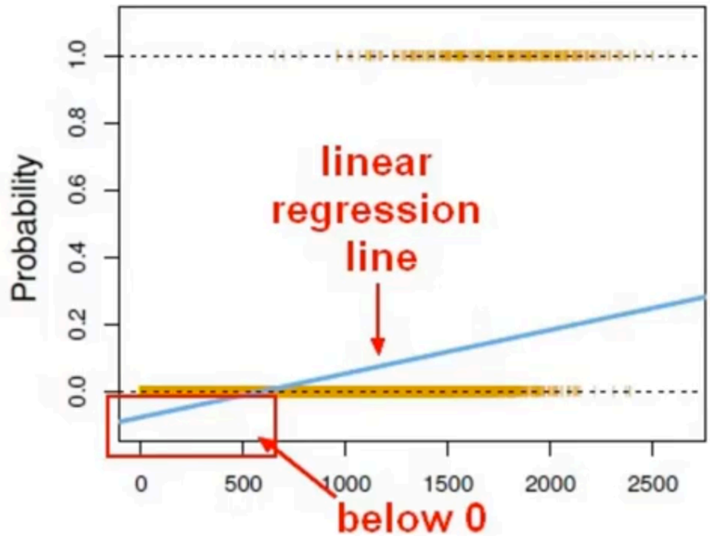
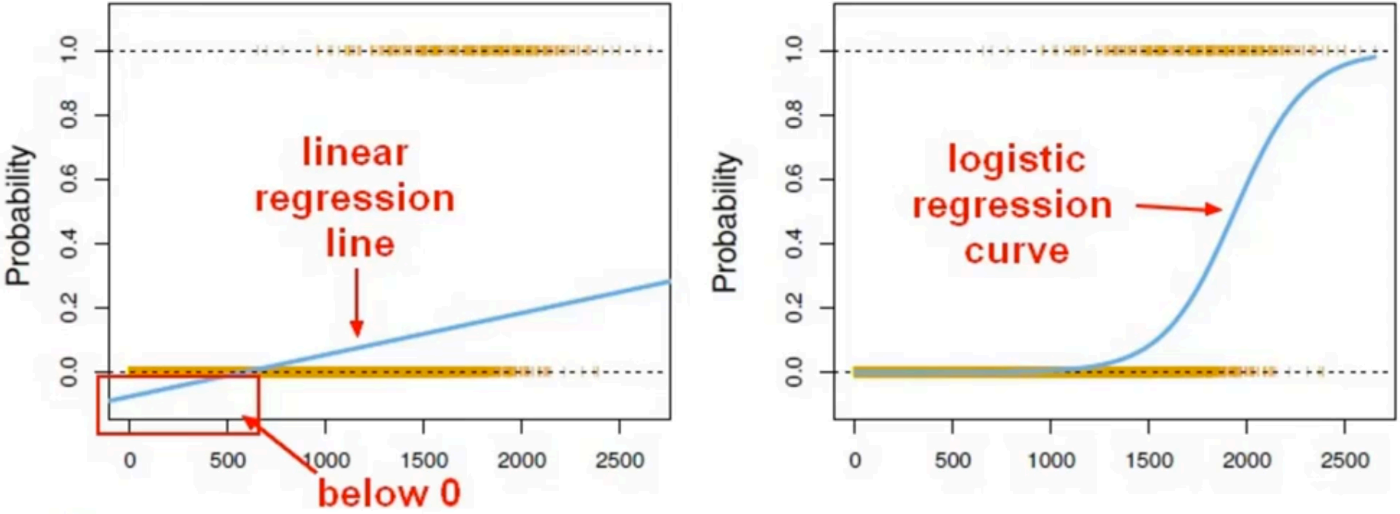
- We want to learn about Logistic Regression as a method for **Classification.**
- Some examples of classification problems:
  - Spam versus “Ham” emails
  - Loan Default (yes/no)
  - Disease Diagnosis
- Above were all examples of Binary Classification

- So far we’ve only seen regression problems where we try to predict a continuous value.
- Although the name may be confusing at first, logistic regression allows us to solve classification problems, where we are trying to predict discrete categories.
- The convention for binary classification is to have two classes 0 and 1.

