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Information Extraction from Social Sites

Yiannis Kompatsiaris

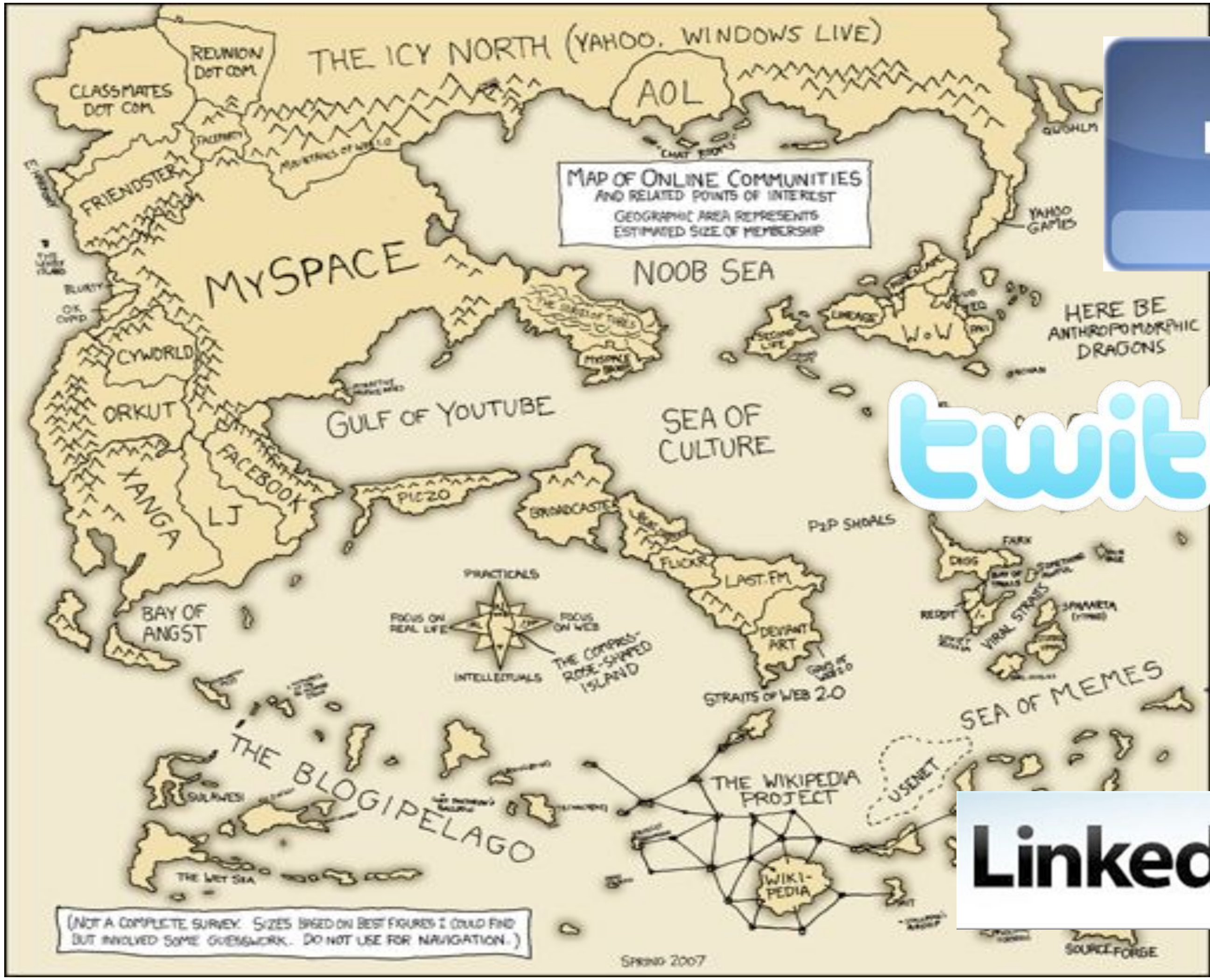
Eirini Yannakidou, Symeon Papadopoulos,
Spyros Nikolopoulos, Elisavet Chatzilari

Athena Vakali, AUTh

Contents

- Introduction
- Clustering in Social Media
- Social media “teacher” of the machine
- Community detection in Social Media
- WeKnowIt project
- Conclusions - Issues

Our world today (already old)



Web 2.0 content
(July 2010)

flickr

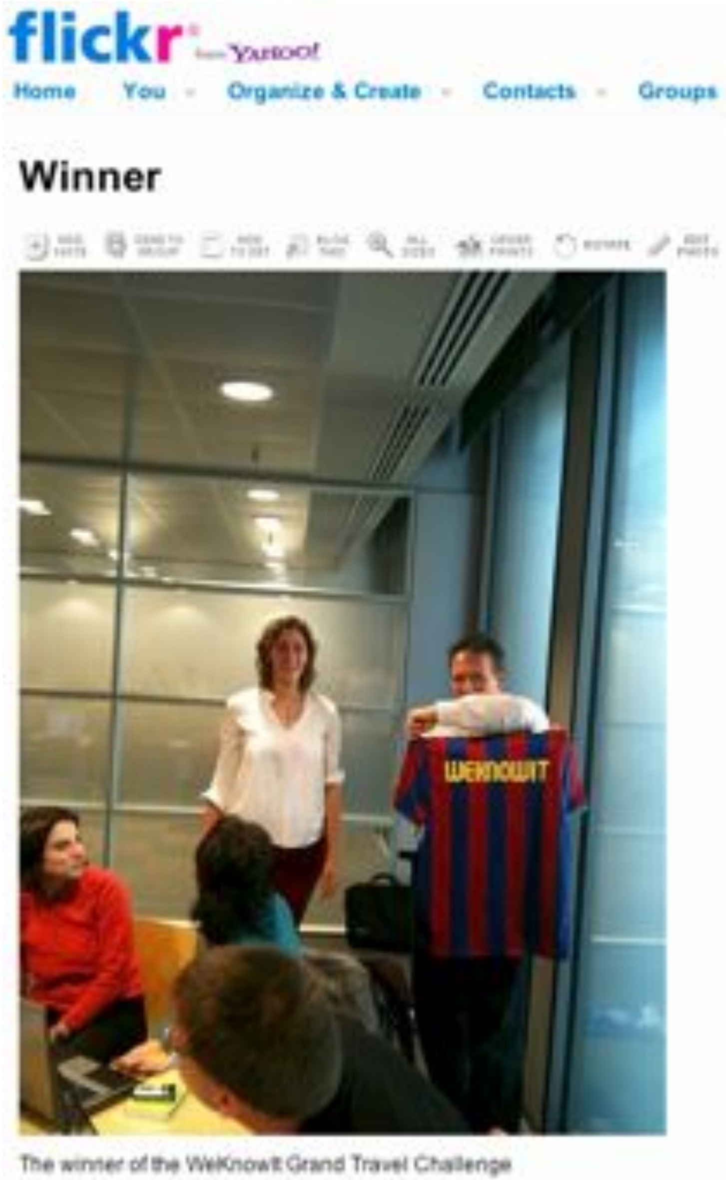
- 3,190 uploads in the last minute
- 3.2 million things geotagged this month
- 4,754,012,299 photos (2 July 2010)

YouTube

- 24h of video content uploaded every minute
- 2 billion movies watched every day

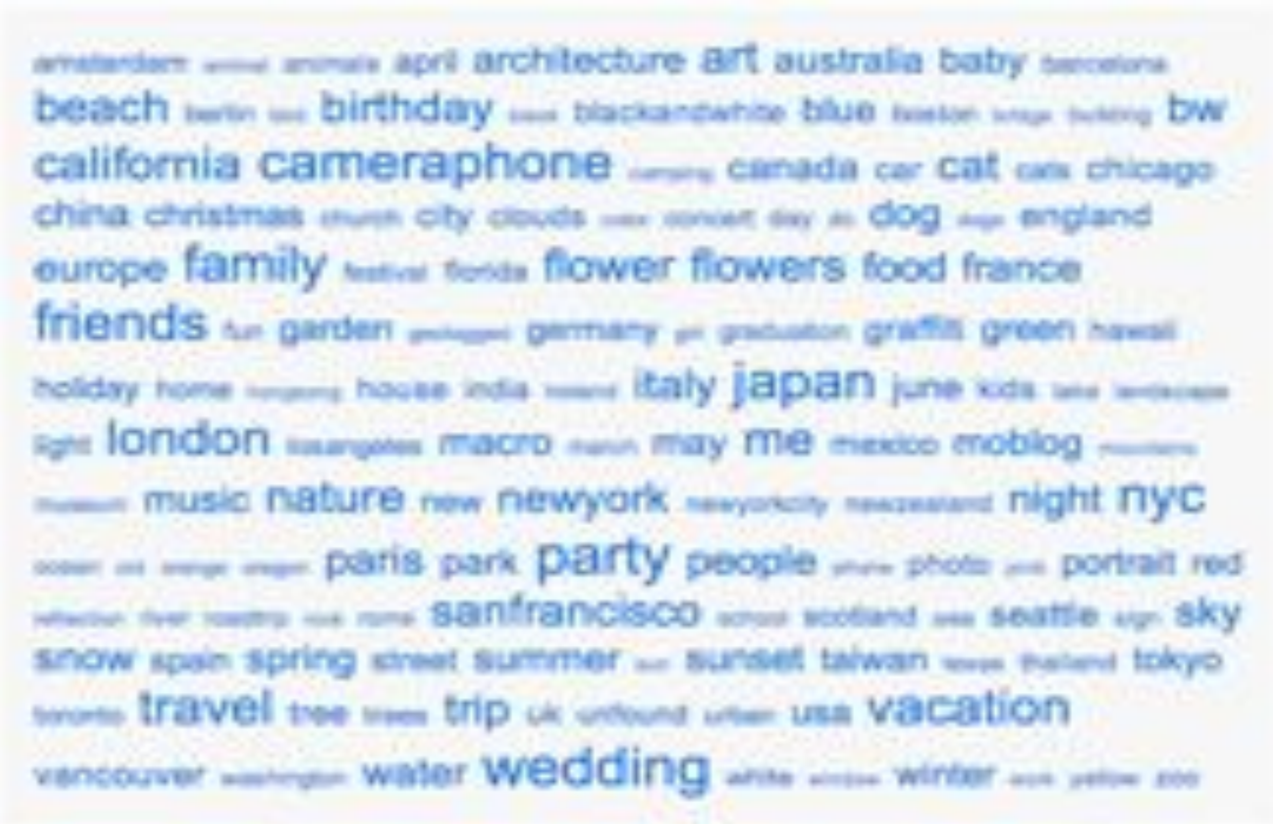
facebook

- More than 400 million active users
- More than 200 million users log on at least once each day
- 2.5 billion photos uploaded each month

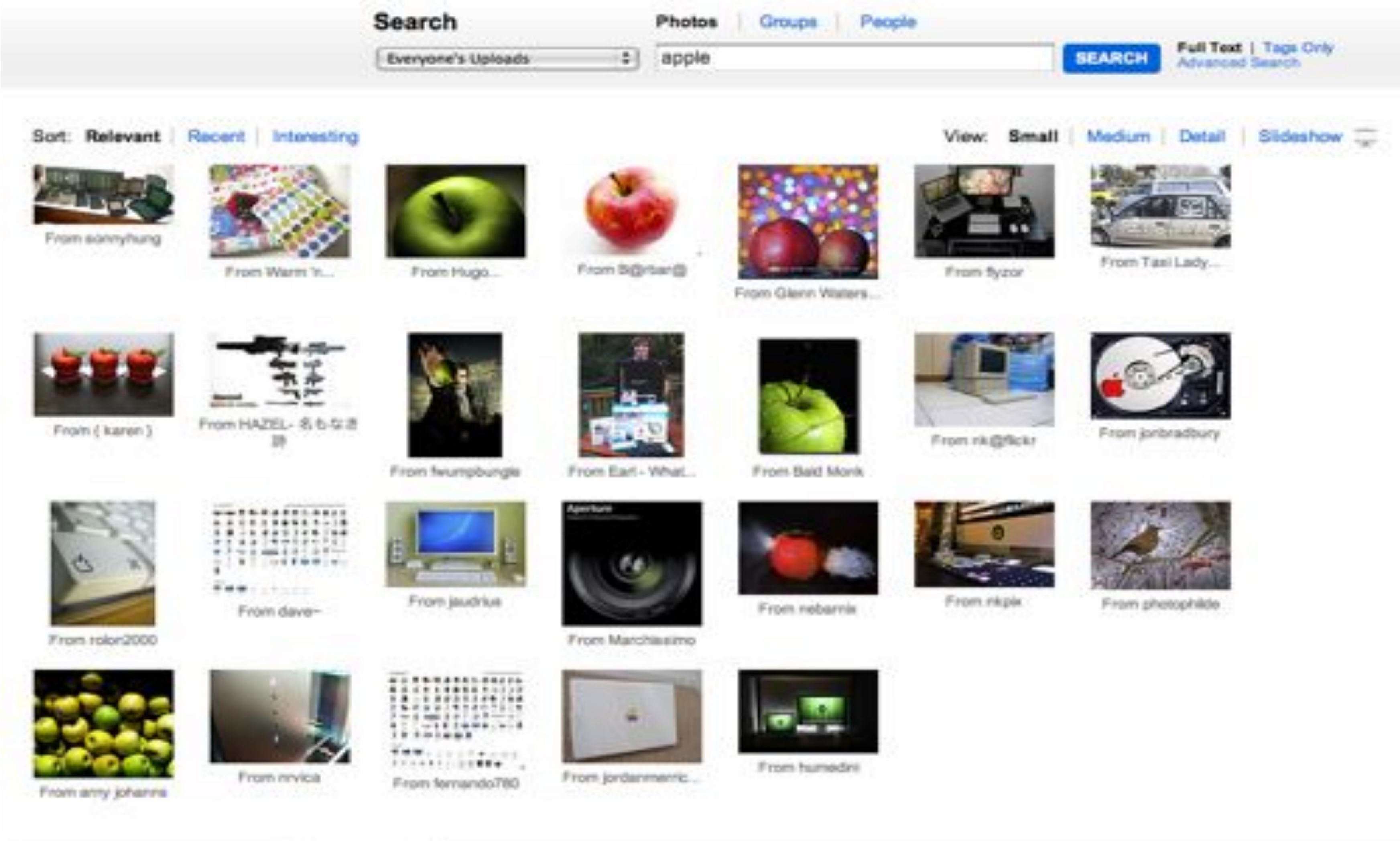


Tags everywhere

Search, Describe content, Extract knowledge



Very low precision

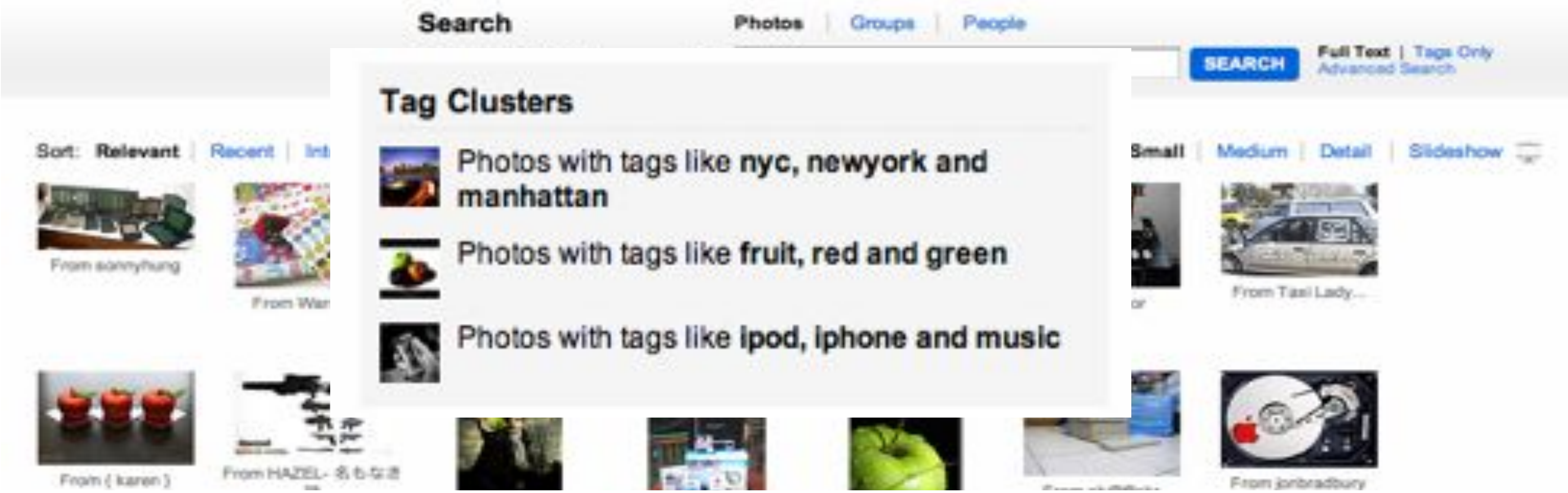


Very low recall

Tags

- Property#1
- Canada
- photo
- image
- digital
- urban
- Halifax
- park
- morning
- afternoon
- night
- Pentax K20D
- Sigma 70-300
- early
- Sackville

Can we improve things?

