California State University
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Machine Learning

Logistic Regression

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What is Machine Learning?

Definition

- Designing and constructing algorithms or methods that give computers the ability to learn from past data, without being explicitly programmed, and then make predictions on future data.

- A set of algorithms that can automatically detect and extract patterns in past data, and then use the extracted patterns to predict future data, or to perform other kinds of decision-making.

Machine Learning Settings

Supervised learning

Learning from labeled observations

Unsupervised learning

Learning from unlabeled observations

Semi-supervised learning

Labels are provided only for a part of the training data

Reinforcement learning

Learning from an agent taking actions in an environment so as to maximize a long-term reward.

Transfer learning

Learning from a dataset while solving a problem, and then applying the extracted knowledge to a different but related dataset/problem.

Active learning

Similar to Semi-Supervised Learning, but the algorithm is able to interactively query the user or some other information source to obtain the labels as needed.

Two Important Approaches of Supervised Learning

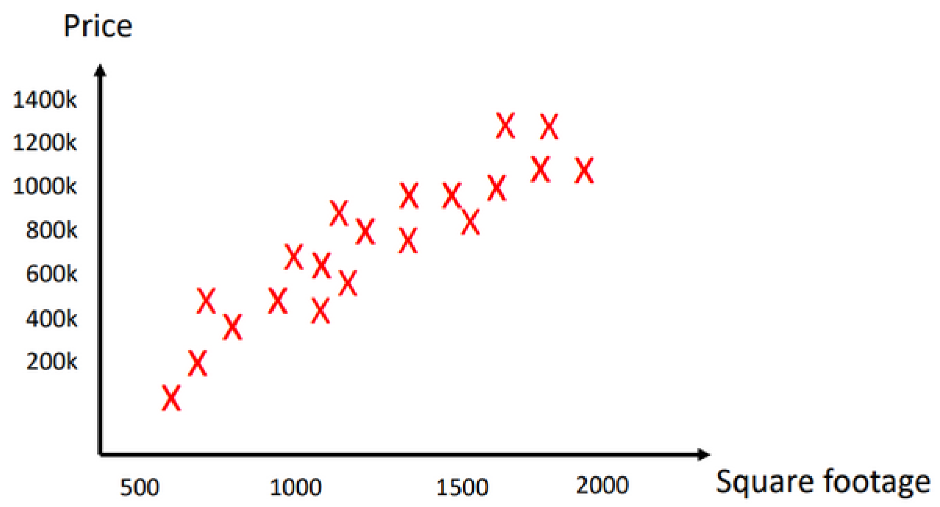
- **Classification**: Predict a discrete valued output for each observation. – Labels are discrete (categorical) – Labels can be binary (e.g., rainy/sunny, spam/non-spam,) or non-binary (e.g., rainy/sunny/cloudy, object recognition (100classes))

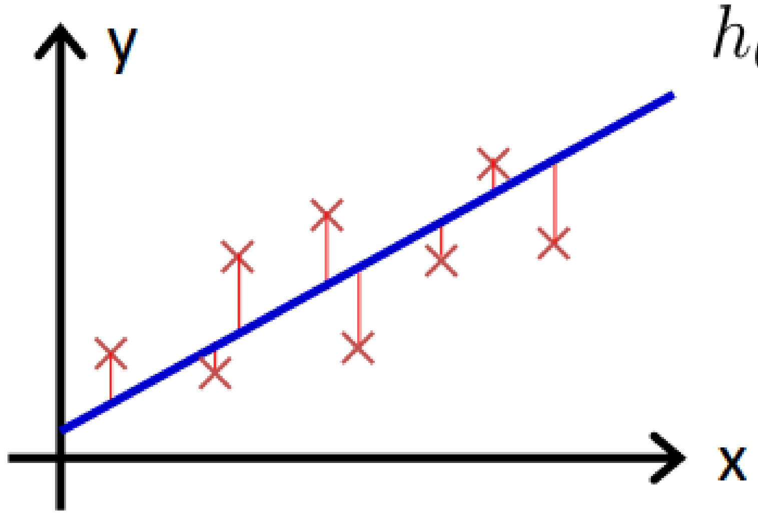
- **Regression**: Predict a continuous valued output for each observation. – Labels are continuous (numeric), e.g., stock price, housing price – Can define 'closeness' when comparing prediction with true values

Linear Regression

- A statistical method to model the relationship between a dependent variable and one or more independent variables.
- Predicts continuous outcomes.
- Simple yet powerful for many real-world applications.
- Linear Regression with single input variable (one feature). It is also called “Univariate Linear Regression.

