

DSC 140B

Representation Learning

Lecture 12 | Part 1

Radial Basis Functions

Recap

- ▶ Linear prediction functions are limited.
- ▶ Idea: transform the data to a new space where prediction is “easier”.
- ▶ To do so, we used **basis functions**.

Overview: Feature Mapping

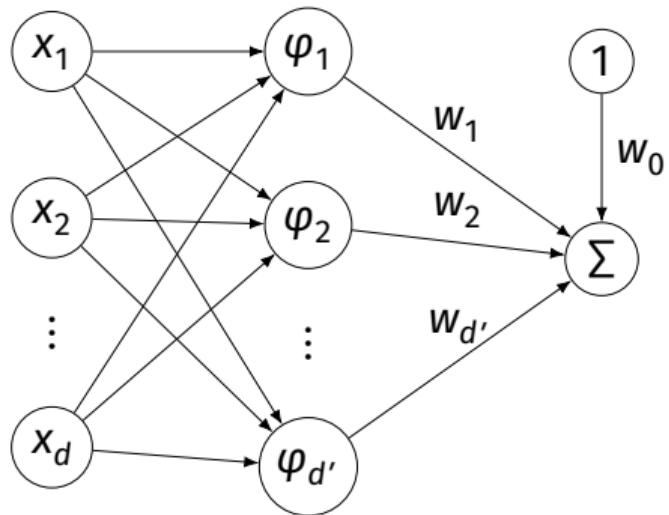
1. Start with data in original space, \mathbb{R}^d .
2. Choose some basis functions, $\varphi_1, \varphi_2, \dots, \varphi_{d'}$
3. Map each data point to **feature space** $\mathbb{R}^{d'}$:

$$\vec{x} \mapsto (\varphi_1(\vec{x}), \varphi_2(\vec{x}), \dots, \varphi_{d'}(\vec{x}))^t$$

4. Fit linear prediction function in new space:

$$H(\vec{x}) = w_0 + w_1 \varphi_1(\vec{x}) + w_2 \varphi_2(\vec{x})$$

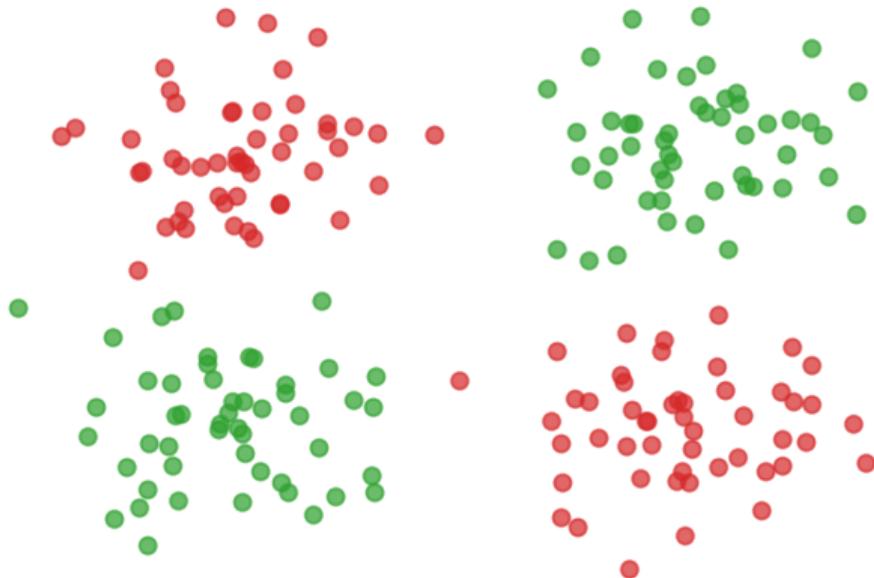
$$H(\vec{x}) = w_0 + w_1 \varphi_1(\vec{x}) + w_2 \varphi_2(\vec{x})$$



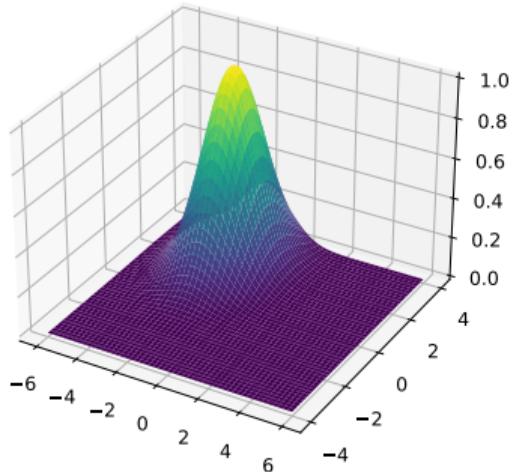
Generic Basis Functions

- ▶ The basis functions we used before were engineered using domain knowledge.
- ▶ They were specific to the problem at hand.
- ▶ **Very manual process!**
- ▶ **Now:** features that work for many problems.

Example



Gaussian Basis Functions



- ▶ A common choice: **Gaussian** basis functions:

$$\varphi(\vec{x}; \vec{\mu}, \sigma) = e^{-\|\vec{x} - \vec{\mu}\|^2 / \sigma^2}$$

- ▶ $\vec{\mu}$ is the center.
- ▶ σ controls the “width”

Gaussian Basis Function

- ▶ If \vec{x} is close to $\vec{\mu}$, $\varphi(\vec{x}; \vec{\mu}, \sigma)$ is large.
- ▶ If \vec{x} is far from $\vec{\mu}$, $\varphi(\vec{x}; \vec{\mu}, \sigma)$ is small.
- ▶ Intuition: φ measures how “similar” \vec{x} is to $\vec{\mu}$.
 - ▶ Assumes that “similar” objects have close feature vectors.

New Representation

- ▶ Pick number of new features, d' .
- ▶ Pick centers for Gaussians $\vec{\mu}^{(1)}, \dots, \vec{\mu}^{(2)}, \dots, \vec{\mu}^{(d')}$
- ▶ Pick widths: $\sigma_1, \sigma_2, \dots, \sigma_{d'}$ (usually all the same)
- ▶ Define i th basis function:

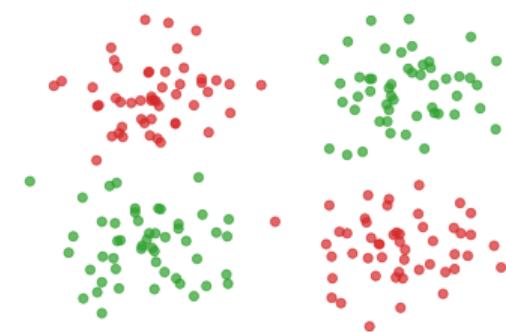
$$\varphi_i(\vec{x}) = e^{-\|\vec{x} - \vec{\mu}^{(i)}\|^2 / \sigma_i^2}$$

New Representation

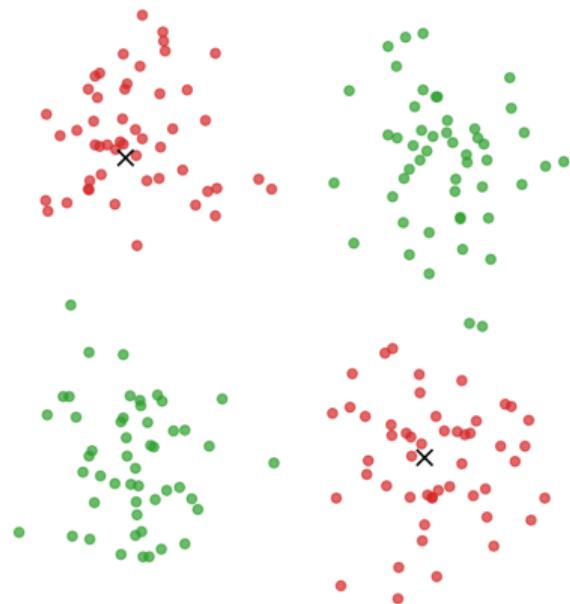
- ▶ For any feature vector $\vec{x} \in \mathbb{R}^d$, map to vector $\vec{\varphi}(\vec{x}) \in \mathbb{R}^{d'}$.
 - ▶ φ_1 : “similarity” of \vec{x} to $\vec{\mu}^{(1)}$
 - ▶ φ_2 : “similarity” of \vec{x} to $\vec{\mu}^{(2)}$
 - ▶ ...
 - ▶ $\varphi_{d'}$: “similarity” of \vec{x} to $\vec{\mu}^{(d')}$
- ▶ Train linear classifier in this new representation.
 - ▶ E.g., by minimizing expected square loss.

Exercise

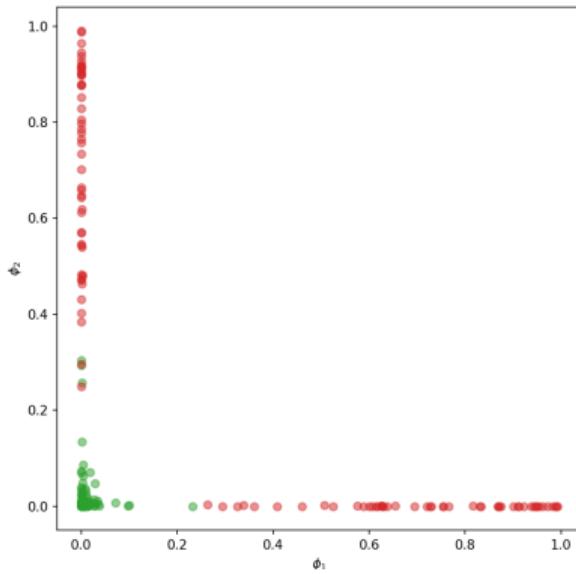
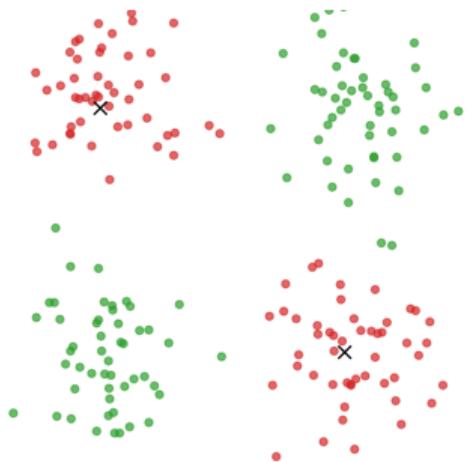
How many Gaussian basis functions would you use, and where would you place them to create a new representation for this data?



Placement



Feature Space



Prediction Function

- ▶ $H(\vec{x})$ is a sum of Gaussians:

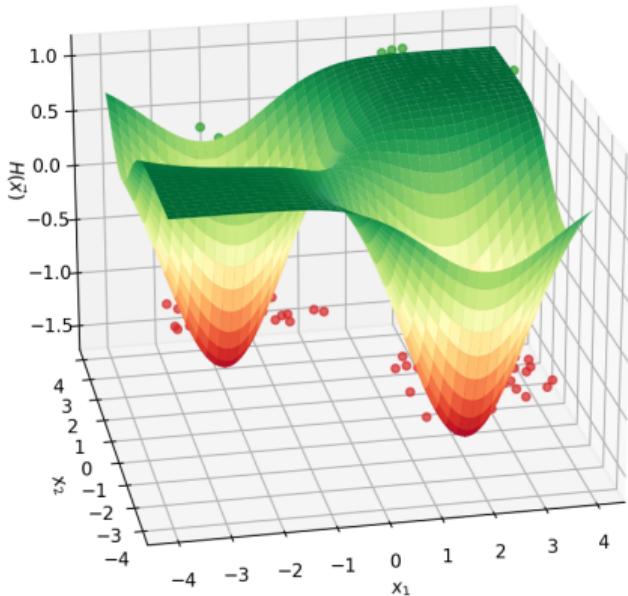
$$\begin{aligned} H(\vec{x}) &= w_0 + w_1 \varphi_1(\vec{x}) + w_2 \varphi_2(\vec{x}) + \dots \\ &= w_0 + w_1 e^{-\|\vec{x}-\vec{\mu}_1\|^2/\sigma^2} + w_2 e^{-\|\vec{x}-\vec{\mu}_2\|^2/\sigma^2} + \dots \end{aligned}$$

Exercise

What does the surface of the prediction function look like?

Hint: what does the sum of 1-d Gaussians look like?

Prediction Function Surface

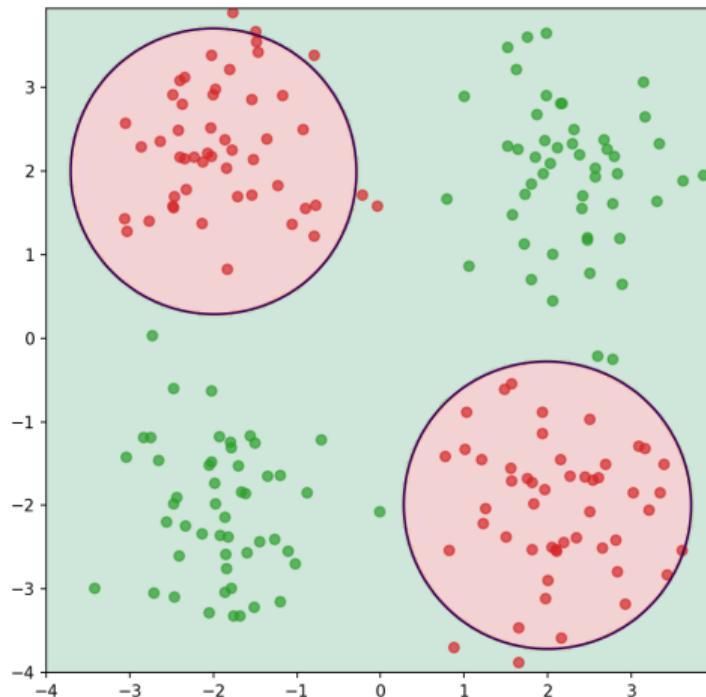


$$H(\vec{x}) = w_0 + w_1 e^{-\|\vec{x} - \vec{\mu}_1\|^2/\sigma^2} + w_2 e^{-\|\vec{x} - \vec{\mu}_2\|^2/\sigma^2}$$

An Interpretation

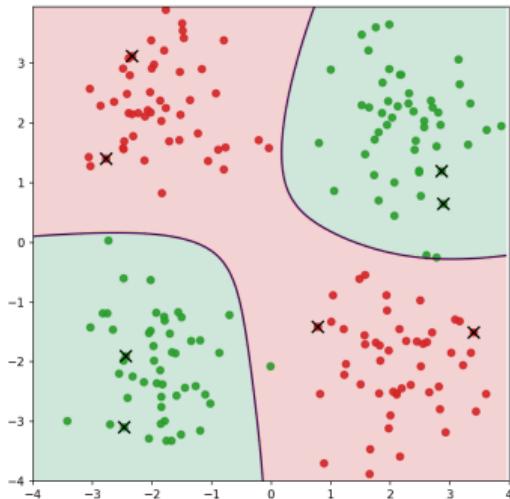
- ▶ Basis function φ_i makes a “bump” in surface of H
- ▶ w_i adjusts the “prominance” of this bump

Decision Boundary

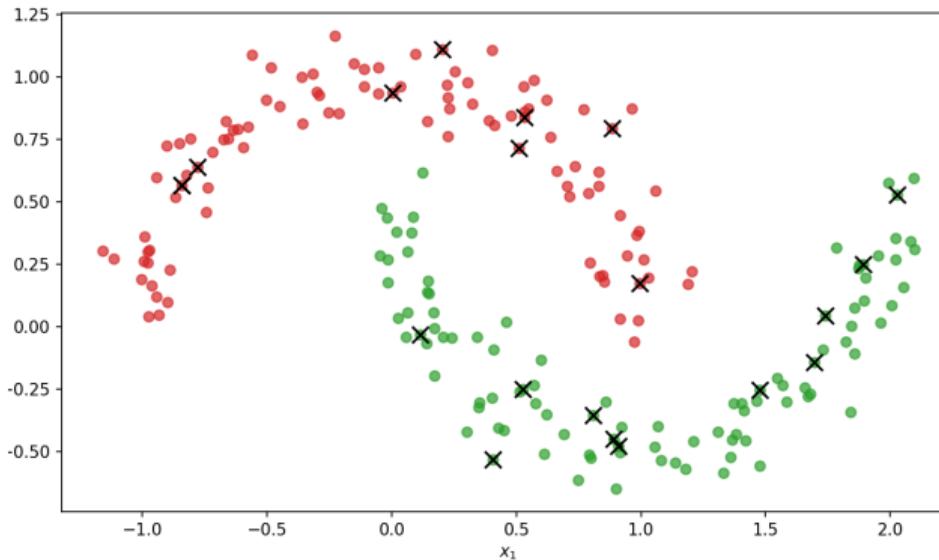


More Features

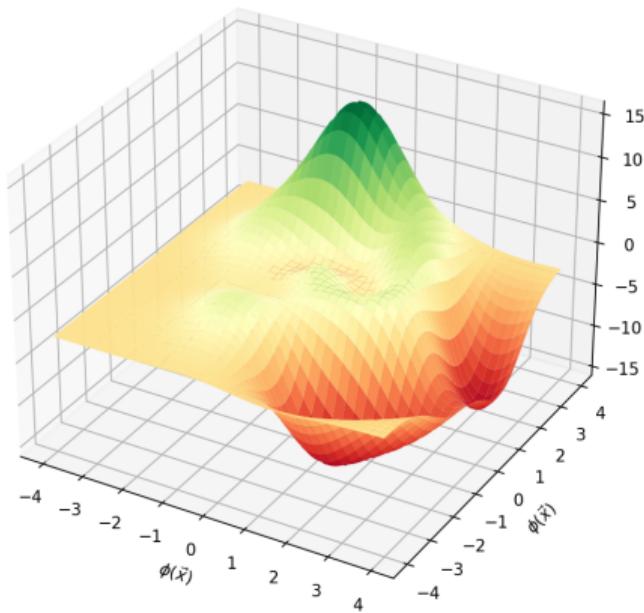
- ▶ By increasing number of basis functions, we can make more complex decision surfaces.



