Improving Understanding and Exploration of Data by Non-Database Experts

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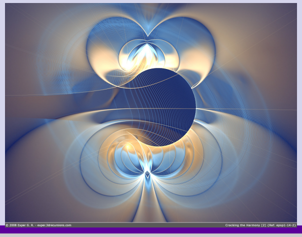
Joint work with lots of great students, including Zainab Zolaktaf, Reza Babanezhad, Jian Xu, Omar AlOmeir, and Janik Andreas

Exploring and understanding data

- More users have more data
- This is particularly challenging for users without much database background
- I like to work with data and users who have real world problems. Then I extend to a more general scenario.
- How can we help users with little database expertise to understand and explore their data?

Exploring and understanding data



- **Exploration**: recommend items beyond the popular items in recommender systems
- **Understand**: help users understand the range of possible answers in data aggregated from multiple sources
- **Exploration** and **understanding**: Ongoing work on exploring and understanding

Exploration: Recommend long tail items
(joint with Zainab Zolaktaf and Reza Babanezhad)

- Standard recommender systems algorithms tend to emphasize popular items
- This tends to cause recommendation consumers to only find things they already know
- But most items are “long tail”
- Presented at ICDE (International Conference on Data Engineering) last week

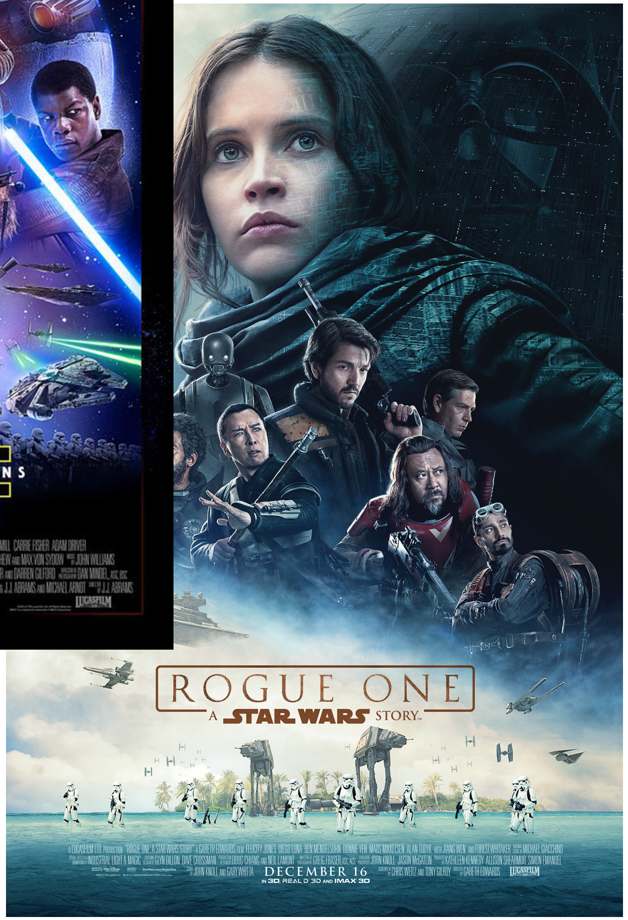
Motivating Example

Top-N recommendation

- Recommend to each user a set of N items from a large collection of items
- Used in Netflix, Amazon, IMDB, etc.

Problem

- Tend to recommend things users are already aware of
- E.g., Suggests “Star Wars: The Force Awakens” to users who have seen “Star Wars: Rogue One”



Motivating Example

- Many recommendation systems
  - Take as input a set of users and their ratings (e.g., ratings on movies)
  - Focus on accurately predicting user preferences based on history
  - Use a subset of data as "gold standard"
- Interaction data often suffers from popularity bias and sparsity
  - Have to recommend popular items to maintain performance accuracy
  - Rich get richer effect
- Accuracy alone is not leading to effective suggestions?

5	4	5	2	3	5
4	5	4			3
1					
5	4				
1			2		

Why long-tail items matter

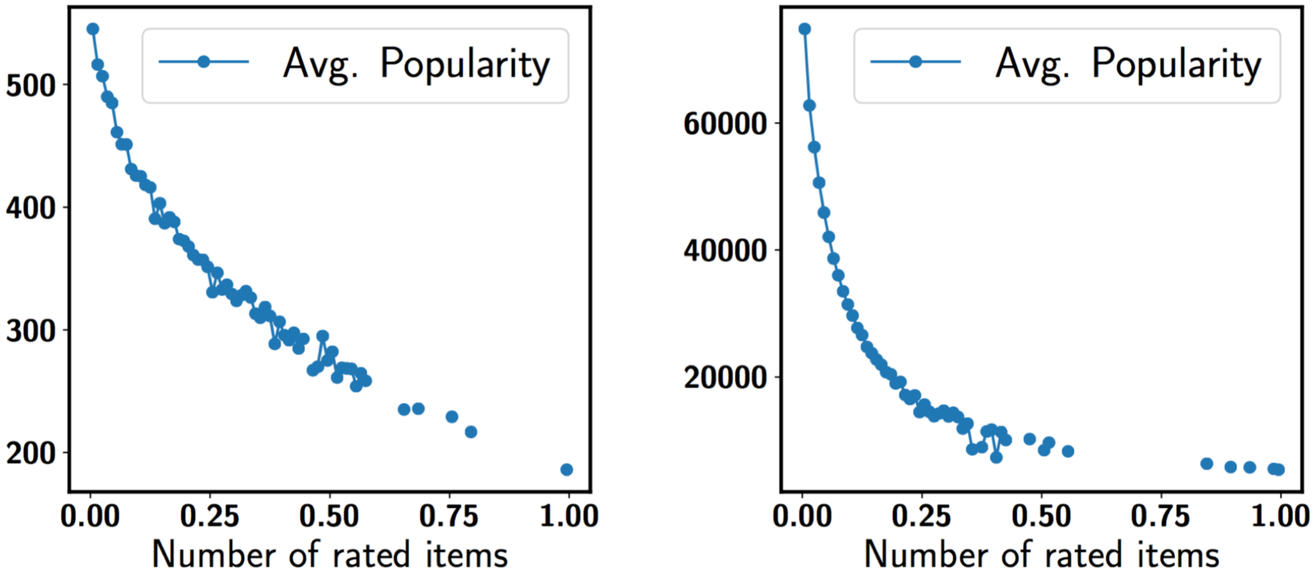
Consumers want

- **Accuracy**
- **Novelty**
- …

Providers of items want

- Keep consumers happy
- Item-space **coverage**
  - Generates revenue
- …

Less focus on popular items



(a) ML-1M (b) Netflix

- Long-tail items
  - Generate the lower 20% of the observations
  - Empirically validated: Correspond to almost 85% of the items in several datasets

