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Advanced Random Walk Techniques for Social Media Analysis

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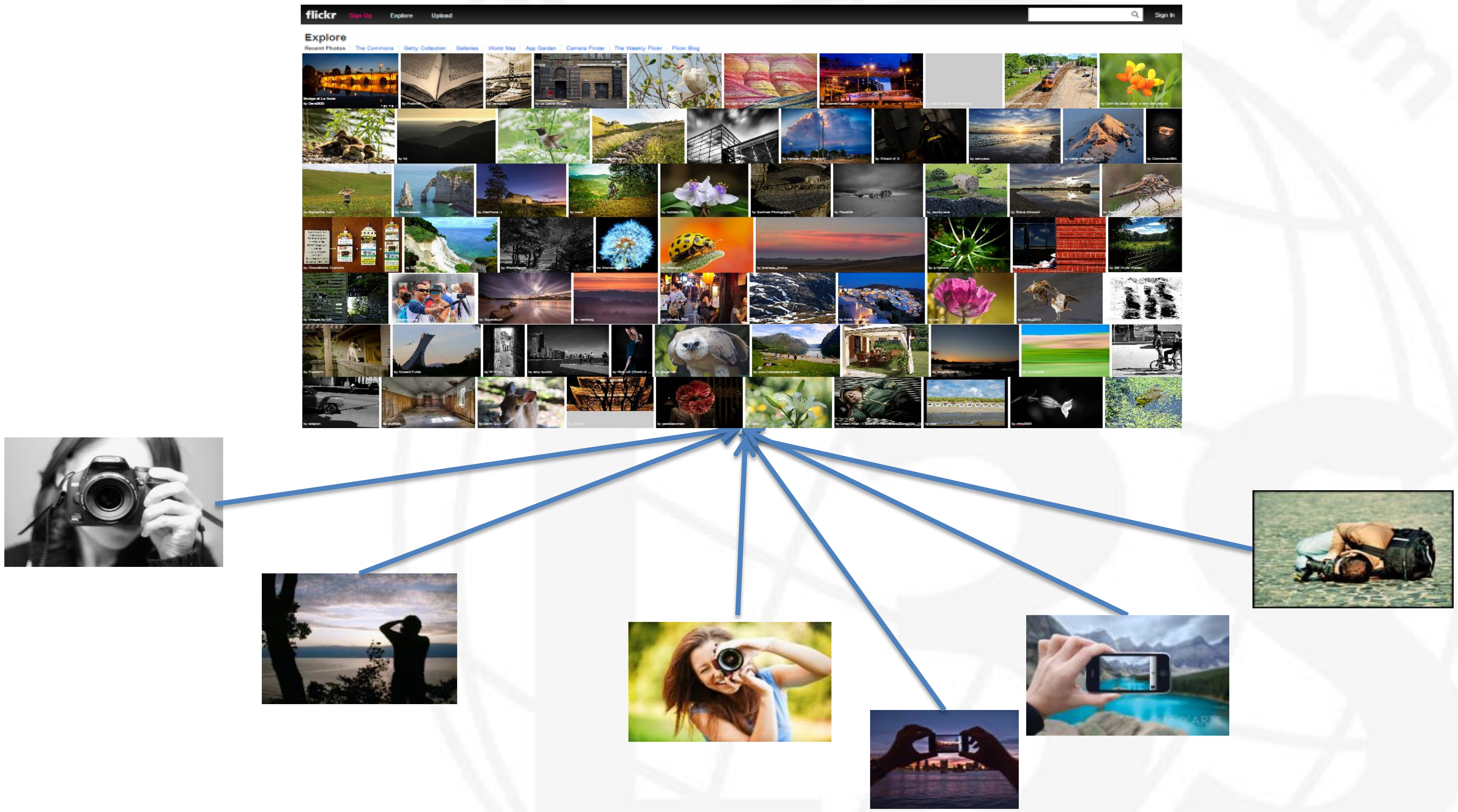
Outline

- Introduction
- Voting Graph
- Adaptive Teleportation Random Walk Model
- Experimental Results
- Conclusion & Future Work

Introduction

- Social media sharing platforms, such as Flickr, users are allowed to upload personalized photos and annotate these photos with freely chosen tags.



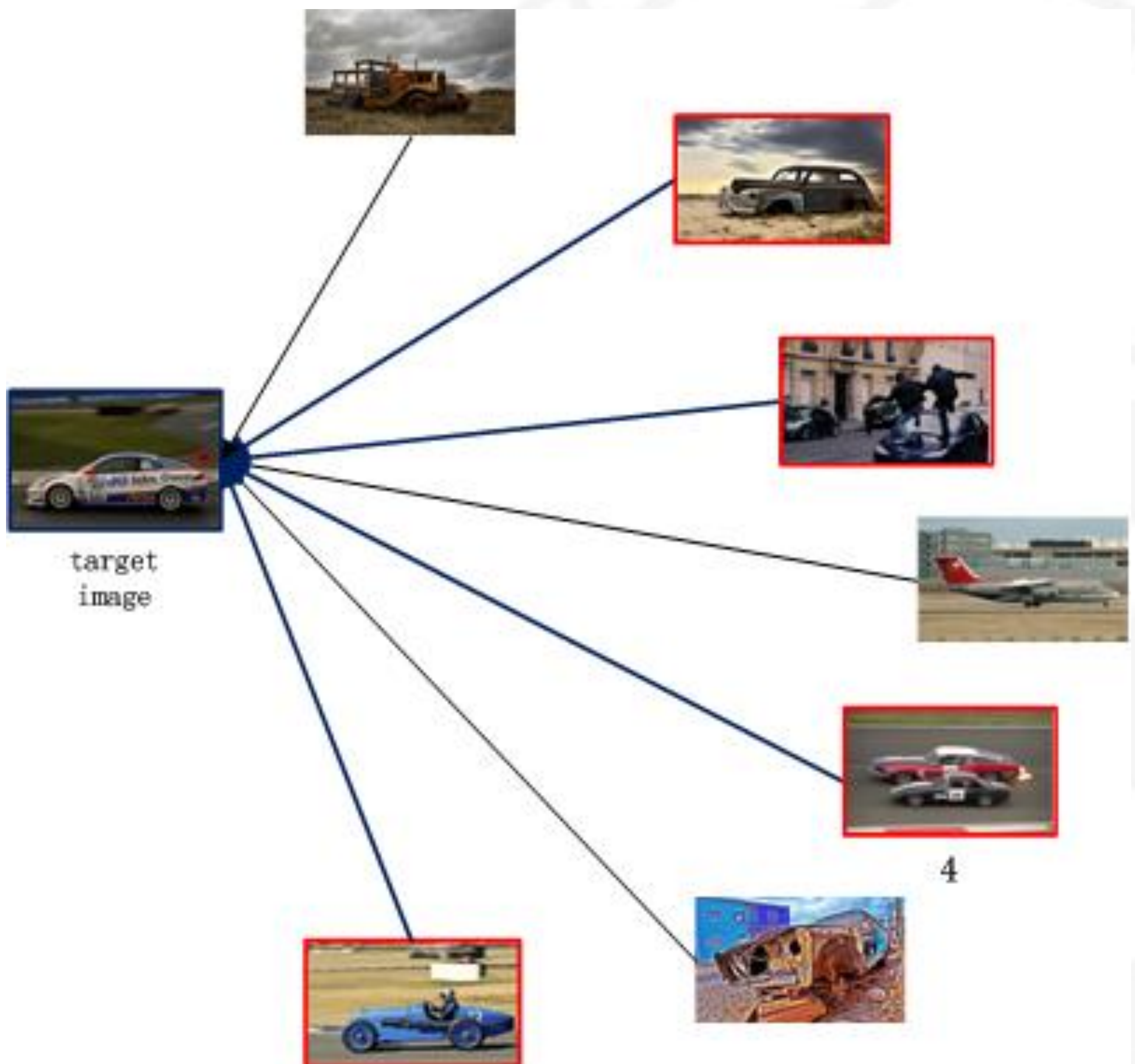
Introduction

- Limitations of tags:
  - Ambiguous, Incomplete and Personalized
  - Lack of relevance information (e.g., tag frequency, order of tags)
- Question:
  - How to accurately and efficiently learn the relevance of a tag with respect to the visual content?

