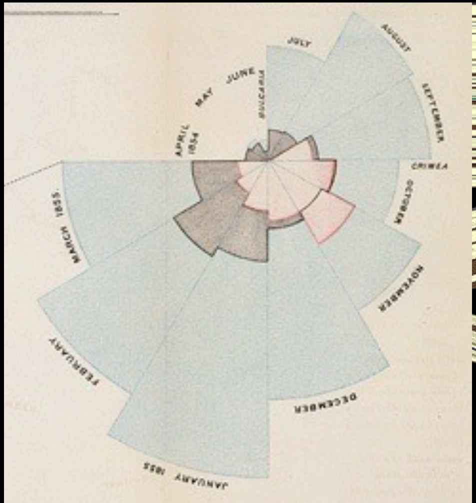
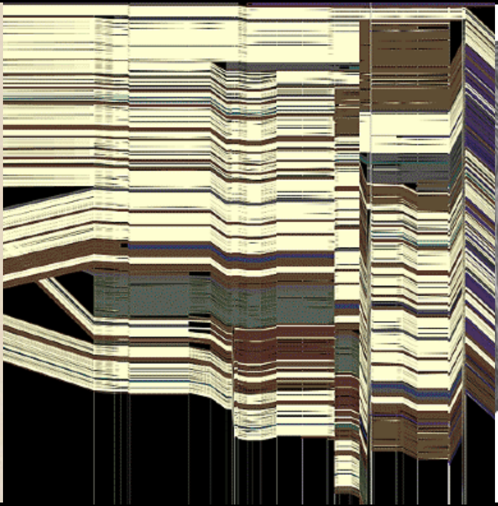
CSE 442 - Data Visualization

Scalable Visualization





Jeffrey Heer University of Washington

Session Outline

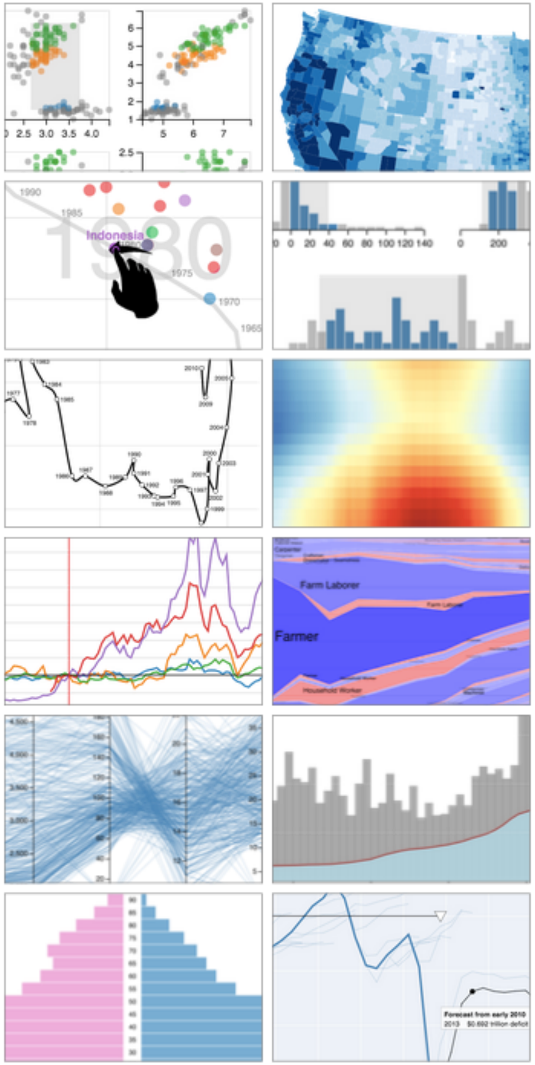
The Varieties of “Big Data”

Scalable Plotting Techniques

Scalable Interaction

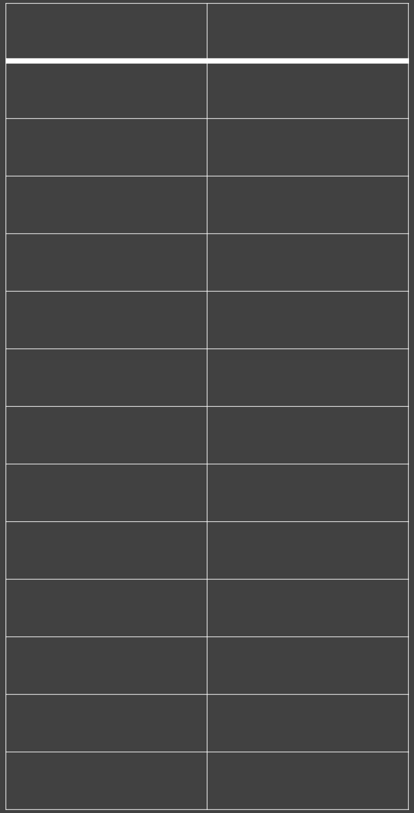
Why Latency Matters

Sampling Methods



The Varieties of ”Big Data”

Tall Data



Lots of records

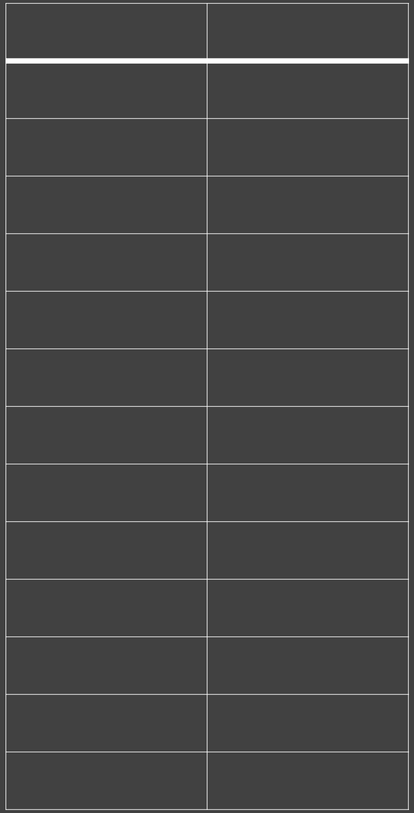
- Large DBs have petabytes or more
- *(but median DB still fits in RAM!)*

How to manage?

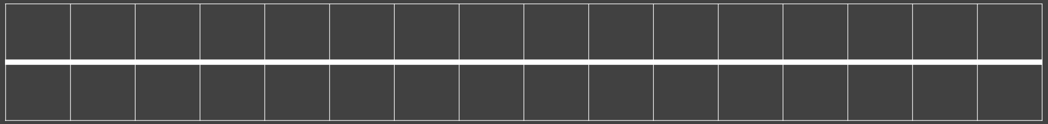
- Parallel data processing
- Reduction: Filter, aggregate
- Sample or approximate

Not just about systems. Consider perceptual / cognitive scalability.

Tall Data



Wide data



Lots of variables (100s-1000s…)

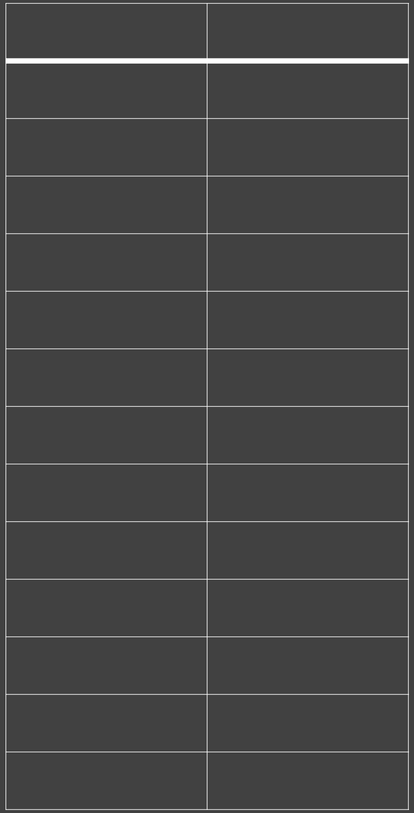
Select relevant subset

Dimensionality reduction

Statistical methods can suggest and order related variables

Requires human judgment

Tall Data



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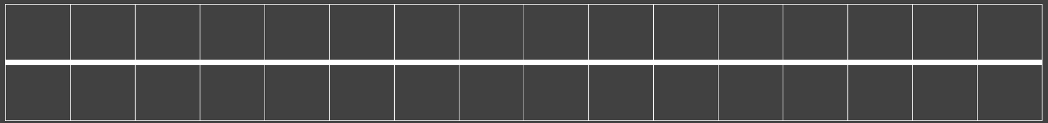
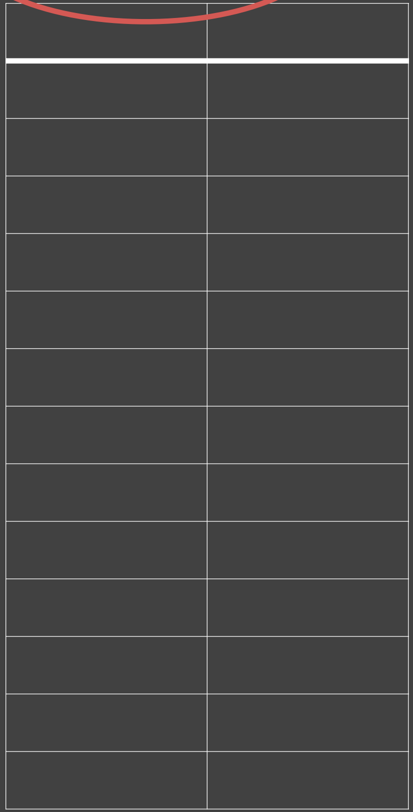
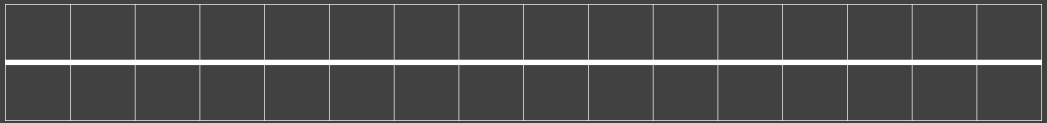


Diverse data

Tall Data



Wide data



Diverse data

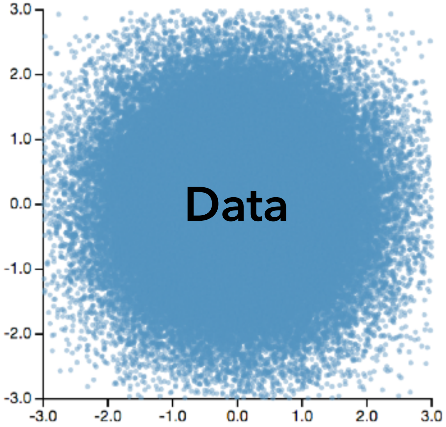
How can we visualize and interact with **billion+ record** databases in real-time?

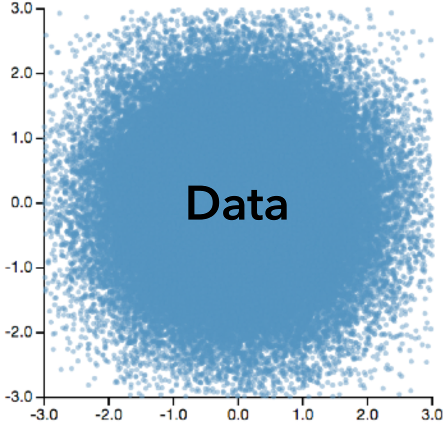
Two Challenges:

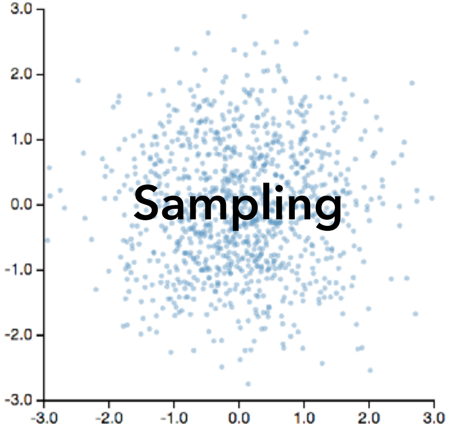
1. Effective **visual encoding**
2. Real-time **interaction**

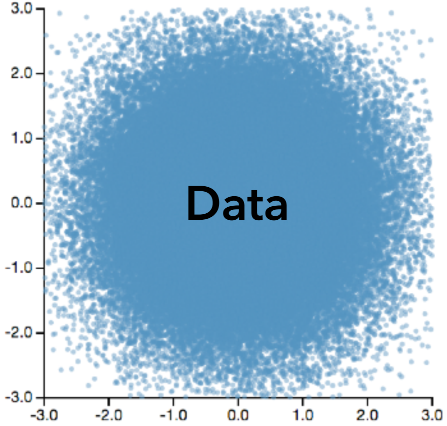
Perceptual and interactive scalability should be limited by the **chosen resolution** of the visualized data, not the number of records.

Scalable Plotting Techniques

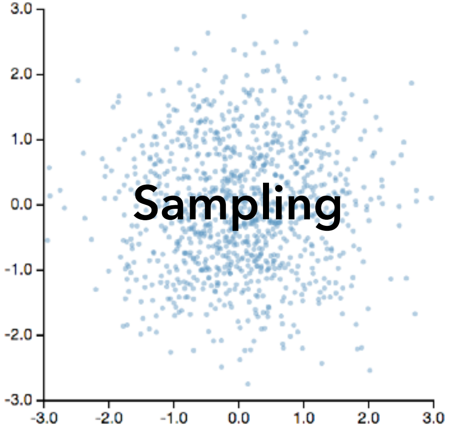

Data
3.0
2.0
1.0
0.0
-1.0
-2.0
-3.0
-3.0
-2.0
-1.0
0.0
1.0
2.0
3.0


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

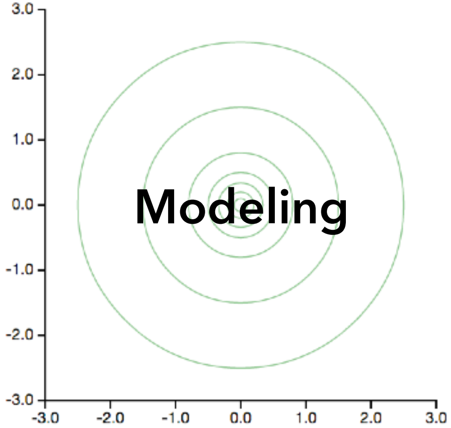

Sampling
3.0
2.0
1.0
0.0
-1.0
-2.0
-3.0
-3.0
-2.0
-1.0
0.0
1.0
2.0
3.0



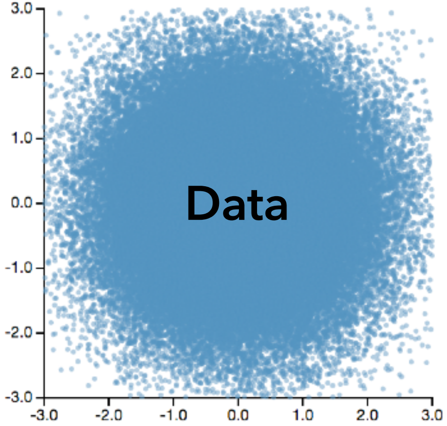
Data



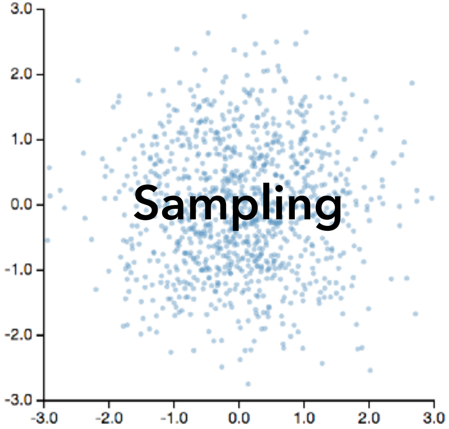
Sampling



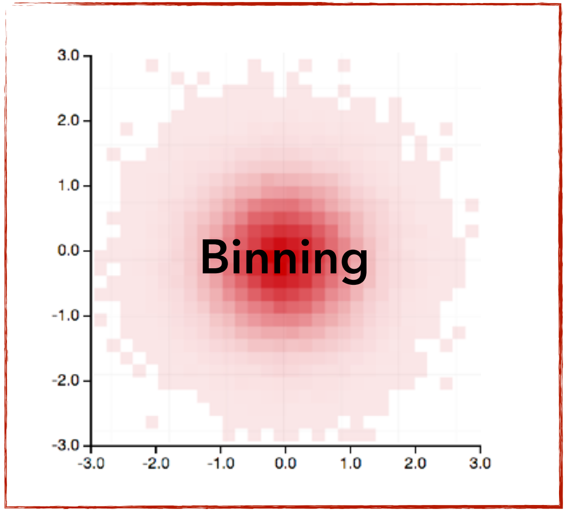
Modeling



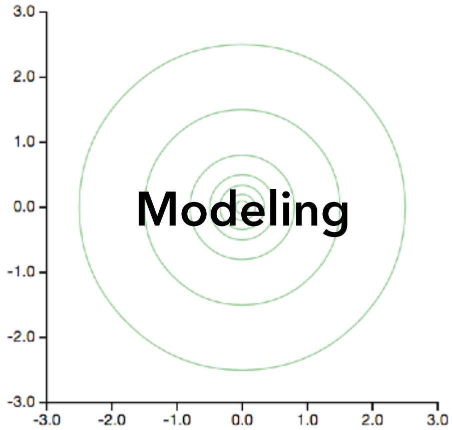
Data



Sampling

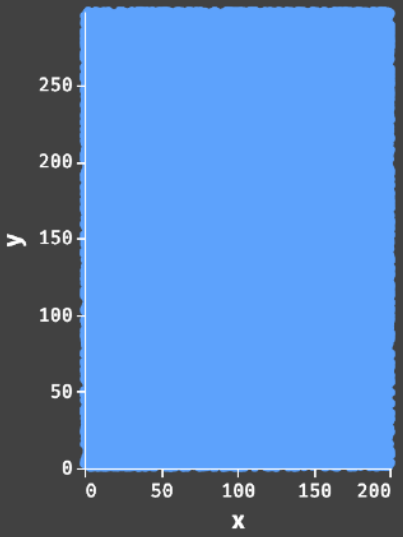


Binning

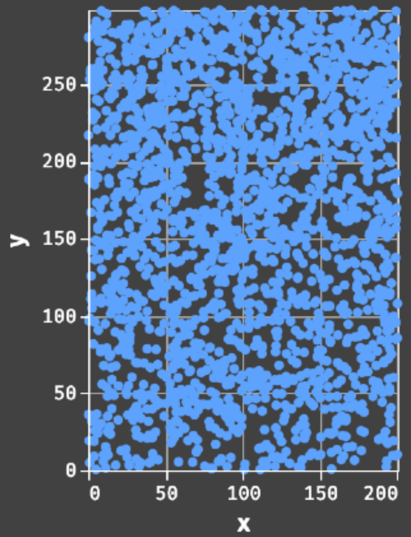


Modeling

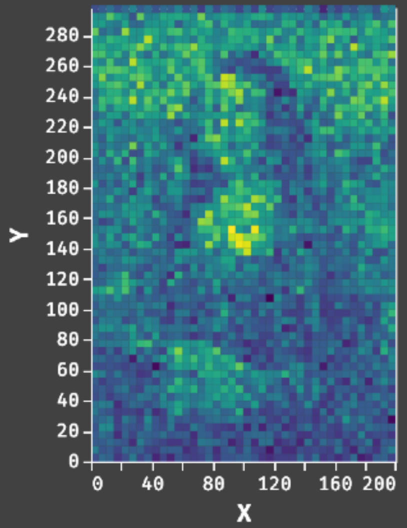
How to **Visualize** a Billion+ Records



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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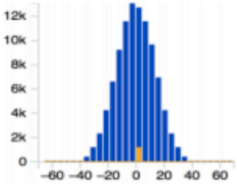
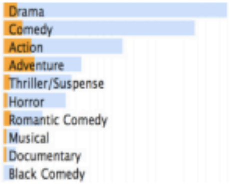
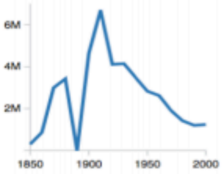
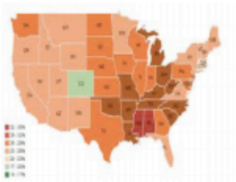
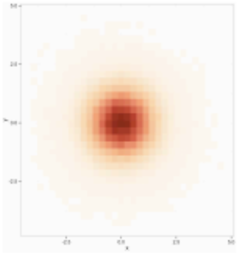
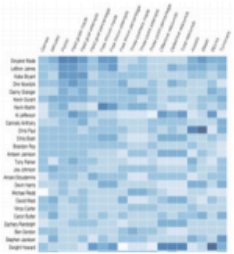
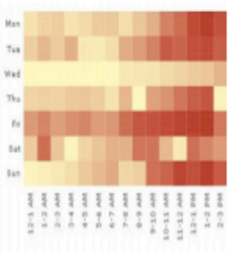
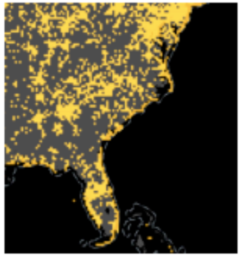
2. Aggregate Count, Sum, Average, Min, Max, ...

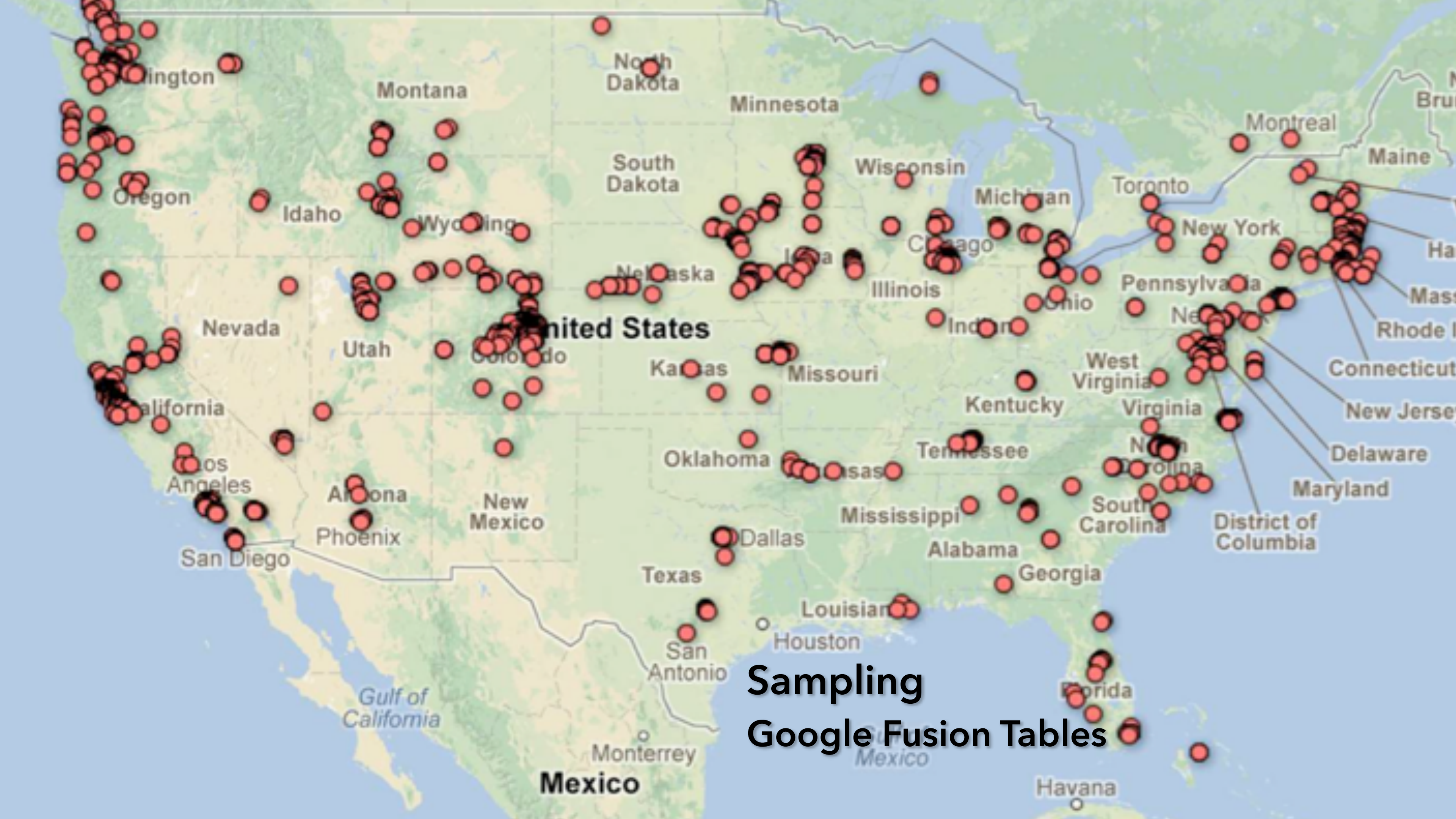
3. Smooth Optional: smooth aggregates [Wickham ’13]

4. Plot Visualize the aggregate values

Binned Plots by Data Type

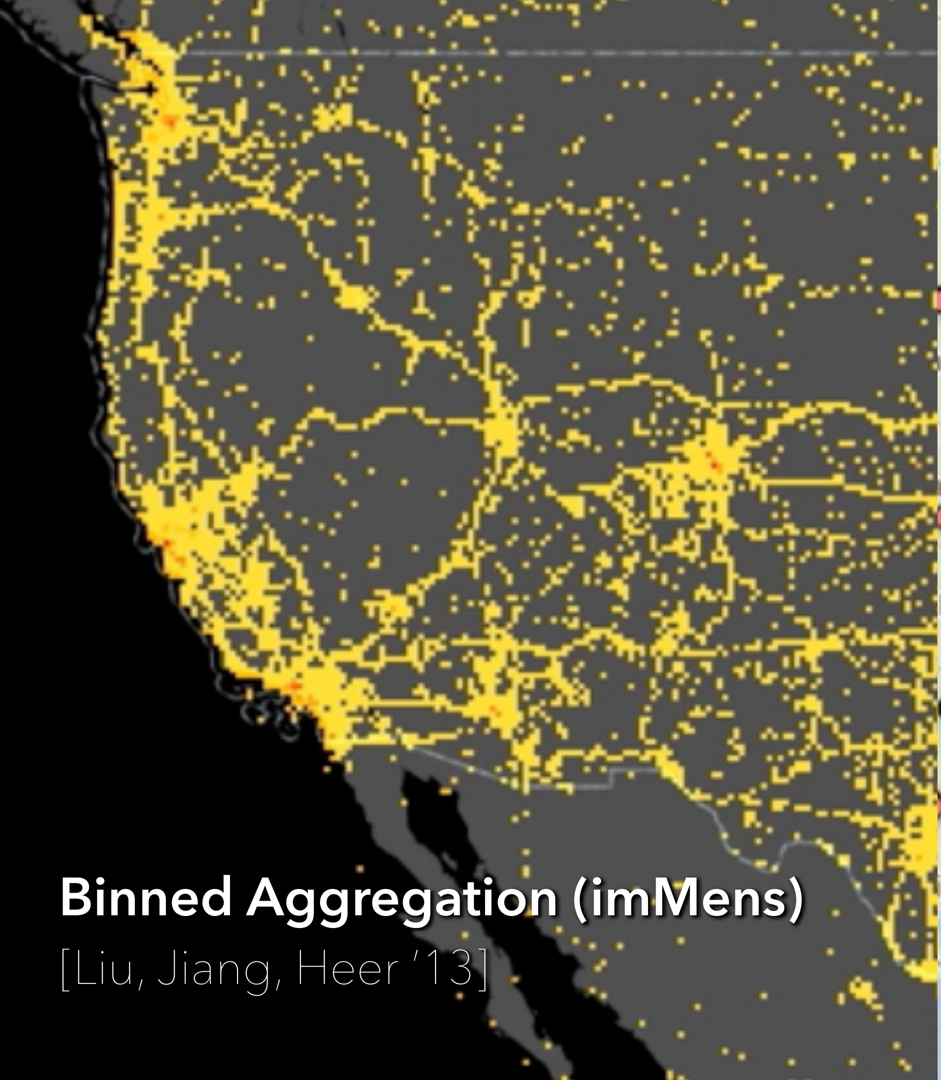
	Numeric	Ordinal	Temporal	Geographic
1D	 Histogram	 Bar Chart	 Line Graph / Area Chart	 Choropleth Map
2D	 Binned Scatter Plot	 Heatmap	 Temporal Heatmap	 Geographic Heatmap

