Query and Answer Models for Keyword Search

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Introduction

- **Keyword Searching :** unstructured method of querying
- greatest advantage: requires no knowledge of the underlying schema
- keyword search in databases:
    - database normalization
    - table joins done on the fly
    - unique characteristics of databases: different types of edges, attributes of nodes, semantics associated with tables
    - physical database design affects performance: availability of indexes on certain columns
- notion of relevance

Representing Data as a Graph

1. Schema Graph:
   - describes the schema of the data
   - meta-level representation of the data
   - constraints the edges that are permissible in the data graph
   - general construction: the tables in the database form the nodes; edges capture some relationship or constraint between the corresponding relations
2. Data Graph:
   - instantiation of its schema graph
   - contains actual data which is split across different nodes and edges
   - general construction: the tuples of the database form the nodes; cross-references like foreign key references, inclusion dependencies, etc., form the edges of the graph
   - nodes can be set according to the granularity required - table, tuple or cell
3. Concept of Node weight and Edge weight

Keyword Query System Model I

1. Data Model:
   - describes the high-level representation of the data in the system
   - reflects the constraints, associations, and organization of the data
   - graph model
2. Query Model:
   - specifies the structure of the input that can be given to the system
   - keyword queries - set of words
   - graph, tree patterns - the user can specify constraints which the answer must satisfy
3. Answer Model:
   - specifies, what an answer to a query is
   - specifies the structure, requirements that it must satisfy according to the semantics of the system
   - common form of representation: graph, tree, tuple, term

Keyword Query System Model II

4. Scoring Model:
   - assigns a score to the answers, based on their relevance
   - notion of relevance - ambigous; returns top scoring answers
   - a simple scheme: higher score to an answer with smaller number of joins
   - most systems use complex rules to assign scores, to improve the quality of the top ranked answers

Object Rank System I

- adapts the notion of PageRank to suit the database setting
- concept of authority: nodes having query terms have authority
- nodes transfer authority to neighbours in a fixed manner
- final score given by the accumulated authority

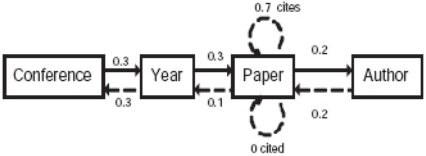
Graph Representation

1. Data graph - labelled graph $D(V_D, E_D)$
2. Schema graph - directed graph $G(V_G, E_G)$
3. Authority Transfer Schema graph $G^A(V_G, E^A)$
   - for each edge $e_G = (u, v)$ in the schema graph, insert two authority transfer edges:
     1. forward edge $e_G^f = (u, v)$ with authority transfer rate: $\alpha(e_G^f)$
     2. backward edge $e_G^b = (v, u)$ with authority transfer rate: $\alpha(e_G^b)$
   - intuition: authority could flow in both directions at different rates

Object Rank System II

4. Authority Transfer Data Graph $D^A(V_D, E_D^A)$
   - for every edge $e = (u, v) \in E_D$, add two edges $e^f = (u, v)$ with authority transfer rate $\alpha(e^f)$ and $e^b = (v, u)$ with authority transfer rate $\alpha(e^b)$
   - e^f be of type e_G^f
   - $OutDeg(u, e_G^f)$ - number of outgoing edges from u of type e_G^f
   - authority transfer rate $\alpha(e^f)$ is defined as:

$$\alpha(e^f) = \begin{cases} \frac{\alpha(e_G^f)}{OutDegree(u, e_G^f)} & ifOutDegree(u, e_G^f) > 0 \\ 0 & ifOutDegree(u, e_G^f) = 0 \end{cases}$$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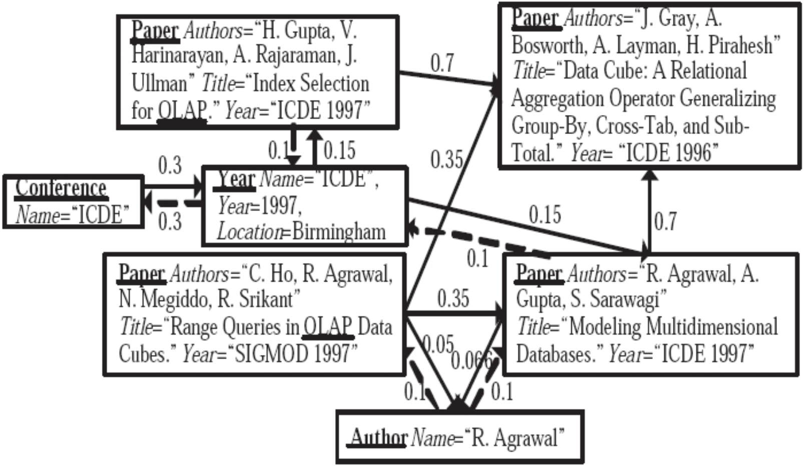
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Paper Authors="J. Gray, A. Bosworth, A. Layman, H. Pirahesh" Title="Data Cube: A Relational Aggregation Operator Generalizing Group-By, Cross-Tab, and Sub-Total." Year= "ICDE 1996"
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Paper Authors="C. Ho, R. Agrawal, N. Megiddo, R. Srikant" Title="Range Queries in OLAP Data Cubes." Year="SIGMOD 1997"
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Paper Authors="R. Agrawal, A. Gupta, S. Sarawagi" Title="Modeling Multidimensional Databases." Year="ICDE 1997"
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Author Name="R. Agrawal"

Object Rank System - Random Surfer Model for Ranking

- initially, large number of random surfers start from objects containing the specified keyword; they traverse the database graph along the edges
- at any point of time, a random surfer at a node does one of the following:
  - move to an adjacent node by moving along an edge
  - jump to a randomly chosen node containing the keyword
- **ObjectRank of a node:** expected percentage of surfers at that node, as time goes to infinity

Keyword-Specific and Global ObjectRanks I

Keyword-Specific ObjectRank

- gives the relevance with respect to a keyword
- w - keyword; $S(w)$ - keyword base set - set of objects that contain w
- $r^w(v_i)$ of node v_i obtained as the solution to:

$$\mathbf{r}^w = d\mathbf{A}\mathbf{r}^w + \frac{(1-d)}{|S(w)|}\mathbf{s}$$

  - $A_{ij} = \alpha(e)$ if there is an edge $e = (v_j, v_i)$ in E_D^A; 0 otherwise
  - $\mathbf{s} = [s_1, ..., s_n]^T$ - base set vector; $s_i = 1$ if $v_i \in S(w)$; 0 otherwise
  - d - damping factor

Global ObjectRank

- gives the general importance regardless of the query
- calculated from the above equation, but with **all** nodes included in the base set

Keyword-Specific and Global ObjectRanks II

Combined ObjectRank

- $r^G(v)$ - Global ObjectRank of v
- $r^w(v)$ - Keyword-specific ObjectRank of v w.r.t w

Combined Rank

$$r^{w,G}(v) = r^w(v).(r^G(v))^g$$

g - Global ObjectRank weight

Multiple-Keyword Queries

extending the random surfer model

- multiple-keyword query : $w_1, \ldots, w_m$
- m independent random surfers, where the i^{th} surfer starts from the keyword base set $S(w_i)$
- **AND** semantics: probability that the m random surfers are simultaneously at node v

$$r_{AND}^{w_1,\ldots,w_m}(v) = \prod_{i=1,\ldots,m} r^{w_i}(v)$$

- **OR** semantics: probability that atleast one of them is at node v

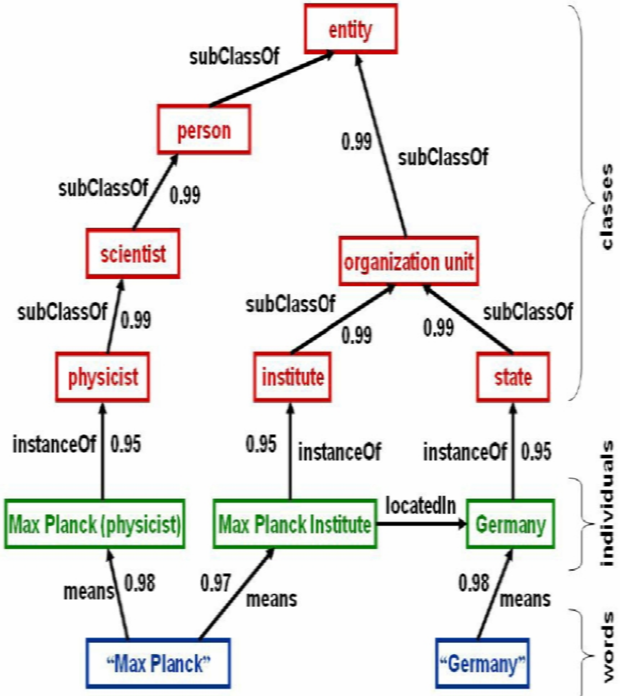
$$r_{OR}^{w_1,\ldots,w_m}(v) = \sum_{i=1,\ldots,m} r^{w_i}(v)$$

