Learning From Data
Lecture 2: Linear Regression & Logistic Regression

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September 23, 2022

Outline

Introduction

Today's Lecture

Supervised Learning (Part I)

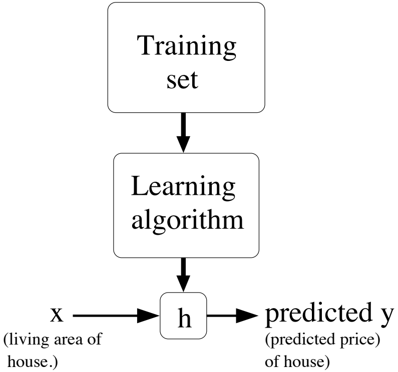
- Linear Regression
- Binary Classification
- Multi-Class Classification

Review: Supervised Learning

- Input space: $\mathcal{X}$, Target space: $\mathcal{Y}$

Review: Supervised Learning

- Input space: $\mathcal{X}$, Target space: $\mathcal{Y}$
- Given training examples, we want to learn a **hypothesis** function $h : \mathcal{X} \rightarrow \mathcal{Y}$ so that $h(x)$ is a "good" predictor for the corresponding y.



Review: Supervised Learning

- y is discrete (categorical): **classification problem**
- y is continuous (real value): **regression problem**

Outline

$h_\theta(x) = \theta_0 + \theta_1 x_1 + \cdots + \theta_n x_n. \quad = \theta^T x.$

Linear Regression

Linear Regression Model

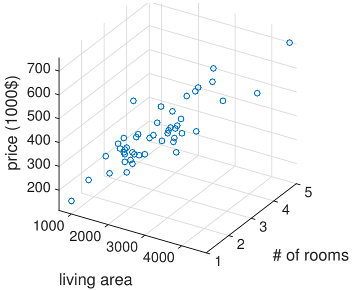
Ordinary Least Square - geometric

Maximum Likelihood Estimation - probablistic

Linear Regression

Example: predict Portland housing price

Living area (ft^2)	# bedrooms	Price ($1000)
x_1	x_2	y
2104	3	400
1600	3	330
2400	3	369
⋮	⋮	⋮



Linear Approximation

A linear model

$$h(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2$$

θ_i's are called **parameters**.

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Using vector notation,

$$h(x) = \theta^T x, \quad \text{where } \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \end{bmatrix}, \quad x = \begin{bmatrix} 1 \\ x_1 \\ x_2 \end{bmatrix}$$

Alternative Notation

$$h(x) = w_1 x_1 + w_2 x_2 + b$$

w_1, w_2 are called **weights**, b is called the **bias**

$$h(x) = w^T x + b, \quad \text{where } w = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}, \quad x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

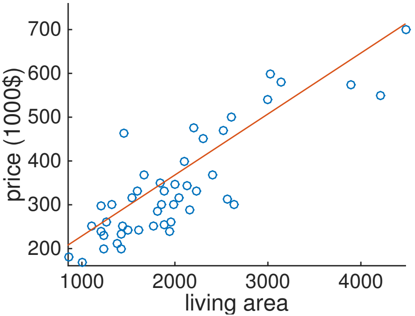
Apply model to new data

Suppose we have the optimal parameters θ , e.g.

```
> h = LinearRegression().fit(X, y)
> theta = h.coef
array([89.60, 0.1392, -8.738])
```

make a prediction of new feature x:

$$\hat{y} = h_\theta(x) = \theta^T x$$



Model Estimation

How to estimate model parameters θ (or w and b) from data?

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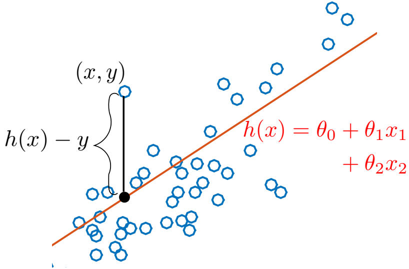
Least Square Estimation



geometric approach

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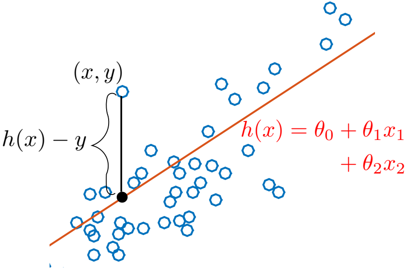
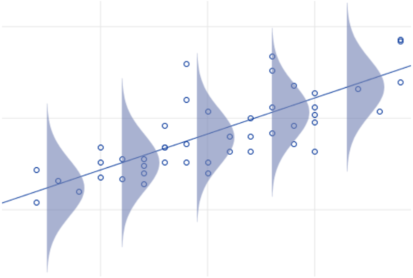


geometric approach

Maximum Likelihood Estimation

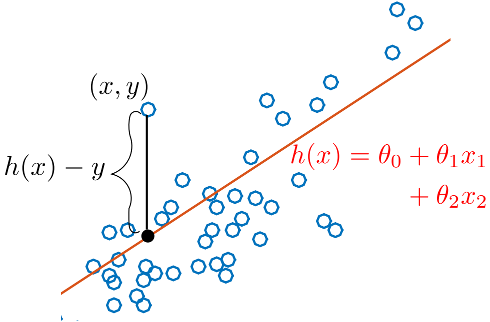


Probabilistic approach

Ordinary Least Square

Cost function:

$$J(\theta) = \frac{1}{2}\sum_{i=1}^{m}(h(x^{(i)}) - y^{(i)})^2$$



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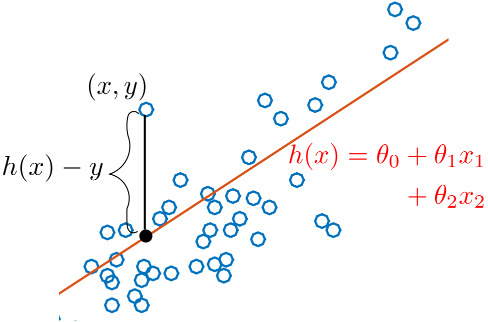

