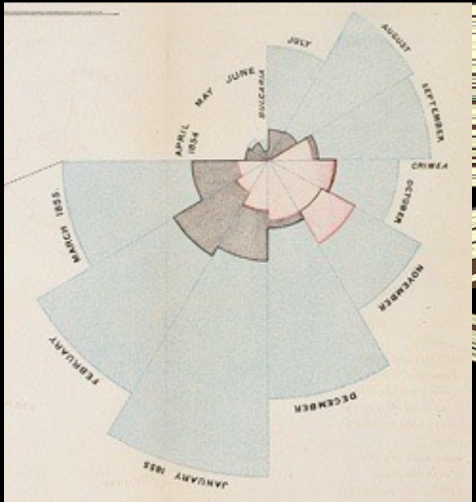
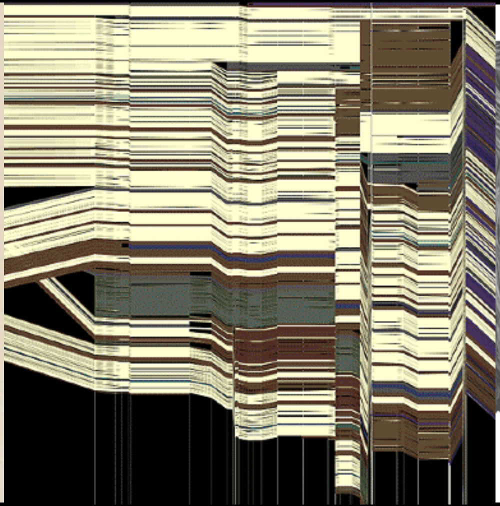
CSE 512 - Data Visualization

Scalability





Jeffrey Heer University of Washington

Session Outline

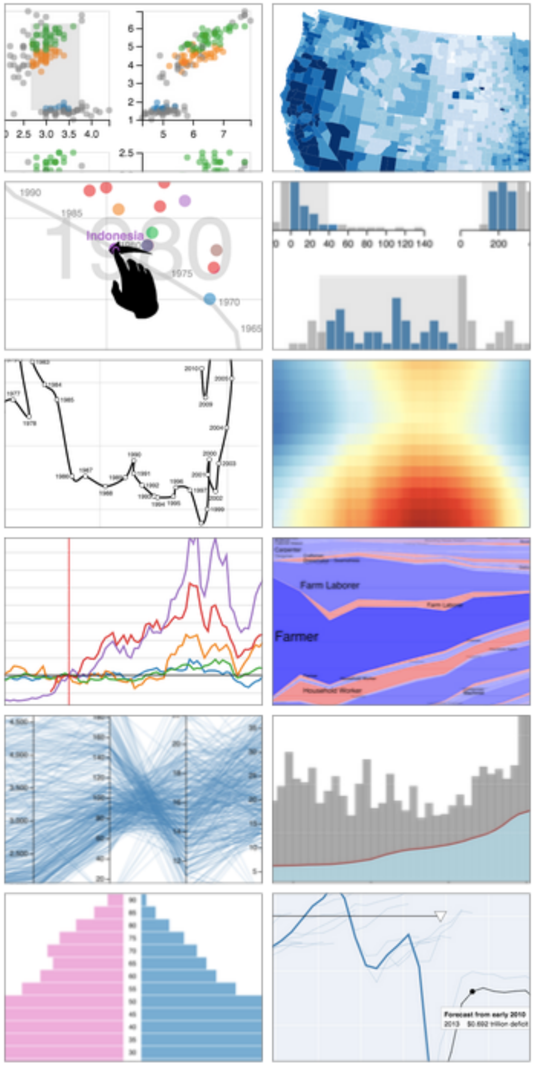
The Varieties of “Big Data”

Scalable Plotting Techniques

Scalable Interaction

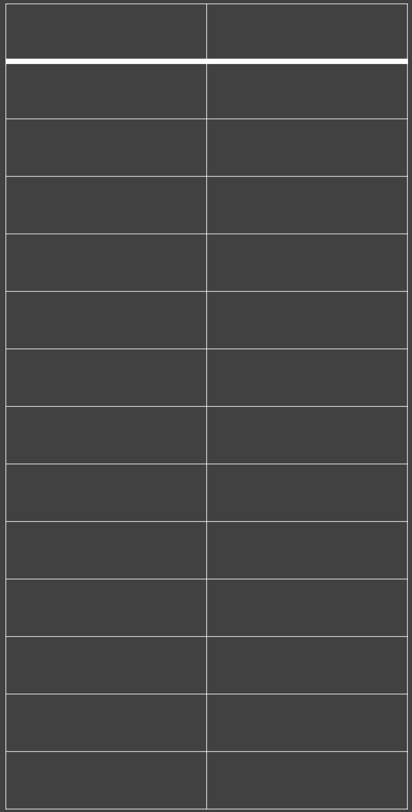
Why Latency Matters

Sampling Methods



The Varieties of "Big Data"

Tall Data



Lots of records

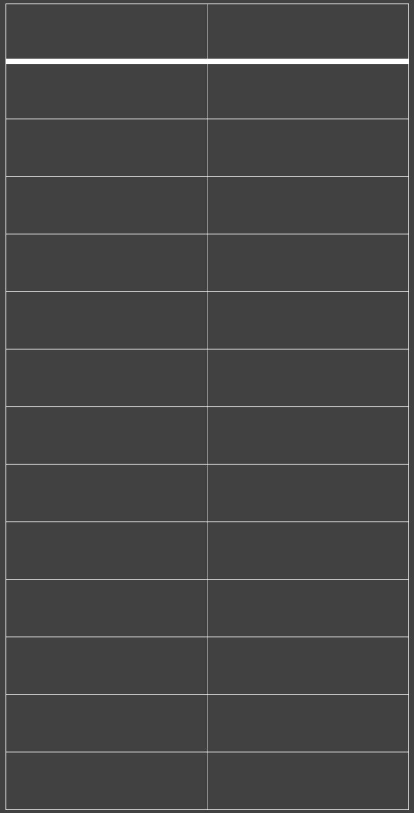
- Large DBs have petabytes or more
- *(but median DB still fits in RAM!)*

How to manage?

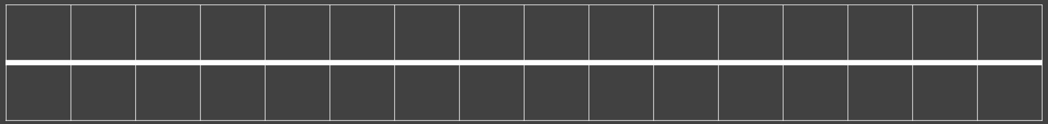
- Parallel data processing
- Reduction: Filter, aggregate
- Sample or approximate

Not just about systems. Consider perceptual / cognitive scalability.

Tall Data



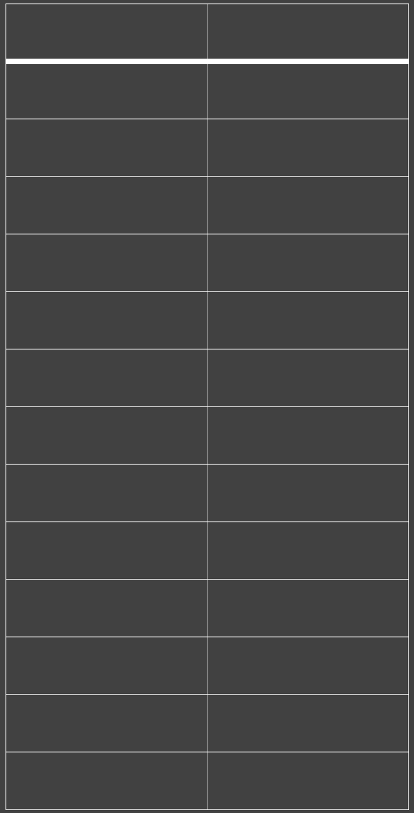
Wide data



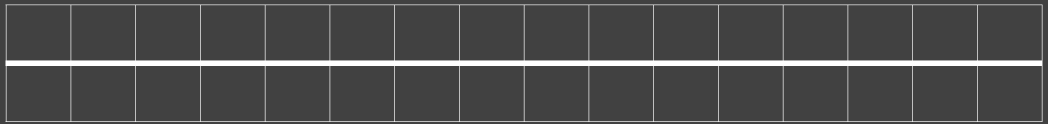
Lots of variables (100s-1000s…)
- Select relevant subset
- Dimensionality reduction
- Statistical methods can suggest and order related variables

Requires human judgment

Tall Data

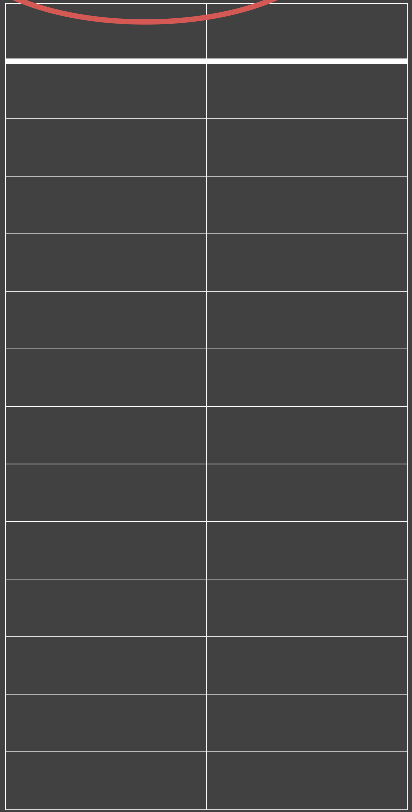


Wide data

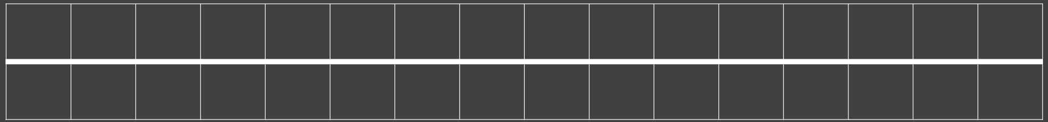


Diverse data

Tall Data



Wide data



Diverse data

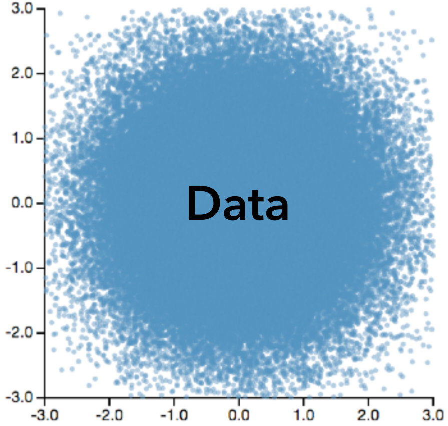
How can we visualize and interact with **billion+ record** databases in real-time?

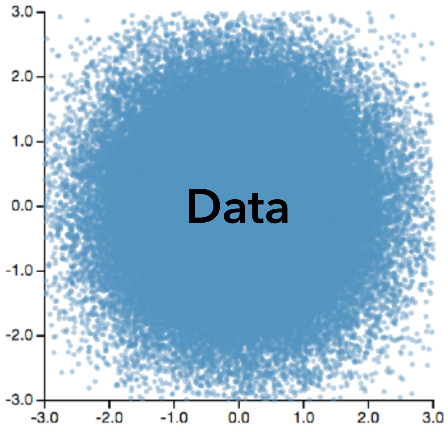
Two Challenges:

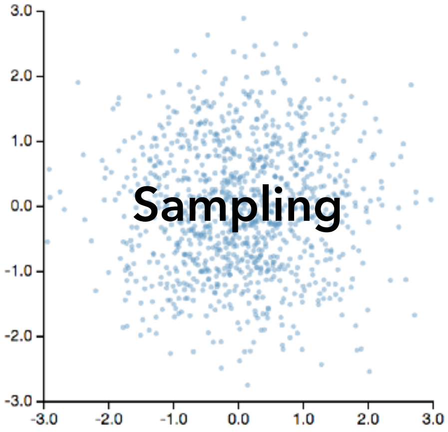
1. Effective **visual encoding**
2. Real-time **interaction**

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

Scalable Plotting Techniques




Data
3.0
2.0
1.0
0.0
-1.0
-2.0
-3.0
-3.0
-2.0
-1.0
0.0
1.0
2.0
3.0


Sampling
3.0
2.0
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-1.0
-2.0
-3.0
-3.0
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0.0
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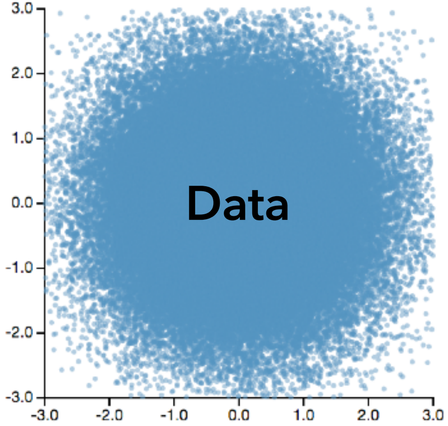
3.0


Data
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2.0
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-2.0
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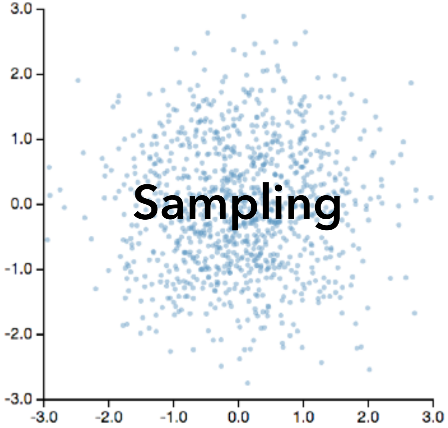
-3.0 -2.0 -1.0 0.0 1.0 2.0 3.0


Sampling
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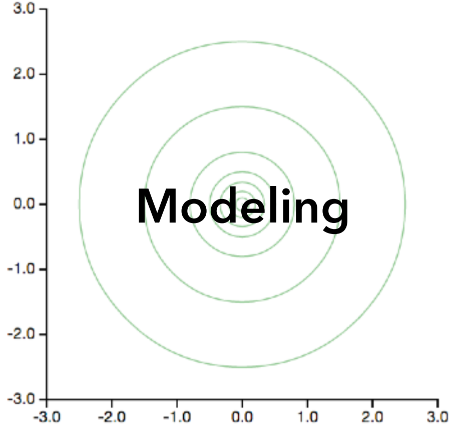
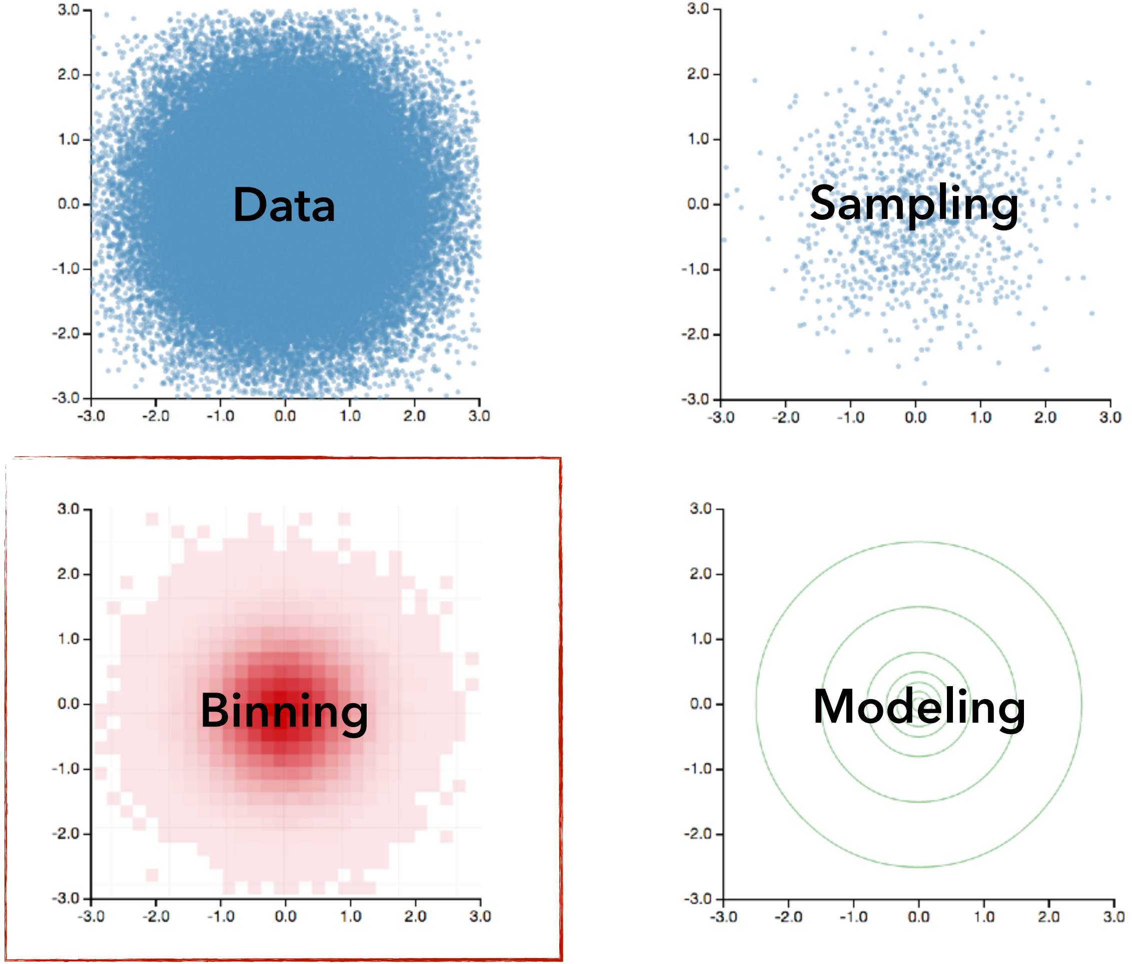
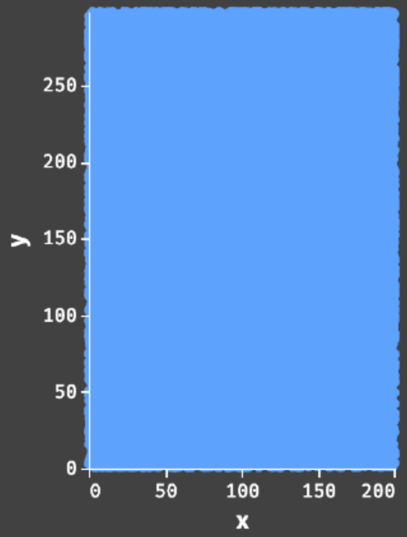
-3.0 -2.0 -1.0 0.0 1.0 2.0 3.0

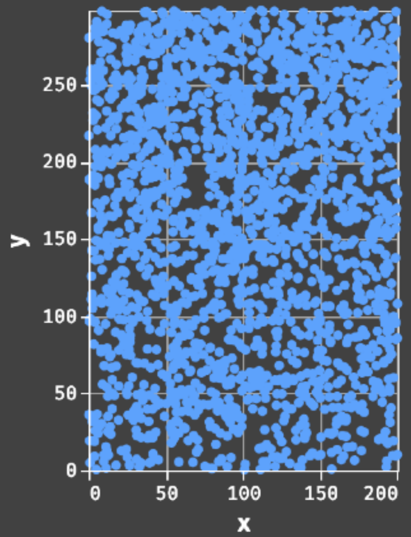

Modeling
3.0
2.0
1.0
0.0
-1.0
-2.0
-3.0
-3.0 -2.0 -1.0 0.0 1.0 2.0 3.0


Data
Sampling
Binning
Modeling
3.0
2.0
1.0
0.0
-1.0
-2.0
-3.0
-3.0 -2.0 -1.0 0.0 1.0 2.0 3.0

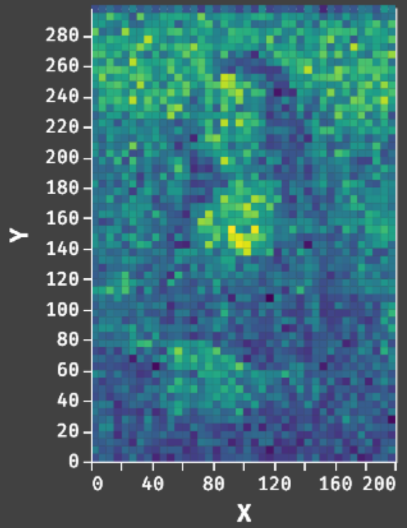
How to **Visualize** a Billion+ Records



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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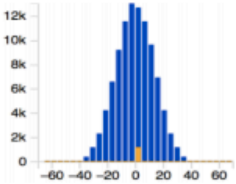
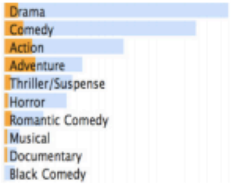
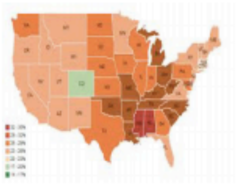
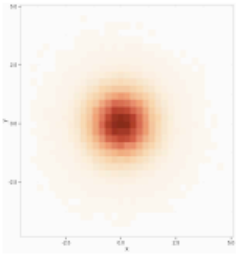
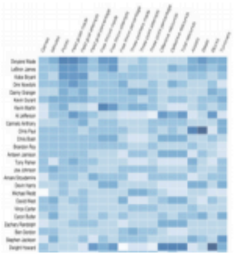
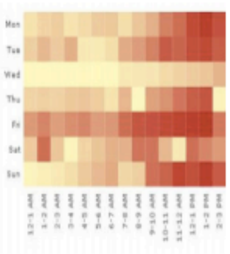
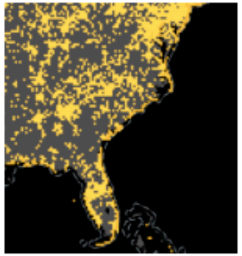
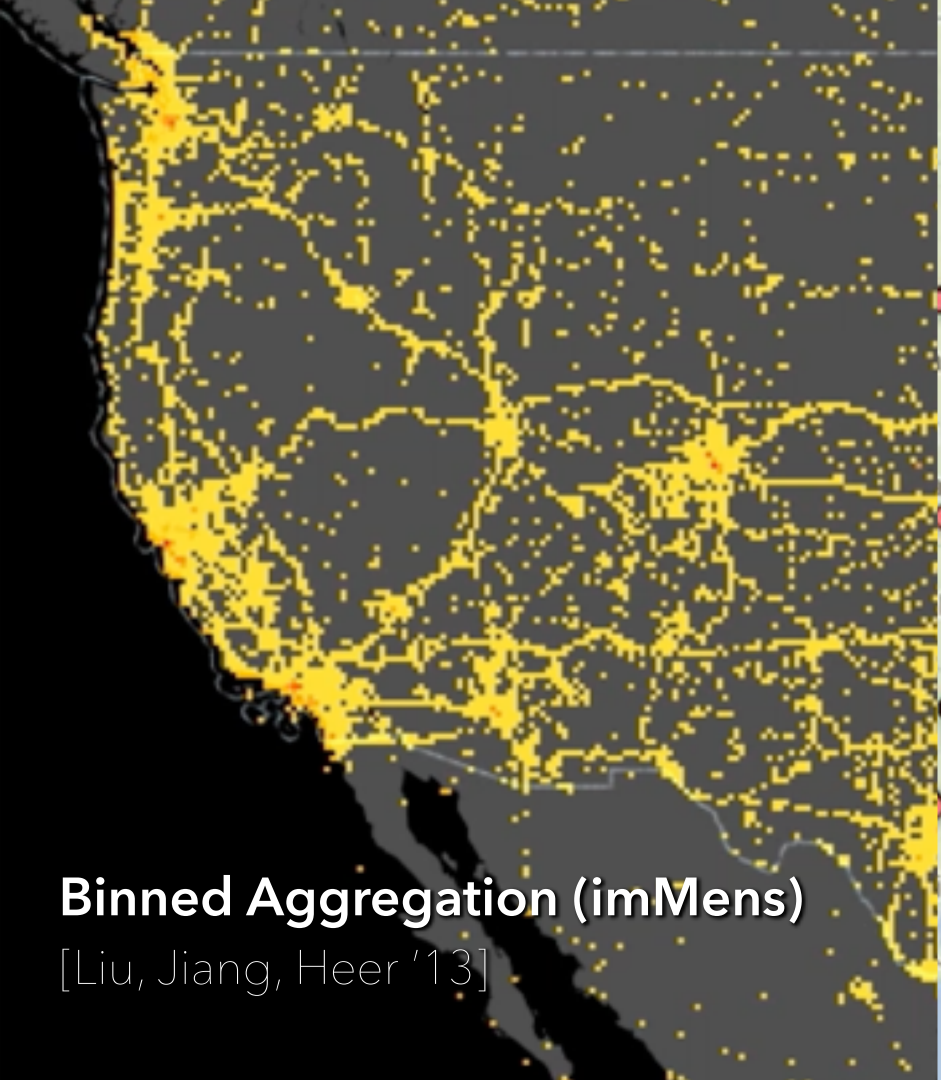
4. Plot Visualize the aggregate values

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

Sampling
Google Fusion Tables

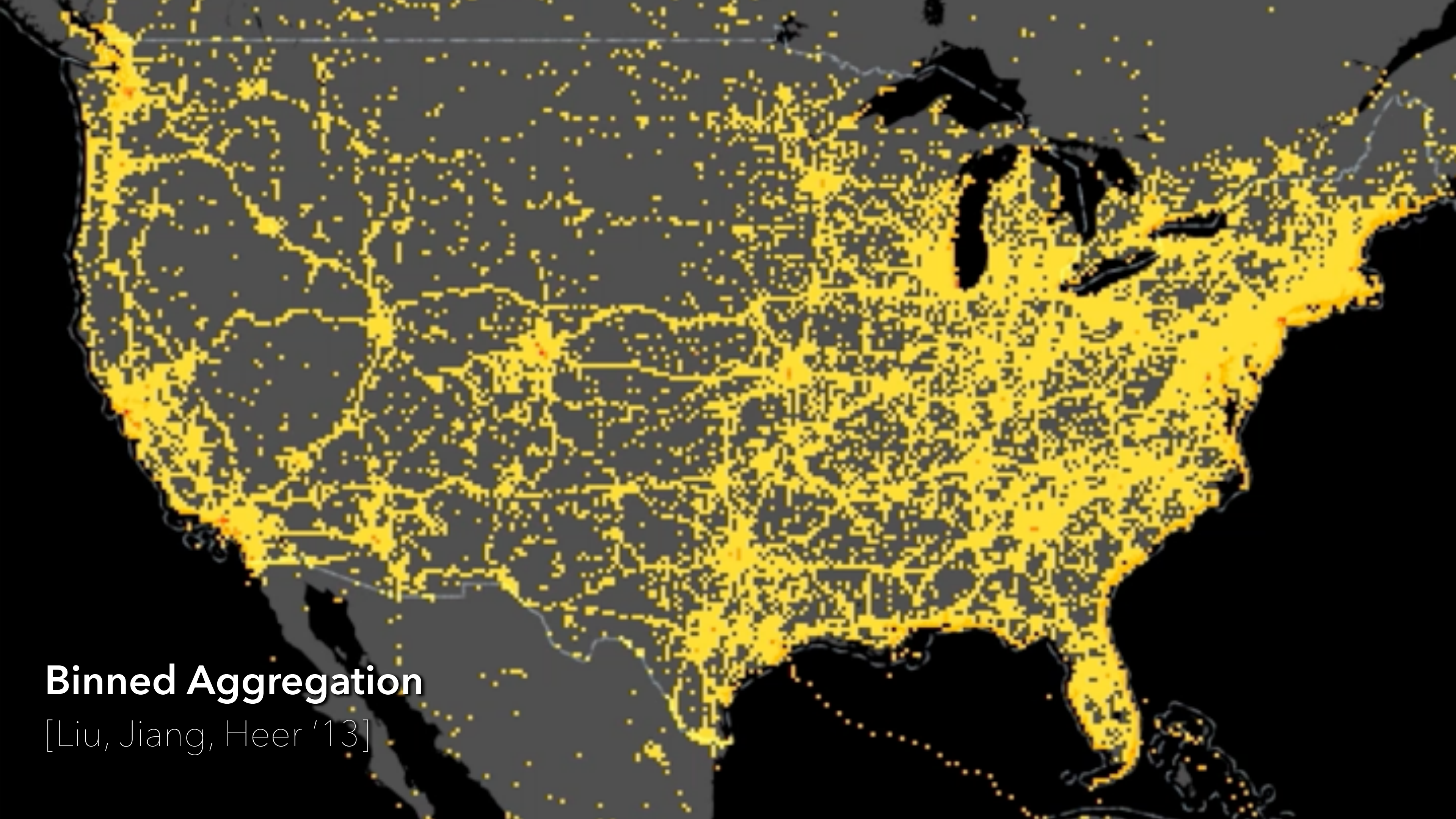


Binned Aggregation (imMens)

[Liu, Jiang, Heer '13]

