Project reading

Project reading

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Detecting Urban Black Holes Based on Human Mobility Data (2015)

1. When instantly detecting *black holes* in a time interval, we propose 1) a candidate selection algorithm that finds candidate grid cells to start from and 2) a spatial expansion algorithm that expands an edge in a candidate grid cell to a black hole. An upper bound of a grid cell's actual flow is defined to help select and prune candidate cells after each black hole is detected.
2. We propose a continuous detection algorithm to further reduce the total cost of black hole detection in multiple time intervals, utilizing both detected results in the previous time interval and historical patterns of black hole over a long period.

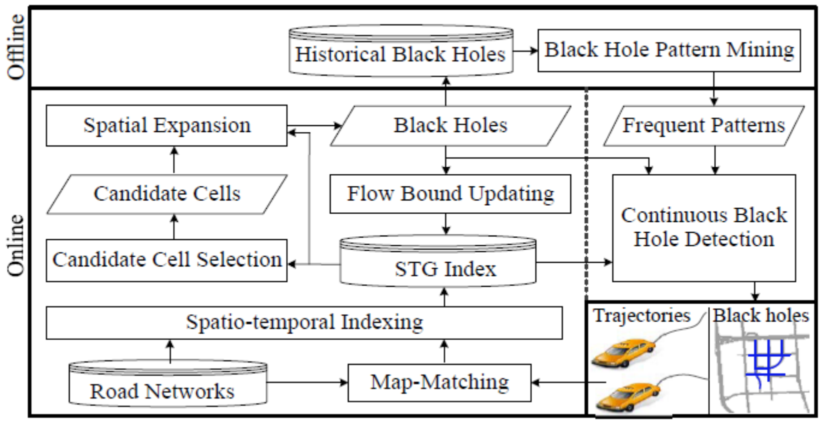


Figure 2: Framework of Black Hole Detection

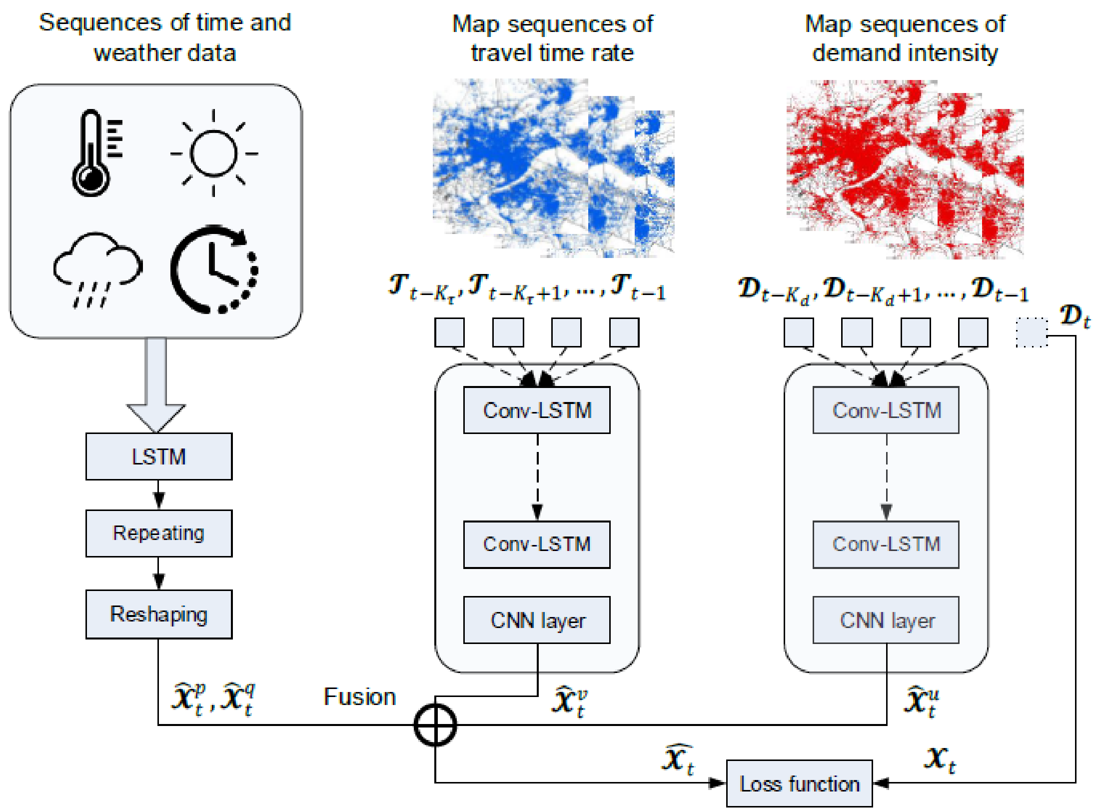
3. We evaluate our method using Beijing road network and real GPS trajectories generated by over 33,000 taxis, and bike trips generated by over 6,300 bikes in New York City. Two case studies demonstrate that our method can detect black holes/volcanos representing unusual events and human mobility patterns that can improve the urban planning of Beijing and the operational efficiency of NYC bike sharing system. The performance evaluation proves that our method outperforms baseline methods.

