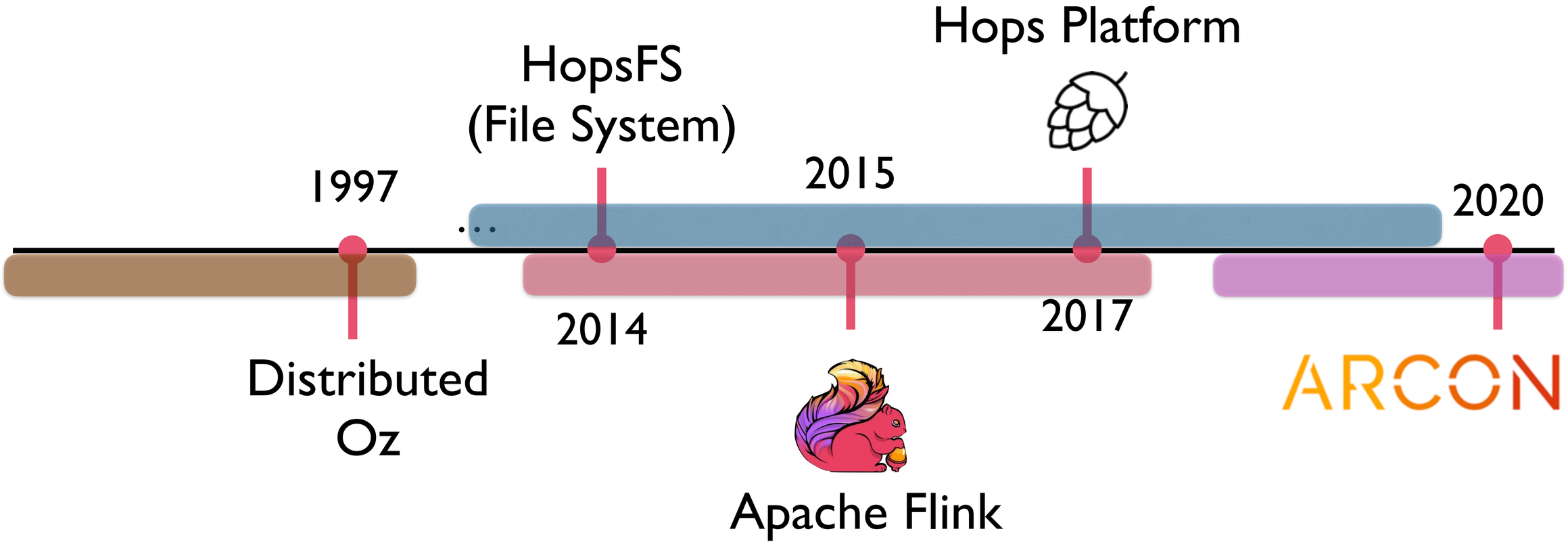
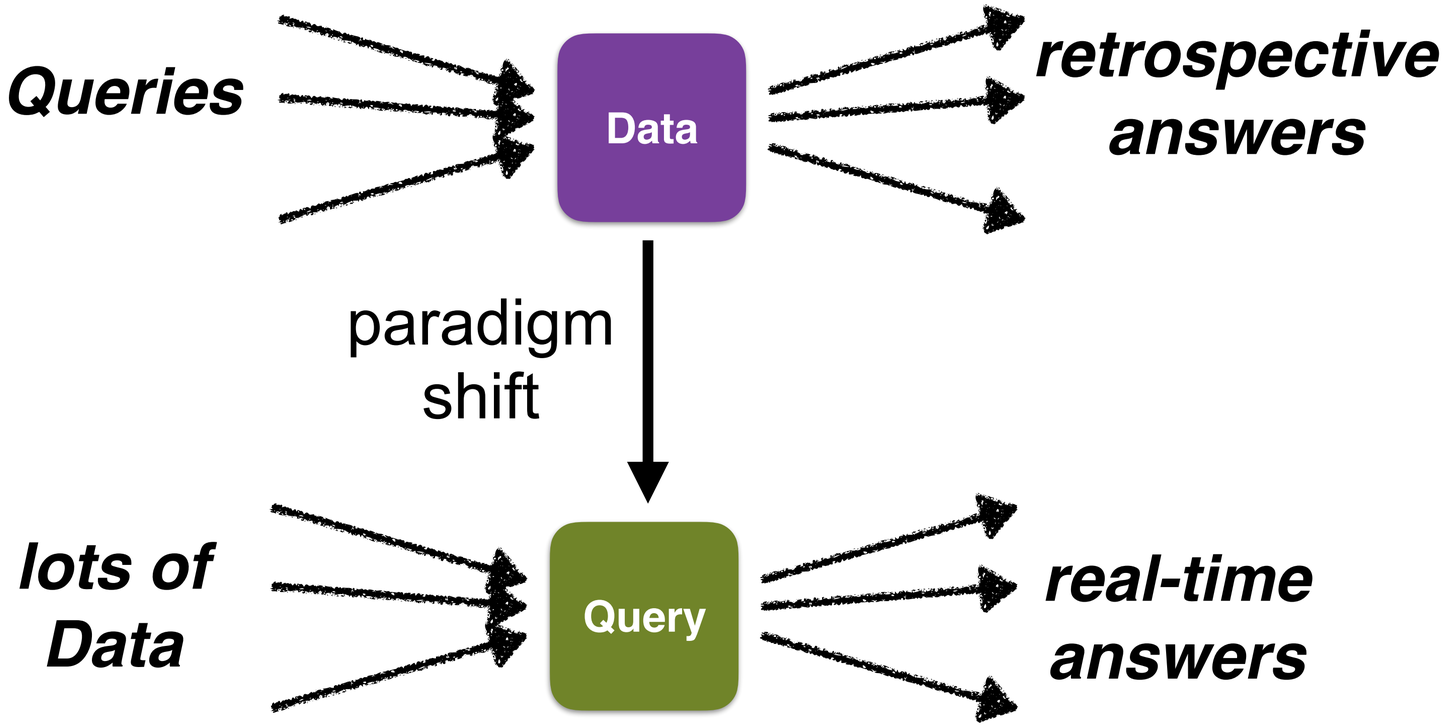
Seamless Batch and Stream Computation on Heterogeneous Hardware with Arcon

Paris Carbone
Research Institutes of Sweden

Open-Source @ DS Group



The Paradigm Shift Some Missed



The Real-Time Analytics Stack

High Level Models	Stream SQL, CEP…
Compute	Flink, Beam, Kafka-Streams, Apex, Storm
Storage	Kafka, Pub/Sub, Kinesis, Pravega…

