Penalized Fast Subset Scanning

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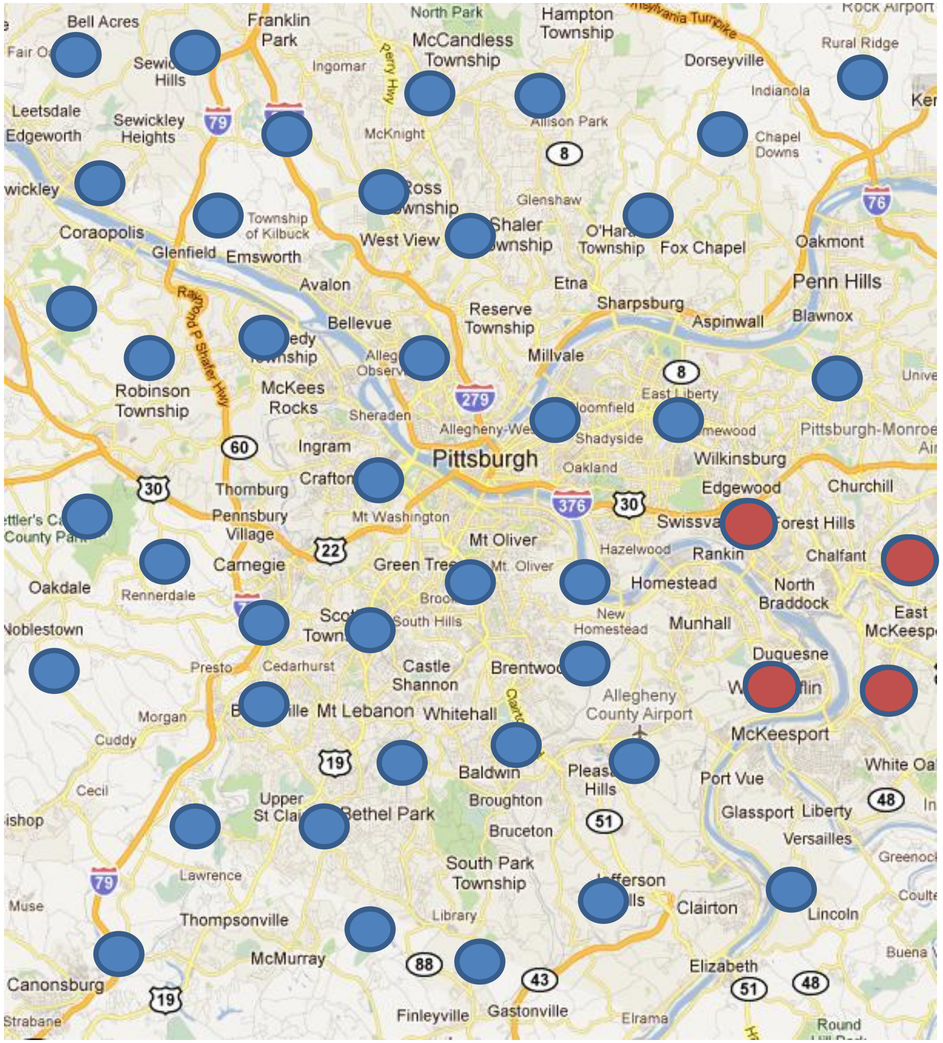
NSF National Science Foundation
WHERE DISCOVERIES BEGIN

Detecting Disease Clusters



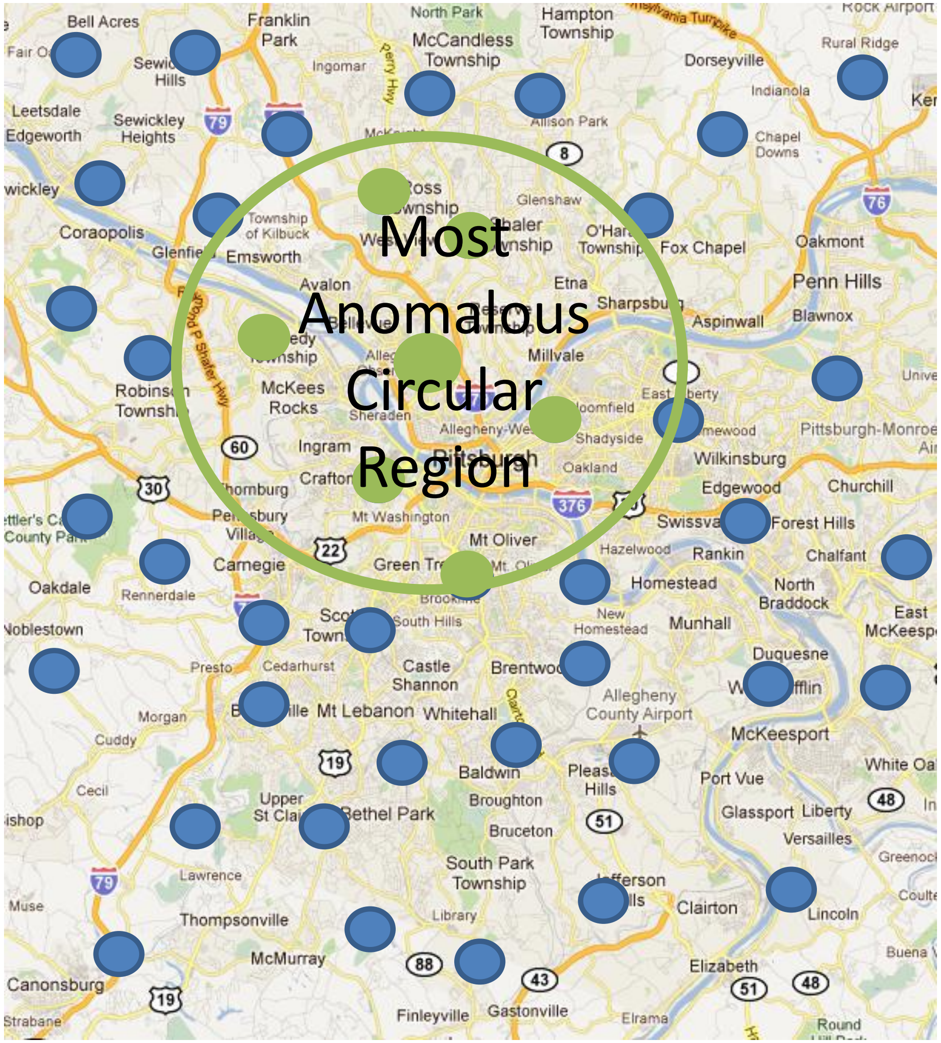
● Location of an informative data stream

- # 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)

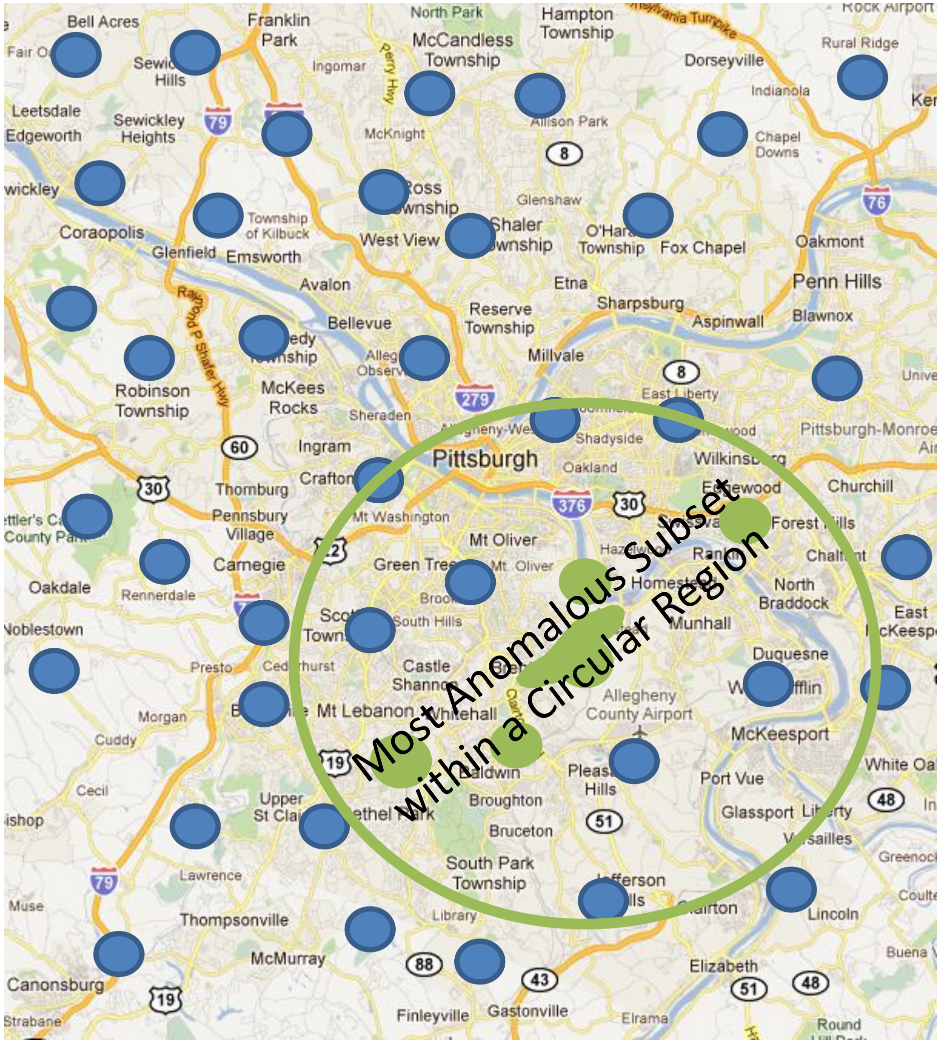
Spatial Scan Statistic
(Circles)

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



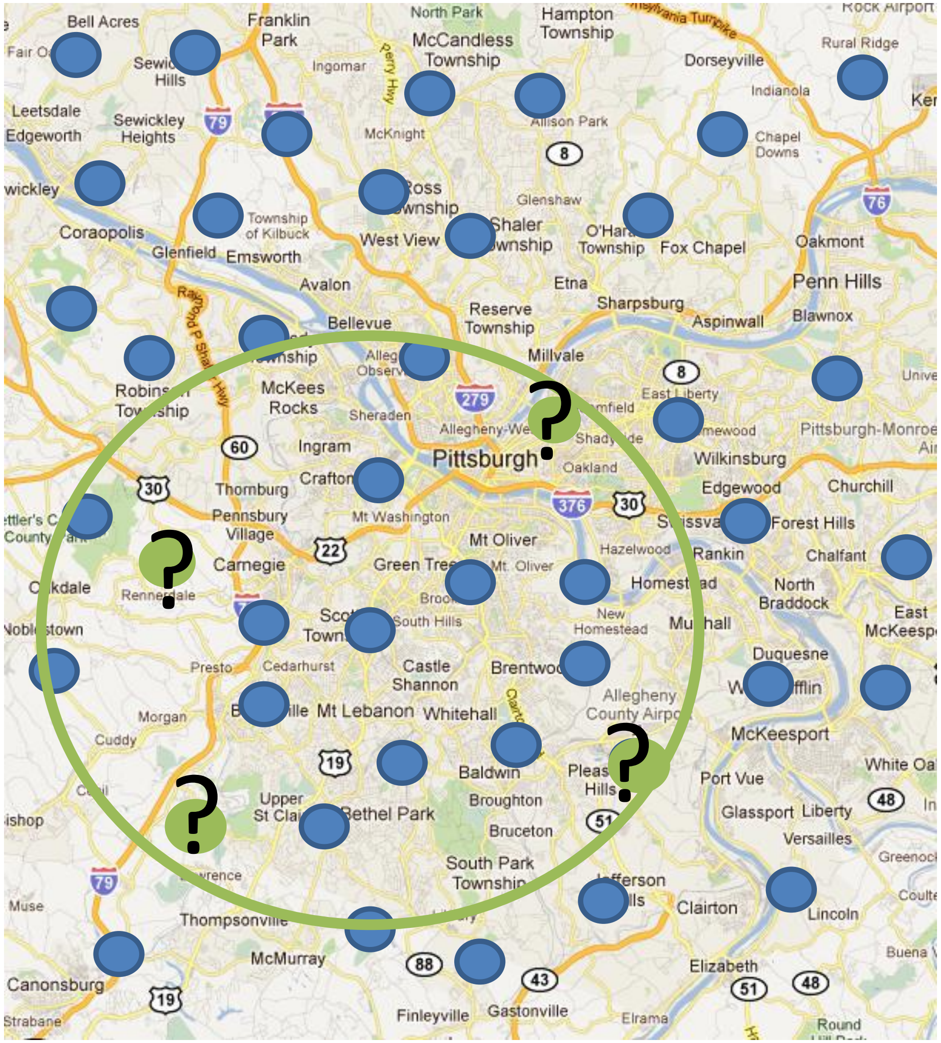
(Neill, 2011)

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

Detecting *Irregular* Disease Clusters



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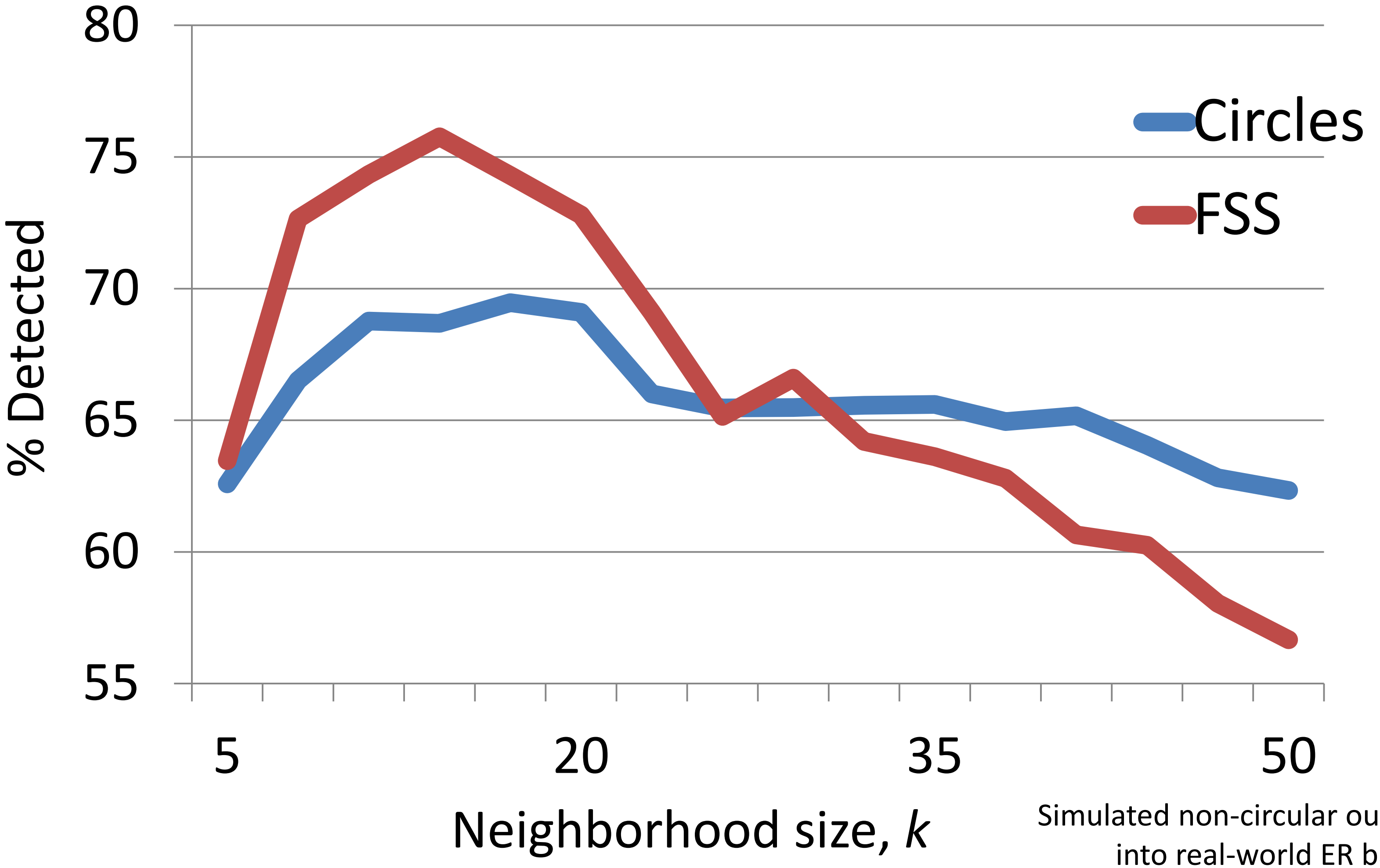
Increases power to detect irregularly shaped disease clusters

