

# Statistical Machine Learning

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Slide credits and other course material can be found at:

[http://www.stats.ox.ac.uk/~palamara/SML\\_BDI.html](http://www.stats.ox.ac.uk/~palamara/SML_BDI.html)

# Supervised Learning

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# Supervised Learning

## Unsupervised learning:

- Visualize, summarize and compress data.
- To “extract structure” and postulate hypotheses about data generating process from “unlabelled” observations  $x_1, \dots, x_N$ .

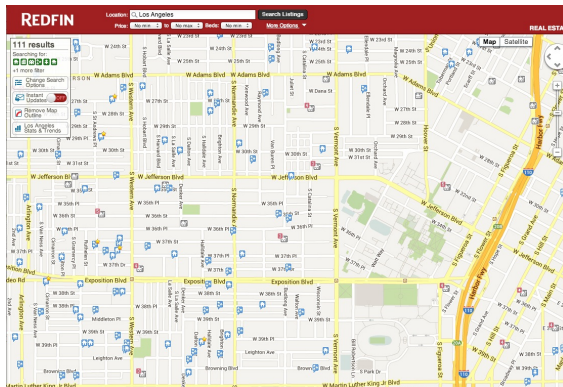
## Supervised learning:

- In addition to the observations of  $X$ , we have access to their response variables / labels  $Y \in \mathcal{Y}$ : we observe  $\{(x_i, y_i)\}_{i=1}^N$ .
- Types of supervised learning:
  - Regression: a numerical value is observed and  $\mathcal{Y} = \mathbb{R}$ .
  - Classification: discrete responses, e.g.  $\mathcal{Y} = \{+1, -1\}$  or  $\{1, \dots, K\}$ .

The goal is to accurately predict the response  $Y$  on new observations of  $X$ , i.e., to **learn a function**  $f: \mathbb{R}^p \rightarrow \mathcal{Y}$ , such that  $f(X)$  will be close to the true response  $Y$ .

# Regression Example: House Price

## Retrieve historical sales records



# Features used to predict

We will use properties of the house, e.g. squared meters, distance from train station, etc.

**3620 South BUDLONG**  
Los Angeles, CA 90007  
Status: Closed


**\$1,510,000**  
Last Sold Price

**14** Beds  
Built: 1956

**6** Baths  
Lot Size: 0.049 Sq. Ft.

**4,418** Sq. Ft.  
Sold On: Jul 25, 2013

Overview Property Details Tour Insights Property History Public Records Activity Schools



Five unit apartment complex within 2 blocks of USC campus, Gate #6. Great for students (most student leases have parents as guarantors). Most USC students live off campus, so housing units like this are always fully leased. Situated on a gated, corner lot, and across from an elementary school, this complex was recently renovated, and has in-unit laundry hook up, wall-unit AC, and 12 parking spaces. It is within a DPS (Department of Public Safety) and Campus Crusader patrolled area. This is a great income generating property, not to be missed!

Property Type: Multi-Family  
Community: Downtown Los Angeles  
MLS#: 22176741

Style: Two Level, Low Rise  
County: Los Angeles

## Property Details for 3620 South BUDLONG, Los Angeles, CA 90007

Details provided by iTech MLS and may not match the public record. [Learn More](#)

