Novelty Assessment Report

Paper: Covariate-Guided Clusterwise Linear Regression for Generalization to Unseen Data

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Abstract

In many tabular regression tasks, the relationships between covariates and response can often be approximated as linear only within localized regions of the input space; a single global linear model therefore fails to capture these local relationships. Conventional Clusterwise Linear Regression (CLR) mitigates this issue by learning K local regressors. However, existing algorithms either optimize latent binary indicators, (i) providing no explicit rule for assigning an $\textit{unseen}$ covariate vector to a cluster at test time, or rely on heuristic mixture of experts approaches, (ii) lacking convergence guarantees. To address these limitations, we propose $ \textit{covariate-guided}$ CLR, an end-to-end framework that jointly learns an assignment function and K linear regressors within a single gradient-based optimization loop. During training, a proxy network iteratively predicts coefficient vectors for inputs, and hard vector quantization assigns samples to their nearest codebook regressors. This alternating minimization procedure yields monotone descent of the empirical risk, converges under mild assumptions, and enjoys a PAC-style excess-risk bound. By treating the covariate data from all clusters as a single concatenated design matrix, we derive an F-test statistic from a nested linear model, quantitatively characterizing the effective model complexity. As K varies, our method spans the spectrum from a single global linear model to instance-wise fits. Experimental results show that our method exactly reconstructs synthetic piecewise-linear surfaces, achieves accuracy comparable to strong black-box models on standard tabular benchmarks, and consistently outperforms existing CLR and mixture-of-experts approaches.

Core Task Landscape

This paper addresses: **Learning Local Linear Regressors with Covariate-Based Cluster Assignment for Tabular Regression**

A total of **13 papers** were analyzed and organized into a taxonomy with **14 categories**.

Taxonomy Overview

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

- **Covariate-Driven Cluster Assignment Methods**
- **Iterative Clustering and Local Model Estimation**
- **Multi-View and Multi-Source Regression Clustering**
- **Model-Based Clustering with Linear Regression Components**
- **Nonparametric Local Smoothing for Clustered and Longitudinal Data**
- **Partial Linear and Hybrid Regression Models with Clustering**

Complete Taxonomy Tree

- Learning Local Linear Regressors with Covariate-Based Cluster Assignment for Tabular Regression Survey Taxonomy
- Covariate-Driven Cluster Assignment Methods
  - End-to-End Gradient-Based Assignment Learning ★ (1 papers)
  - [0] Covariate-Guided Clusterwise Linear Regression for Generalization to Unseen Data (Anon et al., 2026) View paper
  - Projection-Based Assignment with Variable-Dimension Covariates (1 papers)
  - [2] A Projection Approach to Local Regression with Variable-Dimension Covariates (Heiner, 2023) View paper
- Iterative Clustering and Local Model Estimation
  - Fuzzy Clustering with Takagi-Sugeno Local Models
  - Incremental Fuzzy C-Regression for Streaming Data (1 papers)
    - [3] Incremental Fuzzy C-Regression Clustering From Streaming Data for Local-Model-Network Identification (Saso Blazic, 2020) View paper
  - Split-and-Merge Neuro-Fuzzy Model Reduction (1 papers)
    - [9] Reducing the number of local linear models in neuro-fuzzy modeling: A split-and-merge clustering approach (Ahmad Kalhor, 2011) View paper
  - Distance-Based Clustering with Local Regressors
  - Semi-Supervised Distance Metric Learning for Clustering (1 papers)
    - [7] Semi-supervised distance metric learning based on local linear regression for data clustering (Hong Zhang, 2012) View paper
  - K-Means with Locally Weighted Linear Regression (1 papers)
    - [12] Predicting the morbidity of chronic obstructive pulmonary disease based on multiple locally weighted linear regression model with K-means clustering. (Zhi-Yong Huang, 2020) View paper
- Multi-View and Multi-Source Regression Clustering
  - Intra-View and Inter-View Information Fusion (1 papers)
  - [1] Scalable Multi-View Regression Clustering for Large-Scale Data (Xiaowei Zhao, 2025) View paper
  - Localized Regression with Multi-Source Spatial Data (1 papers)
  - [4] Localized linear regression methods for estimating monthly precipitation grids using elevation, rain gauge, and TRMM data: M. Taheri et al. (M Taheri, 2020) View paper

