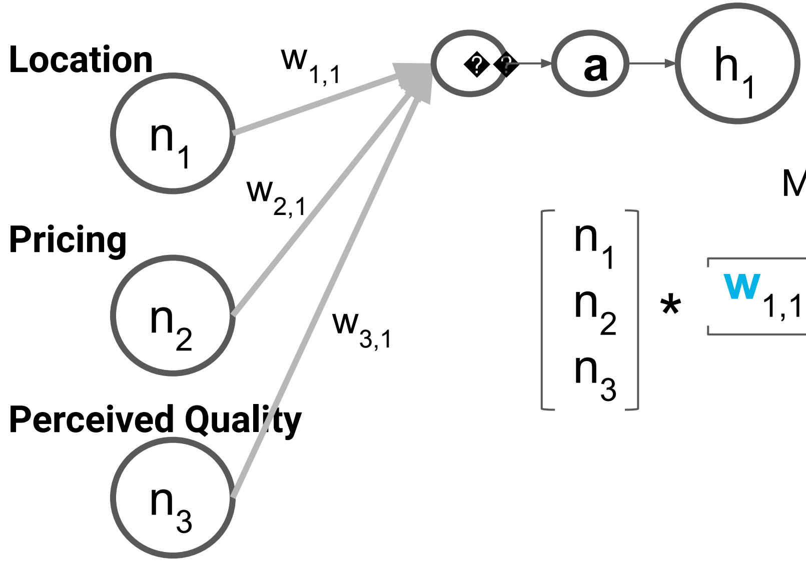


The **distributor** is the **output** of the activation function. It is the **output** of that layer, the final value for that node. It is then used as **input** for the next layer.

**input layer**
**nodes: 3**

**hidden layer**

# For the math lovers in the room:



Matrix notation for one hidden node

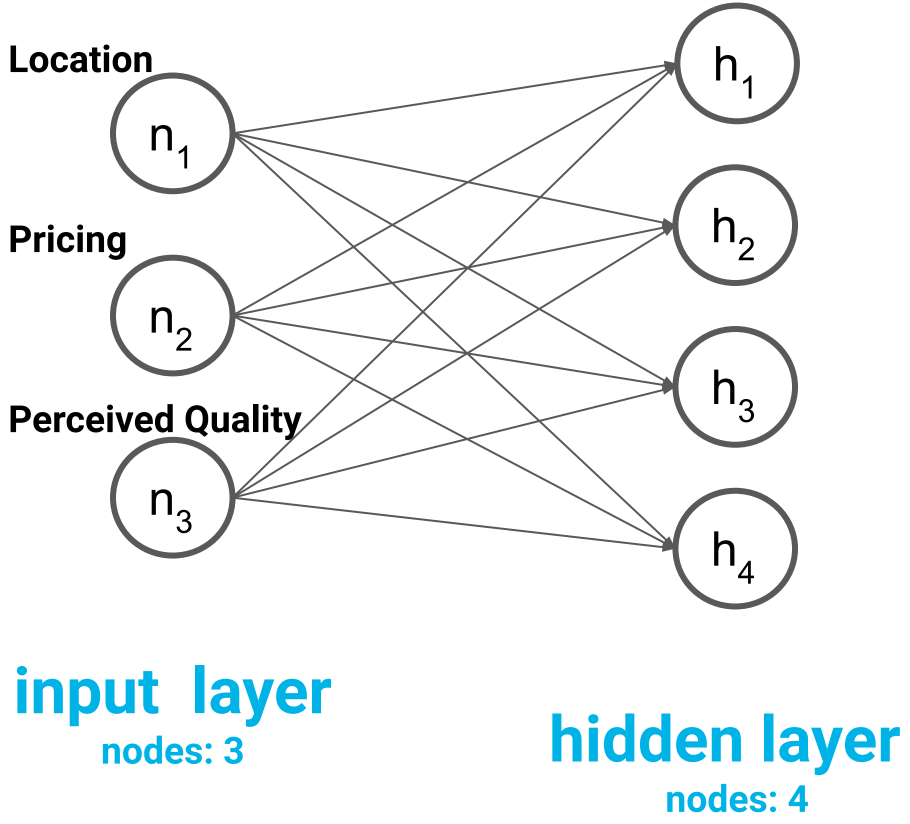
$$\begin{bmatrix} n_1 \\ n_2 \\ n_3 \end{bmatrix} * \begin{bmatrix} w_{1,1} & w_{2,1} & w_{3,1} \end{bmatrix} + b_1 = y_1 \rightarrow f_{a1}(y_1) \rightarrow h_1$$