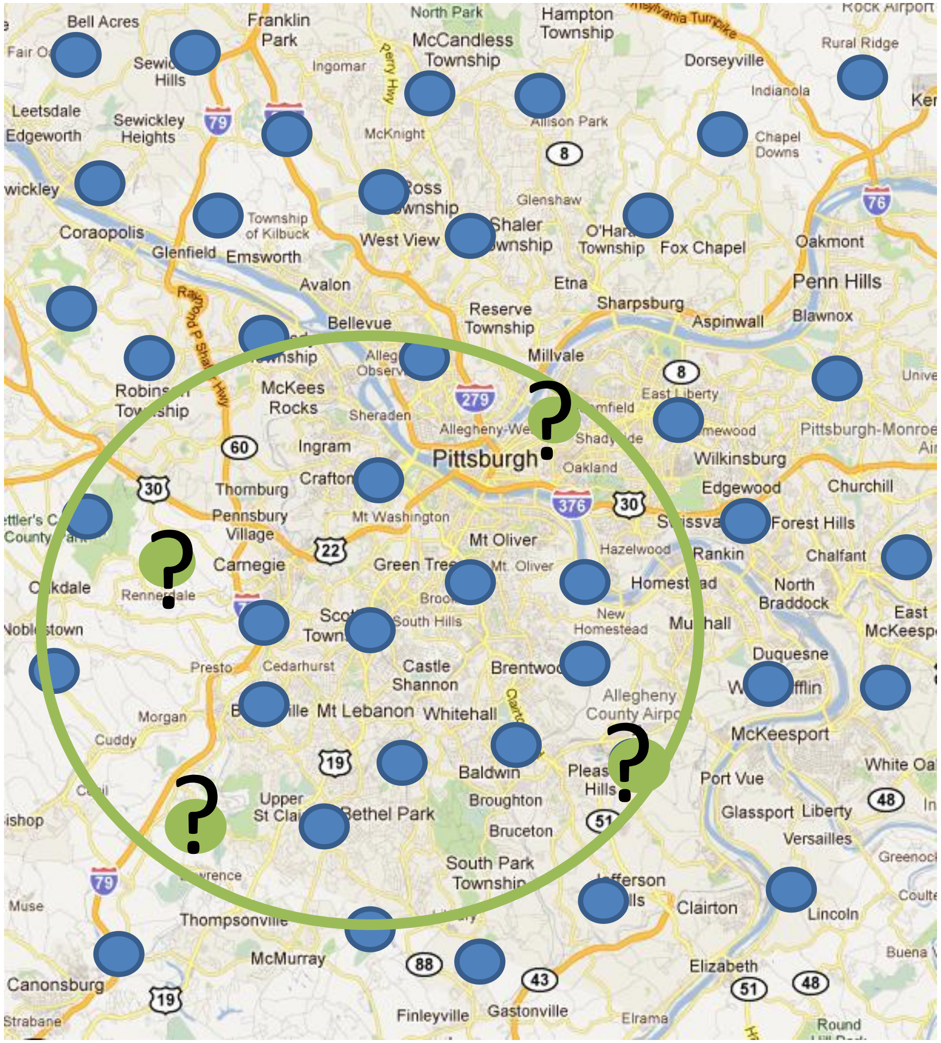
...but may return ***spatially dispersed subsets*** that do not reflect an outbreak of disease

Detection Power for Varying Neighborhood Size



Simulated non-circular outbreaks injected into real-world ER background data.
Fixed false positive rate of 1 per year.

Detecting *Irregular* Disease Clusters



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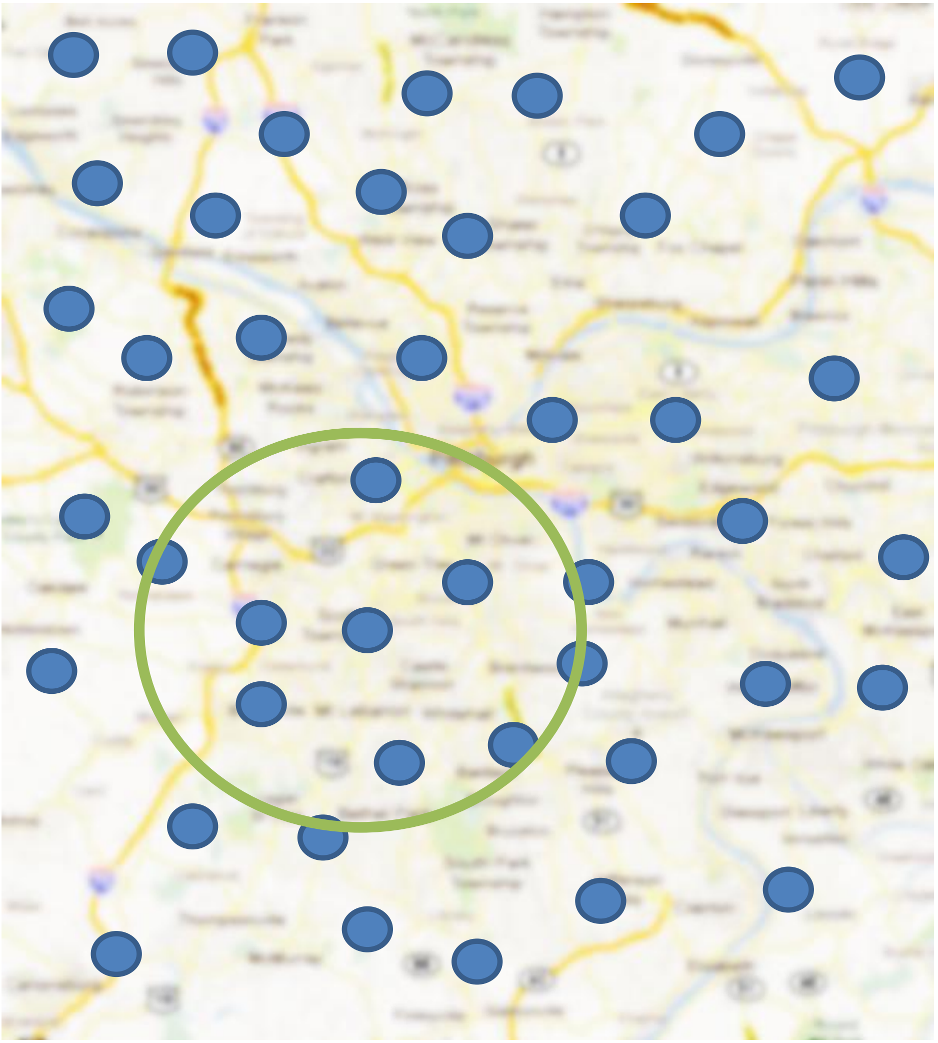
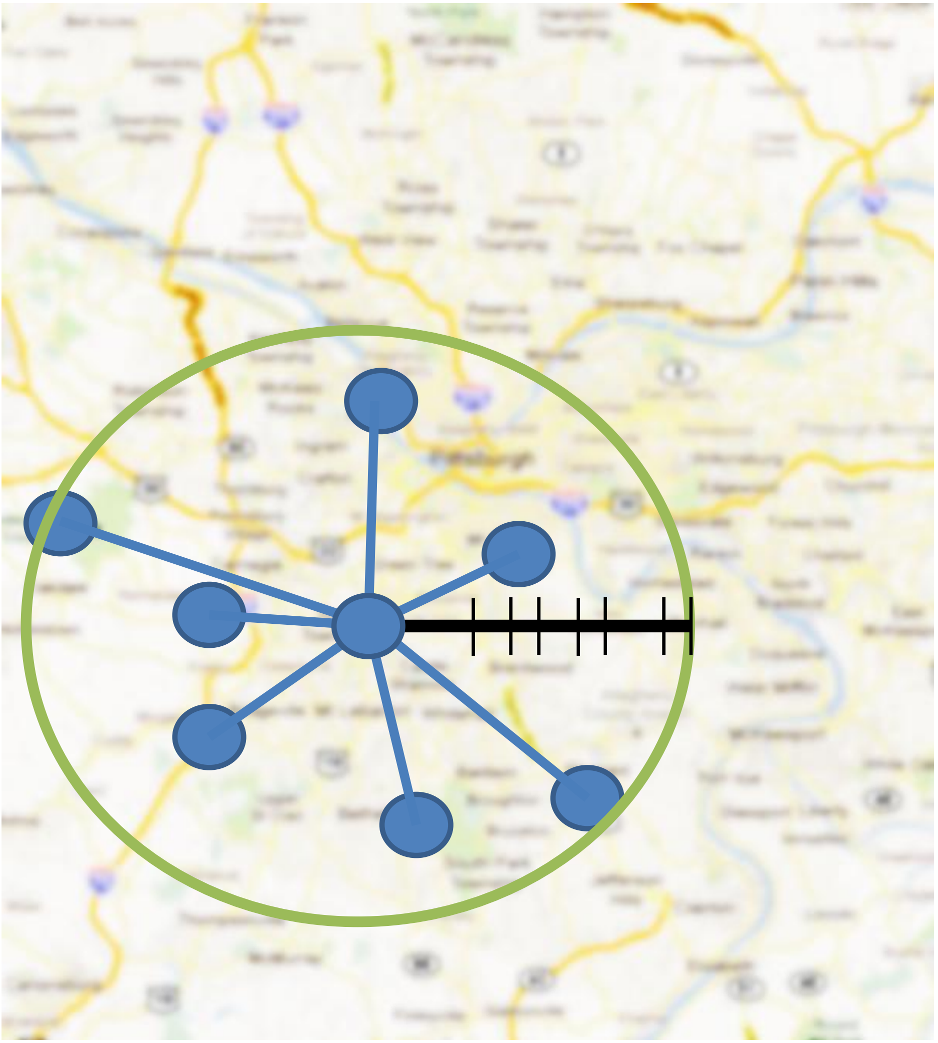


Soft Compactness Constraints

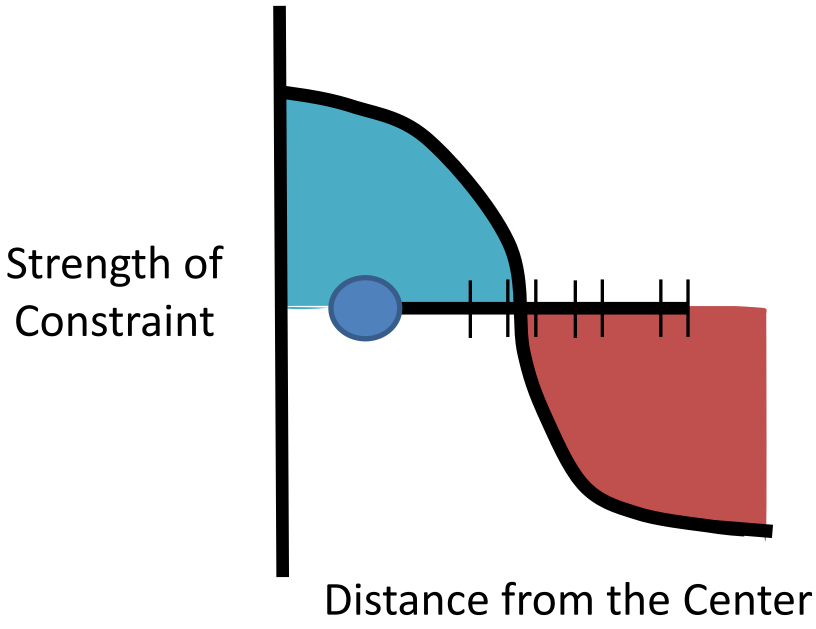
Detecting *Irregular* Disease Clusters



Soft Compactness Constraints

Use the distance of each location from the center as a measure of compactness/sparsity

Detecting *Irregular* Disease Clusters



Soft Compactness Constraints

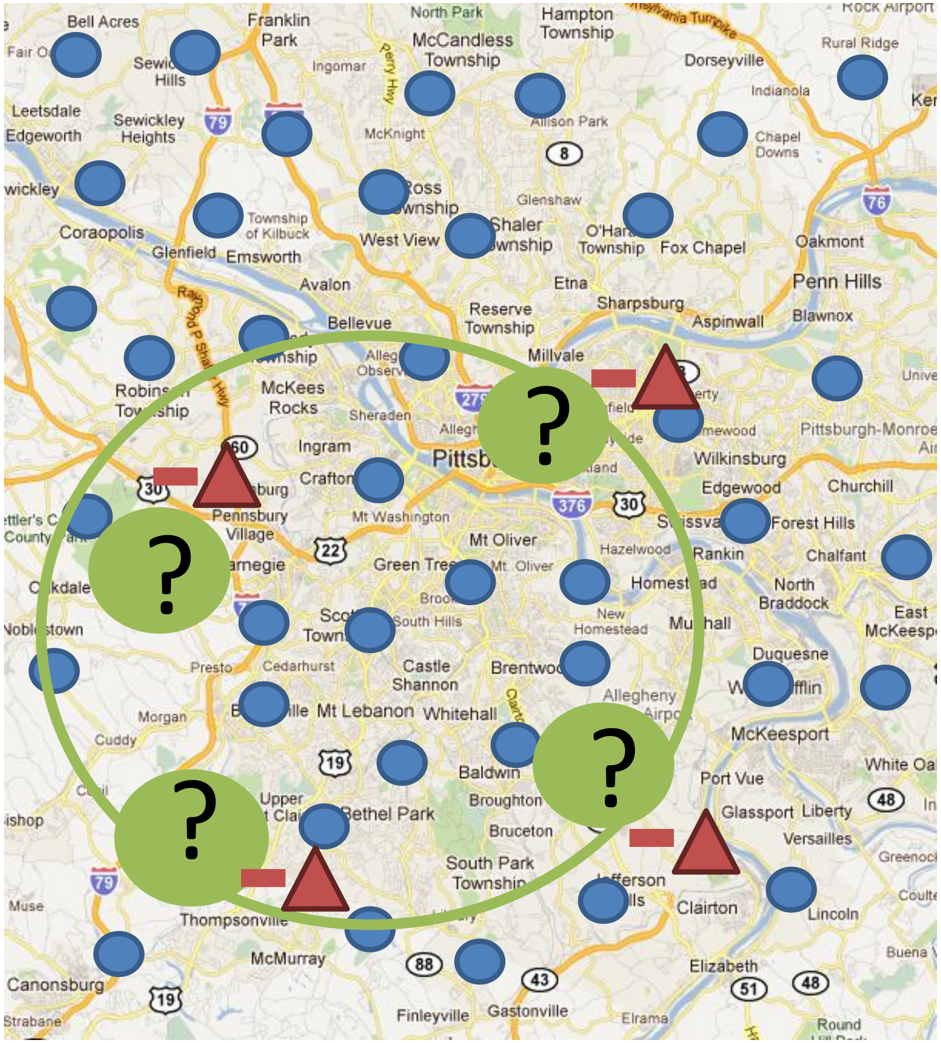
Use the distance of each location from the center as a measure of compactness/sparsity

