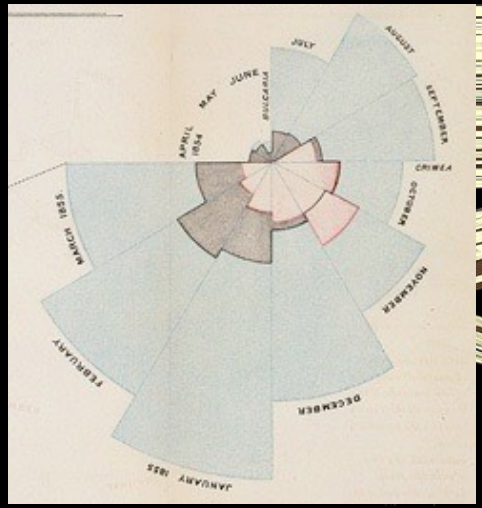
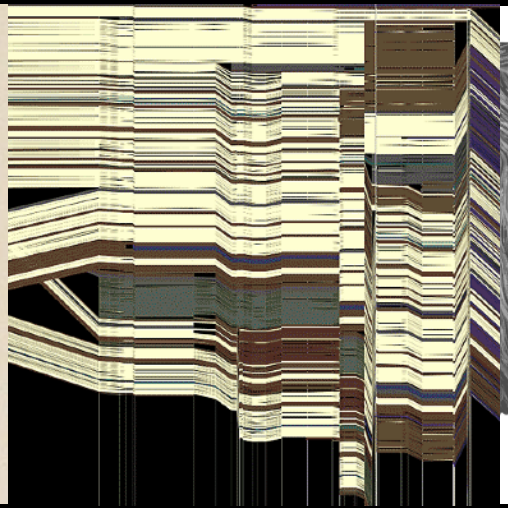
CSE 512 - Data Visualization

Scalable Visualization





Jeffrey Heer University of Washington

Session Outline

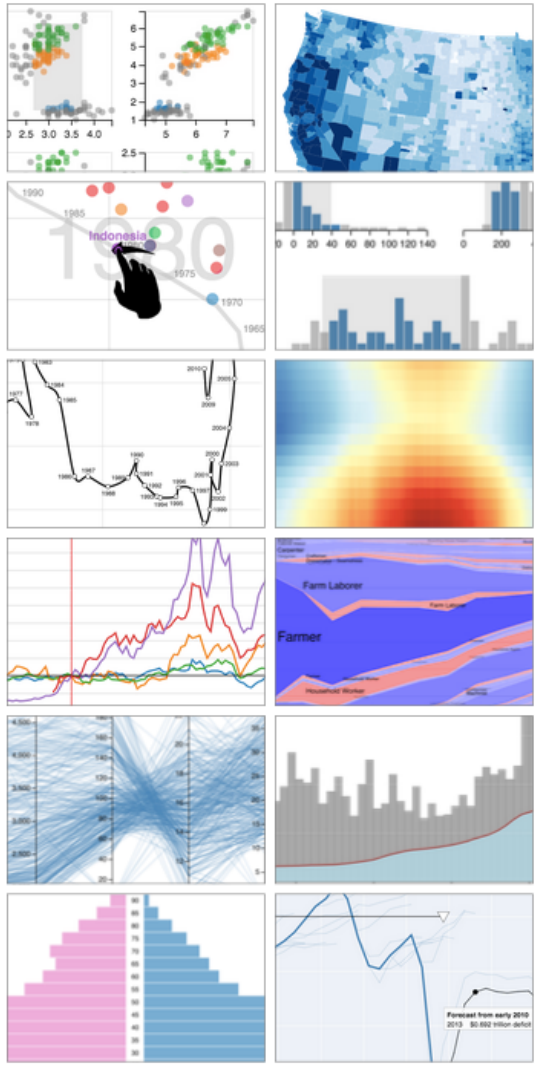
The Varieties of “Big Data”

Scalable Plotting Techniques

Scalable Interaction

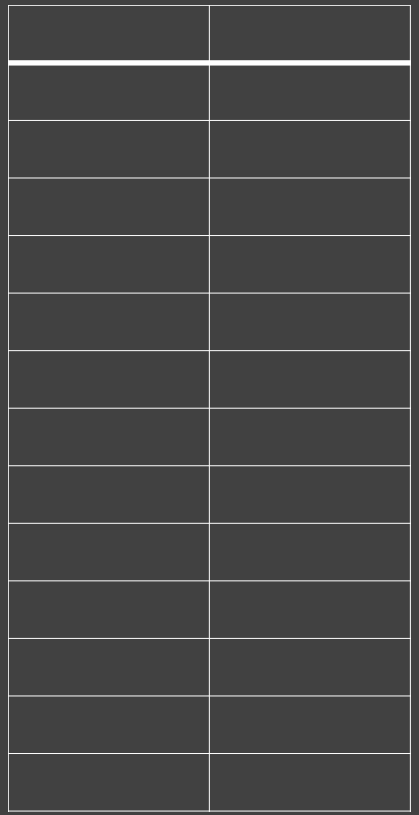
Why Latency Matters

Sampling Methods



The Varieties of “Big Data”

Tall Data



Lots of records

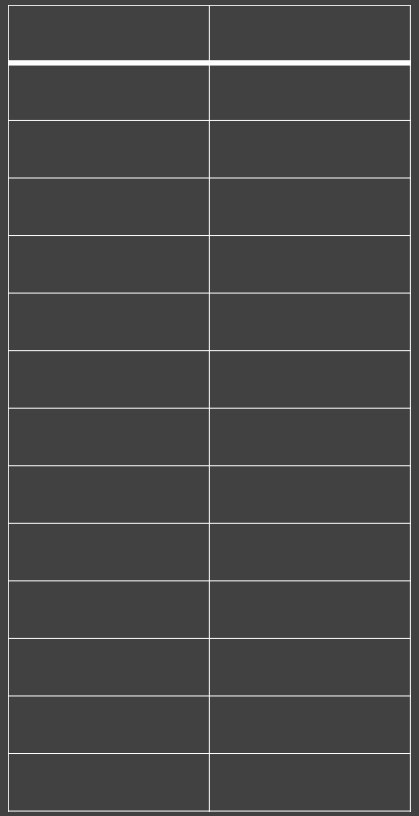
- Large DBs have petabytes or more
- *(but median DB still fits in RAM!)*

How to manage?

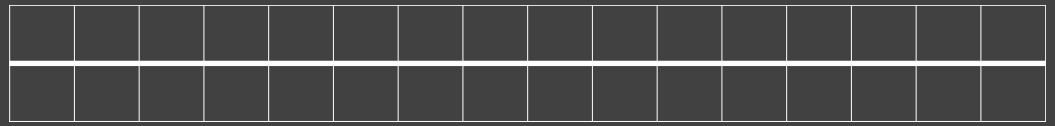
- Parallel data processing
- Reduction: Filter, aggregate
- Sample or approximate

Not just about systems. Consider perceptual / cognitive scalability.

Tall Data



Wide data



Lots of variables (100s-1000s…)

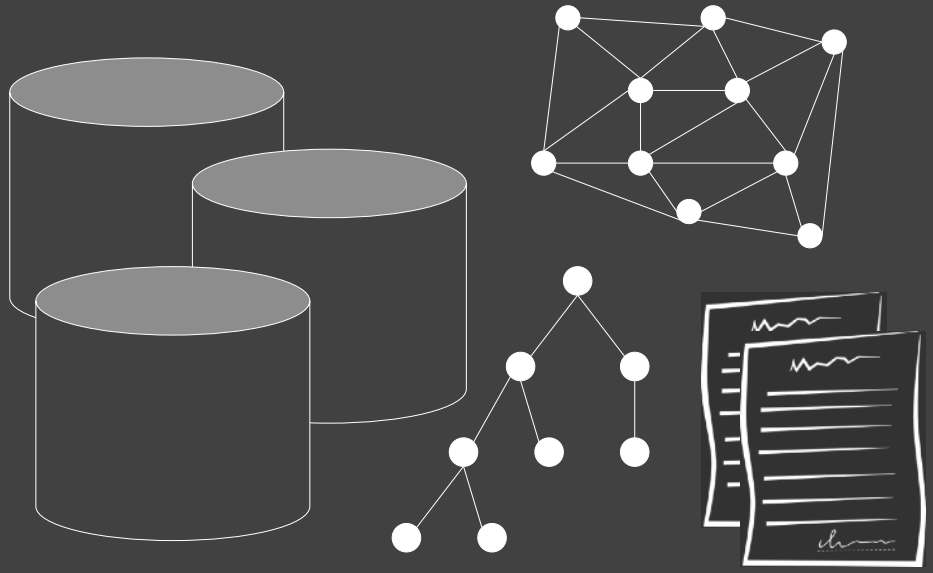
- Select relevant subset
- Dimensionality reduction
- Statistical methods can suggest and order related variables

Requires human judgment

Tall Data

Wide data

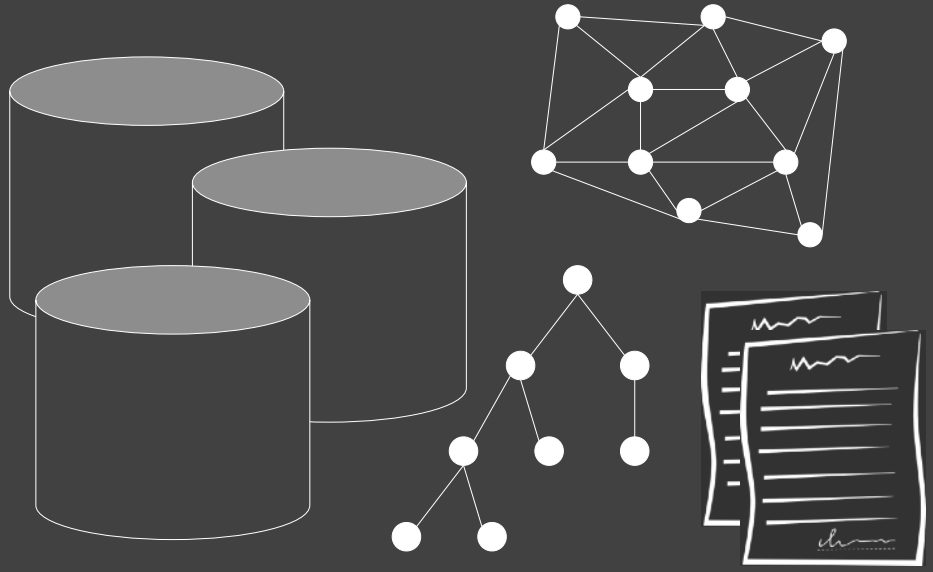
Diverse data



Tall Data

Wide data

Diverse data



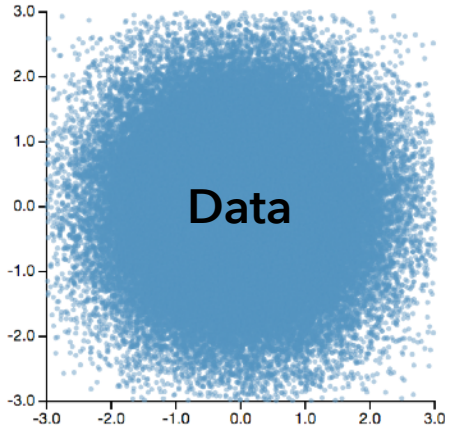
How can we visualize and interact with **billion+ record** databases in real-time?

Two Challenges:

1. Effective **visual encoding**
2. Real-time **interaction**

Perceptual and interactive scalability should be limited by the **chosen resolution** of the visualized data, not the number of records.

Scalable Plotting Techniques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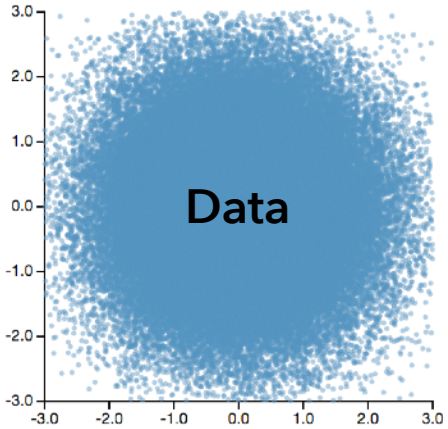
Data
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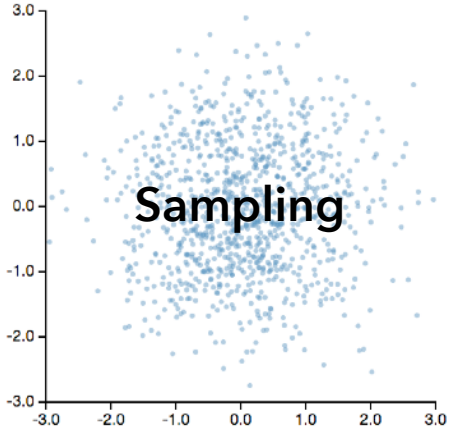
Sampling
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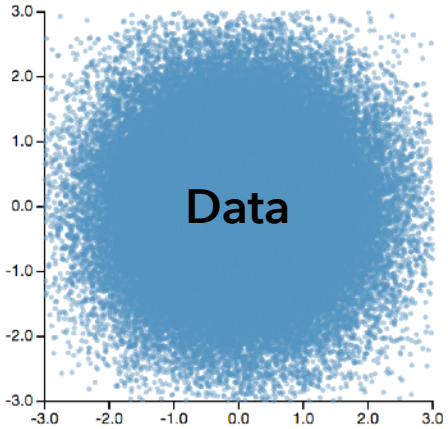
Data
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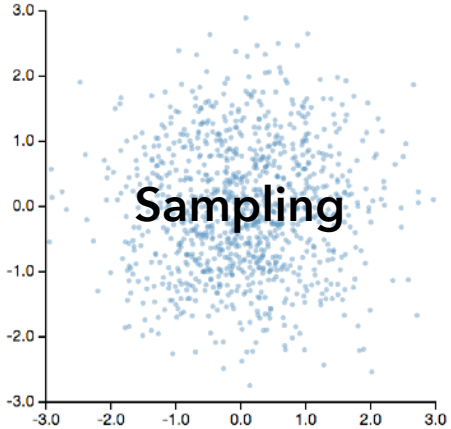
Sampling
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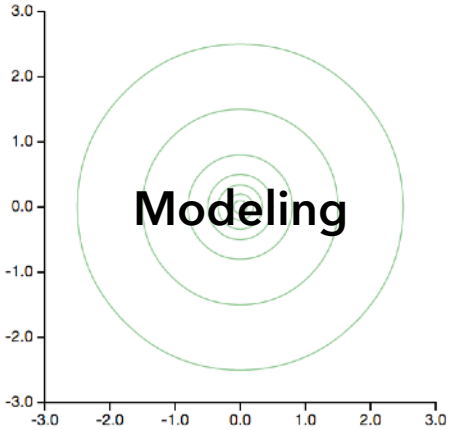
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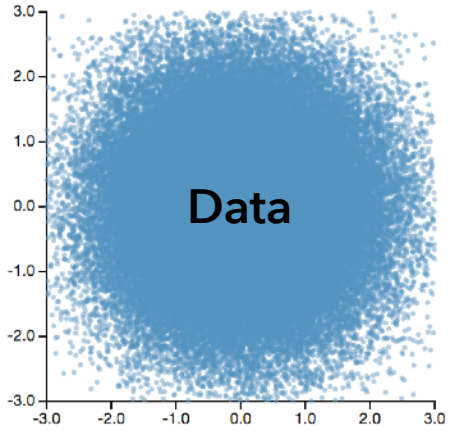
Data
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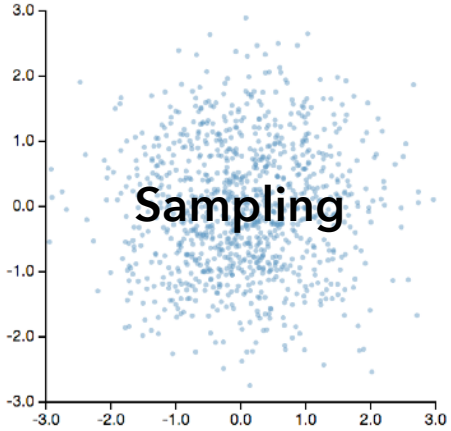
Sampling
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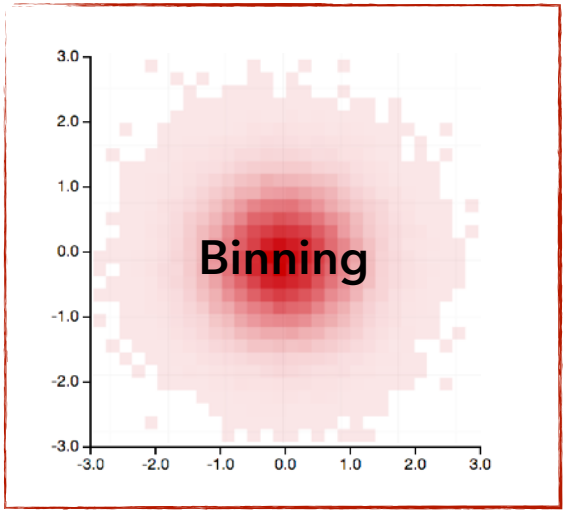
Binning
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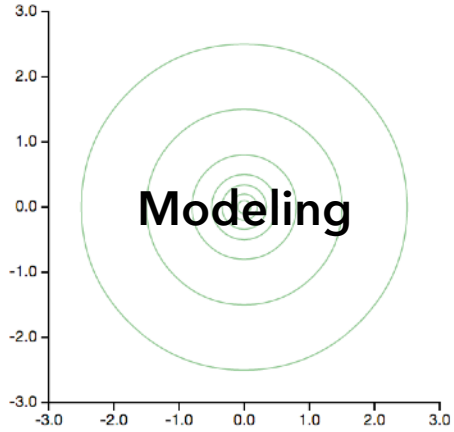
Modeling
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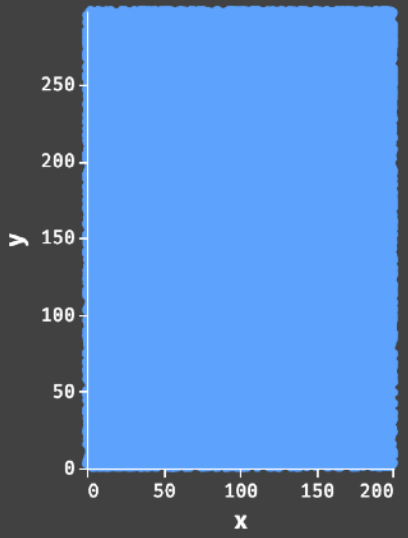
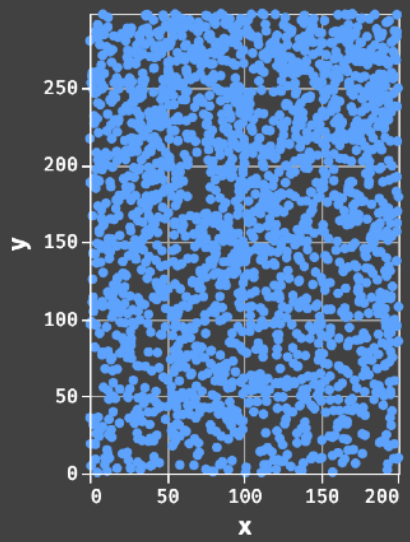
0.0
-1.0
-2.0
-3.0
-3.0 -2.0 -1.0 0.0 1.0 2.0 3.0

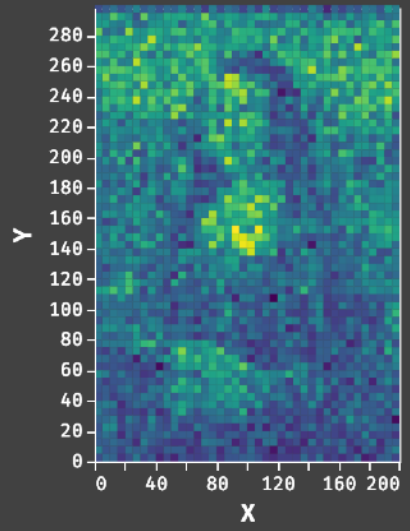
How to **Visualize** a Billion+ Records



Data



Sampling



Binned Aggregation

Decouple the visual complexity from the raw data through aggregation.

Bin > Aggregate (> Smooth) > Plot

1. Bin Divide data domain into discrete “buckets”

Categories: Already discrete (but watch out for high cardinality)

Numbers: Choose bin intervals (uniform, quantile, ...)

Time: Choose time unit: Hour, Day, Month, etc.

Geo: Bin x, y coordinates *after* cartographic projection

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3. Smooth Optional: smooth aggregates [Wickham ’13]

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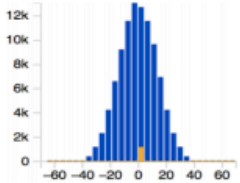
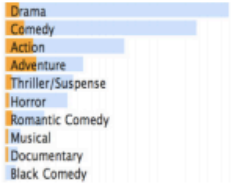
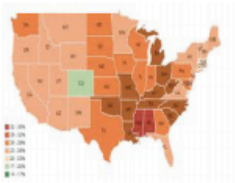
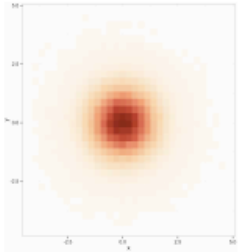
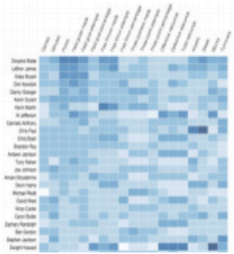
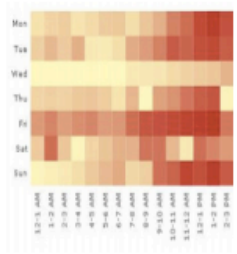
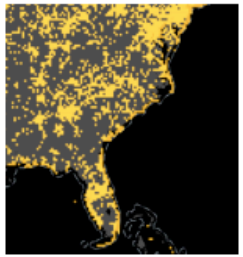
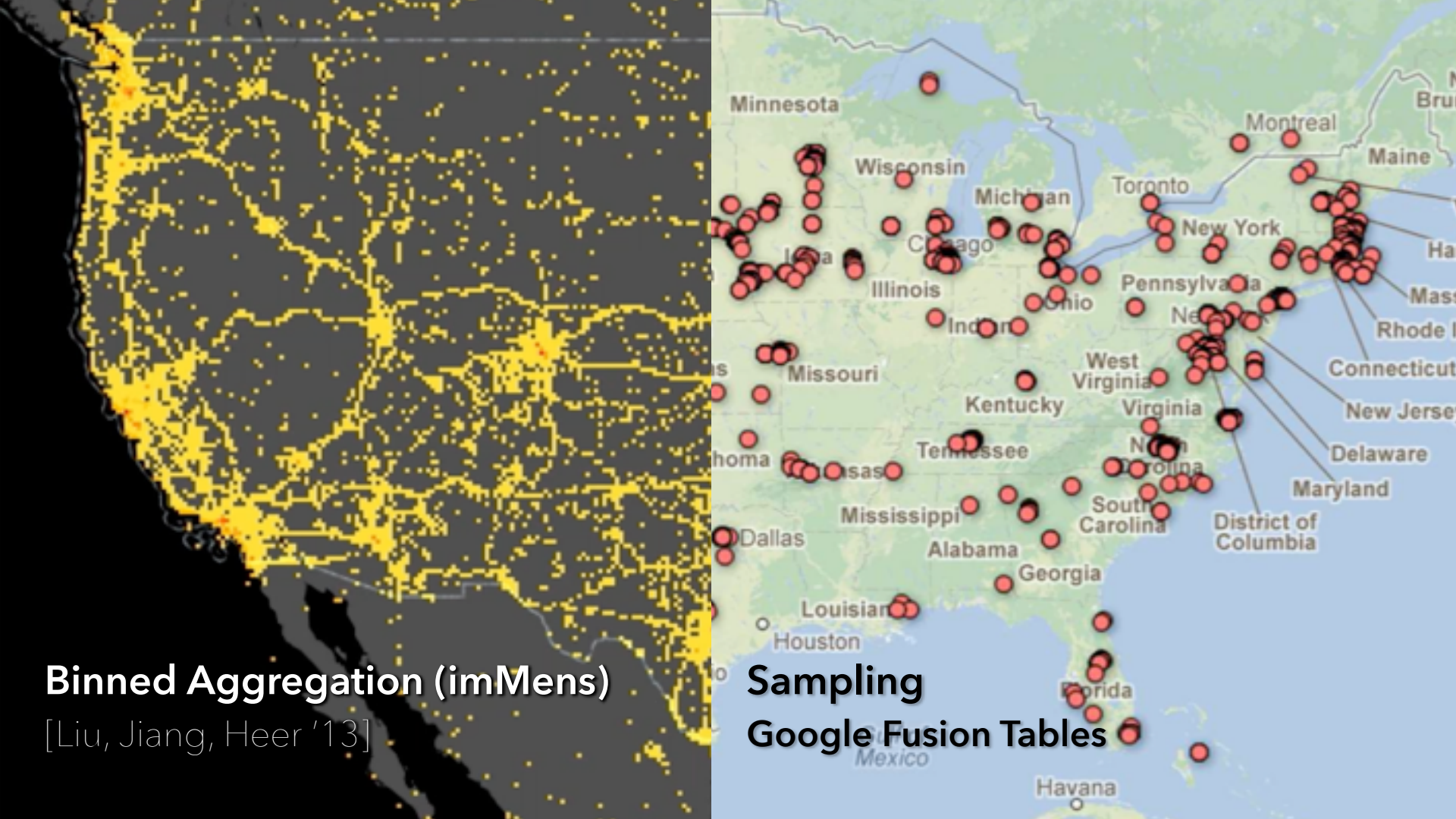
4. Plot Visualize the aggregate values

