

# Homework 1

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## 1 Problem 1

### 1.1 Part 1

#### 1.1.1 (a)

$$L = \prod_{i=1}^N P(x_i|\pi)$$

#### 1.1.2 (b)

Apply logarithm trick:

$$\log(L) = \sum_{i=1}^N \log(P(x_i|\pi))$$

Calculate gradient:

$$\Delta \log(L) = \sum_{i=1}^N \frac{P(x_i|\pi)'}{P(x_i|\pi)} = 0$$

Because

$$\frac{P(x|\pi)'}{P(x|\pi)} = \begin{cases} \frac{1}{\pi} & (x = 1) \\ \frac{-1}{1-\pi} & (x = 0) \end{cases}$$

Taken into gradient equation yields:

$$\frac{k}{\pi} = \frac{N-k}{1-\pi}$$

where  $k$  represents the number of 1s in  $\{x_1, \dots, x_N\}$ . Therefore

$$\hat{\pi}_{ML} = \frac{k}{N}$$

### 1.1.3 (c)

We can regard the observation set as taken from a sample space, where the definition of Bernoulli distribution indicates a portion  $\pi$  of the samples are 1s. The i.i.d nature of the observations shows they are randomly taken from the sample space, so  $\pi N$  of them are 1s is the most probable outcome.

## 1.2 Part 2

### 1.2.1 (a)

$$L = \prod_{i=1}^N P(x_i|\lambda)$$

### 1.2.2 (b)

Apply logarithm trick:

$$\log(L) = \sum_{i=1}^N \log(P(x_i|\lambda))$$

Calculate gradient:

$$\Delta \log(L) = \sum_{i=1}^N \frac{P(x_i|\lambda)'}{P(x_i|\lambda)} = 0$$

Because

$$\frac{P(x|\lambda)'}{P(x|\lambda)} = \frac{x - \lambda}{\lambda}$$

Taken into gradient equation yields:

$$\sum_{i=1}^N \frac{x_i - \lambda}{\lambda} = 0$$

Therefore

$$\hat{\lambda}_{ML} = \frac{\sum_{i=1}^N x_i}{N}$$

### 1.2.3 (c)

From the definition of Poisson distribution,  $x$  represents the number of events happen in a unit amount of time, and  $\lambda$  represents the average number of event occurrences in that amount of time. Clearly the estimation is reasonable given the nature that samples are randomly taken.

## 2 Problem 2

### 2.1 (a)

Using Bayesian rule:

$$\begin{aligned} p(\lambda|x_1, \dots, x_N) &\propto p(x_1, \dots, x_N|\lambda)p(\lambda) \\ &\propto \prod_{i=1}^N p(x_i|\lambda)p(\lambda) \\ &\propto \lambda^{\sum x} e^{-\lambda} \lambda^{a-1} e^{-b\lambda} \\ &\propto \lambda^{(\sum x + a) - 1} e^{-(b+N)\lambda} \end{aligned}$$

Clearly, the posterior of  $\lambda$  is also a Gamma distribution.

$$\lambda \sim \text{Gam}(\sum x + a, N + b)$$

### 2.2 (b)

According to the definition of Gamma distribution:

$$\begin{aligned} E(\lambda) &= \frac{\sum x + a}{N + b} \\ \text{var}(\lambda) &= \frac{\sum x + a}{(N + b)^2} \end{aligned}$$

We can see here the mean and variance of the posterior distribution are both smoothed by factor  $a$  in numerator and  $b$  in denominator. So this relates to Part 2 of Problem 1 as being a normalized version of ML estimate.

## 3 Problem 3

### 3.1 Part 1

#### 3.1.1 (a)

Label	Value
intercept term	23.5473136163
number of cylinders	-0.53624543
displacement	1.27906133
horsepower	-0.05922578
weight	-6.19362742
acceleration	0.24448757
model year	2.83663356

Here, positive sign means input is proportional to output, negative sign means input is inverse proportional to output.

