

# Novelty Assessment Report

**Paper:** Deep Learning for Subspace Regression

**PDF URL:** <https://openreview.net/pdf?id=HF60Lu1Maj>

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## Abstract

It is often possible to perform reduced order modelling by specifying linear subspace which accurately captures the dynamics of the system. This approach becomes especially appealing when linear subspace explicitly depends on parameters of the problem. A practical way to apply such a scheme is to compute subspaces for a selected set of parameters in the computationally demanding offline stage and in the online stage approximate subspace for unknown parameters by interpolation. For realistic problems the space of parameters is high dimensional, which renders classical interpolation strategies infeasible or unreliable. We propose to relax the interpolation problem to regression, introduce several loss functions suitable for subspace data, and use a neural network as an approximation to high-dimensional target function. To further simplify a learning problem we introduce redundancy: in place of predicting subspace of a given dimension we predict larger subspace. We show theoretically that this strategy decreases the complexity of the mapping for elliptic eigenproblems with constant coefficients and makes the mapping smoother for general smooth function on the Grassmann manifold. Empirical results also show that accuracy significantly improves when larger-than-needed subspaces are predicted. With the set of numerical illustrations we demonstrate that subspace regression can be useful for a range of tasks including parametric eigenproblems, deflation techniques, relaxation methods, optimal control and solution of parametric partial differential equations.

### Disclaimer

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## Core Task Landscape

This paper addresses: **Regression of Parametric Linear Subspaces for Reduced Order Modeling**

A total of **50 papers** were analyzed and organized into a taxonomy with **18 categories**.

### Taxonomy Overview

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

- **Subspace Construction and Basis Representation Methods**
- **Subspace Interpolation and Regression Techniques**
- **Parametric Model Order Reduction Frameworks**
- **Application-Specific Parametric ROM**
- **Specialized Techniques and Extensions**

### Complete Taxonomy Tree

- Regression of Parametric Linear Subspaces for Reduced Order Modeling Survey Taxonomy
- Subspace Construction and Basis Representation Methods
  - Linear Subspace Methods
  - Proper Orthogonal Decomposition and Snapshot-Based Methods (4 papers)
    - [2] Parametric model order reduction by machine learning for fluid-structure interaction analysis (SiHun Lee, 2024) [View paper](#)
    - [20] A new method to interpolate POD reduced bases Application to the parametric model order reduction of a gas bearings supported rotor (Dimitri Goutaudier, 2023) [View paper](#)
    - [46] Parametric reduced order models for tricoaxial injection and mixing problems (Chen-Xu Ni, 2024) [View paper](#)
    - [49] Reduced order modeling of parameterized PDEs using time-space parameter principal component analysis (F. de Vuyst, 2009) [View paper](#)
  - Krylov Subspace and Interpolation-Based Methods (4 papers)
    - [6] Identification of dominant subspaces for model reduction of structured parametric systems (Peter Benner, 2024) [View paper](#)
    - [21] Krylov subspace techniques for reduced-order modeling of large-scale dynamical systems (Zhaojun Bai, 2002) [View paper](#)
    - [33] Predicting near optimal interpolation points for parametric model order reduction using regression models (Quirin Aumann, 2021) [View paper](#)
    - [43] Data-Driven Model Reduction by Moment Matching for Linear and Nonlinear Parametric Systems (Zhang Hanqing, 2025) [View paper](#)
  - Randomized and Data-Driven Decomposition (2 papers)
    - [26] Non-intrusive parametric reduced order modeling using randomized algorithms (Dushhyanth Rajaram, 2020) [View paper](#)
    - [38] Randomized Algorithms for Non-Intrusive Parametric Reduced Order Modeling (Dushhyanth Rajaram, 2020) [View paper](#)
  - Nonlinear and Adaptive Subspace Methods
  - Autoencoder-Based Nonlinear Dimensionality Reduction (3 papers)
    - [3] Physics-aware neural network-based parametric model-order reduction of the electromagnetic analysis for a coated component (SiHun Lee, 2025) [View paper](#)
    - [31] Non-intrusive reduced order modeling using convolutional autoencoders (Halder, 2022) [View paper](#)
    - [44] An Artificial Intelligence Framework for Non-Intrusive Reduced Order Modeling (George Drakoulas, 2025) [View paper](#)
  - Locally Adaptive Basis Construction (3 papers)
    - [1] Tensorial parametric model order reduction of nonlinear dynamical systems (Alexander V. Mamonov, 2024) [View paper](#)

