Related Work: OD Prediction

Red: Uncertainty
Blue: Flow Pattern Destination affects the Origin prediction
Orange: Supply Prediction
purple: Graph CN

FCCF: Forecasting Citywide Crowd Flows Based on Big Data (Yu Zheng, SIGSPATIAL 2016)

- Instead of predicting individual movements, investigate a macro-level view of crowd movements by predicting two types of flows of crowds: new-flow and end-flow
- Challenges:
    - Multiple complex factors: e.g., flows has daily and weekly periodic pattern as well as instantaneous changes due to weather and social events
    - Flow dependencies: (intra-region, inter-region)
    - City-scale prediction
- Decompose each type of flow in a region into three ingredients: seasonal, trend, and residual flows, proposing a three-step predictive method to capture each of them.
- To deal with data sparsity and construct a practical city-wide solution, we first divide a city into low-level regions using its road network, and then group adjacent low-level regions with similar crowd flow patterns using graph clustering. The obtained high-level regions have more stable (thus easier to predict) crowd flows, and also provide a meaningful and more manageable representation of the citywide crowd flows
- Based on the Intrinsic Gaussian Markov Random Field (IGMRF), we propose a seasonal model to predict the periodic flow, and a trend model to predict the change of the seasonal pattern over time.
- We propose a spatio-temporal residual model to predict the instantaneous deviations from the periodic patterns of flows, based on the historical flow data of a region and those of its neighbors as well as weather information. The model uses a Bayesian network to capture the transition probability among the regions.

Deep Spatio-Temporal Residual Networks for Citywide Crowd Flows Prediction (Yuzheng, AAAI 2017)

- a deep-learning-based approach, called ST-ResNet, to collectively forecast the in-flow and outflow of crowds in each and every region of a city.
- Challenges:
    - Spatial dependencies
    - Temporal dependencies
    - External influence: weather, events

Matrix Factorization for Spatio-Temporal Neural Networks with Applications to Urban Flow Prediction (Yu Zheng, CIKM, 2019)

- Motivation: Existing deep models have been focusing on capturing spatiotemporal correlations, but overlook **latent region functions**
- Challenges:
    - **Consider latent region function**
    - **Generalize to a variety of deep models**
- 1) a ST feature learner that is employed to capture features of ST correlations for all regions, which can be a sub-network in the existing deep models for capturing ST correlations; 2) a region-specific predictor, which leverages the learned ST features to make a region-specific flow prediction.

Online Spatio-temporal Crowd Flow Distribution Prediction for Complex Metro System (Yuzheng, TKDE, 2020) 未写入参考文献

- three spatiotemporal models to effectively address the network-wide CFD prediction problem (e.g., the model makes 39 a forecast that there are 272 passengers departure from Cenral station between 4:45 PM and 5:00 PM. Among them, 124 passengers will arrive at Bondi Junction, 88 at Redfern, and 42 60 at Stanmore, respectively.)
- Challenges & novelty:
    - Network-wide CFD prediction (only deep neural networks [5,13,14] can do this, but are sensitive to parameters and incomplete inputs)

    - High computation complexity (because too many OD pairs)
    - Dynamic complexity
    - Real-time delayed data collection (a large number of passengers still on their journeys, [5,14,17,18])
- Related work:
    - [3], [5], [18],[23],[14], [17],[24] [25]
    - The first category is the static estimation [31], [32] that focuses on estimating the average OD pairs 210 in a long-term time period, providing
    - The second category is the dynamic model that usually applies to taxi demand prediction and travel time estimation [30], [33]–[37]. (The major problem is real-time delayed data collection)
        - L. Liu, Z. Qiu, G. Li, Q.Wang,W. Ouyang, and L. Lin, "**Contextualized spatial-temporal network for taxi origin-destination demand prediction**," IEEE Transactions on Intelligent Transportation Systems, 2019.
        - M. L. Hazelton, "**Some comments on origin–destination matrix estimation**," Transportation Research Part A: Policy and Practice, vol. 37, no. 10, pp. 811–822, 2003
        - Y. Wang, Y. Zheng, and Y. Xue, "Travel time estimation of a path using sparse trajectories," in Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2014, pp. 25–34.
        - X. Zhou and H. S. Mahmassani, "**Dynamic origin-destination demand estimation using automatic vehicle identification data**," IEEE Transactions on intelligent transportation systems, vol. 7, no. 1, pp. 105–114, 2006.
        - J. Ren and Q. Xie, "**Efficient od trip matrix prediction based on tensor decomposition**," in 2017 18th IEEE International Conference on Mobile Data Management (MDM). IEEE, 2017, pp. 180–185.
        - K. Ashok and M. E. Ben-Akiva, "Estimation and prediction of time-dependent origin-destination flows with a stochastic mapping to path flows and link flows," Transportation science, vol. 36, no. 2, pp. 184–198, 2002.
        - Y. Wang, H. Yin, H. Chen, T. Wo, J. Xu, and K. Zheng, "**Origin-destination matrix prediction via graph convolution: a new**

