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A Deterministic Non-Iterative Approximation Framework using Statistical Weight Assignment for Efficient Data Processing

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ABSTRACT

In many real-world data processing and approximation tasks, existing methods rely heavily on repeated train ing, parameter tuning, and iterative optimization. While these approaches can achieve high accuracy, they often introduce significant computational overhead and increase execution time, making them less suitable for real-time and resource-constrained environments. To overcome these limitations, this paper presents a deterministic and non-iterative approximation framework that eliminates the need for any training phase. The proposed approach is based on direct statistical analysis of input features, where weights are assigned proportionally according to their relative contribution within each data instance. This removes the dependency on learned parameters and ensures a stable and consistent mapping between inputs and outputs. A weighted aggregation mechanism is then applied to combine the feature values, followed by a nonlinear transformation that introduces flexibility in modeling variations within the data. Unlike conventional learning-based models that rely on iterative optimization and parameter updates, the proposed method directly computes the output using deterministic operations, eliminating the need for training. The framework is evaluated on a standard numerical dataset, where it demonstrates reliable approximation capability with reduced processing time and minimal resource usage. Due to its simplicity, deterministic nature, and efficiency, the proposed framework is particularly suitable for applications requiring fast and lightweight computation, such as real-time data analysis, embedded systems, and large-scale numerical processing.

INTRODUCTION

In recent years, data-driven approaches have become essential in a wide range of applications, including housing price estimation, financial analysis, environmental monitoring, and decision support systems. These applications require efficient processing of input data to generate accurate and reliable outputs. Most existing methods are based on models that rely on a training phase, where parameters are learned through iterative optimization techniques. Although such methods can achieve high predictive accuracy, they often involve significant computational cost, longer execution time, and dependence on multiple iterations [1].

The reliance on training and iterative optimization presents several challenges, particularly in scenarios where computational resources are limited or rapid response is required. For instance, real-time systems, embedded platforms, and edge computing environments demand lightweight solutions that can operate efficiently without extensive processing overhead. In such cases, traditional approaches may not be suitable due to their complexity and resource requirements [2].

Another important limitation of existing techniques is the variability introduced by the training process. Since model parameters are typically learned through iterative updates, the final output may depend on initialization conditions and optimization settings. This can lead to inconsistencies across different runs and reduce the reliability of the system in practical deployments. Therefore, there is a clear need for alternative approaches that can provide stable and predictable outputs without relying on iterative learning [3].

To address these challenges, this paper proposes a deterministic and non-iterative approximation framework for efficient data processing. The proposed method eliminates the need for training by directly assigning weights to input features based on their relative contribution within each data instance. This deterministic weight assignment ensures that the model behavior remains consistent and does not depend on external parameters or initialization [4].

Following weight assignment, the framework computes a weighted aggregation of the input features, which is then passed through a nonlinear transformation to generate the output. This combination of weighted aggregation and nonlinear mapping allows the method to capture variations in the data while maintaining a simple computational structure. Since the entire process is executed in a single pass, the proposed approach achieves low computational complexity and fast execution [5].

The effectiveness of the proposed framework is evaluated using a standard numerical dataset. The experimental results show that, although the method does not achieve the same level of accuracy as traditional learning-based models, it pro vides a reasonable approximation with significantly reduced computational overhead. This highlights a trade-off between accuracy and efficiency, where the proposed method prioritizes simplicity, speed, and stability [6].

The main contributions of this work can be summarized as follows:

- A deterministic approximation framework that eliminates the need for training and iterative optimization.
- A statistical weight assignment mechanism that ensures proportional feature contribution.
- A lightweight and single-pass computation process suit able for real-time and resource-constrained environments.

RELATED WORK

In recent years, a variety of approaches have been proposed for data approximation and regression tasks. Traditional methods such as linear regression have been widely used due to their simplicity and interpretability [1]. These methods establish a direct relationship between input features and output values, making them computationally efficient. However, they are often limited in capturing complex nonlinear relationships present in real-world data.

