Literature

Numerical Methods for Deep Learning

Literature Overview

- surveys on deep learning: [5, 30]
- some important works in deep learning: [37, 38, 31, 26, 35, 29, 27, 22, 23, 40, 32],
- applications of deep learning: natural language processing [13, 8, 28], image processing [31, 29], speech processing [24]
- approximation theory: [14, 25]
- PDE-inspired approaches to deep learning: [15, 18]
- optimization: [36, 17, 16, 34, 10, 6, 11]
- numerical methods: overview [3], optimization [33, 12, 4], linear algebra [39, 21], differential equations [2, 1], optimal control [9]
- classical work on adjoints ($\approx$ backpropagation) [7]
- inverse problems: [19, 41, 20]

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