Examples



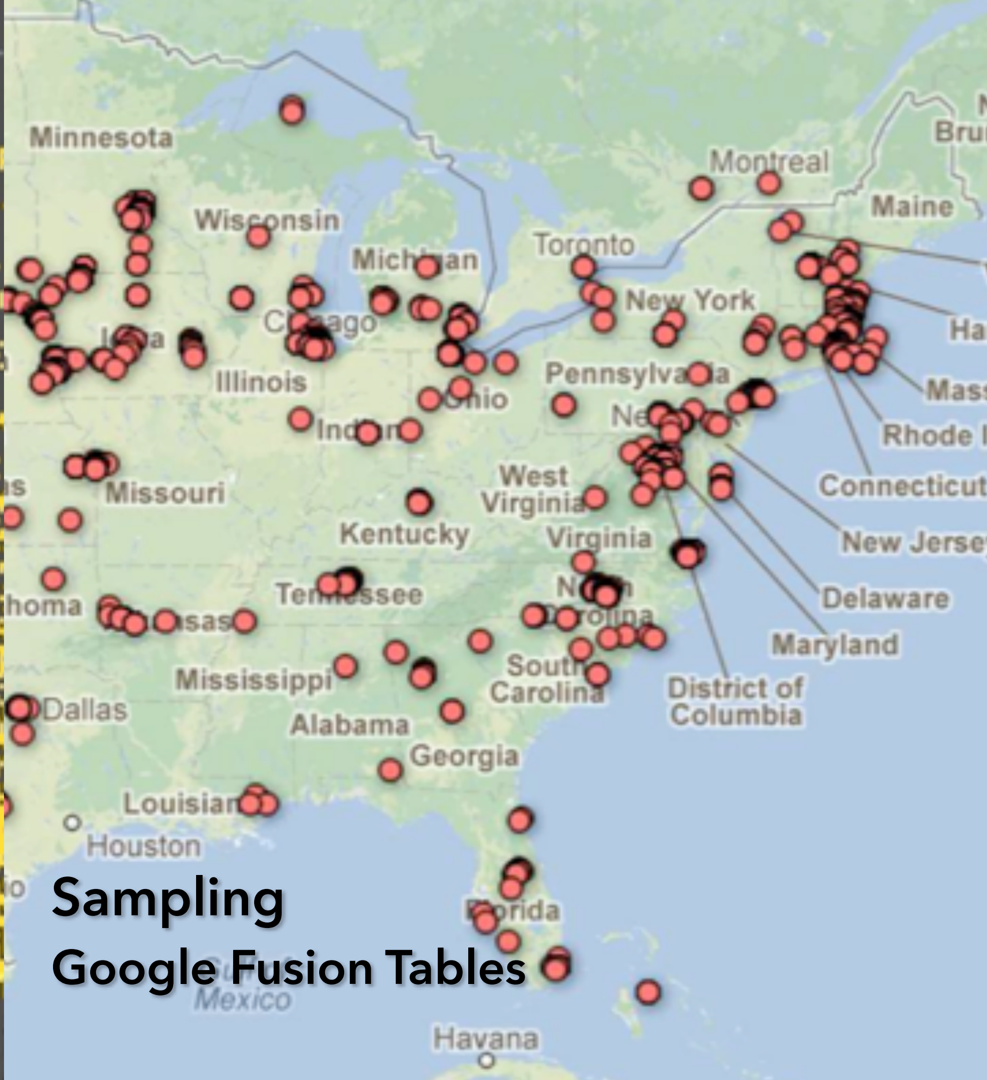
Sampling

Google Fusion Tables



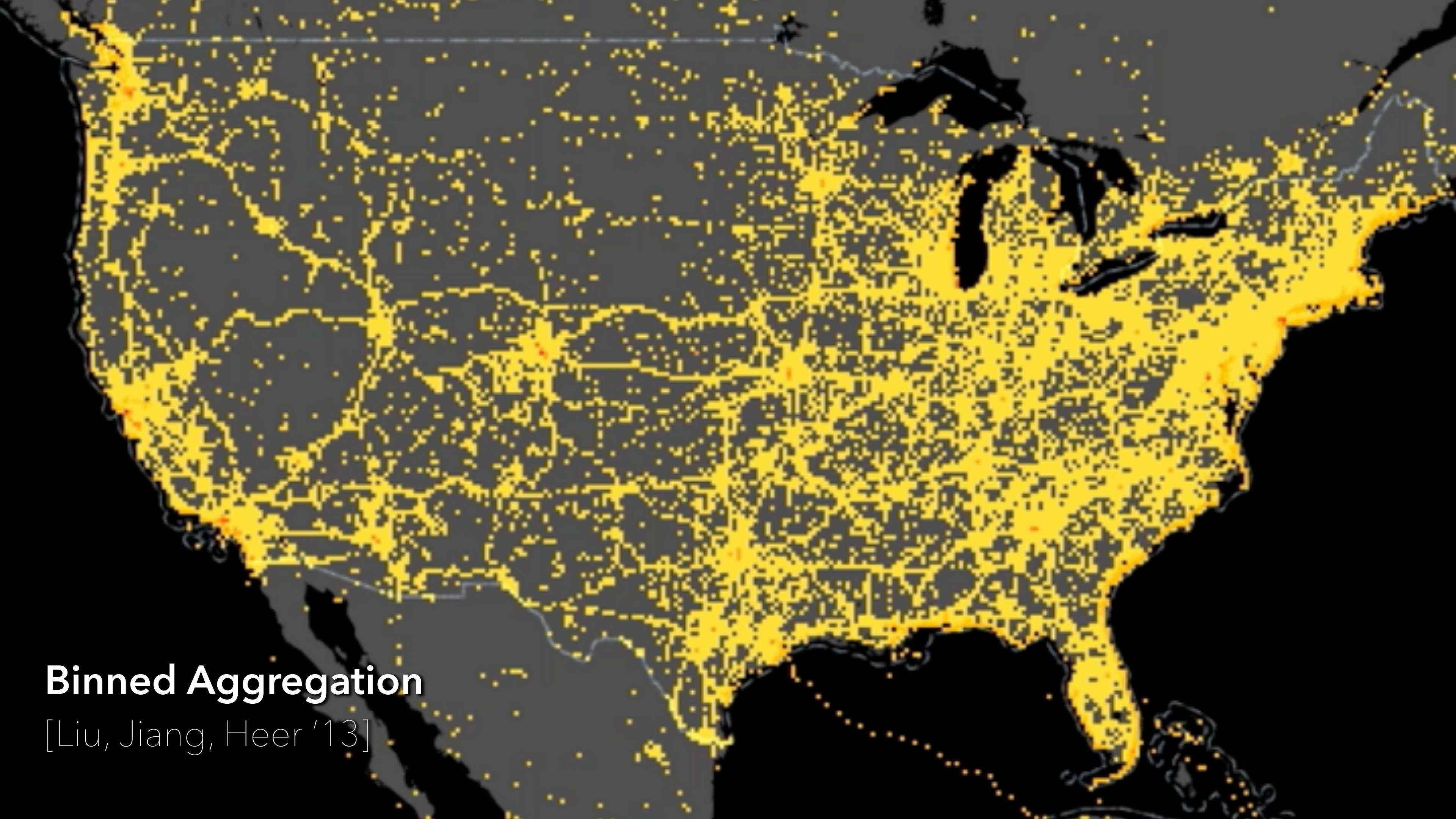
Binned Aggregation (imMens)

[Liu, Jiang, Heer '13]



Sampling

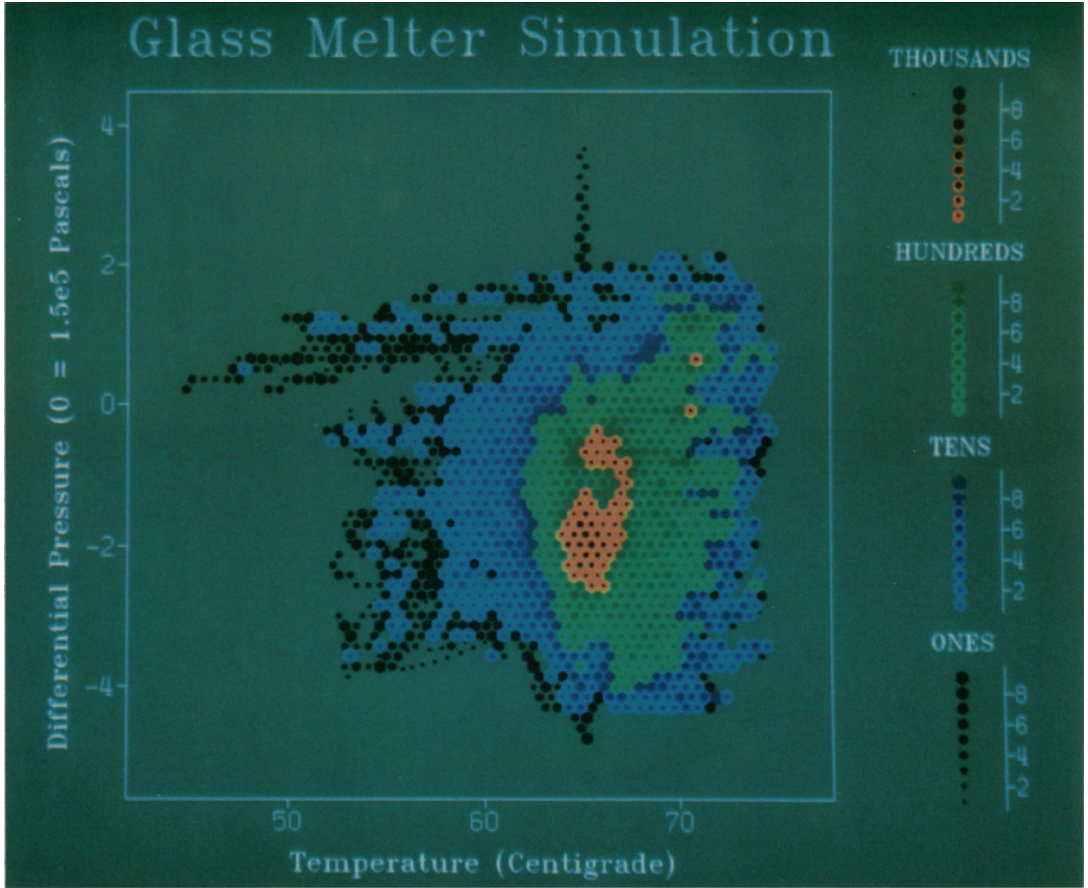
Google Fusion Tables



Binned Aggregation

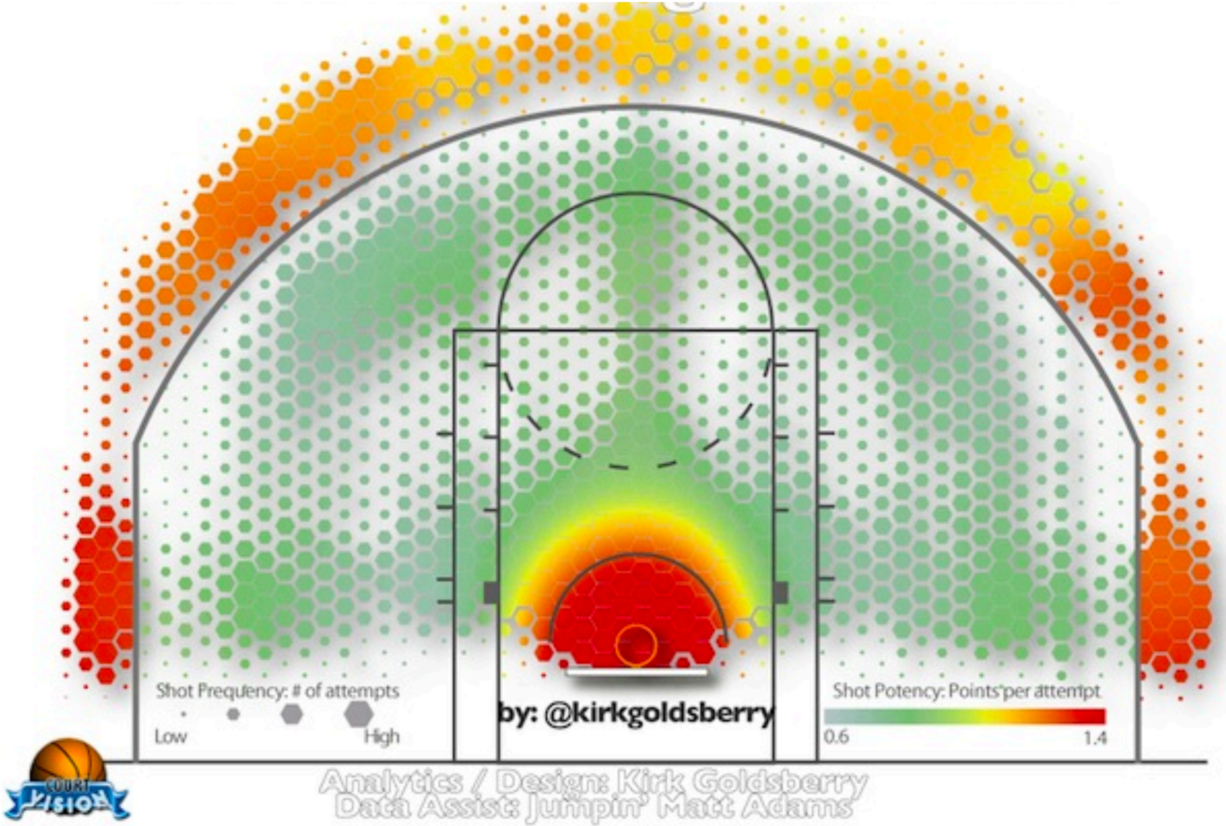
[Liu, Jiang, Heer '13]

Example: Binned Scatter Plots



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

Example: Basketball Shot Chart

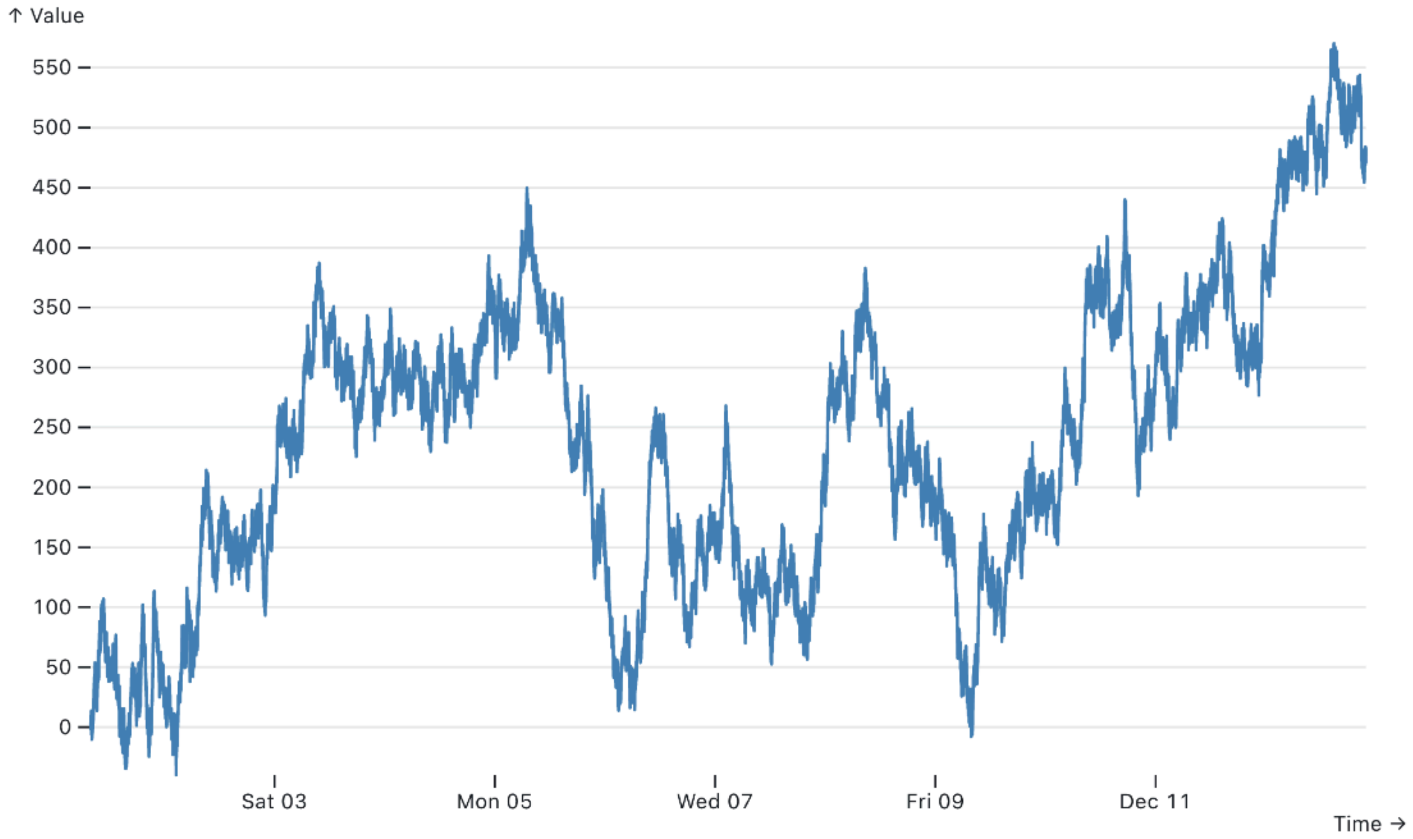


NBA Shooting 2011-12

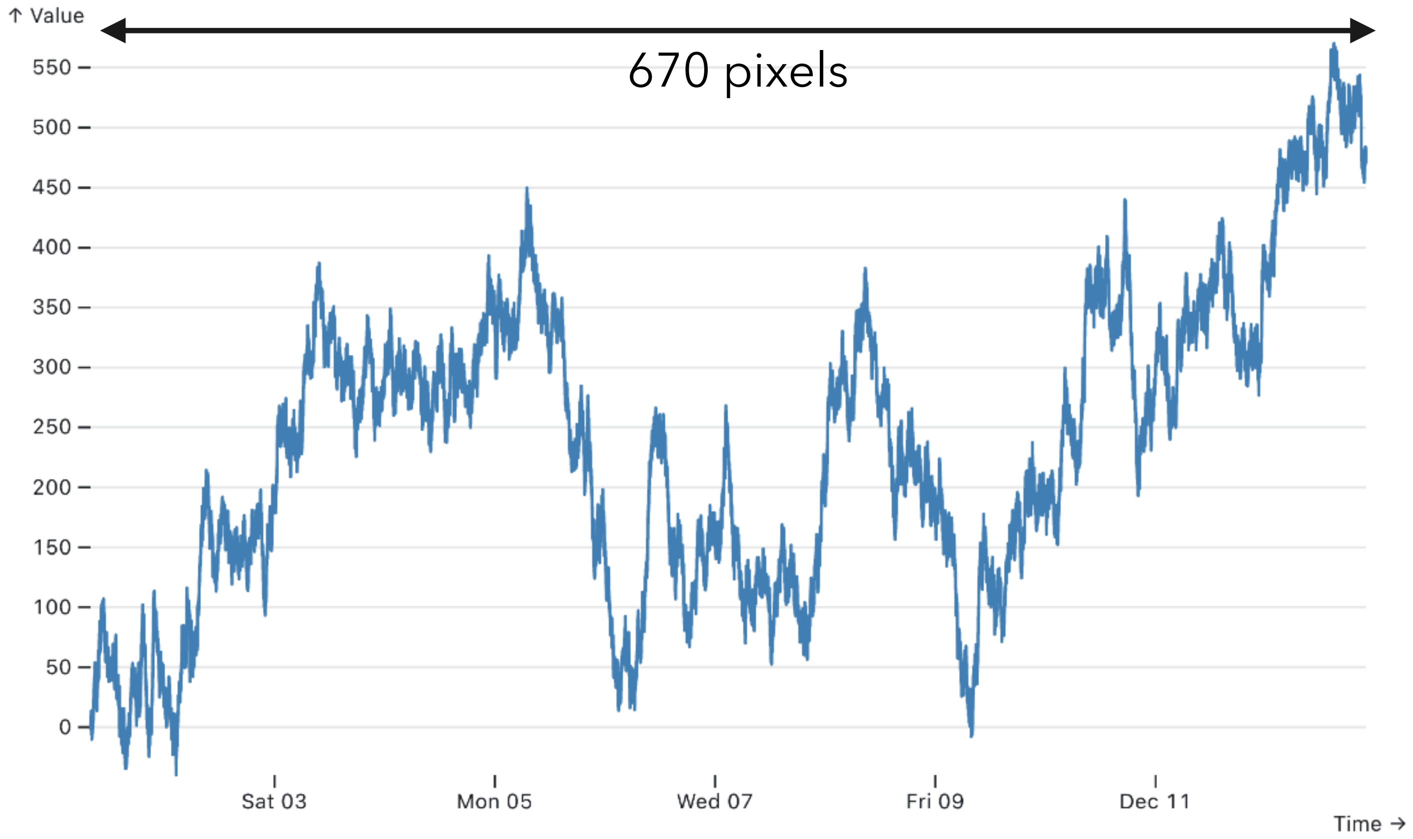
[Goldsberry]

Time Series

Time Series: 1M samples, 1 sample/second

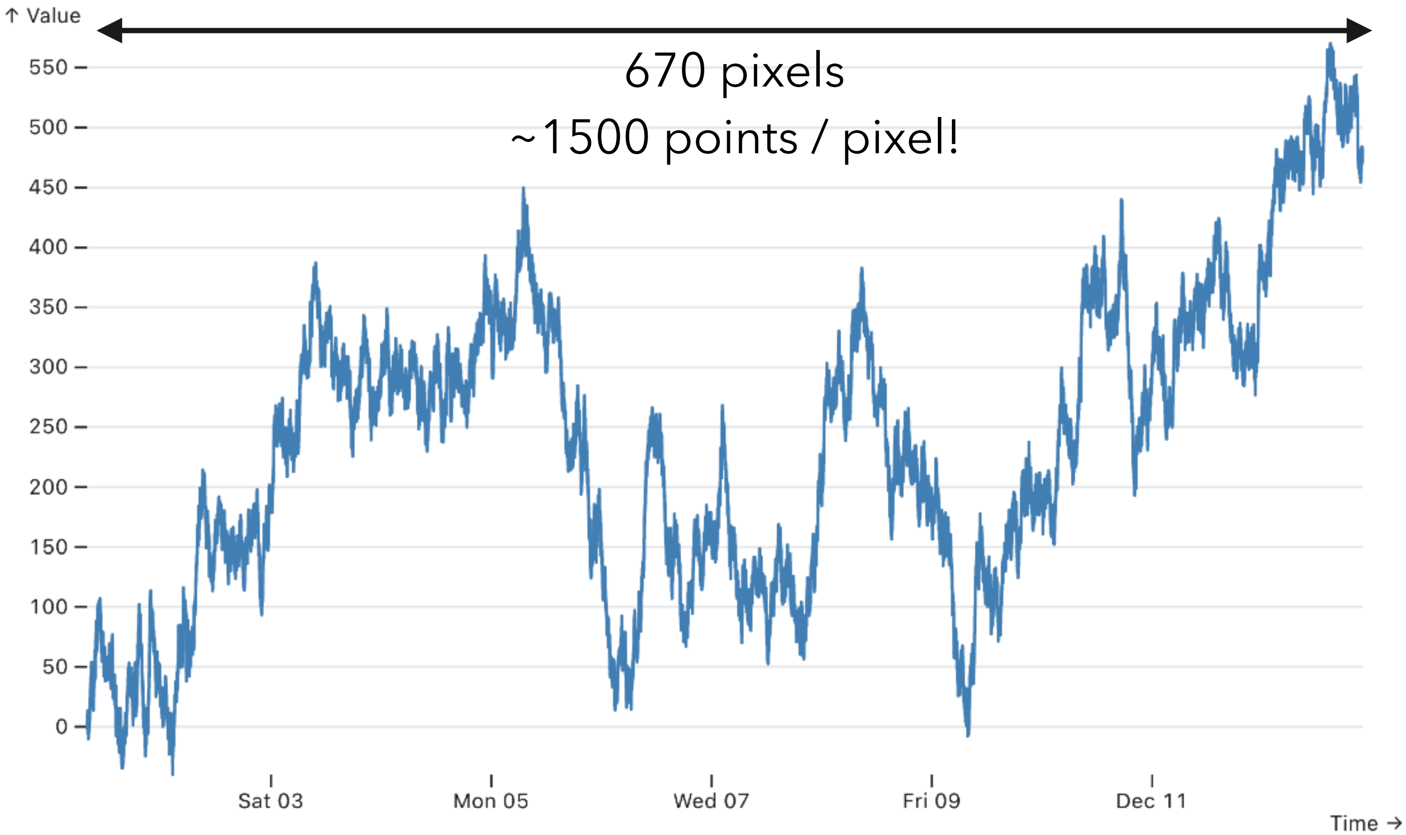


Time Series: 1M samples, 1 sample/second



670 pixels

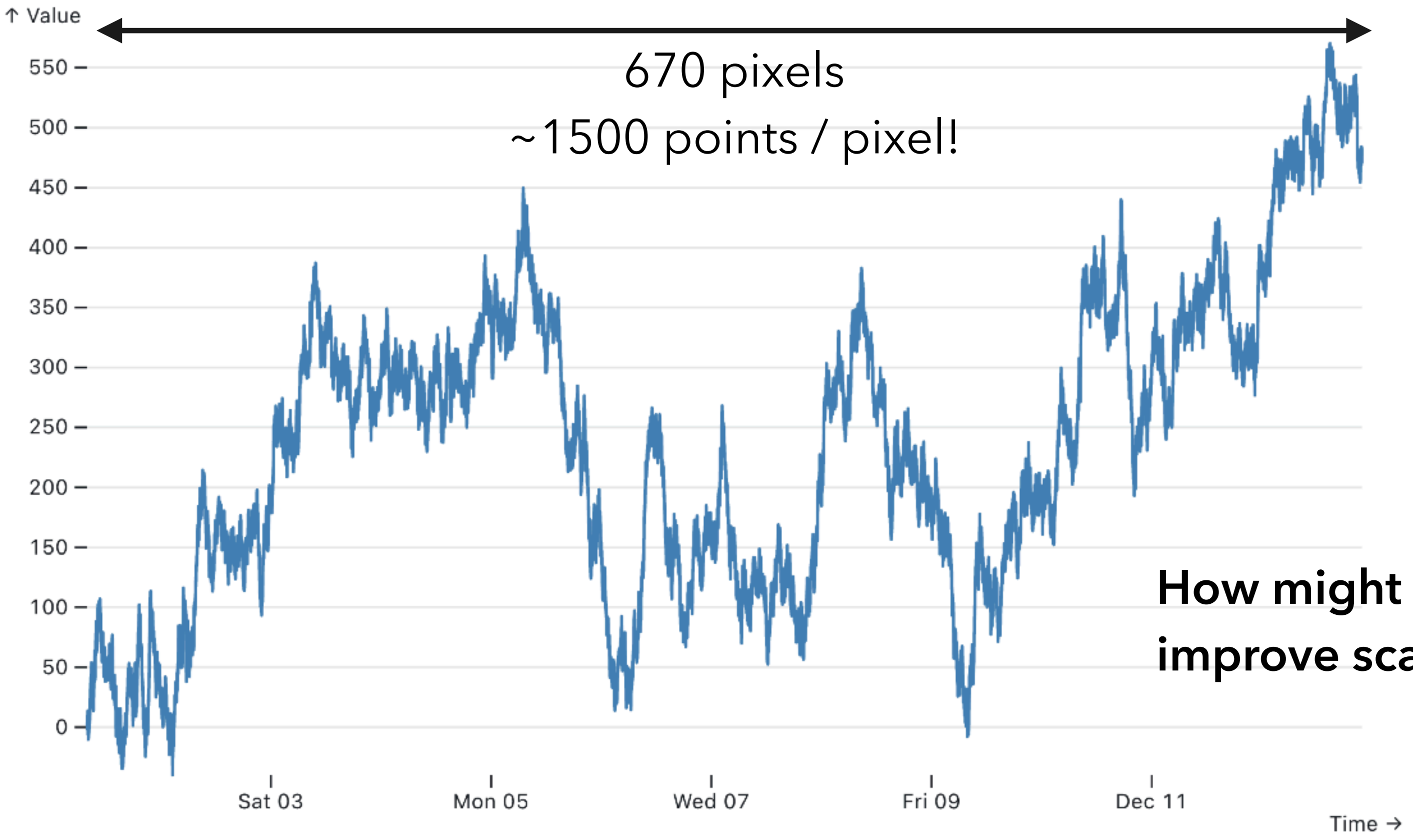
Time Series: 1M samples, 1 sample/second



670 pixels

~1500 points / pixel!

Time Series: 1M samples, 1 sample/second

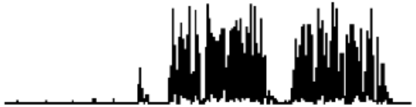


670 pixels

~1500 points / pixel!

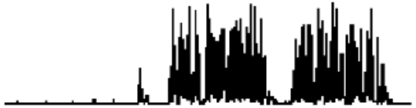
How might we improve scalability?

Time-Series Aggregation [Jugel'14]



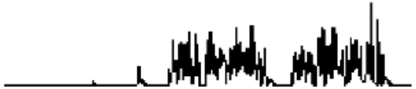
Insight: the resolution is bound by the number of pixels.

Time-Series Aggregation [Jugel'14]



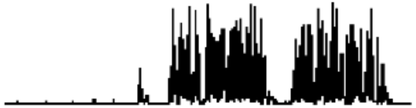
Insight: the resolution is bound by the number of pixels.

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



…this may miss extreme (min, max) values

Time-Series Aggregation [Jugel'14]



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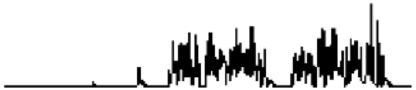
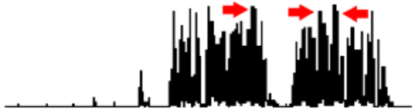


…this may miss extreme (min, max) values

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



…this does better, but still misrepresents

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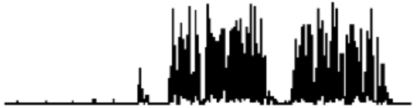

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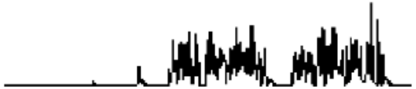

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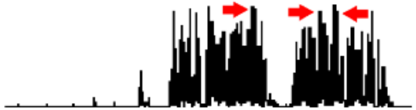
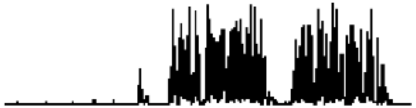


