A Journey Towards Efficient Profiling

Alpine Verification Meeting 2023

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Perun Github: `https://github.com/Perfexionists/perun/`
Paper Demo VM: `10.5281/zenodo.6783242`

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Motivation:
Why Care About Performance?

Performance Bugs Are Everywhere

- Software performance bugs are an omnipresent problem[1]:

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- An internal check for uniqueness
  $\rightarrow$ *hanging effectively forever* for large job batch.

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  - **Cluster computing engine** may *freeze* after an update!
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Apache Spark

- An internal check for uniqueness
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stackoverflow

- A regular expression for stripping whitespaces
  → *34 minutes long outage*.

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Performance Bugs Are Everywhere

- Software performance bugs are an omnipresent problem[1]:
  - **Cluster computing engine** may *freeze* after an update!
  - **Cloud services** may *crash*!
  - **Parsers** may experience significant *slowdown*!

- An internal check for uniqueness
  → *hanging effectively forever* for large job batch.
- A regular expression for stripping whitespaces
  → *34 minutes long outage*.
- One of *Chrome*'s parsers
  → *noticeable slowdown* for long lines.

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Performance Bugs Are Everywhere (yes, even in your code)

- $\mathcal{O}(n^2)$ space implementation of C# constant folding
  $\rightarrow$ *compiler runs out of memory*.
- $\mathcal{O}(n^2)$ pattern matching algorithm in Elasticsearch
  $\rightarrow$ up to $\frac{1}{2}$ *CPU-time spent in* `Regex.simpleMatch`.
- Array used for tags lookup in Vim
  $\rightarrow$ $\mathcal{O}(n^2)$ complexity in the number of matches.
- Godoc source code parsing
  $\rightarrow$ $\mathcal{O}(n^2)$ loop for Go structs definitions.

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- Such bugs usually manifest only under certain conditions.
  - Highly granular analysis may detect them sooner!

How Do We Find The Bugs?

- **Numerous static and dynamic analysis approaches:**
  - Worst-case resource bounds analysis.
  - Anti-patterns detection and log analysis.
  - Performance testing and benchmarking.
  - Profiling (event-based tracing).

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+ Possible formal guarantees.
+ *Soundness*/*Completeness*.
+ Often the only possibility for safety-critical software.

– High skill/tool barrier.
– Scaling issues.
– The analysis *may fail* for complex cases.

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+ Easier tools adoption.
+ Usually scales well.

– Few formal guarantees.
– High-level coarse analysis.

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– Garbage in, garbage out.

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– Potentially significant overhead.

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The Roots of Profiling Inefficiency

Too Much Overhead

- **High granularity** of performance data.
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  3. General profiling optimization techniques.[2]
     - ⇒ The idea: Limit high granularity to **where it actually matters**.

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Recency

- **Recency is important:** it pays off to discover bugs quickly.
  - Recently introduced bugs, as opposed to dormant bugs[3],
    - take on average less time to fix;
    - can be fixed by less experienced developers;
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- Profiling tools generally **ignore project and profiling history**.
- Yet, past profiles coupled with version history are valuable.
  ⇒ The idea: *Reuse profiling data when possible.*

Meet Perun:
Performance Version System

Perun: Beyond Mere Profiling

Perun[4] = Complex Solution for Performance Analysis and Testing

[4] T. Fiedor, J. Pavela, A. Rogalewicz and T. Vojnar: *Perun: Performance Version System*, in Proc. of *ICSME*'22

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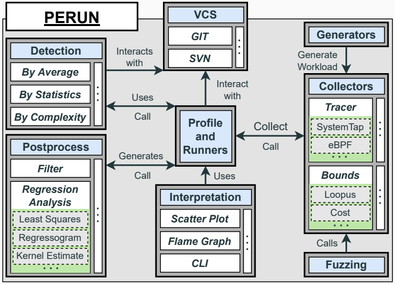

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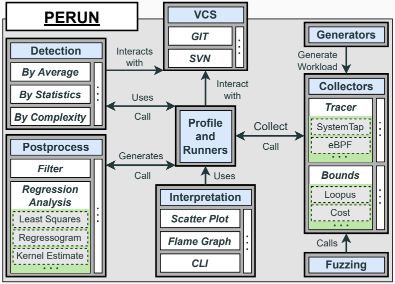

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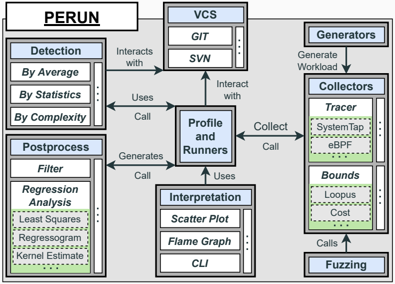

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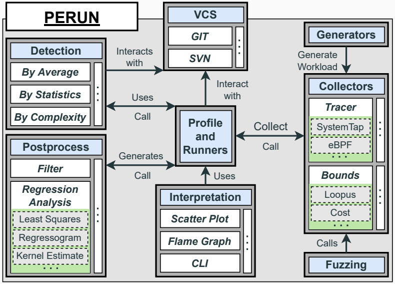

