

Presenting at



2nd BMBF Big Data All Hands Meeting and
2nd Smart Data Innovation Conference
Karlsruhe , October 11.-12., 2017



Efficiently Handling Streams from Millions of Sensors

Jonas Traub – TU Berlin / DFKI

The Growth of the Internet of Things

BY THE YEAR 2020, THERE WILL BE

[IDC, Big Data in IoT, 2014]

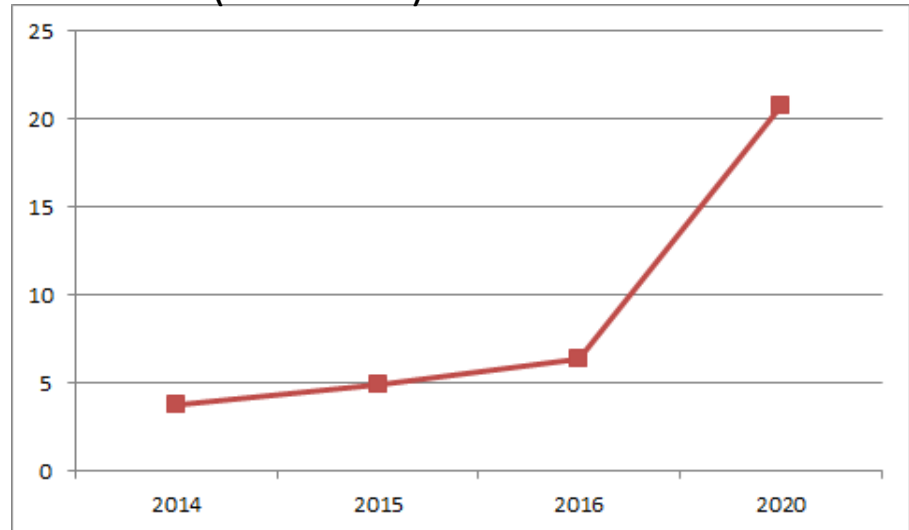
50,000,000,000 connected devices,
creating and sharing

40,000,000,000,000 GB

worth of data across the Internet of Things.

Gartner says 6.4 billion connected "Things" will be in use in 2016 and more than 20 billion in 2020.

Devices (in billions)



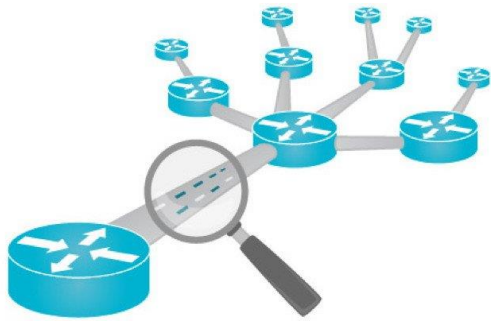
Year

Goal

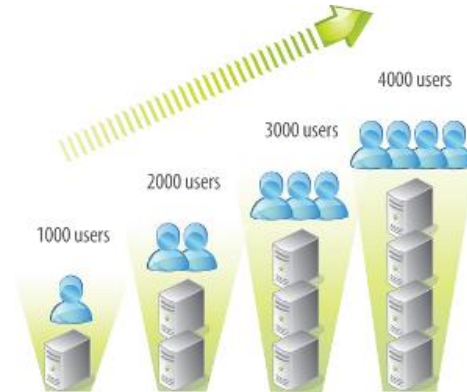
Provide real-time insights based on IoT data.

Problem

- Billions of devices provide real-time data
- Result: Vast amount of data streams



Heavy Network Utilization



Scalability Challenges



Increasing Latencies

Financial Costs

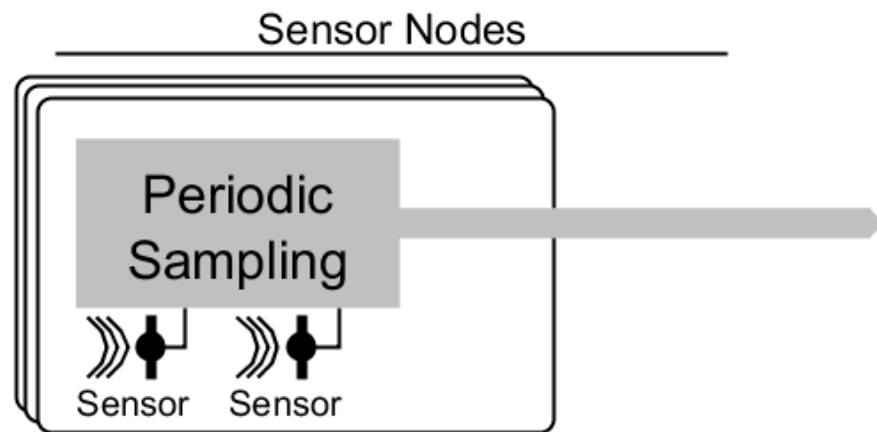


Solution

*Produce and process data streams
based on the data demand of applications.*

State of the Art Approach

Data Stream Production with Periodic Sampling

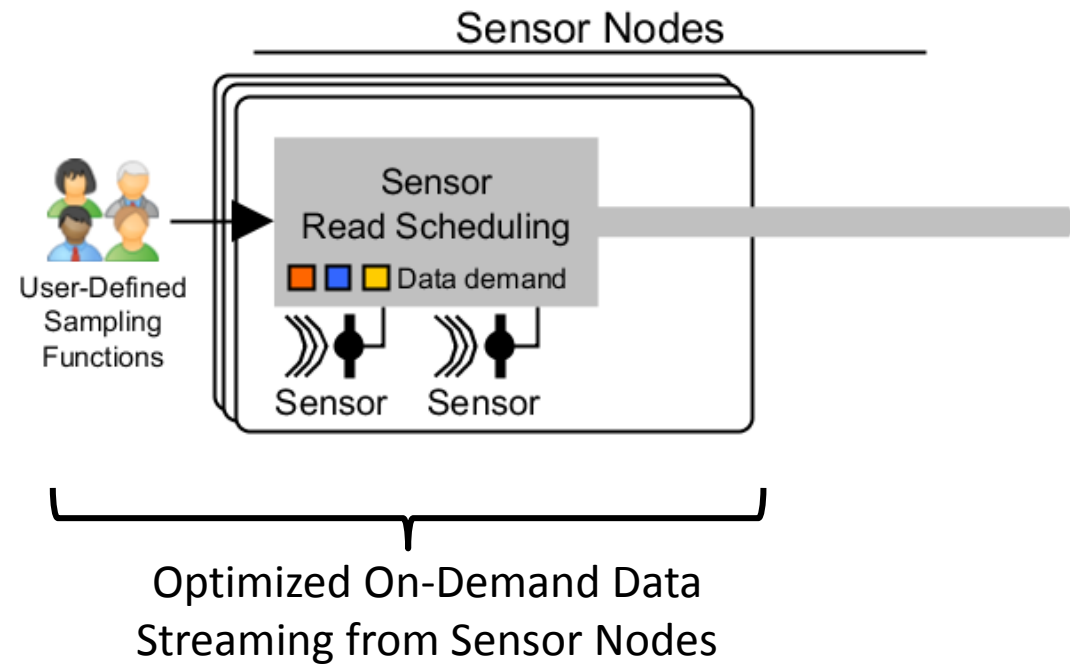


Major Challenges:

- Oversampling
- Missing Adaptivity

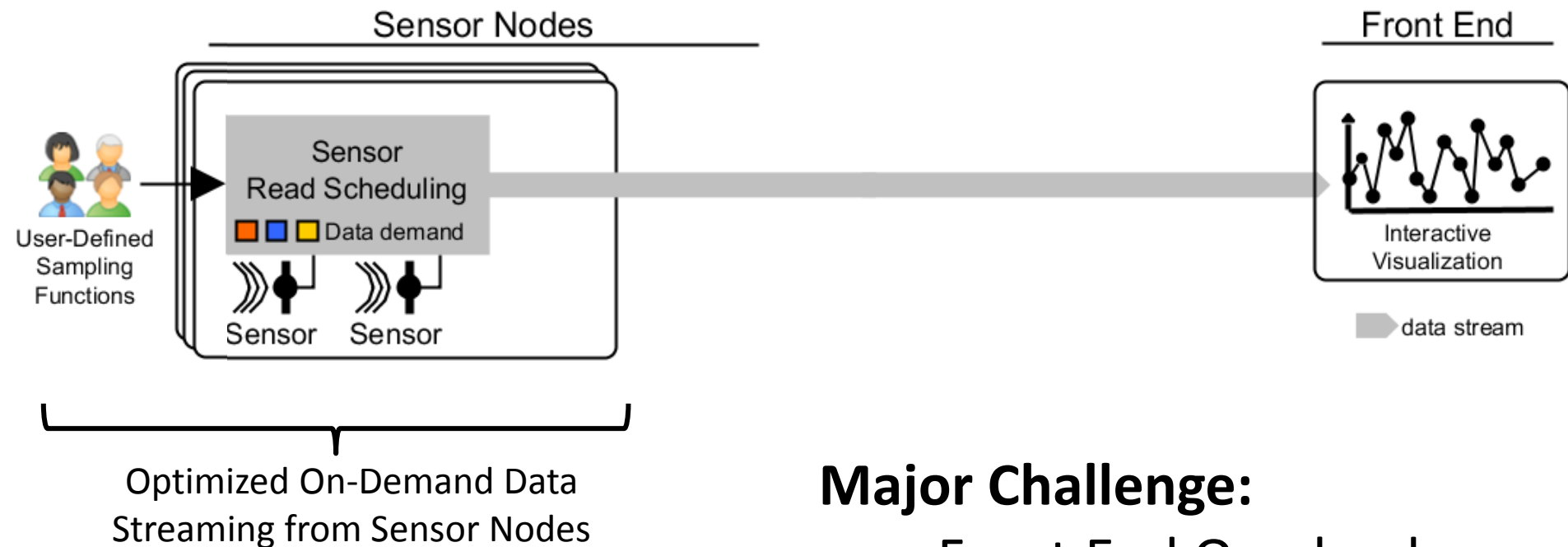
Solution

On-Demand Data Streaming from Sensor Nodes



State of the Art Approach

Provide all Data to Front-End Applications

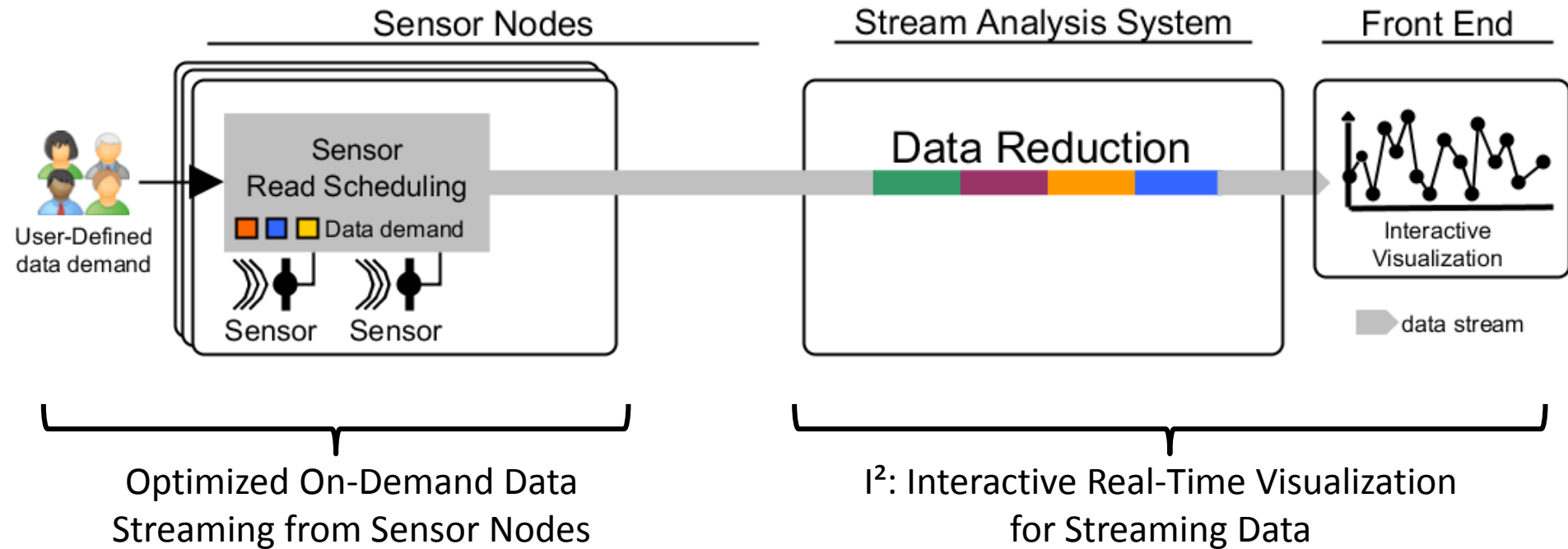


Major Challenge:

- Front End Overload

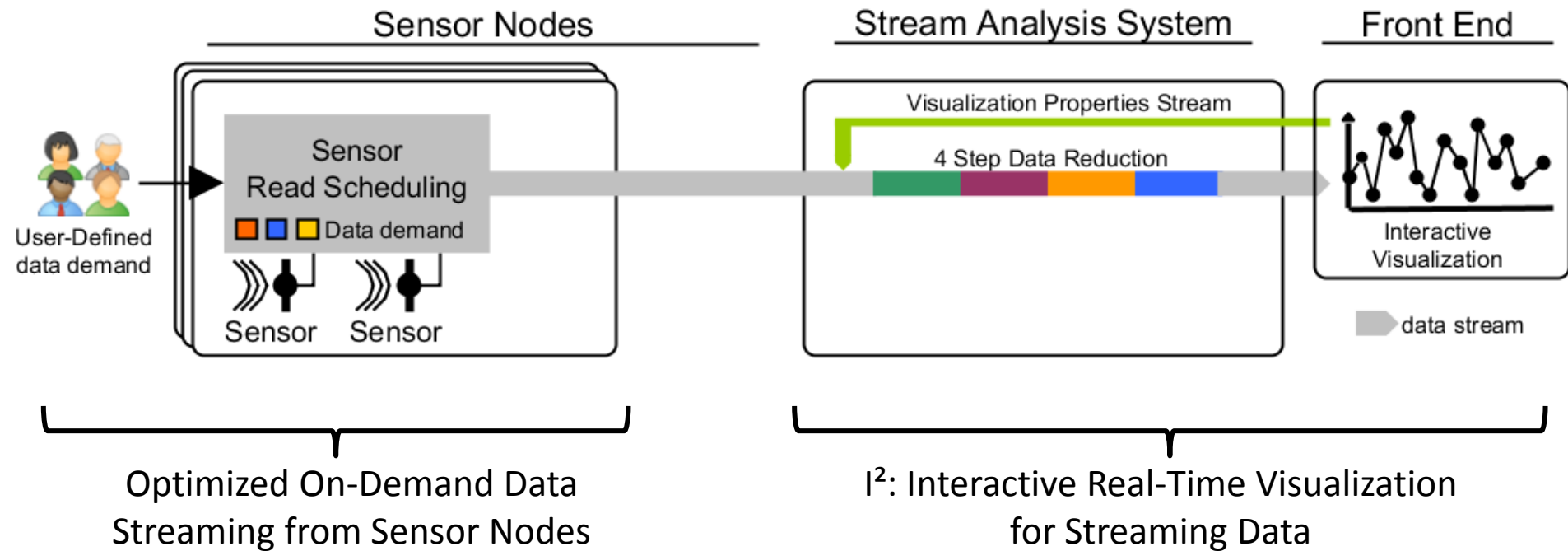
Solution

Adaptive Data Reduction with Streaming Engines



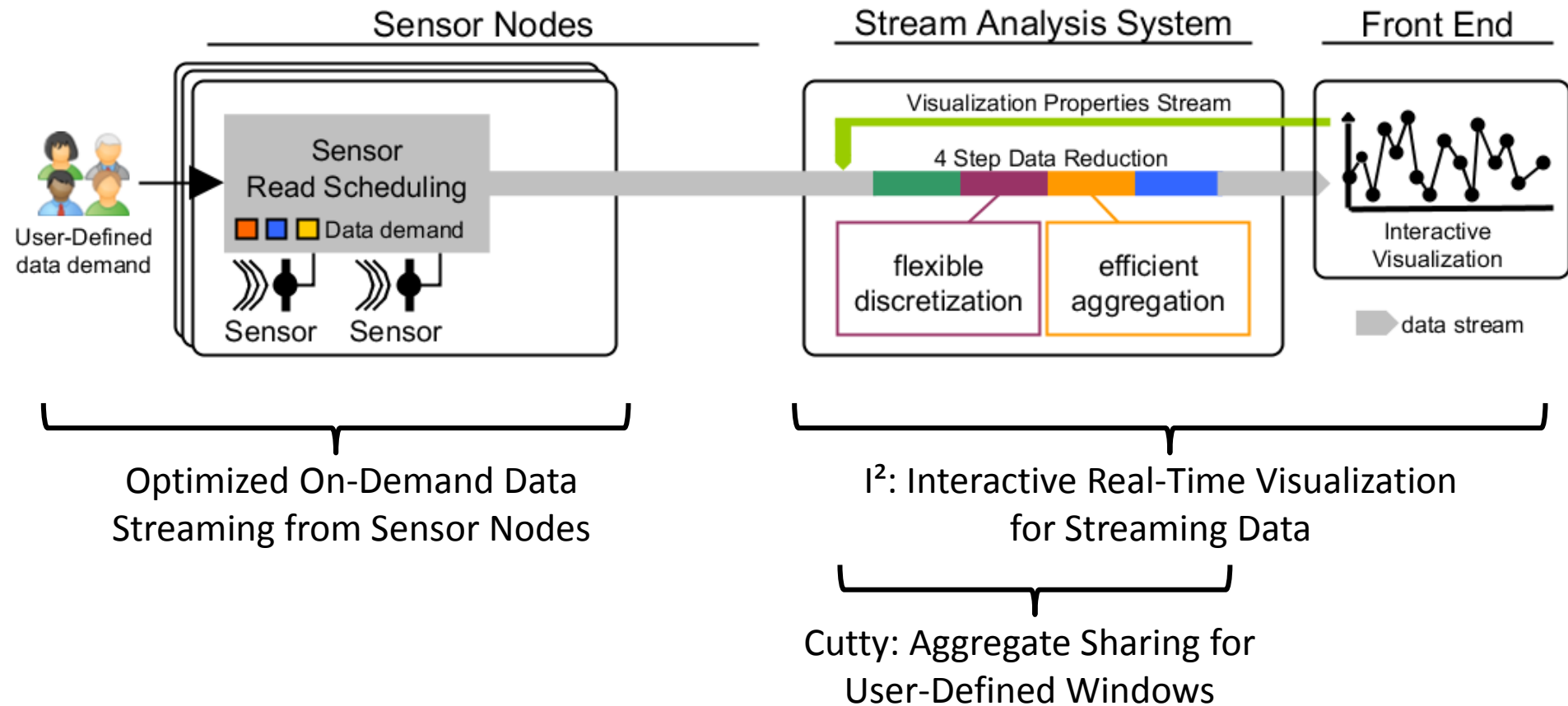
Solution

Adaptive Data Reduction with Streaming



Solution

Efficient Processing of user-defined Windows



Publications

Optimized On-Demand Data Streaming from Sensor Nodes

Jonas Traub¹ Sebastian Breß^{1,2} Tilmann Rabl^{1,2} Asterios Katsifodimos³ Volker Markl^{1,2}