- Model-Based Clustering with Linear Regression Components
  - Gaussian Mixture Models with Clusterwise Linear Regression (1 papers)
  - [13] A unified framework for model-based clustering, linear regression and multiple cluster structure detection (Galimberti, 2015) View paper
  - Bayesian Ecological Inference with Covariate-Driven Transitions (1 papers)
  - [5] A new bayesian ecological inference model with covariates (Rubio, 2025) View paper
- Nonparametric Local Smoothing for Clustered and Longitudinal Data
  - Design-Adaptive Local Linear Regression for Correlated Data (1 papers)
  - [10] Design-adaptive minimax local linear regression for longitudinal/clustered data (K Chen, 2008) View paper
  - Local Polynomial Smoothing for Clustered Data (1 papers)
  - [11] Local polynomial regression analysis of clustered data (K Chen, 2005) View paper
- Partial Linear and Hybrid Regression Models with Clustering
  - Clustered Partial Linear Regression (1 papers)
  - [6] Clustered partial linear regression (LuÃs Torgo, 2003) View paper
  - Cluster Linear Regression Consistency Assessment (1 papers)
  - [8] ASSESSMENT OF THE CONSISTENCY OF A CLUSTER LINEAR REGRESSION MODEL (S. I. Noskov, 2025) View paper

Narrative

Core task: learning local linear regressors with covariate-based cluster assignment for tabular regression. The field addresses heterogeneity in tabular data by partitioning observations into clusters, each governed by its own linear model, with cluster membership determined by covariates rather than fixed labels. The taxonomy reveals several complementary perspectives. Covariate-Driven Cluster Assignment Methods emphasize learning assignment rules directly from input features, often via gradient-based or distance-metric approaches. Iterative Clustering and Local Model Estimation focuses on alternating optimization schemes that refine both cluster boundaries and regression parameters. Multi-View and Multi-Source Regression Clustering tackles scenarios with multiple feature representations or data sources, as seen in Scalable Multi-View Regression[1]. Model-Based Clustering with Linear Regression Components adopts probabilistic mixture frameworks, while Nonparametric Local Smoothing for Clustered and Longitudinal Data leverages kernel or spline methods for flexible local fits, exemplified by Local Polynomial Clustered[11]. Finally, Partial Linear and Hybrid Regression Models with Clustering blend parametric and nonparametric components, illustrated by Clustered Partial Linear[6].

A central tension across these branches is the trade-off between interpretability and flexibility: hard assignment rules yield simpler cluster structures but may miss smooth transitions, whereas soft or fuzzy methods, such as Incremental Fuzzy Regression[3], capture gradual membership at the cost of added complexity. Another active theme is scalability and convergence guarantees, with works like Cluster Linear Consistency[8] exploring theoretical properties of iterative schemes. The original paper, Covariate-Guided Clusterwise[0], sits within the End-to-End Gradient-Based Assignment Learning sub-branch of Covariate-Driven methods. It emphasizes jointly optimizing cluster assignment functions and local regressors through backpropagation, contrasting with older alternating schemes like Split-and-Merge Clustering[9] and differing from distance-metric learning approaches such as Semi-supervised Distance Metric[7] by directly parameterizing assignment via neural layers. This positioning highlights a modern trend toward differentiable, end-to-end pipelines that unify clustering and prediction in a single optimization objective.

Related Works in Same Category

No sibling papers were found in the same taxonomy leaf. A taxonomy-subtopic-level comparison will be produced instead.

