Discovering Statistical Properties for Query Optimization

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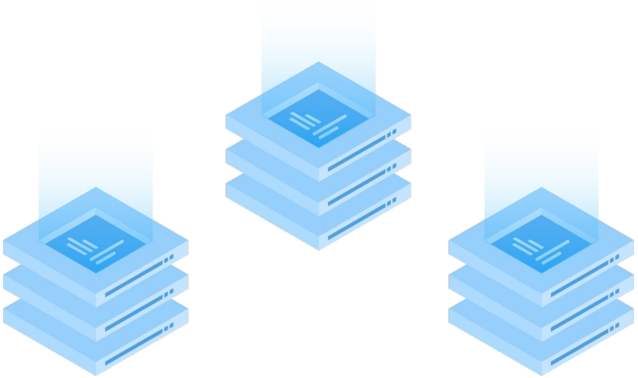
PingCAP TiDB



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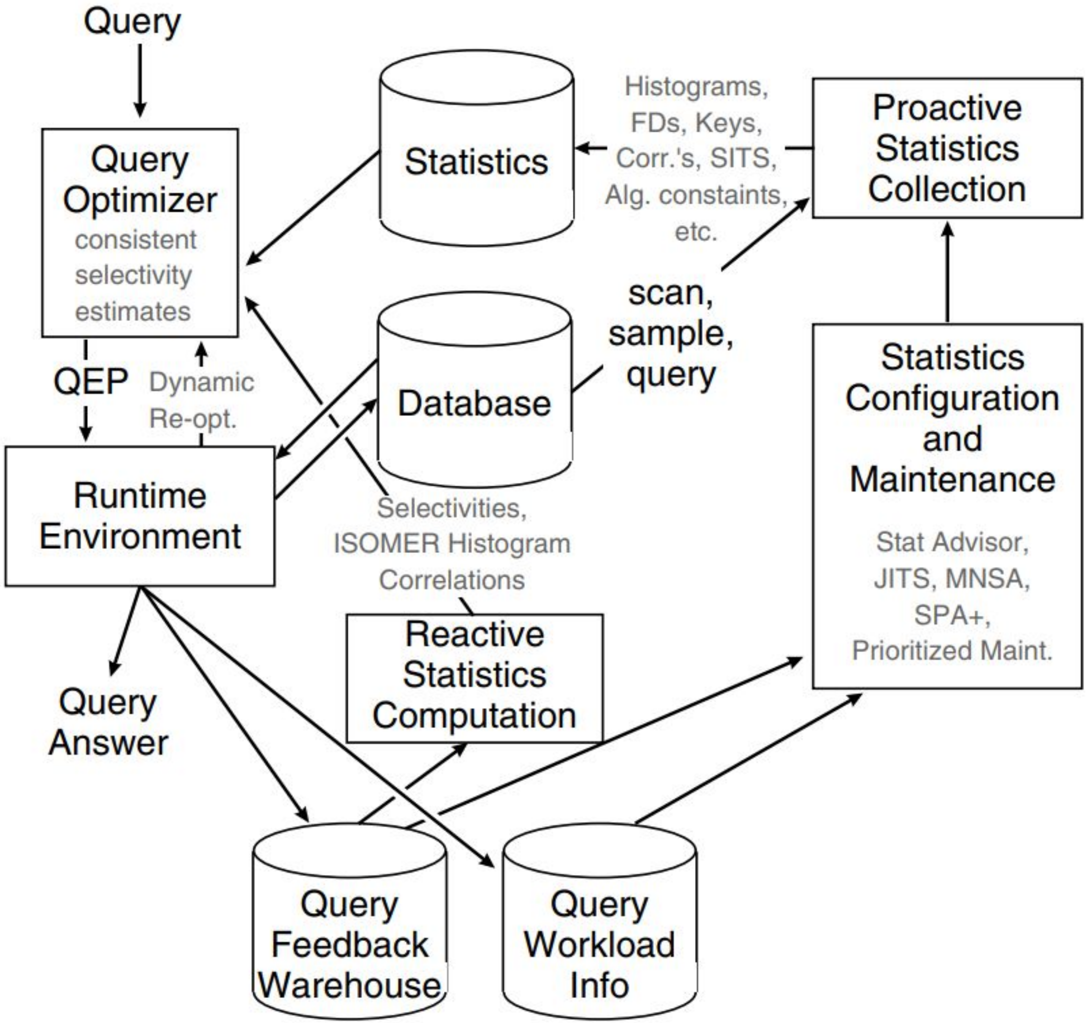
Part I - Introduction to Query Optimization

The Process of Query Optimization

- Enumerate all possible plans by transformation rules (Cascade Optimzier)
- Get the ordinary table/columns cardinality by simple predicate
- Derive cardinality for every subplan
- Estimate the cost of plan and choose the best one


