



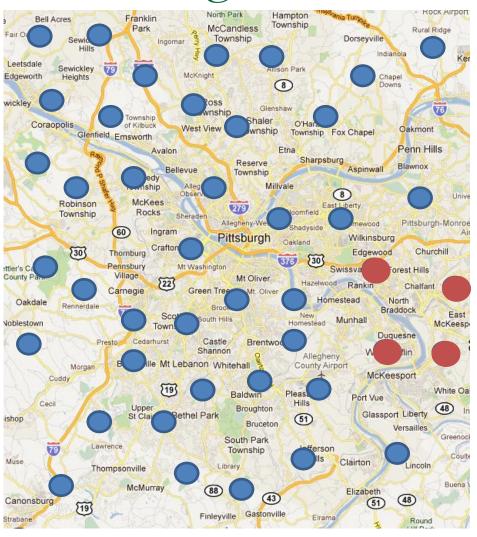
Detecting Irregularly-Shaped Clusters with Star Scan Statistic

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Detecting Disease Clusters

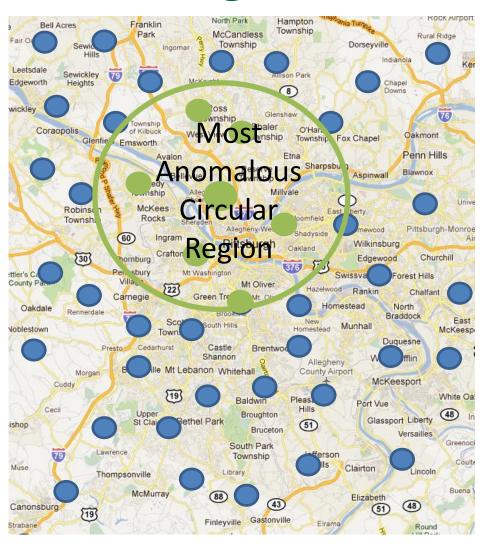


- Location of an informative data stream
 - # of ER visits per Zip Code
 - # of OTC Drug sales per retailer
 - Other novel data sources ...

In the presence of an outbreak, we expect counts of the affected locations to increase.

Effective methods should have high detection power.

Detecting Disease Clusters



(Kulldorff, 1997)

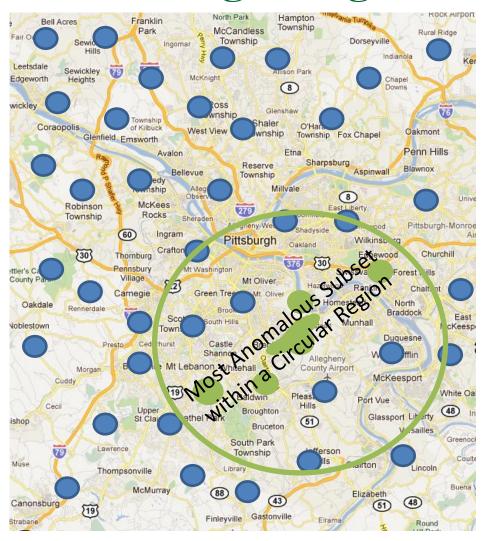
Spatial Scan Statistic (Circles)

Clusters locations by regions constrained by shape

High power to detect disease clusters of the corresponding shape

But what about irregular shaped clusters?

Detecting Irregular Disease Clusters



(Neill, 2012)

Fast Subset Scan

Instead of clustering *ALL locations* within the region together, only the *most anomalous subset of locations* within the region is used

