GENERAL ASSEMBLY

# DATA SCIENCE

## NEURAL NETWORKS AND SVM

# I. ARTIFICIAL NEURAL NETWORKS

# II. SUPPORT VECTOR MACHINES

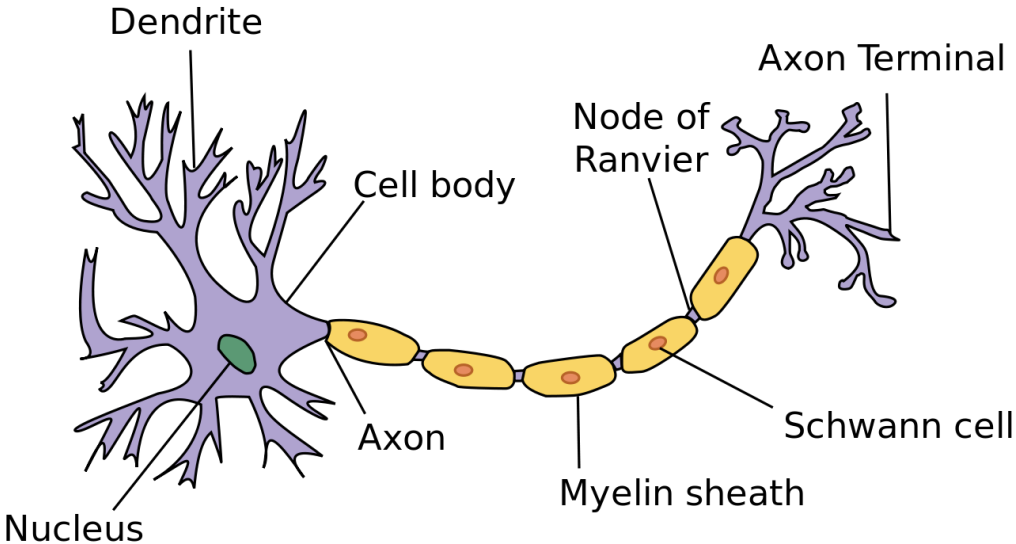
# I. ARTIFICIAL NEURAL NETWORKS

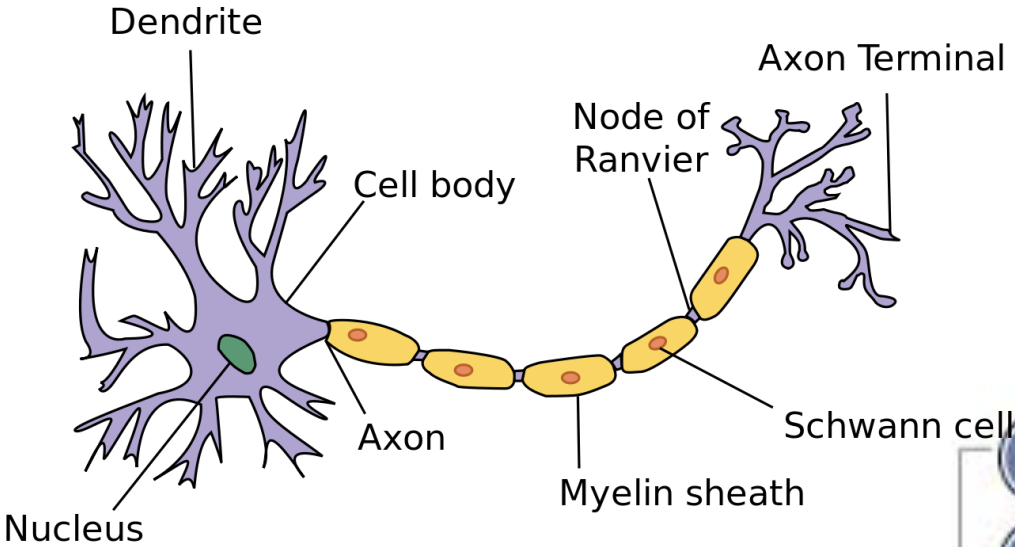
# Artificial Neural Networks

A computational system
comprised of layers and each layer
is built of interconnected perceptrons