- [7] Deep orthogonal decomposition: a continuously adaptive data-driven approach to model order reduction (Franco, 2024) [View paper](#)
    - [32] Local Reduced-Order Modeling for Electrostatic Plasmas by Physics-Informed Solution Manifold Decomposition (Ping-Hsuan Tsai, 2023) [View paper](#)
- Subspace Interpolation and Regression Techniques
  - Manifold Interpolation for Subspace-Valued Functions (3 papers)
  - [13] An online method for interpolating linear parametric reduced-order models (David Amsallem, 2011) [View paper](#)
  - [35] Consistent Parametric Model Order Reduction by Matrix Interpolation for Varying Underlying Meshes (Sebastian Resch-Schopper, 2025) [View paper](#)
  - [37] Parametric model order reduction by matrix interpolation (H Panzer, 2010) [View paper](#)
  - Machine Learning-Based Subspace Regression ★ (6 papers)
  - [0] Deep Learning for Subspace Regression (Anon et al., 2026) [View paper](#)
  - [17] Gaussian process subspace prediction for model reduction (Ruda Zhang, 2022) [View paper](#)
  - [27] Non-intrusive parametric reduced order models with high-dimensional inputs via gradient-free active subspace (Dushhyanth Rajaram, 2020) [View paper](#)
  - [36] Gaussian Process Subspace Regression for Model Reduction (Zhang, 2021) [View paper](#)
  - [47] Non-intrusive model order reduction for parametric radiation transport simulations (Ian Halvic, 2023) [View paper](#)
  - [50] Non-intrusive reduced order modeling of parametric electromagnetic scattering problems through Gaussian process regression (Zhao Ying, 2021) [View paper](#)
  - Optimal Transport and Nonlinear Interpolation (2 papers)
  - [5] Optimal morphings for model-order reduction for poorly reducible problems with geometric variability (Casenave, 2025) [View paper](#)
  - [14] Model order reduction by convex displacement interpolation (Cucchiara S, 2023) [View paper](#)
- Parametric Model Order Reduction Frameworks
  - Projection-Based Parametric ROM
  - Affine and Tensor-Based Parametric ROM (3 papers)
    - [10] Parallel Input-Independent Model Order Reduction for Discrete-Time Parametric Systems (Zhen Li, 2023) [View paper](#)
    - [16] Dominant subspaces of high-fidelity polynomial structured parametric dynamical systems and model reduction (Pawan Goyal, 2024) [View paper](#)
    - [22] Basic ideas and tools for projection-based model reduction of parametric partial differential equations (Roza, 2020) [View paper](#)
  - Non-Affine and Nonlinear Parametric ROM (2 papers)
    - [18] Parametric reduced-order modeling for component-oriented treatment and localized nonlinear feature inclusion (Vlachas, 2024) [View paper](#)
    - [23] Parametric model order reduction of miniaturized energy harvesting modules (Chengdong, 2025) [View paper](#)
  - Non-Intrusive and Data-Driven Parametric ROM (4 papers)
  - [11] A Parametric Dynamic Mode Decomposition for Reduced-Order Modeling of Highly Flexible Aircraft (Tianyi He, 2024) [View paper](#)
  - [15] Parametric reduced-order modeling of unsteady aerodynamics for hypersonic vehicles (Zhiqiang Chen, 2019) [View paper](#)
  - [40] Data-driven Model Reduction for Parameter-Dependent Matrix Equations via Operator Inference (Xuelian Wen, 2025) [View paper](#)
  - [42] Parametric reduced-order models for probabilistic analysis of unsteady aerodynamic applications (T. Bui Thanh, 2008) [View paper](#)
- Application-Specific Parametric ROM
  - Fluid Dynamics and Aerodynamics (3 papers)
    - [12] Model order reduction in fluid dynamics: challenges and perspectives (Quarteroni, 2014) [View paper](#)
    - [29] Reduced-order modeling of large-scale turbulence using Koopman  $\mathbb{H}^2$ -variational autoencoders (Halder, 2025) [View paper](#)
    - [45] Reduced order modeling of thermal convection flows: a reservoir computing approach (Heyder, 2024) [View paper](#)
  - Structural Dynamics and Vibroacoustics (2 papers)
    - [28] Parametric model order reduction of guided ultrasonic wave propagation in fiber metal laminates with damage (Nanda Kishore Bellam Muralidhar, 2021) [View paper](#)
    - [39] Dimensional reduction for parametric projection-based reduced-order models in crash (Mathias Lesjak, 2023) [View paper](#)
  - Electromagnetics and Plasma Physics (2 papers)
    - [9] Inverse scattering for Schrödinger equation in the frequency domain via data-driven reduced order modeling (Tataris, 2025) [View paper](#)
    - [48] Parameter preserving model order reduction for MEMS applications (U. Baur, 2011) [View paper](#)
- Specialized Techniques and Extensions
  - High-Dimensional Parameter Space Reduction (1 papers)
    - [8] A local approach to parameter space reduction for regression and classification tasks (Romor, 2024) [View paper](#)
  - Geometric Variability and Mesh Adaptation (1 papers)
    - [30] LiCROM: Linear-Subspace Continuous Reduced Order Modeling with Neural Fields (Chang Yue, 2023) [View paper](#)
  - Verification, Error Estimation, and Optimization (4 papers)
    - [4] Verification of reduced-order model subspace dimensions and minimal ranks in simple configurations (Ragusa, 2025) [View paper](#)
    - [24] An accelerated subspaces recycling strategy for the deflation of parametric linear systems based on model order reduction (Dionysios Panagiotopoulos, 2023) [View paper](#)
    - [25] Certified Model Order Reduction for parametric Hermitian eigenproblems (Manucci, 2025) [View paper](#)
    - [41] Accelerating optimization of parametric linear systems by model order reduction (Yao Yue, 2013) [View paper](#)
  - Thermal Systems and Eigenproblems (2 papers)
    - [19] Parameterized model order reduction with applications to thermal systems (Daming, 2021) [View paper](#)
    - [34] A Reduced Order Approximation for Identification of Non-linear Material Parameters using Optimal Control Method (M. Bhattacharyya, 2023) [View paper](#)