Increases power to detect irregularly shaped disease clusters

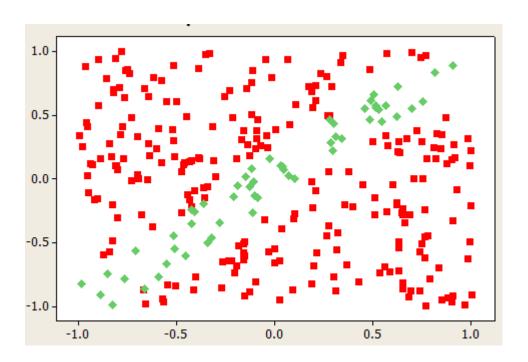
...but returns

unconstrained subsets

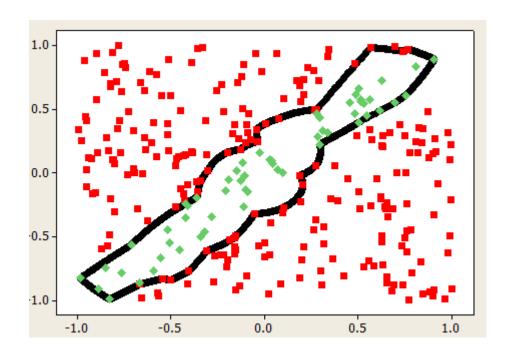
that may not reflect a

pattern of interest

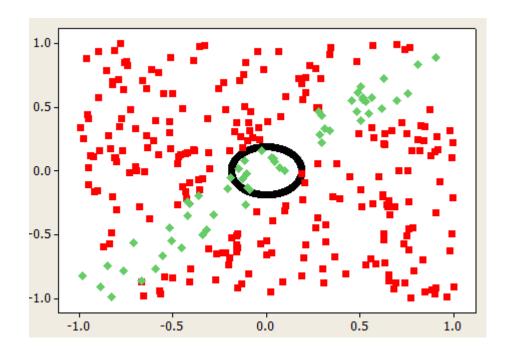
Sample Data



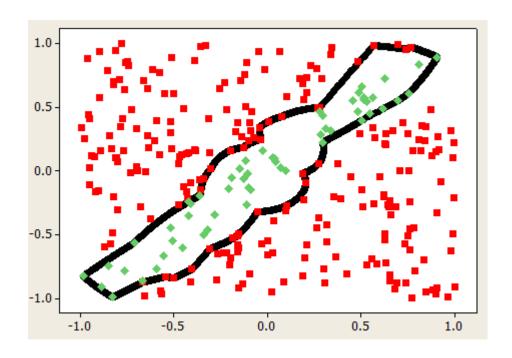
Sample Data: Fast Subset Scanning



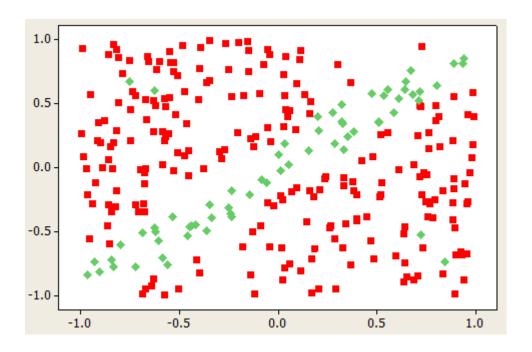
Sample Data: Circles



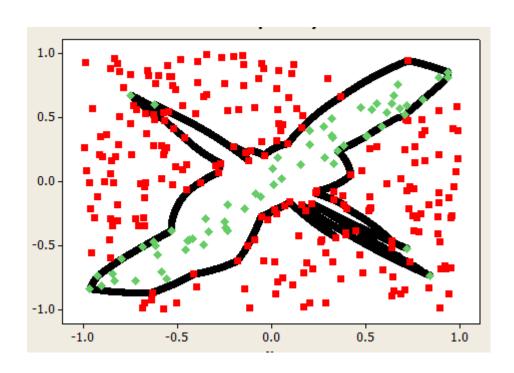
Sample Data: Star Scan



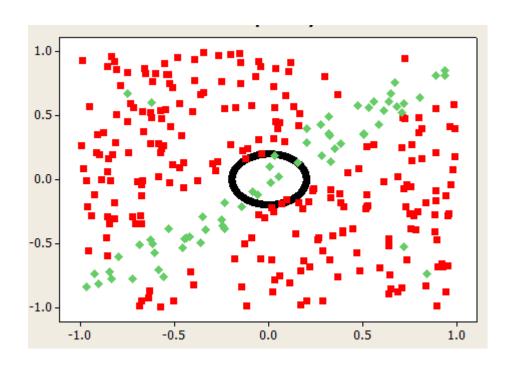
Sample Data with Noise



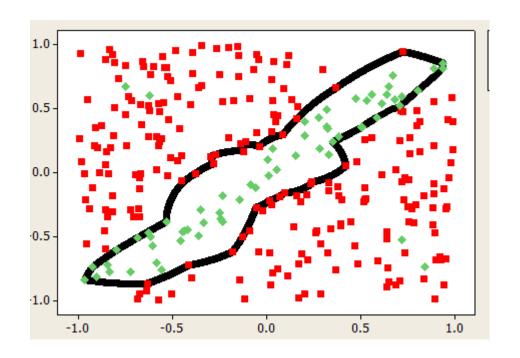
Sample Data with Noise: Fast Subset Scanning



