Fundamentals of Machine Learning

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Weekly Objectives

- Learn the most classical methods of machine learning
 - Rule based approach
 - Classical statistics approach
 - Information theory appraoch
- Rule based machine learning
 - How to find the specialized and the generalized rules
 - Why the rules are easily broken
- Decision Tree
 - How to create a decision tree given a training dataset
 - Why the tree becomes a weak learner with a new dataset
- Linear Regression
 - How to infer a parameter set from a training dataset
 - Why the feature engineering has its limit



LINEAR REGRESSION

How about statistical approach?

(bute 7 (by mas stati)

- http://archive.ics.uci.edu/ml/datasets/Housing
- Housing dataset

 - 13 numerical independent values
 1 numerical dependent value; True / Rulse lake
- approximation process?
- Here.
- (250/2 1/2 Ditz 2001. -(4/1/2 ftm = 2 2/24),
- Our hypothesis is
 - The house value will be the linearly weighted sum of the feature values.
 - $h \cdot \hat{f}(x; \theta) = \theta_0 + \sum_{i=1}^n \theta_i x_i = \sum_{i=0}^n \theta_i x_i$
 - **n** is the number of the feature values.
 - Two aspects: the linearly weight sum (the model), the parameter θ
- The first effort is finding the better θ , just like the thumbtack

Finding θ in Linear Regression

- To make the hypothesis better, we need to find the better $\boldsymbol{\theta}$
 - $h: \hat{f}(x; \theta) = \sum_{i=0}^{n} \theta_i x_i \to \hat{f} = X\theta$

•
$$X = \begin{pmatrix} 1 & \cdots & x_n^1 \\ \vdots & \ddots & \vdots \\ 1 & \cdots & x_n^D \end{pmatrix}, \theta = \begin{pmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_n \end{pmatrix}$$
• The reality would be the noisy, so...
• $f(x;\theta) = \sum_{i=0}^n \theta_i x_i + e = y \to f = X\theta + e = y$
• The difference is the error from the noise, so let's make it minimum

•
$$f(x;\theta) = \sum_{i=0}^{n} \theta_i x_i + e = y \rightarrow f = X\theta + e = Y$$

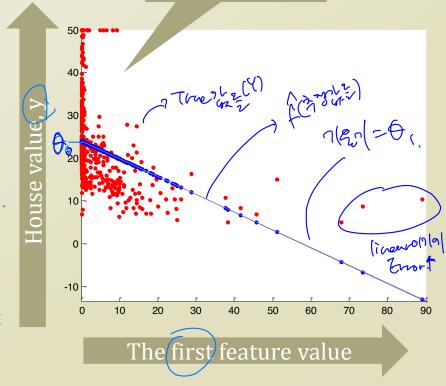
- The difference is the error from the noise, so let's make it minimum
 - $\hat{\theta} = \operatorname{argmin}_{\theta} (f \hat{f})^2 = \operatorname{argmin}_{\theta} (Y X\theta)^2$ $= argmin_{\theta} (Y - X\theta)^{T} (Y - X\theta) = argmin_{\theta} (Y - X\theta)^{T} (Y - X\theta)$ $= argmin_{\theta}(\theta^{T}X^{T}X\theta - 2\theta^{T}X^{T}Y + Y^{T}Y) = argmin_{\theta}(\theta^{T}X^{T}X\theta - 2\theta^{T}X^{T}Y)$
- Now, we need to optimize θ

Optimized θ

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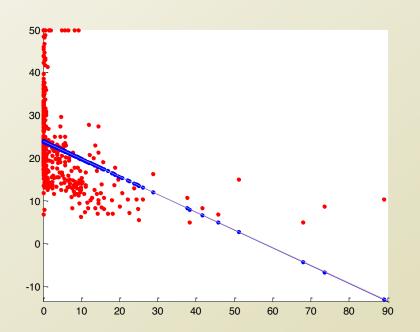
- $\hat{\theta}$ = $argmin_{\theta}(\theta^T X^T X \theta - 2\theta^T X^T Y)$
- Same technique as in Thumbtack
 - $\nabla_{\theta}(\theta^T X^T X \theta 2\theta^T X^T Y) = 0$
 - $2X^TX\theta 2X^TY = 0$
 - $\theta = (X^T X)^{-1} X^T Y$
- Great! We know X and Y, so we can compute θ
- Let's calculate and watch the performance!
 - For demonstration purpose, we limit the dimension to the constant and the first feature
- MLE if error follows the normal distribution

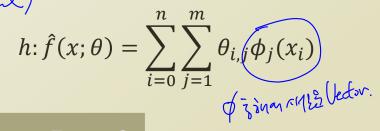


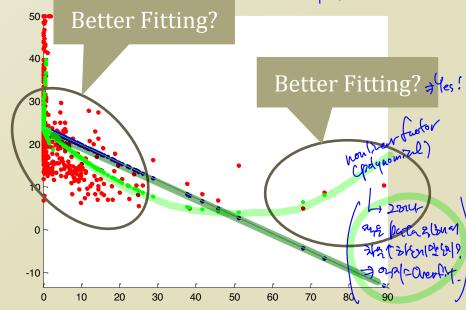


If you want more....

- Actually, you can increase the number of features, a.k.a. dimension
 - You have a value *x* in the previous fitted figure
 - How about adding x^2 , x^3 , x^4? (polywrital) You can improve the result!
- - Is that right?
- We are going to come back!







Too Brittle to Be Used Naively

- What we are doing
 - Approximating a function to the dataset
 - The function can be
 - Discrete logics
 - Statistical model
 - Often, the function type is given
 - The parameters of the functions are the target of the analysis
- Alternatives in finding the parameter
 - MLE or MAP
 - Engineering the features
 - Setting the generalization and the specialization level
- Best choice among the alternatives
 - If we have the perfect data, we will know

