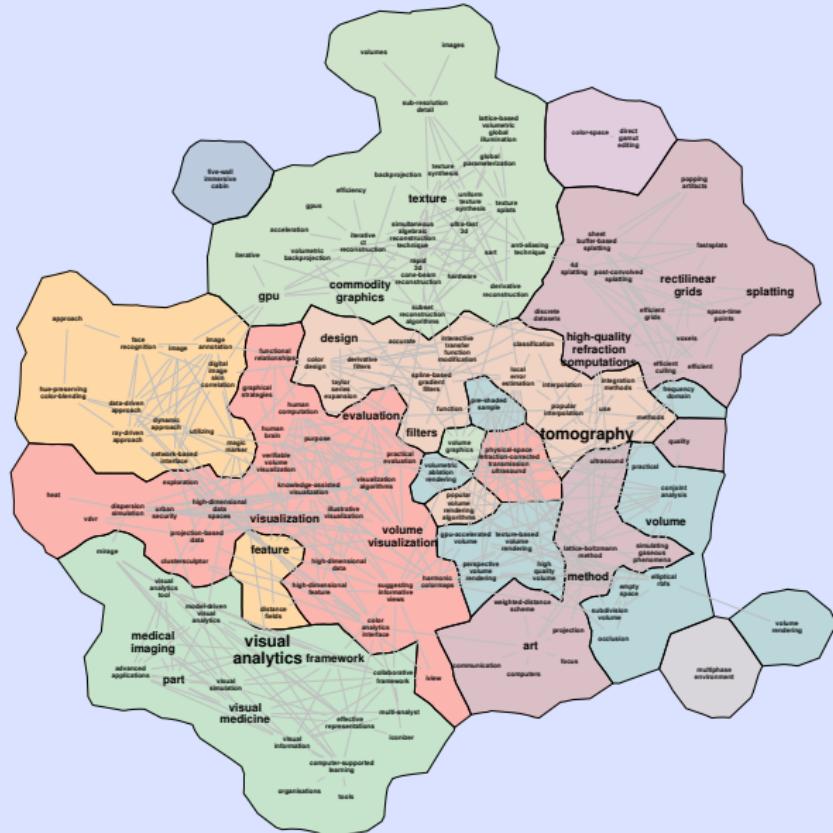


Maps of Computer Science

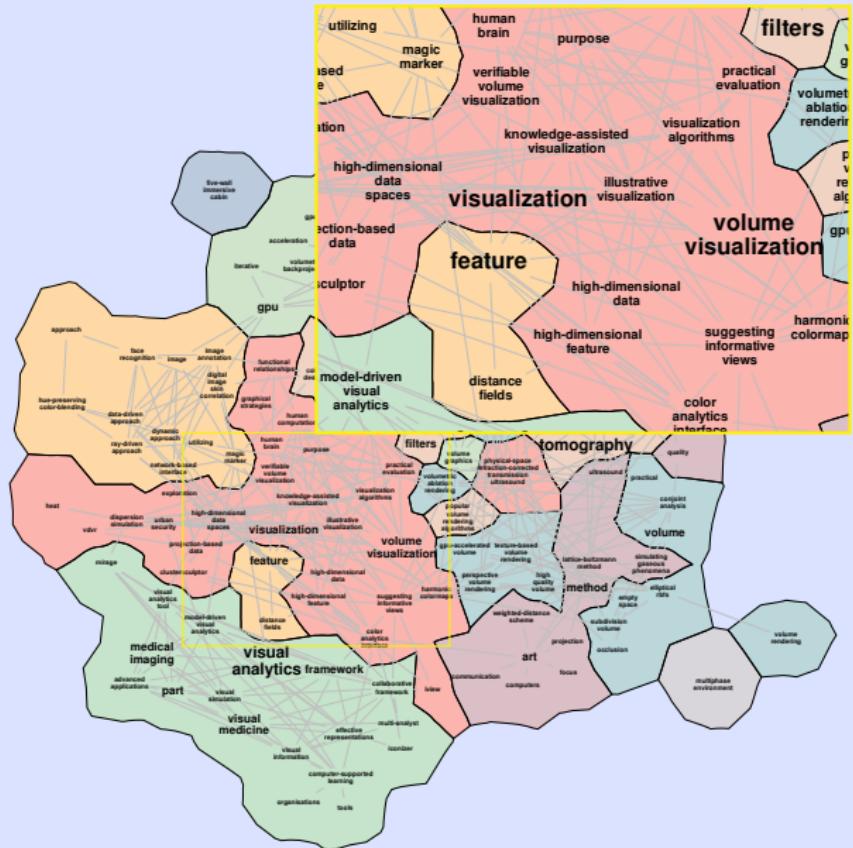
Daniel Fried and Stephen G. Kobourov

Department of Computer Science,
University of Arizona,
<http://mocs.cs.arizona.edu>

Sample Map: Klaus Mueller

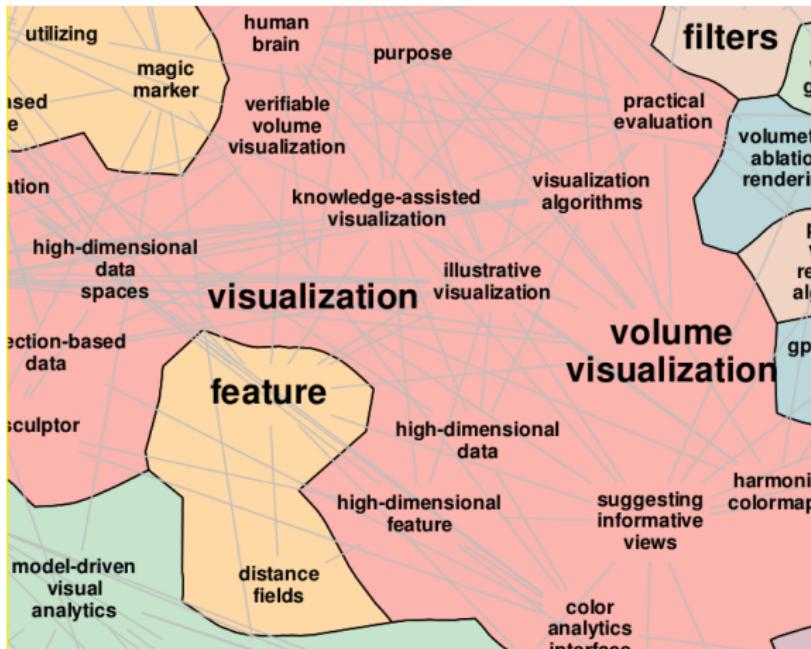


Sample Map: Klaus Mueller



Creating Maps from Paper Titles

- Graph vertices (“cities”): terms representing research topics
- Graph edges (“roads”): term similarity, co-occurrence
- Vertex clusters (“countries”): generally reflect research areas



Visualizations of CS Papers

Dataset: The DBLP bibliography server (DataBase systems and Logic Programming)

Visualizations of CS Papers

Dataset: The DBLP bibliography server (DataBase systems and Logic Programming)

- covers most CS journals/conf. (about 6,000 different ones)
- over 2.1 million indexed publications
- includes titles and bibliographic information

Visualizations of CS Papers

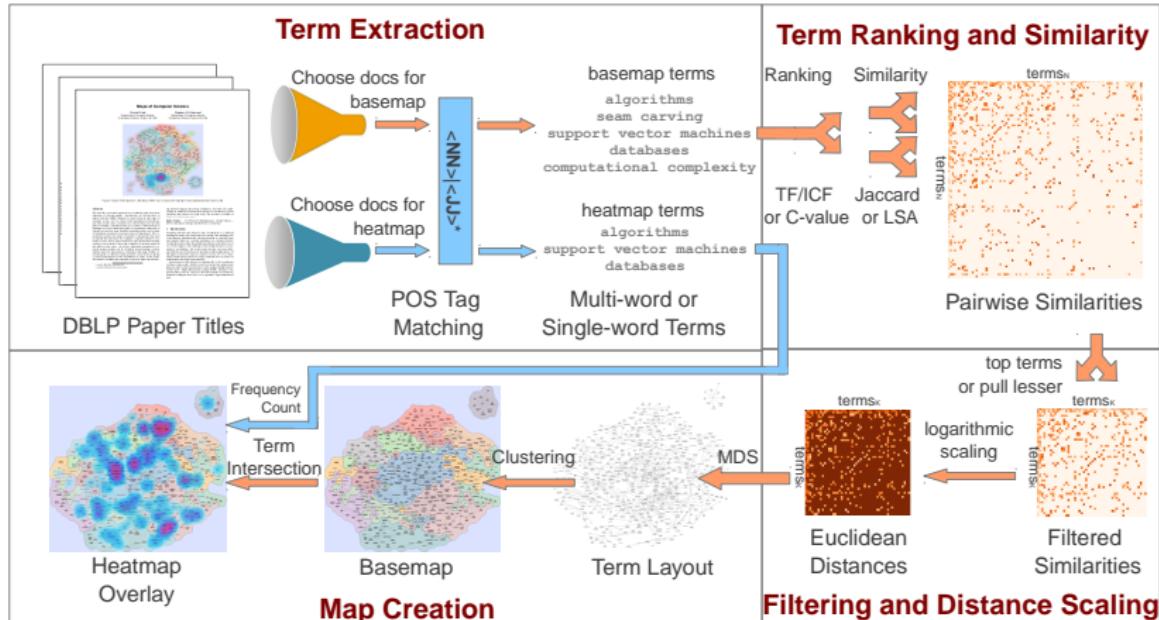
Dataset: The DBLP bibliography server (DataBase systems and Logic Programming)

- covers most CS journals/conf. (about 6,000 different ones)
- over 2.1 million indexed publications
- includes titles and bibliographic information

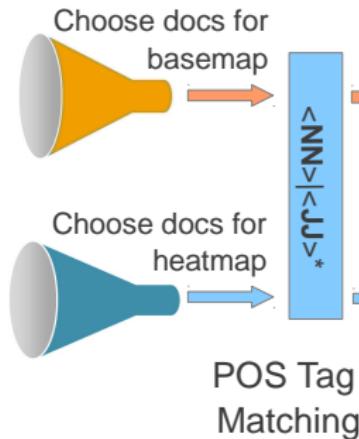
Main problems:

- large dataset (448,374 different words; 2,089,736 phrases)
- short text (only titles, with 10 words on average)

The MoCS System



Term Extraction



basemap terms
algorithms
seam carving
support vector machines
databases
computational complexity

heatmap terms
algorithms
support vector machines
databases

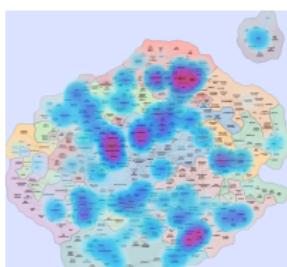
Multi-word or Single-word Terms

Term R

Ranking



TF/ICF or C-value



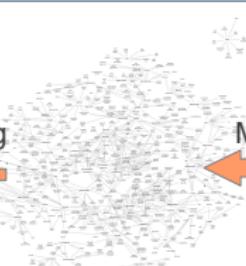
Frequency Count
Term Intersection

Heatmap Overlay



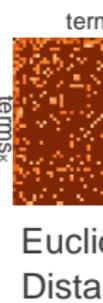
Clustering

Basemap



MDS

Term Layout



termSK

Euclid
Distanc

Euclid
Distanc

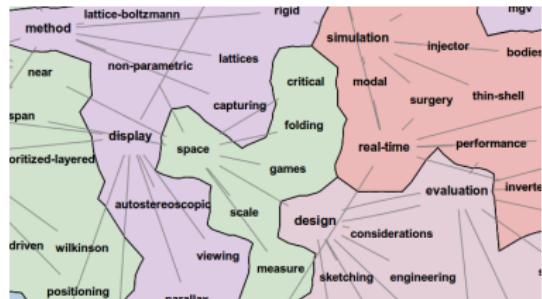
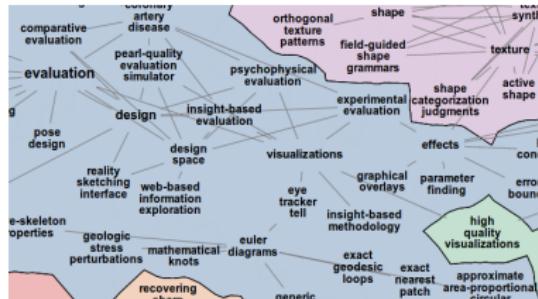
Term Extraction

Multi-word phrases (“collocations”)

- Specificity: “wireless sensor networks” as a type of “network”
- Context: “travelling salesman problem”, not “salesman”
- POS tagging and filtering - Justeson and Katz, 1995

POS	NNS	IN	JJ	NN	NN
word	applications	of	wireless	sensor	networks

- Extract noun and adjective subsequences
- Multi-word, or break up into single words

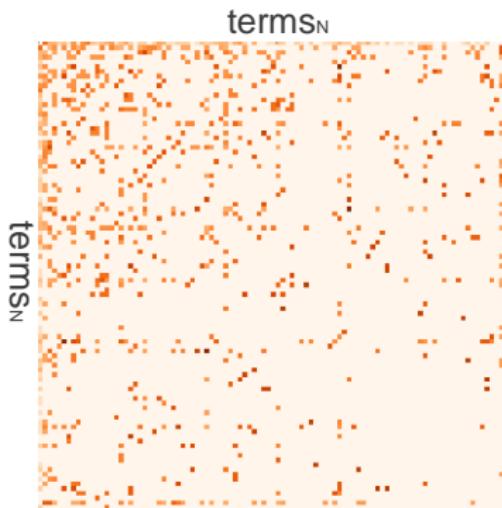
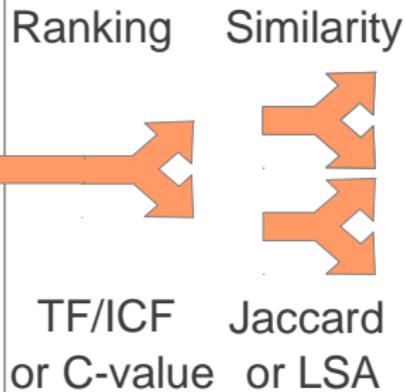


