Predicting Security Attacks in FOSS

Why you want it and one way to do it

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Vuln4Cast 2023 FIRST Technical Colloquium

Talk overview

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

Introduction

The myth of the bleeding edge

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.

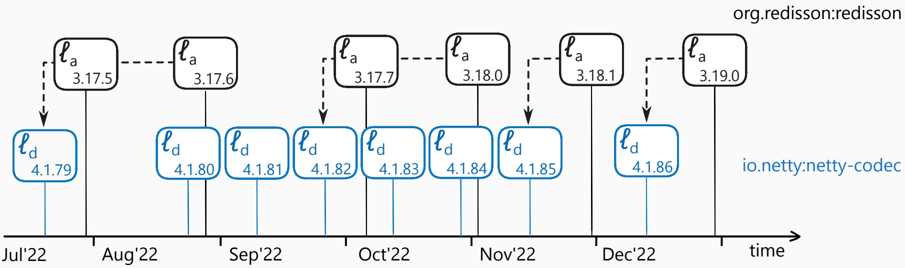
BY **CHRIS HOFFMAN** PUBLISHED AUG 28, 2020

Quick Links

Security Updates 101

What's the Risk, Really?

Some motivation (plz!)



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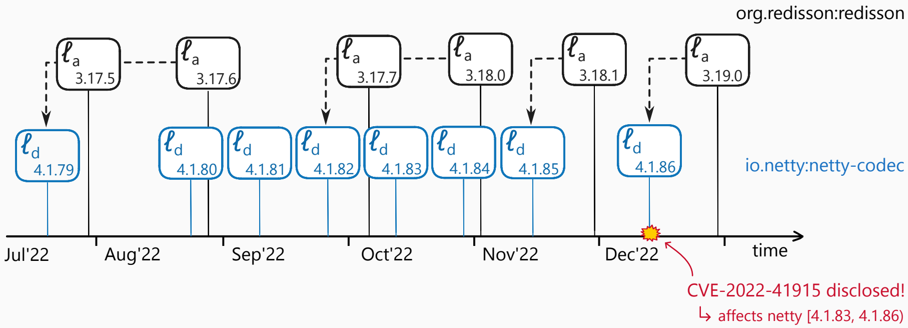

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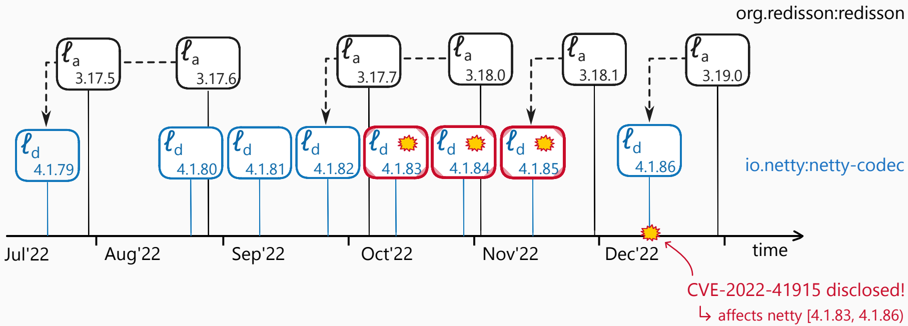

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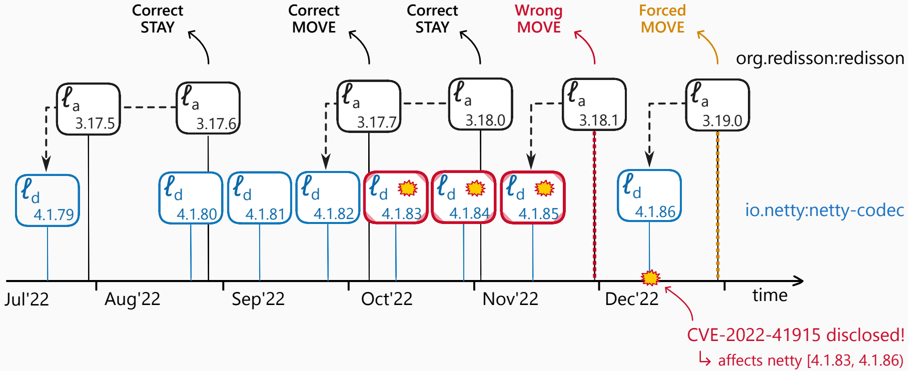
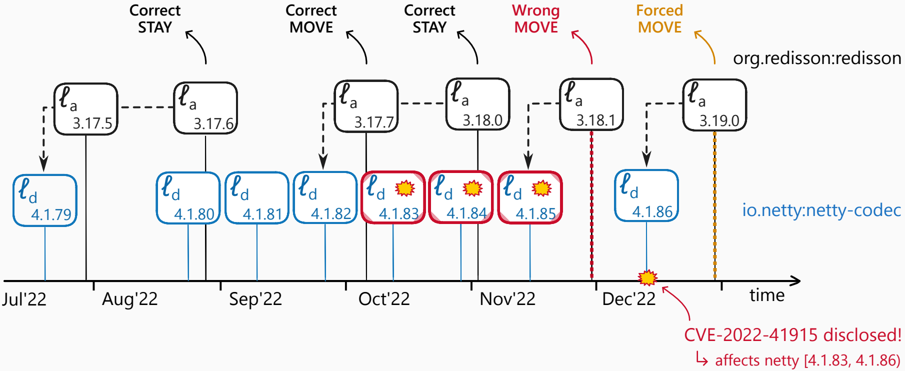


Hindsight!


Correct
STAY
Correct
MOVE
Correct
STAY
Wrong
MOVE
Forced
MOVE
org.redisson:redisson
ℓa 3.17.5
ℓa 3.17.6
ℓa 3.17.7
ℓa 3.18.0
ℓa 3.18.1
ℓa 3.19.0
ℓd 4.1.79
ℓd 4.1.80
ℓd 4.1.81
ℓd 4.1.82
ℓd 4.1.83
ℓd 4.1.84
ℓd 4.1.85
ℓd 4.1.86
io.netty:netty-codec
Jul'22
Aug'22
Sep'22
Oct'22
Nov'22
Dec'22
time
CVE-2022-41915 disclosed!
↳ affects netty [4.1.83, 4.1.86)

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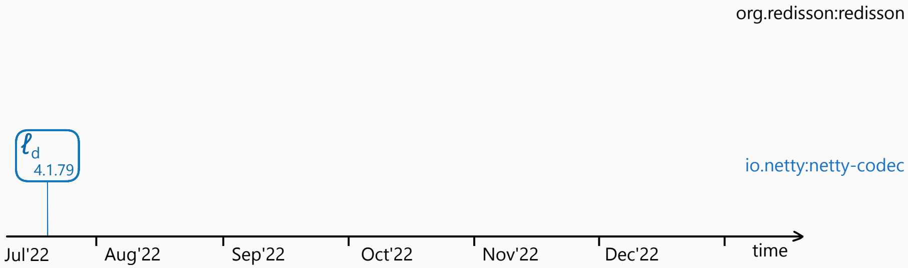
Developer perspective in time:



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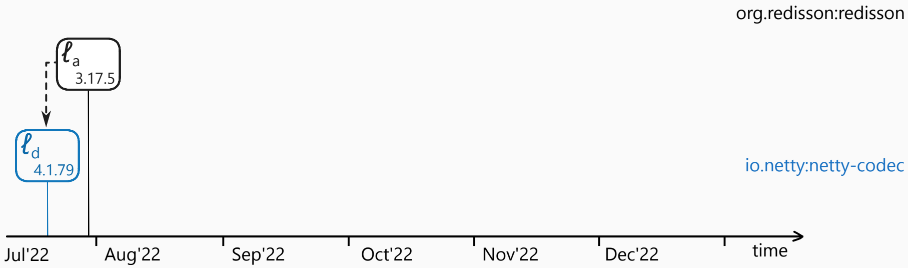

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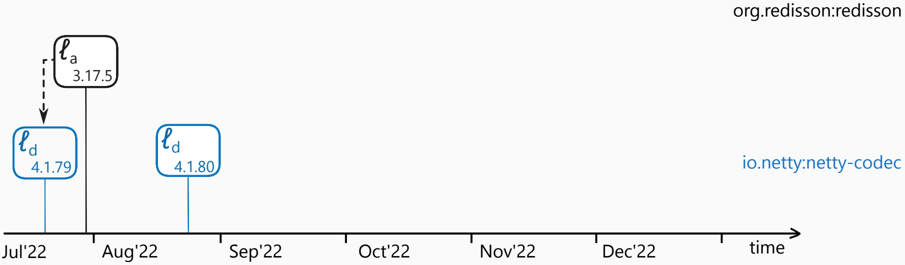

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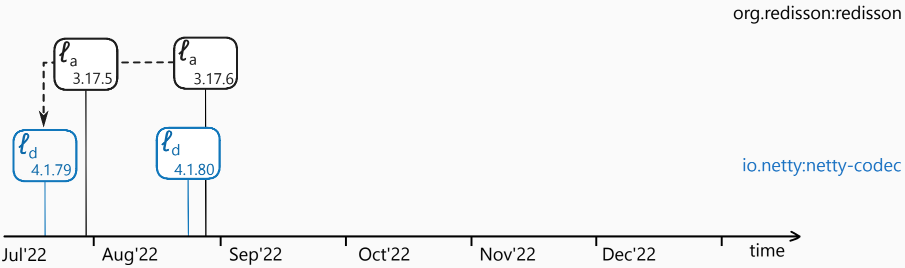

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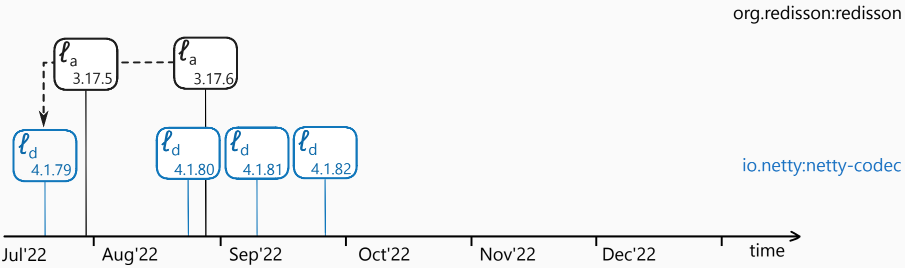

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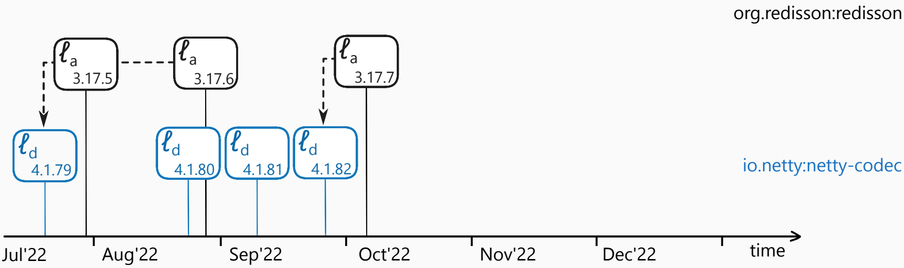

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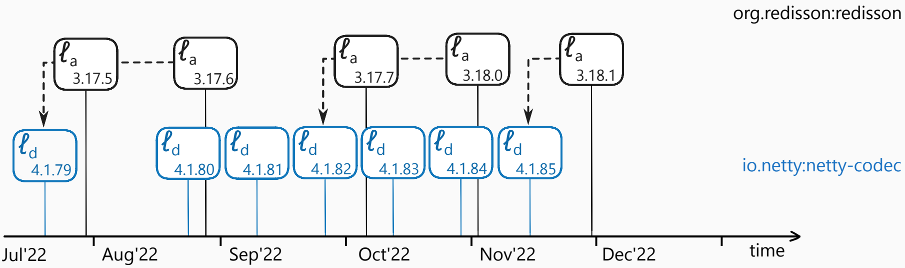

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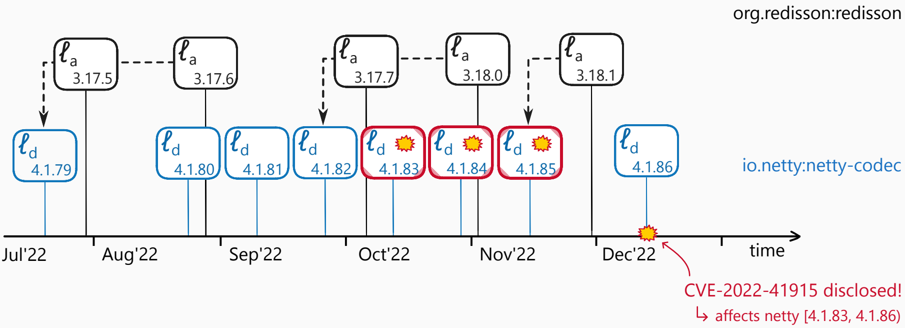

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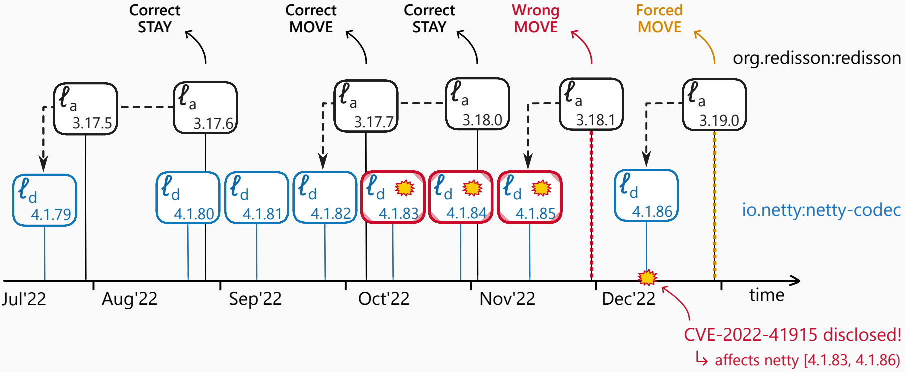