…this does better, but still misrepresents

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
```

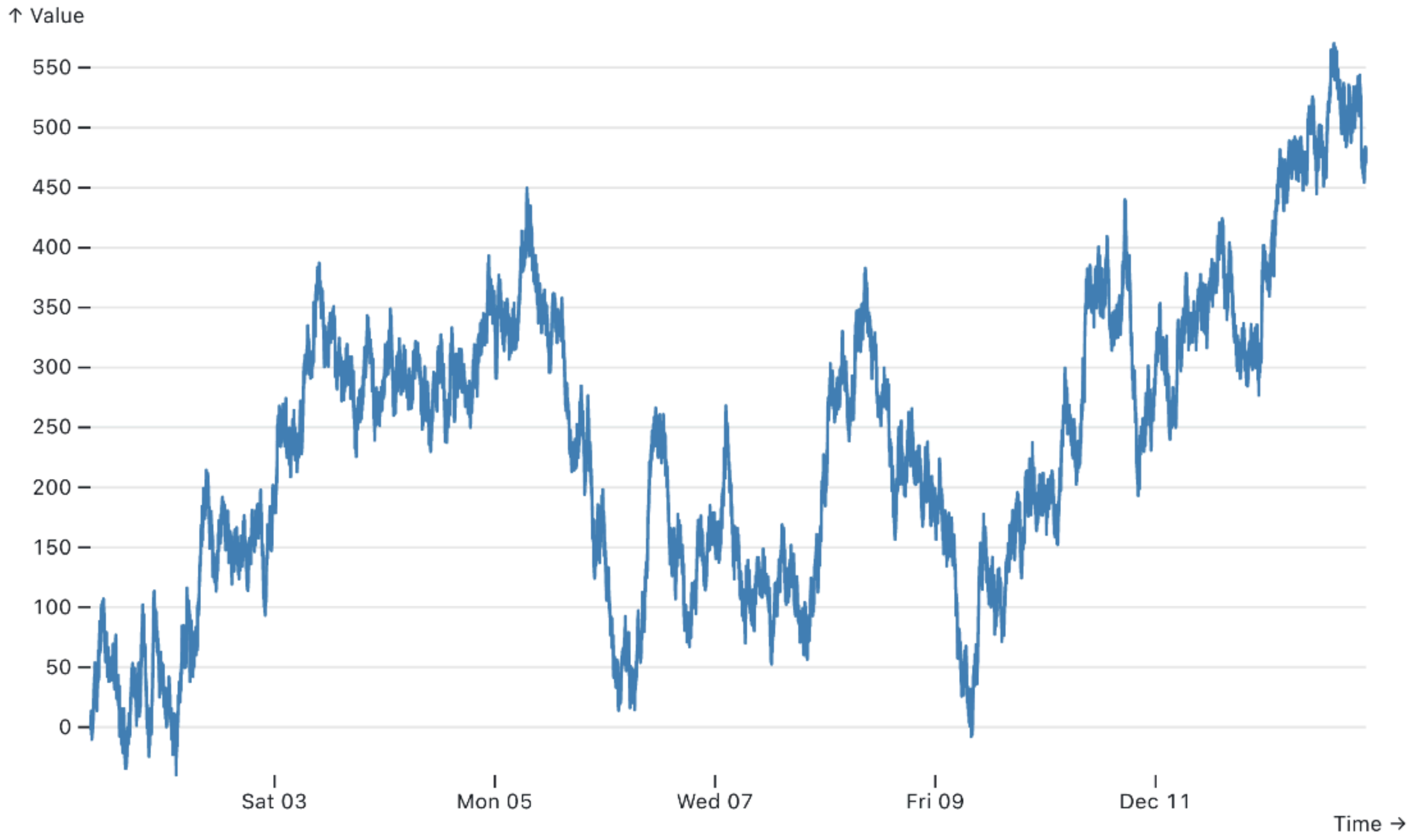
Q: query that returns a time series (t,v)

$t1, $t2: global min/max timestamps

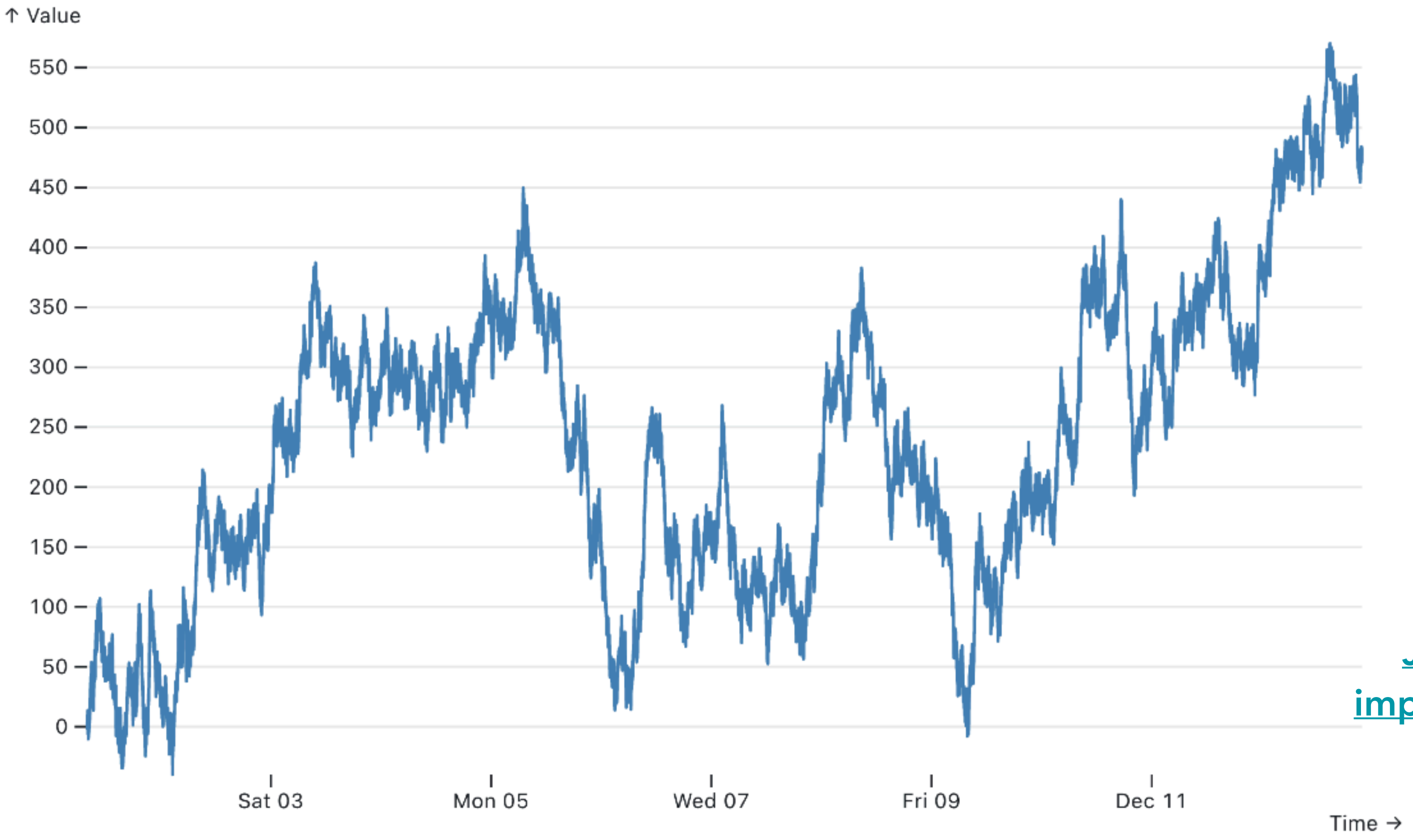
$w: chart width in pixels

$pixel = floor($w(t−$t1)/($t2−$t1))

Time Series: 1M samples, 1 sample/second

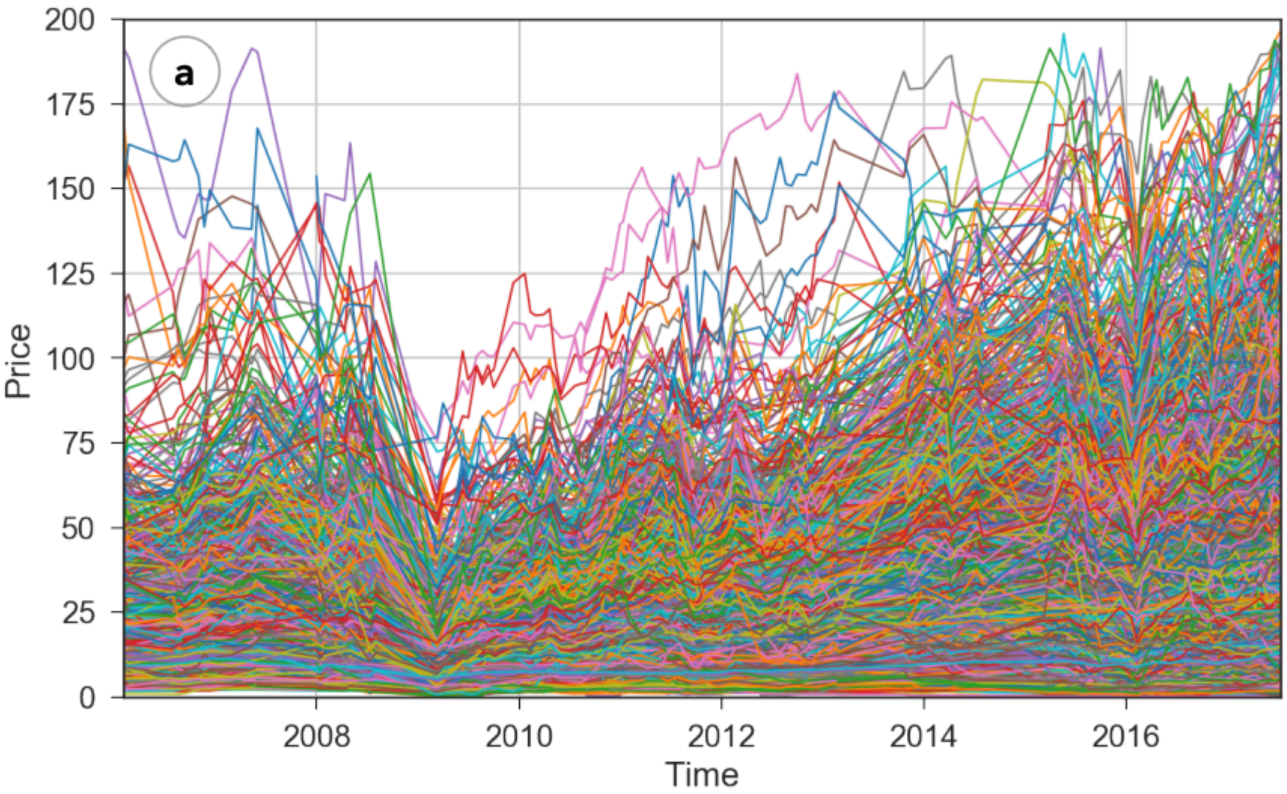


M4: 1M samples -> 2,653 plotted points



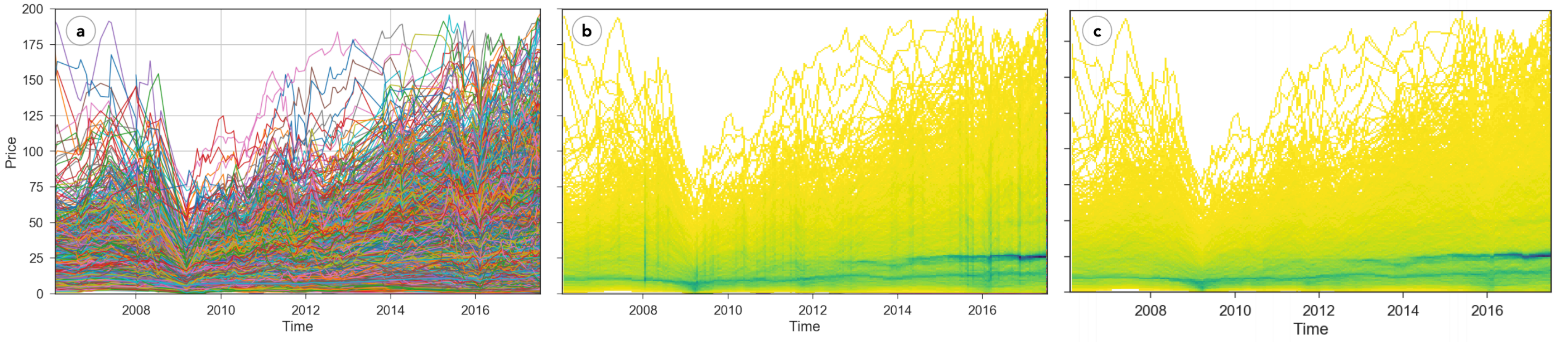
JavaScript implementation

But what about multiple time-series?



Perceptual scalability breaks down…

Density Line Chart [Moritz & Fisher]



Line Chart

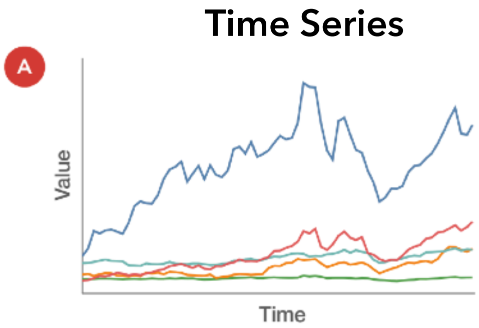
Non-Normalized Heatmap

Normalized “DenseLines”

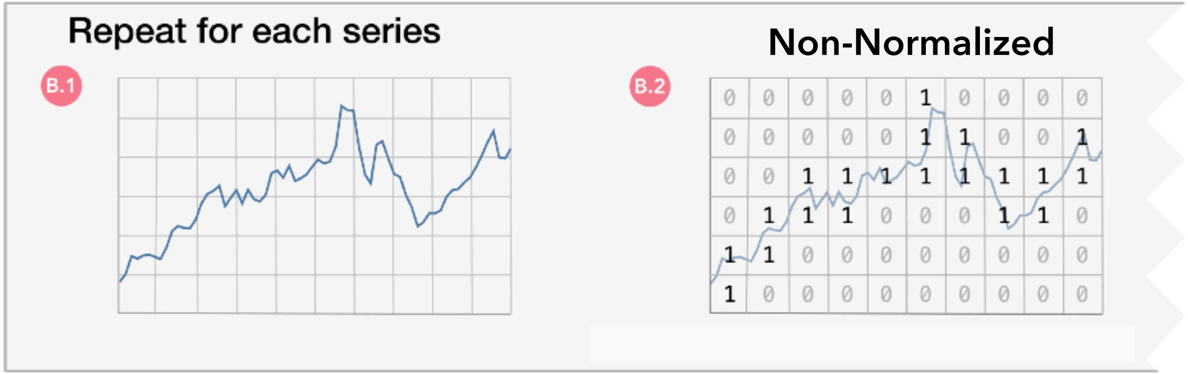
The non-normalized heatmap suffers from artifacts, seen as vertical stripes.

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]



Time Series

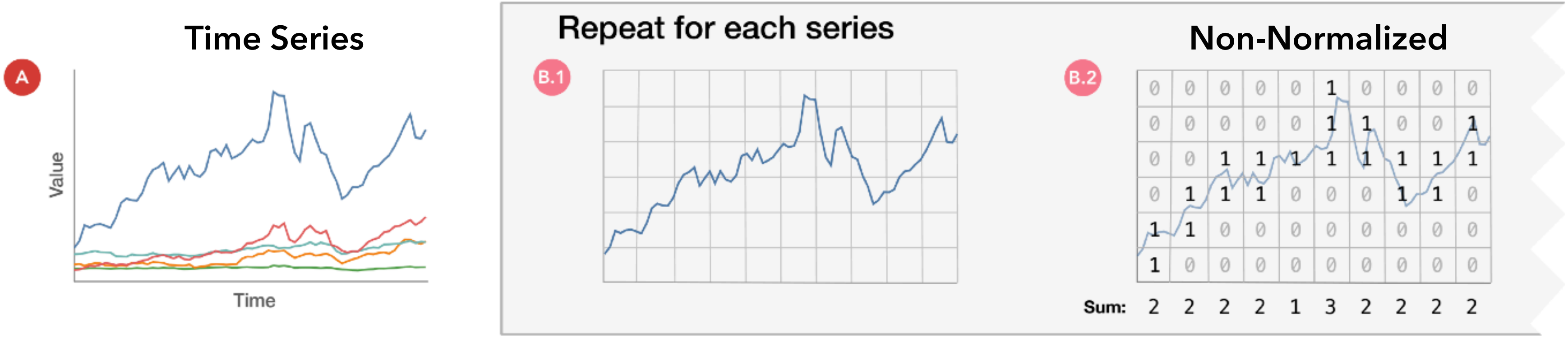


Repeat for each series

Non-Normalized

0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	1	1	0	0	1
0	0	1	1	1	1	1	1	1	1
0	1	1	1	0	0	0	1	1	0
1	1	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0

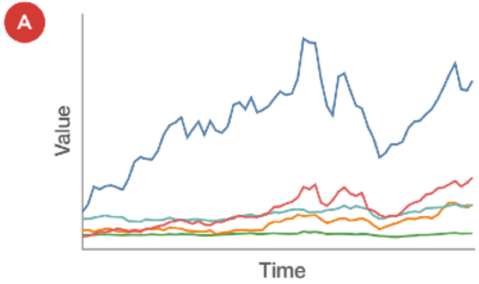
Density Line Chart [Moritz & Fisher]



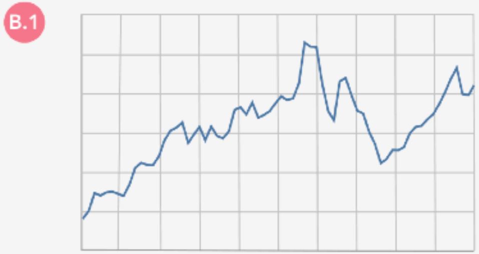
	0	0	0	0	0	1	0	0	0	0
	0	0	0	0	0	1	1	0	0	1
	0	0	1	1	1	1	1	1	1	1
	0	1	1	1	0	0	0	1	1	0
	1	1	0	0	0	0	0	0	0	0
	1	0	0	0	0	0	0	0	0	0
Sum:	2	2	2	2	1	3	2	2	2	2

Density Line Chart [Moritz & Fisher]

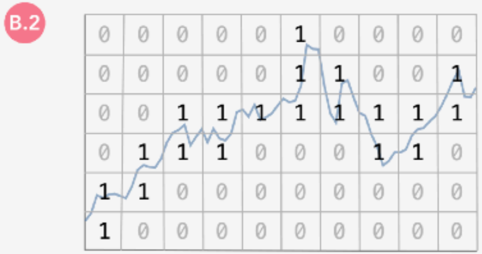
Time Series



Repeat for each series



Non-Normalized



	0	0	0	0	0	1	0	0	0	0
	0	0	0	0	0	1	1	0	0	1
	0	0	1	1	1	1	1	1	1	1
	0	1	1	1	0	0	0	1	1	0
	1	1	0	0	0	0	0	0	0	0
	1	0	0	0	0	0	0	0	0	0
Sum:	2	2	2	2	1	3	2	2	2	2

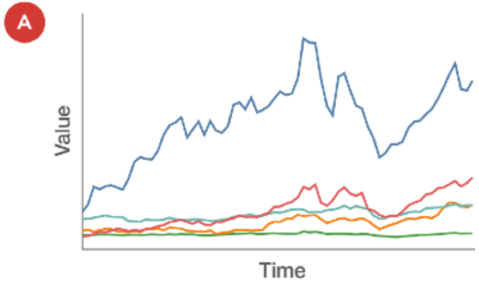
B.3

0	0	0	0	0	0.3	0	0	0	0
0	0	0	0	0	0.3	0.5	0	0	0.5
0	0	0.5	0.5	0.5	0.3	0.5	0.5	0.5	0.5
0	0.5	0.5	0.5	0	0	0	0.5	0.5	0
0.5	0.5	0	0	0	0	0	0	0	0
0.5	0	0	0	0	0	0	0	0	0

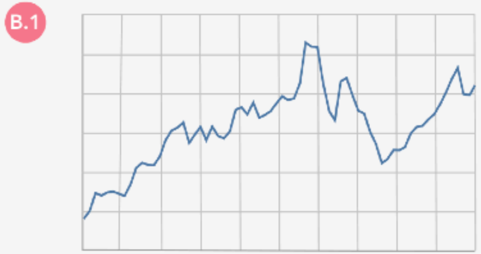
Approx. Arc-Length Normalized

Density Line Chart [Moritz & Fisher]

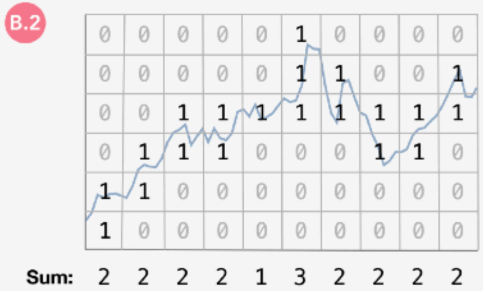
Time Series



Repeat for each series



Non-Normalized



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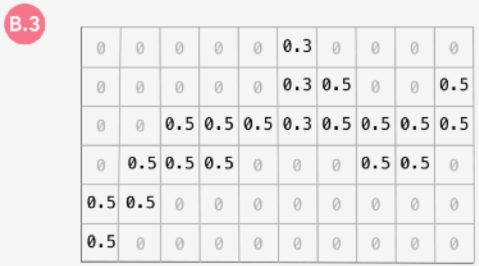
