Technische Universität Berlin

StratoSphere
Above the Clouds

Database Systems and Information Management

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Big Data looks Tiny from the Stratosphere

Data and analyses are becoming increasingly complex!

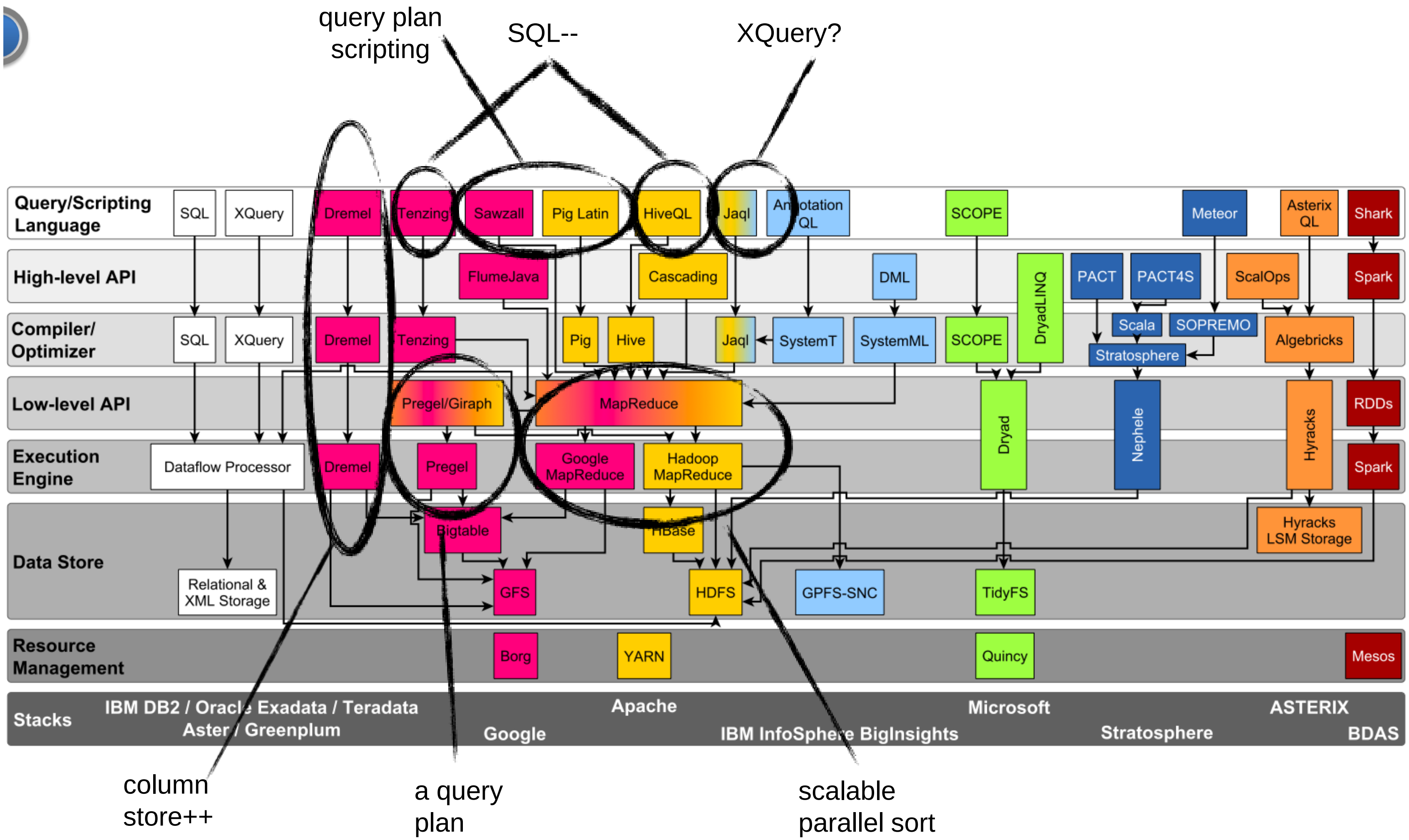
Size	(*volume*)
Freshness	(*velocity*)
Format/Media Type	(*variability*)
Uncertainty/Quality	(*veracity*)
etc.	

