

Extracting Aggregate Answer Statistics for Integration

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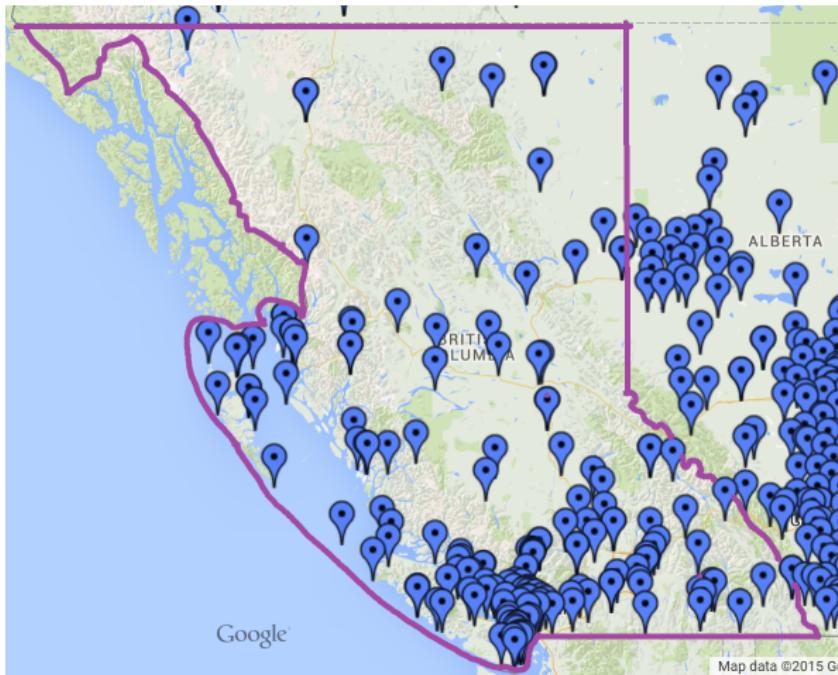


Average high temperature across British Columbia

- Climate change?
 - What is the average high temperature in British Columbia for each year?
 - Averaging across the temperature over the entire province seems reasonable?
 - Query the weather stations to find the average

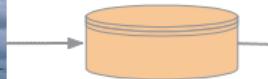


Weather stations not distributed uniformly across BC



Sources have inconsistent values for same data points

- Weather of Vancouver on 11-June-2006?



Location	Avg Temp	Date
Burnaby	21	10-June-06
Vancouver	19	11-June-06
Surrey	18	11-June-06
...

Sources have inconsistent values for same data points

- Weather of Vancouver on 11-June-2006?



Location	Avg Temp	Date
Burnaby	21	10-June-06
Vancouver	19	11-June-06
Surrey	18	11-June-06
...



City	Temp	Date
Burnaby	21	06/10/06
Vancouver	22	06/11/06
Richmond	18	06/12/06
Richmond	18	06/13/06
...

Sources have different coverage and quality

- Coverage: single source contains information about a subset of objects and a subset of object attributes
- Quality: inconsistent or even conflicting values for the same object

Location	Avg Temp	Date
Burnaby	21	10-June-06
Vancouver	19	11-June-06
...

City	Temp	Date
Burnaby	21	06/10/06
Vancouver	22	06/11/06
Richmond	18	06/12/06
Richmond	18	06/13/06
...

City	Temp	Date	...	Total Rain
Burnaby	19	10-June-06	...	0.2
Vancouver	17	11-June-06	...	0.0
Surrey	15	11-June-06	...	0.0
Vancouver	20	12-June-06	...	1.4
...

Location	Temp	Date	Total Snow	Total Rain
Surrey	15	06/11/06	0.0	0.0
Surrey	19	06/12/06	0.0	1.2
...

Aggregate queries

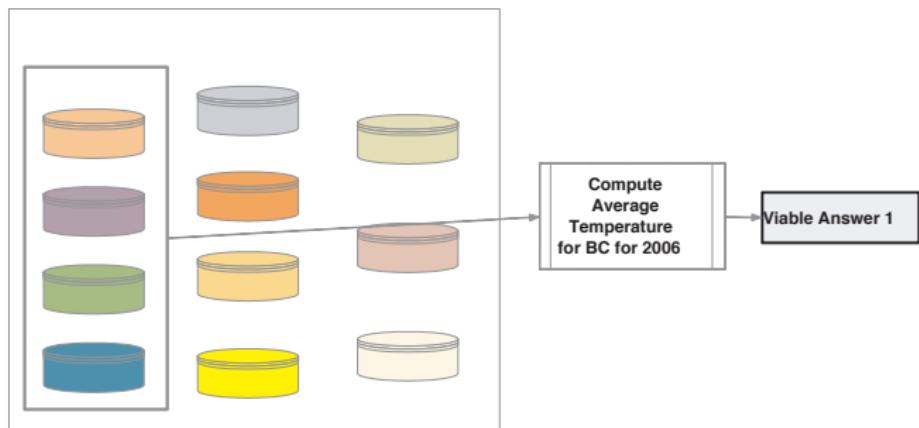
- Group set of data values and calculate informative statistics
 - Sum, Median, Avg ...
- Answering them in integration contexts
 - Requires combining sets of data that are segmented across multiple data sources
- Standard aggregation averages over all the points
 - It is incorrect!
 - Some data points have duplicates across the sources
 - The duplicates can have different values in the sources

Viable answer

- Correct aggregation requires using one value per data point
- Choosing the values from different sources will result in different answers
- Each possible answer called a viable answer
- Which set of sources and value combinations to use?

