

ProfiT-HPC: Architecture and Recommendation System

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Overview

1 Project

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- Goals

2 Architecture

- Implementation
- Development
- Metrics
- PfiTCollect
- Aggregator

3 Recommendation system

- Overview
- Rule based recommendations

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- ProfiT-HPC: Profiling Toolkit for High Performance Computing
- Duration: 01.02.2017 31.01.2020
- Partners:



Project Goals



Goals

Motivation

Comprehensive performance analysis of jobs.

Users get reports with necessary information about the job to evaluate its efficiency and tweak submission parameters or programs if needed.

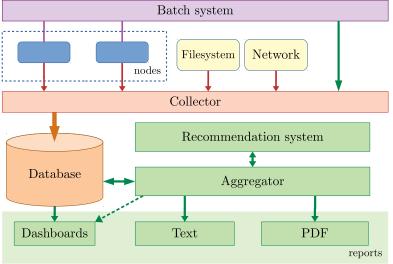
Goals

- Auto generated reports with following data:
 - chosen metrics and performance indicators
 - recommendations to reach higher efficiency
- Improved resources utilization of HPC

Architecture

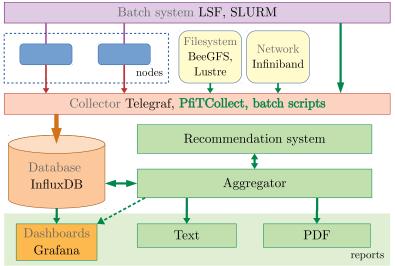
Architecture





Profit-HPC

Architecture Implementation



Implementation

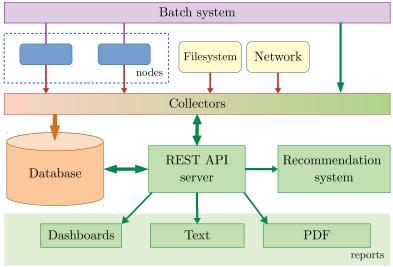


Implementation

Module	Language
PfiTCollect	С
Telegraf plugins	GO, bash
Grafana dashboards	InfluxQL
Aggregator	Python
Text report	Python
PDF report	Python
Recommendation system	Python
Epilog scripts	bash



Alternative architecture





Why modular?

System design

- Every part is independent
- Communicate only via established interface (API, REST)
- Modules can be substituted / reimplemented

Development

- Every site implements module independently
- Easy to substitute dependent modules with stub implementation
- Every module can be encapsulated in its own environment

Dev environment



Modular architecture allows to develop modules of the toolkit with stub implementation of dependencies.

Module	Dependency	Stub type
PfiTCollect	OS & Env	Container
Telegraf plugins	OS & Env	Container
Aggregator	Database	Container
Grafana dashboards	Database	Container
Text report	Aggregator	JSON file
PDF report	Aggregator	JSON file
Recommendation system	Aggregator	Python object
Epilog scripts	Batch system	Bash script

Metrics



Nodes	Processes
CPUMemorySystem	CPU timesMemoryIO
Filesystem	Others
LustreBeeGFSLocal	JobGPUNetwork (Infiniband)

Metrics

PfiTCollect



- light weight metric collector
- implemented for ProfiT to gather metrics fast, without overhead
- substitute for Telegraf and works with InfluxDB

Telegraf

- + Large community
- + Extendable (plugins)
 - Heavy (27 MB Executable)
 - Many dependencies (GO)

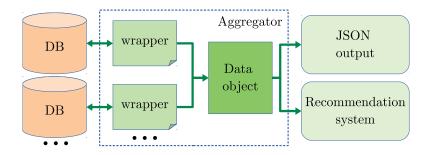
PfiTCollect

- + Very lightweight (\sim 100KB)
- + Easy compilation
 - No external community





- Aggregator Python module to collect the data and pass it further to reports or other parts of the toolkit
- It also provides API to retrieve the data as a Python object



Recommendation system



Recommendation system

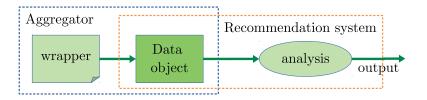
Recommendation system



Definition

Recommendations are comprehensive instructions for users to help with improving efficiency of their jobs

Recommendation system is designed to be completely separated from other parts of the toolkit. Only data should be provided.



