

# REAL-TIME EXPLORATION OF LARGE SPATIOTEMPORAL DATASETS BASED ON ORDER STATISTICS

Original Work By: Cicero Pahins, Nivan Ferreira, and Joao Comba

Presented By: Vaastav Anand

## OUTLINE

- Background
- Motivation
- Quantile Datacube Structure
- Example Visualizations
- Evaluation
- Critique

## SPATIOTEMPORAL DATASETS



"Datasets generated from measuring a set of values across set of locations (spatial dimension) across a time range (temporal dimension)."

PROBLEM: Dataset is too large to perform interactive analysis.

## EXISTING SOLUTIONS

- Precomputed Indices that store aggregations of a given dataset as solutions to this problem.
  - Doesn't take into account data distribution
- Gaussian Cubes that support interactive data modelling by describing data distribution using parametric Gaussian distributions.
  - Based on non-robust statistics (mean + covariance)
  - Can't assume real-world data has a normal distribution

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## PROBLEMS WITH CURRENT SOLUTIONS

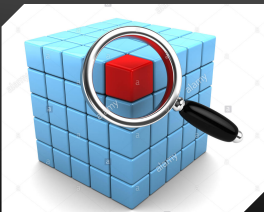
- Memory footprint is too high
- Distributions are approximated using non-robust statistics
- Queries are slow enough to disallow interactive experience
- Queries are limited to count queries

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## QUANTILE DATACUBE STRUCTURE

- A novel datastructure
- Encode data distributions based on robust statistics
- Uses a non-parametric modelling technique called p-digest
- A novel indexing structure that reduces the large memory footprint



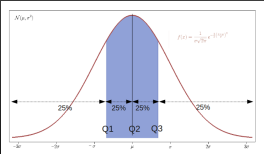
## EXAMPLE QUESTIONS

- "How likely is a flight operated by Delta Airlines to be delayed more than 10 minutes at JFK airport?"
- "How does the distribution of flight delays for two airports compare to each other in the past month?"
- "How unusual are the delays experienced by Delta flights on January 29", 2017?"

## INDEXING SCHEME

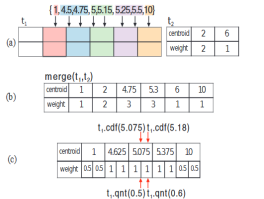
## P-DIGEST DATA SKETCH : T-DIGEST DATA SKETCH

- "Data Sketch": Data Structure that can be easily updated with new or modified data and supports a set of queries whose results approximate queries on the full dataset.
- An optimized version of t-digest data sketch
  - Quantile sketch that supports queries of quantile and cdf estimation.
  - Summarizes the empirical cdf of an input dataset by a set of weighted values called centroids.



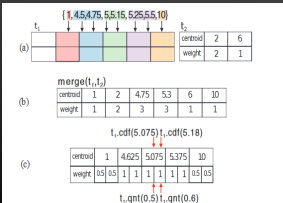
## P-DIGEST DATA SKETCH : T-DIGEST DATA SKETCH

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- An optimized version of t-digest data sketch
  - Quantile sketch that supports queries of quantile and cdf estimation.
  - Summarizes the empirical cdf of an input dataset by a set of weighted values called centroids.
  - Compression Parameter defines the number of centroids
  - Queries for extreme quantiles are made more accurate



## P-DIGEST DATA SKETCH

- "Data Sketch": Data Structure that can be easily updated with new or modified data and supports a set of queries whose results approximate queries on the full dataset.
- An optimized version of t-digest data sketch
  - Reduce centroid storage from 40-80 bytes per centroid array to at most 8 bytes for each of the centroid and weighted arrays. Stored as single chunk of floats
  - If all weight values are 1 then weights are not stored.



## QUERY TYPES

- 3 types
  - Quantile queries
  - CDF queries: Modeled as inverse of quantile queries
  - Pipeline queries: Result of a given query is used as a parameter to another query

Primary Query: **select AGGR from QDR where CONSTRAINTS [group by G]**

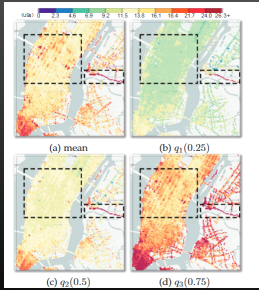
## QUERY ALGORITHM

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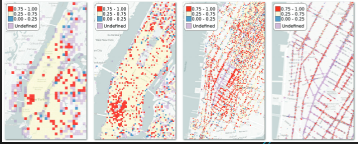
## QUANTILE HEATMAPS

- Instead of using the mean for a given location, use the specified quantile at the location as the aggregate measure
- Quantiles are not sensitive to outliers whereas mean is.
- Powered by QDS's quantile queries



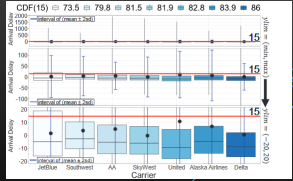
## CDF HEATMAPS

- Instead of showing mean, they show high likely a distribution in a given location is to be smaller than a certain value
- Powered by QDS's cdf query



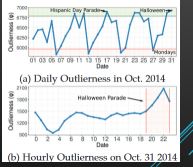
## READABLE UNCERTAINTY VISUALIZATIONS

- Interpreting uncertainty visualizations is not easy.
  - Can have high cognitive load
  - Viz researchers have idioms to shift the cognitive load
  - But existing interactive techniques are not efficient
- QDS's cdf query can allow for this interactivity by computing the result for each box plot.