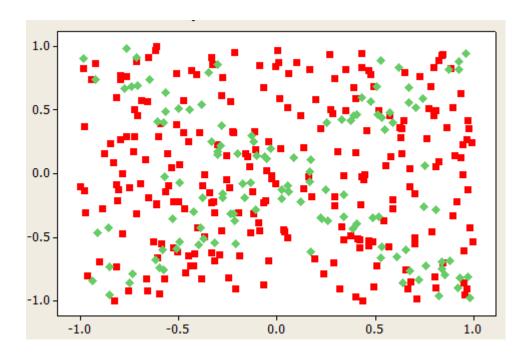
Sample Data with Noise: Circles



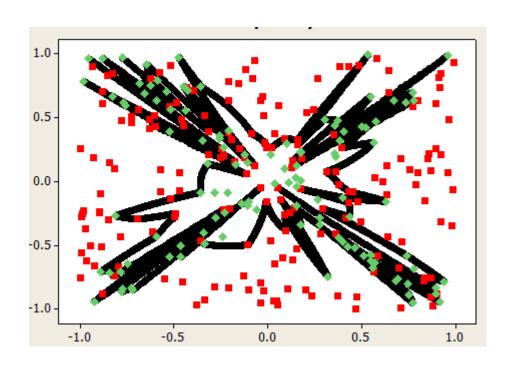
Sample Data with Noise: Star Scan



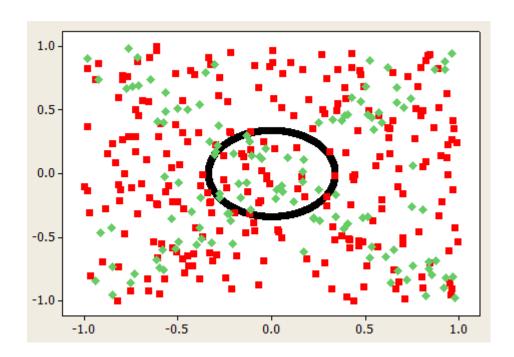
Cross Pattern



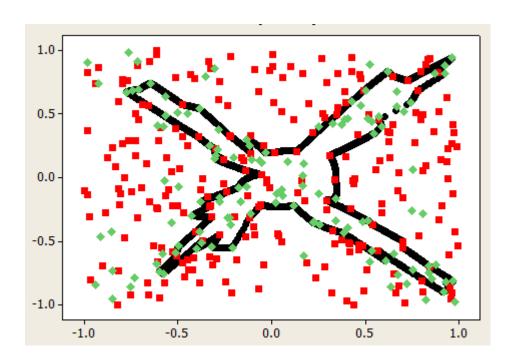
Cross Pattern: Fast Subset Scanning



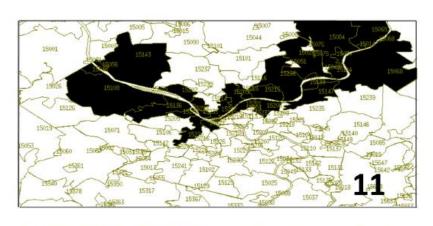
Cross Pattern: Circles

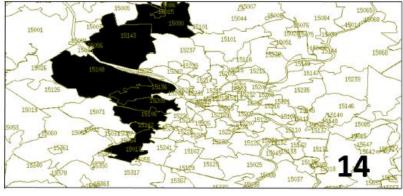


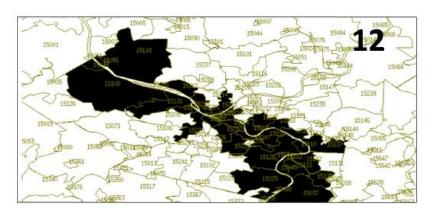
Cross Pattern: Star Scan

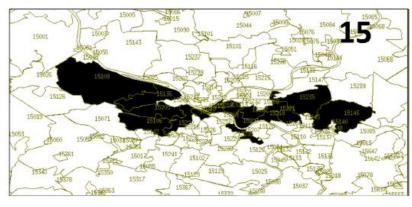


Real-world examples









Star Scan

- We propose a new technique to detect irregularly shaped clusters
- Star Scan maximizes the log-likelihood ratio of a cluster while penalizing the change in radius to form the cluster
- We propose a dynamic programming based solution to find optimal clusters, with penalty terms introduced to control smoothness in the circumference of cluster

