Learning from Large-Scale Online Images

Jianping Fan
Department of Computer Science
UNC-Charlotte

Course Website:
http://webpages.uncc.edu/jfan/itcs5152.html

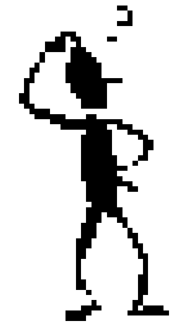
Two Huge Image Sources

- Social images such as Flickr images

- Web images such as Google images

How to harvest both social images and web images for computer vision tasks?

1. Research Motivation



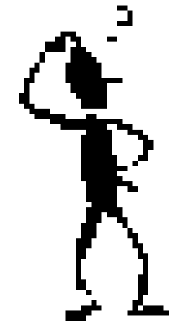
- **Computer Vision Tasks: Why we need large-scale labeled training images?**

  » **Number of objects and concepts could be large;**

  » **Learning complexity for some objects and concepts could be very high!**

Labeling large-scale training images is label-intensive!

1. Research Motivation



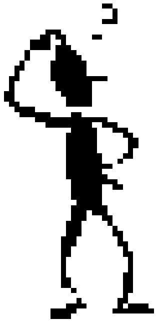
- **What Collaboratively-Tagged Images can do for us?**

  - **They are sufficient to characterize the diverse visual properties of large amounts of objects and concepts;**

  - **They can obtained easily by leveraging the collaborative efforts of Internet users.**

Why not using collaboratively-tagged images for classifier training?

1. Research Motivation

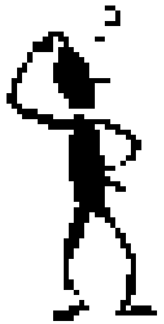


- **What are the problems of collaboratively-tagged images?**

    - **Spam tags & junk images;**
    - **Synonymous & Ambiguous tags;**
    - **Loose tags;**

We call such collaboratively-tagged images as ***weakly-tagged images***!

1. Research Motivation



- **What is the problem of classifier training algorithms?**

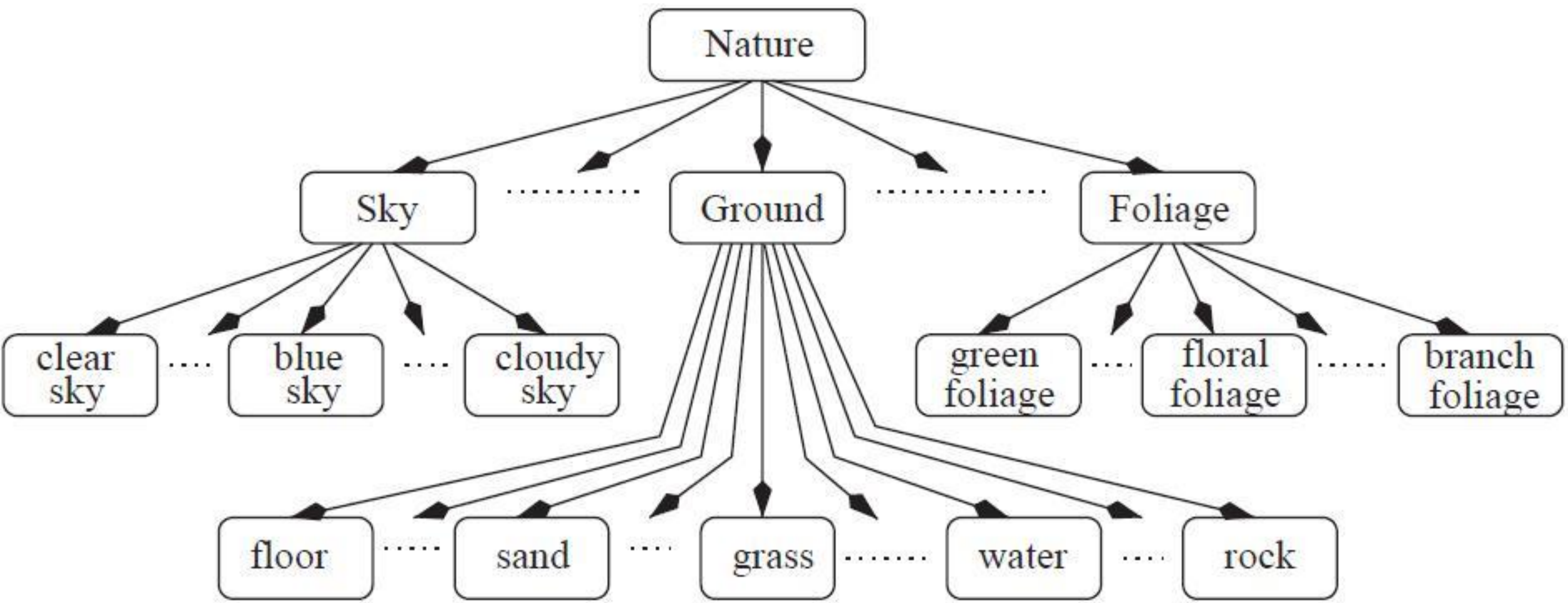
  - **Inter-Task Correlation Exploration;**

  - **Scalability with the number of objects and image concepts;**

  - **Discrimination power for visually-similar objects and image concepts.**

2. Image Crawling

- **Flickr Images & Others**
  - **Keywords for image crawling**



2. Image Crawling

- **Flickr Images & Others**

  - **Images for each keyword**

    ---5000 images and their tags and comments;

    - **Some of these 5000 images are junks;**
    - **Some of these 1000 keywords are synonymous or ambiguous**

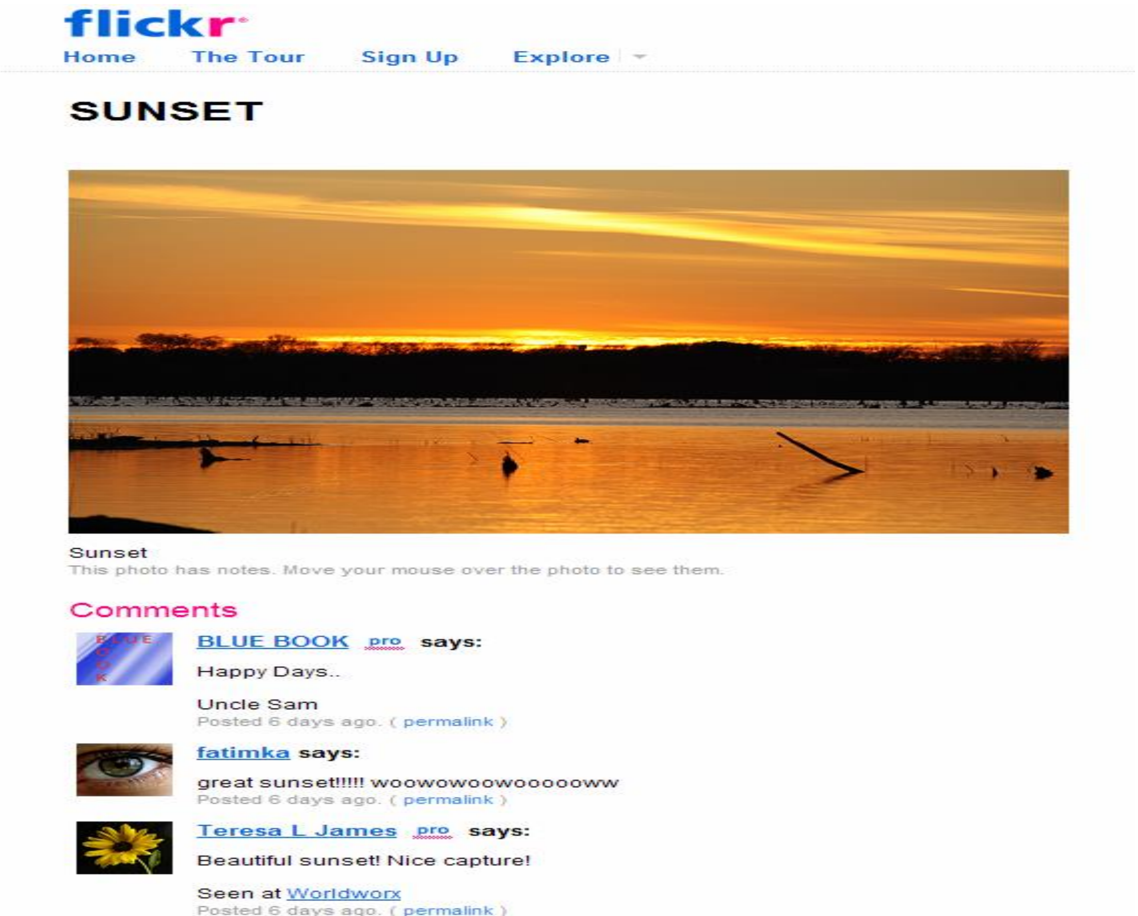
These weakly-tagged images cannot directly be used for classifier training!

- **Image & Tag Cleansing;**

- **Classifier Training with noisy images**

2. Image Crawling

- **Multiple Information Sources**



3. Image Content Representation

- **Multi-Resolution Image Grids**

- **Computational cost for feature extraction**
- **Discrimination power of visual features for classifier training**

