CS 686: Special Topics in Big Data

Managing Geospatial Data

Lecture 19

Today's Agenda

- Q&A from previous class
- Introduction to spatiotemporal data
- P2 dataset specifics
- Geohash
- Spatial Indexes
- Spatial Queries

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Q&A

- Who invented MapReduce?
  - Functional programming languages, way back…
  - Google popularized it
  - Hadoop made it pervasive
- MapReduce 2.0?
  - Hadoop: YARN (Yet Another Resource Negotiatior)
  - Splits up resource management across the cluster
  - Still very much the same old paradigm

Another Question: Why?

- Google has stated that they no longer use MapReduce
  - **But** I am sure the paradigm itself (perhaps not the implementation) is alive and well at Google!
- Spark has recently become more popular for these types of analyses
  - Allows in-memory working sets
- Hadoop, like many "cool" technologies, was over-prescribed
  - It's still a great (the best?) option for processing gigantic amounts of data in a batch fashion

One More Thing

- Turn in:
  - Design doc
  - Project retro
- !!!

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Spatiotemporal Data

- One of the many sources of big data is ***spatiotemporal*** datasets
- These datasets are multidimensional:
  1. Space (geographic location, x-y coordinate, etc.)
  2. Time (could be years, days, even microseconds)
- Besides space and time, a spatiotemporal data point isn't very useful without additional ***features***:
  - Name, Age, ID
  - Speed, Weight, Direction

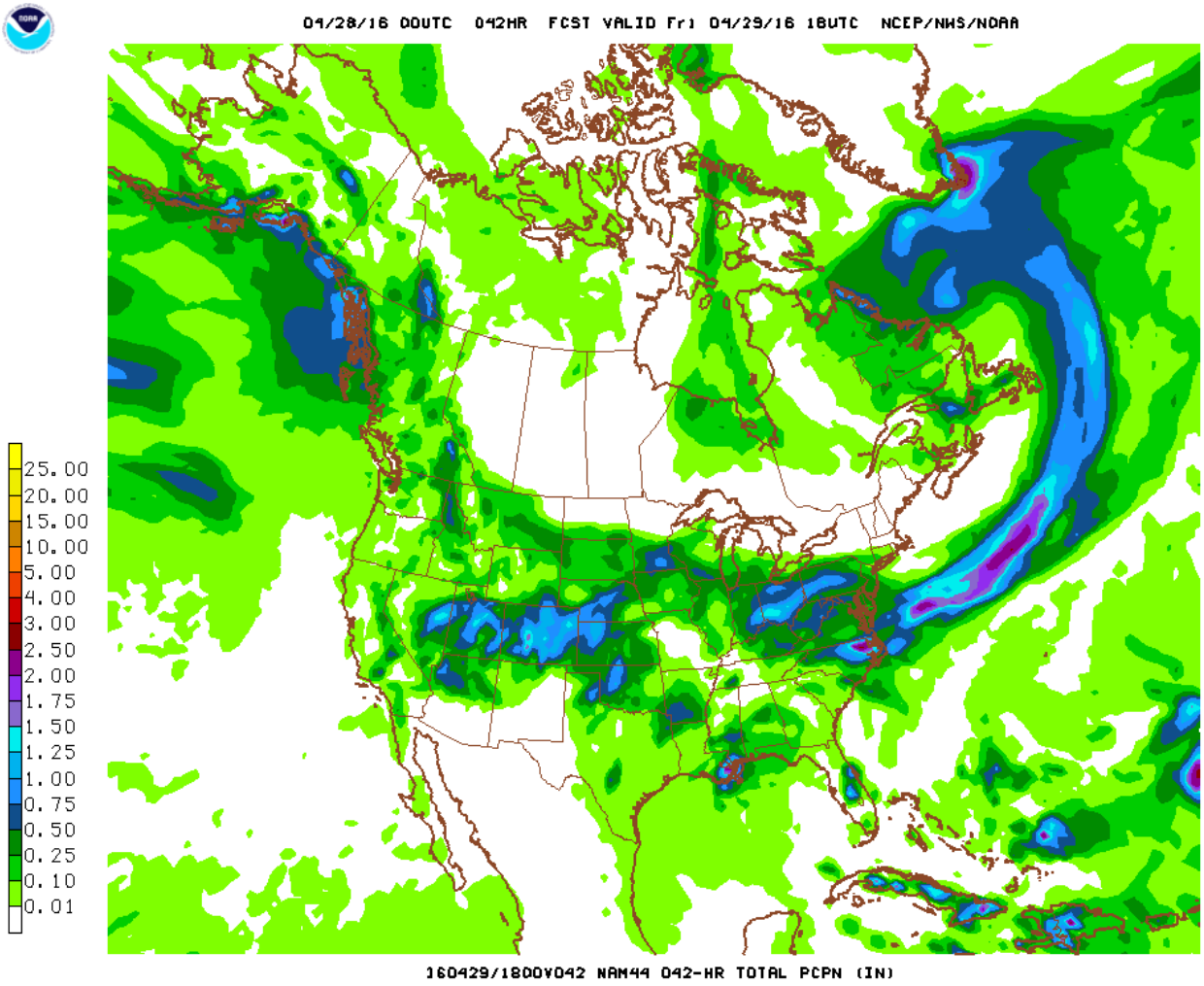
Spatiotemporal Data Sources

- Geographic information systems
  - Electric usage in a city over time
- Object tracking systems
  - GPS, atomic clocks, speed, direction
- Multiplayer games
  - Player location, attributes
- Networked sensors and radars
  - Temperature sensor with Wi-Fi connectivity
  - Cloud cover or reflectivity readings

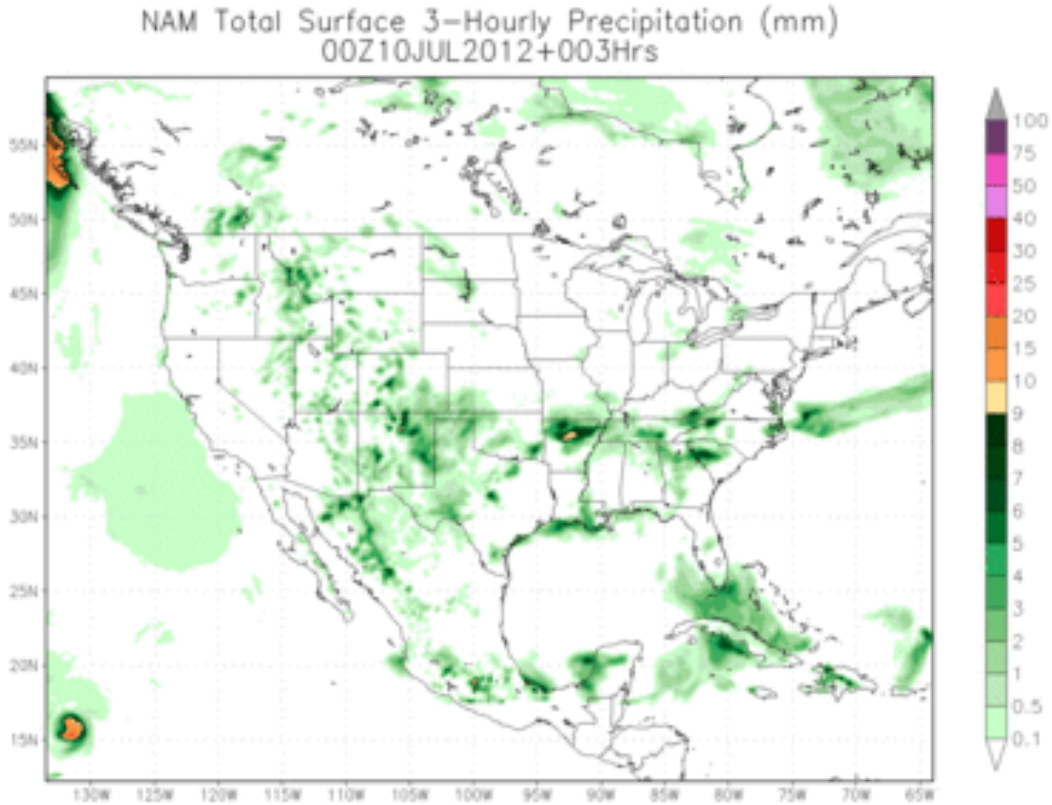
P2 Motivation: NOAA Dataset

- Sourced from NOAA NAM Project
- Some Dimensions/Features:
  - Geospatial: Latitude, Longitude
  - Time Series: Start Time, End Time
  - Temperature
  - Relative Humidity
  - Wind Speed
  - Snow Depth
- ~2 PB (about 20 billion files)