Data

Selection/Grouping	(map/reduce)
Relational Operators	(Join/Correlation)
Extraction & Integration,	(map/reduce or dataflow systems)
ML, Optimization	**(R, S+, Matlab)**
Predictive Models	**(R, S+, Matlab)**
etc.	

Analysis

Overview of Big Data Systems

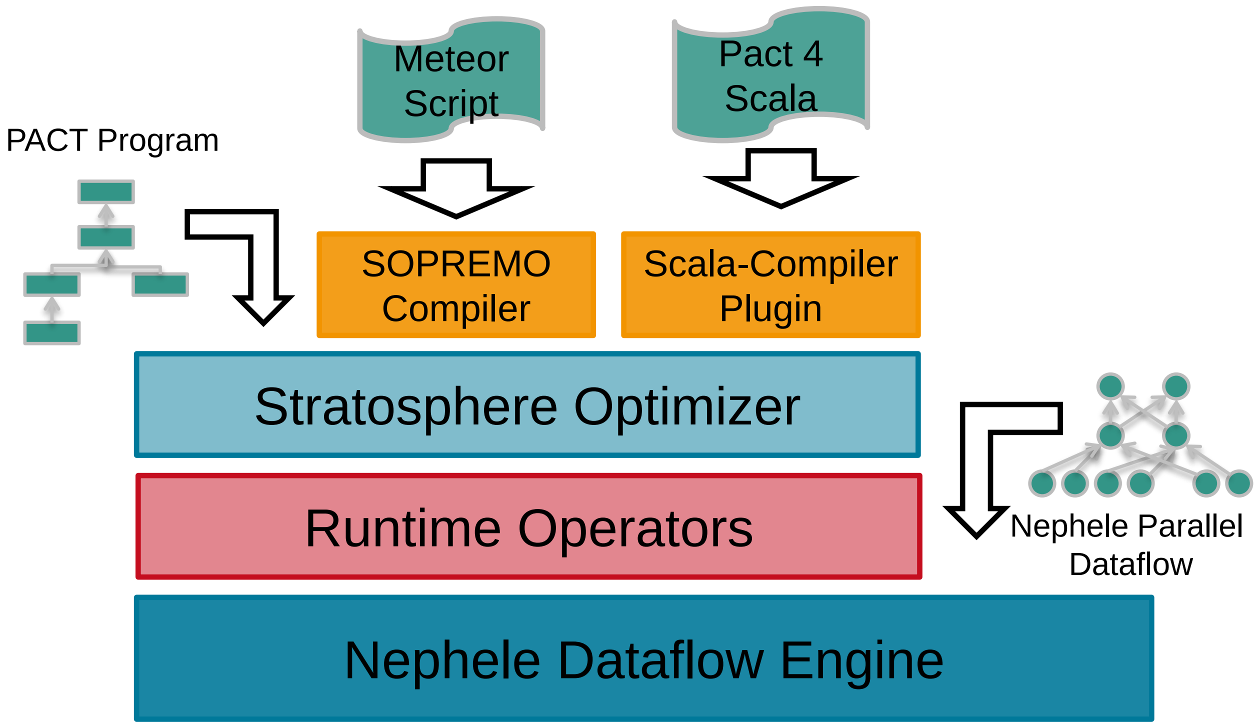


Outline

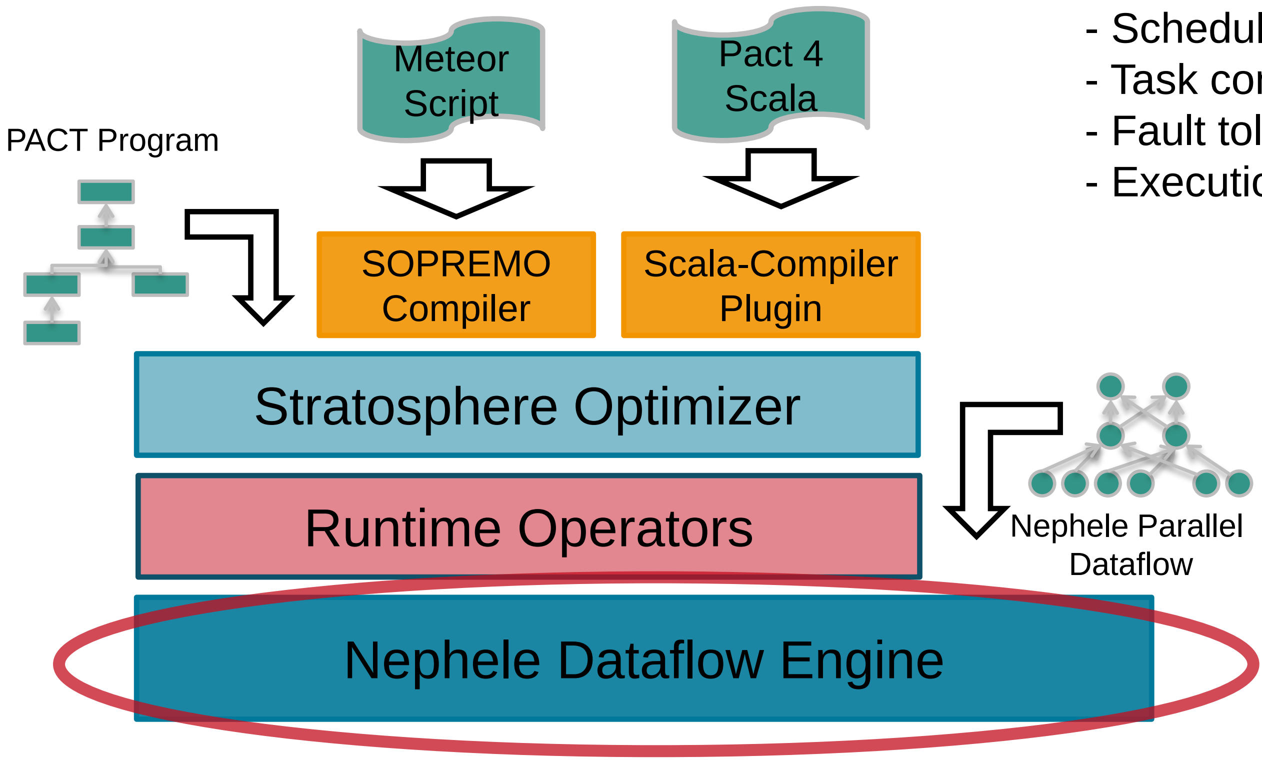
- Stratosphere architecture
  - Layered and flexible stack for massively parallel data management
- The PACT programming model
  - Using second-order functions for data parallelism
- Stratosphere optimizer
  - Deeply embedding Map/Reduce Style UDFs into a query optimizer
- Iterative algorithms in Stratosphere
  - Teaching a dataflow system to execute iterative algorithms with comparable performance to specialized systems

