

# Novelty Assessment Report

**Paper:** Decoupling Dynamical Richness from Representation Learning: Towards Practical Measurement

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## Abstract

Dynamic feature transformation (the rich regime) does not always align with predictive performance (better representation), yet accuracy is often used as a proxy for richness, limiting analysis of their relationship. We propose a computationally efficient, performance-independent metric of richness grounded in the low-rank bias of rich dynamics, which recovers neural collapse as a special case. The metric is empirically more stable than existing alternatives and captures known lazy-to-rich transitions (e.g., grokking) without relying on accuracy. We further use it to examine how training factors (e.g., learning rate) relate to richness, confirming recognized assumptions and highlighting new observations (e.g., batch normalization promote rich dynamics). An eigendecomposition-based visualization is also introduced to support interpretability, together providing a diagnostic tool for studying the relationship between training factors, dynamics, and representations.

### Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

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## Core Task Landscape

This paper addresses: **measuring dynamical richness independent of predictive performance**

A total of **50 papers** were analyzed and organized into a taxonomy with **13 categories**.

### Taxonomy Overview

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

- **Theoretical Frameworks for Dynamics-Performance Decoupling**
- **Dynamical Systems Characterization**
- **Prediction Applications with Dynamical Complexity**
- **Algorithmic and Computational Methods**

### Complete Taxonomy Tree

- measuring dynamical richness independent of predictive performance Survey Taxonomy
- Theoretical Frameworks for Dynamics-Performance Decoupling
  - Feature Learning Dynamics Metrics ★ (2 papers)
  - [0] Decoupling Dynamical Richness from Representation Learning: Towards Practical Measurement (Anon et al., 2026) [View paper](#)
  - [43] Disentangling Rich Dynamics from Feature Learning: A Framework for Independent Measurements (Nam, 2024) [View paper](#)
  - Complexity Quantification Methods (5 papers)
  - [2] A novel method to measure static and dynamic complexity of time series based on visualization curves (Wei Dong, 2023) [View paper](#)
  - [27] Complexity-Based Lambda Layer for Time Series Prediction (Kenneth Brezinski, 2021) [View paper](#)
  - [38] Gas volume fraction measurement and flow pattern identification and analysis in gas-liquid two-phase flow using a multi-source cross-attentional task network (Yufu Liu, 2025) [View paper](#)
  - [45] Complexity of dynamics as variability of predictability (R. Stoop, 2004) [View paper](#)
  - [47] Profiling Visual Dynamic Complexity Using a Bio-Robotic Approach (Qinbing Fu, 2021) [View paper](#)
  - Diversity and Quality Trade-offs (2 papers)
  - [5] Can the Problem-Solving Benefits of Quality Diversity Be Obtained without Explicit Diversity Maintenance? (Ryan Boldi, 2023) [View paper](#)
  - [12] Dynamics-Aware Quality-Diversity for Efficient Learning of Skill Repertoires (Lim, 2022) [View paper](#)
- Dynamical Systems Characterization
  - Nonlinear Optical and Laser Dynamics (2 papers)
  - [1] Dynamical diversity of FWM-induced pulsating solitons in an ultrafast fiber laser (Hongjie Chen, 2025) [View paper](#)
  - [28] Unveiling the dynamical diversity of quantum dot lasers subject to optoelectronic feedback (Ding Shihao, 2023) [View paper](#)
  - Complex System Dynamics Analysis (3 papers)
  - [30] Complex dynamics may limit prediction in marine fisheries (Sarah M. Glaser, 2014) [View paper](#)
  - [35] Node-level resilience loss in dynamic complex networks (Giannis Moutsinas, 2020) [View paper](#)
  - [49] Dynamical diversity and metastability in a hindered granular column near jamming (Luck, 2007) [View paper](#)
  - Biological and Medical Signal Dynamics (3 papers)
  - [24] Characterising Alzheimer's disease with EEG-based energy landscape analysis (Klepl, 2021) [View paper](#)
  - [26] Quantifying cognitive workload in simulated flight using passive, dry EEG measurements (Justin A. Blanco, 2016) [View paper](#)
  - [29] Single-molecule imaging quantifies oncogenic KRAS dynamics for enhanced accuracy of therapeutic efficacy assessment. (Ryoma Yokoi, 2025) [View paper](#)
- Prediction Applications with Dynamical Complexity
  - Time Series Forecasting with Complexity Handling (6 papers)

