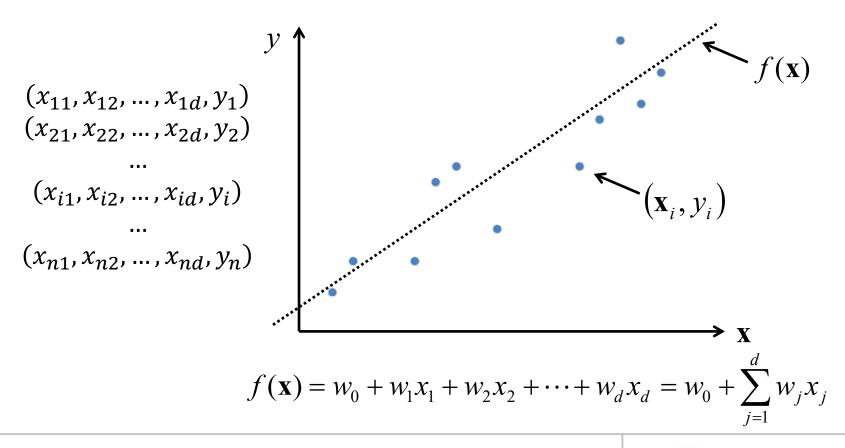


Linear Regression & Additive Linear Model

Find the line which best fits the data

We want to find a line which generalizes the given data



We have n sample data

$$D = \{D_1, D_2, \dots, D_n\}$$
 where $D_i = (\mathbf{x}_i, y_i)$

 $\mathbf{x}_i = (x_{i1}, x_{i2}, \dots, x_{id})$ is an input in d dimensional space y_i is the output for \mathbf{x}_i

Find
$$\mathbf{w} = (w_0, w_1, \dots, w_d)$$
 which minimizes $E(\mathbf{w})$

$$E(\mathbf{w}) = \sum_{i=1}^{n} (f(\mathbf{x}_i) - y_i)^2$$

$$f(\mathbf{x}_i) = w_0 + w_1 x_{i1} + w_2 x_{i2} + \dots + w_d x_{id} = w_0 + \sum_{j=1}^{d} w_j x_{ij}$$

In Other Words

So, our problem can be stated as follows:

Find $\mathbf{w} = (w_0, w_1, \dots, w_d)$ which minimizes $E(\mathbf{w})$ where $E(\mathbf{w}) = \sum_{i=1}^{n} (f(\mathbf{x}_i) - y_i)^2$ $f(\mathbf{x}_i) = w_0 + w_1 x_{i1} + w_2 x_{i2} + \dots + w_d x_{id} = w_0 + \sum_{j=1}^{d} w_j x_{ij}$ $D = \{D_1, D_2, \dots, D_n\} \text{ where } D_i = (\mathbf{x}_i, y_i)$ $\mathbf{x}_i = (x_{i1}, x_{i2}, \dots, x_{id}) \text{ is an input in } d \text{ dimensional space}$ $y_i \text{ is the output for } \mathbf{x}_i$

In Other Words

So, our problem can be stated as follows:

Find
$$\mathbf{w} = (w_0, w_1, \dots, w_d)$$
 which minimizes $E(\mathbf{w})$ where
$$E(\mathbf{w}) = \sum_{i=1}^{n} (f(\mathbf{x}_i) - y_i)^2$$

$$f(\mathbf{x}_i) = w_0 \mathbf{x}_{i0} + w_1 \mathbf{x}_{i1} + w_2 \mathbf{x}_{i2} + \dots + w_d \mathbf{x}_{id} = \sum_{j=0}^{d} w_i \mathbf{x}_{ij}$$

$$D = \{D_1, D_2, \dots, D_n\} \text{ where } D_i = (\mathbf{x}_i, y_i)$$

$$\mathbf{x}_i = (\mathbf{x}_{i0}, \mathbf{x}_{i1}, \mathbf{x}_{i2}, \dots, \mathbf{x}_{id}) \text{ where } \mathbf{x}_{i0} = \mathbf{1} \text{ for } i = 1, \dots, d$$

How to solve this?