### 3.1.2 (b)

$$\mu_{MAE} = 2.67044377205$$

$$\sigma_{MAE} = 0.480117507216$$

## 3.2 Part 2

### 3.2.1 (a)

$p$	$\mu$	$\sigma$
1	3.3875118672114795	0.68638502743433716
2	2.7864791778065361	0.66563803353712114
3	2.6891000472522428	0.6158636996172675
4	2.7235048725782884	0.61841079752286376

Clearly,  $p = 3$  has the best performance.

### 3.2.2 (b)

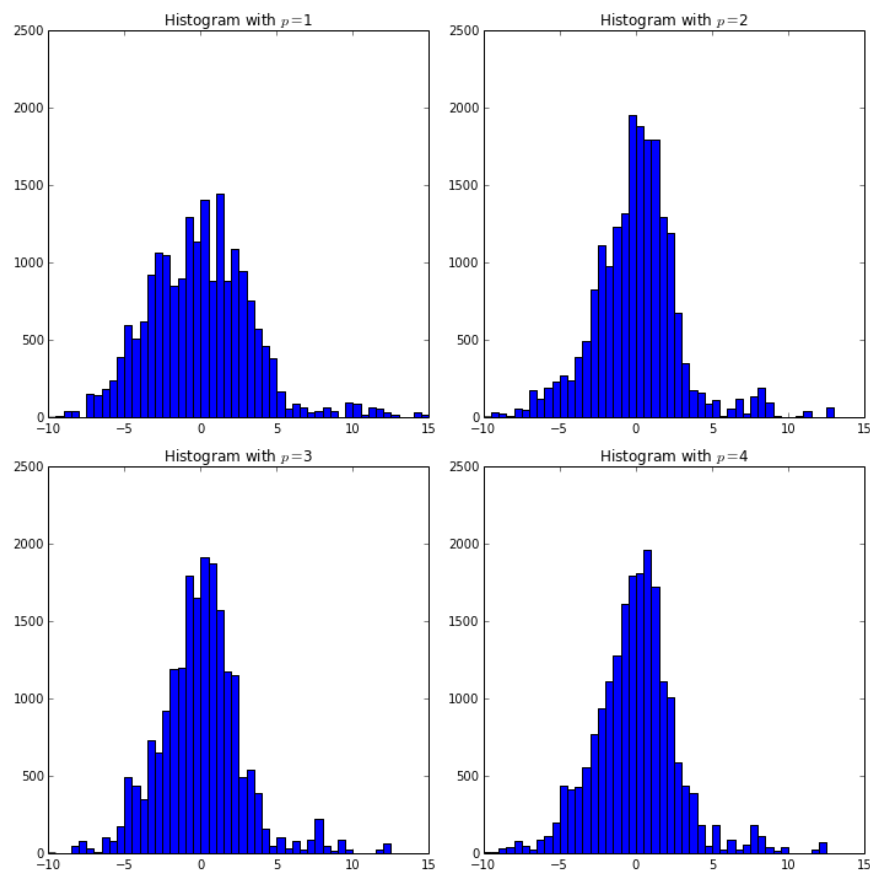


Figure 1: Histograms for each  $p$  value

### 3.2.3 (c)

The maximum likelihood values of mean  $\mu$  and variance  $\sigma$  are calculated as

$$\mu = \frac{\sum_{i=1}^{20000} Err_i}{20000}$$
$$\sigma^2 = \frac{\sum_{i=1}^{20000} (Err_i - \mu)^2}{20000}$$

The log-likelihoods are

$p$ value	log likelihood
1	-53292.1185271
2	-49240.2680536
3	-48466.7455654
4	-49428.5843529

The results here agrees with that of part2(a) in that both show the optimal order is  $p = 3$ . The assumption that the log likelihood of errors is also a measure of the spread of the error range is satisfied. Meaning the larger the log likelihood is, the more concentrated the RMSE errors are, and the better the  $p$  value is.