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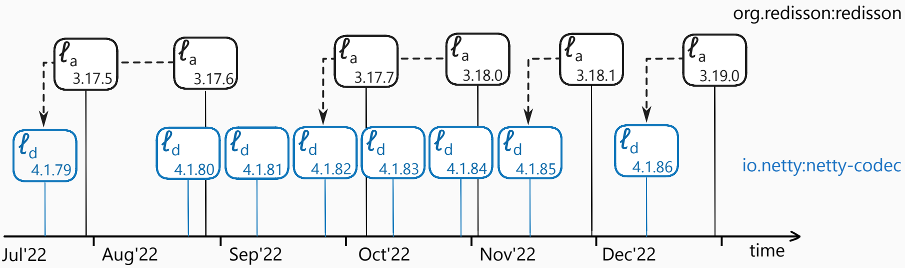

Is there a best time to update?

Questions

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

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

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

- ▷ best time to update?

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

- ▷ measurable software metrics

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    - we study publication of CVEs;
    - keep it high-level, no code analysis.
2. Probability of *exploitation*:
    - we study publication of CVEs;
    - … but check the work of the EPSS!

Background

Work	Goal		Data				Method			Approach			Projects/Libs.		
	Disc.	Pred.	CVEs	Code	VCS	Dep.	Corr.	Clas.	T.Ser.	AH	SA	ML	Language	#	Purport
[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.
[2]	✓				✓		✓	✓				✓	PHP	3	
[16]	✓			✓			✓	✓			✓	✓	Java	4	
[5]	✓			✓	✓			✓		✓			C/C++, PHP, Java, JS, SQL	10	
[11]	✓		✓		✓			✓		✓			C	3	Detect known vulnerabilities (and their correlation to developer activity metrics) from VCS only—e.g. commit churn, peer comments, etc.
[13]	✓		✓		✓		✓			✓			C	1	
[15]	✓		✓		✓		✓			✓	✓		C, ASM	3	
[14]	✓		✓		✓		✓			✓	✓		C, ASM	1	
[6]	✓		✓	✓				✓				✓	C/C++	3	Detect known vulnerabilities (and their correlation to code metrics) from code only—e.g. number of classes, code cloning, cyclomatic complexity, etc.
[8]	✓		✓	✓				✓				✓	Java	7	
[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	

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Most works try to discover current vulnerabilities, not predict future ones

Most works disregard the code dependency tree

Most works do not consider time in their analyses

Disregarded security data

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

Q1 $\Pr(\mathrm{vuln.})$ 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

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- human-in-the-loop metrics, including VCS (#commits, seniority...)

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- ML & statistical analysis to correlate SE metrics to existent vulnerabilities
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- ML & statistical analysis to correlate SE metrics to existent vulnerabilities
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Q1 $\Pr(\text{vuln.})$ as function of time

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

Gap analysis

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

Forecast model

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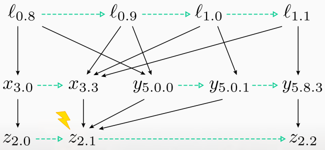
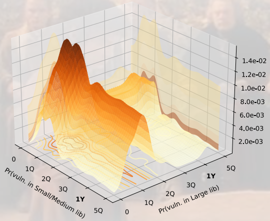
Time Dependency Trees



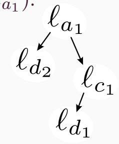


CVE root-lib PDFs

Time Dependency Trees

Dependency Trees in time

$D(\ell_{a_1})$:



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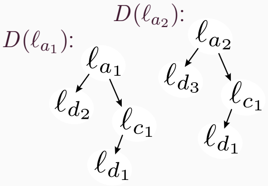

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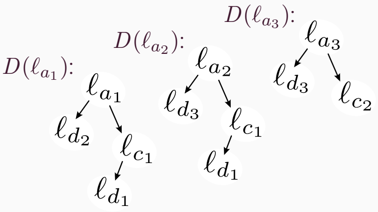

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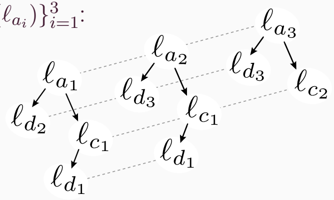
$\{D(\ell_{a_i})\}_{i=1}^{3}$:



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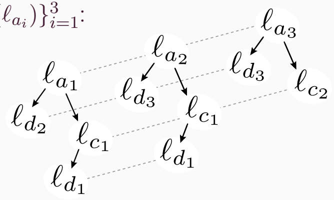

Time Dependency Tree

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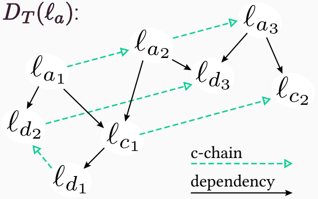

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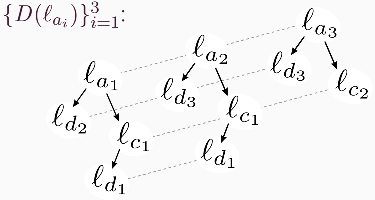

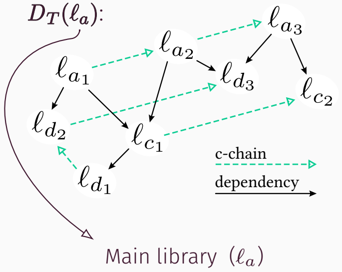

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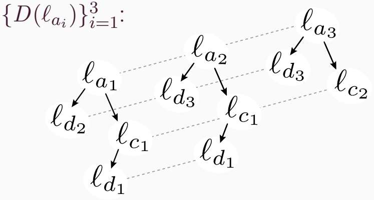

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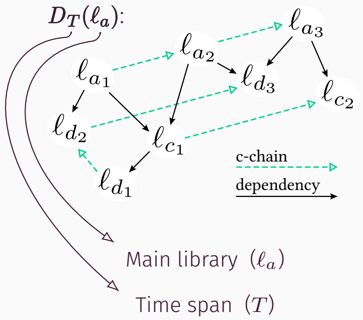

