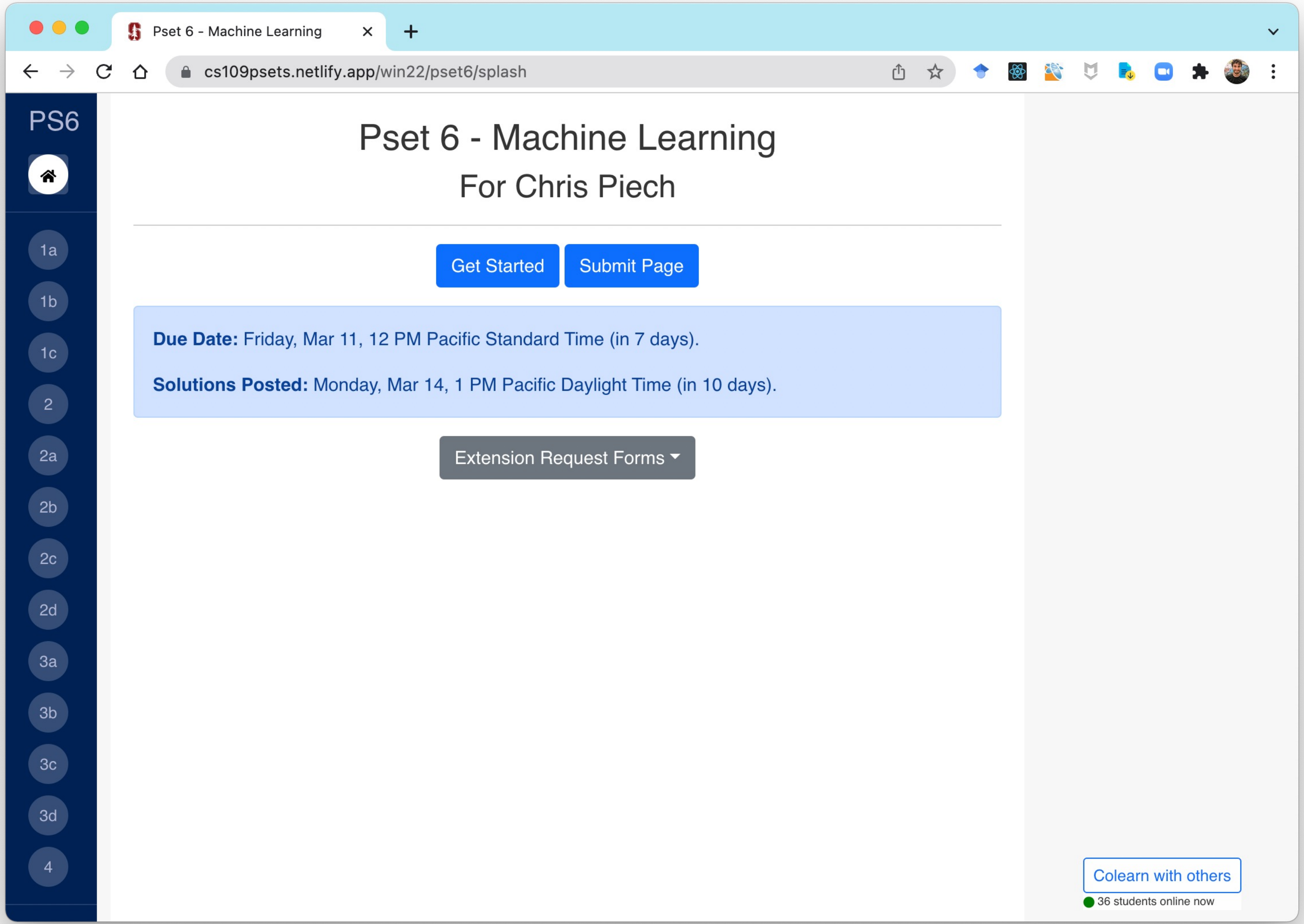
Logistic Regression

Chris Piech
CS109, Stanford University

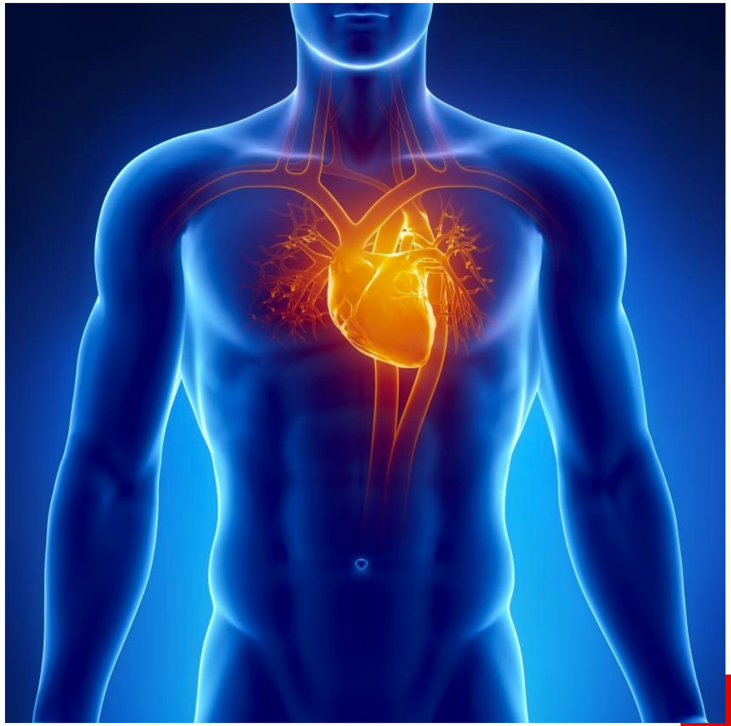
Welcome back from break!

Problem Set #6



Some Fun Times

Heart



Ancestry

23andMe

Netflix

NETFLIX

Creative Challenge

Due next Monday

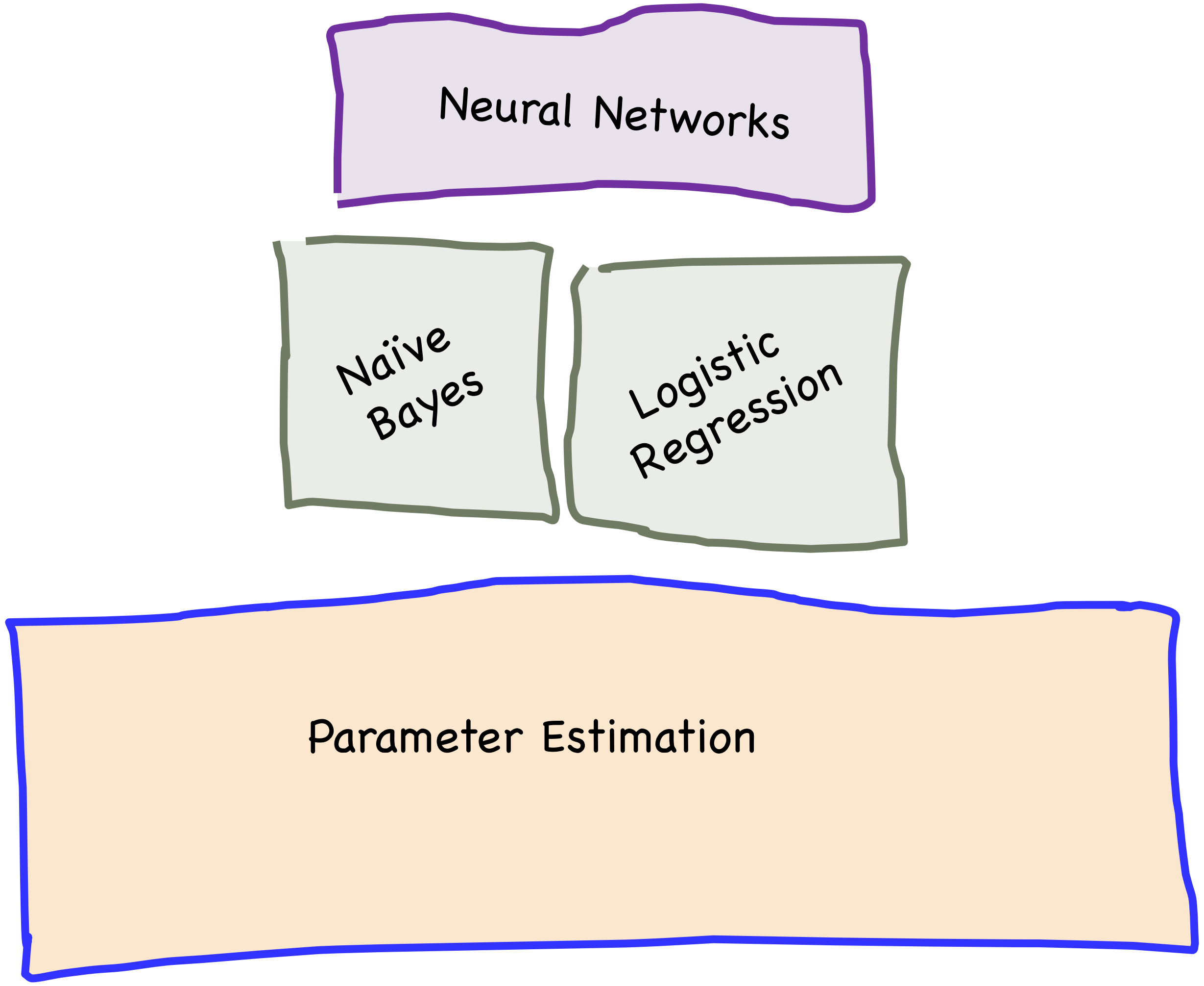
Review

Machine Learning

Great Idea

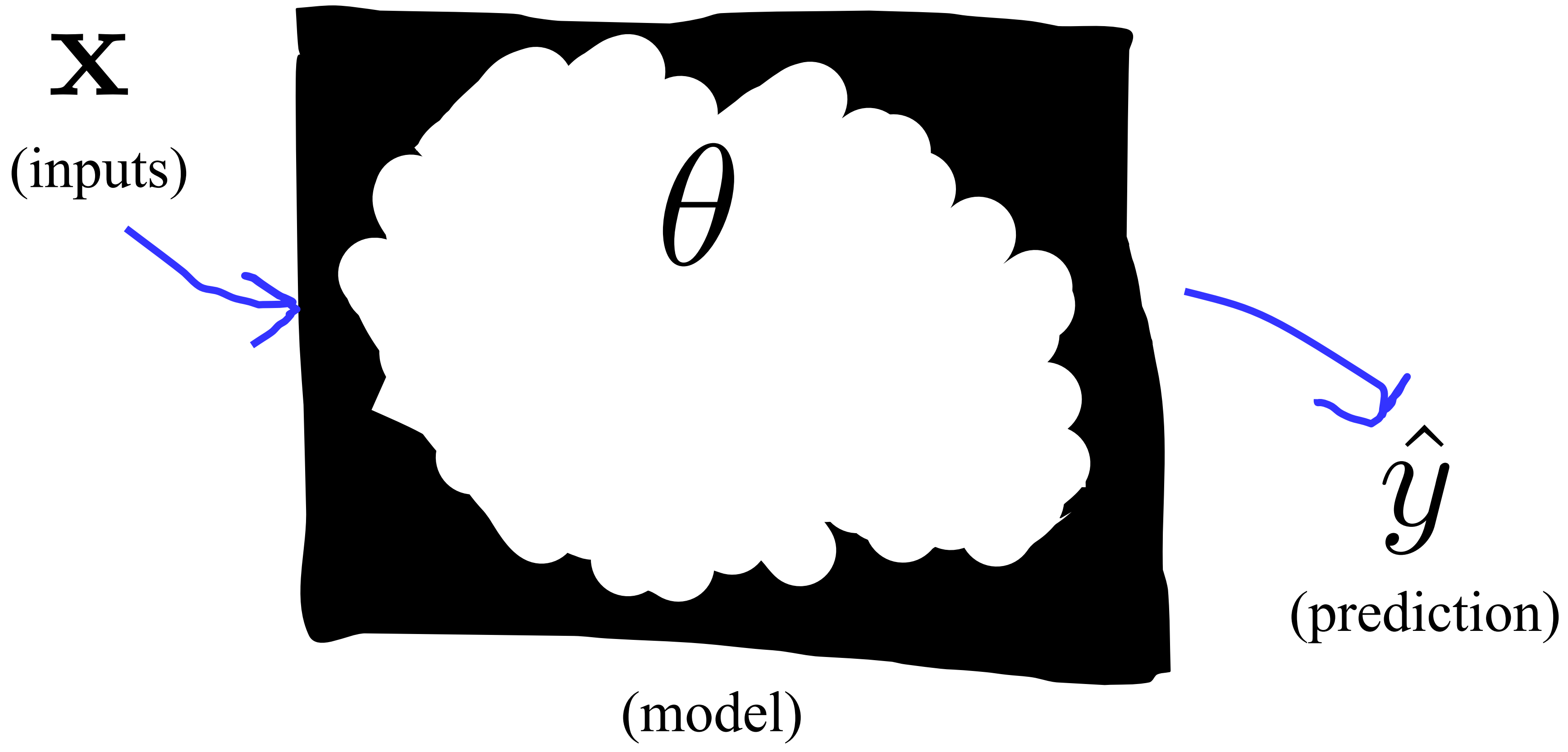
Classification
Algorithms

Theory

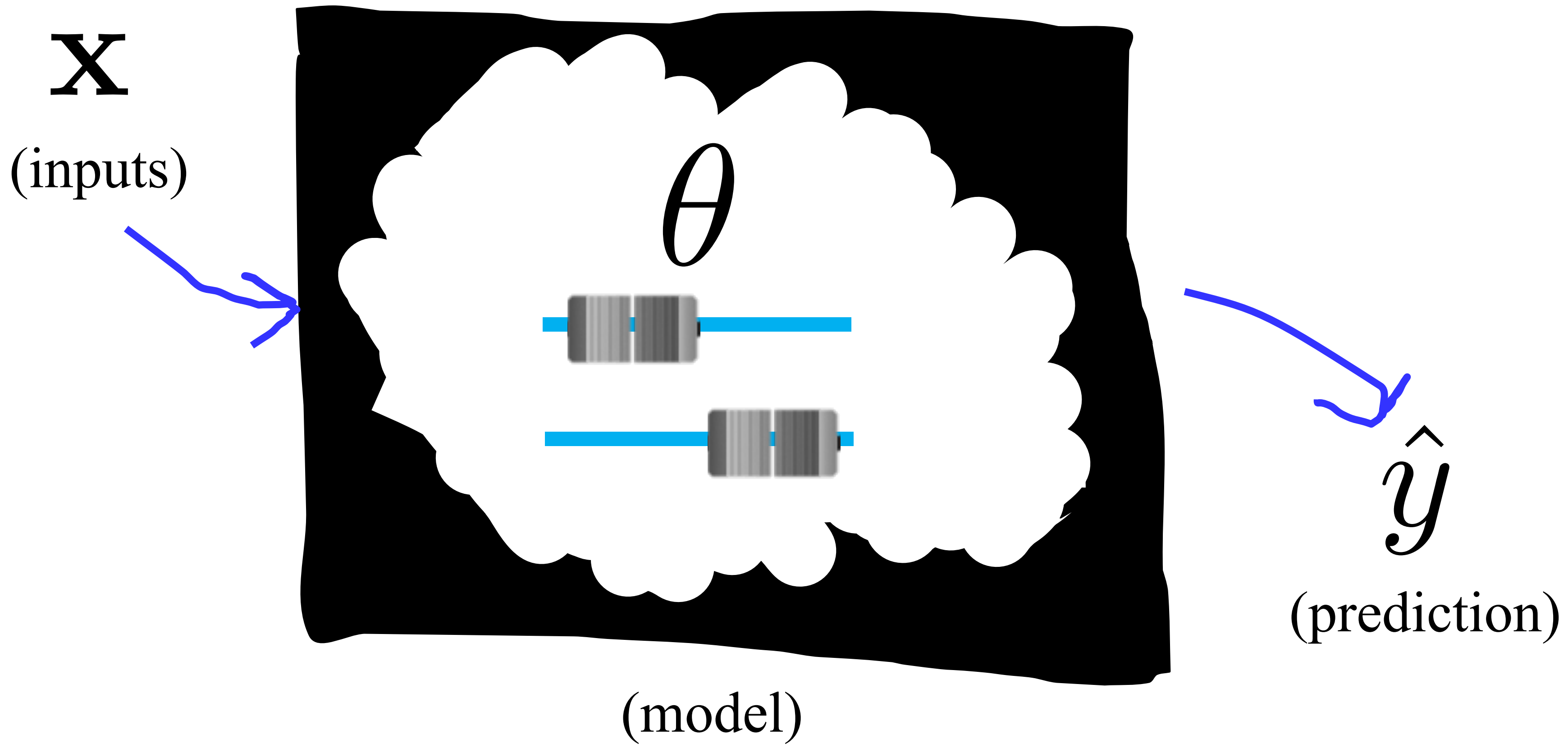


Machine Learning
(aka Applied Probability)

Machine Learning



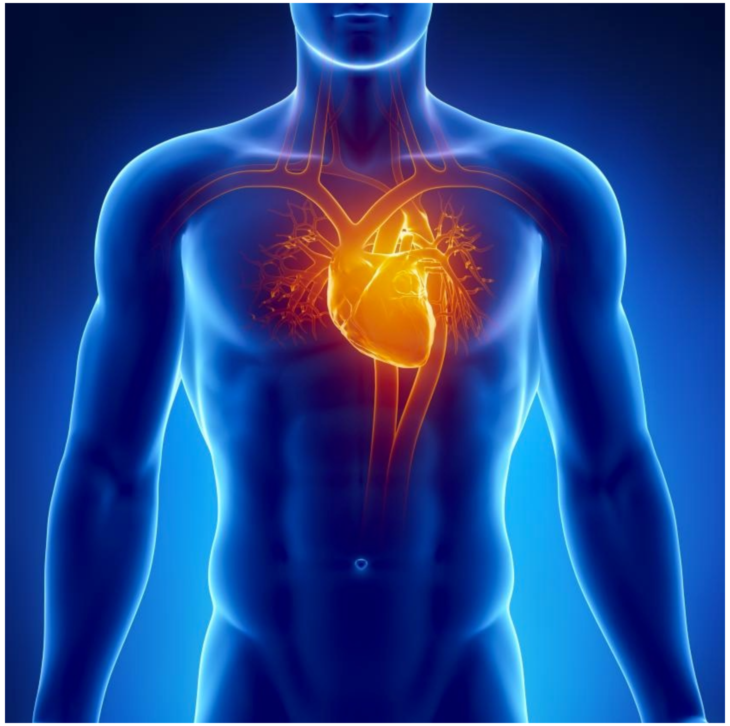
Machine Learning



Classification

Classification Task

Heart



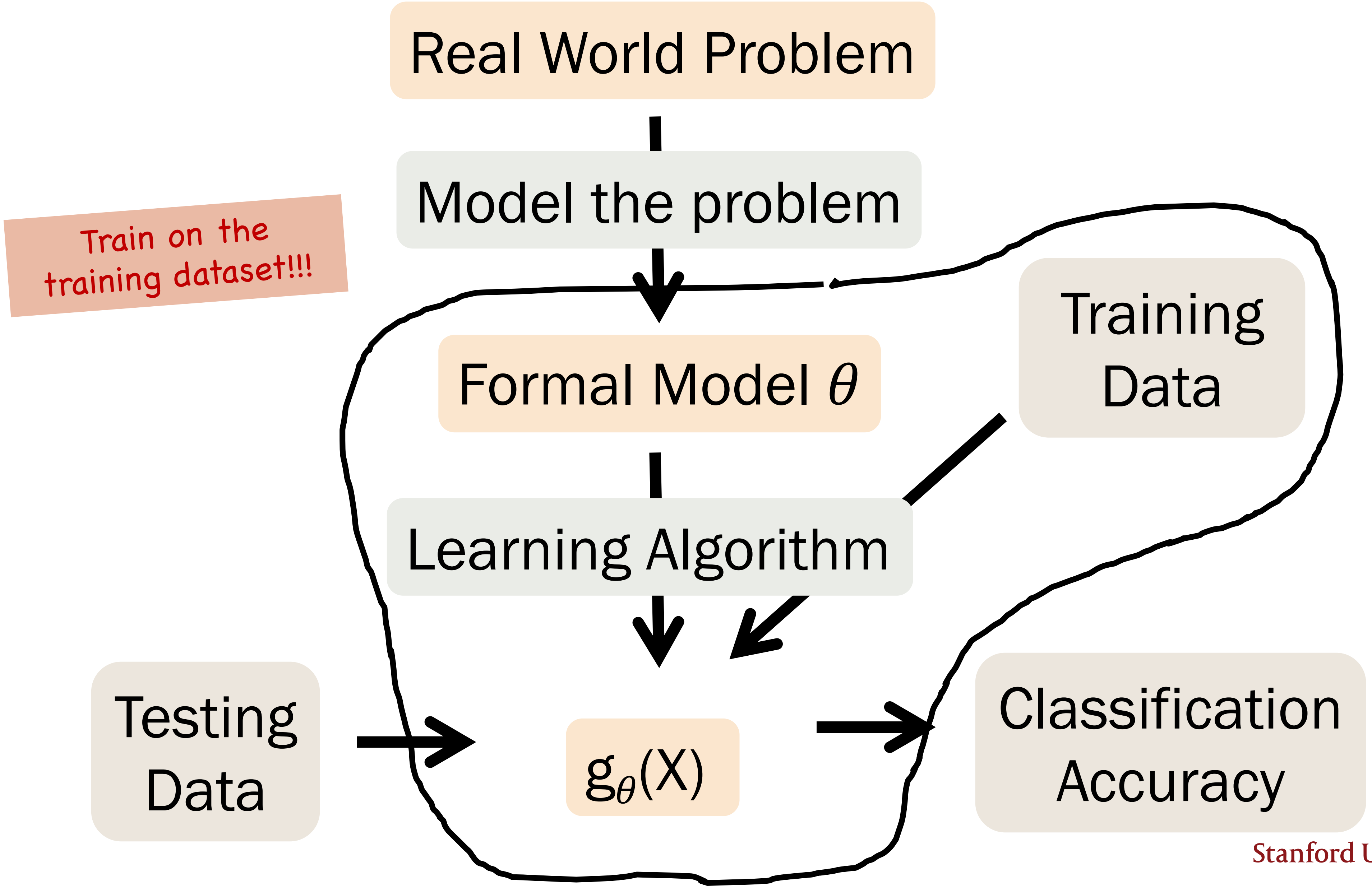
Ancestry

23andMe

Netflix

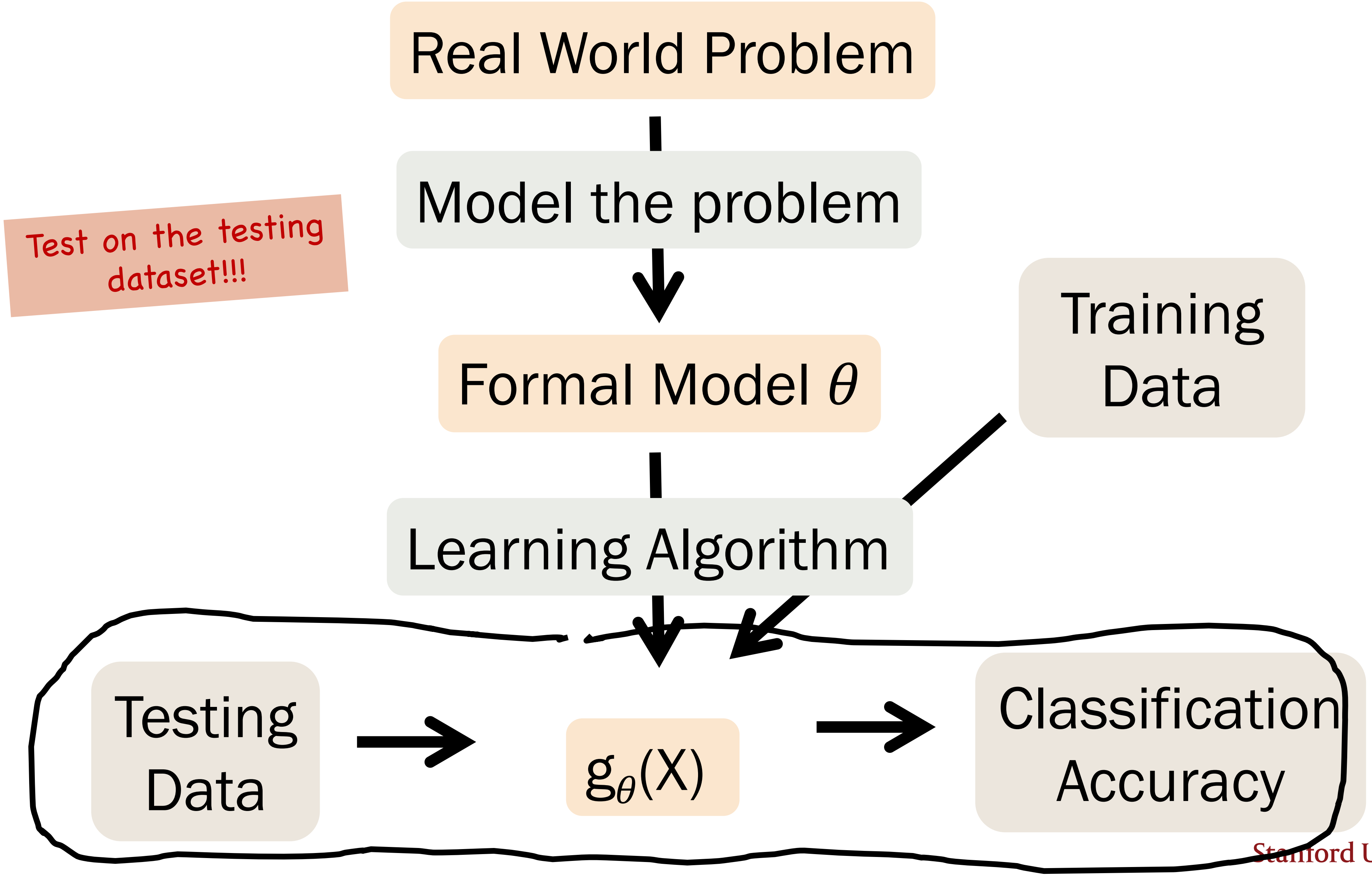
NETFLIX

Training



Real World Problem
Model the problem
Train on the training dataset!!!
Formal Model θ
Training Data
Learning Algorithm
Testing Data
$g_\theta(X)$
Classification Accuracy

Testing


Real World Problem
Model the problem
Formal Model θ
Training Data
Learning Algorithm
Test on the testing dataset!!!
Testing Data
$g_\theta(X)$
Classification Accuracy

Training Data

Assume IID data:

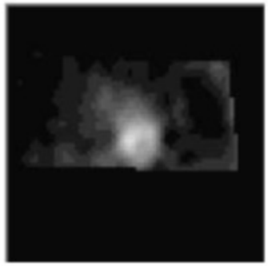
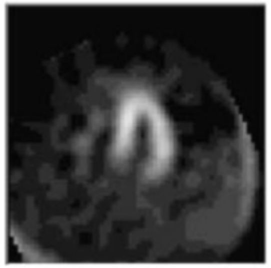
n training datapoints

$$(\mathbf{x}^{(1)}, y^{(1)}), (\mathbf{x}^{(2)}, y^{(2)}), \dots (\mathbf{x}^{(n)}, y^{(n)})$$

$$m = |\mathbf{x}^{(i)}|$$

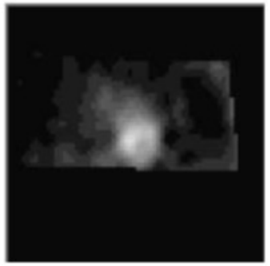
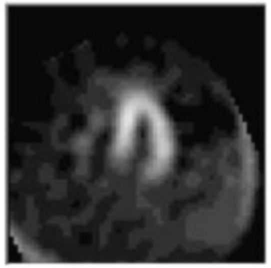
Each datapoint has m features and a single output

Training: Heart Disease Classifier

	ROI 1	ROI 2		ROI m	Output
			...		
Heart 1	0	1		1	0
Heart 2	1	1		1	0
			⋮		⋮
Heart n	0	0		0	1

$g_{\theta}(X)$

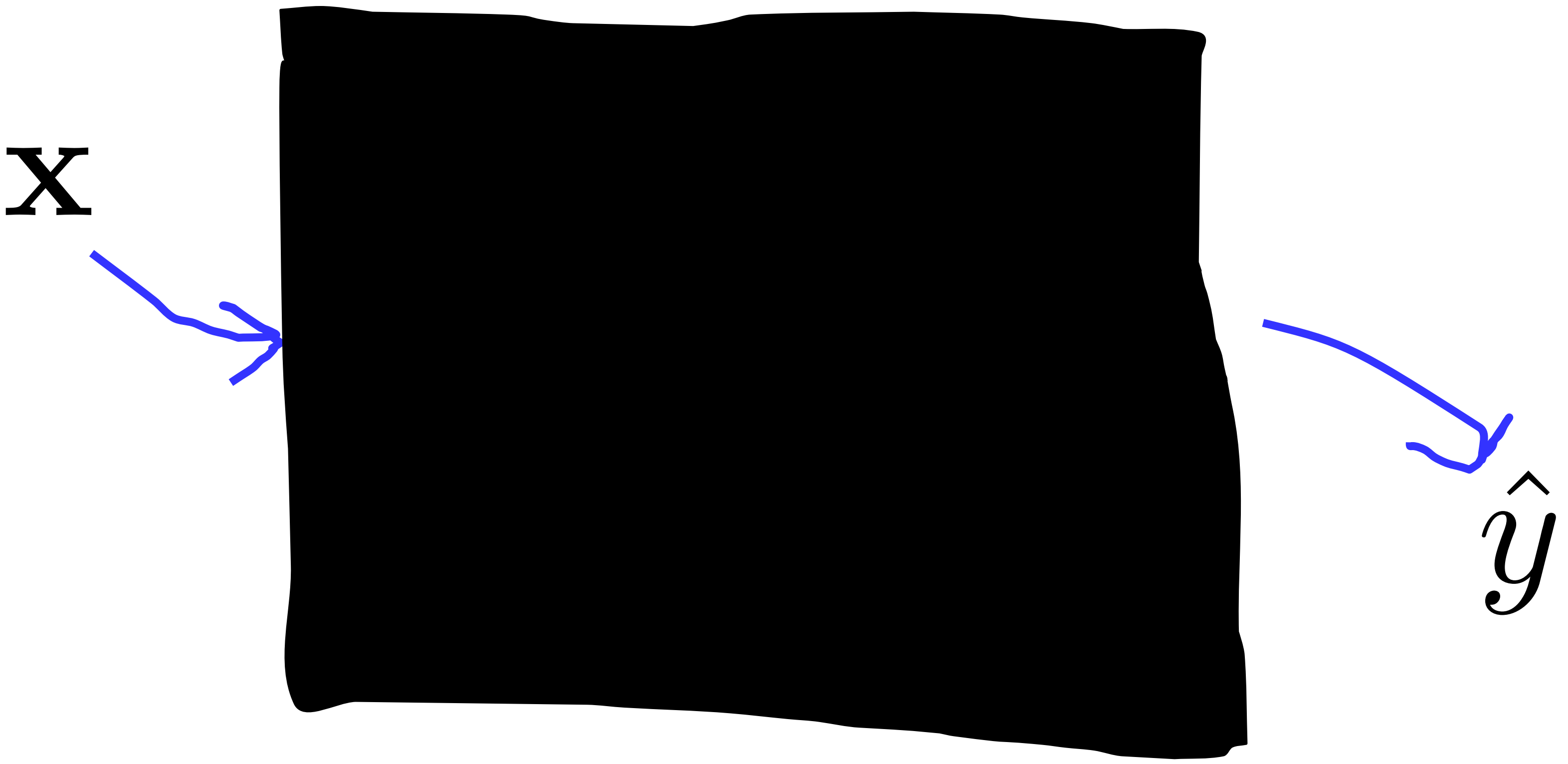
Testing: Heart Disease Classifier

	ROI 1	ROI 2		ROI m	Output
			…		
New Heart	1	0		1	$\boxed{1}$

$g_{\theta}(X)$

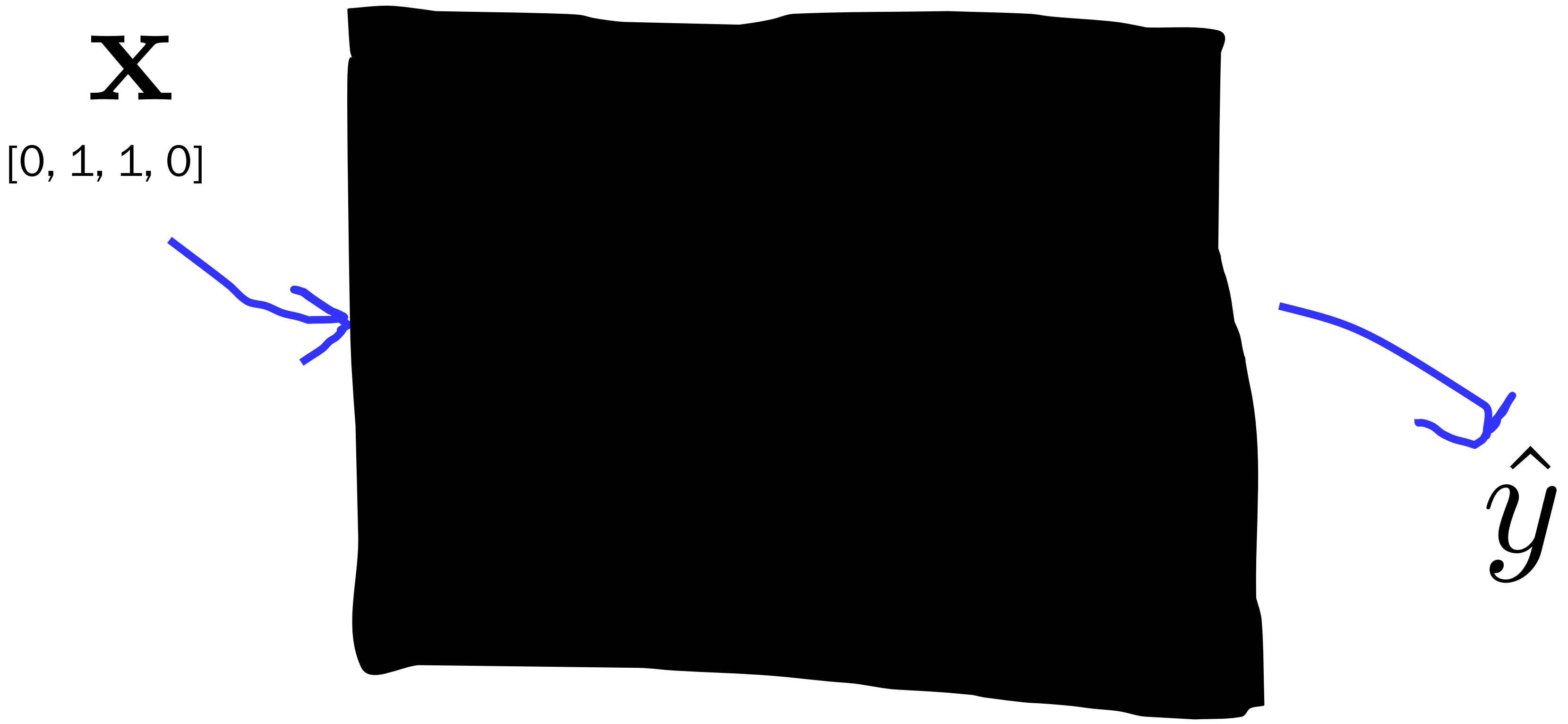
Naïve Bayes Classification

$g_\theta(\mathbf{x})$?