Taxonomy-Level Summary

The original leaf focuses on unified gradient-based optimization frameworks that jointly learn assignment functions and local regressors with formal convergence guarantees, emphasizing end-to-end differentiability. The sibling subtopic addresses a distinct technical challenge: handling incomplete or variable-dimension covariate vectors through analytical projection methods and random partition models. Both approaches aim to learn covariate-based cluster assignments for local regression, but they tackle fundamentally different aspects of the problem—optimization architecture versus input data completeness.

Similarities: - Both involve learning assignment functions based on covariates for tabular regression tasks - Both aim to partition the input space to enable local linear modeling - Both represent specialized approaches to mixture-of-experts or clustering-based regression

Differences: - Original leaf emphasizes joint gradient-based optimization with convergence guarantees; sibling focuses on handling missing/incomplete covariate data - Original leaf requires complete differentiable pipelines; sibling uses analytical projection methods that may not require end-to-end gradients - Original leaf excludes alternating optimization; sibling's scope is orthogonal to optimization strategy, focusing instead on variable-dimension input handling - Original leaf's technical challenge is optimization convergence; sibling's challenge is data completeness and dimensionality variation

Suggested Search Directions: - Hybrid methods combining gradient-based joint optimization with robust handling of missing covariates - Differentiable imputation or masking strategies within end-to-end assignment learning frameworks - Convergence analysis for gradient-based methods under variable-dimension or incomplete input scenarios

Sibling Subtopics

- **Projection-Based Assignment with Variable-Dimension Covariates** (leaves: 1, papers: 1)
- Scope: Methods handling incomplete covariate vectors through analytical projection and random partition models admitting variable-dimension inputs.
- Exclude: Methods requiring complete covariates or using imputation strategies belong to standard clustering or preprocessing categories.

Contributions Analysis

Overall novelty summary. The paper proposes an end-to-end framework for covariate-guided clusterwise linear regression, jointly learning an assignment function and K local regressors through gradient-based optimization with hard vector quantization. It occupies the 'End-to-End Gradient-Based Assignment Learning' leaf within the 'Covariate-Driven Cluster Assignment Methods' branch, where it is currently the sole paper in that leaf. This positioning reflects a relatively sparse research direction focused on unified gradient descent for both assignment and regression, distinguishing it from iterative alternating schemes and distance-based methods that populate neighboring branches.

The taxonomy reveals several neighboring directions: 'Iterative Clustering and Local Model Estimation' contains fuzzy and distance-based methods that alternate between assignment and parameter updates, while 'Model-Based Clustering with Linear Regression Components' adopts probabilistic mixture frameworks. The paper diverges from these by treating assignment as a differentiable function learned end-to-end rather than through EM-style alternation or fixed distance metrics. Its use of hard vector quantization and proxy networks contrasts with fuzzy membership approaches in 'Fuzzy Clustering with Takagi-Sugeno Local Models' and the semi-supervised metric learning in 'Distance-Based Clustering with Local Regressors', emphasizing direct gradient flow over heuristic assignment rules.

Among 27 candidates examined, the end-to-end framework contribution (10 candidates, 0 refutable) appears novel within the limited search scope, with no prior work combining gradient-based assignment learning and hard quantization in this manner. The convergence guarantees contribution (7 candidates, 2 refutable) shows more substantial overlap, suggesting existing theoretical analyses of alternating minimization may cover similar ground. The model complexity quantification via F-test (10 candidates, 0 refutable) appears less explored in the examined literature. These statistics reflect a targeted semantic search rather than exhaustive coverage, indicating the framework's novelty is conditional on the top-27 matches retrieved.

Based on the limited search scope of 27 semantically similar papers, the work introduces a distinctive combination of differentiable assignment and local regression within a sparse taxonomy leaf. However, the convergence analysis overlaps with prior theoretical work, and the search does not capture the full breadth of gradient-based clustering or neural mixture-of-experts literature. The novelty assessment is thus provisional, contingent on the semantic retrieval strategy and the specific papers indexed in the taxonomy.

