



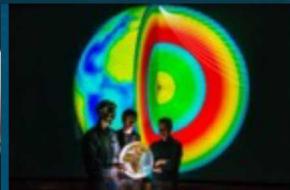
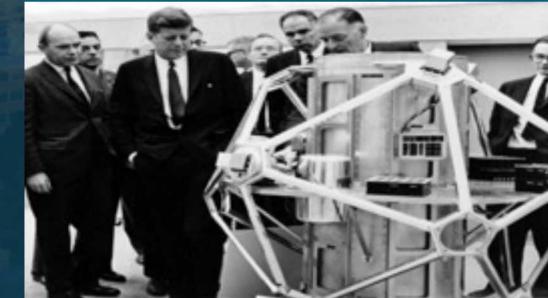
Sandia Research Seminar:

Trajectory Analysis & Constellation Optimization



Sandia
National
Laboratories

SAND2019-4452PE



PRESENTED BY

Christopher G. Valicka, PhD



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- PART 0: Brief Sandia National Laboratories overview

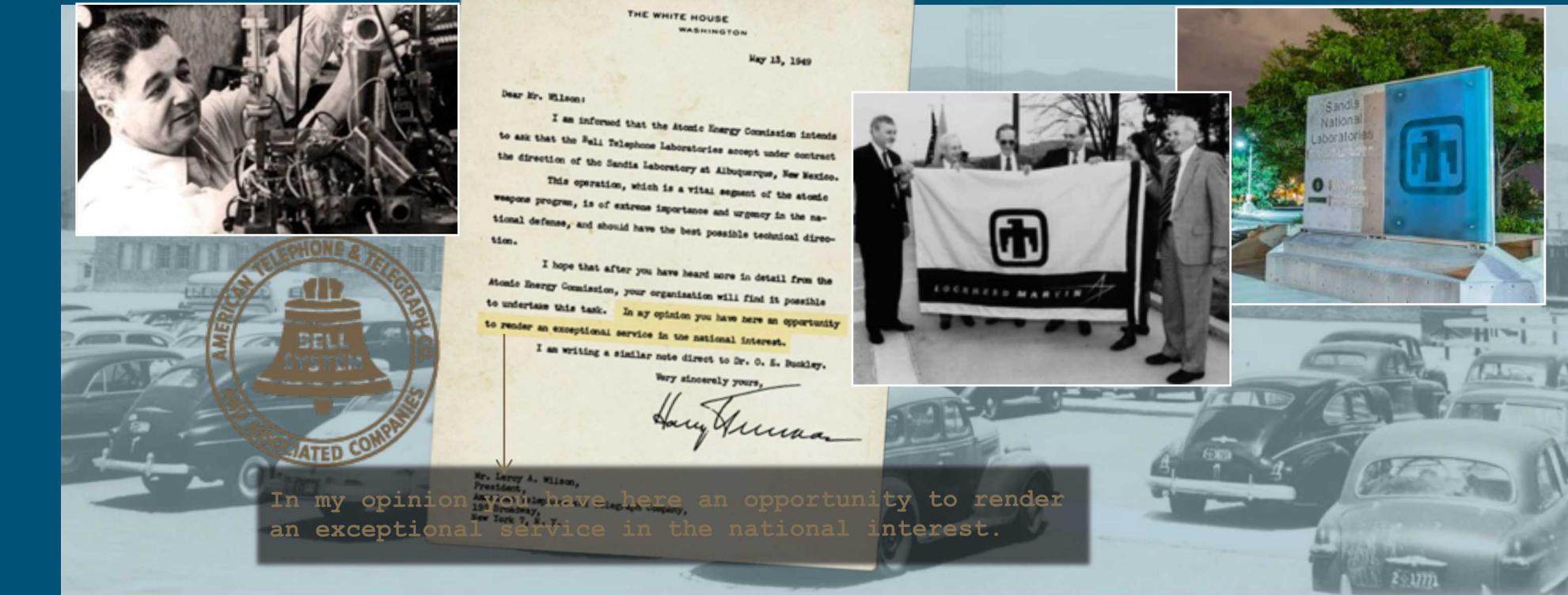
- PART I: Clustering analysis of aircraft trajectory data

- Motivations and applications
- Algorithm implementation details
 - **Tracktable** open source software
- Related problems and future topics

- PART II: Mosaic imaging by sampling and optimization

- Motivations and applications
- Model formulations and solution details
 - **Pyomo** and **GeoPlace** open source software
- Related problems and future topics

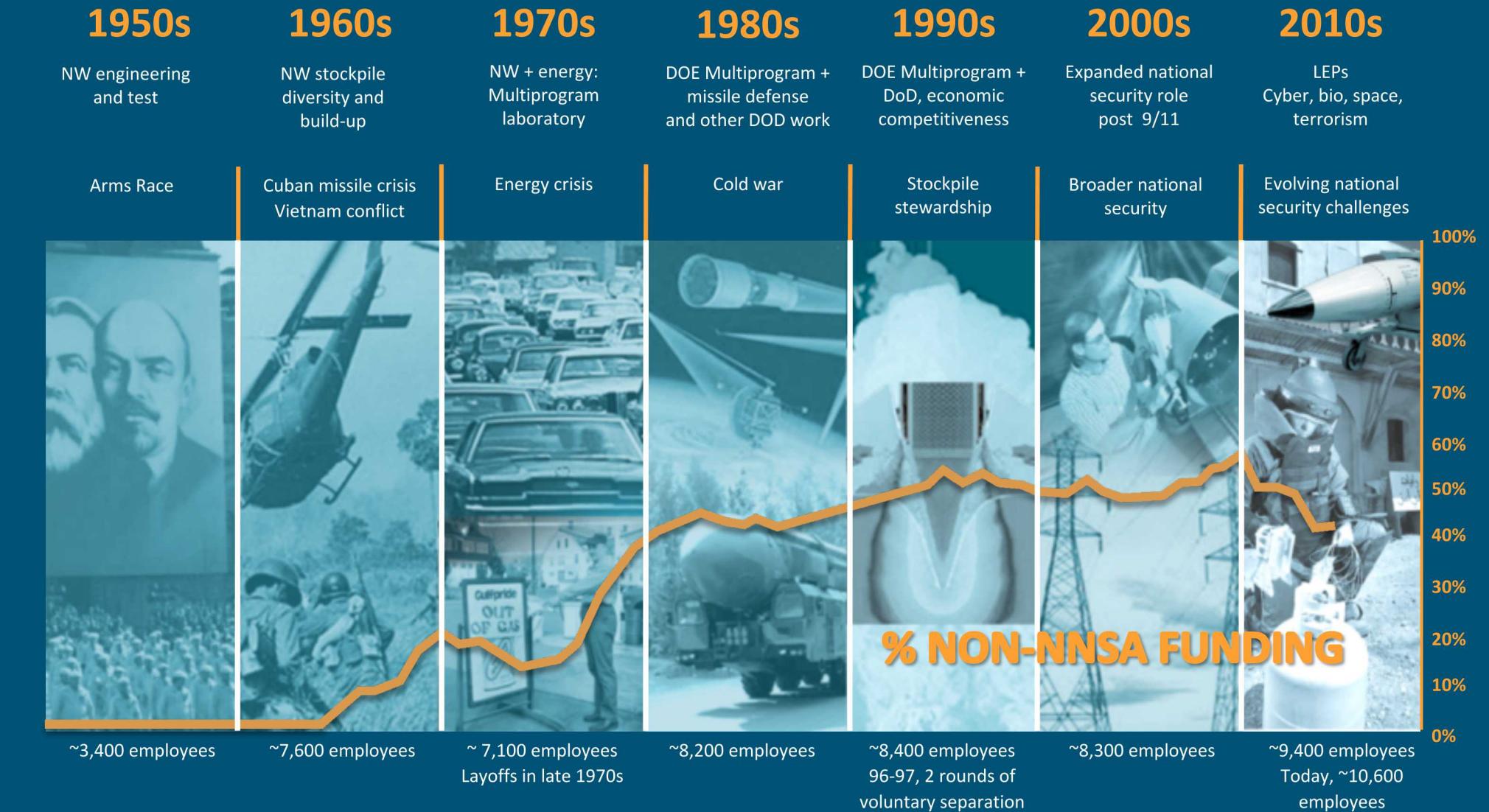
Sandia: An FFRDC for nearly seven decades



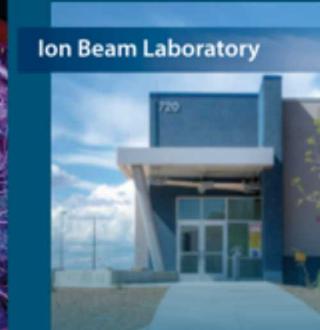
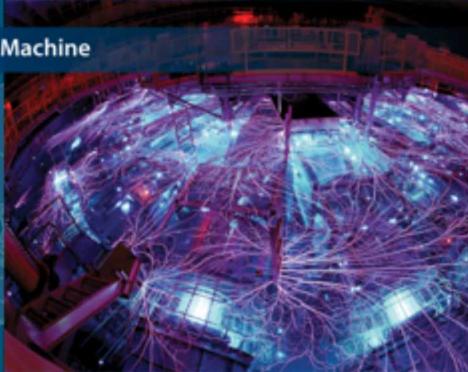
Significant dates

- **July 1945:** Los Alamos creates Z Division at Sandia Base
- **November 1, 1949:** Sandia Laboratory is established and managed by AT&T
- **March 8, 1956:** Sandia's California site is established
- **July 26, 1993:** Martin Marietta wins first Sandia Corporation contract competition
- **April 30, 2017:** Lockheed Martin contract
- **May 1, 2017 – present:** NTESS contract