	0	0	1	1	1	1	1	1	1	1
	0	1	1	1	0	0	0	1	1	0
	1	1	0	0	0	0	0	0	0	0
	1	0	0	0	0	0	0	0	0	0
Sum:	2	2	2	2	1	3	2	2	2	2



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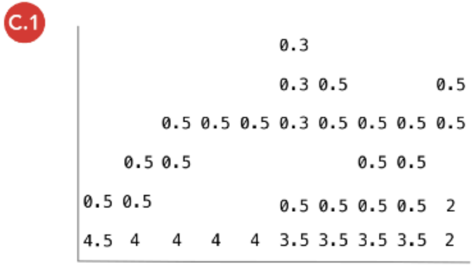
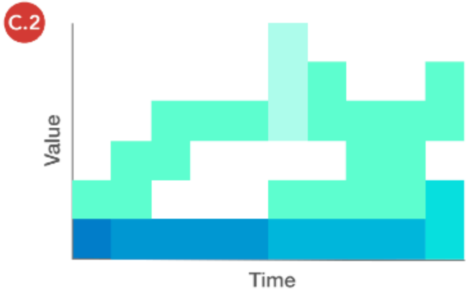
0	0	0	0	0	0.3	0.5	0	0	0.5
0	0	0.5	0.5	0.5	0.3	0.5	0.5	0.5	0.5
0	0.5	0.5	0.5	0	0	0	0.5	0.5	0
0.5	0.5	0	0	0	0	0	0	0	0
0.5	0	0	0	0	0	0	0	0	0



					0.3				
					0.3	0.5			0.5
		0.5	0.5	0.5	0.3	0.5	0.5	0.5	0.5
	0.5	0.5					0.5	0.5	
0.5	0.5				0.5	0.5	0.5	0.5	2
4.5	4	4	4	4	3.5	3.5	3.5	3.5	2

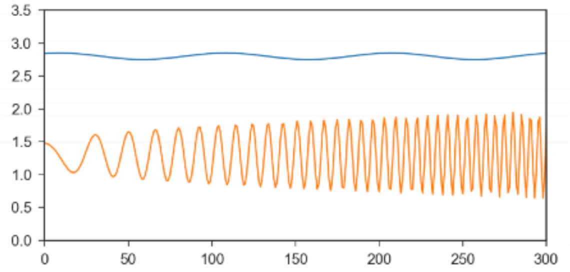


Approx. Arc-Length Normalized

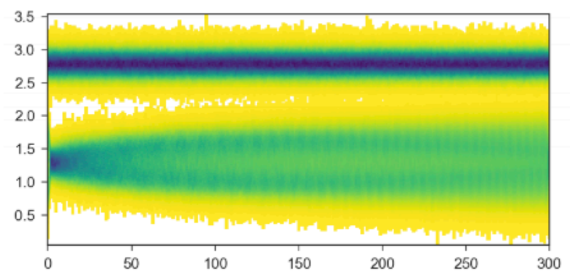
Aggregate

Color

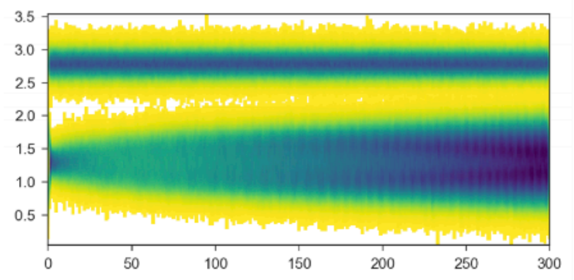
Density Line Chart [Moritz & Fisher]



Example Time Series



10k Series, Normalized



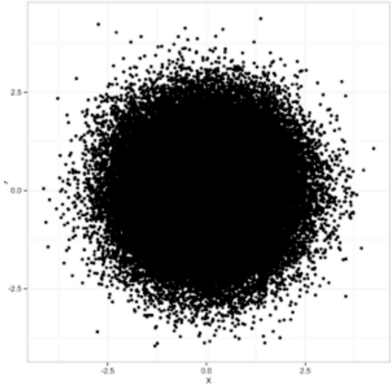
10k Series, Non-Normalized

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

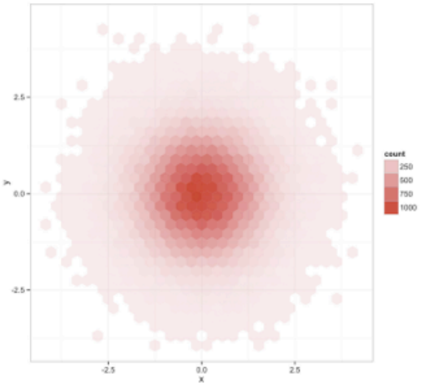
Without normalization, the steep lines are over-represented.

Design Subtleties

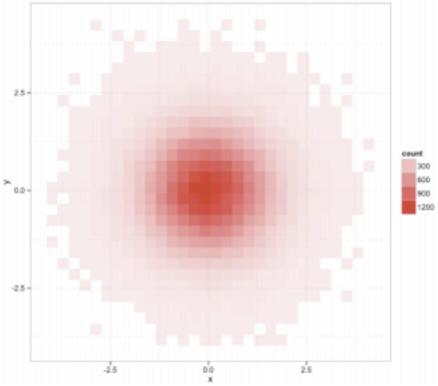
Hexagonal or Rectangular Bins?



100,000 Data Points



Hexagonal Bins

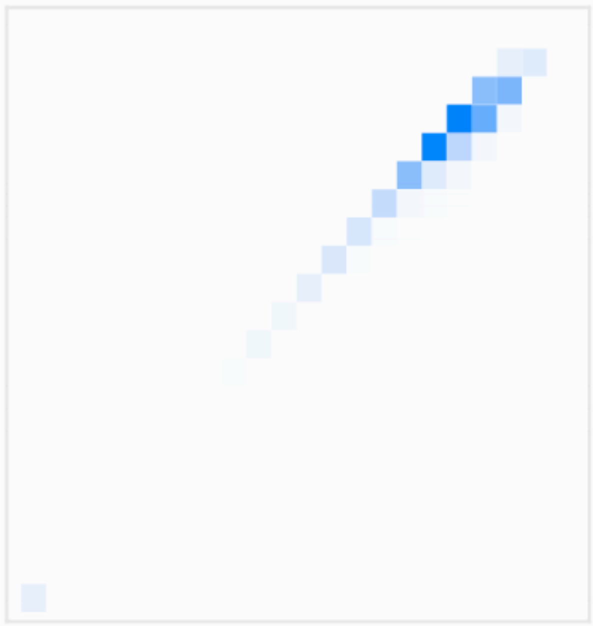


Rectangular Bins

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

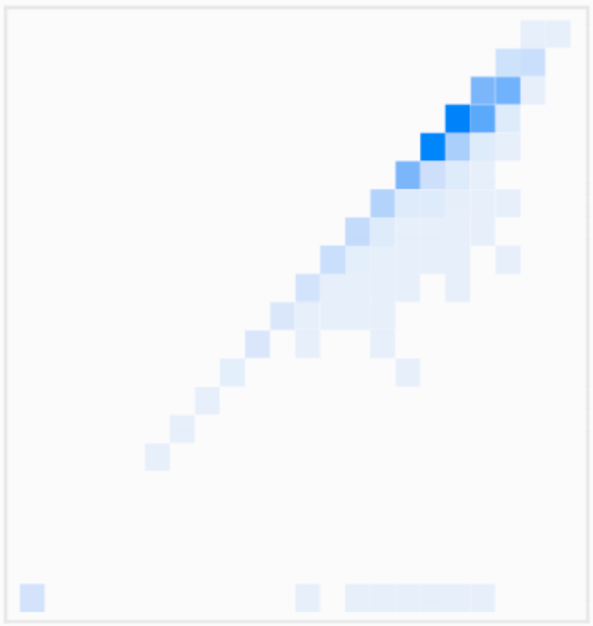
Rectangles support *reuse* and *visual queries*.

Color Scale: Discontinuity after Zero



Standard Color Ramp

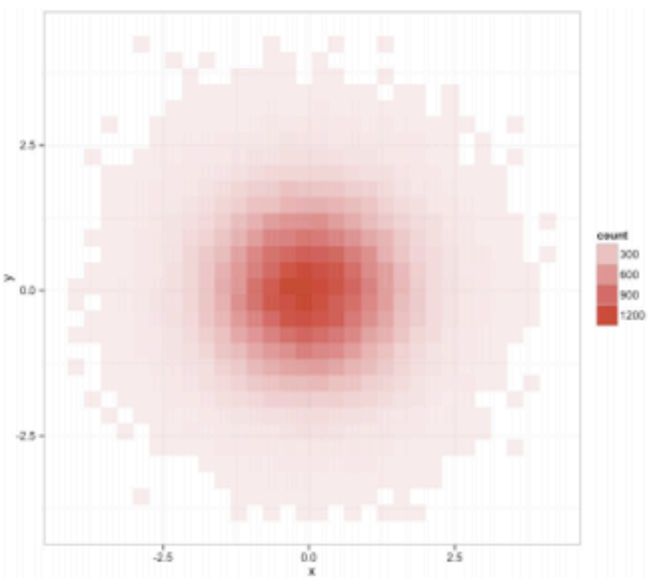
Counts near zero are white.



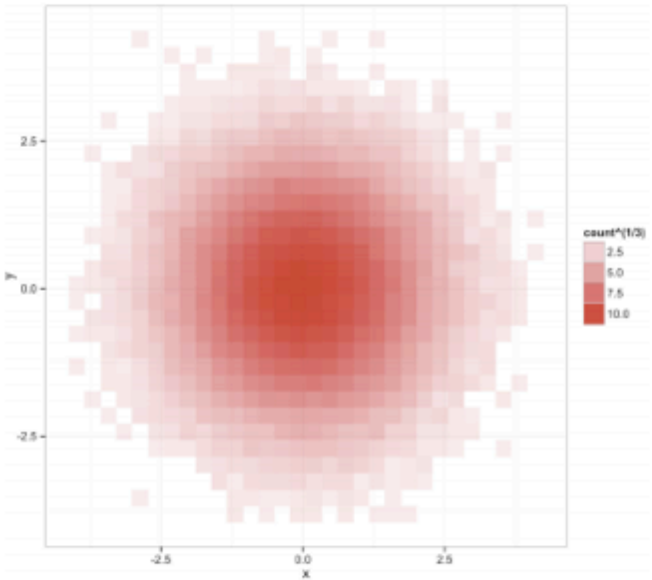
Add Discontinuity after Zero

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 Nov 8~~
Prototype	**Wed Nov 20**
Demo Video	Wed Dec 4
Video Showcase	Thu Dec 5 (in class)
Deliverables	Mon Dec 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.

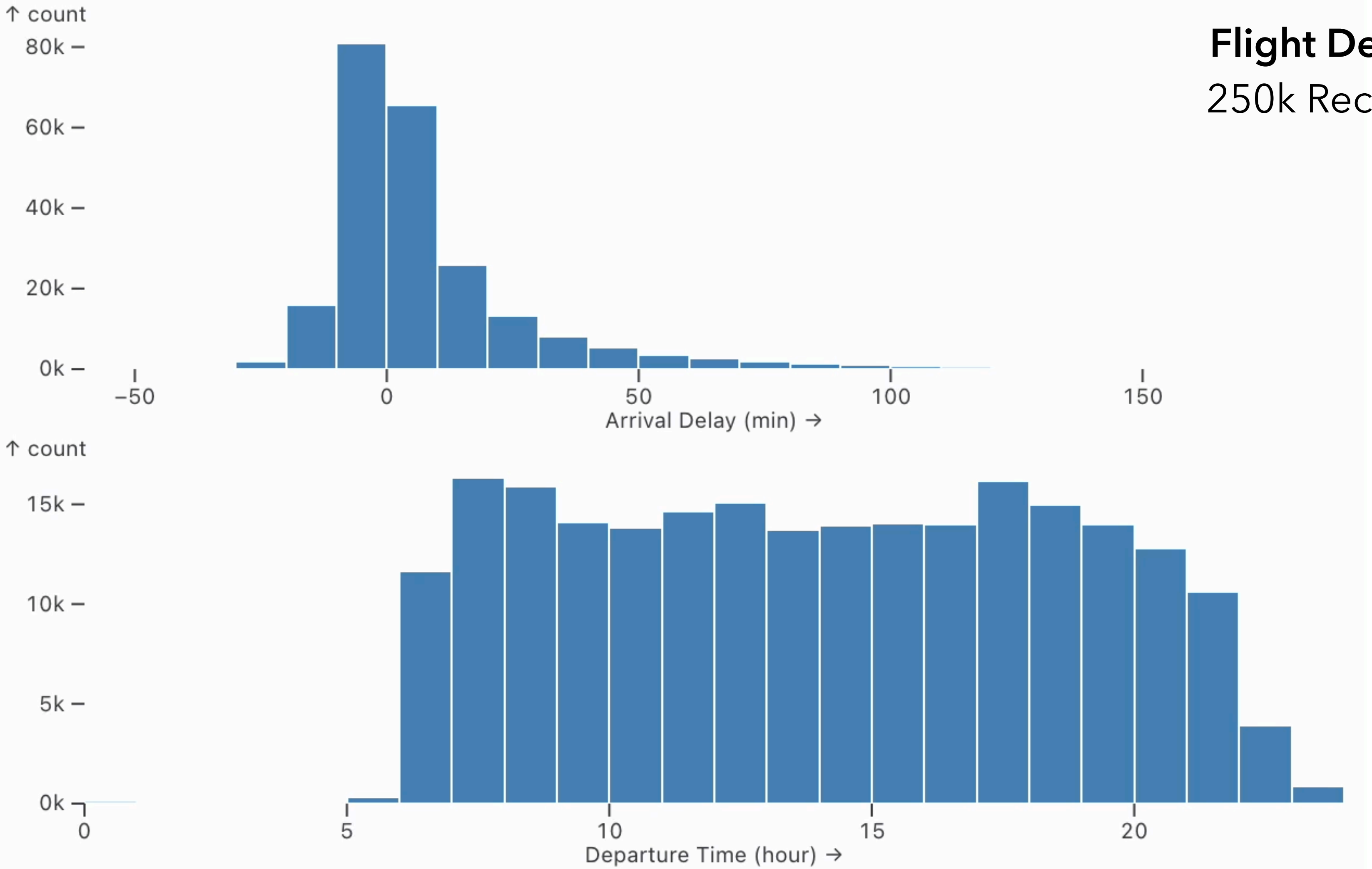
You **are** expected to provide prototype work that communicates your design goals. For example: initial visualizations, sketches, storyboards, and text annotations / idea descriptions.

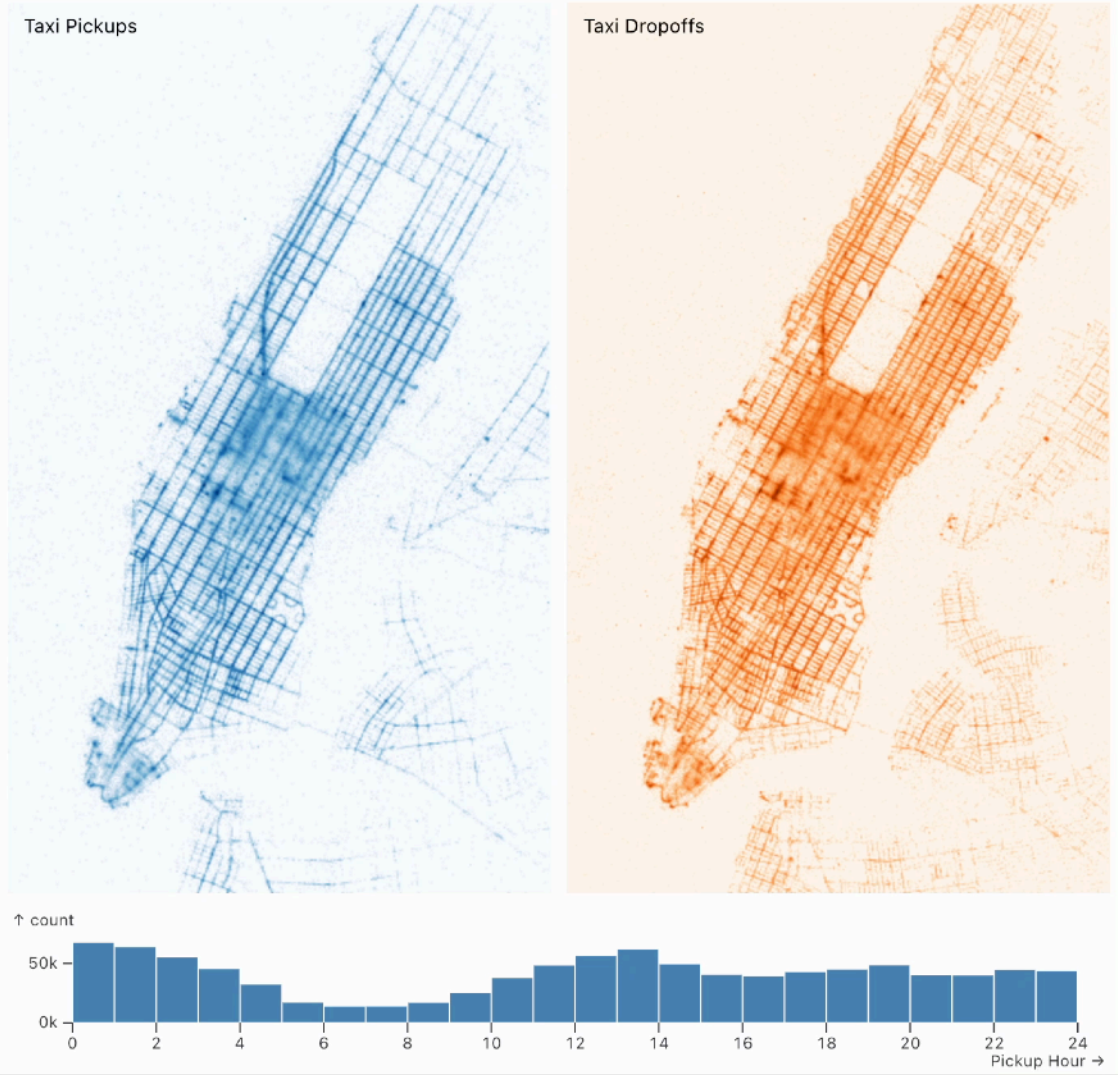
One should get a sense of what you intend to ultimately submit! Also feel free to post questions.

Scalable Interaction

Flight Delays

250k Records

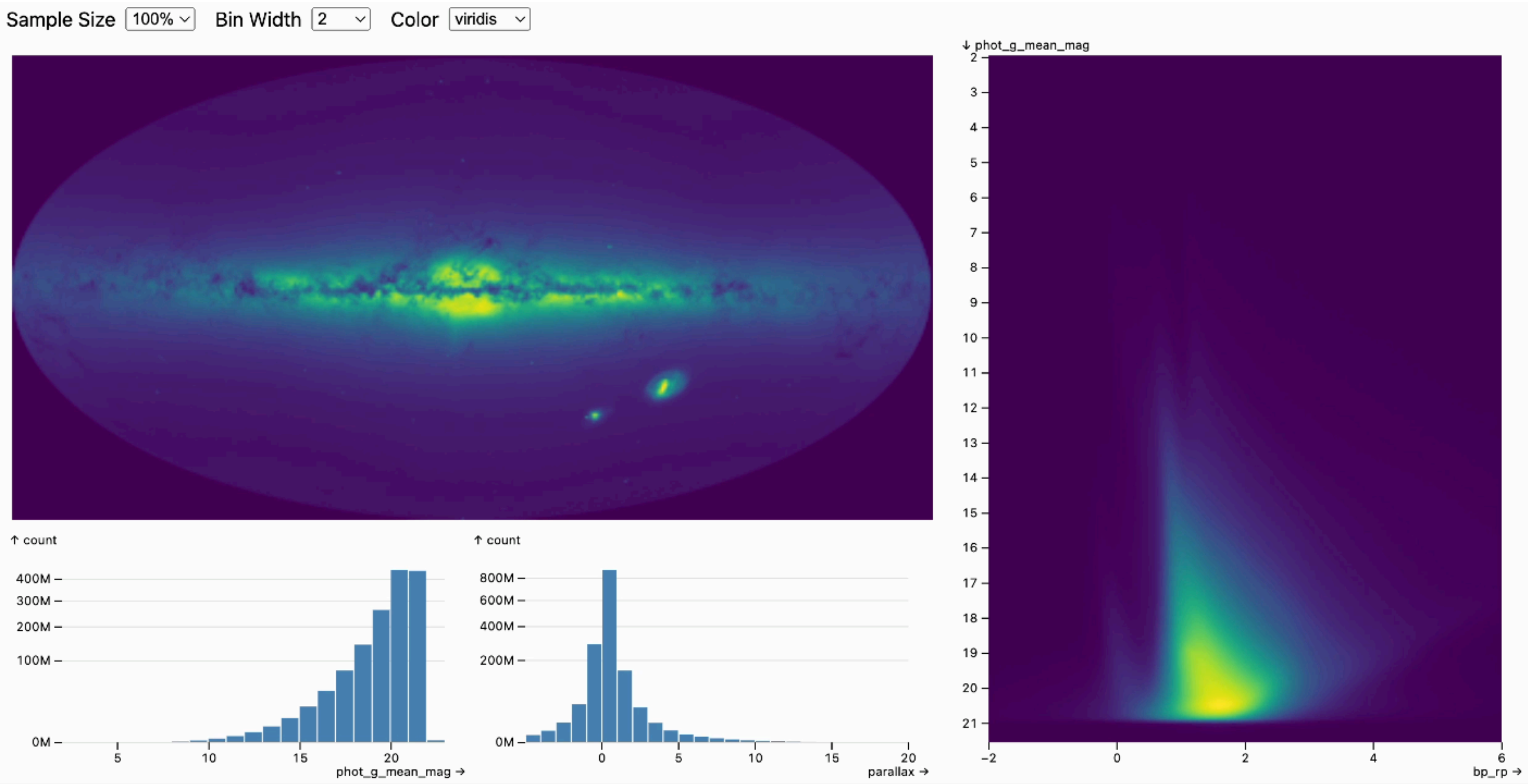