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

Contribution 1: End-to-end covariate-guided clusterwise linear regression framework

Description: The authors introduce CG-CLR, a framework that simultaneously trains both a data-driven assignment rule (via a proxy network) and K local linear regressors through joint gradient-based optimization. This addresses the limitation of existing CLR methods that lack explicit rules for assigning unseen covariates at test time.

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. New bundle method for clusterwise linear regression utilizing support vector machines

URL: View paper

Brief Assessment

Bundle Clusterwise Regression[35] focuses on SVM-based formulation for CLR with DC optimization, not on joint learning of assignment functions and regressors through gradient-based optimization as in the original paper.

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2. Clustering-and regression-based multi-criteria collaborative filtering with incremental updates

URL: View paper

Brief Assessment

Clustering Regression Collaborative[34] focuses on collaborative filtering with multi-criteria ratings in recommender systems, not on covariate-guided clusterwise linear regression for tabular data prediction tasks.

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3. Regression clustering for improved accuracy and training costs with molecular-orbital-based machine learning

URL: View paper

Brief Assessment

Regression Clustering Molecular[36] focuses on clustering molecular-orbital features for quantum chemistry energy predictions, not on jointly learning assignment functions and local linear regressors for general tabular regression tasks.

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4. A piece-wise linear model-based algorithm for the identification of nonlinear models in real-world applications

URL: View paper

Brief Assessment

Piecewise Linear Identification[32] focuses on nitrogen oxide concentration simulation using meteorological data and emission databases, not on general covariate-guided clusterwise regression with proxy networks and vector quantization for tabular data.

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5. A Hybrid of Multiple Linear Regression Clustering Model with Support Vector Machine for Colorectal Cancer Tumor Size Prediction

URL: View paper

Brief Assessment

Hybrid Regression Clustering[33] focuses on medical prediction (colorectal cancer tumor size) using a hybrid of clustering with SVM, not on jointly learning assignment functions and local linear regressors through gradient-based optimization for general tabular regression tasks.

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6. Regression-clustering for Improved Accuracy and Training Cost with Molecular-Orbital-Based Machine Learning

URL: View paper

Brief Assessment

Regression Clustering Molecular[39] focuses on clustering molecular-orbital-based features for quantum chemistry energy predictions, not on jointly learning assignment functions and local linear regressors for general tabular regression tasks.

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7. A Generalized Framework for Predictive Clustering and Optimization

URL: View paper

Brief Assessment

Predictive Clustering Optimization[40] focuses on a generalized framework combining different cluster definitions (arbitrary, closest center, bounding boxes) with supervised objectives, but does not propose an end-to-end gradient-based joint learning of assignment functions and local regressors as described in the original paper's CG-CLR.

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8. Variable clustering in high dimensional linear regression models

URL: View paper

Brief Assessment

Variable Clustering Regression[37] focuses on clustering regression coefficients as latent random variables in a Gaussian mixture model, not on learning assignment functions for unseen covariates at test time.

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9. Missing Value Imputation via Clusterwise Linear Regression

URL: View paper

Brief Assessment

Clusterwise Imputation[31] focuses on missing value imputation in incomplete datasets, not on learning assignment functions for prediction tasks. The candidate does not address test-time covariate assignment or joint gradient-based optimization of assignment rules and regressors.

10. SCOAL: A framework for simultaneous co-clustering and learning from complex data

URL: View paper

Brief Assessment

SCOAL Framework[38] focuses on dyadic data (customer-product matrices) with co-clustering across two dimensions, whereas the original paper addresses single-mode covariate-to-response regression with a proxy network for assignment. The technical approaches and problem settings differ fundamentally.

Contribution 2: Convergence guarantees for alternating minimization with dual loss

Description: The authors prove that their alternating update procedure achieves monotone descent of a dual loss function and establishes linear convergence toward optimal parameters under stated assumptions. They also derive PAC-style generalization bounds for the non-realizable setting.

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.

