Crime Hot-spots Forecasting Phase II

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Crime hotspots forecasting

Understanding patterns in criminal activity allows for the prediction of future crime and enables police precincts to more effectively allocate officers to prevent or respond to incidents.

- ❖ **Goal:** Design a predictive model to identify high-risk "hot spots" in the near future based upon the historical neighborhood crime information of the potential hot region.

- ❖ **Data:** The call-for-service data provided by the Portland, Oregon Police Bureau (PPB) for a 5-year period from March 2012 through the end of December 2016

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Calls-for-service (CFS) records

CATEGORY	CALL GROUPS	final_case_type	CASE DESC	occ_date	x_coordinate	y_coordinate	census_tract
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	1/18/2013	7649793	662388	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	1/5/2013	7651202	661479	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	1/28/2013	7647818	663182	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	2/2/2013	7649298	661246	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	1/13/2013	7650935	661746	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	2/17/2013	7650248	660907	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	1/30/2013	7650289	662464	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	3/13/2013	7650182	664208	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	2/16/2013	7649859	665351	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	3/2/2013	7649894	664127	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	3/29/2013	7649298	661246	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	4/27/2013	7647366	665494	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	4/27/2013	7648668	662094	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	5/2/2013	7650785	661371	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	5/12/2013	7647366	665494	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	5/31/2013	7650022	663852	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	6/1/2013	7648386	663997	100
STREET CRIMES	DISORDER	DISTP	DISTURBANCE - PRIORITY	5/27/2013	7648851	662894	100

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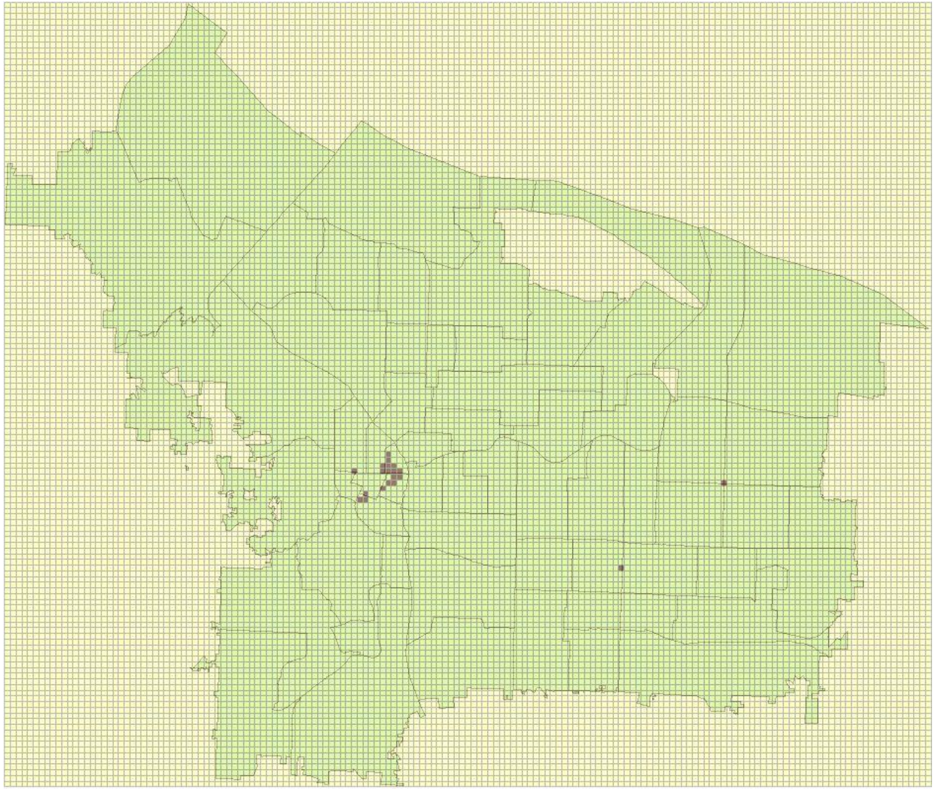
Hot Spots

Crime hotspot maps are a well-established tool for visualization of space–time crime patterns and can be used as a method for prediction of near-repeat crimes.



