Novelty Assessment Report

Paper: Predicting Kernel Regression Learning Curves from Only Raw Data Statistics
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Abstract

We study kernel regression with common rotation-invariant kernels on real datasets including CIFAR-5m, SVHN, and ImageNet. We give a theoretical framework that predicts learning curves (test risk vs. sample size) from only two measurements: the empirical data covariance matrix and an empirical polynomial decomposition of the target function f_*. The key new idea is an analytical approximation of a kernel's eigenvalues and eigenfunctions with respect to an anisotropic data distribution. The eigenfunctions resemble Hermite polynomials of the data, so we call this approximation the \textit{Hermite eigenstructure ansatz} (HEA). We prove the HEA for Gaussian data, but we find that real image data is often ``Gaussian enough'' for the HEA to hold well in practice, enabling us to predict learning curves by applying prior results relating kernel eigenstructure to test risk. Extending beyond kernel regression, we empirically find that MLPs in the feature-learning regime learn Hermite polynomials in the order predicted by the HEA. Our HEA framework is a proof of concept that an end-to-end theory of learning which maps dataset structure all the way to model performance is possible for nontrivial learning algorithms on real datasets.

Core Task Landscape

This paper addresses: **Predicting Kernel Regression Learning Curves from Data Statistics**

A total of **33 papers** were analyzed and organized into a taxonomy with **17 categories**.

Taxonomy Overview

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

- **Theoretical Foundations of Kernel Regression Learning Curves**
- **Empirical Analysis and Validation of Learning Curves**
- **Algorithmic Extensions and Optimization**
- **Kernel Design and Selection**
- **Applied Forecasting and Regression**
- **Related Statistical and Machine Learning Methods**

Complete Taxonomy Tree

- Predicting Kernel Regression Learning Curves from Data Statistics Survey Taxonomy
- Theoretical Foundations of Kernel Regression Learning Curves
  - Spectral and Statistical Mechanics Approaches (4 papers)
  - [1] Spectral bias and task-model alignment explain generalization in kernel regression and infinitely wide neural networks (Canatar, 2020) View paper
  - [8] Out-of-Distribution Generalization in Kernel Regression (AbdÃ¼lkadir Canatar, 2022) View paper
  - [14] Spectrum Dependent Learning Curves in Kernel Regression and Wide Neural Networks (Bordelon, 2022) View paper
  - [23] Statistical mechanics of generalization in kernel regression (Abdulkadir Canatar, 2020) View paper
  - Asymptotic and Power-Law Analysis (4 papers)
  - [5] On the asymptotic learning curves of kernel ridge regression under power-law decay (Li, 2023) View paper
  - [6] Scaling laws are redundancy laws (Bi, 2025) View paper
  - [9] Precise learning curves and higher-order scaling limits for dot product kernel regression (Lechao Xiao, 2022) View paper
  - [22] Learning curves for Gaussian process regression with power-law priors and targets (Jin Hui, 2021) View paper
  - Kernel Eigenstructure and Data Distribution Modeling ★ (2 papers)
  - [0] Predicting Kernel Regression Learning Curves from Only Raw Data Statistics (Anon et al., 2026) View paper
  - [12] A Comprehensive Analysis on the Learning Curve in Kernel Ridge Regression (David Belius, 2024) View paper
- Empirical Analysis and Validation of Learning Curves
  - Real Dataset Benchmarking (2 papers)
  - [2] Asymptotic learning curves of kernel methods: empirical data versus teacherâ student paradigm (S. Spigler, 2020) View paper
  - [30] Asymptotic learning curves of kernel methods: empirical data v.s. Teacher-Student paradigm (Spigler, 2022) View paper
  - Synthetic and Structured Data Studies (2 papers)
  - [27] Kernels and learning curves for Gaussian process regression on random graphs (Peter Sollich, 2009) View paper
  - [28] Random walk kernels and learning curves for gaussian process regression on random graphs (Urry, 2013) View paper
- Algorithmic Extensions and Optimization
  - Stochastic Gradient Descent and Training Dynamics (2 papers)
  - [3] Functional scaling laws in kernel regression: Loss dynamics and learning rate schedules (Li, 2025) View paper
  - [19] Learning Curves of Stochastic Gradient Descent in Kernel Regression (Zhang Hai-han, 2025) View paper
  - Random Features and Approximation Methods (1 papers)
  - [10] Optimal Convergence for Agnostic Kernel Learning With Random Features (Jian Li, 2023) View paper

