Symposium on Software Performance

13th November 2020

A Dynamic Resource Demand Analysis Approach for Stream Processing Systems

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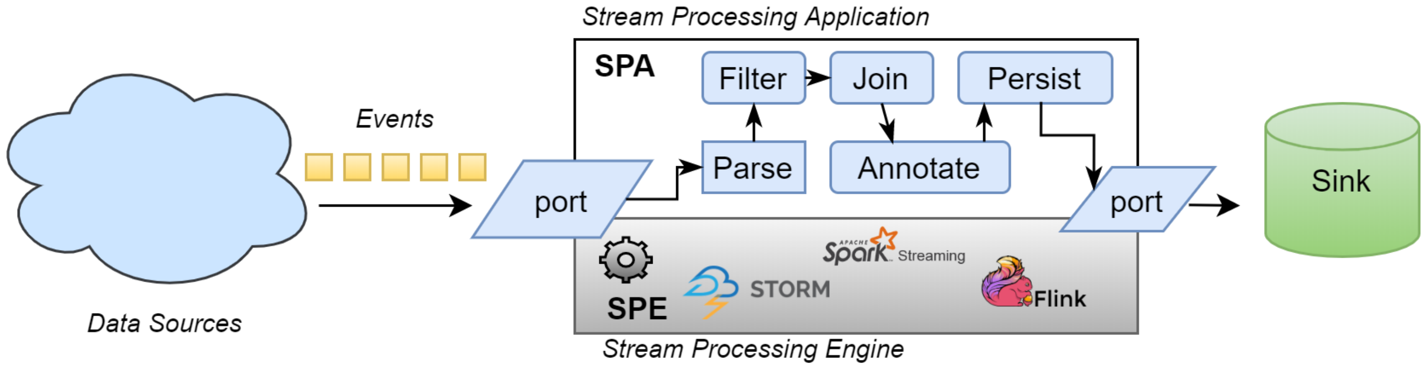
Motivation

- What is Event Stream Processing?



  - Examples: Market feed processing, infrastructure monitoring, fraud detection (Stonebraker, M., et al. 2005)

- **Importance of Performance** for Stream Processing
  - For SPS **performance** is not only a quality of service aspect, but **vital** for the whole business scenario to succeed (Stonebraker, M., et al. 2005)
  - **Crucial need for building scalable systems** to enable the processing of vast amounts of streamed data (Bedini et al. 2013)

Stream Processing Systems Diversity

- Stream Processor Engines (SPE)
- Stream Processing Application (SPA)

SPE	Language Support
Flink	Java, Python
Apex	Java, JavaScript, Python, R, Ruby
IBM Infosphere Streams	SPL (Streams Processing Language), Java, C++
SAP Hana Streaming Analytics	CCL (Continuous Computation Language)
Apache Spark Streaming	Java, Python
Apache Storm	Java, Python, Ruby, Javascript, Perl

➡ **How to compare performance between systems?**

Related Work

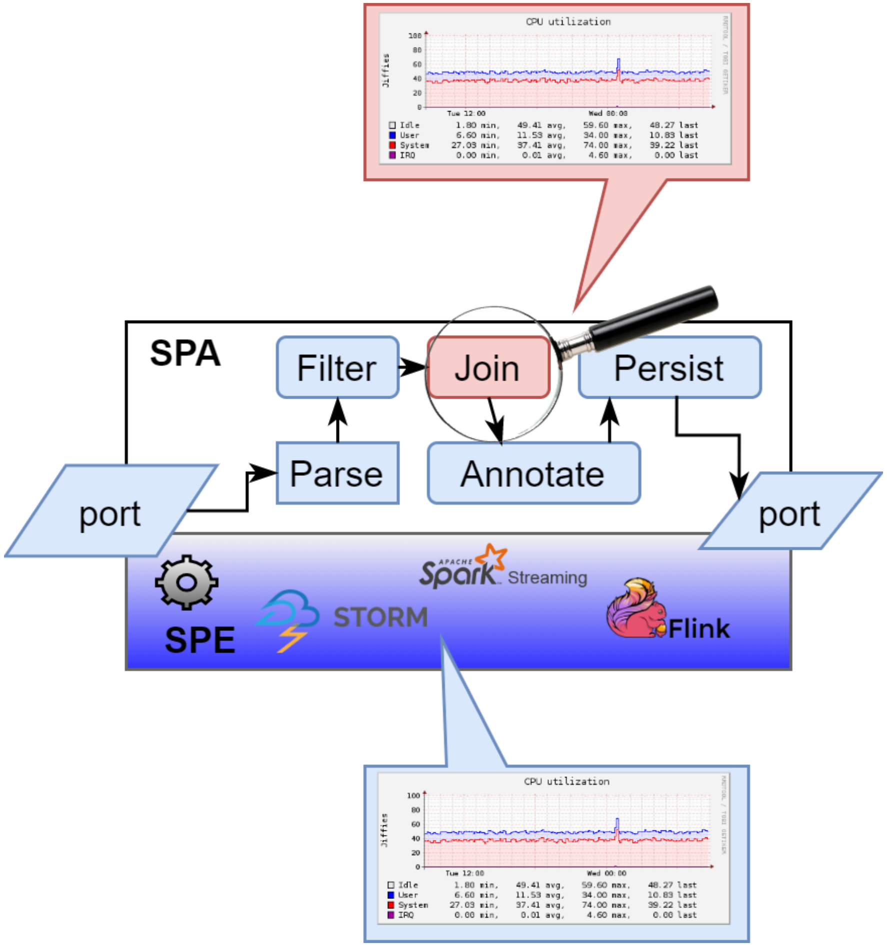
- Related work focuses on **throughput** and **latency**
  - Throughput and latency (Chintapalli, S., et al. 2016)
  - Maximum sustainable throughput (Karimov et al. 2018)
  - Latency measurement for individual processing stages (Dongen et al. 2018+2020)