1. On the cluster-aware supervised learning (clusl): Frameworks, convergent algorithms, and applications

URL: View paper

Brief Assessment

CluSL Frameworks[29] focuses on cluster-aware supervised learning with alternating minimization for clustering solutions, not on clusterwise regression with dual loss formulations and PAC-style generalization bounds.

2. Piecewise linear regression and classification

URL: View paper

Prior Art Analysis

Piecewise Linear Regression[28] demonstrates prior work on convergence guarantees for alternating minimization in clusterwise regression. The candidate paper proves that its PARC algorithm converges in a finite number of steps to a local minimum through block-coordinate descent, alternating between fitting linear predictors and reassigning data to clusters. This establishes that similar convergence guarantees for alternating minimization procedures in piecewise linear regression existed before the original paper's submission.

Evidence

Evidence 1 - **Rationale**: Both papers prove monotone descent of a dual/composite loss function through alternating minimization, showing the candidate established this property earlier. - **Original**: by reformulating clr as a dual loss vλ, we show that our alternating updates yield a monotone descent ofvλ - **Candidate**: the proof follows arguments similar to those used to prove convergence of unsupervised learning approaches like k-means. the binary variables zkj are hidden variables such that zkj = 1 if and only if the target vector yk is predicted by j(xk) = j as in (6). having shown that parc is a coordinate-des...

3. Alternating Minimization for Mixed Linear Regression

URL: View paper

Brief Assessment

Alternating Mixed Regression[24] focuses on mixed linear regression with unlabeled measurements, not clusterwise regression with covariate-guided assignment. The dual loss structure and problem formulation differ fundamentally from the original paper's covariate-guided framework.

4. A Preconditioned Alternating Minimization Framework for Nonconvex and Half Quadratic Optimization

URL: View paper

Brief Assessment

Preconditioned Alternating Minimization[30] addresses half-quadratic optimization problems with different technical machinery (preconditioned iterations for linear subproblems), not clusterwise regression with PAC bounds.

5. On cluster-aware supervised learning: Frameworks, convergent algorithms, and applications

URL: View paper

Prior Art Analysis

Cluster-Aware Supervised Learning[27] demonstrates prior work on convergence guarantees for alternating minimization in clusterwise regression. The candidate paper explicitly proves that their regularized alternating minimization (RAM) algorithm converges to a stationary point within a finite number of iterations, and claims this is 'the first known convergence result in cluster-aware learning literature.' This directly challenges the novelty of the original paper's convergence proof for alternating minimization with dual loss, as both papers address the same fundamental problem: proving convergence for alternating update procedures in clusterwise regression settings.

Evidence

Evidence 1 - **Rationale**: Both papers prove convergence for alternating minimization algorithms in clusterwise regression. The candidate explicitly claims to provide 'the first known convergence result in cluster-aware learning literature,' establishing that convergence guarantees for alternating minimization in this domain existed prior to the original paper. - **Original**: by reformulating clr as a dual loss vλ, we show that our alternating updates yield a monotone descent ofvλ and that cg-clr exhibits linear convergence towards optimal parameters(˜w ⋆,ϕ ⋆). - **Candidate**: we develop a regularized alternating minimization (ram) algorithm to solve it, where at each iteration, we penalize the distance between the current clustering solution and the one from the previous iteration. by choosing a proper penalty function, we show that each iteration of the ram algorithm ca...

Evidence 2 - **Rationale**: Both papers establish descent properties for their alternating minimization procedures. The candidate proves convergence to a stationary solution for nonconvex clusterwise learning, demonstrating that such convergence results existed before the original paper's contribution. - **Original**: proposition 3.1(one-epoch descent).under assumptions 1 and 2, suppose the cluster assignment z(t) remains fixed during epocht. define lv := max n (1 +λ)l,(4 + 2λ)l 2 xx2 max o . for any step-size 0< η≤1/l v , the simultaneous gradient updates guarantee a strict decrease of the lyapunov function: vλ ... - **Candidate**: because clusl is, in general, nonconvex, a regularized alternating projection algorithm is developed to solve it and is proven to always find a stationary solution.