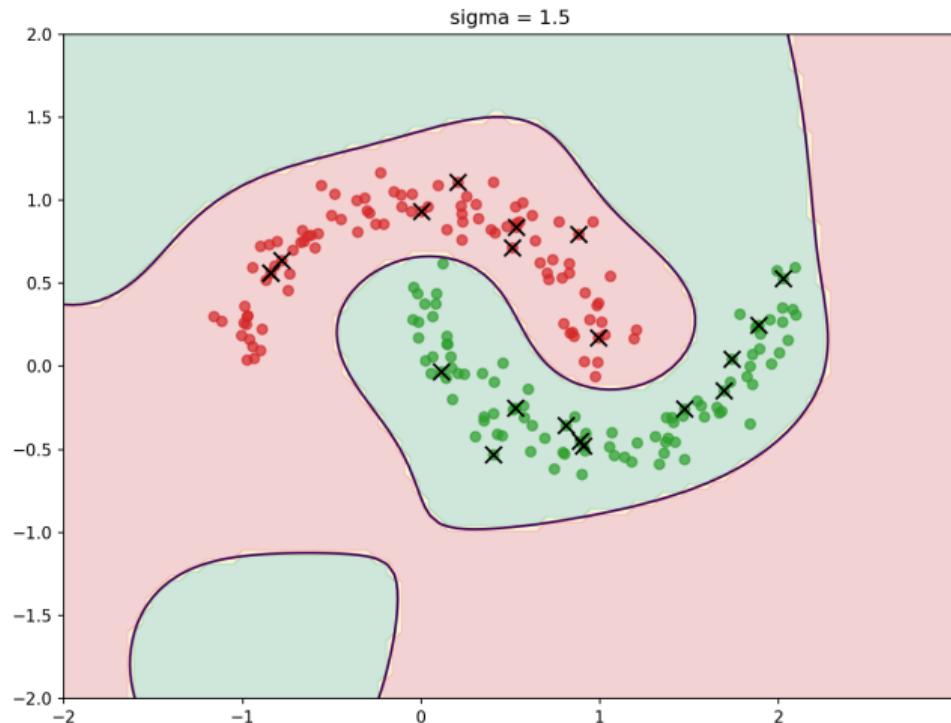
Another Example



Prediction Surface



Decision Boundary



Radial Basis Functions

- ▶ Gaussians are examples of **radial basis functions**.
- ▶ Each basis function has a **center**, \vec{c} .
- ▶ Value depends only on distance from center:

$$\varphi(\vec{x}; \vec{c}) = f(\|\vec{x} - \vec{c}\|)$$

Another Radial Basis Function

- ▶ **Multiquadric:** $\varphi(\vec{x}; \vec{c}) = \sqrt{\sigma^2 + \|\vec{x} - \vec{c}\|} / \sigma$

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Representation Learning

Lecture 12 | Part 2

Radial Basis Function Networks

Recap

1. Choose basis functions, $\varphi_1, \dots, \varphi_{d'}$
2. Transform data to new representation:

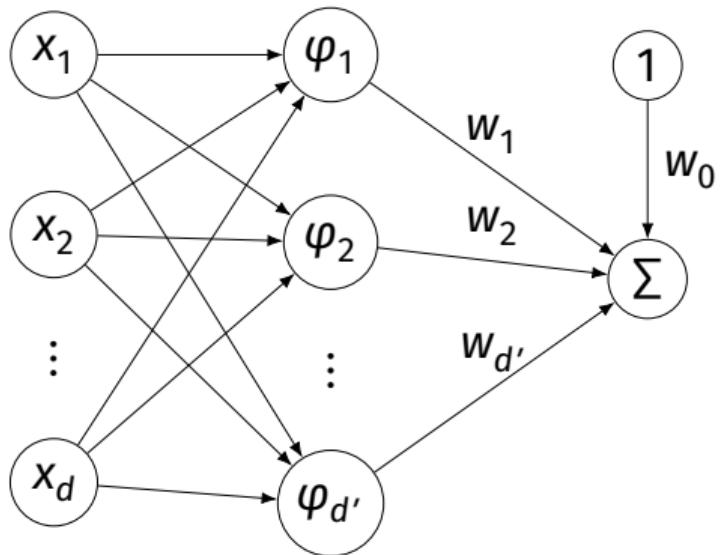
$$\vec{x} \mapsto (\varphi_1(\vec{x}), \varphi_2(\vec{x}), \dots, \varphi_{d'}(\vec{x}))^T$$

3. Train a linear classifier in this new space:

$$H(\vec{x}) = w_0 + w_1 \varphi_1(\vec{x}) + w_2 \varphi_2(\vec{x}) + \dots + w_{d'} \varphi_{d'}(\vec{x})$$

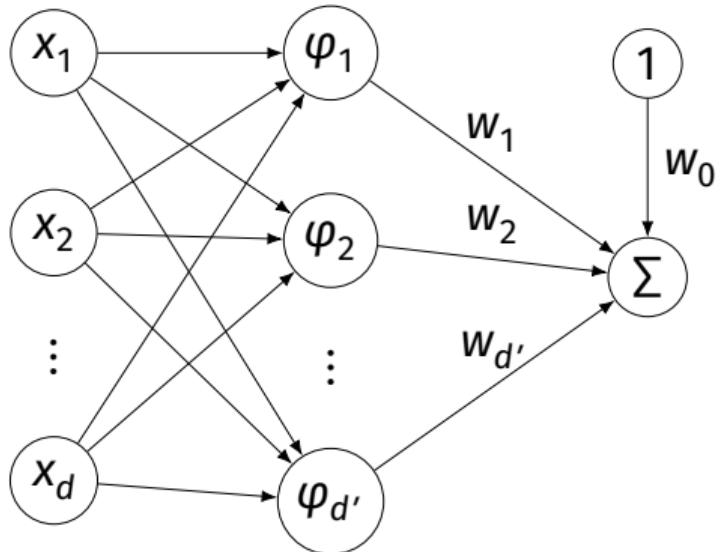
The Model

- The φ are **basis functions**.



$$H(\vec{x}) = w_0 + w_1\varphi_1(\vec{x}) + w_2\varphi_2(\vec{x})$$

Radial Basis Function Networks



If the basis functions are **radial basis functions**, we call this a **radial basis function (RBF) network**.

Training

- ▶ An RBF network has these parameters:
 - ▶ the parameters of each individual basis function:
 - ▶ $\vec{\mu}_i$ (the center)
 - ▶ possibly others (e.g., σ)
 - ▶ w_i : the weights associated to each “new” feature
- ▶ How do we choose the parameters?

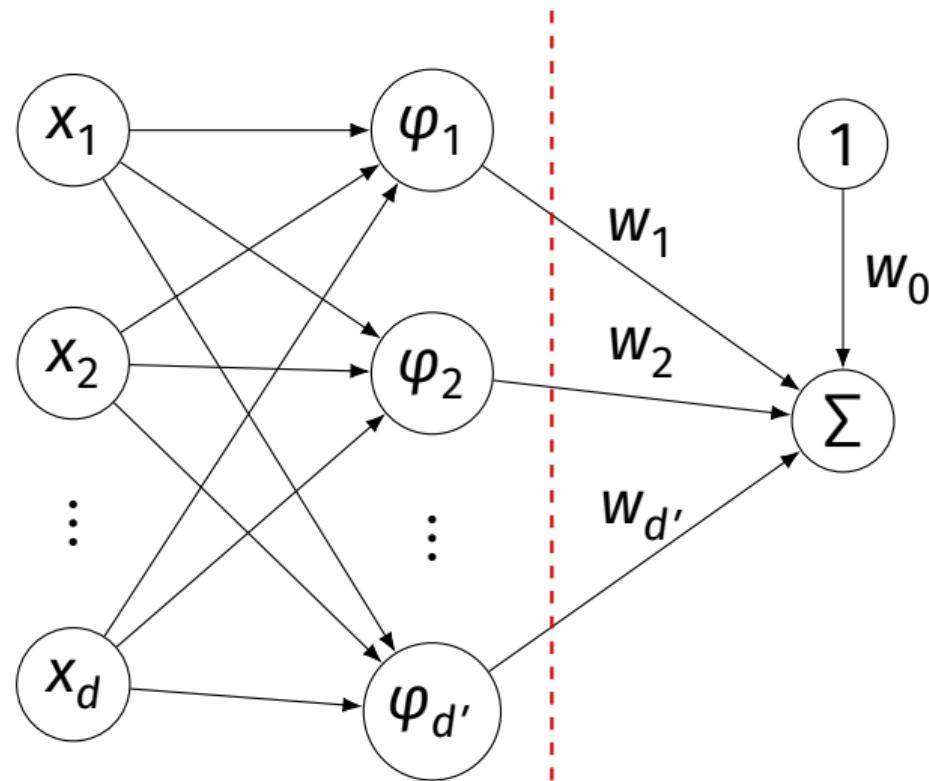
First Idea

- ▶ We can include all parameters in one big cost function, optimize.
- ▶ The cost function will generally be **complicated, non-convex** and thus **hard to optimize**.

Another Idea

- ▶ Break the process into two steps:
 1. Find the parameters of the RBFs *somewhat*.
 - ▶ Some optimization procedure, clustering, randomly, ...
 2. Having fixed those parameters, optimize the w 's.
- ▶ **Linear; easier to optimize.**

Training



Training an RBF Network

1. Choose the form of the RBF, how many.
 - ▶ E.g., k Gaussian RBFs, $\varphi_1, \dots, \varphi_k$.
2. Pick the parameters of the RBFs *somewhat*.
3. Create new data set by mapping
$$\vec{x} \mapsto (\varphi_1(\vec{x}), \dots, \varphi_k(\vec{x}))^T$$
4. Train a linear predictor H_f on new data set
 - ▶ That is, in feature space.

Making Predictions

1. Given a point \vec{x} , map it to feature space:
 $\vec{x} \mapsto (\varphi_1(\vec{x}), \dots, \varphi_k(\vec{x}))^T$
2. Evaluate the trained linear predictor H_f in feature space

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Representation Learning

Lecture 12 | Part 3

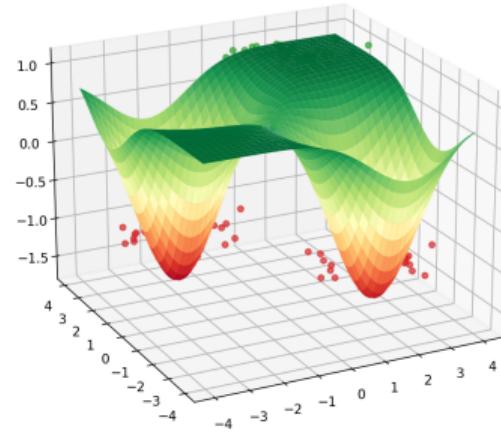
Choosing RBF Locations

Recap

- ▶ We map data to a new representation by first choosing **basis functions**.
- ▶ Radial Basis Functions (RBFs), such as Gaussians, are a popular choice.
- ▶ Requires choosing **center** for each basis function.

Prediction Function

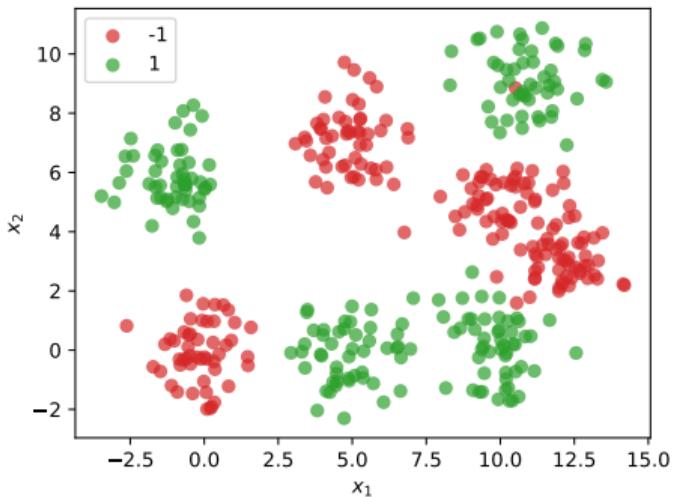
- ▶ Our prediction function H is a surface that is made up of Gaussian “bumps”.



$$H(\vec{x}) = w_0 + w_1 e^{-\|\vec{x} - \vec{\mu}_1\|^2 / \sigma^2} + w_2 e^{-\|\vec{x} - \vec{\mu}_2\|^2 / \sigma^2}$$

Choosing Centers

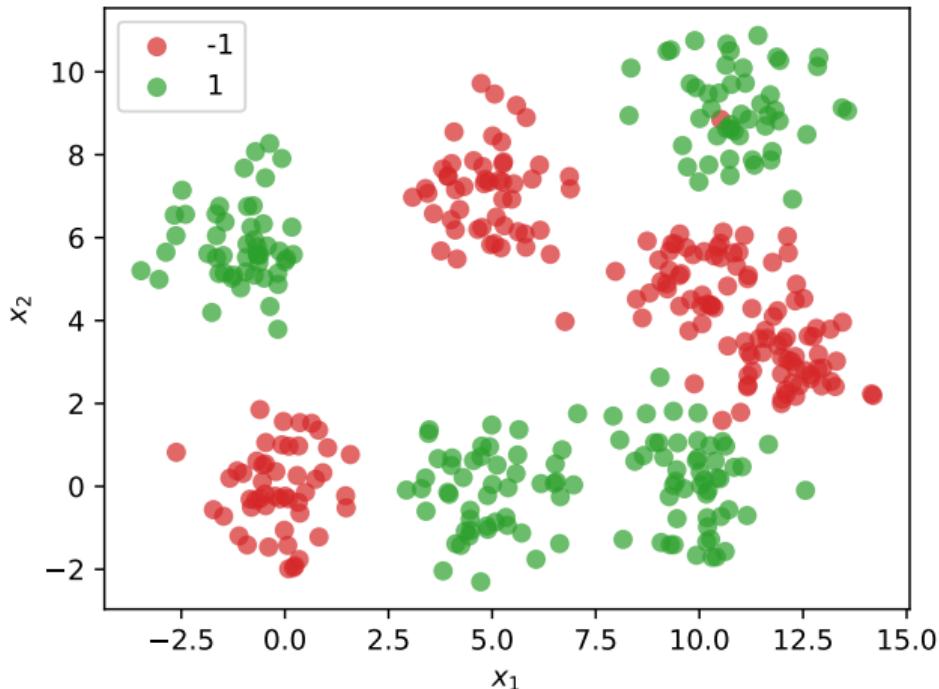
- ▶ Place the centers where the value of the prediction function should be controlled.
- ▶ Intuitively: place centers where the data is.