- [10] High-Accuracy Temporal Prediction via Experimental Quantum Reservoir Computing in Correlated Spins (Hou Yan-jun, 2025) [View paper](#)
- [13] Prediction of the ENSO using Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) supervised learning from other ocean indices (Subhadeep Maishal, 2024) [View paper](#)
- [15] A Combined Landslide Displacement Prediction Model Based on Variational Mode Decomposition and Deep Learning Algorithms (Mengcheng Sun, 2024) [View paper](#)
- [17] Impact of time-history terms on reservoir dynamics and prediction accuracy in echo state networks (Yudai Ebato, 2024) [View paper](#)
- [37] Characterizing Time Series Data Diversity for Wind Forecasting. (Cong Feng, 2017) [View paper](#)
- [41] Improving Long-Term Glucose Prediction Accuracy with Uncertainty-Estimated ProbSparse-Transformer (Wei Huang, 2025) [View paper](#)
- Spatial-Temporal Prediction (4 papers)
- [3] Multivariate Machine Learning Model Based on YOLOv8 for Traffic Flow Prediction in Intelligent Transportation Systems (Fukui Wu, 2025) [View paper](#)
- [4] Fusing visual quantified features for heterogeneous traffic flow prediction (Qinyang Wang, 2024) [View paper](#)
- [20] Model-enhanced spatial-temporal attention networks for traffic density prediction (Qi Guo, 2024) [View paper](#)
- [22] Spatiotemporal Transmission Model to Simulate an Interregional Epidemic Spreading (Li Zitong, 2023) [View paper](#)
- Trajectory Prediction with Diversity Constraints (5 papers)
- [7] Short-Term Target Maneuvering Trajectory Prediction Using DTW-CNN-LSTM (Haifeng Guo, 2025) [View paper](#)
- [16] Criteria: a new benchmarking paradigm for evaluating trajectory prediction models for autonomous driving (Changhe Chen, 2024) [View paper](#)
- [18] Multidimensional Trajectory Prediction of UAV Swarms Based on Dynamic Graph Neural Network (Yu An, 2024) [View paper](#)
- [19] Likelihood-Based Diverse Sampling for Trajectory Forecasting (Ma, 2021) [View paper](#)
- [21] Diverse Trajectory Forecasting with Determinantal Point Processes (Ye Yuan, 2022) [View paper](#)
- Prediction with Uncertainty Quantification (6 papers)
- [6] Non-invasive detection of Parkinson's disease based on speech analysis and interpretable machine learning (Huanqing Xu, 2025) [View paper](#)
- [8] Remaining useful life prediction with uncertainty quantification based on multi-distribution fusion structure (Yuling Zhan, 2024) [View paper](#)
- [14] Diversity entropy-based Bayesian deep learning method for uncertainty quantification of remaining useful life prediction in rolling bearings (Rui Bai, 2023) [View paper](#)
- [25] A Bayesian network of eutrophication models for synthesis, prediction, and uncertainty analysis (Craig A. Stow, 2004) [View paper](#)
- [31] Automated prediction of sudden cardiac death risk using Kolmogorov complexity and recurrence quantification analysis features extracted from HRV signals (U. Rajendra Acharya, 2015) [View paper](#)
- [32] Strategies for reduced-order models for predicting the statistical responses and uncertainty quantification in complex turbulent dynamical systems (Andrew J. Majda, 2018) [View paper](#)
- Domain-Specific Prediction Applications (7 papers)
- [9] Dynamic intelligent prediction approach for landslide displacement based on biological growth models and CNN-LSTM (Ziqian Wang, 2025) [View paper](#)
- [23] Optimizing Production Forecasting in Dynamic Complex Industries with Deep Reinforcement Learning Approaches (Hassina Madjour, 2025) [View paper](#)
- [34] Enhanced Predictive Modeling of Salicylic Acid and Jasmonic Acid Crosstalk in Arabidopsis thaliana Using Multi-Modal Data Fusion and Bayesian Optimization (Lim, 2025) [View paper](#)
- [36] Prediction of coal permeability evolution under true triaxial stress conditions based on optimized deep learning algorithms (Wang Chongyang, 2025) [View paper](#)
- [40] **Prediction of Coal Permeability Evolution under True Triaxial Stress Conditions Based on Optimized Deep Learning Algorithms** (Wang Chongyang, 2025) [View paper](#)
- [42] Prediction of pneumonia-like virus transmission based on machine learning algorithms (T Tang, 2025) [View paper](#)
- [48] SOC Estimation of Lithium-Ion Batteries based on Transfer Learning under Low Temperature Conditions (Xinglong Yang, 2024) [View paper](#)
- Algorithmic and Computational Methods
  - Complexity in Algorithmic Design (4 papers)
  - [11] On the complexity of algorithms with predictions for dynamic graph problems (Heninger, 2023) [View paper](#)
  - [39] Learning and classification of complex dynamics (Ben North, 2002) [View paper](#)
  - [44] Dynamic density: measuring and predicting sector complexity (P Kopardekar, 2002) [View paper](#)
  - [46] Contributions à la gestion du trafic aérien : prédiction des trajectoires par réseaux de neurones et cartes de complexité par maximum d'entropie (Lich, 2024) [View paper](#)
  - Diversity-Enhanced Retrieval and Generation (2 papers)
  - [33] Vendi-RAG: Adaptively Trading-Off Diversity And Quality Significantly Improves Retrieval Augmented Generation With LLMs (Rezaei Mohammad Reza, 2025) [View paper](#)
  - [50] Quantifying genomic connectedness and prediction accuracy from additive and non-additive gene actions. (Morota, 2018) [View paper](#)

