

Efficient Image Retrieval via Decoupling Diffusion into Online and Offline Processing

Fan Yang^{1,2}, Ryota Hinami^{1,2}, Yusuke Matsui¹, Steven Ly^{2,3}, Shin'ichi Satoh^{2,1}

¹The University of Tokyo, Japan

²National Institute of Informatics, Japan

³University of Southern California, USA





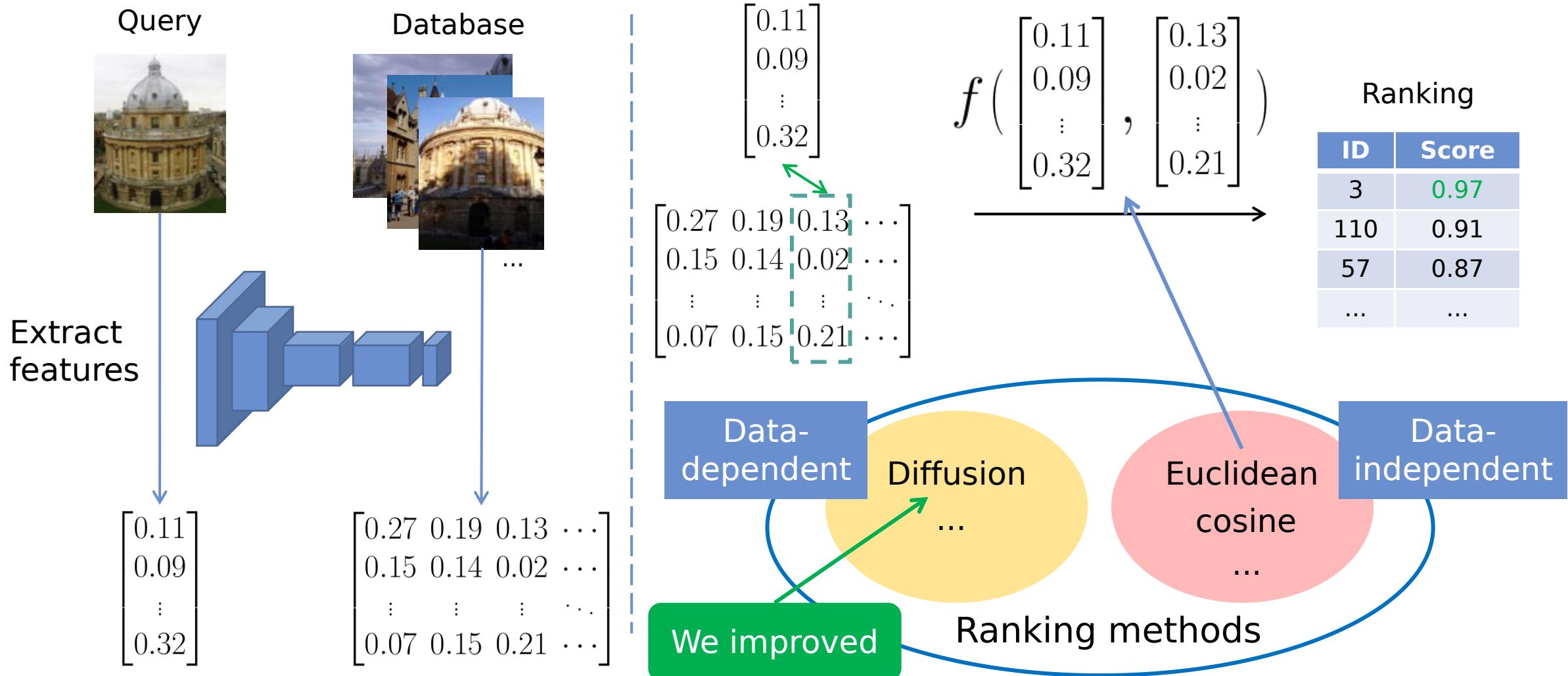
Introduction to Diffusion

Mainly follows Donoser et al. [CVPR2013] and Iscen et al. [CVPR2017]

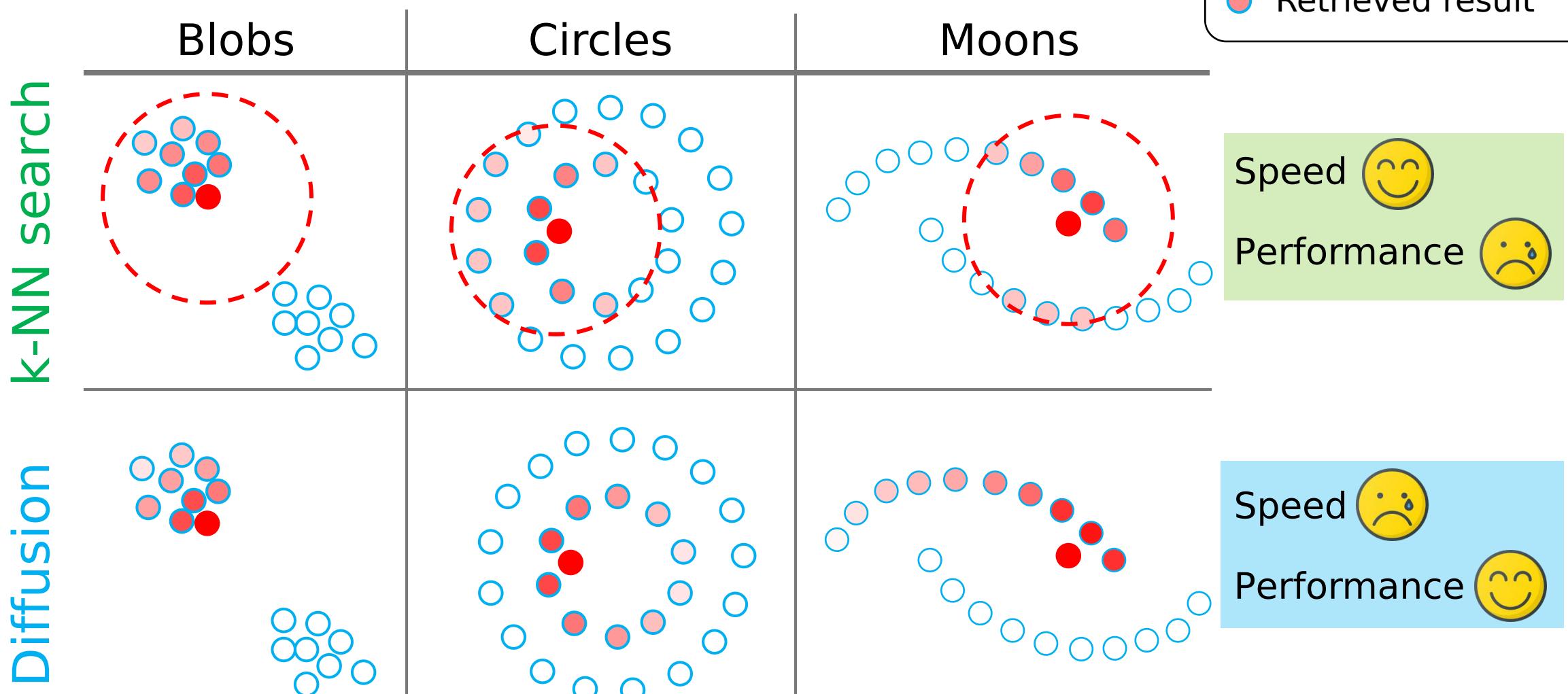
Diffusion processes for retrieval revisited, Donoser et al., CVPR 2013

Efficient diffusion on region manifolds: Recovering small objects with compact cnn representations,
Iscen et al., CVPR 2017