Approaches

1. Every data point as a center
2. Randomly choose centers
3. Clustering

Approach #1: Every Data Point as a Center



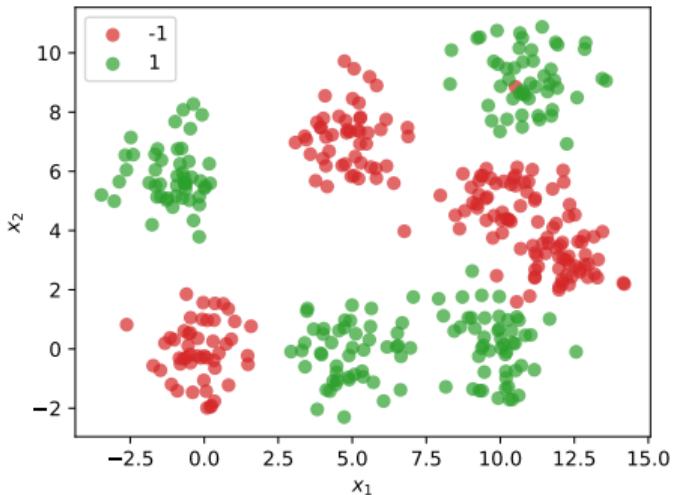
Dimensionality

- ▶ We'll have n basis functions – one for each point.
- ▶ That means we'll have n features.
- ▶ Each feature vector $\vec{\phi}(\vec{x}) \in \mathbb{R}^n$.

$$\vec{\phi}(\vec{x}) = (\phi_1(\vec{x}), \phi_2(\vec{x}), \dots, \phi_n(\vec{x}))^T$$

Problems

- ▶ This causes problems.
- ▶ First: more likely to **overfit**.
- ▶ Second: computationally expensive

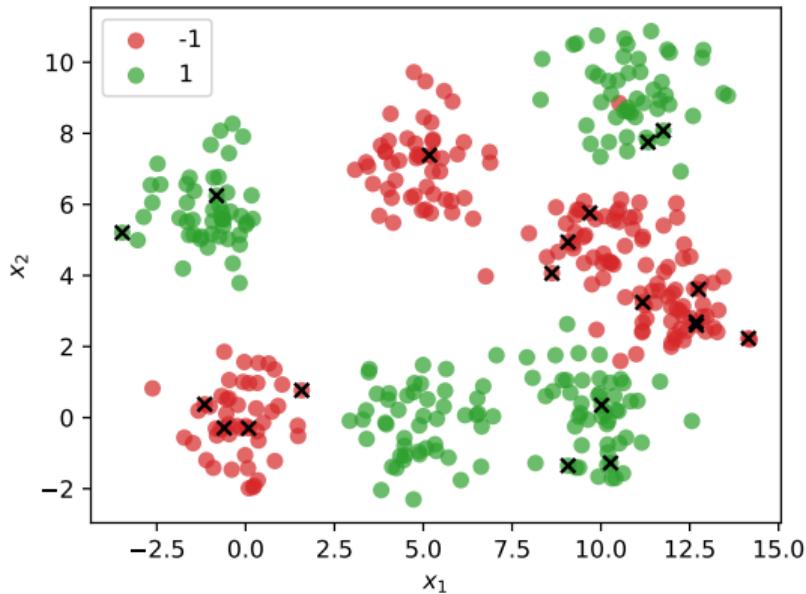


Computational Cost

- ▶ Suppose feature matrix X is $n \times d$
 - ▶ n points in d dimensions
- ▶ Time complexity of solving $X^T X \vec{w} = X^T \vec{y}$ is $\Theta(nd^2)$
- ▶ Usually $d \ll n$. But if $d = n$, this is $\Theta(n^3)$.
- ▶ Not great! If $n \approx 10,000$, then takes > 10 minutes.

Approach #2: A Random Sample

- Idea: randomly choose k data points as centers.



Problem

- ▶ May undersample/oversample a region.
- ▶ More advanced sampling approaches exist.

Approach #3: Clustering

- ▶ Group data points into **clusters**.
- ▶ Cluster centers are good places for RBFs.
- ▶ For example, use k -means clustering to pick k centers.

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Representation Learning

Lecture 12 | Part 4

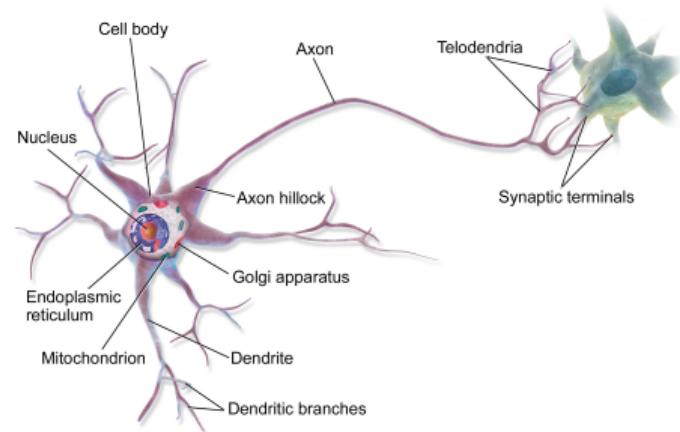
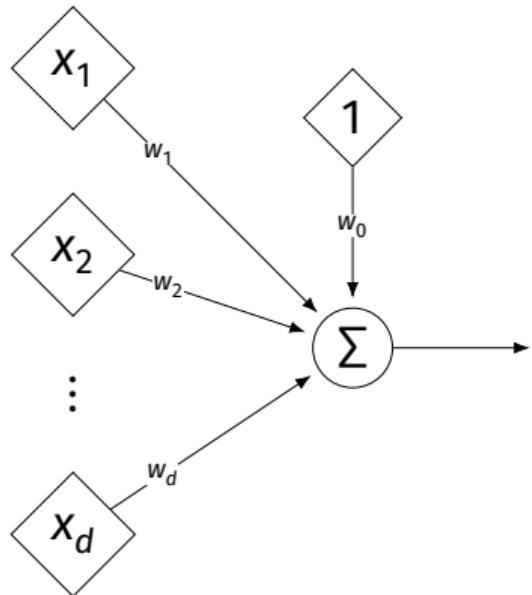
Neural Networks

Beyond RBFs

- ▶ When training RBFs, we fixed the basis functions *before* training the weights.
- ▶ Representation learning was decoupled from learning the prediction function.
- ▶ **Now:** learn representation **and** prediction function together.

Linear Models

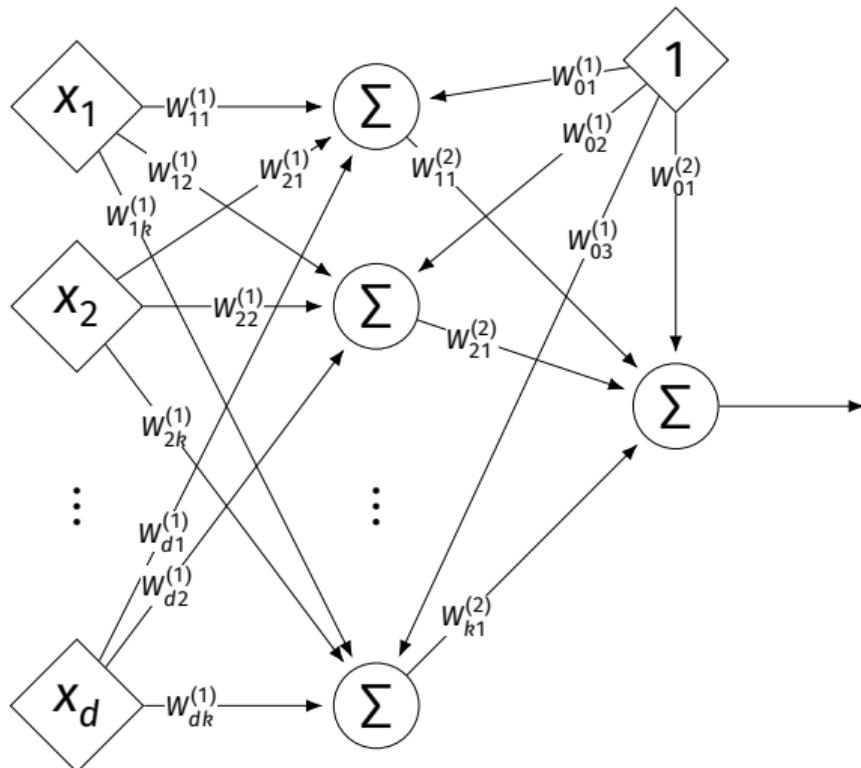
$$H(\vec{x}) = w_0 + w_1x_1 + \dots + w_dx_d$$



Generalizing Linear Models

- ▶ The brain is a **network** of neurons.
- ▶ The output of a neuron is used as an input to another.
- ▶ **Idea:** chain together multiple “neurons” into a **neural network**.

Neural Network¹ (One Hidden Layer)



¹Specifically, a fully-connected, feed-forward neural network

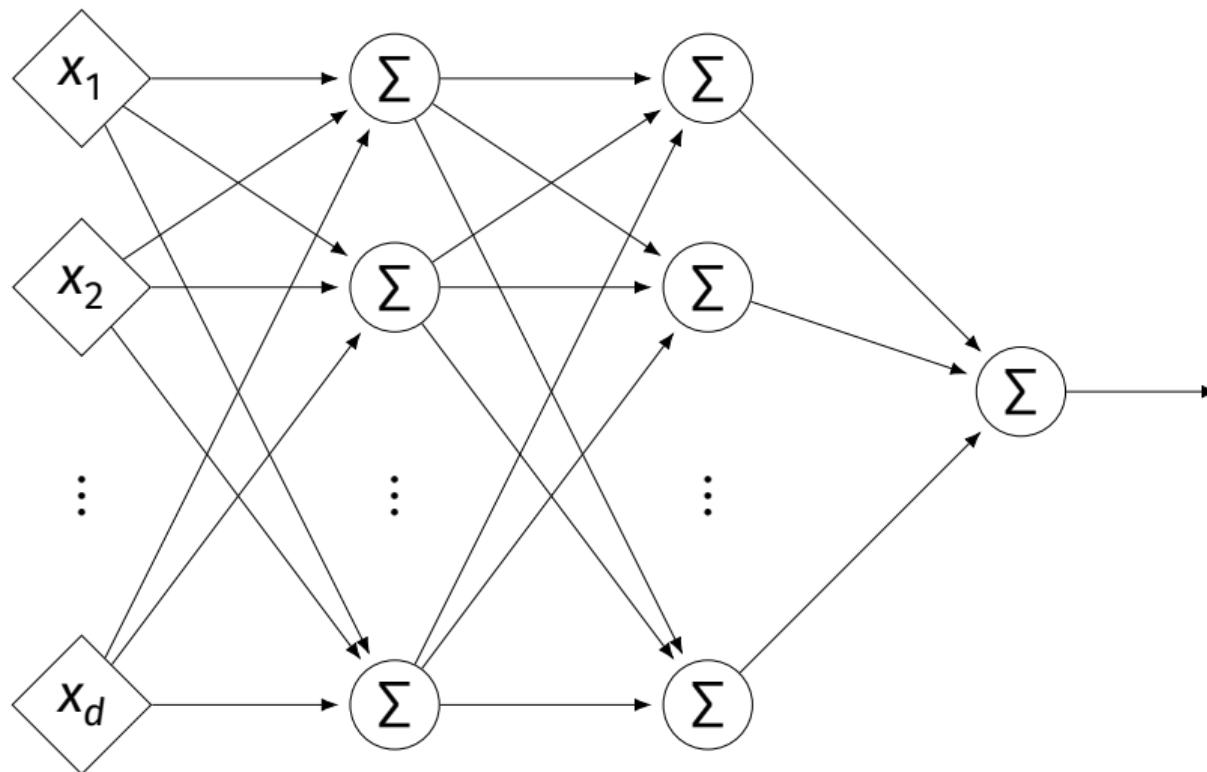
Architecture

- ▶ Neurons are organized into **layers**.
 - ▶ **Input layer**, **output layer**, and **hidden layers**.
- ▶ Number of cells in input layer determined by dimensionality of input feature vectors.
- ▶ Number of cells in hidden layer(s) is determined by you.
- ▶ Output layer can have >1 neuron.

Architecture

- ▶ Can have more than one hidden layer.
 - ▶ A network is “**deep**” if it has >1 hidden layer.
- ▶ Hidden layers can have different number of neurons.

Neural Network (Two Hidden Layers)

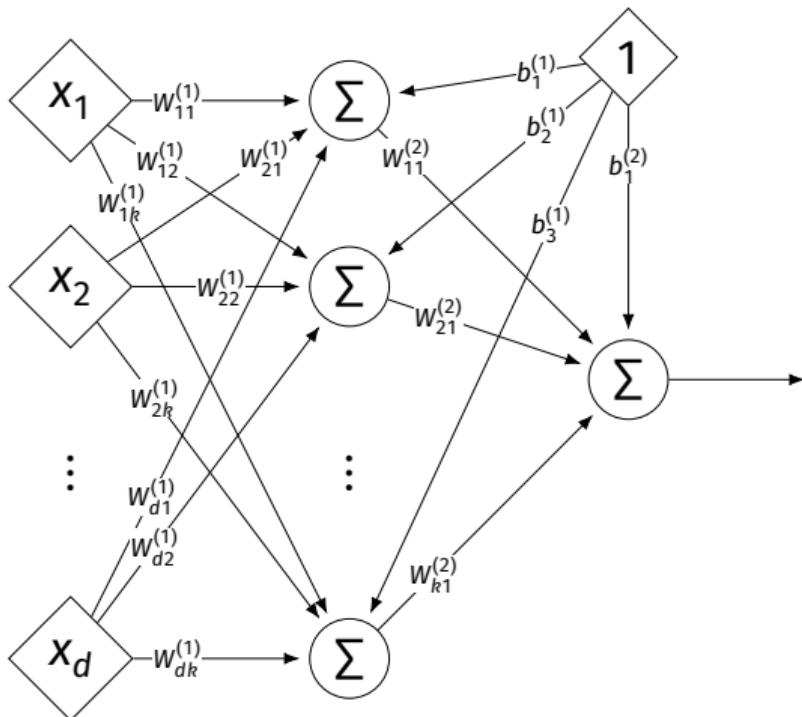


Network Weights

- ▶ A neural network is a type of function.
- ▶ Like a linear model, a NN is **totally determined** by its weights.
- ▶ But there are often many more weights to learn!

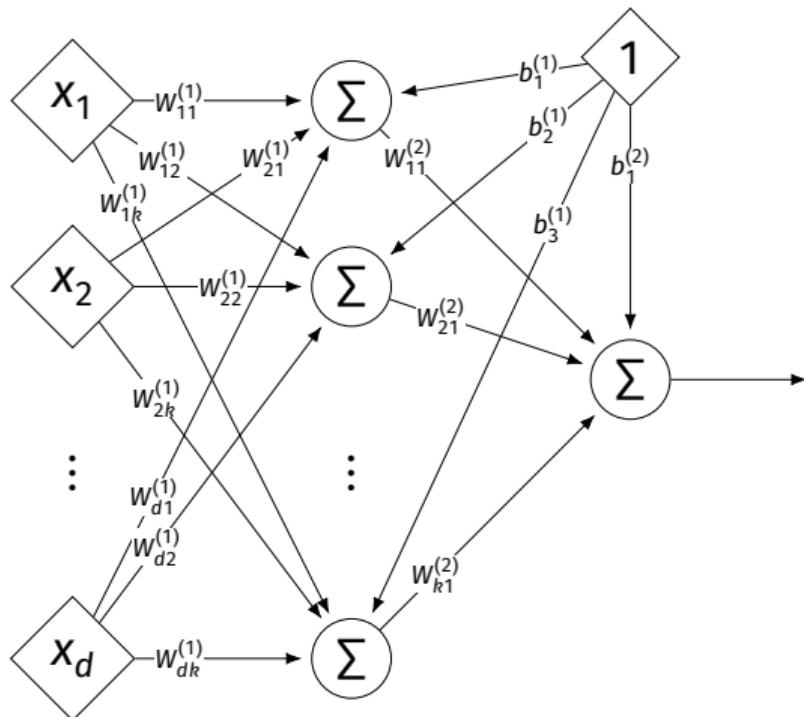
Notation

- ▶ Input is layer #0.
- ▶ $W_{jk}^{(i)}$ denotes weight of connection between neuron j in layer $(i - 1)$ and neuron k in layer i
- ▶ Layer weights are 2-d arrays.



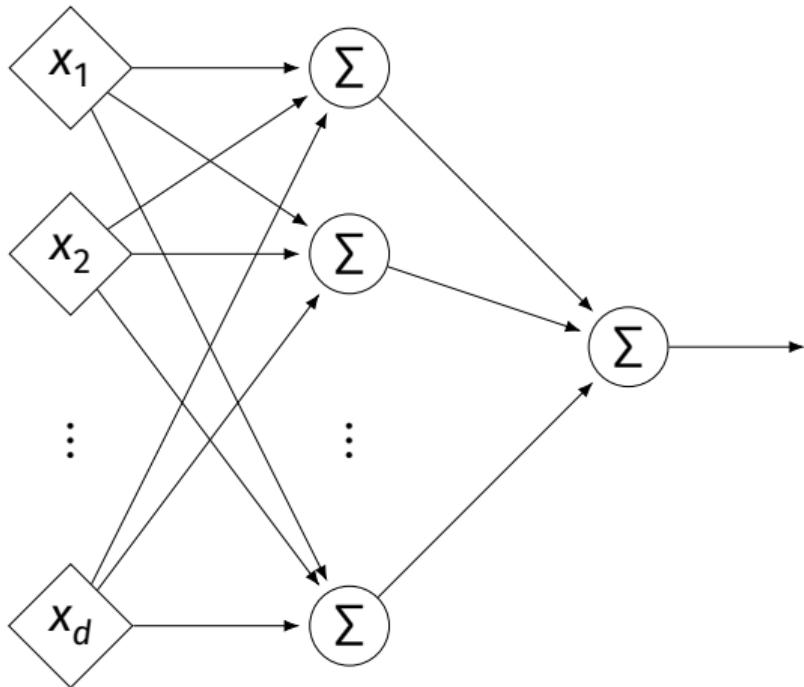
Notation

- ▶ Each hidden/output neuron gets a “dummy” input of 1.
- ▶ j th node in i th layer assigned a bias weight of $b_j^{(i)}$
- ▶ Biases for layer are a vector: $\vec{b}^{(i)}$

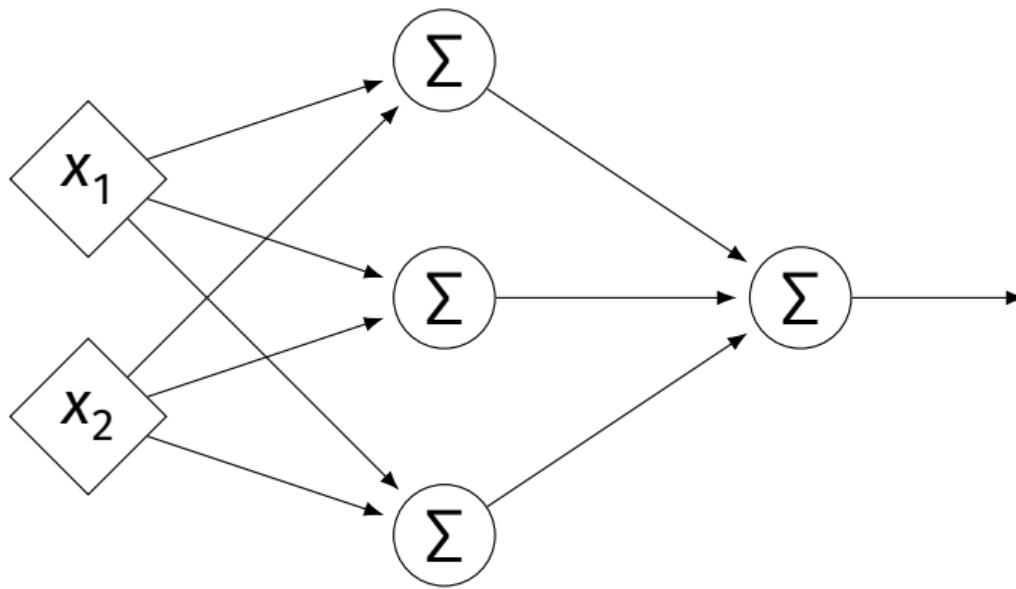


Notation

- ▶ Typically, we will not draw the weights.
- ▶ We will not draw the dummy input, too, but it is there.