- **Data Stream Processing** as a 24/7 execution paradigm

Apache Flink Foundations



Data Streams, Iterations,
Fault Tolerance, Window Aggregation

- Top-level Apache Project
- #1 stream processor (2020)
- Production-Proof

- > 400 contributors
- 100s of deployments

commercial deployments


influenced



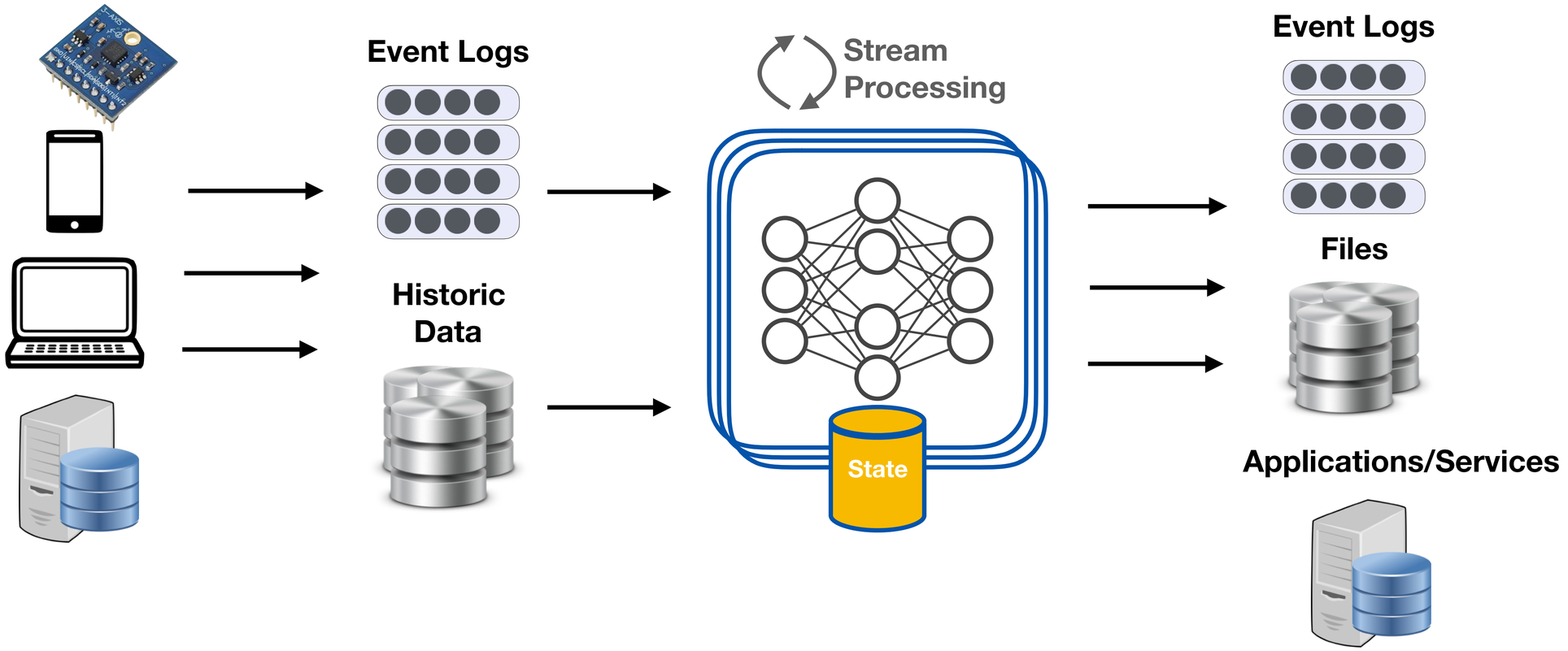






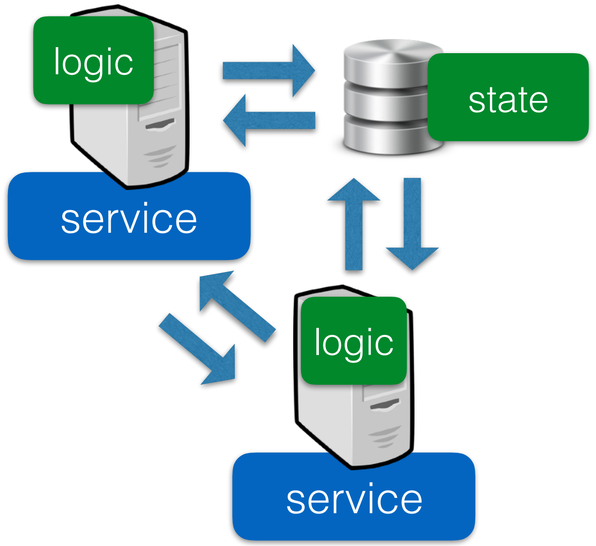



Stream Processors



Actors vs Streams

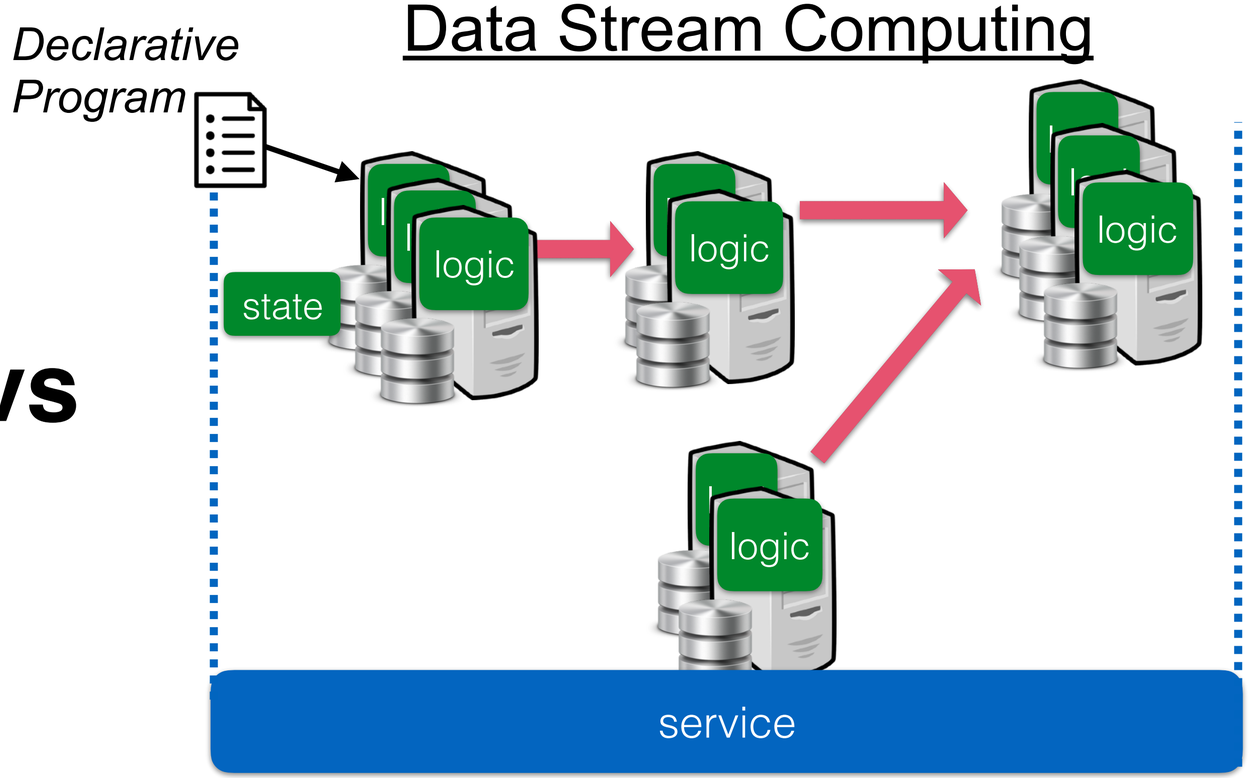
Actor Programming



- Low-Level Event-Based Programming
- Manual/External State
- Not Robust: Manual Fault Tolerance

vs

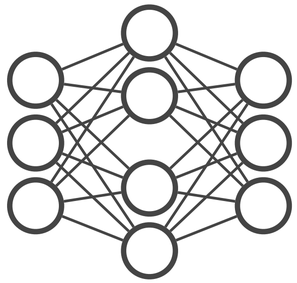
Data Stream Computing



- Declarative Programming
- State Managed by the system
- Robust: Built-in Fault Tolerance