# Artificial Neural Networks

Built to model the animal nervous system


Dendrite
Axon Terminal
Node of
Ranvier
Cell body
Schwann cell
Axon
Myelin sheath
Nucleus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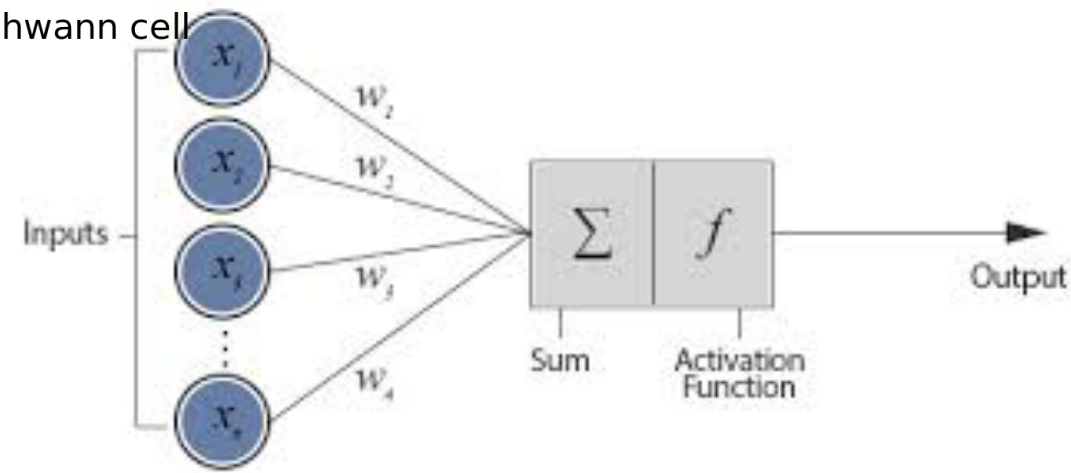

Inputs
$x_1$
$x_2$
$x_3$
$x_n$
$w_1$
$w_2$
$w_3$
$w_4$
$\Sigma$
$f$
Sum
Activation
Function
Output

# Artificial Neural Networks

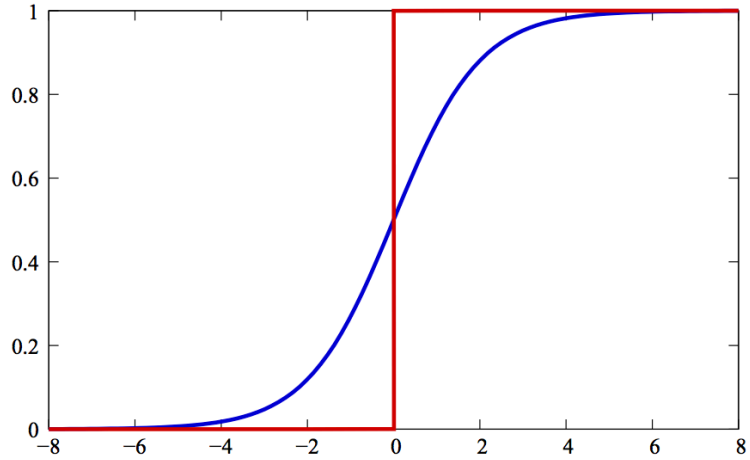
A computational system
comprised of layers and each layer
is built of interconnected perceptrons