> 1）给定time interval的black hole的探测，利用STG index的数据结构，算法上以图论分析为主

> 2）continuous detection algorithm：主要侧重于利用已有black hole信息和flow变化进行update

Short-Term Forecasting of Passenger Demand under On-Demand Ride Services: A Spatio-Temporal Deep Learning Approach (2017)

1. The novel FCL-Net approach characterizes the spatio-temporal properties of the predictors, captures the temporal features of non-spatial time-series variables simultaneously, and coordinates them in one end-to-end learning structure for the short-term passenger demand forecasting.

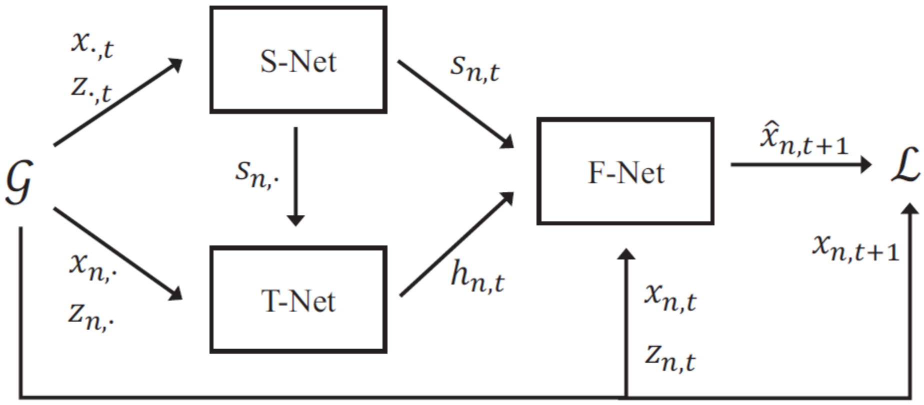


2. We extract the potential predictors affecting short-term passenger demand and assess the feature importance of these predictors via a spatial aggregated random forest.
3. Validated by the real-world on-demand ride services data provided by DiDi Chuxing in a large-scale urban network, the proposed DL structure outperforms five benchmark algorithms, including three conventional time-series prediction methods and two classical DL algorithms.