perspective of passenger demand modeling,” in Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery &Data Mining. ACM, 2019, pp. 1227–1235.

Predicting Taxi-Passenger Demand using Streaming Data (TITS, 2013)

- Motivation
    - An equilibrium fault may lead to one of two scenarios: (Scenario 1) excess of vacant vehicles and excessive competition; (Scenario 2) larger waiting times for passengers and lower taxi reliability. However, a question remains open: Can we guarantee that the taxi spatial distribution over time will always meet the demand? Even when the number of running taxis already does?
    - Existing work: they do not provide any live information about passenger location or the best route to pick-up one in this specific date/time while the GPS data is mainly **a live data stream** (i.e. a time ordered sequence of instances produced in real-time)
- This paper focus on the real-time choice problem **about which is the best taxi stand to go to after a passenger drop-off** (i.e. the stand where we will pick-up another passenger quicker).
- we adapted well-known time series forecasting techniques such as the time varying Poisson model [15] and ARIMA (AutoRegressive Integrated Moving Average) [16]
- Related work: both passenger finding strategies and demand prediction using traditional prediction methods.

DeepSD: Supply-Demand Prediction for Online Car-hailing Services using Deep Neural Networks (ICDE 2017)

- The objective is to predict car-hailing supply and demand in a certain area in the next few minutes
    - Use res-net to incorporate the weather and traffic data
    - Use embedding method to improve prediction accuracy and for discover the similarities among the supply-demand patterns
    - Study the extendability of the model to incorporate new extra attributes

Forecasting short-term subway passenger flow under special events scenarios using multiscale radial basis function networks (TRC 2017) 不放入参考文献中

- Predicting irregular events, This approach does not require any prior information regarding the events and only relies on limited observational subway passenger flow data

Real-time Prediction of Taxi Demand Using Recurrent Neural Networks (TITS 2018)

- Basic idea:
  - For each area, train LSTM
  - Add Mixture Density Networks can help with output a mixture distribution of the demand

The Simpler The Better: A Unified Approach to Predicting Original Taxi Demands based on Large-Scale Online Platforms (KDD 2018)不放入参考文献中

- we leverage the latter paradigm, i.e., **a linear model with massive features, to ease integration of new information** with a unified framework
- Research question: whether a unified simple linear model is able to predict UOTD accurately
- Challenges and Novelty: the prediction model should have both flexibility and accuracy
- As a pilot study, we envision our successful experiences on adopting simple linear models with high-dimensional features can shed light upon other large-scale industrial spatio-temporal prediction problems.

Deep Multi-View Spatial-Temporal Network for Taxi Demand Prediction (AAAI 2018, Didi, Jieping Ye)

- Motivations:
  - Existing non-deep models fail to capture the complex non-linear spatial-temporal correlations
  - None of the existing deep models (LSTM, CNN) consider both spatial and temporal simulaneously

- What they propose:
    - Local CNN to capture the local correlation between the regions to their neighbors
    - Embedding a region graph to capture the correlation between latent semantics of regions.

