

JUDEA PEARL

*WINNER OF THE TURING AWARD*

AND DANA MACKENZIE

THE  
BOOK OF  
WHY



THE NEW SCIENCE  
OF CAUSE AND EFFECT

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