

# **Q & A: Bayesian Learning**

Lecture series „Machine Learning“

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# Quiz: Bayes Rule

- The **Bayes rule** states that for any two random variables  $u, v$  it holds that

$$p(u | v) = \frac{p(v | u)p(u)}{p(v)}$$

- Assume you get tested for a rare disease. You know the following probabilities:

$p(\text{test} = 1 | \text{disease} = 1) = 0.9$       # The test has a false-negative rate of 10%

$p(\text{test} = 1 | \text{disease} = 0) = 0.1$       # The test has a false-positive rate of 10%

$p(\text{disease} = 1) = 0.01$       # 1% of population have the disease

$p(\text{test} = 1) = 0.108$       # 10.8% of population test positive (follows)

- Given that you were tested positive, what is the probability that you have the disease?
  - It is around 20%
  - It is around 8%
  - It is around 1%
  - Cannot say based on the information provided

# Solution: Bayes Rule

- The **Bayes rule** states that for any two random variables  $u, v$  it holds that

$$p(u | v) = \frac{p(v | u) p(u)}{p(v)}$$

- We can apply the Bayes rule as follows:

$$p(disease = 1 | test = 1) = \frac{p(test = 1 | disease = 1) p(disease = 1)}{p(test = 1)}$$

- Plugging in the numbers, we obtain

$$p(disease = 1 | test = 1) = \frac{0.9 \cdot 0.01}{0.108} \approx 0.083$$

- Therefore the probability is around 8%

# Quiz: Coin Tosses

- Assume we toss a coin with unknown parameter  $\theta \in [0,1]$ , and observe as data  $\mathcal{D}$  5 head tosses and 0 tail tosses
- As prior distribution, we assume a Beta distribution as given in the lecture with hyperparameters  $\alpha_h = 5$ ,  $\alpha_t = 5$
- According to the posterior distribution, what is the probability that  $\theta = 1$  ?
  - $p(\theta = 1 | \mathcal{D}) \approx 0.05$
  - $p(\theta = 1 | \mathcal{D}) \approx 0.11$
  - $p(\theta = 1 | \mathcal{D}) \approx 0.3$
  - $p(\theta = 1 | \mathcal{D}) = 0$
  - $p(\theta = 1 | \mathcal{D}) = 1$

# Solution: Coin Tosses

- **Solution:** The posterior distribution is again given by a Beta distribution with parameters  $\alpha_h + N_h = 10$  and  $\alpha_t + N_t = 5$
- The Beta distribution in general is given by

$$\begin{aligned} p(\theta) &= \text{Beta}(\theta \mid \alpha_h, \alpha_t) \\ &= \frac{\Gamma(\alpha_h + \alpha_t)}{\Gamma(\alpha_h)\Gamma(\alpha_t)} \theta^{\alpha_h-1} (1-\theta)^{\alpha_t-1} \end{aligned}$$