- Inductive Bias and Benign Overfitting (1 papers)
- [7] Physics-Informed Interpolator Generalizes Well in Fixed Dimension: Inductive Bias and Benign Overfitting (H Wong, 2025) View paper

- Kernel Design and Selection
  - Polynomial and Hybrid Kernel Analysis (2 papers)
  - [15] Geometry and learning curves of kernel methods with polynomial kernels (Kazushi Ikeda, 2004) View paper
  - [29] Learning curves of polynomial kernel classifiers (Ikeda, 2004) View paper
  - Supervised Kernel Construction (1 papers)
  - [17] Supervised kernel functions from bagging methods (Roig, 2025) View paper
- Applied Forecasting and Regression
  - Energy and Load Forecasting (4 papers)
  - [4] Advanced machine learning approach with dynamic kernel weighting for accurate electrical load forecasting (C. Jeevakarunya, 2025) View paper
  - [11] Calorific Value Forecasting of Coal Gangue with Hybrid Kernel Functionâ Support Vector Regression and Genetic Algorithm (Xiangbing Gao, 2022) View paper
  - [16] Kernel regression for real-time building energy analysis (Matthew Brown, 2012) View paper
  - [21] Short-Term Demand Forecasting Method in Power Markets Based on the KSVMâTCNâGBRT (Guang Yang, 2022) View paper
  - Chemical Property Prediction (1 papers)
  - [13] Alchemical and structural distribution based representation for universal quantum machine learning. (Felix A. Faber, 2017) View paper
  - Time Series Forecasting (1 papers)
  - [26] Prediction of time series data using the lagged dependent variable method (Jin Park, 2025) View paper
- Related Statistical and Machine Learning Methods
  - Support Vector Machines and Statistical Analysis (2 papers)
  - [31] A statistical analysis of soft-margin support vector machines for non-separable problems (Hiroyuki Funaya, 2012) View paper
  - [32] Statistical properties of support vector machines with forgetting factor (Hiroyuki Funaya, 2012) View paper
  - Clustering and Unsupervised Learning (1 papers)
  - [18] Implicit Annealing in Kernel Spaces: A Strongly Consistent Clustering Approach (Debolina Paul, 2022) View paper
  - Kernel Density Estimation and Curve Analysis (2 papers)
  - [20] Kernel Density Estimated Linear Regression (Roshan Kalpavruksha, 2025) View paper
  - [33] Analysing curves using kernel estimators. (ThÃ©o Gasser, 1991) View paper
  - Reinforcement Learning and Dissimilarity Spaces (2 papers)
  - [24] The dissimilarity space: Bridging structural and statistical pattern recognition (Duin, 2012) View paper
  - [25] Adaptive Software-Defined Network Control Using Kernel-Based Reinforcement Learning: An Empirical Study (Y Nurakhov, 2025) View paper

Narrative

Core task: predicting kernel regression learning curves from data statistics. The field organizes around several complementary perspectives. Theoretical Foundations examine how kernel eigenstructure and data distribution shape asymptotic behavior, often drawing on statistical mechanics and spectral analysis to characterize generalization as sample size grows. Empirical Analysis and Validation test these predictions against real datasets, documenting power-law decay and other scaling phenomena. Algorithmic Extensions explore optimization strategies and adaptive methods that exploit learning curve structure, while Kernel Design and Selection address how kernel choice influences curve shape. Applied Forecasting and Regression demonstrate these ideas in domains ranging from energy prediction to load forecasting, and Related Statistical and Machine Learning Methods connect kernel regression to broader themes in nonparametric estimation and neural scaling laws.

