SeeDB: Supporting Fast Visual Analytics

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Motivating Example

- Visualization: First step in analytics

- Census data[1]: age, education, marital-status, sex, race, income, hours-worked etc.
  - A = # attributes in table

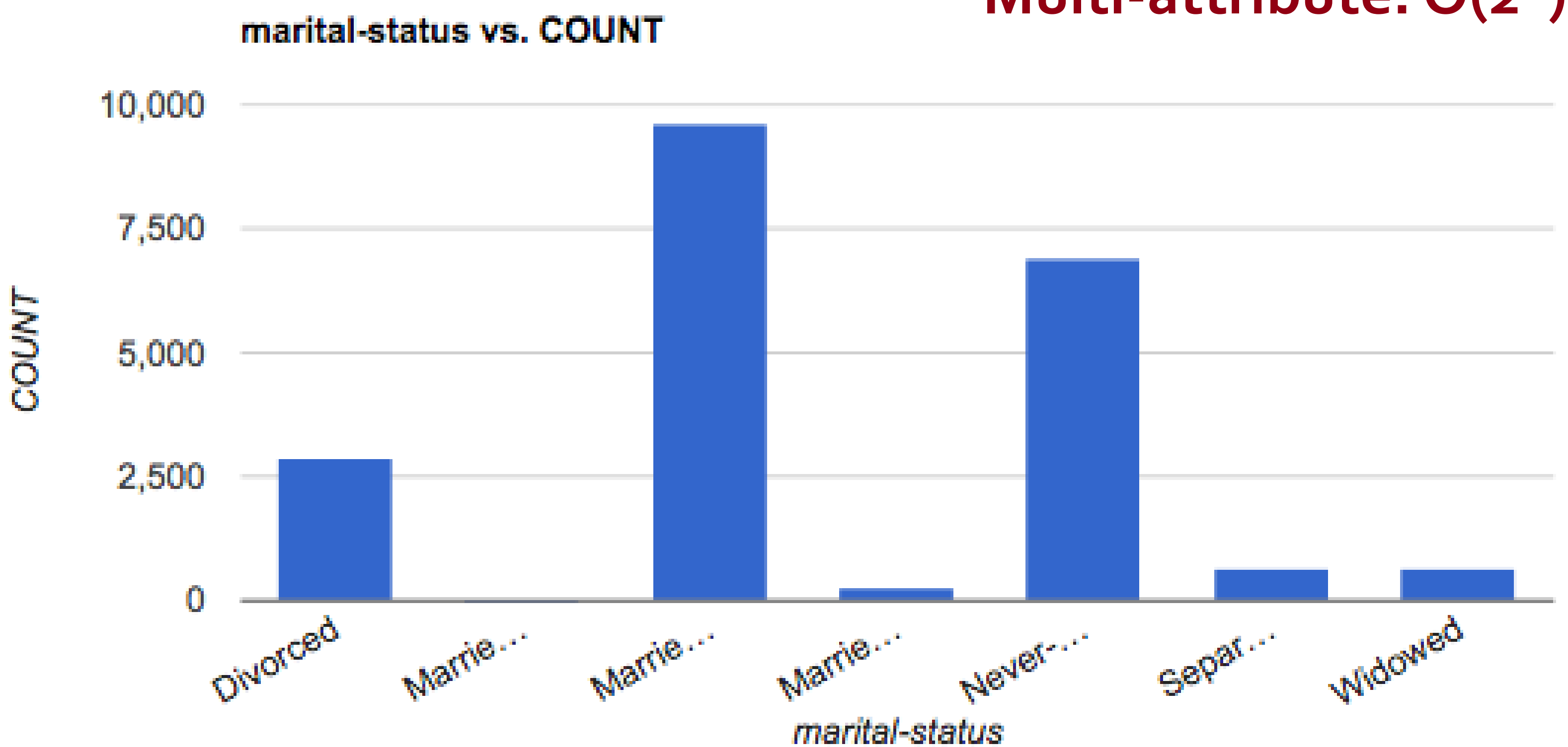
- Task: Socioeconomics of adults who have *never-been-married*

[1]https://archive.ics.uci.edu/ml/datasets/Census+Income

Visualizing Census Data

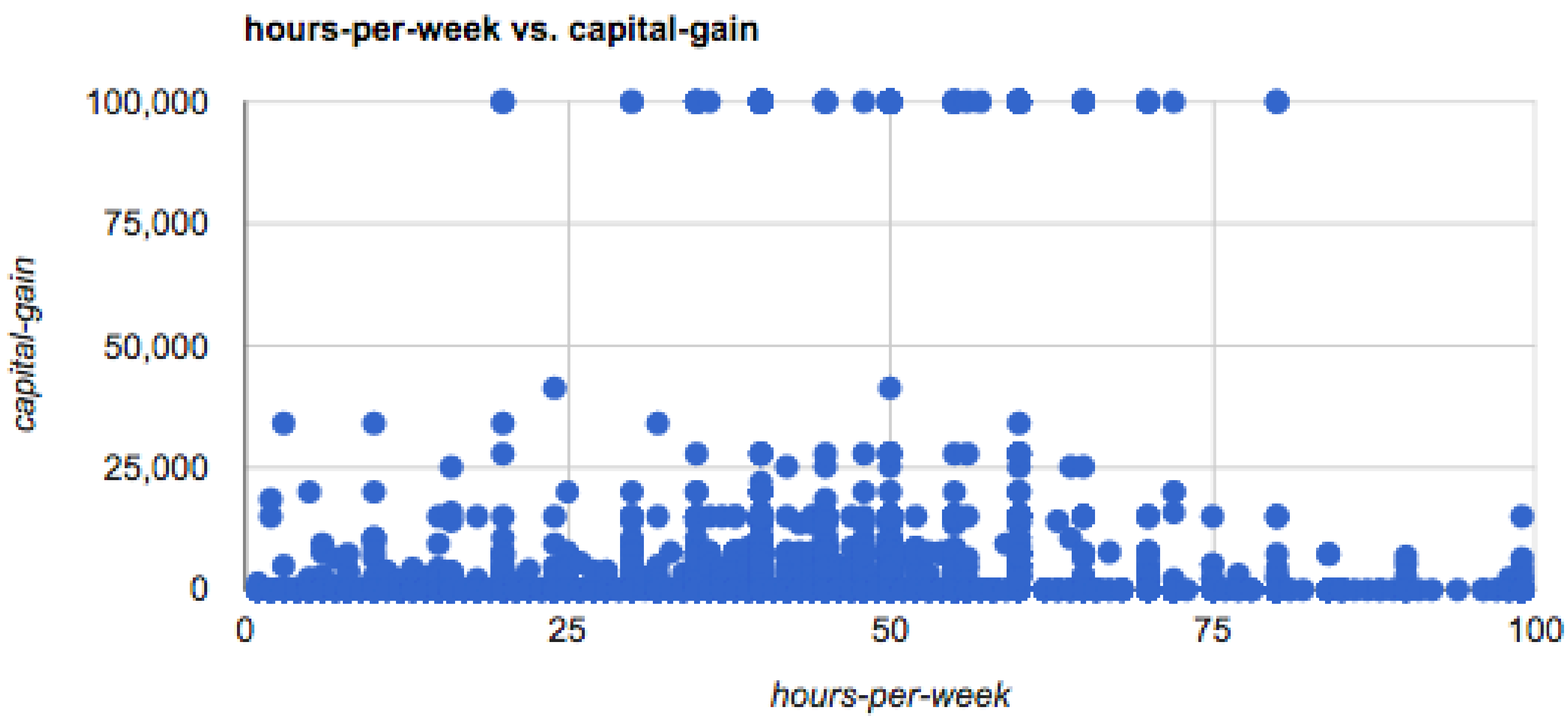
Histograms: O(A)

Multi-attribute: O(2^A)