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Ordinary Least Square

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The **ordinary Least square problem** is:

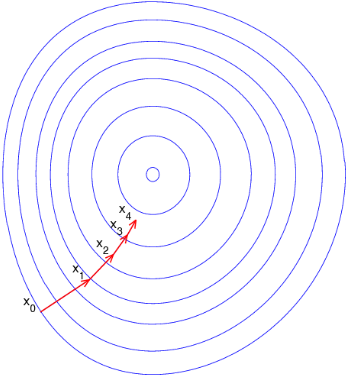
$$\begin{aligned}&\min_{\theta} J(\theta) \\ =&\min_{\theta} \frac{1}{2}\sum_{i=1}^{m}(h(x^{(i)}) - y^{(i)})^2\end{aligned}$$

How to minimize $J(\theta)$?

- Numerical solution: gradient descent, Newton's method
- Analytical solution: normal equation

Gradient descent

A first-order iterative optimization algorithm for finding the minimum of a function $J(\theta)$.



Key idea

Start at an initial guess, repeatedly change θ to decrease $J(\theta)$:

$$\theta := \theta - \alpha \nabla J(\theta)$$

α is the **learning rate**

Review: Convex function

Definition (Convex set)

Let S be a vector space, any subset $C \subseteq S$ is **convex** if for any $x, y \in C$, $0 \leq \lambda \leq 1$, affine combination[1] $\lambda x + (1-\lambda)y \in C$

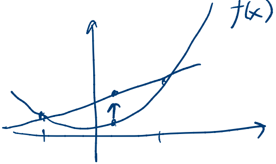
[1] An affine combination is a linear combination where coefficients sum to 1.

Definition (Convex function)

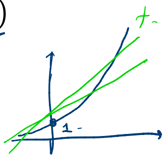
A function $f(x)$ is **convex** on a convex set C if for any $x_1, x_2 \in C$ and $0 \leq \lambda \leq 1$,

$$f(\lambda x_1 + (1-\lambda)x_2) \leq \lambda f(x_1) + (1-\lambda)f(x_2)$$

e.g. C is an interval $[a, b]$



- x^2
- e^x
- $\|x\|_p$
- composition rules.



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e.g. C is an interval $[a, b]$

Theorem

If $J(\theta)$ is convex, gradient descent finds the global minimum.

$\theta := \theta - \alpha \nabla J(\theta)$

For the ordinary least square problem,

$J(\theta) = \frac{1}{2}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2 = \frac{1}{2}\sum_{i=1}^{m}(\theta^T x^{(i)} - y^{(i)})^2$,

$$\nabla J(\theta) = \begin{bmatrix} \frac{\partial J(\theta)}{\partial \theta_1} \\ \vdots \\ \frac{\partial J(\theta)}{\partial \theta_n} \end{bmatrix}, \text{ where } \frac{\partial J(\theta)}{\partial \theta_j} = \frac{\partial}{\partial \theta_j}\frac{1}{2}\sum_{i=1}^{m}(\theta^T x^{(i)} - y^{(i)})^2$$

$$= \frac{1}{2}\sum_{i=1}^{m}\frac{\partial}{\partial \theta_j}(\theta^T x^{(i)} - y^{(i)})^2$$

$$= \frac{1}{2}\sum_{i=1}^{m} 2(\theta^T x^{(i)} - y^{(i)})\frac{\partial}{\partial \theta_j}\theta^T x^{(i)}$$

$$= \sum_{i=1}^{m}(\theta^T x^{(i)} - y^{(i)})x_j^{(i)}$$

$$\frac{\partial}{\partial \theta_j}\theta^T x^{i} = \frac{\partial}{\partial \theta_j}\sum_{j=1}^{n}\theta_j \cdot x_j^{(i)} = \frac{\partial}{\partial \theta_j}\theta_j x_j^{(i)} = x_j^{(i)}$$

For the ordinary least square problem,
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$$= \sum_{i=1}^{m}\left(\theta^T x^{(i)} - y^{(i)}\right) x_j^{(i)}$$

Gradient descent for ordinary least square

Gradient of cost function: $\nabla J(\theta)_j = \sum_{i=1}^{m} \left(\theta^T x^{(i)} - y^{(i)}\right) x_j^{(i)}$
Gradient descent update: $\theta := \theta - \alpha \nabla J(\theta)$

Batch Gradient Descent

```
Repeat until convergence{
    θ_j = θ_j + α Σ_{i=1}^{m} (y^(i) − h_θ(x^(i))) x_j^(i)  for every j
}
```

while θ is not converged:
for j in range(n):
θj = θj + ...

Gradient descent for ordinary least square

Gradient of cost function: $\nabla J(\theta)_j = \sum_{i=1}^{m} \left(\theta^T x^{(i)} - y^{(i)}\right) x_j^{(i)}$
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Batch Gradient Descent

Repeat until convergence{
$\theta_j = \theta_j + \alpha \sum_{i=1}^{m} (y^{(i)} - h_\theta(x^{(i)}))x_j^{(i)}$ for every j
}

θ is only updated after we have seen all m training samples.

