東南大學
SOUTHEAST UNIVERSITY

Efficient Similar Region Search with Deep Metric Learning

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KDD '18: The 24th ACMSIGKDD International Conference on Knowledge Discovery & Data Mining

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2021.04.15

目录

01

问题背景

问题背景

data in city [1] ：

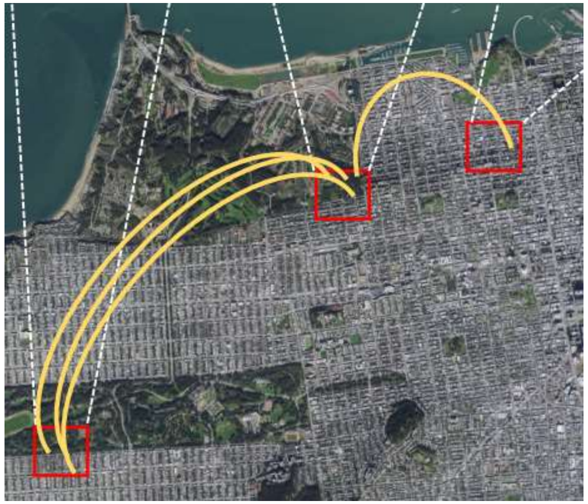
- **POI**
- **Road**
- **Mobility Flow**
- **……**

applications of urban computing：

- **POI recommendation**
- **Chain-store placement recommendation**
- **……**

POI data

Road data



Mobility Flow data[2]

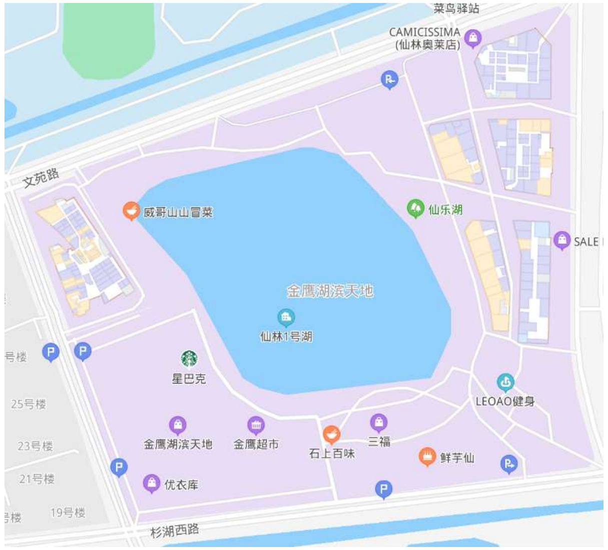
[1] Xu, Y., Shen, Y., Zhu, Y., & Yu, J. (2020). Ar2Net: An attentive neural approach for business location selection with satellite data and urban data. ACM Transactions on Knowledge Discovery from Data, 14(2). https://doi.org/10.1145/3372406

[2] Jenkins, P., Farag, A., Wang, S., & Li, Z. (2019). Unsupervised representation learning of spatial data via multimodal embedding. International Conference on Information and Knowledge Management, Proceedings, 1993–2002. https://doi.org/10.1145/3357384.3358001

问题背景

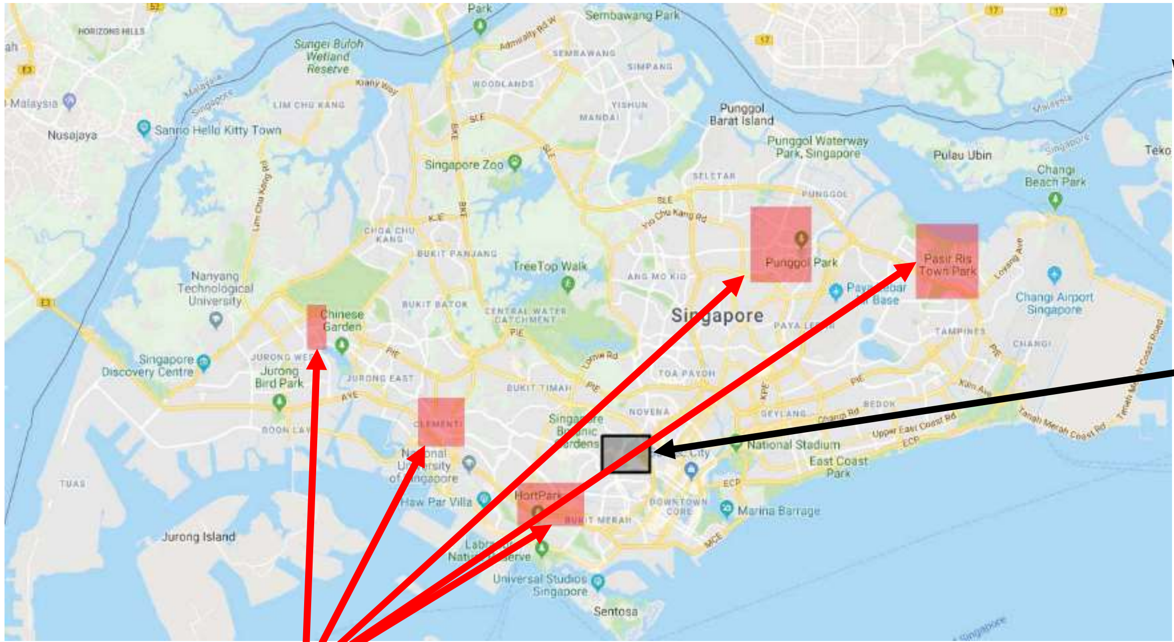
Usage of Similar Area Search：

- **Business site selection**
- **Improving location-based services. （POI recommendation）**
- **Explore unfamiliar cities or regions**
- **……**



问题背景

What is Similar Area Search：



geographical space P

query region R_q

a similarity metric sim(·)

retrieve a set of N regions as $\mathcal{R}$.

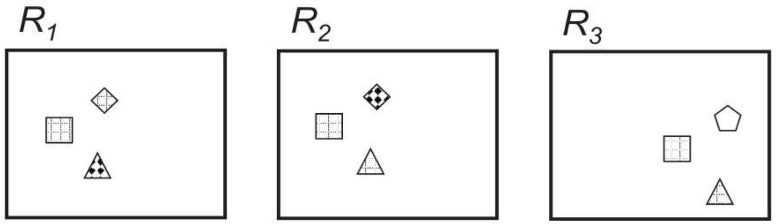
$$sim(R_q, R_i) \geq sim(R_q, R_j), \forall R_i \in \mathcal{R}, \forall R_j \notin \mathcal{R}.$$

问题背景

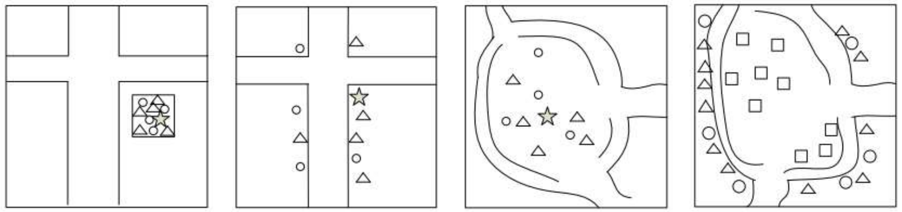
Challenges of Similar Area Search：

- **How to model region similarity**

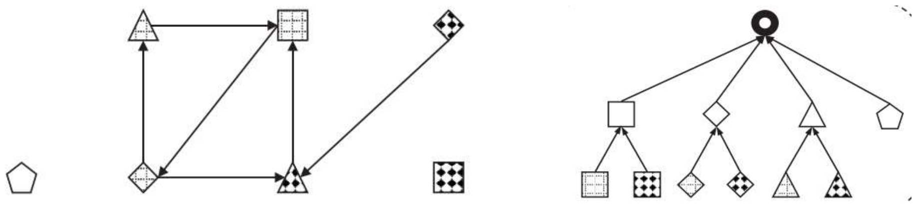
categories of POIs inside[1]



distribution of POIs inside [2]



relations of POIs/categories inside [1]



[1] Jin, X., Lee, D., Oh, B., Lee, K. H., Lee, S., & Chen, L. (2019). Learning region similarity over spatial knowledge graphs with hierarchical types and semantic relations. International Conference on Information and Knowledge Management, Proceedings, 669–678. https://doi.org/10.1145/3357384.3358008
[2] Sheng, C., Zheng, Y., Hsu, W., Lee, M. L., & Xie, X. (2010). Answering Top-k Similar Region Queries. In International Conference on Database Systems for Advanced Applications: Vol. 5981 LNCS (Issue PART 1, pp. 186–201). https://doi.org/10.1007/978-3-642-12026-8_16