The Stratosphere System Stack

Layered approach – several entry points to the system

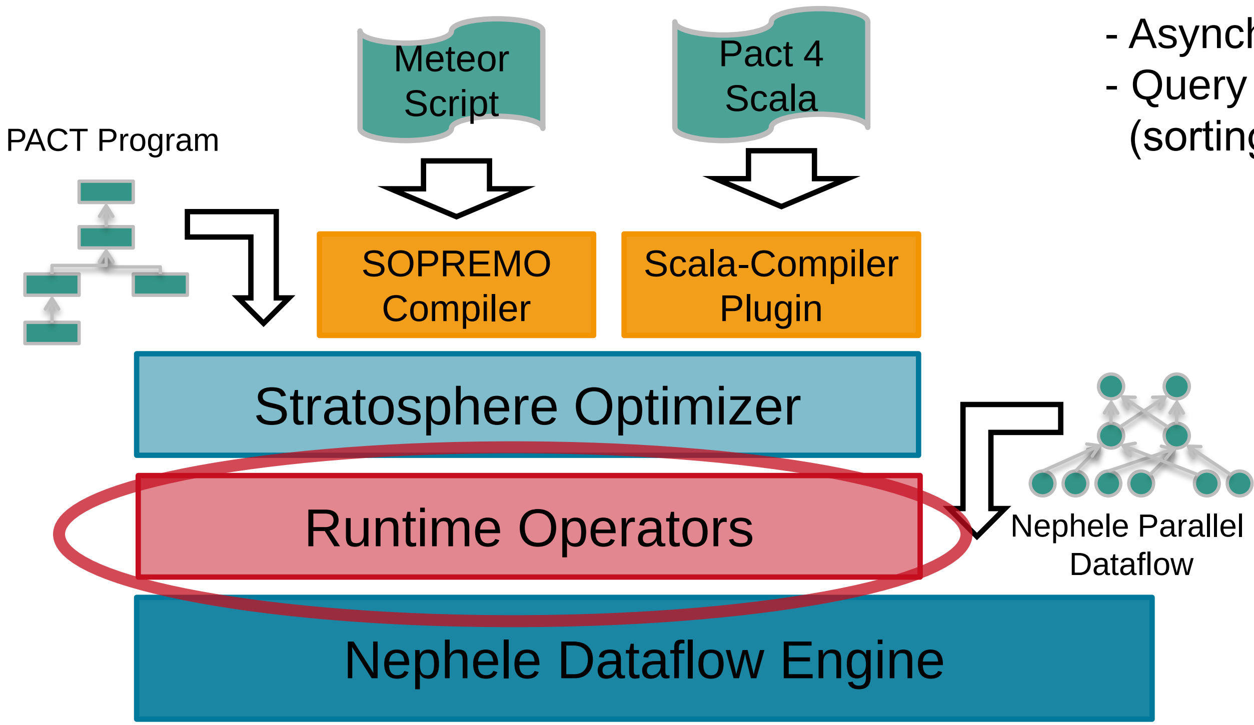


The Stratosphere System Stack



Nephele parallel dataflow engine
- Resource allocation
- Scheduling
- Task communication
- Fault tolerance
- Execution monitoring