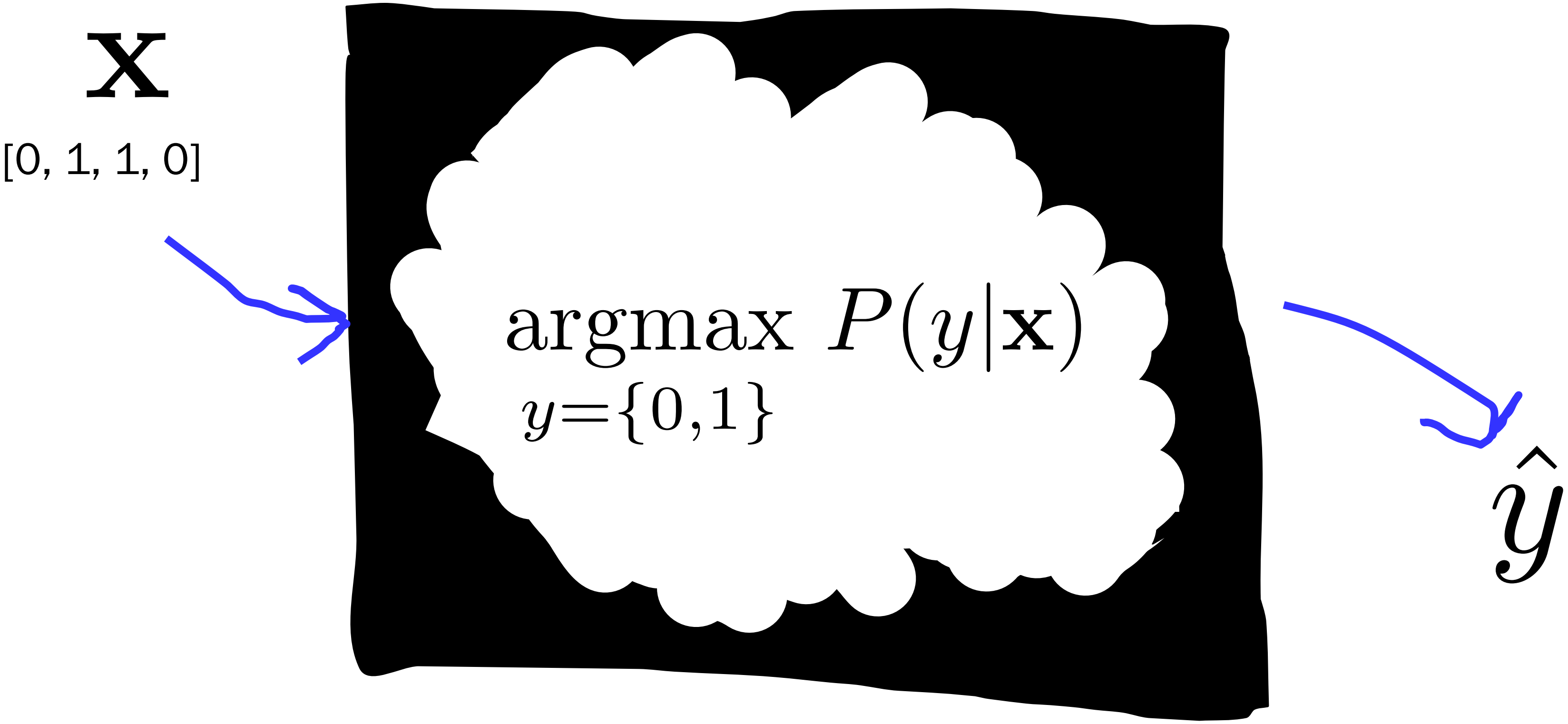
Making a prediction…

$g_\theta(\mathbf{x})$?



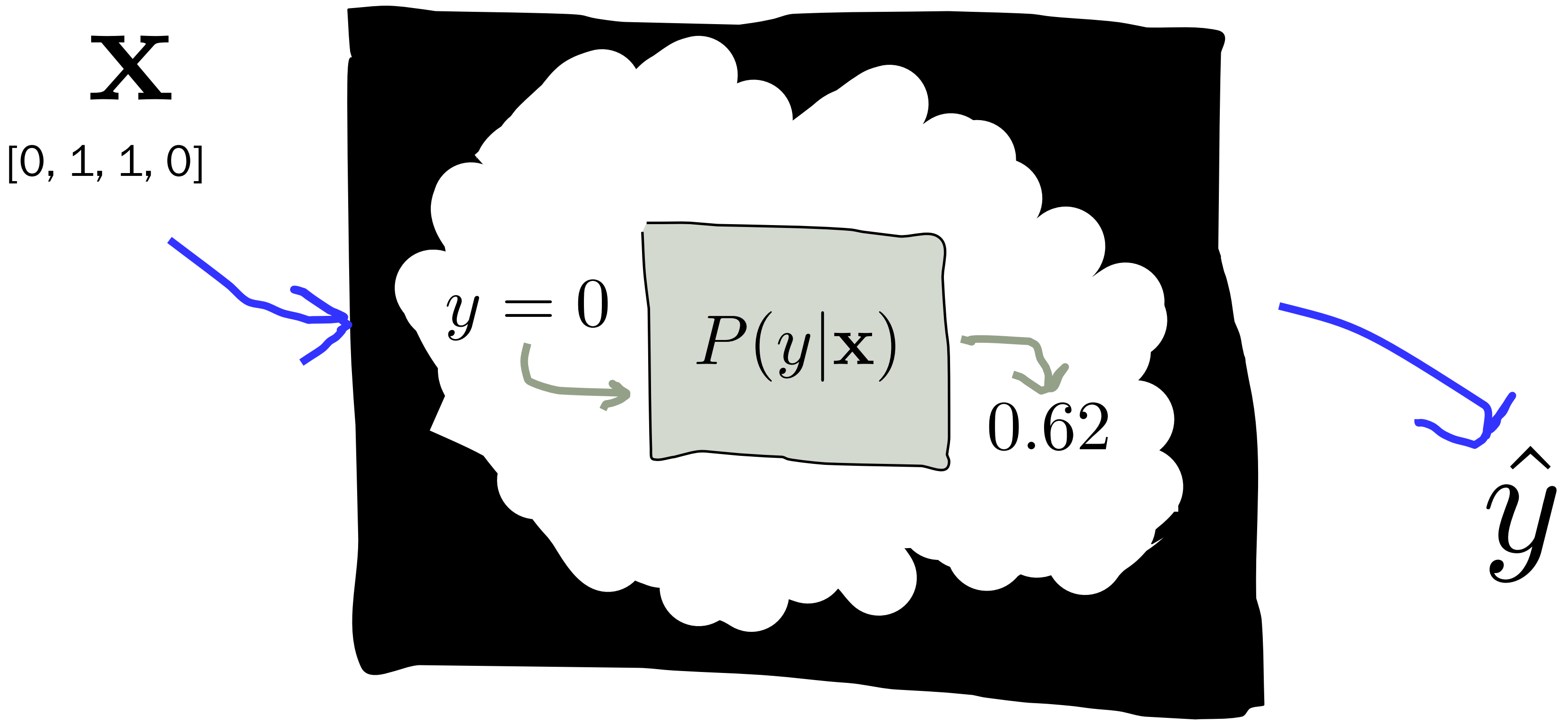
Making a prediction…

$\mathbf{g}_\theta(\mathbf{x})$?



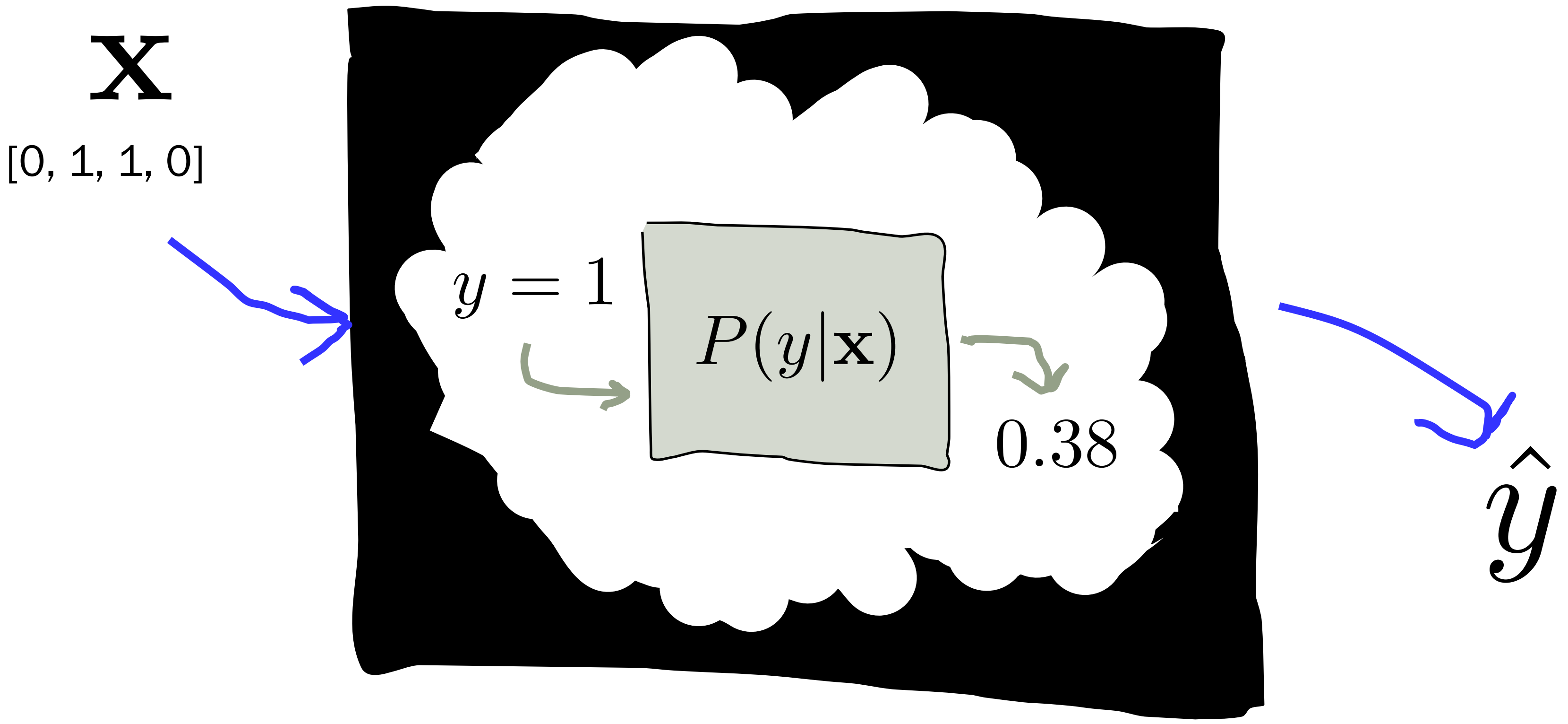
Making a prediction…

$\mathrm{g}_\theta(\mathbf{x})$?



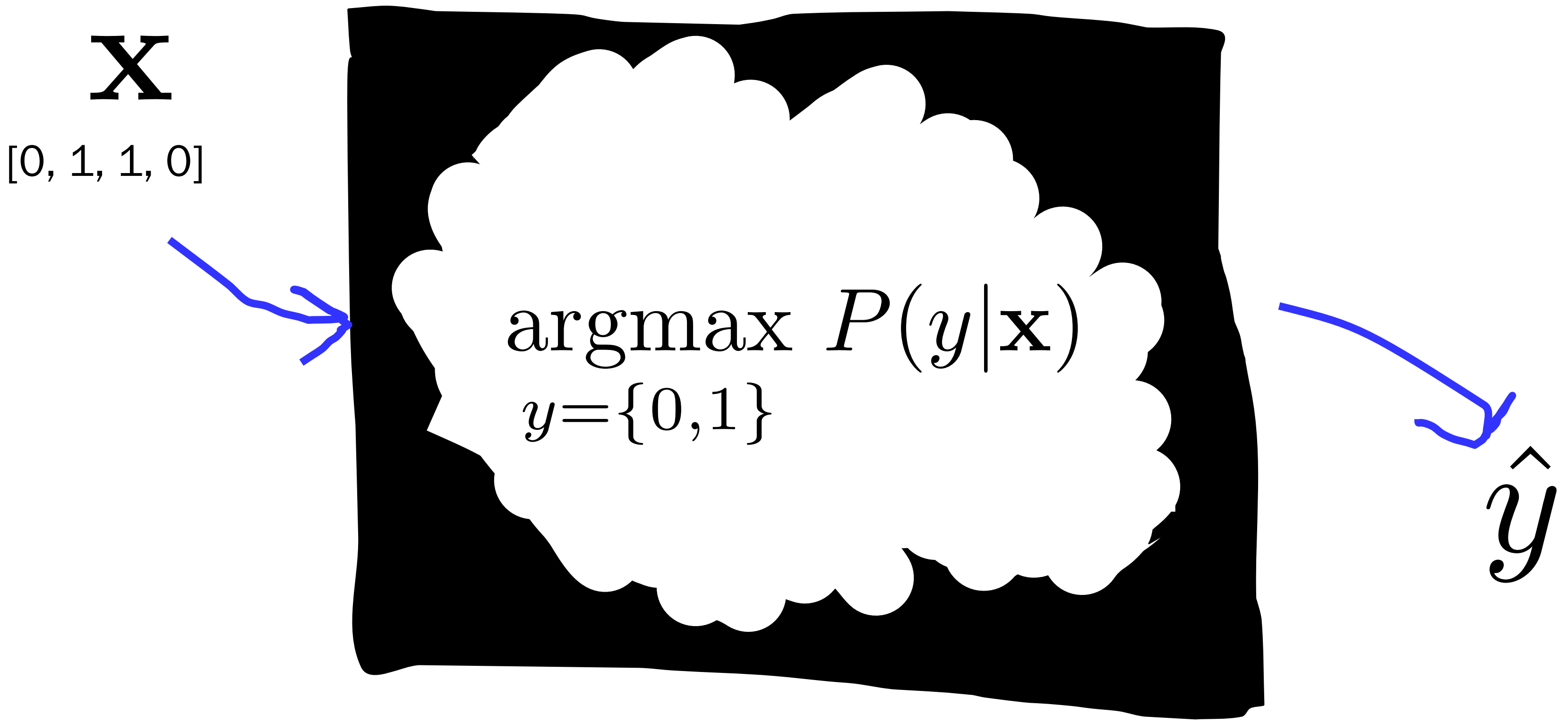
Making a prediction…

$g_\theta(\mathbf{x})$?



Making a prediction…

$g_\theta(\mathbf{x})$?

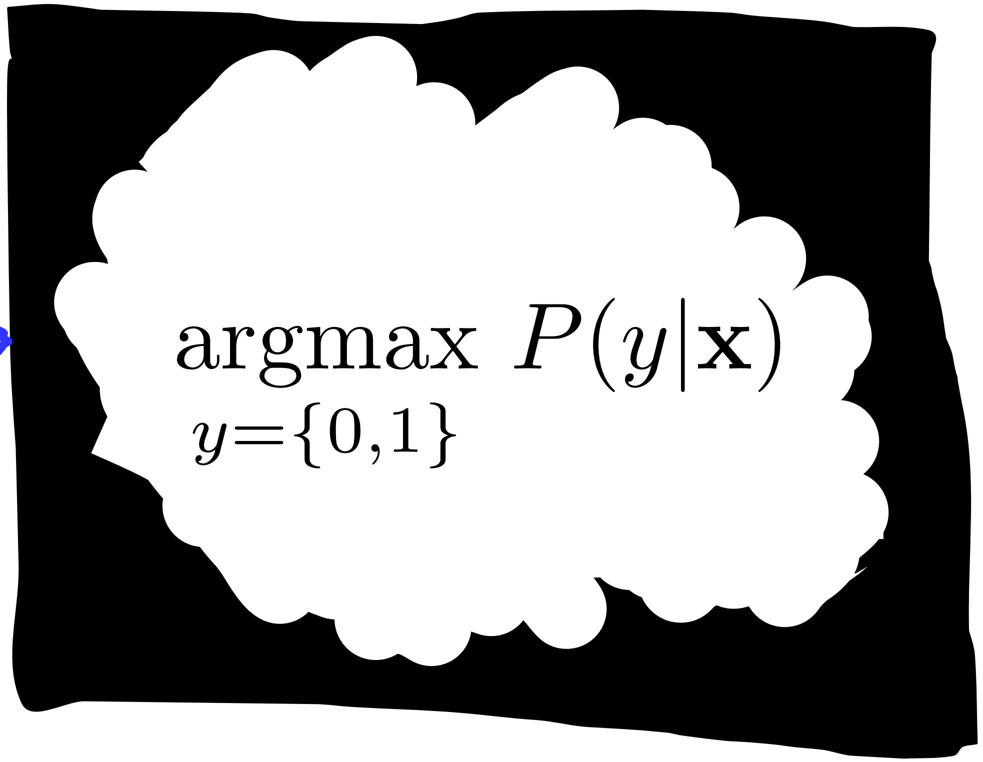


Making a prediction…

$g_\theta(\mathbf{x})$?

$\mathbf{x}$

[0, 1, 1, 0]



$\hat{y} = 0$

Making a prediction…

Big Assumption

Naïve Bayes Assumption:

$$P(\mathbf{x}|y) = \prod_i P(x_i|y)$$

Prediction

Simply chose the class label that is the most likely given the data. Make Naïve Bayes assumption

$$\hat{y} = \arg\max_{y=\{0,1\}} P(Y = y|\mathbf{X} = \mathbf{x})$$

$$= \arg\max_{y=\{0,1\}} \frac{P(Y = y)P(\mathbf{X} = \mathbf{x}|Y = y)}{P(\mathbf{X} = \mathbf{x})}$$

$$= \arg\max_{y=\{0,1\}} P(Y = y)P(\mathbf{X} = \mathbf{x}|Y = y)$$

$$= \arg\max_{y=\{0,1\}} P(Y = y)\prod_i P(X_i = x_i|Y = y)$$

$$= \arg\max_{y=\{0,1\}} \log P(Y = y) + \sum_i \log P(X_i = x_i|Y = y)$$

Must learn params for this

Must learn params for this

Learning Probabilities from Data

Various probabilities you will need to compute for Naive Bayesian Classifier (using **MLE** here):

$$\hat{p}(X_i = 1 | Y = 0) = \frac{(\#\text{ training examples where } X_i = 1 \text{ and } Y = 0)}{(\#\text{ training examples where } Y = 0)}$$

$$\hat{p}(Y = 1) = \frac{(\#\text{ training examples where } Y = 1)}{(\#\text{ training examples})}$$

Learning Probabilities from Data

Various probabilities you will need to compute for Naive Bayesian Classifier (using **MAP with Laplace prior** here):

$$\hat{p}(X_i = 1 | Y = 0) = \frac{(\#\text{ training examples where } X_i = 1 \text{ and } Y = 0) + 1}{(\#\text{ training examples where } Y = 0) + 2}$$

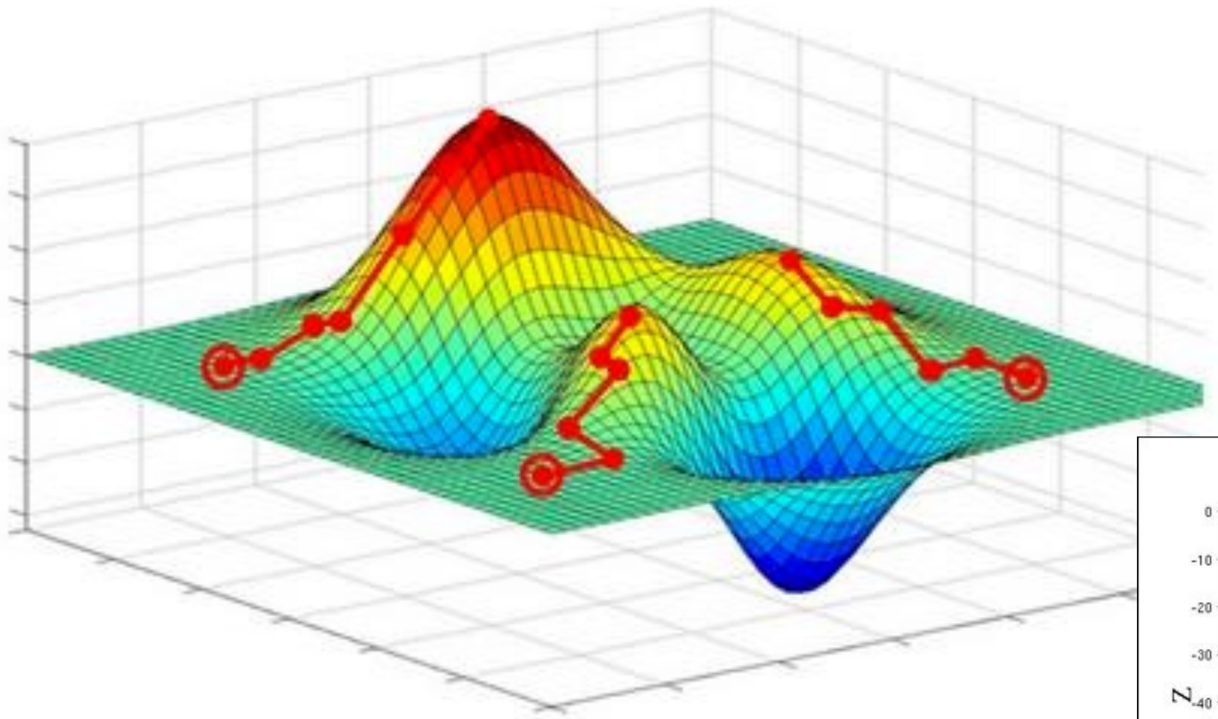
$$\hat{p}(Y = 1) = \frac{(\#\text{ training examples where } Y = 1) + 1}{(\#\text{ training examples}) + 2}$$

Training Naïve Bayes, is estimating parameters for a multinomial (or bernoulli).

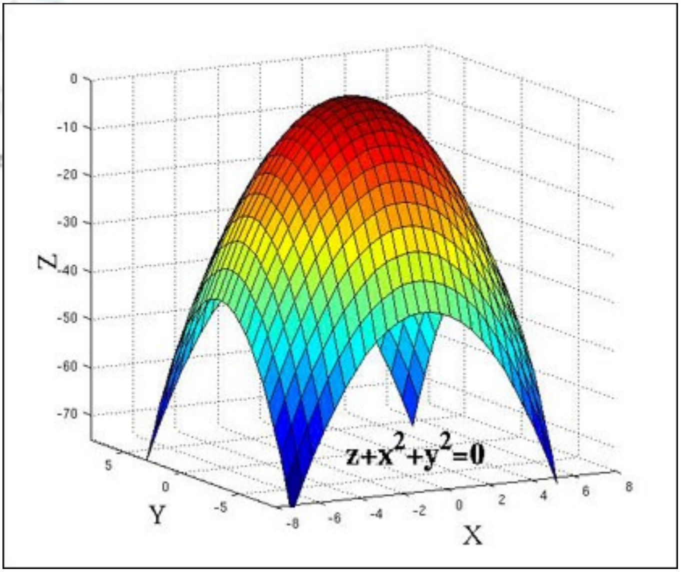
Thus training is just counting.

Optimization

Gradient Ascent



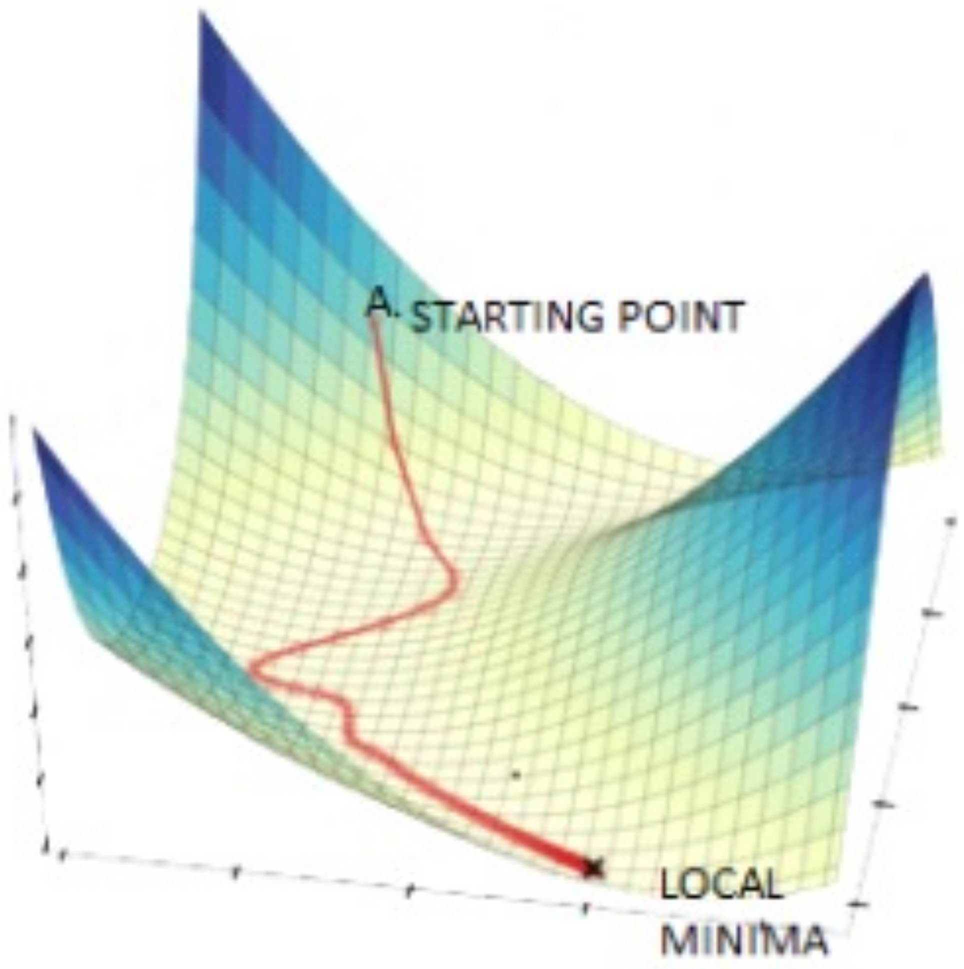
Logistic regression
LL function is
convex



Walk uphill and you will find a local maxima
(if your step size is small enough)

Gradient descent is your bread and butter algorithm for optimization (eg argmax)

Gradient Decent



Walk downhill and you will find a local maxima
(if your step size is small enough)

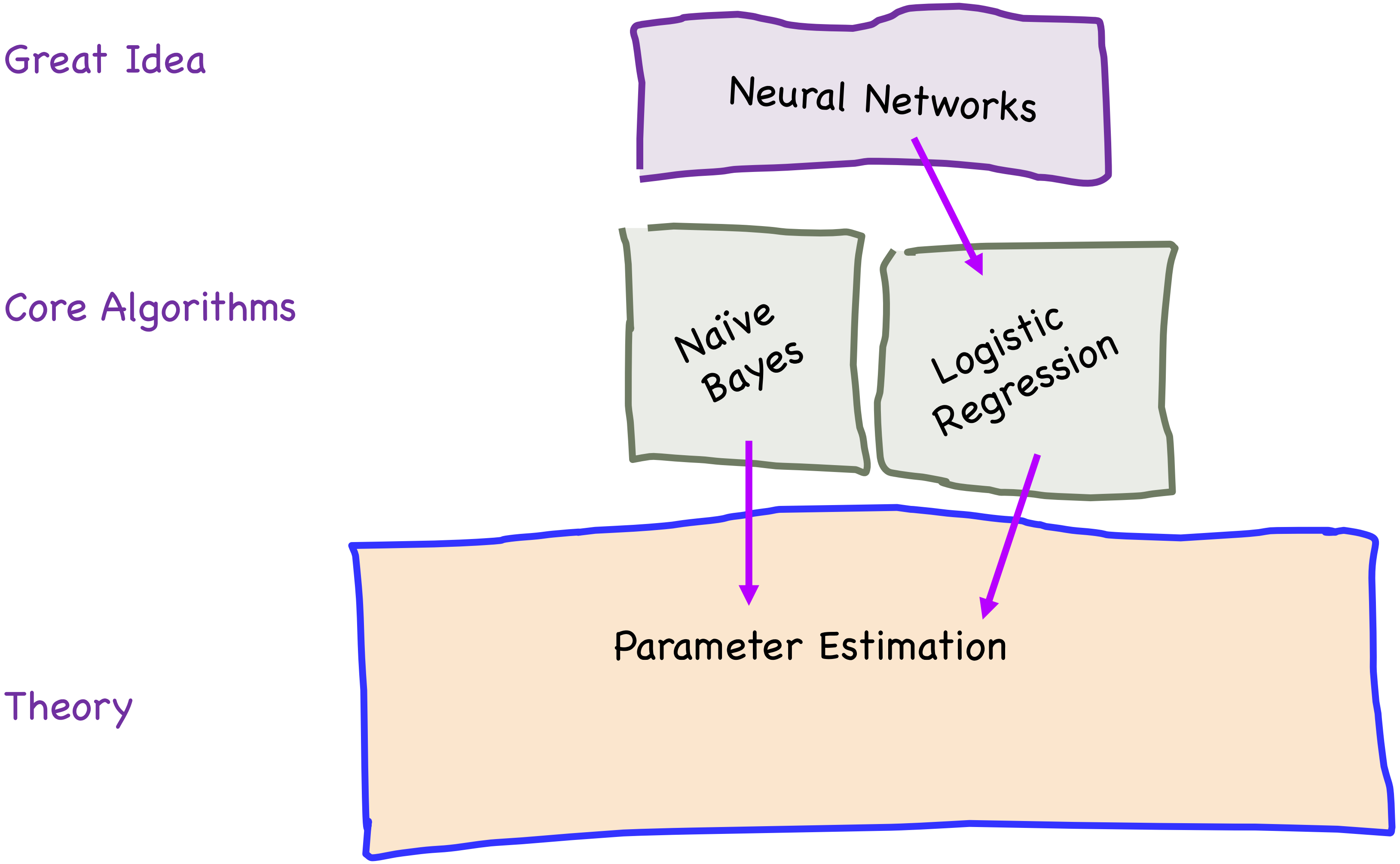
If someone gives you a gradient descent package, you should minimize **negative** log likelihood.

