

About Regression

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Start with two **classification** type regression:

- ▶ Logistic Regression
- ▶ Softmax(Multinomial) regression

the **BIG** idea in here

Assume there is four classes that the classifier is capable to classify:

- ▶ if data x_1 has label $y_1 = 1$, then y_1 can be written as $[1, 0, 0, 0]^T$.
- ▶ if data x_2 has label $y_2 = 2$, then y_2 can be written as $[0, 1, 0, 0]^T$.
- ▶ if data x_3 has label $y_3 = 2$, then y_3 can be written as $[0, 1, 0, 0]^T$.
- ▶ if data x_4 has label $y_4 = 3$, then y_4 can be written as $[0, 0, 1, 0]^T$.
- ▶ if data x_5 has label $y_5 = 4$, then y_5 can be written as $[0, 0, 0, 1]^T$.
- ▶ ...

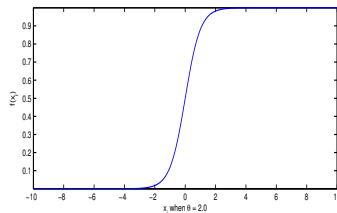
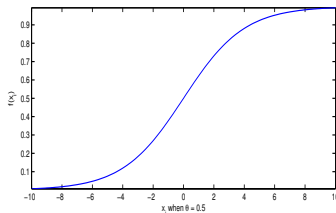
So basically, we want to build a classifier $f(x, \theta)$, such that:

- ▶ $(y_1 = 1) \implies f(x_1, \theta)$ should be as close to $[1, 0, 0, 0]^T$ as possible, e.g., $f(x_1, \theta) = [0.99, 0.005, 0.005, 0]^T$
- ▶ $(y_2 = 2) \implies f(x_2, \theta)$ should be as close to $[0, 1, 0, 0]^T$ as possible, e.g., $f(x_2, \theta) = [0.005, 0.99, 0.005, 0]^T$
- ▶ $(y_3 = 2) \implies f(x_3, \theta)$ should be as close to $[0, 1, 0, 0]^T$ as possible, e.g., $f(x_3, \theta) = [0.005, 0.99, 0.005, 0]^T$
- ▶ $(y_4 = 3) \implies f(x_4, \theta)$ should be as close to $[0, 0, 1, 0]^T$ as possible, e.g., $f(x_4, \theta) = [0.005, 0.005, 0.99, 0]^T$
- ▶ $(y_5 = 4) \implies f(x_5, \theta)$ should be as close to $[0, 0, 0, 1]^T$ as possible, e.g., $f(x_5, \theta) = [0.005, 0.005, 0, 0.99]^T$
- ▶ ...

Let's see the mechanism to achieve this.

Standard Sigmoid function: logistic function

$$\sigma(t) = \frac{1}{1 + \exp(-t)} = \frac{\exp(t)}{\exp(t) + 1} \quad \rightarrow \quad \sigma(\mathbf{x}_i^\top \boldsymbol{\theta}) = \frac{1}{1 + \exp(-\mathbf{x}_i^\top \boldsymbol{\theta})}$$



It's a **squashing function** that maps any real number to a value between 0 ... 1.

Properties of logistic function

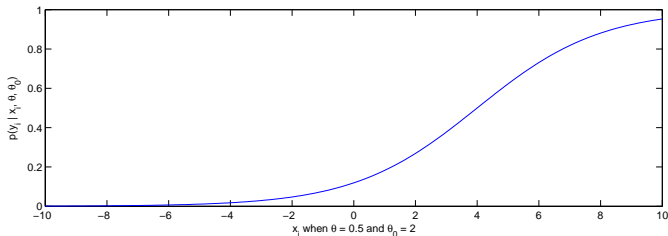
$$1 - \sigma(t) = 1 - \frac{1}{1 + \exp(-t)} = \frac{1 + \exp(-t) - 1}{1 + \exp(-t)} = \frac{\exp(-t)}{1 + \exp(-t)} = \sigma(-t)$$