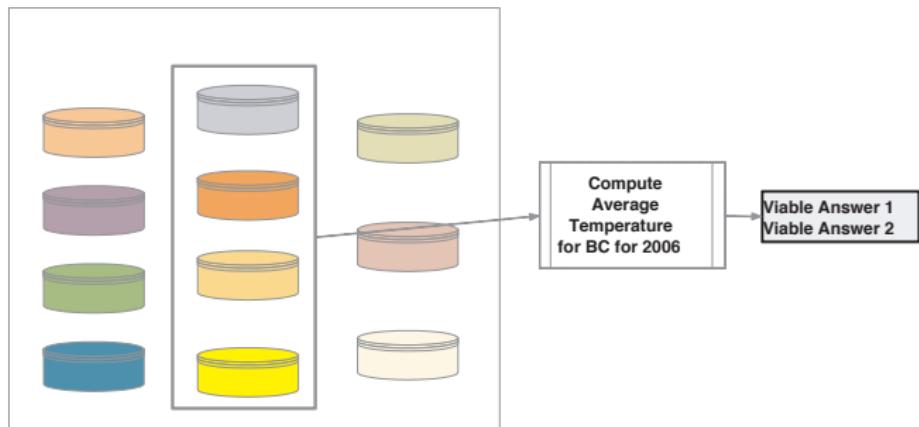
Different combinations of sources and values are possible

- Which set of sources and value combinations to use?



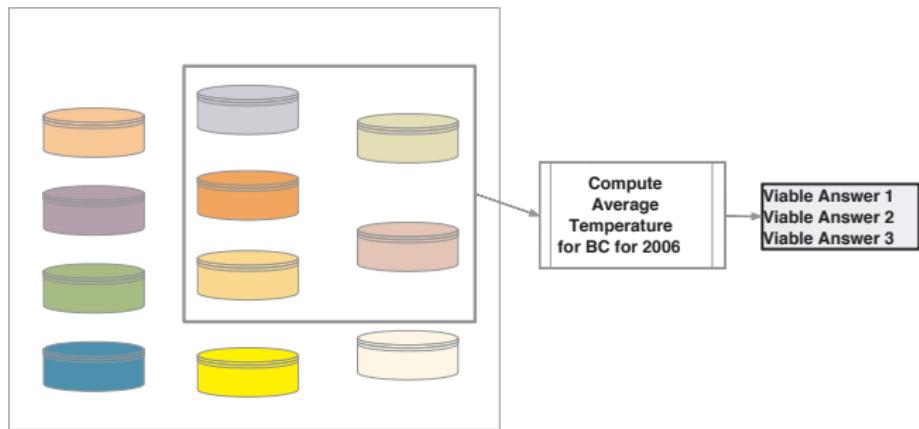
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- Which set of sources and value combinations to use?



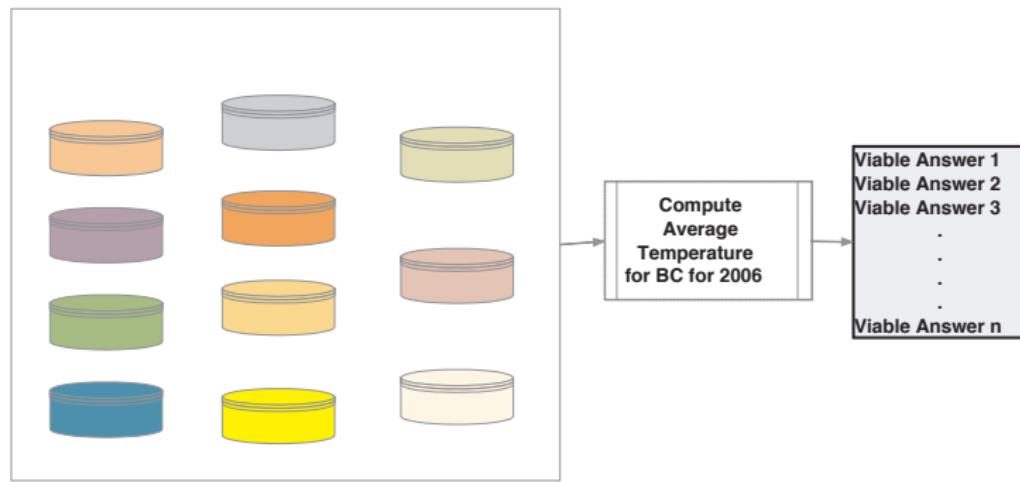
Different combinations of sources and values are possible

- Which set of sources and value combinations to use?



