

# Multilateration Indexing

Data structures and algorithms to improve query performance for geodesic and other complex distance functions



### Agenda

- 1. Hi, I'm Chip!
- 2. Problem Statement
- 3. Multilateration Index
- 4. Query Algorithms
- 5. Experiments
- 6. Results
- 7. Conclusions and Future Work



### Hi, I'm Chip!

## **About Chip**

- Came back to grad school for "fun"
  - It's been fun!
  - Did some research, took some classes. Good times.
- Data and Software Engineer for:
  - KPMG / Deloitte
  - NASA
  - US Air Force
  - SpaceX
  - Passport Health (Medicare/Medicaid)



#### Real World Problems

# Problem Statement

#### Satellite Communications

- Fast Moving
- Extreme accuracy requirement over long distances for laser guidance
- Regularly need to find the closes Satellite/Ground Station/User Terminal (Nearest Neighbor)

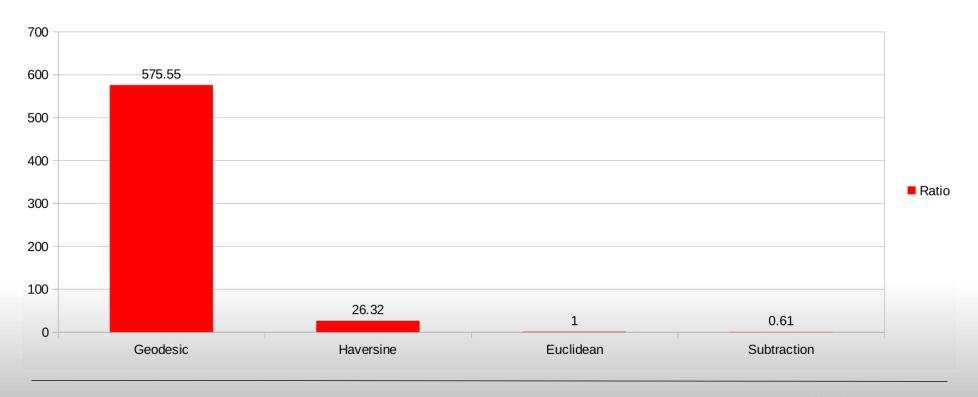
#### Healthcare Network Adequacy

- Ensure that x% of <type of person> is within m miles of <type of health service>
  - 80% of female members over the age of 13 must live within 25 miles of an OB/GYN
  - 80% of members under the age of 16 must live within 25 miles of a pediatrician
  - 90% of members must live within 50 miles of an emergency room
  - ٠ ...



### **Expensive Distance Functions**

# Problem Statement





# Problem Statement

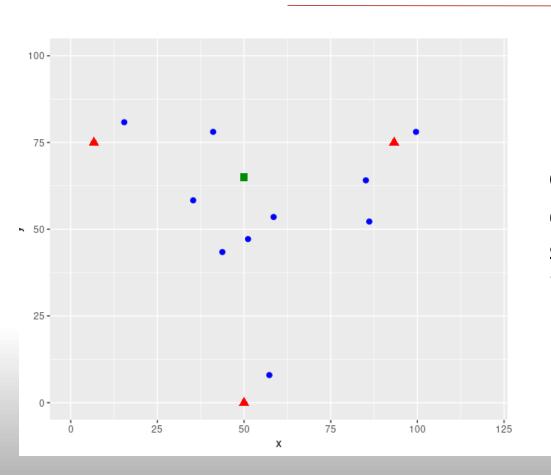
#### **Network Adequacy**

- Given a non-empty set of points P and a non-empty set of query points Q in a metric space M (where P ∩ Q comprises the 'network'), the network is 'completely adequate' for a distance d and a distance function D(a, b) describing the distance between points a and b for a ∈ M and b ∈ M if for every point q (where q ∈ Q) ∃ at least one point p (p ∈ P) 3 D(p, q) <= d. Otherwise the network is 'inadequate.'</li>
- We call a single point q 'adequate' itself, if it satisfies the same condition—i.e.  $\exists$  at least one point p (p  $\in$  P ) D(p, q) <= d.
- If, within P, we consider the largest subset P' ∈ P where P' is 'completely adequate,' then P has a "Network Adequacy Percent (NAP)" of |P'|/|P|. Note that P' can be defined (identically) as the union of all 'adequate' points p ∈ P



### **Nearest Neighbor**

# Problem Statement



Given a set of search points P (blue dots), and a query point Q (green square), determine which of the points in P are closest to the query point Q



