Clustering Applications at Yahoo!

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Outline

- Clustering, in itself, is often not the primary problem
  - Exploratory analysis is rarely needed
- Methods are often tied to the “final” goal

Data	Data	Data	
Problem	Problem	Problem	…
Method	Method	Method	
Issues	Issues	Issues	

Outline

- Advertiser-keyword graph
  (+ social networks)
  - Graph Partitioning
- CTR predictions for ads on webpages
  - Co-clustering
- Query refinement and suggestions
  - Local search methods
- Conclusions

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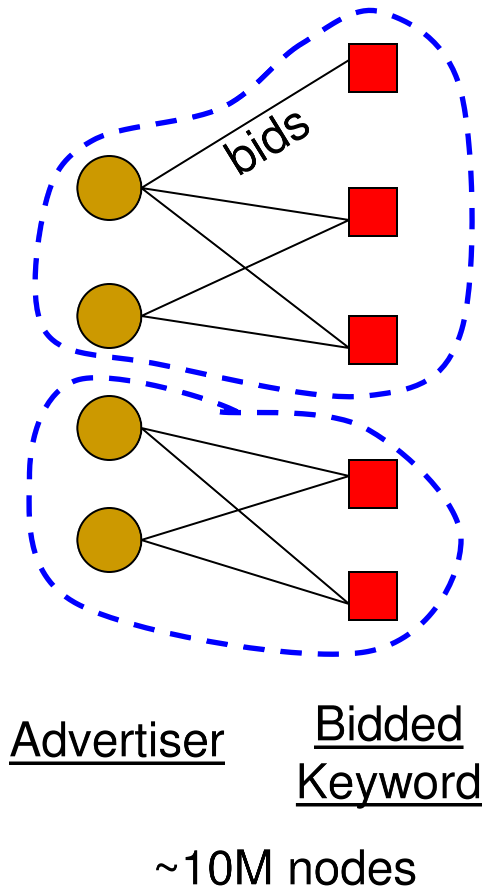
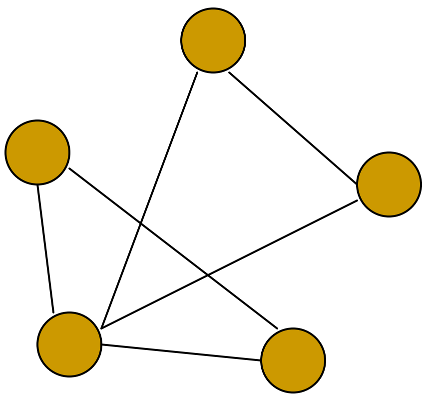
Graph Partitioning (Applications)



- Find clusters of advertisers and keywords
  - Keyword suggestions
  - Running experiments on some “natural” clusters
- Similar:
  - Y! Answers
  - Flickr

Graph Partitioning (Applications)



Who-messages-whom IM graph

~100M nodes

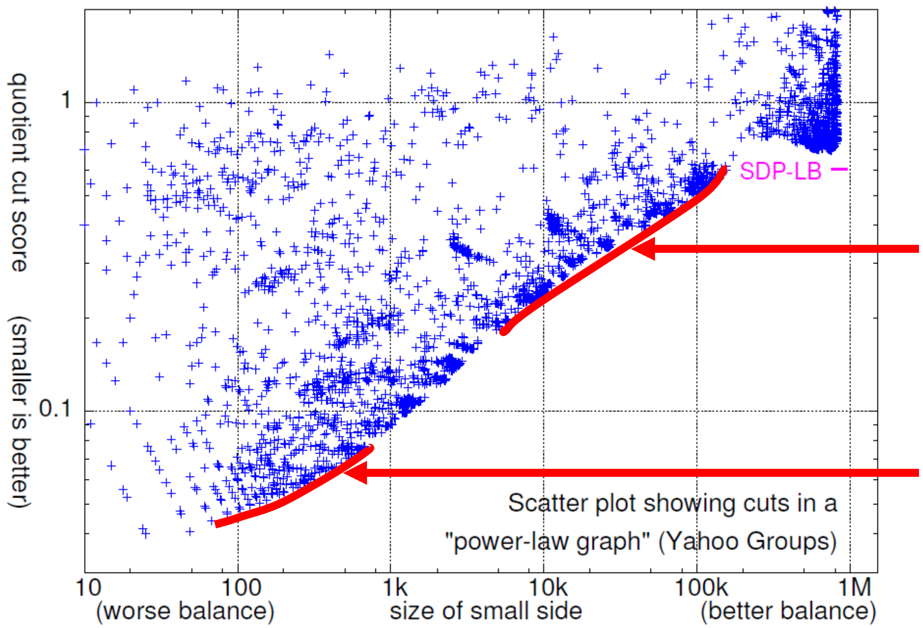
- Find clusters of IM users
  - Targeted advertising
  - Exploratory analysis
- Clusters of the Web Graph
  - Distributed pagerank computation