$$\begin{aligned} \frac{d\sigma(t)}{dt} &= \frac{d\left(\frac{1}{1+\exp(-t)}\right)}{dt} = \frac{\exp(-t)}{(1 + \exp(-t))^2} = \left(\frac{1}{1 + \exp(-t)}\right) \left(\frac{\exp(-t)}{1 + \exp(-t)}\right) \\ &= \sigma(t)(1 - \sigma(t)) \quad \text{it's always positive} \end{aligned}$$

$$\begin{aligned} \frac{d\sigma(-t)}{dt} &= \frac{d\left(\frac{1}{1+\exp(t)}\right)}{dt} = \frac{-\exp(t)}{(1 + \exp(t))^2} = - \underbrace{\left(\frac{1}{1 + \exp(t)}\right)}_{\sigma(-t) \text{ or } 1 - \sigma(t)} \underbrace{\left(\frac{\exp(t)}{1 + \exp(t)}\right)}_{\sigma(t)} \\ &= -\sigma(t)(1 - \sigma(t)) \quad \text{it's always negative} \end{aligned}$$

Logistic Regression

- Finding a **single** Bernoulli probability: $\Pr(y_i = 1 | \underbrace{x_i^T \theta}_p)$:



- Write $\{x_i, 1\} \rightarrow x_i$ and $\{\theta, \theta_0\} \rightarrow \theta$:

$$\Pr(\mathbf{Y}|\mathbf{X}, \theta) = \prod_{i=1}^n \left[\frac{1}{1 + \exp(-x_i^T \theta)} \right]^{y_i} \left[1 - \frac{1}{1 + \exp(-x_i^T \theta)} \right]^{1-y_i}$$

Maximization is performed on the log space:

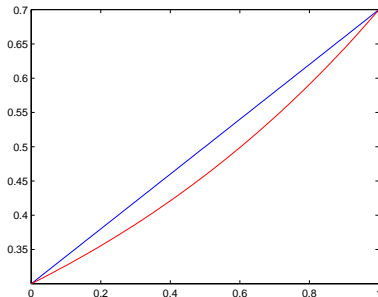
$$C(\theta) = -\log[p(\mathbf{Y}|\mathbf{X}, \theta)] = - \left(\sum_{i=1}^n y_i \log \left[\frac{1}{1 + \exp(-x_i^T \theta)} \right] + (1 - y_i) \log \left[1 - \frac{1}{1 + \exp(-x_i^T \theta)} \right] \right)$$

Think Bernoulli again

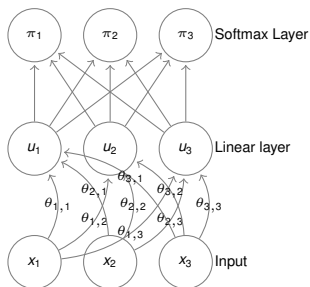
Both functions are the same at end-points $\{0, 1\}$:

$$f_p(x) = (1 - p)^{(1-x)} p^x$$

$$f_p(x) = (1 - p)(1 - x) + px$$



Expand to multiple classes: Softmax



$$\theta_1 = \{\theta_{1,1}, \theta_{1,2}, \theta_{1,3}\} \quad \theta_2 = \{\theta_{2,1}, \theta_{2,2}, \theta_{2,3}\} \quad \theta_3 = \{\theta_{3,1}, \theta_{3,2}, \theta_{3,3}\}$$