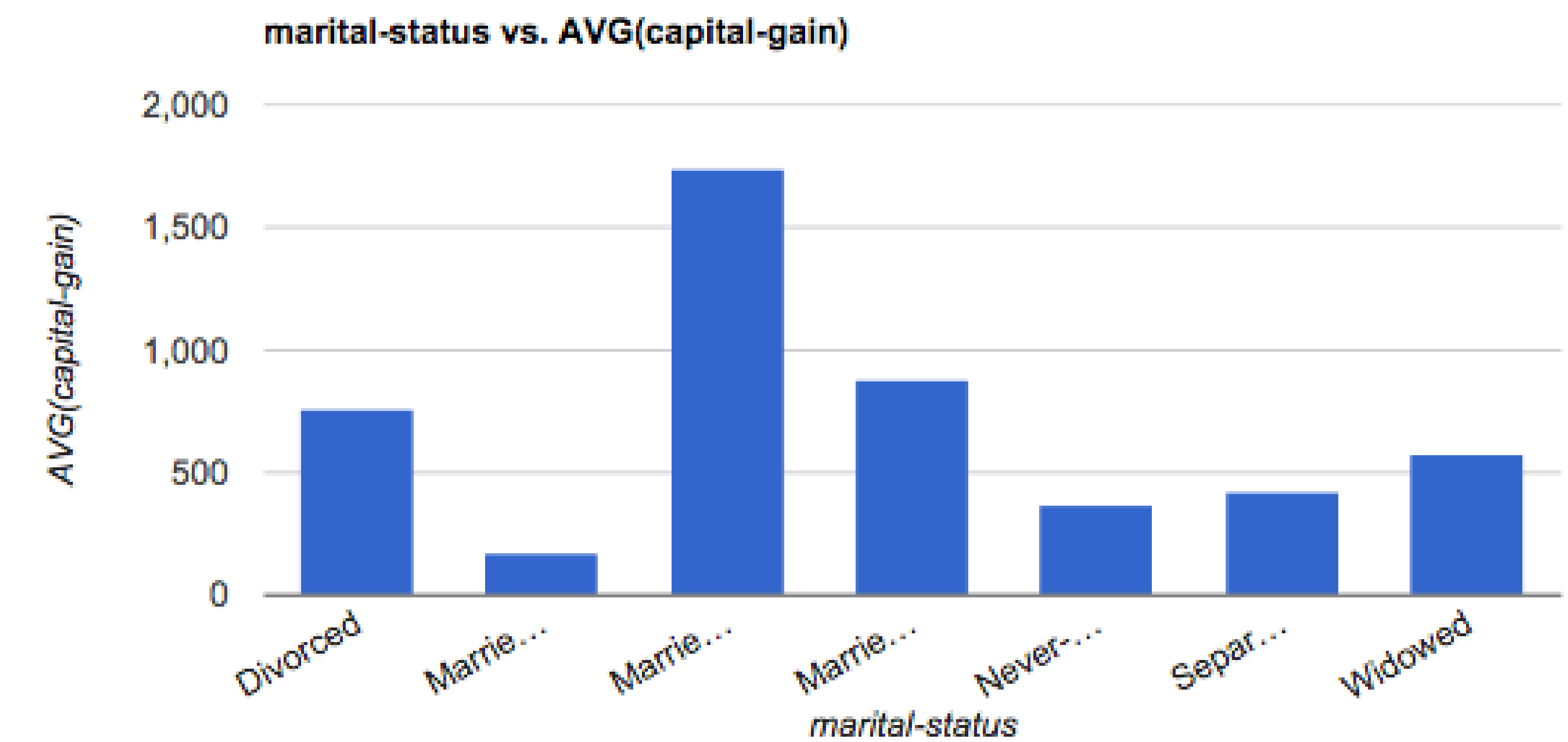
Visualizing Census Data

Pairwise Scatterplot: $O(A^2)$



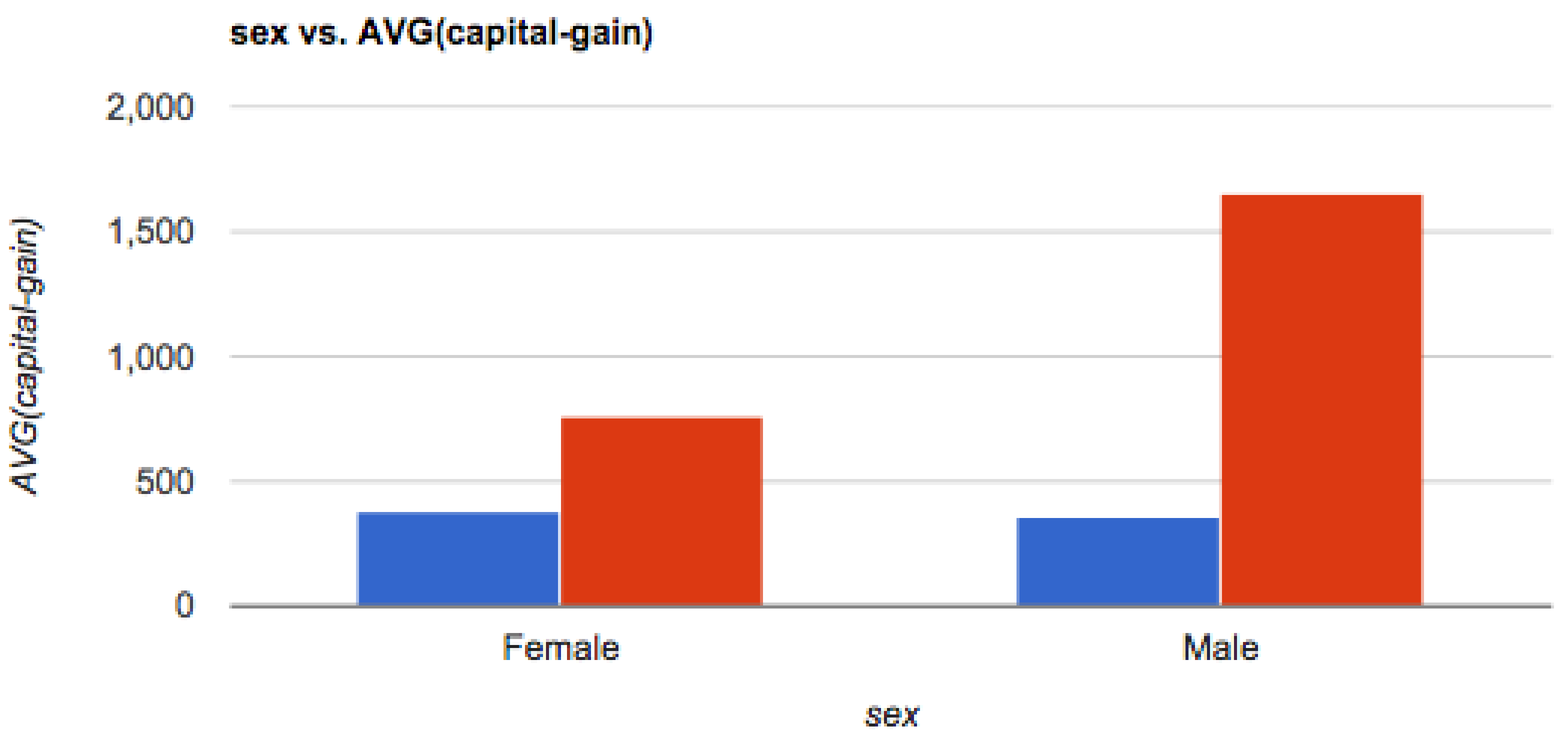
Visualizing Census Data

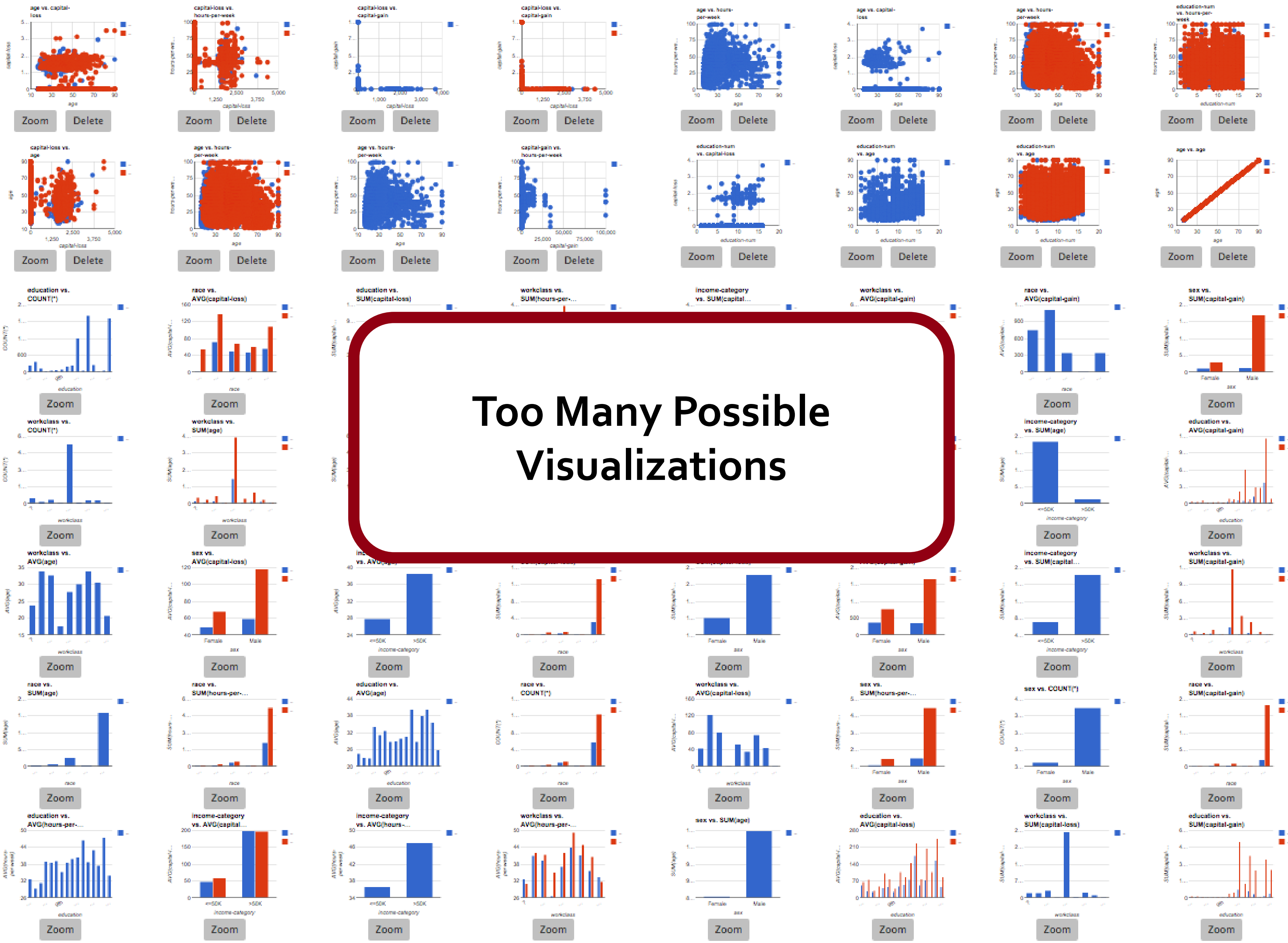
Aggregate View: O(A²)