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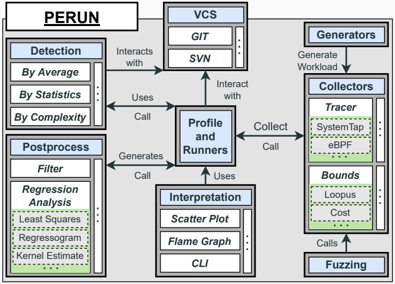

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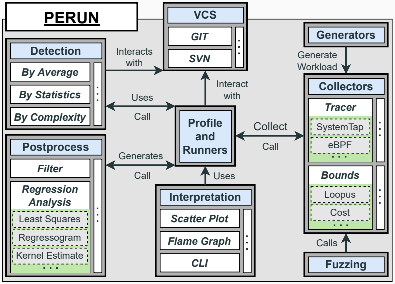

* Often the only steps done by traditional profilers.

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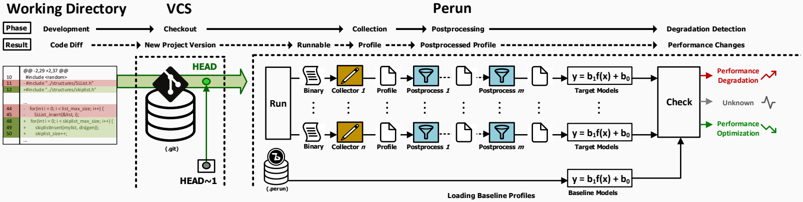
Perun Workflow: Overview

- **Four** major steps: Repository → Profiles → Models → Detection



Perun Workflow: Repository

Working Directory

Phase **Development**

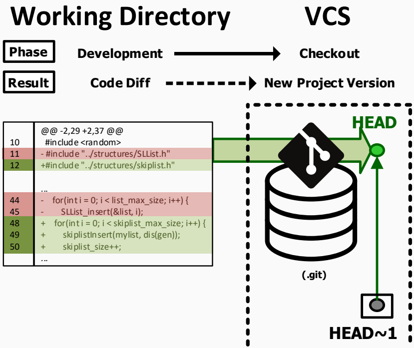
Result **Code Diff**

```
@@ -2,29 +2,37 @@
 #include <random>
- #include "../structures/SLList.h"
+#include "../structures/skiplist.h"

...
-    for(int i = 0; i < list_max_size; i++) {
-        SLList_insert(&list, i);
+    for(int i = 0; i < skiplist_max_size; i++) {
+        skiplistInsert(mylist, dis(gen));
+        skiplist_size++;
...
```

1. We create the project's **working directory**.

Perun Workflow: Repository



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2. We initialize a **VCS** (e.g., Git) for project versioning.

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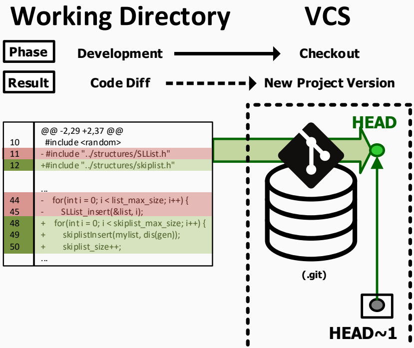
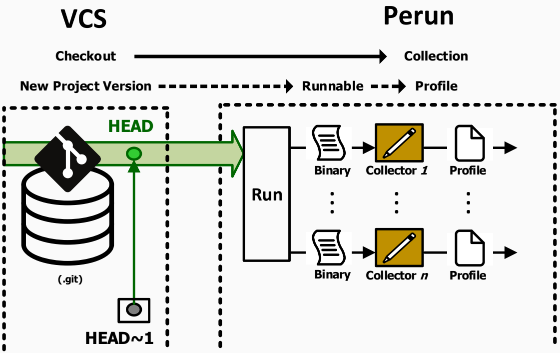


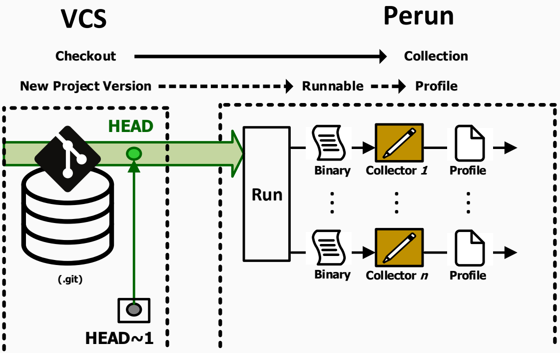
1. We create the project's **working directory**.
2. We initialize a **VCS** (e.g., Git) for project versioning.
3. We initialize **Perun** in the repository alongside the VCS.

Perun Workflow: Profiles



4. We measure project's performance and obtain **profiles**.
    - Profiles are stored within Perun and linked to the corresponding VCS version (e.g., commit).