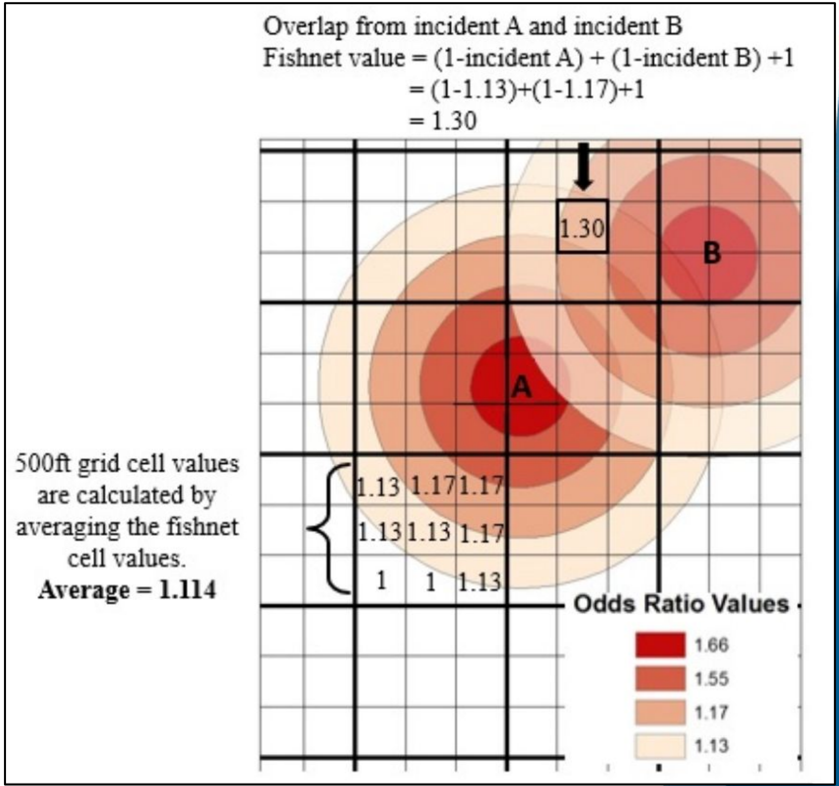
Related work - Monte Carlo simulation

Jerry H. Ratcliffe et al. use geographically smoothed outcome counts to calculate the crime rate.
“Predictive Modeling Combining Short and Long - Term Crime Risk Potential”--- 2016 - ncjrs.gov

Advantage:
Use Monte Carlo simulation to calculate conditional intensity based on the historical events.

Shortage:

Same distance has same influence.

