

Predicting Security Attacks in FOSS

Why you want it and one way to do it

C.E. Budde R. Paramitha F. Massacci

Università di Trento (IT) & Vrije Universiteit (NL)

Vuln4Cast 2023 FIRST Technical Colloquium



Talk overview

1. Introduction
2. Background
3. Forecast model
4. Conclusions

Introduction

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Why You Should Update All Your Software

Updates may sometimes be painful, but they're necessary to keep your devices and data secure on a dangerous internet.

BY **CHRIS HOFFMAN** PUBLISHED AUG 28, 2020



Quick Links

[Security Updates 101](#)

[What's the Risk Really?](#)

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Quick Links

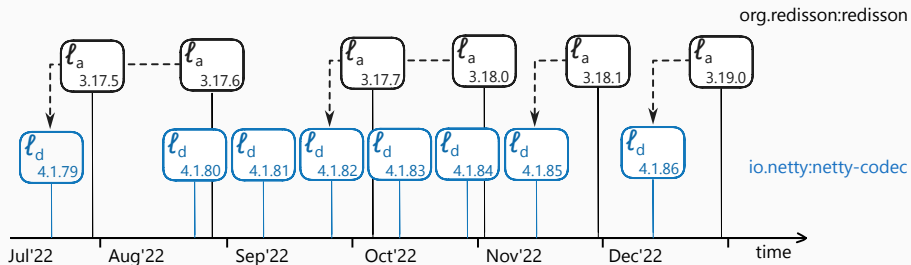
[Security Updates 101](#)

[What's the Risk Really?](#)

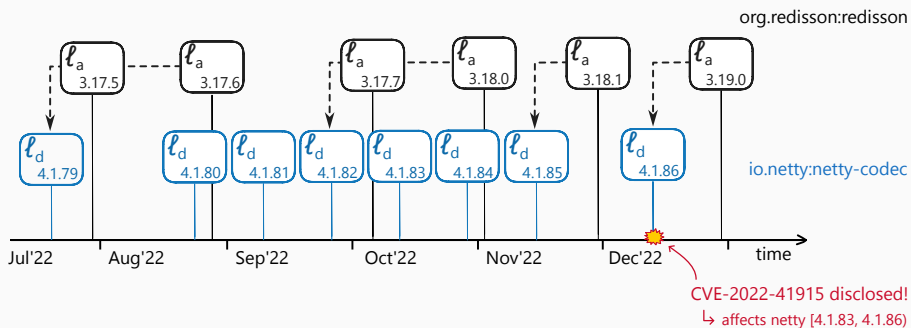


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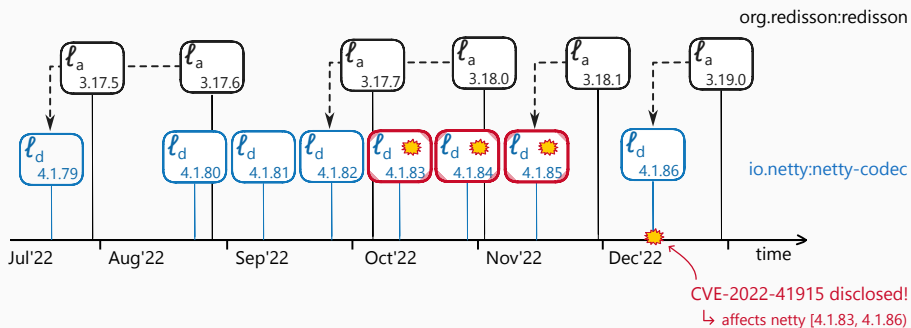
Some motivation (plz!)



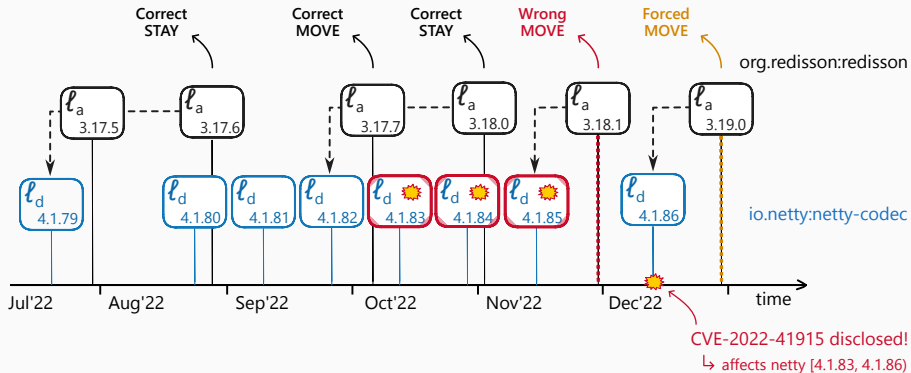
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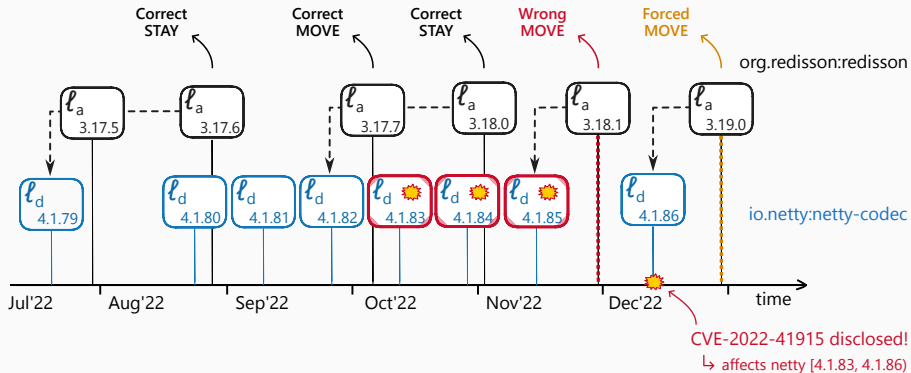


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Hindsight!

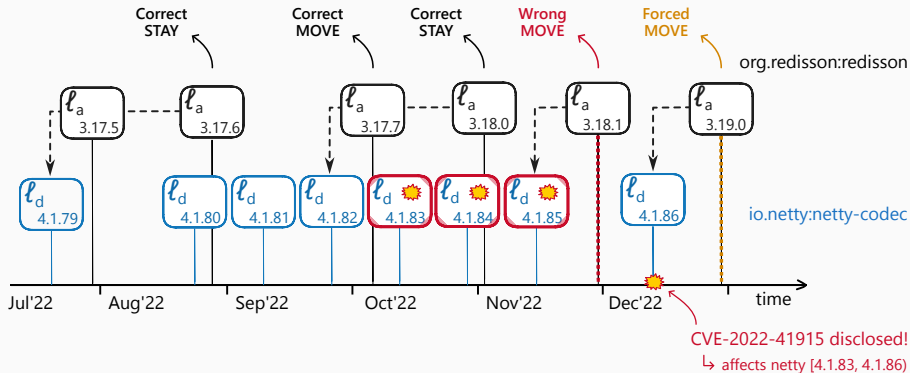


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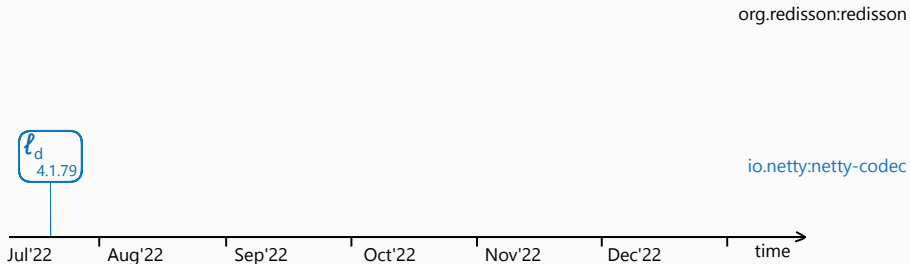


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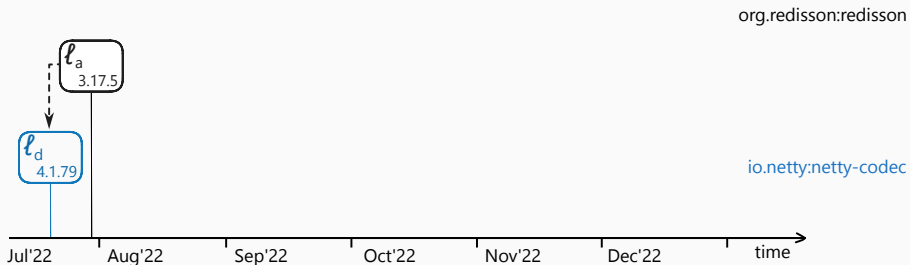
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Developer perspective in time:



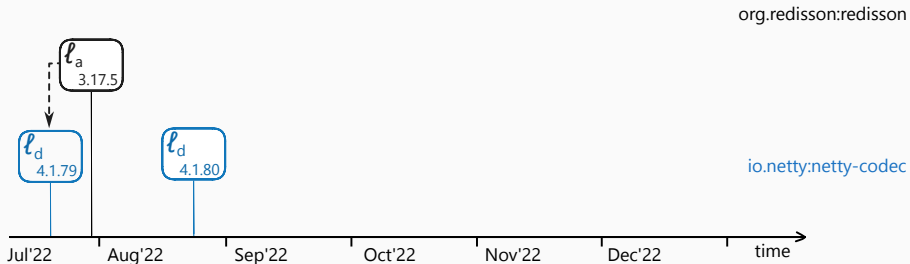
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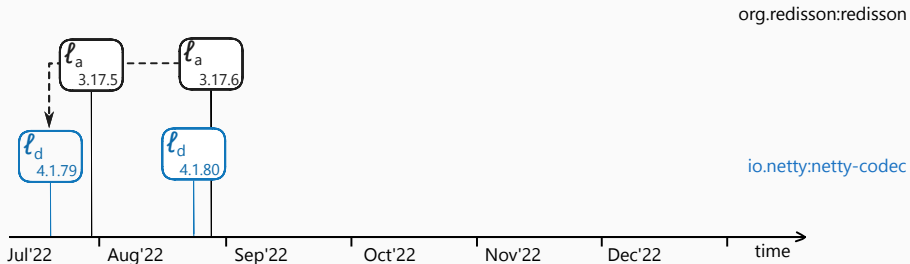
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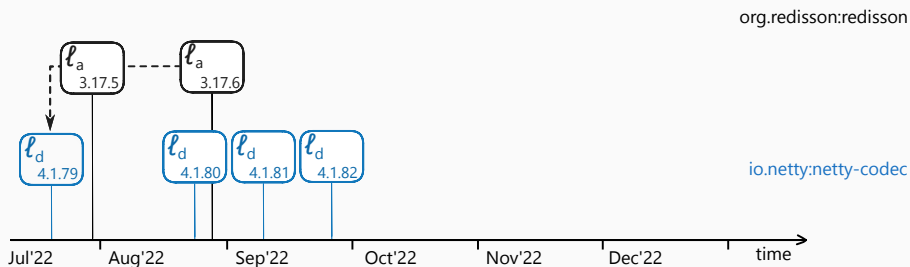
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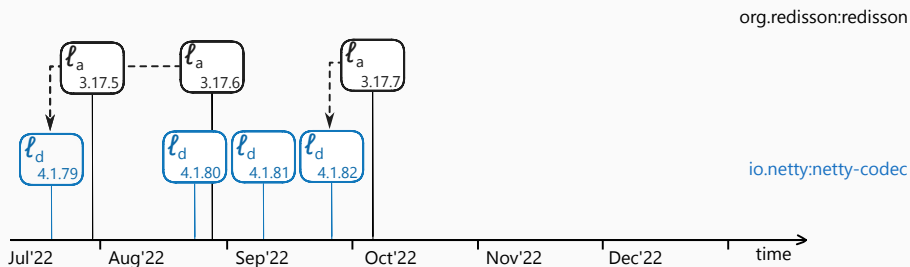
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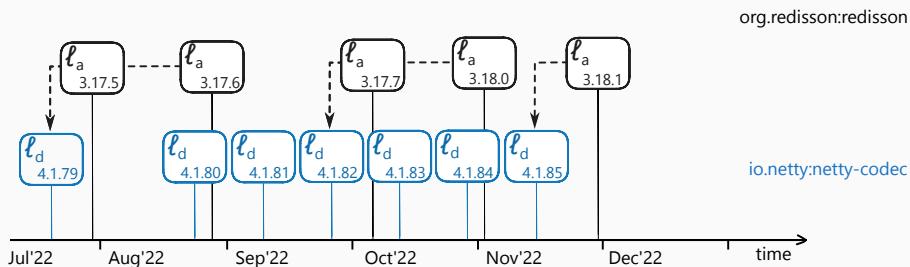
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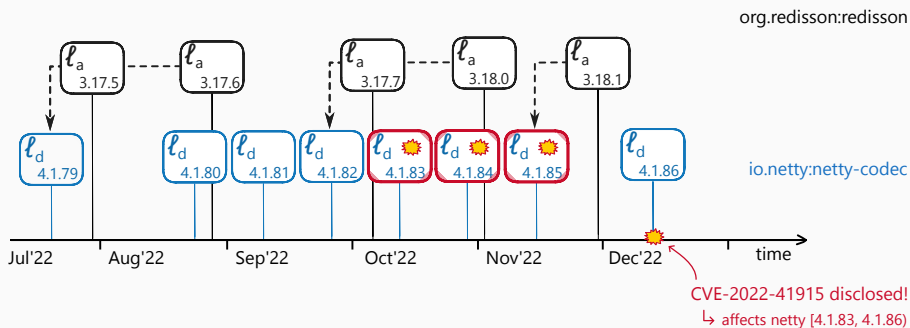
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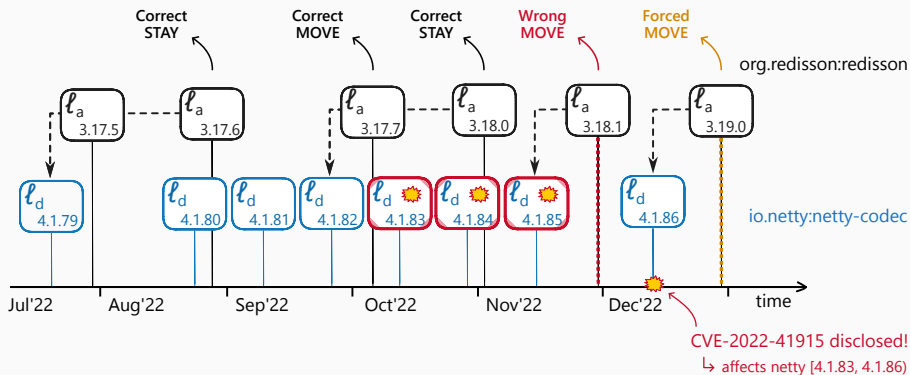
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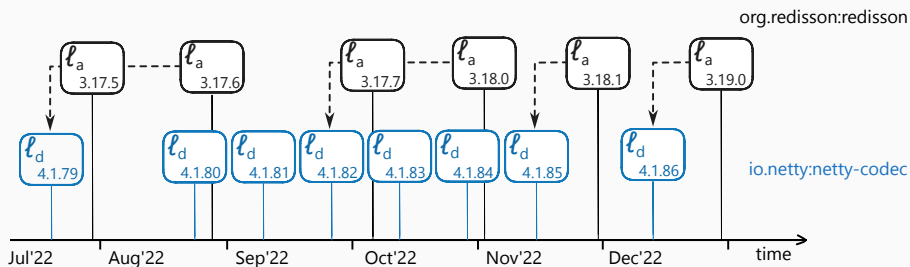
Some motivation (plz!)

Developer perspective in time:



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Developer perspective in time:



Is there a **best time** to update?

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

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

- Q1** How does **time** affect the $\Pr(\text{vuln.})$?
- ▷ best time to update?
- Q2** Which other factors affect $\Pr(\text{vuln.})$?

