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MSI-Multi-Step Interaction Networks for Spatial-Temporal Forecasting

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Abstract:
Spatial-temporal (ST) forecasting is a critical but inherently challenging task in real-world applications such as traffic prediction and urban monitoring[1]. Existing models often struggle to capture complex, long-range dependencies that vary across different locations and time steps[2]. This paper introduces **MSDR: Multi-Step Dependency Relation Networks**, a novel framework designed to address these challenges. MSDR explicitly utilizes hidden states from multiple previous time steps, employing a "dependency relation operation" within a GMSDR (Graph Multi-Step Dependency Relation) block to learn high-quality representations[3]. This block is integrated into an Encoder-Decoder architecture [4]and uses graph convolutions and attention mechanisms to model both spatial and temporal dependencies[5]. We evaluated our model on four public benchmark datasets (NYC Citi Bike, NYC Taxi, PEMS03, and PEMS08). The experimental results demonstrate that GMSDR achieves state-of-the-art performance, consistently outperforming established baselines like DCRNN, STGCN, and GraphWaveNet on all key metrics (RMSE, MAE, and MAPE%)[6666].

1. INTRODUCTION

Spatial-temporal (ST) forecasting has become a cornerstone problem for many real-world applications, including climate forecasting, urban monitoring systems, and, most notably, traffic prediction[7]. Within Intelligent Transportation Systems (ITS), the ability to accurately forecast traffic conditions is essential for improving service quality and operational performance[8].

However, this task is inherently challenging[9]. Traffic data, for example, exhibits complex, non-linear dependencies in both space (the road network) and time (traffic flow over hours or days). Capturing these intricate relationships is the primary hurdle for developing accurate forecasting models.

This paper proposes MSDR, a novel framework that explicitly models **Multi-Step Dependency Relations**. Our approach is motivated by the observation that the current state at one location depends not just on its immediately preceding state but on multiple previous hidden states [10], and that these dependencies vary significantly across different locations[11]. Our model is designed to capture these long-range dependencies to produce more accurate forecasts.

2. PROBLEM DEFINITION

The objective of spatial-temporal forecasting is to predict the signals (e.g., traffic speed, flow, or demand) for the upcoming several time steps, given observations from several historical time steps across a defined traffic network[12].

3. MOTIVATION

The design of MSDR is motivated by three key observations of spatial-temporal data:

1. The temporal representation of a current input (e.g., traffic at time t) is dependent on **multiple previous hidden states**, not just the state at $t-1$[13].
2. The nature of these temporal dependencies **varies greatly at different locations**[14].

3. Despite location variance, **similar patterns of dependencies** can be observed at the *same* location but at *different* time steps (e.g., morning and evening rush hours)[15].

Existing models often fail to capture this complex interplay. Our work is motivated by the need for a model that can explicitly learn these varied, long-range dependencies.

4. METHODOLOGY AND FRAMEWORK

The proposed Multi-Step Dependency Relation (MSDR) framework is built upon two core concepts illustrated in the methodology: the "Computation Process of Temporal Explicit Dependency" and the "Selection Process of Explicit Spatial Dependency"[16]. These concepts are integrated into a complete **GMSDR (Graph Multi-Step Dependency Relation)** block, which forms the basis of a larger Encoder-Decoder architecture[17].

4.1. Core Components

The GMSDR block's operations, as defined by the framework diagram and legend, include[18]:

- **Fully Connected Layer (FC):** For linear transformations of features.
- **Attention (Att):** To weigh the importance of different temporal states and spatial locations.
- **Graph Convolution:** To aggregate information from a node's neighbors, capturing spatial relationships.
- **Leaky Relu:** A non-linear activation function.
- **Add & Concatenate:** Operations to merge features from different paths.

4.2. Modeling Dependencies

Temporal Dependency: The model explicitly captures long-range temporal dependencies. As shown in the "Computation Process" diagram, hidden states from multiple previous time steps (e.g., h_{t-v}, h_{t-1}) are combined[19]. This aggregated temporal information is passed through an Attention mechanism[20]. This allows the model to learn which specific historical steps are most relevant to the current prediction, overcoming a key limitation of standard RNNs.

Spatial Dependency: The framework models spatial dependencies using graph convolutions and an explicit spatial dependency selection process[21]. This allows the model to understand the traffic network structure and how conditions at one location affect others.