Sampling

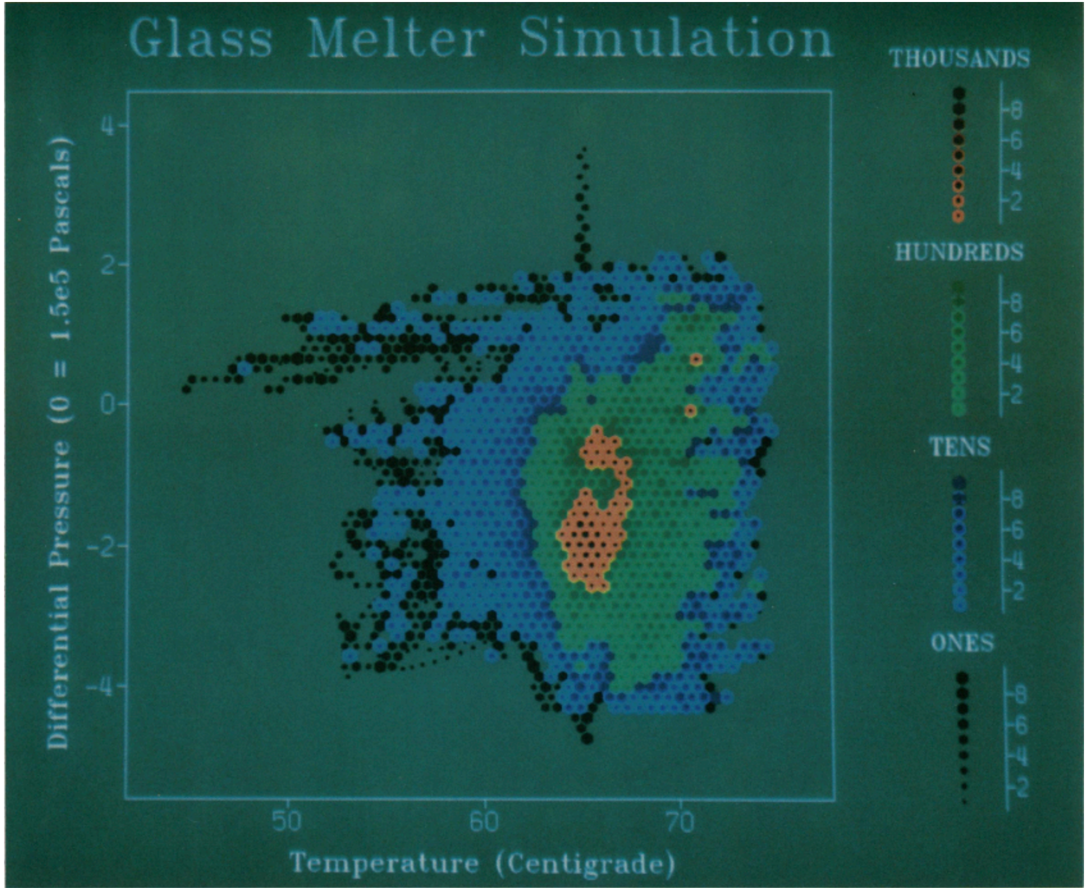
Google Fusion Tables



Binned Aggregation

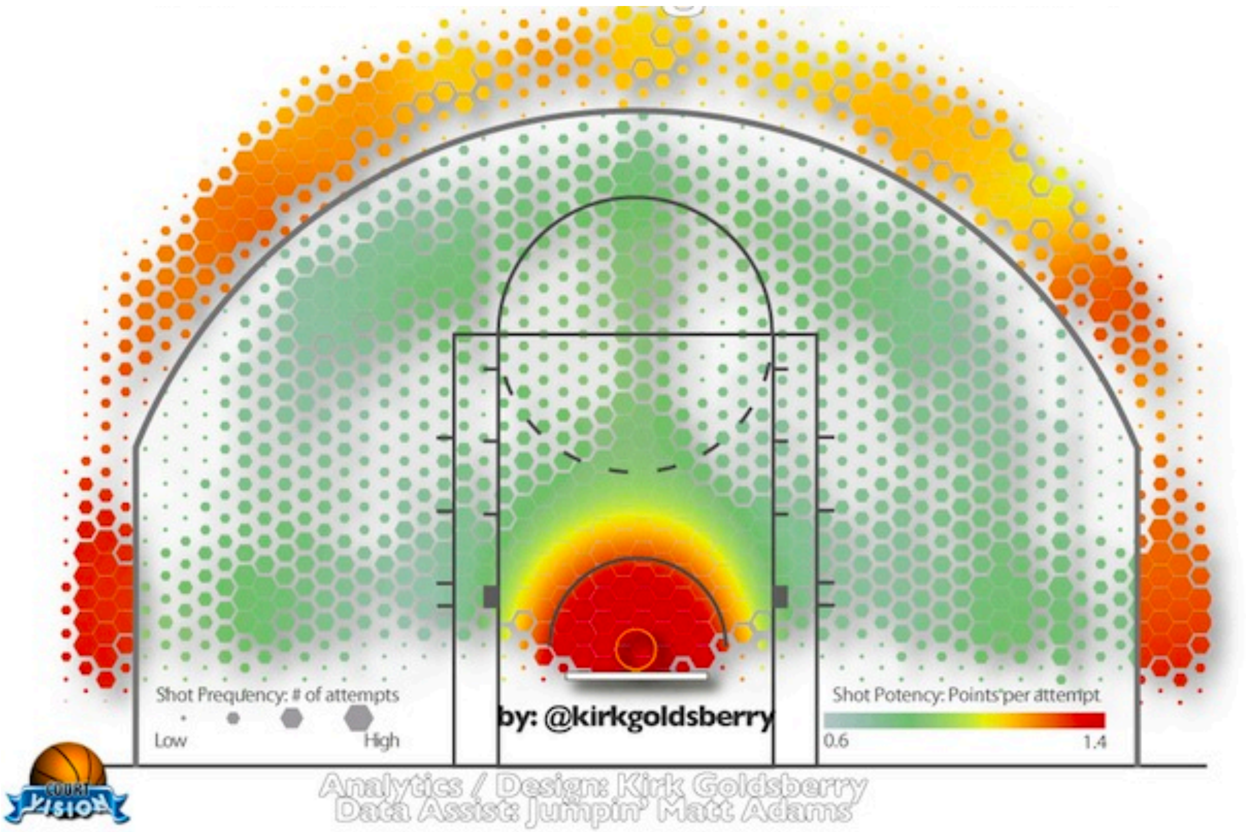
[Liu, Jiang, Heer '13]

Example: Binned Scatter Plots



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

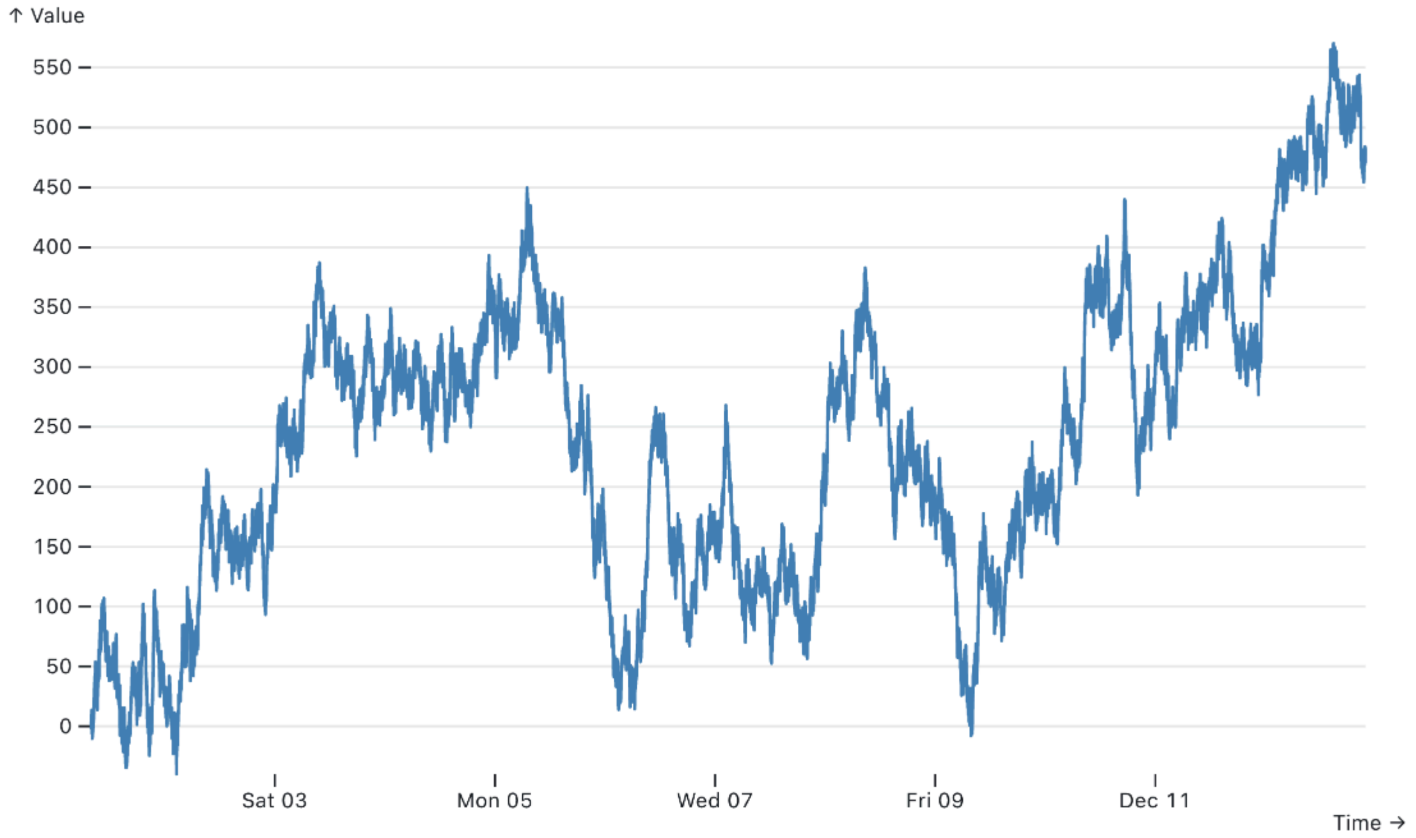
Example: Basketball Shot Chart



NBA Shooting 2011-12
[Goldsberry]

Time Series

Time Series: 1M samples, 1 sample/second



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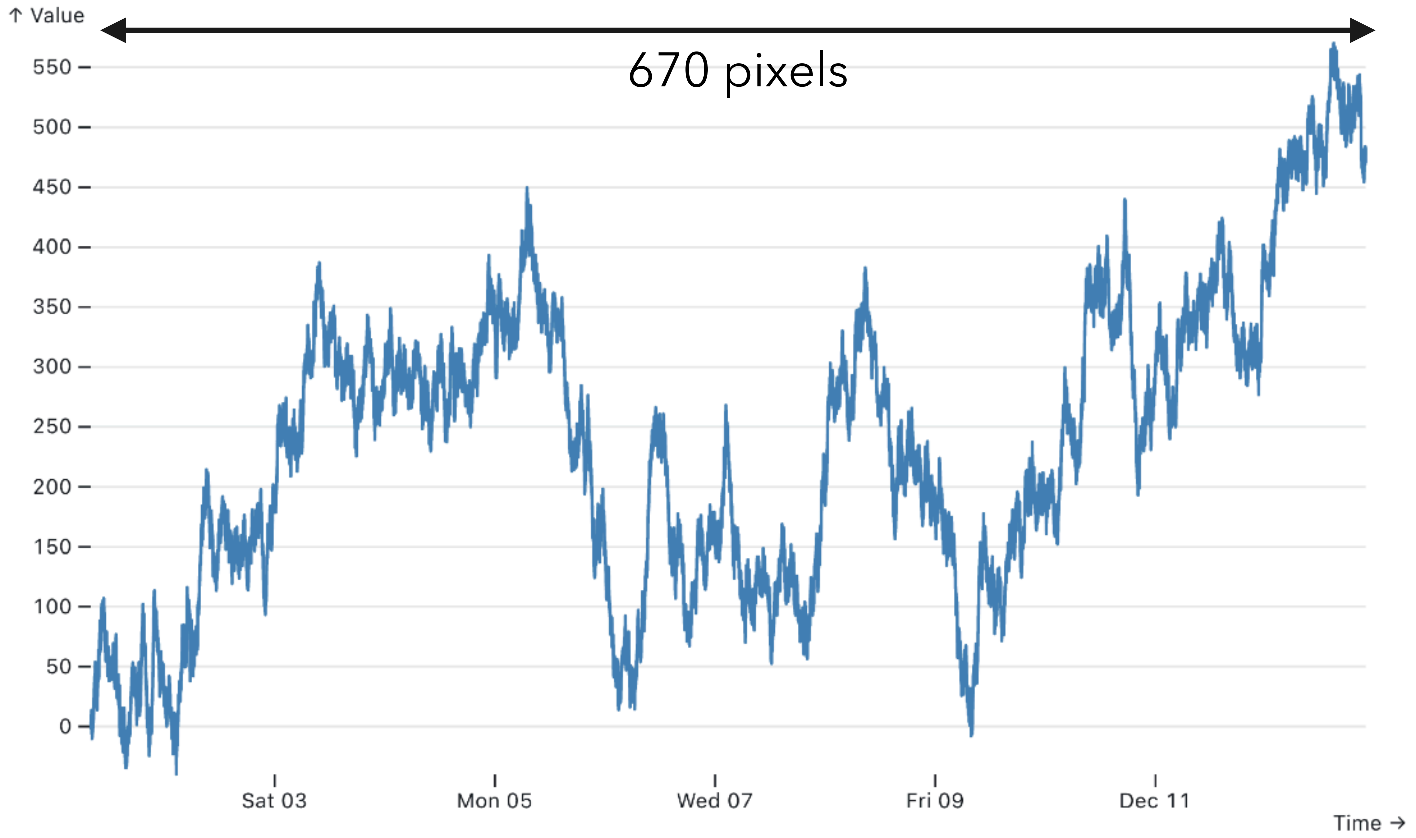

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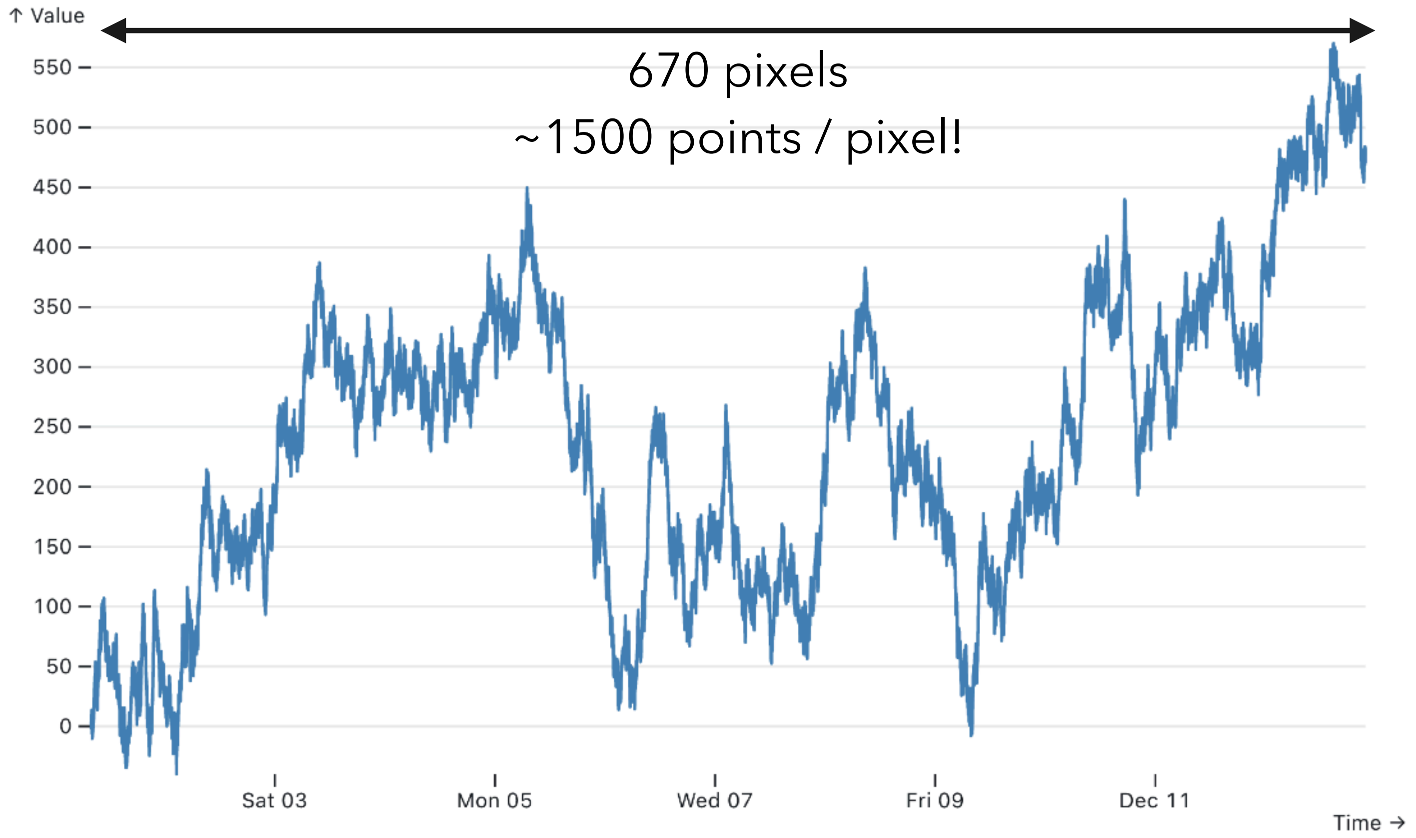

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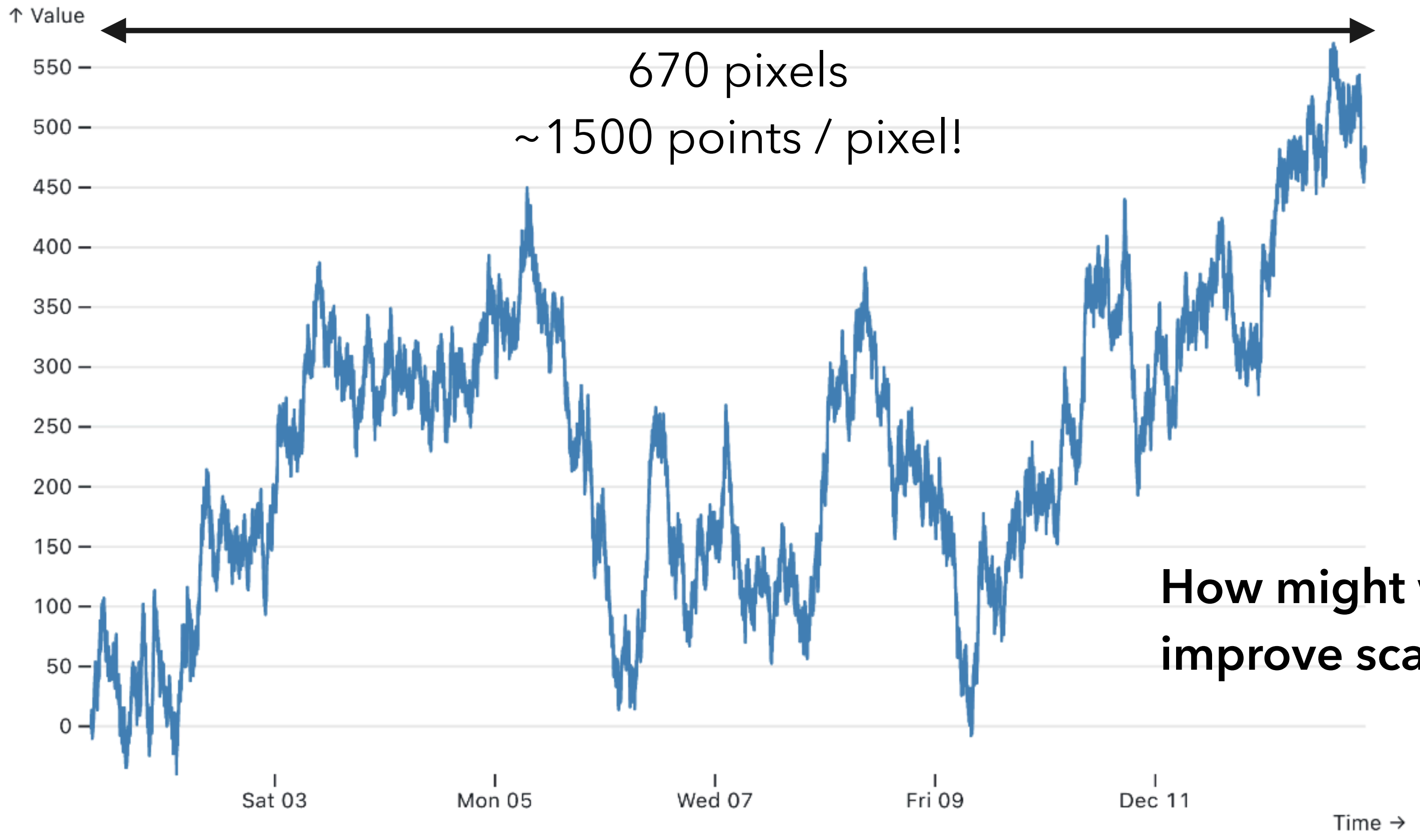
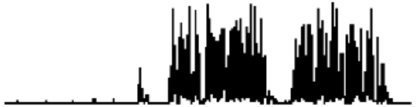


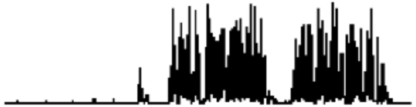
How might we improve scalability?

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

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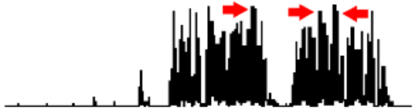
2. Plot min/max values per pixel (2 points/pixel)

   …this does better, but still misrepresents



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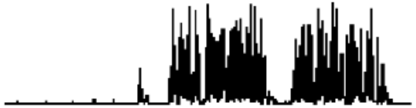

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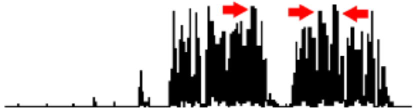


…this does better, but still misrepresents

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

…this provides provable fidelity to the full data!

M4 Data Reduction in the Database

```
SELECT min(t), arg_min(v,t) FROM Q GROUP BY $pixel UNION
SELECT max(t), arg_max(v,t) FROM Q GROUP BY $pixel UNION
SELECT arg_min(t,v), min(v) FROM Q GROUP BY $pixel UNION
SELECT arg_max(t,v), max(v) FROM Q GROUP BY $pixel
```

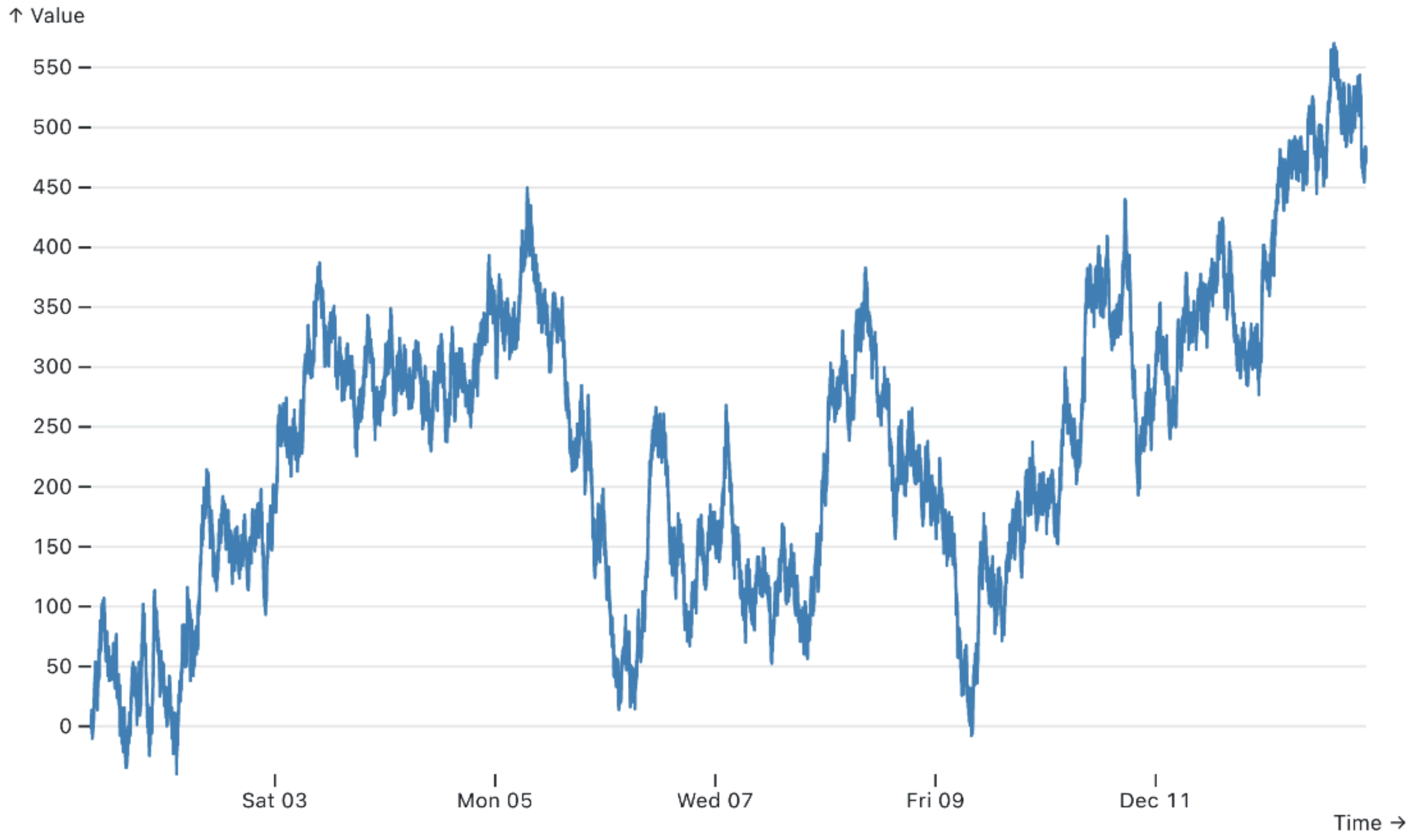
`Q`: query that returns a time series `(t,v)`