Interior Features		
<b>Kitchen Information</b> <ul style="list-style-type: none"> <li>Renovated</li> <li>Oven, Range</li> </ul>	<b>Laundry Information</b> <ul style="list-style-type: none"> <li>In-Unit Laundry</li> </ul>	<b>Heating &amp; Cooling</b> <ul style="list-style-type: none"> <li>Wall Cooling (Unit(s))</li> </ul>
Multi-Unit Information		
<b>Community Features</b> <ul style="list-style-type: none"> <li>Units in Complex (Total): 5</li> </ul> <b>Multi-Family Information</b> <ul style="list-style-type: none"> <li># of Buildings: 5</li> <li># of Units: 1</li> <li>Covered Parking: 1</li> <li>Tenant Pays Electricity, Tenant Pays Gas</li> </ul> <b>Unit 1 Information</b> <ul style="list-style-type: none"> <li># of Beds: 2</li> <li># of Baths: 1</li> <li>Unfurnished</li> <li>Monthly Rent: \$1,700</li> </ul>	<b>Unit 2 Information</b> <ul style="list-style-type: none"> <li># of Beds: 3</li> <li># of Baths: 1</li> <li>Unfurnished</li> <li>Monthly Rent: \$2,250</li> </ul> <b>Unit 3 Information</b> <ul style="list-style-type: none"> <li>Unfurnished</li> </ul> <b>Unit 4 Information</b> <ul style="list-style-type: none"> <li># of Beds: 3</li> <li># of Baths: 1</li> <li>Unfurnished</li> </ul>	<b>Unit 5 Information</b> <ul style="list-style-type: none"> <li>Monthly Rent: \$2,300</li> </ul> <b>Unit 6 Information</b> <ul style="list-style-type: none"> <li># of Beds: 3</li> <li># of Baths: 2</li> <li>Unfurnished</li> <li>Monthly Rent: \$2,325</li> </ul> <b>Unit 8 Information</b> <ul style="list-style-type: none"> <li># of Beds: 3</li> <li># of Baths: 1</li> <li>Monthly Rent: \$2,250</li> </ul>
Property / Lot Details		
<b>Property Features</b> <ul style="list-style-type: none"> <li>Automatic Gate, Car/Code Access</li> </ul> <b>Lot Information</b> <ul style="list-style-type: none"> <li>Lot Size (Sq. Ft.): 8,649</li> <li>Lot Size (Acres): 0.2215</li> <li>Lot Size Source: Public Records</li> </ul>	<ul style="list-style-type: none"> <li>Automatic Gate, Lawn, Sidewalks</li> <li>Corner Lot, Near Public Transit</li> </ul> <b>Property Information</b> <ul style="list-style-type: none"> <li>Updated/Renovated</li> <li>Square Footage Source: Public Records</li> </ul>	<ul style="list-style-type: none"> <li>Tax Parcel Number: 5040017019</li> </ul>
Parking / Garage, Exterior Features, Utilities & Financing		
<b>Parking Information</b> <ul style="list-style-type: none"> <li># of Parking Spaces (Total): 12</li> <li>Parking Space</li> <li>Gated</li> </ul> <b>Building Information</b> <ul style="list-style-type: none"> <li>Total Floors: 2</li> </ul>	<b>Utility Information</b> <ul style="list-style-type: none"> <li>Green Certification Rating: 0.00</li> <li>Green Location: Transportation, Walkability</li> <li>Green Walk Score: 0</li> <li>Green Year Certified: 0</li> </ul>	<b>Financial Information</b> <ul style="list-style-type: none"> <li>Capitalization Rate (%): 6.25</li> <li>Actual Annual Gross Rent: \$128,331</li> <li>Gross Rent Multiple: 11.29</li> </ul>
Location Details, Misc. Information & Listing Information		
<b>Location Information</b> <ul style="list-style-type: none"> <li>Cross Streets: W 36th Pl</li> </ul>	<b>Expense Information</b> <ul style="list-style-type: none"> <li>Operating: \$37,664</li> </ul>	<b>Listing Information</b> <ul style="list-style-type: none"> <li>Listing Terms: Cash, Cash To Existing Loan</li> <li>Buyer Financing: Cash</li> </ul>

Goal: predict price of another house given these properties.

# Classification Example: Lymphoma

We have gene expression measurements  $X$  of  $N = 62$  patients for  $p = 4026$  genes. For each patient,  $Y \in \{0, 1\}$  denotes one of two subtypes of cancer.

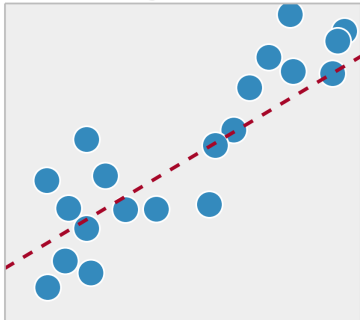
```
> str(X)
'data.frame':  62 obs. of  4026 variables:
 $ Gene 1  : num  -0.344 -1.188  0.520 -0.748 -0.868 ...
 $ Gene 2  : num  -0.953 -1.286  0.657 -1.328 -1.330 ...
 $ Gene 3  : num  -0.776 -0.588  0.409 -0.991 -1.517 ...
 $ Gene 4  : num  -0.474 -1.588  0.219  0.978 -1.604 ...
 $ Gene 5  : num  -1.896 -1.960 -1.695 -0.348 -0.595 ...
 $ Gene 6  : num  -2.075 -2.117  0.121 -0.800  0.651 ...
 $ Gene 7  : num  -1.875 -1.818  0.317  0.387  0.041 ...
 $ Gene 8  : num  -1.539 -2.433 -0.337 -0.522 -0.668 ...
 $ Gene 9  : num  -0.604 -0.710 -1.269 -0.832  0.458 ...
 $ Gene 10 : num  -0.218 -0.487 -1.203 -0.919 -0.848 ...
 $ Gene 11 : num  -0.340  1.164  1.023  1.133 -0.541 ...
 $ Gene 12 : num  -0.531  0.488 -0.335  0.496 -0.358 ...

> str(Y)
 num [1:62] 0 0 0 1 0 0 1 0 0 0 ...
```

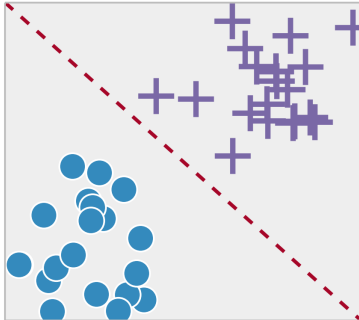
Goal: predict cancer subtype given gene expressions of a new patient.

# Regression VS Classification

Regression



Classification



# Loss function

- Suppose we made a prediction  $\hat{Y} = f(X) \in \mathcal{Y}$  after observing  $X$ .
- How good is the prediction? We can use a **loss function**  $L : \mathcal{Y} \times \mathcal{Y} \mapsto \mathbb{R}^+$  to formalize the quality of the prediction.
- Typical loss functions:
  - **Squared loss** for regression

$$L(Y, f(X)) = (f(X) - Y)^2.$$

- **Absolute loss** for regression

$$L(Y, f(X)) = |f(X) - Y|.$$

- **Misclassification loss** (or **0-1 loss**) for classification

$$L(Y, f(X)) = \begin{cases} 0 & f(X) = Y \\ 1 & f(X) \neq Y \end{cases}.$$

Many other choices are possible, e.g., **weighted misclassification loss**.