> 1) 对Conv-LSTM的延申, 使之可以同时处理spatial, temporal, exogenous dependency
>
> 2) 使用spatial aggregated random forest衡量各个feature对predict的重要程度

MSSTN: Multi-Scale Spatial Temporal Network for Air Pollution Prediction (2019)

1. We suggest to use a multi level graph data structure to better represent the geo-sensory systems and better discover high level spatial temporal patterns. Further we propose a novel deep convolutional neural network named MSSTN for the air pollution prediction task on the proposed data structure.
2. Three subnets are specially designed for MSSTN in order to process multi-scale spatial temporal data explicitly, that are a set of dilated casual convolutional network (DCN) named T-Net, a set of graph convolutional neural networks (ChebNet) named S-Net, and a fusion network with dense connections (MLPs as building blocks) named F-Net



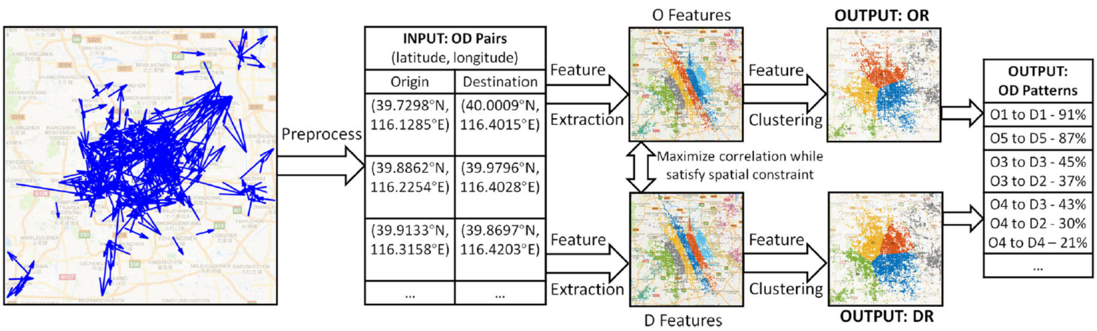
Multi-step inference using a auto-regressive inference procedure.

3. We deploy our model on a real world air pollution datasets, Urban Air Pollution Datasets in North China, and result shows an outstanding performance compared to many state-of-the-art methods.

> 利用空气污染的时空（双层空间）信息进行预测
>
> 使用T-net（DCN）和S-net（GCN）分别处理时空信息，再由F-net（MLPs）整合

Mining Regional Mobility Patterns for Urban Dynamic Analytics (2019)

1. A novel region-aware mobility pattern mining framework. It considers both mobility pattern extraction and OD region partition without overlap.
2. A kernel-based extension to the ACE algorithm for extracting maximal correlated features. KACE is the first algorithm to solve the HGR maximal correlation problem with continuous input and feature constraints.



Algorithm 1 D-dimensional kernelized ACE for clustering.

Require: training samples $\{(x_i, y_i) : i = 1, ..., N\}$

1. Initialize: randomly generate and regularize $f_d(x_i)$, $g_d(y_i), i = 1, \cdots, N, d = 1, \cdots, D$

repeat

2a. **Feature iteration:**

$$f_d(x_i) \leftarrow \frac{\sum_{j=1}^{N} g_d(y_j)K(x_j, x_i)}{N}, K(x_j, x_i) = 1 - \|x_j - x_i\|_2$$

$$g_d(y_i) \leftarrow \frac{\sum_{j=1}^{N} f_d(x_j)K(y_j, y_i)}{N}, K(y_j, y_i) = 1 - \|y_j - y_i\|_2$$

2b. **Regularize:** $f_d(\cdot), g_d(\cdot), d = 1, ..., D$.

$$f_d(x_i) \leftarrow f_d(x_i) - \frac{\sum_i f_d(x_i)}{N}, f_d(x_i) \leftarrow \frac{f_d(x_i)}{\sqrt{\frac{\sum_i f_d(x_i)^2}{N}}}$$

$$g_d(y_i) \leftarrow g_d(y_i) - \frac{\sum_i g_d(y_i)}{N}, g_d(y_i) \leftarrow \frac{g_d(y_i)}{\sqrt{\frac{\sum_i g_d(y_i)^2}{N}}}$$