tiger
grapes
green house
my garden
fransschmit

State-of-the-art

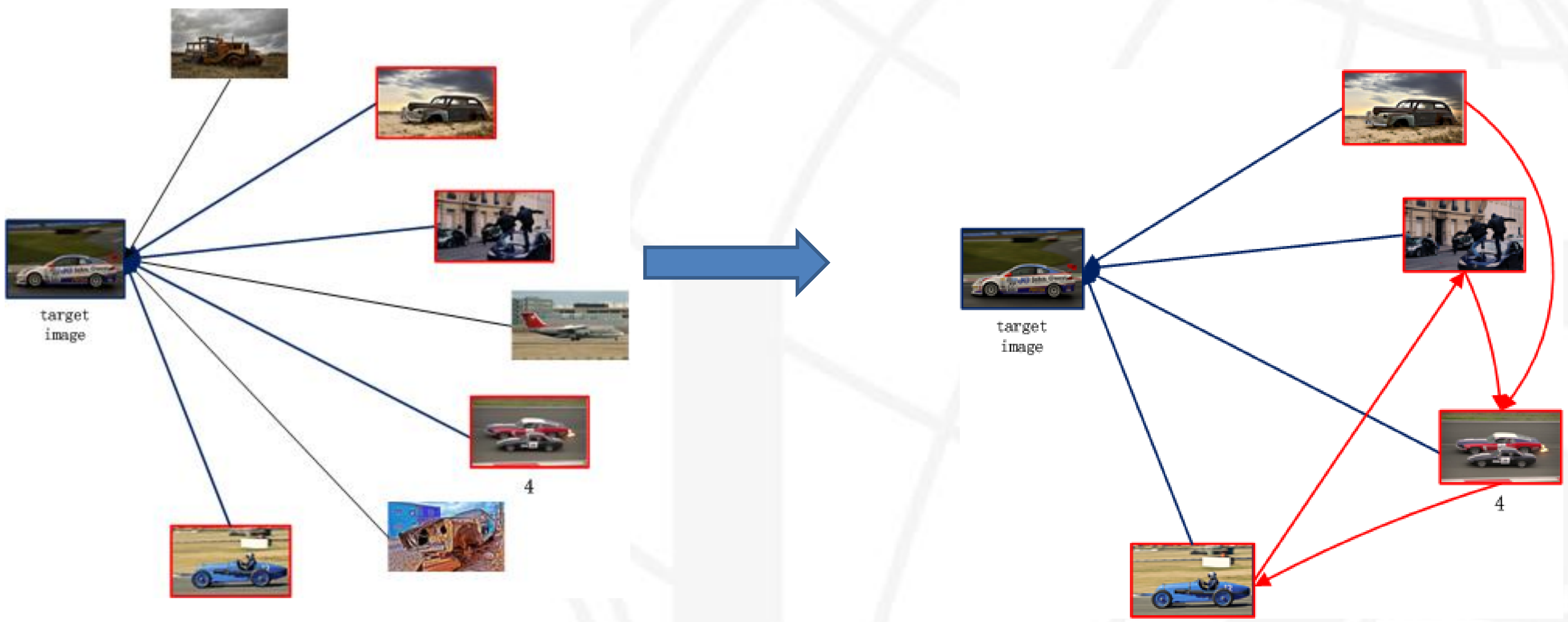
- Neighbor Voting and It's Variants
  - **Assumption:** A tag is considered as relevant to the visual content of a target image if this tag is also used to annotate the *visual neighbor images* of the target image by lots of different users.
  - **Limitation:** Treat the voting power of each neighbor image either equally or simply based on its visual similarity (suffer from the semantic gap problem)



(red frame marks the tagged images)

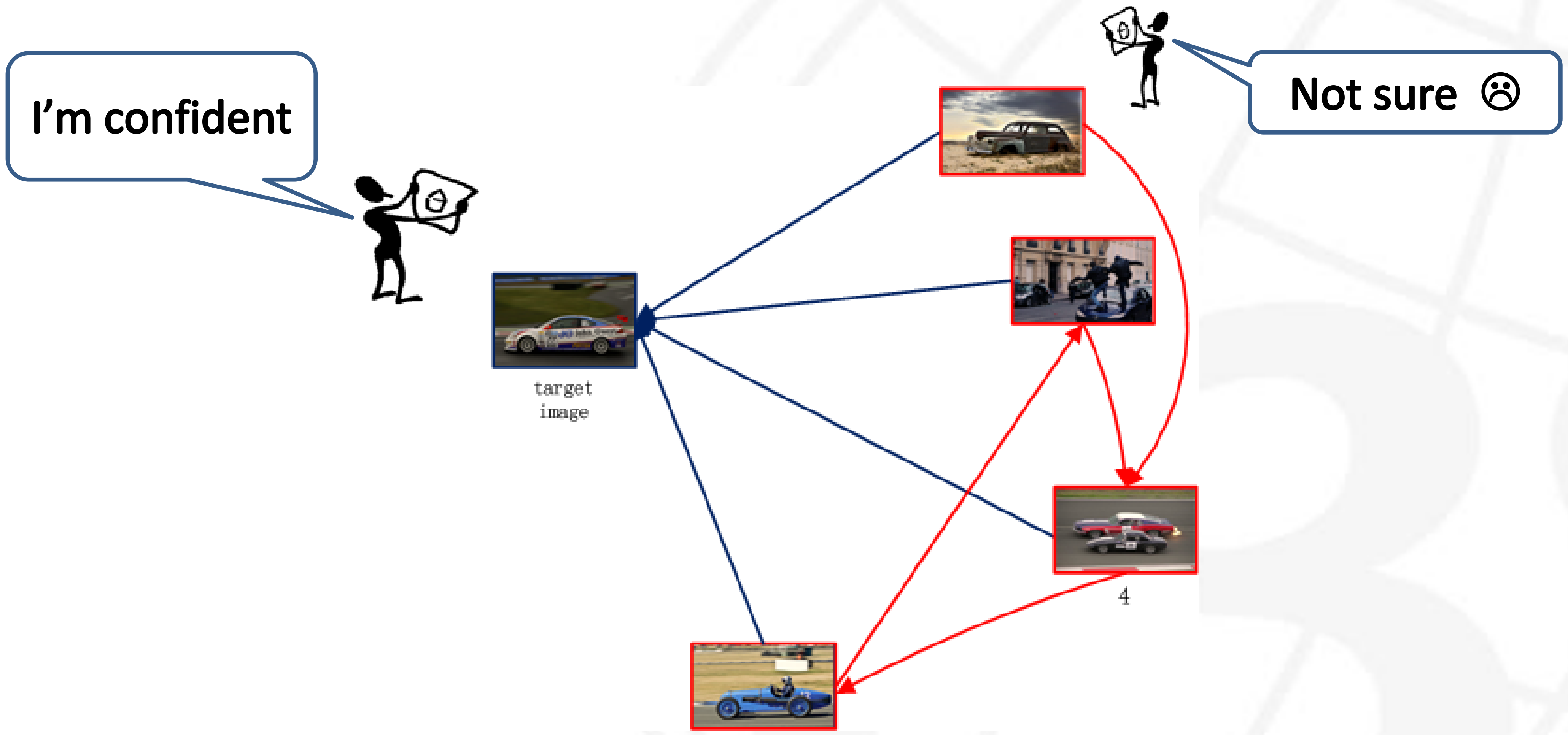
Contribution:

- **1) we exploit the structure information among neighbor images in order to boost the performance.**
  - **Voting Graph**: we construct a novel graph for exploiting the structure relationship information.



Contribution :

- **2) We propose a novel model, called Adaptive Teleportation Random Walk, to seamlessly learn tag relevance through the Voting Graph.**
  - **Confidence factor:** reflects how confidence of a node to vote its out-link neighbors, which will be modeled into the standard random walk process .



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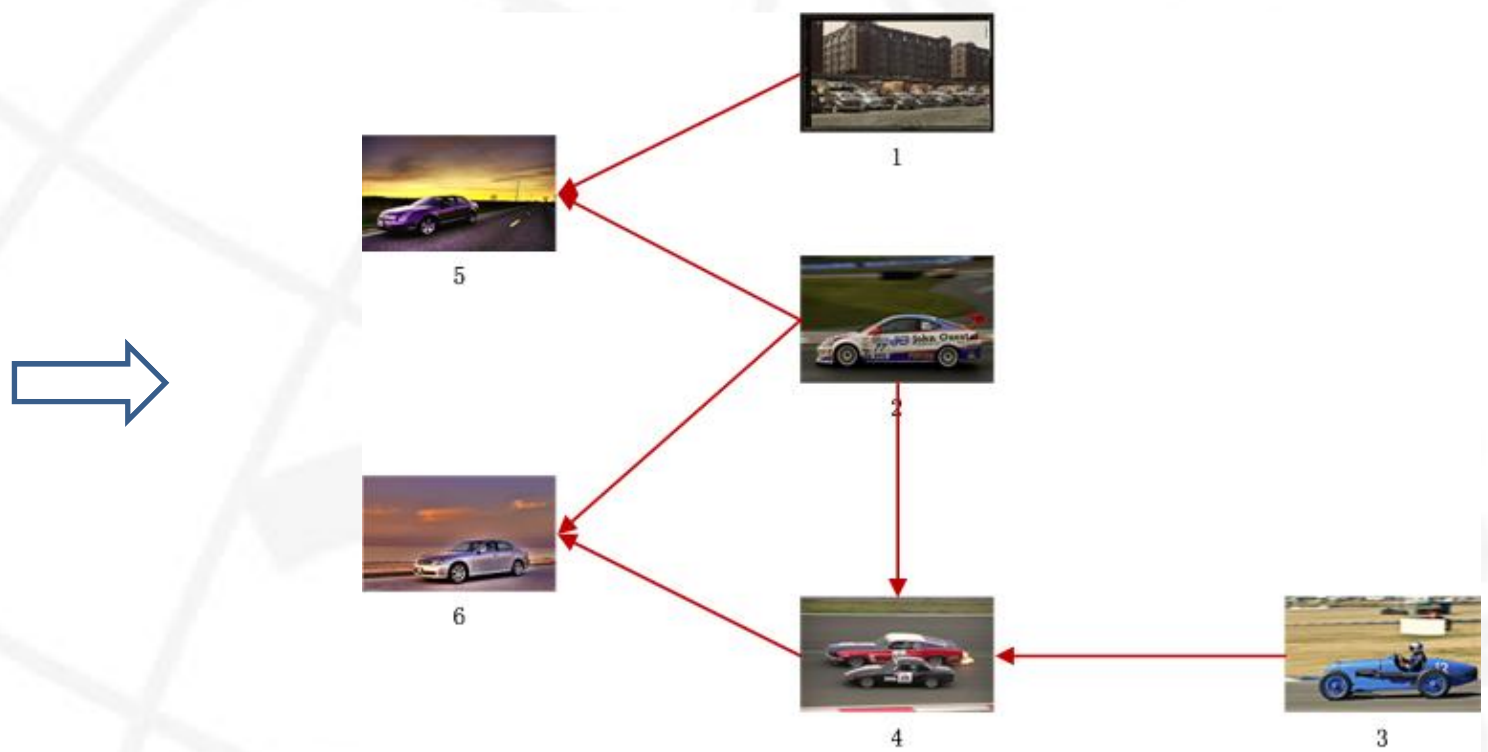
Voting Graph

- **Definition 1**. (*Voting Graph*). A voting graph $G = (V, E)$ is a directed graph where nodes are images in X, i.e., images annotated by a given tag t. There is an edge $e = (i, j) \in E$, if and only if image i appears in $N_k(j)$.