- Q1** How does **time** affect the $\text{Pr}(\text{vuln.})$?
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- ▷ measurable **software metrics**

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1. Unpublished/Undetected vulnerabilities:

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2. Probability of *exploitation*:

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- ... but check [the work of the EPSS!](#)

Background

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Work	Goal		Data				Method			Approach			Projects/Libs.		Purport
	Disc.	Pred.	CVEs	Code	VCS	Dep.	Corr.	Clas.	T-Set.	AH	SA	ML	Language	#	
[4]	✓			✓				✓				✓	C	3	Find vulnerabilities regardless of existent logs such as CVEs (although CWEs may be used). This includes formal methods and static/dynamic code analysis.
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[16]	✓			✓			✓	✓			✓	✓	Java	4	
[5]	✓			✓	✓			✓		✓			C/C++, PHP, Java, JS, SQL	10	
[11]	✓		✓		✓			✓		✓			C	3	
[13]	✓		✓		✓		✓			✓			C	1	Detect known vulnerabilities (and their correlation to developer activity metrics) from VCS only—e.g. commit churn, peer comments, etc.
[15]	✓		✓		✓		✓			✓	✓		C, ASM	3	
[14]	✓		✓		✓		✓			✓	✓		C, ASM	1	
[6]	✓		✓	✓				✓				✓	C/C++	3	
[8]	✓		✓	✓				✓				✓	Java	7	Detect known vulnerabilities (and their correlation to code metrics) from code only—e.g. number of classes, code cloning, cyclomatic complexity, etc.
[23]	✓		✓	✓			✓	✓				✓	Java	4	
[24]	✓		✓	✓			✓					✓	Java	3	
[25]	✓		✓	✓			✓					✓	Java	5	
[21]	✓		✓	✓				✓		✓			C	7	
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[9]	✓		✓	✓	✓			✓		✓			C/C++	8	
[3]	✓		✓	✓	✓		✓				✓		C/C++	5	
[7]	✓		✓	✓	✓		✓	✓			✓	✓	C/C+, Java	1	
[22]	✓		✓	✓	✓		✓				✓	✓	C/C++	2	
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[26]		✓	✓						✓		✓	✓	Agnostic	9	
[10]		✓	✓						✓		✓	✓	Agnostic	25	Time regression to predict vulnerabilities from NVD logs, but the models lack data from the security domain.
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[23]	✓	✓	✓	✓			✓	✓				✓	Java	4	Detect known vulnerabilities (and their correlation to code metrics) from code only—e.g. number of classes, code cloning, cyclomatic complexity, etc.
[24]	✓	✓	✓	✓			✓					✓	Java	3	
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[22]	✓	✓	✓	✓	✓		✓					✓	C/C++	2	
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Disregarded security data

Q2 $\Pr(\text{vuln.})$ as function of **software metrics**

Q1 $\Pr(\text{vuln.})$ as function of **time**

Q2 $\Pr(\text{vuln.})$ as function of **software metrics**

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

Q1 $\Pr(\text{vuln.})$ as function of **time**

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

- ▶ ML & statistical analysis to correlate SE metrics to existent vulnerabilities
- ▶ human-in-the-loop metrics, including VCS (#commits, seniority...)

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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- ▶ time-regression models on CVE publications (\approx FinTech)

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

Forecast model

1. Introduction
2. Background
3. Forecast model
4. Conclusions



Forecast model

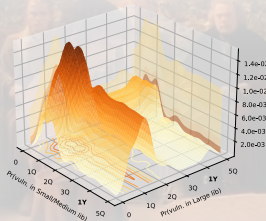
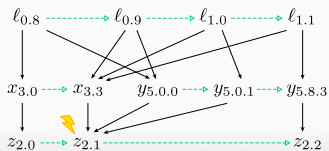
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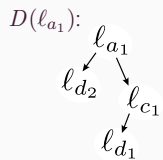
Time Dependency Trees



CVE root-lib PDFs

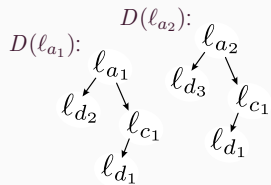
Time Dependency Trees

Dependency Trees in time



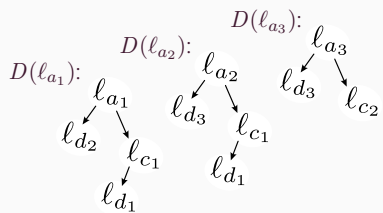
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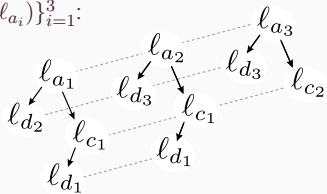
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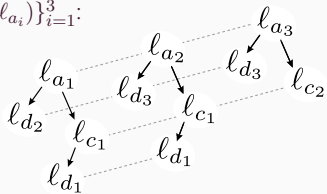
$\{D(l_{a_i})\}_{i=1}^3$:



Time Dependency Trees

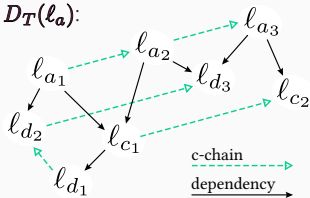
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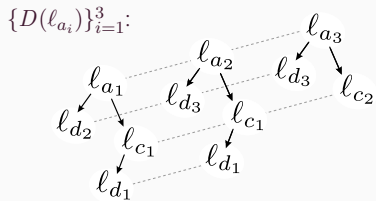
Time Dependency Tree

$D_T(l_a)$:

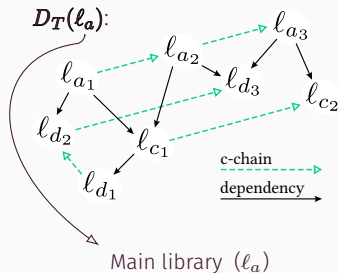


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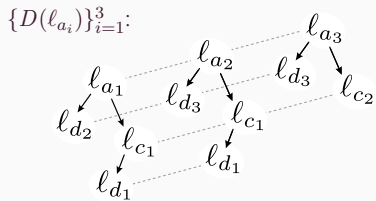


Time Dependency Tree

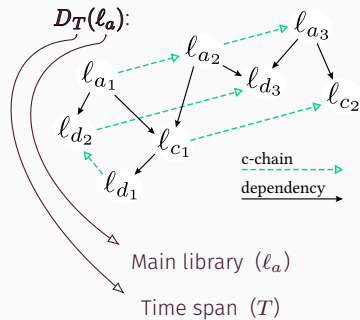


Time Dependency Trees

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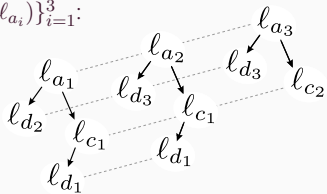
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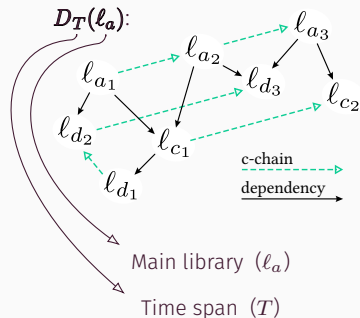
Time Dependency Trees

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Time Dependency Tree



$D_t(l_a) = D(l_{a_1})$
for any time point $t \in T$
after the release of l_{a_1} and
before the release of l_{a_2}

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Properties of TDT $D_T(\ell)$

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Theoretical

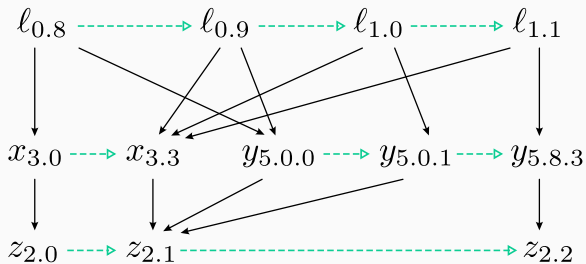
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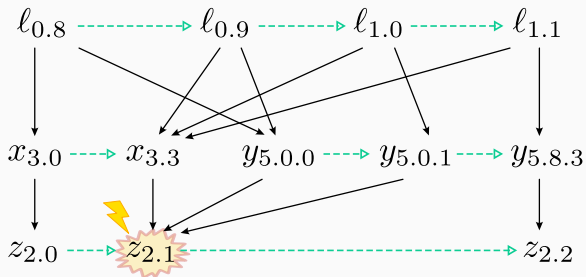
SPoF in time and dependencies

My personal project uses $l_{1.0}$



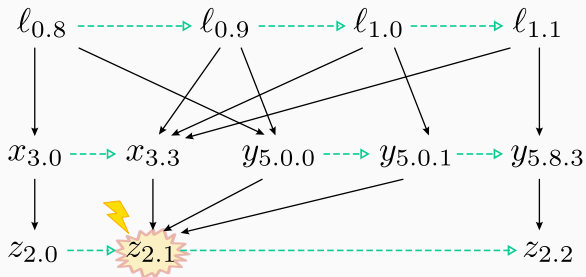
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SPoF in time and dependencies

My personal project uses $l_{1.0}$



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

Theoretical

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- Reachability analysis can spot single-points-of-failure
- Can measure health/risk of development environment