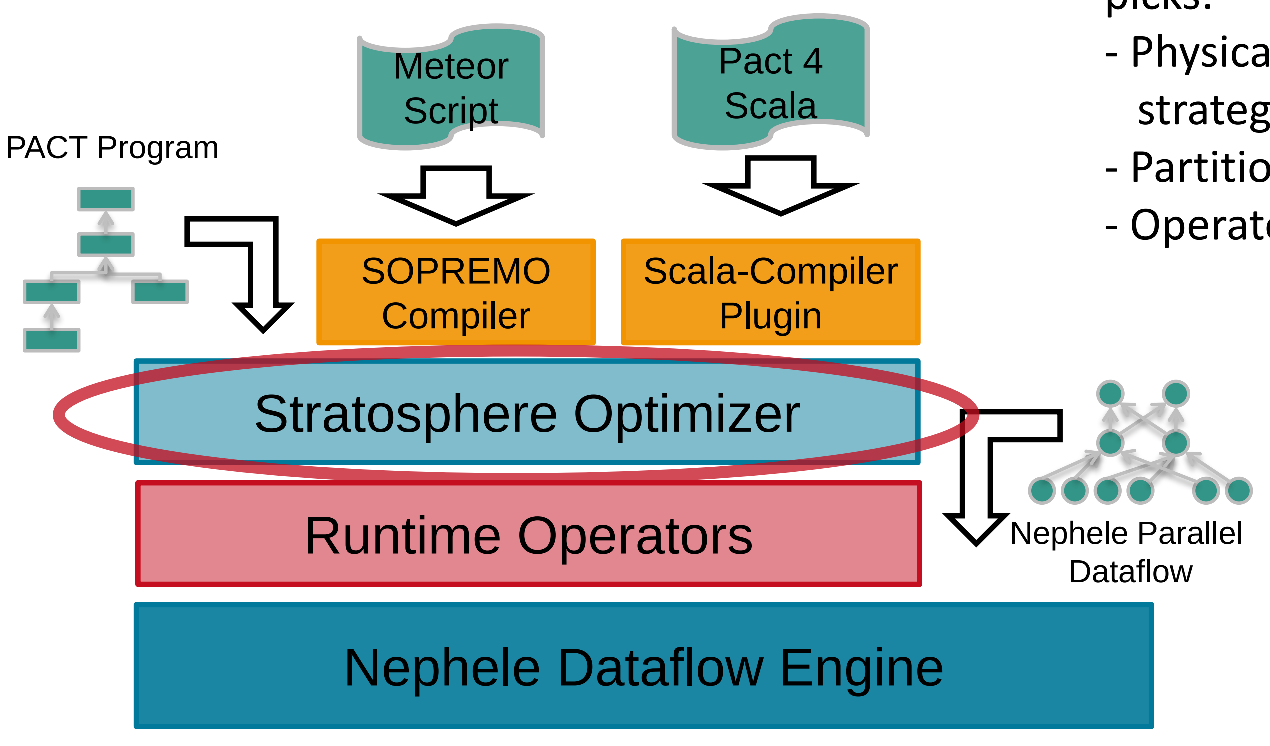
The Stratosphere System Stack



Runtime engine

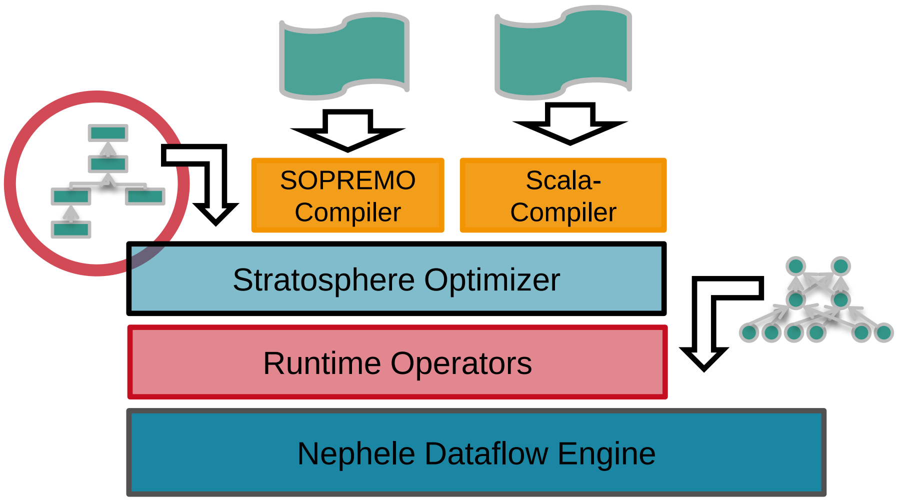
- Memory management
- Asynchronous IO
- Query execution (sorting, hashing, …)

The Stratosphere System Stack



Stratosphere optimizer picks:

- Physical execution strategies
- Partitioning strategies
- Operator order



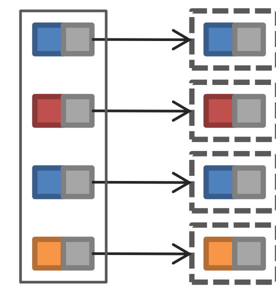
The PACT programming model

Second-order functions for data parallelism

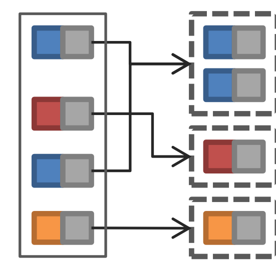
Parallelization Contracts (PACTs)

- Generalize Map/Reduce
- Describe how input is partitioned/grouped as second order function
  - "What is processed together?"
- First-order UDF called once per input group
- Map PACT (record at a time, 1-dimensional)
  - Each input record forms a group
  - Each record is independently processed by UDF
- Reduce PACT (set at a time, 1-dimensional)
  - One attribute is the designated key
  - All records with same key value form a group