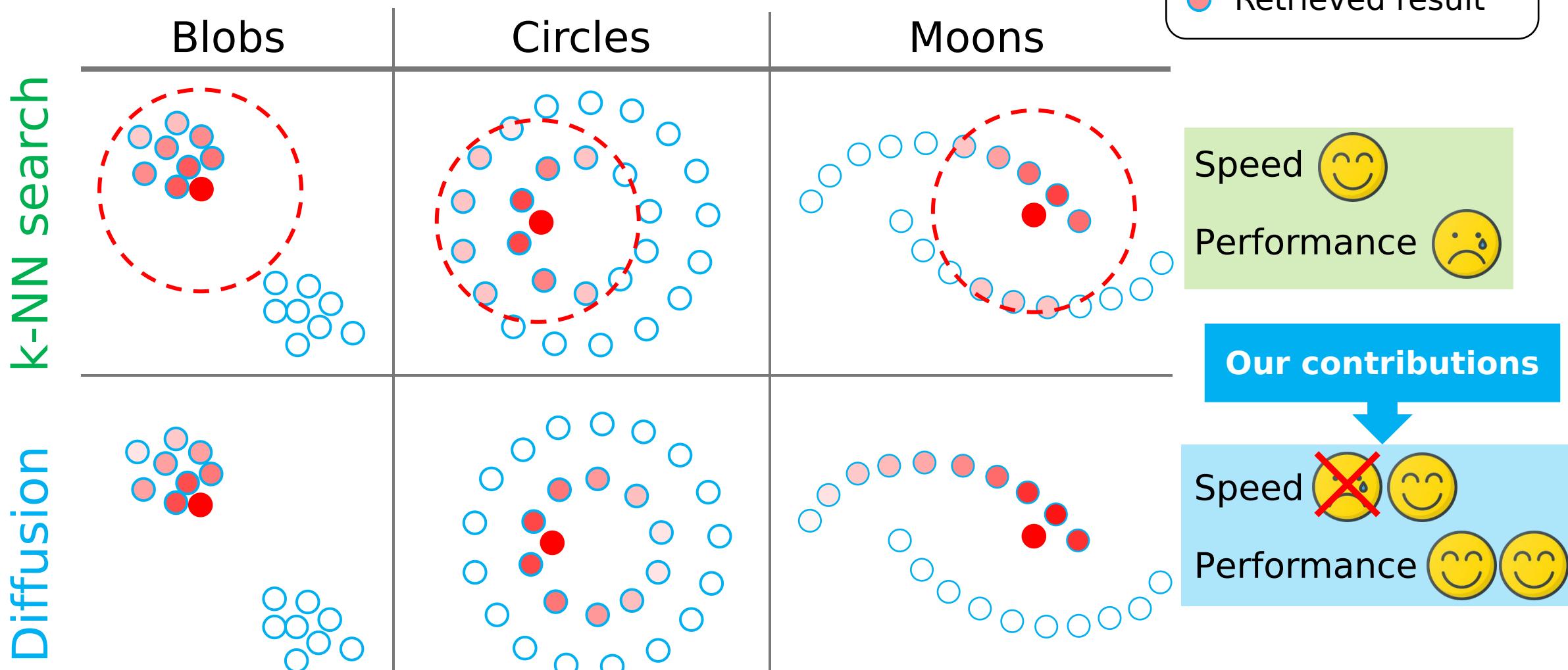
Image Retrieval



K-NN vs. Diffusion

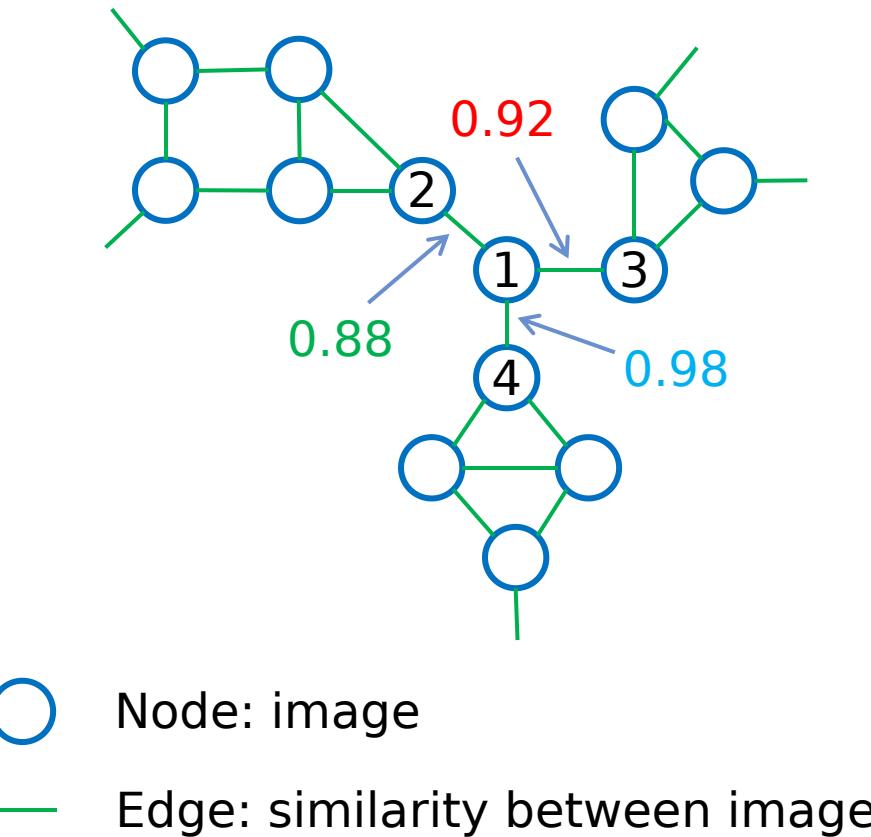


K-NN vs. Diffusion



Preliminaries of Diffusion

- Graph construction



- Step1: Extract features of images
- Step2: Perform k-NN search, using cosine similarity as the metric
e.g.

query: ①

neighbors: ② ③ ④

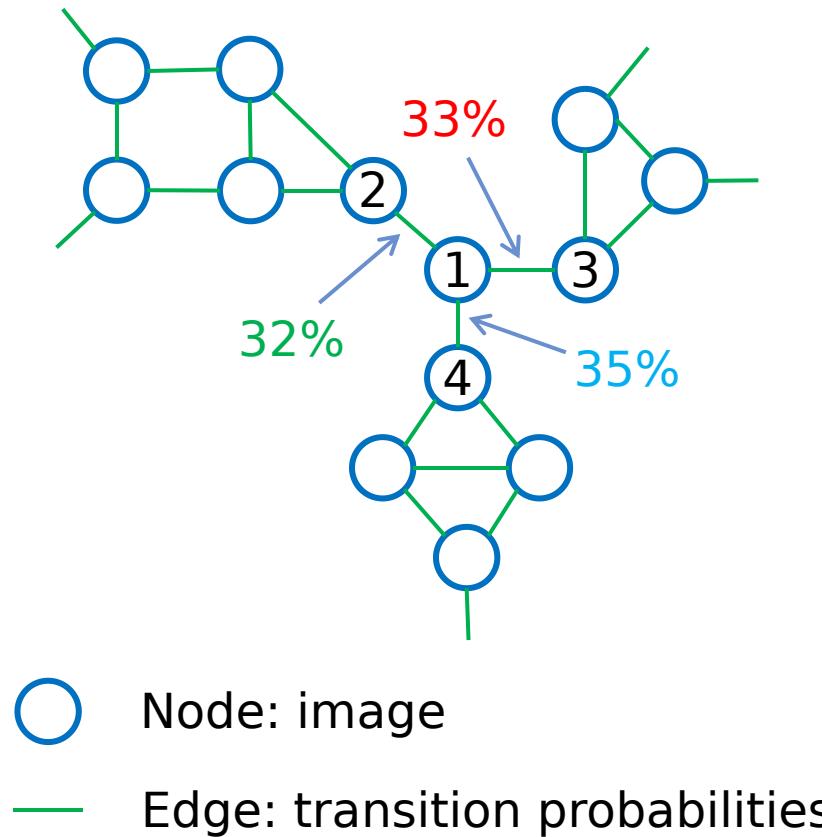
similarities: ①-② 0.88, ①-③ 0.92, ①-④ 0.98

$$\text{affinity matrix } \mathbf{A} = \begin{bmatrix} 0 & 0.88 & 0.92 & 0.98 & \dots \\ 0.88 & 0 & 0 & 0 & \dots \\ 0.92 & 0 & 0 & 0 & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

- Step3: Construct graph with k-NN search results

Preliminaries of Diffusion

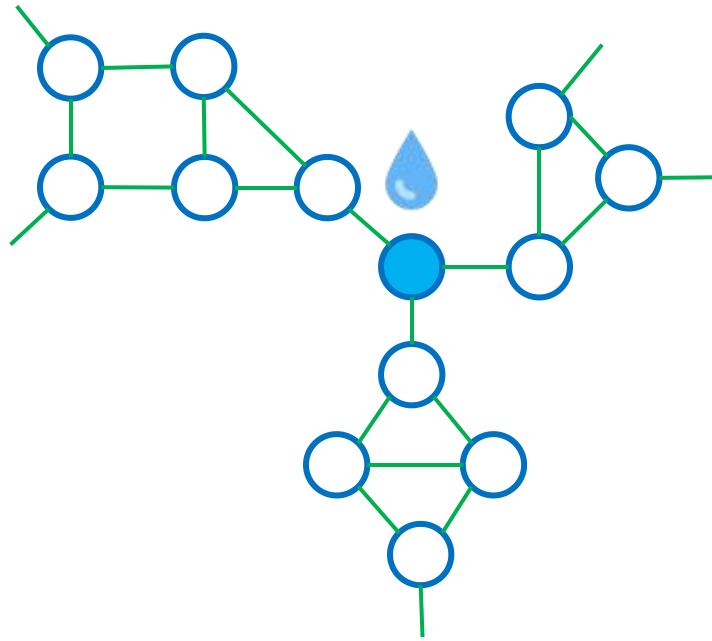
- Graph normalization



- Normalize similarities to transition probabilities:
e.g. $[0.88, 0.92, 0.98] \rightarrow [32\%, 33\%, 35\%]$
 - Popular choices of normalization
 - $S = D^{-1}A$
 - $S = D^{-1/2}AD^{-1/2}$
- transition matrix / stochastic matrix degree matrix
- $$D_{ii} = \sum_{j=0}^n A_{ij}$$

Preliminaries of Diffusion

- Random walk



Node: image

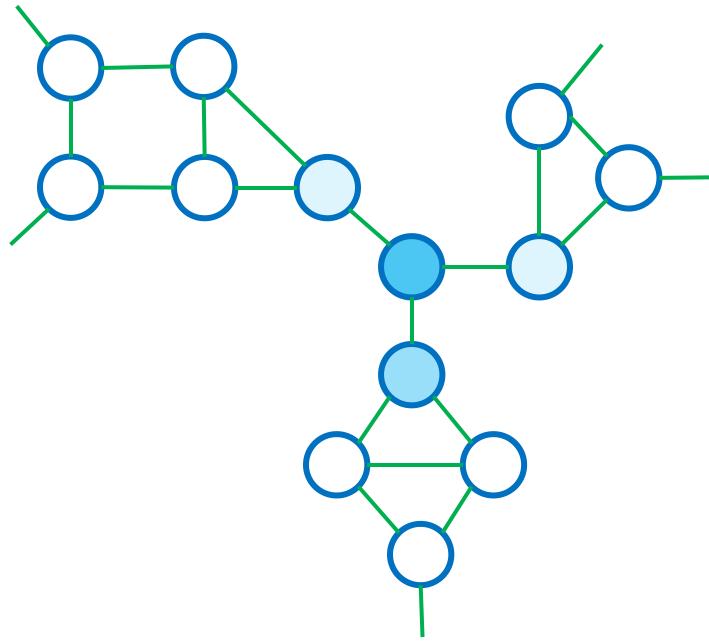


Edge: transition probabilities

- Start from a single node (place a droplet of ink onto the node)