(a) The k-NN of each tagged image (k = 5 in this case)



(b) The resulting voting graph

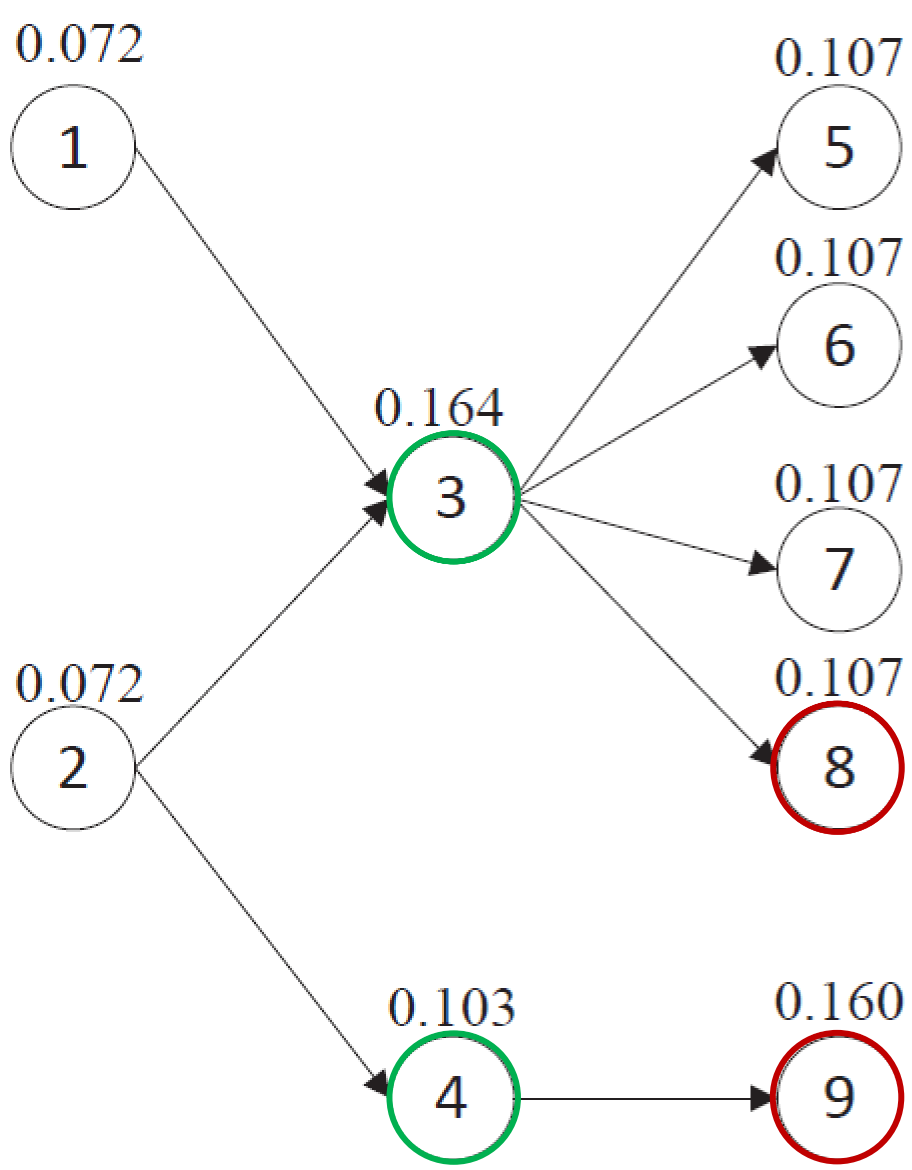
(A solid arrow represents a directed edge from a neighbor image on the right side to the tagged image on the left side.)

Solution via the Voting Graph

- Standard random walk (e.g., PageRank)
  - Succeed in great amount of applications.
  - Use the estimated node importance scores as the tag relevance.

- Question : Is it plausible to run existing random walk (or its variants, like Personalized PageRank)?

Discussion (HOW): standard random walk on voting graph



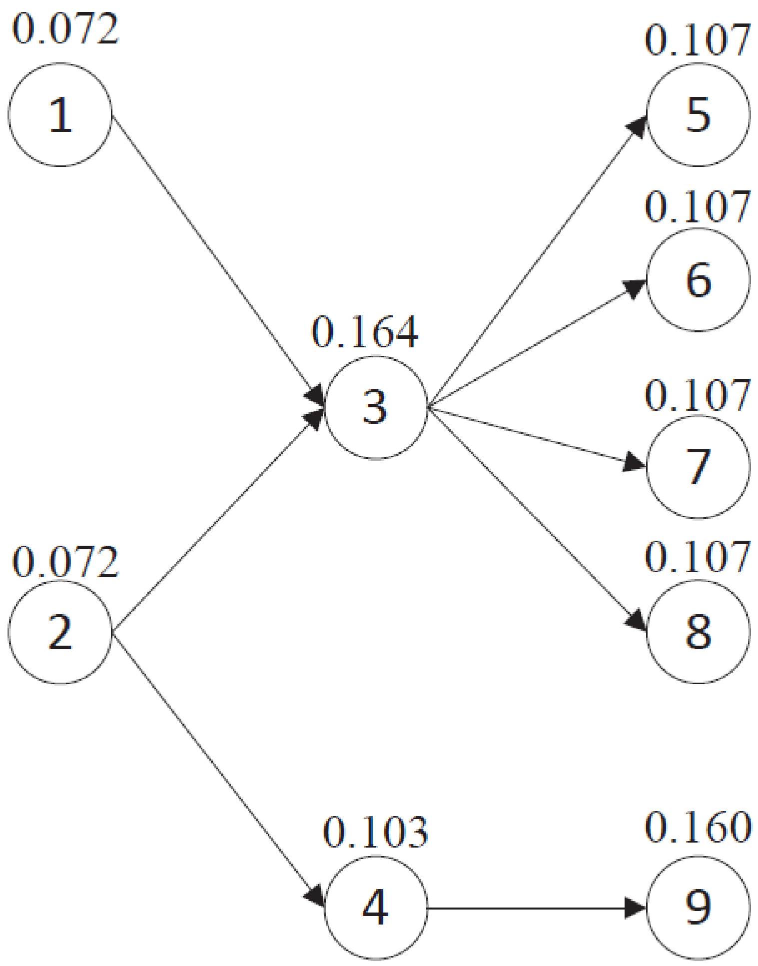
standard random walk model

Intuitively, a good tag relevance learning method should satisfy the following two voting assumptions.

Assumption 1 (authority): The voting impact from a ***highly*** relevant nodes should be higher than the voting impact from a ***less*** relevant voting node.

Assumption 2 (popularity): The voting impact from ***many*** voting nodes should usually be higher than the voting impact from ***fewer*** voting nodes.

Discussion (WHY): standard random walk on voting graph



Results of standard random walk model

- **Analysis :** In the standard random walk (e.g., PageRank), all nodes share the same fixed teleportation probability, determined by the parameter α .