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

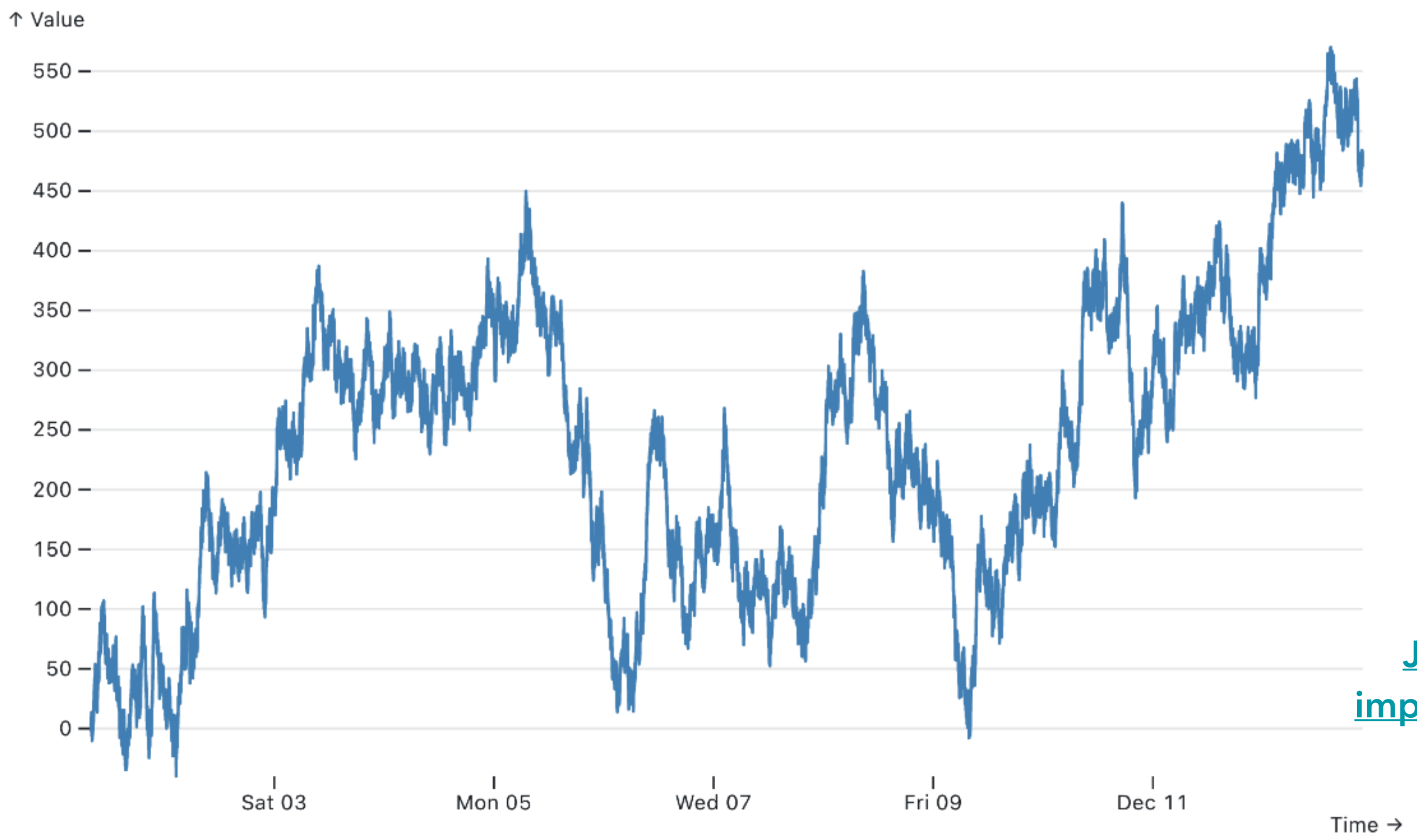
`$w`: chart width in pixels

`$pixel` = `floor($w(t-$t1)/($t2-$t1))`

Time Series: 1M samples, 1 sample/second

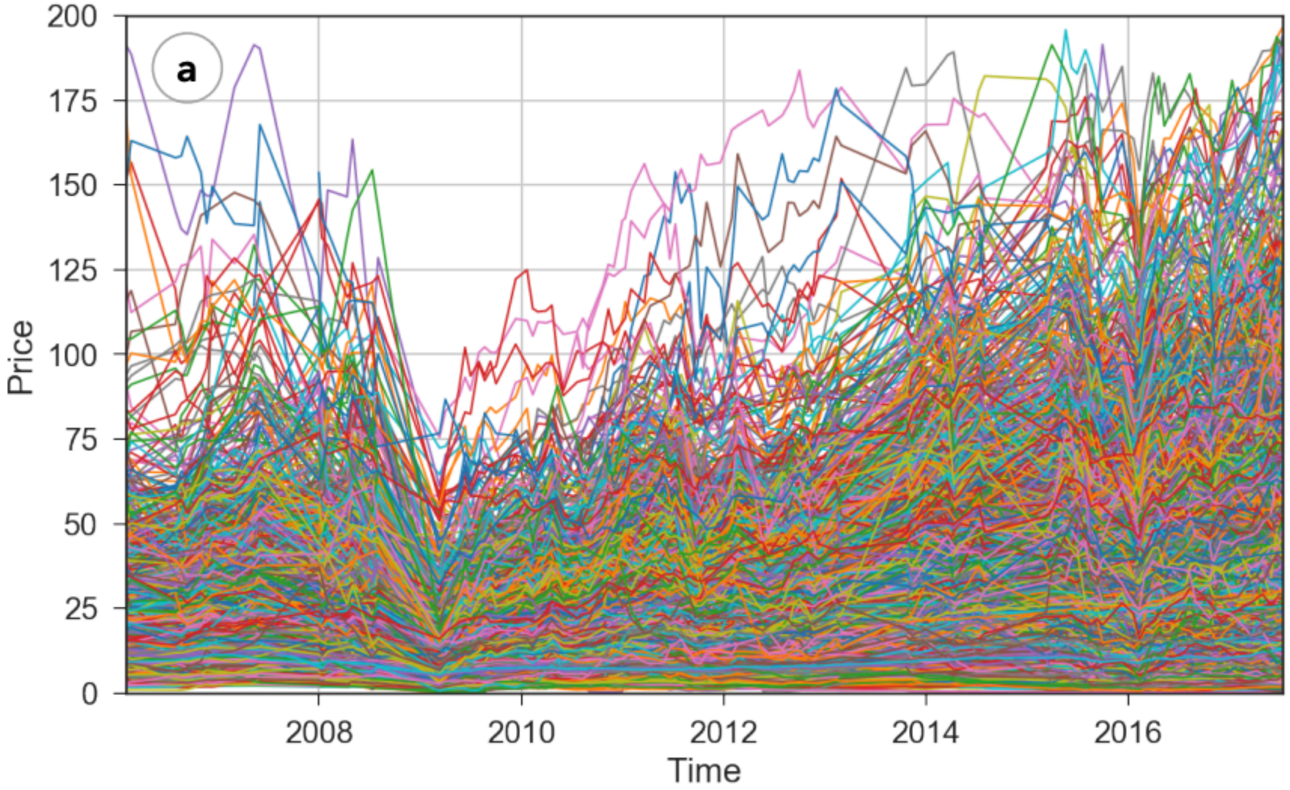


M4: 1M samples -> 2,653 plotted points



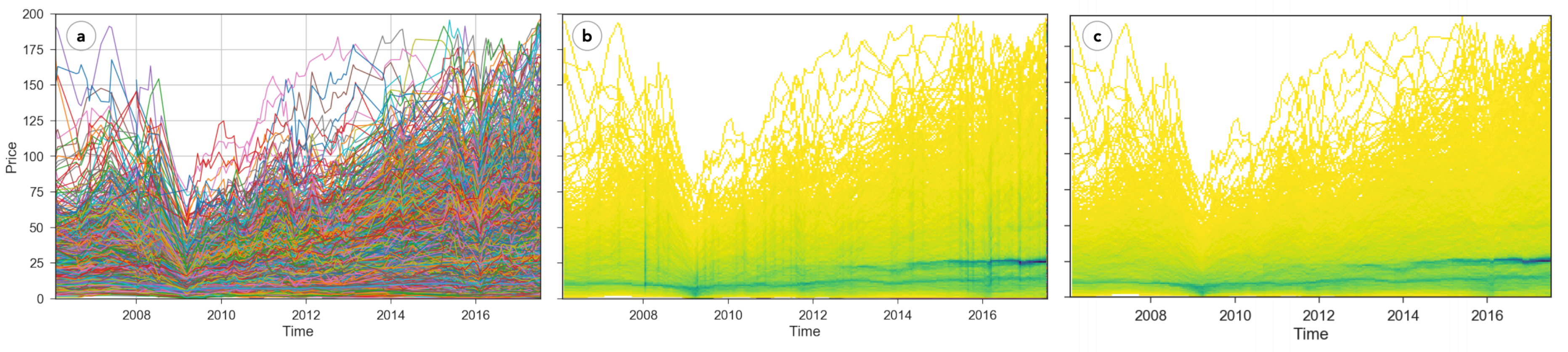
[JavaScript implementation]

But what about multiple time-series?



Perceptual scalability breaks down…

Density Line Chart [Moritz & Fisher]

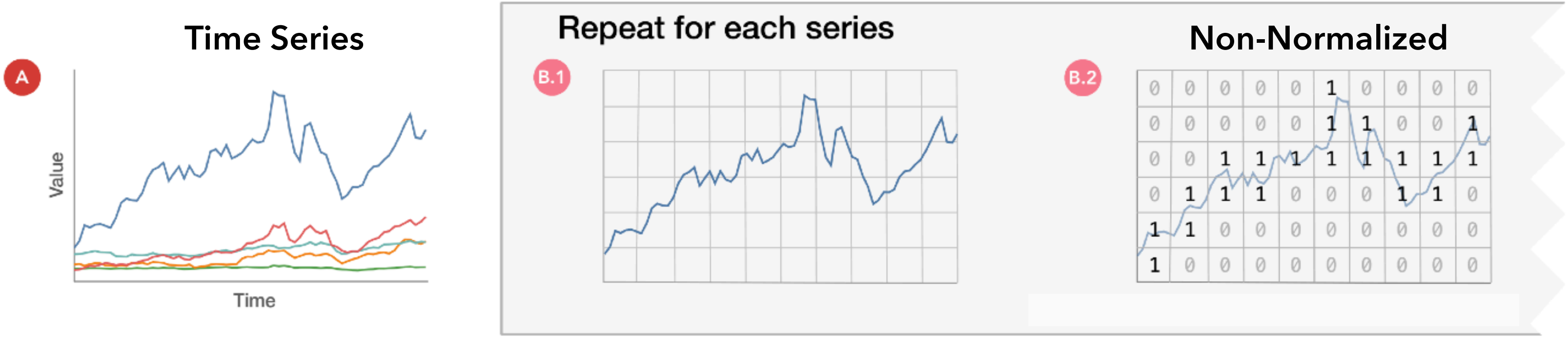


Line Chart | Non-Normalized Heatmap | Normalized "DenseLines"

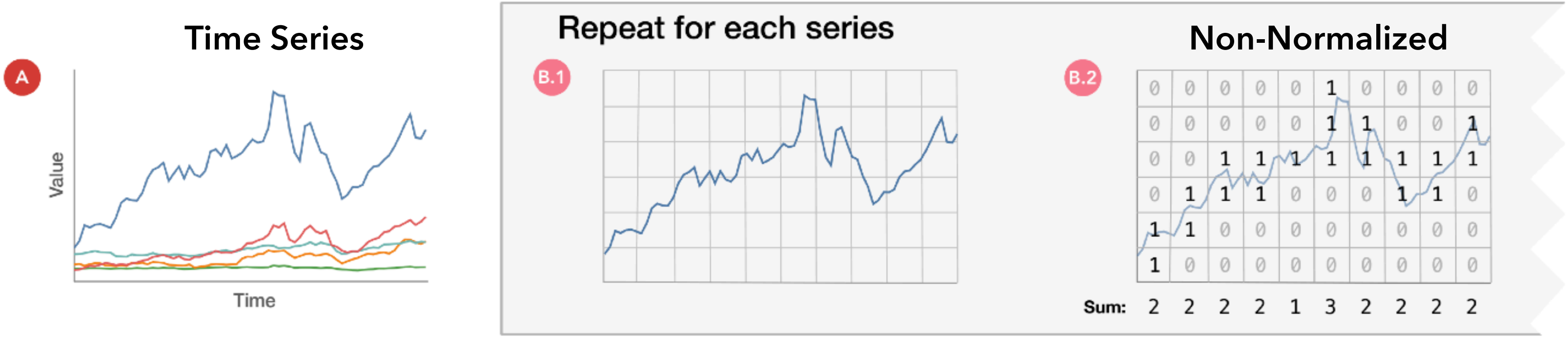
The non-normalized heatmap suffers from artifacts, seen as vertical stripes.

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]

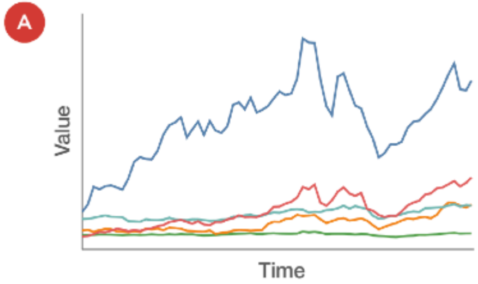


Density Line Chart [Moritz & Fisher]

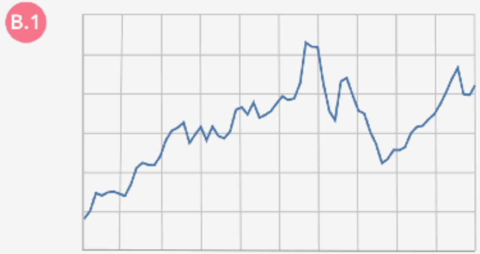


Density Line Chart [Moritz & Fisher]

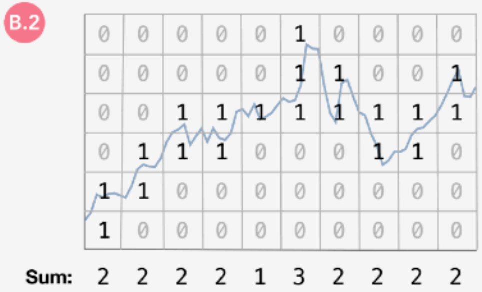
Time Series

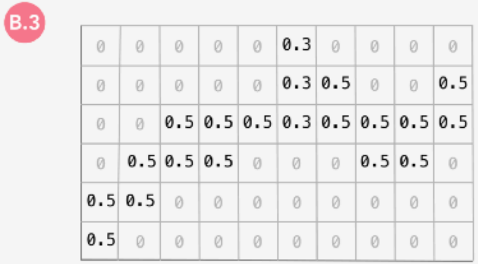


Repeat for each series



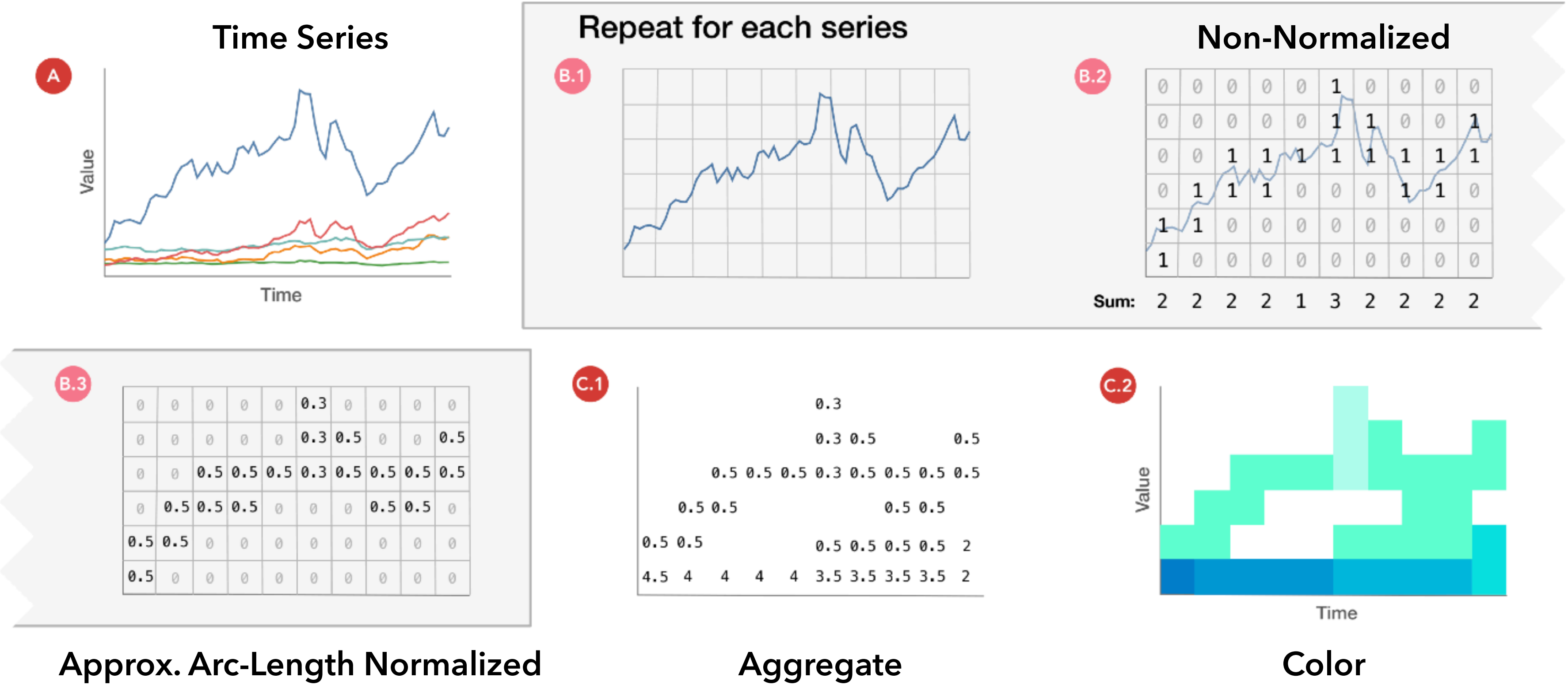
Non-Normalized



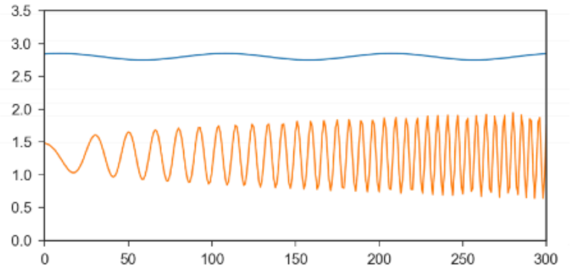


Approx. Arc-Length Normalized

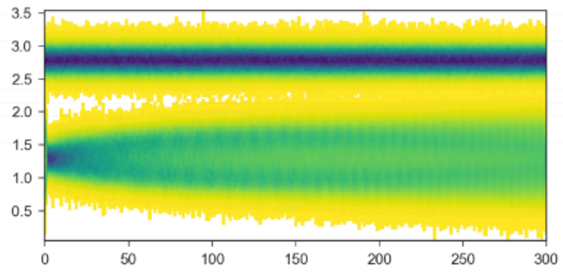
Density Line Chart [Moritz & Fisher]



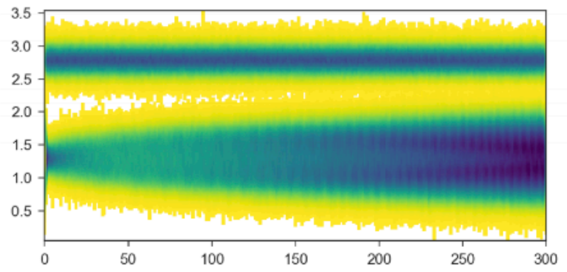
Density Line Chart [Moritz & Fisher]



Example Time Series



10k Series, Normalized



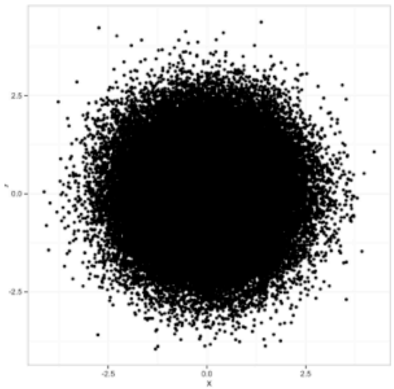
10k Series, Non-Normalized

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

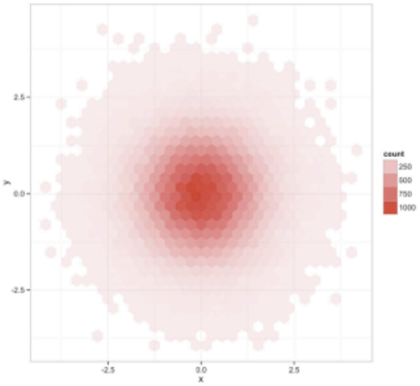
Without normalization, the steep lines are over-represented.

Design Subtleties

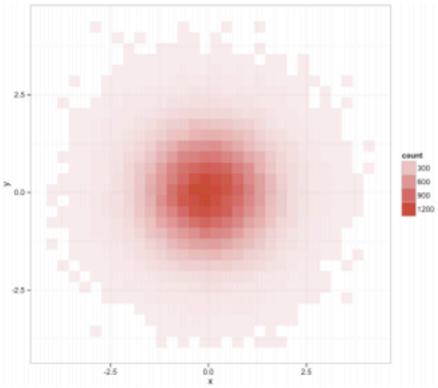
Hexagonal or Rectangular Bins?



100,000 Data Points



Hexagonal Bins

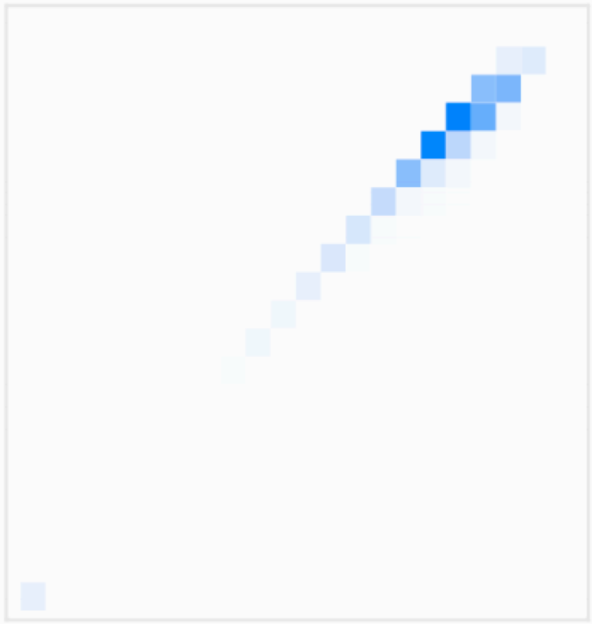


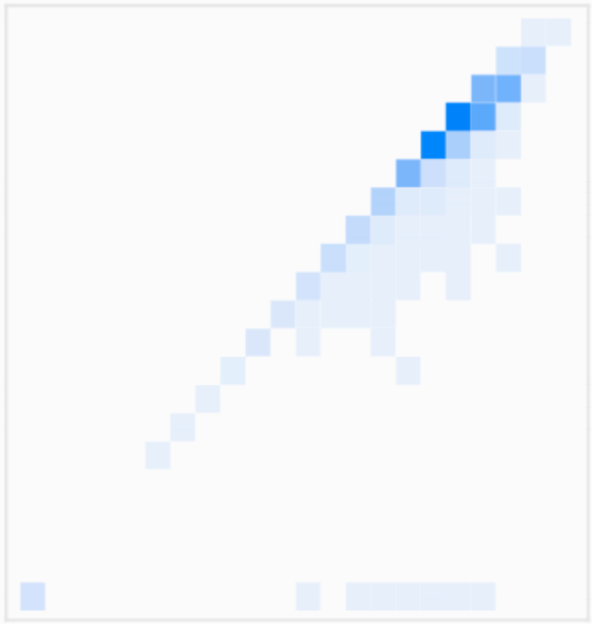
Rectangular Bins

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

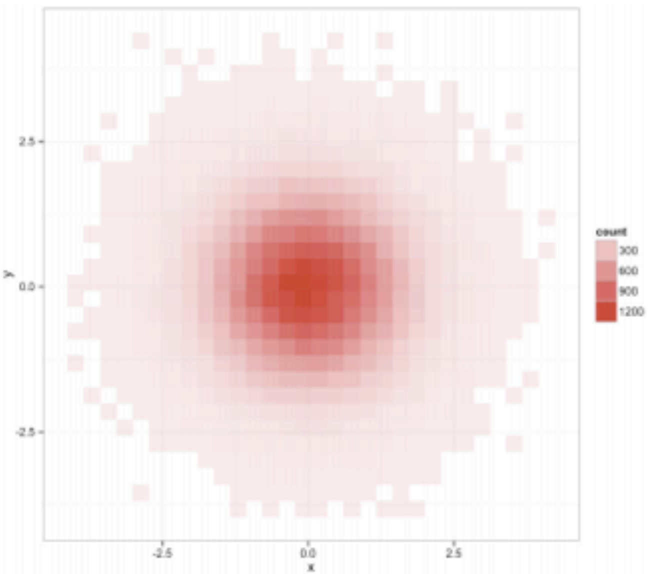




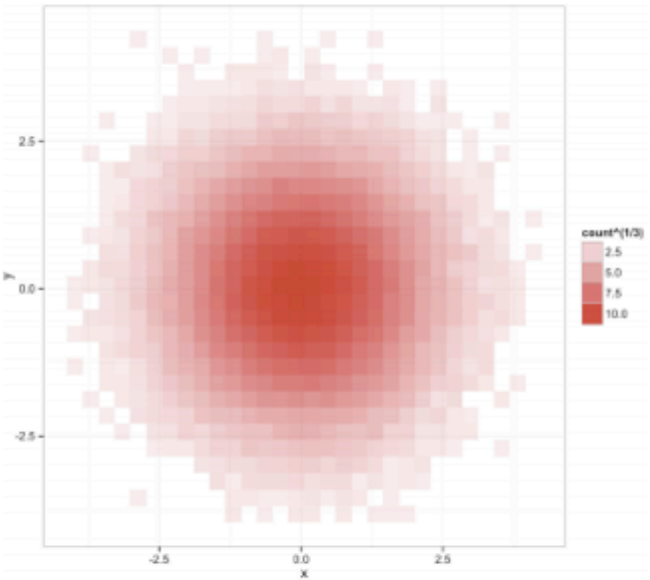
Standard Color Ramp
Counts near zero are white.

Add Discontinuity after Zero
Counts near zero remain visible.

Color Ramps / Scale Transforms



Linear interpolation in RGBA
is not perceptually linear.



Perceptual color spaces
approximate perceptual linearity.

Questions?

Administrivia

Final Project Schedule

~~*Proposal*~~	~~Fri May 16~~
Prototype	**Wed May 28**
Demo Video	Wed Jun 4
Video Showcase	Thu Jun 5 (in class)
Deliverables	Mon Jun 9

Logistics

Final project description posted online

Work in groups of up to 4 people

You should be well on your way at this point!

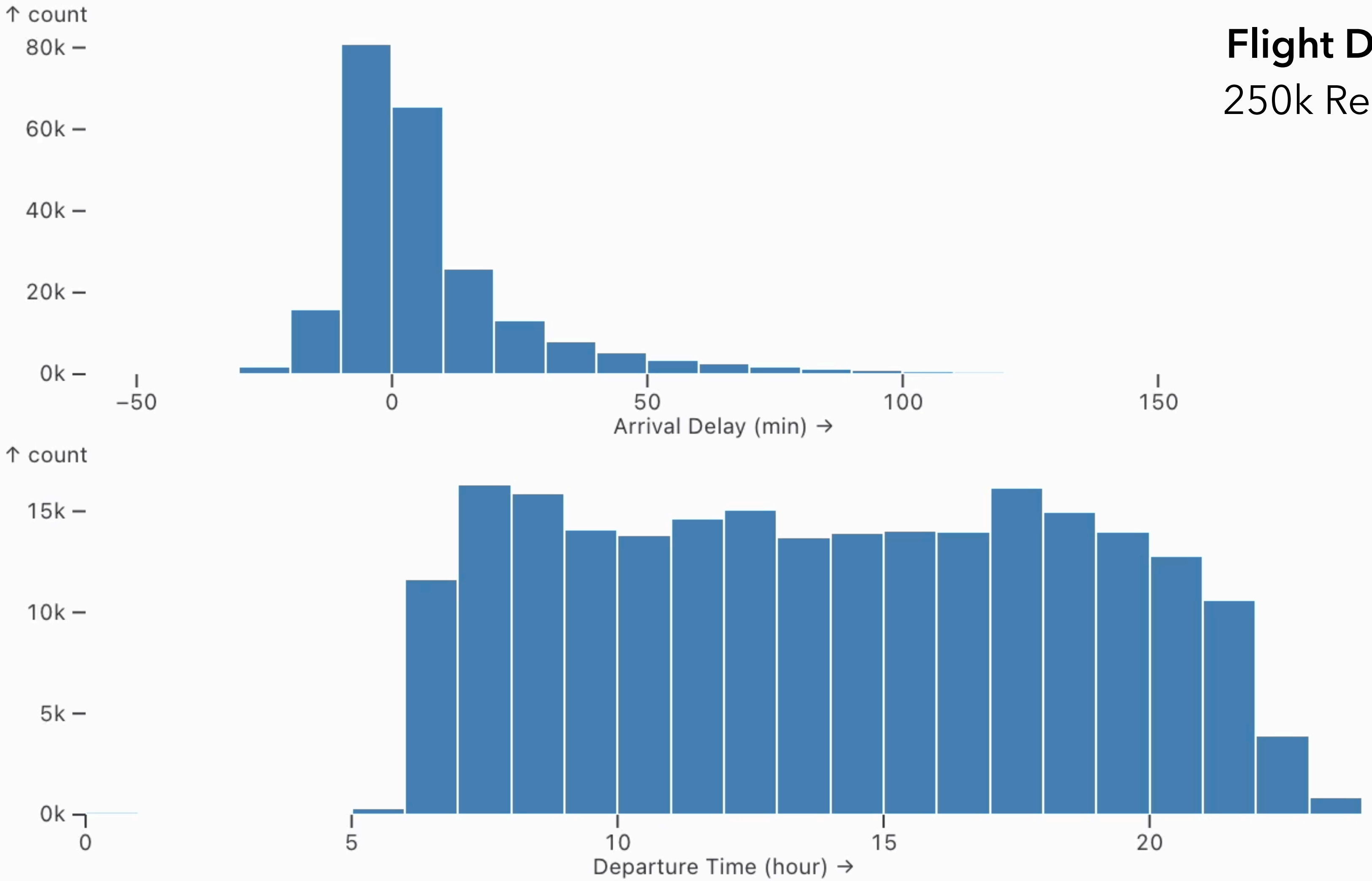
Milestone Prototype

Publish work to GitLab pages for others to examine and share feedback. You **are not** expected to have complete, polished content at this point.

You **are** expected to provide prototype work that communicates your design goals. For example: initial visualizations, sketches, storyboards, and text annotations / idea descriptions.