Perun Workflow: Profiles



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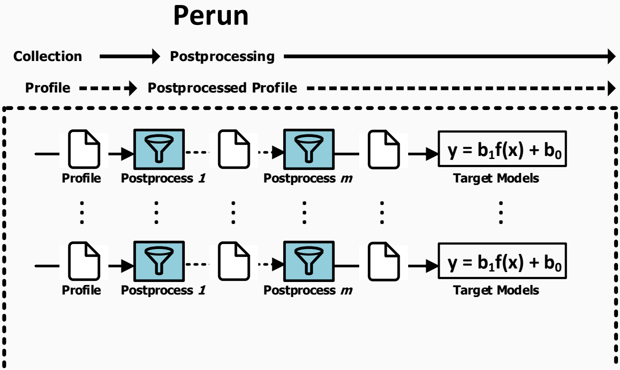
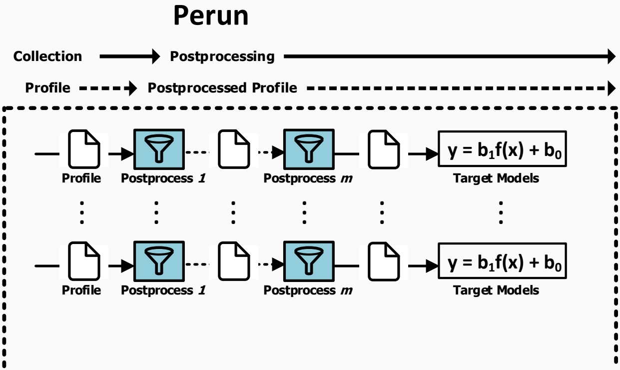


5. We create **performance models** from profiles using postprocessors.
    - Models are stored within Perun alongside the profiles.

Perun Workflow: Models



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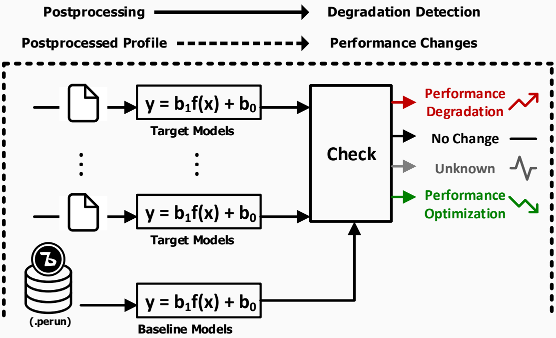

6. We detect **performance changes** using models or directly profiles.
   - Target refers to the current version.
   - Baseline refers to the previous version used for comparison.

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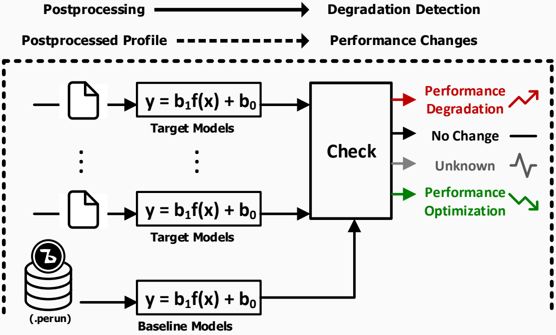

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Perun Demonstration: Finding Performance Changes

CPython: Issue #92356

- **CPython**: Reference C implementation of a Python interpreter.
- **Issue #92356**[5]: A performance regression in `ctypes` module.
  - $\approx$ 8% higher function call overhead (py3.11.0a7 vs. py3.10.4).
  - Replicated using the `pyperformance ctypes` benchmark.

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  - Can Perun help us here?

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2. We **store** a profile for CPython **v3.10.4** ctypes benchmark in Perun.
    - We denote this profile as baseline.
    - Perun handles the *profile-commit* link internally.

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CPython: Detecting Changes

3. CPython v3.11.0a7 **rolls out**.

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4. We **profile** the ctypes benchmark for CPython **v3.11.0a7**.

Perun commands

```
perun collect -c <py3.11.0a7> -a <benchmark> trace -b <files>
```

CPython: Detecting Changes

3. CPython v3.11.0a7 **rolls out**.
4. We **profile** the ctypes benchmark for CPython **v3.11.0a7**.
   - We denote the resulting profile as target.

Perun commands

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perun collect -c <py3.11.0a7> -a <benchmark> trace -b <files>
perun add <target>
```

CPython: Detecting Changes

3. CPython v3.11.0a7 **rolls out**.
4. We **profile** the ctypes benchmark for CPython **v3.11.0a7**.
    - We denote the resulting profile as target.
5. We **compare** the baseline and target profiles.

Perun commands

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4. We **profile** the ctypes benchmark for CPython **v3.11.0a7**.
   - We denote the resulting profile as target.
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   - Perun supports multiple comparison algorithms.
   - For this particular issue, we used *Exclusive-Time Outliers*.

Perun commands

```
perun collect -c <py3.11.0a7> -a <benchmark> trace -b <files>
perun add <target>
perun check -f profiles <baseline> <target>
```

CPython: Regression Detected

Location	**Result**	**T∆ [ms]**	**T∆ [%]**
_ctypes_init_fielddesc	NotInBaseline	77.95	5.23
_ctypes_get_fielddesc	SevereDegradation	52.9	3.55
_ctypes_callproc	Degradation	2.84	0.19
	...		
_ctypes.cpython-311	TotalDegradation	136.92	**9.19**

⋆ T∆: exclusive-time delta of *target* − *baseline*.

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* TΔ: exclusive-time delta of *target* − *baseline*.

- **Root cause** of the issue: repeated calls of an init function.

Function `_ctypes_get_fielddesc`

```
if (!initialized) {
    _ctypes_init_fielddesc();
}
```

CPython: Hotfix

6. We **create** a new hotfix branch and **fix** the issue.

Fixing `_ctypes_get_fielddesc`

```
  if (!initialized) {
+     initialized = 1;
      _ctypes_init_fielddesc();
  }
```

CPython: Hotfix

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```
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  }
```

1. We **Profile** the CPython hotfixed version.

Perun commands

```
perun collect -c <py3.11.0a7-fix> -a <benchmark> trace <...>
```

CPython: Hotfix

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Fixing `_ctypes_get_fielddesc`

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1. We **Profile** the CPython hotfixed version.
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CPython: Issue Fixed!