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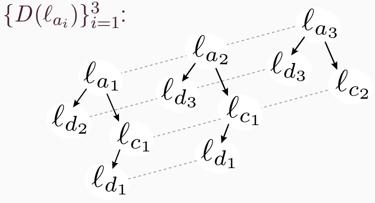
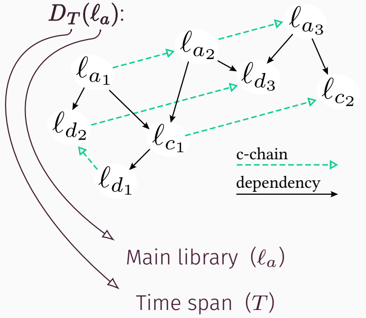


$D_t(\ell_a) = D(\ell_{a_1})$
for any time point $t \in T$
after the release of ℓ_{a_1} and
before the release of ℓ_{a_2}

Time Dependency Tree



Properties of TDT $D_T(\ell)$

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- Reachability analysis can spot single-points-of-failure

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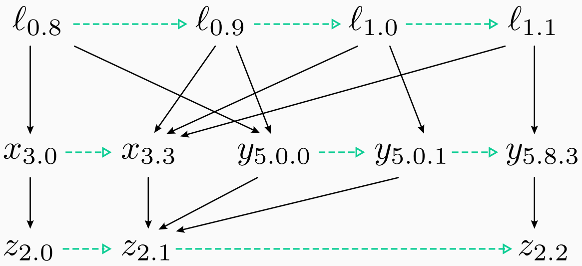

SPoF in time and dependencies

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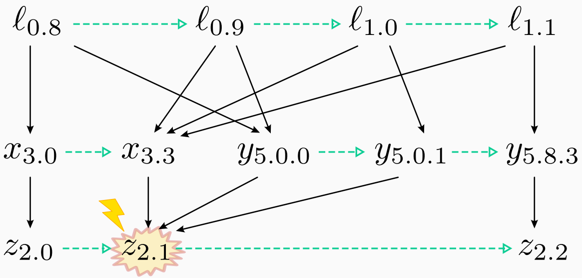

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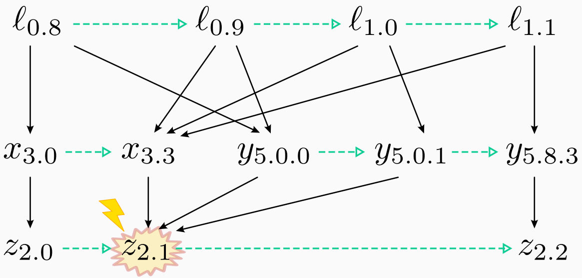

Should I downgrade to $\ell_{0.9}$ or upgrade to $\ell_{1.1}$?

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Theoretical

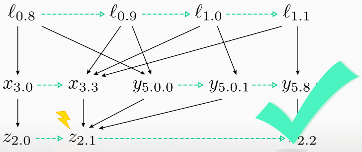
- Minimal graph representation (no lib-version repetition)
- Canonical for library ℓ and time span T
- Natural lifting of dependency trees to time

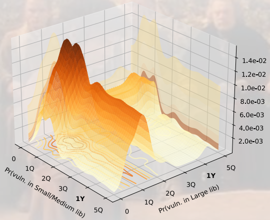
Practical

- **Time-indexing** $D_t(\ell)$ yields the dep. tree at time $t \in T$
- **Library-slicing** $D_T(\ell)\big|_d$ yields *all instances* of dependency d during time T
- Reachability analysis can spot single-points-of-failure
- Can measure health/risk of development environment

Forecast model

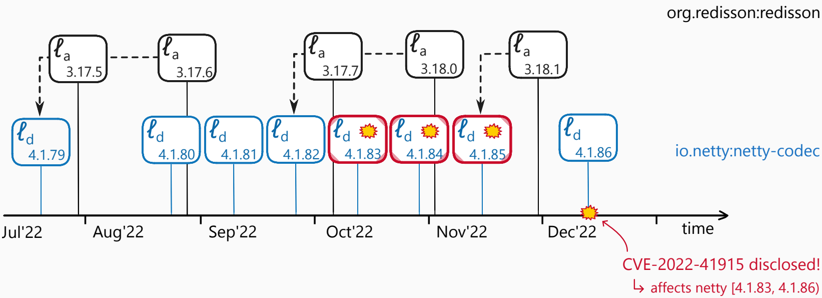
Time Dependency Trees





CVE root-lib PDFs

Publication of CVE since time of code release



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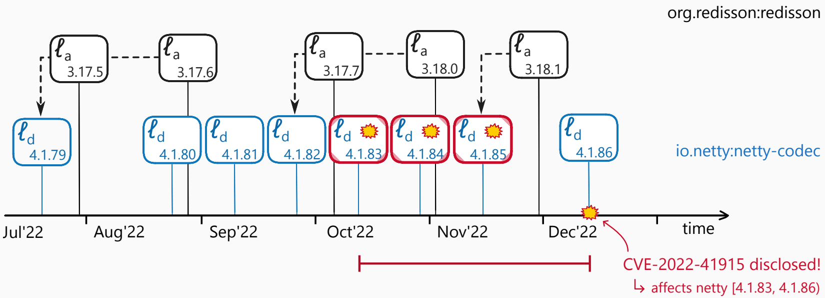

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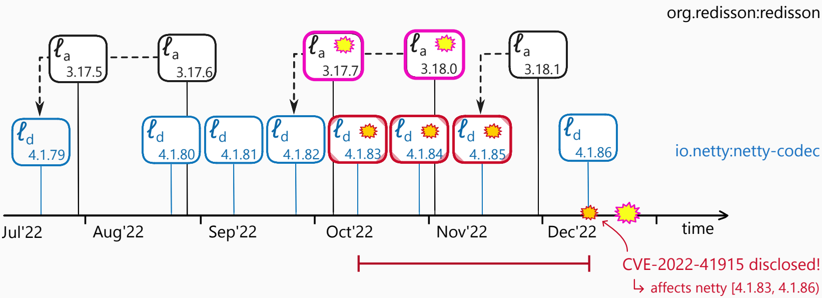

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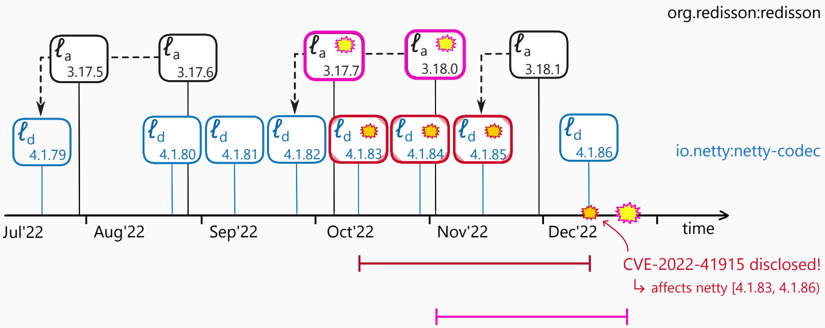