Different combinations of sources and values are possible

- Depending on the choice of sources and value combinations, there can be a whole range of viable answers
- Aggregate query answer is a distribution rather than a single scalar value



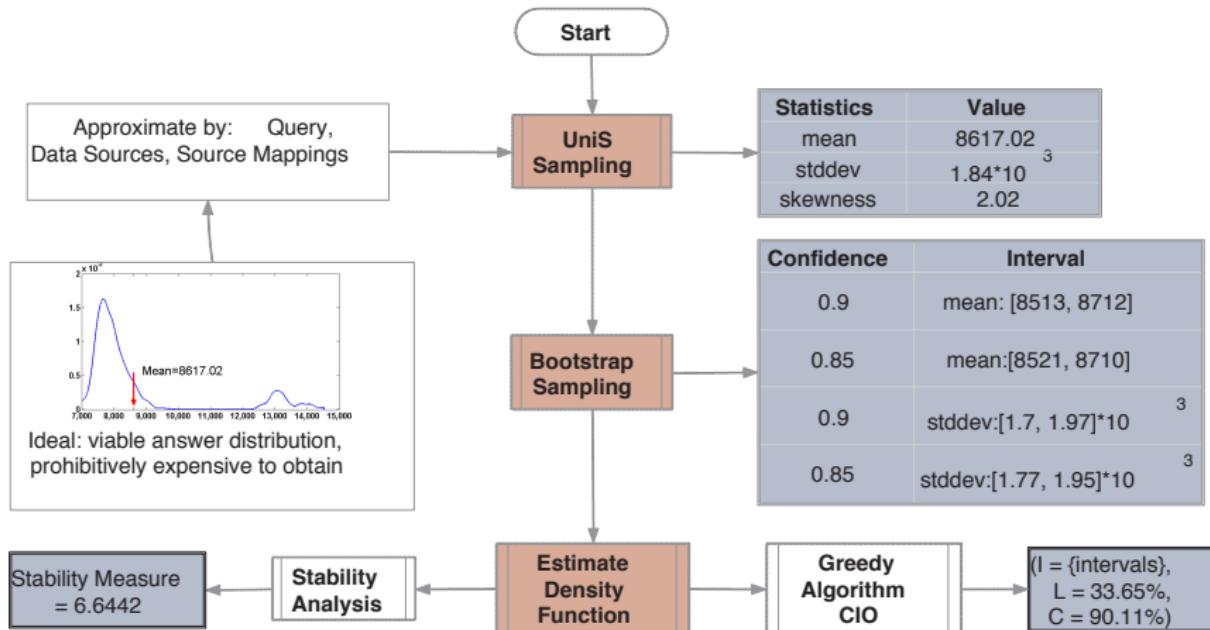
Problem formalization

- Assume meta-information regarding mapping and bindings is available
- Question: What is the viable answer distribution?
 - Enumerating all the possible value combinations is impractical
 - Estimating the exact distribution is infeasible
 - Scalability issues
 - User still has to interpret and analyze

Contributions

- We define aggregate answers as a distribution of viable answers
- We provide summary statistics for the viable answer distribution
 - Key point statistics
 - High coverage intervals
 - Stability score
- We provide algorithms for the efficient extraction of above statistics
- We verify the effectiveness of our methods using real-life and synthetic data