Location	Result	Δ [ms]	Δ [%]	Δ_{old} [ms]	Δ_{old} [%]
	...				
_ctypes_get_fielddesc	MaybeDegradation	0.89	0.06	52.9	3.55
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- The **_ctypes_init_fielddesc** Δ is now negligible.

$\Rightarrow$ Perun leverages **VCS** and **Recency** to successfully discover and help locate performance issues in new project versions as soon as possible.

Efficient Profiling Techniques

Core Concepts of Efficient Profiling

Observation 1

A **subset** of profiled functions is responsible for sizable portion of the overhead while producing **uninteresting performance models**, e.g.:

- Hundreds of millions of times called $\mathcal{O}(1)$ functions.
- Functions with constant-like runtime behaviors.

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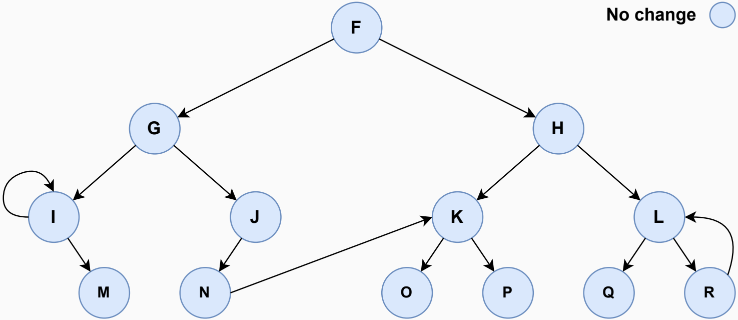
Observation 2

Even **performance-wise** significant functions that are to be profiled may generate substantial amount of records and thus cause **significant** time and space **overhead**.

$\Rightarrow$ Only a subset of the total data may be captured at the cost of profiling precision.

Recency: Diff Tracing

- We identify functions that have *changed* since the last profiling.



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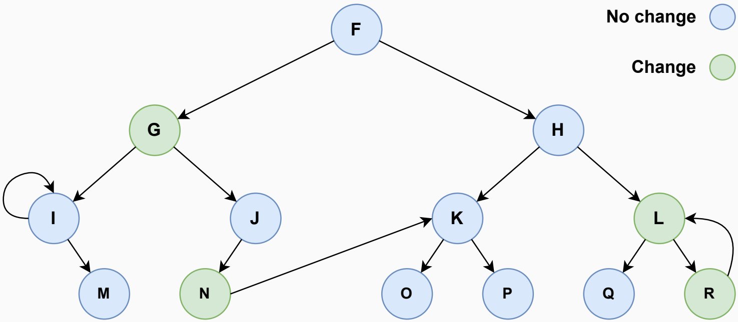
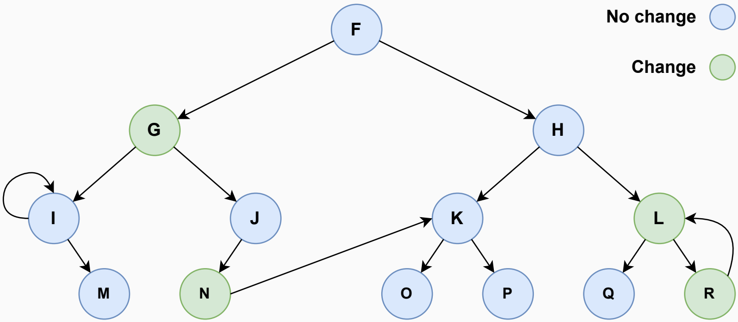


Recency: Diff Tracing

- We identify functions that have *changed* since the last profiling.
  - ⇒ Such functions must be profiled.
- **Challenge:** how to define and detect a *changed function* with respect to performance metrics?

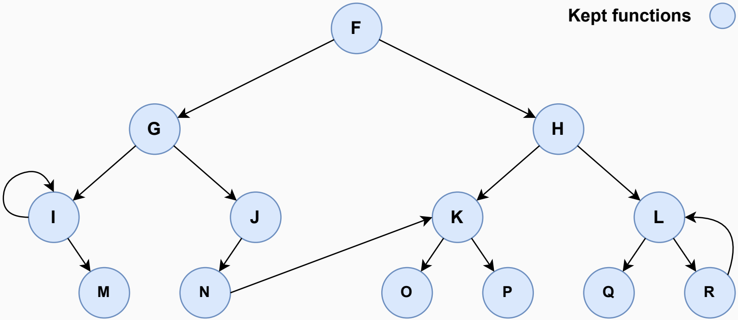


Code Structure: Call Graph Projection

Call Graph Observation

The *number of calls* of a function from a given call site *often grows* with the length that the call stack has upon reaching the call site.