¹Technische Universität Berlin

²German Research Center for Artificial Intelligence (DFKI)

³SAP Innovation Center

jonas.traub@tu-berlin.de

sebastian.bress@dfki.de

rabl@tu-berlin.de

Cutty: Aggregate Sharing for User-Defined Windows

Paris Carbone[†]

Jonas Traub[‡]

Asterios Katsifodimos[‡]

Seif Haridi[†]

Volker Markl[‡]

[†]KTH Royal Institute of Technology
{parisc,haridi}@kth.se

[‡] Technische Universität Berlin & DFKI

I²: Interactive Real-Time Visualization for Streaming Data

Jonas Traub
Technische Universität Berlin
jonas.traub@tu-berlin.de

Nikolaas Steenbergen
German Research Center for
Artificial Intelligence (DFKI)
nikolaas.steenbergen@dfki.de

Philipp M. Grulich
German Research Center for
Artificial Intelligence (DFKI)
philipp.grulich@dfki.de

Tilmann Rabl
Technische Universität Berlin
rabl@tu-berlin.de

Volker Markl
Technische Universität Berlin



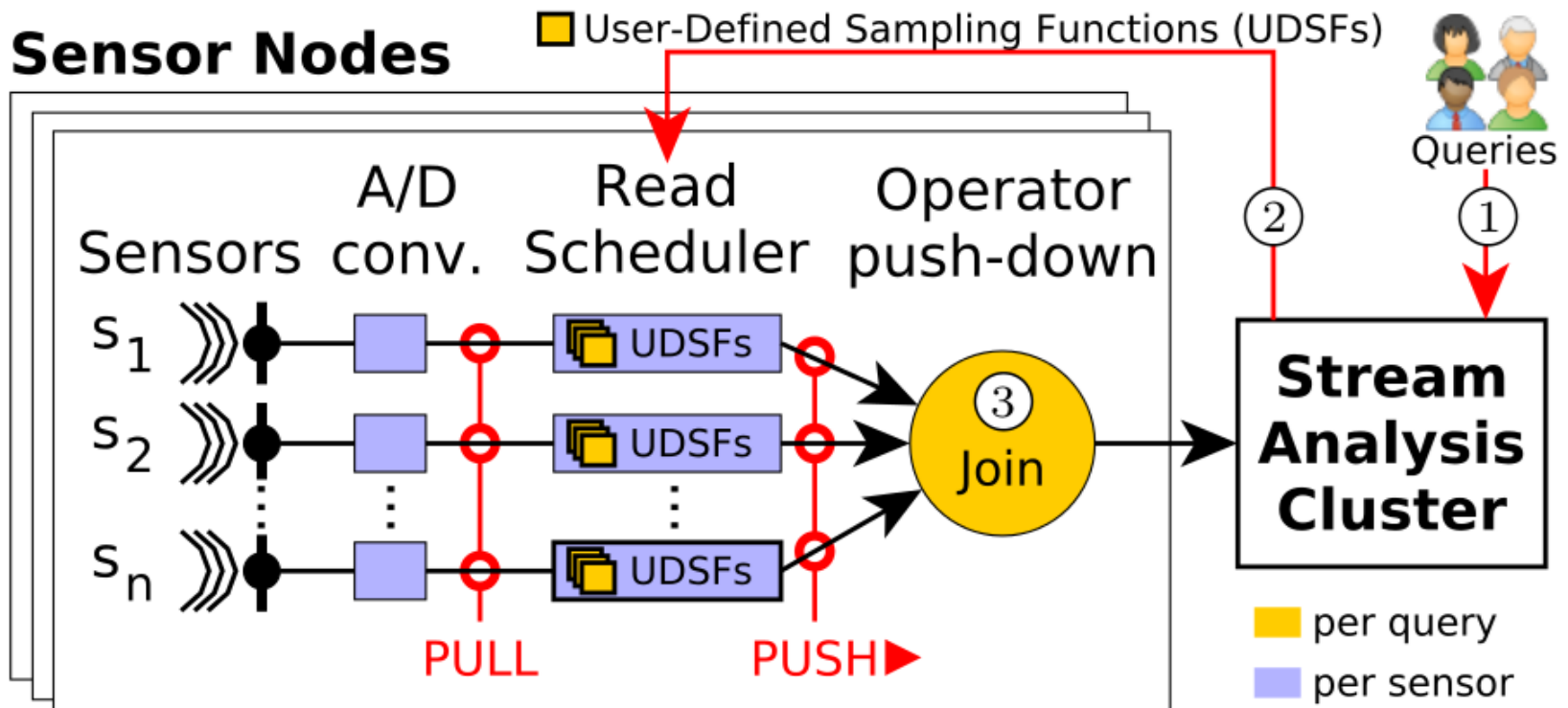
ACM Symposium
on Cloud Computing

Santa Clara, California,
September 25-27, 2017

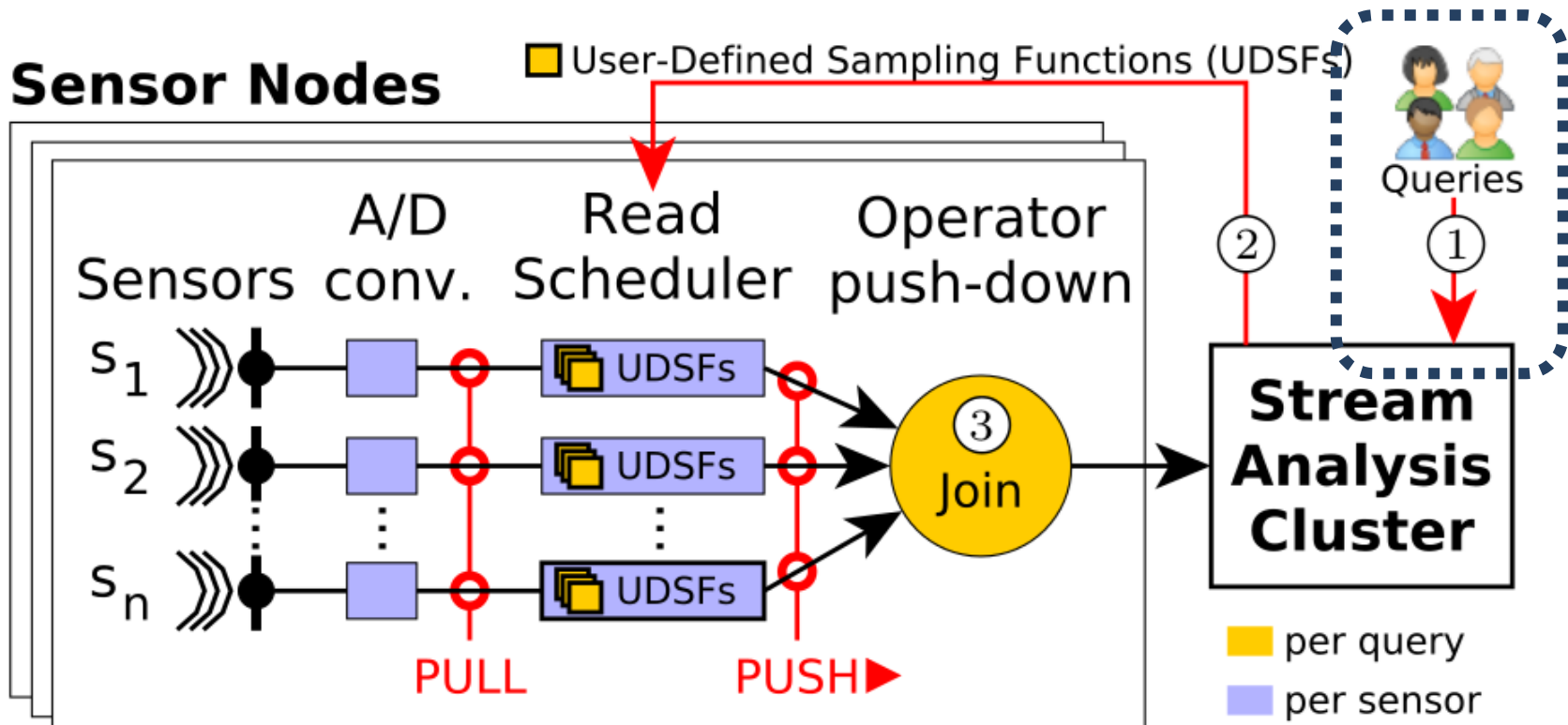
Optimized On-Demand Data Streaming from Sensor Nodes