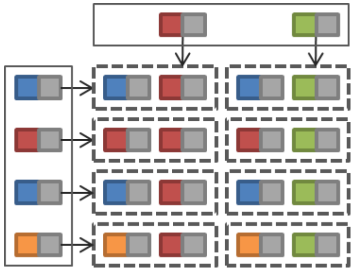
Map PACT



Reduce PACT



More Parallelization Contracts

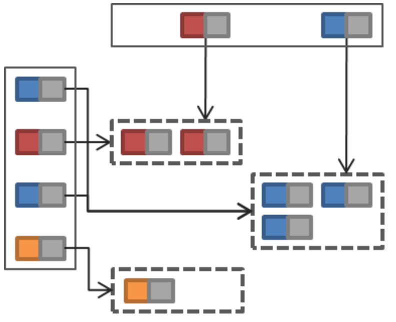


Cross PACT

Each pair of input records forms a group

Distributed Cartesian product

Record-at-a-time, 2-dimensional

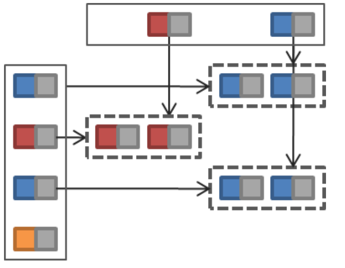


CoGroup PACT

All pairs with equal key values form a group

2D Reduce

Set-at-a-time, 2-dimensional



Match PACT

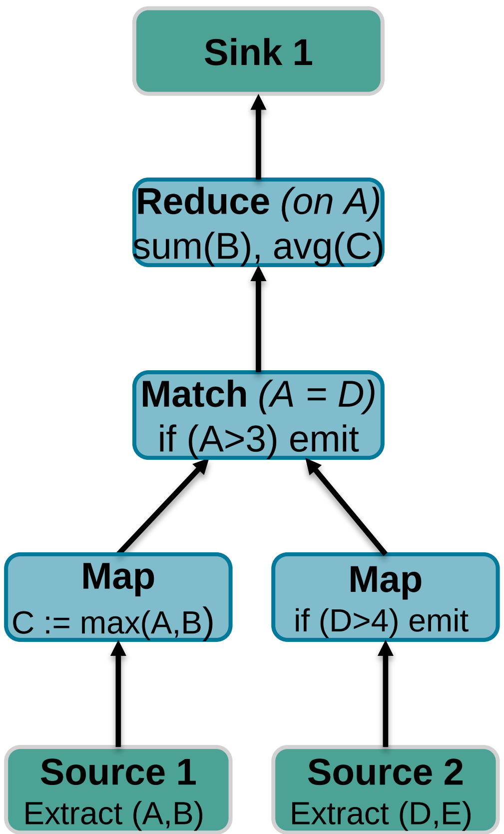
Each pair with equal key values forms a group

Distributed equi-join

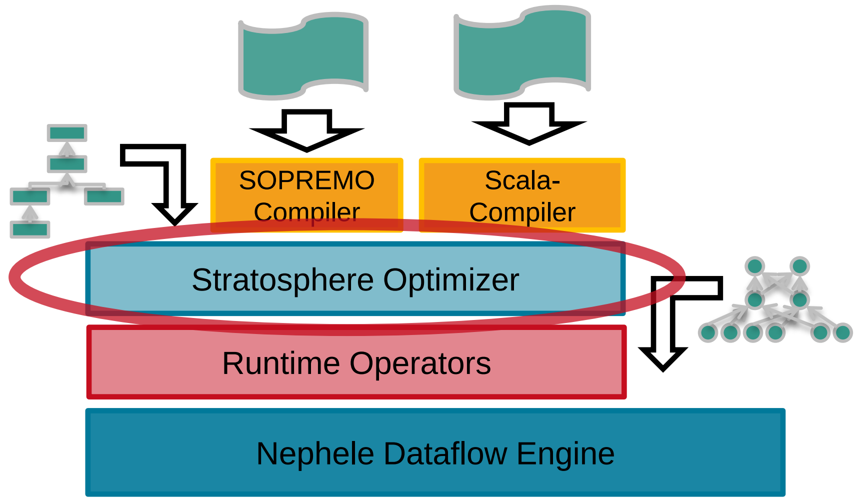
Record-at-a-time, 2-dimensional

- More PACTs currently under consideration
  - For similarity operators, stream processing, etc

PACT Programming Model



- A PACT program is an *arbitrary dataflow DAG* consisting of operators
- An operator consists of
  - A *second-order function* (SOF) signature (PACT)
  - A user-defined first-order function (FOF) written in Java
- PACT programs serve as intermediate representation, but are also exposed to the user
  - To implement UDFs for functionality not supported by Meteor



The Stratosphere Optimizer

Opening the Black Boxes (VLDB 2012)

Optimizer Design

- Cost-based optimizer produces physical execution plan given PACT program
  - Annotates edges with distribution patters, e.g., broadcast, partition
  - Chooses physical execution strategies (e.g., hash/sort)
  - Reorders PACT functions
  - Constructs “Nephele job graph”
- Challenge: Semantics of user-defined functions unknown
  - How to derive correct transformations (this talk)
  - How to cost functions (ongoing work)
  - Mix and match UDFs and native operators (ongoing work)

Optimization Overview

- Approach:
  - Statically analyze user code in each PACT UDFs and extract properties
  - Based on these properties, derive semantically correct transformations
  - Enumerate semantically equivalent plans
- Contribution: How to *deeply embed* MapReduce functions into a query optimizer
  - Parallelization and reordering
  - Applies to data flows composed (in part) of functions written in arbitrary imperative code
  - Exportable to Scope, SQL/MapReduce (e.g., Aster, Greenplum)