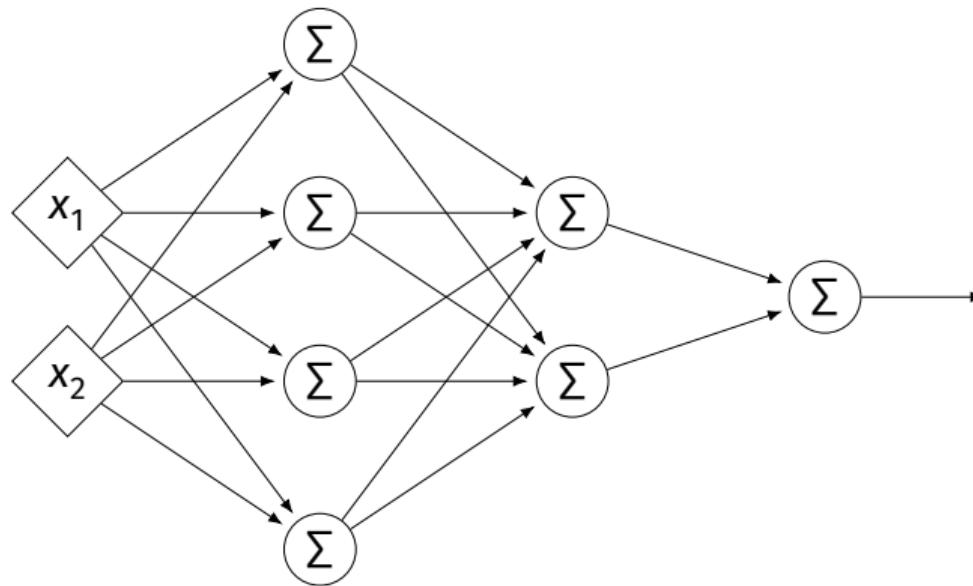
Example



$$W^{(1)} = \begin{pmatrix} 2 & -1 & 0 \\ 4 & 5 & 2 \end{pmatrix} \quad W^{(2)} = \begin{pmatrix} 3 \\ 2 \\ -4 \end{pmatrix}$$

$$\vec{b}^{(1)} = (3, -2, -2)^T \quad \vec{b}^{(2)} = (-4)^T$$

Example



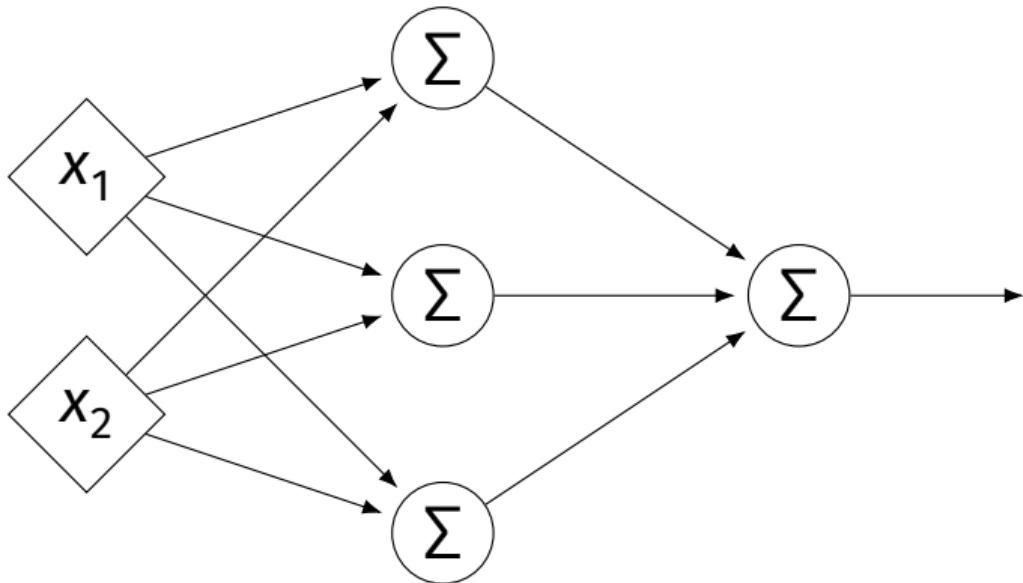
$$W^{(1)} = \begin{pmatrix} 2 & -1 & -3 & 0 \\ 4 & 5 & -7 & 2 \end{pmatrix} \quad W^{(2)} = \begin{pmatrix} 1 & 2 \\ -4 & 3 \\ -6 & -2 \\ 3 & 4 \end{pmatrix} \quad W^{(3)} = \begin{pmatrix} -1 & 5 \end{pmatrix}$$

$$\vec{b}^{(1)} = (3, 6, -2, -2)^T \quad \vec{b}^{(2)} = (-4, 0)^T \quad \vec{b}^{(3)} = (1)^T$$

Evaluation

- ▶ These are “**fully-connected, feed-forward**” networks with one output.
- ▶ They are functions $H(\vec{x}) : \mathbb{R}^d \rightarrow \mathbb{R}^1$
- ▶ To evaluate $H(\vec{x})$, compute result of layer i , use as inputs for layer $i + 1$.

Example



► $\vec{x} = (3, -1)^T$

► $z_1^{(1)} =$

► $z_2^{(1)} =$

► $z_3^{(1)} =$

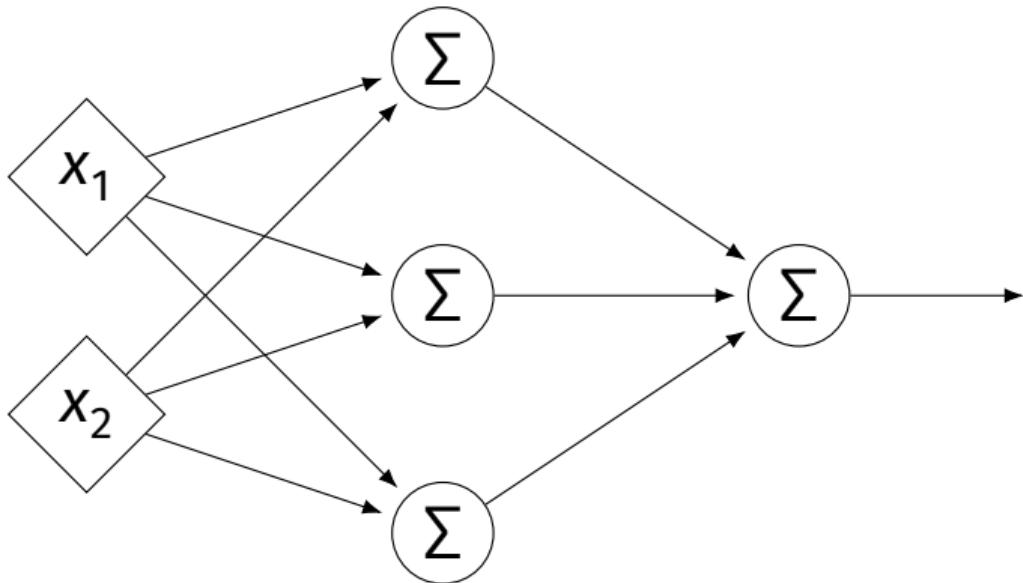
► $z_1^{(2)} =$

$$W^{(1)} = \begin{pmatrix} 2 & -1 & 0 \\ 4 & 5 & 2 \end{pmatrix} \quad W^{(2)} = \begin{pmatrix} 3 \\ 2 \\ -4 \end{pmatrix} \quad \vec{b}^{(1)} = (3, -2, -2)^T \quad \vec{b}^{(2)} = (-4)^T$$

Evaluation as Matrix Multiplication

- ▶ Let $z_j^{(i)}$ be the output of node j in layer i .
- ▶ Make a vector of these outputs: $\vec{z}^{(i)} = (z_1^{(i)}, z_2^{(i)}, \dots)^T$
- ▶ Observe that $\vec{z}^{(i)} = [W^{(i)}]^T \vec{z}^{(i-1)} + \vec{b}^{(i)}$

Example



► $\vec{x} = (3, -1)^T$

► $z_1^{(1)} =$

► $z_2^{(1)} =$

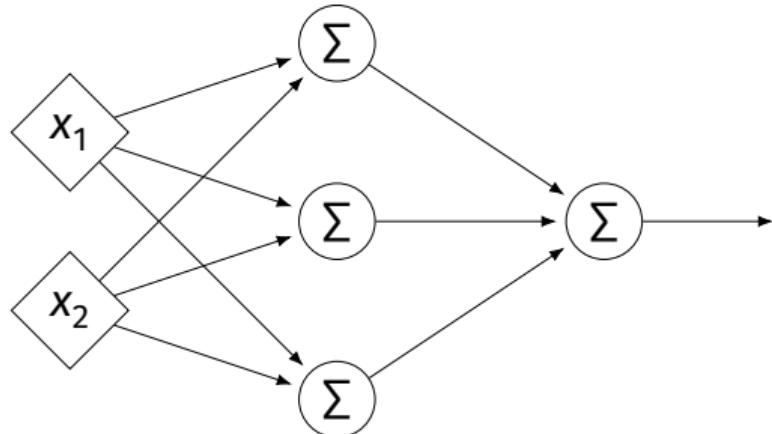
► $z_3^{(1)} =$

► $z_1^{(2)} =$

$$W^{(1)} = \begin{pmatrix} 2 & -1 & 0 \\ 4 & 5 & 2 \end{pmatrix} \quad W^{(2)} = \begin{pmatrix} 3 \\ 2 \\ -4 \end{pmatrix} \quad \vec{b}^{(1)} = (3, -2, -2)^T \quad \vec{b}^{(2)} = (-4)^T$$

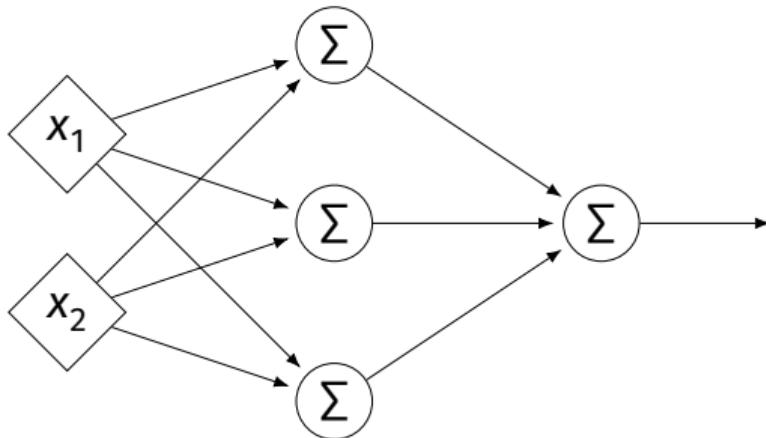
Each Layer is a Function

- ▶ We can think of each layer as a function mapping a vector to a vector.
- ▶ $H^{(1)}(\vec{z}) = [W^{(1)}]^T \vec{z} + \vec{b}^{(1)}$
 - ▶ $H^{(1)} : \mathbb{R}^2 \rightarrow \mathbb{R}^3$
- ▶ $H^{(2)}(\vec{z}) = [W^{(2)}]^T \vec{z} + \vec{b}^{(2)}$
 - ▶ $H^{(2)} : \mathbb{R}^3 \rightarrow \mathbb{R}^1$



NNs as Function Composition

- The full NN is a composition of layer functions.



$$H(\vec{x}) = H^{(2)}(H^{(1)}(\vec{x})) = \underbrace{\left[W^{(2)} \right]^T \left(\left[W^{(1)} \right]^T \vec{x} + \vec{b}^{(1)} \right) + \vec{b}^{(2)}}_{\vec{z}^{(1)}}$$

NNs as Function Composition

- ▶ In general, if there k hidden layers:

$$H(\vec{x}) = H^{(k+1)} \left(\dots H^{(3)} \left(H^{(2)} \left(H^{(1)}(\vec{x}) \right) \right) \dots \right)$$

Exercise

Show that:

$$H(\vec{x}) = [W^{(2)}]^T \left([W^{(1)}]^T \vec{x} + \vec{b}^{(1)} \right) + \vec{b}^{(2)} = \vec{w} \cdot \text{Aug}(\vec{x})$$

for some appropriately-defined vector \vec{w} .

Result

- ▶ The composition of linear functions is again a linear function.
- ▶ The NNs we have seen so far are all equivalent to linear models!
- ▶ For NNs to be more useful, we will need to add **non-linearity**.

Activations

- ▶ So far, the output of a neuron has been a linear function of its inputs:

$$w_0 + w_1 x_1 + w_2 x_2 + \dots$$

- ▶ Can be arbitrarily large or small.
- ▶ But real neurons are **activated** non-linearly.
 - ▶ E.g., saturation.

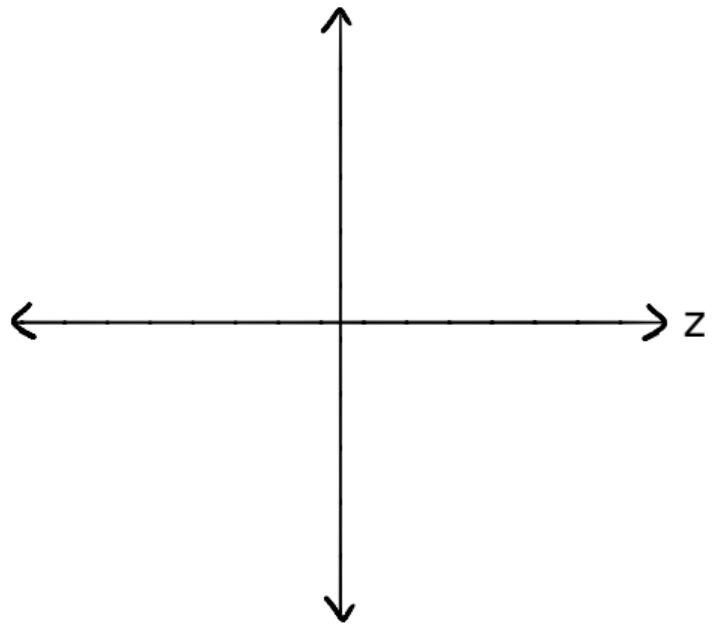
Idea

- ▶ To add nonlinearity, we will apply a non-linear **activation function** g to the output of **each** hidden neuron (and sometimes the output neuron).

Linear Activation

- ▶ The **linear** activation is what we've been using.

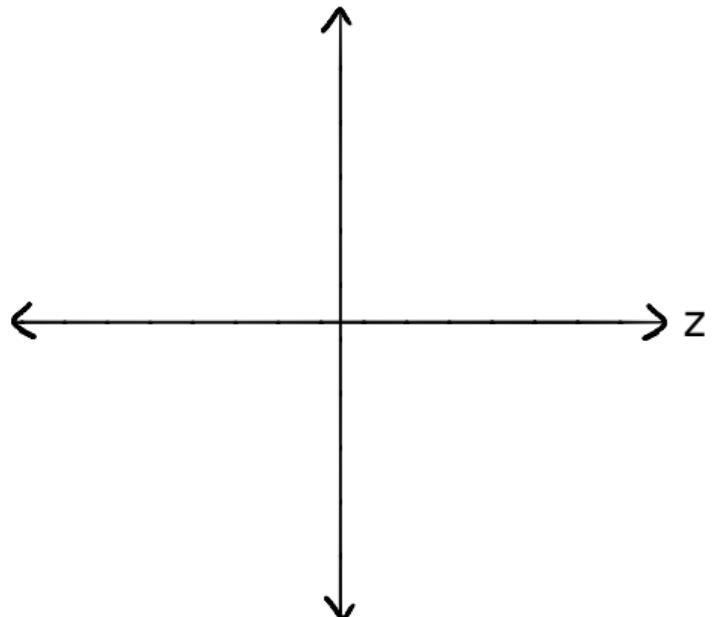
$$\sigma(z) = z$$



Sigmoid Activation

- The **sigmoid** models saturation in many natural processes.