NAM Precipitation Snapshot



Animation


NAM Total Surface 3-Hourly Precipitation (mm)
00Z10JUL2012+003Hrs
55N
50N
45N
40N
35N
30N
25N
20N
15N
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125W
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Learning More

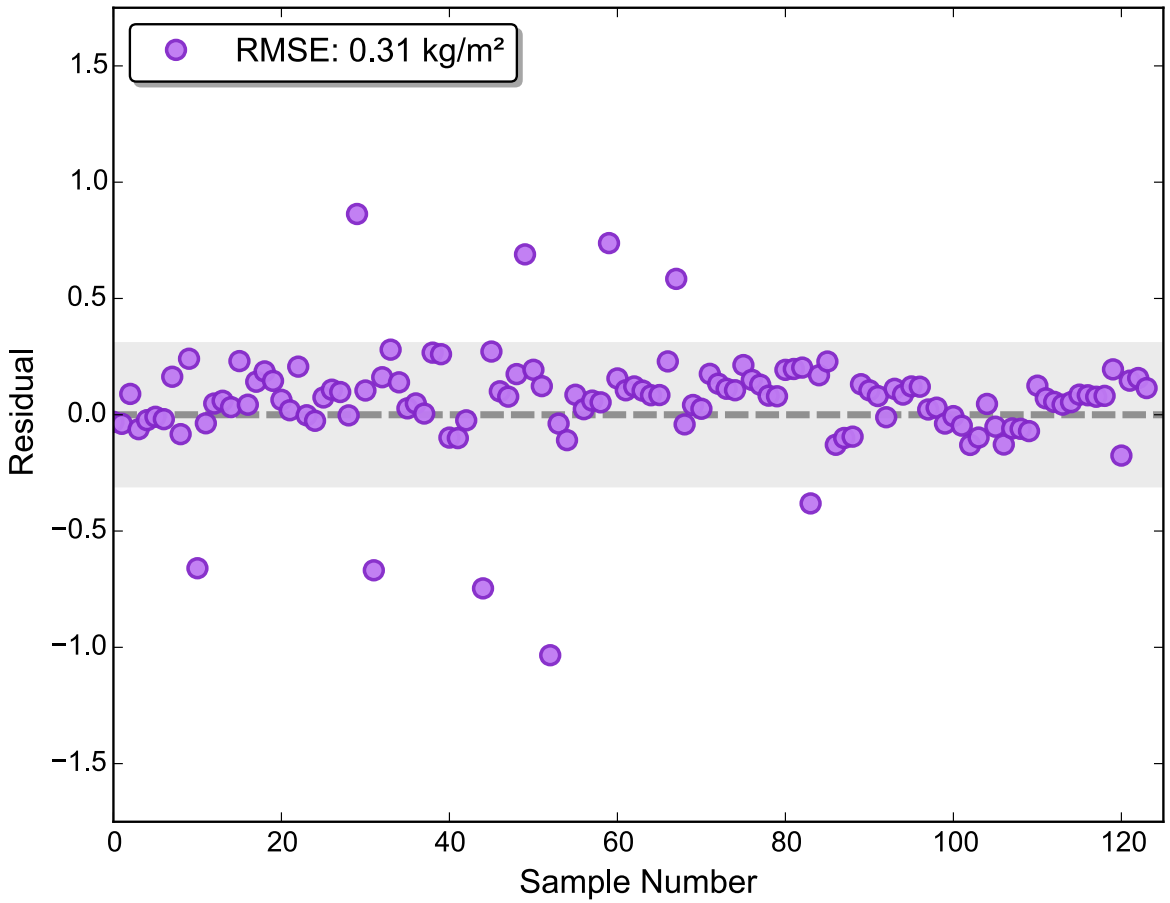
- See:

  https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/north-american-mesoscale-forecast-system-nam

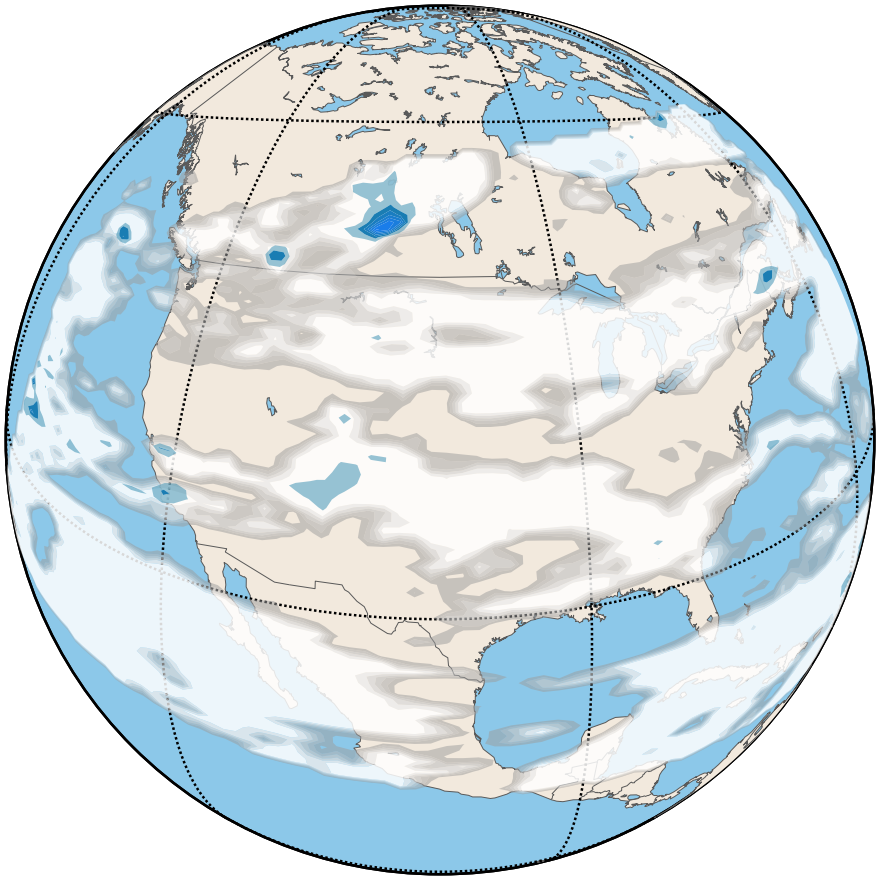
NAM Dataset Applications

- Predicting future weather events or patterns
  - Machine learning
  - Statistics
- Summarizing Information
  - Visualizations
  - Reports
- Exploring relationships between features
  - How does the temperature influence humidity?
  - How does the location influence precipitation?