Batch gradient descent

```
Repeat until convergence{
    θ_j = θ_j + α Σ_{i=1}^m (y^(i) − h_θ(x^(i))) x_j^(i)  for every j
}
```

$$\theta_j = \theta_j + \alpha \sum_{i=1}^{m} (y^{(i)} - h_\theta(x^{(i)}))x_j^{(i)} \quad \text{for every } j$$

Stochastic gradient descent (SGD)

```
Repeat until convergence{
  for i = 1...m {
      θ_j = θ_j + α(y^(i) − h_θ(x^(i))) x_j^(i)  for every j
  }
}
```

$$\theta_j = \theta_j + \alpha(y^{(i)} - h_\theta(x^{(i)}))x_j^{(i)} \quad \text{for every } j$$

θ is updated each time a training example is read

Batch gradient descent

Repeat until convergence{

$\theta_j = \theta_j + \alpha \sum_{i=1}^{m} (y^{(i)} - h_\theta(x^{(i)}))x_j^{(i)}$ for every j

}

Stochastic gradient descent

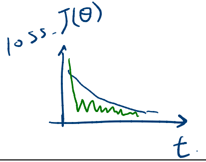
Repeat until convergence{

for $i = 1 \ldots m$ {

$\theta_j = \theta_j + \alpha(y^{(i)} - h_\theta(x^{(i)}))x_j^{(i)}$ for every j

}

}



θ is updated each time a training example is read

- Stochastic gradient descent gets θ close to minimum much faster
- Good for regression on large data

Minimize $J(\theta)$ Analytically

$x^{(i)} \in \mathbb{R}^n \quad i = 1, \dots, m$

The matrix notation

$$X = \begin{bmatrix} — \left(x^{(1)}\right)^T — \\ — \left(x^{(2)}\right)^T — \\ \vdots \\ — \left(x^{(m)}\right)^T — \end{bmatrix}, \quad \vec{y} = \begin{bmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(m)} \end{bmatrix}$$

$X \in \mathbb{R}^{m \times n}$, $\vec{y} \in \mathbb{R}^m$

X is called the **design matrix**.

Minimize $J(\theta)$ Analytically

$$z = \underset{m\times 1}{X\theta} - \underset{m\times 1}{y} = \begin{bmatrix} x^{(1)T}\theta - y^{(1)} \\ x^{(2)T}\theta - y^{(2)} \\ \vdots \\ x^{(m)T}\theta - y^{(m)} \end{bmatrix}$$

$$(X\theta - y)^T(X\theta - y) = z^T z = \sum_{i=1}^{m} z_i^2 = \sum_{i=1}^{n} \left(x^{(i)T}\theta - y^{(i)}\right)^2$$

The matrix notation

$$X = \begin{bmatrix} - \left(x^{(1)}\right)^T - \\ - \left(x^{(2)}\right)^T - \\ \vdots \\ - \left(x^{(m)}\right)^T - \end{bmatrix} \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_n \end{bmatrix}, \quad \vec{y} = \begin{bmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(m)} \end{bmatrix}$$

X is called the **design matrix**. The least square function can be written as

$$J(\theta) = \frac{1}{2}(X\theta - y)^T(X\theta - y)$$

Compute the gradient of $J(\theta)$:   least sq. function

$$\nabla_\theta J(\theta) = \nabla_\theta \left[\frac{1}{2} \underline{(X\theta - y)^T (X\theta - y)} \right]$$

Compute the gradient of $J(\theta)$:

$$\nabla_\theta J(\theta) = \nabla_\theta \left[\frac{1}{2} (X\theta - y)^T (X\theta - y) \right]$$

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$$=$$

Compute the gradient of $J(\theta)$:

$$\nabla_\theta J(\theta) = \nabla_\theta \left[\frac{1}{2} (X\theta - y)^T (X\theta - y) \right]$$
$$= X^T X\theta - X^T y = 0.$$

Since $J(\theta)$ is **convex**, x is a global minimum of $J(\theta)$ when $\nabla J(\theta) = 0$.

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

Compute the gradient of $J(\theta)$:

$$\begin{aligned}\nabla_\theta J(\theta) =& \nabla_\theta \left[\frac{1}{2}(X\theta - y)^T(X\theta - y)\right] \\ =& X^T X\theta - X^T y\end{aligned}$$

Since $J(\theta)$ is **convex**, x is a global minimum of $J(\theta)$ when $\nabla J(\theta) = 0$.

The Normal equation

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

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The Normal equation

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

$(X^T X)^{-1} X^T$ is called the **Moore-Penrose pseudoinverse of** X

Which method to use?

$\min_\theta J(\theta)$

→ more iteration

gradient descent	**normal equation**
iterative solution	exact solution
need to tune α! - distributed gradient descent	faster small-scale problem optimal solution $(X^TX)^{-1}$ → numerical issue
- SGD	

Which method to use?

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Which method to use?

$\frac{1}{2}(X\theta - y)^T(X\theta - y)$

gradient descent	**normal equation**
iterative solution	exact solution
need to choose proper learning parameter α for cost function to converge	numerically unstable when X is ill-conditioned. e.g. features are highly correlated
works well for large number of samples m	solving equation is slow when m is large

Minimize $J(\theta)$ using Newton's Method

Numerically solve for θ in $\nabla_\theta J(\theta) = 0$

Newton's method

Solves real functions $f(x) = 0$ by iterative approximation:

- Start an initial guess x
- Update x until convergence

$$x := x - \frac{f(x)}{f'(x)}$$

Minimize $J(\theta)$ using Newton's Method

Solving $f(x)=0$.