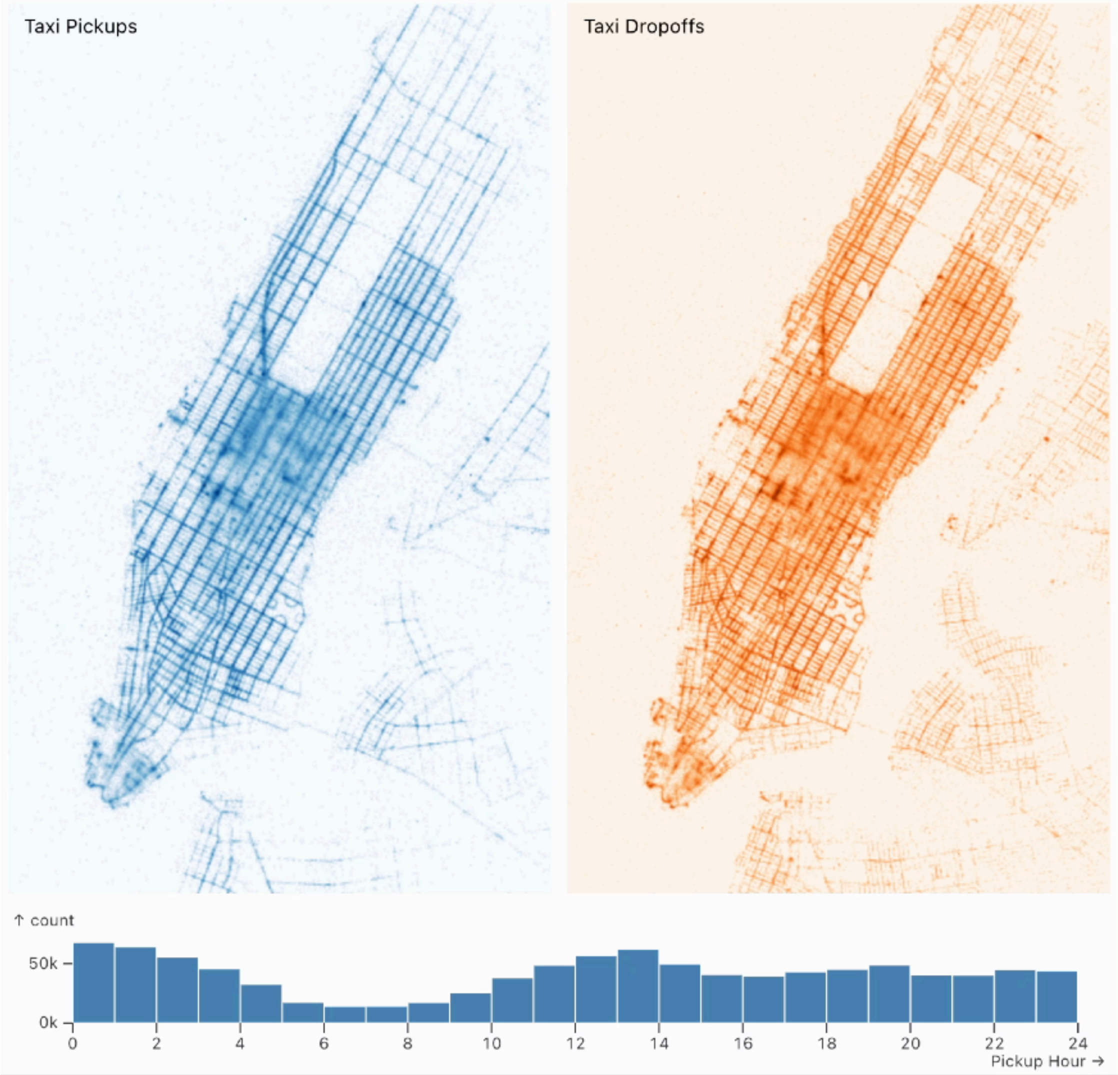
One should get a sense of what you intend to ultimately submit! Also feel free to post questions.

Scalable Interaction



Flight Delays

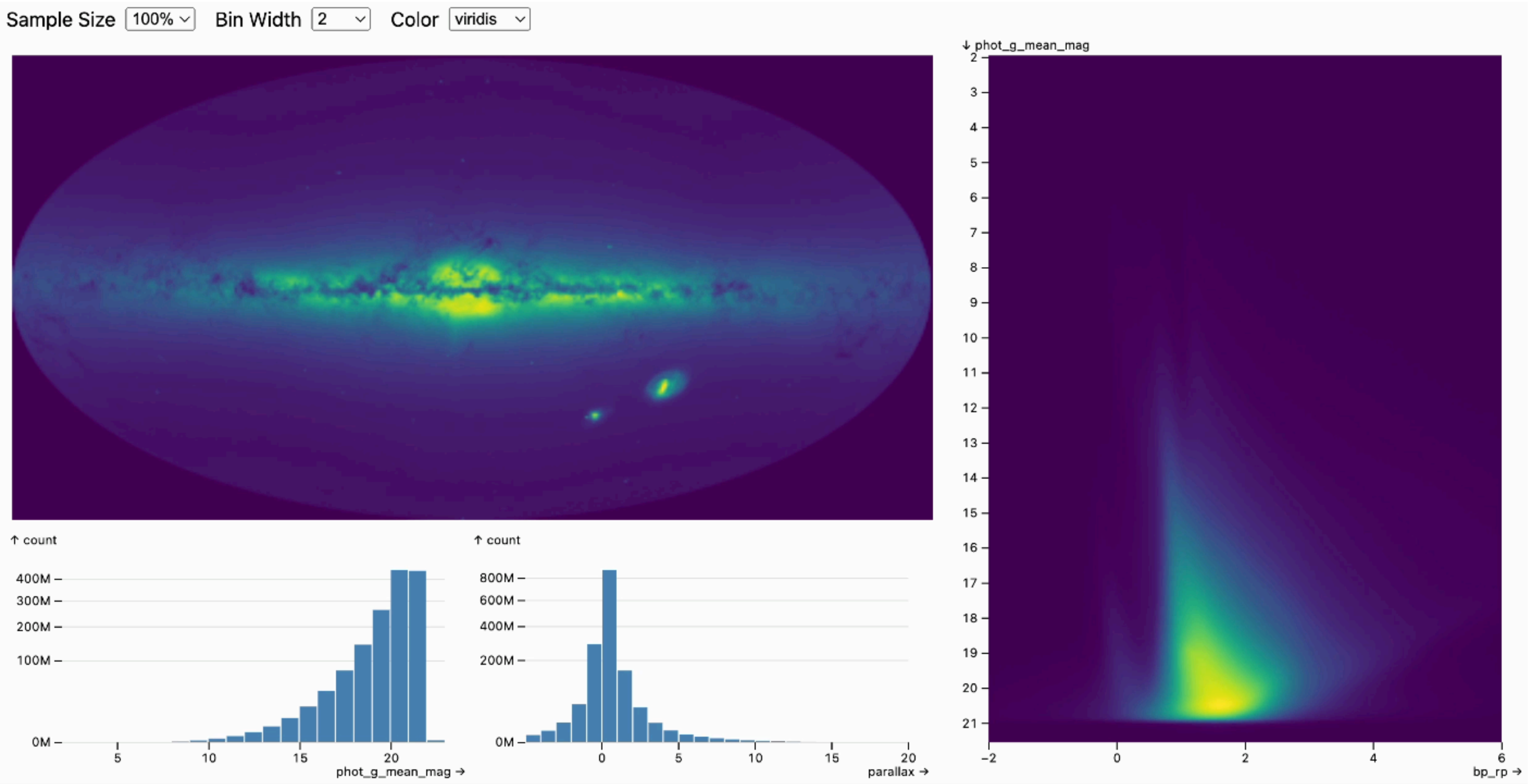
250k Records



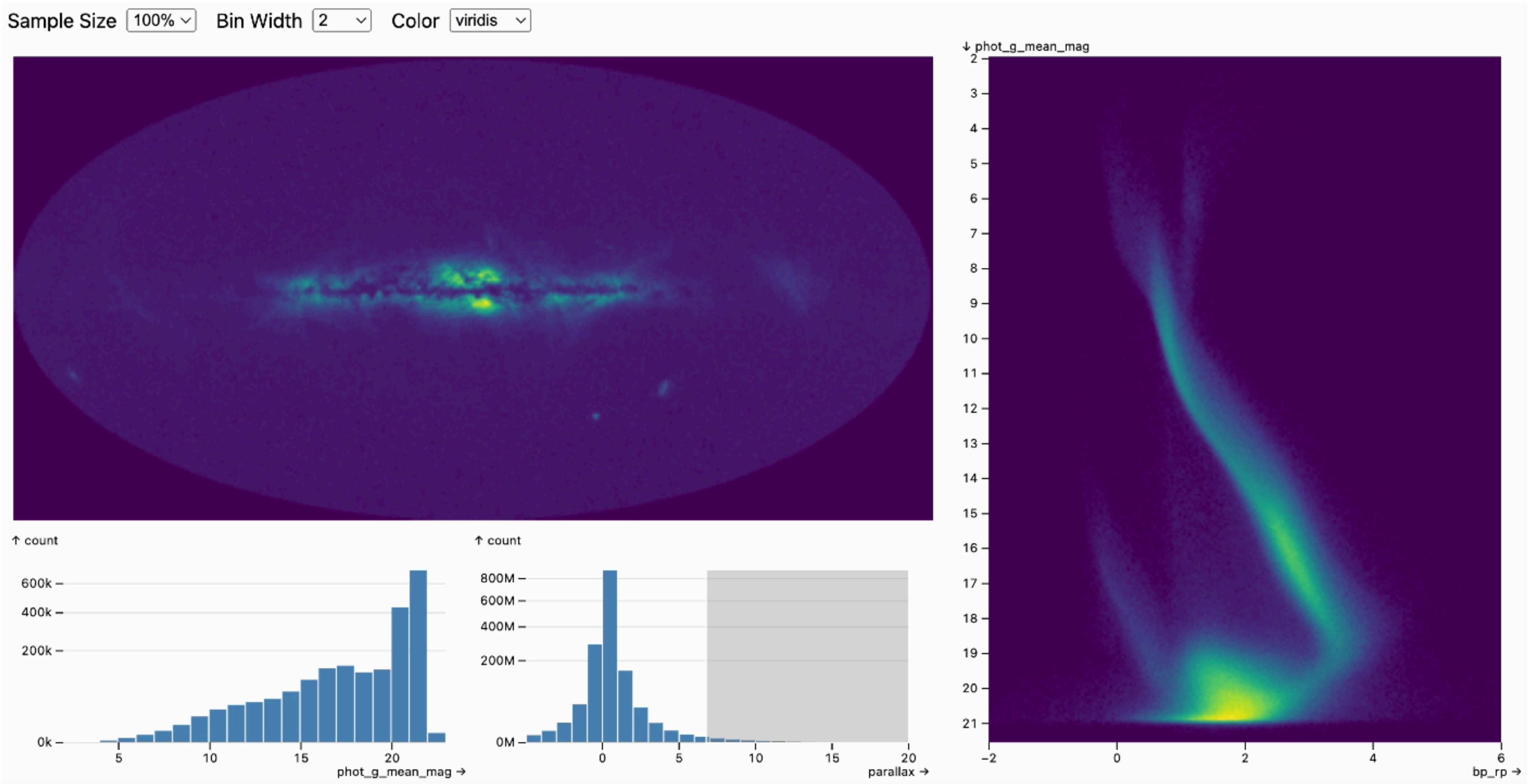
NY Taxi Rides

1M Records

Jan 1-3, 2010



Gaia Star Catalog · 1.8B Records



Gaia Star Catalog · 1.8B Records

Interactive Scalability Strategies

1. Query Database
2. Indexing / Preaggregation
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. Indexing / Preaggregation

3. Prefetching

4. Approximation

Interactive Scalability Strategies

1. Query Database …or alternative data frame implementation

Python: Polars, Vaex, Modin, cuDF

R: dbplyr

All: DuckDB

2. Indexing / Preaggregation

3. Prefetching

4. Approximation

Interactive Scalability Strategies

1. **Query Database**
2. **Indexing / Preaggregation** Query data summaries

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

3. **Prefetching**
4. **Approximation**

Interactive Scalability Strategies

1. **Query Database**
2. **Indexing / Preaggregation**
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. Indexing / Preaggregation

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

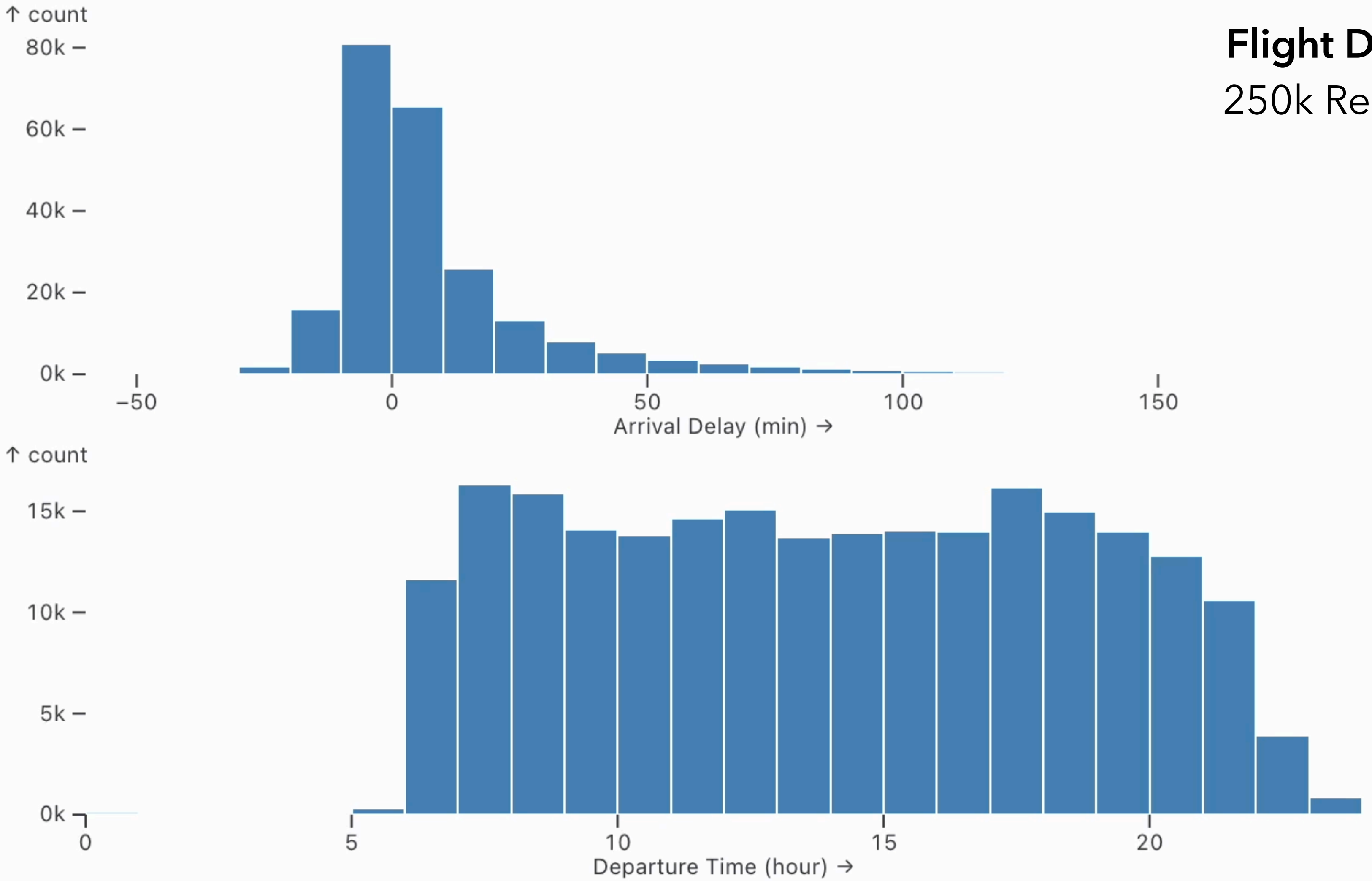
1. **Query Database**
2. **Indexing / Preaggregation**
3. **Prefetching**
4. **Approximation**

These strategies are **not** mutually exclusive!

Systems can apply them in tandem.

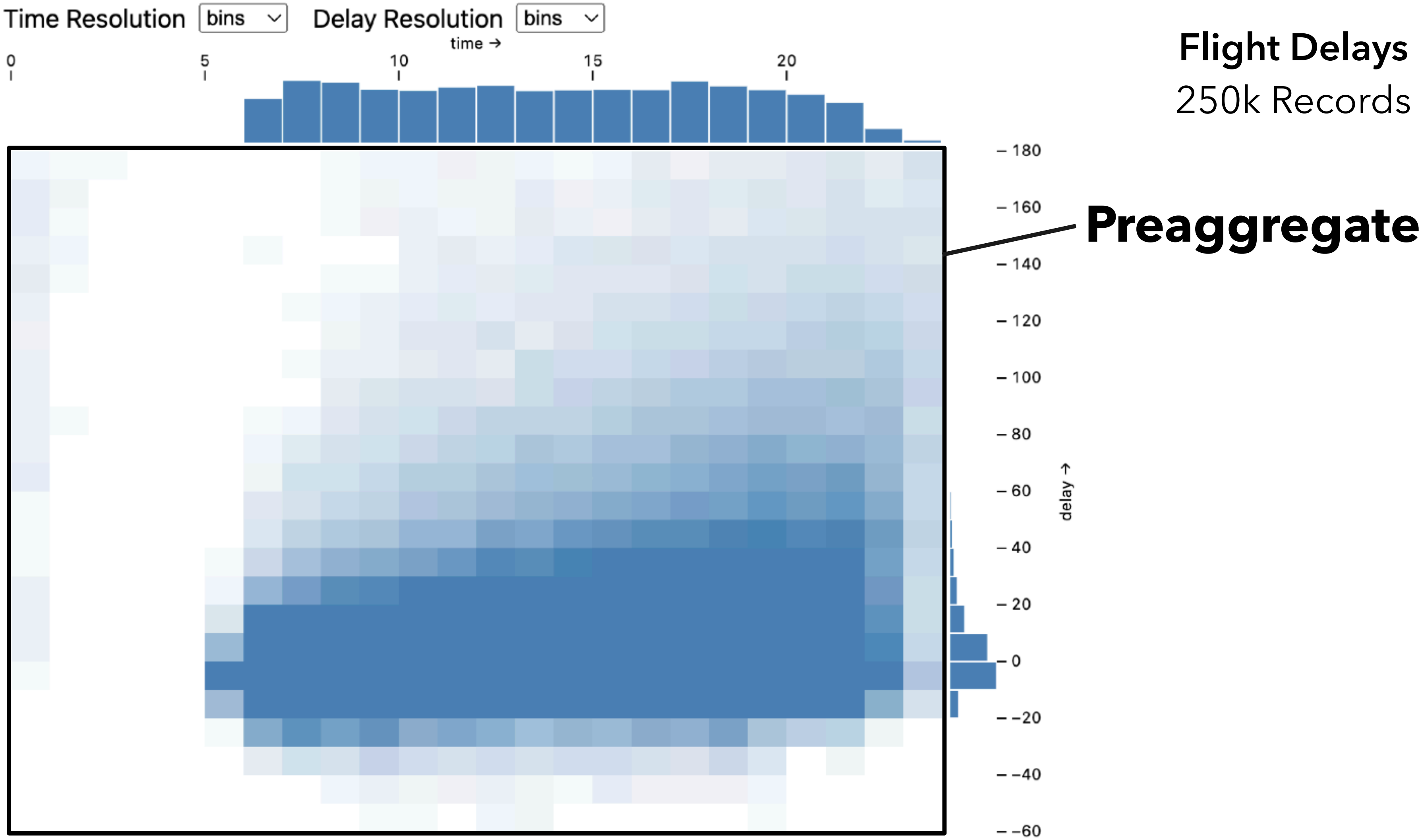
Preaggregation

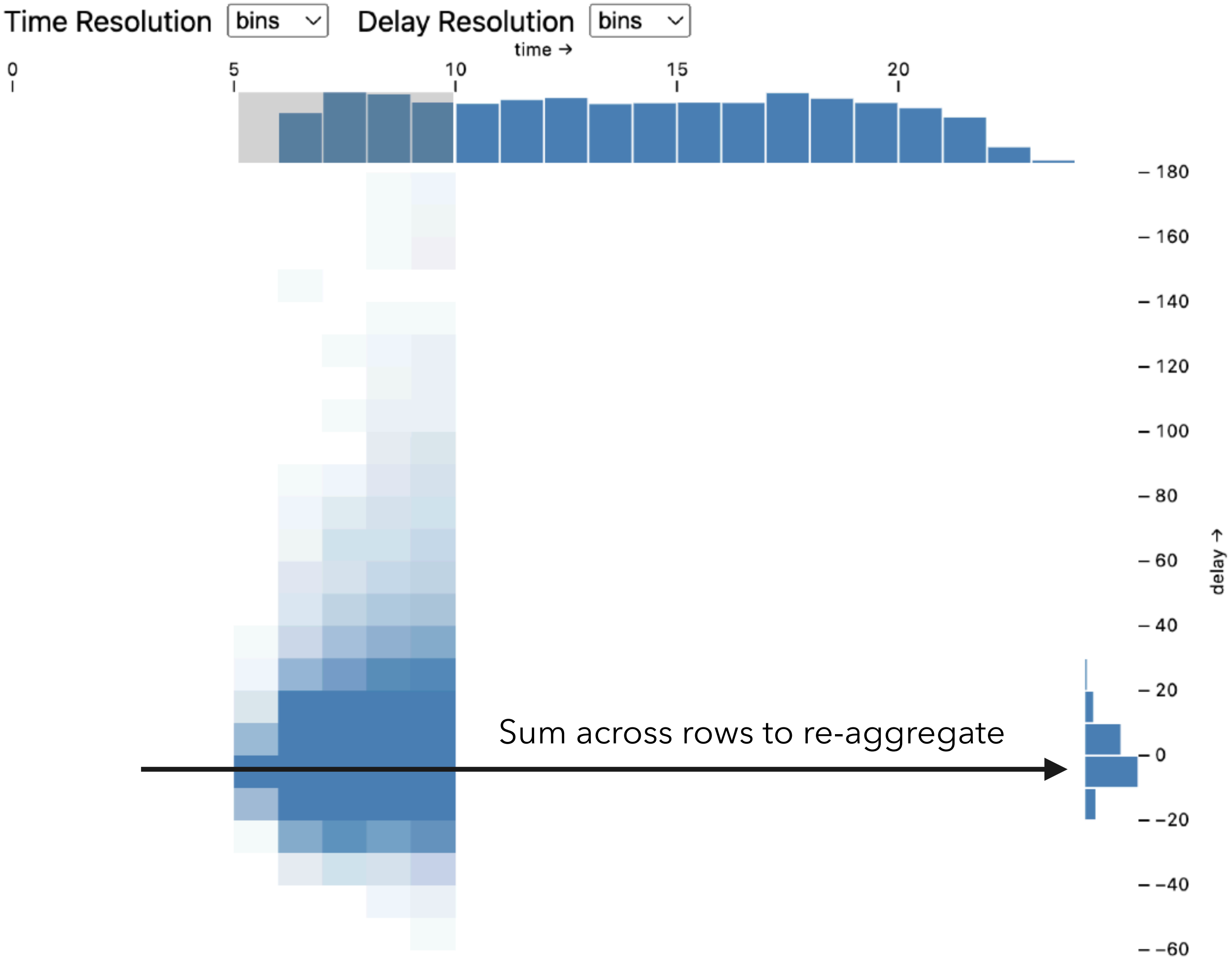
Flight Delays
250k Records



Flight Delays

250k Records



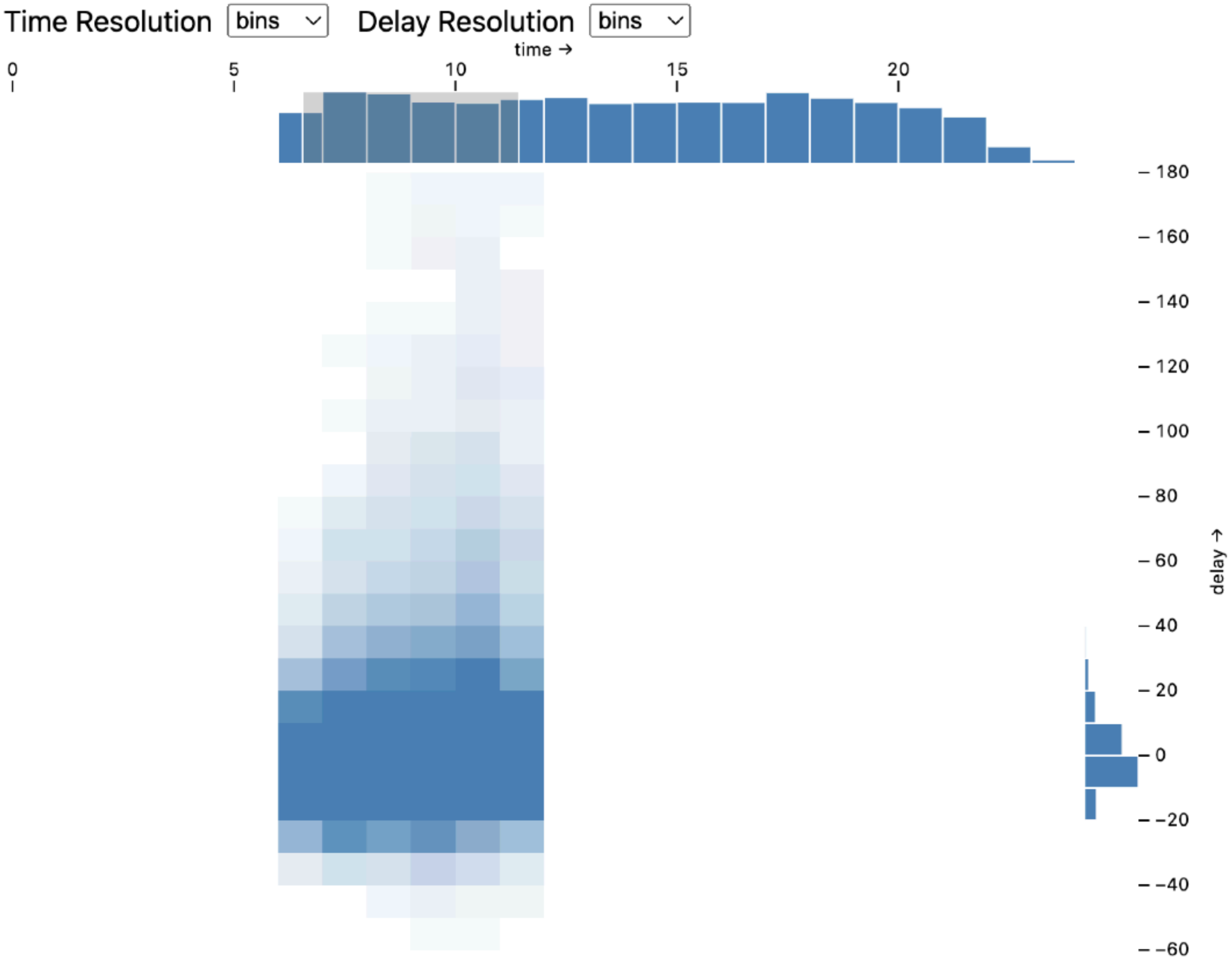


Flight Delays

250k Records

Flight Delays

250k Records



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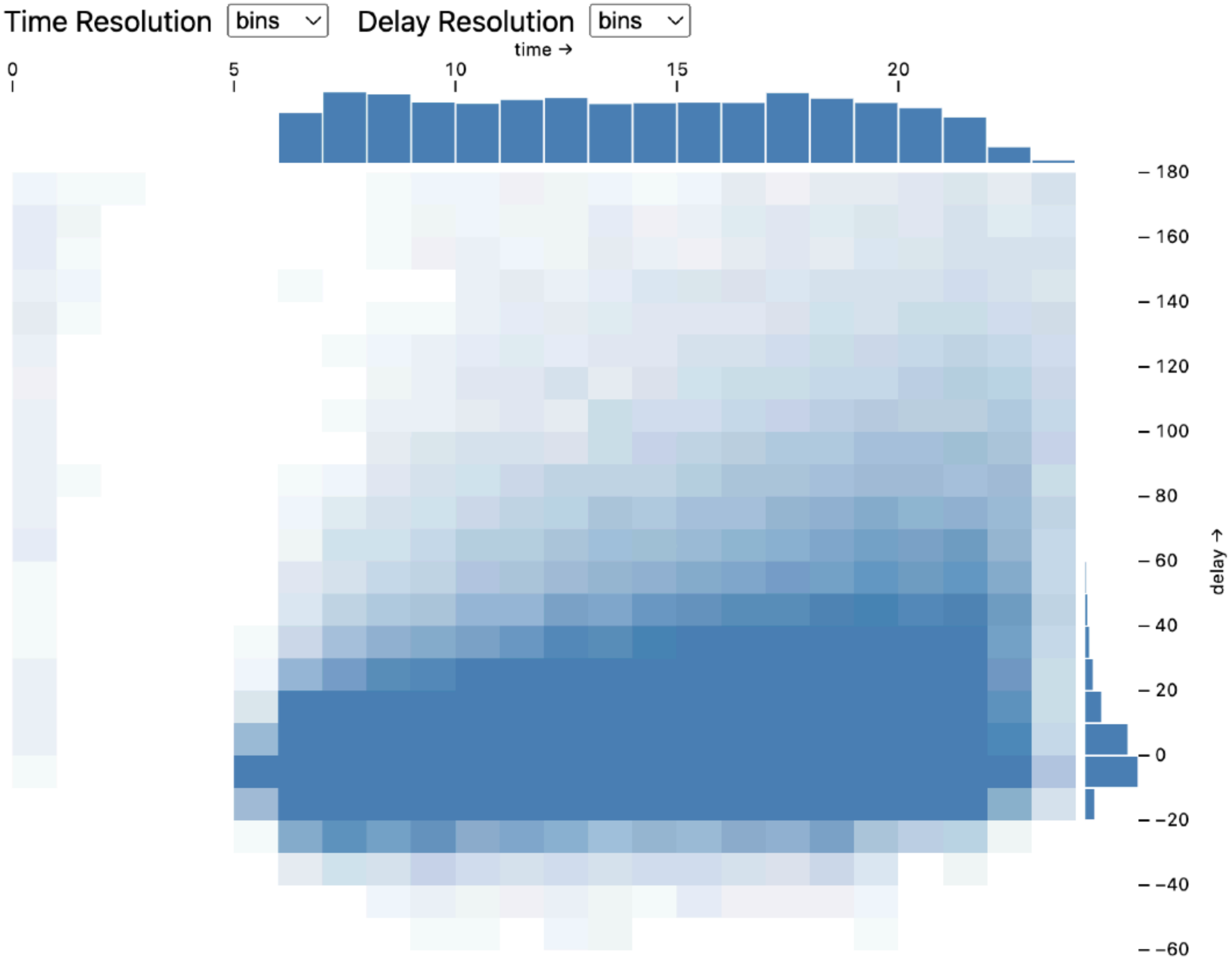

