Joint Hacking and Latent Hazard Rate Estimation

Ziqi Liu  
Department of Computer Science and Technology  
Xi'an Jiaotong University  
ziqilau@gmail.com

Alexander J. Smola  
Machine Learning Department  
Carnegie Mellon University  
alex@smola.org

Kyle Soska  
Department of Electrical and Computer Engineering  
Carnegie Mellon University  
ksoska@cmu.edu

Yu-Xiang Wang  
Machine Learning Department  
Carnegie Mellon University  
yuxiangw@cs.cmu.edu

Qinghua Zheng  
Department of Computer Science and Technology  
Xi'an Jiaotong University  
qhzheng@mail.xjtu.edu.cn

Abstract

In this paper we describe an algorithm for predicting the websites at risk in a long range hacking activity, while jointly inferring the provenance and evolution of vulnerabilities on websites over continuous time. Specifically, we use hazard regression with a time-varying additive hazard function parameterized in a generalized linear form. The activation coefficients on each feature are continuous-time functions constrained with total variation penalty inspired by hacking campaigns. We show that the optimal solution is a 0th order spline with a finite number of adaptively chosen knots, and can be solved efficiently. Experiments on real data show that our method significantly outperforms classic methods while providing meaningful interpretability.

1 Introduction

Websites get hacked, whenever they are subject to a vulnerability that is known to the attacker, whenever they can be discovered efficiently, and, whenever the attacker has efficient means of hacking at his disposal. This combination of knowledge, opportunity, and tools is quite crucial in shaping the way a group of sites receives unwanted attention by hackers. Unfortunately, as an observer we are not privy to either one of these three properties.

Exploits are first discovered by highly skilled hackers who will use them for their own purposes for an extended period of time, as long as there is an ample supply of hackable sites that can be discovered efficiently. Once the opportunity for such hacks diminishes due to exhausted supply, the appropriate vulnerabilities are often published. The available tools increase and they are added to the repertoire of popular rootkits, at the ready disposal of ‘script kiddies’ who will attempt to attack the remaining sites. The increased availability of tools often offsets the reduced opportunity to yield a secondary wave of infections.

In a nutshell, the above leads to the following statistical assumptions on how vulnerability of sites and the infectious behavior occurs. Firstly, sites are only practically vulnerable once a vulnerability is discovered. Second, as time passes, the propensity of an attack might increase or not, but changes in attack behavior are discrete rather than gradual.

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We propose a novel hazard regression model that provides a clear description of the probability a site getting hacked conditioned on its time-varying features, therefore allowing prediction tasks such as finding websites at risk, or inferential tasks such as attributing attacks to certain features as well as identifying change points of the activations of certain features to be conducted with statistical rigor.

Related work. The primary strategy for identifying web-based malware has been to detect an active infection based on features such as small iFrames [9]. This approach has been pursued by both academia (e.g. [1][8] and industry (e.g. [5][10][11]). Soska & Christin [15] propose a data driven (linear classification) approach to identify software packages that were being targeted by attackers to predict the security outcome of websites.

2 Hazard Regression

Hazard regression aims to estimate the chances of survival of a particular event with covariates $x$, as a function of time, such as to better understand the effects of $x$. Instead of directly modeling the cumulative survival distribution, people are interested in the instantaneous rate of dying of any $x$ at any given time $t$, i.e. hazard rate $\lambda(x, t)$. The density of dying at time $t$ is given by $p(t|x) = \lambda(x, t) p(\text{survival until } t|x)$. This leads to a differential equation for the survival probability

$$F(t|x) = \exp \left( - \int_0^t \lambda(x, \tau) d\tau \right).$$

In our case, death amounts to a site being infected and $\lambda(x, t)$ is the rate at which such an infection occurs. An extremely useful fact of hazard regression is that it is additive. That is, if there are two causes with rates $\lambda$ and $\gamma$ respectively, it allows us to add the rates and this leads to $F(t|x) = \exp \left( - \int_0^t \lambda(x, \tau) + \gamma(x, \tau) d\tau \right)$. The reason why this is desirable in our case follows from the fact that we may now model $\lambda$ as the sum of attacks in a generalized linear form.

Most hazard regression approaches are based on the Cox’s proportional hazard model $\lambda(t|x) = \lambda_0(t) \exp(w^T x)$ [3], including parametric models, and nonparametric models with baseline hazard rate $\lambda_0(t)$ unspecified [4]. The proportional assumption may not hold because of the time-varying effect of covariates [2]. As a result, time-dependent effect models that allow $w(t)$ as functions over time for each feature are proposed. Typically people developed time functions based on fractional polynomials [14], or spline functions [7]. Due to the huge parameter space, techniques like reduced rank methods [12] and structured penalized methods [16][17][13] are studied. However those works either search for global smoothing functions or need to pre-specify knots. Typically they work on tens of features. Our work inspired by hacking campaigns aims to identify discrete attack behaviors. We show the optimal solution is a 0th order spline with knots adaptively chosen over continuous time.