To overcome these limitations, more advanced models have been introduced that rely on iterative learning and optimization. Neural-based models and gradient-based approaches adjust parameters through repeated updates to minimize pre diction error [2]. While such methods can achieve high accu racy, they require multiple passes over the data and involve significant computational overhead. This makes them less suitable for applications where fast execution and low resource consumption are required [7].

Several lightweight and approximation-based techniques have also been explored to reduce computational complexity. These include regression trees and ensemble-based methods, which aim to improve prediction performance while maintaining efficiency [3]. Although these approaches reduce complexity compared to deep models, they still depend on a training phase and parameter tuning.

Another line of research focuses on deterministic and rule based methods for data processing. These approaches avoid iterative optimization and instead rely on predefined mathematical formulations to generate outputs [4]. Such methods are generally faster and more stable, but they may struggle to achieve high accuracy when dealing with complex data patterns [8].

Despite these developments, there remains a gap in de signing a framework that is both completely training-free and capable of providing reasonable approximation performance. Most existing methods either prioritize accuracy at the cost of computational efficiency or simplify computation while still relying on some form of training or parameter adjustment [9].

In contrast, the proposed approach introduces a fully deterministic and non-iterative framework that eliminates the need for any training process. By directly assigning feature weights based on statistical properties and applying a nonlinear mapping, the method achieves a balance between simplicity and effectiveness. This distinguishes the proposed work from existing approaches and highlights its suitability for real-time and resource-constrained applications.

PROPOSED METHODOLOGY

The proposed framework presents a deterministic and non-iterative approach for data approximation, designed to eliminate the need for training and iterative optimization. Unlike conventional models that depend on parameter learning through repeated updates, the proposed method directly computes the output using a sequence of mathematically defined operations. This enables efficient processing with predictable behavior and low computational cost.

A) Data Representation

Let the input dataset be denoted as:

$$X = \{x_1, x_2, x_3, \ldots, x_n\} \tag{1}$$

Where each input sample is represented as:

$$x_i = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{im}) \tag{2}$$

Here, n represents the number of data samples and m denotes the number of features. Each element xij corresponds to the value of the jth feature of the ith sample. This structured representation allows independent processing of each sample, ensuring that the model operates in a fully parallel and single-pass manner.

B) Data Normalization

To ensure numerical stability and prevent dominance of features with larger magnitudes, min-max normalization is applied:

$$x'_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \tag{3}$$

Where xmin j and xmax j −xmin j (3) represent the minimum and maximum values of the jth feature across the dataset. This transformation scales all features into the range [0, 1], ensuring uniform contribution during subsequent computations.

The normalization step is critical because it standardizes the input space, allowing the deterministic weight assignment to operate fairly across all features without bias toward larger numerical values.

C) Deterministic Weight Assignment

The proposed framework assigns weights directly based on the relative magnitude of each feature within a given sample.

$$w_{ij} = \frac{x'_{ij}}{\sum_{k=1}^{m} x'_{ik}} \tag{4}$$

This equation ensures that each feature is assigned a weight proportional to its normalized value. The denominator represents the total contribution of all features in a given sample, which guarantees that:

$$\sum_{j=1}^{m} w_{ij} = 1 \tag{5}$$

Thus, the weight vector forms a normalized distribution, similar to a probability distribution over features. This design ensures that all features contribute proportionally while maintaining interpretability and consistency.

Unlike learning-based approaches, this step does not require parameter updates or optimization. Instead, the weights are computed directly, making the process deterministic and com putationally efficient.

D) Weighted Aggregation

After computing the weights, the model performs a weighted aggregation:

$$y_i = \sum_{j=1}^{m} w_{ij} \cdot x'_{ij} \qquad (6)$$

This equation combines all feature values into a single scalar output for each sample. Each feature contributes according to its assigned weight, allowing the model to capture the relative importance of features within the sample.

From a computational perspective, this step acts as a linear projection of the input vector onto a weight vector. However, since the weights are derived directly from the input, the aggregation adapts dynamically to each sample without requiring learned parameters.