Forecast model

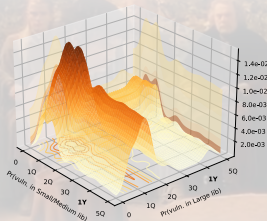
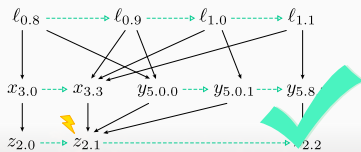
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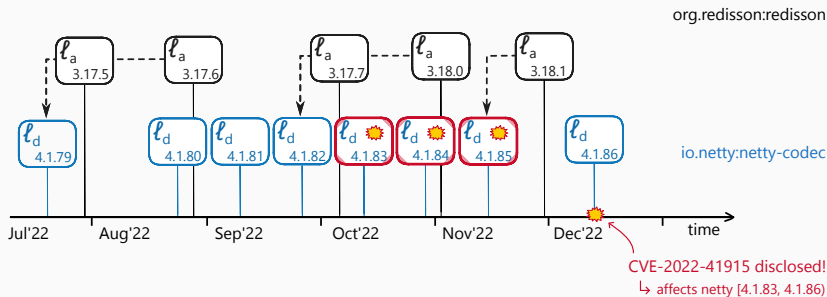
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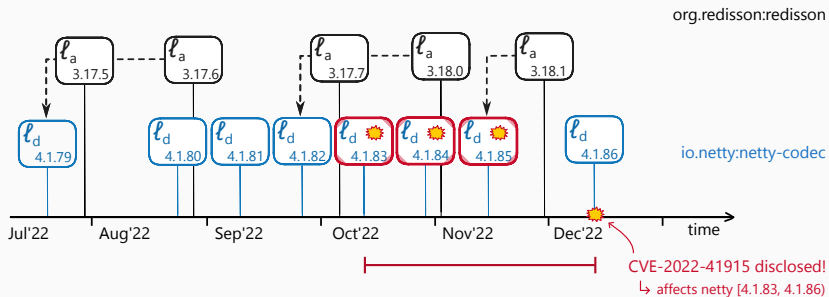


CVE root-lib PDFs

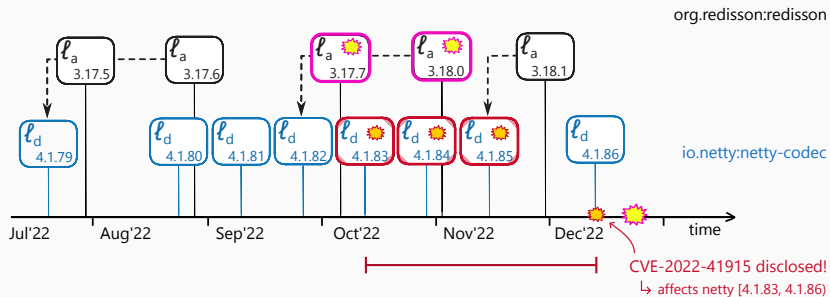
Publication of CVE since time of code release



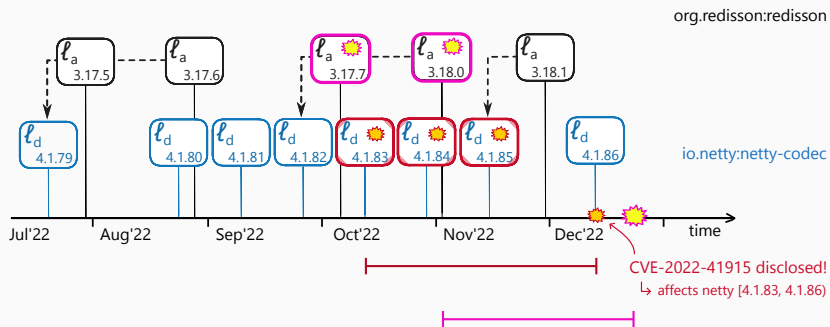
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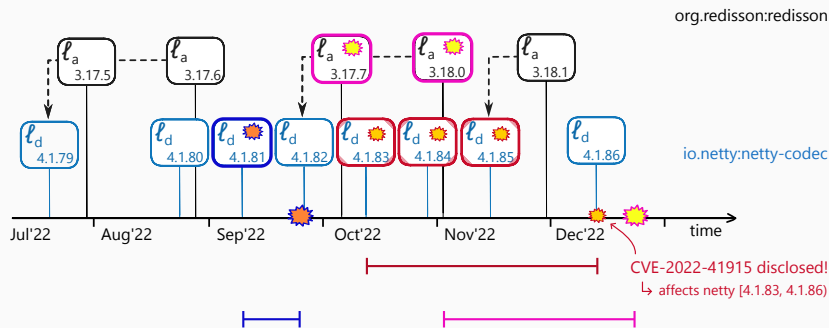
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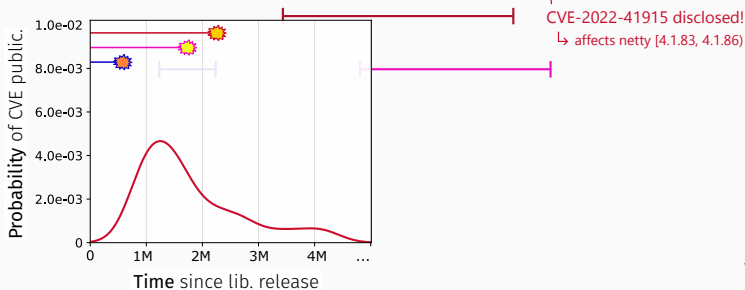
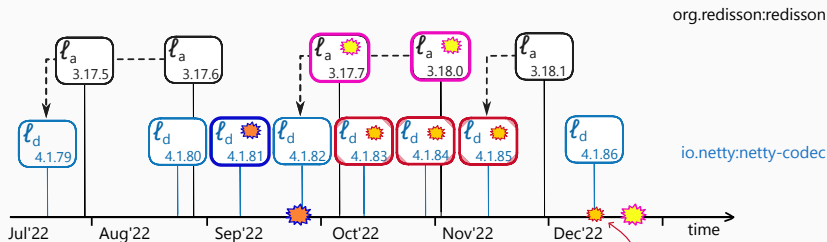
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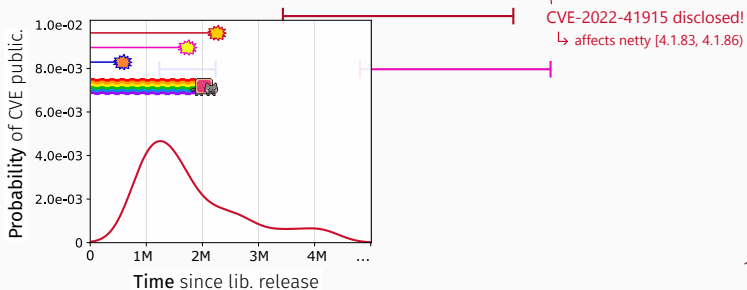
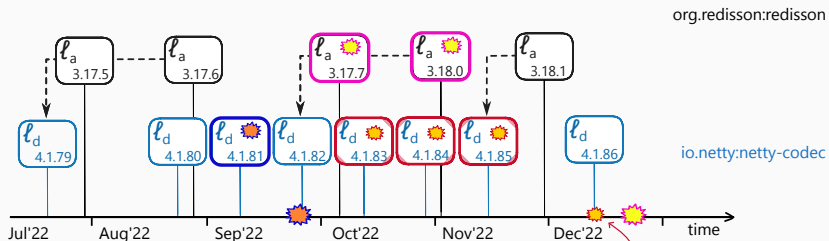
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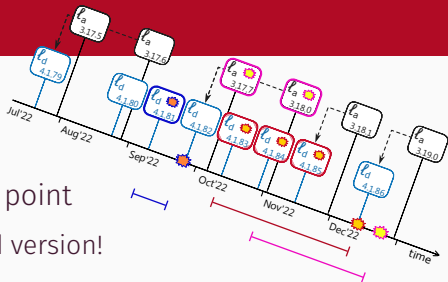


Rules of the game

- ▶ Count each CVE as one data point
 - must choose one affected version!