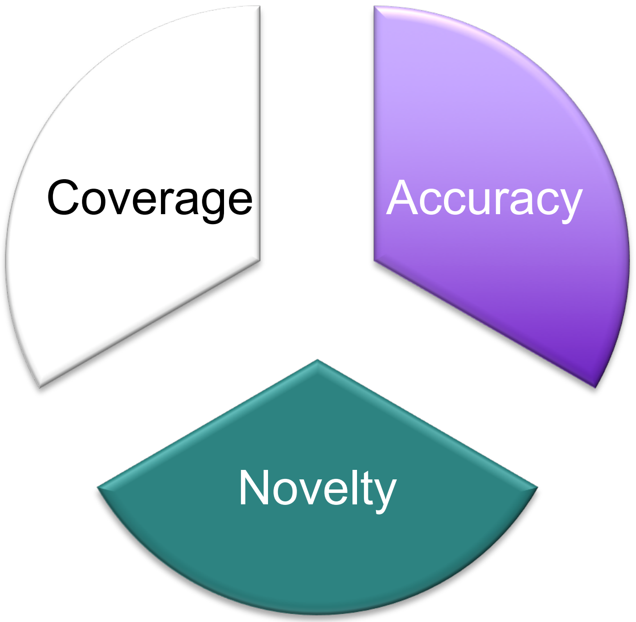
Selected related work

- Accuracy Focused
  - KBV09- Koren, Yehuda, Robert Bell, and Chris Volinsky. "Matrix factorization techniques for recommender systems." *Computer*42.8 (2009).
  - WKL+08- Weimer, Markus, et al. "Cofi rank-maximum margin matrix factorization for collaborative ranking." *Advances in neural information processing systems*. 2008.
- Re-ranking frameworks
  - AK12- Adomavicius, Gediminas, and YoungOk Kwon. "Improving aggregate recommendation diversity using ranking-based techniques." *IEEE Transactions on Knowledge and Data Engineering* 24.5 (2012): 896-911.
  - HCH14- Ho, Yu-Chieh, Yi-Ting Chiang, and Jane Yung-Jen Hsu. "Who likes it more?: mining worth-recommending items from long tails by modeling relative preference." *Proceedings of the 7th ACM international conference on Web search and data mining*. ACM, 2014.
- Evaluation of top-N recommendation
  - CKT10- Cremonesi, Paolo, Yehuda Koren, and Roberto Turrin. "Performance of recommender algorithms on top-n recommendation tasks." *Proceedings of the fourth ACM conference on Recommender systems*. ACM, 2010.
  - Ste11- Steck, Harald. "Item popularity and recommendation accuracy." *Proceedings of the fifth ACM conference on Recommender systems*. ACM, 2011.
  - Ste13- Steck, Harald. "Evaluation of recommendations: rating-prediction and ranking." *Proceedings of the 7th ACM conference on Recommender systems*. ACM, 2013.

Challenges: Accuracy, novelty, and coverage trade-offs

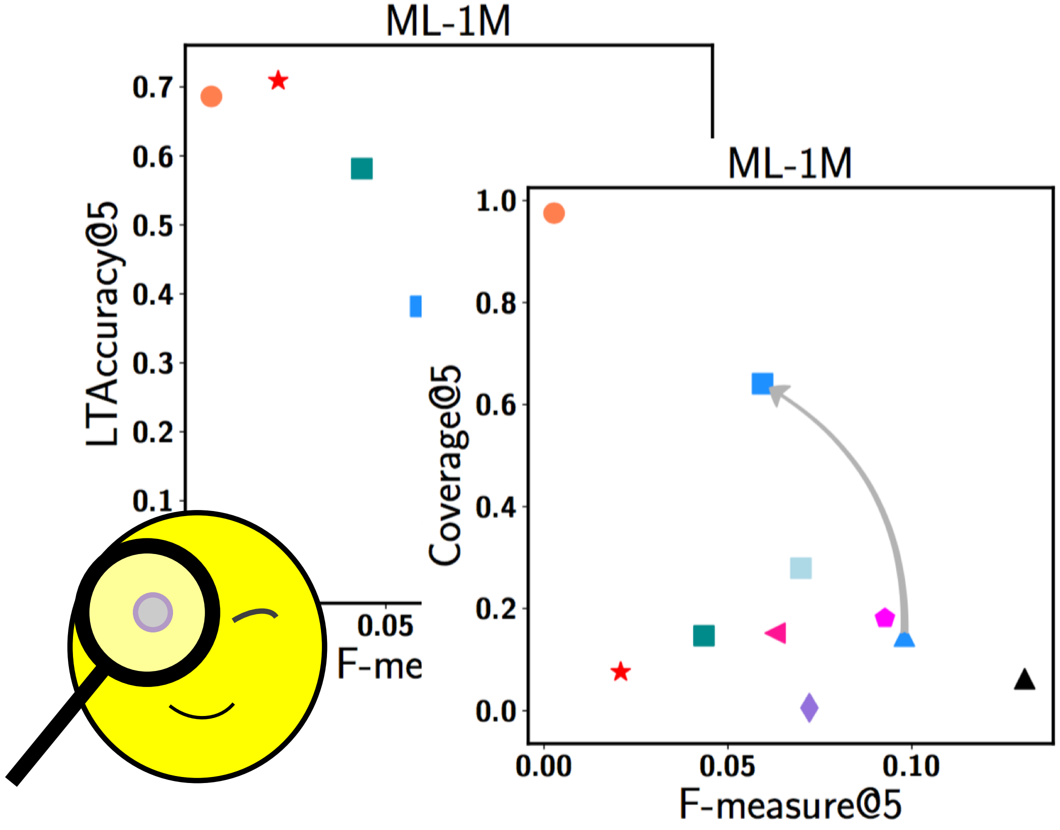
- ✓ Promoting long-tail item can increase novelty [Ste11]
  - Long-tail items are more likely to be unseen
- ✓ Promoting long-tail items increases coverage [Ste11]
  - Generates revenue for providers of items
- × Long-tail promotion can reduce accuracy [Ste11]

