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 $A = |T_1 \bowtie T_2|$
- S_1 , S_2 : independent samples from T_1 and T_2 with sampling probabilities p_1 and p_2
- $\bullet \quad \mathbf{A}^* = |\mathbf{S}_1 \bowtie \mathbf{S}_2|$
- Unbiased estimator $\hat{A} = A^* / p_1 p_2$

Index-Based Sampling

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

Correlated Sampling

- Estimate $A = |T_1 \bowtie T_2|$
- Select a hash function h randomly
 - \circ map the domain of join attribute **a** uniformly into [0, 1]
- S_1, S_2 : tuples in T_1 and T_2 that $h(T_1.a) < p$
- $\bullet \quad \mathbf{A}^* = |\mathbf{S}_1 \bowtie \mathbf{S}_2|$
- Unbiased Estimator $\hat{A} = A^* / p$
- 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

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

К		
a		a
1		1
2		1
3		1
n		1

b

3

n

D

Variance Analysis

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

Bifocal Sampling

- ullet Compute contributions of large $F_i(v_i)$ separately
 - o i.e., detect frequent join attribute values and treat them specially
- Consider $T_1 \bowtie T_2$
 - \circ (dense-dense) For $\boldsymbol{v_i}$ that both $\boldsymbol{F_1(v_i)}$ and $\boldsymbol{F_2(v_i)}$ are large:
 - $\blacksquare \quad \mathbf{A}^* += \mathbf{F}_1(\mathbf{v}_j) \times \ddot{\mathbf{F}}_2(\mathbf{v}_j)$
 - o (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 $T_1 \bowtie T_2$
 - Choose a hash function **h** randomly
 - lacktriangle map the domain of join attribute a uniformly into [0,1]
 - \circ For each join attribute value \mathbf{v}_i :
 - If $F_i(v_i) \ge t_i$, add $(v_i, F_i(v_i))$ to sample
 - Otherwise, if $h(v_i) < p_i = F_i(v_i) / t_i$, add $(v_i, F_i(v_i))$ 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

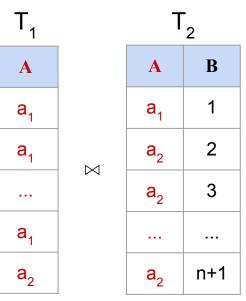
Uniform Sampling for Joins

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):
 - o can be freely interchanged with sampling
- Equi-join
 - Pushing sampling down to both side is hard
 - i.e., SAMPLE(T_1, f_1) \bowtie SAMPLE(T_2, f_2) cannot generate SAMPLE($T_1 \bowtie T_2, f$)
 - However, it is possible to pushing sampling down to one side

Weighted Sampling for Joins

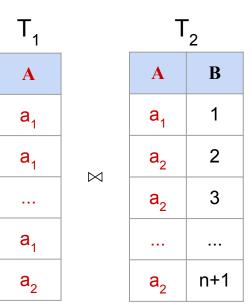
- Attach weights based on the frequency of join attribute values
 - o For hard cases, uniform sampling on either side is infeasible
 - Consider actual join result $T_1 \bowtie T_2$:
 - $\frac{1}{2}$ tuples with $\mathbf{A} = \mathbf{a_1}$
 - $\frac{1}{2}$ tuples with $\mathbf{A} = \mathbf{a}_2$
 - \circ S₁: weighted sampling on T₁
 - Pick each (a_1) with probability proportional to $F_2(a_1) = 1$
 - Pick (a_2) with probability proportional to $F_2(a_2) = n$
 - For each tuple in S_1 :
 - \blacksquare choose one joinable tuple from T, randomly
- Require full frequency statistics on one side
 - o histogram, index



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

Hybrid Sampling

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



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
 - \circ Assume $T_1 \bowtie_{T_1 \land T_2 \land} T_2$
 - \circ For every stratum of T_1 and T_2
 - \circ Weighted sampling on T_1
 - Weight a tuple t by probability proportional to $F_2(t.A)$
 - \circ Weighted sampling on T,
 - Weight a tuple t by probability proportional to $F_1(t.A)$
 - Join two samples
- Correlated sampling: MaxRandJoin
 - Allocate a given sample size amongst different strata
 - o (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

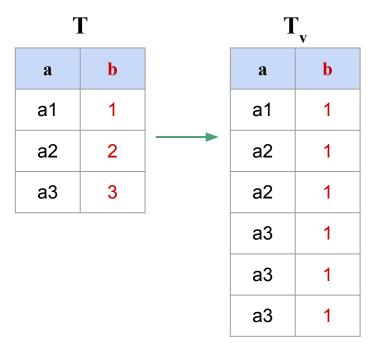
- Frequency-Weighted Sampling
 - Wander Join: uniform sampling from the first table in the walk order
 - Wits, Abe. "Estimating Aggregations over Joins". 2016 (Master Thesis)

- (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



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
 - o **value skew** in aggregated columns
 - outliers
- Convert AQP to CE
 - value skew → frequency skew

Value-Weighted Sampling

ullet Uniform sampling in T_v is equivalent to weighted sampling in T

e.g., SUM(T.b)

 Attach each tuple t a weight proportional to t.b p a b 1/6 a1 1 2/6 a2 2 3/6 a3 3

b a **a**1 a2 a2 **a**3 **a**3 **a**3

p

1/6

1/6

1/6

1/6

1/6

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