**input layer**

**nodes: 3**

**hidden layer**

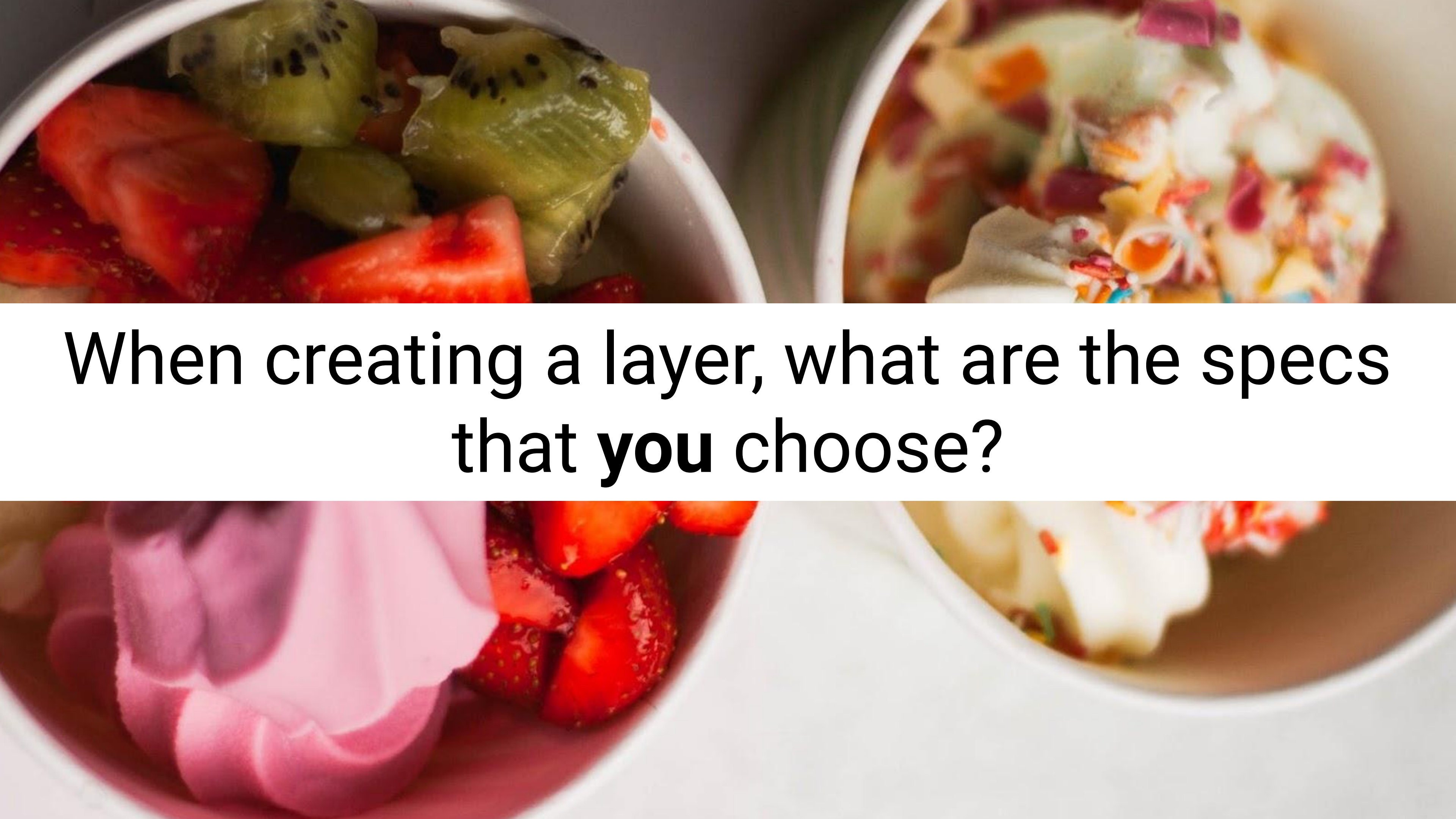
# The full math for a layer:



Matrix notation for one hidden layer

$$\begin{bmatrix} n_1 \\ n_2 \\ n_3 \end{bmatrix} * \begin{bmatrix} w_{1,1} & w_{2,1} & w_{3,1} \\ w_{1,2} & w_{2,2} & w_{3,2} \\ w_{1,3} & w_{2,3} & w_{3,3} \\ w_{1,4} & w_{2,4} & w_{3,4} \end{bmatrix}^T + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix}$$

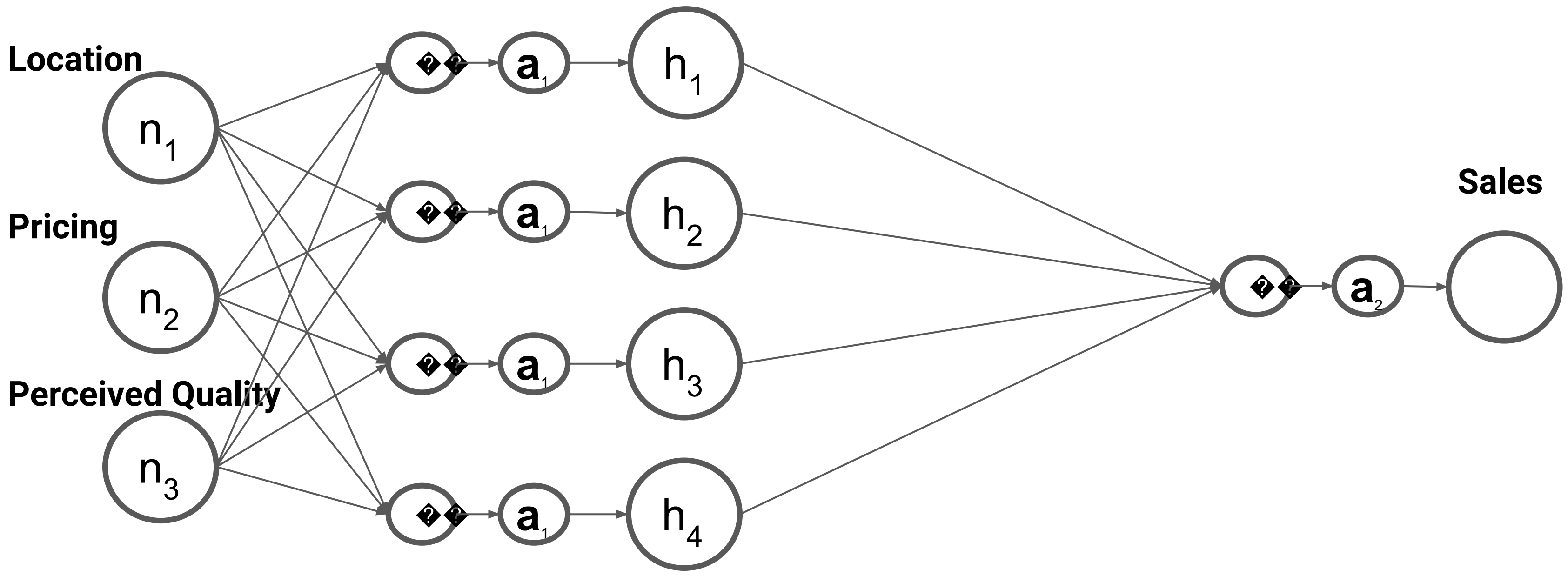
$$\begin{bmatrix} f(y_1) \\ f(y_2) \\ f(y_3) \\ f(y_4) \end{bmatrix} = \begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{bmatrix}$$



## When creating a layer, what are the specs that **you** choose?

## Summary

| Hidden layer variables | You define | Computer figures out |
|---|---|---|
| weights | | ✓ |
| activation function | ✓ | |
| bias | | ✓ |
| number of nodes | ✓ | |