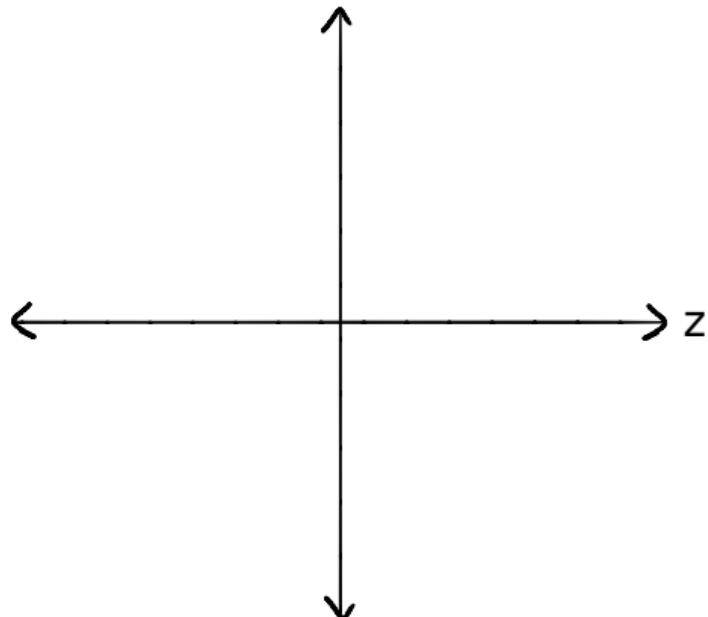
$$\sigma(z) = \frac{1}{1 + e^{-z}}$$



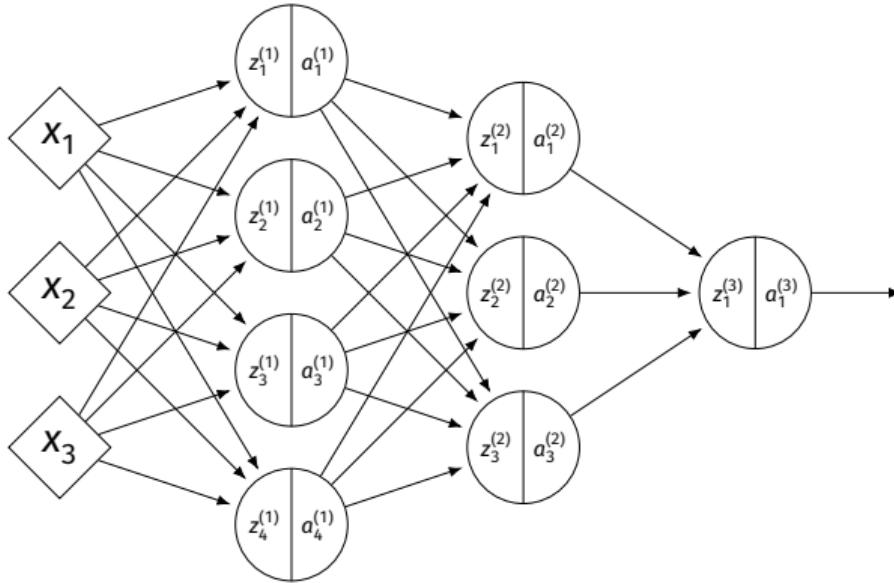
ReLU Activation

- The **Rectified Linear Unit (ReLU)** tends to work better in practice.

$$g(z) = \max\{0, z\}$$

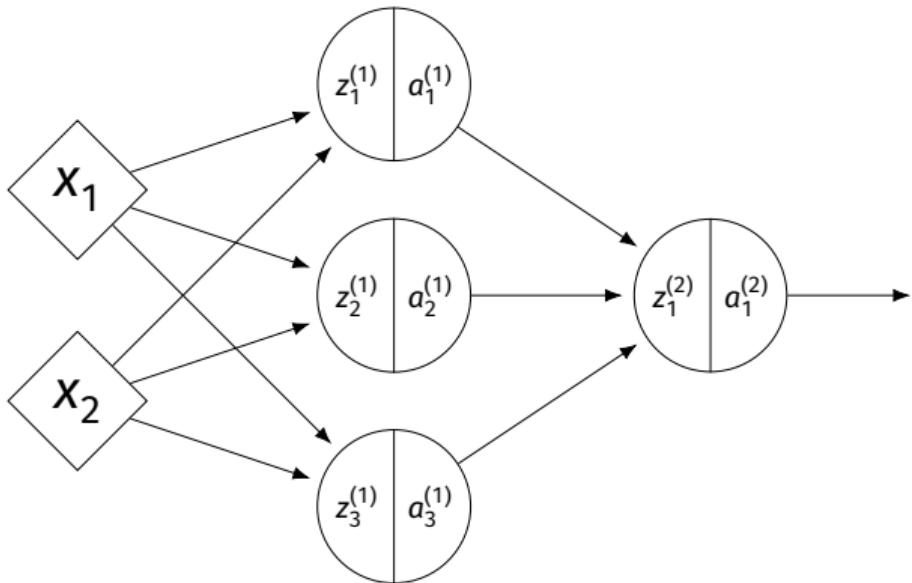


Notation



- ▶ $z_j^{(i)}$ is the linear activation before g is applied.
- ▶ $a_j^{(i)} = g(z_j^{(i)})$ is the actual output of the neuron.

Example



- ▶ $g = \text{ReLU}$
- ▶ Linear output
- ▶ $\vec{x} = (3, -1)^T$
- ▶ $z_1^{(1)} =$
- ▶ $a_1^{(1)} =$
- ▶ $z_2^{(1)} =$
- ▶ $a_2^{(1)} =$
- ▶ $z_3^{(1)} =$
- ▶ $a_3^{(1)} =$
- ▶ $z_1^{(2)} =$

$$W^{(1)} = \begin{pmatrix} 2 & -1 & 0 \\ 4 & 5 & 2 \end{pmatrix} \quad W^{(2)} = \begin{pmatrix} 3 \\ 2 \\ -4 \end{pmatrix} \quad \vec{b}^{(1)} = (3, -2, -2)^T \quad \vec{b}^{(2)} = (-4)^T$$

Output Activations

- ▶ The activation of the output neuron(s) can be different than the activation of the hidden neurons.
- ▶ In classification, **sigmoid** activation makes sense.
- ▶ In regression, **linear** activation makes sense.

Main Idea

A neural network with linear activations is a linear model. If non-linear activations are used, the model is made non-linear.

DSC 140B

Representation Learning

Lecture 12 | Part 5

[Demo](#)

Feature Map

- ▶ We have seen how to fit non-linear patterns with linear models via **basis functions** (i.e., a feature map).

$$H(\vec{x}) = w_0 + w_1\phi_1(\vec{x}) + \dots + w_k\phi_k(\vec{x})$$

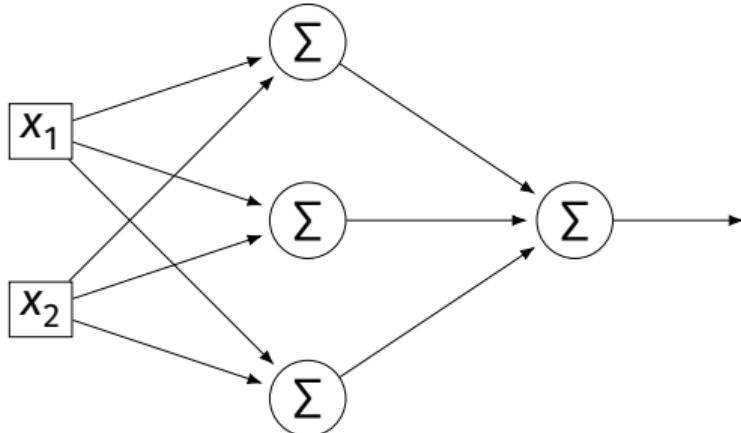
- ▶ These basis functions are fixed **before** learning.
- ▶ **Downside:** we have to choose $\vec{\phi}$ somehow.

Learning a Feature Map

- ▶ **Interpretation:** The hidden layers of a neural network **learn** a feature map.

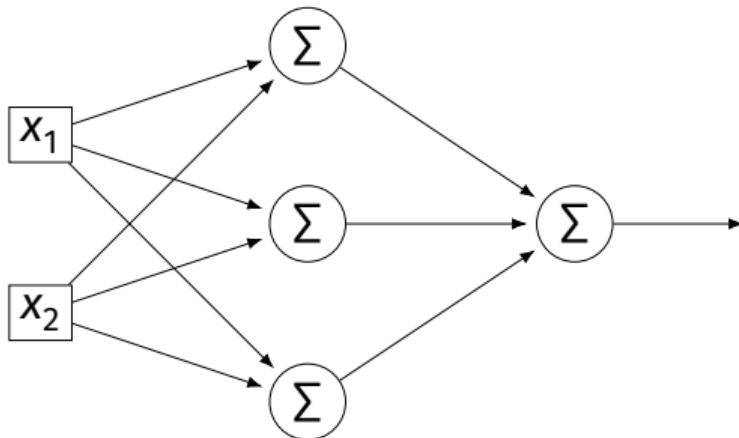
Each Layer is a Function

- ▶ We can think of each layer as a function mapping a vector to a vector.
- ▶ $H^{(1)}(\vec{z}) = [W^{(1)}]^T \vec{z} + \vec{b}^{(1)}$
 - ▶ $H^{(1)} : \mathbb{R}^2 \rightarrow \mathbb{R}^3$
- ▶ $H^{(2)}(\vec{z}) = [W^{(2)}]^T \vec{z} + \vec{b}^{(2)}$
 - ▶ $H^{(2)} : \mathbb{R}^3 \rightarrow \mathbb{R}^1$



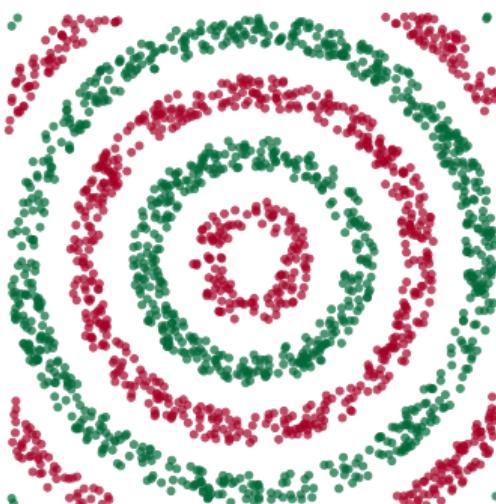
Each Layer is a Function

- ▶ The hidden layer performs a feature map from \mathbb{R}^2 to \mathbb{R}^3 .
- ▶ The output layer makes a prediction in \mathbb{R}^3 .
- ▶ **Intuition:** The feature map is learned so as to make the output layer's job “easier”.



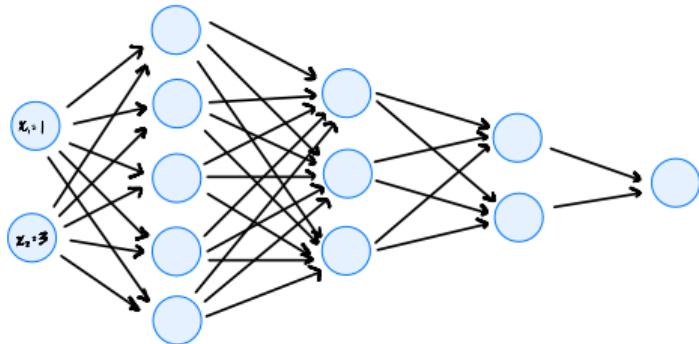
Demo

- ▶ Train a deep network to classify the data below.
- ▶ Hidden layers will learn a new feature map that makes the data linearly separable.

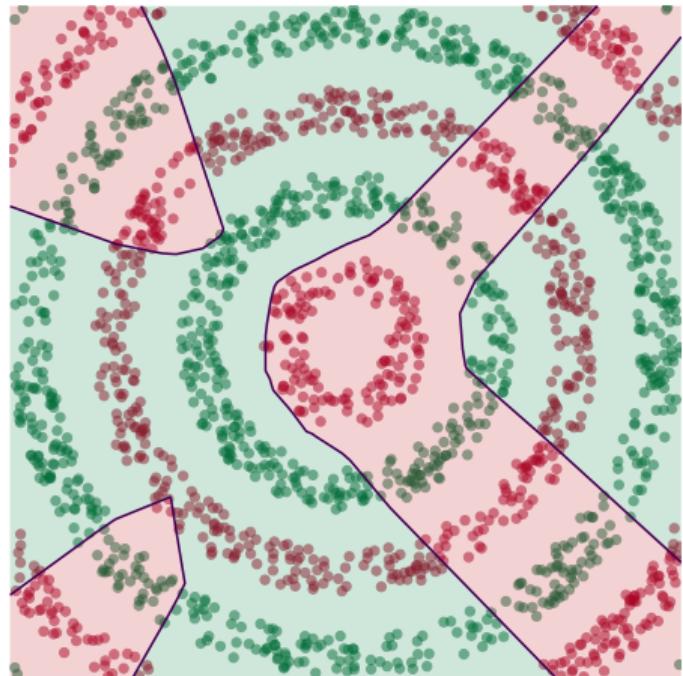


Demo

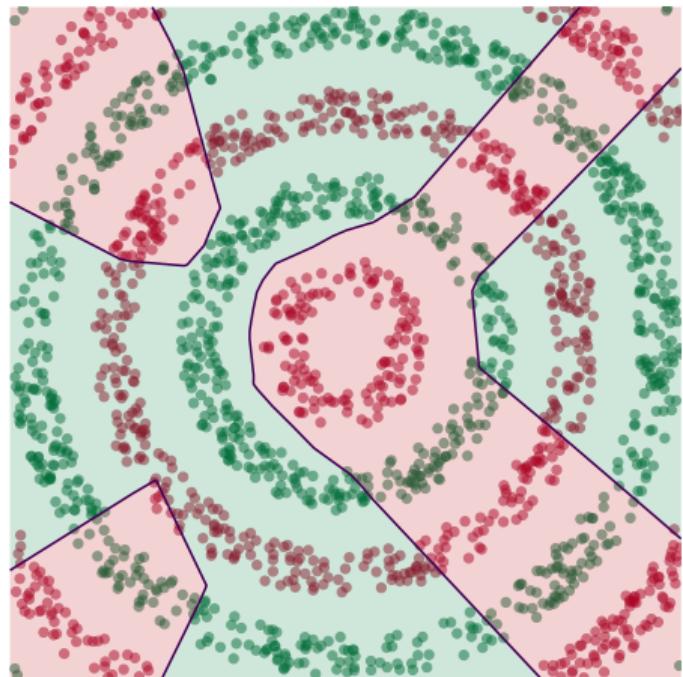
- ▶ We'll use three hidden layers, with last having two neurons.
- ▶ We can see this new representation!
- ▶ Plug in \vec{x} and see activations of last hidden layer.



