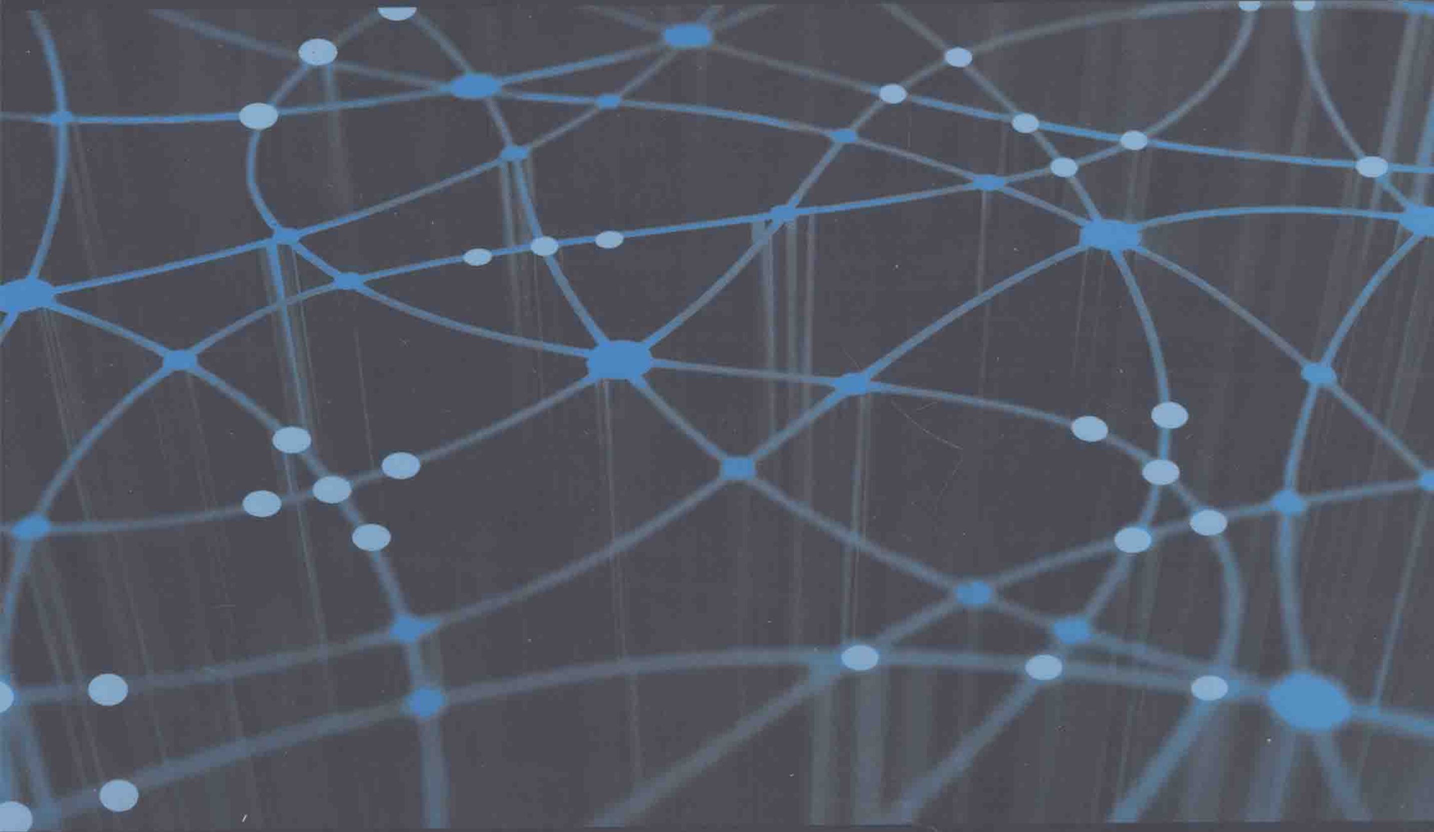
PROBABILISTIC GRAPHICAL MODELS

PRINCIPLES AND TECHNIQUES



DAPHNE KOLLER AND NIR FRIEDMAN

Probabilistic Graphical Models

Principles and Techniques

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Daphne Koller

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To our families

my parents Dov and Ditza
my husband Dan
my daughters Natalie and Maya
D.K.

my parents Noga and Gad
my wife Yael
my children Roy and Lior
N.F.

As far as the laws of mathematics refer to reality, they are not certain, as far as they are certain, they do not refer to reality.

Albert Einstein, 1956

When we try to pick out anything by itself, we find that it is bound fast by a thousand invisible cords that cannot be broken, to everything in the universe.

John Muir, 1869

The actual science of logic is conversant at present only with things either certain, impossible, or entirely doubtful . . . Therefore the true logic for this world is the calculus of probabilities, which takes account of the magnitude of the probability which is, or ought to be, in a reasonable man's mind.

James Clerk Maxwell, 1850

The theory of probabilities is at bottom nothing but common sense reduced to calculus; it enables us to appreciate with exactness that which accurate minds feel with a sort of instinct for which ofttimes they are unable to account.

Pierre Simon Laplace, 1819

Misunderstanding of probability may be the greatest of all impediments to scientific literacy.

Stephen Jay Gould

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