## ON MARKOV NETWORKS

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Abstract. The aim of this paper is to propose an approach based on statistics for studying some Markov networks. As an application, we quote an example related to distributed computing.

## 1. MARKOV NETWORKS AND OPTIMAL SOLUTIONS

The stochastic models where optimization intervenes are usual (cf. for example, [1] and [3]) but their use is more interesting when the stochastic dependence is simple. Hence, the interest of Markov dependence.

Let  $({}^kX_t)_{t\in IN}$ ,  $k\in\{1,...,\nu\}$ , be  $\nu$  homogeneous Markov chains with discrete time (IN) denoting the set of positive integers), defined on a probability space  $(\Omega, \mathcal{A}, \mathcal{P})$ , the state space of the  $k^{\text{th}}$  chain being  $({}^k\chi, {}^k\mathcal{B})$ . We suppose that all these Markov chains verify the Doeblin condition (cf. [5]), and every one of them has only a single ergodic set without cyclically moving subsets. Let  ${}^kP$  be the transition probability of the  $k^{\text{th}}$  chain and let  ${}^kP_t$  be the  $t^{\text{th}}$  step transition probability, given recursively by

$$orall x \in {}^k\chi, \; orall B \in {}^k\mathcal{B}$$
  ${}^kP_t(x,\,B) = \int_{{}^k\chi} {}^kP(x,\,dy)\, {}^kP_{t-1}(y,\,B)\,, \;\; t \geq 2$ 

and let  ${}^k\pi$  be the stationary absolute probability given by

$$\lim_{t\to\infty}{}^kP_t(x,\,B)={}^k\pi(B)\,.$$

Recall that  $\forall B \in {}^k B$ ,

$$k_{\pi(B)} = \int_{k_{\chi}}^{k} \pi(dx)^{k} P(x, B),$$
 (1)

and that the  $k^{\text{th}}$  chain is said to be in permanent regime if  ${}^k\pi$  is taken as initial absolute probability.

Suppose now that  $\forall k \in \{1,...,\nu\}$ ,  ${}^kP$  depends on a parameter  $\theta_k \in {}^k\Theta$ . The Markov  $\nu$  chains are said to constitute a network if there exists a finite number of relations  $\mathcal{R}_h(\theta_1,...,\theta_{\nu})$ ,  $h \in H$ , between the  $\theta_1,...,\theta_{\nu}$ .

The problem we have to examine consists of two stages:

According to the context, to choose a real function f of the  $\theta_1, ..., \theta_{\nu}$  to be optimized; and to fin "solution (s)"  $(\theta_1, ..., \theta_{\nu})$  satisfying the relations  $\mathcal{R}_h(\theta_1, ..., \theta_{\nu})$ ,  $h \in H$ , which optimize the function  $f(\theta_1, ..., \theta_{\nu})$ .

We propose a way for choosing the suitable function f:

Let  $\{{}^kB_i, i \in {}^kI\}$  be a finite  ${}^kB$ -measurable partition of  ${}^k\chi$  and let  ${}^k\mathcal{C}$  be the  $\sigma$ -algebra generated by  $\{{}^kB_i, i \in {}^kI\}$ .

Consider now  $({}^kX_t(\omega))_{t\in[0,\,n]\cap IN}$  a fragment of the trajectory of the  $k^{\text{th}}$  chain (the sample) corresponding to the point  $\omega\in\Omega$ .

For  $({}^kC'^kC') \in ({}^kC)^2$ , we denote by  $n({}^kC \times {}^kC'; \omega)$  the number of direct transitions from  ${}^kC$  to  ${}^kC'$ , and by  $n({}^kC \times {}^kC')$  the corresponding random variable. We know (cf. [3]) that the mathematical expectation  $E[n({}^kC \times {}^kC')]$  is  $n \int_{{}^kC} {}^k\pi(dx, \theta_k) {}^kP(x, {}^kC'; \theta_k)$  and that  $\frac{1}{n} {}^kn({}^kC \times {}^kC')$  is an almost surely consistent estimator (as  $n \to \infty$ ) of  $\int_{{}^kC} {}^k\pi(dx, \theta_k) {}^kP(x, {}^kC'; \theta_k)$ .

