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Evaluation of Temporal Aberration Detection Methods in New York City Syndromic Data

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Objective

To critically evaluate temporal aberration detection methodologies using New York City (NYC) syndromic surveillance data.

Introduction

The NYC syndromic surveillance system has been monitoring syndromes from NYC emergency department (ED) visits for over a decade. We applied several aberration detection methodologies to a time series of ED visits in NYC spiked with synthetic outbreaks. This effort is part of a larger evaluation of the NYC syndromic system, funded by a grant from the Alfred P. Sloan Foundation.

Methods

We tested four aberration detection methodologies: a modified version of the C2 algorithm developed for the Early Aberration Reporting System (EARS) [1], a CUSUM (cumulative sum control chart) algorithm [2], the Holt-Winters exponential smoothing method [3], and an autoregressive integrated moving average (ARIMA) model [4]. We analyzed diarrhea, vomit, influenza-like illness (ILI), fever/flu, and respiratory ED syndrome visits that occurred daily in NYC from 2010-2011.

In order to set thresholds at which an alert is generated, we created synthetic datasets that theoretically contained no outbreaks using data distribution parameters (mean, variance, autocorrelation, day of week patterns, seasonality) derived from historic NYC ED visits. We then ran each method on the synthetic data to develop a series of fixed alert thresholds. To test a method's ability to detect different outbreak types, we added simulated outbreaks to a two-year period of citywide NYC syndromic data. Three outbreak magnitudes were created based on the mean μ and standard deviation σ of residuals that were obtained by applying a regression model to the syndromic time series: small ($M=[\mu+3\sigma]/4$), medium ($M=[\mu+3\sigma]/2$), and large ($M=[\mu+3\sigma]$) [5]. A total of 180 datasets, each containing one outbreak, were created for each of the five syndromes. Of the 900 total datasets, 20% contained a single day spike, 60% had a point source outbreak, and 20% had a propagated outbreak. To compare the performance of these methodologies, we estimated sensitivity, specificity, and timeliness of the signal. Receiver operator curves were generated based on sensitivities and specificities calculated at the various thresholds, and the area under the curves (AUC) were estimated.

Results

The Holt-Winters exponential smoothing method had the highest AUC (0.62) compared with the other three methodologies. Among all the methods, performance varied by outbreak type, as sudden one-day spikes in cases were the most commonly detected (Table).

Outbreak size was also a driving factor in detection ability, as the methods had difficulty detecting small and medium sized increases of all outbreak types. Sensitivity was increasingly poor among all methods as fixed alert rates decreased. Timeliness of the signal was similarly poor.

Conclusions

The Holt-Winters method was the best overall method for detecting outbreaks in our data. Overall, however, the temporal aberration detection methodologies we tested did not perform well for any outbreak type or size. Variability in method performance by outbreak type suggests multiple methods may be ideal for detecting different outbreak features.

Sensitivity of the four tested models running at a fixed alert rate of 0.01 (1 alarm/100 days)

	ARIMA			C2			CUSUM			Holt-Winters		
Size	Spike	PtS	Prop	Spike	PtS	Prop	Spike	PtS	Prop	Spike	PtS	Prop
Overall	8.3	1.7	0.7	10.5	3.4	1.3	6.7	9.6	6.6	9.4	1.0	0.3
Large	20.0	2.1	0.7	21.7	4.7	1.9	13.3	11.5	7.4	23.3	1.7	0.3
Medium	5.0	1.9	0.5	8.3	2.8	0.4	5.0	9.1	3.2	5.0	0.7	0.2
Small	0.0	0.8	0.9	1.7	2.1	1.6	1.7	8.1	9.0	0.0	0.6	0.4

Spike=One day outbreak, PtS=Point source outbreak, Prop=Propagated outbreak

Keywords

Aberration detection methodologies; Syndromic surveillance; Evaluation

References

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