Sandia: A multimission lab



Sites and key facilities: A few examples

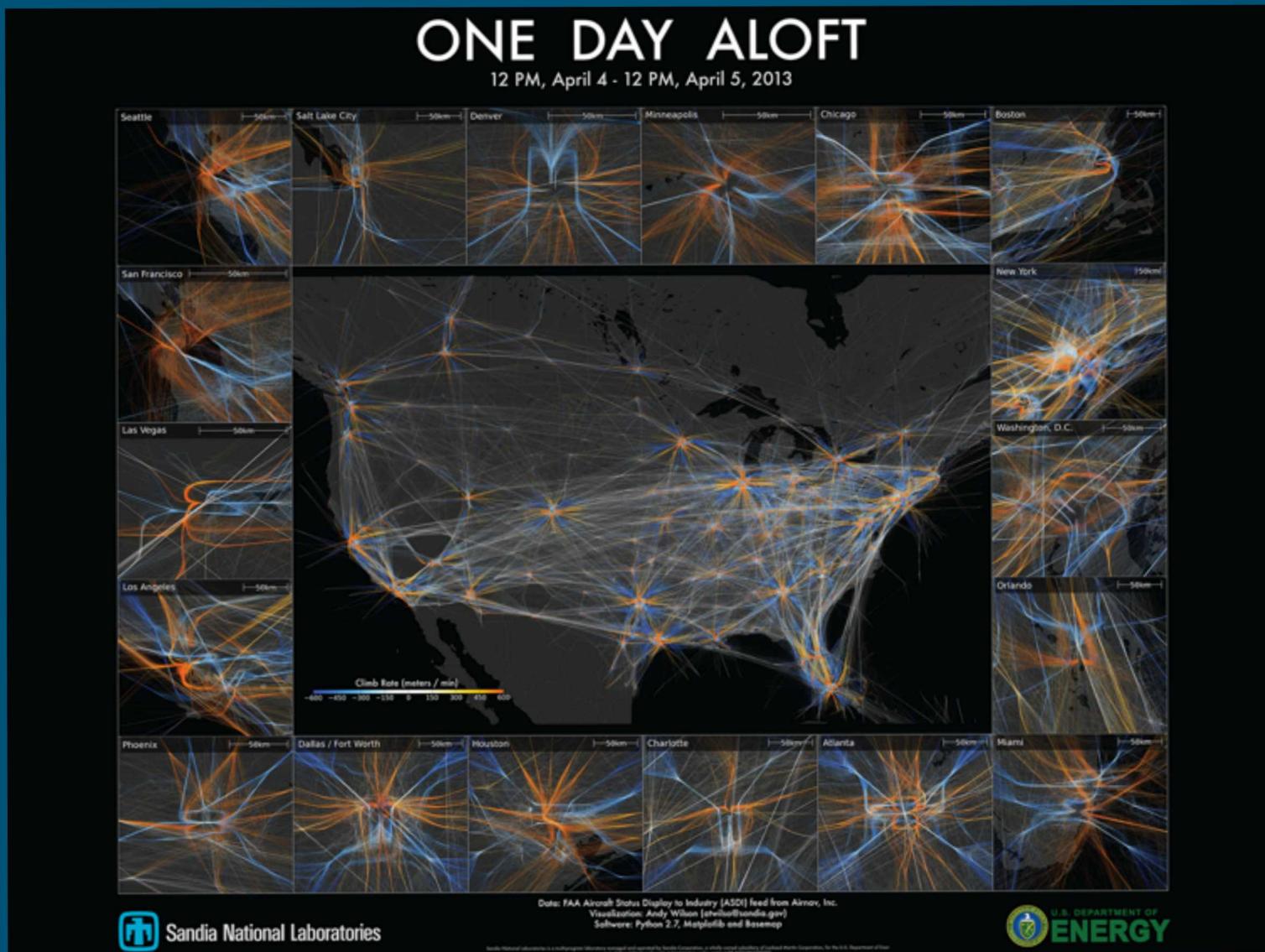




Clustering Analysis of Aircraft Trajectory Data

Motivations and Applications

Nature and Scale of Trajectory Data



Nature and Scale of Trajectory data



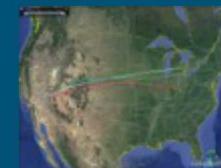
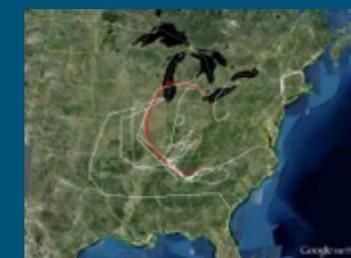
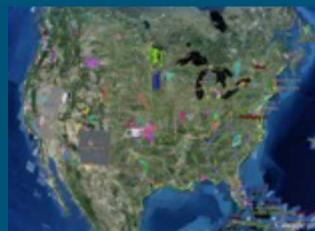
Thanks to GPS and new geolocation technologies, enormous corpuses of position/time data exist:

- Collision avoidance data for aircraft (**ASDI**, ADS-B) and ships (AIS)
- Transponder data from ground vehicles, other moving objects

But...often very little additional information and/or some metadata is untrustworthy

Questions then arise related to comparing trajectories:

- What patterns exist in this dataset?
- Have we seen this pattern before?
- Have we seen a pattern related to this known behavior of interest?
- **Can we group together similar patterns, and...**
- **...can we identify patterns that are unique or unusual (outliers)?**
- Can we forecast where a current trajectory will go based on historical observations?
- Can we identify different types of collective behavior among many trajectories?





Clustering Analysis of Aircraft Trajectory Data

Algorithm Implementation Details

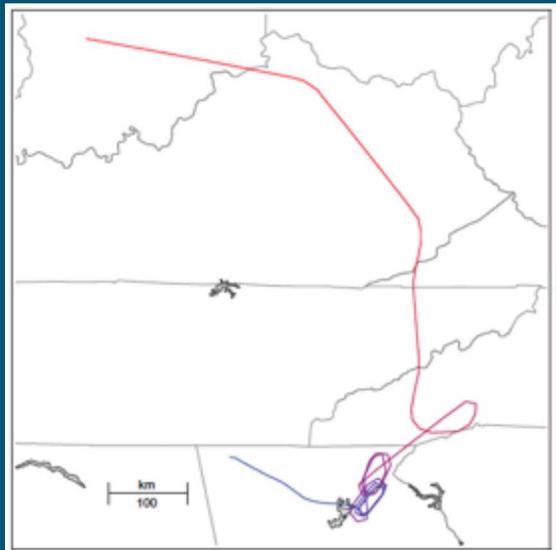
What Does Tracktable Do?



Given a large corpus of trajectory points...



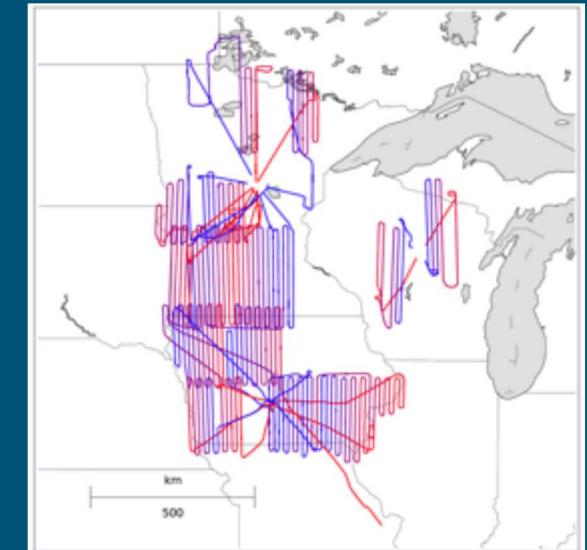
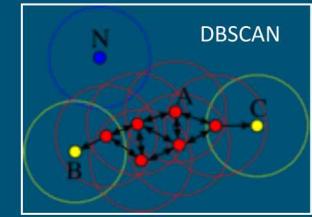
Assemble points into trajectories



Compute features and store in spatial index



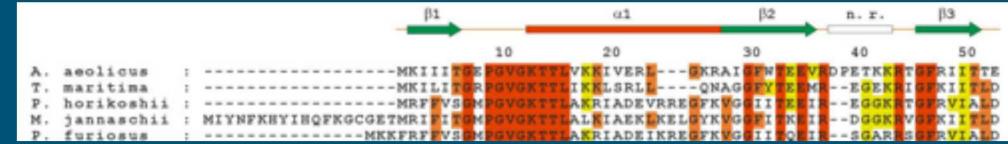
Discover, compare, and forecast patterns



How Does Tracktable Compare?



Previous analyses use computationally expensive, unintuitive curve alignment techniques.



Using intuitive combinations of numerical descriptions, trajectories can be analyzed and compared efficiently:

- End-to-end distance traveled
- Total distance traveled
- Ratio of end-to-end distance traveled to total distance traveled
- Total curvature
- Total amount of turning
- Average heading change
- Area covered by flight (convex hull of points)
- Eccentricity of the convex hull
- Perimeter of convex hull
- Centroid of points
- Centroid of convex hull
- Start/Stop point
- Nearest distance to a given point
- “Distance” from a given specified track
- “Distance” from a given specified shape
- Start/Stop time
- Time nearest to a given point
- Average speed
- Range of speeds
- Max altitude
- Fluctuations of altitude/shape of altitude/time curve
- Difference from historical data
- Most common speed/altitude (cruise)
- Place, time and heading where first seen / last seen (might not be start/stop points)
- Other...

FEATURE LIST

Clustering: DBSCAN



Many different types of clustering algorithms exist (k-means, EM, etc.) but DBSCAN has two nice properties:

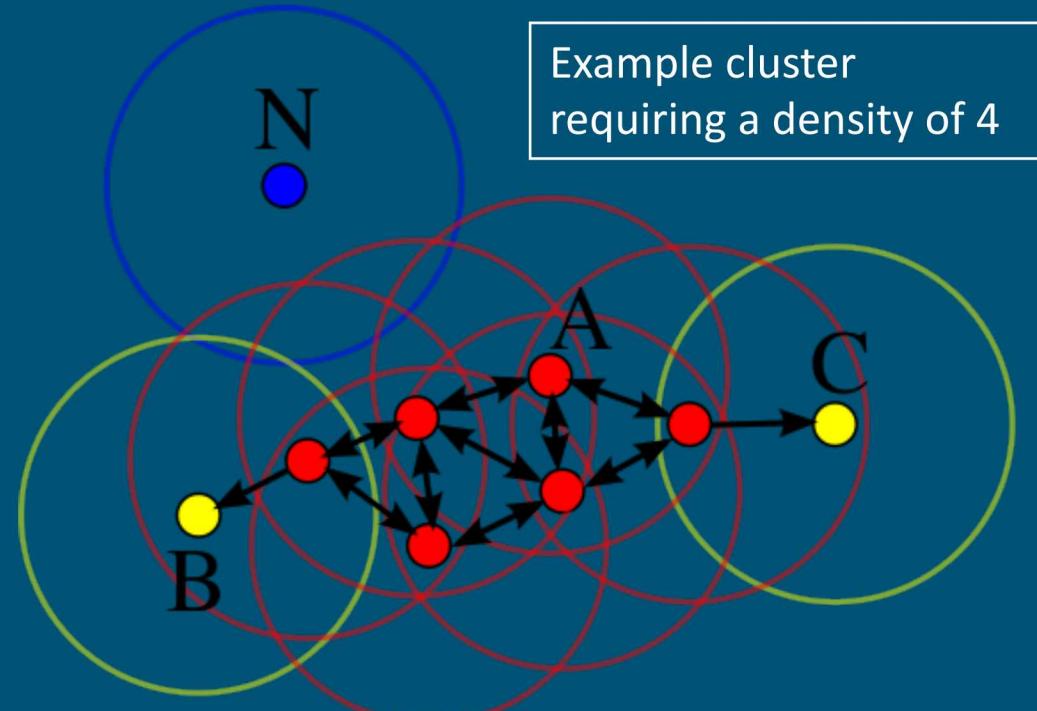
- Doesn't require a pre-defined number of clusters
- Has the notion of noise (outliers)

