<table>
<tr><th></th><th>doc_1</th><th>doc_2</th><th>decision</th><th>id</th></tr>
<tr><th>cases</th><td>
<table>
<tr><th>authors</th><td>Xu Liu
Xiao-Ya Zhang
Wei Peng
Weien Zhou
Wen Yao</td></tr>
<tr><th>title</th><td>A novel meta-learning initialization method for physics-informed neural networks</td></tr>
<tr><th>publication_date</th><td>2022-05-08 00:00:00</td></tr>
<tr><th>source</th><td>SupportedSources.OPENALEX</td></tr>
<tr><th>journal</th><td>Neural Computing and Applications</td></tr>
<tr><th>volume</th><td>34</td></tr>
<tr><th>doi</th><td>10.1007/s00521-022-07294-2</td></tr>
<tr><th>urls</th><td>https://openalex.org/W3185491972
https://doi.org/10.1007/s00521-022-07294-2
http://arxiv.org/pdf/2107.10991</td></tr>
<tr><th>id</th><td>id7202510175119866889</td></tr>
<tr><th>abstract</th><td></td></tr>
<tr><th>versions</th><td></td></tr>
</table>
</td><td>
<table>
<tr><th>authors</th><td>Xu Liu
Xiaoya Zhang
Wei Peng
Weien Zhou
Wen Yao</td></tr>
<tr><th>title</th><td>A novel meta-learning initialization method for physics-informed neural networks</td></tr>
<tr><th>publication_date</th><td>2021-07-23 00:00:00</td></tr>
<tr><th>source</th><td>SupportedSources.INTERNET_ARCHIVE</td></tr>
<tr><th>journal</th><td></td></tr>
<tr><th>volume</th><td></td></tr>
<tr><th>doi</th><td></td></tr>
<tr><th>urls</th><td>https://web.archive.org/web/20210727191145/https://arxiv.org/pdf/2107.10991v1.pdf</td></tr>
<tr><th>id</th><td>id7344450888607918983</td></tr>
<tr><th>abstract</th><td>Physics-informed neural networks (PINNs) have been widely used to solve various scientific computing problems. However, large training costs limit PINNs for some real-time applications. Although some works have been proposed to improve the training efficiency of PINNs, few consider the influence of initialization. To this end, we propose a New Reptile initialization based Physics-Informed Neural Network (NRPINN). The original Reptile algorithm is a meta-learning initialization method based on labeled data. PINNs can be trained with less labeled data or even without any labeled data by adding partial differential equations (PDEs) as a penalty term into the loss function. Inspired by this idea, we propose the new Reptile initialization to sample more tasks from the parameterized PDEs and adapt the penalty term of the loss. The new Reptile initialization can acquire initialization parameters from related tasks by supervised, unsupervised, and semi-supervised learning. Then, PINNs with initialization parameters can efficiently solve PDEs. Besides, the new Reptile initialization can also be used for the variants of PINNs. Finally, we demonstrate and verify the NRPINN considering both forward problems, including solving Poisson, Burgers, and Schr\"odinger equations, as well as inverse problems, where unknown parameters in the PDEs are estimated. Experimental results show that the NRPINN training is much faster and achieves higher accuracy than PINNs with other initialization methods.</td></tr>
<tr><th>versions</th><td></td></tr>
</table>
</td><td>DUPLICATES</td><td>166</td></tr>
</table>