If you are writing optimization yourself, feel free to gradient **ascent** on log likelihood :-)

End Review

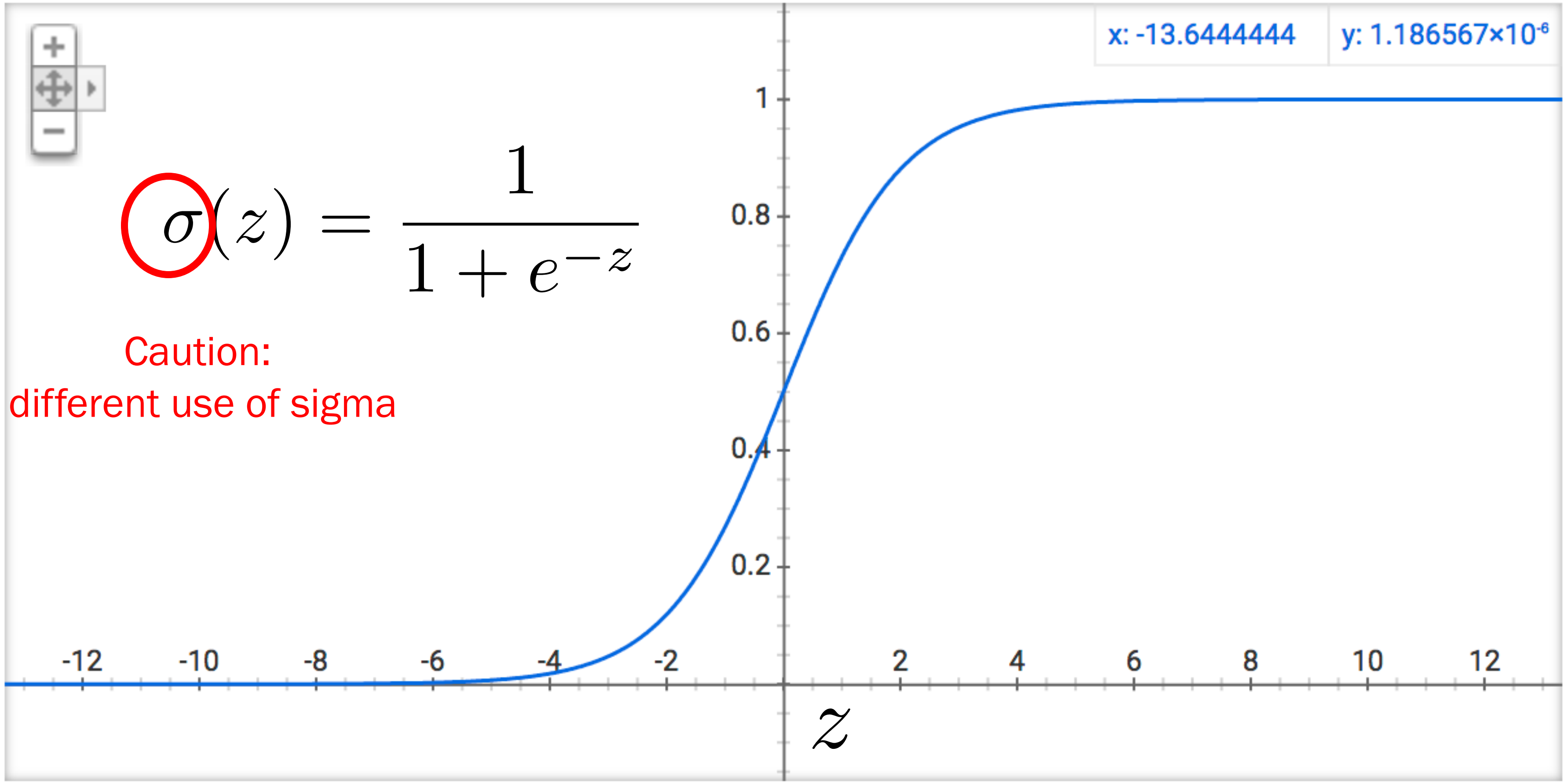
Logistic Regression

Machine Learning *Dependencies*



Chapter 0: Background

Background: Sigmoid Function



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

Caution:
different use of sigma

The sigmoid function squashes z to be a number between 0 and 1

Background: Key Notation

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

Sigmoid function

$$\theta^T \mathbf{x} = \sum_{i=1}^{n} \theta_i x_i$$

$$= \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n$$

Weighted sum
(aka dot product)

$$\sigma(\theta^T \mathbf{x}) = \frac{1}{1 + e^{-\theta^T \mathbf{x}}}$$

Sigmoid function of
weighted sum

Background: Chain Rule

Who knew calculus would be so useful?

$$\frac{\partial f(x)}{\partial x} = \frac{\partial f(z)}{\partial z} \cdot \frac{\partial z}{\partial x}$$

Aka decomposition of composed functions

$$f(x) = f(z(x))$$

Chapter 1: Big Picture

From Naïve Bayes to Logistic Regression

In classification we care about P(Y | **X**)

Recall the Naive Bayes Classifier

- Predict P(Y | **X**)
- Use assumption that $P(\mathbf{X} \mid Y) = P(X_1, X_2, \ldots X_m \mid Y) = \prod_{i=1}^{m} P(X_i \mid Y)$
- That is a pretty big assumption…

Could we model P(Y | **X**) directly?

- Welcome our friend: logistic regression!

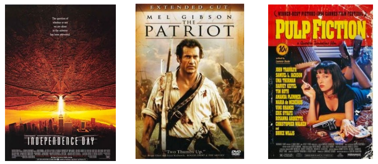
Logistic Regression Assumption

Could we model P(Y | **X**) directly?

- Welcome our friend: logistic regression!

$\mathbf{x}, \theta$

[1, 1, 0]



$P(Y = 1|\mathbf{x})$

0.81

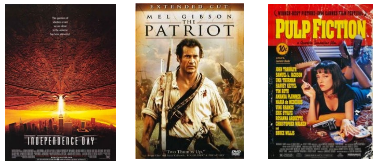
Logistic Regression Assumption

Could we model P(Y | **X**) directly?

- Welcome our friend: logistic regression!

$\mathbf{x}, \theta$

[1, 1, 0]



$P(Y = 1|\mathbf{x})$

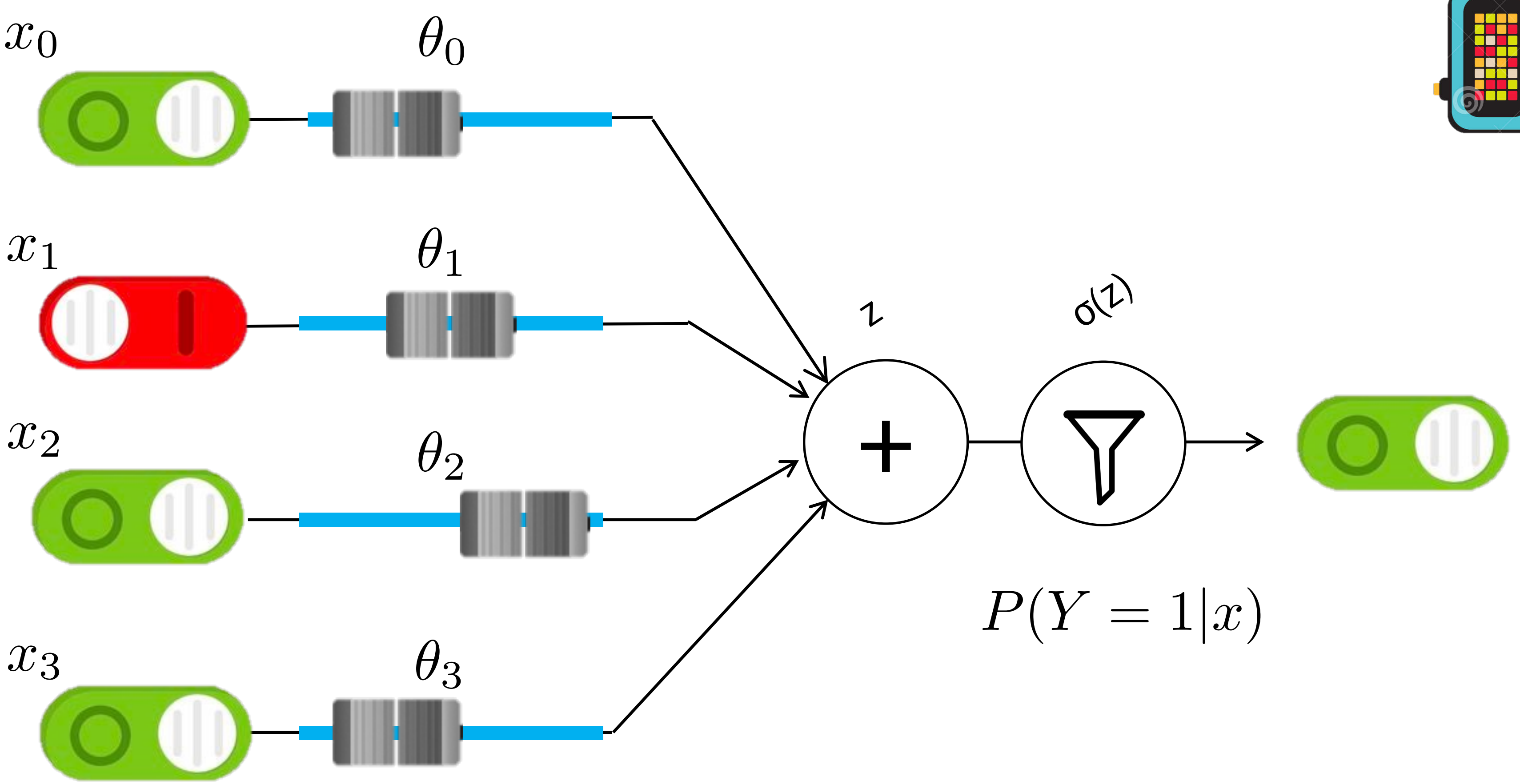
0.81

$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Logistic Regression Assumption

$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Logistic Regression

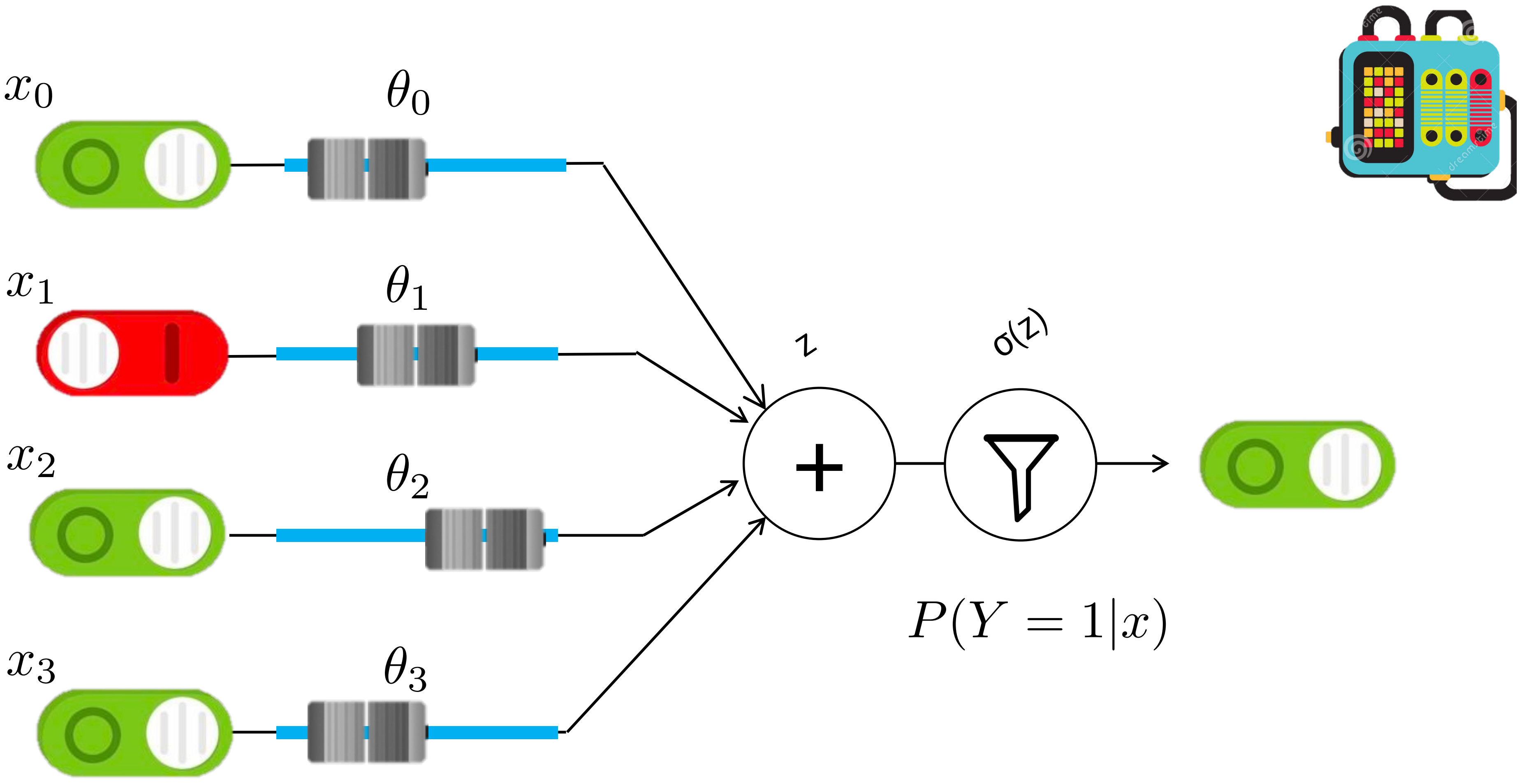


$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Logistic Regression

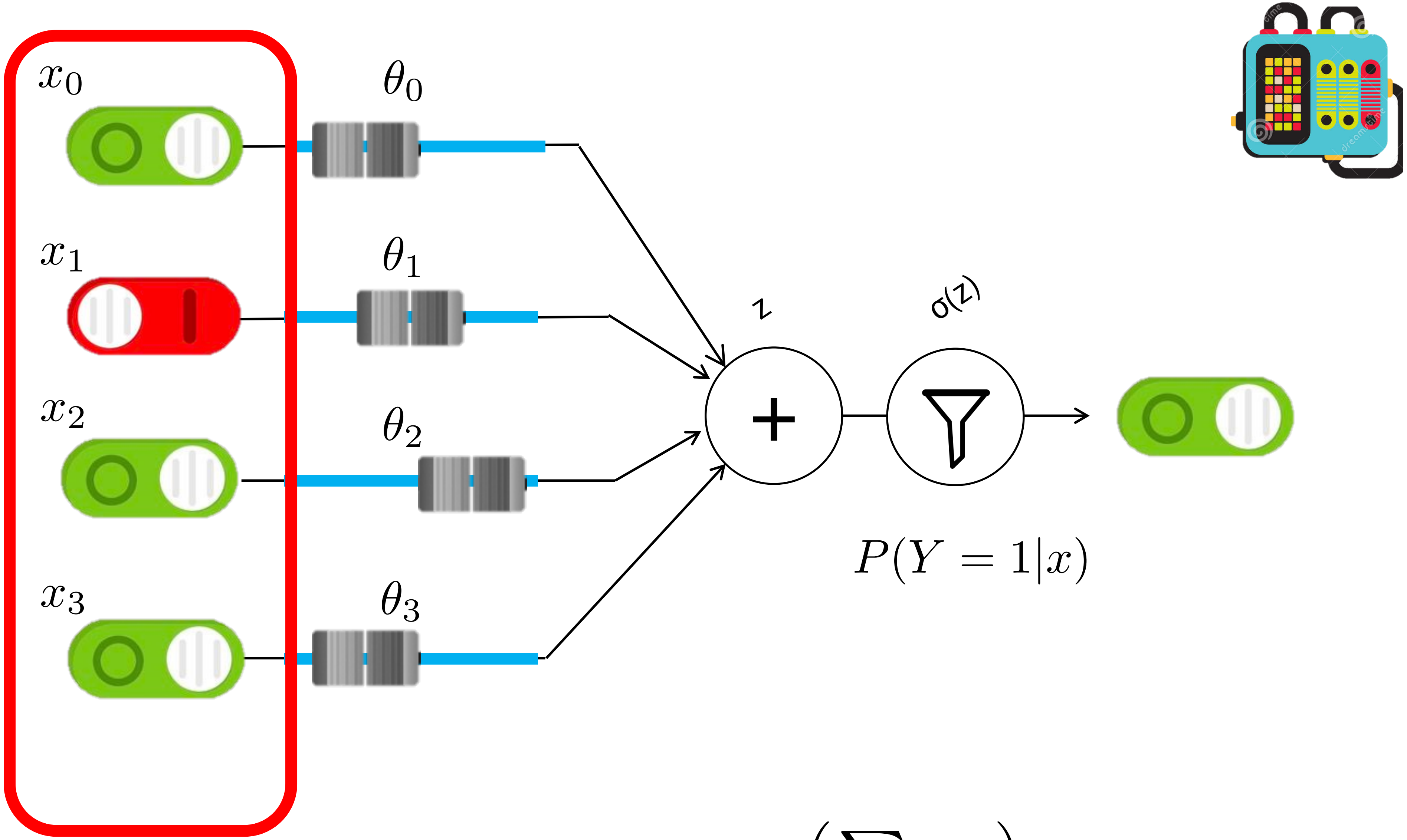
$$P(Y = 1 | \mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Logistic Regression Cartoon



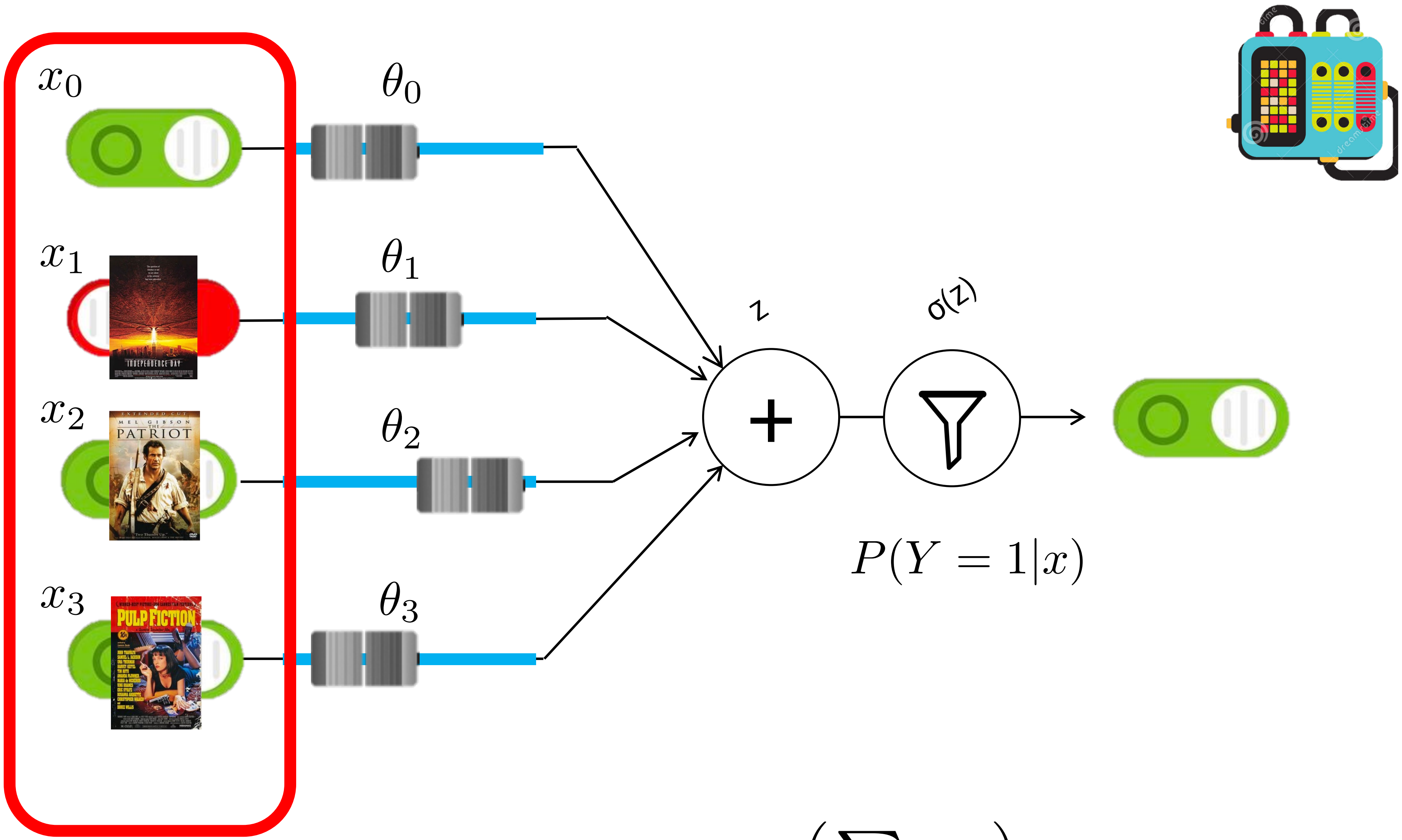
$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Inputs x = [0, 1, 1]



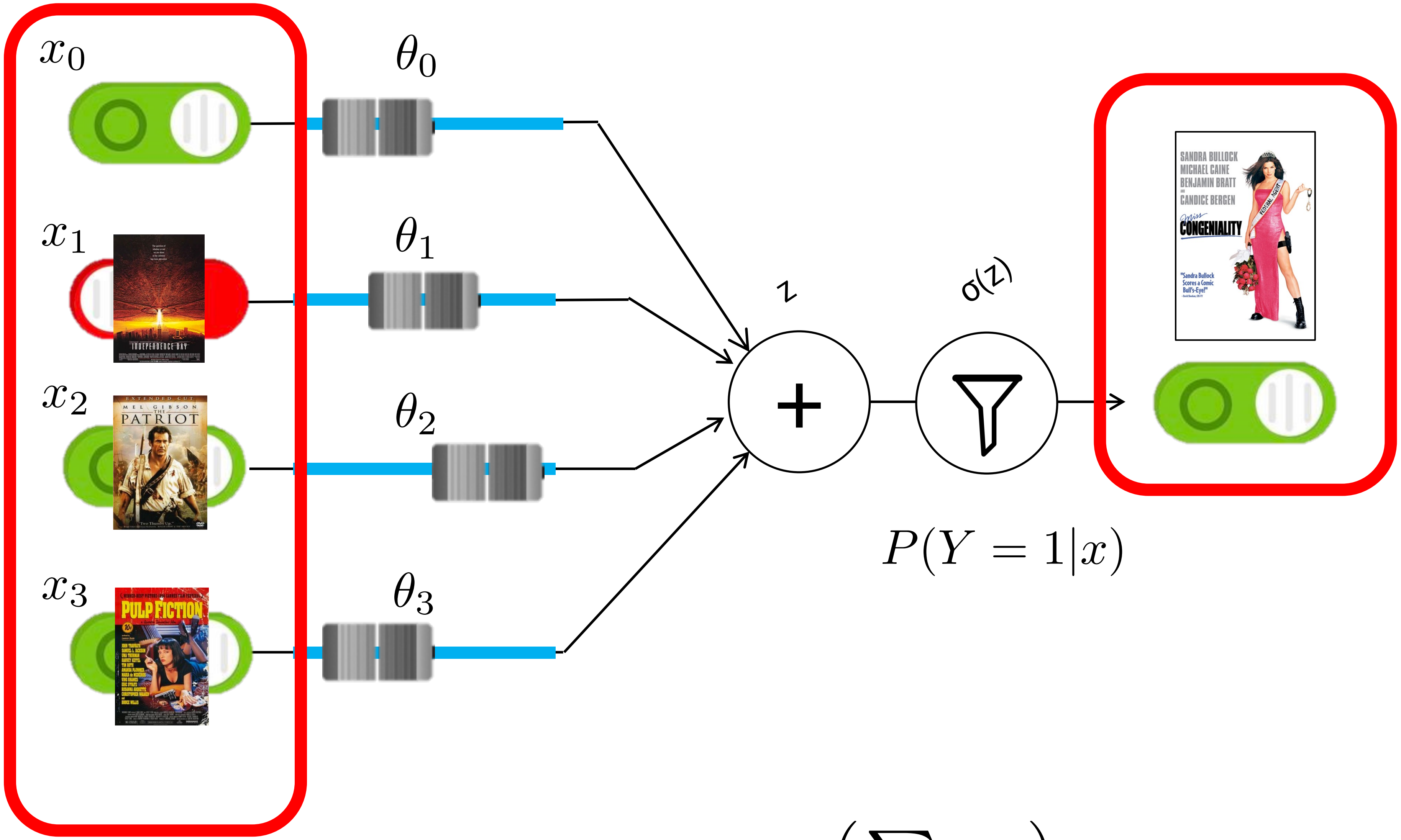
$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Inputs



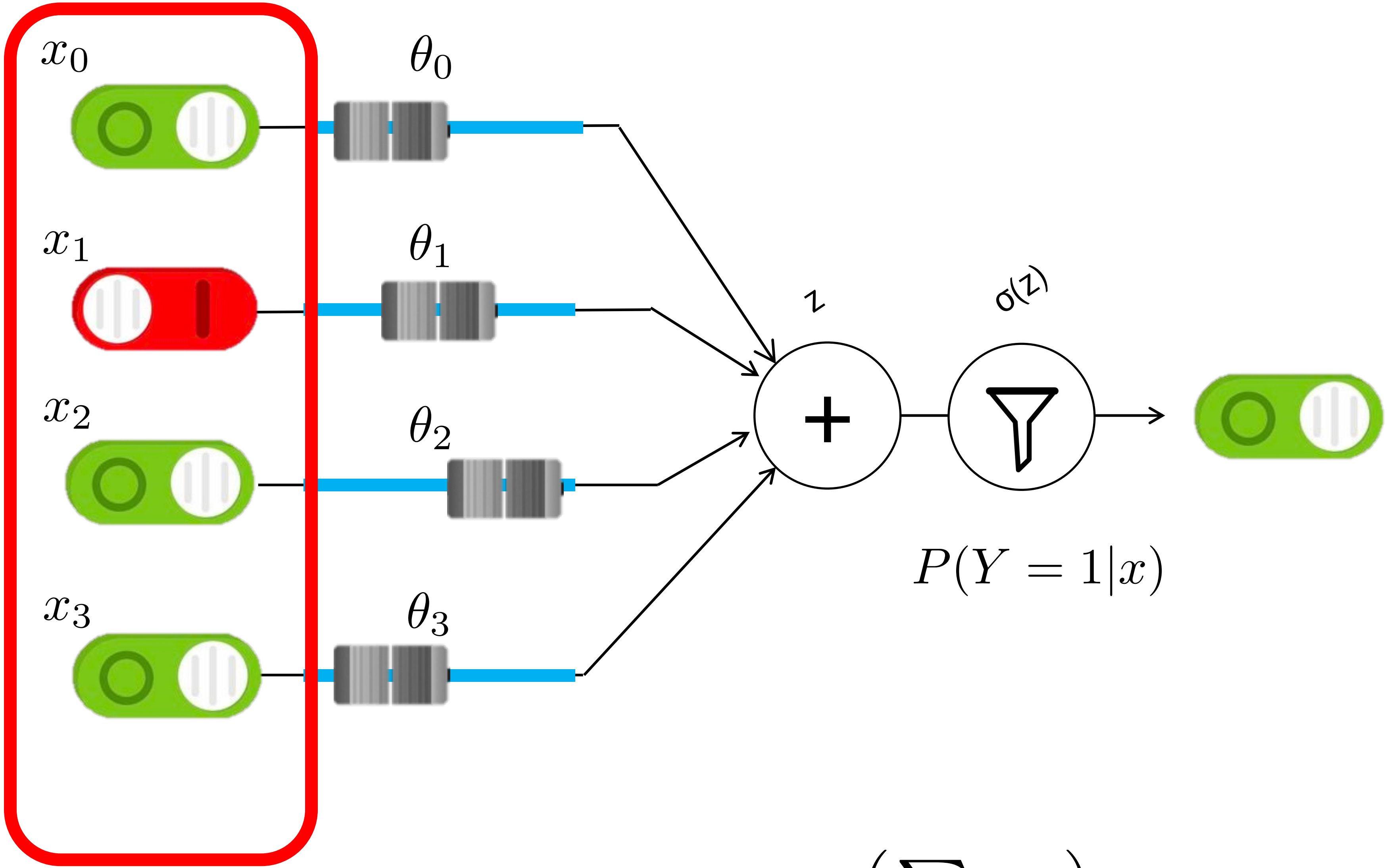
$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Inputs + Output