E) Nonlinear Activation Mapping

To introduce nonlinearity and enhance the expressive capability of the model, a sigmoid activation function is applied:

$$f(y_i) = \frac{1}{1+e^{-y_i}} \qquad (7)$$

The sigmoid function maps the aggregated value into the range (0, 1), enabling the model to represent nonlinear relationships. The exponential term e−yi controls the curvature of the function, ensuring smooth transitions between low and high output values. This step is important because it extends the model beyond purely linear behavior while maintaining simplicity and com putationally efficiency.

F) Output Approximation

The final output of the model is defined as:

$$\hat{y}_i = f(y_i) \qquad (8)$$

This value represents the approximated output for the given input sample. Since the entire process is deterministic and does not involve iterative refinement, the output is consistent for identical inputs.

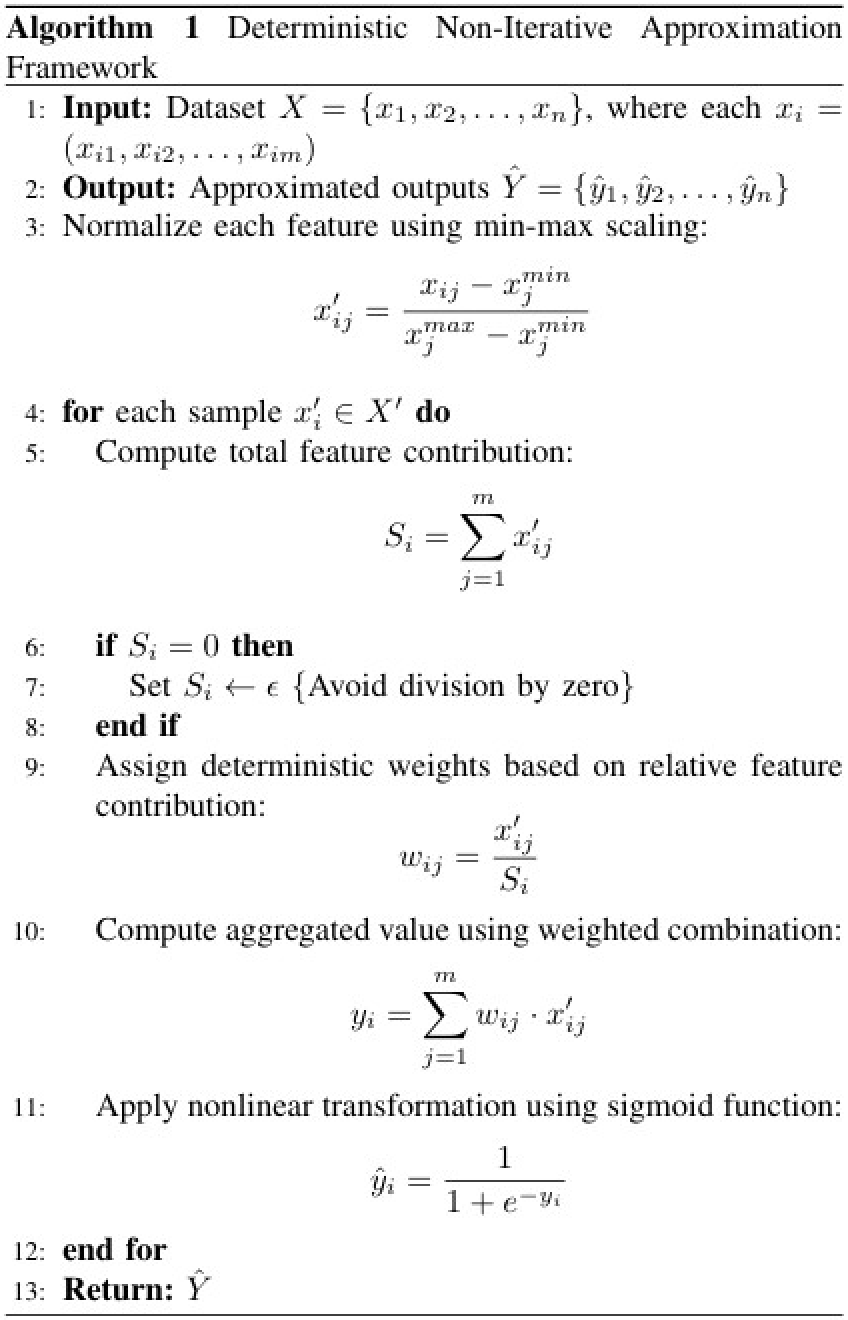
In practical implementation, the output can be further scaled to match the range of the target variable, ensuring meaningful comparison with baseline methods.