Preliminaries of Diffusion

- Random walk



Node: image

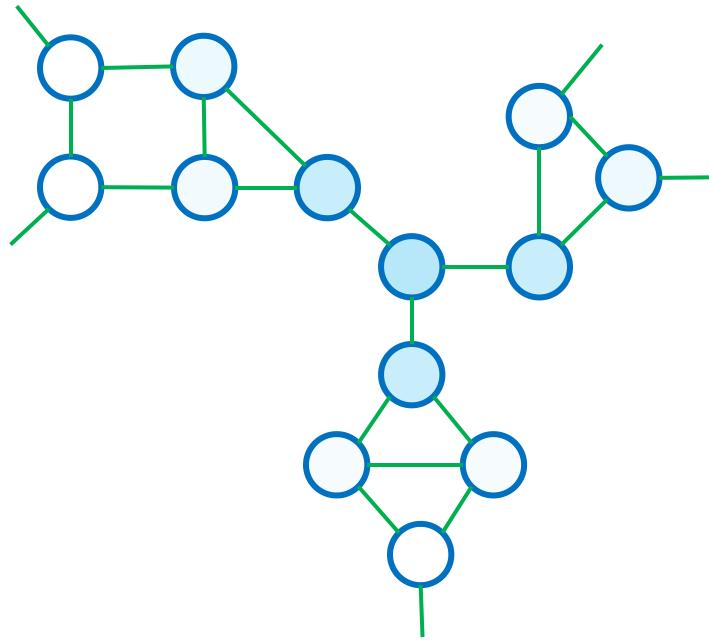


Edge: transition probabilities

- Start from a single node (place a droplet of ink onto the node)
- Random transition to other nodes

Preliminaries of Diffusion

- Random walk



Node: image

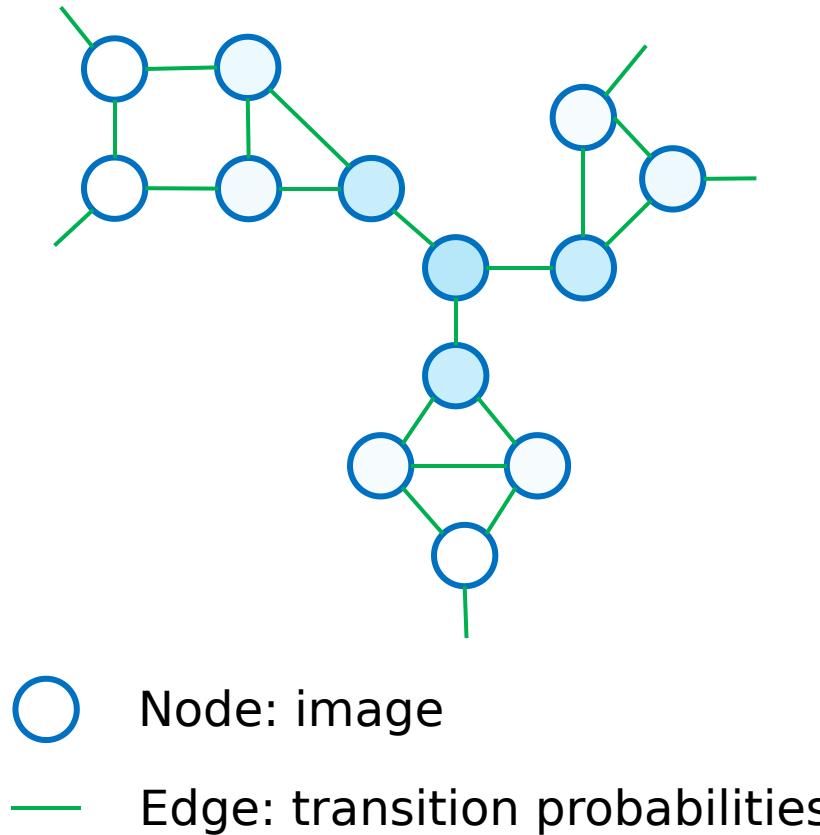


Edge: transition probabilities

- Start from a single node (place a droplet of ink onto the node)
- Random transition to other nodes
- Converge to a stable state

Preliminaries of Diffusion

- Random walk



- Start from a single node (place a droplet of ink onto the node)
- Random transition to other nodes
- Converge to a stable state
- Obtain ranking scores (amount of ink on each node)

ID	Score
1	0.45
4	0.23
3	0.17
2	0.11
...	...

$$\longrightarrow \mathbf{f}^* = [0.45, 0.11, 0.17, 0.23, \dots]^T$$

score vector

Preliminaries of Diffusion

- Random walk step

when $\alpha = 0.99$

$$\mathbf{f}^{t+1} = \underbrace{\alpha \mathbf{S} \mathbf{f}^t}_{\text{99% probability to transition}} + \underbrace{(1 - \alpha) \mathbf{f}^0}_{\text{1% probability to restart}}, \mathbf{f}^0 = [1, 0, 0, \dots]^\top$$

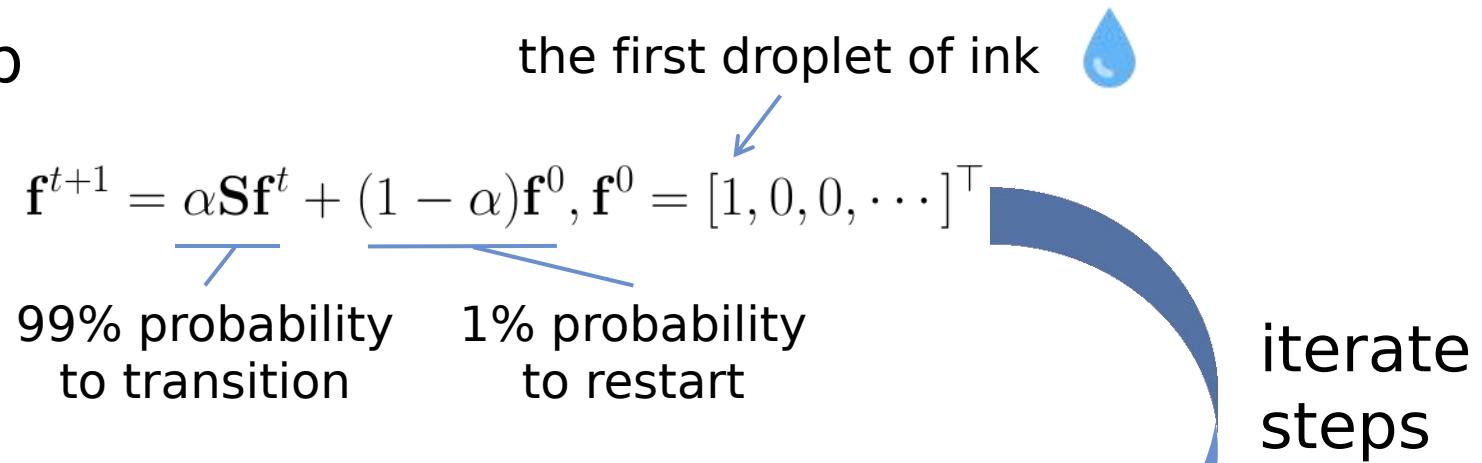
the first droplet of ink



Preliminaries of Diffusion

- Random walk step

when $\alpha = 0.99$



- Closed-form solution

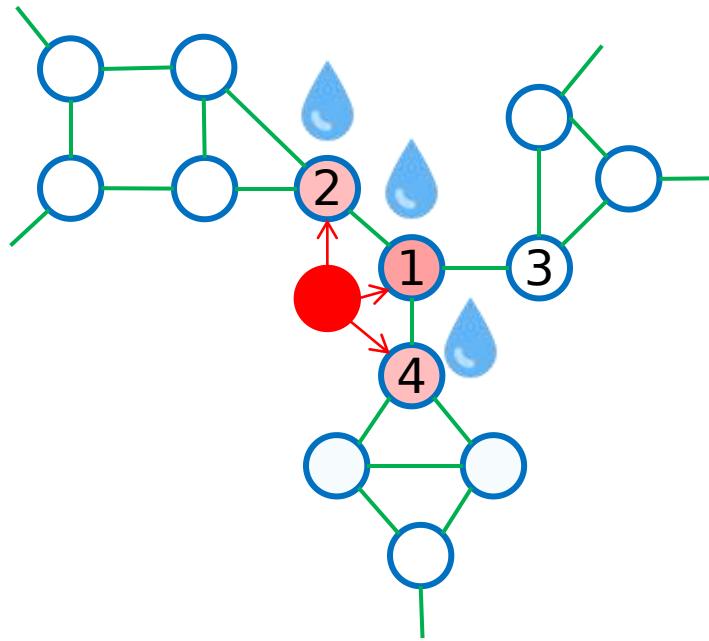
$$\mathbf{f}^* = (1 - \alpha)(\mathbf{I} - \alpha \mathbf{S})^{-1} \mathbf{f}^0$$

score vector Laplacian matrix $\mathcal{L}_\alpha = \mathbf{I} - \alpha \mathbf{S}$

$$\mathbf{f}^* \propto (\mathbf{I} - \alpha \mathbf{S})^{-1} \mathbf{f}^0 \rightarrow \boxed{\mathcal{L}_\alpha \mathbf{f}^* \propto \mathbf{f}^0} \rightarrow \text{solve } \mathbf{Ax} = \mathbf{b}$$