Jonas Traub, Sebastian Breß, Asterios Katsifodimos, Tilmann Rabl, Volker Markl

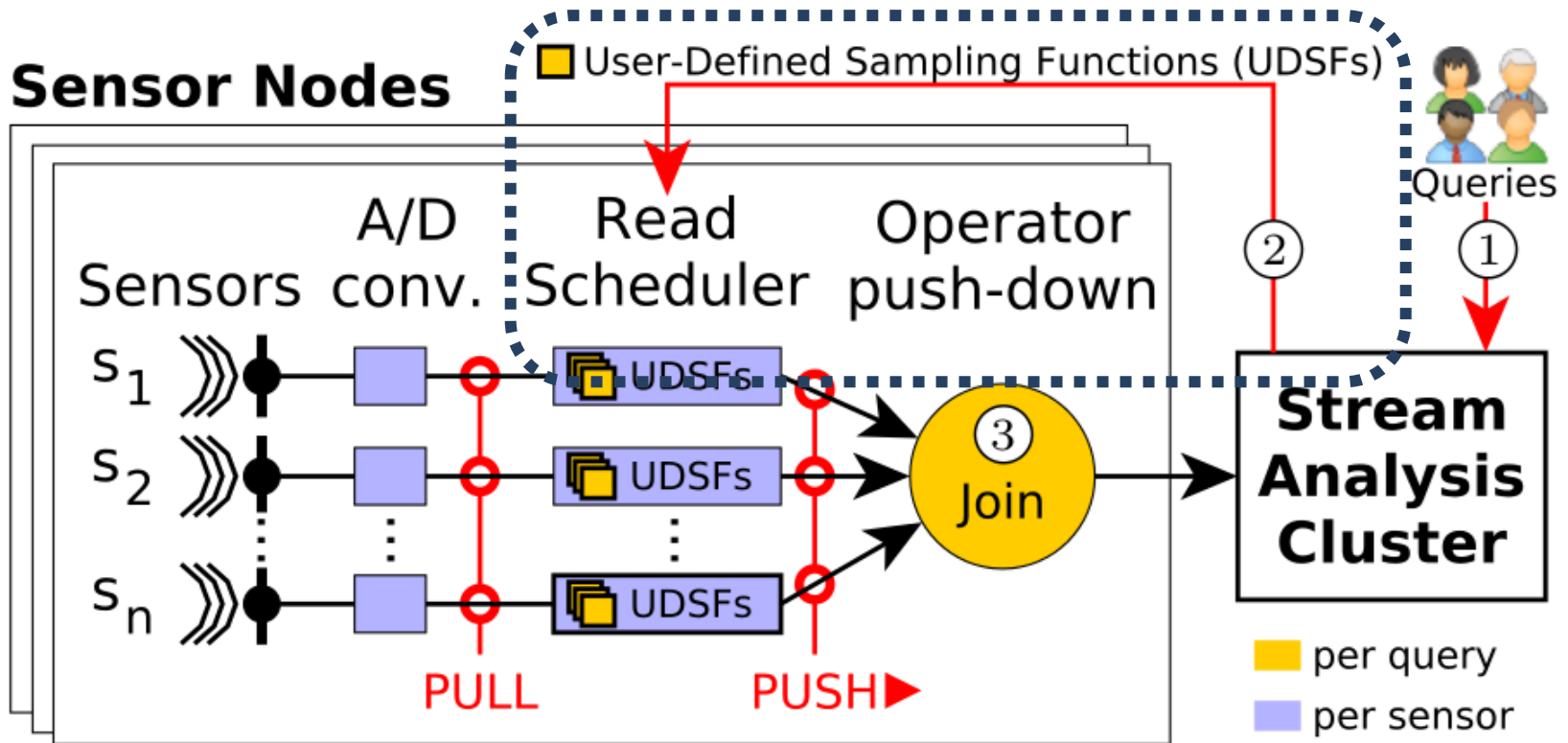
Architecture Overview



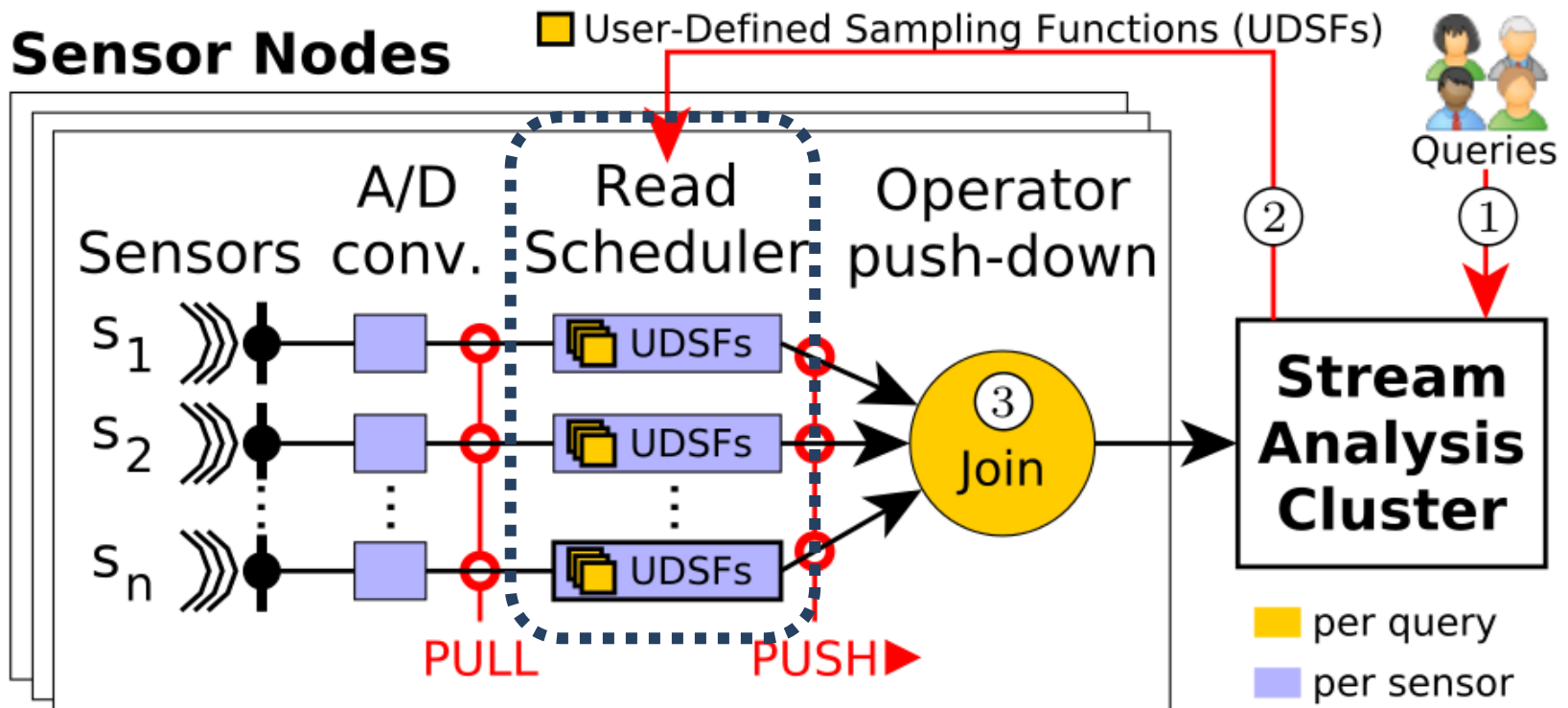
Architecture Overview



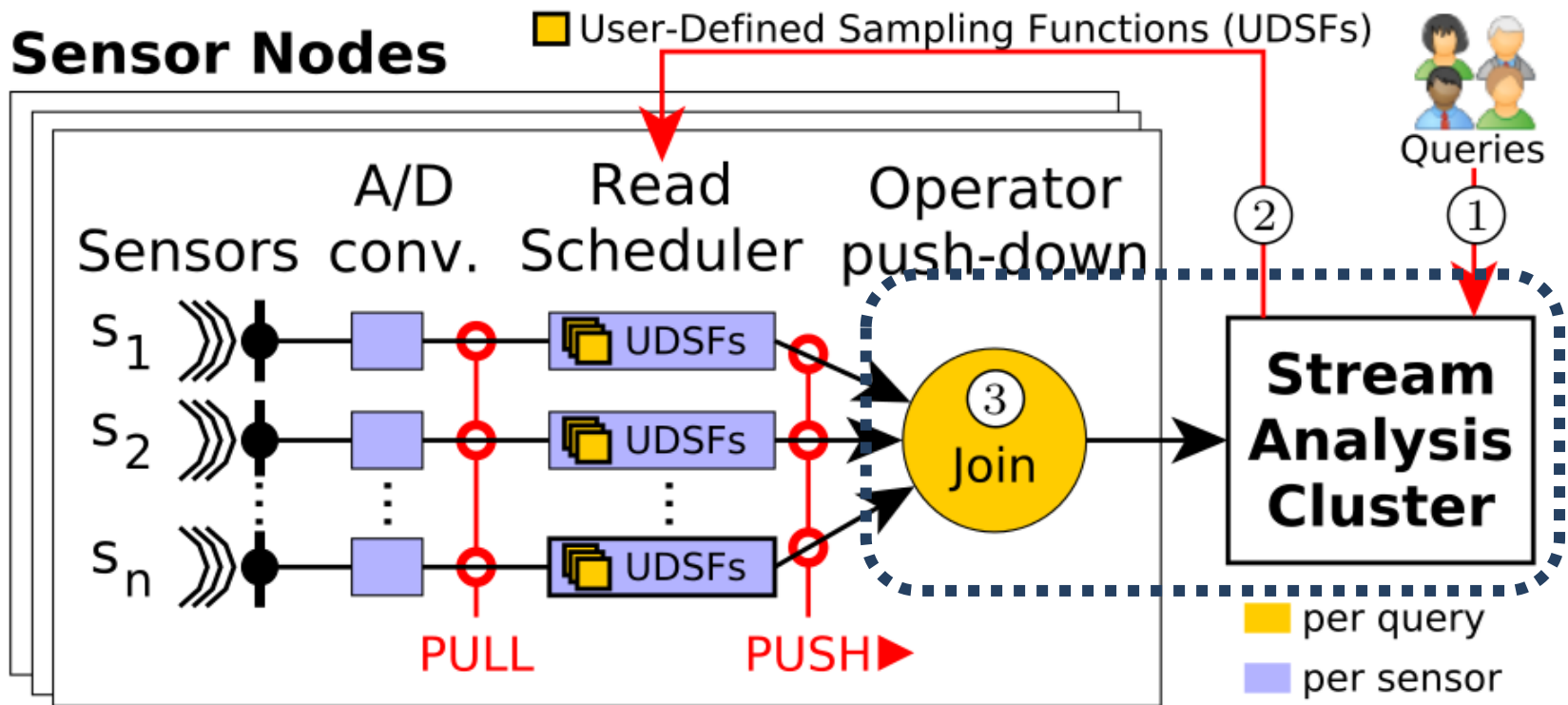
Architecture Overview



Architecture Overview

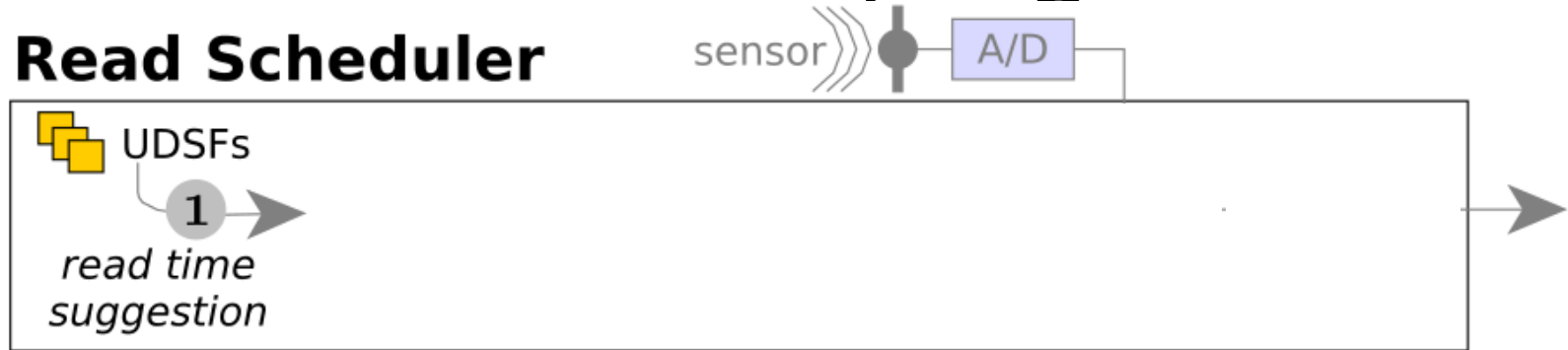


Architecture Overview



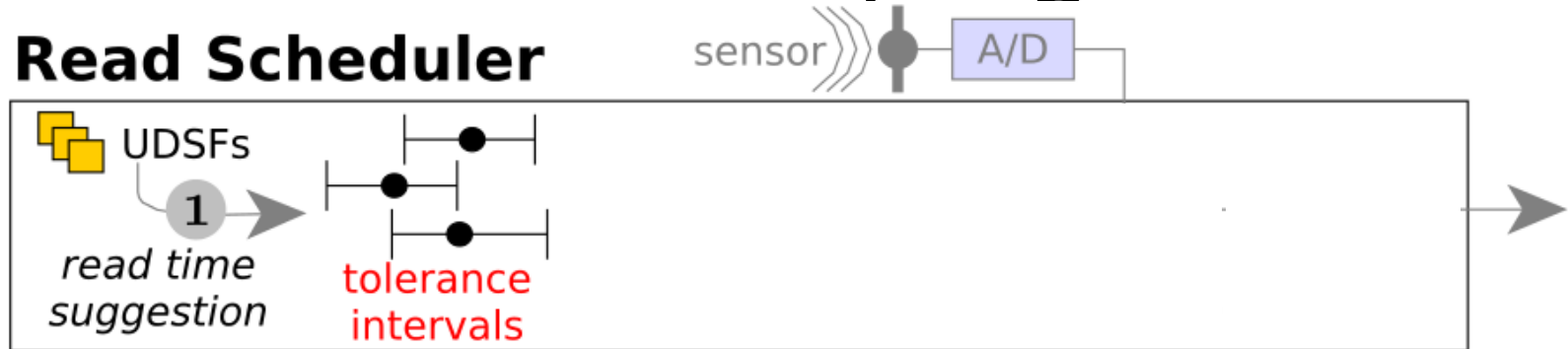