## Narrative

Core task: regression of parametric linear subspaces for reduced order modeling. This field addresses the challenge of efficiently approximating high-dimensional parametric systems by learning low-dimensional subspaces that vary smoothly with parameters. The taxonomy reveals five main branches. Subspace Construction and Basis Representation Methods focus on building effective low-dimensional bases, often through proper orthogonal decomposition or Krylov techniques (Krylov Subspace Techniques[21]). Subspace Interpolation and Regression Techniques develop strategies to predict or interpolate these bases across parameter domains, including classical manifold interpolation (Online Interpolating Models[13]) and modern machine learning approaches (Gaussian Process Subspace[17], Gradient-Free Active Subspace[27]). Parametric Model Order Reduction Frameworks provide overarching methodologies such as moment matching (Moment Matching Reduction[43]) and operator inference (Operator Inference Reduction[40]). Application-Specific Parametric ROM tailors these ideas to domains like fluid dynamics (Fluid Dynamics Challenges[12]), electromagnetics (Physics-aware Electromagnetic Reduction[3]), and structural mechanics. Specialized Techniques and Extensions explore advanced topics including tensor decompositions (Tensorial Parametric Reduction[1]) and neural network-based encoders (Convolutional Autoencoders Reduction[31]).

A particularly active line of work involves machine learning-based subspace regression, where researchers leverage Gaussian processes (Gaussian Subspace Regression[36], Electromagnetic Gaussian Regression[50]) or deep learning to predict parameter-dependent bases without exhaustive precomputation. Deep Subspace Regression[0] sits squarely within this branch, emphasizing neural architectures to regress subspaces directly from parameter inputs. This contrasts with neighboring efforts like Gradient-Free Active Subspace[27], which identifies influential parameter directions without gradient information, and Radiation Transport Reduction[47], which applies subspace methods to challenging transport problems. The main trade-offs center on expressiveness versus computational cost: deep models can capture complex parameter dependencies but require substantial training data, while classical interpolation schemes (Parametric Matrix Interpolation[37]) offer theoretical guarantees at the expense of scalability. Open questions include how to verify subspace quality (Subspace Verification[4]) and how to balance offline training expense against online speedup across diverse applications.

## Related Works in Same Category

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The following **5 sibling papers** share the same taxonomy leaf node with the original paper:

### 1. Gaussian process subspace prediction for model reduction

**Authors:** Ruda Zhang, Simon Mak, David Dunson | **Year/Venue:** 2022 | **URL:** [View paper](#)

#### Abstract

Subspace-valued functions arise in a wide range of problems, including parametric reduced order modeling (PROM), parameter reduction, and subspace tracking. In PROM, each parameter point can be associated with a subspace, which is used for Petrov-Galerkin projections of large system matrices. Previous efforts to approximate such functions use interpolations on manifolds, which can be inaccurate and slow. To tackle this, we propose a novel Bayesian nonparametric model for subspace prediction: th...