Preliminaries of Diffusion

- Handling unseen queries



- Images in database
- A query image

- Decompose transition/stochastic matrix

$$\mathbf{S} = \begin{bmatrix} \mathbf{S}_{qq} & \mathbf{S}_{qd} \\ \mathbf{S}_{dq} & \mathbf{S}_{dd} \end{bmatrix}$$

- Closed-form solution for any new queries

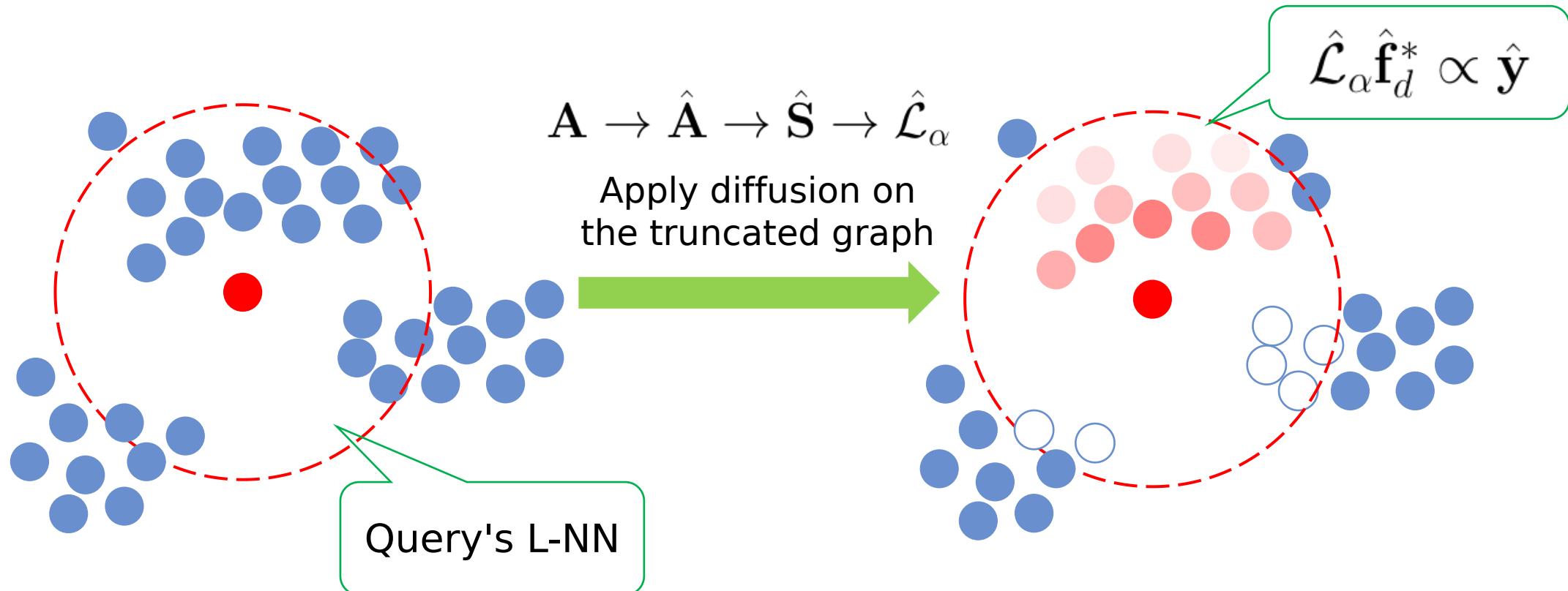
$$(\mathbf{I} - \alpha \mathbf{S}_{dd}) \mathbf{f}_d^* \propto \mathbf{y}, \mathbf{y} = \mathbf{S}_{dq} \mathbf{f}_q^0$$

$$[0.97, 0.88, 0, 0.79, 0, 0, \dots]^T$$

query's NN: 1 2 4

Preliminaries of Diffusion

- Truncation
 - An approach to scale up diffusion for large datasets

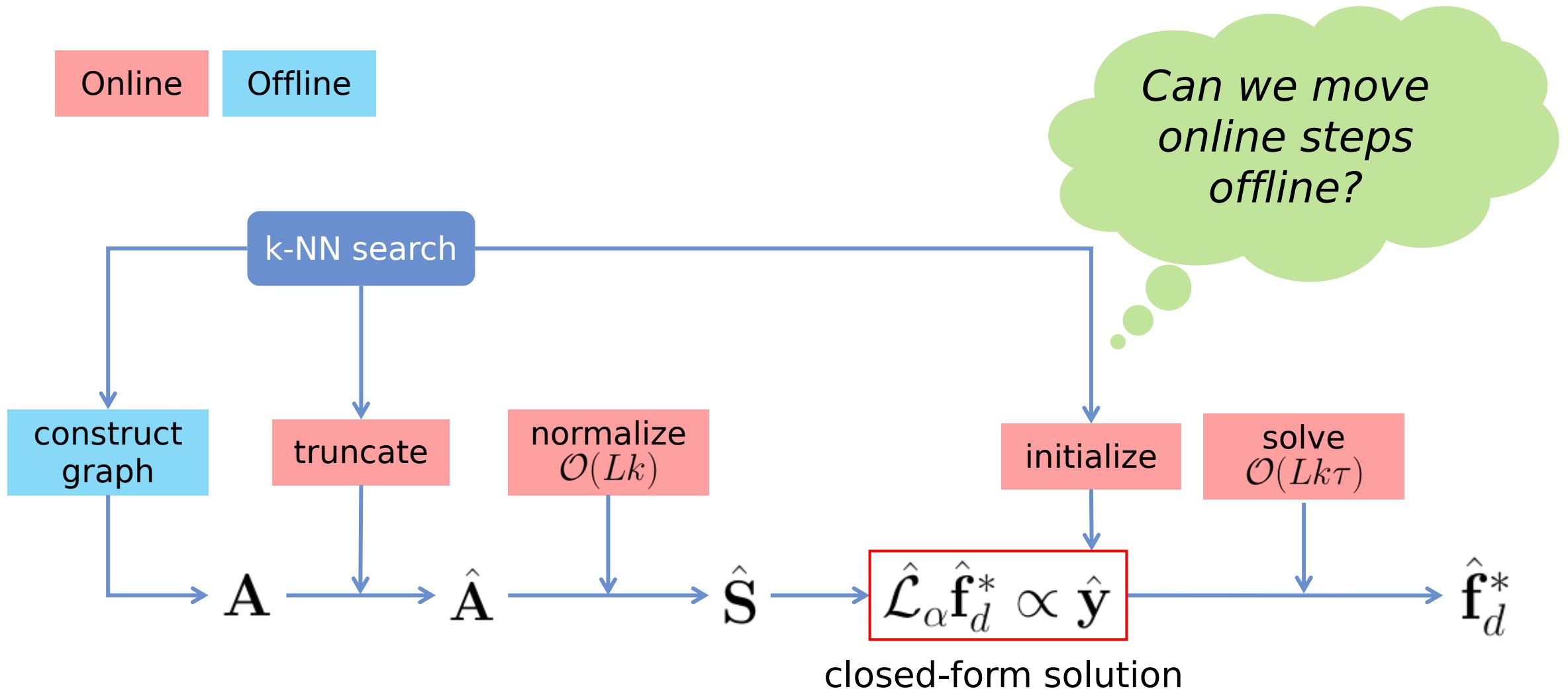




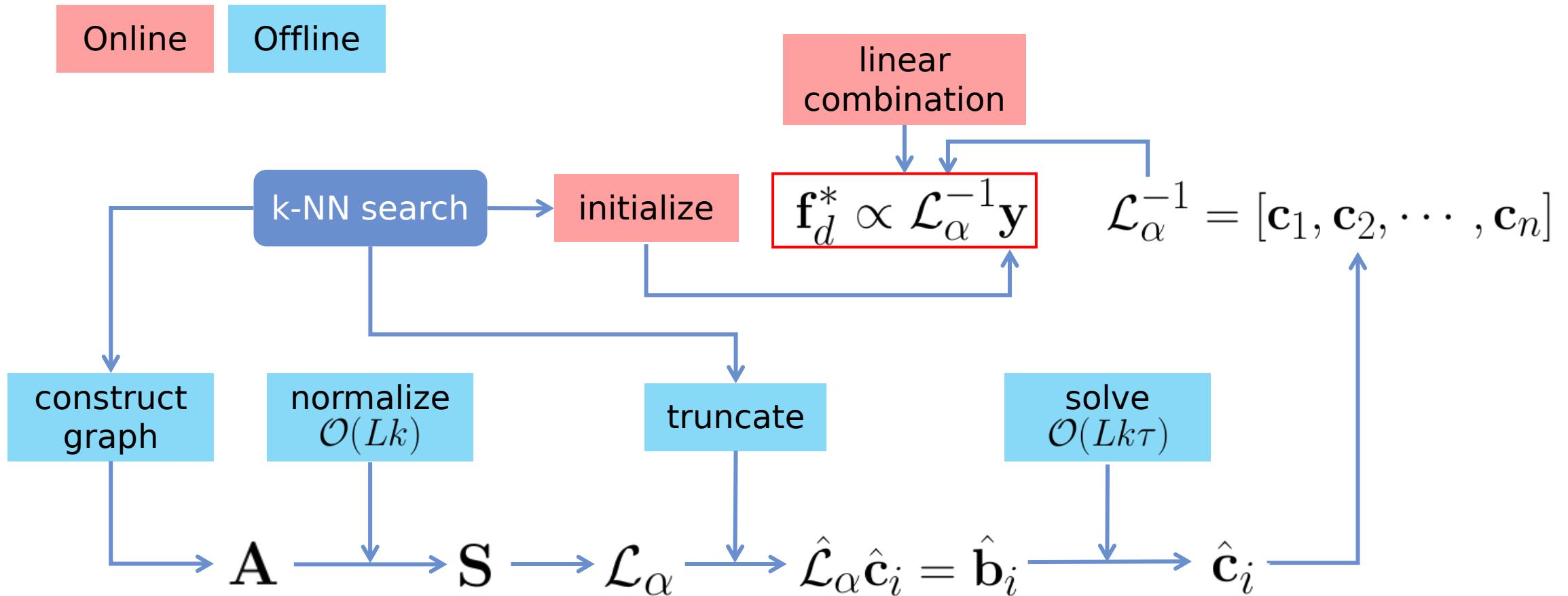
Proposed Method

We propose an efficient diffusion with significant improvement in retrieval performance

