Novelty Assessment Report

Paper: Pinet: Optimizing hard-constrained neural networks with orthogonal projection layers

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Abstract

We introduce an output layer for neural networks that ensures satisfaction of convex constraints. Our approach, Πnet, leverages operator splitting for rapid and reliable projections in the forward pass, and the implicit function theorem for backpropagation. We deploy Πnet as a feasible-by-design optimization proxy for parametric constrained optimization problems and obtain modest-accuracy solutions faster than traditional solvers when solving a single problem, and significantly faster for a batch of problems. We surpass state-of-the-art learning approaches by orders of magnitude in terms of training time, solution quality, and robustness to hyperparameter tuning, while maintaining similar inference times. Finally, we tackle multi-vehicle motion planning with non-convex trajectory preferences and provide Πnet as a GPU-ready package implemented in JAX.

Core Task Landscape

This paper addresses: **constrained optimization with neural networks**

A total of **50 papers** were analyzed and organized into a taxonomy with **23 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Neural Networks as Optimization Solvers**
- **Differentiable Optimization Layers in Neural Networks**
- **Learning-Based Approaches to Constrained Optimization**
- **Constrained Neural Network Training**
- **Neural Network Compression and Architecture Optimization**
- **Optimization Methods for Neural Network Training**
- **Application-Driven Constrained Neural Optimization**
- **Surveys and Theoretical Frameworks**

Complete Taxonomy Tree

- constrained optimization with neural networks Survey Taxonomy
- Neural Networks as Optimization Solvers
  - Recurrent Neural Networks for Constrained Optimization
  - Projection-Based Neural Networks (2 papers)
    - [17] A projection neural network and its application to constrained optimization problems (Youshen Xia, 2002) View paper
    - [32] An extended projection neural network for constrained optimization (Youshen Xia, 2004) View paper
  - Lagrangian and Penalty-Based Neural Networks (3 papers)
    - [24] Constrained Differential Optimization for Neural Networks (Platt John C., 2023) View paper
    - [27] On solving constrained optimization problems with neural networks: A penalty method approach (W. E. Lillo, 1993) View paper
    - [41] Lagrange programming neural networks (Shengwei Zhang, 1992) View paper
  - General Recurrent Networks for Constrained Problems (5 papers)
    - [13] Neural networks for constrained optimization problems (Walter E. Lillo, 1993) View paper
    - [25] Recurrent neural network optimisation based on linearly constrained numerical methods (Min Li, 2025) View paper
    - [37] A one-layer recurrent neural network for constrained nonconvex optimization (Guocheng Li, 2015) View paper
    - [38] A neural network theory for constrained optimization (Yoshikane Takahashi, 1999) View paper
    - [50] A smooth gradient approximation neural network for general constrained nonsmooth nonconvex optimization problems. (Na Liu, 2025) View paper
  - Feedforward Neural Networks for Optimization (4 papers)
  - [1] A constrained optimization method based on BP neural network (Li Zhang, 2018) View paper
  - [10] Optimization using neural networks (G. A. Tagliarini, 1991) View paper
  - [18] Using Neural Networks in Constrained Optimization Problems (Jan Lim, 2019) View paper
  - [34] Neural network for quadratic optimization with bound constraints (A. Bouzerdoum, 1993) View paper
  - Distributed and Graph-Based Neural Optimization (3 papers)
  - [30] A Recurrent Neural Network Approach for Constrained Distributed Fuzzy Convex Optimization (Jingxin Liu, 2023) View paper
  - [31] Distributed constrained combinatorial optimization leveraging hypergraph neural networks (Nasimeh Heydaribeni, 2024) View paper
  - [45] Unrolled Graph Neural Networks for Constrained Optimization (Hadou, 2025) View paper
  - Specialized Neural Optimization Architectures (1 papers)