Graph Partitioning (Methods)

- Basic “Global” spectral partitioning [Ng+/01]
  - Find 2nd eigenvector of the graph Laplacian
  - This embeds all nodes on the real line
  - Split the line in two, to get two clusters
    - Can approximate the optimal conductance cut
  - For more clusters:
    - Use k eigenvectors (for known k), or
    - Split in two, and recurse on each cluster

Graph Partitioning (Methods)

- However, this has problems [Lang/05, Leskovec+/08]:
  - Min. conductance or quotient cuts lead to “small chunks”



Better balance ➔ worse cuts

Large-sized low-quotient cuts are actually just unions of whiskers

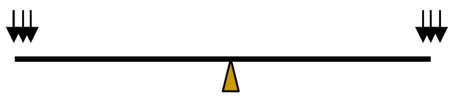
“Whiskers”

Graph Partitioning (Methods)

- However, this has problems:
  - Min. conductance or quotient cuts lead to “small chunks”
    - Balance is not very strongly encouraged
  - Recursive partitioning takes too long
    - Each eigenvector computation yields only a small cluster being broken off
- Two alternatives:
  - More balanced cuts ➔ recursion is faster
  - Unbalanced cuts, but much faster computation

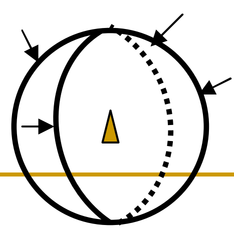
Graph Partitioning (Methods)

- Achieving better balance
  - Combine algorithms (e.g., [Anderson+/08])
    - METIS (more balanced cuts), followed by
    - Flow-based improvement (conductance)
  - Stronger balance constraints



Perfect balance on real line:
NP-Hard

Spectral embedding



Perfect balance on hypersphere:
SDP formulation [Lang/05]

Graph Partitioning (Methods)

- Faster Computation via “local” graph partitioning [Spielman+/04, Anderson+/06]
  - Pick seeds randomly
  - Build local clusters around seed
  - Bite off cluster, and repeat
  - ➡ Time for each iteration is proportional to the size of the local cluster (scalability)
  - ➡ Better for large graphs, or when not all clusters are needed

Graph Partitioning (Issues)

- Many complex networks are very different from planar/mesh-like networks
  - Good small cuts
  - Good large cuts are hard to find, and may not even exist
    - Hard to have a good hierarchical partitioning
- Is conductance really the best objective?
  - METIS+flow finds lower conductance cuts, but
  - Local spectral methods finds more “tightly-knit” cuts [Leskovec+/08]
  - Is there a good compromise?

Graph Partitioning (Issues)

- Speed and Scalability
  - Most implementations have trouble with large graphs, or graphs with some extremely high-degree nodes
  - Map-reduce style partitioning algorithms?