Reward subsets that contain locations close to the center

and

Penalize subsets that contain locations far from the center

Detecting *Irregular* Disease Clusters



Soft Compactness Constraints

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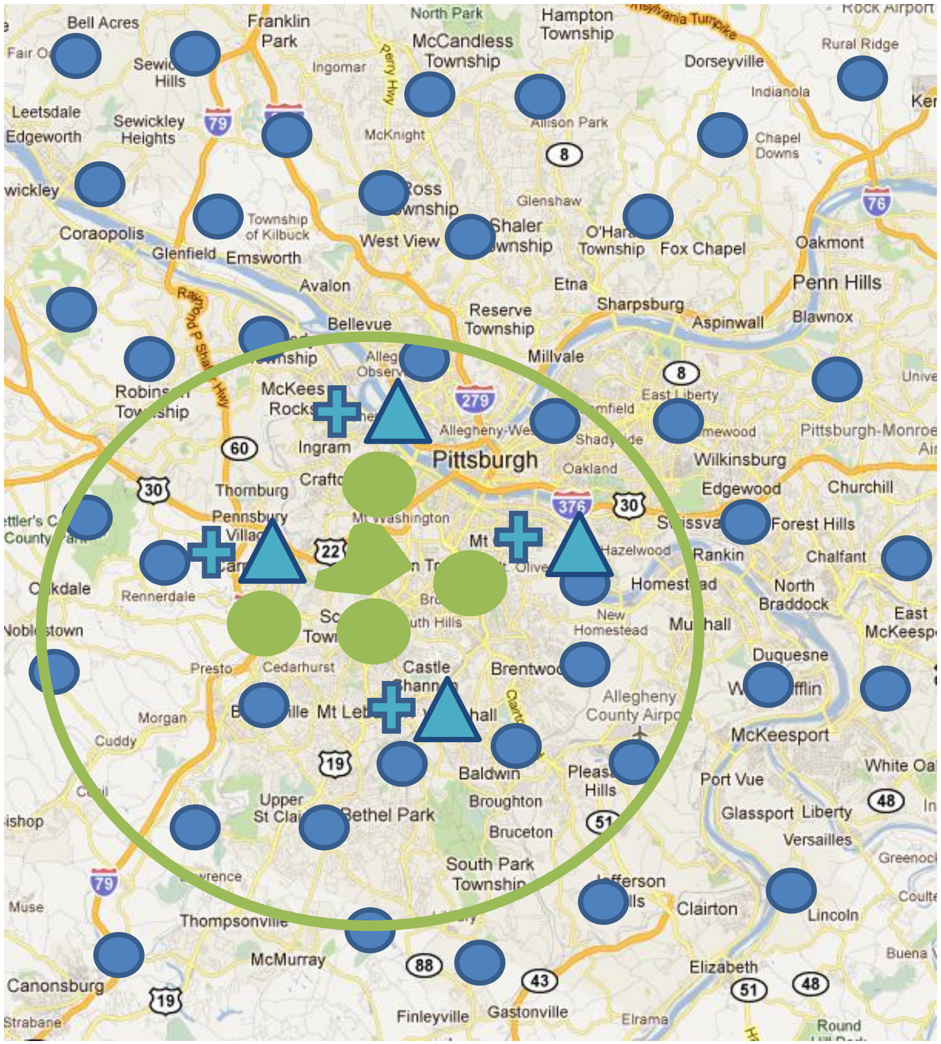
spatially sparse subsets

that do not reflect an outbreak of disease.

This particular subset would be less likely returned as the optimal one when compactness constraints are used

The penalties associated with the distance between the locations and center of the circle would decrease the "score" of the subset

Detecting *Irregular* Disease Clusters



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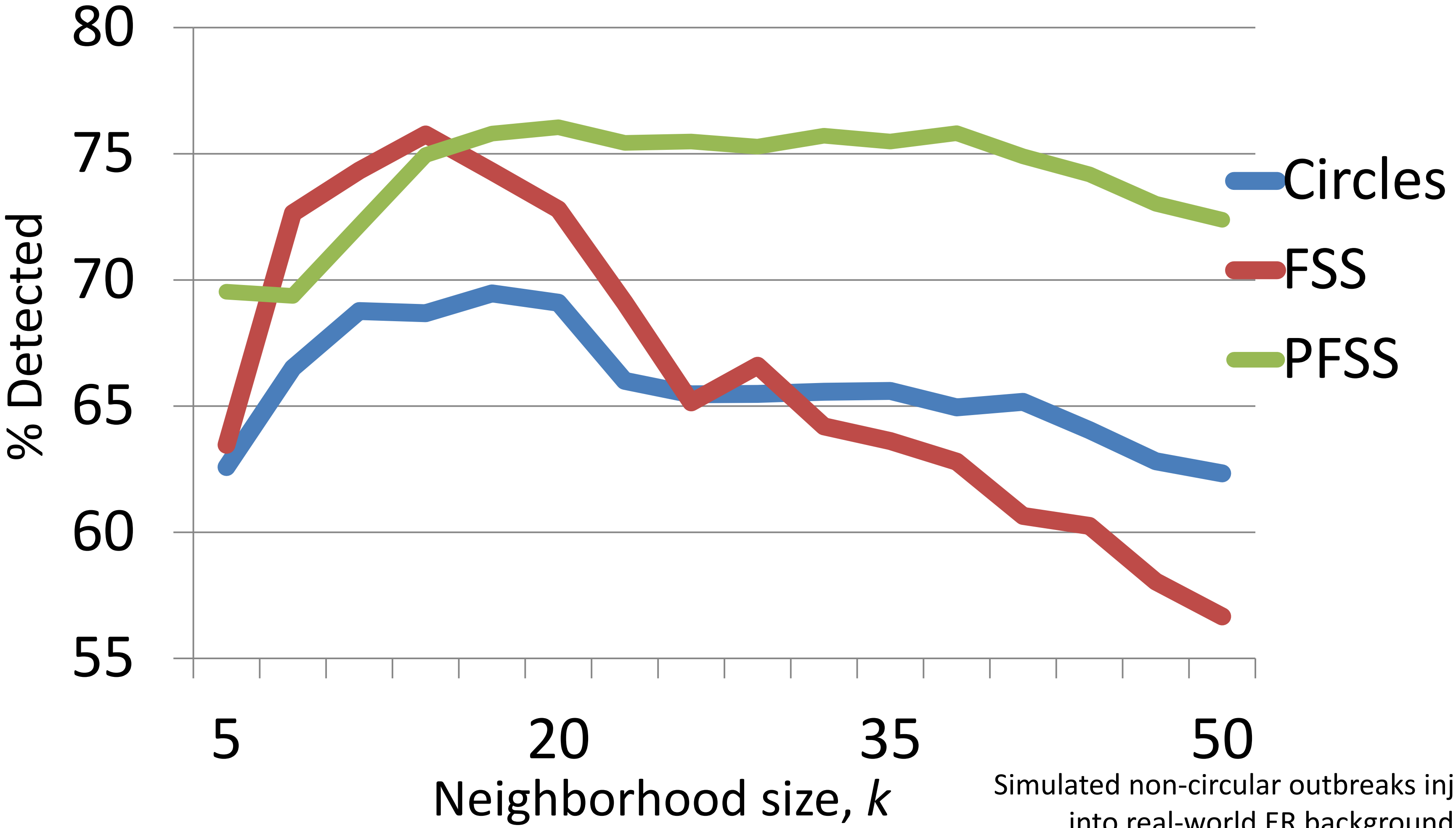
The penalties associated with the distance between the locations and center of the circle would decrease the "score" of the subset

...while increasing the score of compact clusters

Detection Power for Varying Neighborhood Size



Simulated non-circular outbreaks injected into real-world ER background data.
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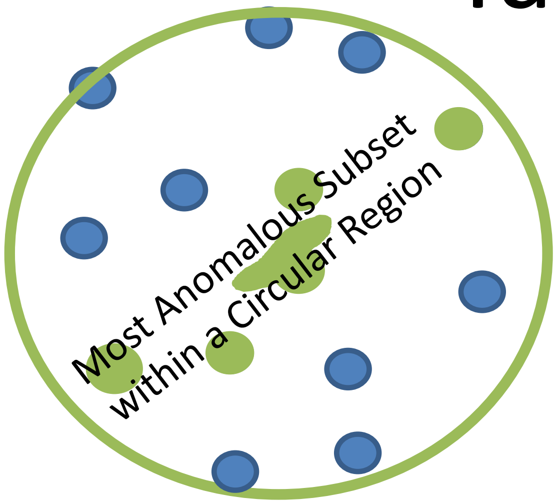
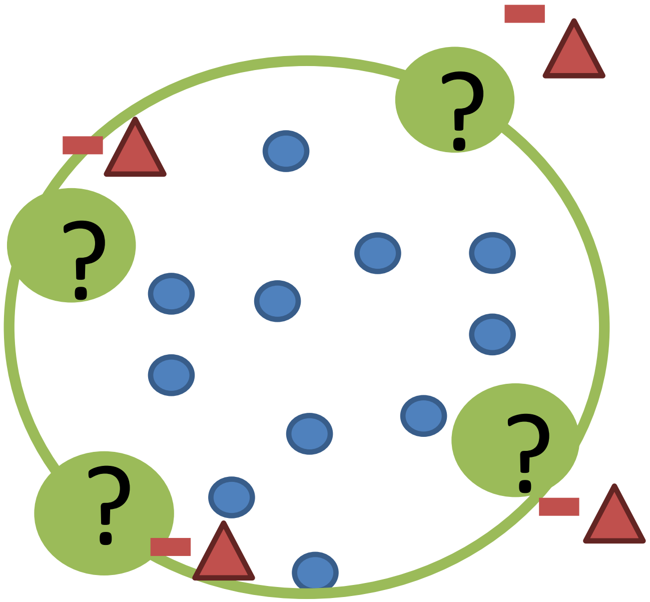
Take-Away Message



The subset scanning approach substantially improves detection power of spatial scan statistics for irregular region shapes



This increased flexibility requires closer attention to choice of neighborhood size, *k*.

Enforcing soft proximity constraints to penalize dispersed subsets addresses this concern and increases overall detection power.

Take-Away Message

Penalized Fast Subset Scanning is very general and provides a framework for incorporating soft constraints into commonly used expectation-based scan statistics.

In the PFSS framework, we demonstrate:

- Exactness: The most anomalous (highest scoring) subset is guaranteed to be identified.
- Efficiency: Only *O(N)* subsets must be scanned in order to identify the most anomalous penalized subset in a dataset containing *N* elements (same as the un-penalized scan).
- Interpretability: Soft constraints may be viewed as the prior log-odds for a given record to be included in the most anomalous penalized subset.

Three Contributions

Additive Linear Time Subset Scanning (ALTSS) property of commonly used expectation-based scan statistics

Efficient computation of the optimal penalized subset for functions satisfying ALTSS

One example of penalty terms: soft proximity constraints

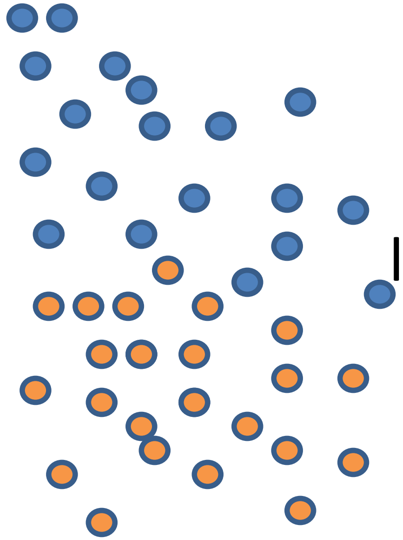
Expectation-based Scan Statistics

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

$$H_0 : x_i \sim \text{Poisson}(\mu_i)$$

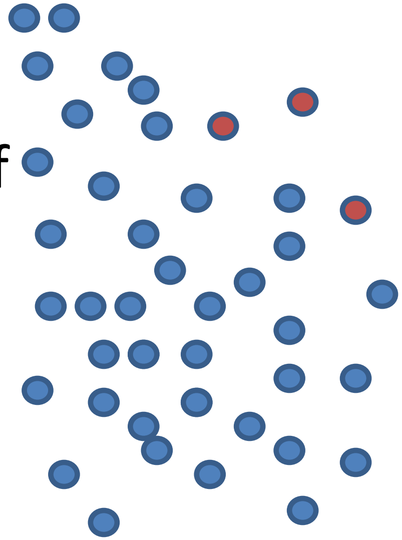
$$H_1 : x_i \sim \text{Poisson}(q\mu_i) \qquad q > 1$$

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



Large number locations with a moderate risk

Small number of locations with a high risk



Additive Linear Time Subset Scanning

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

$$H_0 : x_i \sim Poisson(\mu_i)$$

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

Definition: For a given dataset *D*, the score function *F(S)* satisfies the Additive Linear Time Subset scanning property if for all $S \subseteq D$ we have

$$F(S) = \max_{q>1} F(S|q) \text{ where } F(S|q) = \sum_{s_i \in S} \lambda_i$$

and $\lambda_i$depends only on the observed count x_i, expected count μ_i, and the relative risk, *q*.

Additive Linear Time Subset Scanning

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

Intuition: 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:

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

Additive Linear Time Subset Scanning

Consequence #1: Extremely easy to maximize by including all "positive" elements and excluding all "negative".

Consequence #2: Additional, element-specific, terms may be added to the scoring function while maintaining the additive property.