Recent work highlights tension between universal scaling principles and task-specific structure. Studies like Functional Scaling Laws[3] and Scaling Laws Redundancy[6] investigate how data redundancy and functional form govern asymptotic rates, while Spectral Bias Task Alignment[1] and Spectrum Dependent Curves[14] emphasize that eigenspectrum alignment between kernel and target determines convergence speed. Predicting Kernel Learning Curves[0] sits within the theoretical branch focused on kernel eigenstructure and data distribution modeling, closely aligned with Comprehensive Learning Curve Analysis[12], which also examines how distributional properties drive predictive accuracy. Compared to purely empirical approaches like Power Law Decay[5], the original work emphasizes deriving curve predictions directly from statistical summaries of the data, offering a more mechanistic view of how sample complexity unfolds in kernel methods.

Related Works in Same Category

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

1. A Comprehensive Analysis on the Learning Curve in Kernel Ridge Regression

Authors: David Belius, Tin Sum Cheng, Anastasis Kratsios, Aurelien Lucchi, AurÃ©lien Lucchi | **Year/Venue**: 2024 | **URL**: View paper

Abstract

This paper conducts a comprehensive study of the learning curves of kernel ridge regression (KRR) under minimal assumptions. Our contributions are three-fold: 1) we analyze the role of key properties of the kernel, such as its spectral eigen-decay, the characteristics of the eigenfunctions, and the smoothness of the kernel; 2) we demonstrate the validity of the Gaussian Equivalent Property (GEP), which states that the generalization performance of KRR remains the same when the whitened features ...

Relationship Analysis

Both papers belong to the Kernel Eigenstructure and Data Distribution Modeling category, focusing on theoretical frameworks that predict kernel regression learning curves from data covariance eigenstructure. The original paper introduces the Hermite eigenstructure ansatz (HEA) to predict kernel eigensystems from data covariance for rotation-invariant kernels on real datasets, while the candidate paper provides a comprehensive analysis of learning curves under minimal assumptions, examining the role of kernel spectral eigen-decay, eigenfunction characteristics, and the Gaussian Equivalence Property (GEP). The key difference is that the original paper proposes a specific analytical approximation (HEA using Hermite polynomials) for predicting kernel eigenstructure from raw data statistics, whereas the candidate paper focuses on rigorous bounds and conditions under which generalization performance is determined by eigen-decay, validating when GEP holds across different ridge regularization regimes.

Contributions Analysis

Overall novelty summary. The paper introduces the Hermite eigenstructure ansatz (HEA) to predict kernel regression learning curves from empirical data covariance and polynomial decompositions of the target function. It resides in the 'Kernel Eigenstructure and Data Distribution Modeling' leaf, which contains only two papers total. This leaf sits within the broader 'Theoretical Foundations of Kernel Regression Learning Curves' branch, indicating a relatively sparse research direction focused on mechanistic prediction frameworks rather than purely asymptotic or statistical mechanics approaches. The small sibling count suggests this specific angle—deriving eigenstructure approximations for anisotropic real-world data—is not yet crowded.

The taxonomy reveals neighboring leaves in 'Spectral and Statistical Mechanics Approaches' (four papers) and 'Asymptotic and Power-Law Analysis' (four papers), which address generalization error through replica methods or power-law spectral decay assumptions. The original work diverges by proposing an analytical approximation (HEA) tailored to rotation-invariant kernels and anisotropic distributions, rather than relying on asymptotic limits or generic spectral decompositions. The 'Empirical Analysis and Validation' branch (four papers across two leaves) focuses on measuring exponents on benchmarks, whereas this paper aims to predict curves from raw statistics, bridging theory and empirical structure more directly.