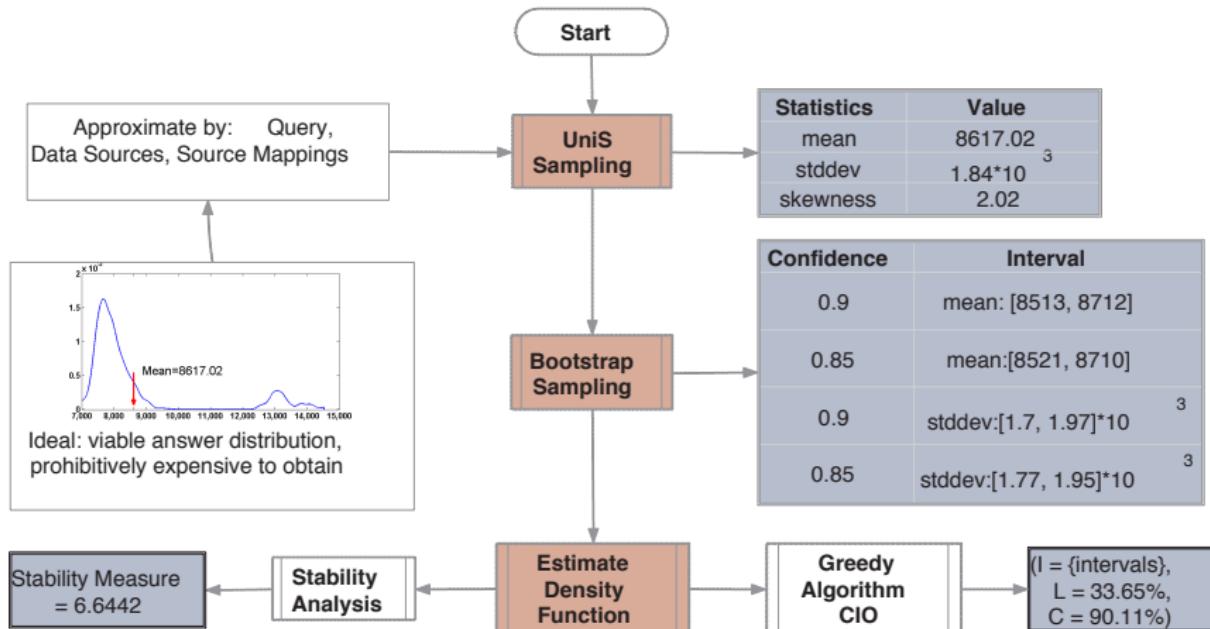
Overview



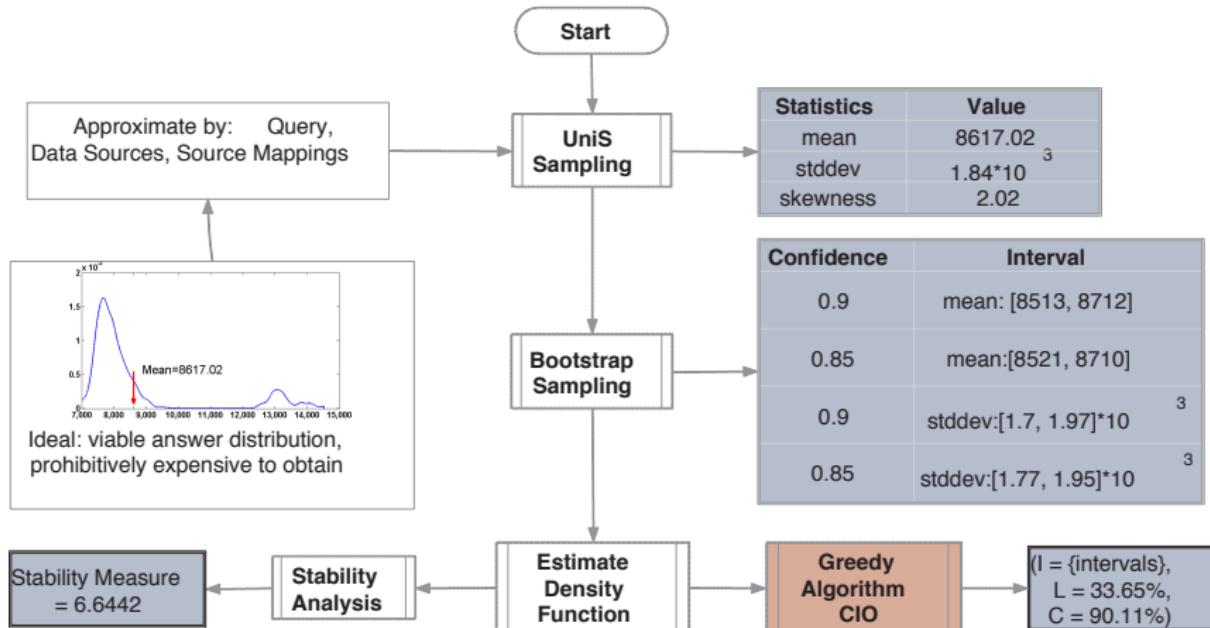
Sampling and point statistics

- Goal: Efficiently approximate viable answer distribution
- Sample a set of viable answers
 - No prior knowledge regarding coverage, accuracy and quality
- Sampling scheme? Uniform sampling
 - Choose sources uniformly at random
 - Stay at source until source is exhausted (all relevant components used)
- Apply bootstrap sampling and bagging
- Apply kernel density estimation

