



AQP++: Connecting Approximate Query Processing with Aggregate Precomputation for Interactive Analytics

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Interactive Analytics

Hardware



Big Data



How to enable interactive analytics over big data?

Two Separate Ideas

1. Approximate Query Processing (AQP)

2. Aggregate Precomputation(AggPre)

Running Example

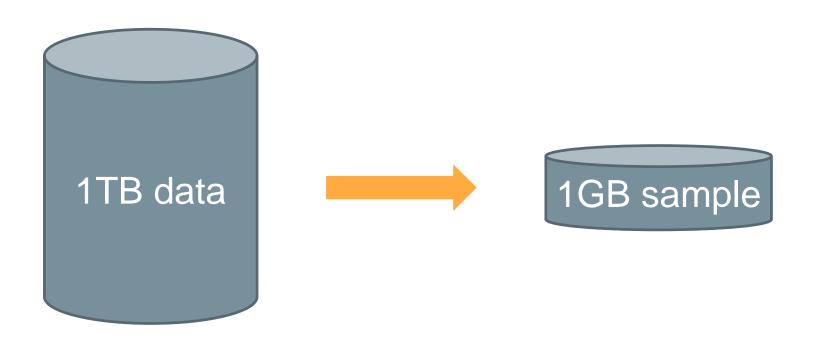
query: SELECT SUM(price) WHERE id in [1000, 9000]

Fact Table

ID	Price	
1	100	
2	50	
1000	900	
9000	70	
12000	500	

Idea 1: AQP

SELECT SUM(price) WHERE id in [1000, 9000]



Idea 2: AggPre

SELECT SUM(price) WHERE id in [1000, 9000]

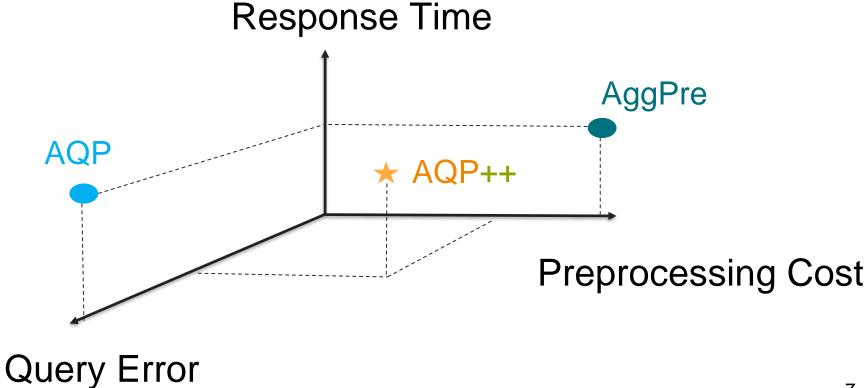
Prefix-Sum Cube[1]

ID	Price	
≤1	100	
≤2	150	
≤999	1.1*10 ⁵	
≤9000	8.1*10 ⁵	
≤12000	9.8*10 ⁵	

SELECT SUM(price)
WHERE id ≤ 999

SELECT SUM(price)
WHERE id ≤ 9000

Tradeoff



How AQP++ works?

SELECT SUM(Price) WHERE id in [1000, 9000]

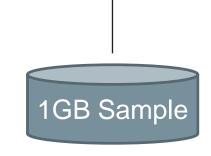
AQP++ estimator

SELECT SUM(Price)
WHERE id in (1100,9000)

Partial Cube

ID	Price
≤500	5.1*10 ⁴
≤1100	9.7*104
≤2000	2.5*10 ⁵
≤4000	4.6*10 ⁵
≤9000	8.1*10 ⁵
≤12000	9.8*10 ⁵

SELECT SUM(Price)
WHERE id in [1000, 1100]



AQP++ Estimator

AQP

q: SELECT f(A) FROM D WHERE condition₁

$$\mathsf{Est} = \hat{q}(S)$$

sample

AQP++

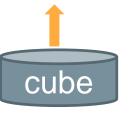
q: SELECT f(A) FROM D

WHERE condition₁

pre: SELECT f(A) FROM D

WHERE condition₂

Est = pre(D) +
$$\{\hat{q}(S) - p\hat{r}e(S)\}$$





Good Properties of AQP++

1. Unify AQP and AggPre.

2. Support any aggregate function that AQP can support (e.g., SUM, COUNT, AVG, VARIANCE).

3. Easy to implement.

Research Challenges

➤ Query Processing

➤ Preprocessing

Query Processing Challenge

SELECT SUM(Salary) WHERE id in [1000, 8000]

