Forecasting software vulnerabilities

Probability Density Functions and Time Dependency Trees

C.E. Budde R. Paramitha F. Massacci

14th March 2024

ProSVED final event symposium

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Those annoying security updates

Those annoying security updates

© [loonylabs](https://loonylabs.files.wordpress.com/2021/01/time-management.jpeg?w=1024)

Is there a best time to update?

Q1 How does time affect the $Pr(\text{vuln.})$?

Q2 Which other factors affect $Pr(\text{vuln.})$?

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Q2 Which other factors affect $Pr(\text{vuln.})$?

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Q2 Which other factors affect $Pr(\text{vuln.})$? \triangleright measurable software metrics

• we study publication of CVEs;

- we study publication of CVEs;
- keep it high-level, no code analysis.

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- 2. Probability of *exploitation*:
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- 2. Probability of *exploitation*:
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	- \cdot ... but check [the work of the EPSS!](https://www.first.org/epss/model)

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 $9/35$

9/35

Q2 Pr(vuln.) as function of software metrics

$Q1$ Pr(vuln.) as function of time

Q2 Pr(vuln.) as function of software metrics

▶ ML & statistical analysis to correlate SE metrics to existent vulnerabilities

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- **Q1** Pr(vuln.) as function of time
	- \triangleright time-regression models on CVE publications (\approx FinTech)

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We propose white-box model(s) to fill these gaps

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▶ Count each CVE as one data point

 \cdot must choose one affected version!

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3.17.5 ℓ

4.1.79 ℓd

Jul'22

 ℓ 3.17.6

> 481 ℓd

 4.82 ℓd

 480 ℓ^{\prime}_q

 $\overline{\bigcup_{\text{Sep 22}}$

 $\ell_{\scriptscriptstyle\rm a}$ -22 ℓ 3.18.0 ℓ a 3.18.1

4.1.83 ℓd

 $4\,$ μ $\ell_{\scriptscriptstyle q}$

 $\begin{array}{c} \n\begin{array}{ccc}\n\text{Oer22} & \text{Nov22} \\
\hline\n\end{array} & \text{Doer22}\n\end{array}$

4.1.85 $\ell_{\scriptscriptstyle q}$

 ℓ 3.19.0

time

 486 $\ell^{}_{\!a}$

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 $\begin{array}{c} \n\sqrt{\frac{1}{2} \cdot \frac{1}{2} \cdot \frac$

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 486 $\ell^{}_{\!a}$

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Used in remote networks

CVEs with the Java keyword

(Own) Code size

15/35

Used in remote networks

Used in remote networks

My favourite correlation

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My favourite correlation

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My favourite correlation

Time from release date of g:a:v to publication date of CVE

On overfitting and rare events

My favourite correlation
On overfitting and rare events

My favourite correlation

On overfitting and rare events

My favourite correlation

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- \blacktriangleright Clusterisation mustn't be too thin
	- few divisions per metric-dimension
	- few metric-dimensions

Enough!

Gimme results

Here ya go

Here ya go

Q1 Pr(vuln.) as function of time **Q2** Pr(vuln.) as function of software metrics

 \triangleright ℓ_A was released on $t_A < t_0$, ℓ_B on $t_B < t_0$, $t_A \bowtie t_B$

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A: $Pr_{A,B}(t) = 1 - S F_A(t + \Delta t_A) CDF_B(t + \Delta t_B)$ where $\Delta t_x = |t_x - t_0|$ vuln. in ℓ_A before change vuln. in ℓ_B after change

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$$
\begin{matrix}\scriptstyle D(\ell_{a_1}): \atop \scriptstyle \ell' \atop \scriptstyle d_2 \\\scriptstyle \ell' \atop \scriptstyle d_1 \end{matrix}
$$

 $\{D(\ell_{a_i})\}_{i=1}^3$:

Dependency Trees in time

Time Dependency Tree

Dependency Trees in time

Time Dependency Tree

Dependency Trees in time

Time Dependency Tree

before the release of ℓ_{a}

• Minimal graph representation (no lib-version repetition)

- Minimal graph representation (no lib-version repetition)
- Canonical for library ℓ and time span T
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- Natural lifting of dependency trees to time

Theoretical

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Practical

• Time-indexing $D_t(\ell)$ yields the dep. tree at time $t \in T$

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Practical

- Time-indexing $D_t(\ell)$ yields the dep. tree at time $t \in T$
- Library-slicing $D_T(\ell)|_d$ yields *all instances* of dependency d during time T

Theoretical

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Practical

- Time-indexing $D_t(\ell)$ yields the dep. tree at time $t \in T$
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- Reachability analysis can spot single-points-of-failure

My personal project uses $\ell_{1,0}$

My personal project uses $\ell_{1,0}$

My personal project uses $\ell_{1,0}$

Should I downgrade to $\ell_{0.9}$ or upgrade to $\ell_{1.1}$?

Theoretical

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- Canonical for library ℓ and time span T
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Practical

- Time-indexing $D_t(\ell)$ yields the dep. tree at time $t \in T$
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- Reachability analysis can spot single-points-of-failure
- Can measure health/risk of development environment

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 $z_{2,0}$ ---- $z_{2,1}$

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	- Base information for probability forecasting

▶ Other metrics to clusterise libraries for PDF-fitting

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Questions?

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