DBSCAN requires

- A neighborhood density
- A neighborhood radius

Tracktable implements a variation of DBSCAN

- `sklearn.cluster` Python package includes an implementation



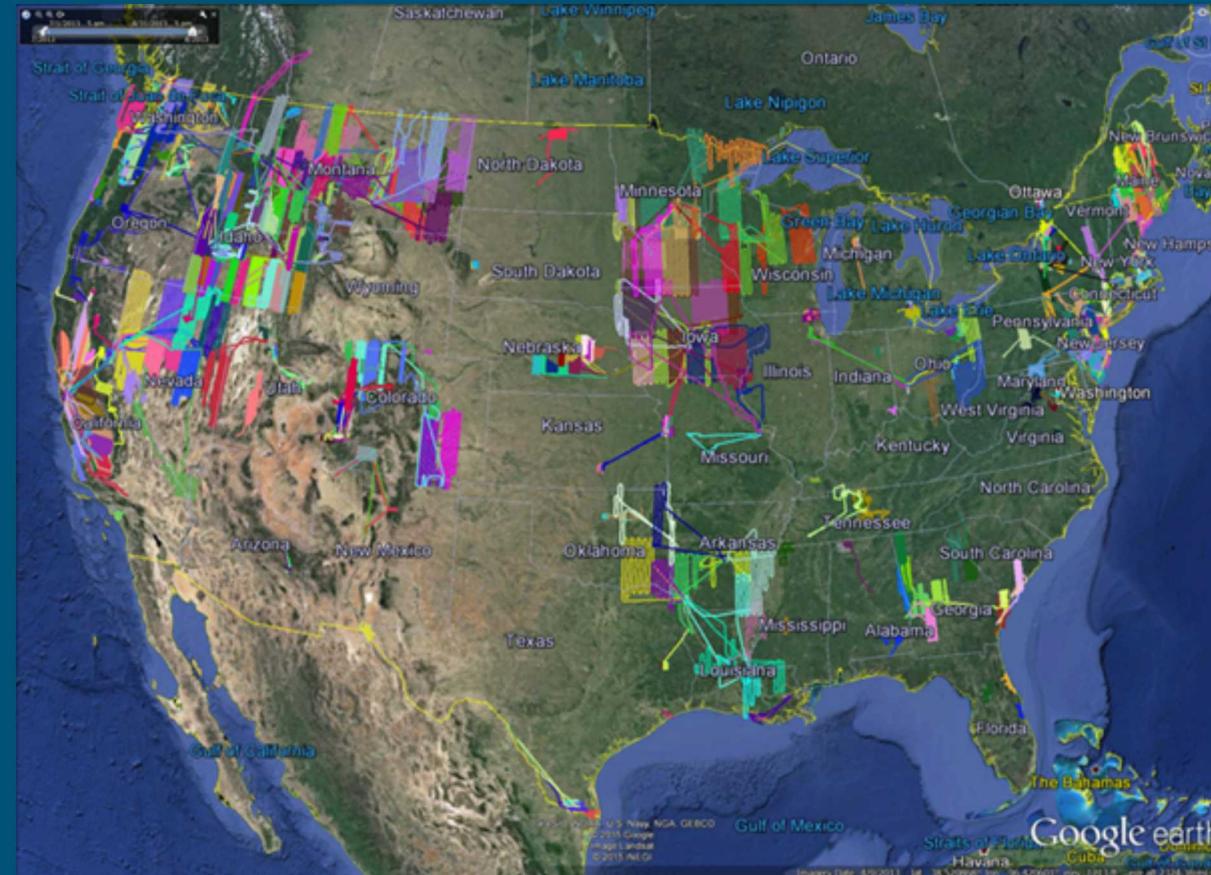
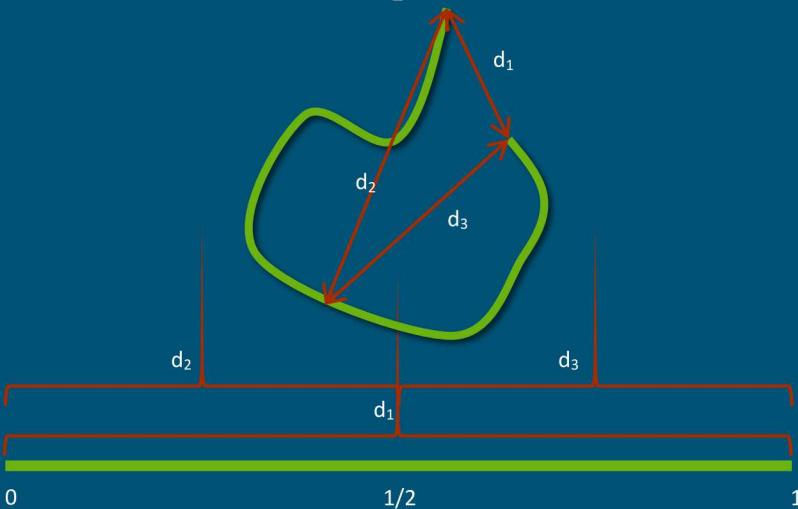
Clustering Pattern Discovery: Mapping flights



Clustered 1 month of ASDI data from July of 2013 according to shape features

Discovered a large cluster of mapping flights across the US

- Mapping/aerial surveillance flights are regularly used to produce commercial and scientific maps



Clustering Pattern Discovery: Oil Rig Helicopters

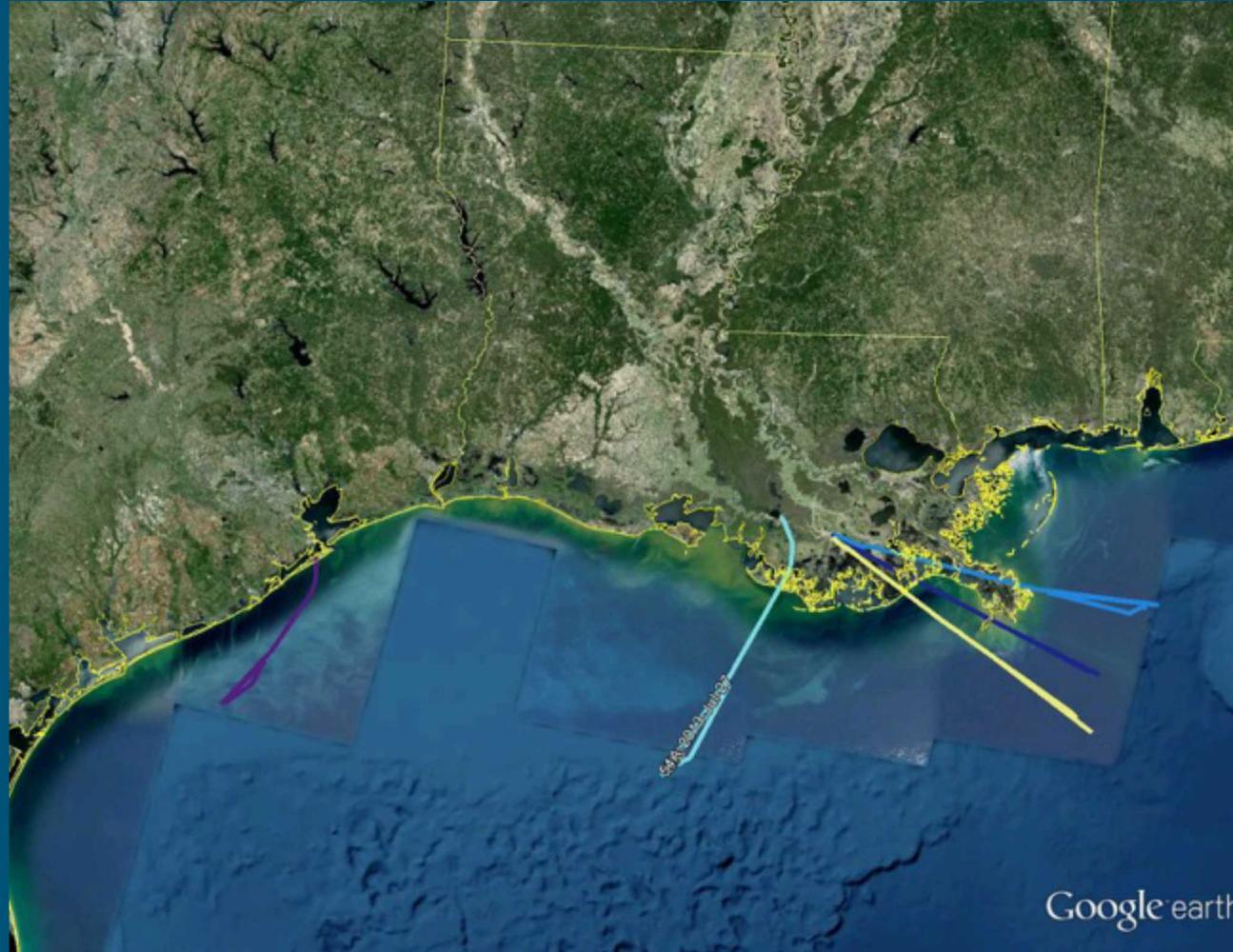
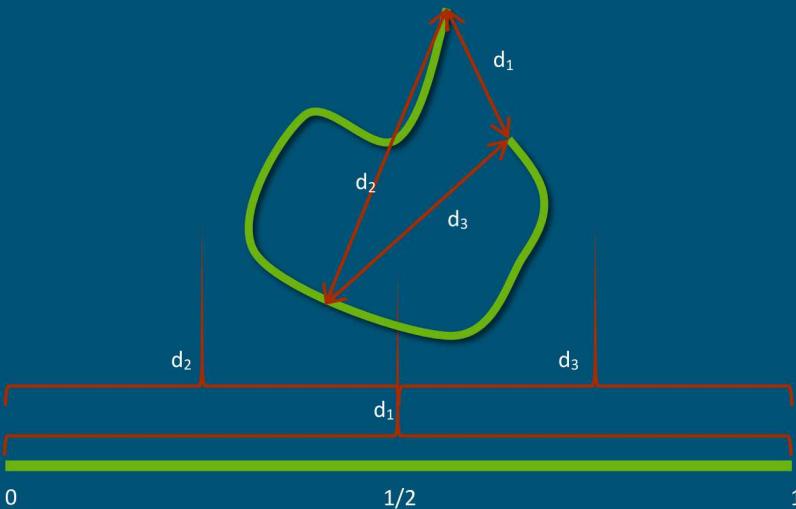


5 helicopter flights from July 2013

All helicopters belong to the same petrochemical company

- They fly people/equipment out to oil rigs

Spatial proximity was coincidental



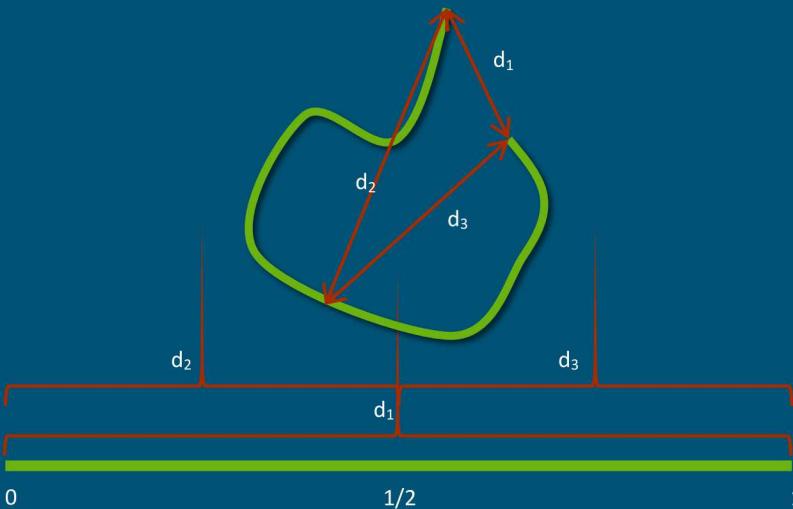
Clustering Pattern Discovery: Boeing Test Flights