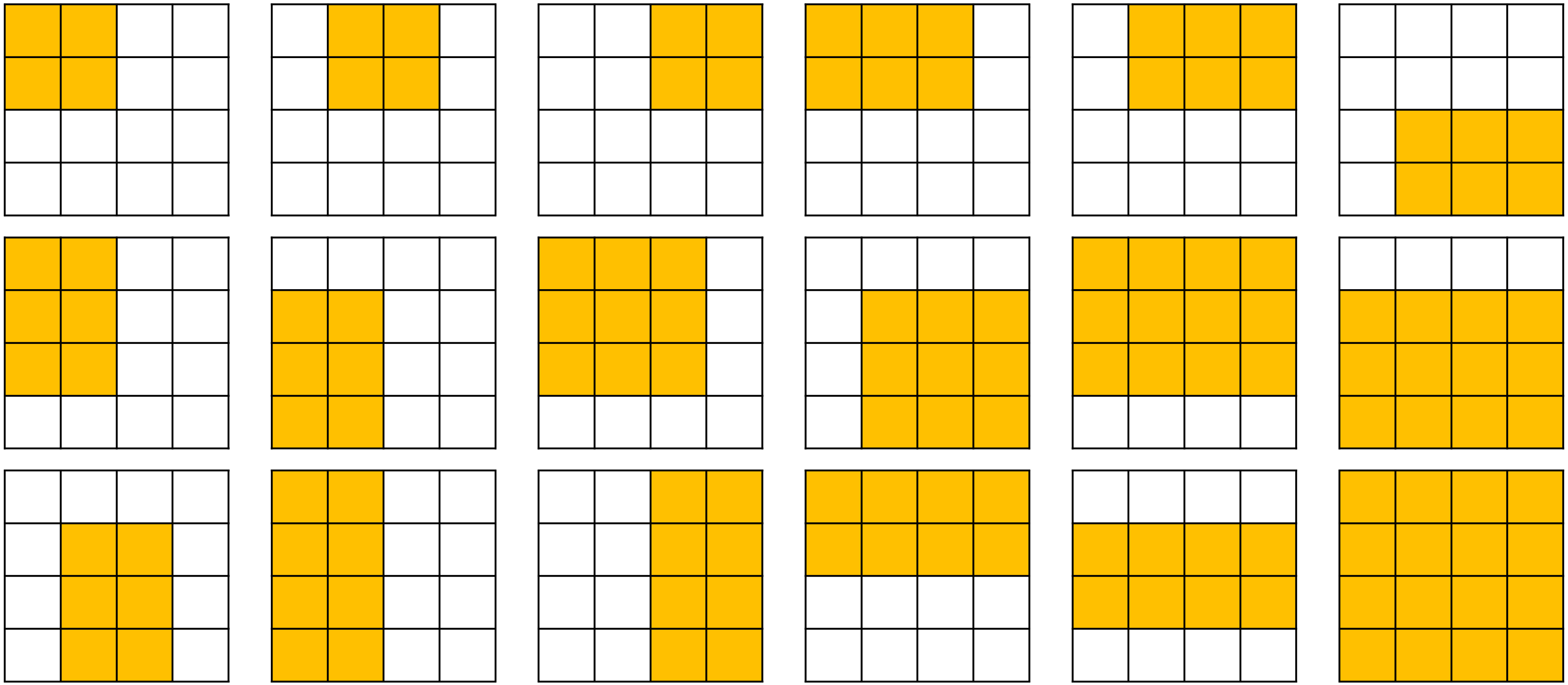
问题背景

Challenges of Similar Area Search：

- **Efficiency of similar region search**

Assume:
2 <= width <= 4
2 <= height <= 4

$$\mathcal{O}(n^2m^2)$$



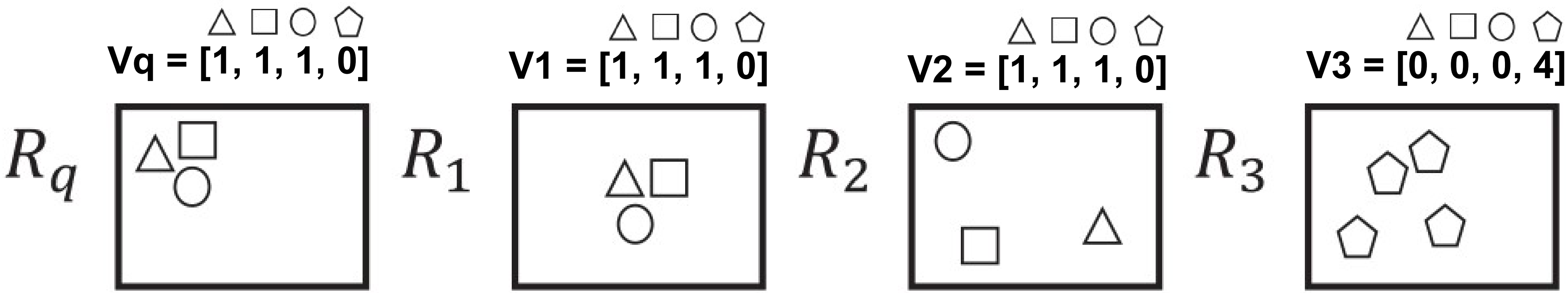
02

区域相似性

区域相似性

What affects the similarity：

- categories of POIs in the region

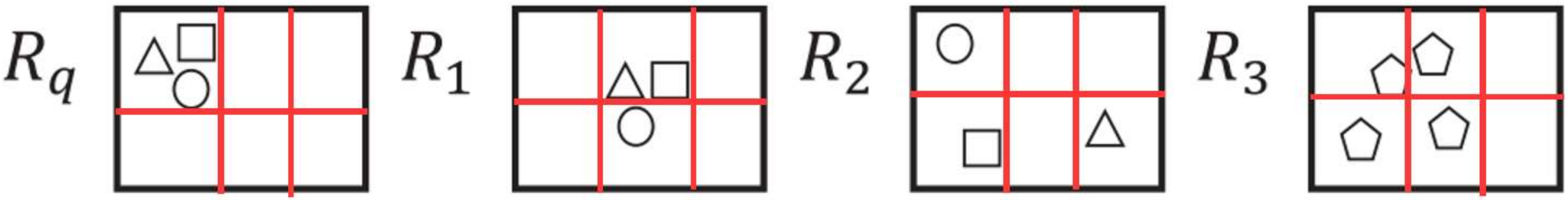


区域相似性

What affects the similarity：

- Relative locations of the objects in a region

△ □ ○ ⬠	△ □ ○ ⬠	△ □ ○ ⬠	△ □ ○ ⬠
Vq_11 = [1, 1, 1, 0]	V1_11 = [0, 0, 0, 0]	V2_11 = [0, 0, 1, 0]	V3_11 = [0, 0, 0, 1]
Vq_12 = [0, 0, 0, 0]	V1_12 = [1, 1, 0, 0]	V2_12 = [0, 0, 0, 0]	V3_12 = [0, 0, 0, 1]
Vq_13 = [0, 0, 0, 0]	V1_13 = [0, 0, 0, 0]	V2_13 = [0, 0, 0, 0]	V3_13 = [0, 0, 0, 0]
Vq_21 = [0, 0, 0, 0]	V1_21 = [0, 0, 0, 0]	V2_21 = [0, 1, 0, 0]	V3_21 = [0, 0, 0, 1]
Vq_22 = [0, 0, 0, 0]	V1_22 = [0, 0, 1, 0]	V2_22 = [0, 0, 0, 0]	V3_22 = [0, 0, 0, 1]
Vq_23 = [0, 0, 0, 0]	V1_23 = [0, 0, 0, 0]	V2_23 = [1, 0, 0, 0]	V3_23 = [0, 0, 0, 0]