As all useful information contained in the sample relatively to the partition  $\{{}^kB_i, i \in {}^kI\}$  is given by  $n({}^kC \times {}^kC'; \omega), ({}^kC, {}^kC') \in ({}^kC)^2,$  f may be chosen as a function of  $\frac{1}{n}E[n({}^kC \times {}^kC')], ({}^kC, {}^kC') \in ({}^kC)^2.$ 

More precisely, according to the context of the problem, in order to take advantage of information, we propose to choose a set of characteristic pairs  $\binom{k}{C}$ ,  $\binom{k}{C'}$   $\in$   $\binom{k}{C}$ , namely  $\binom{k}{C} = \{\binom{k}{C_1}, \binom{k}{C'_1}, ..., \binom{k}{C_r}, \binom{k}{C'_r}\}$ .

We then define f as function of the parameters  $\theta_1, ..., \theta_{\nu}$ :

$$f(\theta_1,...,\theta_{
u}) = \psi(\int_{{}^kC}{}^k\pi(dx,\,\theta_k)\,{}^kP(x,\,{}^kC';\,\theta_k)\,,$$
  $({}^kC,\,{}^kC')\in{}^k\mathcal{G}\,,\,\,k\in\{1,...,
u\})\,.$ 

f being chosen, we have to find the  $\nu$ -uples  $(\theta_1, ..., \theta_{\nu}) \in \mathcal{R}_h(\theta_1, ..., \theta_{\nu})$ ,  $h \in H$ , which optimize f, or in the absence of such optimal solutions, to find solutions which make f as close as possible to its optimal value. For the convenience of the formulation, we can express the optimization in the form of a maximization.

## 2. APPLICATION TO A DISTRIBUTED COMPUTING PROBLEM

Consider the following network of  $\nu$  homogeneous finite Markov chains. Its  $k^{\text{th}}$  Markov chain has  ${}^kr$  states,  ${}^k\chi=\{1,...,{}^kr\},{}^kr_1,{}^kr_2,{}^kr_3$  being integers >0 such that  ${}^kr_1+{}^kr_2+{}^kr_3<{}^kr$ . Let us denote

$$^kB_1 = \{1,...,^kr_1\},$$
 $^kB_2 = \{^kr_1 + 1,...,^kr_1 + ^kr_2\},$ 
 $^kB_3 = ^kr_1 + ^kr_2 + 1,...,^kr_1 + ^kr_2 + ^kr_3\},$ 
 $^kB_4 = ^kr_1 + ^kr_2 + ^kr_3 + 1,...,^kr\}.$ 

The entries of the transition matrix  ${}^kP=({}^kp_{ij})$  are described as follows

$$\forall i \in {}^kB_1, \; \sum_{j \in {}^kB_1} {}^kp_{ij} = 1 - a_k \; ext{and} \; \sum_{j \in {}^kB_2} {}^kp_{ij} = a_k, \; ext{where} \; a_k \in ]0, \, 1[;$$

$$orall i \in {}^kB_2, \ \sum_{j \in {}^kB_2} {}^kp_{ij} = 1 - b_k \ ext{and} \ \sum_{j \in {}^kB_3} {}^kp_{ij} = b_k, ext{ where } b_k \in ]0, 1[;$$
 $orall i \in {}^kB_3, \ \sum_{j \in {}^kB_3} {}^kp_{ij} = 1 - c_k \ ext{and} \ \sum_{j \in {}^kB_4} {}^kp_{ij} = c_k, ext{ where } c_k \in ]0, 1[;$ 
 $orall i \in {}^kB_4, \ \sum_{j \in {}^kB_1} {}^kp_{ij} = 1.$ 

For the other (i, j),  $k p_{ij} = 0$ .

The  $\nu$  chains are connected into a network by the following relations:

$$\forall (i, i') \in {}^kB_1 \times {}^{k+1}B_2,$$

$$\sum_{j \in {}^{k}B_{2}} {}^{k}p_{ij} + \sum_{j \in {}^{k+1}B_{3}} {}^{k+1}p_{i'j} = 1 \text{ for } k \in \{1, ..., \nu - 1\}$$
 (2)

and  $\forall (i, i') \in {}^{\nu}B_1 \times {}^{1}B_2$ ,

$$\sum_{j\in{}^{\boldsymbol{\nu}}B_2}{}^{\boldsymbol{\nu}}p_{ij} + \sum_{j\in{}^1B_3}{}^1p_{i'j} = 1.$$