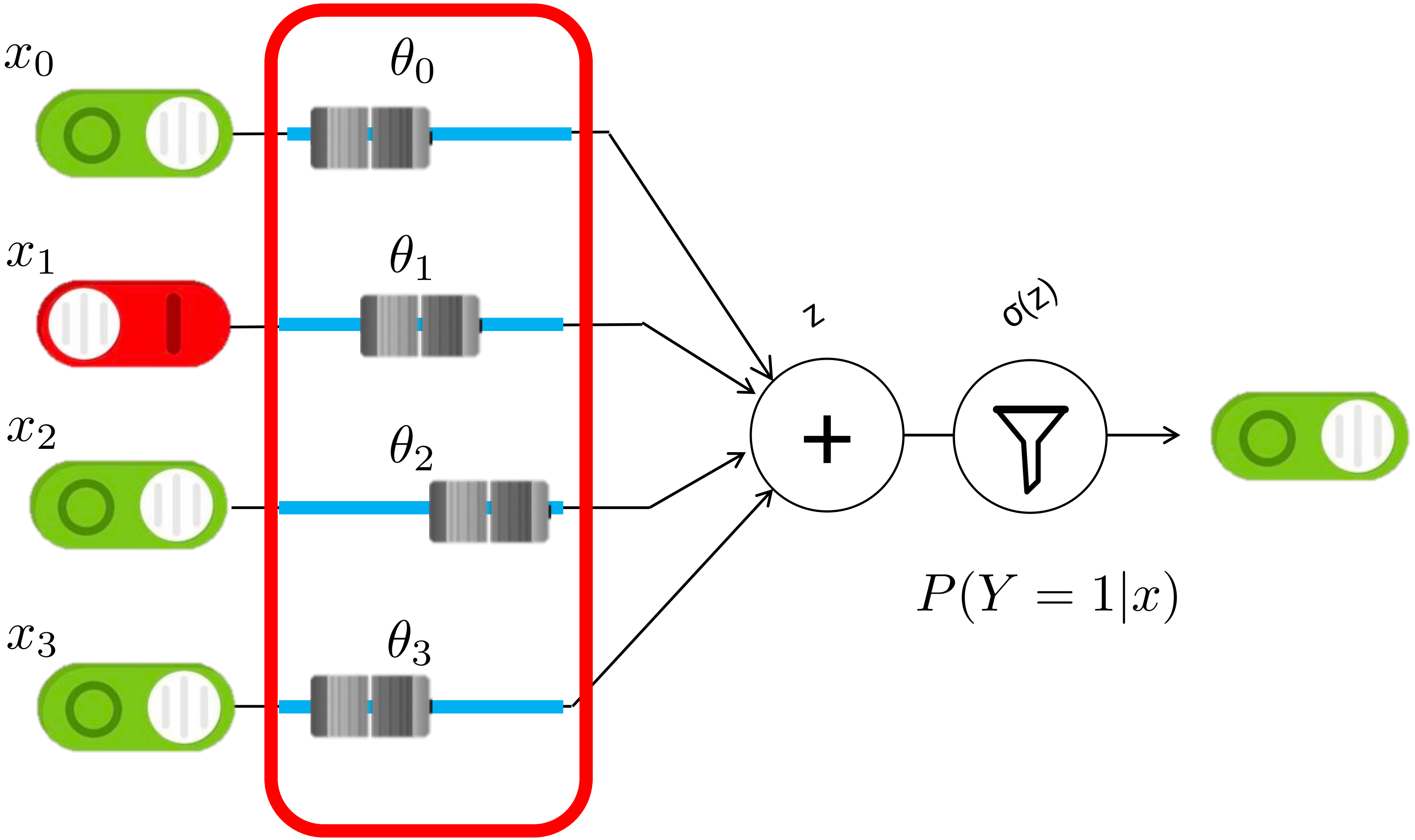
$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Inputs



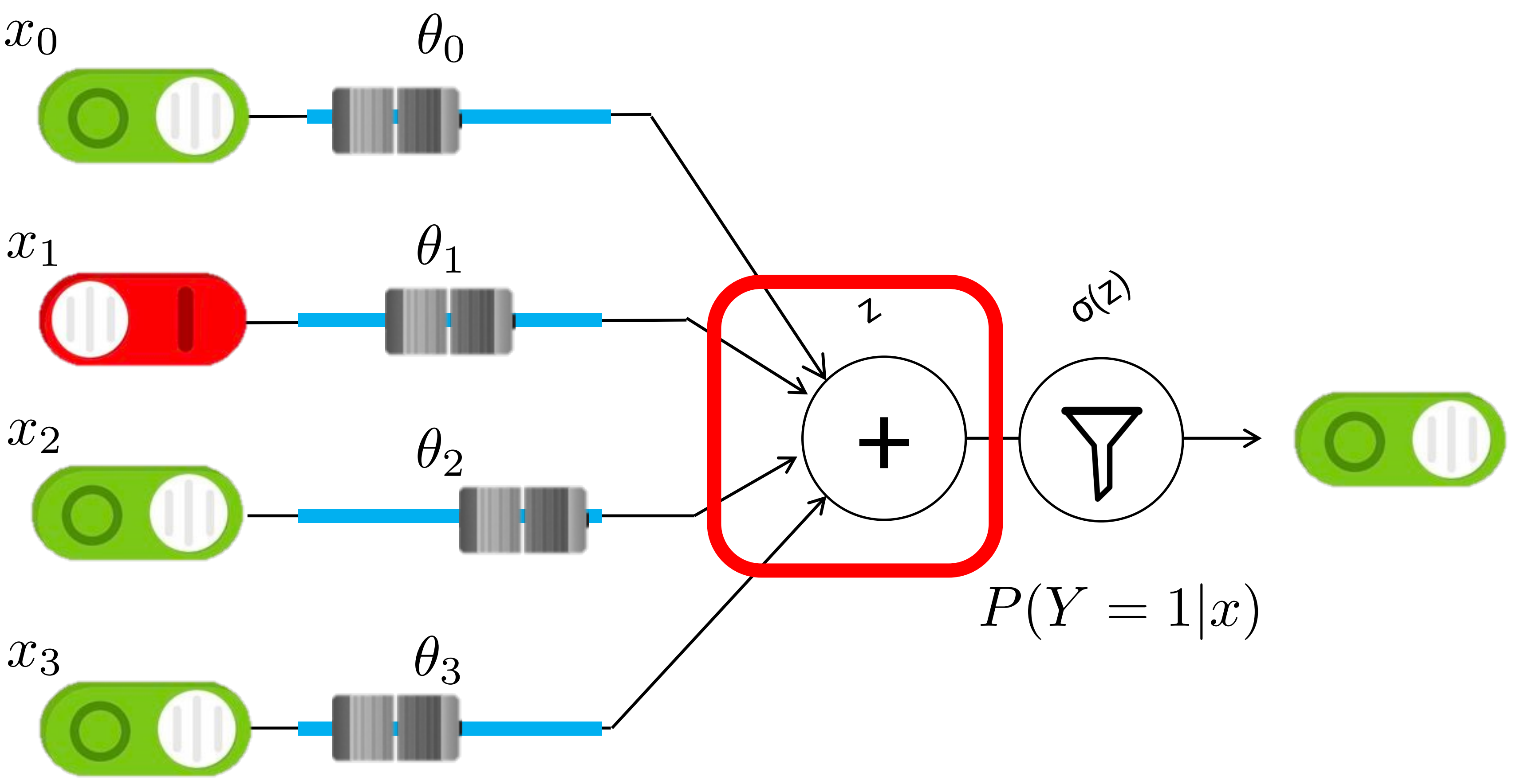
$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Weights



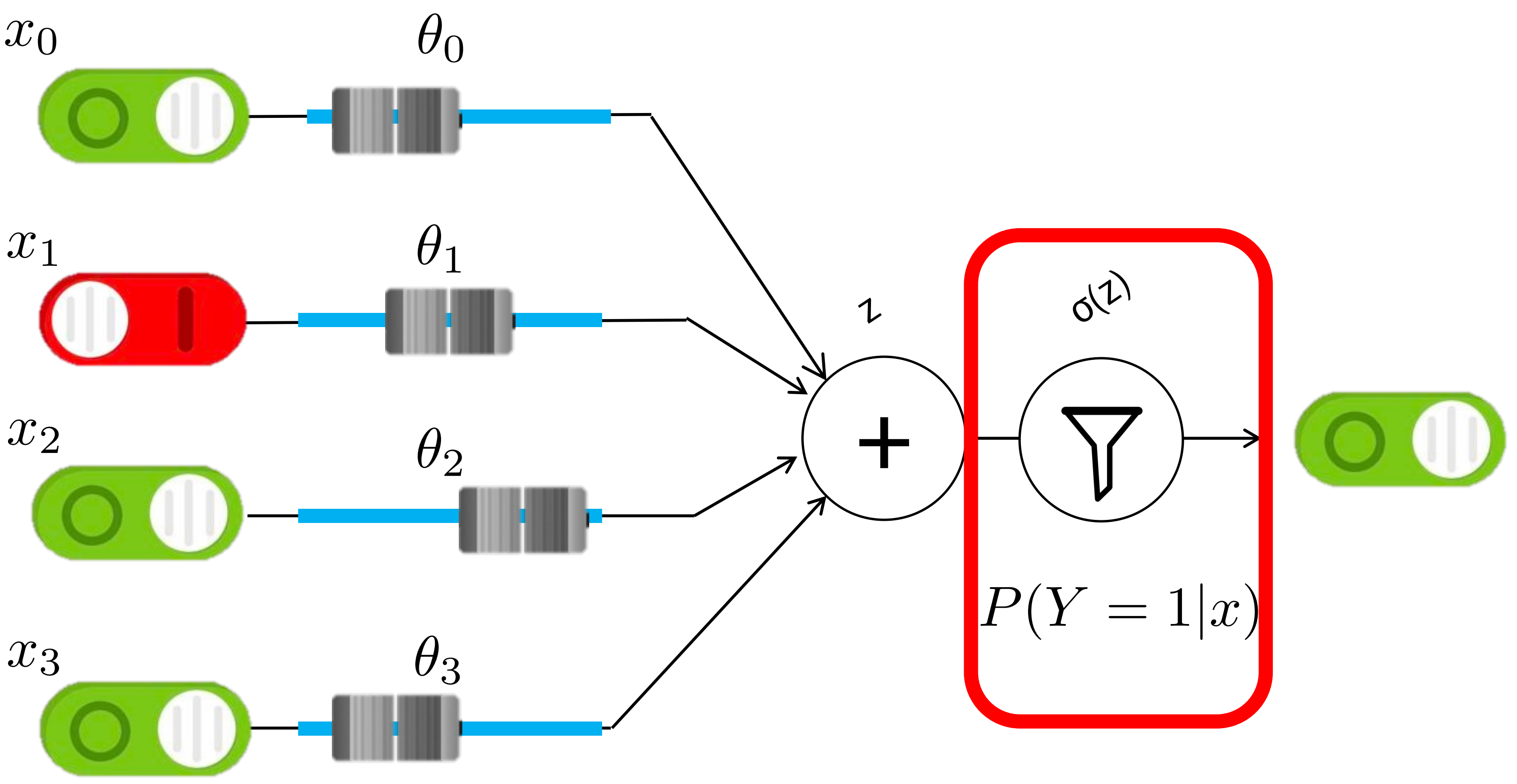
$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Weighed Sum



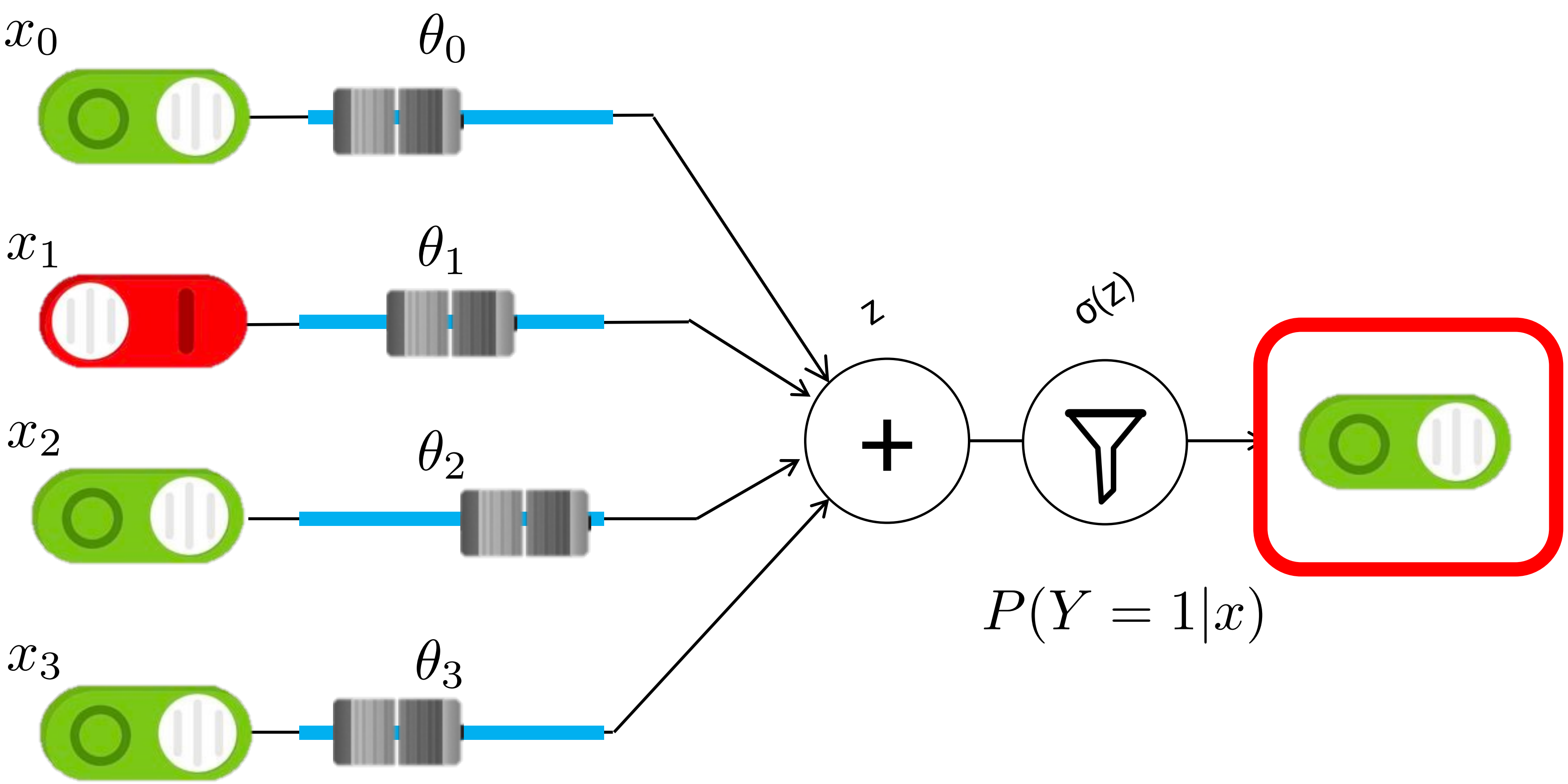
$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Squashing Function



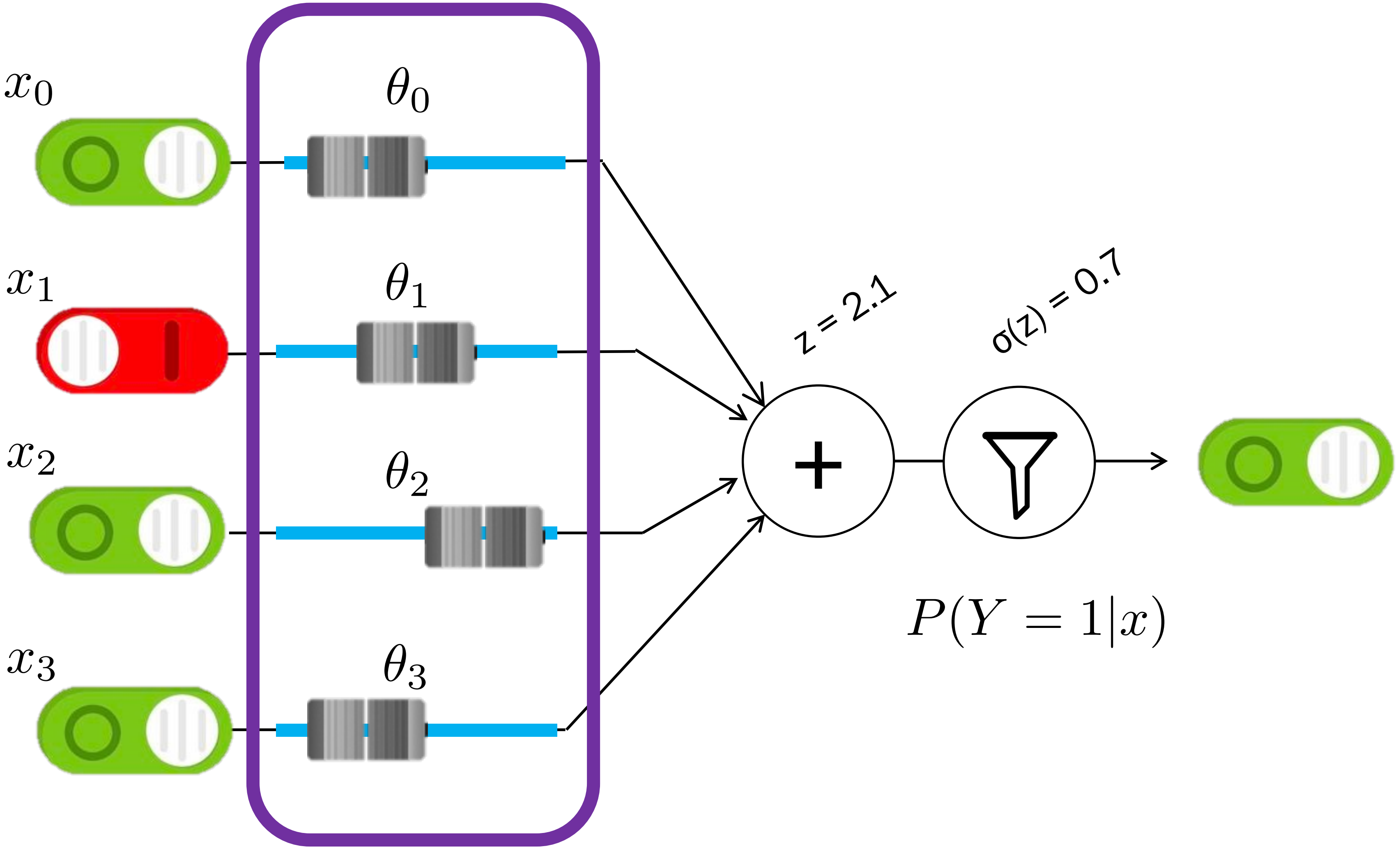
$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Prediction



$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Parameters Affect Prediction



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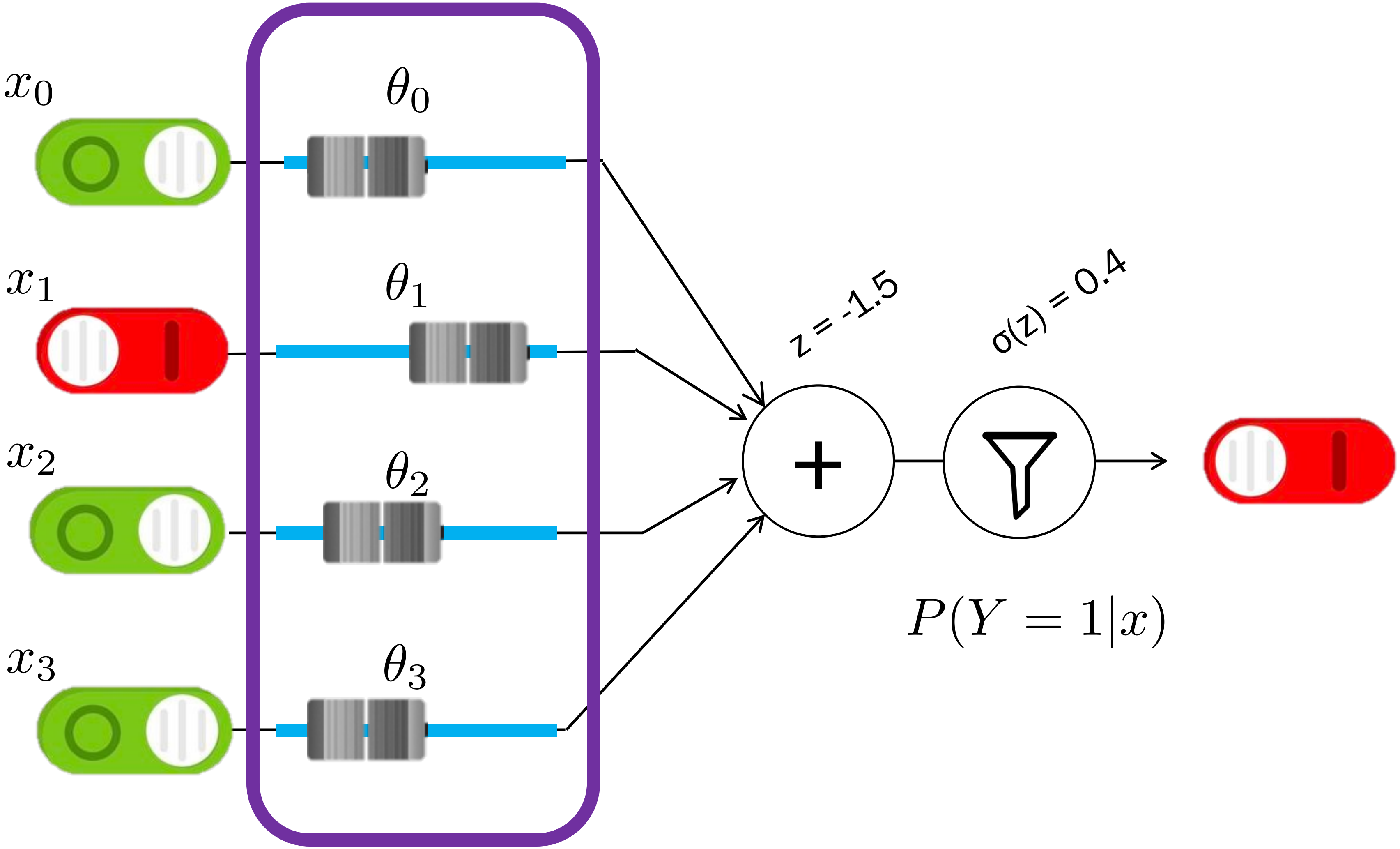

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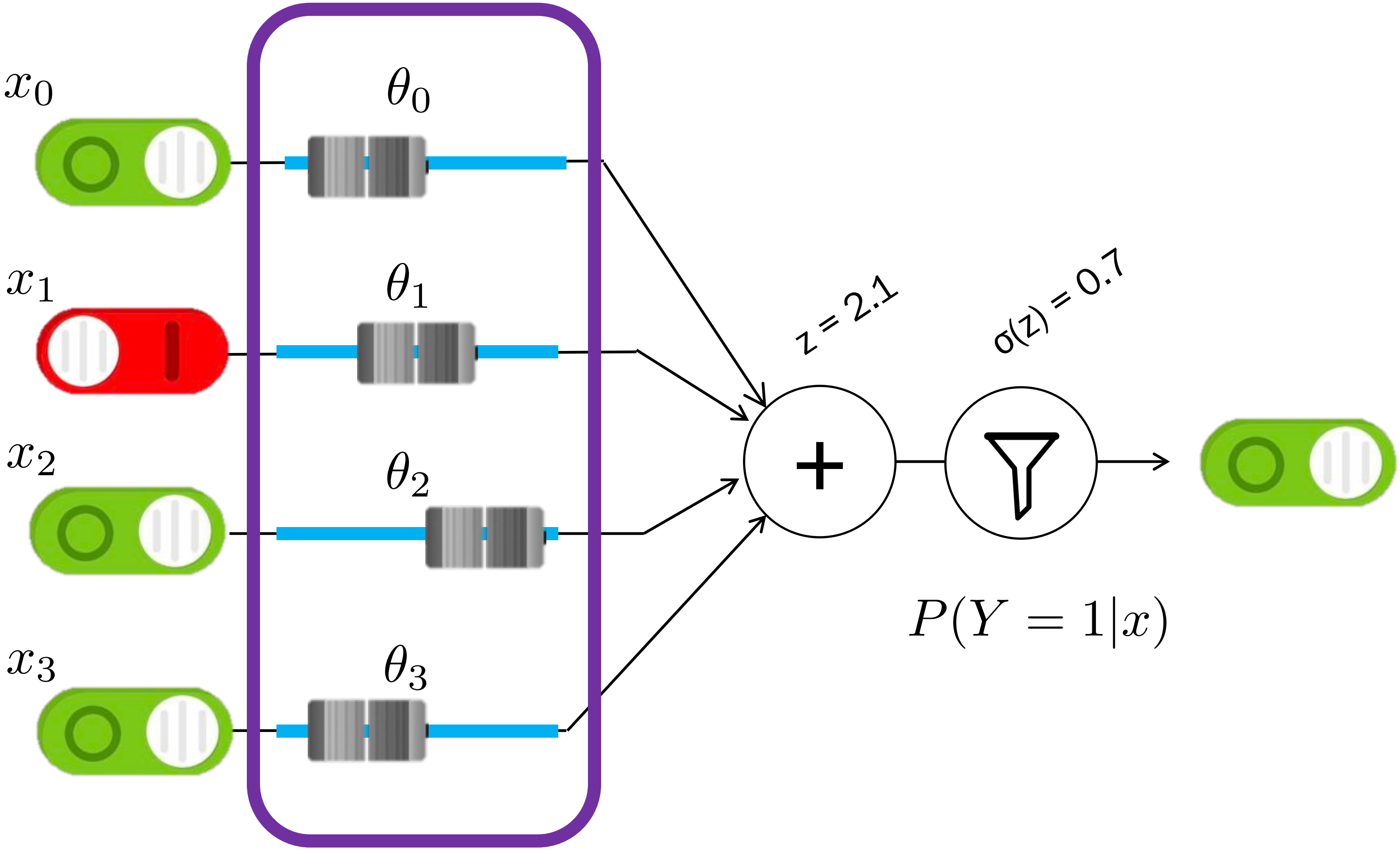
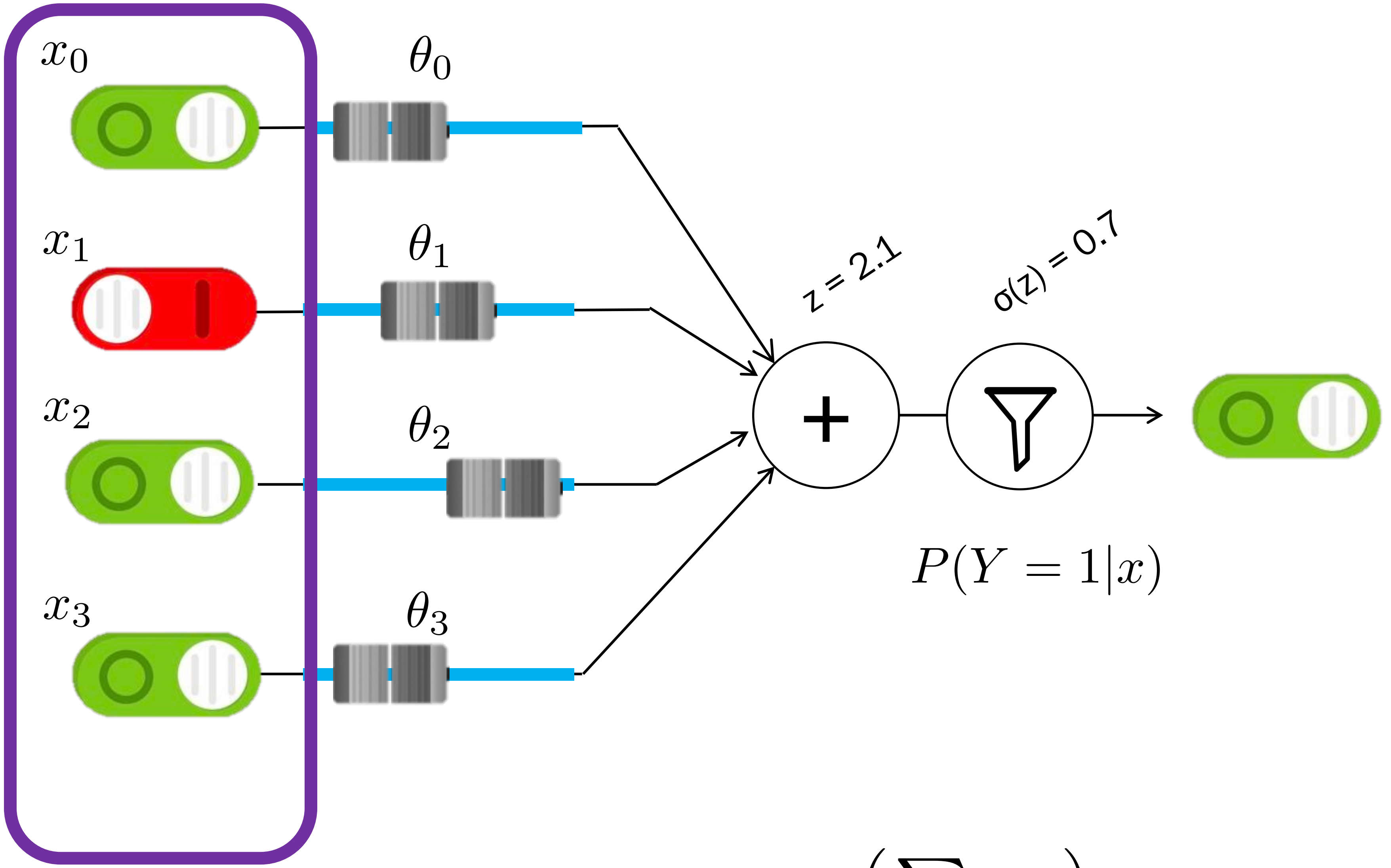
Parameters Affect Prediction



$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

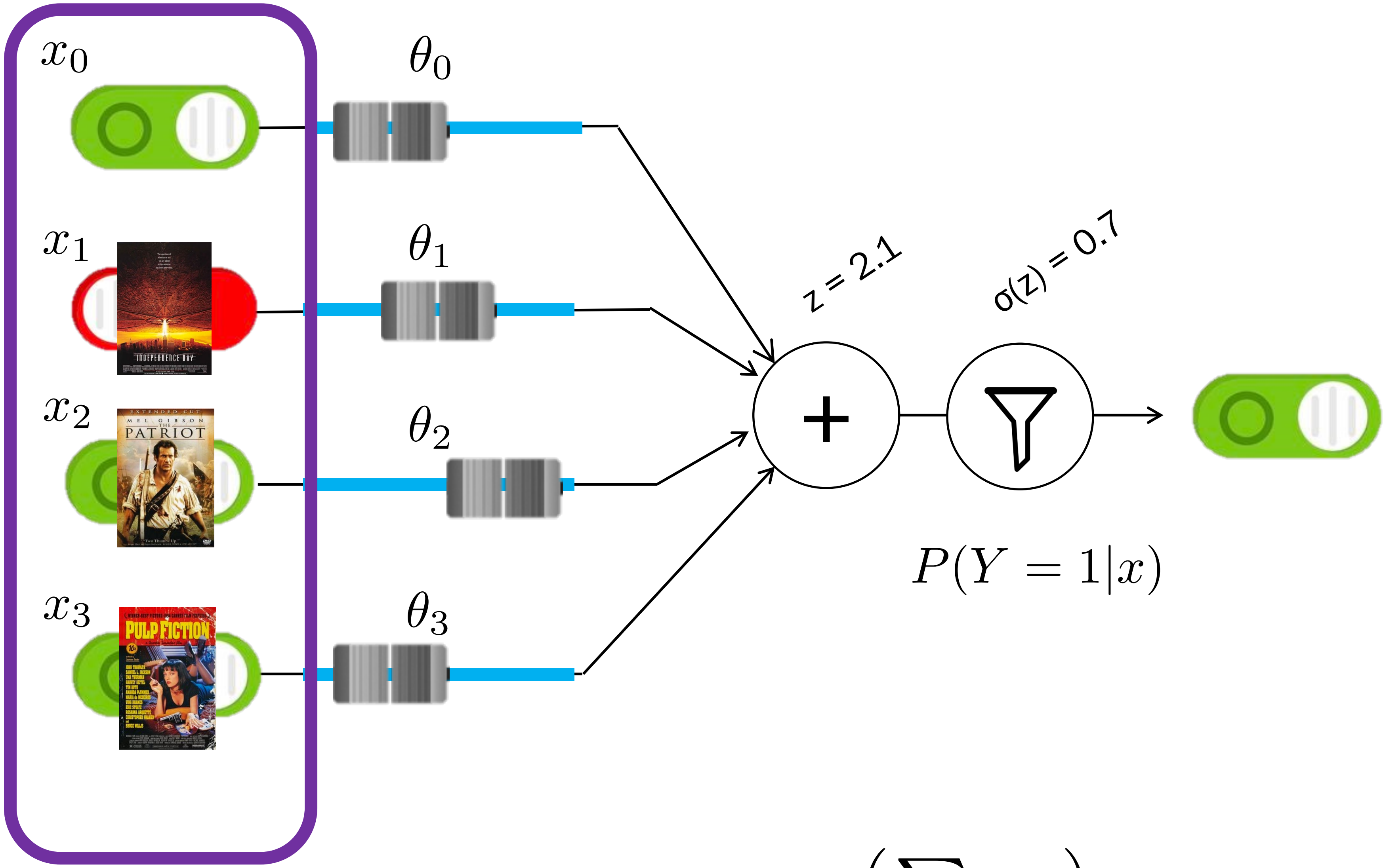
Stanford University

Different Predictions for Different Inputs



$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Different Predictions for Different Inputs