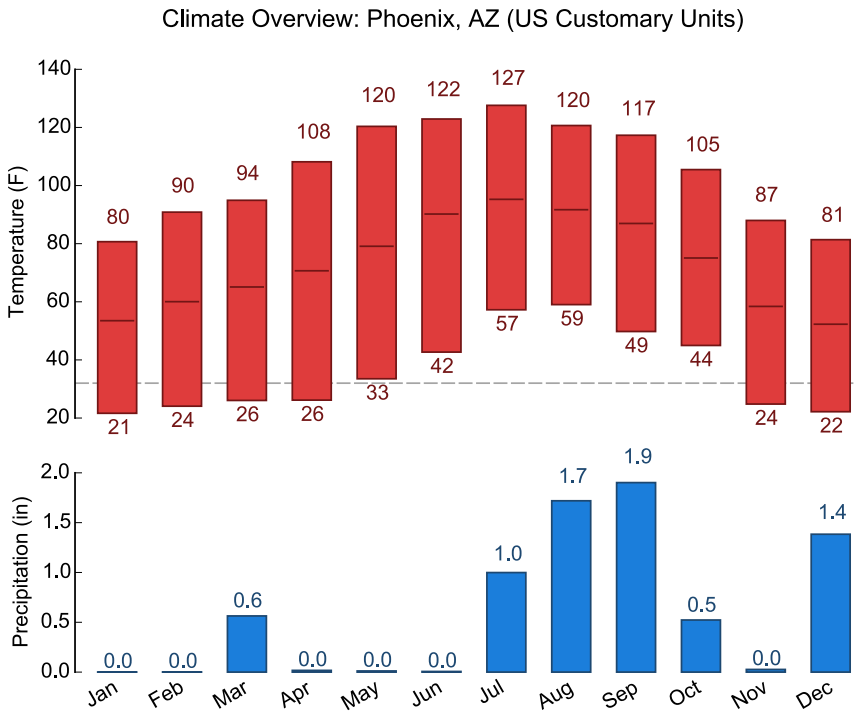
Predicting Rainfall: Wyoming

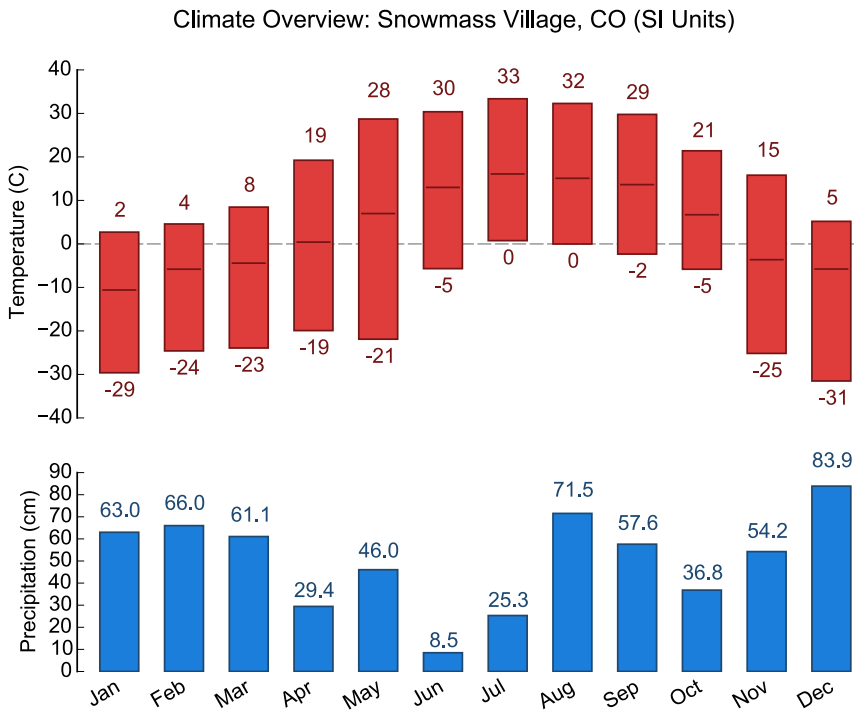


Contour Visualization



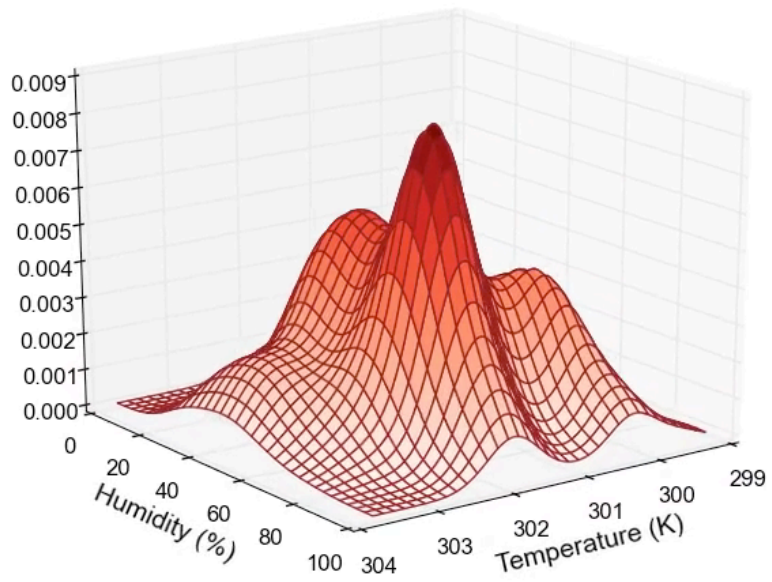
Climate Chart



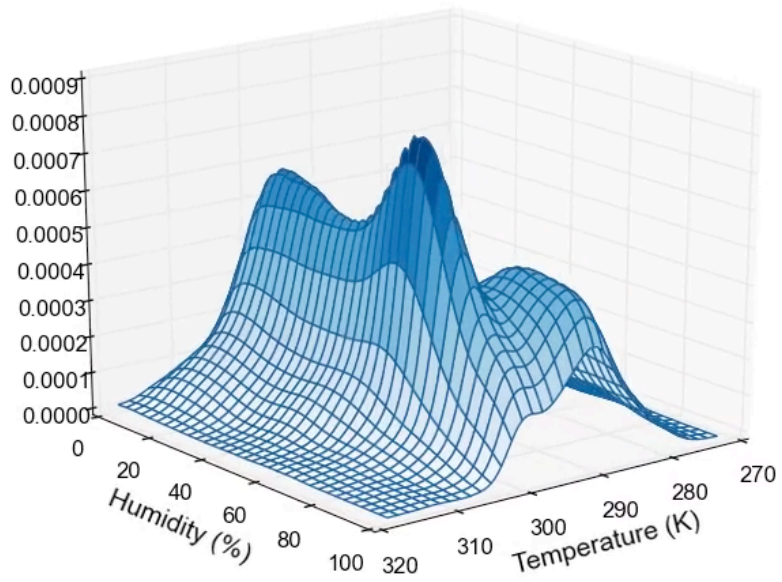


Relationships: Temp & Humidity

PDF(Temperature ∩ Humidity): Florida, USA



PDF(Temperature ∩ Humidity): Continental United States



Gathering Insights

- This dataset contains a wealth of information, but extracting insights from the data is challenging
- Multiple dimensions
- Storage requirements: where do we put all of it?
- Querying the data
  - (*knowledge discovery*)

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NAM Dataset Specifics

- The source data is stored in GRIB format
- Can be read and manipulated via the NetCDF library: https://www.unidata.ucar.edu/software/netcdf/
- We'll use a condensed version of the dataset for P2 instead

Condensed NAM

- Tab-delimited features (no fancy formats)
- We'll consider only 2D feature data
  - No elevation information
- Each .tdv file contains a month of readings **sampled** from the original source
  - nam_201501.tdv – January 2015

File Format

- Each line contains a single record
- Each record begins with:
  1. Time of reading (UNIX timestamp)
  2. Geohash location (more on this later!)
- Then, the remaining features (~56)
  - null if no reading existed

Some Interesting Features

- visibility
- pressure
- vegetation
- lightning
- temperature
- wind speed
- preciptation
- snow cover, snow depth

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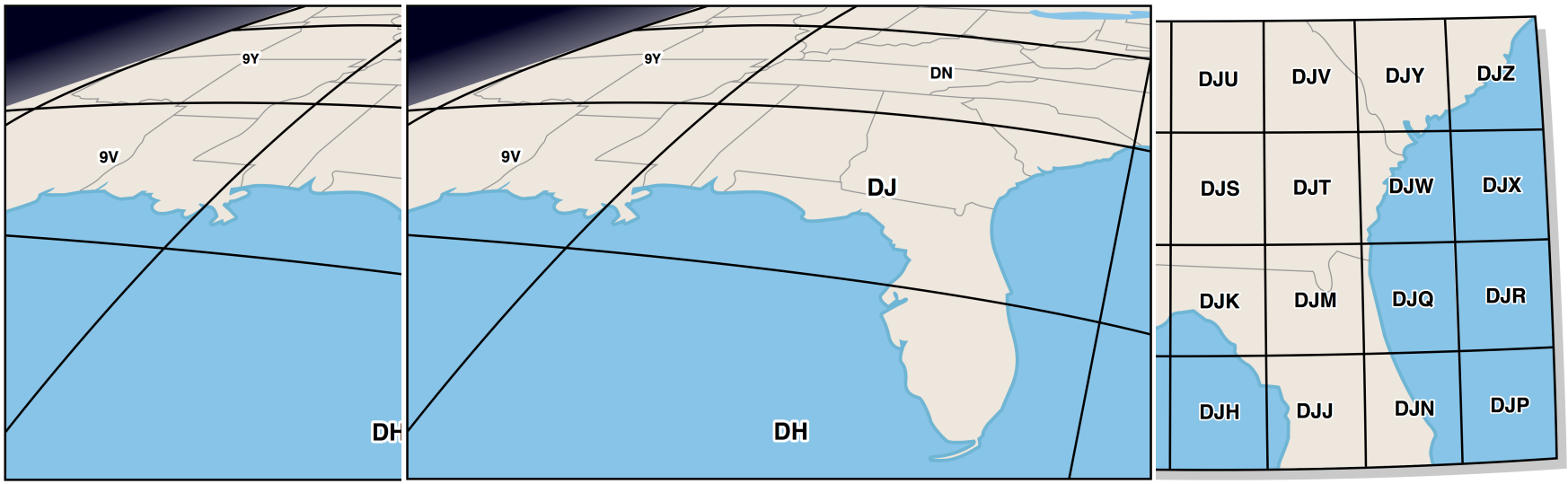
Spatial Queries