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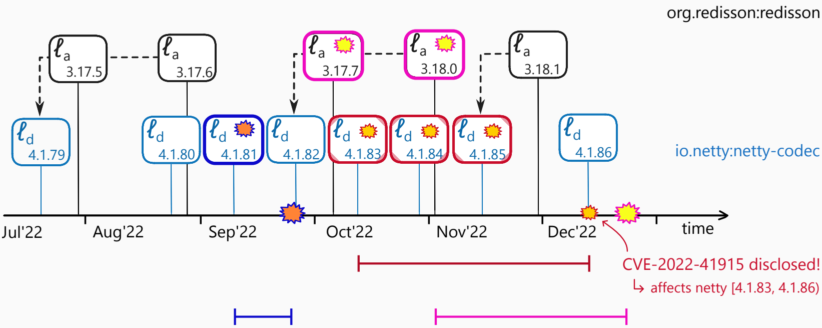

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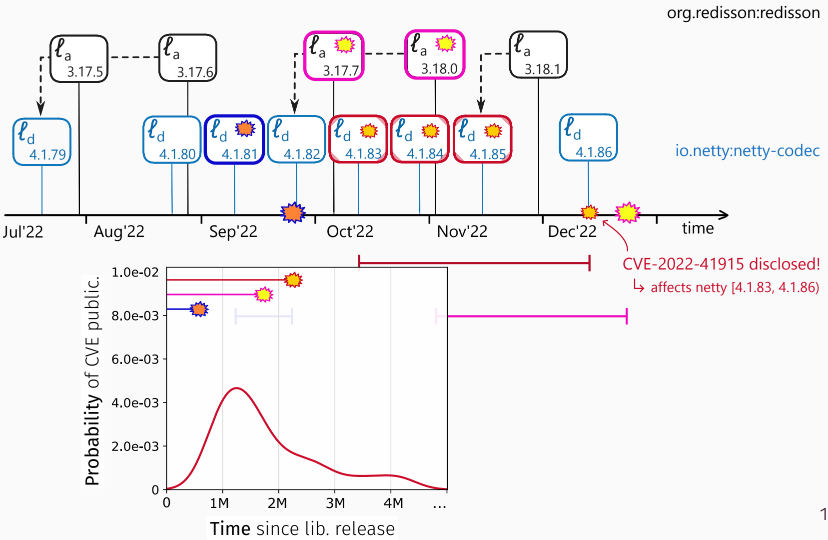

Rules of the game

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

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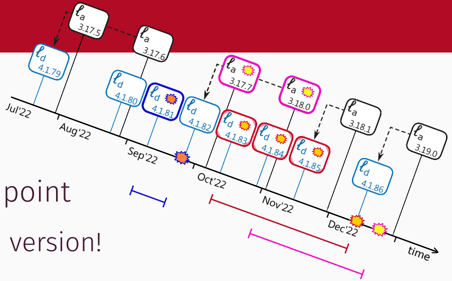

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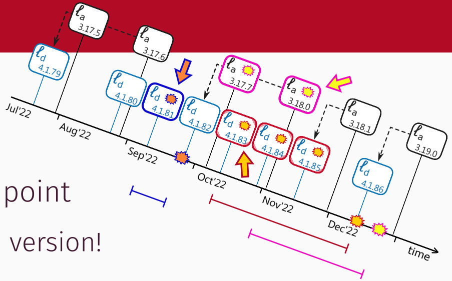

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    🍏 🍊

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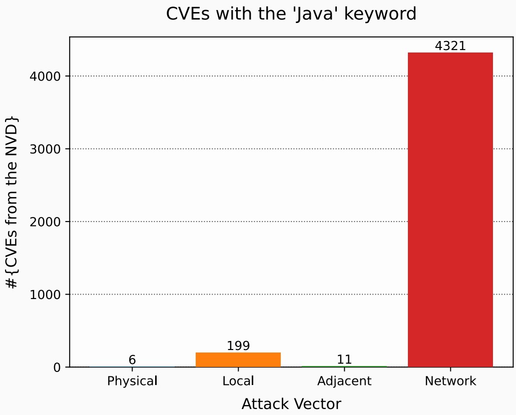
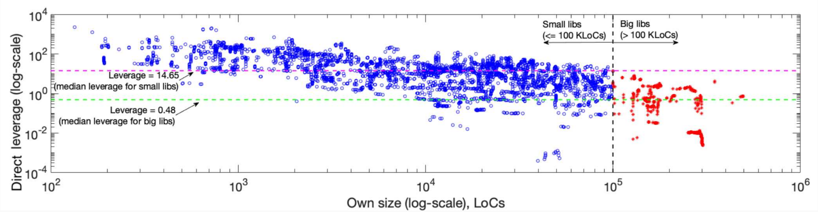
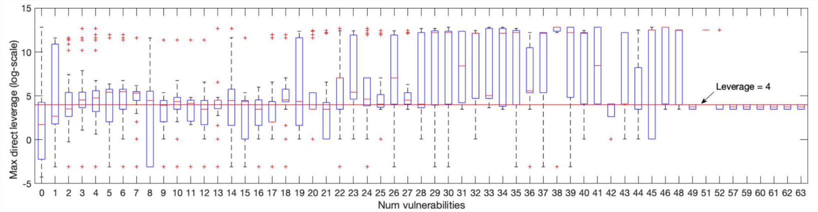
Used in remote networks



(Own) Code size





Security-relevant code metrics

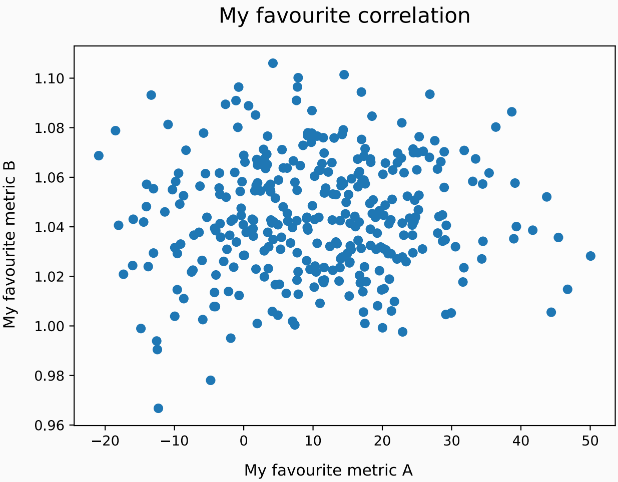
Work	Goal: Disc.	Goal: Pred.	Data: CVEs	Data: Code	Data: VCS	Data: Dep.	Method: Corr.	Method: Clas.	Method: T.Ser.	Approach: AH	Approach: SA	Approach: ML	Projects/Libs.: Language	Projects/Libs.: #	Purport
[4]	✓			✓				✓				✓	C	3	Find vulnerabilities regardless of existent logs such as CVEs (although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