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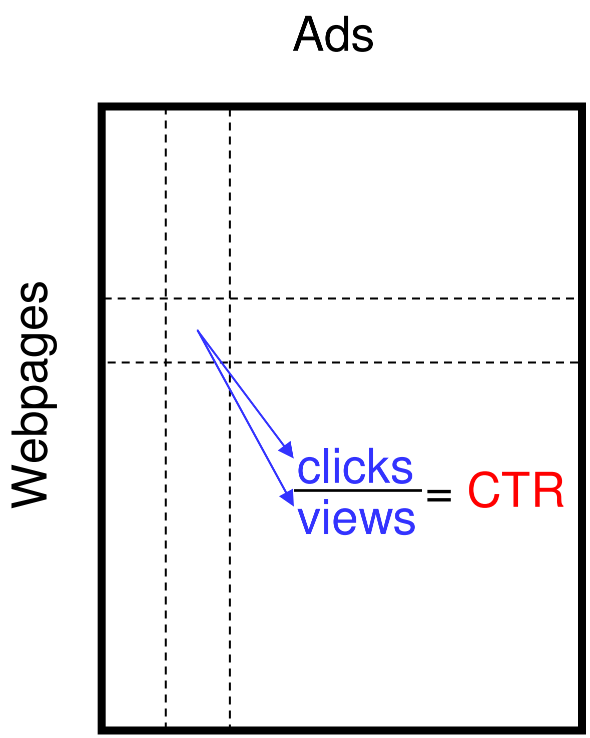
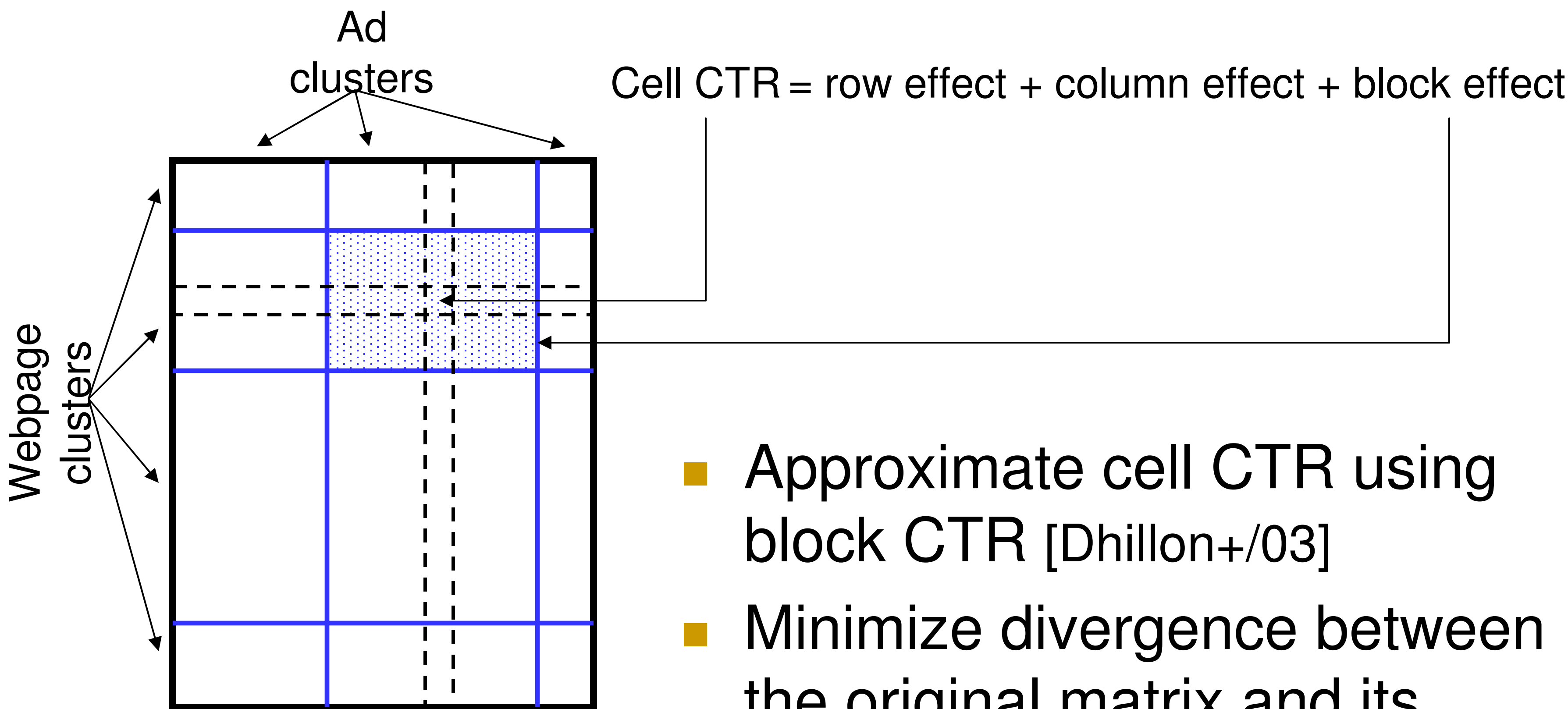
Co-clustering (Applications)



- The Content Match problem
  - Predict click-thru rate (CTR)
  - Extreme sparsity
    - Few views
    - Even fewer clicks

Co-clustering (Methods)



- Approximate cell CTR using block CTR [Dhillon+/03]
- Minimize divergence between the original matrix and its reconstruction

➨ Combats sparsity

Co-clustering (Issues)

- Picking the right number of clusters
  - Use MDL [Chakrabarti+/2004]
- Handling new ads/pages
  - Combine co-clustering with feature-based prediction models [Agarwal+/2007]
- Handling extra information
  - E.g., if each page and ad can be categorized into a taxonomy [Chakrabarti+/2007]
  - Can the taxonomy be automatically modified?

