Interpreting Log Error

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Let $\hat{P}$ be an estimate of the target value P. Say in the training we have obtained

$$\log\left(1+P\right)=\log\left(1+\hat{P}\right)\pm\hat{\epsilon} \tag{1}$$

where $\hat{\epsilon}$ is some estimate [1] of the test error and

$$\hat{\epsilon}\ll 1\ll \hat{P}, \tag{2}$$

then

$$P\approx\hat{P}\left(1\pm\hat{\epsilon}\right),\quad \hat{P}\approx P\left(1\pm\hat{\epsilon}\right). \tag{3}$$

In other words, the error $\hat{\epsilon}$ for $\log(1+\hat{P})$ translates [2] to the percentage-error $100\hat{\epsilon}$ % for $\hat{P}$.

Proof. From (1), we have $\log\left[\left(1+P\right)/(1+\hat{P})\right]=\pm\hat{\epsilon}$, that is,

$$P=-1+e^{\pm\hat{\epsilon}}\left(1+\hat{P}\right) \tag{4}$$

Since $\hat{\epsilon}$ is relatively small, e.g. $\hat{\epsilon}\approx 0.01$ (see (2)), by Taylor series,

$$e^{\pm\hat{\epsilon}}\approx 1\pm\hat{\epsilon} \tag{5}$$

Substitue (5) into (4), we have

$$\begin{aligned} P&\approx\hat{P}\pm\hat{\epsilon}\hat{P}\pm\hat{\epsilon}\\ &\approx\hat{P}\left(1\pm\hat{\epsilon}\right) \end{aligned} \tag{6}$$

Notice that in the last step leading to (6), we drop the term $\pm\hat{\epsilon}$ since $\hat{\epsilon}\ll\hat{P}$ and $\hat{\epsilon}\ll\hat{\epsilon}\hat{P}$ (see (2)). This proves the first approximation in (3).

Next, from (6), we estimate that

$$\hat{P}\approx P\left(1\pm\hat{\epsilon}\right), \tag{7}$$

which can be derived by substituting the following approximation into (6):

$$\frac{1}{1\mp\hat{\epsilon}}=1\pm\hat{\epsilon}+\hat{\epsilon}^2\pm\hat{\epsilon}^3+\ldots\approx 1\pm\hat{\epsilon}.$$

This proves the second approximation in (3). □

[1] For example, we may take $\hat{\epsilon}$ to be the worst (largest) root mean square error from cross validations.

[2] By the way, (3) also hold for the case when $\log P=\pm\hat{\epsilon}+\log\hat{P}$ under the same assumption (2). The proof is similar.