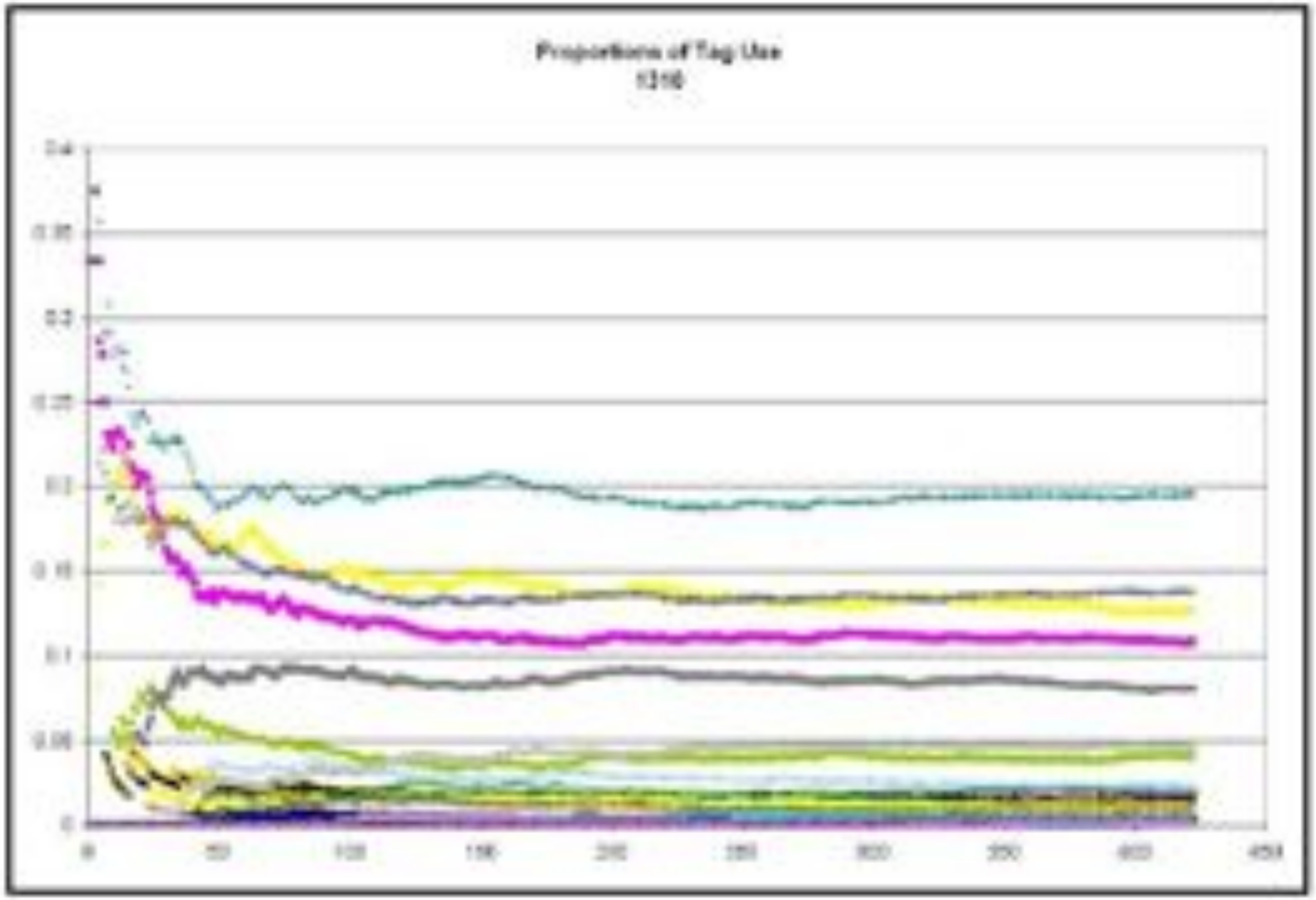


By combining information from many photos - tags, it seems that we can

Stable patterns

in tagging systems over time

Stable tagging patterns




flickr
Deutsches Eck from Ehrenbreitstein Fortress, Koblenz, Germany
When you're high up on the hill above Koblenz at Ehrenbreitstein Fortress you can get a great panoramic view of the city and the surrounding area.
by schaengel
121 comments 69 faves
Tagged with koblenz, ehrenbreitstein ...
Taken on November 15, 2009, uploaded November 17, 2009
See more of schaengel photos, or visit his profile.
Low-level
Time
Geo
User Profile
Groups
Social network
Caption
Tags
Favs
Comms

… and more: Travel trends using flickr

Trace Flickr users from a chronologically ordered set of geographically referenced photos

Who are the Italians and who are the Americans?

MIT SENSEABLE CITY LAB, "The World's eyes"

What else we can do?

Tags that are "representative" for a geographical area

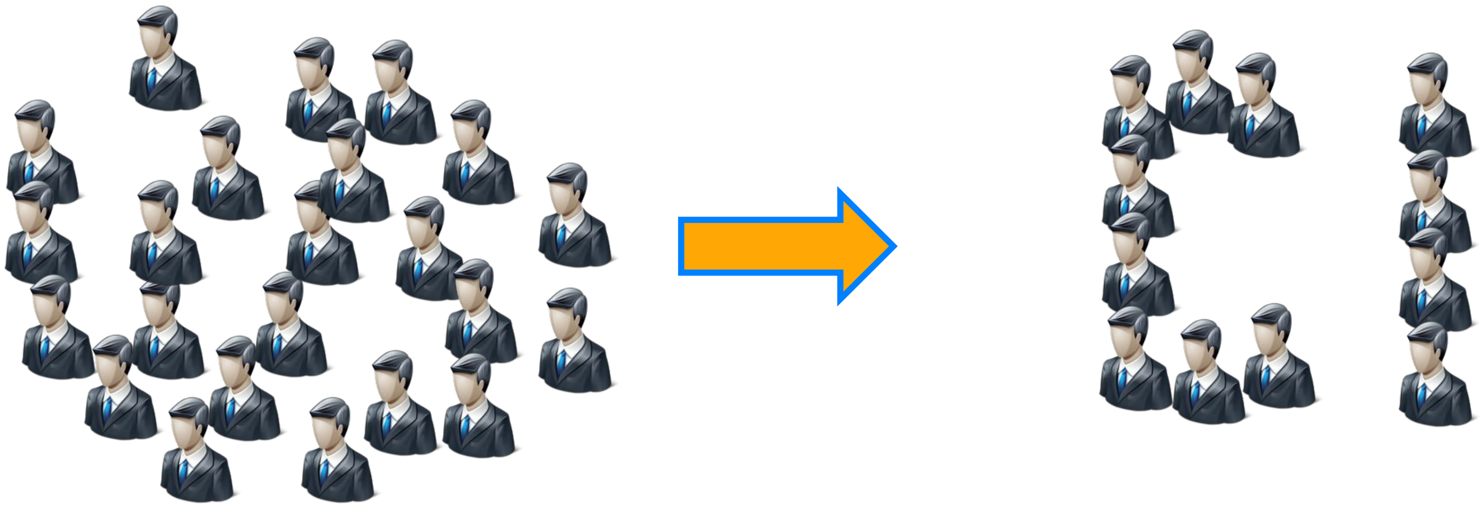
Contribute to our understanding of the world

- 1. Clustering of photos
  - K-means, based on their location [Kennedy07]
- 2. Rank each cluster's tags
- 3. Get tags above a certain threshold

Representative tags for San Francisco [Kennedy07]

Collective Intelligence, PeopleWeb, Crowdsourcing, Wisdom of crowds …

Collective Intelligence is the Intelligence which emerges from the collaboration, competition and coordination among individuals.



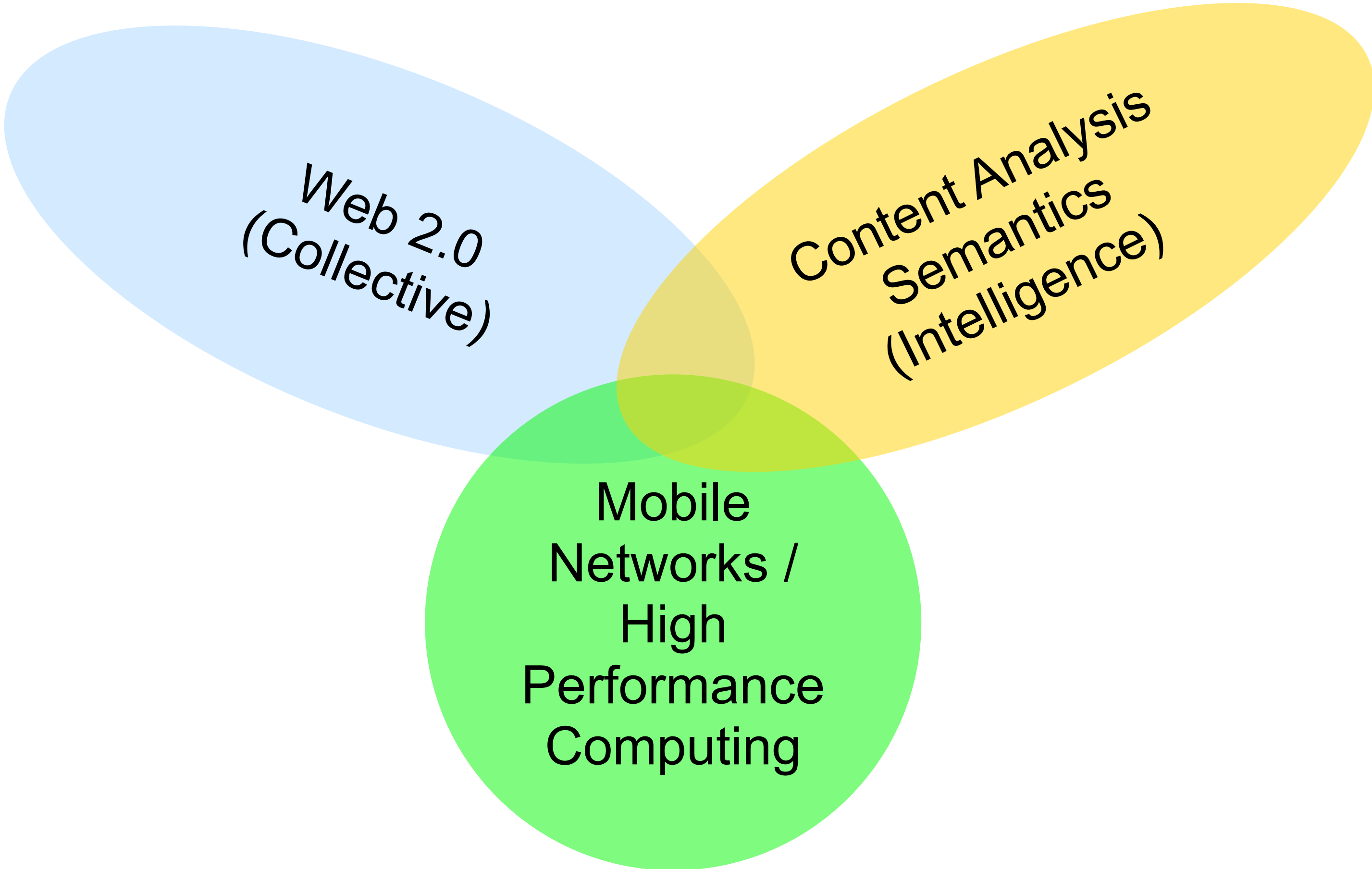
...an Intelligence greater than the sum of the individuals' intelligence

CI and Web 2.0?

- Analyze user-generated content, such as tags that are manually assigned to photos, and its relation to context over time, space and social connectivity
- Sources
  - Tags
  - Content
  - Social info
  - Time, Location
  - Other sources (e.g. Wikipedia)

http://www.iyouit.eu

Why today?


Web 2.0
(Collective)
Content Analysis
Semantics
(Intelligence)
Mobile
Networks /
High
Performance
Computing

A "simple" example

Uses the GPS in cellular phones to gather traffic information, process it, and distribute it back to the phones in real time

- online, real-time data processing
- privacy-preservation
- data efficiency, i.e. not requiring excessive cellular network

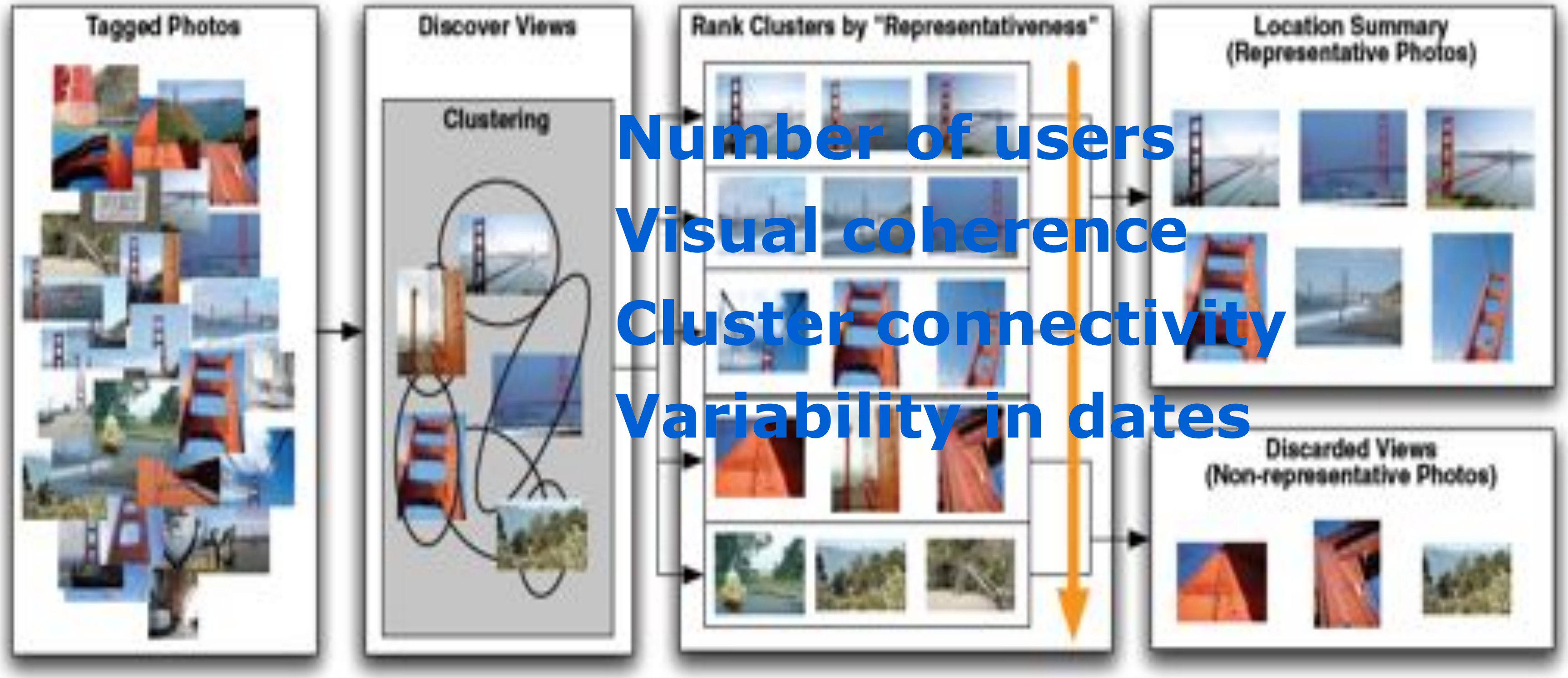
Mobile Century Project: http://traffic.berkeley.edu/mobilecentury.html

Image search - Tourism

- Linguistic processing of semi-structured sources
  - Wikipedia, Geoplanet
- Statistical analysis for ranking
  - User Queries
  - Flickr tags

Generating photo summaries

- **Problem formulation**: Having identified a tag x as representative of a cluster, compute a set of photos that are representative for that tag



Number of users
Visual coherence
Cluster connectivity
Variability in dates

Generating photo summaries for geographic objects in [Kennedy07]

Sample photo summaries of events [Quack08]

DATASET: Divide the earth's surface into square tiles of 200m2
70000 geographic tiles
220000 geotagged photos from Flickr
After preprocessing, 73000 photos were assigned to clusters
Manually labeling of 700 clusters

"Oxford Geek nights"
"Movie premiere Italy"
"Exhibition gallery paris"

The most commonly identified event (single day covered by a single photographer)

Auto annotation & geo-location

# Images	222'757
Size Metadata	1.1 GB
Size Features	111 GB
# Images assigned to clusters	73'236
# Similarities computed	217'330'144
# Similarities > 0	751'457

[Quack08]

EpiCollect: Science - epidemiology example

A scientist or member of the public collects and records data, photos and videos then sends this information to a central web-based database

- e.g. to document the presence of an animal or plant species that are “representative” for a geographical area
- Location information – maps
- Citizen scientists

EpiCollect: Linking Smartphones to Web Applications for Epidemiology, Ecology and Community Data Collection, David M. Aanensen, Derek M. Huntley, Edward J. Feil, Fada'a al-Own, Brian G. Spratt

Relevant activities

collective intellect

http://traffic.berkeley.edu

FixMyStreet

Mobnotes beta
The World, Around You!