**Proposition 1.** With the partition  $\{{}^kB_1, {}^kB_2, {}^kB_3, {}^kB_4\}$  of  ${}^k\chi$ , the  $k^{\text{th}}$  Markov chain is lumpable. The lumped chain is an homogeneous Markov chain with four states; its transition matrix  ${}^kM = ({}^km_{su})$  is

the following:  ${}^km_{11} = 1 - a_k$ ,  ${}^km_{12} = a_k$ ,  ${}^km_{22} = 1 - b_k$ ,  ${}^km_{23} = b_k$ ,  ${}^km_{33} = 1 - c_k$ ,  ${}^km_{34} = c_k$ ,  ${}^km_{14} = 1$ .

The other kmsu are equal to zero.

The  $\nu$  lumped chains are connected into a network by the relations

$$\begin{cases}
 a_k + b_{k+1} - 1 = 0, & k \in \{1, ..., \nu - 1\}, \\
 a_{\nu} + b_1 - 1 = 0,
\end{cases}$$
(3)

the parameters being  $\theta_k = (a_k, b_k)$ .

Indeed, it is easy to complete the description of the matrix  ${}^kP$  by writing:  $\forall i \in {}^kB_1$ ,  $\sum\limits_{j \in {}^kB_3} {}^kp_{ij} = 0$ ,  $\sum\limits_{j \in {}^kB_4} {}^kp_{ij} = 0$ , and so on. We then see that for every pair  $({}^kB_s, {}^kB_u)$ ,  $s, u \in \{1, 2, 3, 4\}$ ,  $\sum\limits_{i \in {}^kB_u} {}^kp_{ij}$ ,  $i \in {}^kB_u$ 

 ${}^kB_s$ , depends uniquely on s (but does not depend on i individually). The common value of the sums  $\sum_{j \in {}^kB_u} {}^kp_{ij}$ ,  $i \in {}^kB_s$ , is the  ${}^km_{su}$  of the

transition matrix of the  $k^{\text{th}}$  lumped Markov chain (cf. [6]). Because of (2), the lumped chains are connected by relations (3).

We rediscover then the network of the dining philosophers problem studied in [2].

**Proposition 2.** For every  $k \in \{1,...,\nu\}$  the initial  $k^{\text{th}}$  Markov chain satisfies the conditions of §1. With the partition  $\{{}^kB_1, {}^kB_2, {}^kB_3, {}^kB_4\}$  and in permanent regime, we have

$$egin{aligned} E[n(^kB_1 imes ^kB_1)] &= rac{n(1-a_k)b_kc_k}{D_k} \,, \ E[n(^kB_2 imes ^kB_2)] &= rac{na_k(1-b_k)c_k}{D_k} \,, \ E[n(^kB_3 imes ^kB_3)] &= rac{na_kb_k(1-c_k)}{D_k} \,, \end{aligned}$$

$$E[n({}^{k}B_{1} \times {}^{k}B_{2})] = E[n({}^{k}B_{2} \times {}^{k}B_{3})] =$$
 $E[n({}^{k}B_{3} \times {}^{k}B_{4})] = E[n({}^{k}B_{4} \times {}^{k}B_{1})] = \frac{na_{k}b_{k}c_{k}}{D_{k}},$ 

where  $D_k = a_k b_k + b_k c_k + c_k a_k + a_k b_k c_k$ . The other  $E[n(^k B_s \times ^k B_u)]$  are equal to zero.

In particular,

$$egin{aligned} E[n(^kB_1 imes^k\chi)] &= nrac{b_kc_k}{D_k}\,,\;\; E[n(^kB_2 imes^k\chi)] = nrac{a_kc_k}{D_k}\,,\ E[n(^kB_3 imes^k\chi)] &= nrac{a_kb_k}{D_k}\,,\;\; E[n(^kB_4 imes^k\chi)] = nrac{a_kb_kc_k}{D_k}\,. \end{aligned}$$