… via Static Code Analysis

```
void match (Record left,
                 Record right,
                 Collector col) {
 Record out = copy (left);
 if (left.get(0) > 3) {
   double a = right.get(2);
   out.set(2,1.0/a);
  }
  out.set(1, 42);
  out.set(3,right.get(0));
  out.set(4,right.get(1));
  out.set(5,right.get(2));
  col.emit (out);
  }
```

Feasible:

1. Record data model, fixed API for
2. No control flow between operators

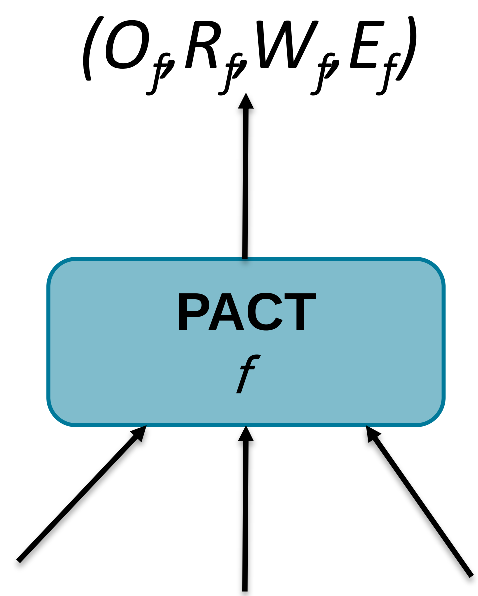
Correct:

- Difficulty comes from different code paths
- Correctness guaranteed through conservatism
- Add to *R*,*W* when in doubt

Opening the Black Boxes …

Analyze user code to discover:

- <u>Output schema O_f:</u> Schema of output record given schema of input record(s)
- <u>Read set R_f:</u> Attributes of the input record(s) that might influence output
- <u>Write set W_f:</u> Attributes of the output record(s) that might have different values from respective input attributes
- <u>Emit cardinality E_f:</u> Bounds on records emitted per call (1, >1, …)



Code Analysis Algorithm

```
void match (Record left,
            Record right,
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  Record out = copy (left);
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  out.set(1, 42);
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  out.set(4,right.get(1));
  out.set(5,right.get(2));
  col.emit (out);
}
```
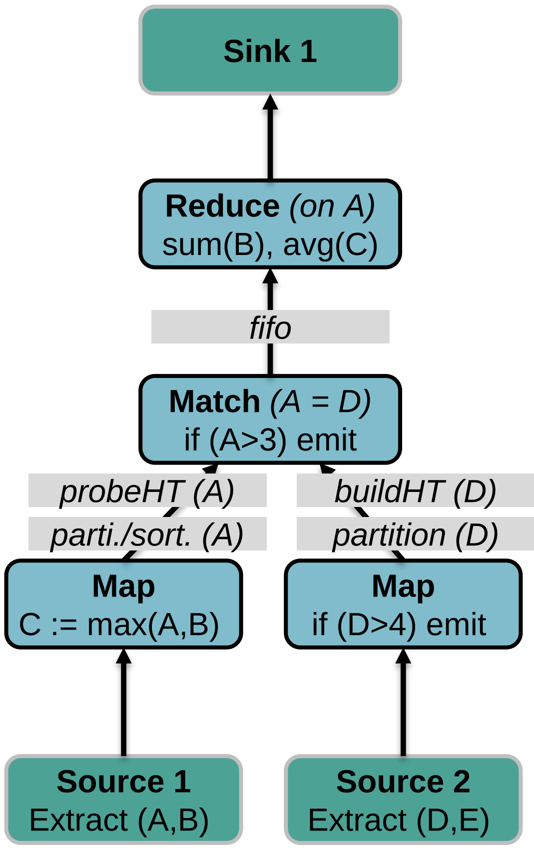

- R_f from get statements
- W_f by backwards traversal of data flow graph starting from emit statement
- E_f by traversing control flow graph

$Input_1$ = [A,B,C]
$Input_2$ = [D,E,F]
Output = [A,B,C,D,E,F]