#### Relationship Analysis

Both papers belong to the Machine Learning-Based Subspace Regression category, using statistical learning methods to map parameters to reduced-order subspaces. The original paper proposes deep neural networks with specialized loss functions for subspace regression, introducing an embedding technique to predict larger-than-needed subspaces and demonstrating applications across eigenproblems, POD, and iterative solvers. The candidate paper develops a Gaussian process model (GPS) for subspace prediction on the Grassmann manifold, providing a Bayesian probabilistic framework with uncertainty quantification and analytical predictive distributions, focusing primarily on parametric reduced order modeling applications.

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### 2. Non-intrusive parametric reduced order models with high-dimensional inputs via gradient-free active subspace

**Authors:** Dushyanth Rajaram, Raphael H. Gautier, Christian Perron, Olivia J. Pinon-Fischer, Dimitri Mavris | **Year/Venue:** 2020 | **URL:** [View paper](#)

#### Abstract

This work presents the development of a method for the construction of parametric, interpolation-based non-intrusive Reduced Order Models (ROMs) for predicting field outputs when the input parameter space is high-dimensional. The Proper Orthogonal Decomposition (POD) is used to decrease the dimensionality of the field outputs. Instead of directly approximating the map between the input parameters and the low-dimensional POD subspace, the proposed method trains Gaussian processes to simultaneousl...

#### Relationship Analysis

Both papers belong to the Machine Learning-Based Subspace Regression category, using machine learning to map parameters to reduced subspaces for ROM. The candidate paper uses Gaussian processes with gradient-free active subspace discovery to handle high-dimensional input parameters and construct non-intrusive POD-based ROMs, while the original paper employs deep neural networks with novel subspace embedding techniques and specialized loss functions to directly regress parametric linear subspaces. The key difference is that the candidate focuses on discovering low-dimensional input subspaces via Gaussian processes on product manifolds, whereas the original paper introduces redundancy by predicting larger-than-needed output subspaces using deep learning with grassmannian-aware losses.

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### 3. Gaussian Process Subspace Regression for Model Reduction

**Authors:** Zhang, Ruda, Mak, Simon, Dunson, et al. (6 authors total) | **Year/Venue:** 2021 • arXiv.org | **URL:** [View paper](#)

#### Abstract

Subspace-valued functions arise in a wide range of problems, including parametric reduced order modeling (PROM). In PROM, each parameter point can be associated with a subspace, which is used for Petrov-Galerkin projections of large system matrices. Previous efforts to approximate such functions use interpolations on manifolds, which can be inaccurate and slow. To tackle this, we propose a novel Bayesian nonparametric model for subspace prediction: the Gaussian Process Subspace regression (GPS) ...

#### Relationship Analysis

Both papers belong to the Machine Learning-Based Subspace Regression category, using data-driven approaches to learn mappings from parameters to subspaces for reduced order modeling. The original paper employs deep neural networks with novel loss functions and a subspace embedding technique to predict parametric linear subspaces, while the candidate paper uses Gaussian Process regression on the Grassmann manifold to provide probabilistic subspace predictions with uncertainty quantification. The key difference is that the original paper focuses on deterministic neural network predictions with embedding strategies to improve accuracy, whereas the candidate paper offers a Bayesian nonparametric framework that naturally provides uncertainty estimates and analytical predictive distributions.

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### 4. Non-intrusive model order reduction for parametric radiation transport simulations

**Authors:** Ian Halvic, Jean C. Ragusa, Jean C Ragusa | **Year/Venue:** 2023 • Journal of Computational Physics | **URL:** [View paper](#)

## Abstract

We present a parametric, non-intrusive reduced-order model (ROM) for multigroup radiation transport, addressing the high computational cost and resource requirements associated with transport simulations in scenarios involving multiple queries. To achieve this, we employ Proper Orthogonal Decomposition (POD) to learn a groupwise reduced basis representation of the observed data (obtained from full-order simulations). We utilize Gaussian Process Regression and Multivariate Adaptive Regression Splines...