► Linear Layer

$$u_1 = \mathbf{x}^T \theta_1 = \sum_{i=1}^3 x_{1,i} \theta_{1,i}$$

$$u_2 = \mathbf{x}^T \theta_2 = \sum_{i=1}^3 x_{2,i} \theta_{2,i}$$

$$u_3 = \mathbf{x}^T \theta_3 = \sum_{i=1}^3 x_{3,i} \theta_{3,i}$$

► Softmax Layer

$$\pi_1 \equiv \Pr(y_i = 1 | \mathbf{x}_i, \theta) = \frac{\exp(u_1)}{\sum_{k=1}^3 \exp(u_k)} = \frac{\exp(\mathbf{x}_i^T \theta_1)}{\sum_{k=1}^3 \exp(\mathbf{x}_i^T \theta_k)}$$

$$\pi_2 \equiv \Pr(y_i = 2 | \mathbf{x}_i, \theta) = \frac{\exp(u_2)}{\sum_{k=1}^3 \exp(u_k)} = \frac{\exp(\mathbf{x}_i^T \theta_2)}{\sum_{k=1}^3 \exp(\mathbf{x}_i^T \theta_k)}$$

$$\pi_3 \equiv \Pr(y_i = 3 | \mathbf{x}_i, \theta) = \frac{\exp(u_3)}{\sum_{k=1}^3 \exp(u_k)} = \frac{\exp(\mathbf{x}_i^T \theta_3)}{\sum_{k=1}^3 \exp(\mathbf{x}_i^T \theta_k)}$$

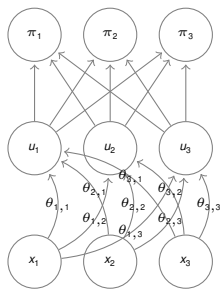
► $\pi_1 + \pi_2 + \pi_3 = 1!$

► easily extend them to multiple K arbitrary classes

Relationship between 2-class Softmax and Logistic regression

$$\begin{aligned}\pi_1 \equiv \pi(y_i = 1 | \mathbf{x}_i, \boldsymbol{\theta}) &= \frac{\exp(\mathbf{x}^T \boldsymbol{\theta}_1)}{\exp(\mathbf{x}^T \boldsymbol{\theta}_1) + \exp(\mathbf{x}^T \boldsymbol{\theta}_2)} \\&= \frac{1}{1 + \exp(\mathbf{x}^T (\boldsymbol{\theta}_2 - \boldsymbol{\theta}_1))} \\&= \frac{1}{1 + \exp(\mathbf{x}^T (-\boldsymbol{\theta}))} \\&= \frac{\exp(\mathbf{x}^T \boldsymbol{\theta})}{\exp(\mathbf{x}^T \boldsymbol{\theta}) + 1}\end{aligned}$$

Softmax in our three class example



$$\pi_{1:\text{Data Scientist}} = \frac{\exp(u_1)}{\sum_{i=1}^3 u_i} = \frac{\exp(\mathbf{x}^T \boldsymbol{\theta}_1)}{\sum_{i=1}^3 \exp(\mathbf{x}^T \boldsymbol{\theta}_i)}$$

$$\pi_{2:\text{Scholar}} = \frac{\exp(u_2)}{\sum_{i=1}^3 u_i} = \frac{\exp(\mathbf{x}^T \boldsymbol{\theta}_2)}{\sum_{i=1}^3 \exp(\mathbf{x}^T \boldsymbol{\theta}_i)}$$

$$\pi_{3:\text{CEO}} = \frac{\exp(u_3)}{\sum_{i=1}^3 u_i} = \frac{\exp(\mathbf{x}^T \boldsymbol{\theta}_3)}{\sum_{i=1}^3 \exp(\mathbf{x}^T \boldsymbol{\theta}_i)}$$

	attribute 1	attribute 2	attribute 3	Occupation
Attendee 1	50	64	1.2	Data scientist
Attendee 2	23	23	15	Scholar
Attendee 3	50	80	3.2	Data scientist
...
Attendee N	5	90	25	CEO
Attendee N+1	60	43	12	?