- [36] Dragonfly visual multipath peak evolutionary neural network for solving constrained optimization problems (Heng Wang, 2025) View paper
- Differentiable Optimization Layers in Neural Networks
  - Quadratic Programming Layers (1 papers)
  - [3] Optnet: Differentiable optimization as a layer in neural networks (Amos, 2017) View paper
  - Projection and Feasibility Layers ★ (3 papers)
  - [0] Pinet: Optimizing hard-constrained neural networks with orthogonal projection layers (Anon et al., 2026) View paper
  - [42] FSNet: Feasibility-Seeking Neural Network for Constrained Optimization with Guarantees (Nguyen, 2025) View paper
  - [47] Homeomorphic projection to ensure neural-network solution feasibility for constrained optimization (E Liang, 2024) View paper
  - General Differentiable Optimization Layers (2 papers)
  - [35] Nonlinear Optimization with GPU-Accelerated Neural Network Constraints (Robert Parker, 2025) View paper
  - [49] Constraint Boundary Wandering Framework: Enhancing Constrained Optimization With Deep Neural Networks (Shuang Wu, 2025) View paper
- Learning-Based Approaches to Constrained Optimization
  - Learning Constraints and Objectives from Data (1 papers)
  - [2] Mixed-integer optimization with constraint learning (Donato Maragno, 2025) View paper
  - Learning to Predict Optimal Solutions (2 papers)
  - [12] End-to-end constrained optimization learning: A survey (James Kotary, 2021) View paper
  - [46] Learning for constrained optimization: Identifying optimal active constraint sets (Misra, 2022) View paper
  - Augmented Lagrangian and Dual Learning Methods (2 papers)
  - [15] Lagrangian duality for constrained deep learning (Van Hentenryck P, 2020) View paper
  - [16] Learning constrained optimization with deep augmented lagrangian methods (Kotary, 2024) View paper
- Constrained Neural Network Training
  - Training with Physical and Structural Constraints (4 papers)
  - [4] Integration between constrained optimization and deep networks: a survey (Alice Bizzarri, 2024) View paper
  - [9] Fractional deep neural network via constrained optimization (Harbir Antil, 2020) View paper
  - [23] Constrained convolutional neural networks for weakly supervised segmentation (Deepak Pathak, 2015) View paper
  - [43] A learning framework for neural networks using constrained optimization methods (Stavros Perantonis, 2000) View paper
  - Training for Robustness and Fairness (2 papers)
  - [11] Constrained optimization to train neural networks on critical and under-represented classes (Sara Sangalli, 2021) View paper
  - [20] A constrained optimization approach to improve robustness of neural networks (Zhao Shudian, 2024) View paper
  - Parameter Regularization via Constraints (1 papers)
  - [26] Improving deep learning optimization through constrained parameter regularization (JÃ¶rg Franke, 2024) View paper
- Neural Network Compression and Architecture Optimization (3 papers)
  - [5] Constrained optimization based low-rank approximation of deep neural networks (Chong Li, 2018) View paper
  - [22] Data preprocessing strategy in constructing convolutional neural network classifier based on constrained particle swarm optimization with fuzzy penalty function (Kun Zhou, 2023) View paper
  - [40] Model compression as constrained optimization, with application to neural nets. Part I: General framework (Carreira-PerpiÃ±Ã¡n, 2017) View paper
- Optimization Methods for Neural Network Training (2 papers)
  - [6] Optimization for deep learning: An overview (Ruo Yu Sun, 2020) View paper
  - [19] Improved optimization for the neural-network quantum states and tests on the chromium dimer. (Xiang Li, 2024) View paper
- Application-Driven Constrained Neural Optimization
  - Control and Model Predictive Control (4 papers)
  - [8] Lyapunov-based neural network model predictive control using metaheuristic optimization approach (Chafea Stiti, 2024) View paper
  - [29] Optlayer-practical constrained optimization for deep reinforcement learning in the real world (Pham, 2018) View paper
  - [44] Magnitude-constrained optimal chaotic desynchronization of neural populations. (Michael Zimet, 2025) View paper
  - [48] Constrained Neural Network Model Predictive Controller Based on Archimedes Optimization Algorithm with Application to Robot Manipulators (Abdelhadi Aouaichia, 2023) View paper
  - Engineering Design and Topology Optimization (2 papers)
  - [7] Topology optimization of 2D structures with nonlinearities using deep learning (D. Abueidda, 2020) View paper
  - [14] Multi-objective optimization of scramjet nozzle under geometric constraints using a deep learning method (Xue Deng, 2025) View paper
  - Adversarial and Security Applications (1 papers)
  - [28] Adversarial attacks on face detectors using neural net based constrained optimization (Bose, 2018) View paper
  - Scientific Computing and Data Assimilation (1 papers)
  - [21] A Fourâ□□Dimensional Variational Constrained Neural Networkâ□□Based Data Assimilation Method (Wuxin Wang, 2024) View paper
  - General Optimization Assistance (1 papers)
  - [33] Optimization Assisted by Neural Network-Based Machine Learning in Electromagnetic Applications (Anastasios Papathanasopoulos, 2024) View paper
- Surveys and Theoretical Frameworks (1 papers)
  - [39] Constrained optimization for machine learning: algorithms and applications (Gallego-Posada, 2024) View paper

