TDD25
Distributed Systems

Distributed Stream Processing

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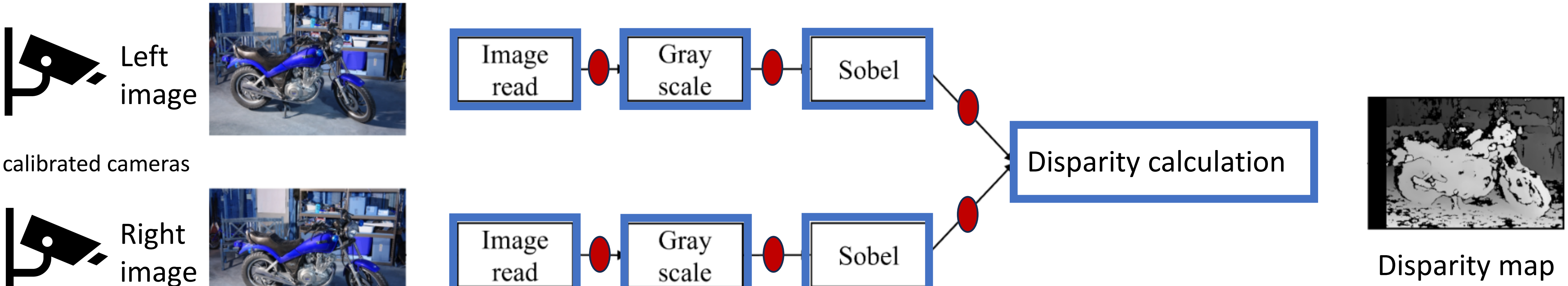
Data Stream

- Possibly infinite sequence of stream elements
- Elements can be values of base type, structs, strings, images, video frames, …,
  key-value pairs,
  time-stamped or indexed
- Encoding: can be
  - binary-native (platform-specific, not portable – use at best within same computer),
  - binary-portable (framework-specific), or
  - text-based (e.g. CSV, JSON, YAML, XML) – wasteful in space and time, but universally portable and even human-readable
- Streams may have a fixed or varying **data rate** (*velocity*, #elements per second)
- In certain stream processing applications, some stream elements might even be **malformed** due to errors in preceding stages – needs be handled at processing

Stream Processing Application

- **Stream sources** (input streams)
  - E.g., from sensors, network connection, (continuous) database query, file read position
- **Stream sinks** (output streams)
  - E.g., to display, file, actuators
- **Stream processing tasks / stream operators**
  - Transform input to output streams by elementwise computation or aggregate input stream elements (e.g., elements with same key)
  - executed whenever new data has arrived
    - execution of a task instance can be input-triggered or time-triggered)
    - may thus exist as long as the overall application itself.
  - Can be stateless or stateful
  - Have input and/or output **ports** that connect to streams from stream sources, to stream sinks or to/from other stream operators' ports
- **Internal streams** connect (ports of) multiple dependent stream processing tasks
  - Stream-**producer** tasks/ports forward data to stream-**consumer** tasks/ports

Example Application: Stereo Depth Estimation

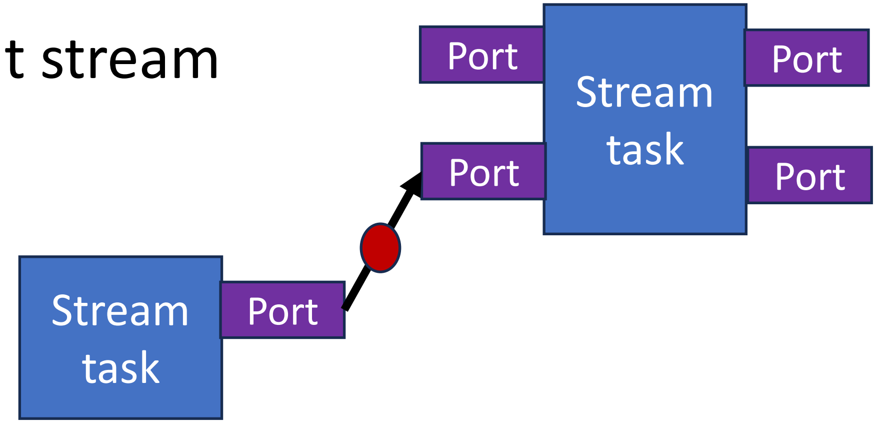


Workflow describing a complex stream processing pipeline

- **Tasks**: stream-processing tasks, stream operators
  - Input and output **ports** – one per input and per output stream
- **Streams**: FIFO-queue-buffered dataflow

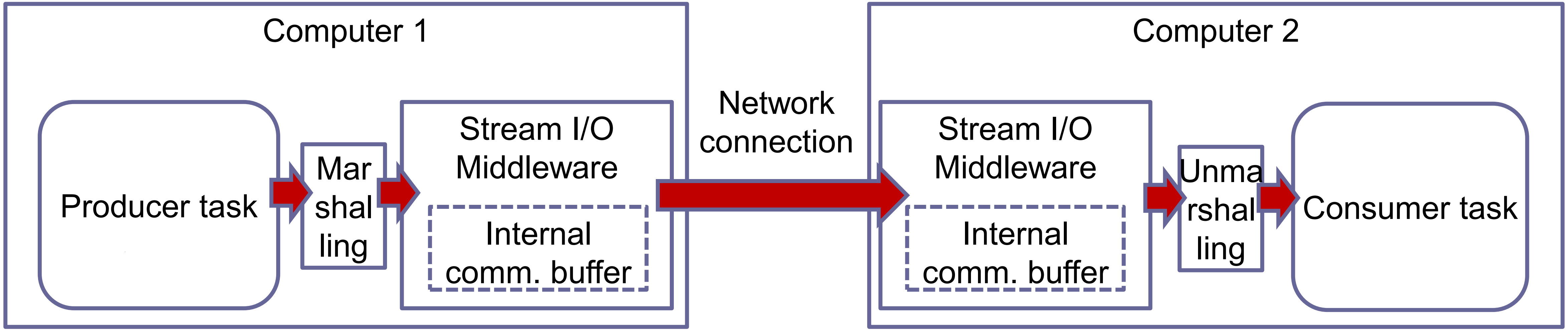
Formally: A bipartite directed acyclic graph (DAG)

G = (Tasks, Streams, Data-flow edges)



Stream Processing Systems

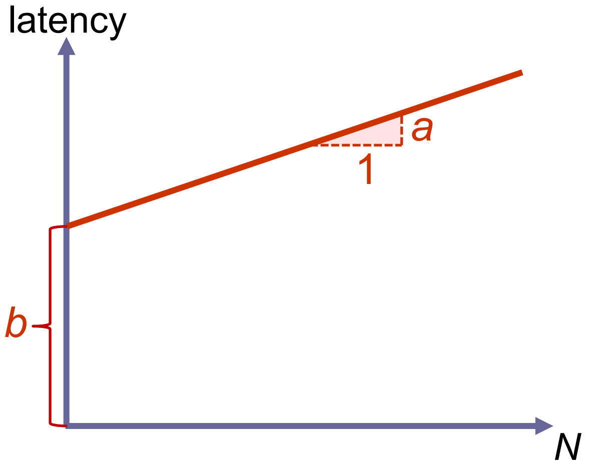
- Where a stream's producer and consumer are mapped to different computers, we need **middleware** and **glue code** (cf. CORBA for RPC/RMI) to mask heterogeneity.



- Optionally, windowing (batching) techniques can be used to aggregate multiple subsequent stream elements to coarser-grained units of further processing and forwarding
  - Often done for input streams from stream sources

Background: Work Agglomeration by Batching

Goal: Reduce average per-element overheads in communication and processing



- **Time** (latency) for **communicating** a message of *N* bytes is usually linear in *N*:

  $T_{msg}(N) = a*N + b$ for constants* $a, b > 0$

  (* a, b still depend e.g. on network distance between sender and receiver)

  - *a*: **per-byte transfer time**, network throughput - typically *a* ~ few nanoseconds
    - limited by network connection bandwidth
  - *b*: **per-message transfer overhead** (usually, ***b* >> *a***) - typically *b* ~ microseconds
    - due to network software overheads, message headers (metadata, e.g. addresses, checksums), routing, physical network delays

- **Time** for elementwise **processing** (loading, parsing, transforming, storing) a batch of *M* elements is often linear in *M*:

  $T_{transf}(M) = c*M + d$ for constants $c, d > 0$

  - *c*: **per-element processing time**
    - Limited by memory bandwidth and computational bandwidth of the processor
  - *d*: **batch-processing startup time**
    - Due to memory latency, parsing overheads, launching processes/threads/kernels, etc.

→ Communicating messages and processing batches of **1** element size is possible, but very **inefficient**.
The larger the batch size, the lower the amortized per-element overheads (*b* / #elements in message, *d* / *M*).

