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<tr><th>authors</th><td>Quercus Hernandez
Alberto Badias
David Gonzalez
Francisco Chinesta
Elias Cueto</td></tr>
<tr><th>title</th><td>Deep learning of thermodynamics-aware reduced-order models from data</td></tr>
<tr><th>publication_date</th><td>2021-03-09 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>
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<tr><th>urls</th><td>https://web.archive.org/web/20200728224405/https://arxiv.org/pdf/2007.03758v1.pdf</td></tr>
<tr><th>id</th><td>id-4766093536009297256</td></tr>
<tr><th>abstract</th><td>We present an algorithm to learn the relevant latent variables of a large-scale discretized physical system and predict its time evolution using thermodynamically-consistent deep neural networks. Our method relies on sparse autoencoders, which reduce the dimensionality of the full order model to a set of sparse latent variables with no prior knowledge of the coded space dimensionality. Then, a second neural network is trained to learn the metriplectic structure of those reduced physical variables and predict its time evolution with a so-called structure-preserving neural network. This data-based integrator is guaranteed to conserve the total energy of the system and the entropy inequality, and can be applied to both conservative and dissipative systems. The integrated paths can then be decoded to the original full-dimensional manifold and be compared to the ground truth solution. This method is tested with two examples applied to fluid and solid mechanics.</td></tr>
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<tr><th>source</th><td>SupportedSources.INTERNET_ARCHIVE</td></tr>
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