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

Additive Linear Time Subset Scanning

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$$F_{penalized}(S) = \max_{q>1} \sum_{s_i \in S} [\, \overbrace{x_i(\log q) + \mu_i(1-q) + \boldsymbol{\Delta}_i}^{\text{“Total Contribution” } \gamma_i \text{ of record } s_i \text{ for fixed risk, } q} \,]$$

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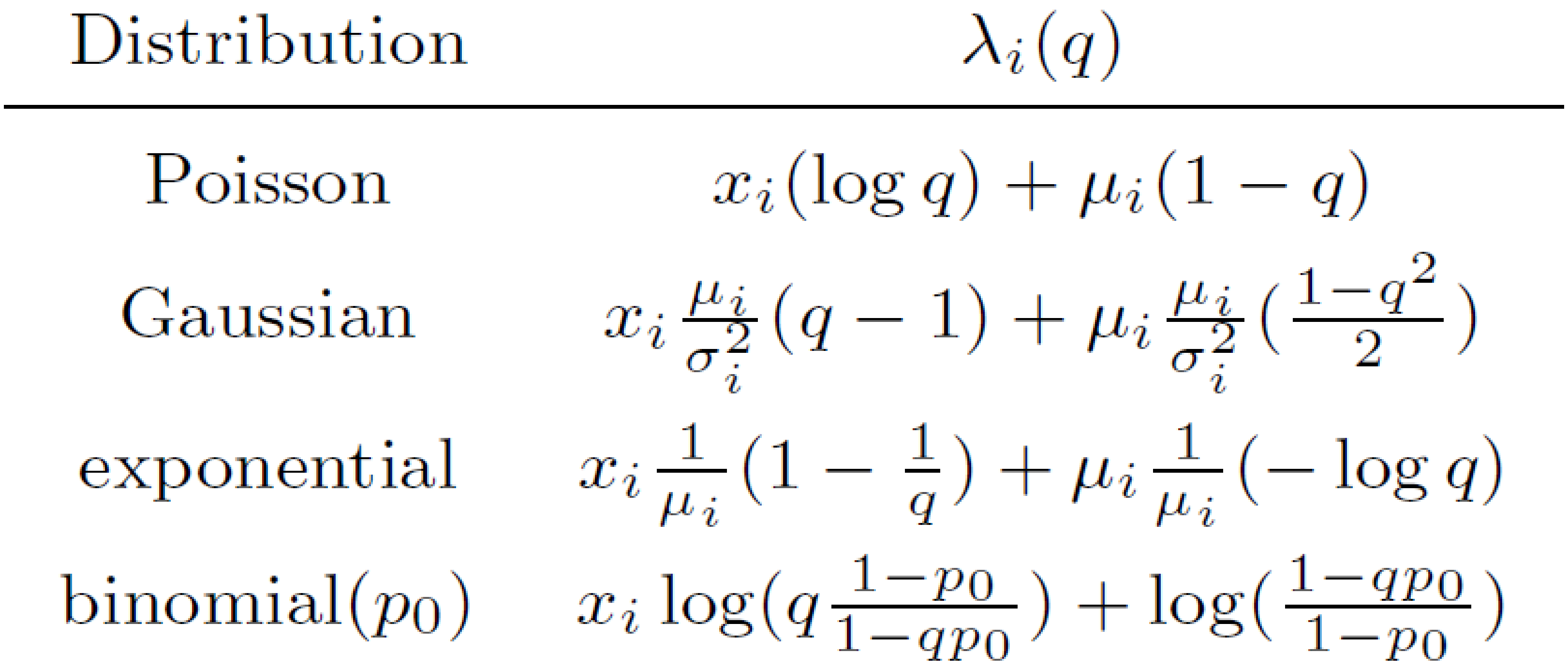
Additive Linear Time Subset Scanning



Distribution	$\lambda_i(q)$
Poisson	$x_i(\log q) + \mu_i(1-q)$
Gaussian	$x_i \frac{\mu_i}{\sigma_i^2}(q-1) + \mu_i \frac{\mu_i}{\sigma_i^2}(\frac{1-q^2}{2})$
exponential	$x_i \frac{1}{\mu_i}(1-\frac{1}{q}) + \mu_i \frac{1}{\mu_i}(-\log q)$
binomial(p_0)	$x_i \log(q \frac{1-p_0}{1-qp_0}) + \log(\frac{1-qp_0}{1-p_0})$

Three Contributions

Additive Linear Time Subset Scanning (ALTSS) property of commonly used expectation-based scan statistics

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One example of penalty terms: soft proximity constraints

Penalized Fast Subset Scanning

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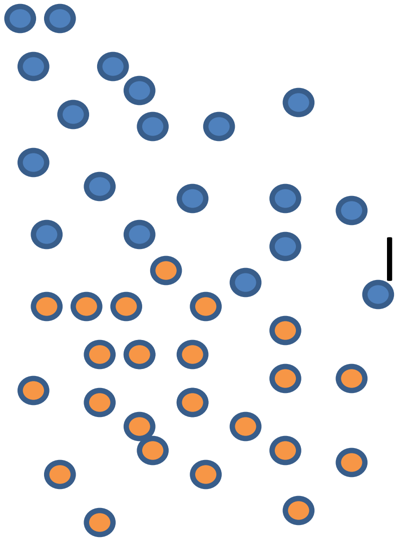
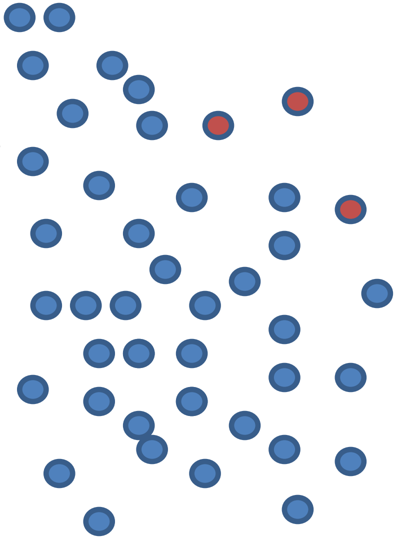


Large number locations with a moderate risk

Small number of locations with a high risk



… but the ALTSS property requires evaluating the function at a *fixed* risk.

How do we optimize over the entire range *q > 1 ?*

Penalized Fast Subset Scanning

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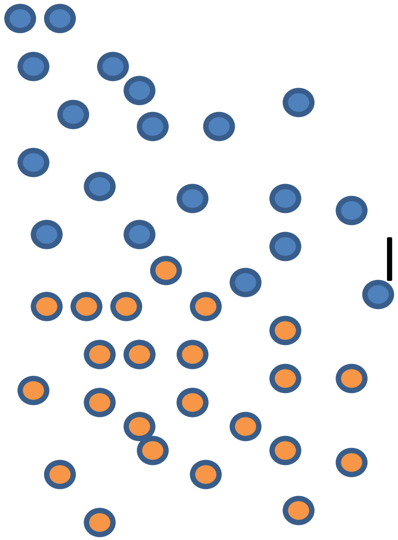

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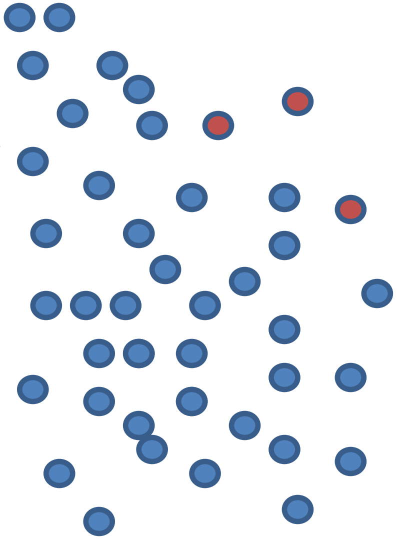
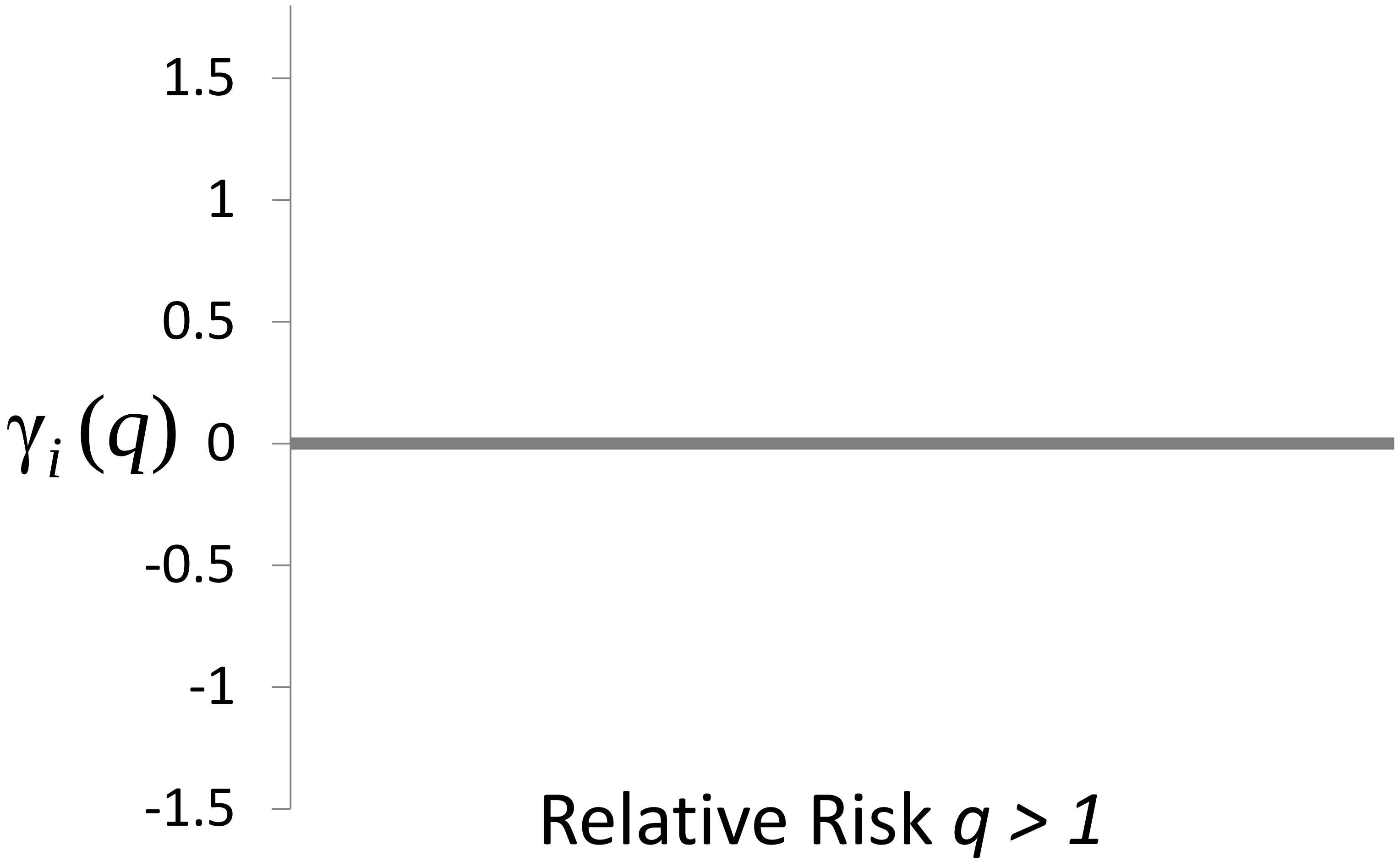


Theorem: The optimal subset $S^* = \arg\max_S F_{pen}(S)$ maximizing a penalized expectation-based scan statistic satisfying the ALTSS property may be found be evaluating only *O(N)* subsets, where *N* is the total number of data elements.