Among 27 candidates examined, no contribution was clearly refuted. The HEA for rotation-invariant kernels (7 candidates, 0 refutable) and theoretical proofs for Gaussian data (10 candidates, 0 refutable) appear novel within the limited search scope. The learning curve prediction framework (10 candidates, 0 refutable) also shows no substantial prior overlap. The analysis does not claim exhaustive coverage—only that top-K semantic matches and citation expansion yielded no direct precedents. The sparse taxonomy leaf and zero refutations suggest the HEA concept and its application to real image data are relatively unexplored in the examined literature.

Given the limited search scale (27 candidates) and the paper's placement in a two-paper leaf, the work appears to occupy a distinct niche within kernel regression theory. The taxonomy structure indicates that while spectral and asymptotic methods are established, mechanistic prediction from data statistics via Hermite approximations is less developed. Acknowledging the search scope, the analysis suggests the HEA framework and its empirical validation on real datasets represent a substantive contribution, though a broader literature review might reveal related ideas in adjacent fields not captured by the current taxonomy.

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

Contribution 1: Hermite eigenstructure ansatz (HEA) for rotation-invariant kernels

Description: The authors introduce an analytical approximation that expresses kernel eigenvalues and eigenfunctions in terms of Hermite polynomials of the data. This ansatz depends only on the empirical data covariance matrix and kernel level coefficients, enabling prediction of kernel eigenstructure without constructing or diagonalizing kernel matrices.

This contribution was assessed against **7 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. Nonorthogonal optical waveguides and resonators

URL: View paper

Brief Assessment

Nonorthogonal Optical Waveguides[39] applies Hermite polynomials to optical waveguide modes in physical systems with oblique coordinates, not to kernel regression eigenstructure prediction for machine learning datasets. The contexts are fundamentally different: optical propagation versus statistical learning theory.

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2. Estimation of spectral distributions of a class of high-dimensional linear processes

URL: View paper

Brief Assessment

Spectral Distributions Processes[37] focuses on eigenvalue estimation for high-dimensional linear processes and covariance matrices, not on kernel eigenstructure approximation using Hermite polynomials for rotation-invariant kernels in machine learning contexts.

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3. Short-time Fourier transform: two fundamental properties and an optimal implementation

URL: View paper

Brief Assessment

Short Time Fourier[34] focuses on shift and rotation invariance properties of the short-time Fourier transform with Hermite-Gaussian kernels in time-frequency analysis, not on kernel eigenstructure prediction for machine learning applications using Hermite polynomials of empirical data.

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4. Polymeromorphic complex ItÃ´-Hermite and Zernike functions: a systematic study, spectral analysis and applications

URL: View paper

Brief Assessment

Polymeromorphic Hermite Functions[35] focuses on mathematical extensions of Hermite polynomials in complex domains and rotationally symmetric systems, not on kernel regression eigenstructure prediction or machine learning applications.

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5. Closed-form expressions for time-frequency operations involving Hermite functions

URL: View paper

Brief Assessment

Time Frequency Hermite[36] focuses on closed-form expressions for time-frequency operations (product, convolution, correlation, WDF, AF) involving Hermite functions, not on kernel eigenstructure approximation or machine learning applications.

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6. A solar flux density calculation for a solar tower concentrator using a two-dimensional hermite function expansion

URL: View paper

Brief Assessment

Solar Flux Hermite[38] applies two-dimensional Hermite function expansion to solar flux density calculations for solar tower concentrators, not to kernel eigenstructure analysis or machine learning contexts.

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7. Simultaneously band and space limited functions in two dimensions, and receptive fields of visual neurons

URL: View paper

Brief Assessment

Band Space Limited[40] focuses on simultaneously band and space limited functions for visual neuron receptive fields, using Hermite polynomials in a different mathematical context (Gaussian spaces, Mehler's formula). The original paper's HEA predicts kernel eigenstructure from data covariance for machine learning applications, which is a distinct contribution.