2c. **Gram-Schmidt:**

for $d = 1$ to D **do**

  for $k = 1$ to $d - 1$ **do**

$$f_d(x) \leftarrow f_d(x) - \frac{\langle f_k(x), f_d(x)\rangle}{\langle f_k(x), f_k(x)\rangle} f_k(x)$$

$$g_d(x) \leftarrow g_d(x) - \frac{\langle g_k(x), g_d(x)\rangle}{\langle g_k(x), g_k(x)\rangle} g_k(x)$$

  end for

end for

until $\mathbb{E}[f_{1,2\cdots D}(x)^T g_{1,2\cdots D}(y)]$ stops to increase

3. **Output:** Region label of each point x_i and y_i

3a. $OR(x_i) \leftarrow$ Linkage cluster of $f_{1,\cdots,D}(x_i), i = 1, \cdots, N$ with maximum cluster number N_x,

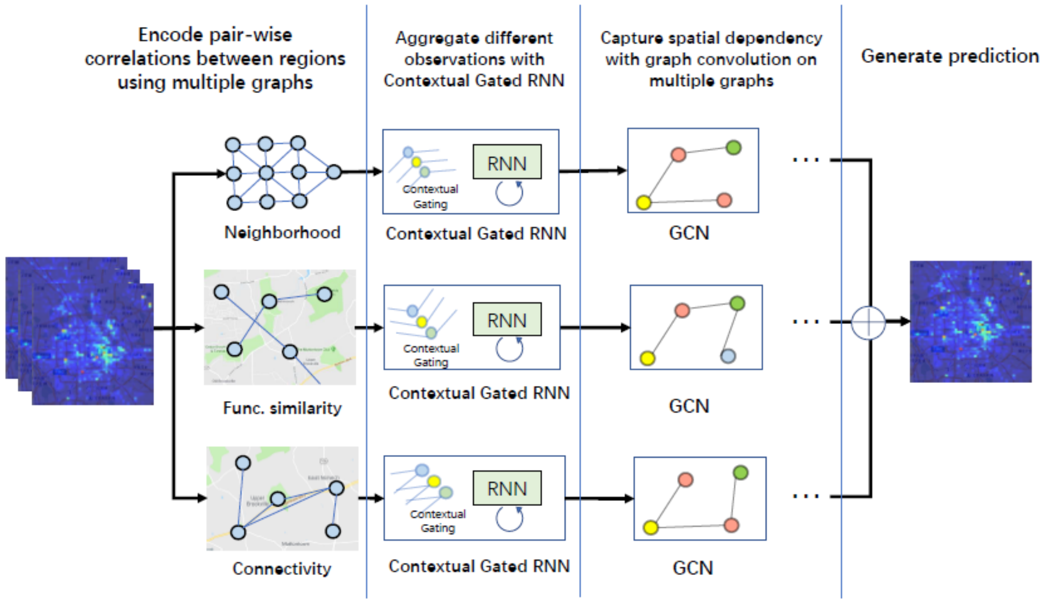
3b. $DR(y_i) \leftarrow$ Linkage cluster of $g_{1,\cdots,D}(y_i), i = 1, \cdots, N$ with maximum cluster number N_y