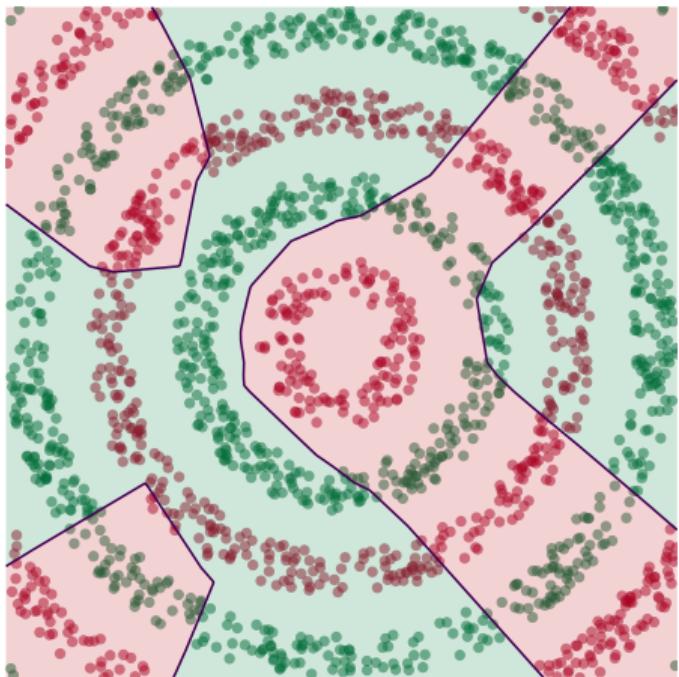
Learning a New Representation



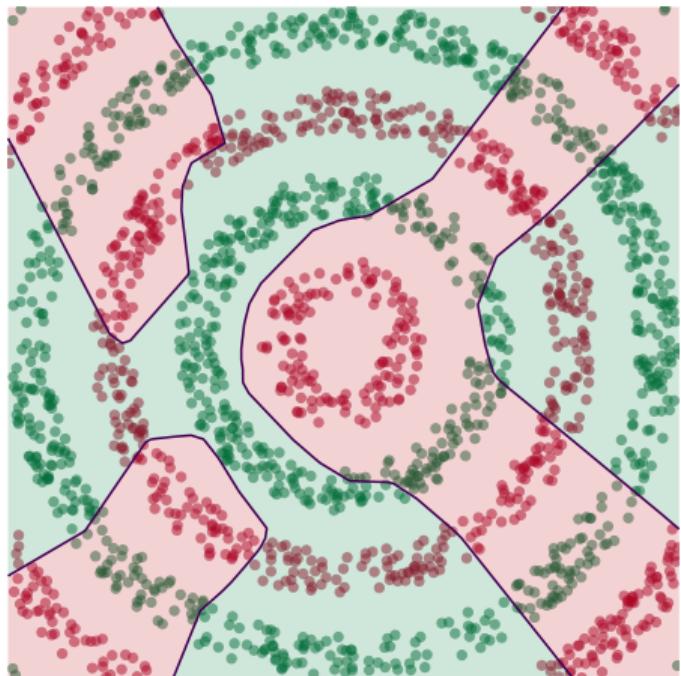
Learning a New Representation



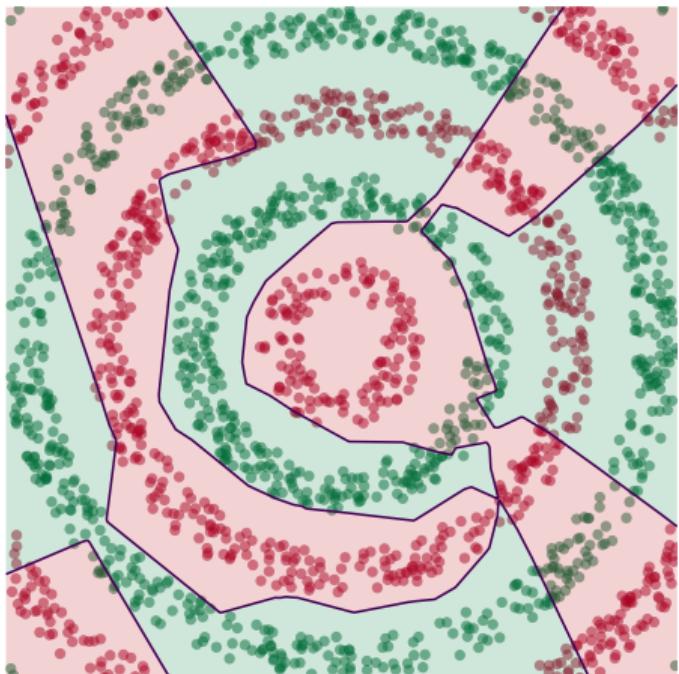
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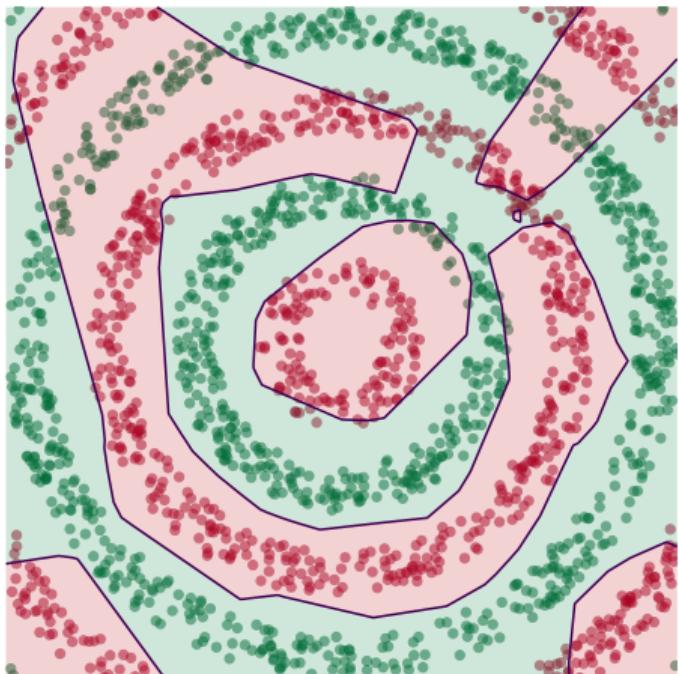
Learning a New Representation



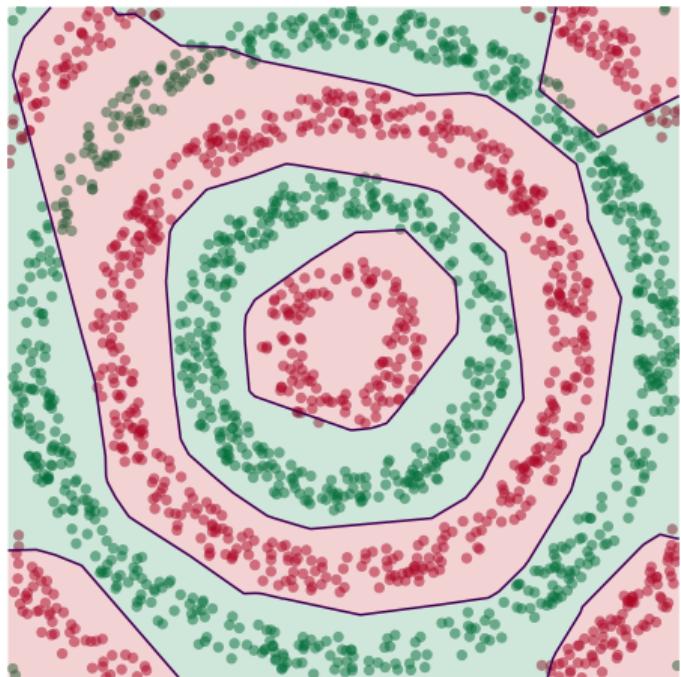
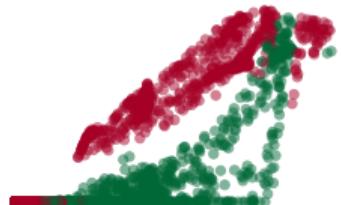
Learning a New Representation



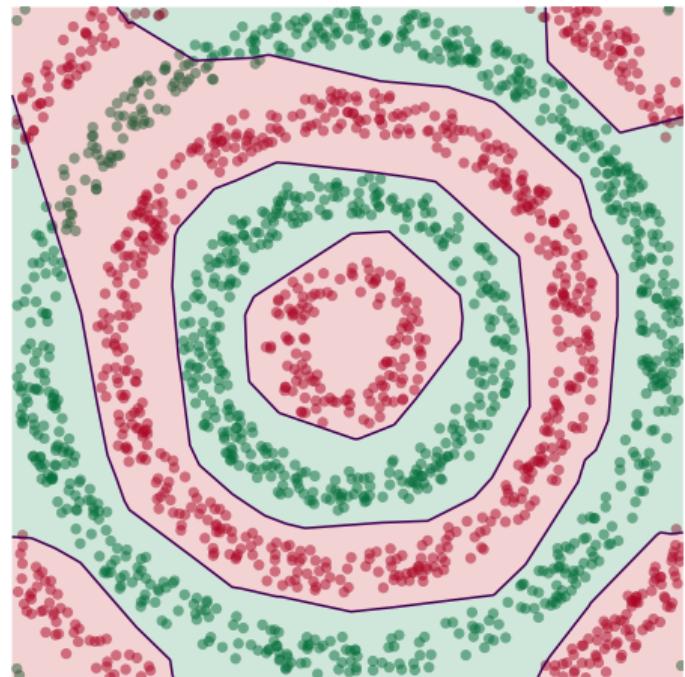
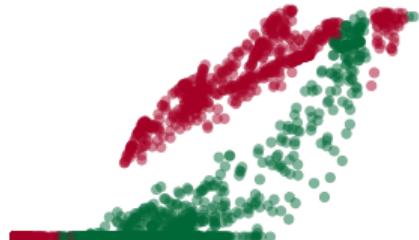
Learning a New Representation



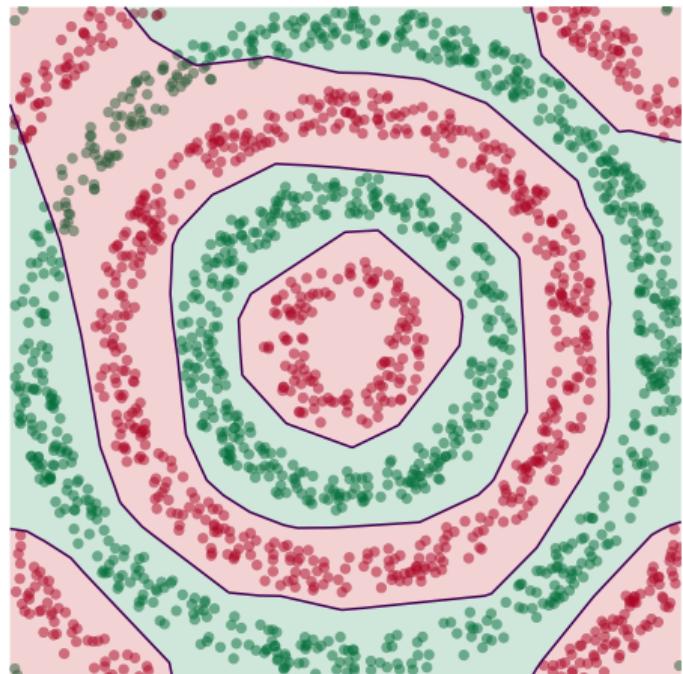
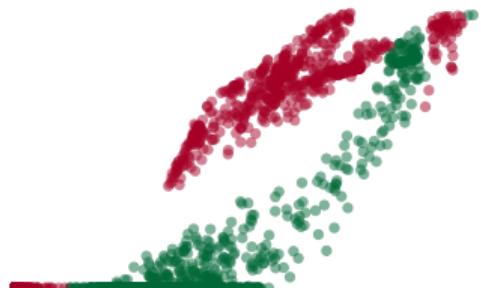
Learning a New Representation



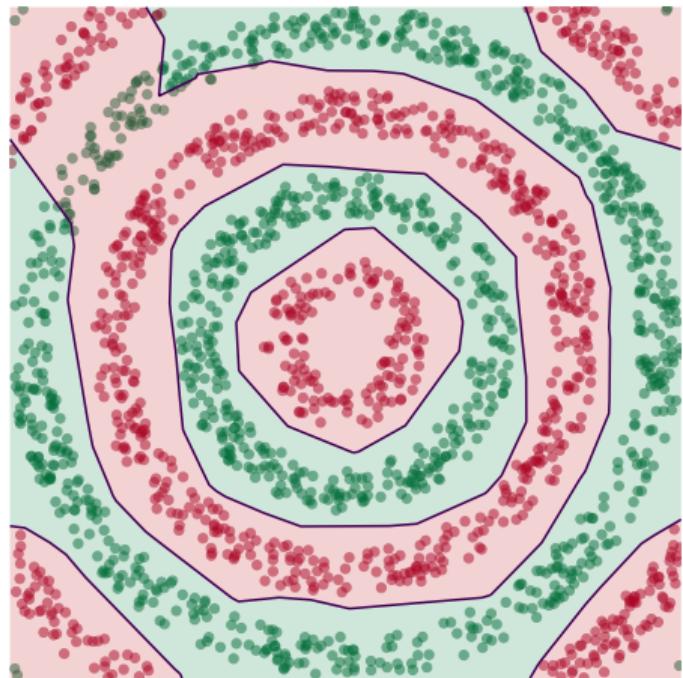
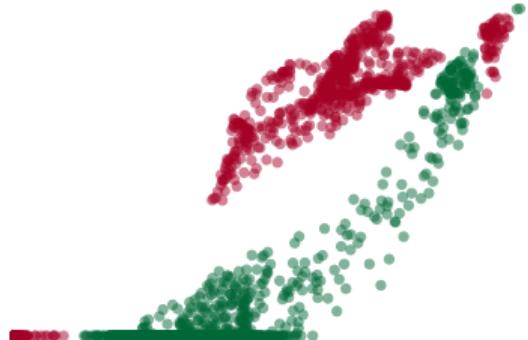
Learning a New Representation



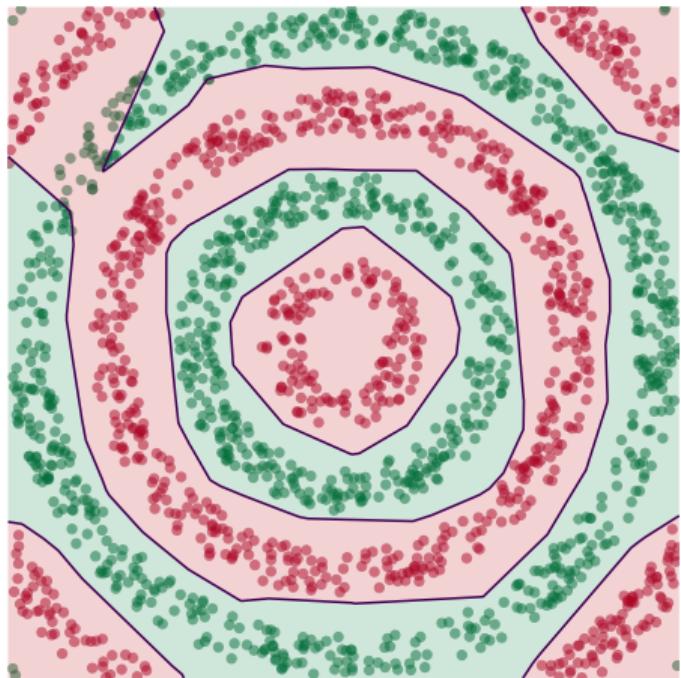
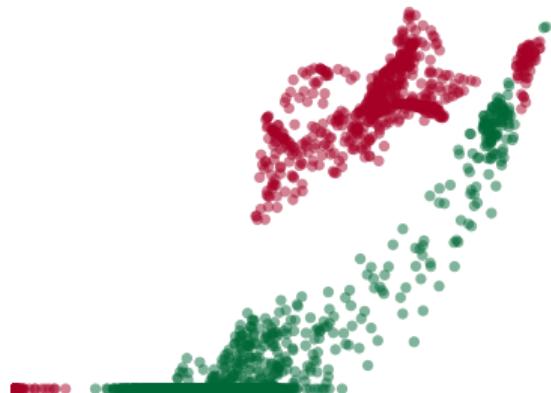
Learning a New Representation



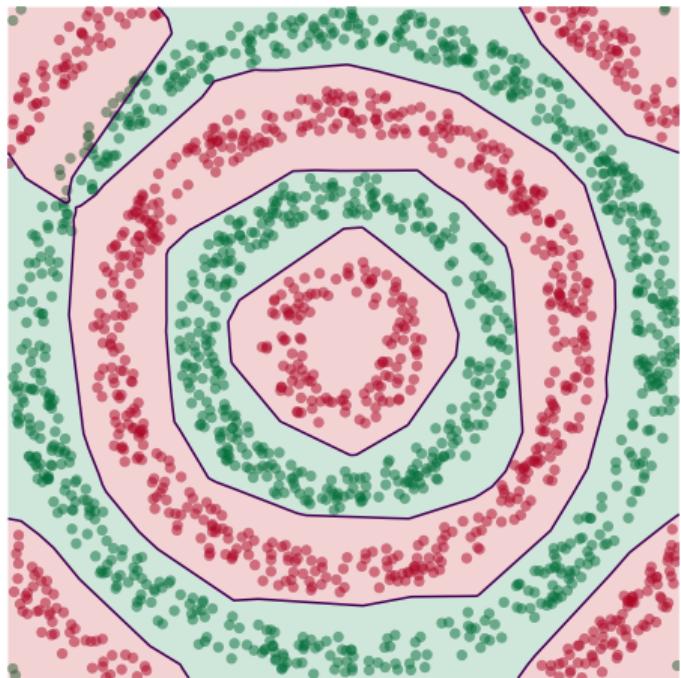
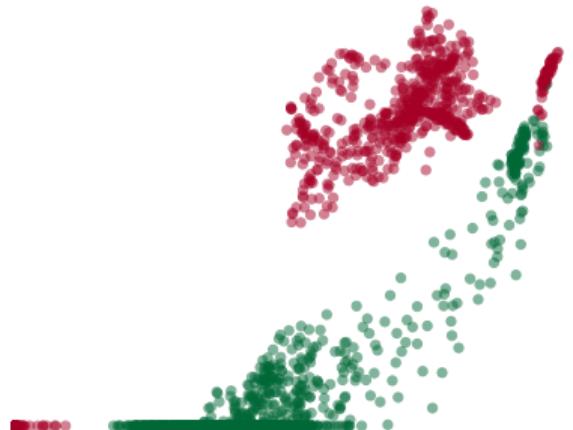
Learning a New Representation