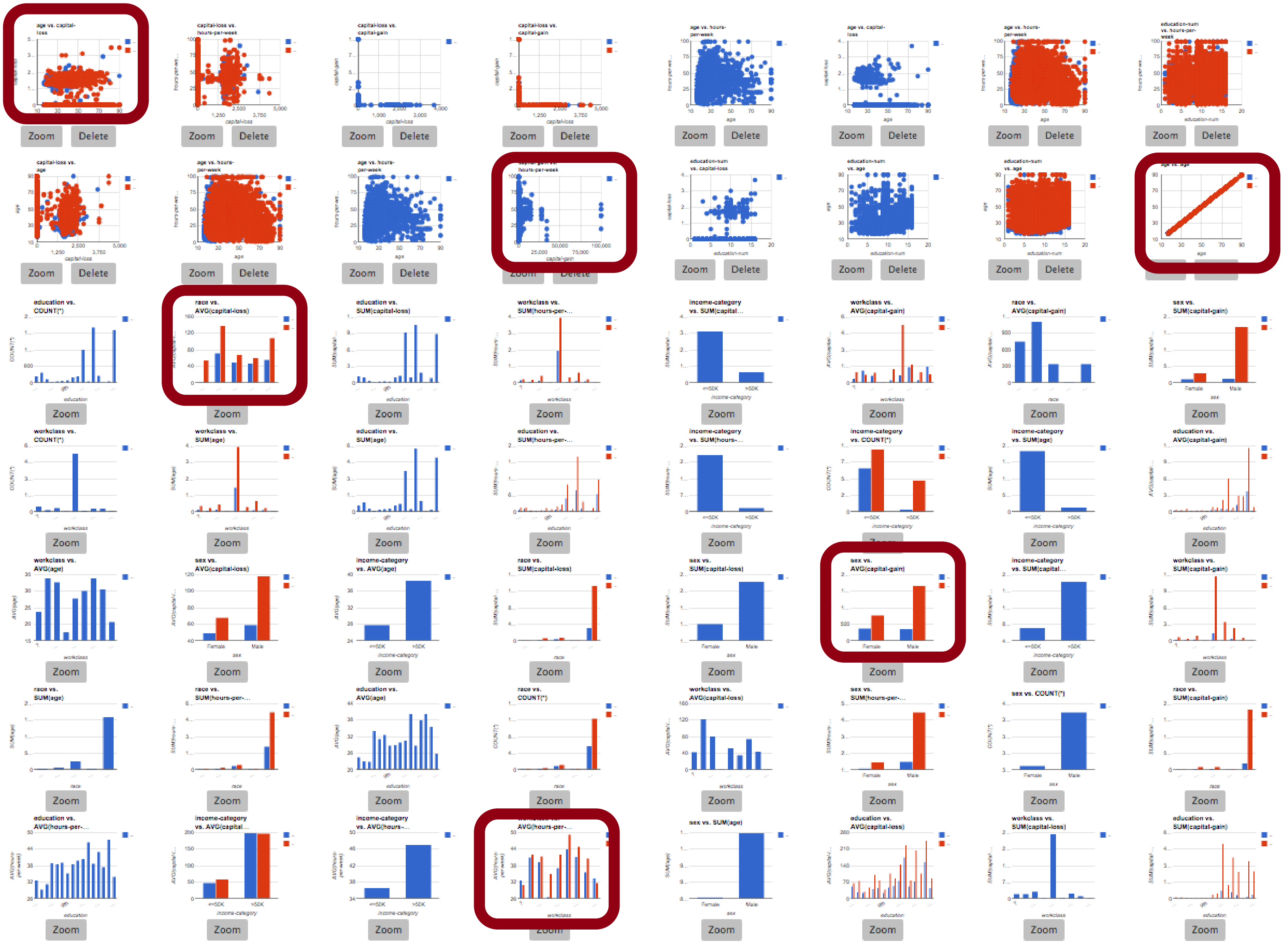
Visualizing Census Data

Comparative visualizations: O(A²)

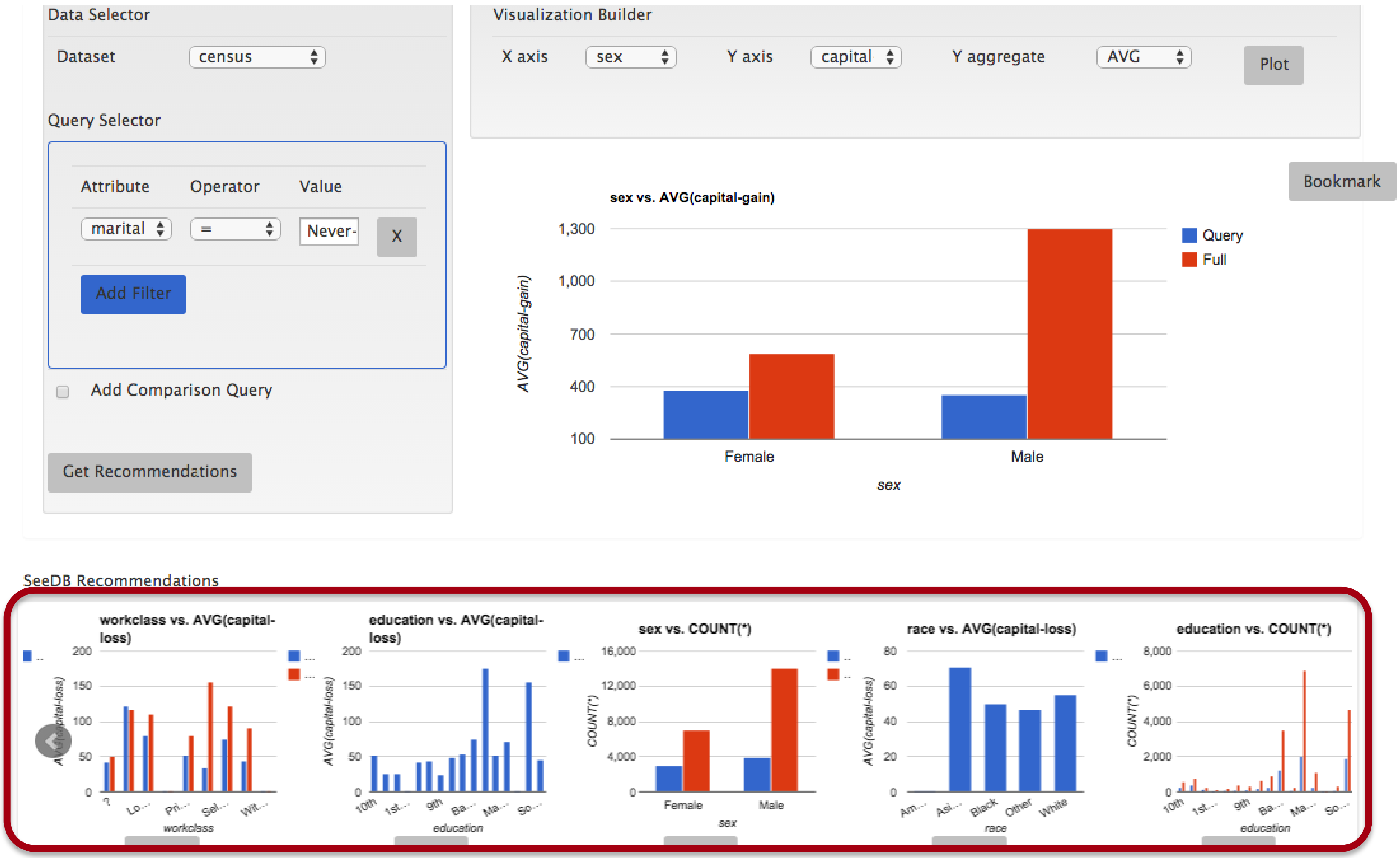




Too Many Possible Visualizations



SeeDB: a visualization recommender



Related Work

- Visualization tools:
  - ManyEyes, Tableau/Polaris, Fusion Tables, Spotfire
  - Tableau and Spotfire recommendations (Aesthetics)
- Some Automation: VizDeck, Profiler, Voyager
- Scagnostics: interesting-ness of scatterplots
  - Graph-theoretic metrics

