Physics Informed Temporal Multimodal Multivariate Learning for Short-Term Traffic State Prediction

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Introduction Heterogeneous nature of traffic makes it difficult to accurately predict the short-term traffic states. The adverse impact of unstable traffic prediction influences the quality of life, economic output, and social trust of information. To overcome these challenges, recent studies have addressed spatiotemporal correlations, however, limited only to neighbouring correlations not far distant non-contiguous locations. As another important statistical perspective, travel time distributions have shown *two or more modes as distinct peaks* in the probability distribution function due to the mixes of driving patterns and vehicle types (Guo, Rakha, and Park 2010). However, travel state bimodality has not been considered in traffic state prediction.

Temporal Multimodal Multivariate Learning (TMML) by (Park et al. 2022) addressed the above limitations by indirectly learning and transferring online information from multiple modes of probability distributions and multiple variables across different time stages. This paper advances TMML with two contributions: 1) extends data-driven part by incorporating physics knowledge to decouple spurious correlations, 2) relaxes Gaussian noise assumption by developing dynamic graphical deep learning that accomodates the bimodality.

Partial information gain from multimodal distribution and multivariate correlation has been left unaddressed, possibly due to the main focus of reinforcement learning (RL) on games and simple control problems with a lack of generalization to real-world problems. In a sequence of transfer learning, the RL does not utilize the covariance structure and ignore multimodal and multivariate gains in the reward function. Hybrid deep learning traffic studies extract spatiotemporal correlations (Zhang 2021), but static graph is unable to capture dynamic nature of traffic. Recent adaptive adjacency graphs (Kong et al. 2022) however does not consider multimodality. This study develops a novel Graph Convolutional method to efficiently accommodate evolving adjacency graph based on multimodal distributions.

Methodology The distinguishable aspect of the physics-informed and -regularized (PIR) model in the hierarchical update steps is the use of new information obtained from TMML (fig. 1). We first predict the chosen state variable at the next time interval $t+1$ using the measurement from the previous time interval t. In the update step, the predicted state is corrected using the noisy measurements at $t+1$. Clustering identifies similar travel time distributions. The global correlation between non-contiguous cells of an entire map are estimated by using Expectation Maximization. The optimal distribution of the data over K clusters are determined by maximizing the lower bound of the log of the likelihood. We decouple the spurious correlations first and then use the entropy method to estimate the mixture of multimodal and multivariate distributions. Since the mixture could be non-Gaussian and non-linear, providing an accurately estimated distribution rather than just mean and standard deviation will increase the accuracy of updating the error covariance matrix.
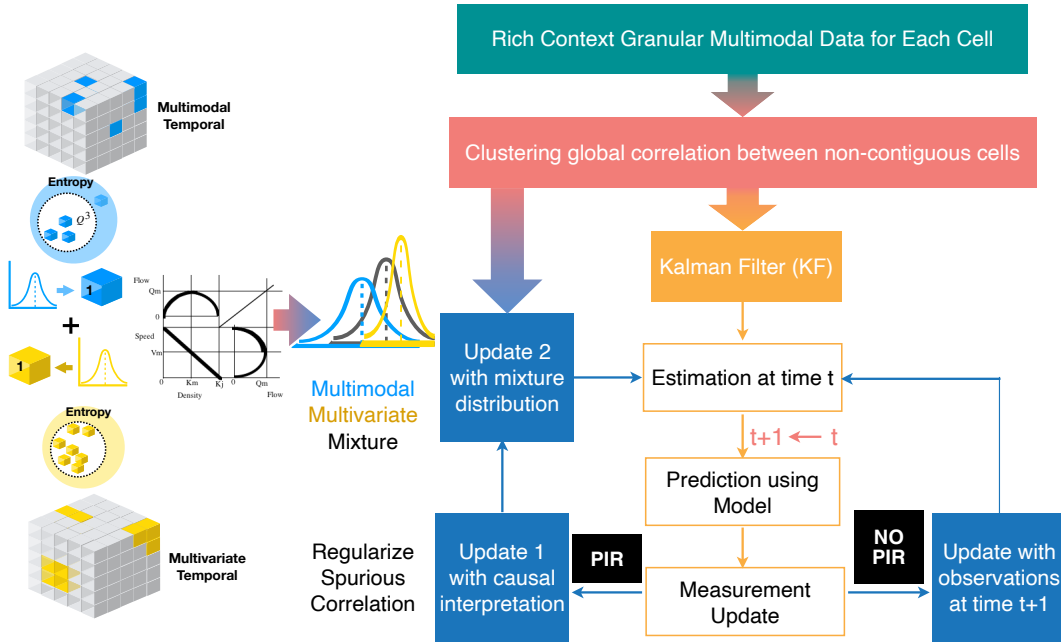

Figure 1   Physics-informed and -regularized (pir) KF in the hierarchical update steps

Prediction-Collection Step: We project the state at time t using the prediction at previous time $t-1$ as $\hat{x}_t^- = A\hat{x}_{t-1}^+ + B\mu_t$ and error covariance of state as $P_t^- = P_{t-1}^+ A^T + Q$. We determine the Kalman Gain at time t as $K_t = P_t^- H^T (H P_t^- H^T + R)^{-1}$ where H is the connection matrix between the state vector and the measurement vector and R & Q are Gaussian noise vectors. Z_t is the observations used to correct the predicted estimate. Observations considered for KF model with Physics Informed Regularization (PIR) is different than that for no-PIR. Z_t for KF-no PIR are the

speed observations on a given day while, in case of KF-PIR, Z_t are the observations drawn through two steps as described in fig. 1.