  - ➢ Easy to measure
  - ➢ But no insights into the resource demands

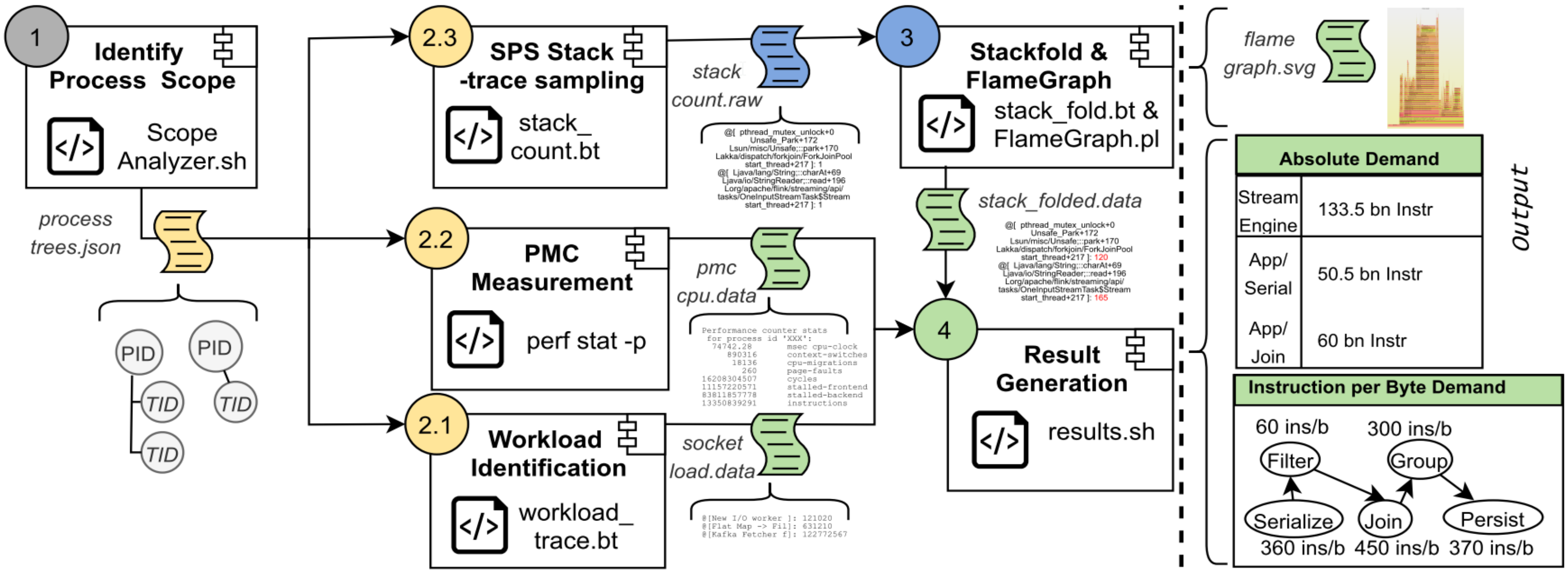
- Resource efficiency becomes increasingly important for stream processing
  - IoT edged computing with limited resources (e.g. Raspberry Pi 3) (Xhafa, F., et al. 2020)
  - Cost advantage in large-scale deployments

Idea

- Measuring resource demand of **individual operations** of the streaming application **and the engine** itself …
  - without language centric tools (e.g. Java Profiler),
  - dynamically (applicable for running applications),
  - without source code knowledge
  - and production safe (non-disruptive performance overhead)