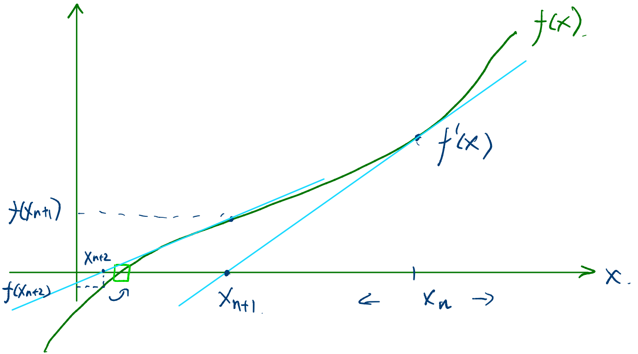
$$f(x) = f'(x)(x - x_n) + f(x_n) = 0$$

$$x = x_n - \frac{f(x)}{f'(x)}$$

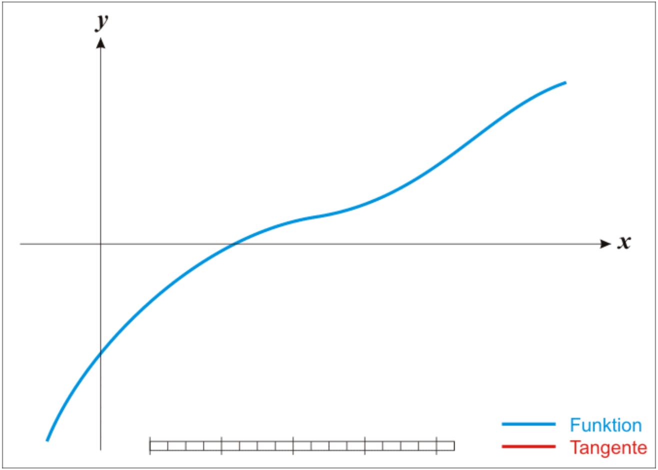
Geometric intuition of Newton's method

At step $n+1$: x_n, $y_n = f(x_n)$.

- Find tangent line of f at (x_n, y_n)
- $x_{n+1} \leftarrow$ x-intercept of the tangent line
- $y_{n+1} \leftarrow f(x_{n+1})$



Newton's Method Demo



https://en.wikipedia.org/wiki/File:NewtonIteration_Ani.gif

Minimize $J(\theta)$ using Newton's Method

$$\theta = \theta - \frac{f(\theta)}{f'(\theta)}$$

Newton's method for optimization $\min_\theta J(\theta)$

Use newton's method to solve $\nabla_\theta J(\theta) = 0$:

$f(\theta)$

- θ is one-dimensional:

$$\theta := \theta - \frac{J'(\theta)}{J''(\theta)}$$

$J'(\theta)$

$J''(\theta)$

Minimize $J(\theta)$ using Newton's Method

Newton's method for optimization $\min_\theta J(\theta)$

Use newton's method to solve $\nabla_\theta J(\theta) = 0$:

Hession of $J(\theta)$:

$$H(\theta) = \begin{bmatrix} \frac{\partial^2 J}{\partial \theta_1^2} & \frac{\partial^2 J}{\partial \theta_1 \partial \theta_2} & \cdots & \frac{\partial^2 J}{\partial \theta_1 \partial \theta_n} \\ \frac{\partial^2 J}{\partial \theta_2 \partial \theta_1} & \ddots & & \vdots \\ \frac{\partial^2 J}{\partial \theta_n \partial \theta_1} & \cdots & & \frac{\partial^2 J}{\partial \theta_n \partial \theta_n} \end{bmatrix}$$

$(n \times n)$

- θ is one-dimensional:

$$\theta := \theta - \frac{J'(\theta)}{J''(\theta)}$$

- θ is multidimensional:

$$\theta = \theta - H^{-1}(\theta) \nabla J(\theta)$$

where H is the Hessian matrix of $J(\theta)$.

a.k.a Newton-Raphson method

Newton's Method for Optimization

```
Initialize θ
While θ has not coverged {
  θ := θ − H^{-1}(θ)∇J(θ)
}
```

Newton's Method for Optimization

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Performance of Newton's method:

- Needs fewer interations than batch gradient descent

Newton's Method for Optimization

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n×n

Performance of Newton's method:

- Needs fewer interations than batch gradient descent
- Computing H^{-1} is time consuming

Newton's Method for Optimization

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Initialize θ
While θ has not coverged {
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Performance of Newton's method:

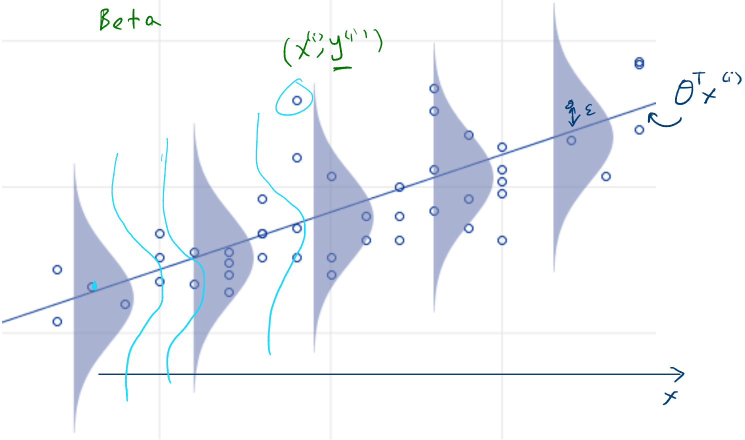
- Needs fewer interations than batch gradient descent
- Computing H^{-1} is time consuming
- Faster in practice when n is small