Proof by Picture

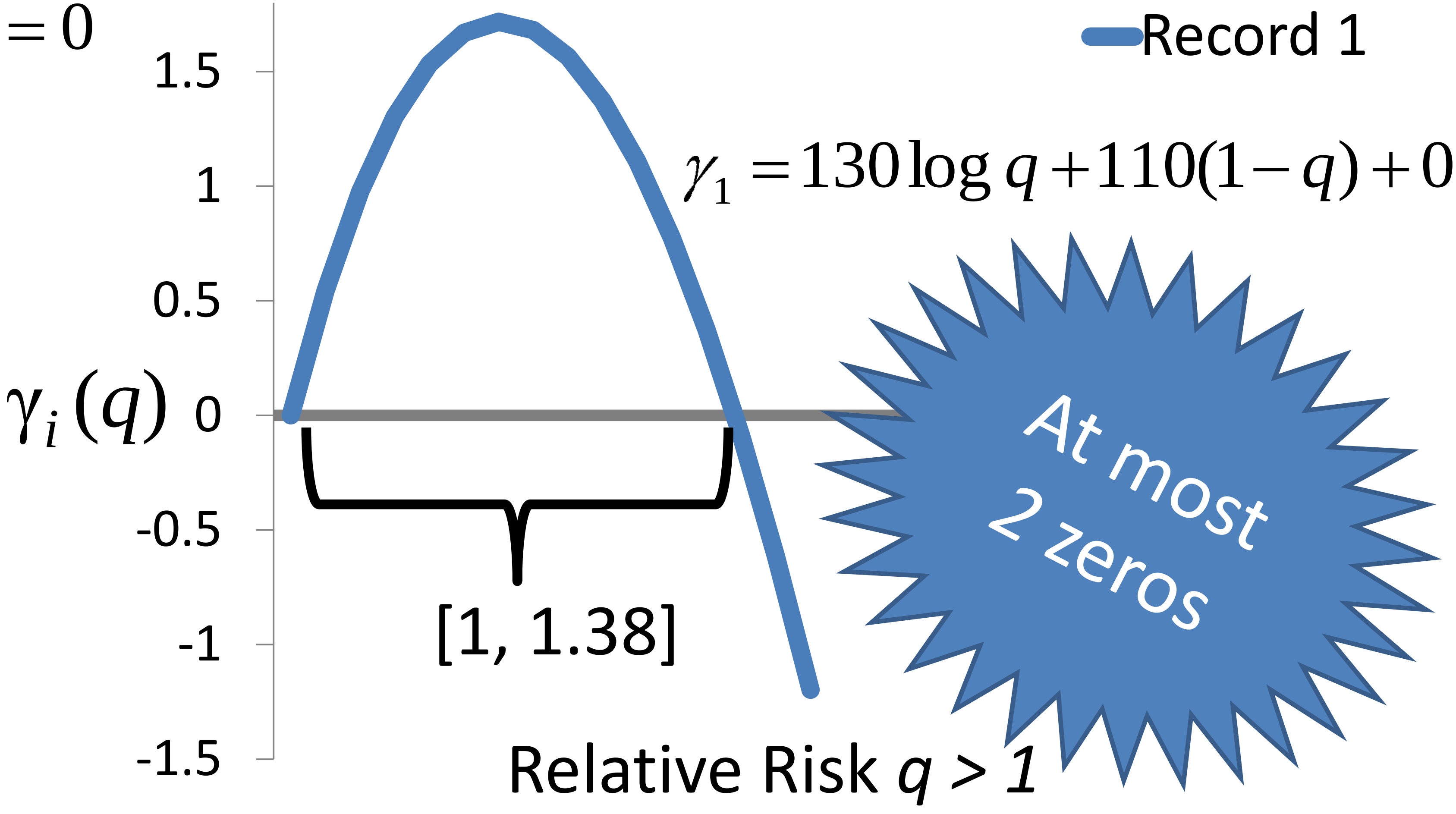


$$x_1 = 130$$

$$\mu_1 = 110$$

$$\Delta_1 = 0$$

Proof by Picture



$$\gamma_1 = 130 \log q + 110(1 - q) + 0$$

Proof by Picture

$$x_1 = 130$$

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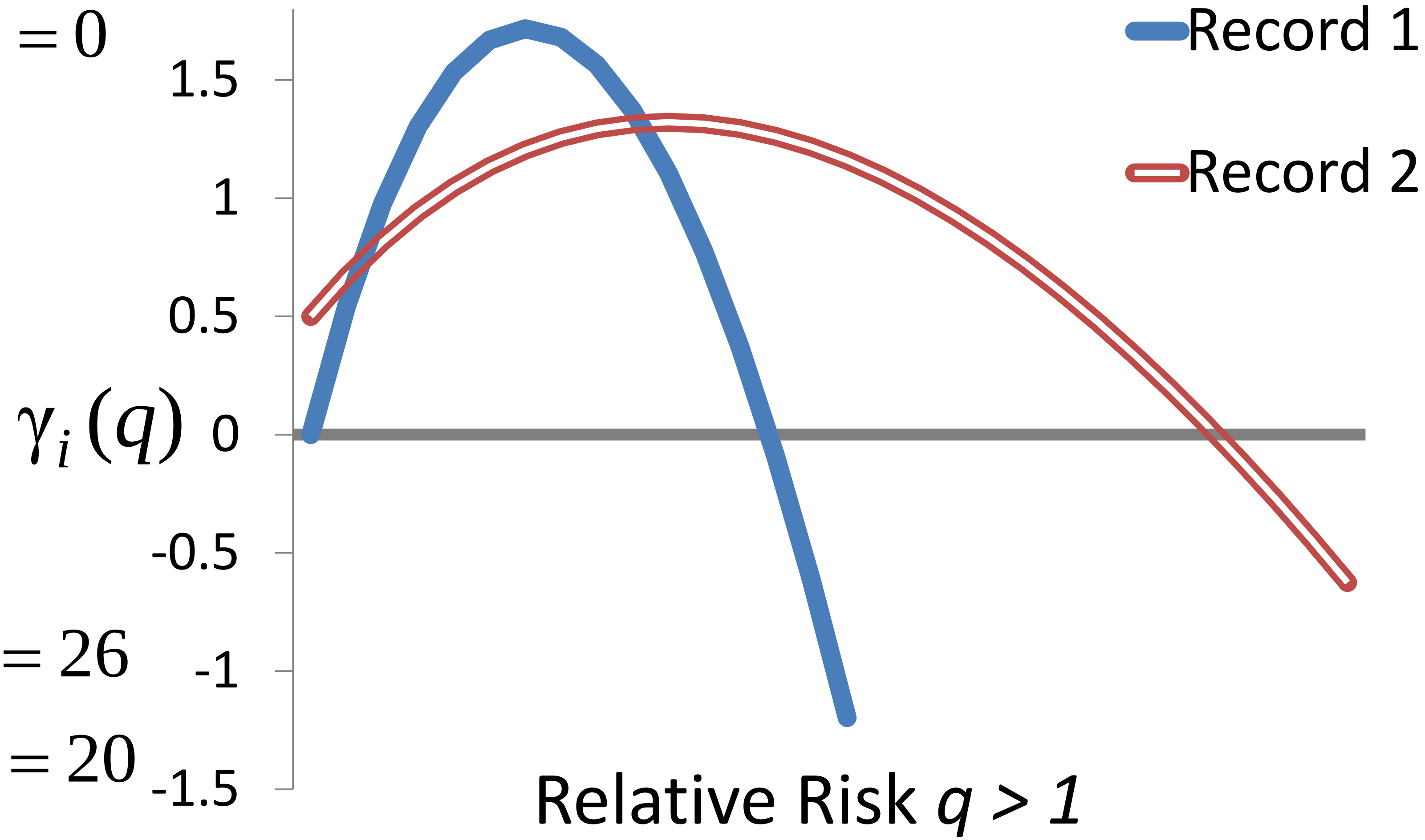


$$x_2 = 26$$

$$\mu_2 = 20$$

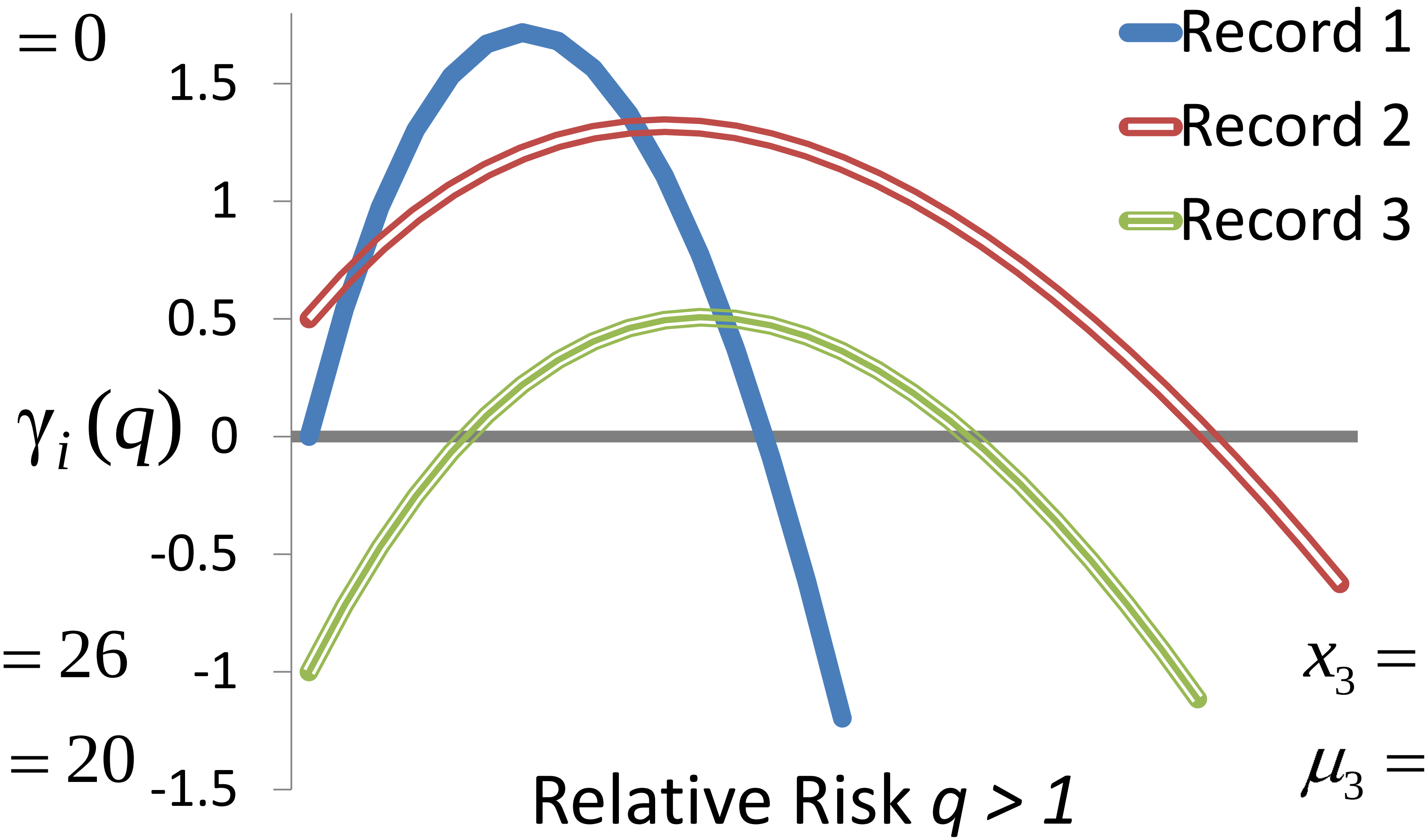
$$\Delta_2 = 0.5$$

$x_1 = 130$

$\mu_1 = 110$

$\Delta_1 = 0$

Proof by Picture



$x_2 = 26$

$\mu_2 = 20$

$\Delta_2 = 0.5$

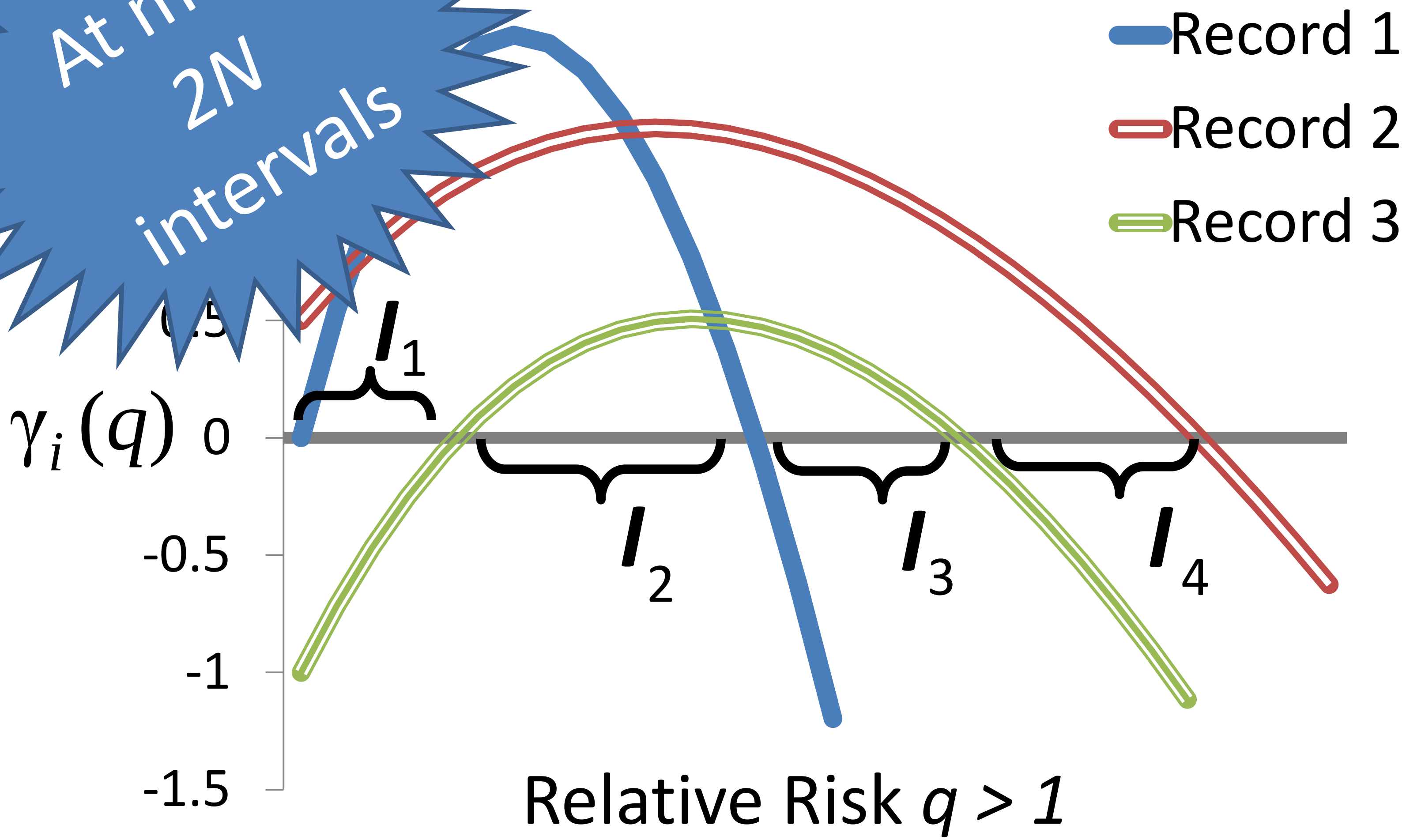
$x_3 = 40$

$\mu_3 = 30$

$\Delta_3 = -1$

Proof by Picture

At most 2N intervals



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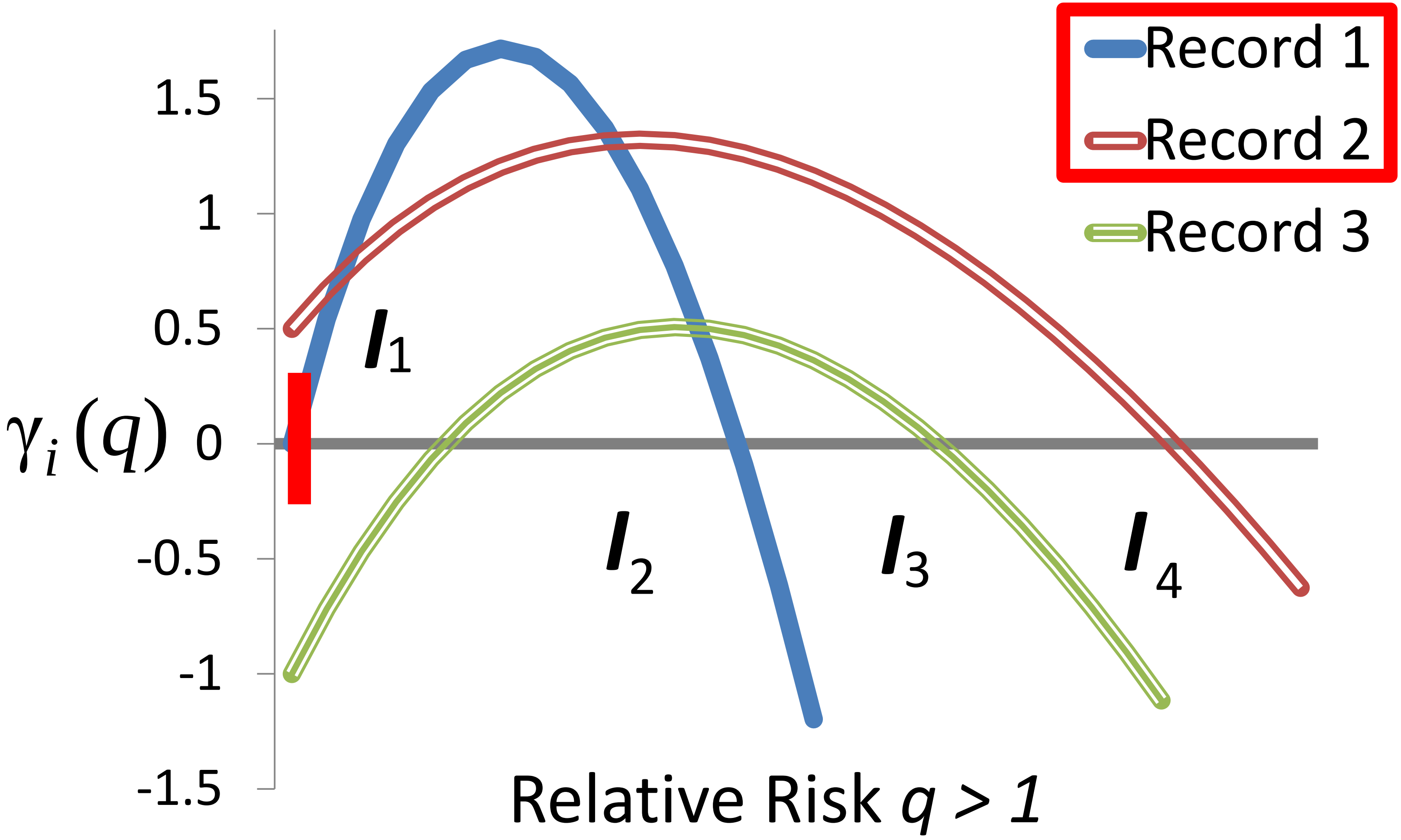