## Relationship Analysis

Both papers belong to the Machine Learning-Based Subspace Regression category, focusing on learning mappings from parameters to reduced subspaces for computational efficiency. The original paper develops deep learning methods with novel loss functions and embedding techniques for general subspace regression across diverse applications (eigenproblems, POD, iterative solvers), while the candidate paper applies established techniques (POD with Gaussian Process Regression and MARS) specifically to parametric radiation transport simulations in a non-intrusive manner. The key difference is that the original paper contributes new theoretical frameworks and neural network architectures for subspace learning, whereas the candidate paper demonstrates practical application of existing methods to a specific physics domain without introducing new subspace regression techniques.

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## 5. Non-intrusive reduced order modeling of parametric electromagnetic scattering problems through Gaussian process regression

**Authors:** Zhao Ying, Ying Zhao, Li Liang, Liang Li, Li Kun, et al. (6 authors total) | **Year/Venue:** 2021 • arXiv.org | **URL:** [View paper](#)

## Abstract

This paper is concerned with the design of a non-intrusive model order reduction (MOR) for the system of parametric time-domain Maxwell equations. A time- and parameter-independent reduced basis (RB) is constructed by using a two-step proper orthogonal decomposition (POD) technique from a collection of full-order electromagnetic field solutions, which are generated via a discontinuous Galerkin time-domain (DGTD) solver. The mapping between the time/parameter values and the projection coefficient...

## Relationship Analysis

Both papers belong to the Machine Learning-Based Subspace Regression category, using data-driven approaches to learn mappings from parameters to reduced subspaces for parametric problems. The original paper focuses on deep neural networks with novel loss functions and subspace embedding techniques for various applications including eigenproblems and PDEs, while the candidate paper specifically applies Gaussian process regression combined with POD for electromagnetic scattering problems in a non-intrusive framework. The key difference is that the original paper develops general neural network architectures with theoretical justifications for subspace embedding, whereas the candidate paper uses GPR with SVD-based feature extraction tailored to time-domain Maxwell equations.

## Contributions Analysis

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

### Contribution 1: Mathematical formulation of subspace regression problem

**Description:** The authors formulate subspace regression as a statistical learning problem where a parametric model maps parameters to linear subspaces on the Grassmann manifold. They demonstrate applications across eigenproblems, reduced order modeling, iterative methods, and optimal control.

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. Interpolation-based parametric reduced-order models via Galerkin projection and dynamic mode decomposition

**URL:** [View paper](#)

#### Brief Assessment

Interpolation-based Galerkin DMD[77] focuses on interpolating DMD modes on Grassmann manifolds for parametric ROMs in fluid dynamics, not on formulating a general statistical learning framework for subspace regression across diverse applications (eigenproblems, deflation, optimal control, etc.).

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### 2. Grassmannian diffusion maps based dimension reduction and classification for high-dimensional data

**URL:** [View paper](#)

#### Brief Assessment

Grassmannian Diffusion Maps[74] focuses on nonlinear dimensionality reduction for embedding high-dimensional data using random walks on the Grassmann manifold, not on parametric subspace regression for eigenproblems and reduced order modeling as formulated in the original paper.

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### 3. Grassmannian Dimensionality Reduction Using Triplet Margin Loss for Ume Classification of 3d Point Clouds

**URL:** [View paper](#)

#### Brief Assessment

Grassmannian Triplet Margin[73] focuses on classification of 3D point clouds using Grassmannian dimensionality reduction with metric learning, not on parametric subspace regression for eigenproblems and reduced order modeling.

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### 4. Sparse Grassmannian embeddings for hyperspectral data representation and classification

**URL:** [View paper](#)

#### Brief Assessment

Sparse Grassmannian Embeddings[79] focuses on hyperspectral data classification using subspace representations on the Grassmann manifold with distance-based embeddings and SVMs. It does not formulate a parametric regression problem mapping parameters to subspaces for eigenproblems, reduced order modeling, or optimal control applications.

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### 5. Joint normalization and dimensionality reduction on Grassmannian: a generalized perspective

**URL:** [View paper](#)

#### Brief Assessment

Joint Normalization Grassmannian[78] focuses on dimensionality reduction and discriminative subspace learning using Riemannian optimization on Grassmann manifolds, not on parametric subspace regression for eigenproblems and reduced order modeling as formulated in the original paper.