User-Defined Sampling Functions

Read Scheduler



- Provide an abstraction to define the data demand of applications.
- Upon a sensor read, request the next sensor read.

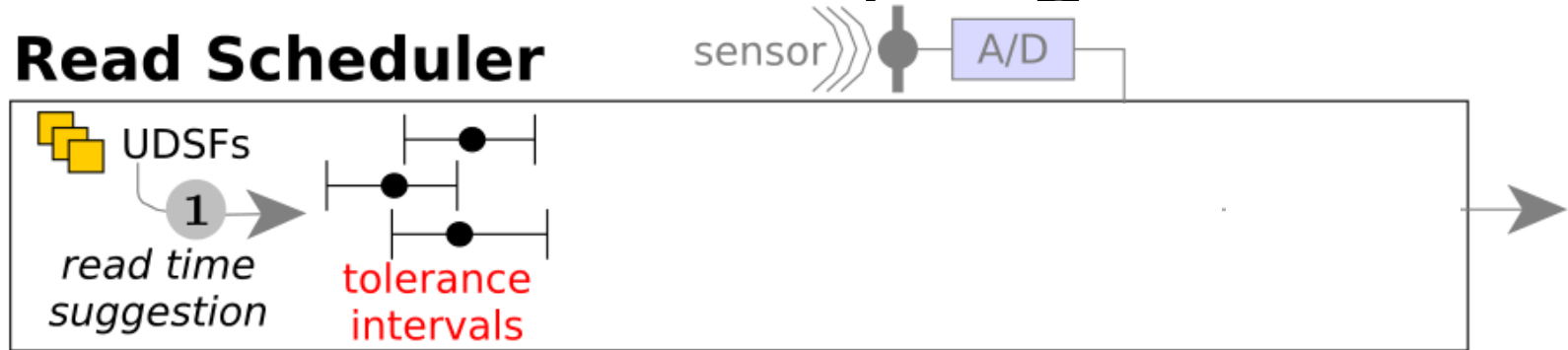
User-Defined Sampling Functions



- Provide an abstraction to define the data demand of applications.
- Upon a sensor read, request the next sensor read.
- Make read time tolerances explicit.

