



ΚΥΚΛΟΣ ΣΕΜΙΝΑΡΙΩΝ ΣΤΑΤΙΣΤΙΚΗΣ ΜΑΡΤΙΟΣ 2018

Guido Consonni

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Learning Markov Equivalence Classes of Directed Acyclic Graphs: an Objective Bayes Approach

ΤΕΤΑΡΤΗ 21/3/2018

13:30

**ΑΙΘΟΥΣΑ Τ201, 2^{ος} ΟΡΟΦΟΣ,
ΝΕΟ ΚΤΙΡΙΟ Ο.Π.Α. (ΤΡΟΙΑΣ 2)**

ΠΕΡΙΛΗΨΗ

A Markov equivalence class contains all the Directed Acyclic Graphs (DAGs) encoding the same conditional independencies, and is represented by a Completed Partially Directed DAG (CPDAG), also named Essential Graph (EG).

We approach the problem of model selection among noncausal sparse Gaussian DAGs by directly scoring EGs, using an objective Bayes method. Specifically, we construct objective priors for model selection based on the Fractional Bayes Factor, leading to a closed form expression for the marginal likelihood of an EG.

Next we propose an MCMC strategy to explore the space of EGs, possibly accounting for sparsity constraints, and illustrate the performance of our method on simulation studies, as well as on a real dataset.

Our method is fully Bayesian and thus provides a coherent quantification of inferential uncertainty, requires minimal prior specification, and shows to be competitive in learning the structure of the data-generating EG when compared to alternative state-of-the-art algorithms.



AUEB STATISTICS SEMINAR SERIES MARCH 2018

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WEDNESDAY 21/3/2018

13:30

**ROOM T201, 2nd FLOOR,
NEW AUEB BUILDING (TRIAS 2)**

ABSTRACT

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