Windowing Techniques

- Application-specific **windowing** techniques can be applied (e.g. to stream sources) to **aggregate** multiple subsequent stream elements into coarser-grained units of work for further processing
  - A generalization of **batching**
  - Trades higher throughput (lower per-element overhead) for longer latency for some stream elements
    - Granularity of work becomes large enough to reduce per-element overhead (e.g. for data transfers in larger packets) and possibly use parallel computing or accelerators in tasks to speed up processing.
    - But waiting for more input elements to arrive in order to form larger batches also increases end-to-end latency for the earlier ones – linearly with the batch/window size
  - Whenever the current window on an input stream is considered **full**,
    it will be **dispatched** as a packet for further stream processing,
    and the window on the input stream is moved (slided or tumbled).

Windowing Techniques

When is a window considered **full** for the application?

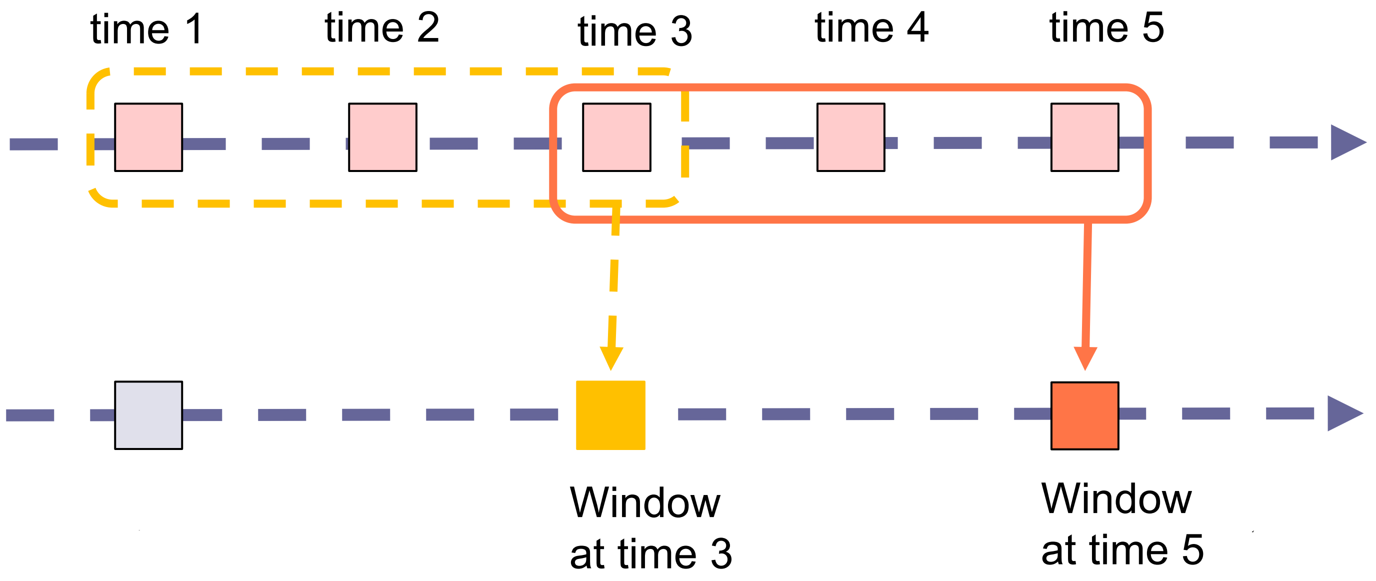
- **Capacity based**: if it contains *K* elements or no further elements can be stored
  - Corresponds to traditional batching (as used e.g. in ANN training and inference)
- **Wallclock time based**: whenever *S* seconds have passed since the window was moved last (also if there is some capacity left)
- **Timestamp based**: if an element with a timestamp newer than some threshold *S*' since the timestamp of the oldest element in the window has arrived
  - Time-based windowing may produce window instances that contain varying amounts of elements.

Subsequent window instances may overlap or not

- **Tumbling window**: The window is moved so the next window instance contains only new elements. Different window instances contain different stream elements.
- **Sliding window**: Subsequent window instances overlap partially so that recent stream history is considered together with the elements arrived since the last move.

Windowing Example: Spark Streaming

- Can define a sliding window over a source DStream



Window length (here 3)
Slide length (here 2)
→ Overlap size (here 1)

Every time the window slides over a source DStream, the source elements that fall within the window are forwarded as input to a Spark batch-processing computation (as an “RDD”)

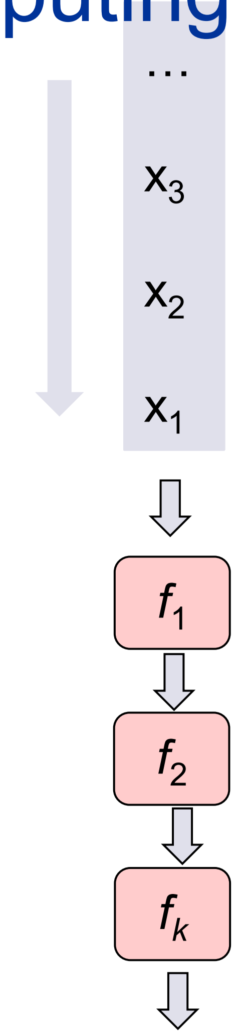
```
# Example:  Reduce last 30 seconds of data, every 10 seconds:
windowedWordCounts =    \
  pairs.reduceByKeyAndWindow( lambda x, y: x + y, lambda x, y: x - y, 30, 10 )
```

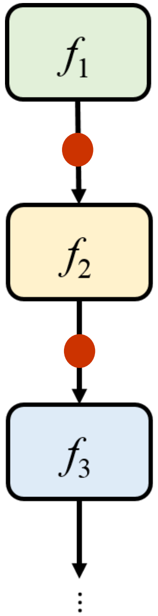
Pipelining (algorithmic design pattern in parallel computing)

Applicable if a sequence of dependent computations/tasks (f_1, f_2, ..., f_k) is elementwise applied to data sequence $\boldsymbol{x} = (x_1, x_2, x_3, ..., x_n)$

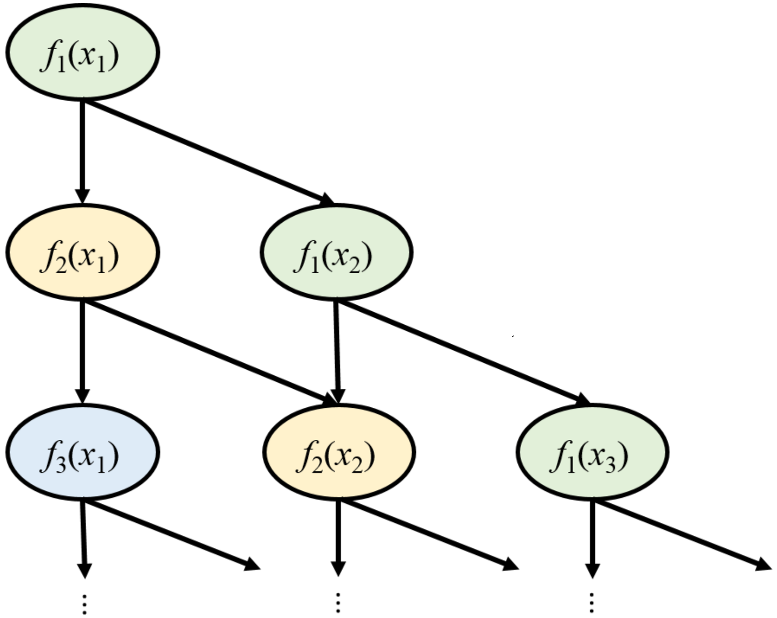
For fixed x_j, must compute $f_i(x_j)$ before $f_{i+1}(x_j)$

… and $f_i(x_j)$ before $f_i(x_{j+1})$ if the tasks f_i have a *run-time state* (*stateful tasks*)





Pipeline stage/task dependence graph



Task instances dependence graph (trace)

Remark: It is possible to explicitly create a new one-shot task for each instantiation (input) $f_i(x_j)$ of a pipeline task f_i. However, this involves high runtime overhead for dynamic task creation, resource allocation/mapping and scheduling. For long-running pipelines with statically predictable task workloads it is often better to have each pipeline task assigned to a fixed resource for executing all its instances.