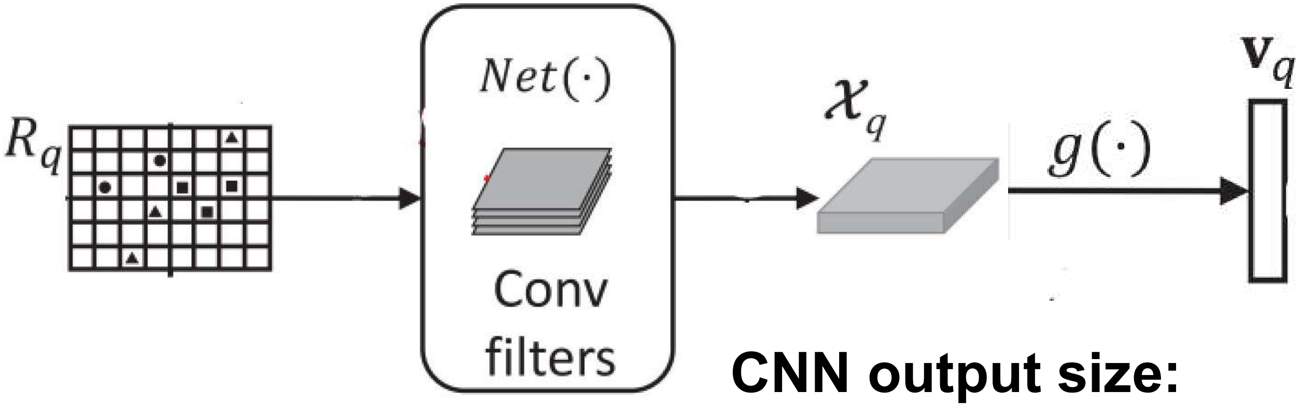


区域相似性

How to extract regional features：

- Relative locations of the objects in a region

Input size:
width1 * height1 * channel size



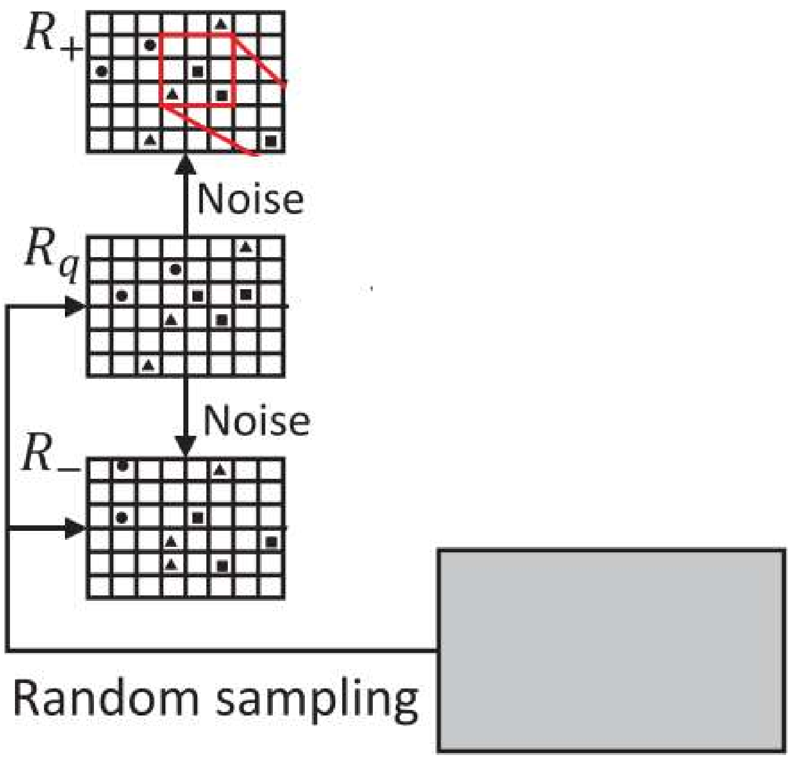
Vq size:
1* K

CNN output size:
width2 * heigh2 * K

区域相似性

How to get the data whether the regions are similar or not：

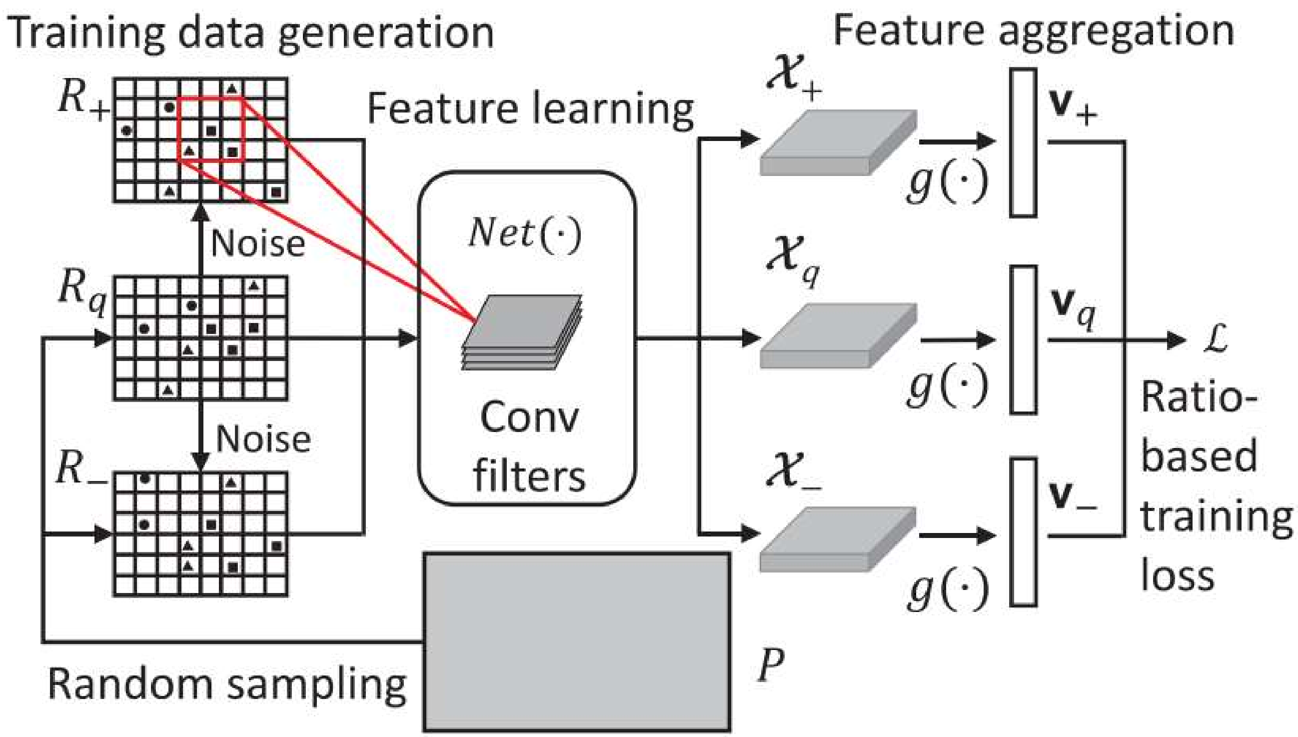
- **Hand-made**



- **randomly removing objects**
- **adding random objects at random locations**
- **randomly shifting the locations**