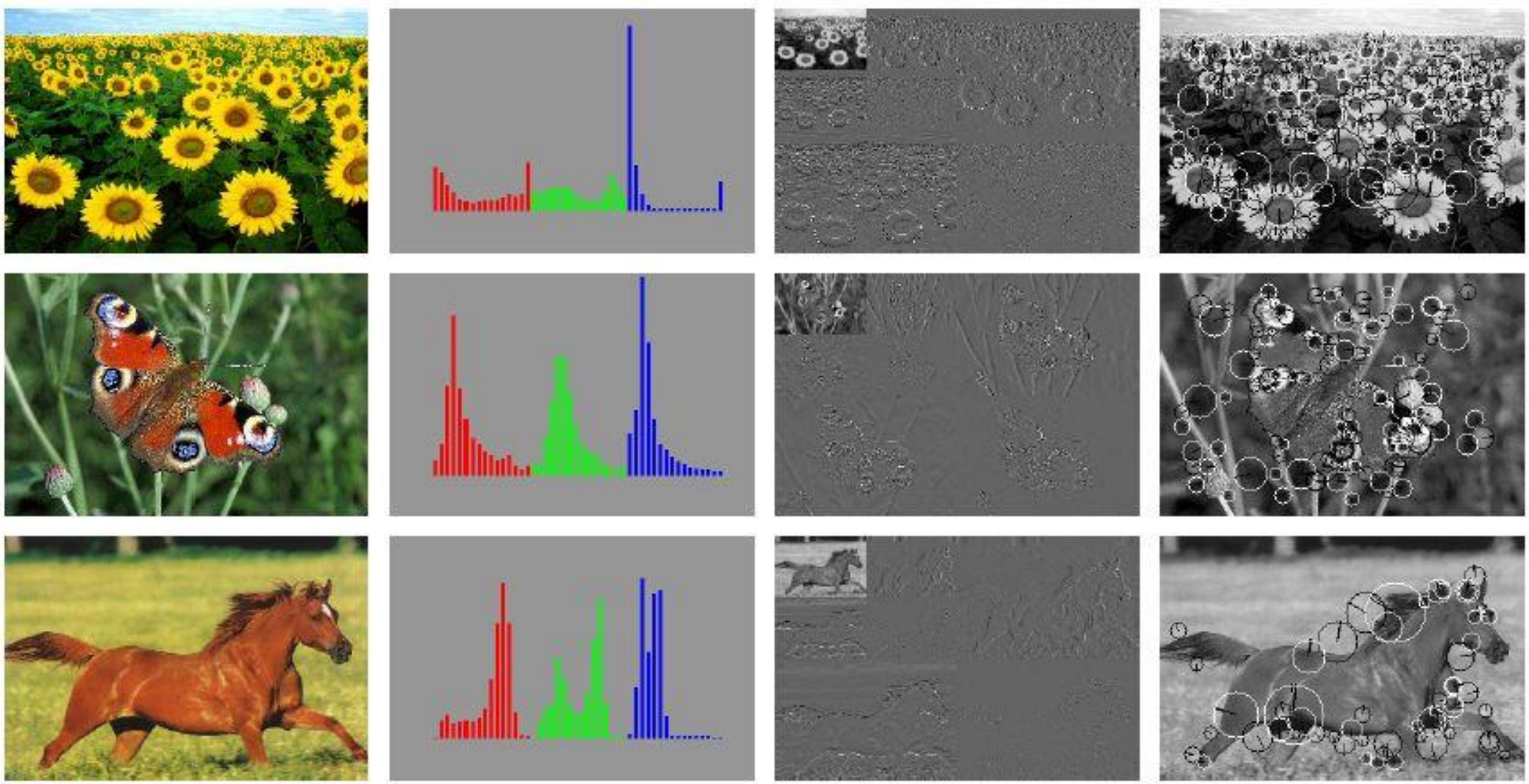
3. Image Content Representation

- **Multi-Resolution Image Grids**

- **Object information characterization at certain accuracy;**
- **Good trade-off between computational cost and accuracy.**

4. Image Similarity Characterization

- **Multi-Modal Visual Features & Mixture-of-Kernels**



4. Image Similarity Characterization

- **Mixture-of-Kernels**

$$\kappa(x, y) = \sum_{l=1}^{\tau} \alpha_l \kappa_l(x, y), \qquad \sum_{l=1}^{\tau} \alpha_l = 1$$

- **Image distributions under different feature subsets may have different statistical properties**

- **One kernel cannot handle such diversity!**

5. Junk Image Filtering

- **Positive Comments *vs.* Negative Comments**

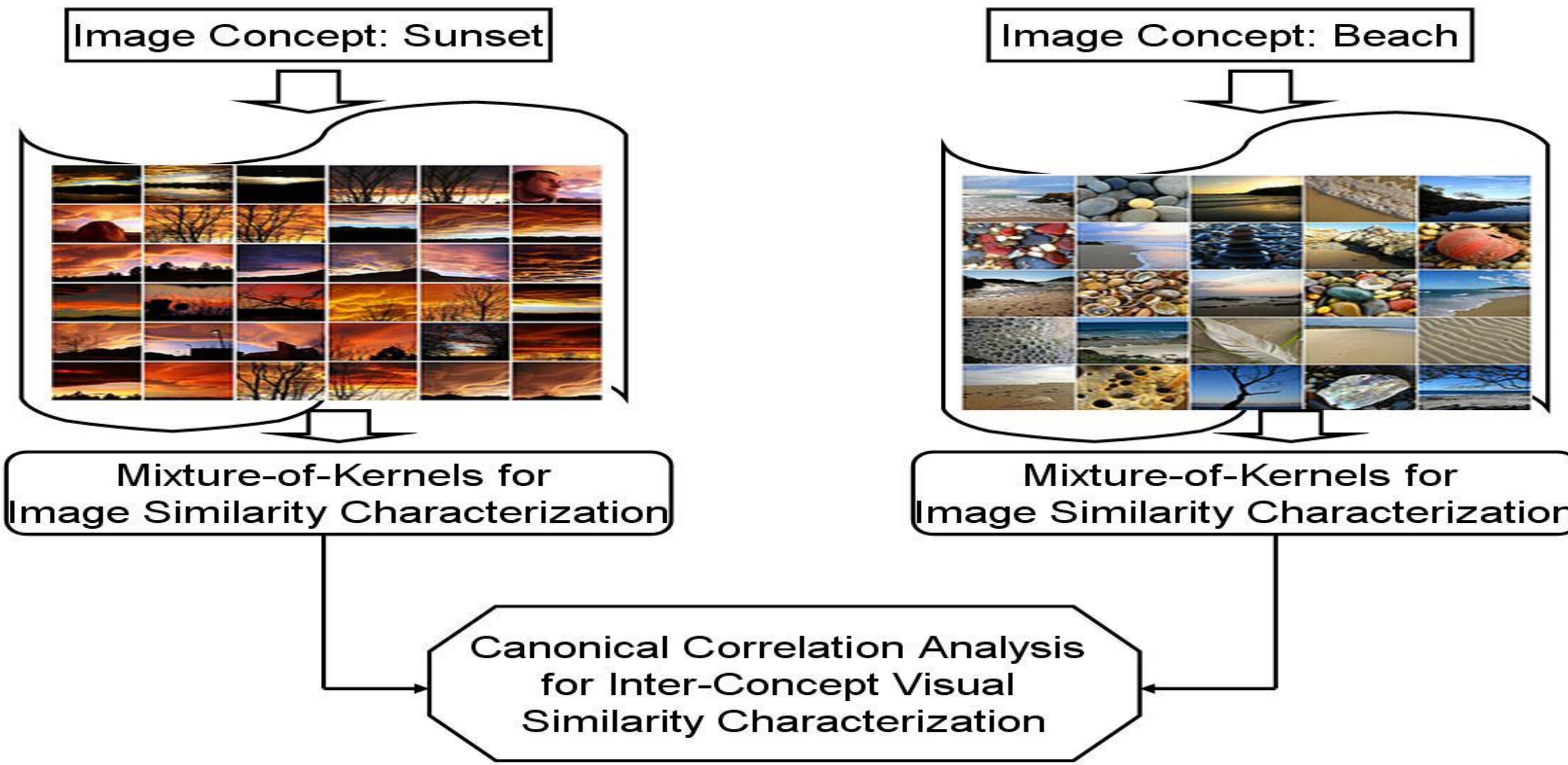
$$PMI(C,\Phi) = \sum_{i=1}^{N} \log \frac{P(C \cap P\_word_i)}{P(C)P(P\_word_i)}$$

$$PMI(C,\Psi) = \sum_{i=1}^{N} \log \frac{P(C \cap N\_word_i)}{P(C)P(N\_word_i)}$$

$$PMI(C) = PMI(C,\Phi) - PMI(C,\Psi)$$

6. Visual Concept Network

- **Kernel Canonical Correlation Analysis**



6. Visual Concept Network

- **Kernel Canonical Correlation Analysis**

$$\gamma(C_i, C_j) = \max_{\theta, \vartheta} \frac{\theta^T \kappa(S_i)\kappa(S_j)\vartheta}{\sqrt{\theta^T \kappa^2(S_i)\theta \cdot \vartheta^T \kappa^2(S_j)\vartheta}}$$

$$\kappa(S_i) = \sum_{x_l, x_m \in S_i} \kappa(x_l, x_m) \quad \kappa(S_j) = \sum_{x_h, x_k \in S_j} \kappa(x_h, x_k)$$

$$\kappa(S_i)\kappa(S_i)\theta - \lambda_\theta^2 \kappa(S_i)\kappa(S_i)\theta = 0$$

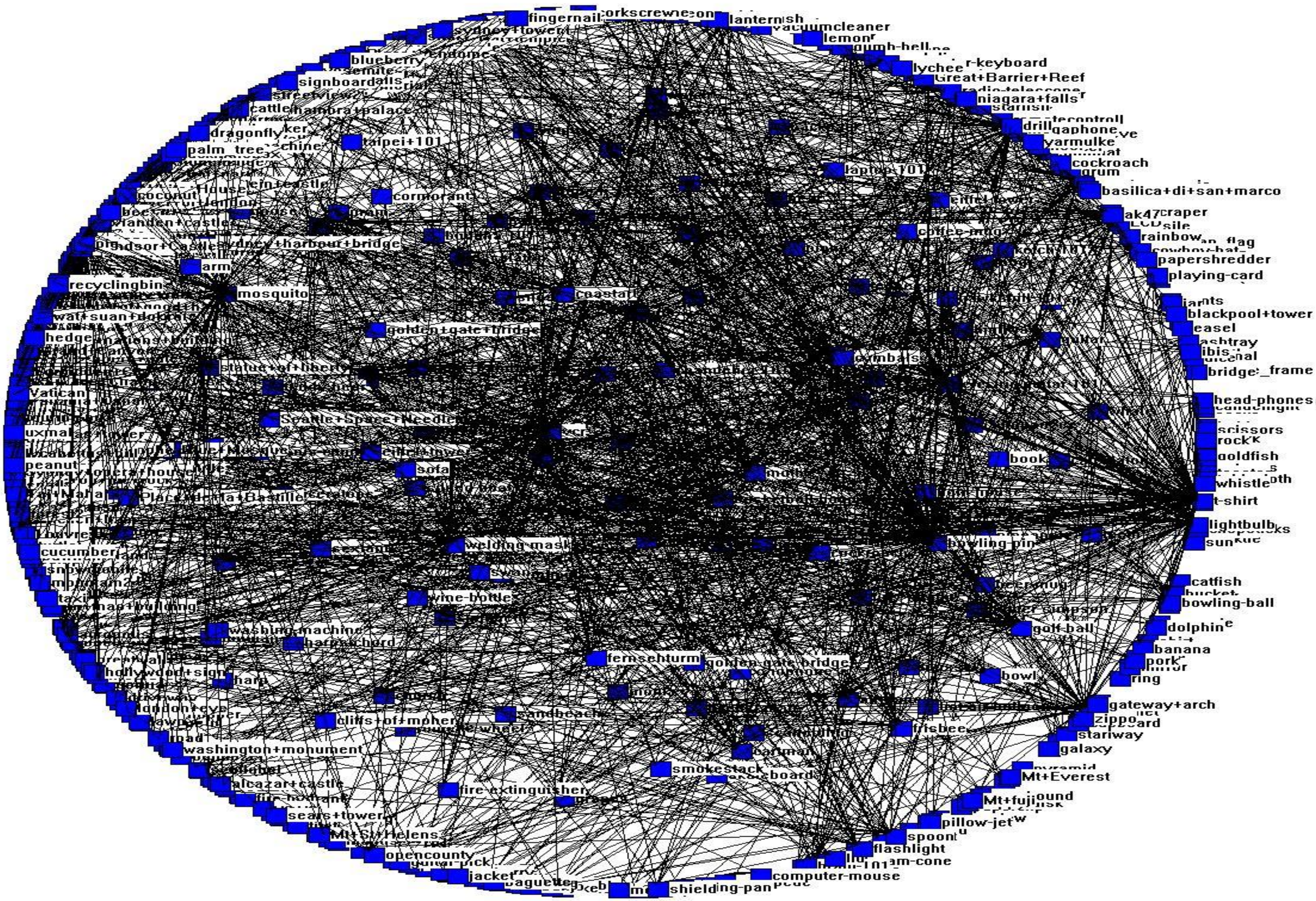
$$\kappa(S_j)\kappa(S_j)\vartheta - \lambda_\vartheta^2 \kappa(S_j)\kappa(S_j)\vartheta = 0$$