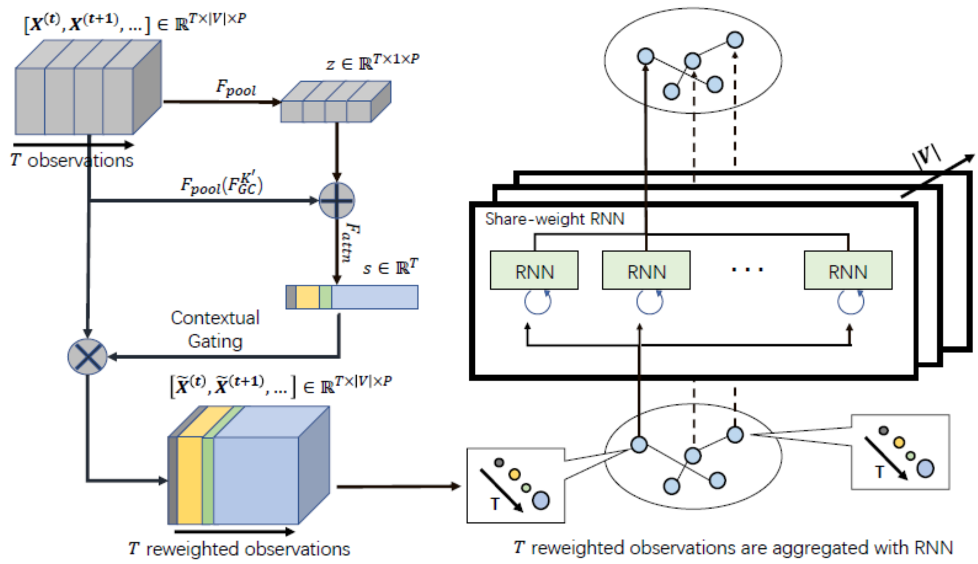
3. A thorough evaluation of KACE towards both feature and cluster results with real world data. Feature evaluation shows KACE has tradeoff between correlation and distribution kurtosis thus features are easier to be clustered. Cluster results show the versatility of our approach in disentangling complicated mobility patterns comparing with both traditional methods and state-of-the-art clustering algorithms.
4. Comprehensive case studies of both New York City and Beijing with real taxi data. Urban dynamics analysis of NYC reveals people's travel patterns between different functionalities in the city. A three-year analysis of Beijing's mobility patterns reveals its city development and urban sprawl through years.

> region-aware mobility pattern mining, view the problem as: regional dependency between OR and DR is maximized; points inside each cluster are close to each other.
>
> Kernelized ACE; Gram-Schmidt othogonalization; cluster high-dimensional features into O/D region labels using linkage clustering methods

Spatio-temporal Multi-Graph Convolution Network for Ride-Hailing Demand Forecasting (2019)

1. We identify non-Euclidean correlations among regions in ride-hailing demand forecasting and propose to encode them using multiple graphs. Then we further leverage the proposed multi-graph convolution to explicitly model these correlations.
2. We propose the Contextual Gated RNN (CGRNN) to incorporate the global contextual information when modeling the temporal dependencies.





3. We conduct extensive experiments on two large-scale real-world datasets, and the proposed approach achieves more than 10% relative error reduction over state-of-the-art baseline methods for ride-hailing demand forecasting.

> 使用历史需求数据预测Region-level ride-hailing demand，主要贡献在于将region间的dependency从Euclidean距离变化为了neighborhood, similarity, connectivity的multiple graph。在三个层面上，都使用CGRNN以汇总不同时间的信息，并用multi-graph convolution得到region间的correlation。最后用全连接网络从feature得到预测结果。

Urban ride-hailing demand prediction with multiple spatio-temporal information fusion network (2020)

1. fuse multiple graph-level structure representation and pixel-level situation representation to obtain a superior joint representation in ride-hailing demand prediction tasks.

2. propose the Multiple Spatio-Temporal Information Fusion Networks (MSTIF-Net) to better fuse multiple
   situation awareness information and graphs representation. MSTIF-Net model integrates structures of Graph Convolutional Neural Networks (GCN), Variational Auto-Encoders (VAE) and Sequence to Sequence Learning (Seq2seq) model to obtain the joint latent representation of urban ride-hailing situation that contain both Euclidean spatial features and non-Euclidean structural features, and capture the spatio-temporal dynamics
3. We transfer hybrid GCN model from station-based or network-based scenarios to grid-based scenarios by adjacency matrices modeling without any additional network data.