区域相似性

Framework：



$g(\cdot)$: global max-pooling

$$sim(R_1, R_2) = \frac{1}{1 + ||\mathbf{v}_1 - \mathbf{v}_2||_2}.$$

$$d_+ = ||Net(x_q) - Net(x_+)||_2$$

$$d_- = ||Net(x_q) - Net(x_-)||_2$$

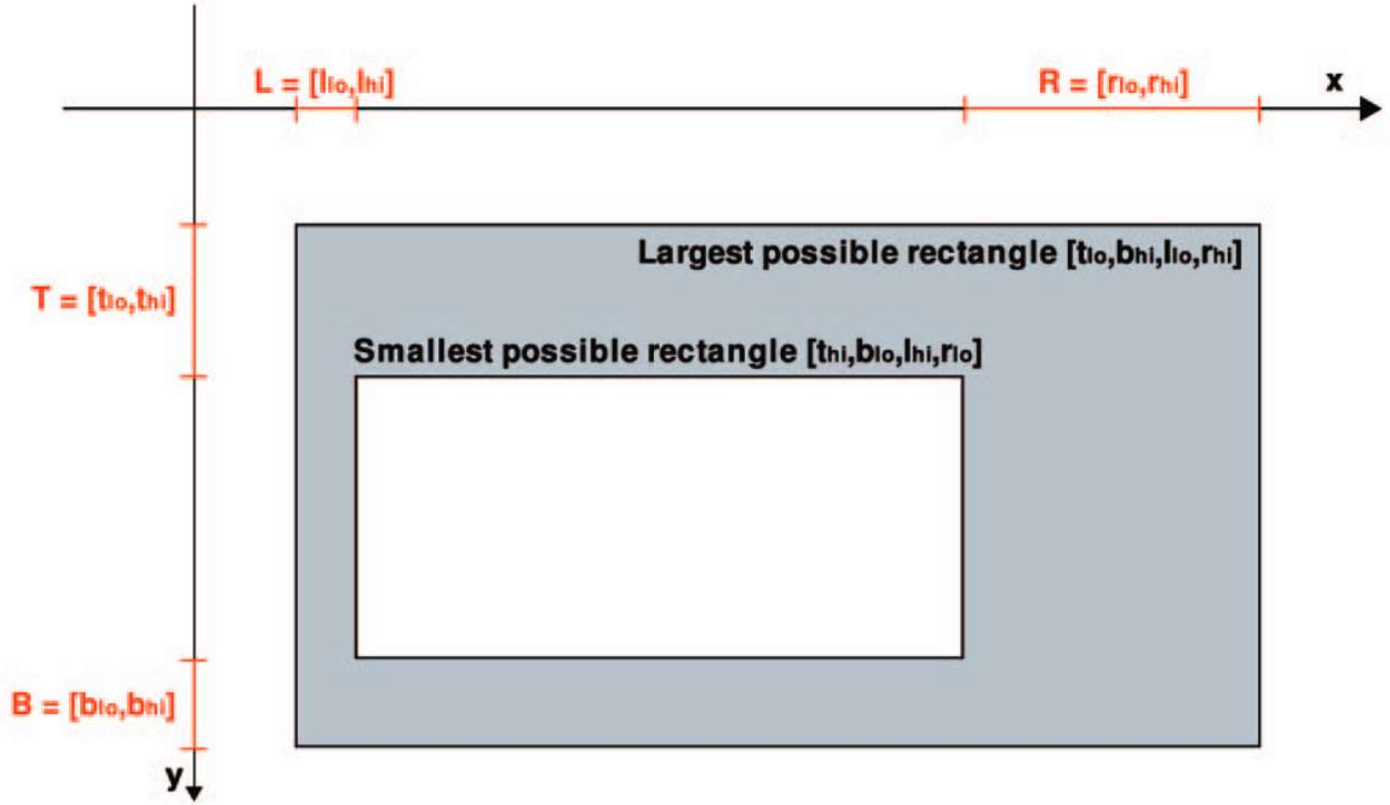
$$\mathcal{L} = \sum_{(x_q, x_+, x_-)} max\{0, d_+ - d_- + \delta\} + \lambda||Net(\cdot)||_2.$$

03

搜索算法

搜索算法

What are the candidate areas:



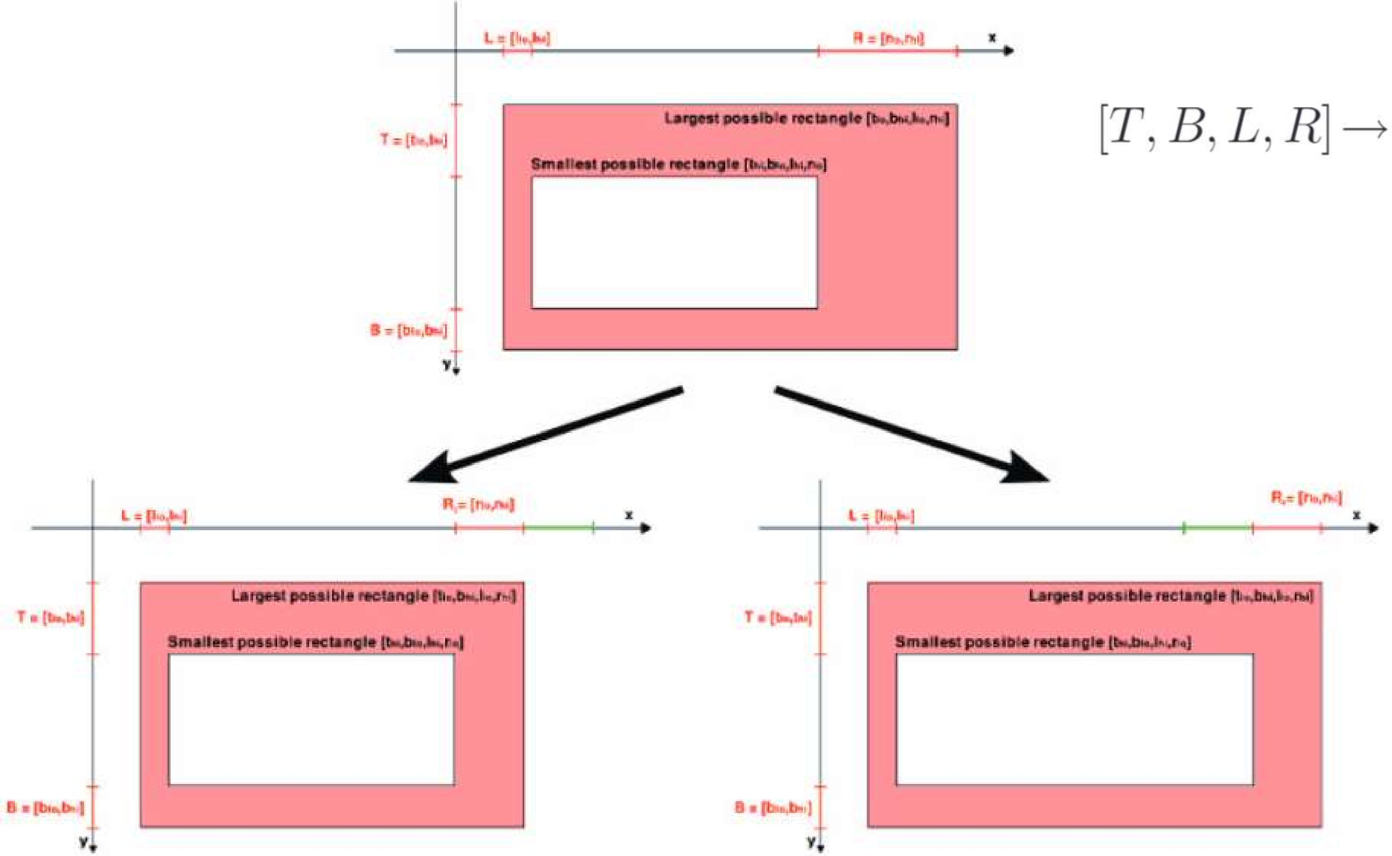
$$[T, B, L, R]$$

$$T = [t_{low}, t_{high}] \quad \text{etc.}$$

[1] Lampert, C. H., Blaschko, M. B., & Hofmann, T. (2009). Efficient subwindow search: A branch and bound framework for object localization. IEEE Transactions on Pattern Analysis and Machine Intelligence, 31(12), 2129–2142. https://doi.org/10.1109/TPAMI.2009.144

搜索算法

How to decompose search area:



$$[T, B, L, R] \rightarrow [T, B, L, R_1] \dot{\cup} [T, B, L, R_2]$$

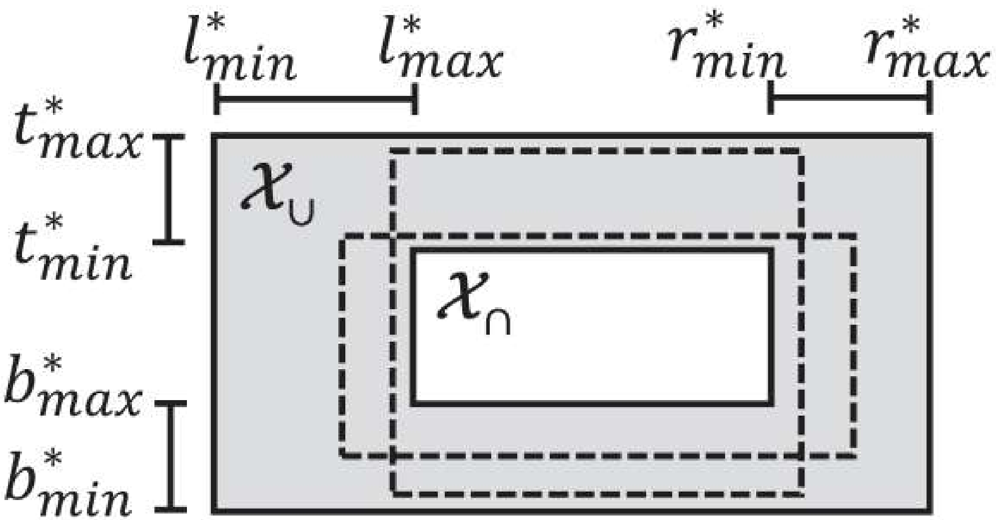
$$R_1 := \left[r_{lo}, \left\lfloor \frac{r_{lo}+r_{hi}}{2} \right\rfloor\right]$$

$$R_2 := \left[\left\lfloor \frac{r_{lo}+r_{hi}}{2} \right\rfloor + 1, r_{hi}\right]$$

