

Neural networks through ice cream

Objectives:

- To *fluently* use the *vocabulary* of neural networks
- To connect familiar past algorithms to neural 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.

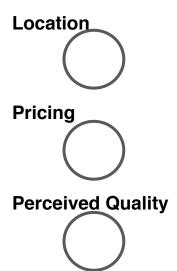




Problem summary



Variables



Variables

Location



Perceived Quality

Target

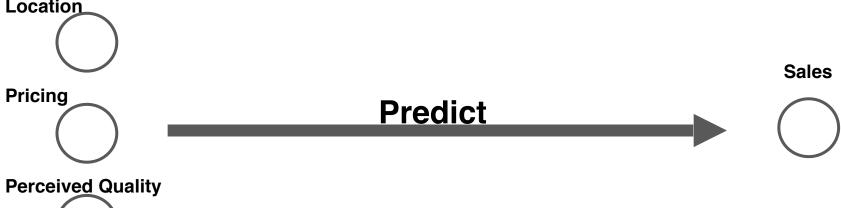


Variables Target

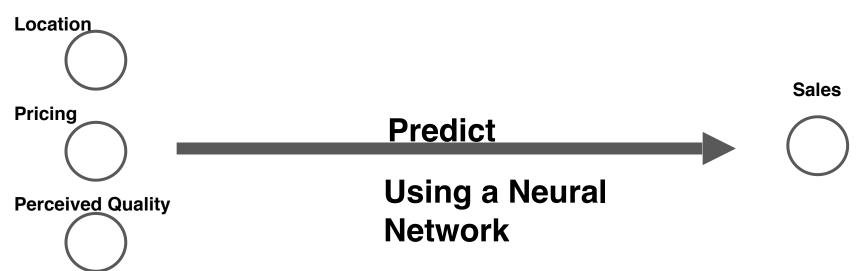


Variables Target

Location



Variables Target





Vocabulary



Variables

Target

Location

Pricing

Perceived Quality

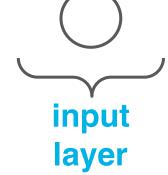


Variables





Perceived Quality



Target



Variables



Target

Location





input layer nodes: 3



Target

Variables

Location

Pricing

Perceived Quality

input layer





Variables

Target

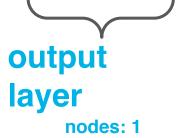
Location

Pricing

Perceived Quality

input layer





Variables

Location

Pricing

Perceived Quality



nodes: 3







Target

Sales



output layer

Variables

Location

Pricing

Perceived Quality