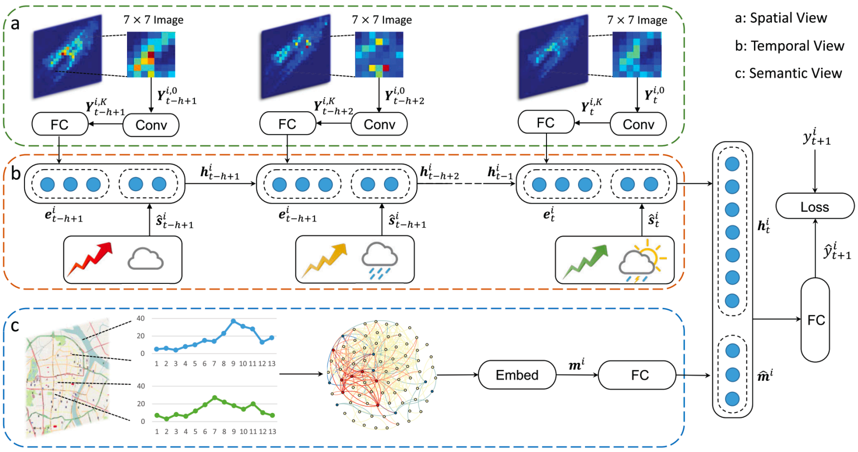

Figure 1: The Architecture of DMVST-Net. (a). The spatial component uses a local CNN to capture spatial dependency among nearby regions. The local CNN includes several convolutional layers. A fully connected layer is used at the end to get a low dimensional representation. (b). The temporal view employs a LSTM model, which takes the representations from the spatial view and concatenates them with context features at corresponding times. (c). The semantic view first constructs a weighted graph of regions (with weights representing functional similarity). Nodes are encoded into vectors. A fully connected layer is used at the end for jointly training. Finally, a fully connected neural network is used for prediction.

DeepUrbanMomentum: An Online Deep-Learning System for Short-Term Urban Mobility Prediction (AAAI 2018)未加入参考文献

- Motivation: short term is important because of some rate event such as disaster and earthquake, the mobility is not dependent on long-term patterns
- continuously take the recent momentary mobility as the input and predict next short-term urban human mobility as the output
- Data: A raw GPS log dataset was collected anonymously from approximately 1.6 million mobile phone users in Japan over a three-year period

Parallel Architecture of Convolutional Bi-Directional LSTM Neural Networks for Network-Wide Metro Ridership Prediction (TITS 2018)

- Consider both spatial (use CNN) and temporal features (use LSTM)
- Related Work:
    - Statistical models: GWR(geographically weighted regression), ARIMA

    - Computational intelligence: SVM, CNN, LSTM
- Comments: CNN here only considered nearby spatial relationship….that's why GCNN maybe better

Contextualized Spatial–Temporal Network for Taxi Origin-Destination Demand Prediction (TITS 2019)

- Motivation:
    - The main problem stems from the mismatch between supply and demand caused by inaccurate taxi demand prediction, which results in a large number of taxis gathering in some busy areas and causing oversupply, while in other remote areas the distribution of taxis was extremely sparse. The solution to this issue involves taxi demand prediction, which estimates the future taxi demand and helps to allocate the taxis to each region in advance.
    - we believe it is suboptimal to preallocate the taxi into each region-based **solely on the taxi origin demand**
- Challenges and novelty:
    - how to capture the diverse spatial-temporal contextual information to learn the demand patterns
    - local spatial context (**geo correlation**) + global correlation context (**semantic correlation**)
- Related Work: taxi demand prediction has attracted a wide range of research interest and achieved notable successes [6], [7], [12]–[14], [33, 23,7, 34, 11]
    - Y. Tong et al., "**The simpler the better: A unified approach to predicting original taxi demands based on large-scale online platforms**," in Proc. ACM SIGKDD, Aug. 2017, pp. 1653–1662.
    - H. Yao et al. (2018). "**Deep multi-view spatial-temporal network for taxi demand prediction**." [Online]. Available: https://arxiv.org/abs/1802. 08714
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    - X. Qian, S. V. Ukkusuri, C. Yang, and F. Yan, "**Forecasting short-term taxi demand using boosting-GCRF**," 2017.
    - J. Ke, H. Zheng, H. Yang, and X. M. Chen, "**Short-term forecasting of passenger demand under on-demand ride services: A spatio-temporal deep learning approach,**" J. Transp. Res. C, Emerg. Technol., vol. 85, pp.

591–608, Dec. 2017.

- D. Wang, W. Cao, J. Li, and J. Ye, “**DeepSD: Supply-demand prediction for online car-hailing services using deep neural networks**,” in Proc. ICDE, Apr. 2017, pp. 243–254.
- J. Xu, R. Rahmatizadeh, L. Bölöni, and D. Turgut, “**Real-time prediction of taxi demand using recurrent neural networks**,” IEEE Trans. Intell. Transp. Syst., vol. 19, no. 8, pp. 2572–2581, Aug. 2018.