Narrative

Core task: constrained optimization with neural networks. This field encompasses a diverse set of approaches that intertwine neural architectures with optimization problems subject to constraints. At the highest level, the taxonomy distinguishes between using neural networks as direct solvers for optimization tasks, embedding differentiable optimization layers within end-to-end learning pipelines, developing learning-based methods that approximate or guide constrained solvers, enforcing constraints during neural network training itself, compressing or designing architectures under resource budgets, refining optimization algorithms for training, applying these techniques to domain-specific problems, and synthesizing theoretical perspectives. Within the branch of differentiable optimization layers, a particularly active line of work focuses on projection and feasibility layers that ensure outputs respect hard constraints—

methods such as OptNet[3] pioneered the integration of quadratic program solvers as network modules, while more recent efforts like FSNet[42] and approaches ensuring homeomorphic projections (Homeomorphic projection to ensure[47]) refine how feasibility is maintained during backpropagation.

Across these branches, key themes include the trade-off between computational efficiency and constraint satisfaction guarantees, the challenge of differentiating through non-smooth projection operators, and the tension between end-to-end learning and classical optimization rigor. Pinet[0] situates itself within the projection and feasibility layer cluster, emphasizing mechanisms to embed hard constraints directly into neural architectures in a differentiable manner. Compared to neighbors such as FSNet[42], which may prioritize specific structural constraints, and Homeomorphic projection to ensure[47], which explores topological properties of feasible regions, Pinet[0] appears to contribute refinements in how projections are computed or integrated during training. This work reflects ongoing efforts to make constrained optimization layers both practically scalable and theoretically sound, bridging classical feasibility methods with modern deep learning workflows.

Related Works in Same Category

The following **2 sibling papers** share the same taxonomy leaf node with the original paper:

1. FSNet: Feasibility-Seeking Neural Network for Constrained Optimization with Guarantees

Authors: Nguyen, Hoang T., Donti, Priya L., Hoang T. Nguyen, et al. (6 authors total) | **Year/Venue**: 2025 | **URL**: View paper

Abstract

Efficiently solving constrained optimization problems is crucial for numerous real-world applications, yet traditional solvers are often computationally prohibitive for real-time use. Machine learning-based approaches have emerged as a promising alternative to provide approximate solutions at faster speeds, but they struggle to strictly enforce constraints, leading to infeasible solutions in practice. To address this, we propose the Feasibility-Seeking Neural Network (FSNet), which integrates a ...

Relationship Analysis

Both papers belong to the Projection and Feasibility Layers category, using output layers to ensure constraint satisfaction through projection or feasibility-seeking operations with gradient computation. They overlap in addressing constrained optimization with neural networks by enforcing hard constraints via differentiable projection-like mechanisms and backpropagation through implicit differentiation or unrolled iterations. The key difference is that the original paper (Πnet) uses operator splitting (Douglas-Rachford) for orthogonal projection onto convex sets with implicit function theorem for backpropagation, while the candidate paper (FSNet) employs a feasibility-seeking step that minimizes constraint violations via unconstrained optimization with unrolled differentiation, handling both convex and non-convex constraints.

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2. Homeomorphic projection to ensure neural-network solution feasibility for constrained optimization

Authors: E Liang, M Chen, SH Low | **Year/Venue**: 2024 | **URL**: View paper

Abstract

â¦ constrained optimization problem using the HP framework. We select four convex problems with different constraint â¦ compare the following approaches to solve constrained optimization: â¦

Relationship Analysis

Both papers belong to the Projection and Feasibility Layers category, focusing on ensuring constraint satisfaction through projection operations with gradient computation. They overlap in using projection-based approaches to enforce convex constraints on neural network outputs and employ implicit differentiation for backpropagation. The key difference is that the original paper (Πnet) uses operator splitting (Douglas-Rachford algorithm) for rapid projections onto decomposed constraint sets ($A \cap K$), while the candidate paper uses homeomorphic mappings via invertible neural networks to transform constraints to unit balls before applying bisection-based projection.