So, substitute into the neural network, you hope to get a set of $\boldsymbol{\theta}$, such that:

$$\mathbf{x}^{(1)} = (50, 64, 1.2) \Rightarrow (\pi_{1:\text{Data Scientist}} = 1, \pi_{2:\text{Scholar}} = 0, \pi_{3:\text{CEO}} = 0)$$

$$\mathbf{x}^{(2)} = (23, 23, 15) \Rightarrow (\pi_{1:\text{Data Scientist}} = 0, \pi_{2:\text{Scholar}} = 1, \pi_{3:\text{CEO}} = 0)$$

$$\mathbf{x}^{(3)} = (50, 80, 3.2) \Rightarrow (\pi_{1:\text{Data Scientist}} = 1, \pi_{2:\text{Scholar}} = 0, \pi_{3:\text{CEO}} = 0)$$

...

$$\mathbf{x}^{(N)} = (5, 90, 25) \Rightarrow (\pi_{1:\text{Data Scientist}} = 0, \pi_{2:\text{Scholar}} = 0, \pi_{3:\text{CEO}} = 1)$$

An unique perfect $\boldsymbol{\theta}$ suitable for all the data obviously do *NOT* exist. We need to find a $\boldsymbol{\theta}$ which minimize the sum of cost.

Minimize cost function example: Softmax

- ▶ Logistic regression:

$$p(\mathbf{Y}|\mathbf{X}, \boldsymbol{\theta}) = \prod_{i=1}^N \left[\frac{1}{1 + \exp(-\mathbf{x}_i^T \boldsymbol{\theta})} \right]^{y_i} \left[1 - \frac{1}{1 + \exp(-\mathbf{x}_i^T \boldsymbol{\theta})} \right]^{1-y_i}$$

- ▶ Softmax:

$$p(\mathbf{Y}|\mathbf{X}, \boldsymbol{\theta}) = \prod_{i=1}^N \prod_{k=1}^K \left[\frac{\exp(\mathbf{x}_i^T \boldsymbol{\theta}_k)}{\sum_{l=1}^K \exp(\mathbf{x}_i^T \boldsymbol{\theta}_l)} \right]^{y_{i,k}}$$

we write y_i as an indicator vector, e.g., [100], [101]

$$\mathcal{C}(\boldsymbol{\theta}) = - \sum_{i=1}^N \sum_{k=1}^K \underbrace{y_{i,k} \log \left[\frac{\exp(\mathbf{x}_i^T \boldsymbol{\theta}_k)}{\sum_{l=1}^K \exp(\mathbf{x}_i^T \boldsymbol{\theta}_l)} \right]}_{\substack{p(x) \\ \log(q(x))}} \quad \text{note the cross entropy form: } H(p, q) = - \sum_x p(x) \log(q(x))$$

$$= - \sum_{i=1}^N \sum_{k=1}^K y_{i,k} \left[\log \exp(\mathbf{x}_i^T \boldsymbol{\theta}_k) - \log \sum_{l=1}^K \exp(\mathbf{x}_i^T \boldsymbol{\theta}_l) \right]$$

- ▶ What is cross entropy?

Cost function: Cross Entropy

Minimize the cost function: Cross Entropy can be thought of “how much” deviates between the “true” density $p(x)$ and recovered density “ $q(x)$ ”.

$$\begin{aligned} H(p, q) &= E_p[-\log q] \\ &= - \sum_x p(x) \log q(x) \\ &= \sum_x \left[\underbrace{-p(x) \log q(x) + p(x) \log(p(x))}_{\text{Cross Entropy}} \underbrace{- p(x) \log(p(x))}_{\text{Entropy}} \right] \\ &= \sum_x \underbrace{-p(x) \log p(x)}_{\text{Entropy}} + \sum_x p(x) \log \frac{p(x)}{q(x)} \\ &= H(p) + D_{\text{KL}}(p||q), \end{aligned}$$

Question If minimising **cross entropy loss** is equivalent of maximising multinomial likelihood estimation, then minimising **square loss** is equivalent of maximising what likelihood estimation?