$$r_t = \boxed{\alpha P^T r_{t-1}} + \boxed{(1-\alpha) v}$$

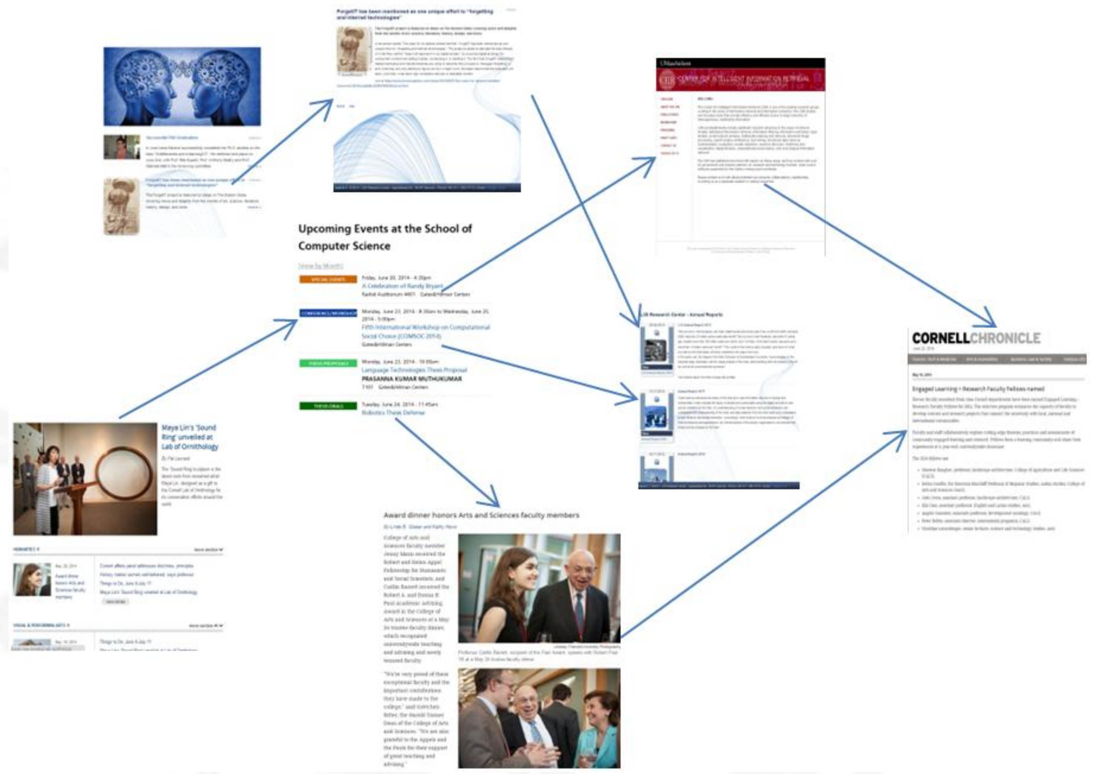
jump to it neighbors

jump to an arbitrary node

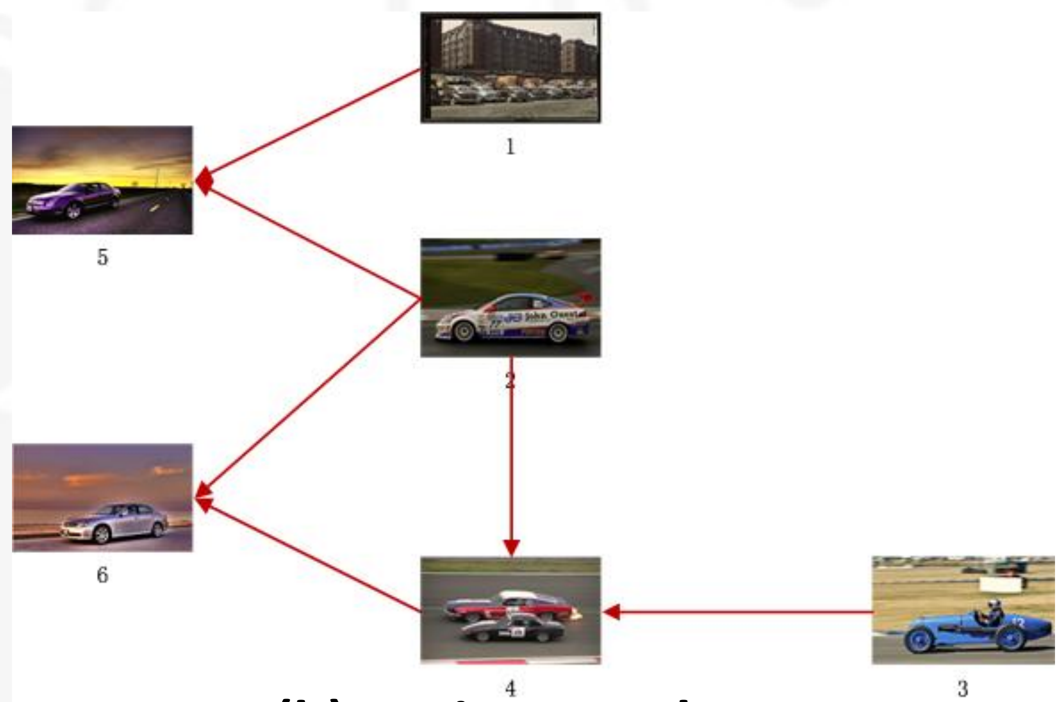
- **Example:** Node 3 has 4 out-link neighbors, while node 4 only has one out-link neighbor.

Discussion (WHY): standard random walk on voting graph

- **Traditional Web Link Graph vs Voting Graph:**
  - Web link graph (heterogeneous) :
    - 1) ***nodes*** of the graph probably come from different concepts.
    - 2) ***links*** can be freely added by the content owners.
  - Voting Graph (homogeneous) :
    - 1) ***nodes*** in voting graph are the images annotated by the same concept (i.e., tag), which can be considered as the exemplars of that concept.
    - 2) ***links*** *are* strictly constrained by their visual similarity.



(a) Web Link Graph



(b) Voting Graph

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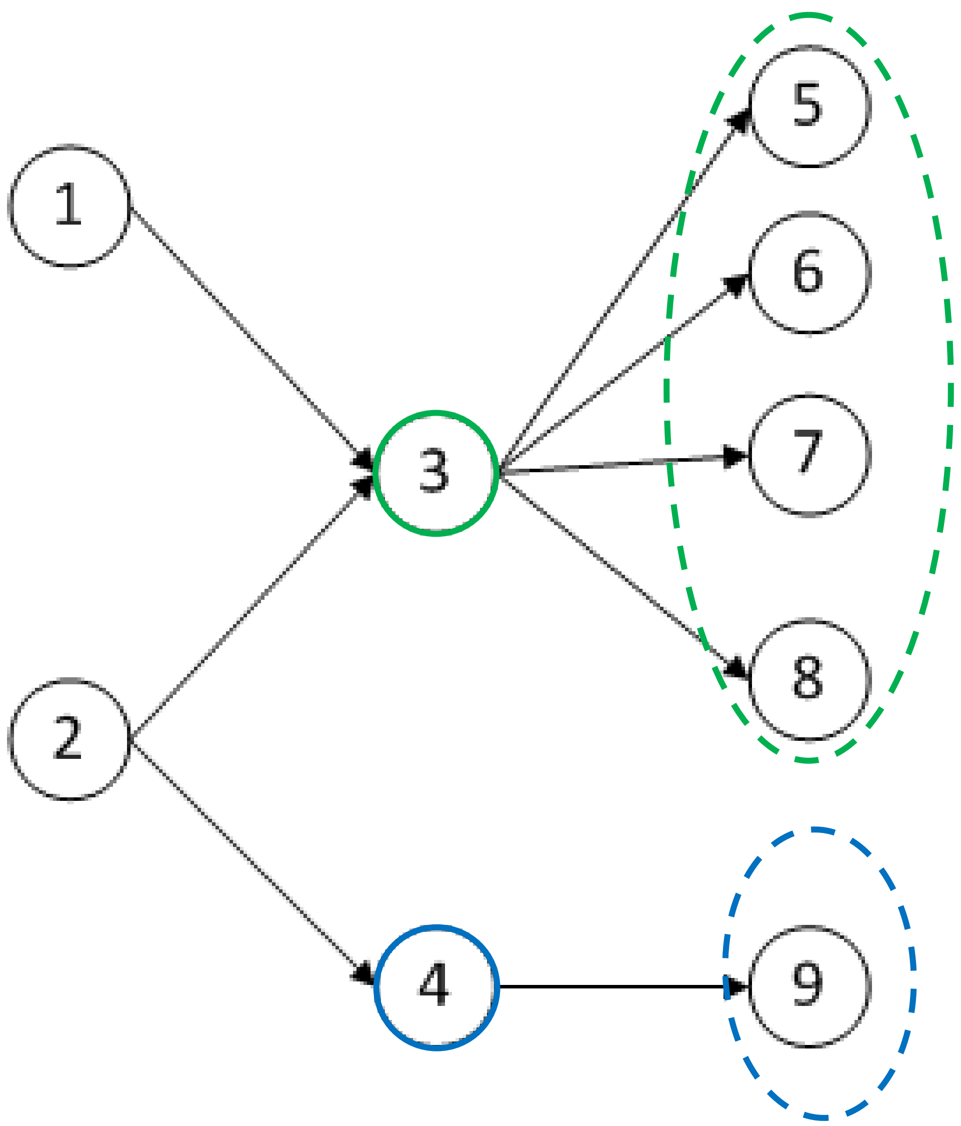
Confidence factor



Observation:

1) All the images can be considered as the exemplars of the given concept.

2) Image with many out-link neighbors should be more relevant to that concept.

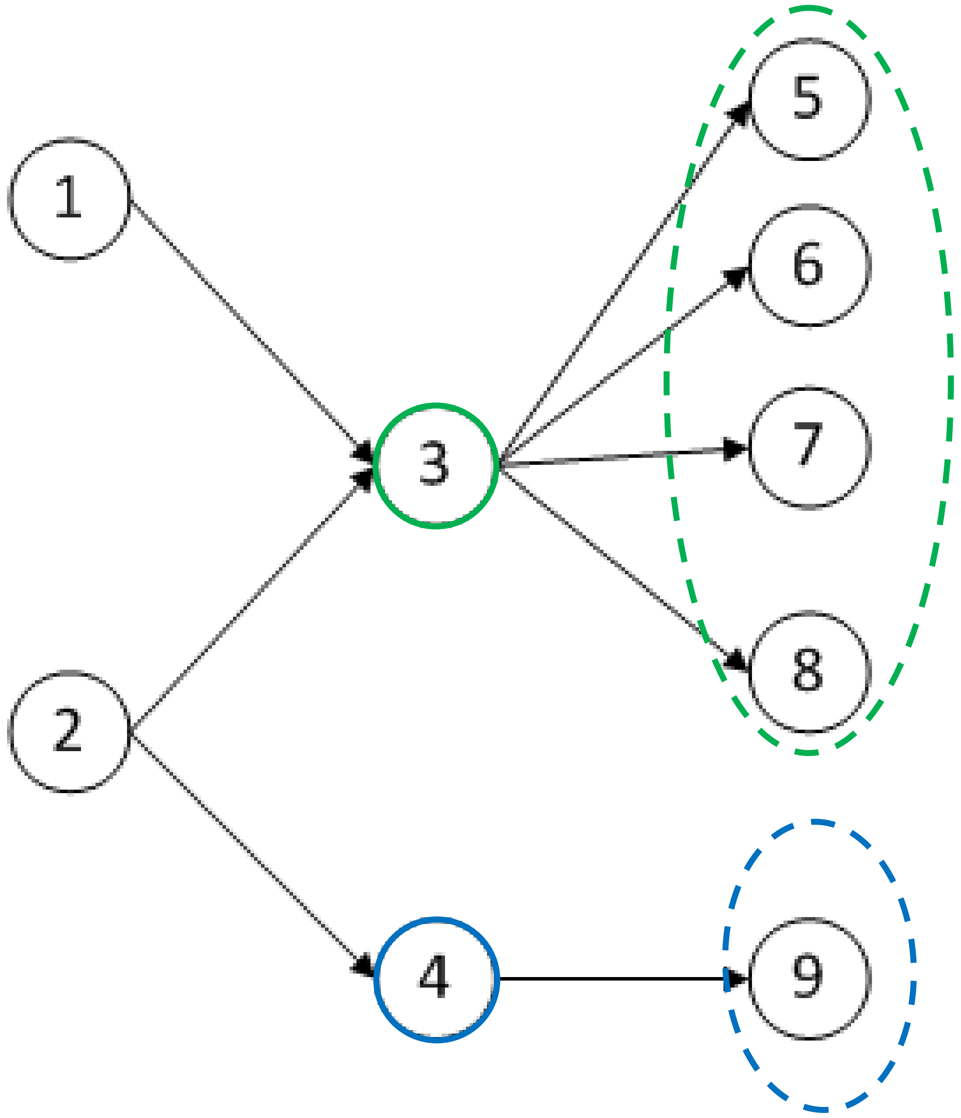
Confidence Factor:

It reflects the confidence of a node walks to its our-link neighbors.

$$c_i = \frac{(d_i^+)^\gamma}{\max_j (d_j^+)^\gamma}$$

Idea: Nodes with a large number of out-link neighbors will comparably devote larger scores for voting on their out-link neighbors than those nodes with less out-link neighbors.