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## 6. Intrinsic Grassmann averages for online linear, robust and nonlinear subspace learning

URL: [View paper](#)

### Brief Assessment

Intrinsic Grassmann Averages[76] focuses on computing intrinsic averages on the Grassmann manifold for PCA and kernel PCA applications, not on parametric subspace regression as a statistical learning problem with neural networks for reduced order modeling.

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## 7. Parametric reduced-order modelling and mode sensitivity of actuated cylinder flow from a matrix manifold perspective

URL: [View paper](#)

### Brief Assessment

Matrix Manifold Cylinder[80] focuses on sensitivity analysis and interpolation of POD modes on Grassmann manifolds for fluid flow applications, not on formulating subspace regression as a statistical learning problem with neural networks and loss functions.

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## 8. Multi-view Spectral Clustering on the Grassmannian Manifold With Hypergraph Representation

URL: [View paper](#)

### Brief Assessment

Multi-view Spectral Grassmann[72] focuses on multi-view clustering using hypergraph representations on the Grassmannian manifold, not parametric subspace regression for eigenproblems or reduced order modeling as in the original paper.

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## 9. Parametric reduced-order modeling and mode sensitivity of actuated cylinder flow from a matrix manifold perspective

URL: [View paper](#)

### Brief Assessment

Matrix Manifold Cylinder[71] focuses on parametric reduced-order modeling for fluid dynamics using POD modes on Grassmann manifolds, not on general subspace regression as a statistical learning problem across diverse applications like eigenproblems, iterative methods, and optimal control.

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## 10. Adapting Projection-Based Reduced-Order Models using Projected Gaussian Process

URL: [View paper](#)

### Prior Art Analysis

Projected Gaussian Process[75] demonstrates that the problem of learning mappings from parameters to linear subspaces on the Grassmann manifold was formulated and solved prior to the original paper. The candidate explicitly frames the adaptation of POD basis as 'a supervised statistical learning problem, for which the goal is to learn a mapping from the parameter space to the grassmann manifold that contains the optimal subspaces.' This directly addresses the same mathematical formulation claimed as novel by the original paper, which states they provide 'mathematical formulation of subspace regression problem' where 'a parametric model maps parameters to linear subspaces on the Grassmann manifold.' Both papers formulate the identical problem: learning functions that map parameter spaces to subspaces represented as points on the Grassmann manifold.

### Evidence

Evidence 1 - **Rationale:** Both papers explicitly formulate the problem of learning mappings from parameter spaces to the Grassmann manifold. The candidate demonstrates this was done prior to the original submission, directly challenging the novelty of the 'mathematical formulation of subspace regression problem' contribution. - **Original:** we consider regression on grassmannian. we approach the regression under review as a conference paper at iclr 2026 problem by specifying loss function and using neural networks as parametric models to accommodate high-dimensional parameter spaces pervasive in practical problems. more specifically, o... - **Candidate:** we propose a projected gaussian process (pgp) and formulate the problem of adapting the pod basis as a supervised statistical learning problem, for which the goal is to learn a mapping from the parameter space to the grassmann manifold that contains the optimal subspaces.

Evidence 2 - **Rationale:** Both papers establish mathematical frameworks for mapping parameters to the Grassmann manifold. The candidate's formulation using exponential/logarithm maps and tangent spaces represents a complete mathematical framework for the same problem, predating the original paper's formulation. - **Original:** let  $v : \mathbb{R}^p \rightarrow \text{gr}(k, n)$  be a function that maps the space of parameters  $r \in \mathbb{R}^p$  to the subset of grassmanian represented as the set of tall full rank matrices  $v(r)$ . we assume that parameters  $r$  are sampled from distribution  $r \sim p_r$  and that dataset  $d = \{(r_1, v_1), \dots, (r_m, v_m)\}$  of  $m$  i.i.d. samples is... - **Candidate:** a mapping is firstly established between the euclidean space and the horizontal space of an orthogonal matrix that spans a reference subspace in the grassmann manifold. a second mapping from the horizontal space to the grassmann manifold is established through the exponential/logarithm maps between ...