# Single Perceptron

Takes in input and uses an activation function in order to output

# Single Perceptron

$$f_{log}(z) = \frac{1}{1 + e^{-z}}$$




$f_{log}$ is called logistic function

**NOTE:**
A single perception can be like a logistic regression in and of itself!

Takes in input and uses an activation function in order to output

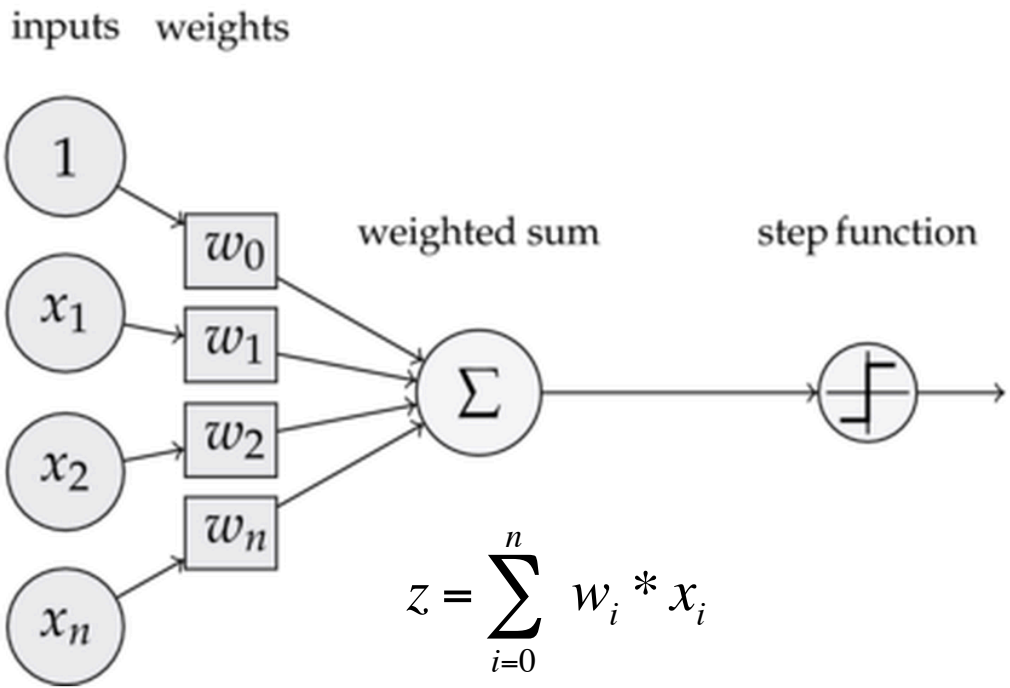
# Single Perceptron

But what is z? A weighted sum on the inputs!

$$z = \sum_{i=0}^{n} w_i * x_i$$

Where w is the weight on input x

# Single Perceptron




$$z = \sum_{i=0}^{n} w_i * x_i$$

$$f_{log}(z) = \frac{1}{1 + e^{-z}}$$

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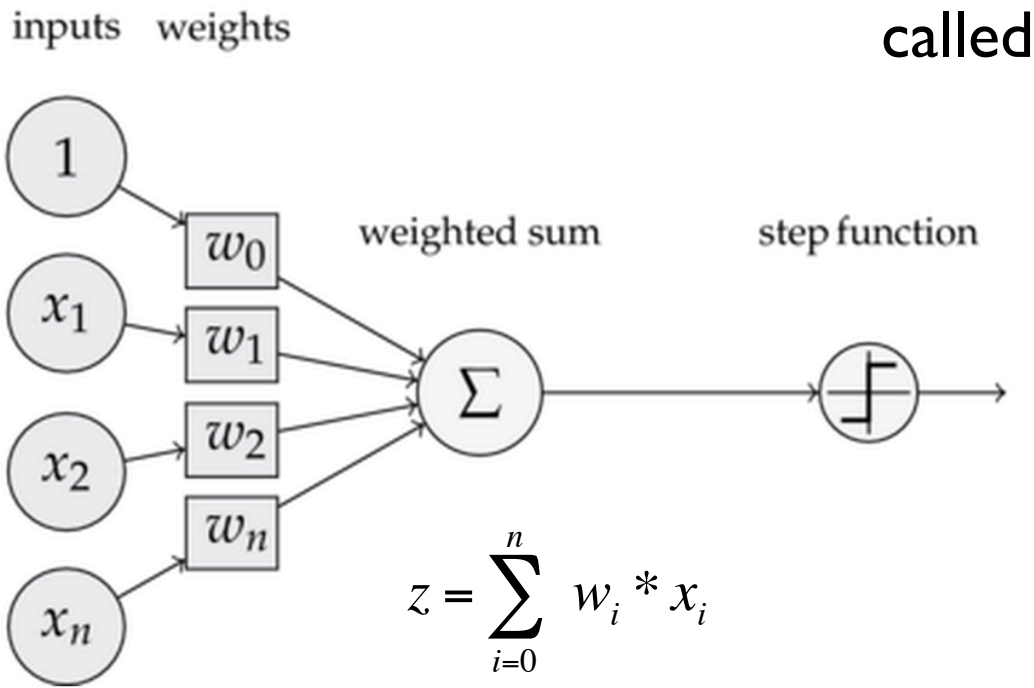
# Single Perceptron