- In classification, if estimated probabilities  $\hat{p}(k)$  for each class  $k \in \mathcal{Y}$  are returned, **log-likelihood loss** (or **log loss**)  $L(Y, \hat{p}) = -\log \hat{p}(Y)$  is often used.



# Risk

- paired observations  $\{(x_i, y_i)\}_{i=1}^N$  viewed as i.i.d. realizations of a random variable  $(X, Y)$  on  $\mathcal{X} \times \mathcal{Y}$  with joint distribution  $P_{XY}$

## Risk

For a given loss function  $L$ , the **risk**  $R$  of a learned function  $f$  is given by the expected loss

$$R(f) = \mathbb{E}_{P_{XY}} [L(Y, f(X))],$$

where the expectation is with respect to the true (unknown) joint distribution of  $(X, Y)$ .

- The risk is unknown, but we can compute the **empirical risk**:

$$R_N(f) = \frac{1}{N} \sum_{i=1}^N L(y_i, f(x_i)).$$

# Hypothesis space and Empirical Risk Minimization

- Hypothesis space  $\mathcal{H}$  is the space of functions  $f$  under consideration.
- **Inductive bias**: necessary assumptions on “plausible” hypotheses
- Find best function in the space of hypothesis  $\mathcal{H}$  minimizing the risk:

$$f_{\star} = \operatorname{argmin}_{f \in \mathcal{H}} \mathbb{E}_{X,Y} [L(Y, f(X))]$$

- **Empirical Risk Minimization (ERM)**: minimize the empirical risk instead, since we typically do not know  $P_{X,Y}$ .

$$\hat{f} = \operatorname{argmin}_{f \in \mathcal{H}} \frac{1}{N} \sum_{i=1}^N L(y_i, f(x_i))$$

- How complex should we allow functions  $f$  to be? If hypothesis space  $\mathcal{H}$  is “too large”, ERM will overfit. Function

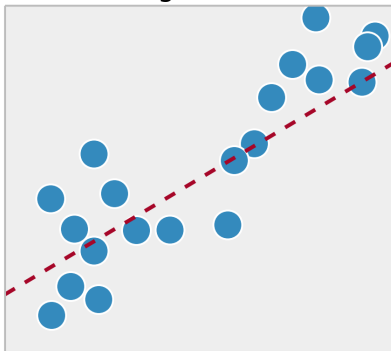
$$\hat{f}(x) = \begin{cases} y_i & \text{if } x = x_i, \\ 0 & \text{otherwise} \end{cases}$$

will have zero empirical risk, but is useless for generalization, since it has simply “memorized” the dataset.

# Linear Regression

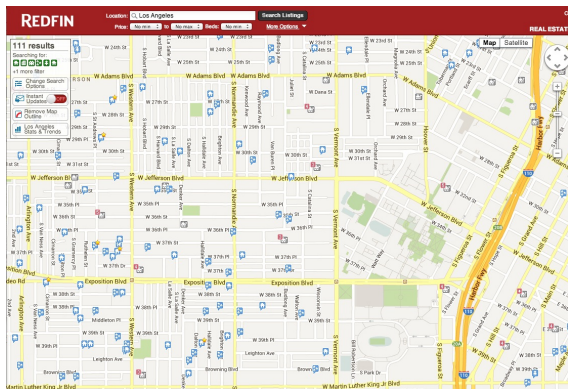
We will use the framework of linear regression, which should be familiar to you, to illustrate some of the key concepts of supervised learning.

Regression



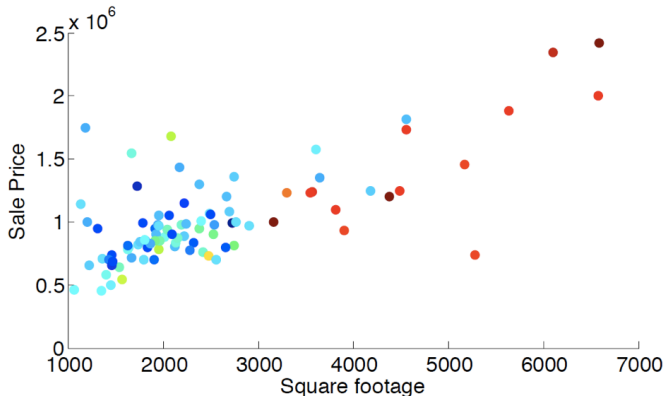
# Linear regression: predicting the sale price of a house

**We will use the house price example.**  
(This will be our training data)



# Correlation between square footage and sale price

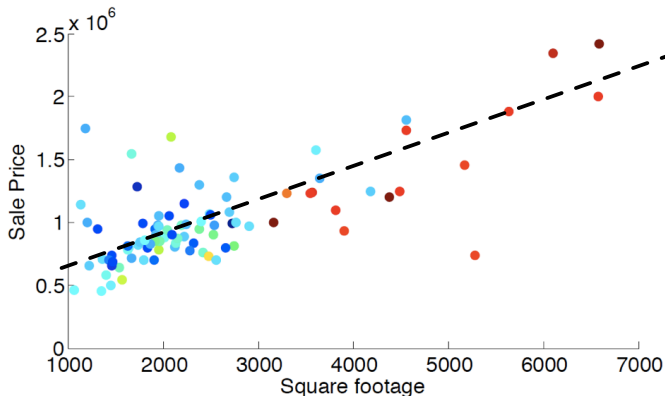
The size of a house is a good predictor of its price.