Rule based recommendations



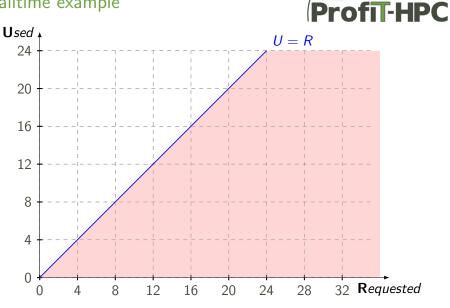
Rules are natural way to give recommendations in current systems by experts

Example

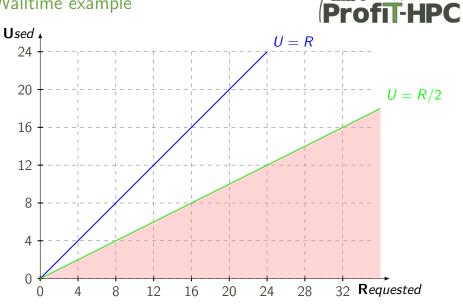
Case Users request high wall time, resulting to long pending state Rule If runtime of the job is half or less than requested walltime (runtime \leq requested/2) Advice Request less walltime

However, deriving such rules are complicated, even for such simple cases...

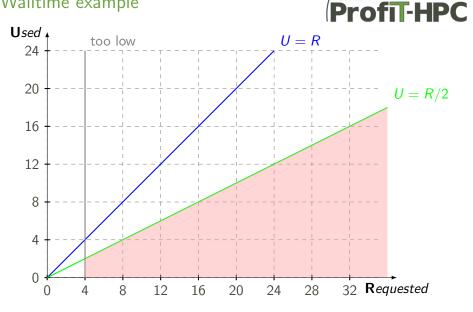
Walltime example



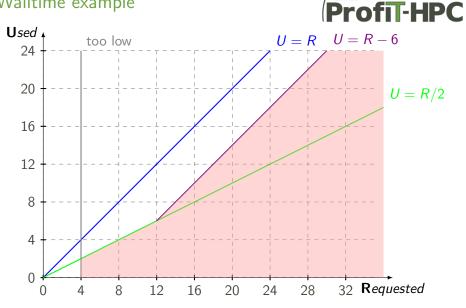
Walltime example



Walltime example



Walltime example



Rules and Attributes



Attribute is a property of the job with predefined values

 $A \in \{V_1, V_2, ..., V_n\}$

For example, used_walltime attribute might be LOW or NORM

Rule is a set of attributes with specified values

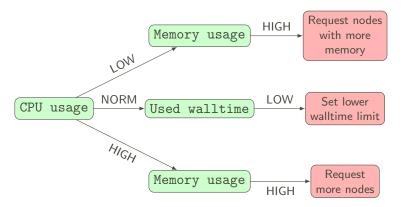
$$R: A_1 = V_1 \& A_2 = V_2 \& \dots \& A_k = V_k$$

For example, *fix_requested_walltime* rule might be formed by attributes like *used_walltime* = LOW & *cpu_usage* = NORM

Decision trees



The set of the rules can be represented and visualized as a decision tree





Anomaly detection

Anomaly detection



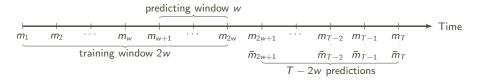
General problem

Calculate anomaly score of a program using measurements during a runtime



Anomaly detection implementation





- **1** Neural Network is trained on previous measurements every time step
- 2 It makes prediction for the next time step
- 3 Prediction is compared to the observed value and anomaly score is calculated

Anomaly Score



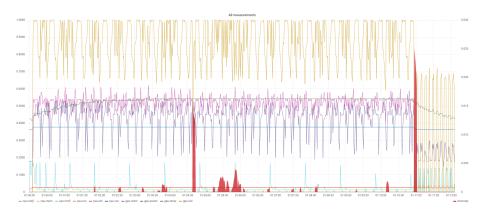
Threshold

- Points with higher anomaly score than threshold considered to be anomalous
- Threshold dynamically calculated using standard deviation of previous points
- Adjustable with parameters (scaling and smoothing)

Anomaly detection example



Anomaly detection of GPU utilization with neural networks



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Anomaly detection challenges



- Such anomaly detection mechanism produces false positive results, especially when a program has various runtime phases
- Measurements usually have large amount of noise
- Measurements sometimes don't have patterns
- Proposed anomaly detection models were trained using measurements which were taken *every second*



Thank you! Questions?

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