Program Hierarchy in Flink

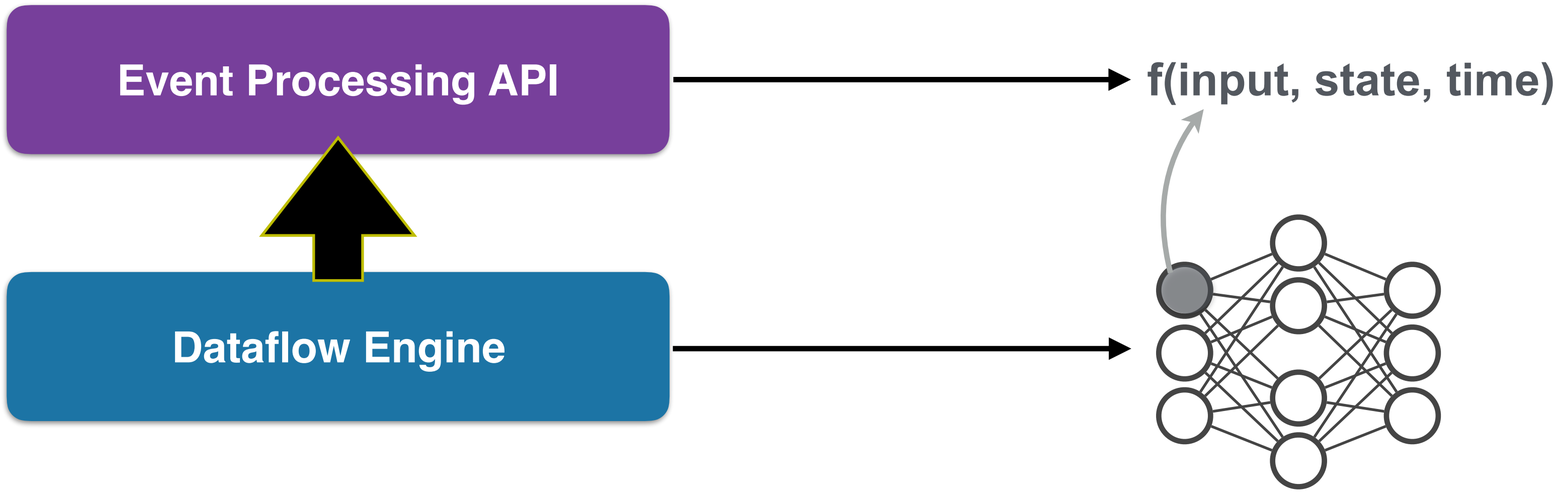
Dataflow Engine



Automates

- Fault Tolerance
- Scalability
- Monitoring/IO Management

Program Hierarchy in Flink

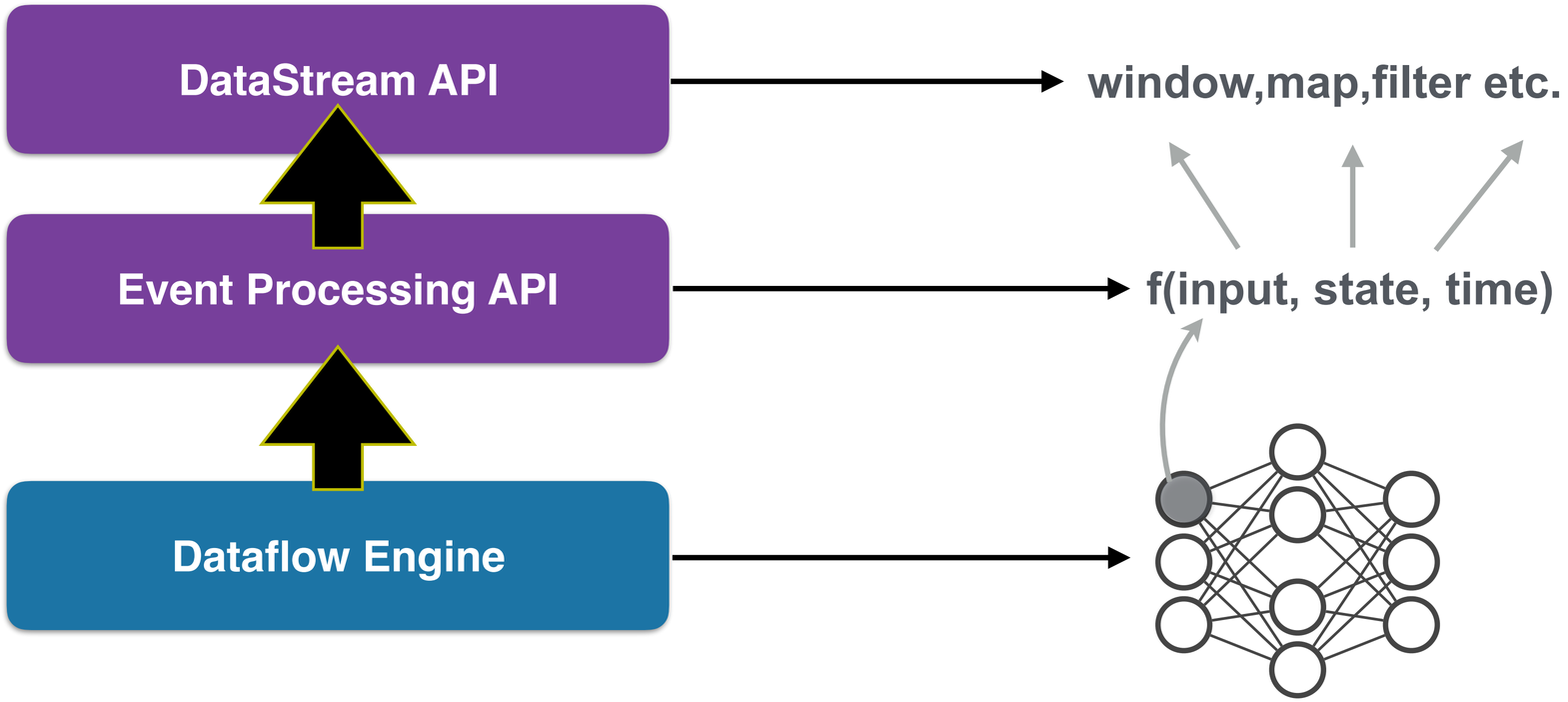


Automates

- Dynamic program state
- Operations on out-of-order streams

- Fault Tolerance
- Scalability
- Monitoring/IO Management

Program Hierarchy in Flink



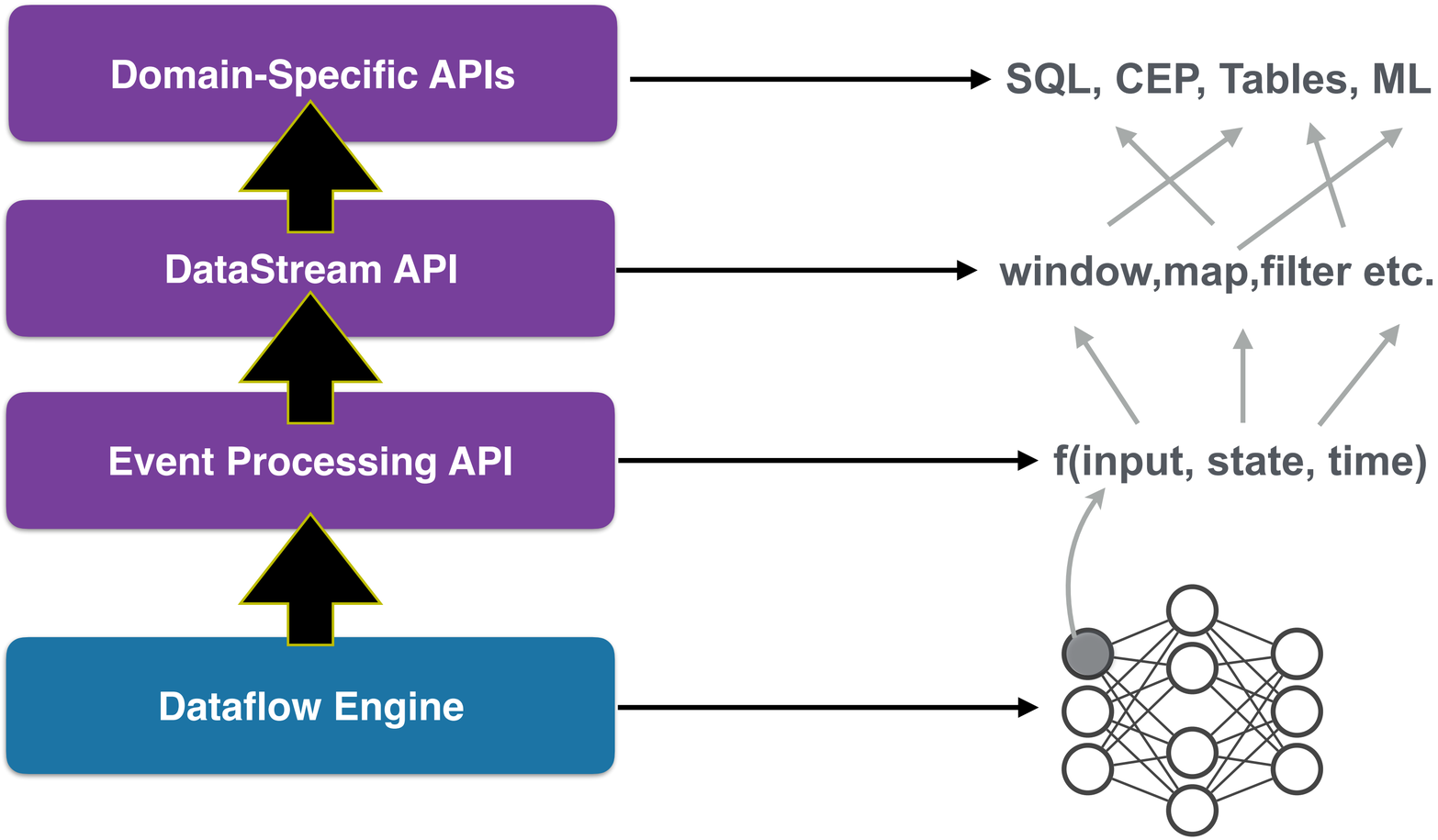
Automates

- Higher-Order Streaming Functions
- Event Windowing (sessions, time etc.)

- Dynamic program state
- Operations on out-of-order streams

- Fault Tolerance
- Scalability
- Monitoring/IO Management

Program Hierarchy in Flink



Automates

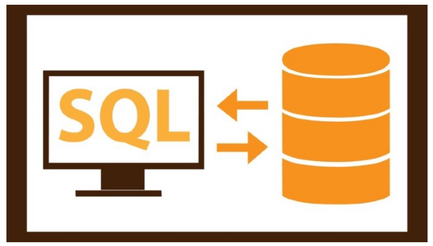
- Fully Declarative Programming
- Event Patterns, Relations etc.

- Higher-Order Streaming Functions
- Event Windowing (sessions, time etc.)

- Dynamic program state
- Operations on out-of-order streams

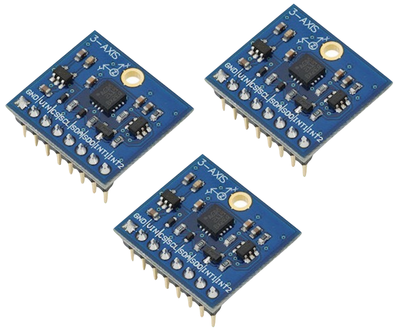
- Fault Tolerance
- Scalability
- Monitoring/IO Management

Declarative Streaming Examples



```
SELECT
  HOUR(r.rideTime) AS hourOfDay,
  AVG(f.tip) AS avgTip
FROM
  Rides r,
  Fares f
WHERE
  r.rideId = f.rideId AND
  NOT r.isStart AND
  f.payTime BETWEEN r.rideTime - INTERVAL '5' MINUTE AND r.rideTime
GROUP BY
  HOUR(r.rideTime);
```

Average Tip per Hour with Stream SQL



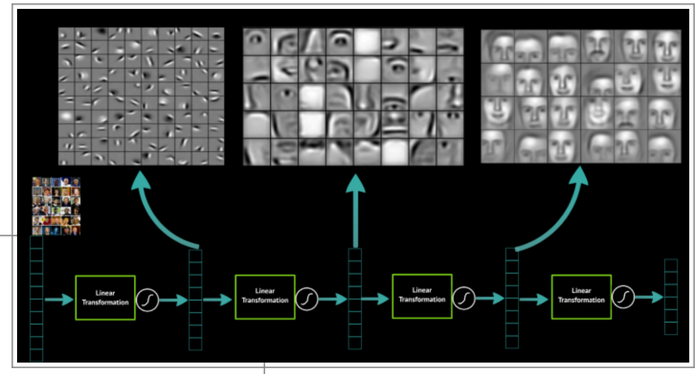
```
val completedRides = Pattern
 .begin[TaxiRide]("start").where(_.isStart)
 .next(“end").where(!_.isStart)

CEP.pattern[TaxiRide](allRides,
completedRides.within(Time.minutes(120)))
```

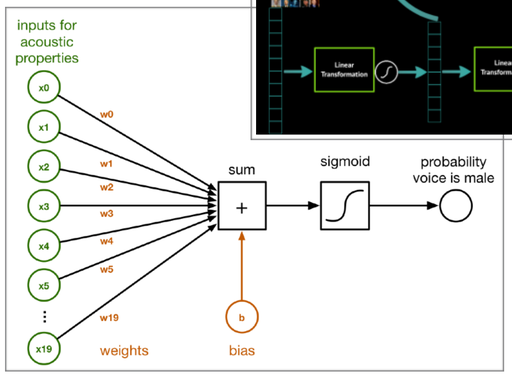
Completed Taxi Rides within 120min with Complex Event Processing

Data Pipelines Today

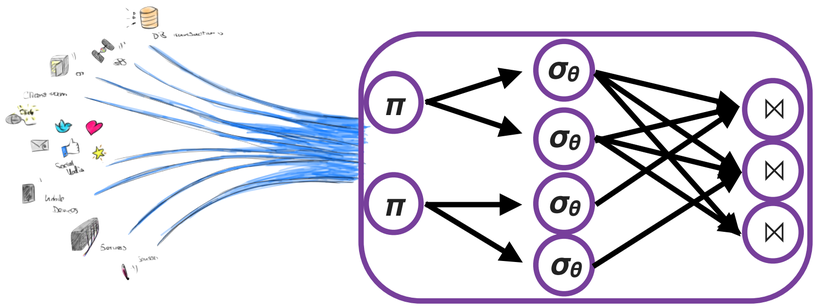
- Many Frameworks/Frontends for different needs
- (ML Training & Serving, SQL, Streams, Tensors, Graphs)



Feature Learning



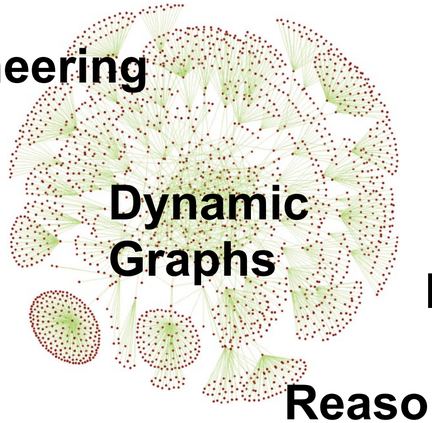
Tensor Programming



Streams

AI

Feature Engineering



ML

Model Serving

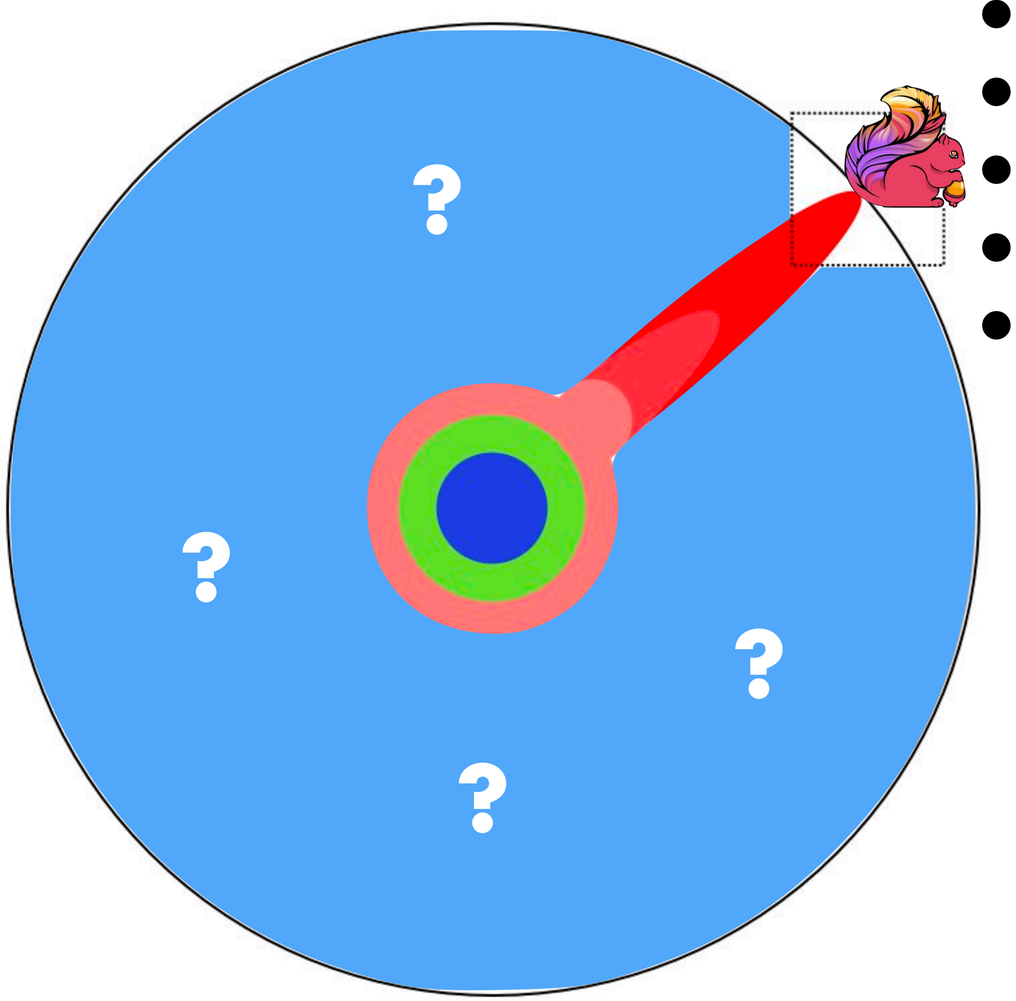
Reasoning

RL

Simulation tasks

The Bigger Picture

Data Processing



Data Streams

- scalable, fault tolerant analytics
- event-based business logic
- out-of-order computation
- dynamic relational tables (SQL)
- event pattern-matching (CEP)

but what about deeper analytics…

- tensors
- graph algorithms
- deep learning
- feature learning
- reinforcement learning
- ….