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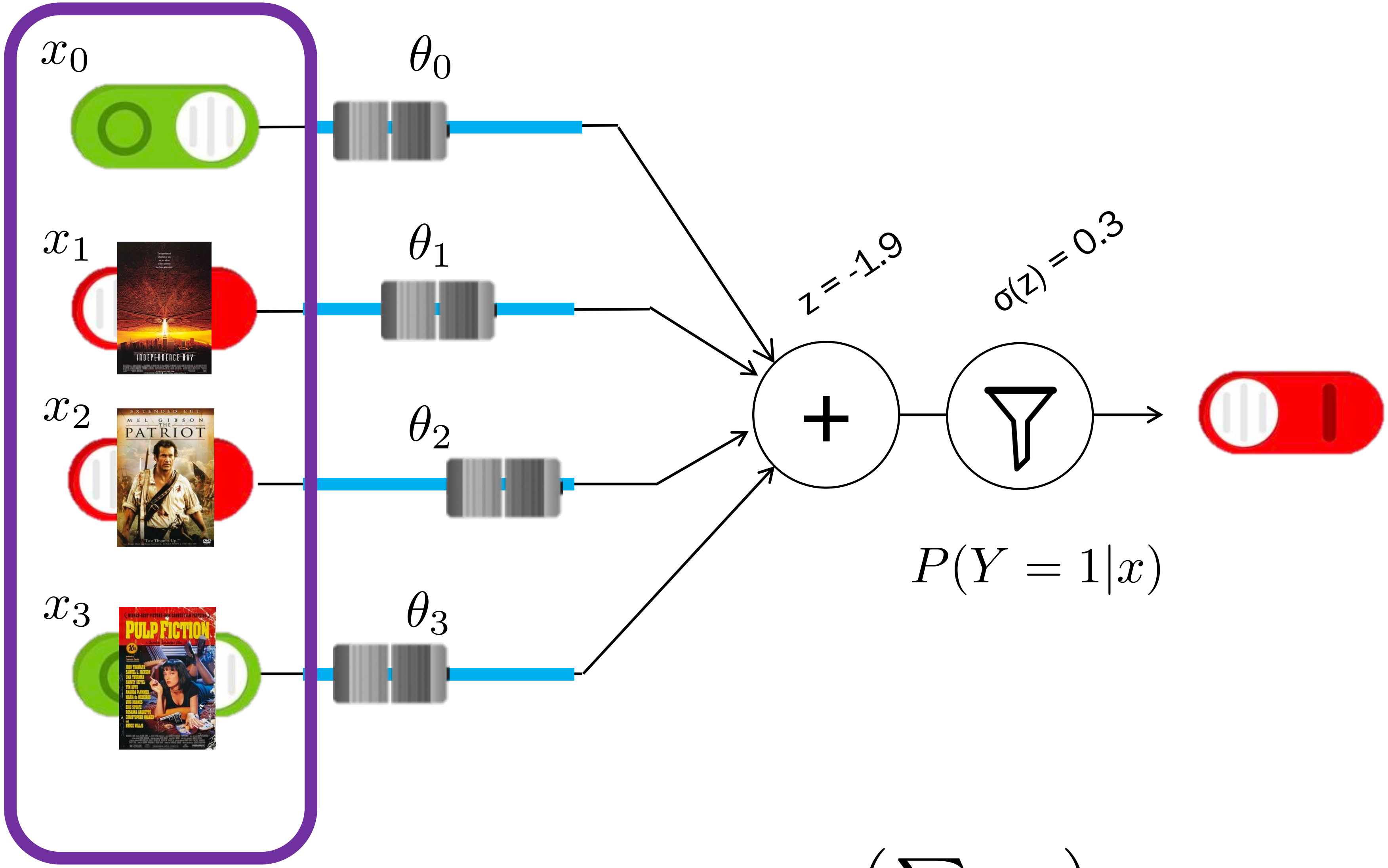
Different Predictions for Different Inputs



$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right)$$

Logistic Regression Assumption

Model *conditional* likelihood P(Y | **X**) directly

- Model this probability with *logistic* function:

$$P(Y=1|\mathbf{X}) = \sigma(z) \text{ where } z = \theta_0 + \sum_{i=1}^{m} \theta_i x_i$$

- For simplicity define $x_0 = 1$ so $z = \theta^T \mathbf{x}$

- Since $\mathrm{P}(Y = 0 \mid \mathbf{X}) + \mathrm{P}(Y = 1 \mid \mathbf{X}) = 1$:

$$P(Y=1|X=\mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

$$P(Y=0|X=\mathbf{x}) = 1 - \sigma(\theta^T \mathbf{x})$$

Recall:
Sigmoid function

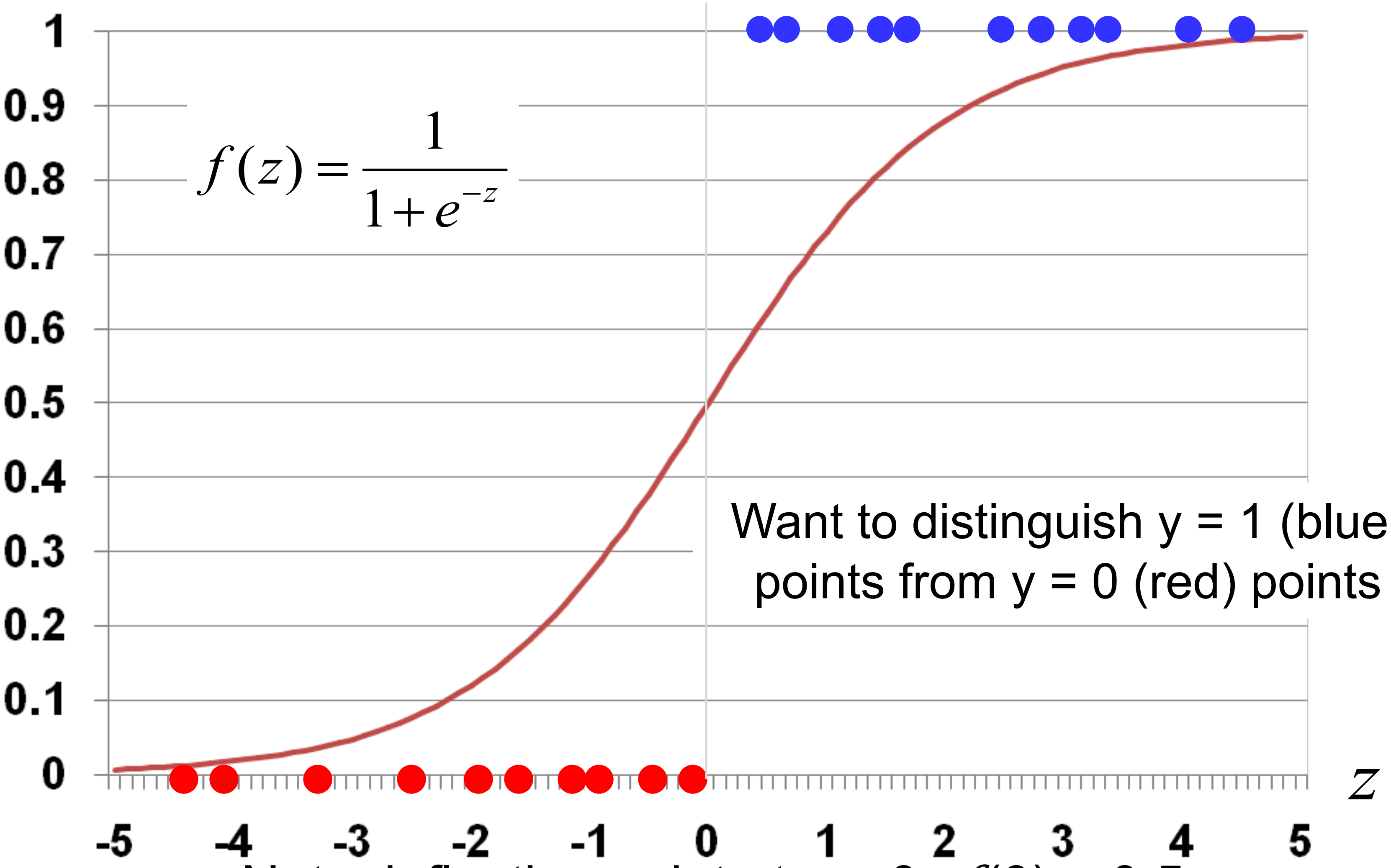
$$\sigma(z) = \frac{1}{1+e^{-z}}$$

Big Assumption

Logistic Regression Assumption:

$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

The Sigmoid Function



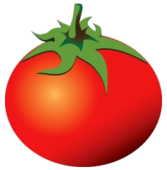
$$f(z) = \frac{1}{1+e^{-z}}$$

Want to distinguish y = 1 (blue) points from y = 0 (red) points

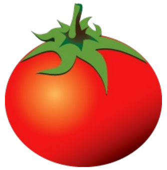
Note: inflection point at z = 0. $f(0) = 0.5$

What is in a Name

Regression Algorithms

Linear Regression 

Classification Algorithms

Naïve Bayes 

Logistic Regression 

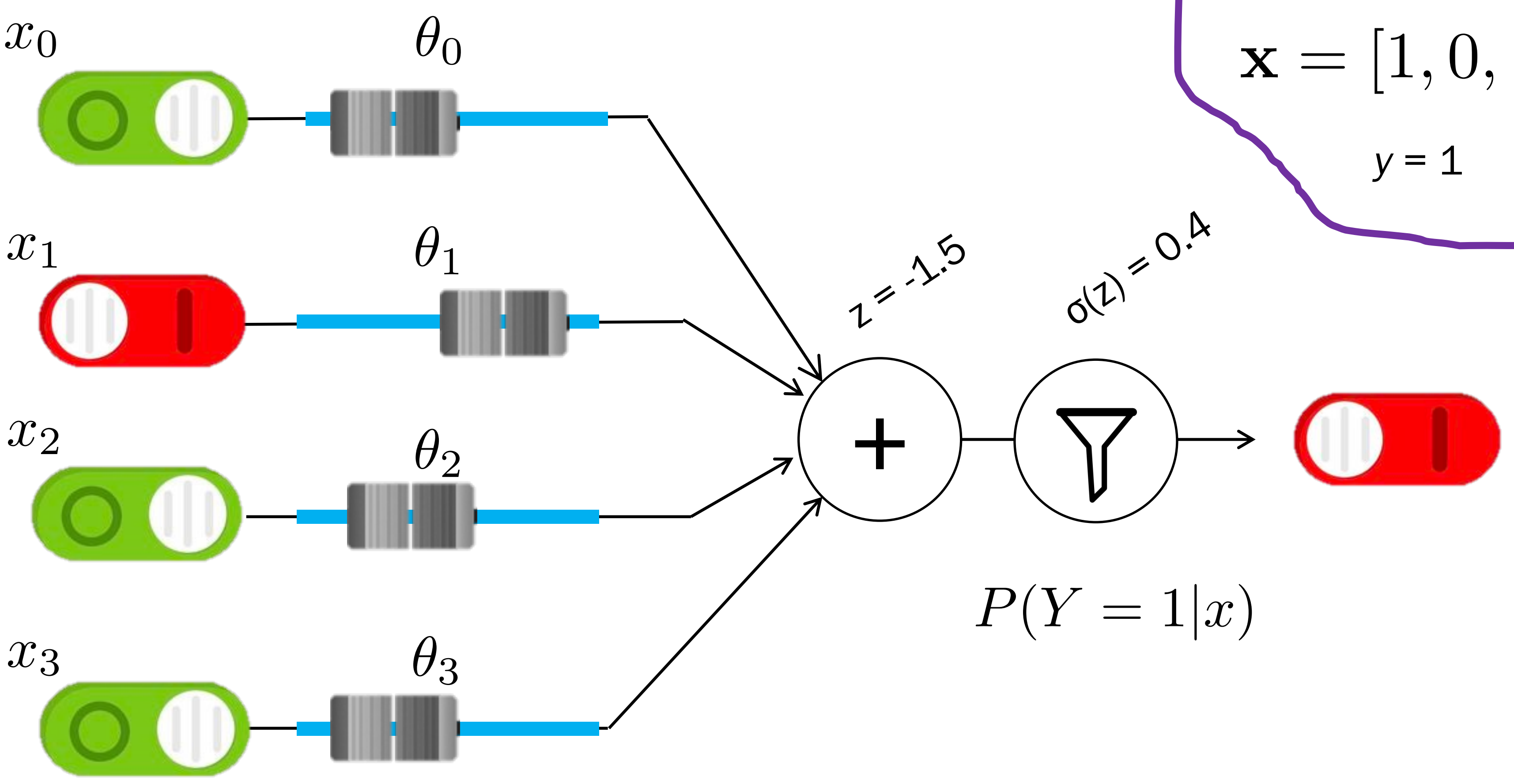
Awesome classifier,
terrible name

If Chris could rename it he would call it: Sigmoidal Classification

What makes for a “smart” logistic regression algorithm?

Logistic regression gets its ***intelligence*** from its thetas (aka its parameters)

How Do We Learn Parameters?



Let's say that:

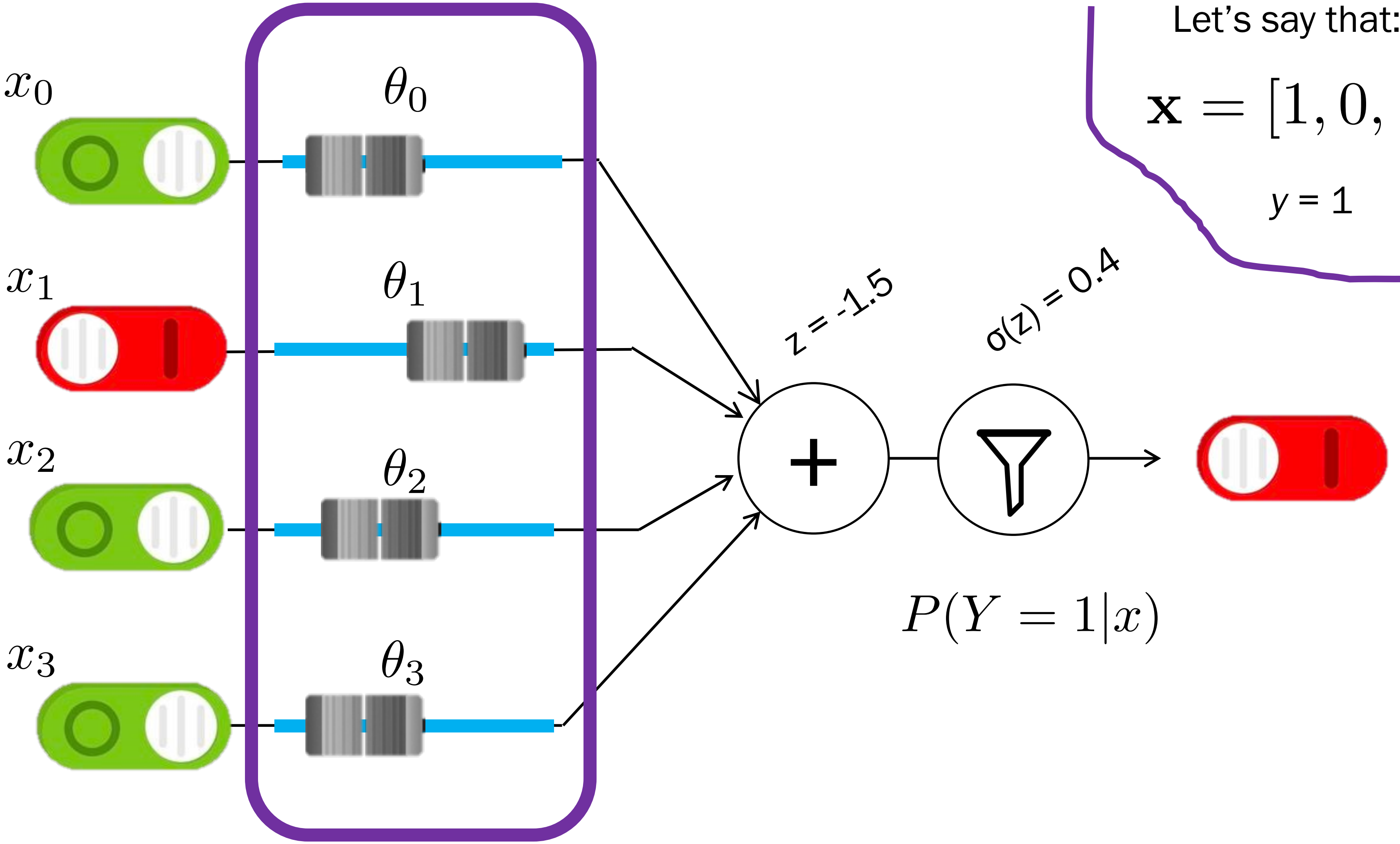
$$\mathbf{x} = [1, 0, 1, 1]$$

y = 1

$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\Big(\sum_i \theta_i x_i\Big) = 0.4$$

Data looks unlikely

How Do We Learn Parameters?



Let's say that:

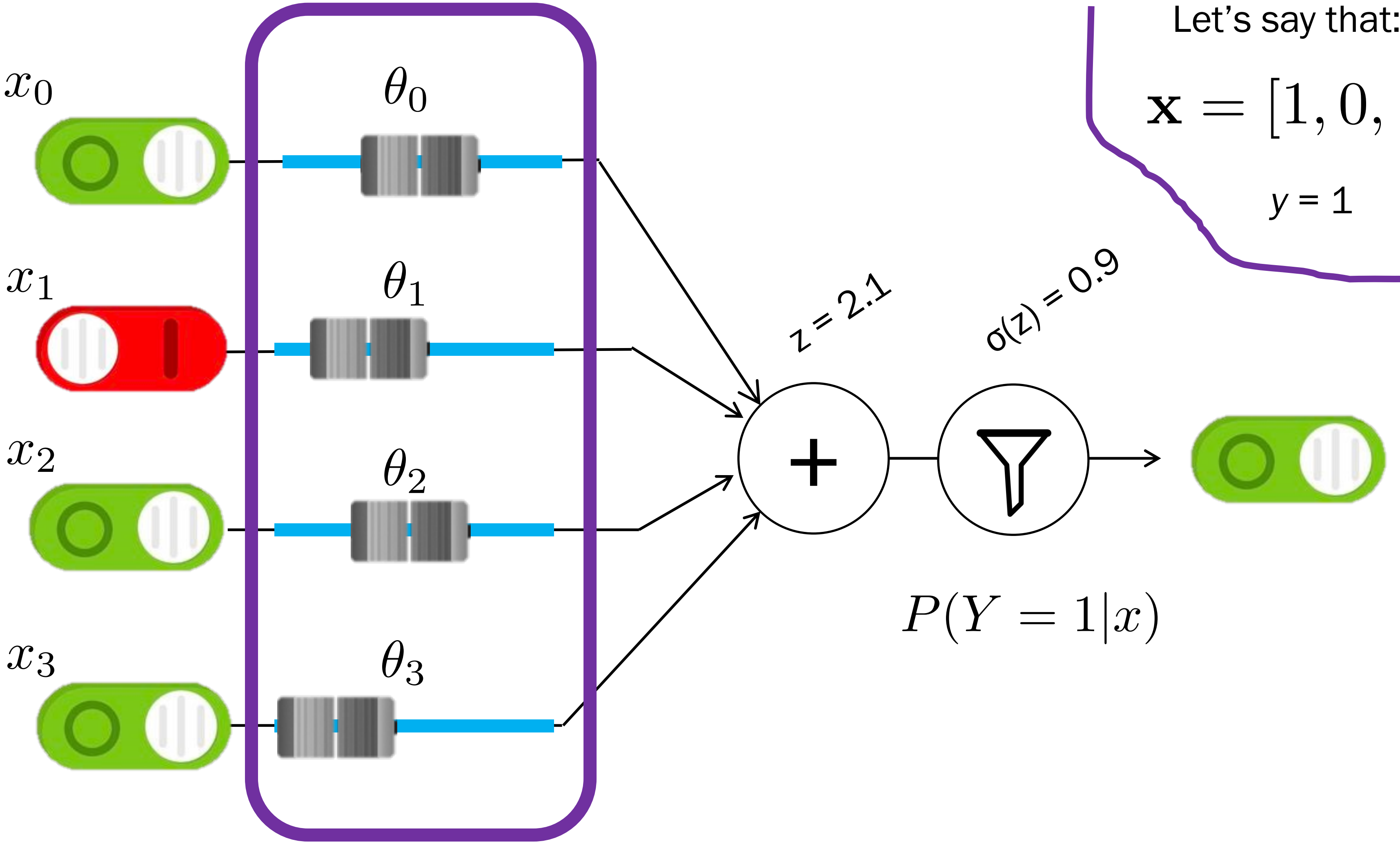
$$\mathbf{x} = [1, 0, 1, 1]$$

$y = 1$

Data looks unlikely

$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\Big(\sum_i \theta_i x_i\Big) = 0.4$$

How Do We Learn Parameters?



Let's say that:

$$\mathbf{x} = [1, 0, 1, 1]$$

$y = 1$

$$P(Y = 1|\mathbf{X} = \mathbf{x}) = \sigma\left(\sum_i \theta_i x_i\right) = 0.9$$

Data is much more likely!

Maximum Likelihood Estimation

Chose your parameter estimates

Parameter μ: 5 Parameter σ: 1.1

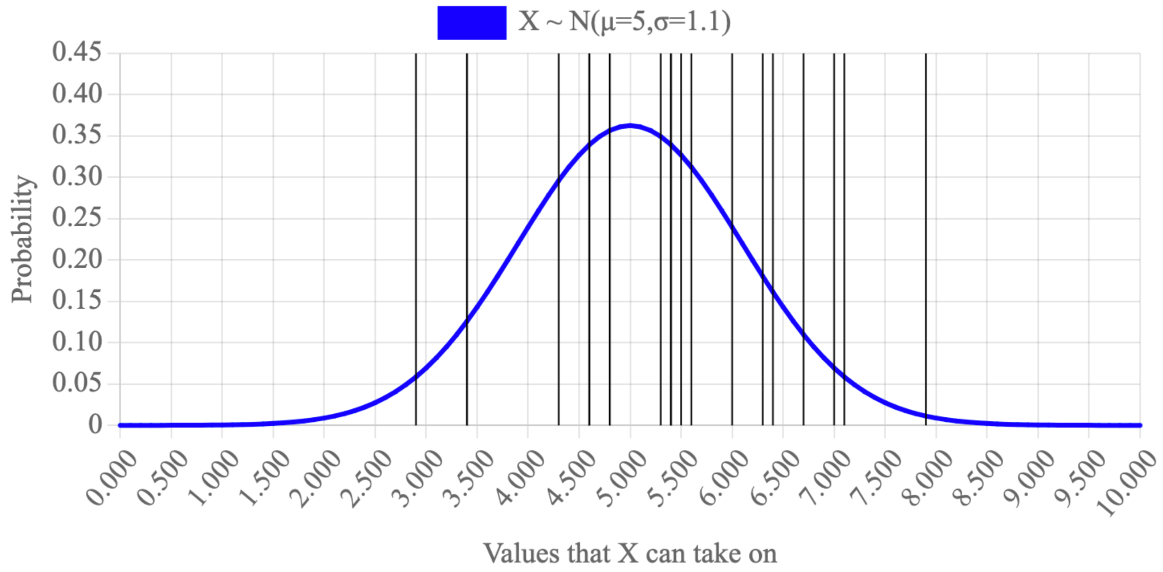
Likelihood of the data given your params

Likelihood: 5.204152095194613e-16

Log Likelihood: -314.1

Best Seen: -311.2

Your Gaussian



Math for Logistic Regression

1 Make logistic regression assumption

$$P(Y=1|X=\mathbf{x}) = \sigma(\theta^T\mathbf{x})$$
$$P(Y=0|X=\mathbf{x}) = 1-\sigma(\theta^T\mathbf{x})$$

Often call this $\hat{y}$

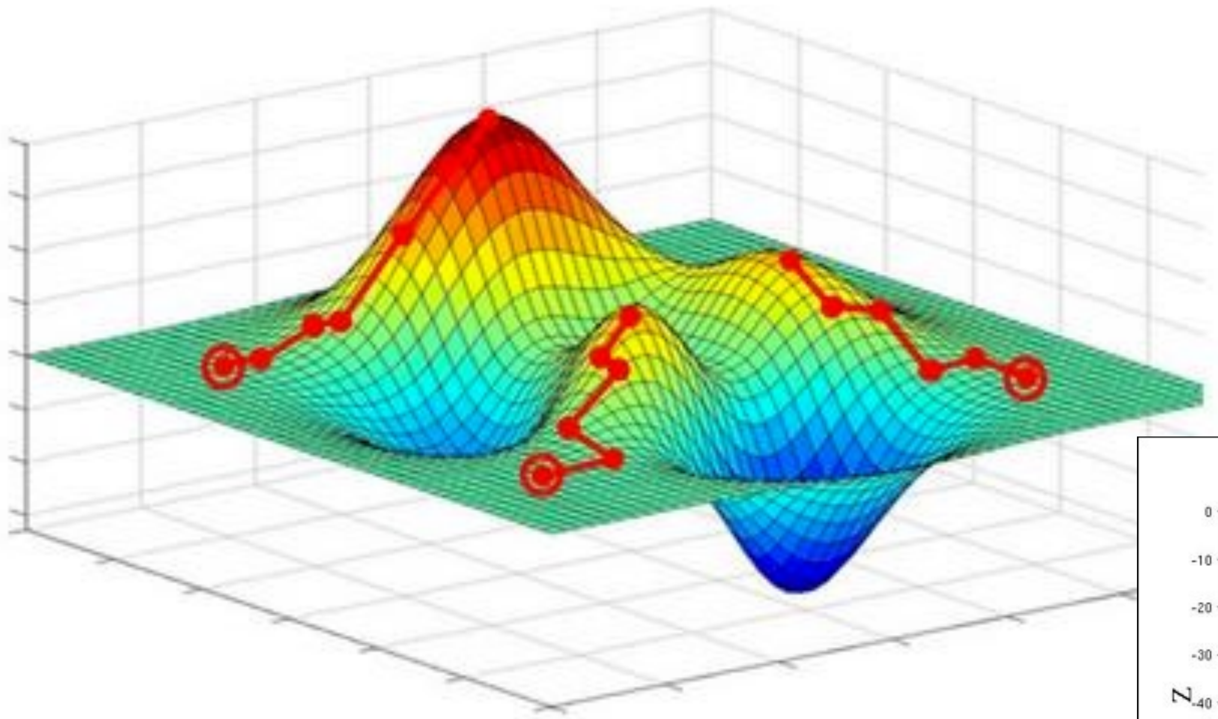
2 Calculate the log likelihood for all data

$$LL(\theta) = \sum_{i=0}^{n} y^{(i)} \log \sigma(\theta^T\mathbf{x}^{(i)}) + (1-y^{(i)}) \log[1-\sigma(\theta^T\mathbf{x}^{(i)})]$$

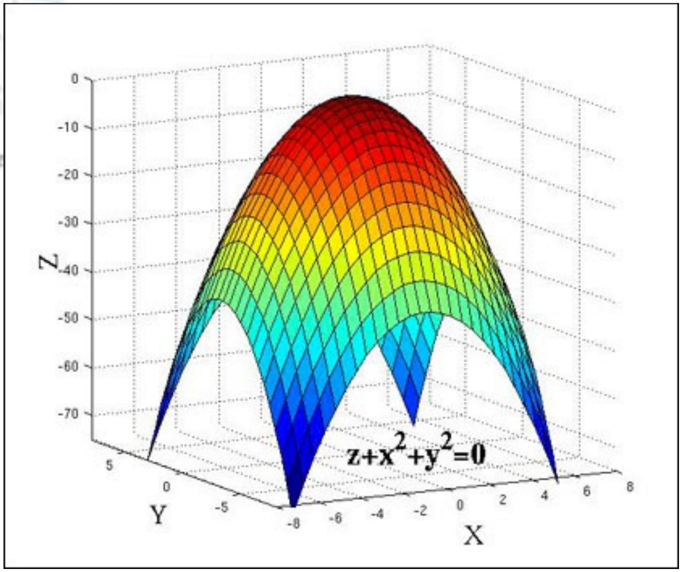
3 Get derivative of log likelihood with respect to thetas

$$\frac{\partial LL(\theta)}{\partial \theta_j} = \sum_{i=1}^{n} \left[y^{(i)} - \sigma(\theta^T\mathbf{x}^{(i)})\right] x_j^{(i)}$$

Gradient Ascent



Logistic regression LL function is convex



Walk uphill and you will find a local maxima
(if your step size is small enough)

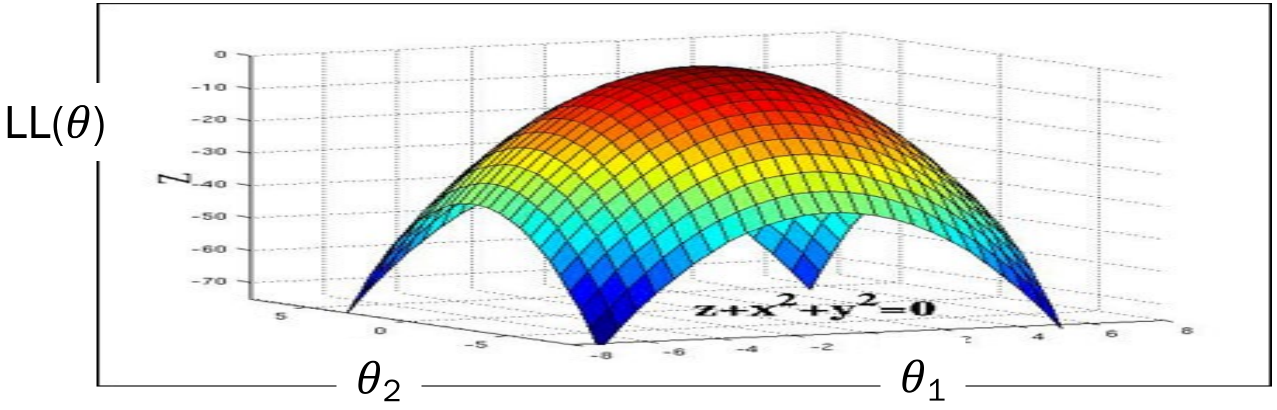
Gradient Ascent Step

$$\frac{\partial LL(\theta)}{\partial \theta_j} = \sum_{i=0}^{n} \left[y^{(i)} - \sigma(\theta^T \mathbf{x}^{(i)}) \right] x_j^{(i)}$$

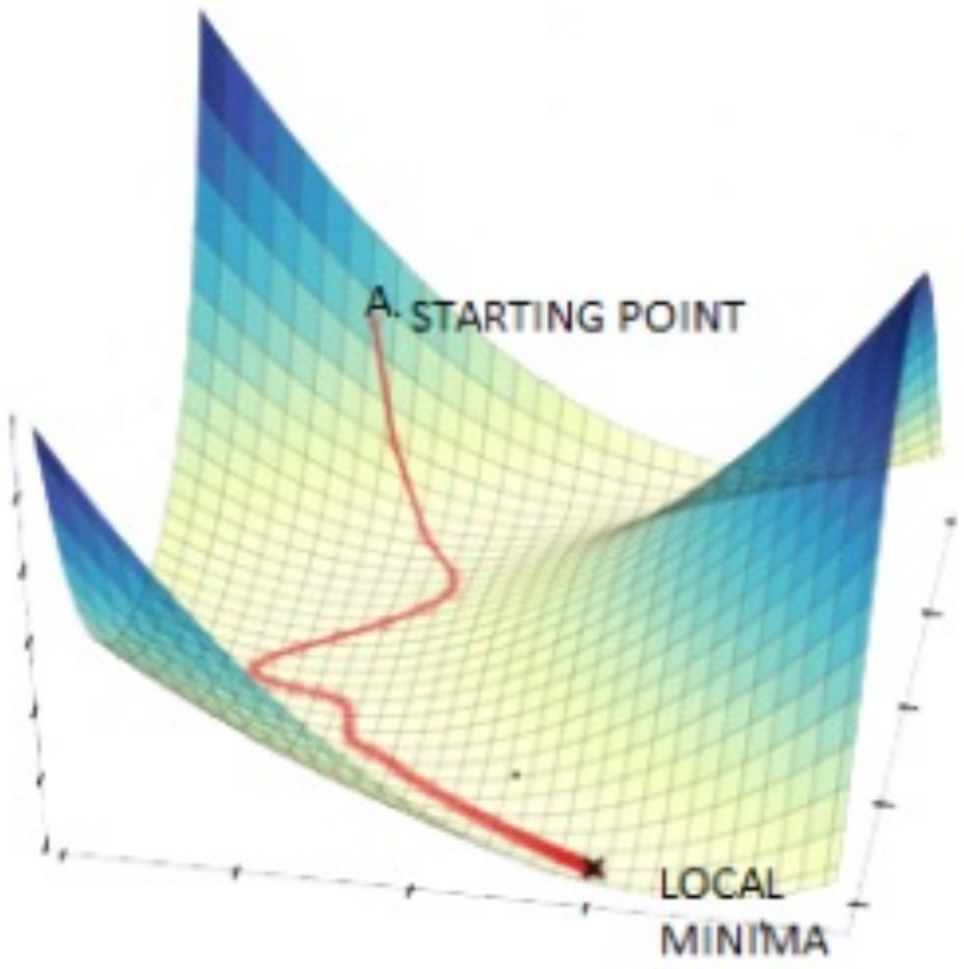
$$\theta_j^{\text{new}} = \theta_j^{\text{old}} + \eta \cdot \frac{\partial LL(\theta^{\text{ old}})}{\partial \theta_j^{\text{old}}}$$

$$= \theta_j^{\text{old}} + \eta \cdot \sum_{i=0}^{n} \left[y^{(i)} - \sigma(\theta^T \mathbf{x}^{(i)}) \right] x_j^{(i)}$$

Do this for all thetas!