Boeing test flights from its factory to a test field near Moses Lake in eastern Washington

Flights occurred over the month of July in 2013

Slightly different routes all with very similar 2-D shapes

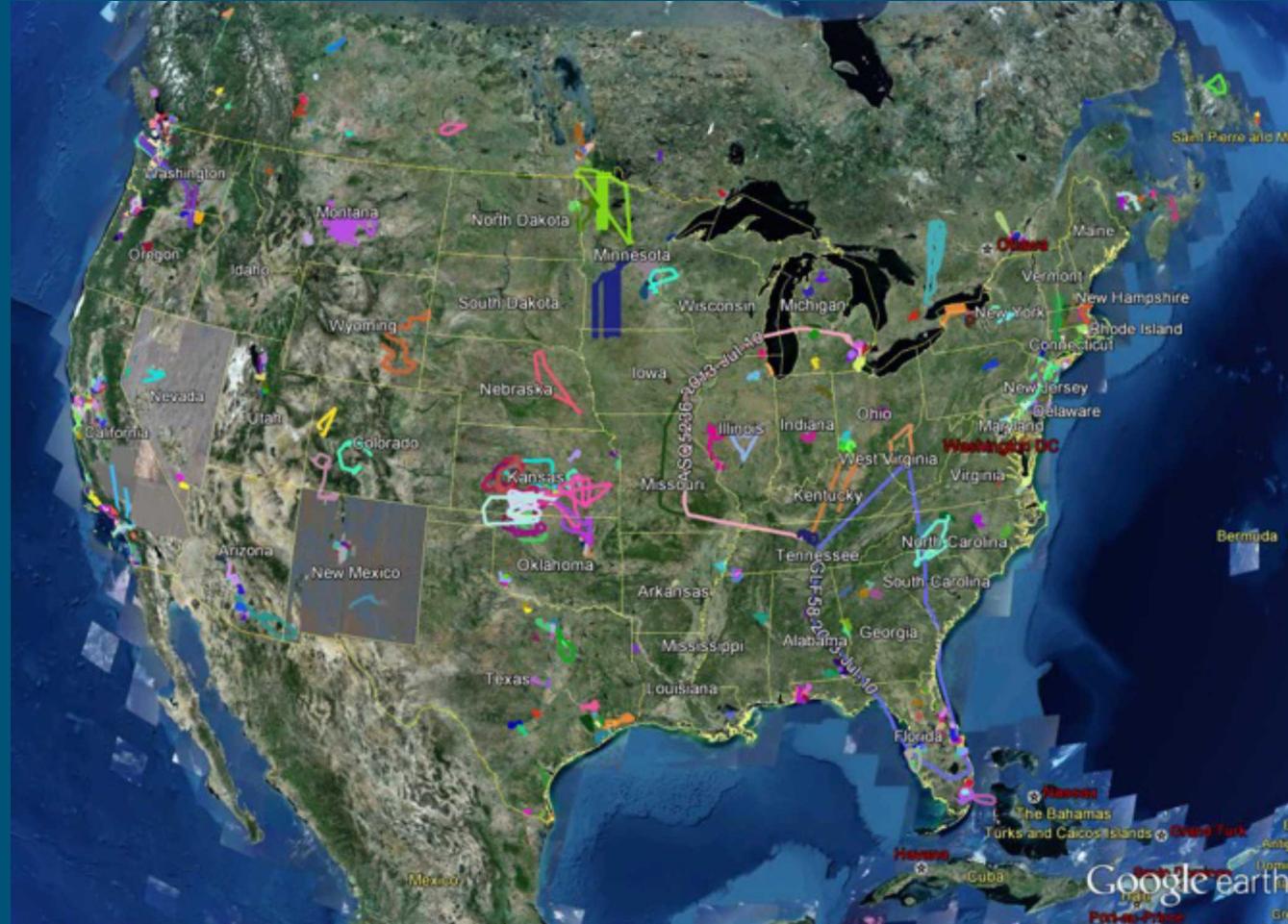
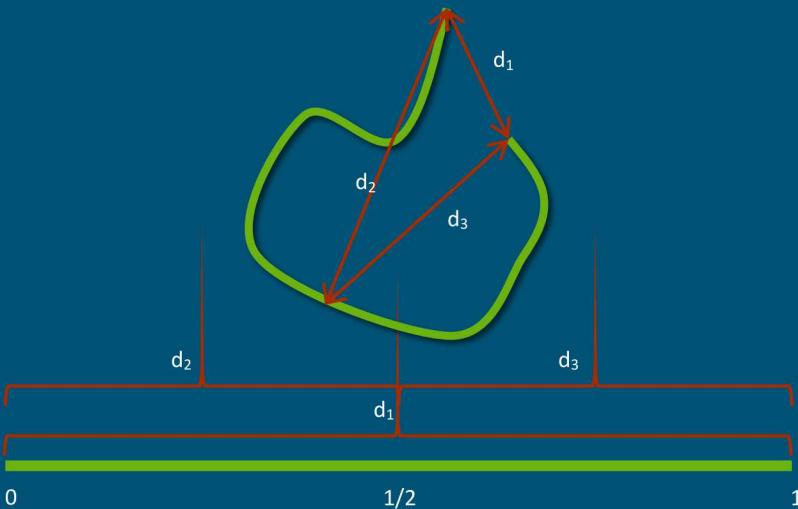


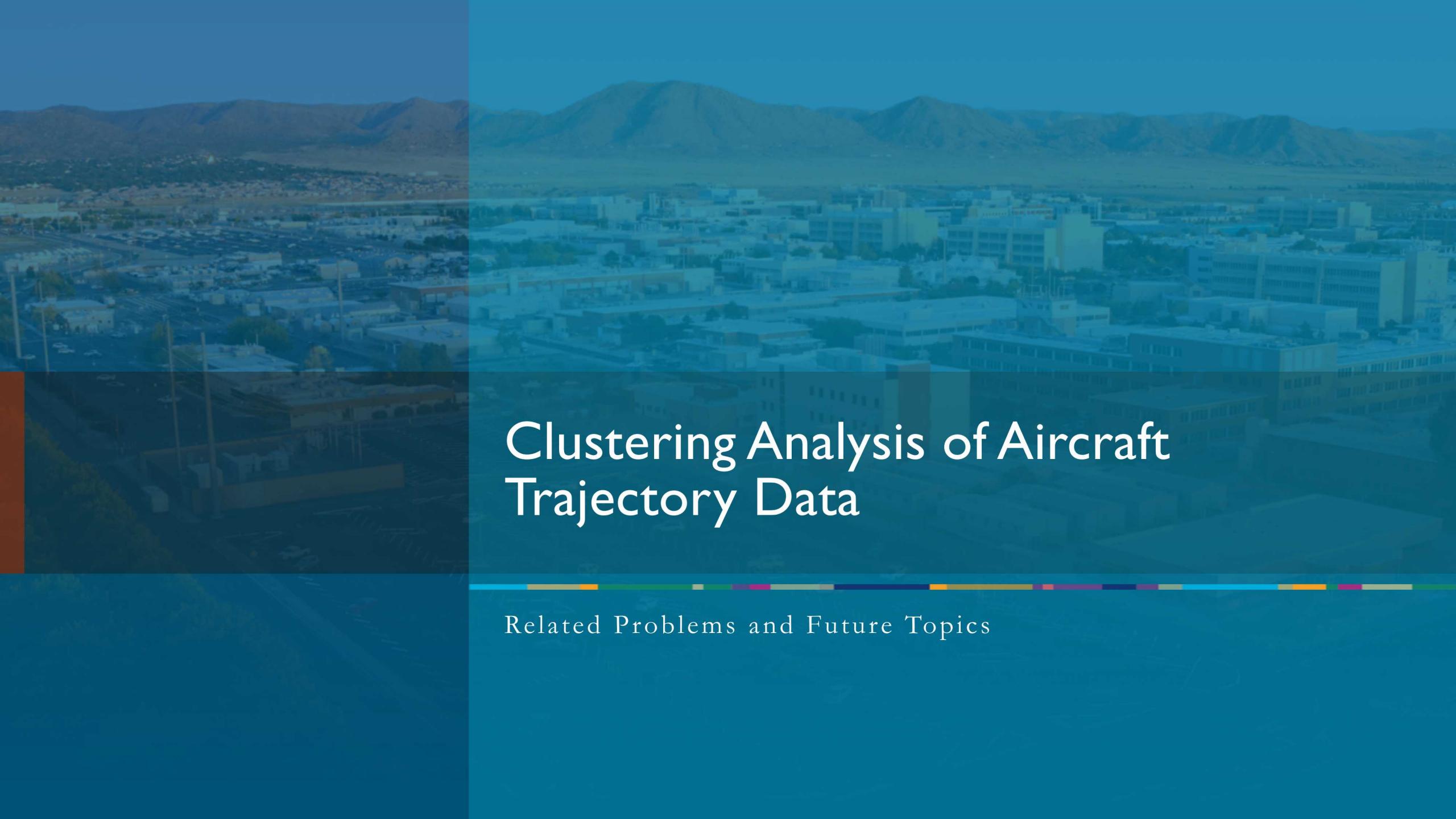
Clustering Pattern Discovery: Outliers



If we use the same feature vector and cluster over one day of flights, we also get a noise cluster

This graphic represents around 700 outliers out of a total of 50,000 flights from July 10th, 2013