6. Visual Concept Network

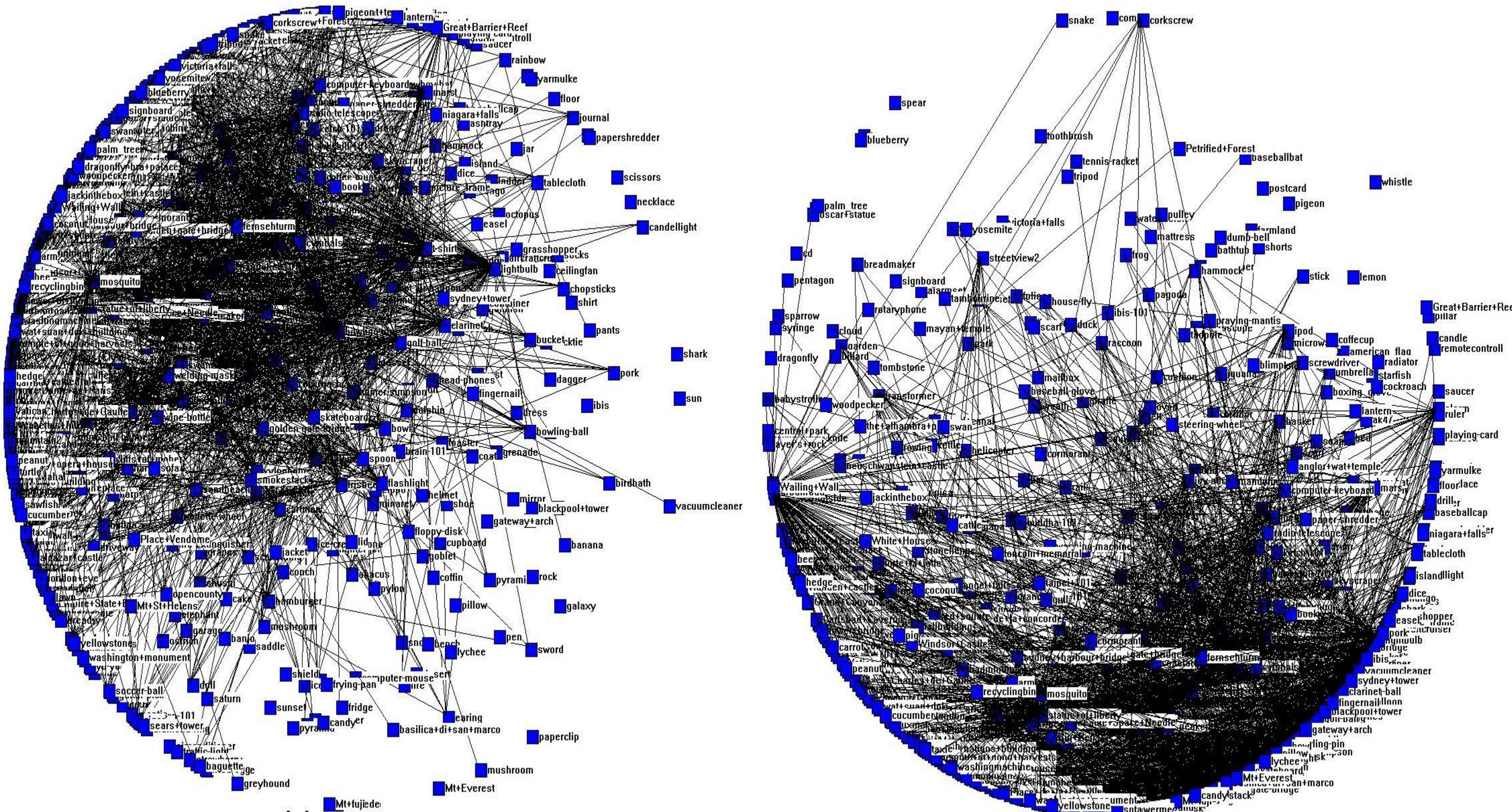
- **Kernel Canonical Correlation Analysis**

concept pair	γ	concept pair	γ	concept pair	γ	concept pair	γ
urbanroad-streetview	0.99	cat-dog	0.81	kerb-saucer	0.28	tweezer-corn	0.19
frisbee-pizza	0.80	dolphin-cruiser	0.73	fridge-vest	0.29	journal-grape	0.19
moped-bus	0.75	habor-outview	0.71	stick-cupboard	0.29	sheep-greatwall	0.26
monkey-humanface	0.71	guitar-violin	0.71	mushroom-moon	0.32	whistle-watermelon	0.28
lightbulb-firework	0.69	mango-broccoli	0.69	cannon-ruler	0.41	snake-ipod	0.31
porcupine-lion	0.68	bridge-warship	0.68	tombstone-crab	0.42	helicopter-city	0.63
doorway-street	0.65	statue-building	0.68	pylon-highway	0.61	LCD-container	0.65
windmill-bigben	0.63	cat-lion	0.66	beermug-bar	0.62	sailboat-cruiser	0.66

6. Visual Concept Network



6. Visual Concept Network

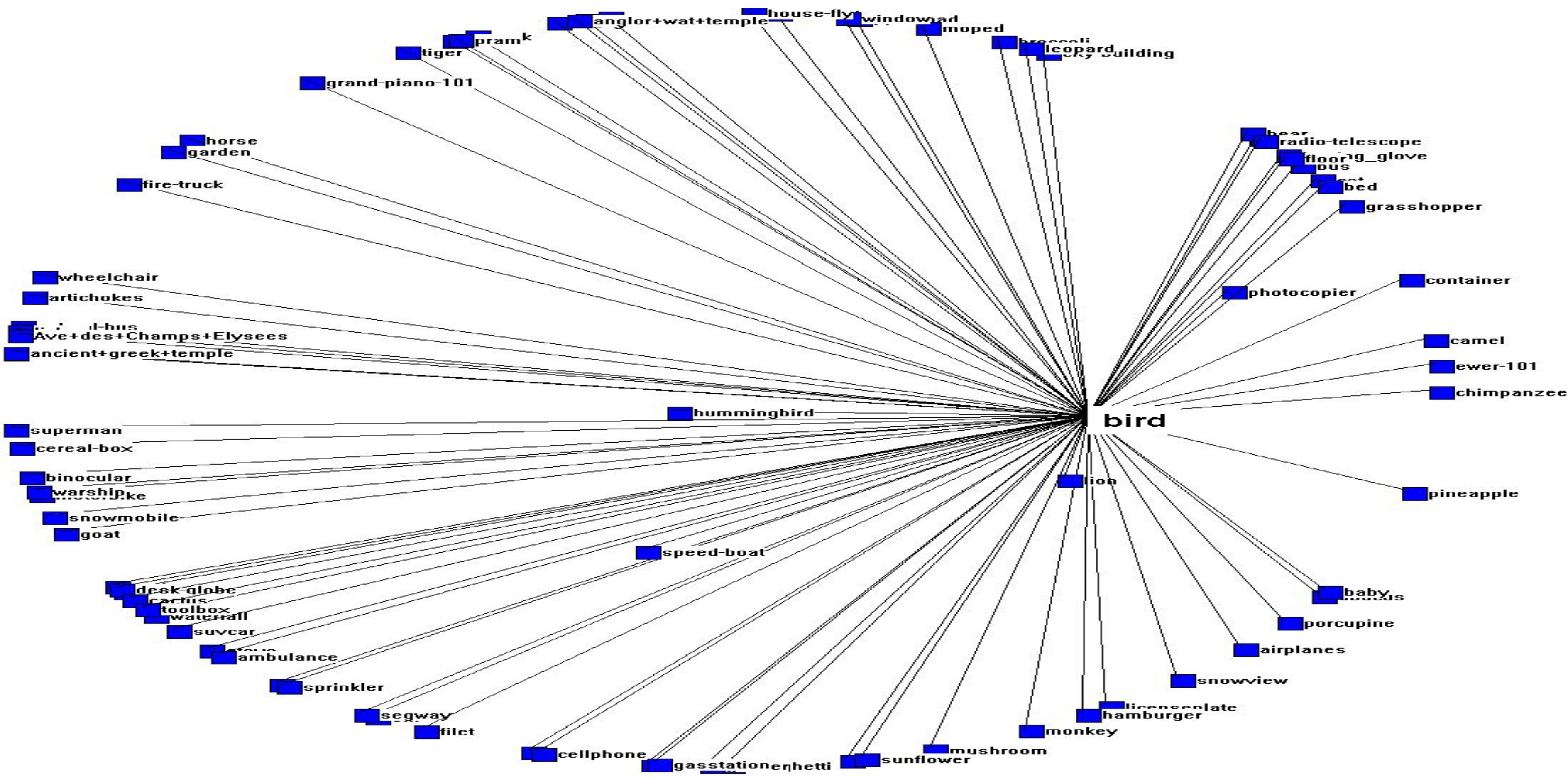


(a)

