An Introduction to Machine Learning

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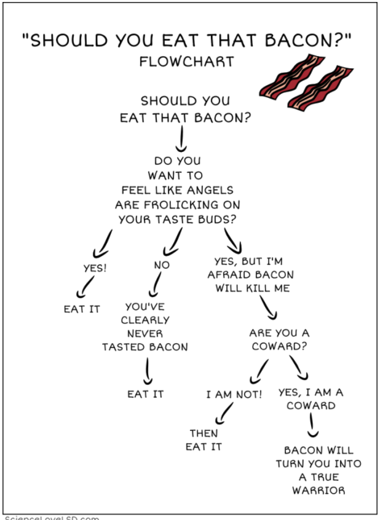
What is Classification?

- Email: Spam/Not Spam
- Sports Outcomes: Win/Loss
- Disease Prediction: Positive/Negative test results


"SHOULD YOU EAT THAT BACON?" FLOWCHART
SHOULD YOU EAT THAT BACON?
DO YOU WANT TO FEEL LIKE ANGELS ARE FROLICKING ON YOUR TASTE BUDS?
YES!
EAT IT
NO
YOU'VE CLEARLY NEVER TASTED BACON
EAT IT
YES, BUT I'M AFRAID BACON WILL KILL ME
ARE YOU A COWARD?
I AM NOT!
THEN EAT IT
YES, I AM A COWARD
BACON WILL TURN YOU INTO A TRUE WARRIOR
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How do we Classify?

- Support Vector Machines (SVM)
- Neural Network
- **Logistic Regression**

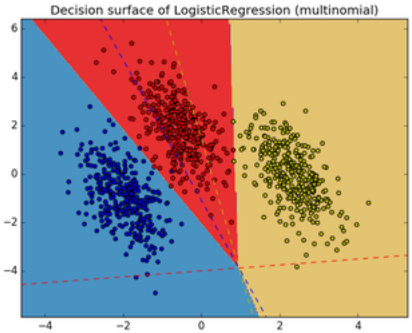

Figure 1: Logistic Regression

Introduction to Logistic Regression

- Hypothesis representation function, $h_\theta(x)$
- Basic Binary Classification, 0 or 1. This is the output of the hypothesis function (y)
- Can be whether a trait occurs or not, absence or presence of what you want to predict
- Threshold value for deciding when to be positive or negative

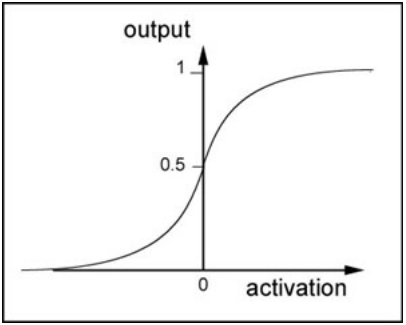

Figure 2: Sigmoid Activation Function

Features and Data

- Features are specific traits about a given subject in the data.
- Examples being: size, color, shape, weight, etc..
- Subject is the item in question
- Example: A golf gall is 42.67 cm, white, spherical, and weighs 1.62 oz
- Two types features: Qualitative and Quantitative.
- Two types of data, training and testing

Hypothesis Function

- Want $0 \leq h_\theta(x) \leq 1$
- Threshold for classification: 0.5 (This is up to you and may change for different data sets)
- If $h_\theta(x) \geq 0.5$, predict "y=1"
- If $h_\theta(x) < 0.5$, predict "y=0"
- $h_\theta(x) = g(\theta^T x)$ where θ is the matrix representing our coefficients, and x is the values of the features of our data.
- $h_\theta(x) = g(\theta_0 + \theta_1 x_1 + ... + \theta_n x_n)$
- $g(z) = \frac{1}{1+e^{-z}}$

Decision Boundary

- $h_\theta(x) = g(\theta_0 + \theta_1 x_1 + ... + \theta_n x_n)$
- Predict "y=1" if $\theta_0 + x_1 + x_2 + ... + x_n \geq 0$
- Otherwise predict "y=0"

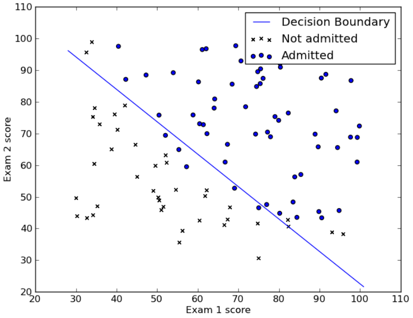

Figure 3: Decision Boundary Example

Cost Function

$$cost(h_\theta(x), y) = \begin{cases} -log(h_\theta(x)) & \text{if y=1} \\ -log(h_\theta(1-x)) & \text{if y=0} \end{cases}$$

- The cost function "punishes" the algorithm for incorrect predictions with very high costs(approaching infinity) and "rewards" the algorithm for correct predictions with low costs (approaching 0)
- If "y=1" and our predicted value from $h_\theta(x)$ is "y=1" then our cost goes to 0, because the prediction was accurate
- If "y=1" and our predicted value from $h_\theta(x)$ is "y=0" then our cost goes to infinity to teach the algorithm that this was an incorrect prediction
- Eventually we want our algorithm to only generate low costs

Cost Function (Cont.)