Regression Example: Housing Price





$$h_\theta(x) = \theta_0 + \theta_1 x$$

$$\theta_0, \theta_1 = ?$$

Cost Function in Linear Regression

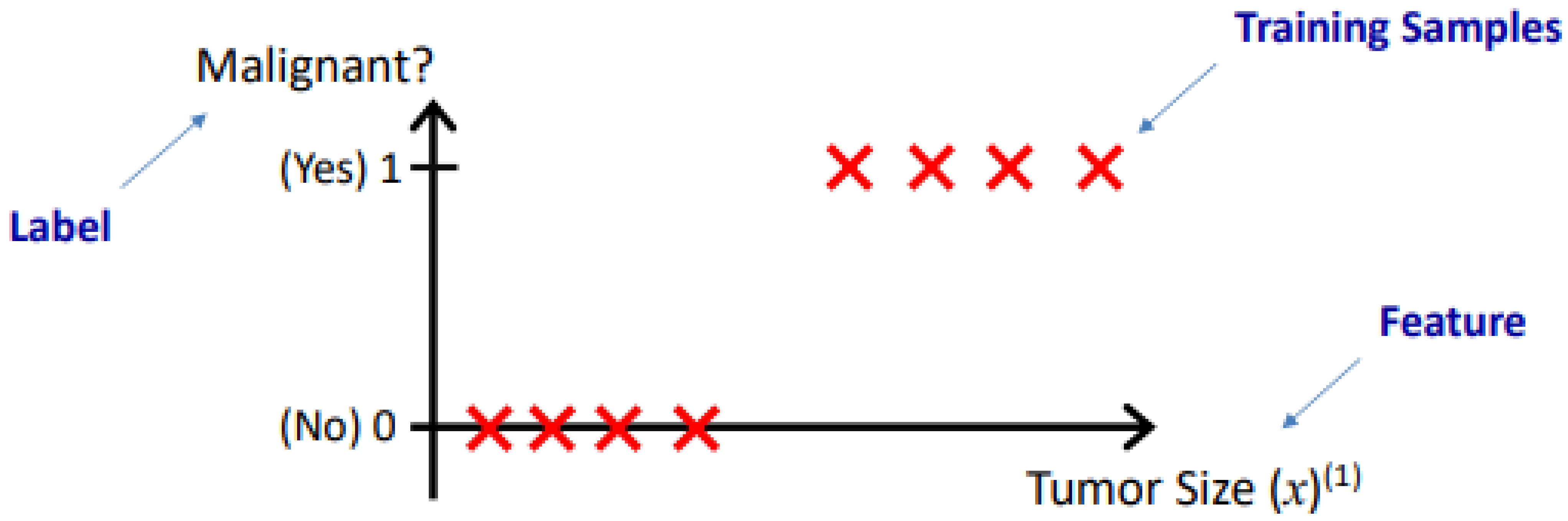
- The Cost Function, J(θ0,θ1), quantifies the error between the predicted values and actual values in the training data.
- It helps measure how well the model fits the data.