Confidence factor



Teleportation Probability in Our Method :

1) It is determined jointly by parameter α and the confidence factor c_i

2) Formalized as :

$$\underbrace{\boxed{(1-\alpha)}}_{\text{prior teleportation probability}} + \underbrace{\boxed{(1-c_i)\times\alpha}}_{\text{observed teleportation probability}}$$

Adaptive Teleportation Random Walk Model

- The novel adaptive teleportation random walk process is then formulated as follow:

$$r_t(j) = \alpha \sum_i c_i P_{ij} r_{t-1}(i) + \alpha v_j \sum_i (1 - c_i) r_{t-1}(i) + (1 - \alpha) v_j, \quad (5)$$

Where $p_{ij} = \frac{w_{ij}}{\sum_{k \in N_k(i)} w_{ik}}$ indicates the transition probability

Adaptive Teleportation Random Walk Model

- Mathematical Property

THEOREM 2. *The iteration of Eq.5 converges to*

$$\mathbf{r}_\pi = (1-\alpha)(I - \alpha(\mathbf{P}^T\Lambda + \mathbf{v}\mathbf{e}^T(I-\Lambda)))^{-1}\mathbf{v}$$

PROOF. Eq.5 can be rewritten in the matrix form

$$\mathbf{r}_t = \alpha\mathbf{P}^T\Lambda\mathbf{r}_{t-1} + \alpha\mathbf{e}^T(I-\Lambda)\mathbf{r}_{t-1}\mathbf{v} + (1-\alpha)\mathbf{v} \quad (7)$$
$$= \alpha\mathbf{P}^T\Lambda\mathbf{r}_{t-1} + \alpha\mathbf{v}\mathbf{e}^T(I-\Lambda)\mathbf{r}_{t-1} + (1-\alpha)\mathbf{v} \quad (8)$$
$$= \alpha(\mathbf{P}^T\Lambda + \mathbf{v}\mathbf{e}^T(I-\Lambda))\mathbf{r}_{t-1} + (1-\alpha)\mathbf{v} \quad (9)$$

Let $\mathbf{Q} = \mathbf{P}^T\Lambda + \mathbf{v}\mathbf{e}^T(\mathbf{I}-\Lambda)$, then we have

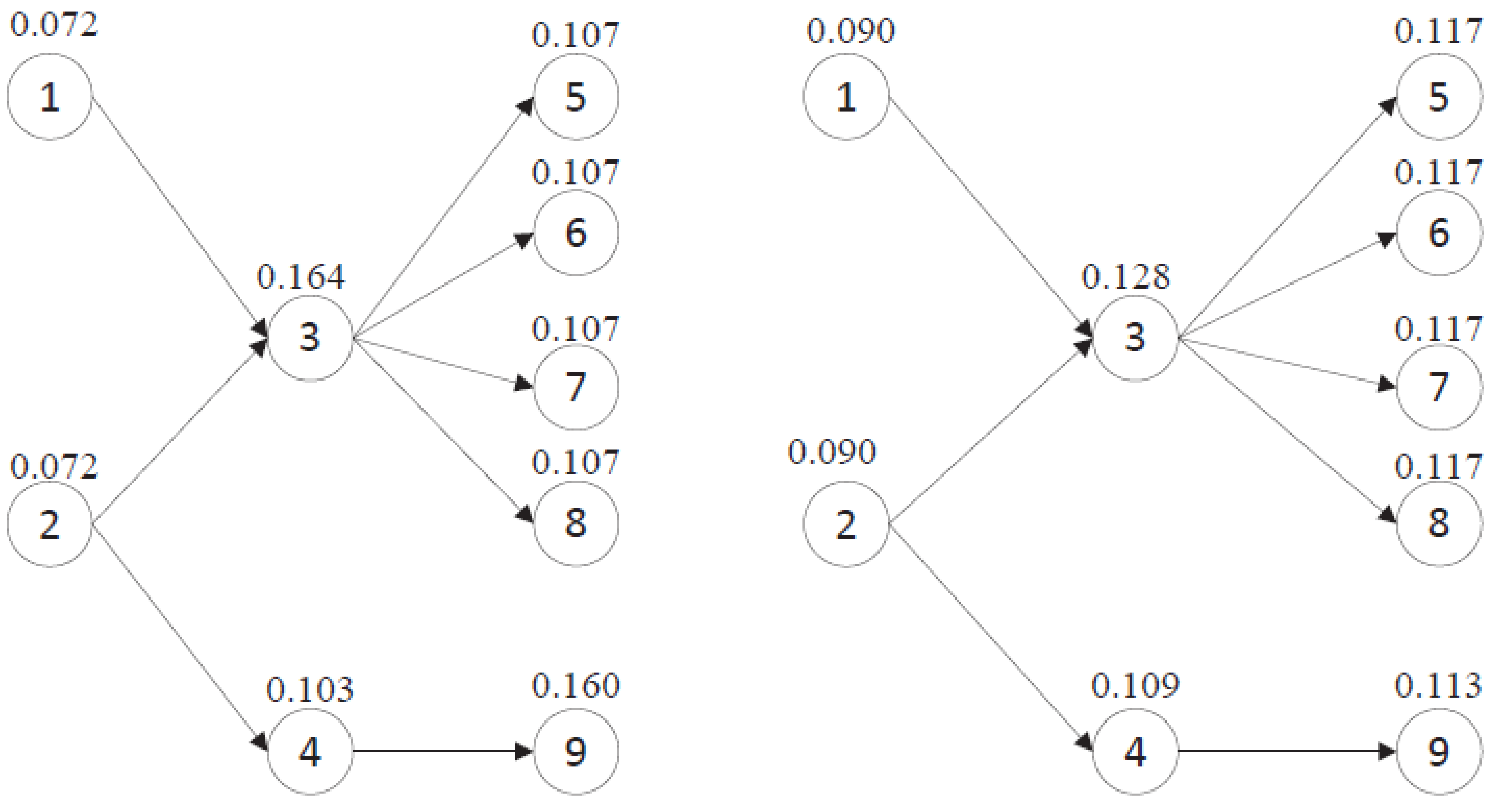
$$\mathbf{r}_t = \alpha\mathbf{Q}\mathbf{r}_{t-1} + (1-\alpha)\mathbf{v}, \quad (10)$$

and thus we have

$$\mathbf{r}_\pi = \lim_{n\to\infty}(\alpha\mathbf{Q})^n\mathbf{r}_0 + (1-\alpha)(\sum_{i=1}^{n}(\alpha\mathbf{Q})^{i-1})\mathbf{v} \quad (11)$$

Note that transition matrix P has been row normalized to 1, and v is the probabilistic relevance score (i.e., $\sum_i v_i = 1$). For $0 < \alpha < 1$, there exists $\delta < 1$, such that $\alpha < \delta$, and we can derive that

Examples of Our Method vs Standard Random Walk



(a) standard random walk model

(b) our model

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EXPERIMENTS

- Datasets
  - NUS-WIDE
    - 269,648 images
    - 265-D global features.
    - 81 concepts are used as the ground-truth.
  - MIR Flickr
    - 25,000 images
    - 305-D global features (LIRE)
    - 17 potential concepts are used as the ground-truth

Statistics	NUS-WIDE	MIR Flickr
# of images	269,648	25,000
# of unique tags	425,059	80,997
# of unique owners	47,721	9,862
avg # of tags per image	19.31	8.94
avg # of owner's tagged images	5.03	2.53

- Evaluation Metrics
  - Precision@K
    - measures the ranking quality of the top results
  - MAP
    - measures the ranking quality of the entire list

- Baseline Methods
  - Neighbor Voting (NV)
  - Weighted Neighbor Voting (NV-W)
  - Random Walk(RW)
  - Weighted Random Walk (RW-W).

Comparisons with Other Methods

- The evaluation results on both NUS-WIDE and MIR Flickr datasets

Method	NUS-WIDE		MIR Flickr	
	MAP	P@100	MAP	P@100
NV	0.3766	0.7406	0.2918	0.8906
NV-W	0.3778	0.7480	0.2921	0.8935
RW	0.3526	0.6336	0.2869	0.8571
RW-W	0.3531	0.6359	0.2871	0.8559
GV	0.3788 † ‡	0.7453 †	0.2921	0.8918
GV-W	<u>0.3790</u> † ‡	<u>0.7501</u> † ‡	<u>0.2923</u>	<u>0.8965</u> ‡

The † (‡) indicates statistical significance at p-value<0.05 using the Student's t-test with regard to the baseline NV (NV-W).