Critical Limitations

Complex Analytics

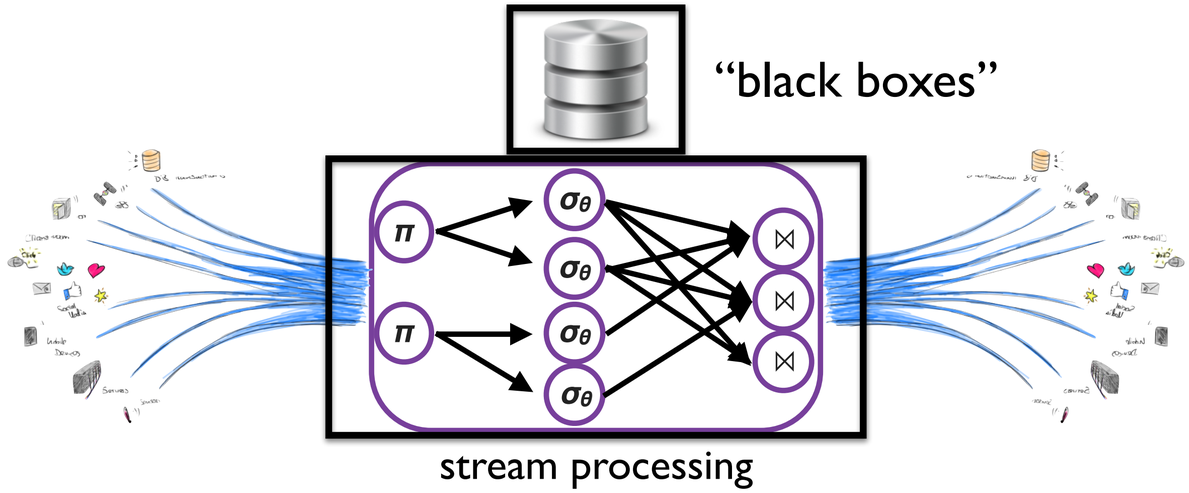
- Highly Skewed Data-Parallel KV Ops
- Beyond Data-Parallel KV ops
  - Graph Data
  - Large Matrices
- Task-Parallel Computation
- Bulk-Synchronous/Window Iterations

State Reuse

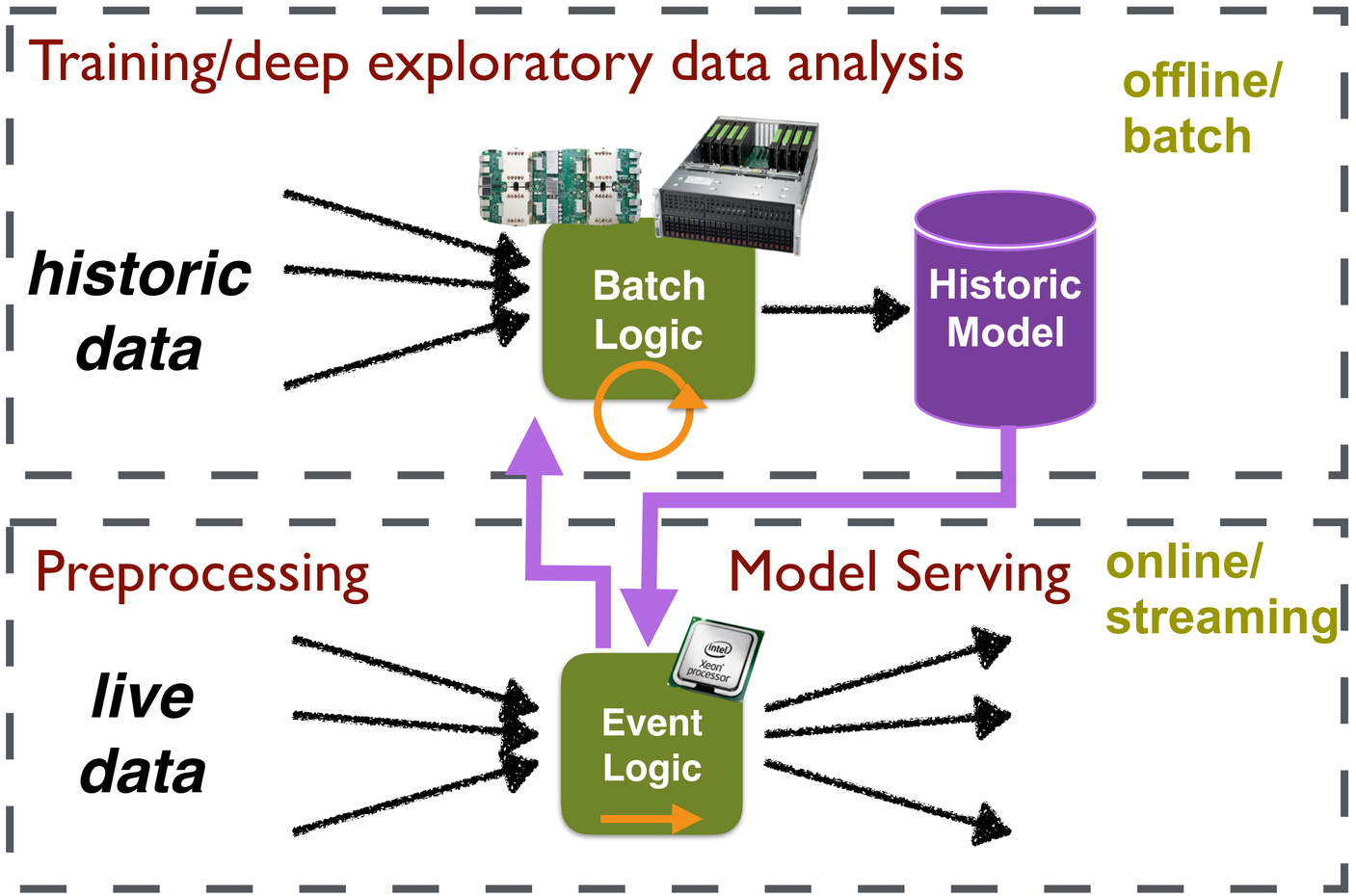
- Accessing Stream State *Externally*
  - Materialized Views (Relational)
  - Feature Matrices (ML)
  - Edge Stream State (Graphs)
- Parallelizing Stateful Ops *Internally*
  - Global Window Aggregation

Compute/HW Sharing

- Escaping the JVM
  - Code Generation for Accelerators
  - SIMD, Vectorization
  - Better Fusion Capabilities
  - Flexible, Dynamic Reconfiguration



