

Problem 1:

$$(a) P(x_1, x_2, \dots, x_n | \pi, r) = \prod_{i=1}^n \binom{x_i + r - 1}{x_i} \pi^{x_i} (1 - \pi)^r$$

$$= \prod_{i=1}^n \binom{x_i + r - 1}{x_i} \pi^{\sum x_i} (1 - \pi)^{Nr}$$

$$(b) \frac{\partial P(x_1, \dots, x_n | \pi, r)}{\partial \pi} = 0$$

$$-Nr(1-\pi)^{Nr-1} \hat{\pi}_{ML}^{\sum x_i} + (\sum x_i) \hat{\pi}_{ML}^{\sum x_i - 1} (1 - \hat{\pi}_{ML})^{Nr} = 0$$

$$\hat{\pi}_{ML} = \frac{\sum x_i}{\sum x_i + Nr}$$

$$(c) P(\pi | x_1, \dots, x_n) \propto \pi^{\sum x_i} (1 - \pi)^{Nr} \cdot \pi^{a-1} (1 - \pi)^{b-1}$$

$$\propto \pi^{\sum x_i + a - 1} (1 - \pi)^{Nr + b - 1}$$

$$\text{So } P(\pi | x_1, \dots, x_n) = \text{Beta}(\sum x_i + a, Nr + b)$$

$$\frac{\partial}{\partial \pi} \text{Beta}(\sum x_i + a, Nr + b) = 0 \Rightarrow$$

$$\hat{\pi}_{map} = \frac{\sum x_i + a - 1}{\sum x_i + a + Nr + b}$$

(d) as shown in (c):

$P(\pi | x_1, \dots, x_n)$  is a Beta distribution.

$\sim \text{Beta}(\sum x_i + a, Nr + b)$ .

QED.

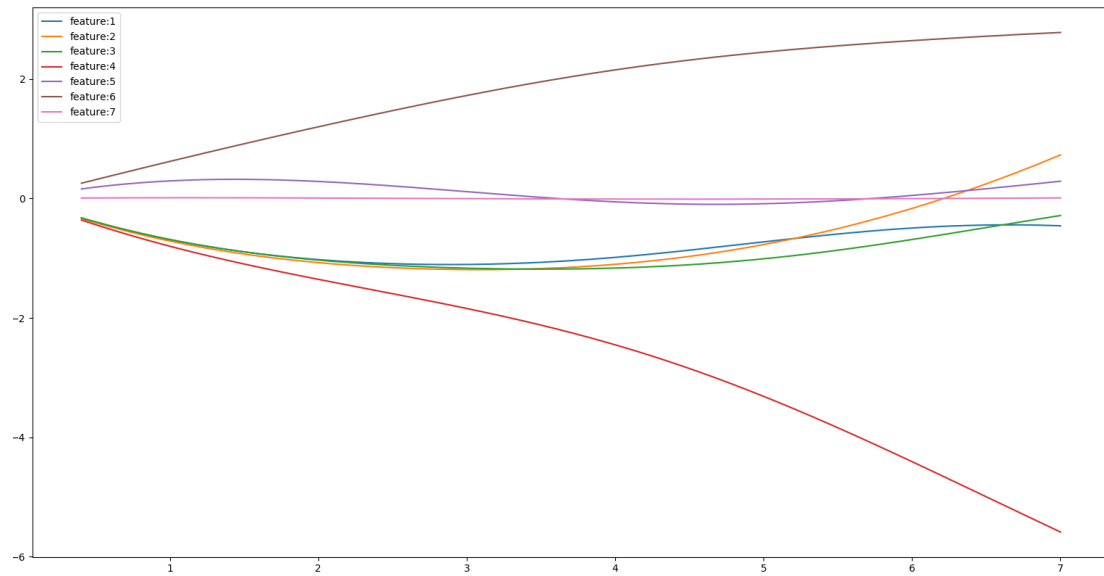
(e) the mean is  $\frac{\sum x_i + a}{\sum x_i + a + N + b}$

the variance is  $\frac{\alpha \beta}{(\alpha + \beta)^2 (\alpha + \beta + 1)}$ ,  $\alpha = \sum x_i + a$ ,  $\beta = N + b$

$\hat{\pi}_{map}$  is really close to the mean of distribution  
And when  $\alpha$  and  $\beta$  are all zero, the mean is  
equals to  $\hat{\pi}_{ML}$