Analysis on different categories

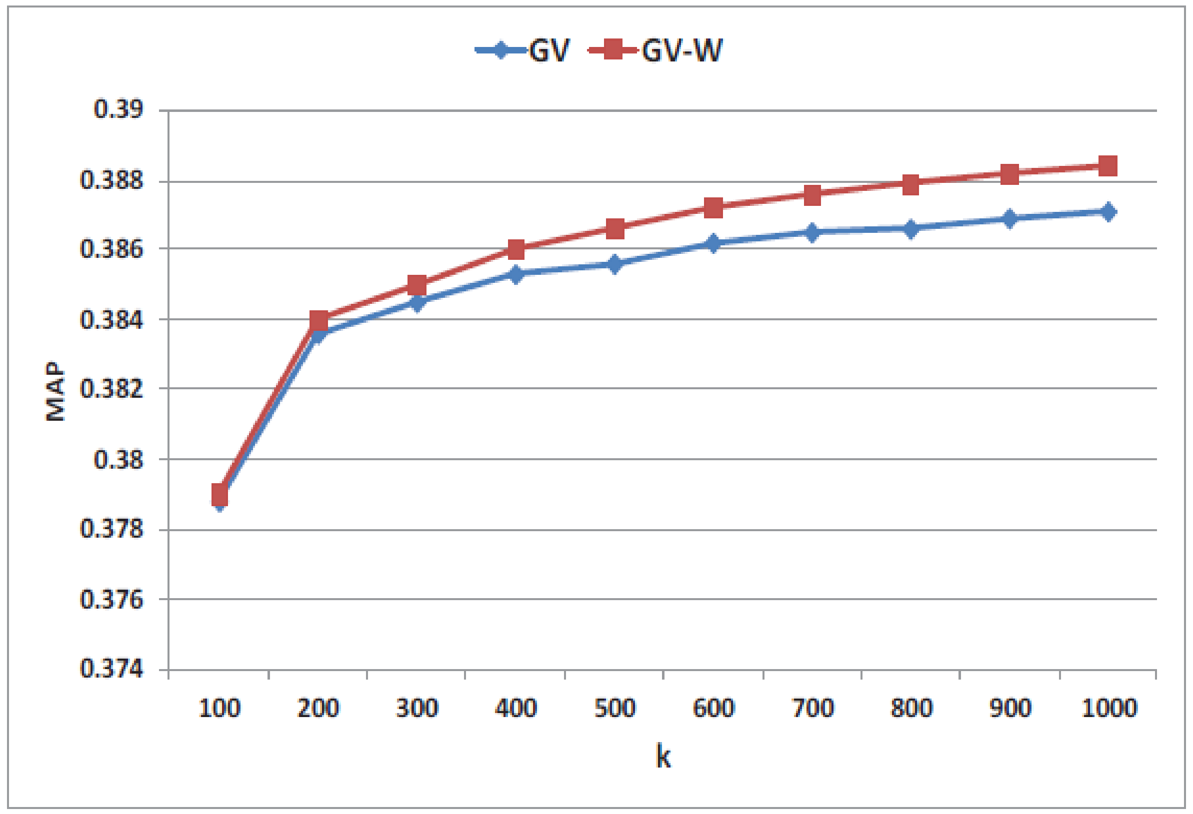
Table 3: Group Analysis on NUS-WIDE based on the metric MAP. The underline indicates the best performance.

Category	NV	NV-W	RV	RV-W	GV	GV-W
Events	0.332	0.333	0.285	0.286	<u>0.337</u>	0.335
Scene	0.344	0.347	0.317	0.317	0.345	<u>0.347</u>
People	0.391	0.394	0.376	0.377	0.395	<u>0.396</u>
Objects	0.438	0.438	0.403	0.403	<u>0.440</u>	0.439

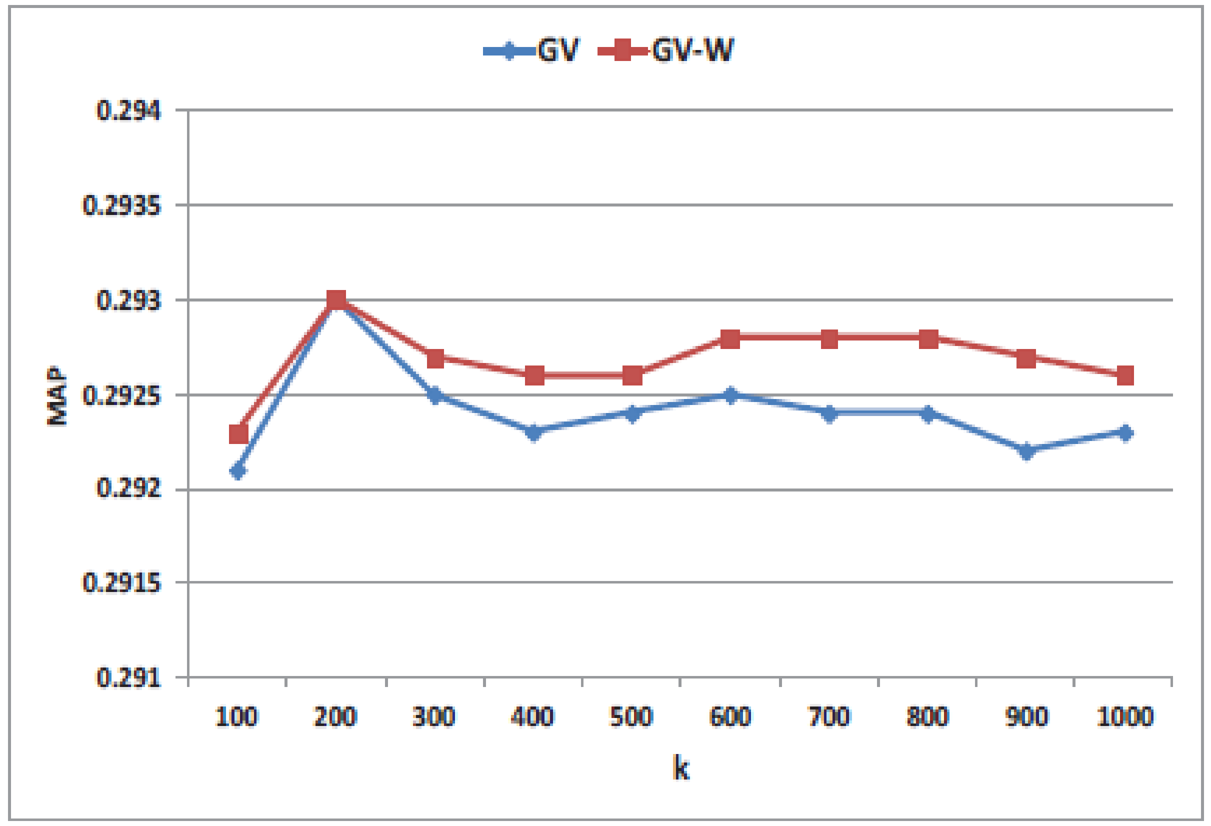
6 categories: *events* (e.g., dancing), *scene* (e.g., sky), *people* (e.g., police), *objects(e.g.*, horses), *program* (e.g., sports), and *graphics(e.g*., map).

