# Image Retrieval with Reciprocal and Shared Nearest Neighbors

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# Outline

# Content-based image retrieval

"Rank database images in decreasing order of expected relevance to the query."

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**modern systems:** **large scale**, **efficient** and **effective** search

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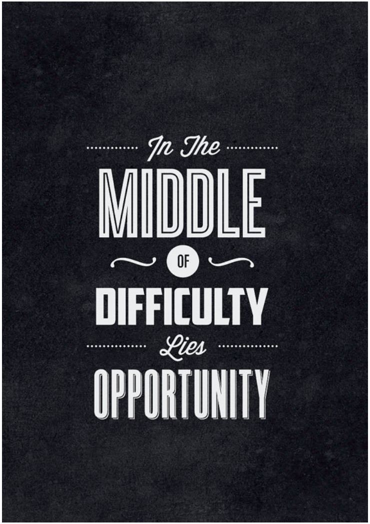
**the difficulty:** inherent **asymmetry** of $k$-nearest neighborhoods

"If $u$ is the among the $k$-NN of $v$, it is not necessarily the case that $v$ be among the $k$-NN of $u$."




"Albert Einstein"

# Getting some intuition . . .

**the needs**

- build high-relevance neighborhoods $\rightarrow$ **adjacency**
- exploit neighborhood information to assess images relationship $\rightarrow$ **structure**

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**. . . organize them**

- the direct neighborhood
- the indirect neighborhood

# So far

## enhancing the query result

- geometrical re-ranking [Fischler & Bolles, 1981; Jégou *et al.* 2008]
- redefinitions of the visual vocabulary [Nister & Stewenius 2006]
- alterations of distance measure [Jégou *et al.* 2010]
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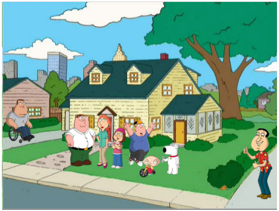
## notion of shared neighborhood

- reciprocity based set partition strategy [Qin *et al.* 2011]
- relevant-set correlation clustering model (RSC) [Houle 2008]
- shared neighbors as a secondary rank-based similarity measure [Houle *et al.* 2010]
- bipartite shared-neighbor algorithm for object-based visual query suggestion [Hamzaoui *et al.* 2013]

The promise!

# Our point-of-view



exploit the degree of association among the $k$-NN neighborhoods

- "denoise" the primary similarity measure
- extract adjacency and structural information among neighborhoods within the image space

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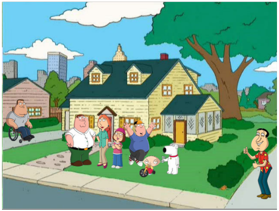

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2 re-reranking mechanisms in isolation or in combined manner

- 3 extended shared-neighbor based similarity measures $\rightarrow$ **indirect neighborhood**
- maximum reciprocal rank criterion $\rightarrow$ **direct neighborhood**

# Outline

# Shared nearest neighbors [Houle et al. 2010]

## Interesting notes

“Two images in the shortlist that share many database images are likely to be more similar than two other ones sharing few relevant ones.”

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"Comparing the neighborhoods of the images in the shortlist can serve for the comparison of the images themselves."

$$SNN_k(t,u) = \mathcal{N}_k(t) \cap \mathcal{N}_k(u)$$

where $t, u$ images in the $k$-shortlist of $q$ and $\mathcal{N}_k(;)$ the shortlist

$\rightarrow$ $|SNN_k(t,u)|$: the basis for a query result re-ranking function

# Shared neighbors illustration

Balliol College, Oxford

**image** $\mathbf{x}$

$\mathcal{N}_9(\mathbf{x})$

**image** $\mathbf{y}$

$\mathcal{N}_9(\mathbf{y})$

# Shared neighbors illustration

## Balliol College, Oxford

**image** $\mathbf{x}$ $\qquad\qquad$ $\mathcal{N}_{\mathbf{9}}(\mathbf{x})$

$$\mathcal{SNN}_{\mathbf{9}}(\mathbf{x}, \mathbf{y}) = \mathcal{N}_{\mathbf{9}}(\mathbf{x}) \cap \mathcal{N}_{\mathbf{9}}(\mathbf{y})$$

**image** $\mathbf{y}$ $\qquad\qquad$ $\mathcal{N}_{\mathbf{9}}(\mathbf{y})$

# Metrics for neighborhoods

- **Jaccard**

$$j_k(x,y) = \frac{|SNN_k(x,y)|}{|\mathcal{N}_k(x) \cup \mathcal{N}_k(y)|}$$

$\rightarrow$ distribution of shared neighbors

- **Set Correlation** [Houle *et al.* 2010]

$$sc_k(x,y) = \frac{|\mathcal{D}|}{|\mathcal{D}| - k}\left(\frac{|SNN_k(x,y)|}{k} - \frac{k}{|\mathcal{D}|}\right)$$

where $\mathcal{D}$ the image database set
$\rightarrow$ neighborhood size as a fraction of the database size

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"Jaccard and Set Correlation are sensitive to the membership and size of neighborhoods but not to their order."