Overview of Previous Method

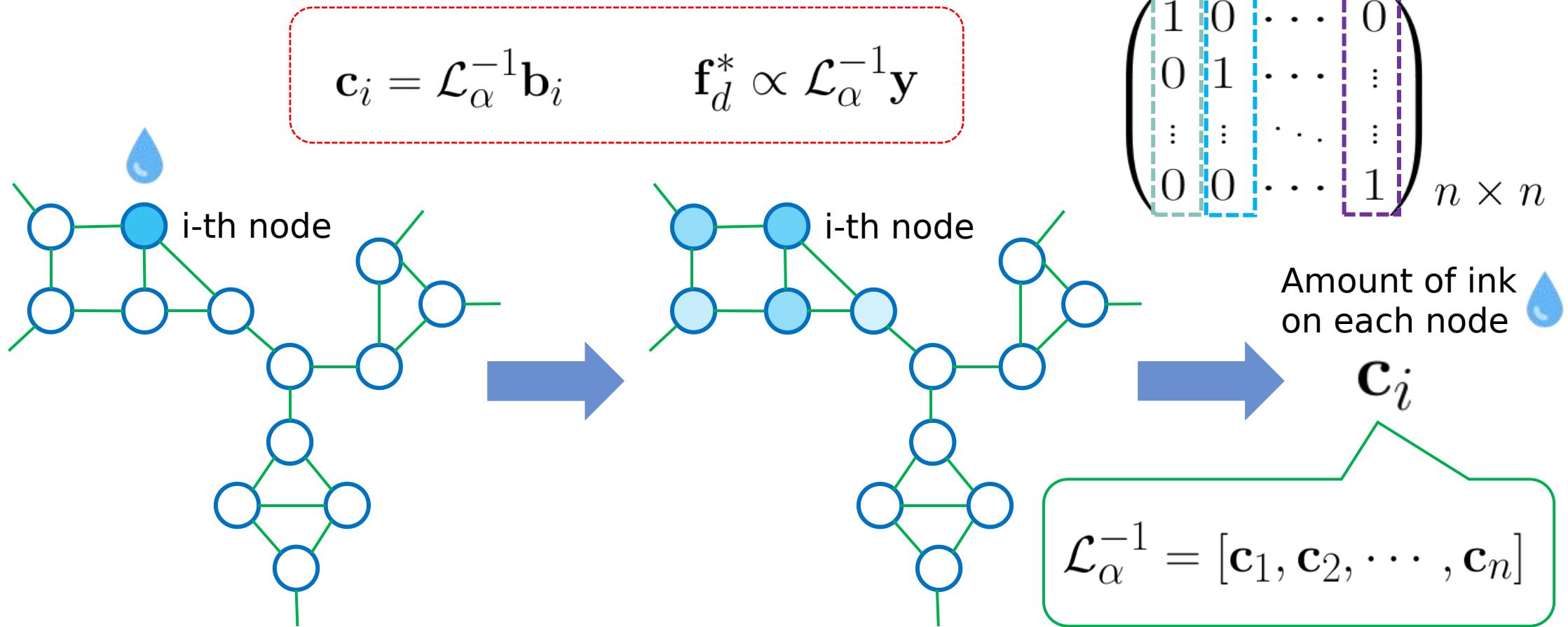


Overview of proposed method



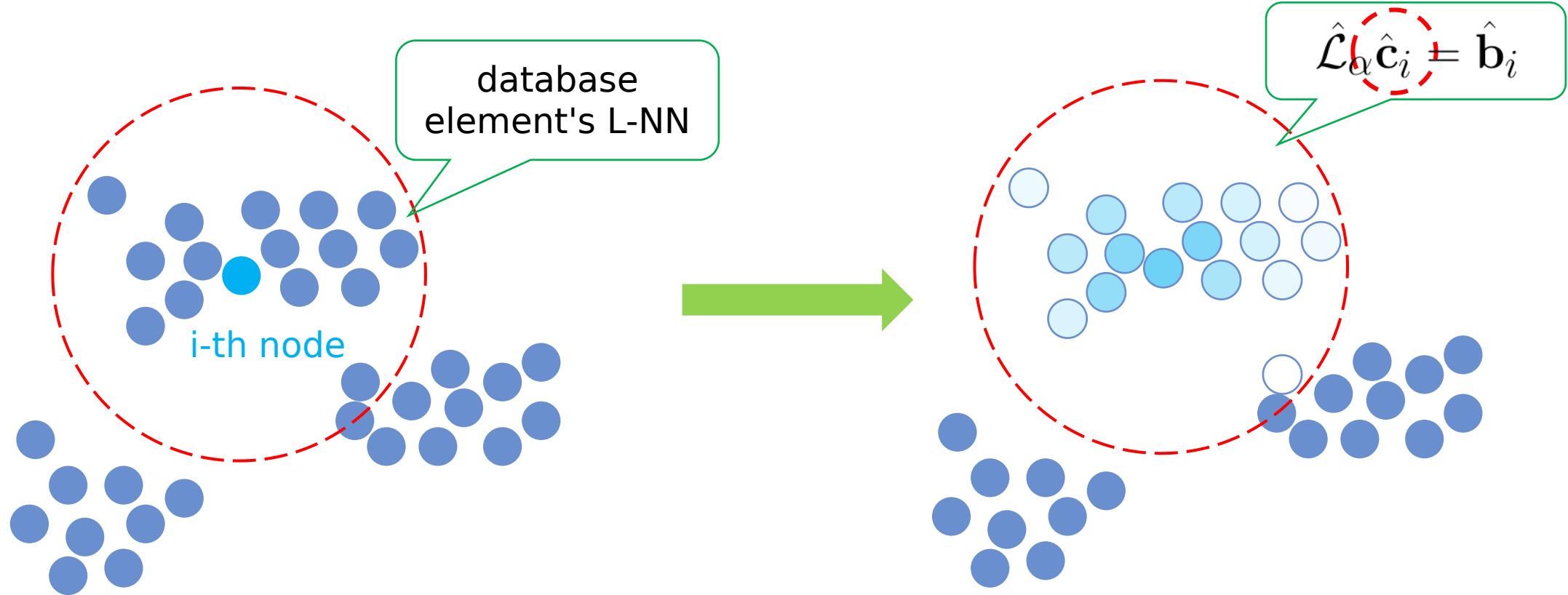
Proposed Method

- Offline Pre-computations

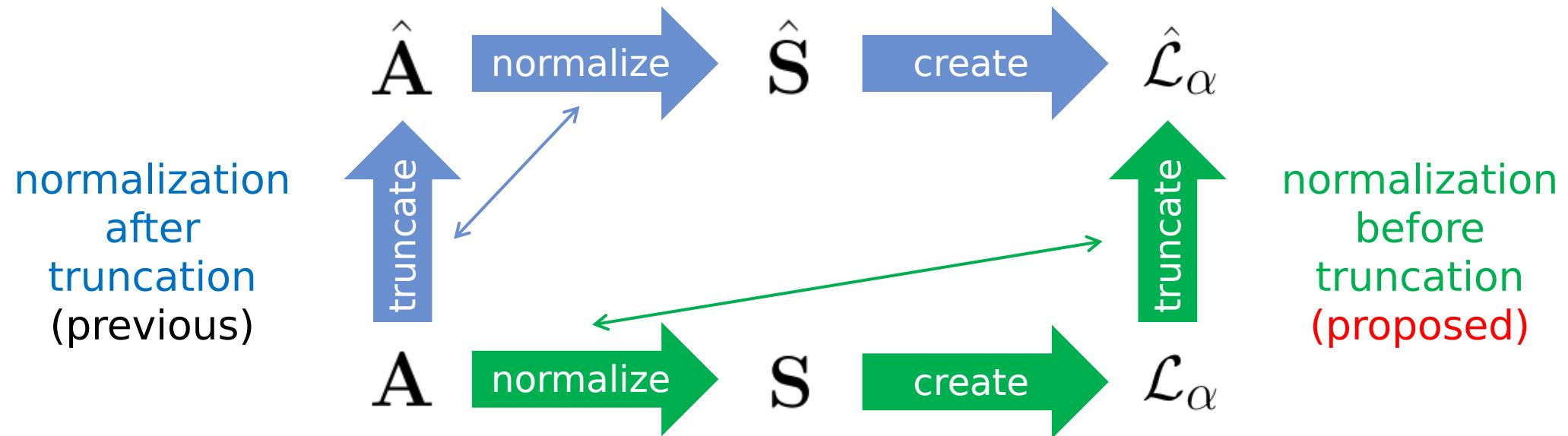


Proposed Method

- Database-side truncation



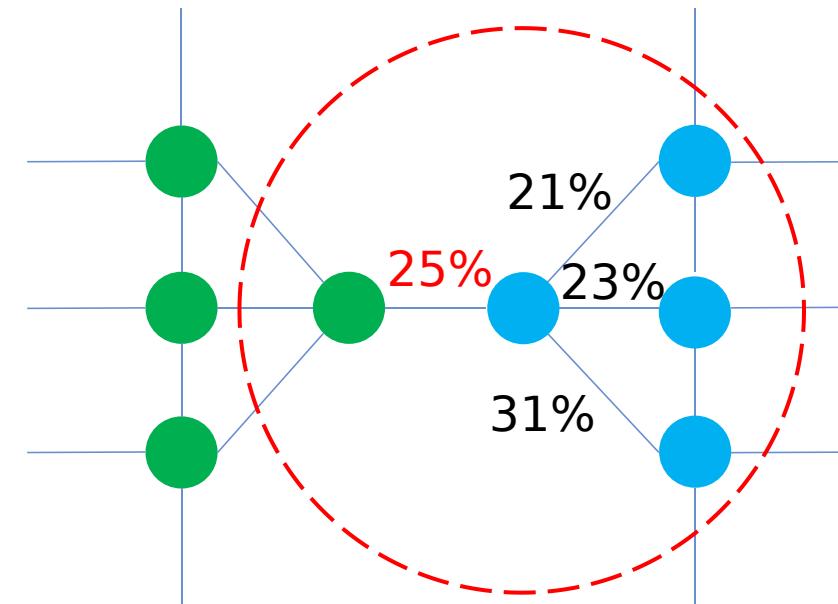
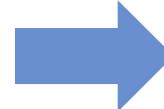
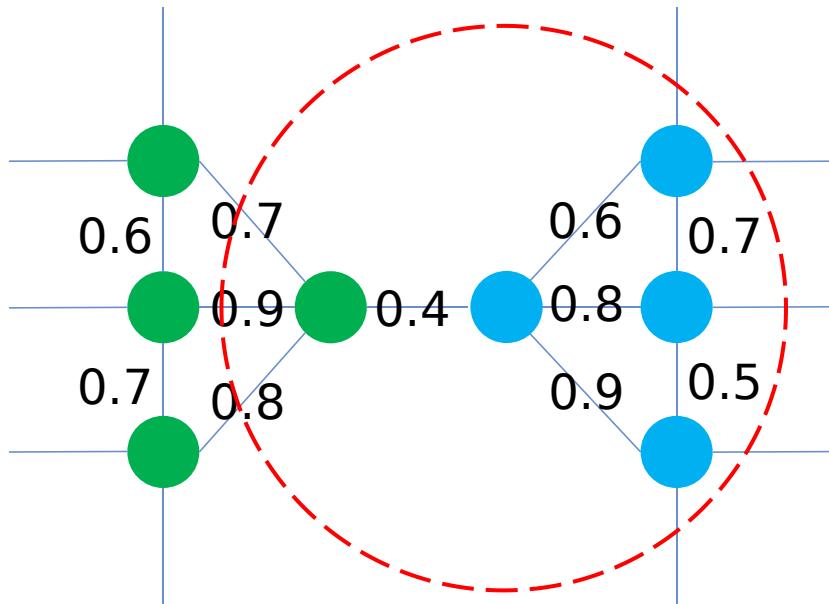
Early Truncation vs. Late Truncation



Early Truncation

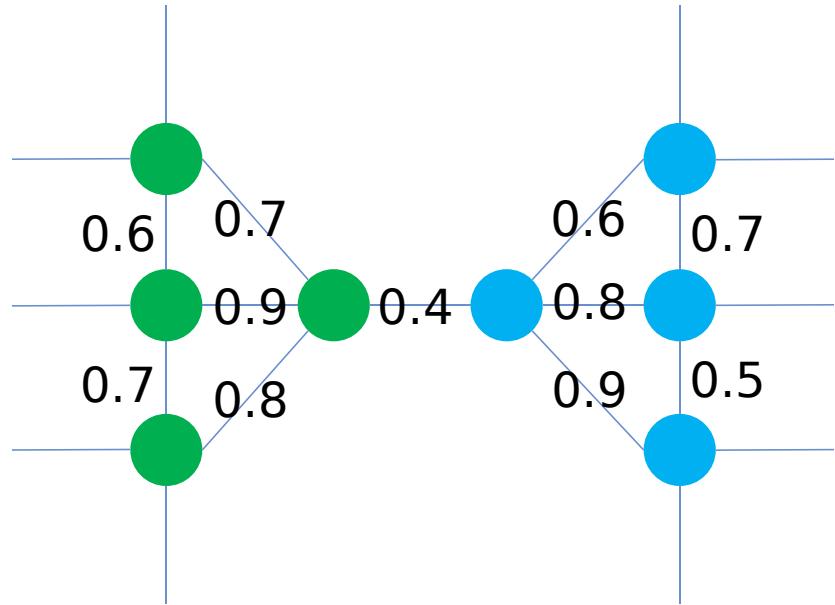
$$S = D^{-1/2} A D^{-1/2}$$

A truncate \hat{A} normalize \hat{S} We call this subgraph normalization