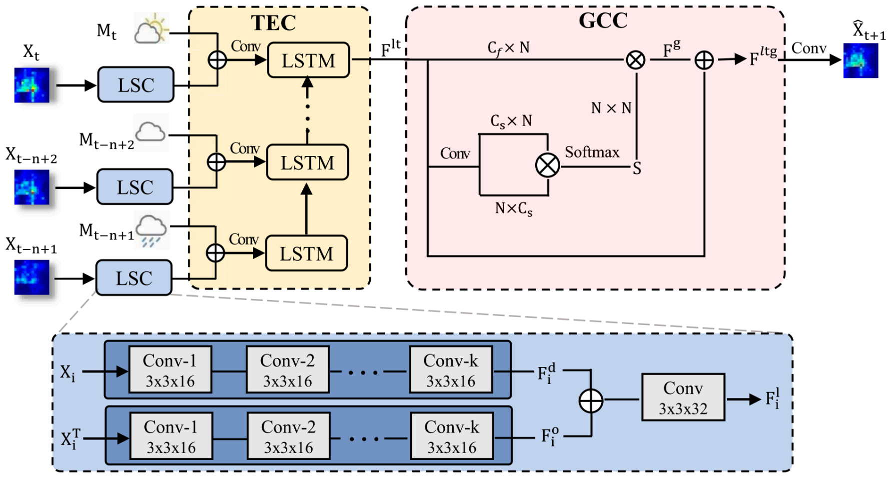
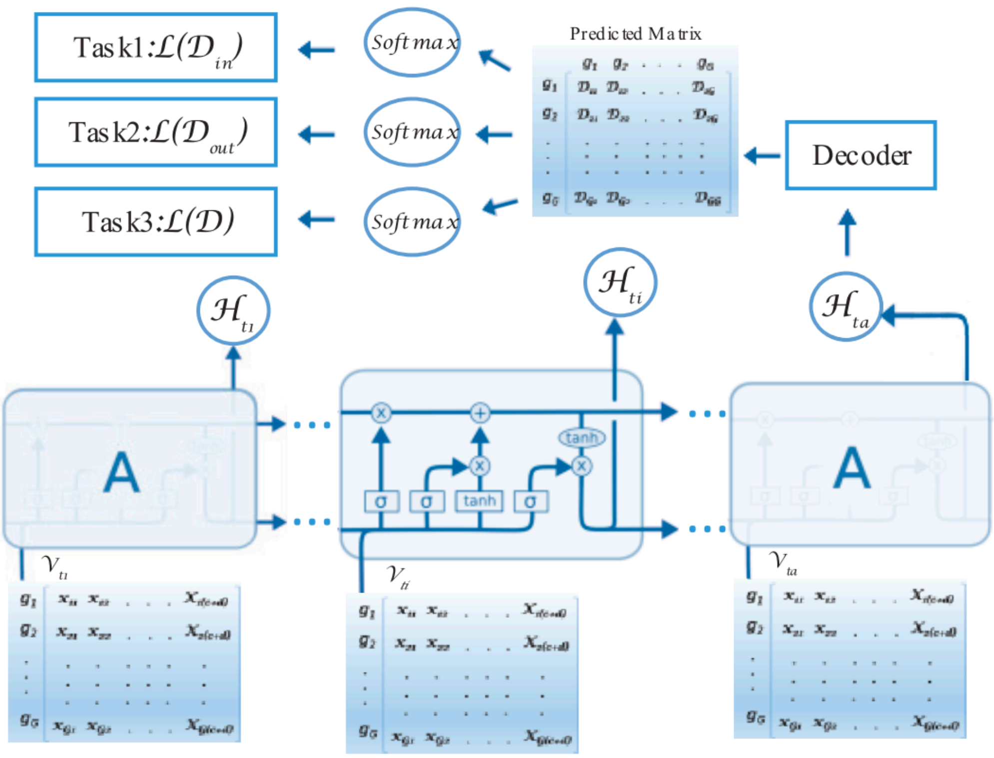


