

# ELEN 4903 Machine Learning

## HW1

Name: Wenbo Song

UNI: ws2505

### Problem 1

(a) Because  $x_1, x_2 \dots x_n$  are i.i.d, given that  $p(x_i|\pi) = \pi^{x_i}(1 - \pi^{1-x_i})$  the joint likelihood of  $(x_1, \dots, x_N)$  is shown as follow

$$\begin{aligned} p(x_1, x_2 \dots x_n|\pi) &= p(x_1|\pi) \dots \dots p(x_n|\pi) \\ &= (\pi^{x_1}(1 - \pi^{1-x_1})) \dots \dots (\pi^{x_N}(1 - \pi^{1-x_N})) \\ &= \pi^{\sum_{i=1}^n x_i} (1 - \pi)^{\sum_{i=1}^n 1-x_i} \end{aligned}$$

(b) The maximum likelihood estimates  $\hat{\pi}_{ML} = \operatorname{argmax}(\pi^{\sum_{i=1}^n x_i} (1 - \pi)^{\sum_{i=1}^n 1-x_i})$

To find  $\hat{\pi}_{ML}$ , we want to calculate the gradient of  $\pi^{\sum_{i=1}^n x_i} (1 - \pi)^{\sum_{i=1}^n 1-x_i} = 0$  and the solution is the  $\hat{\pi}_{ML}$ .

$$\nabla_{\pi} \pi^{\sum_{i=1}^n x_i} (1 - \pi)^{\sum_{i=1}^n 1-x_i} = 0$$

$$\frac{\sum_{i=1}^n x_i}{\pi} - \sum_{i=1}^n x_i - N + \sum_{i=1}^n x_i = 0$$

We get the solution

$$\pi = \frac{\sum_{i=1}^n x_i}{N}$$

(c) We want to find  $\Pr(\pi|X) = \frac{\Pr(X|\pi)\Pr(\pi)}{\Pr(X)}$

Then we have

$$\hat{\pi}_{map} = \operatorname{argmax} \Pr(\pi|X)$$

$$= \operatorname{argmax} \frac{\Pr(X|\pi) \Pr(\pi)}{\Pr(X)}$$

$$= \operatorname{argmax} \Pr(X|\pi) \Pr(\pi)$$

$$= \operatorname{argmax} \prod_{x_i \in X} \Pr(X_i|\pi) \Pr(\pi)$$

We write the equation in log form

$$\begin{aligned} \operatorname{argmax} \Pr(\pi|X) &= \operatorname{argmax} \log \Pr(\pi|X) \\ &= \operatorname{argmax} \log \prod_{x_i \in X} \Pr(X_i|\pi) \Pr(\pi) \\ &= \operatorname{argmax} \sum \log \Pr(x_i|\pi) + \Pr(\pi) \end{aligned}$$

We want to find  $\hat{\pi}_{map}$  which is the  $\pi$  that let

$$\frac{1}{\pi} \sum_{i=1}^n x_i - \frac{1}{1-\pi} \sum_{i=1}^n (1-x_i) + \frac{\alpha-1}{\pi} - \frac{\beta-1}{1-\pi} = 0$$

Solve the equation we have

$$\hat{\pi}_{map} = \frac{\sum x_i + \alpha - 1}{n + \beta + \alpha - 2}$$

(d) if we know that  $\pi$  is followed beta distribution, we have

$$P(\pi) = \text{Beta}(\pi|a, b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \pi^{a-1} (1-\pi)^{b-1}$$

from Bayes rule

$$P(\pi|x_1, \dots, x_n) = \frac{P(x_1, \dots, x_n|\pi)P(\pi)}{\int_0^1 P(x_1, \dots, x_n|\pi)P(\pi)d\pi}$$

We can write  $p(\pi|x) \propto p(x|\pi)p(\pi)$

Multiply the two we have

$$P(\pi|x_1, \dots, x_n) \propto \pi^{\sum_{i=1}^n x_i + a - 1} (1-\pi)^{\sum_{i=1}^n (1-x_i) + b - 1}$$

We can recognize this as  $P(\pi|x_1, \dots, x_n) = \text{Beta}(\sum_{i=1}^n (x_i + a), \sum_{i=1}^n (1-x_i) + b)$

So, it's a Beta distribution.

(e) The mean of  $\pi$  is  $E[X] = \frac{1}{1+\frac{\beta}{\alpha}}$  where  $\alpha = \sum_{i=1}^n x_i + a$ ,  $\beta = \sum_{i=1}^n (1-x_i) + b$

So we can get that  $E[X] = \frac{1}{1 + \frac{\sum_{i=1}^n (1-x_i) + b}{\sum_{i=1}^n x_i + a}}$

The variance of  $\pi$  is  $\text{var}(X) = E[(X - u)^2] = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$