User-Defined Sampling Functions

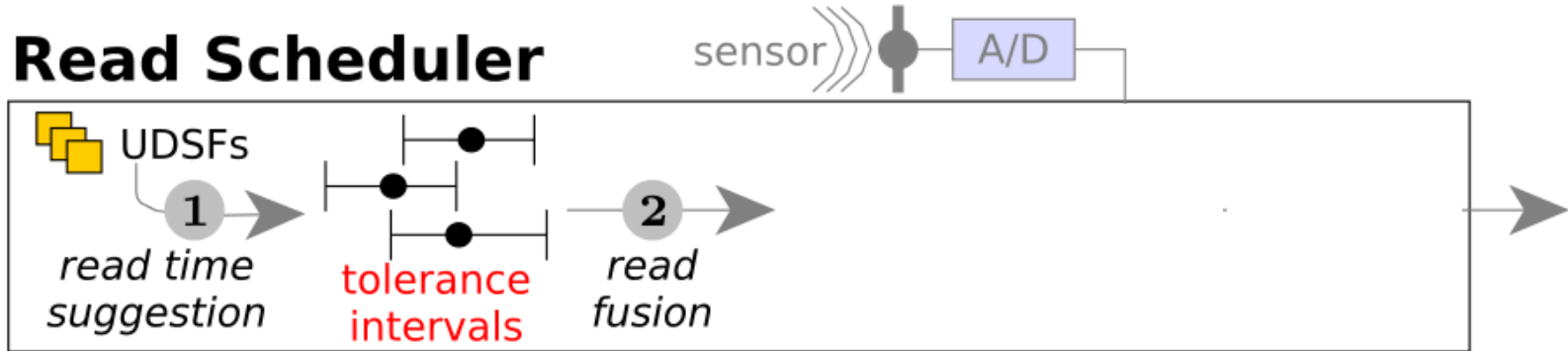
Read Scheduler



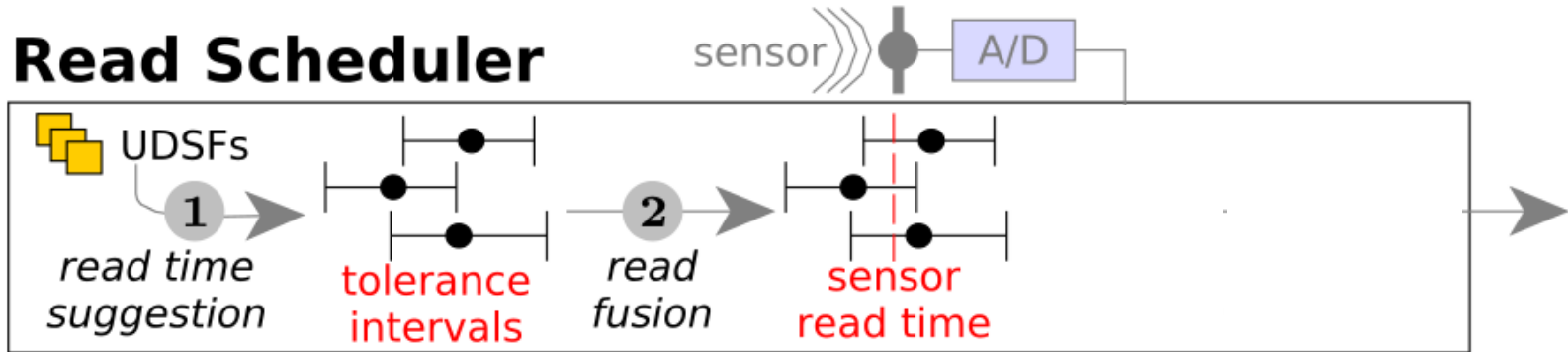
Enable **adaptive sampling techniques** to **reduce data transmission**

e.g., Adam [Trihinas '15], FAST [Fan '14], L-SIP [Gaura '13]

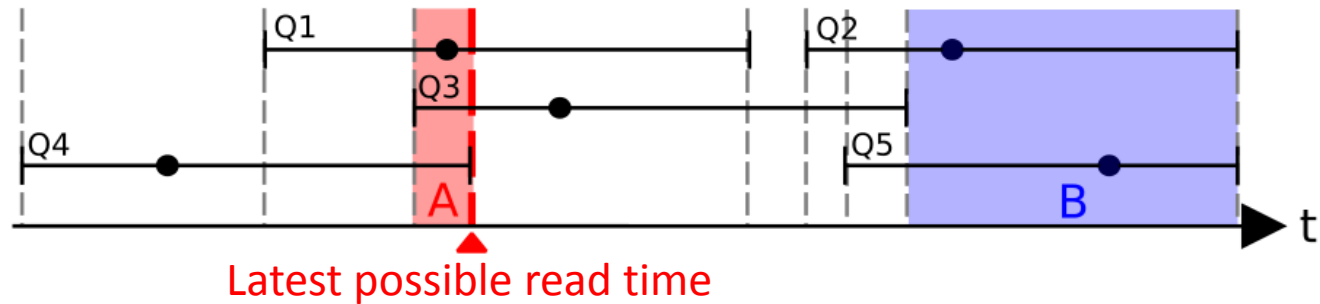
Sensor Read Fusion



Sensor Read Fusion



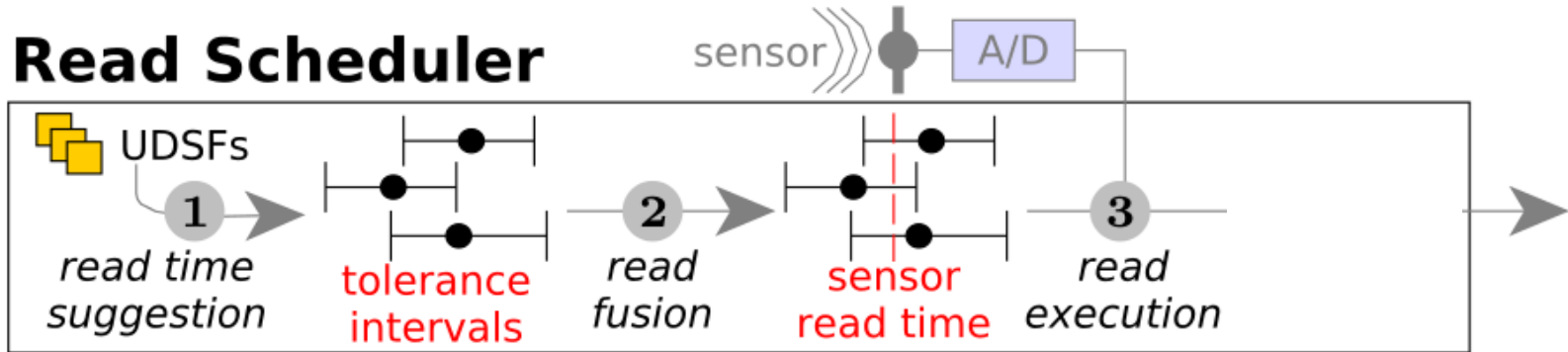
1) Minimize Sensor Reads and Data Transfer:



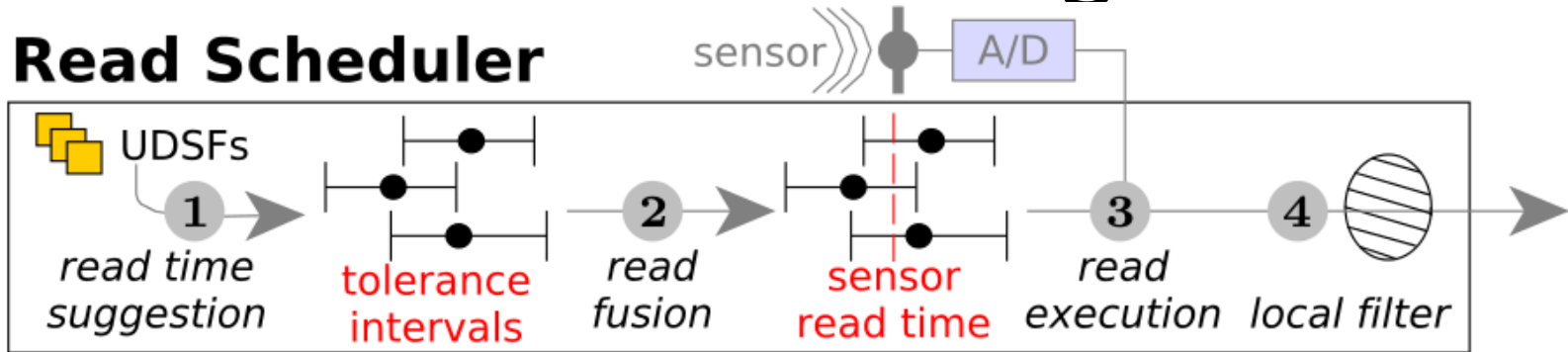
2) Optimize Sensor Read Times:

- Check the paper for all details on the read time optimizer!

Read Scheduler



Local Filtering



Optimized On-Demand Data Streaming from Sensor Nodes

Jonas Traub, Sebastian Breß, Asterios Katsifodimos, Tilmann Rabl, Volker Markl

Wrap-Up:

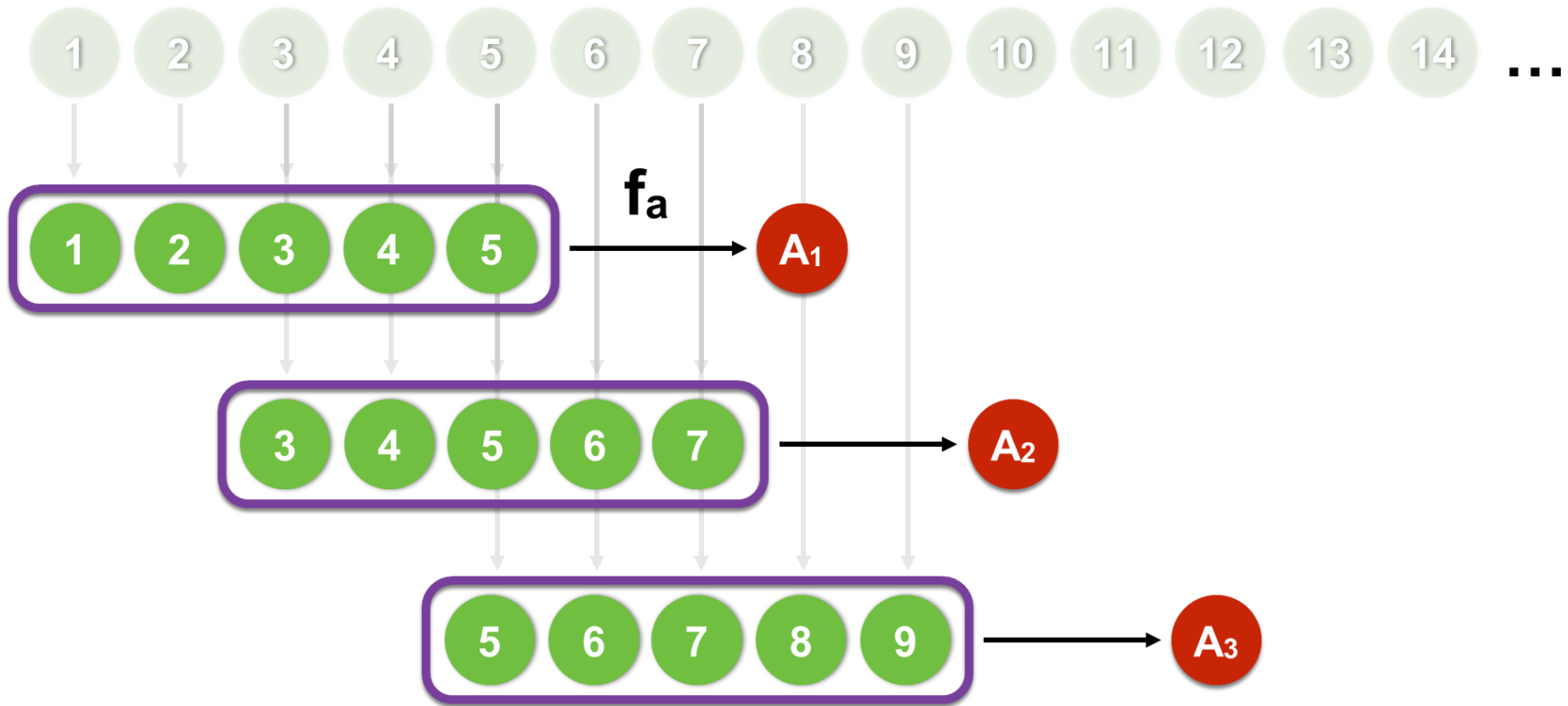
Tailor Data Streams to the Demand of Applications

