Classification

- Email : Spam / Not Spam?
- Online Transactions: Fraudulent (Yes / No)?
- Tumor: Malignant / Benign?

In all of these problems the variable that we're trying to predict is a variable y that we can think of as taking on two values either zero or one, either spam or not spam, fraudulent or not fraudulent, related malignant or benign.

$y \in \{0, 1\}$

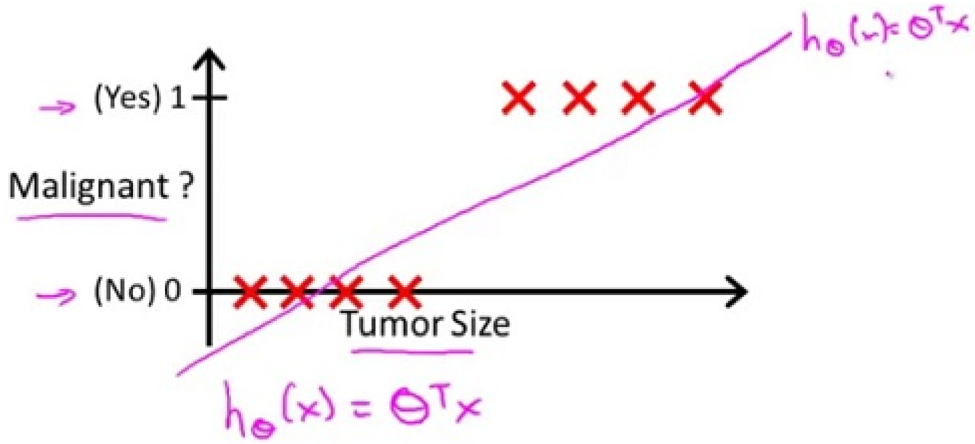
0: "Negative Class" (e.g., beningn tumor)

1: "Positive Class" (e.g., malignant tumor)

Another name for the class that we denote with zero is the negative class, and another name for the class that we denote with one is the positive class. So zero we denote as the benign tumor, and one, positive class we denote a malignant tumor.

How do we develop a classification algorithm?

Example of a training set for a classification task for classifying a tumor as malignant or benign.So one thing we could do given this training set is to apply the Linear regression algorithm to this data set and just try to fit the straight line to the data.

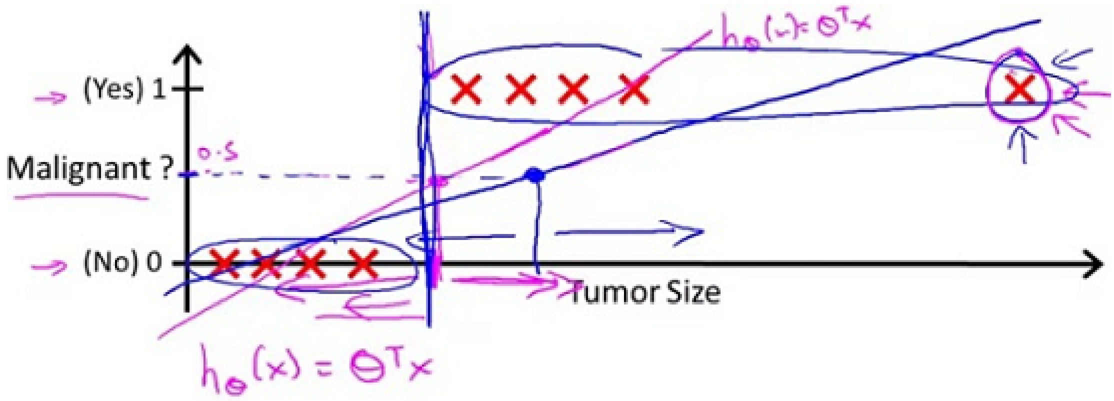


If we want to make predictions one thing we could try doing is then **threshold classifier**:

Threshold classifier output $h_\theta(x)$ at 0.5:

If $h_\theta(x) \geq 0.5$, predict "$y = 1$":

If $h_\theta(x) < 0.5$, predict "$y = 0$":



However, this method doesn't work well because classification is not actually a linear function.

Other problem about what would happen if we were to use linear regression for a classification problem is if for classification we know that y is either zero or one. But if we are using linear regression where the hypothesis can output values that are much larger than one or less than zero, even if all of our training examples have labels y equals zero or one.

Classification: $y = 0$ or 1

$h_\theta(x)$ can be > 1 or < 0

Video Question: Which of the following statements is true?

- If linear regression doesn't work on a classification task as in the previous example shown in the video, applying feature scaling may help.
- If the training set satisfies $0 \leq y^{(i)} \leq 1$ for every training example $(x^{(i)}, y^{(i)})$, then linear regression's prediction will also satisfy $0 \leq h_\theta(x) \leq 10$ for all values of x.
- If there is a feature x that perfectly predicts y, i.e. if $y = 1$ when $x \geq c$ and $y = 0$ whenever $x < c$ (for some constant c), then linear regression will obtain zero classification error.

> None of the above statements are true.

Summary

To attempt classification, one method is to use linear regression and map all predictions greater than 0.5 as a 1 and all less than 0.5 as a 0. However, this method doesn't work well because classification is not actually a linear function.

The classification problem is just like the regression problem, except that the values we now want to predict take on only a small number of discrete values. For now, we will focus on the **binary classification problem** in which y can take on only two values, 0 and 1.

(Most of what we say here will also generalize to the multiple-class case.) For instance, if we are trying to build a spam classifier for email, then $x^{(i)}$ may be some features of a piece of email, and y may be 1 if it is a piece of spam mail, and 0 otherwise. Hence, $y \in 0, 1$. 0 is also called the negative class, and 1 the positive class, and they are sometimes also denoted by the symbols "$-$" and "$+$." Given $x^{(i)}$, the corresponding $y^{(i)}$ is also called the label for the training example.