Judging Changes in Key Criteria for Badger Bounce Back

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The proposed criteria

Symptoms:

1. *Downward trajectory of influenza-like illnesses (ILI) reported within a 14-day period.*
2. *Downward trajectory of COVID-like syndromic cases reported within a 14-day period.*
3. *Cases: Downward trajectory of positive tests as a percent of total tests within a 14-day period.*

Hospitals:

- *Criteria are currently under development in partnership with Wisconsin healthcare stakeholders.*

Discussion

1. The aim of the analysis is to enable a decision: have measures of Wisconsin population health changed enough to move from one stage to another in stepping down from Safer at Home?   The decision is an assessment that Wisconsin public health is in a 'new state' that will continue in the near future and justifies the change to the new stage.
2. The change to be detected is stated as 'downward trajectory within a 14-day period'. The 'downward trajectory' language has a strong basis in policy positions developed over the past few weeks, including alignment with White House Guidelines issued 16 April 2020. DHS proposes to use a linear regression applied to daily counts (or in the case of per cent positive cases, the daily per cents) and assess whether the upper bound of a 95% confidence interval is less than zero.   There may be no options other than some kind of estimate of 'downward trajectory' as the trigger.
    a. From the language of the Badger Bounce Back plan, any negative slope is good enough to move to phase 1 from Safer At Home. The slope just needs to pass the threshold test.
    b. The week of 26 April, AFI DSI group members had a technical discussion of simple linear regression versus regression using Poisson assumptions. At the state level, the counts are far from zero and more sophisticated assumptions did not yield much difference in estimates of slope from ordinary least squares approach.
3. As the ultimate trigger is a negative slope for the most recent 14 days for the three gating measures, other plots related to the three gating measures should complement the study. In addition to plotting a 14-day slope and 95% CI every day in a time series, keep an eye on the original data using control charts.   The control chart provides a robust method to detect shifts in performance over time and enable decisions. (see below). Control charts could be built to detect changes from baseline performance or to provide evidence that the current performance is x% lower "on average" than the preceding period. Control

charts can accommodate modest serial correlation and other issues that concern statisticians in linear regression.

Other Issues for follow-up.

1. Restricting to 14-day windows ignores history too much so any method should plot and use the relevant history.
2. Using state-wide measures may be critical to decision making but of course ignores important county to county variation. Some counties will have 'flat' measurements. An alternate criterion could be that majority of counties (or 75% or 80%?) show no increase in the core measures AND the state-wide measures show decrease.

Background on Control Charts

1. A standard method to assess change in system measurements uses control charts, outlined by Walter Shewhart for industrial applications 90+ years ago. Control charts have been used extensively in health care for the past 30 years to monitor clinical and administrative processes. Many Wisconsin health care leaders will have seen and used control charts in their own systems. See appendix for references of control charts applied to infection modeling.
2. Shewhart developed the control chart method to enable system managers to distinguish a system with signals of 'assignable' or 'special 'causes from a system that had no such signals. Systems with no evidence of special causes are "in a state of statistical control", which implies that in the absence of interventions by managers or exogenous events, short term predictions are feasible. Simple models of random variation serve as a starting point to describe a sequence of measurements with no evidence of special causes.
3. In the Wisconsin public health application, we seek to detect signals of special cause: either improvement in key measures to support decision to move to new stage in Badger Bounce Back OR signs that there are more cases/infections (in order to increase interventions).
4. Construction of a suitable control chart requires an initial baseline to establish a mean level of performance and estimation of variability. Then the analyst applies a small set of rules to examine the chart for signals of assignable or special variation.
    a. Shewhart's 'criterion 1' looks for points beyond a certain distance from the mean, typically mean +/- 3 * estimate of standard deviation. (Justification from Chebyshev Inequality). Generally, the estimate of standard deviation is a robust estimate using the average of local variation throughout the series rather than a global standard deviation as global estimates may include variation from special causes, reducing the effectiveness of the chart.
    b. A second rule useful to detect shifts considers 8 consecutive values above or below the center line. (Statistical Quality Control Handbook (1956) Western Electric Company, p. 26)
    c. Serial correlation or clumping will tend to show up as signals of special cause. This is a feature, not a bug, it forces subject matter experts to interact and reflect

on the meaning of the data plotted in time order. Extreme serial correlation will show up in the plot of the running record and obviates the need for elaborate statistical summaries.

5. Percentages other than those derived from sampling that justify the binomial distribution are usefully charted using an 'individuals' chart. Short-term variation is derived from the absolute range of day to day values. You can plot both the absolute ranges and the raw data in a pair of control charts to reveal signals of special causes in either variability, mean level or both.
6. A control chart for relatively rare events relies on the Poisson distribution (so called c-chart). In this case, the center line is the average of the counts and the upper and lower control limits are given by the average counts +/- 3*sqrt(average counts). As you can see from the limit formula, this chart asserts the Poisson nature of variation and invites the data to contradict the assertion.
    a. There are other versions of charts that rely on the Poisson model, e.g. a chart that plots days between events (the limits will be based on the exponential distribution). This is particularly useful when most days yield 'zero' events. This chart can be easy to explain by relating to safety series 'This job site has gone 75 days without injury.'