Gradient Decent



Walk downhill and you will find a local maxima
(if your step size is small enough)

Gradient Descent with Negative LL

Assume some loss function with known derivative $\dfrac{\partial \text{ Loss}}{\partial \theta_j}$

$$\theta_j^{\text{new}} = \theta_j^{\text{old}} - \eta \cdot \frac{\partial \text{ Loss}}{\partial \theta_j}$$

Gradient Descent with Negative LL

Assume some loss function with known derivative $\frac{\partial \text{ Loss}}{\partial \theta_j}$

$$\theta_j^{\text{new}} = \theta_j^{\text{old}} - \eta \cdot \frac{\partial \text{ Loss}}{\partial \theta_j}$$

$$= \theta_j^{\text{old}} - \eta \cdot \frac{\partial \text{ Negative}LL}{\partial \theta_j}$$

$$= \theta_j^{\text{old}} + \eta \cdot \sum_{i=0}^{n} \left[y^{(i)} - \sigma(\theta^T \mathbf{x}^{(i)}) \right] x_j^{(i)}$$

Gradient Descent with Negative LL

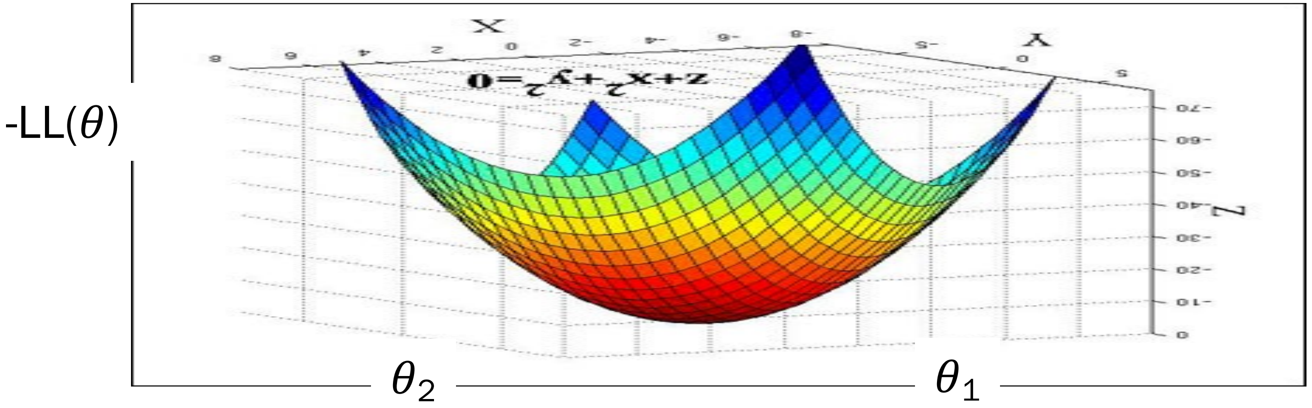
Assume some loss function with known derivative $\frac{\partial \text{ Loss}}{\partial \theta_j}$

$$\theta_j^{\text{new}} = \theta_j^{\text{old}} - \eta \cdot \frac{\partial \text{ Loss}}{\partial \theta_j}$$

...exactly the same

$$= \theta_j^{\text{old}} - \eta \cdot \frac{\partial \text{ Negative}LL}{\partial \theta_j}$$

$$= \theta_j^{\text{old}} + \eta \cdot \sum_{i=0}^{n} \left[y^{(i)} - \sigma(\theta^T \mathbf{x}^{(i)}) \right] x_j^{(i)}$$



What does this look like in code?

$$\theta_j^{\text{new}} = \theta_j^{\text{old}} + \eta \cdot \frac{\partial LL(\theta^{\text{ old}})}{\partial \theta_j^{\text{old}}}$$

$$= \theta_j^{\text{old}} + \eta \cdot \sum_{i=0}^{n} \left[y^{(i)} - \sigma(\theta^T \mathbf{x}^{(i)}) \right] x_j^{(i)}$$

Logistic Regression Training

Initialize: $\theta_j = 0$ **for all** $0 \leq j \leq m$

Calculate all θ_j

Logistic Regression Training

Initialize: θ_j = 0 for all 0 ≤ j ≤ m

Repeat many times:

gradient[j] = 0 for all 0 ≤ j ≤ m

Calculate all gradient[j]*'s based on data*

θ_j += η * gradient[j] for all 0 ≤ j ≤ m

Logistic Regression Training

Initialize: $\theta_j = 0$ for all $0 \le j \le m$

Repeat many times:

gradient[j] = 0 for all $0 \le j \le m$

For each training example (x, y):

For each parameter j:

Update gradient[j] *for current training example*

θ_j += η * gradient[j] for all $0 \le j \le m$

Logistic Regression Training

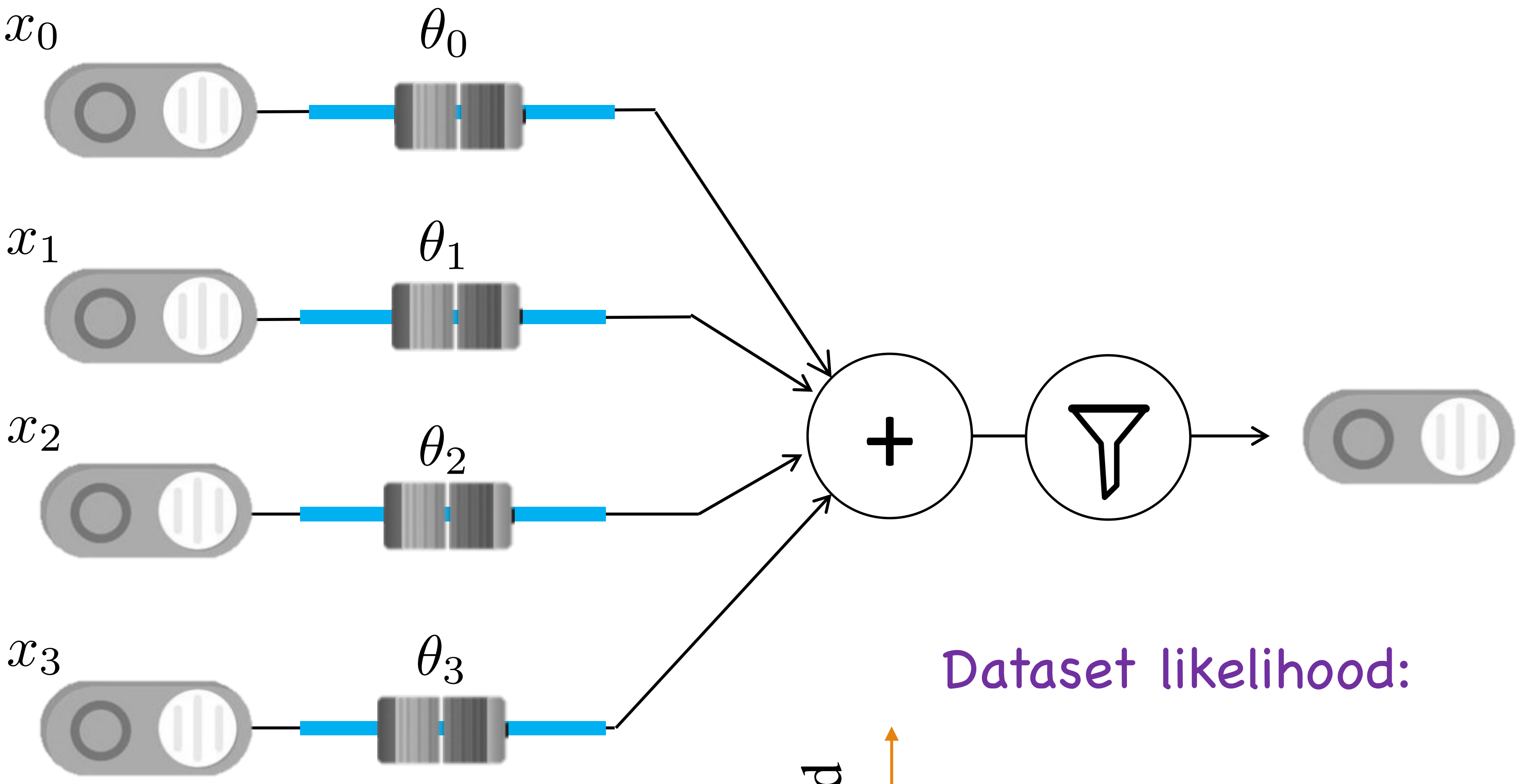
```
Initialize: θ_j = 0 for all 0 ≤ j ≤ m
```

```
Repeat many times:
    gradient[j] = 0 for all 0 ≤ j ≤ m

    For each training example (x, y):

        For each parameter j:
```

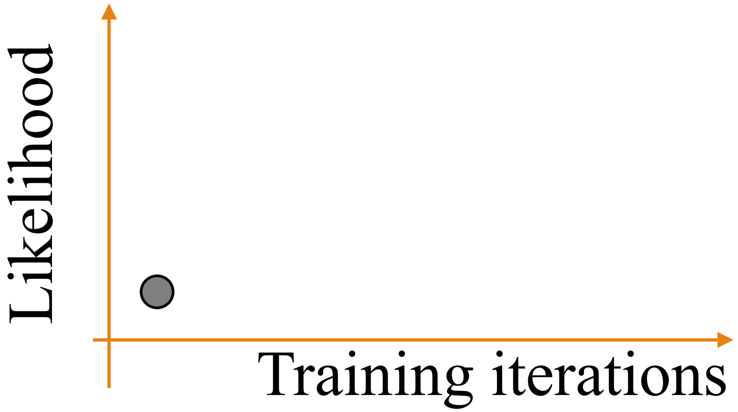
gradient[j] $\mathrel{+}= x_j \left(y - \dfrac{1}{1 + e^{-\theta^{\mathrm{T}} \mathbf{x}}} \right)$

θ_j += η * gradient[j] for all $0 \le j \le m$

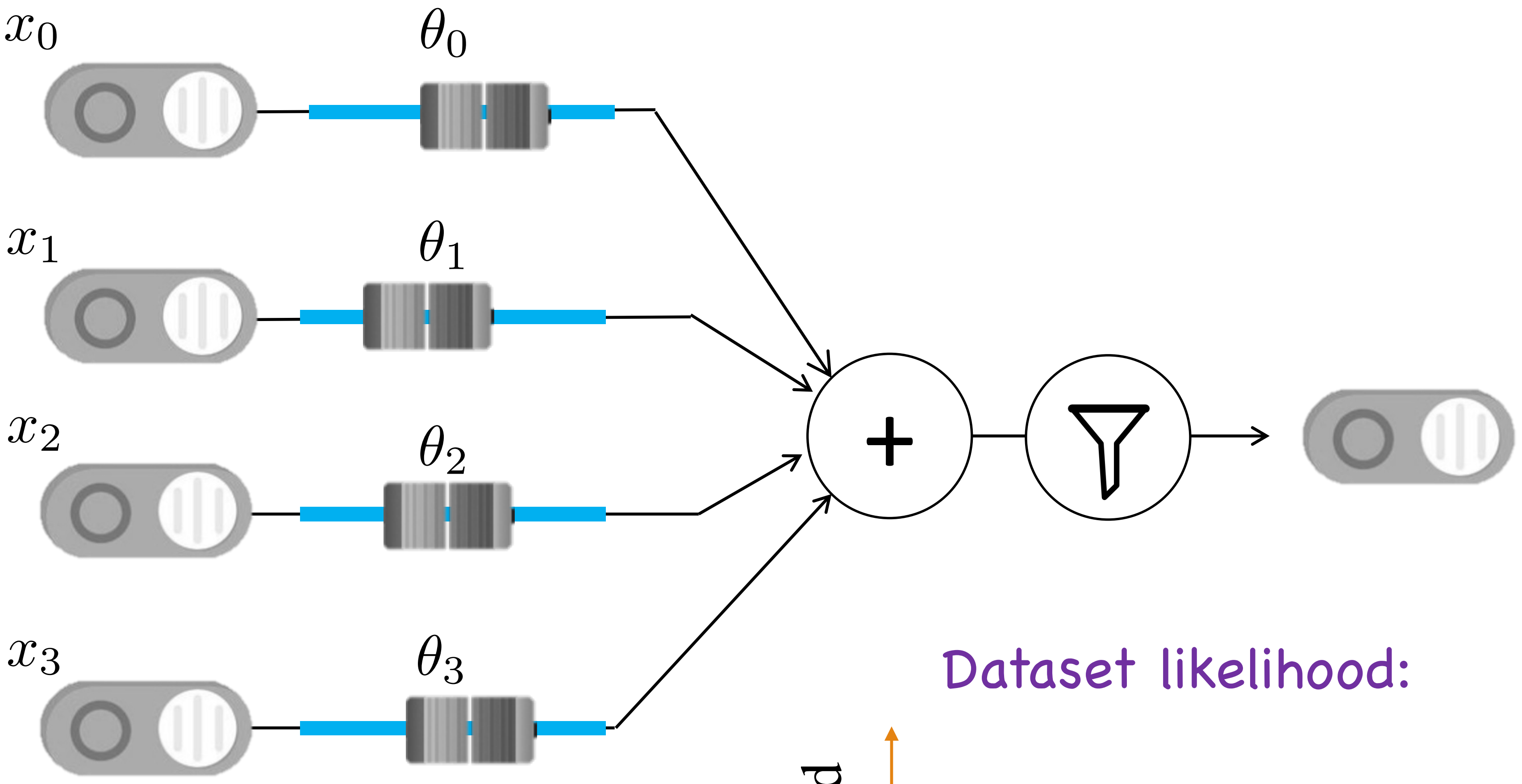
Training



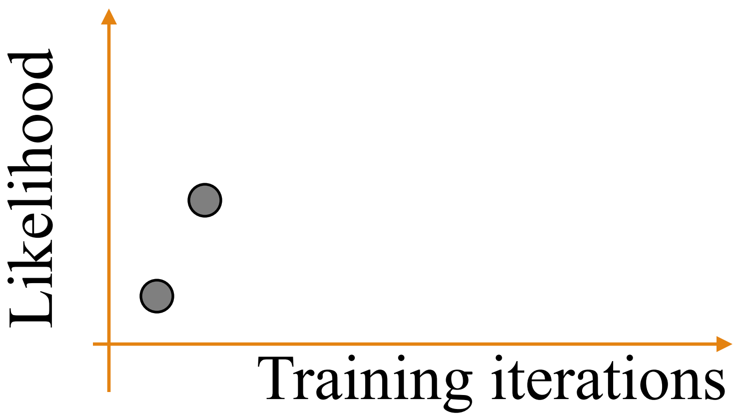
Dataset likelihood:



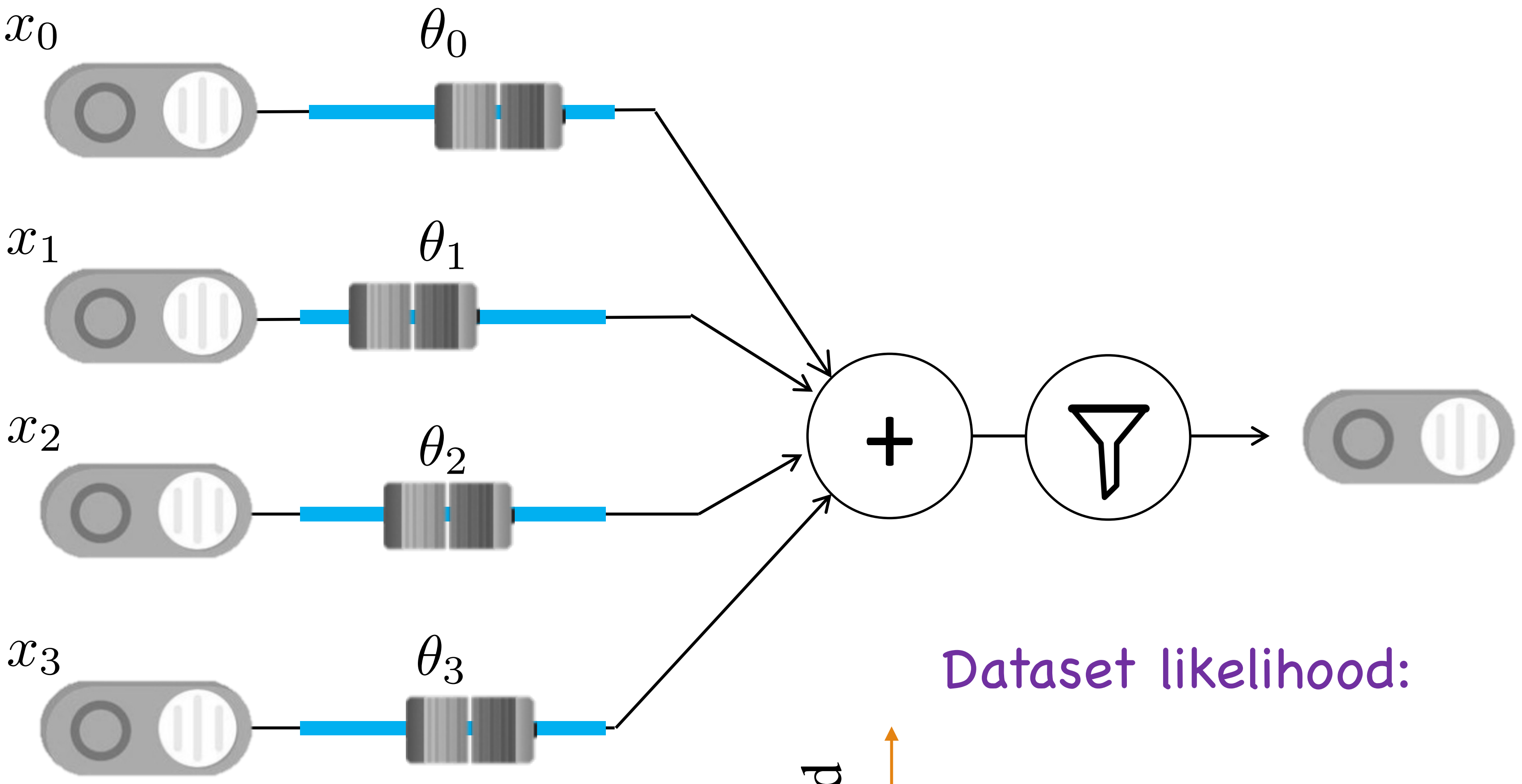
Training



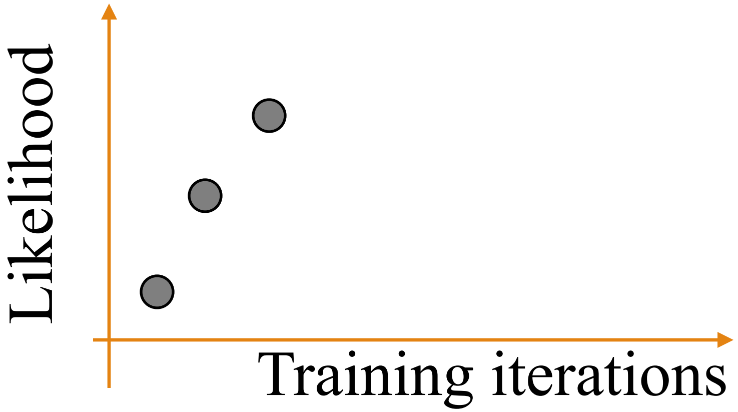
Dataset likelihood:



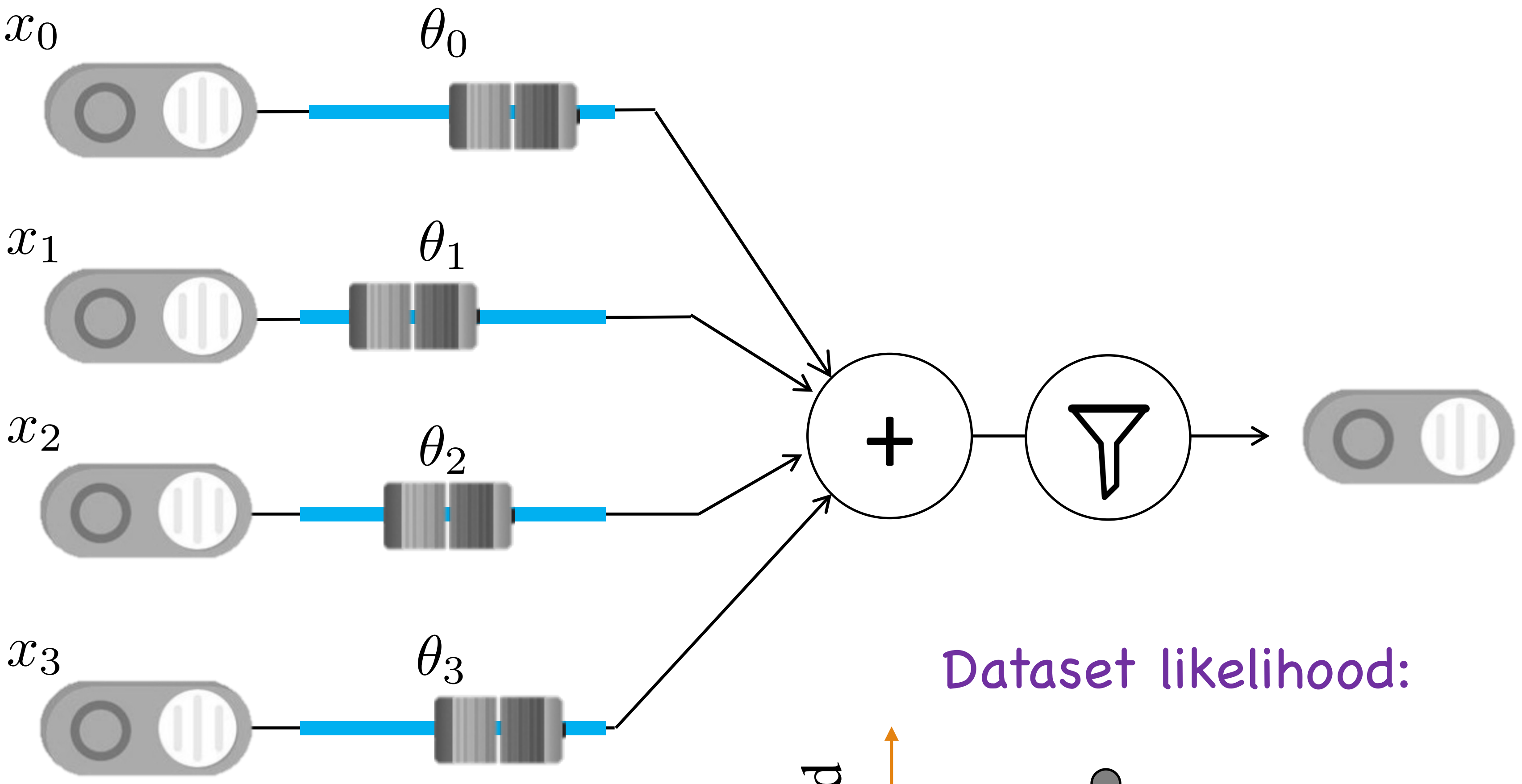
Training



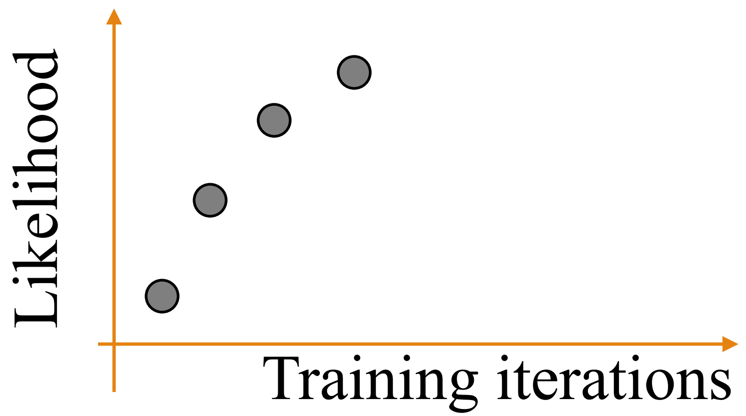
Dataset likelihood:



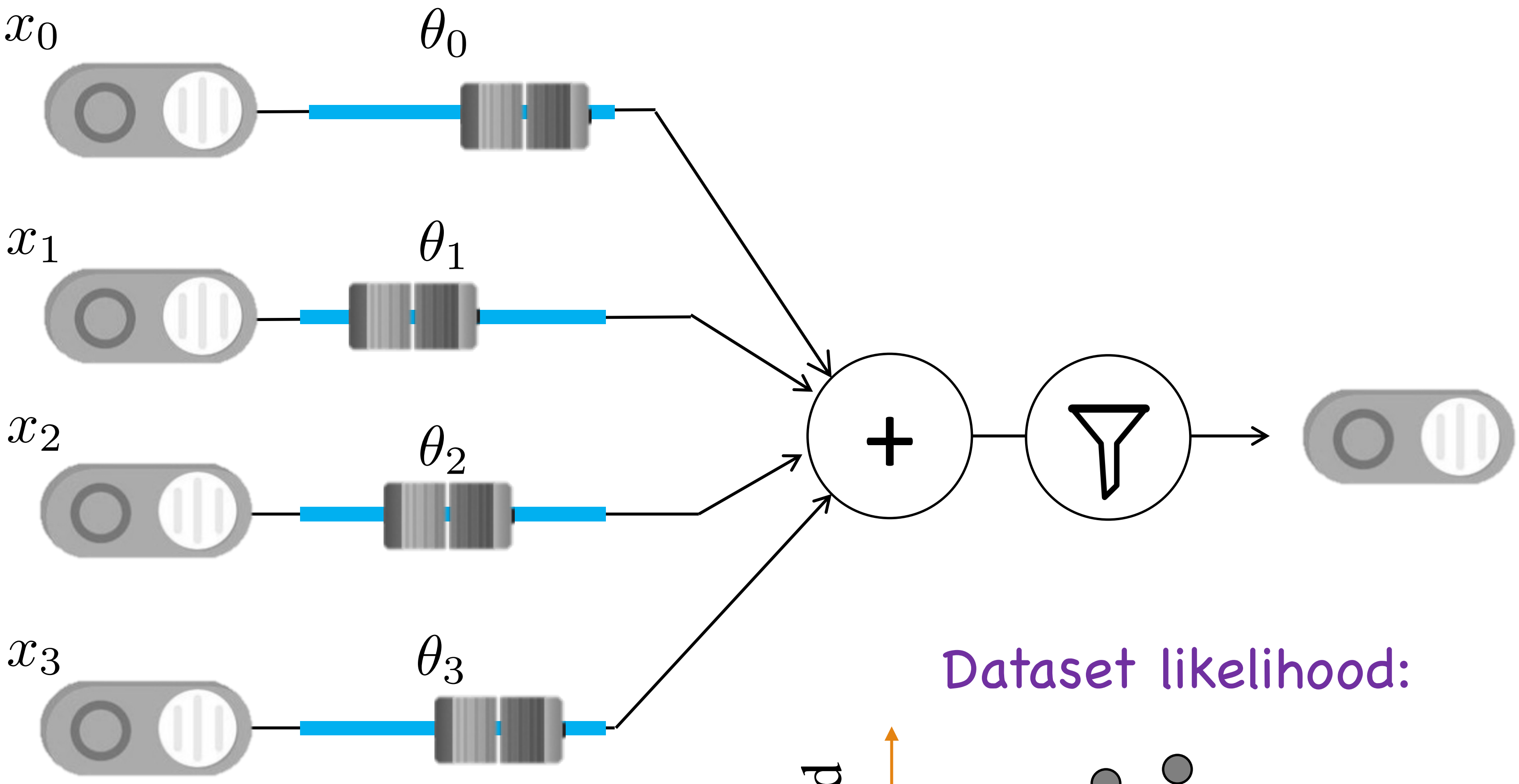
Training



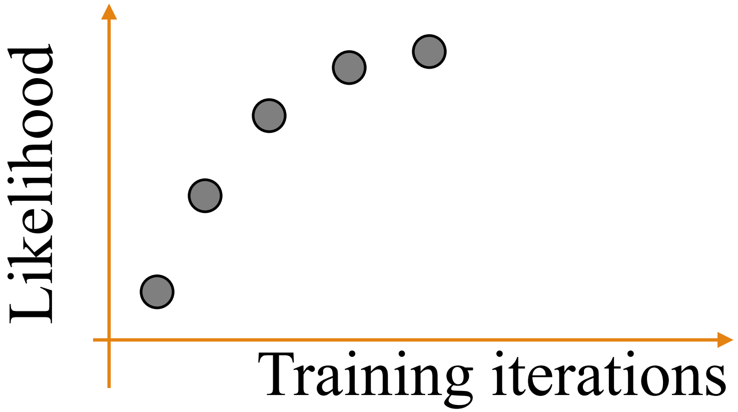
Dataset likelihood:



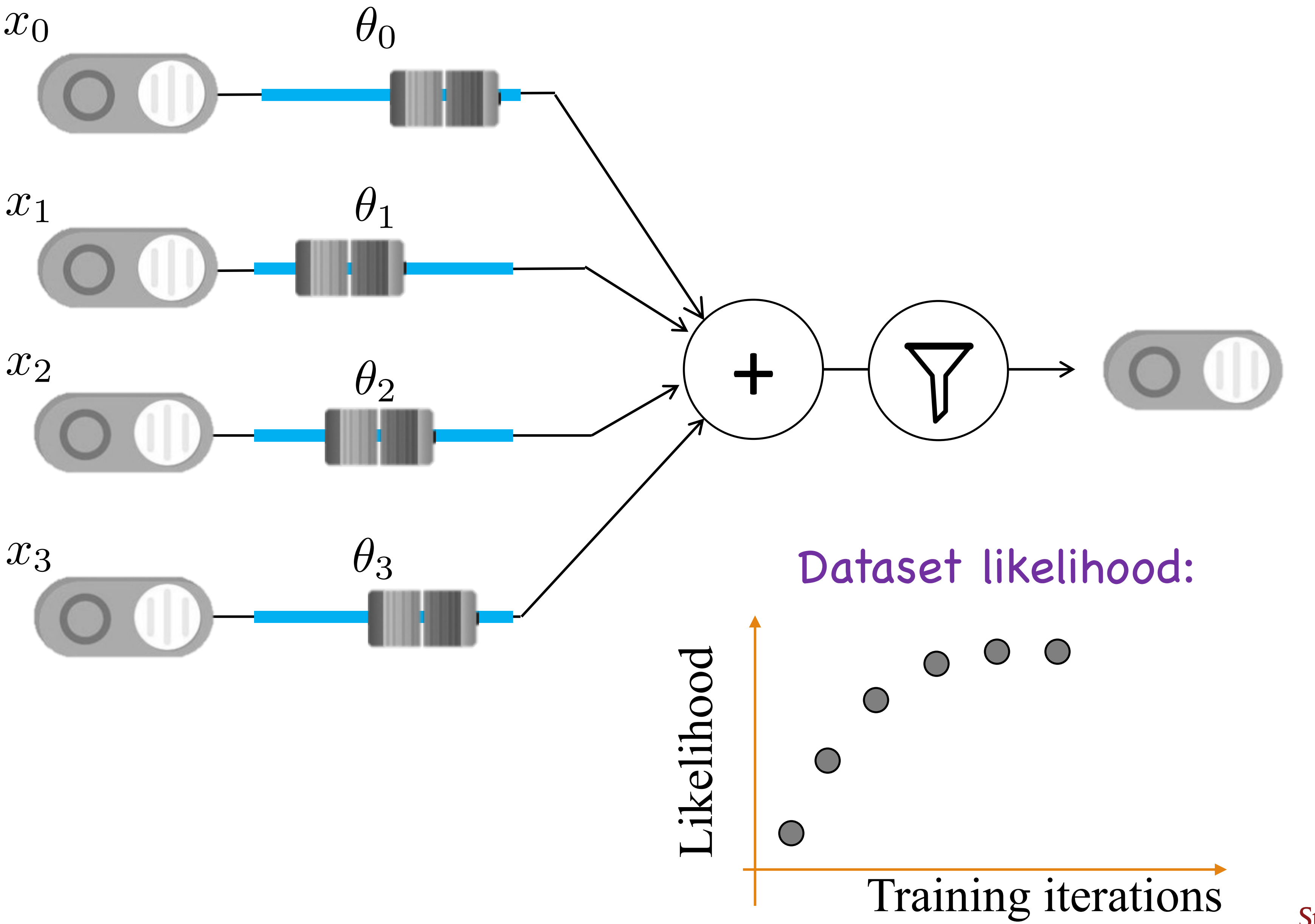
Training



Dataset likelihood:



Training



x_0
θ_0
x_1
θ_1
x_2
θ_2
x_3
θ_3
+
Dataset likelihood:
Likelihood
Training iterations

Don’t forget:

x_j is j-th input variable and $x_0 = 1$.