- Querying spatial data is a whole subject in itself
- If I gave you lat-lon pairs in the dataset, you could use those to perform simple spatial queries
  - If lat is >= something && lat <= something else:

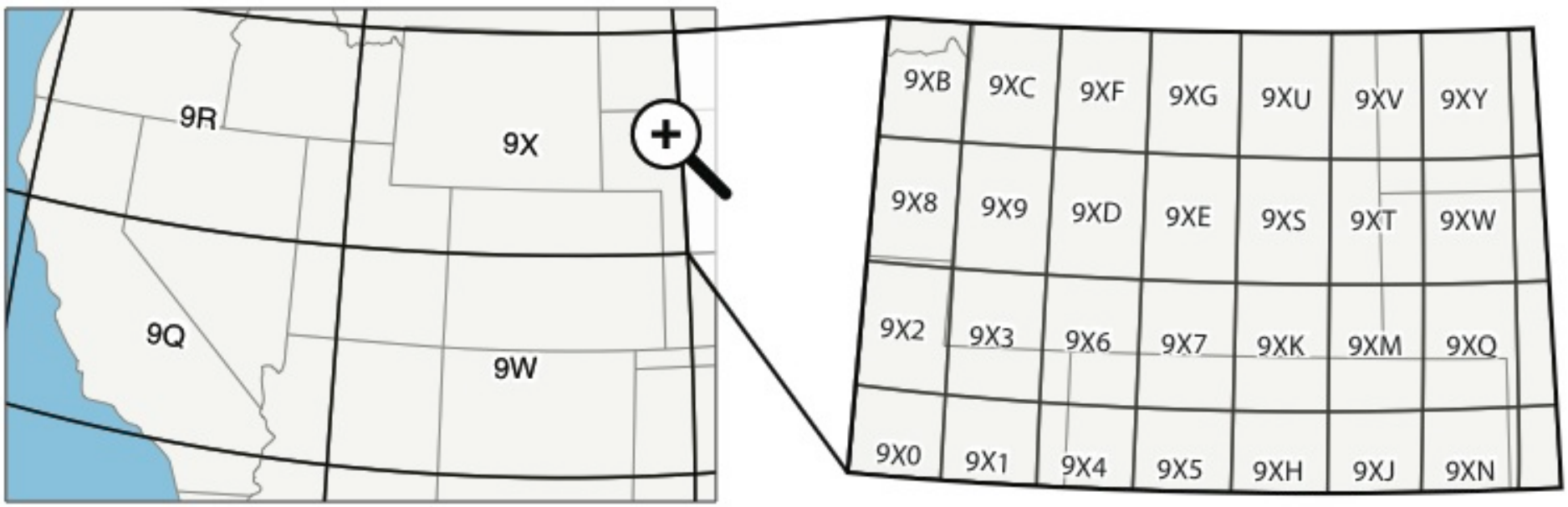
    blah blah blah();

    etc();
- A **better** option is to use the Geohash algorithm
  - Maps the earth to base32 strings
  - Defines a spatial **hierarchy** we can exploit

The Geohash Algorithm (1/2)



The Geohash Algorithm (2/2)



Geohash Details

- We use the ***Geohash*** algorithm to represent the spatial location associated with our sensor readings
  - Maps 2D spatial locations to 1D strings
  - Precision is determined by string length
- 9Q8YVT1F ➔ Kudlick Classroom
  - Similar string prefixes refer to similar locations
- Want to support range queries? Just match more or less of the string prefix

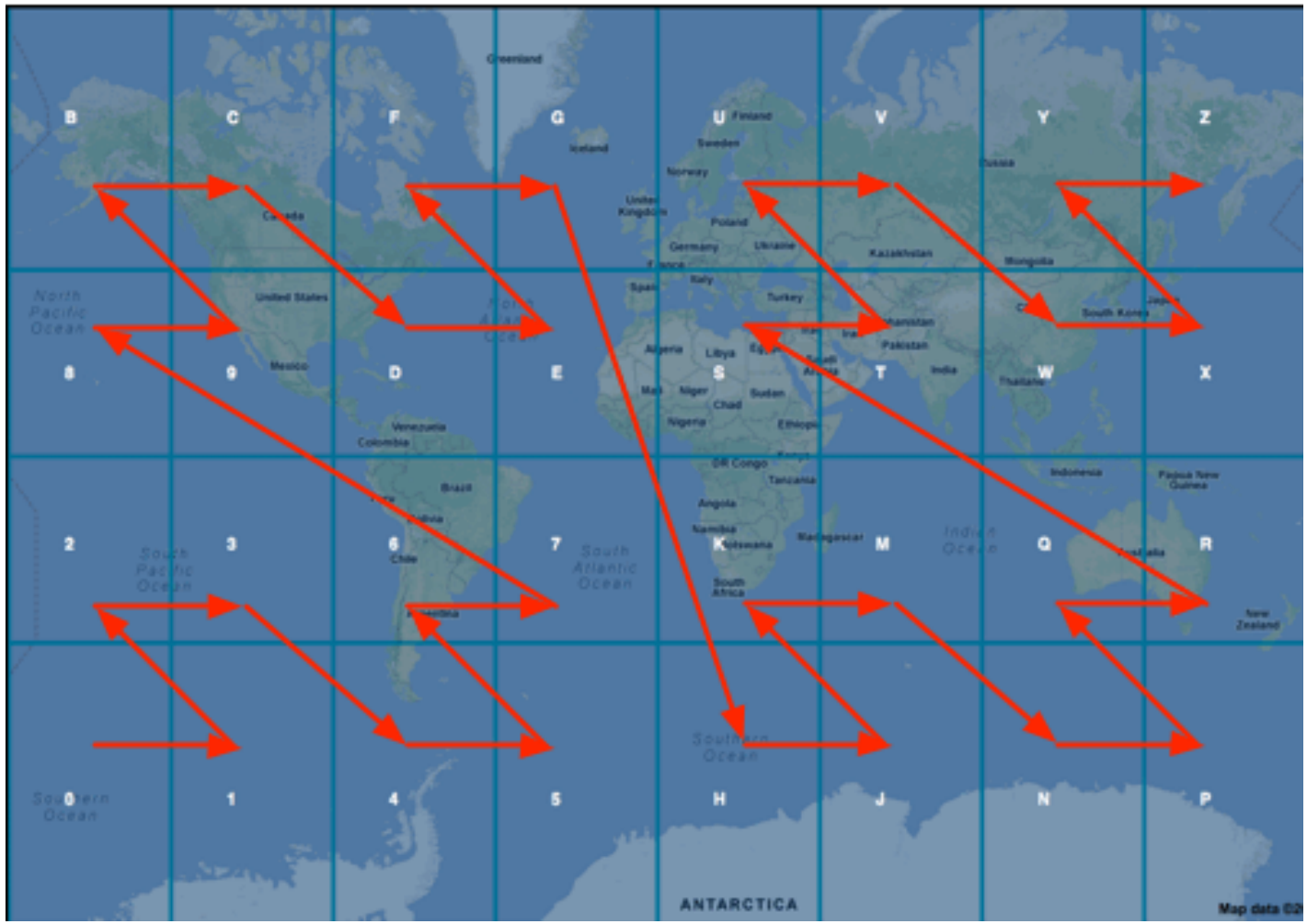
Geohash Resolutions

- Spatiotemporal data is not always evenly distributed
  - Compare the density of New York City and Glenwood Springs, Colorado
- Hash: 9XJQBF
  - 9XJQ = 20x30 km
  - 9X = 600x1000 km
- However, for our dataset, the data **IS** evenly distributed!
  - Fixed grid

Geohash Implementation

- Divides the bounding boxes in half with each binary bit added to the string
  - 1 bit = left or right half of the earth
  - 2 bits = top or bottom half of the left/right half
  - And so on…
- Uses 32 alphanumeric characters (Base 32)
  - 32 characters = 5 bits per character (5 divisions)
  - Omits some letters to avoid forming words

Z-Order Curve



Source: http://www.bigdatamodeling.org/2013/01/intuitive-geohash.html

Geohash Fun Facts

- Originally designed to allow users to share short URLs that represent locations
- Similar implementations have been used to identify locations for businesses, government
  - Ireland's proof-of-concept ***openpostcode*** can uniquely identify all locations within the UK
- Play with it! http://geohash.gofreerange.com