Recurring Issues



Framework/Library Silos

↓

Fragmented Codebases/Runtimes

↓

Unshared Hardware

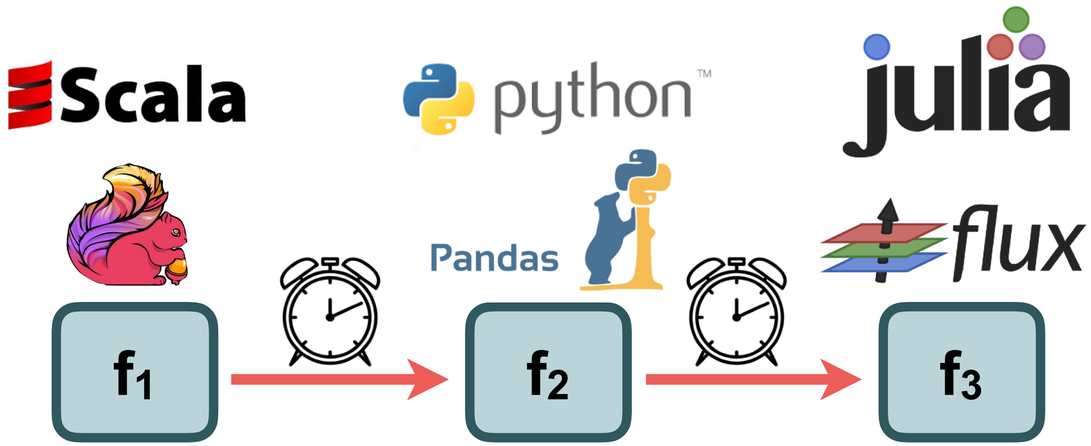
↓

Over-materialization of results

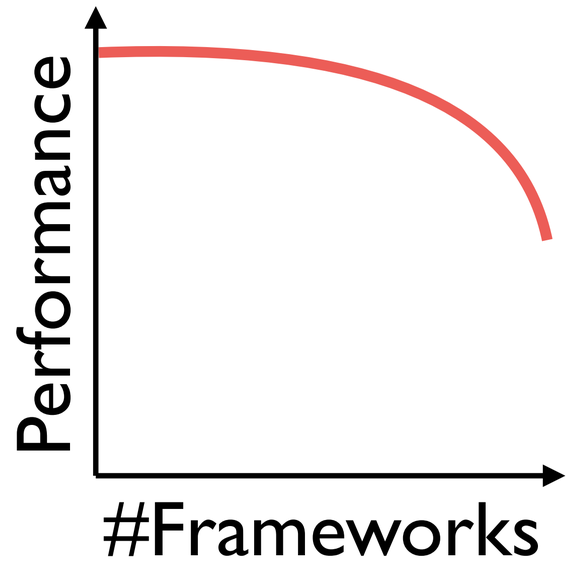
↓

Ridiculously Unoptimal Pipelines

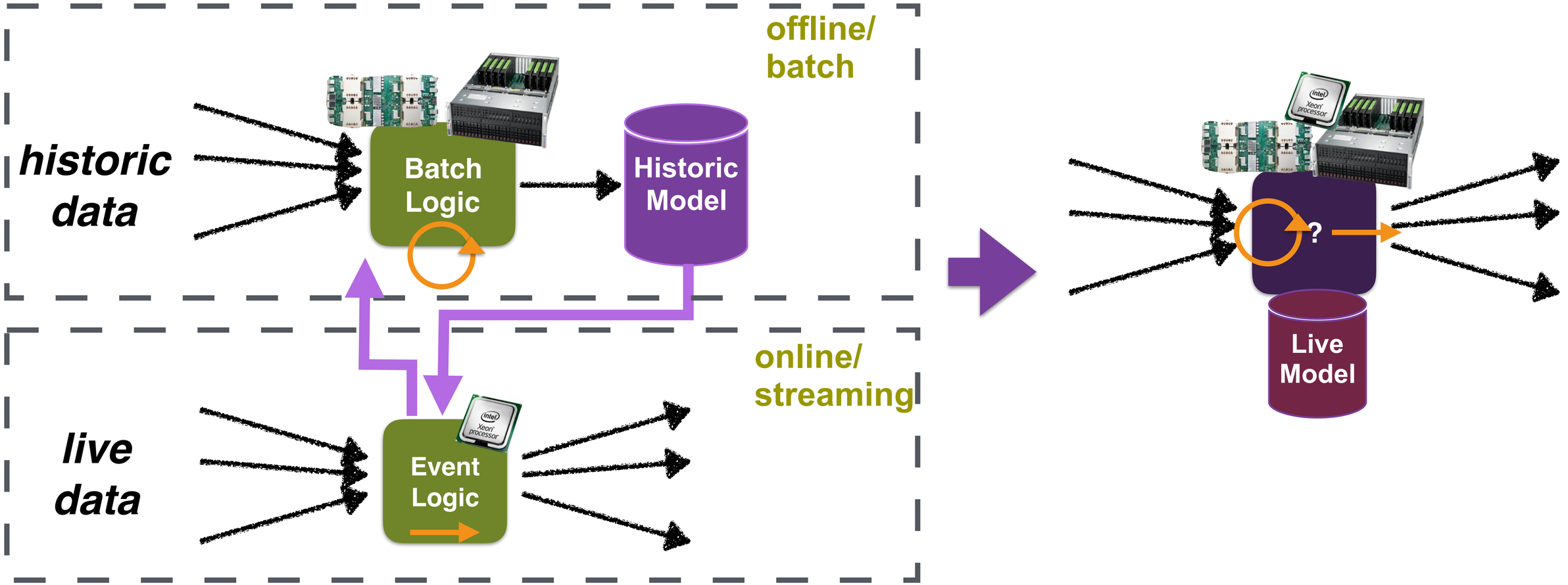
The Problem



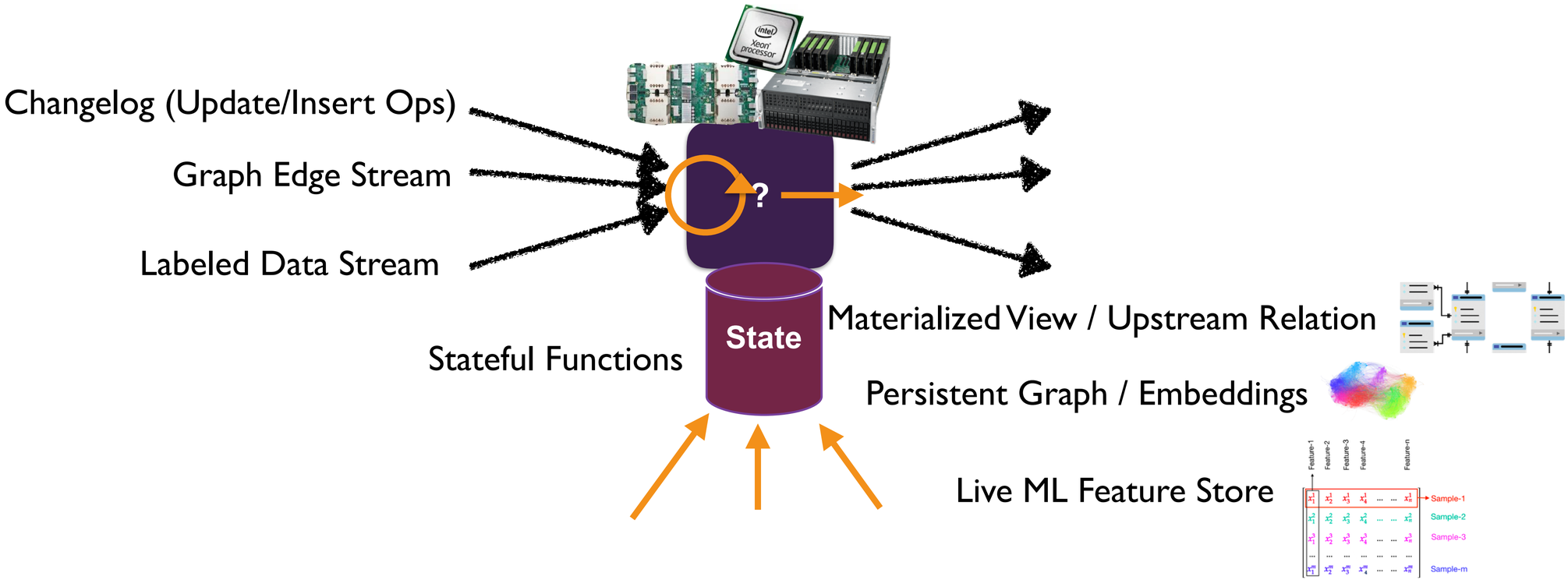
- No cross-optimisation is possible, e.g. resource sharing
- Data movement costs (⟶)