Find
$$\mathbf{w} = (w_0, w_1, \dots, w_d)$$
 which minimizes $E(\mathbf{w})$ where
$$E(\mathbf{w}) = \sum_{i=1}^{n} (f(\mathbf{x}_i) - y_i)^2$$

$$f(\mathbf{x}_i) = w_0 \mathbf{x}_{i0} + w_1 \mathbf{x}_{i1} + w_2 \mathbf{x}_{i2} + \dots + w_d \mathbf{x}_{id} = \sum_{j=0}^{d} w_i \mathbf{x}_{ij}$$

$$D = \{D_1, D_2, \dots, D_n\} \text{ where } D_i = (\mathbf{x}_i, y_i)$$

$$\mathbf{x}_i = (\mathbf{x}_{i0}, \mathbf{x}_{i1}, \mathbf{x}_{i2}, \dots, \mathbf{x}_{id}) \text{ where } \mathbf{x}_{i0} = 1 \text{ for } i = 1, \dots, d$$

x and y are given values E is a quadratic function of w's

- There are various ways to solve
- Here, the SIMPLEST one will be presented

Quadratic Function Optimization

- At the point which minimizes $E(\mathbf{w}) = \sum_{i=1}^{\infty} (f(\mathbf{x}_i) - y_i)^2$

$$\frac{\partial}{\partial w_j} E(w_0, w_1, \dots, w_d) = 0 \text{ for } j = 0, \dots, d$$

That is

$$\frac{\partial}{\partial w_j} E(\mathbf{w}) = \sum_{i=1}^n \left(\frac{\partial}{\partial w_j} (f(\mathbf{x}_i) - y_i)^2 \right) = \sum_{i=1}^n 2x_{ij} (f(\mathbf{x}_i) - y_i) = 0 \quad j \ge 0$$

$$f(\mathbf{x}_i) = w_0 x_{i0} + w_1 x_{i1} + w_2 x_{i2} + \dots + w_d x_{id} = \sum_{i=0}^d w_i x_{ij}$$

Quadratic Function Optimization

$$E(\mathbf{w}) = \sum_{i=1}^{n} (f(\mathbf{x}_i) - y_i)^2$$

$$\frac{\partial}{\partial w_0} E(\mathbf{w}) = \sum_{i=1}^n x_{i0} \left(f(\mathbf{x_i}) - y_i \right) = 0$$

$$\frac{\partial}{\partial w_1} E(\mathbf{w}) = \sum_{i=1}^n x_{i1} \left(f(\mathbf{x_i}) - y_i \right) = 0$$

$$\frac{\partial}{\partial w_d} E(\mathbf{w}) = \sum_{i=1}^n x_{id} \left(f(\mathbf{x_i}) - y_i \right) = 0$$

 $\frac{\partial}{\partial w_0} E(\mathbf{w}) = \sum_{i=1}^n x_{i0} \left(f(\mathbf{x_i}) - y_i \right) = 0$ $\frac{\partial}{\partial w_1} E(\mathbf{w}) = \sum_{i=1}^n x_{i1} \left(f(\mathbf{x_i}) - y_i \right) = 0$ There are d variables d equations. If we solve the equation system, we can obtain

$$\mathbf{w} = (w_0, w_1, \cdots, w_d)$$

$$f(\mathbf{x}_i) = w_0 x_{i0} + w_1 x_{i1} + w_2 x_{i2} + \dots + w_d x_{id} = \sum_{j=0}^{a} w_i x_{ij}$$

Quadratic Function Optimization

$$\sum_{i=1}^{n} x_{i0}(f(\mathbf{x_i}) - y_i) = 0 \qquad \longrightarrow \sum_{i=1}^{n} x_{i0}(w_0 x_{i0} + w_1 x_{i1} + \dots + w_d x_{id} - y_i) = 0$$

$$\sum_{i=1}^{n} x_{i1} (f(\mathbf{x_i}) - y_i) = 0 \longrightarrow \sum_{i=1}^{n} x_{i1} (w_0 x_{i0} + w_1 x_{i1} + \dots + w_d x_{id} - y_i) = 0$$

$$\sum_{i=1}^{n} x_{id}(f(\mathbf{x_i}) - y_i) = 0 \qquad \longrightarrow \sum_{i=1}^{n} x_{id}(w_0 x_{i0} + w_1 x_{i1} + \dots + w_d x_{id} - y_i) = 0$$