For Project 2

- I'll give you a class that can convert Geohashes to lat-longs, and vice versa
- It's written by me, so um, watch out!
  - (No seriously, it does work!)
- Feel free to use your own library or favorite spatial data structures library for this

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- **Spatial Indexes**
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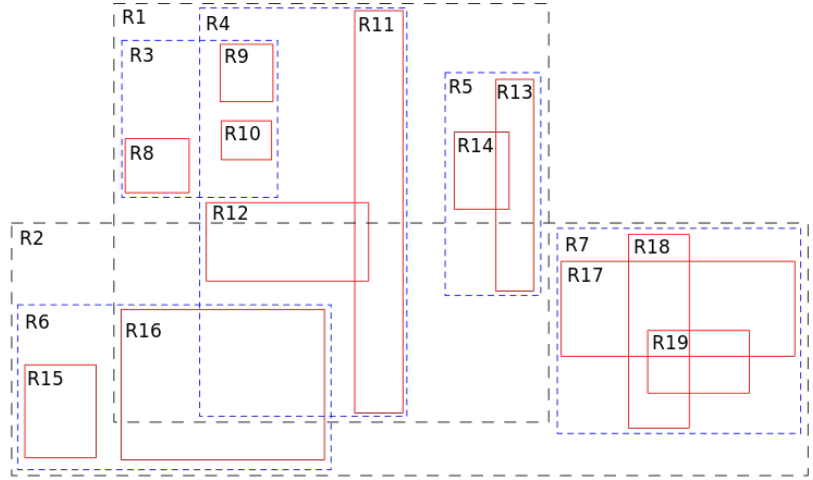
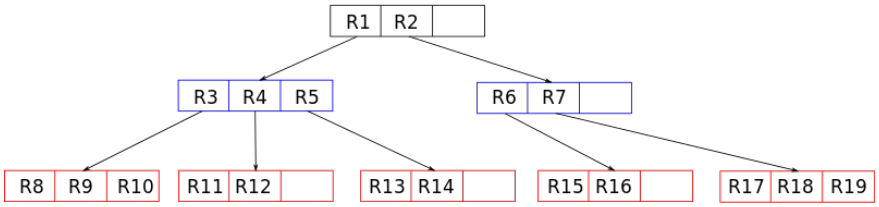
Spatial Indexing: R-Trees

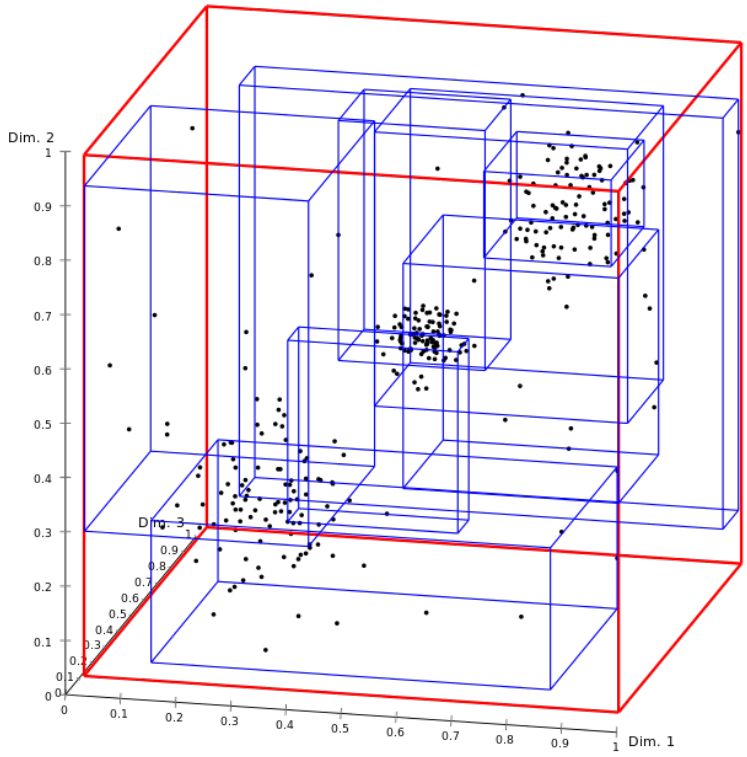
- **R-Trees** are a widely-used spatial index
- Share many similarities with B-Trees, but support spatial features:
  - Multiple dimensions
  - Intersection, containment queries
  - Nearest neighbor search





R-Tree Drawbacks

- R-Trees can be overwhelmed by extremely large datasets
- Query performance decreases as the number of leaves in the tree expands
  - Too much precision



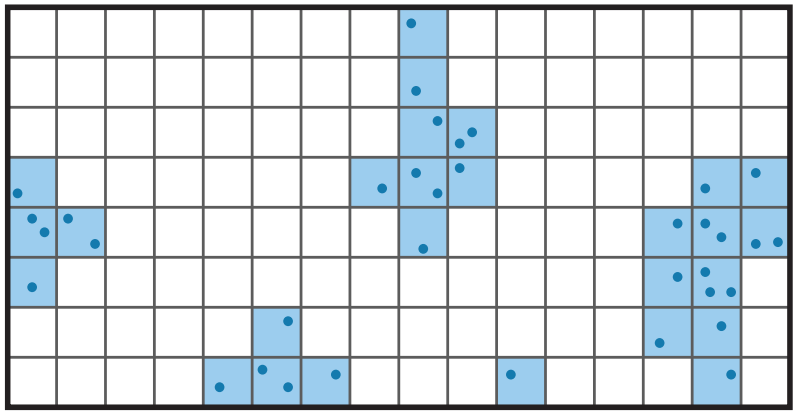
Alternative: Geoavailability Grid

- ***Bitmap index*** for spatial data
- Provides a coarse-grained representation of the spatial locations of information in the system
  - Limits the maximum memory consumption
  - May produce false positives
- Eliminates geographic regions from queries that do not contain relevant data

Bitmap Indexing

- Also known as: ***bit arrays*** or ***bitsets***
- Used in several areas:
  - Relational database management systems
  - Decision support systems
  - Data warehousing
- Just a stream of bits!
  - 01101000 01100101
  - 01101100 01101100
  - 01101111

Geoavailability Grid

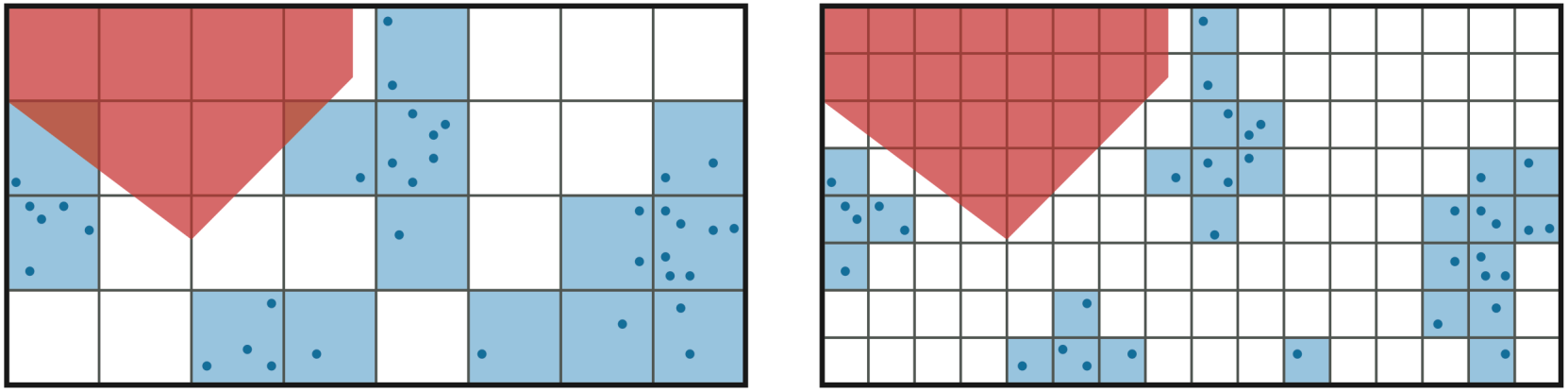


0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
1	0	0	0	0	0	0	1	1	1	0	0	0	0	1	1
1	1	0	0	0	0	0	0	1	0	0	0	0	1	1	1
1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0
0	0	0	0	1	1	1	0	0	0	1	0	0	0	1	0