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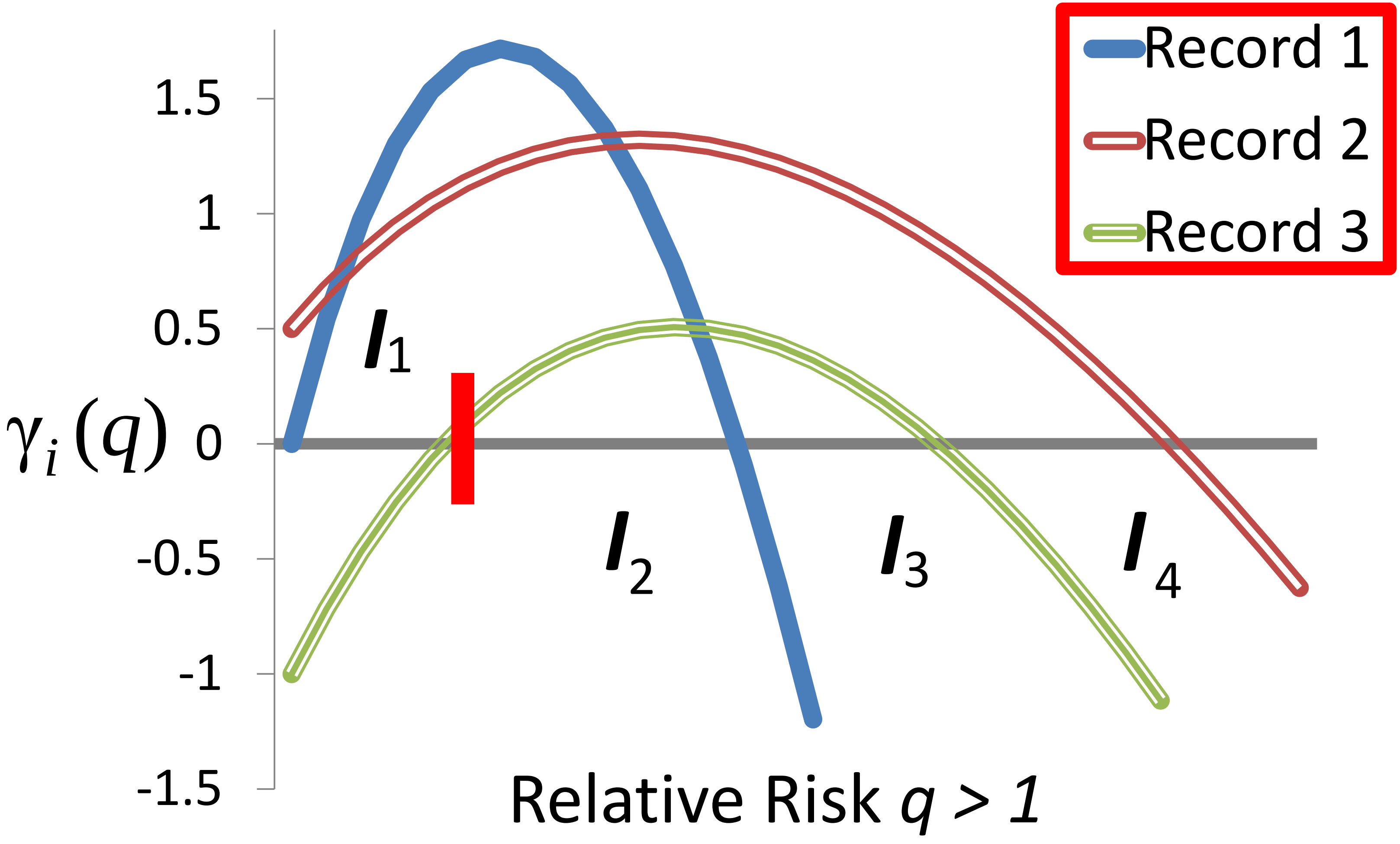

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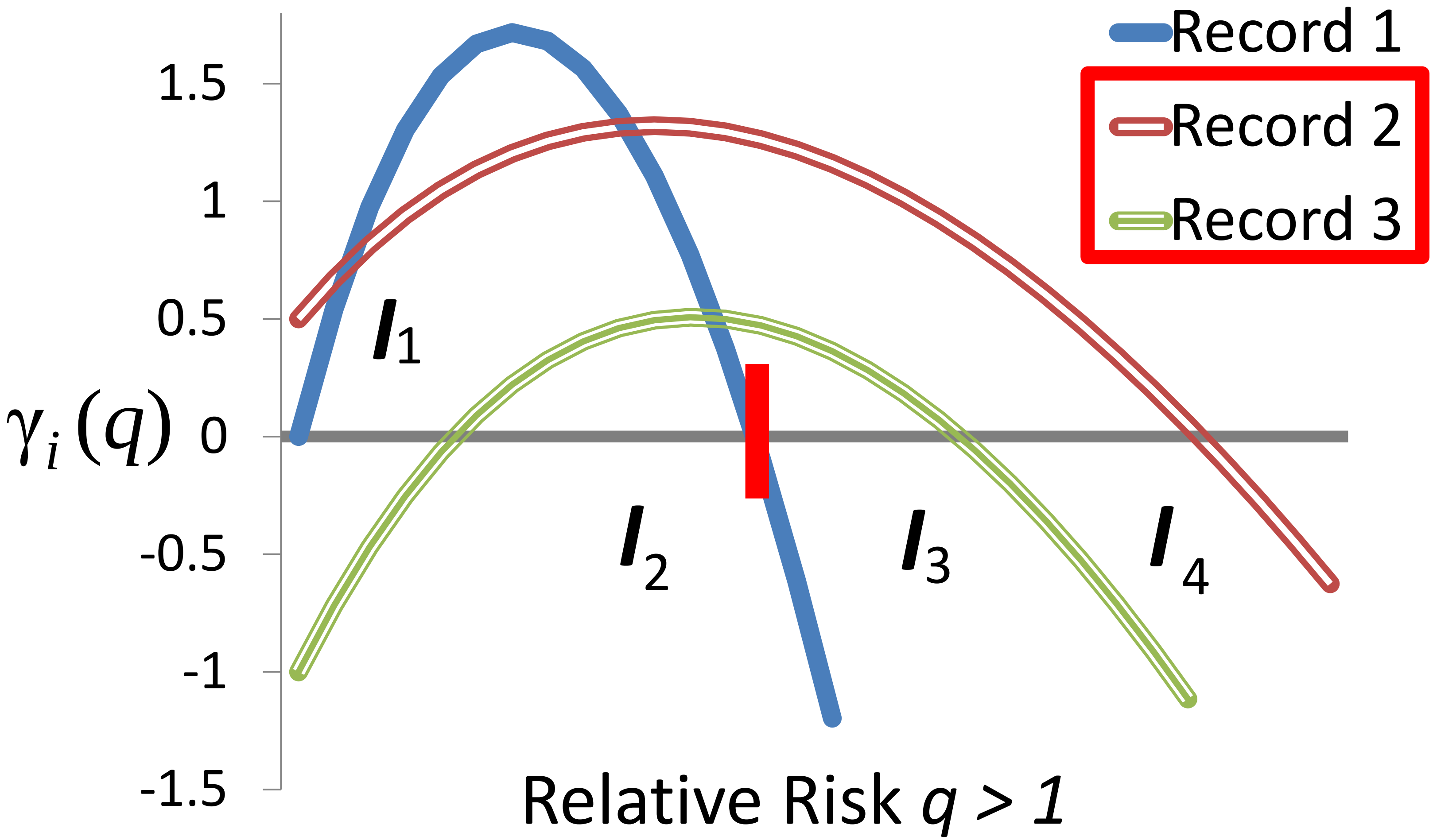

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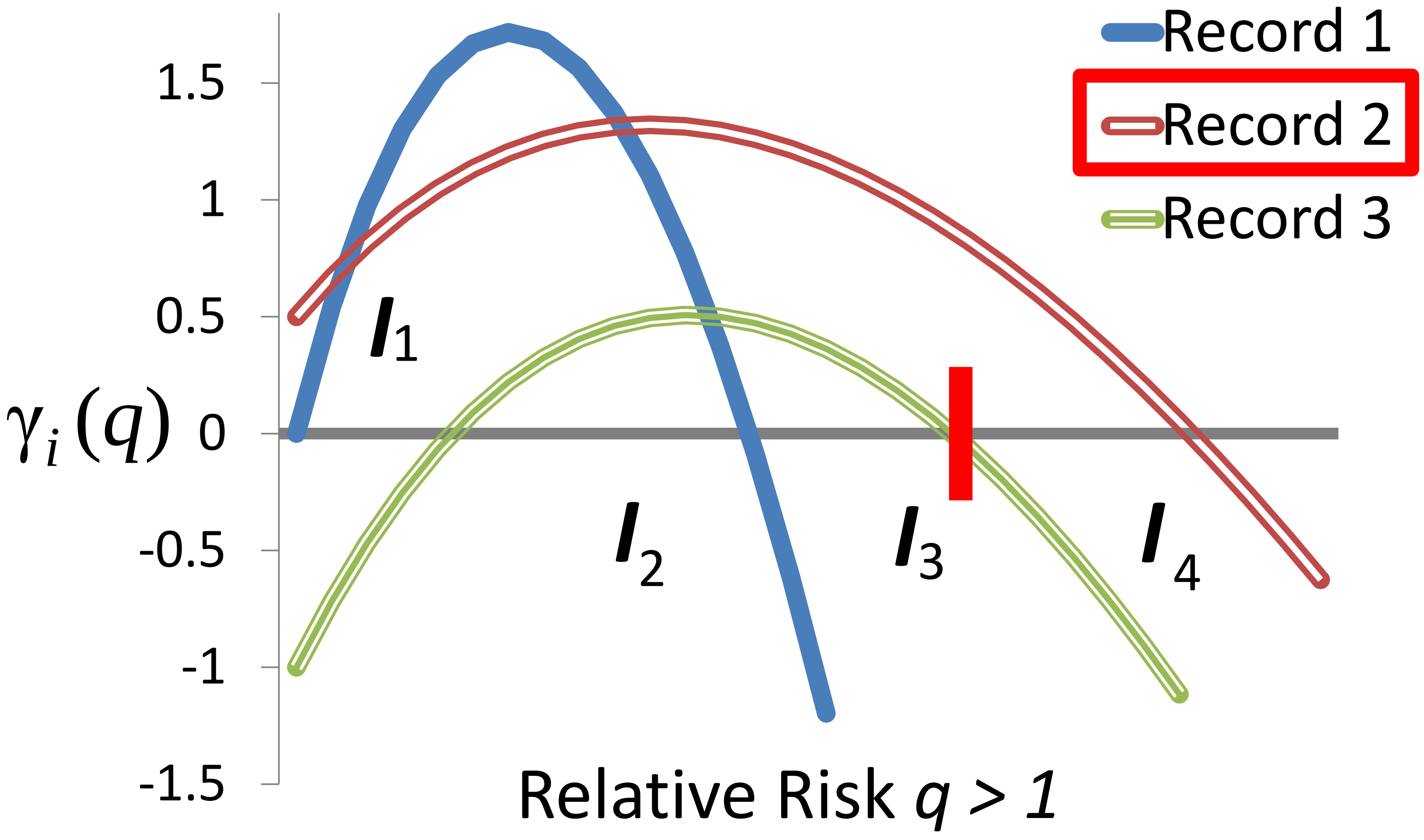

Three Contributions

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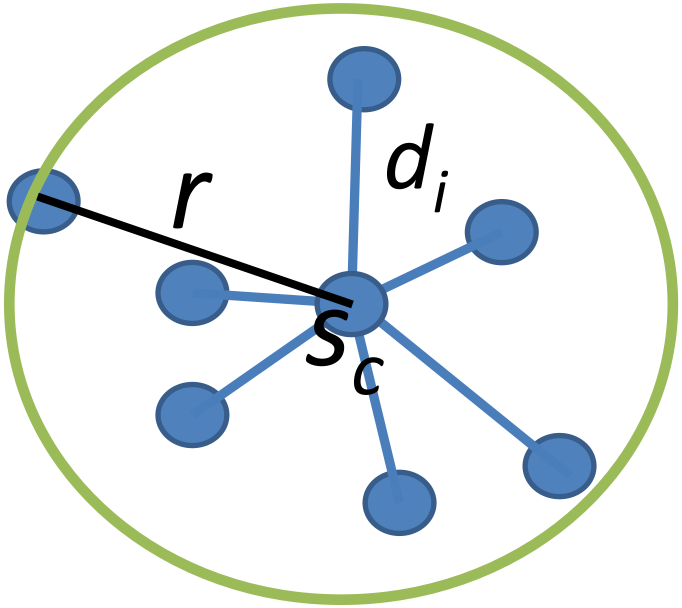
Soft Proximity Constraints

Penalized Fast Subset Scanning allows additional spatial information to be included; rewarding spatial compactness and penalizing dispersed subsets within a local neighborhood.



Center location and its *k-1* nearest neighbors

$$\Delta_i = h\left(1 - \frac{2d_i}{r}\right)$$

h is the strength of the constraint

$$\Delta_i = -h \leftrightarrow h$$

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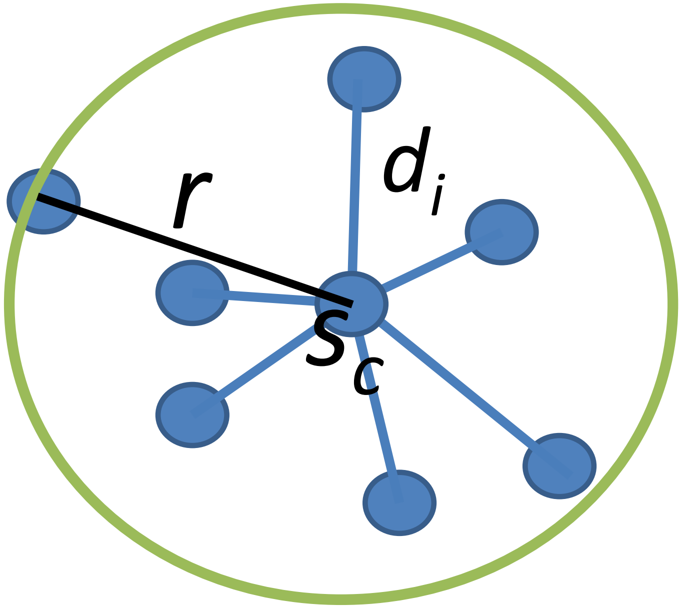

Center location and its *k-1* nearest neighbors

$$\log\left(\frac{p_i}{1-p_i}\right)=\Delta_i$$

The center location is e^h times more likely to be included in the optimal subset than the *k-1* nearest neighbor.