$$w_0 \sum_{i=1}^{n} x_{i0} x_{i0} + w_1 \sum_{i=1}^{n} x_{i0} x_{i1} + w_2 \sum_{i=1}^{n} x_{i0} x_{i2} + \dots + w_d \sum_{i=1}^{n} x_{i0} x_{id} = \sum_{i=1}^{n} x_{i0} y_i$$



$$w_0 \sum_{i=1}^{n} x_{i1} x_{i0} + w_1 \sum_{i=1}^{n} x_{i1} x_{i1} + w_2 \sum_{i=1}^{n} x_{i1} x_{i2} + \dots + w_d \sum_{i=1}^{n} x_{i1} x_{id} = \sum_{i=1}^{n} x_{i1} y_i$$

 $w_0 \sum_{i=1}^{n} x_{id} x_{i0} + w_1 \sum_{i=1}^{n} x_{id} x_{i1} + w_d \sum_{i=1}^{n} x_{id} x_{i2} + \dots + w_d \sum_{i=1}^{n} x_{id} x_{id} = \sum_{i=1}^{n} x_{id} y_i$

Quadratic Function Optimization $\mathbf{A}\mathbf{w} = \mathbf{b}$

$$\mathbf{A} = \begin{pmatrix} \sum_{i=1}^{n} x_{i0} x_{i0}, \sum_{i=1}^{n} x_{i0} x_{i1}, \dots, \sum_{i=1}^{n} x_{i0} x_{id} \\ \sum_{i=1}^{n} x_{i1} x_{i0}, \sum_{i=1}^{n} x_{i1} x_{i1}, \dots, \sum_{i=1}^{n} x_{i1} x_{id} \\ \dots \\ \sum_{i=1}^{n} x_{id} x_{i0}, \sum_{i=1}^{n} x_{id} x_{i1}, \dots, \sum_{i=1}^{n} x_{id} x_{id} \end{pmatrix} \qquad \mathbf{w} = \begin{pmatrix} w_{0} \\ w_{1} \\ \dots \\ w_{d} \end{pmatrix}$$

$$\mathbf{b} = \begin{pmatrix} \sum_{i=1}^{n} x_{i0} y_{i} \\ \sum_{i=1}^{n} x_{i1} y_{i} \\ \dots \\ \sum_{i=1}^{n} x_{id} y_{i} \end{pmatrix}$$

$$\mathbf{w} = \begin{pmatrix} w_0 \\ w_1 \\ \dots \\ w_d \end{pmatrix}$$

$$\mathbf{b} = \begin{pmatrix} \sum_{i=1}^{n} x_{i0} y_i \\ \sum_{i=1}^{n} x_{i1} y_i \\ \dots \\ \sum_{i=1}^{n} x_{id} y_i \end{pmatrix}$$

Quadratic Function Optimization

Using given data, let's define X and Y

$$(x_{11}, x_{12}, \dots, x_{1d}, y_1)$$

 $(x_{21}, x_{22}, \dots, x_{2d}, y_2)$
 \dots
 $(x_{n1}, x_{n2}, \dots, x_{nd}, y_n)$

$$\mathbf{X} = \begin{pmatrix} x_{10}, x_{11}, x_{12}, \dots, x_{1d} \\ x_{20}, x_{21}, x_{22}, \dots, x_{2d} \\ \dots \\ x_{n0}, x_{n1}, x_{n2}, \dots, x_{nd} \end{pmatrix} \quad \mathbf{Y} = \begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{pmatrix}$$

- Then,

$$\mathbf{A} = \begin{pmatrix} \sum_{i=1}^{n} x_{i0} x_{i0}, \sum_{i=1}^{n} x_{i0} x_{i1}, \dots, \sum_{i=1}^{n} x_{i0} x_{id} \\ \sum_{i=1}^{n} x_{i1} x_{i0}, \sum_{i=1}^{n} x_{i1} x_{i1}, \dots, \sum_{i=1}^{n} x_{i1} x_{id} \\ \dots \\ \sum_{i=1}^{n} x_{id} x_{i0}, \sum_{i=1}^{n} x_{id} x_{i1}, \dots, \sum_{i=1}^{n} x_{id} x_{id} \end{pmatrix} = \mathbf{X}^{T} \mathbf{X} \qquad \mathbf{b} = \begin{pmatrix} \sum_{i=1}^{n} x_{i0} y_{i} \\ \sum_{i=1}^{n} x_{i1} y_{i} \\ \dots \\ \sum_{i=1}^{n} x_{id} y_{i} \end{pmatrix} = \mathbf{X}^{T} \mathbf{Y}$$