Clustering Analysis of Aircraft Trajectory Data

Related Problems and Future Topics

Related Problems: Find a Similar Flight

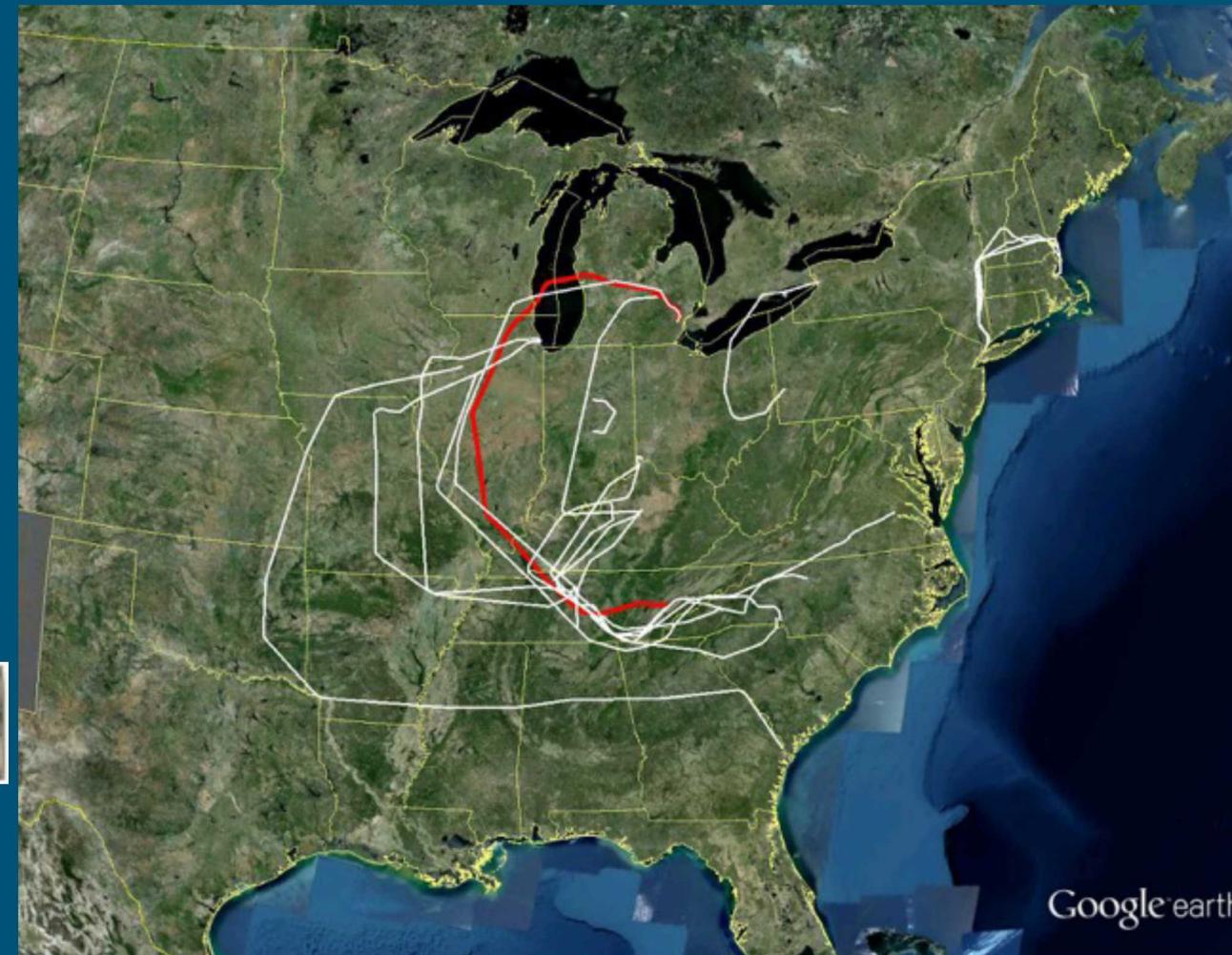


Consider the red flight, and look at just two features:

- Ratio of length to end-to-end distance
- Aspect ratio of convex hull

A search for flights with similar values gives the white flights

This is an example of a fast, shape-invariant search

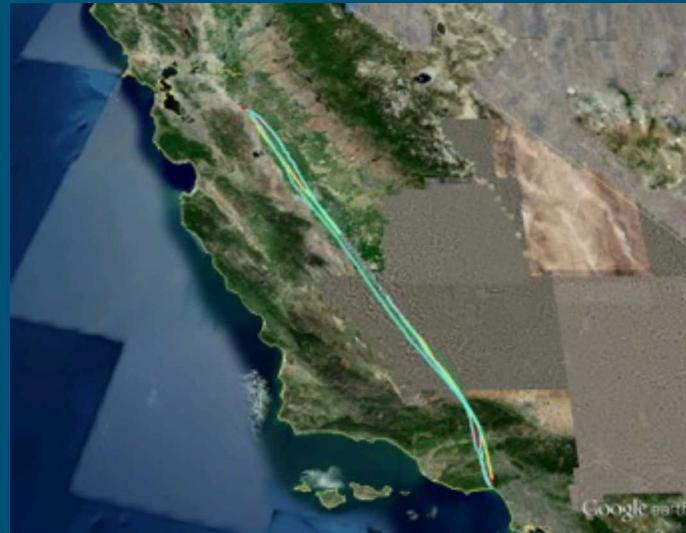


Related Problems: Collective Behavior

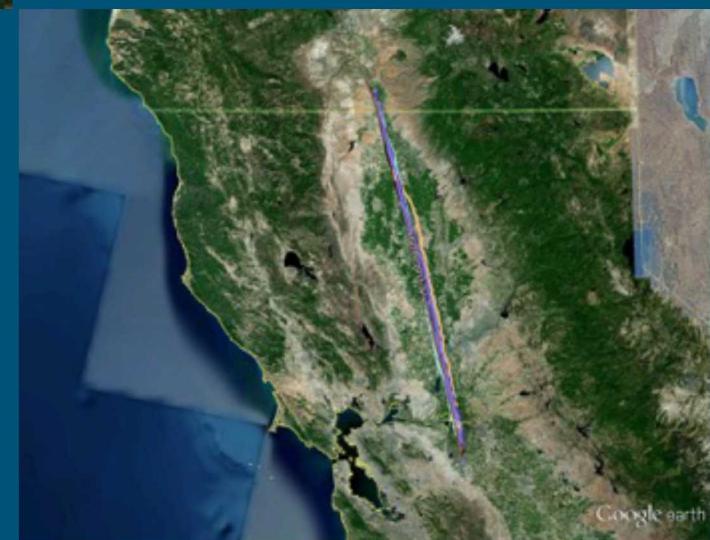


Find flights that followed the same path around the same time

A group of 6 Cessna's all flew from Los Angeles to Tracy on the morning of July 10th.



... and then from Tracy to Redding around noon on July 10th.



Automated parameter selection for clustering analysis

Automated feature selection for clustering, forecasting, and trajectory comparison

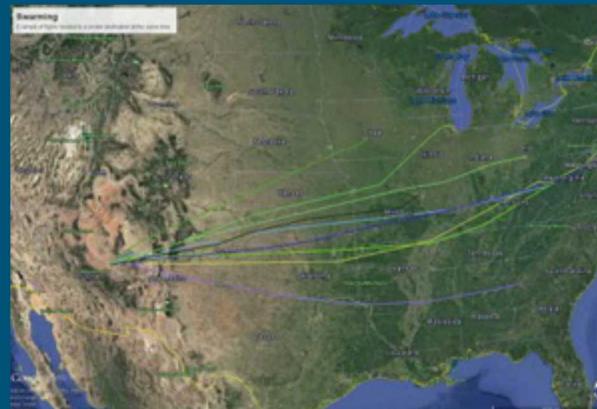
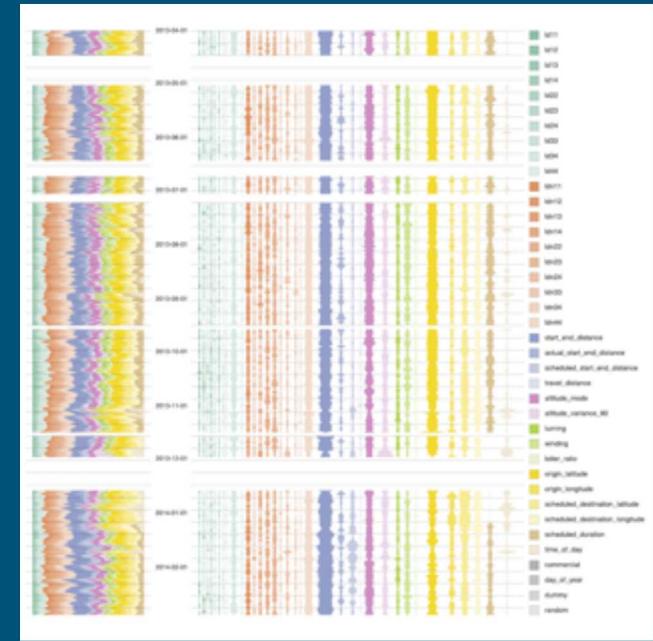
- Dimensionality reduction techniques
- Suitability of specific features across different trajectory data sets

Forecasting and prediction of various trajectory features

- To date, we have explored destination/source/location forecasting

Sub-trajectory lexicon for behaviors

Additional topics in coordinated behavior of trajectories





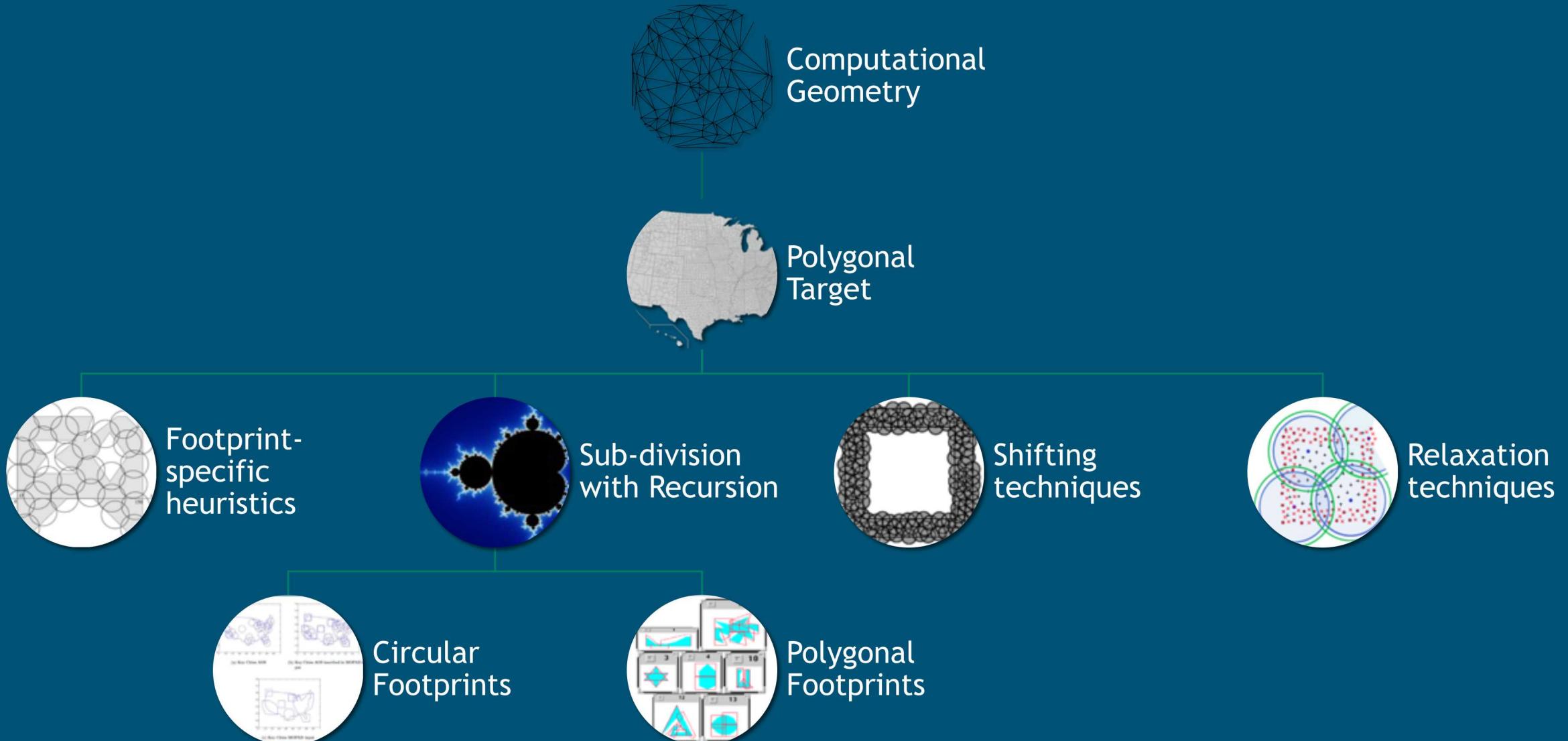
Mosaic Imaging by Sampling and Optimization

