Elements of statistical learning: Chapter 2

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Content

Introduction

Supervised learning

Goal is to use *inputs* to predict *outputs*.

- inputs are also referred to as *predictors*, *features* or *independent variable*
- outputs are also referred to as *response* or *dependent variables*

The outputs may be

- quantitative (takes values in $\mathbb{R}$)
- qualitative (also known as categorical or discrete)
  - Ordered (e.g. small, medium or large)
  - Unordered (e.g. pass or fail, on or off)

Regression vs classification

We use *regression* to predict quantitative outputs and *classification* to predict qualitative outputs.

Notations

For different predictors $\{X_k\}_{k=1}^{p}$ across different observations $i = 1, \cdots, n$ denote

$X_{i,k}$	for random variable and $x_{i,k}$ for an observation
X_i	for a $p \times 1$ vector of variables $- i.e. X_i = [X_{i,1}, \cdots, X_{i,p}]'$
$\boldsymbol{X}$	for a $N \times p$ matrix of variables across different obvs

In other words

$$\boldsymbol{X} = \begin{bmatrix} X_{11} & \cdots & X1p \\ X_{21} & \cdots & X2p \\ \vdots & \ddots & \vdots \\ X_{n1} & \cdots & X_{np} \end{bmatrix} = \begin{bmatrix} X_1' \\ X_2' \\ \vdots \\ X_n' \end{bmatrix}$$

Therefore, denotes (X_i, Y_i) as the random variables and (x_i, y_i) as the observed values at i.

Linear models and least squares

To predict Y (which would be denoted by $\hat{Y}$), we use the linear regression model, which may be expressed as

$$Y_i = \beta_0 + \beta_1 X_{i,1} + \cdots + \beta_p X_{i,p} + \epsilon_i, \quad i = 1, \cdots, n \tag{1}$$

or as

$$Y_i = \beta_0 + \sum_{k=1}^{P} \beta_k X_{i,k} + \epsilon_i, \quad i = 1, \cdots, n \tag{2}$$

or as

$$Y_i = X_i' \beta + \epsilon_i, \quad , i = 1, \cdots, n \tag{3}$$

where $X_i = [1, X_{i,1}, \cdots, X_{i,p}]'$ and $\beta = [\beta_0, \beta_1, \cdots, \beta_p]'$ are $(p+1) \times 1$ vectors.

In matrix notation, the above can be expressed as

$$\boldsymbol{Y} = \boldsymbol{X}\beta + \boldsymbol{\epsilon} \tag{4}$$

which if expanded is expressed as follows

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} 1 & X_{1,1} & X_{1,2} & \cdots & X_{1,p} \\ 1 & X_{2,1} & X_{2,2} & \cdots & X_{2,p} \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ 1 & X_{n,1} & X_{n,2} & \cdots & X_{n,p} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix} \tag{5}$$

Least squares estimation

The least squares estimation in one approach to fit the model. In essence, we find the coefficiens β that minimize the sum of squared residuals. Thus, we wish to minimize $RSS(\beta)$

$$\arg\min_{\beta} RSS(\beta) \text{ or } (\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta})'(\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta})$$

The above can be rearranged and expanded to (which is not necessary, as chain rule can be used)

$$\begin{aligned}
(\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta})'(\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}) &= (\boldsymbol{y}' - \boldsymbol{\beta}'\boldsymbol{X}')(\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}) \\
&= \boldsymbol{y}'\boldsymbol{y} - \boldsymbol{y}'\boldsymbol{X}\boldsymbol{\beta} - \boldsymbol{\beta}'\boldsymbol{X}'\boldsymbol{y} + \boldsymbol{\beta}'\boldsymbol{X}'\boldsymbol{X}\boldsymbol{\beta}
\end{aligned}$$

