# Non-parametric copula-based estimator of transition matrices for high-order Markov chains

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ABSTRACT

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## Contents

1	Introduction	4
2	Motivation	4
3	Copula-based transition matrices	4
4	Estimation and inference	6
	4.1 Estimation	6
	4.2 Inference	6
5	Measuring causality in high-dimensional Markov chains	6
6	Monte Carlo simulations	6
	6.1 Bootstrap bias-corrected estimator of Granger causality measures	6
	6.1.1 Bootstrap bias-correction	6
	6.1.2 Simulation study	6
	6.2 Empirical size and power	6
7	Empirical application	6
8	Conclusion	6
9	Appendix: Proofs	8

#### 1 Introduction

#### 2 Motivation

Consider the simple case of a two-state first-order stationary Markov chain, such as the one depicted below

$$1 - r_{1|2} \bigcirc S_1 \bigcirc S_2 \bigcirc 1 - r_{2|1}$$

with an *unknown* transition matrix

$$\mathbf{P} = \begin{bmatrix} 1 - r_{1|2} & r_{1|2} \\ r_{2|1} & 1 - r_{2|1} \end{bmatrix}$$

where

$$r_{i|j} = P[X_t = i \mid X_{t-1} = j], \quad i, j \in \{1, 2\}$$
 (1)

In such scenarios, estimating the conditional probabilities  $r_{i|j}$  is rather straightforward. Consider observing a sequence of states for individual entities at times t-1 and t. The probability of transitioning from one state to another can be estimated by calculating the ratio of the entities that transitioned from, say, S1 to S2 in the period t-1 to t to the total number of entities that began at state S1 at t-1. In other words:

$$r_{i|j} = \frac{n_{ij}}{\sum_{j} n_{ij}} \tag{2}$$

Now, instead let us consider that the Markov chain under consideration is of order p with a transition probability

$$r_{j_0|j_1,\dots,j_p} = P[X_t = j_0 \mid X_{t-1} = j_1,\dots,X_{t-p} = j_p], \quad j_k \in \{1,2\}, \quad \text{for } k = 0,1,\dots,p$$
 (3)

Evidently, estimating the transition probabilities is no longer trivial. In what follows, we propose methods for estimating the transition probabilities for Markov chains of high-order.

### 3 Copula-based transition matrices

First, let us consider the case of a third-order stationary Markov chain with a transition matrix

$$r_{j_0|j_1,\dots,j_3} = P[X_t = j_0 \mid X_{t-1} = j_1, X_{t-2} = j_2, X_{t-3} = j_3]$$

we may express this transition matrix as

$$r_{j_0|j_1,\cdots,j_3} = P[X_t = j_0, X_{t-1} = j_1, X_{t-2} = j_2 \mid X_{t-3} = j_3] / P[X_{t-1} = j_1, X_{t-2} = j_2 \mid X_{t-3} = j_3]$$
 (4)

Furthermore, note that

$$P[X_{t} = j_{0}, X_{t-1} = j_{1}, X_{t-2} = j_{2} \mid X_{t-3} = j_{3}] = \sum_{l=0,1} \sum_{m=0,1} \sum_{n=0,1} (-1)^{(l+m+n)} \times P[X_{t} \leq j_{0} - l, X_{t-1} \leq j_{1} - m, X_{t-2} \leq j_{2} - n \mid X_{t-3} = j_{3}]$$

$$(5)$$

where we know from the Theorem of Sklar (1959) that the joint conditional distribution function on the right hand side of relationship (4) can be expressed by its marginal conditional distributions and a copula function capturing their respective dependence, - i.e.

$$P[X_{t} \leq j_{0} - l, X_{t-1} \leq j_{1} - m, X_{t-2} \leq j_{2} - n \mid X_{t-3} = j_{3}] = F(j_{0} - l, j_{1} - m, j_{2} - n \mid j_{3})$$

$$= C(F(j_{0} - l \mid j_{3}), F(j_{1} - m \mid j_{3}), F(j_{2} - n \mid j_{3}))$$

$$(6)$$

Therefore, using relationship (6), we may express (5) as follows

$$P[X_{t} = j_{0}, X_{t-1} = j_{1}, X_{t-2} = j_{2} \mid X_{t-3} = j_{3}] = \sum_{l=0,1} \sum_{m=0,1} \sum_{n=0,1} (-1)^{(l+m+n)} \times C(F(j_{0} - l \mid j_{3}), F(j_{1} - m \mid j_{3}), F(j_{2} - n \mid j_{3}))$$

$$(7)$$

Therefore, the transition matrix (4) can alternatively be expressed as

$$r_{j_0|j_1,\dots,j_3} = \frac{\sum_{l=0,1} \sum_{m=0,1} \sum_{n=0,1} (-1)^{(l+m+n)} C(F(j_0-l \mid j_3), F(j_1-m \mid j_3), F(j_2-n \mid j_3))}{\sum_{m=0} \sum_{1} \sum_{n=0,1} (-1)^{(m+n)} C(F(j_1-m \mid j_3), F(j_2-n \mid j_3))}$$
(8)

In the following Proposition these results are extended to a Markov chain of order p.

**Proposition 1** For a Markov chain of order p, the copula-based transition matrix  $r_{j_0|j_1,\dots,j_p}$  is expressed as follows

$$r_{j_0|j_1,\dots,j_p} = \frac{\sum\limits_{l_0=0,1} \dots \sum\limits_{l_p=0,1} (-1)^{(l_0+\dots+l_p)} C(F(j_0-l_0\mid j_p),\dots,F(j_{p-1}-l_{p-1}\mid j_p))}{\sum\limits_{l_1=0} \dots \sum\limits_{l_p=0,1} (-1)^{(l_1+\dots+l_p)} C(F(j_1-l_1\mid j_p),\dots,F(j_{p-1}-l_{p-1}\mid j_p))}$$
(9)

where F(. | .) is a conditional distribution function and  $C(u_0, \cdot, u_p)$  is a copula function in  $[0, 1]^{p+1}$ .

- 4 Estimation and inference
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- 6 Monte Carlo simulations
- 6.1 Bootstrap bias-corrected estimator of Granger causality measures
- 6.1.1 Bootstrap bias-correction
- 6.1.2 Simulation study
- 6.2 Empirical size and power
- 7 Empirical application
- 8 Conclusion

## References

Sklar, M. (1959). Fonctions de repartition an dimensions et leurs marges. *Publ. inst. statist. univ. Paris*, 8:229–231.

9 Appendix: Proofs