Allows for θ_0 to be an intercept.

Classification with Logistic Regression

Training: determine parameters θ_j (for all $0 \leq j \leq m$)

- After parameters θ_j have been learned, test classifier

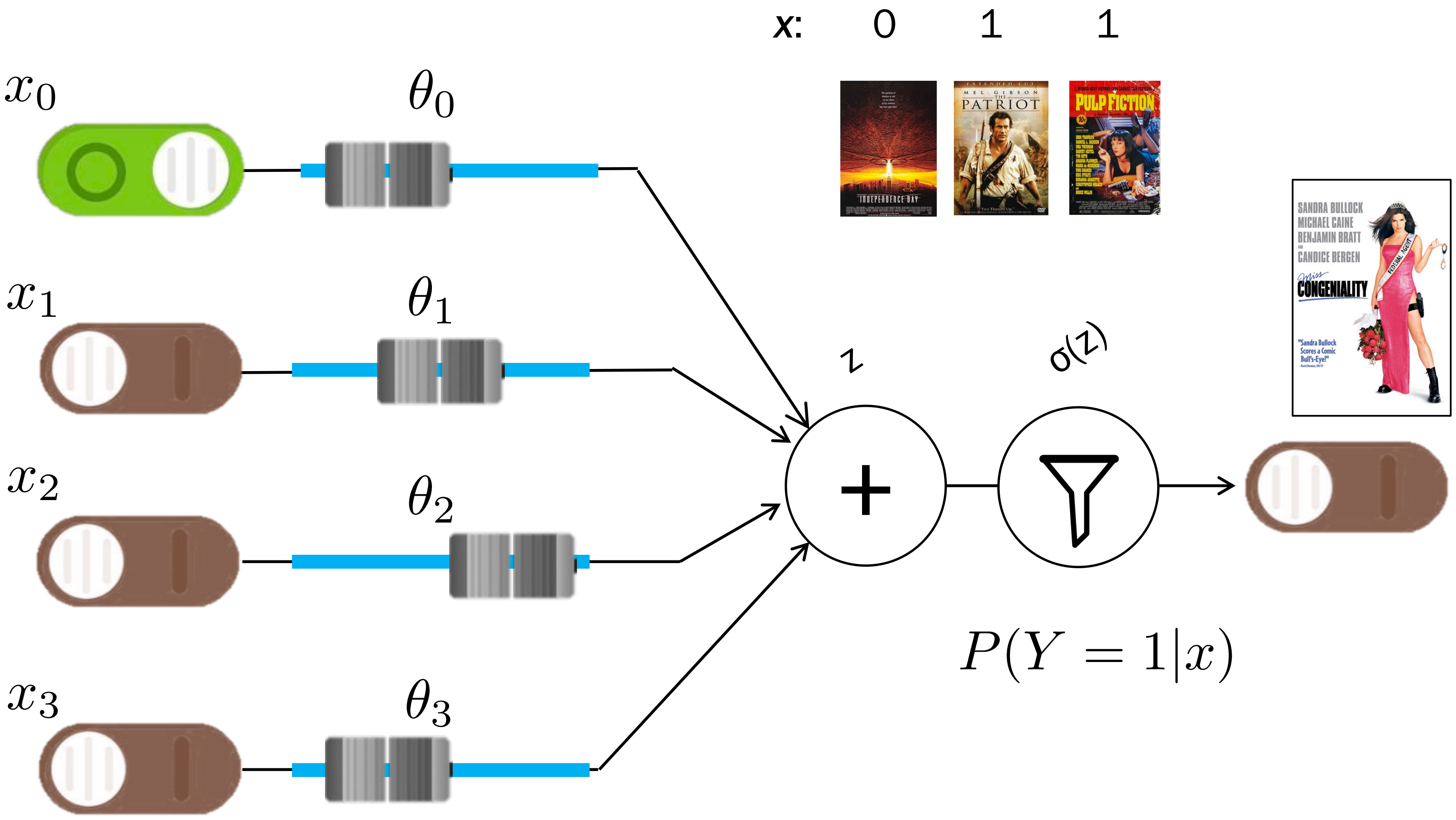
To test classifier, for each new (test) instance ***X***:

- Compute: $p = P(Y = 1 \mid \boldsymbol{X}) = \dfrac{1}{1 + e^{-z}}$, where $z = \theta^T \mathbf{x}$

- Classify instance as: $\hat{y} = \begin{cases} 1 & p > 0.5 \\ 0 & \text{otherwise} \end{cases}$

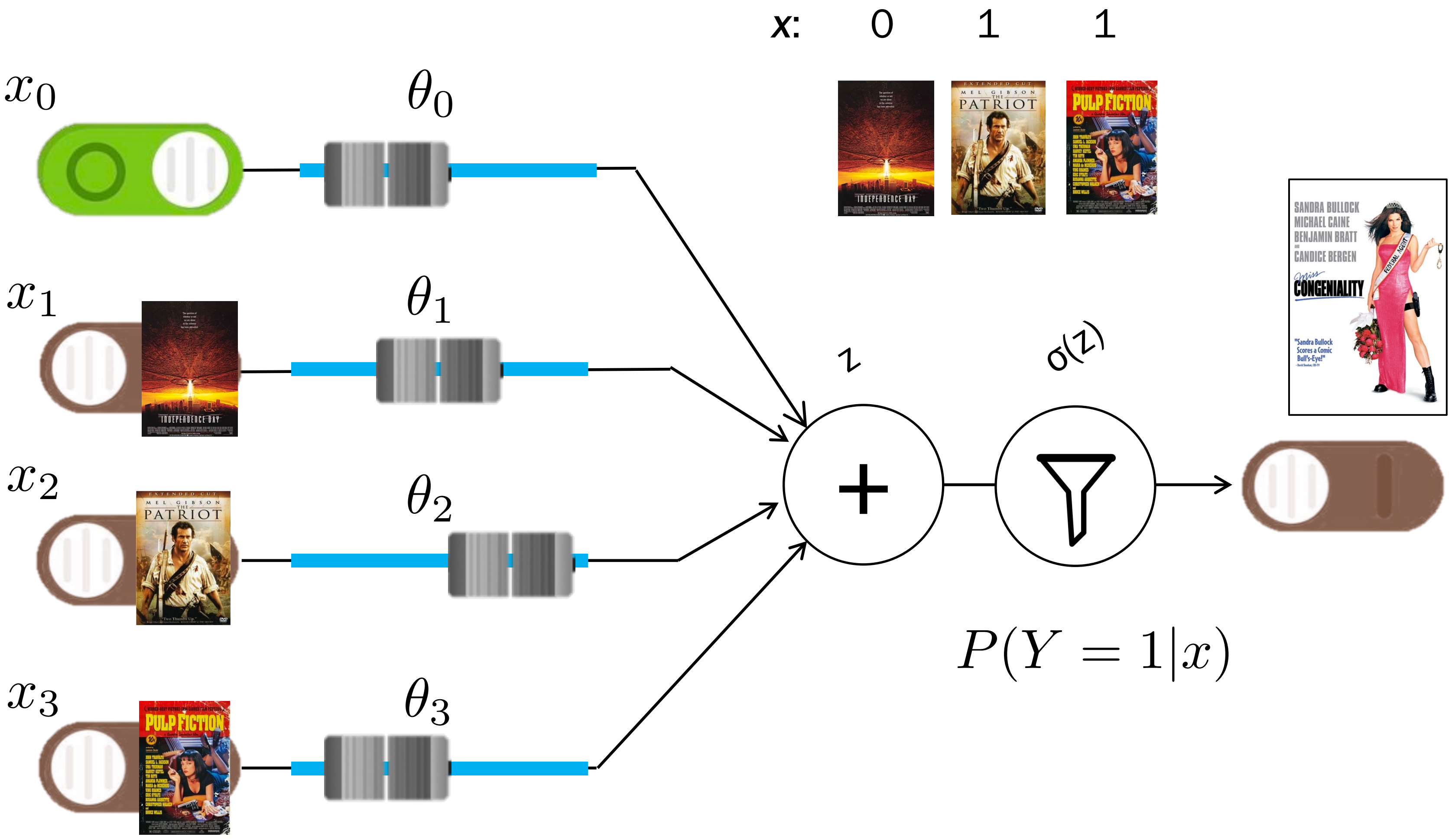
- Note about evaluation set-up: parameters θ_j are **not** updated during "testing" phase

Prediction



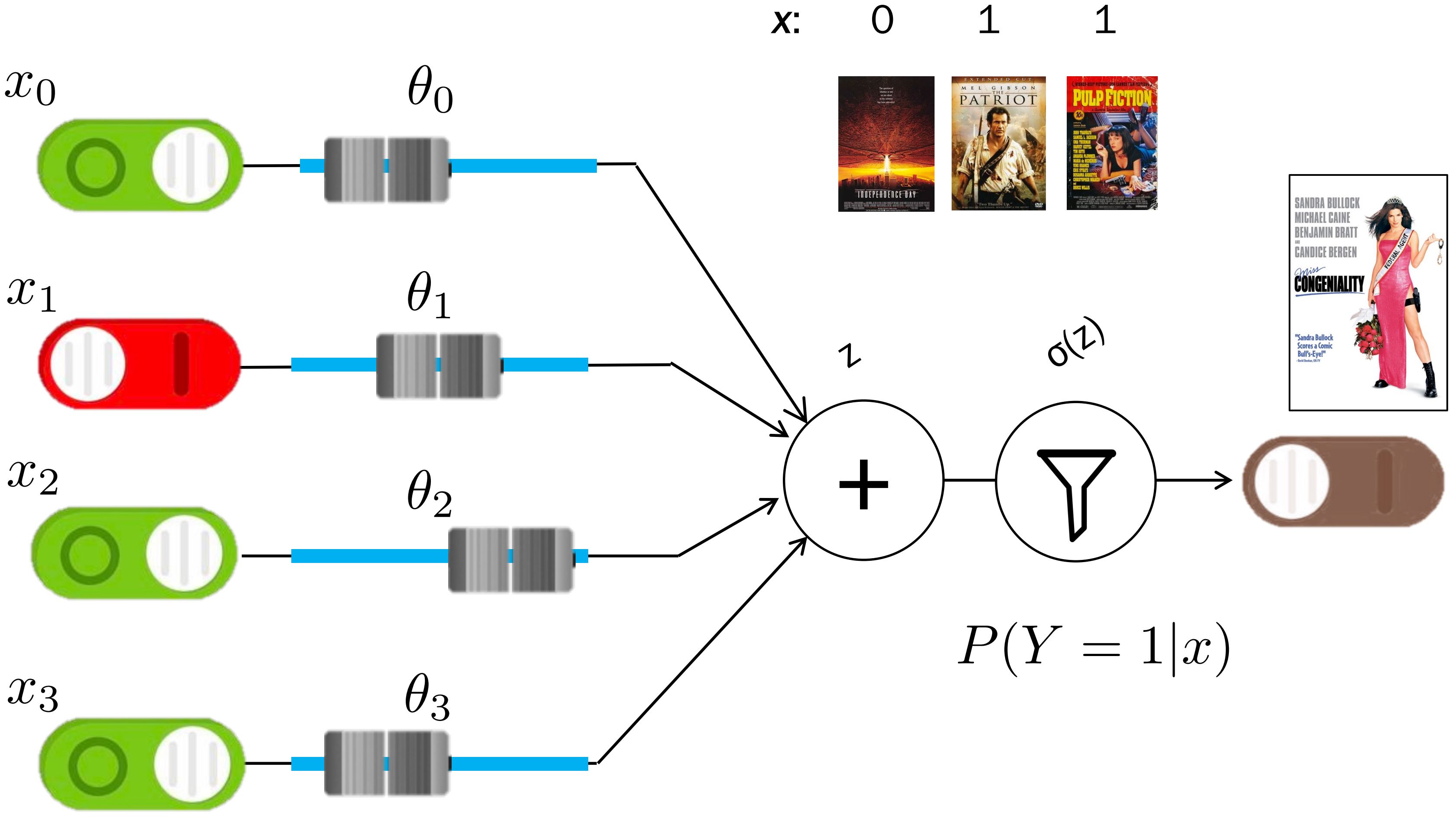
$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

Prediction



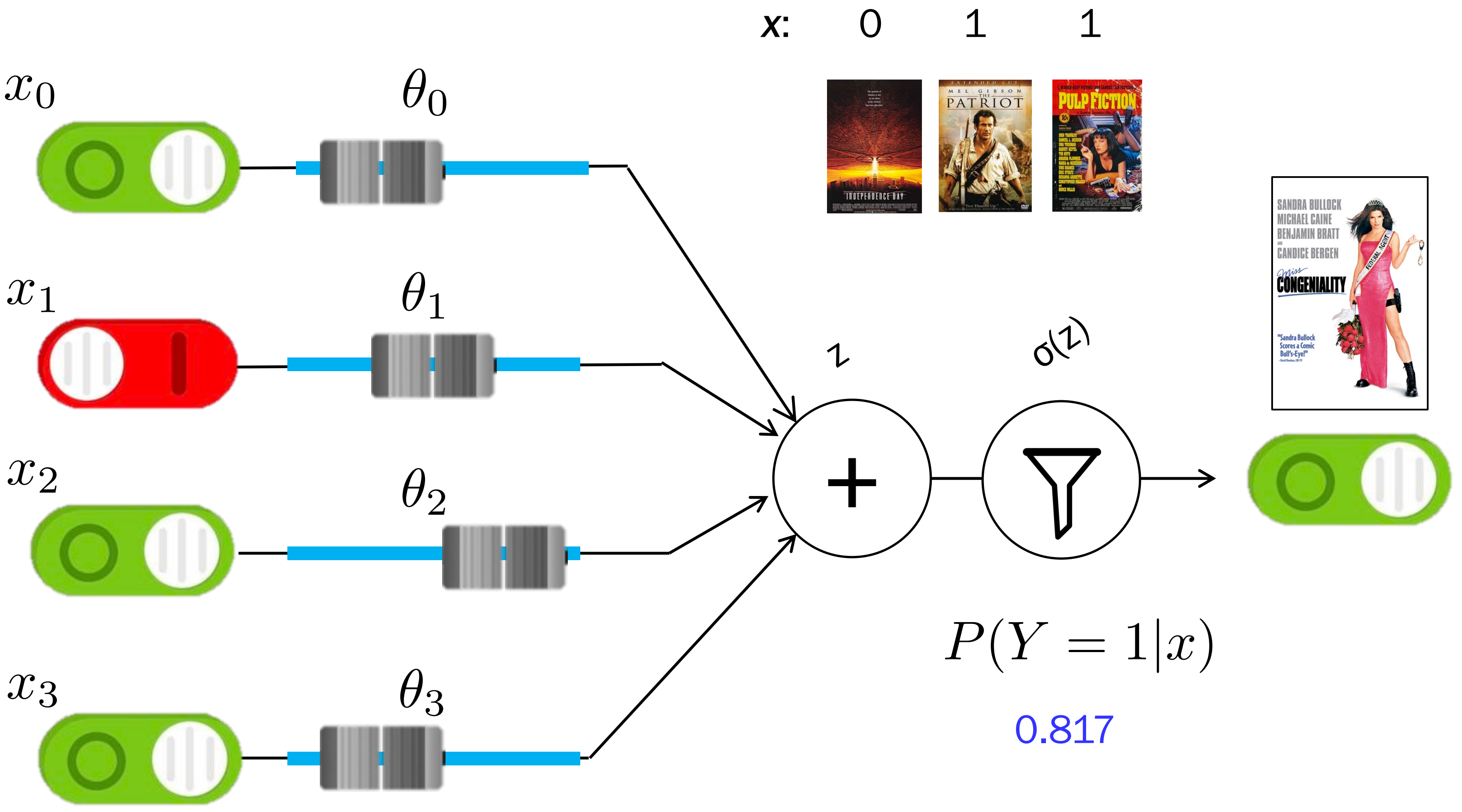
$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

Prediction



$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

Prediction



$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

Chapter 2: How Come?

Logistic Regression

1. Make logistic regression assumption

$$P(Y=1|X=\mathbf{x}) = \sigma(\theta^T\mathbf{x})$$
$$P(Y=0|X=\mathbf{x}) = 1-\sigma(\theta^T\mathbf{x})$$

Often call this $\hat{y}$

2. Calculate the log probability for all data

$$LL(\theta) = \sum_{i=0}^{n} y^{(i)} \log \sigma(\theta^T\mathbf{x}^{(i)}) + (1-y^{(i)}) \log[1-\sigma(\theta^T\mathbf{x}^{(i)})]$$

3. Get derivative of log probability with respect to thetas

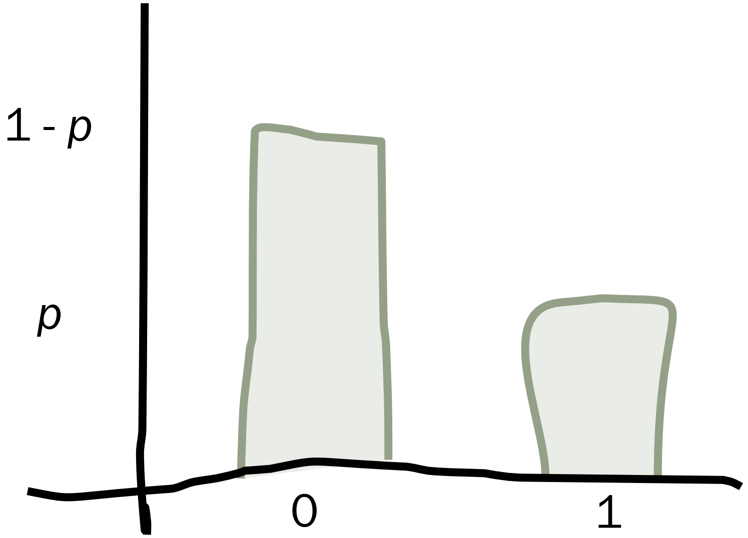
$$\frac{\partial LL(\theta)}{\partial \theta_j} = \sum_{i=1}^{n} \left[y^{(i)} - \sigma(\theta^T\mathbf{x}^{(i)}) \right] x_j^{(i)}$$

How did we get that LL function?

Recall: PMF of Bernoulli

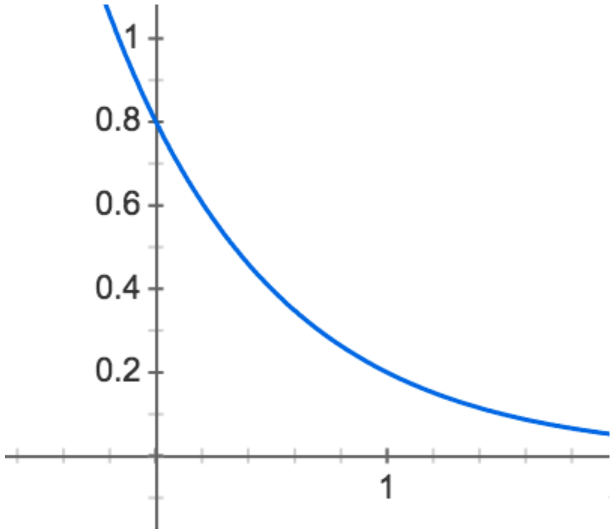
- Y ~ Ber(p)
- Probability mass function: $P(Y = y)$

PMF of Bernoulli



$$P(Y = y) = p^y(1-p)^{1-y}$$

PMF of Bernoulli (p = 0.2)



$$P(Y = y) = 0.2^y(0.8)^{1-y}$$

Log Probability of Data

$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

$$P(Y = 0|X = \mathbf{x}) = 1 - \sigma(\theta^T \mathbf{x})$$

Implies

$$P(Y = y|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})^y \cdot \left[1 - \sigma(\theta^T \mathbf{x})\right]^{(1-y)}$$

For IID data

$$L(\theta) = \prod_{i=1}^{n} P(Y = y^{(i)}|X = \mathbf{x}^{(i)})$$

$$= \prod_{i=1}^{n} \sigma(\theta^T \mathbf{x}^{(i)})^{y^{(i)}} \cdot \left[1 - \sigma(\theta^T \mathbf{x}^{(i)})\right]^{(1-y^{(i)})}$$

Take the log

$$LL(\theta) = \sum_{i=1}^{n} y^{(i)} \log \sigma(\theta^T \mathbf{x}^{(i)}) + (1 - y^{(i)}) \log[1 - \sigma(\theta^T \mathbf{x}^{(i)})]$$

How did we get that gradient?

Sigmoid has a Beautiful Slope

True fact about
sigmoid functions

$$\frac{\partial}{\partial z}\sigma(z) = \sigma(z)[1 - \sigma(z)]$$

Sigmoid has a Beautiful Slope

$$\frac{\partial}{\partial \theta_j} \sigma(\theta^T x)?$$

$$\frac{\partial}{\partial z} \sigma(z) = \sigma(z)[1 - \sigma(z)]$$

---

where $z = \theta^T x$

$$\frac{\partial}{\partial \theta_j} \sigma(\theta^T x) = \frac{\partial}{\partial z} \sigma(z) \cdot \frac{\partial z}{\partial \theta_j}$$

Chain rule!

$$\frac{\partial}{\partial \theta_j} \sigma(\theta^T x) = \sigma(\theta^T x)[1 - \sigma(\theta^T x)] x_j$$

Plug and chug

Sigmoid, you should be a ski hill

Sigmoid has a Beautiful Slope

$$\hat{y} = \sigma(\theta^T x)$$

$$\frac{\partial \hat{y}}{\partial \theta_j} = \sigma(\theta^T x)[1 - \sigma(\theta^T x)]x_j$$

$$= \hat{y}(1 - \hat{y})x_j$$

[pedagogical pause]

ARE YOU READY???

I think I'm Ready…

$$\frac{\partial LL(\theta)}{\partial \theta_j}$$

Where

$$LL(\theta) \;\; = \sum_{i=1}^{n} y^{(i)} \log \sigma(\theta^T \mathbf{x}^{(i)}) + (1 - y^{(i)}) \log[1 - \sigma(\theta^T \mathbf{x}^{(i)})]$$

This is Sparta!!!!!

This is ~~Sparta~~!!!!!

Stanford

Think About Only One Training Instance

$$LL(\theta) = \sum_{i=1}^{n} y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log[1 - \hat{y}^{(i)}]$$

We only need to calculate the gradient for one training example!

$$\frac{\partial}{\partial x} \sum_i f(x, i) = \sum_i \frac{\partial}{\partial x} f(x, i)$$

We will pretend we only have one example

$$LL(\theta) = y \log \hat{y} + (1 - y) \log[1 - \hat{y}]$$

We can sum up the gradients of each example to get the correct answer

First, imagine only one example

$$LL(\theta) = y \log \hat{y} + (1 - y) \log[1 - \hat{y}]$$

Where $\hat{y} = \sigma(\theta^T \mathbf{x})$

$$\frac{\partial LL(\theta)}{\partial \theta_j} = \frac{\partial LL(\theta)}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \theta_j}$$

CHAIN RULZ!

First, imagine only one example

$$LL(\theta) = y \log \hat{y} + (1-y) \log[1-\hat{y}]$$

Where $$\hat{y} = \sigma(\theta^T \mathbf{x})$$

$$\frac{\partial LL(\theta)}{\partial \theta_j} = \frac{\partial LL(\theta)}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \theta_j}$$

CHAIN RULZ!

$$= \frac{\partial LL(\theta)}{\partial \hat{y}} \hat{y}(1-\hat{y}) x_j$$

Already did that one

$$= \left[\frac{y}{\hat{y}} - \frac{1-y}{1-\hat{y}}\right] \hat{y}(1-\hat{y}) x_j$$

Derive this one

$$= (y - \hat{y}) x_j$$

Simplify

Make it Simple

$$LL(\theta) = y \log \hat{y} + (1 - y) \log[1 - \hat{y}]$$

Where $$\hat{y} = \sigma(\theta^T \mathbf{x})$$

$$\frac{\partial LL(\theta)}{\partial \theta_j} = \frac{\partial LL(\theta)}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \theta_j}$$

CHAIN RULZ!

$$= \frac{\partial LL(\theta)}{\partial \hat{y}} \hat{y}(1 - \hat{y}) x_j$$

Already did that one

$$= \left[\frac{y}{\hat{y}} - \frac{1 - y}{1 - \hat{y}}\right] \hat{y}(1 - \hat{y}) x_j$$

Derive this one

$$= (y - \hat{y}) x_j$$

Simplify

Now, all the data

$$LL(\theta) = \sum_{i=1}^{n} y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log[1 - \hat{y}^{(i)}]$$

$$\hat{y}^{(i)} = \sigma(\theta^T \mathbf{x}^{(i)})$$

Derivative of sum…

$$\frac{\partial LL(\theta)}{\partial \theta_j} = \sum_{i=1}^{n} \frac{\partial}{\partial \theta_j} \left[y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log[1 - \hat{y}^{(i)}] \right]$$

$$= \sum_{i=1}^{n} [y^{(i)} - \hat{y}^{(i)}] x_j^{(i)}$$

See last slide

$$= \sum_{i=1}^{n} [y^{(i)} - \sigma(\theta^T \mathbf{x}^{(i)})] x_j^{(i)}$$

Some people don't like hats…

Now, all the data

$$\frac{\partial LL(\theta)}{\partial \theta_j}$$

$$= \sum_{i=1}^{n} [y^{(i)} - \sigma(\theta^T \mathbf{x}^{(i)})] x_j^{(i)}$$

Logistic Regression

1 Make logistic regression assumption

$$P(Y = 1|X = \mathbf{x}) = \sigma(\theta^T \mathbf{x})$$

$$P(Y = 0|X = \mathbf{x}) = 1 - \sigma(\theta^T \mathbf{x})$$

2 Calculate the log probability for all data

$$LL(\theta) = \sum_{i=1}^{n} y^{(i)} \log \sigma(\theta^T \mathbf{x}^{(i)}) + (1 - y^{(i)}) \log[1 - \sigma(\theta^T \mathbf{x}^{(i)})]$$

3 Get derivative of log probability with respect to thetas

$$\frac{\partial LL(\theta)}{\partial \theta_j} = \sum_{i=1}^{n} \left[y^{(i)} - \sigma(\theta^T \mathbf{x}^{(i)}) \right] x_j^{(i)}$$

The Hard Way

$$LL(\theta) = y \log \sigma(\theta^T \mathbf{x}) + (1-y)\log[1 - \sigma(\theta^T \mathbf{x})]$$

$$\begin{aligned}
\frac{\partial LL(\theta)}{\partial \theta_j} &= \frac{\partial}{\partial \theta_j} y \log \sigma(\theta^T \mathbf{x}) + \frac{\partial}{\partial \theta_j}(1-y)\log[1 - \sigma(\theta^T \mathbf{x}] \\
&= \left[\frac{y}{\sigma(\theta^T x)} - \frac{1-y}{1-\sigma(\theta^T x)}\right]\frac{\partial}{\partial \theta_j}\sigma(\theta^T x) \\
&= \left[\frac{y}{\sigma(\theta^T x)} - \frac{1-y}{1-\sigma(\theta^T x)}\right]\frac{\partial}{\partial \theta_j}\sigma(\theta^T x) \\
&= \left[\frac{y - \sigma(\theta^T x)}{\sigma(\theta^T x)[1-\sigma(\theta^T x)]}\right]\sigma(\theta^T x)[1-\sigma(\theta^T x)]x_j \\
&= \left[y - \sigma(\theta^T x)\right] x_j
\end{aligned}$$

Phew!

Chapter 3: Philosophy
(if time)

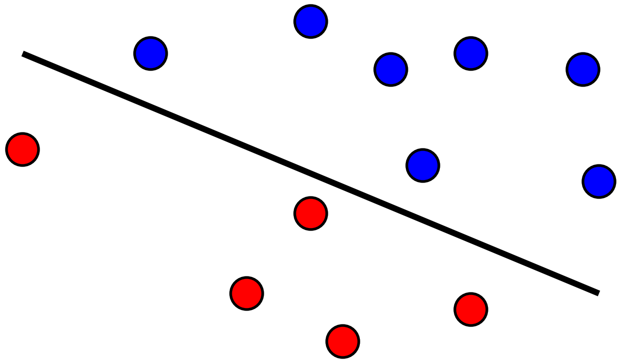
Choosing an Algorithm?