Boston Citizens Connect

iSpot
your place to share nature

AMPHIBIANS & REPTILES · BIRDS · FUNGI & LICHENS · FISH · INVERTEBRATES · MAMMALS · PLANTS · OTHER ORGANISMS

DOPPLR

Dopplr helps you share your … travel …. and exchange tips … presents this **collective intelligence** - the travel patterns and advice … as the Social Atlas.

Research Fields and Issues

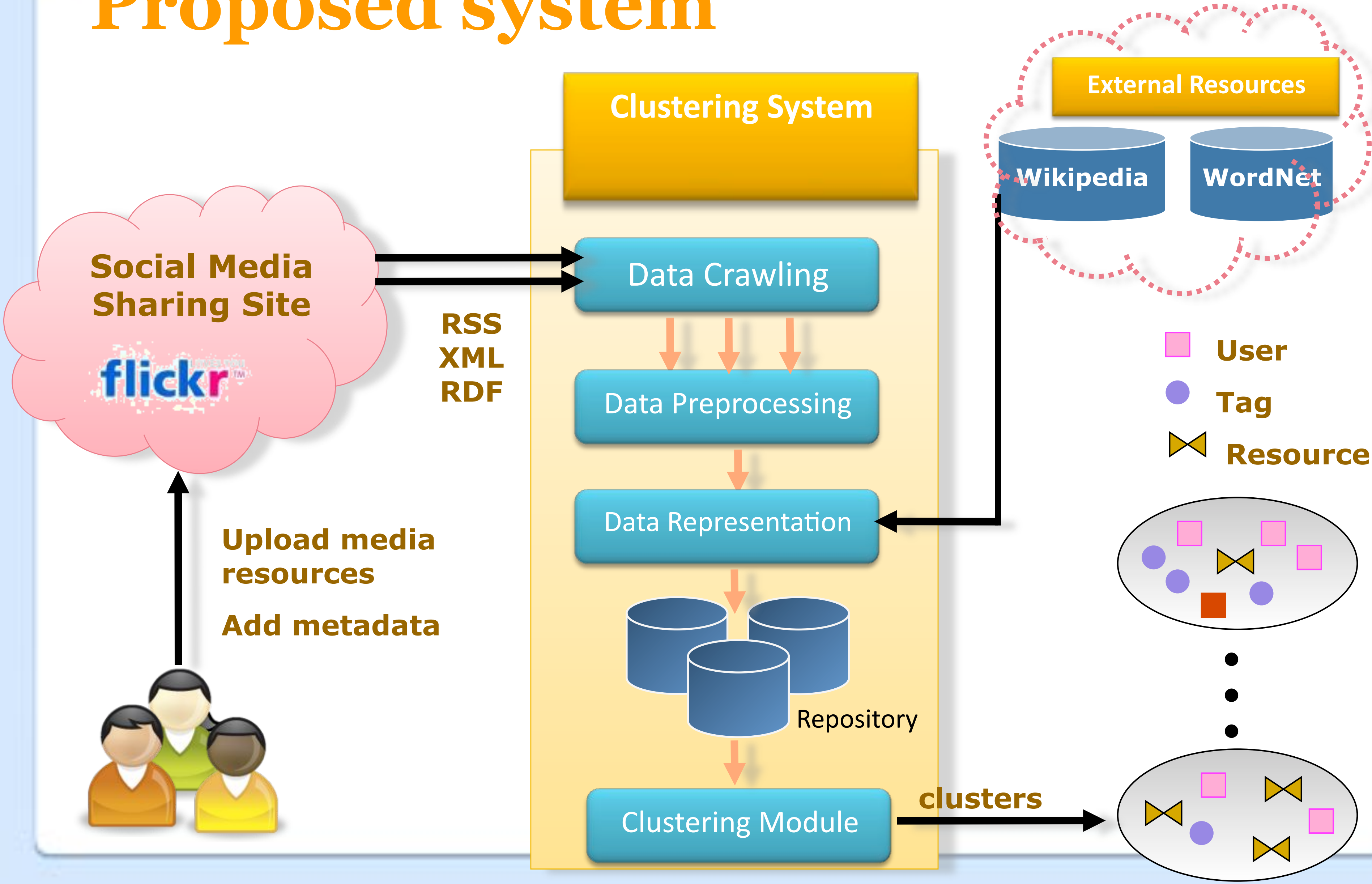
- Statistical analysis, machine learning, data mining, pattern recognition, social network analysis
- Clustering
- Graph theory
- Image, text, video analysis
- Information extraction
- Fusion techniques
- Trust, security, privacy
- Performance, scalability
  - speed, storage, power, grids, clouds

Clustering for Social Media

Clustering Approaches

- Tag-Based
- Content-Based
- Time-based

Proposed system



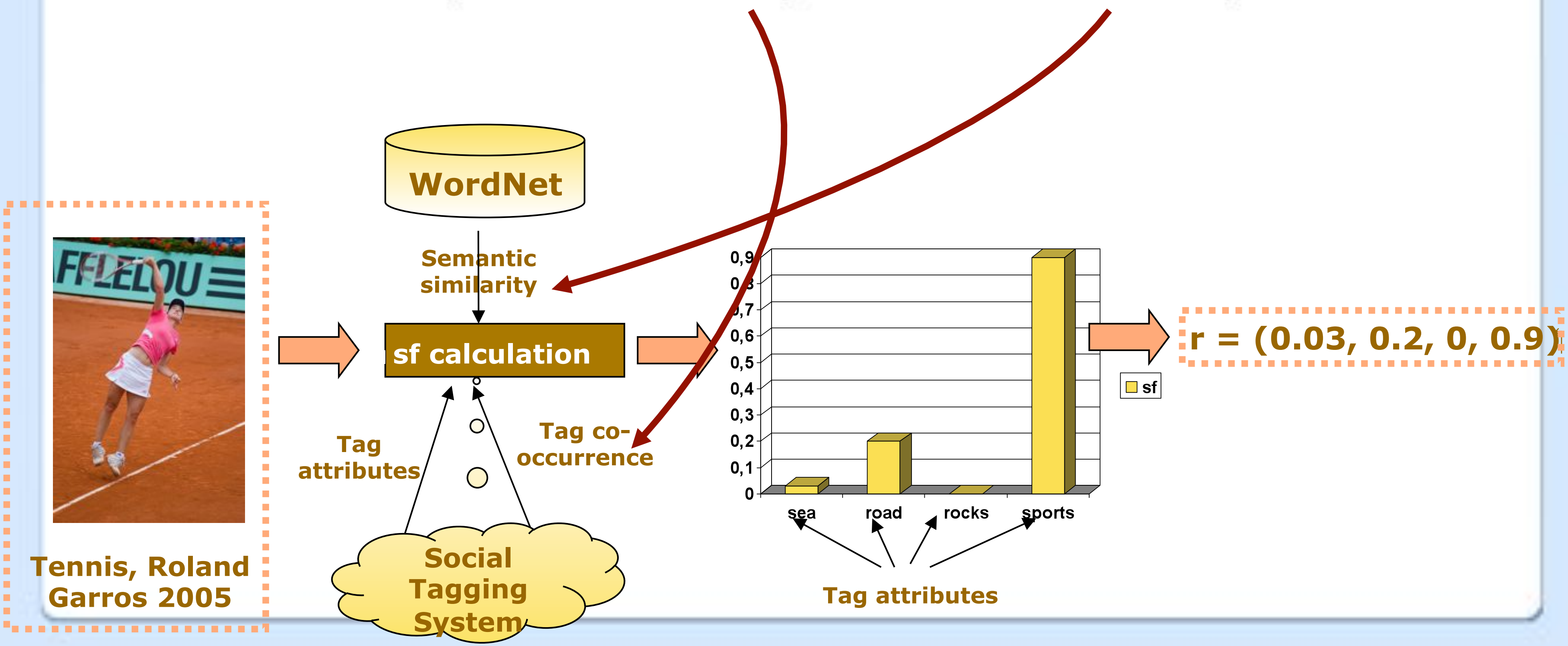
Tag-based Clustering (I)

- **1. Vector data model**
- Assume **n** resources and **d** attribute-tags
  - **d:** a representative set of tags
- A resource representation in vector space (**sf**) is based on semantic similarity and tag co-occurrence between the resource's tags and the attribute-tags
- A resource $\mathbf{r_i}$ is represented by a **d**-dimensional vector $\mathbf{r_i} = (\mathbf{sf_1}, \mathbf{sf_2}, \ldots, \mathbf{sf_d})$
- All resources can be represented by an **n** x **d** matrix

Tag-based Clustering (II)

- **2. Clustering on n (resources, r) x d (attributes) matrix (K-means, Hierarchical, COBWEB)**

$$SS(t_x, t_y) = w * SoS(t_x, t_y) + (1 - w) * SeS(t_x, t_y)$$



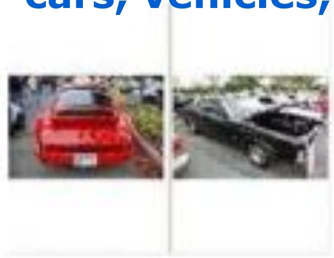
Tag-based Clustering - Experimental Results

- **Dataset:** 3000 images downloaded from Flickr
- Meaningful subdomains of **roadside**:

buildings, roof, street, road

(a)

cars, vehicles, race



(b)

people, street, festival

(c)

- Different clusters for the **ambiguous tag** *wave, rock:*

wave, sea, ocean

(a)

wave, person, hand

(b)

rocks, stone, rockyside

rock, music, band

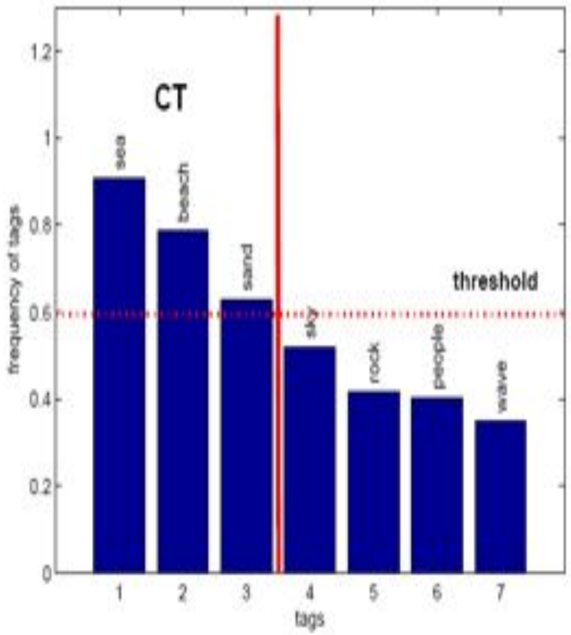
Tag & Content-based Clustering

- After performing tag-based clustering, low-level features of resources are used for cluster refinement
- Outlier Detection (mahalanobis distance)
- For each resource the following visual descriptors are extracted:
    - Scalable Color, $\mathcal{SC}$
    - Color Structure, $\mathcal{CS}$
    - Color Layout, $\mathcal{CL}$
    - Edge Histogram, $\mathcal{EH}$
    - Homogenous Texture, $\mathcal{HT}$
- A single image feature vector per each resource is produced, encompassing all descriptors normalized in [0,1]
- Feature extraction and distances between image feature vectors are according to MPEG-7 XM.

Evaluation Method

- **<u>Definition:</u>** Cluster Topic, CT, are the tags that have frequency in cluster's resources annotation over a threshold **T.**

- **Evaluation Metrics**
- Precision $$Pr\left(C_j\right) = \frac{|C_j \cap RR(C_j)|}{|C_j|}$$
- Recall $$R\left(C_j\right) = \frac{|RR(C_j) \cap C_j|}{|RR(C_j)|}$$
- F-Measure $$F\left(C_j\right) = \frac{2 * Pr\left(C_j\right) * R\left(C_j\right)}{Pr\left(C_j\right) + R\left(C_j\right)}$$