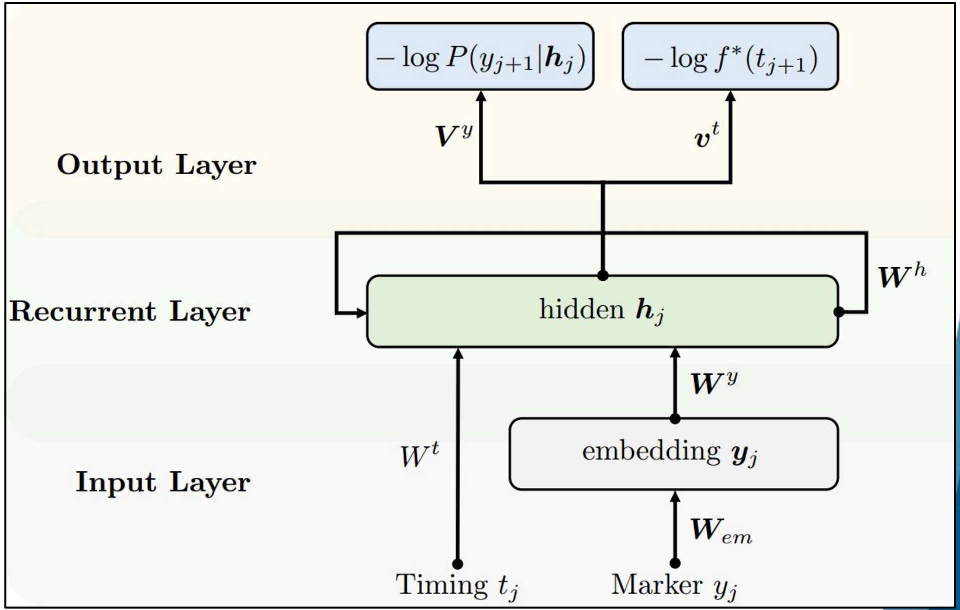


Related work

N Du et al. use recurrent neural network to predict the location and time of the next stop for taxi.
“Recurrent marked temporal point processes: Embedding event history to vector” --- SIGKDD 2016

Advantage: use recurrent neural network to Simulate conditional intensity function.

Shortage: Predict the future event of a point based on its historical information. Ignore the influence of other points.



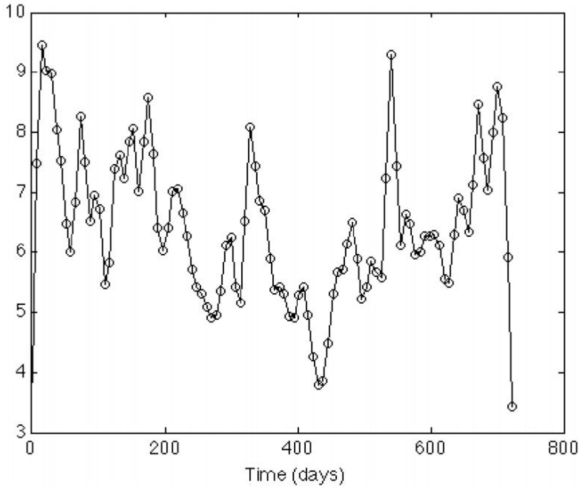
Related work

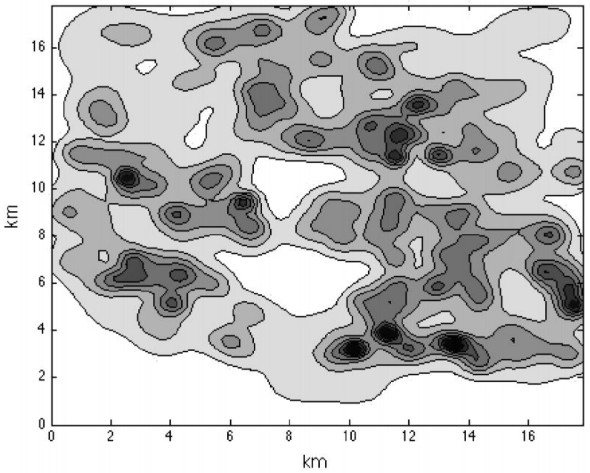
Mohler, George O., et al. use Self-Exciting Point Process Model to predict crime risk.

“Self-Exciting Point Process Modeling of Crime” --- JASA 2011

Advantage: use Poisson process to determine background rate and estimate a function g to estimate the space-time influence of historical events.

Shortage: The g function use the distances of time and coordinates, which mean wherever the location (x,y), if the distances of time and coordinates are the same, the space-time influence are same.





Spatio-Temporal Point Process

Temporal point processes are mathematical abstractions for many different phenomena across a wide range of domains. In seismology, marked temporal point processes have originally been widely used for modeling earthquakes and aftershocks. In computational finance, temporal point processes are very active research topics in econometrics. In sociology, temporal-spatial point processes have been used to model networks of criminals.

The behavior of a spatial-temporal point process N is typically modelled by specifying a functional form for $\lambda(t,x,y)$, which represents the expected rate of events at time t and location (x,y), given all the observations up to time t. Within a space-time window S , S= $[t-\Delta t,t],[x-\Delta x,x+\Delta x],[y-\Delta y,y+\Delta y]$, $\lambda(t,x,y)$, is the conditional intensity function for the occurrence of a new event given the history H:

$$\lambda(t, x, y) = \mathbb{P}\{\text{event in } t \mid \text{events in } S\} \qquad (1)$$