**input layer**
nodes: 3

**hidden layer**
nodes: 4

**output layer**
one node

## Summary so far:

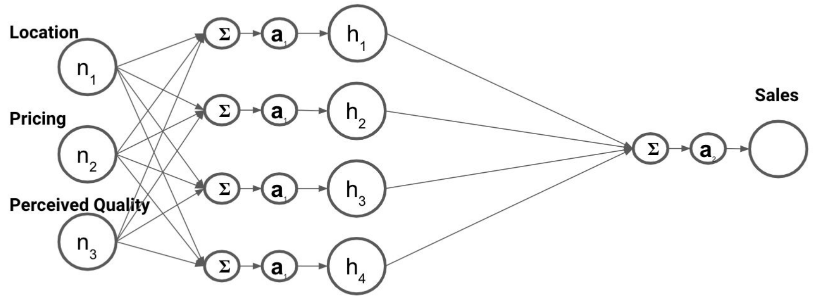
What you choose when building a neural network:

At the ***network*** level:

- Number of input variables
- Number of hidden layers
- If it is a classification or regression problem

At the ***layer*** level:

- The number of nodes
- The activation function



## What else can we adjust?

## What you choose when building a neural network:

At the ***network*** level:

- Number of input variables
- Number of hidden layers
- If it is a classification or regression problem
- **Batch size**
- **Number of epochs**
- **Learning rate & optimizer**
- **Regularization type and lambda**

At the ***layer*** level:

- The number of nodes
- The activation function

## Batches and Epochs are about data processing

That's a lot of math and a lot of data. The dataset is split into chunks and passed through the network one chunk at a time.

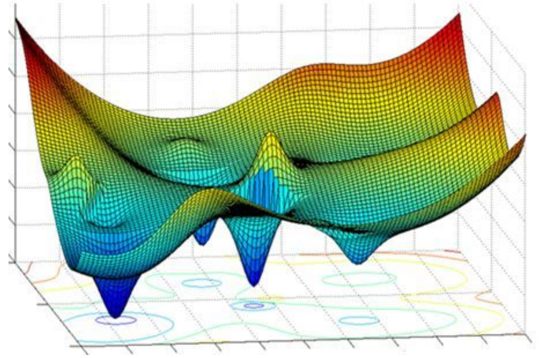
***Batch*** defines the number of observations in each "chunk".

***Epochs*** are how many times you want the whole dataset to go through the network.

All the **batches** = one **epoch**.

# **Learning rate** is from gradient descent

| **Scenario** | **Cost/Loss Function** |
|---|---|
| Regression | MSE |
| Binary classification | Cross-Entropy (Logarithmic loss) |
| Multi-class classification | Softmax of Cross-Entropy |



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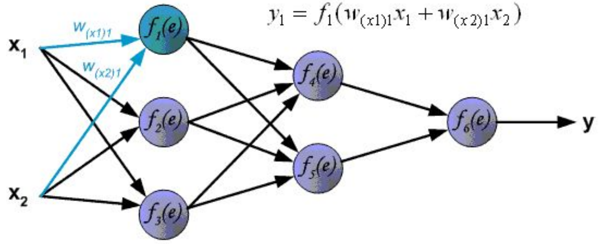
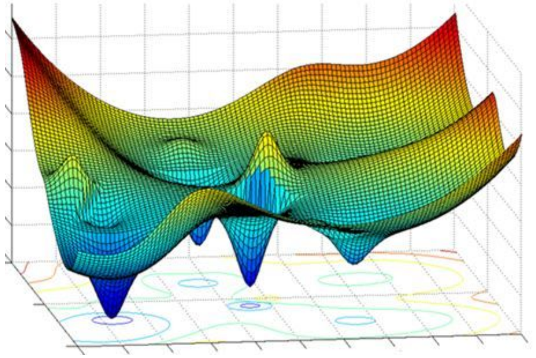


# Optimizer is how the gradient is calculated

| Options |
|---|
| sgd |
| rmsprop |
| Adagrad |
| Adadelta |
| Adam |
| And more! |



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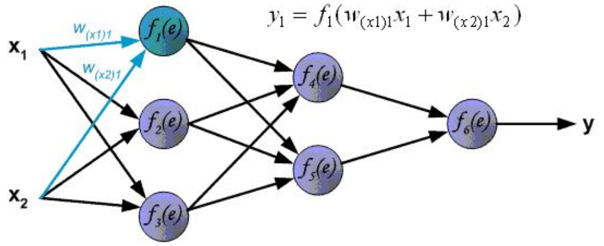


## **Regularization** - adjusts the weights  by layer

Adding a set penalization term at each collector node.