Contribution 2: Theoretical proofs of HEA for Gaussian data

Description: The authors formally prove that the Hermite eigenstructure ansatz holds exactly for Gaussian data distributions in two limiting regimes: for wide Gaussian kernels and for dot-product kernels with fast-decaying level coefficients. These theorems provide rigorous justification for when the ansatz is valid.

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. Interlacing eigenvectors of large Gaussian matrices

URL: View paper

Brief Assessment

Interlacing Eigenvectors[48] focuses on eigenvector overlaps between principal minors of Gaussian matrices under Dyson Brownian motion, not on kernel eigenstructure or the Hermite eigenstructure ansatz for kernel regression on Gaussian data distributions.

2. Spectral Mixture Kernels for Multi-Output Gaussian Processes

URL: View paper

Brief Assessment

Spectral Mixture Kernels[50] focuses on multi-output Gaussian processes with spectral mixture kernels for modeling cross-covariances between channels. It does not address eigenstructure of kernels on Gaussian data distributions or provide theoretical proofs about Hermite eigenstructure ansatz.

3. Ensemble-regularized Kernel density estimation with applications to the ensemble Gaussian mixture filter

URL: View paper

Brief Assessment

Ensemble Kernel Density[52] focuses on kernel density estimation for ensemble filtering methods with Gaussian mixture models, not on eigenstructure of kernels on Gaussian data distributions or the Hermite eigenstructure ansatz.

4. Gaussian Process Kernels for Pattern Discovery and Extrapolation

URL: View paper

Brief Assessment

Gaussian Process Kernels[51] focuses on deriving kernels for pattern discovery via spectral densities modeled as Gaussian mixtures. It does not address eigenstructure of kernels on Gaussian data distributions or provide theoretical proofs about Hermite eigenstructure ansatz.

5. Universality of kernel random matrices and kernel regression in the quadratic regime

URL: View paper

Brief Assessment

Kernel Random Matrices[44] studies kernel matrices in the quadratic regime $n \asymp d^2$ with general covariance structures, not the Hermite eigenstructure ansatz for Gaussian data distributions.

6. Reconstructing QCD spectral functions with Gaussian processes

URL: View paper

Brief Assessment

QCD Spectral Functions[49] focuses on reconstructing spectral functions in quantum chromodynamics using Gaussian process regression, not on proving eigenstructure properties of kernels on Gaussian data distributions. The paper addresses a completely different domain (particle physics) with different objectives (spectral function reconstruction).

7. The Distribution of the Largest Eigenvalue in the Gaussian Ensembles

URL: View paper

Brief Assessment

The candidate paper (Largest Eigenvalue Distribution[56]) focuses on the distribution of the largest eigenvalue in Gaussian random matrix ensembles, not on kernel eigenstructure or the Hermite eigenstructure ansatz for kernel regression on Gaussian data.

8. Informed Spectral Normalized Gaussian Processes for Trajectory Prediction

URL: View paper

Brief Assessment

Informed Spectral Normalized[55] focuses on continual learning methods for spectral normalized Gaussian processes in trajectory prediction, not on theoretical proofs about eigenstructure of kernels on Gaussian data distributions or Hermite polynomial decompositions.

9. Generalized Spectral Kernels

URL: View paper

Brief Assessment

Generalized Spectral Kernels[53] focuses on approximating arbitrary kernels using spectral representations with Fourier transforms and Bochner's theorem. It does not address eigenstructure of kernels on Gaussian data distributions or provide proofs about Hermite eigenstructure ansatz.

10. Asymptotic Gaussian Fluctuations of Eigenvectors in Spectral Clustering

URL: View paper

Brief Assessment

Asymptotic Gaussian Fluctuations[54] focuses on eigenvector fluctuations in spectral clustering for spike random matrix models, not on proving the Hermite eigenstructure ansatz for Gaussian data distributions with rotation-invariant kernels.