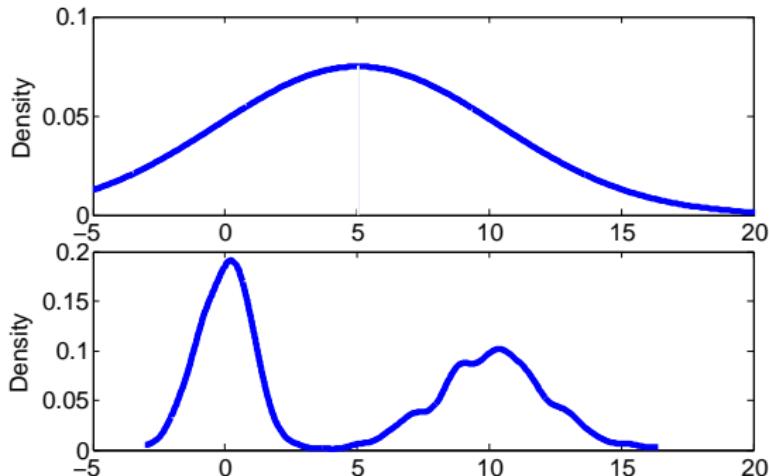
Overview



Overview



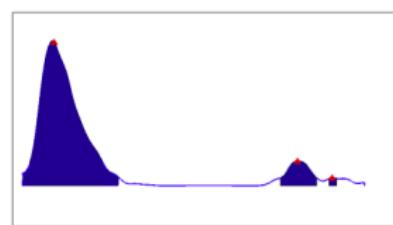
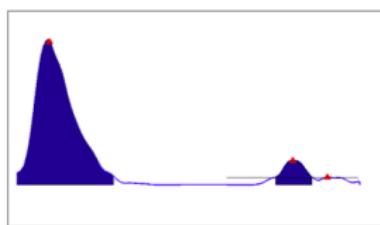
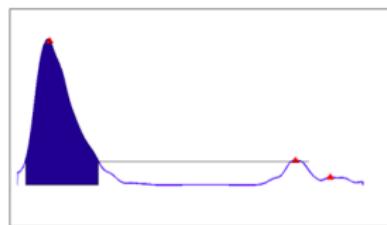
High coverage intervals and optimization



- Point statistics such as mean and variance are insufficient
- Statistics that convey shape information are needed!

High coverage intervals and optimization

- Goal: Communicate shape information about viable answer distribution
- Greedy algorithm CIO
 - Minimize interval length so that coverage of viable answers is above a certain threshold

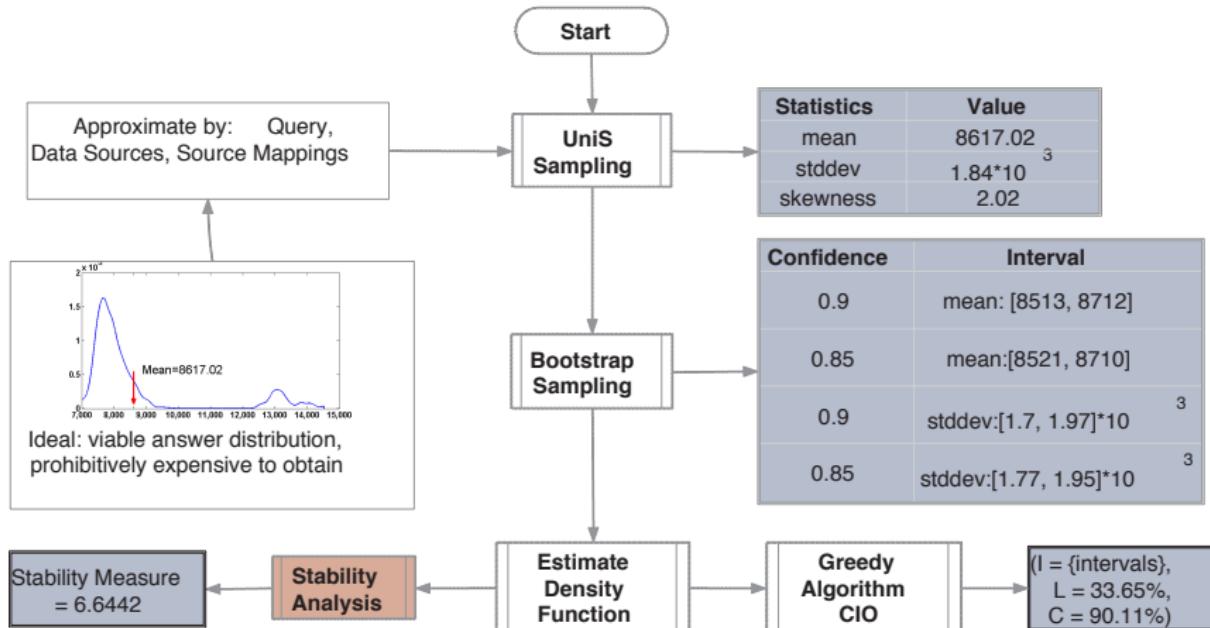


(a) initial high coverage interval finding

(b) intermediate

(c) high coverage intervals that are above our threshold ($\theta\%$)

Overview



Stability score

- Goal: How much change is caused in the estimated distribution when some sources leave?
- Quantify the change as the distance between two probability distributions
 - The original viable answer distribution
 - The viable answer distribution when some of the sources are removed
- Obtain stability analytically for the L_2 measure
- Helps prioritize re-evaluation and updating of queries need updating when sources are updated

Empirical study

- Dataset
 - Synthetic data
 - D2 - Mixtures of four Gaussians
 - D3 - Mixture of Gaussians, Cauchy and Gamma
 - Real-life data
 - C - Monthly Canadian climate data for the year 2006, from 1672 stations for 104 districts
- Aggregate query: Sum temperature data over 500 components from datasets