Term Ranking and Similarity

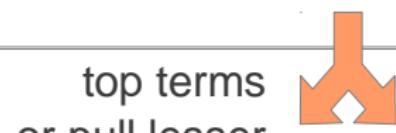
top terms
algorithms
carving
vector machines
bases
al complexity

top terms
algorithms
vector machines
bases

word or
d Terms



Pairwise Similarities



Term Ranking

- Simplest possible ranking: by frequency

Term Ranking

- Simplest possible ranking: by frequency
- TF-IDF: *term frequency – inverse document frequency*
 - Extra difficult due to short titles (IDF is meaningless)

Term Ranking

- Simplest possible ranking: by frequency
- TF-IDF: *term frequency – inverse document frequency*
 - Extra difficult due to short titles (IDF is meaningless)
- TF-ICF: *term frequency – inverse corpus frequency*
 - Expensive

Term Ranking

- Simplest possible ranking: by frequency
- TF-IDF: *term frequency – inverse document frequency*
 - Extra difficult due to short titles (IDF is meaningless)
- TF-ICF: *term frequency – inverse corpus frequency*
 - Expensive
- Best results: C-Value - Frantzi et al, 2000
 - ① Term frequency: +
 - ② Length of the term: +
 - ③ Occurrences nested in other terms: -
 - ④ Number of these other terms: +

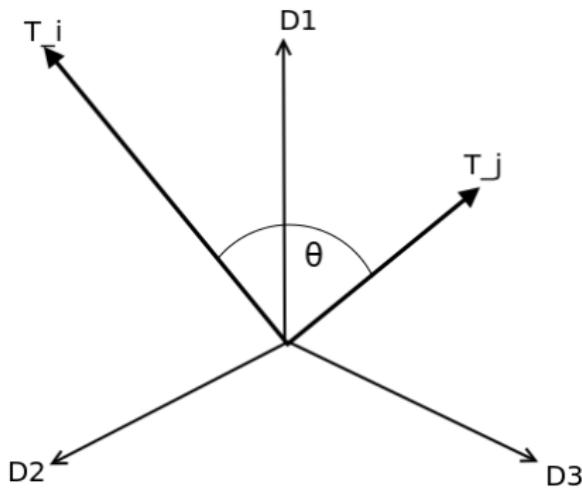
Term Similarity: LSA and Cosine

- Term-document matrix A
- Latent Semantic Analysis (LSA) - decompose A
- Cosine distance - compare angles

$$Dist(T_i, T_j) = \frac{T_i \cdot T_j}{\|T_i\| \|T_j\|}$$

- Small angle (large cosine): similar terms
- Large angle (small cosine): dissimilar terms

	D_1	D_2	\dots	D_n
T_1	$tf_{1,1}$	$tf_{1,2}$	\dots	$tf_{1,t}$
T_2	$tf_{2,1}$	$tf_{2,2}$	\dots	$tf_{2,t}$
\vdots	\vdots	\vdots	\vdots	\vdots
T_t	$tf_{n,1}$	$tf_{n,2}$	\dots	$tf_{n,t}$



Term Similarity: Jaccard Coefficient

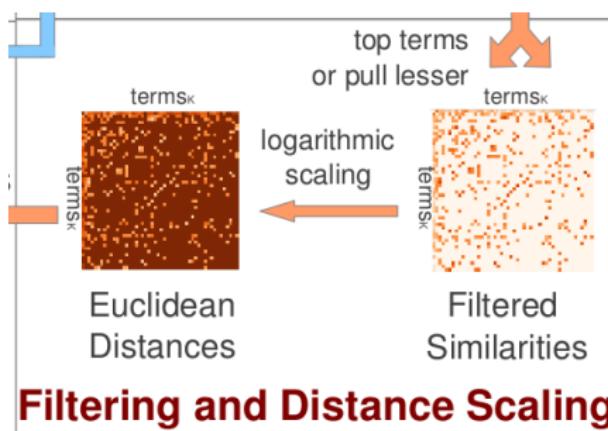
- Idea: terms are similar if they are used together in titles
- Treat as set similarity: S_i is the set of documents with term i
- Jaccard coefficient:

$$Jacc(S_i, S_j) = \frac{|S_i \cap S_j|}{|S_i \cup S_j|}$$

- Extra difficult due to multi-word terms
- Partial match Jaccard: count co-occurrence if terms overlap

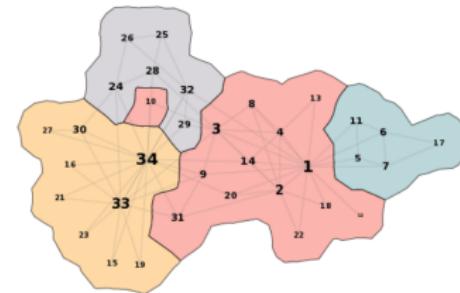
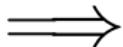
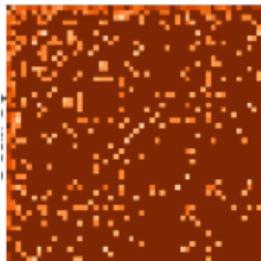
Filtering and Distance Scaling

- LSA and Jaccard return similarity values between 0 and 1
- Convert to distances for graph drawing
- Inverse logarithmic spacing
- Top Terms: only plot N highest-ranked terms
- Pull Lesser Terms: plot K most similar terms for each term t



Making a Map with GMap

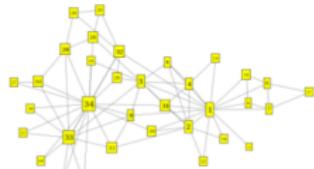
- Input: vertex-weighted, edge-weighted graph $G = (V, E)$
- Output: map, with clusters as countries and vertices as cities
- GMap: a framework for embedding + clustering + mapping
 - different algorithms: embedding, clustering, mapping
 - different overlays: journal profile, author profile, paper profile



GMap Overview

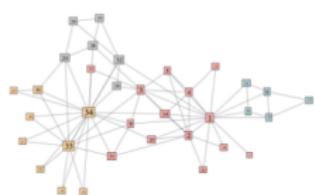
- Embedding

- *scalable force-directed method*
- iterative improvement
- minimal energy \Rightarrow good layout



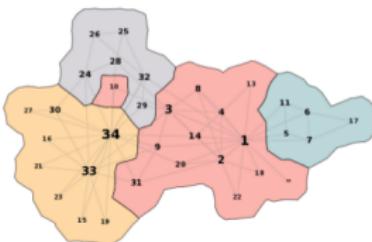
- Clustering

- *modularity clustering*
- group vertices such that:
- high edge density *within* groups
- low edge density *between* groups

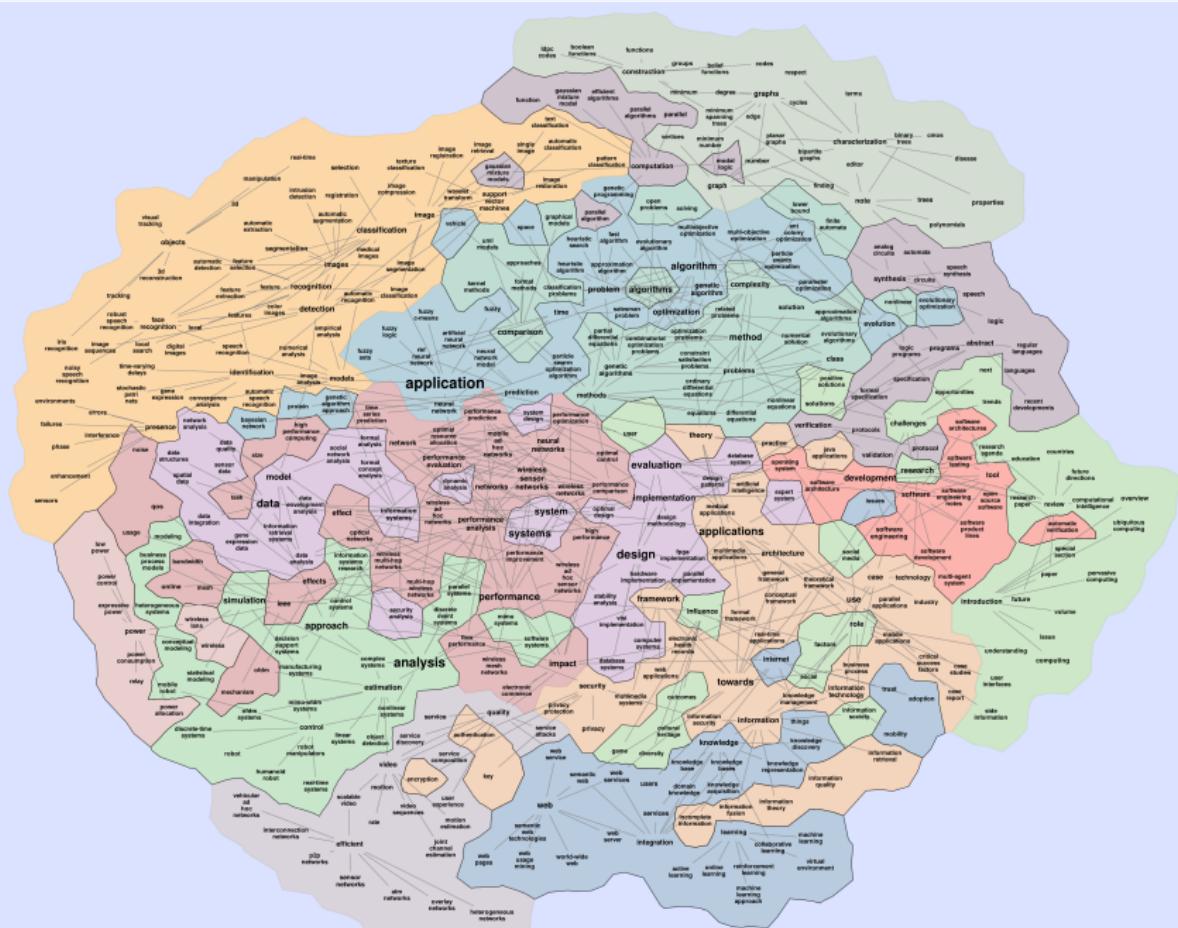


- Mapping

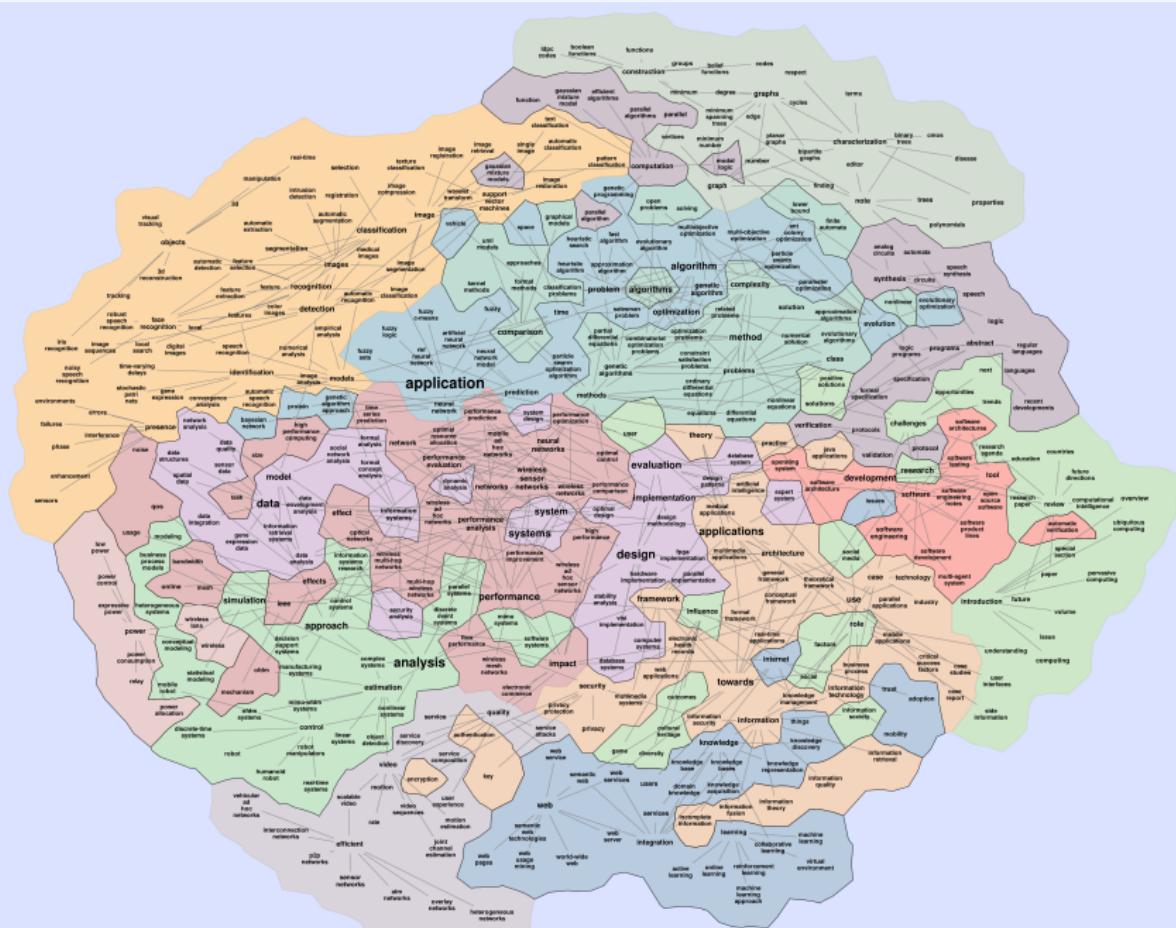
- *modified Voronoi Diagram*
- add bounding box
- add dummy points to get nice borders