Self-exciting point process

The self-exciting point process are often used to model events that are clustered together in time and space. A commonly used form for such models is a spatial-temporal generalization of the Hawkes model, where the conditional intensity function λ(t,x,y) may be written as:

$$\lambda(t, x, y) = \mu(x, y) + \sum_{\substack{t_k, x_k, \\ y_k, m_k \in S}} \nu(t - t_k, x - x_k, y - y_k, m_k) \qquad (2)$$

The functions μ and g represent the prior probability and historical influence, respectively. Often μ is modelled as merely a function of the space-time point (t,x,y), and every historical event in the given space-time window elevates the conditional intensity based on the kernel v(t, x, y, m)

Self-exciting point process

Here we remodel the historical influence function as a recurrent process as follows:

$$\nu(t, x, y) = a * \nu(t-1, x, y) + b * g_{t-1}(x, y, m) \qquad (4)$$

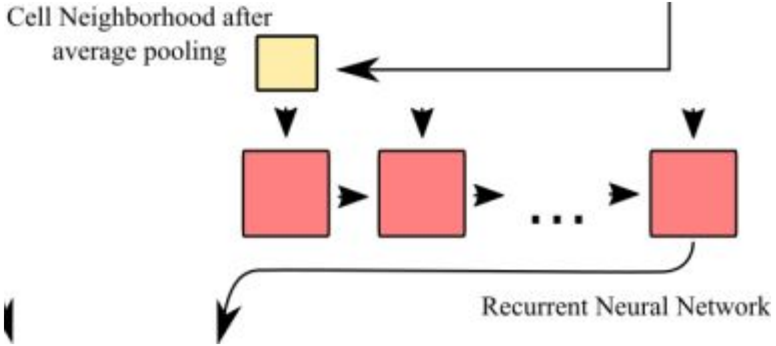
Where

$$g_t(x, y, m) = \sum_{\substack{x_k, y_k \\ m_k \in S_t}} z(x, y, x_k, y_k, m_k) \qquad (5)$$

Recurrent neural network model the historical influence function

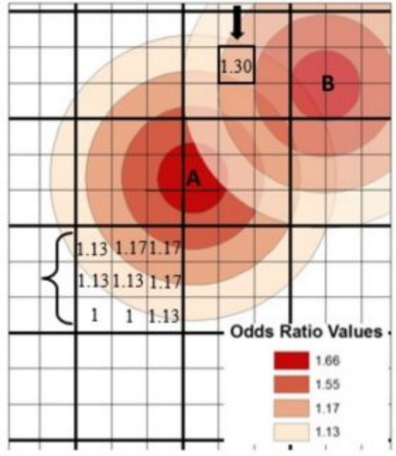
Using Recurrent neural network to model the historical influence function :

$$\nu(t, x, y) = a * \nu(t-1, x, y) + b * g_{t-1}(x, y, m) \qquad (4)$$

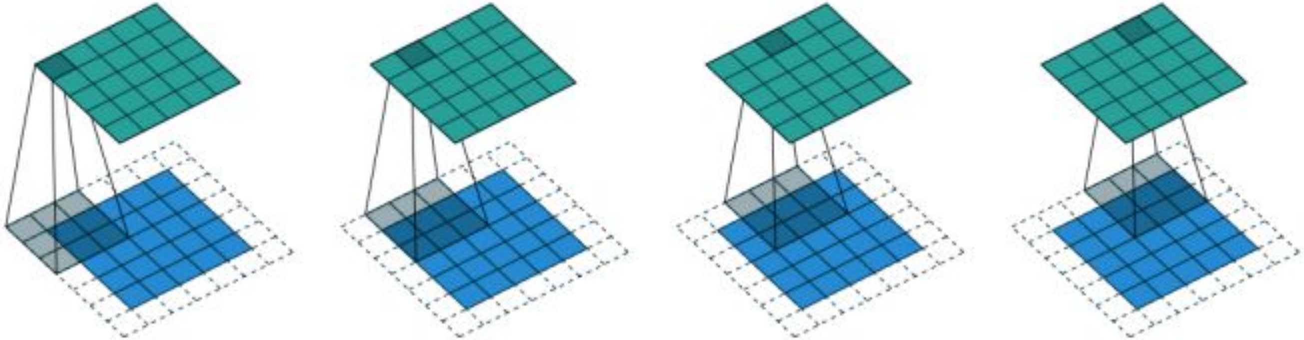


Transposed Convolution model to simulate spatial influence function

Using Transposed convolution to model the spatial influence function :