"Small neighborhoods appear more reliable than larger ones."

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"We desire to increase the relative weight of less relevant images (bottom of the shortlist) at the expense of highly relevant ones (top of the shortlist)."

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## The alternative

- **Sigmoid**

$$sgm_k(x,y) = \frac{1}{1 + exp(-a * (\frac{|SNN_k(x,y)|}{k} - b))},$$

slope $a$: controls the type of mapping (gradual to steep)

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$\rightarrow$ still sensitive to neighborhood size $k$

# Extending neighborhood measures

**The idea:** integrate the basic shared neighbor-based scores across the full range of neighborhood size and discover neighbors adopting a sophisticated strategy to refine all neighborhoods

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*improving the indirect neighborhood*

- **Extended Jaccard**

$$\bar{j}_k(x,y) = \sum_{k'=1}^{k} j_{k'}(x,y) \frac{1}{\sum_{l=1}^{k'} \delta_l(x,y)},$$

with

$$\delta_l(x,y) = \begin{cases} 1, & \text{if } |SNN_l(x,y)| > 0 \\ 0, & \text{otherwise} \end{cases}$$

$\rightarrow$ consider only non zero contributions

# Extending neighborhood measures

- **Extended Set Correlation**

$$\overline{sc}_k(x, y) = \sum_{k'=1}^{k} \frac{sc_{k'}(x, y)}{k'}$$

- **Extended Sigmoid**

$$\overline{sgm}_k(x, y) = \sum_{k'=1}^{k} \frac{sgm_{k'}(x, y)}{k'}$$

$\rightarrow$ normalize depending on $k$

**note:** initial $k$ can vary ($k_0 \leq 1$)

# Outline

Introduction

Comparing neighborhoods

**Maximum Reciprocal Rank**

Experiments

Discussion

# Maximum Reciprocal Rank

**The novelty**

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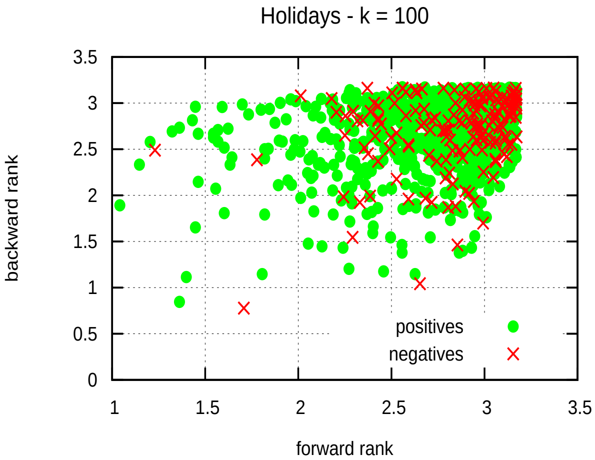
*improving the direct neighborhood*

$$\mathcal{R}_k(x) = k\text{-}\mathsf{arg}\min_{y \in \mathcal{D}} r(x, y)$$

→ a symmetric dissimilarity measure
→ identification of neighbors with high degree of mutual relevance

# Maximum Reciprocal Rank



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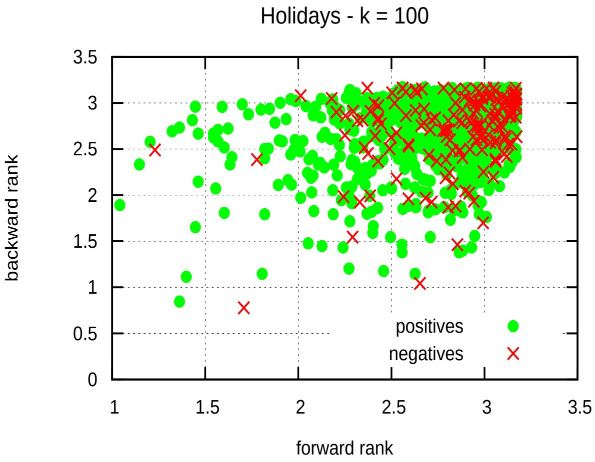



"The density of positive examples is high when both the forward and backward rank indicate high relevance, whereas most negative examples have a poor forward or backward rank or both."