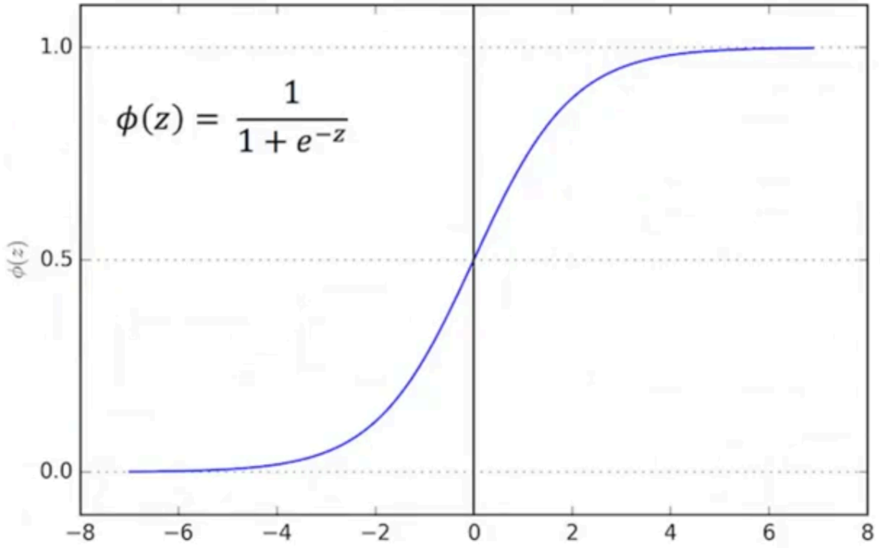
- We can’t use a normal linear regression model on binary groups. It won’t lead to a good fit:



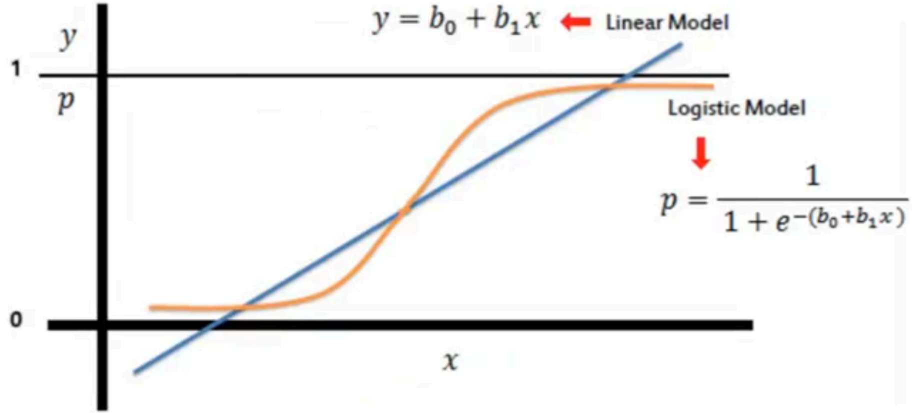
- Instead we can transform our linear regression to a logistic regression curve.



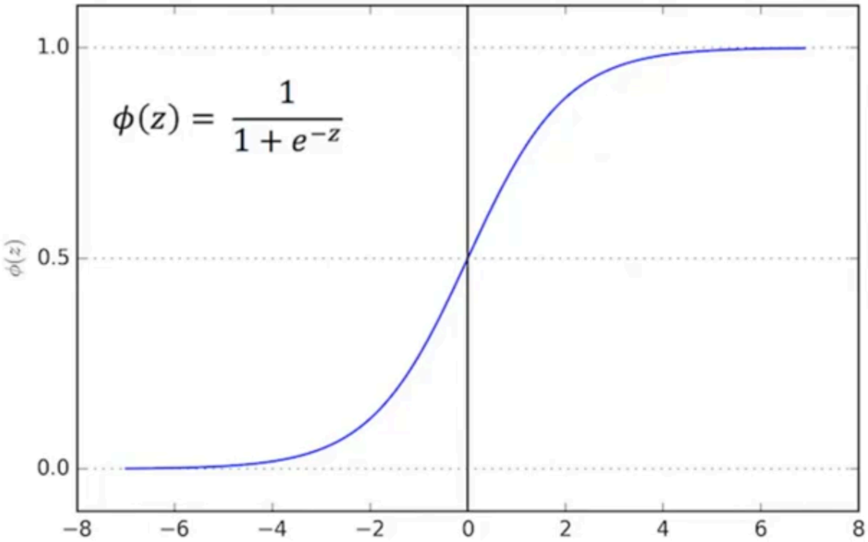
- The Sigmoid (aka Logistic) Function takes in any value and outputs it to be between 0 and 1.