Flight Delays

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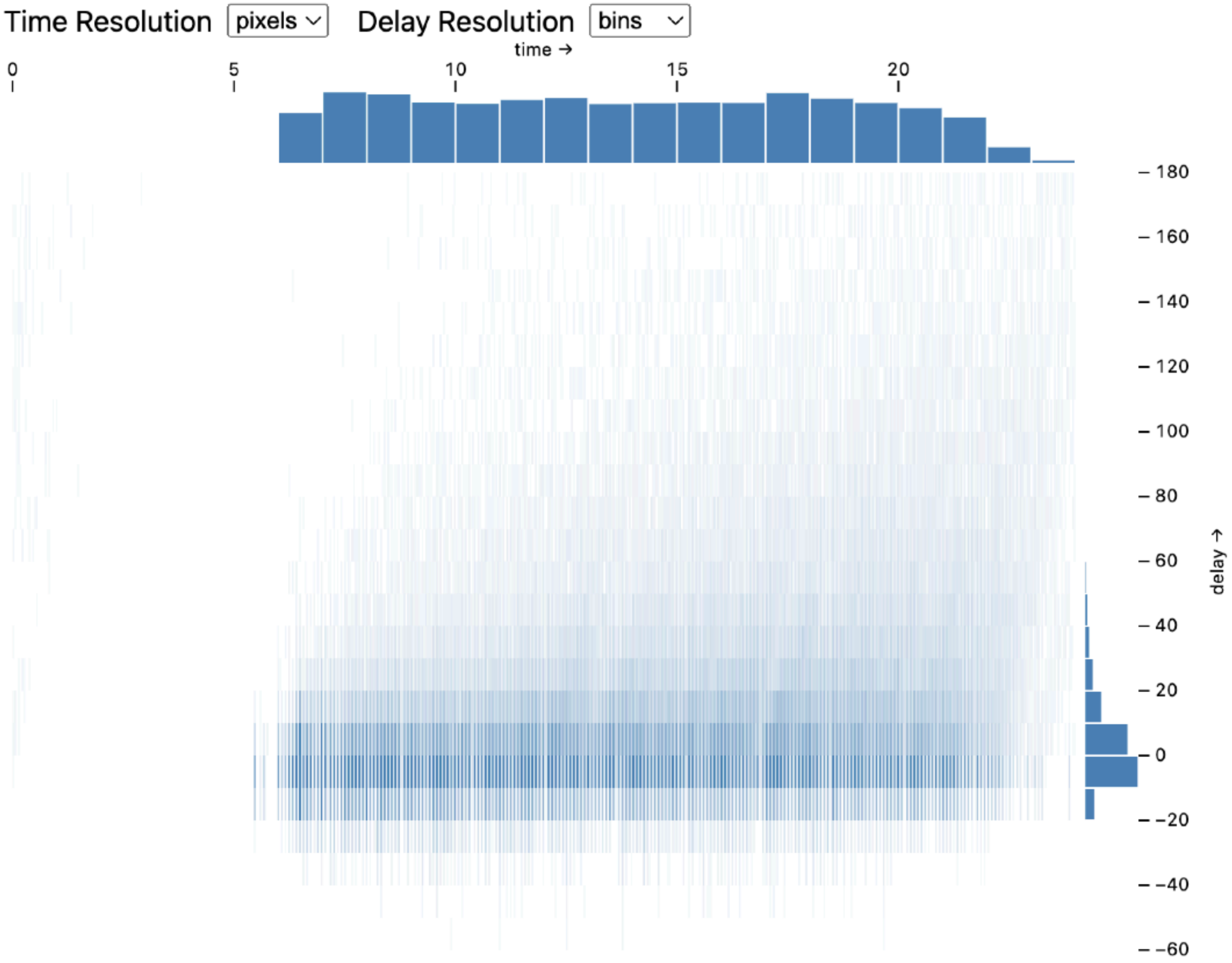

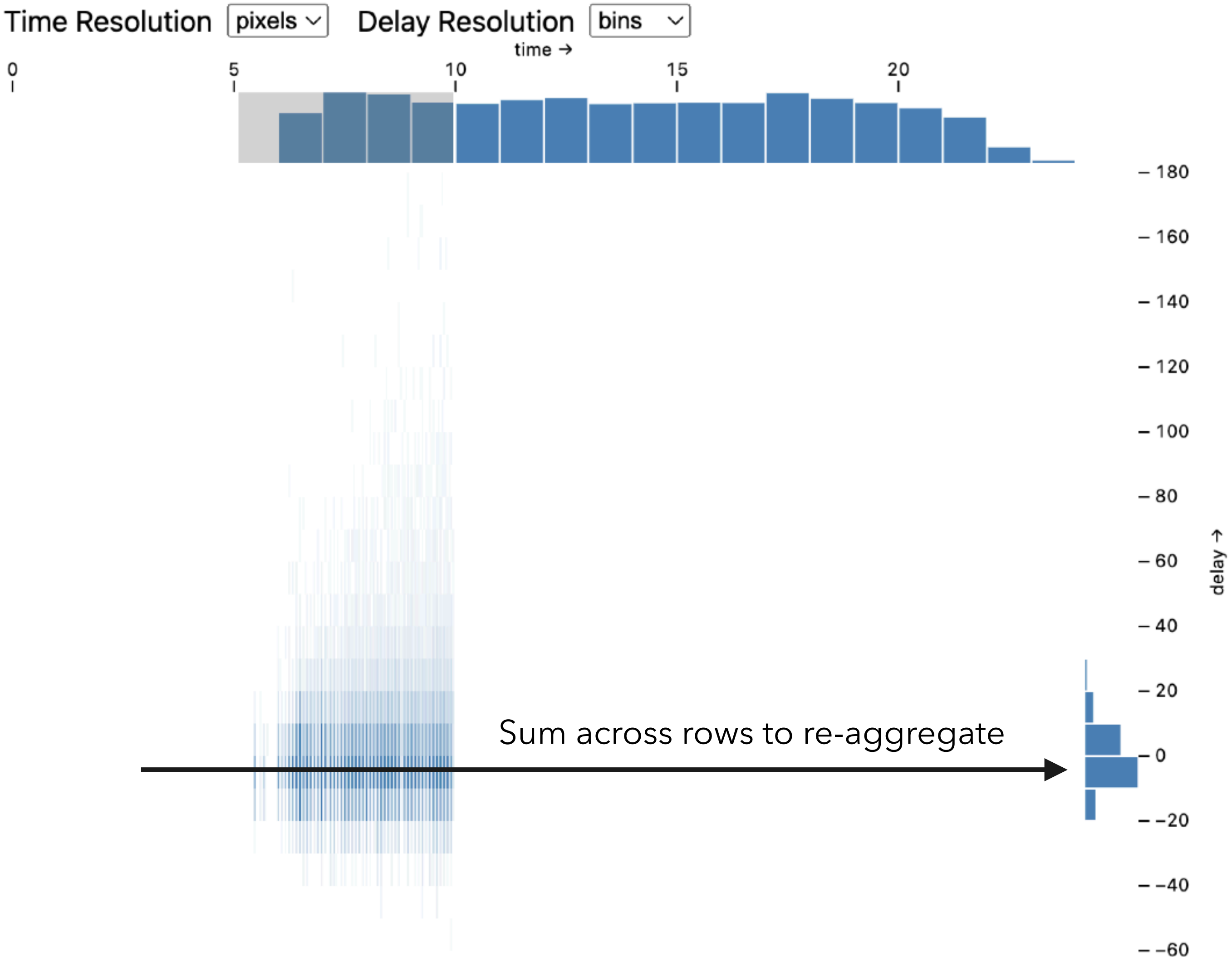

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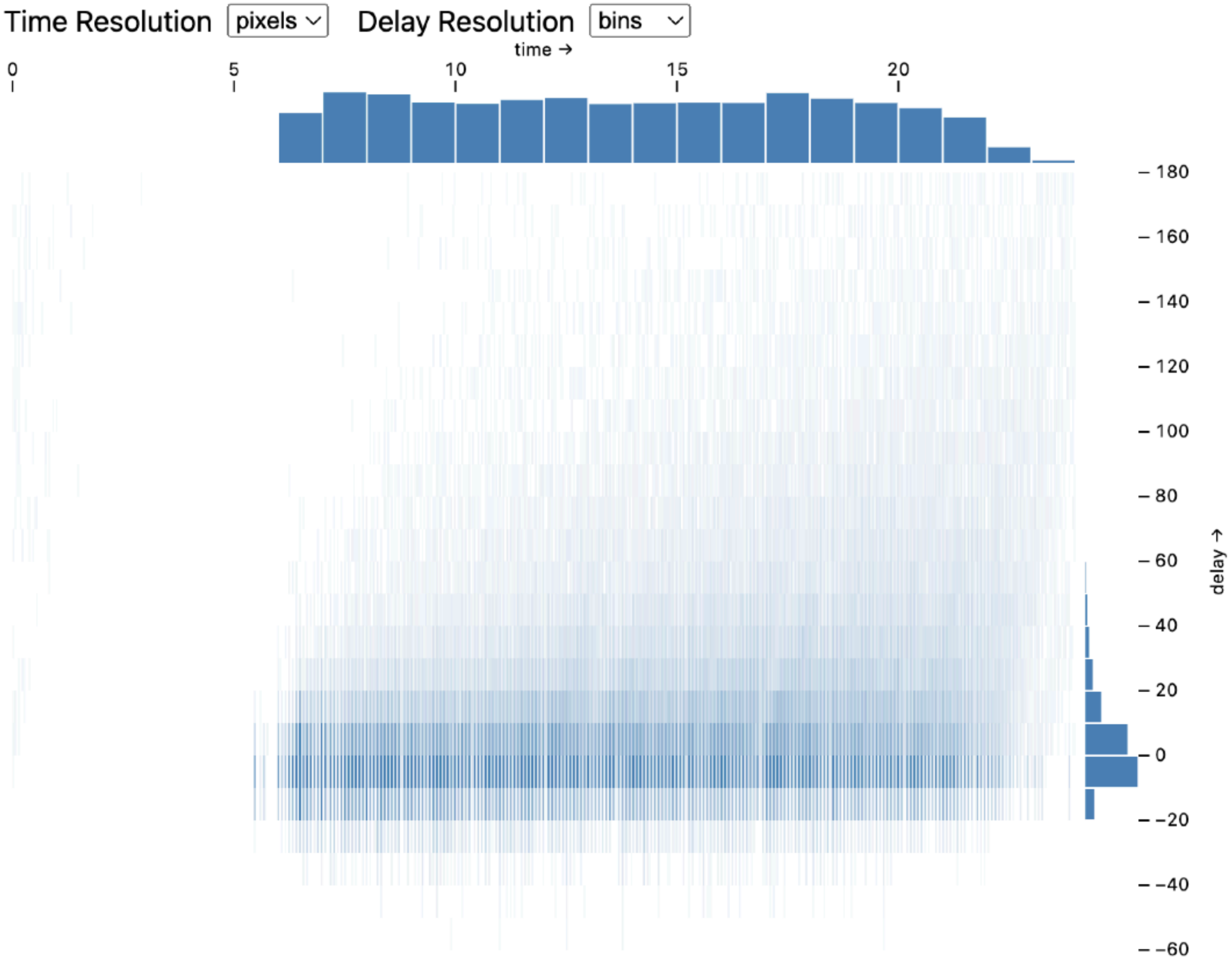
250k Records

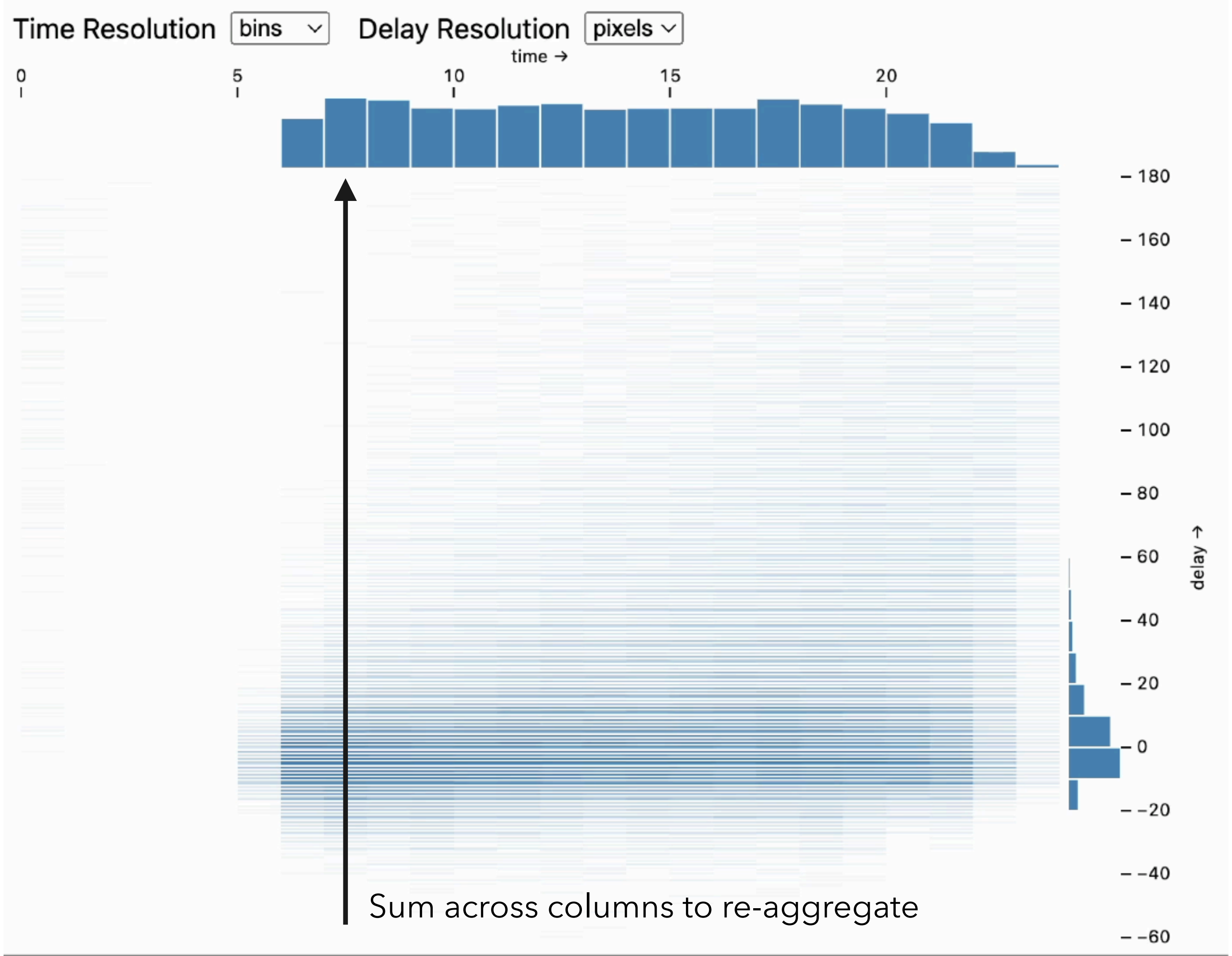


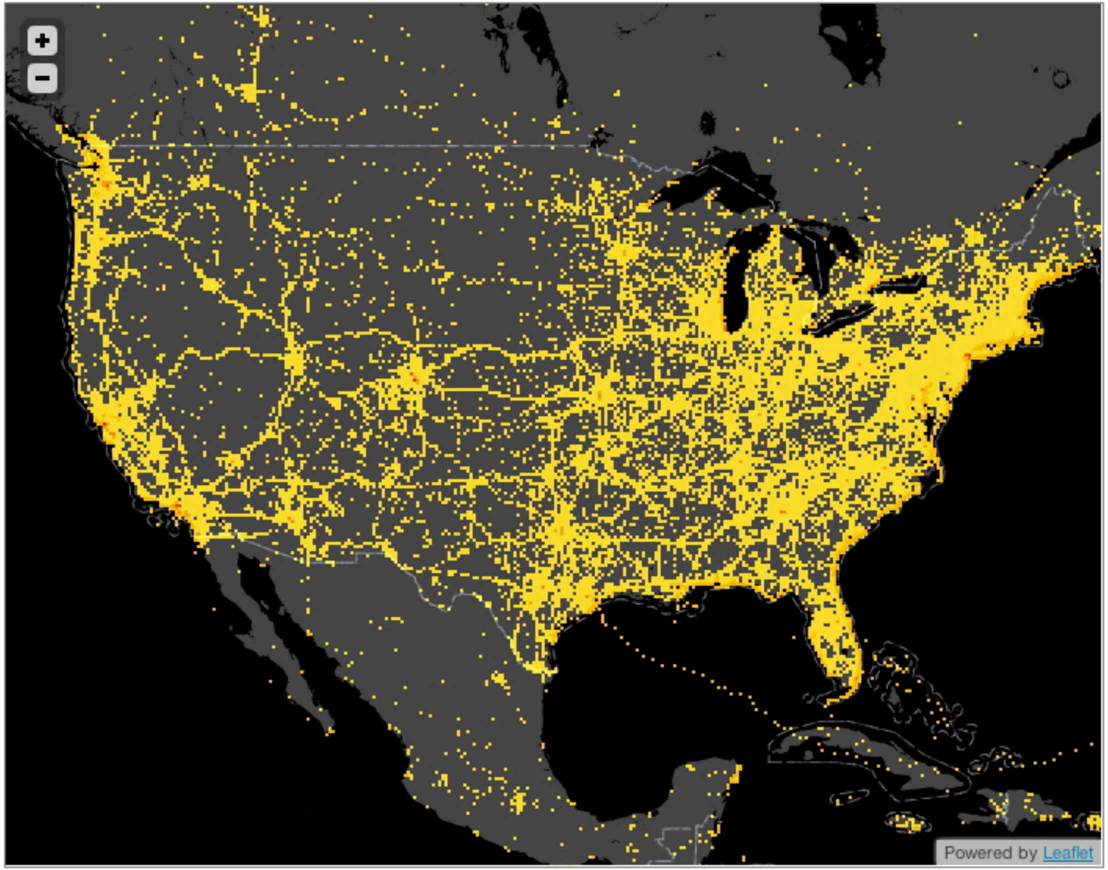
Flight Delays

250k Records

Flight Delays

250k Records





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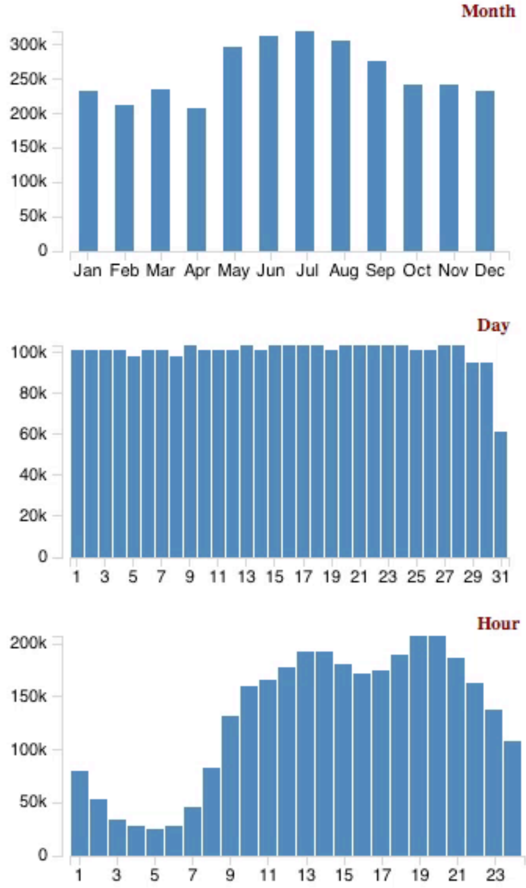

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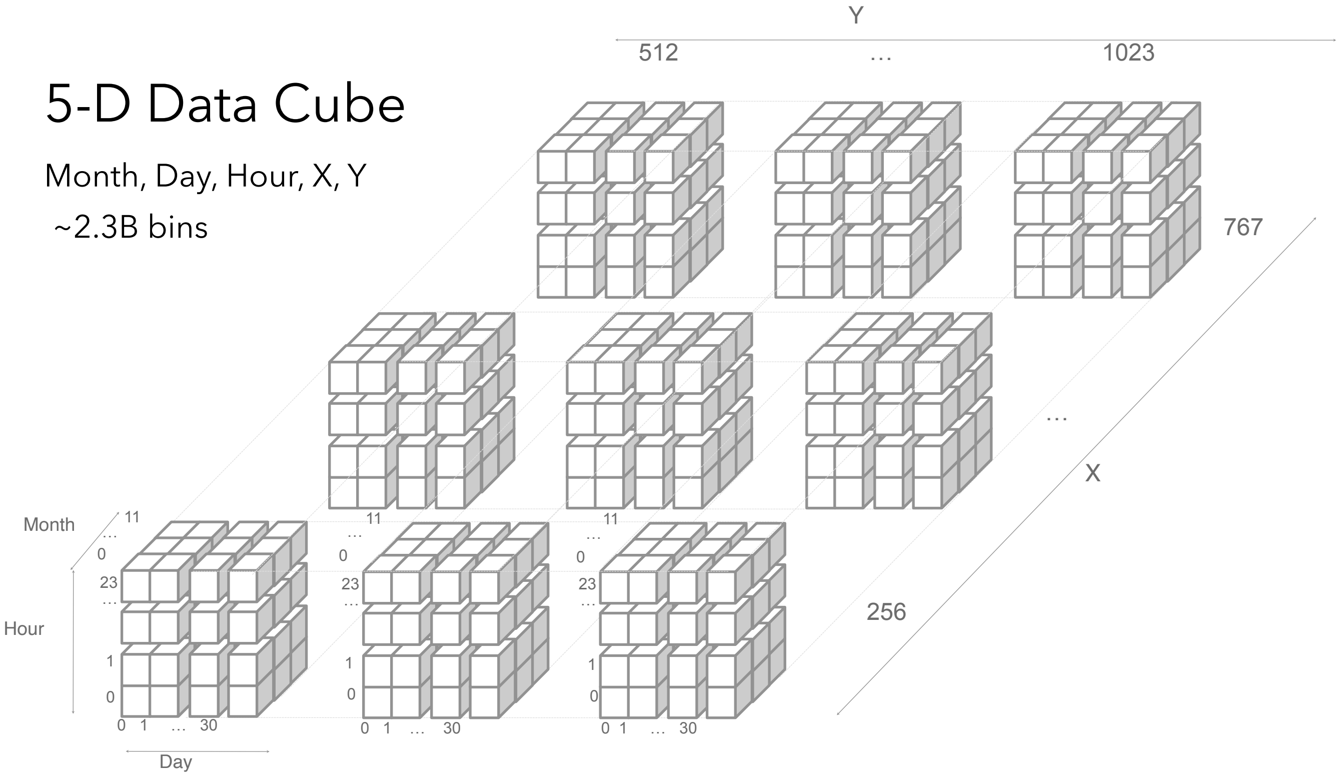
5-D Data Cube