NY Taxi Rides

1M Records

Jan 1-3, 2010

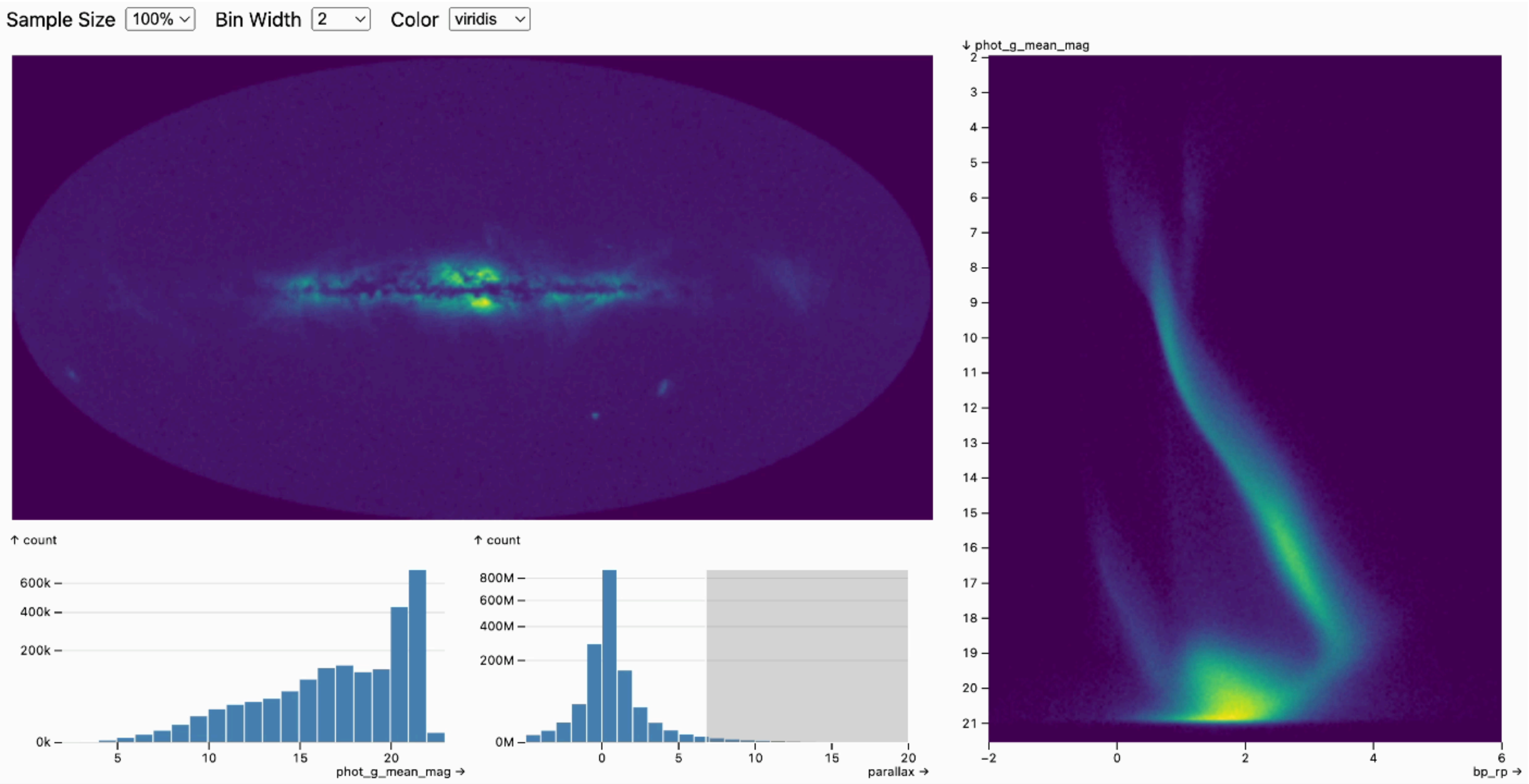


Sample Size 100%

Bin Width 2

Color viridis

Gaia Star Catalog · 1.8B Records



Sample Size 100%

Bin Width 2

Color viridis

Gaia Star Catalog · 1.8B Records

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**

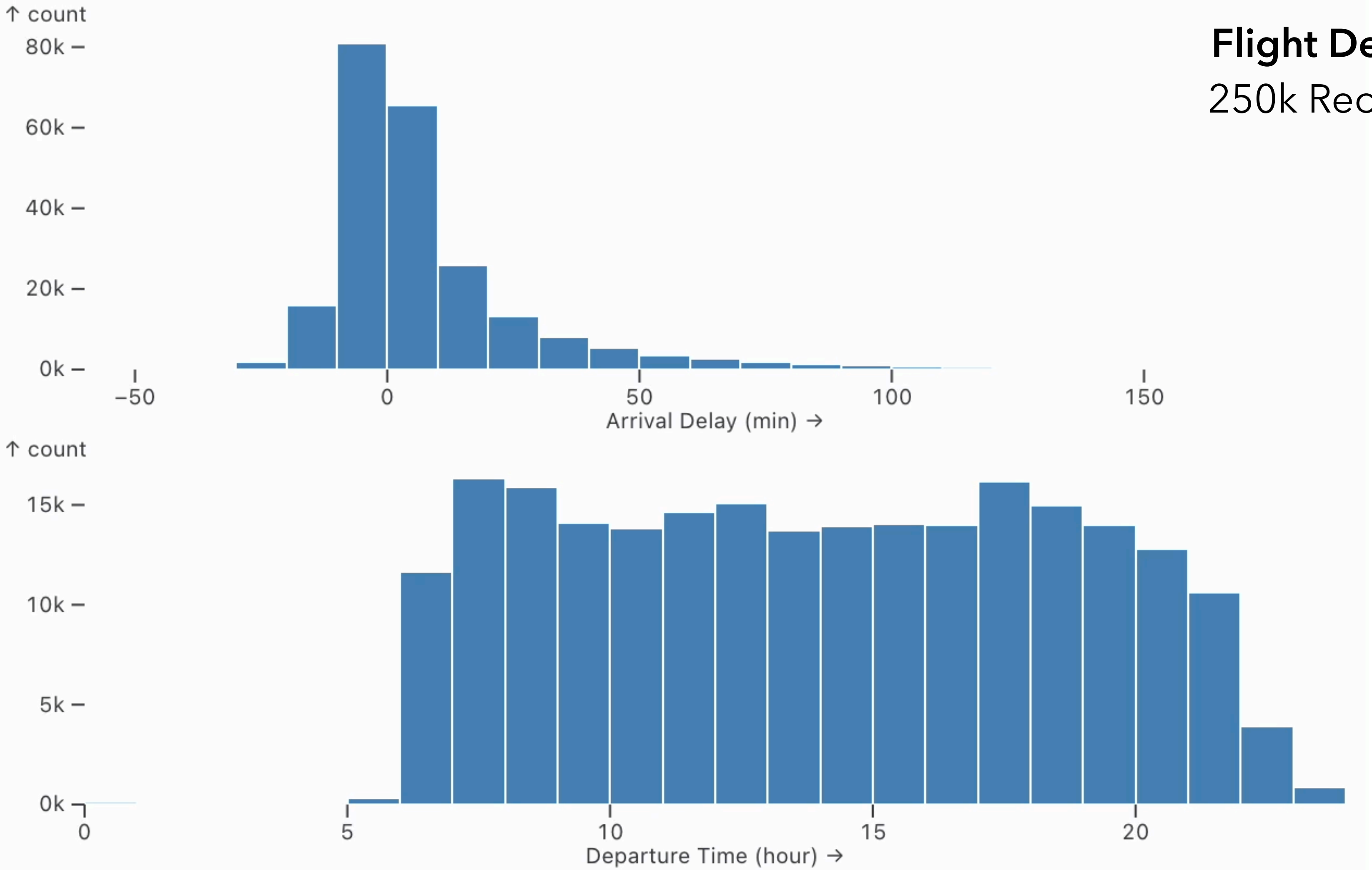
These strategies are **not** mutually exclusive!

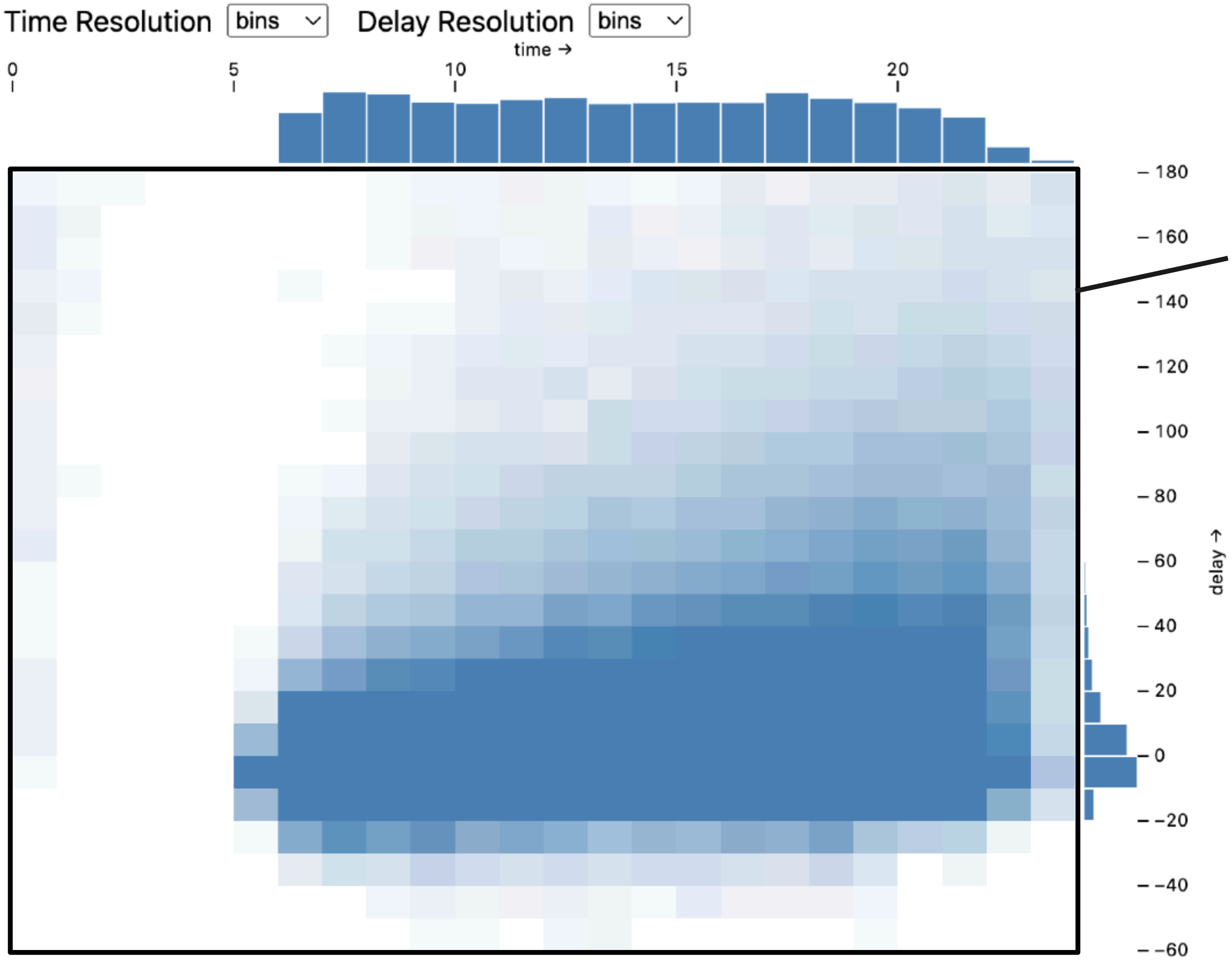
Systems can apply them in tandem.

Client-Side Indexes

Flight Delays

250k Records





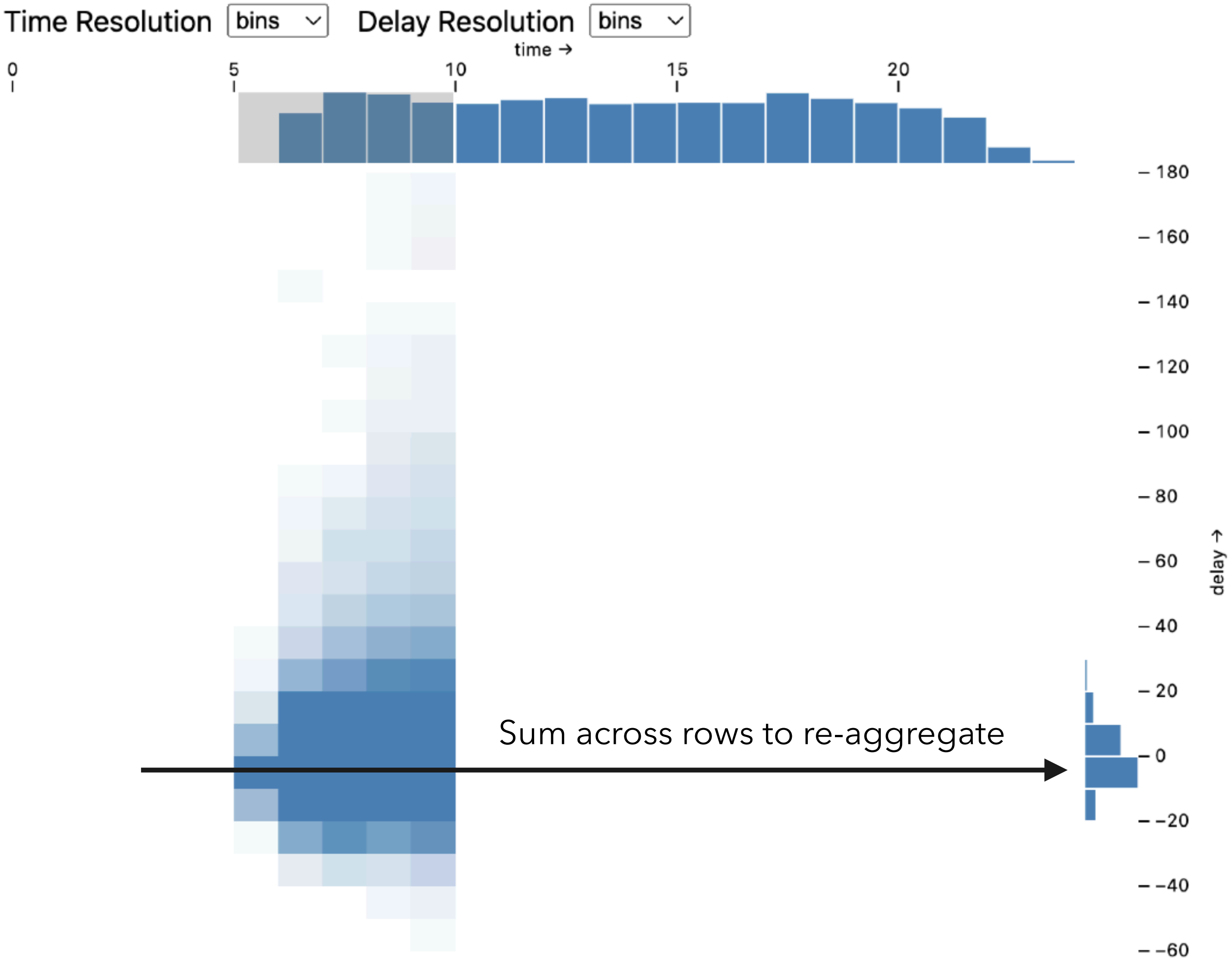
Flight Delays

250k Records

Preaggregate

Flight Delays

250k Records



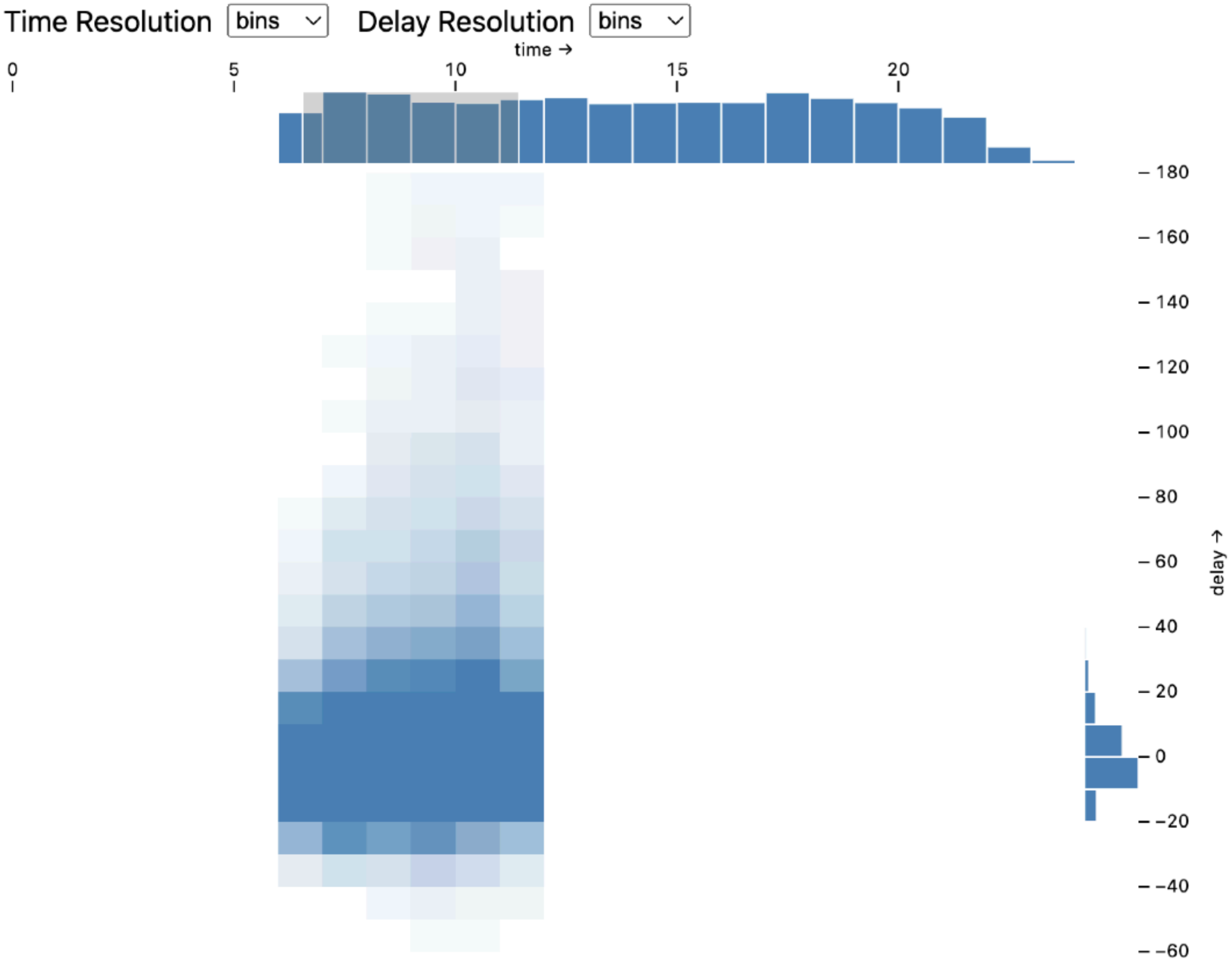
Time Resolution bins

Delay Resolution bins

Sum across rows to re-aggregate

Flight Delays

250k Records

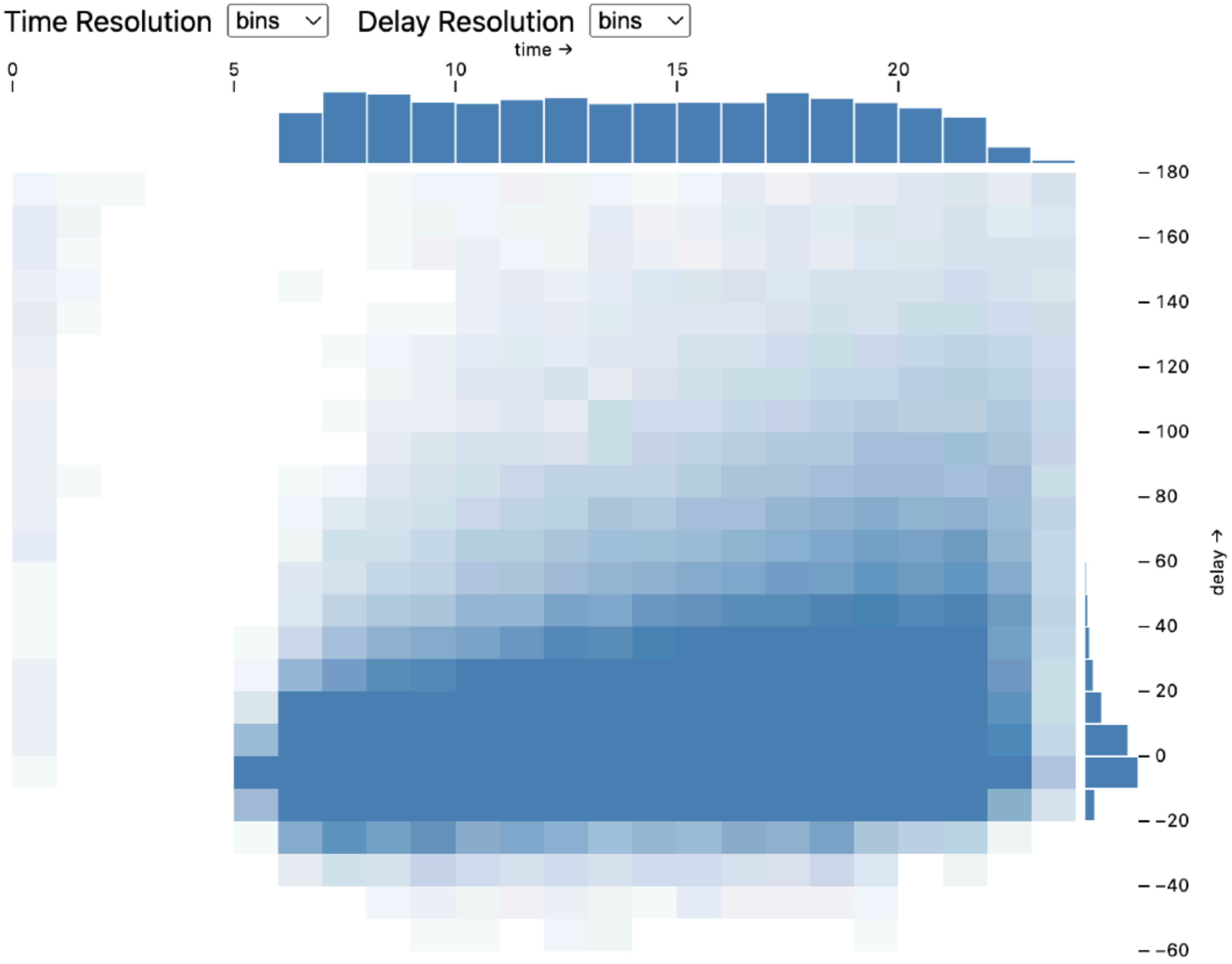


Time Resolution bins

Delay Resolution bins

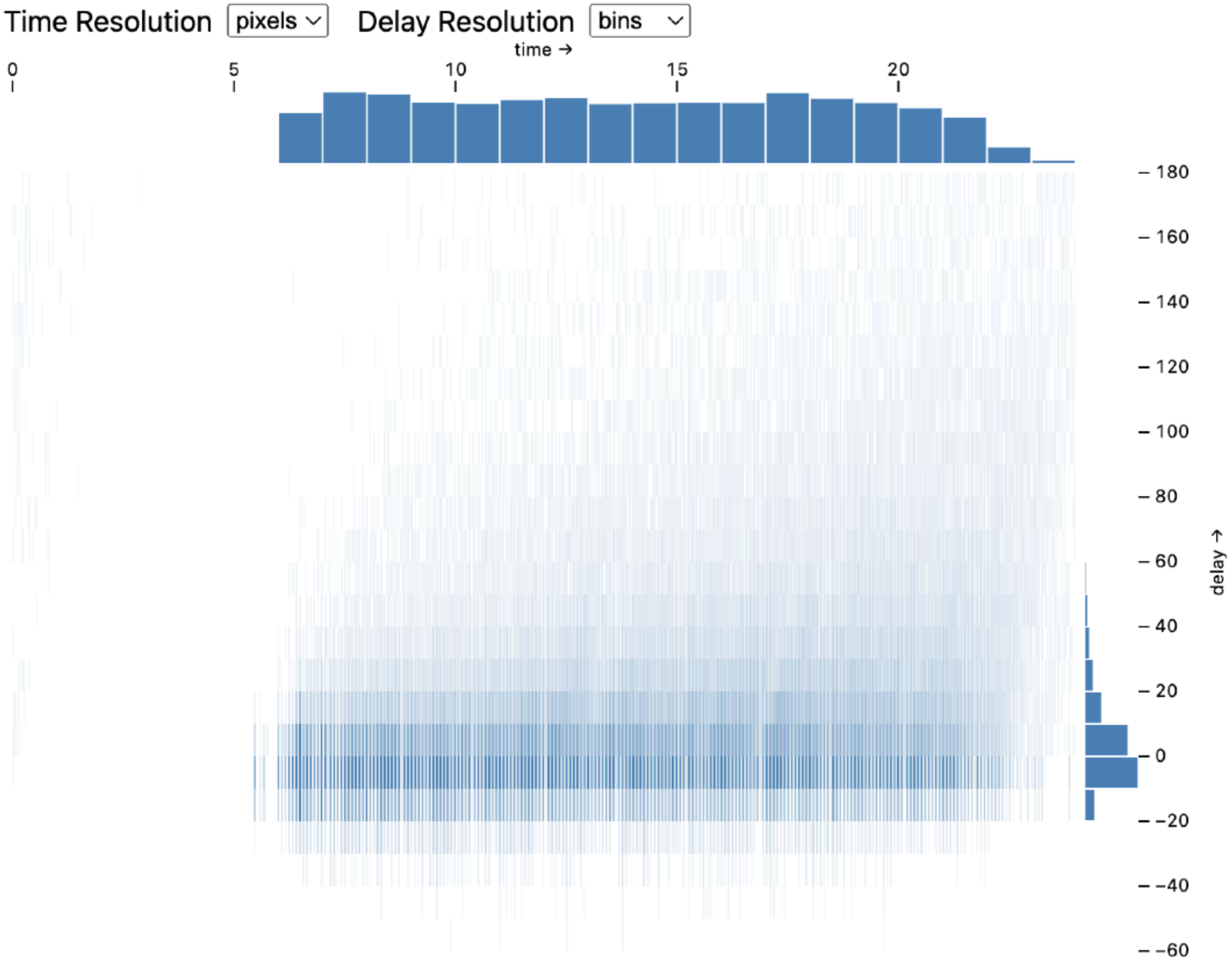
Flight Delays

250k Records



Flight Delays

250k Records

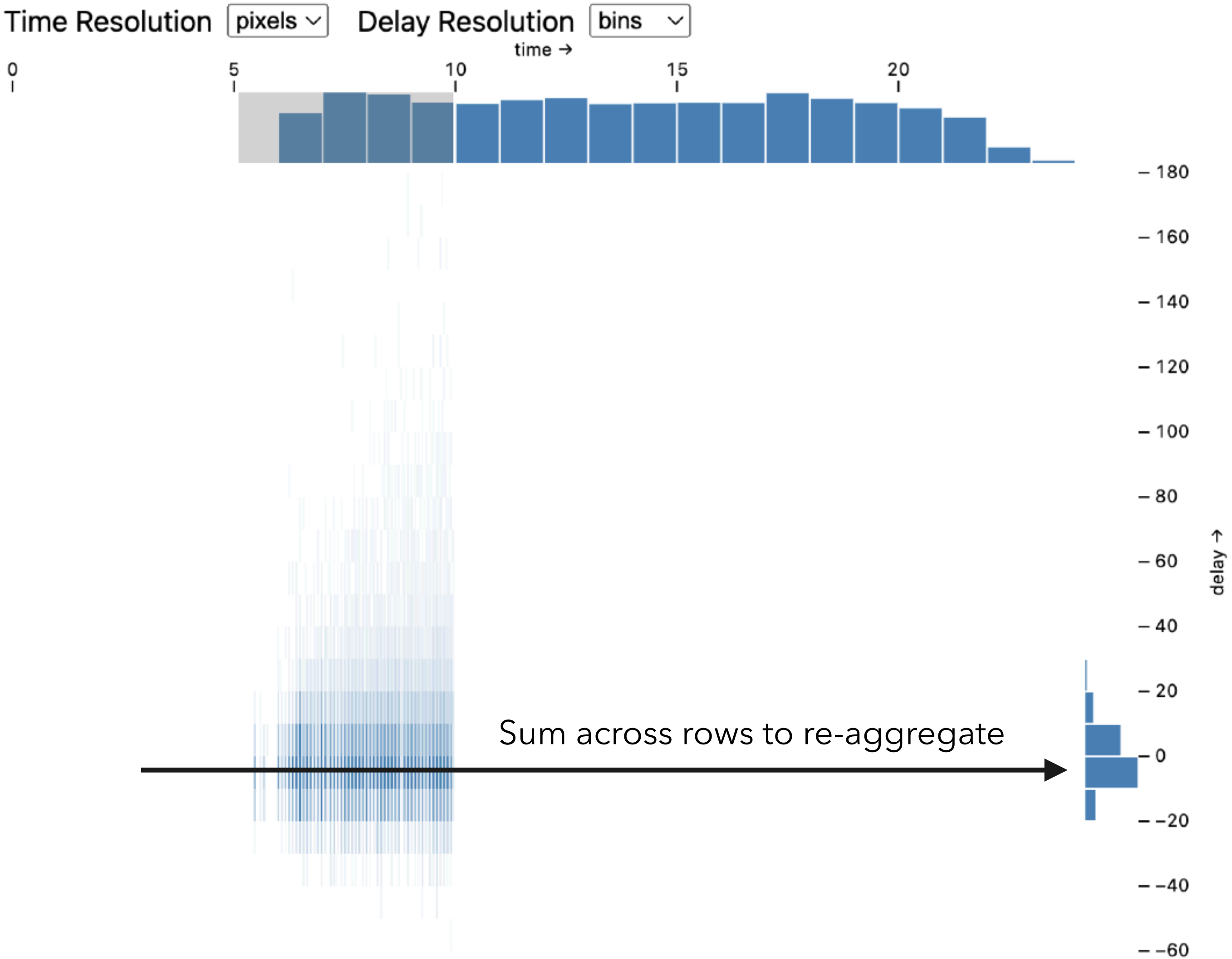


Time Resolution: pixels

Delay Resolution: bins

Flight Delays

250k Records



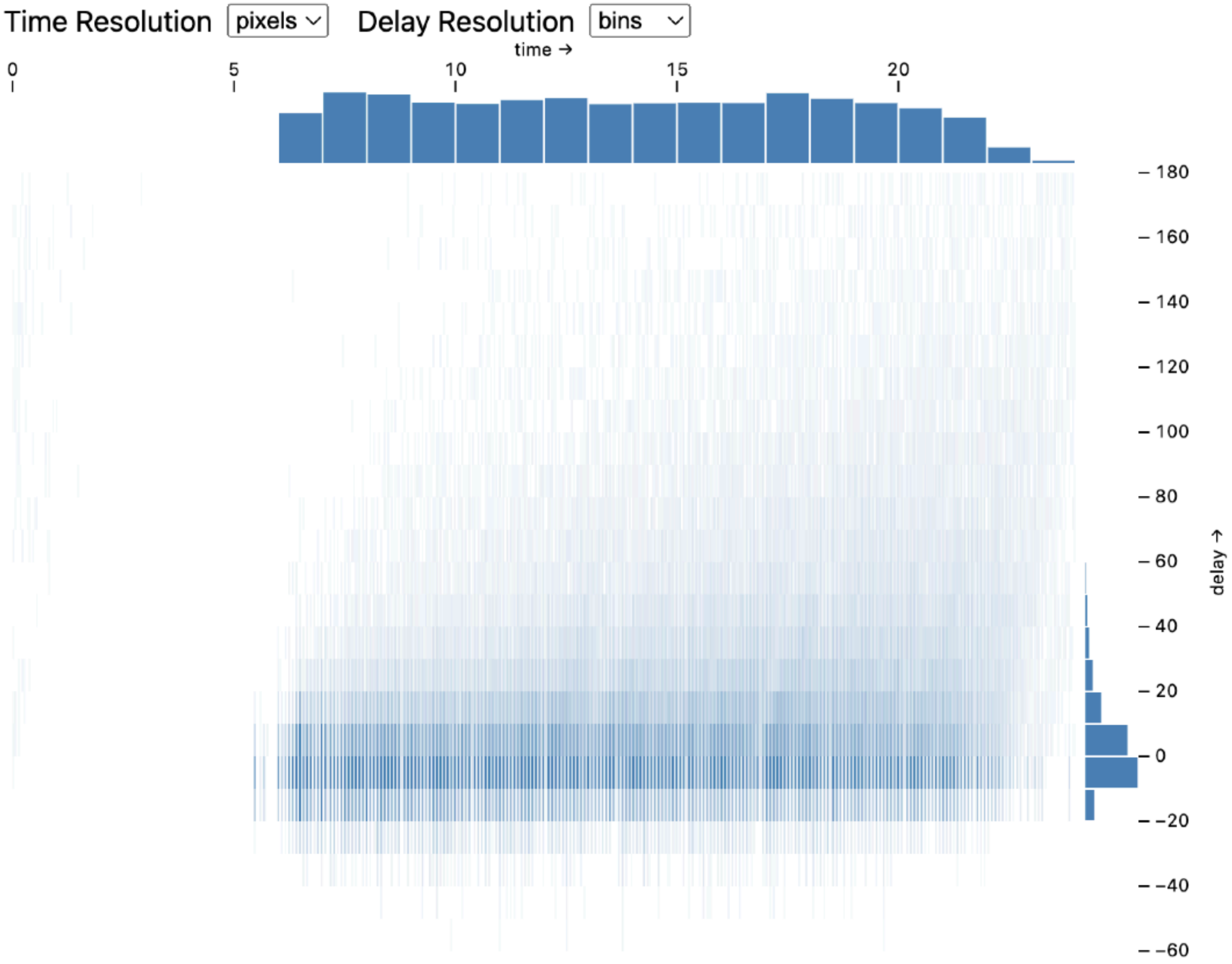
Time Resolution pixels

Delay Resolution bins

Sum across rows to re-aggregate

Flight Delays

250k Records

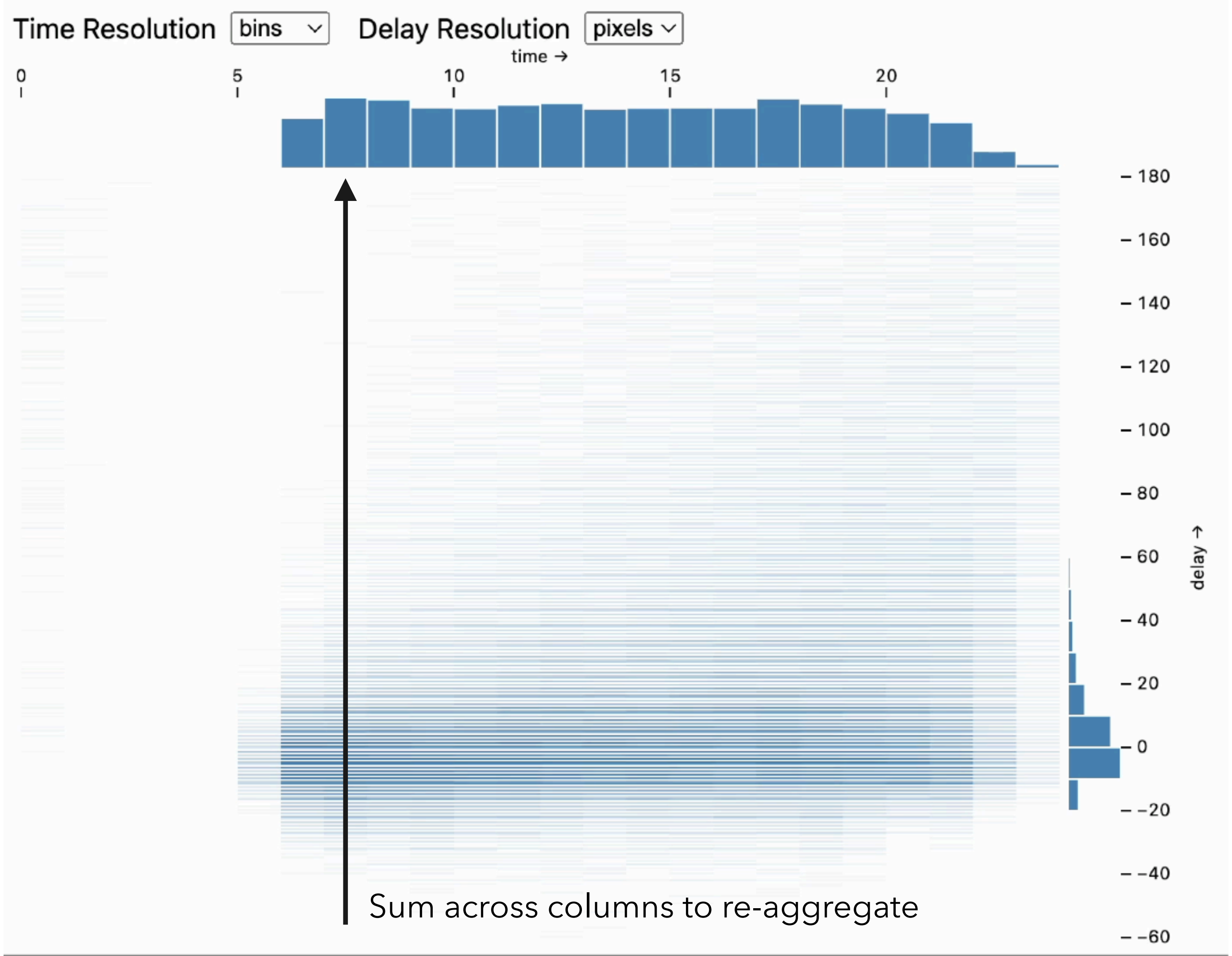


Time Resolution: pixels

Delay Resolution: bins

Flight Delays

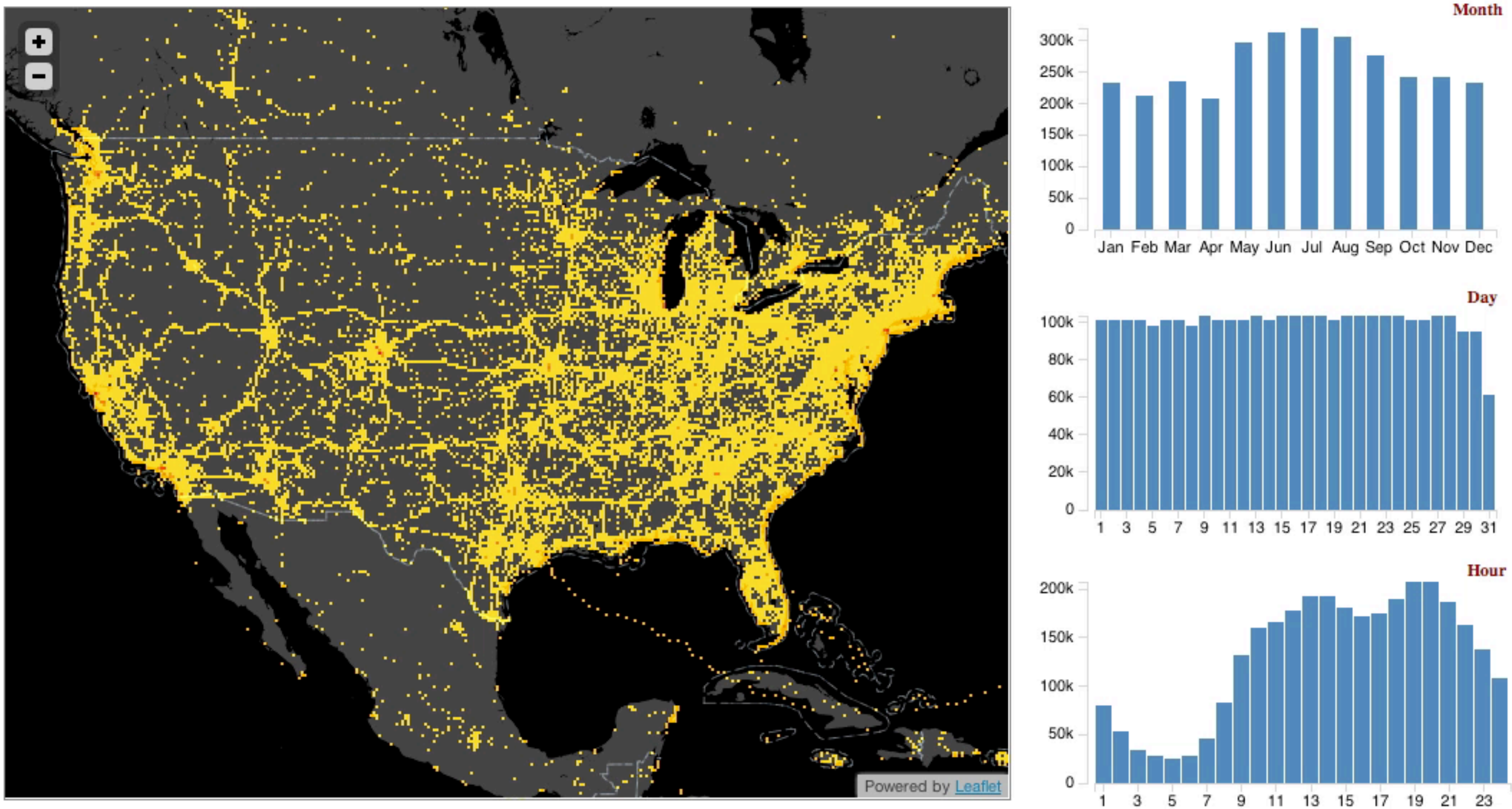
250k Records



Time Resolution: bins

Delay Resolution: pixels

Sum across columns to re-aggregate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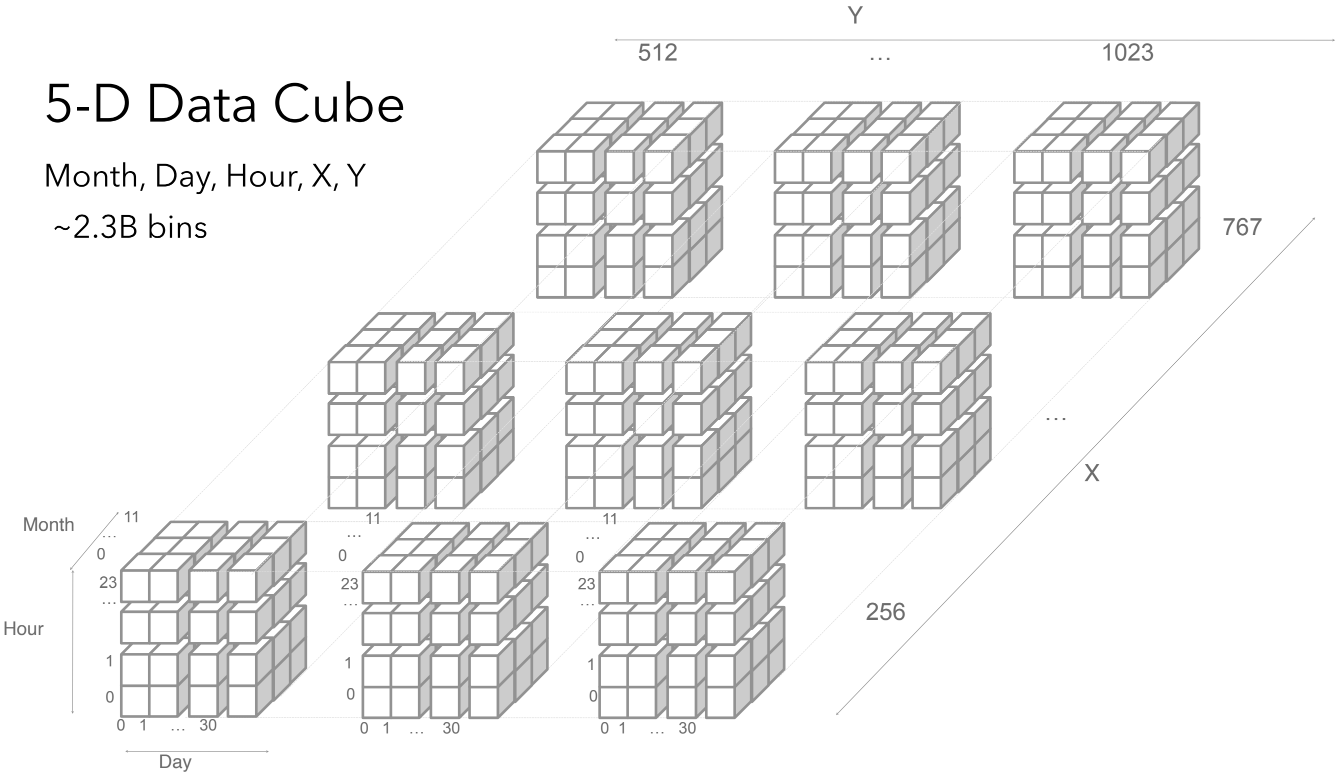
5-D Data Cube

Month, Day, Hour, X, Y

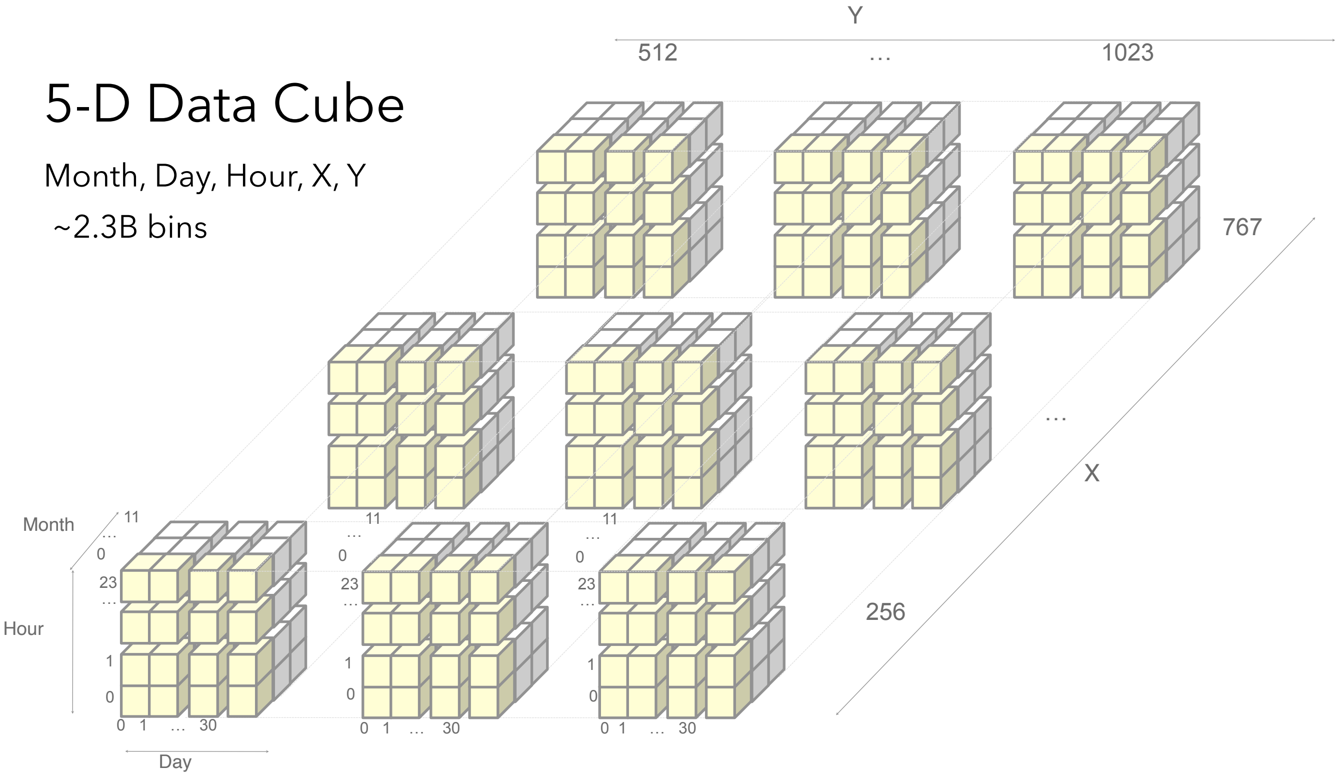
~2.3B bins

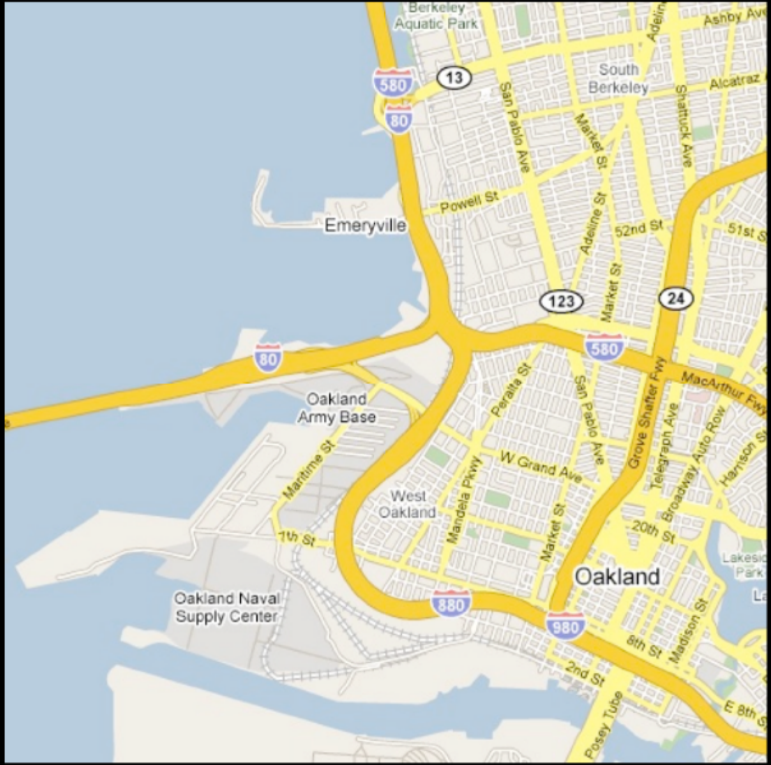


5-D Data Cube

Month, Day, Hour, X, Y

~2.3B bins





Berkeley
Aquatic Park
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Adeline
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South
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Alcatraz
San Pablo Ave
Market St
Shattuck Ave
Powell St
Adeline St
52nd St
51st St
Emeryville
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Market St
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MacArthur Fwy
Oakland
Army Base
Peralta St
San Pablo Ave