Note: colors are not important here

# Roughly linear relationship

The size of a house is a good predictor of its price.



Sale price  $\approx$  price\_per\_sqft  $\times$  square\_footage + fixed\_expense

# Linear regression (ordinary least squares)

## Setup

- Input:  $\mathbf{x} \in \mathbb{R}^D$  (covariates, predictors, features, etc)
- Output:  $y \in \mathbb{R}$  (responses, targets, outcomes, outputs, etc)
- **Hypotheses:**  $h_{\theta, \theta_0} : \mathbf{x} \rightarrow y$ , with  $h_{\theta, \theta_0}(\mathbf{x}) = \theta_0 + \sum_d \theta_d x_d = \theta_0 + \boldsymbol{\theta}^T \mathbf{x}$   
 $\boldsymbol{\theta} = [\theta_1 \ \theta_2 \ \dots \ \theta_D]^T$ : **weights, parameters**.  $\theta_0$  is the intercept (also called bias).
- Training data:  $\mathcal{D} = \{(\mathbf{x}_n, y_n), n = 1, 2, \dots, N\}$
- We will use the **squared loss** (differentiable):

$$(\text{sale price} - \text{prediction})^2 = (y_n - h_{\boldsymbol{\theta}}(\mathbf{x}_n))^2$$

- Could use other loss functions, e.g. **absolute loss**:

$$|\text{sale price} - \text{prediction}| = |y_n - h_{\boldsymbol{\theta}}(\mathbf{x}_n)|$$

# How do we learn parameters?

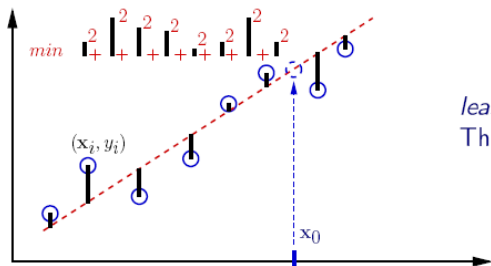
## Minimize prediction error on training data

- Hypothesis:

$$y = h_{\theta}(x) = \theta_0 + \theta_1 x$$

- We chose to minimize the squared loss. Empirical risk:

$$R_N(\theta) = \frac{1}{N} \sum_{n=1}^N (y_n - h_{\theta}(\mathbf{x}_n))^2$$



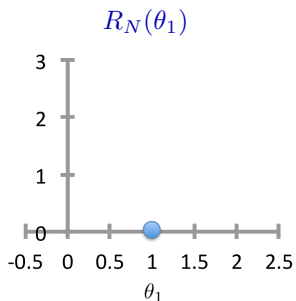
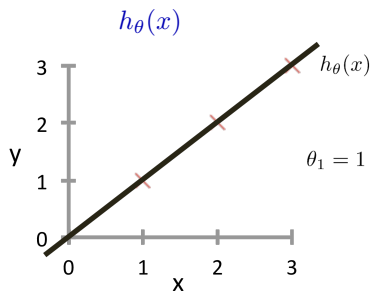
*least squares (LSQ)*

The fitted line is used as a predictor



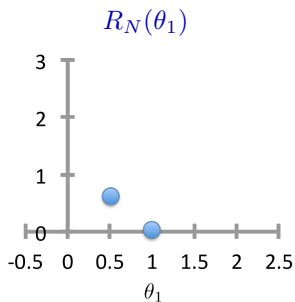
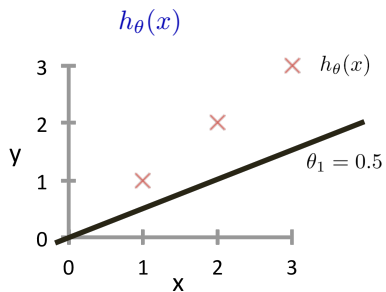
# Intuition behind the squared loss

