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A Physics-Informed Neural Network Approach for Traffic Flow Prediction Using Burgers' Equation

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Abstract:

Traffic congestion in urban environments poses a significant challenge due to increasing vehicle density and complex traffic dynamics. Traditional traffic prediction models, including statistical and deep learning approaches, often fail to capture nonlinear traffic behavior and require large volumes of data.

This paper proposes a Physics-Informed Neural Network (PINN) approach for traffic flow prediction based on the one-dimensional viscous Burgers' Equation. The proposed model integrates deep learning with physical laws by embedding the governing partial differential equation into the loss function, ensuring both accuracy and physical consistency.

The model is trained using a hybrid strategy that combines sparse data with physics-based collocation points. A composite loss function incorporating data loss, physics loss, and boundary constraints is optimized using Adam and L-BFGS optimizers.

Experimental results demonstrate that the model achieves high prediction accuracy with a relative L2 error of approximately 0.42%, while requiring significantly less training data compared to conventional approaches. The model effectively captures nonlinear traffic phenomena such as shock waves and shows strong generalization capability.

The proposed approach highlights the potential of integrating physics-based modeling with deep learning for efficient and reliable traffic prediction in intelligent transportation systems.

Keywords — **Traffic Flow Prediction, Physics-Informed Neural Networks, Burgers' Equation, Deep Learning, Intelligent Transportation Systems**

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I. INTRODUCTION

Traffic congestion has become a critical issue in modern urban environments due to rapid urbanization and the increasing number of vehicles. It leads to increased travel time, fuel consumption, and environmental pollution, making efficient traffic management an essential requirement for intelligent transportation systems (ITS).

Accurate traffic flow prediction plays a vital role in improving traffic control, congestion management, and route optimization. Traditional statistical models such as ARIMA rely on linear assumptions and fail to capture the nonlinear and dynamic nature of traffic flow. Machine learning and deep learning approaches, including Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) networks, have improved prediction performance but require large volumes of data and often lack interpretability.

On the other hand, physics-based models describe traffic flow using mathematical equations derived from conservation laws. Models such as the Burgers' Equation can effectively capture nonlinear phenomena like shock waves in traffic flow. However, these models are difficult to apply directly to real-world data due to noise and variability.

To address these limitations, this paper proposes a Physics-Informed Neural Network (PINN) approach for traffic flow prediction. The proposed method integrates deep learning with physical laws by embedding the governing Burgers' Equation into the loss function. This hybrid approach enables the model to learn from both data and physics, resulting in improved accuracy, better generalization, and reduced dependency on large datasets.

II. LITERATURE RREVIEW

Traffic flow prediction has been widely studied using various approaches in intelligent transportation systems. Early methods relied on statistical models such as Auto-Regressive Integrated Moving Average (ARIMA), which assume linear relationships and fail to capture complex nonlinear traffic behaviour.

Machine learning techniques, including Support Vector Machines (SVM) and Random Forests, improved prediction accuracy by learning patterns from historical data. Deep learning models such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks further enhanced performance by capturing temporal dependencies in traffic data. However, these models require large datasets and often act as black-box systems, lacking interpretability.

Physics-based traffic models describe traffic flow using mathematical equations derived from physical principles. The Burgers' Equation is commonly used to model nonlinear traffic phenomena such as shock waves. While these models provide strong theoretical foundations, they lack flexibility when applied to real-world noisy data.

Recently, Physics-Informed Neural Networks (PINNs) have emerged as a promising approach that integrates deep learning with physical laws. By embedding governing equations into the loss function, PINNs enable learning from both data and physics, improving accuracy and generalization. This work builds upon this concept and applies PINNs for efficient traffic flow prediction.

III. METHODOLOGY

The proposed system utilizes a Physics-Informed Neural Network (PINN) to model traffic flow as a function of space and time. The objective is to learn the traffic velocity distribution by integrating both observational data and physical laws.

A fully connected feedforward neural network is used, where the inputs to the model are spatial coordinate (x) and time (t), and the output is the traffic velocity u(x,t). The network consists of multiple hidden layers with nonlinear activation functions, enabling it to approximate complex spatio-temporal relationships.

The governing physical model is based on the one-dimensional viscous Burgers' Equation, which describes nonlinear traffic flow dynamics. Instead of solving the equation directly, the model incorporates it into the training process by minimizing the residual of the differential equation.

A composite loss function is defined to train the network effectively. It consists of data loss, which measures the difference between predicted and actual values, and physics loss, which enforces the governing equation. Additionally, boundary and initial condition losses are included to ensure that the solution satisfies physical constraints.

