

## Gibbsian conditioning

Let  $(\Omega, \mathcal{F}, \mathbb{P})$  a probability space on which we consider a sequence of iid discrete random variables  $(X_n)_{n \geq 1}$  with law  $\mathbb{P}(X_n = \pm 1) = 1/2$ . Let  $M_n = (X_1 + \dots + X_n)/n$  the empirical mean of the first  $n$  variables. Fix  $\varepsilon > 0$  and  $m \in ]-1, 1[$  and let  $B_n$  be the set  $B_n = \{\omega \in \Omega : M_n(\omega) \in [m, m + \varepsilon]\}$ . We want to study the limit law as  $n \rightarrow \infty$  of the  $k$ -ple  $(X_1, \dots, X_k)$  when  $(X_1, \dots, X_n)$  is conditioned on the event  $B_n$ . More precisely fix  $k \geq 1$  and let  $\mu_n$  be the law of  $(X_1, \dots, X_k)$  conditional on  $B_n$ :

$$\mu_n(x_1, \dots, x_k) = \mathbb{P}(X_1 = x_1, \dots, X_k = x_k | B_n) = \frac{\mathbb{P}(X_1 = x_1, \dots, X_k = x_k, B_n)}{\mathbb{P}(B_n)}.$$

Our aim is to prove that the family  $\{\mu_n\}_{n \geq 1}$  converge weakly to the law  $\rho_\lambda^k$  on  $\{-1, 1\}^k$  for which all the components are independent and

$$\rho_\lambda^k(x_1, \dots, x_k) = \rho_\lambda(x_1) \cdots \rho_\lambda(x_k)$$

where  $\rho$  is the discrete probability on  $\{-1, 1\}$  given by

$$\rho_\lambda(x) = \frac{e^{\lambda x}}{e^\lambda + e^{-\lambda}} \quad \text{for } x = -1, 1$$

where  $\lambda \in \mathbb{R}$  is a fixed number which is determined by the fact that the mean of the measure  $\rho_\lambda$  should be  $m$ :

$$m = \sum_{x=-1,1} x \rho_\lambda(x) = \frac{e^\lambda - e^{-\lambda}}{e^\lambda + e^{-\lambda}} = \tanh(\lambda).$$

To prove this weak convergence result you need to understand the discussion on ‘‘Gibbsian conditioning’’ in the ‘‘Poly 4’’ of the lecture notes and proceed as follows:

- a) Start by proving the statement for  $k = 1$ . Note that for any continuous function

$$\sum_{x_1 = \pm 1} f(x_1) \mu_n(x_1) = \frac{\mathbb{E}[f(X_1)1_{B_n}]}{\mathbb{E}[1_{B_n}]} = \frac{\mathbb{E}[L_n(f)1_{B_n}]}{\mathbb{E}[1_{B_n}]}$$

where  $L_n(f) = \frac{1}{n} \sum_{i=1}^n f(X_i)$  is the mean of  $f$  with respect to the empirical measure of the random vector  $(X_i)_{1 \leq i \leq n}$ . Observe also that  $B_n = \{L_n(h) \in [m, m + \varepsilon]\}$  where  $h: \{-1, +1\} \rightarrow \mathbb{R}$  is the identity function given by  $h(x) = x$ . Then

$$\sum_{x_1 = \pm 1} f(x_1) \mu_n(x_1) = \frac{\mathbb{E}[L_n(f)1_{L_n(h) \in [m, m + \varepsilon]}]}{\mathbb{E}[1_{L_n(h) \in [m, m + \varepsilon]}]}$$

Use Sanov theorem (Theorem 7 of Poly 4) and Proposition 1 and Corollary 2 of Poly 4 to deduce a large deviation principle for  $\mu_n$ . Conclude that  $\mu_n \rightarrow \rho_\lambda$ .

- b) Follow the discussion on ‘‘Gibbsian conditioning’’ in the ‘‘Poly 4’’ of the lecture notes to extend the argument to  $k > 1$ . For the purpose of the exam it is enough to prove the statement for  $k = 2$ : that is we want to prove that conditionally on  $B_n$ , the pair  $(X_1, X_2)$  converge weakly to a pair of independent variables each of them with law  $\rho_\lambda$ . (with  $\lambda$  depending on  $m$ ).