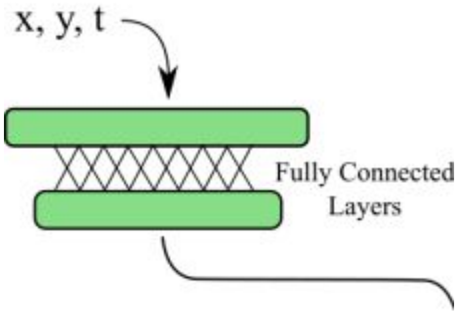


$$i_t(x, y, m) = \sum_{x_k : x-\Delta x}^{x+\Delta x} \sum_{y_k : y-\Delta y}^{y+\Delta y} z(x, y, x_k, y_k, m) \quad (5)$$



Multi-layers perceptron to estimate prior probability function

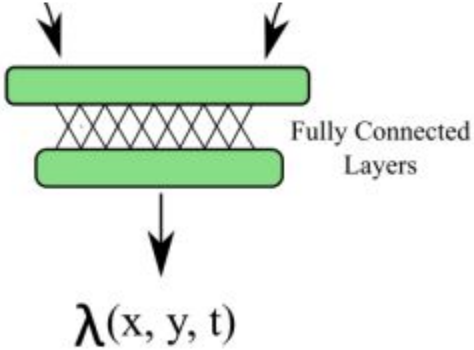
Use multi-layers perceptron model to estimate prior probability function.