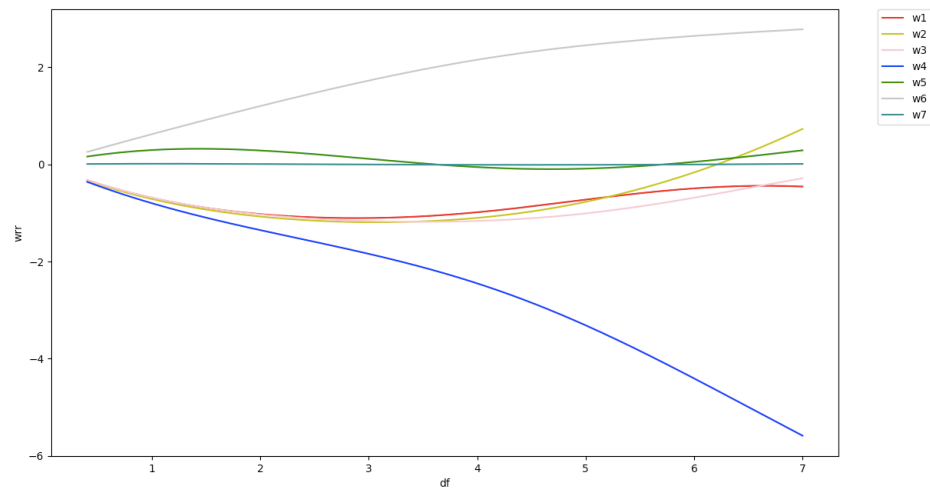
So we can get that  $\text{var}(X) = \frac{(\sum_{i=1}^n x_i + a)(\sum_{i=1}^n (1-x_i) + b)}{(\sum_{i=1}^n x_i + a + \sum_{i=1}^n (1-x_i) + b)^2 (\sum_{i=1}^n x_i + a + \sum_{i=1}^n (1-x_i) + b + 1)}$

Relations:  $\hat{\pi}_{ML}$  is unbiased but potentially has high variance, by contrast,  $\hat{\pi}_{map}$  is biased but has a lower variance than  $\hat{\pi}_{ML}$

## Problem 2

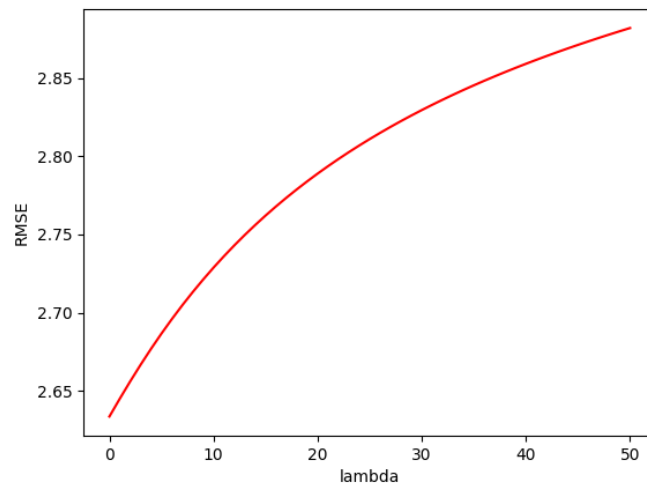
### Part 1

(a) For  $\lambda = 0, 1, 2, 3, \dots, 5000$  the relation between wr and  $df(\lambda)$  is shown as following graph



(b) We can see that  $w_4$  and  $w_6$  stand out than other features, which indicates that the  $w_4$ , car weight and the  $w_6$ , car year has more influence than the other features.

(c) The root mean squared error on the test set is shown as follow:

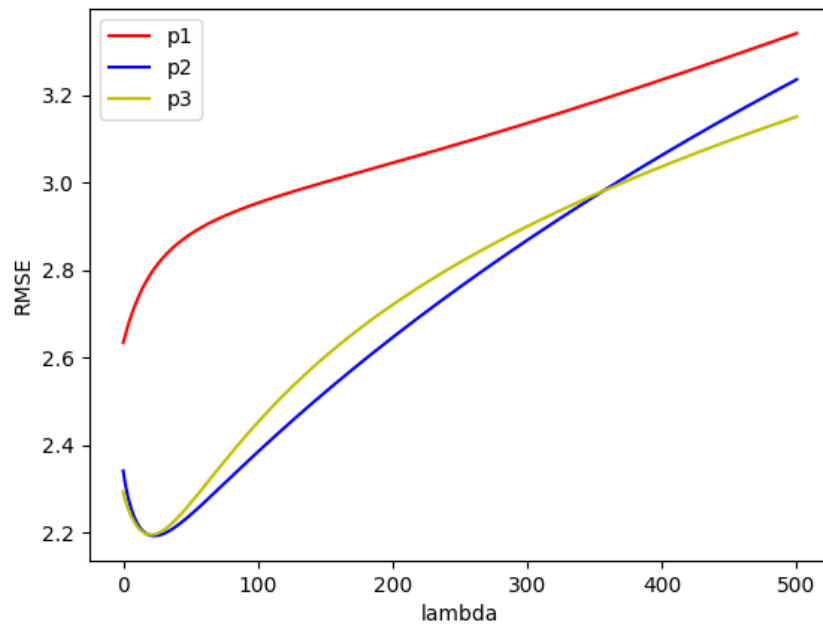


When  $\lambda$  decrease, we can find that eh RMSE decrease, which will lead to a better result, so in this case, we can choose the minimum lambda to get the optimal value.

When  $\lambda$  is 0, the regression became the least square regression. So in this case, we can choose the square regression to get a better performance.

Part2.

(d) The RMSE for  $p = 1, 2, 3$  can be seen as follow:



Based on this plot, we can see that when  $\lambda < 500$ ,  $p = 2$  and  $p = 3$  has very similar performance. Before  $\lambda = 300$ , we can choose  $p2$ , after  $\lambda = 300$  before  $\lambda = 500$ , we can choose  $p3$ .

For  $\lambda$ , we can see that when  $\lambda = 20$ , all three regression,  $p1$ ,  $p2$ ,  $p3$  has the relatively smallest values, so in this problem, we can choose  $\lambda$  to be 20.