Recommending Visualizations

I. How to find relevant visualizations?
   – Interesting-ness or **utility metric**

I. How to make recommendations efficiently?
   – Scale to large number of rows
   – Curse of dimensionality
   – Interactive time scales

I. How to find relevant visualizations?

Visualization Utility

- Utility depends on data (distribution), query, metadata, context, user preferences, aesthetics

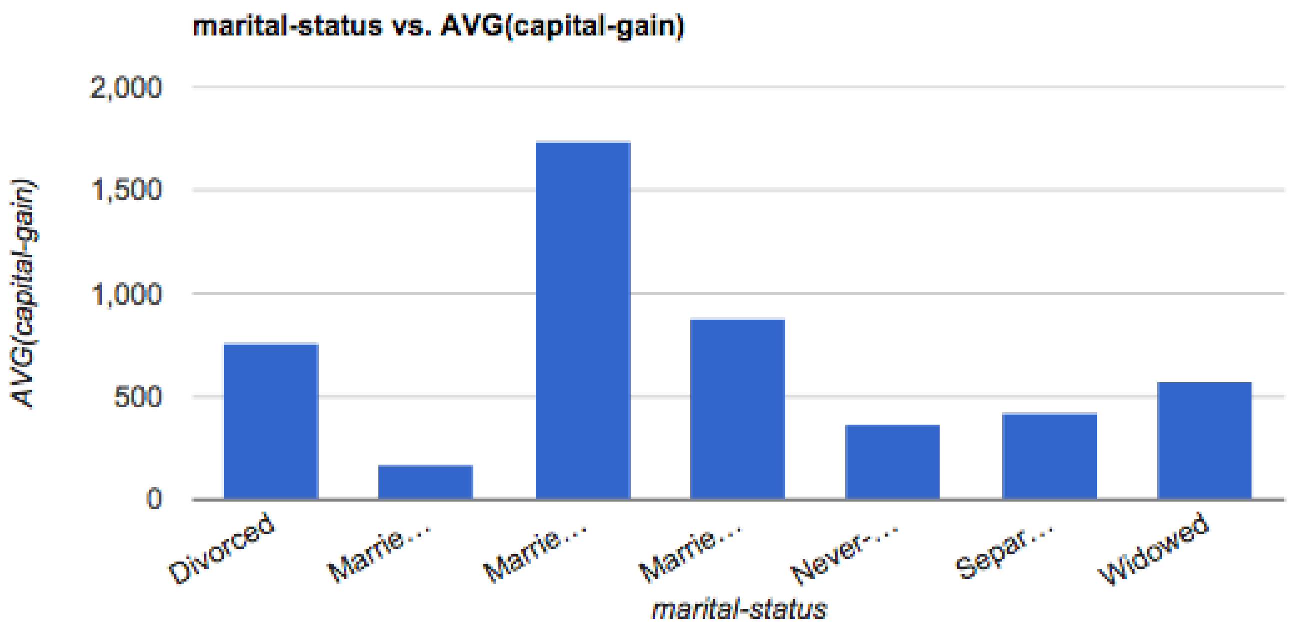
- U = f (data, query, metadata)

- Why?
  - Captures significant part of user interest
  - Independent of "external" data
  - Necessary for cold starts

SeeDB Visualizations

Bar charts/Aggregate Visualizations

- Aggregates essential for large datasets
- Large fraction of common visualizations



SeeDB Visualizations

- $V_i = (d : \text{dimension}, m : \text{measure}, f : \text{aggregate})$

  X-axis Y-axis

- AGGREGATE + GROUP BY queries

SELECT d, f(m) FROM table GROUP BY d
WHERE selection_predicate

The greatest value of a picture is when it forces us to notice what we never expected to see

Tukey, Exploratory Data Analysis 1977

What is unexpected (different from expected trends) is interesting

Deviation-based Utility Metric

Q : SELECT * from census WHERE marital-status = ‘Never-married’

Table: *D*, Data selected by Q: Q_D

{d} : race, work-type, sex etc.

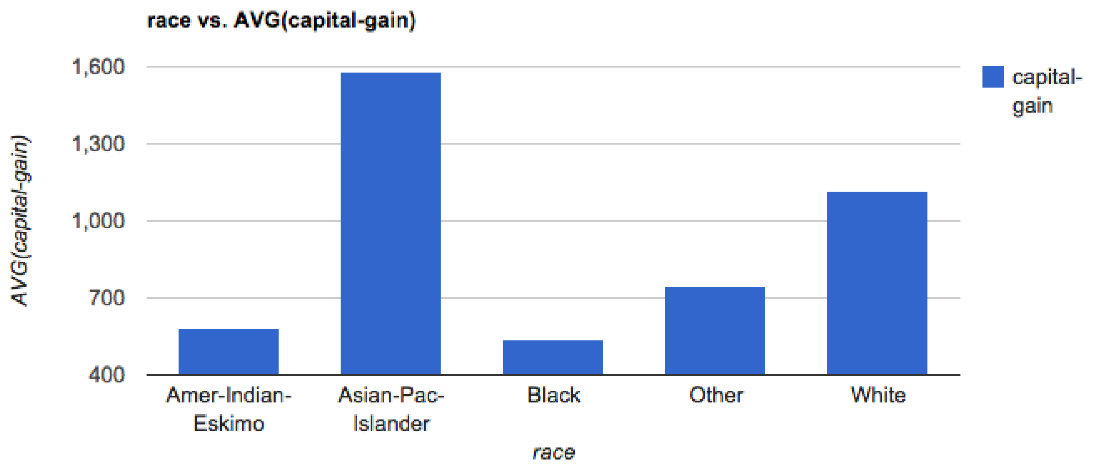
{m} : capital-gain, capital-loss, hours-per-week

{f} : COUNT, SUM, AVG

Computing Expected Trend

V_i: Race vs. AVG(capital-gain)

SELECT race, AVG(capital-gain) FROM census
GROUP BY race



$P[V_i(D)]$

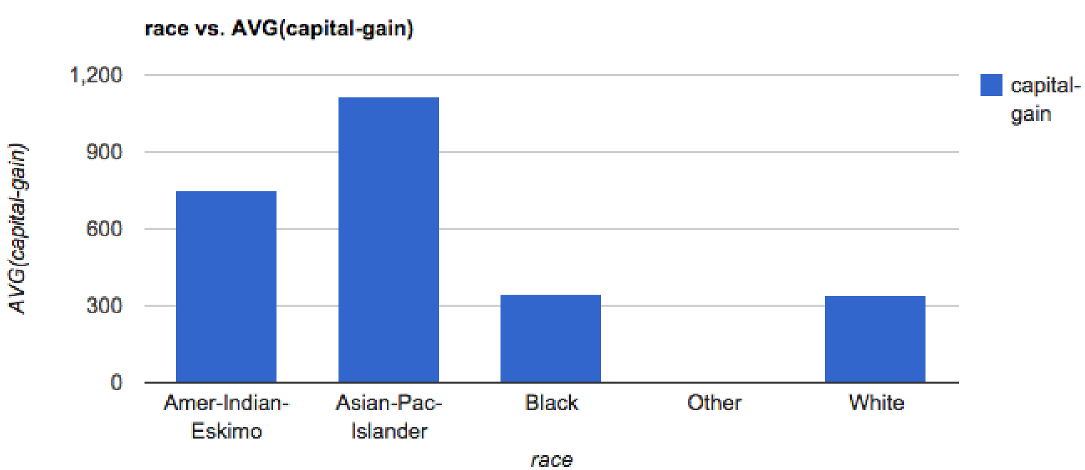
Expected

Distribution

Computing Actual Trend

V_i: Race vs. AVG(capital-gain)

SELECT race, AVG(capital-gain) FROM census GROUP BY race WHERE marital-status='Never-married'