Indeed, with the indicated partition of  $k\chi$ , the  $k^{th}$  lumped chain has only one ergodic set without cyclically moving subsets and satisfies the conditions of §1. Let us denote by  ${}^k\mu=({}^k\mu_1,{}^k\mu_2,{}^k\mu_3,{}^k\mu_4)$  its absolute stationary probability. Solving (1), i.e.  ${}^k\mu.{}^kM={}^k\mu$ , we have

$$^{k}\mu_{1}=rac{b_{k}c_{k}}{D_{k}}\,,\ ^{k}\mu_{2}=rac{a_{k}c_{k}}{D_{k}}\,,\ ^{k}\mu_{3}=rac{a_{k}b_{k}}{D_{k}}\,,\ ^{k}\mu_{4}=rac{a_{k}b_{k}c_{k}}{D_{k}}\,.$$

Then,

Then,
$$E[n({}^{k}B_{s} \times {}^{k}B_{u})] = n \sum_{i \in {}^{k}B_{s}} \sum_{i \in {}^{k}B_{u}} {}^{k}\pi_{i} \cdot {}^{k}p_{ij}$$

$$= n \sum_{i \in {}^{k}B_{s}} {}^{k}\pi_{i} \cdot \sum_{i \in {}^{k}B_{u}} {}^{k}p_{ij}$$

$$= n \sum_{i \in {}^{k}B_{s}} {}^{k}\pi_{i} \cdot {}^{k}m_{su} \quad \text{(because of the lumpability)}$$

$$= n {}^{k}\mu_{s} \cdot {}^{k}\mu_{su} .$$

In particular,  $\forall s \in \{1, 2, 3, 4\}$ 

$$E[n({}^{k}B_{s}\times{}^{k}\chi)]=n\sum_{u=1}^{4}{}^{k}\mu_{s}.{}^{k}m_{su}=n{}^{k}\mu_{s}.$$

Let us examine now the problem of choosing a suitable and workable function f following our method indicated in §1. Let us recall that, because of its context (exposed in [2]), one "privileges" the access to state 3 of the  $k^{th}$  lumped chain, i.e. to the set  ${}^kB_3$  of the  $k^{th}$  initial chain. Thus, we take

 ${}^k\mathcal{G} = \left\{{}^kB_3 \times {}^k\chi\right\}.$ 

For every k, we suggest maximizing  $\frac{1}{n}E[n(^kB_3\times ^k\chi)]$ , viz. minimizing  $\frac{n}{E[n(k_{B_3} \times k_{\chi})]}$ , so that, globally, under constrains (3), we minimize

$$\sum_{k=1}^{\nu} \frac{n}{E[n({}^{k}B_{3} \times {}^{k}\chi)]} = \sum_{k=1}^{\nu} \frac{D_{k}}{a_{k}b_{k}}.$$

This leads to the same result as [2], found by another approach. Let the  $c_k$ 's be fixed, and consider the  $\theta_k$ 's  $(\theta_k = (a_k, b_k))$  as tuning parameters. f, as indicated in §1, is here the concave function

$$f[(a_1,\,b_1),...,(a_
u,\,b_
u)] = -\sum_{k=1}^
u \left[ (1+c_k) + rac{c_k}{a_k} + rac{c_k}{b_k} 
ight].$$

The Lagrange multipliers method used by [2] for lumped chains proves that there exists only one optimal solution, which is

$$((a_1, b_1), ..., (a_k, b_k), ..., (a_{\nu}, b_{\nu})) = (\frac{1}{1 + \rho_1}, \frac{\rho_{\nu}}{1 + \rho_{\nu}}), ..., (\frac{1}{1 + \rho_k}, \frac{\rho_{k-1}}{1 + \rho_{k-1}}), ..., (\frac{1}{1 + \rho_{\nu}}, \frac{\rho_{\nu-1}}{1 + \rho_{\nu-1}}),$$

where 
$$ho_k = \sqrt{rac{c_{k+1}}{c_k}}$$
, for  $k \in \{1,...,\nu-1\}$  and  $ho_{
u} = \sqrt{rac{c_1}{c_{
u}}}$ .