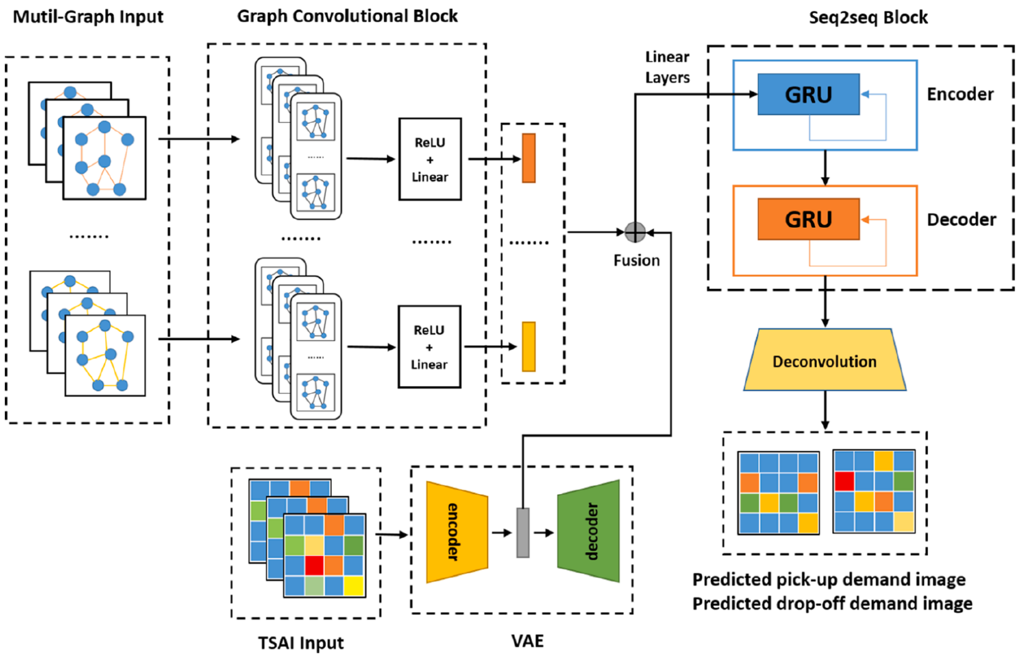


Fig. 5. Overview of the Multiple Spatio-Temporal Information Fusion Network Model for urban ride-hailing demand prediction.

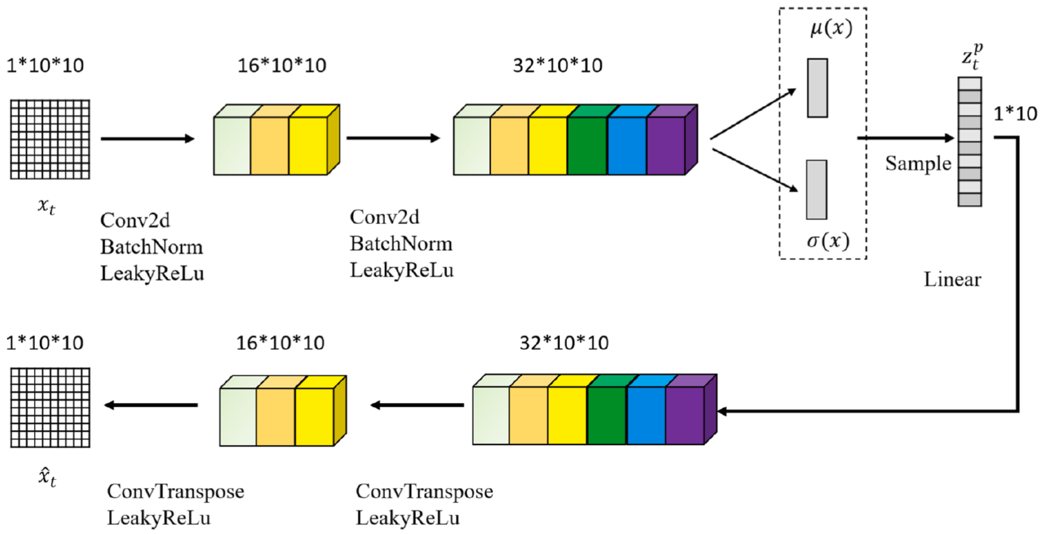


Fig. 6. Computational framework for Conv-VAE. Both of Encoder and Decoder are parameterized with convolutional neural networks. And the dimension of output z is 1×10.