Binned Plots by Data Type

	Numeric	Ordinal	Temporal	Geographic
1D	 Histogram	 Bar Chart	 Line Graph / Area Chart	 Choropleth Map
2D	 Binned Scatter Plot	 Heatmap	 Temporal Heatmap	 Geographic Heatmap

Examples


Montana
North Dakota
Minnesota
Montreal
Maine
South Dakota
Wisconsin
Toronto
Oregon
Idaho
Michigan
New York
Illinois
Pennsylvania
Nevada
Utah
Missouri
West Virginia
Kentucky
Virginia
Connecticut
New Jersey
Delaware
Maryland
Oklahoma
Tennessee
Mississippi
South Carolina
District of Columbia
Alabama
Georgia
New Mexico
Phoenix
San Diego
Dallas
Texas
Houston
San Antonio
Gulf of California
Monterrey
Mexico
Havana
Sampling
Google Fusion Tables

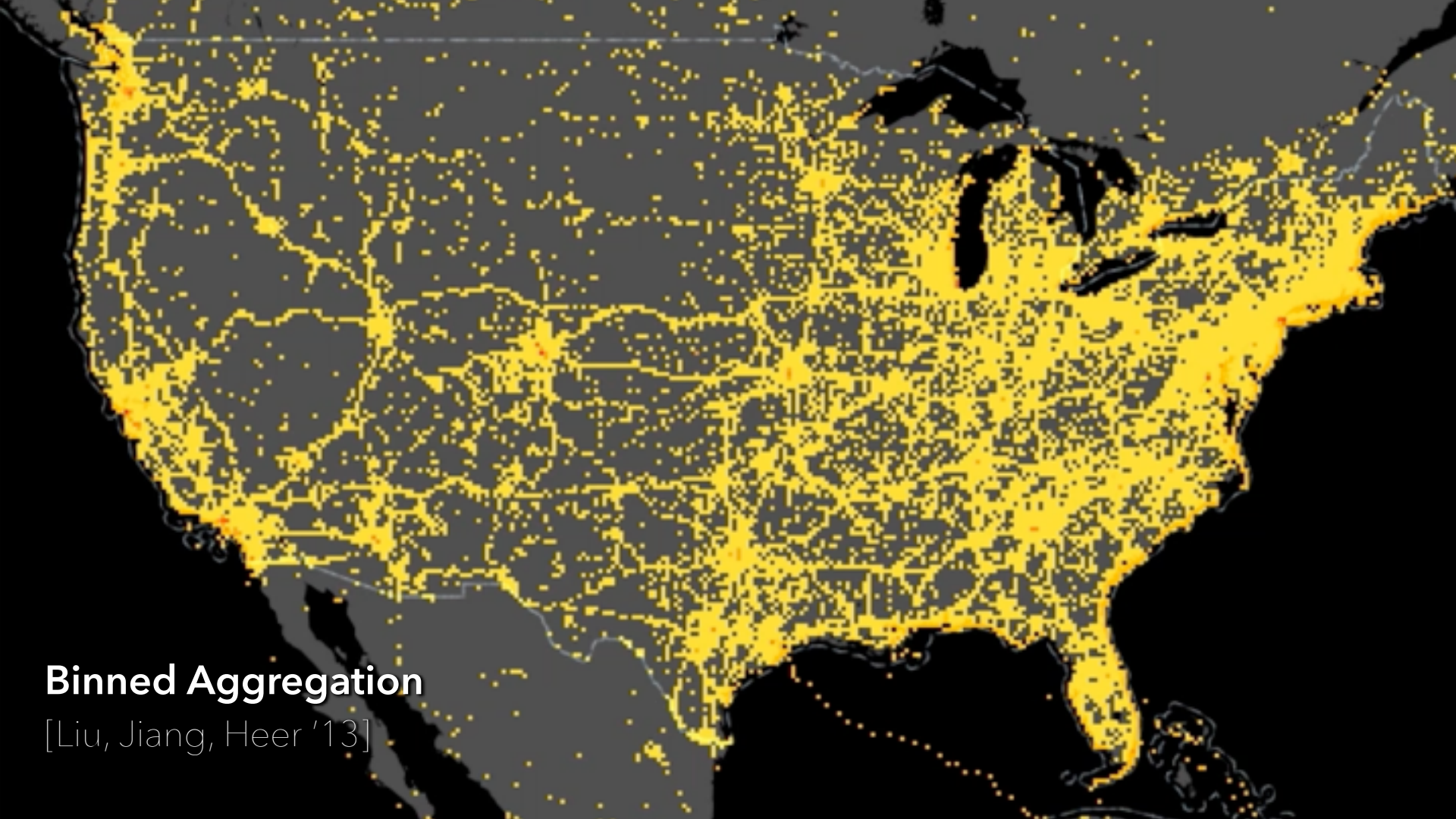


Binned Aggregation (imMens)

[Liu, Jiang, Heer '13]

Sampling

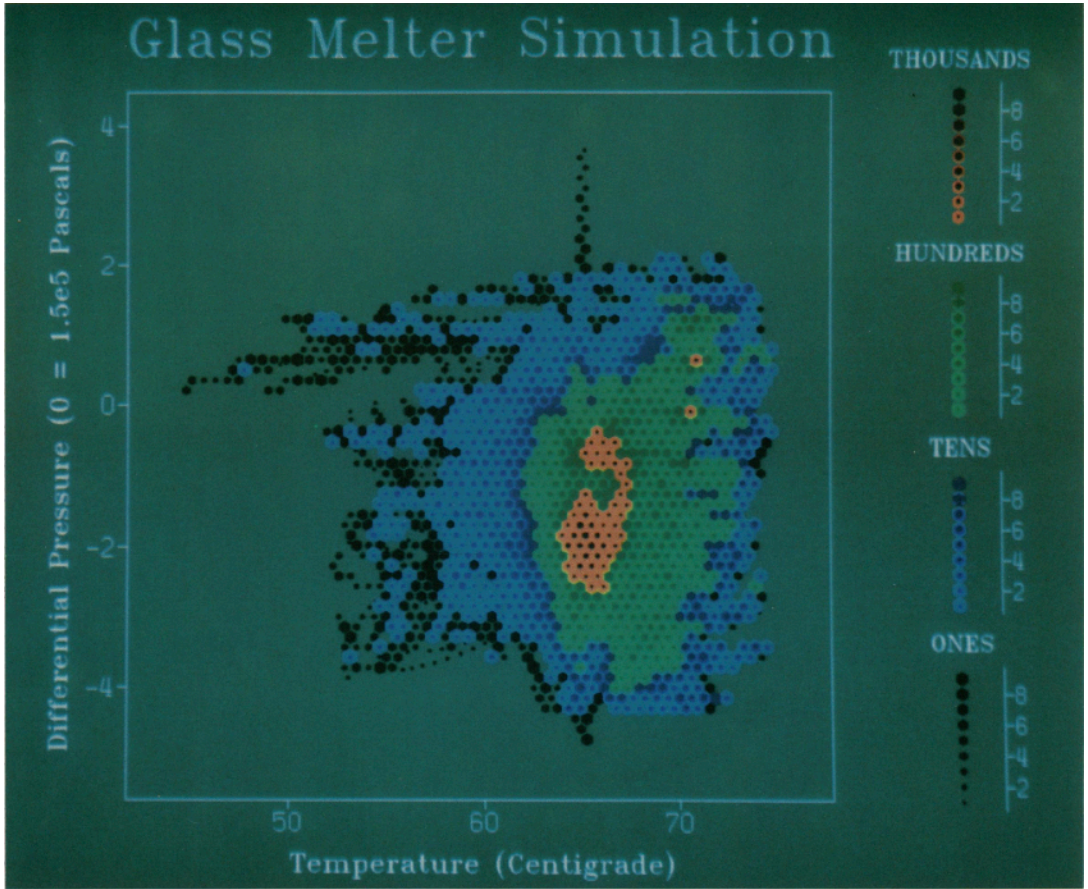
Google Fusion Tables



Binned Aggregation

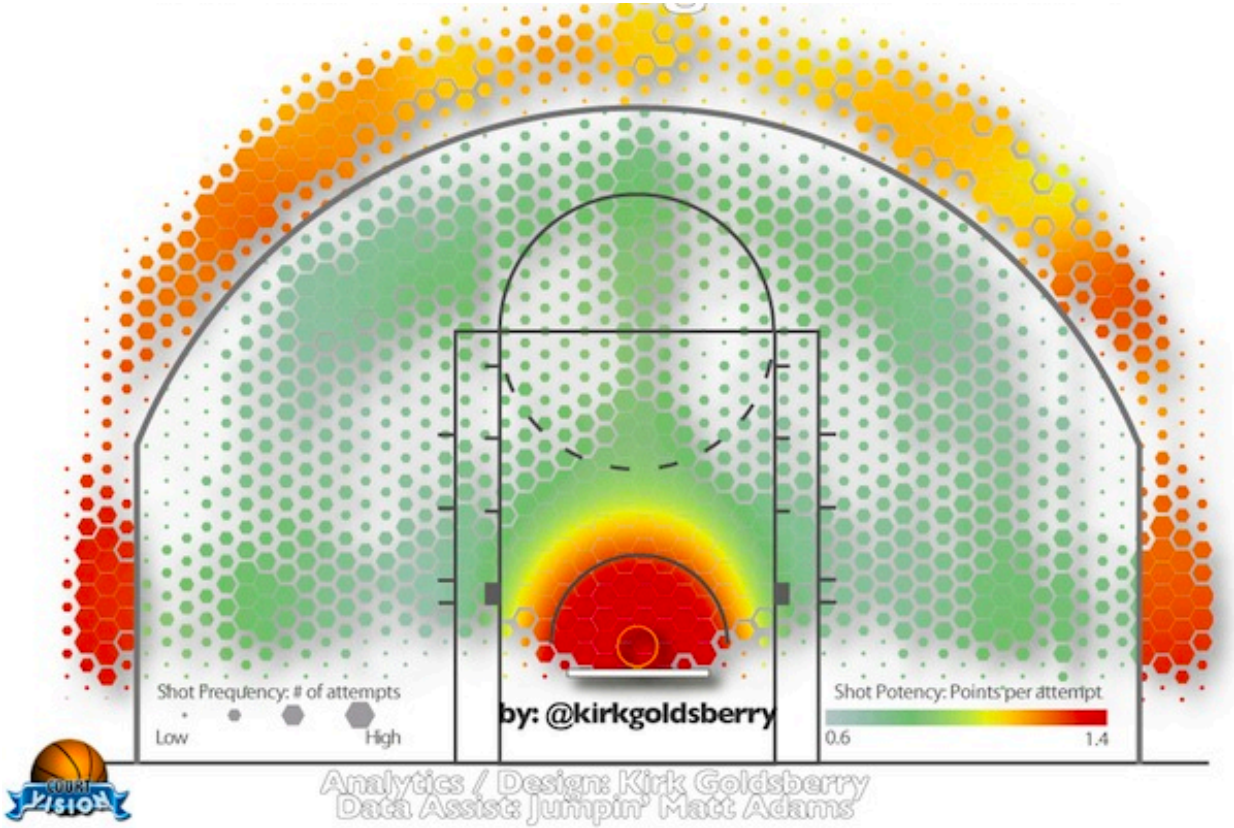
[Liu, Jiang, Heer '13]

Example: Binned Scatter Plots



Scatterplot Matrix Techniques for Large N [Carr et al. '87]

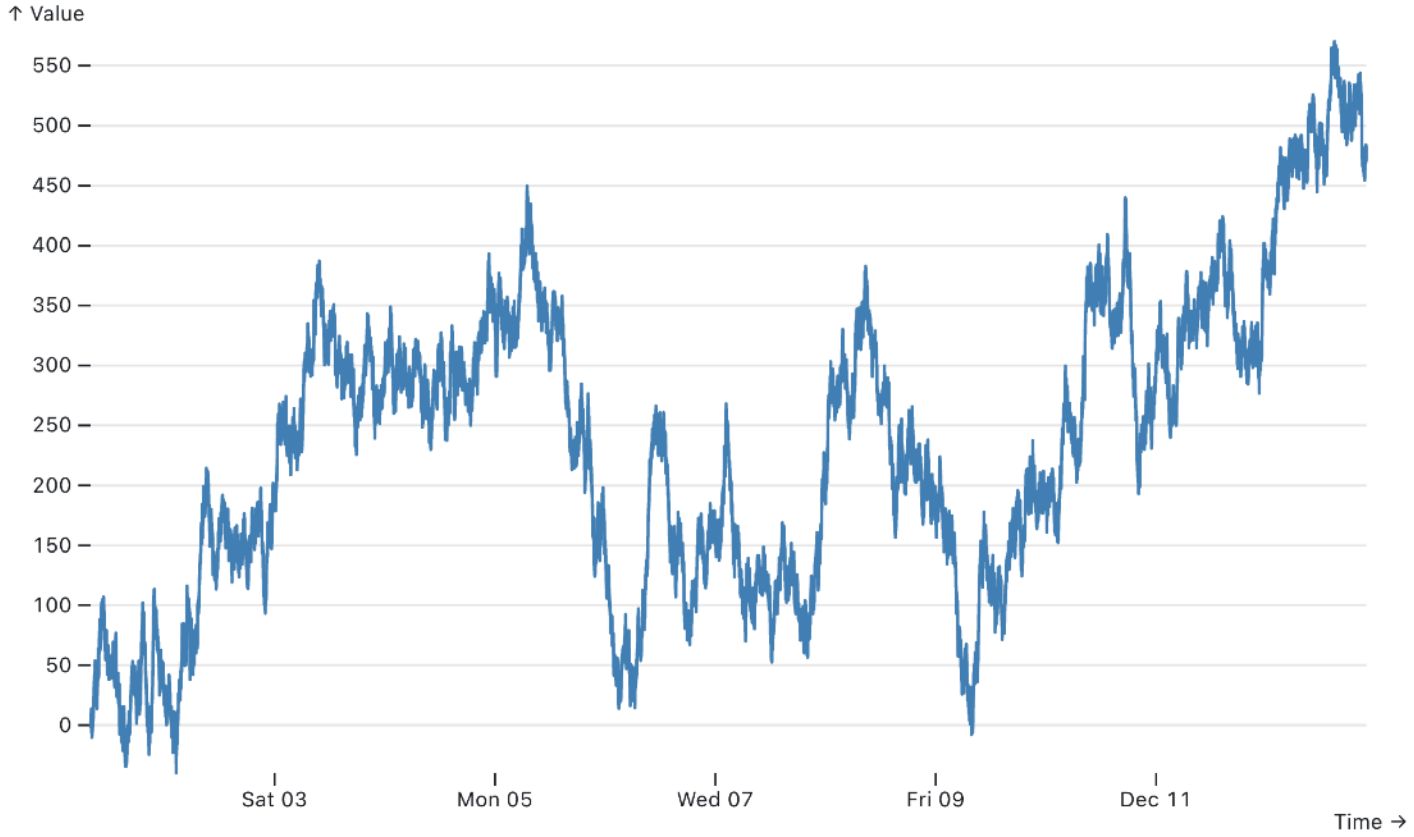
Example: Basketball Shot Chart



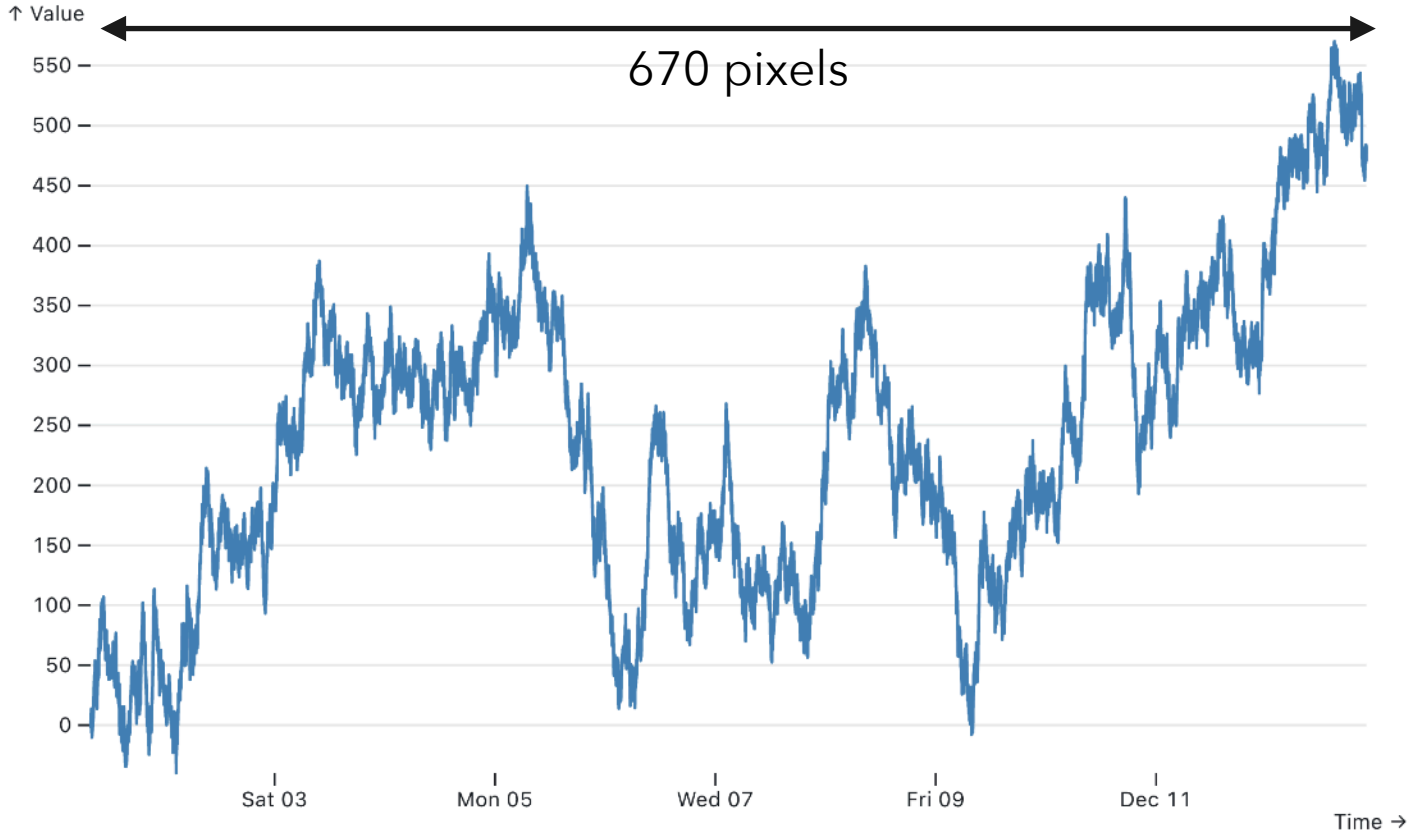
NBA Shooting 2011-12
[Goldsberry]

Time Series

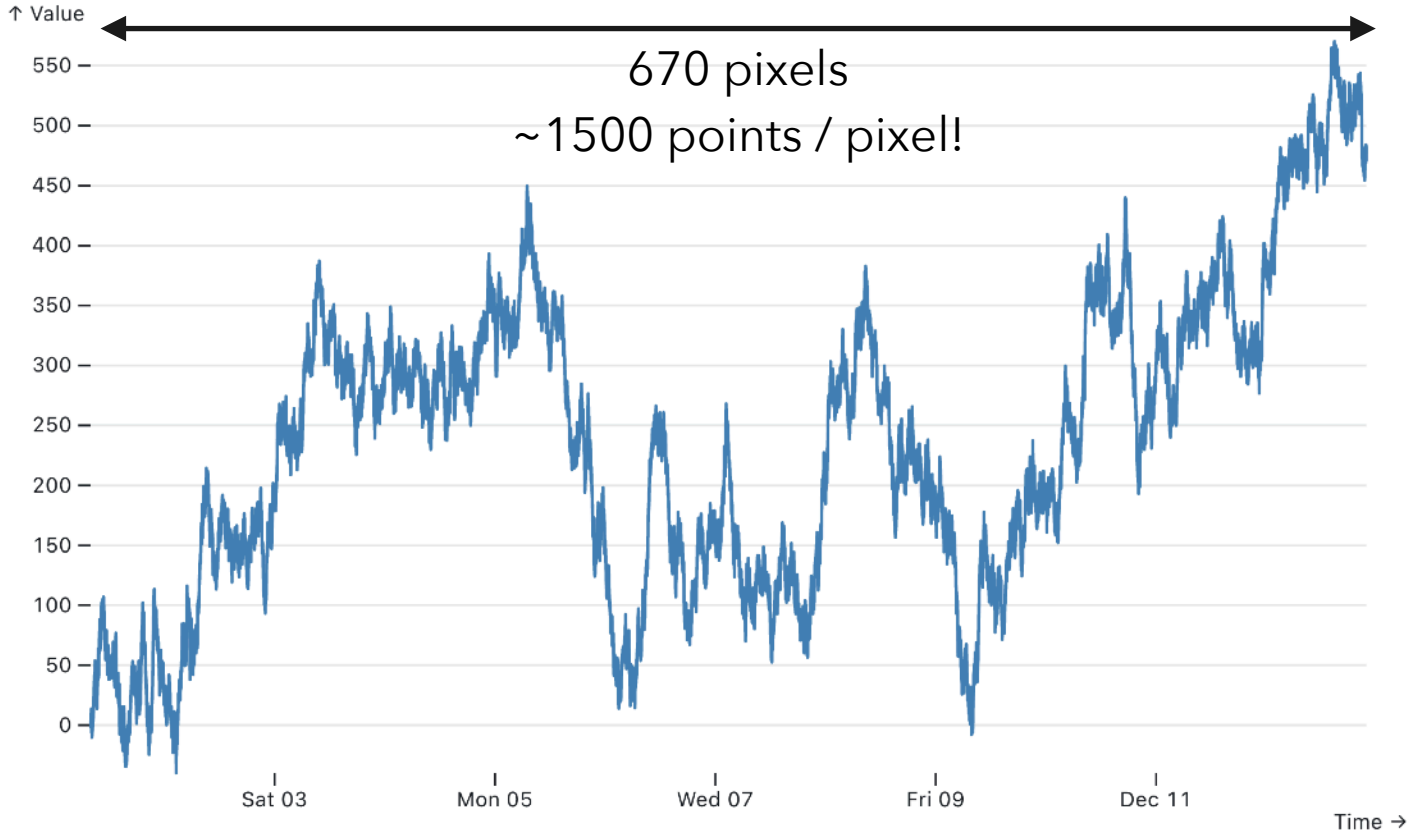
Time Series: 1M samples, 1 sample/second



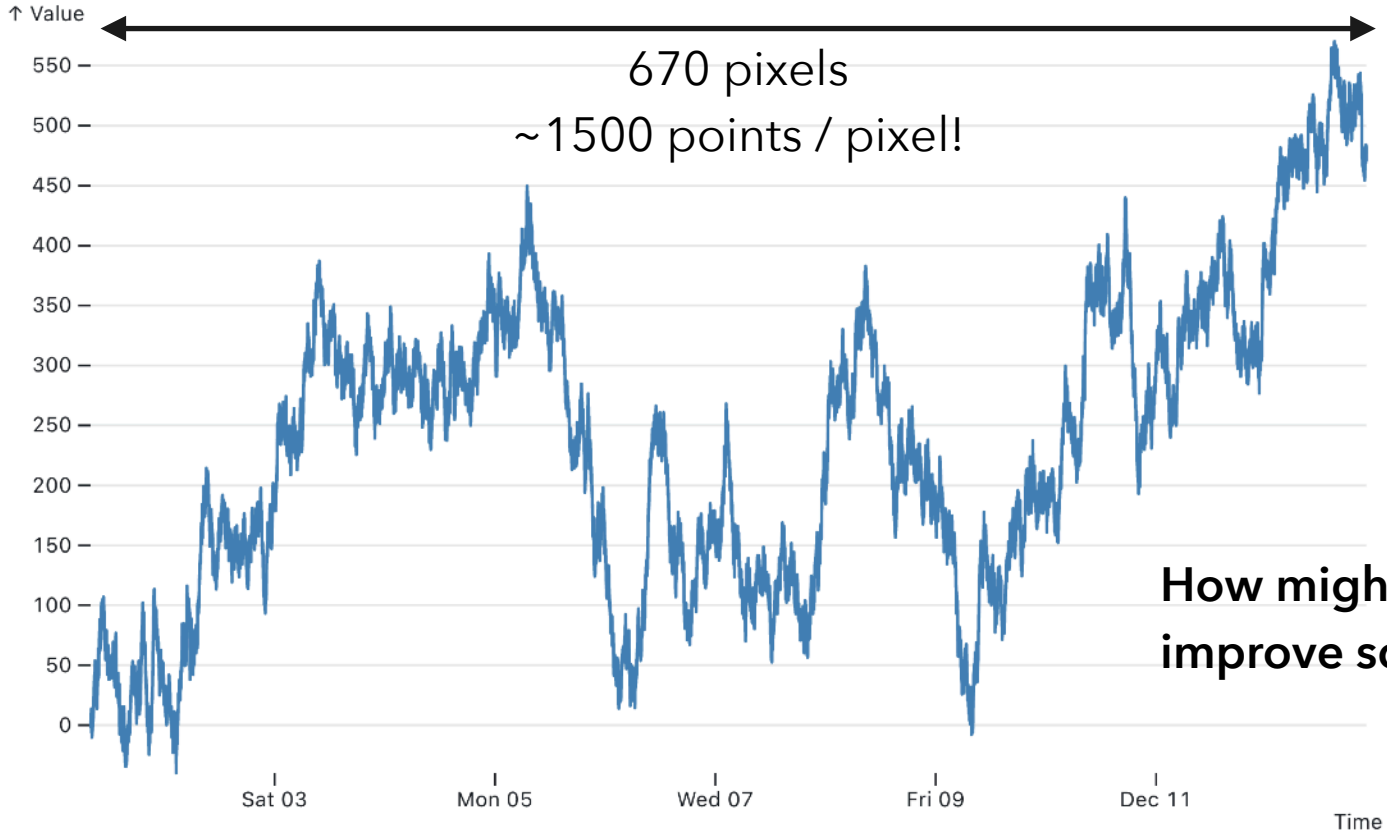
Time Series: 1M samples, 1 sample/second



Time Series: 1M samples, 1 sample/second

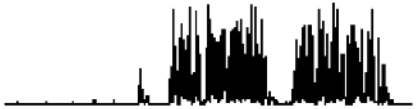


Time Series: 1M samples, 1 sample/second



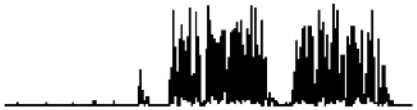
How might we improve scalability?

