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Discussion Paper

Deep learning for finance: deep portfolios

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Abstract

We explore the use of deep learning hierarchical models for problems in financial prediction and classification. Financial prediction problems – such as those presented in designing and pricing securities, constructing portfolios, and risk management – often involve large data sets with complex data interactions that currently are difficult or impossible to specify in a full economic model. Applying deep learning methods to these problems can produce more useful results than standard methods in finance. In particular, deep learning can detect and exploit interactions in the data that are, at least currently, invisible to any existing financial economic theory.

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