

Hypergeometric

①  $R \sim \text{Unif}([0, N])$     ②  $R \sim \text{Unif}([1, N-1])$

$D = (n, r) = (z, 1)$

③ Uninformative prior

$p(R) = ?$

$p(z=1 | N, R, n=2) = \text{Unif} ?$

$p(R) \propto \frac{1}{R(N-R)}$

$\frac{\binom{R}{z} \binom{N-R}{n-z}}{\binom{N}{n}} = \frac{2R(N-R)}{N(N-1)}$

uninformative prior

$p(R) = \frac{\text{Const}}{R(N-R)}, R=1, \dots, N-1$

$p(R | D=(z, 1), N) = \frac{\text{Const}}{R(N-R)} \cdot \binom{R}{z} \binom{N-R}{n-z} =$

$= \frac{\text{Const}}{z(n-z)} \cdot \binom{R-1}{z-1} \binom{N-R-1}{n-z-1}$

$\sum_{a=0}^b \binom{a}{x} \binom{b-a}{y-x} = \binom{b+1}{y+1}$

$\sum_{z=0}^b \binom{R}{z-1} \binom{N-R-1}{n-z-(z-1)} = \binom{N}{n-1}$

④ Binomial monkey prior

$g = \text{pr}[\text{cracklin}]$

$E[R] = gN$   
 $\text{Var}[R] = Ng(1-g)$

$p(R|N) = \binom{N}{R} g^R (1-g)^{N-R}$

$p(D|N) = \sum_{R=0}^N p(D|N, R) p(R|N) = \sum_{R=0}^N \frac{\binom{R}{z} \binom{N-R}{n-z}}{\binom{N}{n}} \binom{N}{R} g^R (1-g)^{N-R}$

$\binom{R}{z} \binom{N-R}{n-z} \binom{N}{R} = \binom{N}{n} \binom{n}{z} \binom{N-n}{R-z}$

$$= \binom{n}{2} \sum_{R=2}^{N-(n-2)} \binom{N-n}{R-2} g^R (1-g)^{N-R} = \sum_{R=2}^{N-n} \binom{N-n}{R-2} g^{R-2} (1-g)^{N-n-(R-2)}$$

$$= \binom{n}{2} \cdot g^2 (1-g)^{n-2} - 1$$

$$P(R|D, N) = \text{Const} \cdot \binom{N}{R} g^R (1-g)^{N-R} \binom{R}{2} \binom{N-R}{n-2} =$$

$$= \text{Const} \cdot \binom{N-n}{R-2} g^{R-2} (1-g)^{N-R-n+2} = \text{Const} \cdot \binom{N-n}{R-2} g^{R-2} (1-g)^{(N-n)-(R-2)}$$

$$= \text{Const} \cdot \binom{N-n}{R-2} g^{R-2} (1-g)^{(N-n)-(R-2)}$$

$$E[R|D, N] = 2 + (N-n)g \pm \sqrt{(N-n)g(1-g)}$$

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Энтропия

$(p_1, p_2, \dots, p_n)$

«мера неопределенности»

$$H_n(p_1, \dots, p_n) = - \sum_i p_i \log p_i$$

$$h(mn) = h(m) + h(n)$$

$$h(n) = c \cdot \log n$$

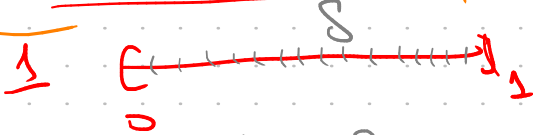
-  $H_n$  - мер.

-  $h(n) = H_n\left(\frac{1}{n}, \dots, \frac{1}{n}\right)$  - базисный мер по  $n$

- композибельность

$$H_3(p_1, p_2, p_3) = H_2(p_1, p_2+p_3) + (1-p_1) \cdot H_2\left(\frac{p_2}{p_2+p_3}, \frac{p_3}{p_2+p_3}\right)$$