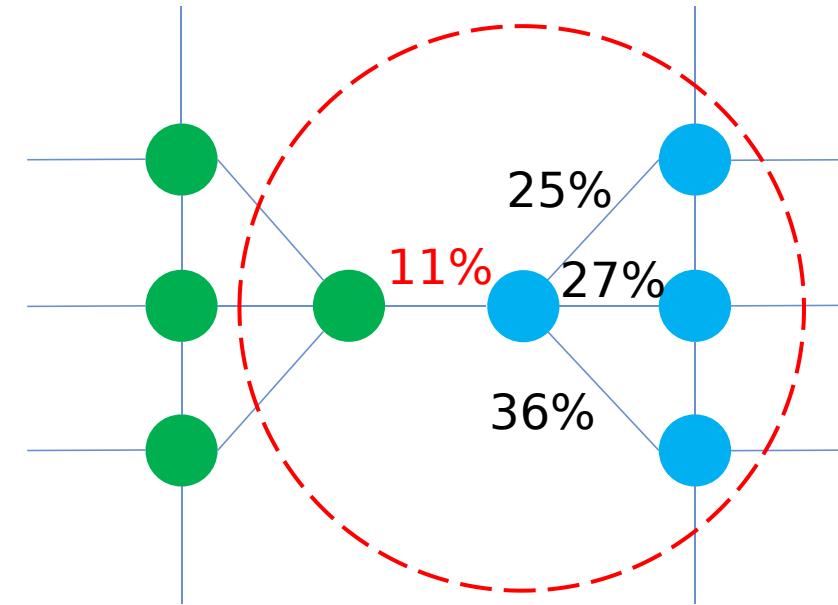


Late Truncation

$$S = D^{-1/2} A D^{-1/2}$$

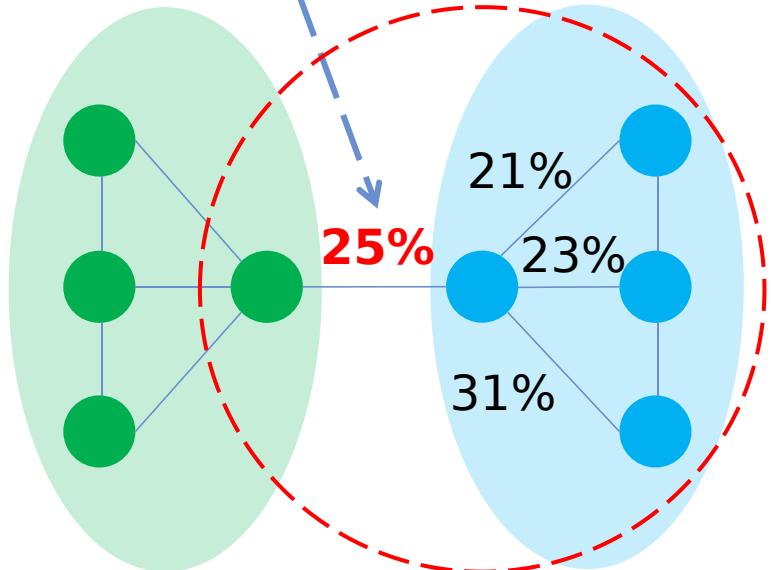


In real implementation, we apply truncation to Laplacian

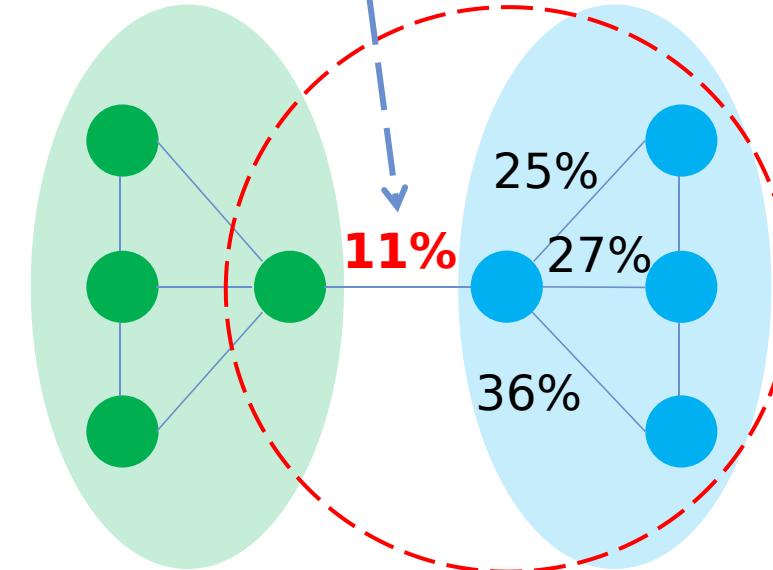


Early Truncation vs. Late Truncation

Early truncation utilizes the **truncated graph** in normalization and results in **misleading high transition probabilities** to partial manifolds after truncation



Late truncation utilizes the **complete graph** in normalization which avoids the problem in early truncation