- The Shewhart charts are a reasonable starting point for analysis of general system performance to complement a focus on 14 days slopes.
    - Cumulative sum (cusum) charts and exponentially weighted moving average (EWMA) charts have been developed to detect relatively small shifts in average level; interpretation and explanation are more involved than for standard Shewhart charts.
    - See Box, Luceño, Del Carmen Paniagua-Quiñones, *Statistical Control by Monitoring and Adjustment* (2009) Wiley for examples of methods that apply to systems that feature controllable interventions and structure that are modeled by integrated moving average (IMA) series.

Appendix: control chart references

From draft of paper being submitted this week to *International Journal for Quality in Health Care* (a discussion of Shewhart control chart ideas implemented in this Shiny app: https://iecodesign.shinyapps.io/Hybrid_Shewhart_chart_COVID/)

> The bulk of previous studies using Shewhart charts in an epidemiological context have focused on infection control and hospital epidemiology.[i,ii,iii,iv,v] More relevant to our approach is a relatively sparse literature based on use of control charts to enable timely detection of unusual patterns in public health data.[vi] A 1946 study tracked a poliomyelitis epidemic with *X*-bar charts, suggesting that "the industrial control chart may prove to be of general usefulness in many kinds of epidemiological work."[vii(p. 1510)] Shewhart *U*-charts have been used to track disease cases and hospital referrals as a dynamic warning system for health authorities, care providers, and the general public, and thus "reduced the possibility of precipitating adverse events by indicating appropriate reactions to normal variations in sampling." [viii(p.280)]

Researchers have used moving average, exponentially weighted moving average, and/or cumulative sum charts for signaling the start or end of outbreaks, [ix,x,xi] enabling rapid detection and "subsequent timely public health actions to decrease unnecessary morbidity and mortality." [xii(3309)] Woodall's 2006 review highlighted opportunities for public health surveillance and encouraged further investigation of public health applications with control charts.[xiii] Previous research has suggested that "of the many tools used by continuous quality improvement, perhaps the most important for the epidemiologist to understand is the control chart."[xiv(p102)]

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[i] Benneyan JC. Statistical quality control methods in infection control and hospital epidemiology, part I introduction and basic theory. *Infection Control & Hospital Epidemiology*. 1998 Mar;19(3):194-214.
[ii] Arantes A, Carvalho ED, Medeiros EA, Farhat CK, Mantese OC. Use of statistical process control charts in the epidemiological surveillance of nosocomial infections. *Revista de saude publica*. 2003;37:768-74.
[iii] Gomes IC, Mingoti SA, Oliveira CD. A novel experience in the use of control charts for the detection of nosocomial infection outbreaks. *Clinics*. 2011;66(10):1681-9.
[iv] Sellick JA. The use of statistical process control charts in hospital epidemiology. *Infection Control & Hospital Epidemiology*. 1993 Nov;14(11):649-56.
[v] Brewer JH, Gasser CS. The affinity between continuous quality improvement and epidemic surveillance. *Infection Control & Hospital Epidemiology*. 1993 Feb;14(2):95-8.
[vi] Qian YH, Su J, Shi P, He EQ, Shao J, Sun N, Zu RQ, Yu RB. Attempted early detection of influenza A (H1N1) pandemic with surveillance data of influenza-like illness and unexplained pneumonia. Influenza and other respiratory viruses. 2011 Nov;5(6):e479-86.
[vii] Rich WH, Terry MC. The industrial" control-chart" applied to the study of epidemics. *Public Health Reports*. 1946 Oct 18;61(42):1501-11.
[viii] Hanslik T, Boelle PY, Flahault A. The control chart: an epidemiological tool for public health monitoring. *Public Health*. 2001 Jul 1;115(4):277-81.
[ix] Steiner SH, Grant K, Coory M, Kelly HA. Detecting the start of an influenza outbreak using exponentially weighted moving average charts. *BMC medical informatics and decision making*. 2010 Dec;10(1):37.
[x] Williamson GD, Hudson WG. A monitoring system for detecting aberrations in public health surveillance reports. *Statistics in medicine*. 1999 Dec 15;18(23):3283-98.
[xi] Bjerkedal T, Bakketeig LS. Surveillance of congenital malformations and other conditions of the newborn. *International Journal of Epidemiology*. 1975 Mar 1;4(1):31-6.
[xii] Vanbrackle L, Williamson GD. A study of the average run length characteristics of the National Notifiable Diseases Surveillance System. *Statistics in Medicine*. 1999 Dec 15;18(23):3309-19.
[xiii] William H. Woodall, "The Use of Control Charts in Health-Care and Public-Health Surveillance", *Journal of Quality Technology*, Vol. 38, No. 2, April 2006
[xiv] Simmons BP, Kritchevsky SB. Epidemiologic approaches to quality assessment. *Infection Control & Hospital Epidemiology*. 1995 Feb;16(2):101-4