Using the Electronic Medical Record to Reduce both the Delay and the Workload Required to Detect an Influenza Epidemic

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OBJECTIVE

This work uses a mathematical model of a plausible influenza epidemic to begin to test the influence of single-case detection algorithms (CDA) on the performance of a syndromic surveillance system (SSS).

BACKGROUND

Measures aimed at controlling epidemics of infectious diseases critically benefit from early outbreak recognition [1]. Through a manual electronic medical record (EMR) review of 5,127 outpatient encounters at the Veterans Administration health system (VA), we previously developed CDAs aimed at uncovering individuals with influenza-like illness (ILI). In this work, we evaluate the impact of using CDAs of varying statistical performance on the time and workload required to find a community-wide influenza outbreak through a VA-based SSS. The CDAs utilize various logical arrangements of EMR data, including ICD-9 codes, structured clinical parameters, and/or an automated analysis of the free-text of the full clinical note. The 18 ILI CDAs used here are limited to the most successful representatives of ICD-9-only and EMR-based case detectors.

METHODS

An age-structured spatiotemporal influenza epidemic model was created in Matlab for 30 zip codes in and around Baltimore, MD. The model also determined the probability that an ILI case would present at the VA. We applied each of the 18 different CDAs to EMR data extracts, and generated 18 distinct real-world substrate datasets of daily ILI encounters at the VA. We then injected the same modeled, facticious epidemic into the background dataset derived from each ILI CDAs. Epidemics were detected by running the SatScan software [2] prospectively, starting on the day when the epidemic was injected and then each of the 50 subsequent days. “True positive” (TP) SatScan alerts ($p < 0.001$) were those uniquely found in the injected dataset of a particular CDA. False alerts were those also found in a corresponding uninjected dataset. For each CDA, epidemic injections and outbreak detection routines were repeated each week of the test year (8/02-8/03).

RESULTS

Time to the first SatScan alert decreased with increasing CDA sensitivity, but most of those initial detections were false alerts (Figure, left panel). Improvements in timeliness of true outbreak detection was significant, but modest, decreasing from 42 ± 1 days to 39 ± 1 days from the worse to the best-performing CDAs. The most desirable CDAs were those that coupled sensitivities above 75% with high specificity or positive predictive value. Compared to ICD-9-only CDAs, the best EMR-based CDAs could attain the 3-day drop in outbreak detection delay, and yet do so with a ~15-fold reduction in the false-alert rate (Figure, right panel).

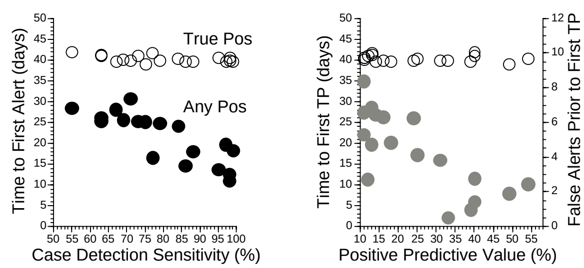

Figure – *Left panel.* Delay at detecting a community-wide influenza epidemic (y-axis) as a function of CDA sensitivity at detecting individual ILI cases (x-axis). Each circle corresponds to the mean value for 52 separate epidemics, each injected on a different week of the year. Delay to the first SatScan alert (black circles) decreased with CDA sensitivity, but delay to the first true positive alert (open circles) did not. *Right panel.* CDAs with increased positive predictive value (x-axis) maintained true outbreak detection timeliness (left y-axis, open circles) but were associated with large decreases in false alerts (right y-axis, grey circles).

CONCLUSIONS

Case detection methods that take advantage of information from the EMR can lower both the delay and the workload required to find an influenza epidemic.

REFERENCES

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