4. We conduct extensive experiments on two large-scale real-world datasets, and the proposed approach achieves superior performance than other state-of-art baseline methods for urban traffic prediction.

> 同时使用TSAI和graph (distance, interaction, correlation)信息, 综合多种方法

Short-term demand forecasting for online car-hailing using ConvLSTM networks (2021)

1. The online ride-hailing order information with spatio-temporal feature information is processed into pictures.
2. The Conv-LSTM neutral network is introduced to predict images.

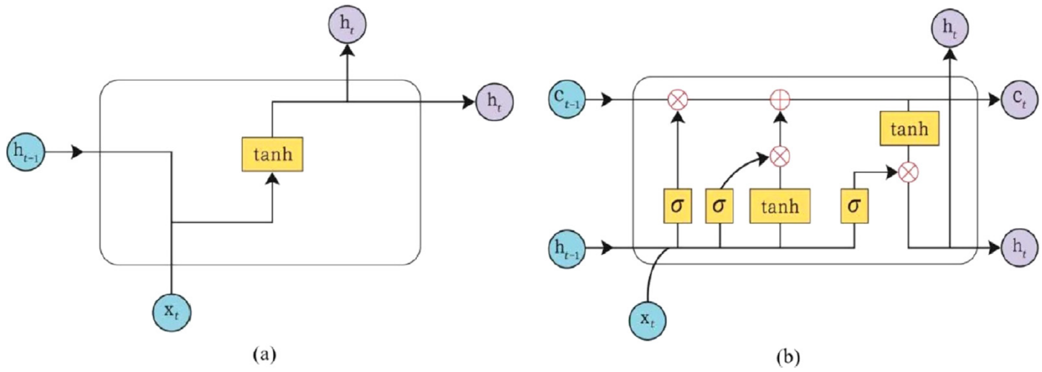


Fig. 1. (a) RNN model (b) FC-LSTM model.

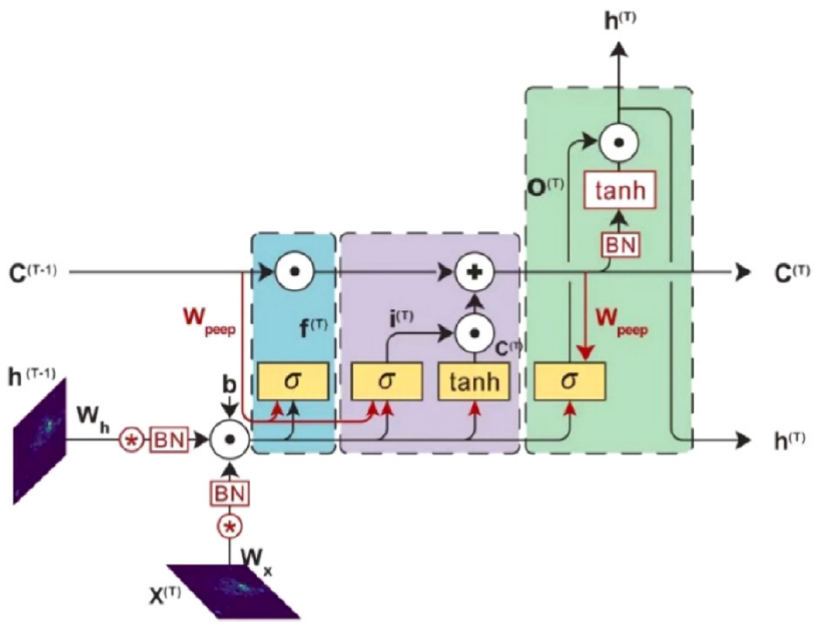


Fig. 4. Conv-LSTM Cell diagram.

3. A real case was studied to demonstrate the feasibility of this neutral network in dealing with short-term forecasting of online car-hailing demand.

> 将每一时刻的空间信息视为图片（矩阵），通过将LSTM的输入改为卷积，实现同时利用FC-LSTM对时间信息的处理优势和Conv对图片信息的处理优势