Time-Series Aggregation [Jugel'14]



Insight: the resolution is bound by the number of pixels.

Time-Series Aggregation [Jugel'14]

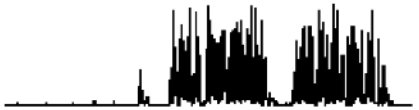


Insight: the resolution is bound by the number of pixels.

1. Compute average value per pixel (1 point/pixel)

…this may miss extreme (min, max) values

Time-Series Aggregation [Jugel'14]



Insight: the resolution is bound by the number of pixels.

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   …this may miss extreme (min, max) values

2. Plot min/max values per pixel (2 points/pixel)

   …this does better, but still misrepresents

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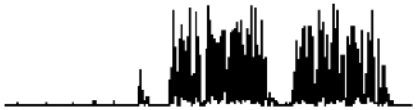

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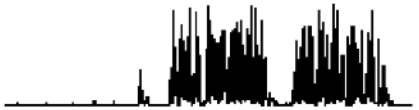
3. M4: min/max values & timestamps (4 points/pixel)



…this provides provable fidelity to the full data!

Data Reduction in the Database

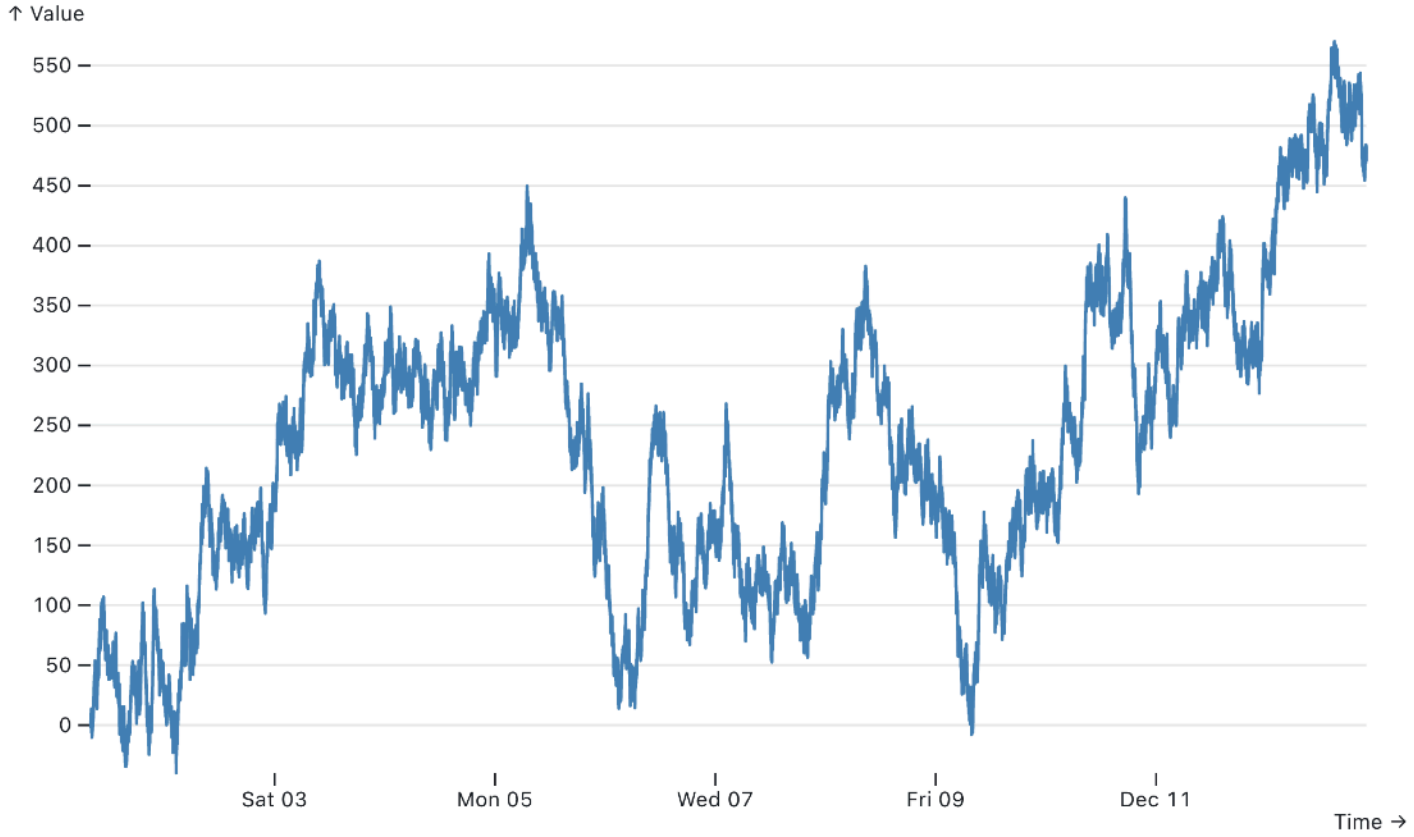
```
SELECT t,v FROM Q JOIN
(SELECT round($w*(t-$t1)/($t2-$t1)) as k,   --define key
        min(v) as v_min, max(v) as v_max,   --get min,max
        min(t) as t_min, max(t) as t_max    --get 1st,last
        FROM Q GROUP BY k) as QA            --group by k
ON k = round($w*(t-$t1)/($t2-$t1))          --join on k
       AND (v = v_min OR v = v_max OR       --&(min|max|
            t = t_min OR t = t_max)         -- 1st|last)
```

`Q`: query that returns a time series `(t,v)`

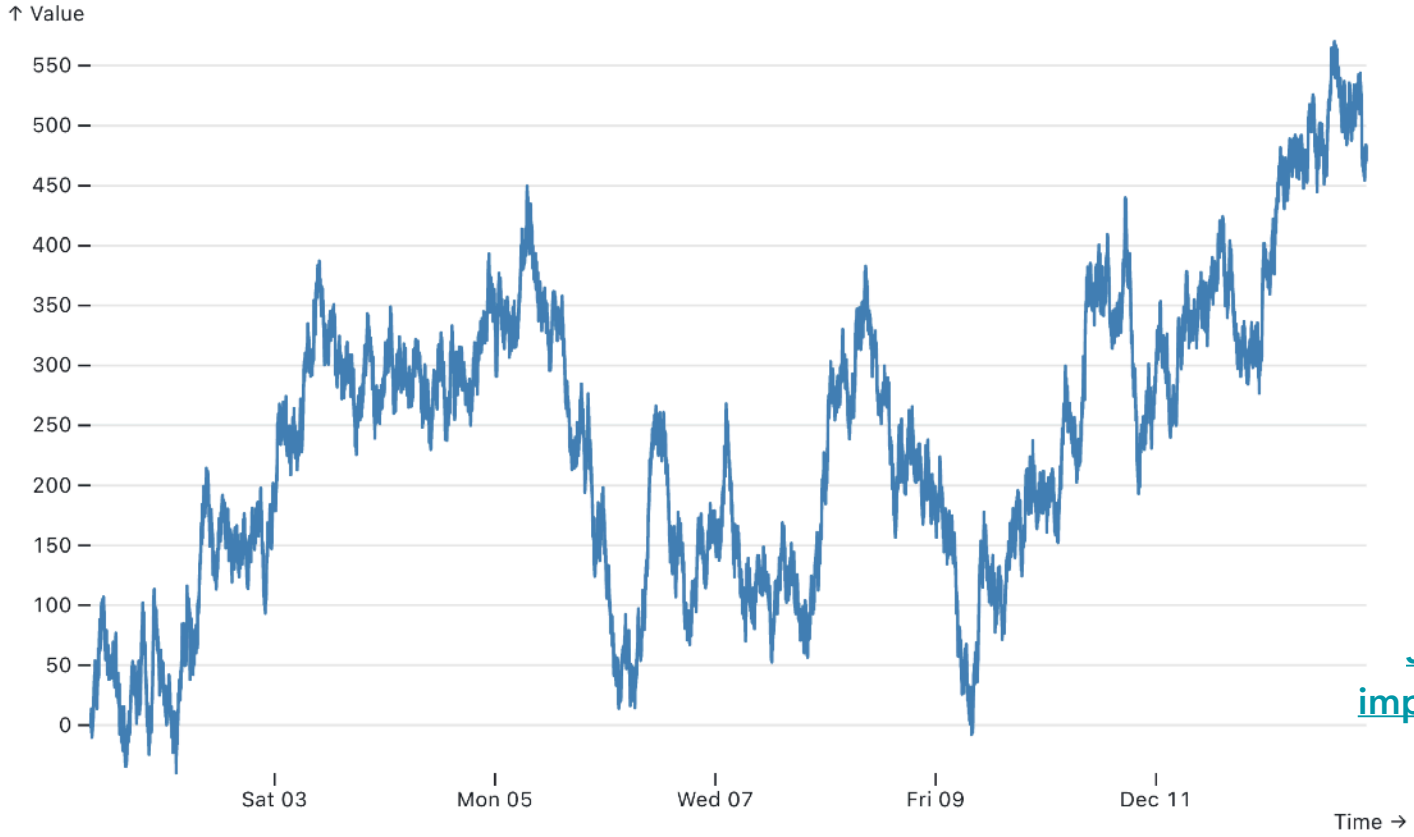
`$w`: chart width in pixels

`$t1, $t2`: global min/max timestamps

Time Series: 1M samples, 1 sample/second

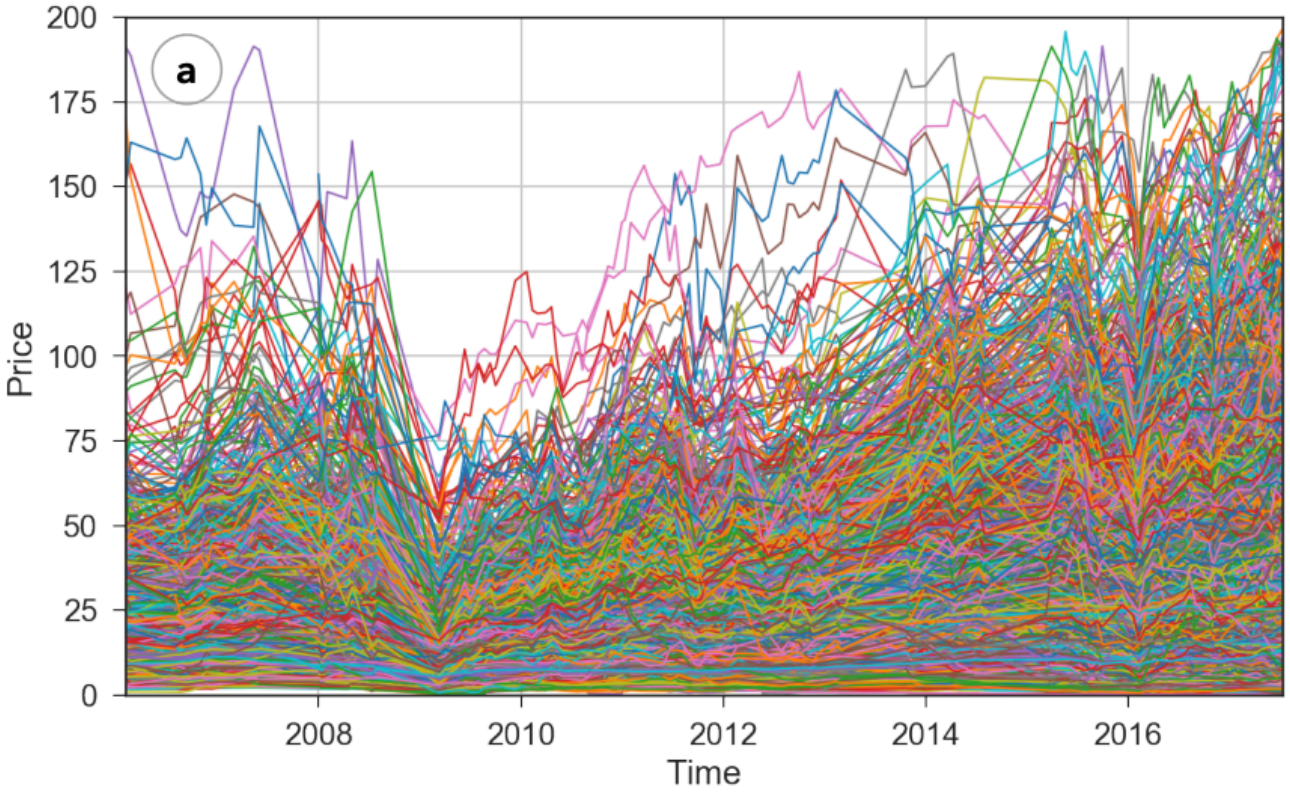


M4: 1M samples -> 2,653 plotted points



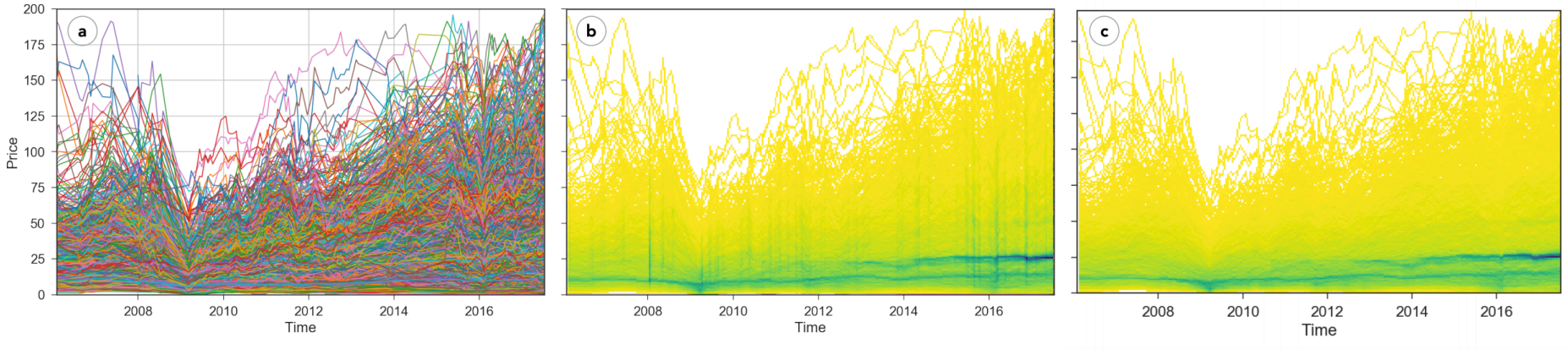
JavaScript implementation

But what about multiple time-series?



Perceptual scalability breaks down…

Density Line Chart [Moritz & Fisher]

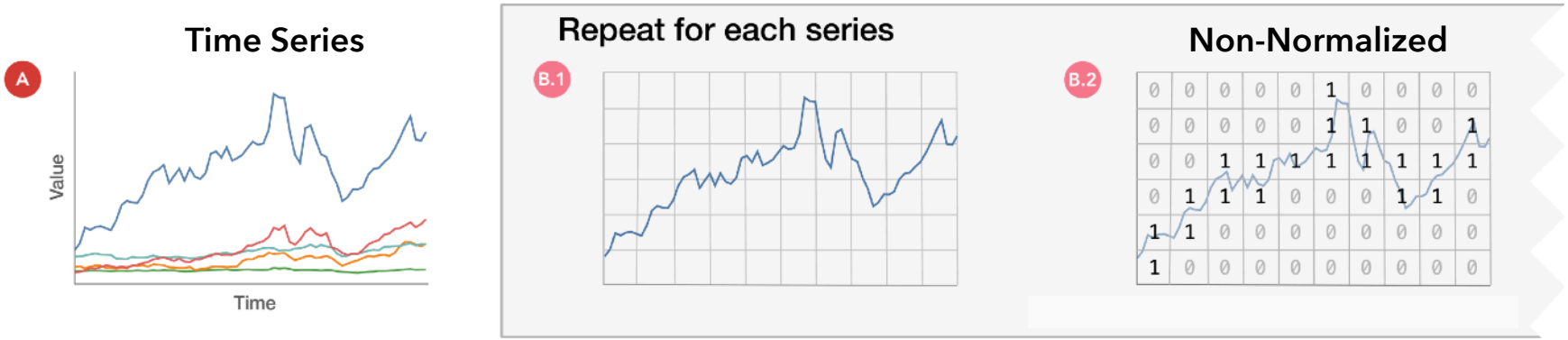


Line Chart | Non-Normalized Heatmap | Normalized "DenseLines"

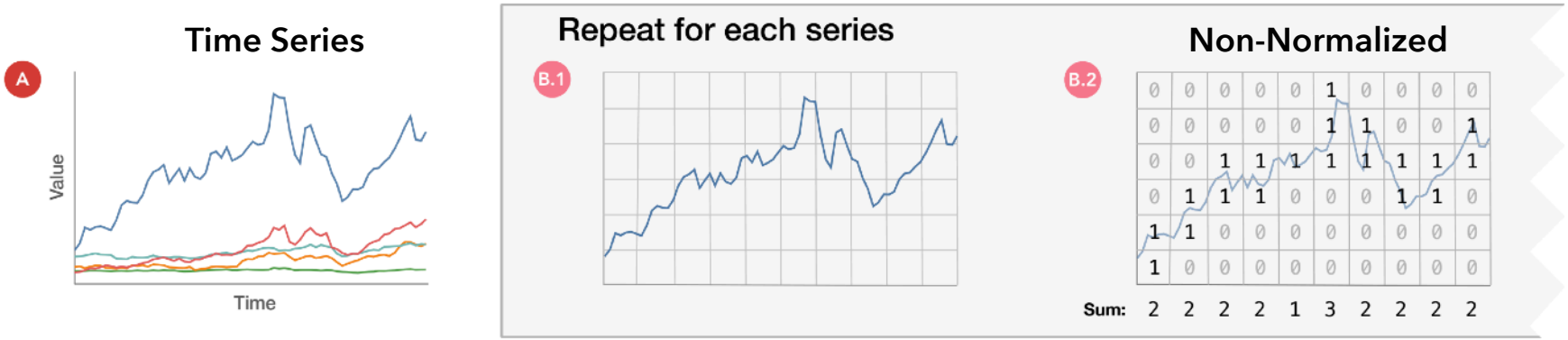
The non-normalized heatmap suffers from artifacts, seen as vertical stripes.

Binned charts convey high points across the top, a collective dip in stocks during the crash of 2008, and two distinct bands of $25 and $15 stocks.

Density Line Chart [Moritz & Fisher]



Density Line Chart [Moritz & Fisher]



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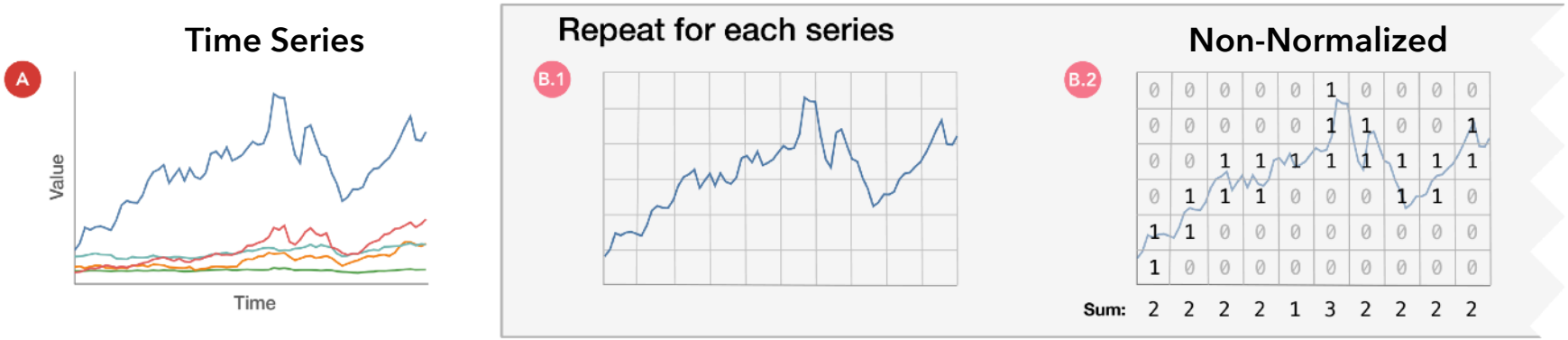

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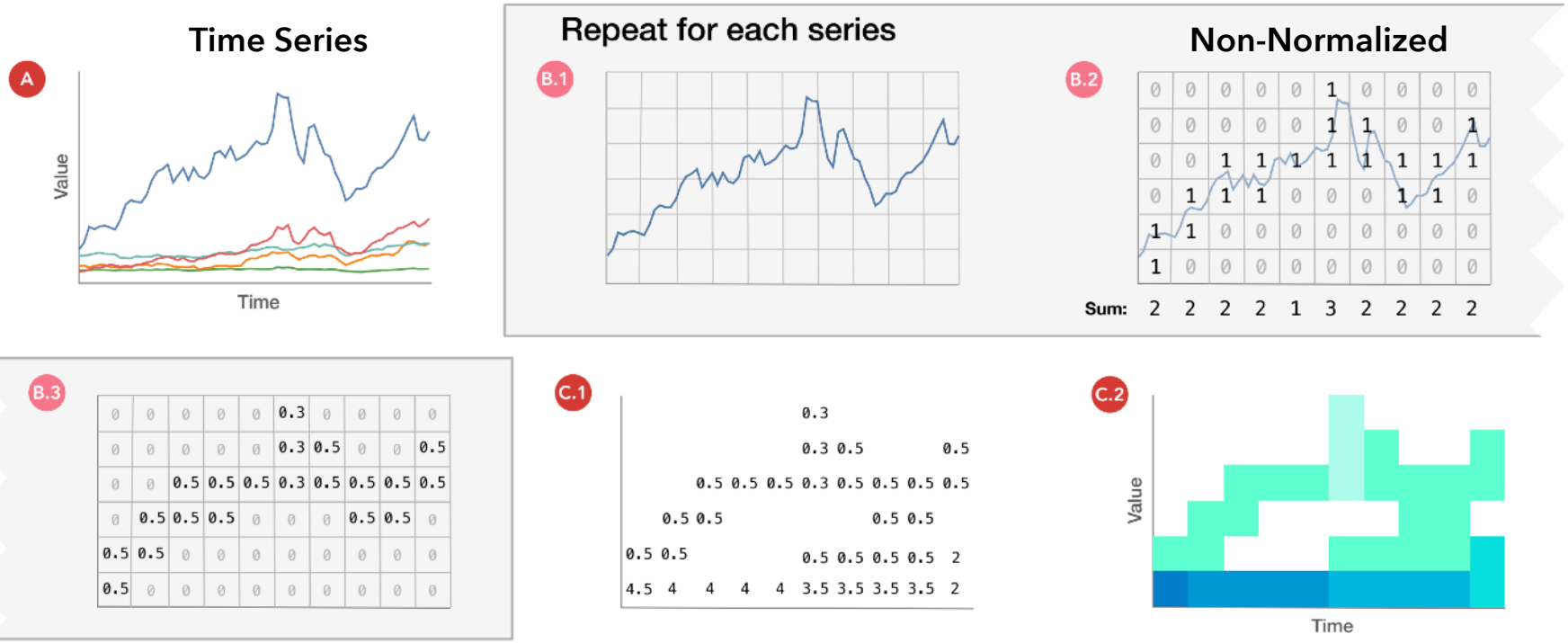
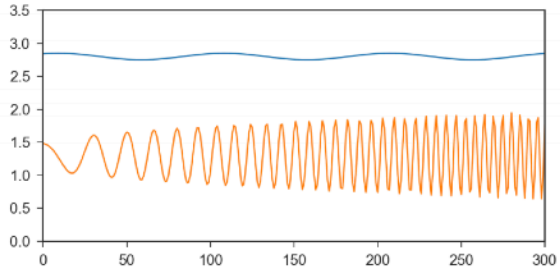
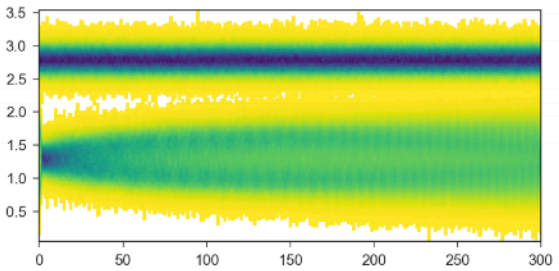


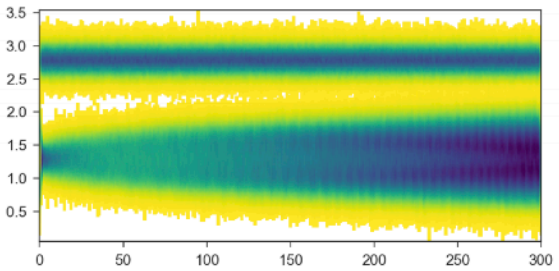
Density Line Chart [Moritz & Fisher]



Example Time Series



10k Series, Normalized



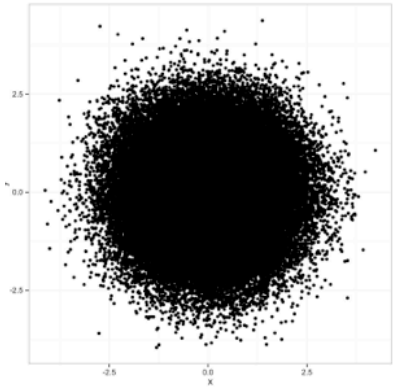
10k Series, Non-Normalized

The density of the second group appears to increase to the right!