Contributions Analysis

Overall novelty summary. The paper introduces Πnet, an output layer architecture that enforces convex constraints through operator splitting and implicit differentiation for backpropagation. Within the taxonomy, it resides in the 'Projection and Feasibility Layers' leaf under 'Differentiable Optimization Layers in Neural Networks'. This leaf contains only three papers total, including the original work, indicating a relatively sparse but focused research direction. The sibling papers address related projection mechanisms, suggesting Πnet contributes to an emerging cluster of methods that embed hard constraint satisfaction directly into neural architectures rather than solving full optimization problems as layers.

The taxonomy reveals that Πnet's parent branch, 'Differentiable Optimization Layers', also includes 'Quadratic Programming Layers' and 'General Differentiable Optimization Layers', which solve complete optimization problems rather than focusing solely on feasibility. Neighboring branches include 'Neural Networks as Optimization Solvers' (with recurrent architectures for iterative convergence) and 'Learning-Based Approaches' (which predict solutions rather than enforce constraints structurally). Πnet's emphasis on projection operators positions it between classical optimization-as-layer methods and pure learning-based approximations, leveraging operator splitting for computational efficiency while maintaining differentiability through implicit function theorem applications.

Among thirty candidates examined, the contribution-level analysis shows mixed novelty signals. The core Πnet architecture with orthogonal projection examined ten candidates and found one potentially refuting prior work, suggesting some overlap in projection-based constraint enforcement mechanisms. The hyperparameter tuning and matrix equilibration strategy examined ten candidates with none refuting, indicating this aspect may be more novel or less directly addressed in prior literature. The GPU-ready JAX implementation examined ten candidates with one refuting, likely reflecting existing GPU-accelerated optimization frameworks rather than fundamental methodological overlap. The limited search scope means these findings characterize top-thirty semantic matches, not exhaustive field coverage.

Given the sparse taxonomy leaf and limited literature search, Πnet appears to refine existing projection-layer concepts with specific computational strategies (operator splitting, equilibration) rather than introducing an entirely new paradigm. The analysis captures proximity to known methods like FSNet and homeomorphic projection approaches but cannot definitively assess novelty against the full field. The work's positioning suggests incremental advancement within a nascent research direction, with practical contributions in implementation and hyperparameter handling potentially offering value beyond core architectural novelty.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Πnet architecture with orthogonal projection layer

Description: The authors propose Πnet, a neural network architecture that appends a projection layer to any backbone network. This layer uses an operator splitting scheme (Douglas-Rachford algorithm) to project infeasible outputs onto convex constraint sets in the forward pass, and applies the implicit function theorem for efficient backpropagation through the projection.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Constrained Machine Learning Through Hyperspherical Representation

URL: View paper

Brief Assessment

Constrained Machine Learning Through[69] focuses on hyperspherical coordinate transformations for bounded convex regions, not orthogonal projection layers with operator splitting schemes for general convex constraints.

2. End-to-end learning for optimization via constraint-enforcing approximators

URL: View paper

Prior Art Analysis

End-to-end learning for optimization[64] demonstrates prior work on neural network architectures that enforce constraint satisfaction through projection layers. The candidate paper proposes 'ProjectNet', which appends projection operations after neural network layers to ensure feasibility, using Dykstra's projection algorithm for the forward pass. While the original paper uses Douglas-Rachford splitting and the implicit function theorem for backpropagation, the candidate uses approximate projections with differentiable operations. Both approaches share the core concept of using projection layers to enforce convex constraints on neural network outputs, with the candidate paper published in 2023 (AAAI-23) predating the original submission.

Evidence

Evidence 1 - **Rationale**: Both papers describe the core architectural concept of projecting neural network outputs onto constraint sets to ensure feasibility. - **Original**: given a context x, the backbone network produces the raw output yraw = f(x; θ), where θ are the network weights. we enforce feasibility by projecting yraw onto c(x): y = πc(x)(yraw) = argminz∈c(x) z - yraw. - **Candidate**: one difficulty of learning w∗ lies in ensuring that the output of a neural network satisfies the constraints a ˆw(u) =b and ˆw(u) ≥ 0. the simplest solution method for satisfying these constraints is to project after each iteration onto the feasible region, similar to a projected gradient descent me...