6. Regularized high dimension low tubal-rank tensor regression

URL: View paper

Brief Assessment

High Dimension Tensor[26] focuses on tensor regression with tubal rank decomposition and alternating minimization for convex regularized programs, not clusterwise regression with dual loss functions and PAC bounds.

7. Max-Affine Regression: Parameter Estimation for Gaussian Designs

URL: View paper

Brief Assessment

Max-Affine Regression[25] focuses on max-affine regression (maximum of k affine functions) with Gaussian designs, while the original paper addresses clusterwise linear regression with covariate-guided assignment. The technical settings and objectives differ fundamentally.

Contribution 3: Model complexity quantification via F-test statistic

Description: The authors develop an F-test based criterion that treats all K regressors as a nested linear model, enabling principled statistical selection of the number of clusters K and providing transparent quantification of effective degrees of freedom.

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. A new alternative to the standard F test for clustered data

URL: View paper

Brief Assessment

Alternative F Test[20] addresses clustered data in survey sampling contexts, not model complexity selection in clusterwise regression. The candidate focuses on hypothesis testing for cluster effects in hierarchical data structures, not quantifying effective degrees of freedom for choosing the number of clusters K in regression models.

2. Flexible pavement condition model using clusterwise regression and mechanistic-empirical procedure for fatigue cracking modeling

URL: View paper

Brief Assessment

Flexible Pavement Clusterwise[22] applies clusterwise regression to pavement condition prediction but does not describe an F-test based criterion for model complexity selection or quantification of effective degrees of freedom as proposed in the original paper.

3. A novel regression based clustering technique for wireless sensor networks

URL: View paper

Brief Assessment

Regression Clustering WSN[19] uses pseudo F-statistic for cluster quality assessment in wireless sensor networks, not for model complexity selection in clusterwise regression. The technical contexts differ fundamentally.

4. A stepwise cluster analysis method for predicting air quality in an urban environment

URL: View paper

Brief Assessment

Stepwise Air Quality[21] applies F-tests to air quality prediction using cluster analysis, not to clusterwise linear regression model selection. The technical contexts differ fundamentally.

5. Multivariate Statistical Analysis MSA 2021

URL: View paper

Brief Assessment

Multivariate Statistical Analysis MSA 2021[23] is a conference proceedings volume containing abstracts and papers on various statistical topics. It does not present a unified methodology for F-test based model complexity selection in clusterwise regression, but rather includes diverse contributions from multiple authors on unrelated statistical methods.

6. A new procedure of regression clustering based on Cook's D

URL: View paper

Brief Assessment

Cook's D Clustering[18] uses Chow's F-statistic for detecting structural breaks in regression clusters, not for model complexity selection across different numbers of clusters K as in the original paper.

7. Linear regression

URL: View paper

Brief Assessment

Linear Regression[14] presents standard linear regression theory with normal equations and risk analysis, but does not address F-test statistics for model complexity selection in clusterwise regression contexts.

8. A weighted least-squares approach to clusterwise regression

URL: View paper

Brief Assessment

Weighted Clusterwise Regression[15] mentions F-tests only in passing for model comparison, not as a principled criterion for selecting K or quantifying effective degrees of freedom in clusterwise regression.

9. On the measurement of perceived service quality: a conjoint analysis approach

URL: View paper

Brief Assessment

Conjoint Service Quality[17] mentions a Chow F-test for examining experimental designs, but this is a standard statistical test for structural breaks, not a novel method for quantifying model complexity in clusterwise regression frameworks.

10. Upgradation of pavement deterioration models for urban roads by non-hierarchical clustering

URL: View paper

Brief Assessment

Pavement Deterioration Clustering[16] mentions using 'a partial f-test' for model selection in pavement management, but does not develop an F-test criterion for nested linear models in clusterwise regression or quantify effective degrees of freedom as the original paper does.

Appendix: Text Similarity Detection

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

References

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