Deep Spatio-Temporal Residual Networks for Citywide Crowd Flows Prediction

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Main Goal

Predicting crowd flows in a city.

Why ?

- To be able to manage traffic.
- Lack of safety when massive crowds of people streamed into a strip region.
  - $\rightarrow$ Stampede at Shanghai New Year's celebration kills 36

Figure 1: Massive crowds of people in Paris during World Cup (2018)

Proposed method

Deep-learning-based approach to collectively forecast the inflow and outflow of crowds in each and every region of a city.

→ method called *ST-ResNet* (Spatio-Temporal Residual Networks)

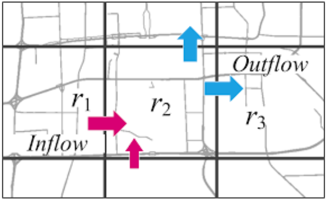

Figure 2: Inflow and outflow

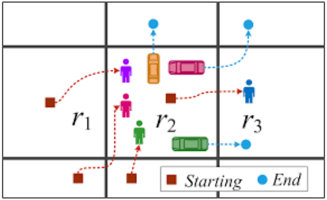

Figure 3: Measurement of flows

Introduction - Method

Proposed method

Deep-learning-based approach to collectively forecast the inflow and outflow of crowds in each and every region of a city.

$\rightarrow$ method called *ST-ResNet* (Spatio-Temporal Residual Networks)

- What is include ?
  - Number of pedestrian
  - Number of car
  - Number of people traveling on public transportation systems (e.g. metro, bus)

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- What is include ?
  - Number of pedestrian
  - Number of car
  - Number of people traveling on public transportation systems (e.g. metro, bus)
- How to get the necessary data ?
  - Mobile phone signals (for pedestrians)
  - GPS trajectories (for vehicles)
- Thus, we can obtain a set of trajectories $\mathbb{P}$ where each trajectory $Tr \in \mathbb{P}$, $Tr = (g_1, g_2, ..., g_k)$ *with* $g_k \in \mathbb{R}^2$ is a list of coordinates (longitude and latitude).

Introduction - Difficulties

1. Spatial dependencies

Inflow of a region is affected by outflows of nearby regions.

- After an event occured in a specific place, the inflow of nearby regions will increase.

2. Temporal dependencies

The flow of crowds in a region is affected by more or less recent time intervals.

- Traffic congestion at 8 AM will affect that of 9 AM.
- Traffic conditions during morning rush hours may be similar on consecutive workday.

3. External influence

Some external factors may change the flow of crowds.

- Weather, events, etc.

Partition the city

Many ways to partition a city. In this method, the city is partitioned into an $I \times J$ grid map based on longitude and latitude.

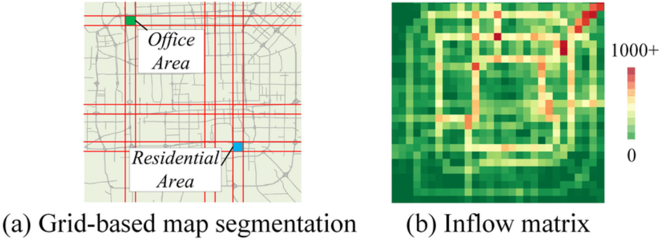

Figure 4: Regions in Beijing

Formulation of Crowd Flows Problem

Definition (Inflow & Outflow)

For a cell (i, j) that lies at the i^{th} row and j^{th} column of the grid, the inflow and outflow of the crowds at the time interval t are defined as:

$$x_t^{in,i,j} = \sum_{Tr \in \mathbb{P}} |\{k > 1 | g_{k-1} \notin (i,j) \wedge g_k \in (i,j)\}|$$

$$x_t^{out,i,j} = \sum_{Tr \in \mathbb{P}} |\{k \geq 1 | g_k \in (i,j) \wedge g_{k+1} \notin (i,j)\}|$$

where

- $\mathbb{P}$: a collection of trajectories at the t^{th} time interval
- $Tr : g_1 \rightarrow g_2 \rightarrow ... \rightarrow g_{|Tr|}$: a specific trajectory in $\mathbb{P}$
- g_k : the geospatial coordinate (i.e. longitude and latitude)
- $|.|$: the cardinal

Thus, at the t^{th} time interval, inflow and outflow in all the city can be denoted as a tensor $\mathbf{X}_t \in \mathbb{R}^{2 \times I \times J}$ where $(\mathbf{X}_t)_{0,i,j} = x_t^{in,i,j}$ and $(\mathbf{X}_t)_{1,i,j} = x_t^{out,i,j}$.