Differentiating with respect to β yields

$$\begin{aligned}\frac{\partial RSS(\beta)}{\partial\beta} &= 0 - \boldsymbol{X'y} - \boldsymbol{X'y} + 2\beta\boldsymbol{X'X} \\ &= -2\boldsymbol{X'y} + 2\beta\boldsymbol{X'X}\end{aligned}$$

and as this is a minimization problem

$$\begin{aligned}\frac{\partial RSS(\beta)}{\partial\beta} &= 0 \\ -2\boldsymbol{X'y} + 2\beta\boldsymbol{X'X} &= 0 \\ \beta\boldsymbol{X'X} &= \boldsymbol{X'y}\end{aligned}$$

and thus so long as $\boldsymbol{X'X}$ is non-singular, the LS estimator of $\hat{\beta}$ is

$$\hat{\beta} = (\boldsymbol{X'X})^{-1}\boldsymbol{X'y} \tag{6}$$

Logit models

Now let us consider the case , where the dependent variable Y_i can assume only two categories (say win or lose), and hence two discrete values (i.e. $Y_i = 0$ or $Y_i = 1$), where as the vector of independent variables are continuous, say $X_i \in \mathbb{R}^p$.
In order to restrict Y_i to 0 and 1. In this case it would make sense to make the probability of $Y_i = 1$ and not the value of Y_i itself. This leads to a probability model, which specifies the the probbility of the outcome as a function of the predictor:

$$\begin{aligned} P[Y_i = 1] &= P[X_i, \beta] && (7) \\ P[Y_i = 0] &= 1 - P[X_i, \beta] && (8) \end{aligned}$$

Since P is a probability, it is bounded between 0 and 1. The regression equation may be revived by briefly denoting

$$P(X_i, \beta) = X_i' \beta$$

As we wish the pobability to vary monotically with X, we may use a *sigmoid* function:

$$P(X_i, \beta) = \frac{\exp(\beta' X_i)}{1 + \exp(\beta' X_i)} \tag{9}$$

Let us denote $Z_i = \beta' X_i$, then

$$\lim_{z \to \infty} \frac{\exp(z)}{1 + \exp(z)} = 1$$

and

$$\lim_{z \to -\infty} \frac{\exp(z)}{1 + \exp(z)} = 0$$

Therefore,

$$P[Y_i = 1] = \frac{\exp(\beta' X)}{1 + \exp(\beta' X)}$$

and

$$P[Y_i = 0] = \frac{1}{1 + \exp(\beta' X)}$$

Alternatively, one could look at the odd $P[Y_i = 1]/P[Y_i = 0]$, which may be expressed as

$$\begin{aligned} \frac{P[Y_i = 1]}{P[Y_i = 0]} &= \frac{\exp(\beta' X)}{1 + \exp(\beta' X)}[1 + \exp(\beta' X)]. \\ &= \exp(\beta' X). \end{aligned}$$

now taking the logarithm from both sides will yield

$$\log(odds) = \beta' X \tag{10}$$

where now $\log(odds)$ is no longer bounded by 0 and 1.

Nearet-neighbour algorithm

- A non-parametric approach used for both *classification* and *regression*
- Input consists of the k closest training examples in the feature space.
- Output depends on whether $K - NN$ is used or classification or regression.
- For classification, the output is a class membership
- For regression, this value is the average of the k nearest neighbbours
- Specifically it can be defined as

$$\hat{Y}(x) = \frac{1}{k} \sum_{x_i \in N_k(x)} y_i, \tag{11}$$

  where $N_k(x)$ is the neighbourhood of x defined by the k closest points x_i in the training sample.
- In other words, find the k nearest neighbours with x_i closest to x, and average their responses y_i.

L2 loss function

- Let random variables $X \in \mathbb{R}^p$ and $Y \in \mathbb{R}$ with joint distribution function $F(x, y)$.
- A function $g(X)$ is sought after for predicting Y, given values of the input X.
- This theory requires a loss function $L(Y, g(X))$ for penalizing errors in prediction.
- The most common and convenient is squared error loss

$$L(Y, g(X)) = (Y - g(X))^2 \tag{12}$$

which gives us the following criterion

$$EPE = \mathbb{E}[(Y - g(X))^2] \tag{13}$$

EXTRA: Some probability recap

The expectation operator $\mathbb{E}$ is defined for discrete and continuous variables as follows

- Discrete variables:

$$\mathbb{E}(X) = \sum_{i \in k} p_i x_i$$

  where k are the number of categories. E.g. A coin has two possible states of head (quantified as 1) and tail (quantified as 0) with equal probability. Therefore, the expectated value of the outcome of a coin toss is

$$\mathbb{E}(X) = 0.5 \times 0 + 0.5 \times 1 = 0.5$$

- Continuous variables:

$$\mathbb{E}[X] = \int_{\mathbb{R}} x f(x) dx$$

if density $f(x)$ exists. Otherwise,

$$\mathbb{E}[X] = \int_{\mathbb{R}} x dF(x)$$

(noting that $dF(X)/dx = f(x)$)