## OUTLIER EXPLORATION

- Finding outliers requires users to inspect a large number of data slices over time and space.
- QDS can retrieve approx. distributions over an arbitrary portion of the data very quickly.
- Authors define an outlier measure supported by QDS's pipeline query.



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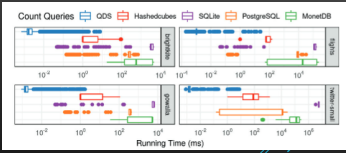
## MEMORY FOOTPRINT

- Comparable memory footprint with HashedCubes.
- Better for some datasets, Worse for other datasets

Overall summary of the relevant information for building QDS.									
dataset	size	index schema(bits)	payload schema	QDS Memory/Time	HC Memory/Time	QDS Memory/Time	HC Memory/Time	QDS Memory/Time	HC Memory/Time
lightbike	4.5 M dayOfWeek (3), hourOfDay (5), time (16), lat (25), lon (25)	NA	NA	455 MB/7s	276 MB/7s	455 MB/7s	276 MB/7s	455 MB/7s	276 MB/7s
gsmalls	8.4 M dayOfWeek (3), hourOfDay (5), time (16), lat (25), lon (25)	NA	NA	713 MB/13s	369 MB/13s	713 MB/13s	369 MB/13s	713 MB/13s	369 MB/13s
twitter-small	208.6 M dayOfWeek (3), time (16), lat (17), lon (17)	NA	NA	1.1 GB/10.5m	2.7 GB/10.5m	1.1 GB/10.5m	2.7 GB/10.5m	1.1 GB/10.5m	2.7 GB/10.5m
hailu	120.8 M dayOfWeek (3), time (16), lat (25), lon (25)	NA	NA	1.6 GB/10.5m	4.2 GB/10.5m	1.6 GB/10.5m	4.2 GB/10.5m	1.6 GB/10.5m	4.2 GB/10.5m
Nights	121.7 M dayOfWeek (3), time (16), lat (25), lon (25)	NA	NA	1.6 GB/10.5m	4.2 GB/10.5m	1.6 GB/10.5m	4.2 GB/10.5m	1.6 GB/10.5m	4.2 GB/10.5m
green-taxi-small	40 M dayOfWeek (3), hourOfDay (5), time (16), lat (25), lon (25)	NA	NA	1.2 GB/10.5m	3.0 GB/10.5m	1.2 GB/10.5m	3.0 GB/10.5m	1.2 GB/10.5m	3.0 GB/10.5m
green-taxi	40 M dayOfWeek (3), hourOfDay (5), time (16), lat (25), lon (25)	NA	NA	1.2 GB/10.5m	3.0 GB/10.5m	1.2 GB/10.5m	3.0 GB/10.5m	1.2 GB/10.5m	3.0 GB/10.5m
yellow-taxi-small	786 M dayOfWeek (3), hourOfDay (5), time (16), lat (25), lon (25)	NA	NA	9.3 GB/24.4m	21.8 GB/24.4m	9.3 GB/24.4m	21.8 GB/24.4m	9.3 GB/24.4m	21.8 GB/24.4m
yellow-taxi	786 M dayOfWeek (3), hourOfDay (5), time (16), lat (25), lon (25)	NA	NA	9.3 GB/24.4m	21.8 GB/24.4m	9.3 GB/24.4m	21.8 GB/24.4m	9.3 GB/24.4m	21.8 GB/24.4m

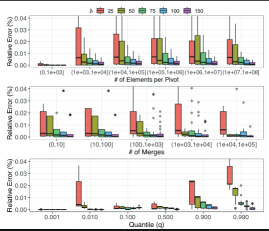
## PERFORMANCE

- Measures the performance of count queries.
- QDS is faster than HashedCubes, MonetDB, SQLite, PostgreSQL
- MonetDB, SQLite, PostgreSQL don't provide effective mechanisms for spatial filtering with temporal and categorical constraints.



## P-DIGEST APPROXIMATION ERROR

- The error rate is fairly low for low quantiles, high merges, and low # of elements per pivot
  - More accurate when data broken down into more parts
  - Accurate for small input data
  - Large values of compression parameter better for higher quantile estimation.
- The error measured is the relative error of the estimated quantile to the actual empirical quantile

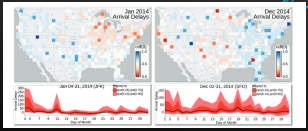


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## WHAT-WHY-HOW FRAMEWORK

- What?
  - Large Static Spatiotemporal datasets
- Why?
  - Better Memory Footprint
  - Quicker Results -> More Interactive exploration
  - Robust Metrics + Visualizing Uncertainty
- How?
  - QDS - New Datastructure for storing indices of spatiotemporal datasets
  - New queries that can approximate quantiles + cdf.



## STRENGTHS

- Thorough performance eval
  - Good comparisons vs believable baselines
- Built on/Promotes usage of Robust Statistics
- Allows for exploration of uncertainty in datasets.



## WEAKNESSES

- Lack of Validation: No User Study
  - One of the goals was more interactivity. Can't validate w/o user study.
- Lack of Error Estimation
  - The distributions are approximations but currently the user has no way of knowing how good the approximation is
- Lack of Detail: Building QDS with a dataset. (minor)
  - Needs more detail about how to specify the schema
- Meta Comment: Should use a spellchecker. (minor)



## CONCLUSION

- Presents QDS: a fast in-memory data structure
  - Supports uncertainty exploration + data distribution estimation
  - Designed for large static spatiotemporal datasets
- Source Code: <https://github.com/cicero/qds>
- Video: <https://vimeo.com/262669555>