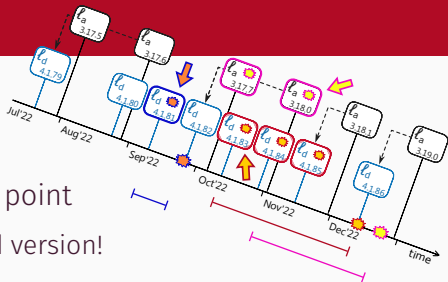
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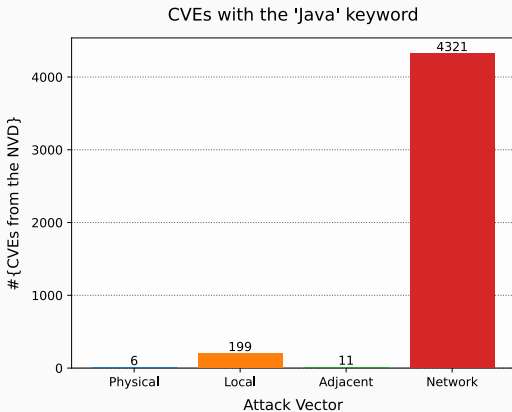
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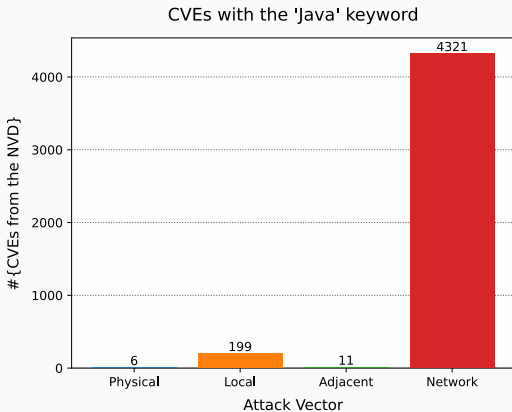
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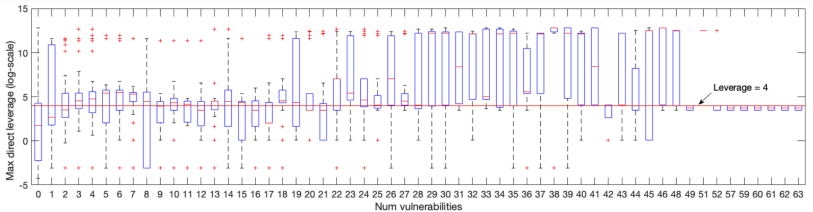
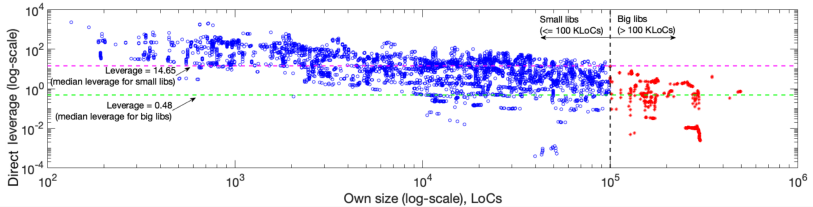
Security-relevant code metrics



Used in remote networks

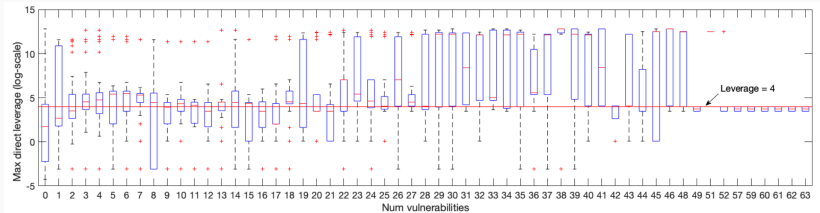
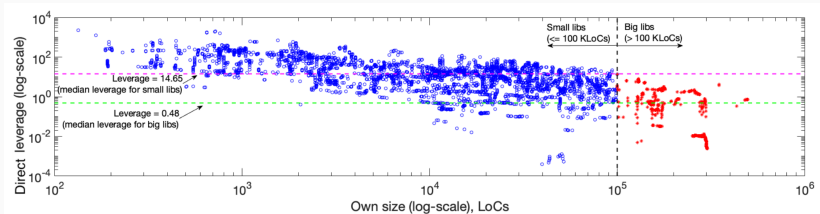


Security-relevant code metrics



Security-relevant code metrics

(Own) Code size



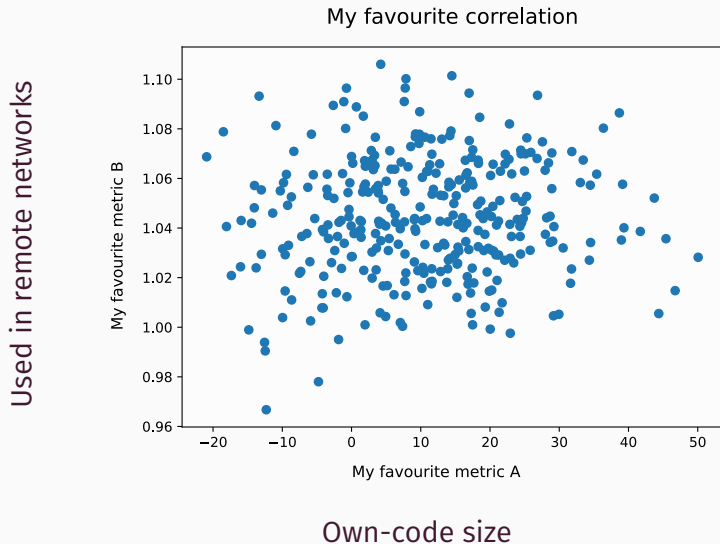
Security-relevant code metrics

Work	Goal		Data				Method			Approach			Projects/Libs.		Purport
	Disc.	Pred.	CVEs	Code	VCS	Dep.	Corr.	Clas.	T.Self.	AH	SA	ML	Language	#	
[4]	✓			✓				✓				✓	C	3	Find vulnerabilities regardless of existent logs such as CVEs (although CWEs may be used).
[2]	✓				✓		✓	✓				✓	PHP	3	
[16]	✓			✓			✓	✓			✓	✓	Java	4	
[5]	✓			✓	✓			✓		✓			C/C+, PHP, Java, JS, SQL	10	
[11]	✓		✓		✓			✓		✓			C	3	
[13]	✓		✓		✓		✓			✓			C	1	Detect known vulnerabilities (and their correlation to developer activity metrics) from VCS only—e.g. commit churn, peer comments, etc.
[15]	✓		✓		✓		✓		✓	✓			C, ASM	3	
[14]	✓		✓		✓		✓		✓	✓			C, ASM	1	
[6]	✓		✓	✓				✓				✓	C/C+	3	
[8]	✓		✓	✓				✓				✓	Java	7	Detect known vulnerabilities (and their correlation to code metrics) from code only—e.g. number of classes, code cloning, cyclomatic complexity, etc.
[23]	✓		✓	✓			✓	✓			✓	✓	Java	4	
[24]	✓		✓	✓			✓				✓		Java	3	
[25]	✓		✓	✓			✓				✓		Java	5	
[21]	✓		✓	✓				✓		✓			C	7	
[1]	✓		✓	✓	✓		✓	✓				✓	C/C+	>150k	Detect known vulnerabilities (and their corr. to code and developer activity metrics) from both code and VCS, but without considering the effect of dependencies in their propagation.
[9]	✓		✓	✓	✓			✓		✓			C/C+	8	
[3]	✓		✓	✓	✓		✓				✓		C/C+	5	
[7]	✓		✓	✓	✓		✓	✓			✓	✓	C/C+, Java	1	
[22]	✓		✓	✓	✓		✓	✓			✓	✓	C/C+	2	
[18]	✓		✓	✓	✓	✓		✓		✓			Java	500	Detect known vulnerabilities using code or VCS, via dependency-aware models that can find the offending code to help correcting it (own vs. third-party libraries).
[12]	✓		✓	✓		✓		✓				✓	Java	>300k	
[19]	✓		✓	✓	✓	✓	✓	✓			✓		Java, Ruby, Python	450	
[17]	✓		✓	✓		✓		✓		✓			Java	200	
[26]		✓	✓					✓		✓	✓		Agnostic	9	Time regression to predict vulnerabilities from NVD logs, but the models lack data from the security domain.
[10]		✓	✓					✓			✓	✓	Agnostic	25	
[20]		✓	✓					✓		✓			Agnostic	5	

