Sampling over Joins

Cardinality Estimation

New Publications

- Yu, Feng, et al. "CS2: a new database synopsis for query estimation." SIGMOD 2013
- Lohman, Guy M. "Is query optimization a “solved” problem." wp.sigmod.org 2014
- Leis, Viktor, et al. "How good are query optimizers, really?." VLDB 2015
- Vengerov, David, et al. "Join size estimation subject to filter conditions." VLDB 2015
- Leis, Viktor, et al. "Cardinality Estimation Done Right: Index-Based Join Sampling." CIDR 2017
- Yu Chen and Ke Yi. "Two-Level Sampling for Join Size Estimation" SIGMOD 2017

*...the **cost model** may introduce errors of at most **30%** for a given cardinality, but the **cardinality model** can quite easily introduce errors of **many orders of magnitude**!*

Lohman, Guy M. "Is query optimization a “solved” problem." wp.sigmod.org 2014

Estimation Methods

- Sampling
    - Independent Sampling
    - Index-Based Sampling
    - Correlated Sampling
    - Bifocal Sampling

- Sketches
    - AGMS sketch

Independent Sampling

- Estimate $\mathbf{A} = |\mathbf{T_1} \bowtie \mathbf{T_2}|$
- $\mathbf{S_1}, \mathbf{S_2}$: independent samples from $\mathbf{T_1}$ and $\mathbf{T_2}$
  - with sampling probabilities $\mathbf{p_1}$ and $\mathbf{p_2}$
- $\mathbf{A^*} = |\mathbf{S_1} \bowtie \mathbf{S_2}|$
- Unbiased estimator $\hat{\mathbf{A}} = \mathbf{A^*} / \mathbf{p_1 p_2}$

Index-Based Sampling

- Estimate $\mathbf{A} = |\mathbf{T_1} \bowtie \mathbf{T_2}|$
- $\mathbf{S_1}$: uniform sample from $\mathbf{T_1}$
- Use the index on $\mathbf{T_2}$ to compute $\mathbf{A^*} = |\mathbf{S_1} \bowtie \mathbf{T_2}|$
- Unbiased Estimator $\hat{\mathbf{A}} = (|\mathbf{T_1}| \,/\, |\mathbf{S_1}|) \bullet \mathbf{A^*}$

Correlated Sampling

- Estimate $\mathbf{A} = |\mathbf{T_1} \bowtie \mathbf{T_2}|$
- Select a hash function $\mathbf{h}$ randomly
  - map the domain of join attribute $\mathbf{a}$ uniformly into $\mathbf{[0, 1]}$
- $\mathbf{S_1}$, $\mathbf{S_2}$: tuples in $\mathbf{T_1}$ and $\mathbf{T_2}$ that $\mathbf{h(T_i.a) < p}$
- $\mathbf{A^* = |S_1 \bowtie S_2|}$
- Unbiased Estimator $\mathbf{\hat{A} = A^* / p}$

- Highly selective filter conditions (indirectly) falling on the join attribute?
  - Star/snowflake schema

Vengerov, David, et al. "Join size estimation subject to filter conditions" VLDB 2015

Frequency Skew

- $\mathbf{R} \ltimes \mathbf{S}$
- Independent & Index-Based Sampling
  - If $\mathbf{a = 1}$ is not chosen for $\mathbf{R}$, then $\hat{\mathbf{A}} = \mathbf{0}$
- Correlated Sampling
  - If $\mathbf{h(1) > p}$, then $\hat{\mathbf{A}} = \mathbf{0}$

R

a
1
2
3
...
n

$\bowtie$

S

a	b
1	1
1	2
1	3
...	...
1	n

Variance Analysis

- Let $\mathbf{F_i(v_j)}$ be the frequency of join attribute value $\mathbf{v_j}$ in table $\mathbf{T_i}$
- $\mathbf{var(\hat{A})}$ is correlated to some forms of $\mathbf{F_i(v_j)}$
- Highly skewed data: some large $\mathbf{F_i(v_j)}$ may dominate the variance

Vengerov, David, et al. "Join size estimation subject to filter conditions" VLDB 2015

Bifocal Sampling

- Compute contributions of large $F_i(v_j)$ separately
  - i.e., detect frequent join attribute values and treat them specially

- Consider $T_1 \bowtie T_2$
  - (dense-dense) For v_j that both $F_1(v_j)$ and $F_2(v_j)$ are large:
    - $A^* \mathrel{+}= F_1(v_j) \times F_2(v_j)$
  - (sparse-dense, dense-sparse, sparse-sparse) Otherwise:
    - A^* += estimations of index-based method for $T_1 \bowtie T_2$ and $T_2 \bowtie T_1$
- Require indexing on both tables

Ganguly, Sumit, et al. "Bifocal sampling for skew-resistant join size estimation." SIGMOD 1996

End-Biased Sampling

- Bias the sample towards keeping the frequent join attribute values

- Consider $\mathbf{T_1} \bowtie \mathbf{T_2}$
  - Choose a hash function $\mathbf{h}$ randomly
    - map the domain of join attribute a uniformly into $\mathbf{[0, 1]}$
  - For each join attribute value $\mathbf{v_j}$:
    - If $\mathbf{F_i(v_j)} >= \mathbf{t_i}$, add $(\mathbf{v_j}, \mathbf{F_i(v_j)})$ to sample
    - Otherwise, if $\mathbf{h(v_j)} < \mathbf{p_j} = \mathbf{F_i(v_j)} / \mathbf{t_i}$, add $(\mathbf{v_j}, \mathbf{F_i(v_j)})$ to sample
- Require exact counts of each join attribute value

Estan, Cristian, and Jeffrey F. Naughton. "End-biased samples for join cardinality estimation." ICDE 2006