Expectation-Based Scan Statistics

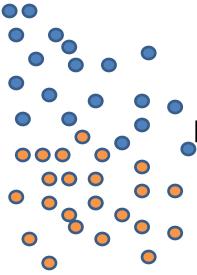
For location S_i

Observed: $x_i H_0: x_i \sim \mu_i$

Expected: μ_i

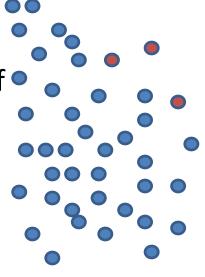
 $H_1: x_i \sim q\mu_i \quad q > 1$

$$F(S) = \max_{q>1} \log \frac{P(Data \mid H_1(S))}{P(Data \mid H_0)}$$



Large number locations with a moderate risk

Small number of locations with a high risk



Additive Linear Time Subset Scanning

$$F(S) = \max_{q>1} \log \frac{P(Data \mid H_1(S))}{P(Data \mid H_0)} \qquad H_0: x_i \sim \mu_i \\ H_1: x_i \sim q\mu_i \qquad q > 1$$

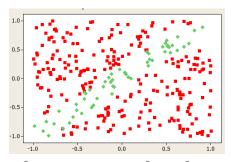
Conditioning ALTSS functions on the relative risk, q, allows the function to be written as an **additive** set function over the data elements s_i contained in S.

Poisson example:

$$F(S) = \max_{q>1} \sum_{S_i \in S} x_i (\log q) + \mu_i (1 - q)$$

Conditioning on relative risk

By conditioning on relative risk (q) each element is either "positive" or "negative"



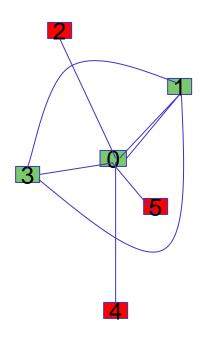
- This simplifies the maximization over subsets
 - Include only the points whose contribution to LLR are positive

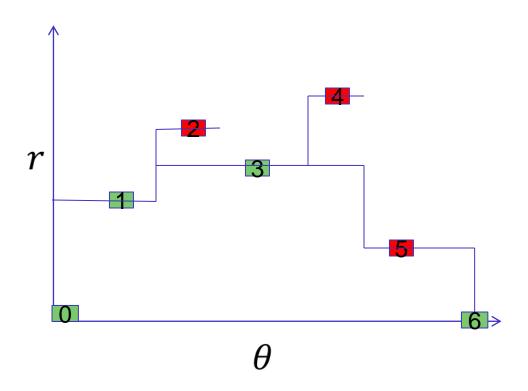
$$F(S) = \max_{q>1} \sum_{s_i \in S} [x_i(\log q) + \mu_i(1-q)]$$

Star Scan: Fundamentals

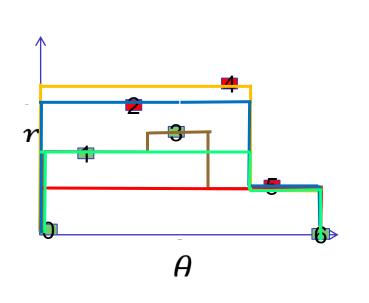
- The score of subset (S) is dependent on the following four characteristics
 - \Box Cumulative sum of observed: $\sum x_i = X(S)$
 - □ Cumulative sum of expected: $\sum \mu_i = \mu(S)$
 - \Box Total change in radius to form a subset : R(S)
- We propose a dynamic programming based solution to find optimal subset that maximizes the score of subset (S)
- $F_{starscan}(S \mid q) = F_{exp}(S|q) + \lambda * R(S)$