Bitmap Storage Requirements

- The resolution of the geoavailability grid determines the number of bits that must be stored
- Each node in the system maintains a geoavailability grid for each feature type it contains
- Higher precision maps require more bits, but provide greater reductions in search space

Resolution vs. Search Space Reduction



Bitmap Compression

- Bitmaps are compact, but massive datasets still require large amounts of bits
- The smaller the geoavailability grids, the more data can be held in memory
- Most bitmap implementations use run-length encoding (RLE) to reduce their size

Run-Length Encoding

- RLE is one of the simplest forms of compression
- Consider a binary string: 00000011111110001
- Run-length encoded: 60713011
- Geoavailability grids use Enhanced Word-Aligned Hybrid compression (EWAH)
  - More resilient to data with low sparsity
  - Better compression ratio than standard RLE
  - Increases the speed of bitwise operations

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- **Spatial Queries**

Brute-force Approach

- Submit queries to all nodes, scan over records
  - **This is what we'll do in P2**
- Issues:
  - Wasted processing on nodes with no matches
  - Not scalable
  - High latencies
- A better approach: ***decompose*** the query and distribute it only to relevant nodes

Query Evaluation Process

1. User submits a polygon and feature constraints
   - "Give me humidity values for San Francisco in July"

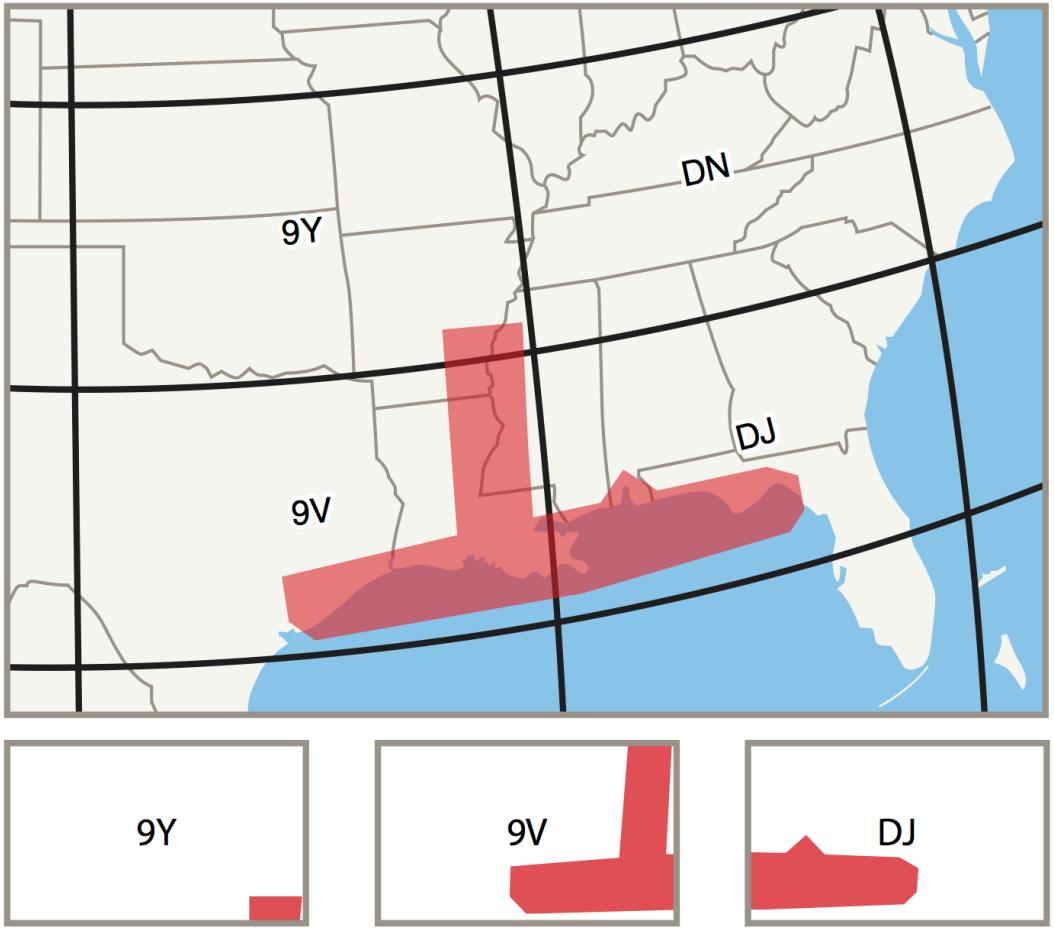
2. The query is *decomposed* into multiple *subqueries* based on Geohash boundaries

3. Subqueries are distributed to individual storage nodes for processing

Representing Polygon Queries

- Users are provided a scrollable, zoomable map with standard polygon/rectangle drawing tools
- Each component of the input polygon is represented by <latitude, longitude> pairs
- Coordinate pairs are stored by creation order and serialized to a binary format