- Multivatiate continuous variable

$$\mathbb{E}[g(X_1, \cdots, X_n)] = \int_{x_1} \cdots \int_{x_n} g(x_1, \cdots, x_n) dF(x_1, \cdots, x_n)$$

and where the density $f(x_1, \cdots, x_n)$ exists

$$\mathbb{E}[g(X_1, \cdots, X_n)] = \int_{x_1} \cdots \int_{x_n} g(x_1, \cdots, x_n) f(x_1, \cdots, x_n) dx_1 \cdots dx_n$$

Finally, note that

$$F(x, y) = F(x \mid y)F(y)$$
$$F(x, y) = F(y \mid x)F(x)$$

Therefore, returning to (13)

$$\begin{aligned}
\mathbb{E}[(Y - g(X))^2] &= \int_x \int_y (y - g(x))^2 dF(y, x) \\
&= \int_x \int_y (y - g(x))^2 f(y, x) dy dx \\
&= \int_x \int_y (y - g(x))^2 f(y \mid x) f(x) dy dx \\
&= \int_x \mathbb{E}_{y|x}[(Y - g(X))^2 \mid X] f(x) dx \\
&= \mathbb{E}_X \mathbb{E}_{Y|X}[(Y - g(X))^2 \mid X]
\end{aligned}$$

- As the above expression is conditioned on X, there is no longer any dependency between X and the function g.
- furthermore, $[Y - g]^2$ is a convex function and we may minimize to solve for g

$$
\begin{aligned}
g(x) &= \arg\min_g \mathbb{E}_{y|x}[(Y - g(X))^2 \mid X = x] \\
&\rightarrow \frac{\partial}{\partial g} \int [y - g]^2 f(y \mid x) dy = 0 \\
&\rightarrow \int \frac{\partial}{\partial g} [y - g]^2 f(y \mid x) dy = 0 \\
&\rightarrow -2 \int [y - g] f(y \mid x) dy = 0 \\
&\rightarrow 2g \int f(y \mid x) dy = 2 \int y f(y \mid x) dy \\
&\rightarrow 2g \int f(y \mid x) dy = 2\mathbb{E}_{Y|X}[Y \mid X = x]
\end{aligned}
$$

Note that

$$\int_{\mathbb{R}} f(y \mid x) dy = 1$$

- Thus

$$\mathbb{E}[Y \mid X = x] = g(x)$$

- This conditional function is also known as the regression function. Thus, the best predictor of Y at any point $X = x$ is the conditional mean.

L1 loss function

- The L2 loss function is analytically more desirable, but an L1 criteria of the sort
$$\mathbb{E}[|Y - g(X)|]$$
is more robust to outliers. We may express (13) in the following manner using the L1 criteria:
$$\mathbb{E}[|Y - g(X)|] = \int \int |Y - g(X)| f(x, y) dy dx$$
where as before it may be expressed as
$$\mathbb{E}_X \mathbb{E}_{Y|X}[|Y - g(X)| | X]$$
and minimized by differentiating with respect to g - i.e.
$$\frac{\partial}{\partial g} \int |y - g(x)| f(y \mid x) dy = 0$$

The latter can be approxmiated by

$$
\begin{aligned}
\frac{\partial}{\partial g}\int |y-g| f(y \mid x) dy = & \quad \frac{\partial}{\partial g}\lim_{n\to\infty}\frac{1}{n}\sum_{i=1}^{n}|y_i-g| \\
\approx & \quad \frac{\partial}{\partial g}\frac{1}{n}\sum_{i=1}^{n}|y_i-g|
\end{aligned}
\tag{14}
$$

Note that the absolute function is piecewise

$$
|y_i-g|= \begin{cases} y_i-g, & y_i-g>0 \\ g-y_i, & y_i-g<0 \\ 0, & y_i=g \end{cases}
$$

So that taking the derivative is not continuous at zero

$$\frac{\partial}{\partial g}|y_i - g| = \begin{cases} -1, & y_i - g > 0 \\ 1, & y_i - g < 0 \\ 0, & y_i = g \end{cases}$$

which is very similar to a sign function - i.e.