- Backed by experiments on CCSDS and CPython projects (87–96 %).



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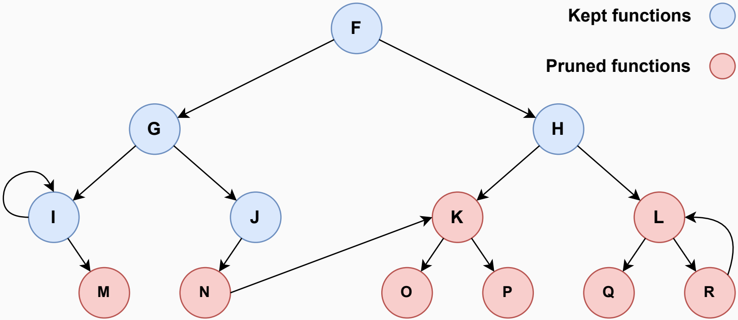

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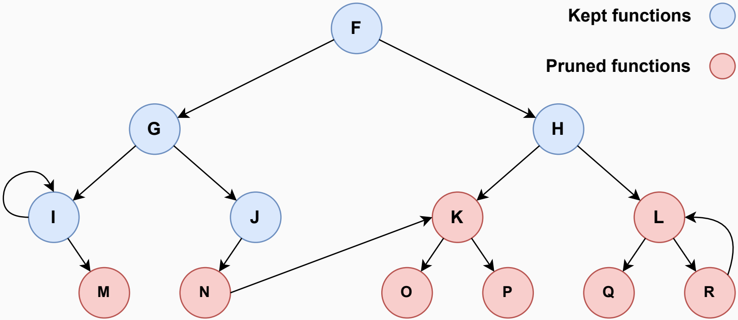
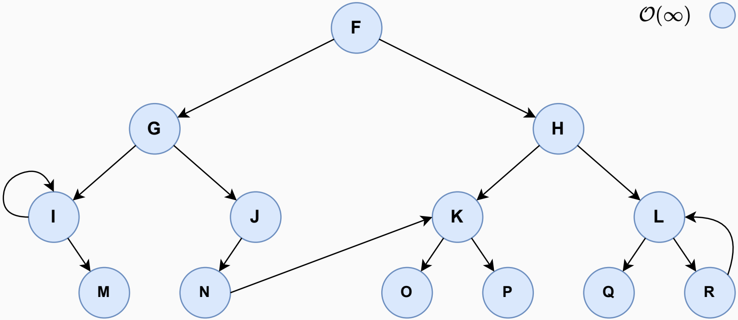
- **Challenge:** how to define the *Call Graph Depth* with respect to the *Call Graph Observation*?



Expected Performance: Performance Baseline

- *Static:*
- *Dynamic:*



Expected Performance: Performance Baseline

- *Static:* We do not profile functions below certain complexity.
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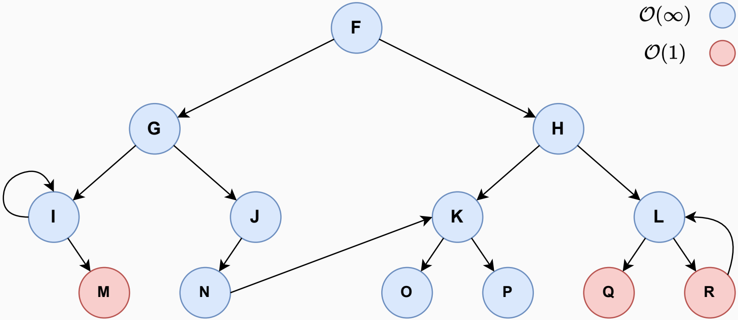

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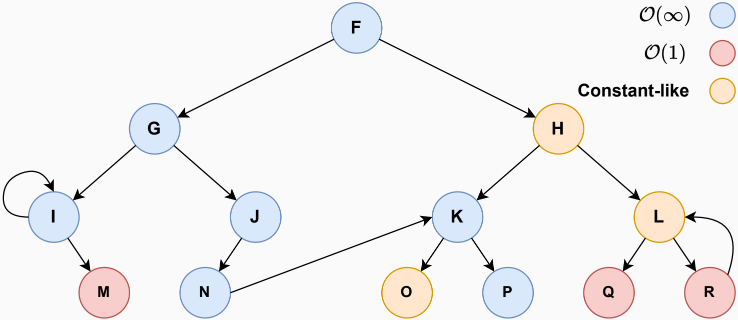