ID	Price
≤500	5.1*10 ⁴
≤1100	9.7*104
≤2000	2.5*10 ⁵
≤4000	4.6*10 ⁵
≤9000	8.1*10 ⁵
≤12000	9.8*10 ⁵

(500,1100]	(1100,9000]	(9000,12000]
(500,2000]	(1100,12000]	$(-\infty,500]$
(500,4000]	(2000,4000]	$(-\infty,1100]$
(500,9000]	(2000,9000]	$(-\infty,2000]$
(500,12000]	(2000,12000]	$(-\infty,4000]$
(1100,2000]	(4000,9000]	$(-\infty,9000]$
(1100,2000]	(4000,9000]	(-∞,9000]
(1100,4000]	(4000,12000]	(-∞,12000]

Too many precomputed queries!

How to **efficiently** find the best one?

Step1: Get Candidates

SELECT SUM(Salary) WHERE id in [1000, 8000]

ID	Price
≤500	5.1*104
≤1100	9.7*104
≤2000	2.5*10 ⁵
≤4000	4.6*10 ⁵
≤9000	8.1*10 ⁵
≤12000	9.8*10 ⁵



Candidates

pre 1: (500, 4000]

pre 2: (500, 9000]

pre 3: (1100, 4000]

pre 4: (1100, 9000]

pre 5: Ø

Step 2: Estimate Errors

SELECT SUM(Salary) WHERE id in [1000, 8000]

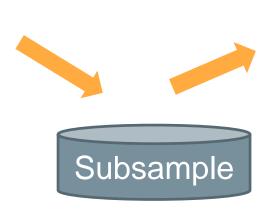
pre 1: (500, 4000]

pre 2: (500, 9000]

pre 3: (1100, 4000]

pre 4: (1100, 9000]

pre 5: Ø



Err(pre 1): 2.5%

Err(pre 2): 1.2%

Err(pre 3): 2%

Err(pre 4): 1%

Err(pre 5): 10%

Research Challenges

➤ Query Processing

> Preprocessing

Preprocessing Challenge

Partial Cube 1

ID	Price
≤500	5.1*10 ⁴
≤1100	9.7*104
≤2000	2.5*10 ⁵
≤4000	4.6*10 ⁵
≤9000	8.1*10 ⁵
≤12000	9.8*10 ⁵

Partial Cube 2

ID	Price
≤1	100
≤2	150
≤3	1150
≤4	1200
≤5	1330
≤6	1600

Partial Cube 3

ID	Price
≤2000	2.5*10 ⁵
≤4000	4.6*10 ⁵
≤6000	6.3*10 ⁵
≤8000	7.5*10 ⁵
≤10000	8.9*10 ⁵
≤12000	9.8*10 ⁵

Too many possible cubes!

Given a space budget, how to find the best cube?

Theoretical Result

ID	Price
≤2000	2.5*10 ⁵
≤4000	4.6*10 ⁵
≤6000	6.3*10 ⁵
≤8000	7.5*10 ⁵
≤10000	8.9*10 ⁵
≤12000	9.8*10 ⁵

Equal partition is optimal when:

- 1. Condition column has no duplicate.
- 2. Aggregate column and condition column are independent.

Hill Climbing for General Case

Basic Idea

- Initialization: Equal partition.
- Adjustment: Move one partition point to form a better cube.

Two Issues

- 1. How to efficiently compute the error of cube?
- 2. Which point & where to move?