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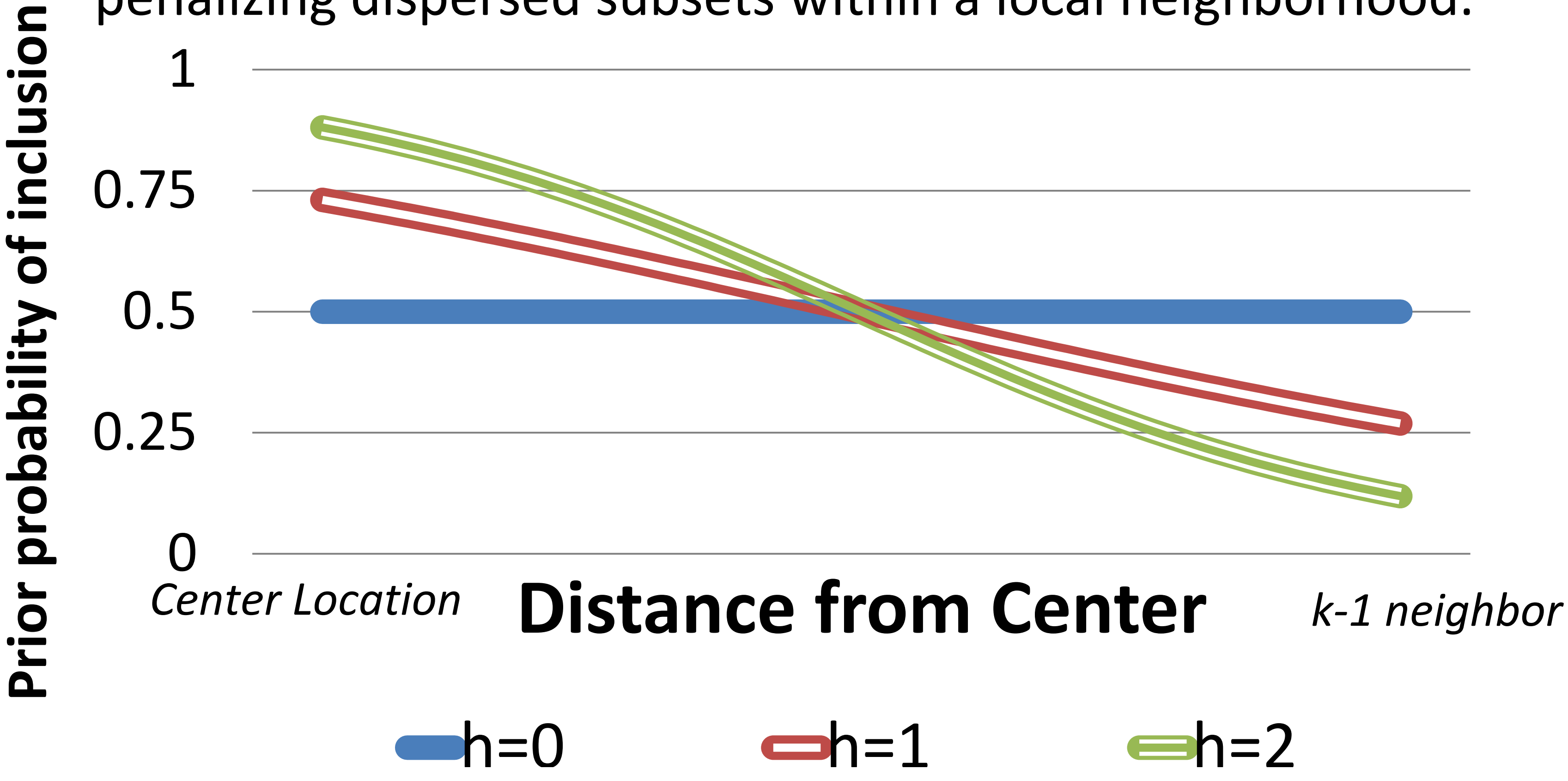


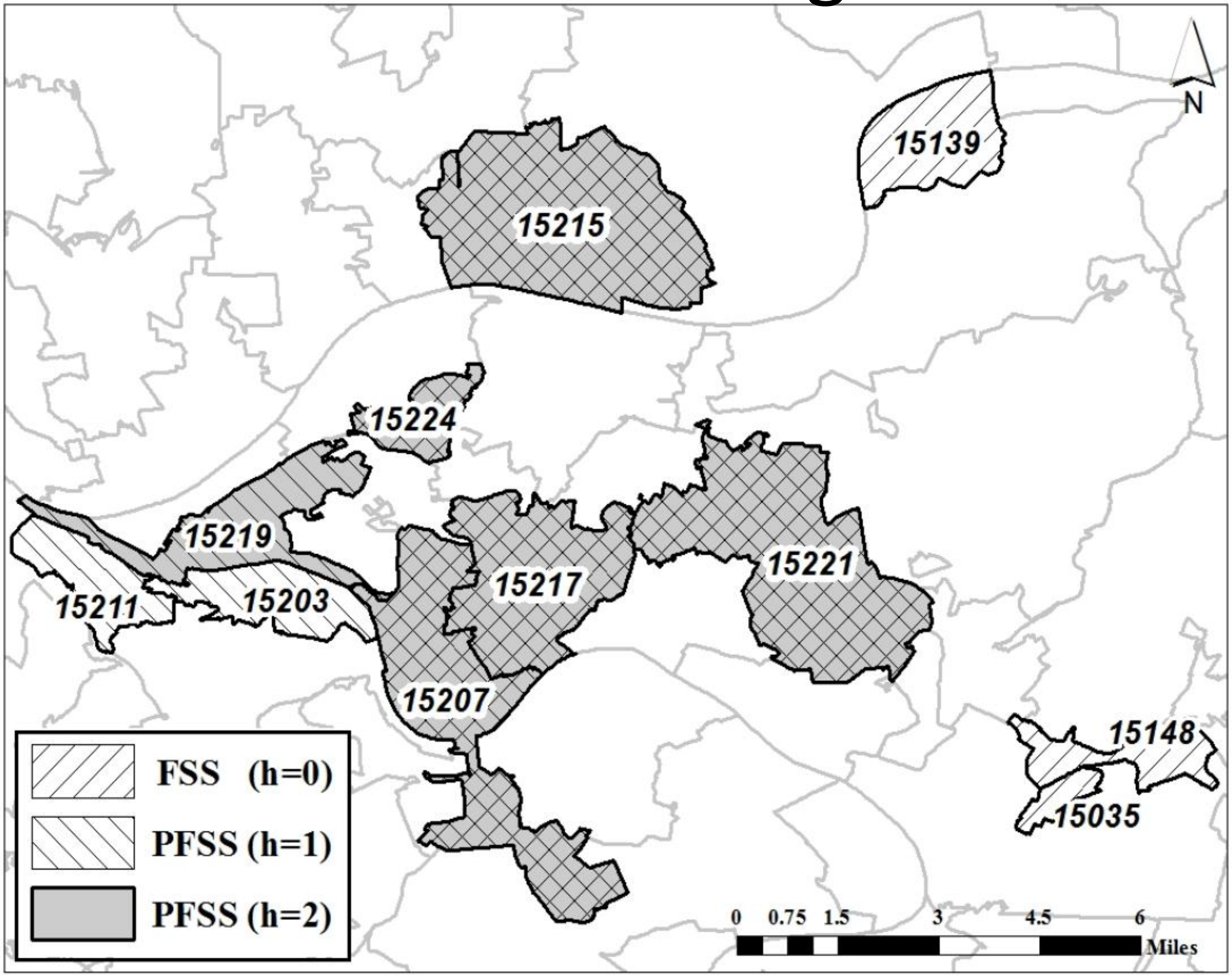
Evaluation: Emergency Department Data

Two years of admissions from Allegheny County Emergency Departments

The patient's home zip code is used to tally the counts at each location

Centriods of 97 Zip Codes were used as locations

Demonstration on Background Data



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

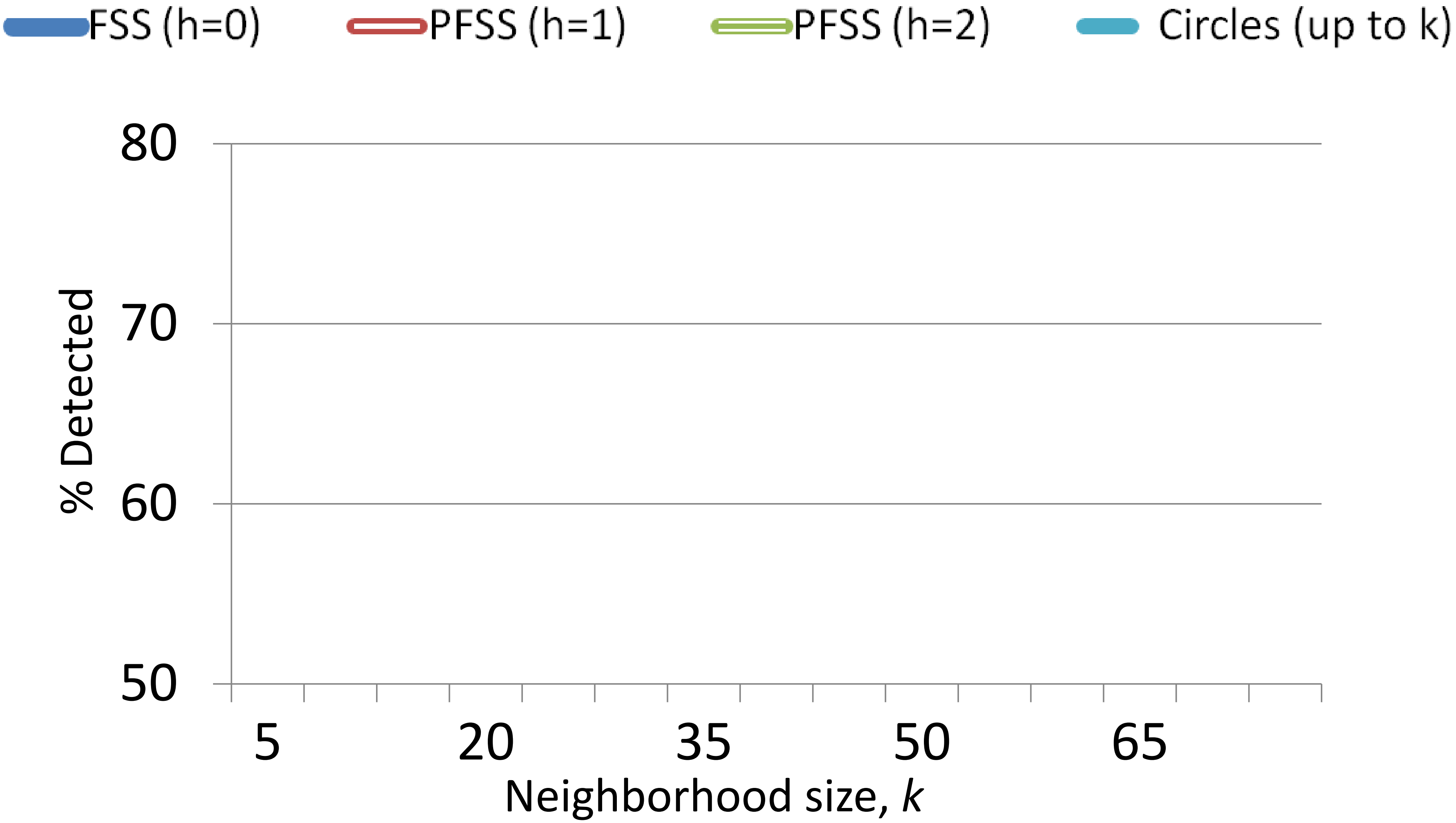
Infection

How many infected people in an area?

Demographic data

Increased ER visits with respiratory complaints

Comparison of Detection Power for BARD Simulated Attacks



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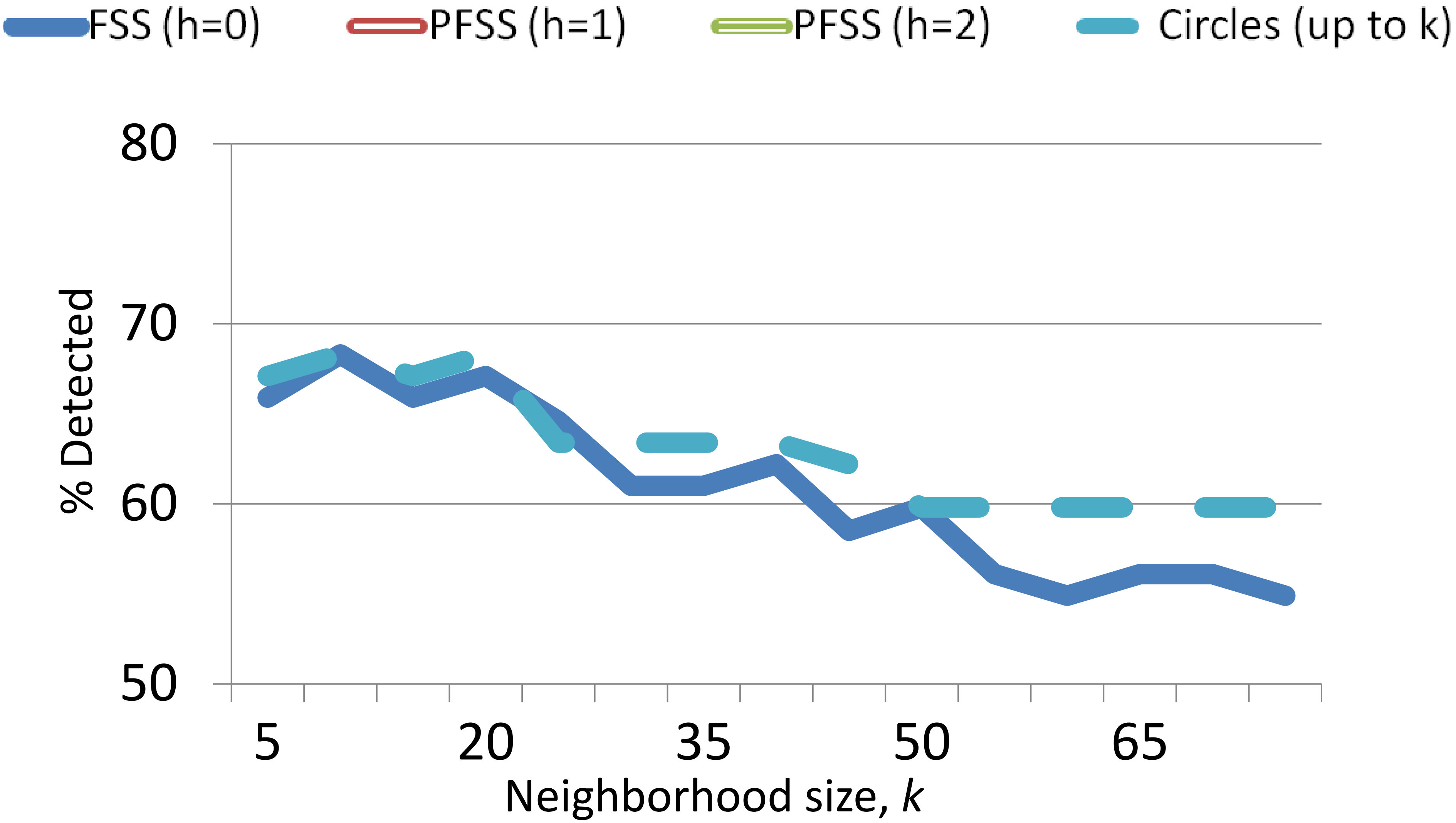