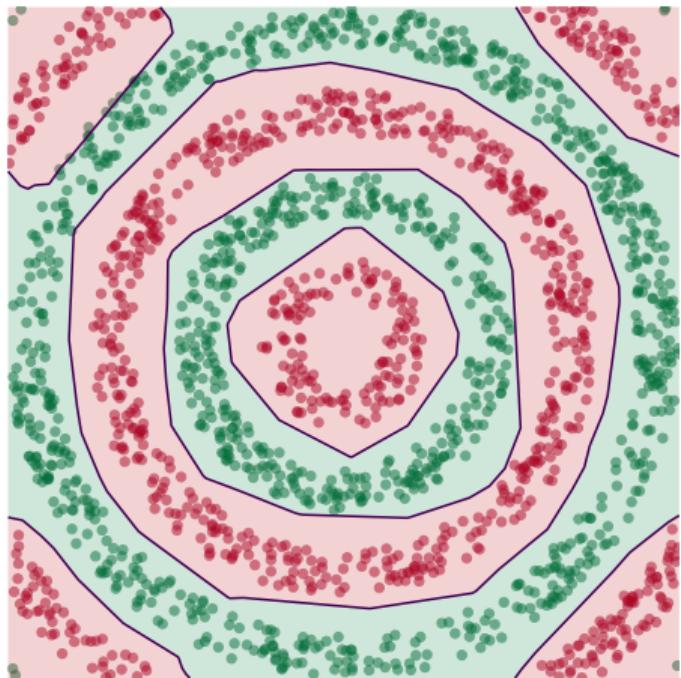
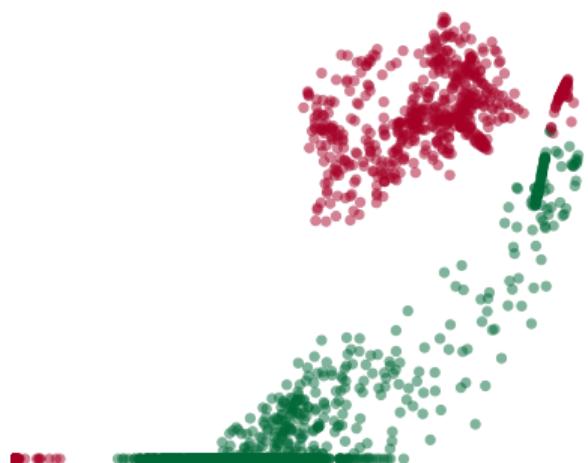
Learning a New Representation



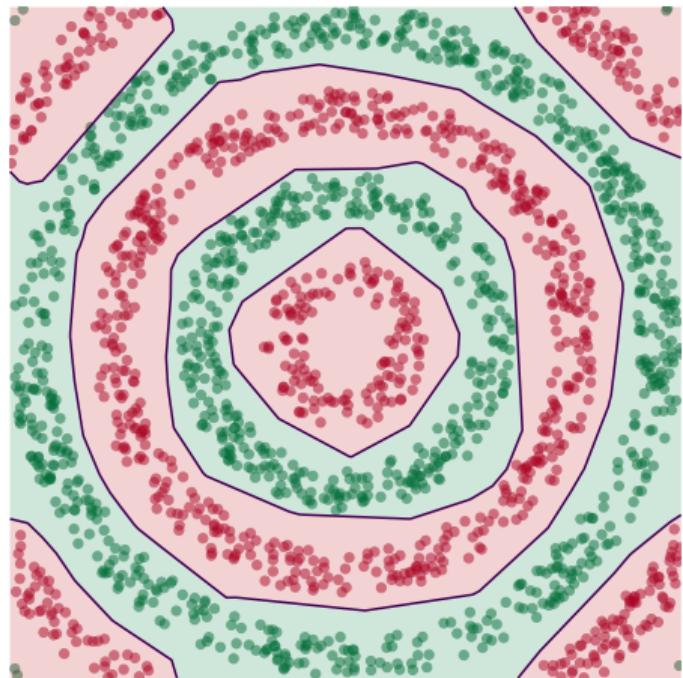
Learning a New Representation



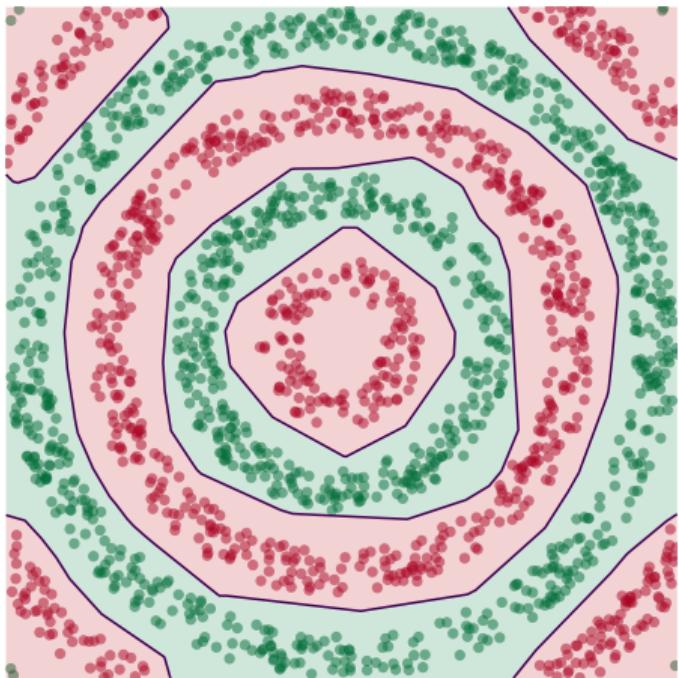
Learning a New Representation



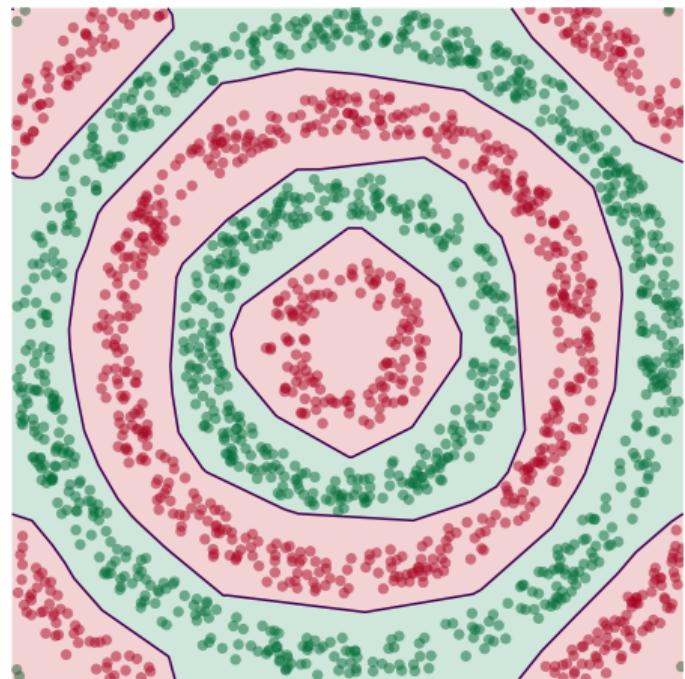
Learning a New Representation



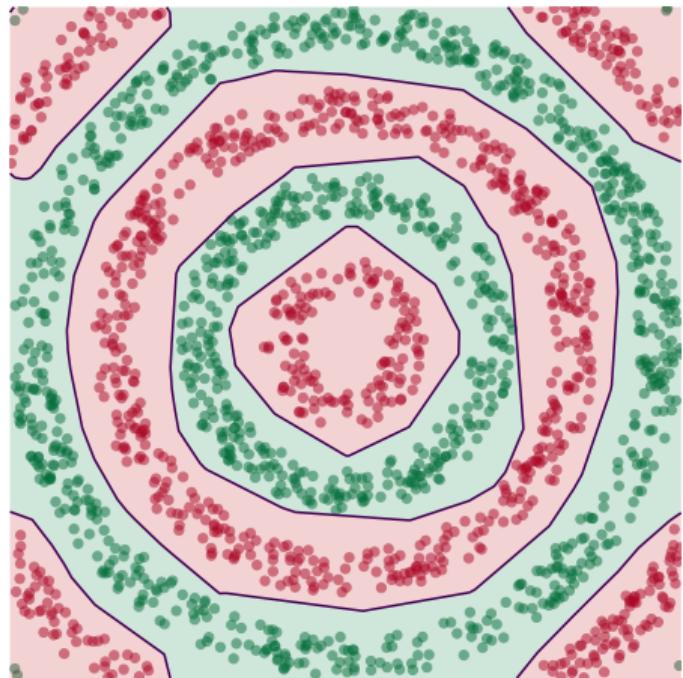
Learning a New Representation



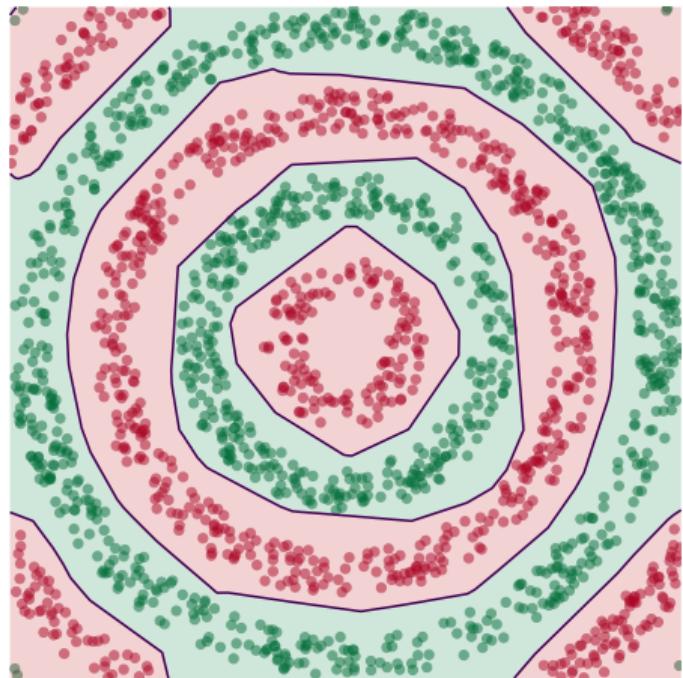
Learning a New Representation



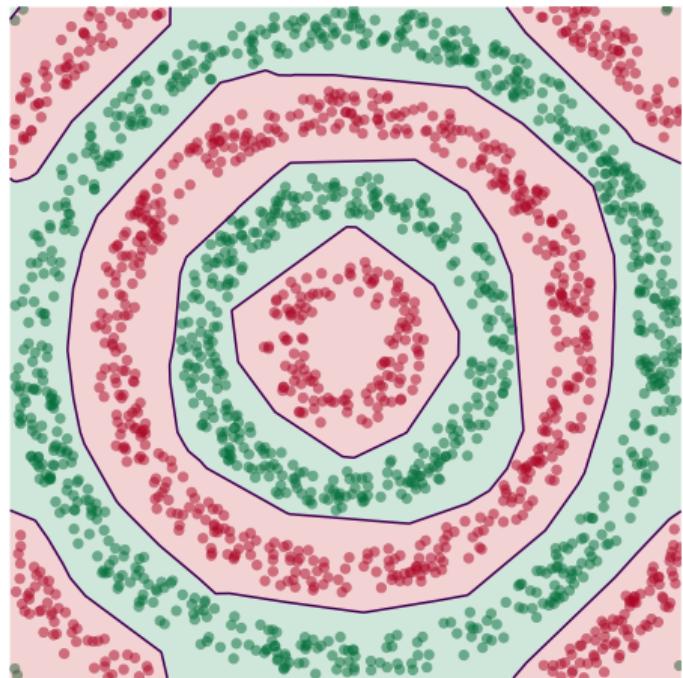
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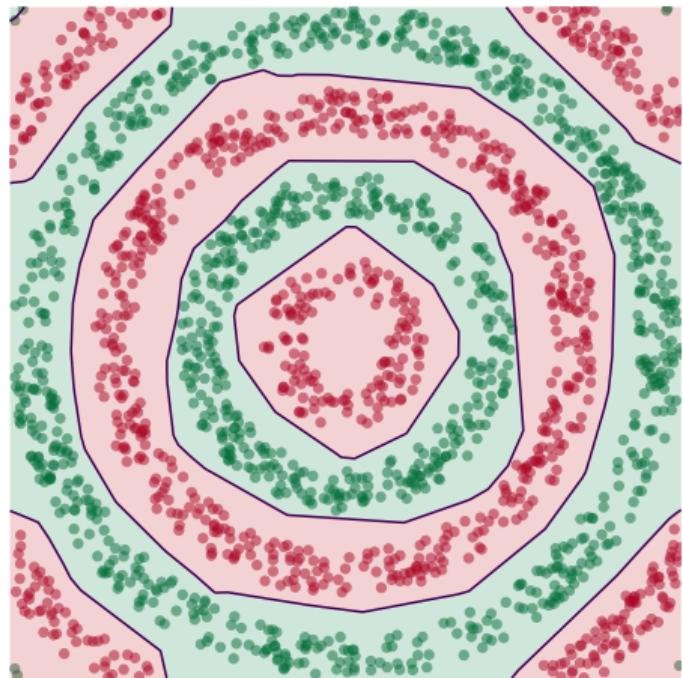
Learning a New Representation



