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<tr><th>authors</th><td>Tian Qin
Alex Beatson
Deniz Oktay
Nick McGreivy
Ryan P. Adams</td></tr>
<tr><th>title</th><td>Meta-PDE: Learning to Solve PDEs Quickly Without a Mesh</td></tr>
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