## Narrative

Core task: measuring dynamical richness independent of predictive performance. This field addresses a fundamental tension in machine learning and complex systems: how to quantify the intrinsic complexity or diversity of a system's internal dynamics without conflating it with task-specific accuracy. The taxonomy reflects four main branches. Theoretical Frameworks for Dynamics-Performance Decoupling develop formal metrics and conceptual tools to separate dynamical properties from prediction quality, often drawing on information theory and feature learning perspectives (e.g., Decoupling Dynamical Richness[0], Disentangling Rich Dynamics[43]). Dynamical Systems Characterization focuses on classical and modern techniques for analyzing temporal evolution, attractors, and complexity measures in physical and biological systems (e.g., Quantum Reservoir Computing[10], EEG Energy Landscape[24]). Prediction Applications with Dynamical Complexity examines domains where rich dynamics coexist with forecasting tasks—such as traffic flow (YOLOv8 Traffic Flow[3], Visual Features Traffic[4]), climate (ENSO RNN LSTM[13]), and landslide prediction (CNN LSTM Landslide[9])—highlighting the interplay between model expressiveness and practical performance. Algorithmic and Computational Methods provide diversity-aware optimization and sampling strategies (Quality Diversity Without Maintenance[5], Determinantal Point Processes[21]) that maintain behavioral variety alongside objective optimization.

A particularly active line of work explores quality-diversity algorithms and diversity metrics that preserve exploration in evolutionary and reinforcement learning settings, balancing novelty with performance (Dynamics Aware Quality Diversity[12], Likelihood Diverse Sampling[19]). Another contrasting theme emerges in reservoir computing and recurrent architectures, where internal state complexity is leveraged for temporal prediction (Time History Reservoir[17], Quantum Reservoir Computing[10]), yet the relationship between reservoir richness and generalization remains subtle. Decoupling Dynamical Richness[0] sits squarely within the Theoretical Frameworks branch, specifically addressing Feature Learning Dynamics Metrics. Its emphasis on decoupling aligns closely with Disentangling Rich Dynamics[43], which also seeks to isolate dynamical properties from task outcomes. Compared to diversity-focused works like Quality Diversity Without Maintenance[5] or Determinantal Point Processes[21], which operate in optimization contexts, Decoupling Dynamical Richness[0] appears more concerned with intrinsic characterization of learning trajectories, offering a complementary lens on how systems evolve internally regardless of their final predictive success.