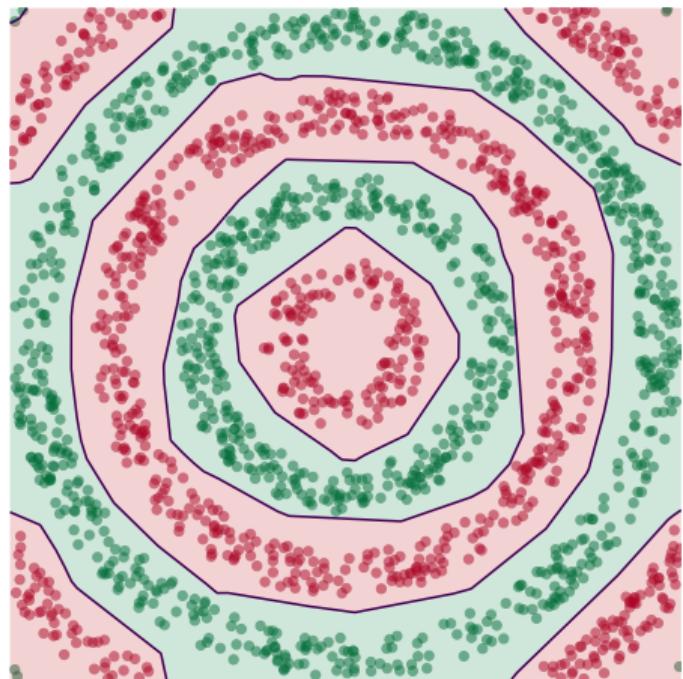
Learning a New Representation



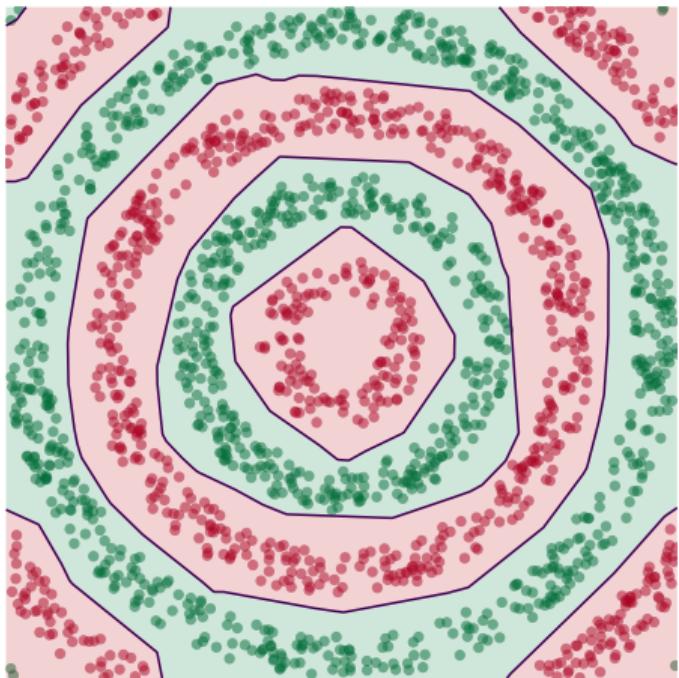
Learning a New Representation



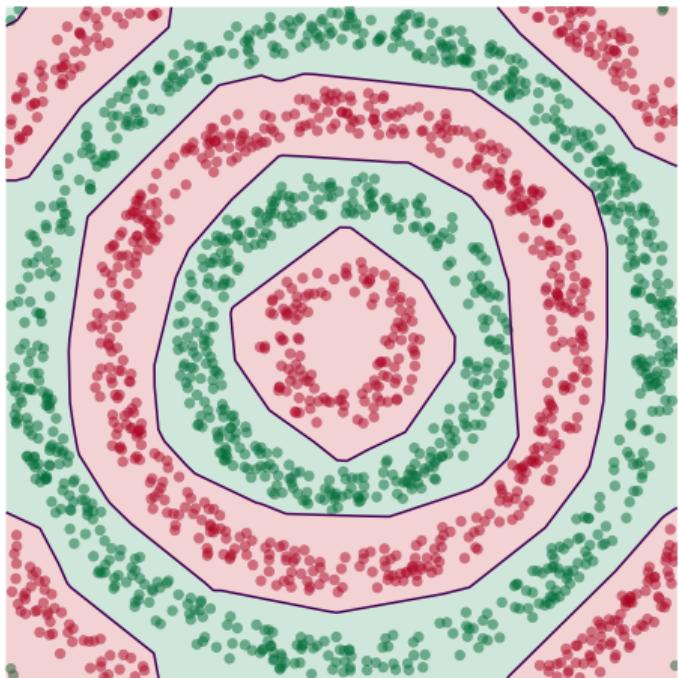
Learning a New Representation



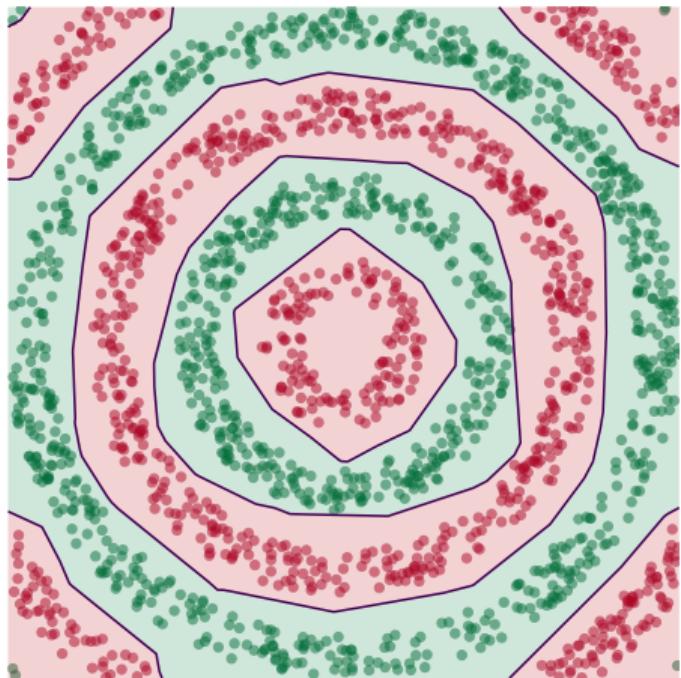
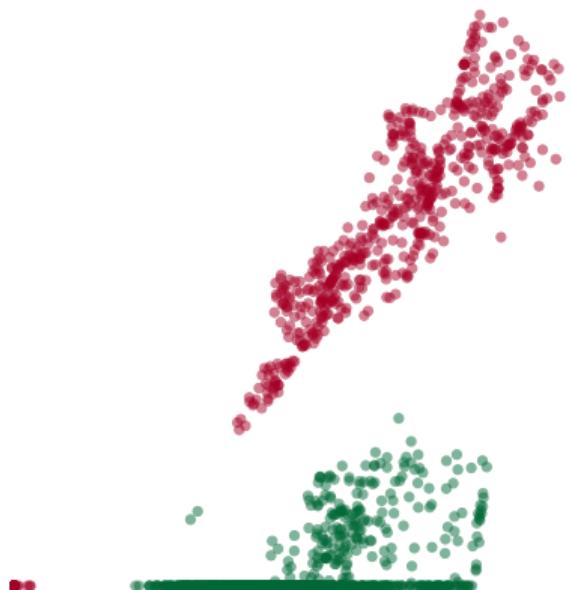
Learning a New Representation



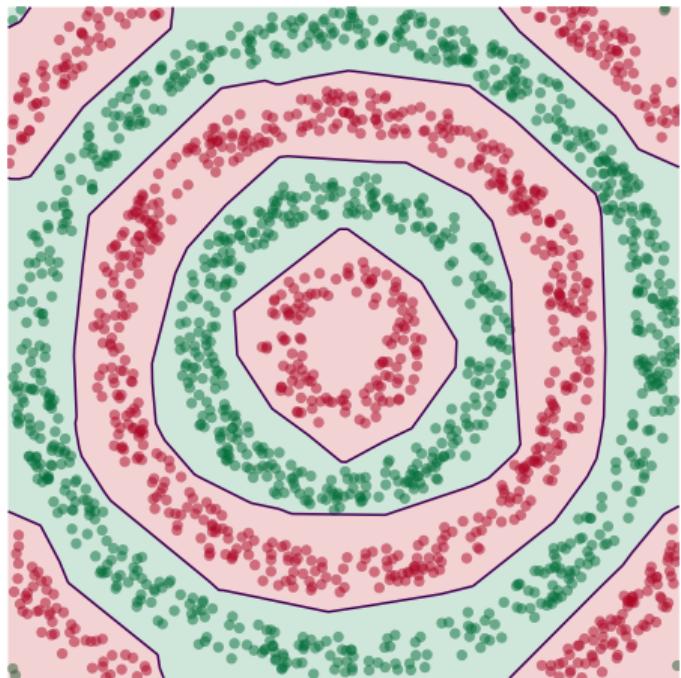
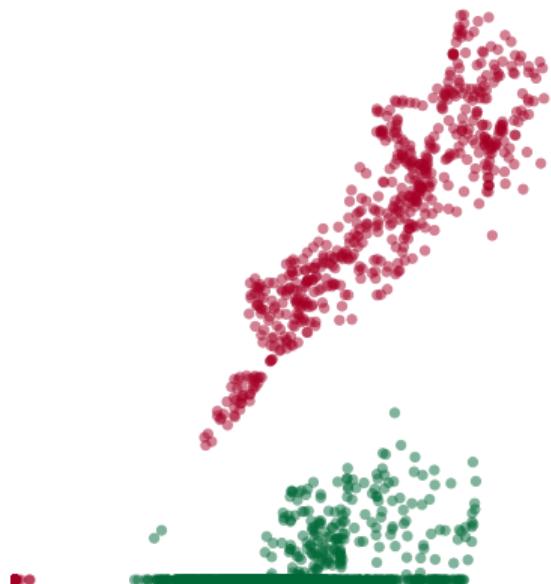
Learning a New Representation



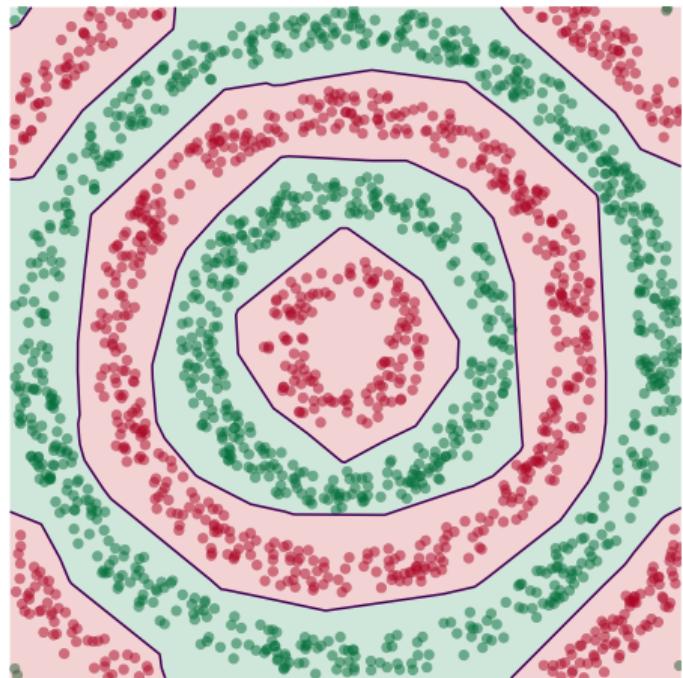
Learning a New Representation



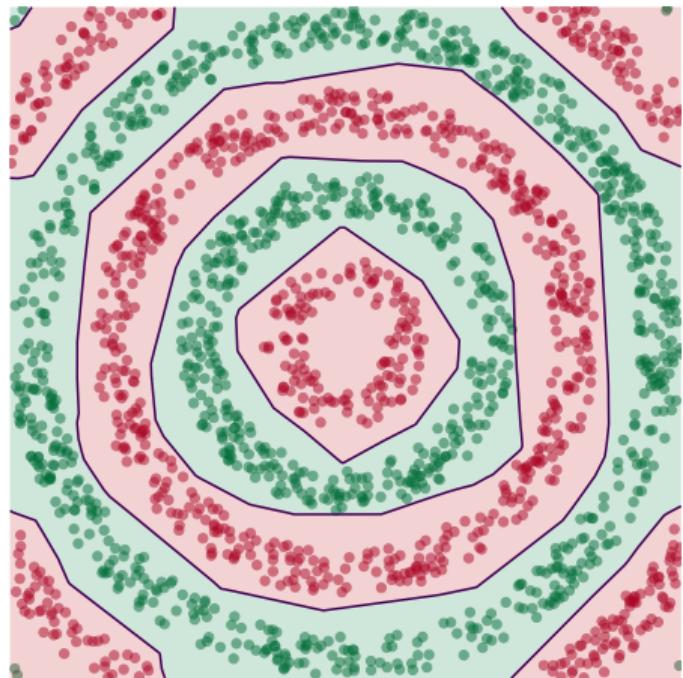
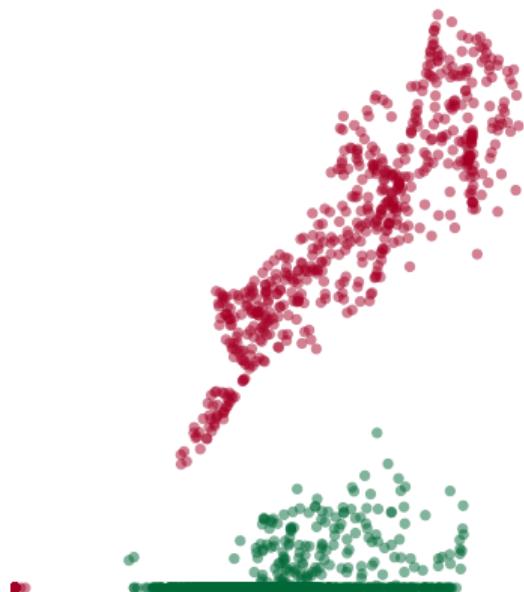
Learning a New Representation



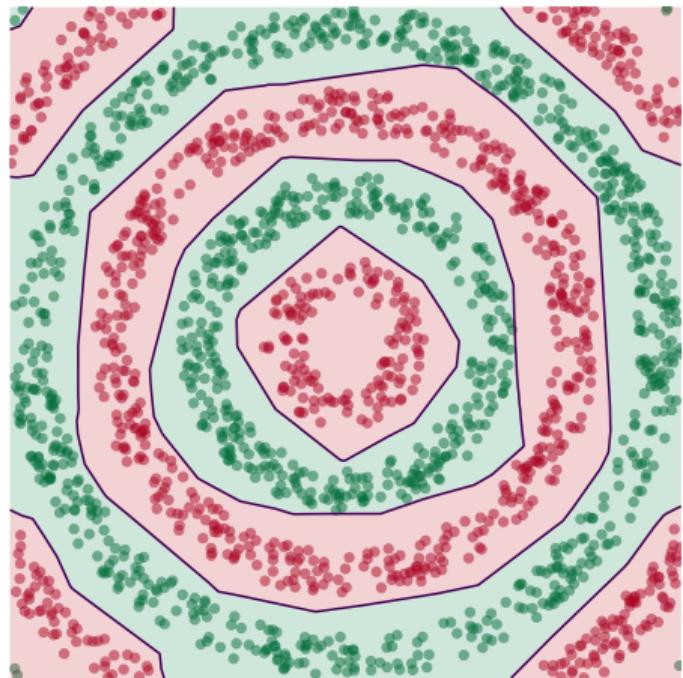
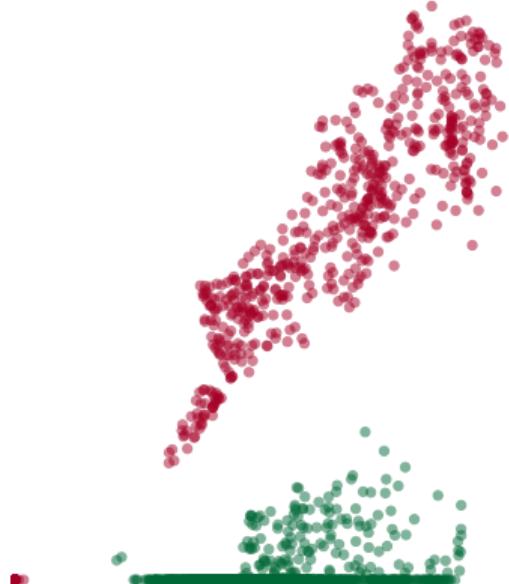
Learning a New Representation



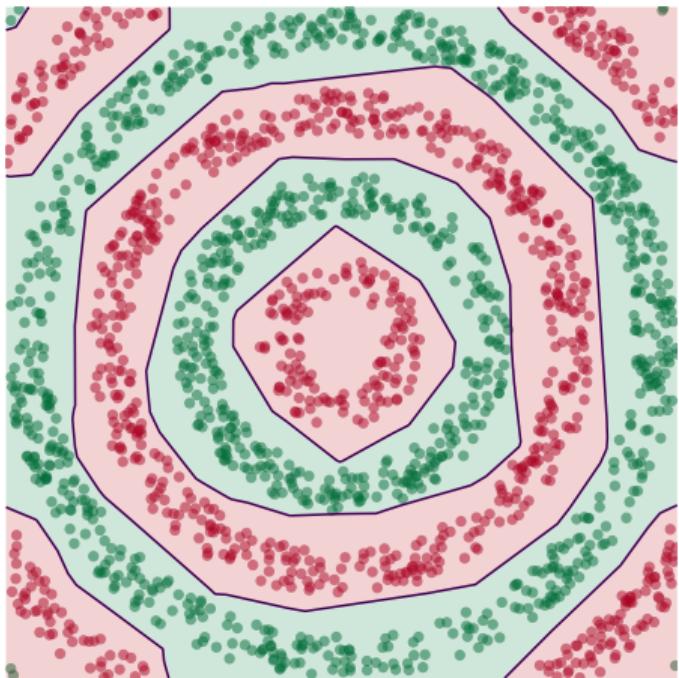
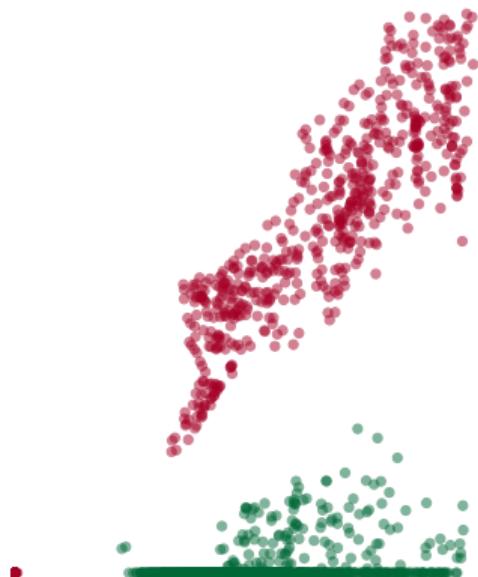
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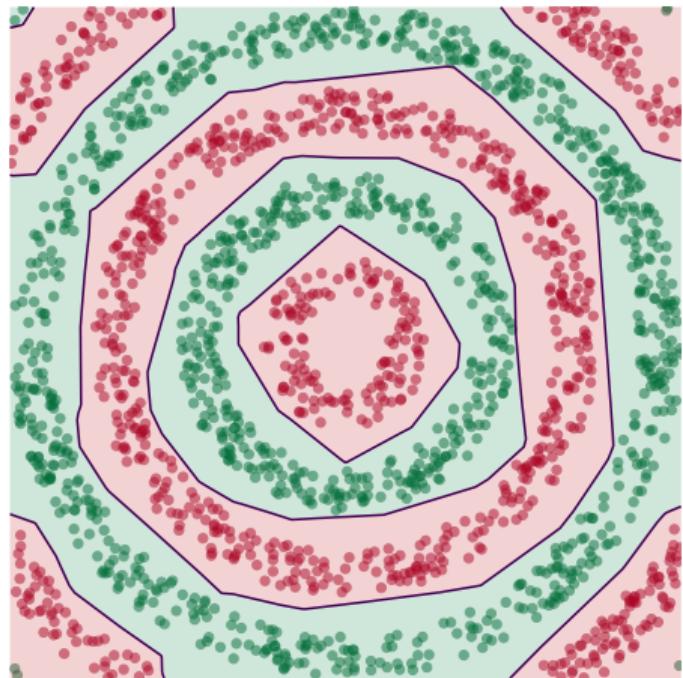
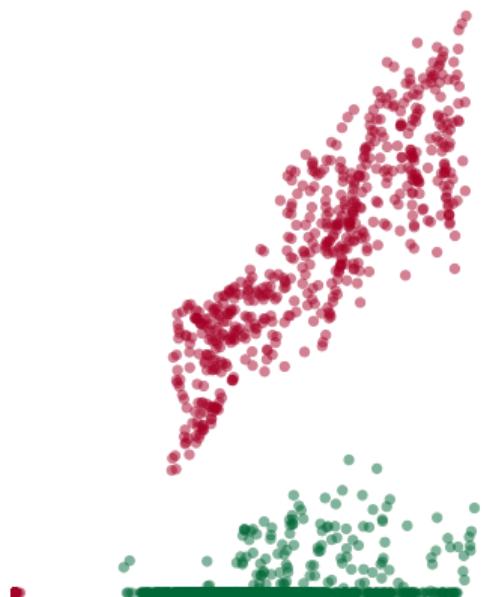
Learning a New Representation



Learning a New Representation



Learning a New Representation



Deep Learning

- ▶ The NN has learned a new **representation** in which the data is easily classified.