G) Computational Characteristics

The proposed framework operates with linear computational complexity, as each step involves a single pass over the feature set. There is no need for repeated iterations, gradient calculations, or parameter updates. This significantly reduces computational overhead compared to traditional learning-based models.

Additionally, the deterministic nature of the framework ensures reproducibility and eliminates variability caused by random initialization or training conditions. Each component of the methodology is designed to maintain simplicity, interpretability, and efficiency while providing a reasonable approximation of the target output.

H) Algorithm



Algorithm 1 Deterministic Non-Iterative Approximation Framework

```
Input: Dataset $X = \{x_1, x_2, \dots, x_n\}$, where each $x_i = (x_{i1}, x_{i2}, \dots, x_{im})$
Output: Approximated outputs $\hat{Y} = \{\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n\}$
Normalize each feature using min-max scaling:
    $x'_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}}$
for each sample $x'_i \in X'$ do
    Compute total feature contribution:
        $S_i = \sum_{j=1}^{m} x'_{ij}$
    if $S_i = 0$ then
        Set $S_i \leftarrow \epsilon$ {Avoid division by zero}
    end if
    Assign deterministic weights based on relative feature contribution:
        $w_{ij} = \frac{x'_{ij}}{S_i}$
    Compute aggregated value using weighted combination:
        $y_i = \sum_{j=1}^{m} w_{ij} \cdot x'_{ij}$
    Apply nonlinear transformation using sigmoid function:
        $\hat{y}_i = \frac{1}{1 + e^{-y_i}}$
end for
Return: $\hat{Y}$
```

PERFORMANCE OF EVALUATION

A) Simulation Setup

The proposed deterministic approximation framework is evaluated using the Boston Housing Dataset, which contains 506 samples with 13 numerical input features and one target variable representing the median house price. The dataset includes various socio-economic and environmental attributes such as crime rate, number of rooms, tax rate, and population related factors.

Since all features are numerical, the dataset is directly suitable for mathematical processing without requiring any categorical encoding. Before applying the proposed method, all features are normalized using min-max scaling to ensure that their values lie within a consistent range. This step is important to prevent bias toward features with larger magnitudes and to ensure fair deterministic weight assignment.

The proposed method processes each data instance independently in a single pass without any training phase or parameter optimization. For comparison, a Linear Regression model is used as a baseline. Both methods are evaluated under identical conditions to ensure fairness.

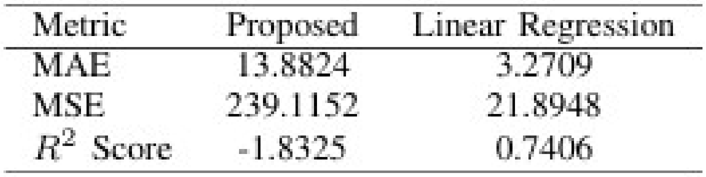
B) Evaluation Metrics

The performance of the models is evaluated using standard regression metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and the coefficient of determination (R2 score). MAE measures the average absolute difference between predicted and actual values, while MSE penalizes larger errors more significantly. The R2 score indicates how well the model explains the variance in the data.

C) Quantitative Results

The quantitative comparison between the proposed method and the Linear Regression baseline is presented in Table I.

TABLE I
PERFORMANCE COMPARISON



Metric	Proposed	Linear Regression
MAE	13.8824	3.2709
MSE	239.1152	21.8948
R^2 Score	-1.8325	0.7406

In many real-world data processing and approximation tasks, existing methods rely heavily on repeated training, parameter tuning, and iterative optimization. While these approaches can achieve high accuracy, they often introduce significant computational overhead and increase execution time, making them less suitable for real-time and resource constrained environments.