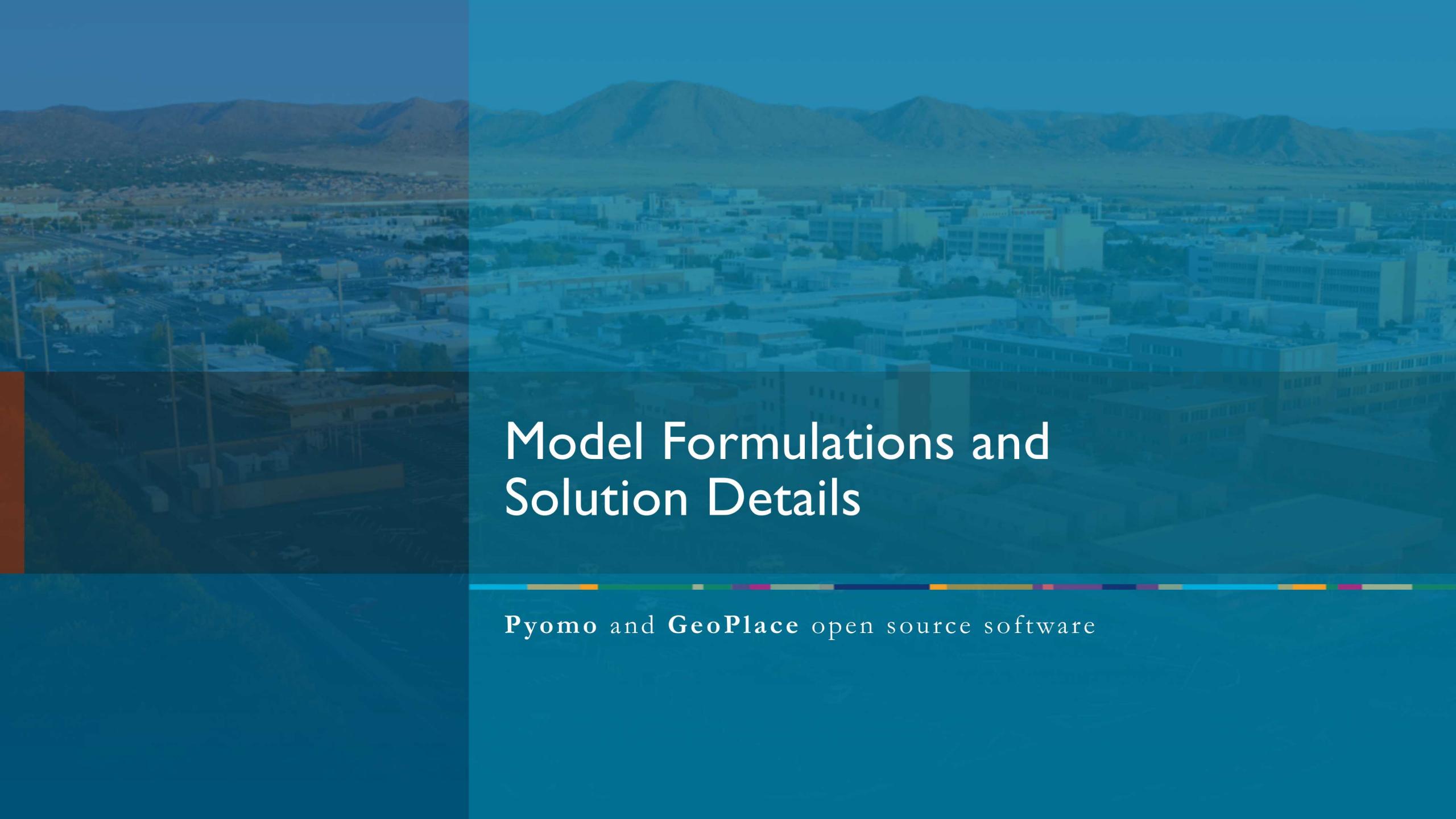
Motivations and Applications

Optimization of Spatial Coverage



Applied Coverage Techniques





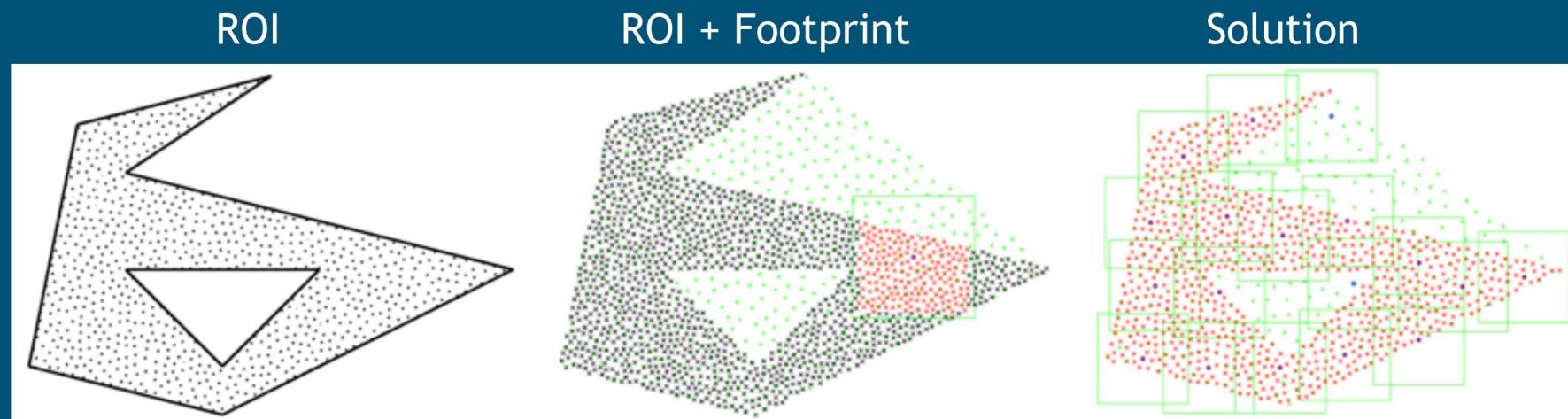
Model Formulations and Solution Details

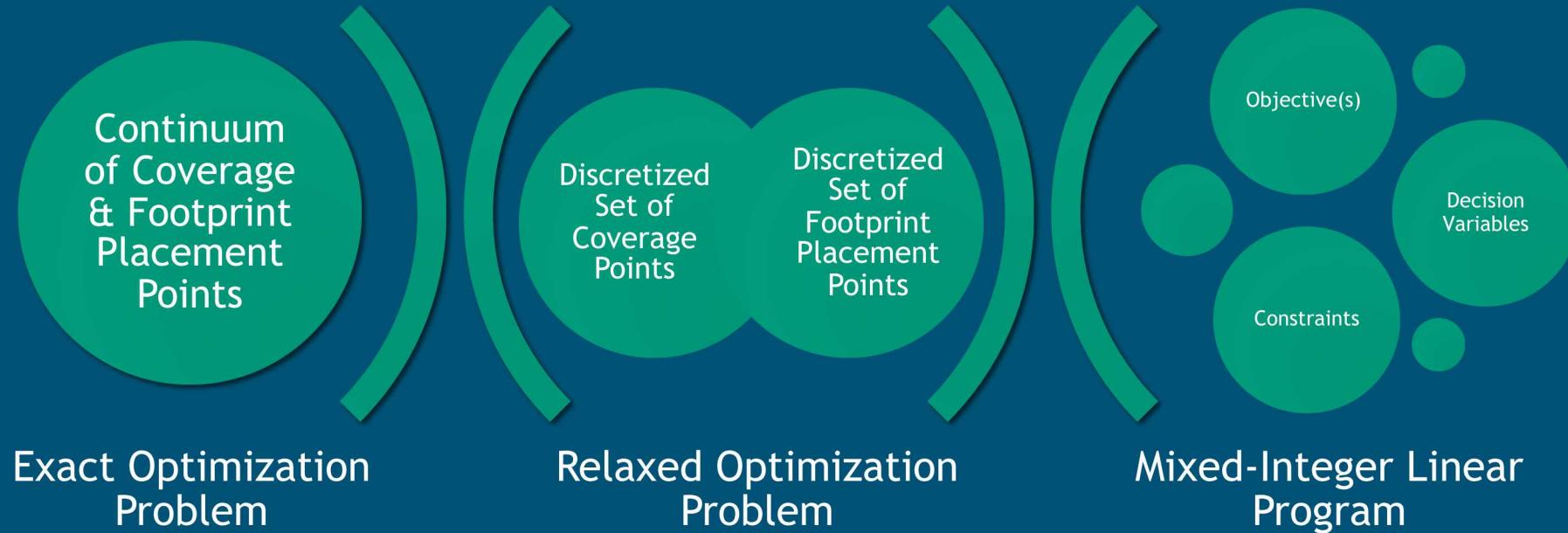
Pyomo and **GeoPlace** open source software

Details of Our Spatial Coverage Problem

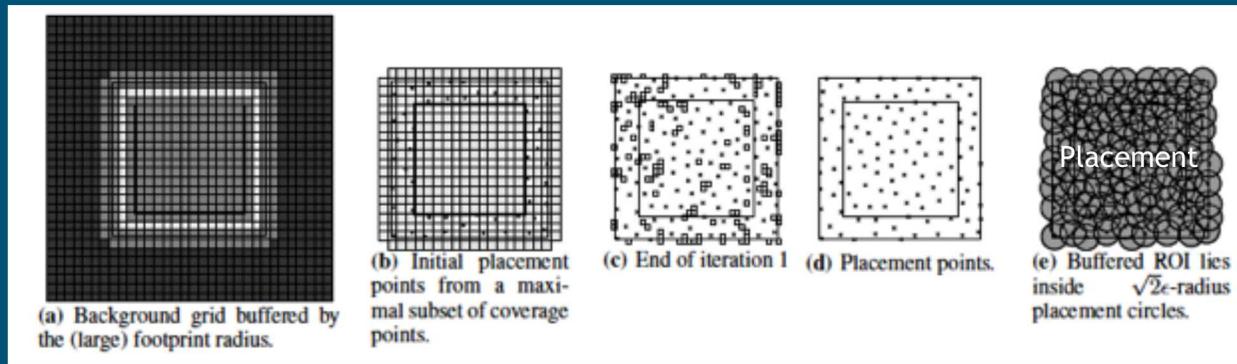
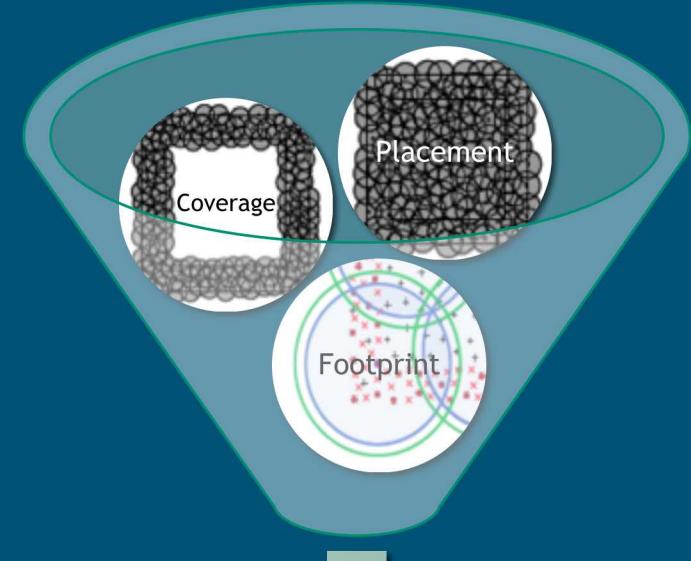
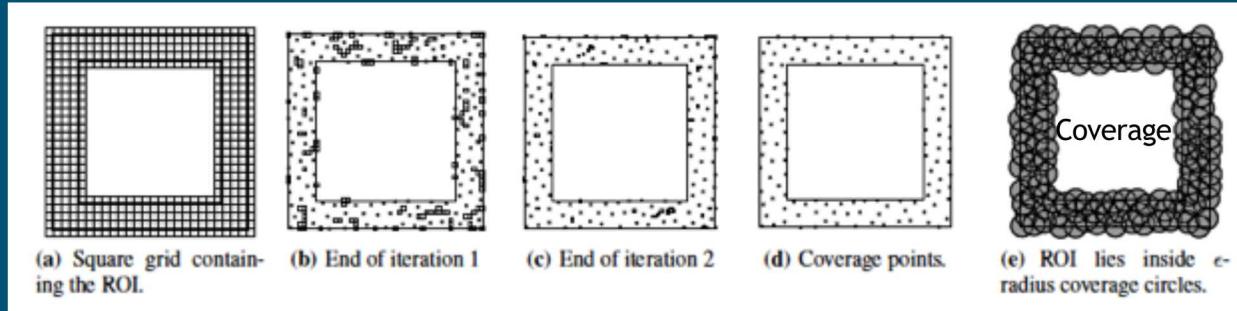