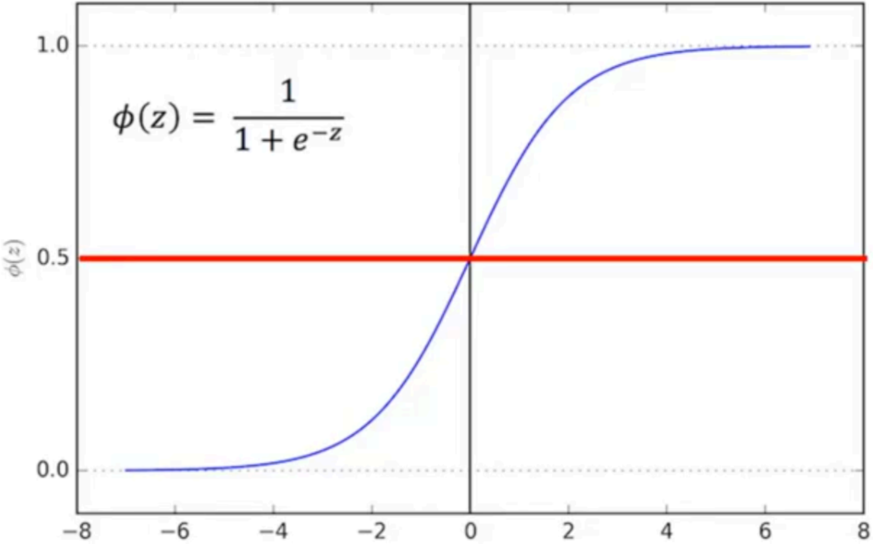
- This means we can take our Linear Regression Solution and place it into the Sigmoid Function.



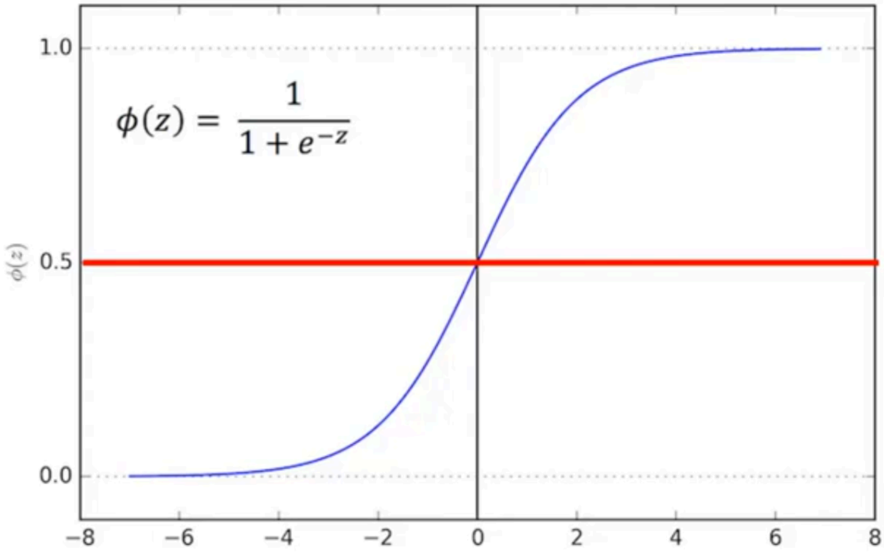
- This results in a probability from 0 to 1 of belonging in the 1 class.



- We can set a cutoff point at 0.5, anything below it results in class 0, anything above is class 1.



- We use the logistic function to output a value ranging from 0 to 1. Based off of this probability we assign a class.



- After you train a logistic regression model on some training data, you will evaluate your model’s performance on some test data.
- You can use a confusion matrix to evaluate classification models.

- We can use a confusion matrix to evaluate our model.
- For example, imagine testing for disease.

n=165	**Predicted: NO**	**Predicted: YES**
Actual: NO	50	10
Actual: YES	5	100

Example: Test for presence of disease
NO = negative test = False = 0
YES = positive test = True = 1

n=165	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

Basic Terminology:

- True Positives (TP)
- True Negatives (TN)
- False Positives (FP)
- False Negatives (FN)

n=165	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

Accuracy:

- Overall, how often is it **correct**?
- (TP + TN) / total = 150/165 = 0.91

n=165	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

Misclassification Rate (Error Rate):

- Overall, how often is it **wrong**?
- (FP + FN) / total = 15/165 = 0.09

Type I error
(false positive)

Type II error
(false negative)