input layer nodes: 3 **Using a Neural Network**









hidden layer

Target

Sales



output layer

Variables

Location

Pricing

Perceived Quality

input layer

nodes: 3

Using a Neural Network









hidden layer

nodes: 4



Sales



output layer



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



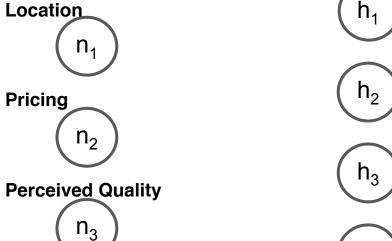
input layer nodes: 3

hidden layer nodes: 4 Sales

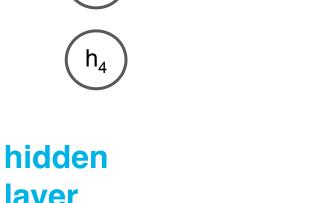


output layer

We need some notation to make this work



input hidder nodes: 3 layer

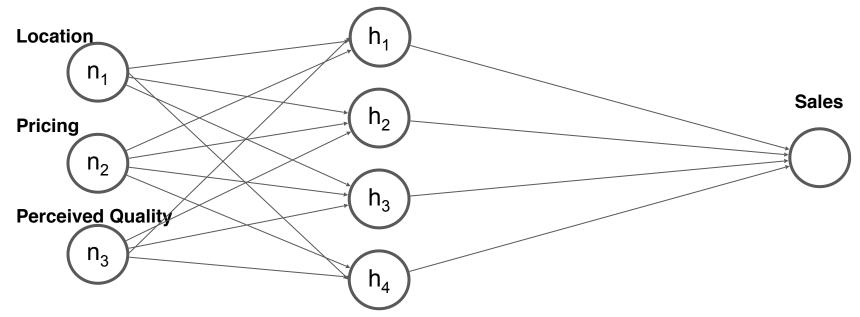


Sales



output layer

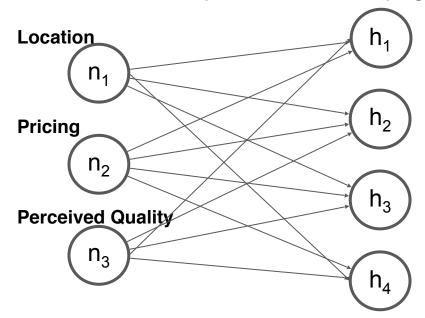
May have seen diagrams like this



input layer nodes: 3

hidden layer output layer

For simplicity we are only going to focus on one layer

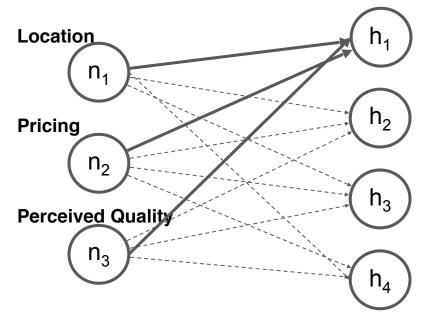


input layer

hidden layer

nodes. 1

And specifically the first node in the hidden layer

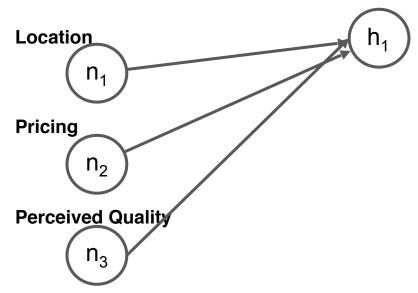


input layer nodes: 3

hidden layer

nodee. 1

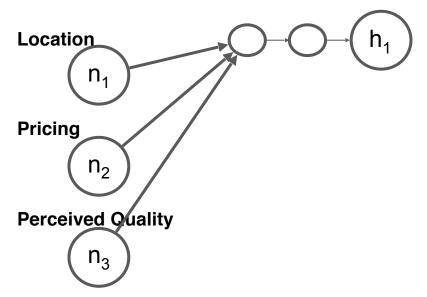
Problem: this common diagram isn't representative