Month, Day, Hour, X, Y

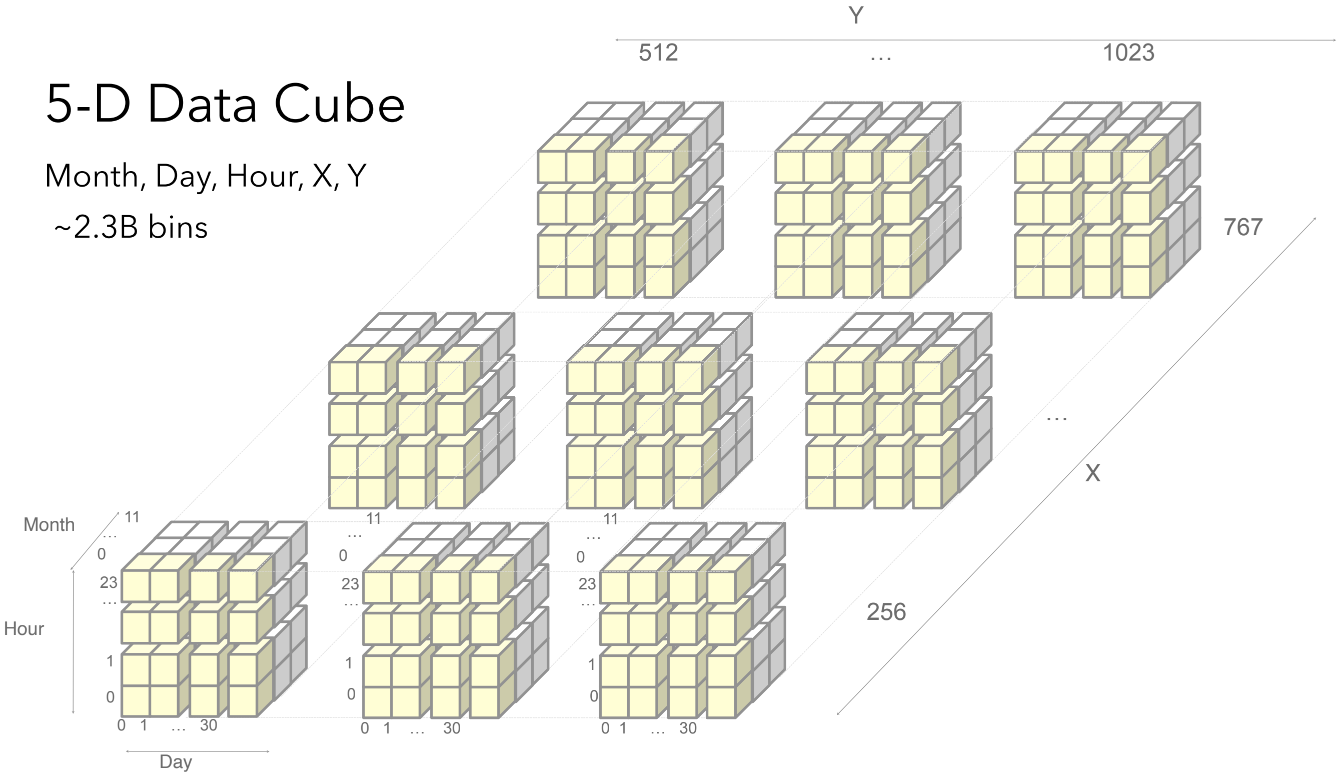
~2.3B bins

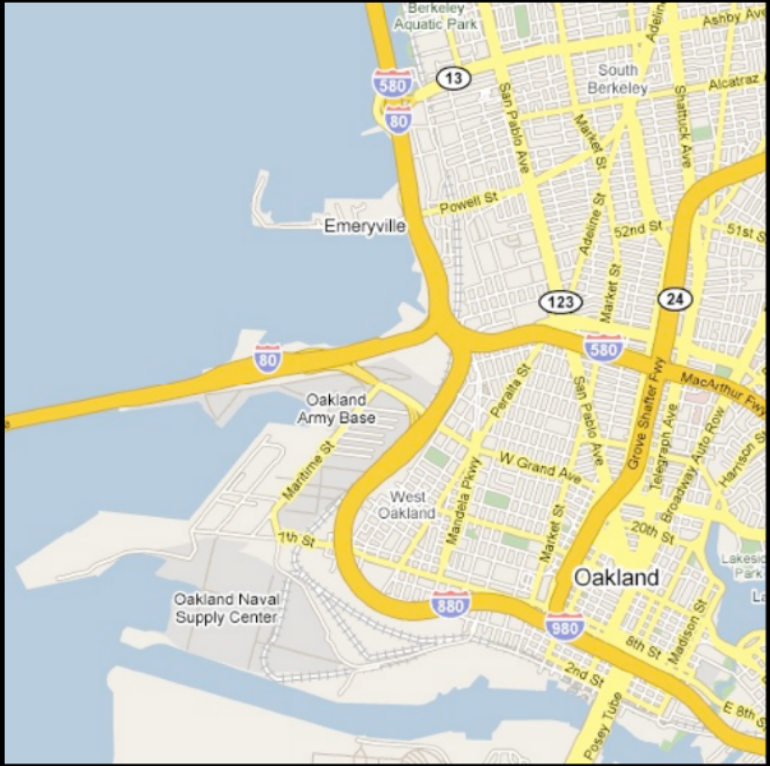


5-D Data Cube

Month, Day, Hour, X, Y

~2.3B bins





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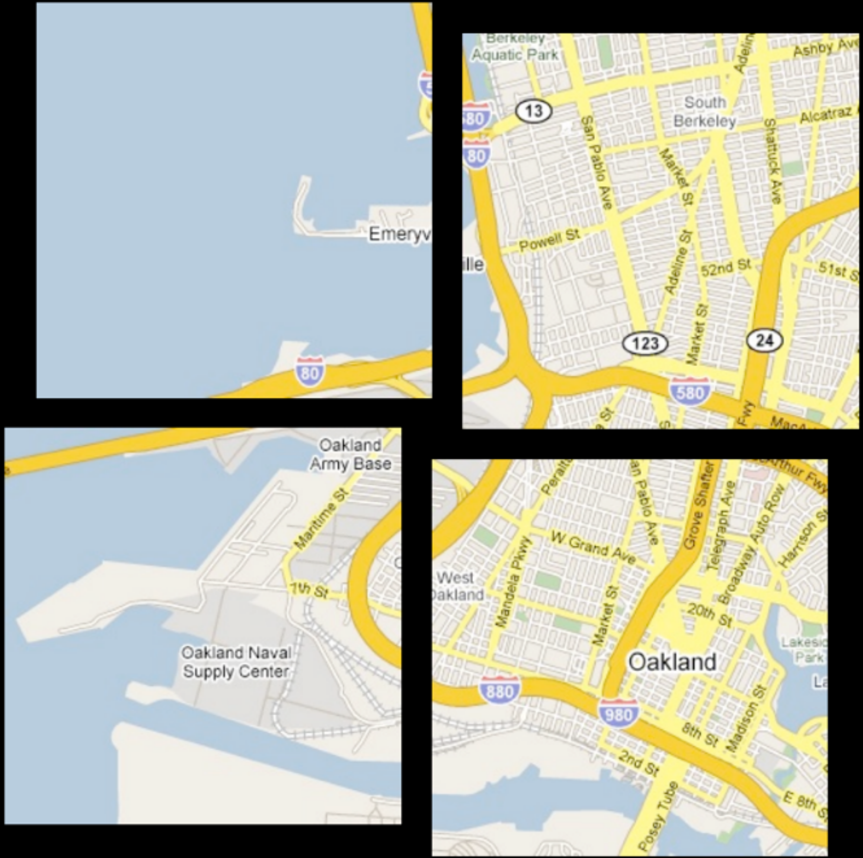
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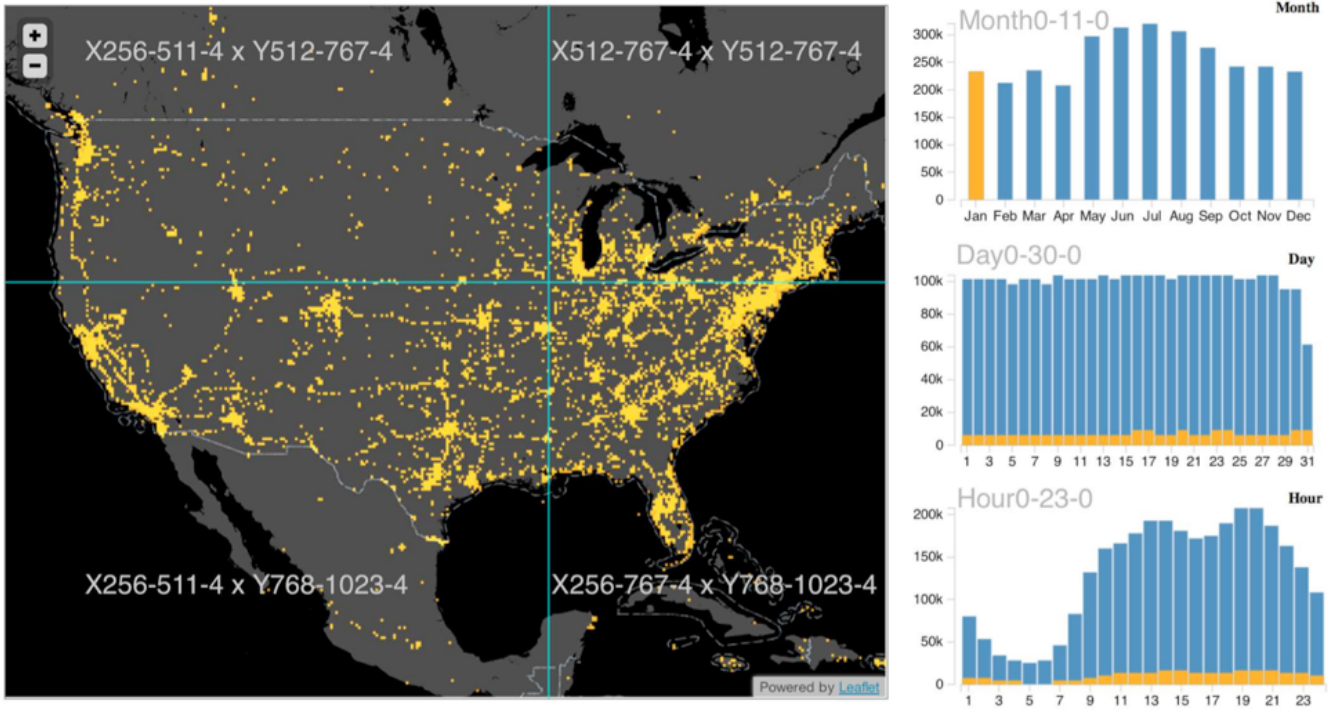
2nd St
E 8th
Posey Tube

Multivariate Data Tiles

1. Send data, not pixels
2. Embed multi-dim data



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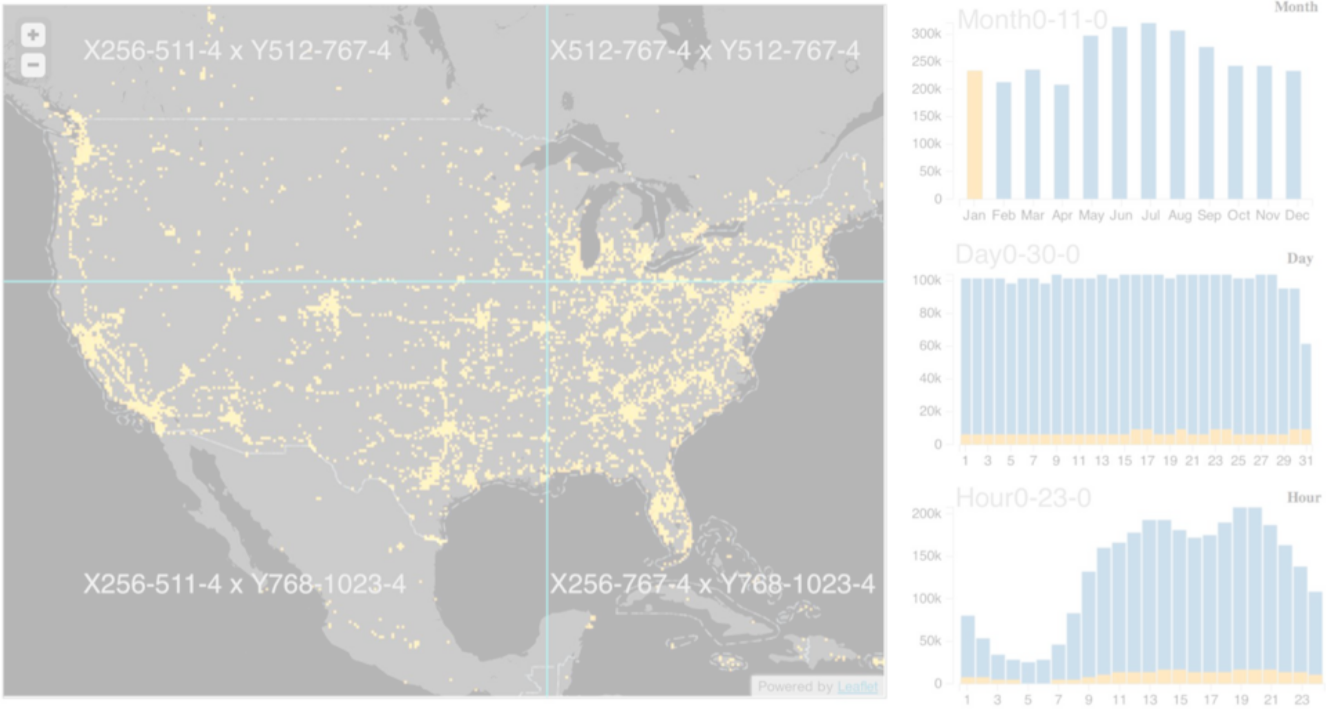

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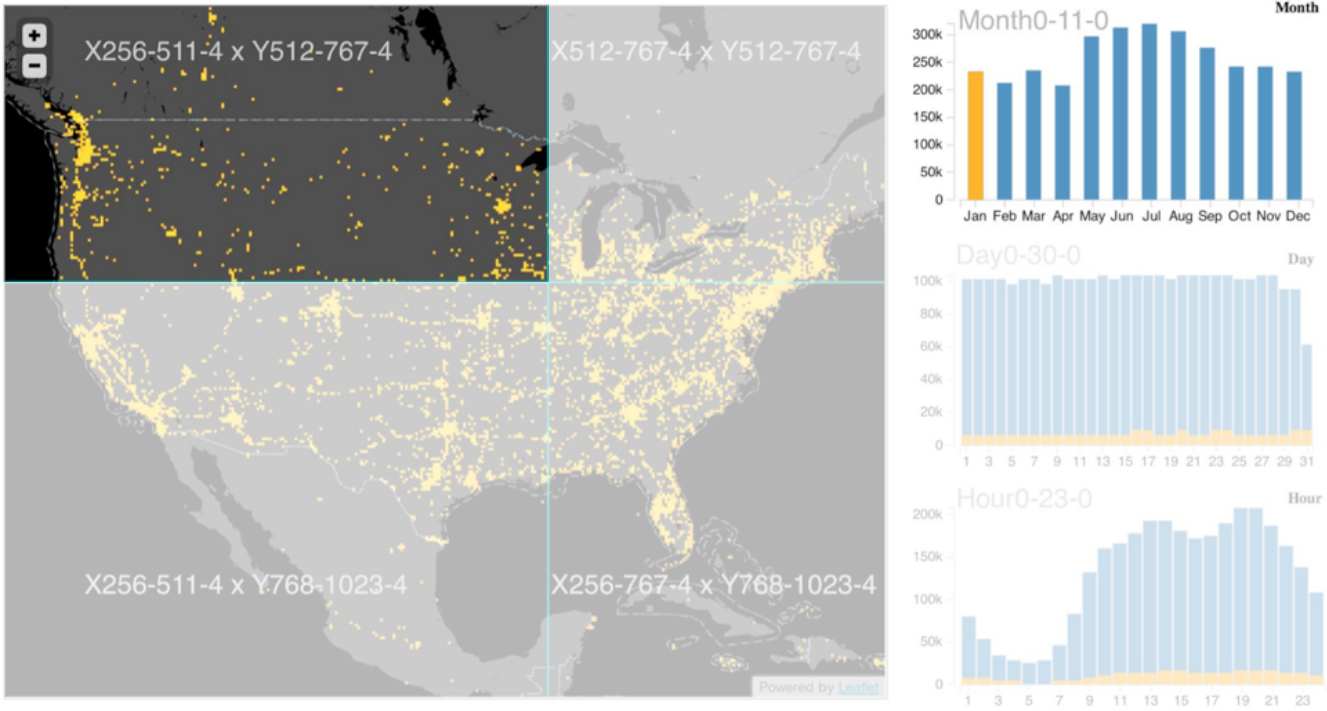
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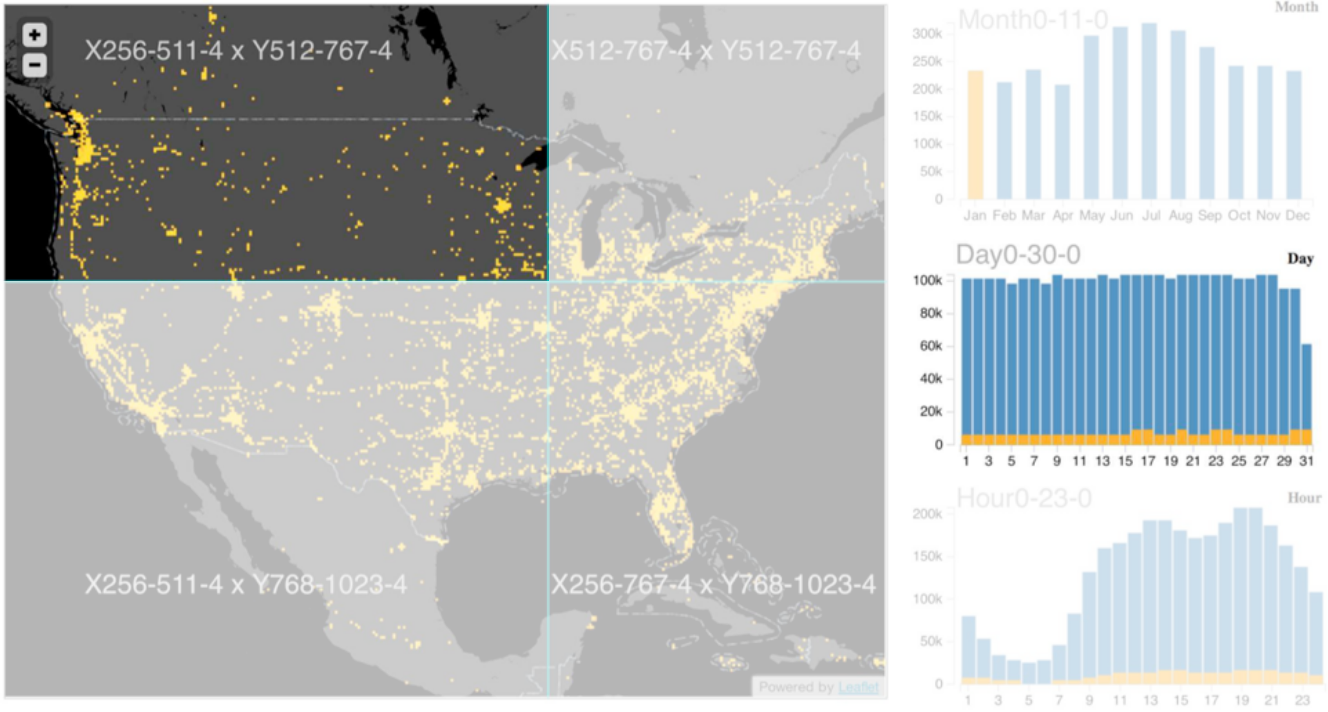
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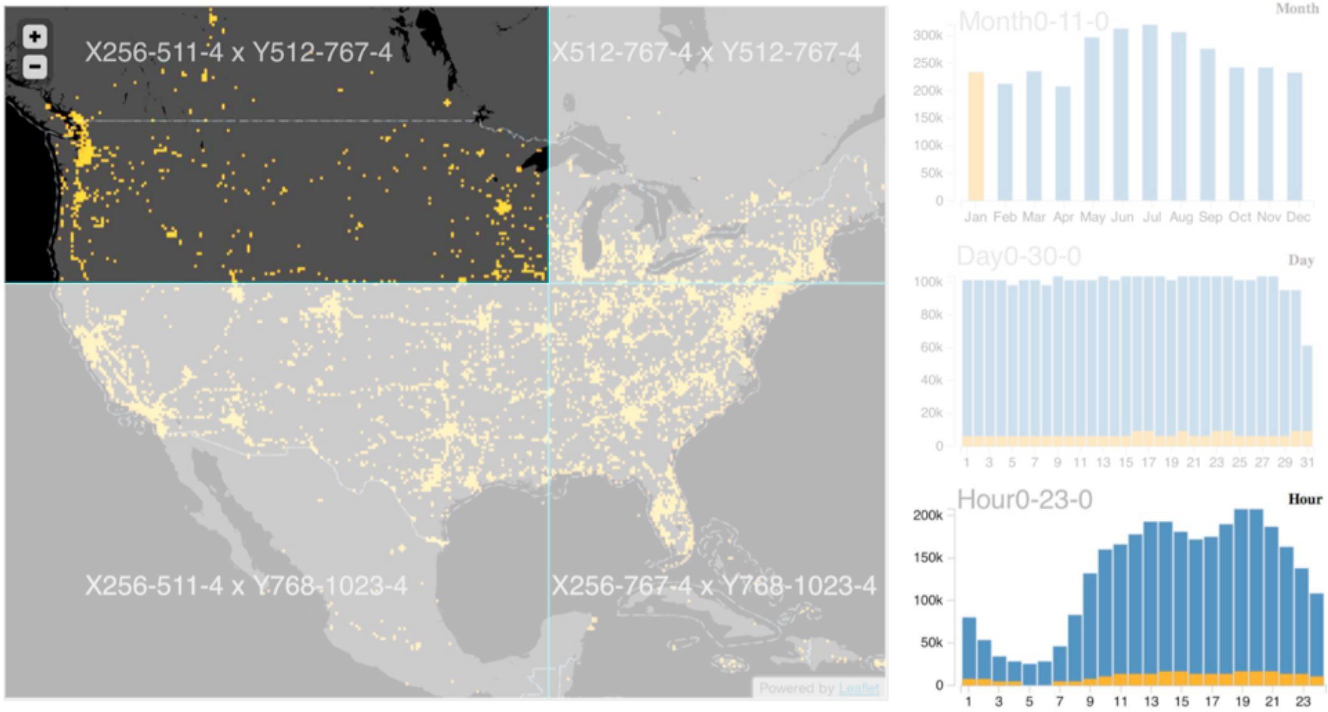
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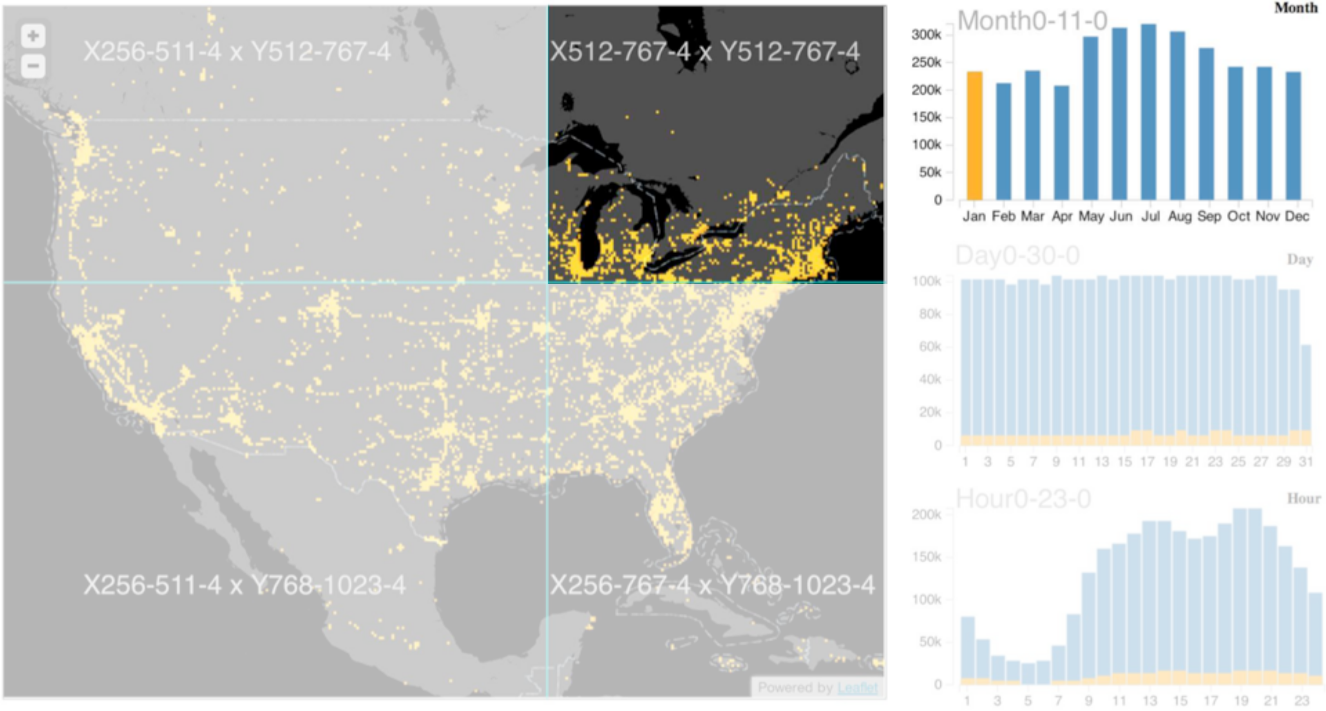
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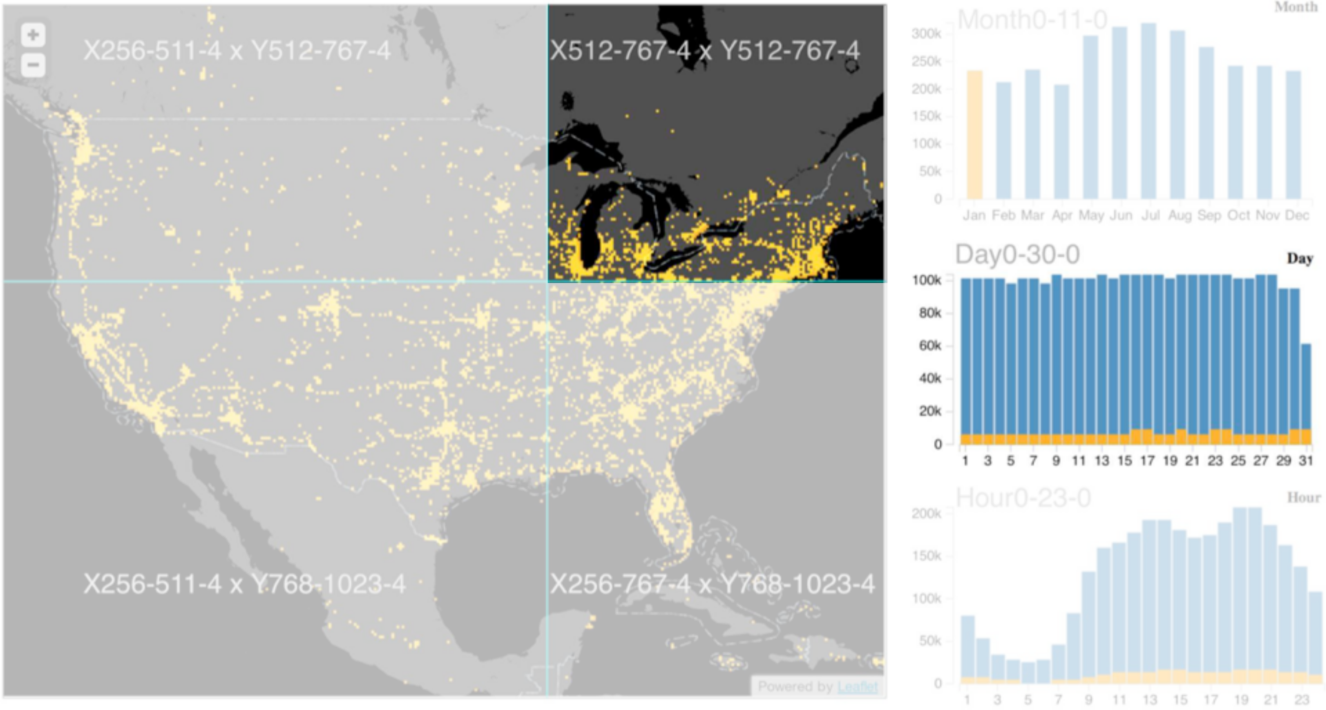

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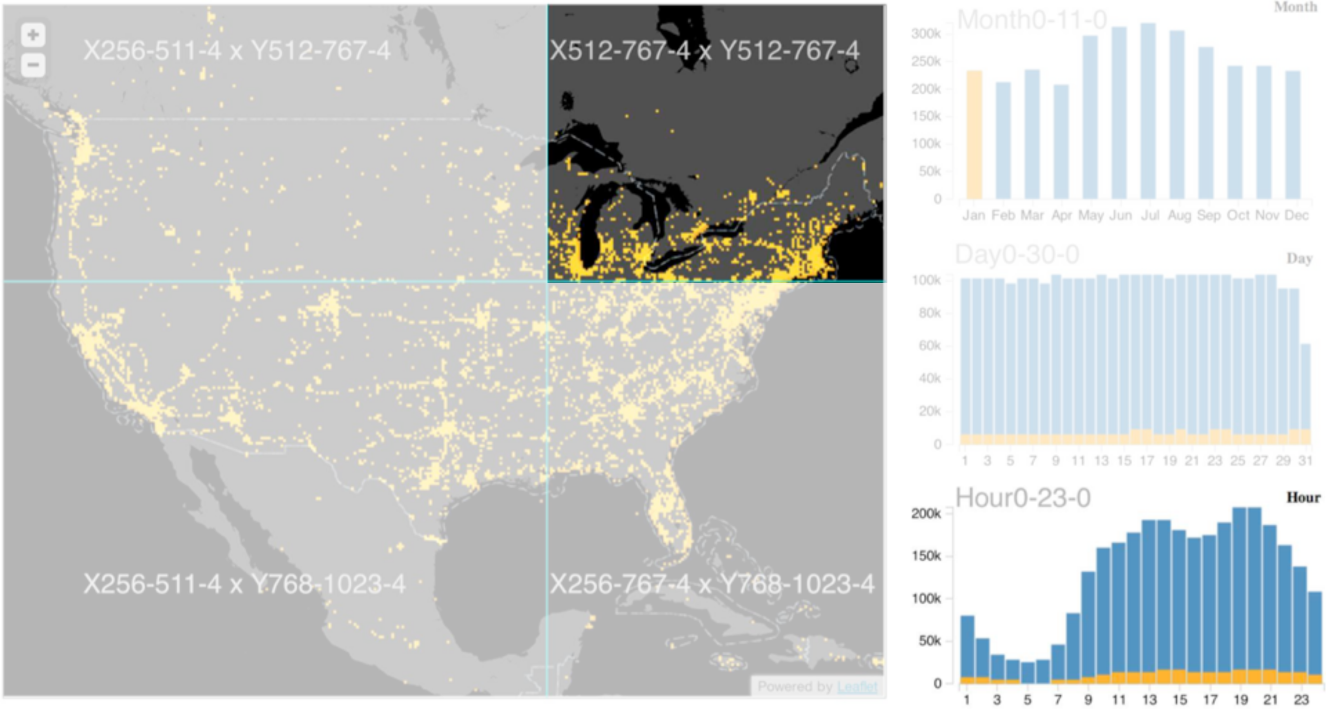