Pipelining

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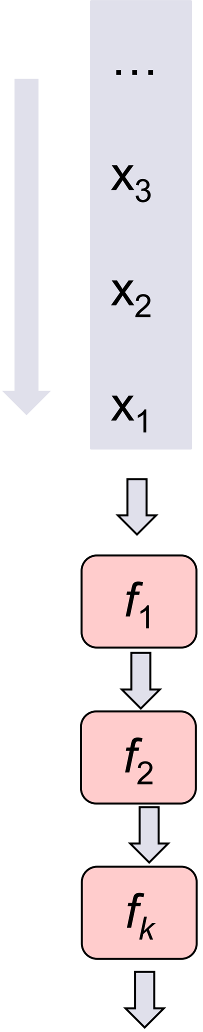


Parallelizability: Overlap execution of all f_i for k subsequent x_j

Round 1: compute $f_1(x_1)$

Round 2: compute $f_1(x_2)$ *and* $f_2(x_1)$

Round 3: compute $f_1(x_3)$ *and* $f_2(x_2)$ *and* $f_3(x_1)$

...

At k rounds we reach the steady state of the pipeline (all tasks are active). After round n, the pipeline starts draining (no new elements entering).

Total time*:* $O\ (\ (n+k)\ \mathbf{max}_i\ (\ time(f_i)\ ))$ if we have k processors

Still, requires good mapping of the tasks f_i to a fixed set of processing resources for even load balancing – often, static mapping (done before running)

Leveraging More Parallelism: Stream Farming

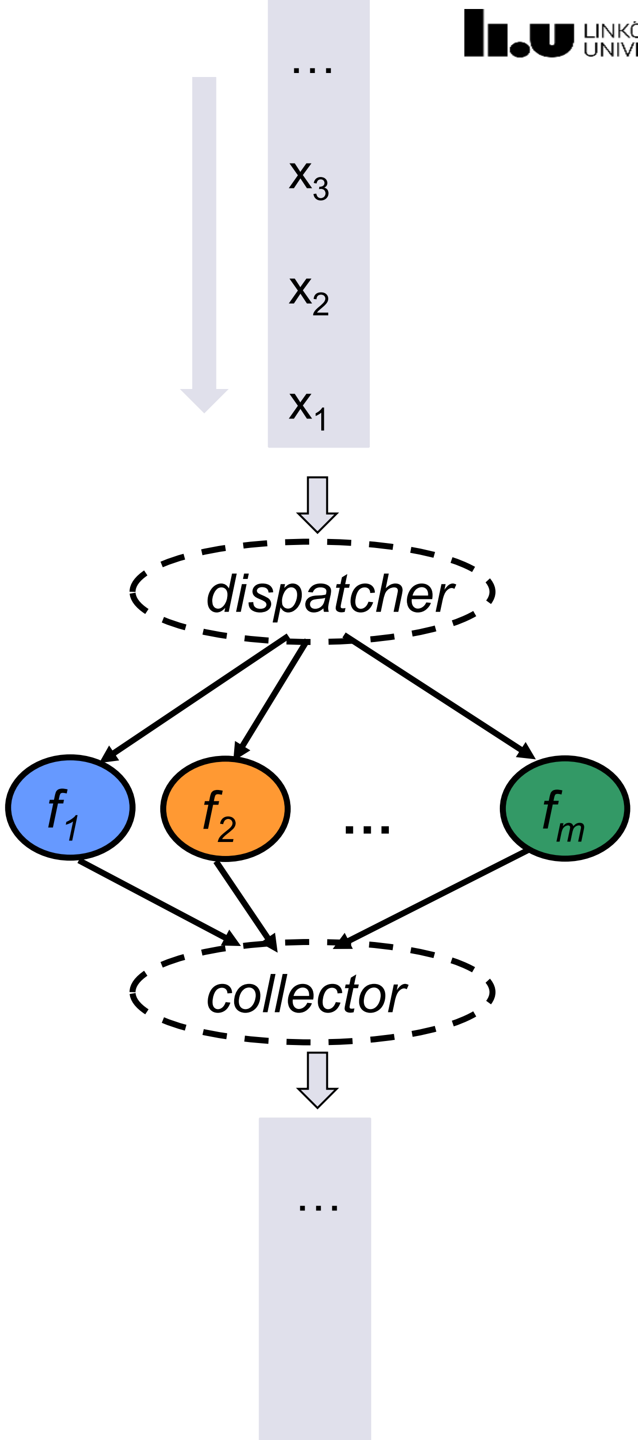
A heavy pipeline stage/task *f* can easily dominate the overall time!

Idea: Speed up that task by parallel processing of multiple subsequent data packets where this is acceptable for the application,
by distributing the computation of *f* across multiple resources
(**stream farming** – also known as “replication parallelism”)

- For **stateless** tasks: Not a problem. E.g., dispatch data round-robbin.
- For **stateful** tasks: must observe application-specific constraints, e.g. if state is key-specific, might be OK to process elements with different keys separately, while computations of elements with same key have to take place in same f_i in their original order.
- Needs a **dispatcher** task (dynamic scheduler) and a **collector** task (putting result stream in right order). These manager tasks will also consume some resources.

Caution: In many cases, the original order of stream elements must be maintained after processing, i.e. in the output stream.

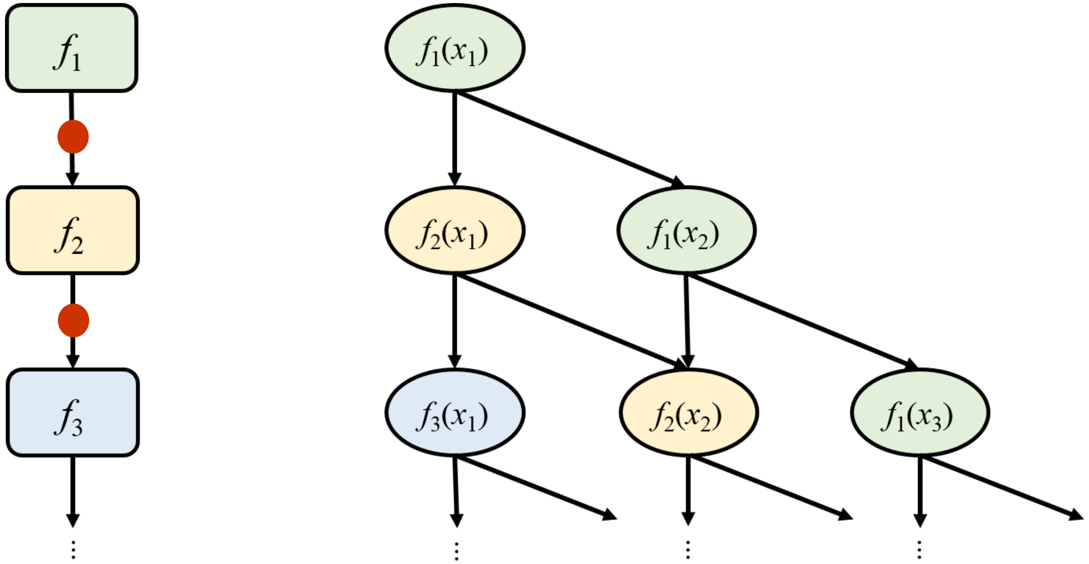
An alternative is to allow **internally parallel** task implementations.



Foundations: Dataflow Programming

Executing stream-processing tasks in a pipeline

→ Trace of *partially dependent* task instances



Well-established **execution models** for such **data flow graphs** of periodic tasks have been defined in the literature, e.g.

- **Kahn Process Networks** (KPN)
  - assumes FIFO channels with **unbounded** buffering capacity (for unknown number of in-flight task instances)
    → any fixed buffering capacity might be insufficient
    (could deadlock if not handling backpressure by slowing down upstream tasks)
- **Synchronous Data Flow** (SDF)
  - assumes **fixed, statically known data production / consumption rates** for each task instance
    → fixed buffering capacities sufficient
- ...

Stream-Processing Frameworks

- API for application writer to specify the stream-processing pipeline DAG structure, other pipeline properties, and the stream-processing tasks' implementations
- Framework provides deployment, resource management, portable communication (middleware), buffering, windowing
- Varying support for distribution, heterogeneous nodes, parallel tasks, accelerator usage, fault tolerance, stream encryption, portability of stream operator specifications, etc.