Many trade-offs in choosing learning algorithm

- Continuous input variables
  - Logistic Regression easily deals with continuous inputs
  - Naive Bayes needs to use some parametric form for continuous inputs (e.g., Gaussian) or "discretize" continuous values into ranges (e.g., temperature in range: <50, 50-60, 60-70, >70)
- Discrete input variables
  - Naive Bayes naturally handles multi-valued discrete features by using multinomial distribution for $P(X_i \mid Y)$
  - Logistic Regression requires some sort of representation of multi-valued discrete data (e.g., one hot vector)
  - Say $X_i \in \{A, B, C\}$. Not necessarily a good idea to encode X_i as taking on input values 1, 2, or 3 corresponding to A, B, or C.

Discrimination Intuition

- Logistic regression is trying to fit a **line** that separates data instances where *y* = 1 from those where *y* = 0



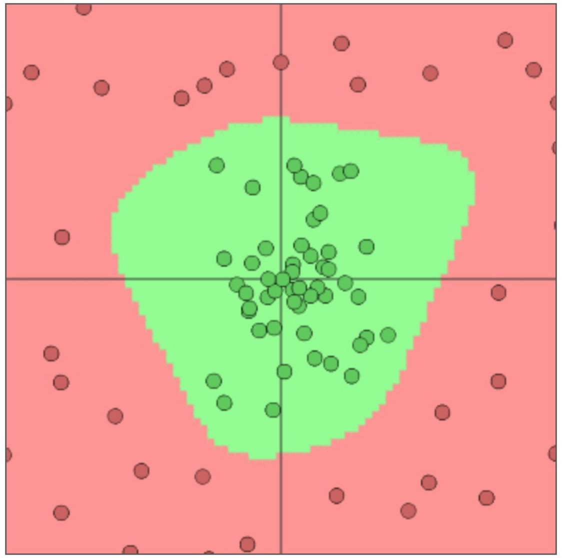
$$\theta^T \mathbf{x} = 0$$

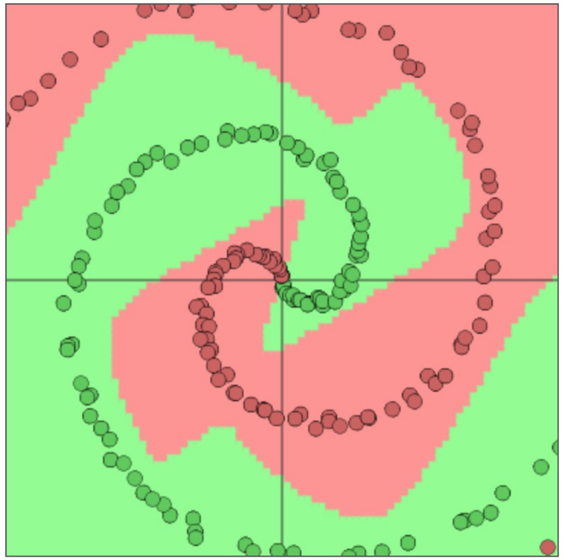
$$\theta_0 x_0 + \theta_1 x_1 + \cdots + \theta_m x_m = 0$$

- We call such data (or the functions generating the data) "**linearly separable**"
- **Naïve bayes is linear too** as there is no interaction between different features.

Some Data Not Linearly Seperable

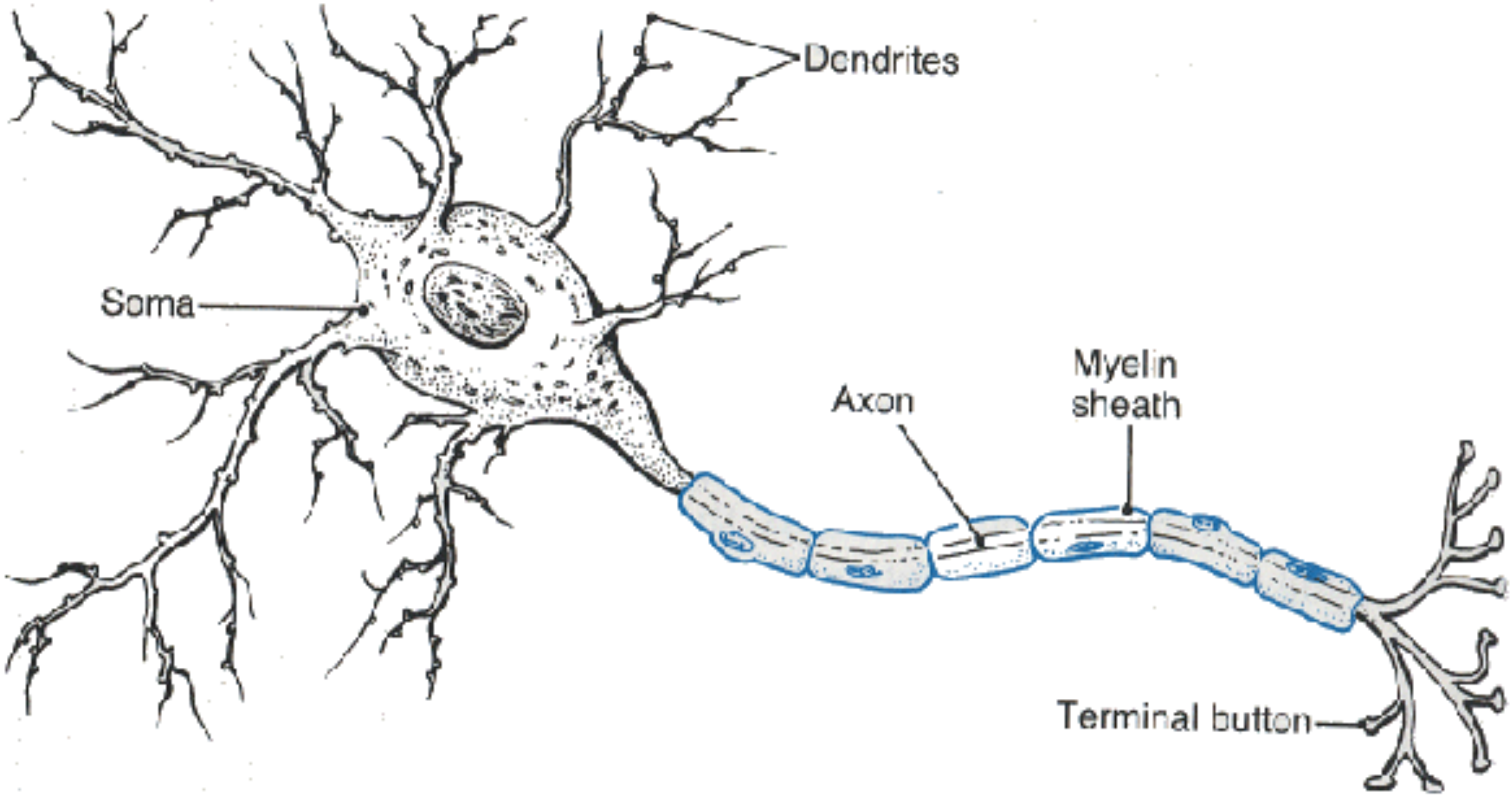
Some data sets/functions are not separable



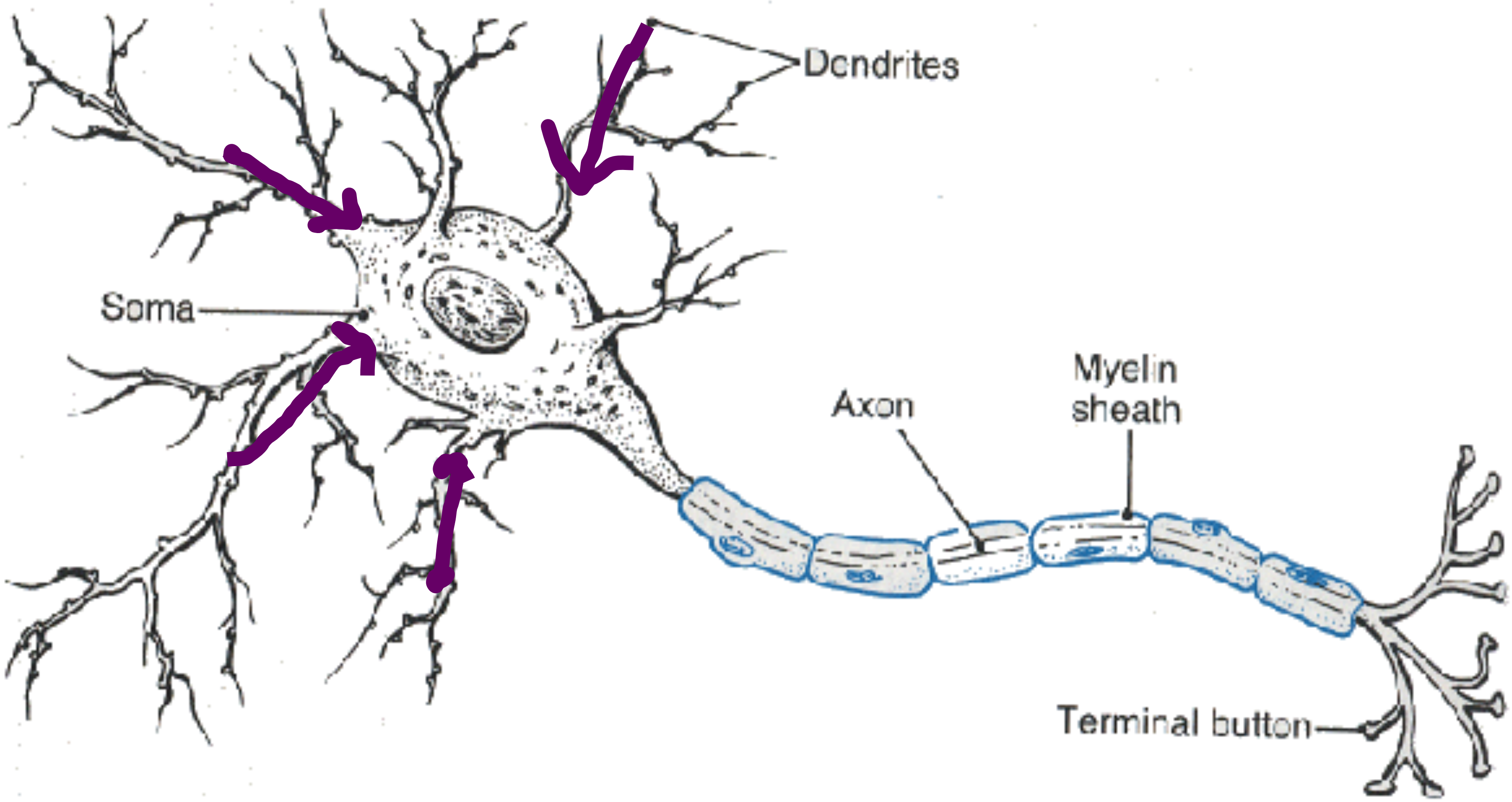


- Not possible to draw a line that successfully separates all the $y = 1$ points (green) from the $y = 0$ points (red)
- Despite this fact, logistic regression and Naive Bayes still often work well in practice

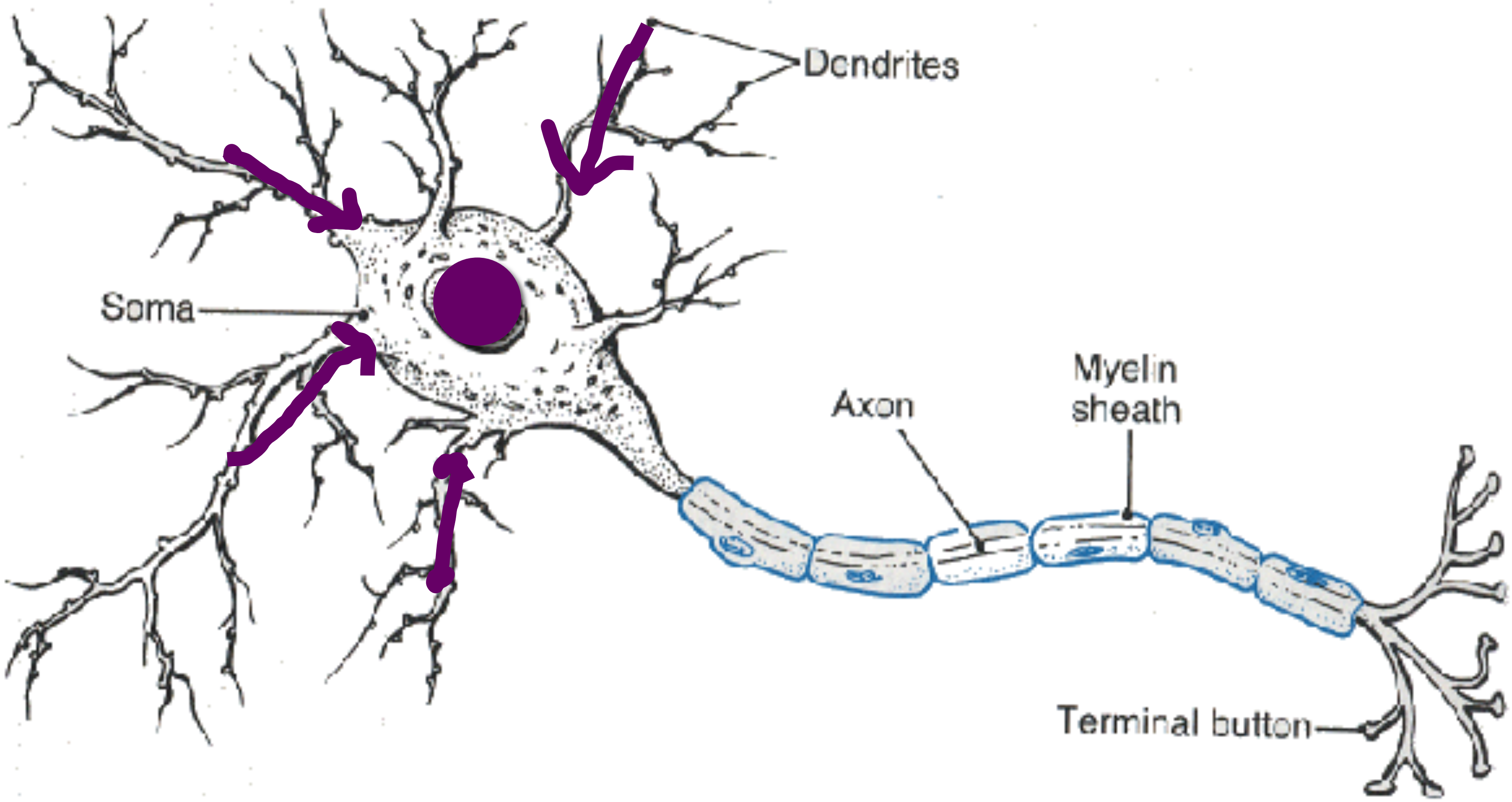
Neuron



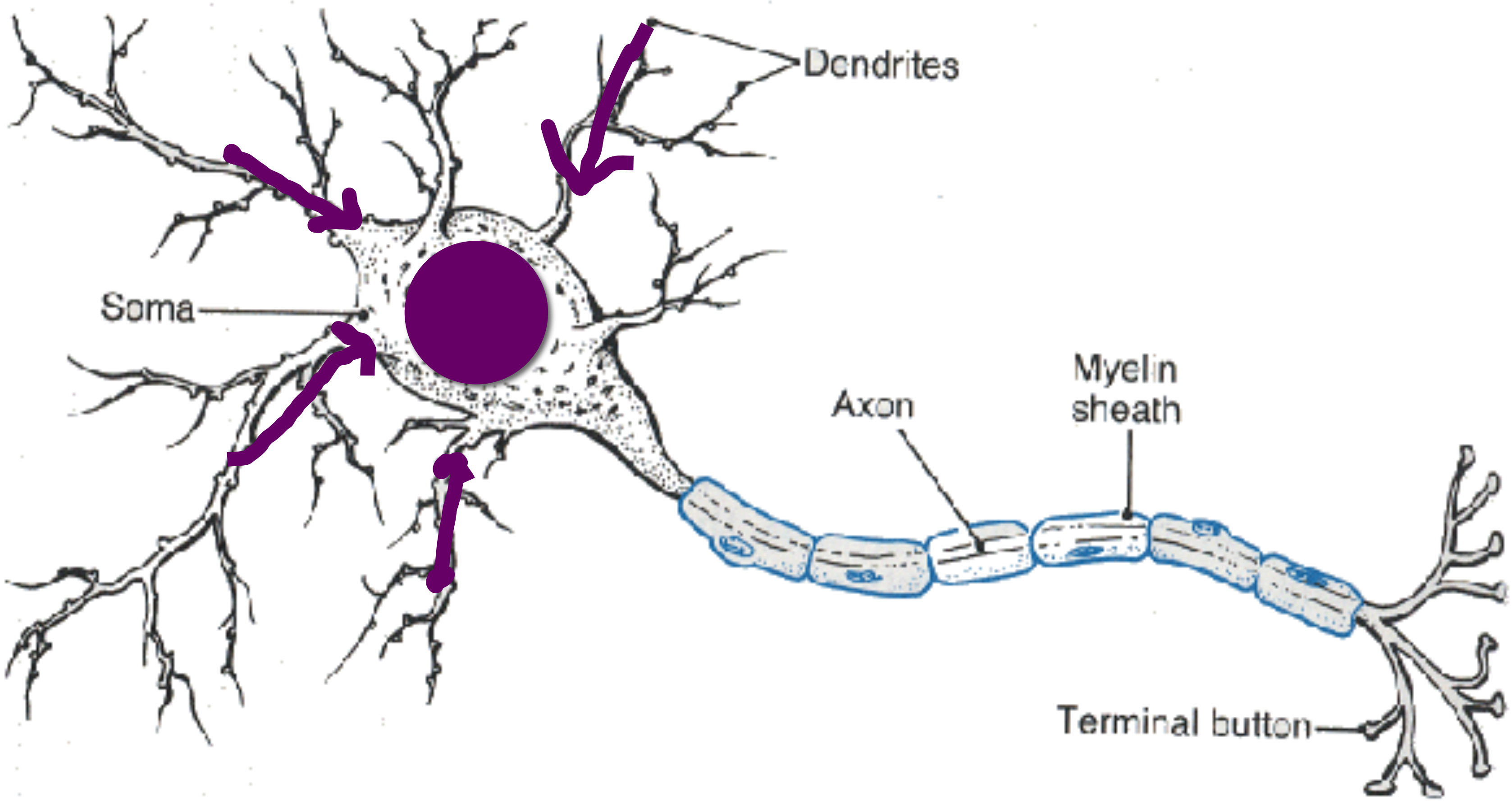
Neuron



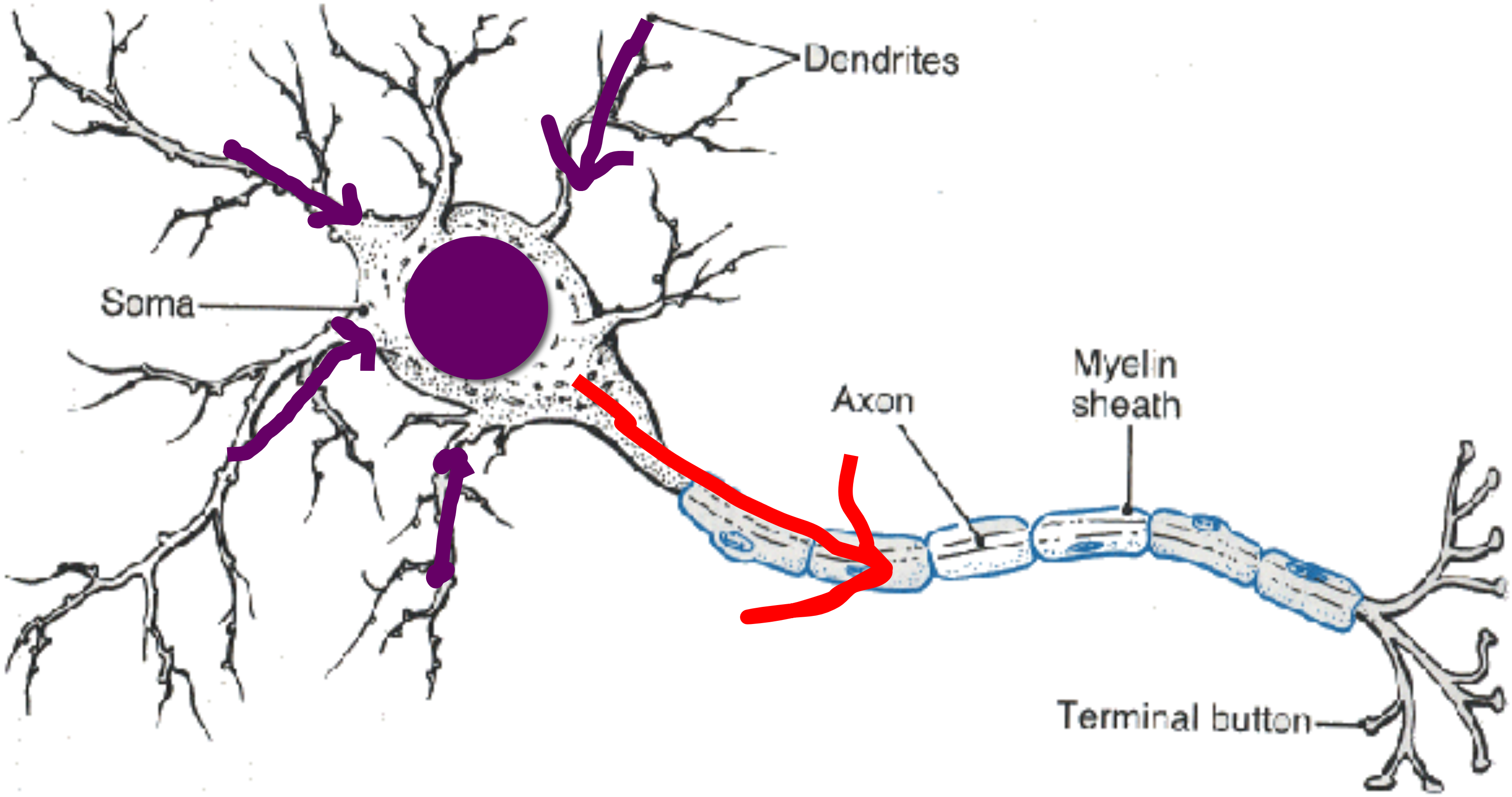
Neuron



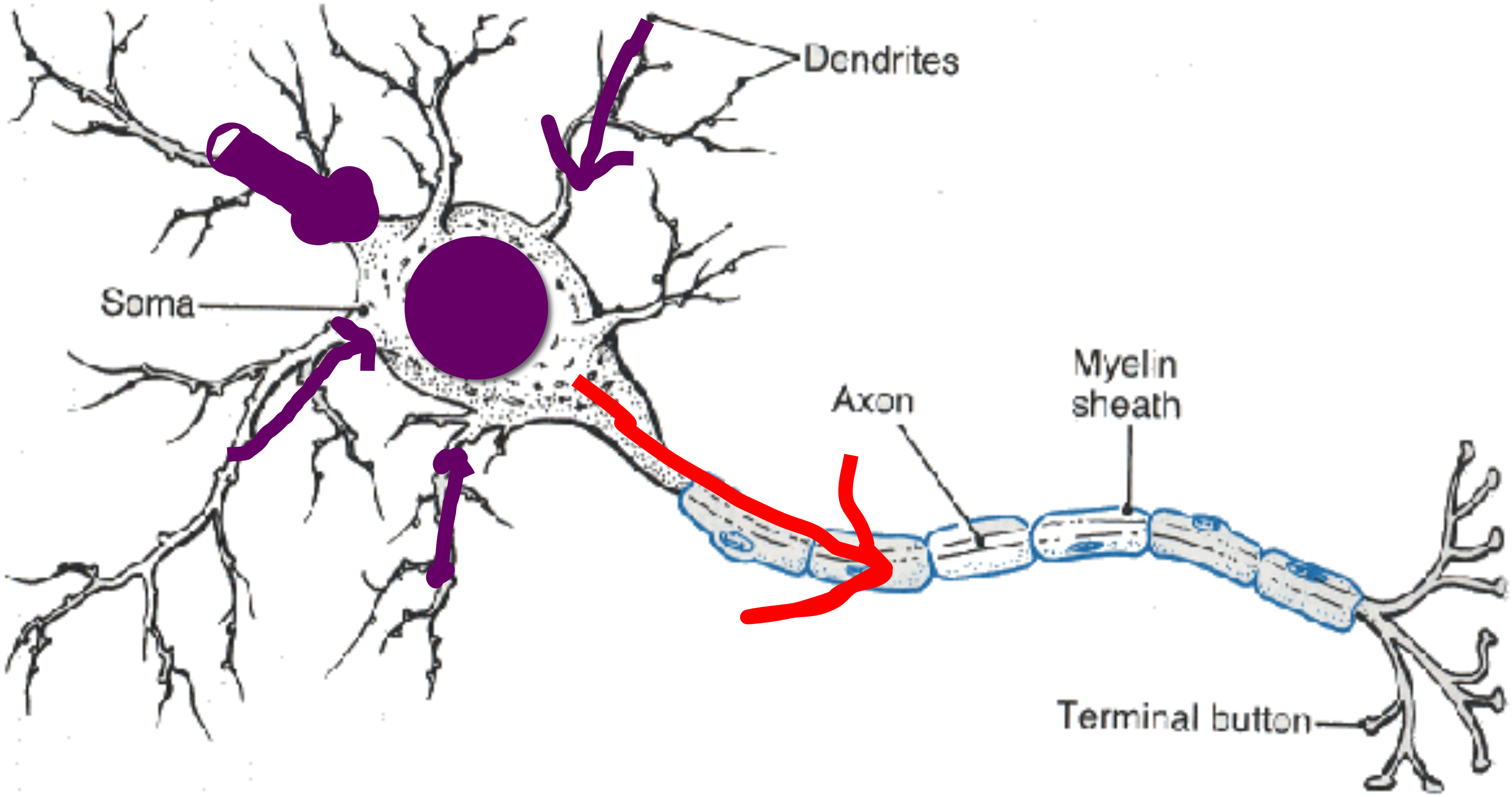
Neuron



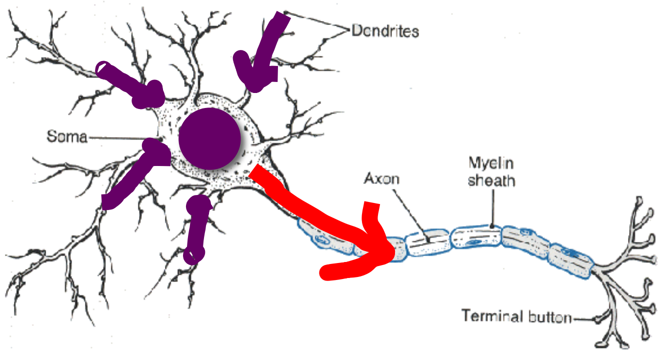
Neuron

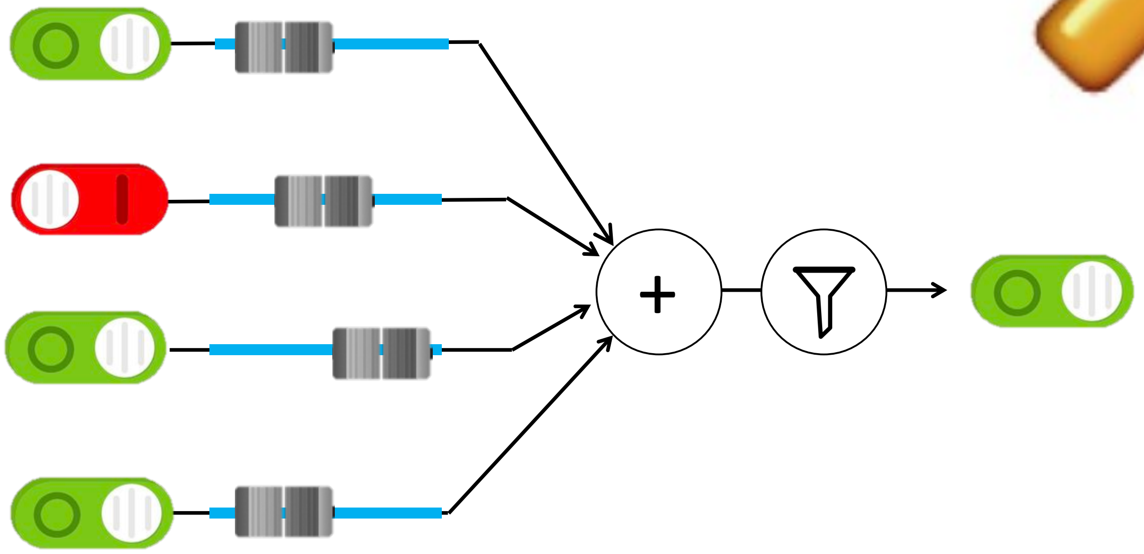


Some inputs are more important



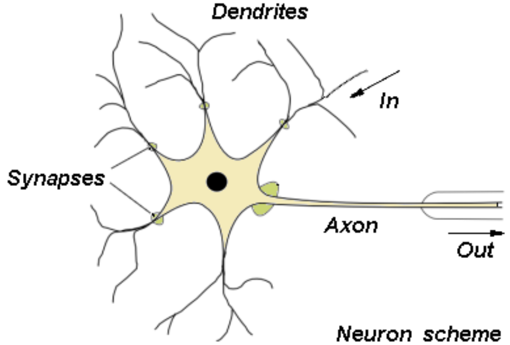
Artificial Neurons

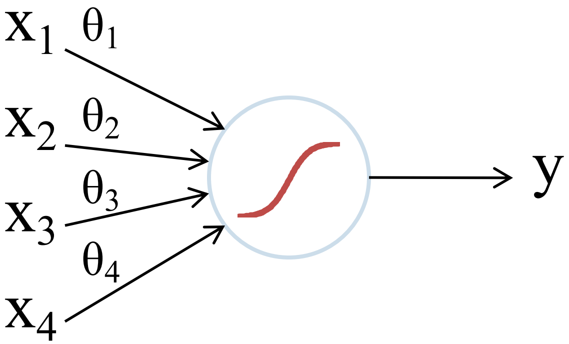




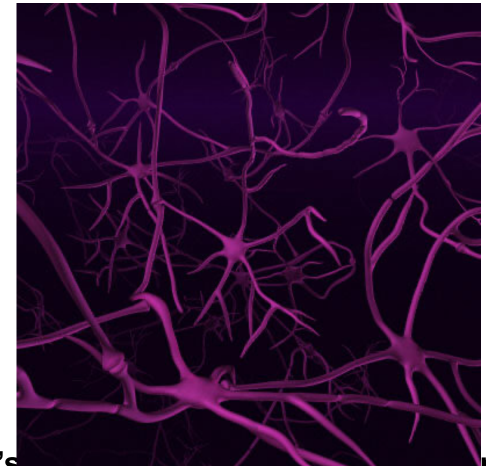
Biological Basis for Neural Networks

A neuron

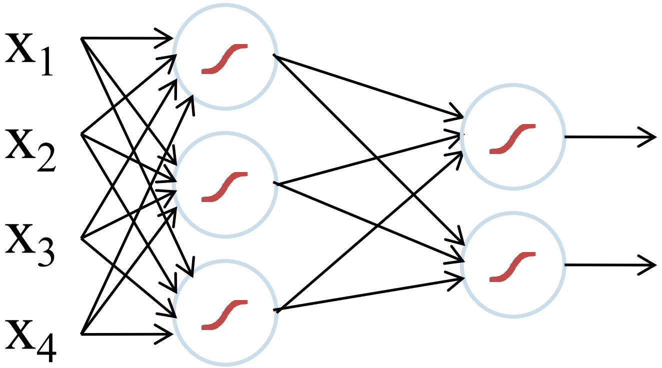




Your brain



Actually, it’s probably someone else’s brain



(aka Neural Networks)

Deep learning is (at its core) many logistic regression pieces stacked on top of each other.

Computer Vision

Alpha GO

Revolution in AI

Computers Making Art

Basically just many logistic regression cells
And lots of chain rule…

Next up: Ethics