If f(z) if above a threshold, generally called theta, then the neuron "fires"

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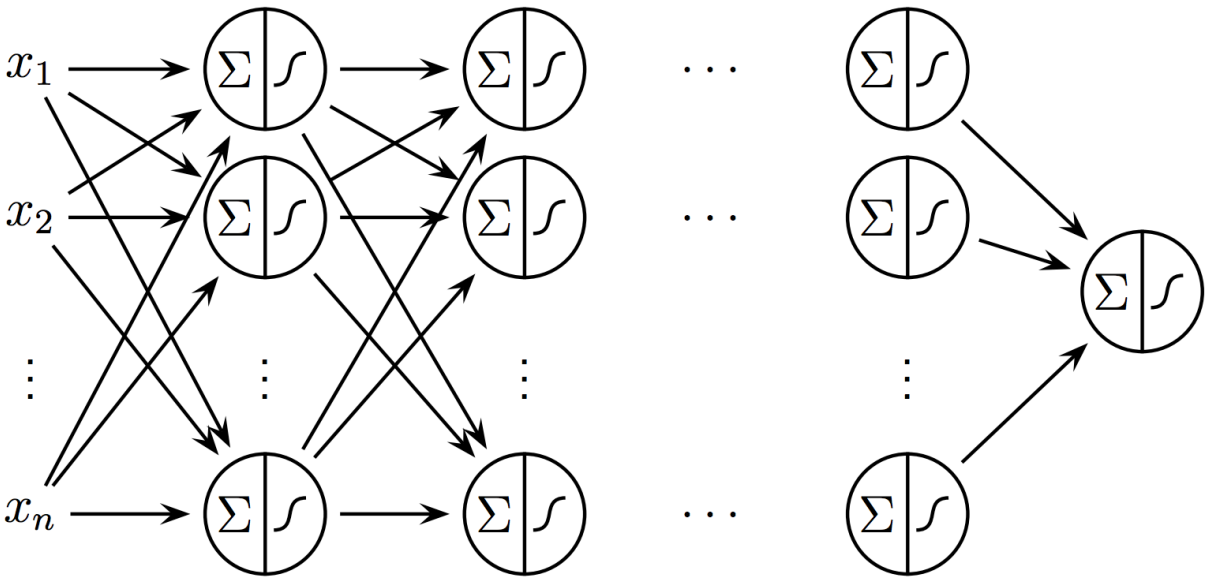
Artificial Neural Networks are
also known as multi layer perceptrons

A multi layer perceptrons (MLP) is a finite acyclic graph. The nodes are neurons with logistic activation.



