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MichaÃ«l Bauerheim
BÃ©nÃ©dicte Cuenot</td></tr>
<tr><th>title</th><td>Performance and accuracy assessments of an incompressible fluid solver coupled with a deep Convolutional Neural Network</td></tr>
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