Fig. 3. The architecture of the proposed Contextualized Spatial-Temporal Network (CSTN) for taxi origin-destination demand prediction. X_i denotes the OD matrix in time interval i, while X_i^T is the DO matrix called in our work. M_i is the meteorological data. C_{lt} is the channel number of feature F^{lt} and C_s is the channel number of F_s. N is the total number of the regions. “$\oplus$” denotes feature concatenation and “$\otimes$” refers to the dot product operation. CSTN consists of three components for three types of context modeling respectively. The LSC module feeds X_i and X_i^T into a Two-View ConvNet to respectively learn the local spatial context from the origin view and destination view and then combines the output of the two ConvNet. The TEC module recurrently takes the local feature F_i^l generated by LSC and the meteorological data M_i to learn the temporal evolution context of the taxi demand with a ConvLSTM. The GCC module computes the similarity between all regions and generates the global correlation feature of each region by summing the features of all regions with the similarity weights.

Origin-Destination Matrix Prediction via Graph Convolution: a New Perspective of Passenger Demand Modeling (KDD 2019)

- Ride-hail application
- Challenges:
  - simultaneously consider (1) the quantity ofpassenger demands from a given region and (2) the final destinations of these demands.
  - Spatial and Temporal feature fusion
  - Data Sparsity (Method: GCNN, consider two kinds of neighbours in our grid embedding part and they are Geographical Neighbors and Semantic Neighbors based on whether two grids are geographically close or connected by passenger demands.)
- Multi-tasks:

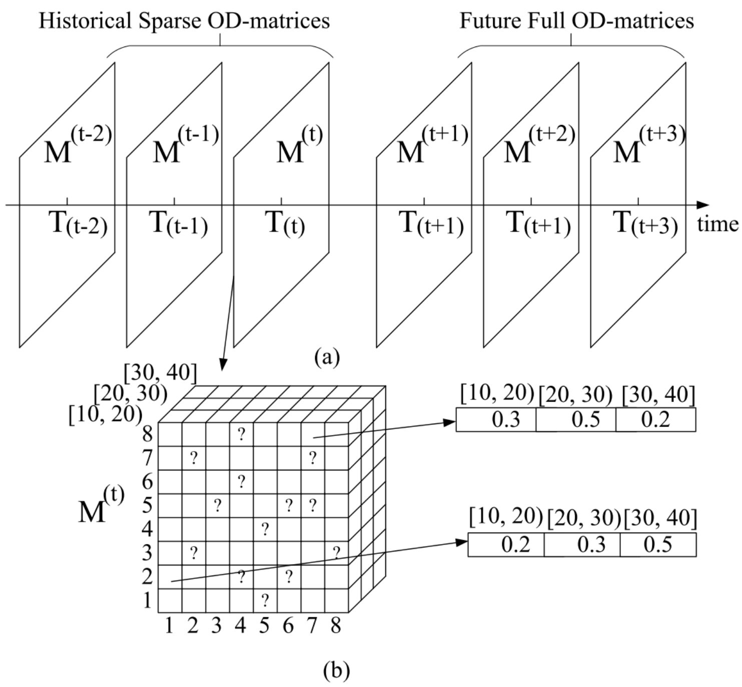
    - 1) predict the numbers of specific incoming
    - and 2) outgoing demands in each grid at different time slots.
- Related work:
    - [7, 12, 14, 18, 27]
        - Dingxiong Deng, Cyrus Shahabi, Ugur Demiryurek, et al. 2016. Latent space model for road networks to predict time-varying traffic. SIGKDD (2016).
        - Minh X Hoang, Yu Zheng, and Ambuj K Singh. 2016. **FCCF: forecasting citywide crowd flows based on big data**. SIGSPATIAL (2016).
        - Renhe Jiang, Xuan Song, Zipei Fan, et al. 2018. **DeepUrbanMomentum: An Online Deep-Learning System for Short-Term Urban Mobility Predictio**n. AAAI (2018).
        - Jiangtao Ren and Qiwei Xie. 2017. **Efficient OD Trip Matrix Prediction Based on Tensor Decomposition**. MDM (2017).
        - Junbo Zhang, Yu Zheng, and Dekang Qi. 2017. **Deep Spatio-Temporal Residual Networks for Citywide Crowd Flows Prediction**. AAAI (2017).