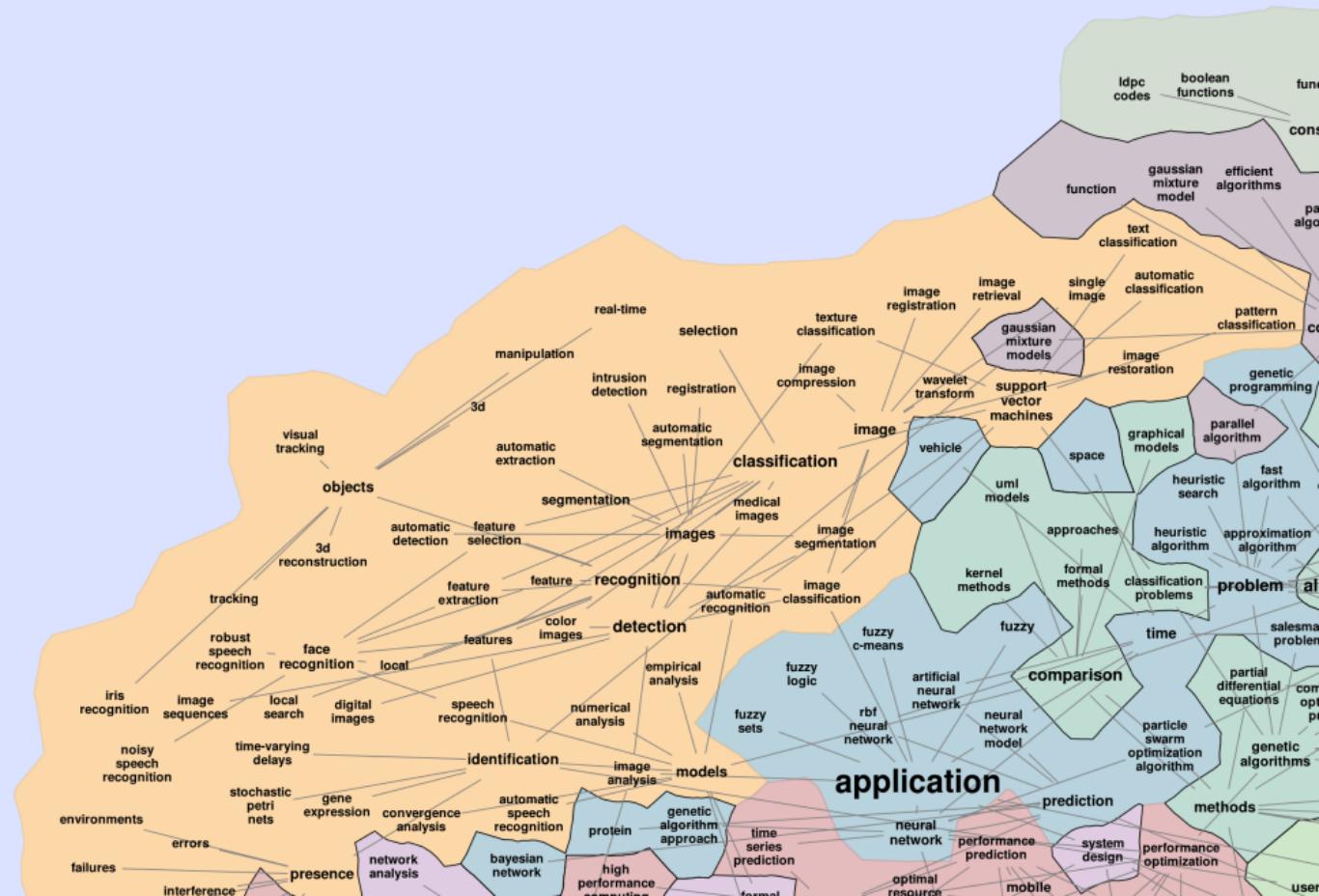
Base Map of CS



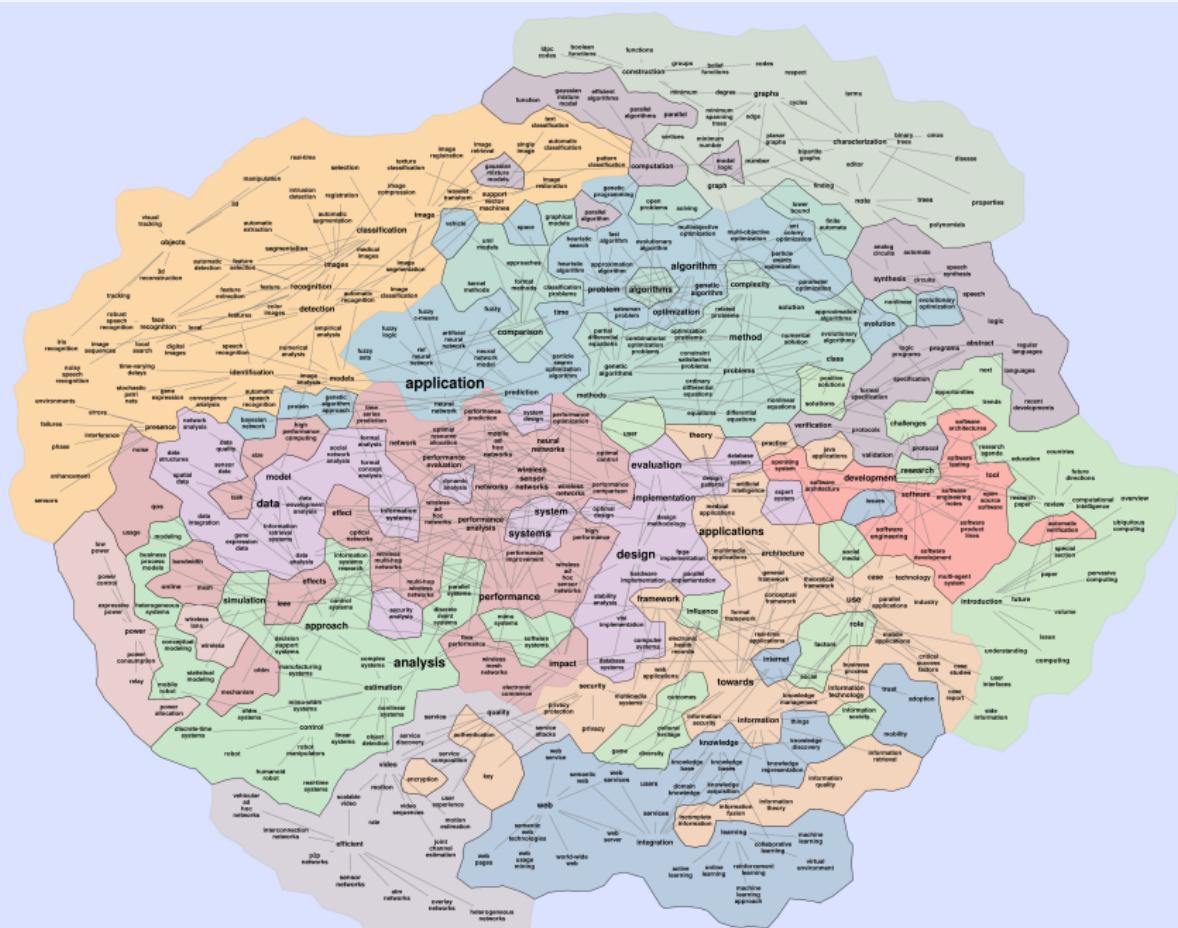
Base Map of CS



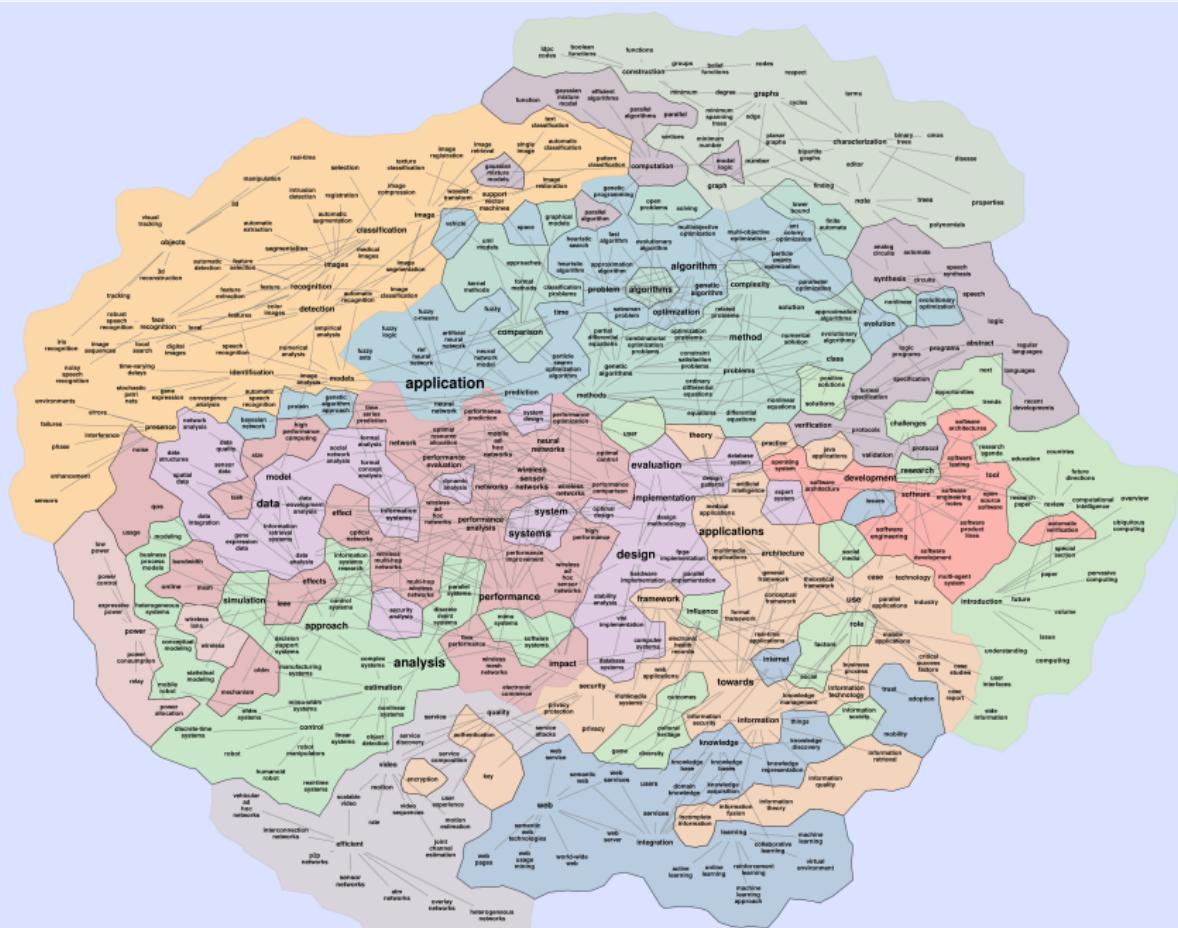
Base Map of CS



Base Map of CS



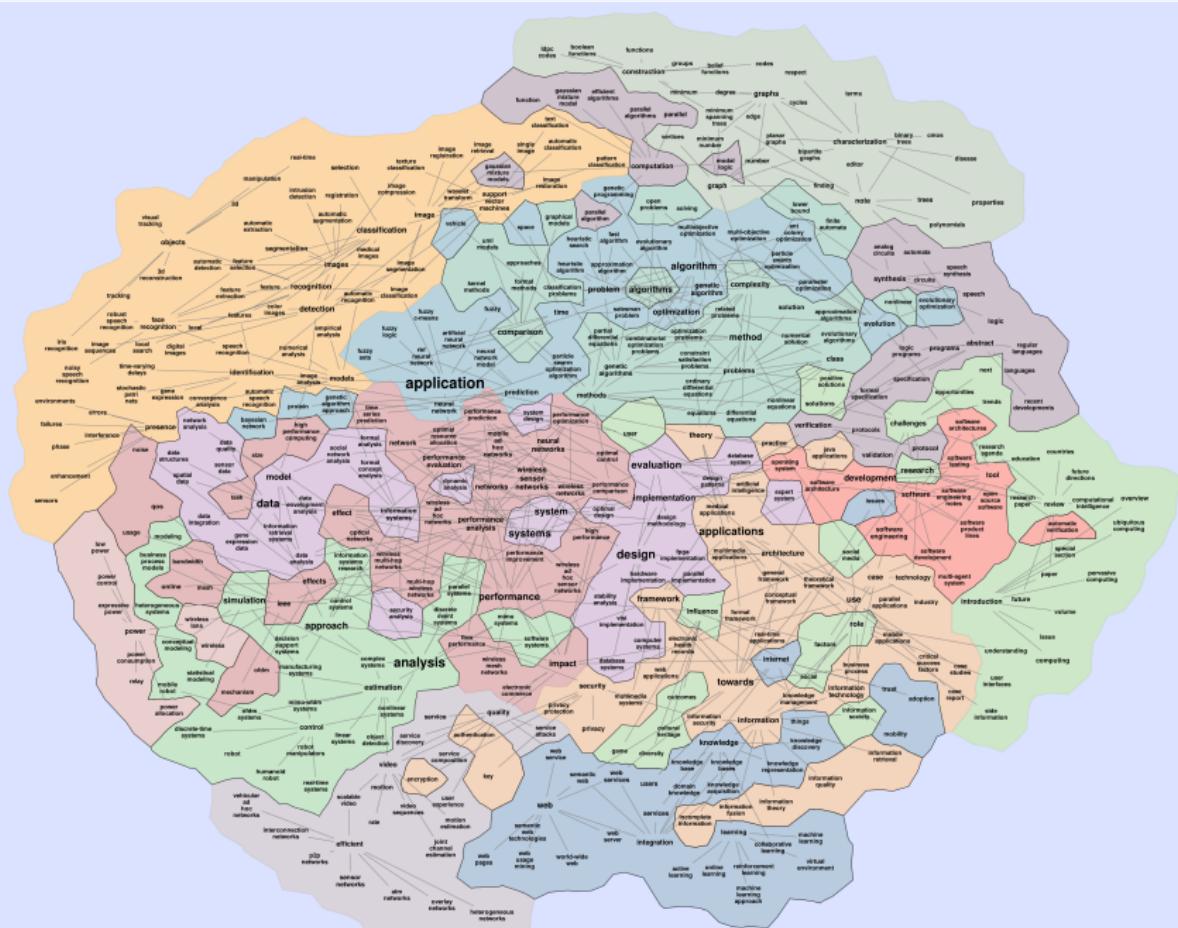
Base Map of CS



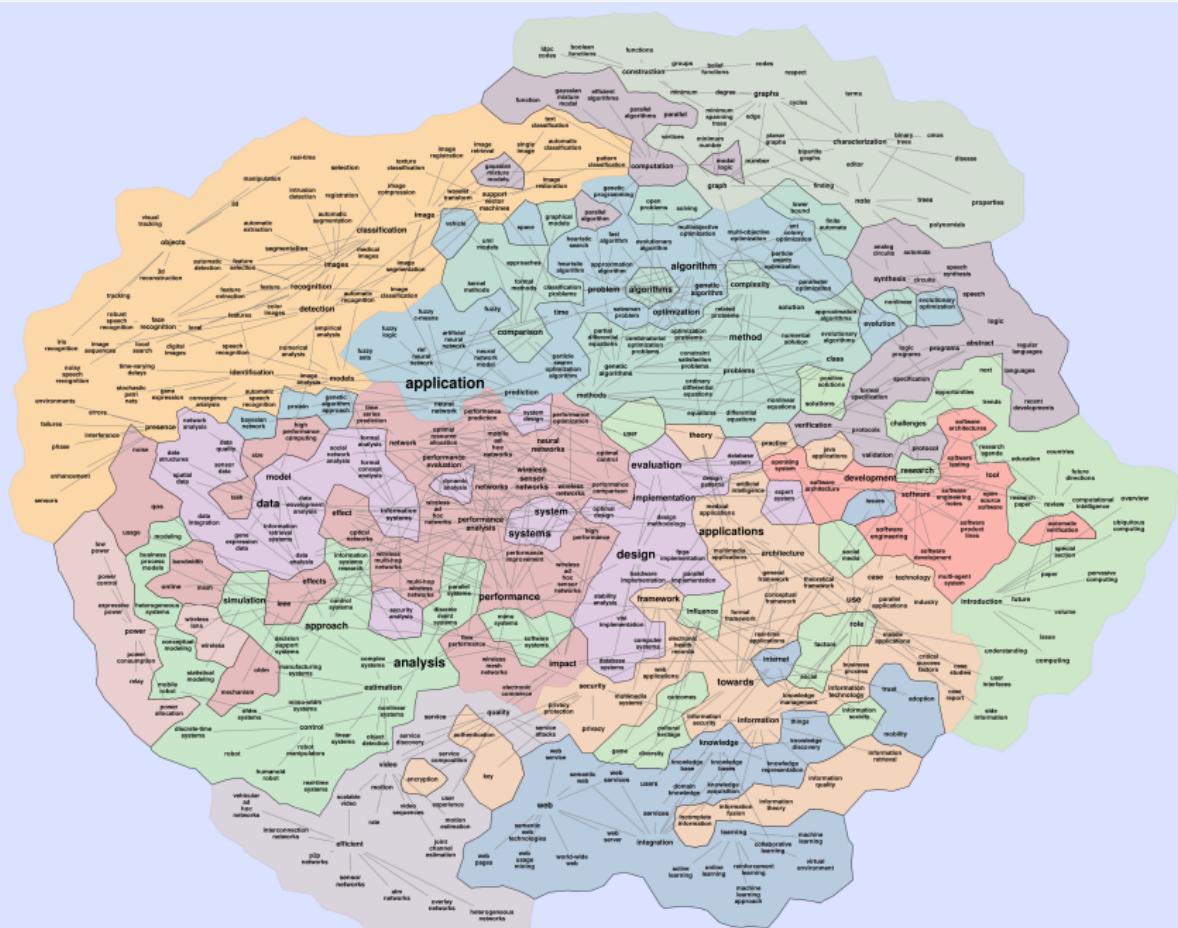
Base Map of CS



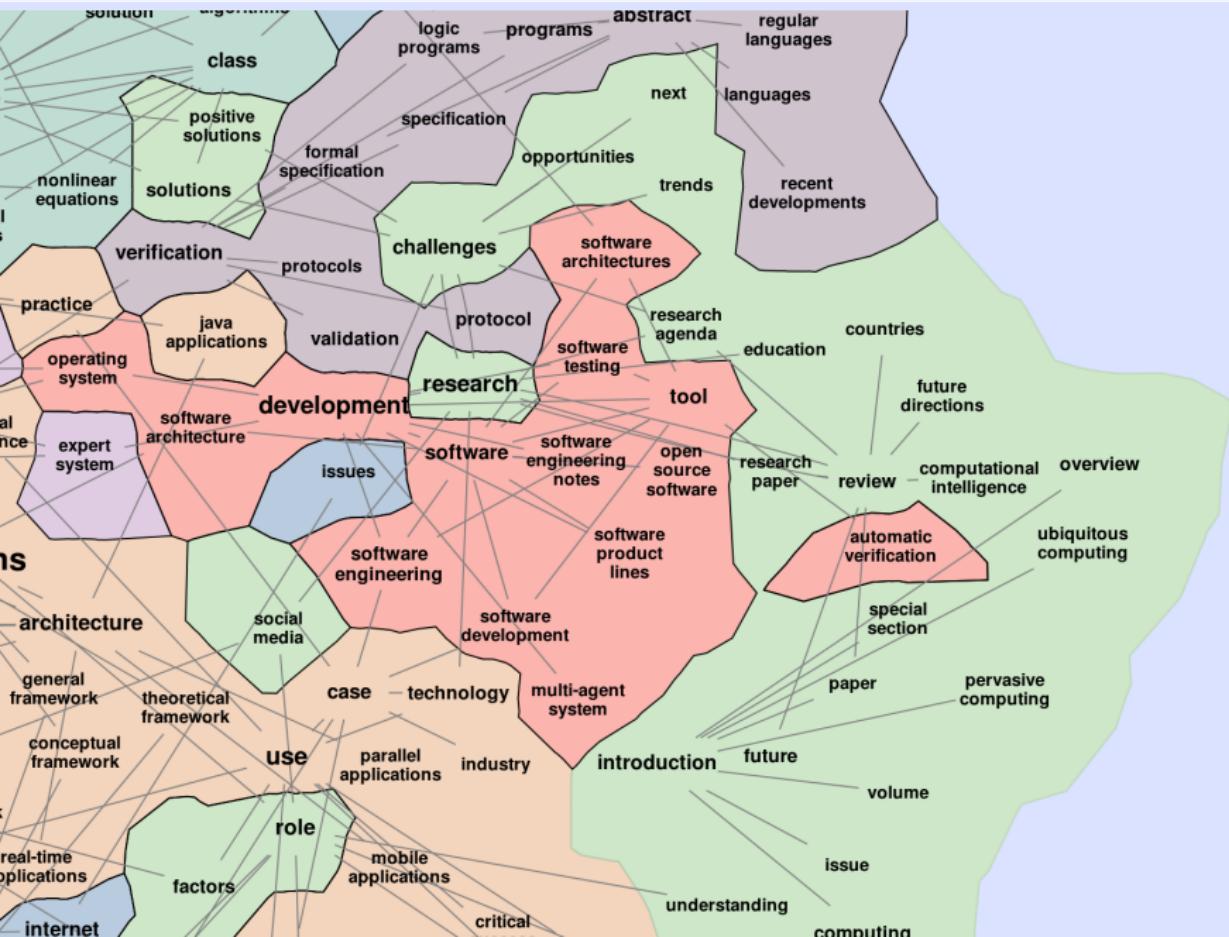
Base Map of CS



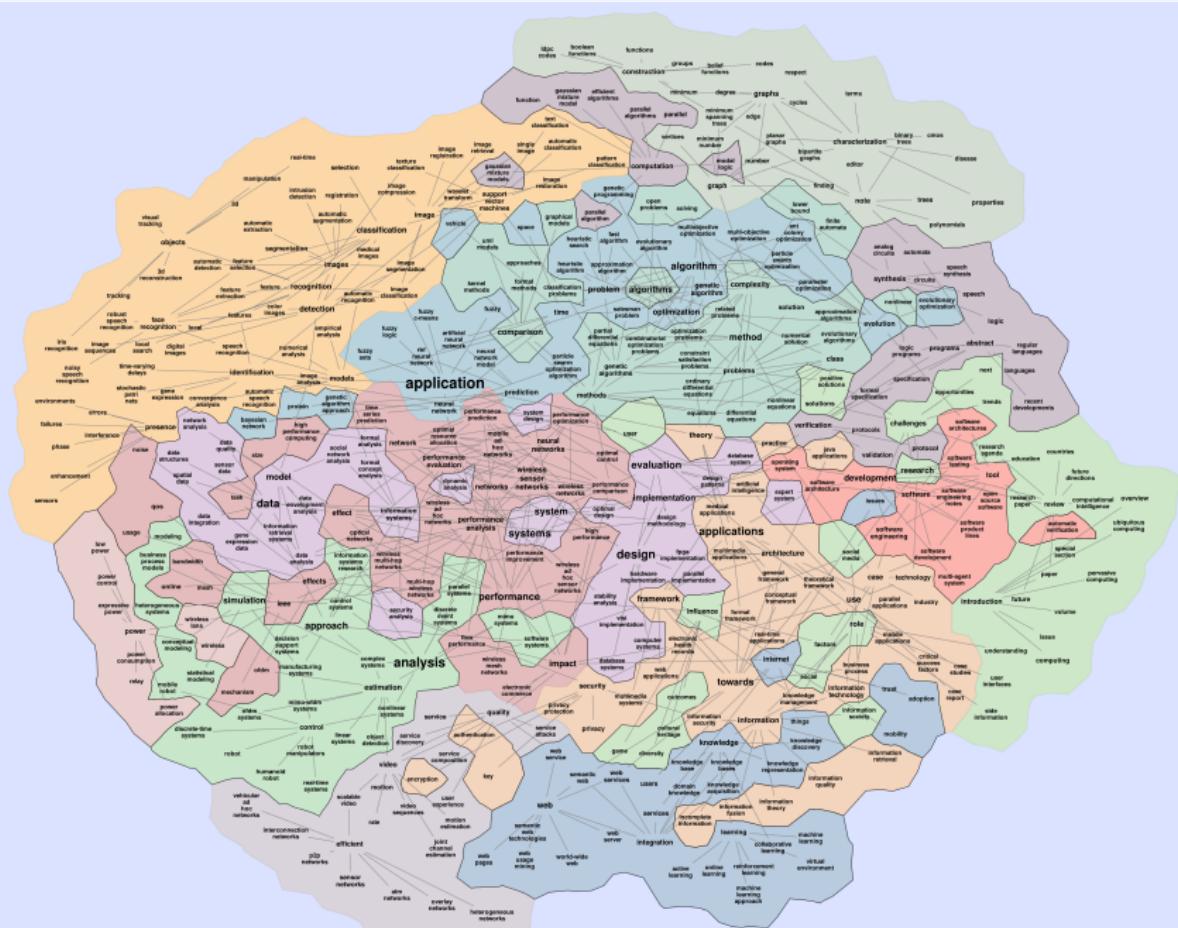
Base Map of CS



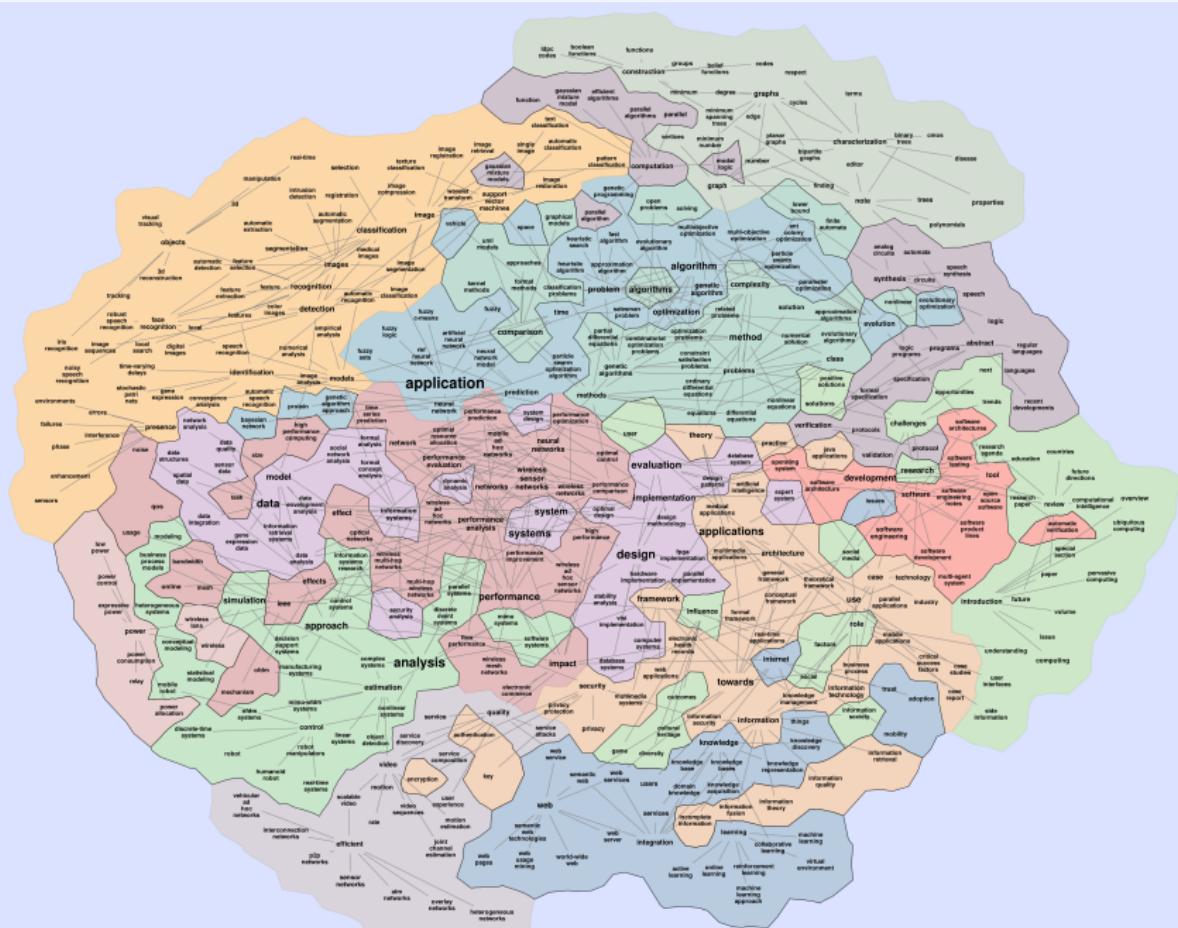
Base Map of CS