Assume  $x \in \mathbb{R}$



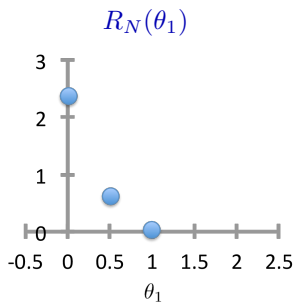
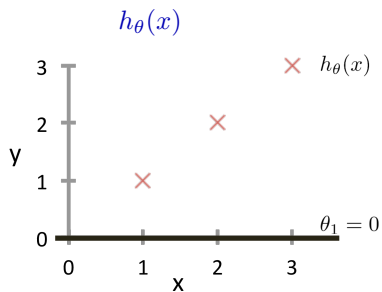
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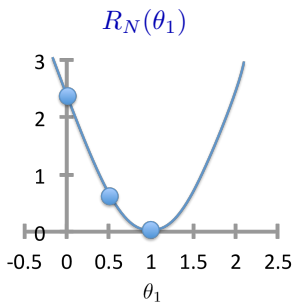
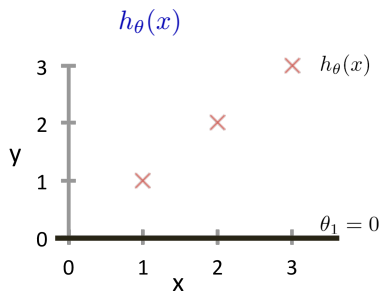
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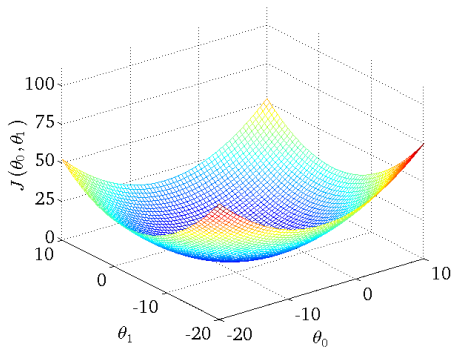


# Intuition behind the squared loss

Assume  $x \in \mathbb{R}$

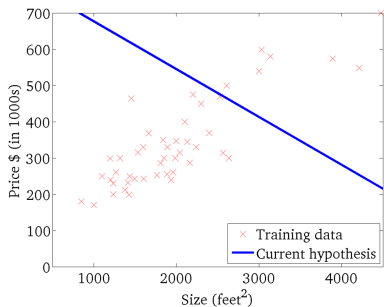


# Intuition behind the squared loss

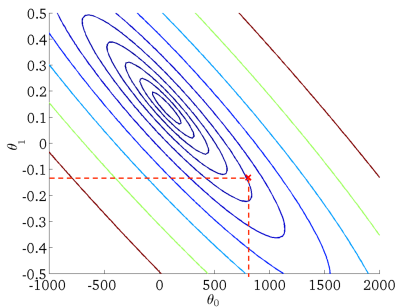


# Intuition behind the squared loss

$$h_{\theta}(x)$$

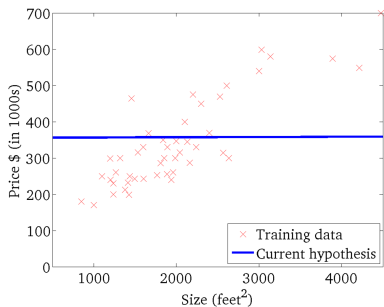


$$R_N(\theta_0, \theta_1)$$

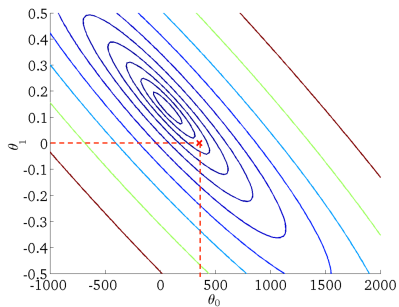


# Intuition behind the squared loss

$$h_{\theta}(x)$$

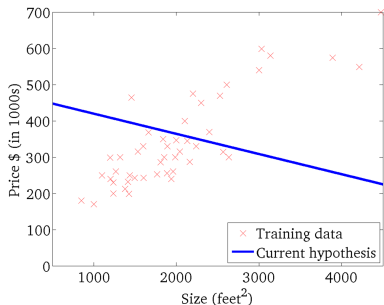


$$R_N(\theta_0, \theta_1)$$

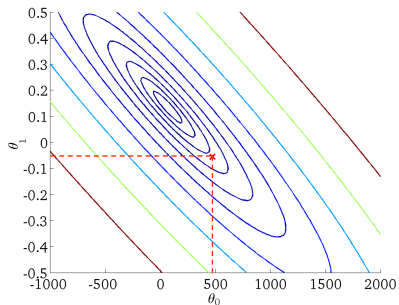


# Intuition behind the squared loss

$$h_{\theta}(x)$$



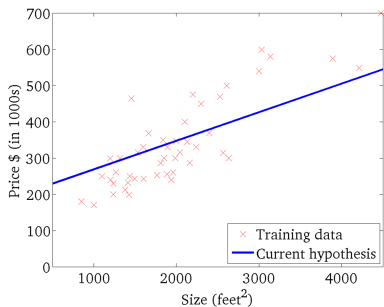
$$R_N(\theta_0, \theta_1)$$



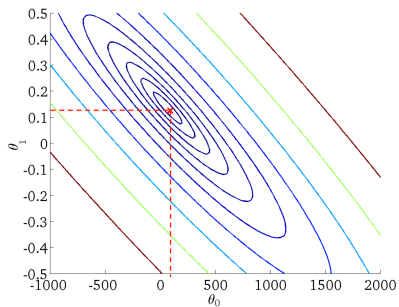


# Intuition behind the squared loss

$$h_{\theta}(x)$$



$$R_N(\theta_0, \theta_1)$$



# A simple case: $x$ is just one-dimensional ( $D=1$ )

## Squared loss

(dropping the  $1/N$  for simplicity)

$$R_N(\boldsymbol{\theta}) = \sum_n [y_n - h_{\boldsymbol{\theta}}(\mathbf{x}_n)]^2 = \sum_n [y_n - (\theta_0 + \theta_1 x_n)]^2$$

## Analytical solution

For linear regression, the minimization can be done in closed form.

