Modern approaches for component-wise boosting:

Automation, efficiency, and distributed computing with application to the medical domain

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Daniel Schalk

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Supervisor: Prof. Dr. Bernd Bischl
Referees: Prof. Dr. Matthias Schmid, PD Dr. Fabian Scheipl
Chair of the examination panel: Prof. Dr. Christian Heumann

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