

# Group Homework 2

## ○ Histogram Problem

- Imagine a random variable  $X$  such that,  $P_X(k) = \pi_k, k \in 1, \dots, N$
- Suppose we draw  $n$  independent observations from  $X$  and form a random vector  $C = (C_1, \dots, C_N)^T$  where  $C_k$  is the number of times where the observed value is  $k$

- $C$  is then a *histogram* and has a *multinomial distribution*:

$$P_{C_1, \dots, C_N}(c_1, \dots, c_N) = \frac{n!}{\prod_{k=1}^N c_k!} \prod_{j=1}^N \pi_j^{c_j}$$

- Note that  $\pi = (\pi_1, \dots, \pi_w)$  are probabilities and thus:  $\pi_i \geq 0$  ,  $\sum \pi_i = 1$

- 1. Derive the ML estimate for parameters  $\pi_k, k \in \{1, \dots, N\}$

- *hint*: If you know about lagrange multipliers, use them! Otherwise, keep in mind that minimizing for a function  $f(a,b)$  constraint to  $a+b=l$  is equivalent to minimizing for  $f(a, l-a)$ .

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2. Derive the MAP solution using Dirichlet priors:

► One possible prior model over  $\pi_k$  is the *Dirichlet Distribution*:

$$P_{\Pi_1, \dots, \Pi_N}(\pi_1, \dots, \pi_N) = \frac{\Gamma(\sum_{j=1}^N u_j)}{\prod_{j=1}^N \Gamma(u_j)} \prod_{j=1}^N \pi_j^{u_j-1}$$

► where  $u$  is the set of *hyper-parameters* (prior parameters to solve) and

$$\Gamma(x) = \int_0^\infty e^{-t} t^{x-1} dt$$

is the Gamma function.

► You should show that the posterior is equal to:

$$P_{\Pi|C}(\pi|c) = \frac{\Gamma(\sum_{j=1}^W c_j + u_j)}{\prod_{k=1}^W \Gamma(c_j + u_j)} \prod_{j=1}^W \pi_j^{c_j+u_j-1}$$

3. Compare the MAP estimator with that of ML in part (I). What is the role of this prior compared to ML?