Base Map of CS



Base Map of CS



Base Map of CS



Heatmap Profiles

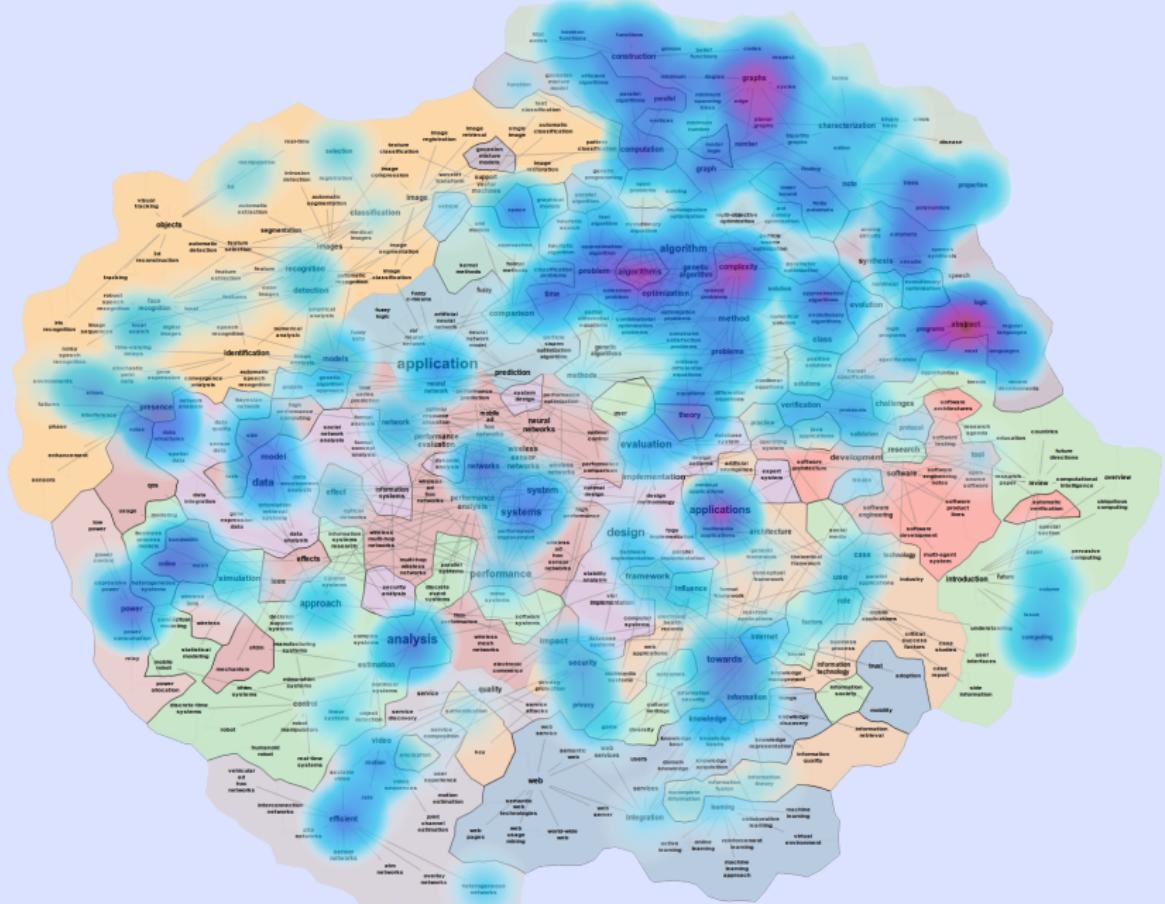
- Visualize an author, conference, journal, or timeframe
- Want to see intensity of term usage and spread over the map
- Extract terms in same way as basemap
- Count frequencies of term intersection

$$\hat{I}(t) = \frac{\log(tf(t) + \beta)}{\max_{\hat{t}} \log(tf(\hat{t}) + \beta)}$$

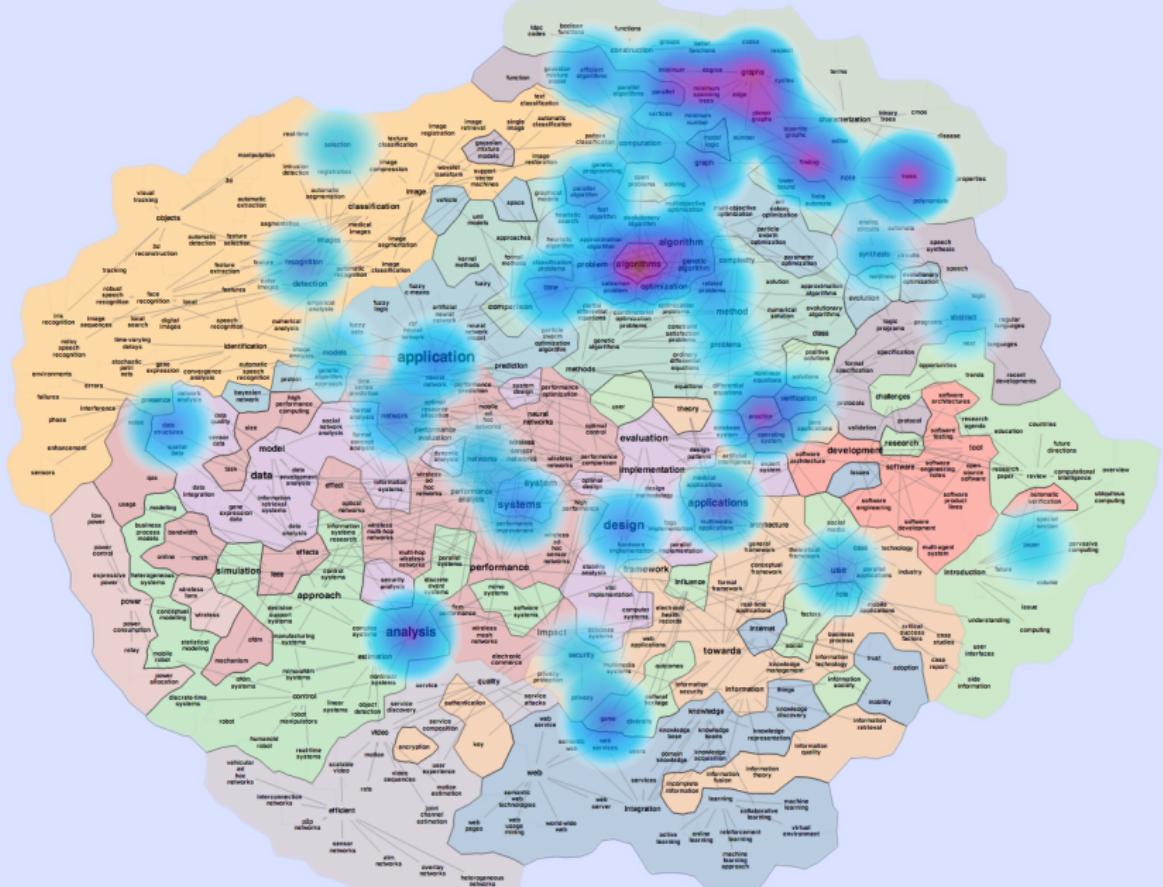
$tf(t)$: frequency of term t in heatmap query