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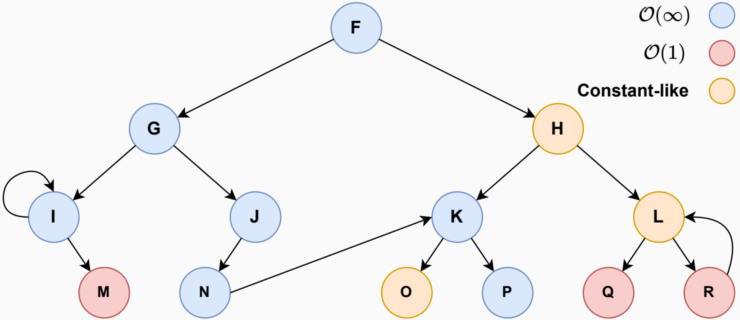
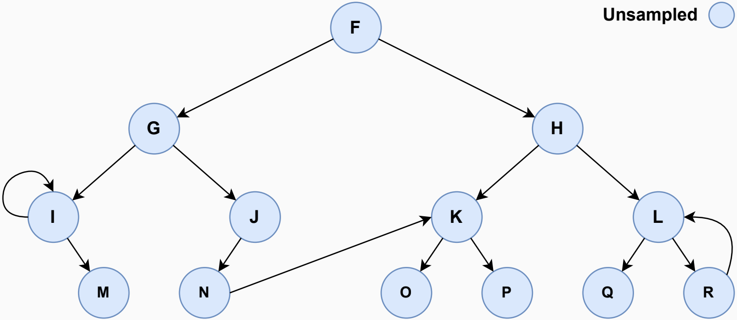


Profiling Process Refining: Sampling Control

- Only a subset of performance data are necessary for sufficiently precise models.



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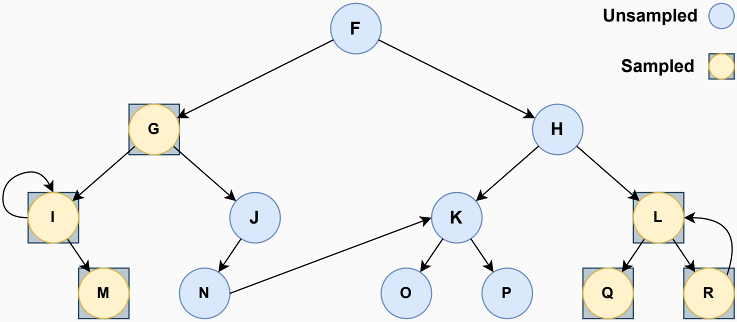

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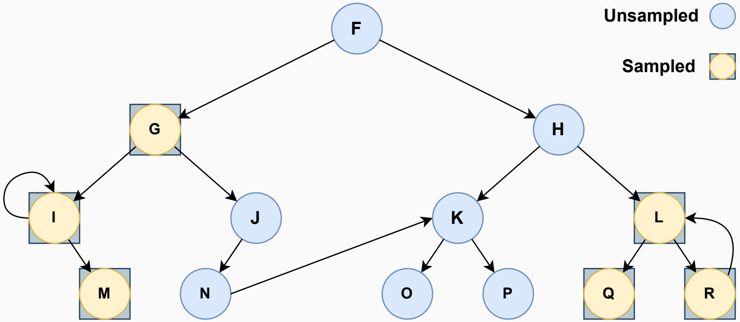
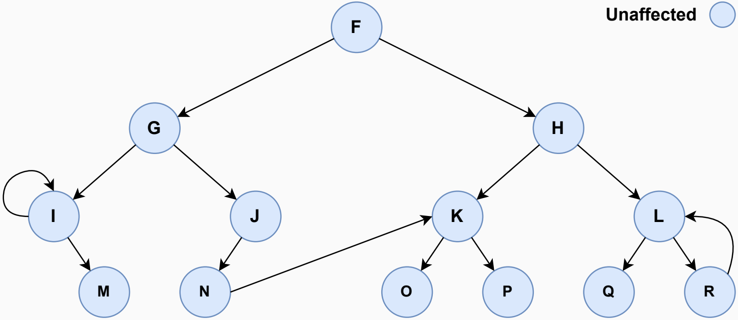


Optimization Pipelines

- Key idea: **combine** the aforementioned approaches.



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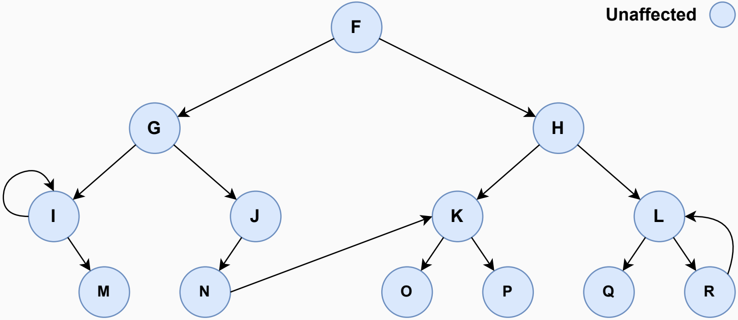

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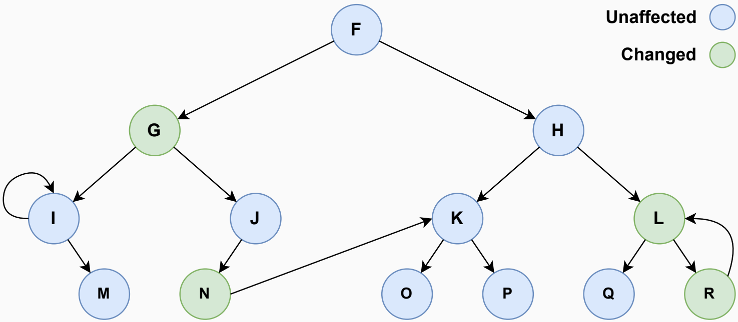