In the first update step of KF-PIR, if there are conflicting observations from multimodal and multivariate clusters at the same time and location, then the original cell distribution of observation is investigated. If spurious correlations are reckoned, then they are filtered using the coefficient of variation parameter given by $CV = \frac{\sigma}{\mu}$ to identify extent of variability with respect to the mean of distribution. Once the conflicting observations are resolved, in the second step, a mixture of multimodal and multivariate distributions is estimated using cross-entropy method. The relative entropy between the true distribution f and the mixture of multimodal and multivariate distributions g parameterized by θ is minimized using $\boldsymbol{\theta}_g^* = \underset{\boldsymbol{\theta}_g}{\arg\min} - \int_{\mathbf{x} \in \mathcal{X}} f^*(\mathbf{x}) \log g\left(\mathbf{x} \,|\, \boldsymbol{\theta}_g\right) d\mathbf{x}$. The cross-entropy-method uses a multi-level algorithm to estimate $\boldsymbol{\theta}_g^*$ iteratively. Specifically, the parameter $\boldsymbol{\theta}_k$ at iteration k is used to find new parameters $\boldsymbol{\theta}_{k'}$ at the next iteration k'.

The multivariate fundamental diagram will be further considered in the regularization step by the conference. Deep learning will be presented to overcome the limitations of Kalman Filtering (KF). Clustering on TMCs as explained previously is performed for each time interval t. We employed a more efficient method of evolving the adjacency matrix than (Li et al. 2021) which is capable to capture geographical adjacency as well as dynamic traffic flow. The dynamic adjacency graph used in Graph Convolutional Neural (GCN) network will assign weights according to semanticity in road traffic flow during time interval t. For example, similar weights will be assigned to two or more distant locations where the traffic patterns show similarity.
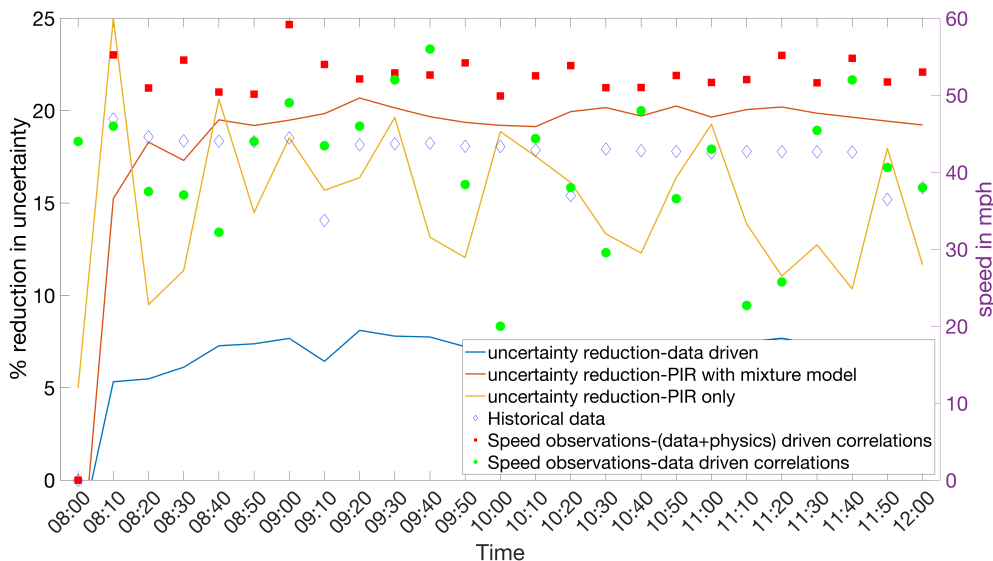
Results & Conclusion

Figure 2   **Percent change in uncertainty of KF prediction when PIR with mixture is considered.**

KF with both PIR and mixture model shows the superior performance with total uncertainty reduction of 19% compared to traditional-KF without any updates, while KF with only PIR reduce uncertainty by 14% and TMML (Park et al. (2022) data-driven model by 5% as shown in fig. 2. GCN with dynamic adjacency model is expected to further reduce uncertainty in prediction than highest performing KF model considering GCN do not restrict noise to be Gaussian unlike KF.

The route suggestion that users receive at the outset of their commute may not be optimal when they are on the road due to the uncertainty in travel time prediction. More reliable traffic predictions can be achieved by capturing unobserved heterogeneity by analyzing a mixture of multiple probability distributions. This study enhanced the author's data-driven model Park et al. (2022) by using physics of traffic flow to regularize factitious correlations improving the prediction accuracy significantly. Traditional deep learning models overlook the time-dependent spatial correlations which results in degradation of prediction performance. The new family of deep learning models enhanced with cross-entropy-based mixture estimation of multimodal distribution presents a superior performance in travel time prediction against the TMML-PIR model. The model developed in this study takes advantage of explored correlated link to reduce prediction uncertainty for unexplored one. This paper opens appealing research opportunities in the study of deep learning models based on information-theoretic decision making that exhibits nontrivial indirect learning from spatiotemporal correlation.

Acknowledgments

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