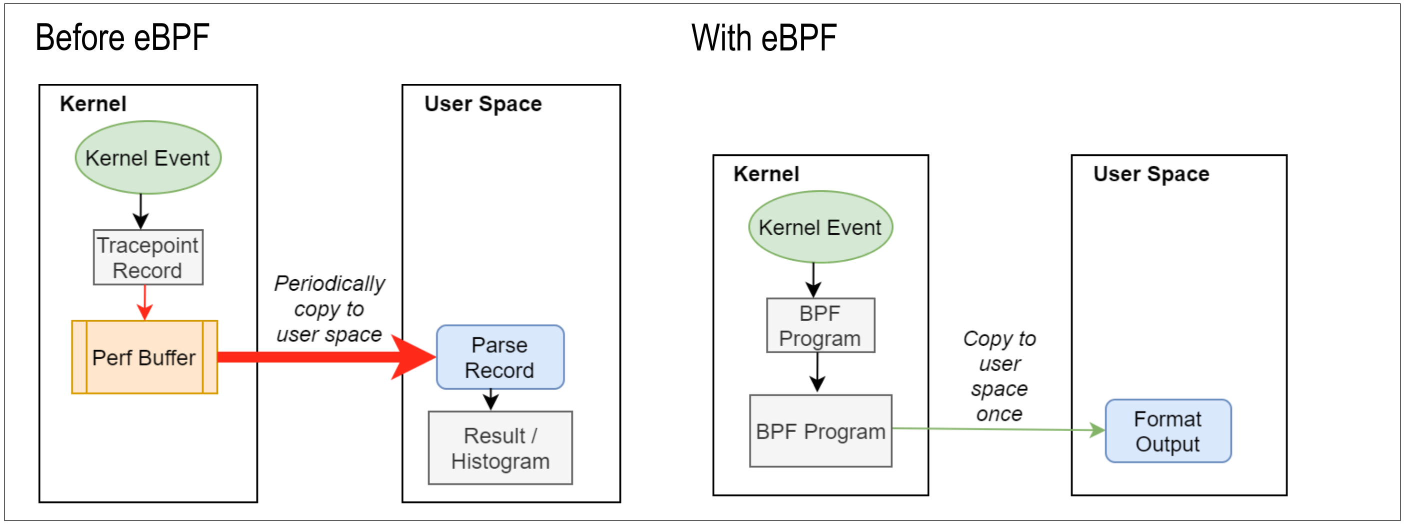
Toolchain



- (1) Collect all PIDs and TIDs of the SPE and Application
- (2.1) Trace consumed events/data in bytes
- (2.2) For all PIDs identified in step 1, count the number of cycles and instructions via PMC
- (2.3) For the PID of the streaming application sample stack traces at 999 Hz
- (3+4) Combine the results from 2.1 – 2.3 to calculate the absolute CPU demand for the SPE and application, as well as the individual cpu/byte demand for every processing task

Technology

- **eBPF** (Extended Berkley Package Filter) – Step 2.2
  - Added to the Linux Kernel in release 3.18 (KernelNewbies 2014)
  - Allows to process events in Kernel space
  - Bpftrace is a high-level language for eBPF
  - Enables efficient stack sampling (Phase 2.3) and Workload tracing (Phase 2.1)



Gregg, B. (2019)

Technology

- **PMC** (Performance Monitoring Counters) – Step 2.2 (Gregg, B. 2019)

  - Programmable counters on the CPU
  - Dedicated registers on the CPU to collect performance metrics
    - Counting the number of cycles or instructions costs practically no performance overhead