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$$

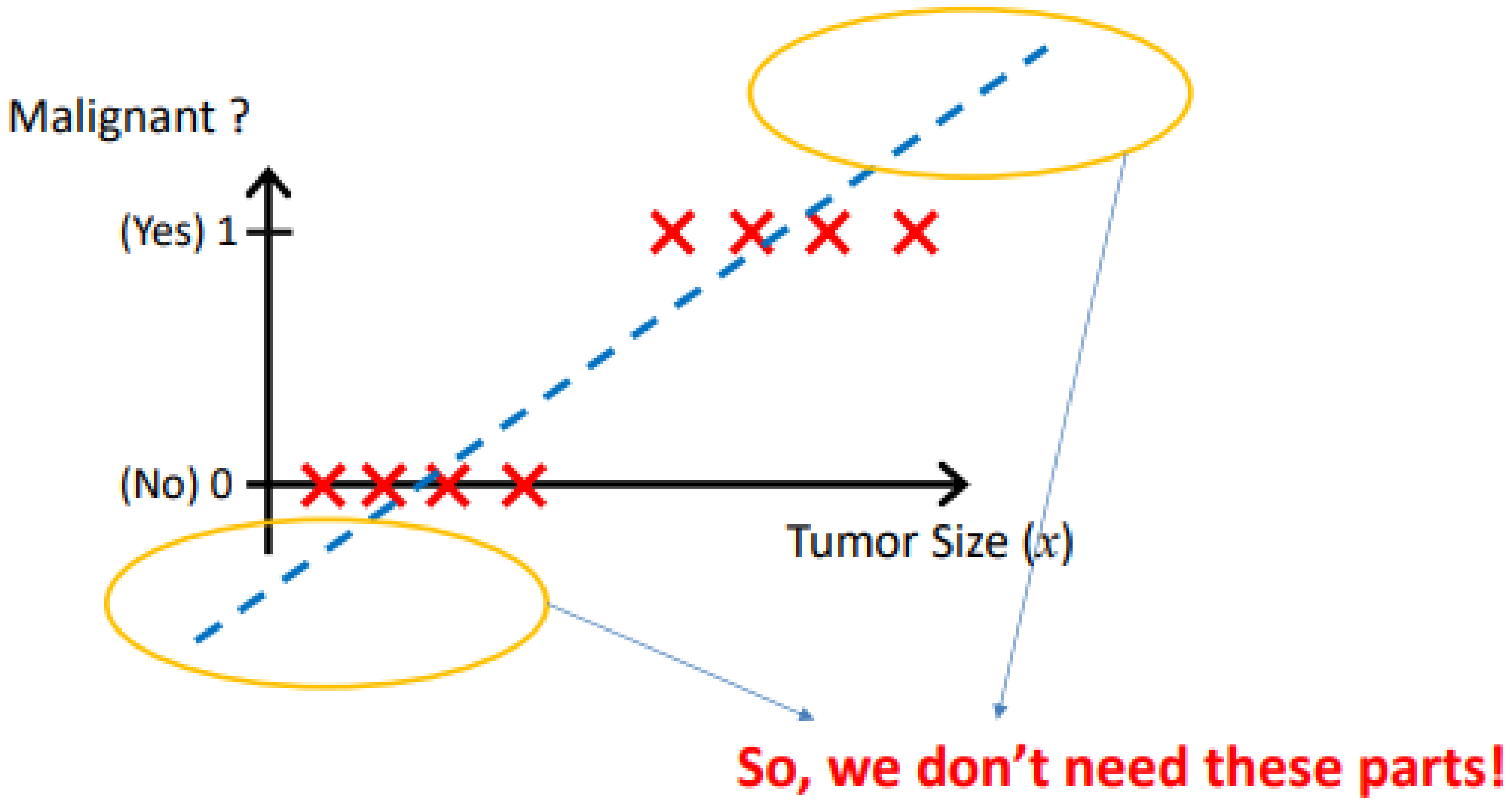
Logistic Regression

- Logistic Regression is a statistical model used for binary classification, where the goal is to predict one of two possible classes (e.g., 0 or 1) based on input features.
- It applies a sigmoid function to the linear combination of input features and weights, which maps any real-valued number to a probability between 0 and 1.
- The model is trained using maximum likelihood estimation, typically minimizing the log loss (cross-entropy) function to find the best-fitting parameters for classification.

:Predicting if a Tumor is Malignant or Not based on tumor size (so, we need a classifier):



we know that for our classifier, the output should be either 1 or 0!