3 Attributing Hacks

3.1 Additive hazard function and variational maximum likelihood

The blacklist may not always immediately discover whether a site has been taken over. The probability that this happens in some time interval $[t_i, T_i]$ is given by $F(t_i, x_i) - F(T_i, x_i)$, named “interval censoring”. On another hand, the absence of evidence of an infection does not mean the evidence of absence. In other words, all we know is that the site survived until time $T$, named “right censoring”. The probability is thus given by $F(T, x_i)$. Time $T$ denotes the end of the observation. Given intervals $[t_i, T_i]$ of likely infection for site $i \in \{1, ..., n\}$, at time $T$ we have the following likelihood for the observed data:

$$\prod_{i \in \text{hacked}} [F(t_i, x_i) - F(T_i, x_i)] \prod_{i \in \text{hacked}} F(T, x_i).$$

It remains to specify the hazard function $\lambda(x, t)$. We do not wish to make strong parametric assumptions, but since $x \in \mathbb{R}^d$ is high-dimensional, estimating $\lambda(x, t)$ completely non-parametrically
We evaluate the out-of-sample predictive power measured by log-likelihood and conduct case studies where we abuse the notation to denote

$\text{Theorem 1}$

The data used for evaluation was sourced from the work of Soska et al. [15] and was compromised as a collection of interval censored sites from backlists and right censored sites randomly sampled from .com domains[1].

4.1 Real-World Data

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\[1\] A .com zone file is the list of all registered .com domains at the time.
All the sites were drawn from The Wayback Machine\footnote{The Wayback Machine is a service that archives parts of the web.} when archives were available at appropriate dates. A total of 49,347 blacklists were collected between 2011 to 2013, include a blacklist of predominately phishing\footnote{A phishing website is a website that impersonates another site such as a bank, typically to trick users and steal credentials.} and search redirection attacks \cite{8}. The .com zone files during the same period are random sampled, served as right censored sites with a total of 336,671.

We automatically extracted raw tags and attributes from webpages, that served as features (a total of 159,000 features). These tags and attributes could be like \texttt{<br>}, or \texttt{<meta> WordPress 2.9.2</meta>}. Our corpus of features corresponds to a very large set of distinct and diverse software packages or content management systems.

### 4.2 Real-World Numeric Results

![Convergence on training data](left) and test data (right) respectively.

The baseline method is the classic Cox Proportional model (Cox) \cite{3} which have been extensively used for hazard regression and survival analysis. It’s parametrized based on the features with constant coefficients over time. We use \(\ell_1\) to denote the model penalized with \(\|Dw^\top\|_1\).

An experimental comparison between our models and Cox on the aforementioned dataset are reported in Figure 1 (left and right). Apparently the Cox model underfit the data quite a bit. Our “monotone” model allows only monotone hazard rate underfit the data a little but still significantly outperforms Cox. It is well expected that “non-monotone” model without any constraint overfit the data severely. “\(\ell_1+\)non-monotone” model which is well regularized performs the best. This result clearly shows that the latent hazard rate recovered by our model is much better than the Cox’s model. To achieve such accuracy, our model uses only around 3 times parameter size compared with Cox model.

#### 4.2.1 Real-World Case Study

In this section, we manually inspect the model’s ability to automatically discover known security events. Figure 2 (left) demonstrates some of the differences between the monotone and non-monotone models by following the hazard assigned to features that correspond to Wordpress 3.5.1. In early 2013, our dataset recorded a few malicious instances of Wordpress 3.5.1 sites (among some benign ones). These initial samples appeared to be part of a small scale test or proof of concept by the adversary to demonstrate their ability to exploit the platform. Both models detect these security events and respond by assigning a non-zero hazard.

Following the small scale test was a lack of activity for a few weeks, during which the non-monotone model relaxes its hazard rate back down to zero, just before an attack campaign on a much larger scale is launched. This example illustrates once a vulnerability for a software package is known,
that package is always at risk, even if it is not actively being exploited. On the other hand, the non-monotone model captures the notion that adversaries tend to work in batches or attack campaigns. Previous work [15] has shown that it is economically efficient for adversaries to compromise similar sites in large batches, and after a few attack campaigns, most vulnerable websites tend to be ignored. This phenomena is shown in Figure 2 (left) where Wordpress 3.2.1 was attacked in late 2011 and then subsequently ignored with the exception of a few small attacks that were likely orthogonal to the underlying software and any observable content features.

It can be observed from Figure 2 (right) that a number of distinct Wordpress distributions experienced a change-point in the summer of 2011. This phenomena was present in several of the most popular versions of Wordpress in the dataset including versions 2.8.5, 2.9.2 and 3.2.1. This type of correlation between the hazard of features corresponding to different versions of a software package is expected. This correlation often occurs when adversaries exploit vulnerabilities which are present in multiple versions of a package, or plugins and third party add-ons that share compatibility across the different packages.

5 Conclusion

In this paper, we propose a novel survival analysis-based approach to model the latent process of websites getting hacked over time. The proposed model attempts to solve a variational total variation penalized optimization problem, and we show that the optimal function can be linearly represented by a set of step functions with the jump points known to as ahead of time. The results suggest that by correctly recovering the latent hazard rate, our model significantly outperforms the classic Cox model. Compared with known time-dependent hazard regression models, our models work on several orders of larger feature space. Most importantly, identifying the changes of each feature’s susceptibility over time can help people understand the latent hacking campaigns and leverage these insights to take appropriate actions.

In future, further works can be made to study the relations among potential correlated features by investigating the structures (e.g. low rank) of the coefficient matrix $w \in \mathbb{R}^{d \times T}$, or via deeper transformation. On the other hand, the same model (variants) can be used in many other settings to study consumer spending behaviors, marriage, animal habits and so on.

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