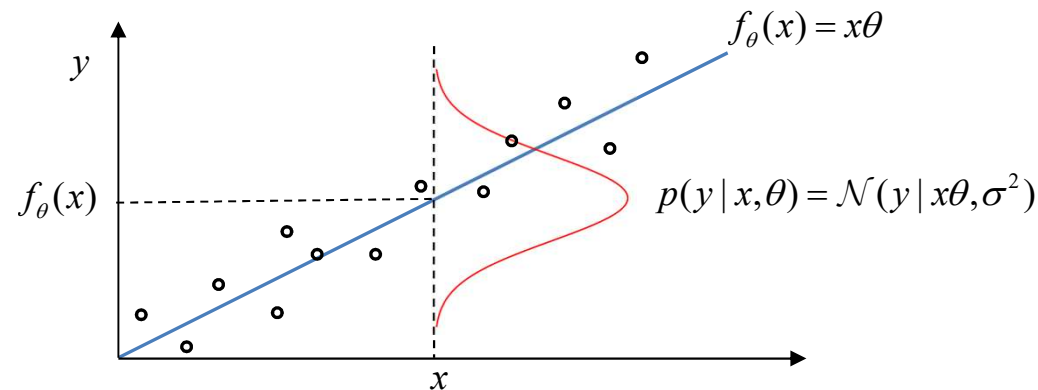
so the posterior in our case is

$$\begin{aligned} p(\theta \mid \mathcal{D}) &= \text{Beta}(\theta \mid 10, 5) \\ &= \frac{\Gamma(15)}{\Gamma(10)\Gamma(5)} \theta^9 (1-\theta)^4 \end{aligned}$$

- Clear that  $p(\theta = 1 \mid \mathcal{D}) = 0$

# Quiz: Bayesian Linear Regression

- Assume a univariate Bayesian linear regression model  $f_\theta(x) = x\theta$ :



- On a given data set  $\mathcal{D}$ , we train two models: model A with hyperparameter  $\sigma = 1$  and model B with hyperparameter  $\sigma = 10$ . Everything else stays the same.
- What can we say about the variance of the posterior distribution  $p(\theta | \mathcal{D}) = \mathcal{N}(\theta | \mu_{pos}, \sigma_{pos}^2)$  of models A and B?
  - Variance of posterior distribution for model B is **higher** than for model A
  - Variance of posterior distribution for model B is **lower** than for model A
  - Variance of posterior distribution is **identical** for both models
  - Cannot say based on the information provided

# Solution: Bayesian Linear Regression

- **Solution:** the posterior distribution is given by

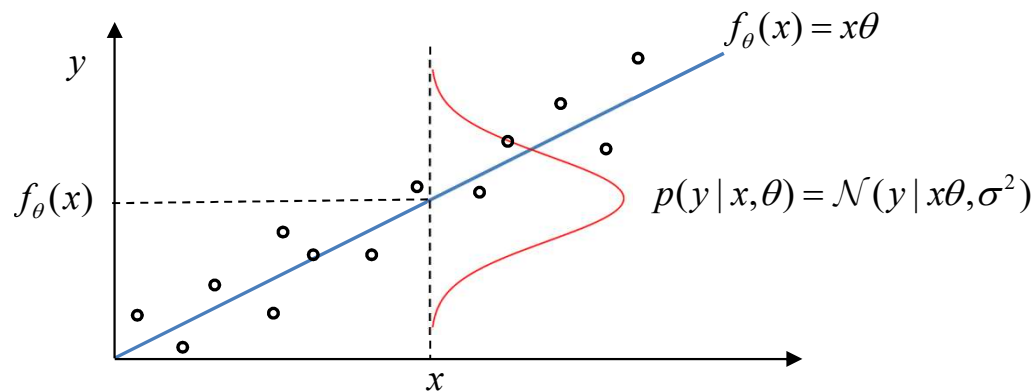
$$p(\theta | \mathbf{y}, \mathbf{X}) = \mathcal{N}(\theta | \bar{\theta}, A^{-1})$$

$$\text{where } A = \underbrace{\sigma^{-2} \mathbf{X}^T \mathbf{X}}_{\in \mathbb{R}_{>0}} + \sigma_p^{-2} \quad \text{and} \quad \bar{\theta} = \sigma^{-2} A^{-1} \mathbf{X}^T \mathbf{y}$$

- As can be seen, increasing the data variance  $\sigma$  leads to smaller  $A$  and therefore higher variance

# Solution: Bayesian Linear Regression

- **Intuitive Explanation:** increasing the size of the hyperparameter  $\sigma$  corresponds to the assumption that the data fluctuates more strongly around an assumed true model  $\theta^*$  :



- The more noise/fluctuations there are in the data, the less the data tells us about the true model
- Therefore, at the same data size set, the remaining uncertainty about what the true model is will be higher if  $\sigma$  is higher
- Therefore, the variance of the posterior distribution is higher