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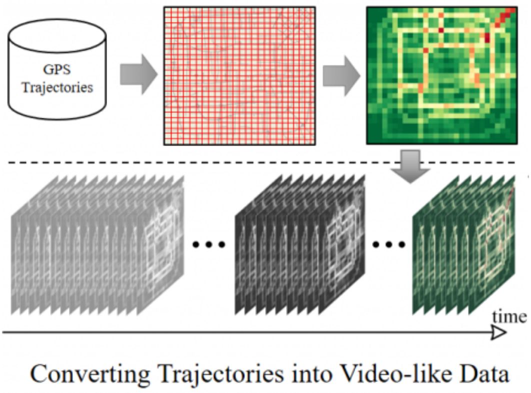


Figure 5: Processing data

Definition (Deep residual network)

Convolution neural networks whose structure is composed of residual units:

$$\mathbf{X}^{(l+1)} = \mathbf{X}^{(l)} + \mathcal{F}(\mathbf{X}^{(l)})$$

where $\mathbf{X}^{(l)}$ and $\mathbf{X}^{(l+1)}$ are the input and output af the l^{th} residual unit.

Such networks can be trained even with more than 100 layers.

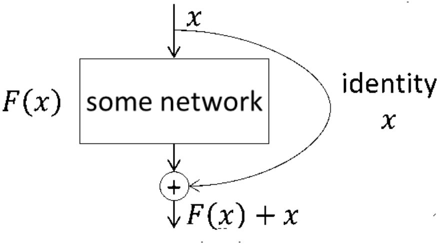


Figure 6: Residual Unit

ST-ResNet - Model Details

- Recall the objective:
  - Find a function f which predict X_n given $(X_{n-1}, X_{n-2}, ..., X_0) = H_t$
    - we will use neural networks to approximate f
    - learn $f_\theta : \mathbb{R}^{2n \times I \times J} \to \mathbb{R}^{2 \times I \times J}$

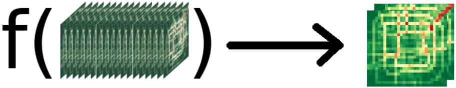


Figure 7: Objective

- Recall the difficulties :
  - temporal dependencies
  - spatial dependencies
  - external influences

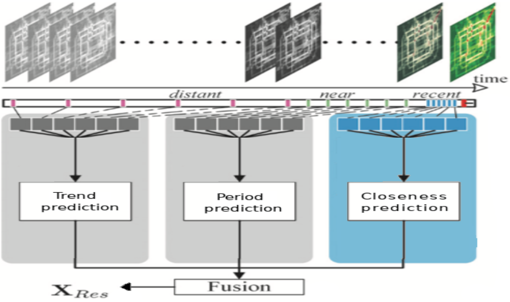
We will build our model f_θ to cope with these difficulties.

Dealing with the temporal dependencies difficulty

ST-ResNet summarize the temporal properties of crowds flows into three categories:

- Temporal **closeness** $\mathbf{X}_c$ $\rightarrow$ function of $\left[\mathbf{X}_{t-l_c}, \mathbf{X}_{t-(l_c-1)}, \ldots, \mathbf{X}_{t-1}\right]$
- Temporal **period** $\mathbf{X}_p$ $\rightarrow$ function of $\left[\mathbf{X}_{t-l_p.p}, \mathbf{X}_{t-(l_p-1).p}, \ldots, \mathbf{X}_{t-p}\right]$
- Temporal **trend** $\mathbf{X}_q$ $\rightarrow$ function of $\left[\mathbf{X}_{t-l_q.q}, \mathbf{X}_{t-(l_q-1).q}, \ldots, \mathbf{X}_{t-q}\right]$

Use three networks to model these properties and dynamically aggregates the three outputs (as shown on the figure).