- **Figure 4: The architecture of the multi-task LSTM.**

Stochastic Origin-Destination Matrix Forecasting Using Dual-Stage Graph Convolutional, Recurrent Neural Networks (ICDE,2020)

- We model a travel cost as a distribution because when traveling between a pair of OD regions and address the problem of forecasting complete, near future OD matrices from sparse, historical OD matrices. (**This is for predicting travel cost/time**)



- Figure 2: Stochastic Origin-Destination Matrix Forecasting

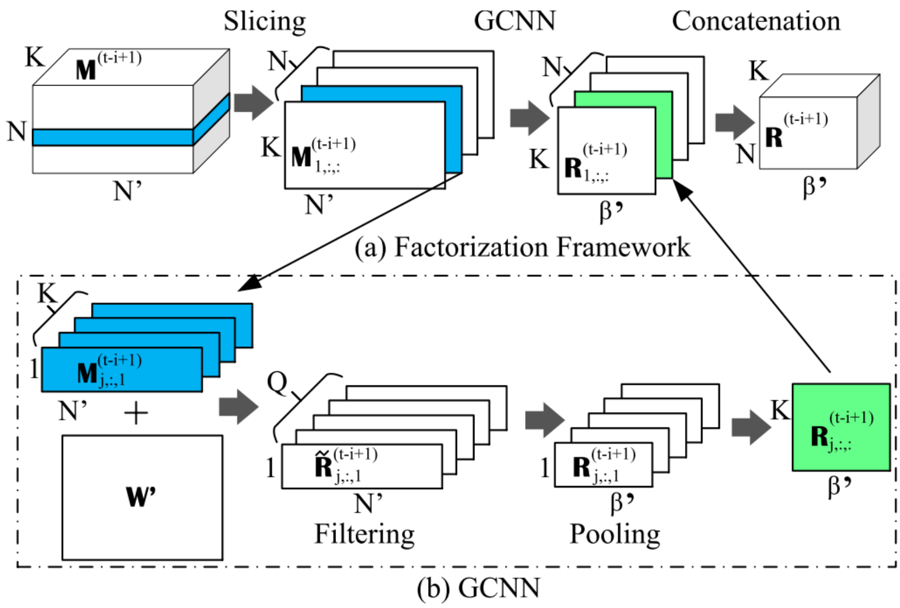


Figure 4: Spatial Factorization for $\boldsymbol{R}$

- Challenges &novelty
  - Data Sparseness
  - Spatio-temporal Correlations —> graph convolution

Real-time forecasting of metro origin-destination matrices with high-order weighted dynamic mode decomposition (arXiv 2021)未加入参考文献

- for short-term metro OD matrices forecasting. DMD uses Singular Value Decomposition (SVD) to extract low-rank approximation from OD data, and a high-order vector autoregression model is estimated on the reduced space for forecasting.
- Challenges:
  - High dimensionality
  - Sparsity (because of the short term)
  - Delayed data availability
  - Temporal dynamics

LSGCN: Long Short-Term Traffic Prediction with Graph Convolutional Networks (IJCAI 2020)

- Graph convolution networks for traffic both long and short term prediction

Traffic Flow Prediction via Spatial Temporal Graph Neural Network (WWW 2020)

- a novel spatial temporal graph neural network for traffic flow prediction. It combines positional **graph neural layer**, recurrent neural network layer and transformer layer to better capture the complex relations between roads from both spatial and temporal aspects.
- Related Work:
  - Graph Neural Network is widely used in modeling the underlying relationships of non-Euclidean data [43]. It can be generally categorized into recurrent graph neural networks (RecGNNs) [34], convolutional graph neural networks (ConvGNNs) [4], graph au- toencoders (GAEs) [5], and spatial-temporal graph neural networks.
  - Convolutional Neural Networks [22] and generalized Graph Convolution Neural Networks (GCN) [19] provide new insights to capture spatial information but they can not directly deal with time series problems.
- Method:
  - 1) the spatial graph neural network (S-GNN) layers, which aim to capture the spatial relations between the roads through the traf- fic network;
  - 2) the GRU layer, which is to capture the temporal relation sequentially (or local temporal dependency); and
  - 3) the transformer layer, which aims to directly capture the long-range temporal dependence in the sequence (or global temporal depen- dence). Note that the S-GNN layer is utilized to model the spatial relation between the nodes and it is applied to both the input and the hidden representations of the GRU unit as shown in Figure 1. Both the GRU layer and the transformer layer are used to capture the temporal dependency for each node individually, while they capture the dependency from different perspectives.