Impact of Parameters

- Impact of Parameter *k*



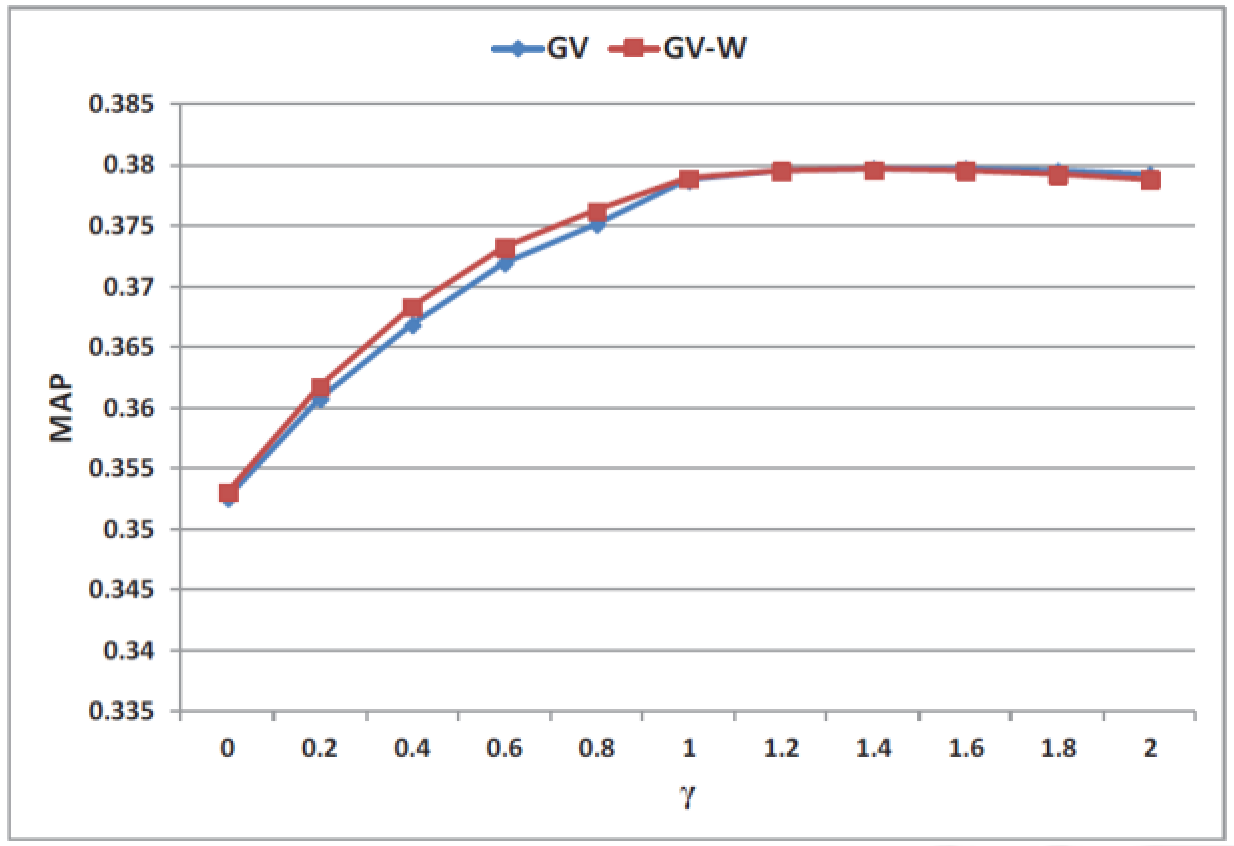
NUS-WIDE



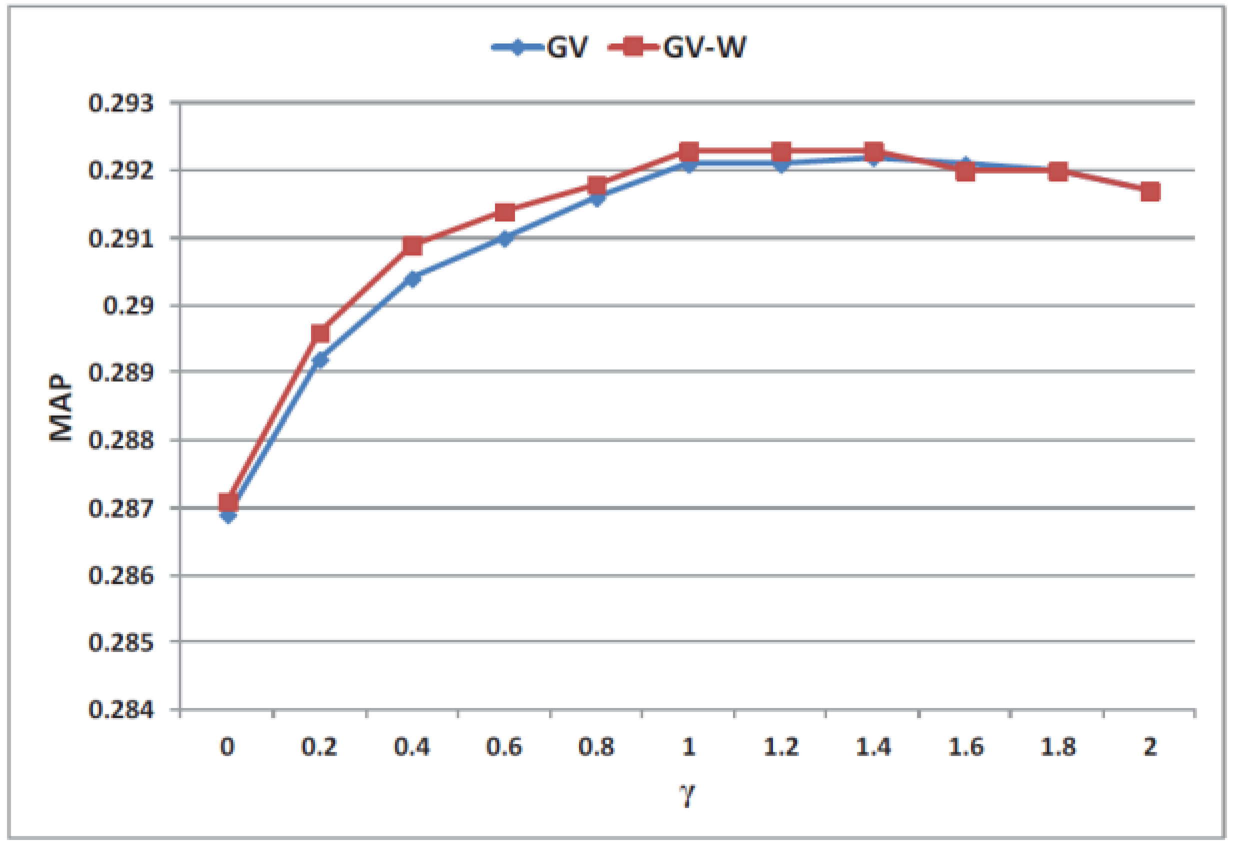
MIR Flickr

- *k* represents the number of nearest neighbors considered and controls the density of the voting graph.

Impact of Parameter γ



NUS-WIDE



MIR Flickr

- γ controls how the number of out-link neighbors affects the confidence value.

$$\gamma = \begin{cases} 1.0: & \text{linearly proportional to the number of its out-link neighbors.} \\ 0.0: & \text{regress to the standard random walk model.} \\ +\infty: & \text{nodes with less number of out-link neighbors will be omitted.} \end{cases}$$

Impact of Parameter α and σ

- α controls the prior teleportation probability.
  - our methods are not very sensitive to as compared with the case of standard random walk based methods.
- σ affects the sensitivity of the similarity measure
  - when σ is ***small***, neighbor images which are ***very close to*** the target image will have a ***larger similarity***.
  - when σ is ***large***, all neighbor images will tend to have ***similar voting powers***.
  - optimal value: the average distance of all images.

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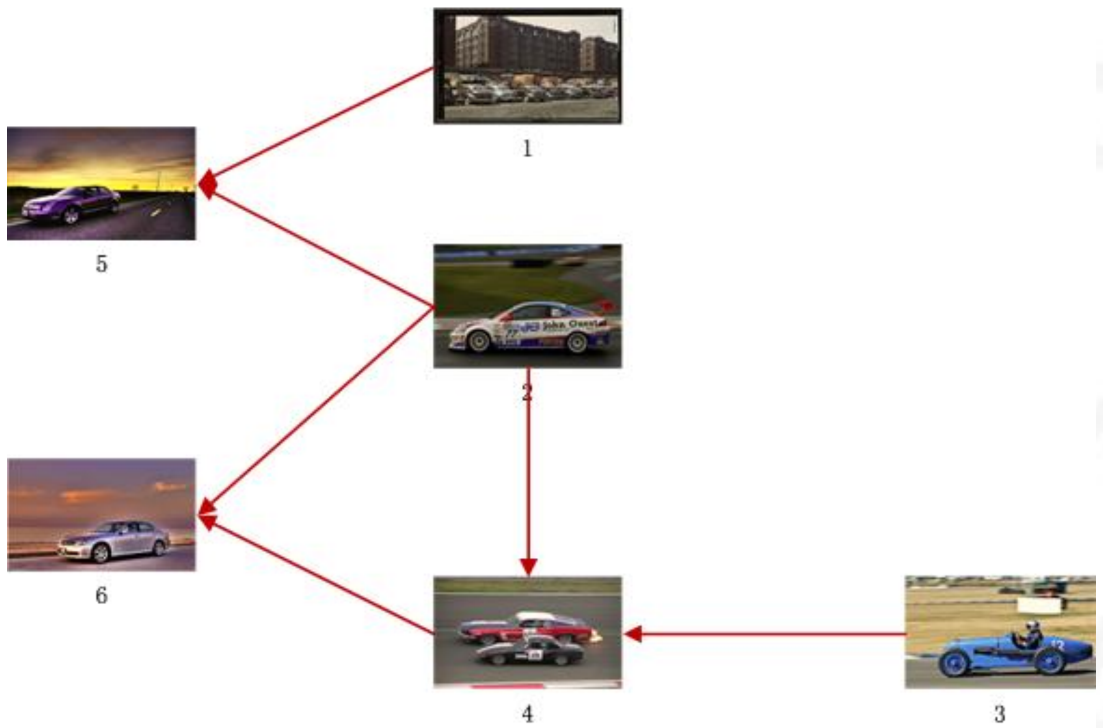
CONCLUSIONS

- We propose the **Voting Graph** to exploiting the relationships among visual neighbors.
  - structured (graph) voting, rather than flat voting.
- We presented a novel framework, called **Adaptive Teleportation Random Walk Model**, to seamlessly integrate confidence factor the into to random walk process.
- Theoretically analyze the **Mathematical Property**:
  - prove that the proposed model can converge to a stationary distribution
  - give its closed-form solution