- **Examples**:
  - StreamIt (https://groups.csail.mit.edu/cag/streamit)
  - Spark-Streaming
  - Apache Storm (https://storm.apache.org)
  - Apache Flink (https://flink.apache.org)
  - Apache Kafka Streams (https://kafka.apache.org)
  - SkePU-Streaming

SkePU-Streaming

Reference:

Distributed Pipelining of Portable Data-Parallel Skeleton Computations for the Heterogeneous Edge-Cloud Continuum
Int. J. of Parallel Programming, to appear, 2026

August Svensson, Fabio Crugnola, August Ernstsson,
Sajad Khosravi, Sebastian Litzinger, Alexander Lindskog,
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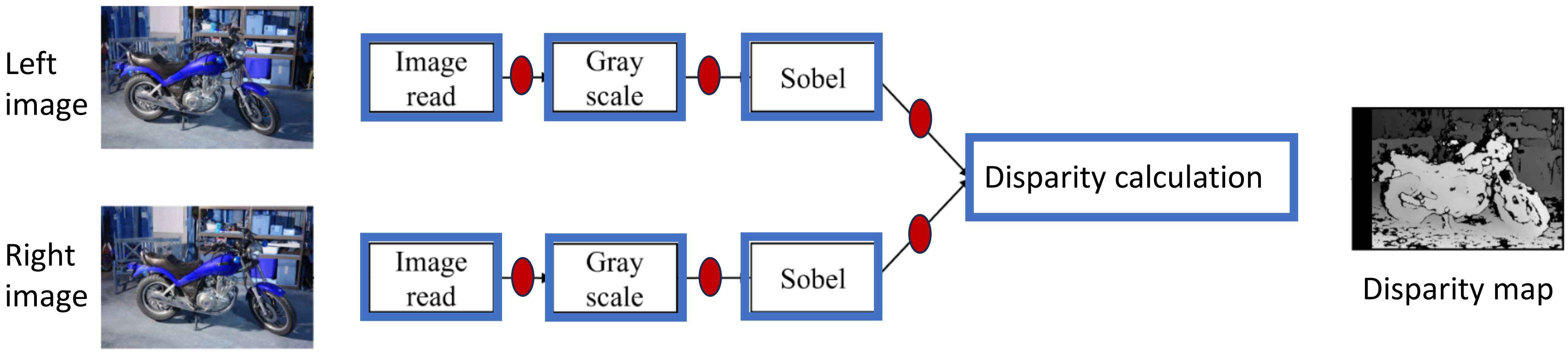
Adaptive Software for the Heterogeneous Edge-Cloud Continuum

SWEDISH FOUNDATION *for* STRATEGIC RESEARCH

This work has been partly funded by SSF project FUS21-0033 ASTECC (https://astecc.gitlab-pages.liu.se/).

Application Model



Focus here:

Workflows describing complex stream processing pipelines

- Tasks: Multi-variant stream-processing tasks
  - Characterized by workload, intra-task parallelism (**moldable** tasks), algorithmic/platform-specific variants for heterogeneous systems …

Embrace heterogeneity, intra-task parallelism

- Streams: FIFO-buffered dataflow (cf. Kahn Processing Networks)

Encapsulation, explicit inter-task (here, pipeline) parallelism

Formally: A bipartite DAG (Tasks, Streams, Data-flow edges)

Challenges

- Native execution on heterogeneous distributed hardware
- Convenient, portable, high-level specification of
  - Heterogeneous intra-task parallelism
  - Pipeline flow structure and properties to connect the tasks
- Automatic deployment to a distributed target system
- Easy reconfiguration

Skeleton programming, e.g. SkePU: Single source, many backends

Can this be achieved with an (if possible, non-intrusive) extension of SkePU?

SkePU

https://skepu.github.io

- C++-based high-level programming framework for heterogeneous parallel systems
  - Developed since 2010 as an open-source effort at Linköping University, Sweden.
- Provides a set of **multi-variadic skeletons** for common data-parallel patterns such as map, reduce, stencil, scan, ...
  - **Generic in**: operand number (**arity**), operand **shape**, operand **access pattern** (elementwise, random-access, neighborhood region, …), **element type**, and **user function** (per-element operator)
  - Can be parameterized with problem-specific sequential C++ code (**user-functions**), resulting in **skeleton instances** which can be invoked like hand-written C++ functions.

```
#include <skepu>

int main ()
{
 skepu::Matrix<int> m(5, 5);

 auto sum_function = skepu::Reduce(     // Matrix sum reduction
     [](int a, int b) { return a + b; }
 );

 std::cout << "Matrix␣Sum:␣" << sum_function(m) << std::endl;
}
```

Data-container for 2D skeleton operands

Builds a Reduce skeleton instance

User function (here, lambda)

SkePU https://skepu.github.io

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  - Can be parameterized with problem-specific sequential C++ code (**user-functions**), resulting in **skeleton instances** which can be invoked like hand-written C++ functions.
- Each skeleton provides **multiple backends**
  - parallel and accelerator-specific implementations (called backends) for the various native parallel programming models for CPU (sequential C++, OpenMP), single- and multi-GPU execution (OpenCL, CUDA), …
  - Static or dynamic backend selection
  - Separately for each skeleton instance call, or use global default settings, or use SkePU's auto-tuning backend selection
- STL-like array-based generic **data-container** abstractions
  - Vector<>, Matrix<>, Tensor3<>, Tensor4<>
  - Wrapping C/C++ array operands to be used in skeleton instance calls
  - Memory management, coherent software caching, transfers, and some other run-time optimizations

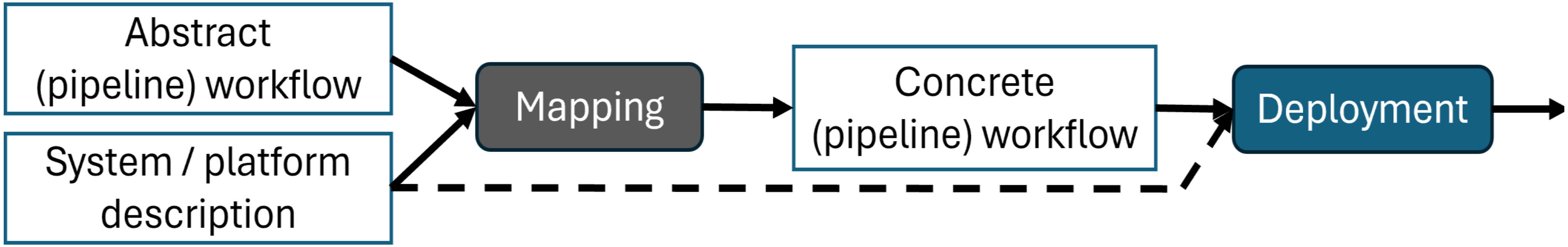
Abstract and Concrete Workflows

Abstract workflow:

- Directed bipartite graph (tasks, data-flow nodes, data-flow edges)

Concrete workflow:

- Abstract workflow + Mapping/deployment information for target system


Abstract (pipeline) workflow
System / platform description
Mapping
Concrete (pipeline) workflow
Deployment

SkePU-Streaming Design (1)

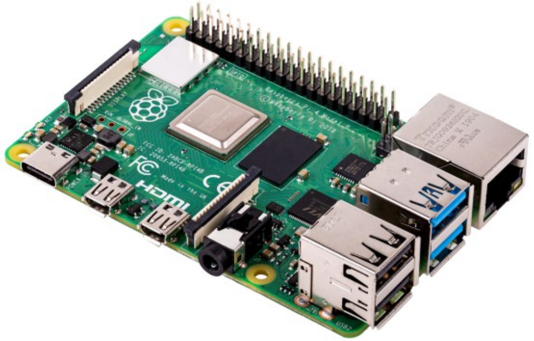
- **Global pipeline workflow and properties** are defined in a pipeline workflow description in (customized) JSON format

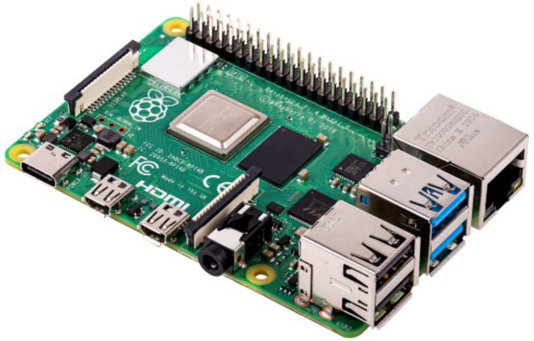
  Main structure:

  - List of named **hosts** (possible deployment targets)
    - each host with properties (usually included from separate specification file)

Hosts specification

```
resources {
    hosts: [
        { id: rbpi_2
          executor_affinity: "0"
          crosscompile: True
          sysroot: "/home/fabcr/Documents/rbpisysroot"
          host: "192.168.0.102"
          cxx: "aarch64-linux-gnu-g++"
          arch: "aarch64-linux-gnu"
        }
        { id: rbpi_3
          crosscompile: True
          …
        }
       …
    ]
}
```





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SkePU-Streaming Design (1)

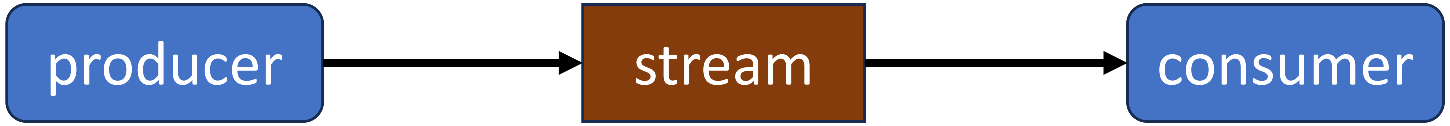
- **Global pipeline workflow and properties** are defined in a pipeline workflow description in (customized) JSON format