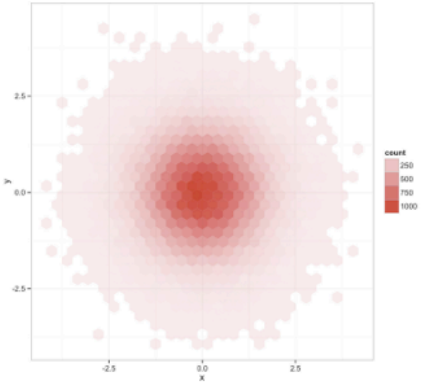
Without normalization, the steep lines are over-represented.

Design Subtleties

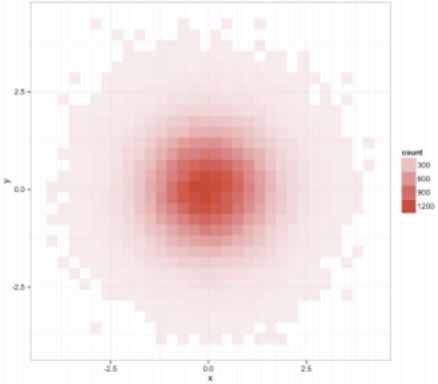
Hexagonal or Rectangular Bins?



100,000 Data Points



Hexagonal Bins

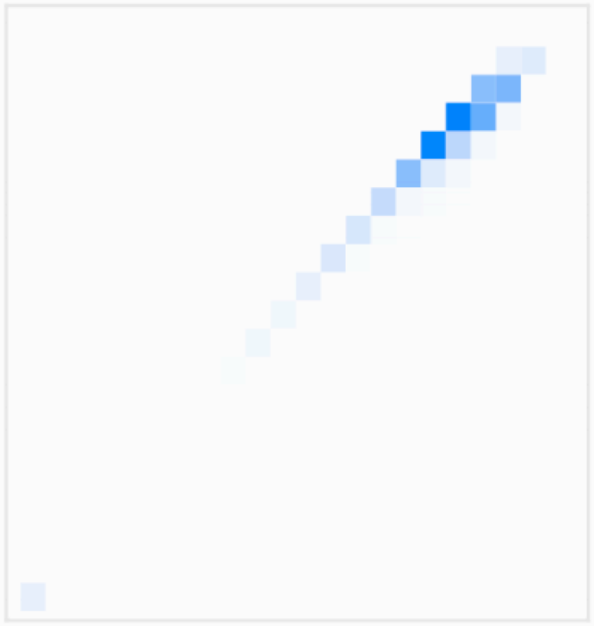


Rectangular Bins

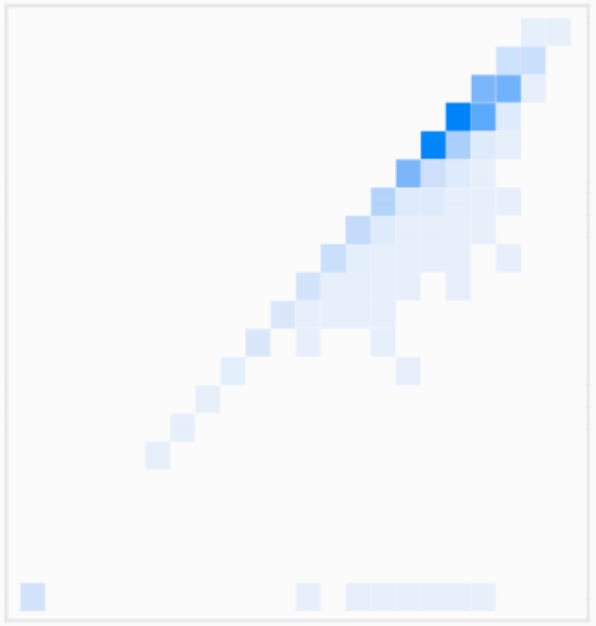
Hex bins better estimate density for 2D plots, but the *improvement is marginal* [Scott 92].

Rectangles support *reuse* and *visual queries*.

Color Scale: Discontinuity after Zero

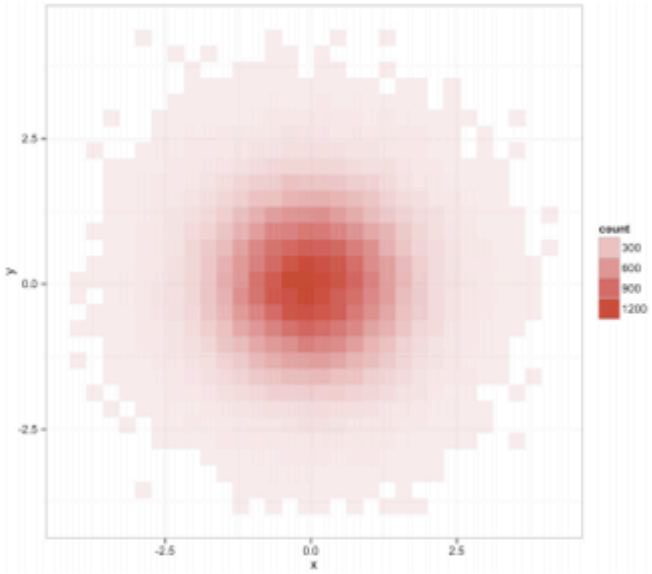


Standard Color Ramp
Counts near zero are white.

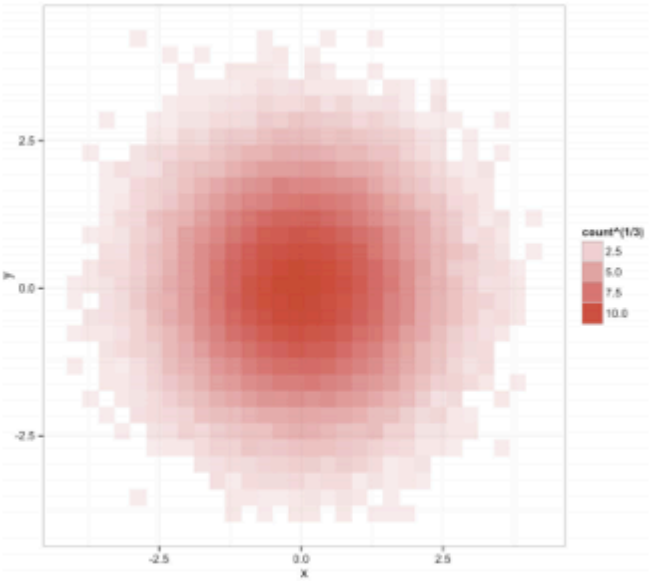


Add Discontinuity after Zero
Counts near zero remain visible.

Color / Opacity Ramps



Linear interpolation in RGBA
is not perceptually linear.



Perceptual color spaces
approximate perceptual linearity.

Scalable Interaction

Interactive Scalability Strategies

1. Query Database
2. Client-Side Indexing / Data Cubes
3. Prefetching
4. Approximation

Interactive Scalability Strategies

1. Query Database Offload to a scalable backend…

Tableau, for example, issues aggregation queries.

Analytical databases are designed for fast, parallel execution.

But round-trip queries to the DB may still be too slow…

2. Client-Side Indexing / Data Cubes

3. Prefetching

4. Approximation

Interactive Scalability Strategies

1. Query Database …or alternative data frame implementation

Python: Vaex, Polars, Modin, cuDF

R: dbplyr

All: DuckDB

2. Client-Side Indexing / Data Cubes

3. Prefetching

4. Approximation

Interactive Scalability Strategies

1. Query Database

2. Client-Side Indexing / Data Cubes Query data summaries

Build sorted indices or data cubes to quickly re-calculate aggregations as needed on the client.

3. Prefetching

4. Approximation

Interactive Scalability Strategies

1. Query Database

2. Client-Side Indexing / Data Cubes

3. Prefetching Request data *before* it is needed

Reduce latency by speculatively querying for data before it is needed. Requires prediction models to guess what is needed.

4. Approximation

Interactive Scalability Strategies

1. **Query Database**
2. **Client-Side Indexing / Data Cubes**
3. **Prefetching**
4. **Approximation** Give fast, approximate answers

Reduce latency by computing aggregates on a sample, ideally with approximation bounds characterizing the error.

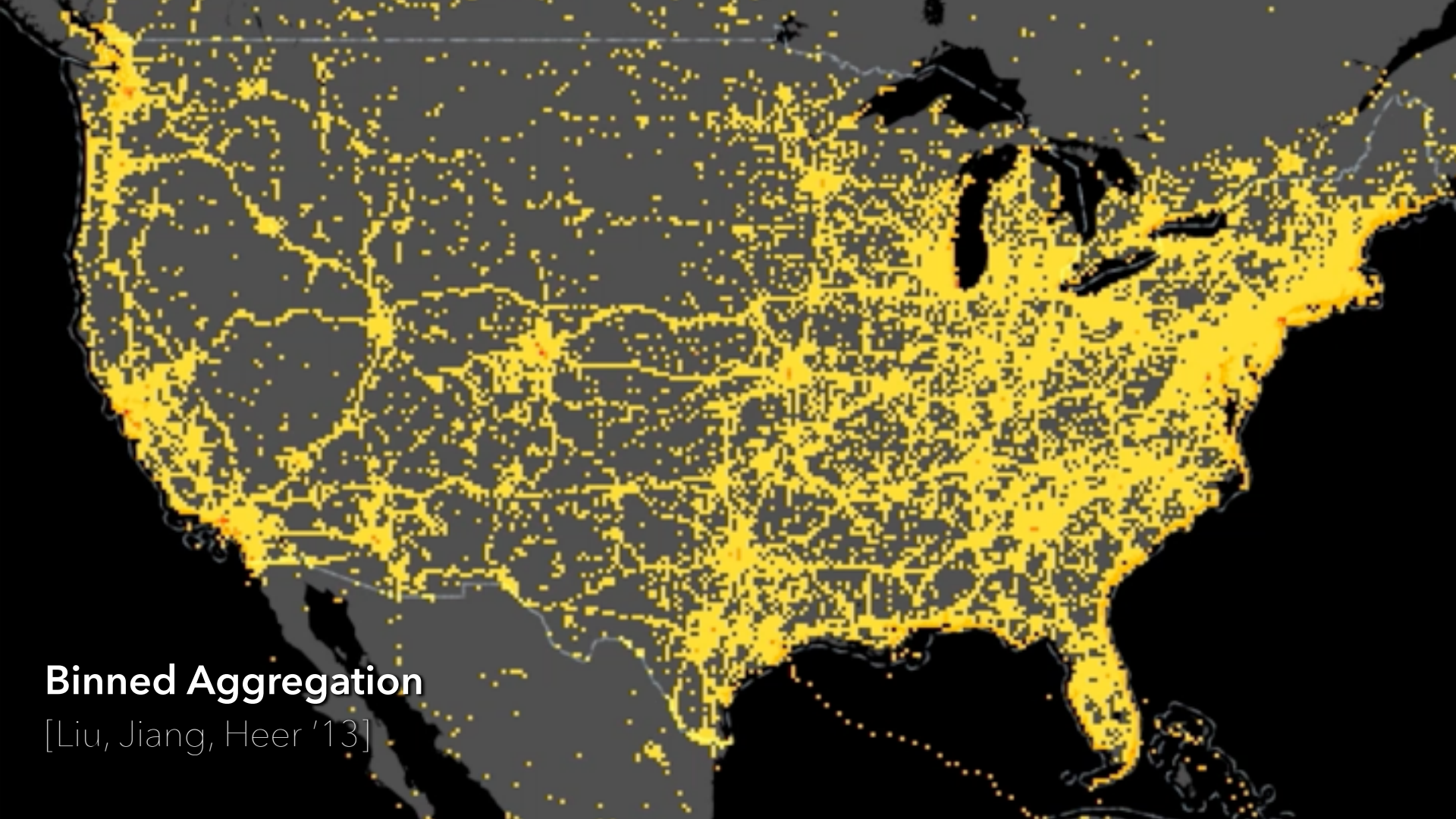
Interactive Scalability Strategies

1. **Query Database**
2. **Client-Side Indexing / Data Cubes**
3. **Prefetching**
4. **Approximation**

These strategies are **not** mutually exclusive!

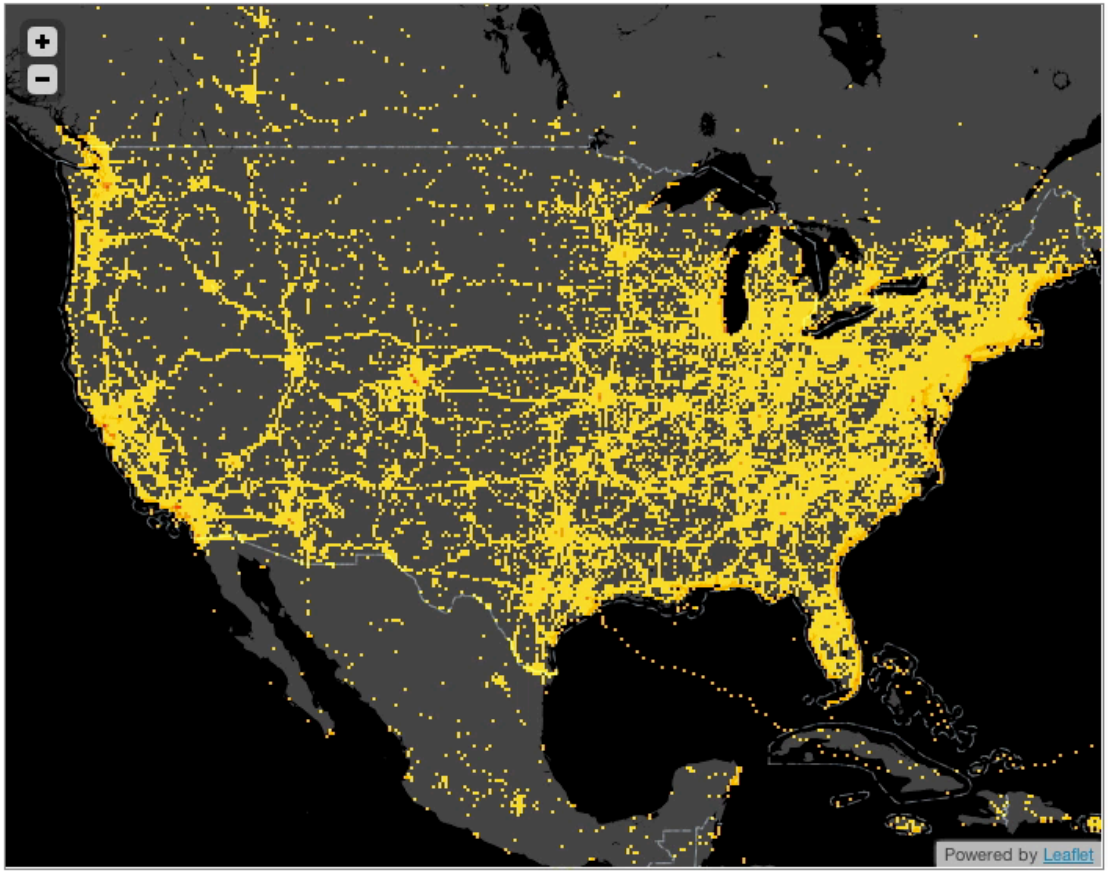
Systems can apply them in tandem.

Client-Side Indexes



Binned Aggregation

[Liu, Jiang, Heer '13]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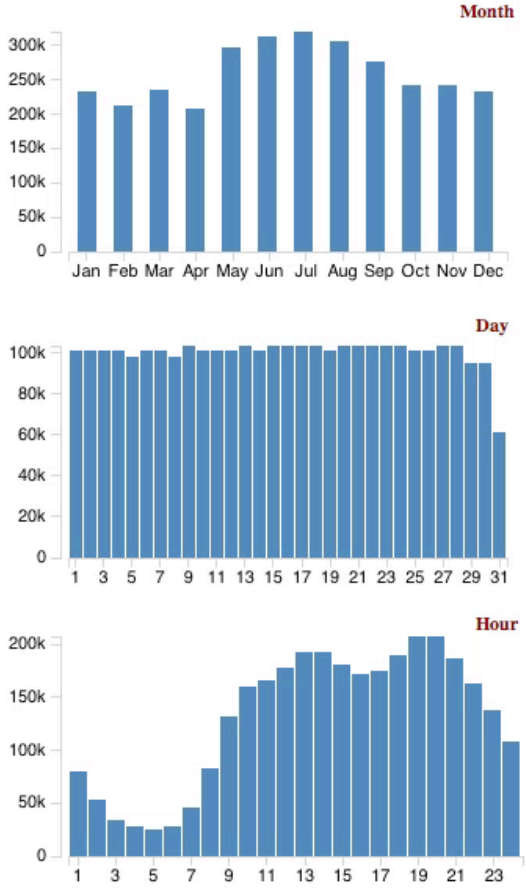
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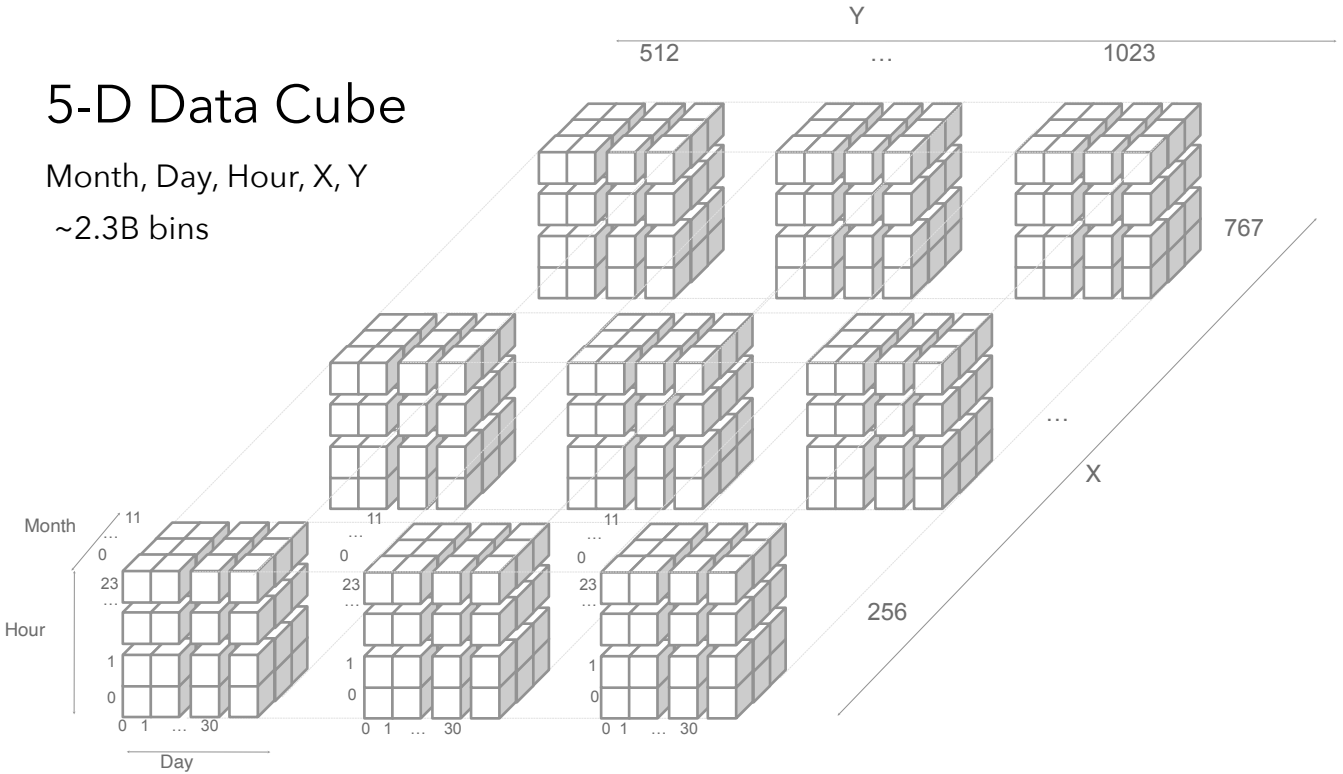
5-D Data Cube