- Define data demand: User-Defined Sampling Functions
- Schedule sensor reads and data transfer on-demand
- Optimize read times globally - for all users and queries

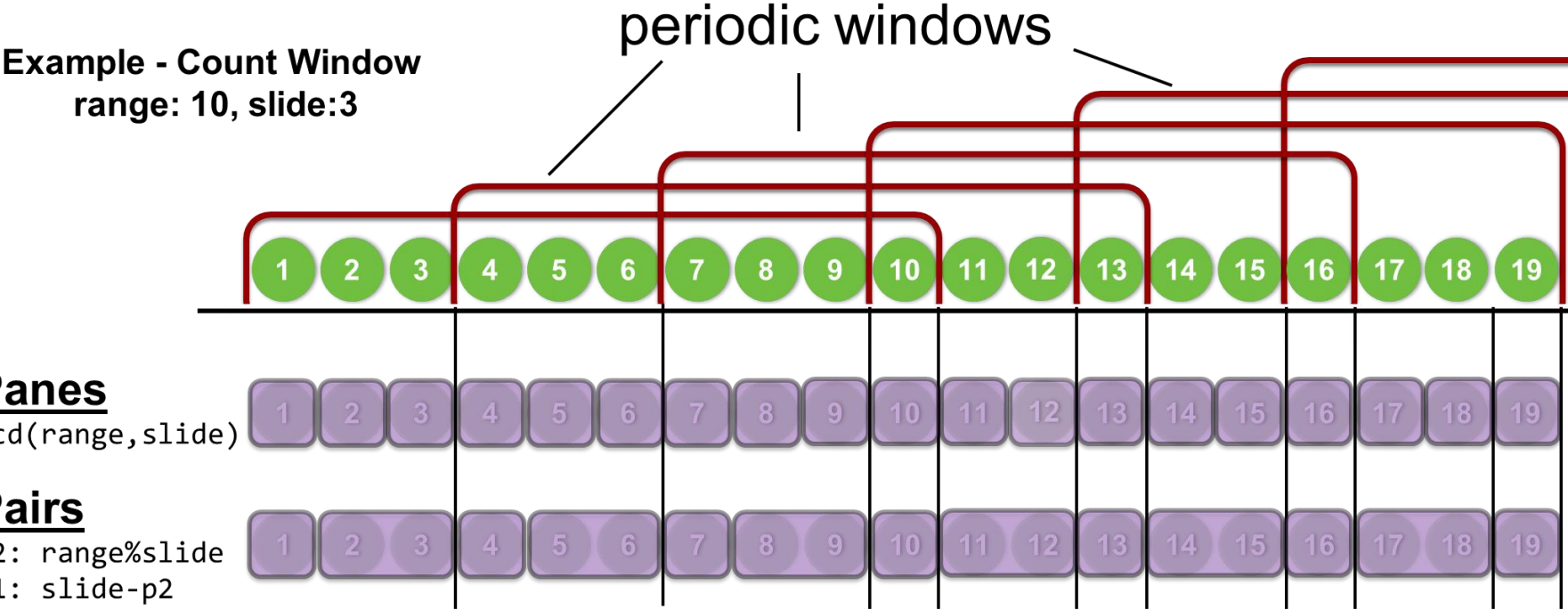
Cutty: Aggregate Sharing for User-Defined Windows