**Identify stationary points by taking derivative with respect to parameters and setting to zero**

$$\frac{\partial R_N(\boldsymbol{\theta})}{\partial \theta_0} = 0 \Rightarrow -2 \sum_n [y_n - (\theta_0 + \theta_1 x_n)] = 0$$

$$\frac{\partial R_N(\boldsymbol{\theta})}{\partial \theta_1} = 0 \Rightarrow -2 \sum_n [y_n - (\theta_0 + \theta_1 x_n)] x_n = 0$$

$$\frac{\partial R_N(\boldsymbol{\theta})}{\partial \theta_0} = 0 \Rightarrow -2 \sum_n [y_n - (\theta_0 + \theta_1 x_n)] = 0$$

$$\frac{\partial R_N(\boldsymbol{\theta})}{\partial \theta_1} = 0 \Rightarrow -2 \sum_n [y_n - (\theta_0 + \theta_1 x_n)] x_n = 0$$

**Simplify these expressions to get “Normal Equations”**

$$\sum y_n = N\theta_0 + \theta_1 \sum x_n$$

$$\sum x_n y_n = \theta_0 \sum x_n + \theta_1 \sum x_n^2$$

We have two equations and two unknowns. Solving we get:

$$\theta_1 = \frac{\sum (x_n - \bar{x})(y_n - \bar{y})}{\sum (x_i - \bar{x})^2} \quad \text{and} \quad \theta_0 = \bar{y} - \theta_1 \bar{x}$$

where  $\bar{x} = \frac{1}{n} \sum_n x_n$  and  $\bar{y} = \frac{1}{n} \sum_n y_n$ .

# Why is minimizing $R_N$ sensible?

## Probabilistic interpretation

- Noisy observation model

$$Y = \theta_0 + \theta_1 X + \eta$$

where  $\eta \sim \mathcal{N}(0, \sigma^2)$  is a Gaussian random variable

- Likelihood of one training sample  $(x_n, y_n)$

$$p(y_n | x_n; \boldsymbol{\theta}) = \mathcal{N}(\theta_0 + \theta_1 x_n, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{[y_n - (\theta_0 + \theta_1 x_n)]^2}{2\sigma^2}}$$

# Probabilistic interpretation (cont'd)

## Log-likelihood of the training data $\mathcal{D}$ (assuming i.i.d)

$$\begin{aligned}\mathcal{LL}(\boldsymbol{\theta}) &= \log P(\mathcal{D}) \\ &= \log \prod_{n=1}^N p(y_n|x_n) = \sum_n \log p(y_n|x_n) \\ &= \sum_n \left\{ -\frac{[y_n - (\theta_0 + \theta_1 x_n)]^2}{2\sigma^2} - \log \sqrt{2\pi\sigma} \right\} \\ &= -\frac{1}{2\sigma^2} \sum_n [y_n - (\theta_0 + \theta_1 x_n)]^2 - \frac{N}{2} \log \sigma^2 - N \log \sqrt{2\pi} \\ &= -\frac{1}{2} \left\{ \frac{1}{\sigma^2} \sum_n [y_n - (\theta_0 + \theta_1 x_n)]^2 + N \log \sigma^2 \right\} + \text{const}\end{aligned}$$

What is the relationship between minimizing  $R_N$  and maximizing the log-likelihood?

# Maximum likelihood estimation

## Estimating $\sigma$ , $\theta_0$ and $\theta_1$ can be done in two steps

- Maximize over  $\theta_0$  and  $\theta_1$

$$\max \log P(\mathcal{D}) \Leftrightarrow \min \sum_n [y_n - (\theta_0 + \theta_1 x_n)]^2 \leftarrow \text{That is } R_N(\boldsymbol{\theta})!$$

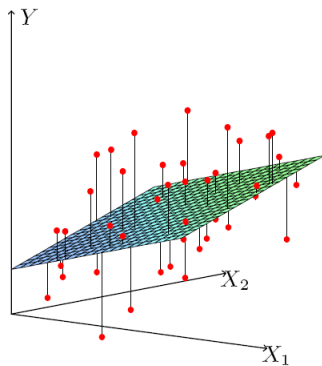
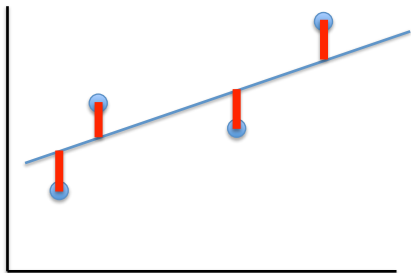
- Maximize over  $s = \sigma^2$  (we could estimate  $\sigma$  directly)

$$\log P(\mathcal{D}) = -\frac{1}{2} \left\{ \frac{1}{\sigma^2} \sum_n [y_n - (\theta_0 + \theta_1 x_n)]^2 + N \log \sigma^2 \right\} + \text{const}$$

$$\frac{\partial \log P(\mathcal{D})}{\partial s} = -\frac{1}{2} \left\{ -\frac{1}{s^2} \sum_n [y_n - (\theta_0 + \theta_1 x_n)]^2 + N \frac{1}{s} \right\} = 0$$

$$\rightarrow \sigma^{*2} = s^* = \frac{1}{N} \sum_n [y_n - (\theta_0 + \theta_1 x_n)]^2$$