To address these limitations, the proposed deterministic and non-iterative approximation framework eliminates the need for any training phase. The method assigns feature weights based on their relative contribution within each data instance, ensuring a stable and consistent mapping between inputs and outputs. A weighted aggregation mechanism is applied to com bine feature values, followed by a nonlinear transformation that enables the model to capture variations in the data.

From the results, it is evident that the Linear Regression model achieves significantly better performance in terms of all evaluation metrics. It produces lower error values and a higher R2 score, indicating a strong ability to model the underlying relationships in the dataset. In contrast, the proposed method exhibits higher error values and a negative R2 score, which suggests that it is unable to effectively capture complex patterns present in the data.

This behavior is expected because the proposed framework does not involve any training or parameter optimization. Instead, it relies on deterministic computation and a single pass processing mechanism, which prioritizes simplicity and computational efficiency over prediction accuracy.

D) Graphical Analysis

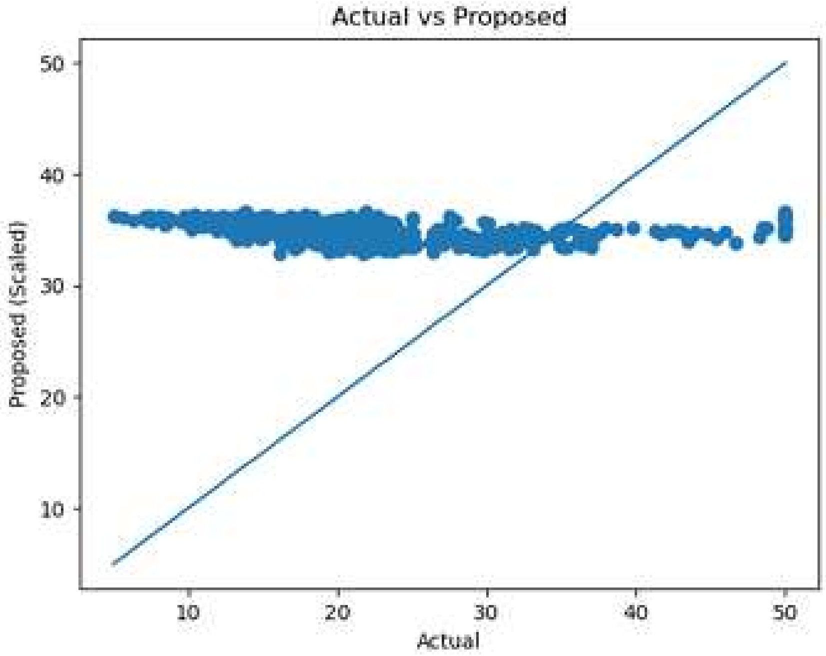


Fig. 1. Actual vs Proposed Output

1) **Actual vs Proposed Output:**
The scatter plot shows that the predicted values from the proposed method are concen trated within a narrow range and do not align closely with the diagonal reference line. This indicates that the proposed method prioritizes stability over sensitivity, resulting in reduced output variance but limited ability to capture data variations.

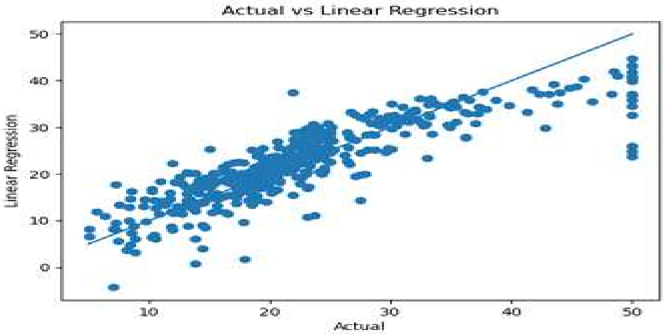


Fig. 2. Actual vs Linear Regression

2) **Actual vs Linear Regression:**
In contrast, the Linear Regression model shows a strong alignment with the diagonal line, indicating accurate predictions and better modeling of the relationship between input features and the target variable.