[1] Lampert, C. H., Blaschko, M. B., & Hofmann, T. (2009). Efficient subwindow search: A branch and bound framework for object localization. IEEE Transactions on Pattern Analysis and Machine Intelligence, 31(12), 2129–2142. https://doi.org/10.1109/TPAMI.2009.144

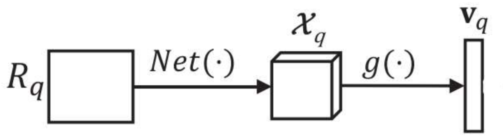
搜索算法

How to define the lower bound:



$$d = \sqrt{\sum_{k\in[1,K]}(\mathbf{v}_q[k]-\mathbf{v}_c[k])^2}$$

Recall: global pooling to represent region



global pooling is monotone increasing

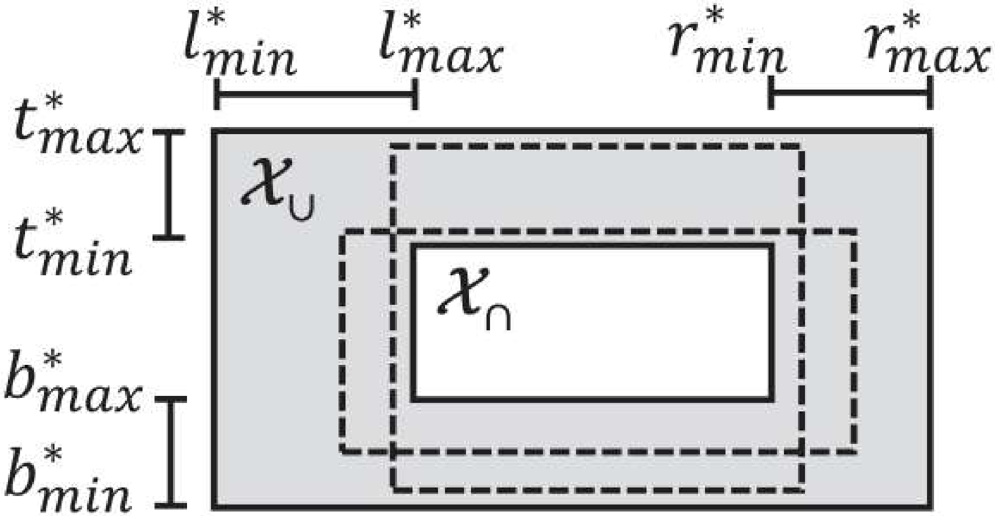
$$\mathcal{X}_\cap \subset \mathcal{X}_c \subset \mathcal{X}_\cup, \forall \mathcal{X}_c \in \mathcal{S}$$

$$g(\mathcal{X}_\cap) \leq g(\mathcal{X}_c) \leq g(\mathcal{X}_\cup)$$

i.e., $\mathbf{v}_\cap[k] \leq \mathbf{v}_c[k] \leq \mathbf{v}_\cup[k], \forall k \in [1, K]$

搜索算法

How to define the lower bound:



$$d = \sqrt{\sum_{k\in[1,K]}(\mathbf{v}_q[k]-\mathbf{v}_c[k])^2}$$

Given: $\mathcal{X}_\cap \subset \mathcal{X}_c \subset \mathcal{X}_\cup, \forall \mathcal{X}_c \in \mathcal{S}$.

$$\mathbf{v}_\cap[k] \le \mathbf{v}_c[k] \le \mathbf{v}_\cup[k], \forall k \in [1,K]$$

It can be deduced that:

(i) $(\mathbf{v}_q[k]-\mathbf{v}_c[k])^2 \ge (\mathbf{v}_q[k]-\mathbf{v}_\cap[k])^2$, if $\mathbf{v}_\cap[k] \ge \mathbf{v}_q[k]$.

(ii) $(\mathbf{v}_q[k]-\mathbf{v}_c[k])^2 \ge (\mathbf{v}_q[k]-\mathbf{v}_\cup[k])^2$, if $\mathbf{v}_\cup[k] \le \mathbf{v}_q[k]$.

Lower bound:

$\mathbf{v}_\cap[k] > \mathbf{v}_q[k]$ as k_1 $\quad$ $\mathbf{v}_\cup[k] < \mathbf{v}_q[k]$ as k_2

$$\hat{f}(\mathcal{S}|\mathcal{X}_q) = \sqrt{\sum_{k_1}(\mathbf{v}_q[k_1]-\mathbf{v}_\cap[k_1])^2 + \sum_{k_2}(\mathbf{v}_q[k_2]-\mathbf{v}_\cup[k_2])^2}$$

搜索算法

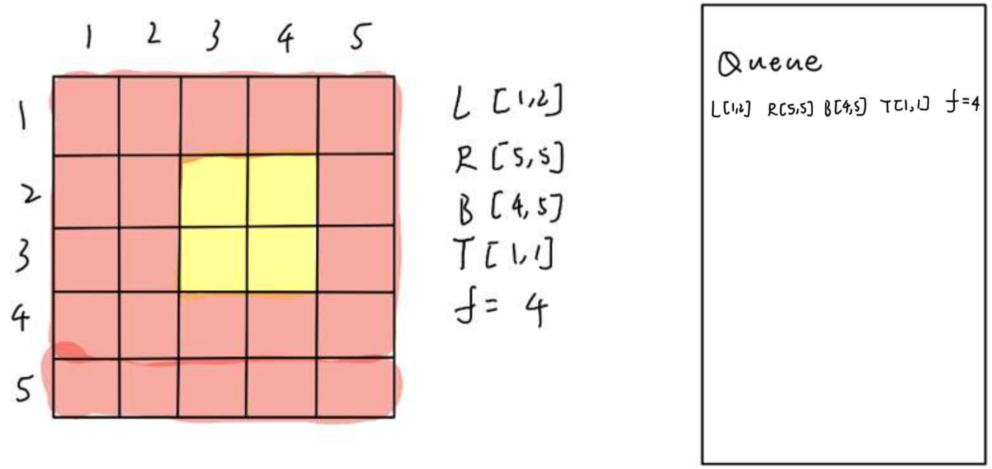
Search proceduce:

Algorithm 1: ExactSFRS

Input: Initial search space $\mathcal{S}_{\forall}$, query feature region $\mathcal{X}_q$, distance lower bound $\hat{f}(\cdot)$

Output: top-N similar feature regions $\mathcal{F}$

begin
  $\mathcal{F} \leftarrow \emptyset$; $Q \leftarrow \emptyset$;
  $Q.Insert(\mathcal{S}_{\forall})$;
  repeat
    repeat
      $\mathcal{S}' \leftarrow Q.RetrieveTop()$;
      split $\mathcal{S} \rightarrow \mathcal{S}_1 \cup \mathcal{S}_2$;
      $Q.Insert((\hat{f}(\mathcal{S}_1|\mathcal{X}_q), \mathcal{S}_1))$;
      $Q.Insert((\hat{f}(\mathcal{S}_2|\mathcal{X}_q), \mathcal{S}_2))$;
    until $|\mathcal{S}'| = 1$;
    $\mathcal{F} \leftarrow \mathcal{F} \cup \mathcal{S}'$;
  until $|\mathcal{F}| = N$;
end



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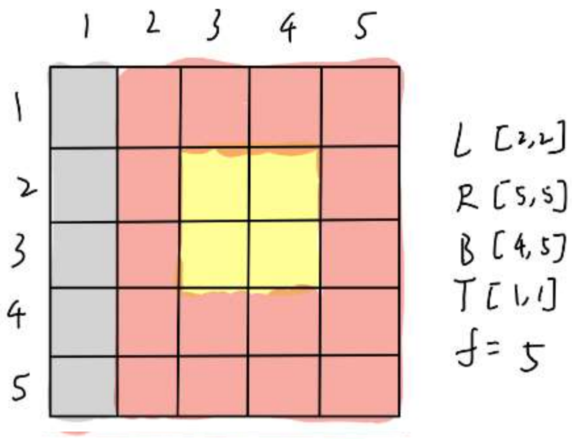
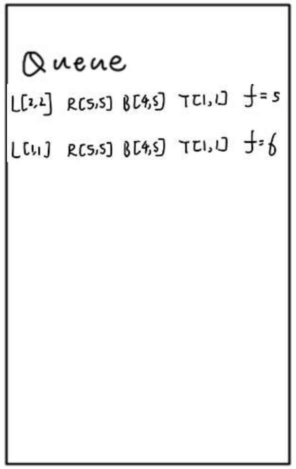
```
begin
    F ← ∅; Q ← ∅;
    Q.Insert(S_∀);
    repeat
        repeat
            S' ← Q.RetrieveTop() ;
            split S → S_1 ∪ S_2;
            Q.Insert((f̂(S_1|X_q), S_1)) ;
            Q.Insert((f̂(S_2|X_q), S_2)) ;
        until |S'| = 1;
        F ← F ∪ S';
    until |F| = N;
end
```





