

# Regression

Greg Grudic

# Admin

- If you haven't, please send in your survey.

# Your Concerns

1. Math Skills
2. Matlab
3. Workload

# Matlab

- The link to the matlab page is:  
[http://www.mathworks.com/academia/student\\_version/](http://www.mathworks.com/academia/student_version/)
- Almost all of the ITS lab machines have matlab

# Questions?

# To Do...

- Homework 1 is on the class web page
- Please read next weeks lecture notes before next class...

## Lecture Goal

- Basic definitions
- Introduction to Regression
  - Least squares regression
  - Ridge Regression
  - Lasso Regression
  - Kernels
  - Kernel Ridge Regression

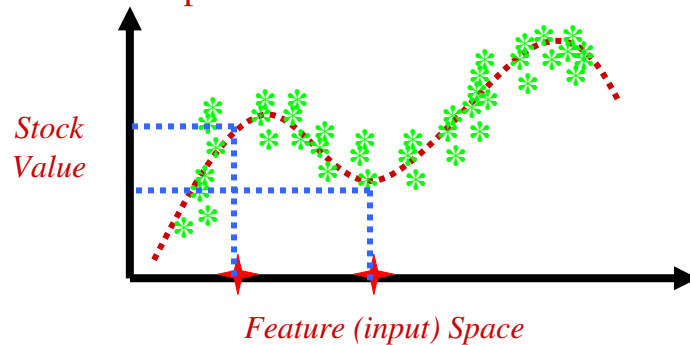
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## Learning Regression Models

- Collect Training data
- Build Model: stock value =  $F(\text{feature space})$
- **Make a prediction**



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## My Favorite Regression Example:



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## Human-to-Robot Skill Transfer (ICRA96)

- **Problem:** Human demonstrates a task via teleoperation.
  - Object locate and approach task.
  - 1024 raw pixel inputs and 2 actuator outputs.
- **Learning Data:** 4 demonstrations of task sequence.
  - 2000 to 5000 learning examples (~2 to 5 min).
- **Learning Time:** ~5 min. on SPARC 20.
- **Model Size / Evaluation Speed:** < 500 Kb, ~5 Hz.
- **Autonomous control of robot using model:**
  - No failures in 30 random trials.

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# Ridge Regression

Given learning data:

$$\{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)\}, \text{ where } \mathbf{x}_i \in \mathfrak{R}^d, y_i \in \mathfrak{R}$$

Define:  $\mathbf{G} = \begin{pmatrix} g_{11} & \cdots & g_{1K} \\ \vdots & \ddots & \vdots \\ g_{N1} & \cdots & g_{NK} \end{pmatrix}$  and  $\bar{g}_i = \frac{1}{N} \sum_{a=1}^N g_{ai}$

Where:

1. Linear Ridge:  $g_{ij} = x_{ij}$  and  $K = d$
2. Kernel Ridge:  $g_{ij} = K(\mathbf{x}_i, \mathbf{x}_j)$  and  $K = N$   
↖ Kernel Matrix

# Ridge Coefficients

$$\mathbf{X} = \begin{pmatrix} g_{11} - \bar{g}_1 & \cdots & g_{1K} - \bar{g}_K \\ \vdots & \ddots & \vdots \\ g_{N1} - \bar{g}_1 & \cdots & g_{NK} - \bar{g}_K \end{pmatrix} = \mathbf{G} - \begin{pmatrix} \bar{g}_1 & \cdots & \bar{g}_K \\ \vdots & \ddots & \vdots \\ \bar{g}_1 & \cdots & \bar{g}_K \end{pmatrix}$$

$$\left( \hat{\beta}_1^{ridge}, \dots, \hat{\beta}_K^{ridge} \right)^T = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I})^{-1} \mathbf{X}^T \mathbf{y}$$

$$\hat{\beta}_0^{ridge} = \left[ \frac{1}{N} \sum_{i=1}^N y_i \right] - \left[ \sum_{j=1}^K \bar{g}_j \hat{\beta}_j^{ridge} \right]$$

## Learned Models

- Linear

$$\hat{y} = \hat{\beta}_0 + \sum_{j=1}^d \hat{\beta}_j x_j$$

- Kernel

$$\hat{y} = \hat{\beta}_0 + \sum_{i=1}^N \hat{\beta}_i K(\mathbf{x}_i, \mathbf{x})$$