SELECT SUM(A) FROM table WHERE C

SELECT f(A) FROM table WHERE C

SELECT f(A) FROM table WHERE C₁, C₂, ... C_n

SELECT f(A)FROM table WHERE $C_1, C_2, ..., C_n$ GROUP-BY G

```
SELECT f(A)

FROM table_1, table_2

WHERE table_1.PK = table_2.FK & C_1, C_2, ... C_n

GROUP-BY G
```

Exp: Setup

- > Environment
 - Windows
 - 16 GB RAM, 1TB HDD
 - Visual Studio C++

➤ Dataset

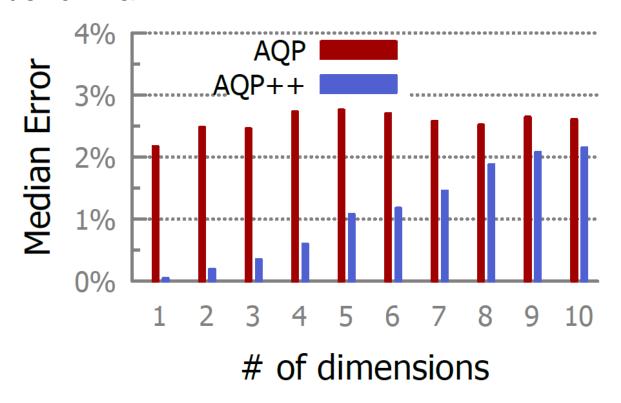
- TPCD benchmark (100GB, 600 million, skewness=2)
- BigData benchmark (100GB, 752 million)
- TLCTrip (200GB, 1400 million)

➤ Default Parameter

- Sample ratio: 0.05%
- Cube size: 50000
- Query selectivity: 0.5% to 5%

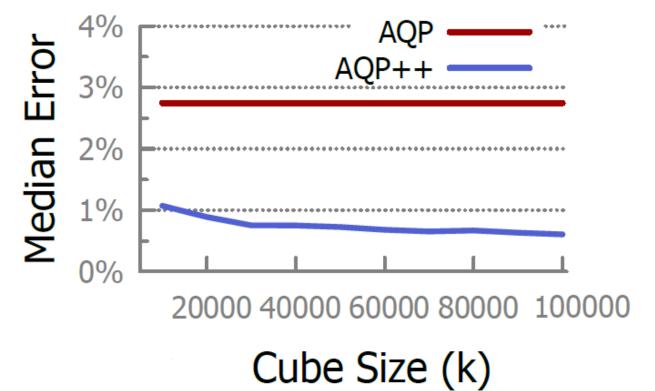
AQP++ can scale up to 10 dims

TPCD benchmark



A small cube can improve quality a lot

BigData benchmark



Performance Summary

TPCD benchmark 2-dim Query

	Preprocessing Cost		Response	Average
	Space	Time	Time	Error
AQP	51.2 MB	5.6 min	0.58 sec	2.56%
AggPre	> 10 TB	> 1 day	< 0.01 sec	0.00%
AQP++	51.9 MB	9.8 min	0.64 sec	0.28%

AQP++ can be up to 10X more accurate!

Related Work

- Alex Galakatos, Andrew Crotty, Emanuel Zgraggen, Carsten Binnig, and Tim Kraska.
 "Revisiting reuse for approximate query processing." VLDB'2017
- Yongjoo Park, Ahmad Shahab Tajik, Michael Cafarella, and Barzan Mozafari. "Database learning: Toward a database that becomes smarter every time. " SIGMOD'2017
- Bolin Ding, Silu Huang, Surajit Chaudhuri, Kaushik Chakrabarti, and Chi Wang. "Sample+ seek: Approximating aggregates with distribution precision guarantee." SIGMOD'2016
- Jiannan Wang, Sanjay Krishnan, Michael J. Franklin, Ken Goldberg, Tim Kraska, and Tova Milo. "A sample-and-clean framework for fast and accurate query processing on dirty data." SIGMOD'2014
- Niranjan Kamat, Prasanth Jayachandran, Karthik Tunga, and Arnab Nandi. "Distributed and interactive cube exploration." ICDE'2014
- Ruoming Jin, Leonid Glimcher, Chris Jermaine, and Gagan Agrawal. "New sampling-based estimators for OLAP queries." ICDE'2006

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Key Takeaways



- AQP++: Connect AQP with Aggregate Precomputation
- Achieve a better tradeoff among preprocessing cost, response time, and query quality.
- Up to 10x more accurate than AQP.



https://github.com/sfu-db/aqppp

Thank You! Q&A