The training process uses a hybrid optimization strategy. Initially, the Adam optimizer is used for faster convergence, followed by the L-BFGS optimizer for fine-tuning and improving accuracy. This combination ensures stable training and better convergence of the model.

$$\frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} = \nu \frac{\partial^2 u}{\partial x^2}$$

IV. RESULTS AND DISCUSSIONS

The proposed Physics-Informed Neural Network (PINN) model was evaluated using traffic flow data generated based on the Burgers' Equation. The objective was to analyze the model's ability to accurately capture nonlinear traffic dynamics and generalize across spatio-temporal domains.

During training, the model exhibited stable convergence, with the total loss decreasing significantly over iterations. The combination of data loss and physics loss ensured that the model learned both observed patterns and underlying physical behavior.

The predicted traffic flow results closely match the reference solution, demonstrating high accuracy. The model effectively captures nonlinear phenomena such as shock waves and smooth transitions in traffic density, which are essential characteristics of real-world traffic systems.

Visualization of the results using contour plots and surface plots shows strong agreement between predicted and actual values across both space and time. These visualizations confirm the model's capability to represent complex traffic patterns.

The model achieves a relative L2 error of approximately 0.42%, indicating high prediction accuracy. Compared to traditional machine learning and deep learning approaches, the proposed method requires significantly less training data while maintaining strong performance.

Overall, the results demonstrate that integrating physical laws into neural networks improves prediction accuracy, generalization, and reliability in traffic flow modeling.

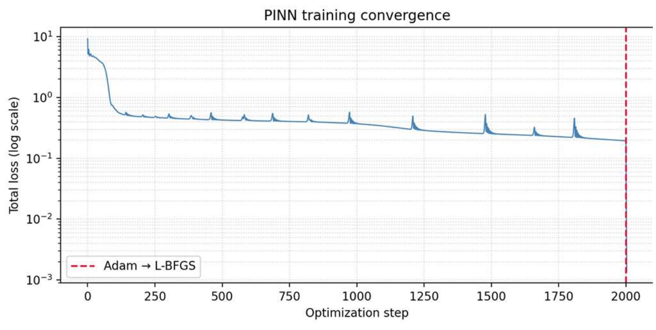

Fig. 1 Training Loss Convergence of the PINN Model

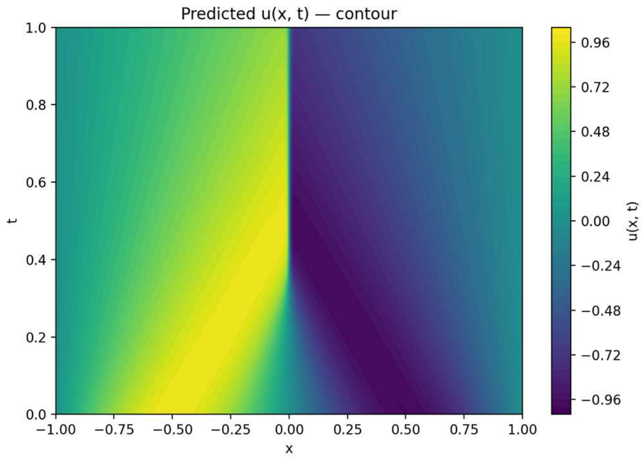

Fig. 2 Contour Plot of Predicted Traffic Flow over Space and Time

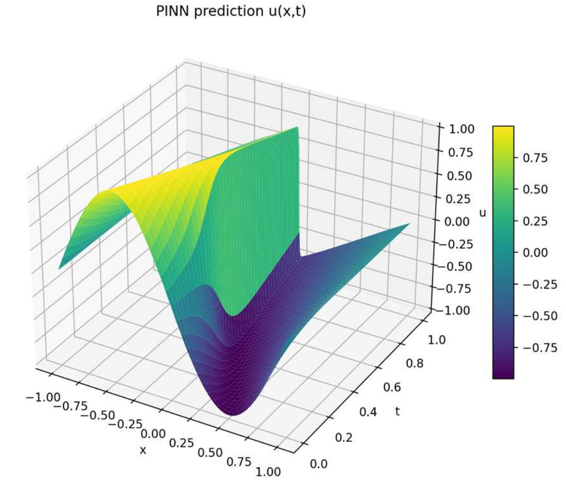

Fig. 3 Surface Visualization of Traffic Velocity Predicted by the PINN Model

CONCLUSION

This paper presented a Physics-Informed Neural Network (PINN) approach for traffic flow prediction using the Burgers' Equation. The proposed method integrates deep learning with physical laws, enabling accurate modeling of nonlinear traffic dynamics while maintaining physical consistency.

The model demonstrated high prediction accuracy with a relative L2 error of approximately 0.42% and required significantly less training data compared to traditional approaches. It effectively captured important traffic phenomena such as shock waves and smooth transitions.

The results highlight the potential of combining data-driven methods with physics-based modeling for intelligent transportation systems. Future work can focus on extending the model to real-world traffic datasets, multi-lane traffic scenarios, and real-time prediction systems.

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