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Universiteit Leiden



The handle <http://hdl.handle.net/1887/3170176> holds various files of this Leiden University dissertation.

Author: Rossum, A.C. van

Title: Nonparametric Bayesian methods in robotic vision

Issue date: 2021-06-03

**Nonparametric Bayesian Methods
in Robotic Vision**

Nonparametric Bayesian Methods in Robotic Vision

PROEFSCHRIFT

ter verkrijging van
de graad van Doctor aan de Universiteit Leiden,
op gezag van Rector Magnificus Prof. dr. ir. H. Bijl,
volgens besluit van het College voor Promoties
te verdedigen op donderdag 3 juni 2021
klokke 12:30 uur

door

Anne Cornelis van Rossum,

geboren te Dirksland
in 1980

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SIKS Dissertation Series No. 2021-11

The research reported in the thesis has been carried out under the auspices of SIKS, the Dutch Research School for Information and Knowledge Systems.

ISBN 978-94-6423-258-5

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“

The study of mental objects with reproducible properties is called mathematics.

”

The Mathematical Experience (Davis and Hersch, 1981)

“

The study of physical objects with reproducible properties is called science.

”

The dawning of the age of stochasticity, Mathematics: frontiers and perspectives
(Mumford, 2000)

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