Month, Day, Hour, X, Y

~2.3B bins

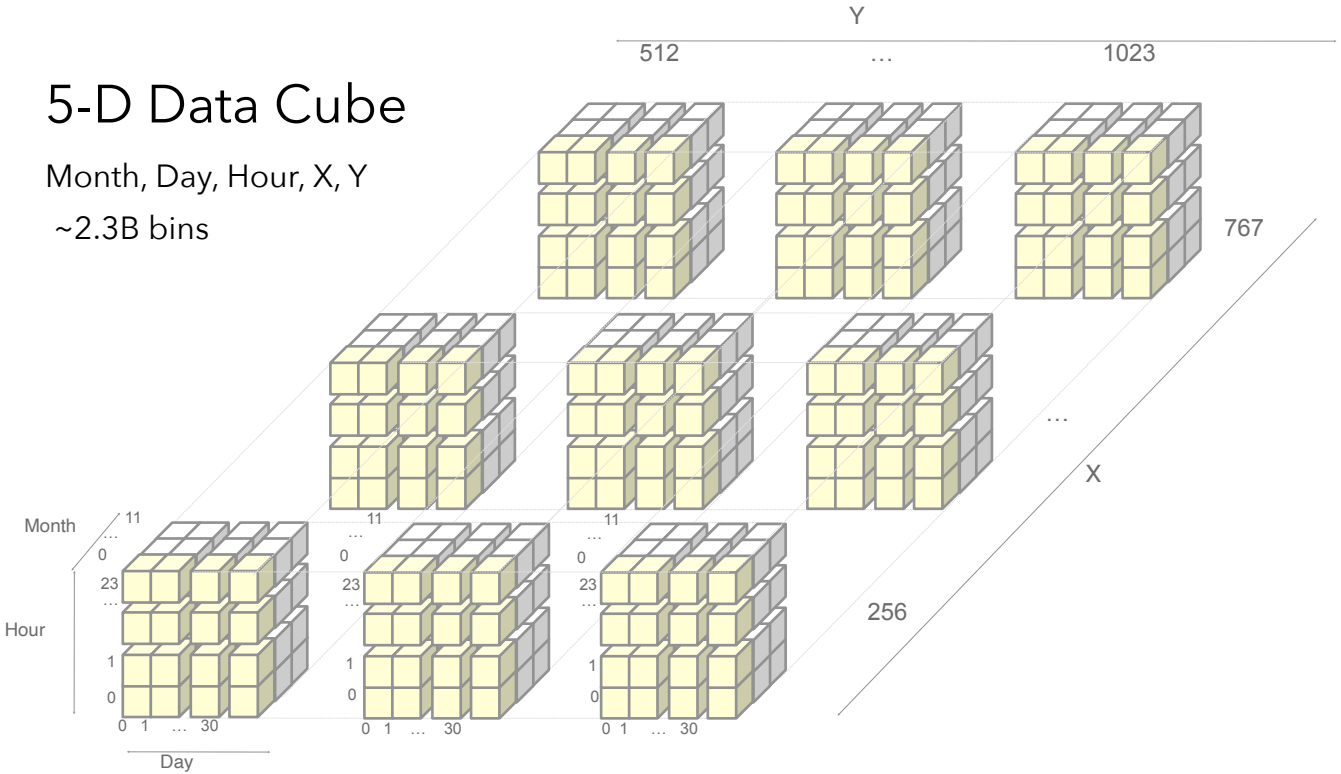


SPHERE

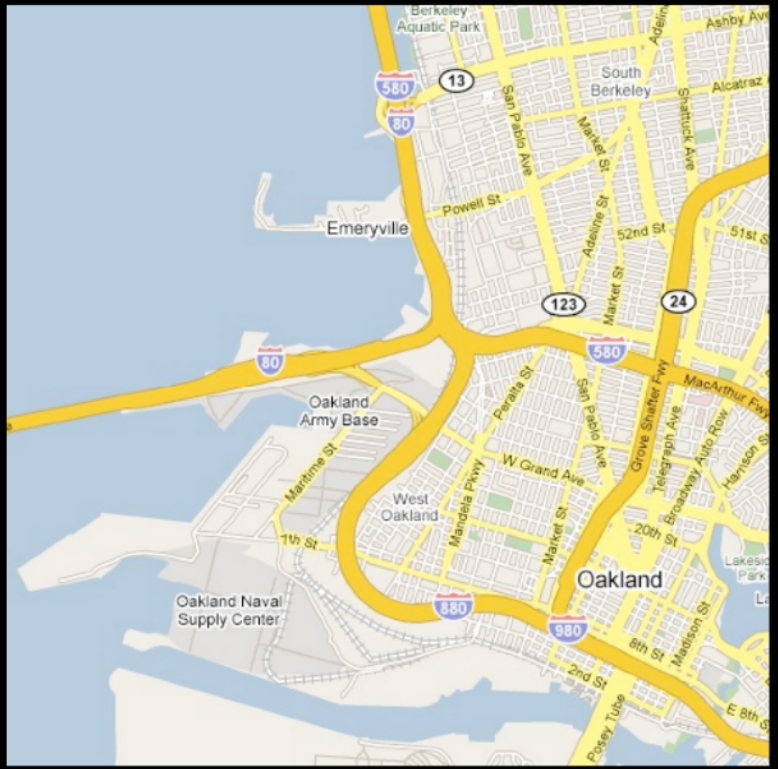
5-D Data Cube

Month, Day, Hour, X, Y

~2.3B bins



SPHERE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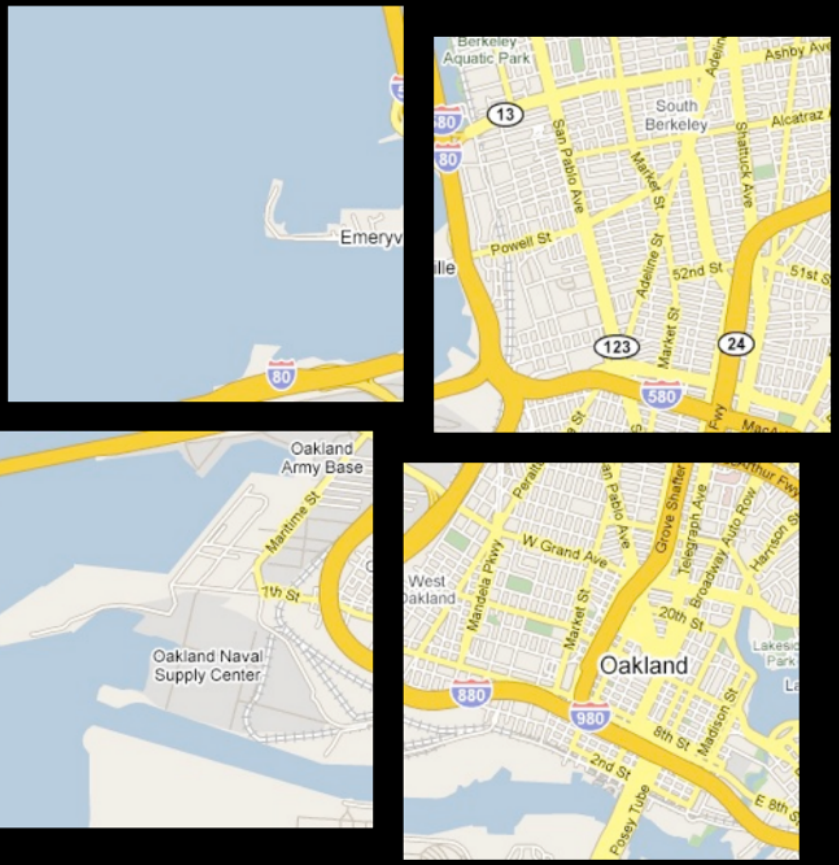
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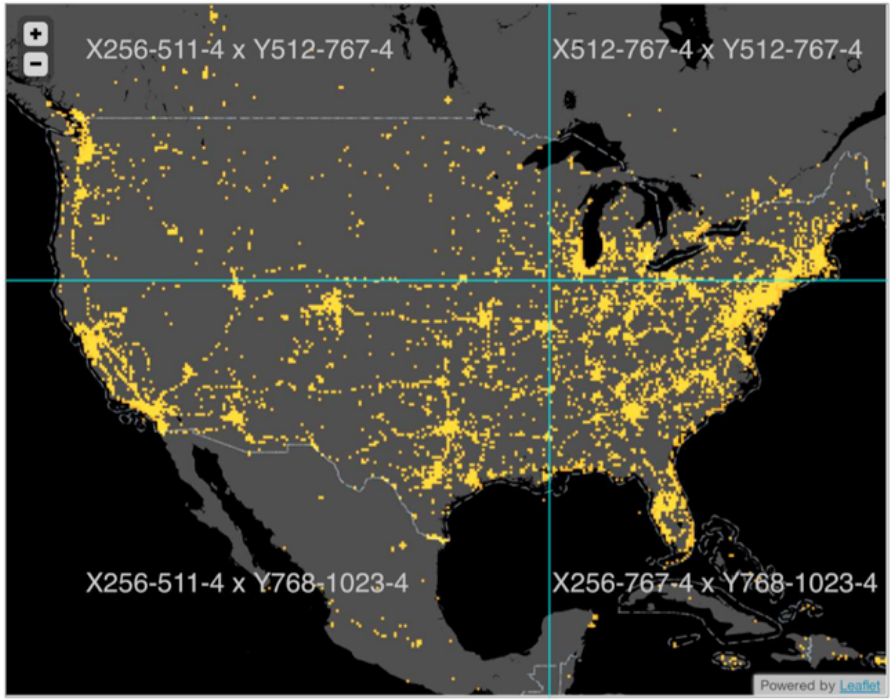
SPHERE