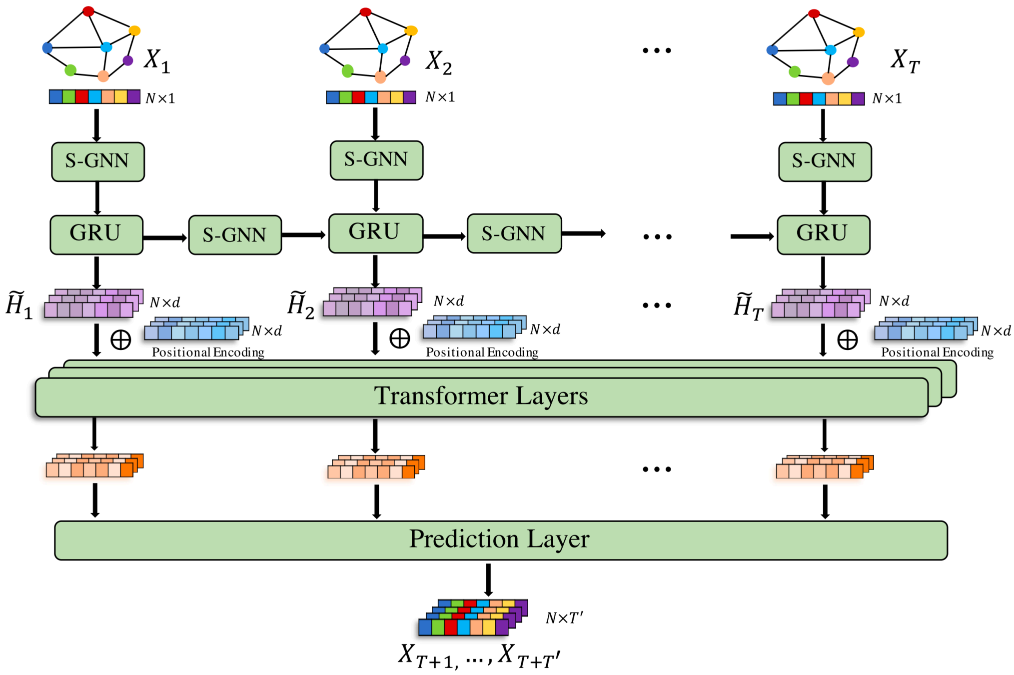
- 

Figure 1: The Proposed Spatial Temporal Graph Neural Network Framework

Spatiotemporal Adaptive Gated Graph Convolution Network for Urban Traffic Flow Forecasting (CIKM 2020)

- spatiotemporal correlation of urban traffic flow and construct a dynamic weighted graph by seeking both **spatial neighbors and semantic neighbors of road nodes.**
- Multi-head self-attention temporal convolution network is utilized to capture **local and long-range temporal dependencies** across historical observations.

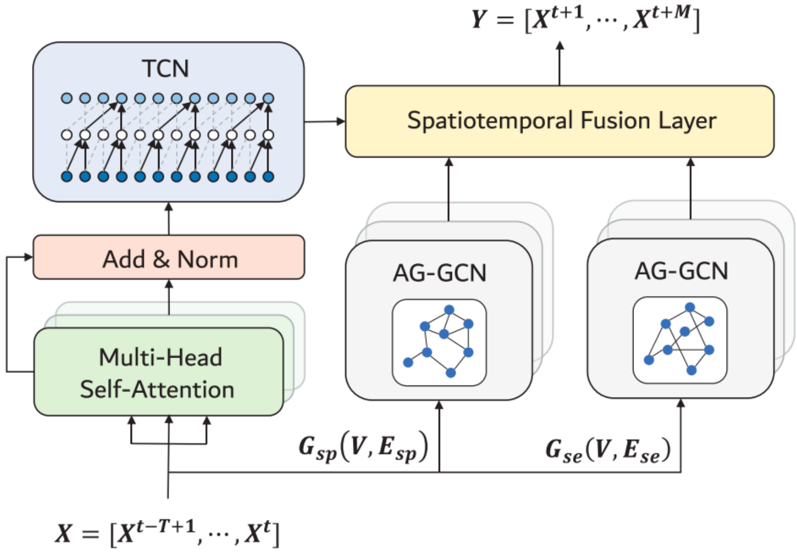


Figure 3: Model Overview of Spatiotemporal Adaptive Gated Graph Convolution Network (STAG-GCN).