Dynamic Programming for Star Scan

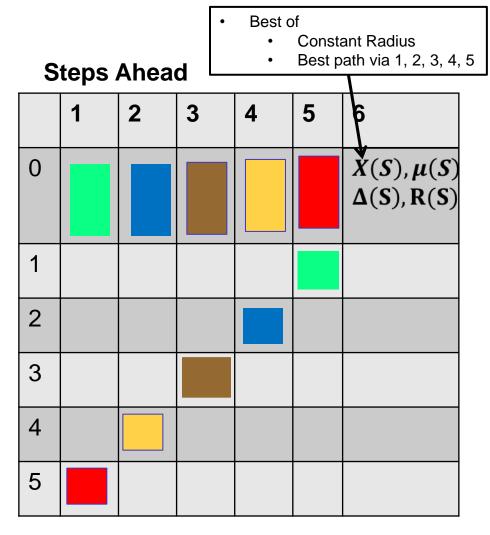




Dynamic Programming for Star Scan



Start Location



Star Scan generalizes FSS and Circles

 The penalty parameter can be used to generalize Star Scan

$$F_{starscan}(S | q) = F_{exp}(S | q) + \lambda * R(S)$$

- λ is the penalization parameter
 - High value of λ: Circles (Kulldorff, 1997)
 - Low value of λ: Fast Subset Scan (Neill, 2012)

Star Scan: Challenges

Dynamic programming is easy for a given relative risk (q) as each element is either "positive" or "negative", that is,

$$F_{starscan}(S | q) = F_{exp}(S | q) + \lambda * R(S)$$

$$F^*(q) = \max_{S} F_{starscan}(S | q)$$

However the optimal score F* is given by

$$F^* = \max_{q>1} \max_{S} F_{starscan}(S | q)$$

DP for Star Scan: Solutions

We can either grid search for the values of q in the range of possible values

 Or use branch and bound technique in order to find the optimal value of q

Bayesian Aerosol Release Detector

(BARD)

Hogan et al; 2007

Simulates anthrax spores released over a city

Two models drive the simulator:

Dispersion

Which areas will be affected?