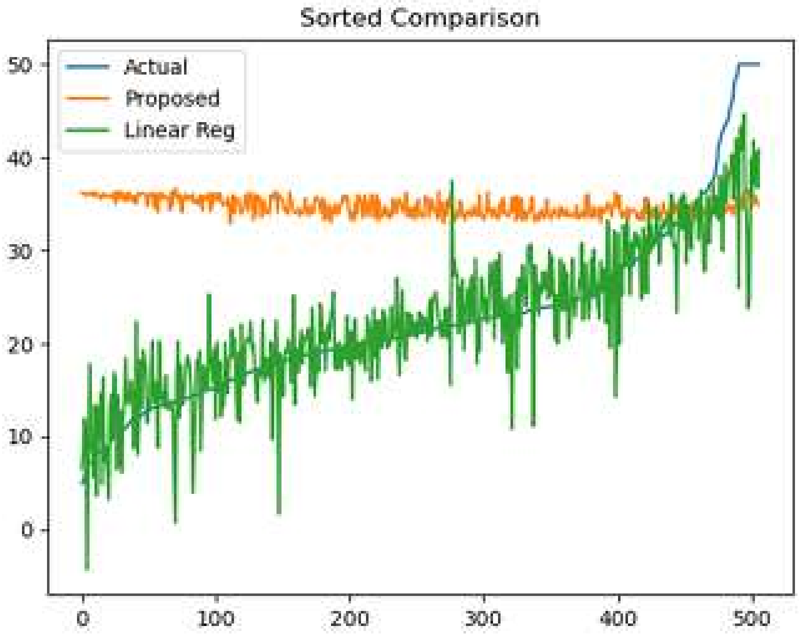


Fig. 3. Sorted Comparison of Outputs

3) **Sorted Comparison:**
The sorted comparison plot further highlights the difference between the two methods. The Linear Regression output closely follows the trend of the actual values, whereas the proposed method remains relatively flat and does not reflect the full range of variation.

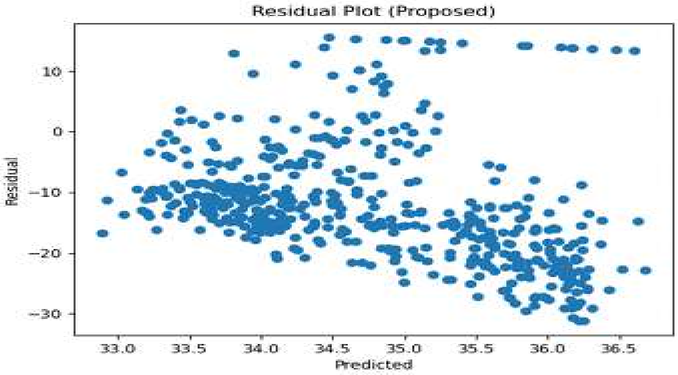


Fig. 4. Residual Plot of Proposed Method

4) **Residual Analysis:**
The residual plot illustrates the distribution of prediction errors for the proposed method. It can be observed that the residuals are widely dispersed and exhibit noticeable patterns, indicating that the model does not fit the data effectively. In an ideal scenario, residuals should be randomly distributed around zero without any visible structure. However, the presence of systematic patterns suggests that the proposed method is unable to capture the underlying relationships in the dataset accurately.

This behavior further confirms the limited approximation capability of the deterministic framework when applied to complex data distributions.