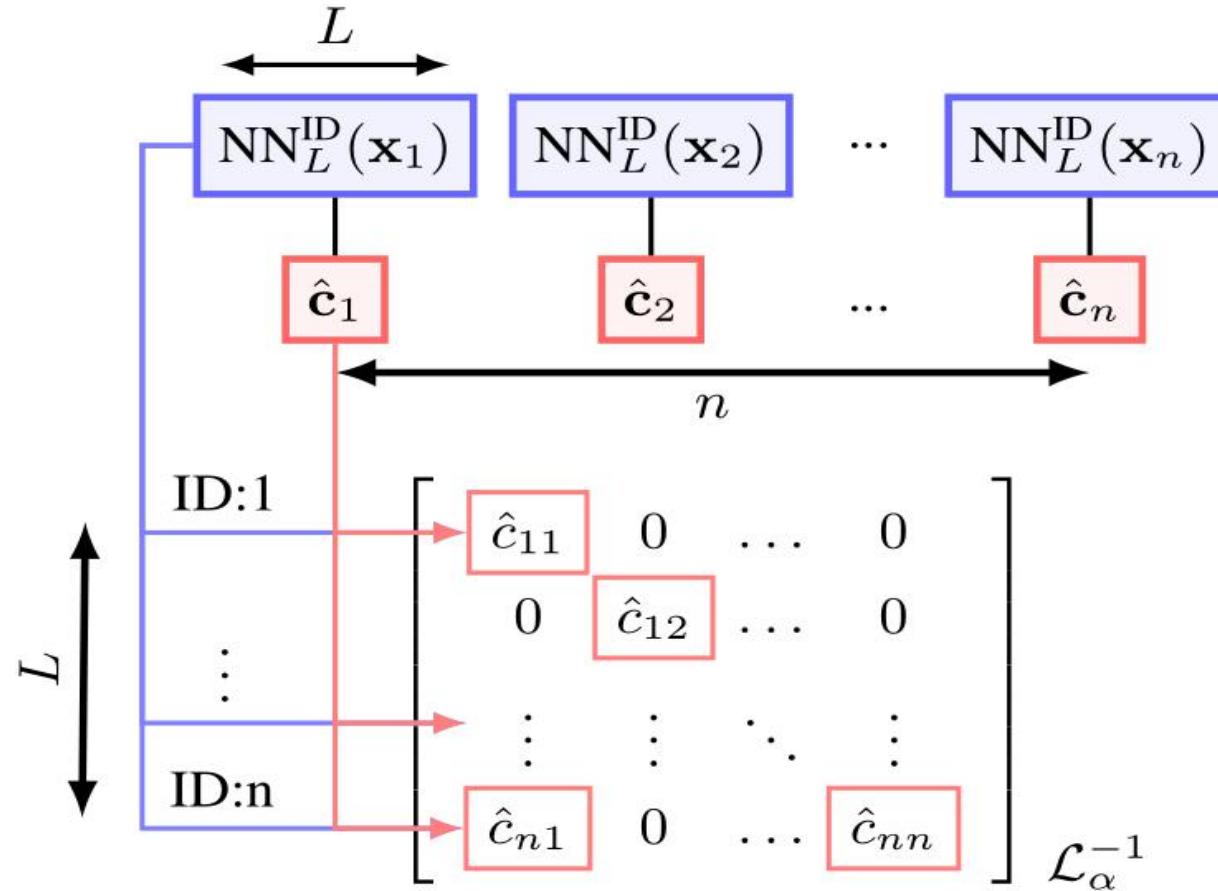


Proposed Method

- Sparsified structure

$$\hat{\mathcal{L}}_\alpha \hat{\mathbf{c}}_i = \hat{\mathbf{b}}_i$$

We maintain a sparsified inverse of Laplacian, which takes $O(L^*n)$ memory.
 $L \ll n$ (e.g. $L=2k$, $n=100k$)



Proposed Method

- Online search

Algorithm 1 Online search

```
1: Input  $\mathcal{Q} = \{\mathbf{q}_1, \dots, \mathbf{q}_m\} \leftarrow$  a new query
2: Output  $\mathbf{f}_d^* \leftarrow$  a new array of  $n$  zeros
3: for  $i \leftarrow 1$  to  $m$  do
4:   obtain  $\text{NN}_k^{\text{SIM}}(\mathbf{q}_i), \text{NN}_k^{\text{ID}}(\mathbf{q}_i)$  by  $k$ -NN search
5:   for  $j \leftarrow 1$  to  $k$  do
6:      $\text{col\_id} \leftarrow \text{NN}_k^{\text{ID}}(\mathbf{q}_i)[j]$ 
7:      $\text{weight} \leftarrow \text{NN}_k^{\text{SIM}}(\mathbf{q}_i)[j]$ 
8:      $\text{row\_ids} \leftarrow \text{NN}_L^{\text{ID}}(\mathbf{x}_{\text{col\_id}})$  from sparsified  $\mathcal{L}_\alpha^{-1}$ 
9:      $\mathbf{f}_d^*[\text{row\_ids}] \leftarrow \mathbf{f}_d^*[\text{row\_ids}] + \text{weight} * \hat{\mathbf{c}}_{\text{col\_id}}$ 
10: Aggregate scores in  $\mathbf{f}_d^*$  to image level if needed
```

$$\mathbf{f}_d^* \propto \mathcal{L}_\alpha^{-1} \mathbf{y}$$
$$\mathcal{L}_\alpha^{-1} = [\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_n]$$

This algorithm computes the above linear combination



Experiments and Results

We show that our method improved both the speed and the performance

Datasets

The Oxford Buildings

[James Philbin](#), [Relja Arandjelović](#) and [Andrew Zisserman](#)

Overview

The Oxford Buildings Dataset consists of 5062 images collected manually annotated to generate a comprehensive ground truth over which an object retrieval system can be evaluated.

Groundtruth Queries

The following image shows all 55 queries used to evaluate performance.



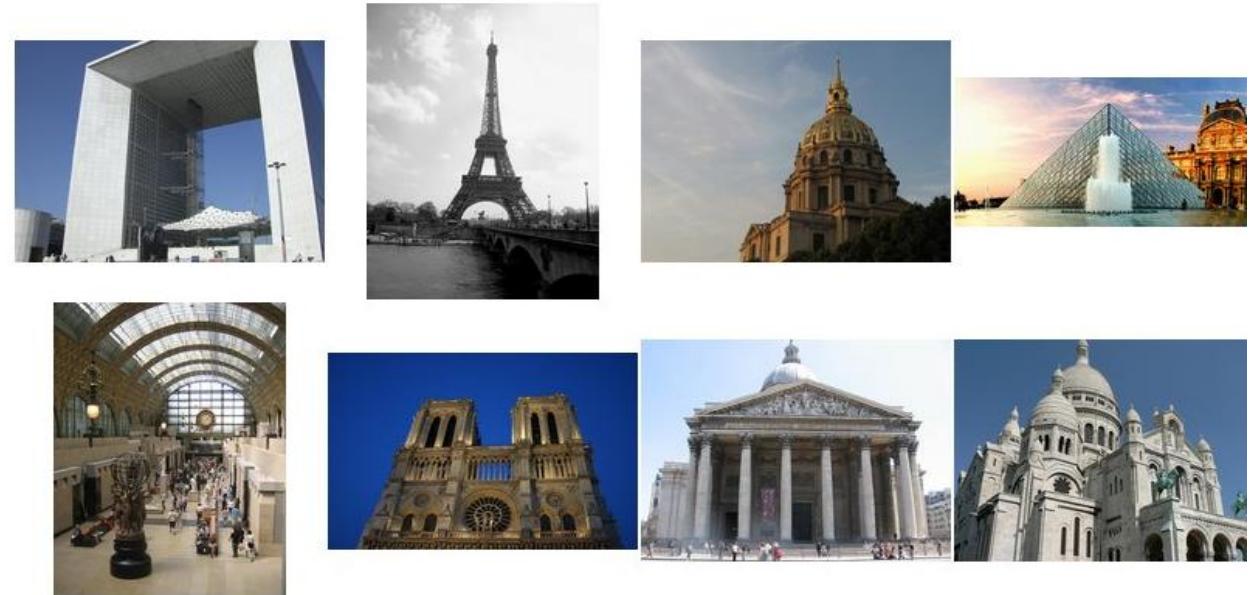
55 query
5062 gallery

The Paris Dataset

[James Philbin](#) and [Andrew Zisserman](#)

Overview

The Paris Dataset consists of 6412 images collected from [Flickr](#) by searching for particular Paris landmarks.