Quadratic Function Optimization

$$\mathbf{w} = \left(\mathbf{X}^T \mathbf{X}\right)^{-1} \left(\mathbf{X}^T \mathbf{Y}\right)$$

$$f(\mathbf{x}_i) = w_0 x_{i0} + w_1 x_{i1} + w_2 x_{i2} + \dots + w_d x_{id} = \sum_{j=0}^d w_i x_{ij}$$

$$(x_{11}, x_{12}, ..., x_{1d}, y_1)$$

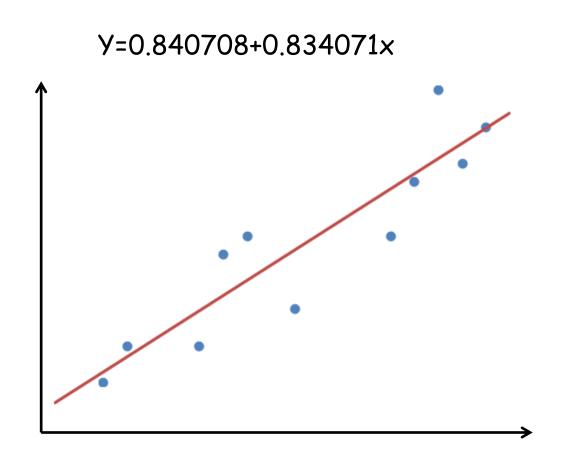
 $(x_{21}, x_{22}, ..., x_{2d}, y_2)$
...
 $(x_{n1}, x_{n2}, ..., x_{nd}, y_n)$

$$\mathbf{X} = \begin{pmatrix} 1, x_{11}, x_{12}, \dots, x_{1d} \\ 1, x_{21}, x_{22}, \dots, x_{2d} \\ \dots \\ 1, x_{n1}, x_{n2}, \dots, x_{nd} \end{pmatrix} \qquad \mathbf{Y} = \begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{pmatrix}$$

$$\mathbf{Y} = \begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{pmatrix}$$

Example

```
(2, 2)
(3, 4)
(6, 4)
(7, 9)
(8, 10)
(10, 6)
(14, 10)
(15, 13)
(16, 18)
(17, 14)
(18, 16)
```



Example

$$\mathbf{A} = \mathbf{X}^T \mathbf{X} = \begin{pmatrix} 11,116 \\ 116,1552 \end{pmatrix}$$

$$\mathbf{b} = \mathbf{X}^T \mathbf{Y} = \begin{pmatrix} 106 \\ 1392 \end{pmatrix}$$

$$\mathbf{w} = (A)^{-1}(b) = \begin{pmatrix} 0.840708 \\ 0.834071 \end{pmatrix}$$

Generalized Version of Linear Regression

Linear Regression

$$f(\mathbf{x}) = w_0 + w_1 x_1 + w_2 x_2 + \dots + w_d x_d = w_0 + \sum_{j=1}^d w_j x_j$$

- Find ws so that f(x) best fits given data
- Generalized Linear Regression
 - Instead of single variables, let's use pre-determined functions

of **x**,
$$h(x)$$
\$
$$f(\mathbf{x}) = w_0 + w_1 h_1(\mathbf{x}) + w_2 h_2(\mathbf{x}) + \dots + w_d h_d(\mathbf{x}) = w_0 + \sum_{j=1}^d w_j h_j(\mathbf{x})$$

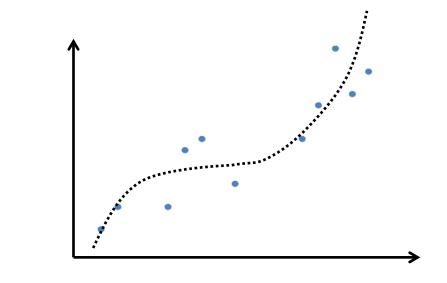
Find w's so that f(x) best fits given data