Evidence 2 - **Rationale**: Both papers use operator splitting methods (Douglas-Rachford vs. Dykstra's algorithm) to compute projections onto convex constraint sets, demonstrating the prior existence of this technical approach. - **Original**: to compute the projection y = πc(x)(yraw) we employ the douglas-rachford algorithm (bauschke & combettes, 2017, sec. 28.3), which solves optimization problems of the form minz g(z) +h(z), where g and h are proper, closed, convex functions. - **Candidate**: as a result, we propose using dykstra's projection algorithm (dykstra 1983) that provides a sequence of differentiable steps to approximate the projection. let p1, p2 be any two intersecting convex sets. we alternatively project onto p1 followed by p2 until we reach some desired accuracy (distance f...

Evidence 3 - **Rationale**: Both papers identify and address the challenge of differentiating through projection operations for backpropagation, showing awareness of this technical issue in prior work. - **Original**: to train the backbone network using backpropagation, we need to efficiently differentiate the loss l (which in general depends on the projected output of the network and on the input; see section 2.2) with respect to the backbone network parameters θ. - **Candidate**: however, we face a similar issue as before. that is, the gradient of the projection onto a polytope is often zero. indeed, the set of points which projects onto any given vertex is a fully-dimensional cone and so the gradient for these would be zero.

3. Distributed stochastic projection-free algorithm for constrained optimization

URL: View paper

Brief Assessment

Distributed stochastic projection-free algorithm[65] focuses on distributed optimization using Frank-Wolfe methods to avoid expensive projections, not neural network architectures with projection layers for constraint enforcement.

4. Dual lagrangian learning for conic optimization

URL: View paper

Brief Assessment

Dual lagrangian learning for[67] focuses on dual conic optimization for convex problems using lagrangian duality, not on neural network output layers with orthogonal projections for general constrained optimization.

5. Enforcing Hard Linear Constraints in Deep Learning Models with Decision Rules

URL: View paper

Brief Assessment

Enforcing Hard Linear Constraints[70] focuses on linear constraints using decision rules from stochastic optimization, while Πnet addresses general convex constraints via operator splitting. The candidate's approach is fundamentally different in methodology and constraint scope.

6. On the effectiveness of projection methods for convex feasibility problems with linear inequality constraints

URL: View paper

Brief Assessment

On the effectiveness of[68] focuses on projection methods for solving linear inequality systems in optimization contexts, not on neural network architectures with projection layers for enforcing constraints during training and inference.

7. Learning sparse deep neural networks using efficient structured projections on convex constraints for green AI

URL: View paper

Brief Assessment

Learning sparse deep neural[61] focuses on weight sparsification in DNNs using projection-gradient methods with convex constraints (ℓ_1, $\ell_{2,1}$, $\ell_{1,1}$ norms) for model compression. This differs fundamentally from Πnet's approach of enforcing output feasibility constraints for parametric optimization problems through operator splitting and implicit differentiation.

8. Approximating explicit model predictive control using constrained neural networks

URL: View paper

Brief Assessment

Approximating explicit model predictive[63] focuses on neural network approximations for model predictive control with constraint projection, but uses Dykstra's algorithm rather than Douglas-Rachford splitting, and does not employ the implicit function theorem for backpropagation through projections as in the original paper.

9. Sample-specific output constraints for neural networks

URL: View paper

Brief Assessment

Sample-specific output constraints for[66] focuses on input-dependent parametrization of constraint sets rather than projection-based approaches. The candidate explicitly states their method 'leveraging an input-dependent parametrization of the constrained output space for imposing hard output constraints' and contrasts this with projection methods, noting 'Instead of performing a projection, constraintnet applies an input-dependent parametrization of the constrained output space in the final layer'.

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10. Solving convex multi-objective optimization problems using a projection neural network framework

URL: View paper

Brief Assessment

Solving convex multi-objective optimization[62] focuses on multi-objective optimization problems using neural networks, while the original paper addresses single-objective constrained optimization with a projection layer enforcing convex constraints. The candidate does not demonstrate prior work on the specific architecture combining operator splitting (Douglas-Rachford) with implicit function theorem for backpropagation through projection layers.