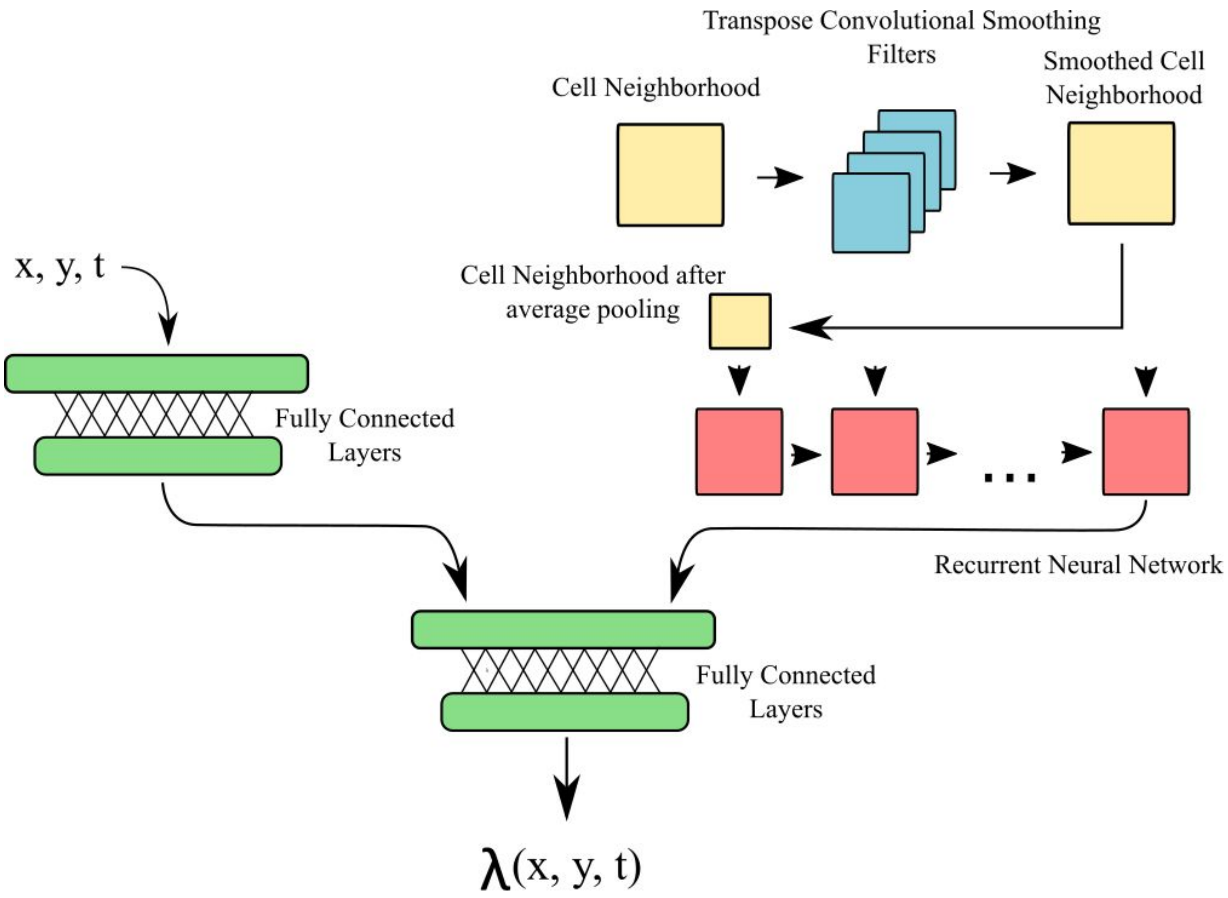
$$\mu(x, y)$$

Multi-layers perceptron to predict conditional intensity function

Use multi-layers perceptron model to estimate prior probability function.



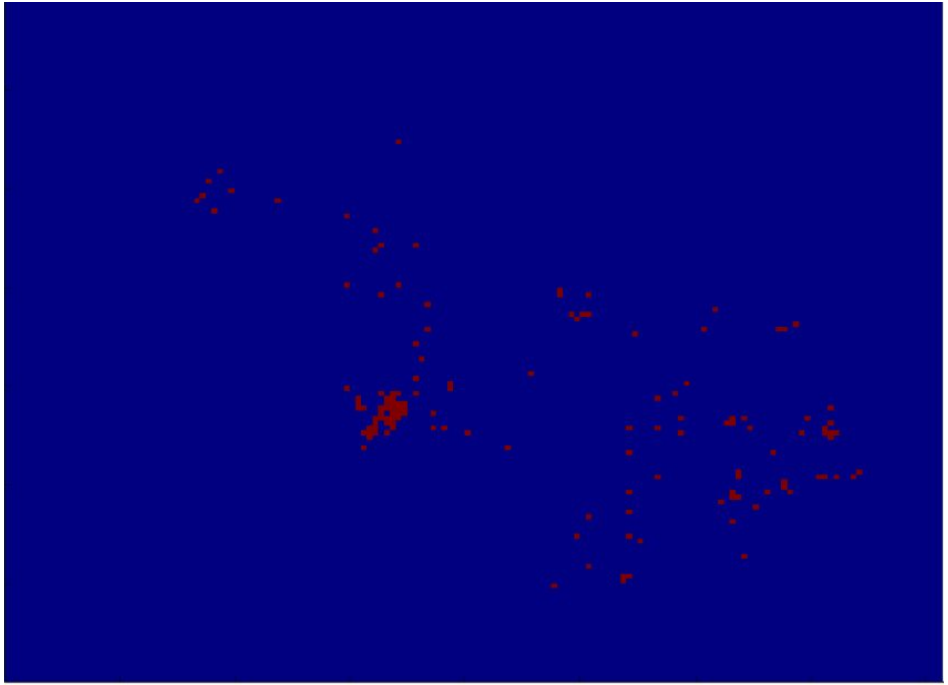
Architecture of TCLSTM



Experiments data construction

- 235 potential hot cells
- Total 1797 days data
- 5 class label (level 0 ~ 4)
- Total 36506 Samples ：

  number of lvl4 samples: 5790
  number of lvl3 samples: 7679
  number of lvl2 samples: 7679
  number of lvl1 samples: 7679
  number of lvl0 samples: 7679



- Training samples : 29202; Validation samples: 3652; Testing samples: 3652

Thank You!