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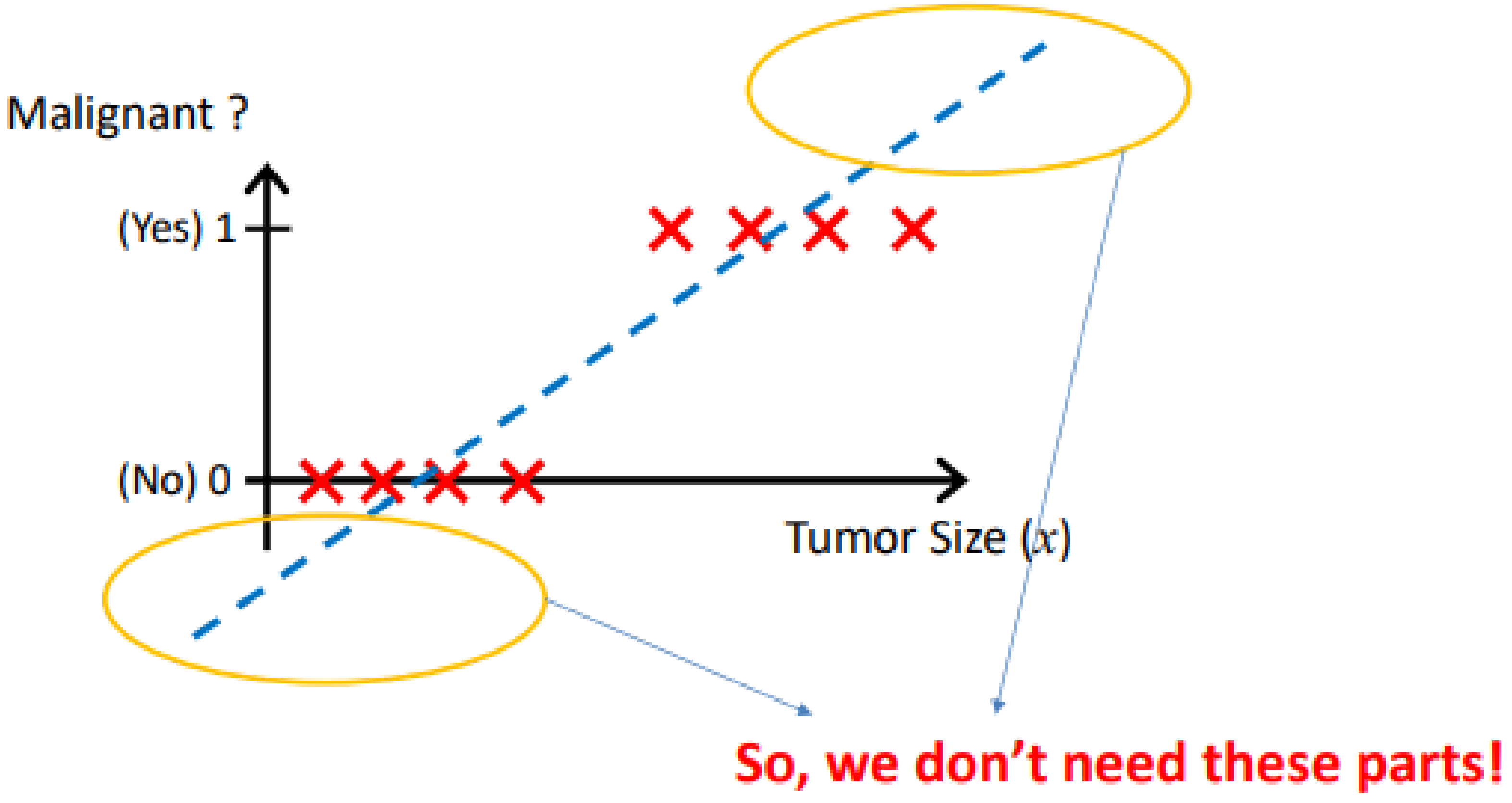
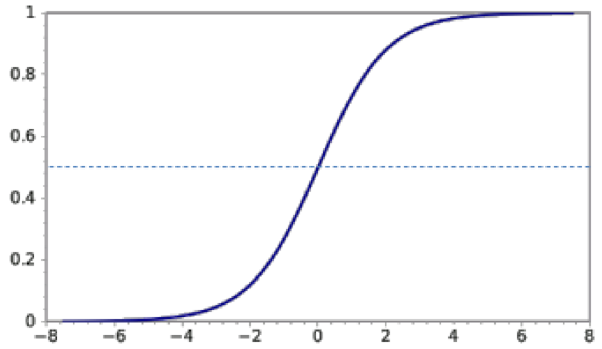


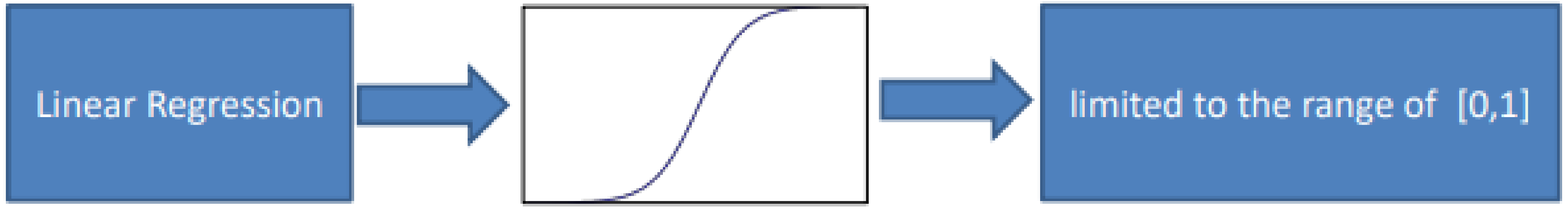
$$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n$$