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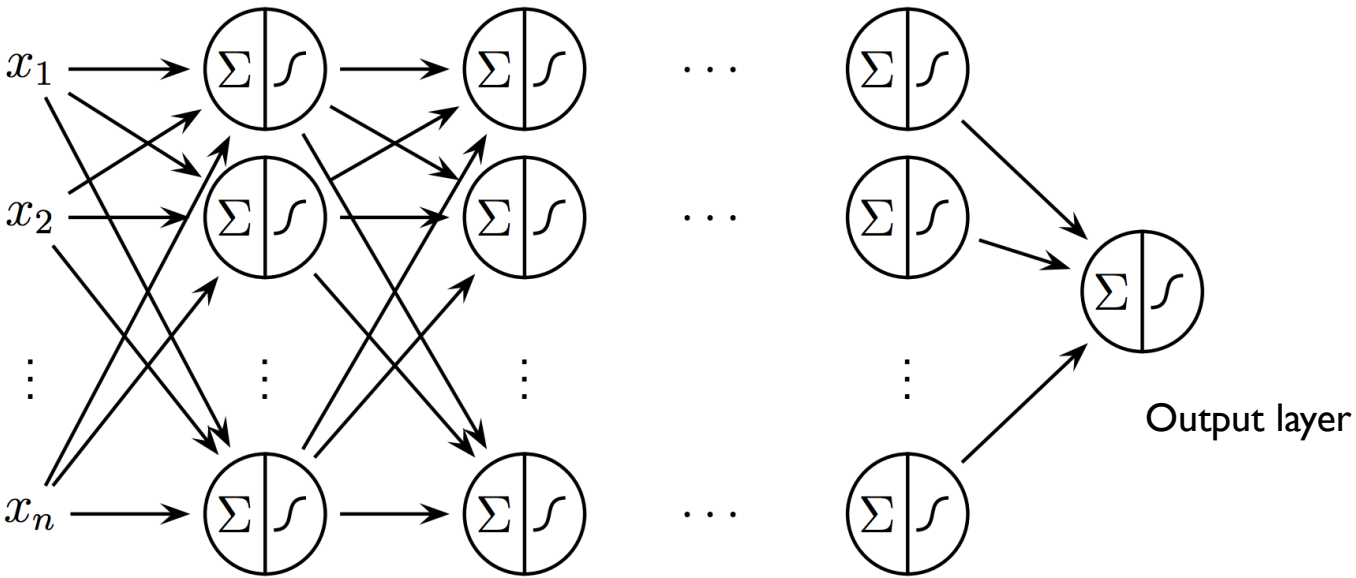

But how does it learn?!

# Back-Propagation

As we train the model we update the sigmoid function weights in order to get the best predictions possible

If an observation goes through the model and is outputted as False when it should have been True, The logistic functions in the single perceptrons are changed slightly

# Pros

- Online model (updates as you go)
  - Doesn't need to be fit all of the time
- Very fast predictions
- Can approximate almost any type of function
- Can be used in a supervised and unsupervised manner
- Super cool

# Cons

- Requires many training samples to be considered good
- Hard to describe what is happening
- Requires a lot of hardware / computation power
- Slow to train
- Sklearn only has unsupervised version
- Other versions are difficult to use

The most advanced ANN's use thousand's of neurons which is a lot right?

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Sure but my dog has billions…….