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Deep Multi-Scale Convolutional LSTM Network for Travel Demand and Origin-Destination Predictions (TITS 2020)

- “visualize” the travel demands in the city at a particular moment as an image, where each small area is considered as a pixel and its travel demand as the corresponding pixel value.
- OD Tensor, to represent OD flows that can preserve most of the geographical information of the OD flow
- Nothing new…. Related work sucks

Attention-Based Deep Ensemble Net for Large- Scale Online Taxi-Hailing Demand Prediction (TITS 2020)不放入参考文献中
Spatio-Temporal Ensemble Method for Car-Hailing Demand Prediction (TITS 2020)不放入参考文献中

- Motivation: single model is limited so we use ensemble learning
- The first paper proposed **universal** framework can be applied to (1) taxi-hailing and

2) air quality

- The second paper SUCKs

A residual spatio-temporal architecture for travel demand forecasting (TRC 2020)

- Good summary of existing work and their limitations:
    - Insufficient representation of travel demand
    - Naive modeling
    - Insufficient spatio-temporal exporation
- Proposed a model that contains three parts:
    - (1). A spatial correlation embedding (SCE) module, which is constructed by employing fully convolutional neural network (FCNs);
    - (2). A spatio-temporal dependencies approximating (STDA) module, which is achieved by involving a hybrid module consisting of extended Conv-LSTMs (CE-LSTMs), LSTMs and CNNs; and
    - (3). A residual connection (RC) module, which reformulates the prediction problem as a **learning residual function** with regard to the travel density in each time interval. The

Building Personalized Transportation Model for Online Taxi-Hailing Demand Prediction (IEEE TRANSACTIONS ON CYBERNETICS, 2020)

- (Temporal Personalization): The attention mechanism is used to represent time information (e.g., the day of the week) as a personalized temporal feature map. The input feature map can be multiplied by the personalized temporal feature map to refine the extracted information for each region. WHY??????
- (Spatial Personalization): The personalized spatial feature map, which contains information extracted from different regions in a city, will be adapted to the distinct local geographical attributes. THIS IS NOT PERSONALIZATION!!!

Is Travel Demand Actually Deep? An Application in Event Areas Using Semantic Information (TITS 2020)

- explore time-series data and **semantic information combinations** using machine learning and deep learning techniques in the context of creating a prediction model that is able to capture in **real-time future stressful situations** of the studied transportation system
- Related work
    - A summary about the dispatching methods "Zhao et al. [16] use entropy and the temporal correlation of human mobility to measure the demand uncertainty at the building block level. "
    - [16] K. Zhao, D. Khryashchev, J. Freire, C. Silva, and H. Vo, "**Predicting taxi demand at high spatial resolution: Approaching the limit of predictability**," in Proc. IEEE Int. Conf. Big Data, Dec. 2016, pp. 833–842.

Predicting Taxi Demand at High Spatial Resolution: Approaching the Limit of Predictability (Big Data 2016)

- 1. Given a predictive algorithm α, considering both the randomness and temporal correlation of the taxi demand sequence, what is the upper bound of the potential accuracy that a predictive algorithm α can reach?
- 2. Given an upper bound of potential accuracy, which predictor has a better performance given the trade-off between the computation time and the accuracy?

Short-Term Demand Forecasting for on-Demand Mobility Service (TITS 2020)

- the model **outputs distributions of future demand rather than point estimations**, which contributes to **quantifying uncertainties** in future OMS demand and framing more robust real-time operation policies for OMS industry.

Taxi Demand Prediction Using Parallel Multi-Task Learning Model (TITS 2020)

- Motivation:
    - existing work ignores the correlations between taxi pick-up demand and the drop-off demand
    - There would be inter-correlation between one's pick-up and drop-off locations
    - So they adopt multi-task learning to capture the internal correlations

Data-Driven Multi-step Demand Prediction for Ride-hailing Services Using Convolutional Neural Network (arXIv 2019)

- Motivation:
    - Existing work focus on temporal correlation
    - This work use CNN for considering spatial correlation

Short-Term Prediction of Passenger Demand in Multi-Zone Level: Temporal Convolutional Neural Network with Multi-Task Learning (TITS 2020)