Contribution 3: Learning curve prediction framework from raw data statistics

Description: The authors develop an end-to-end framework that maps minimal dataset statistics directly to kernel regression performance predictions. By combining the HEA with existing kernel eigenframework results, they predict test error curves using only data covariance and target function decomposition, without requiring kernel matrix construction.

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. Retrieval of Physical Parameters With Deep Structured Kernel Regression

URL: View paper

Brief Assessment

Deep Structured Kernel[47] focuses on multioutput regression for physical parameter retrieval in remote sensing applications, not on predicting learning curves from data covariance statistics.

2. Bayesian Kernel Regression for Functional Data

URL: View paper

Brief Assessment

Bayesian Kernel Regression[46] focuses on functional output regression where the output is a function (e.g., spectra, probability distributions), not on predicting learning curves from data covariance statistics. The candidate addresses a different problem domain (functional data analysis) rather than kernel regression performance prediction.

3. Generalization error rates in kernel regression: The crossover from the noiseless to noisy regime

URL: View paper

Brief Assessment

Noiseless Noisy Crossover[41] focuses on characterizing generalization error decay rates in kernel regression across different noise regimes, not on predicting learning curves from minimal dataset statistics like data covariance and target function decomposition.

4. Pseudo-labeling for Kernel Ridge Regression under Covariate Shift

URL: View paper

Brief Assessment

Pseudo Labeling Covariate[42] focuses on kernel ridge regression under covariate shift with pseudo-labeling for model selection, not on predicting learning curves from raw data statistics. The paper addresses a different problem (domain adaptation) using different methodology (imputation-based model selection).

5. Asymptotic learning curves of kernel methods: empirical data versus teacherâstudent paradigm

URL: View paper

Brief Assessment

Asymptotic Learning Curves[2] focuses on teacher-student paradigms with Gaussian random fields and lattice-based theoretical analysis, not on predicting learning curves directly from raw data covariance and target function statistics without kernel matrix construction.

6. Package CovRegpy: Regularized covariance regression and forecasting in Python

URL: View paper

Brief Assessment

CovRegpy Package[43] focuses on covariance regression and portfolio optimization methods for financial applications, not on predicting kernel regression learning curves from data statistics.

7. Universality of kernel random matrices and kernel regression in the quadratic regime

URL: View paper

Brief Assessment

Kernel Random Matrices[44] predicts kernel regression performance in the quadratic regime but does not claim to predict learning curves from only data covariance and target function decomposition without kernel matrix construction.

8. Scaling laws are redundancy laws

URL: View paper

Brief Assessment

Scaling Laws Redundancy[6] focuses on deriving scaling exponents from spectral redundancy in kernel regression, not on predicting learning curves from raw data statistics. The candidate's framework maps spectral tail indices to power-law exponents, while the original develops the HEA to predict kernel eigenstructure from data covariance.

9. A Comprehensive Analysis on the Learning Curve in Kernel Ridge Regression

URL: View paper

Brief Assessment

Comprehensive Learning Curve Analysis[12] focuses on kernel ridge regression learning curves under minimal assumptions with emphasis on spectral eigen-decay and feature properties. The original paper's framework specifically maps data covariance and target function decomposition to predictions using the Hermite Eigenstructure Ansatz (HEA), which is not addressed in this candidate.

10. A theory of high dimensional regression with arbitrary correlations between input features and target functions: sample complexity, multiple descent curves and a â¦

URL: View paper

Brief Assessment

High Dimensional Regression[45] focuses on ridge regression with arbitrary correlations between features and targets, deriving exact error formulas. While both papers predict learning curves, the candidate does not use the Hermite Eigenstructure Ansatz (HEA) or kernel eigenframework that are central to the original paper's approach of mapping data covariance directly to kernel regression performance without kernel matrix construction.

Appendix: Text Similarity Detection

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

References

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