http://deepdreamgenerator.com/

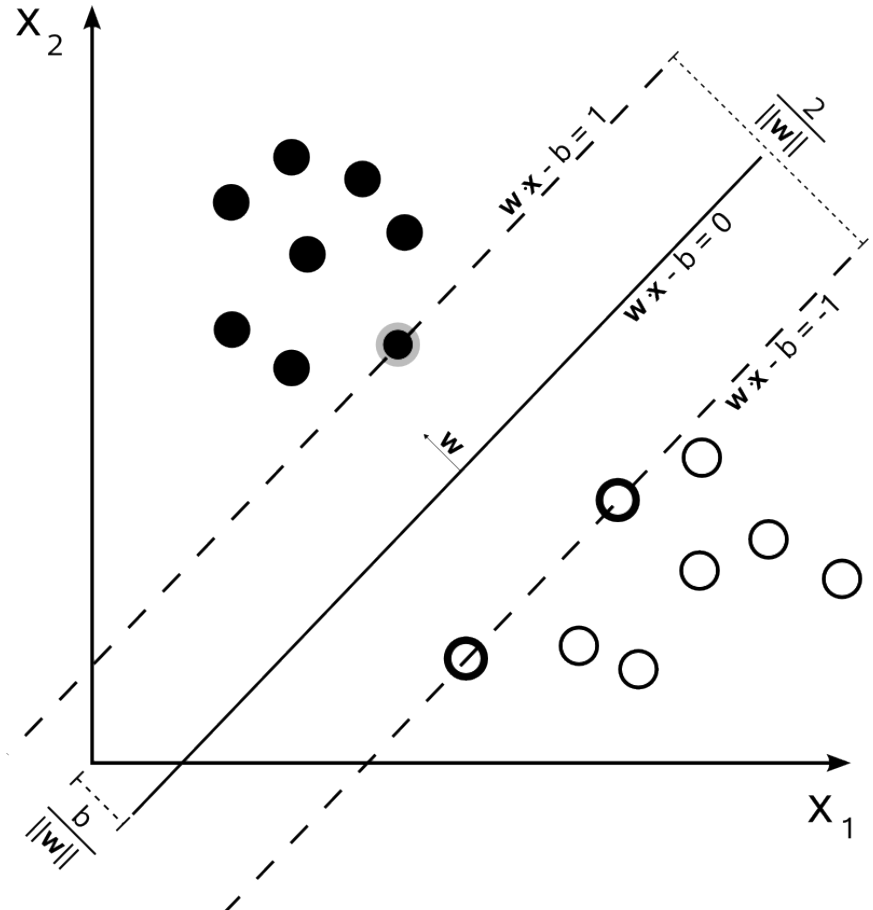
Google uses a supervised neural network to recognize content in photos.

http://deepdreamgenerator.com/

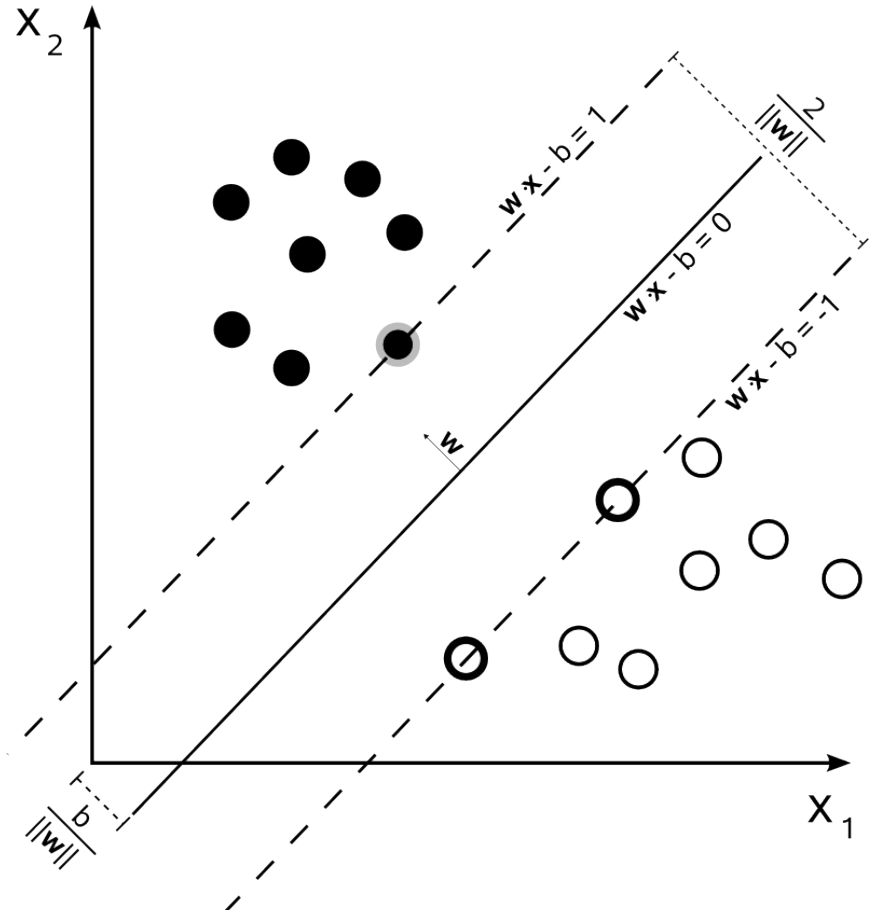
Turns out if you input an image you can ask the neural network to try and “re-create” the image as well