- A small number ($\sim 10\text{-}100$) of footprints (images) are required to:
 - Cover a region of interest (ROI) on the earth.
 - No gaps are allowed, some overlap between footprints is desirable.
- The ROI is modeled as a polygon, sometimes with holes.
- Footprints are nearly convex and have good aspect ratios when projected on Earth.





Algorithm (continued)



Mixed-integer linear
program



Mixed-Integer Programs

Formulation and Solution Descriptions

Mixed-Integer Programs

$$\begin{aligned}
 & \min \sum_t^T \delta_t \\
 \text{s.t. } & \sum_j^{J(c)} \delta_j \geq 1 \quad \forall c \in C, \\
 & \delta_t \in \{0, 1\} \quad \forall t \in T.
 \end{aligned}$$

Equation 1: Basic coverage

$$\begin{aligned}
 & \min \sum_t^T \delta_t + \sigma \sum_{(i,j)}^D f(i,j) \phi_{i,j}, \\
 \text{s.t. } & \sum_j^{J(c)} \delta_j \geq 1 \quad \forall c \in C, \\
 & \delta_t \leq 1 \quad \forall t \in T, \\
 & \delta_t \in \{0, 1\} \quad \forall t \in T, \\
 & \phi_{i,j} \geq \delta_i + \delta_j - 1, \quad \forall (i, j) \in D, \\
 & \phi_{i,j} \leq \delta_i, \quad \forall (i, j) \in D, \\
 & \phi_{i,j} \leq \delta_j, \quad \forall (i, j) \in D,
 \end{aligned}$$

Equation 2: Coverage penalizing overlap

$$\sum_t^T \delta_t (1 - \sigma_1 h(t)) + \sigma_2 \sum_{(i,j)}^D f(i,j) \phi_{i,j}$$

Equation 3: Coverage penalizing overlap, rewarding efficiency

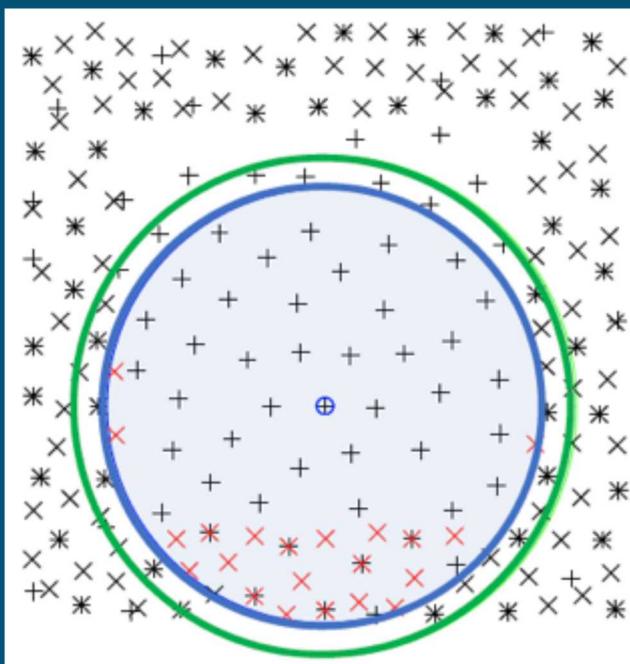
Notation:

- Let T denote the set of (potential) footprint placement points,
- C is the set of required coverage points,
- $J(c)$ are the set of placements $j \in J$ that would cover $c \in C$,
- $\phi_{ij} \in \{0,1\}$ denotes whether or not placement pair (i,j) has footprints placed at both points,
- $b(t)$ is the number of coverage points covered by placing a footprint at placement point t .

Mixed-Integer Programs

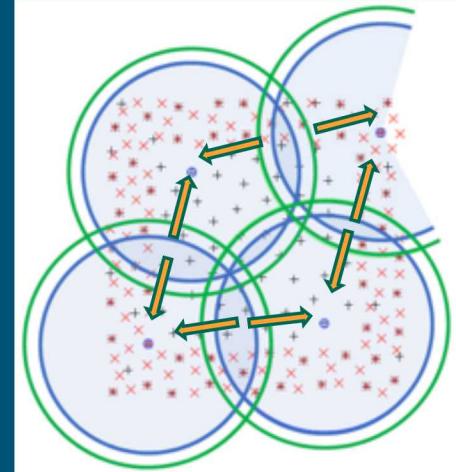
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 & \delta_t \in \{0, 1\} \quad \forall t \in T.
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Equation 1: Basic coverage



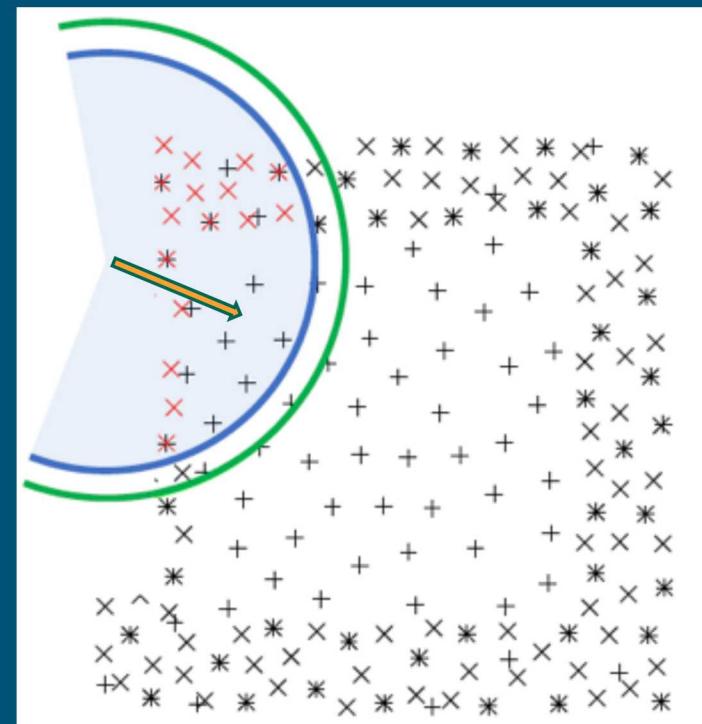
$$\begin{aligned}
 & \min \sum_t \delta_t + \sigma \sum_{(i,j)}^D f(i,j) \phi_{i,j}, \\
 \text{s.t.} \quad & \sum_j \delta_j \geq 1 \quad \forall c \in C, \\
 & \delta_t \leq 1 \quad \forall t \in T, \\
 & \delta_t \in \{0, 1\} \quad \forall t \in T, \\
 & \phi_{i,j} \geq \delta_i + \delta_j - 1, \quad \forall (i, j) \in D, \\
 & \phi_{i,j} \leq \delta_i, \quad \forall (i, j) \in D, \\
 & \phi_{i,j} \leq \delta_j, \quad \forall (i, j) \in D,
 \end{aligned}$$

Equation 2: Coverage penalizing overlap



$$\sum_t \delta_t (1 - \sigma_1 h(t)) + \sigma_2 \sum_{(i,j)}^D f(i,j) \phi_{i,j}$$