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## Related Works in Same Category

The following **1 sibling papers** share the same taxonomy leaf node with the original paper:

### 1. Disentangling Rich Dynamics from Feature Learning: A Framework for Independent Measurements

**Authors:** Nam, Yoonsoo, Fonseca, Nayara, Yoonsoo Nam, et al. (18 authors total) | **Year/Venue:** 2024 | **URL:** [View paper](#)

#### Abstract

In machine learning, it is widely believed that dynamic feature transformation (the rich regime) enhances predictive performance. However, this link does not always hold, and existing richness measures rely on correlated factors - such as performance or parameter norms - which can complicate the analysis of feature learning. We introduce (1) a measure that quantifies the rich regime independently of performance, and (2) interpretable feature metrics for visualization. Leveraging low-rank bias, o...

#### △ Similarity Notice

This paper appears to be a published or revised version of the original paper. Both papers propose the same DLR metric based on minimum projection operators, use identical experimental setups (e.g., label-encoded MNIST, grokking on modular arithmetic), and present the same core contributions including the connection to neural collapse and eigendecomposition-based visualization. The candidate paper may represent a later submission or accepted version with minor revisions.

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## Contributions Analysis

**Overall novelty summary.** The paper proposes a computationally efficient metric for measuring dynamical richness in neural networks that does not rely on predictive accuracy. It sits within the Feature Learning Dynamics Metrics leaf of the taxonomy, which contains only two papers total. This is a notably sparse research direction, suggesting the problem of decoupling dynamics from performance remains underexplored. The sibling paper in this leaf also addresses disentangling rich dynamics from task outcomes, indicating a nascent but focused line of inquiry.

The taxonomy reveals that neighboring leaves pursue related but distinct goals. Complexity Quantification Methods (five papers) measure temporal or spatial complexity through entropy and information theory, while Diversity and Quality Trade-offs (two papers) balance exploration with optimization in evolutionary algorithms. The original paper bridges these areas by grounding its richness metric in low-rank bias rather than entropy or diversity maintenance, positioning it at the intersection of feature learning theory and dynamical systems characterization without direct overlap with prediction-oriented branches.

Among thirty candidates examined, none clearly refute the three core contributions. The Dynamical Low-Rank Measure examined ten candidates with zero refutable matches, as did the connection to neural collapse and the eigendecomposition visualization method. This suggests that within the limited search scope, the specific combination of low-rank bias as a richness proxy, its theoretical link to neural collapse, and the proposed visualization approach appear novel. The absence of refutations may reflect both the sparse literature in this exact niche and the limited scale of the search.

Based on the top-thirty semantic matches and taxonomy structure, the work appears to occupy a relatively unexplored corner of the field. The Feature Learning Dynamics Metrics leaf is small, and no examined candidates provide overlapping prior work for any contribution. However, the search scope is inherently limited, and a broader survey might reveal related metrics or visualizations in adjacent communities not captured here.

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

### Contribution 1: Dynamical Low-Rank Measure (DLR)

**Description:** The authors propose a computationally efficient metric called DLR that quantifies dynamical richness in neural networks by comparing activations before and after the last layer. This metric is grounded in the low-rank bias of rich dynamics and operates independently of predictive performance, enabling direct evaluation of training dynamics without referencing accuracy.

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. The low-dimensional neural architecture of cognitive complexity is related to activity in medial thalamic nuclei

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

##### Brief Assessment

Low Dimensional Thalamic[80] focuses on low-dimensional manifolds in whole-brain fMRI dynamics during cognitive tasks, not on measuring dynamical richness in neural network training via low-rank projections of layer activations.

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#### 2. How connectivity structure shapes rich and lazy learning in neural circuits

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

##### Brief Assessment

Connectivity Rich Lazy[71] focuses on how initial weight structure (particularly effective rank) influences rich vs. lazy learning regimes in neural circuits, not on proposing a computational metric for measuring dynamical richness during training. The candidate examines initialization effects on learning dynamics rather than developing performance-independent metrics for quantifying richness.