Not all users receptive of long-tail items



Challenges: Recommendation system evaluation

- Need to assess multiple aspects
  - Accuracy, novelty, and coverage
  - No single measure that combines all aspects. Report trade-offs?
- Need to consider real-world settings
  - Datasets are sparse
  - Users provide little feedback
- Test ranking protocols [Ste13, CKT10]
  - Do not reward popularity-biased algorithms
  - Offline accuracy should be close to what user experiences in real-world



Solution overview: GANC

A Generic top-N recommendation framework that provides customized balanced between Accuracy, Novelty, and Coverage

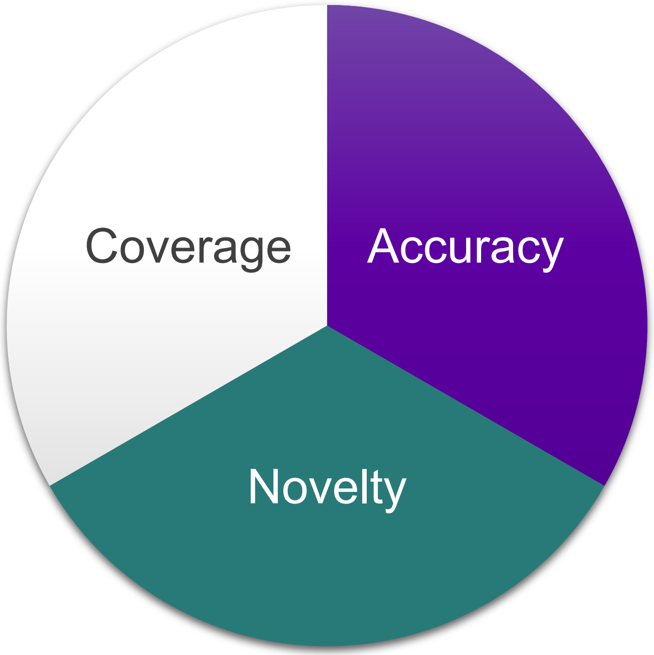
Objective: Assign top-N sets to all users

Find $\mathcal{P} = \{\mathcal{P}_u\}_{u=1}^{|\mathcal{U}|}$, the collection of top-N sets to maximize

$$v(P) = \sum_u v_u(P_u)$$

$$= \sum_u (1-\theta_u) a(P_u) + \theta_u c(P_u)$$

$$= \sum_u (1-\theta_u) \sum_{i \in P_U} a(i) + \theta_u \sum_{i \in P_U} c(i)$$



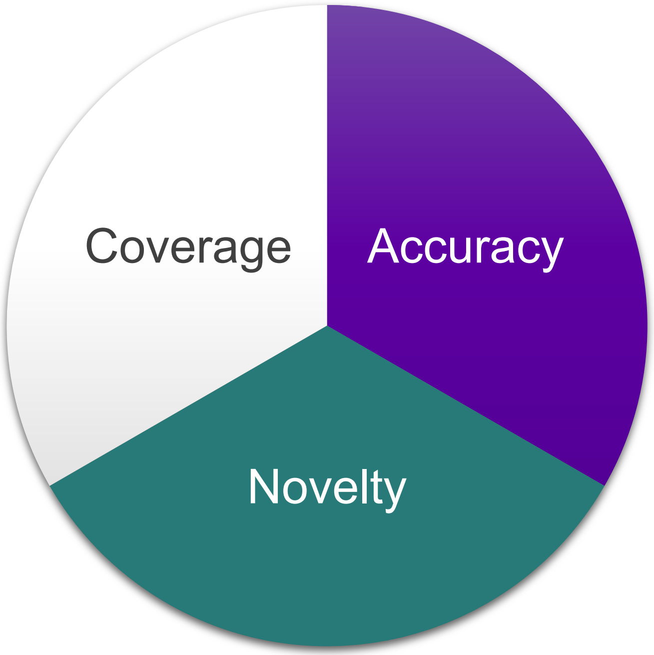
Solution overview: GANC

Main features of our solution

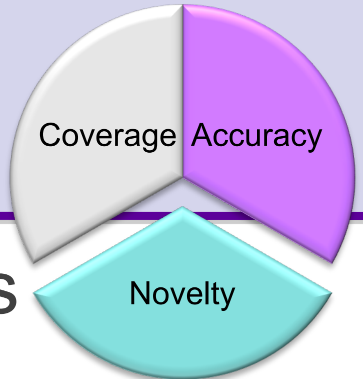
1. Directly infer user long-tail novelty preference θ_u from interaction data

   Customize trade-off parameters per user

2. Integrate θ_u into a generic re-ranking framework
   - θ_u independent of any base recommender
   - Plugin a suitable base recommender w.r.t. factors such as dataset density



Long-tail novelty preference model (θ_u)



We created and evaluated 4 long-tail novelty preference models

(1) Activity

- Number observations in the train set (e.g., number of rated items)
- Does not distinguish between long-tail and popular items

(2) Normalized long-tail measure

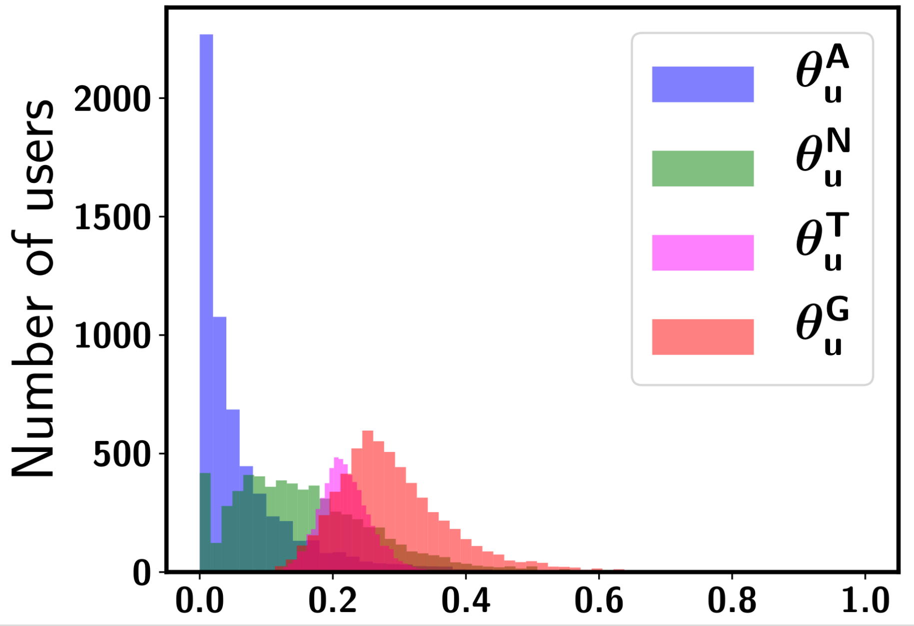
- Ratio of long-tail items rated in train set
- Does not consider if user liked item

