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	authors	<ul style="list-style-type: none">Ferran AletAdarsh K. JeewajeeMaria BauzaAlberto RodriguezTomas Lozano-PerezLeslie Pack Kaelbling	authors	<ul style="list-style-type: none">Alet, FerranBauza, MariaJeewajee, Adarsh K.Kaelbling, Leslie PackLozano-Perez, TomasRodriguez, Alberto	DUPLICATES	306
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	abstract	We explore the use of graph neural networks (GNNs) to model spatial processes in which there is no a priori graphical structure. Similar to finite element analysis, we assign nodes of a GNN to spatial locations and use a computational process defined on the graph to model the relationship between an initial function defined over a space and a resulting function in the same space. We use GNNs as a computational substrate, and show that the locations of the nodes in space as well as their connectivity can be optimized to focus on the most complex parts of the space. Moreover, this representational strategy allows the learned input-output relationship to generalize over the size of the underlying space and run the same model at different levels of precision, trading computation for accuracy. We demonstrate this method on a traditional PDE problem, a physical prediction problem from robotics, and learning to predict scene images from novel viewpoints.	abstract	We explore the use of graph neural networks (GNNs) to model spatial processes in which there is no a priori graphical structure. Similar to finite element analysis, we assign nodes of a GNN to spatial locations and use a computational process defined on the graph to model the relationship between an initial function defined over a space and a resulting function in the same space. We use GNNs as a computational substrate, and show that the locations of the nodes in space as well as their connectivity can be optimized to focus on the most complex parts of the space. Moreover, this representational strategy allows the learned input-output relationship to generalize over the size of the underlying space and run the same model at different levels of precision, trading computation for accuracy. We demonstrate this method on a traditional PDE problem, a physical prediction problem from robotics, and learning to predict scene images from novel viewpoints.Comment: Accepted to ICML 201		
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