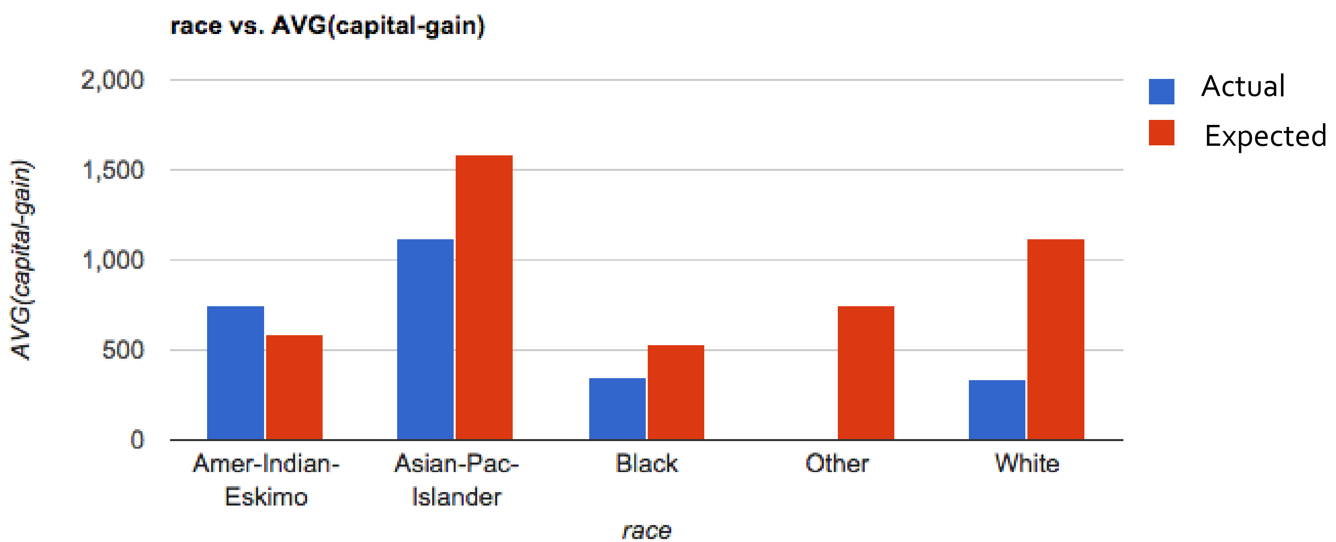
$P[V_i(D_Q)]$

Actual

Distribution

Computing Utility

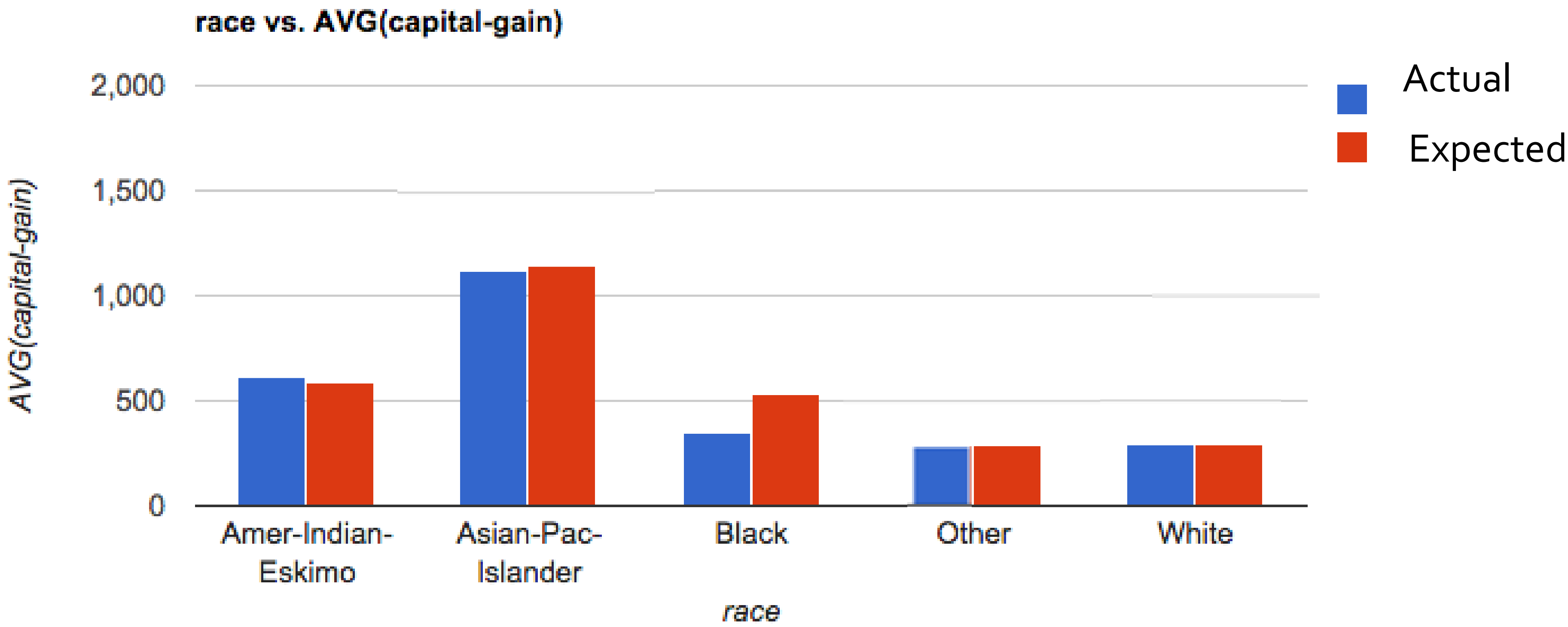
$V_i : P[V_i(D)]$ (expected), $P[V_i(D_Q)]$ (actual)



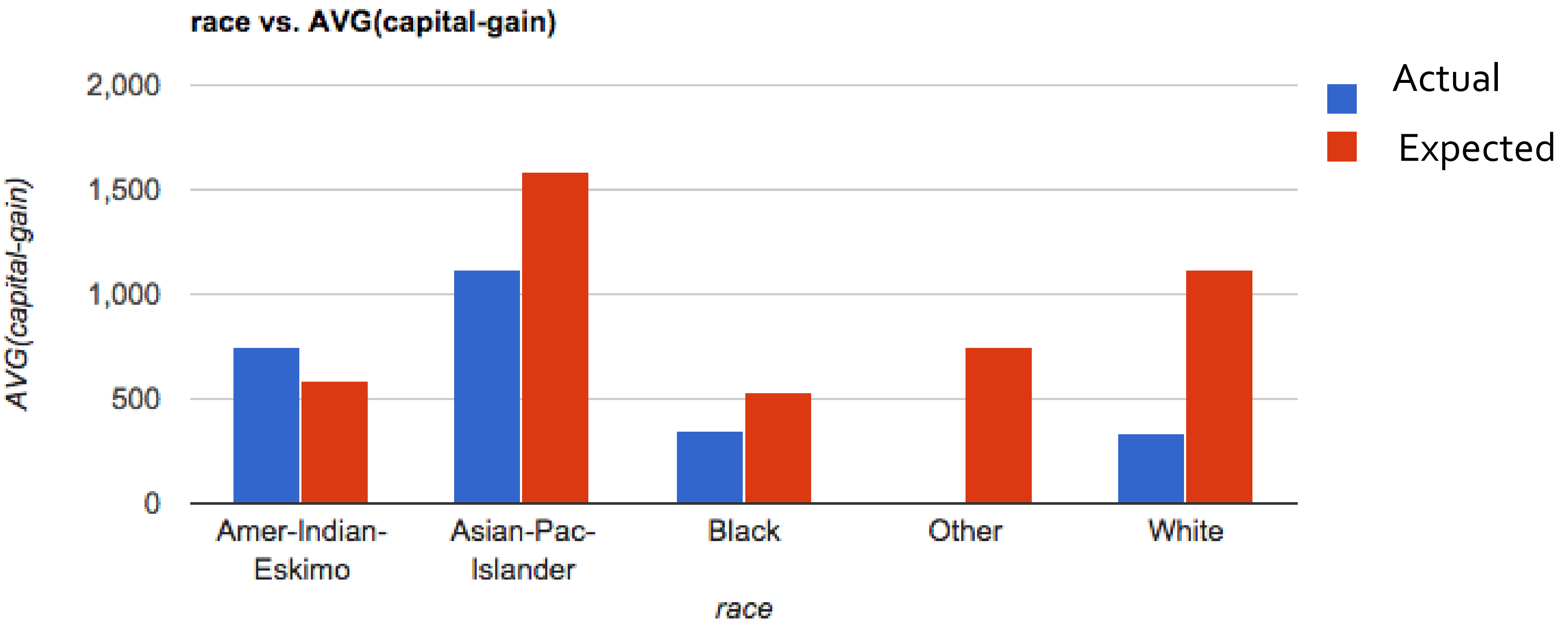
$$\mathbf{U}(V_i) = \Delta(\mathbf{P}[V_i(Q_D)], \mathbf{P}[V_i(D)])$$

Δ = EMD, L2 etc.

Low Utility Visualization



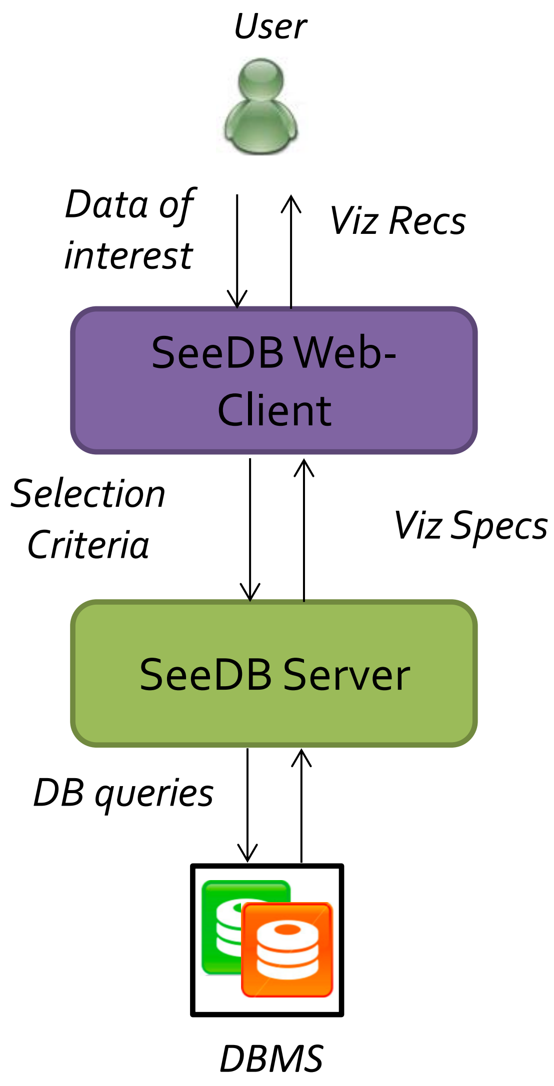
High Utility Visualization



II. How to make recommendations efficiently?

SeeDB Architecture

- Middleware on top of DB
- Data processing delegated to DBMS
- Any SQL-compliant DBMS



Challenges

D = # dimensions, M = # measures,

F = # aggregate functions

- D * M * F potential visualizations
- 2 * D * M * F queries to the DBMS
- Each query (potentially) scans full dataset
- Computation wasted on low-utility views

How do we make recommendations efficiently?

