Integrating Web and Database Searches

CPS 296.1

Topics in Database Systems

Roadmap

- ➢ Rank aggregation: merging ranked results from different searches
  - Fagin et al. "Optimal Aggregation Algorithm for Middleware." *PODS*, 2001
- Proximity search: finding all shortest paths in the link structure of a database
  - Goldman et al. "Proximity Search in Databases." *VLDB*, 1998
- WSQ: enhancing database queries with Web searches
  - Goldman and Widom. "WSQ/DSQ: A Practical Approach for Combined Querying of Databases and the Web." *SIGMOD*, 2000

Rank aggregation problem

- Each object R is graded using m different criteria
  - Grades are $x_1, x_2, \ldots, x_m$
  - Example: each grade measures the relevance of R for a particular search term
- The combined grade is calculated by an aggregation function $t(x_1, x_2, \ldots, x_m)$
  - Example: weighted sum, min, max, etc.
- Problem: find the top k objects with the highest combined grade

Modes of access

- Sorted: sequentially request a list of objects (with their grades) ranked according to one criterion (from highest to lowest)
  - Conceptually, there are m lists $L_1, L_2, \ldots, L_m$, one for each criterion
  - Example: search an image database for a list of "red" pictures, ranked by their "redness"
- Random: request the grade of an object according to one criterion
  - Example: query an image database for the "redness" of one particular picture

Assumptions

- Individual scores are in the interval [0, 1]
- Aggregation function is monotone
  - If $x_i \leq x'_i$ for every i, then $t(x_1, x_2, \ldots, x_m) \leq t(x'_1, x'_2, \ldots, x'_m)$
  - Examples: min, sum
  - Not an example: $1 - \text{sum}(x_1, x_2, \ldots, x_m)$
- Cost per sorted access (one object, one score): c_S
- Cost per random access (one object, one score): c_R

Naïve algorithm

- For each criterion, do sorted access to retrieve all objects and their grades
  - That is, access all L_i's
- Calculate the combined grades for all objects
- Pick the top k
- ➢ Accesses the entire database
- ➢ Does not use the fact that L_i's are sorted

FA (Fagin's Algorithm)

- Do sorted access in parallel to all L_i's, until there are k "matches"
  - A "match" is an object that has been seen in all L_i's
- For each object that has been seen, do random accesses to get all its grades
- Calculate the combined grades and pick the top k

➢ Pop quiz
  - Why not just consider the k matches?
  - Why not consider objects seen after the k matches?

➢ Needs to remember lots of objects: large buffer size

➢ Does not use the aggregation function effectively

TA (Threshold Algorithm)

- Do sorted access in parallel to all L_i's
  - Whenever an object is seen, do random accesses to get all its grades, and compute the combined grade
  - Remember up to k objects with top combined grades
  - Calculate the threshold value $\tau = t(\underline{x}_1, \underline{x}_2, \ldots, \underline{x}_m)$, where $\underline{x}_i$'s are the bottom grades seen so far
  - If we have seen at least k objects whose combined grade is at least τ, stop
- Output the top k objects we remembered

Intuition behind TA

- τ serves as an upper bound on the combined grade for objects that have never been seen
- When we stop, the top k objects we have remembered all have combined grade of at least τ

➢ The top k we have are the top k overall

- "Gather what information you need to allow you to know the top k answers, and then halt"

FA versus TA

- TA never stops later than FA
  - FA's stopping condition (k matches) implies that TA's stopping condition (k objects above threshold) has already been satisfied
- TA requires only bounded buffers (to remember the top k objects)
- TA may perform more random accesses

Instance optimality

- **A**: a class of algorithms
- **D**: a class of legal inputs to algorithms
- *cost*(A, D): cost of running algorithm A with input D
- An algorithm $B \in \mathbf{A}$ is instance optimal over **A** and **D** if for every $A \in \mathbf{A}$ and every $D \in \mathbf{D}$,

  $$cost(B, D) = O(\ cost(A, D)\ )$$

  - That is, $cost(B, D) \leq c \cdot cost(A, D)\ ) + c'$, where c is called the optimality ratio