$$sgn(z) = \begin{cases} -1, & z < 0 \\ 1, & z > 0 \\ 0, & z = 0 \end{cases}$$

which implies that we may express (14) as

$$\begin{aligned} \frac{\partial}{\partial g} \int |y - g| f(y \mid x) dy &= 0 \\ \frac{1}{n} \sum_{i=1}^{n} -sgn(y_i - g) &= 0 \\ \sum_{i=1}^{n} sgn(y_i - g) &= 0 \end{aligned}$$

The mean squared error at a nominated test point x_0 for a *deterministic* model of the form

$$Y = f(X) = \exp(-8||X||^2)$$

without any measurement errors, can be obtained by

$$\begin{aligned} MSE(x_0) &= \mathbb{E}_T[(f(x_0) - \hat{y}_0)^2] \\ &= \mathbb{E}_T[(f(x_0) \underbrace{-\mathbb{E}_T(\hat{y}_0) + \mathbb{E}_T(\hat{y}_0)}_{\text{add and deduct}} - \hat{y}_0)^2] \end{aligned}$$

Noting that by noting $\underbrace{f(x_0) - \mathbb{E}_T(\hat{y}_0)}_{a}$ and $\underbrace{\mathbb{E}_T(\hat{y}_0) - \hat{y}_0}_{a}$, the above is equivalent to $\mathbb{E}_T[(a+b)^2]$, and such can be expanded as follows

$$\begin{aligned} MSE(x_0) &= \mathbb{E}_T[(f(x_0) - \mathbb{E}_T(\hat{y}_0))^2 + (\mathbb{E}_T(\hat{y}_0) - \hat{y}_0)^2 \\ &+ 2[(f(x_0) - \mathbb{E}_T(\hat{y}_0))(\mathbb{E}_T(\hat{y}_0) - \hat{y}_0)] \end{aligned}$$

which may further get expanded as

$$
\begin{aligned}
MSE(x_0) &= \mathbb{E}_T[(f(x_0) - \mathbb{E}_T(\hat{y}_0))^2 + (\mathbb{E}_T(\hat{y}_0) - \hat{y}_0)^2 \\
&+ 2f(x_0)\mathbb{E}_T(\hat{y}_0) - 2f(x_0)\hat{y}_0 - 2\mathbb{E}_T(\hat{y}_0)\mathbb{E}_T(\hat{y}_0) + 2\mathbb{E}_T(\hat{y}_0)\hat{y}_0] \\
&= \mathbb{E}_T[(f(x_0) - \mathbb{E}_T(\hat{y}_0))^2] + \mathbb{E}_T[(\mathbb{E}_T(\hat{y}_0) - \hat{y}_0)^2] \\
&+ 2f(x_0)^2 - 2f(x_0)\hat{y}_0 - 2f(x_0)^2 + 2f(x_0)\hat{y}_0 \\
&= \mathbb{E}_T[(f(x_0) - \mathbb{E}_T(\hat{y}_0))^2] + \mathbb{E}_T[(\mathbb{E}_T(\hat{y}_0) - \hat{y}_0)^2]
\end{aligned}
$$

Note that by definition

- Variance: $\mathbb{E}_T[(f(x_0) - \mathbb{E}_T(\hat{y}_0))^2]$; and
- Bias: $\mathbb{E}_T[(\mathbb{E}_T(\hat{y}_0) - \hat{y}_0)]$

Thus,

$$MSE(x_0) = \sigma_T^2(\hat{y}_0) + Bias^2(\hat{y}_0) \tag{15}$$

Proofs of eq 2.26 and 2.27

Assume we know that the relationship between X and Y linear and follows the relationship

$$Y_i = X_i'\beta + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2) \tag{16}$$

and the model is fitted using the LS estimator, which is

$$\hat{\beta} = (X'X)^{-1}X'Y$$

which may alternatively be expressed as

$$\begin{aligned} \hat{\beta} = (X'X)^{-1}X'(X\beta + \epsilon) &= (X'X)^{-1}(X'X)\beta + (X'X)^{-1}X'\epsilon \\ &= \beta + (X'X)^{-1}X'\epsilon \end{aligned}$$

Thus, the linear model (16) can be expressed as

$$\begin{aligned} Y_i = X_i'[\beta + (X'X)^{-1}X'\epsilon] &= X_i'\beta + X_i'(X'X)^{-1}X'\epsilon \\ &= X_i'\beta + X(X'X)^{-1}X_i\epsilon \end{aligned}$$

Thus, at a nominated test point x_0, we have

$$\begin{aligned} \hat{y}_0 &= x_0'\beta + X(X'X)^{-1}x_0\epsilon \\ \hat{y}_0 &= x_0'\beta + \sum_{i=1}^{N} l_i(x_0)\epsilon_i \end{aligned}$$

where $l_i(x_0)$ is the $i-$th elemenet of the N vector $X(X'X)^{-1}x_0$.