Paris Cabone, **Jonas Traub**, Asterios Katsifodimos, Seif Haridi, Volker Markl

Streaming Window Aggregation



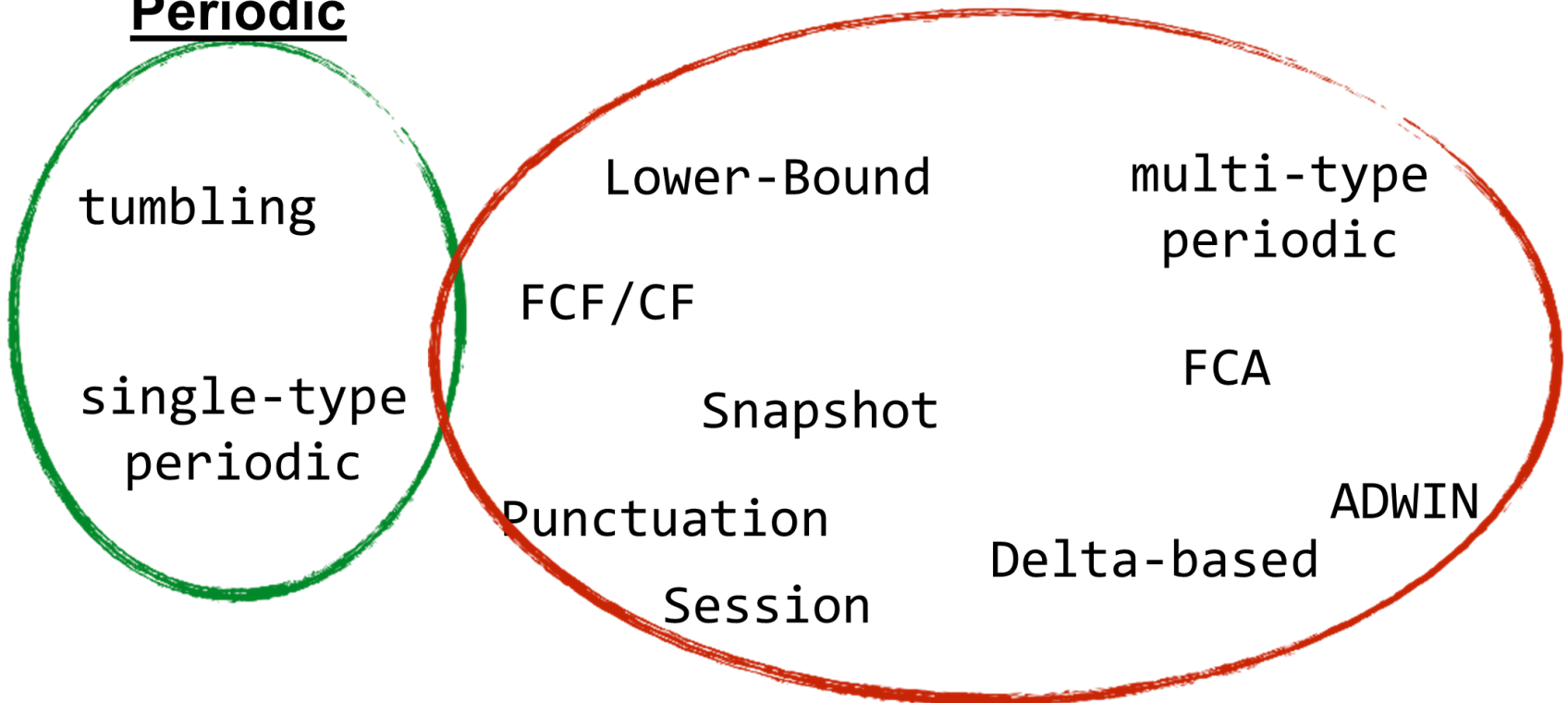
Stream Slicing



Applicability of Stream Slicing

Non-Periodic

Periodic

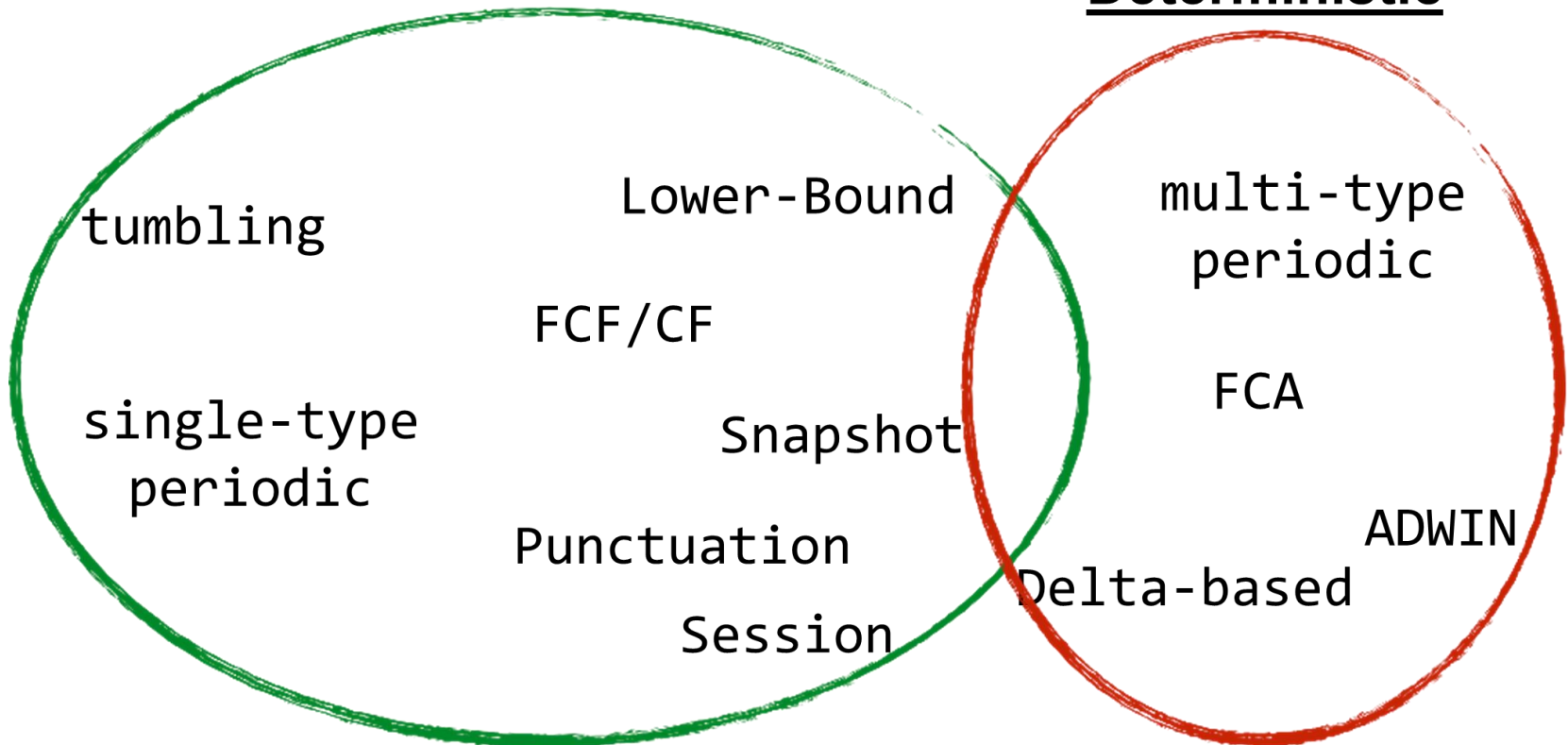


No slicing for the majority of window types
Can we do better?

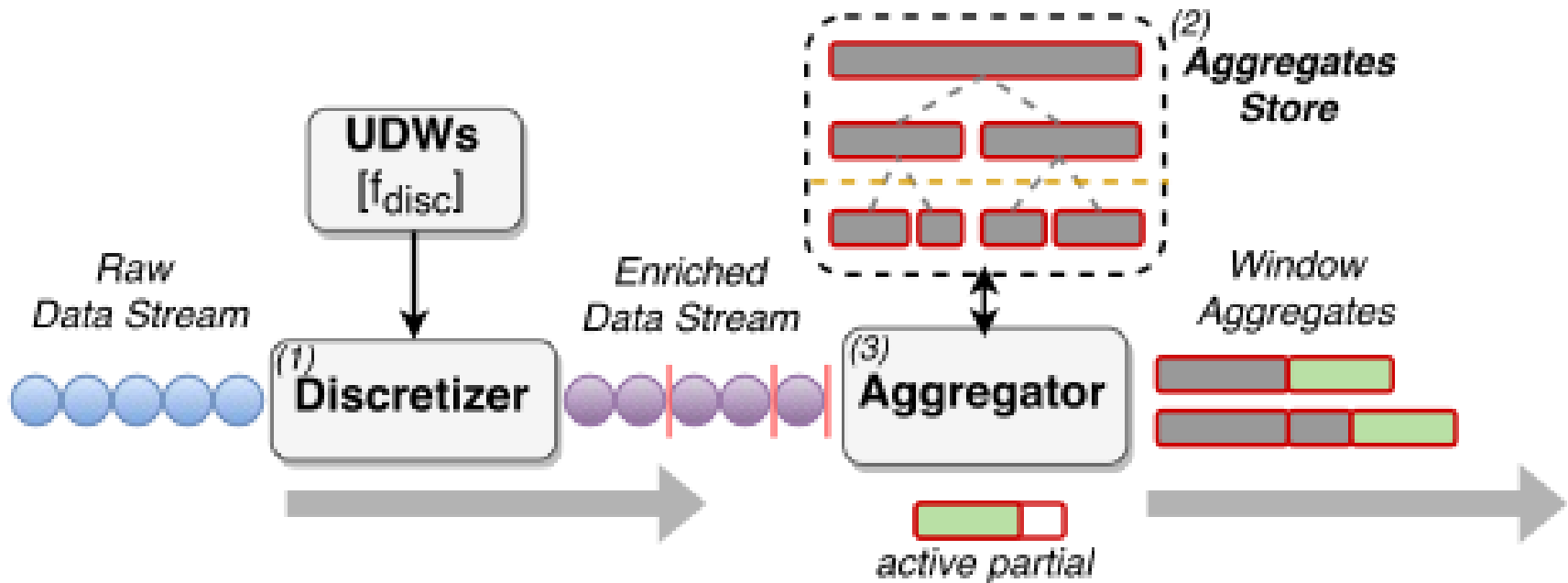
Yes, we can do better!

Deterministic

Non-Deterministic



Cutty Overview



Cutty: Aggregate Sharing for User-Defined Windows

Paris Cabone, Jonas Traub, Asterios Katsifodimos, Seif Haridi, Volker Markl

Wrap-Up:

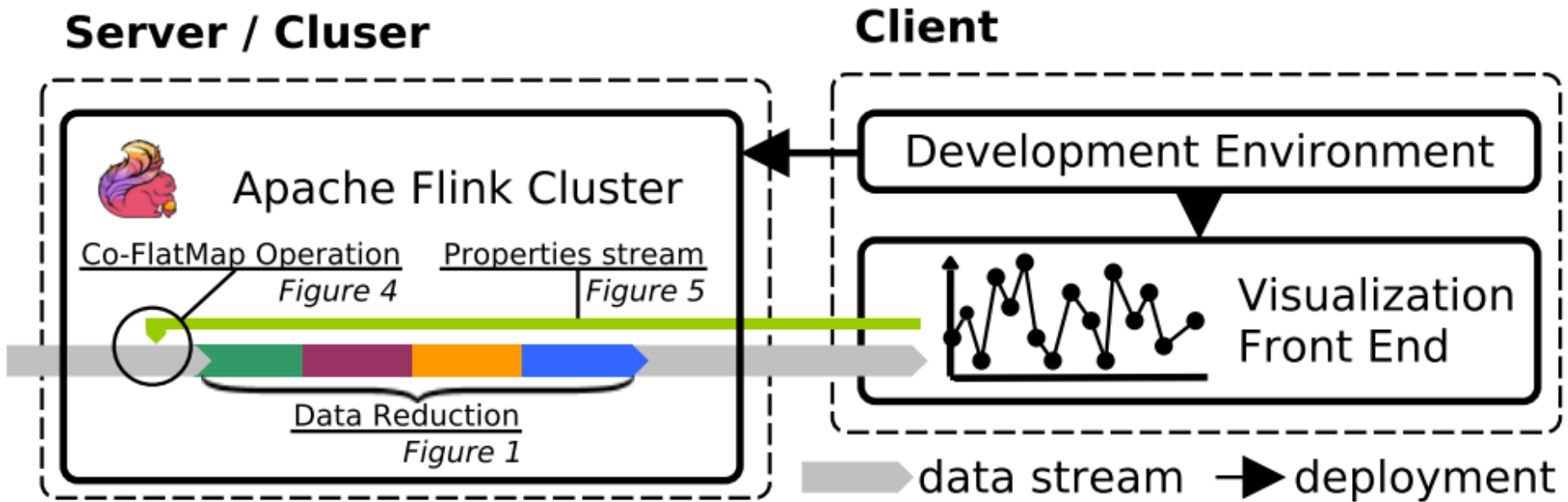
Enable Stream Slicing beyond Simple Tumbling and Sliding Windows

- Cutty enables Stream Slicing for a broad class of windows
- Cutty combines Stream Slicing, On-the-fly Aggregation, Aggregate Sharing, and Aggregate Trees

I²: Interactive Real-Time Visualization for Streaming Data

Jonas Traub, Nikolaas Steenbergen, Philipp Grulich, Tilmann Rabl, Volker Markl

Architecture Overview



Check out our Flink Forward Talk



Berlin, Sep 11-13, 2017

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INTERACTIVE REAL-TIME VISUALIZATION FOR STREAMING DATA WITH APACHE FLINK AND APACHE ZEPPELIN

JONAS TRAUB
RESEARCH ASSOCIATE,
TECHNISCHE UNIVERSITÄT BERLIN

PHILIPP GRULICH
RESEARCH ASSISTANTS,
GERMAN RESEARCH CENTRE FOR ARTIFICIAL INTELLIGENCE



youtube.com/watch?v=JNbq239JkK4

The Big Picture