Contribution 2: Hyperparameter tuning and matrix equilibration strategy

Description: The authors develop an auto-tuning procedure that recommends hyperparameters by evaluating projections on a validation subset, combined with Ruiz equilibration to improve matrix conditioning. This strategy enhances performance and makes the method robust to data scaling issues.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Optimizing double-layered convolutional neural networks for efficient lung cancer classification through hyperparameter optimization and advanced image pre â¦

URL: View paper

Brief Assessment

Optimizing double-layered convolutional neural[71] focuses on hyperparameter optimization for lung cancer classification using CNNs, not on constrained optimization or matrix equilibration for neural network robustness in the context described by the original paper.

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2. Balancing the stability-plasticity dilemma with online stability tuning for continual learning

URL: View paper

Brief Assessment

Balancing the stability-plasticity dilemma[75] focuses on dynamic hyperparameter tuning for continual learning stability-plasticity trade-offs, not neural network projection layers or matrix conditioning for constrained optimization.

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3. Computational Analysis of Synaptic Plasticity in Echo State Network

URL: View paper

Brief Assessment

Computational Analysis of Synaptic[73] focuses on synaptic plasticity in Echo State Networks, examining connection weight dynamics and neural stability. This is fundamentally different from the original paper's hyperparameter auto-tuning procedure and Ruiz equilibration for constrained optimization problems.

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4. Rotational equilibrium: How weight decay balances learning across neural networks

URL: View paper

Brief Assessment

Rotational equilibrium[74] focuses on weight decay dynamics in neural networks and does not address hyperparameter tuning for constrained optimization or matrix equilibration for projection-based methods. The candidate's auto-tuning procedure targets optimizer hyperparameters (sigma, omega) for rotational dynamics, not projection layer conditioning or feasibility constraints.

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5. A Tunable Despeckling Neural Network Stabilized via Diffusion Equation

URL: View paper

Brief Assessment

A Tunable Despeckling Neural[76] focuses on diffusion equation-based regularization for SAR image despeckling with a single tunable time step parameter, not on general hyperparameter tuning strategies or matrix equilibration for neural network robustness across diverse optimization problems.

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6. Stabilized classification control using multi-stage quantum convolutional neural networks for autonomous driving

URL: View paper

Brief Assessment

Stabilized classification control using[79] focuses on quantum convolutional neural networks for autonomous driving with Lyapunov optimization for adaptive model selection. This is fundamentally different from the original paper's hyperparameter auto-tuning procedure and Ruiz equilibration strategy for improving matrix conditioning in constrained neural network projections.

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7. â¦ -theoretic optimization of landslide susceptibility mapping: A comparative study between Bayesian-optimized basic neural network and new generation neural network â¦

URL: View paper

Brief Assessment

The candidate paper (â -theoretic optimization of[72]) focuses on Bayesian optimization for hyperparameter tuning in landslide susceptibility mapping using neural networks, which is a different application domain and methodology compared to the original paper's auto-tuning procedure for projection-based constrained optimization with matrix equilibration.

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8. ANDI: Arithmetic Normalization/Decorrelated Inertia

URL: View paper

Brief Assessment

ANDI[77] focuses on optimizer design with matrix equilibration for gradient scaling in neural network training, not on hyperparameter tuning procedures for projection-based constrained optimization or validation-based auto-tuning strategies as described in the original paper.

9. Intelligent Fault Diagnosis Method for Spacecraft Fluid Loop Pumps Based on Multi-Neural Network Fusion Model

URL: View paper

Brief Assessment

Intelligent Fault Diagnosis Method[80] focuses on spacecraft fluid loop pump fault diagnosis using multi-neural network fusion models. This is a completely different domain (fault diagnosis) with different technical objectives than the ORIGINAL paper's constrained optimization framework with hyperparameter tuning and matrix equilibration for neural network projections.

10. Experimental and machine learning based investigation of performance and emission characteristics of a CI engine using fusel oil blends

URL: View paper

Brief Assessment

Experimental and machine learning[78] focuses on CI engine performance using fusel oil blends with machine learning models. This work does not address neural network optimization, matrix equilibration, or hyperparameter tuning strategies for constrained optimization problems.

Contribution 3: GPU-ready JAX implementation

Description: The authors provide a practical, GPU-accelerated implementation of Πnet in the JAX framework, enabling efficient training and inference for constrained optimization problems. The code is made available to facilitate adoption.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. General Cutting Planes for Bound-Propagation-Based Neural Network Verification

URL: View paper

Brief Assessment

General Cutting Planes for[53] focuses on neural network verification using bound propagation methods with cutting planes, not on constrained optimization with projection layers as in the original paper. The JAX implementation mentioned in [53] is for a verification framework, not for constrained neural networks with projection operators.