# Linear regression when $x$ is D-dimensional



# Linear regression when $\mathbf{x}$ is D-dimensional

$R_N(\boldsymbol{\theta})$  in matrix form

$$R_N(\boldsymbol{\theta}) = \sum_n [y_n - (\theta_0 + \sum_d \theta_d x_{nd})]^2 = \sum_n [y_n - \boldsymbol{\theta}^T \mathbf{x}_n]^2$$

where we have redefined some variables (by augmenting)

$$\mathbf{x} \leftarrow [1 \ x_1 \ x_2 \ \dots \ x_D]^T, \quad \boldsymbol{\theta} \leftarrow [\theta_0 \ \theta_1 \ \theta_2 \ \dots \ \theta_D]^T$$

which leads to

$$\begin{aligned} R_N(\boldsymbol{\theta}) &= \sum_n (y_n - \boldsymbol{\theta}^T \mathbf{x}_n)(y_n - \mathbf{x}_n^T \boldsymbol{\theta}) \\ &= \sum_n \boldsymbol{\theta}^T \mathbf{x}_n \mathbf{x}_n^T \boldsymbol{\theta} - 2y_n \mathbf{x}_n^T \boldsymbol{\theta} + \text{const.} \\ &= \left\{ \boldsymbol{\theta}^T \left( \sum_n \mathbf{x}_n \mathbf{x}_n^T \right) \boldsymbol{\theta} - 2 \left( \sum_n y_n \mathbf{x}_n^T \right) \boldsymbol{\theta} \right\} + \text{const.} \end{aligned}$$



# $R_N(\boldsymbol{\theta})$ in new notations

## Design matrix and target vector

$$\mathbf{X} = \begin{pmatrix} \mathbf{x}_1^T \\ \mathbf{x}_2^T \\ \vdots \\ \mathbf{x}_N^T \end{pmatrix} \in \mathbb{R}^{N \times (D+1)}, \quad \mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{pmatrix}$$

## Compact expression

$$R_N(\boldsymbol{\theta}) = \|\mathbf{X}\boldsymbol{\theta} - \mathbf{y}\|_2^2 = \left\{ \boldsymbol{\theta}^T \mathbf{X}^T \mathbf{X} \boldsymbol{\theta} - 2 (\mathbf{X}^T \mathbf{y})^T \boldsymbol{\theta} \right\} + \text{const}$$

# Solution in matrix form

## Compact expression

$$R_N(\boldsymbol{\theta}) = \|\mathbf{X}\boldsymbol{\theta} - \mathbf{y}\|_2^2 = \left\{ \boldsymbol{\theta}^T \mathbf{X}^T \mathbf{X} \boldsymbol{\theta} - 2 (\mathbf{X}^T \mathbf{y})^T \boldsymbol{\theta} \right\} + \text{const}$$

## Gradients of Linear and Quadratic Functions

- $\nabla_{\mathbf{x}} \mathbf{b}^T \mathbf{x} = \mathbf{b}$
- $\nabla_{\mathbf{x}} \mathbf{x}^T \mathbf{A} \mathbf{x} = 2\mathbf{A} \mathbf{x}$  (symmetric  $\mathbf{A}$ )

## Normal equation

$$\nabla_{\boldsymbol{\theta}} R_N(\boldsymbol{\theta}) \propto \mathbf{X}^T \mathbf{X} \boldsymbol{\theta} - \mathbf{X}^T \mathbf{y} = 0$$

This leads to the linear regression solution<sup>1</sup>

$$\boldsymbol{\theta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

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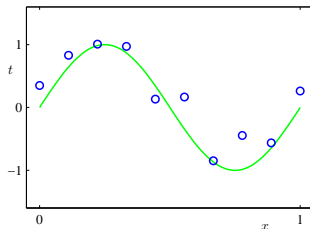
<sup>1</sup>Also see PRML book, Section 3.1.2 for a geometric interpretation.

# Mini-Summary

- Linear regression is the linear combination of features  
 $f : \mathbf{x} \rightarrow y$ , with  $f(\mathbf{x}) = \theta_0 + \sum_d \theta_d x_d = \theta_0 + \boldsymbol{\theta}^T \mathbf{x}$
- If we minimize residual sum of squares as our learning objective, we get a closed-form solution of parameters
- Probabilistic interpretation: maximum likelihood if assuming residual is Gaussian distributed
- D-dimensional case leads to compact expressions in matrix form.

# Nonlinear basis functions

Can we learn non-linear functions?



**We can use a nonlinear mapping**

$$\phi(\mathbf{x}) : \mathbf{x} \in \mathbb{R}^D \rightarrow \mathbf{z} \in \mathbb{R}^M$$

where  $M$  is the dimensionality of the new feature/input  $\mathbf{z}$  (or  $\phi(\mathbf{x})$ ). Note that  $M$  could be either greater than  $D$  or less than or the same.