Revisiting Compute Systems



Example Applications



The Arcon Vision

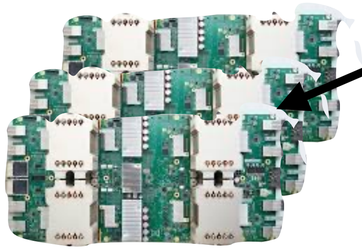
Unified Declarative Programming

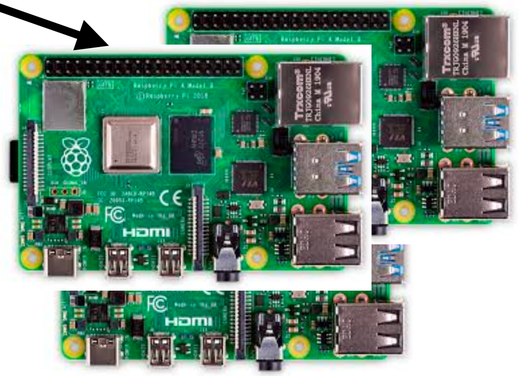
Tensors DataFrames DataStreams Graphs

Cross-Compile
Optimise²
and Generate Code

Arcon

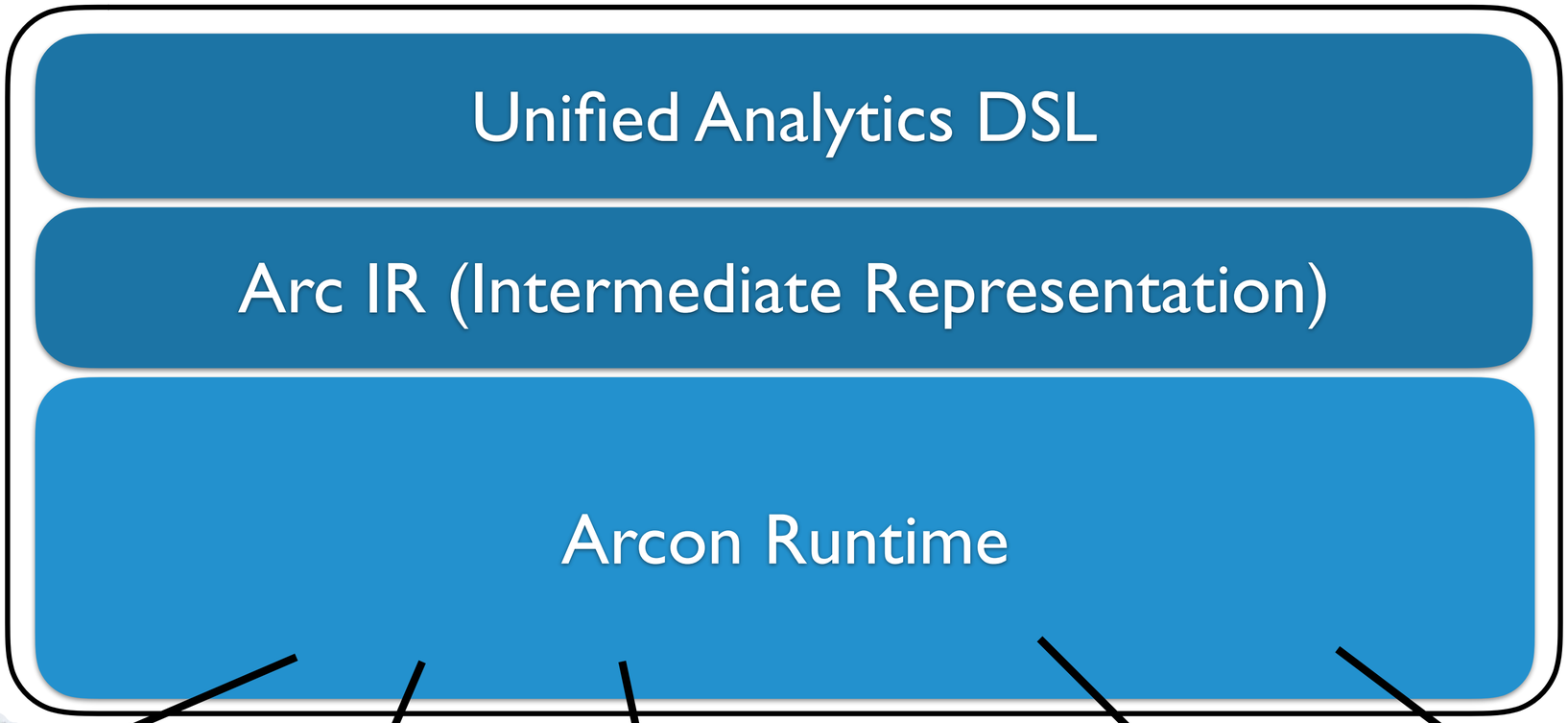
3.5mil eur
SSF funding

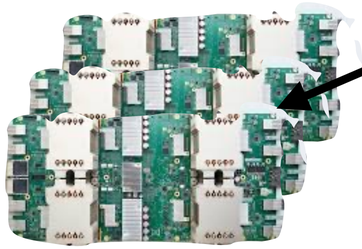


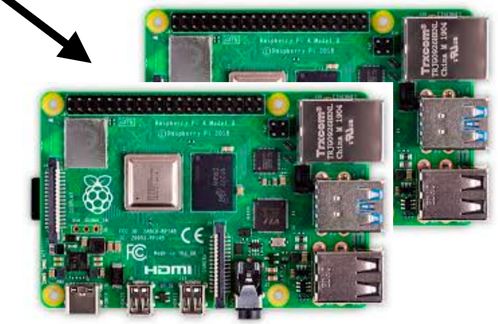


Shared Native Execution

The Arcon Architecture

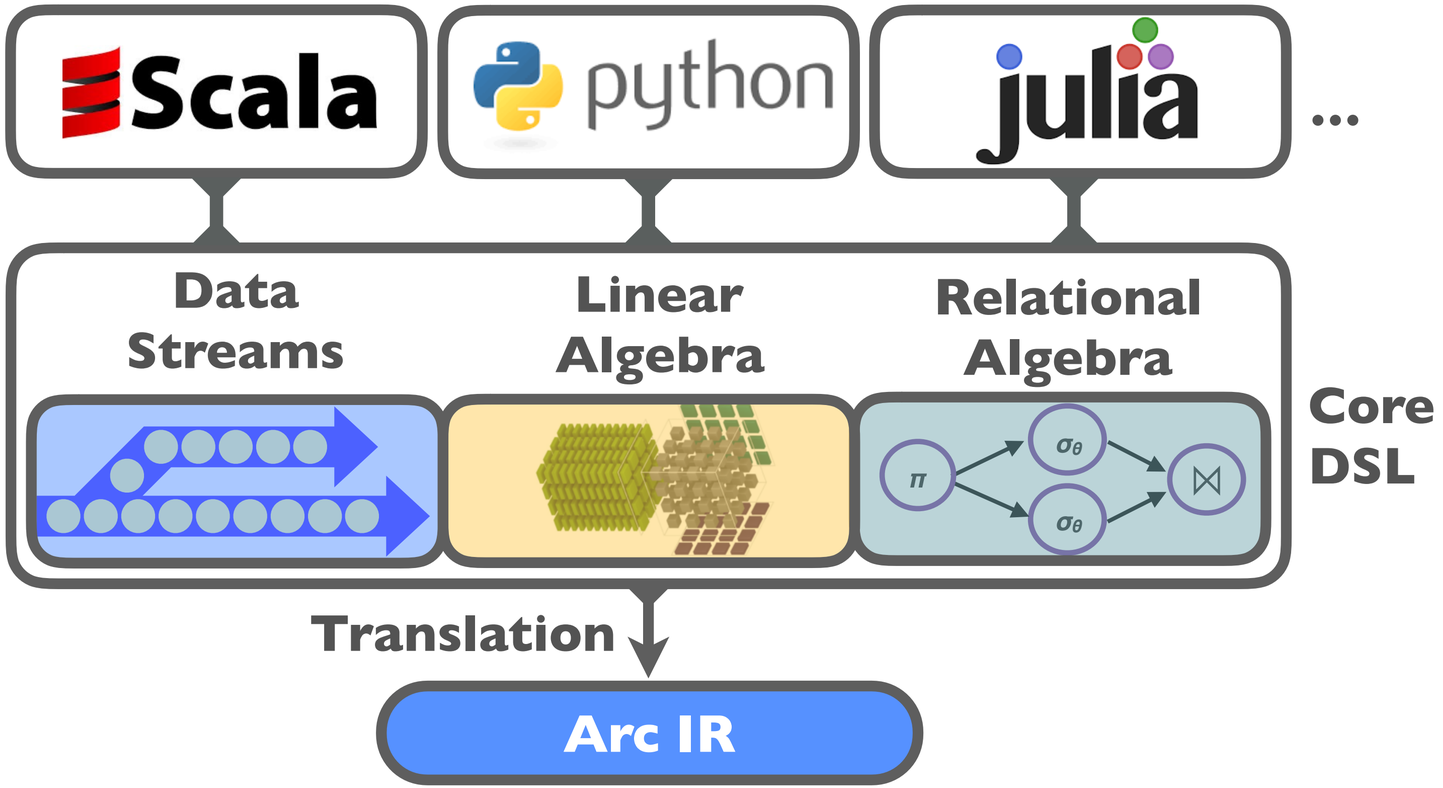






Unified Analytics DSL

- Host language-agnostic core
- Compositional
- First-class citizen support for:
  - *streams, tensors, relations*



DSL Philosophy

Comprehensions (e.g., DataSets + Matrices)

```
1  @lib def vectorizeComment(c: Comment) = { /* UDF */ }
2  @lib def vectorizeUser(u: User) = { /* UDF */ }                    ❶
3
4  optimize {                                                         ❷
5    // Join "Comments" and "Users" and vectorize the result
6    val features = for {
7      c <- Comments // DataBag[Comment]
8      u <- Users    // DataBag[User]
9      if u.user_id == c.user_id
10   } yield vectorizeComment(c) ++ vectorizeUser(u)
11   // Convert the DataBag "features" into matrix "X"
12   val X = Matrix(features)                                         ❸
13   // Filter rows that have values > 10 in the third column
14   val M = X.forRows(row => row(2) > 10)                            ❹
15   // Calculate the mean for each column
16   val means = M.forCols(col => mean(col))                          ❺
17   // Deviation of each cell of "M" to the cell's column mean
18   val U = M - Matrix.fill(M.nRows, M.nCols)((i,j) => means(j))
19   // Compute the covariance matrix
20   val C = 1 / (U.nRows - 1) * U ** U.t                             ❻
21 }
```

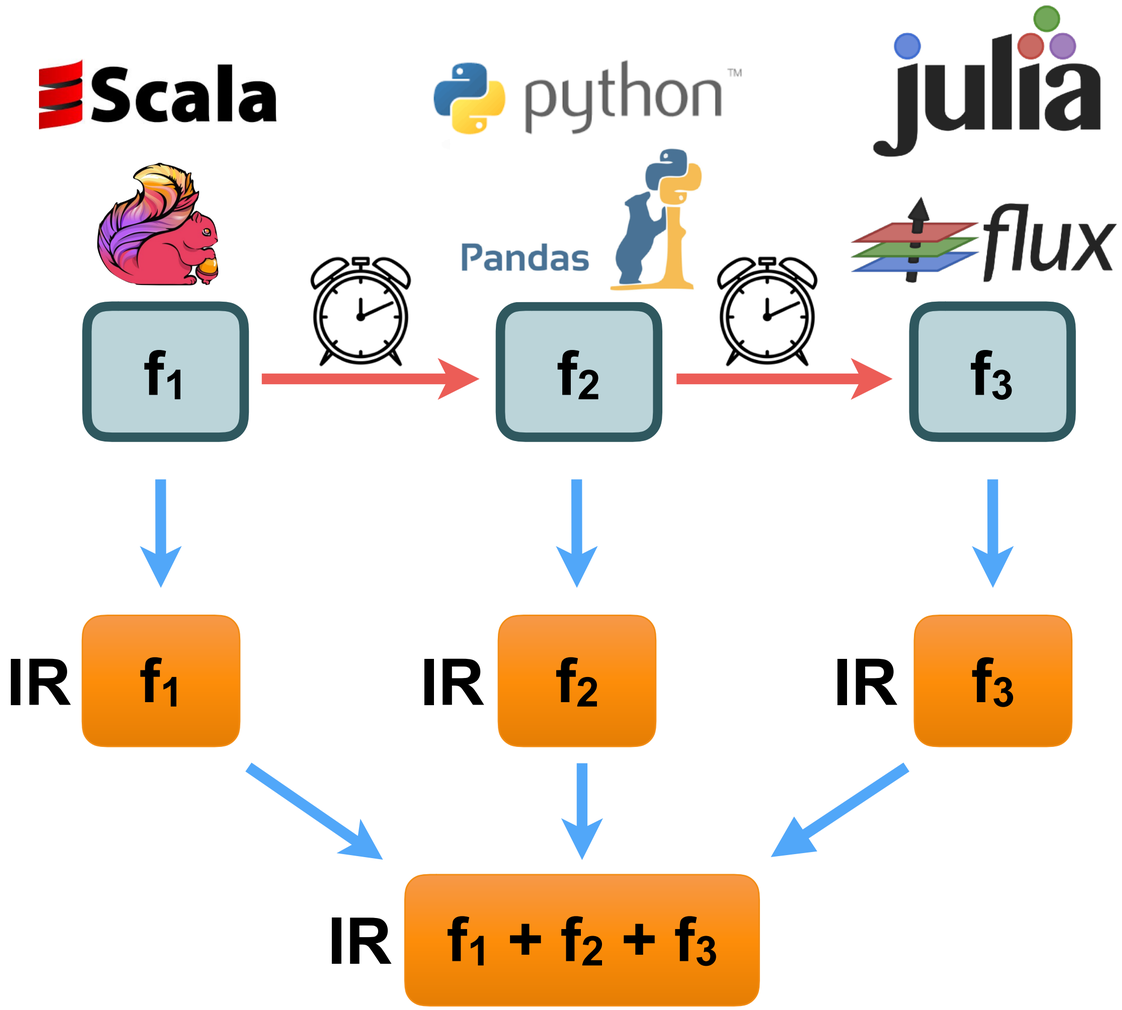
Example taken from Lara DSL

DSL Extensions

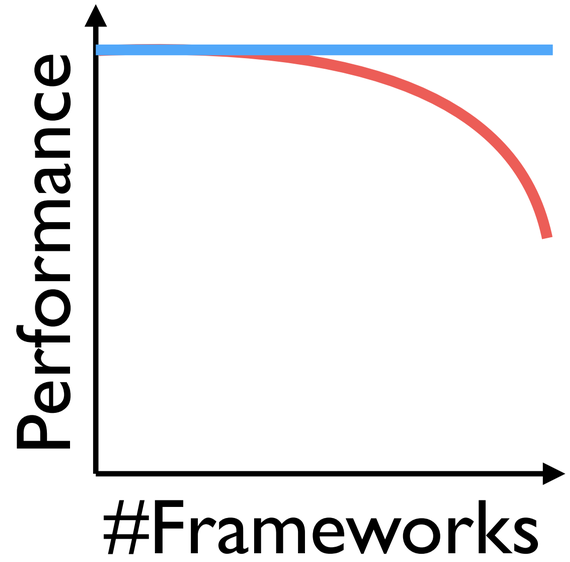
Comprehensions for Data Streams

```
  for {
    w <- features.window(length=10, stride=60) //
Window[Feature] with 10 sec length, 1 min stride
  } yield {
    // Convert the Window "w" into matrix "X"
    val X = Matrix(w)
    // Filter rows that have values > 10 in the third column
    val M = X.forRows(row => row(2) > 10)
    // Calculate the mean for each column
    val means = M.forCols(col => mean(col))
    // Deviation of each cell of "M" to the cell's column mean
    val U = M - Matrix.fill(M.nRows, M.nCols)((i,j) =>
means(j))
    // Compute the covariance matrix
    val C = 1 / (U.nRows - 1) * U ** U.t
    // ...
  }
}
```

IR Intuition



- No cross-optimisation is possible, e.g. resource sharing
- Data movement costs (⟶)



Arcon Compiler Pipeline

Arcon

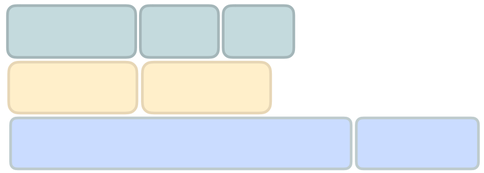
Unified Analytics DSL

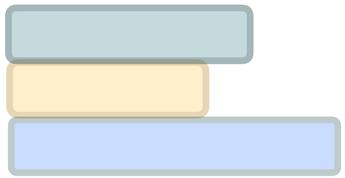
Arc (High Level IR)

