

cases	doc_1		doc_2		decision	id
	authors	<ul style="list-style-type: none">Suryanarayana MadduDominik SturmChristian L. MllerIvo F. Sbalzarini	authors	<ul style="list-style-type: none">Suryanarayana MadduDominik SturmChristian L. MllerIvo F. Sbalzarini	DUPLICATES	244
	title	Inverse-Dirichlet Weighting Enables Reliable Training of Physics Informed Neural Networks	title	Inverse-Dirichlet Weighting Enables Reliable Training of Physics Informed Neural Networks		
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	urls	<ul style="list-style-type: none">http://arxiv.org/pdf/2107.00940v1http://arxiv.org/abs/2107.00940v1http://arxiv.org/pdf/2107.00940v1	urls	<ul style="list-style-type: none">https://web.archive.org/web/20210708070044/https://arxiv.org/pdf/2107.00940v1.pdf		
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	abstract	We characterize and remedy a failure mode that may arise from multi-scale dynamics with scale imbalances during training of deep neural networks, such as Physics Informed Neural Networks (PINNs). PINNs are popular machine-learning templates that allow for seamless integration of physical equation models with data. Their training amounts to solving an optimization problem over a weighted sum of data-fidelity and equation-fidelity objectives. Conflicts between objectives can arise from scale imbalances, heteroscedasticity in the data, stiffness of the physical equation, or from catastrophic interference during sequential training. We explain the training pathology arising from this and propose a simple yet effective inverse-Dirichlet weighting strategy to alleviate the issue. We compare with Sobolev training of neural networks, providing the baseline of analytically ϵ -optimal training. We demonstrate the effectiveness of inverse-Dirichlet weighting in various applications, including a multi-scale model of active turbulence, where we show orders of magnitude improvement in accuracy and convergence over conventional PINN training. For inverse modeling using sequential training, we find that inverse-Dirichlet weighting protects a PINN against catastrophic forgetting.	abstract	We characterize and remedy a failure mode that may arise from multi-scale dynamics with scale imbalances during training of deep neural networks, such as Physics Informed Neural Networks (PINNs). PINNs are popular machine-learning templates that allow for seamless integration of physical equation models with data. Their training amounts to solving an optimization problem over a weighted sum of data-fidelity and equation-fidelity objectives. Conflicts between objectives can arise from scale imbalances, heteroscedasticity in the data, stiffness of the physical equation, or from catastrophic interference during sequential training. We explain the training pathology arising from this and propose a simple yet effective inverse-Dirichlet weighting strategy to alleviate the issue. We compare with Sobolev training of neural networks, providing the baseline of analytically μ -optimal training. We demonstrate the effectiveness of inverse-Dirichlet weighting in various applications, including a multi-scale model of active turbulence, where we show orders of magnitude improvement in accuracy and convergence over conventional PINN training. For inverse modeling using sequential training, we find that inverse-Dirichlet weighting protects a PINN against catastrophic forgetting.		
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