Flickr 100k
as distractors

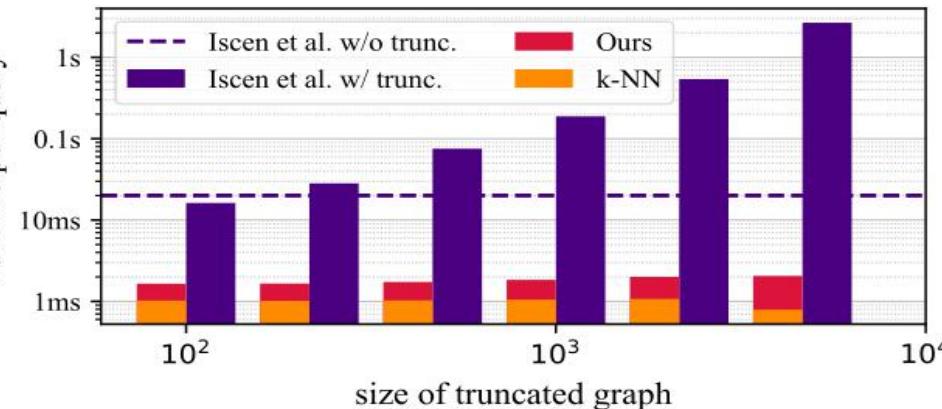
55 query
6412 gallery

Experiment Settings

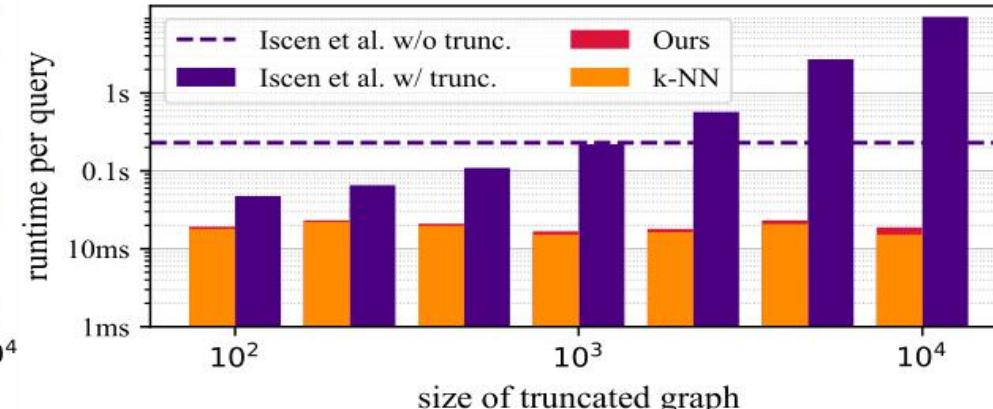
- Features
 - 512-d and 1,024-d R-MAC descriptors based on VGG and ResNet respectively (provided online by Iscen et al. <https://github.com/ahmetius/diffusion-retrieval>)
- Parameters
 - We follow the parameters in previous works and we confirm that deviating from these parameters results in worse performance
- Library
 - We use Facebook FAISS (<https://github.com/facebookresearch/faiss>) to conduct k-NN search

Runtime Computational Efficiency

- We evaluate the computational efficiency between k-NN search, Iscen's method [CVPR2017], and our proposed method



(a) Oxford5k



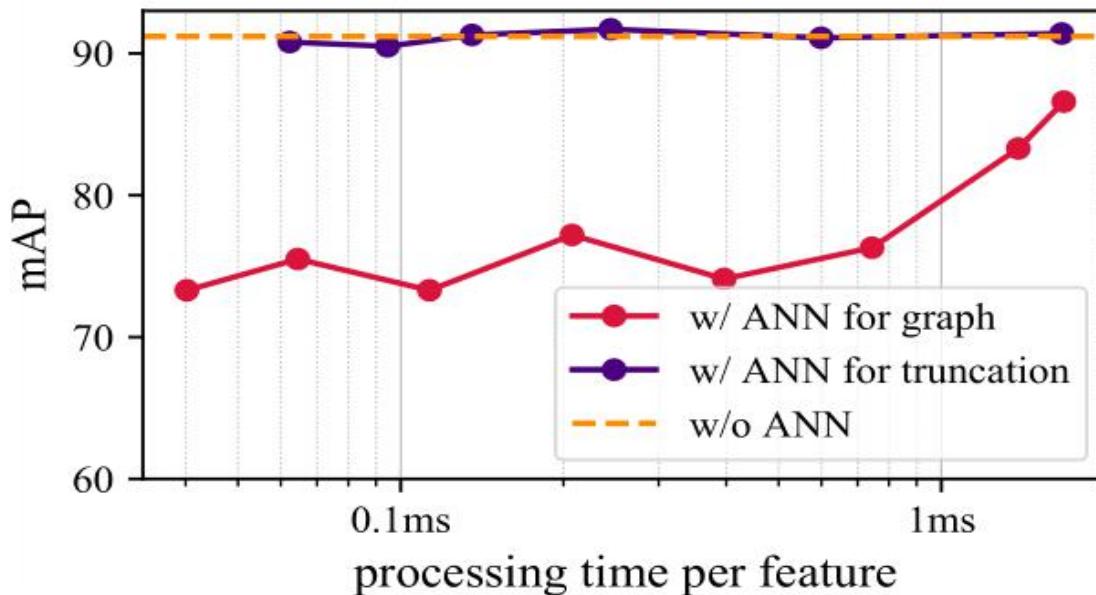
(b) Oxford105k

speed
proposed method \approx k-NN search

Efficient diffusion on region manifolds: Recovering small objects with compact cnn representations,
Iscen et al., CVPR 2017

Pre-computational Efficiency

- We adopt ANN (approximate nearest neighbor) search to accelerate the offline computation



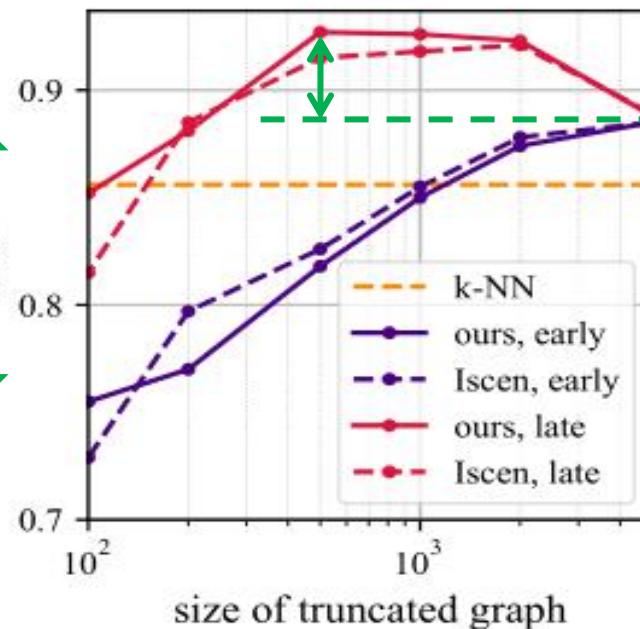
- Truncation only requires a coarse set of the top results
- Graph construction is negatively affected by even small differences in the scores

100k~ Images	Ours	Iscen's [CVPR2018]
Offline Time Cost	~6mins	a few hours

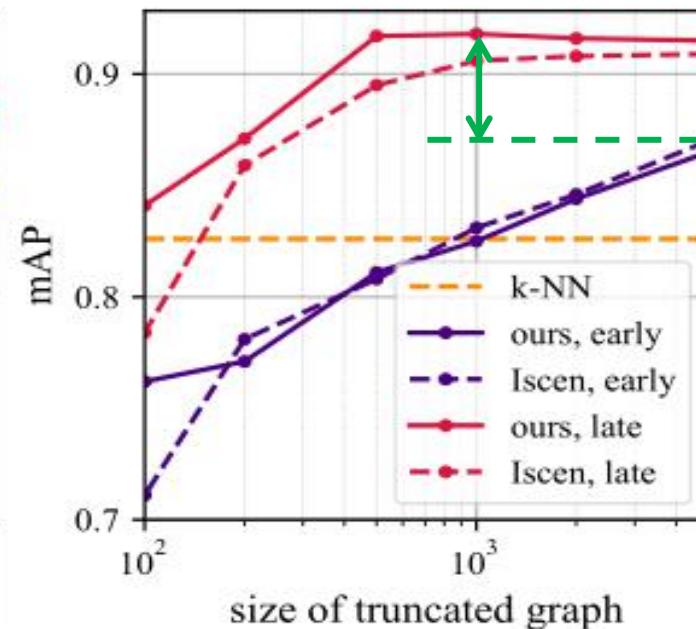
Fast spectral ranking for similarity search, Iscen et al., CVPR 2018

Influence of Subgraph Normalization

- We show the effectiveness of our proposed late truncation by using our proposed method and Iscen's method [CVPR2017]



(a) Oxford5k



(b) Oxford105k

Efficient diffusion on region manifolds: Recovering small objects with compact cnn representations,
Iscen et al., CVPR 2017

Comparison to Other Methods

Method	Feature	Global	Regional	Oxf5k	Oxf105k	Par6k	Par106k
k-NN search	R-MAC (VGG)	✓	4%	79.5	72.1	84.5	77.1
k-NN + AQE (Chum et al. 2007)		✓		85.4	79.7	88.4	83.5
Iscen's diffusion (Iscen et al. 2017)		✓		85.7	82.7	94.1	92.5
Proposed diffusion		✓		89.7	86.8	94.7	92.9
k-NN search	R-MAC (ResNet)	✓	5%	83.9	80.8	93.8	89.9
k-NN + AQE (Chum et al. 2007)		✓		89.6	88.3	95.3	92.7
Iscen's diffusion (Iscen et al. 2017)		✓		87.1	87.4	96.5	95.4
Proposed diffusion		✓		92.6	91.8	97.1	95.6
R-match (Razavian et al. 2016)	R-MAC (VGG)	✓	✓	81.5	76.5	86.1	79.9
R-match + AQE (Chum et al. 2007)		✓	✓	83.6	78.6	87.0	81.0
Iscen's diffusion (Iscen et al. 2017)		✓	✓	93.2	90.3	96.5	92.6
Proposed diffusion		✓	✓	91.8	88.6	93.9	89.2
R-match (Razavian et al. 2016)	R-MAC (ResNet)	✓	✓	93.5	91.2	96.1	93.8
R-match + AQE (Chum et al. 2007)		✓	✓	88.1	85.7	94.9	91.3
Iscen's diffusion (Iscen et al. 2017)		✓	✓	91.0	89.6	95.5	92.5
Proposed diffusion		✓	✓	95.8	94.2	96.9	95.3
Proposed diffusion w/ late fusion		✓	✓	95.9	94.8	97.6	95.6
Proposed diffusion w/ late fusion		✓	✓	96.2	95.2	97.8	96.2

Table 1: Performance comparison with the state of the art. We used R-MAC features extracted with VGG (Radenović, Tolias, and Chum 2016) and ResNet101 (Gordo et al. 2016).



Thank you!

Fan Yang
2018/11/13
