# A Robust Expectation-Based Spatial Scan Statistic Daniel B. Neill and Maheshkumar R. Sabhnani

School of Computer Science, Carnegie Mellon University, Pittsburgh, PA 15213

# OBJECTIVE

This paper describes a new expectation-based scan statistic that is robust to outliers (individual anomalies at the store level that are not indicative of outbreaks). We apply this method to prospective monitoring of over-the-counter (OTC) drug sales data, and demonstrate that the robust statistic improves timeliness and specificity of outbreak detection.

## BACKGROUND

The expectation-based scan statistic [1-2] is a variant of the spatial and space-time scan statistics [3-4] that enables timely and accurate detection of disease outbreaks by accounting for spatial and temporal variation in baseline disease rates. The expectation-based method first infers the expected count for each spatial location by time series analysis, and then finds spatial regions with counts that are significantly higher than expected. Our SSS system [5] is currently using this method for daily, nationwide monitoring of OTC sales data from the National Retail Data Monitor [6].

Our experience with prospective surveillance of OTC sales has revealed that *outliers* (individual stores with counts that are much higher than expected) are a common source of false positives. These outliers are not due to disease outbreaks, but instead reflect a variety of unmodeled events in the OTC data, including data irregularities, bulk purchases, inventory movements, and promotional sales. Because we expect an outbreak to increase counts in multiple stores in the affected area, while only a small proportion of stores are outliers, we can accurately distinguish between these potential causes of an increase in counts.

#### METHODS

Our robust scan statistic model assumes that all counts  $c_i$  are Poisson distributed with mean equal to the product of the (known) expectation  $b_i$  and an (un-known) relative risk  $q_i$ . The robust statistic compares the null hypothesis  $H_0$  of no clusters to the set of alternative hypotheses  $H_1(S)$ , each representing a cluster in some region S, using a likelihood ratio statistic. Under  $H_0$ , each  $q_i$  is equal to 1 with probability 1- $\epsilon$ , and equal to some outlier value  $o_i$  with probability  $\epsilon$ . Under  $H_1(S)$ , each  $q_i$  is equal to q (inside S) or 1 (outside S) with probability 1- $\epsilon$ , and equal to some outlier value  $o_i$  with probability  $\epsilon$ .

The probability of outliers  $\varepsilon$  must be provided in advance; for  $\varepsilon = 0$ , this statistic is identical to the original expectation-based statistic. Maximum likelihood estimation is used to determine the values of q, the

values of each o<sub>i</sub>, and whether each count is an outlier under the null and alternative hypotheses. Randomization testing is performed by generating each count according to whether or not it is an outlier under the null. More details of this approach are given in [7].

# RESULTS

We compared the robust scan statistic (with a range of  $\varepsilon$  values from 10<sup>-10</sup> to .25) to the standard expectation-based scan statistic for semi-synthetic data: simulated respiratory outbreaks injected into real store-level OTC sales data for western Pennsylvania. The robust statistic reduced the proportion of false positives in the baseline data from 66% to 9%, with higher  $\varepsilon$  corresponding to fewer false positives. For a fixed false positive rate of 1/month, detection power was maximized for an intermediate value of  $\varepsilon = .05$ , detecting 95.4% of outbreaks in an average of 5.1 days. The non-robust statistic ( $\varepsilon = 0$ ) detected only 62.4% of outbreaks in an average of 5.7 days.

## CONCLUSIONS

The robust scan statistic is a useful method for reducing the number of false positives due to outliers, thus increasing our power to detect true outbreaks. We have also developed expectation-based statistics that are robust to small fluctuations in rate and to distributional assumptions respectively; these statistics can also be used to improve detection power in practice.

#### References

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Further Information: Daniel B. Neill, <u>neill@cs.cmu.edu</u> www.cs.cmu.edu/~neill and www.autonlab.org