Goals:

- Interactive latencies
- No wasted resources on low-utility views

Strategies:

1. Run-time pruning framework
2. Systems-level optimizations

Run-time Pruning Framework

- Identify views with low-utility early, weed out

- Running estimates of utility based on samples

- Techniques:
  - Confidence Interval-based Pruning
  - Multi-Armed Bandit Pruning*

Multi-Armed Bandit

Slot Machines	S_1	S_2	S_3	S_4	…	S_n
Reward Distributions	R_1	R_2	R_3	R_4		R_n
Estimates	$\mathbf{r_1}$	$\mathbf{r_2}$	$\mathbf{r_3}$	$\mathbf{r_4}$		$\mathbf{r_n}$

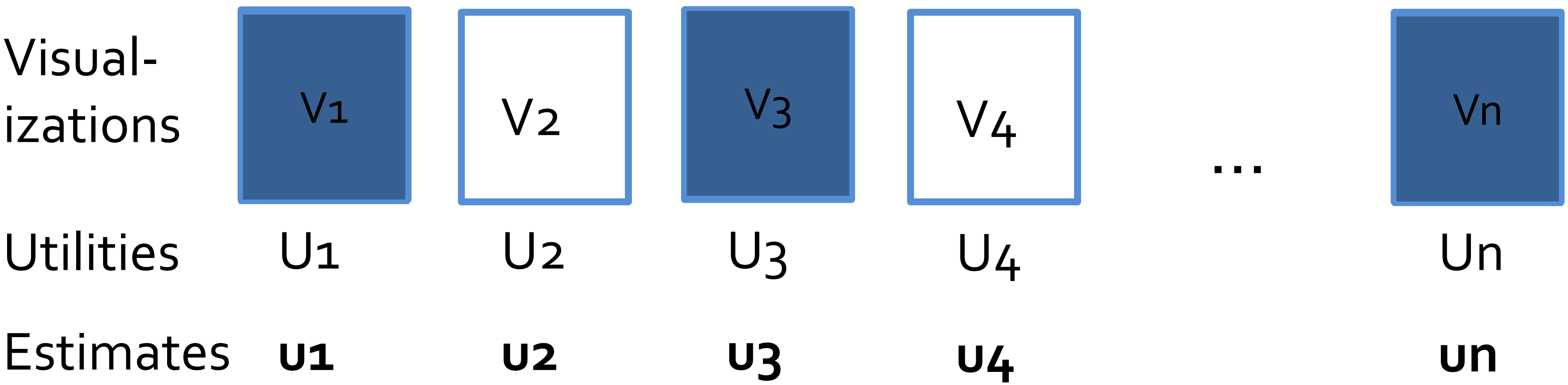
Which machines to play and in what order to maximize reward?

Multi-Armed Bandit

Slot Machines	S1	S2	S3	S4	…	Sn
Reward Distributions	R1	R2	R3	R4		Rn
Estimates	**r1**	**r2**	**r3**	**r4**		**rn**

Use estimates to guide choice of machine

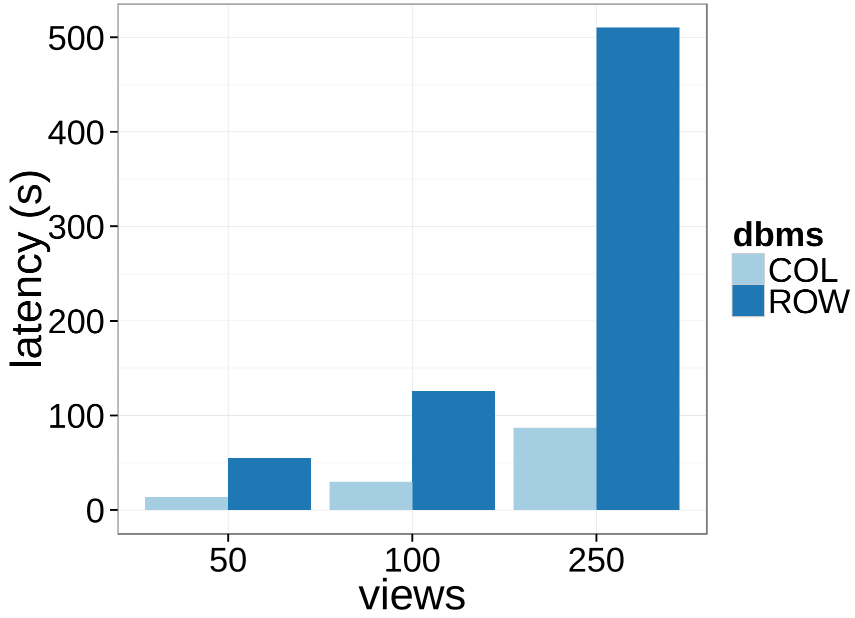
Multi-Armed Bandit Pruning



- Rank views by utility
- Find maximum utility views
- Compute various Δ_i
- *Discard* V_n or *accept* V_1

Systems-level optimizations

- Each visualization = 2 SQL queries



- Latency > 100s
- Minimize number of queries and scans

Systems-level optimizations

- Combine aggregate queries on Q_D and D

- Combine multiple aggregates

  (d1, m1, f1), (d1, m2, f1) → (d1, [m1, m2], f1)

- Combine multiple group-bys*

  (d1, m1, f1), (d2, m1, f1) → ([d1, d2], m1, f1)

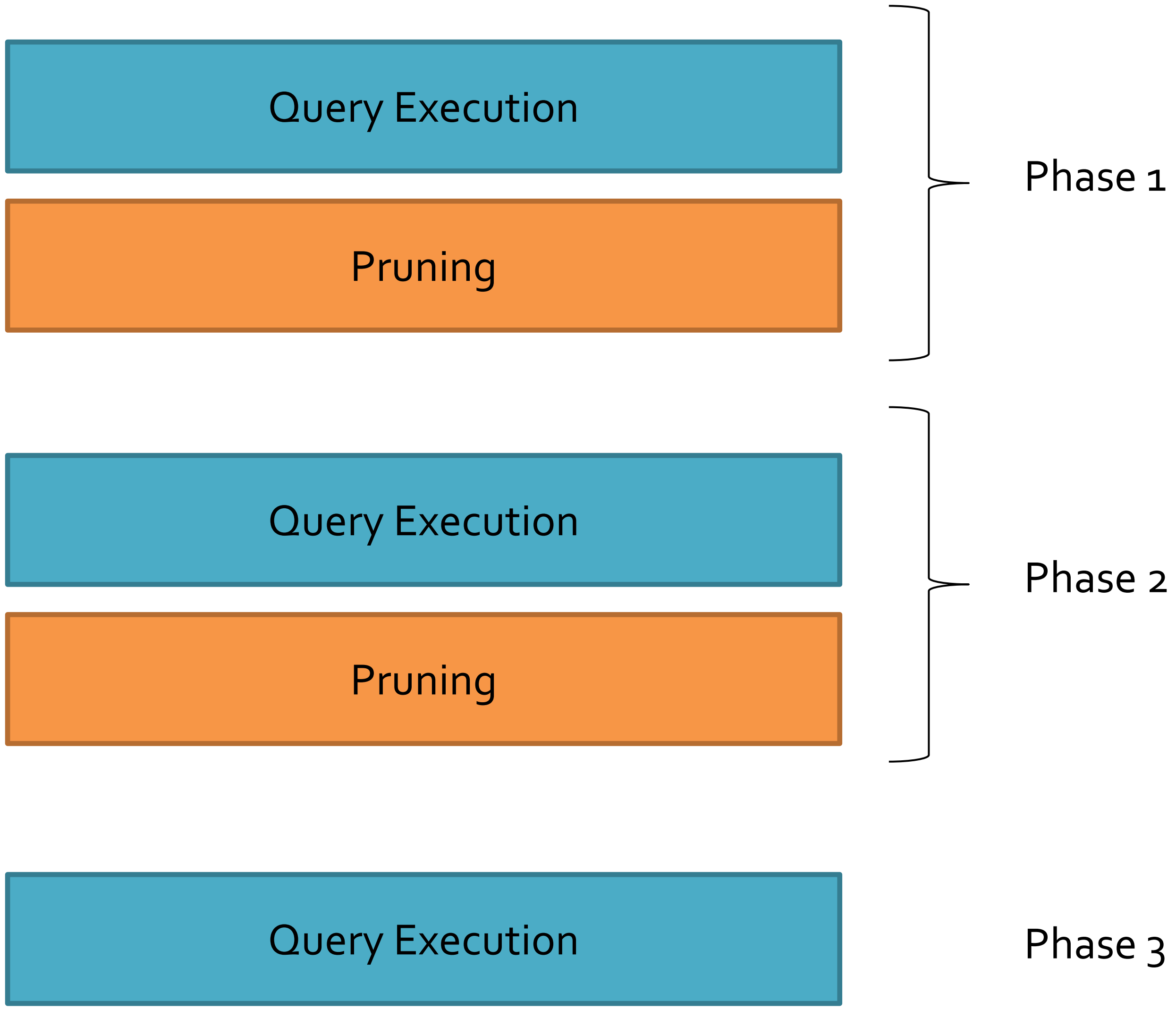
- Parallel Query Execution

Combining Multiple Group-bys

- Too few group-bys leads to many table scans
- Too many group-bys hurt performance
  - # groups = Π (# distinct values per attributes)
- Optimal group-by combination ≈ bin-packing
  - Bin volume = log S (max number of groups)
  - Volume of items (attributes) = log ($|a_i|$)
  - Minimize # bins s.t.