Security-relevant code metrics

Used in remote networks

Own-code size

Security-relevant code metrics



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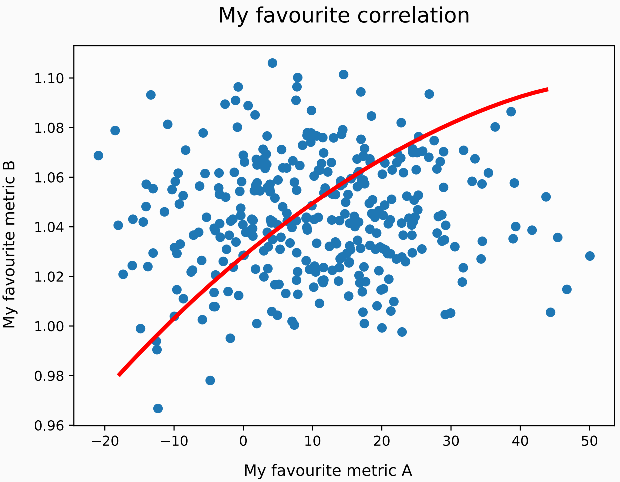

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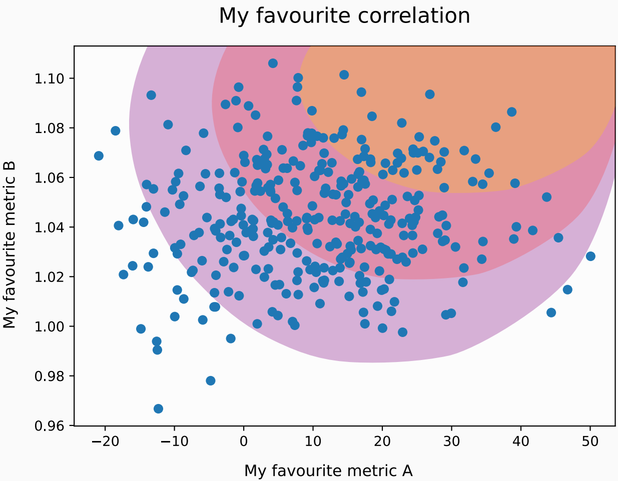

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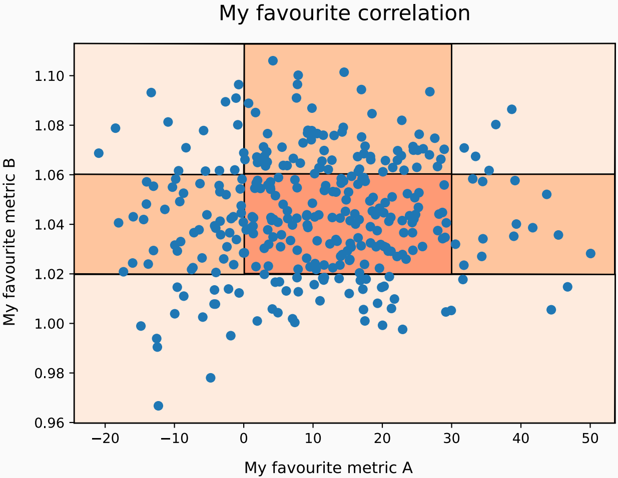

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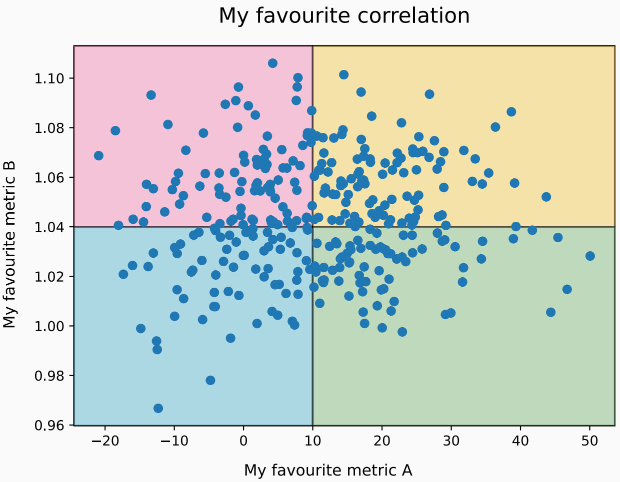

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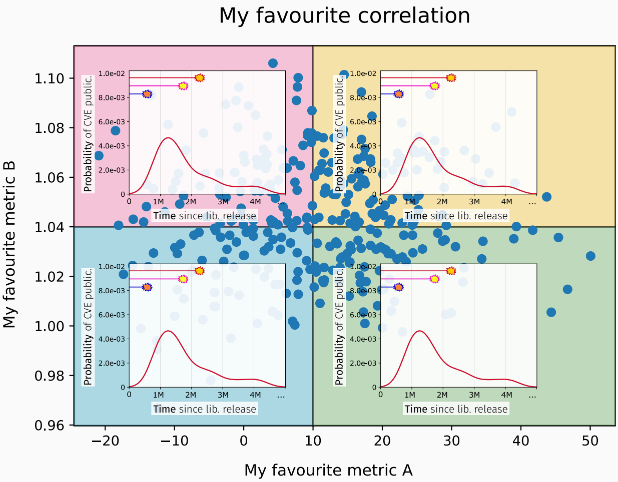

Own-code size

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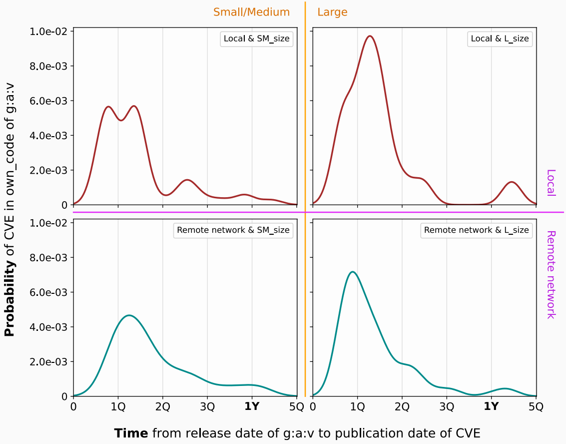
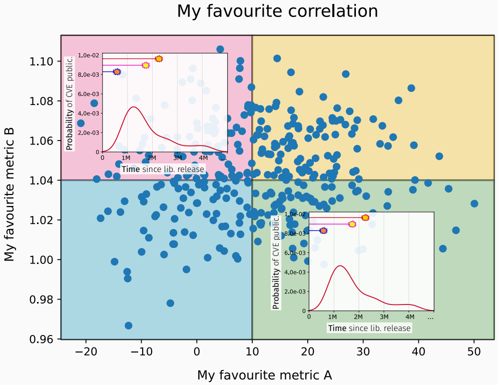