Linear Regression Model $h\theta(x) = \theta^T x$

Sigmoid Function

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





$$h_\theta(\boldsymbol{x}) = \boldsymbol{\theta}^T \boldsymbol{x}$$

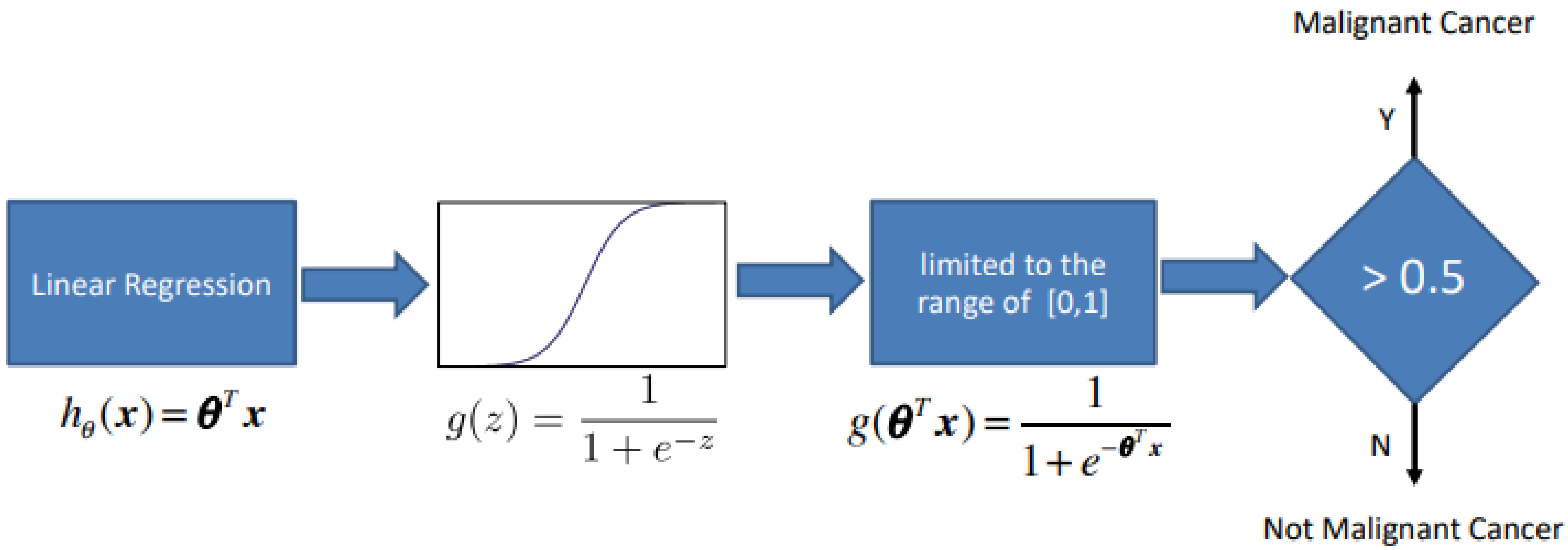
$$g(z) = \frac{1}{1 + e^{-z}}$$

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

New approach for output prediction:

$$h_\theta(\boldsymbol{x}) = g(\boldsymbol{\theta}^T \boldsymbol{x}) = \frac{1}{1 + e^{-\boldsymbol{\theta}^T \boldsymbol{x}}}$$

So, Now the NEW $h_\theta(x)$ is limited to the range of [0,1].



New Cost function:

$$J(\boldsymbol{\theta}) = J(\theta_0, \theta_1, \dots, \theta_n)$$

$$= -\frac{1}{m} \sum_{i=1}^{m} \left[y^{(i)} \log h_\theta(\boldsymbol{x}^{(i)}) + (1 - y^{(i)}) \log(1 - h_\theta(\boldsymbol{x}^{(i)})) \right]$$

Note: $y = 0$ or 1 always

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Thank You

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