You can choose no regularization, lasso, or ridge.

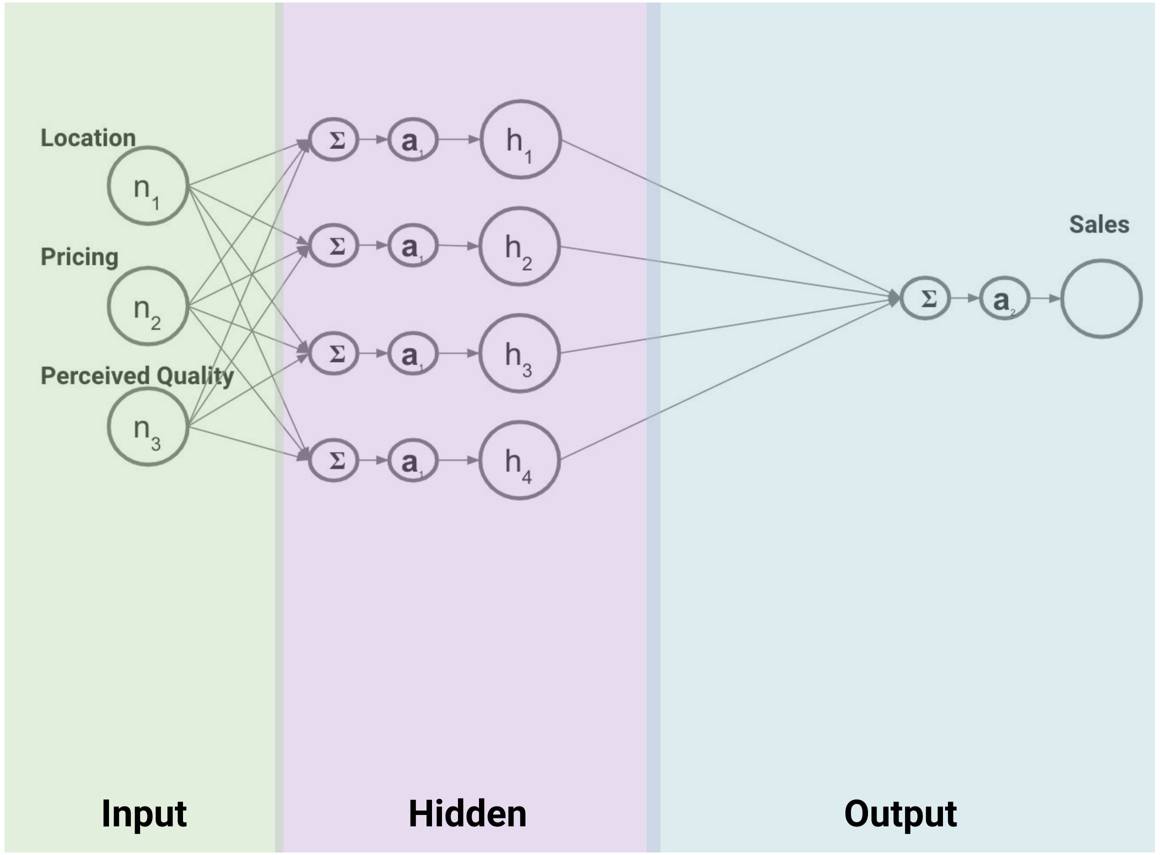
# Write in sentences what this code does

```
model = Sequential()
model.add(Dense(32, activation='relu', input_dim=100))
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['accuracy'])

# Generate dummy data
import numpy as np
data = np.random.random((1000, 100))
labels = np.random.randint(2, size=(1000, 1))

# Train the model, iterating on the data in batches of 32 samples
model.fit(data, labels, epochs=10, batch_size=32)
```