Uniform Sampling for Joins

Sampling as a Relational Operator

- Push sampling operator down the tree towards leaves
- Guarantee the equivalence of uniform-sampling semantics
- Selection, projection(without duplicate removal):
  - can be freely interchanged with sampling
- Equi-join
  - Pushing sampling down to both side is hard
    - i.e., $\mathbf{SAMPLE(T_1, f_1)} \bowtie \mathbf{SAMPLE(T_2, f_2)}$ cannot generate $\mathbf{SAMPLE(T_1 \bowtie T_2, f)}$
  - However, it is possible to pushing sampling down to one side

Chaudhuri, Surajit, Rajeev Motwani, and Vivek Narasayya. "On random sampling over joins." SIGMOD 1999

Weighted Sampling for Joins

- Attach weights based on the frequency of join attribute values
  - For hard cases, uniform sampling on either side is infeasible
  - Consider actual join result $\mathbf{T_1} \bowtie \mathbf{T_2}$:
    - ½ tuples with $\mathbf{A = a_1}$
    - ½ tuples with $\mathbf{A = a_2}$
  - $\mathbf{S_1}$: weighted sampling on $\mathbf{T_1}$
    - Pick each $\mathbf{(a_1)}$ with probability proportional to $\mathbf{F_2(a_1) = 1}$
    - Pick $\mathbf{(a_2)}$ with probability proportional to $\mathbf{F_2(a_2) = n}$
  - For each tuple in $\mathbf{S_1}$:
    - choose one joinable tuple from $\mathbf{T_2}$ randomly
- Require full frequency statistics on one side
  - histogram, index

T_1

A
a_1
a_1
...
a_1
a_2

$\bowtie$

T_2

A	**B**
a_1	1
a_2	2
a_2	3
...	...
a_2	n+1

Chaudhuri, Surajit, Rajeev Motwani, and Vivek Narasayya. "On random sampling over joins." SIGMOD 1999

Hybrid Sampling

- What if only partial frequency statistics are available?
  - i.e., statistics for all values with high frequency
    - all $(v_j, F_i(v_j))$ that $F_i(v_j) > t$
- Hybrid sampling strategy
  - Partition the domain into two sets of values
  - high-frequency (in T_2)
    - S_1^{hi}: weighted sampling on T_1
    - J^{hi}: $S_1^{hi} \bowtie T_2$, n^{hi}: $|T_1^{hi} \bowtie T_2|$
  - low-frequency (in T_2)
    - J^{lo}: $T_1^{lo} \bowtie T_2$
  - Combine J^{hi} and J^{lo} with probability proportional to n^{hi} and $|J^{lo}|$
- Require scans on both tables

T_1

A
a_1
a_1
...
a_1
a_2

$\bowtie$

T_2

A	B
a_1	1
a_2	2
a_2	3
...	...
a_2	n+1

Chaudhuri, Surajit, Rajeev Motwani, and Vivek Narasayya. "On random sampling over joins." SIGMOD 1999

Stratified Sampling over Joins

- Each join attribute value as a stratum
- Non-correlated sampling: ***StratJoin***
  - Assume $\mathbf{T_1} \bowtie_{\mathbf{T1.A = T2.A}} \mathbf{T_2}$
  - For every stratum of $\mathbf{T_1}$ and $\mathbf{T_2}$
  - Weighted sampling on $\mathbf{T_1}$
    - Weight a tuple t by probability proportional to $\mathbf{F_2(t.A)}$
  - Weighted sampling on $\mathbf{T_2}$
    - Weight a tuple t by probability proportional to $\mathbf{F_1(t.A)}$
  - Join two samples
- Correlated sampling: ***MaxRandJoin***
  - Allocate a given sample size amongst different strata
  - (near-)optimal allocation: proportional allocation

Kamat N, Nandi A. A Unified Correlation-based Approach to Sampling Over Joins. SSDBM 2017

Joins in AQP

Improve Joins in AQP

- Frequency-Weighted Sampling
    - Wander Join: uniform sampling from the first table in the walk order
    - Wits, Abe. “Estimating Aggregations over Joins”. 2016 (Master Thesis)

- (Bifocal) Sampling for AQP?
    - Star/snowflake schema
        - Cardinality differences between two tables can be very large
        - TPC-H: 97.4% of the joined tuples occur on the probe side

How does CE relate to AQP?

- CE is equivalent to ***COUNT(*)*** in AQP

- ***SUM()*** in AQP can be converted to CE
    -

T

a	**b**
a1	1
a2	2
a3	3

$\rightarrow$

$\mathbf{T_v}$

a	**b**
a1	1
a2	1
a2	1
a3	1
a3	1
a3	1

Skews in CE and AQP

- CE: **frequency skew** only
  - i.e., some attribute values appear more frequently
- AQP: **frequency skew, value skew**
  - **frequency skew** in group-by columns
    - some groups contain more tuples
  - **value skew** in aggregated columns
    - outliers
- Convert AQP to CE
  - value skew ➔ frequency skew

Value-Weighted Sampling

- Uniform sampling in $\mathbf{T_v}$ is equivalent to weighted sampling in $\mathbf{T}$
  - e.g., **SUM(T.b)**
- Attach each tuple **t** a weight proportional to **t.b**

T

p	a	b
1/6	a1	1
2/6	a2	2
3/6	a3	3

$\mathbf{T_v}$

a	b	p
a1	1	1/6
a2	1	1/6
a2	1	1/6
a3	1	1/6
a3	1	1/6
a3	1	1/6

Ding, Bolin, et al. "Sample+ Seek: Approximating Aggregates with Distribution Precision Guarantee." SIGMOD 2016

Improve Joins in AQP #2

- Value-Weighted + Frequency-Weighted?

- Outlier Detection