

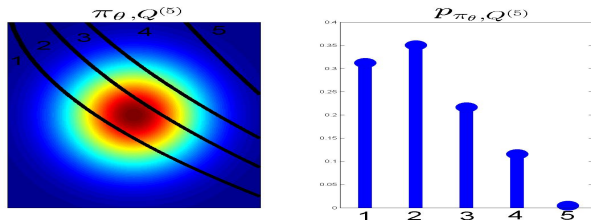
# Most Likely Maximum Entropy for Population Analysis: a case study in decompression sickness prevention

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## Problem Formulation

- $\Theta \subset \mathbb{R}^d$  space of parameters  $\theta$ ,  $\pi_\theta$  probability distribution over  $\Theta$ ,
- $Q$  a  $L$ -partition of  $\Theta$  :  $\Theta = \bigcup_{\ell=1}^L Q_\ell$ ,  $Q_i \cap Q_j = \emptyset, i \neq j$ ,
- $p_{\pi_\theta, Q}$  the probability law induced by  $\pi_\theta$  on  $Q$  :  $p_{\pi_\theta, Q_\ell} = \int_{Q_\ell} d\pi_\theta$ .



$\tilde{p}_{Q^{(n)}}$  empirical estimate of  $p_{\pi_\theta, Q^{(n)}}$ ,  $\nu_n = \frac{N_n}{\sum_{n'=1}^N N_{n'}}$ .

- Data : samples from distributions laws  $\{p_{\pi_\theta, Q^{(n)}}\}_{n=1}^N$  determined by  $N$  distinct  $L$ -partitions :  $G_i^n \sim p_{\pi_\theta, Q^{(n)}}, i = 1, \dots, N_n, n = 1, \dots, N$ ,  $G_i^n \in \{1, \dots, L\}$ .
- Goal : **Determination of  $\pi_\theta$  from the  $N$  observed samples.**
- Log-likelihood :

$$\mathcal{L}(\pi_\theta) = - \sum_{n=1}^N \nu_n \left[ \mathcal{D}_{KL}(\tilde{p}_{Q^{(n)}} || p_{\pi_\theta, Q^{(n)}}) + \sum_{n=1}^N H(\tilde{p}_{Q^{(n)}}) \right]$$

$\mathcal{D}_{KL}$  : Kullback-Leibler divergence;  $H$  : Shannon entropy.

## NPMLE

- support of  $\hat{\pi}_\theta$  is confined to  $\mathcal{P}$ , ( $|\mathcal{P}| = K$ ) a subset of the intersections of the elements of  $\{Q^{(n)}\}_{n=1}^N$  elements,
- only the probability mass  $\mathbf{w}$  of the sets in  $\mathcal{P}$  can be estimated.
- non uniqueness the solution

$$\operatorname{argmax}_{\mathbf{w}} \sum_{n=1}^N \sum_{\ell=1}^L \tilde{p}_{Q_\ell^{(n)}} \log \mathbf{B}_\ell^{(n)} \mathbf{w}$$

$\mathbf{B}_\ell^{(n)}$  the  $\ell$ -th row of a  $(L \times K)$  binary matrix describing the link between observations  $G_i^n$  and elements of  $\mathcal{P}$ .

- optimization very fast with the modification of Vertex Exchange Method (Harmann et al, Statistics & Probability Letters(2007)).

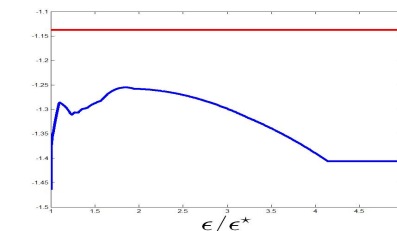
## Most Likely Maxent

- In the large sample where  $(N_n \rightarrow \infty)$  we should have  $\tilde{p}_{Q^{(n)}} \rightarrow p_{\pi_\theta, Q^{(n)}}$
- Dudik et al. (Journal of Machine Learning Research, 2007) propose a generalized maxent estimator of the form :  $\operatorname{argmin}_{\pi \in \mathcal{P}} [\mathcal{D}_{KL}(\pi || q_0) + U(E_\pi[\tilde{p}_Q])]$  with specific choice of  $U$  to express  $\ell_1$  or  $\ell_2$ -regularization, and where features  $\tilde{p}_Q$  are obtained from the same empirical distribution.
- We propose to estimate  $\pi_\theta$  as the Rényi-maxent (quadratic programming) that best matches observed frequencies :  $\epsilon^* \geq 0$  the smallest value of  $\epsilon$  for which there exists a solution to