$$\Sigma_i \log(|a_i|) <= \log S$$

Interleaving Optimizations

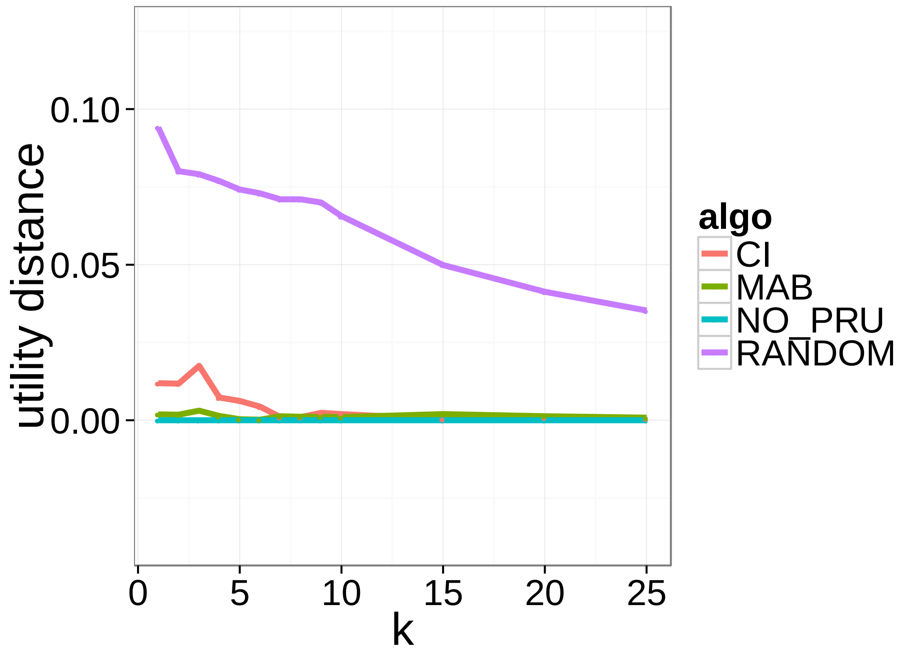


Evaluation

Evaluation

- Performance Study
  - Latency, accuracy
  - Variety of synthetic and real datasets
- User Study (ongoing)
  - Controlled Study
  - Trends, Interactions, Surveys

Pruning Optimizations

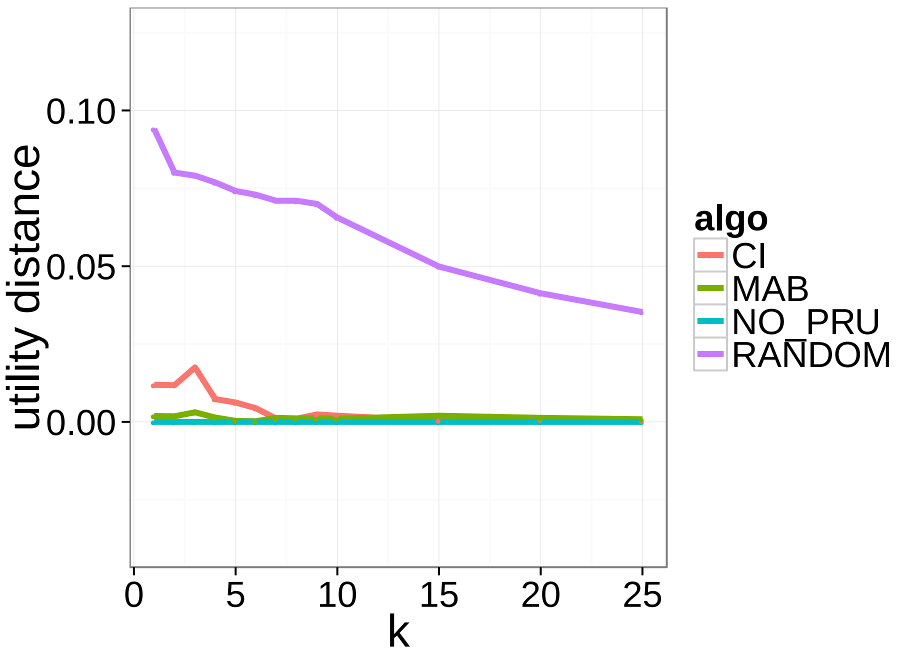


Utility Distance for BANK

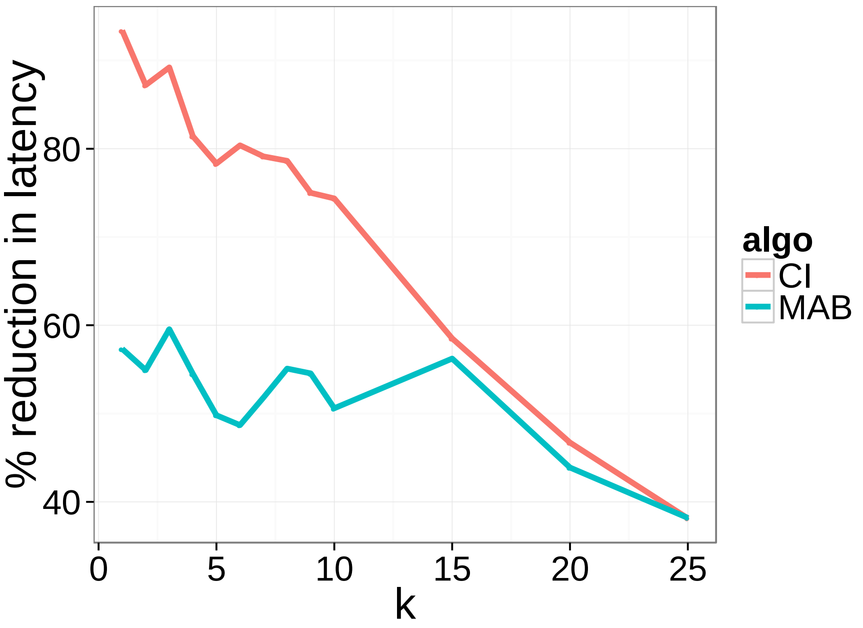
Utility Distance =

Δ (*Utility of real top-k, Utility of SeeDB top-k*)