Proof of equation 2.27

Here, since our target is no longer deterministic (pay attention to the error term in (16), the expected prediction error can be written as

$$EPE(x_0) = \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}(y_0 - \hat{y}_0)^2 \tag{17}$$

which as before may get expanded to

$$\begin{aligned}
EPE(x_0) &= \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[(y_0 - g(x_0)) + (g(x_0) - \hat{y}_0)]^2 \\
&= \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[(y_0 - g(x_0))^2] \\
&+ 2\mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[(y_0 - g(x_0))(g(x_0) - \hat{y}_0)] \\
&+ \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[(g(x_0) - \hat{y}_0)^2]
\end{aligned}$$

The first term $\mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[(y_0 - g(x_0))^2]$ is independent of the training set and as such can be expressed as

$$\begin{aligned}\mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[(y_0 - g(x_0))^2] &= \mathbb{E}_{y_0|x_0}[(y_0 - g(x_0))^2] \\ &= \int (y_0 - g(x_0))^2 f(y \mid x)dy\end{aligned}$$

and as $\mathbb{E}(y_0) = g(x_0)$ the first term is nothing but the conditional variance σ^2.

The second term can be factorized as before to get

$$\begin{aligned}\mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[(y_0 - g(x_0))(g(x_0) - \hat{y}_0)] &= \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[y_0 g(x_0)] - \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[y_0\hat{y}_0] \\ &- \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[g(x_0)^2] \\ &+ \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[g(x_0)\hat{y}_0]\end{aligned}$$

$\hat{y}_0$ is dependent on T and $g(x_0) = \mathbb{E}[y_0]$, so it is a constant term that we can reduce above to

$$= g(x_0)\mathbb{E}_{y_0|x_0}[y_0] - \mathbb{E}_{y_0|x_0}[y_0\mathbb{E}_T[\hat{y}_0]] - g(x_0)^2 + g(x_0)\mathbb{E}_{y_0|x_0}\mathbb{E}_T[\hat{y}_0]$$

noting that

$$\mathbb{E}_{y|x_0}[y_0] = \int y_0 f(y_0 \mid x_0)dy = g(x_0)$$

and for the 2nd term in relationship

$$\mathbb{E}_{y_0|x_0}[y_0\mathbb{E}_T[\hat{y}_0]] = \mathbb{E}_T[\hat{y}_0]\mathbb{E}_{y_0|x_0}[y_0] = \mathbb{E}_T[\hat{y}_0]g(x_0)$$

and the last term we get

$$g(x_0)\mathbb{E}_{y_0|x_0}\mathbb{E}_T[\hat{y}_0] = g(x_0)\mathbb{E}[\hat{y}_0]$$

Therefore, since $\mathbb{E}_{y_0|x_0}[y_0] = g(x_0)$

$$\begin{aligned}
\mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[(y_0 - g(x_0))(g(x_0) - \hat{y}_0)] &= g(x_0)\mathbb{E}_{y_0|x_0}[y_0] - \mathbb{E}_{y_0|x_0}[y_0\mathbb{E}_{\mathcal{T}}[\hat{y}_0]] \\
&- g(x_0)^2 + g(x_0)\mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[\hat{y}_0] \\
&= g(x_0)^2 - g(x_0)\mathbb{E}_{\mathcal{T}}[\hat{y}_0] \\
&- g(x_0)^2 + g(x_0)\mathbb{E}_{\mathcal{T}}[\hat{y}_0] = 0
\end{aligned}$$

Thus,

$$\begin{aligned}
EPE(x_0) &= \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[(y_0 - g(x_0))^2] + \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[(g(x_0) - \hat{y}_0)^2] \\
&= \sigma^2 + \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[(g(x_0) - \hat{y}_0)^2] \\
&= \sigma^2 + \underbrace{\mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[g(x_0)^2] - 2\mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[g(x_0)\hat{y}_0]} + \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[\hat{y}_0^2]
\end{aligned}$$