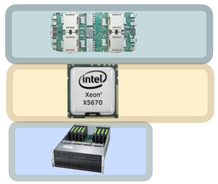
Logical Dataflow IR

Physical Dataflow IR

Binaries







Arc IR

- A minimal yet feature-complete set of read/write-only types and expressions

```
program     ::= { declaration } lambda
declaration ::= macro id ( { id , } ) = expr ;
              | type id = type ; // Type alias
              | fn id | { type , } | ( type ) = lambda ;
lambda      ::= | { id : type , } | expr
type        ::= id | valueType | builderType | struct type
valueType   ::= Unit | bool | i8 | i16 |...
              | Simd [ type ]
              | Vec [ type ]
              | Dict [ type , type ]
              | Stream [ type ]
builderType ::= Appender [ type ]
              | Merger [ type , binop ]
              | StreamAppender [ type ]
              | Windower [ type , type ]
              |...
struct type ::= { { type , } }
expr        ::= opExpr | letExpr
opExpr      ::= ( expr )
              | id
              | literal
              | type ( expr ) // Type cast
              | for ( iterator , expr , lambda )
              | merge ( expr , expr )
              | result ( expr )
              | if ( expr , expr , expr )
              | cudf [ id , type ] ( { expr , } )
              | drain ( expr , expr )
              | builderConstr
              | opExpr binop opExpr
              |...
```

```
letExpr     ::= let id : type = opExpr ; expr
binop       ::= + | - | * | / |...
              | id
literal     ::= scalarLiteral
              | [ { expr , } ] // Vec literal
              | { { expr , } } // Struct literal
              | () // Unit literal
iterator    ::= expr | iter ( expr , expr , expr )
              | next ( expr )
              | keyby ( expr , lambda )
              |...
builderConstr ::= Appender [ type ]
              | Merger [ type , binop ]
              | StreamAppender [ type ]
              | Windower [ type , type ] ( lambda , lambda,
                  lambda )
              |...
```

Read More

[Paper] Arc: An IR for Batch and Stream Programming @ DBPL19

[Code] https://github.com/cda-group/arc

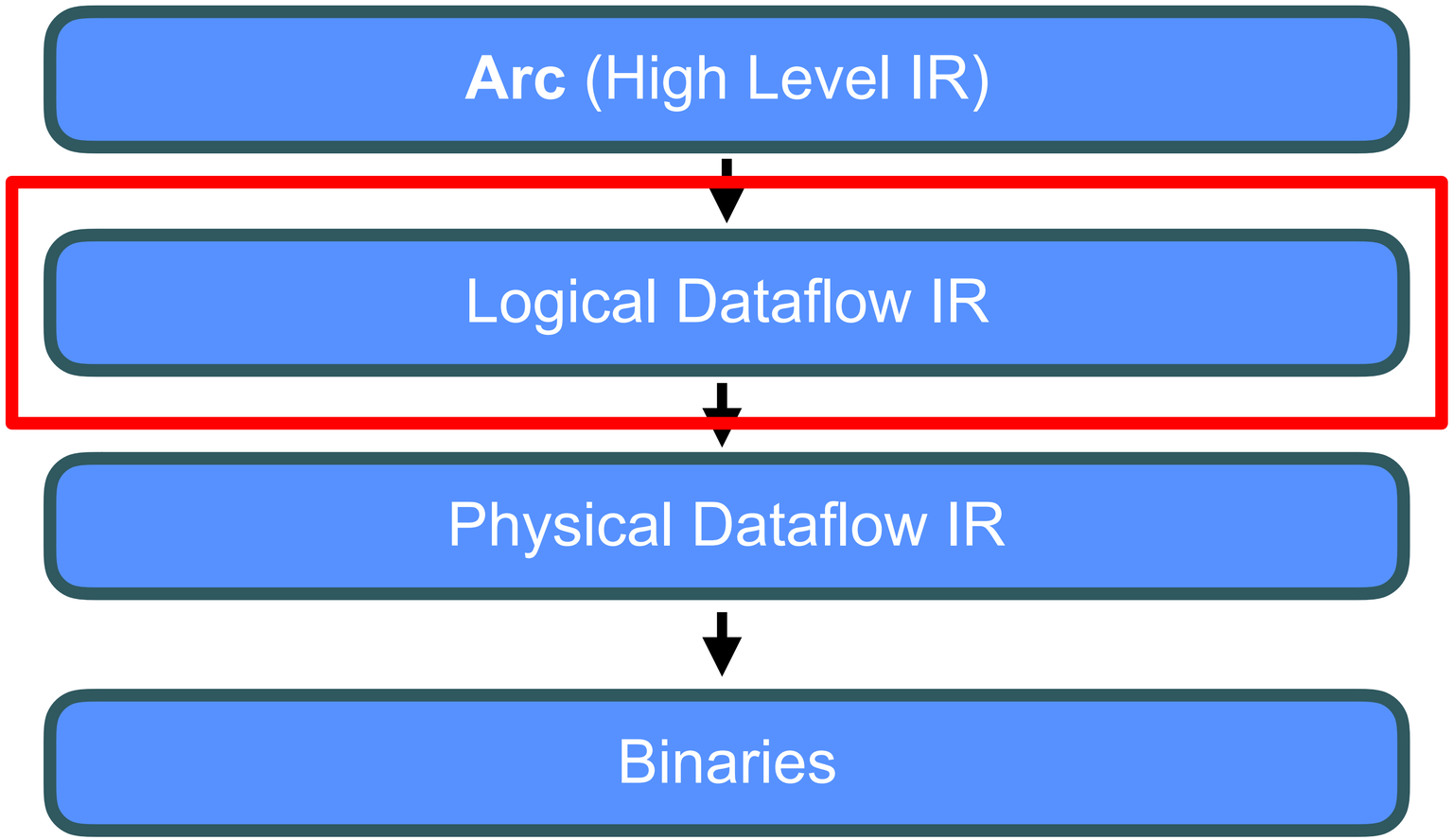
RI.
SE

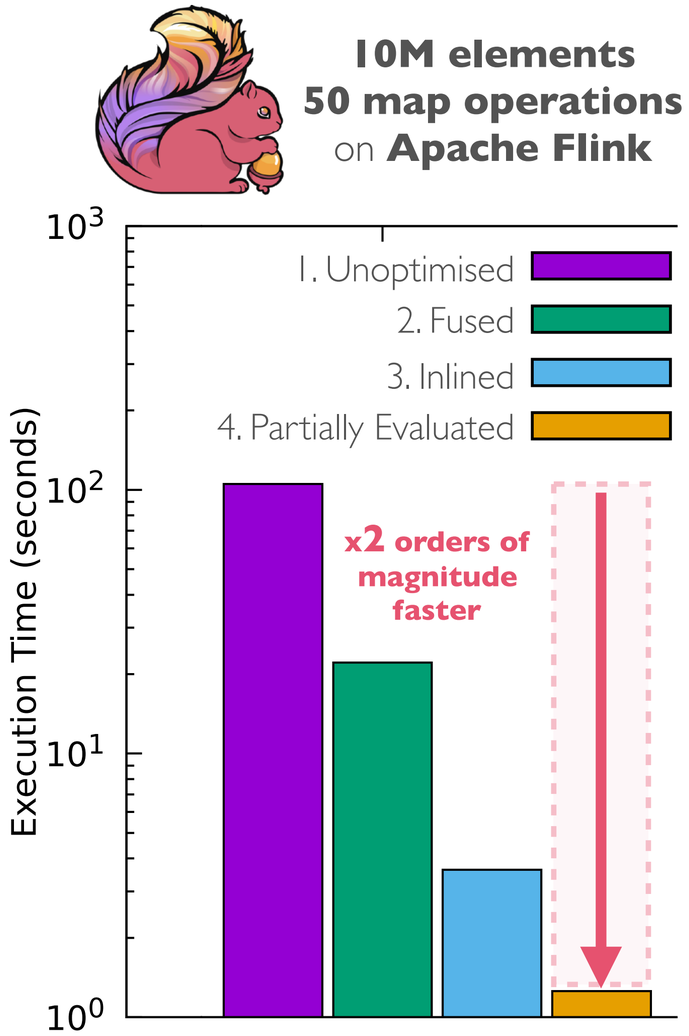
Arc Optimisations

- Arc supports **both** compiler and dataflow optimisations. (Compiler toolchain in MLIR)
  - **Compiler**: Loop unrolling, partial evaluation,
  - **Dataflow**: Operator fusion, fi ssion, reordering, specialisation, ...

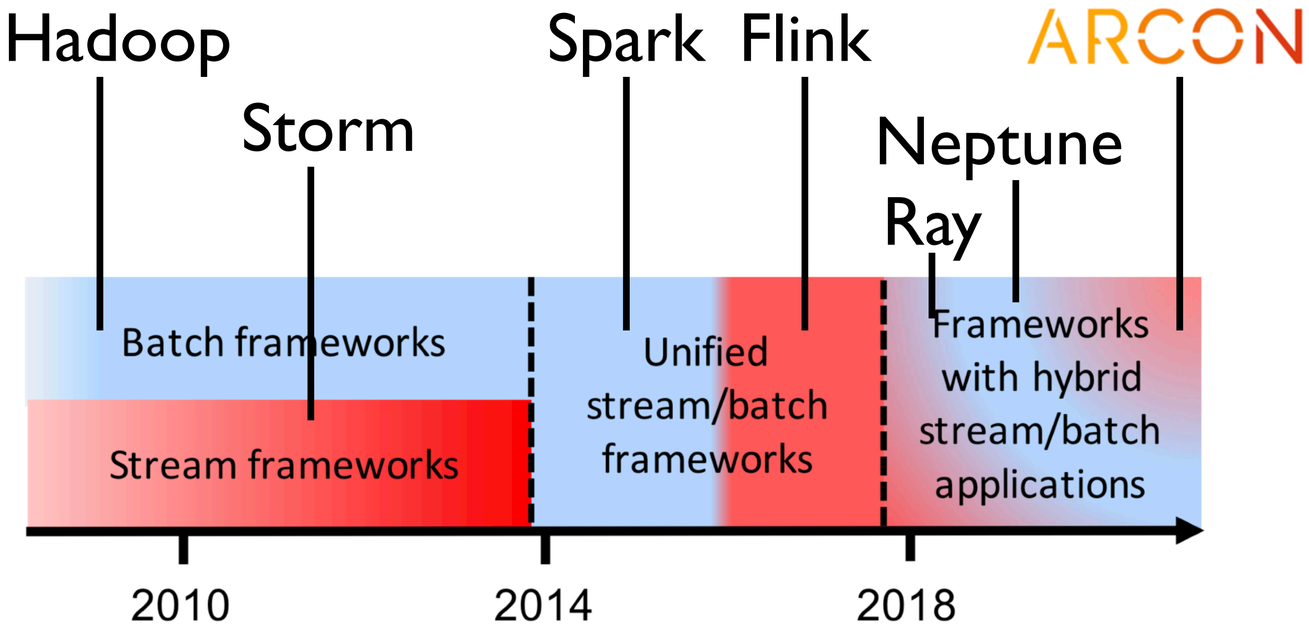
Unlocking Speed

Arc can boost even existing frameworks





Next-Gen is Hybrid

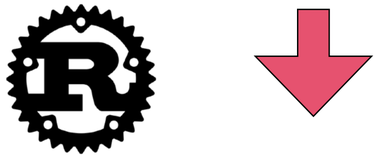


Neptune: Scheduling Suspendable Tasks for Unified Stream/Batch Applications SOCC 2019