Pruning Optimizations



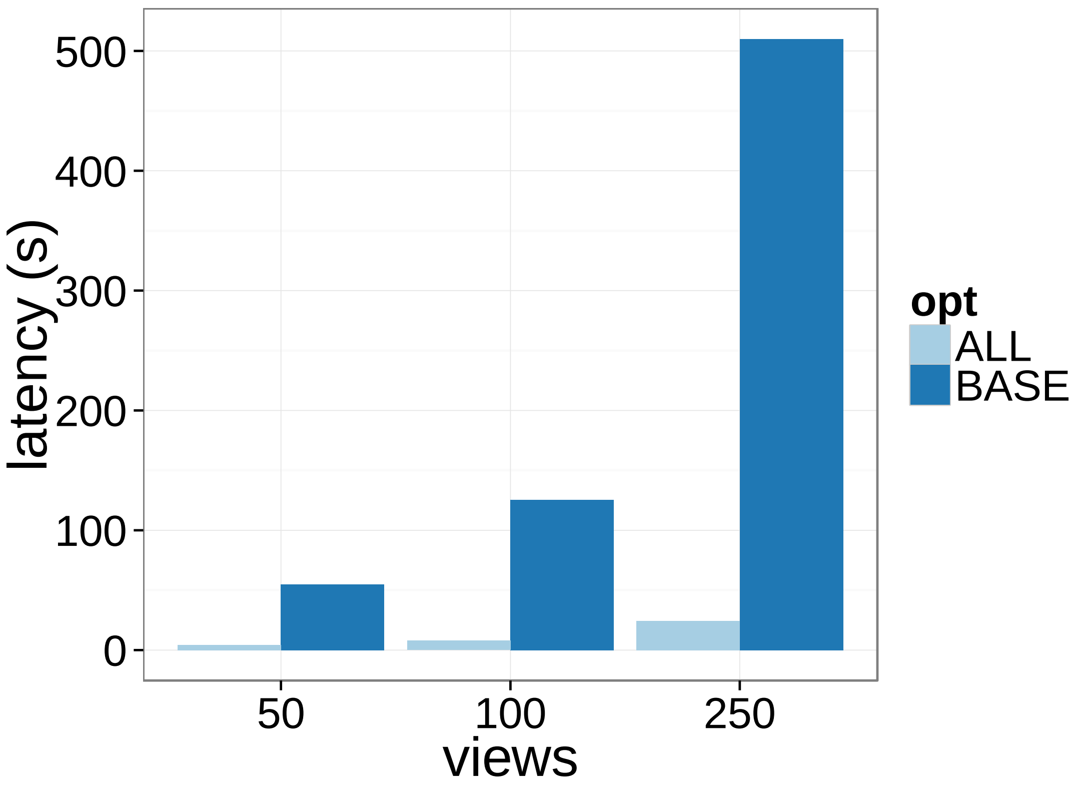
Utility Distance for BANK



Latency Reduction for BANK

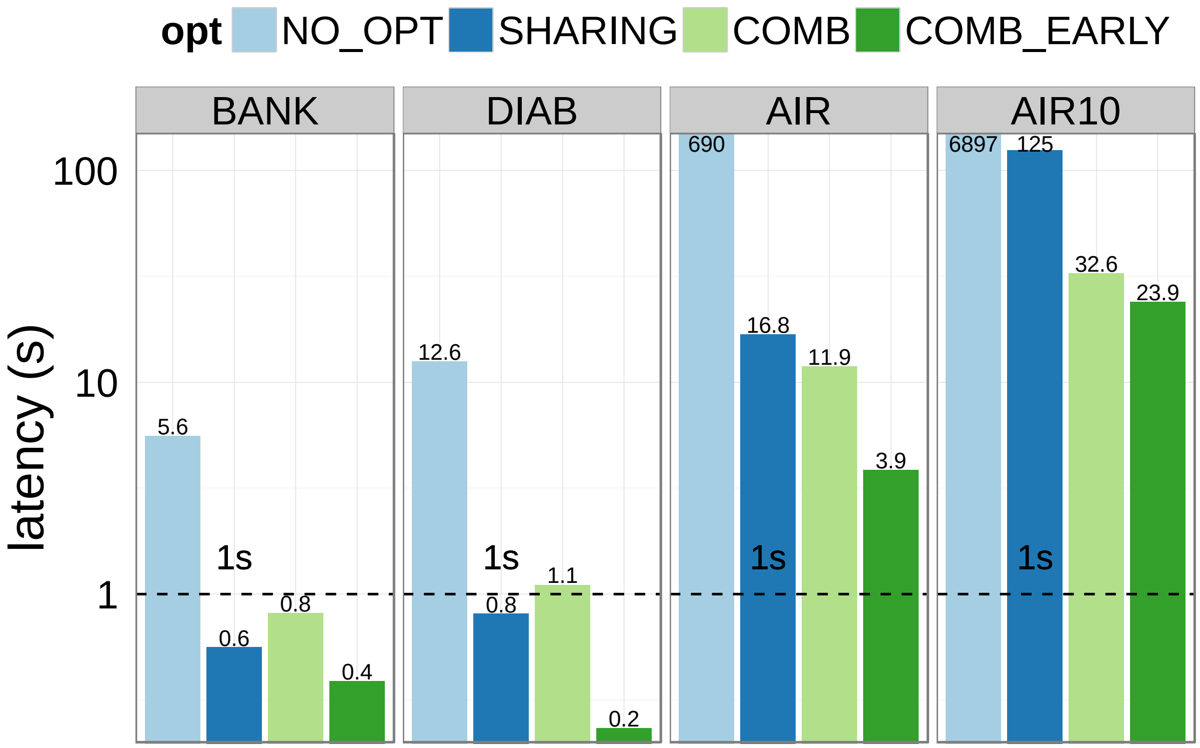
Pruning can reduce latency by 50 - 90% w/o significant hit in accuracy

Systems-level Optimizations



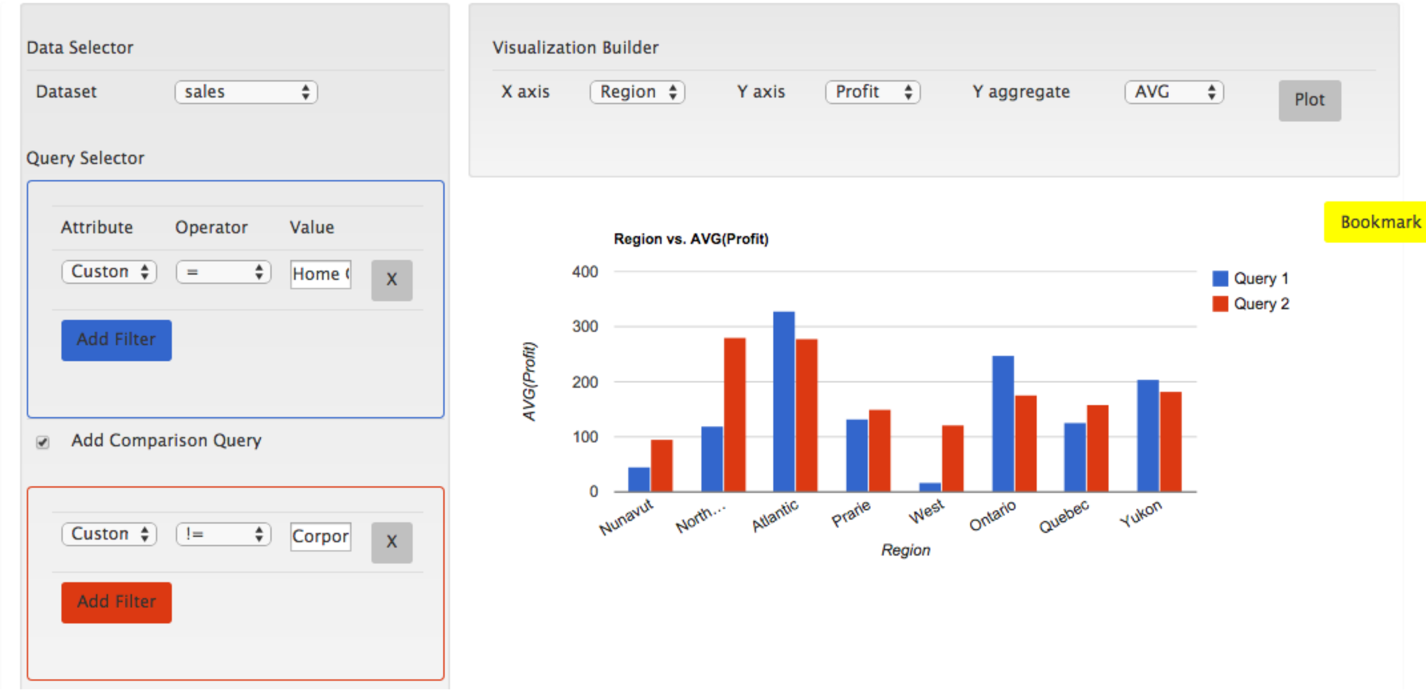
Combination of systems optimizations reduce latency 25X to ~ 10s

Putting it together



SeeDB returns results in < 4 s for small and medium-sized data

User Study



Data Selector
Dataset
sales
Query Selector
Attribute
Operator
Value
Custon
=
Home (
X
Add Filter
Add Comparison Query
Custon
!=
Corpor
X
Add Filter
Visualization Builder
X axis
Region
Y axis
Profit
Y aggregate
AVG
Plot
Bookmark
Region vs. AVG(Profit)
400
300
200
100
0
AVG(Profit)
Nunavut
North…
Atlantic
Prarie
West
Ontario
Quebec
Yukon
Region
Query 1
Query 2

User Quotes

"I liked the recommendations because it allowed for a quick starting point"

"They showed a compelling abstract of the data. It made the data comprehensible"

"It's a great tool for proposing an initial set of queries for a new dataset"

"Recommendations helped in finding some interesting aspects of the data I wouldn't have checked myself"

"I was more likely to stick to suggestions than come up with my own thoughtful or new ideas"

User study stats: I

- Prefer tool with recommendations: 100%
  - High bar on quality
- Recommendations sped up analysis: 85%
- Recommendations Rating: 75% (>= helpful)
  - Deviation-based metric performs well

User study stats: II

- More charts explored with recommendations
  - No_rec (11) vs. Rec (14) [p-value: 0.1]
- Number of bookmarks
  - No_rec (3.5) vs. Rec (3.6) [p-value: 0.5]
  - Context and user preferences
- Expert users expect sophisticated statistics

SeeDB Summary

- Visualization recommender for analytics
- Deviation-based utility to capture relevance
- Run-time pruning can provide a 4X speedup and systems-level optimizations 25X
- Users prefer a tool with recommendations
- Ongoing work: incorporate other relevance metrics (other distance metrics, context etc.)

Thanks and Questions!

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