Maximum Likelihood Estimation

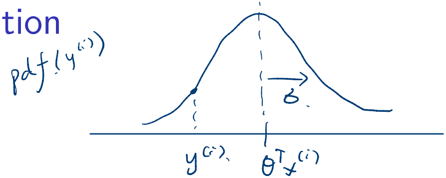
Consider target y is modeled as

$$y^{(i)} = \theta^T x^{(i)} + \epsilon^{(i)}$$

and $\epsilon^{(i)}$ are *independently and identically distributed (IID)* to Gaussian distribution $\mathcal{N}(0, \sigma^2)$



Maximum Likelihood Estimation



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$$y^{(i)} = \theta^T x^{(i)} + \epsilon^{(i)}$$

and $\epsilon^{(i)}$ are *independently and identically distributed (IID)* to Gaussian distribution $\mathcal{N}(0, \sigma^2)$, then

$$p(\epsilon^{(i)}) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left(-\frac{\epsilon^{(i)2}}{2\sigma^2}\right)}$$

$$\epsilon^{(i)} = y^{(i)} - \theta^T x^{(i)}$$

Given $x^{(i)}, y^{(i)}$.

$$p(y^{(i)} \mid x^{(i)}; \theta) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left(-\frac{(y^{(i)} - \theta^T x^{(i)})^2}{2\sigma^2}\right)}$$

Maximum Likelihood Estimation

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and $\epsilon^{(i)}$ are *independently and identically distributed (IID)* to Gaussian distribution $\mathcal{N}(0, \sigma^2)$, then

$$p(\epsilon^{(i)}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{{\epsilon^{(i)}}^2}{2\sigma^2}\right)$$

Maximum Likelihood Estimation

Consider target y is modeled as

$$y^{(i)} = \theta^T x^{(i)} + \epsilon^{(i)}$$

and $\epsilon^{(i)}$ are *independently and identically distributed (IID)* to Gaussian distribution $\mathcal{N}(0, \sigma^2)$, then

$$p(\epsilon^{(i)}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{{\epsilon^{(i)}}^2}{2\sigma^2}\right)$$

$$p(y^{(i)}|x^{(i)};\theta) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y^{(i)} - \theta^T x^{(i)})^2}{2\sigma^2}\right)$$

Maximum Likelihood Estimation

$$y = \begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix} \qquad p(y_1, \dots, y_m | X; \theta) = \prod_{i=1}^{m} p(y^{(i)} | X; \theta)$$

$$= p(y^{(i)} | x^{(i)}; \theta)$$

The **likelihood** of this model with respect to θ is

$$L(\theta) = p(\vec{y}|X;\theta) = \prod_{i=1}^{m} p(y^{(i)}|x^{(i)};\theta)$$

Maximum Likelihood Estimation

The **likelihood** of this model with respect to θ is

$$L(\theta) = p(\vec{y}|X;\theta) = \prod_{i=1}^{m} p(y^{(i)}|x^{(i)};\theta)$$

Maximum likelihood estimation of θ:

$$\theta_{MLE} = \operatorname*{argmax}_{\theta} L(\theta)$$

Maximum Likelihood Estimation

We compute log likelihood,

$$\log L(\theta) = \log \prod_{i=1}^{m} p(y^{(i)}|x^{(i)};\theta) = \sum_{i=1}^{m} \log p(y^{(i)}|x^{(i)};\theta)$$

$$= \sum_{i=1}^{m} \log\left(\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y^{(i)} - \theta^T x^{(i)})^2}{2\sigma^2}\right)\right)$$

Maximum Likelihood Estimation

We compute log likelihood,

$$\log L(\theta) = \log \prod_{i=1}^{m} p(y^{(i)}|x^{(i)};\theta) = \sum_{i=1}^{m} \log p(y^{(i)}|x^{(i)};\theta)$$

$$= \sum_{i=1}^{m} \log \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y^{(i)} - \theta^T x)^2}{2\sigma^2}\right)$$

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$\epsilon^{i} \sim \mathcal{N}(0, \sigma^2)$ iid

$$= m \log \frac{1}{\sqrt{2\pi\sigma^2}} - \frac{1}{\sigma^2} \cdot \frac{1}{2} \sum_{i=1}^{m} (y^{(i)} - \theta^T x^{(i)})^2$$

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Under the assumptions on $\epsilon^{(i)}$, least-squares regression corresponds to the maximum likelihood estimate of θ.

Linear Regression Summary

How to estimate model parameters θ (or w and b) from data?

- Least square regression (geometry approach)
- Maximum likelihood estimation (probabilistic modeling approach)

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How to solve for solutions ?

- normal equation (close-form solution)
- gradient descent
- newton's method

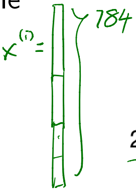
Outline

Logistic Regression

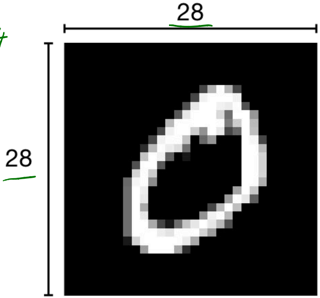
A binary classification problem

Classify binary digits

- Training data: 12600 grayscale images of handwritten digits



- Each image is represent by a vector $x^{(i)}$ of dimension $28 \times 28 = 784$
- Vectors $x^{(i)}$ are normalized to [0,1]



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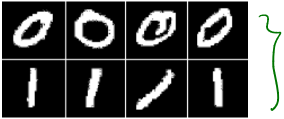

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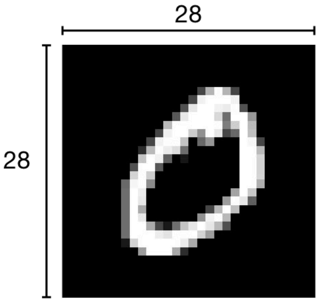