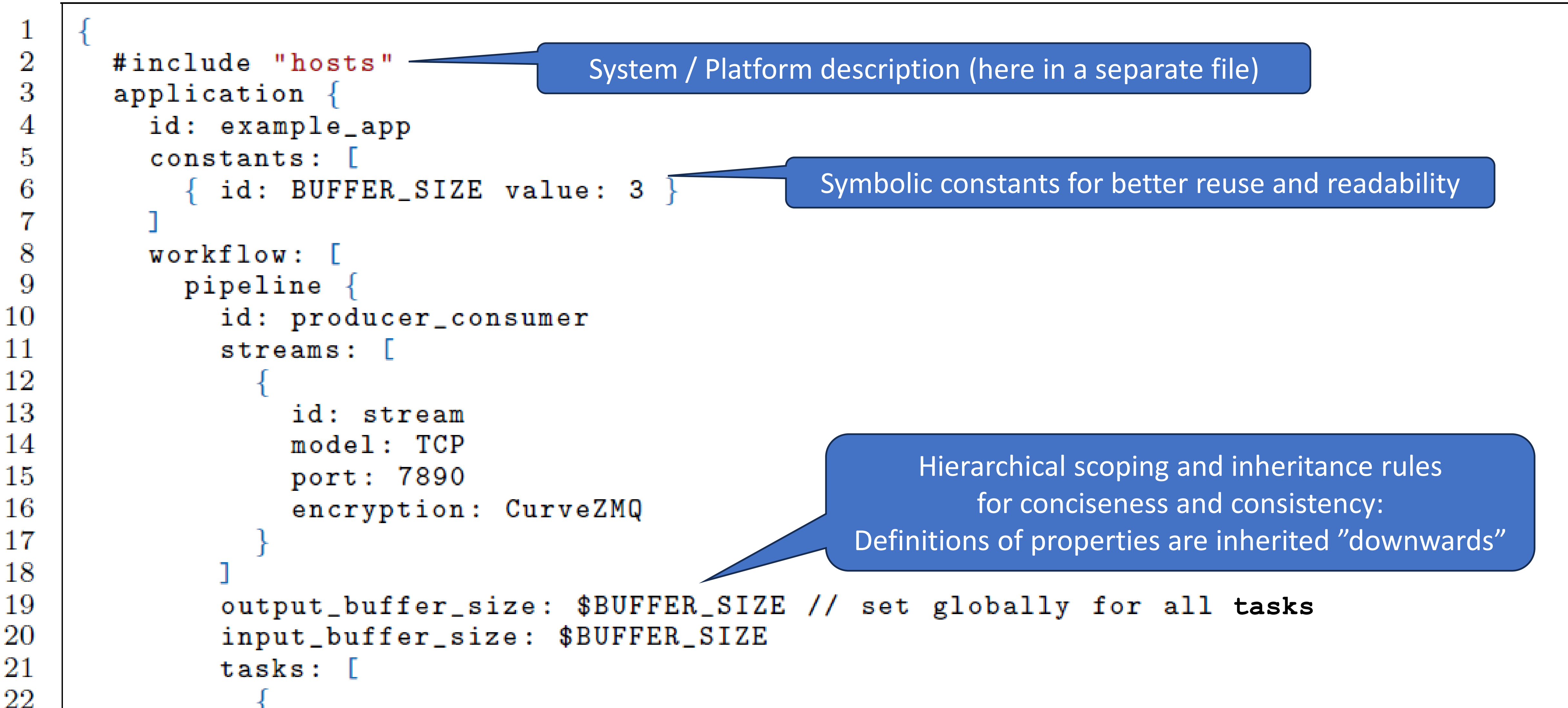
  Main structure:

  - List of named **hosts** (possible deployment targets)
    - each host with properties (usually included from separate specification file)
  - List of named **streams**
    - each stream with properties (e.g., buffering capacity, encryption scheme, transfer method)

Example

Producer-Consumer pipeline





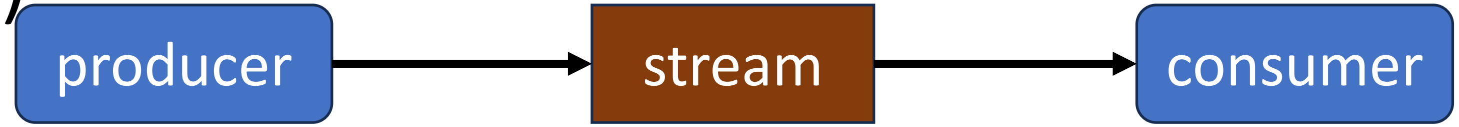
```
{
  #include "hosts"
  application {
    id: example_app
    constants: [
      { id: BUFFER_SIZE value: 3 }
    ]
    workflow: [
      pipeline {
        id: producer_consumer
        streams: [
          {
            id: stream
            model: TCP
            port: 7890
            encryption: CurveZMQ
          }
        ]
        output_buffer_size: $BUFFER_SIZE // set globally for all tasks
        input_buffer_size: $BUFFER_SIZE
        tasks: [
          {
```

System / Platform description (here in a separate file)

Symbolic constants for better reuse and readability

Hierarchical scoping and inheritance rules
for conciseness and consistency:
Definitions of properties are inherited ”downwards”

Example (cont.)



```
tasks: [
  {
    id: producer
    host: $rbpi_2
    output_streams: [$stream]
    variants: [
      skepu {
        id: producer_variant_1
        backend: openmp
        build: {
          type: make
          source: "examples/producer-consumer/producer"
          output: "producer"
        }
      }
    ]
  }
  {
    id: consumer
    host: $rbpi_3
    input_streams: [$stream]
    variants: [
      skepu {
```

Producer task is a stream source: no input stream operand

External backend selection

Consumer task is a stream sink: no output stream operand

SkePU-Streaming Design (1)

- **Global pipeline workflow and properties** are defined in a pipeline workflow description in (customized) JSON format

  Main structure:

  - List of named **hosts** (possible deployment targets)
    - each host with properties (usually included from separate specification file)
  - List of named **streams**
    - each stream with properties (e.g., buffering capacity, encryption scheme, transfer method)
  - List of named **stream-processing tasks**, each with
    - Ingoing and outgoing streams (ports, operands) – variadic
    - Task properties and mapping information (resource assignment, core pinning)
    - **Implementation variants** (current options: SkePU with backends; sequential C++, OpenMP)
      - Each with deployment information: source directory/files, compilation flags etc.
      - One of them set as default variant (usually, SkePU)

  Extensions over JSON:

  #include, expressions, symbolic constants, C/C++ comments, simplified syntax { } ,

  Implementation: Custom JSON parser based on pyparsing module.

SkePU-Streaming Design (2)

- Each **stream-processing task** is defined as a separate SkePU program
  - Source code and local makefile located in its own subdirectory
  - Portable multi-backend data-parallelism
    - Skeleton instance parallelism limited to resources within one node
  - **Access to stream operands**
    by new skepu::io standard library extensions overloading operators <<, >>
    and specifying the accessed input or output port number

Producer Task, Source Code

```
#include <skepu>
#include <skepu-streaming>

int main ()
{
 skepu::io::streams::init();

 skepu::Matrix<int> m(5, 5);

 skepu::io::streams::endless ( []() {
     … // produce m
     skepu::io::output_stream[0] << m;
 });
}
```

The stream-processing task body

endless() construct iterates until all input streams see *EndOfStream* (default)

Flushes and serializes matrix container m contents to first output stream (output port 0)

Consumer Task, Source Code

```
#include <skepu>
#include <skepu-streaming>

int main ()
{
 skepu::io::streams::init();
 skepu::Matrix<int> m(5, 5);

 auto sum_function = skepu::Reduce(      // Matrix sum reduction
     [](int a, int b) { return a + b; }
 );

 skepu::io::streams::endless( [&]() {
     if (!(skepu::io::input_stream[0] >> m)) continue;
     std::cout << "Matrix␣Sum:␣" << sum_function(m) << std::endl;
 });
}
```