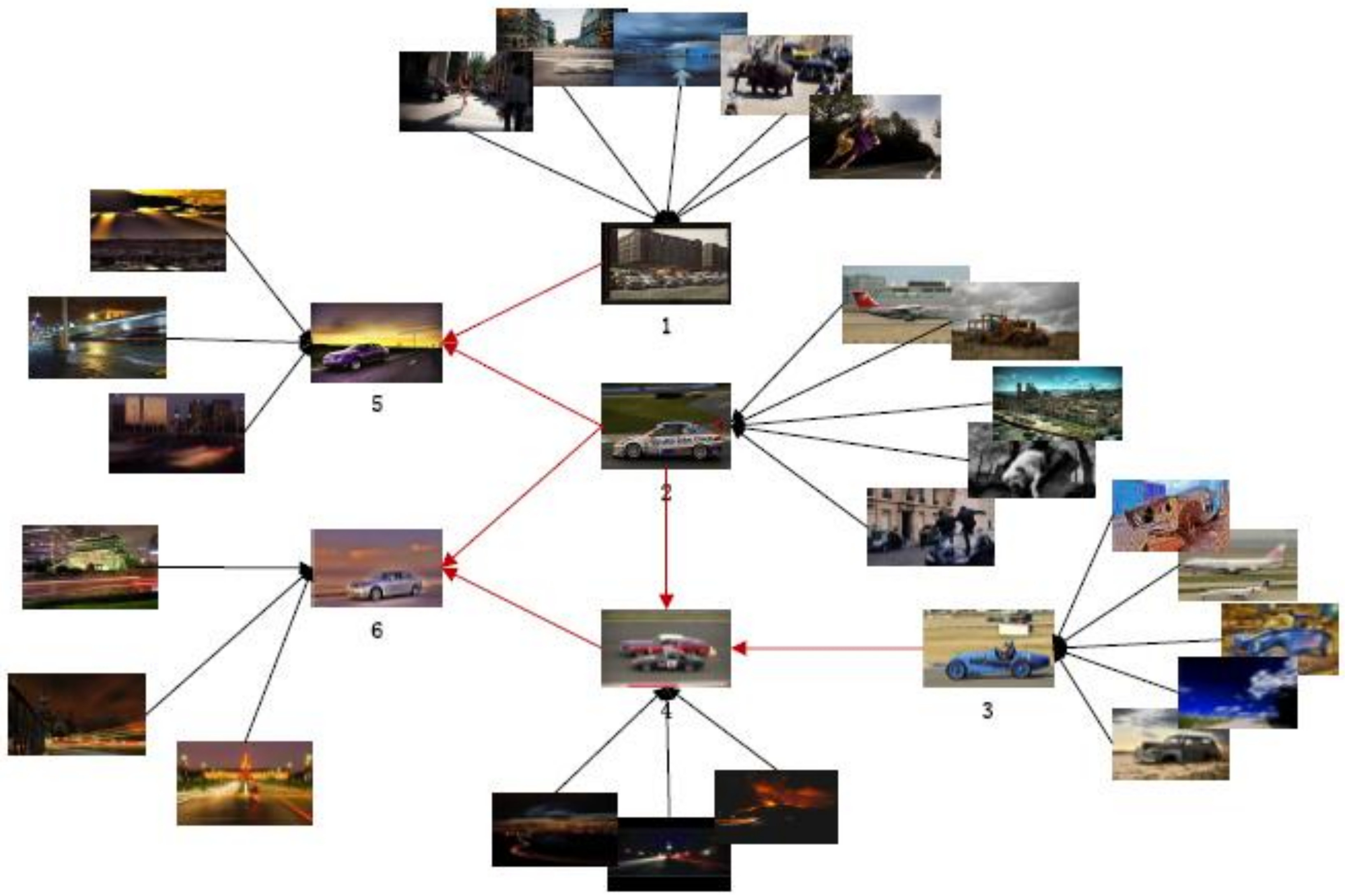
- **Future work**
  - Apply the proposed method in other applications, such as web search, query recommendation.
  - Reduce the incorrect relationships in the graph (semantic information)

THANKS & QUESTION?

Voting Graph vs k-NN Graph



(b) The resulting voting graph

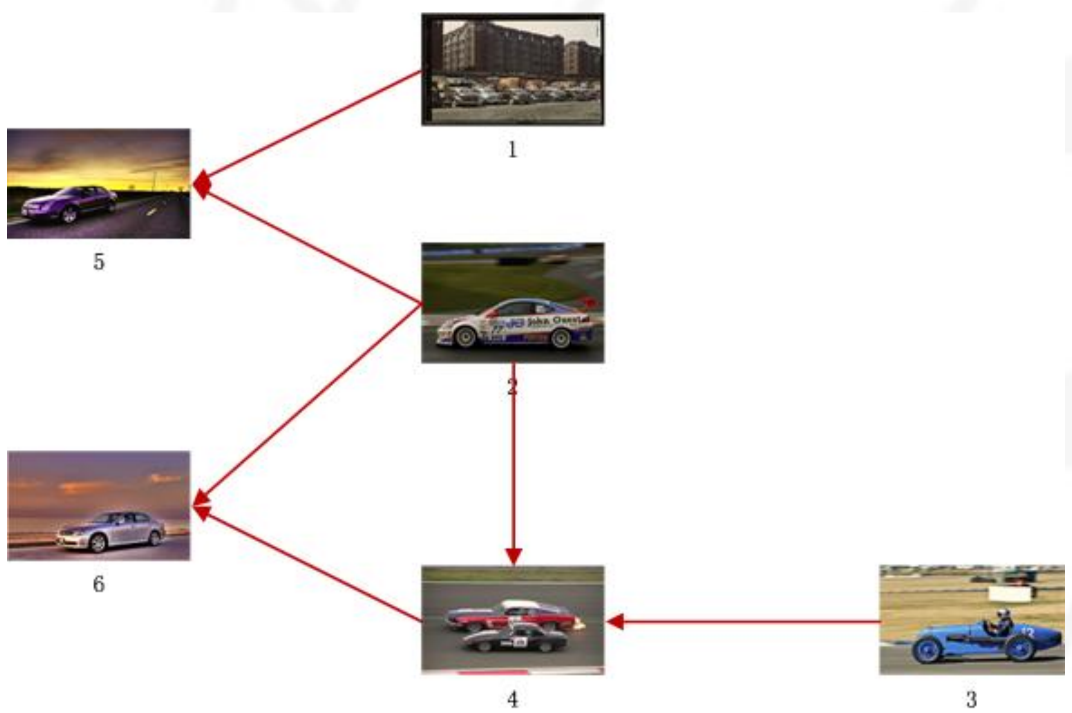


(c) The resulting k-NN graph

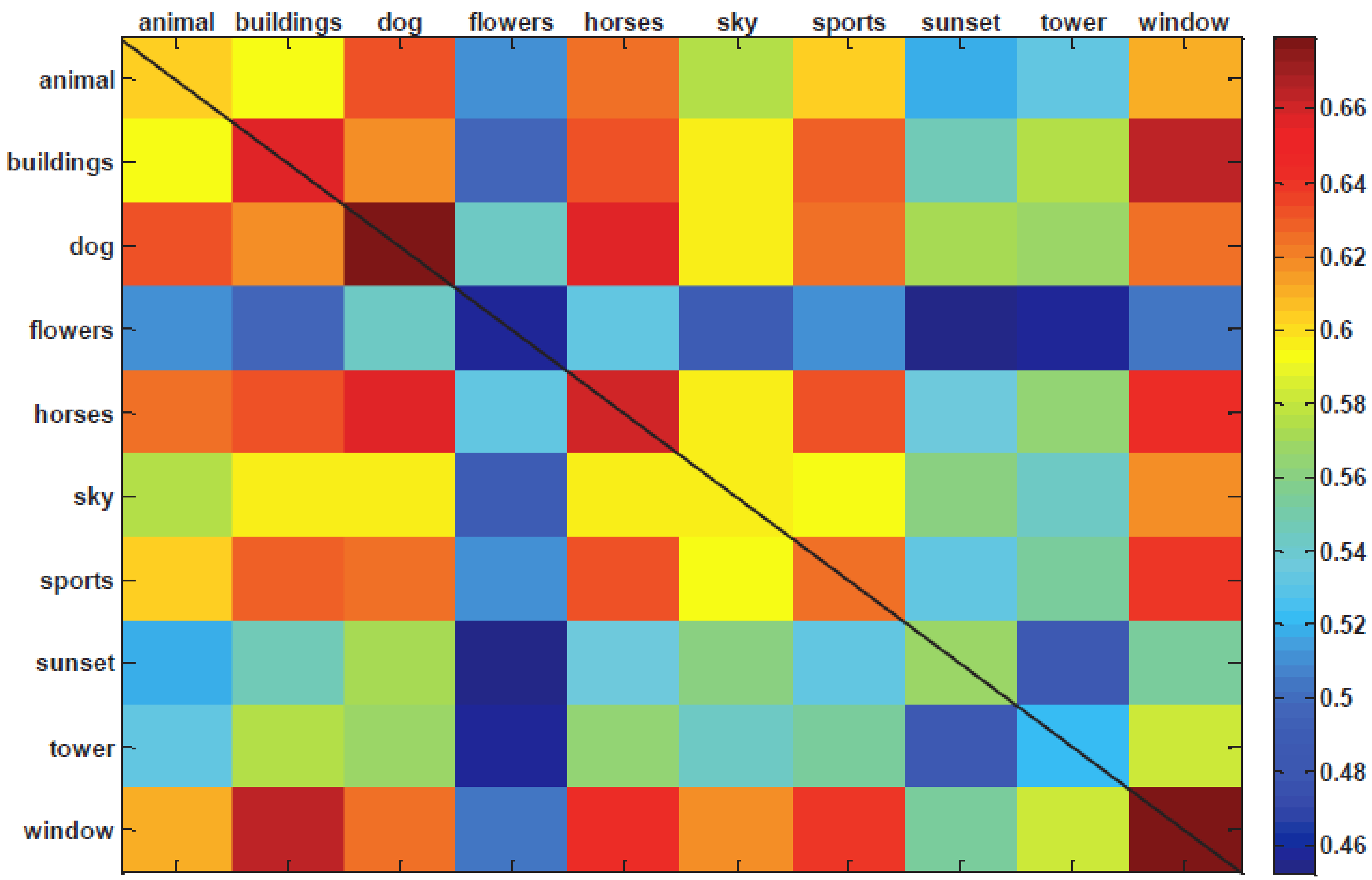
Interpretation of Existing Approaches via Voting Graph

- Use the in-degree of each node *i* (i.e., d_i^+)
  - equivalent to standard ***Neighbor Voting***.

- Further take into account the weight of the edges
  - equivalent to the **Weighted Neighbor Voting** algorithm



An illustration of the limitations of neighbor voting methods.



Intra-Class Similarity (diagonal blocks)

Inter-Class Similarity (non-diagonal blocks)

(Note: Warmer colors indicate *higher* visual similarities, Colder colors indicate *lower* visual similarities)

(e.g., the **intra-class similarity** of the concept `flower' is much smaller than its corresponding **inter-class similarity** with the concept 'horse‘)