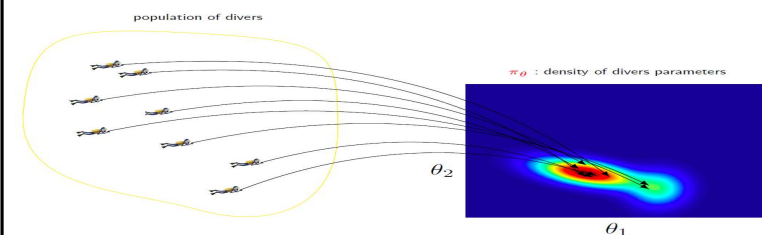
$$\tilde{\pi}_\theta^\epsilon = \operatorname{argmax}_{\pi} h_2(\pi) \text{ s.t. } \left\| \Sigma^{(n)-1/2} (p_{\pi_\theta, Q^{(n)}} - \tilde{p}_{Q^{(n)}}) \right\|_\infty \leq \epsilon, \forall n,$$

$h_2(\cdot)$  : Rényi-entropy of order 2;  $\Sigma^{(n)}$  :  $L \times L$  covariance matrix of the empirical distribution of  $\tilde{p}_{Q^{(n)}}$ .

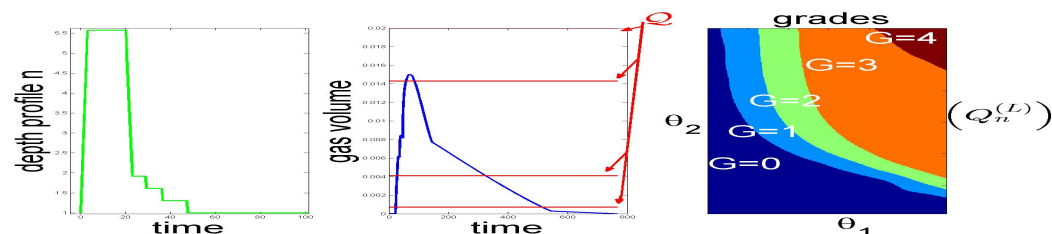
- We propose to use likelihood to chose the degree of regularization  $\tilde{\pi}_\theta^{ml} = \operatorname{argmax}_{\tilde{\pi}_\theta^\epsilon, \epsilon > \epsilon^*} \mathcal{L}(\tilde{\pi}_\theta^\epsilon)$



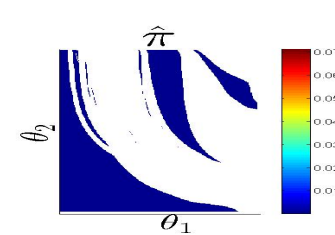
## Application : Decompression sickness



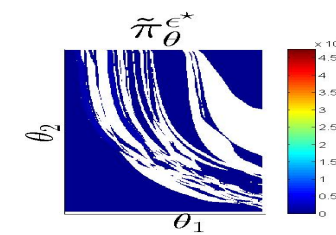
- Accidents due to formation of gas bubbles due to a fast decrease in diver's depth (fast reduction of pressure)
- Only the maximum gas volume  $B(\theta, P_i)$  is measured through a (known) quantification  $Q \rightarrow$  grades
- From observations of grades  $G_i$  we only know that  $\theta_i \in \{\theta : Q(B(\theta, P_i)) = G_i\}$ .



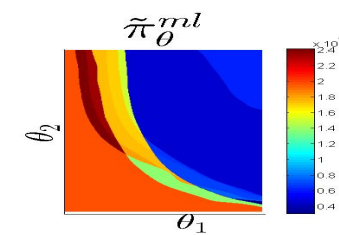
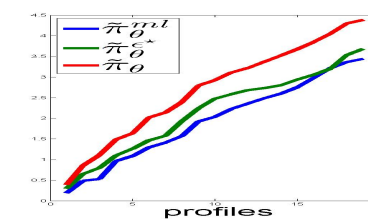
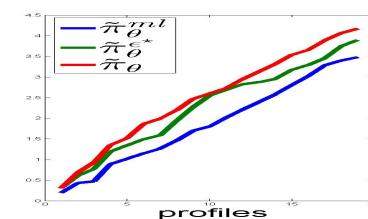
## Results



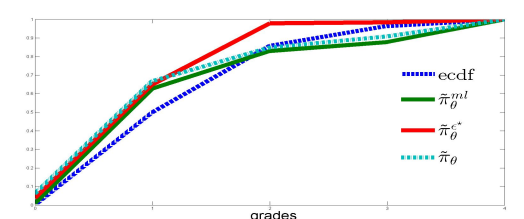
unstable solution not physically plausible  
biological model of a population



has larger support than  $\hat{\pi}_\theta$ ,  
still large regions with zero mass



smoother, more plausible and stable,  
better for prediction



- Leave-one-out-cross-validation, compare kolmogorov and total variation distances between estimated and observed frequencies.

- $\pi_\theta^{ml}$  the most efficient estimator in terms of prediction.