Query
Query Optimizer
consistent selectivity estimates
Statistics
Histograms, FDs, Keys, Corr.'s, SITS, Alg. constaints, etc.
Proactive Statistics Collection
Database
scan, sample, query
QEP
Dynamic Re-opt.
Runtime Environment
Statistics Configuration and Maintenance
Stat Advisor, JITS, MNSA, SPA+, Prioritized Maint.
Selectivities, ISOMER Histogram Correlations
Reactive Statistics Computation
Query Answer
Query Feedback Warehouse
Query Workload Info

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Most Common Statistics : Histogram

- Bucket Scheme
  - Equi-Width
  - Equi-Depth
  - Max Diff
  - V-Optimial
- Estimation Scheme
  - Continuous Spread Assumption
  - Four Level Tree

What do We Need More for Modern Databases?

- Correlation Discovery
- ‘soft’ Functional Dependency
- Algebraic constraints
- Holes in joins
- Workload-aware Methods
- Incremental Maintance

Part II - Proactive Methods

How do we estimate multiple predicates?

- attribute value independece assumption
    - the distributions of individual attributes are independent of each other
- join uniformity assumption
    - a tuple from one relation is equally likely to join with any tuple from the second relation

Automated Correlation Discovery

- Consider a table with tree attributes:
  - Education
  - Income
  - Home-holder
- some of the correlations between attributes might be indirect ones, mediate by others.
  - a high-school dropout who owns a successful Internet startup is more likely to own a home than a highly educated beach bum.

E	I	H	$P(E, I, H)$
h	l	f	0.27
h	l	t	0.03
h	m	f	0.105
h	m	t	0.045
h	h	f	0.005
h	h	t	0.045
c	l	f	0.135
c	l	t	0.015
c	m	f	0.063
c	m	t	0.027
c	h	f	0.006
c	h	t	0.054
a	l	f	0.018
a	l	t	0.002
a	m	f	0.042
a	m	t	0.018
a	h	f	0.012
a	h	t	0.108

Conditionally Independent

- $P(H = h \mid E = e, I = i) = P(H = h \mid I = i)$
- We just need hold some marginal distribution
  - $P(E)$
  - $P(I \mid E)$
  - $P(H \mid I)$
- Then $P(H, E, I) = P(E)\,P(I \mid E)\,P(H \mid I)$

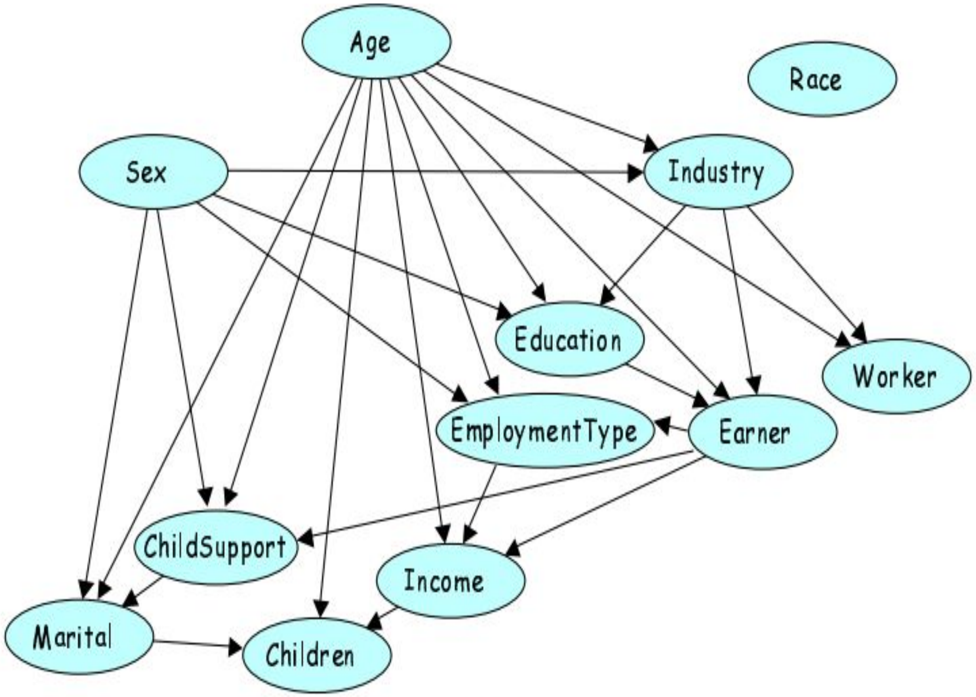
E	$P(E)$
h	0.5
c	0.3
a	0.2

I	E	$P(I \mid E)$
l	h	0.6
m	h	0.3
h	h	0.1
l	c	0.5
m	c	0.3
h	c	0.2
l	a	0.1
m	a	0.3
h	a	0.6