Own-code size

On overfitting and rare events



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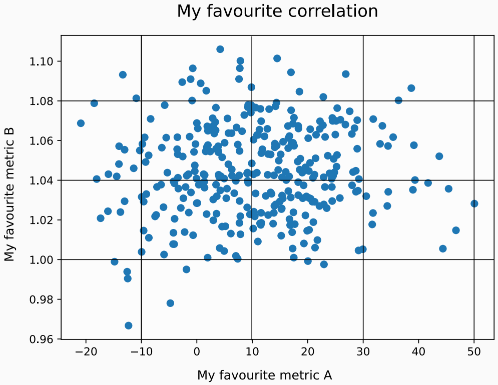

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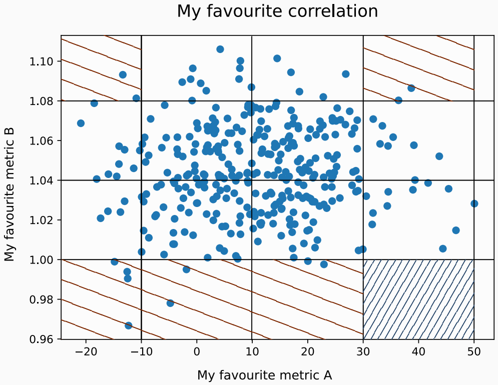

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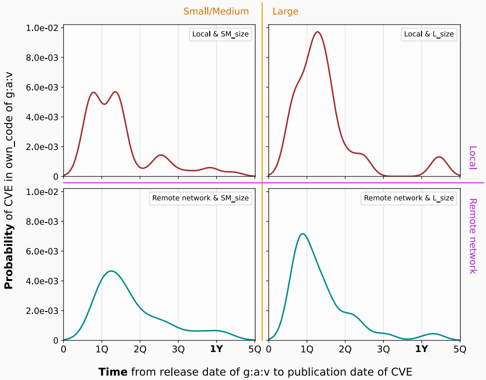
On overfitting and rare events

- 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!

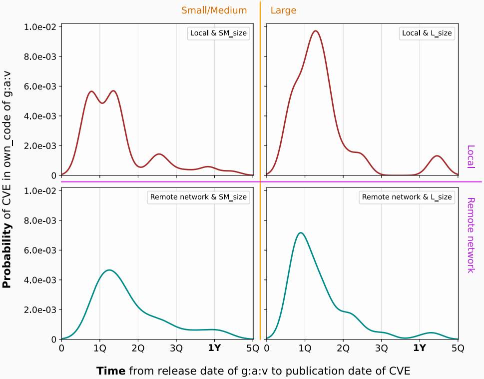
Gimme results

Here ya go



Small/Medium
Large
Local & SM_size
Local & L_size
Remote network & SM_size
Remote network & L_size
Local
Remote network
1.0e-02
8.0e-03
6.0e-03
4.0e-03
2.0e-03
0
0
1Q
2Q
3Q
1Y
5Q
Probability of CVE in own_code of g:a:v
Time from release date of g:a:v to publication date of CVE

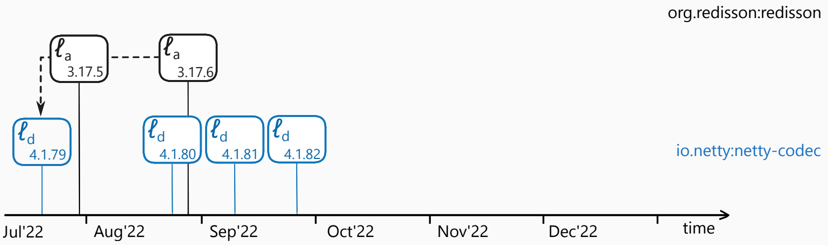
Here ya go



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

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

Survival analysis on library update



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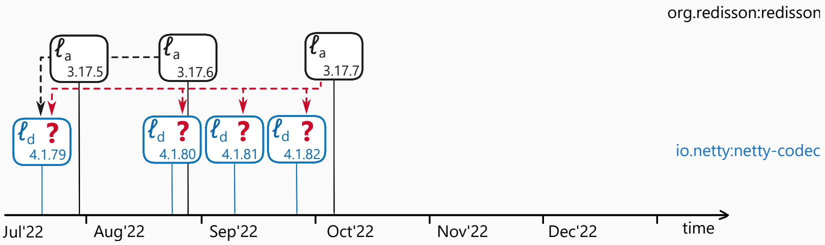

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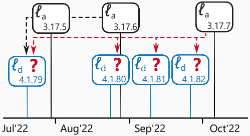

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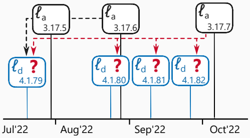

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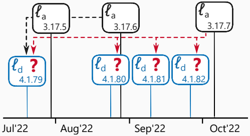

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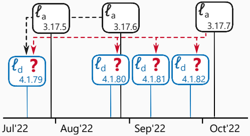

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vuln. in ℓ_A before change vuln. in ℓ_B after change

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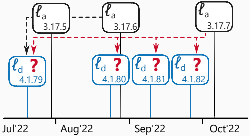

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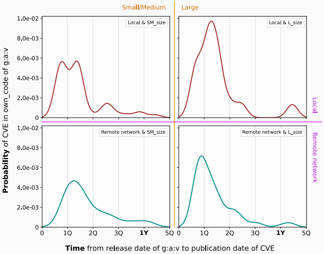
vuln. in ℓ_A before change   vuln. in ℓ_B after change



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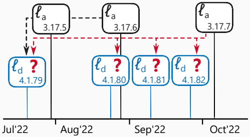

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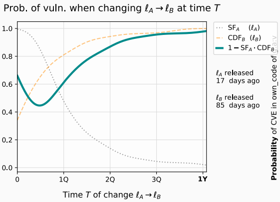
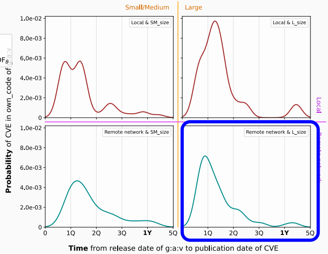
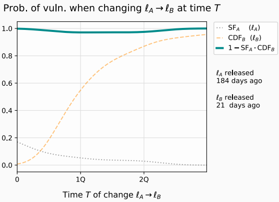


$t_A = 17$ days
$t_B = 85$ days





$t_A = 184$ days
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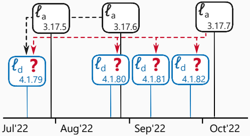
Survival analysis on library update



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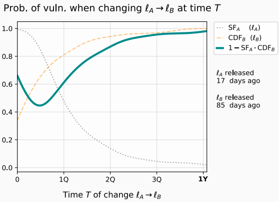

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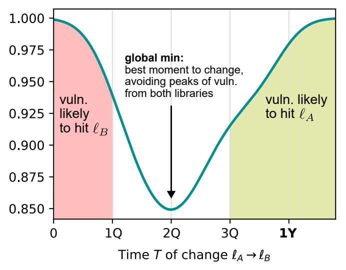