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#### 3. Model Reduction Captures Stochastic Gamma Oscillations on Low-Dimensional Manifolds

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

##### Brief Assessment

Stochastic Gamma Manifolds[76] focuses on model reduction of gamma oscillations in spiking neural networks through Markovian methods, not on measuring dynamical richness in general neural network activations using low-rank projections as proposed in the original paper.

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#### 4. Unsupervised discovery of demixed, low-dimensional neural dynamics across multiple timescales through tensor component analysis

URL: [View paper](#)

##### Brief Assessment

Tensor Component Analysis[74] focuses on discovering demixed, low-dimensional neural dynamics across multiple timescales in biological neural recordings, not on measuring dynamical richness in artificial neural network training dynamics using low-rank projections of activations.

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#### 5. Complex harmonics reveal low-dimensional manifolds of critical brain dynamics

URL: [View paper](#)

##### Brief Assessment

Complex Harmonics Manifolds[78] focuses on dimensional reduction of critical brain dynamics using wave equation mathematics for neuroscience applications, not on measuring dynamical richness in neural network training through low-rank projections of activations.

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#### 6. High-dimensional neuronal activity from low-dimensional latent dynamics: a solvable model

URL: [View paper](#)

##### Brief Assessment

Low Dimensional Latent[72] focuses on analyzing neuronal activity in biological systems through low-dimensional latent dynamics in recurrent neural networks, not on measuring dynamical richness in artificial neural network training via low-rank projections of activations.

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#### 7. Low-dimensional dynamics for working memory and time encoding

URL: [View paper](#)

##### Brief Assessment

Low Dimensional Working Memory[73] focuses on analyzing neural activity trajectories in biological systems (nonhuman primates) to understand working memory and time encoding through dimensionality analysis. The candidate does not address measuring dynamical richness in artificial neural networks during training, which is the core focus of the original paper's DLR metric.

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#### 8. Nonlinear manifold learning in functional magnetic resonance imaging uncovers a low-dimensional space of brain dynamics

URL: [View paper](#)

##### Brief Assessment

Nonlinear Manifold fMRI[75] focuses on dimensionality reduction for fMRI brain imaging data using nonlinear manifold learning techniques, not on measuring dynamical richness in neural network training dynamics through low-rank projections of activations.

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#### 9. Large-scale neural dynamics in a shared low-dimensional state space reflect cognitive and attentional dynamics

URL: [View paper](#)

##### Brief Assessment

Shared Low Dimensional State[79] focuses on low-dimensional latent states in brain dynamics during cognitive tasks, not on measuring dynamical richness in neural network training via low-rank projections of activations.

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#### 10. Latent embeddings: An essential representation of brain-environment interactions

URL: [View paper](#)

##### Brief Assessment

Latent Brain Environment[77] focuses on dimensionality reduction techniques (PCA, t-SNE, UMAP, CEBRA) for neuroscience data to extract interpretable latent embeddings from brain-environment interactions. This is fundamentally different from DLR, which measures dynamical richness in neural network training by comparing activations before and after the last layer using low-rank projections.

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### Contribution 2: Connection between DLR and neural collapse

**Description:** The authors establish that their proposed metric recovers neural collapse conditions (NC1 and NC2) as a special case when the feature kernel operator is a minimum projection operator. This theoretical connection extends the applicability of their metric beyond labeled classification tasks to more general settings.

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. Implicit geometry of next-token prediction: From language sparsity patterns to model representations

URL: [View paper](#)

##### Brief Assessment

Next Token Geometry[60] focuses on next-token prediction in language models and establishes connections to nuclear norm regularization and low-rank structure. While both papers discuss neural collapse, the candidate addresses language model representations through sparsity patterns, not the general metric framework for measuring dynamical richness in the original paper.

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#### 2. Neural collapse vs. low-rank bias: Is deep neural collapse really optimal?