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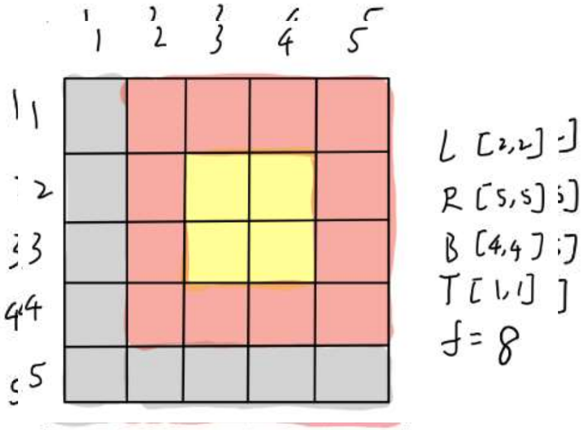

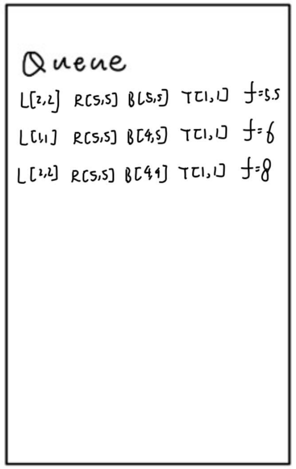

搜索算法

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  - **repeat**
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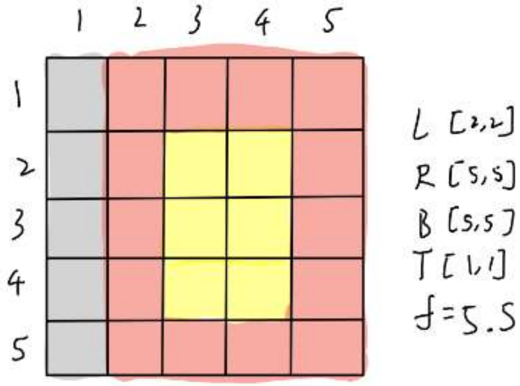
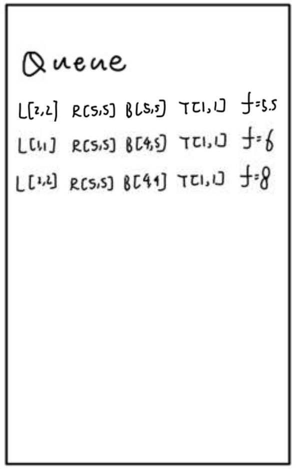
    - $Q.Insert((\hat{f}(\mathcal{S}_2|\mathcal{X}_q), \mathcal{S}_2))$;
  - **until** $|\mathcal{S}'| = 1$;
  - $\mathcal{F} \leftarrow \mathcal{F} \cup \mathcal{S}'$;
- **until** $|\mathcal{F}| = N$;

end





an area found!

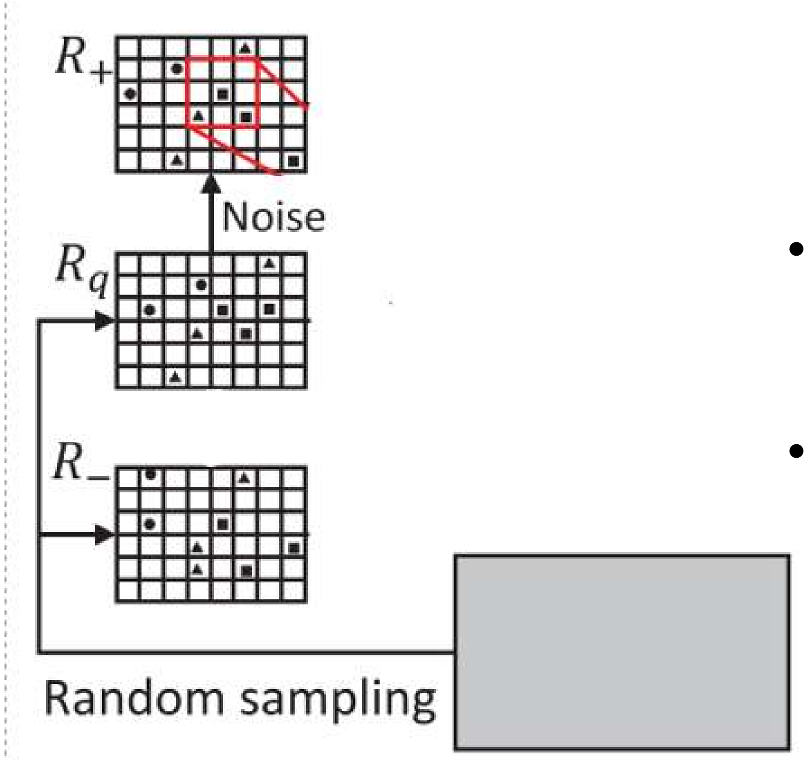
04

实验

实验

How to get the test data：

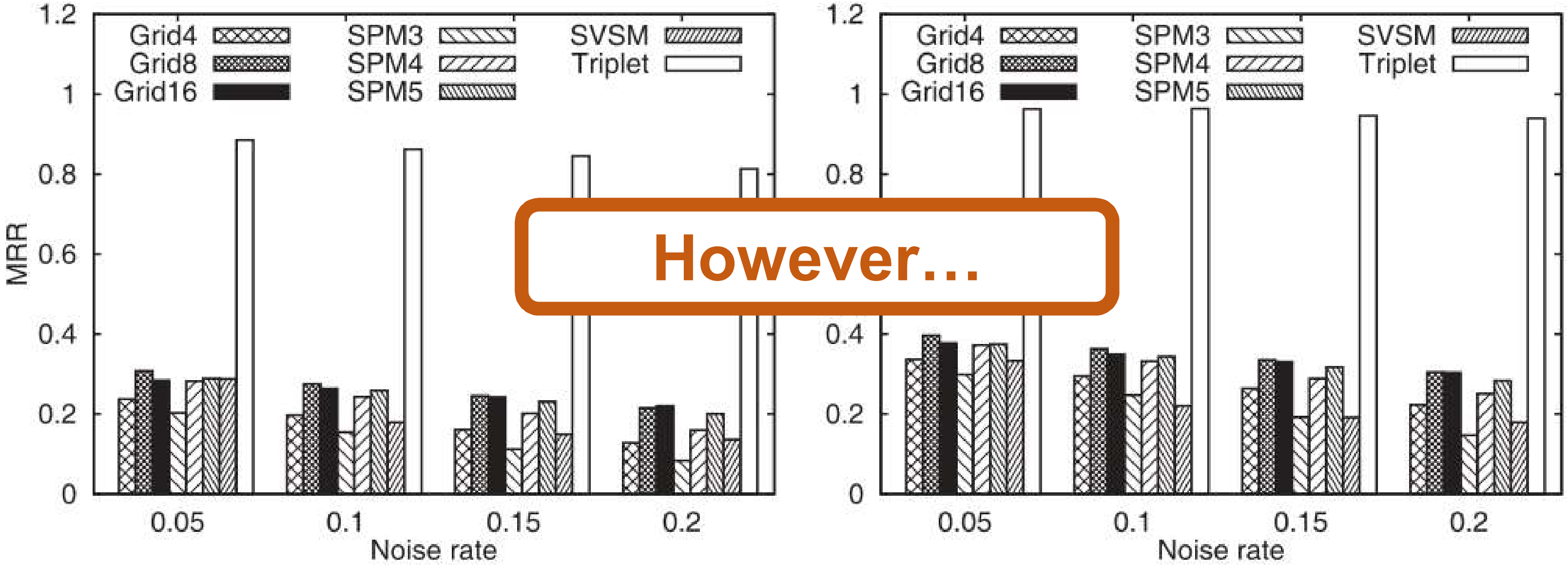
- **Also hand-made**



- **randomly sample 2000 regions that contains more than 50 objects as the test queries**
- **The height and width of a region vary from 640m to 3km**
- **candidate regions are constrained by 0.5wq ≤ wc ≤ 2wq and 0.5hq ≤ hc ≤ 2hq**

