TRUST BUT VERIFY Optimistic Visualizations of Approximate Queries for Exploring Big Data

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HCI and DMX **Microsoft Research**



What's the distribution of flight distances?

\$ wget https://www.transtats.bts.gov/download.zip

- -> Done
- \$ import download.zip
- -> Done
- \$ SELECT bin(distance), count(*) FROM flights
- -> Running Query. Please wait ...

Visual Analysis



Computer by Simple Icons from the Noun Project analyst by Gregor Cresnar from the Noun Project

Big Data Visual Analysis

Query finished!



\$ SELECT bin(distance), count(*) FROM flights



\$ SELECT bin(distance), count(*)
 FROM flights
 WHERE airline = 'hi'

-> Running Query. Please wait ...

State of the Art in Big Data Exploration

Distributed Systems Expensive and high latency.

Indexes (Data Cubes) Requires pre computation and limited queries.

Sampling

Use a representative subset of the data.

Rubik's Cube by Aleks from the Noun Project Cluster servers by Branis Panos from the Noun Project

Sampling and Approximate Query Processing (AQP)

Use a representative subset of the data and estimate the true values of aggregate results.

Sampling and Approximate Query Processing (AQP)

Use a representative subset of the data and estimate the true values of aggregate results. Decide on acceptable uncertainty or timeout

Sum of 25% = 42

Estimate

Sum of 100 % = 168 ±10 Uncertainty

Progressive Visualization with Online Aggregation

Growing sample - continuously improving results

Analysts watch updates until bounds errors are low enough

Query finished!

- \$ SELECT bin(distance), count(*)
 FROM flights
 WHERE airline = 'hi'
- -> No Results
- \$ SELECT bin(distance), count(*)
 FROM flights
 WHERE airline = 'ha'
- -> Running Query. Please wait ...

Hawaiian Airlines

Challenges with AQP

Approximate results → Convey uncertainty Probabilistic guarantees Unbounded errors Arbitrary aggregation or joins

Optimistic Visualization A UX approach to challenges with AQP traditionally treated as database problems.

Optimistic Visualization

Assume that approximation is mostly right but offer a way to detect and recover from mistakes.

Analysts use initial estimates, run precise query in background, and confirm results later.

Gives users confidence in using AQP.

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්ට ≍ Massive drop off after Sep 2001 Remember 25M Exact data loaded (18s) 20M Сlж 3 decades of llights 15M 10M 5M U Exact data loaded (50s) ආ ≍ Spike near 0 minutes Loading exact data. 400k 300k 200k 100k 0 History Clear History Reset App

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Remember	

Load more data

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Expect almost no errors: 0.3%

What have you learned?

Year

Continue exploration without waiting

Evaluation

Lab Study 5 users Flight delay data (170 Million records)

1 hour each

Case Study 3 teams Product insights, Social media, Bing ~1+ hour exploration

Findings from the study

AQP works: "seeing something right away at first glimpse is really great"

Optimism works: "I was thinking what to do next— and I saw that it had loaded, so I went back and checked it . . . [the passive update is] very nice for not interrupting your workflow."

Need for guarantees: "[with a competitor] I was willing to wait 70-80 seconds. It wasn't ideally interactive, but it meant I was looking at **all** the data."

Findings from the study (cont)

"When I'm using your system, there is a path that I need to follow."

"Now that I've been sitting here for an hour, after I go back, it makes a lot of sense [to have these annotations], but as I was doing it, I was thinking, 'I want to move on, I want to move on."

Conclusions

Fundamental problems with AQP addressed as **UX problem**

Gives analysts confidence in AQP

Future: Alerting, Remembering, Progressive + Optimistic

AQP needs Multi-Disciplinary Solutions

Implications for the Database Community

HILDA at SIGMOD 2017

What Users Don't Expect about Exploratory Data Analysis on **Approximate Query Processing Systems**

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ABSTRACT

Pangloss implements "Optimistic Visualization", a method that gives analysts confidence to use approximate results for exploratory data analysis. In this paper, we outline how analysts' experience with an approximate visualization system did not match their intuitions. These observations have implications for the design of future data exploration systems that expose uncertainty. We also describe requirements for approximate query engines to enable the next generation of exploratory visualization systems.

CCS CONCEPTS

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data system: it allows users to explore their data through fast, approximate queries; users can then request precise responses with slow queries over the full data. In the first phase, the engine that drives Pangloss, called "Sample+Seek" [3], returns approximate results in interactive time with an overall uncertainty level.

This is a new experience for users. Pangloss requires users to work with a new uncertainty model, with two-round queries, and to directly face the implications of uncertainty. We see all of these as important and valuable changes in a world that increasingly embraces AQP; however, they can be surprising for users. These user stories will allow us to begin to design for interacting with

Trust But Verify: Optimistic Visualizations for AQP

Fundamental problems with AQP addressed as UX problem

Optimistic Visualization gives analysts confidence in AQP

Integrates well into existing Visual Analysis tools

Future: Alerting, Remembering, Progressive

Details: <u>bit.ly/2pwQQg7</u>

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Query finished!

Backup Slides

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Histogram of Distances for Hawaiian Airlines

Distribution Uncertainty

Within Distribution Uncertainty

Outside Distribution Uncertainty

Error: 4 Sum: 12

Distribution Uncertainty

Origin

Remember

Filtering can show new groups

new predicate → new query → different sample → different groups

Precise results can show new groups

Approximate

Carrier

Precise

Vocabulary of visual cues

Heatmap

Barchart