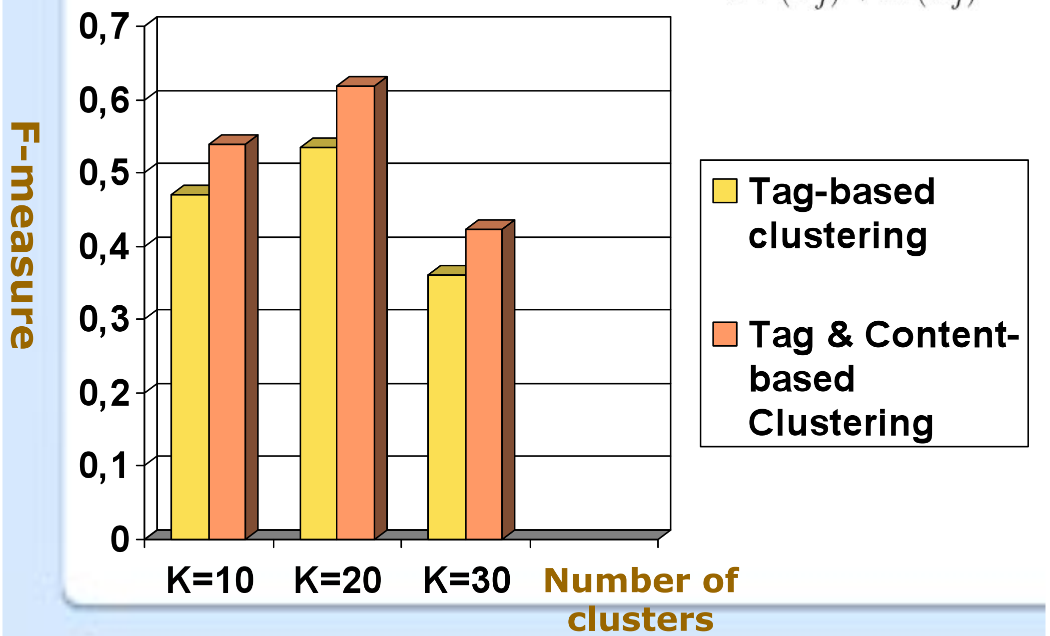


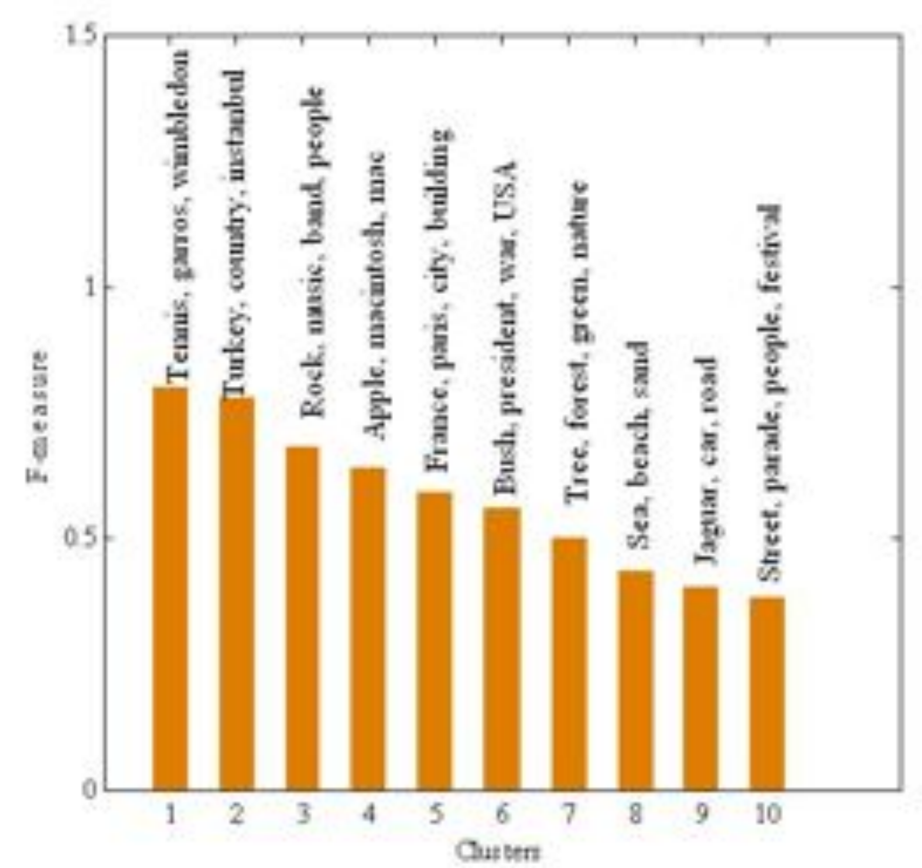
Tag & Content-based Clustering – Experimental Results

Dataset: 10000 images (with their tags) downloaded from Flickr

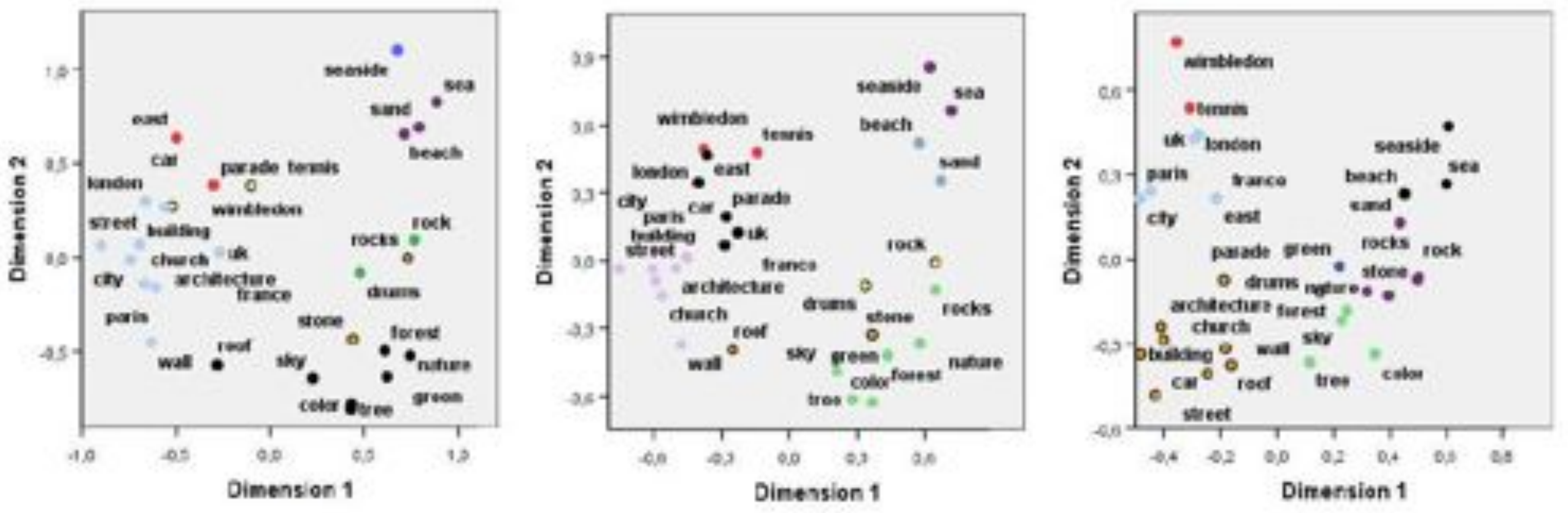
Evaluation: Manual annotation and use of F-Measure.

$$F(C_j) = \frac{2 * Pr(C_j) * R(C_j)}{Pr(C_j) + R(C_j)}$$





Experimental Results (II)



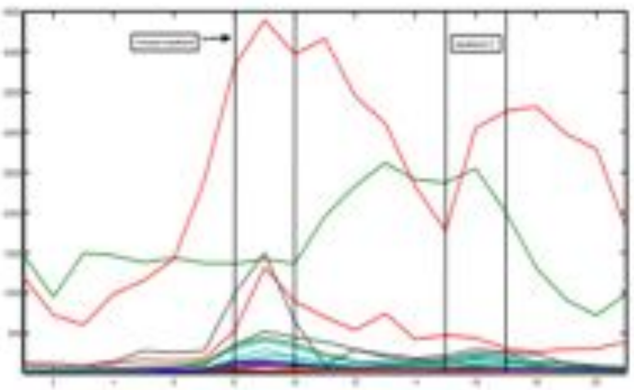
(a) $w = 0.2$ (b) $w = 0.5$ (c) $w = 0.8$

Attributes Assignment to k=8 clusters,

$\mathcal{W}$: weighting factor of semantic similarity against similarity derived from tag co-occurrence

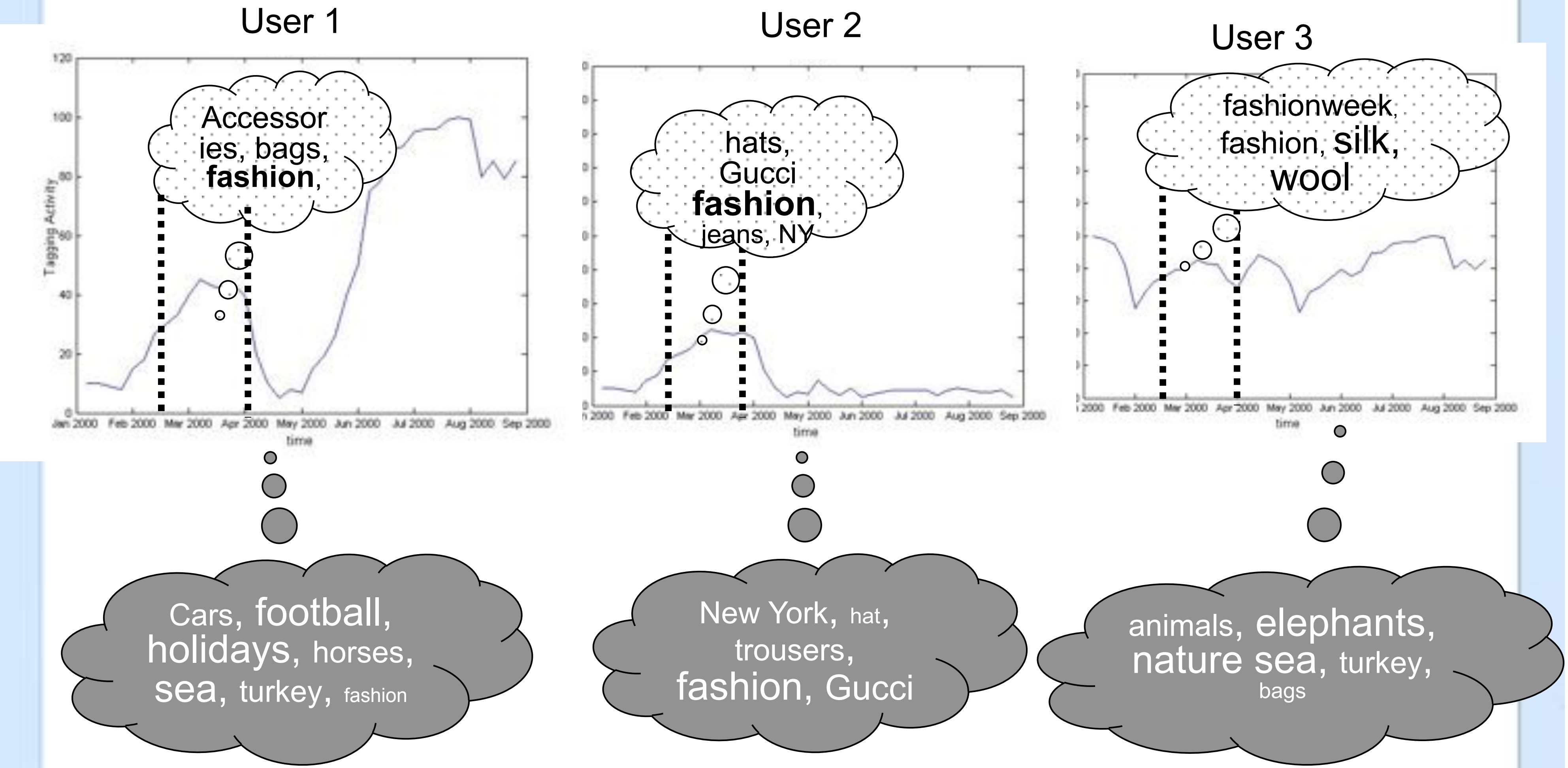
Why consider time?

- Most approaches analysis of “static” views of users-tags
- Events, Trends change user interests
- Users Tagging Behavior changes over time
- Time is a fundamental dimension in analysis of users and tags in a social tagging system



E.g. : Prediction of first weekend box-office revenues using tweets

Many times, a user's targeted interest is hidden in the general tagging activity….

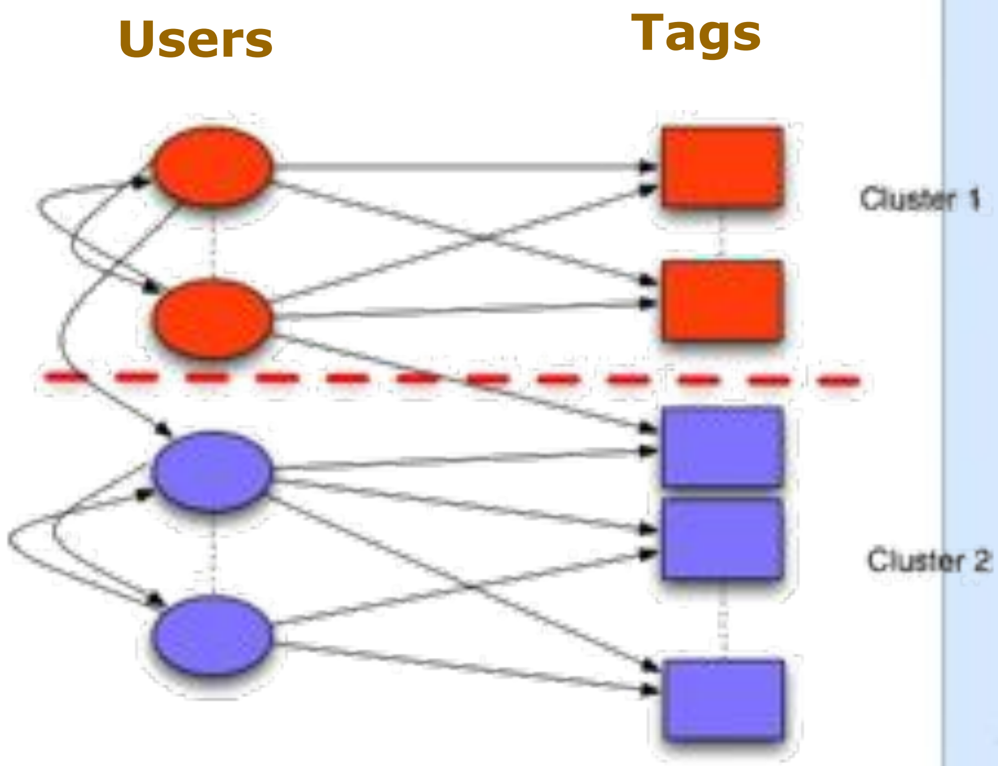


Time-aware user/tag clustering

Static user/tag clusters	Time-aware user/tag clusters
Find user/tags groups that relate to a topic	Find user/tags groups that relate to a topic at specific time periods (e.g. people interested in fashion every August and March, that new collections are announced)
Group together users that use similar tags during the entire time span	Discriminate between users' regular interests (spread over the entire time span) and occasional interests (highlighted in specific time periods)

Clustering vs Co-clustering

- Given a multi-dimensional data matrix, co-clustering refers to **simultaneous** clustering along multiple dimensions
- In a two-dimensional case it is simultaneous clustering of rows and columns
- Most traditional clustering algorithms cluster along a single dimension



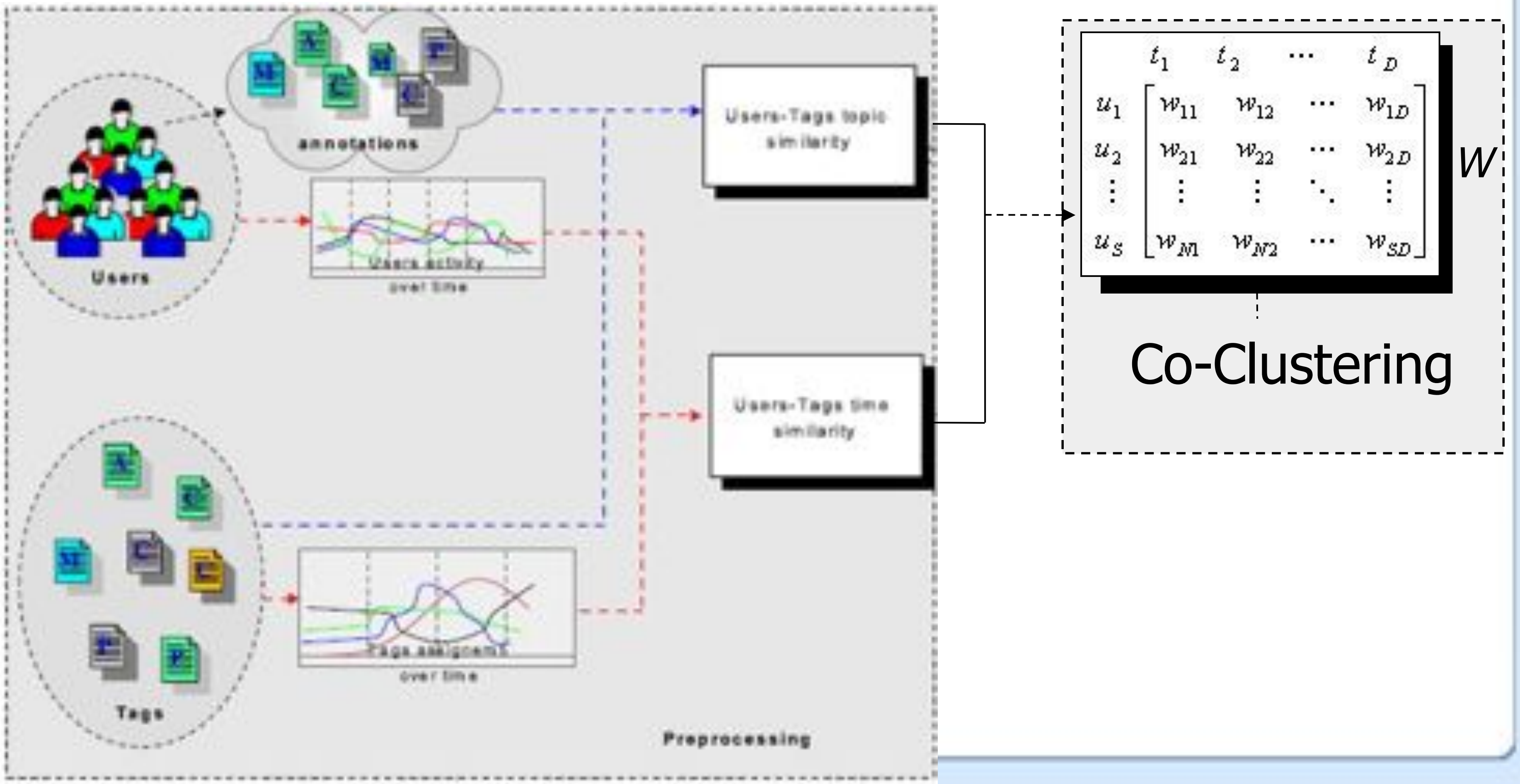
Co-Clustering Example

- Text is represented as a Matrix D
  - rows denote documents
  - columns denote the words
  - matrix elements D_{ij} denote occurrence of word j in document i
- Co-clustering is applied to discover blocks in matrix D
  - correspond to a group of documents (rows) characterized by a group of words (columns)
- In our case we want a user – tag time dependent matrix: D (user, tag)