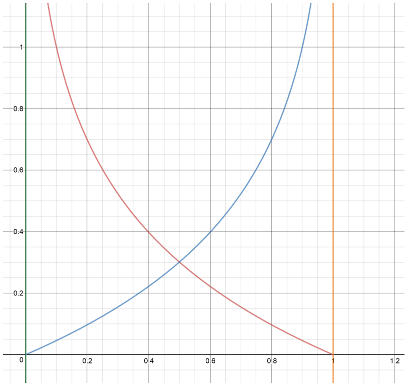

Figure 4: Cost Function for Classification

- Red is $-log(x)$, for when $y = 1$, so if $h_\theta = 1$, cost $= 0$
- Blue is $-log(1 - x)$ for when $y = 0$, so if $h_\theta = 0$, cost $= 0$

Combining the Cost Function

- Combined,
  $cost((h_\theta(x)) = -y_i log(h_\theta(x_i)) - (1 - y_i)log(h_\theta(1 - x_i))$
- if y = 1,
  $cost((h_\theta(x), y) = -y_i log(h_\theta(x_i)) - 0$
- if y = 0,
  $cost((h_\theta(x), y) = 0 - (1 - y_i)log(h_\theta(1 - x_i))$
- So then,
  $J(\theta) = \frac{1}{m}\left[\sum_{i=1}^{m} cost(h_\theta(x_i), y_i)\right]$
- Finally,
  $J(\theta) = \frac{1}{m}\left[\sum_{i=1}^{m} -y_i log(h_\theta(x_i)) - (1 - y_i)log(h_\theta(1 - x_i))\right]$
- And therefore the derivative with respect to θ_j,
  $\frac{\partial}{\partial\theta_j} J(\theta) = \sum_{i=1}^{m} [h_\theta(x_i) - y_i] ({}^j x_i)$

Minimizing the Cost Function with Gradient Descent

- Search for the set of coefficients that will minimize the next step in our cost function by calculating the slope of surrounding coefficients of the current data point. Chose the next data point with the smallest value.

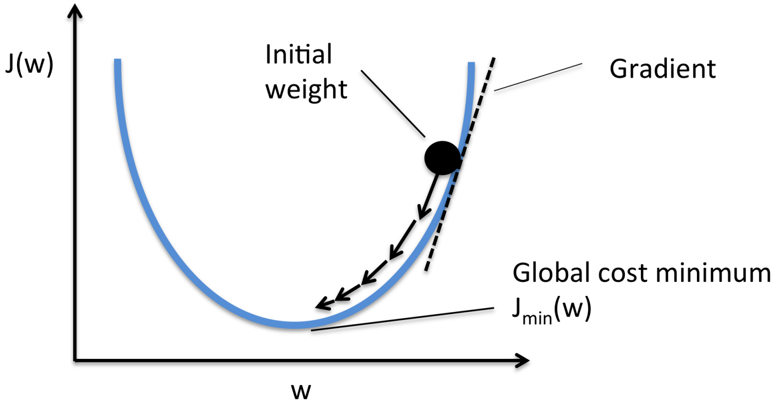

Figure 5: Minimizing the Cost Function with Gradient Descent

Minimizing the Cost Function with Gradient Descent

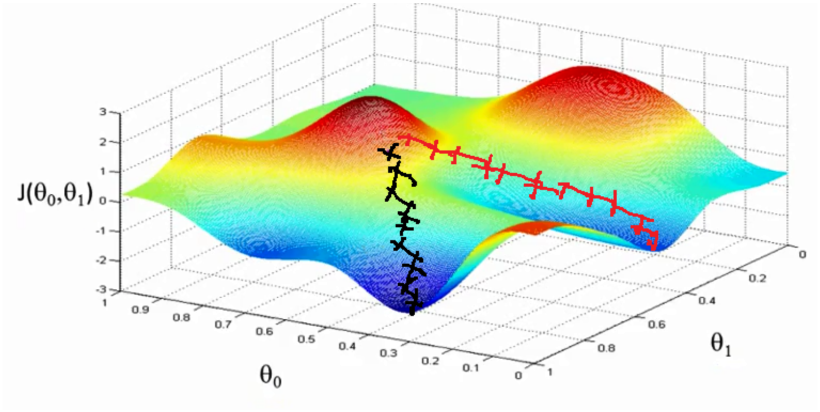

Figure 6: Gradient Descent Visualization

Minimizing the Cost Function with Gradient Descent

- We want to minimize J(θ)
- Repeat: $\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$ such that we are simultaneously updating all θ_j
- $\frac{\partial}{\partial \theta_j} J(\theta) = \sum_{i=1}^{m} \left[h_\theta(x_i) - y_i \right] ({}^j x_i)$
- Therefore our gradient descent will look like the following:
  Repeat: $\theta_j := \theta_j - \alpha \sum_{i=1}^{m} \left[h_\theta(x_i) - y_i \right] ({}^j x_i)$

Putting it All Together

- So we can classify positive and negative examples using a training set, then predict on "real" data.
- We train the hypothesis function with the cost function, and improve the cost using gradient descent.
- This creates a decision boundary, which we can then use to classify our data.
- By minimizing the cost function we train our hypothesis to create the best possible decision boundary.

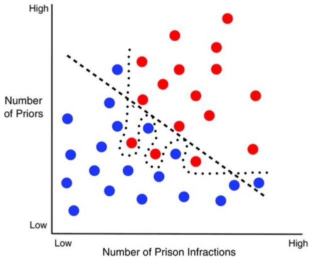

Figure 7: Decision Boundary

Sources

- Stanford University Machine Learning Course Via Coursera
- Andrew Ng
- kaleko on github
- Kaggle Databases

Lab! - Iris Classification

Figure 8: Iris Classification

Lab Setup

- https://github.com/spencer-hanson/HackCU-Machine-Learning
- Clone the entire repository
- Make sure you have the proper python dependencies installed by running "./install.sh" in your command line (for linux)