β : small constant

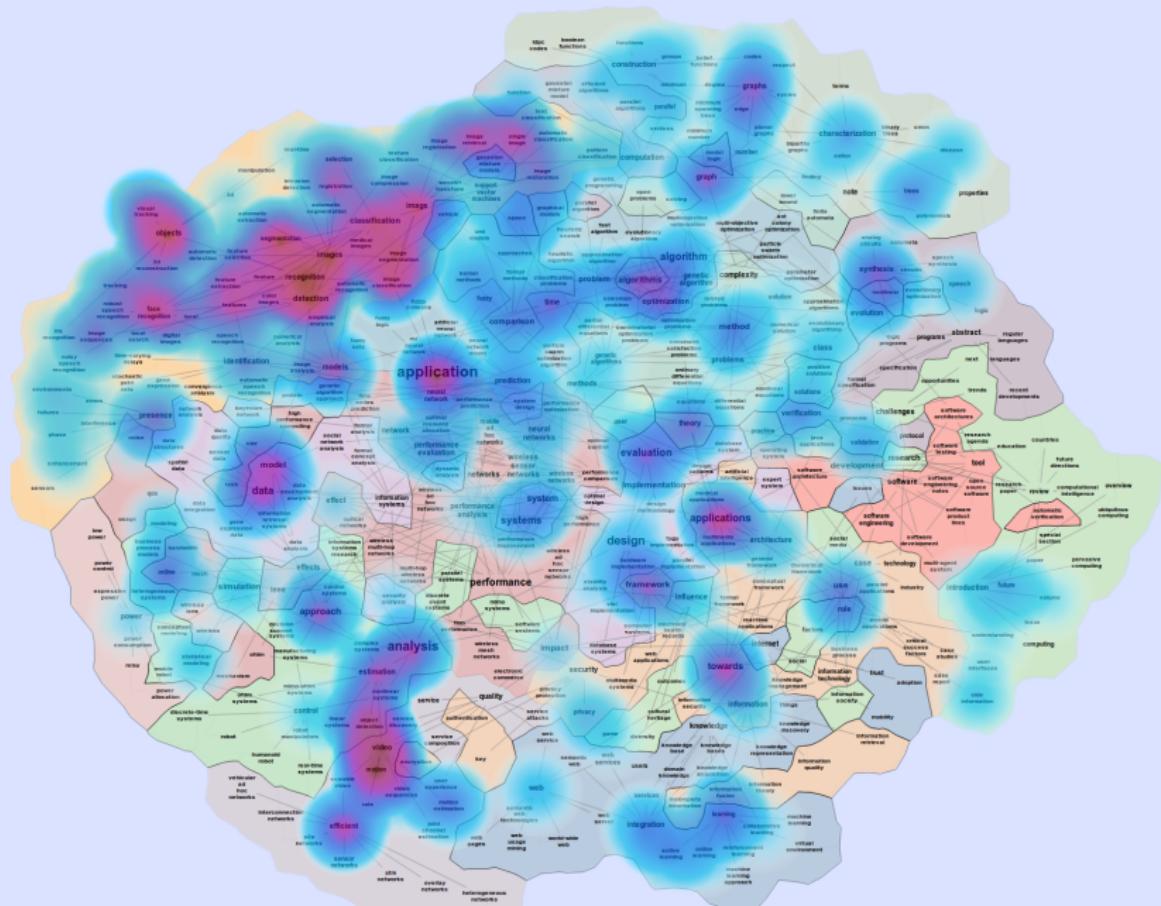
Symposium on Theory of Computing



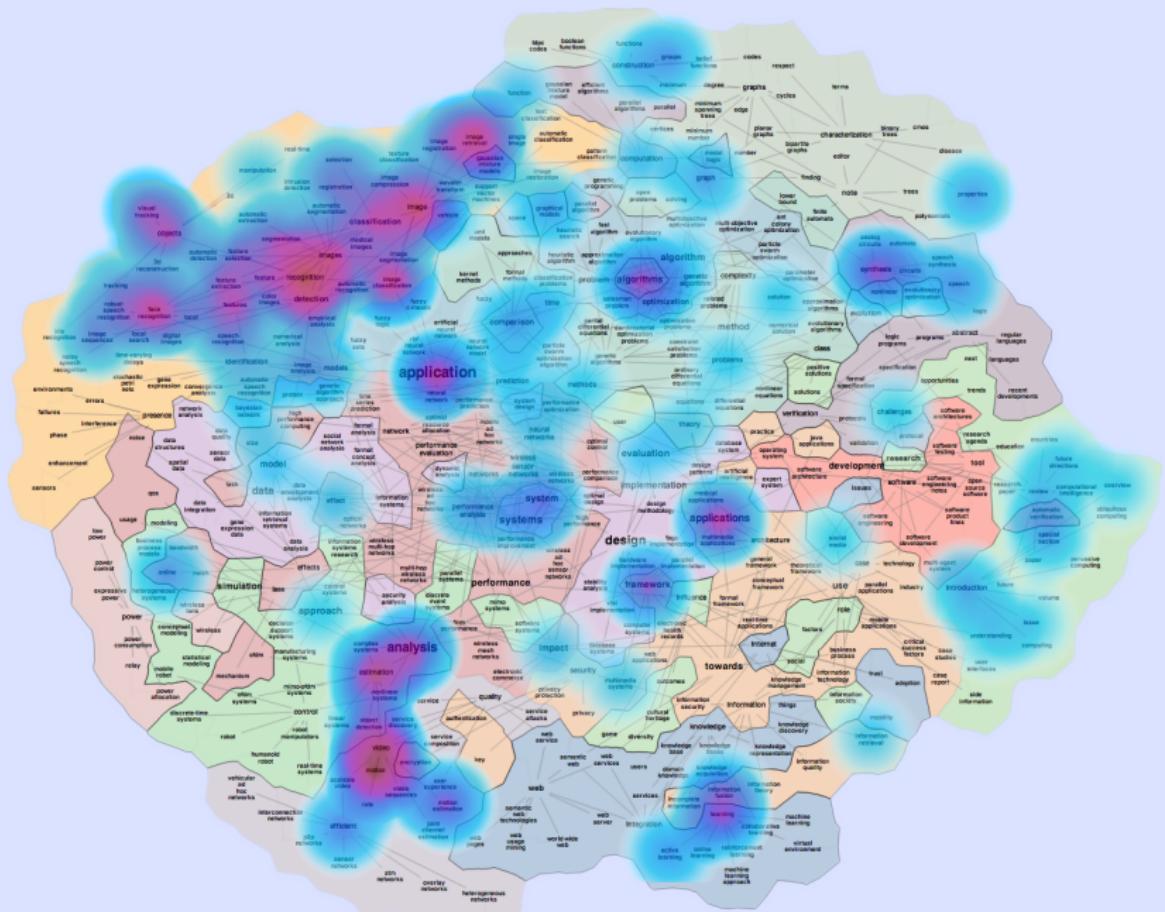
Robert E. Tarjan



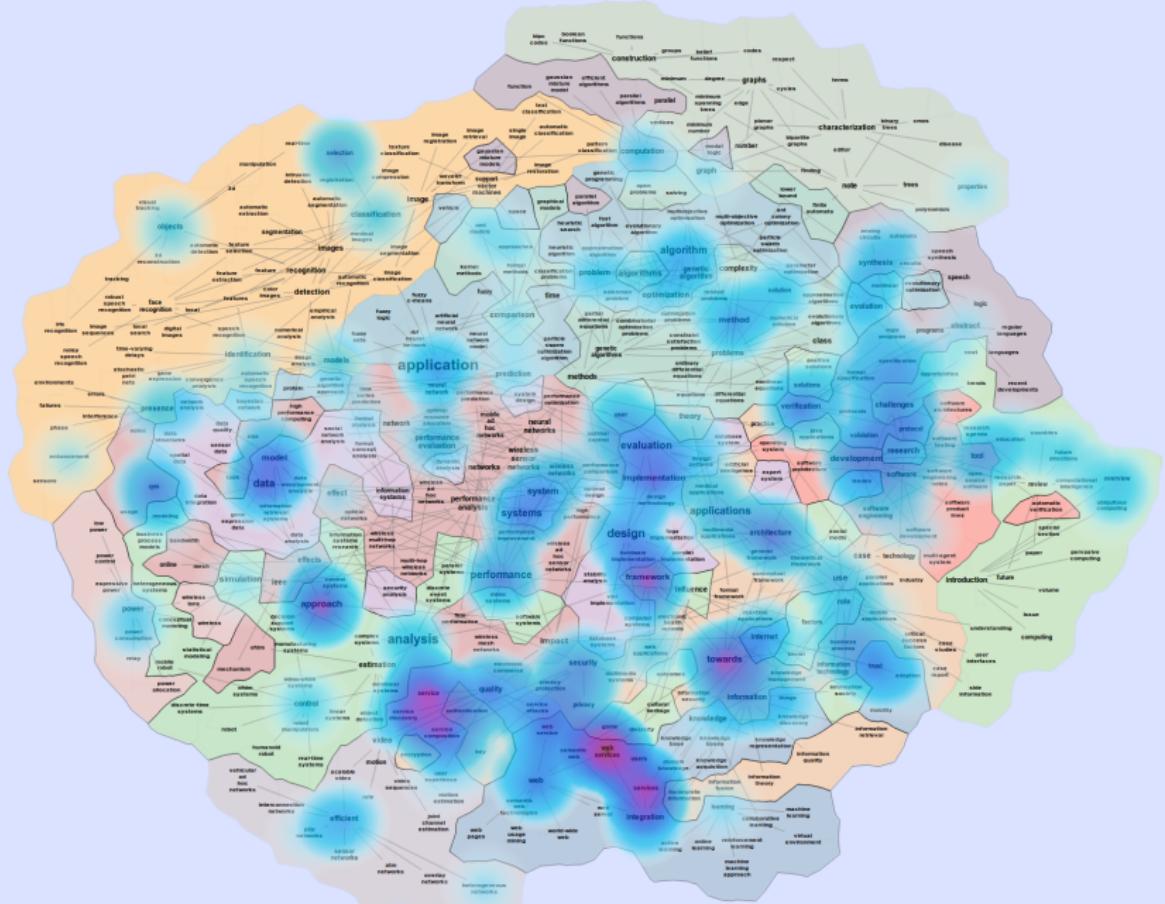
Computer Vision and Pattern Recognition



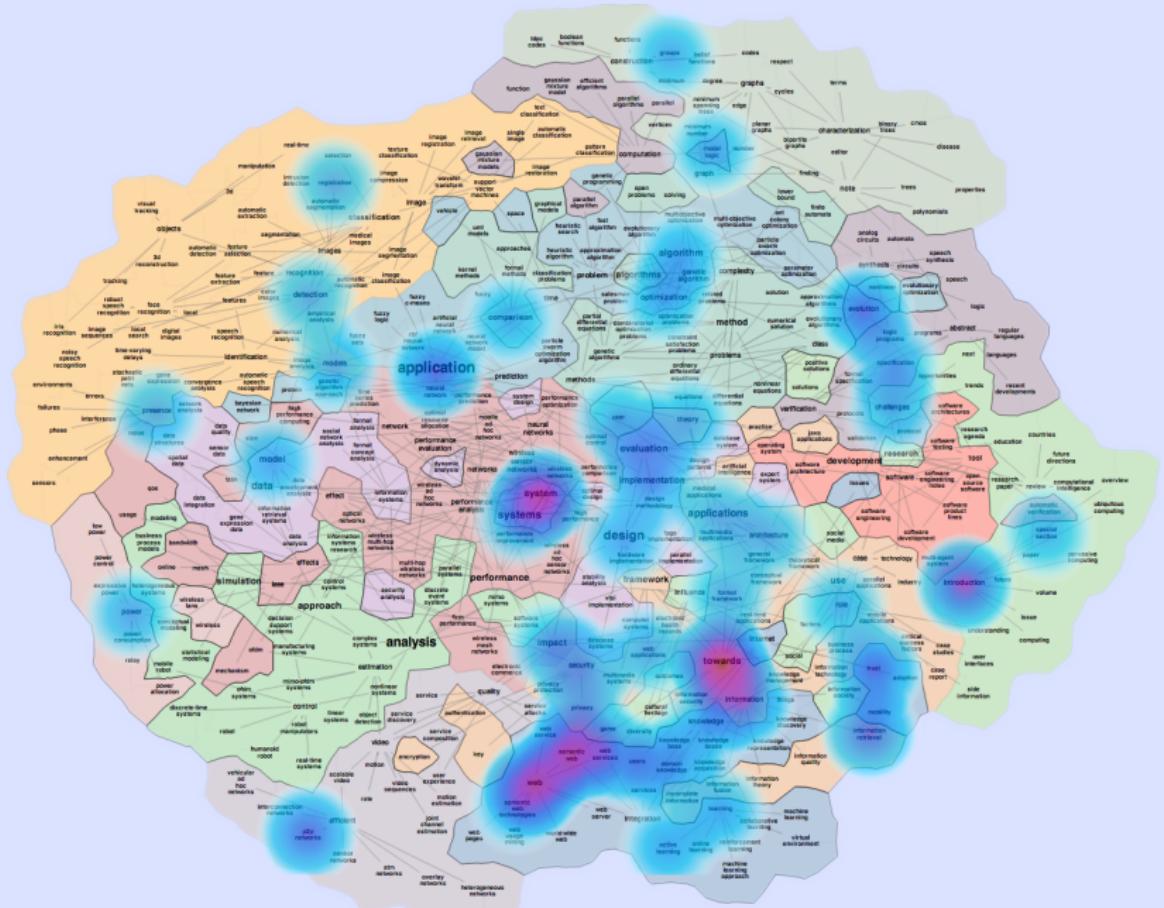
Thomas S. Huang



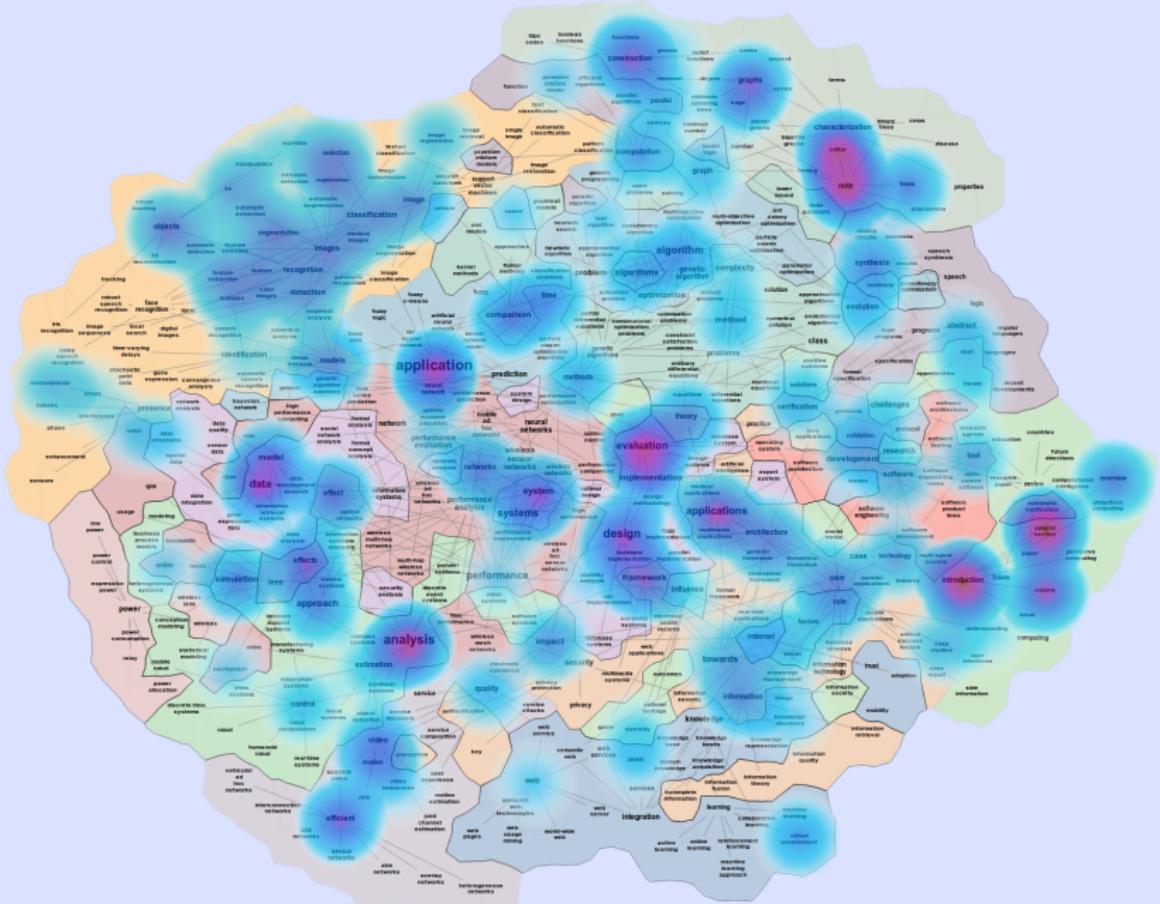
International Conference on Web Services



Wolfgang Nejdl



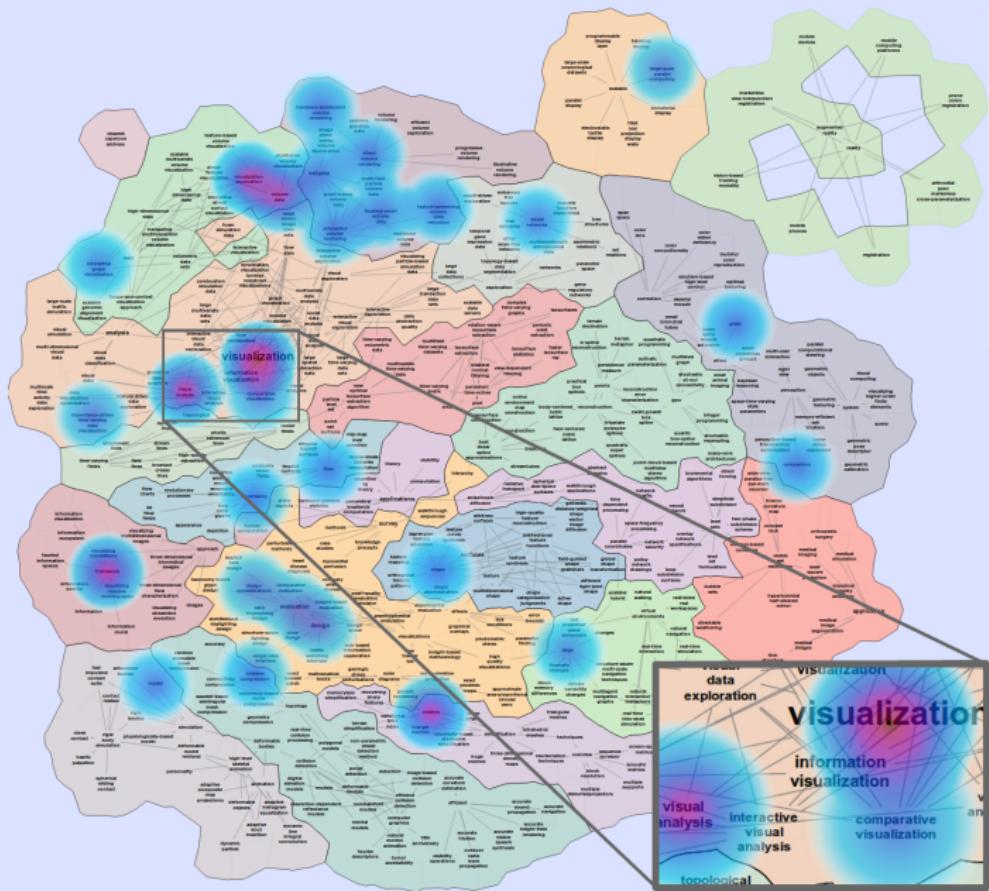