(3) TFIDF-Measure

- Incorporates rating and popularity of items
- Does not consider view of other users

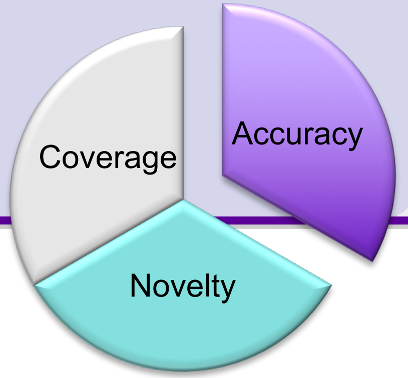
(4) Generalized measure

- Optimization approach
- Incorporates rating information, popularity of items, and view of other users



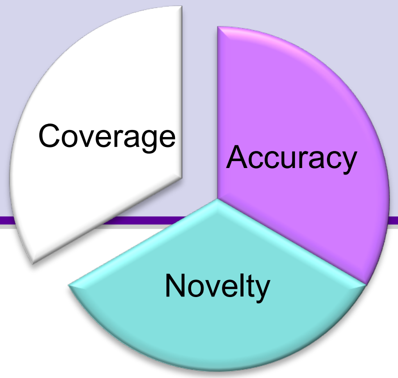
ML-1M (More dense)

GANC: Accuracy recommenders



- Focuses on making accurate suggestions
- Evaluated existing models from literature
  - PureSVD [CKT10]
  - Regularized SVD [KBV09]
  - Most Popular [CKT10]

GANC: Coverage recommenders



- Focus on increasing coverage
  - Random coverage recommender
  - Static coverage recommender
    - Consider how many times the item was rated in the past
      - Gain of recommending an item is proportionate to the inverse of its frequency in train set
  - Dynamic coverage recommender
    - Consider how many times item has been recommended so far
      - Gain of recommending an item is proportionate to the inverse of item recommendation frequency

Empirical Evaluation

Dataset	#Ratings	#Users	#Items	Density	Long-Tail %
ML-100K	100K	943	1682	6.30	66.98
ML-1M	1M	6,040	3,706	4.47	67.58
ML-10M	10M	69,878	10,677	1.34	84.31
MT-200k	172,506	7,969	13,864	0.16	86.84
Netflix	98,754,394	459,497	17,770	1.21	88.27

- ML = Movie Lens MT = Movie Tweetings.
- ML, MT, and Netflix these are common recommender datasets
- Datasets have varying level of density
- Long-tail items correspond to approximately 85% in three datasets

Empirical Evaluation

- Performance metrics
  - Local ranking accuracy metrics
    - Precision, Recall, F-measure
  - Long-tail promotion metrics
    - LTAccuracy (emphasizes novelty and coverage), Stratified Recall (emphasizes novelty and accuracy)
  - Coverage metrics
    - Coverage, Gini

- Test ranking protocol [Ste13, CKT10]
  - "All unrated items test ranking protocol"
    - Generate the top-N set of each user, by ranking all items that do not appear in the train set of that user
    - Closer to accuracy the user experiences in real-world settings

Algorithms Compared

- Re-ranking frameworks for rating prediction
  - Regularized SVD (RSVD)
  - Resource Allocation (5D)
  - Ranking-based Techniques (RBT)
  - Personalized Ranking adaptation (PRA)
- Report results for two variants of each algorithm