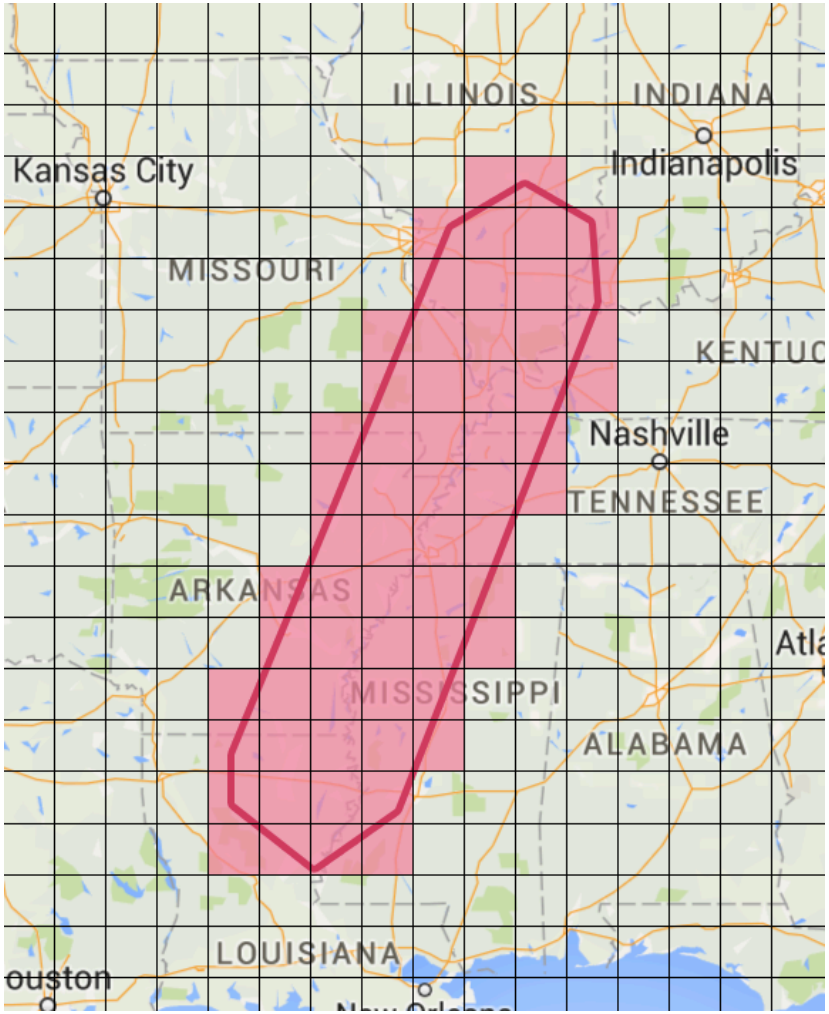
Spatial Decomposition



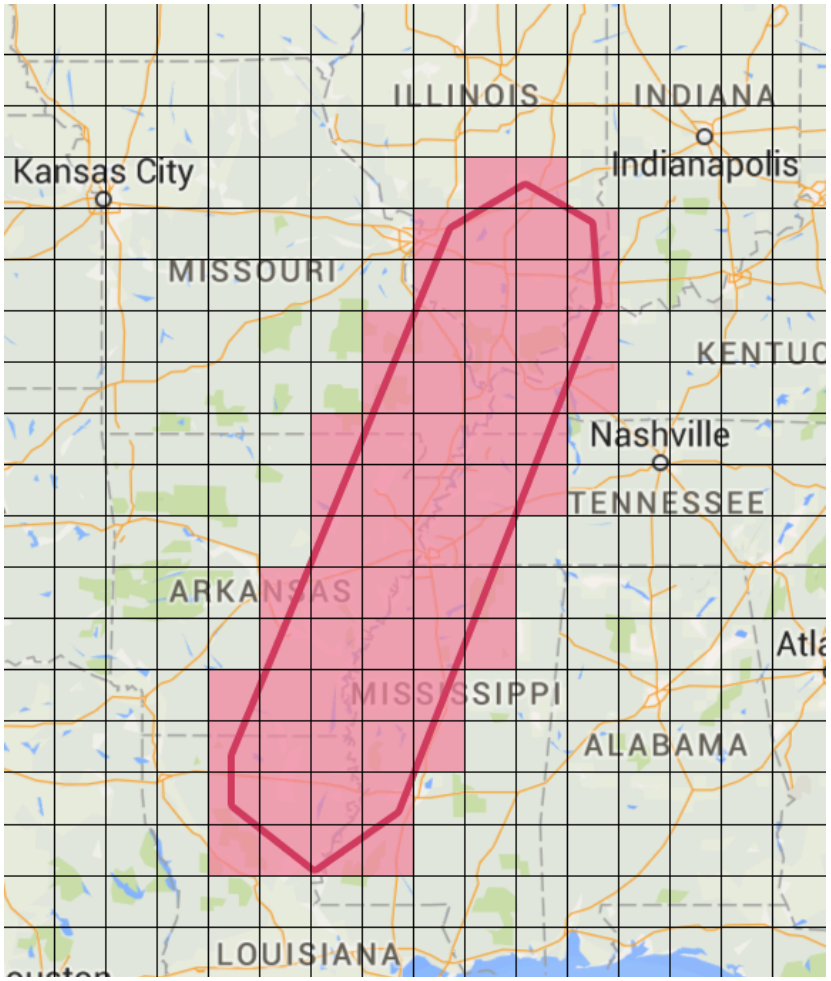
Geoavailability Evaluation

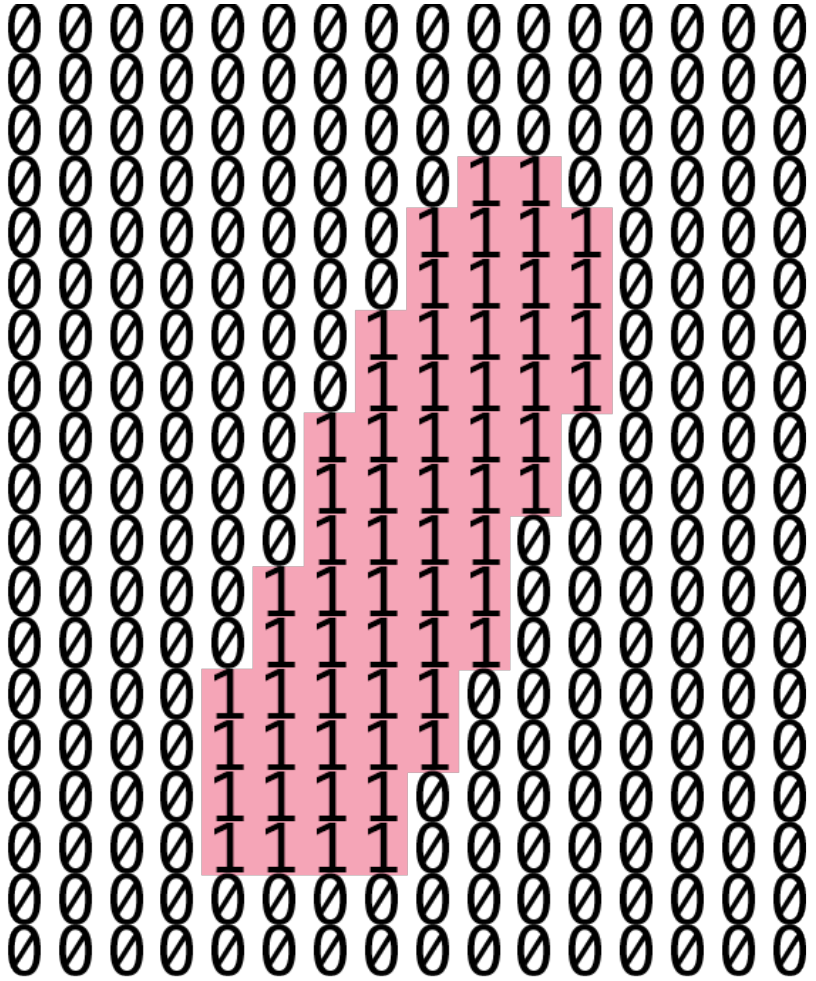
- Query polygons are transformed into query bitmaps
  - Uses standard graphics routines
  - Can be GPU accelerated
- A bitwise AND is performed between the query bitmap and each geoavailability grid
  - If the result is an empty set, the storage node does not contain relevant data

Polygon Transformation [1/2]



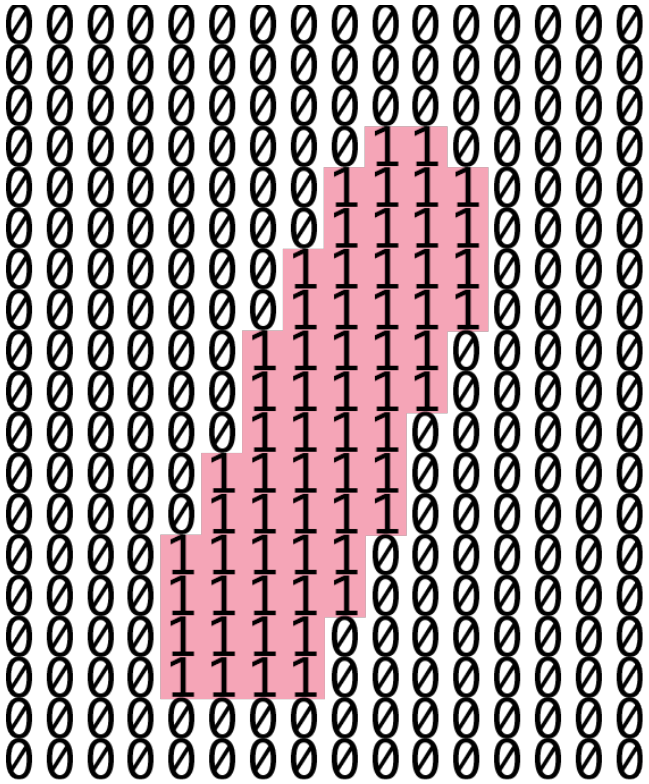
Polygon Transformation [2/2]