(b)

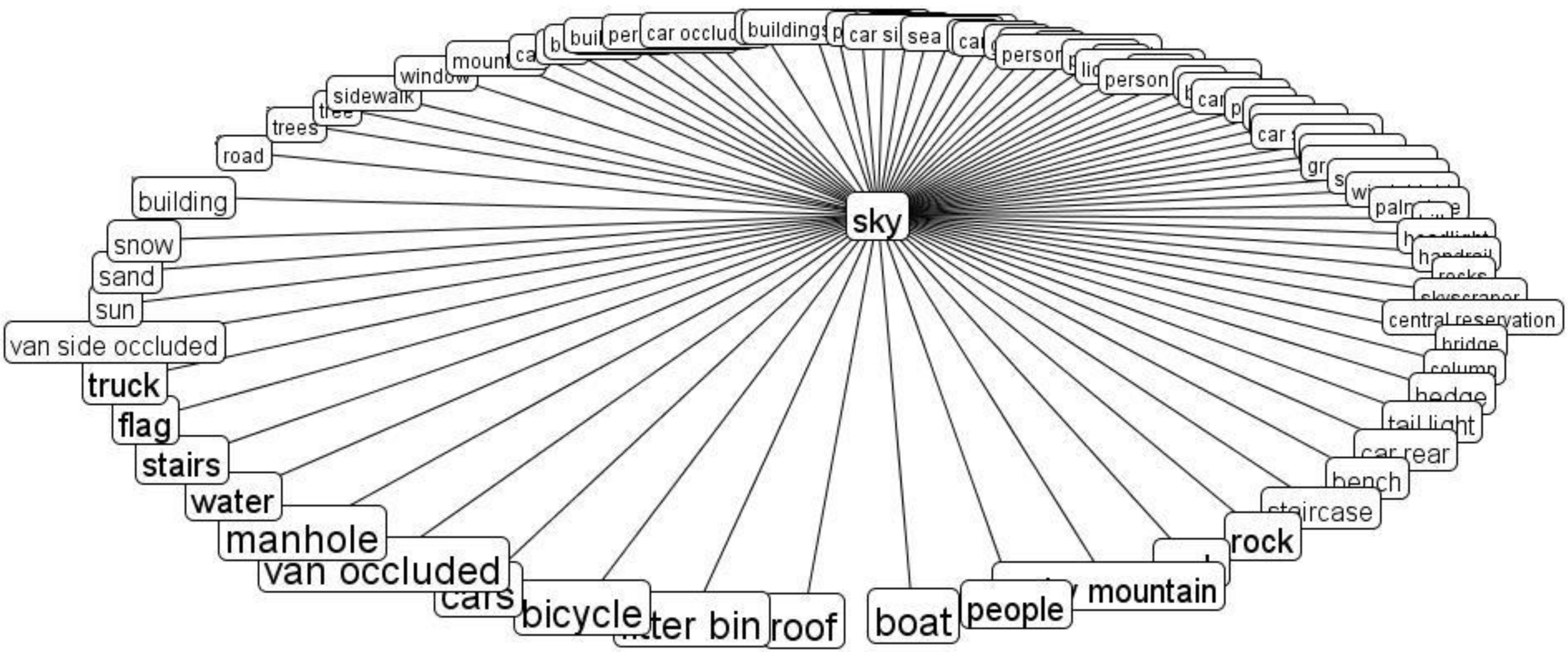
6. Visual Concept Network

- **First-Order Nearest Neighbors**



6. Visual Concept Network

- **First-Order Nearest Neighbors**



6. Visual Concept Network

- **Why we need a visual concept network?**
  - **Inter-Related Learning Tasks, e.g., inter-related objects and concepts;**
  - **Discrimination power of classifiers, e.g., if our classifiers can identify the visually-similar objects and concepts, they will have better discrimination power.**

7. Cross-Modal Tag Cleansing

- **Synonymous Tags: Visual Similarity**

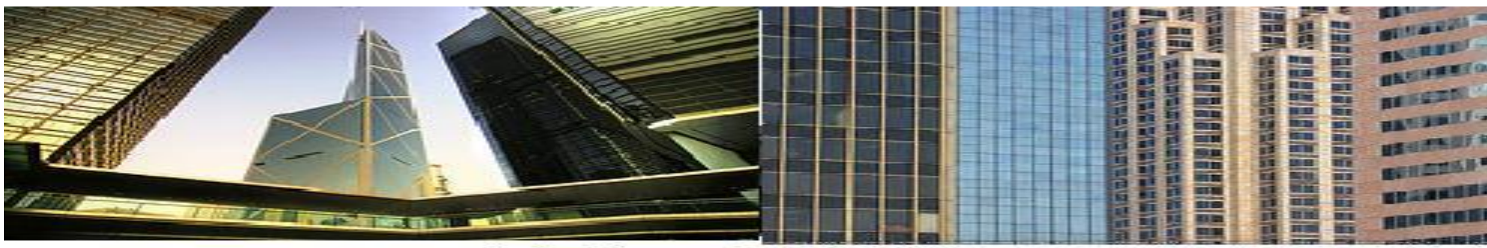
(a) Auto

(b) Automobile

(c) Car

7. Cross-Modal Tag Cleansing

- **Ambiguous Tags: Visual Diversity**



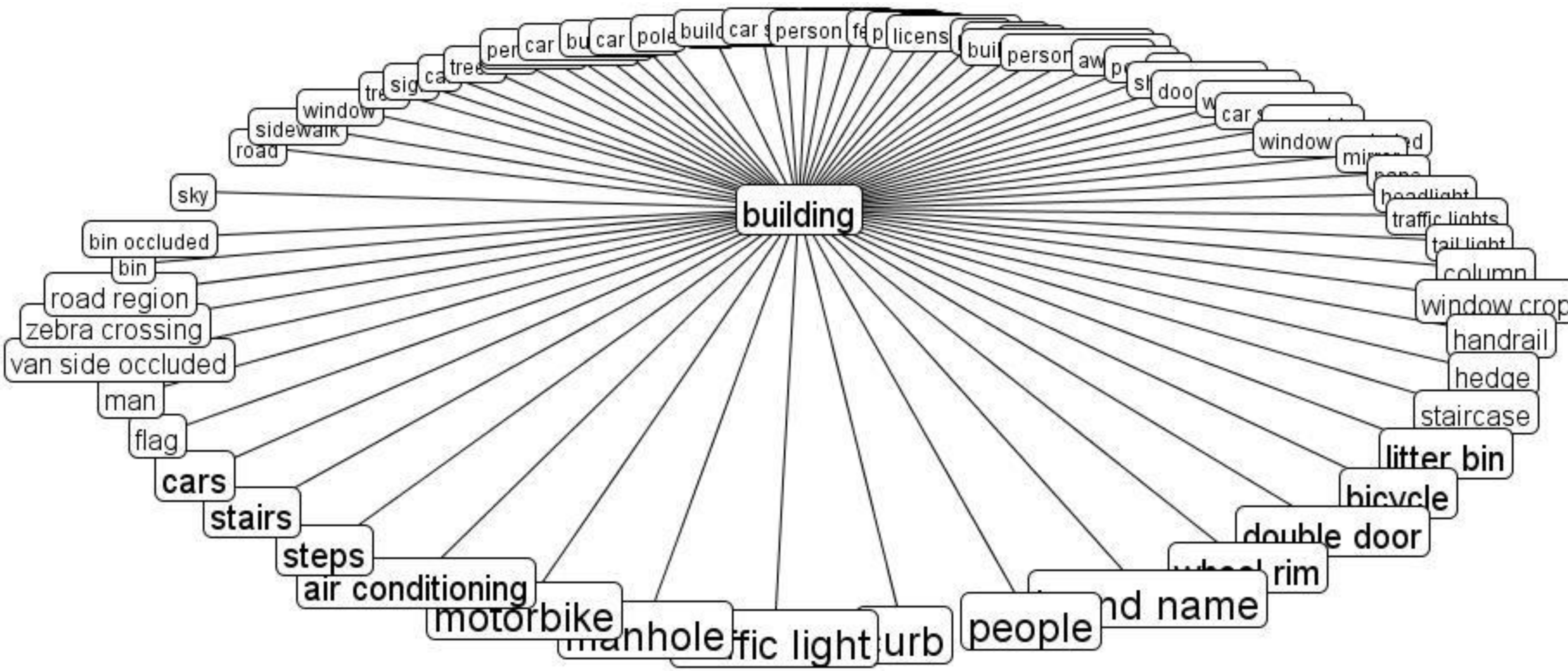
(a) Bank Office

(b) River Bank

(c) Cloud Bank

8. Inter-Related Classifier Training

- **Which Object and Concepts are correlated?**



Our visual concept network can provide a good environment for this task!

8. Inter-Related Classifier Training

- **How to model such inter-concept correlation?**

  ----Structured Max-Margin Networking

  - **Support Vector Machine (SVM)**

    ----It is able to handle high-dimensional issue effectively, but it cannot model the inter-related structure!

  - **Graphical Models such as CRF**

    ----It is able to model the inter-related structure effectively, but it cannot handle high-dimensional issue!

Our learning situation is both high-dimension and correlation structure!