The NAGA System

- semantic search engine

Data Model :

- Knowledge graph: directed, weighted, labeled multi-graph $G = (V, E, L_V, L_E)$
- facts: binary relationships derived from the web
- represented as an edge together with its end nodes e.g. $e(u, v)$, $l(u) = MaxPlanck(physicist)$, $l(e) = bornInYear$, $l(v) = 1858$
- witnesses of a fact: the pages from which it has been extracted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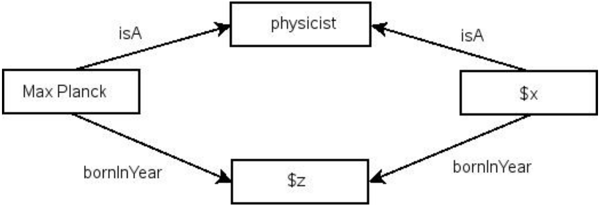
NAGA - Graph Pattern Query Model I

- connected, directed graph
- nodes, edges can be labeled with variables or constants
- fact template: edge label and the two node labels. e.g. `AlbertEinstein friendOf $x`
- answer - subgraph of the data graph, that has valid objects which can take the place of the variables and also satisfy the edge constraints

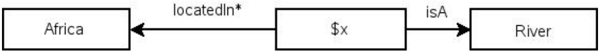
Queries supported:

1. Discovery query: to discover pieces of information
   e.g. to find physicists who were born in the same year as Max Planck:

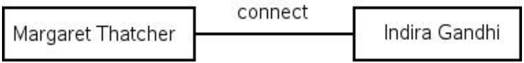


NAGA - Graph Pattern Query Model II

2. Regular expression query: to find out some particular path connecting pieces of information
   e.g. to find out the rivers located in Africa:



3. Relatedness query: to find out a broad relationship between pieces of information
   e.g. How are Margaret Thatcher and Indira Gandhi related?



NAGA - Answer Model I

- matching path: e.g. `Nile locatedIn Egypt, Egypt locatedIn Africa` is a valid match for `$x locatedIn* Africa`
- Answer Graph- subgraph of the knowledge graph such that:
  - for each fact template in the query, there is a matching path
  - each fact in the answer is part of only one matching path
  - each vertex of the query is bound to exactly one vertex of answer
- for query $q = q_1 q_2 \ldots q_n$, find subgraph g for which $P(g|q)$ is the highest

NAGA - Answer Model II

confidence value of a fact

$$P_{conf}(f) = \frac{1}{n}\sum_{i=1}^{n} acc(f, p_i).tr(p_i)$$

- p_i : witnesses of f
- $acc(f, p)$: estimated accuracy with which f was extracted from p
- $tr(p)$: trust in p - computed by an algorithm similar to PageRank

informativeness of a fact

- $P_{finfo}(f)$ - depends on number of witnesses, query
  e.g. query:`AlbertEinstein isA $x` - `AlbertEinstein isA physicist` ranked higher than `AlbertEinstein isA politician`
  $\frac{|W(\texttt{AlbertEinstein isA physicist})|}{\sum_{\$x} |W(\texttt{AlbertEinstein isA \$x})|}$
  query: `$x isA physicist`
  $\frac{|W(\texttt{AlbertEinstein isA physicist})|}{\sum_{\$x} |W(\texttt{\$x isA physicist})|}$