Trans. on Visualization and Computer Graphics (TVCG)



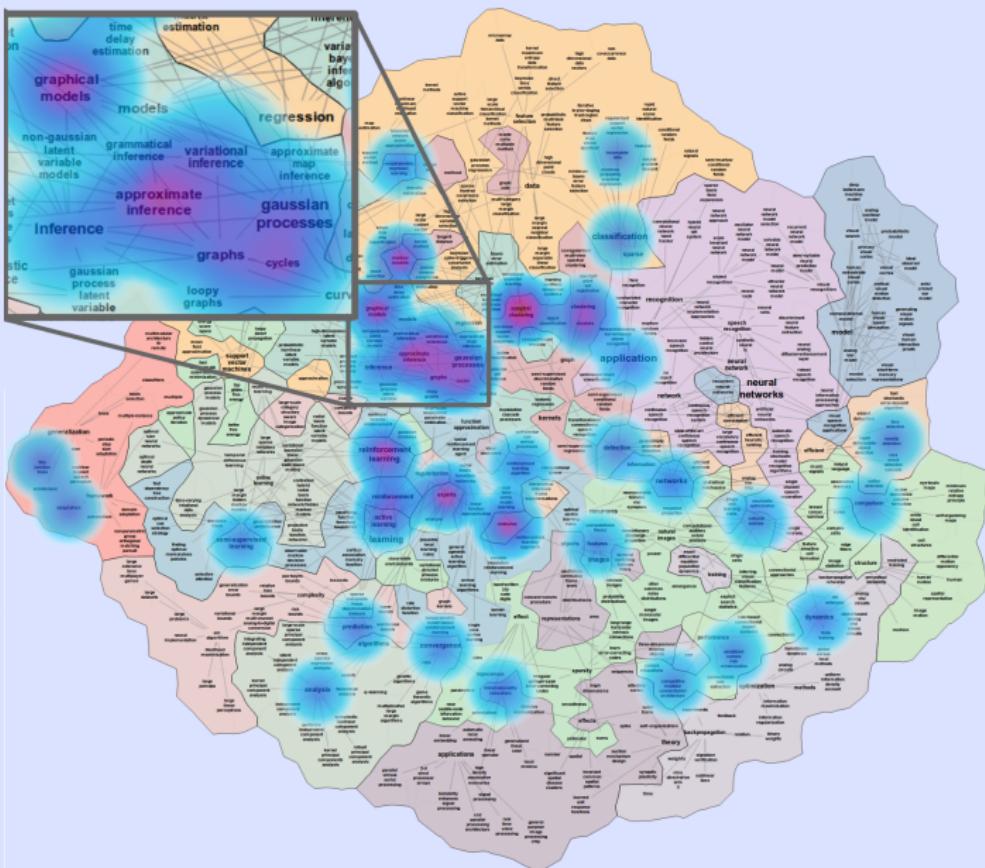
Using DBLP Metadata

- Separate queries for basemaps and heatmaps
- DBLP metadata allows query variation
 - by venue: 1,324 journals; 6,904 conferences
 - by author: 1,237,445 authors
 - by date: 1950 - present
- Visualize authors in the context of their venues
- Visualize change in a venue's research focus over time