Softmax or multinomial regression objective function

$$\mathcal{C}(\theta) = - \sum_{i=1}^N \sum_{k=1}^K y_{i,k} \left[\log \left(\frac{\exp(\mathbf{x}_i^T \theta_k)}{\sum_{l=1}^K \exp(\mathbf{x}_i^T \theta_l)} \right) \right]$$

How may we find:

$$\arg \min_{\theta} \mathcal{C}(\theta)$$

We solve it using Gradient descend.

Find the derivatives of Multinomial regression

$$C(\theta) = - \sum_{i=1}^N \sum_{k=1}^K y_{i,k} \left[\log \left(\frac{\exp(\mathbf{x}_i^T \theta_k)}{\sum_{l=1}^K \exp(\mathbf{x}_i^T \theta_l)} \right) \right]$$

Let $Z_k = \mathbf{x}_i^T \theta_k$, we have,

$$\begin{aligned} \frac{\partial C(\theta)}{\partial Z_k} &= \sum_{i=1}^N \frac{\partial \left(- \sum_{k=1}^K y_{i,k} \left[\log \left(\frac{\exp(Z_k)}{\sum_{l=1}^K \exp(Z_l)} \right) \right] \right)}{\partial Z_k} \\ &= \sum_{i=1}^N \left[\frac{\exp(Z_k)}{\sum_{l=1}^K \exp(Z_l)} - y_{i,k} \right] \quad \text{see next page} \\ \Rightarrow \frac{\partial C(\theta)}{\partial Z} &= \sum_{i=1}^N \begin{bmatrix} \frac{\exp(Z_1)}{\sum_{l=1}^K \exp(Z_l)} - y_{i,1} \\ \vdots \\ \frac{\exp(Z_K)}{\sum_{l=1}^K \exp(Z_l)} - y_{i,K} \end{bmatrix} = \sum_{i=1}^N \left(\frac{\exp(Z)}{\sum_{l=1}^K \exp(Z_l)} - y_i \right) \end{aligned}$$

If we were to differentiate with respect to θ :

$$\frac{\partial C(\theta)}{\partial \theta} = \frac{\partial C(\theta)}{\partial Z} \frac{\partial Z}{\partial \theta} = \sum_{i=1}^N \mathbf{x}_i \left[\frac{\exp(\mathbf{x}_i^T \theta)}{\sum_{l=1}^K \exp(\mathbf{x}_i^T \theta_l)} - y_i \right]^T$$

Derivative for Softmax regression

$$p_k = \frac{\exp^{z_k}}{\sum_l \exp^{z_l}} \quad C = - \sum_k y_k \log p_k, \quad \text{where } \sum_k y_k = 1$$

when $k = i$:

$$\frac{\partial p_k}{\partial z_k} = \frac{\partial \left(\frac{\exp^{z_k}}{\sum_l \exp^{z_l}} \right)}{\partial z_k} = \frac{\partial \left(\frac{\exp^{z_k}}{\exp^{z_k} + \sum_{l \neq k} \exp^{z_l}} \right)}{\partial \exp(z_k)} \times \frac{\partial \exp^{z_k}}{\partial z_k}$$

We know the identity:

$$\frac{\partial \frac{x}{x+c}}{\partial x} = \frac{\partial x(x+c)^{-1}}{\partial x} = (x+c)^{-1} - x(x+c)^{-2} = \frac{(x+c) - x}{(x+c)^2} = \frac{c}{(x+c)^2}$$

Therefore,

$$\begin{aligned} \frac{\partial p_k}{\partial z_k} &= \frac{\partial \left(\frac{\exp^{z_k}}{\exp^{z_k} + \sum_{l \neq k} \exp^{z_l}} \right)}{\partial \exp(z_k)} \times \frac{\partial \exp^{z_k}}{\partial z_k} = \frac{\sum_{l \neq k} \exp^{z_l}}{(\sum_{l=1}^K \exp^{z_l})^2} \times \exp^{z_k} \\ &= \frac{\sum_{l \neq k} \exp^{z_l}}{(\sum_{l=1}^K \exp^{z_l})} \times \frac{\exp^{z_k}}{(\sum_{l=1}^K \exp^{z_l})} = p_k(1 - p_k) \end{aligned}$$