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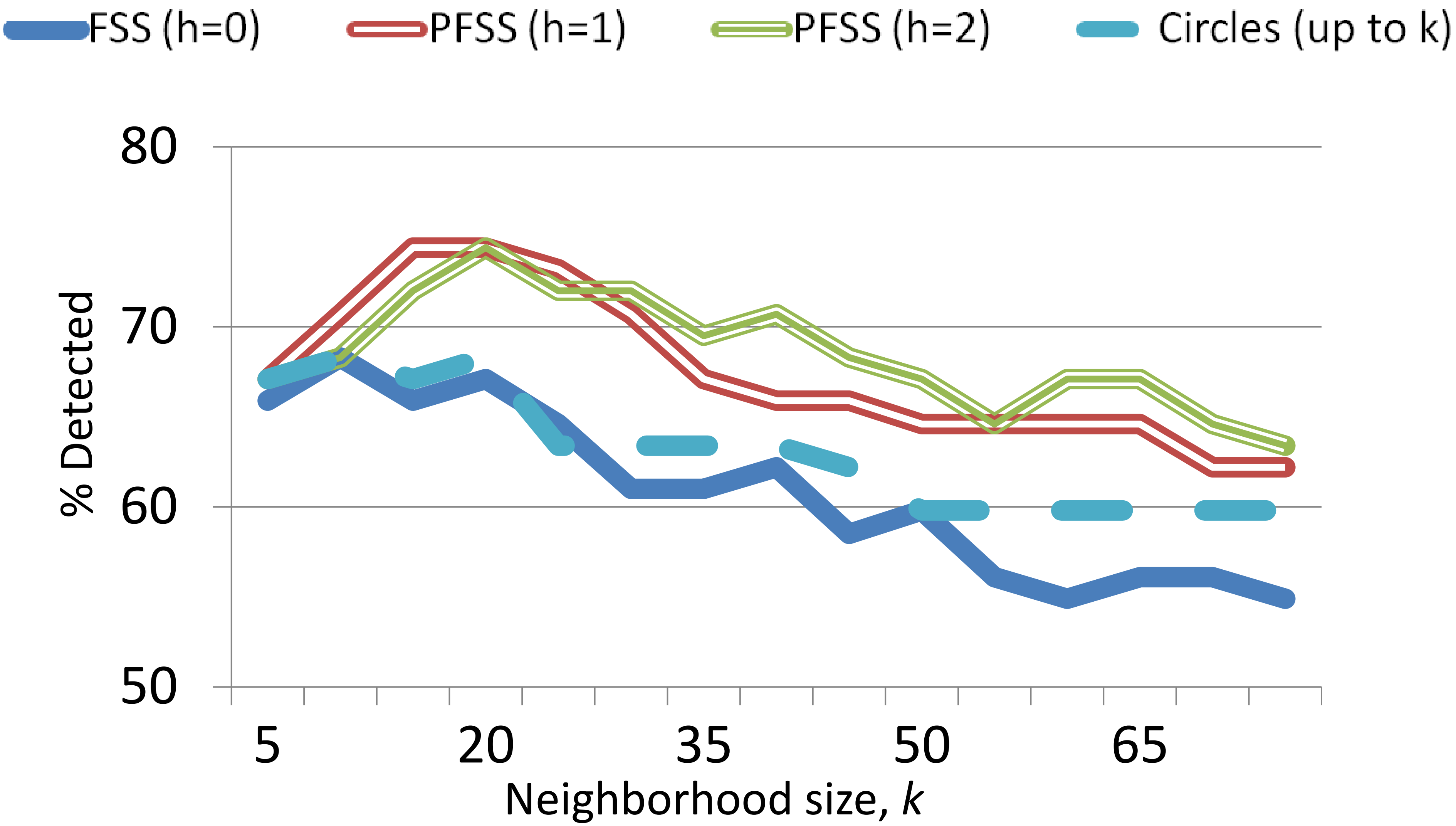
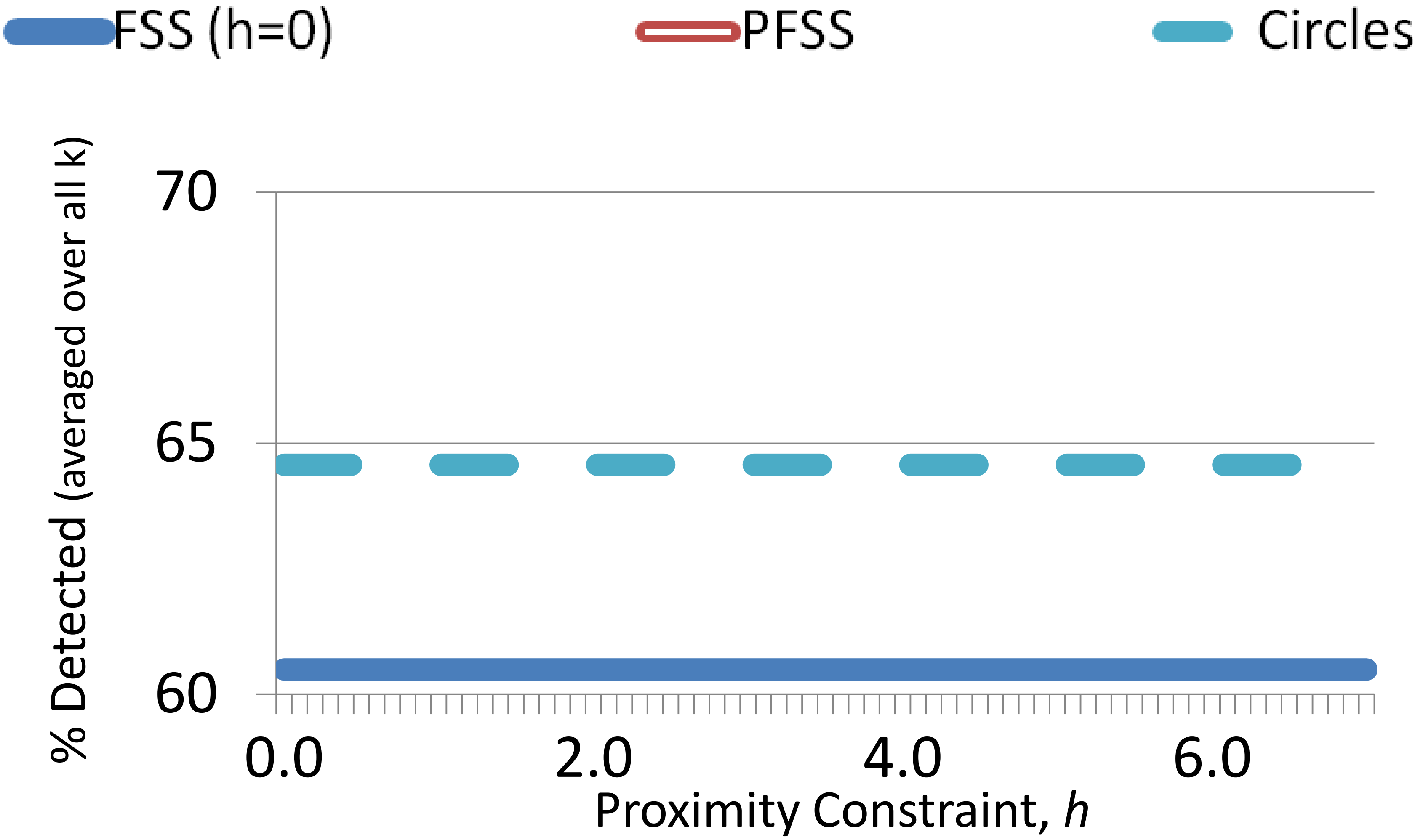


Average Detection Power for Varying Proximity Constraint Strength



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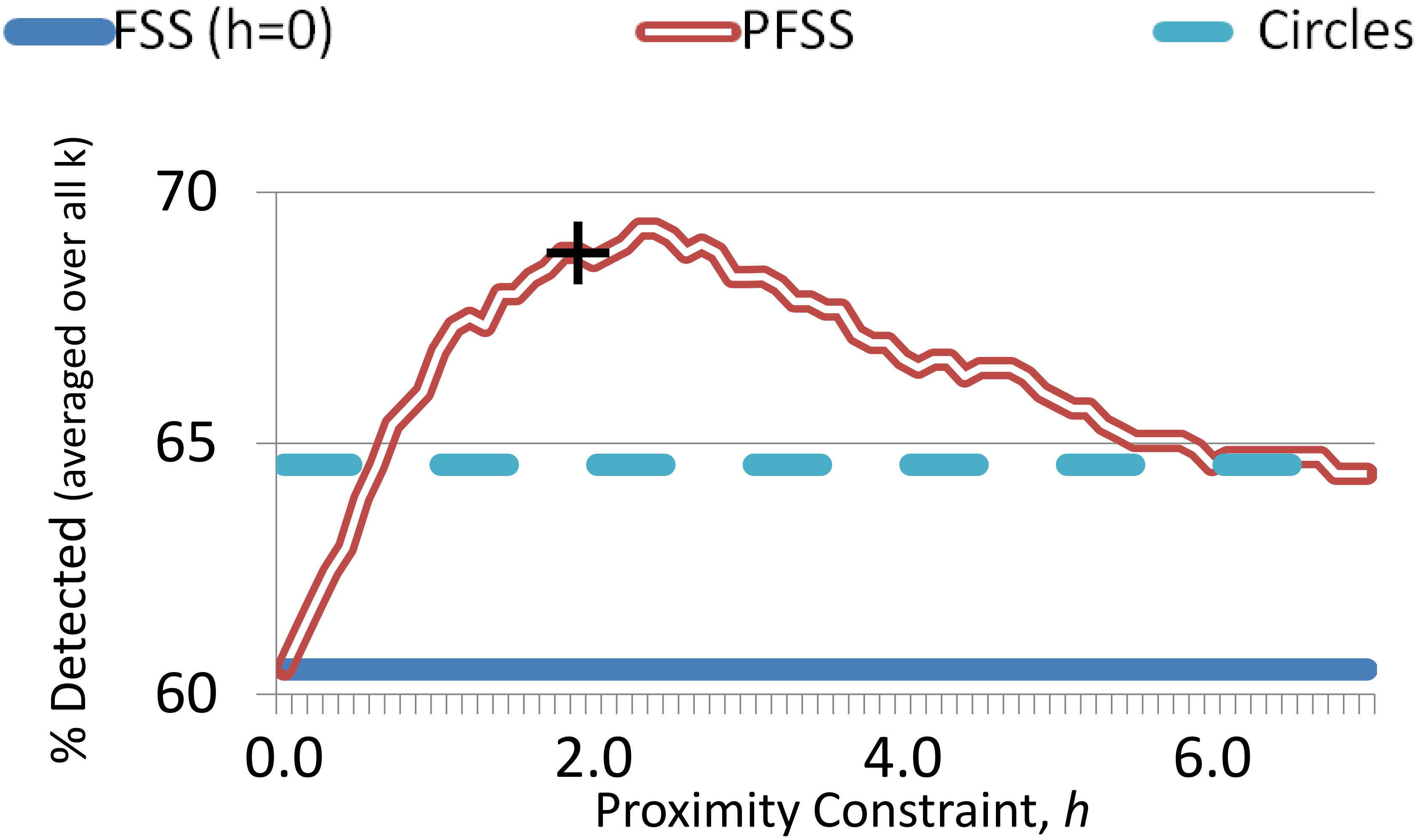

Conclusions

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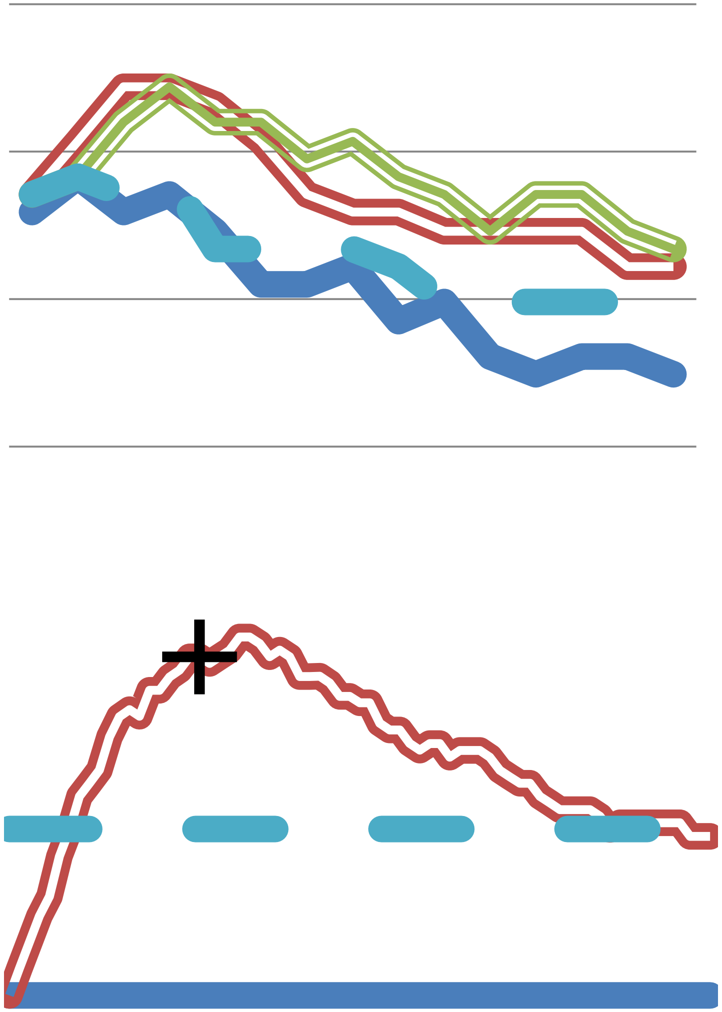

We applied PFSS with soft proximity constraints to the task of detecting simulated anthrax bio-attacks.

PFSS showed higher detection power and robustness to both neighborhood size, *k*, and proximity constraint, *h*.

Other types of soft constraints…

Temporal consistency to help detect and track patterns that change the affected subset over time. Penalizes abrupt changes that do not reflect a relevant pattern type.

Potential future work:
Soft connectivity constraints that reward inter-connectivity based on an underlying graph structure.

Thank you

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