The proposed approach (I): Overview

- Build a matrix of user activity over time: U(user, time)
- Build a matrix of tag activity over time: T(tag, time)
- Combine these two matrixes: TeS(user, tag)
  - Temporal connection is introduced, but
  - Tag – User connection is not taken into account
- Build a matrix of users and tags based on tag semantics SeS(user, tag)
- Combine TeS and SeS and apply co-clustering: Sim(user, tag)
  - Both temporal and tag – user connections are introduced

The proposed approach (II): The Co-Clustering algorithm



The proposed approach (III): Details

Focus on time locality

- Division of total time in timeframes of size τ
- Representation of users and tags activity in each timeframe (vector model)
    - Number of tags a **user** has assigned and number of times a **tag** has been used, during each timeframe
- Combination of the two matrixes: Inner product

Focus on tag – user similarity

- Compute similiarities between users and tags based on tag semantics
- Similarity metric: WordNet *Wu & Palmer*

Joint use of tag and time similarity

- Similarity metric: Dot product $\rightarrow$ $(u_i, t_j) = SemSim(u_i, t_j) * TemSim(u_i, t_j)$

[I. S. Dhillon, "Co-clustering documents and words using bipartite spectral graph partitioning," in *7th SIGKDD]*

Experimentation – Input parameters

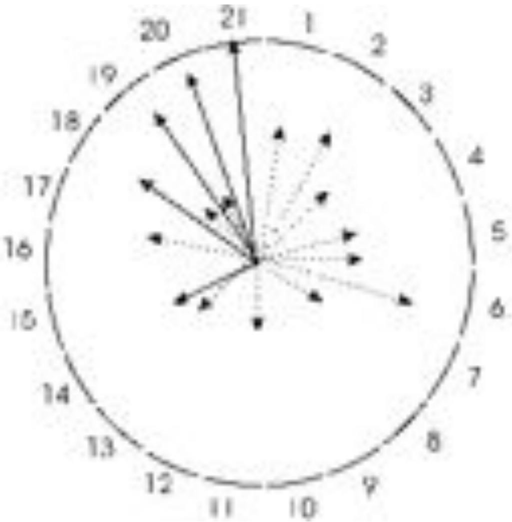
- **Data workload:** 6764 images from Flickr over a time period of 1 year (Sept 2007-Aug 2008) that referred to 4 topics (ancient Greece, Olympics, earthquake and weddings)
  - Pre-processing
    - Remove invalid tags
    - Remove tags with frequency < 1
    - Keep compound valid tags
      - 1218 users, 2496 tags, 210 days
- **Size of timeframes:** τ = 1, 10, 30 days
- **Number of clusters:** k = 7, 10, 12

Experimentation – the τ parameter

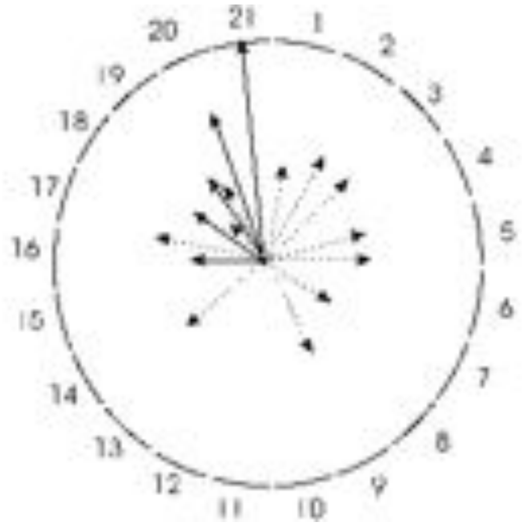
- By changing the value of τ, we can discriminate between users occasional and regular interests

User	$\tau = 30$	$\tau = 100$
User1	olympics2008, beijing, flame, opening ceremony	ancientgreece, acropolis, parthenon, archaeology, ancientcivilizations
User2	earthquake, china, disaster, ruin, disasterassistanceresponseteam	wedding, organizing, party

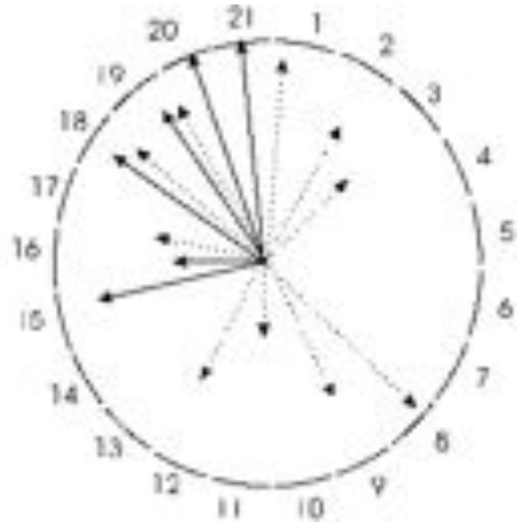
Experimentation – Clusters Visualization



Tags distribution in a cluster



User1' s tags distribution

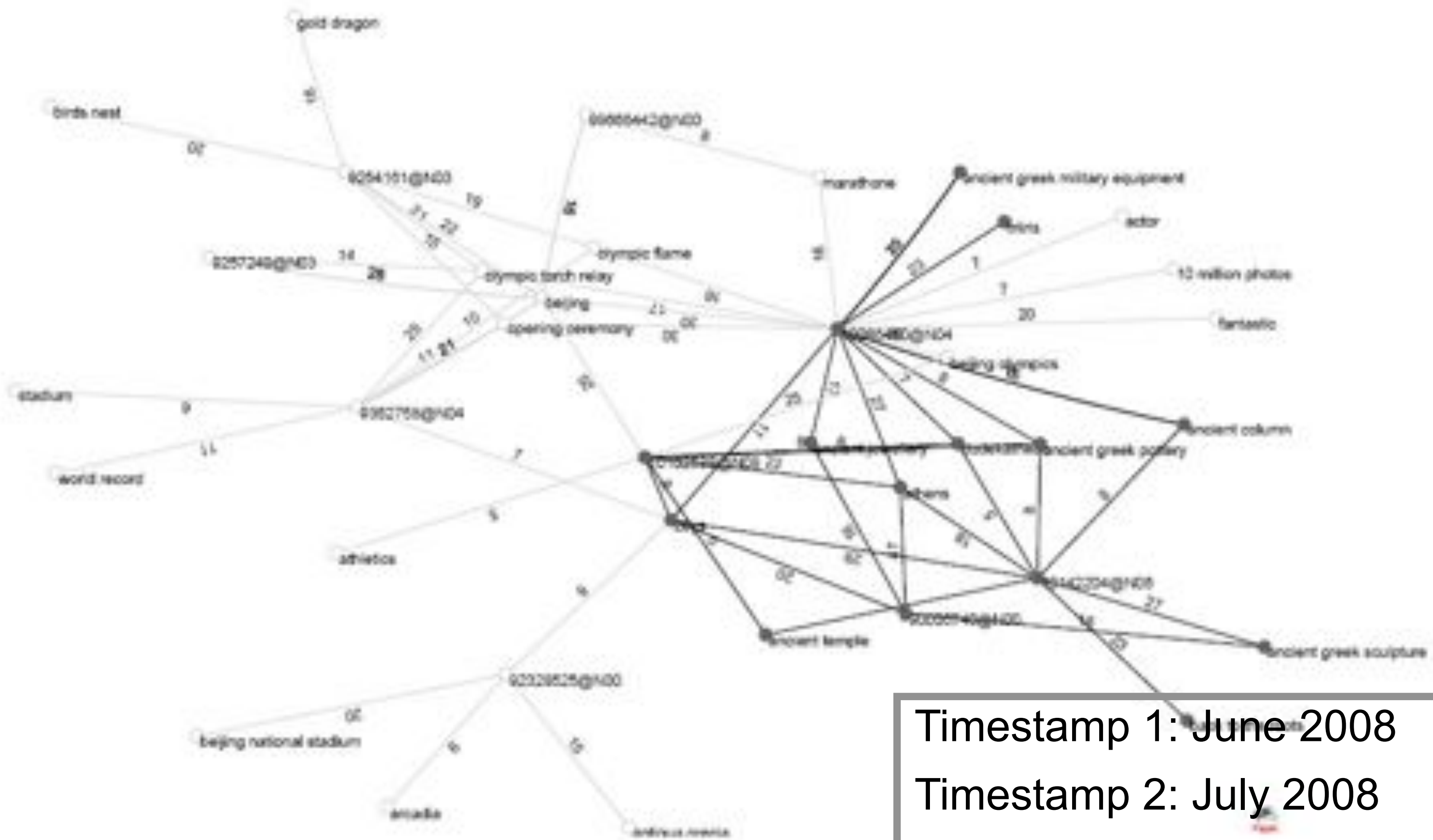


User2' s tags distribution

⟶ Olympics –related tags

⋯→ Ancient Greece –related tags

Cluster evolution (timestamp 1)

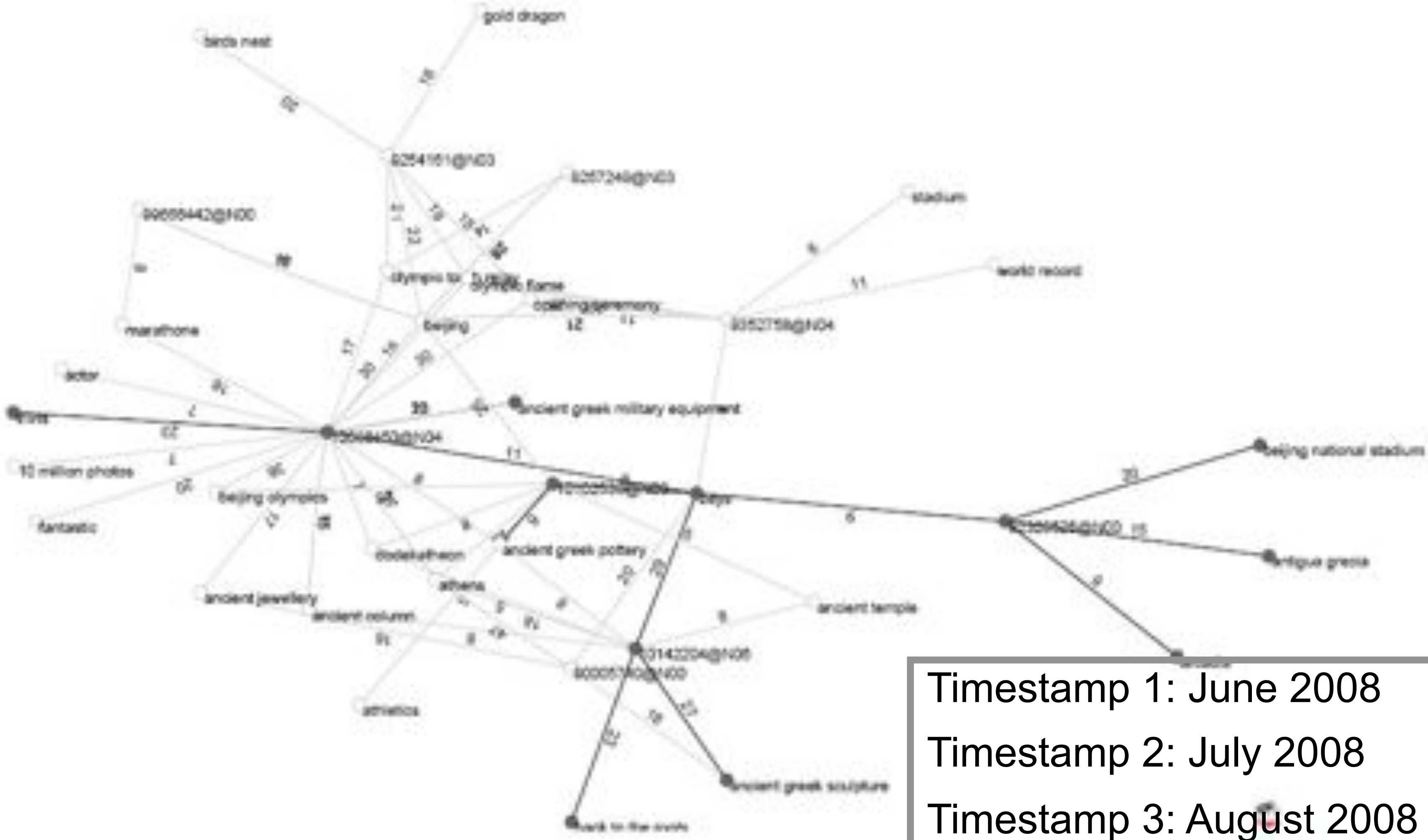


Timestamp 1: June 2008

Timestamp 2: July 2008

Timestamp 3: August 2008

Cluster evolution (timestamp 2)