NAGA - Answer Model III

confidence and informativeness of query q_i

$$P_{conf}(q_i|g) = \prod_{f \in match(q_i,g)} P_{conf}(f)$$
$$P_{info}(q_i|g) = \prod_{f \in match(q_i,g)} P_{finfo}(f|q_i)$$

probability of the query being generated by g

$$\tilde{P}(q_i|g) = \beta P_{conf}(q_i|g) + (1-\beta)P_{info}(q_i|g)$$
$$P(q_i|g) = \alpha\tilde{P}(q_i|g) + (1-\alpha)\tilde{P}(q_i)$$

where, $\tilde{P}(q_i)$ gives different weights to fact templates

estimate probability of an answer graph, given the query

$$P(g|q) \sim P(q|g)P(g)$$

where, $P(q|g) = \prod_{i=1}^{n} P(q_i|g)$

NAGA - Scoring Model

Scoring model captures the following:

1. Confidence:
   - certainity about a specific fact
   - independent of the query and the popularity of the fact
   - facts extracted from authoritative pages, with high accuracy, will be given a higher score
2. Informativeness:
   - relevance of a fact for a given query
   - dependent on the formulation of the query
   - fact deemed to be relevant if it is highly visible in the web
   - intuition: the more the number of pages that state the fact, the higher is the likelihood that the fact is true and is important
3. Compactness of the resulting graph:
   - implicitly captured by the likelihood of the graph given the query
   - likelihood is the product over the probabilities of its component facts

Conclusion

- Other systems studied: System by Goldman et. al. for search incorporating the notion of proximity, DBXplorer, DISCOVER, BANKS, System by Hristidis et. al. for IR style Keyword search, Proximity Search in Type-Annotated Corpora and FleXPath
- Keyword Searching is an important paradigm for searching in databases
- methods of querying: set of words, graph/tree patterns
- answer models: from rows in the database, to trees and graphs
- different semantics: OR, AND, proximity
- scoring models: number of joins, complex combinations of node and edge scores, concept of authority, probabilities etc.
- future work:
  - oriented towards incorporating more semantics into the search systems
  - alternate structure for answers which will make it more intuitive
  - fine tuning of the scoring model, based on feedback from the user - instead of having a static function

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DBXplorer

- Answer: row that contains all keywords
- rows may be either from single tables, or by joining tables connected by foreign-key relationships
- ranking of rows - by the number of joins involved

DISCOVER

- Answer: Minimal Total Joining Networks of Tuples (MTJNT)
- MTJNT - Joining Network of Tuples that satisfy Totality and Minimality requirements
- Joining Network of Tuples j is a tree of tuples where for each pair of adjacent tuples $t_i, t_j \in j$, where $t_i \in R_i, t_j \in R_j$, there is an edge (R_i, R_j) in the schema graph and $(t_i \bowtie t_j) \in (R_i \bowtie R_j)$
- Total: answer graph should contain ALL the words in the query
- Minimal: if any node is removed from the answer graph, then either, it becomes disconnected or it is no longer total
- ranking of rows - by the number of joins involved

IR style Keyword search by Hristidis et. al.

- idea: use the underlying RDBMS, to efficiently process a keyword query. incorporates IR techniques of proximity, in answering keyword queries on a database. Contemporary RDBMS possess efficient querying capabilities for text attributes, but
- data, query model - same as that in DISCOVER
- Scoring model:
  - for each textual attribute a_i in T, the joining tree of tuples, find single-attribute score using the IR engine employed in the underlying database
  - final score: combination of single-attribute scores using *Combine* $Combine(Score(A, Q), size(T)) = \frac{\sum_{a_i \in A} Score(a_i, Q)}{size(T)}$
- AND semantics: 0 score for tuple trees that don't have **all** keywords; else, score given by *Combine* function
- OR semantics: score given by the *Combine* function

The BANKS System I

Data Graph - tuples: nodes and edges: foreign key - primary key relationships

Answer Model

- connection tree - a directed rooted tree containing **all** the keywords
- keywords nodes form the leaves of the tree
- root node - the information node; is a common vertex from where there exists path to all the keyword nodes

Scoring Model

- overall relevance score of an answer tree:
  - additive combination: $(\mathbf{1} - \lambda)\mathbf{Escore} + \lambda\mathbf{Nscore}$
  - multiplicative combination: $\mathbf{Escore} \times \mathbf{Nscore}^{\lambda}$

