

Frequentist v.s. Bayesian

Usually, we face problems that given samples to find out the the hypothesis conditions (parameters). In statistics, that is to maximize:

$$P(\text{Hypotheses}|\text{Samples})$$

In general, there're 2 major parties for this type of question: Frequentist and Bayesian.

Frequentist

Frequentist inference based on likelihood, and does not require a prior hypothesis on probability, which is actually the MLE routine, Maximum Likelihood Estimation.

$$L(\theta|x_i) = \prod_{\{i=1\}}^n P(x_i|\theta)$$

To maximize the likelihood is to maximize its 'log' transformation:

$$\log(L(\theta|x_i)) = \log\left(\prod_i P(x_i|\theta)\right) = \sum_i \log(P(x_i|\theta))$$

take partials with respect to θ and set it equal to 0:

$$\frac{\partial \log(L(\theta|x_i))}{\partial \theta} = \frac{\partial \log \prod_i P(x_i|\theta)}{\partial \theta} = \frac{\partial \sum_i \log P(x_i|\theta)}{\partial \theta} = 0$$

simplify the function and get the MLE estimator for θ .

Therefore, for MLE estimator:

$$\begin{aligned}\theta_{MLE} &= \operatorname{argmax}_{\theta} P(X|\theta) \\ &= \operatorname{argmax}_{\theta} \log P(X|\theta) \\ &= \operatorname{argmax}_{\theta} \log \prod_i P(x_i|\theta) \\ &= \operatorname{argmax}_{\theta} \sum_i \log P(x_i|\theta)\end{aligned}$$

Bayesian

Bayesian inference is based on Bayes' Theorem, where it considers about probabilities for both samples and hypotheses, thus requires the probability for prior hypothesis. It follows a MAP (Maximum A Posteriori Estimation) routine.

$$\begin{aligned}\theta_{MAP} &= \operatorname{argmax}_{\theta} P(X|\theta)P(\theta) \\ &= \operatorname{argmax}_{\theta} \log P(X|\theta)P(\theta) \\ &= \operatorname{argmax}_{\theta} \log \prod_i P(x_i|\theta)P(\theta) \\ &= \operatorname{argmax}_{\theta} \sum_i \log P(x_i|\theta)P(\theta)\end{aligned}$$