Co-clustering (Issues)

- Iterative process (hard for map-reduce)
  - Factor-3 approximation by just clustering webpages and ads separately [Dasgupta+/2008]

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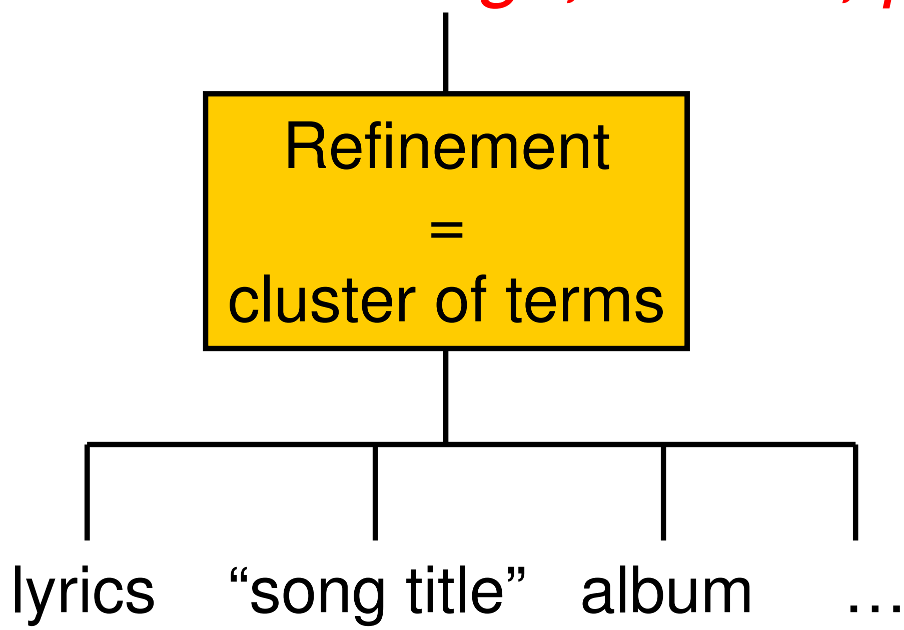
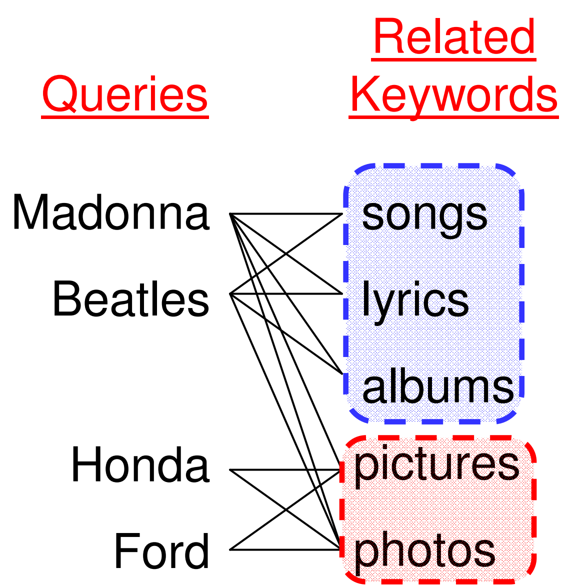
Query Refinement

- User inputs ambiguous query *("madonna")*
- Search engine asks:
  "*Did you mean: songs, videos, pictures?*"



Query Refinement

- Suppose we could relate queries with keywords



Query Refinement (Problem)

- Different from plain bipartite graph partitioning
  - Don’t confuse users!
    - only 3 or fewer clusters for each query
    - only a few easily-distinguishable clusters overall
- Clustering quality now also depends on
  - the query workload
  - the algo that picks the “top-3” clusters for any query

Query Refinement (Method)

- Can optimally pick top-k clusters for any query [Wang+/2009]
  - for a wide range of matching functions
  - only if clusters are disjoint
- Iteratively improve clustering via local search
  - Move a keyword to a new cluster
  - Update top-k clusters for all queries in workload
  - Repeat

Query Refinement (Issues)

- Iterative ➔ slow
  - Each iteration has to go over the entire historical query logs
  - Optimality guarantees?
  - Modeling issues:
    - How do we present a cluster to the user?
    - Cluster naming?
    - How does a user interact with a cluster?

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Conclusions

- Standalone clustering applications are rare!
  - Constraints on clustering
    - What use will it serve (as in query refinement)?
    - What is the desired “natural” cluster size?
  - Clustering for predictions (e.g., CTR)
    - Missing values
    - Extreme sparsity
  - Combining clustering with explore-exploit

Conclusions

- Even for standalone clustering:
  - Scalability concerns
    - 10s to 100s of millions of nodes
    - Skewed degree distributions
    - Algorithms amenable to map-reduce
  - The right “balance” relaxation
    - Tradeoffs between cluster “compactness”, conductance, and partition sizes
    - Is it even reasonable to require balance?

References

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