Binary classification: $\mathcal{Y} = \{0, 1\}$

- negative class: $y^{(i)} = 0$
- positive class: $y^{(i)} = 1$

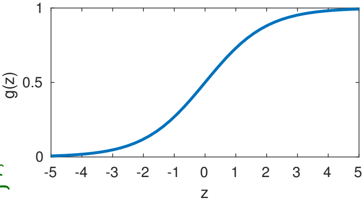
Logistic Regression Hypothesis Function

Sigmoid function

$$g(z) = \frac{1}{1 + e^{-z}}$$

- $g : \mathbb{R} \to (0, 1)$
- $g'(z) =$ g(z) (1 − g(z))

Homework



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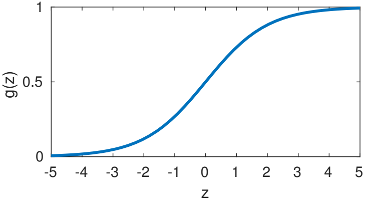

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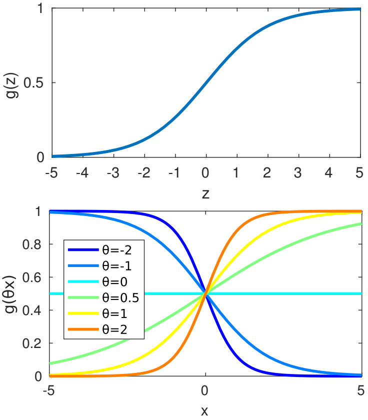

Hypothesis function for logistic regression:

$$h_\theta = g(\theta^T x) = \frac{1}{1 + e^{-\theta^T x}}$$

Review: Bernoulli Distribution

A discrete probability distribution of a binary random variable $x \in \{0, 1\}$:

$y^{(i)} | x^{(i)} \sim \mathcal{N}(\theta^T x^{(i)}, \sigma^2)$

$$p(x) = \begin{cases} \lambda & \text{if } x = 1 \\ 1 - \lambda & \text{if } x = 0 \end{cases}$$
$$= \lambda^x (1 - \lambda)^{1-x}$$

Maximum likelihood estimation for logistic regression

Logistic regression assumes $y|x$ is **Bernoulli distributed**.

- $p(y = 1 \mid x; \theta) = h_\theta(x)$
- $p(y = 0 \mid x; \theta) = 1 - h_\theta(x)$

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$$p(x;\lambda) = \lambda^x (1-\lambda)^{1-x}$$

$$p(y \mid x; \theta) = (h_\theta(x))^y (1 - h_\theta(x))^{1-y}$$

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Given m **independently generated** training examples, the likelihood function is:

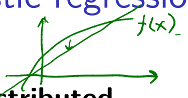
$y \log h_\theta(x) + (1-y)\log(1-h_\theta(x))$

$$L(\theta) = p(\vec{y}|X; \theta) = \prod_{i=1}^{m} p(y^{(i)}|x^{(i)}; \theta)$$

$$l(\theta) = \log(L(\theta)) = \sum_{i=1}^{m} y^{(i)} \log h_\theta(x^{(i)}) + (1 - y^{(i)}) \log(1 - h_\theta(x^{(i)}))$$

Maximum likelihood estimation for logistic regression

① f is concave iff −f is convex ②



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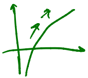

$$L(\theta) = p(\vec{y}|X; \theta) = \prod_{i=1}^{m} p(y^{(i)}|x^{(i)}; \theta)$$

$$l(\theta) = \log(L(\theta)) = \sum_{i=1}^{m} y^{(i)} \log h_\theta(x^{(i)}) + (1 - y^{(i)}) \log(1 - h_\theta(x^{(i)}))$$

$l(\theta)$ is concave!

Maximum likelihood estimation for logistic regression

$$l(\theta) = \sum_{i=1}^{m} y^{(i)} \log h_\theta(x^{(i)}) + (1 - y^{(i)}) \log(1 - h_\theta(x^{(i)}))$$

Solve $\text{argmax}_\theta \, l(\theta)$ using gradient ascent:

$$h_\theta(x^{(i)}) = g(\theta^T x^{(i)})$$

$$\frac{\partial}{\partial \theta_j} h_\theta(x^{(i)}) = g(\theta^T x^{(i)})(1 - g(\theta^T x^{(i)})) \frac{\partial}{\partial \theta_j} \theta^T x^{(i)}$$

$$= h_\theta(x^{(i)})(1 - h_\theta(x^{(i)})) x_j^{(i)} \quad x_j^{(i)}$$

$$\frac{\partial l(\theta)}{\partial \theta_j} = \sum_{i=1}^{m} y^i \frac{1}{h_\theta(x^{(i)})} \frac{\partial}{\partial \theta_j} h_\theta(x^{(i)}) + \frac{1 - y^{(i)}}{1 - h_\theta(x^{(i)})} (-1) \cdot \frac{\partial}{\partial \theta_j} h_\theta(x^{(i)})$$

$$= \sum_{i=1}^{m} \left[y^i (1 - h_\theta(x^i)) x_j^i - (1 - y^i) h_\theta(x^i) \, x_j^{(i)} \right]$$

$$= \sum_{i=1}^{m} \left[y^i (1 - h_\theta(x^i)) - (1 - y^i) h_\theta(x^i) \right] x_j^{(i)}$$

$$= \sum_{i=1}^{m} \left(y^i - h_\theta(x^i) \right) x_j^{(i)}$$

$$g(\theta^T x^{(i)})$$

Maximum likelihood estimation for logistic regression

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$$\frac{\partial l(\theta)}{\partial \theta_j} = \sum_{i=1}^{m} \left(y^{(i)} - h_\theta(x^{(i)}) \right) x_j^{(i)}$$