Dealing with the spatial dependencies difficulty

ST-ResNet employs convolution-based residual networks to model nearby and distant spatial dependencies between any two regions of the city.

- Need very large citywide dependencies (each node in output depends on all nodes in input)
- For 32×32 grid and 3×3 kernel convolution $\rightarrow$ at least 15 layers
- Use residual networks to this end (with 26 layers in practice)

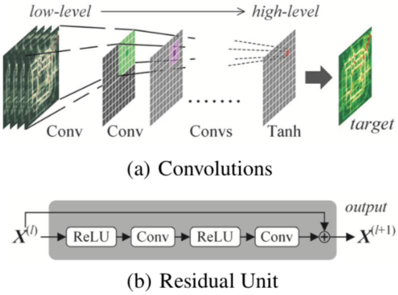


Figure 8: Convolutional and residual units

Dealing with the external influences difficulty

Adding a fourth component : the *external influence* component. This component is approximate by a simple two-fully-connected neural network where inputs are some features manually extracted from external datasets.

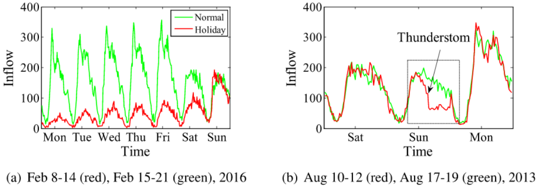


Figure 9: Effect of holidays and weather on Office Area of Beijing

Figure 10: External component

Global architecture

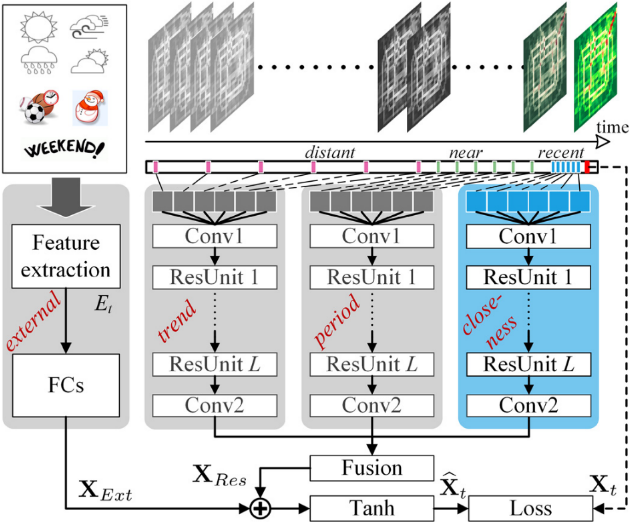


Figure 11: ST-ResNet Architecture

Experiment

Experiments are made on two differents datasets:

- **TaxiBJ** - Taxicab GPS trajectories
  - Time interval : $30min$
  - Grid map size : $(32, 32)$
  - Number of taxi: 34000+
  - Available time interval: 22459
  - External influence data : holidays, weather, temperature, wind speed
- **BikeNYC** - Bike trajectories
  - Time interval : $60min$
  - Grid map size : $(16, 8)$
  - Number of bikes: 6800+
  - Available time interval: 4392
  - External influence data : holidays

