fast machine learning
for science

State Space Models for Scientific Time Series Applications

We investigate the application of state space models (SSMs) to a diverse set of scientific time series tasks. In particular, we benchmark the performance of SSMs against a set of baseline neural networks across three domains: magnet quench prediction, gravitational wave signal classification (LIGO), and neural phase estimation. Our analysis evaluates both computational efficiency—quantified by the number of mathematical operations—and task-specific performance metrics. Results suggest that SSMs offer a favorable trade-off between accuracy and computational efficiency, making them a possible alternative to conventional deep learning models in scientific settings.

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Session Classification: Posters and coffee