

# Elements of statistical learning: Chapter 2

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# 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  $i = 1, \dots, n$  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.  $X_i = [X_{i,1}, \dots, X_{i,p}]'$

$\mathbf{X}$  for a  $N \times p$  matrix of variables across different obs

In other words

$$\mathbf{X} = \begin{bmatrix} X_{11} & \cdots & X_{1p} \\ X_{21} & \cdots & X_{2p} \\ \vdots & \ddots & \vdots \\ X_{n1} & \cdots & X_{np} \end{bmatrix} = \begin{bmatrix} X'_1 \\ X'_2 \\ \vdots \\ X'_n \end{bmatrix}$$

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

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

or as

$$Y_i = \beta_0 + \sum_{k=1}^p \beta_k X_{i,k} + \epsilon_i, \quad i = 1, \dots, n \quad (2)$$

or as

$$Y_i = X_i' \beta + \epsilon_i, \quad i = 1, \dots, n \quad (3)$$

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

In matrix notation, the above can be expressed as

$$\mathbf{Y} = \mathbf{X}\beta + \epsilon \quad (4)$$

which if expanded is expressed as follows

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

# Least squares estimation

The least squares estimation is one approach to fit the model. In essence, we find the coefficients  $\beta$  that minimize the sum of squared residuals.

Thus, we wish to minimize  $RSS(\beta)$

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

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

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

Differentiating with respect to  $\beta$  yields

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

and as this is a minimization problem

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

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

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



# 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 probability of the outcome as a function of the predictor:

$$P[Y_i = 1] = P[X_i, \beta] \quad (7)$$

$$P[Y_i = 0] = 1 - P[X_i, \beta] \quad (8)$$

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 probability to vary monotonically with  $X$ , we may use a *sigmoid* function:

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

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

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

and

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

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.

# Nearest-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 for classification or regression.
- For classification, the output is a class membership
- For regression, this value is the average of the  $k$  nearest neighbours
- Specifically it can be defined as

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

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

$$L(Y, g(X)) = (Y - g(X))^2 \quad (12)$$

which gives us the following criterion

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

## 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 expected value of the outcome of a coin toss is

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

- Continuous variables:

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

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

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

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

- Multivariate continuous variable

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

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

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

Finally, note that

$$F(x, y) = F(x | y)F(y)$$

$$F(x, y) = F(y | x)F(x)$$

Therefore, returning to (13)

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



- 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  $g$

$$g(x) = \arg \min_g \mathbb{E}_{y|x}[(Y - g(X))^2 | X = x]$$

$$\rightarrow \frac{\partial}{\partial g} \int [y - g]^2 f(y | x) dy = 0$$

$$\rightarrow \int \frac{\partial}{\partial g} [y - g]^2 f(y | x) dy = 0$$

$$\rightarrow -2 \int [y - g] f(y | x) dy = 0$$

$$\rightarrow 2g \int f(y | x) dy = 2 \int y f(y | x) dy$$

$$\rightarrow 2g \int f(y | x) dy = 2\mathbb{E}_{Y|X}[Y | X = x]$$

Note that

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

- Thus

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

- 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.

$$\frac{\partial}{\partial g} \int |y - g(x)| f(y | x) dy = 0$$

The latter can be approximated by

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

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.

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

which implies that we may express (14) as

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

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

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

which may further get expanded as

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

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,

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

## Proofs of eq 2.26 and 2.27

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

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

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 element 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

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

which as before may get expanded to

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

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

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

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

The second term can be factorized as before to get

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

$\hat{y}_0$  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

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

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

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

Thus,

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

Noting that

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

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

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

noting that

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

Hence

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