4.3. GMSDR Framework

The GMSDR block combines these elements. It takes multiple historical hidden states as input, processes them through graph convolution and attention layers, and outputs a new, refined hidden state[22]. This GMSDR block is then used as the repeating unit within a sequence-to-sequence (Seq2Seq) Encoder-Decoder structure to process entire time series and generate multi-step forecasts[23].

5. EXPERIMENTAL SETUP

To validate the performance of the proposed GMSDR model, a series of comprehensive experiments were conducted, following the structure outlined in the agenda[24].

5.1. Datasets

The model was evaluated on four real-world public benchmark datasets[25252525252525]:

1. **NYC Citi Bike**
2. **NYC Taxi**
3. **PEMS03**
4. **PEMS08**

5.2. Evaluation Metrics

The performance was measured using standard regression metrics.

- For **NYC Citi Bike** and **NYC Taxi** datasets, the metrics were **RMSE** (Root Mean Square Error), **MAE** (Mean Absolute Error), and **PCC** (Pearson Correlation Coefficient)[2626].
- For **PEMS03** and **PEMS08** datasets, the metrics were **MAE**, **MAPE(%)** (Mean Absolute Percentage Error), and **RMSE**[2727].

5.3. Baseline Models

The GMSDR model was compared against a wide array of baseline methods, including[28282828]:

- **Statistical:** HA (Historical Average).
- **Classic RNN:** FC-LSTM.
- **Spatio-Temporal Graph Networks:** DCRNN, STGCN, STG2Seq, GraphWaveNet, CCRNN, ASTGCN(r), STSGCN, and STFGNN.

5.4. Experimental Design

The evaluation consisted of four distinct experiments[29]:

- **Experiment I: Main Results**: A direct quantitative comparison of GMSDR against all baseline models on traffic demand prediction and traffic flow prediction[30303030].
- **Experiment II: Parameter Analysis**: An analysis of the model's sensitivity to the hyperparameter K, measuring the "Value of K" against "RMSE" on all four datasets[31].
- **Experiment III: Ablation Study**: A study to validate the contribution of the model's components by comparing the full "E-Spatial" model against two simpler variants: "D-Spatial" and "Simple"[32].
- **Experiment IV: Case Study**: A qualitative analysis visualizing the model's prediction ("Our Model") against the "Ground Truth" and the "FC-LSTM" baseline in two scenarios: "Traffic Flow with Multiple peaks" and "Traffic Flow with Smooth Data" [33].

6. RESULTS AND DISCUSSION

6.1. Experiment I: Main Results

The GMSDR model demonstrated superior performance across all datasets.

- **Traffic Demand Prediction:** On the NYC Citi Bike and NYC Taxi datasets, GMSDR achieved the lowest RMSE (2.7218 and 8.6533, respectively) and MAE (1.6760 and 4.9831), and the highest PCC (0.8107 and 0.9711), outperforming all baselines including CCRNN and GraphWaveNet[3434].
- **Traffic Flow Prediction:** On the PEMS03 and PEMS08 datasets, GMSDR again achieved the best scores on all metrics, with an MAE of 15.78 (PEMS03) and 16.36 (PEMS08), and the lowest MAPE and RMSE, surpassing STFGNN and STSGCN[3535].

6.2. Experiment III: Ablation Study

The ablation study confirmed the importance of the model's design. The full model ("E-Spatial") consistently outperformed the simpler "D-Spatial" and "Simple" variants across all metrics on all four datasets[36]. For example, on PEMS08, the MAE for "E-Spatial" was 16.36, compared to 17.54 for "D-Spatial" and 18.33 for "Simple," validating the effectiveness of the explicit spatial dependency component[37].

6.3. Experiment IV: Case Study

The case study visualizations show the model's predictive accuracy.

- **Multiple Peaks:** In volatile traffic, our model's predictions closely tracked the ground truth, capturing the sharp peaks and valleys far better than the FC-LSTM model[38].
- **Smooth Data:** Even in less volatile conditions, our model's predictions provided a much tighter fit to the ground truth data, demonstrating its precision[39].

7. CONCLUSION

This paper introduced MSDR, a novel network for spatial-temporal forecasting. We have demonstrated that the MSDR model can **explicitly utilize hidden states from previous multiple time steps** and learn high-quality representations from them[40].

The proposed **dependency relation operation** proves highly effective at **capturing long-range dependencies** by modeling the interactions between historical hidden states and the current time step's input[41]. The comprehensive experimental results on four public benchmarks validate that our GMSDR model achieves new state-of-the-art performance, outperforming previous methods in accuracy and robustness[42424242].

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