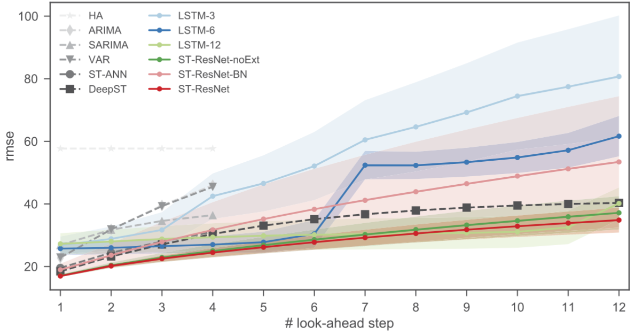


Figure 12: Multi-step ahead prediction on TaxiBJ dataset

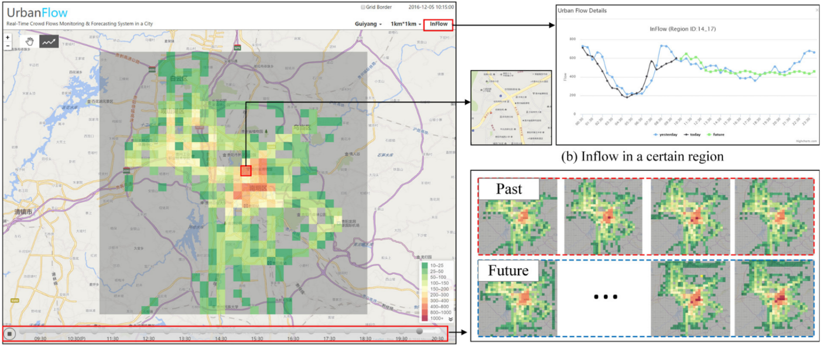
Experiment

Table 6
Comparisons with baselines on TaxiBJ and BikeNYC. Results of ARIMA, SARIMA, VAR and DeepST on BikeNYC are taken from [3]. For RNN-based models and ST-ResNet variants, we run each of them 10 times and show "mean ± standard deviation".

Model	RMSE	
	TaxiBY	BikeNYC
HA	57.69	21.578
ARIMA	22.78	10.07
SARIMA	26.88	10.56
VAR	22.88	9.92
ST-ANN	19.57	7.58
DeepST	18.18	7.43
RNN-3	26.68 ± 3.41	9.01 ± 0.50
RNN-6	30.03 ± 1.60	8.61 ± 0.42
RNN-12	45.51 ± 2.01	12.41 ± 0.84
RNN-24	51.12 ± 1.99	12.53 ± 0.14
RNN-48	43.42 ± 1.20	12.76 ± 0.18
RNN-336	39.61 ± 0.77	10.74 ± 0.35
LSTM-3	26.81 ± 2.80	8.67 ± 0.33
LSTM-6	26.07 ± 1.87	9.56 ± 0.64
LSTM-12	27.59 ± 3.69	9.90 ± 0.67
LSTM-24	25.69 ± 2.25	11.34 ± 0.44
LSTM-48	27.80 ± 2.87	12.36 ± 0.87
LSTM-336	40.68 ± 1.08	10.54 ± 0.13
GRU-3	22.97 ± 1.11	8.76 ± 0.37
GRU-6	23.64 ± 1.14	8.57 ± 0.22
GRU-12	27.40 ± 3.72	9.68 ± 0.51
GRU-24	27.01 ± 1.58	12.27 ± 0.77
GRU-48	28.56 ± 3.71	12.71 ± 0.93
GRU-336	40.27 ± 2.30	10.76 ± 0.33
ST-ResNet	**17.17** ± **0.21** (12 residual units)	6.32 ± 0.13 (4 residual units)
ST-ResNet-noExt	17.26 ± 0.38 (12 residual units)	\
ST-ResNet-AVG1	19.07 ± 0.30 (12 residual units)	6.44 ± 0.19 (4 residual units)
ST-ResNet-AVG2	18.04 ± 0.15 (12 residual units)	**5.99** ± **0.09** (4 residual units)

Figure 13: Results for TaxiBJ dataset (left) and BikeNYC dataset (right)

Visualization



(a) Web user interface of UrbanFlow

(b) Inflow in a certain region

(c) Heatmaps in past & future

Figure 14: Web interface of the UrbanFlow

Conclusion

- Forecast the flow of crowds collectively in each and every region of a city
- Performances beyond at least 6 baseline methods
- Future works :
  - Model to predict with irregular regions
  - Consider other types of flows

    $\rightarrow$ bus, phone signals data, metro card swiping data
- Since, other methods have been developped to improve citywide crowd flows prediction
  - MVGCC
  - ST-DCCNAL (overcome ST-ResNet)