input layer nodes: 3

hidden layer

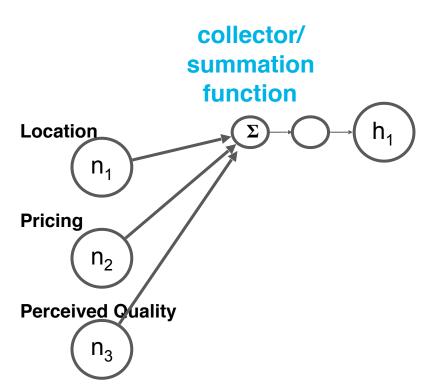
What is shown as one is really three



input layer nodes: 3

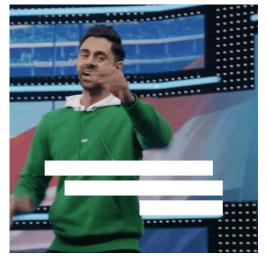
hidden layer

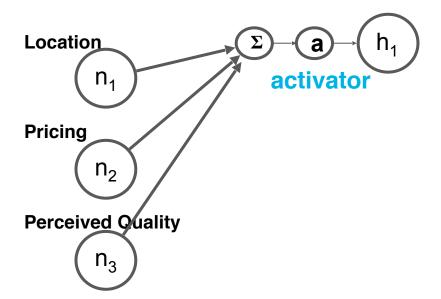




input layer nodes: 3

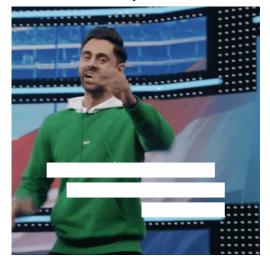
hidden layer

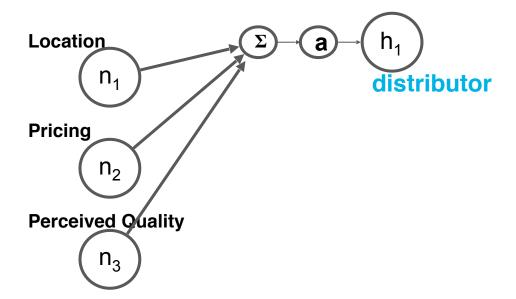




input layer nodes: 3

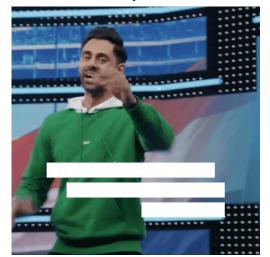
hidden layer

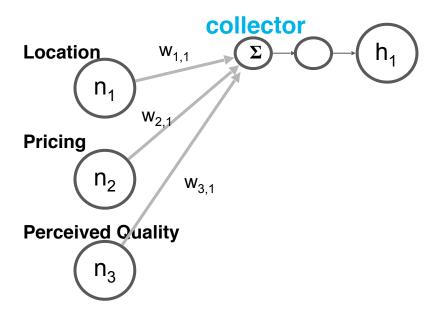




input layer nodes: 3

hidden layer

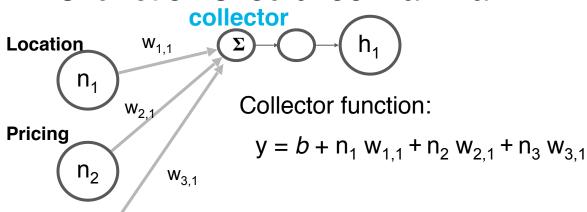




input layer nodes: 3

hidden layer

This function should look familiar



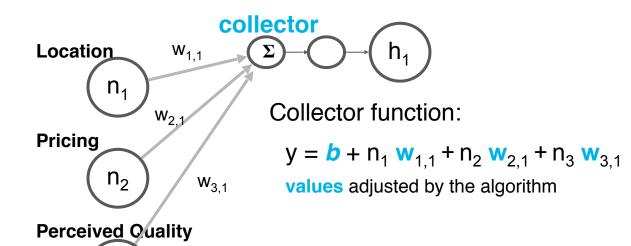
Perceived Quality

 n_3

input

layer nodes: 3

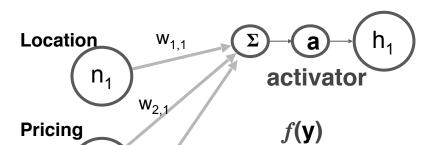
hidden layer



input layer nodes: 3

 n_3

hidden layer



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

m₂ w_{3,1} written as:

 $f(b + n_1 w_{1,1} + n_2 w_{2,1} + n_3 w_{3,1})$

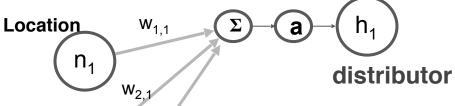
The **activator** is specified for **each** layer. Nodes within a layer all use the same activation function

input layer

Perceived Quality

 n_3

hidden layer



Pricing

 n_2 $w_{3,1}$

Perceived Quality

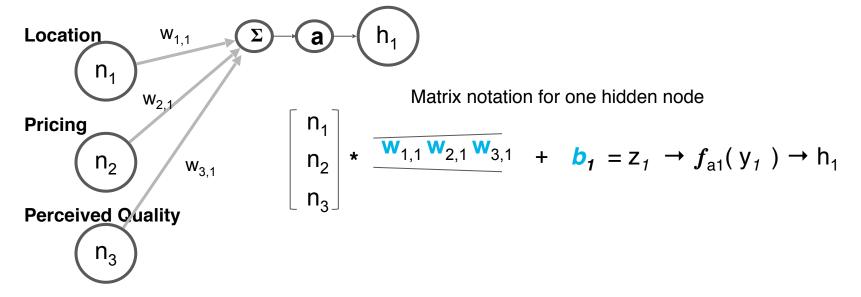
n₃

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

hidden layer

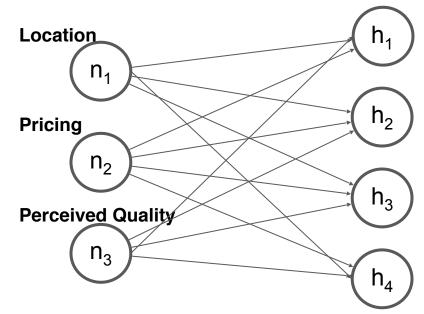
For the math lovers in the room:



input layer nodes: 3

hidden layer

The full math for a layer:



input layer nodes: 3

hidden layer Matrix notation for one hidden layer

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

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

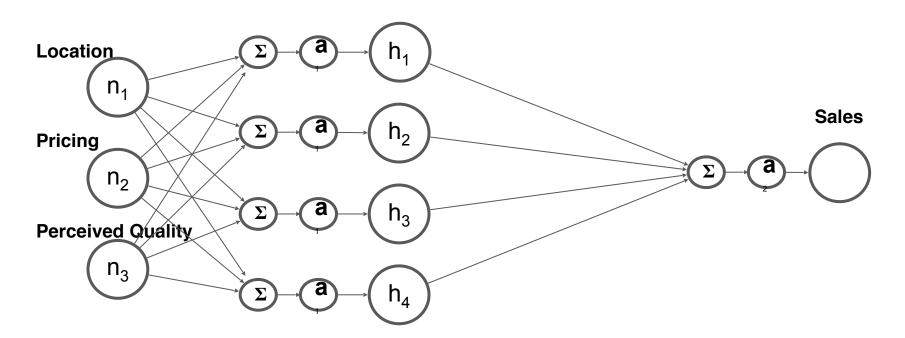


When creating a layer, what are the specs that **you** choose?



Summary

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



input layer nodes: 3

hidden layer output layer

Summary so far:

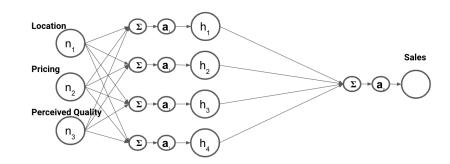
What you choose when building a neural network:

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".

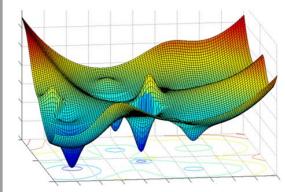
Epochs are how many times you want the whole dataset to go through the network.

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

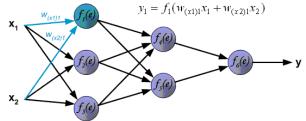


Learning rate is from gradient descent

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

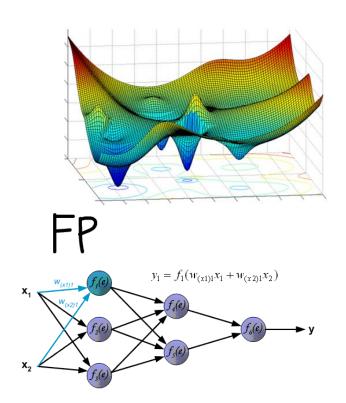






Optimizer is how the gradient is calculated

Options
sgd
rmsprop
Adagrad
Adadelta
Adam
And more!



Regularization - adjusts the weights by layer

Adding a set penalization term at each collector node.

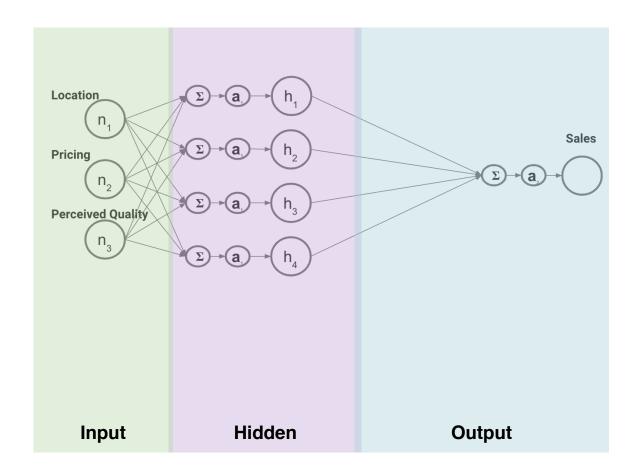
You can choose no regularization, lasso, or ridge.

Write in sentences what this code does

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.

Pre-