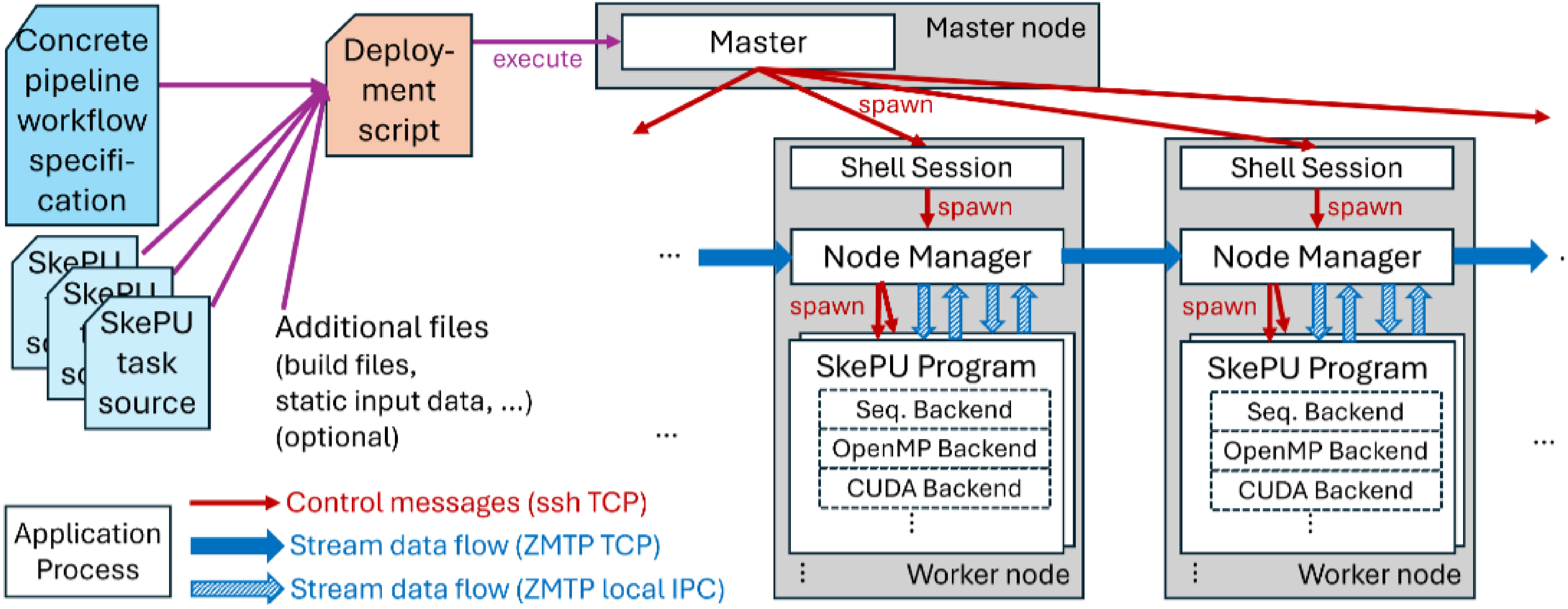
No backends chosen here
→ external global settings apply

Deserialize to matrix container m from first input stream (inp. port 0)

The stream-processing task body

Implementation

Deployment of a SkePU-Streaming workflow and runtime management



Implementation Details (1)

NodeManager component handles external routing
and feeds SkePU application with stream elements

Communication library based on ZeroMQ (https://zeromq.org)

- ZeroMQ Message Transport Protocol (ZMTP)
- For node-manager – node-manager communication (TCP)
  and node-manager – SkePU communication (Unix domain sockets)
- **Serializers** implemented for skepu::Vector and skepu::Matrix containers
  - Before serialization, the container contents are flushed to main memory
- We use binary encoding for performance reasons,
  and because SkePU seldom is used for text processing.
- For TCP stream **encryption and decryption** as requested by the workflow, we use for now the CurveZMQ mechanism provided by ZeroMQ

Implementation Details (2)

Deployment script

- turns into the **master process**
  - Parses the pipeline description
  - Resolves eventual IP addresses of hostnames, and for each task opens up an SSH connection to the worker node specified in the concrete workflow for that task
  - Generates a global Makefile
  - Builds and transfers task binary to respective target node (alternatively, local compilation)
  - Launches execution of node manager and SkePU task processes
- Implemented in Python, as not considered performance-critical
- Concurrency needed e.g. for transferring multiple files concurrently

Experiments: ASTECC Testbed

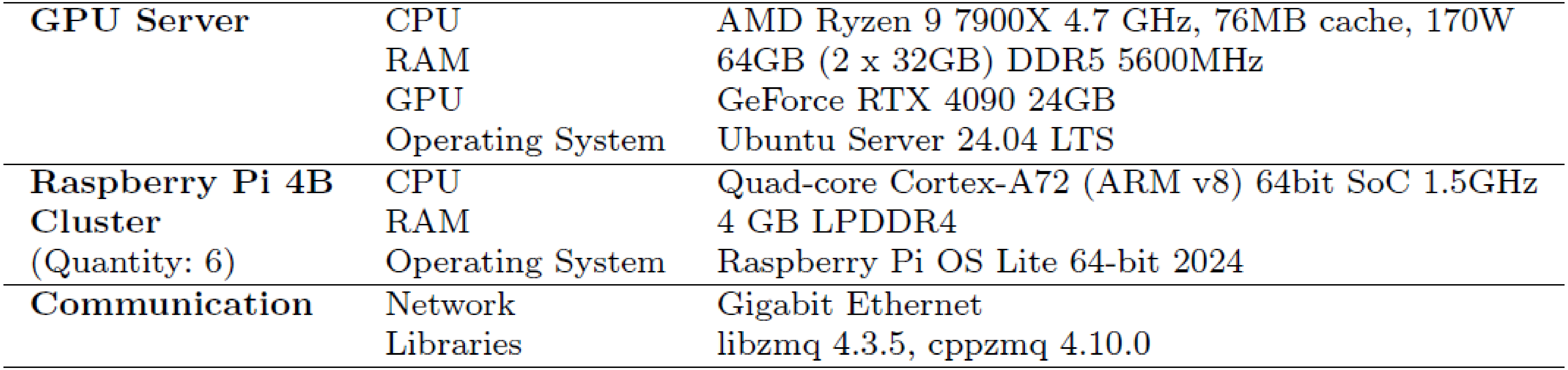
Mapping targets:

”Cloud”:

- GPU server
  - AMD Ryzen 9 7900X, 12 cores, 5.6 GHz
  - Nvidia RTX 4090

”Device, Edge resources”:

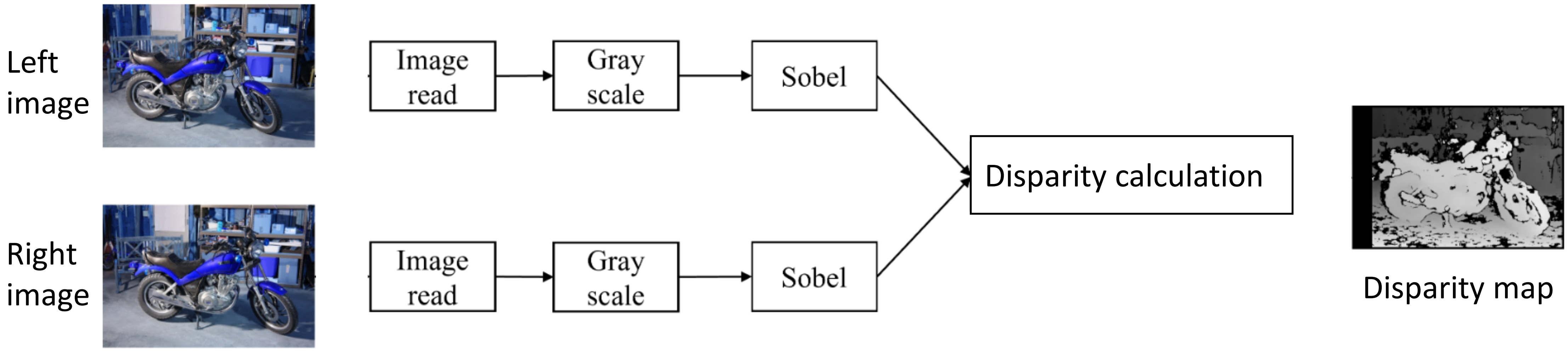
- Raspberry Pi 4B
  - Quad-core ARM Cortex A72, 1.5 GHz



GPU Server	CPU	AMD Ryzen 9 7900X 4.7 GHz, 76MB cache, 170W
	RAM	64GB (2 x 32GB) DDR5 5600MHz
	GPU	GeForce RTX 4090 24GB
	Operating System	Ubuntu Server 24.04 LTS
Raspberry Pi 4B Cluster (Quantity: 6)	CPU	Quad-core Cortex-A72 (ARM v8) 64bit SoC 1.5GHz
	RAM	4 GB LPDDR4
	Operating System	Raspberry Pi OS Lite 64-bit 2024
Communication	Network	Gigabit Ethernet
	Libraries	libzmq 4.3.5, cppzmq 4.10.0

Example Application

Stereo Depth Estimation (SDE)