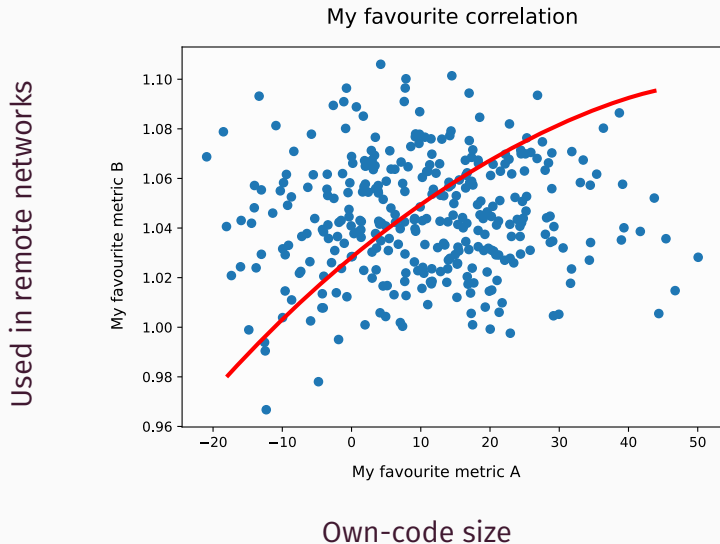
Used in remote networks

Own-code size

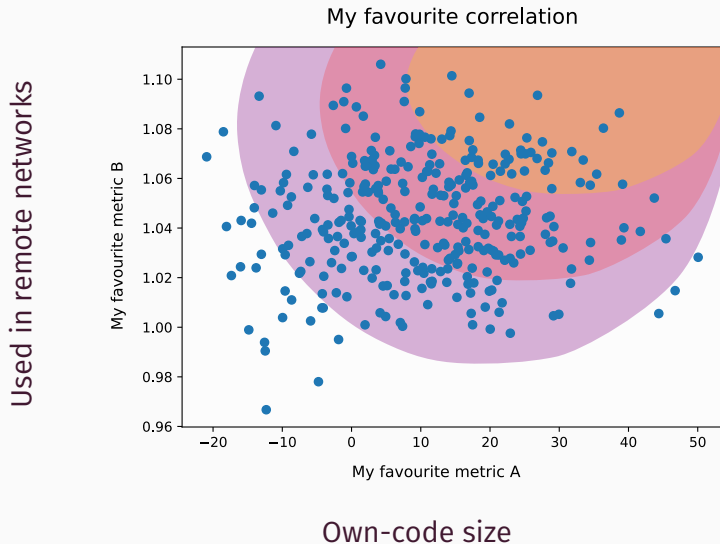
Security-relevant code metrics



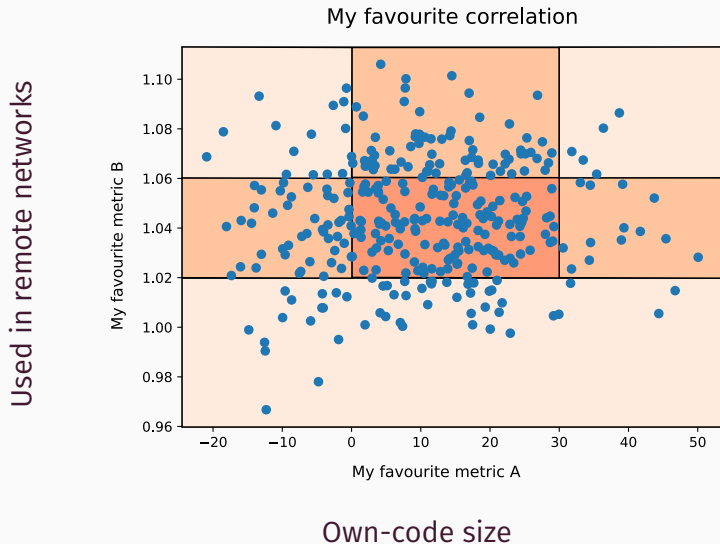
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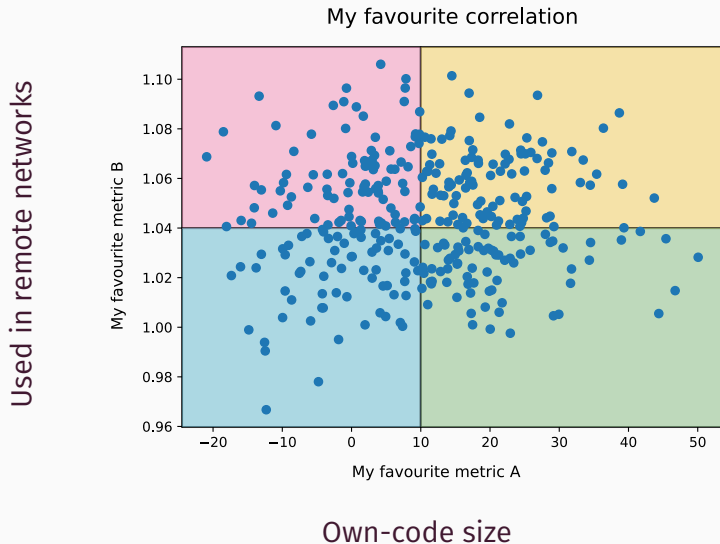
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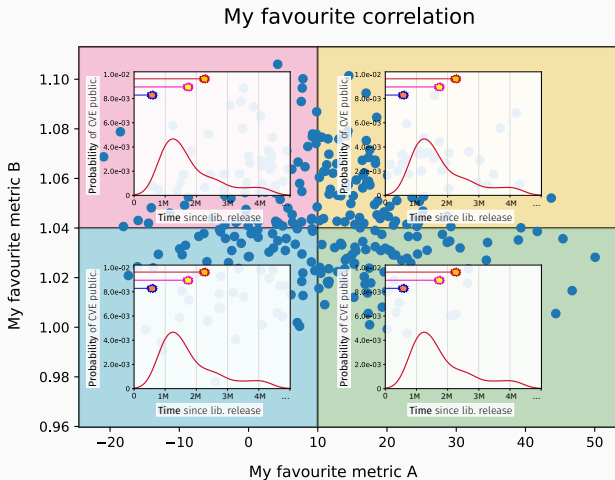


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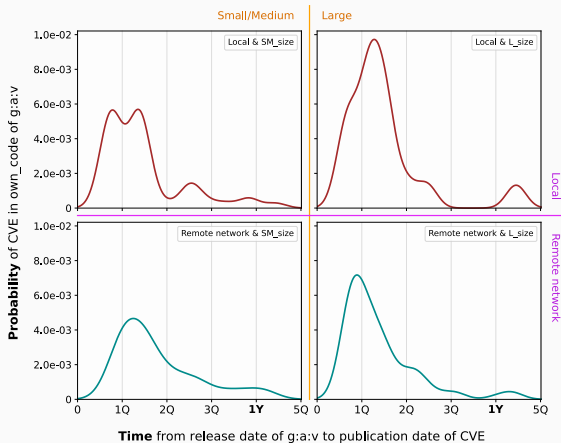
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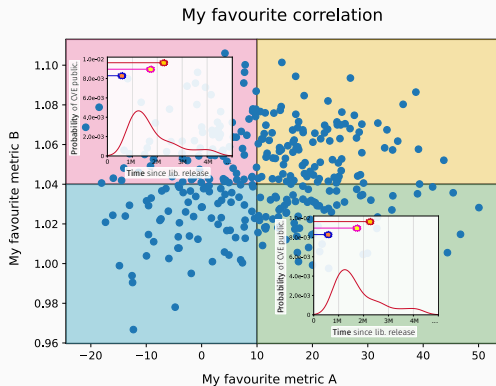
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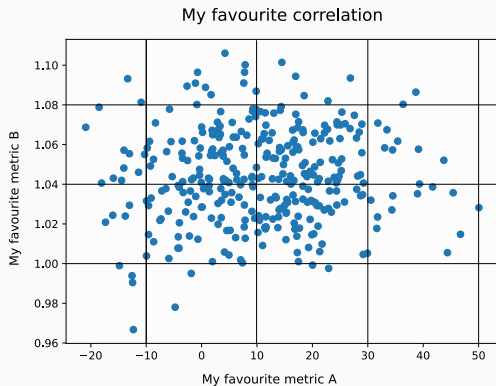


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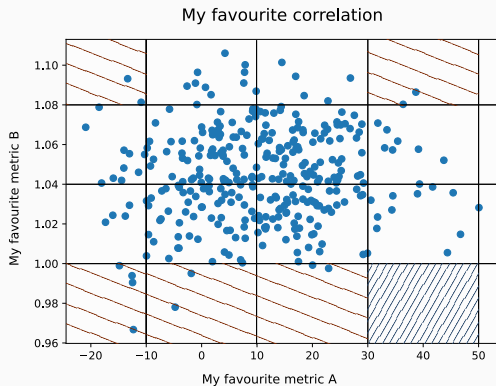
On overfitting and rare events



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On overfitting and rare events

- ▶ Count each CVE as one data point
- ▶ Discriminate per development environment
- ▶ Discriminate per library type

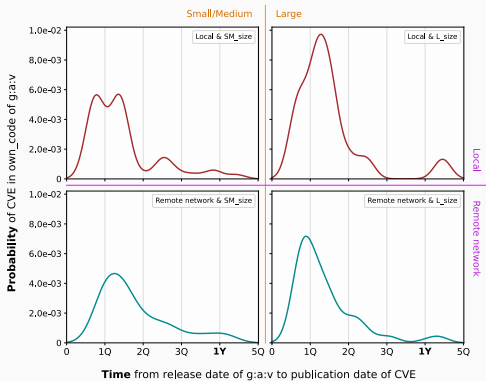
On overfitting and rare events

- ▶ Count each CVE as one data point
- ▶ Discriminate per development environment
- ▶ Discriminate per library type
- ▶ Clusterisation mustn't be too thin
 - few divisions per metric-dimension
 - few metric-dimensions

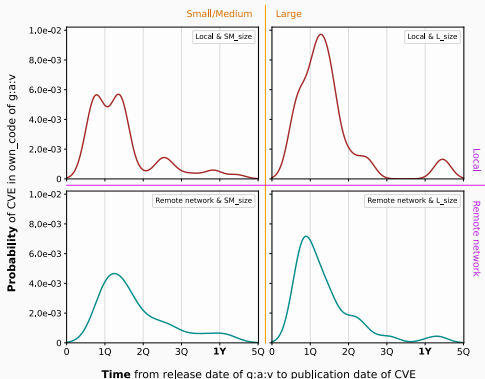
Enough!