Derivative for Softmax regression

when $k \neq i$, We know the identity:

$$\frac{\partial \frac{y}{z+c}}{\partial z} = \frac{\partial y(z+c)^{-1}}{\partial z} = -\frac{y}{(z+c)^2}$$

$$\begin{aligned}\frac{\partial p_k}{\partial z_i} &= \frac{\left(\frac{\partial \frac{\exp^{z_k}}{\exp^{z_i} + \sum_{l \neq i} \exp^{z_l}}}{\partial \exp(z_i)} \right) \times \frac{\partial \exp^{z_i}}{\partial z_i}}{\partial \exp(z_i)} \\ &= -\frac{\exp^{z_k}}{(\sum_{l=1}^K \exp^{z_l})^2} \times \exp^{z_i} \\ &= -\frac{\exp^{z_i}}{(\sum_{l=1}^K \exp^{z_l})} \times \frac{\exp^{z_k}}{(\sum_{l=1}^K \exp^{z_l})} = -p_i p_k\end{aligned}$$

Derivative for Softmax regression

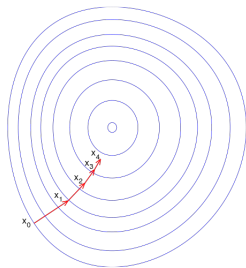
$$\frac{\partial p_k}{\partial z_i} = \begin{cases} p_i(1 - p_i), & i = k \\ -p_i p_k, & i \neq k \end{cases}$$

$$\begin{aligned} \frac{\partial \mathcal{C}}{\partial z_i} &= - \sum_k y_k \frac{\partial \log p_k}{\partial z_i} \\ &= - \sum_k y_k \frac{1}{p_k} \frac{\partial p_k}{\partial z_i} \\ &= -y_i(1 - p_i) - \sum_{k \neq i} y_k \frac{1}{p_k} (-p_k p_i) \\ &= -y_i(1 - p_i) + \sum_{k \neq i} y_k (p_i) \\ &= -y_i + y_i p_i + \sum_{k \neq i} y_k (p_i) \\ &= p_i \left(\sum_k y_k \right) - y_i \\ &= p_i - y_i \end{aligned}$$

Gradient Descent for multinomial regression

$$\mathbf{x}_{n+1} = \mathbf{x}_n - \alpha_n \nabla f(\mathbf{x}_n), \quad n \geq 0$$

$$\mathcal{C}(\boldsymbol{\theta}) = - \sum_{i=1}^N \sum_{k=1}^K y_{i,k} \log \left[\frac{\exp(\mathbf{x}_i^T \boldsymbol{\theta}_k)}{\sum_{l=1}^K \exp(\mathbf{x}_i^T \boldsymbol{\theta}_l)} \right] + \frac{\lambda}{2} \sum_{k=1}^K \sum_{j=1}^m \theta_{k,j}^2$$



$$\boldsymbol{\theta}^{n+1} = \boldsymbol{\theta}^n - \alpha_n \left(\sum_{i=1}^N \mathbf{x}_i \left[\frac{\exp(\mathbf{x}_i^T \boldsymbol{\theta})}{\sum_{l=1}^K \exp(\mathbf{x}_i^T \boldsymbol{\theta}_l)} - y_i \right]^T + \lambda \boldsymbol{\theta}^n \right), \quad n \geq 0$$

What's this $\frac{\lambda}{2} \sum_{k=1}^K \sum_{j=1}^m \theta_{k,j}^2$ business? It's the **regulariser** we added.