Left image

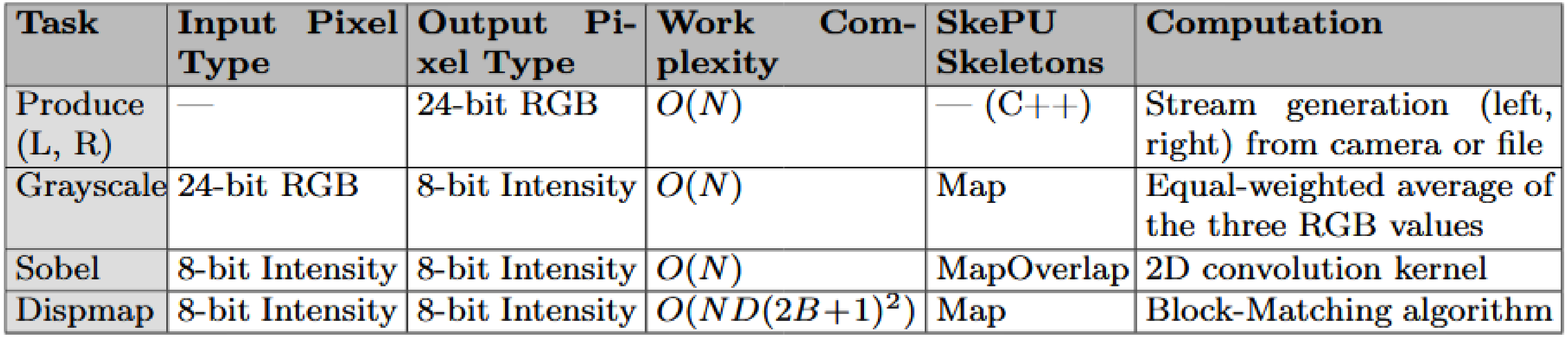
Right image

Image read → Gray scale → Sobel

Image read → Gray scale → Sobel

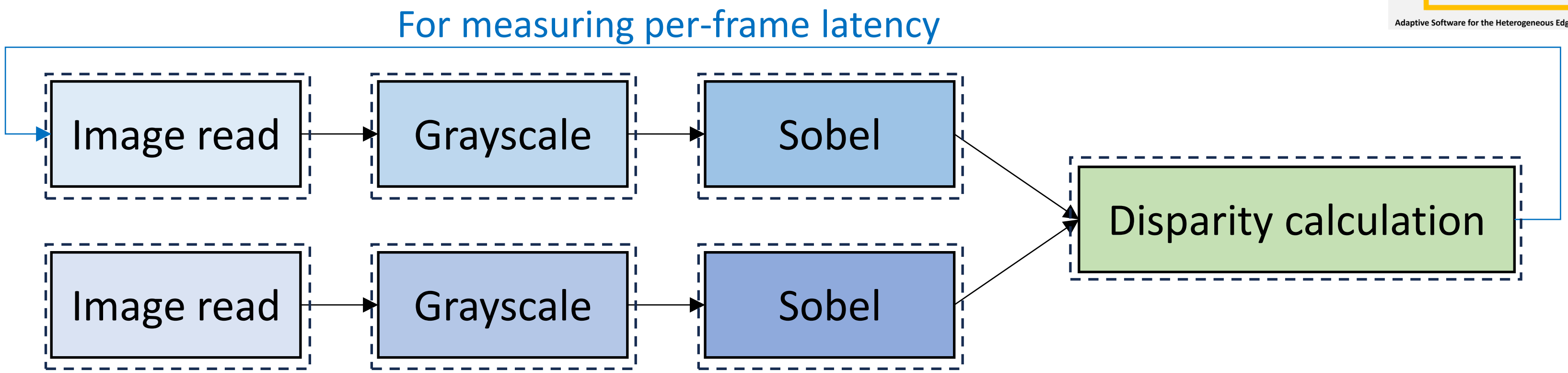
Disparity calculation

Disparity map

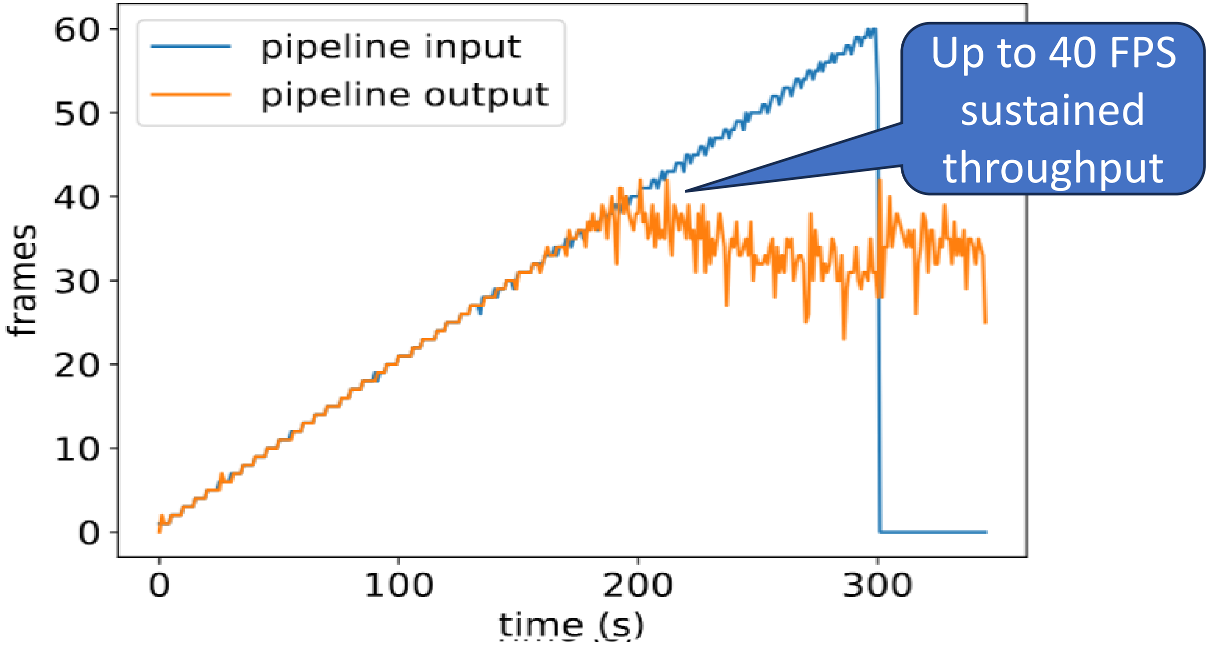


Task	Input Pixel Type	Output Pixel Type	Work Complexity	SkePU Skeletons	Computation
Produce (L, R)	—	24-bit RGB	$O(N)$	— (C++)	Stream generation (left, right) from camera or file
Grayscale	24-bit RGB	8-bit Intensity	$O(N)$	Map	Equal-weighted average of the three RGB values
Sobel	8-bit Intensity	8-bit Intensity	$O(N)$	MapOverlap	2D convolution kernel
Dispmap	8-bit Intensity	8-bit Intensity	$O(ND(2B+1)^2)$	Map	Block-Matching algorithm

Fully distributed mapping



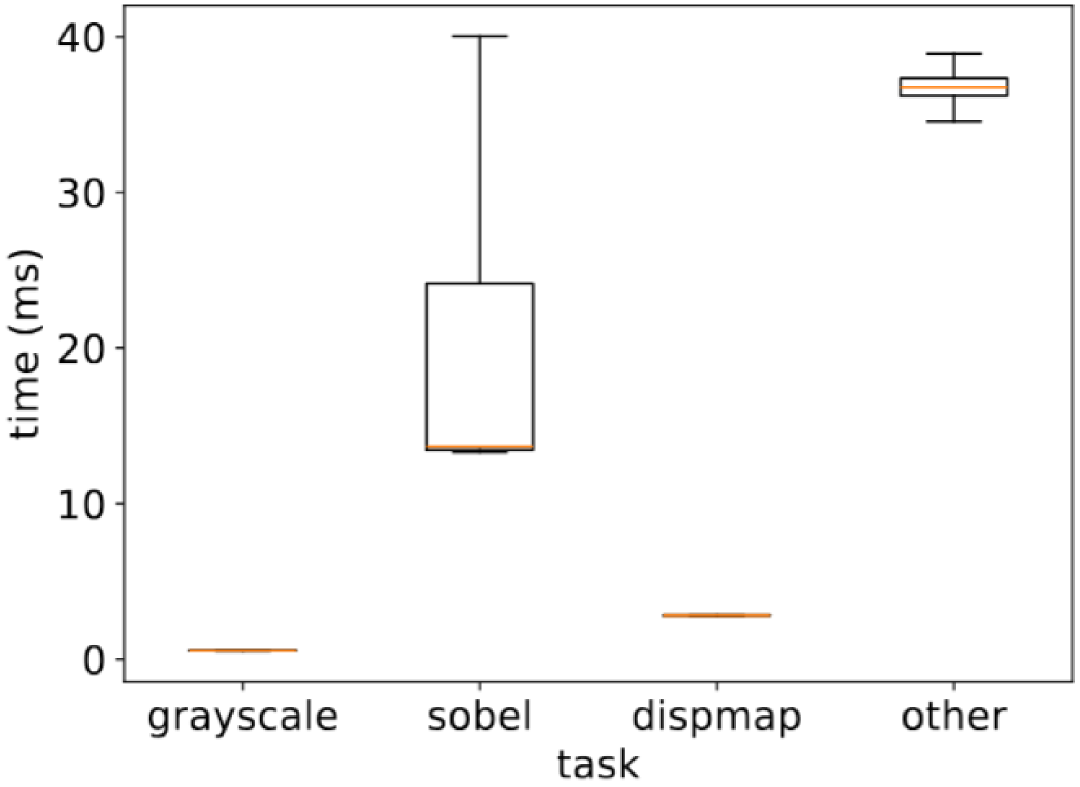
- 741x500px video source starting at 1 FPS and increasing by 1 FPS every 5 seconds
- One pipeline task per node
- Disparity calculation task on GPU server, GPU backend selected; f. other tasks: OpenMP