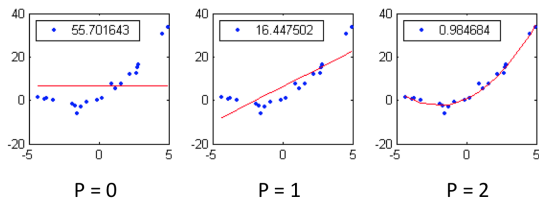
# Nonlinear basis functions

Can we learn non-linear functions?

**We can use a nonlinear mapping**

$$\phi(\mathbf{x}) : \mathbf{x} \in \mathbb{R}^D \rightarrow \mathbf{z} \in \mathbb{R}^M$$

For instance, we could use polynomials of increasing order,  $\phi_k(\mathbf{x}_i) = \mathbf{x}_i^k$



With the new features, we can apply our learning techniques to minimize our errors on the transformed training data

- for linear methods, prediction is still based on  $\theta^T \phi(\mathbf{x})$

# Regression with nonlinear basis functions

## Residual sum squares

$$\sum_n [\boldsymbol{\theta}^T \boldsymbol{\phi}(\mathbf{x}_n) - y_n]^2$$

where  $\boldsymbol{\theta} \in \mathbb{R}^M$ , the same dimensionality as the transformed features  $\boldsymbol{\phi}(\mathbf{x})$ .

**The linear regression solution can be formulated with the new design matrix**

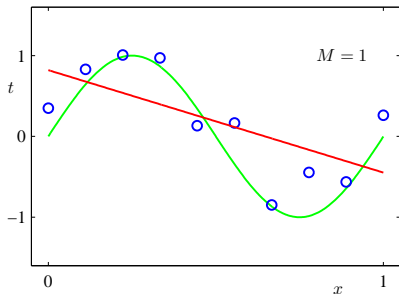
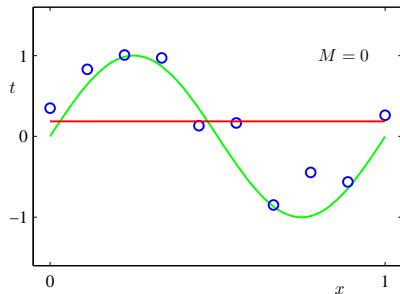
$$\mathbf{\Phi} = \begin{pmatrix} \boldsymbol{\phi}(\mathbf{x}_1)^T \\ \boldsymbol{\phi}(\mathbf{x}_2)^T \\ \vdots \\ \boldsymbol{\phi}(\mathbf{x}_N)^T \end{pmatrix} \in \mathbb{R}^{N \times M}, \quad \boldsymbol{\theta}^{\text{LMS}} = (\mathbf{\Phi}^T \mathbf{\Phi})^{-1} \mathbf{\Phi}^T \mathbf{y}$$

# Regression with nonlinear basis functions

## Polynomial basis functions

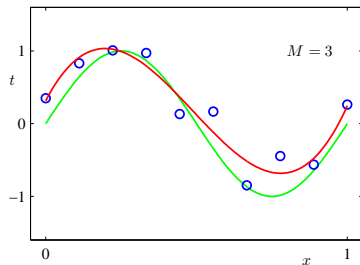
$$\phi(x) = \begin{bmatrix} 1 \\ x \\ x^2 \\ \vdots \\ x^M \end{bmatrix} \Rightarrow f(x) = \theta_0 + \sum_{m=1}^M \theta_m x^m$$

Fitting samples from a sine function: **underfitting** as  $f(x)$  is too simple

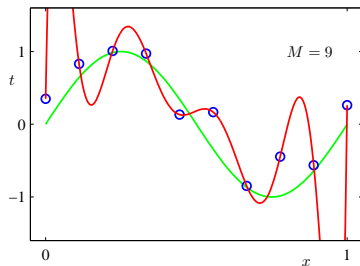


# Adding high-order terms

**M=3**



**M=9: overfitting**



More complex features lead to better results on the training data, but potentially worse results on new data, e.g., test data!



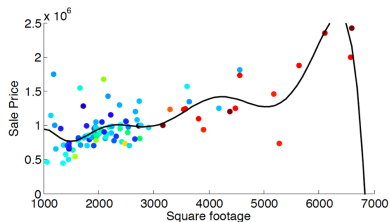
# Overfitting

Parameters for higher-order polynomials are very large

	$M = 0$	$M = 1$	$M = 3$	$M = 9$
$\theta_0$	0.19	0.82	0.31	0.35
$\theta_1$		-1.27	7.99	232.37
$\theta_2$			-25.43	-5321.83
$\theta_3$			17.37	48568.31
$\theta_4$				-231639.30
$\theta_5$				640042.26
$\theta_6$				-1061800.52
$\theta_7$				1042400.18
$\theta_8$				-557682.99
$\theta_9$				125201.43

# Overfitting can be quite disastrous

Fitting the housing price data with  $M = 7$



Note that the price would go to zero (or negative) if you buy bigger ones!  
**This is called poor generalization/overfitting.**