Linear Regression

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

where

$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \quad \mathbf{X} = \begin{pmatrix} \mathbf{x}_1^T \\ \mathbf{x}_2^T \\ \vdots \\ \mathbf{x}_n^T \end{pmatrix} = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ x_{21} & \cdots & x_{2p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix} \quad \boldsymbol{\beta} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{pmatrix} \quad \boldsymbol{\epsilon} = \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{pmatrix}$$

You have seen it so many times! There is an analytical solution to it:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} = \left(\sum \mathbf{x}_i \mathbf{x}_i^T \right)^{-1} \left(\sum \mathbf{x}_i y_i \right).$$

Linear Regression

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You have seen it so many times! There is an analytical solution to it:

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$$R^2 = 1 - \frac{\sum_i \left(\overbrace{y_i - \hat{y}_i}^{r_i} \right)^2}{\sum_i (y_i - \bar{y})^2}$$

- ▶ the better linear regression fits the data relative to a simple average, the closer the value of R^2 is to 1.
- ▶ If the chosen model fits worse than a horizontal line, then R^2 is negative

Polynomial Regression

For each of the data pairs (x_i, y_i) :

$$y_i = a_0 + a_1 x_i + a_2 x_i^2 + \cdots + a_m x_i^m + \varepsilon_i$$

The model can be written as a system of **linear equations**:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 & \cdots & x_1^m \\ 1 & x_2 & x_2^2 & \cdots & x_2^m \\ 1 & x_3 & x_3^2 & \cdots & x_3^m \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & x_n^2 & \cdots & x_n^m \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ \vdots \\ a_m \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{bmatrix},$$

or,

$$\vec{y} = \mathbf{X}\vec{a} + \vec{\varepsilon}.$$

Ordinary least squares estimation is:

$$\hat{\vec{a}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \vec{y}.$$

Imagine we have the following setting:

A particular company “*develops and markets products for the early detection of target organ damage and management of cardiovascular and renal disease.*”. In five years time, this company will have 10000 employees worldwide, HR needs a good model to reward its employees:

- ▶ has $N = 10000$ number of employees.
- ▶ has $q = 45$ working departments throughout the world.
- ▶ each department has N_q number of employees, i.e, $N = \sum_j^q n_j$
- ▶ The HR has collected $p = 6$ attributes from each employees, including:
 - ▶ utilisation hours
 - ▶ yrs of experience
 - ▶ salary
 - ▶ last year's rating
 - ▶ number of awards received
 - ▶ market value
- ▶ each y_i is the amount of “shared” profit each employee should receive.

Mixed effect model

- In the matrix form:

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{Z}\gamma + \varepsilon$$

- write down the dimensionality:

$$\underbrace{\mathbf{y}}_{N \times 1} = \underbrace{\underbrace{\mathbf{X}}_{N \times p} \underbrace{\beta}_{p \times 1}}_{N \times 1} + \underbrace{\underbrace{\mathbf{Z}}_{N \times q} \underbrace{\gamma}_{q \times 1}}_{N \times 1} + \underbrace{\varepsilon}_{N \times 1}$$

- substitute numbers into:

$$\underbrace{\mathbf{y}}_{10000 \times 1} = \underbrace{\underbrace{\mathbf{X}}_{10000 \times 6} \underbrace{\beta}_{6 \times 1}}_{10000 \times 1} + \underbrace{\underbrace{\mathbf{Z}}_{10000 \times 45} \underbrace{\gamma}_{45 \times 1}}_{10000 \times 1} + \underbrace{\varepsilon}_{10000 \times 1}$$

$$\mathbf{X} = \begin{bmatrix} \text{utilisation hours} & \text{yrs of experience} & \text{salary} & \text{last year's rating} & \text{number of clients} & \text{market value} \\ 1 & 64.97 & 0 & 1 & 6087 & 4.87 \\ 1 & 53.92 & 0 & 0 & 6700 & 4.68 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 56.07 & 0 & 1 & 6430 & 4.73 \end{bmatrix}$$

- \mathbf{z}_i is a **one-hot** vector, indicating which Department the employee belong to.