#### (Advanced) Nearest Neighbor

# Problem Statement

- Constraints beyond typical NN problems:
  - Constant motion pre-processing must happen repeatedly and quickly
  - Expensive distance function D(a, b)
  - Queries specify subsets of points in P and Q
- Includes "kNN":
  - Find the nearest k neighbors out of the set P



#### **Comparing Solutions**

# Problem Statement

#### 1. Training Time Complexity

the O() (typically in terms of |P|) required to pre-process the points p if any

#### 2. Memory Space

the memory requirements of the structures resulting from pre-processing

#### 3. Prediction Time Complexity

the O() required to find the closest point p ∈ P for a single query point q

#### 4. Insertion/Move Complexity

• the O() complexity required to add or move (or remove) a point  $p \in P$  (or  $q \in Q$ )



### **Comparing Solutions**

# Problem Statement

- Training Time Complexity
  - the O() (typically in terms of |P|) required to pre-process the points p if any
- 2. Memory Space
  - the memory requirements of the structures resulting from pre-processing
- 3. Prediction Time Complexity
  - the O() required to find the kN N ∈ P for a single point q
- 4. Insertion/Move Complexity
  - the O() complexity required to add or move (or remove) a point p ∈ P

Most solutions optimize for #3



# Problem Statement

### **Existing NN Solutions**

#### Brute Force

Compare every point to each other and sort the resulting distances

#### 2. Space Partitioning Trees

- Recursively divide points into smaller and smaller areas to reduce search space
- Examples: k-d trees and ball trees

#### 3. Locality Sensitive Hashing

Project points to lower dimensions while attempting to maintain distance relationships

#### 4. Graph Based Search

- Create a network of locally nearest-neighbors
- Example: Facebook's FAISS



# Multilateration Index

#### Proposing a Solution

- The Multilateration Index
  - Store distances from fixed points, rather than coordinates
  - i.e. Store distances from three points around the globe for geospatial applications

#### Benefits:

- Allows direct comparison of distances using simple subtraction
- Can be quickly calculated and updated (particularly vs. graph and space partitioning)
- Allows error checking (many combinations of distances are impossible, unlike coordinates)
- Is easily augmented with additional data that does not affect optimization



# Multilateration Index

## Example Index:

Index	X	у	d1	d2	d3
8	15.42852	80.83634	10.50105	78.09115	87.91872
4	35.32139	58.321179	33.12763	60.331164	60.14001
6	41.08036	78.065907	34.51806	52.310835	78.57382
2	43.7394	43.418684	48.67639	58.768687	43.86772
7	51.14533	47.157734	52.44704	50.520446	47.17164
1	58.52396	53.516719	56.10157	40.877779	54.1913
9	85.13531	64.090063	79.19169	13.627535	73.08916
5	86.12714	52.201894	82.6355	23.900247	63.48392
3	57.28944	7.950161	83.99465	76.108693	10.78615
10	99.60833	78.055071	92.95982	7.008032	92.48557