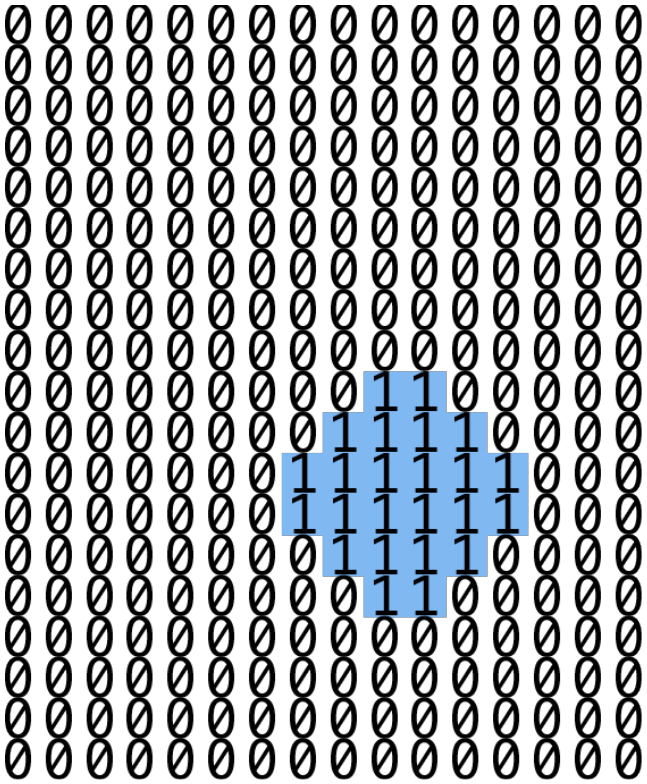


Intersection Queries

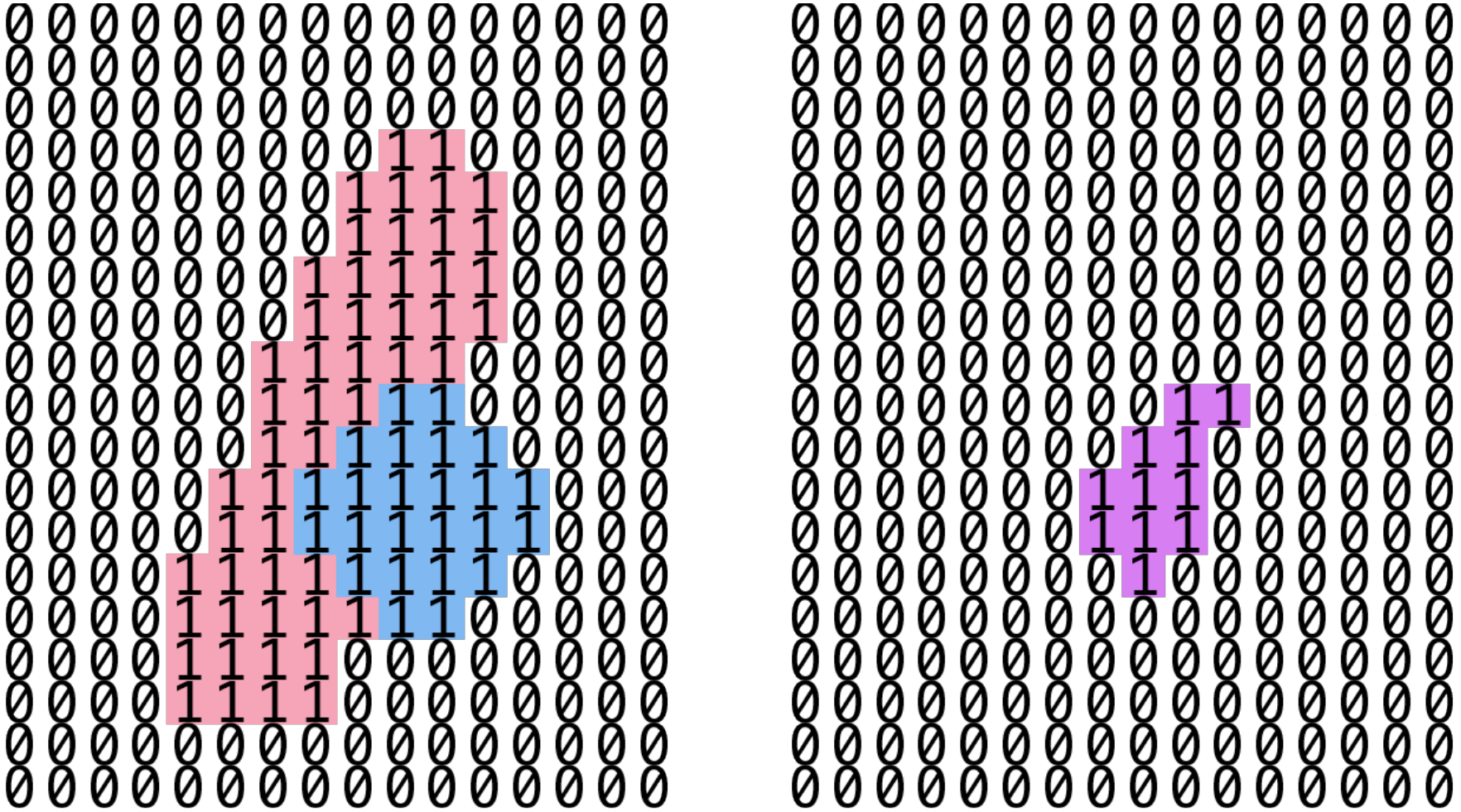
Query



Data



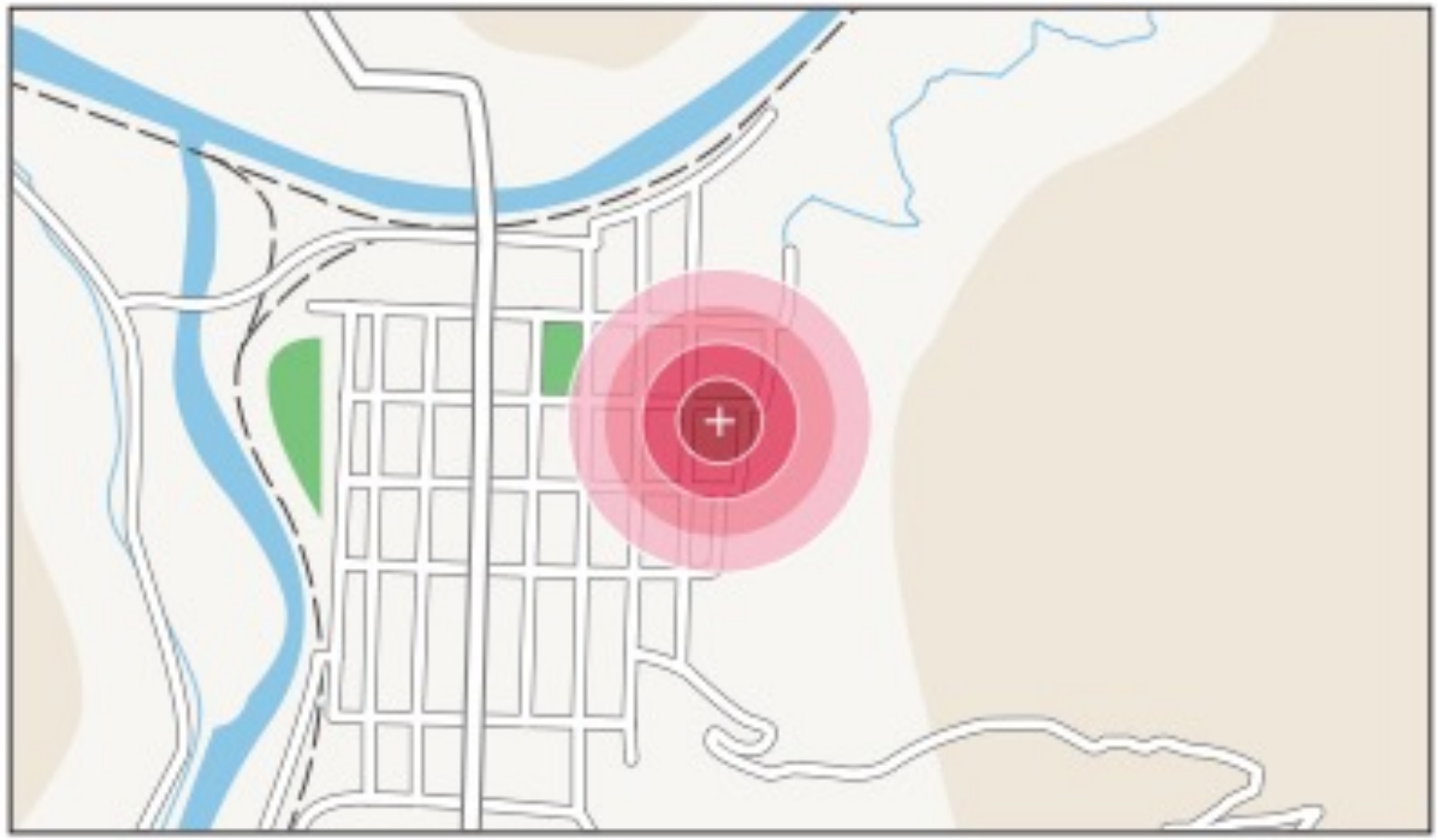
Bitwise AND



Proximity Queries

- Retrieves relevant records near a starting coordinate pair
  - "Where's the nearest coffee shop?"
- Successively larger *annuli* are generated around the starting location and evaluated against the geoavailability grid
- The search stops when a match is found, or a specified maximum area has been covered

Proximity Query Example



Constrained Proximity Queries

- In some cases, users may wish to constrain a proximity query to a particular region
  - "Find the nearest coffee shop in Santa Clara county"
- Requires constraining geometry
  - US **T**opologically **I**ntegrated **G**eographic **E**ncoding and **R**eferencing (TIGER) spatial dataset
  - Includes counties, states, administrative boundaries

Constrained Proximity Example

Performance Evaluation

- Geoavailability Grids are based on space efficient, fast data structures: **bitmaps**
- Query evaluation speeds can be boosted by using GPU acceleration
- The real question: are they faster than R-Trees?

Geoavailability Grid Lookup

Bitmap Resolution	Lookup Time (ms)	Standard Deviation (ms)
2^{25}	0.012	0.021
2^{30}	0.163	0.203
2^{35}	0.723	0.289

Query Performance Comparison