Gimme results

Here ya go



Here ya go



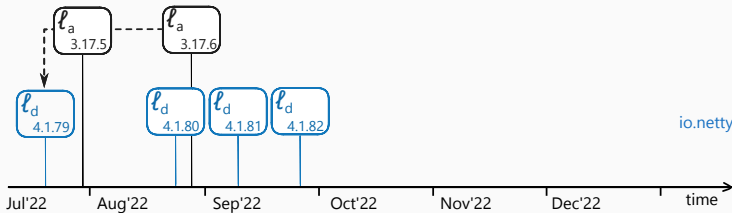
Q1 Pr(vuln.) as function of time

Q2 Pr(vuln.) as function of software metrics

Survival analysis on library update

org.redis:redis

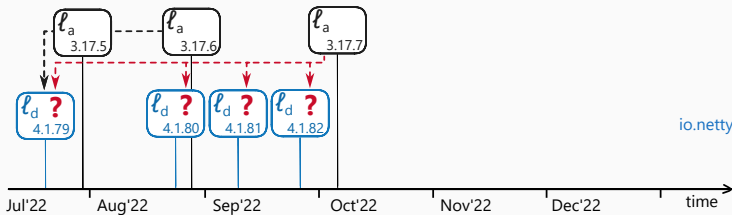
io.netty:netty-codec



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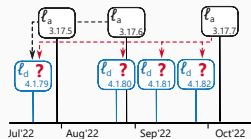
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Survival analysis on library update

$A \xrightarrow{t} B$ means that we change from dependency ℓ_A to ℓ_B in t time units counting from t_0 ("today").

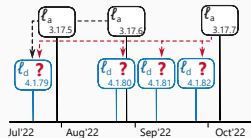
▷ ℓ_A was released on $t_A < t_0$, ℓ_B on $t_B < t_0$, $t_A \not\ll t_B$



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



Q: $\Pr_{A,B}(t) =$ probability of vuln. of $A \xrightarrow{t} B$ as a function of t

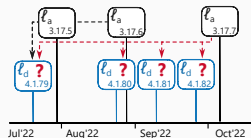
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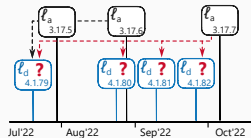
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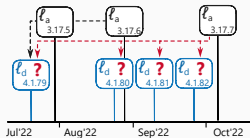
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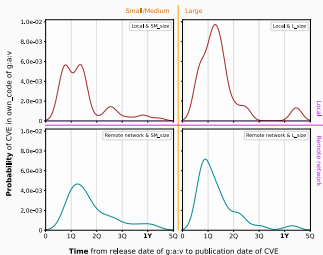
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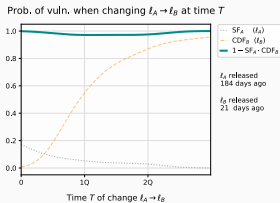
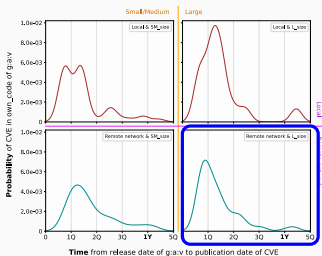
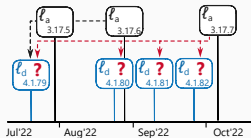
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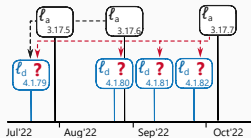
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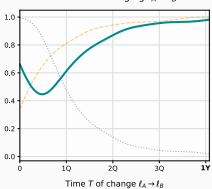
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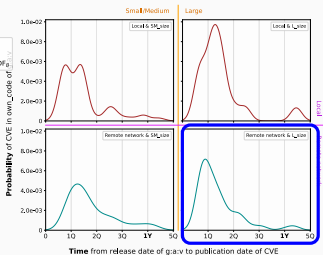
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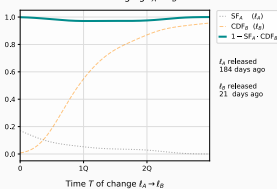
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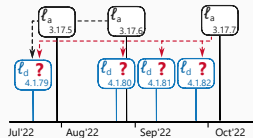
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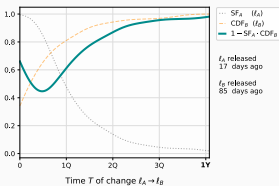
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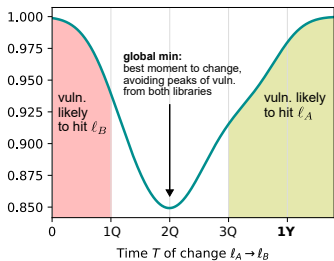
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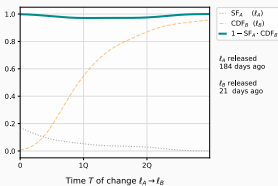
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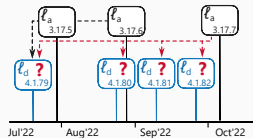
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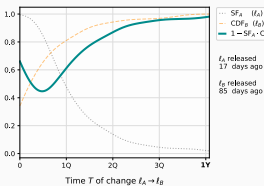
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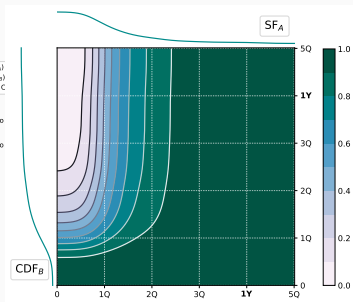
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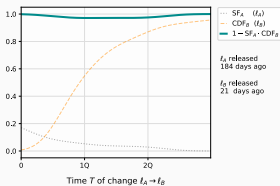
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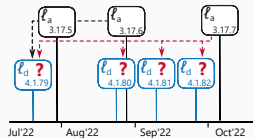
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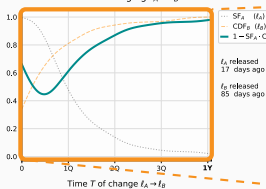
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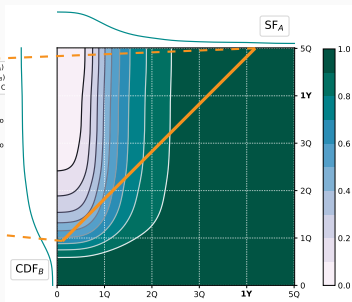
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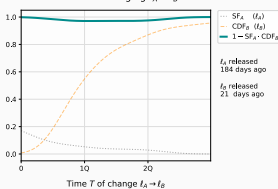
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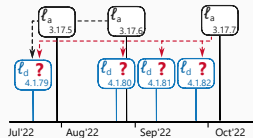
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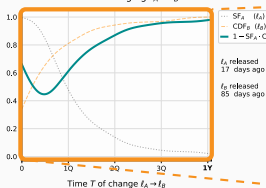
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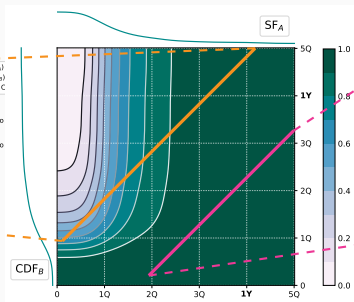
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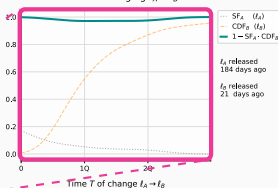
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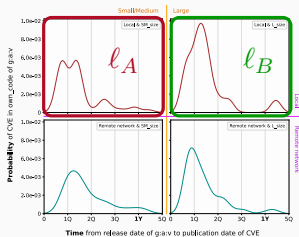
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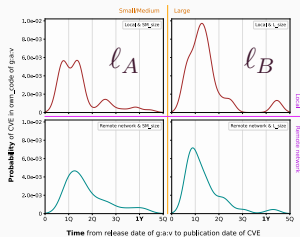
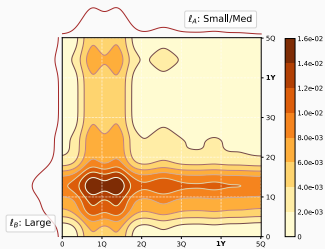
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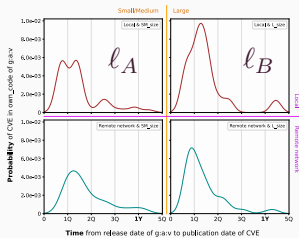
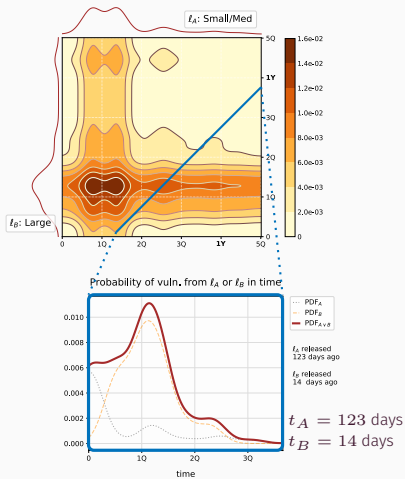
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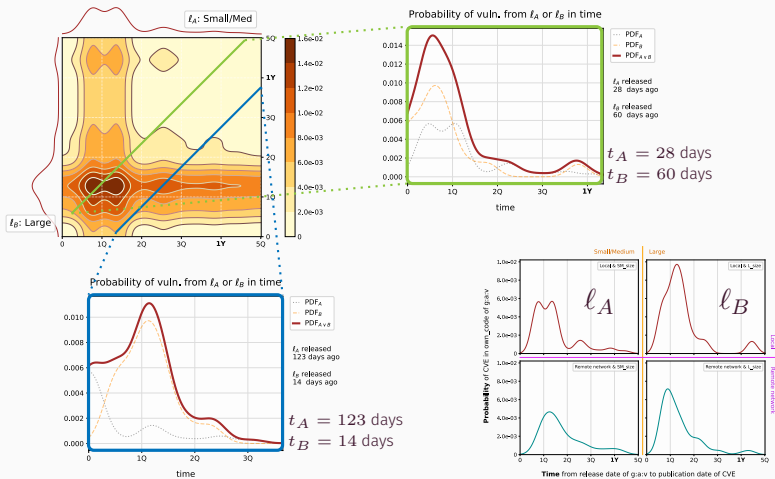
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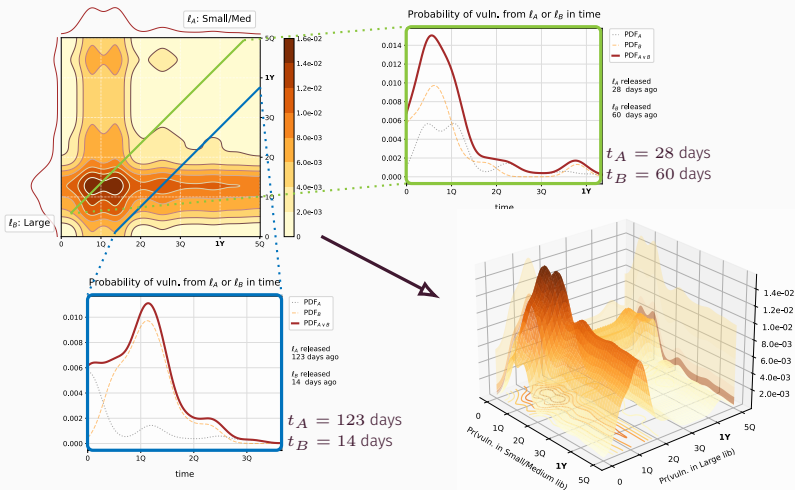
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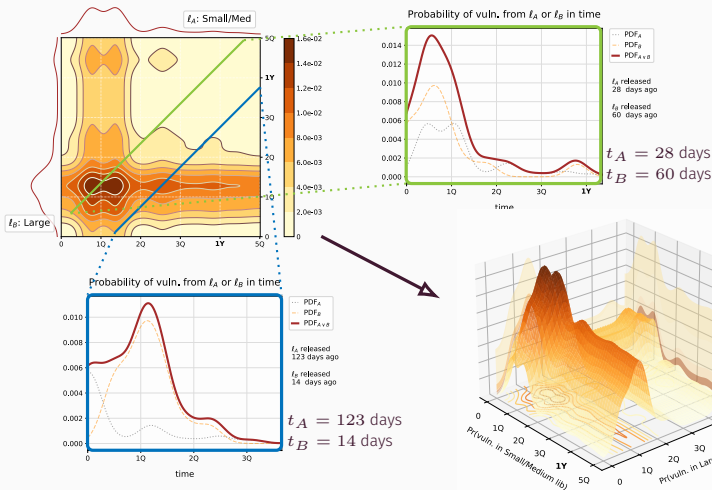
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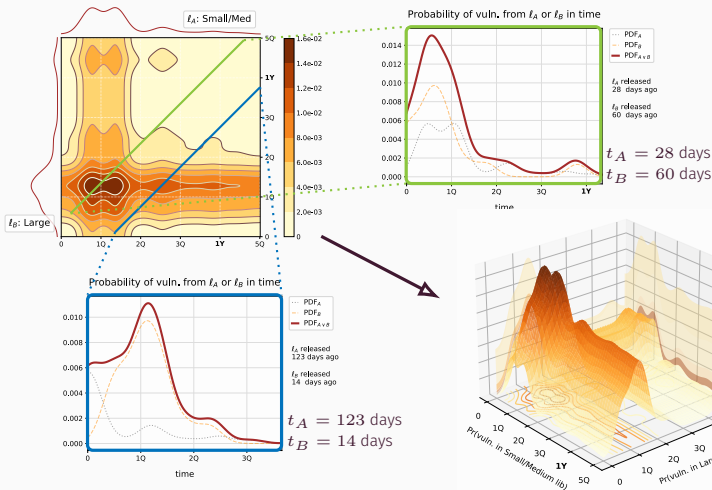