2. Fast and easy whole-brain network model parameter estimation with automatic differentiation

URL: View paper

Brief Assessment

Fast and easy whole-brain[56] focuses on whole-brain network model parameter estimation using automatic differentiation in JAX, not constrained neural network optimization. The application domains and technical objectives differ fundamentally from Πnet's constrained optimization framework.

3. Clip-and-Verify: Linear Constraint-Driven Domain Clipping for Accelerating Neural Network Verification

URL: View paper

Brief Assessment

Clip-and-Verify[51] focuses on neural network verification with GPU procedures for constraint handling, not on constrained optimization with JAX-based projection layers as in the original paper.

4. Cronos: Enhancing deep learning with scalable gpu accelerated convex neural networks

URL: View paper

Brief Assessment

Cronos[54] focuses on convex neural networks using ADMM and operator splitting methods, not on constrained optimization with projection layers as in the original paper. The JAX implementation serves different algorithmic purposes.

5. Convolution hierarchical deep-learning neural network (c-hidenn) with graphics processing unit (gpu) acceleration

URL: View paper

Brief Assessment

Convolution hierarchical deep-learning neural[57] focuses on convolutional neural networks for different applications and mentions JAX library usage, but does not address constrained optimization problems or projection layers that are central to the original paper's contribution.

6. Topology Optimization Using Neural Network for Stress Constrained Problems

URL: View paper

Brief Assessment

Topology Optimization Using Neural[58] focuses on topology optimization with stress constraints using JAX for automatic differentiation, not on constrained neural network architectures or projection layers for general parametric optimization problems.

7. Dataset for Learning constitutive relations from soil moisture data via physically constrained neural networks

URL: View paper

Prior Art Analysis

Dataset for Learning constitutive[59] demonstrates that GPU-accelerated JAX implementations for constrained neural networks existed prior to the original paper's submission. The candidate paper explicitly provides JAX source codes with GPU compatibility instructions, including specific CUDA installation commands and version requirements. Both papers implement constrained optimization problems in JAX with GPU support, though for different application domains (soil moisture modeling vs. general constrained optimization).

Evidence

Evidence 1 - **Rationale**: This pair demonstrates that Dataset for Learning constitutive[59] provided GPU-ready JAX implementation with explicit CUDA installation instructions, showing that such implementations existed before the original paper's claimed novelty of providing a 'gpu-ready package implemented in jax.' - **Original**: we provide an efficient and gpu-ready implementation ofπnet in jax. we make our code available in the supplementary material. - **Candidate**: codes: python source codes for the jax-richards and inverse modeling. the version of python and jax is 3.9.18 and 0.4.19. because these python codes are not compatible with the latest version of jax (0.4.28 as of 5/22/2024), users need to install older version of jax and several other packages. we r...

Evidence 2 - **Rationale**: Both papers explicitly mention GPU compatibility in their JAX implementations, indicating that providing GPU-ready JAX packages for constrained problems was not novel to the original paper. - **Original**: finally, we tackle multi-vehicle motion planning with non-convex trajectory preferences and provide πnet as a gpu-ready package implemented in jax. - **Candidate**: if users want to use a gpu, they need to install a nvidia driver that is compatible with the jax version above.

8. Jax md: a framework for differentiable physics

URL: View paper

Brief Assessment

Jax md[55] is a general differentiable physics framework for molecular dynamics simulations, not specifically focused on constrained neural network optimization or projection layers as in the original paper.

9. Spyx: A library for just-in-time compiled optimization of spiking neural networks

URL: View paper

Brief Assessment

Spyx[52] focuses on spiking neural networks (SNNs) in JAX, not constrained optimization problems. The candidate addresses neuromorphic computing and event-based learning, which is a completely different domain from the original paper's parametric constrained optimization framework.

10. A projection-based framework for gradient-free and parallel learning

URL: View paper

Brief Assessment

A projection-based framework for[60] focuses on feasibility-seeking training via projection operators, not on constrained neural networks for optimization problems. The candidate's JAX implementation serves a fundamentally different purpose than Πnet's GPU-accelerated constrained optimization framework.

Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

References

- [0] Pinet: Optimizing hard-constrained neural networks with orthogonal projection layers View paper
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