Comparison with re-rankings models for rating-prediction

Dense dataset

- ML-1M

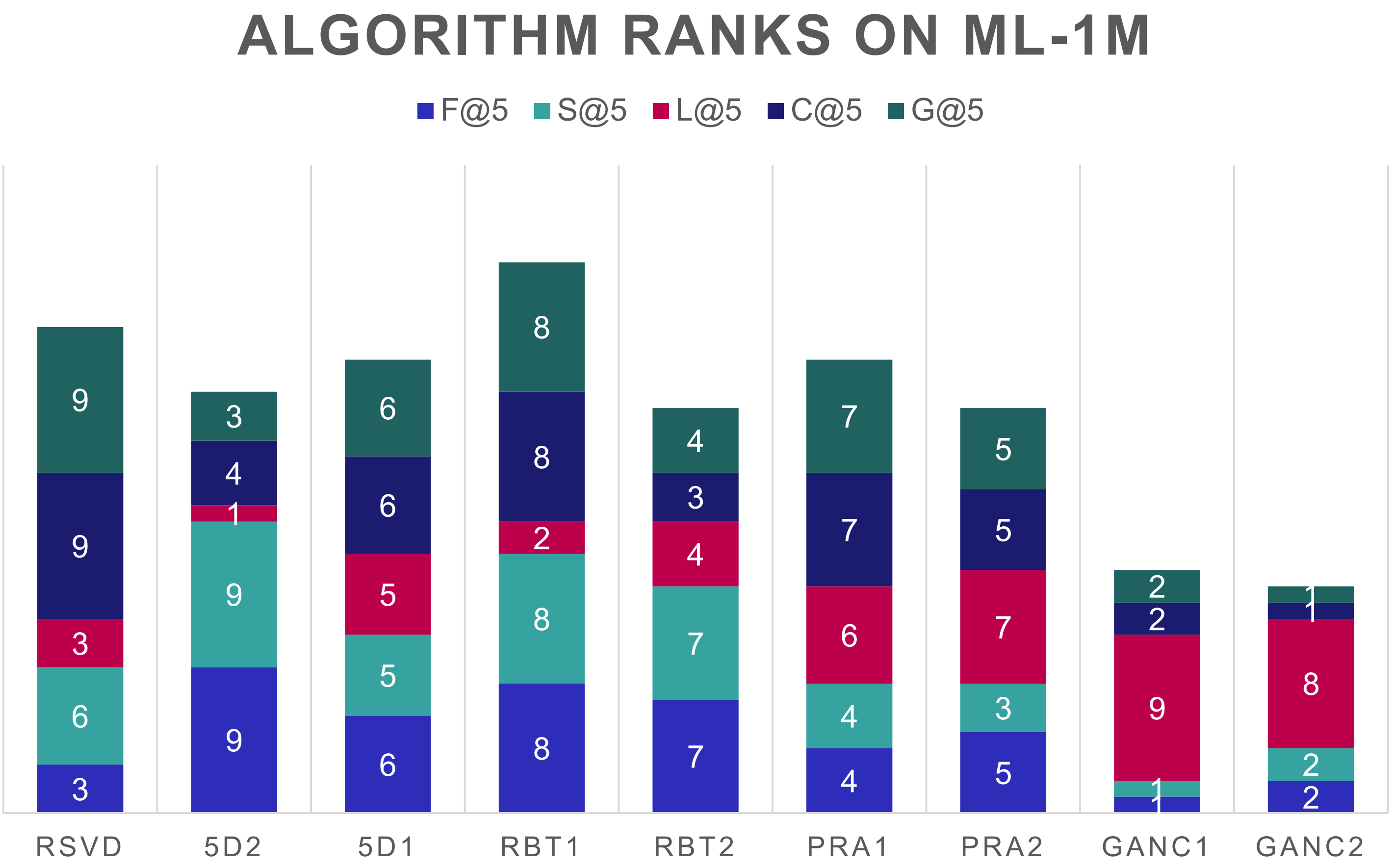
RSVD is base accuracy recommender

Lower height is better

- Corresponds to better rank

GANC outperforms RSVD in all metrics

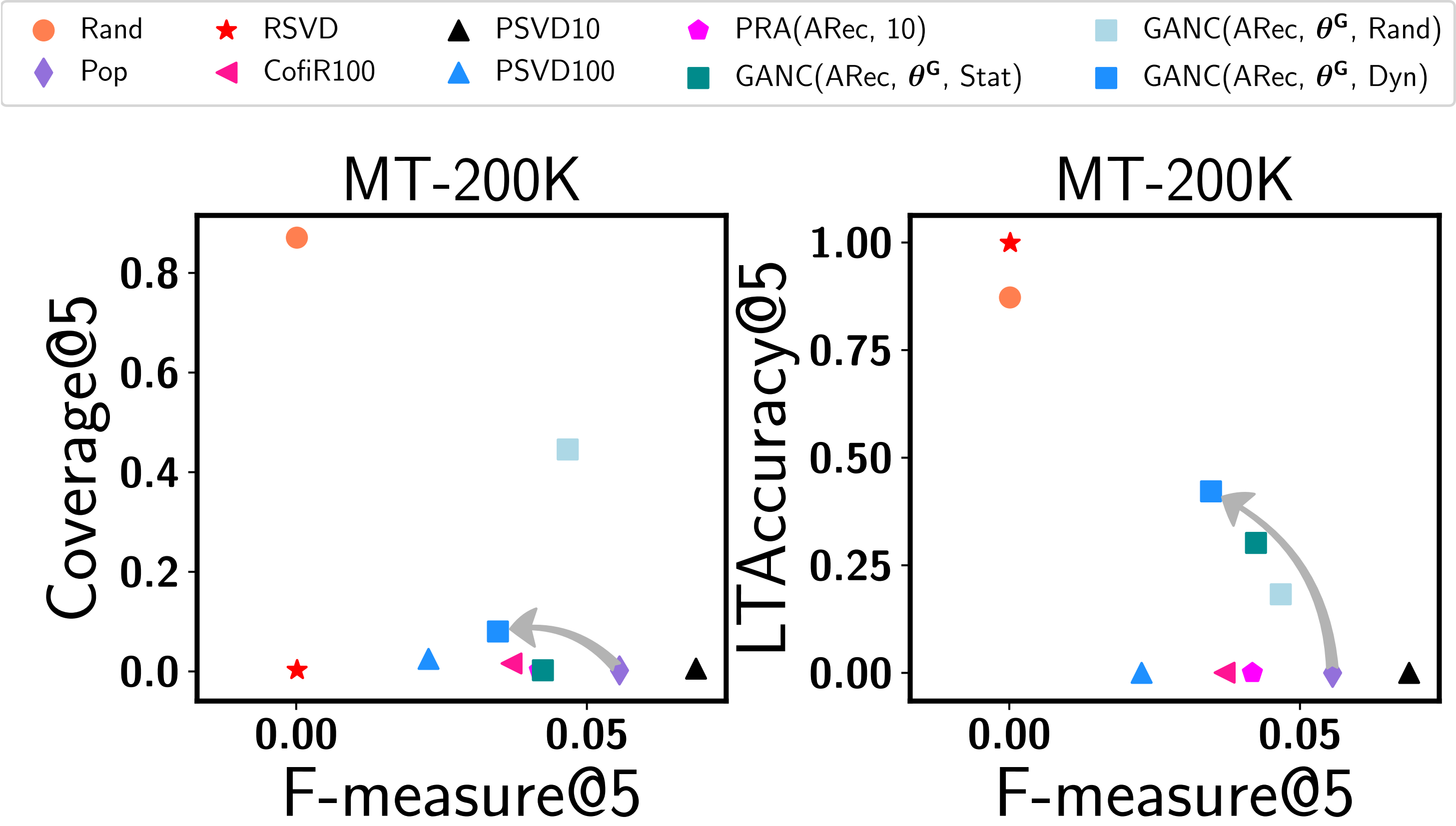
GANC obtains lowest overall performance across 5 metrics



(F)measure@5 (S)tratified Recall@5 (L)Taccuracy@5 (C)overage@5 (G)ini@5

Changing accuracy recommenders explores tradeoffs between accuracy and coverage

- GANC allows different accuracy recommenders
- Plugging the non-personalized algorithm Pop as accuracy recommender
- Competitive with more sophisticated algorithms like CofiR100