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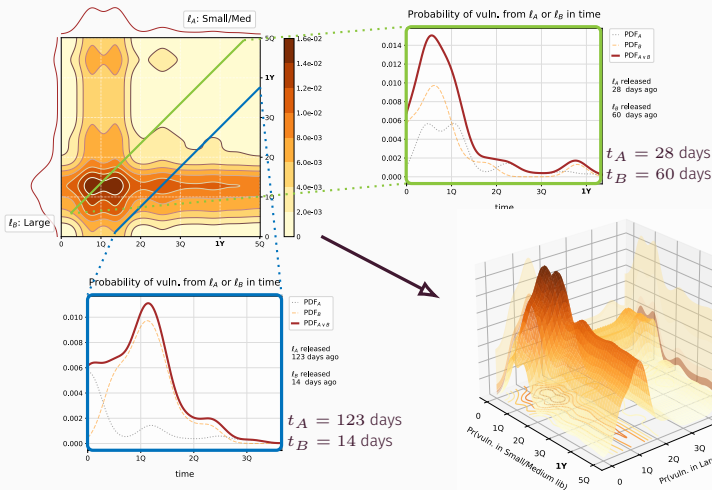
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Forecast model

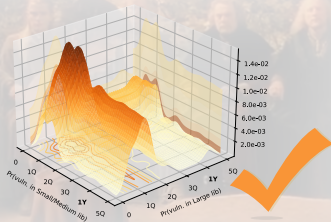
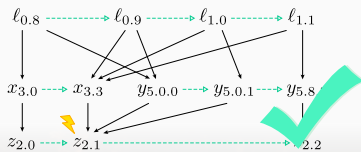
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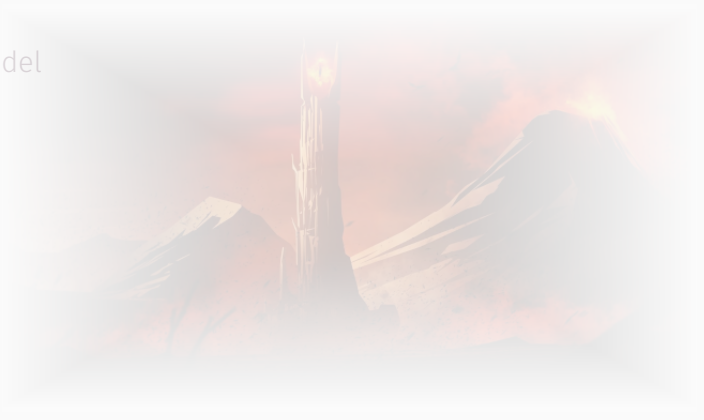
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CVE root-lib PDFs

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Questions?



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Why you want it and one way to do it

C.E. Budde R. Paramitha F. Massacci

Università di Trento (IT) & Vrije Universiteit (NL)

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