Multivariate Data Tiles

1. Send data, not pixels
2. Embed multi-dim data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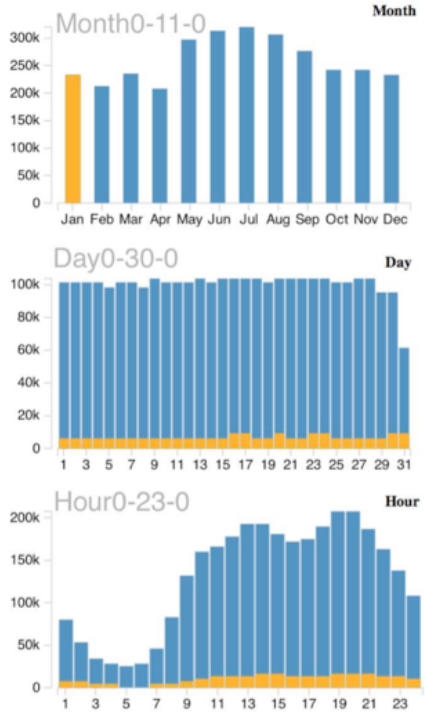
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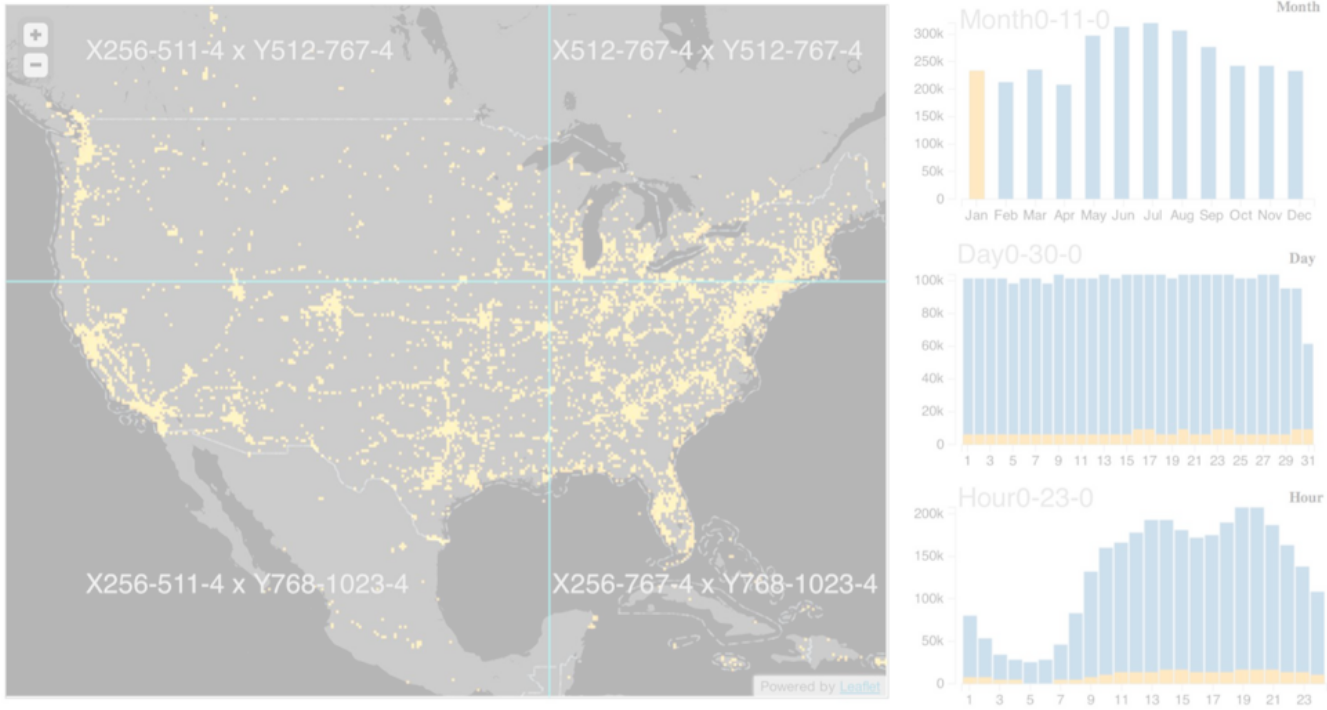
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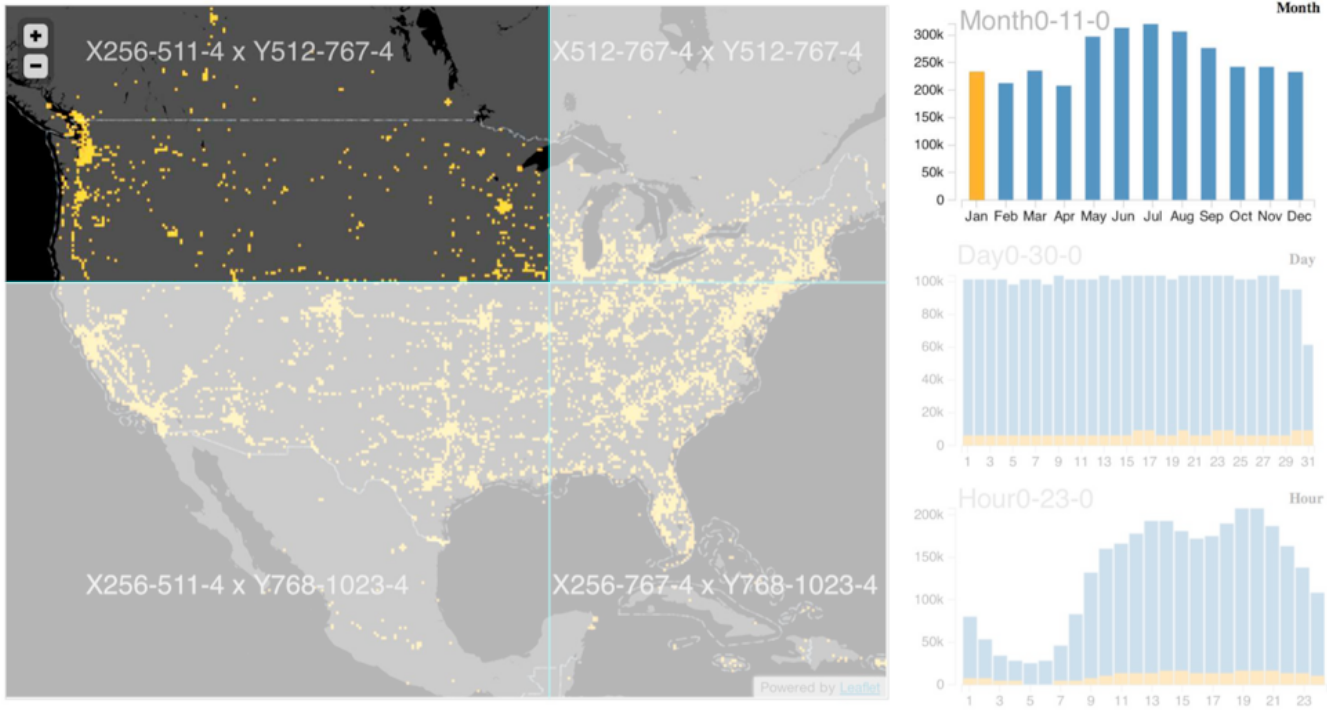
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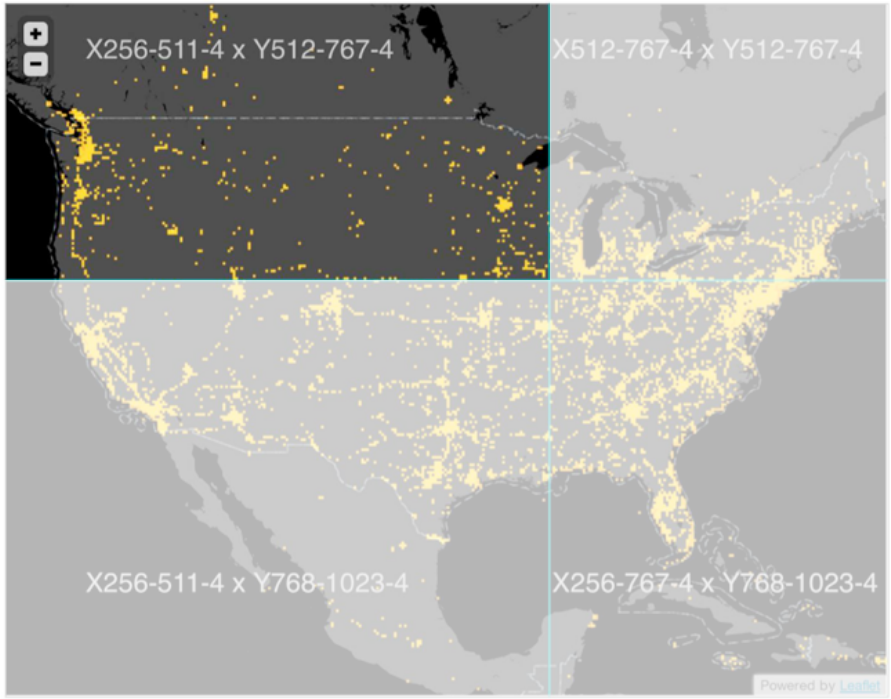
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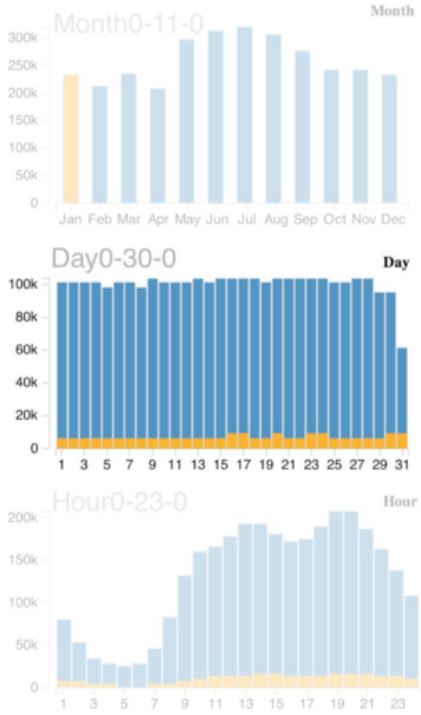
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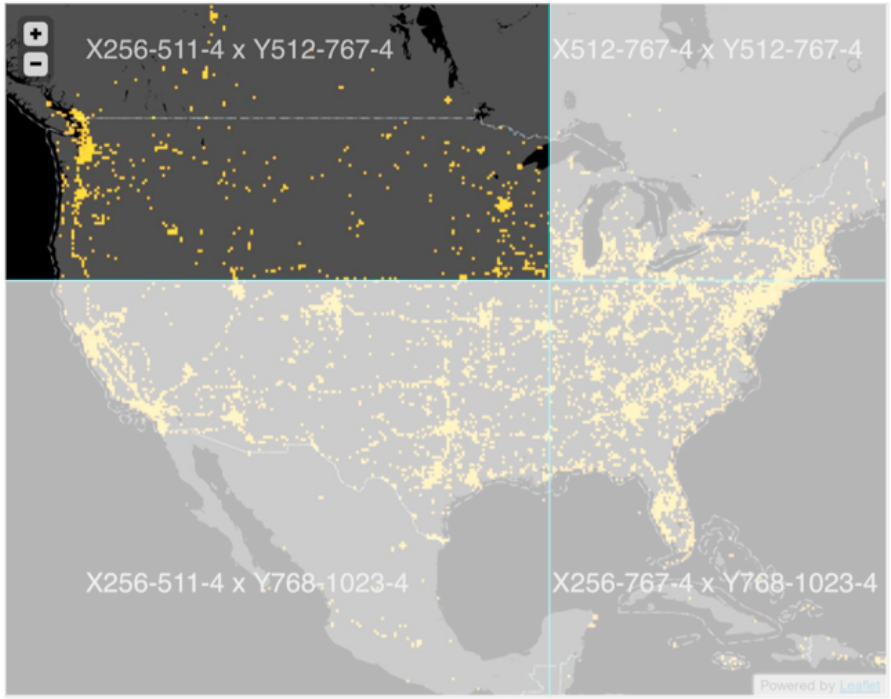
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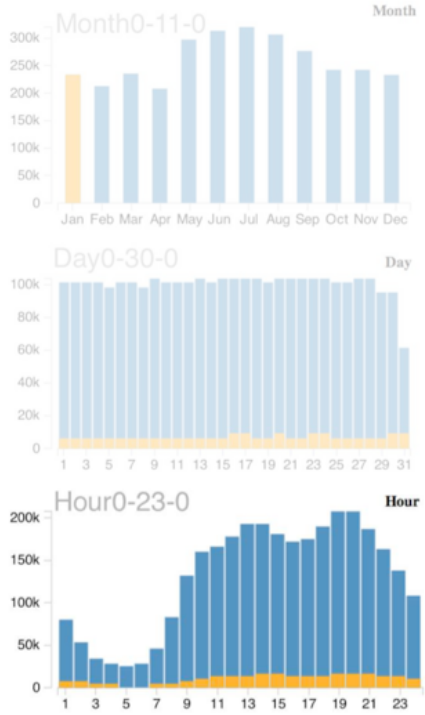
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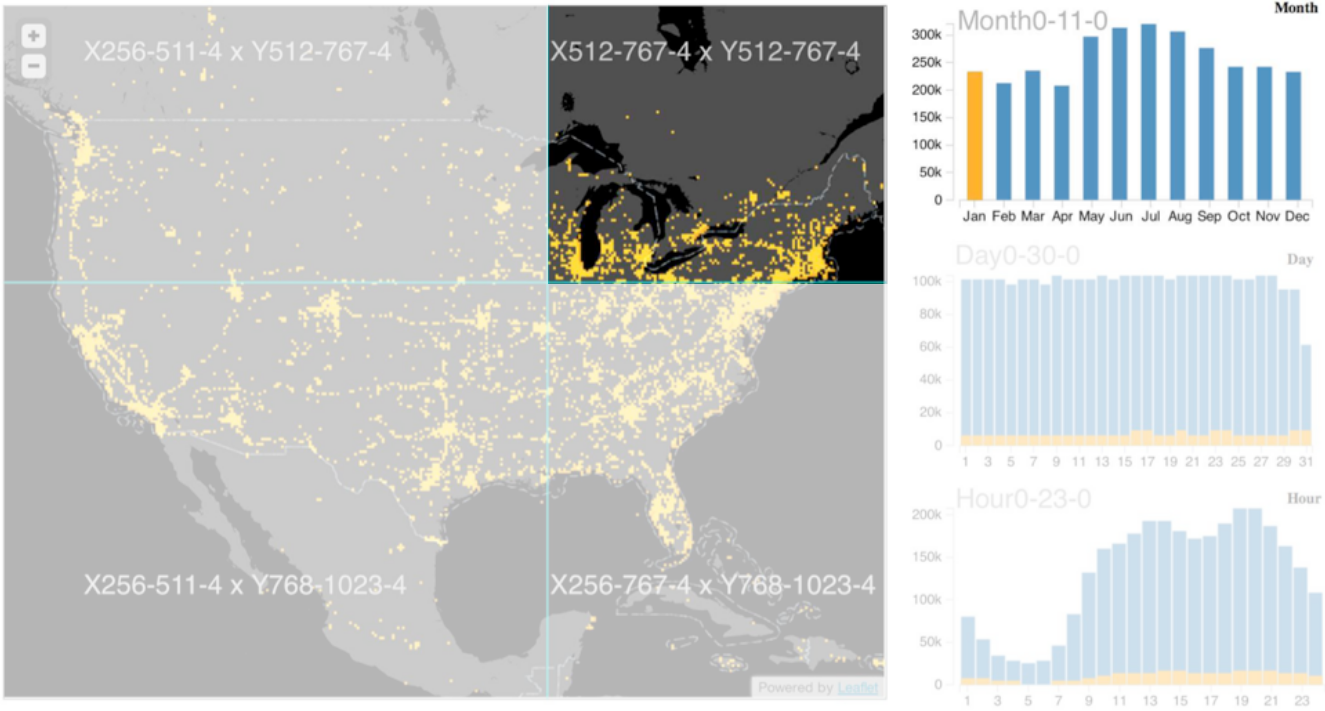
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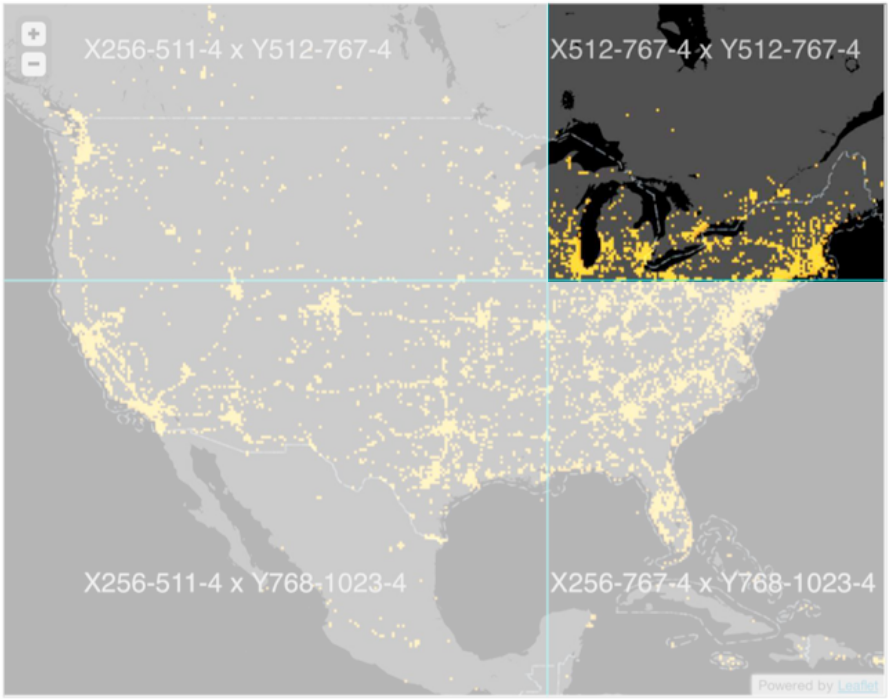
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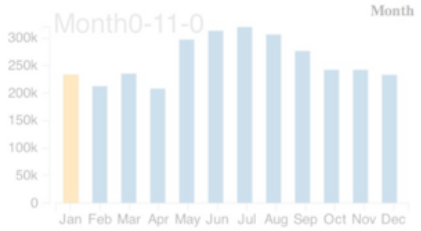
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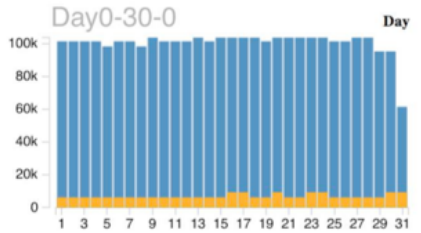
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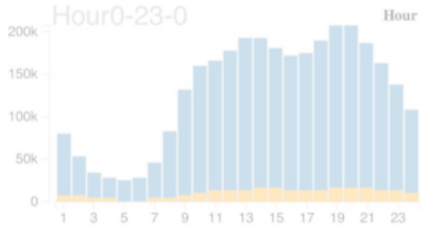
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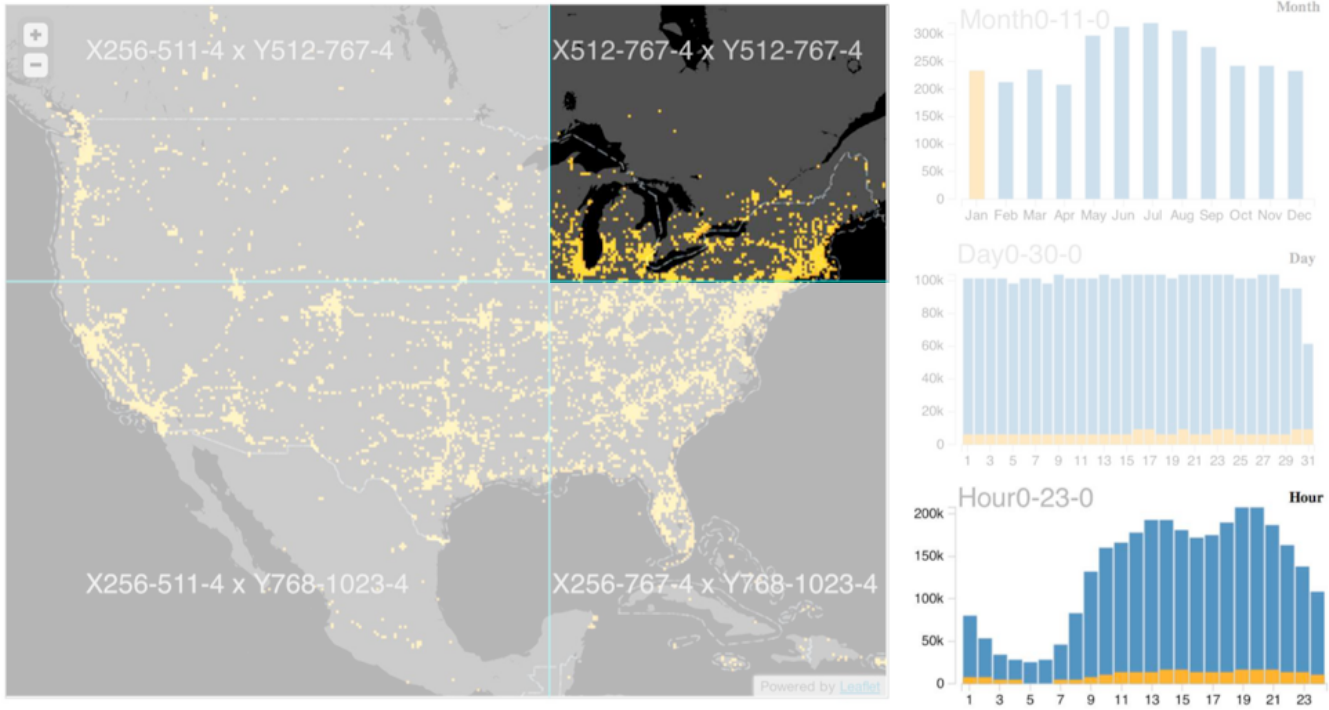
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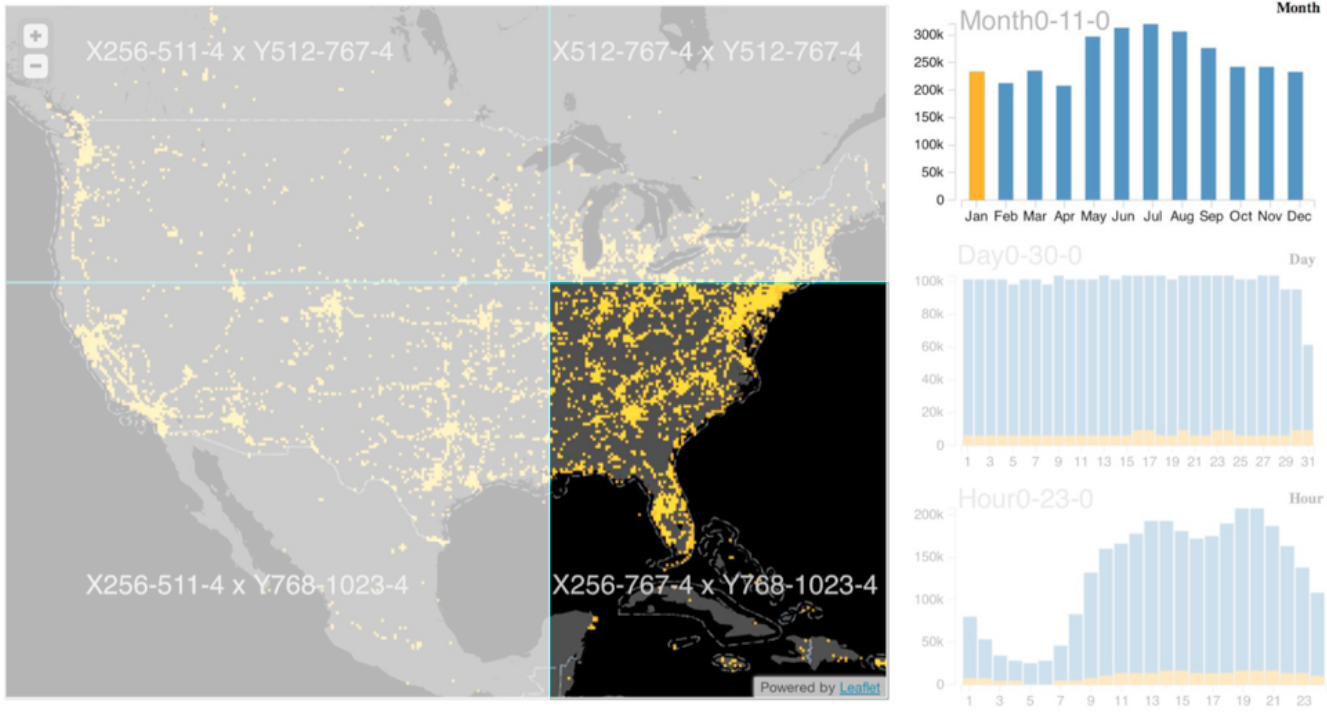
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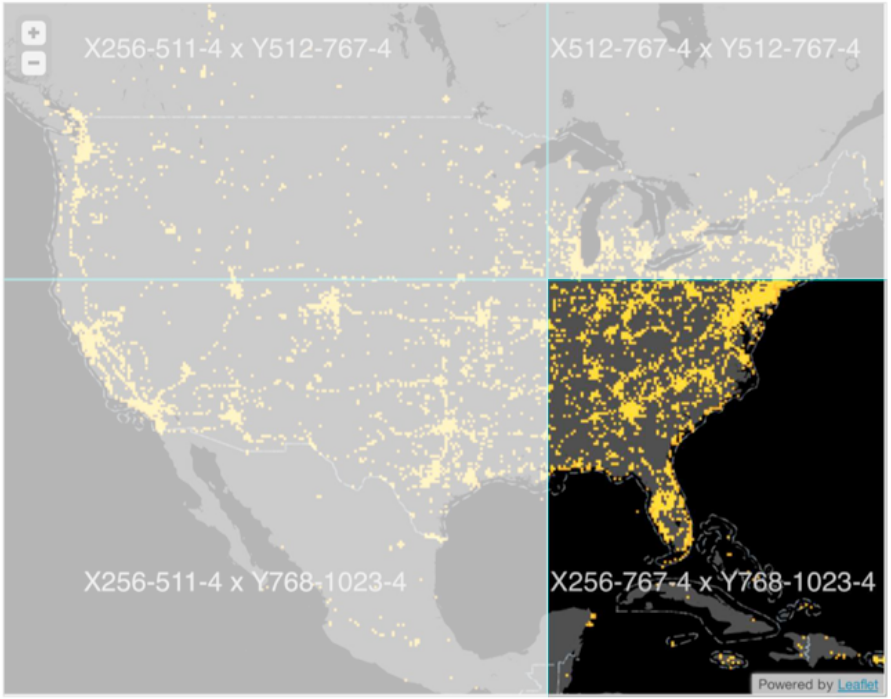
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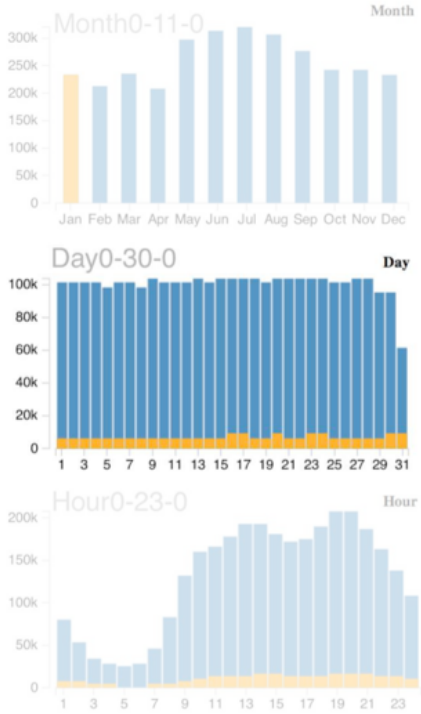
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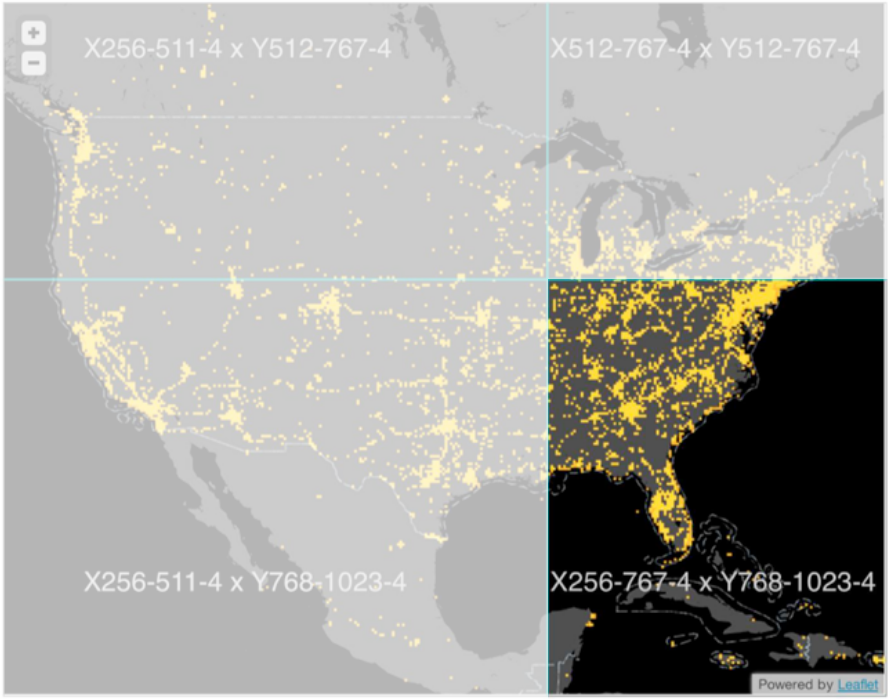
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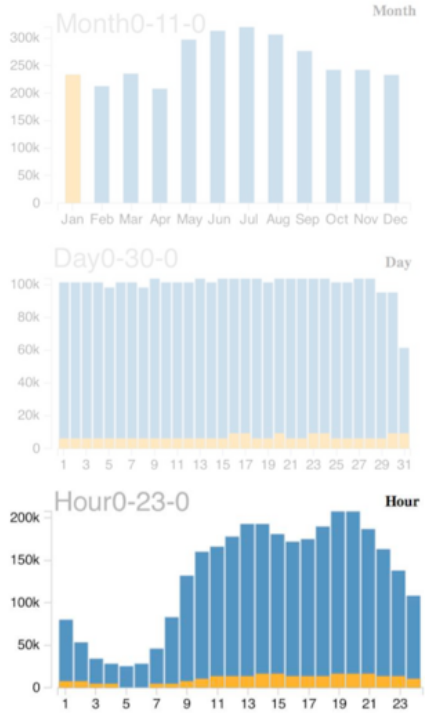
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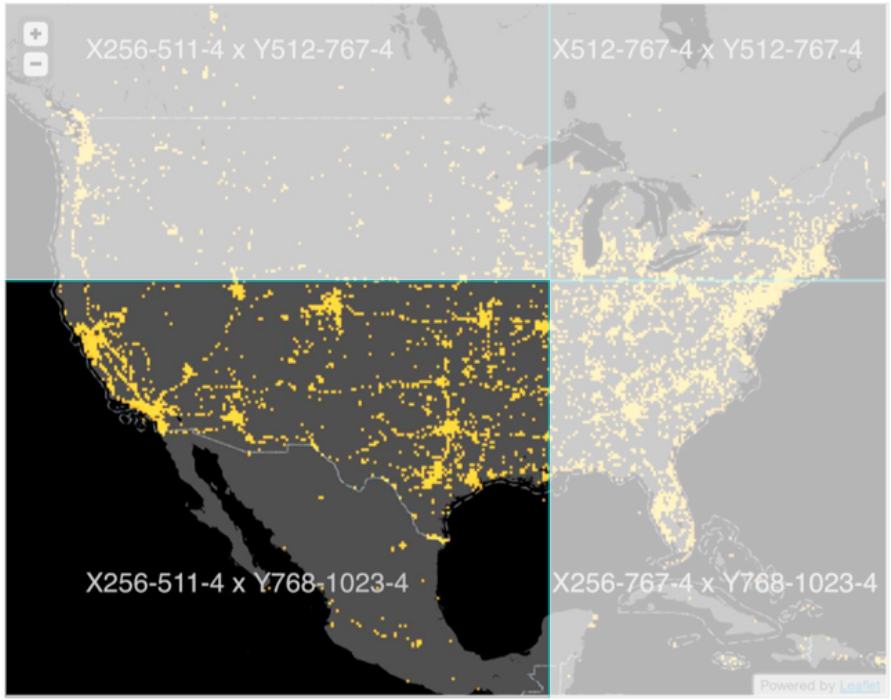
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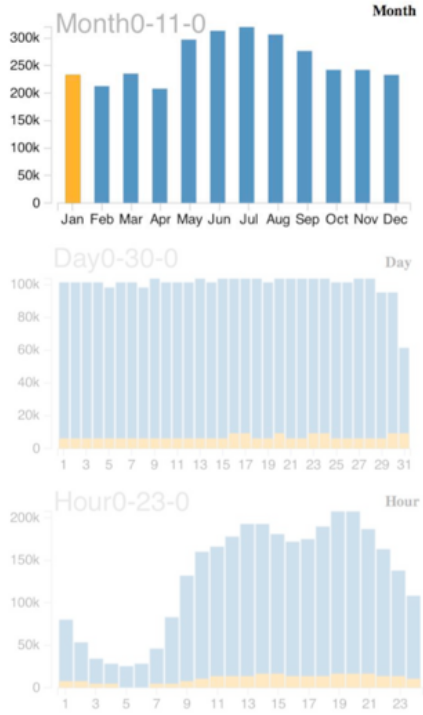
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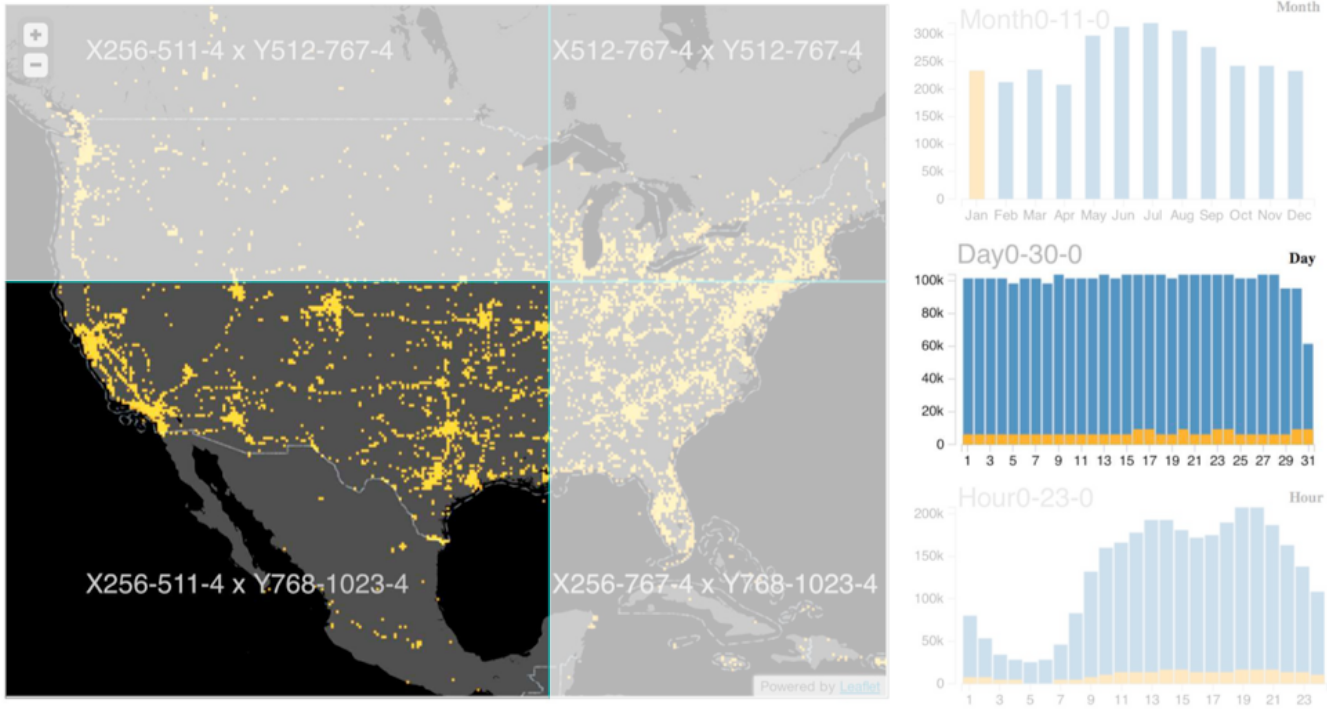
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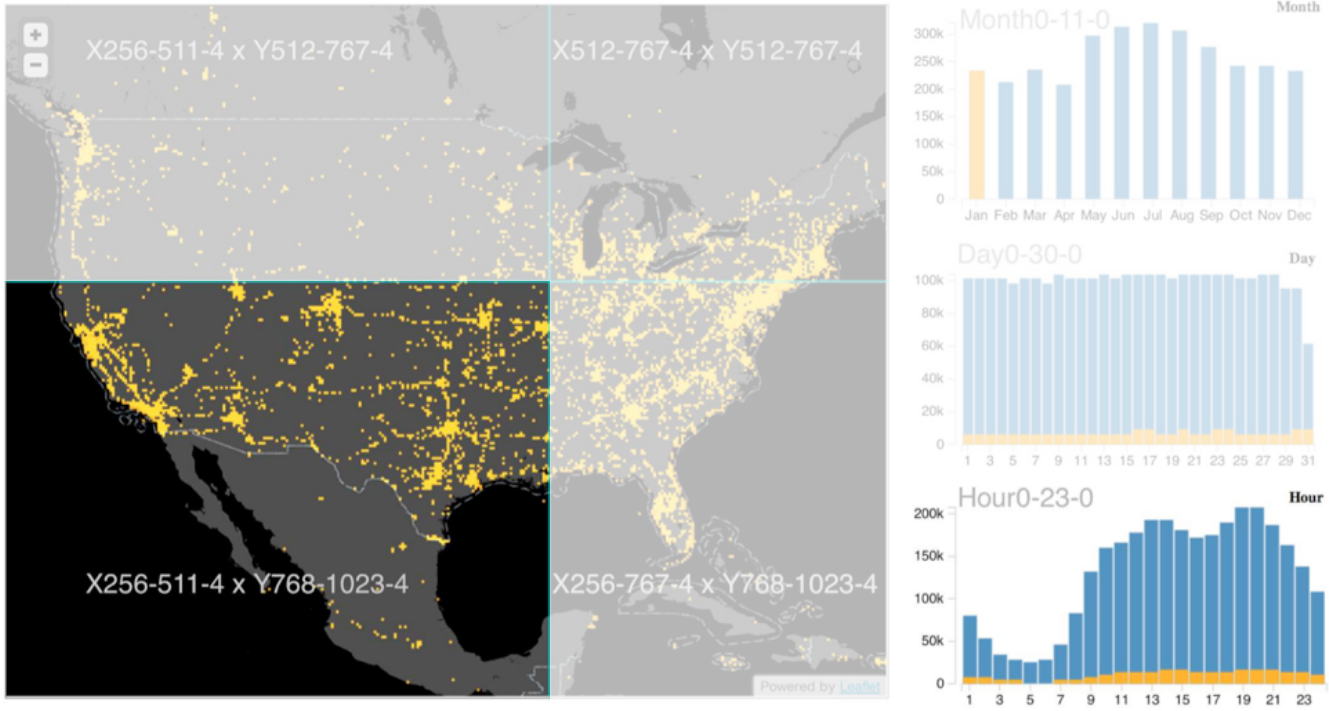
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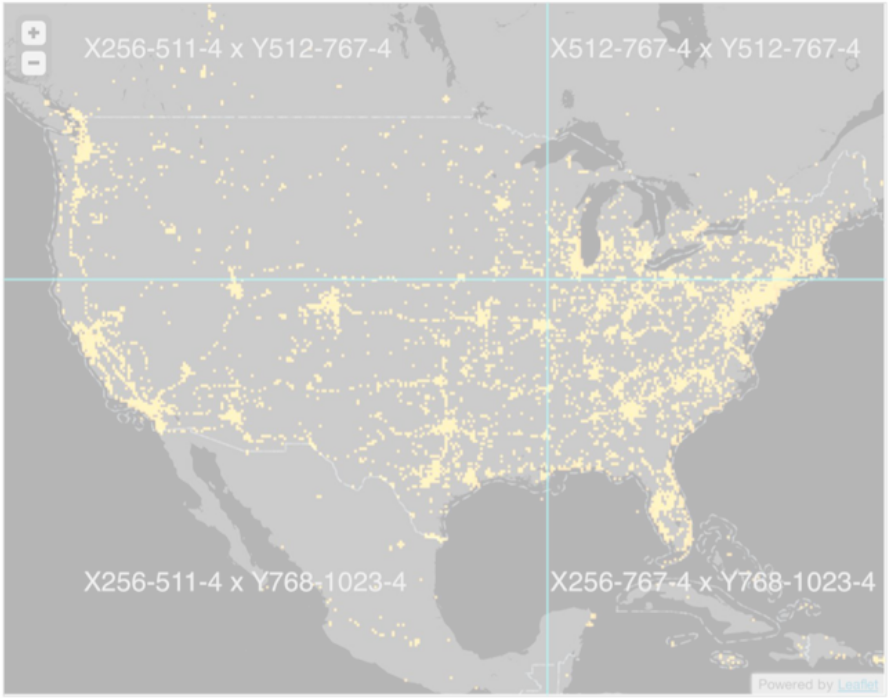
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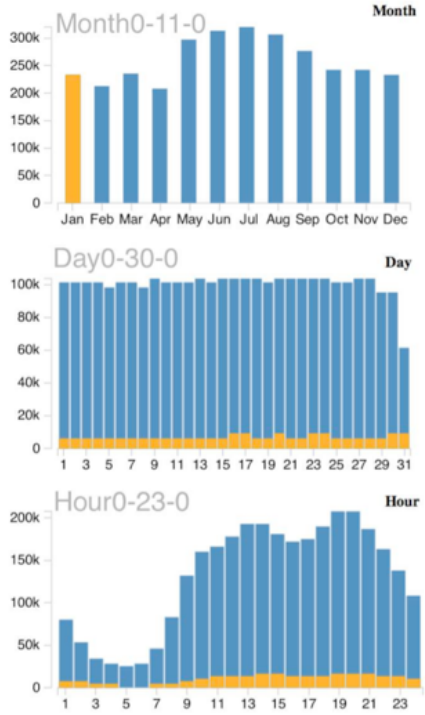
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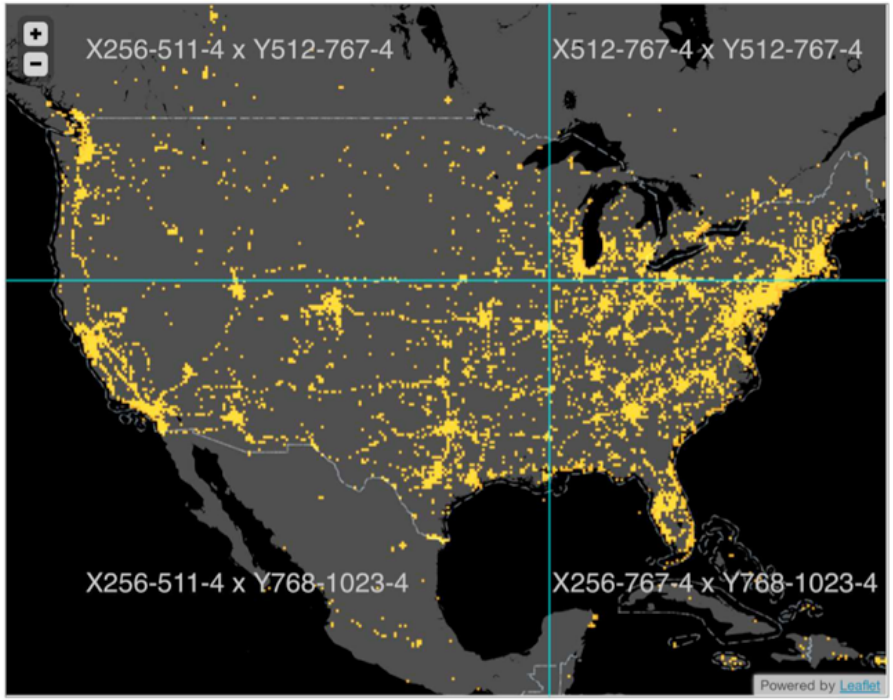
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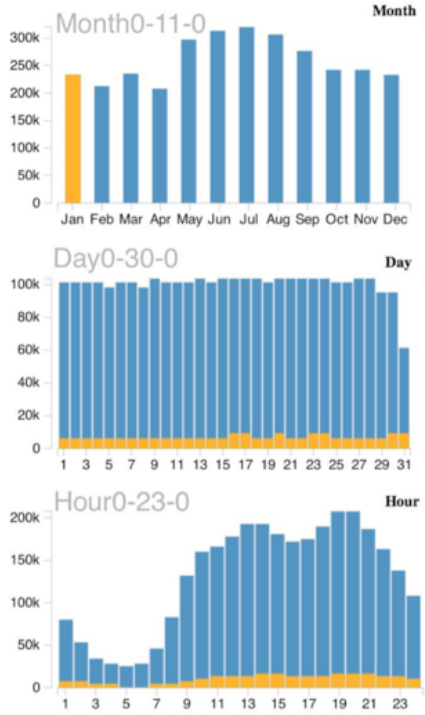
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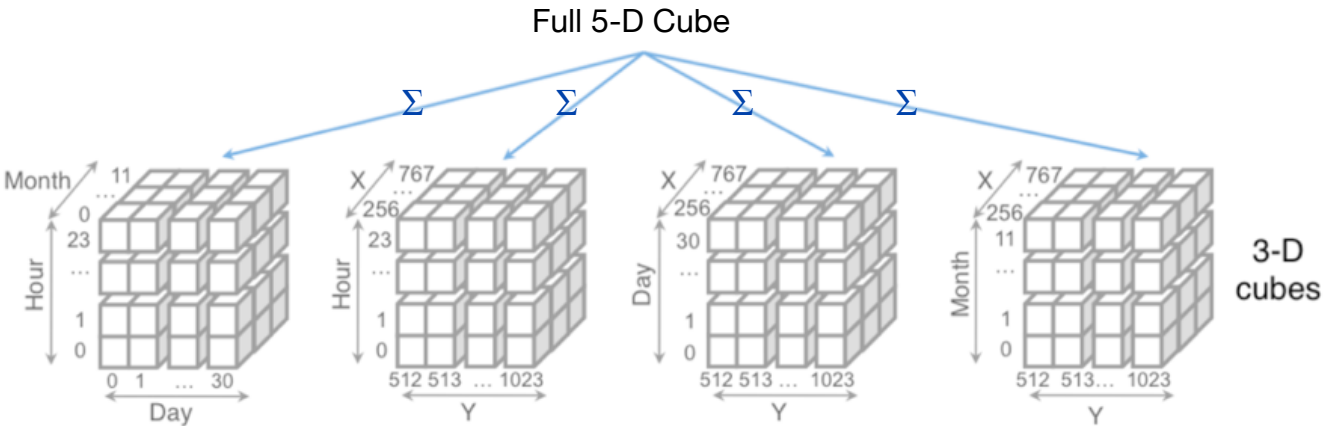
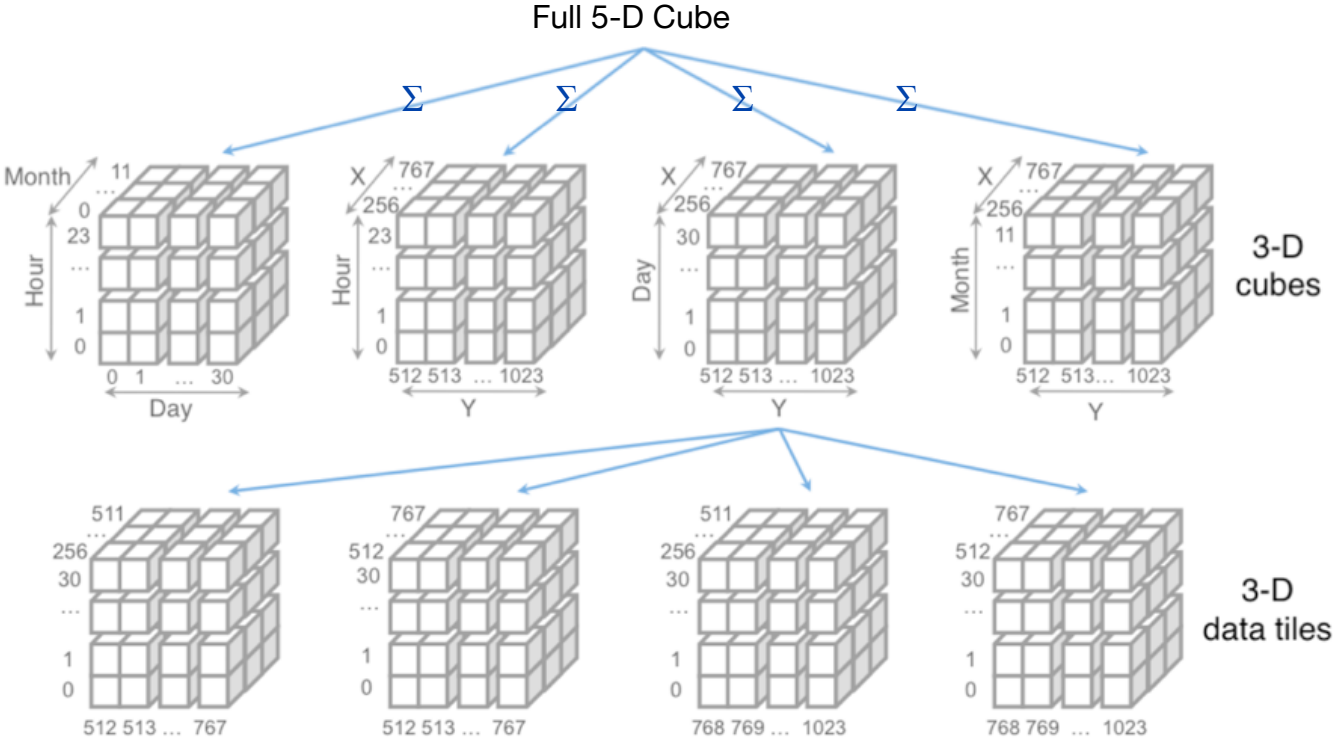
Full 5-D Cube