Grove Shafter Fwy
Telegraph Ave
Broadway Auto Row
Harrison St
Maritime St
W Grand Ave
West
Oakland
Mandela Pkwy
Market St
20th St
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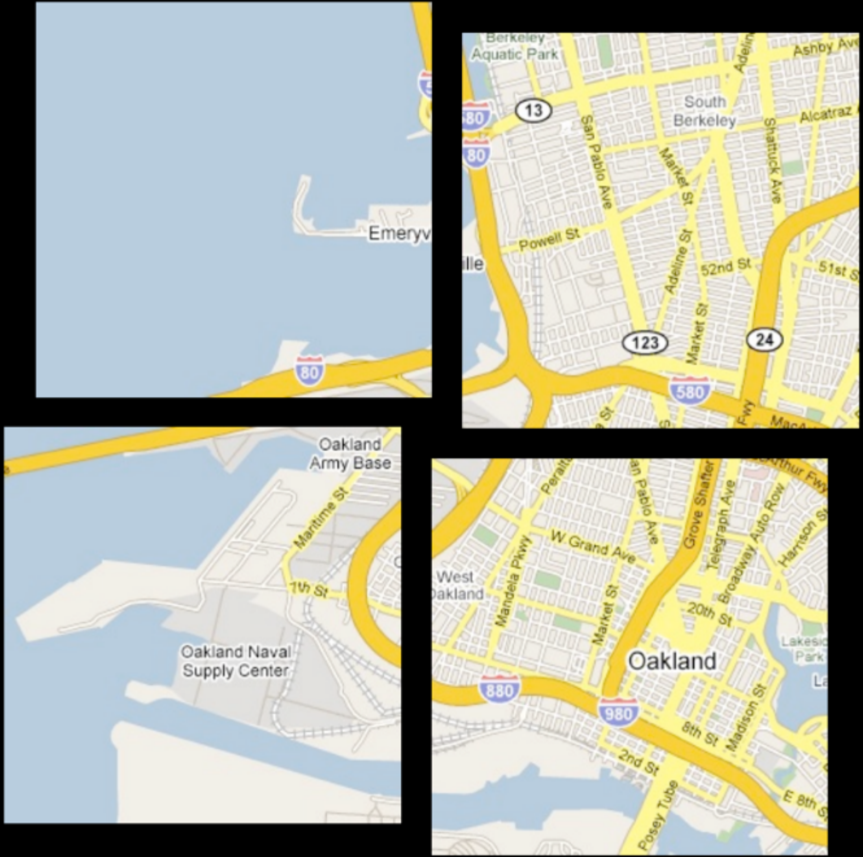
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Adeline St
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Supply Center
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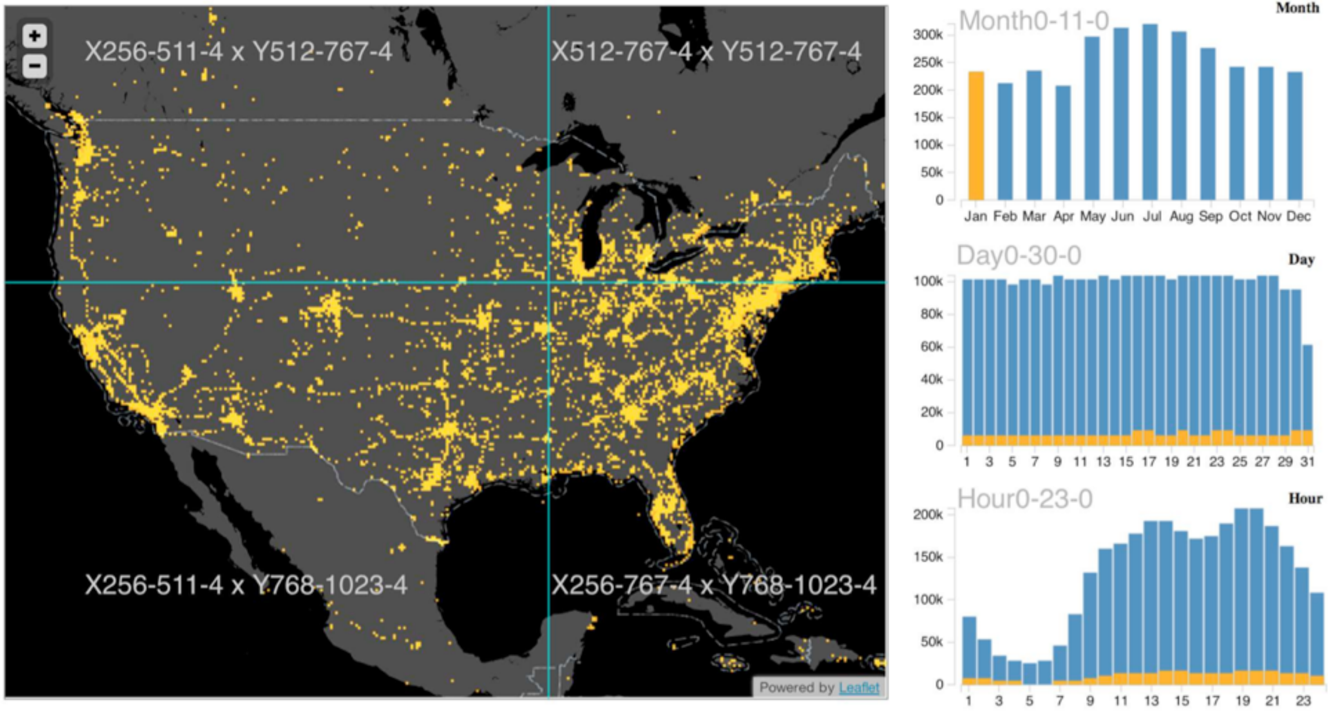
an Pablo Ave
Grove Shafter
Telegraph Ave
Broadway Auto Row
Arthur Fwy
Harrison St
Market St
20th St
Oakland
Lakesid
Park
880
980
8th St
Madison St
2nd St
E 8th St
Posey Tube

Multivariate Data Tiles

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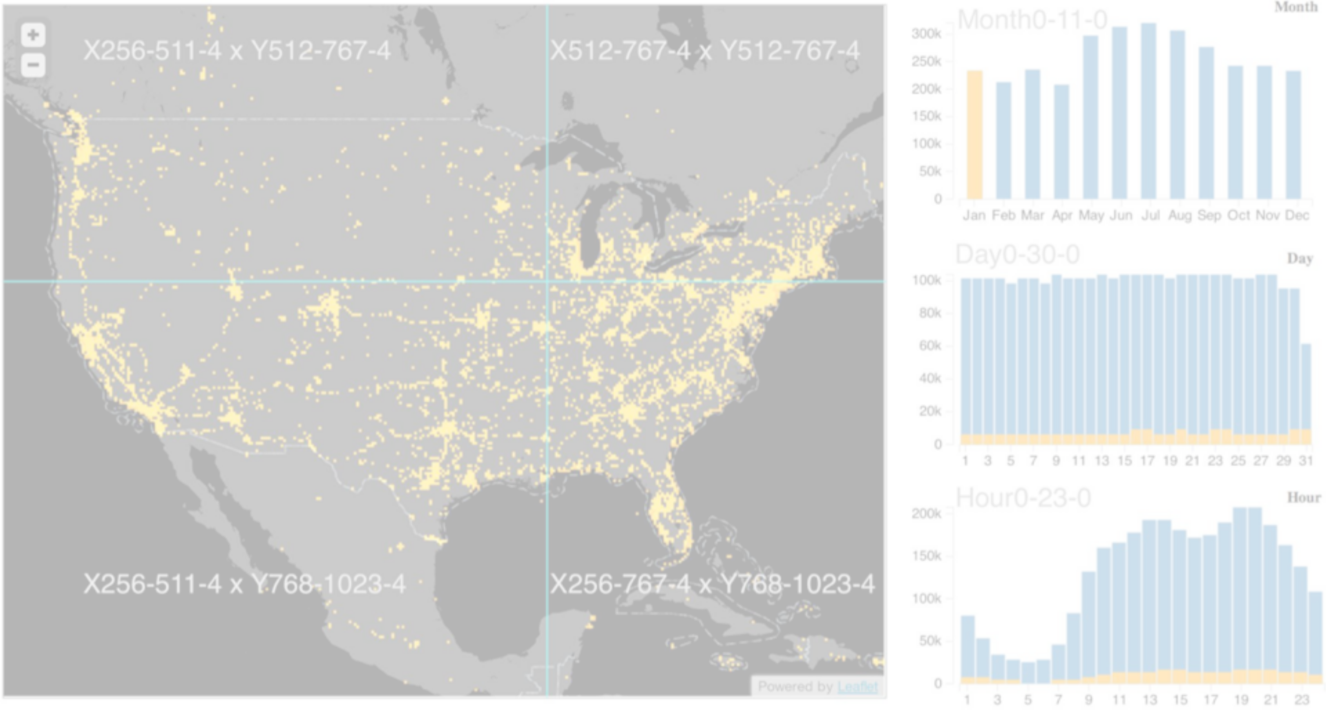
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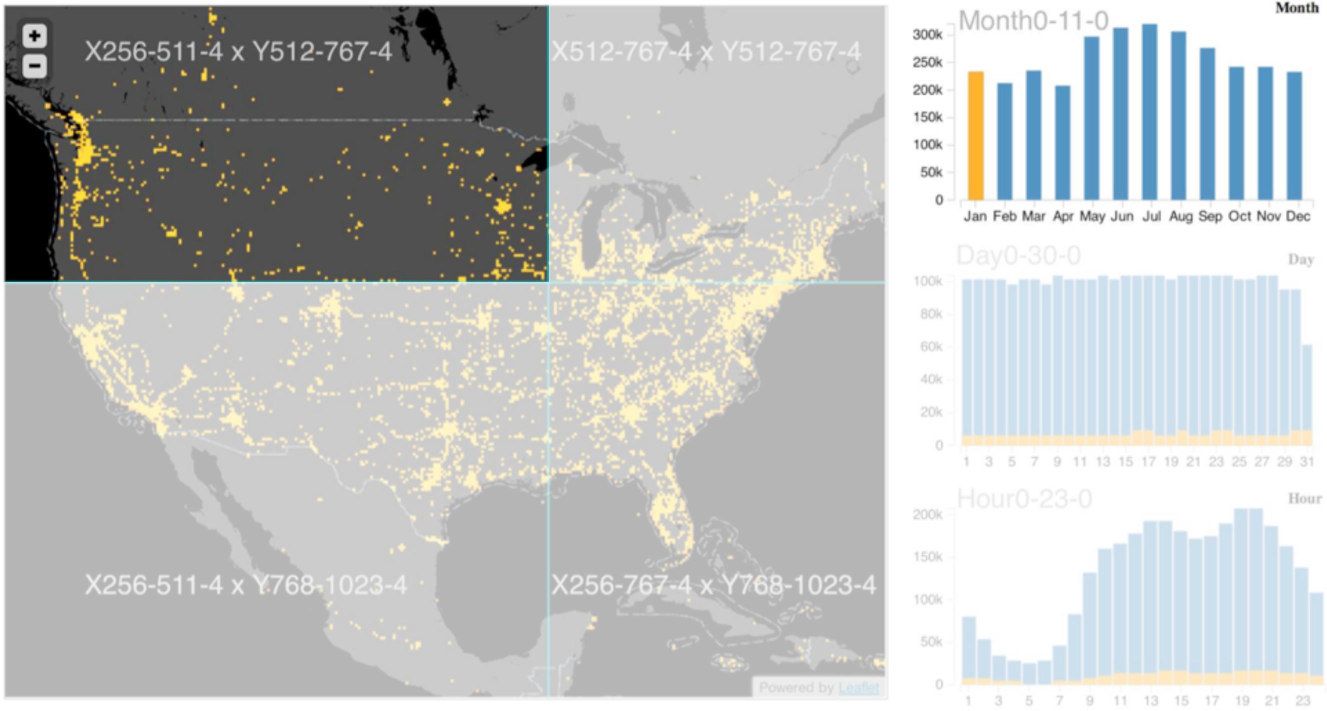
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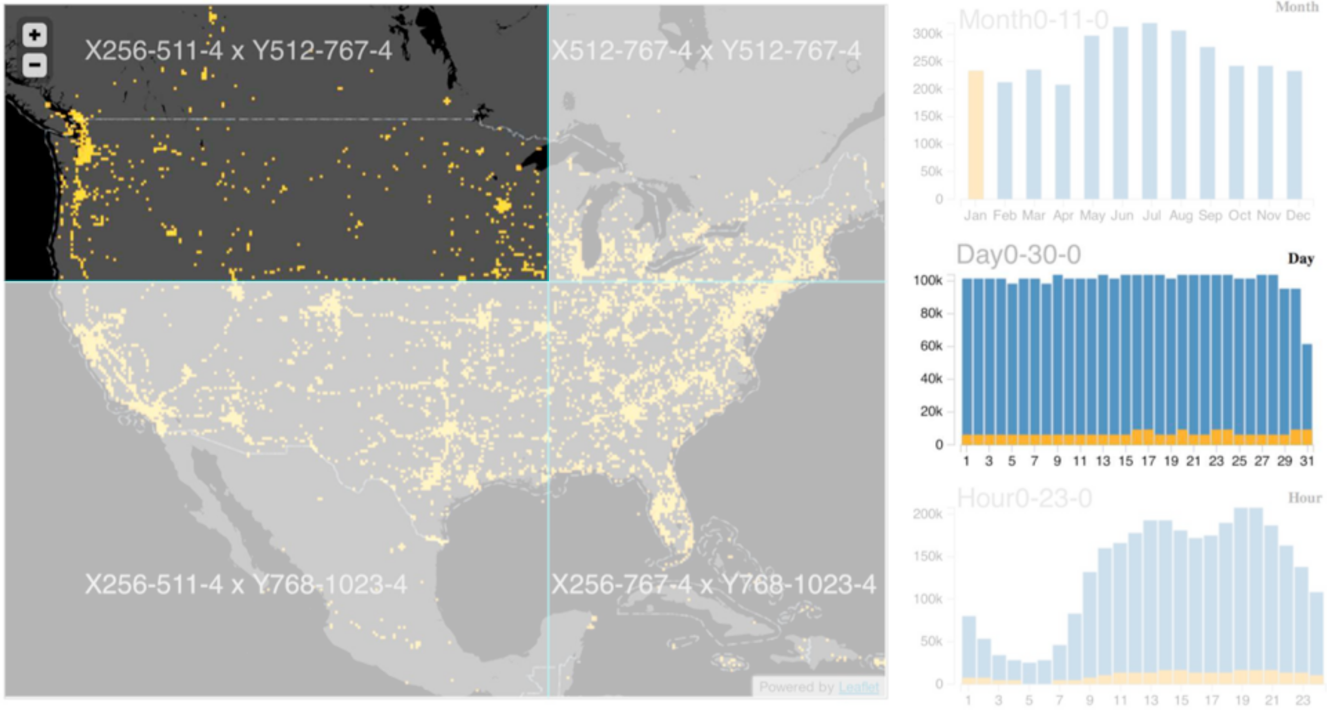
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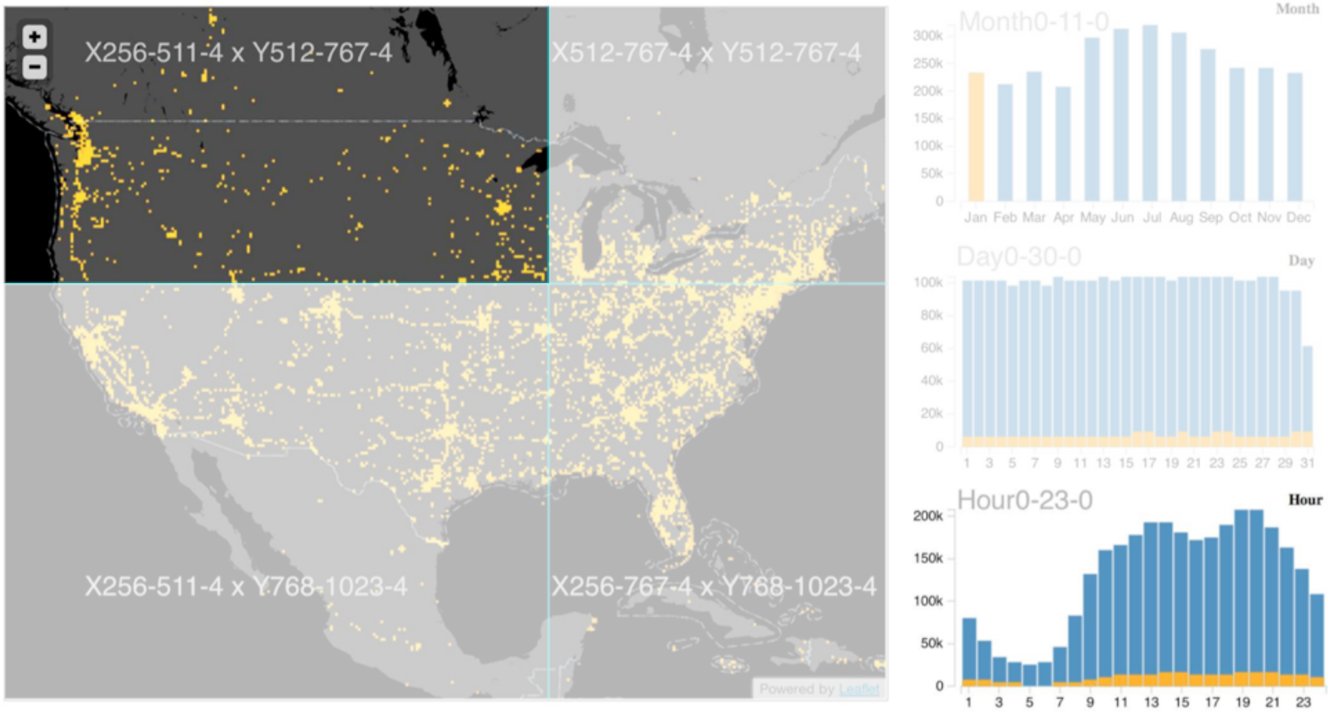
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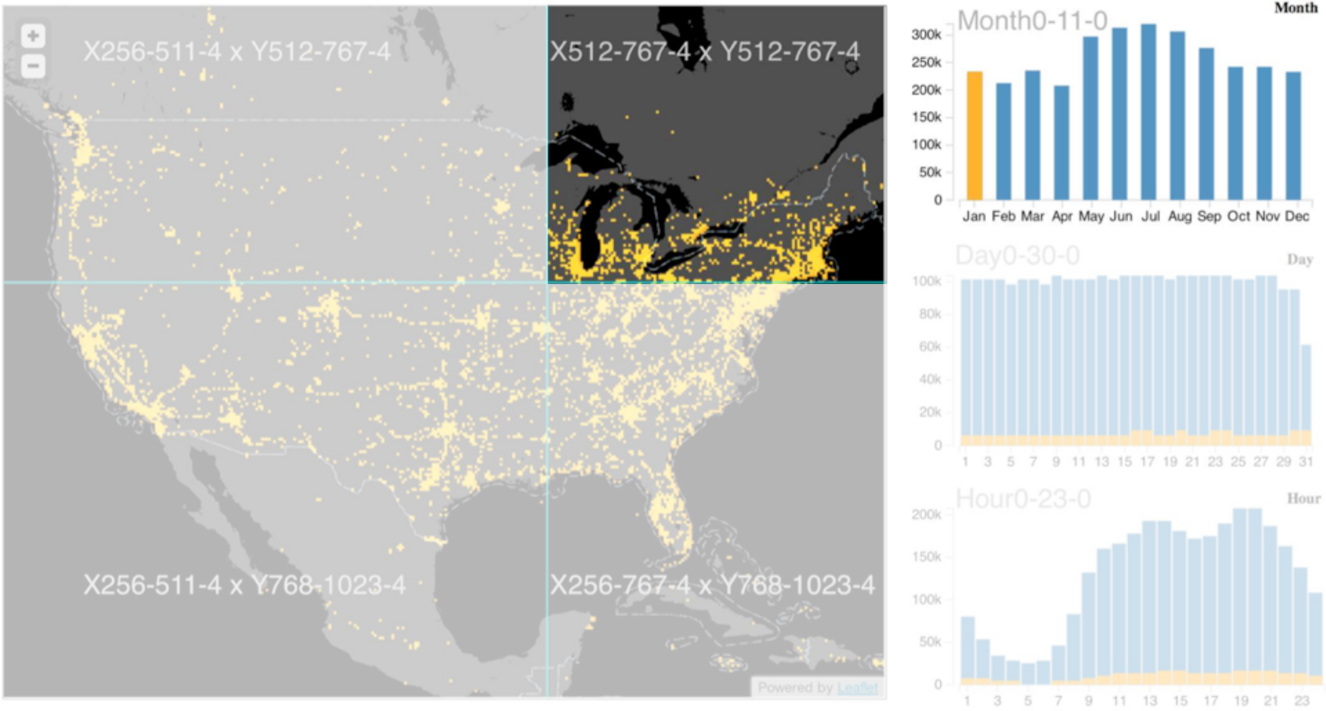
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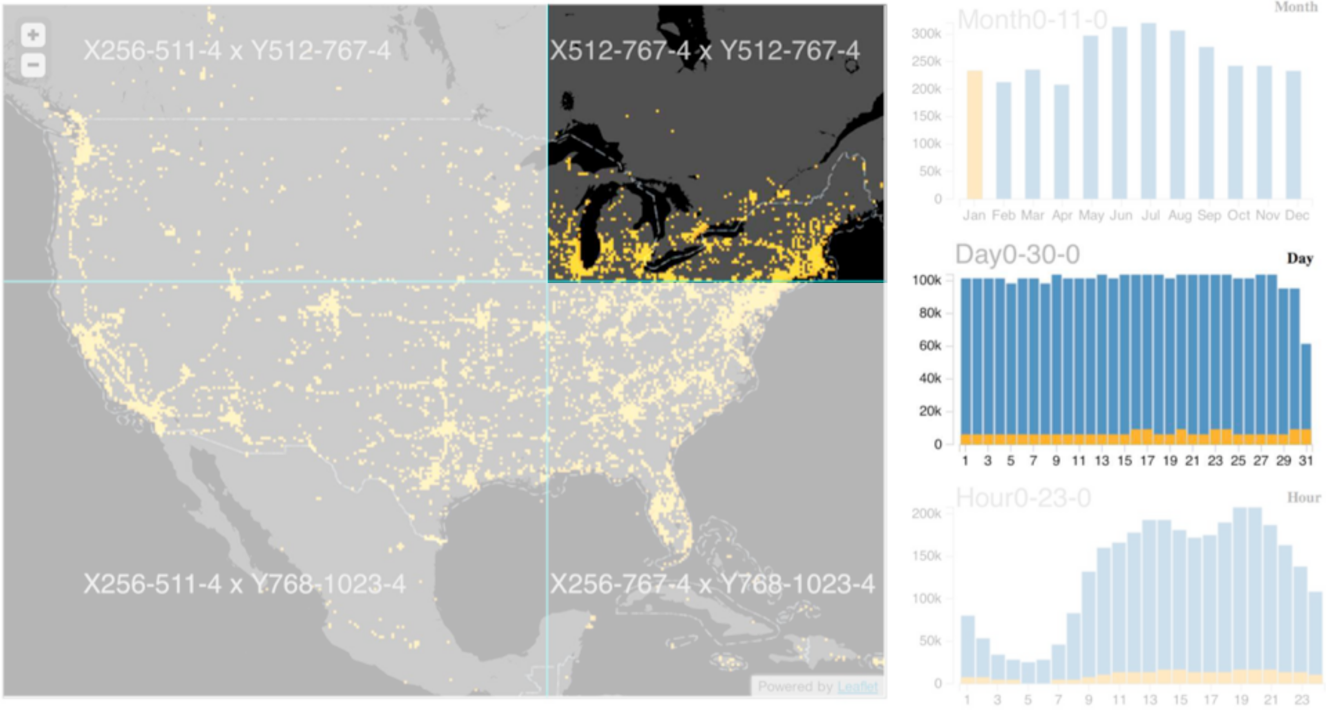
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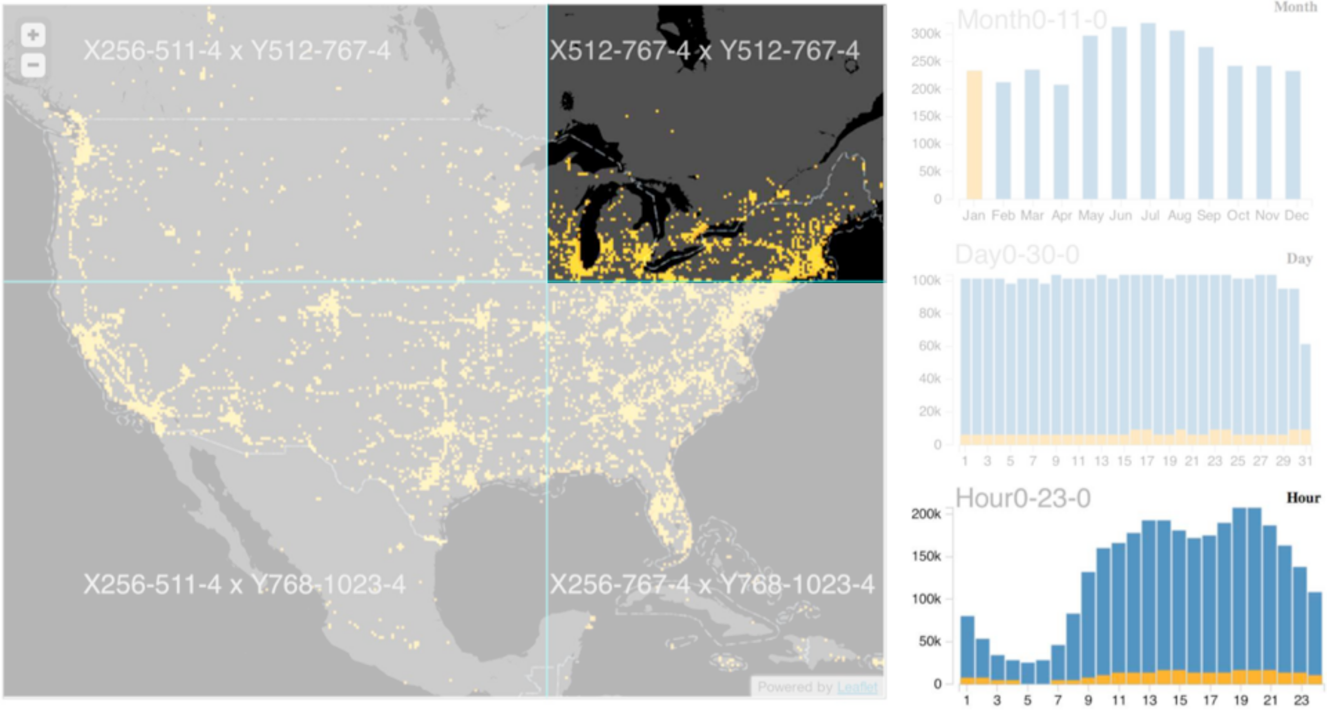

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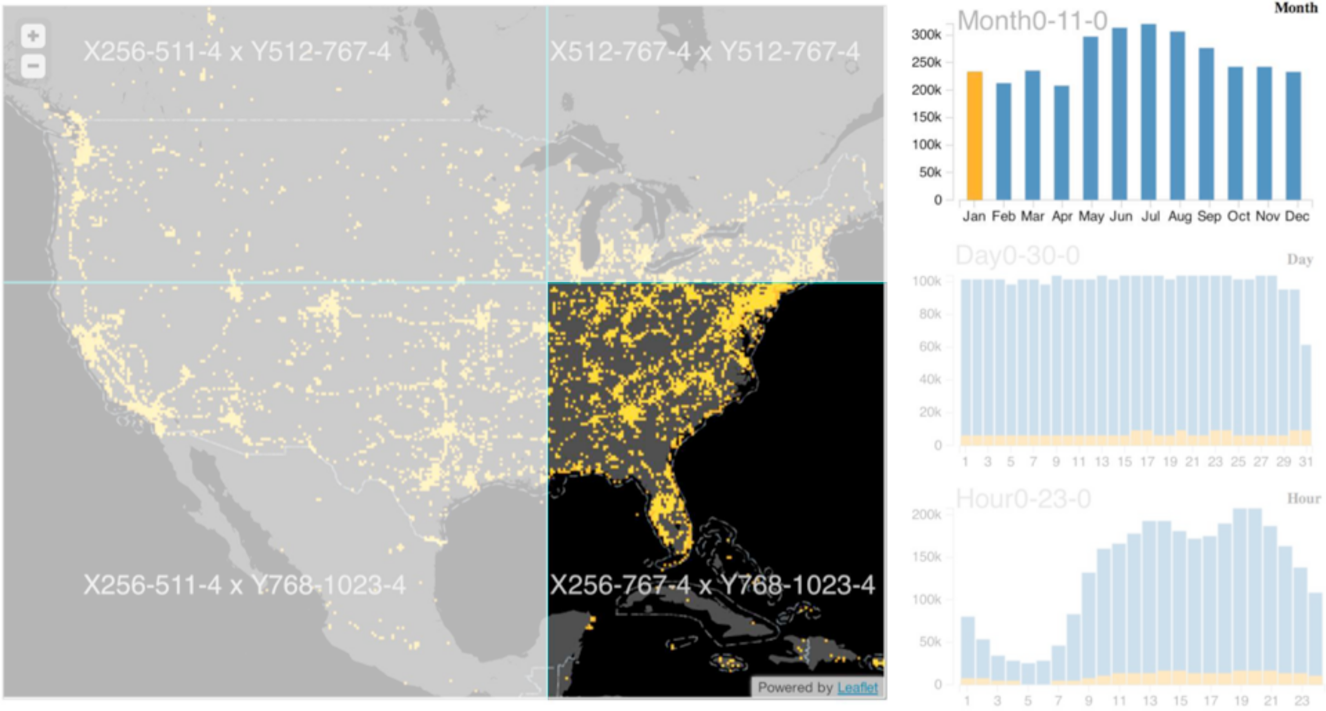
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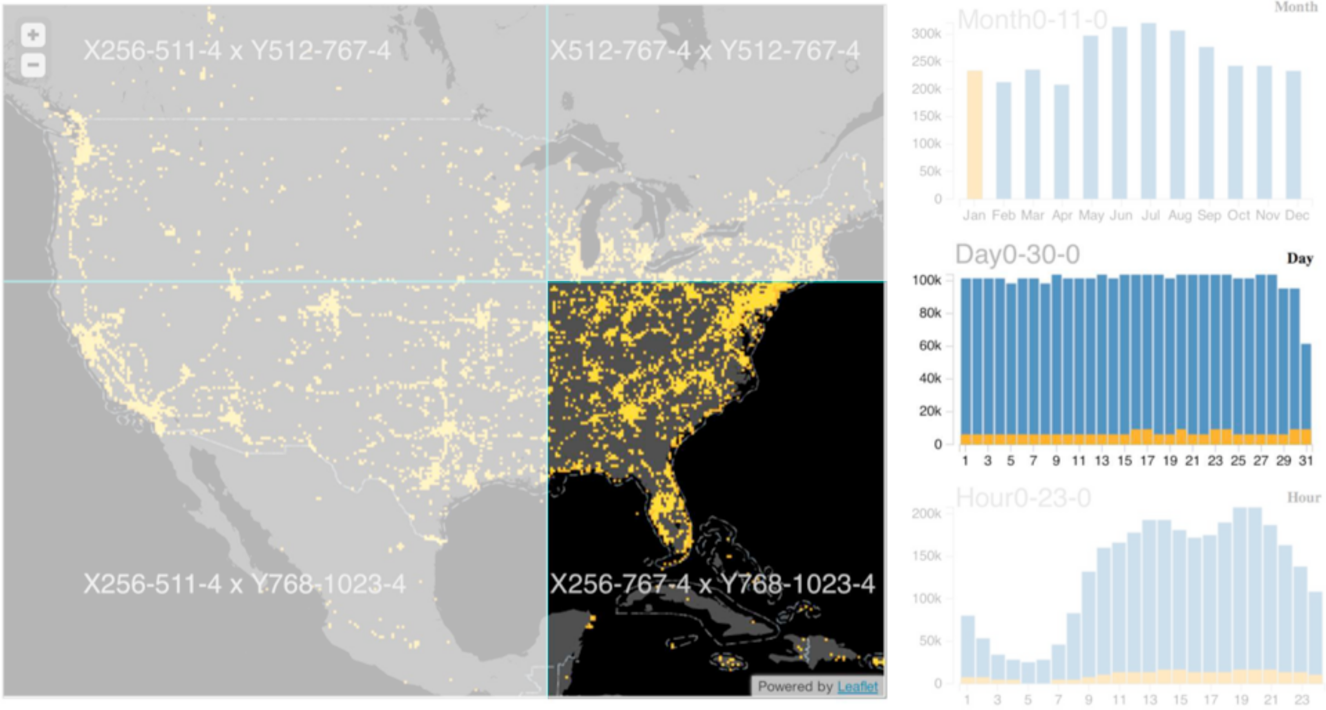
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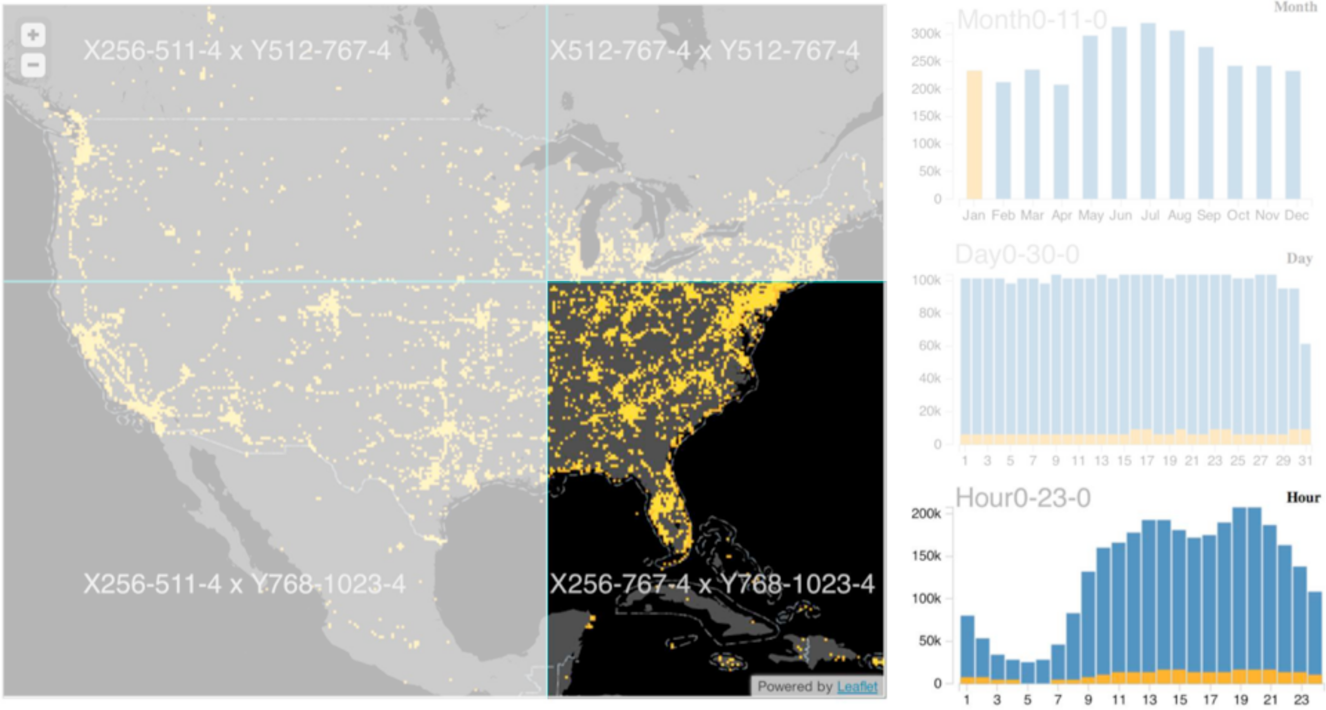
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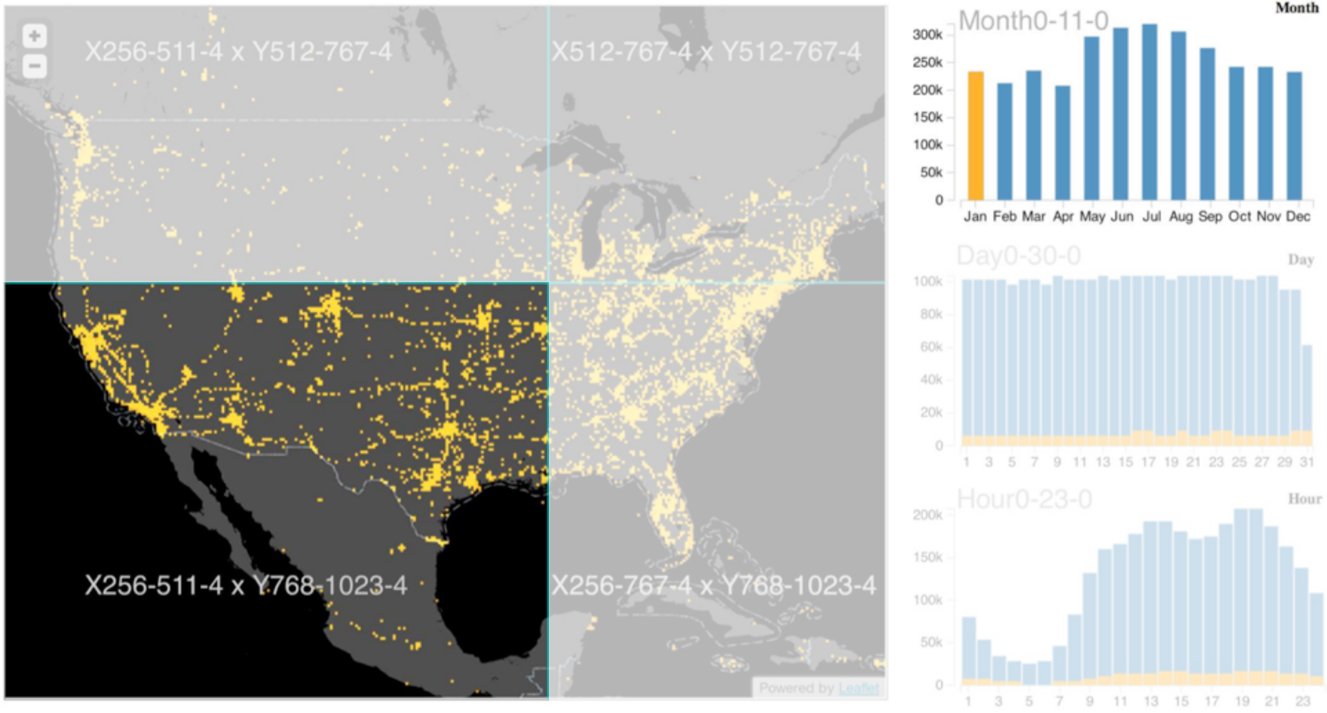
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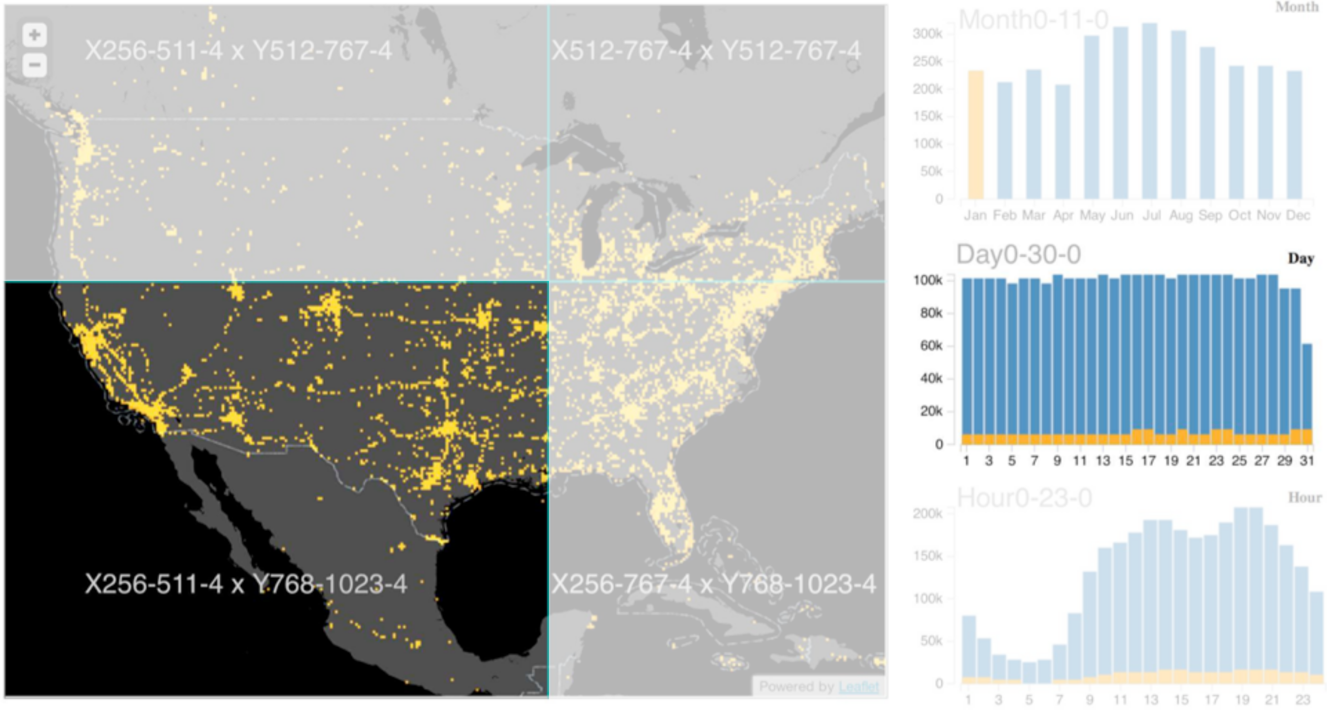
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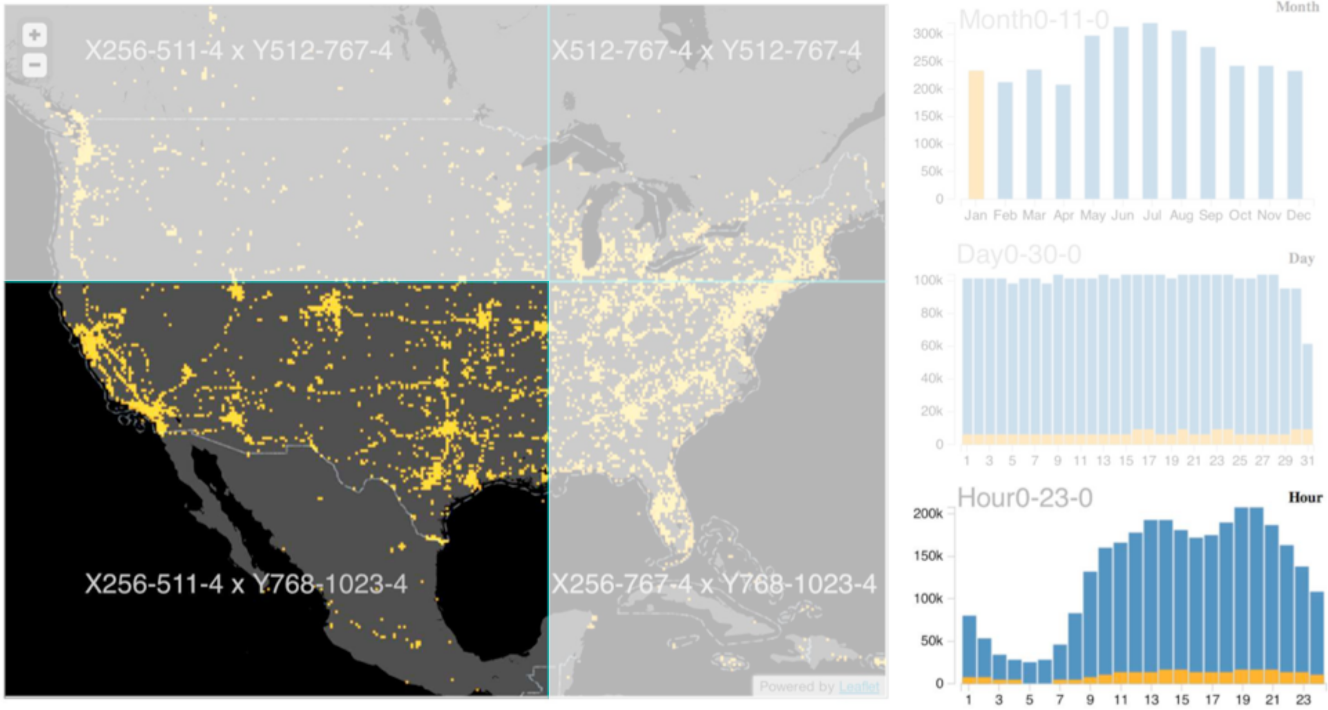

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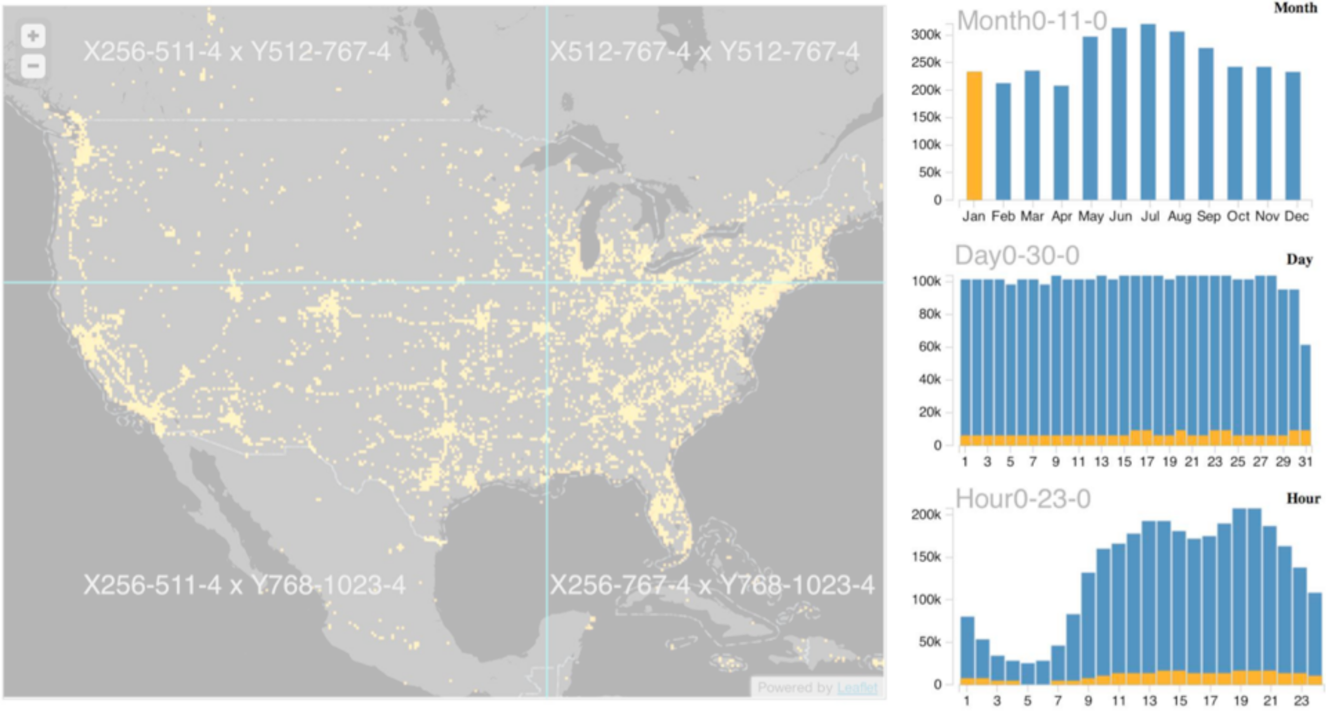

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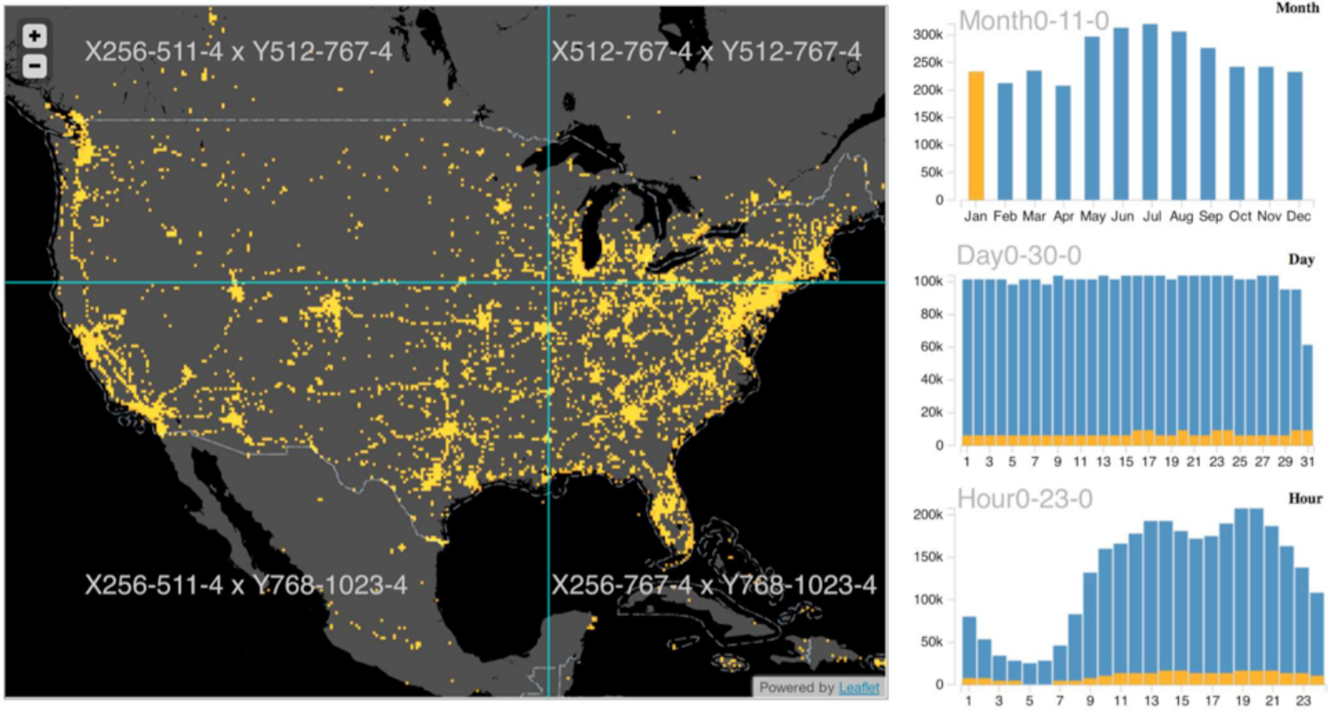
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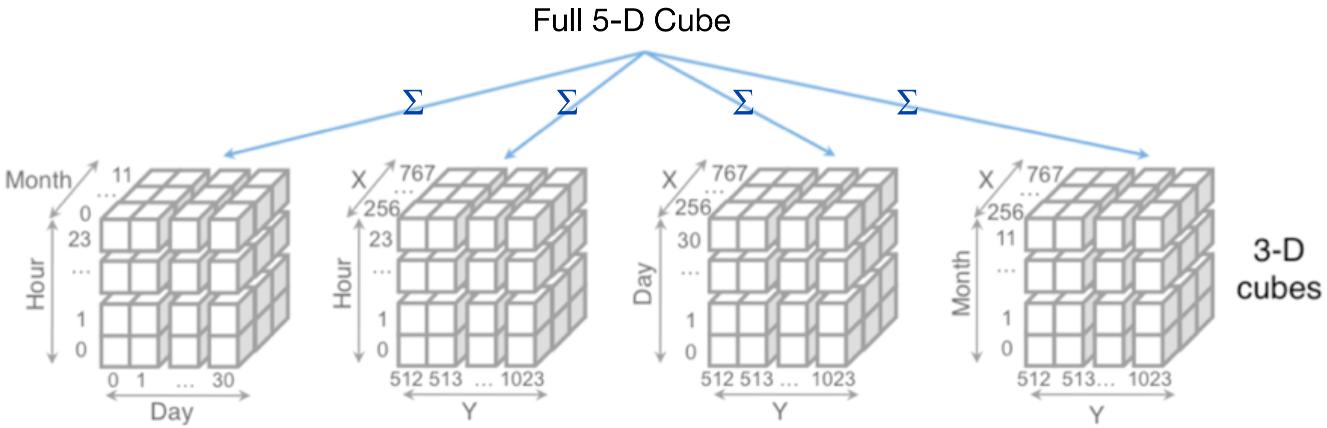
Full 5-D Cube

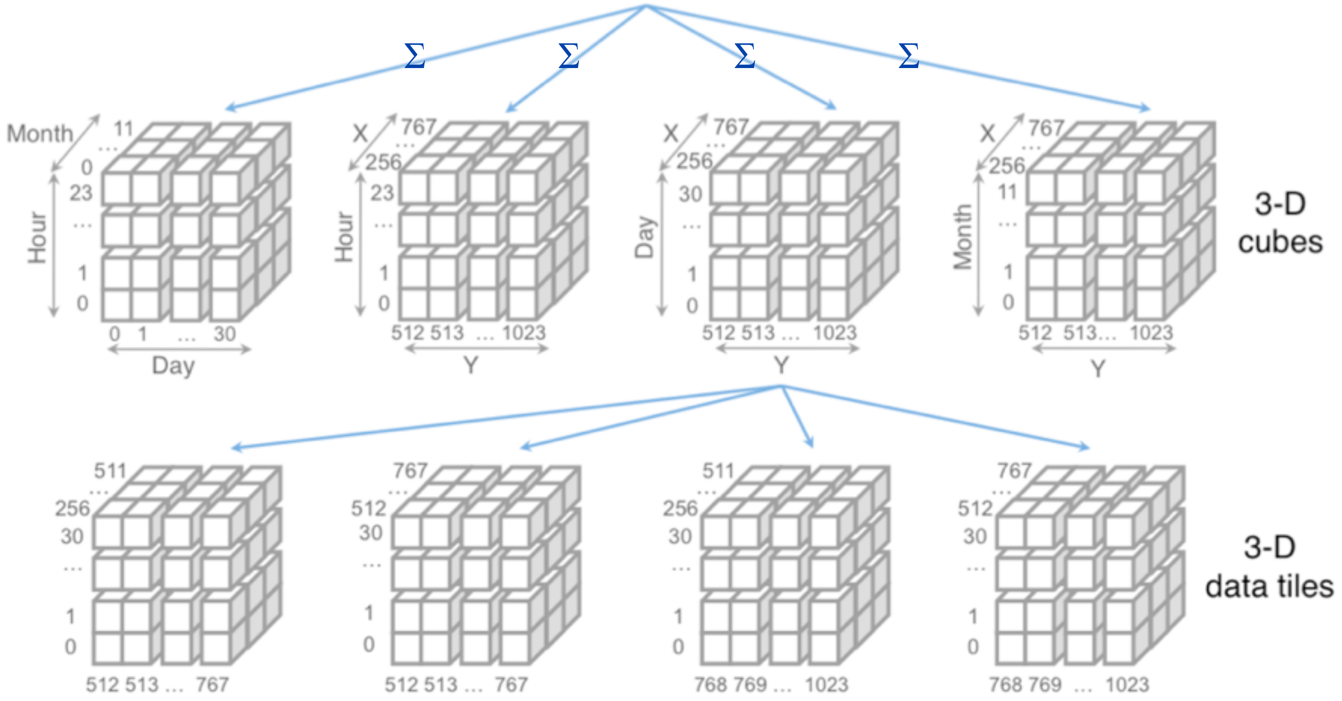


Full 5-D Cube

3-D cubes