# Outline

# Datasets

Diversity

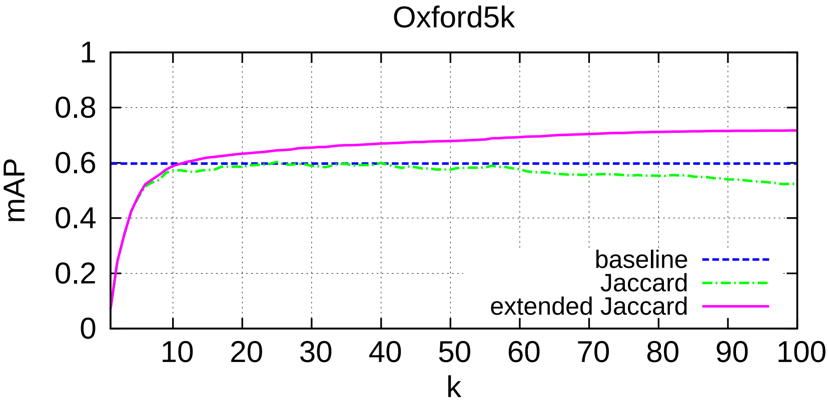
images - queries - description

Paris6k: 6412 - 55 - Paris landmarks

Oxford5k: 5062 - 55 - 11 distinct Oxford buildings

Holidays: 1491 - 500 - small groups of images

# Jaccard vs. extended Jaccard



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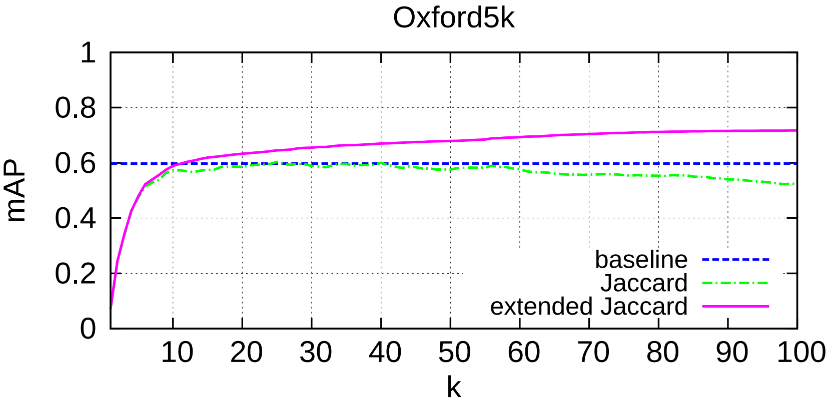
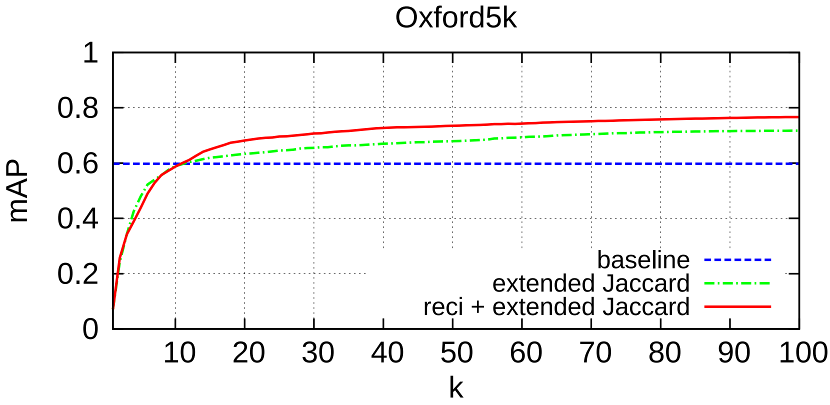



"The extension of the measure appears more stable & increasing over $k$."