Evidence 3 - **Rationale:** Both papers address the same fundamental problem: learning how subspaces (represented as basis matrices) vary with parameters. The candidate's formulation for adapting POD basis across parameter space is mathematically equivalent to the original's 'subspace regression' formulation, demonstrating prior work on this problem. - **Original:** in linear space  $\mathbb{R}^n$  we define  $k$ -dimensional subspace  $s(w) = w\alpha$ ,  $\alpha \in \mathbb{R}^k$  by specifying tall full rank matrix  $w \in \mathbb{R}^{n \times k}$ . matrices  $w_1$  and  $w_2$  represent the same subspace if there is an invertible matrix  $g$  such that  $w_1 = w_2g$ . the equivalence class of such matrices is denoted by  $[w]$ . the set of all  $k$ -dimensi... - **Candidate:** utilizing the snapshot data from solving full-order governing equations, the proper orthogonal decomposition (pod) computes the optimal basis modes that represent the data, and a rom can be constructed in the low-dimensional vector subspace spanned by the pod basis. for parametric governing equation...

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## Contribution 2: Loss functions for subspace data suitable for neural network training

**Description:** The authors introduce multiple loss functions that satisfy invariance requirements for Grassmannian data, including a stochastic variant based on least squares that scales better computationally as subspace dimensions increase.

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. Accurate 3D action recognition using learning on the Grassmann manifold

URL: [View paper](#)

#### Brief Assessment

Accurate Action Recognition[56] focuses on action recognition using Grassmann manifolds with statistical modeling (wrapped Gaussians) rather than neural network training with scalable loss functions for subspace regression.

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### 2. Domain adaptation as optimal transport on Grassmann manifolds

URL: [View paper](#)

#### Brief Assessment

Domain Adaptation Transport[58] focuses on optimal transport-based domain adaptation on Grassmann manifolds for computer vision tasks, not on developing loss functions for neural network training on Grassmannian data with computational scalability considerations.

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### 3. Grassmann pooling as compact homogeneous bilinear pooling for fine-grained visual classification

URL: [View paper](#)

#### Brief Assessment

Grassmann Pooling Classification[54] focuses on visual classification using Grassmann manifolds for pooling CNN features, not on designing loss functions for general subspace regression in neural networks with scalability considerations.

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### 4. Microsecond Federated SVD on Grassmann Manifold for Real-time IoT Intrusion Detection

URL: [View paper](#)

#### Brief Assessment

Federated SVD Grassmann[59] focuses on SVD-based anomaly detection in IoT networks using Grassmann manifold optimization, not on developing loss functions for neural network training on Grassmannian data. The candidate addresses a different application domain (intrusion detection) with different technical objectives (federated SVD optimization) rather than proposing loss functions for subspace regression in neural networks.

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### 5. Projection metric learning on Grassmann manifold with application to video based face recognition

URL: [View paper](#)

#### Brief Assessment

Projection Metric Learning[52] focuses on learning Mahalanobis-like matrices on Grassmann manifolds for video face recognition using projection metric, not on developing loss functions for neural network training of subspace regression problems.

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### 6. Cross-View Approximation on Grassmann Manifold for Multiview Clustering

URL: [View paper](#)

#### Brief Assessment

Cross-View Grassmann Clustering[55] focuses on multiview clustering using grassmann manifold approximation for clustering tasks, not on developing loss functions for neural network training of subspace regression problems.

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### 7. Grassmann Neighborhood Preserving Autoencoder for Image Set Classification

URL: [View paper](#)

#### Brief Assessment

Grassmann Neighborhood Autoencoder[60] focuses on reconstruction loss for autoencoders on Grassmann manifolds, while the original paper introduces multiple loss functions (including stochastic variants) specifically designed for subspace regression tasks with scalability considerations. The candidate's differential geometric approach to reconstruction differs from the original's regression-oriented loss functions.

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### 8. A Riemannian gossip approach to subspace learning on Grassmann manifold

URL: [View paper](#)

#### Brief Assessment

Riemannian Gossip Subspace[57] focuses on decentralized subspace learning using Riemannian distance-based consensus terms for gossip protocols, not on loss functions for neural network training with scalability considerations.

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### 9. Spatio-Temporal Tensor Analysis on Product Grassmann Manifolds and its Application to Action Recognition

URL: [View paper](#)

#### Brief Assessment

Spatio-Temporal Tensor Grassmann[53] focuses on representing spatio-temporal tensors on product Grassmann manifolds for action recognition tasks, using distance-based discriminative analysis rather than neural network training with loss functions. The candidate does not address loss function design for neural network optimization on Grassmannian data.

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### 10. Discriminant locality preserving projection on Grassmann Manifold for image-set classification

URL: [View paper](#)

#### Brief Assessment

Discriminant Locality Grassmann[51] focuses on discriminant analysis and locality preservation for image-set classification on Grassmann manifolds, not on developing loss functions for neural network training with scalability properties for subspace regression tasks.