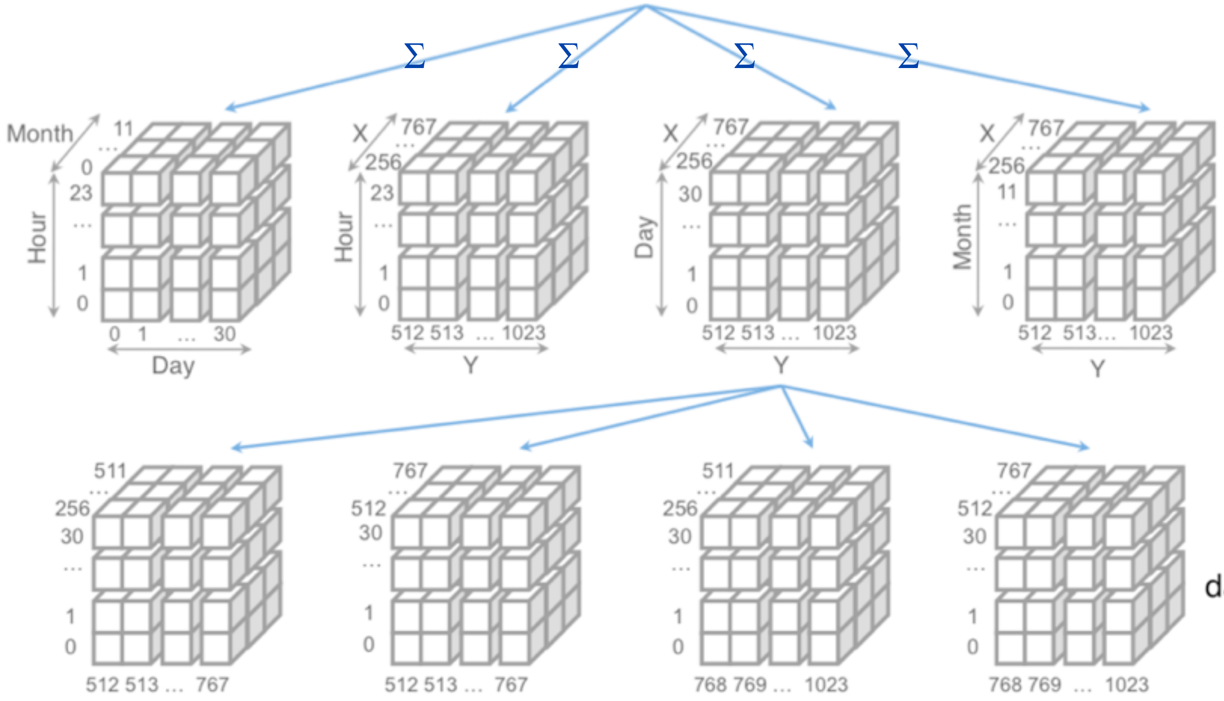
For any pair of 1D or 2D binned plots, the maximum number of dimensions needed to support brushing & linking is **four**.

Full 5-D Cube



13 3-D Data Tiles

Full 5-D Cube → ~2.3B bins

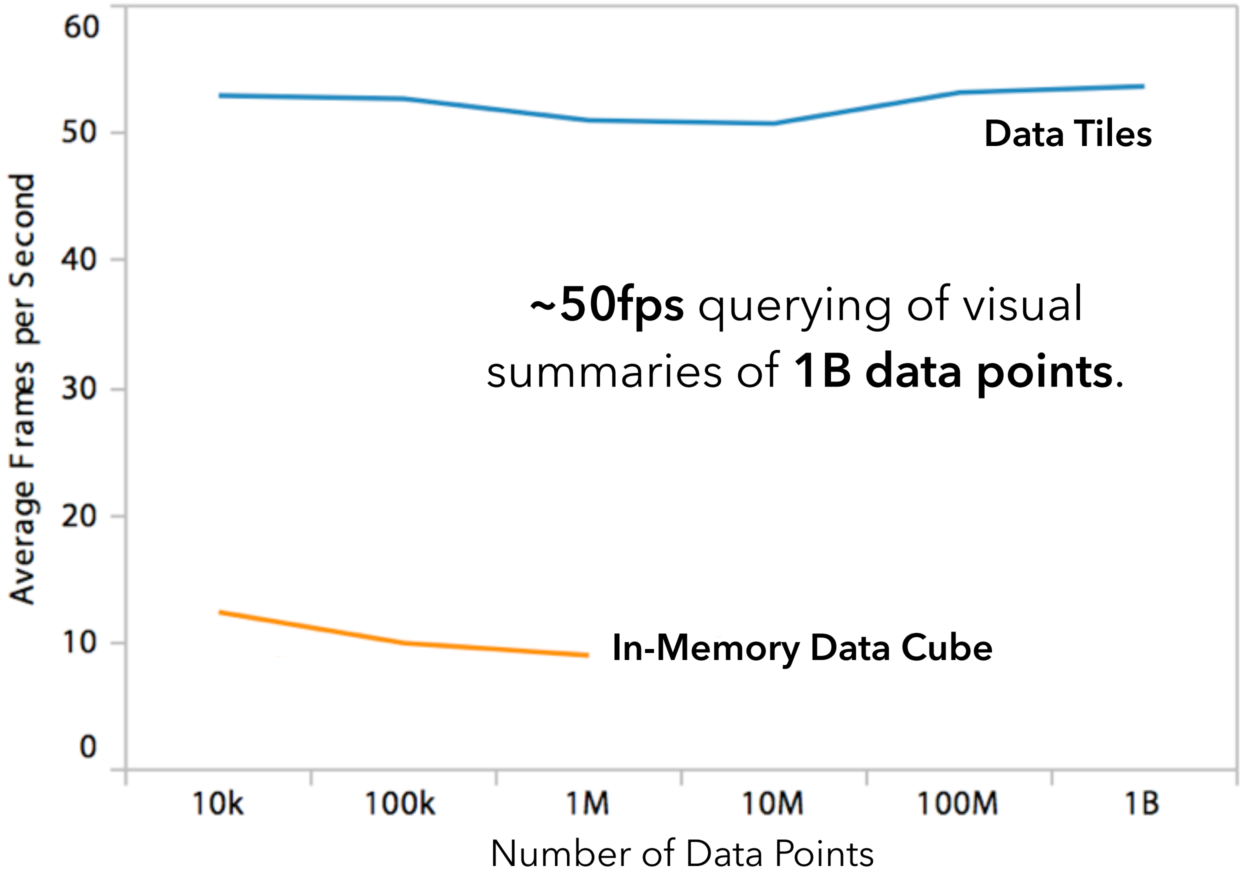


3-D cubes

3-D data tiles

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

5 dimensions x 50 bins/dim x 25 plots



~50fps querying of visual summaries of **1B 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]

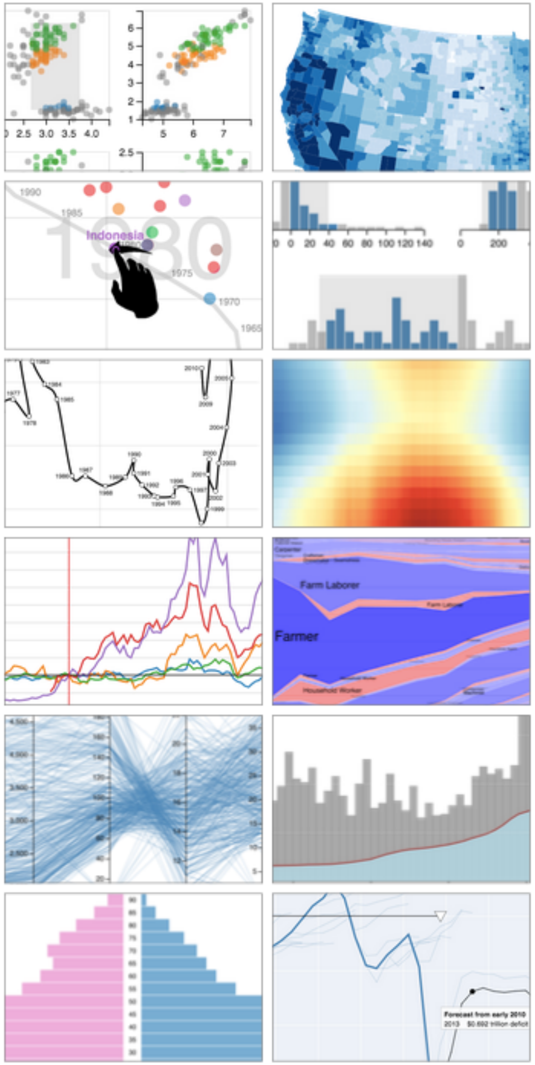
Sampling Methods

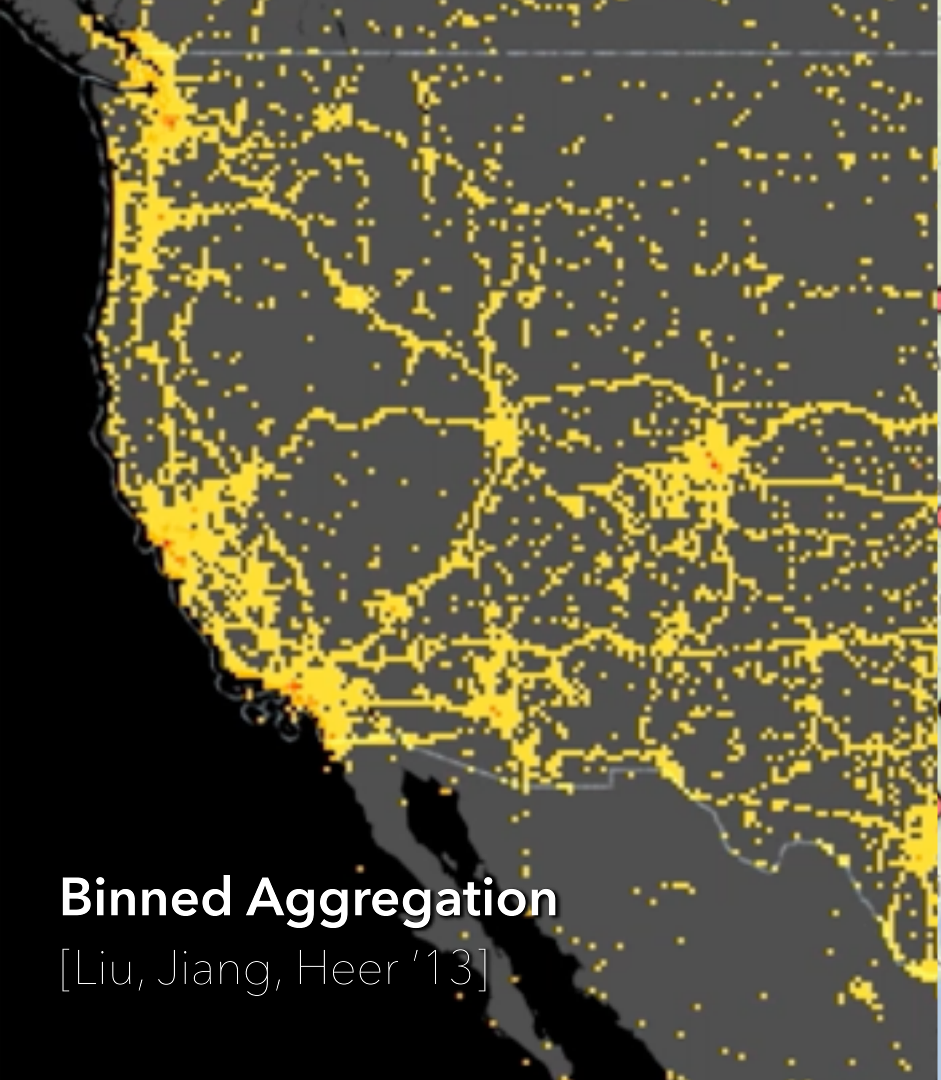
Common Sampling Methods

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.

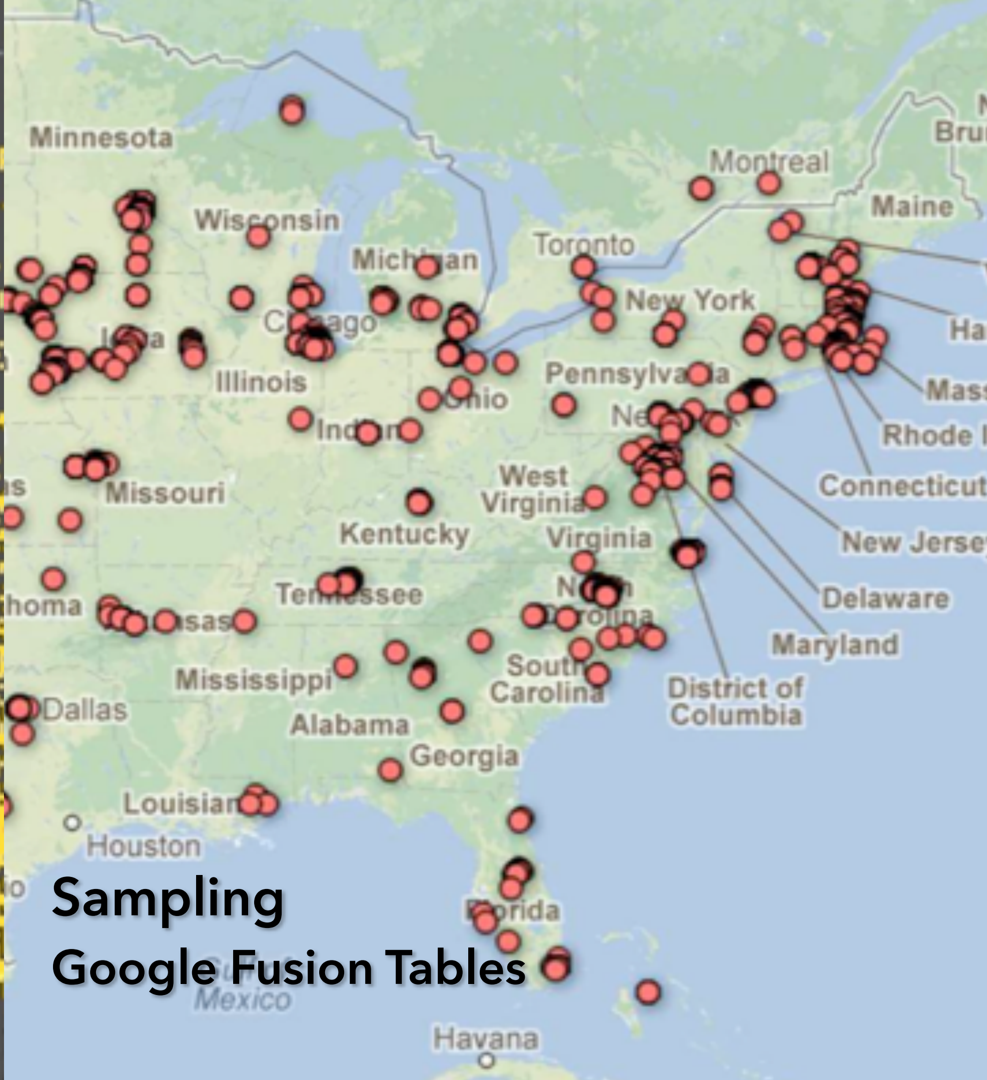
Stratified: Sample within groups, ensure coverage and balance across those categories.





Binned Aggregation

[Liu, Jiang, Heer '13]



Sampling

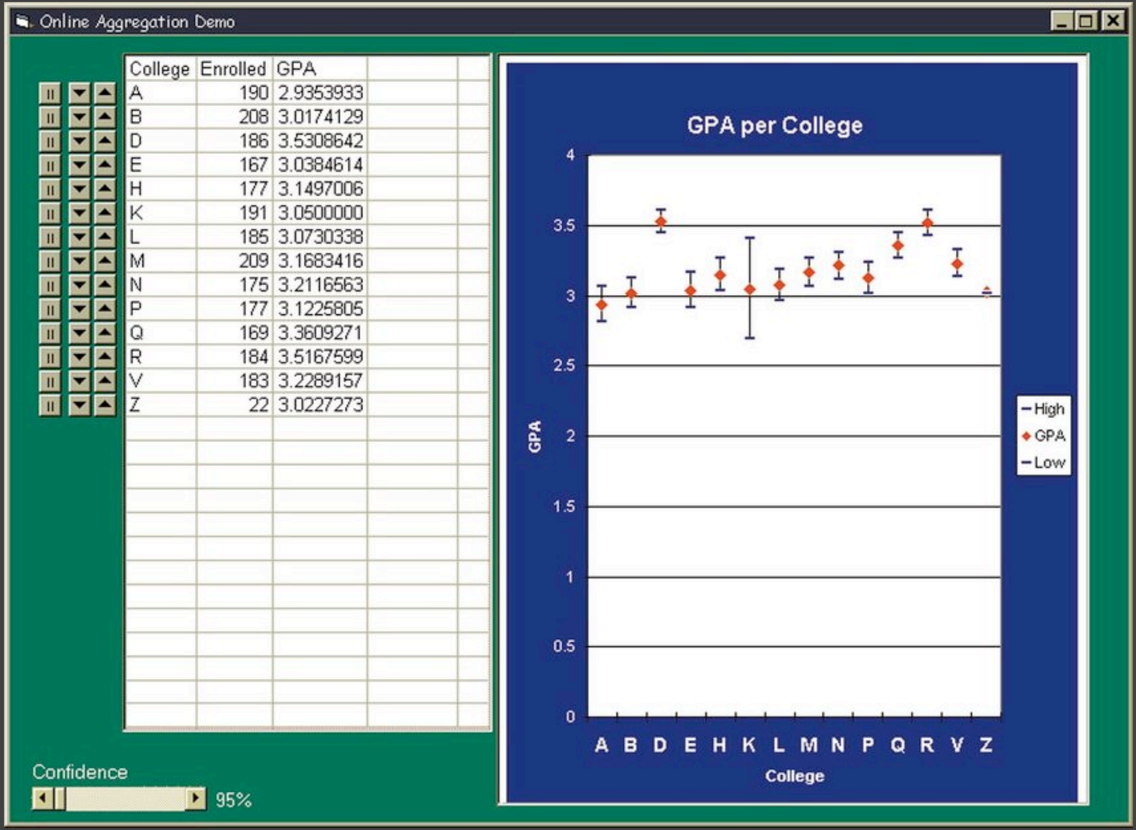
Google Fusion Tables

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.


Online Aggregation Demo

College	Enrolled	GPA
A	190	2.9353933
B	208	3.0174129
D	186	3.5308642
E	167	3.0384614
H	177	3.1497006
K	191	3.0500000
L	185	3.0730338
M	209	3.1683416
N	175	3.2116563
P	177	3.1225805
Q	169	3.3609271
R	184	3.5167599
V	183	3.2289157
Z	22	3.0227273

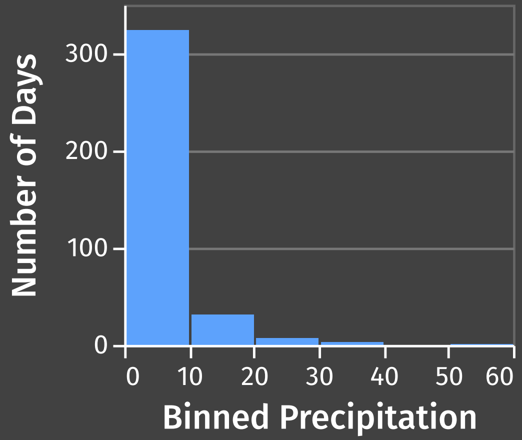
Confidence 95%

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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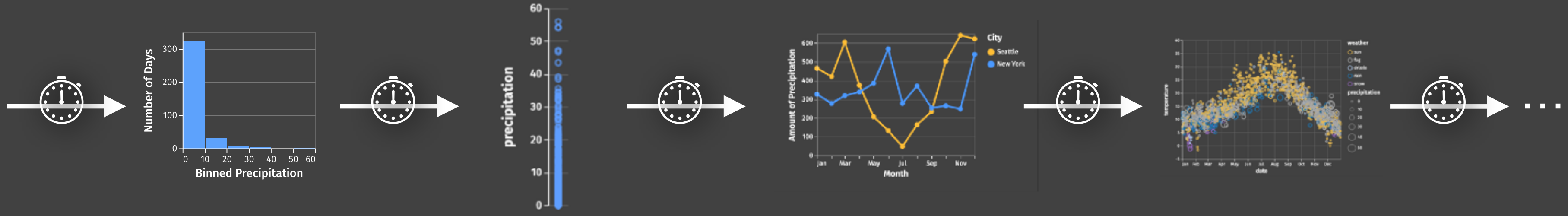
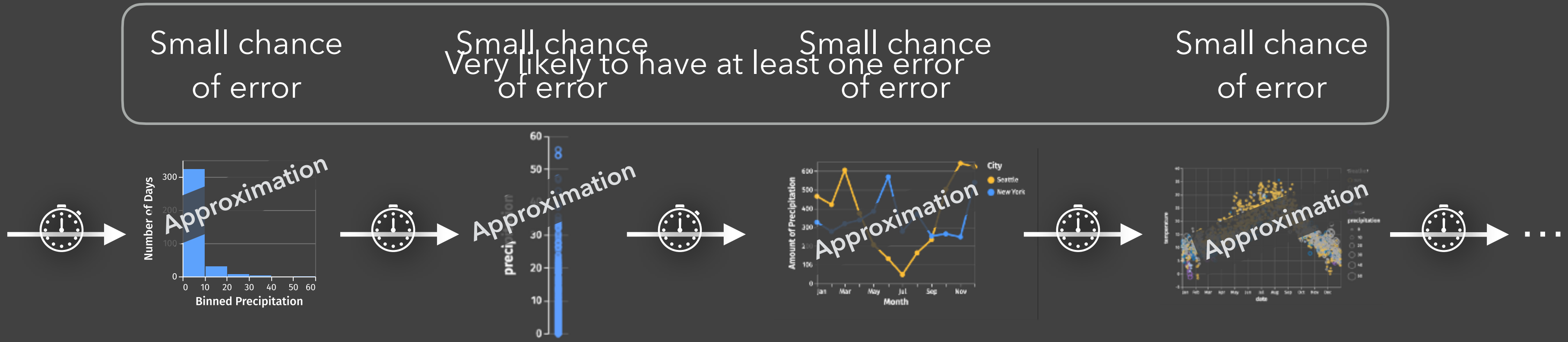
Binned Precipitation



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

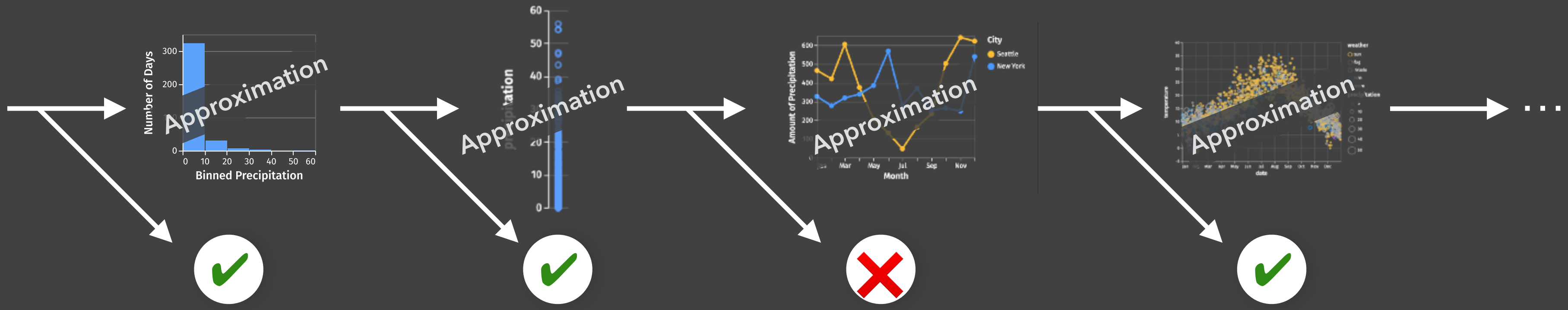
Optimistic Visualization

Trust but Verify

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

Optimistic Visualization

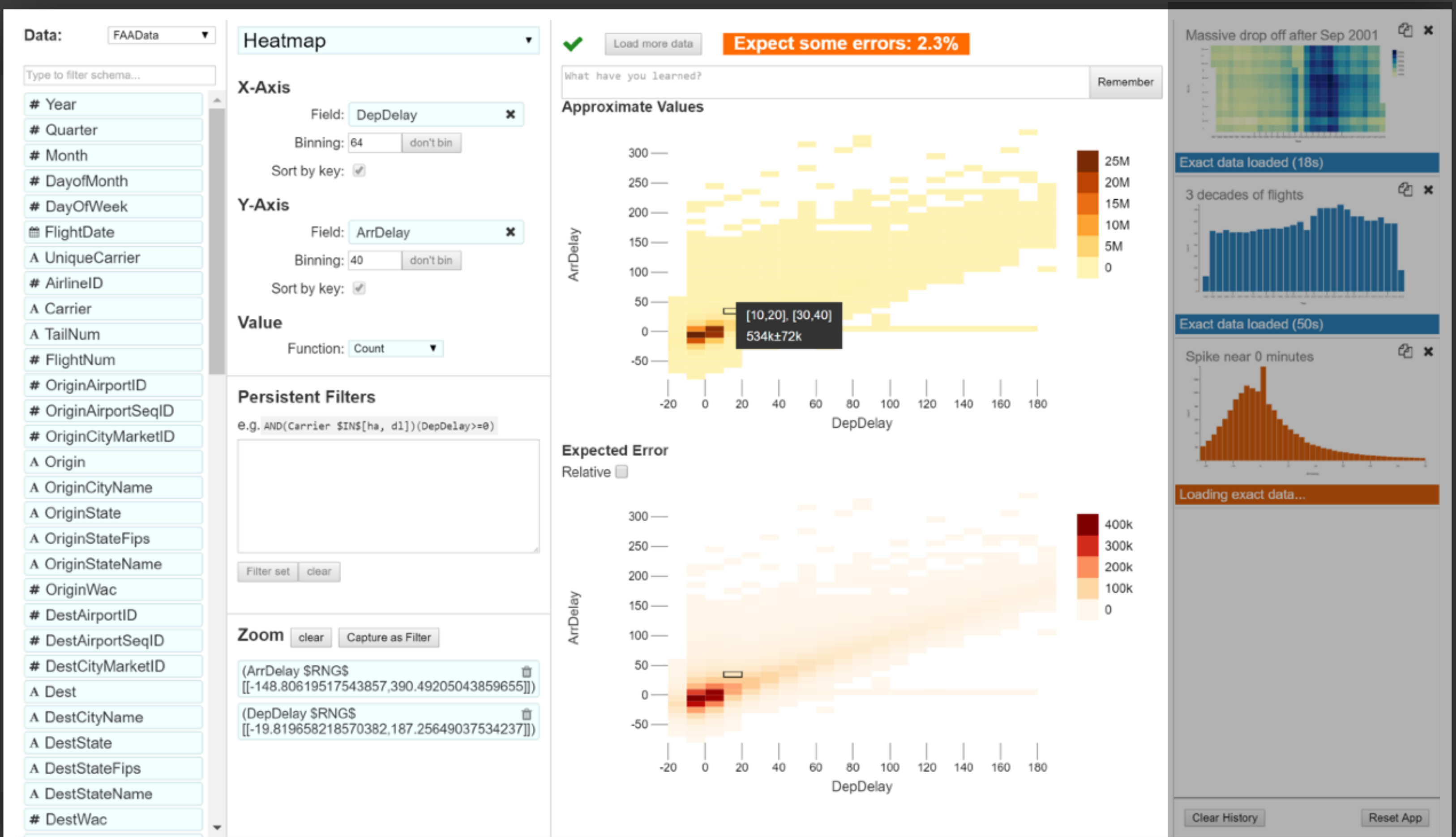
Trust but Verify. Moritz et al. *CHI 2017*.



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



Data: FAAData

Heatmap

X-Axis

Field: DepDelay

Binning: 64

Sort by key: ☑

Y-Axis

Field: ArrDelay

Binning: 40

Sort by key: ☑

Value

Function: Count

Persistent Filters

e.g. `AND(Carrier $IN$[ha, dl])(DepDelay>=0)`

Zoom

(ArrDelay RNG [[-148.80619517543857,390.49205043859655]])

(DepDelay RNG [[-19.819658218570382,187.25649037534237]])

Expect some errors: 2.3%

