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# Linear Regression

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# Content

- Linear Regression: Definition
- Linear Regression: Property\*
- Linear Regression: Interpretation\*
- Linear Regression: Some Modifications



# Recap: Machine Learning Definition

- Definition1
- Machine learning allows computers to observe input and produce a desired output, either by example by identifying latent patterns in the input
- Data
  - What type of input? What type of output?
- Patterns = Algorithm
  - Intuition (empirical) / Objective (theoretical)



# Recap: Machine Learning Definition

- Definition2
- Using Experience to gain expertise
- Programs that
  - Learn Rules from data
  - Adapt to changes
  - Improve performance with experience



# Recap: Machine Learning Definition

- Definition3
- Fitting a function to data
- Fitting: Optimization, what parameters can we change
- Function: Model, loss function
- Data: Data/model assumptions? How we use data?



We start with  
Linear  
Regression



# Why Start Here

- Well-known algorithm
- Not strictly a “machine learning” algorithm
- Can learn about fundamentals with a simple example





# Example

- I run a real estate website. I want to list properties for sale and provide estimates of how much they will sell for
- Goal: Predict home prices
- Data: Previous home sales
  - Housing facts: size, bedrooms, age, neighborhood, listing price
- How do I do this



# Data Model

- Assume dependent variable ( $y$ ) can be modeled by a linear function of the input variables ( $x$ )
- $Y = wx + b$
- 2 dimensions
  - Compute  $x$  and  $b$  from two points
- Solution
  - Given  $y$  and  $x$ , solve for  $w$  and  $b$



# Regression

- Data  $\{(x_i, y_i)\}_{i=1}^N$   $x_i \in \mathbb{R}^M$   $y_i \in \mathbb{R}$
- Learn: a mapping from  $x$  to real valued  $y$ 
  - $f(x)=y$
- Examples
  - GPAs
  - Stock price
  - Miles per gallon
  - Age of author

# Fitting a function to data

- Fitting: solve for  $w$  given  $y$  and  $x$
- Function: linear function
- Data: assume dependent variable linear combination of independent variables
- Minimize a function:
  - What function are we minimizing?

# What is the goal?

- In Statistics:
  - linear regression is an approach for modeling the relationship between a scalar dependent variable  $y$  and one or more explanatory variables (or independent variables) denoted  $X$ ." (Wikipedia)
- ML goal: predict correctly the next example
  - Minimize: reduce prediction error

# Loss Functions

- Machine learning algorithms minimize loss functions
  - Or some substitute for a loss function
  - The best solution minimizes the loss function\*
- Definition
  - A function that maps between (true label, prediction) -> non-negative number
  - 0 = perfect prediction

# Loss: What We Minimize

- Loss measures the badness of our prediction
- What's a good loss function?
  - It depends on task and goals
- Regression loss function?
  - Proposal: How far are you from the correct answer

# Sum of Squares Loss

- $f(x) - y$
- $(f(x) - y)^2$
- $\sum_{i=1}^n (f(x_i) - y_i)^2$
- $\sum_{i=1}^n (w \cdot x_i - y_i)^2$



# Goal of Learning

- True error
- $\sum_{i=1}^{\infty} (w \cdot x_i - y_i)^2$
- We need infinite data to measure this

## Goal of Learning (Cont'd)

- If we can't measure true error, how do we judge learning success?
- Should an algorithm maximize performance on observed data?
- Proposal: Measure error on the given data
  - Call this the “training data”
  - Is this a good idea?

# Measuring Error

- Very bad idea for Machine learning (not that bad for statistics)
- Recall: machine learning cares about prediction (the future)
  - How well will the system do once deployed?
- Memorizing the training data is easy

# Generalization

- Generalization
  - The ability of an algorithm to generalize knowledge learned from observed data to new data
- Simple example: memory based classifier
  - Binary classification
  - Train: remember each example
  - Test: if we have seen an example before, report label
    - Otherwise, guess randomly
- Train error: 0%, test error: 50%