For any pair of 1D or 2D binned plots, the maximum number of dimensions needed to support brushing & linking is **four**.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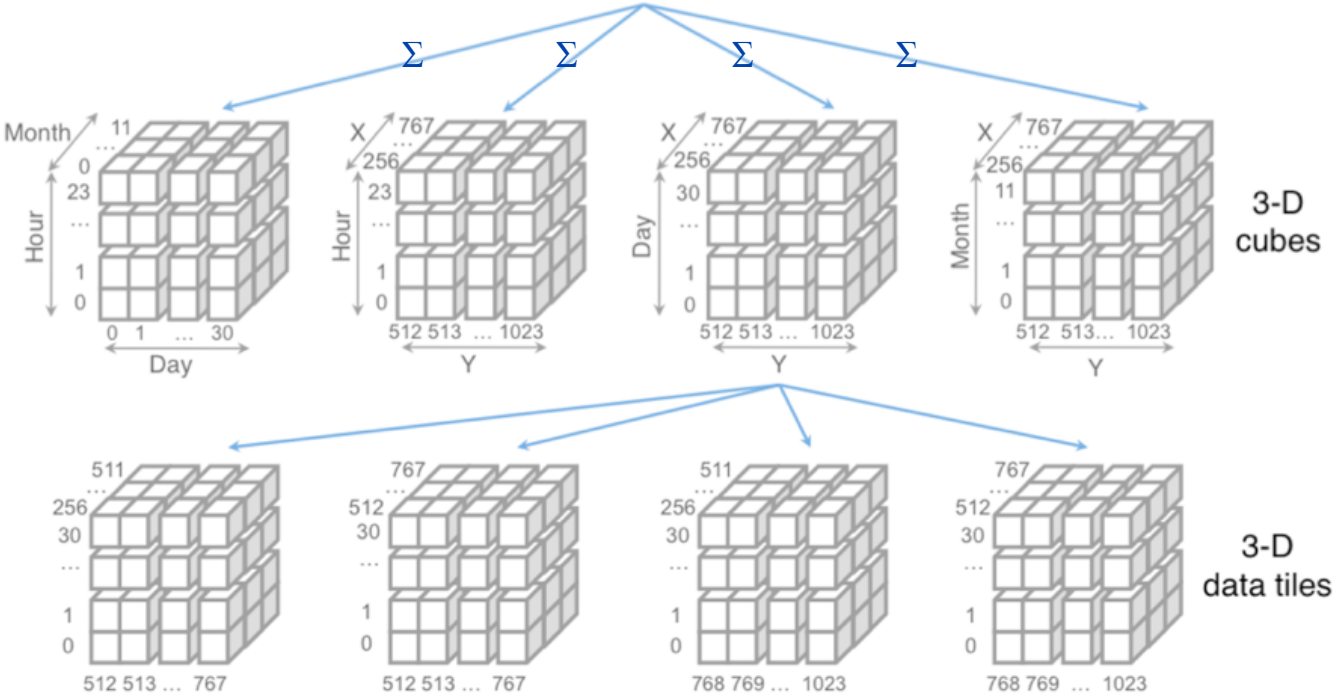
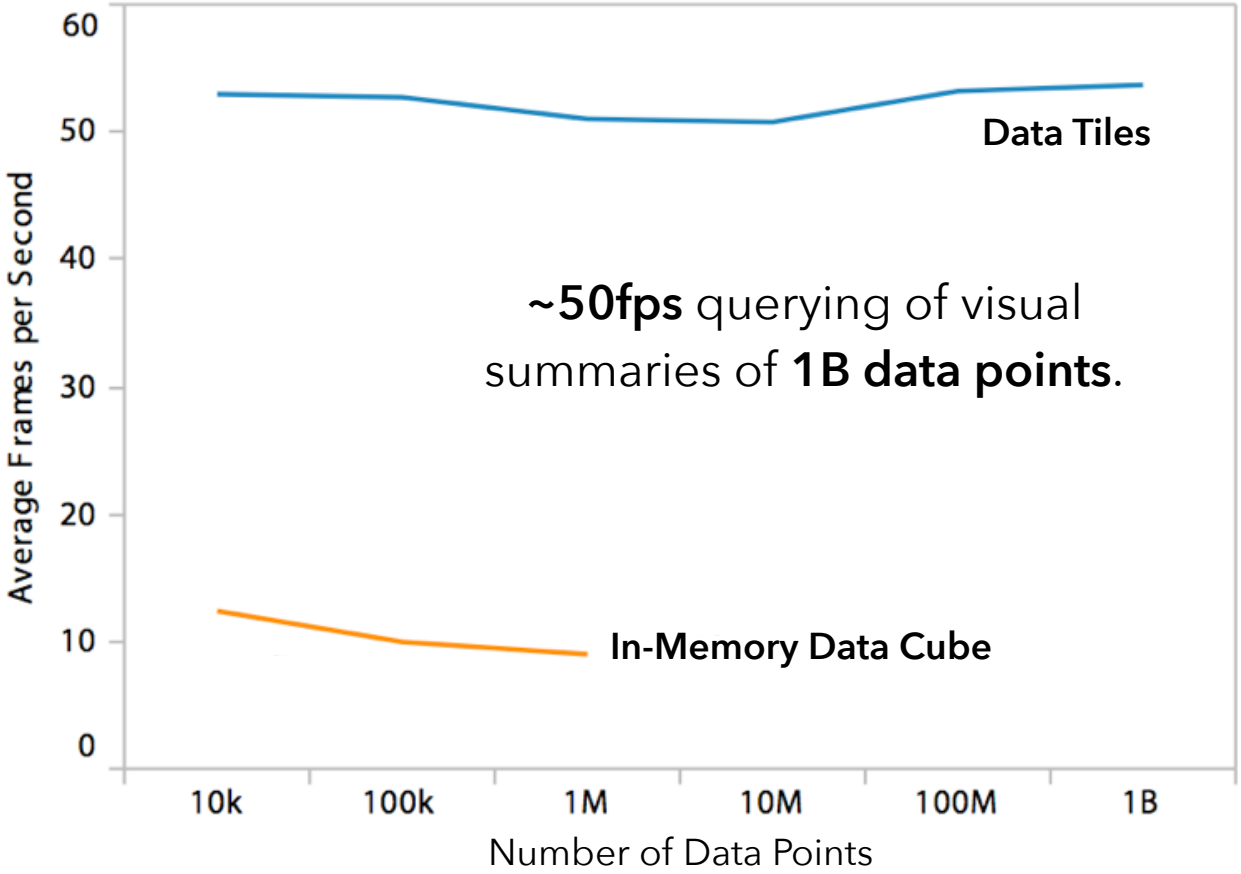
3-D cubes
3-D data tiles
13 3-D Data Tiles

Full 5-D Cube → ~2.3B bins



13 3-D Data Tiles → ~17.6M bins (in 352KB!)

5 dimensions x 50 bins/dim x 25 plots



Limitations and Questions

But where do the multivariate data tiles come from?

They must be provided by a backend server. This can be time-consuming, particularly if supporting deep levels of zooming.

Does super-low-latency interaction really matter?

Is it worth it to go to all of this trouble? (Short answer: yes!)

High latency leads to reduced analytic output [Liu & Heer, InfoVis 2014]

Why Latency Matters

Prior Work

Higher latency entails higher action costs, subjects satisfice by selecting strategies that *reduce short-term effort* with no guarantee that the final outcome is optimized. [Gray & Boehm-Davis]

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> When the cost of acquiring information is increased, subjects change strategy and rely more on working memory. [Ballard et al]

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When confronted with increased latencies, users resort to more mental planning, at times making fewer errors and performing better on tasks with *verifiable outcomes*. [O'Hara & Payne]

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But what about *open, exploratory analysis tasks*?

Experiment Design

2 (Latency) x 2 (Scenario) Design

Latency: +0ms / +500ms

Scenario: Mobile Check-ins / FAA Flight Delays

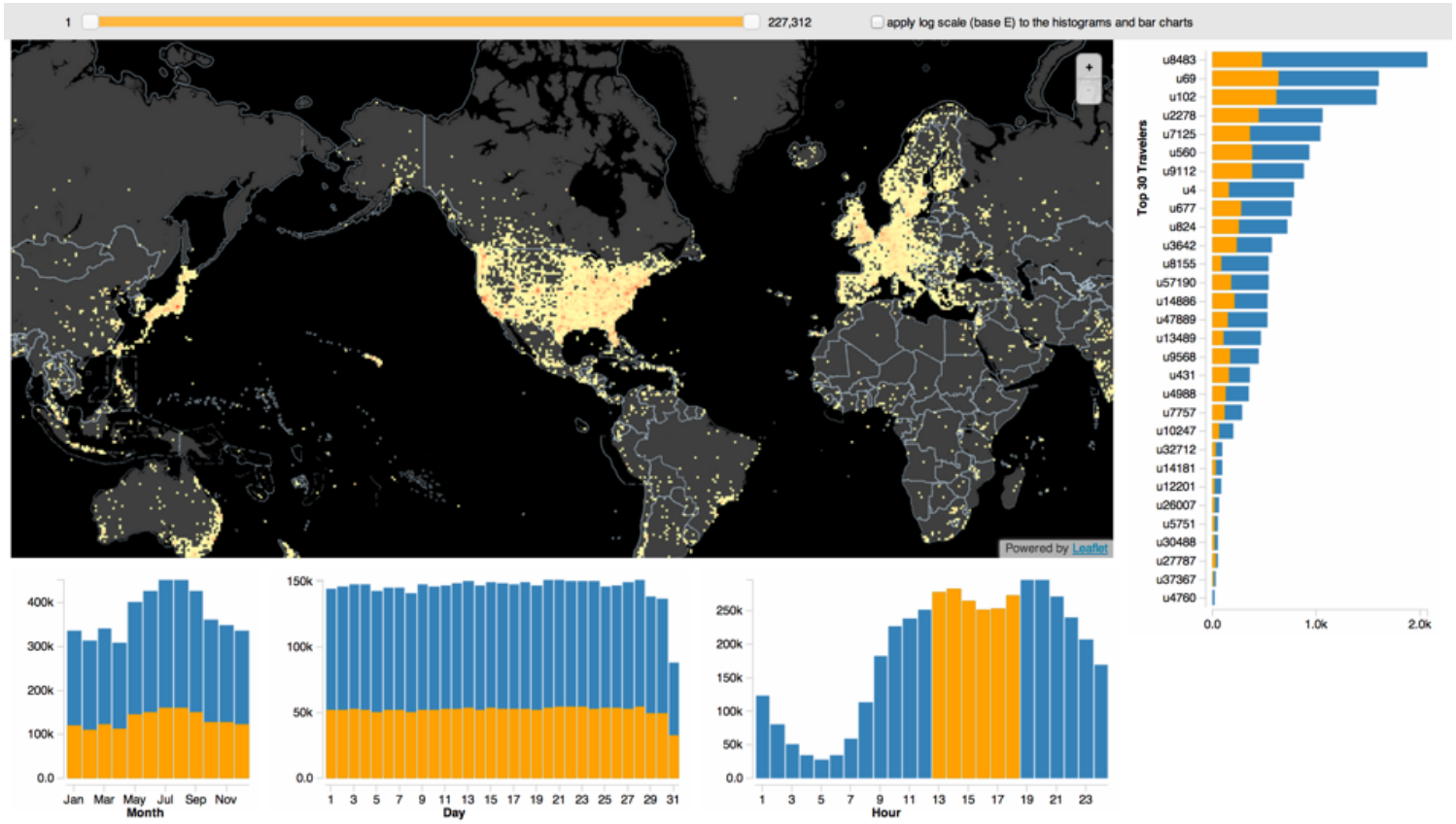
Exploratory Analysis Tasks (2 per session)

imMens with brush, pan, zoom, adjust scales

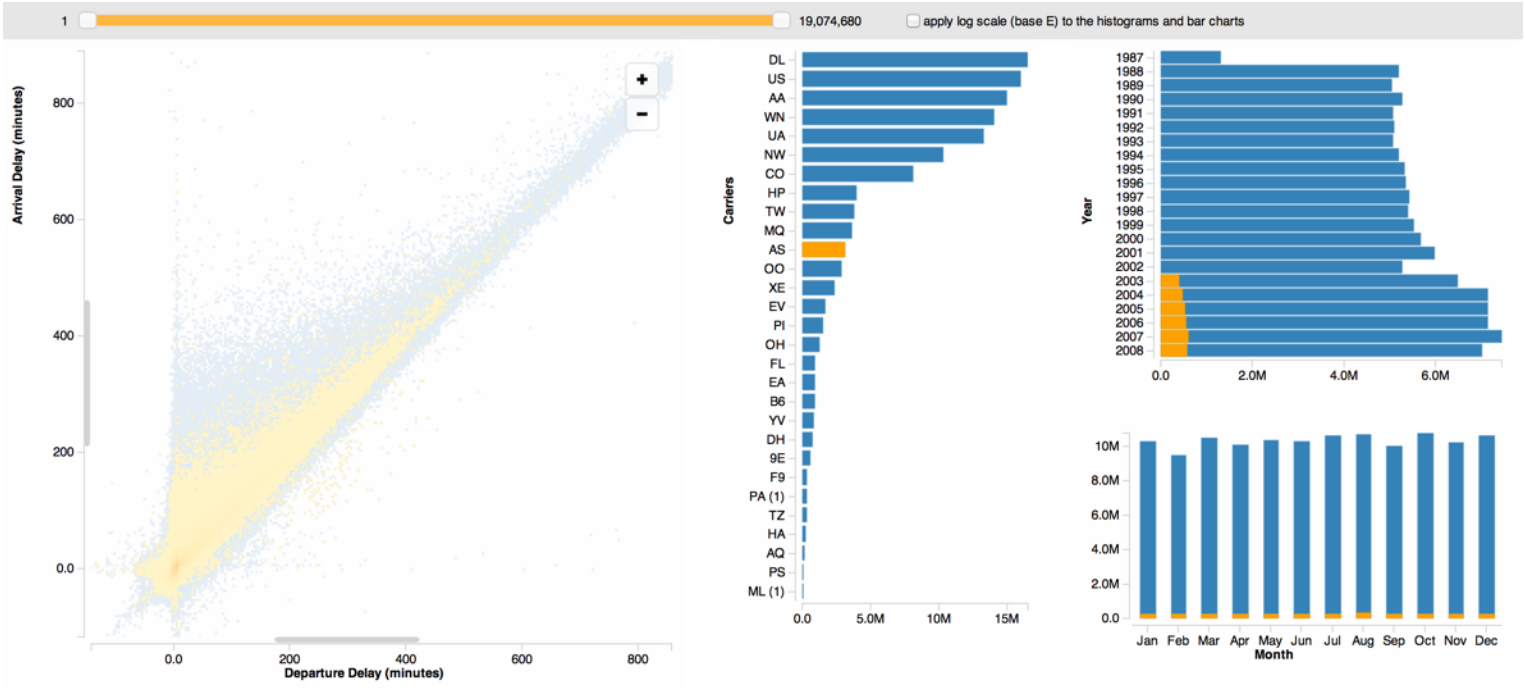
Users asked to explore data and share findings

Log events, record audio and screen capture

16 subjects, all familiar with data analysis + vis



4.5m Mobile Check-Ins



140m FAA Flight Delay Records

Data Collection & Analysis

Event Log Analysis

Analyze triggered & processed user input events

Assess data set coverage (# unique tiles)

Verbal Protocol Analysis

Think-aloud protocol: verbalize thought process

Transcribe sessions; Code actions and insights

Analyze number and type of coded events

Latency Study Results

Higher latency leads to…

Latency Study Results

Higher latency leads to…

Reduced user activity and data set coverage

Latency Study Results

Higher latency leads to…

Reduced user activity and data set coverage

Significantly fewer brushing actions

Latency Study Results

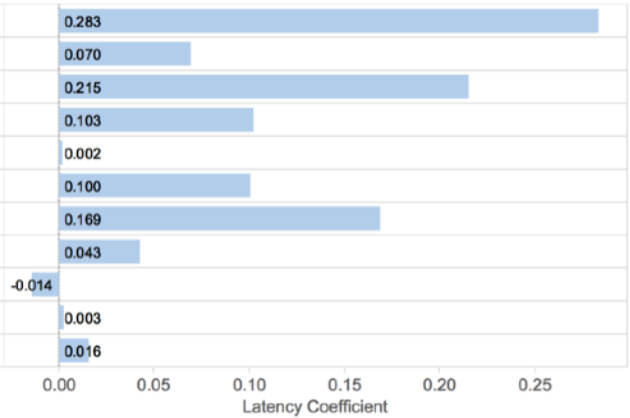
Higher latency leads to…

Reduced user activity and data set coverage

Significantly fewer brushing actions

Less observation, generalization & hypothesis

Verbal Category	likelihood-ratio test: Chisq(1, N=32)	p value	significance
Observation	5.4812	0.01922	*
Observation (Single View)	1.5706	0.2101	
Observation (Multiple Views)	3.3119	0.06878	.
Generalization	8.9763	0.002735	**
Generalization (Single View)	0.2641	0.6073	
Generalization (Multiple Views)	8.5054	0.003541	**
Hypothesis	8.3999	0.003752	**
Question	0.7416	0.3891	
Interface	0.4651	0.4953	
Recall	0.0202	0.8869	
Simulation	0.6983	0.4033	



Latency Study Results

Higher latency leads to…

Reduced user activity and data set coverage

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Interaction effect: Exposure to delay reduces subsequent performance in low-latency interface.