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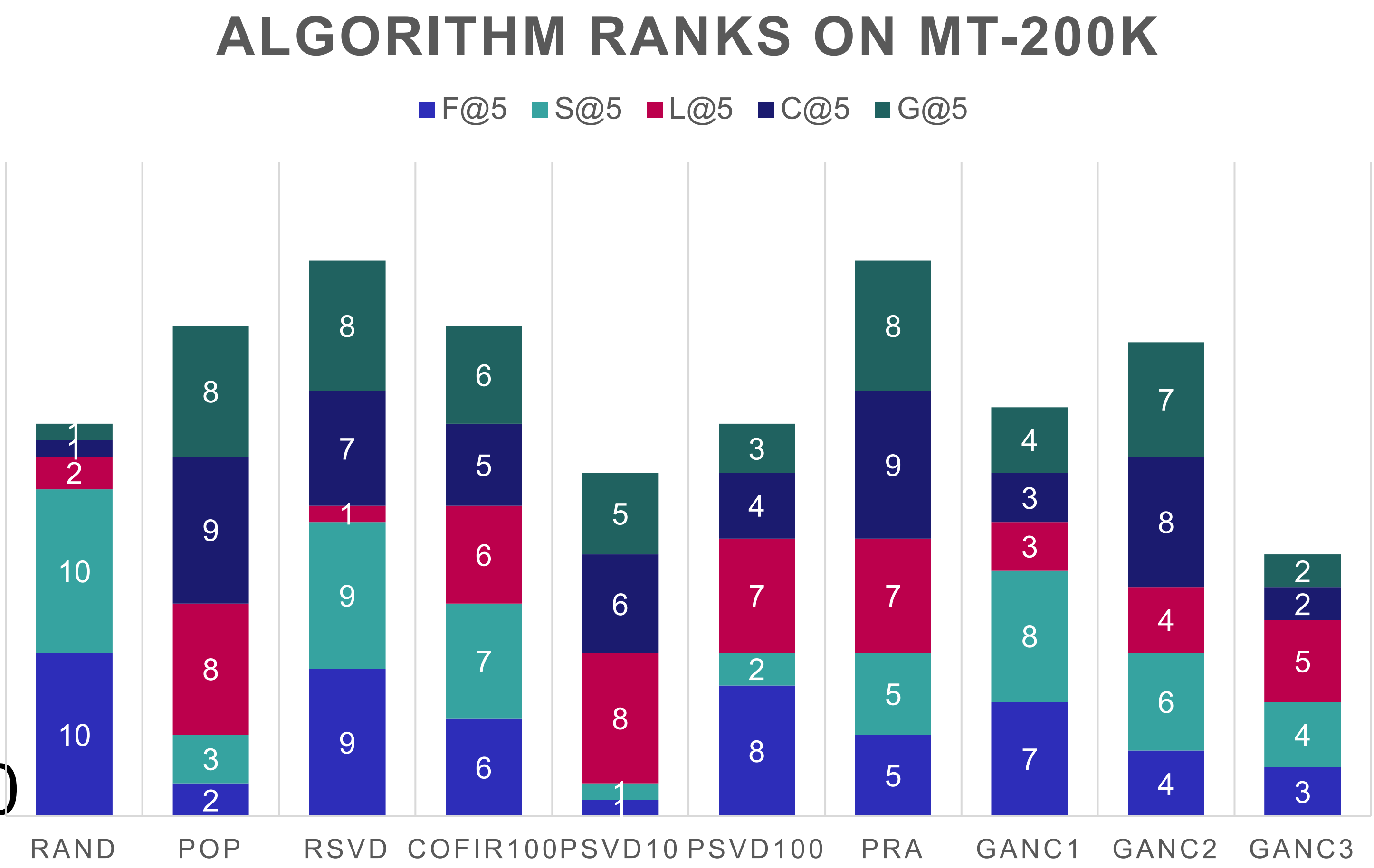
Comparison with top-N recommendation algorithms

- Sparse dataset
  - MT-200K
- Pop is base accuracy recommender
- Lower height is better
  - Corresponds to better rank
- Three variations of GANC competitive with more PSVD100 and Cofi100



(F)measure@5 (S)tratified Recall@5 (L)Taccuracy@5 (C)overage@5 (G)ini@5

Act 2

- The first part of the talk described how to help users explore data beyond the most popular in a recommendation setting
- Next we'll help users understand the range of possible answers in data aggregated from multiple sources
- Published in Extending DataBase Technology (EDBT) 2015 (joint with Zainab Zolaktaf and Jian Xu)

Looking for climate change: what is the average high temperature across BC for each year?

- Averaging across readings over the entire province seems reasonable
- But there are problems, e.g., inconsistent values

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
...	...	...

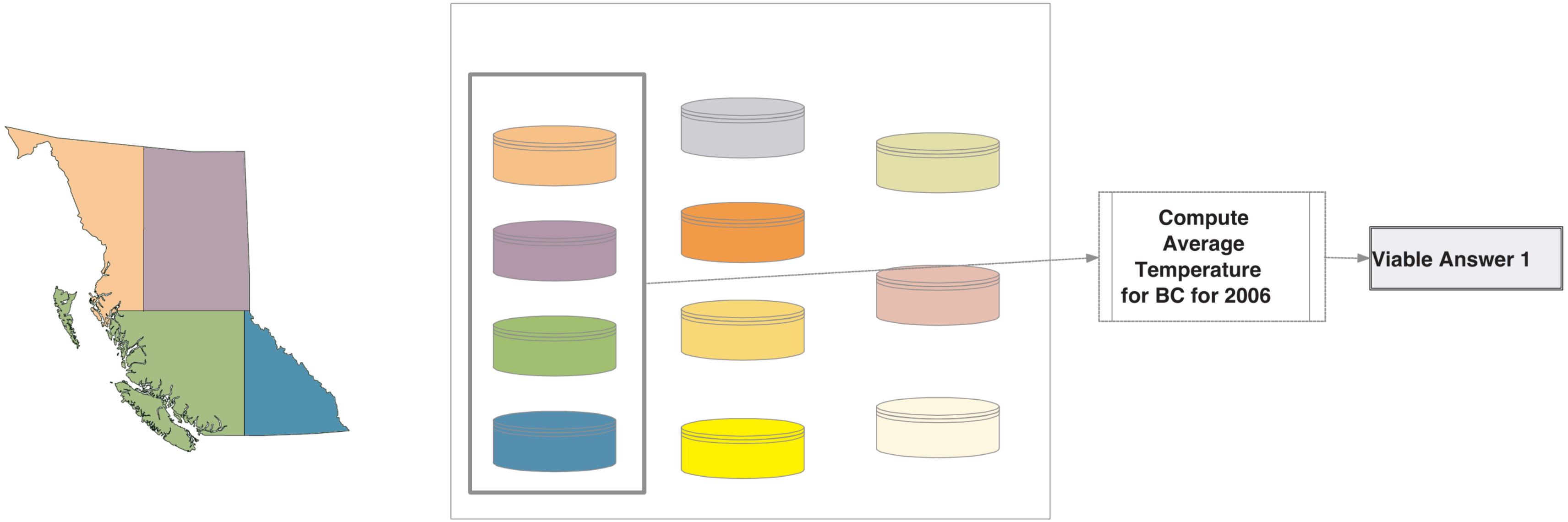
City	Temp	Date	...	Total Rain
Burnaby	19	10-June-06	...	0.2
Vancouver	17	11-June-06	...	0.0
Surrey	15	11-June-06	...	0.0
Vancouver	20	12-June-06	...	1.4
...	...	...	...	...