Equation 3: Coverage penalizing overlap, rewarding efficiency



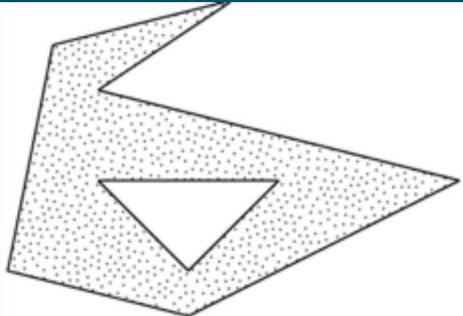
Examples

Problem Instances and Solutions with *GeoPlace*

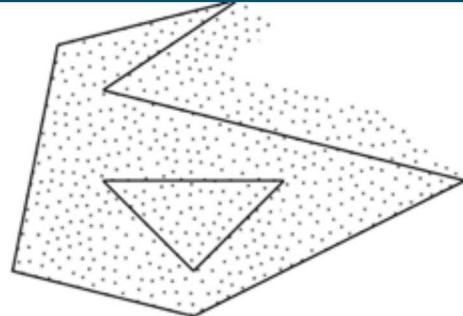
Examples



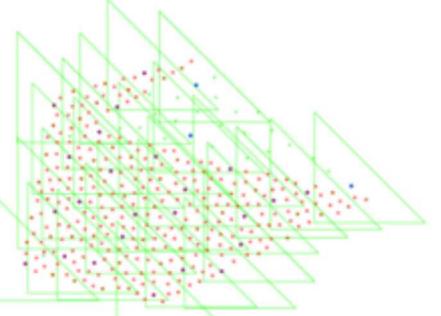
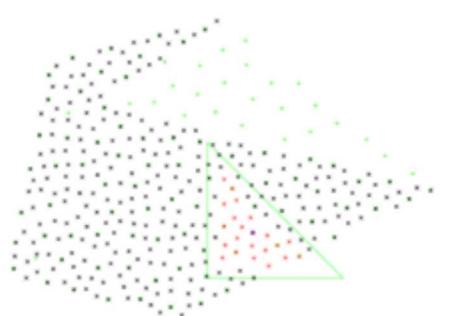
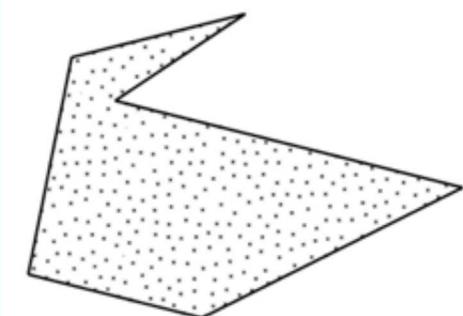
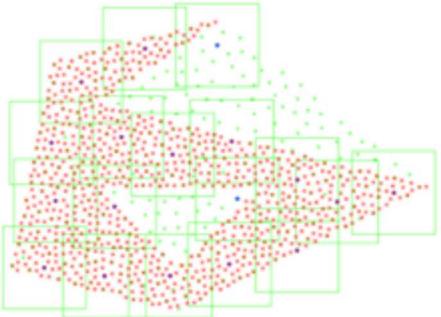
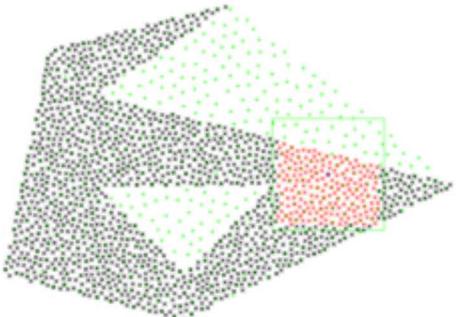
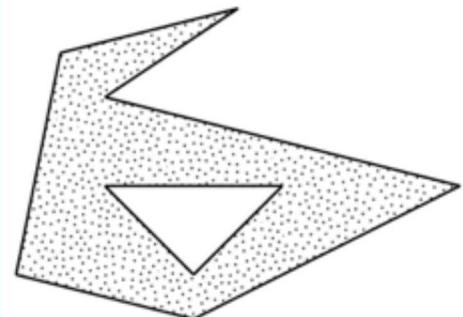
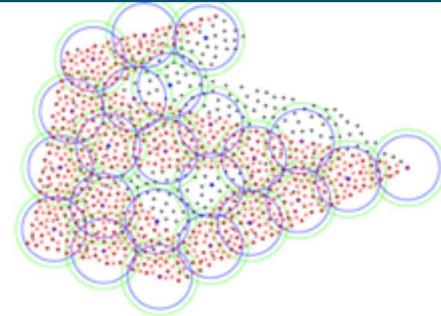
Coverage



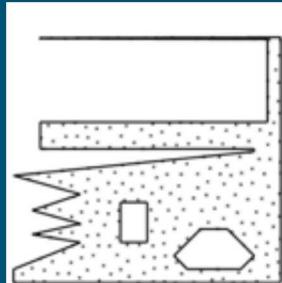
Placement



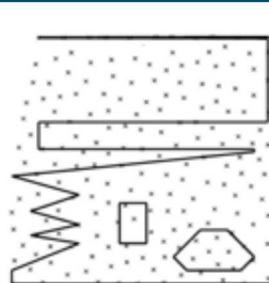
Solution



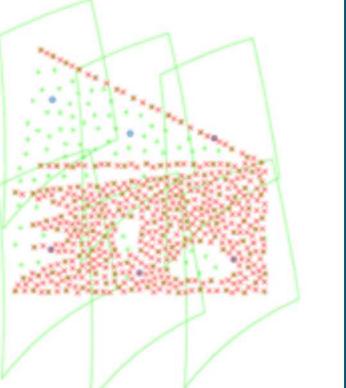
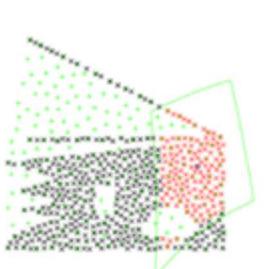
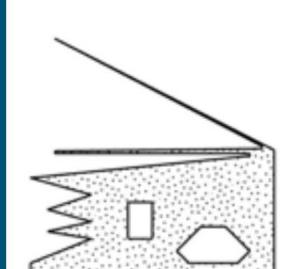
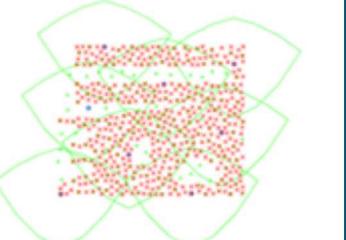
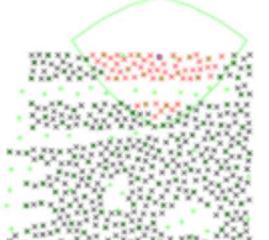
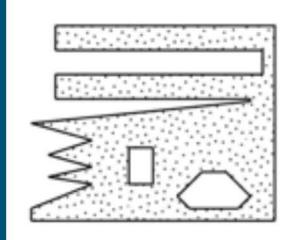
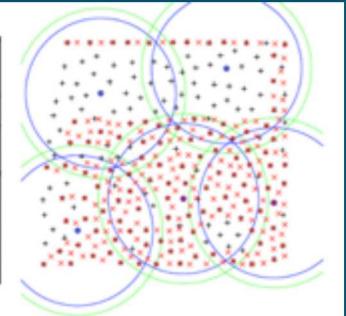
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Placement

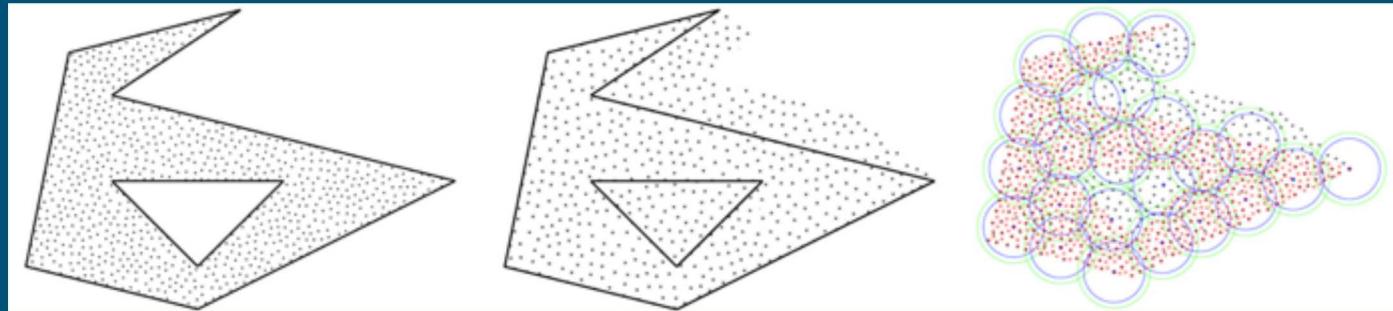


Solution

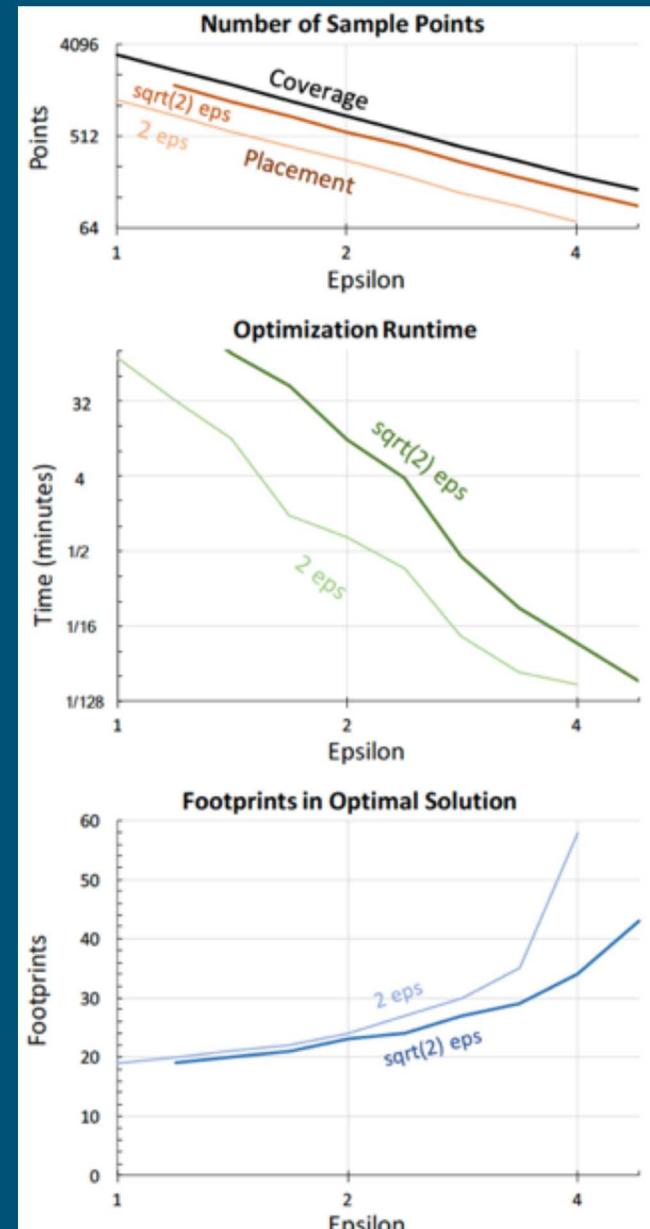


Note: Placements are optimal given fixed coverage and placement points and footprints.

Examples (continued)



- Problem instances were solved using both CPLEX (commercial license) and Gurobi (free academic use license)
 - Optimality gap tolerance was set to 0.01%
 - Solved on a 64-core workstation with 2.4GHz AMD processors and 512GB RAM
- Source code:
 - Available at <https://github.com/cgvalic/GeoPlace>
 - C++
 - Coverage and placement point generation
 - Visualization
 - Python
 - Mixed-integer linear program models (www.pyomo.org)
 - Solver interface





Extensions

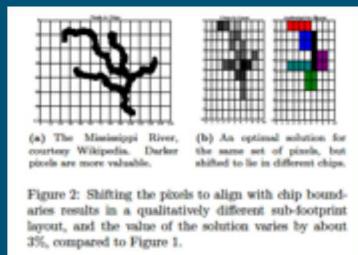
Ideas for Future Research

Related Problems and Future Topics

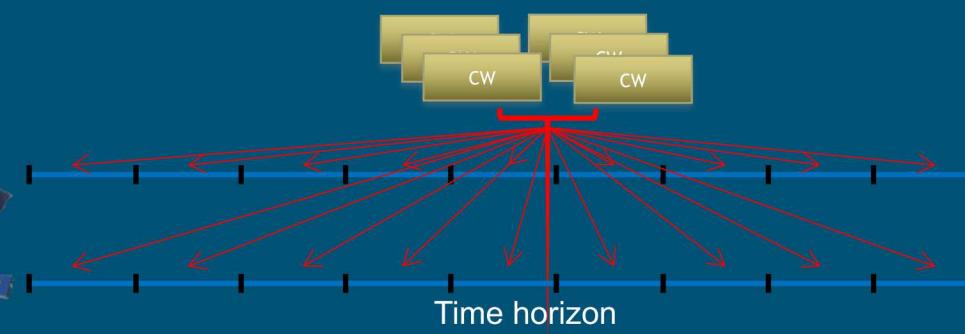


○ Alternative mosaics

- Multiple intra-mosaic footprint shapes
- Accommodate relative motion of satellite
- Accommodate cooperative sensing of disparate satellites
- Placement with priorities and uncertainty



○ Constellation job scheduling problems



Research and Development Themes

- Adaptive models: objectives, states and constraints
- Scalable online solutions



Example schedule with model that allows certain collection windows to run concurrently.



Questions?