# Assumption for Linear Regression

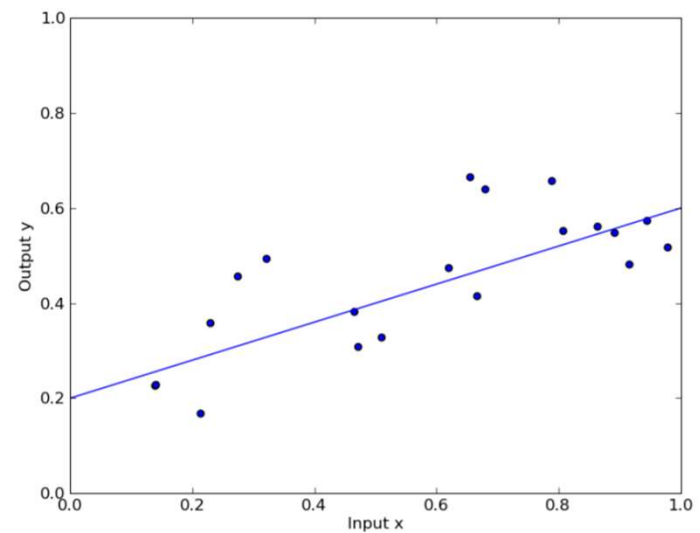
- We assumed output ( $y$ ) is linear combination of inputs
- This is wrong
  - Rarely is data actually linear
- But realistic assumption may be too complex
- A reasonable middle ground?

# Noise from a Gaussian Distribution

- Assume output permuted by Gaussian noise
- $y = wx + \varepsilon$
- $\varepsilon \sim N(\mu, \sigma^2), \mu = 0, \sigma^2 = 1$
- The data isn't really generated in this way
  - Assume that it is for sake of modeling (Law of Large Numbers)

# Probability of Output

- $p(y|x, w, \sigma^2)$
- $= N(y, \sigma^2)$
- $= N(wx, \sigma^2)$





## Two common methods

- Ordinary Least Square vs Maximum Likelihood
- They will reach the same solution to the data (mostly)

# Maximum Likelihood

- Likelihood = probability of observing data
- Writing likelihood
  - Assume data generated from our linear regression

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A horizontal brushstroke with a green-to-blue gradient, featuring a textured, painterly appearance with visible brush marks and a soft edge.

# Blackboard Session

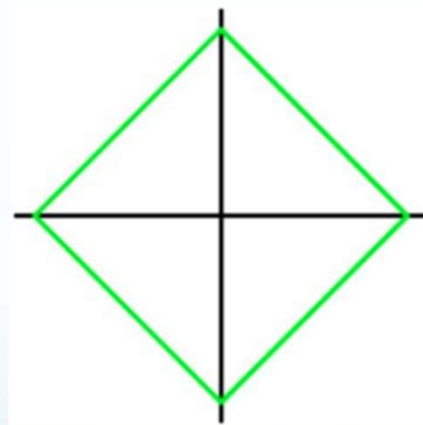
# Bias?

- Gaussians: Maximum likelihood estimate is biased
  - This is ok if we have infinite data
  - We never have infinite data!
- Overfitting: avoid it by favoring certain solutions
- Regularization
  - Add term to objective to favor different considerations
  - What should we favor: simpler is better → favor small weights

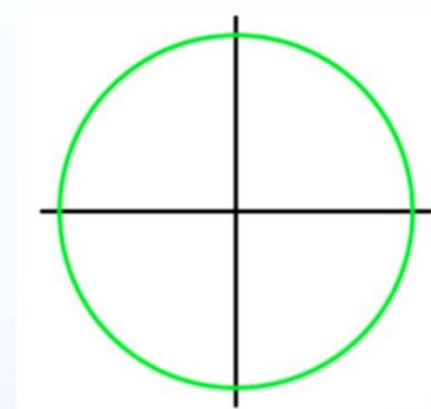
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# Blackboard Session for Regularization