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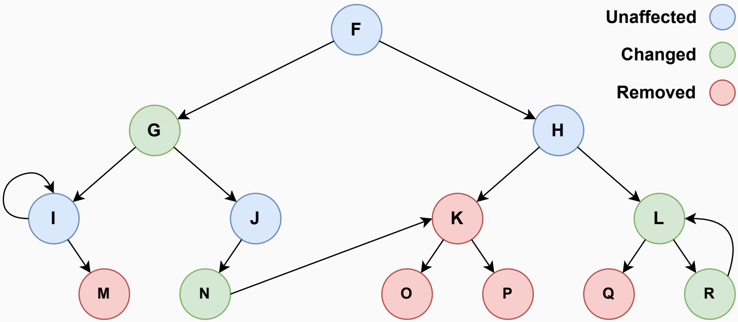

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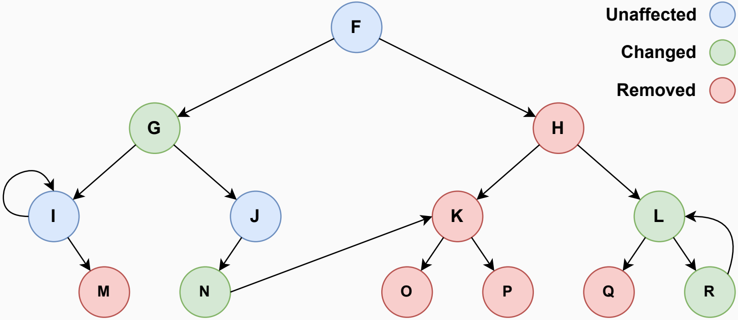

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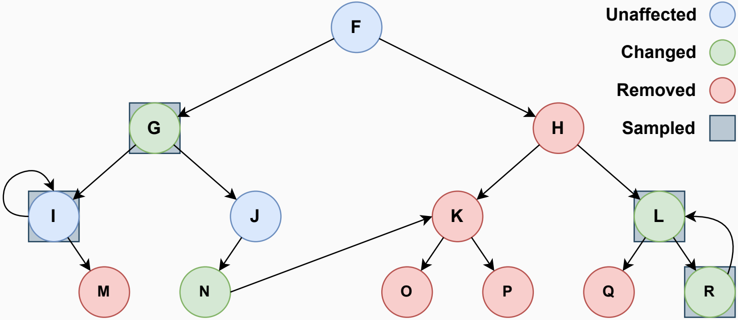

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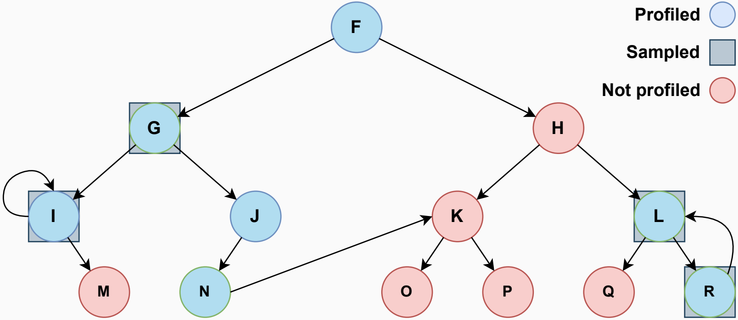

Preliminary Experimental Evaluation

- So far, we have conducted two case studies (more in progress):
  1. (RQ1) *How significant is the impact of the individual optimizations on the profiling process?*
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	open122	**CPython**	**Gedit**	**emacs**	**vim**
LoC	10,000	500,000	35,000	400,000	480,000
$\lvert\mathcal{F}_P\rvert$	83	1,883/1,227	569	1,826	4,382
branch	2984883	3.8/2.7	3-36	2.71	8.2
$\texttt{runs}_{opt}$	5/10	0/1	2/3	2/3	2/3
$\texttt{runs}_{\pi}$	5/10	0/1	5/5	5/5	5/5

Results: CPython

Python3

Pipeline	Total [s]	Data [MiB]	$\|\mathcal{F}_P\|$	$Cov_{\mathcal{H}}$ [%]	$\delta_{\mathcal{H}}$	$U_{\mathcal{F}_P}$ [%]	$O_{\mathcal{F}_P}$ [%]
no-opt	39,304.19	164,022.73	53,360.00				
π_{10}	14,514.99	56,907.35	39,981.00	40.00	1.00	2.02	3.38
π_{25}	3,847.49	11,482.11	28,741.00	20.00	1.00	2.56	5.59
π_{50}	3,425.64	9,339.42	26,826.00	20.00	1.00	2.79	6.34
π_{75}	2,647.76	5,602.77	24,419.00	20.00	1.00	3.55	6.43
π_{90}	1,683.27	1,572.93	5,471.00	20.00	1.00	0.00	3.85
no-prof	577.58						