➢ Much stronger than worst-case optimality

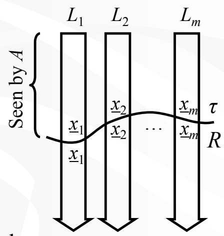
Instance optimality of TA

- **A**: the class of all algorithms that do not make mistakes or wild guesses
  - "No wild guesses" means no random access for R unless R has been seen in sorted access
- **D**: the class of all possible inputs
- TA is instance optimal over **A** and **D**, with optimality ratio of at most $m + m(m-1)\ c_R / c_S$

Intuition behind TA's instance optimality

- Say an algorithm A stops sooner than TA on some input (i.e., one of the top k picked by A has combined grade less than τ)
- Construct another input by inserting a new object R right below where A stops looking
- Then A will make an mistake by failing to pick R

➢ See paper for a rigorous proof and other results



Related work: Quick-Combine

- Güntzer et al. "Optimizing Multi-Feature Queries in Image Databases." *VLDB*, 2000
- Instead of doing sorted access on all Li's in parallel, choose one L_i to access next
- Prefer the list in which grades are declining at the fastest rate, so we can lower the threshold value faster
  - Rate is measured by the decrease in successive grades, weighted by $|\partial t / \partial x_i|$

➢ $|\partial t / \partial x_i|$ may be undefined (e.g., min)

➢ Quick-Combine may beat TA in some cases, but is not instance optimal unless we ensure every L_i is accessed every now and then

Extending TA

- What if we only need approximate answers? TA_θ
  - Example: Web search, with lots of good-quality answers
- What if we have no sorted access for some criteria? TA_Z
  - Example: find good restaurants near me (sorted and random accesses for restaurant ratings, random access only for distances)
- What if we have no random access at all? NRA
  - Example: Web search engines, which typically do not allow you to enter a URL and get its ranking
- What if consider the relative costs of random and sorted accesses? CA

Adding approximation: TA_θ

- A θ-approximation ($\theta > 1$) to the top k answers is a collection of k objects, such that
  - For each R among these k objects, and for each R' not among these these k objects, $\theta\, t(R) \geq t(R')$
- TA_θ: same as TA, except that the stopping condition is "we have seen at least k objects whose combined grade is at least τ / θ"

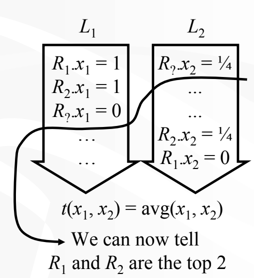
Restricting sorted access: TA_Z

- Suppose we only have sorted access to L_i for $i \in Z$
- TA_Z: same as TA, except
  - Only do sorted accesses to L_i's where $i \in Z$
  - Use $\underline{x}_j = 1$ to calculate the threshold if sorted access to L_j is not allowed ($j \notin Z$)

➢ Intuition: The first object that we see in L_j (if we could) can have grade 1

No random access: NRA

- Key observation: Sometimes we do not have to know all individual grades of R in order to tell that R is among the top k
- Use bounds!



NRA

- Do sorted access in parallel to all L_i's; at each depth:
  - Maintain bottom grades $\underline{x}_1, \underline{x}_2, \ldots, \underline{x}_m$ seen in the lists
  - For each object R, calculate the lower and upper bounds for its combined grade
    - If x_i is not available, use 0 in calculating lower bound, and use $\underline{x}_i$ in calculating upper bound
  - Maintain a current top k list containing the k objects with the largest lower bounds (ties are broken by upper bounds)
- Stopping condition
  - For every R not in the current top k list, the calculated upper bound for R is less than the calculated lower bound for all objects in the current top k list

➢ Lots of note-keeping!

Combined algorithm: CA

- A compromise between TA (lots of random accesses) and NRA (no random accesses)
  - Uses random accesses, but considers their cost relative to sorted access
- Suppose $h = \lfloor c_R / c_S \rfloor \geq 1$
- CA: same as NRA, except
  - Every h steps, pick an object with missing individual grades (see paper for details on which object to pick)
  - Do random accesses to get the missing grades, and then recalculate the bounds

Summary

- A very practical problem (rank aggregation)
- A simple algorithm (TA) and various extensions
  - Nothing wild; just clean implementations of remarkably simple ideas (thresholds, bounds)
  - But the amazing thing is that these simple algorithms are unbeatable for any input (instant optimality)!