8. Inter-Related Classifier Training

- **How to model such inter-concept correlation?**

$$P(C_j, X) = \frac{1}{Z} exp \left(\sum_{C_j \in \Xi_j} f(C_j, X) + \sum_{C_j \in \Xi_j} \sum_{C_i \in \Xi_i} f(C_j, C_i, X) \right)$$

$$Z = \sum_{j=1}^{T} exp \left(\sum_{C_j \in \Xi_j} f(C_j, X) + \sum_{C_j \in \Xi_j} \sum_{C_i \in \Xi_i} f(C_j, C_i, X) \right)$$

8. Inter-Related Classifier Training

- **How to model such inter-concept correlation?**

$$P(C_j|X) \propto P(C_j, X) \propto exp\left(\sum_{C_j \in \Xi_j} f(C_j, X) + \sum_{C_j \in \Xi_j} \sum_{C_i \in \Xi_i} f(C_j, C_i, X)\right)$$

$$H_{C_j}(X) = argmax\left(\sum_{C_j \in \Xi_j} f(C_j, X) + \sum_{C_j \in \Xi_j} \sum_{C_i \in \Xi_i} f(C_j, C_i, X)\right)$$

8. Inter-Related Classifier Training

- **How to model such inter-concept correlation?**

$$f(C_j, X) = sign\left(\sum_{l=1}^{N}\sum_{m=1}^{\tau} \beta_{lj} Y_{lj} \alpha_m \kappa_m(X_{lj}, X) + b\right)$$

$$f(C_j, C_i, X) = sign\left(\sum_{j=1}^{M}\sum_{l=1}^{N}\sum_{m=1}^{\tau} \hat{\beta}_{lj} Y_{lj} \hat{\alpha}_m \kappa_m(X_{lj}, X) + b\right)$$

8. Inter-Related Classifier Training

- **How to model such inter-concept correlation?**

$$\min_{\beta} \max_{\alpha} \sum_{r=1}^{\tau} \alpha_l \Psi(r) + \min_{\hat{\beta}} \max_{\hat{\alpha}} \sum_{r=1}^{\tau} \hat{\alpha}_l \Phi(r)$$

Subject to:

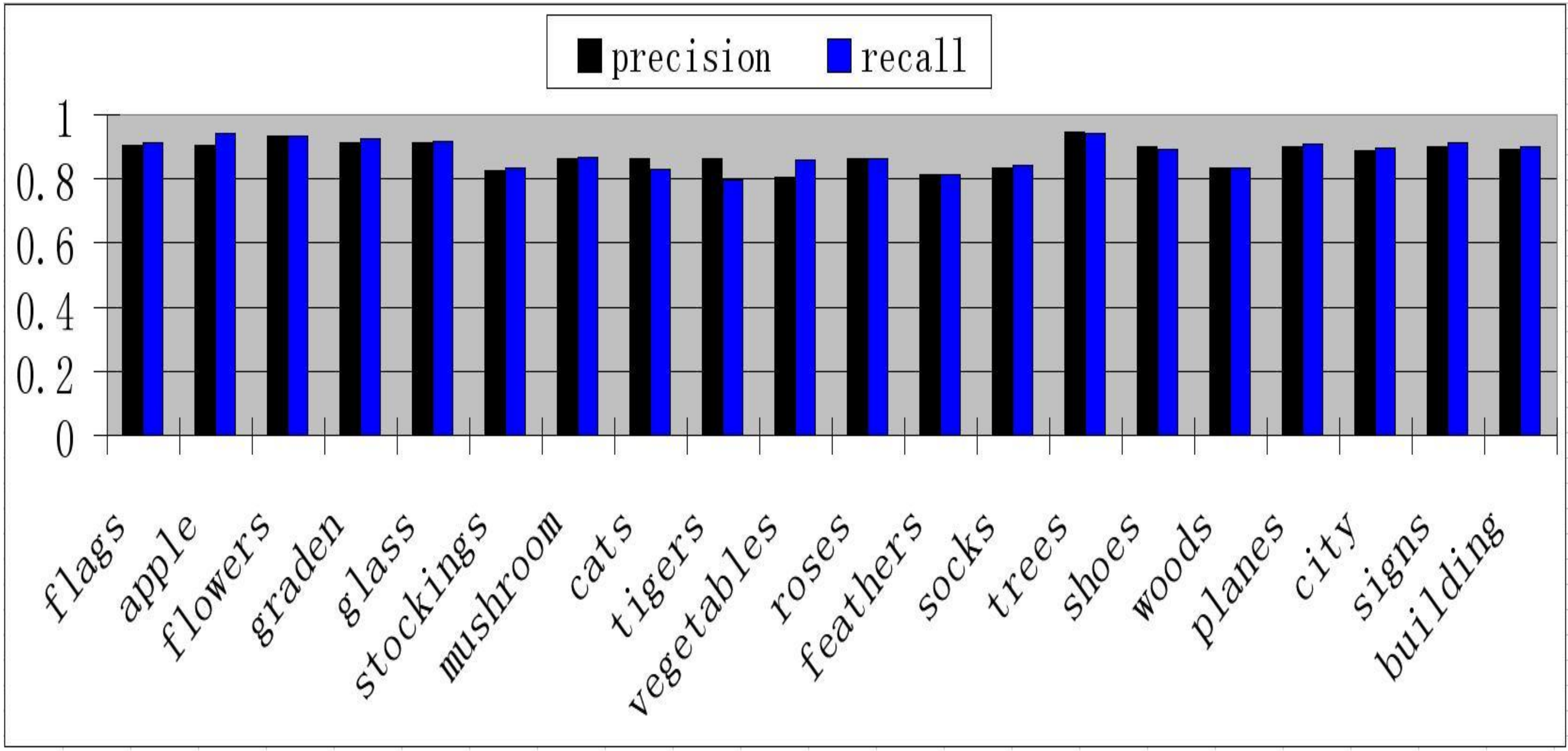
$$\forall_{l=1}^{N}: \quad 0 \le \beta_l \le \lambda, \quad \sum_{l=1}^{N} \beta_l Y_l = 0; \quad \forall_{r=1}^{\tau}: \quad \alpha_r \ge 0, \quad \sum_{r=1}^{\tau} \alpha_r = 1$$

$$\forall_{i=1}^{N} \ \forall_{j=1}^{M}: \quad 0 \le \hat{\beta}_{ij} \le \frac{M}{2\lambda}, \quad \sum_{j=1}^{M} \sum_{i=1}^{N} \hat{\beta}_{ij} Y_{ij} = 0; \quad \forall_{r=1}^{\tau}: \quad \hat{\alpha}_r \ge 0, \quad \sum_{r=1}^{\tau} \hat{\alpha}_r = 1$$

$$\Psi(r) = \sum_{l,m=1}^{N} \beta_l \beta_m Y_l Y_m \kappa_r(X_l, X_m) - \sum_{l=1}^{N} \beta_l \qquad \Phi(r) = \sum_{j=1}^{M} \sum_{i=1}^{N} \sum_{h=1}^{M} \sum_{l=1}^{N} \hat{\beta}_{ih} Y_{ih} \hat{\beta}_{jl} Y_{jl} \kappa_r(X_{ih}, X_{jl}) - \sum_{j=1}^{M} \sum_{i=1}^{N} \hat{\beta}_{ij}$$

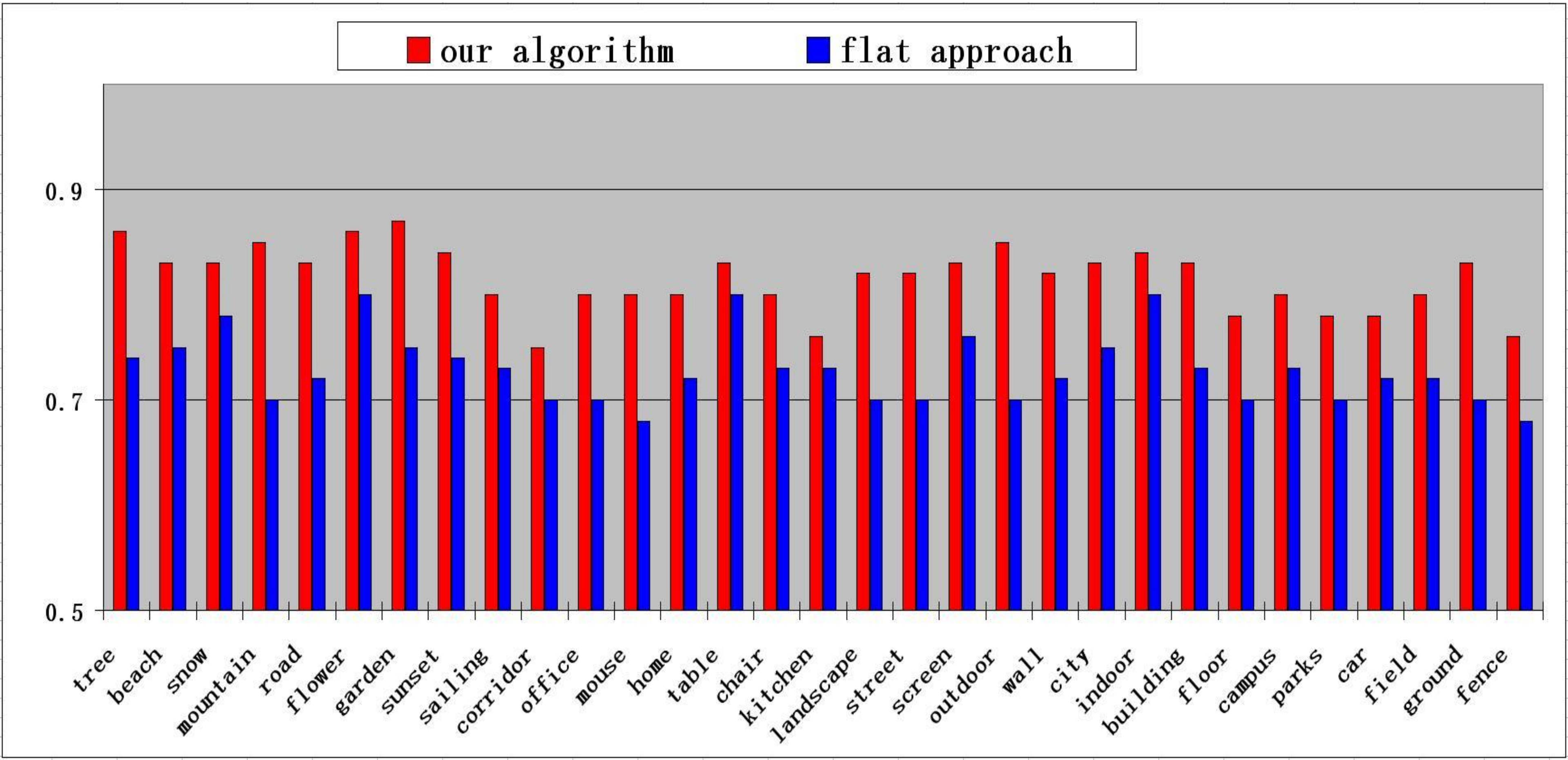
9. Algorithm Evaluation

- **Junk Image Filtering**



9. Algorithm Evaluation

- **Inter-related Classifier Training**



9. Algorithm Evaluation

- **Computational Cost for classifier training**
  - **Our Algorithm** $O(\hat{M} \times T) \cdot O(\tau N^3)$
  - **GentleBoosting** $O(T^2) \cdot O(\widetilde{N}^3)$
- **Computational Cost for image classification**
  - **Our Algorithm** $O(\hat{M} + T)$
  - **GentleBoosting** $O(T^2)$

Web Image Indexing

- Research Motivation
- Image and Auxiliary Text Extraction
  - Image-Block Generation
  - Image Clustering
- Automatic Image-Text Alignment
  - Term-Image Relevance Estimation
  - Term Correlation Network
  - Relevance Refinement
- Evaluation