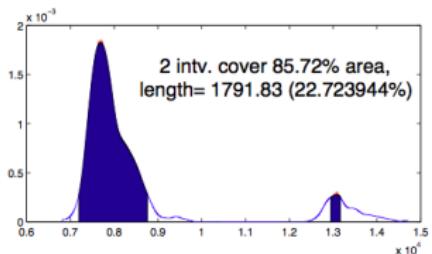
Bootstrapping vs Direct inference

- Bootstrapping helps derives tighter confidence intervals for point statistics
 - Smaller confidence intervals represent more reliable estimates
 - Improvement ratio $i_r = \frac{\text{len}(Cl_{di})}{\text{len}(Cl_{boot})}$

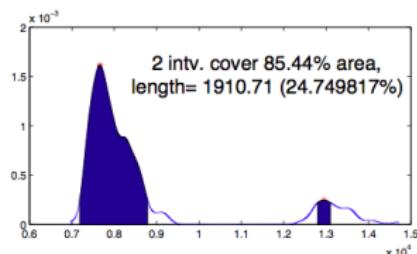
$ S_{unis} $	$1 - \alpha$	max i_r	avg i_r
200	0.8	4.248	2.556
200	0.9	3.309	2.119
400	0.8	2.896	2.001
400	0.9	2.293	1.655

Greedy algorithm output

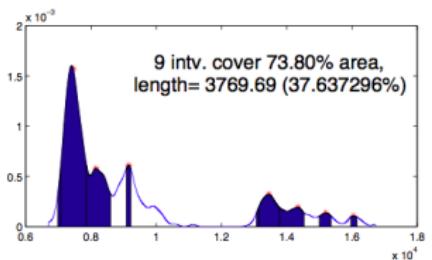
- By returning dense areas, the intervals cover a small percentage of the range of data



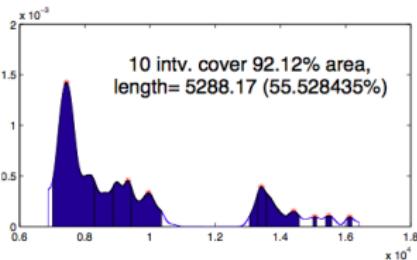
(a) S_1 (Climate Data C)



(b) S_2 (Climate Data C)



(c) S_3 (Synthetic data D3)



(d) S_4 (Synthetic data D3)

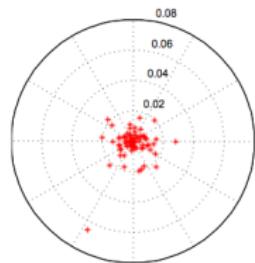
High coverage intervals

- Optimal Slicing: slice the area under the distribution into 4028 slices
- Optimal Slicing vs Greedy Algorithm CIO
 - Optimal Slicing returns tighter intervals, but does not guarantee the continuity of returned intervals

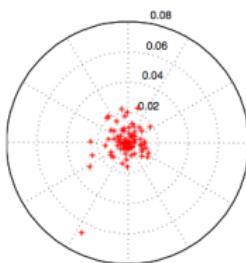
Fig	Greedy	Optimal	Cover	Greedy/Optimal
a	0.2272	0.2272	85.72%	1.0
b	0.2475	0.2475	85.44%	1.0
c	0.3764	0.2724	73.82%	1.38
d	0.5552	0.5150	92.12%	1.08

Stability score

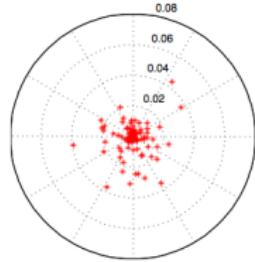
- Closer to the center, and the more dense around the center, the more stable the result



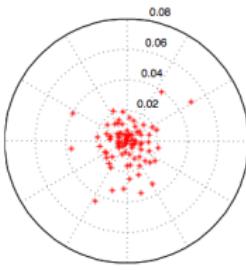
(a) S_1 L_2 score=6.5882



(b) S_2 L_2 score=6.4139



(c) S_3 L_2 score=6.4217



(d) S_4 L_2 score=6.3204

Selected related work

- Data Fusion - assumes a single true answer
 - Bleiholder, Jens, and Felix Naumann. "Data fusion." ACM Computing Surveys (CSUR) 41.1 (2008): 1.
 - Dong, Xin Luna, and Felix Naumann. "Data fusion: resolving data conflicts for integration." Proceedings of the VLDB Endowment 2.2 (2009): 1654-1655.
- Value-level heterogeneity in the Flight and Stock domain, due to sources applying different semantics
- No single true answer
 - Li, Xian, et al. "Truth finding on the deep web: is the problem solved?." Proceedings of the VLDB Endowment 6.2 (2012): 97-108.
- Applications in probabilistic databases

Future work

- Investigate the stability analysis
- Improve uniS sampling to consider quality and coverage
- Make inferences regarding data and sources based on non-normality of estimated viable distribution
 - Multi-modal distributions can indicate mapping problems
 - Find homogeneous sources that apply similar semantics