# Regularization Behavior

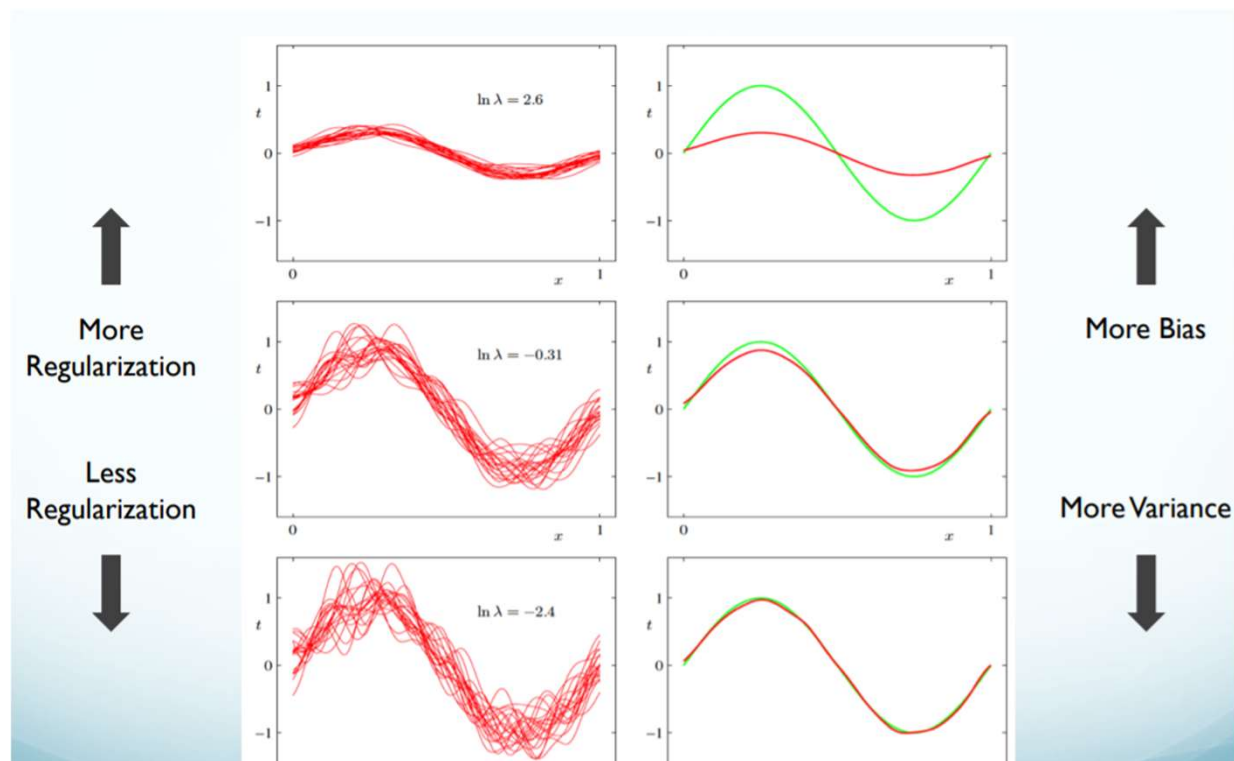


$q=1$  L1 (Lasso)



$q=2$  L2 (quadratic)

# Parameter Tradeoff





# Interpretation

- [http://reliawiki.org/index.php/Simple Linear Regression Analysis](http://reliawiki.org/index.php/Simple_Linear_Regression_Analysis)

# Property

- [https://en.wikipedia.org/wiki/Gauss%E2%80%93Markov\\_theorem](https://en.wikipedia.org/wiki/Gauss%E2%80%93Markov_theorem)
- <https://statisticsbyjim.com/regression/gauss-markov-theorem-ols-blue/>

# Paper

- Find your interest
  - <https://arxiv.org/>
  - Some problem in real world (predicting crowdfunding success, predicting housing/car/stock price, image, speech, language processing)
- Read more papers (literature review)
- Think about what makes you different from previous work
- Prepare data/methodology
- Experiments
- Write the paper

# Examples

- Some volunteers please~

My example

# A different story --- Reviewing paper

- Find some fields you like
- Read many many many paper
- Reformat them
- Think about some future directions
- Write the paper

Examples~



# Some Possible Fields

- Various of Predictions (stock, used car, crowdfunding, housing...
- <https://www.kaggle.com/competitions>
- <https://www.kaggle.com/datasets>
- <https://elitedatascience.com/datasets>
- CV, NLP, Speech