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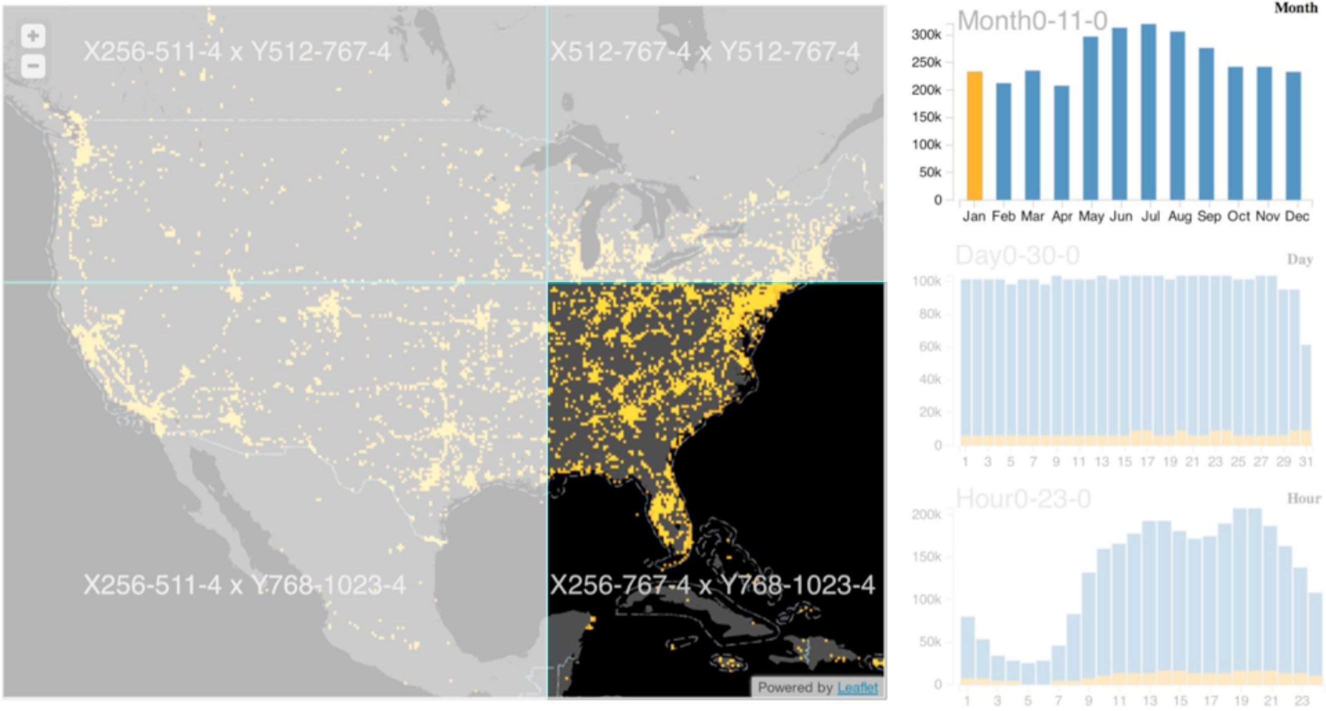

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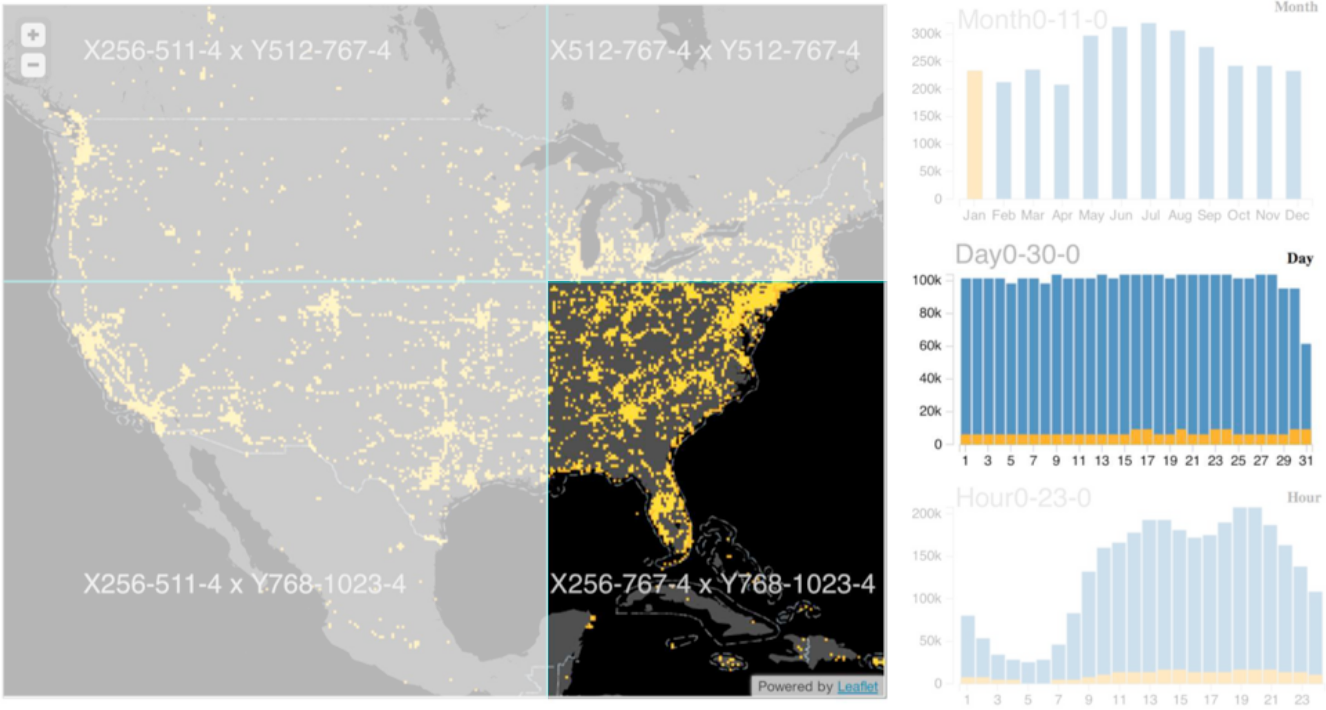

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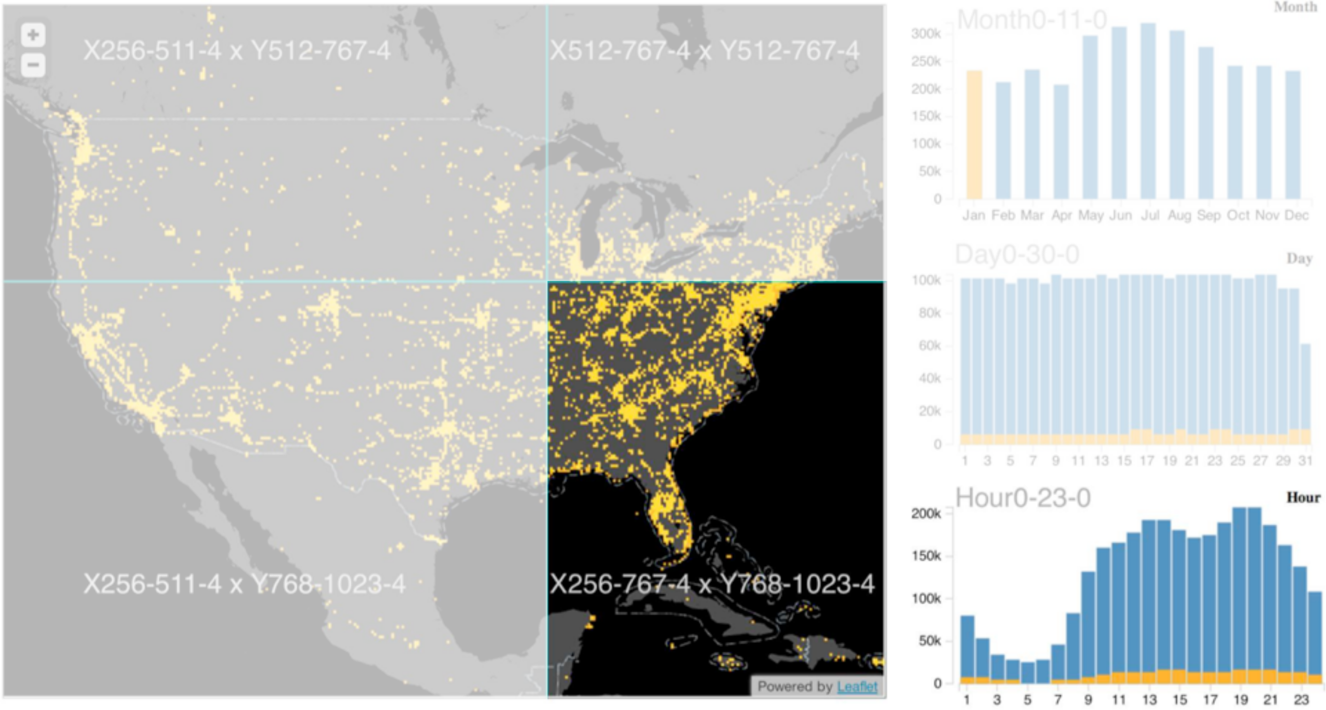

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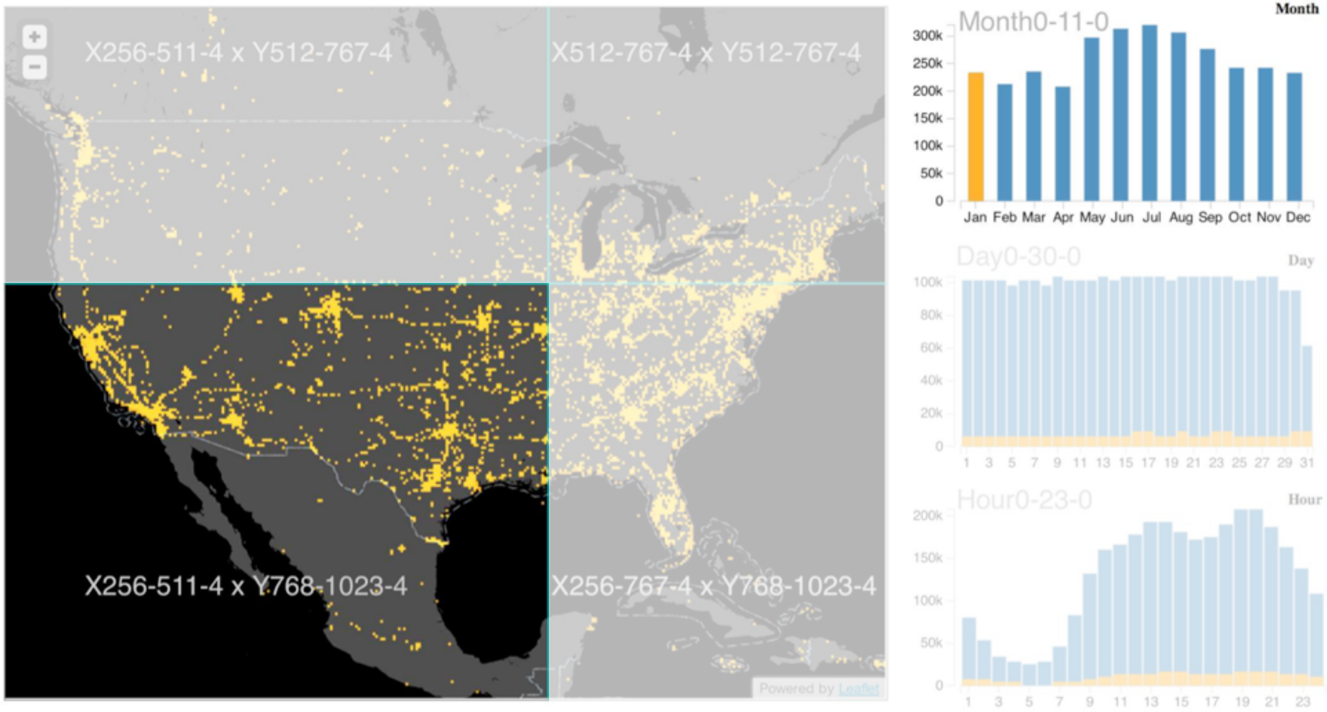

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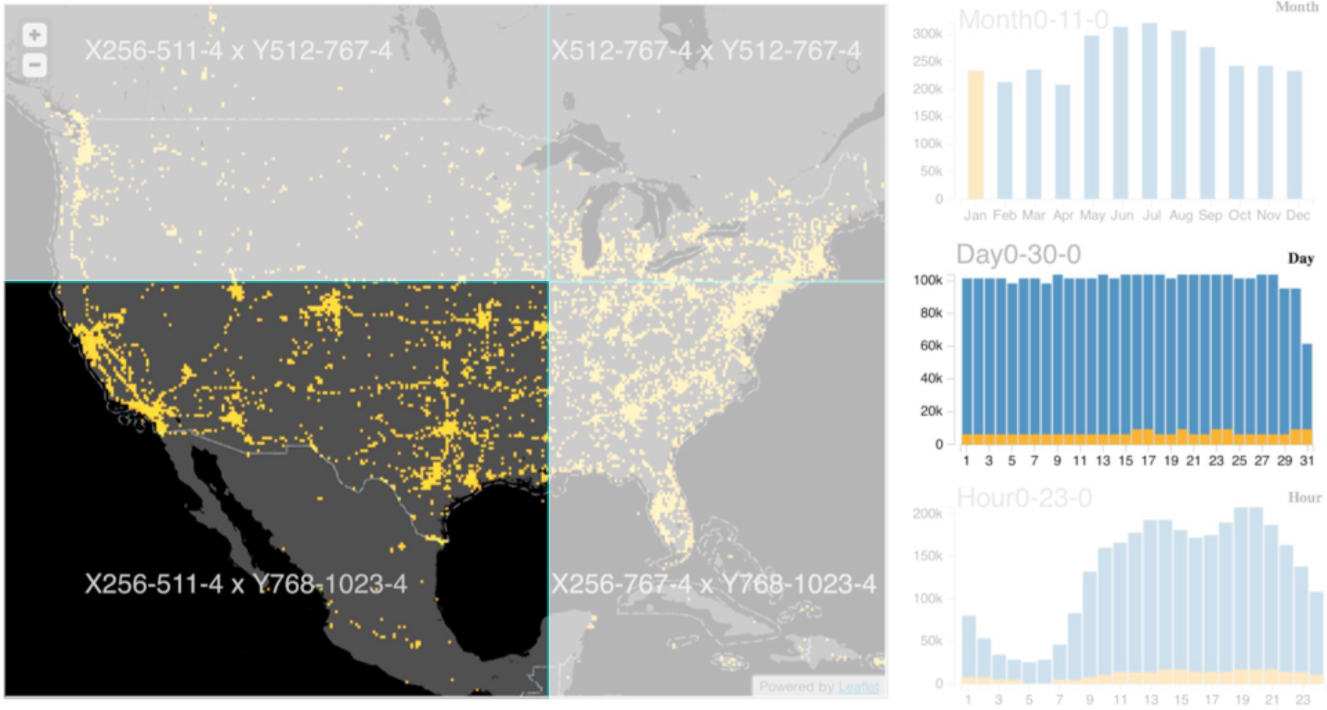

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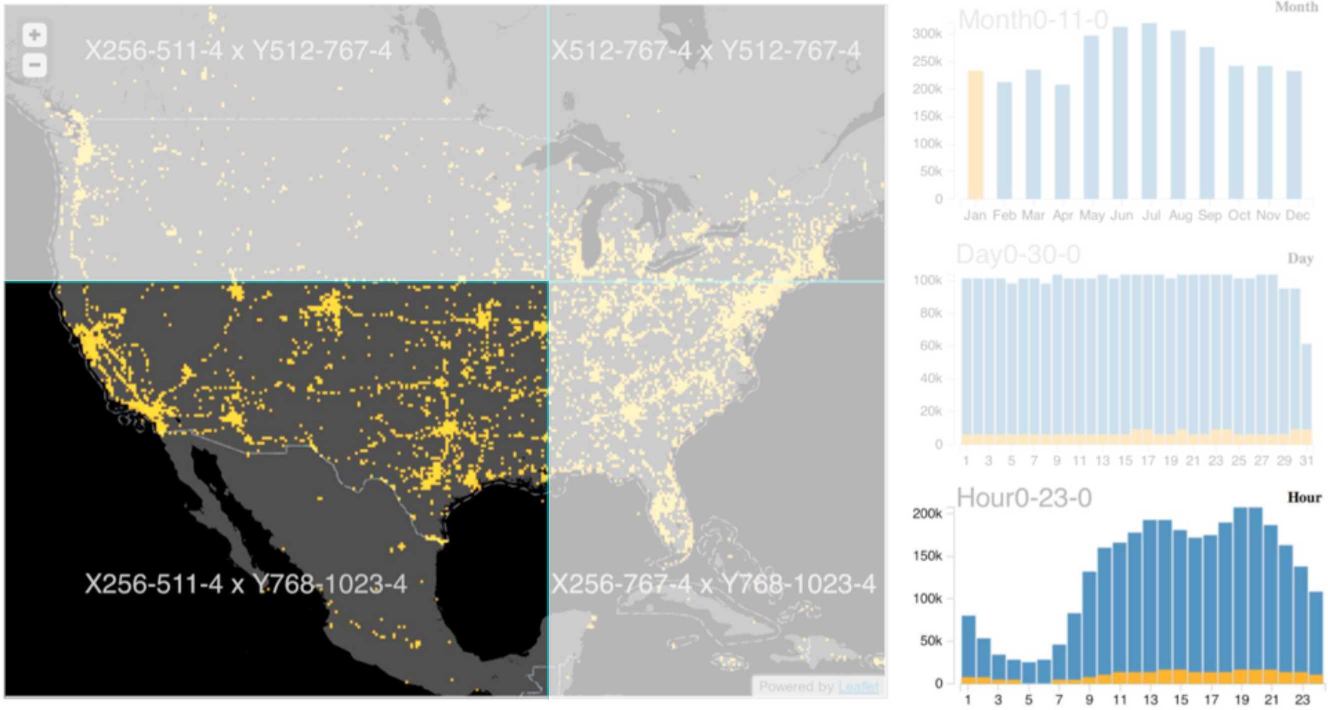

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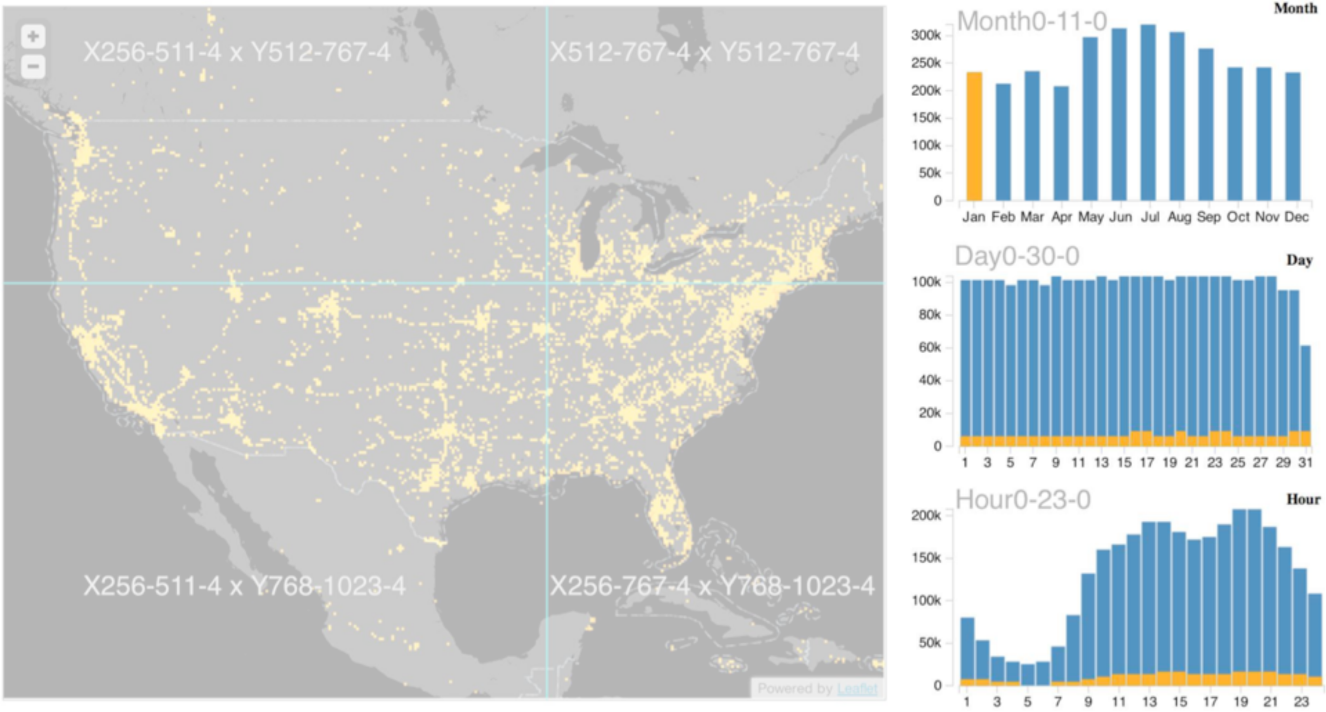
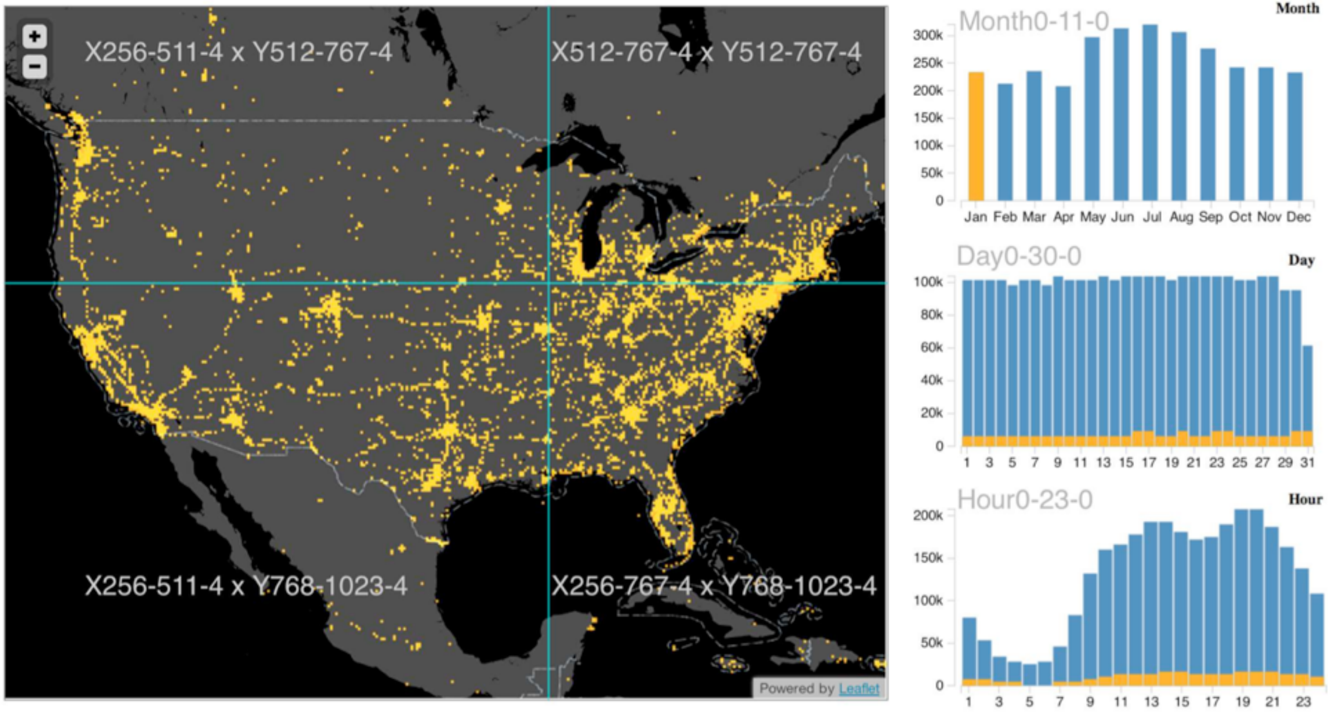
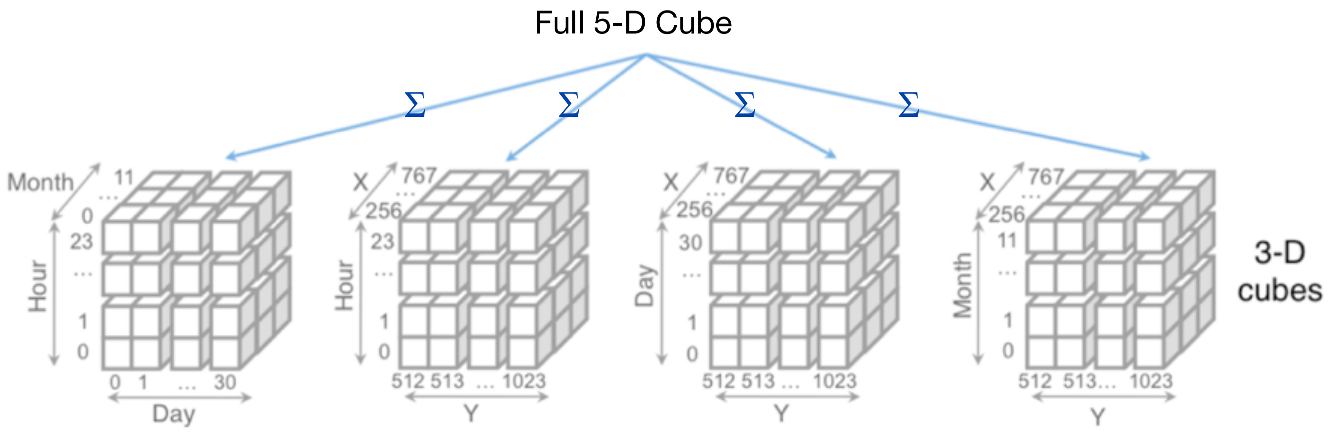


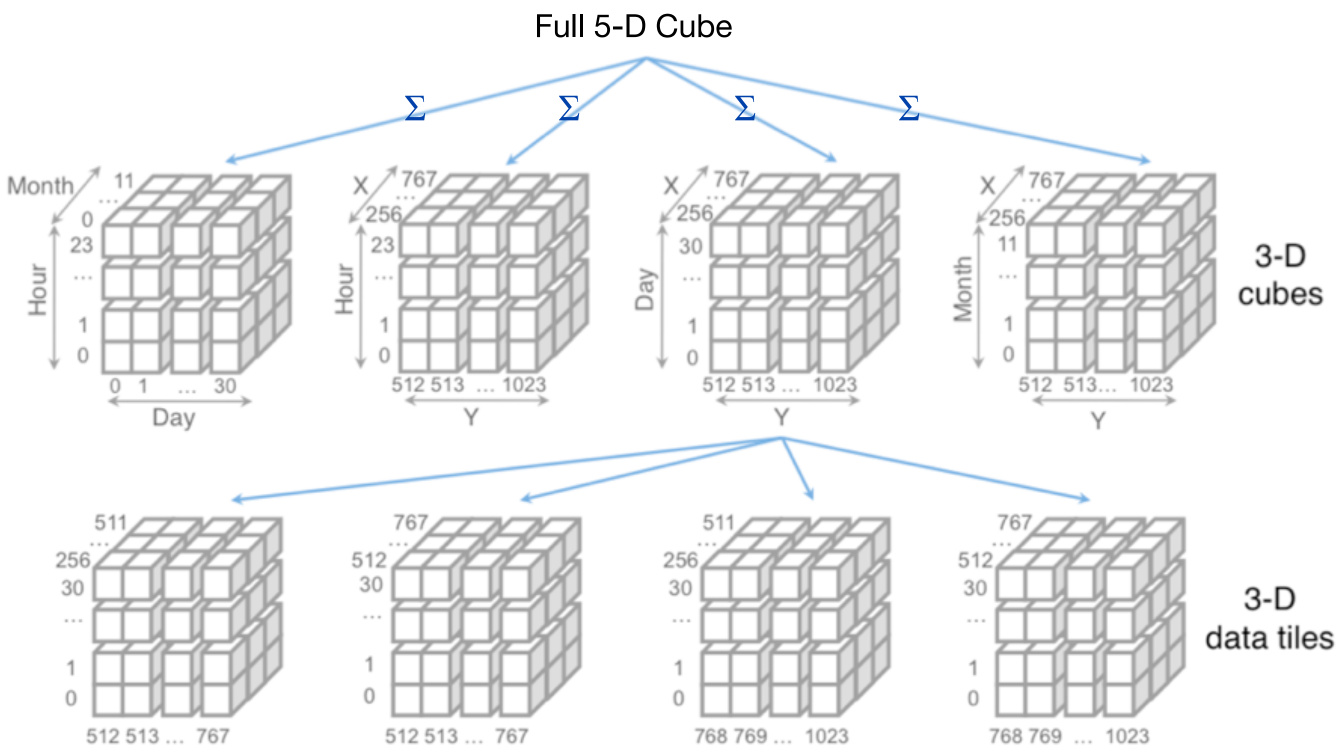
X256-511-4 x Y512-767-4
X512-767-4 x Y512-767-4
X256-511-4 x Y768-1023-4
X256-767-4 x Y768-1023-4
Powered by Leaflet
Month0-11-0
Month
300k
250k
200k
150k
100k
50k
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Day0-30-0
Day
100k
80k
60k
40k
20k
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31
Hour0-23-0
Hour
200k
150k
100k
50k
0
1 3 5 7 9 11 13 15 17 19 21 23


X256-511-4 x Y512-767-4
X512-767-4 x Y512-767-4
X256-511-4 x Y768-1023-4
X256-767-4 x Y768-1023-4
Powered by Leaflet
Month0-11-0
Month
300k 250k 200k 150k 100k 50k 0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Day0-30-0
Day
100k 80k 60k 40k 20k 0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31
Hour0-23-0
Hour
200k 150k 100k 50k 0
1 3 5 7 9 11 13 15 17 19 21 23

Full 5-D Cube

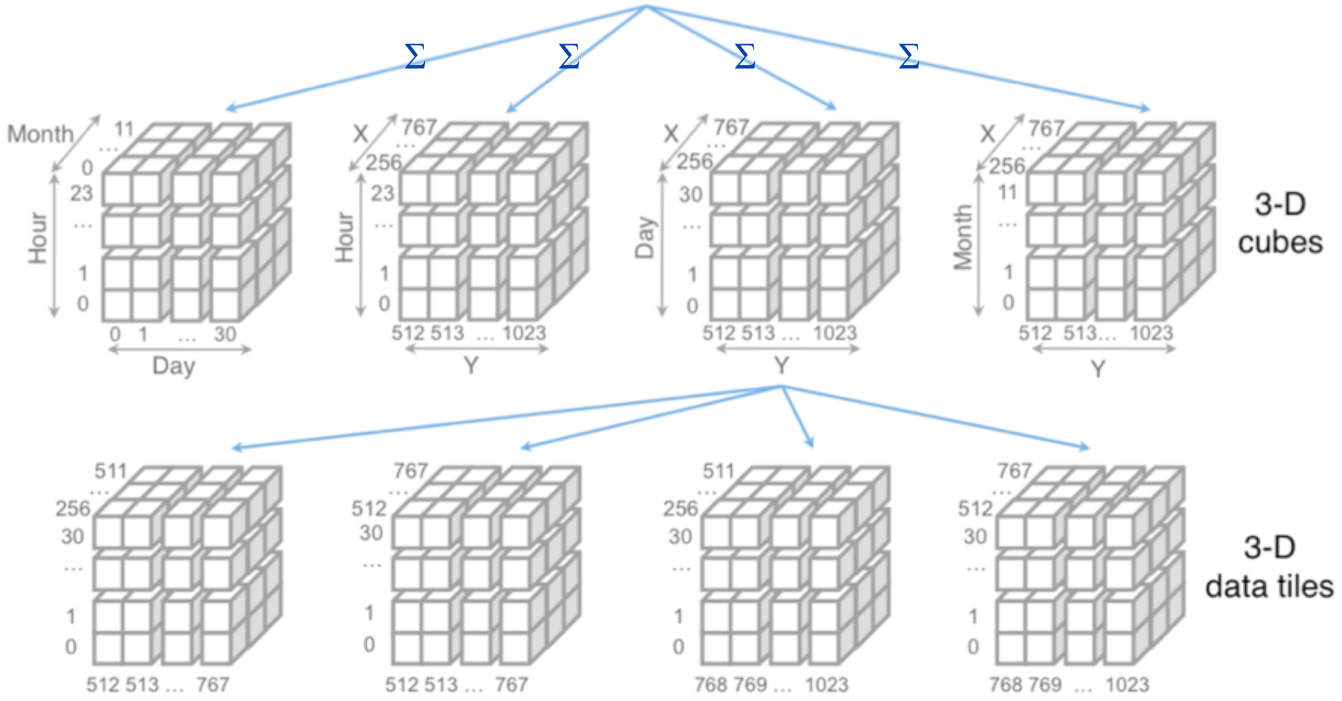


For any pair of 1D or 2D binned plots, the maximum number of dimensions needed to support brushing & linking is **four**.