H	I	$P(H \mid I)$
t	l	0.1
f	l	0.9
t	m	0.3
f	m	0.7
t	h	0.9
f	h	0.1

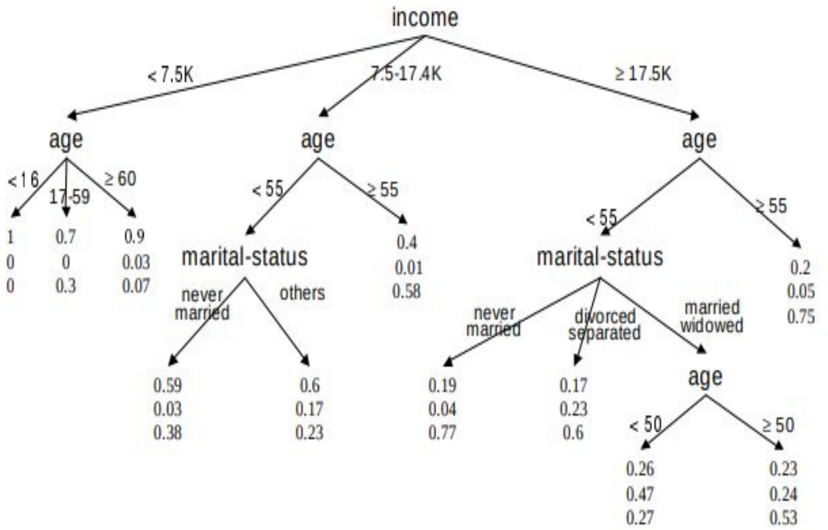
Use Graphical Model to detect correlation

- We can build a Bayesian network which consists of two component
  - a DAG whose nodes correspond to A_1, … , A_n, edges denote a direct dependency of A_i on its parents(A_i)
  - conditional probability distribution



Age
Race
Sex
Industry
Education
Worker
EmploymentType
Earner
ChildSupport
Income
Marital
Children

(a)



income
< 7.5K
7.5-17.4K
≥ 17.5K
age
age
age
< 16
17-59
≥ 60
1
0
0
0.7
0
0.3
0.9
0.03
0.07
< 55
≥ 55
marital-status
0.4
0.01
0.58
never married
others
0.59
0.03
0.38
0.6
0.17
0.23
< 55
≥ 55
marital-status
0.2
0.05
0.75
never married
divorced separated
married widowed
0.19
0.04
0.77
0.17
0.23
0.6
age
< 50
≥ 50
0.26
0.47
0.27
0.23
0.24
0.53

(b)

Part III - Reactive Methods

Feedback based Histogram

- monitor queries on specified column gathering estimated and actual cardinalities
- create/refine maximum-entropy distribution at given condition

Max Entropy Principle

- We define every bucket as $\{l_i, r_i, f_i\}$, of which f_i is relative frequency.
- $H(R) = - sum(m_i / ln (m_i / h_i))$
- Use this principle to determine the boundaries

Meeting a Space Budget - Prunning

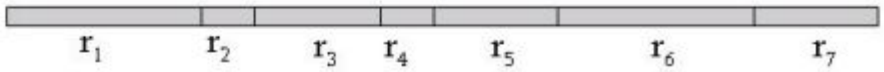


Figure 6: Set of bins before pruning

$$
\begin{array}{ll}
h_1 = 4 & m_1 = 0.2 \\
h_2 = 2 & m_2 = 0.1 \\
h_3 = 3 & m_3 = 0.1 \\
h_4 = 2 & m_4 = 0.2 \\
h_5 = 3 & m_5 = 0.3 \\
h_6 = 4 & m_6 = 0.05 \\
h_7 = 3 & m_7 = 0.05 \\
max = 5 & k = 7
\end{array}
$$

Meeting a Space Budget - Prunning

$$err(r_x, r_{x+1}) = h_x \left| \frac{m_x}{h_x} - \left(\frac{m_x + m_{x+1}}{h_x + h_{x+1}}\right) \right| + h_{x+1} \left| \frac{m_{x+1}}{h_{x+1}} - \left(\frac{m_x + m_{x+1}}{h_x + h_{x+1}}\right) \right| \qquad (6)$$

The error equals zero if and only if two bins imply uniformity.
In this example merging bins 1,2 and 4,5 minimizes the error because:
$err(r_1, r_2) = 4(|\frac{0.2}{4} - \frac{0.2+0.1}{4+2}|) + 2(|\frac{0.1}{2} - \frac{0.2+0.1}{4+2}|) = 0$
$err(r_4, r_5) = 2(|\frac{0.2}{2} - \frac{0.2+0.3}{2+3}|) + 3(|\frac{0.3}{3} - \frac{0.2+0.3}{2+3}|) = 0$

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Thank You !

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