Contributions

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Dataset

Dataset [About the Data](#) [Resources](#)

Monthly Data Report for 2006

Metadata including Station Name, Province, Latitude, Longitude, Revision, Climate ID, WMO ID, TC ID

PORT LANGLEY TELEGRAPH TRAIL, BRITISH COLUMBIA

Latitude	49°04'40.800" N	Longitude	122°57'03.800" W	Elevation	74.00 m
Climate ID	1102012	WMO ID	7174	TC ID	

Product Data [No related data is available for this station](#) [Advanced Search](#)

Historical Search Options [Monthly Data \(1950-2007\)](#) [CSV](#) [XLS](#) [Download Data](#)

Previous Year [2005](#) [2006](#) [Next Year](#) **2007** [Previous Year](#) [2006](#) [Next Year](#) **2008** [Previous Year](#) [2007](#) [Next Year](#)

Monthly Data Report for 2006

Month	Mean Max Temp (°C)	Mean Min Temp (°C)	Mean Precip (mm)	Ext Max Temp (°C)	Ext Min Temp (°C)	Total Precip (mm)	Snow on Ground (cm)	Blust of Wind (km/h)	Ext of Wind (km/h)
Jan	8.1	4.0	6.0	12.0	-1.0	491.0	0.0	491.0	0
Feb	9.2	6.5	4.4	13.0	-5.5	79.0	2.4	81.4	0
Mar	10.7	2.8	4.70	14.9	-2.8	98.0	10.8	102.4	0
Apr	13.8	4.6	9.2	17.0	4.8	16.4	0.0	16.4	0
May									
Jun	24.2	13.4	18.1	34.8	9.8	4.1	0.0	4.1	0
Jul	23.8	13.8	17.8	33.8	13.8	0.0	0.0	0.0	15
Aug	21.8	9.8	19.8	31.8	9.0	121.0	0.0	121.0	0
Sep	15.0	5.8	10.4	21.5	-4.0	95.4	0.0	95.4	0
Oct	9.8	2.7	8.1	13.8	-12.8	62.0	0.0	62.0	38
Nov	6.0	1.8	3.8	13.0	-3.8	183.0	0.0	183.0	0
Dec									

Summary, average and extreme values are based on the data above.

Notes on Data Quality

Legend:

- = More than one occurrence and estimated
- = Trace
- = Estimated
- = Missing
- = More than one occurrence

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Preliminaries

- Bootstrap sampling and bagging
- Kernel density estimation
- Distance measures for distributions

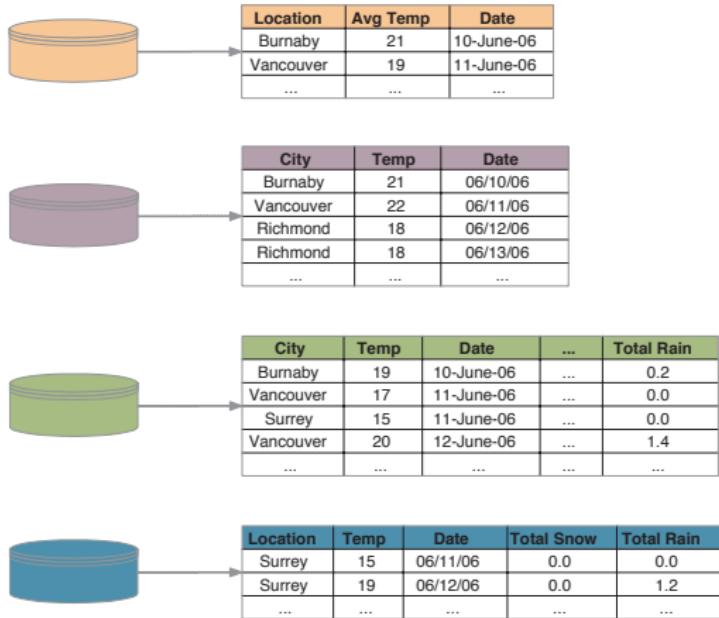
Finding high coverage intervals - optimization approach

Given a density function $f_X^{\mathcal{D}}$ for a distribution defined on a finite range, a coverage threshold $0 \leq \theta \leq 1$, and a constant t representing the number of modes, the CIO problem finds k intervals I_1, I_2, \dots, I_k where $k \leq t$, to minimize $\sum_{i=1}^k |I_i|$ subject to $\sum_{i=1}^k \int_{I_i} f_X^{\mathcal{D}}(x) dx \geq \theta$.

$$\begin{aligned} & \underset{k, I_1, \dots, I_k}{\text{minimize}} && \sum_{i=1}^k |I_i| \\ & \text{subject to} && \sum_{i=1}^k \int_{I_i} f_X^{\mathcal{D}}(x) dx \geq \theta. \end{aligned}$$