Noting that

$$\begin{aligned}
\mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[(g(x_0) - \mathbb{E}_{\mathcal{T}}[\hat{y}_0])^2] &= \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[g(x_0)^2] - 2\mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[g(x_0)\hat{y}_0] \\
&+ \mathbb{E}_{y_0|x_0}\mathbb{E}_{\mathcal{T}}[\hat{y}_0]^2
\end{aligned}$$

The expression in the brackets can be substituted with

$$\mathbb{E}_{y_0|x_0}\mathbb{E}_T[(g(x_0) - \mathbb{E}_T[\hat{y}_0])^2] - \mathbb{E}_{y_0|x_0}\mathbb{E}_T[\hat{y}_0]^2$$

which implies

$$\begin{aligned} EPE(x_0) &= \mathbb{E}_{y_0|x_0}\mathbb{E}_T[(y_0 - g(x_0))^2] + \mathbb{E}_{y_0|x_0}\mathbb{E}_T[(g(x_0) - \hat{y}_0)^2] \\ &= \sigma^2 + \mathbb{E}_{y_0|x_0}\mathbb{E}_T[(g(x_0) - \mathbb{E}_T[\hat{y}_0])^2] \\ &- \mathbb{E}_{y_0|x_0}\mathbb{E}_T[\hat{y}_0]^2 + \mathbb{E}_{y_0|x_0}\mathbb{E}_T[\hat{y}_0^2] \end{aligned}$$

noting that

$$\sigma_T^2(\hat{y}_0) = \mathbb{E}_T[\hat{y}_0^2] - \mathbb{E}_T[\hat{y}_0]^2$$

Hence

$$\begin{aligned} EPE(x_0) &= \sigma^2(y_0 \mid x_0) + \mathbb{E}_{y_0|x_0}\mathbb{E}_T[(g(x_0) - \mathbb{E}_T[\hat{y}_0])^2] + \sigma_T^2(\hat{y}_0) \\ &= \sigma^2(y_0 \mid x_0) + Bias^2(\hat{y}_0) + \sigma_T^2(\hat{y}_0) \end{aligned}$$

Maximum likelihood estimation

For a random sample $\{y_i\}_{i=1}^N$ from a density function $P_\theta[y]$ indexed by some parameters θ, the likelihood function is

$$L(\theta) = \prod_{i=1}^{N} P_\theta[y_i] \tag{18}$$

while the log-likelihood function is given by

$$l(\theta) = \sum_{i=1}^{N} P_\theta[y_i] \tag{19}$$

Assuming with the additive error model is of the form

$$Y = g_\theta(X) + \varepsilon, \quad \varepsilon \sim N(g_\theta(X), \sigma^2)$$

then the log-likelihoof function of data is derived as follows:

We know that the conditional normal distribution function is

$$F(y \mid g_\theta(x)) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{y} \exp\left(\frac{-(y - g_\theta(x))^2}{2\sigma^2}\right)$$

with a density function

$$f(y \mid g_\theta(x)) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(\frac{-(y - g_\theta(x))^2}{2\sigma^2}\right)$$

thus,

$$\begin{aligned}
l(\theta) &= \sum_{i=1}^{N} \log\left(\frac{1}{\sigma\sqrt{2\pi}} \exp\left(\frac{-(y - g_\theta(x))^2}{2\sigma^2}\right)\right) \\
&= N \log\left(\frac{1}{\sigma\sqrt{2\pi}}\right) + \sum_{i=1}^{N} \log\left(\exp\left(\frac{-(y - g_\theta(x))^2}{2\sigma^2}\right)\right) \\
&= -N \log(\sigma\sqrt{2\pi}) + \sum_{i=1}^{N} \left(\frac{-(y - g_\theta(x))^2}{2\sigma^2}\right)
\end{aligned}$$

$$
\begin{aligned}
l(\theta) &= -N\log(\sigma\sqrt{2\pi}) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}(y_i - g_\theta(x_i))^2 \\
&= -N\log(\sigma) - N\log(\sqrt{2\pi}) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}(y_i - g_\theta(x_i))^2 \\
&= -N\log(\sigma) - \frac{N}{2}\log(2\pi) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}(y_i - g_\theta(x_i))^2
\end{aligned}
$$

which is the proof of equation (2.35) in the book.