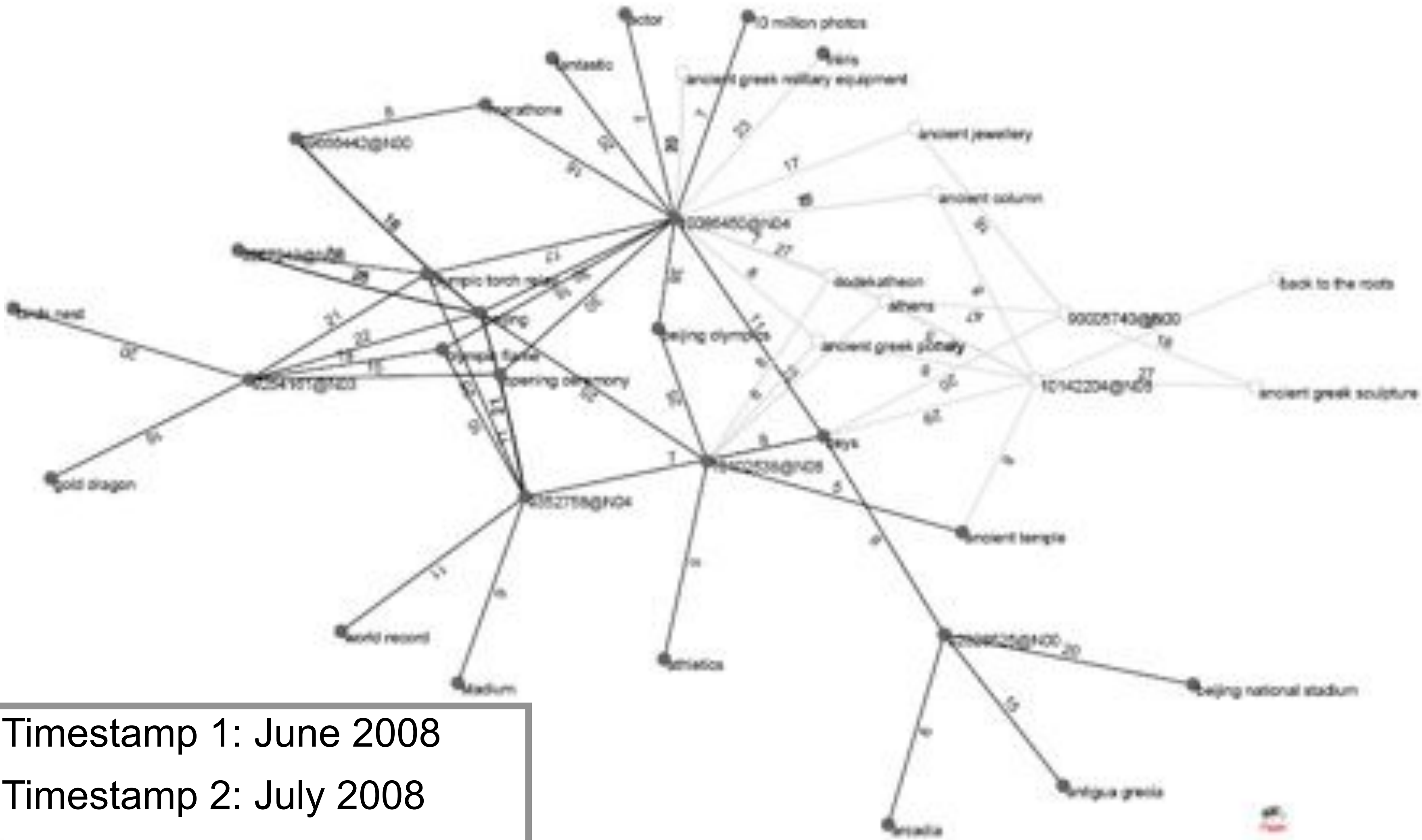


Timestamp 1: June 2008

Timestamp 2: July 2008

Timestamp 3: August 2008

Cluster evolution (timestamp 3)



Timestamp 1: June 2008

Timestamp 2: July 2008

Timestamp 3: August 2008

Use Cases

- Capturing trends, interests, periodic activities of users in specific time periods
- Community-based tag recommendation
- Personalization (time-aware user profiles)
- Fighting spam on social web sites (by discriminating regular and occasional users)

Social Media “teacher” of the machine

Exploiting clustering for machine learning

Objective: Develop a framework able to create strongly annotated training samples from weakly annotated images

Problems:

- Object detection schemes require region-detail annotations
- Manual annotation is laborious and time consuming

Tagged images

sand, wave, rock, sky

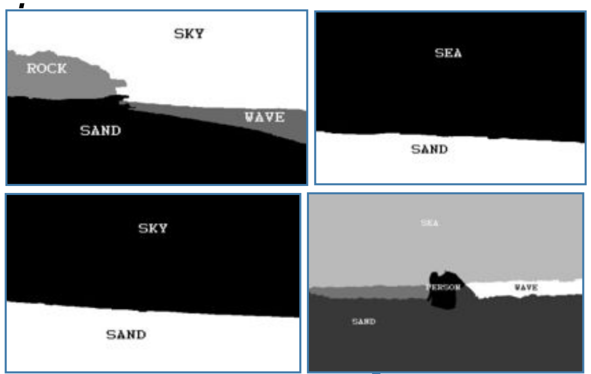
sea, sand

sand, sky

person, sand, wave, see

Social information + Image analysis

Region-detail annotated images



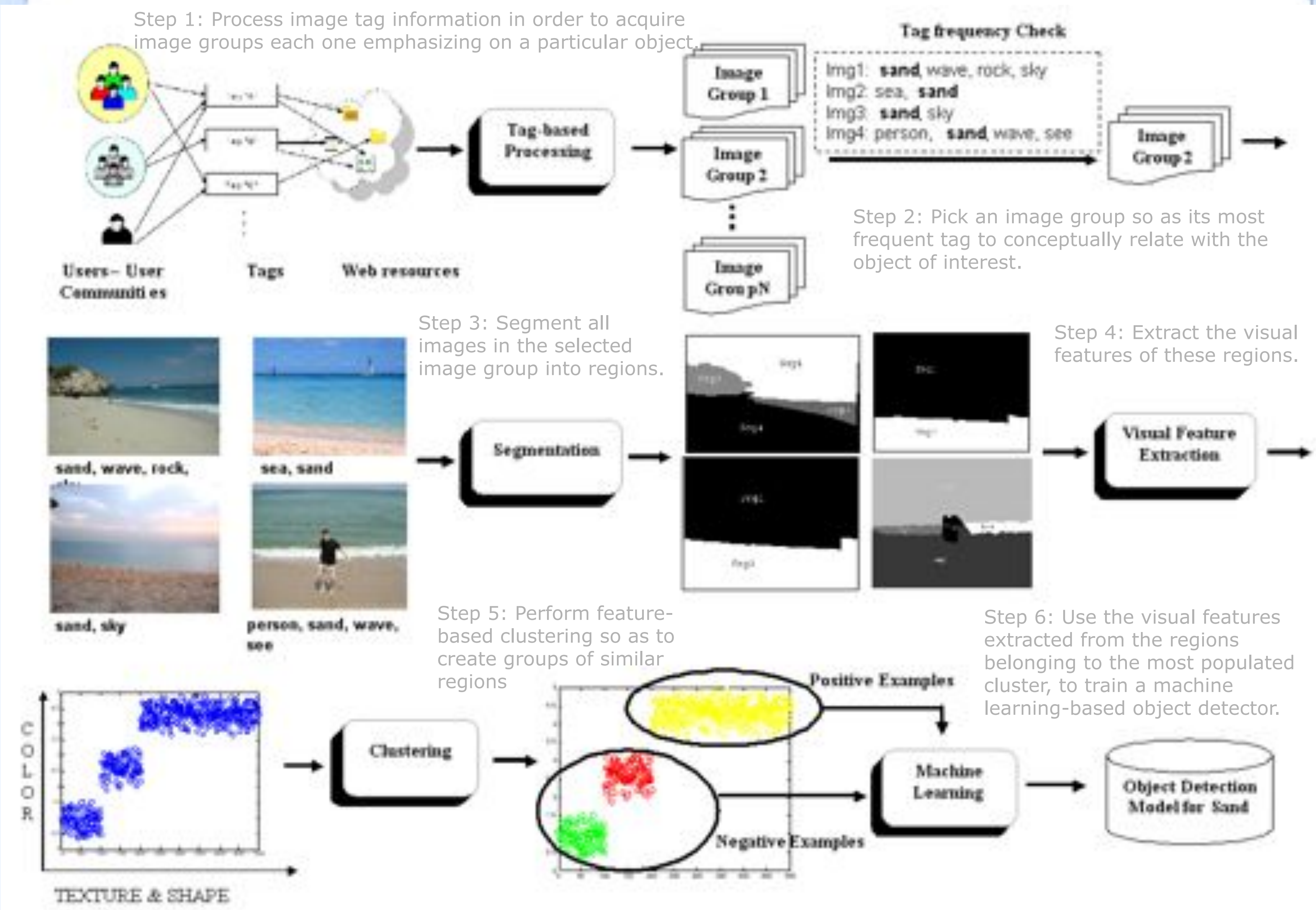
[Chatzilari09]

Machine Learning

Object Detectors

Solutions:

- Exploit user tagged images from social sites like flickr
- Combine techniques operating on tag and visual information space



Step 1: Process image tag information in order to acquire image groups each one emphasizing on a particular object.
Users – User Communities
Tags
Web resources
Tag-based Processing
Image Group 1
Image Group 2
Image Group N
Tag frequency Check
Img1: sand, wave, rock, sky
Img2: sea, sand
Img3: sand, sky
Img4: person, sand, wave, see
Image Group 2
Step 2: Pick an image group so as its most frequent tag to conceptually relate with the object of interest.
sand, wave, rock, sky
sea, sand
sand, sky
person, sand, wave, see
Step 3: Segment all images in the selected image group into regions.
Segmentation
Step 4: Extract the visual features of these regions.
Visual Feature Extraction
Step 5: Perform feature-based clustering so as to create groups of similar regions
COLOR
TEXTURE & SHAPE
Clustering
Positive Examples
Negative Examples
Step 6: Use the visual features extracted from the regions belonging to the most populated cluster, to train a machine learning-based object detector.
Machine Learning
Object Detection Model for Sand

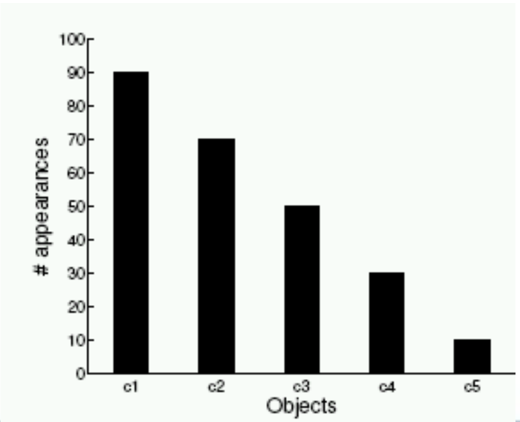
Tag-based processing

[Giannakidou08]

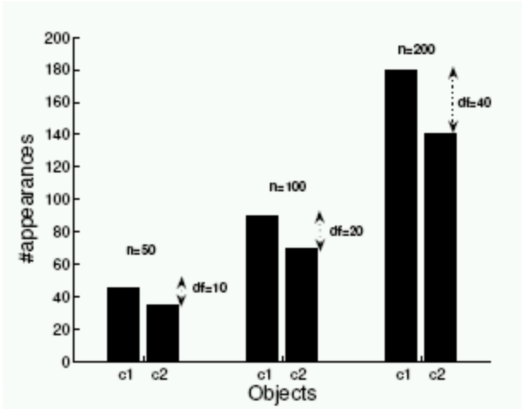
SEMSOC output example

SEMSOC, vector space model where each image is projected onto a space defined by the most prominent tags

Distribution of objects based on their frequency rank



Absolute difference between 1st and 2nd most highly ranked objects increases as n increases



Segmentation & Visual Descriptors

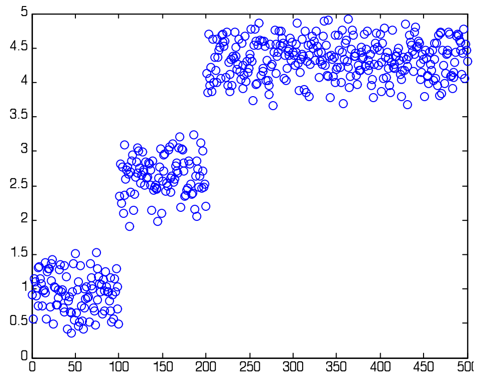
- Segmentation
  - K-means with connectivity constraint (KMCC)

[Mezaris et al., 2004]

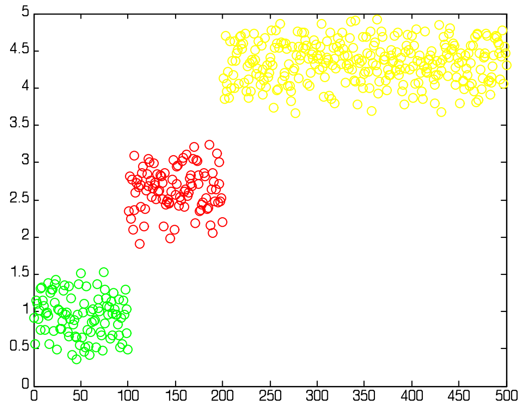
- Visual Descriptors
  - MPEG-7 standard
    - *Dominant Color , Color Layout, Color Structure, Scalable Color, Edge Histogram, Homogeneous Texture, Region Shape.*

[Bober et al., 2001], [Manjunath et al., 2001].

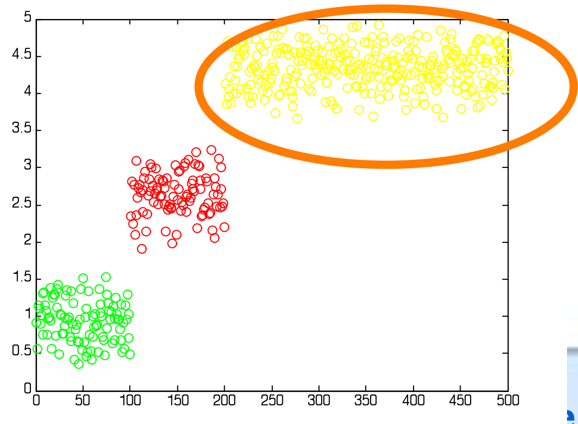
Region-based Clustering & Cluster Selection Region clustering



- Perform segmentation and visual feature extraction from all images in an image group (Identified by SEMSOC)

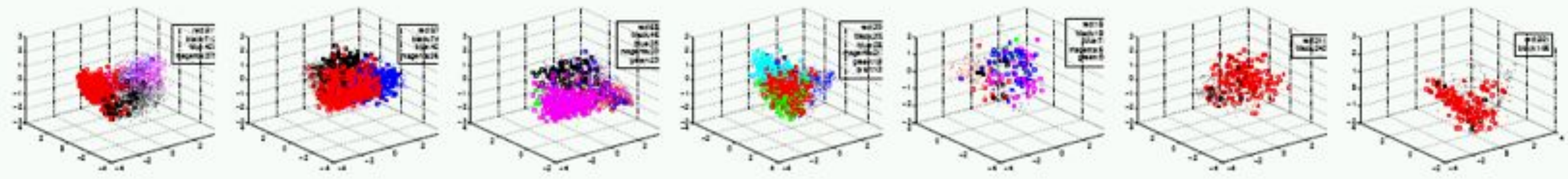


- Perform clustering based on visual features to gather together regions depicting the same object



- Pick the most populated cluster as the one representing the most frequently appearing tag of the group

Experimental Results – Cluster Selection



(a) Sky (b) Sea (c) sand (d) Person (e) Boat (f) Vegetation (g) Rock

Setting:

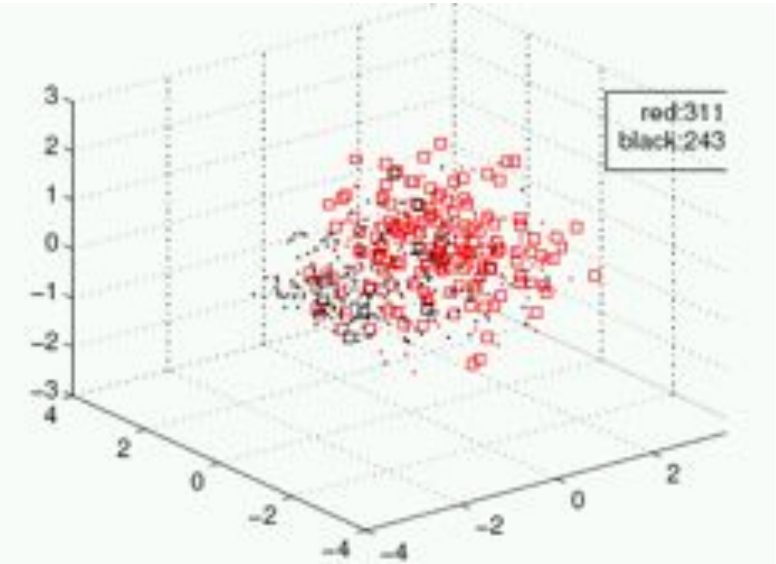
- Visualise the way regions are distributed among clusters
- Use shape-code (squares) to indicate the regions of interest and color-code to indicate a cluster's rank (largest cluster: red)
- Ideally all squares should be painted red and all dots should be painted differently

Goal:

- Validate our theoretical claim that the most populated cluster contains the majority of regions depicting the object of interest