Up to 40 FPS sustained throughput

For reference:
Executing the entire pipeline with only sequential tasks on a single Raspberry Pi 4 gives a throughput of 0.065 FPS ...

Fully Distributed Mapping: Breakdown of End-to-End Latency

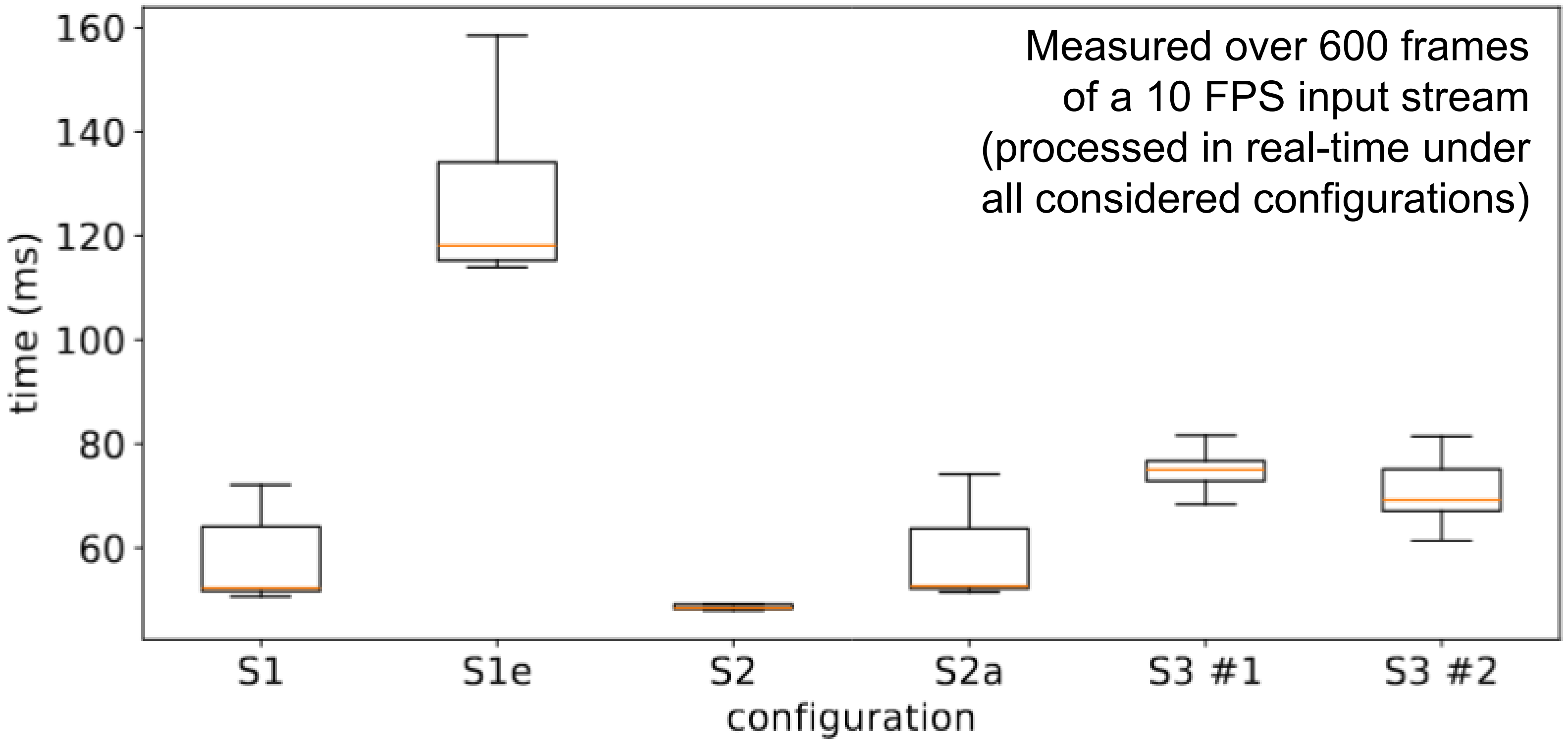


Measured over 600 frames of a 10 FPS input stream (processed in real-time under all considered configurations)

- Disparity calculation (dispmap) is the heaviest task, but executing on the GPU server (RTX 4090) it is not the performance bottleneck.
- “Other” includes 4 network jumps and the intermediate buffering/queuing.

End-to-End Latency Experiments

S1e: Deploying **encrypted** messages on all internal streams with the fully distributed mapping more than doubles end-to-end latency



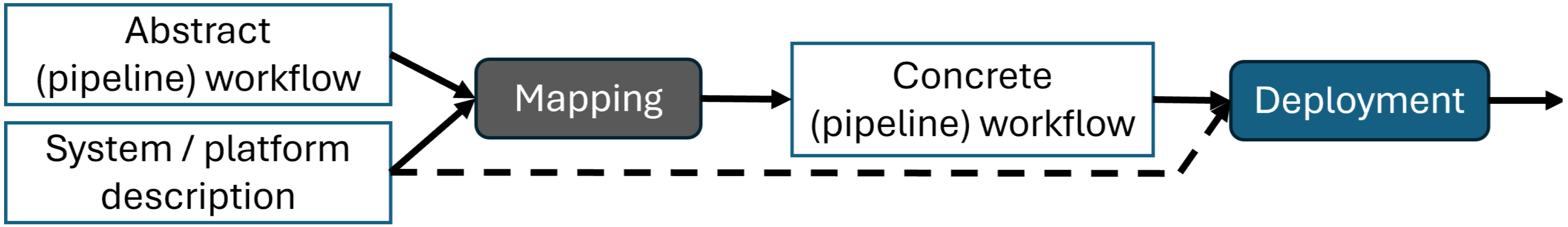
Measured over 600 frames of a 10 FPS input stream (processed in real-time under all considered configurations)

S2: Co-locating Grayscale and Sobel tasks on one node (reduced distribution) saves transfers → shorter latency

S3: Deploying *two* concurrent SDE pipelines time-sharing the same resources only increases latency for each of them a little.

Future Work

- Address some inefficiencies in the prototype
- Further example applications
- More configuration options, e.g. DVFS (in progress)
- Coupling with (crown-scheduling based) optimizer for mapping and resource allocation [Khosravi *et al*. FMEC'24]


Abstract (pipeline) workflow
System / platform description
Mapping
Concrete (pipeline) workflow
Deployment

- Monitoring, tracing, live performance visualization
- Dynamic redeployment for dynamically changing application population
- **Thesis projects available!**

References

SkePU: https://skepu.github.io

SkePU-Streaming:

A. Svensson, F. Crugnola, A. Ernstsson, S. Khosravi, S. Litzinger, A. Lindskog, C. Kessler: ”SkePU-Streaming: Distributed Pipelining of Portable Data-Parallel Skeleton Computations for the Heterogeneous Edge-Cloud Continuum.” Accepted for publication in *International Journal of Parallel Programming*, Feb. 2026, to appear.

General overview:

H. Isah et al.: “A Survey of Distributed Data Stream Processing Frameworks.” *IEEE Access*, 2019.

Foundations (Kahn Process Networks, Synchronous Data Flow):

G. Kahn: ”The semantics of a simple language for parallel programming.” Proc. IFIP Congress on Information Processing. North-Holland, 1974.

E. A. Lee, D. G. Messerschmitt: ”Synchronous Data Flow.” *Proceedings of the IEEE* 75(9), 1987.