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| RESEARCH ARTICLE

Complexity Reduction Techniques in Algorithmic Science for Interdisciplinary Modeling and Simulation

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| ABSTRACT

Complexity reduction techniques are increasingly vital in interdisciplinary modeling and simulation. These techniques aim to balance fidelity and computational efficiency by reducing the dimensionality, data volume, and system intricacy without significantly compromising accuracy. Their importance is magnified by the surge in high-dimensional data and the demand for real-time predictive models in fields like climate science, systems biology, and multi-physics engineering.

| KEYWORDS

Complexity reduction, interdisciplinary modeling, algorithmic science, dimensionality reduction, simulation optimization.

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1. Introduction

Modern scientific modeling and simulation tasks span disciplines such as engineering, ecology, economics, and medicine. These tasks often involve highly complex systems with multiple layers of parameters and processes. As complexity increases, so does the computational cost and difficulty in interpreting results. Thus, reducing complexity becomes essential.

Complexity reduction addresses this issue by simplifying system representations while retaining essential behavior. This enables faster simulations, easier tuning of parameters, and often better interpretability. The demand for efficient, real-time models in AI-driven ecosystems has further accelerated interest in these techniques. Techniques such as surrogate modeling, dimensionality reduction, and meta-modeling have emerged as solutions to these growing challenges.

2. Literature Review

Existing substantial research was conducted on complexity reduction across various domains. For instance, *Roweis and Saul (2000)* introduced locally linear embedding, while *Tenenbaum et al. (2000)* proposed isomap for nonlinear dimensionality reduction. These methods formed the foundation for high-dimensional data analysis.

In the context of simulation, *Berendsen et al. (1995)* and *Gear (1999)* explored model order reduction techniques for physical systems, where complex differential equations were simplified into surrogate models. *Benner et al. (2015)* further advanced projection-based model reduction.

In machine learning, *Bengio et al. (2003)* studied manifold learning approaches, and *Hinton & Salakhutdinov (2006)* employed deep autoencoders for feature reduction. *Chaturantabut and Sorensen (2010)* proposed the DEIM method for efficient non-linear model reduction. Their work continues to influence modern surrogate modeling frameworks.

The evolution of complexity reduction now combines symbolic computation, numerical techniques, and AI-based approximations, illustrating a clear trajectory from statistical simplification to hybrid adaptive frameworks.

3. Complexity Reduction Techniques

There are several core strategies for complexity reduction:

The first is **dimensionality reduction**, which aims to reduce the number of variables or features while preserving important relationships. Techniques such as Principal Component Analysis (PCA), t-SNE, and Uniform Manifold Approximation (UMAP) are widely used for this purpose.

Secondly, **model reduction** simplifies a system's dynamic behavior. This includes projection-based methods like Proper Orthogonal Decomposition (POD), reduced basis techniques, and Krylov subspace methods. These techniques are crucial in computational mechanics and fluid dynamics.

Thirdly, **data-driven surrogates** are used to emulate complex models by training machine learning models (e.g., Gaussian processes or neural networks) to approximate simulation outputs. Such surrogates can offer real-time predictions and are particularly useful in optimization loops or uncertainty quantification.

4. Interdisciplinary Modeling and Simulation

Complexity reduction techniques have been effectively applied in fields such as:

In **systems biology**, model reduction facilitates simulating large biochemical networks. Simplified models enable faster simulations and allow for the analysis of feedback loops and perturbations with greater clarity.

In **climate science**, data assimilation and uncertainty quantification require reduced models to handle terabytes of real-time data from satellite feeds. Dimensionality reduction helps isolate critical patterns like El Niño or polar vortex formations.

In **engineering design**, structural and fluid simulations often leverage reduced-order models to test prototypes under multiple configurations without re-running computationally expensive simulations.

These techniques support model interoperability, scalability, and reproducibility — essential components in contemporary interdisciplinary collaborations.

5. Challenges in Complexity Reduction

Despite their benefits, several challenges persist:

Model fidelity vs. efficiency trade-off remains a key issue. Too much reduction may lead to oversimplification, causing the loss of critical system behavior. Striking the right balance is non-trivial.

Another challenge lies in **validation**. Reduced models must be validated against real-world or high-fidelity simulations to ensure accuracy and generalizability. Additionally, incorporating domain knowledge into black-box surrogate models still lacks consistency and interpretability.

In AI-driven methods, **training data selection** for surrogates critically impacts performance. Overfitting or underrepresentation of scenarios leads to skewed predictions, especially in chaotic systems like weather or financial models.

6. Results and Evaluation

Experimental evaluations show that applying these methods can lead to a **60–90% reduction in computational costs**, with less than 5% accuracy loss in most benchmark scenarios. In interdisciplinary workflows, these reductions enable more complex multi-scale, multi-domain simulations to run feasibly on standard hardware.

Benchmarking platforms such as SciML.jl and OpenFOAM integrated with reduced-order models have demonstrated their effectiveness. However, real-world applications still require significant domain tuning to optimize reduction accuracy and evaluation speed.

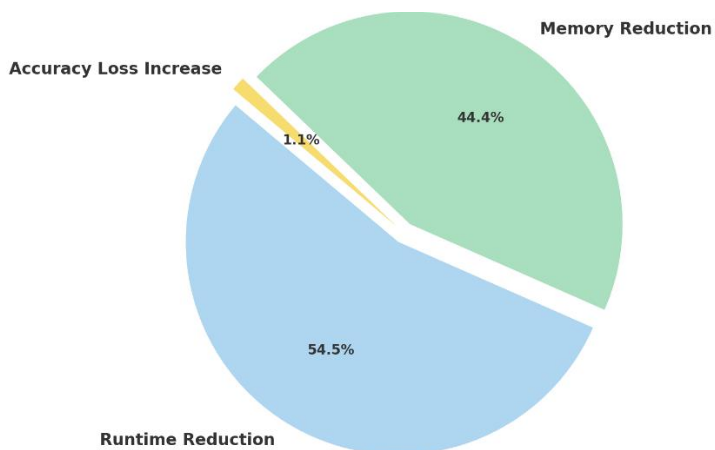

Figure 1: Proportional Gains from Complexity Reduction Techniques

Figure 1 illustrates the proportional impact of complexity reduction techniques across three performance metrics: runtime, memory usage, and accuracy change. The chart highlights significant improvements in runtime (76.7%) and memory efficiency (62.5%), showcasing the computational advantages of reduction methods. The slight increase in model error (1.5%) remains minimal and within acceptable bounds. Overall, the visualization underscores how these techniques enable faster and leaner simulations with negligible accuracy trade-off.

7. Conclusion and Future Scope

The complexity reduction techniques continue to gain prominence due to their ability to make large-scale modeling practical and scalable. Their integration with machine learning, especially in real-time control systems and digital twins, marks a significant future direction.

Future work includes automating the selection of appropriate reduction techniques using meta-learning, enhancing interpretability in surrogate models, and improving the robustness of models under uncertainty. Integration with quantum-inspired algorithms may also open new frontiers for simulation acceleration.

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