# II. SUPPORT VECTOR MACHINES

Constructs a hyperplane to separate classes in space


X2
X1
wx - b = 1
wx - b = 0
wx - b = -1
||w||2
w
||w||b

We want to maximize the width of the margin



What if there is no easy hyperplane?

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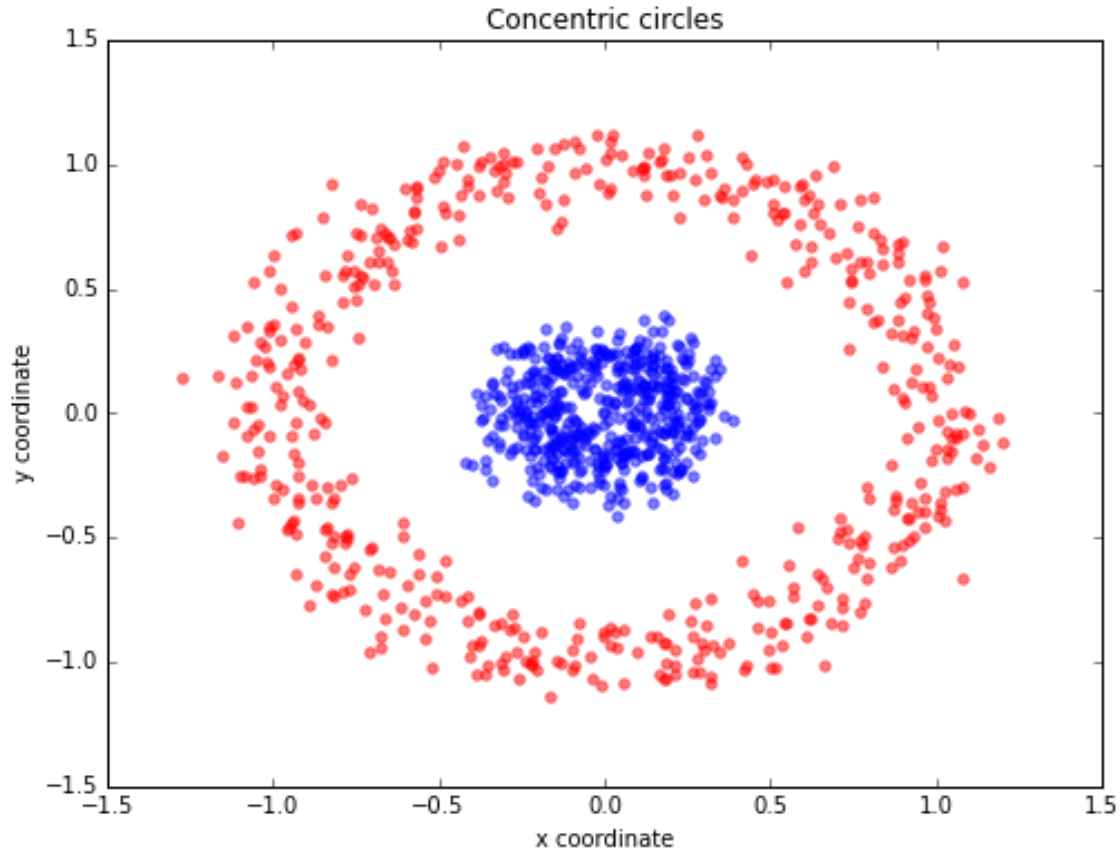
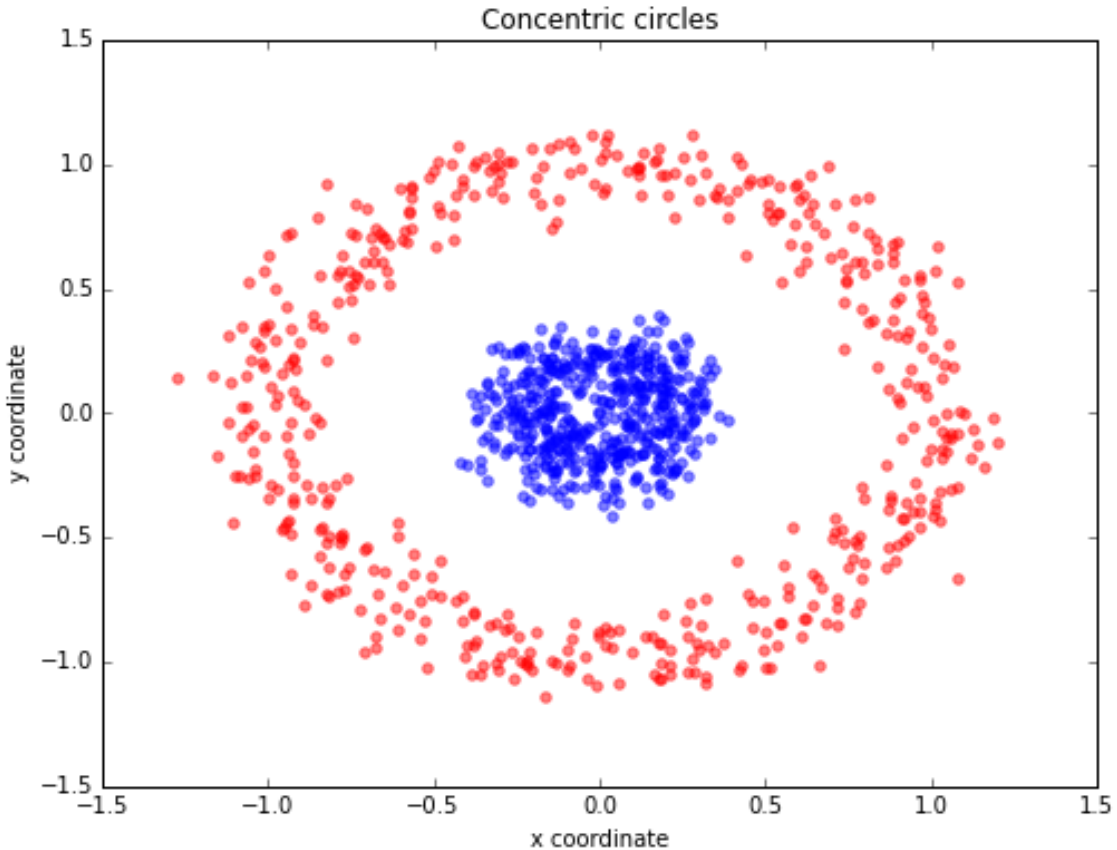
easy hyperplane?

Walk with me on this,
a mathematical journey


Concentric circles
y coordinate
x coordinate
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5




Pretty much no hyperplane will separate this out, but what if we could add a third dimension?

Q. OK fine, but what if I have 100 predictors? How many dimensions should I project into?

A. An arbitrary amount, possible infinite..

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A. An arbitrary amount, possible infinite..

OK but this can take time..

# Kernel Trick

We assume a certain shape of the data and the kernel trick saves us MASSIVE computation time

# Kernel Trick

**Example:**

Linear ( assumes a linear boundary)
Poly ( assumes a curved boundary)
Gaussian ( assumes a spherical boundary)

# Pros

- Very fast training and predicting with kernel trick
- Built on solid mathematical foundation (unlike ANN)
- Very common and in sklearn

# Cons

- A lot of "guess work" with kernels
- Hard to grasp math behind it (ok if you accept the black box)