

A Generalization of the Standard AMOC Curve

Yanna Shen, Weng-Keen Wong, Gregory F. Cooper
RODS Laboratory, Center of Biomedical Informatics
University of Pittsburgh, Pittsburgh, Pennsylvania

OBJECTIVE

We introduce a new measure for evaluating alerting algorithms, which is a generalization of the standard AMOC curve [1]. For a given rate of false positive alerts, the new measure estimates the time between when an alert is raised and when clinicians are expected to detect the outbreak on their own. We call this measure the *Expected Warning Time* (EWT).

BACKGROUND

The Activity Monitoring Operating Characteristic (AMOC) curve is a useful and popular method for assessing the performance of algorithms that detect outbreaks of disease [1]. As it is typically applied in biosurveillance, the AMOC curve plots the expected time to detection (since the outbreak began) as a function of the false alert rate. An ideal algorithm has zero false alerts and a detection time of zero. An alternative, conceptually equivalent version of the AMOC curve plots ($T - \text{detection_time}$) as a function of the false alert rate, where T is a maximum meaningful detection time. We focus on this version.

METHODS

We now introduce a simple model of clinician outbreak detection. Although simple, we believe this model can serve as a useful first-order approximation for estimating the expected time that clinicians (or more generally, diagnosticians of any kind) will take to detect a particular type of outbreak of some disease D (e.g., an outbreak due to outdoor, airborne release of anthrax spores).

The model assumes that people with D are diagnosed independently of each other. Let p denote the probability that a person with D is diagnosed as having D upon presentation with that disease. Let $\text{time}(i)$ be a function that maps patient case i to the time at which that patient presented with D to clinicians. Assume that patient cases with D are consecutively numbered from 1 to M , where case 1 denotes the first patient and M denotes the last patient to present to clinicians with D during the current outbreak. For a given alerting threshold u , there will be a false alerting rate and a time t at which the alerting score first exceeds u during an outbreak (e.g., using a test set of simulated cases). Many such thresholds are considered.

Under the above assumptions, the following equation expresses the expected warning time (EWT):

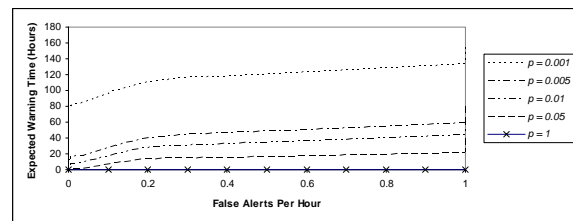
$$EWT(t) = \max(0, \text{time}(M) - t)(1 - p)^M + \sum_{i=1}^M \max(0, \text{time}(i) - t)p(1 - p)^{i-1}$$

The first term is the warning time if clinicians never detect the outbreak on their own, multiplied by the probability of that occurring. The second term (the sum) considers that clinicians first diagnose the outbreak on the i^{th} case; each possible value of i is considered.

For various values of p , we derived the EWT for the PANDA detection algorithm when it was applied to simulated cases of inhalational anthrax [2].

RESULTS

When $p = 0$ (not shown) the EWT curve is an AMOC curve. The figure below shows the results of applying PANDA to the simulated dataset when $p > 0$. As clinician detection proficiency (p) increases, EWT decreases, as expected. If $p \geq 0.05$ and the *false alert rate* ≤ 1 per month, then EWT is less than 34 minutes. Thus, according to this analysis, PANDA would be most helpful when clinicians have less than a 5% chance of diagnosing a case of inhalational anthrax on their own.



CONCLUSIONS

We introduced a generalization of the standard AMOC curve that models the possibility that clinicians will detect outbreaks on their own. These EWT curves provide a promising new approach for analyzing outbreak detection algorithms.

REFERENCES

- [1] Fawcett T, Provost F. Activity monitoring: Noticing interesting changes in behavior. In: *Proceedings of International Conference on Knowledge Discovery and Data Mining* (1999) 53-62.
- [2] Cooper GF, Dash DH, Levander, JD, Wong WK, Hogan WR, Wagner MM. Bayesian biosurveillance of disease outbreaks. In: *Proceedings of the Conference on Uncertainty in Artificial Intelligence* (2004) 94-104.