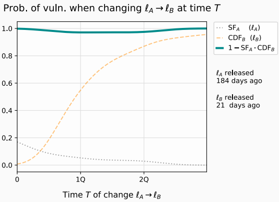

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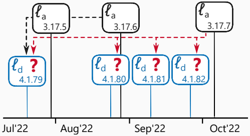

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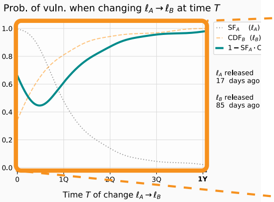
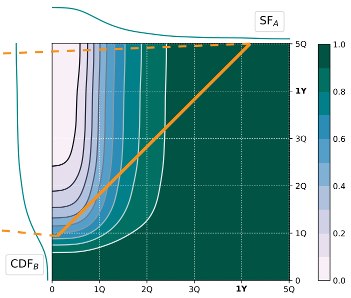
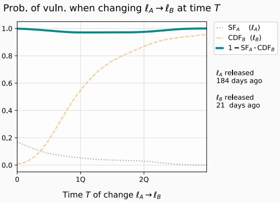


$t_A = 17$ days
$t_B = 85$ days

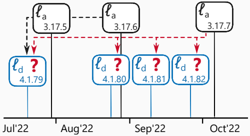




$t_A = 184$ days
$t_B = 21$ days

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").



- $\triangleright$ 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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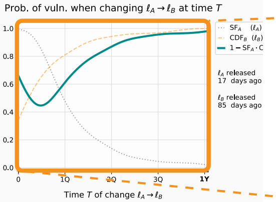

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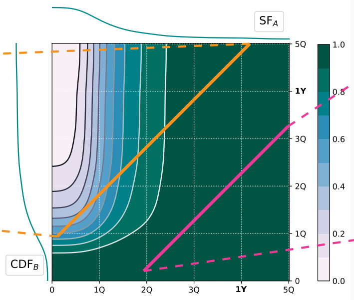

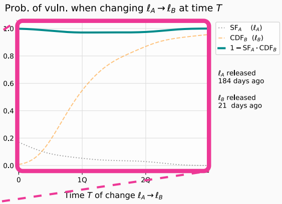

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Vulnerabilities from any dependency

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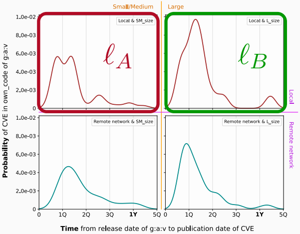

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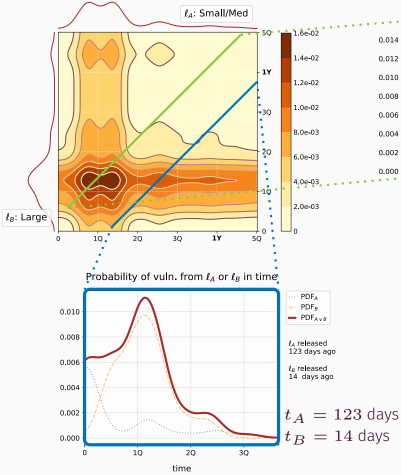

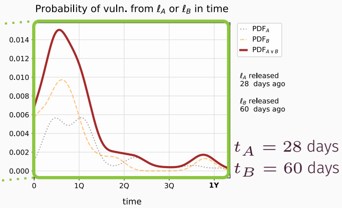

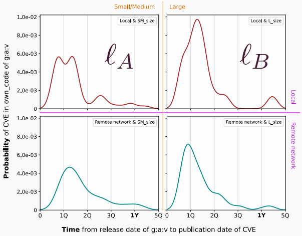

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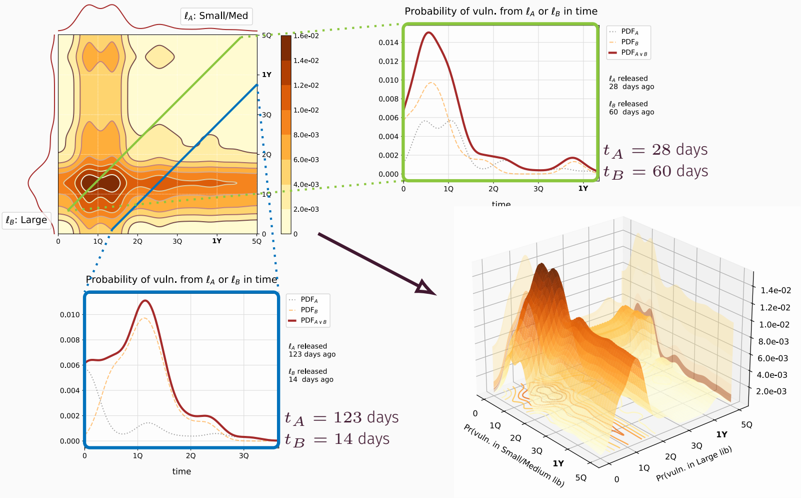

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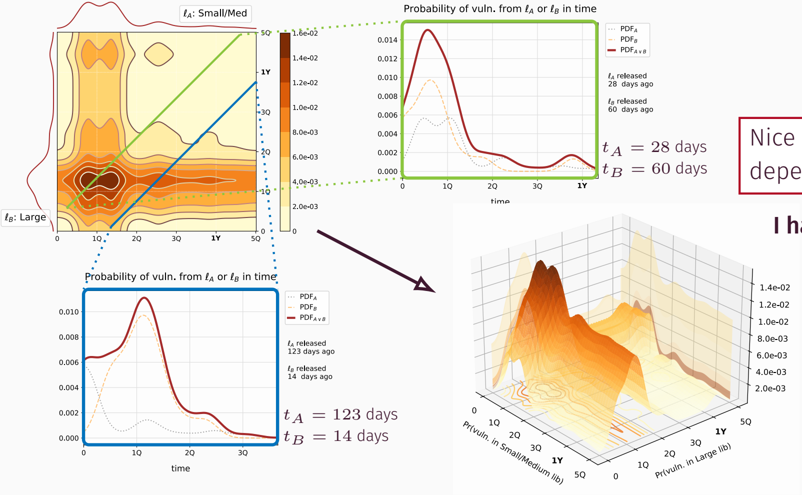
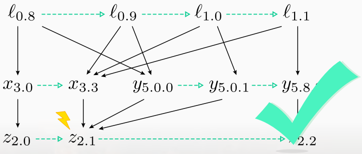


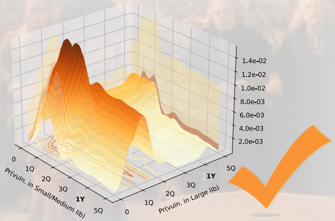
Nice for 2 dependencies...

I have 2000 TDTs!

Forecast model

Time Dependency Trees





CVE root-lib PDFs

Conclusions

Some things done

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  - Aggregate dependency and code-evolution data

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  - Base information for probability forecasting

Some things done

Some things to be done

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Questions?

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Why you want it and one way to do it

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