Query Routing Mechanisms in Self-organizing Search Systems

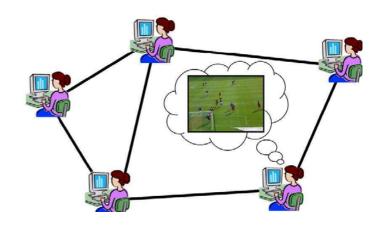
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Outline

- Self-organizing search systems
- Routing algorithm
- Confusability of queries
- Experimental trials
- Conclusions and future work

Self-organizing Search Systems

- A set of interacting components creating a desired outcome
 - Evolves in time and space
 - Inspired in sociology, biology
- Goal: search for information
- Properties:
 - Scalability
 - Adaptability
 - Robustness

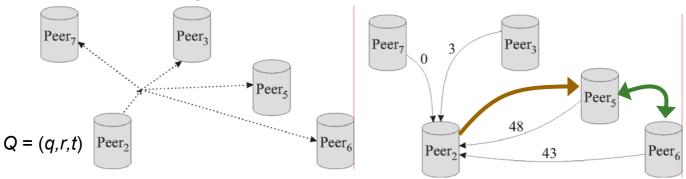


Metric Semantic Overlay

- Self-organizing system over a P2P network
- Metric space as data model
- Structure:
 - Peers
 - Data stored in the corresponding peer of underlying P2P network
 - Query history, list of exploration peers
 - Relationships
 - Exploited for query routing
 - Created by analyzing queries and their answers

Relationships

Created according to peers' answers to the processed query

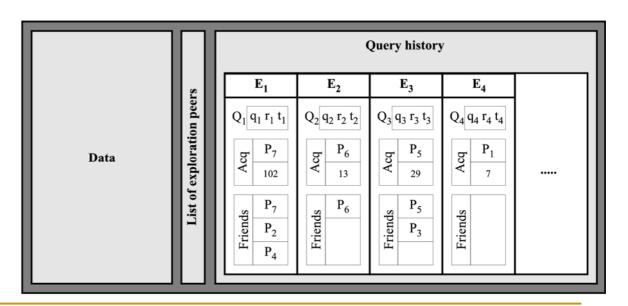


- Acquaintance
 - Peer returning the biggest part of the answer

 - Acquaintance relationship: between Peer₂ and Peer₅
- Friends
 - Peers returning the significantly-large part of the answer
 - \neg Friends(Q₃) = {Peer₅, Peer₆}
 - Friend relationships: between each pair of friends

Peer

- Query history
 - List of entries $E_1, ..., E_n$ representing the relationships
 - Each entry contains metadata about a processed query:
 - Query object, radius, timestamp
 - Acquaintance
 - List of friends



Query Routing

- At each peer P, a query Q=(q,r,t) is evaluated:
 - Inspect all entries of query history and take ones most relevant to Q
 - Forward Q to the acquaintances of these entries
 - In case of few relevant entries, Q is forwarded to some exploration peers.
 - If there is no more relevant entry, do:
 - Evaluate Q on local data
 - Ask all friends to answer Q
 - Return all answers to P_{start}

Relevancy of Entries

- By means of Confusability
 - □ $conf(Q,Q_t) \rightarrow [0,1]$
 - It measures closeness and extent of queries.
 - Identical queries: conf(Q,Q) = 1
 - □ Queries Q_t having $conf(Q,Q_t) \ge ct_{high}$ are highly relevant to Q_t
 - \square Queries Q_t having $conf(Q,Q_t) < ct_{low}$ are irrelevant to Q_t
 - □ Parameters: $ct_{low} = 0.3$ $ct_{high} = 0.8$

Measures of Confusability

- A new range query Q=(q,r,t), a template query $Q_t=(q_t,r_t,t_t)$
 - $\Box conf(Q,Q_t) \rightarrow [0,1]$
- Exponential function
 - □ *B* is constant, depends on data:
 - B = 1 / most frequent distance d
- Adaptive exponential function
 - Adapts to varying radii
- Adaptive Gaussian-like function
 - Overlapping queries are very similar
 - $d(q,q_t) \le r$

$$Exp(Q,Q_t) = e^{-B d(q,q_t)}$$

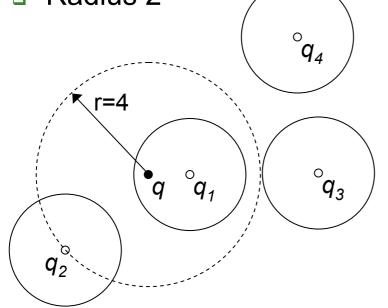
$$aExp(Q,Q_t) = e^{-\frac{\ln ct_{low}}{-r-r_t}d(q,q_t)}$$

