# Bayesian Machine Learning, MLE, MAP - II

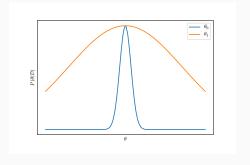
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## **Fully Bayesian Approach**

• MLE and MAP do not give us uncertainty.



**Figure 1:** More uncertainty around  $\theta_0$  than  $\theta_1$ 

- P(Next Toss = H| Data)
- What value of  $\theta$  should be used?
- Answer: Use all the possible values of  $\theta$ .
- $P(\text{Next Toss} = H|Data) = \int P(\text{Next Toss} = H, \theta| \text{ Data})d\theta$ Why?
- Marginalization!  $p(x) = \int_{Y} p(x, y) dy$
- Note that the conditioning above is only over the observed data or evidence.

#### Predictive Distribution for the Coin Toss Problem if $\theta$ is known

- Let c be a random variable that is assigned the value 1 if head results after tossing a coin and 0 if tail results after tossing a coin.
- Question: What is  $P(\text{Next Toss} = c | \theta)$ ?
- Answer:  $\theta^c (1-\theta)^{1-c}$ . Why?
- Suppose c = 0. Then  $P(Tails|\theta) = (1 \theta)$ .

- Let us consider the case where we have a Beta prior for our coin toss problem. What is the predictive distribution, given we have observed some data?
- Answer:  $P(\text{Next} = c | \mathcal{D}, a, b) = \int P(\text{Next} = c, \theta | \mathcal{D}, a, b) d\theta$
- From the chain rule of probability, we have the following:

$$P(AB|CDE) = \frac{P(ABCDE)}{P(CDE)} = \frac{P(A|BCDE)P(BCDE)}{P(CDE)}$$

$$= P(A|BCDE)P(B|CDE)$$

- In our case, the integrand  $P(\text{Next} = c, \theta | \mathcal{D}, a, b)$  therefore becomes,  $P(\text{Next} = c, |\theta, \mathcal{D}, a, b)P(\theta | \mathcal{D}, a, b)$
- If  $\theta$  is known, then  $P(\text{Next} = c | \theta, \mathcal{D}, a, b) = P(\text{Next} = c | \theta)$ . Why?
- This is because we know the actual model parameter distribution. The data *cannot* affect it. What about a and b affecting the prior? They do not concern us anymore either, since we actually know the parameters.
- ullet The predictive distribution is,

$$\int_{\theta} \theta^{c} (1-\theta)^{1-c} \frac{\Gamma(n_{H}+n_{T}+a+b)\theta^{n_{H}+a-1}(1-\theta)^{n_{T}+b-1}d\theta}{\Gamma(n_{H}+a)\Gamma(n_{T}+b)}$$

$$= \frac{\Gamma(n_H + n_T + a + b)}{\Gamma(n_H + a)\Gamma(n_T + b)} \int_{\theta} \theta^{n+h+a-1+c} (1 - \theta)^{n_T + b - c} d\theta$$

$$= \frac{\Gamma(n_H + n_T + a + B)\Gamma(c + n_H + a)\Gamma(n_T + b - c + 1)}{\Gamma(n_H + a)\Gamma(n_T + b)\Gamma(1 + n_H + a + n_T + b)}$$