实验

Effectiveness：

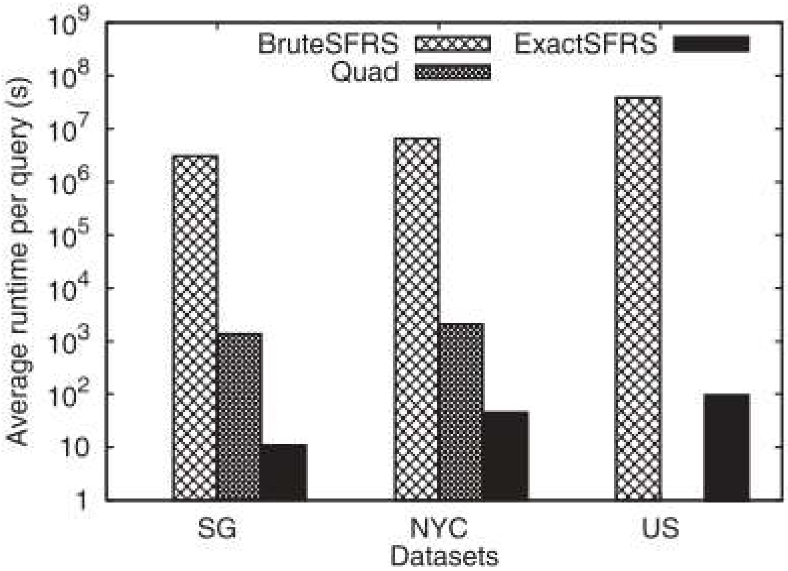


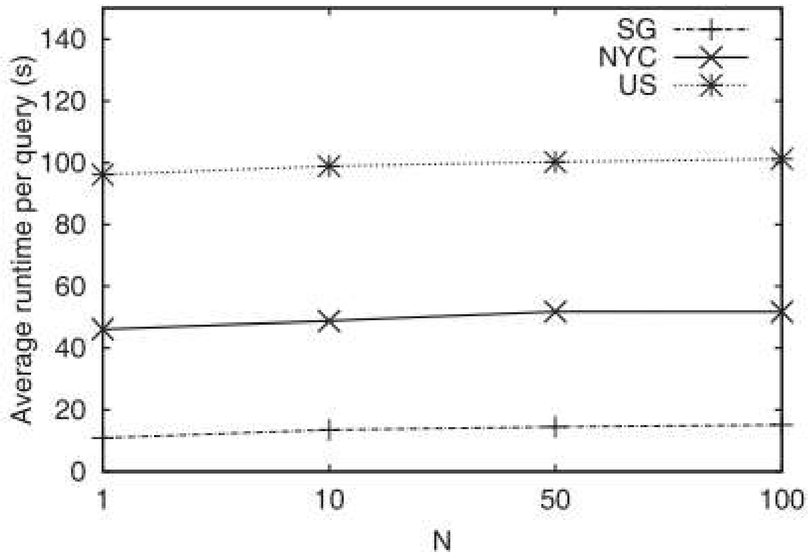
However…

(a) MRR-SG　　(b) HR@10-SG

实验

Efficiency:





05

讨论

还可以做点什么...区域相似性

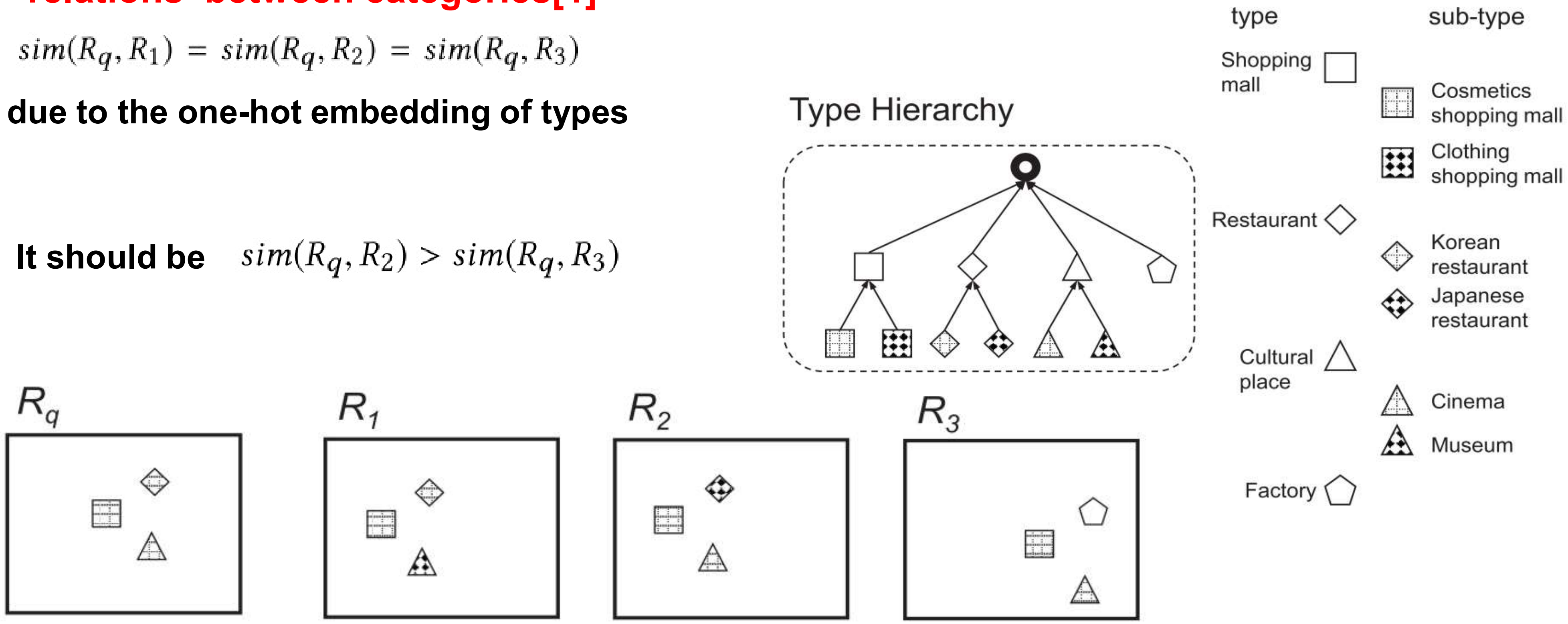
What else can be done：

- **relations between categories[1]**

$$sim(R_q, R_1) = sim(R_q, R_2) = sim(R_q, R_3)$$

due to the one-hot embedding of types

It should be $sim(R_q, R_2) > sim(R_q, R_3)$

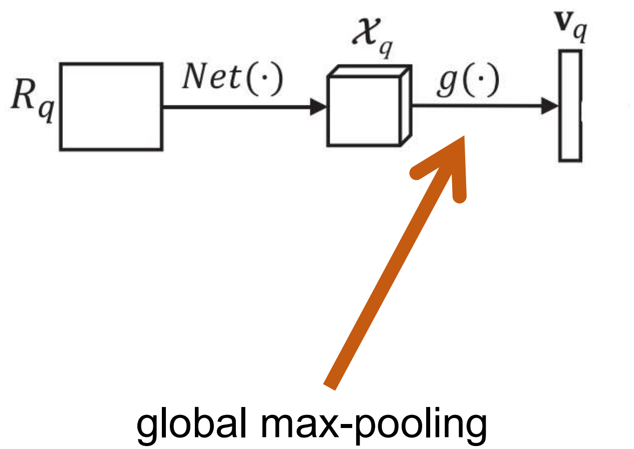


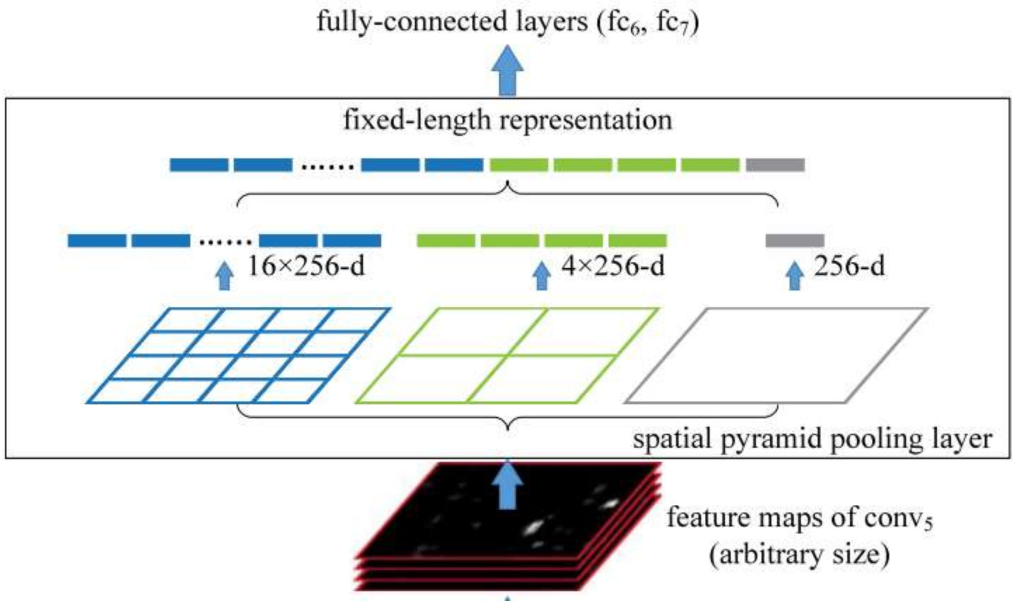
[1] Jin, X., Lee, D., Oh, B., Lee, K. H., Lee, S., & Chen, L. (2019). Learning region similarity over spatial knowledge graphs with hierarchical types and semantic relations. International Conference on Information and Knowledge Management, Proceedings, 669–678. https://doi.org/10.1145/3357384.3358008