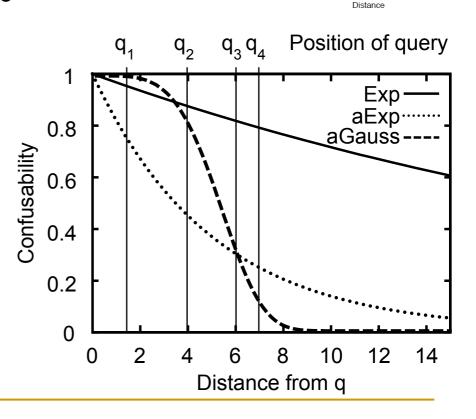
$$aGauss(Q,Q_t) = e^{-B d(q,q_t)^C}$$

$$B = \frac{\ln ct_{low}}{(-r - r_t)^C} \qquad C = \frac{\ln \frac{\ln ct_{high}}{\ln ct_{low}}}{\ln \frac{r}{r + r_t}}$$

Measures of Confusability – Example

- 2-d data, uniform distr., Euclidean dist.
 - Most-frequent distance 30.0
 - Exp function: B=1/30
 - □ Radius 2

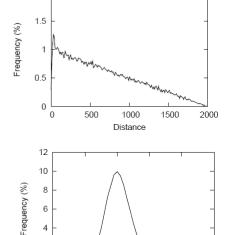




2000

Experimental Comparison

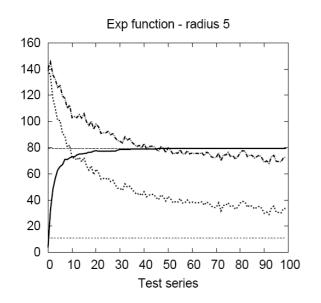
- Synthetic dataset 100,000 2-d vectors
 - [0;1,999] x [0;49] space
 - Each peer contains 50 objects having the same x-coordinate
- Real-life dataset 100,000 image features
 - Subset of CoPhIR dataset
 - Each peer contains 50 objects following
 M-Chord data-distribution principles

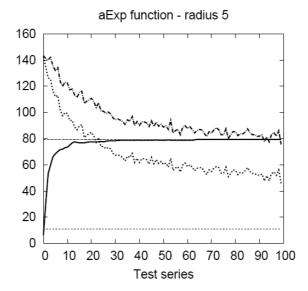


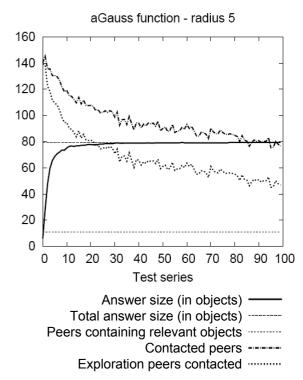
Distance

- List of exploration peers is initialized to just 50 random peers.
- Repeating the batch:
 - Training queries 50 random objects, varying radii
 - □ Testing queries 5 objects, same radius

Experiment Results – 2-d, rad=5

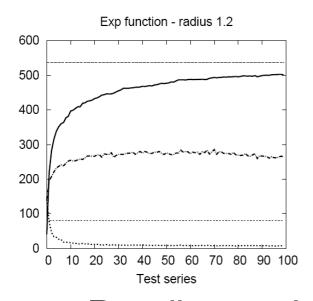


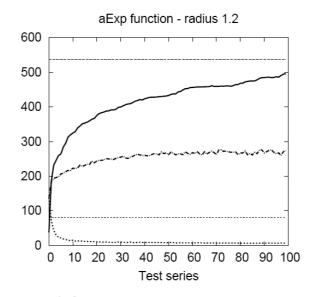


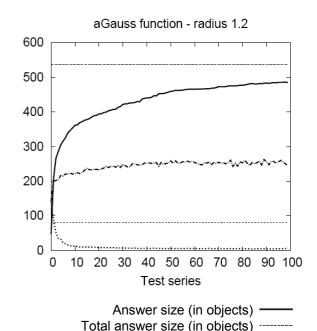


- Recall nearly 100%
- Costs increased for aExp and aGauss
 - These functions are below Exp, so more exploration peers are used.

Experiment Results – CoPhIR, rad=1.2







Peers containing relevant objects -----

Exploration peers contacted

Contacted peers -----

- Recall nearly 90%
- Costs almost identical
 - □ Distance to the nearest neighbor is quite large, so Exp returns low values too. ⇒ The same number of exploration peers.

Conclusions

Contribution

- Adaptive functions focus more on similar queries (overlapping)
- Adaptive functions are data independent.
- Navigation is more focused
 - Contacting fewer peers that are promising to contain data

Future work

- Advanced filtering techniques to decrease costs
- Detecting when the system is adapted (learned)
- Management of query history