Weather data

Gaussian plumes

Infection

How many infected people in an area? Demographic data

Increased ER visits with respiratory complaints

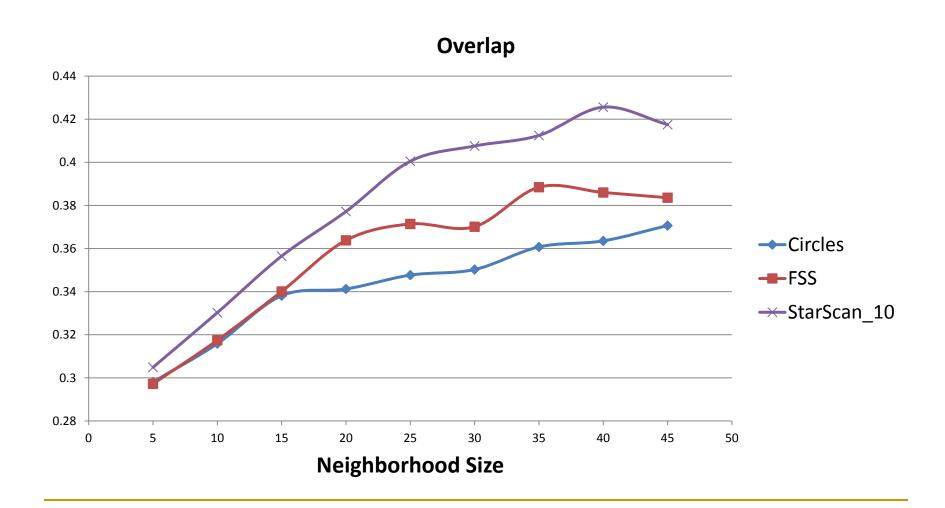
Results: Spatial Overlap

$$Overlap = \frac{A \cap B}{A \cup B} = \frac{}{}$$

$$Overlap = 1$$
 Perfect Match

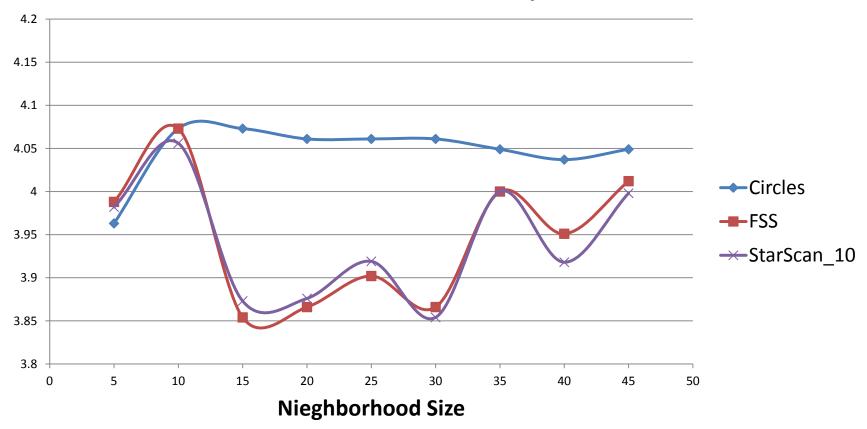
$$Overlap = 0$$
 Completely Disjoint

BARD Results: Spatial Overlap

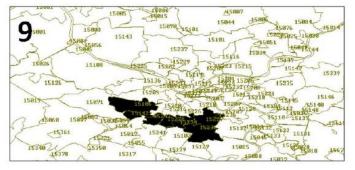


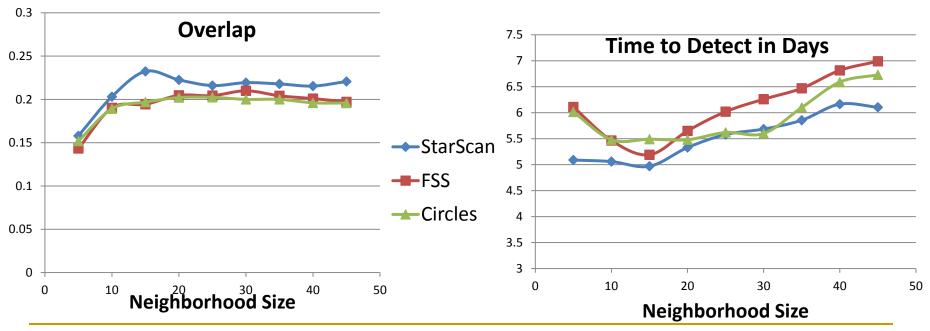
BARD Results: Time to Detect at a fixed fpr

Time to Detect in Days

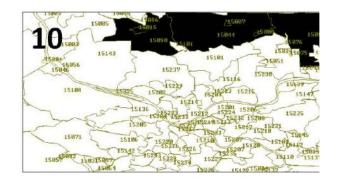


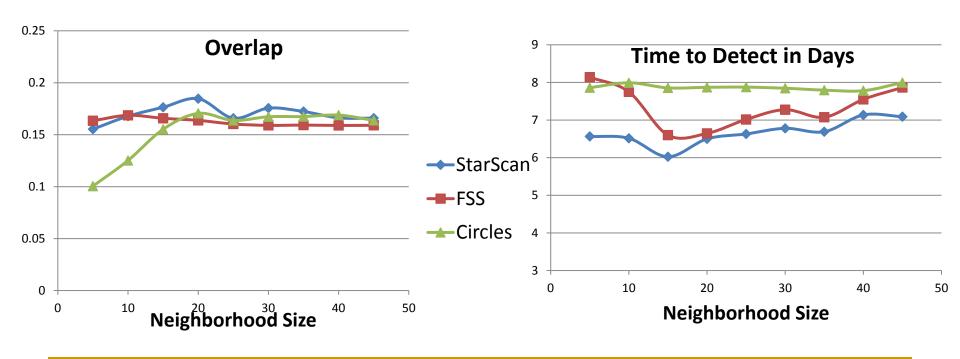
Simulated Injects in real-world Emergency Department data.





Simulated Injects (continued)





Conclusion

- We propose StarScan to find irregularly-shaped clusters more accurately than either the circular scan or unconstrained fast subset scan
- StarScan was compared with circular scan and fast localized subset scan on simulated respiratory outbreaks and bioterrorist anthrax attacks injected into real-world Emergency Department data
- Given a small amount of labeled training data, StarScan learns appropriate penalties for both compact and elongated clusters, resulting in improved detection performance