For example,
$$f(x) = w_0 + w_1 \sin(\pi x) + w_2 e^x$$

Example

Find the 3rd order Polynomial which best fits the data

(2, 2) (3, 4) (6, 4) (7, 9) (8, 10) (10, 6) (14, 10) (15, 13) (16, 18) (17, 14) (18, 16)

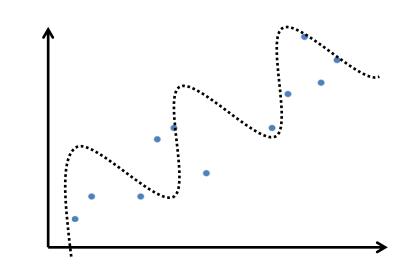


Use this model $f(x) = w_0 + w_1 h_1(x) + w_2 h_2(x) + w_3 h_3(x)$ where, $h_1(x) = x$, $h_2(x) = x^2$, $h_3(x) = x^3$

Example

You think that the given data are periodic

(2, 2) (3, 4) (6, 4) (7, 9) (8, 10) (10, 6) (14, 10) (15, 13) (16, 18) (17, 14) (18, 16)



You may use $f(x) = w_0 + w_1 h_1(x) + w_2 h_2(x)$ where, $h_1(x) = x$, $h_2(x) = \sin(ax)$

How to solve this???

Find $\mathbf{w} = (w_0, w_1, \dots, w_k)$ which minimizes $E(\mathbf{w})$ where $E(\mathbf{w}) = \sum_{i=1}^{n} (f(\mathbf{x}_i) - y_i)^2$ $f(\mathbf{x}_i) = w_0 h_0(\mathbf{x}_i) + w_1 h_1(\mathbf{x}_i) + \dots + w_k h_k(\mathbf{x}_i) \quad \text{where } h_0(\mathbf{x}_i) = 1$ $D = \{D_1, D_2, \dots, D_n\}$ $D_i = (\mathbf{x}_i, y_i)$ $\mathbf{x}_i = (x_{i1}, x_{i2}, \dots, x_{id})$

How to solve this

Solution

$$\mathbf{w} = \left(\mathbf{H}^T \mathbf{H}\right)^{-1} \left(\mathbf{H}^T \mathbf{Y}\right)$$

Where

$$\mathbf{H} = \begin{pmatrix} h_0(\mathbf{x}_1), h_1(\mathbf{x}_1), \dots, h_k(\mathbf{x}_1) \\ h_0(\mathbf{x}_2), h_1(\mathbf{x}_2), \dots, h_k(\mathbf{x}_2) \\ \dots \\ h_0(\mathbf{x}_n), h_1(\mathbf{x}_n), \dots, h_k(\mathbf{x}_n) \end{pmatrix} \qquad \mathbf{Y} = \begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{pmatrix}$$

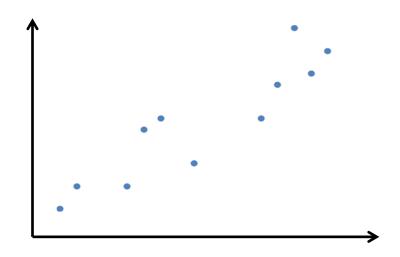
Example

Find the 3rd order Polynomial which best fits the data

- (2, 2)
- (3, 4)
- (6, 4)
- (7, 9)
- (8, 10)
- (10, 6)
- (14, 10)
- (15, 13)
- (16, 18)
- (17, 14)
- (18, 16)

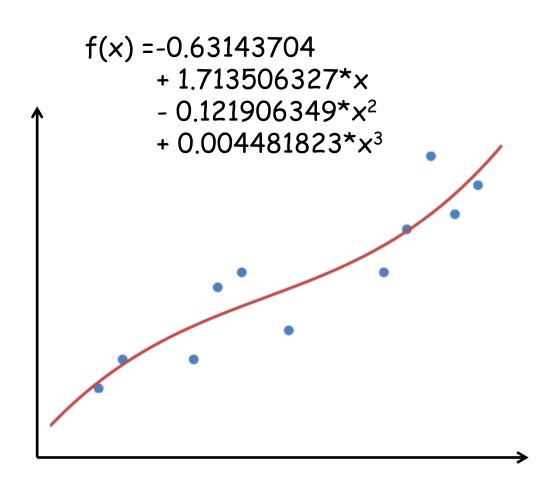
$$f(x) = w_0 + w_1 h_1(x) + w_2 h_2(x) + w_3 h_3(x)$$

where,
$$h_1(x) = x$$
, $h_2(x) = x^2$, $h_3(x) = x^3$



Example

(2, 2) (3, 4) (6, 4) (7, 9) (8, 10) (10, 6) (14, 10) (15, 13) (16, 18) (17, 14) (18, 16)