Python2

Pipeline	Total [s]	Data [MiB]	$\|\mathcal{F}_P\|$	$Cov_{\mathcal{H}}$ [%]	$\delta_{\mathcal{H}}$	$U_{\mathcal{F}_P}$ [%]	$O_{\mathcal{F}_P}$ [%]
no-opt	43,568.59	171,842.30	34,356.00				
π_{10}	20,704.52	73,768.39	25,432.00	50.00	1.00	2.42	3.57
π_{25}	11,421.38	37,963.51	18,833.00	40.00	1.00	3.41	4.63
π_{50}	8,674.45	26,793.04	15,300.00	40.00	1.00	2.96	4.77
π_{75}	5,270.95	12,825.88	6,969.00	30.00	1.00	2.74	0.00
π_{90}	3,345.23	4,800.91	3,180.00	20.00	1.00	0.00	0.00
no-prof	527.19						

Conclusion

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- We believe **profiling efficiency can be significantly improved**.
  - Reuse of historic profiling data when possible.
  - General profiling optimizations and their combinations.
- **Ongoing and Future work:**
  - Further improving the **efficiency**, **granularity** and **precision**.
  - Support for more **languages**, performance **metrics**, existing **tools**.

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- In no particular order:
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    - Czech Science Foundation Project 23-06506S
    - JCMM PhD Talent Scholarship Programme

A Journey Towards Efficient Profiling

Alpine Verification Meeting 2023

Jiří Pavela

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Perun Github: `https://github.com/Perfexionists/perun/`
Paper Demo VM: `10.5281/zenodo.6783242`

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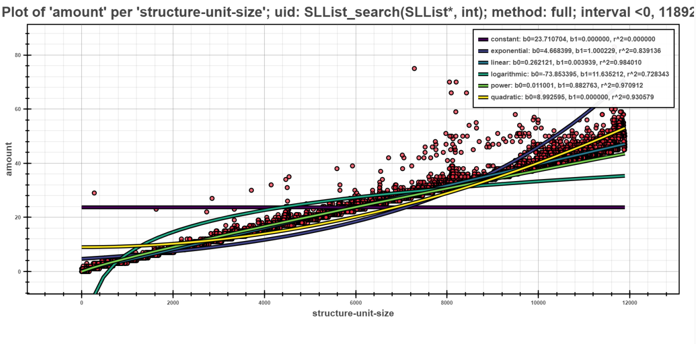
JCMM PhD Talent Scholarship Programme

Perun Workflow: Models Example

- Models in Perun are **mathematical functions** of the input size or **statistical summaries** describing the main features of the profile.



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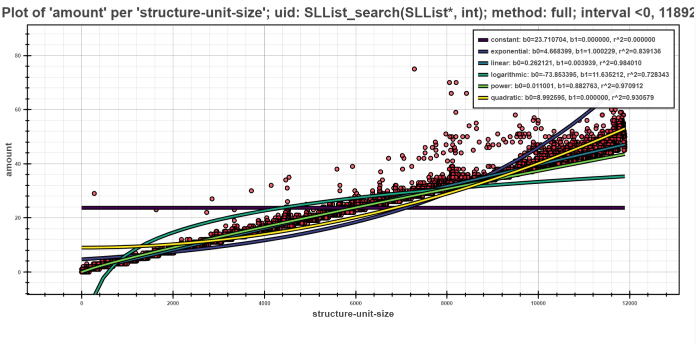

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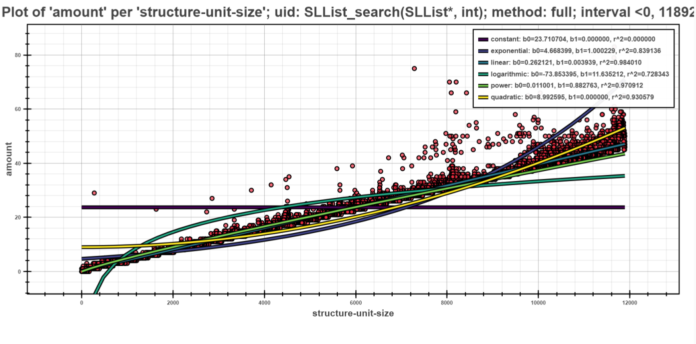
- For example, in regression analysis:
  - the curve is described using **function** $y = b_1 f(x) + b_0$,



Perun Workflow: Models Example

- Models in Perun are **mathematical functions** of the input size or **statistical summaries** describing the main features of the profile.
- For example, in regression analysis:
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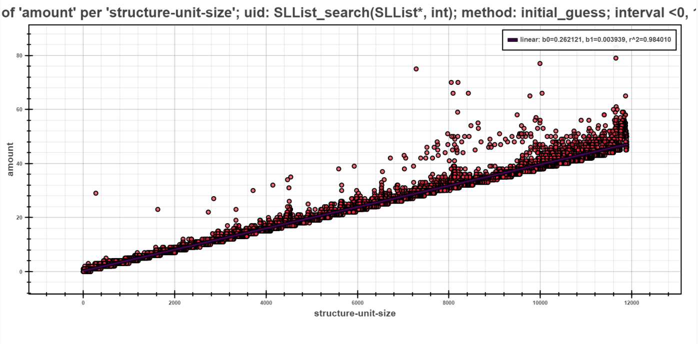
  - and the model quality as **coefficient of determination** R^2.



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  - *Integral Comparison*
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    - Standard deviation multiple $\quad \overline{X} - k \cdot \sigma < x < \overline{X} - k \cdot \sigma$