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Different interactions exhibit varied sensitivity to latency. Brushing is highly sensitive!

Latency Study Results

Higher latency leads to…

Reduced user activity and data set coverage

Significantly fewer brushing actions

Less observation, generalization & hypothesis

Interaction effect: Exposure to delay reduces subsequent performance in low-latency interface.

Different interactions exhibit varied sensitivity to latency. Brushing is highly sensitive!

In short: milliseconds matter! And optimizing for latency was not a waste of time… 😅

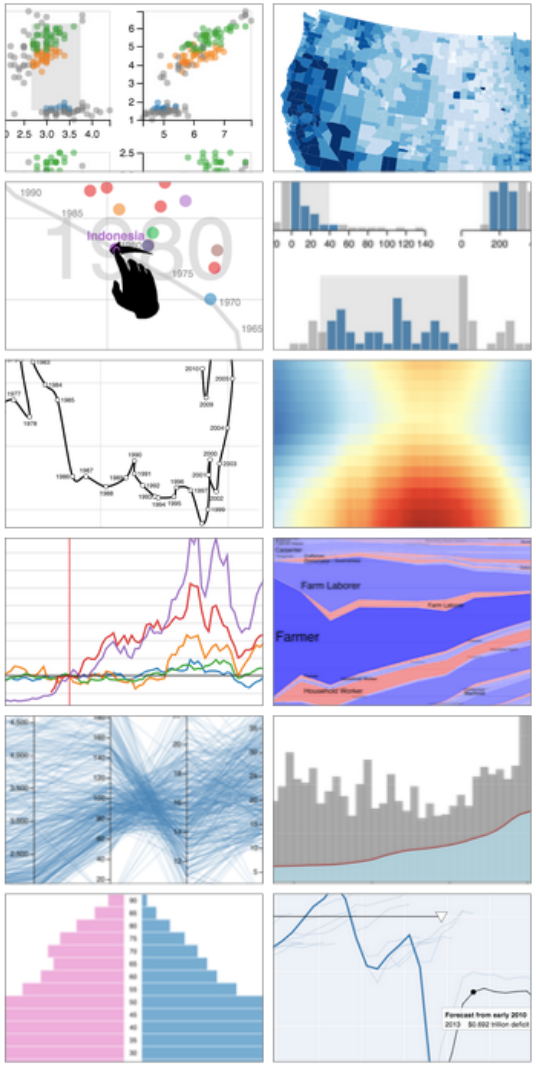
Sampling Methods

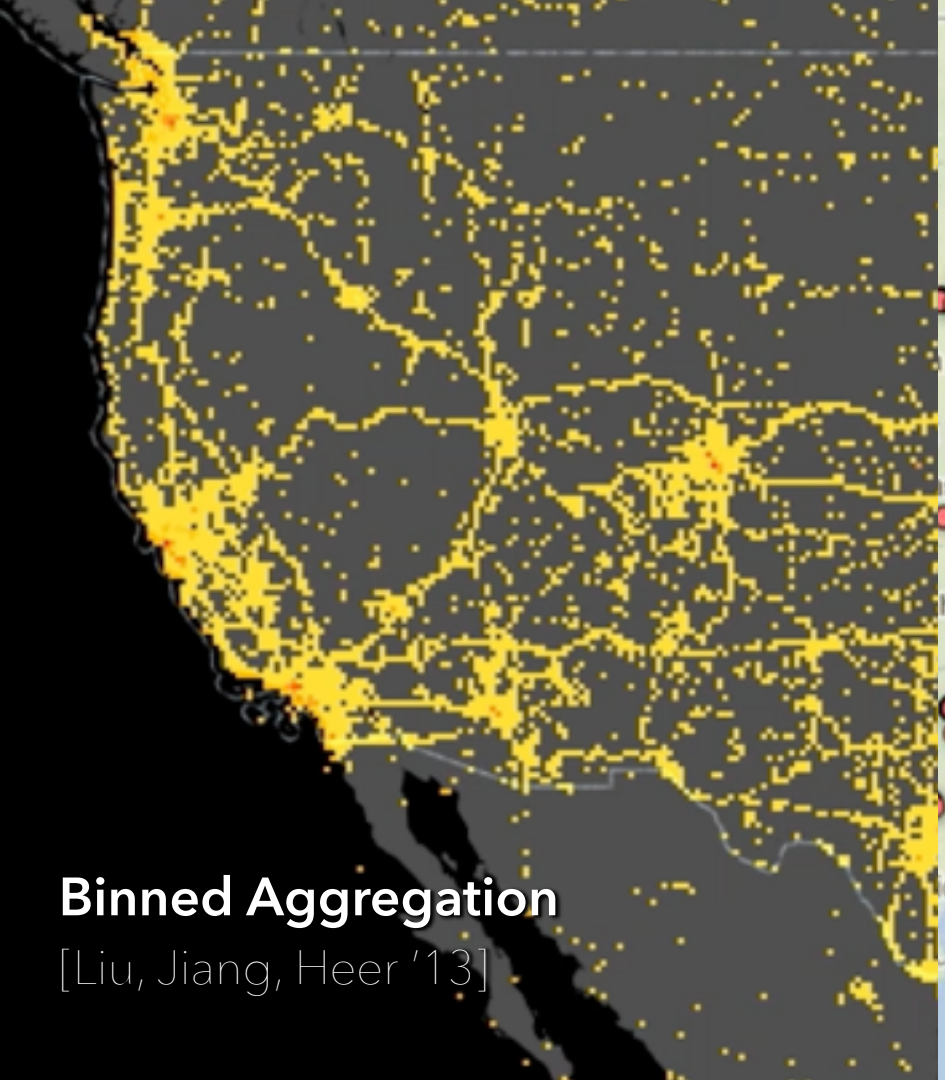
Common Sampling Methods

First-N: Useful for transformation, but not inference.

Random: Good default, but may miss features of interest. Possible in one pass via reservoir sampling, or faster if stored in randomized order.

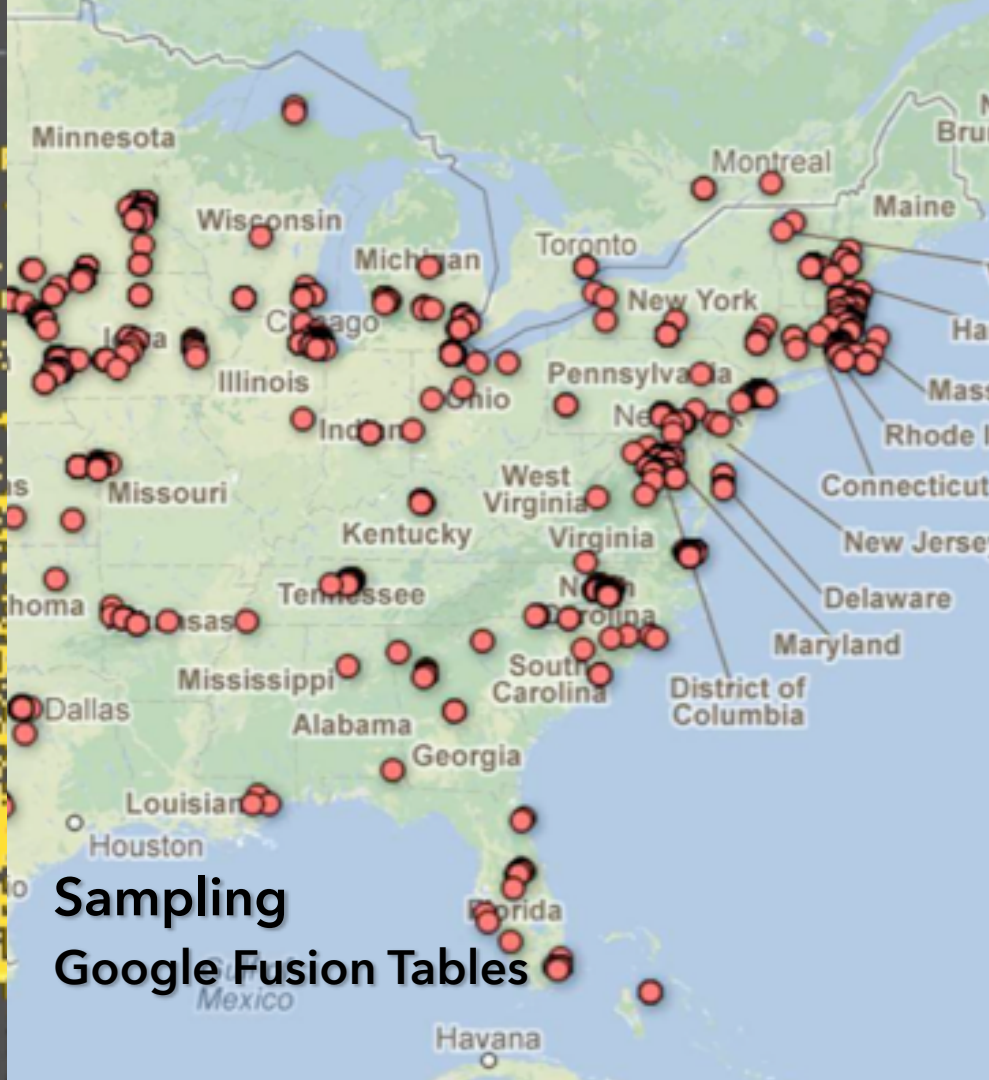
Stratified: Sample within groups, ensure coverage and balance across those categories.





Binned Aggregation

[Liu, Jiang, Heer '13]



Sampling

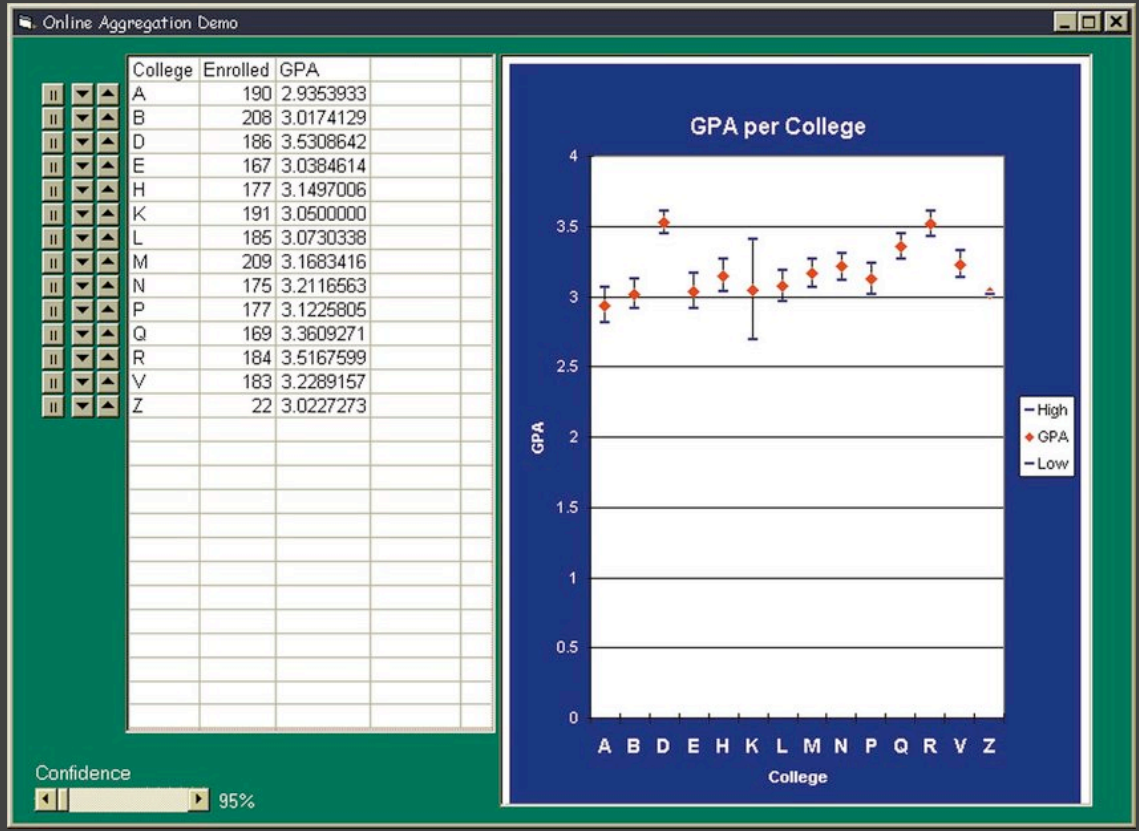
Google Fusion Tables

Online Aggregation [Hellerstein, Haas, Wang '97]

Provide dynamic, *progressive* results as queries run: see results over growing samples.

Visualize current results with confidence intervals to convey uncertainty of estimate.

Challenge: difficult to ensure truly random sampling.

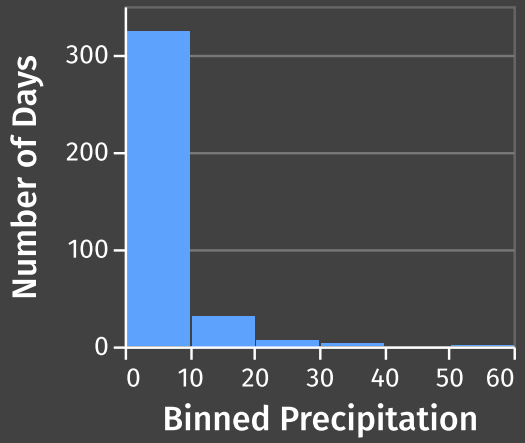


What if data is too large to query in a reasonable time?

Trust, but Verify: Optimistic Vis

[Moritz, Fisher, Ding & Wang '17]

Strategies: Query Database, Approximation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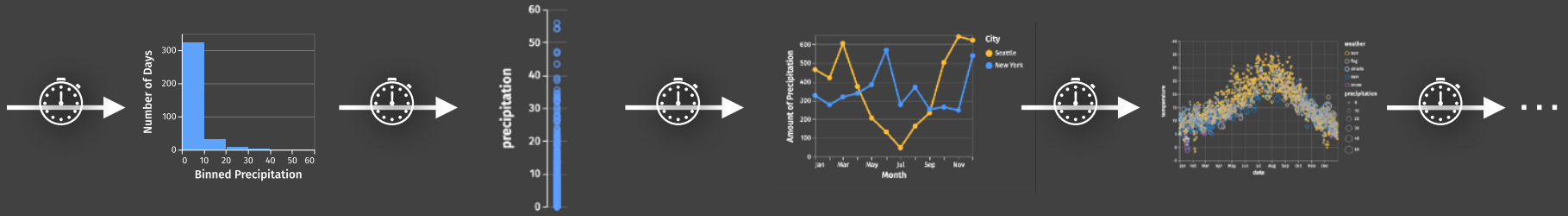


Latencies reduce engagement
and lead to fewer observations.

The Effect of Interactive Latency. Liu, Heer. *IEEE InfoVis 2014.*

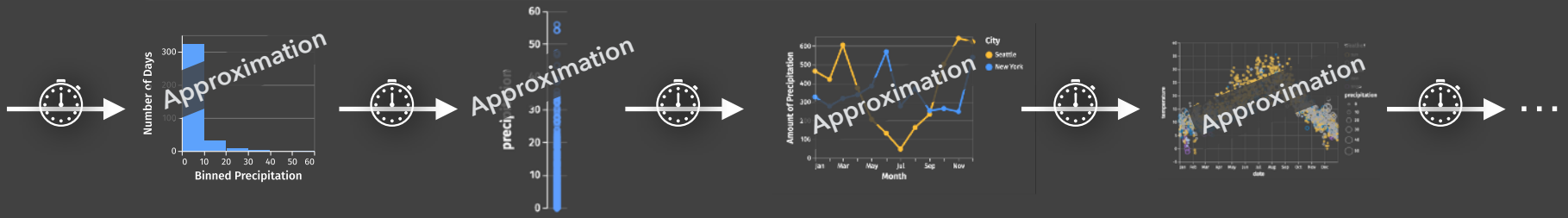
Small chance of error

Small chance of error

Very likely to have at least one error

Small chance of error

Small chance of error



Approximation: Trade Accuracy for Speed

Approximate query processing (AQP)
Uncertainty estimation in statistics
Uncertainty visualization
Probabilistic programming
Approximate hardware

Pick your poison:

1. Trust the approximation, or
2. Wait for everything to complete.

Optimistic Visualization

Trust but Verify

What if we think of the
issues with approximation as
user experience problems?

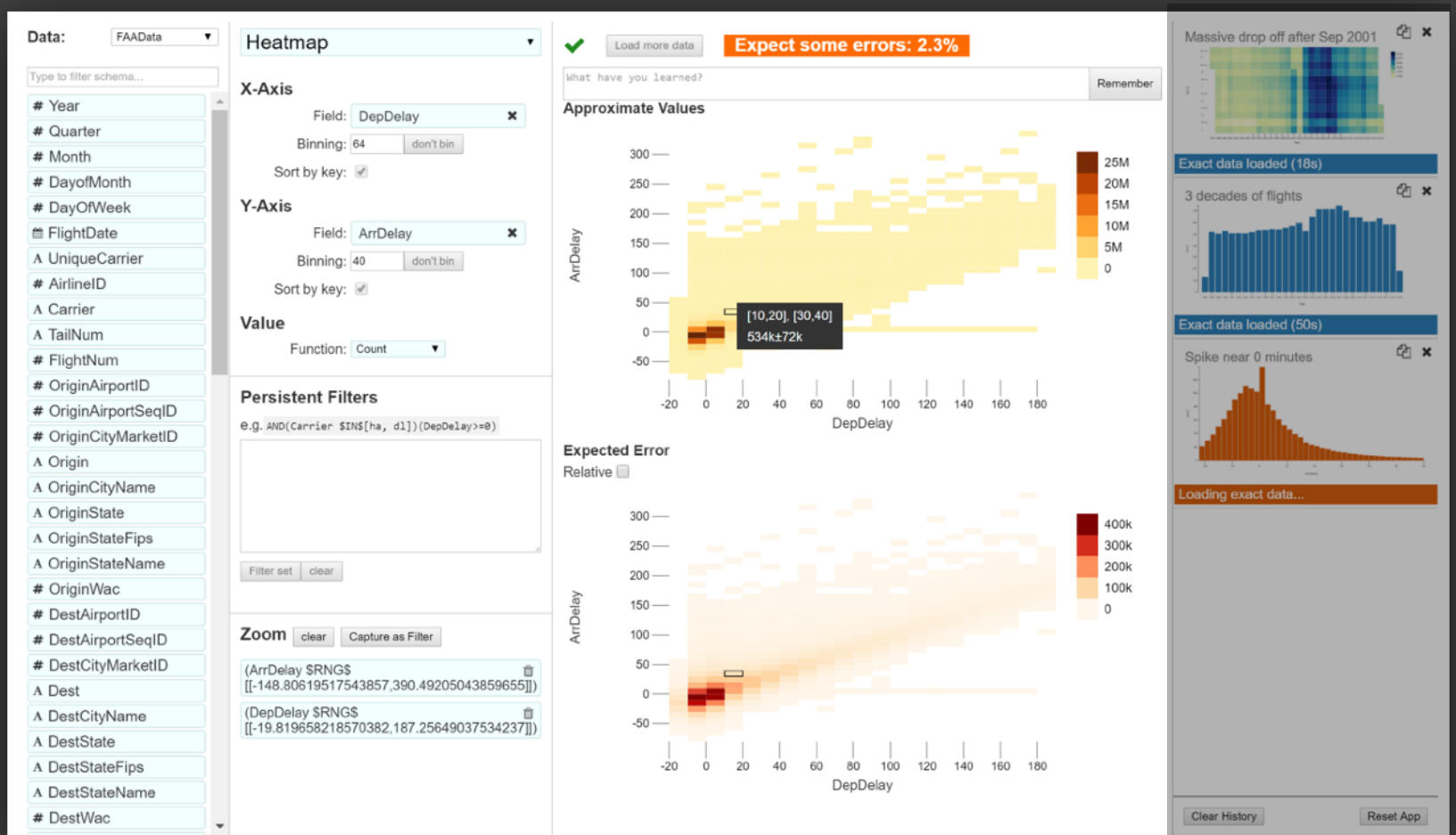
Optimistic Visualization

Trust but Verify. Moritz et al. *CHI 2017.*

1. Analysts uses initial estimates.
2. Precise queries run in the background.
3. System confirms results. Analyst detects errors.

Analysts can use approximations and also trust them.

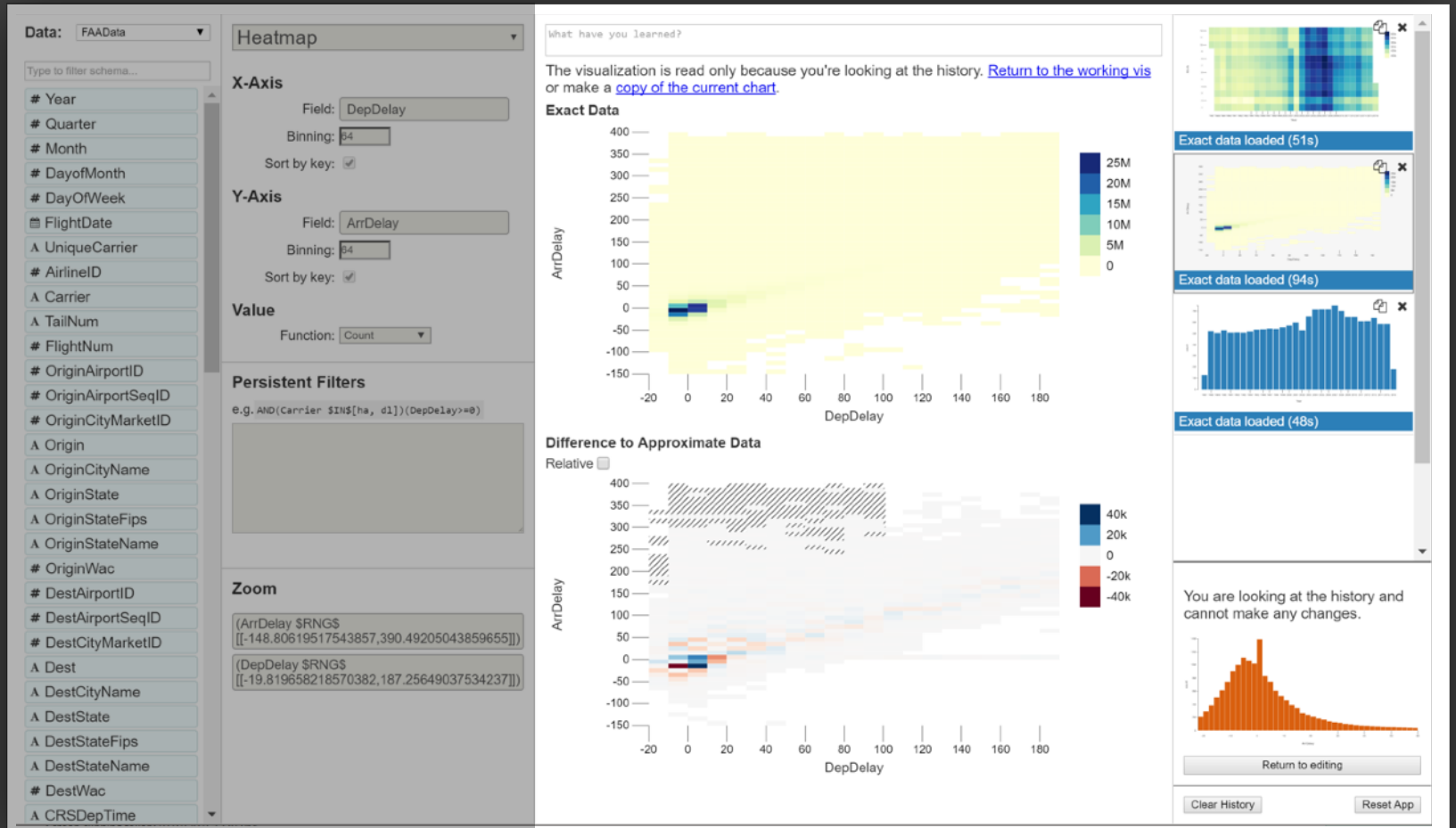
Optimistic Visualization



Visualize Uncertainty

Show a History of Previous Charts

Help Analysts Confirm Results



Evaluation

Case studies with teams at Microsoft who brought in their own data.

Approximation works

“seeing something right away at first glimpse is really great”

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.”

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.”

In Conclusion…

Two Challenges:

1. Effective **visual encoding**
2. Real-time **interaction**

Perceptual and interactive scalability should be limited by the **chosen resolution** of the visualized data, not the number of records.

Bin > Aggregate (> Smooth) > Plot

1. **Bin** Divide data domain into discrete “buckets”
2. **Aggregate** Count, Sum, Average, Min, Max, ...
3. **Smooth** *Optional*: smooth aggregates [Wickham ’13]
4. **Plot** Visualize the aggregate values

Interactive Scalability Strategies

1. **Query Database**
2. **Client-Side Indexing / Data Cubes**
3. **Prefetching**
4. **Approximation**

These strategies are **not** mutually exclusive!
Systems can apply them in tandem.