Research Motivation

- Leveraging large-scale web images with reliable labels for vision tasks
  - Most modern web-pages are composed by Images and auxiliary texts
  - Image labels can be learned from the auxiliary texts

- Challenges
  - Most of text terms are weakly related or even irrelevant to the semantics of the web images in the same hosted webpage

Image-Text Alignment Framework

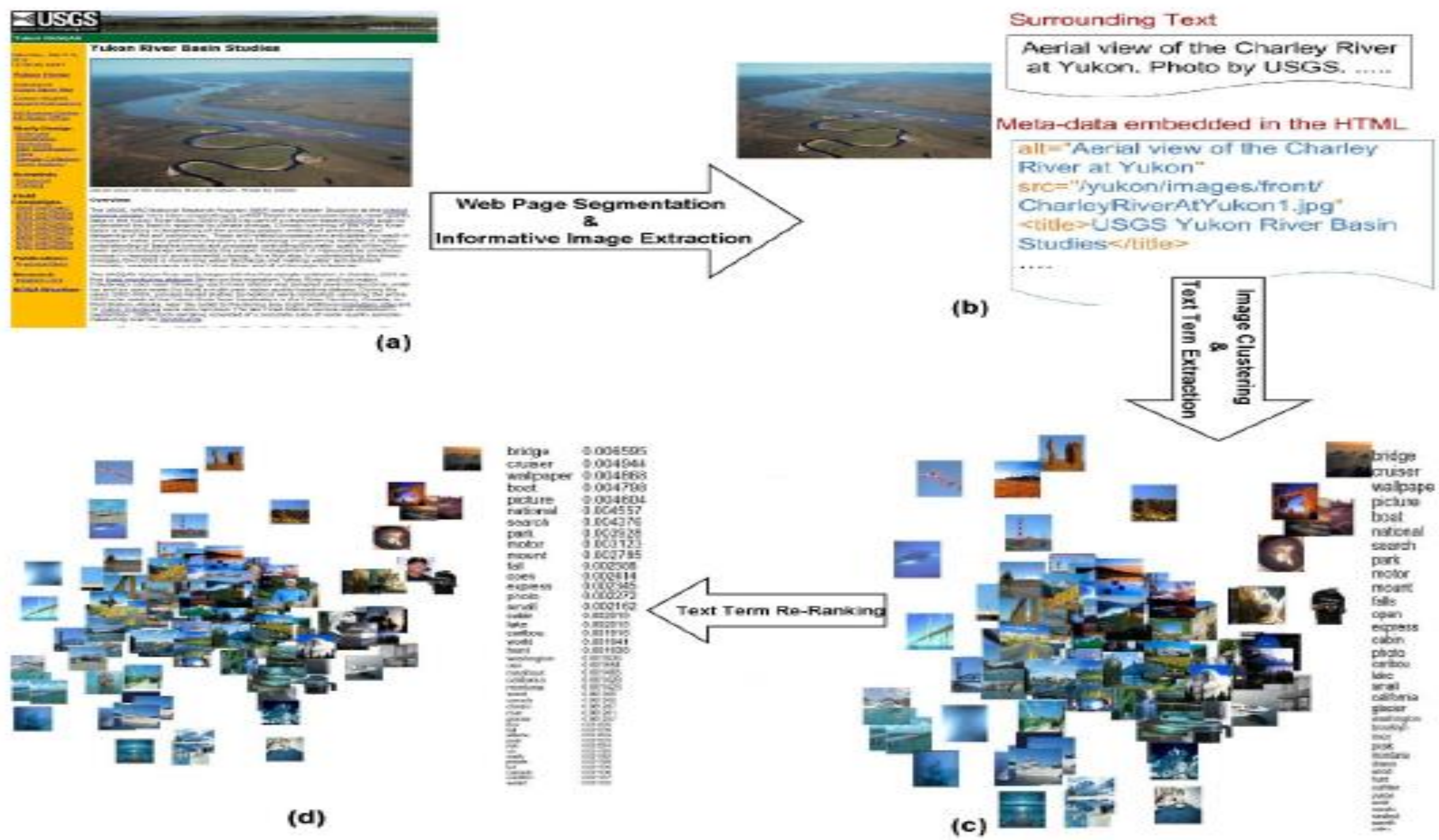
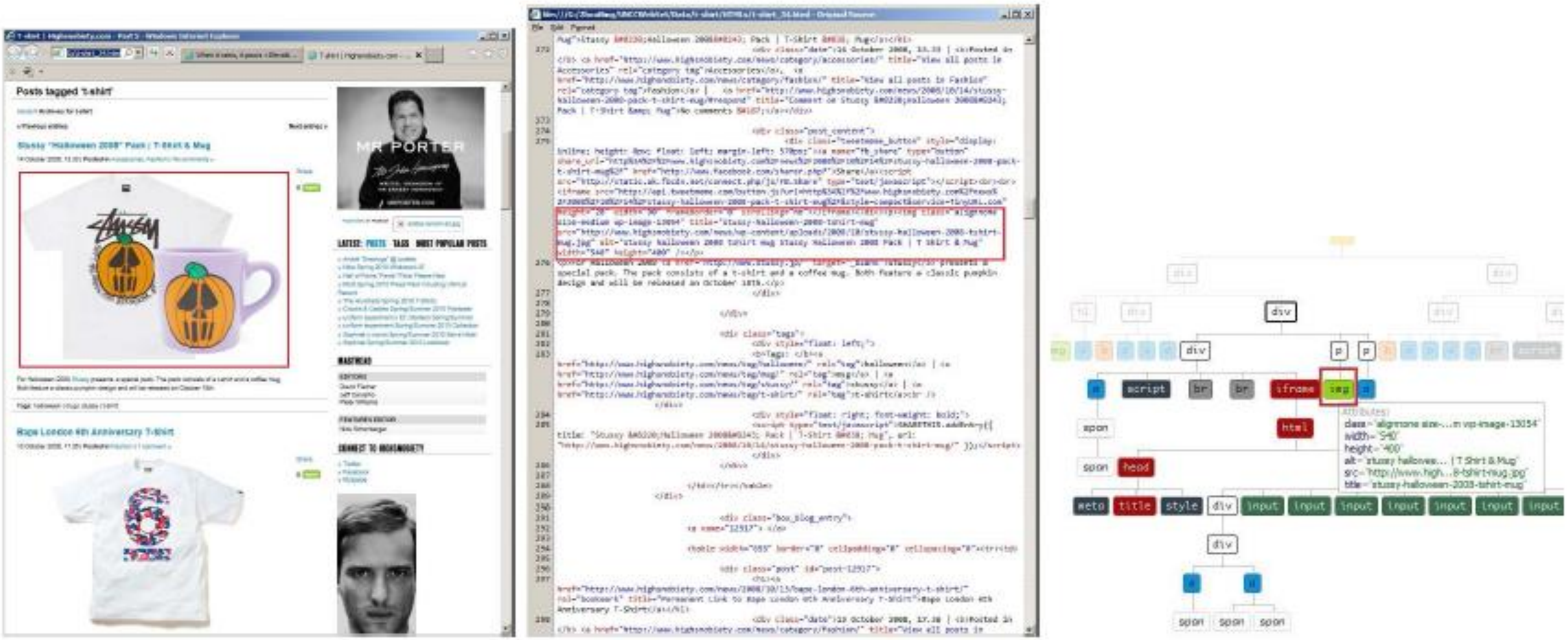


Figure 1: The illustration of the key components of our image-text alignment scheme: (a) web page; (b) image-block pair; (c) image cluster and ranked auxiliary text terms; (d) image cluster and re-ranked auxiliary text terms.

- **Text-Image Alignment for Web Image Indexing**



(a) A web page rendered by IE (b) The html document (c) The DOM-Tree

WWW2010, TPAMI2012

Image and Auxiliary Text Extraction

- Informative Image Extraction
  - Plenty of “noise” images: navigation menus, advertisement images, snippet previews,…
  - Still a open problem in the research community
- Method
  - Aspect ratio (>0.2 or <5)
  - Image size (min(width, height) > 60 pixel)
  - Not perfect but can produce satisfied results
  - Unsupervised and computationally efficient

Image and Auxiliary Text Extraction

- Auxiliary text extraction
  - The text content in a webpage is diverse and most of them are irrelevant to the images in the webpage
- Assumption: texts which are visually close to the web image are more likely to be related to the semantics of the image
- Webpage segmentation
  - Visually-based: precise but computationally expensive
  - DOM(Document Object Model) based: computationally efficient

Image and Auxiliary Text Extraction

- DOM-based region growing for most relevant text block(s) extraction
  - the corresponding image node in the DOM-tree is set as the start point
  - a upward growing search is performed until it reaches any text node
  - the inner texts embedded in the text node(s)are extracted as the text block(s)

Image and Auxiliary Text Extraction

- Meta data embedded i
  - Alternate text
  - Image titles
  - Image filename
  - Webpage title

Surrounding Text

Aerial view of the Charley River at Yukon. Photo by USGS. .....

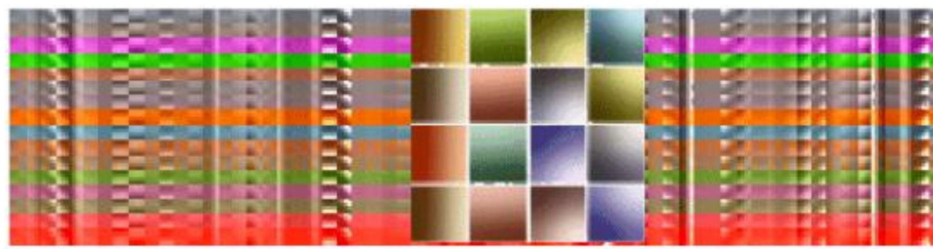
Meta-data embedded in the HTML source

alt="Aerial view of the Charley River at Yukon"
src="/yukon/images/front/CharleyRiverAtYukon1.jpg"
<title>USGS Yukon River Basin Studies</title>
....