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
...	...	...	...	...

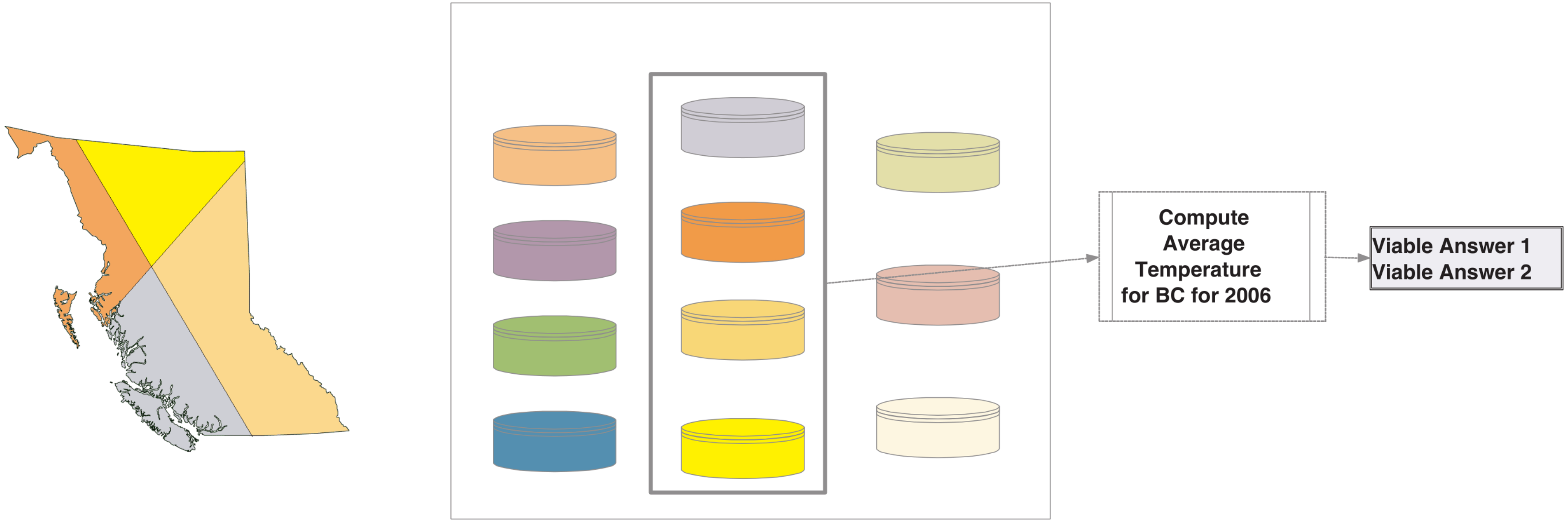
In this work, we helped users understand aggregation query results from multiple sources

- Answering queries in integration contexts requires combining sets of data that are segmented across multiple sources
- Averaging over all the points doesn't work
  - Some data points have duplicates across the sources
  - The duplicates may have different values in the sources
  - Which set of sources and value combinations do we use?
  - We define a ***viable*** answer as a possible answer

Way #1 to compute average temp



Way #2 to compute average temp



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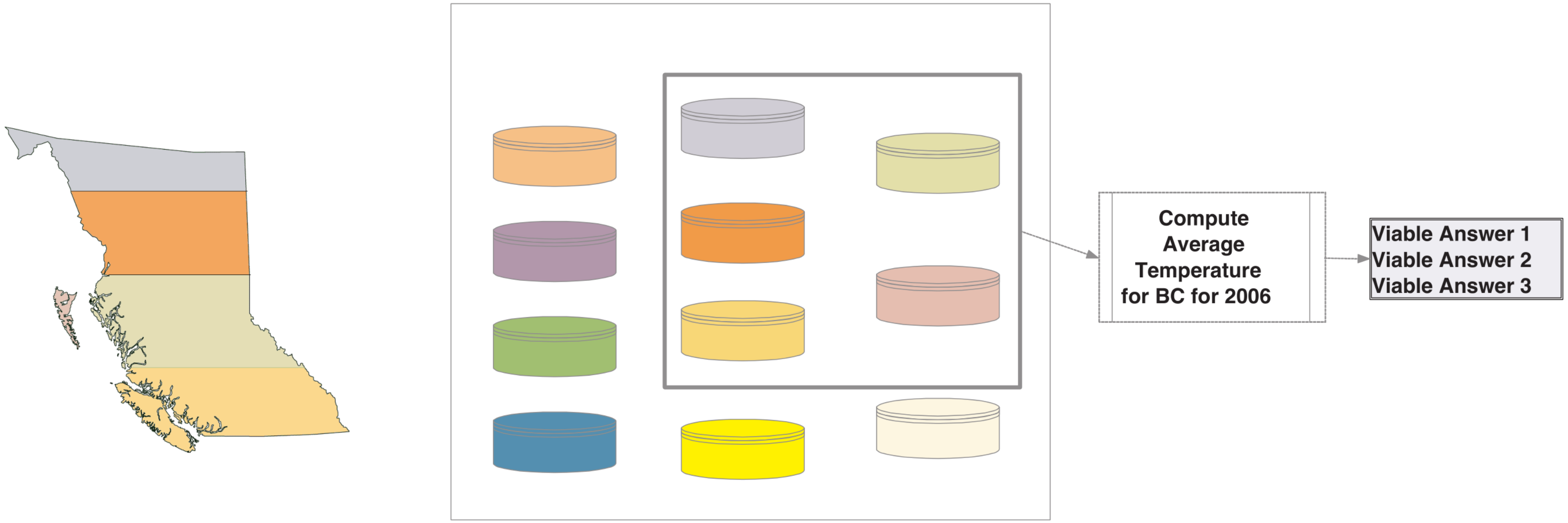
Way #3 to compute average temp