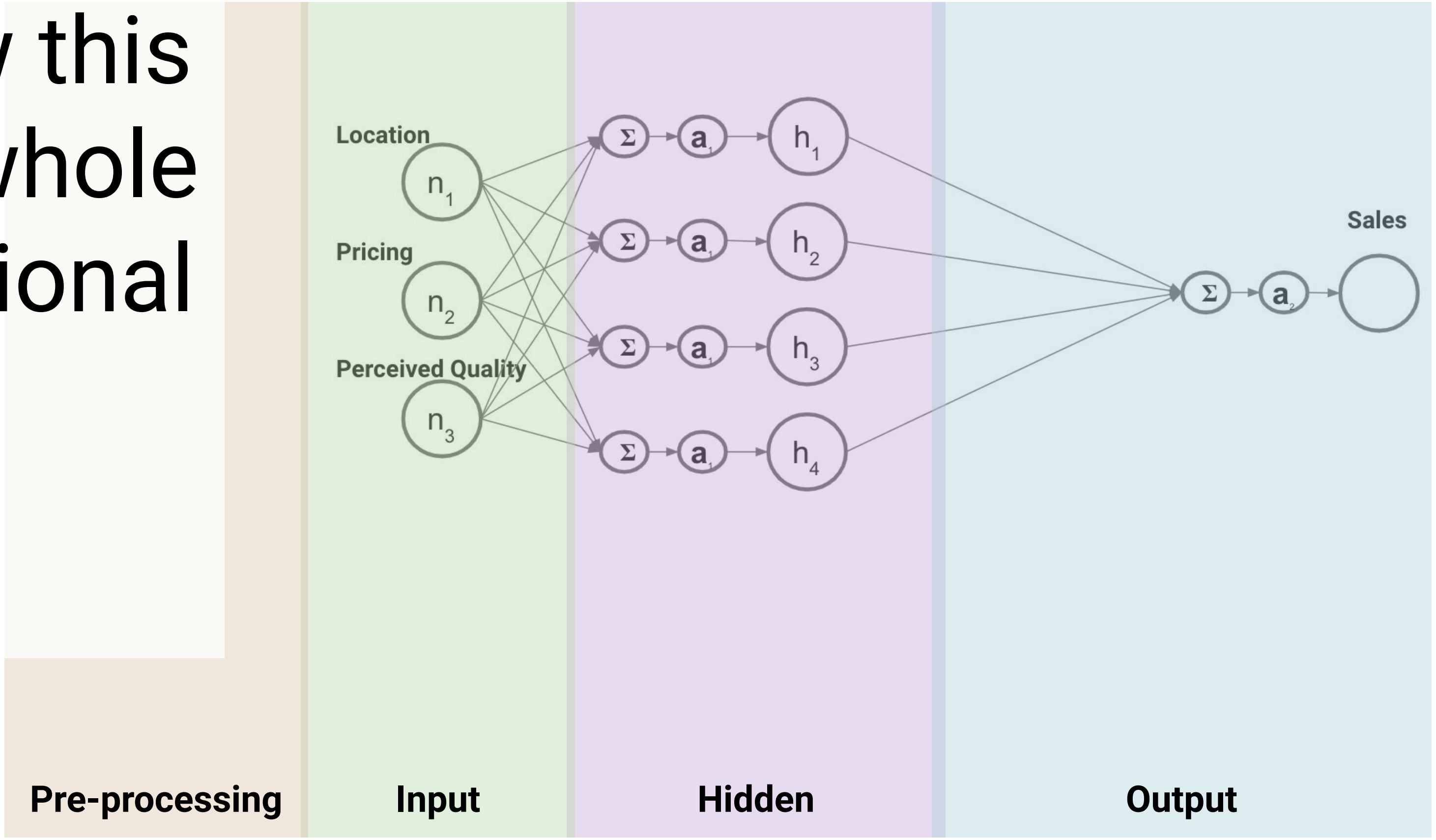
Even without learning Keras explicitly, you should be able to recognize keywords and concepts based on this review.

Dense = fully connected to all previous nodes

# While we have covered this:



# Know this is a whole additional area.



# Exit ticket