Image Clustering

- Image as a bag of visual words

- Codebook



- Dista

$$d(\mathbf{x}_m, \mathbf{x}_n) = \sum_{\forall i} \frac{|\mathrm{ASPH}_m(i) - \mathrm{ASPH}_n(i)|}{1 + \mathrm{ASPH}_m(i) + \mathrm{ASPH}_n(i)} + \sum_{\forall j} \frac{|\mathrm{CSPH}_m(j) - \mathrm{CSPH}_n(j)|}{1 + \mathrm{CSPH}_m(j) + \mathrm{CSPH}_n(j)}. \quad (1)$$

Image Clustering

- Clustering method: Affinity propagation
- Image pair wise similarity is taken as the negative distance between these two images
- Text blocks belong to the same image cluster are merged as a single joint text document
- Text terms are extracted from this document using NLTK tool kit

Automatic Image-Text Alignment

- Term-Image relevance estimation

$$\rho(C,t) = \frac{\sum_{x\in\Theta(t)} P(x,t)}{\sum_{y\in\Theta}\sum_{r\in\mathcal{W}} P(y,r)}, \qquad (2)$$

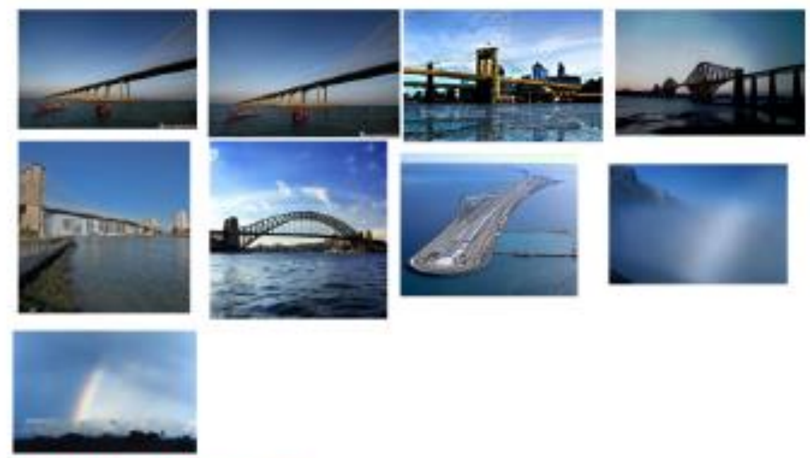
- Image clusters with ranked terms by relevance score

Auxiliary Terms: **portrait, mount rushmore, national monument, south dakota, arch, nature, canvas, joshua tree, california, mountain, mist, glacier, national park, montana, brooklyn bridge**

Automatic Image-Text Alignment

- Image clusters with ranked terms by relevance score

Auxiliary Terms: river, national park, zambia, pool, africa, age, news, tiger, brain, pond, united states, popularity, uniform, green, pan, vegetable, source, vitamin a, potassium, peak season, ...



Auxiliary Terms: brooklyn bridge, bridge, rainbow, island, completion, peak, sunset, traffic, gallery, photo, dawn, front, devil , tree, order, transfer, water, causeway, history, harbour, prince edward island, ...

Term Correlation Network

- Terms are not alone but inter-related
  - Multiple terms can have similar meaning
  - Some terms can have multiple senses under different context
  -
- Inter-term correlation characterization
  - Term co-occurrences
  - Semantic similarity from WordNet

Term Correlation Network

- Term co-occurrences
- Semantic

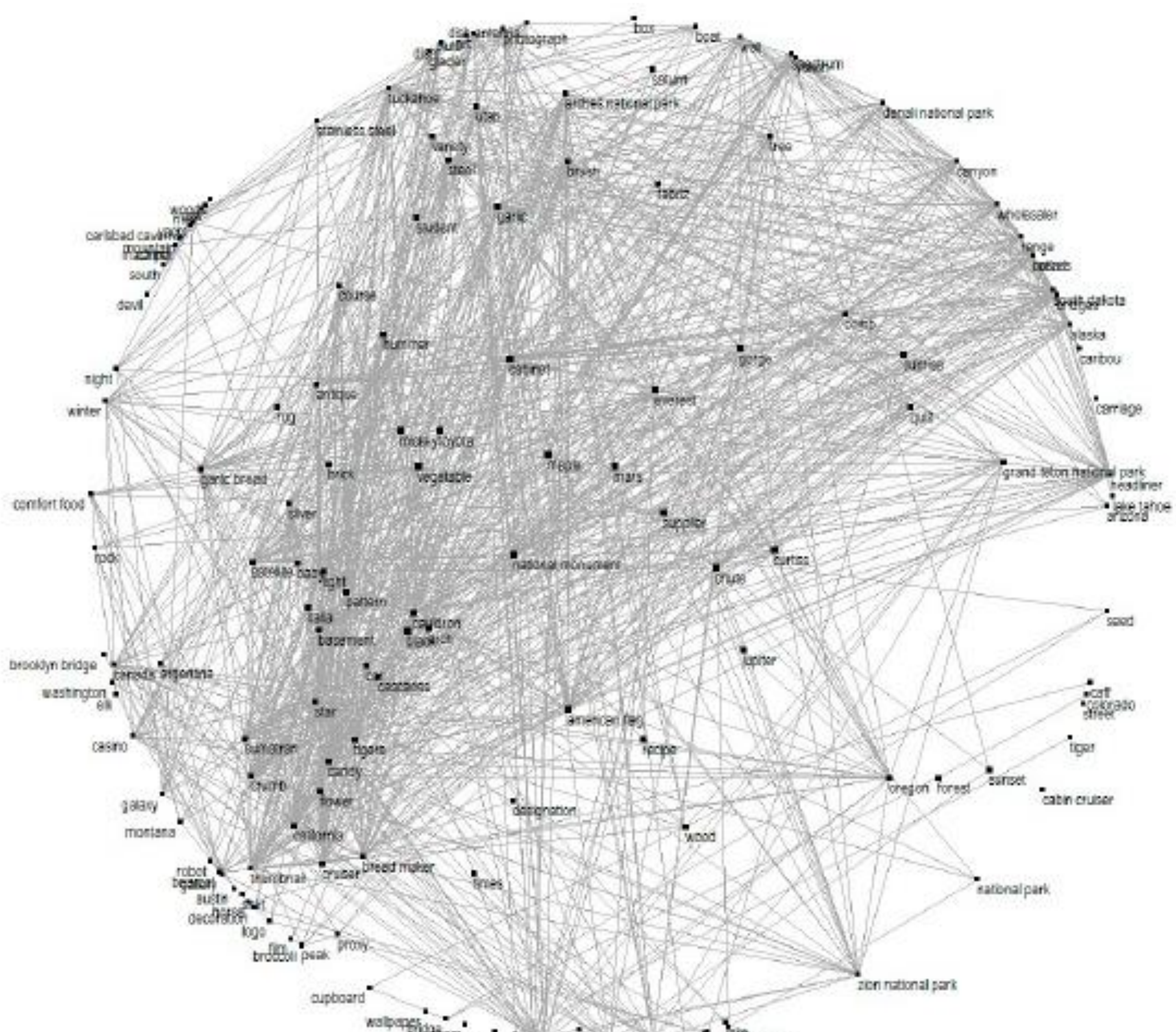
$$\beta(t_i, t_j) = -P(t_i, t_j) log \frac{P(t_i, t_j)}{P(t_i) + P(t_j)},$$

- Integrati

$$\gamma(t_i, t_j) = P(t_i, t_j) \cdot \log \frac{L(t_i, t_j)}{2 \cdot D}$$

$$\phi(t_i, t_j) = \alpha \cdot \gamma(t_i, t_j) + (1 - \alpha) \cdot \beta(t_i, t_j),$$

Visualization of the term correlation network



Relevance Refinement

- Random walk over term correlation network

- Transmission $$\phi_{ij} = \frac{\phi(i,j)}{\sum_k \phi(i,k)},$$

- Random walk process

$$\rho_k(t) = \theta \sum_{j \in \Omega_j} \rho_{k-1}(j)\phi_{tj} + (1-\theta)\rho(C,t),$$

Refinement example

(a)

(b) **Auxiliary Terms:** photo, tiger, friendship, oct, animal, photograph, tag, carrot, caribou, cat, meow, chimpanzee, wallpaper, format, wife, stab, source, bridge, inspiration, turnip, balloon, calla lily, kid, golf, ...

(c) **Re-ranked Terms:** friendship, chimpanzee, tag, tiger, animal, oct, photo , photograph, cat, carrot, caribou, meow, stab, yukon, shark, usmc, balloon, source, calla lily, achievement, launch, stride, ...

- **Text-Image Alignment for Web Image Indexing**

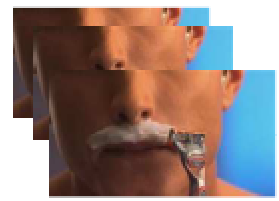
Cluster No.: 3598, 10 duplicates

Phrase list 1: sterilization equipment, water, sterilizer, china mainland
Phrase list 2: autoclave, sterilizer, water, china mainland, manufacturer
Phrase list 3: retort, heating, sterilizer, water, china mainland, manufacturer
Phrase list 4: sterilizer, water, china mainland, manufacturer
Phrase list 5: sterilization equipment, water, sterilizer, china mainland, manufacturer
....
Aggregation: sterilizer, sterilization equipment, water, retort, manufacturer, ….

Cluster No.: 6244, 13 duplicates

Phrase list 1: cimarron, roper, saddle, roper saddle, horse, ...
Phrase list 2: cimarron, roper, saddle, roper saddle,...
Phrase list 3: saddle, roper, roper saddle, horse, sale
Phrase list 4: roper saddle, saddle, cimarron, horse
....
Aggregation: saddle, roper, roper saddle, cimarron, ….

Cluster No.: 16263, 33 duplicates



Phrase list 1: face, area, drive stick, rule safety
Phrase list 2: face, grip, play tennis, tennis racket
Phrase list 3: face, , tennis racket, maintenance
Phrase list 4: face, shaver, tennis preparation tip,.
....
Aggregation: face, shaver, gillete, ….

Cluster No.: 29906, 8 duplicates

Phrase list 1: pisa feb, pisa, leaning tower, location, photo
Phrase list 2: pisa, leaning tower, location, photo
Phrase list 3: pisa, location, leaning tower, photo
Phrase list 4: pisa, leaning tower, photo….
Aggregation: pisa, learning tower, pisa feb, location, ….

Cluster No.: 35950, 27 duplicates

Phrase list 1: venture snowmobile, indonesia
Phrase list 2: venture snowmobile, arctic, snowmobile, ...
Phrase list 3: venture snowmobile, snowmobile
Phrase list 4: venture snowmobile, snowmobile manufacture
Aggregation: venture snowmobile, snowmobile, ….

Near-duplicates share similar semantics!