What have you learned?

Approximate Values

[10,20], [30,40]
534k±72k

Expected Error

Relative □

Massive drop off after Sep 2001

Exact data loaded (18s)

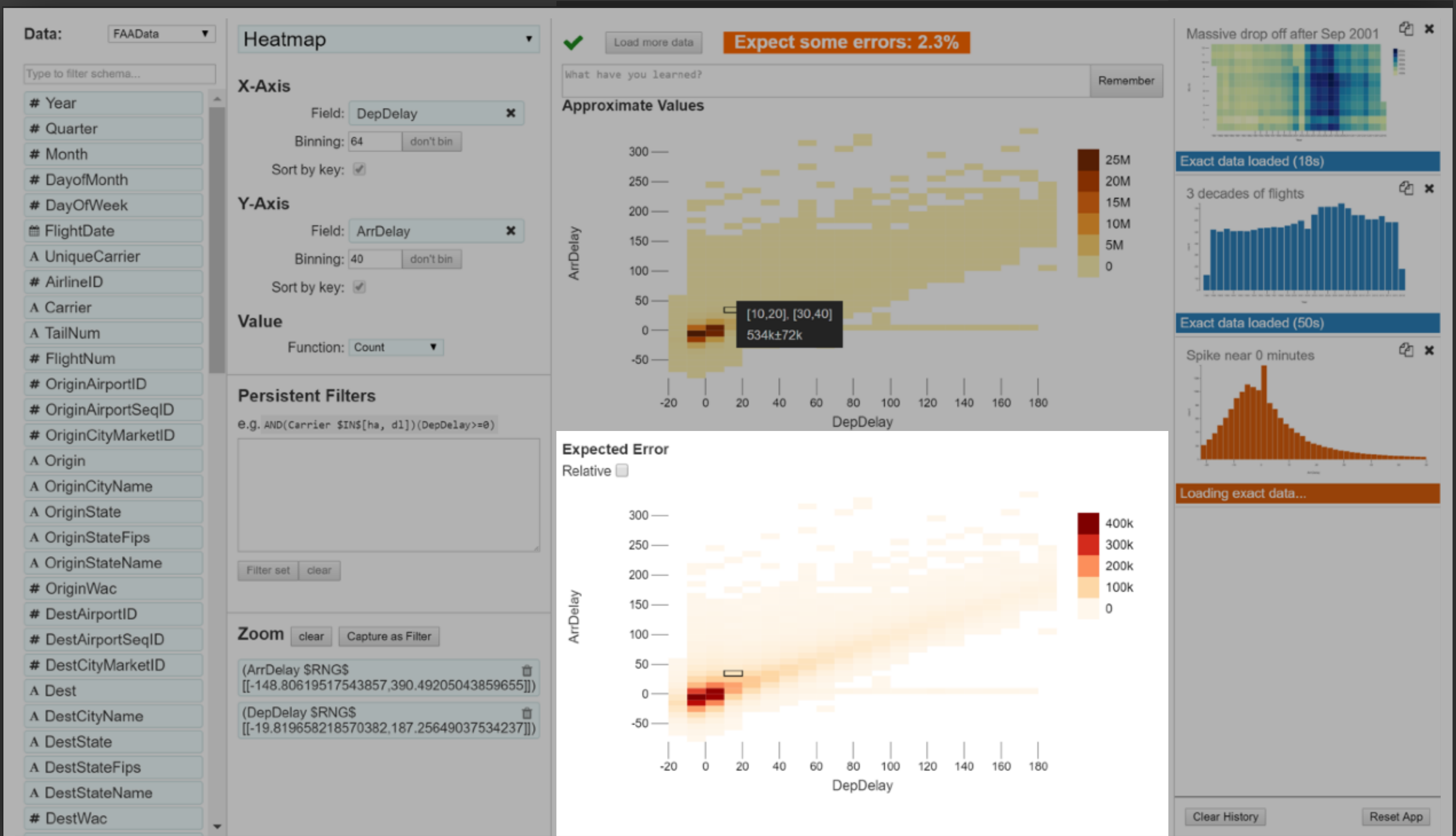
3 decades of flights

Exact data loaded (50s)

Spike near 0 minutes

Loading exact data...

Visualize Uncertainty



Data: FAAData

Heatmap

X-Axis

Field: DepDelay

Binning: 64

Sort by key: ☑

Y-Axis

Field: ArrDelay

Binning: 40

Sort by key: ☑

Value

Function: Count

Persistent Filters

e.g. `AND(Carrier $IN$[ha, dl])(DepDelay>=0)`

Zoom

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(DepDelay RNG [[-19.819658218570382,187.25649037534237]])

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534k±72k

Expected Error

Relative □

Massive drop off after Sep 2001

Exact data loaded (18s)

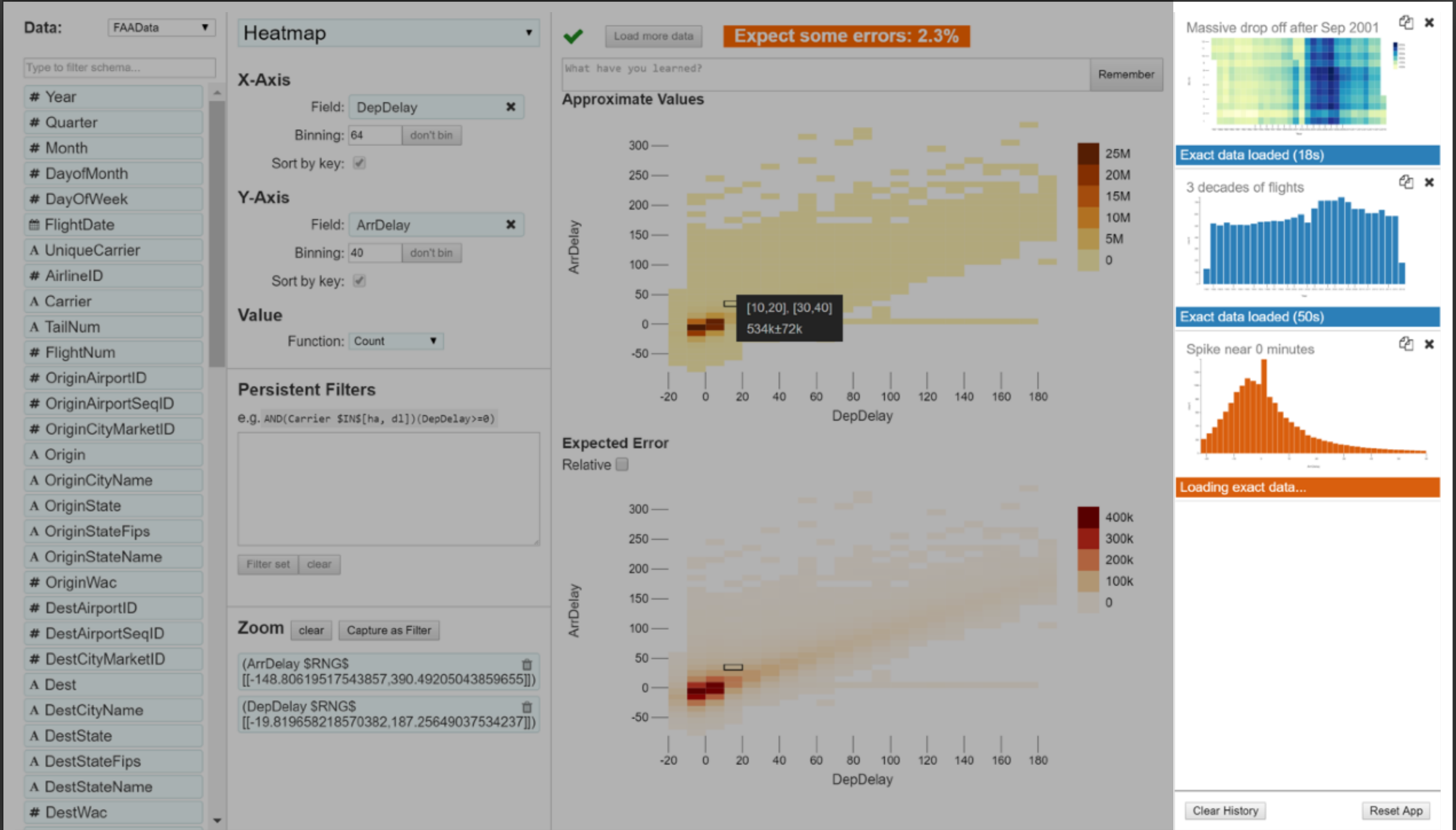
3 decades of flights

Exact data loaded (50s)

Spike near 0 minutes

Loading exact data...

Show a History of Previous Charts



Data: FAAData

Heatmap

X-Axis

Field: DepDelay

Binning: 64

Sort by key: ☑

Y-Axis

Field: ArrDelay

Binning: 40

Sort by key: ☑

Value

Function: Count

Persistent Filters

e.g. `AND(Carrier $IN$[ha, dl])(DepDelay>=0)`

Zoom

(ArrDelay RNG [[-148.80619517543857,390.49205043859655]])

(DepDelay RNG [[-19.819658218570382,187.25649037534237]])

Expect some errors: 2.3%

Approximate Values

[10,20], [30,40]
534k±72k

Expected Error

Relative □

Massive drop off after Sep 2001

Exact data loaded (18s)

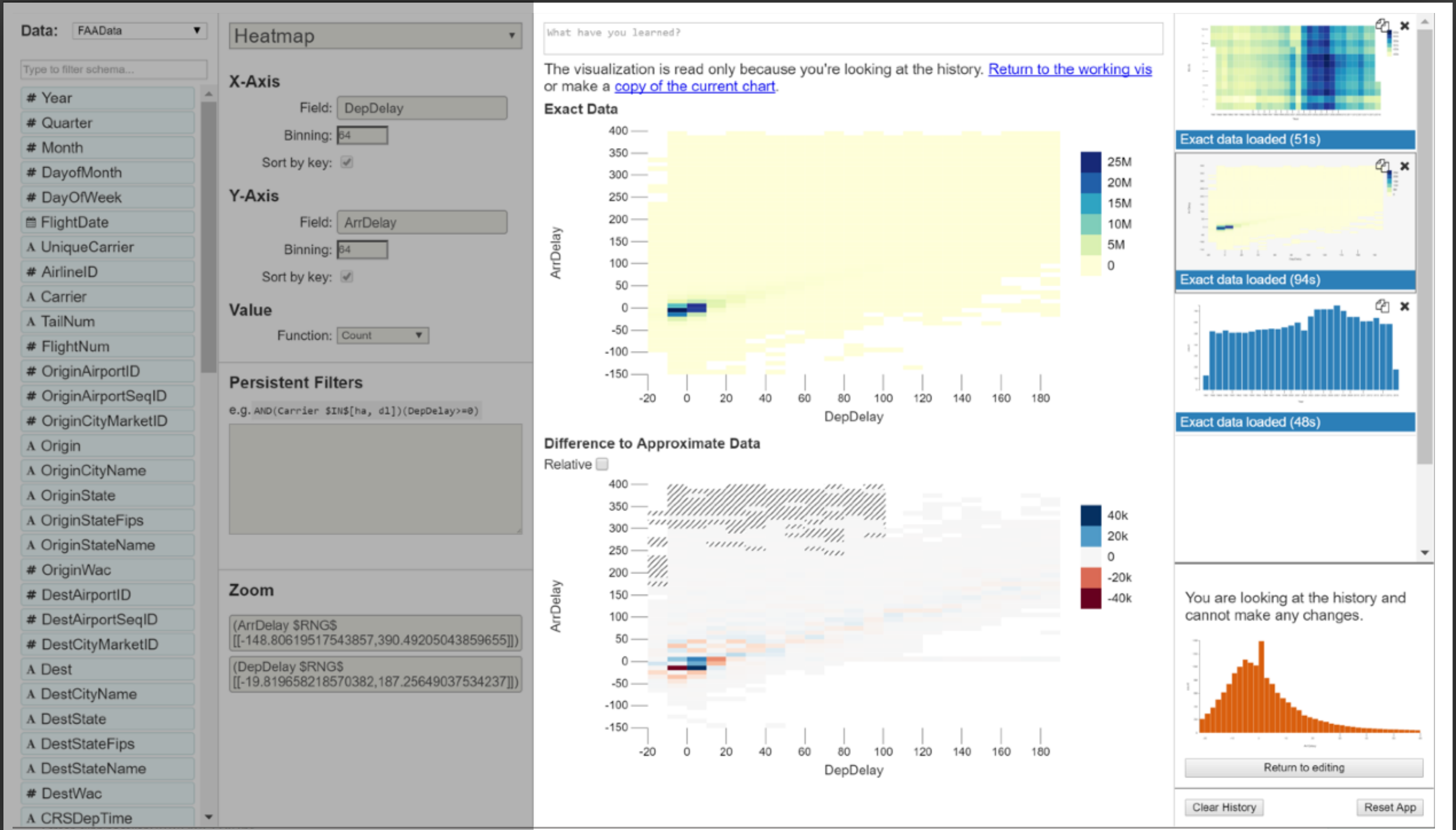
3 decades of flights

Exact data loaded (50s)

Spike near 0 minutes

Loading exact data...

Help Analysts Confirm Results



Data: FAAData

Heatmap

X-Axis

Field: DepDelay

Binning: 64

Sort by key: ☑

Y-Axis

Field: ArrDelay

Binning: 64

Sort by key: ☑

Value

Function: Count

Persistent Filters

e.g. AND(Carrier IN[ha, dl])(DepDelay>=0)

Zoom

(ArrDelay RNG [[-148.80619517543857,390.49205043859655]])

(DepDelay RNG [[-19.819658218570382,187.25649037534237]])

What have you learned?

The visualization is read only because you're looking at the history. Return to the working vis or make a copy of the current chart.

You are looking at the history and cannot make any changes.

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.