Garefalakis, Karanasos, Pietzuch

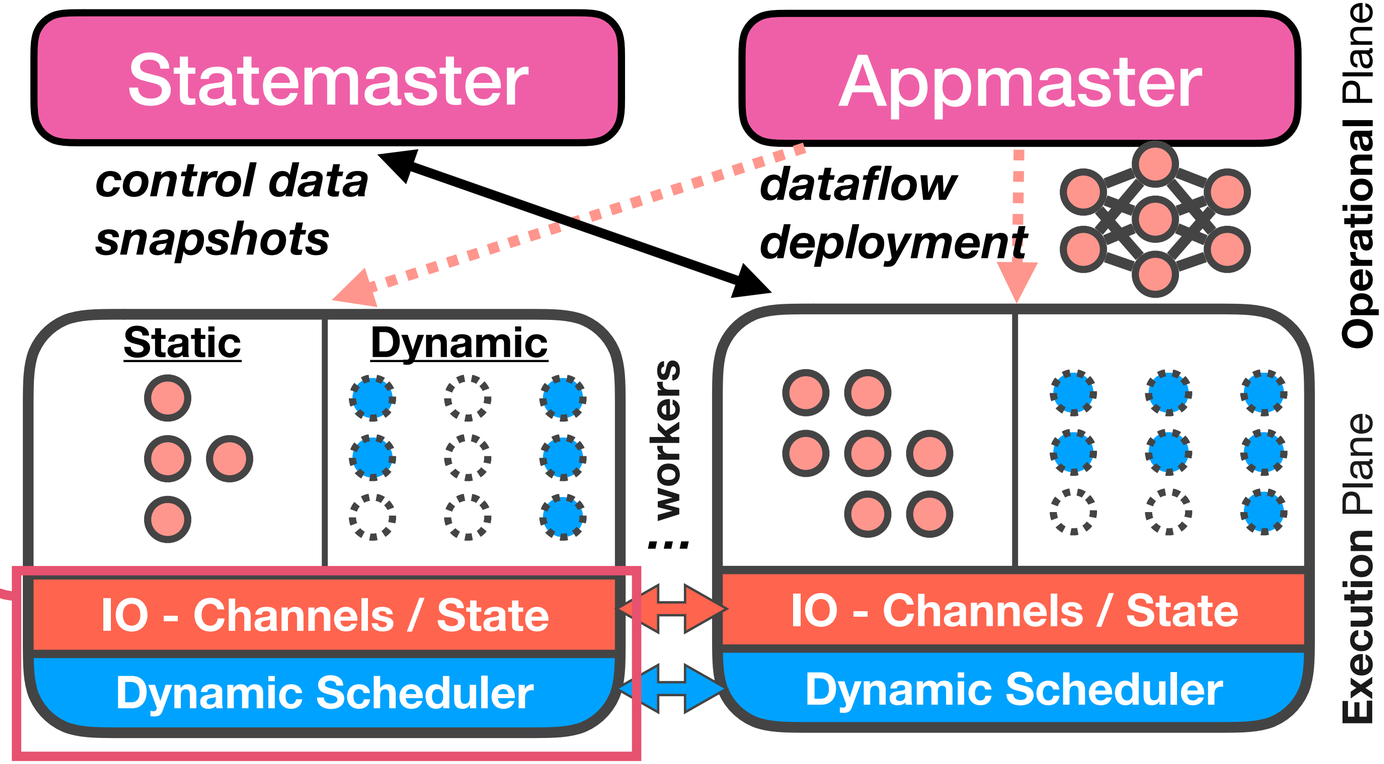
Arcon : A Runtime Capable for Unified Analytics

- performance critical libraries
- hardware native optimisations needed

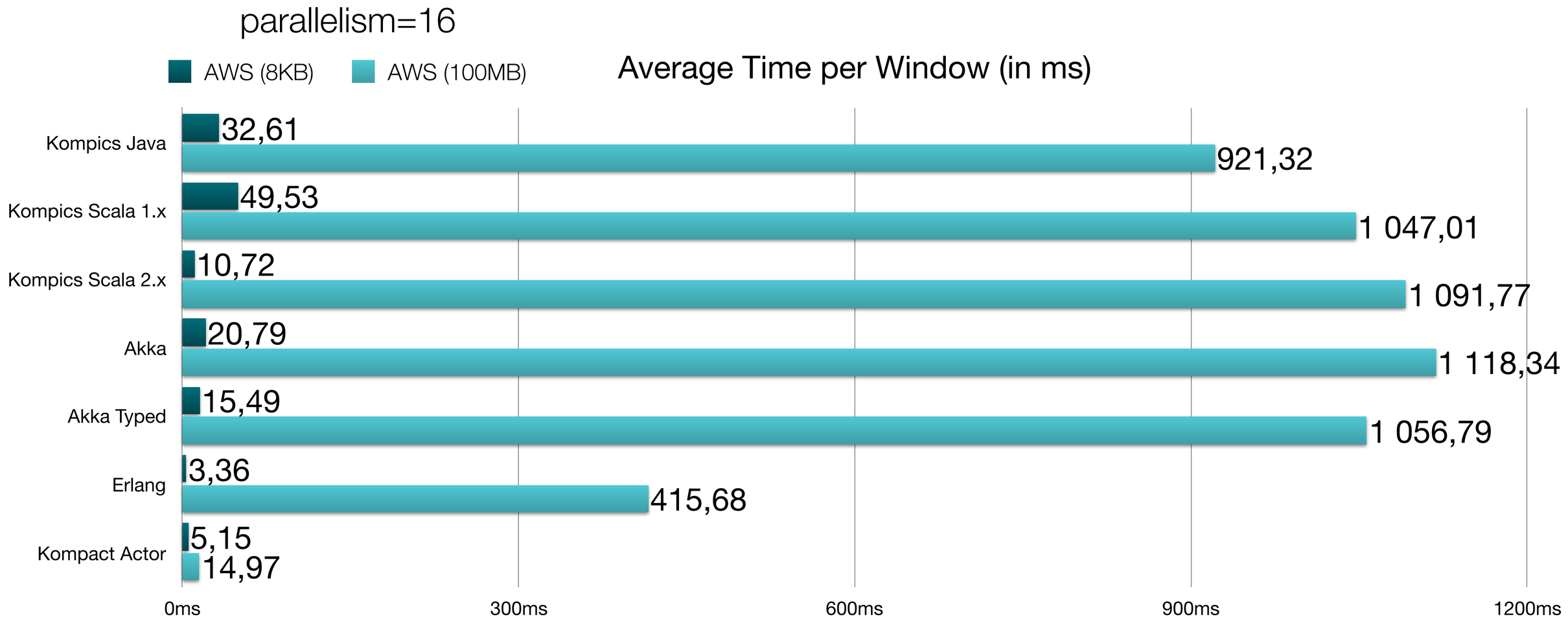


Kompact Middleware

- Message Driven Actor Framework
- Written in Rust (memory safety)
- Complex Type Checking
- High Performance

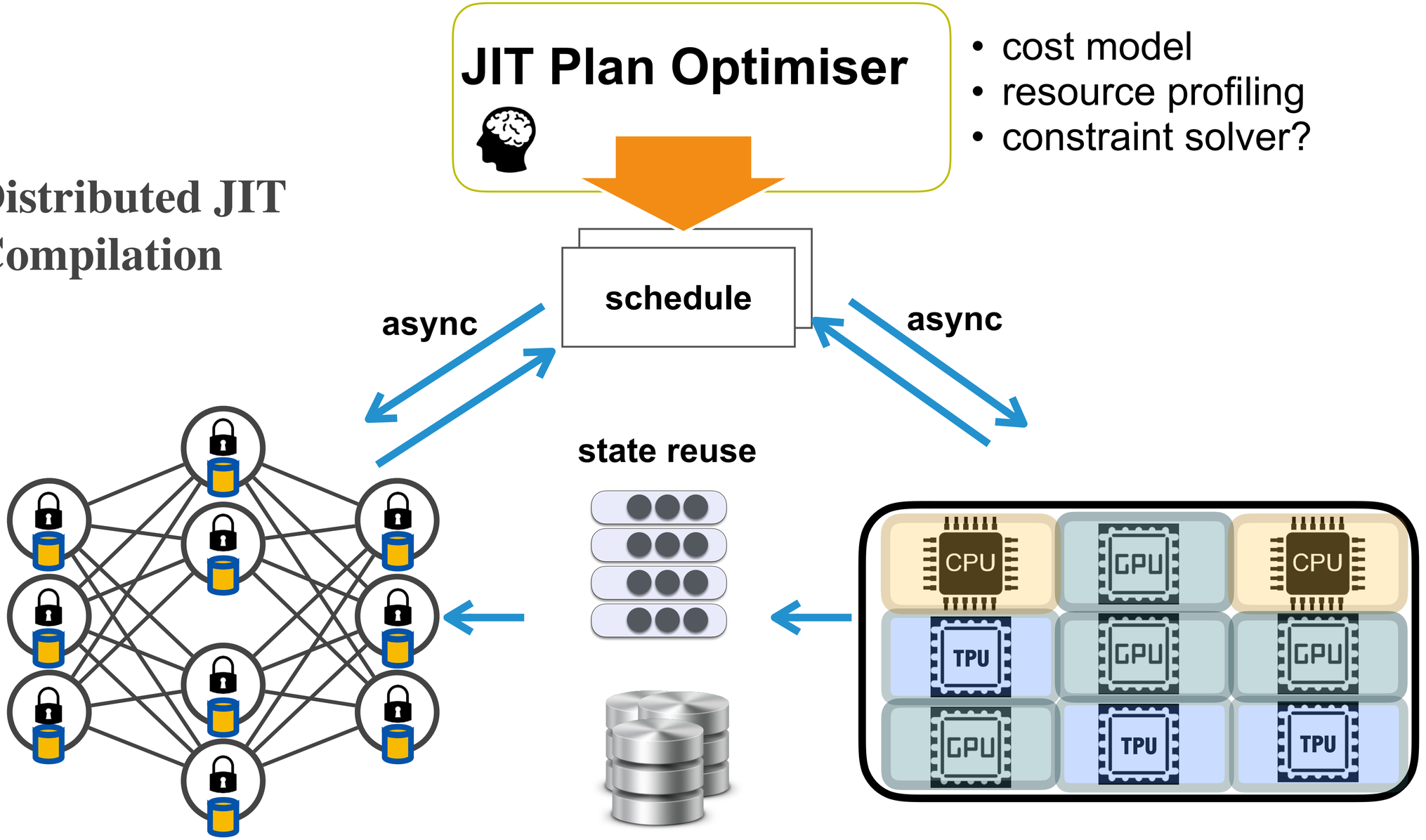


Streaming Windows Results



RI.
SE

Distributed JIT Compilation



- cost model
- resource profiling
- constraint solver?

The Team

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Seif Haridi

Max Meldrum

Klas Segeljakt

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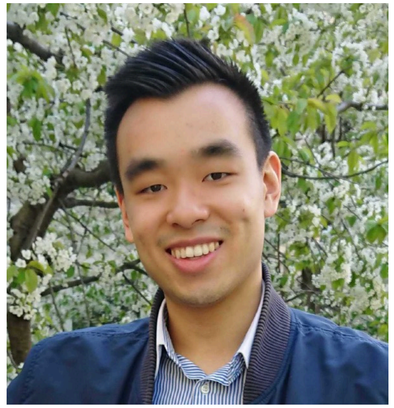
Khoa Dinh

Harald Ng



Mikolaj Robakowski

More Info

Code: https://github.com/cda-group/arc

https://github.com/cda-group/arcon

Project: https://cda-group.github.io