# Using reciprocity



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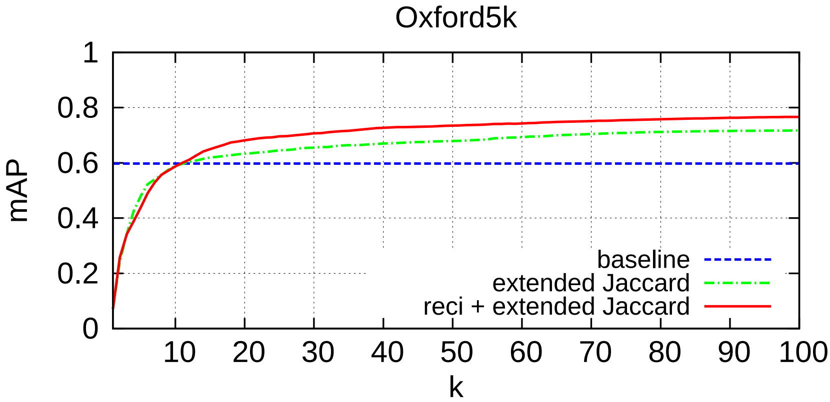


"The use of maximum reciprocal rank criterion boosts image retrieval performance."

# mAP evaluation
## $(1 \leq k \leq 200)$

| Dataset | Oxford5k | Paris6k | Holidays | |
|---|---|---|---|---|
| Method | BOF | BOF | BOF | VLAD |
| | 1M | 500k | 200k | 64 centroids |
| baseline | 0.598 | 0.691 | 0.549 | 0.571 |
| (Qin *et al.* 2011) | 0.814 | 0.803 | - | - |
| $\mathcal{N}_k$ & $\overline{j}_k$ | 0.701 | 0.752 | 0.582 | 0.606 |
| $\mathcal{N}_k$ & $\overline{sc}_k$ | 0.700 | 0.748 | 0.581 | 0.602 |
| $\mathcal{N}_k$ & $\overline{sgm}_k$ | 0.724 | 0.783 | 0.589 | 0.607 |
| $\mathcal{R}_k$ & $\overline{j}_k$ | 0.737 | 0.768 | 0.685 | 0.655 |
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$\rightarrow$ extended measures outperform their non-extended counterparts

$\rightarrow$ similar performance over all three variants

# Varying initial neighborhood size $k_0$

| Oxford5k | | |
|---|---|---|
| Method | $k_0 = 1$ | $k_0 = 20$ |
| $\mathcal{R}_k$ & $\overline{j}_k$ | 0.737 | **0.779** |
| $\mathcal{R}_k$ & $\overline{sc}_k$ | 0.734 | 0.777 |
| $\mathcal{R}_k$ & $\overline{sgm}_k$ | 0.746 | 0.761 |

| Paris6k | | |
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| Method | $k_0 = 1$ | $k_0 = 80$ |
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$\rightarrow$ $k_0$ association with dataset structure

# Retrieval examples

query | Retrieved images

rank 1 | rank 2 | rank 3 | rank 4 | rank 5

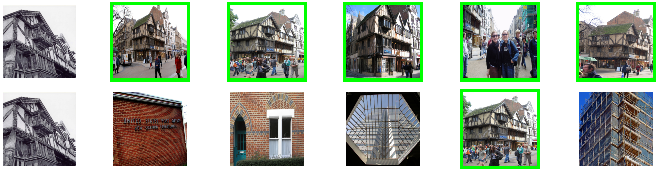
$\mathcal{R}_k$ & $\bar{j}_k$

$k$-nn


Paris6k

$\mathcal{R}_k$ & $\bar{j}_k$

$k$-nn



Oxford5k

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**Holidays**

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$\mathcal{R}_k$ & $\overline{sgm}_k$

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**Holidays**

"The combined use of reciprocity and shared-neighbor information enhance the quality of similarity search."

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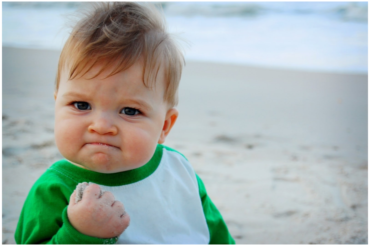
# The contribution



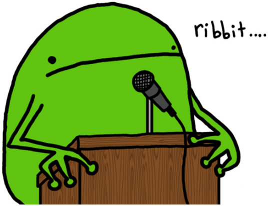
1. 3 neighborhood similarity measures suitable for use in shared-neighbor based re-ranking scheme
2. the extension of measures integrates efficiently their values across a range of the neighborhood size
3. maximum reciprocal rank criterion improves on the degree of relevance in the shortlists

# A review

- \+ a simple but uniform and principled framework for integrating the structural information obtained by image neighborhoods
- \+ free of parameter tuning and optimisation processes
- – the overhead of the computation & storage of the shortlists grows linearly with database size $\rightarrow$ common problem with the main competing method [Qin *et al.* 2011]

# Outline

# Thank you for your attention!




## Questions

Picture credits: Google image retrieval!