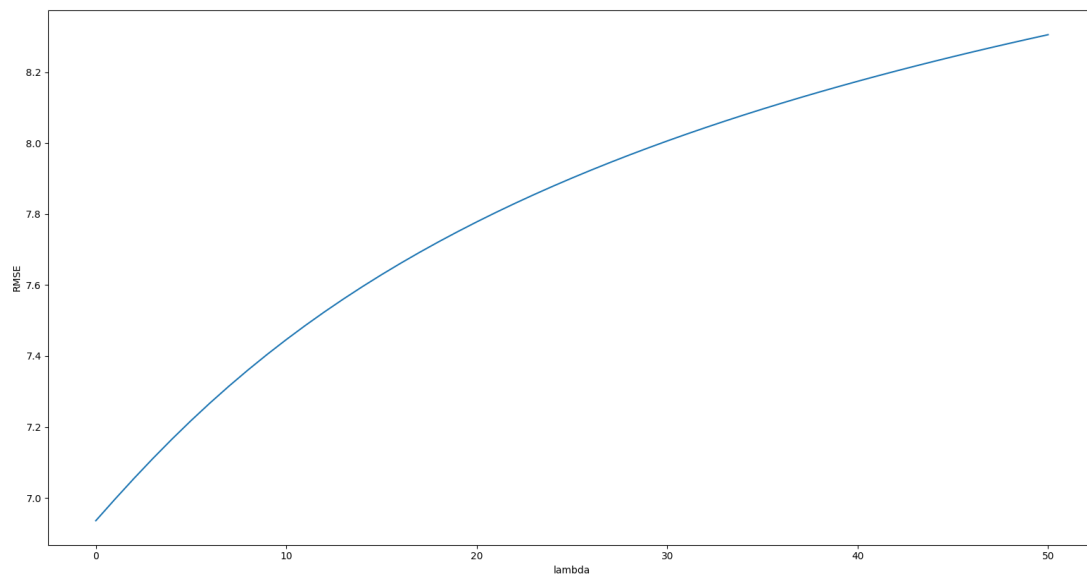
## Problem2:

### Part 1.(a)



(b) It seems the fourth and the sixth dimension have greater influence on “y” than other dimensions. When  $\lambda$  is small, these two dimensions are much more influential than others. And it becomes less obvious when  $\lambda$  increases.

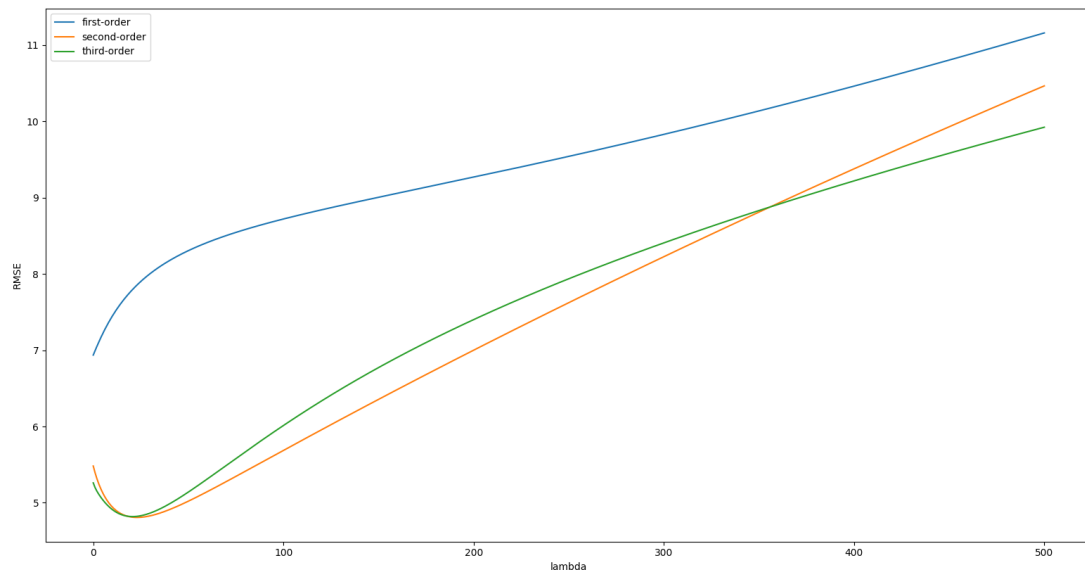
(c).



I would choose  $\lambda=0$ , in other words I would choose least square regression.

## Part 2.

(d)



I think  $p = 2$  is better. Because the RMSE of second order and third order is very similar, so I prefer to predict the result with less features since it can save calculation resource.

The primary goal of using  $\lambda$  is preventing overfitting. In the case of first order regression, there is no issue about overfitting. So when  $\lambda$  increase the RMSE just increase. And In the case of second and third order regression, the overfitting may affect our prediction. Thus we introduce a proper  $\lambda$  (about 25) to handle this, and it works good. However, if  $\lambda$  is too big it will still increase the RMSE.