WWW2010, TPAMI2012

Evaluation

- Data set
  - 500, 000 web pages crawled from the Internet
  - 5,000,000 informative image have been extracted
  - Randomly select 5,000 images for evaluation because of the computational cost consideration

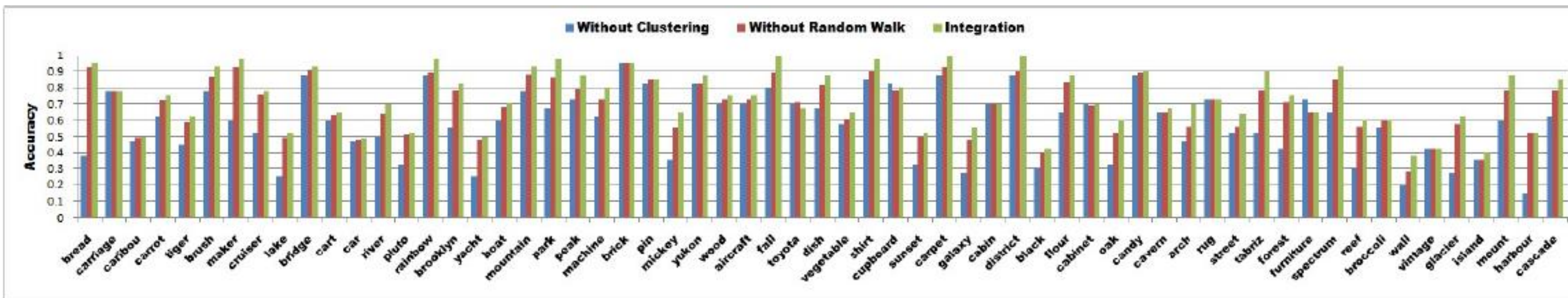
- Evaluation metrics
  - Accuracy rate

$$\varrho = \frac{\sum_{i=1}^{N} \delta(L_i, R_i)}{N},$$

$$\delta(x,y) = \begin{cases} 1, & x = y, \\ 0, & otherwise \end{cases}$$

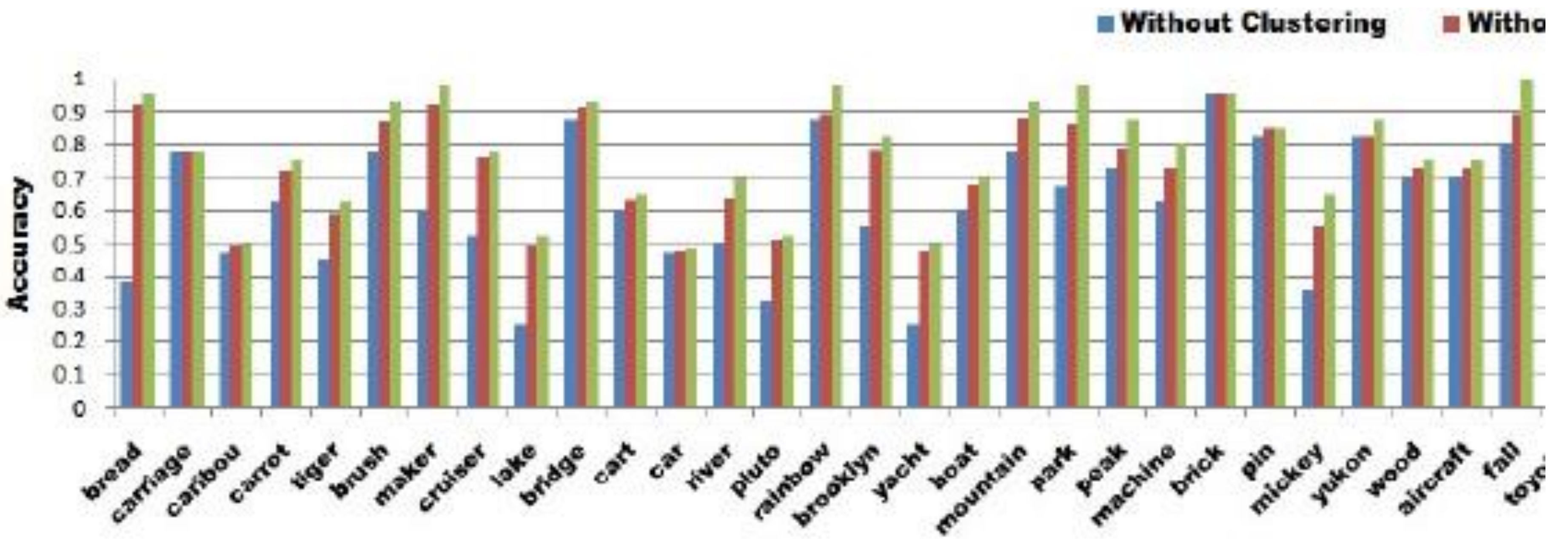
Results

- Effectiveness of image clustering and random walk for refinement



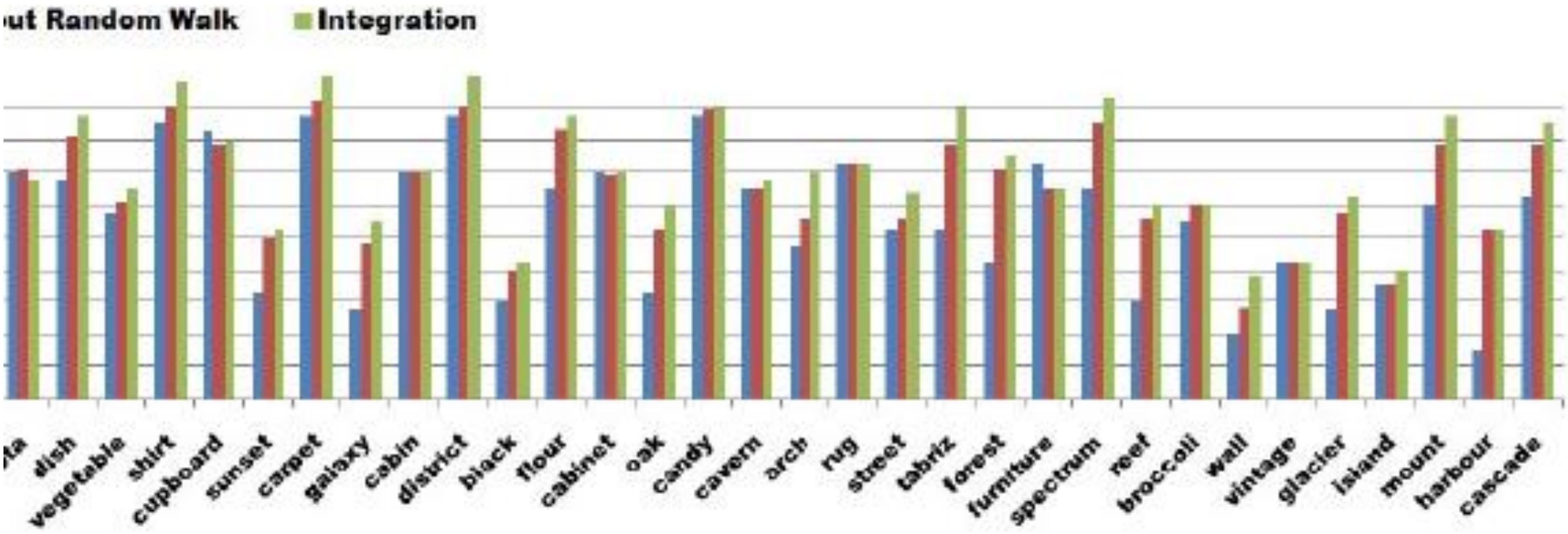
- Average accuracy: without clustering = 0.5828; Without random walk = 0.6939; Integration = 0.7373

Results



Without Clustering
Witho
Accuracy
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
bread
carriage
caribou
carrot
tiger
brush
maker
cruiser
lake
bridge
cart
car
river
pluto
rainbow
brooklyn
yacht
boat
mountain
park
peak
machine
brick
pin
mickey
yukon
wood
aircraft
fall

Results



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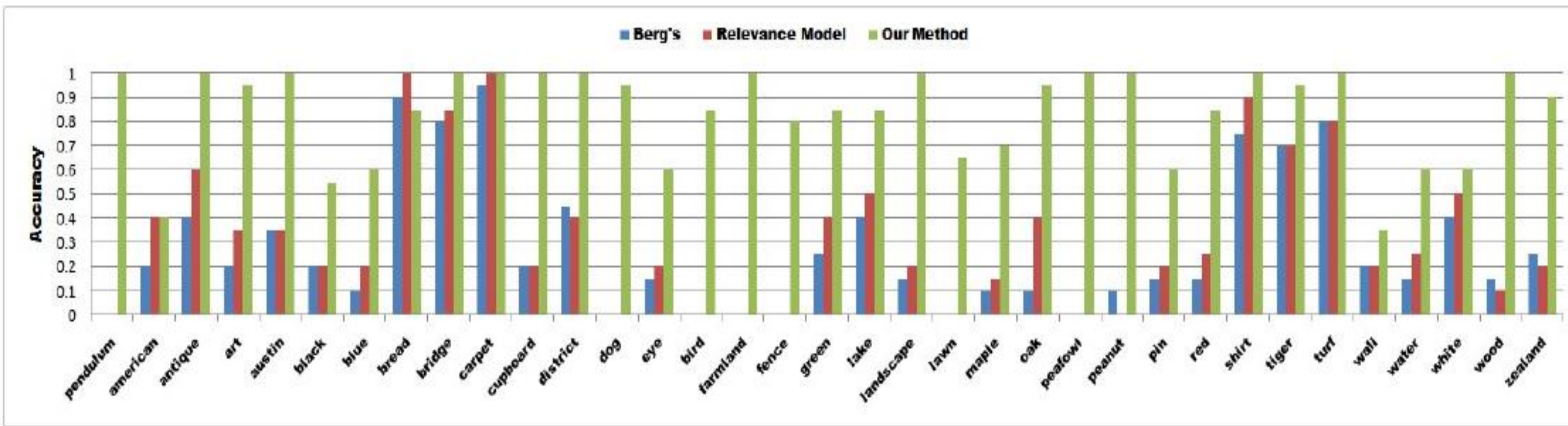
cabin
district
black
flour
cabinet
oak
candy
cavern
arch
rug
street
tabriz
forest
furniture
spectrum
reef
broccoli
wall
vintage
glacier
island
mount
harbour
cascade

Results

- Compare with other image-text alignment model
- Models (both are supervised ones)
  - Berg’s
  - Cross-media relevance model
- Each concept we randomly select 60% samples as training samples and the other as test
- Our method was compared to the two methods on the test partion

Results



- Average accuracy: Berg's = 0.2771; Relevance Model = 0.3286; Our method = 0.8400