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**Transfer learning of deep material network for seamless structure-property predictions.** (English) Zbl 07095675

Comput. Mech. 64, No. 2, 451-465 (2019).

Summary: Modern materials design requires reliable and consistent structure-property relationships. The paper addresses the need through transfer learning of deep material network (DMN). In the proposed learning strategy, we store the knowledge of a pre-trained network and reuse it to generate the initial structure for a new material via a naive approach. Significant improvements in the training accuracy and learning convergence are attained. Since all the databases share the same base network structure, their fitting parameters can be interpolated to seamlessly create intermediate databases. The new transferred models are shown to outperform the analytical micromechanics methods in predicting the volume fraction effects. We then apply the unified DMN databases to the design of failure properties, where the failure criteria are defined upon the distribution of microscale plastic strains. The Pareto frontier of toughness and ultimate tensile strength is extracted from a large-scale design space enabled by the efficiency of DMN extrapolation.

### MSC:

74 Mechanics of deformable solids

### Keywords:

multiscale modeling; machine learning; micromechanics; nonlinear plasticity; failure analysis; materials design

**Full Text:** DOI

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