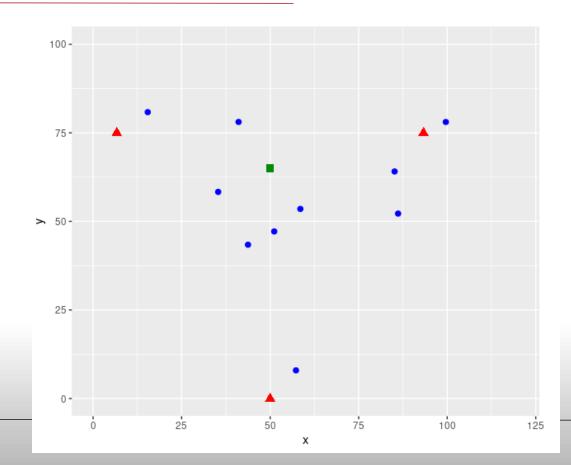


### Example Walkthrough Step 1:

3 Red Triangles: Reference Points

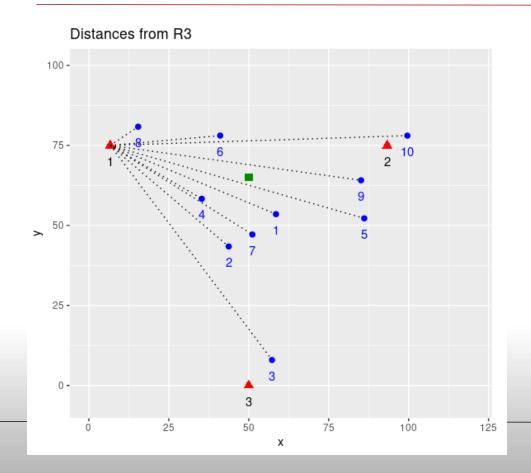
10 Blue Dots: Search Points

1 Green Square: Query Point





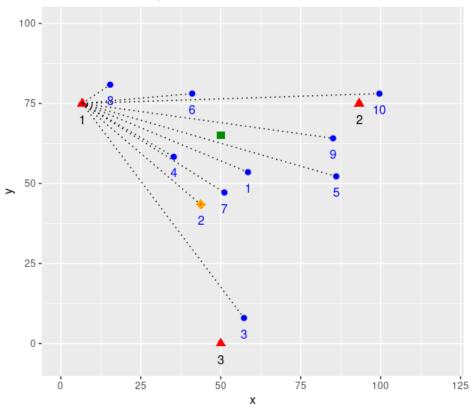
## Example Walkthrough Step 2:





### Example Walkthrough Step 3:

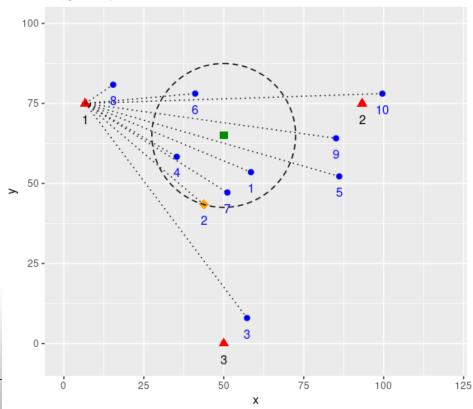






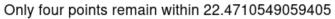
### Example Walkthrough Step 4:

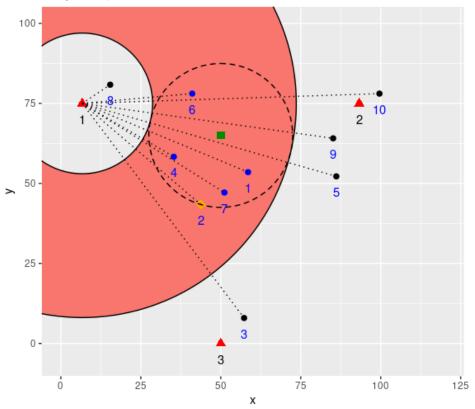
#### Only four points remain within 22.4711 units





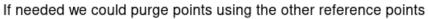
### Example Walkthrough Step 5:

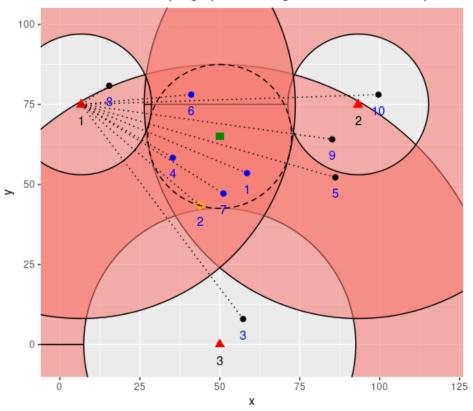






### Example Walkthrough Step 6:

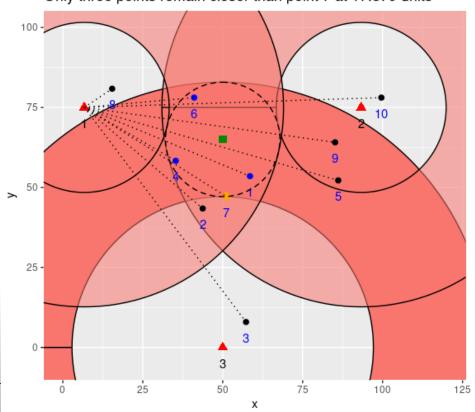






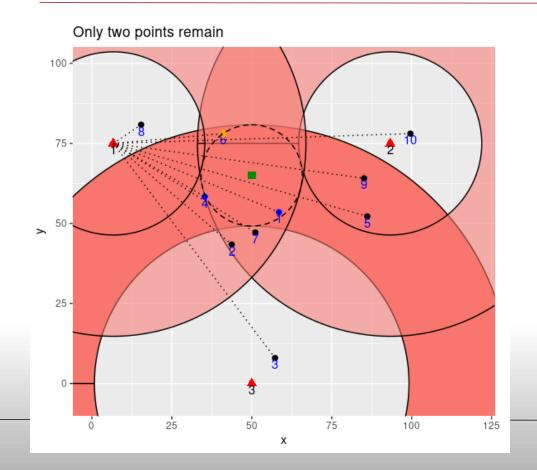
### Example Walkthrough Step 7:







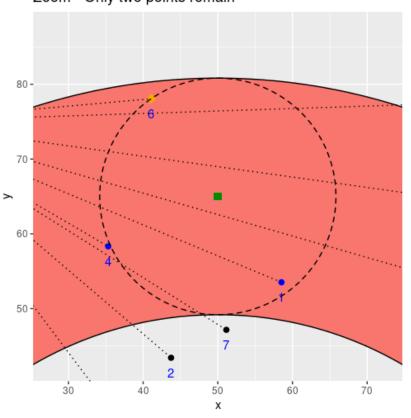
### Example Walkthrough Step 8:





## Example Walkthrough Step 9:

Zoom - Only two points remain





## **Experiments**

#### **Experiment Setup**

#### Nearest Neighbor:

- Use Open Source "ANN" Software
- Modify popular Scikit-Learn to run our algorithms
- Use custom geodesic data set (since none already existed)
- Use existing Euclidean and Angular data sets for comparison

#### Network Adequacy:

- Use Postgresql due to geodesic distance support
- No strong alternatives exist in SQL so we compare to naive use of "st\_distance"

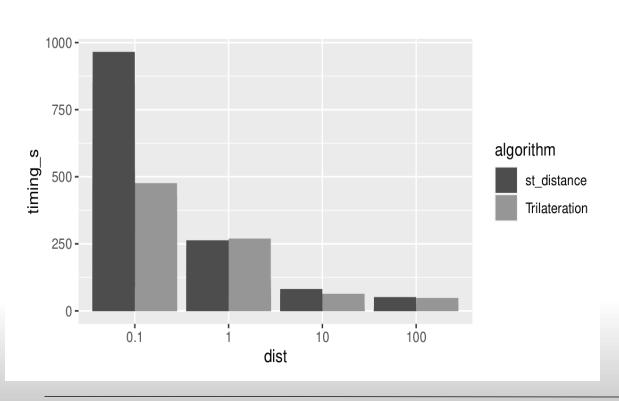
#### Data

150,000 Points near Louisville, KY divided into 10 Categories when needed



## Results

### **SQL NA Timings:**



#### Good:

50% faster on sparse data (NAP <~ 50%)</li>

#### Bad:

 No major difference for dense data (NAP >~ 80%)



### Results

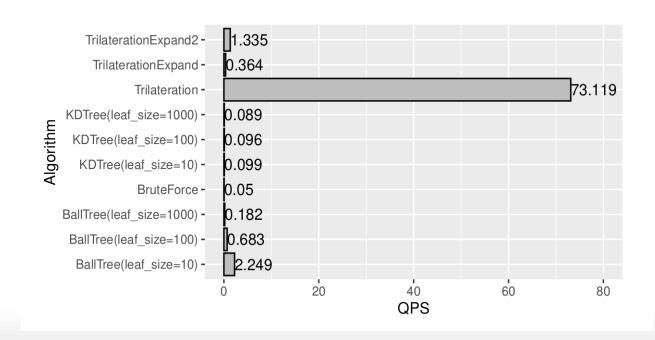
#### Cython Nearest Neighbor

#### Good:

- 50x faster on Geodesic
  Nearest-Neighbor queries
  than other algorithms
- Also fast pre-processing times not included in the 50x value

#### Bad:

 Horrible performance on Euclidean and other simple distance functions





# Objectives Met!

# Conclusions & Future Work

#### The Good:

- We were able to improve performance in SQL and Scikit-Learn for complex distance functions
- We are reasonably optimized for training time, memory space, and insert/move time complexity as well as query performance

## But nothing's perfect...

 We did NOT create a magical algorithm that improves in the universal case, but we have good bounds on where our algorithm will be useful in advance



# Conclusions & Future Work

#### So many things...

There are many, many avenues of research we think this opens up for future work:

- This is new code and can likely be optimized:
  - Parallelization should be easy but distributed computing versions were not implemented here for compatibility with our testing libraries
  - Precision is extremely high; in fact with 64-bit distances and meter units, we are precise to atomic levels measuring on earth. This is unnecessary and probably slows us down.
- The Index values themselves have other uses...
  - These can be used as an alternate coordinate system instead of Lat/Long
  - "Geohashing" based on Trilateration distances could be valuable
- Search for other domains with complex distance functions:
  - Protein folding? Recommendation Systems? Cryptography?
  - Non-metric space applications?



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