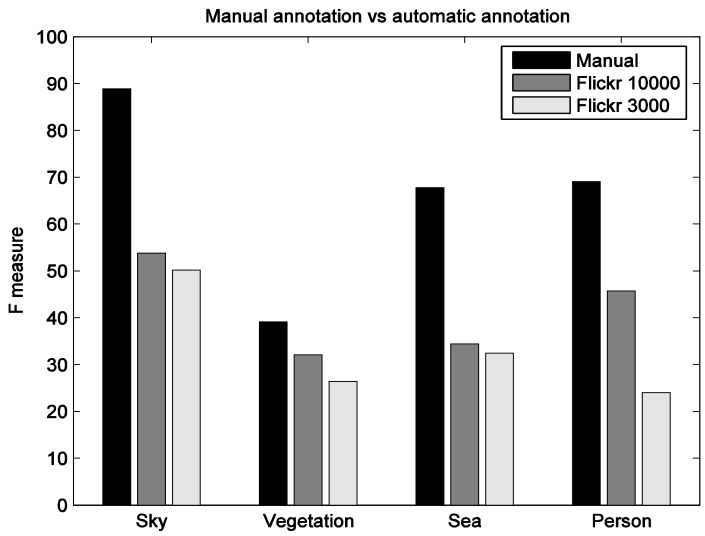
Conclusions:

- Our claim is valid in 5 (i.e., sky, sea, person, vegetation, rock) and not valid in 2 (i.e., boat, sand) cases



Vegetation in magnification

Experimental Results - Man. vs Autom. trained object detectors



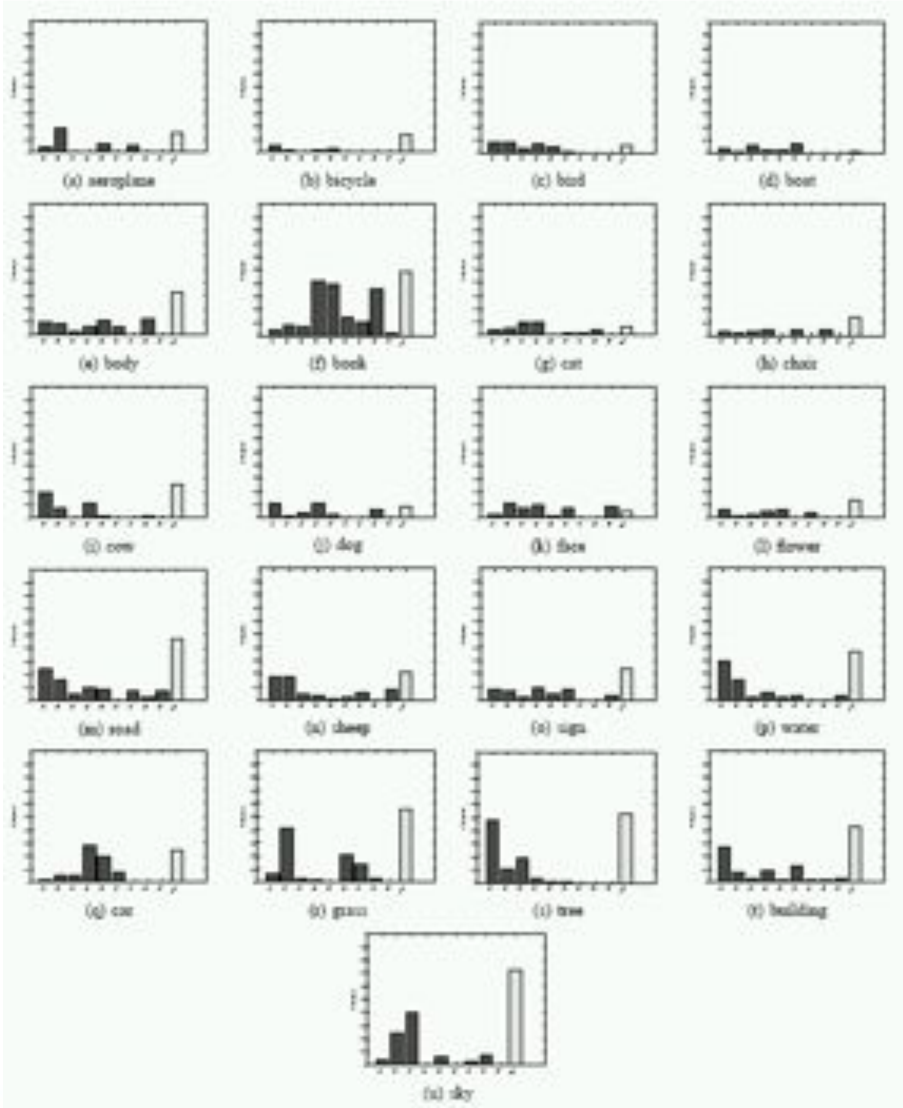
Observations:

- Performance lower than manually trained detectors
- Consistent performance improvement as the dataset size increases

Experimental Results – MSRC Dataset (21 objects)

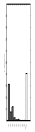
Observations:

- In 5 cases the objects were too diversiform to be described by the employed feature space (not even the manual annotations performed well)
- In 5 cases the annotation we got from Flickr groups were not appropriate
- In 6 cases, our method has failed to select the appropriate cluster
- In 5 cases our method worked well



Experimental Results - MSRC vs Flickr groups Target object: Tree

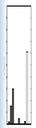
Tree object



Good example: Semantic objects are correctly assigned to clusters and the most-populated cluster corresponds to the target object)

Experimental Results - MSRC vs Flickr groups Target Object: Sky

Sky object

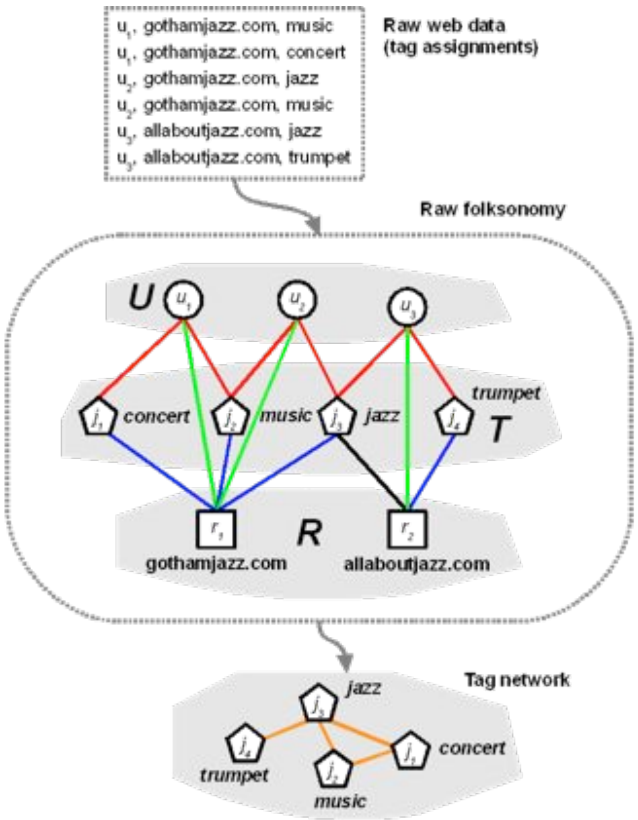


Bad example: Sky regions are split in many clusters and the most populated cluster contains noise regions

Community Detection

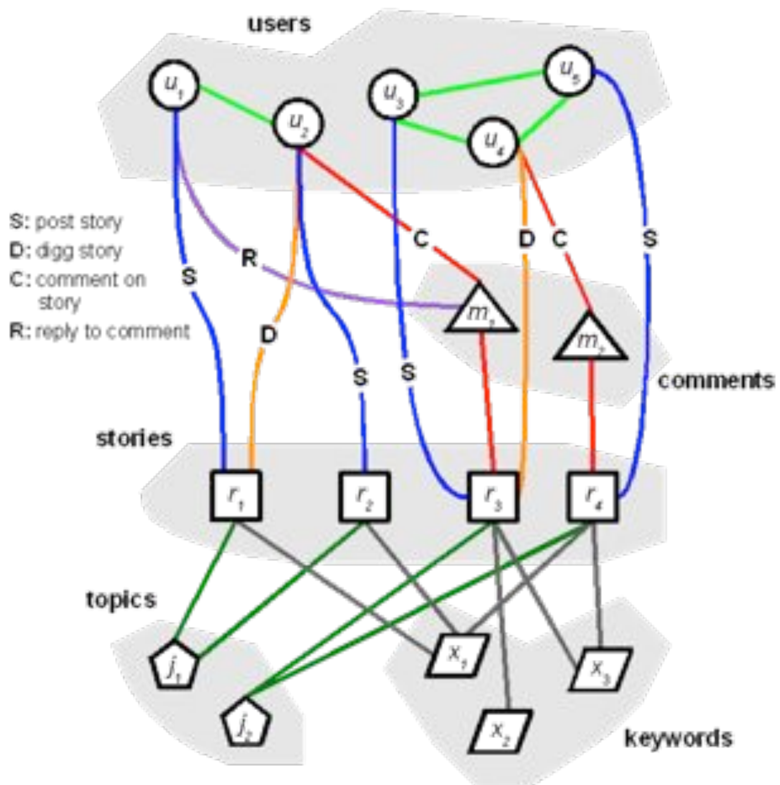
Examples of Social Media networks

Folksonomy (Delicious)



Mika, P. (2005) Ontologies Are Us: A Unified Model of Social Networks and Semantics. Proceedings of the 4th International Semantic Web Conference (ISWC 2005), Springer Berlin / Heidelberg, pp. 522-536

MetaGraph (Digg)



Lin, Y., Sun, J., Castro, P., Konuru, R., Sundaram, H., and Kelliher, A. (2009) MetaFac: community discovery via relational hypergraph factorization. Proceedings of KDD '09, ACM, pp. 527-536

Challenges in Social Media network mining

No prior assumptions about structure:

- Complex & evolving structure
- No possibility for knowing structural features (e.g. number of clusters on a graph) in advance

→ Unsupervised

Scale

- Tens of millions of active users frequently contributing loads of content links + metadata (tags, comments, ratings)

→ Efficient - scalable

Quality

- Spam is very common. Only a portion of user contributions is worth further analysis.

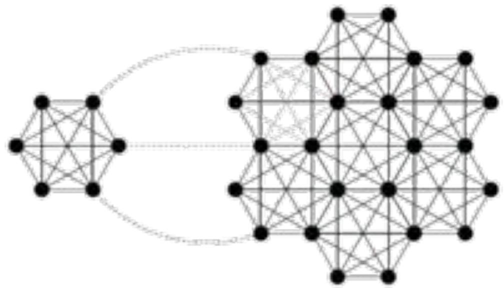
→ Noise resilient

What is a community in a network?

Group of vertices that are more densely connected to each other than to the rest of the network.

Multiple definitions to quantify communities:

Fortunato S. (2010) Community detection in graphs. Physics Reports486: 75-174



- Global: N-cut, conductance, modularity
- Local: Local modularity, (μ,ε)-cores
- Ad hoc: Label propagation, dynamic synchronization

Related to clustering, but: (a) not necessary to know number of communities, (b) computationally more efficient

In Social Media, we focus on local definitions, because of the properties of Social Media networks: efficiency-scalability and noise resilience.

Global vs. Local

- **Global:** Process the whole graph to derive a partition into communities
  - \+ Abundant research
  - \+ Good results (community quality, algorithm efficiency)
  - Not practical for huge graphs or for real-time applications
- **Local:** Incremental process of the graph and output communities (streaming)
  - Relatively little research
  - Great potential for demanding applications

Approach illustration

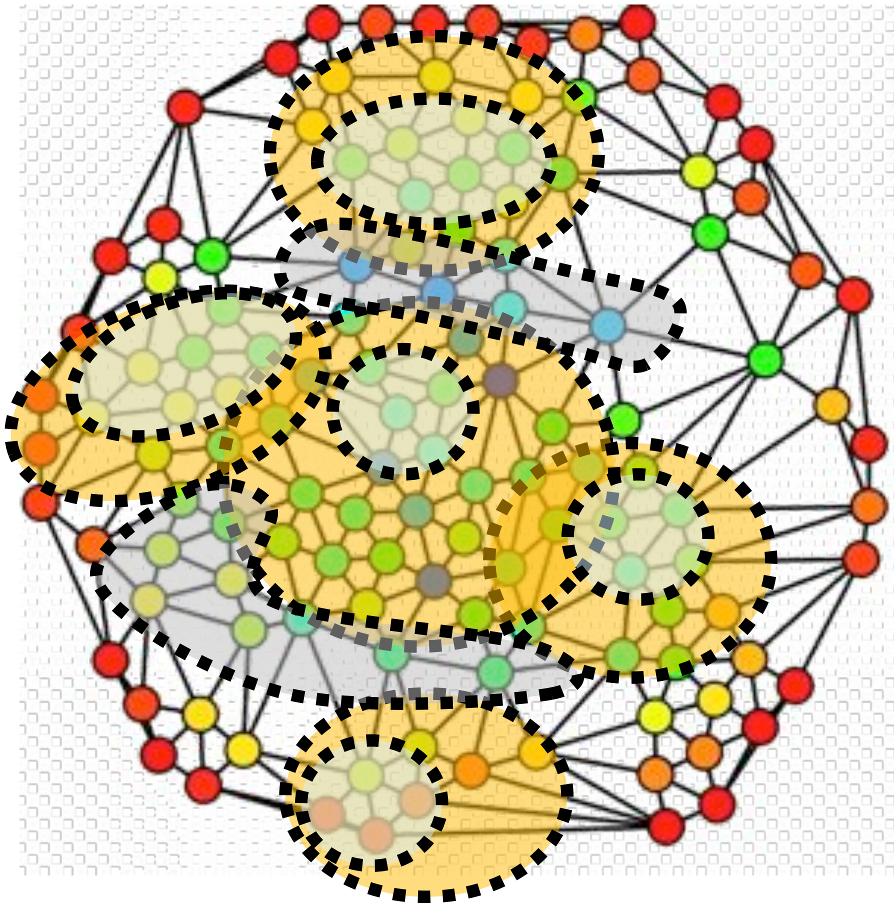
Two-step process:

•1st step:

(μ, ε) – core detection

- 2nd step:
  Local expansion

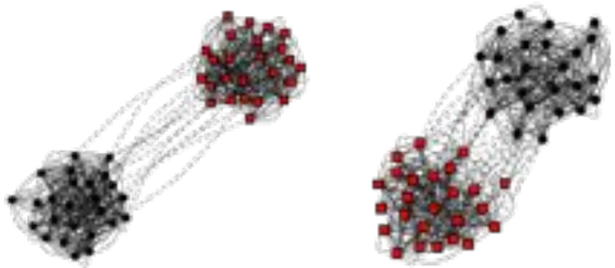
- 3rd step:
  Characterization of remaining vertices as *hubs* or *outliers*



Experiments on Synthetic Community Networks

- Synthetic networks according to method of Newman and Girvan.

$$S_{PAR} = \{N, K, z_{tot}, p_{out}, s_{var}\}$$



(a) $p_{out} = 0.01$ (b) $p_{out} = 0.08$

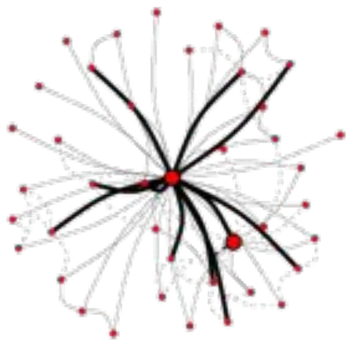
Change complexity of underlying communities.

	F_C			NMI		
p_{out}	BB	BB'	GN	BB	BB'	GN
0.01	100	100	100	1.0	1.0	1.0
0.05	100	100	100	1.0	1.0	1.0
0.1	100	100	50	1.0	1.0	0.86
0.15	100	99	50	1.0	.98	0.86
0.20	99	74	50	0.98	0.84	0.86
0.25	24	24	0	0.54	0.56	0.02

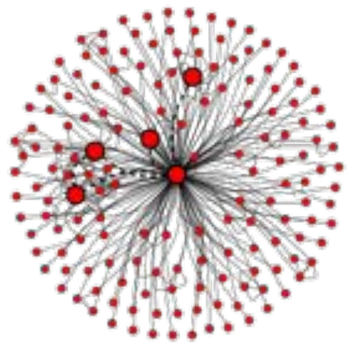
Change relative sizes of underlying communities.