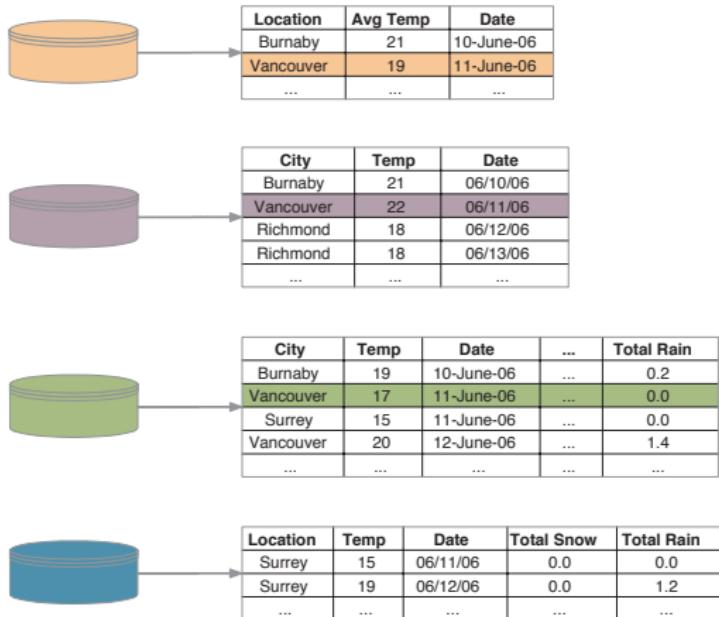
Heterogeneity

- Heterogeneity at three levels
 - Schema-level



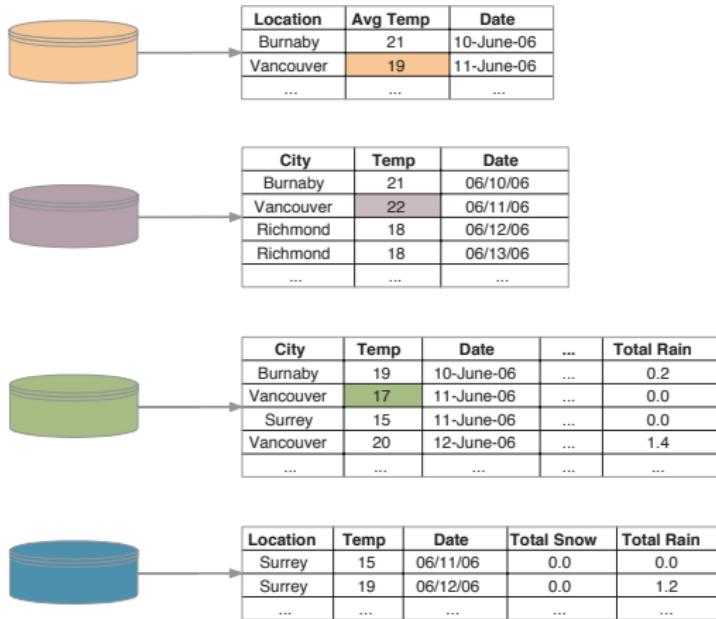
Heterogeneity

- Heterogeneity at three levels
 - Schema-level
 - Instance-level



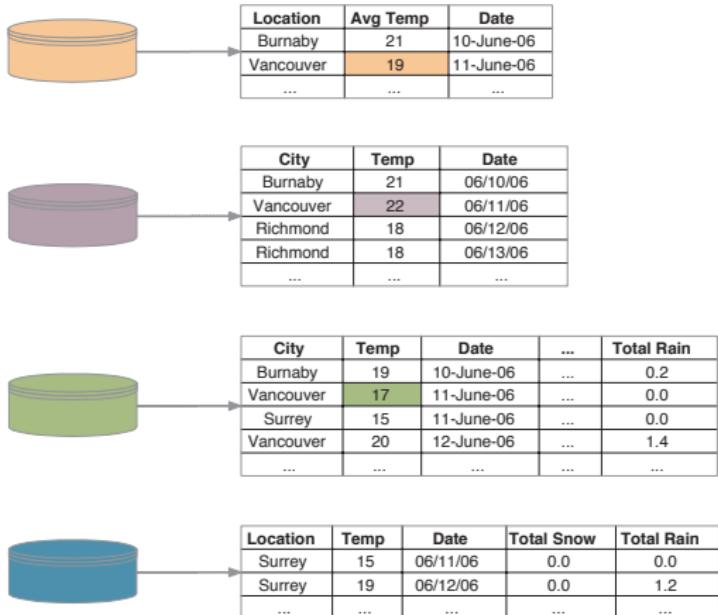
Heterogeneity

- Heterogeneity at three levels
 - Schema-level
 - Instance-level
 - Value-level



Value-level Heterogeneity

- Focus of our work is on value-level heterogeneity
 - Problem exists in various domains, e.g., stock, flight, weather domain
- Prior work assumes a single true answer exists, which we do not



Processing overhead of operations

- KDE dominates the processing overhead for extracting statistics
- Sampling the viable answers dominates the overall time needed for sampling and extracting statistics