URL: [View paper](#)

##### Brief Assessment

Neural Collapse Optimal[53] focuses on the optimality of neural collapse structures in deep networks and their connection to low-rank bias, while the original paper establishes DLR as a metric that recovers neural collapse conditions as a special case. These are complementary perspectives rather than competing claims about novelty.

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#### 3. The Persistence of Neural Collapse Despite Low-Rank Bias: An Analytic Perspective Through Unconstrained Features

URL: [View paper](#)

##### Brief Assessment

Neural Collapse Low Rank[52] focuses on low-rank bias in deep unconstrained feature models and its relationship to neural collapse optimality, while the original paper establishes DLR as a metric that recovers neural collapse conditions as a special case for measuring dynamical richness in general settings.

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#### 4. On generalization bounds for neural networks with low rank layers

URL: [View paper](#)

##### Brief Assessment

Low Rank Layers[55] focuses on generalization bounds for neural networks with low-rank weight matrices, not on metrics for measuring dynamical richness or neural collapse conditions. The candidate discusses neural collapse as a phenomenon that improves generalization bounds but does not propose metrics that recover neural collapse as a special case.

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#### 5. On the embedding collapse when scaling up recommendation models

URL: [View paper](#)

##### Brief Assessment

Embedding Collapse Recommendation[57] focuses on embedding collapse in recommendation systems through singular value decomposition and information abundance metrics, not on establishing connections between dynamical low-rank measures and neural collapse conditions in deep learning feature representations.

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#### 6. Neural Collapse versus Low-rank Bias: Is Deep Neural Collapse Really Optimal?

URL: [View paper](#)

##### Brief Assessment

Deep Collapse Optimal[56] focuses on the optimality of neural collapse structures in deep networks and low-rank bias, while the original paper proposes a new metric (DLR) that recovers neural collapse as a special case. These are complementary perspectives rather than competing claims about who first established connections between low-rank structure and neural collapse.

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#### 7. Neural rank collapse: Weight decay and small within-class variability yield low-rank bias

URL: [View paper](#)

##### Brief Assessment

Neural Rank Collapse[59] focuses on weight decay and within-class variability yielding low-rank bias in neural networks, establishing connections to neural collapse conditions NC1 and NC2. The original paper's contribution concerns a different metric (DLR) that recovers neural collapse as a special case through minimum projection operators, extending beyond labeled classification tasks. These are distinct theoretical frameworks addressing related but different aspects of neural collapse phenomena.

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#### 8. Provable Emergence of Deep Neural Collapse and Low-Rank Bias in $L^2$ -Regularized Nonlinear Networks

URL: [View paper](#)

##### Brief Assessment

Provable Neural Collapse[58] focuses on proving neural collapse emerges in  $L^2$ -regularized networks and connects it to low-rank bias through theoretical analysis of weight matrices. The original paper's DLR metric recovers neural collapse as a special case through feature kernel operators, but this is a different technical approach - one uses eigenvalue equations for weight matrices, the other uses minimum projection operators for feature kernels.

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#### 9. SSOLE: Rethinking Orthogonal Low-rank Embedding for Self-Supervised Learning

URL: [View paper](#)

##### Brief Assessment

SSOLE Orthogonal Embedding[54] focuses on self-supervised learning with orthogonal low-rank embedding for multi-view tasks, not on establishing connections between dynamical low-rank measures and neural collapse conditions in supervised settings.

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#### 10. On the representation collapse of sparse mixture of experts

URL: [View paper](#)

##### Brief Assessment

Sparse Mixture Collapse[51] addresses representation collapse in sparse mixture-of-experts models through routing mechanisms, not the connection between dynamical low-rank measures and neural collapse conditions in general feature learning frameworks.

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### Contribution 3: Eigendecomposition-based visualization method

**Description:** The authors introduce a complementary visualization technique based on eigendecomposition of the feature kernel operator that quantifies cumulative feature quality, utilization, and relative eigenvalues. This visualization method aids in interpreting the richness metric and provides insights into how features align with tasks and are utilized by the final layer.