  λ - controls relative weightage
- *Nscore* of a tree : average of node scores of (i) leaf nodes (ii) root node

The BANKS System II

- *Escore* of a tree : $1/(1+\sum_{e} Escore(e))$, where $Escore(e)$ - normalized score of individual edges
- gives lower relevance to larger trees

Bidirectional Search : Scoring Model

- $s(T, t_i)$ - score of answer tree T with respect to keyword t_i: defined as the sum of the edge weights on the path from the root of T to the leaf containing t_i
- aggregate edge-score E of T: $\sum_i s(T, t_i)$.
- tree node prestige N: sum of the node prestiges of the leaf nodes and the answer root
- Prestige: computed by a biased random walk, where, the probability of moving along a particular edge is inversely proportional to its edge weight
- overall tree score: $\mathbf{EN}^{\lambda}$
  λ controls relative weightage

Search incorporating the notion of proximity by Goldman et. al.

- proximity measured as the shortest distance between nodes
- query model: pair of queries
  Find Query:
  - specifies the type of the answer e.g. objects of type `movie`
  - defines *FindSet*: set of objects that can potentially be the answer

  Near Query: specifies the keywords that define a *NearSet*.
- idea: rank *FindSet* objects based on proximity to *NearSet* objects
- *bond* between *FindSet* object f and *NearSet* object n:
  $b(f, n) = \frac{r_F(f) r_N(n)}{d(f,n)^t}$
  - $r_F(f)$ - ranking of f in *FindSet*, F; $r_N(n)$ - ranking of n in *NearSet*, N
  - $d(f, n)$ - distance between f and n
  - t - tuning component
- Scoring model:
  - Additive : $score(f) = \sum_{n \in N} b(f, n)$
  - Maximum : $score(f) = max_{n \in N} b(f, n)$
  - Beliefs : $score(f) = 1 - \prod_{n \in N} (1 - b(f, n))$

Proximity Search in Type-Annotated Corpora

- query model: `type=atype` `NEAR` $S_1 S_2 \ldots S_k$
- candidate answer token: any token connected to a descendant of `atype`
- nearness is a function of:
  - matching selectors
  - frequency of selectors in the corpus
  - distance of selectors from the candidate answer
- scoring model:
  - $\mathit{energy}(s)$: similar to inverse document frequency (IDF)
  - $\mathit{gap}(w, s)$: number of tokens present between a candidate token and a matched selector
  - energy received: $\mathit{energy}(s)\mathit{decay}(\mathit{gap}(w, s))$, where $\mathit{decay}(g)$ is a function of the gap
  - decay function is automatically learned - found that its not monotonically decreasing with gap, as was expected
  - score of a candidate a:
    $\mathit{score}(a) = \oplus_s \oslash_i \mathit{energy}(s_i)\mathit{decay}(\mathit{gap}(s_i, a))$
    s_i: multiple occurrences of s near a

FleXPath I

- query model - *tree pattern query* (TPQ) (T, F):
  - T: rooted tree with nodes denoting variables; edges denoting structural predicates - parent-child (pc), ancestor-descendant (ad) relationships
  - F: predicate expression - specifies constraints on the contents of the nodes
  - distinguished node: usually, the root node; designated as the answer
- query relaxation:
  - replacing `parent-child` by `ancestor-descendant` predicate
  - dropping an `ancestor-descendant` constraint
  - promoting a `contains` predicate to the parent
- Predicate Penalty: measures the extend of the loss of context, when a predicate is dropped to get the relaxed query
  $penaltyOfDropping(pc(\$i, \$j)) = \frac{\#_{pc}(t_i,t_j)}{\#_{ad}(t_i,t_j)} w_Q(pc(\$i, \$j))$
  where, $w_Q(p)$ - weight of the predicate - measure of its importance

FleXPath II

- score of an answer- *ss*: structural score; *ks*:keyword score
- $ss = \sum_{p \in P} w_Q(p) - \sum_{p \in S} \pi(p)$
  - P: set of all predicates in the original query, Q
  - S: set of predicates that have been dropped from P to obtain relaxed version
  - $\pi(p)$: penalty incurred for dropping predicate p
- final score:
  - structure first: (ss, ks)
  - keyword first: (ks, ss)
  - arithmetic function that combines *ks* and *ss*