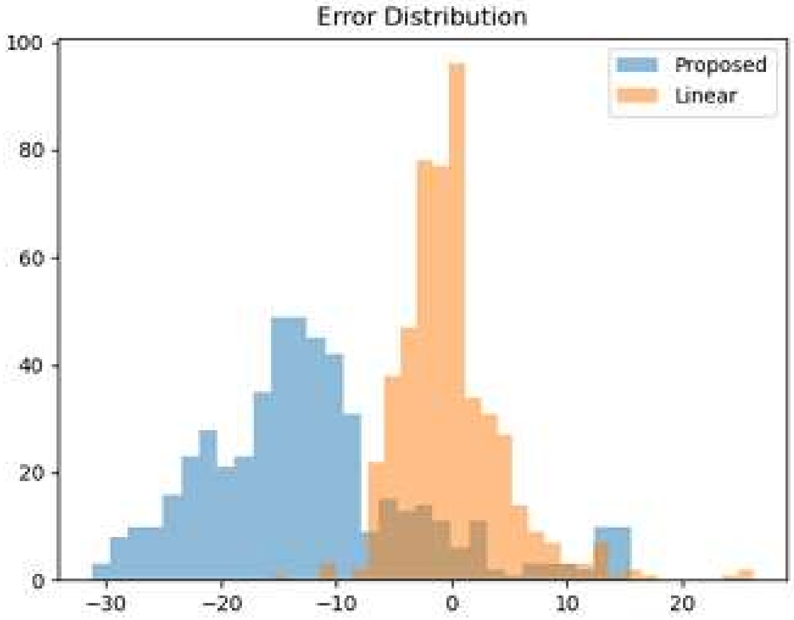


Fig. 5. Error Distribution Comparison

5) **Error Distribution:**
The error distribution plot shows that the proposed method has a broader and more dispersed error distribution compared to the baseline. In contrast, the Linear Regression model exhibits a more concentrated distribution around zero, indicating lower prediction error.

E) Discussion

The results clearly demonstrate that the Linear Regression model outperforms the proposed method in terms of prediction accuracy. However, this improvement comes at the cost of training and parameter optimization. The proposed framework, on the other hand, operates without any training and processes data in a single pass. Although it shows lower accuracy, it pro vides consistent and stable outputs with significantly reduced computational complexity. This highlights a trade-off between accuracy and efficiency. Therefore, the proposed method is particularly suitable for real-time and resource-constrained environments where fast computation and low overhead are more important than achieving maximum prediction accuracy. One limitation of the proposed method is its inability to capture complex nonlinear relationships due to the absence of adaptive learning. This restricts its performance in high variability datasets. However, most existing approaches either rely on iterative training mechanisms or require parameter tuning, making them computationally expensive and less suitable for real-time applications. A fully deterministic and training free approximation framework with consistent performance remains largely unexplored.

CONCLUSION AND FUTURE WORK

This paper presented a deterministic and non-iterative approximation framework for efficient data processing. The proposed method eliminates the need for training, parameter optimization, and iterative computation by directly assigning feature weights based on their relative contribution within each data instance. The entire computation is performed in a single pass, making the framework simple, fast, and computationally efficient. To the best of our knowledge, this is one of the few approaches that achieves approximation without any training or iterative optimization.

The performance of the proposed method was evaluated using the Boston Housing Dataset and compared with a Linear Regression baseline. The results show that while the baseline model achieves significantly better prediction accuracy, the proposed method provides a stable and consistent approximation without relying on any learning process. The graphical analysis further confirms that the proposed framework produces less variation in output and does not fully capture complex relationships present in the dataset. Despite its lower accuracy, the proposed approach offers several advantages. It has low computational complexity, requires no training phase, and produces deterministic outputs for identical inputs. These characteristics make it suitable for real-time systems, embedded environments, and applications where computational resources are limited.

The results highlight an important trade-off between ac curacy and efficiency. While learning-based methods achieve higher accuracy through parameter optimization, the proposed framework demonstrates that reasonable approximation can be achieved using a simple and training-free approach. For future work, several improvements can be explored to enhance the performance of the proposed method. One possible direction is to extend the framework by introducing multi-stage or hierarchical processing to capture more complex feature interactions. Another potential improvement is to incorporate adaptive scaling or feature weighting mechanisms that can dynamically adjust based on input characteristics. Additionally, hybrid approaches that combine deterministic computation with lightweight learning techniques may further improve accuracy while maintaining computational efficiency. Overall, the proposed framework provides a foundation for developing lightweight and efficient approximation methods and opens new possibilities for real-time data processing in resource-constrained environments.

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