	F_C			NMI		
s_{var}	BB	BB'	GN	BB	BB'	GN
1.1	100	100	100	1.0	1.0	1.0
1.5	100	100	100	1.0	1.0	1.0
1.6	99.5	100	100	0.99	1.0	1.0
1.7	88	98	100	0.82	0.96	1.0
1.8	85.5	97	100	0.79	0.95	1.0
1.9	58.5	87	90	0.68	0.82	0.88
2.0	12.5	80	82	0.45	0.73	0.81
2.5	0	62	75	0.45	0.63	0.72

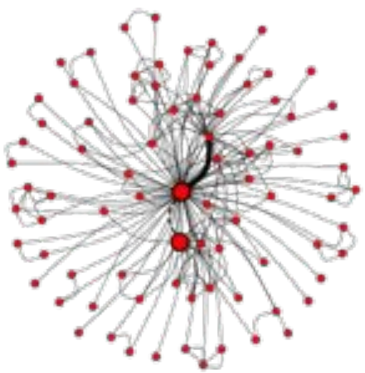
LYCOS iQ Tag Network



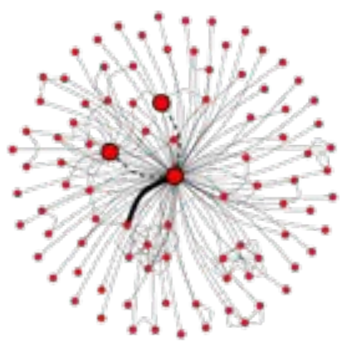
(a) Music



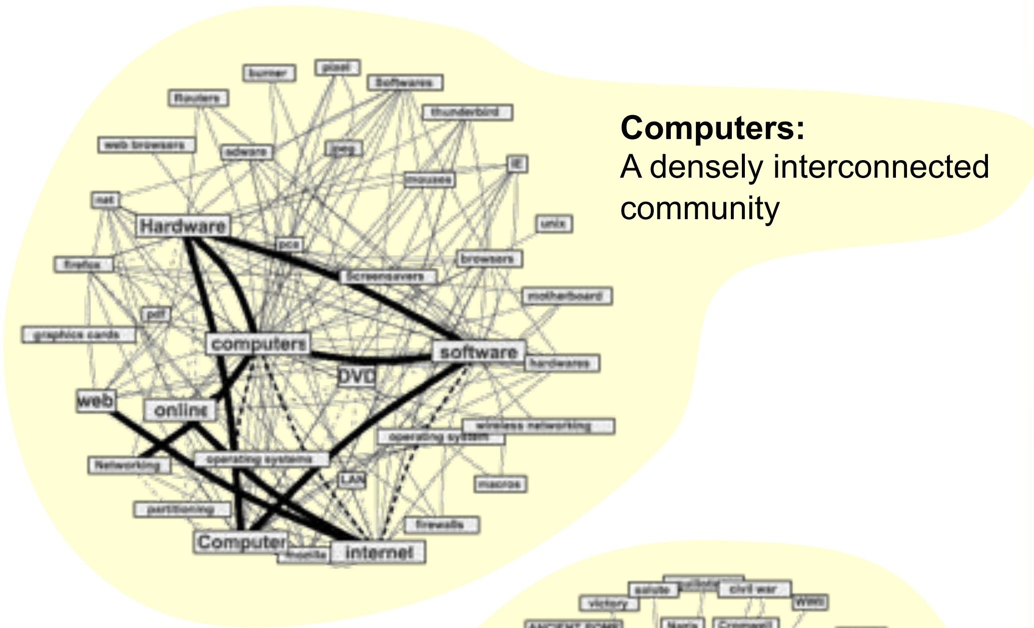
(b) Science

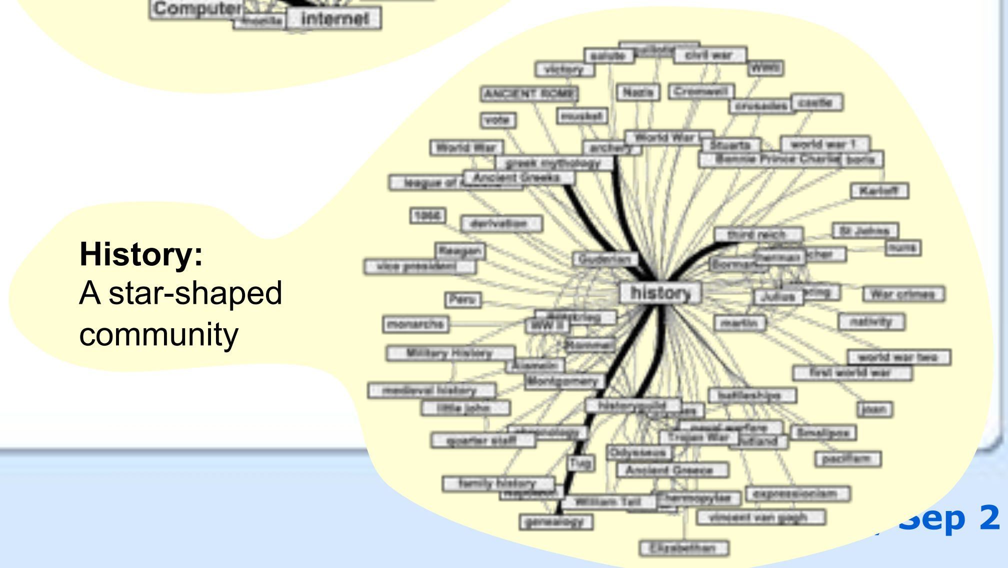


(c) Film



(d) Animals





Hybrid Photo Clustering

Goal:

- Group large photo collections into clusters based on how much they are related to each other
- Assist browsing and navigation by means of a map-based application
- Detect landmark and event clusters.

Combine both visual features *and* tags

- Two kinds of similarity (visual and tag networks) are complementary to each other
- Many times one photo has missing tags or is hard to interpret visually
- Graph-based approach - superimpose visual and tag graphs
- Use photo cluster features for classification to landmarks/events

Results

- Higher quality clusters by use of both visual and tag similarity instead of only each one of them.
- Clusters can be used for landmark and event detection.
- Integrated in CSG prototype and ClustTour stand-alone demo.

Overview of approach

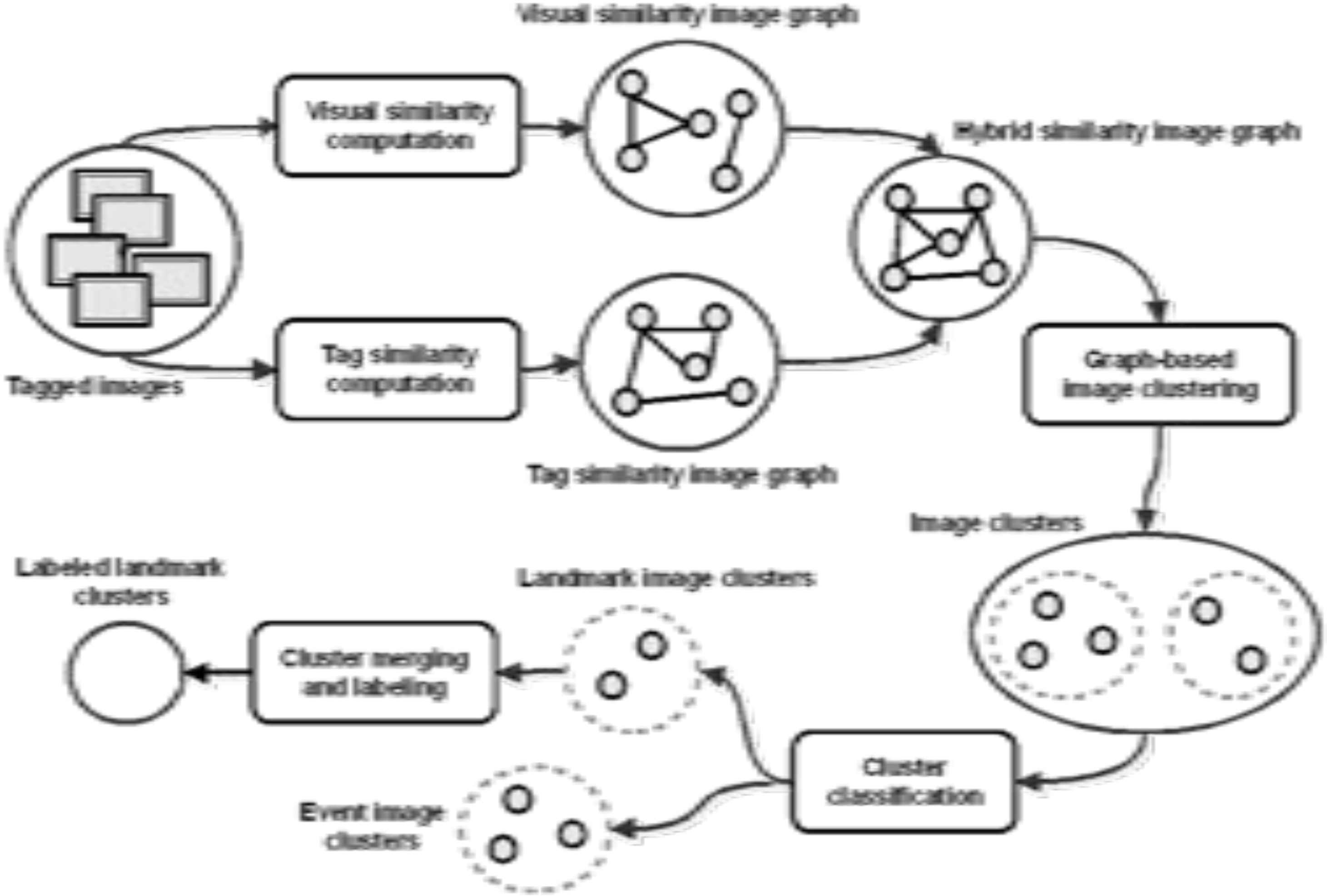


Photo clustering results (1)

User study (involving 20 people)

- Users where shown photo clusters and they were asked to judge how relevant the photos of each cluster were related to each other
- Each cluster was produced by different notion of similarity (tag-only, visual-only, hybrid). Obviously, users were not aware of this information
- Hybrid clusters were found to be of superior quality (highest F-measure)

Algorithm	Precision	Recall	F-measure	κ-statistic
SCAN-VIS	0.980	0.178	0.301	**0.925**
SCAN-TAG	0.910	0.197	0.323	0.688
SCAN-HYB	0.898	**0.246**	**0.387**	0.637
EXP-VIS	**0.985**	0.178	0.301	0.895
EXP-TAG	0.929	0.201	0.331	0.709

Photo clustering results (2)

Geographic localization of results was also found to be very high.
Most clusters correspond to landmarks or events.

EVENTS

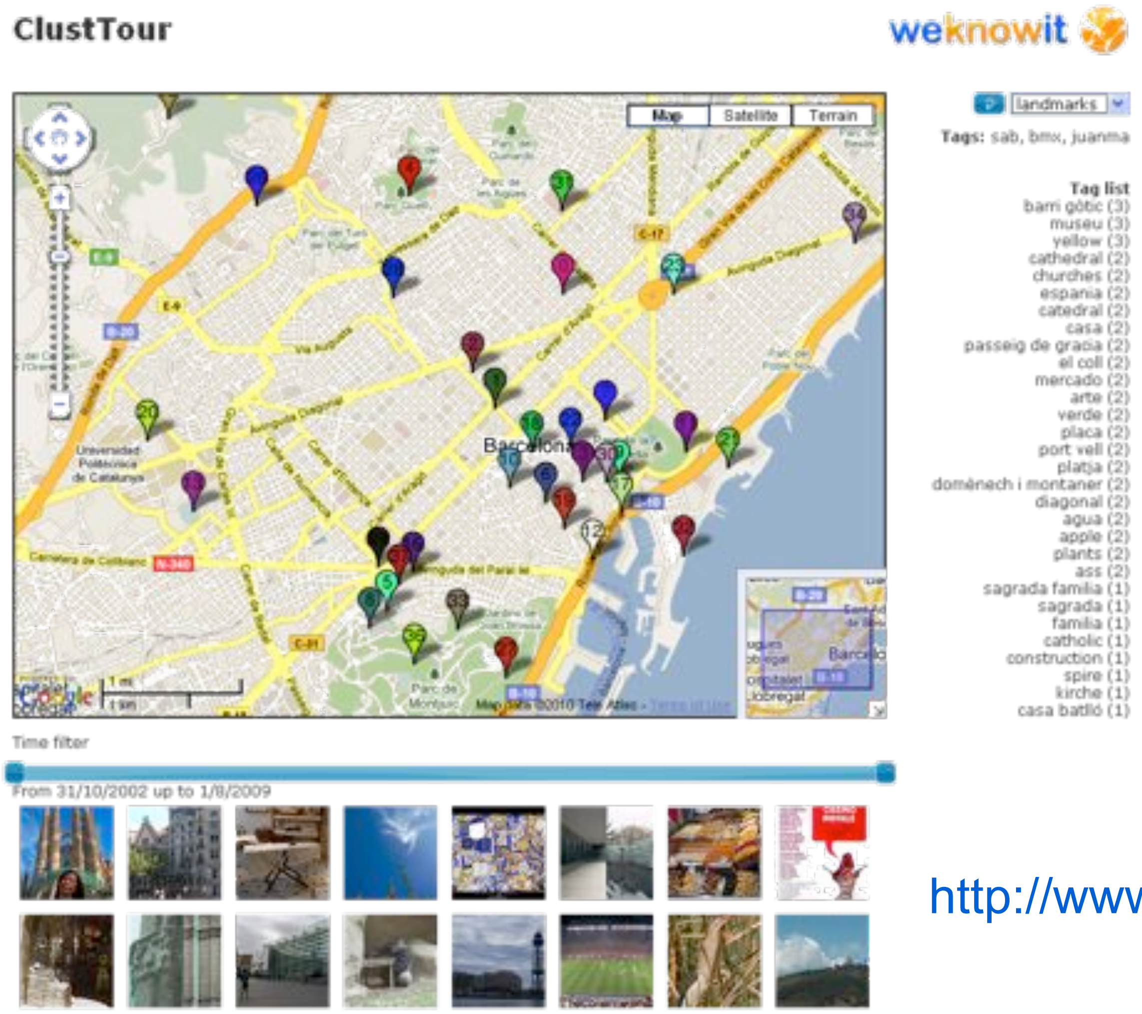
Sample results:
[Visual] vs. [Tag] vs. [Visual + Tag]

VISUAL

HYBRID

TAG

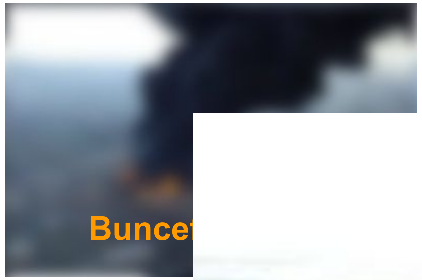
ClustTour demo: City exploration by means of photo clusters



http://www.clusttour.gr

WeKnowIt and CI

Personal Intelligence



Profile of contributor

>> What to send where,

e.g. location, age

Media Intelligence

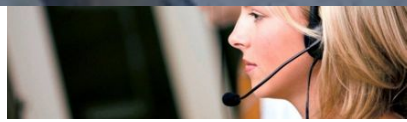
se

on

Organizati

Trust and feedback

>> Determine trustworthiness and hub-structures by SNA



Further Issues

- Not all data always available (e.g. User queries, fb)
- Long tail is forgotten (e.g. flu trends in 3rd world countries)
- “More data, less analysis”,....
- Applications and commercialization
- Efficiency of semantics and analysis
- Real integration
  - not just sum of different analysis
  - formal framework and approach
  - representation
- User interaction – Interfaces

Thank you!


sky
tower
vegetation
ground
road
<rdf:Description rdf:about="http://www.iti.gr/ontologies/INSTANCES#Sky_0">

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