Stocastic Gradient Ascent

```
Repeat until convergence{
  for i = 1...m {
      θ_j = θ_j + α(y^(i) − h_θ(x^(i)))x_j^(i)   for every j
  }
}
```

- Update rule has the same form as least square regression, but with different hypothesis function h_θ

Binary Digit Classification

$\theta^T x$

Using the learned classifier

Given an image x, the predicted label is

$$\hat{y} = \begin{cases} 1 & g(\theta^T x) > 0.5 \\ 0 & \text{otherwise} \end{cases}$$

$g(\theta^T x) \in (0,1)$

Binary digit classification results

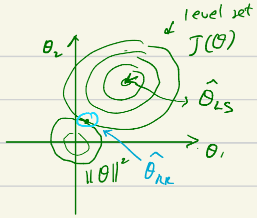
	sample size	accuracy
Training	16200	100%
Testing	1225	100%

- Testing accuracy is 100% since this problem is relatively easy.

Q: label imbalance?

focal loss

Homework Preview



① Ridge regression $\min_\theta J(\theta)$

$$J(\theta) = \| y - X\theta \|^2 + \lambda \|\theta\|^2$$

$tr(\theta^T\theta)$

- underdetermined $X\theta = y$ $m < n$
- prevent overfitting
- highly correlated variables. $(X^TX)^{-1}$ ← numerical issues

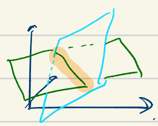
$$\hat{\theta}_{RR} = (X^TX + \lambda I)^{-1} X^T y.$$

when $\lambda \to 0$, $\hat{\theta}_{RR} \to \hat{\theta}_{LS}$

② over-parameterized model :

Implicit Bias of Gradient Descent.

Given an under-determined system



$$y = Ax \quad \text{full rank}$$

$$= \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

assuming A has full row rank.

$\min_x \| y - Ax \|$

GD: Let $x_0 = 0$

update: $x_k = x_{k-1} - \alpha \nabla f(x)$.

$x^\infty \to x_{LN}$

Definition Least Norm Solution of a Linear System :

$$x_{LN} = \arg\min_x \|x\|$$

$$\text{s.t. } Ax = y.$$

$$x_{LN} = A^T(AA^T)^{-1}y$$

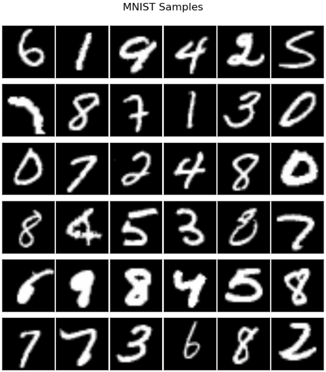
↑ not the same as $(A^TA)^{-1}A^Ty$

Outline

Multi-class classification

Each data sample belong to one of $k > 2$ different classes.

$$\mathcal{Y} = \{1, \ldots, k\}$$



Given new sample $x \in \mathbb{R}^k$, predict which class it belongs.

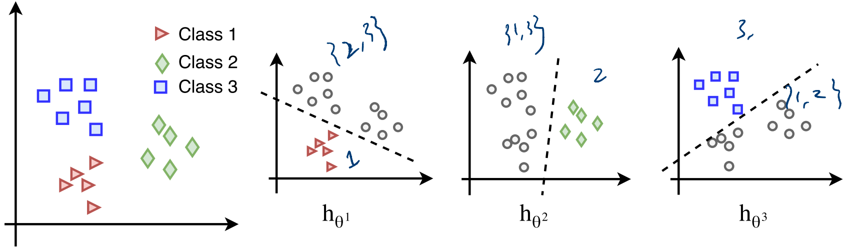
Naive Approach: Convert to binary classification

One-Vs-Rest

Learn k classifiers $h_1, \ldots, h_k$. Each h_i classify one class against the rest of the classes.

Given a new data sample x, its predicted label $\hat{y}$:

$$\hat{y} = \operatorname*{argmax}_i h_i(x)$$



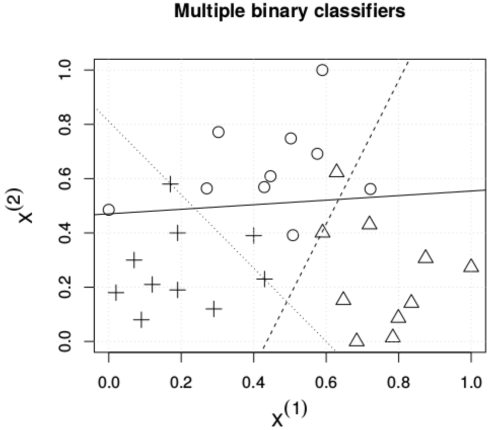
Multiple binary classifiers

100 samples, 20 classes

5 positive samples for each h_i

Drawbacks of One-Vs-Rest:

- Class unbalance: more negative samples than positive samples
- Different classifiers may have different confidence scales



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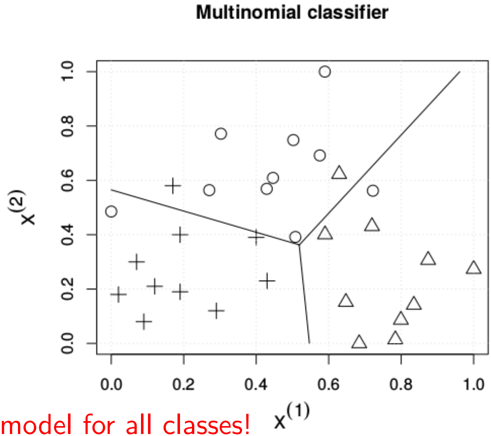


Learn one model for all classes!