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## Contribution 3: Subspace embedding technique with theoretical justification

**Description:** The authors propose predicting larger-than-needed subspaces to simplify the learning problem. They provide theoretical justification showing this reduces mapping complexity for elliptic eigenproblems and makes mappings smoother on the Grassmann manifold, which aligns with neural network inductive biases.

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. Safe and reliable diffusion models via subspace projection

URL: [View paper](#)

#### Brief Assessment

Safe Subspace Projection[66] focuses on removing unwanted concepts from text-to-image diffusion models by projecting embeddings onto complementary subspaces. This is fundamentally different from the original paper's subspace embedding technique for reduced-order modeling, which predicts larger-than-needed subspaces to simplify learning problems in parametric PDEs and eigenproblems.

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### 2. Semi-Supervised Deep Subspace Embedding for Binary Classification of Sella Turcica

URL: [View paper](#)

#### Brief Assessment

Semi-Supervised Subspace Embedding[67] focuses on medical image classification using subspace embedding for feature representation in a semi-supervised learning context, not on predicting larger-than-needed subspaces to simplify learning problems for parametric systems like eigenproblems or PDEs as in the original paper.

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### 3. Subspace-Guided Feature Reconstruction for Unsupervised Anomaly Localization

URL: [View paper](#)

#### Brief Assessment

Subspace-Guided Feature Reconstruction[70] focuses on anomaly localization in industrial manufacturing using subspace construction for feature reconstruction, not on subspace regression for reduced order modeling or eigenproblems. The subspace techniques serve fundamentally different purposes in different application domains.

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### 4. Expandable Subspace Ensemble for Pre-Trained Model-Based Class-Incremental Learning

URL: [View paper](#)

#### Brief Assessment

Expandable Subspace Ensemble[61] focuses on class-incremental learning with task-specific adapter subspaces for continual learning, not on subspace regression for reduced-order modeling or eigenproblems as in the original paper.

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### 5. Safree: Training-free and adaptive guard for safe text-to-image and video generation

URL: [View paper](#)

#### Brief Assessment

Safree Training-Free Guard[62] focuses on identifying and projecting away from toxic concept subspaces in text embeddings for safe image/video generation, not on learning larger subspaces to simplify regression problems for reduced-order modeling as in the original paper.

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### 6. Fractionalization paves the way to local projector embeddings of quantum many-body scars

URL: [View paper](#)

#### Brief Assessment

Fractionalization Projector Embeddings[63] focuses on quantum many-body scar states in physical systems, not reduced order modeling or neural network training for subspace regression problems.

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### 7. Universal Domain Alignment Framework for Classification and Regression Tasks

URL: [View paper](#)

#### Brief Assessment

Universal Domain Alignment[65] focuses on aligning embedding subspaces between source and target domains for classification/regression tasks, not on predicting larger-than-needed subspaces to simplify learning problems in reduced order modeling contexts.

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### 8. Adaptive graph-guided joint soft clustering and distribution alignment for cross-load and cross-device rotating machinery fault transfer diagnosis

URL: [View paper](#)

#### Brief Assessment

Adaptive Graph Clustering[64] focuses on weighted subspace alignment for domain adaptation in fault diagnosis, not on predicting larger-than-needed subspaces to simplify learning problems or theoretical justifications about mapping complexity on Grassmann manifolds.

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### 9. Unsupervised Domain Adaptation on Person Reidentification Via Dual-Level Asymmetric Mutual Learning

URL: [View paper](#)

#### Brief Assessment

Dual-Level Asymmetric Learning[68] focuses on person re-identification using heterogeneous networks (CNN and ViT) to learn from different feature subspaces for domain adaptation. This is fundamentally different from the original paper's subspace embedding technique for reduced-order modeling and eigenproblems, which involves predicting larger-than-needed linear subspaces to simplify regression problems on Grassmann manifolds.

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### 10. Graph-Embedding Balanced Transfer Subspace Learning for Hyperspectral Cross-Scene Classification

URL: [View paper](#)

#### Brief Assessment

Graph-Embedding Transfer Subspace[69] focuses on hyperspectral cross-scene classification using graph-embedding and balanced distribution adaptation in transfer learning, not on predicting larger-than-needed subspaces to simplify learning problems or providing theoretical justification for elliptic eigenproblems and Grassmann manifold smoothness.

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## Appendix: Text Similarity Detection

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

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