还可以做点什么...区域相似性

What else can be done：

- **feature aggregation method within a grid**





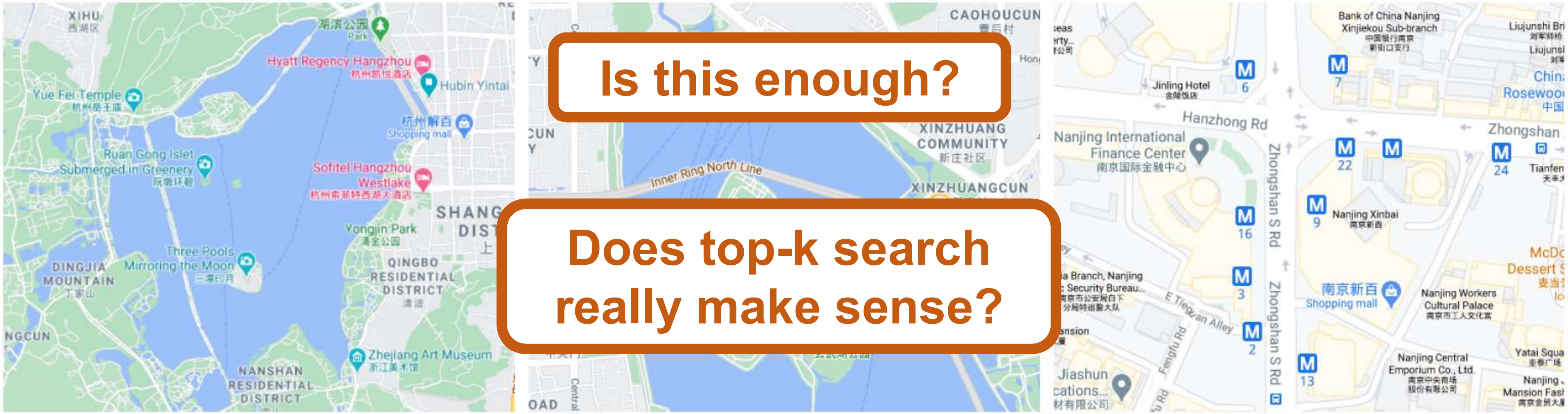
[1]

[1] He, K., Zhang, X., Ren, S., & Sun, J. (2015). Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 37(9), 1904–1916. https://doi.org/10.1109/TPAMI.2015.2389824

还可以做点什么...区域相似性

What else can be done：

- **Dynamic surroundings impact --- What kind of area do users really want ?**



(a) Hangzhou - West Lake (b) Nanjing - Xuanwuhu Park (c) Nanjing - XinJieKou

Is this enough?

Does top-k search really make sense?

[1] He, K., Zhang, X., Ren, S., & Sun, J. (2015). Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 37(9), 1904–1916. https://doi.org/10.1109/TPAMI.2015.2389824

谢谢大家

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1. Querying and Exploring Geospatial Data

1.1 Querying spatio-textual (geo-textual) data streams

Selected publications:

- SSTD: A Distributed System on Streaming Spatio-Textual Data, PVLDB 2020
- STAR: A Distributed Stream Warehouse System for Spatial Data. SIGMOD Conference 2020: 2761-2764 (Demo)
- Distributed Publish/Subscribe Query Processing on the Spatio-Textual Data Stream (ICDE 17)
- Diversity-aware top-k publish/subscribe on text stream (SIGMOD 15)
- Temporal spatial-keyword top-k publish/subscribe on geo-textual data stream (ICDE15 and demo in VLDB14)
- Boolean spatial-keyword publish/subscribe on geo-textual data stream (SIGMOD13 and demo in VLDB14)

1.2 Data exploration for spatial data: Region search & topic exploration

Selected publications:

- SURGE: Continuous Detection of Bursty Regions Over a Stream of Spatial Objects (TKDE19, ICDE18)
- Finding attribute-aware similar regions for data analysis (PVLDB 19)
- Efficient Similar Region Search with Deep Metric Learning (KDD 18)
- Efficient Selection of Geospatial Data on maps for Interactive Visualized Exploration (SIGMOD 18)
- Towards Best Region Search for Data Exploration (SIGMOD 2016)
- Topic Exploration in Spatio-Temporal Document Collections(SIGMOD 2016, VLDBJ19)

1.2 Spatial keyword queries

- On Spatial Pattern Matching (ICDE’17, VLDBJ’19)
- Answering the m-closest keywords query (SIGMOD 15)
- Search regions of interest for user exploration (VLDB14)
- Distributed spatial keyword querying on road networks (EDBT14)
- An evaluation of 12 geo-spatial indexes (VLDB13). Code available here.
- An overview paper on spatial-keyword querying (invited paper in ER)
- Route planning: answering queries like “a most popular route such that it passes by shopping malls, restaurant, and pı
- Efficient processing of several types of spatial keyword queries (VLDB09, PVLDB10, SIGMOD11a). Code for our SI TODS
- Efficient algorithms and cost models for reverse spatial-keyword k-nearest neighbor search (SIGMOD11b, TODS14)
- Efficient spatial keyword search in trajectory databases (unpublished paper)

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2. Spatial Data Mining and Spatial-temporal Data Mining

2.1 Intelligent transportation using trajectory data

Selected Publications:

- Online Anomalous Trajectory Detection with Deep Generative Sequence Modeling, ICDE2020
- Spatial Transition Learning on Road Networks with Deep Probabilistic Models, ICDE 2020
- Learning Travel Time Distributions with Deep Generative Model. (WWW 2019)

2.1 Data driven smart city applications

- Periodic-CRN: A Convolutional Recurrent Model for Crowd Density Prediction with Recurring Periodic Patterns (IJCAI, 2018)
- Efficient Similar Region Search with Deep Metric Learning (KDD 2018)

2.3 Spatial graph mining, POI recommendation & prediction

- Densely Connected User Community and Location Cluster Search in Location-Based Social Networks, SIGMOD2020
- Context-aware Deep Model for Joint Mobility and Time Prediction, WSDM 2020

4. Recommendation, POI recommendation and User Behaviour Modeling

4.1 Recommendation and group recommendation

Selected publications:

- HyperML: A Boosting Metric Learning Approach in Hyperbolic Space for Recommender Systems. WSDM 2020 (**Best paper award runner-up**)
- Global Context Enhanced Graph Nerual Networks for Session-based Recommendation, SIGIR 2020
- Interact and Decide: Medley of Sub-Attention Networks for Effective Group Recommendation (SIGIR 19)
- Group Recommendation based on topic models(KDD14)

4.2 POI recommendation

- HME: A Hyperbolic Metric Embedding Approach for Next-POI Recommendation, SIGIR 2020
- A new POI recommentdation approach, which performs better than previous approaches in experiments (SIGIR 2015)
- SAR: A sentiment-aspect-region model for user preference analysis and POI/user recommendation. The model provides explanations for recommendation results. (ICDE 2015)
- A general graph model for recommendation in heterogeneous networks and its applications in event-based social networks (ICDE 2015)
- Diversity-aware POI recommendation (AAAI 2015)
- Time-aware POI recommendation (SIGIR13, CIKM14). Datasets available here
- Mining significant semantic locations from user generated GPS data for recommendation (PVLDB10)

4.3 User behaviour modeling

- W4: Discovering spatio-temporal topics for individual users and its various applications, e.g., requirement-aware POI recommendation (KDD13, TOIS15). Datasets available here