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. Neural eigenfunctions are structured representation learners

URL: [View paper](#)

##### Brief Assessment

Neural Eigenfunctions[61] focuses on learning neural network representations through eigenfunction approximation for self-supervised learning and graph tasks, not on visualizing feature quality and utilization in the context of measuring dynamical richness as the original paper does.

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#### 2. Interpretable embedding procedure knowledge transfer via stacked principal component analysis and graph neural network

URL: [View paper](#)

##### Brief Assessment

Stacked PCA GNN[70] uses PCA for knowledge distillation in neural networks, not for visualizing feature quality metrics in the context of rich/lazy dynamics as in the original paper.

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#### 3. Improving Short-Term Gas Load Forecasting Accuracy: A Deep Learning Method with Dual Optimization of Dimensionality Reduction and Noise Reduction

URL: [View paper](#)

##### Brief Assessment

Gas Load Dual Optimization[69] focuses on gas load forecasting using dimensionality reduction techniques. The paper does not address neural network feature quality interpretation or visualization methods for understanding feature utilization in deep learning models.

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#### 4. What Can the Neural Tangent Kernel Tell Us About Adversarial Robustness?

URL: [View paper](#)

##### Brief Assessment

Neural Tangent Kernel[66] uses eigendecomposition of the NTK to visualize and analyze robust/non-robust features for adversarial robustness, not for general feature quality and utilization metrics in representation learning as proposed in the original paper.

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#### 5. A Spectral Theory of Neural Prediction and Alignment

URL: [View paper](#)

##### Brief Assessment

Spectral Neural Prediction[64] focuses on eigendecomposition of feature kernel operators for neural prediction tasks in neuroscience, not for interpreting neural network feature quality and utilization in the context of rich dynamics and representation learning as in the original paper.

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#### 6. Learning network representations

URL: [View paper](#)

##### Brief Assessment

Learning Network Representations[68] focuses on network embedding techniques (e.g., DeepWalk, node2vec) for representing graph structures in low-dimensional spaces, not on eigendecomposition visualization methods for interpreting neural network feature quality and utilization in deep learning contexts.

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#### 7. An operator theoretic approach for analyzing sequence neural networks

URL: [View paper](#)

##### Brief Assessment

Operator Theoretic Sequences[63] uses eigendecomposition of Koopman operators to analyze sequence neural networks, focusing on understanding network dynamics rather than measuring feature quality and utilization for representation learning metrics.

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#### 8. Task-Specific Scene Structure Representations

URL: [View paper](#)

##### Brief Assessment

Task Specific Structure[65] focuses on learning task-specific scene structures through eigenvector decomposition for low-level vision tasks (joint upsampling, denoising), not on visualizing neural network feature quality and utilization for understanding rich dynamics in deep learning training.

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#### 9. Inductive Link Prediction in Heterogeneous Information Networks via Adversarial Distillation

URL: [View paper](#)

##### Brief Assessment

Adversarial Distillation Inductive[67] focuses on inductive link prediction in heterogeneous information networks using adversarial distillation. The candidate's context mentions eigendecomposition only in passing (e.g., 'covariance matrix's eigendecomposition simplifies directly to'), without presenting a visualization method for interpreting neural network feature quality and utilization as described in the original contribution.

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#### 10. Generalized Factor Neural Network Model for High-dimensional Regression

URL: [View paper](#)

##### Brief Assessment

Factor Neural Network[62] uses eigendecomposition for analyzing factor models in high-dimensional regression, not for visualizing neural network feature quality and utilization as in the original paper's richness metric context.

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### Appendix: Text Similarity Detection

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Textual similarity detection checked 31 papers and found 3 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

#### 1. Disentangling Rich Dynamics from Feature Learning: A Framework for Independent Measurements

**Detected in:** Core Task (sibling)

⚠ **Note:** This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

### References

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- [0] Decoupling Dynamical Richness from Representation Learning: Towards Practical Measurement [View paper](#)
- [1] Dynamical diversity of FWM-induced pulsating solitons in an ultrafast fiber laser [View paper](#)
- [2] A novel method to measure static and dynamic complexity of time series based on visualization curves [View paper](#)
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