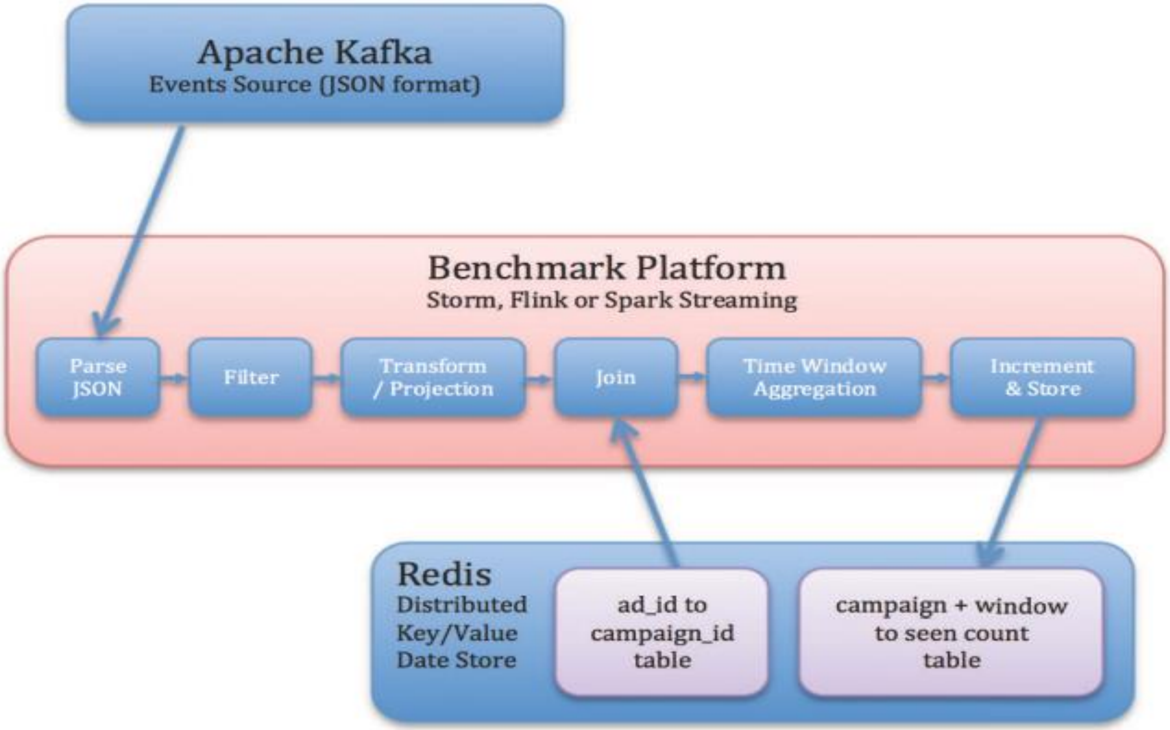
  - PMCs need to be supported by a hypervisor in virtualized environments
    - Supported by Xen
    - Available in AWS since 2017

  - Access to PMC via the perf_events utility
  - BPF tracers may call the perf_events utility to access PMC information

Gregg, B. (2019)

Experiment

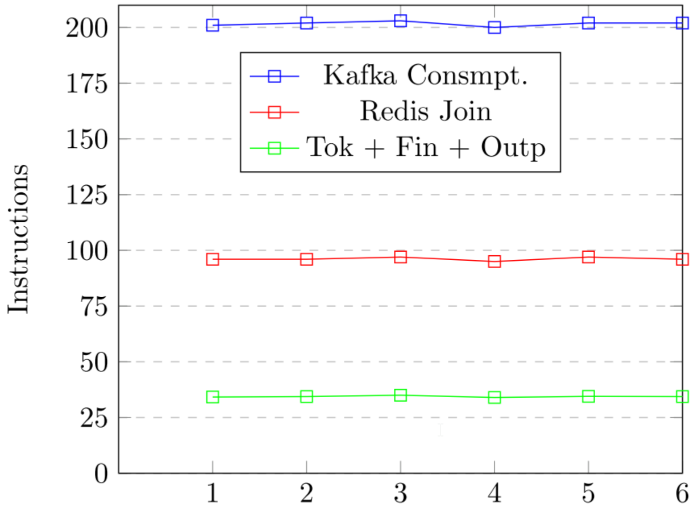
- Execute the Yahoo streaming benchmark (Chintapalli, S., et al. 2016) and measure the performance demand of Apache Flink in a single-node configuration
- Measured with two load variants 2k events/s and 4k events/s



(Chintapalli, S., et al. 2016)

Experiment

- Methodnames are obtained via the java symbol names (requires jdk-debug package)
- For each processing task the actual consumed CPU instructions can be collected
- Results are consistent for measurments >30min (distribution of CPU consumption among tasks)
- Minor processing tasks such as the „filter“ are not visible due to their neglectable performance impact
- No considerable performance overhead during measurement



CPU instructions for processing 1 Byte from Kafka

	2k Instr	2k IPC	4k Instr	4k IPC
Application	810 bil	0.73	1661 bil	0.75
SPE/Cluster	13.5 bil	0.29	12.5 bil	0.29
SPE/Client	1.0 bil	0.24	1.9 bil	0.23

Average CPU Instructions

Conclusion

- ✓ Dynamically applicable (but JVM symbol translation requires startup parameter)
- ✓ No source-code knowledge required (task dependency cannot be reverse-engineered)
- ✓ Small performance overhead during monitoring (when samplingrate <= 999 Hz)
- ✓ Broad support of different SPEs (eBPF part of Linux Kernel)
- ✓ Extensive insights into the actual resource consumption of SPE and SPA

- ○ Major operations are visible but low performance operations might be neglected (e.g. Filter operation)
- ○ Sampling induces high disk utilization after monitoring for dumping the stacktrace (spare ressources in production scenarios necessary)

Future Work

Yahoo Streaming Benchmark

- Fully integrate toolchain into the Yahoo Streaming Benchmark
- Benchmark the resource efficiency of contemporary SPS

Performance Prediction

- Yielded metrics can be integrated into a model-based performance prediction approach
- Example: Scalability predictions based on the Palladio Component Model (Becker, S., et al. 2009)

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Thank you for your attention!

Questions?

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