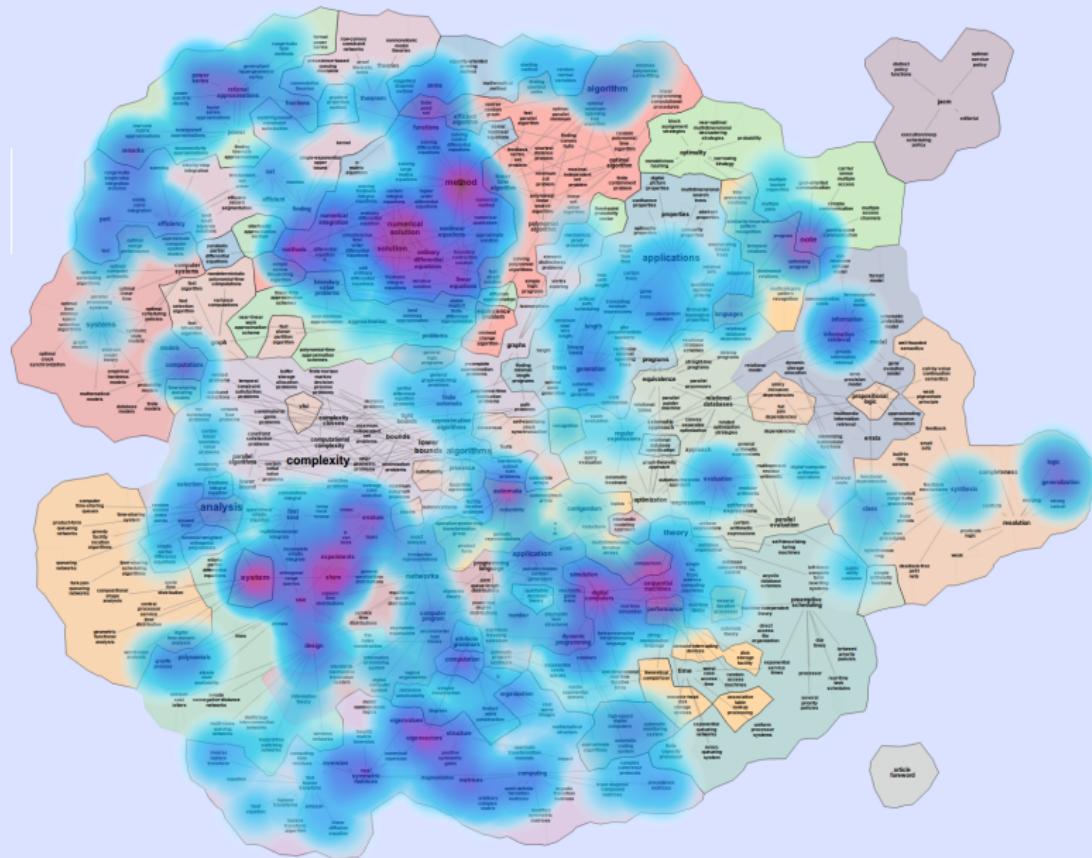
Author Heatmaps: Kwan-Liu Ma over TVCG



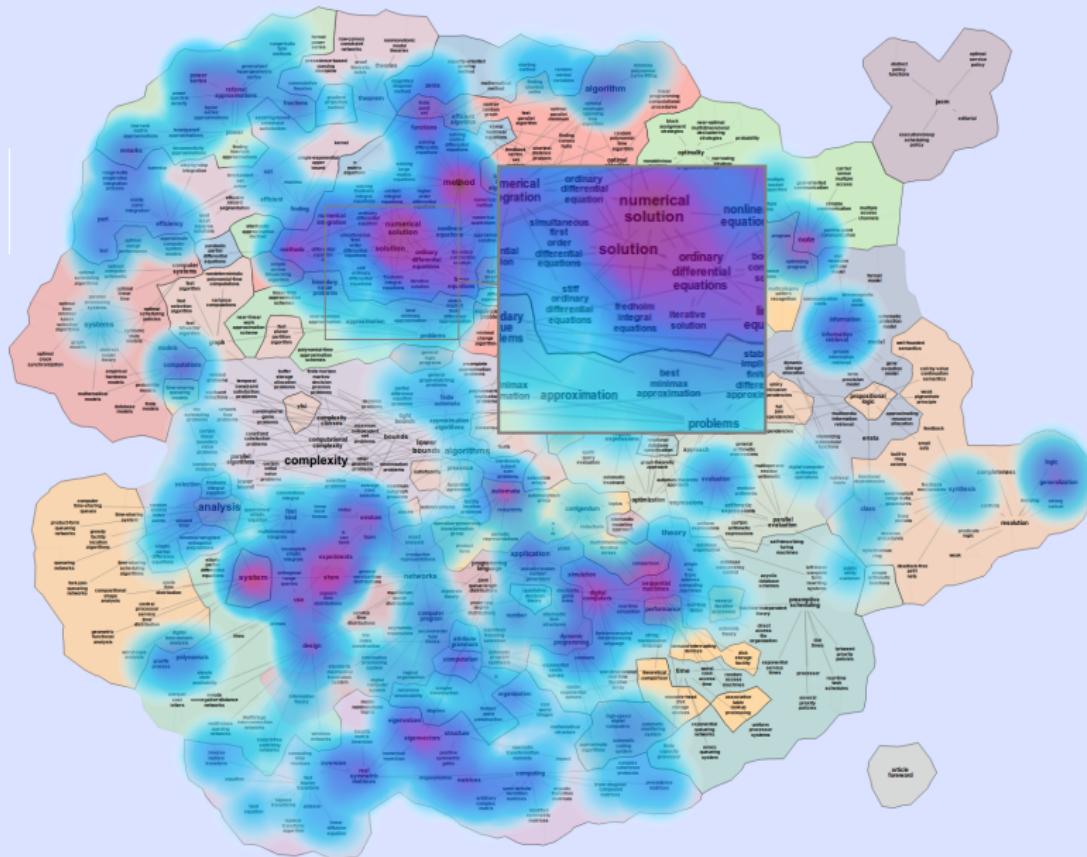
Author Heatmaps: Michael I. Jordan over NIPS



