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# Reduction of Alert Fatigue with Decision Analysis using Boosting Dynamics and Bayesian Methods

Gobind Singh[??*†], Boaz Avitall[??] and Hui Lu[??]

[*]Correspondence: gsingh6@uic.edu
[??]Department of Bioengineering, University of Illinois at Chicago, 808 S. Wood St., Chicago, US
Full list of author information is available at the end of the article
[†]Equal contributor

**Abstract**

**Background:** The rate of Alert Fatigue is defined as the number of alerts ignored by clinical staff. Normally, alerts are generated, independent of context, by any number of devices or systems.

**Objective:** (1) To test our hypothesis that the dynamical weights of boosting associated with nearer to boundaries classification, relates to clinical points of interest, (2) to increase the number of alerts relating to care and management(3) to provide criteria for meaningful medical use relating to effect size, feature variability, and group differences.

**Methods:** Two data sets were obtained. Alert classification labels are defined using bayes credible intervals, association mapping, generative mixture, and expert priors using the roulette method. Prior distribution over the boosting weights dynamics, alert classification, is determined using kernel density estimator. Expert prior distribution for alert classification, are determined with a trained cardiologist using the roulette method. Boosting is calibrated over the two groups, ICU and at-home telehealth. Validation of prior estimates is determined through convergence of posteriors, between large ICU and small telehealth data-sets. The overlap between the joint posterior distriubtions of the hard vs easy points is what determines statistically significant difference. Power curve analysis of effect size is determined. Causal modeling of time of day, gender, and geography are also explored. A hierarchical model over top alert-type features is explored. A loss likelihood function for the prediction of care is defined as the sum over a probability distribution of the number of alerts, the distribution of time between alerst, using a weibull prior, and the predicted number of alerts not yet seen.

**Keywords:** boosting, empirical bayes methods, meaningful clinical use, alert fatigueboosting; bayesian methods; meaningful clinical use; alert fatigue

## Introduction

Medical alerts have been shown to provide positive benefit: such as reduced blood sugar variability [**?**], and improved prescribing safety [**?**]. Currently, the extent of preventable medical error is estimated at 40,000 fatalities per year [**?**]. The need for improved medical alerts has been recognized in a recent Joint Commission and FDA statement. The percentage of alerts currently being ignored, or alert fatigue, is estimated at 70-80% [**?**]. The purpose of this study is to link model complexity with visual information for a clinically meaningful alert. Recently, we were involved with a telehealth, at-home monitoring study, which recorded patient vital sign readings, twice daily, for an approximate several month interval. A publicly available

dataset is sampled as well for comparative analysis. The dynamics of Adaboost weights have been shown to distinguish 'easy' from 'hard' classification points[**?**]. Data mining techniques are applied to handle features common to clinical data: high-dimensionality, variously scaled measures, group differences, and time series issues. Three types of clinical alert are identified, static, sequential, and drifting. Further, global monitoring over the combined feature space is achieved. Finally, to address the issue of alert fatigue, results are graphically interpretable. Decision tree, forest plot, and sequence logo are presented.

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*Sub-sub-sub heading for section* Text for this sub-sub-sub-heading ... In this section we examine the growth rate of the mean of $Z_0$, $Z_1$ and $Z_2$. In addition, we examine a common modeling assumption and note the importance of considering the tails of the extinction time $T_x$ in studies of escape dynamics. We will first consider the expected resistant population at $vT_x$ for some $v > 0$, (and temporarily assume $\alpha = 0$)

$$E\big[Z_1(vT_x)\big] = E\bigg[\mu T_x \int_0^{v\wedge 1} Z_0(uT_x)\exp\big(\lambda_1 T_x(v-u)\big)\,du\bigg].$$

If we assume that sensitive cells follow a deterministic decay $Z_0(t) = xe^{\lambda_0 t}$ and approximate their extinction time as $T_x \approx -\frac{1}{\lambda_0}\log x$, then we can heuristically estimate the expected value as

$$\begin{aligned} E\big[Z_1(vT_x)\big] &= \frac{\mu}{r}\log x \int_0^{v\wedge 1} x^{1-u}x^{(\lambda_1/r)(v-u)}\,du \\ &= \frac{\mu}{r}x^{1-\lambda_1/\lambda_0 v}\log x \int_0^{v\wedge 1} x^{-u(1+\lambda_1/r)}\,du \\ &= \frac{\mu}{\lambda_1-\lambda_0}x^{1+\lambda_1/rv}\left(1-\exp\left[-(v\wedge 1)\left(1+\frac{\lambda_1}{r}\right)\log x\right]\right). \quad (1) \end{aligned}$$

Thus we observe that this expected value is finite for all $v > 0$ (also see [**?**, **?**, **?**, **?**, **?**]).

**Competing interests**
The authors declare that they have no competing interests.

**Author's contributions**
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**Tables**
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