Computational Mathematics for AI: Numerical Methods and Distributed Computing for Deep Learning on Big Data

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1 Introduction

This document outlines the protocol for a systematic literature review (SLR) on computational mathematics for AI, focusing on numerical methods and distributed computing techniques for deep learning on big data. The review will follow the PRISMA guidelines (?) and Kitchenham's methodology for SLRs in software engineering (?).

2 Background

2.1 Rationale

As deep learning models grow in complexity and data volumes continue to increase, there is a critical need to understand and optimize the computational methods underpinning these systems. This review aims to synthesize current knowledge on numerical methods and distributed computing techniques specifically applied to deep learning in big data contexts.

2.2 Objectives

The primary objectives of this SLR are:

1. To identify and categorize state-of-the-art numerical methods used in deep learning for big data.

2. To evaluate the effectiveness of various distributed computing techniques for scaling deep learning to big data problems.

3. To compare these methods and techniques in terms of computational efficiency, scalability, and accuracy.

4. To identify emerging trends and future directions in this field.

3 Research Methodology

This study employs a comprehensive approach combining two systematic literature reviews (SLRs) with subsequent meta-analysis and network analysis. The methodology is structured into seven distinct phases:

3.1 Phase 1: Planning and Protocol Development

3.1.1 Research Questions

For SLR 1 (Numerical Methods):

RQ1.1 What are the state-of-the-art numerical methods used in deep learning for big data?

RQ1.2 How do these methods perform in terms of computational efficiency and accuracy?

For SLR 2 (Distributed Computing Techniques):

RQ2.1 What distributed computing techniques are used for scaling deep learning to big data problems?

RQ2.2 How effective are these techniques in terms of scalability and performance?

3.1.2 Literature Review Classification Framework

We will use Cooper's taxonomy (**?**) to classify the literature in both SLRs:

This classification will be applied to each included study during the data extraction phase. It will help us to:

- Systematically categorize the nature and scope of each study
- Identify patterns and trends in the literature
- Ensure a balanced representation of different types of research in our review

Table 1: Adaptation of Cooper's Literature Review Taxonomy

Characteristic	Categories
(a) Focus	Research outcomes, Research methods, Theories, Practices or applications
(b) Goal	Integration, Criticism, Identification of central issues
(c) Perspective	Neutral representation, Espousal of position
(d) Coverage	Exhaustive, Exhaustive with selective citation, Representative, Central or pi
(e) Organization	Historical, Conceptual, Methodological
(f) Audience	Specialized scholars, General scholars, Practitioners or policymakers, Genera

- Tailor our findings to different audience needs
- Guide our analysis and synthesis of the literature

The classification results will be used in Phase 6 (Study Classification and Bias Assessment) to provide additional context for interpreting our findings and identifying gaps in the current research landscape.

3.1.3 Search Strategy Development

PICO-based search strings for each SLR:

SLR 1:

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(("deep learning" OR "neural network*") AND
("numerical method*" OR "optimization algorithm*") AND
("big data" OR "large-scale") AND
(efficiency OR accuracy))
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SLR 2:

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(("deep learning" OR "neural network*") AND
("distributed computing" OR "parallel processing" OR
"GPU acceleration" OR "federated learning") AND
("big data" OR "large-scale") AND
(scalability OR performance))
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3.1.4 Information Sources

IEEE Xplore, ACM Digital Library, SpringerLink, Scopus, Web of Science, JSTOR, AIS

3.1.5 Eligibility Criteria

Inclusion:

- Studies from 2019-2024
- Peer-reviewed journal articles and conference papers
- English language publications
- Directly addressing the respective SLR focus

Exclusion:

- Studies not focusing on big data scenarios
- Publications without clear methodological details
- Review papers

3.2 Phase 2: Literature Search and Study Selection

1. Execute search strategy on selected databases
2. Import results to reference management software
3. Remove duplicates
4. Initial screening of titles and abstracts
5. Full-text assessment of potentially eligible studies
6. Document selection process using PRISMA flow diagram

3.3 Phase 3: Data Extraction and Quality Assessment

3.3.1 Data Extraction

Using a standardized, pre-piloted form to extract:

- Bibliographic information
- Methods/techniques used
- Problem domain and dataset characteristics
- Performance metrics
- Hardware and software environment
- Key findings and limitations

3.3.2 Quality Assessment

Two-phase process using 7-element criteria:

1. Minimum quality threshold
2. Rigour, credibility, and relevance

Quality threshold: 75% positive responses, 75% inter-rater reliability (Krippendorff's q ¿ 0.8)

3.4 Phase 4: Data Synthesis for Individual SLRs

For each SLR:

- Narrative synthesis of findings
- Categorization of methods/techniques
- Analysis of performance metrics

3.5 Phase 5: Combined Analysis

3.5.1 Meta-Analysis

- Random-effects model for common outcome measures
- Forest plots for combined effect sizes
- Subgroup analyses for different categories

3.5.2 Network Analysis

- Comprehensive network graph
- Community detection
- Centrality measure analysis

3.6 Phase 6: Study Classification and Bias Assessment

3.6.1 Study Classification

Classify all studies according to Cooper's taxonomy:

- Focus, Goal, Perspective, Coverage, Organization, Audience

3.6.2 Assessment of Meta-Bias

- Funnel plot examination
- Egger's test for small-study effects

3.7 Phase 7: Synthesis and Reporting

- Compare and contrast findings from both SLRs
- Identify synergies between numerical methods and distributed computing techniques
- Discuss trade-offs between efficiency, scalability, and accuracy
- Highlight emerging trends and future research directions
- Assess confidence in cumulative evidence using GRADE approach
- Prepare final report following PRISMA guidelines

This phased approach ensures a systematic and comprehensive review of computational mathematics for AI in big data contexts, combining insights from numerical methods and distributed computing techniques.

4 Discussion

This systematic review will provide a comprehensive overview of the current state of numerical methods and distributed computing techniques for deep learning on big data. The findings will be interpreted considering the strength of evidence, applicability, and generalizability. Limitations of the review and the included studies will be discussed, and implications for future research will be outlined.