We then infer the following result:

Suppose that the  ${}^kp_{ij}$ ,  $(i, j) \in [{}^kB_3 \times ({}^kB_3 \cup {}^kB_4)] \cup ({}^kB_4 \times {}^kB_1)$ , be fixed, and consequently, so are the  $c_k$ 's and suppose that the  ${}^kp_{ij}$ ,  $(i, j) \in [{}^kB_1 \times ({}^kB_1 \cup {}^kB_2)] \cup [{}^kB_2 \times ({}^kB_2 \cup {}^kB_3)]$ , be tuning parameters. Then

Proposition 3. The initial Markov network has the following optimal solutions:

\* For the first chain, the  ${}^1p_{ij}$ ,  $(i, j) \in [{}^1B_1 \times ({}^1B_1 \cup {}^1B_2)]$ , are such that

$$\forall i \in {}^{1}B_{1}, \ \sum_{j \in {}^{1}B_{1}} {}^{1}p_{ij} = \frac{\rho_{1}}{1 + \rho_{1}} \ and \ \sum_{j \in {}^{1}B_{2}} {}^{1}p_{ij} = \frac{1}{1 + \rho_{1}};$$

the  ${}^{1}p_{ij}$ ,  $(i, j) \in [{}^{1}B_{2} \times ({}^{1}B_{2} \cup {}^{1}B_{3})]$ , are such that

$$\forall i \in {}^{1}B_{2}, \sum_{j \in {}^{1}B_{2}} {}^{1}p_{ij} = \frac{1}{1 + \rho_{\nu}} \text{ and } \sum_{j \in {}^{1}B_{3}} {}^{1}p_{ij} = \frac{\rho_{\nu}}{1 + \rho_{\nu}}.$$

\* For the  $k^{th}$  chain,  $k \in \{2,...,\nu\}$ , the  ${}^{k}p_{ij}$ ,  $(i,j) \in [{}^{1}B_{1} \times ({}^{1}B_{1} \cup {}^{1}B_{2})]$ , are such that

$$\forall i \in {}^{k}B_{1}, \sum_{j \in {}^{k}B_{1}} {}^{k}p_{ij} = \frac{\rho_{k}}{1 + \rho_{k}} \text{ and } \sum_{j \in {}^{k}B_{2}} {}^{k}p_{ij} = \frac{1}{1 + \rho_{k}};$$

the  ${}^kp_{ij}$ ,  $(i, j) \in [{}^kB_2 \times ({}^kB_2 \cup {}^kB_3)]$ , are such that

$$\forall i \in {}^{k}B_{2}, \sum_{j \in {}^{k}B_{2}}{}^{k}p_{ij} = \frac{1}{1 + \rho_{k-1}} \text{ and } \sum_{j \in {}^{k}B_{3}}{}^{k}p_{ij} = \frac{\rho_{k-1}}{1 + \rho_{k-1}}.$$

Among these optimal solutions is the following particular one:

For the first chain

$$orall (i,j) \in ({}^{k}B_{1} \times {}^{k}B_{1}), \ ^{1}p_{ij} = rac{
ho_{1}}{{}^{1}r_{1}(1+
ho_{1})};$$
 $orall (i,j) \in ({}^{k}B_{1} \times {}^{k}B_{2}), \ ^{1}p_{ij} = rac{1}{{}^{1}r_{2}(1+
ho_{1})};$ 
 $orall (i,j) \in ({}^{k}B_{2} \times {}^{k}B_{2}), \ ^{1}p_{ij} = rac{1}{{}^{1}r_{2}(1+
ho_{
u})};$ 
 $orall (i,j) \in ({}^{k}B_{2} \times {}^{k}B_{3}), \ ^{1}p_{ij} = rac{
ho_{
u}}{{}^{1}r_{3}(1+
ho_{
u})}.$ 

• For the  $k^{\text{th}}$  chain,  $k \in \{2, ..., \nu\}$ ,

$$orall (i,j) \in ({}^kB_1 imes {}^kB_1), \ \ {}^kp_{ij} = rac{
ho_k}{{}^kr_1(1+
ho_k)};$$
 $orall (i,j) \in ({}^kB_1 imes {}^kB_2), \ \ {}^kp_{ij} = rac{1}{{}^kr_2(1+
ho_k)};$ 
 $orall (i,j) \in ({}^kB_2 imes {}^kB_2), \ \ {}^kp_{ij} = rac{1}{{}^kr_2(1+
ho_{k-1})};$ 
 $orall (i,j) \in ({}^kB_2 imes {}^kB_3), \ \ {}^kp_{ij} = rac{
ho_{k-1}}{{}^kr_3(1+
ho_{k-1})}.$ 

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