Contributions of this part

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

Contributions of this part

- We defined aggregate answers as a distribution of viable answers
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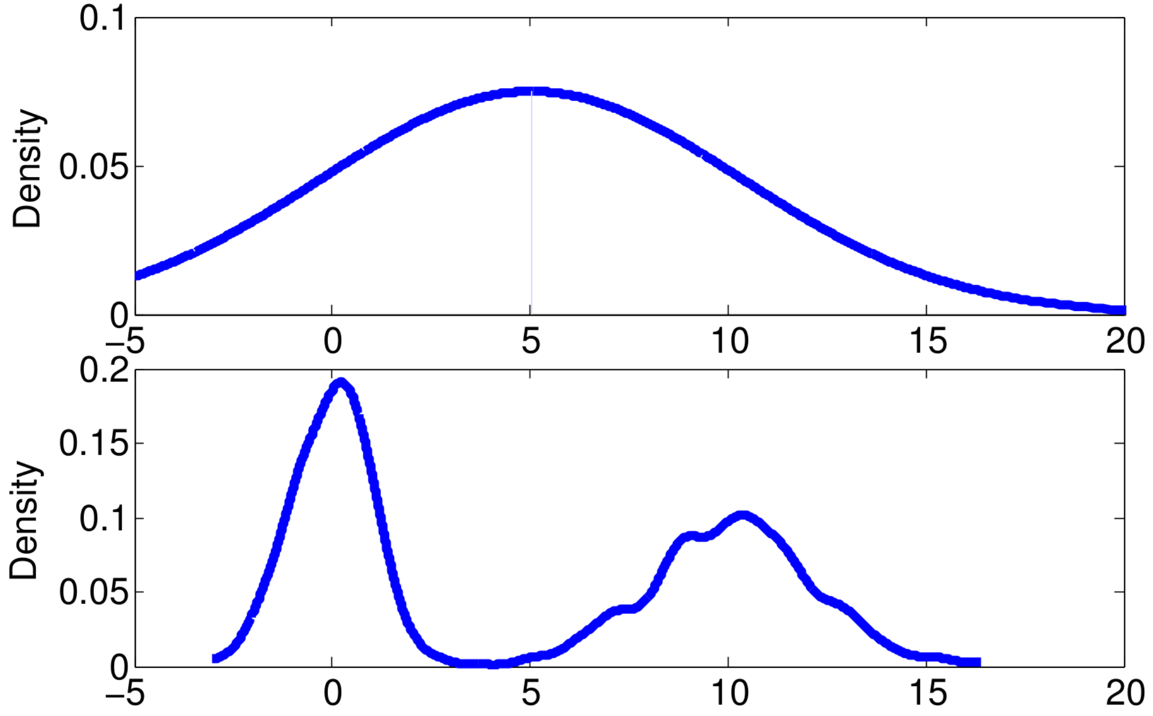
    - Key point statistics
    - **High coverage intervals**
    - Stability score
- We verified the effectiveness of our methods using real-life and synthetic data

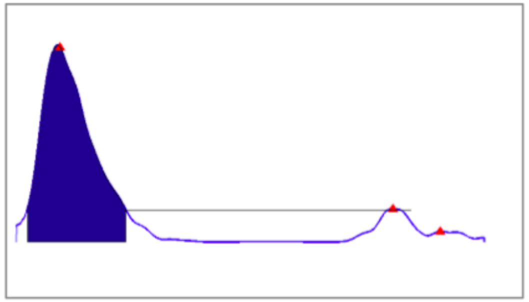
High coverage intervals and optimization

Point statistics such as mean and variance are insufficient

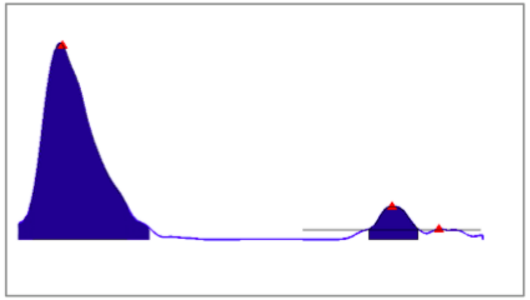


Computing high coverage intervals

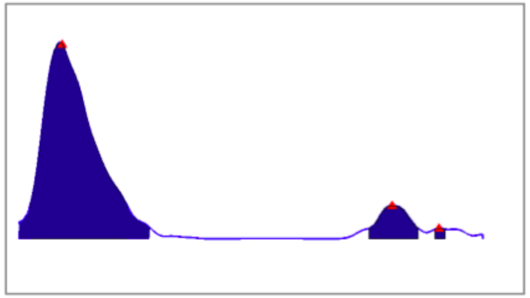
- The ideal, full viable answer distribution is prohibitively expensive to obtain
- We used sampling, bootstrapping and a greedy algorithm to minimize interval length so that coverage of viable answers is above a set threshold



(a) initial high coverage interval finding



(b) intermediate



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

Act three: ongoing work

Understand: help users understand data provenance (joint work with Omar AlOmeir)

- Database researchers have done a great job of exploring different provenance definitions and how to calculate it
- However, this information is difficult to understand by non-DBA users, which makes it hard for users to trust their data
- We created a desirable set of features for provenance exploration systems and implemented such a system
- Our case study was on Global Legal Entity Identifiers
- We're looking for more data

Understand: help users understand open data (joint work with Janik Andreas)

- Governments are increasingly creating open data sites
- However, these open data sites are hard to use – it's hard to find the data that users are looking for
- We're doing a case study on local data to look at some common open data issues:
  - Quality – granularity and details of available data
  - Metadata and data formatting
  - Availability and completeness

Understand: how can we help users understand why they got the wrong answer?

I'd love to have more people to work with

- If you have data or ideas that you think would fit in, I'd love to talk… especially if you are looking for a postdoc position!