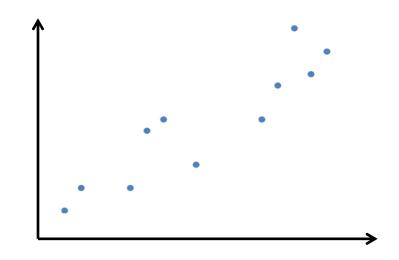


Example

You think that the given data are periodic

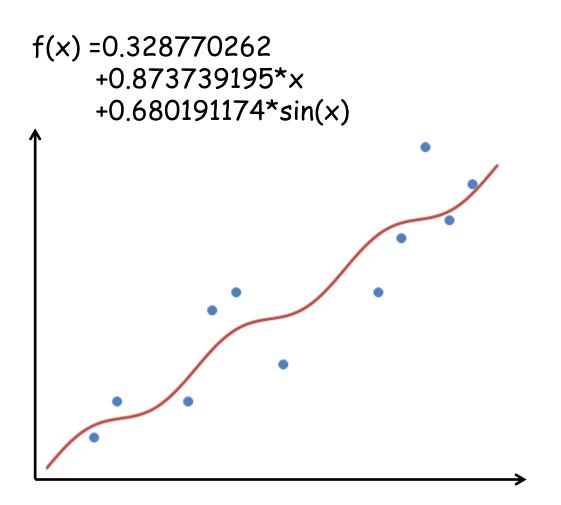
$$f(x) = w_0 + w_1 h_1(x) + w_2 h_2(x)$$

where, $h_1(x) = x$, $h_2(x) = \sin(ax)$



Example

(2, 2) (3, 4) (6, 4) (7, 9) (8, 10) (10, 6) (14, 10) (15, 13) (16, 18) (17, 14) (18, 16)



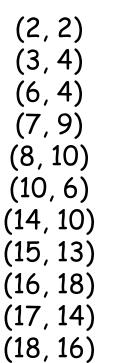
Example: Kernel Regression

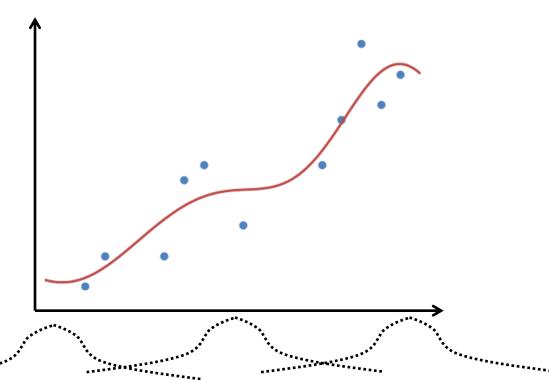
You can find a linear combination of given kernel functions

$$f(x) = w_0 + w_1 h_1(x) + w_2 h_2(x) + w_3 h_3(x)$$
where, $h_1(x) = \exp\left(\frac{-(x-1)^2}{18}\right)$, $h_2(x) = \exp\left(\frac{-(x-9)^2}{18}\right)$,
$$h_3(x) = \exp\left(\frac{-(x-18)^2}{18}\right)$$

Example

$$f(x) = 5.76 - 3.64 \exp\left(\frac{-(x-1)^2}{18}\right) + 2.40 \exp\left(\frac{-(x-9)^2}{18}\right) + 10.82 \exp\left(\frac{-(x-18)^2}{18}\right)$$





Another Approaches

Solving Linear Equations

Simplest Approach for Linear Regression

Another Approaches to Solve Linear Regression

- Gradient Descent Approach
- Maximum Likelihood Estimation Approach
- => Both give the same solution as SLE gives

Then, Why?

 Both are well-known, useful and important methods to solve problems in ML domain