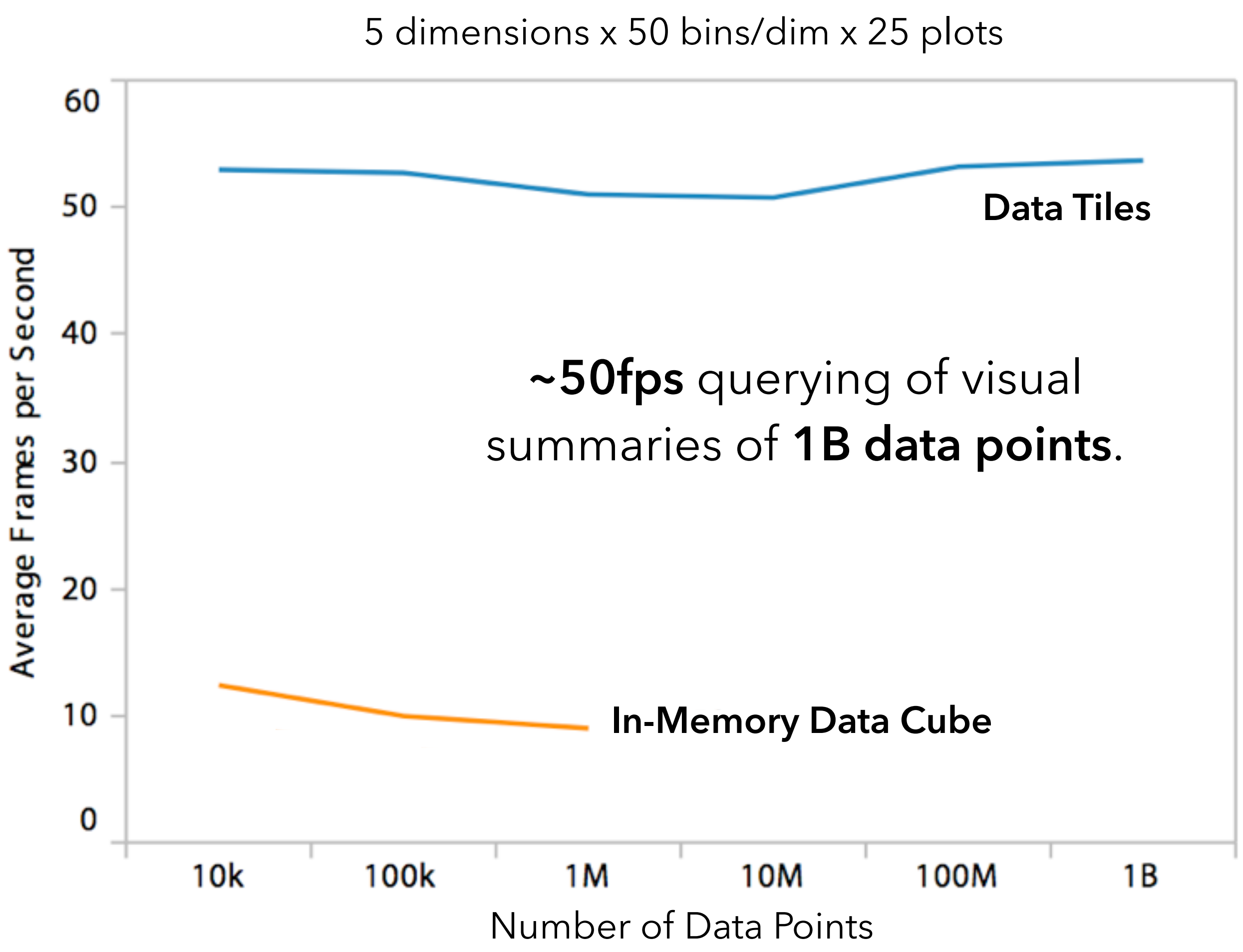


13 3-D Data Tiles

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
Average Frames per Second
60
50
40
30
20
10
0
Data Tiles
~50fps querying of visual summaries of 1B data points.
In-Memory Data Cube
10k
100k
1M
10M
100M
1B
Number of Data Points

Limitations and Questions

But where do the multivariate data tiles come from?

They must be computed, either ahead of time or on-the-fly. Up to the 100M point range, an analytic database can do this on the fly. In the 1B point range, pre-computation avoids delays.

We can also *prefetch*: we can start computing new data tiles as soon as the pointer enters a chart, before a selection is made.

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]

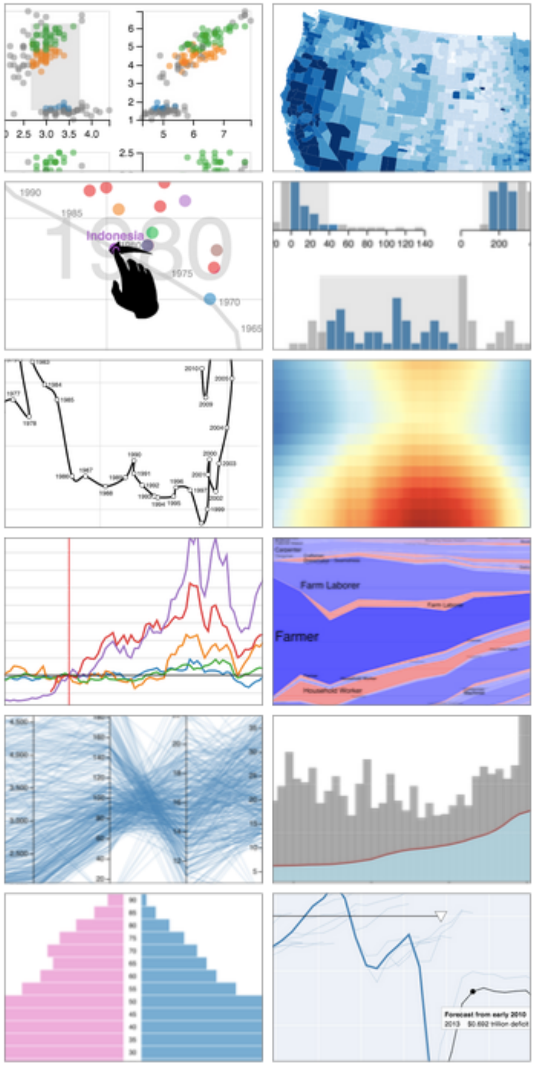
Sampling Methods

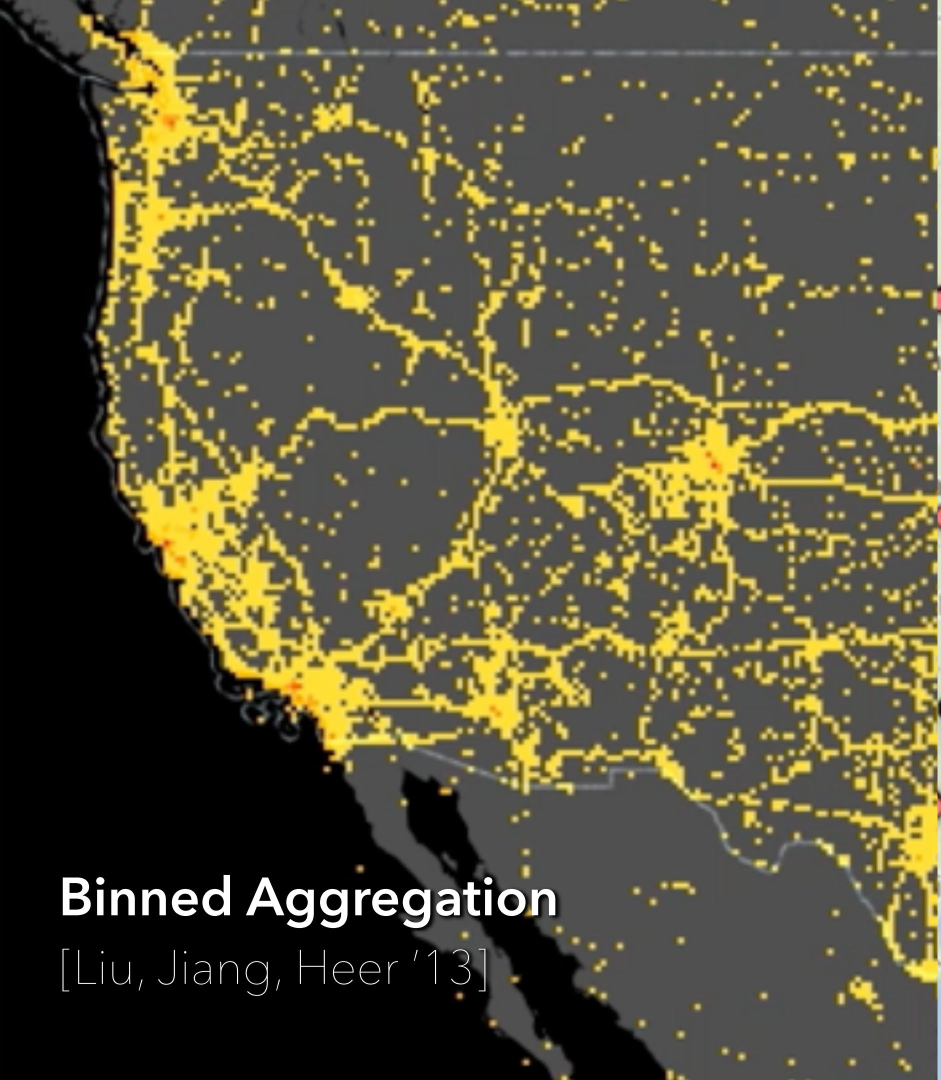
Common Sampling Methods

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

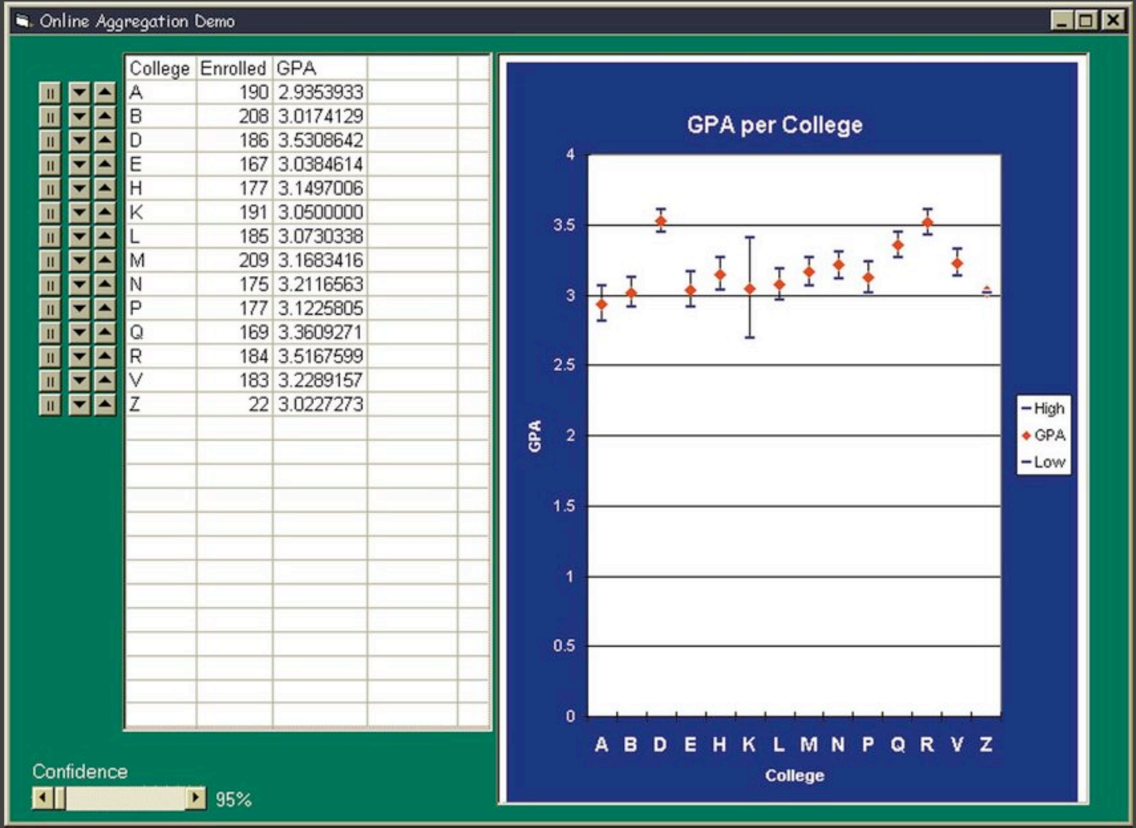
Google Fusion Tables

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.

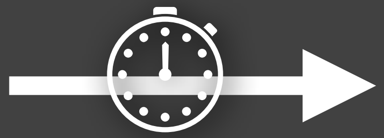


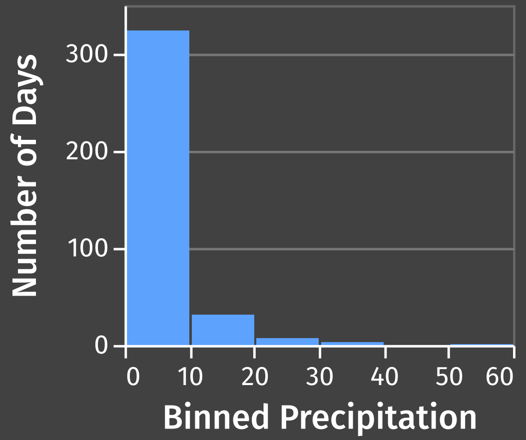
What if data is too large to query in a reasonable time?

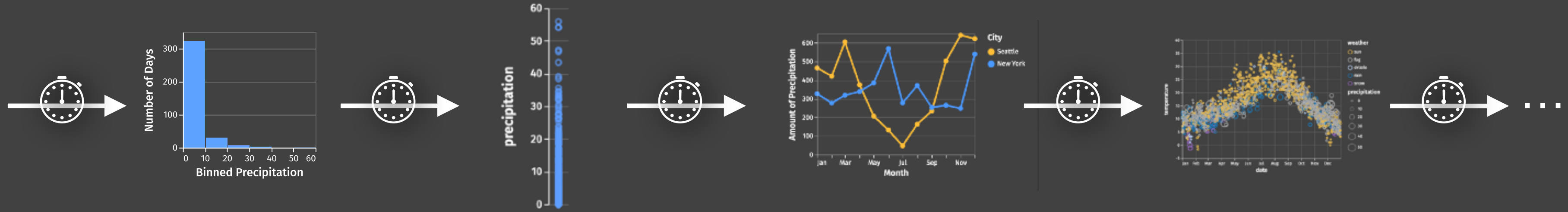
Trust, but Verify: Optimistic Vis

[Moritz, Fisher, Ding & Wang '17]

Strategies: Query Database, Approximation




Number of Days
300
200
100
0
0
10
20
30
40
50
60
Binned Precipitation



Latencies reduce engagement
and lead to fewer observations.

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

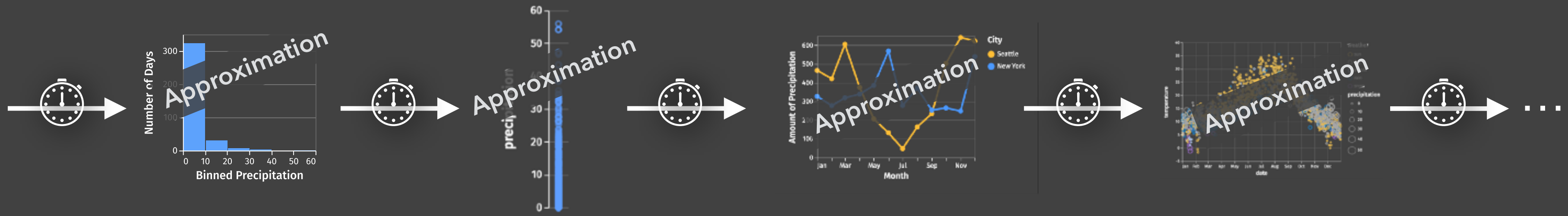
Small chance of error

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.

This glass
is half full

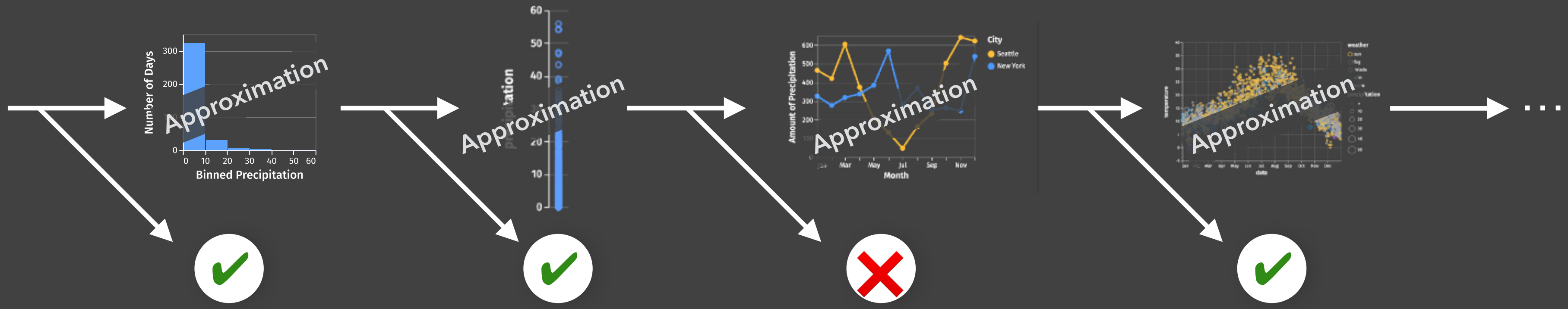
Optimistic Visualization

Trust but Verify

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

Optimistic Visualization

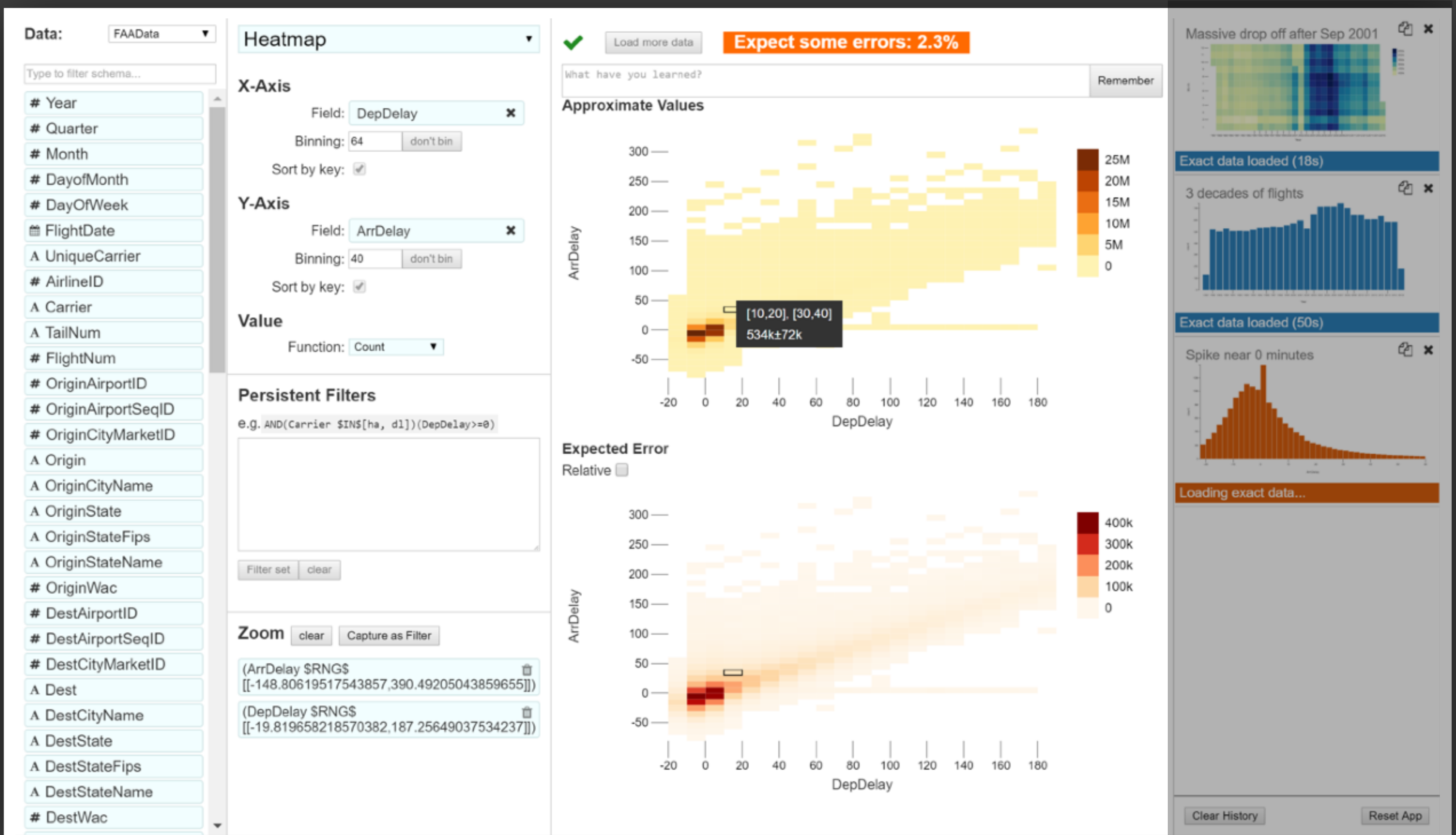
Trust but Verify. Moritz et al. *CHI 2017*.



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.

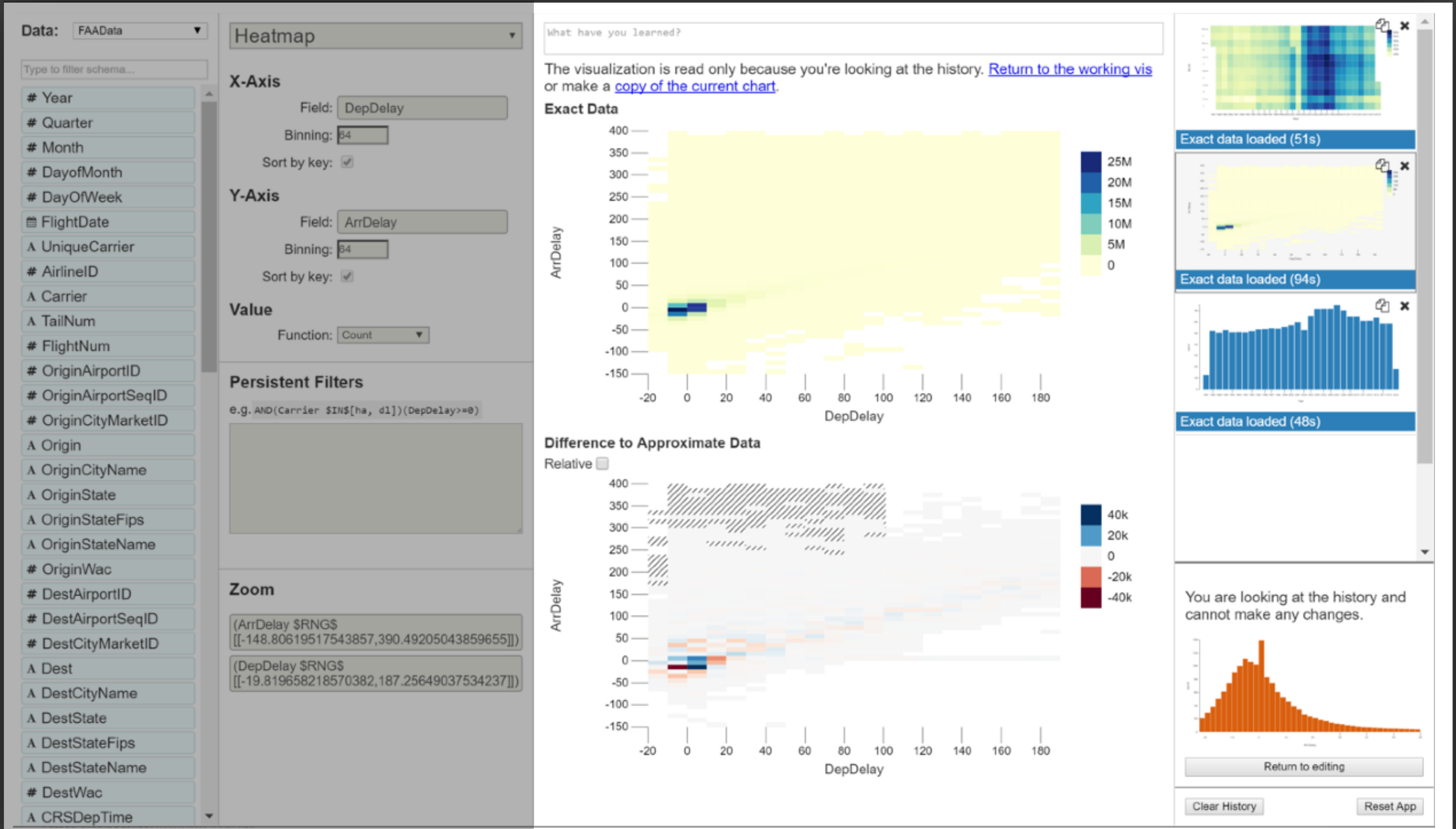
Optimistic Visualization



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.