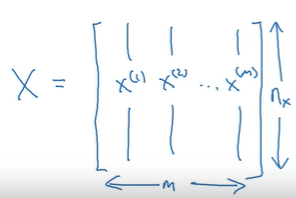
**Week 2 – Notes**

**Binary Classification**

The notation used throughout the course:

 - features: one example per column (m columns) nx features (rows)

A picture containing text

Description automatically generated - targets: one target per column

**Logistic Regression**

**Text

Description automatically generated with medium confidenceWhiteboard

Description automatically generated with medium confidenceIcon

Description automatically generated**

**Logistic Regression Cost Function**

We denote

Text

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We cannot define the loss function as below because it isn’t convex

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We define it as

Text

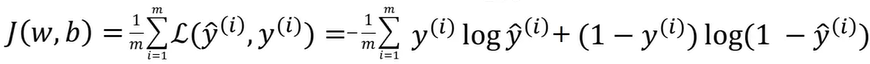
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The cost function is the average of all loss functions for each pair of y and y hat

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**Gradient Descent**



We want to minimize J(w, b) – the cost function

The derivative represents the slope of the function in a point

With d we denote derivatives and with sigma we denote partial derivatives

This algorithm implies moving towards the minimum values of the function by repeatedly subtracting from each parameter the value given by alpha (learning rate) \* the derivative of the function with respect to that parameter

**Derivatives**

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Computes what’s the ratio between the change in the value of the function and the change of the variable, if we increase the variable just by a little (represents the height / width of the triangle that we draw it with the hypotenuse as being the tangent)

**More Derivative Examples**

In machine learning the log always denotes the ln

**Computation graph**

Forward pass -> compute the outputs of the network

Backward pass -> Compute the gradients / derivatives

**Computing derivatives**

**Diagram

Description automatically generated**

In this course, dvar is the notation of the derivative of the cost function with respect to the variables

To compute the derivative of J with respect to a, we use the chain rule:

 = Text

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To compute derivates we can use the defined formula, or to use the definition, but in which we consider x0 to be a small value, such as 0.001

**Logistic Regression Gradient Descent**

Diagram

Description automatically generated

We have to update w1, w2 and b; for example w1 := w1 – alpha \* dw1

**Gradient Descent on m Examples**

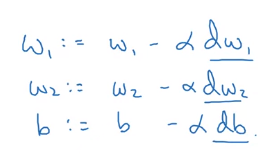
The superscript notation denotes the indices / number of the data example

Text

Description automatically generated

We initialize J, dw1, dw2 and db with 0 and we compute them by adding the value computed in relation with each training example; after that we divide each variable with the number of examples

One iteration of the gradient descent means that we update w1, w2 and b:



Because we want to avoid having many for loops, we’ll use the vectorized implementation