Review: Multinomial Distribution

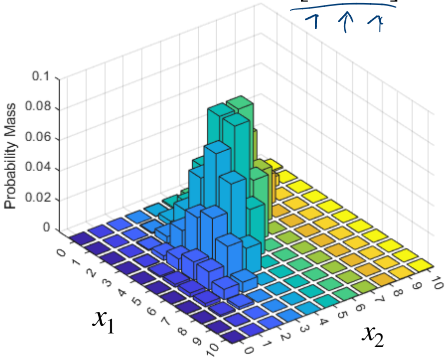
Models the probability of counts for each side of a k-sided die rolled m times, each side with independent probability ϕ_i

3-sided die.

$$\phi_1 + \cdots + \phi_k = 1$$

$$k = 3,\ n = 10 \qquad \phi = \left[\frac{1}{2}, \frac{1}{3}, \frac{1}{6}\right]$$

$\phi = [\frac{1}{6}, \frac{1}{6} \ldots \frac{1}{6}]$



Extend logistic regression: Softmax Regression

Assume $p(y|x)$ is **multinomial distributed**, $k = |\mathcal{Y}|$

Extend logistic regression: Softmax Regression

Assume $p(y|x)$ is **multinomial distributed**, $k = |\mathcal{Y}|$

Hypothesis function for sample x:

$$h_\theta(x) = \begin{bmatrix} p(y=1|x;\theta) \\ \vdots \\ p(y=k|x;\theta) \end{bmatrix} = \frac{1}{\sum_{j=1}^{k} e^{\theta_j^T x_j}} \begin{bmatrix} e^{\theta_1^T x} \\ \vdots \\ e^{\theta_k^T x} \end{bmatrix} = \text{softmax}(\theta^T x)$$

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{(z_j)}}$$

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$x \in \mathbb{R}^n$

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{(z_j)}}$$

Parameters: $\theta = \begin{bmatrix} - & \theta_1^T & - \\ & \vdots & \\ - & \theta_k^T & - \end{bmatrix}$ } k.

n.

Softmax Regression

Given $(x^{(i)}, y^{(i)}), i = 1, \ldots, m$, the log-likelihood of the Softmax model is

$$\ell(\theta) = \sum_{i=1}^{m} \log p(y^{(i)}|x^{(i)}; \theta)$$
$$= \sum_{i=1}^{m} \log \prod_{l=1}^{k} p(y^{(i)} = l|x^{(i)})^{\mathbf{1}\{y^{(i)}=l\}}$$

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samples

classes

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&= \sum_{i=1}^{m} \log \prod_{l=1}^{k} p(y^{(i)} = l | x^{(i)})^{\mathbf{1}\{y^{(i)} = l\}} \\
&= \sum_{i=1}^{m} \sum_{l=1}^{k} \mathbf{1}\{y^{(i)} = l\} \log \underline{p(y^{(i)} = l | x^{(i)})} \\
&= \sum_{i=1}^{m} \sum_{l=1}^{k} \mathbf{1}\{y^{(i)} = l\} \log \frac{e^{\theta_l^T x^{(i)}}}{\sum_{j=1}^{k} e^{\theta_j^T x^{(i)}}}
\end{aligned}$$

Softmax Regression

Derive the stochastic gradient descent update:

- Find $\nabla_{\theta_l} \ell(\theta)$

$$\nabla_{\theta_l} \ell(\theta) = \sum_{i=1}^{m} \left[\left(\mathbf{1}\{y^{(i)} = l\} - P\left(y^{(i)} = l | x^{(i)}; \theta \right) \right) x^{(i)} \right]$$

Property of Softmax Regression

- Parameters $\theta_1, \ldots \theta_k$ are not independent: $\sum_j p(y = j|x) = \sum_j \phi_j = 1$
- Knowning $k - 1$ parameters completely determines model.

Invariant to scalar addition

$$p(y|x;\theta) = p(y|x;\theta - \psi)$$

Proof.

Relationship with Logistic Regression

When K = 2,

$$h_\theta(x) = \frac{1}{e^{\theta_1^T x} + e^{\theta_2^T x}} \begin{bmatrix} e^{\theta_1^T x} \\ e^{\theta_2^T x} \end{bmatrix}$$

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Replace $\theta = \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix}$ with $\theta* = \theta - \begin{bmatrix} \theta_2 \\ \theta_2 \end{bmatrix} = \begin{bmatrix} \theta_1 - \theta_2 \\ 0 \end{bmatrix}$,

$$h_\theta(x) = \frac{1}{e^{\theta_1^T x - \theta_2^T x} + e^{0x}} \begin{bmatrix} e^{(\theta_1 - \theta_2)^T x} \\ e^{0^T x} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{e^{(\theta_1 - \theta_2)^T x}}{1 + e^{(\theta_1 - \theta_2)^T x}} \\ \frac{1}{1 + e^{(\theta_1 - \theta_2)^T x}} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1}{1 + e^{-(\theta_1 - \theta_2)^T x}} \\ 1 - \frac{1}{1 + e^{-(\theta_1 - \theta_2)^T x}} \end{bmatrix} = \begin{bmatrix} g(\theta *^T x) \\ 1 - g(\theta *^T x) \end{bmatrix}$$

When to use Softmax?

- When classes are mutually exclusive: use Softmax
- Not mutually exclusive: multiple binary classifiers may be better