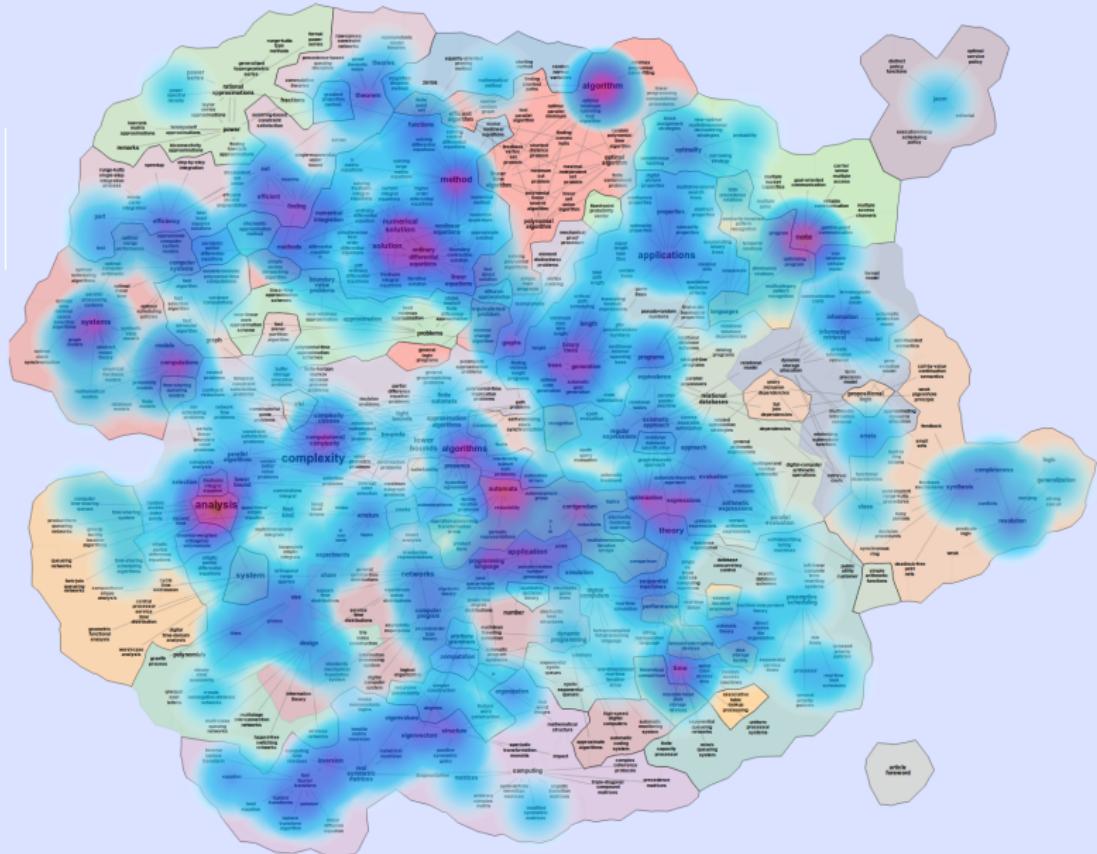
Temporal Heatmaps: JACM 1954-1963



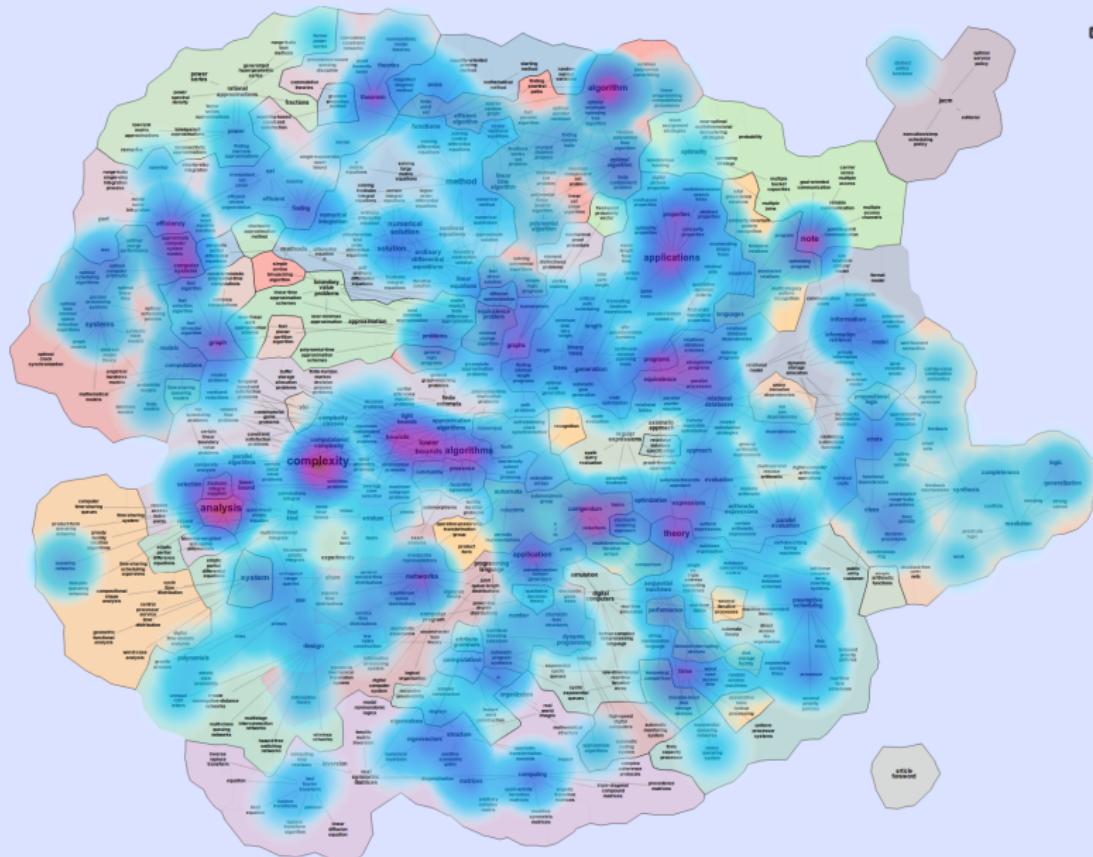
Temporal Heatmaps: JACM 1954-1963



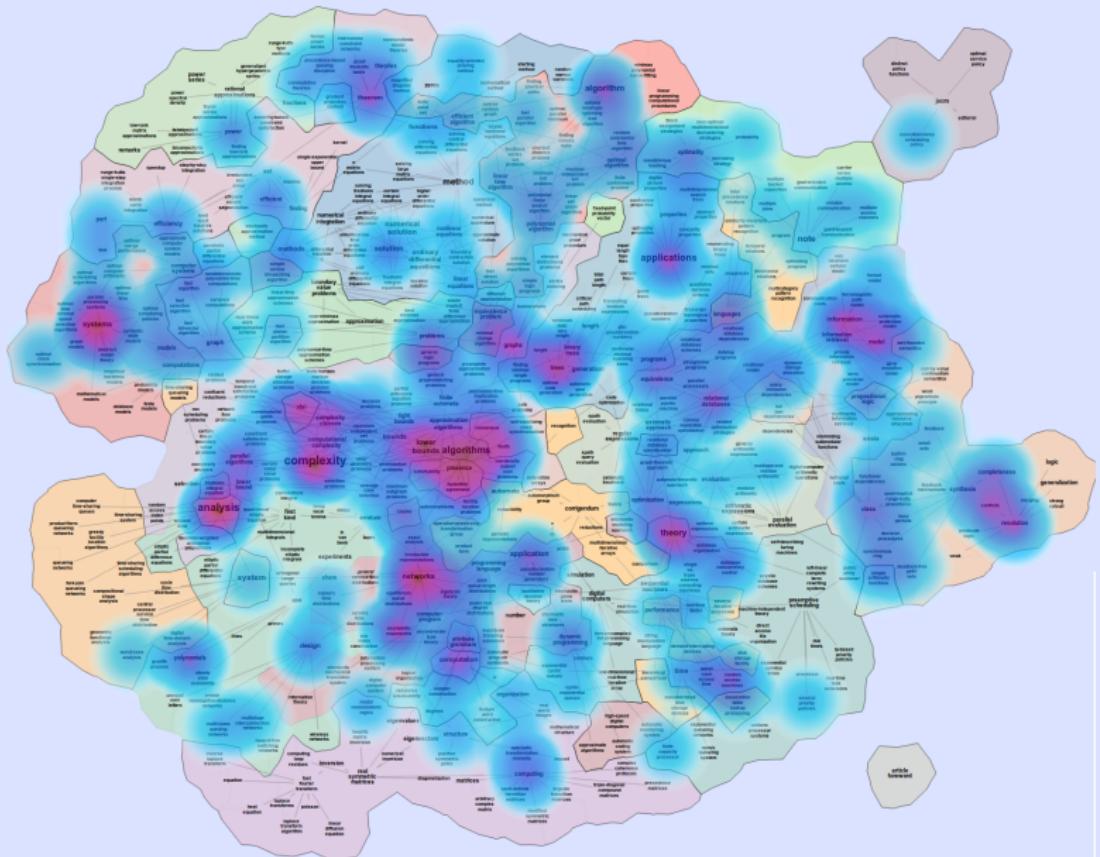
Temporal Heatmaps: JACM 1964-1973



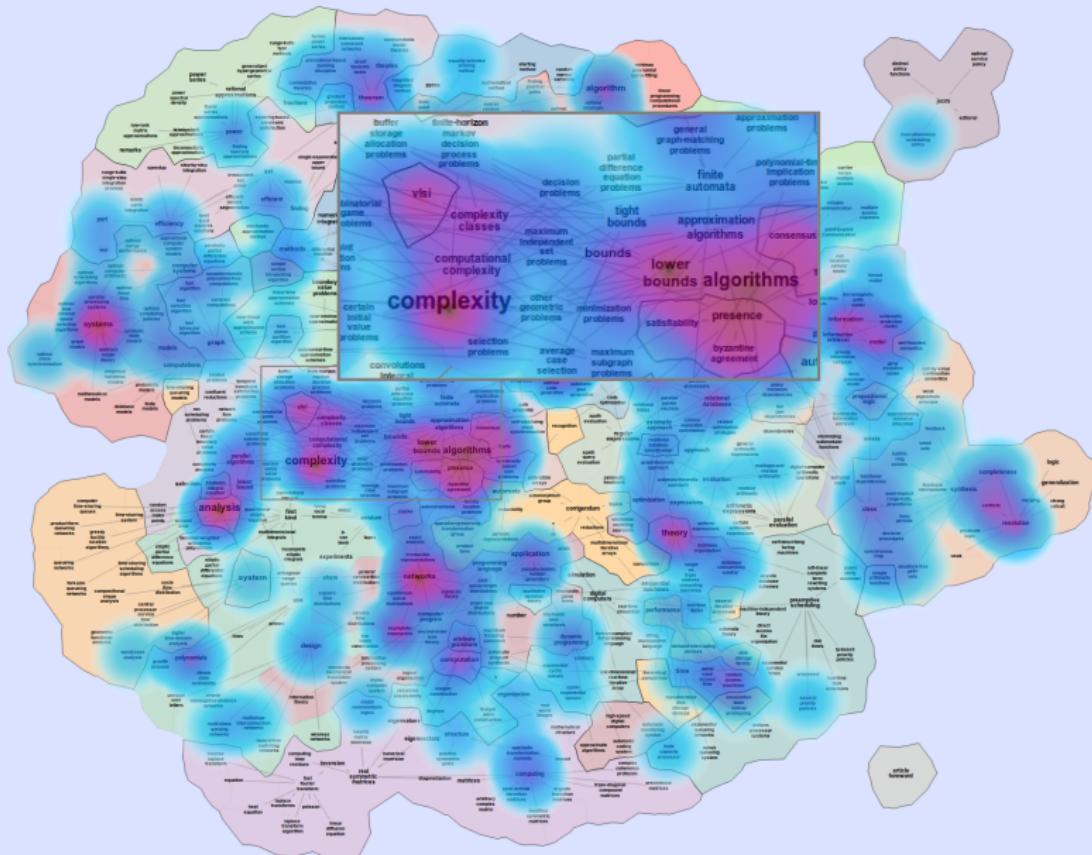
Temporal Heatmaps: JACM 1974-1983



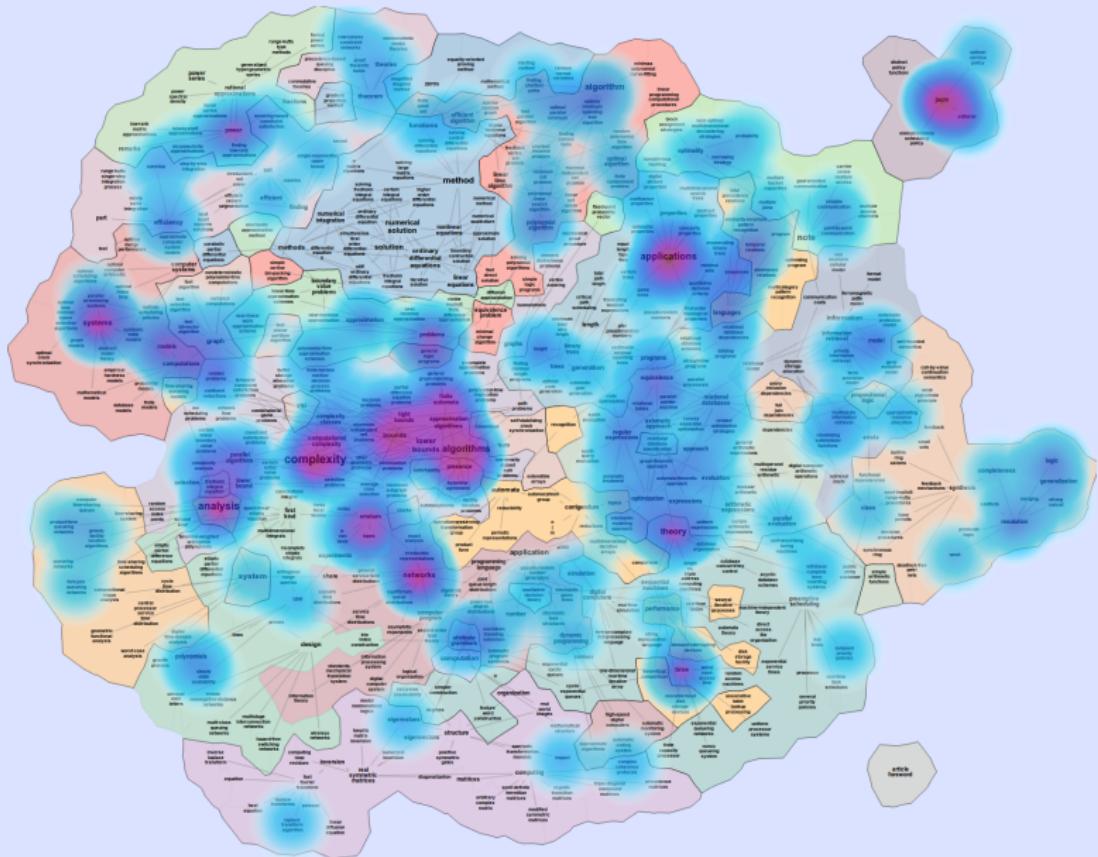
Temporal Heatmaps: JACM 1984-1993



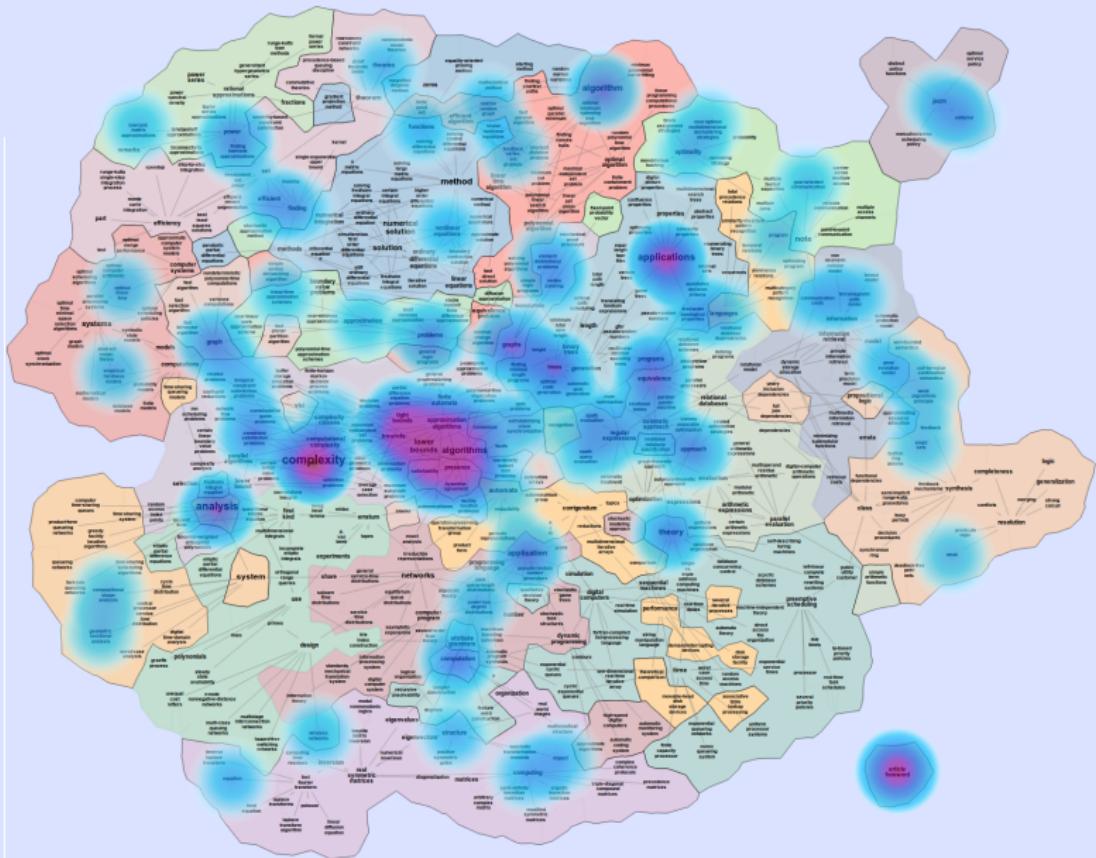
Temporal Heatmaps: JACM 1984-1993



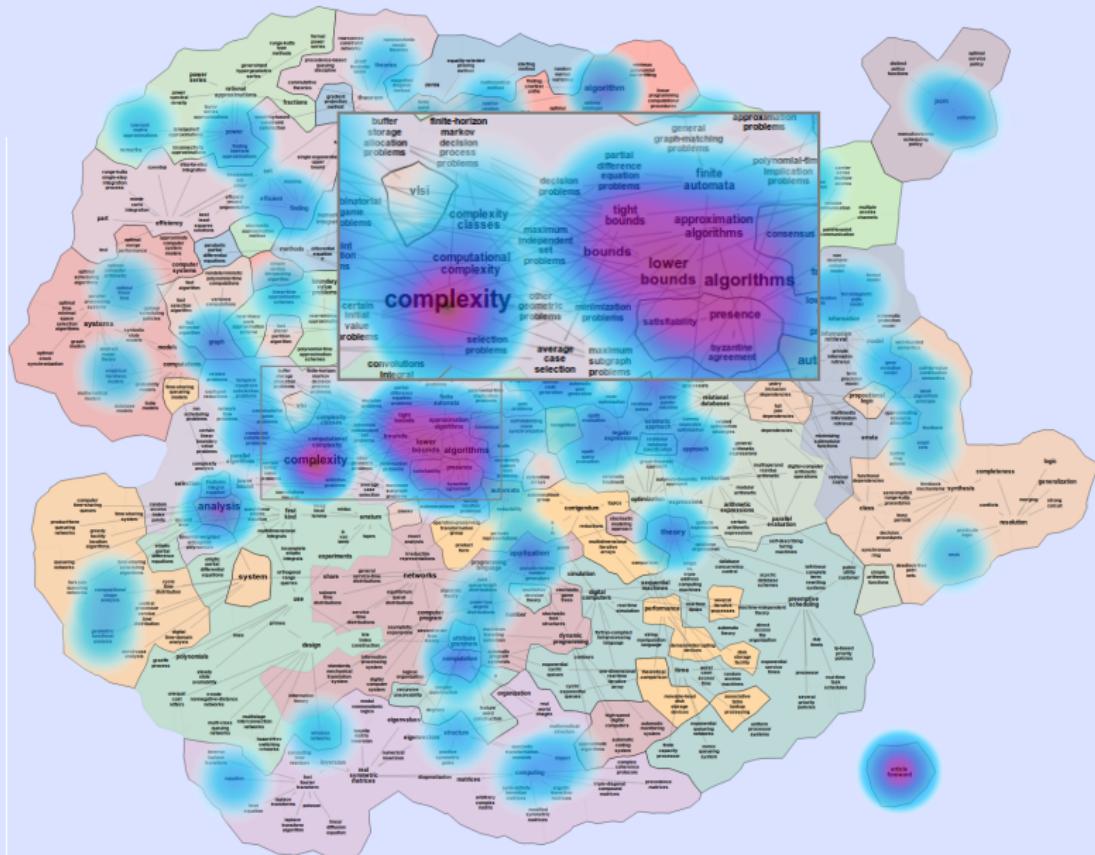
Temporal Heatmaps: JACM 1994-2003



Temporal Heatmaps: JACM 2004-2013



Temporal Heatmaps: JACM 2004-2013



- Can vary basemap and heatmap queries independently
- Runtime varies: a few seconds for an author, about a minute for 60,000 doc sample of all papers
- Open source, modular, extensible – add your own term similarity, ranking, etc. functions:
`github.com/dpfried/mocs`
- Interactive web interface: `mocs.cs.arizona.edu`

Future Work

- Dealing with sparsity: using abstracts and full papers
- Reducing map fragmentation with contiguous country maps
- Try on paper corpora from other domains
 - PubMed
 - arXiv
- Map validation: consistency and recall (expert evaluation)

Thanks!