Если "Укрупнение"  $\mathcal{I}$ ,  $\leftarrow$  при  $\delta$ -коор.  $(p_1, \dots, p_n)$



$$\delta = \frac{1}{N}$$

$N$  раз  $\delta$  раз делится  $\leftarrow$  и  $n$  раз

$$p_i = \frac{N_i}{N}$$

$n^N$  возм.  $n$ -векторов  
 $(N_1, N_2, \dots, N_n)$

$$P_{\mathcal{I}}(p_1, \dots, p_n) = n^{-N}$$

$$= \frac{N!}{N_1! N_2! \dots N_n!}$$

$p_1, \dots, p_n \rightarrow \max$

$$\log N! = N \log N - N + O(\sqrt{N})$$

$$\log \frac{N!}{N_1! N_2! \dots N_n!} = N \log N - N - \sum_{i=1}^n (N_i \log N_i - N_i) + O(\sqrt{N})$$

$$= N \log N - N - \sum_{i=1}^n p_i \cdot N (\log N + \log p_i) + \sum_{i=1}^n N_i + O(\sqrt{N})$$

$$= -N \sum_{i=1}^n p_i \log p_i + O(\sqrt{N})$$

6 Maximum entropy principle

$$KL(p||q) = \sum_i p_i \log \frac{p_i}{q_i}$$

$\rightarrow$  min  
"const"

- условие  $E[X] = m$

$$H = - \sum_{i=1}^6 p_i \log p_i \rightarrow \max_{p_i}$$

$$p_1 + \dots + p_6 = 1, p_i \geq 0$$

$$p_1 + 2p_2 + \dots + 6p_6 = m$$

$$L = - \sum_{i=1}^6 p_i \log p_i - \lambda \sum_i i p_i - \mu \sum p_i$$

$$\frac{\partial L}{\partial p_i} = -\log p_i - 1 - \lambda i - \mu = 0$$

$$p_i = e^{-\lambda i - \mu - 1}$$

$$e^{-\mu-1} \sum_{i=1}^6 e^{-\lambda i} = 1$$

$$e^{-\mu-1} \cdot \sum_{i=1}^6 i \cdot e^{-\lambda i} = m$$

$$m = \frac{\sum i e^{-\lambda i}}{\sum e^{-\lambda i}}$$

$$\mu = \log \sum e^{-\lambda i} - 1$$

⑦ Пример Max Ent: найти  $p(x)$ ,  $x \in \mathbb{R}$ , given макс. ent.  
с зад.  $\mu, \sigma^2$

$$H(p) = \int_{-\infty}^{\infty} p(x) \log p(x) dx \xrightarrow{p} \max$$

$$\int p(x) dx = 1, \quad \int x p(x) dx = \mu, \quad \int (x-\mu)^2 p(x) dx = \sigma^2$$

$$\begin{aligned} L(p, \lambda_0, \lambda_1, \lambda_2) = & \int p(x) \log p(x) dx - \lambda_0 \left(1 - \int p(x) dx\right) - \\ & - \lambda_1 \left(\mu - \int x p(x) dx\right) - \lambda_2 \left(\sigma^2 - \int (x-\mu)^2 p(x) dx\right) \end{aligned}$$

$$p + \delta p(x)$$

$$\delta L = \int (\delta p(x) \left( \log p(x) + 1 + \lambda_0 + \lambda_1 x + \lambda_2 (x-\mu)^2 \right) dx$$

$$0 + \delta p(x)$$

$$0 = \log p(x) + 1 + \lambda_0 + \lambda_1 x + \lambda_2 (x-\mu)^2$$

$$p(x) = e^{-1 - \lambda_0 - \lambda_1 x - \lambda_2 (x-\mu)^2}$$

$$p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2}$$

$H(q, p)$

$$\forall q: H(q) \leq H(p)$$

$$0 \leq KL(q||p) = \int q(x) \log \frac{q(x)}{p(x)} dx = -H(q) - \int q(x) \log p(x) dx$$

$$\int q(x) \left( -\frac{1}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} (x-\mu)^2 \right) dx =$$

$$= -\frac{1}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \int (x-\mu)^2 q(x) dx =$$

$$= -\frac{1}{2} \log(2\pi\sigma^2) - \frac{1}{2} = -H(p)$$

$$H[N(x|\mu, \sigma^2)] = -E_N \left[ -\frac{1}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} (x-\mu)^2 \right] =$$

$$= \frac{1}{2} \log(2\pi\sigma^2) + \frac{1}{2\sigma^2} E_N [(x-\mu)^2] = \frac{1}{2} \log(2\pi\sigma^2) + \frac{1}{2}$$

$$0 \leq KL(q||p) = -H(q) + H(p) \rightarrow H(p) \geq H(q)$$