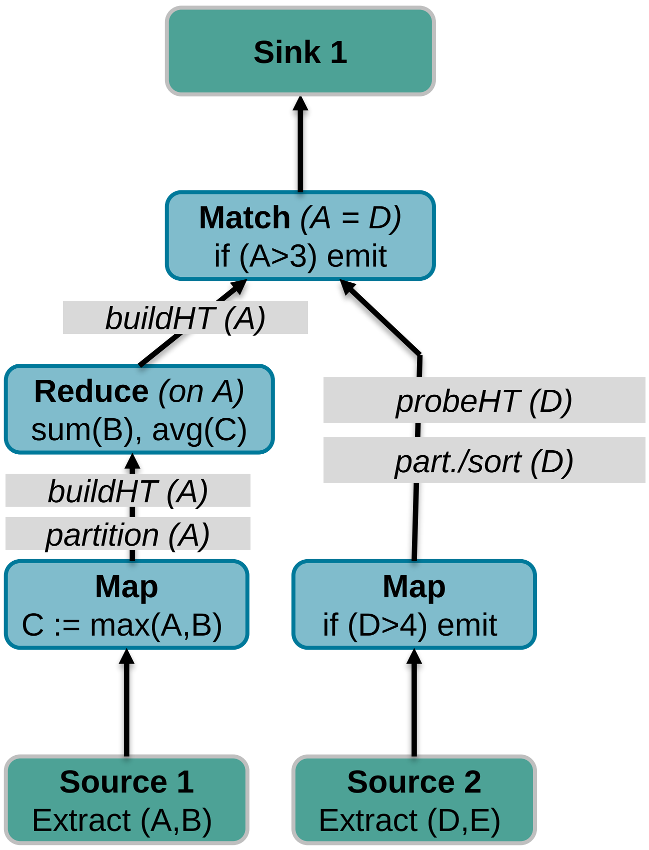
R_f = {A,B,C,D,E,F}
W_f = {B,C}
E_f = 1

Automatic Parallelization



- Optimizer can pick partitioning strategies
  - From PACT signature
- E.g., for Match: broadcast, partition, SFR
- Partitioning strategies propagated top-down as interesting properties
- Can infer preserved partitioning via R/W sets
  - Identifies *pass-through UDFs*
- A Reduce does not always imply a physical sort operator

Operator Reordering



- Reordering PACTs
  - Reduce data volume
  - Introduce new partitioning opportunities
- Reordering, partitioning, and physical operators in one stage
  - “Optimal” execution plan
- Powerful transformations using *read and write conflicts*
- Can “emulate” most relational optimizations without knowing operator semantics

Example Transformations

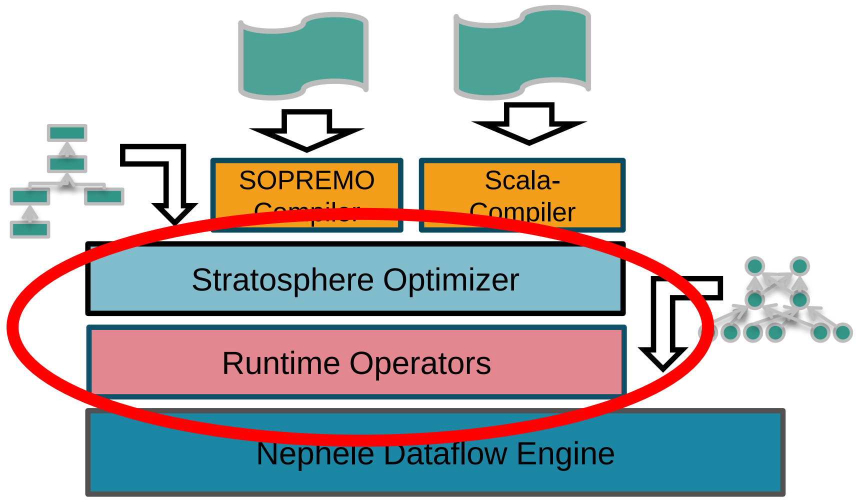
Theorem 1: *Two Map operators can be reordered if their UDFs have only read-read conflicts*

Theorem 2: *For a Map and a Reduce, we need in addition the Reduce key groups to be preserved*

Enabled optimizations:

- ✓ Selection push-down
- ✓ (Bushy) join reordering
- ✓ Aggregation push-down
  - ✓ Equivalent to invariant grouping transformation [Chaudhuri & Shim 1994]
- ✓ Reordering of non-relational Reduce functions

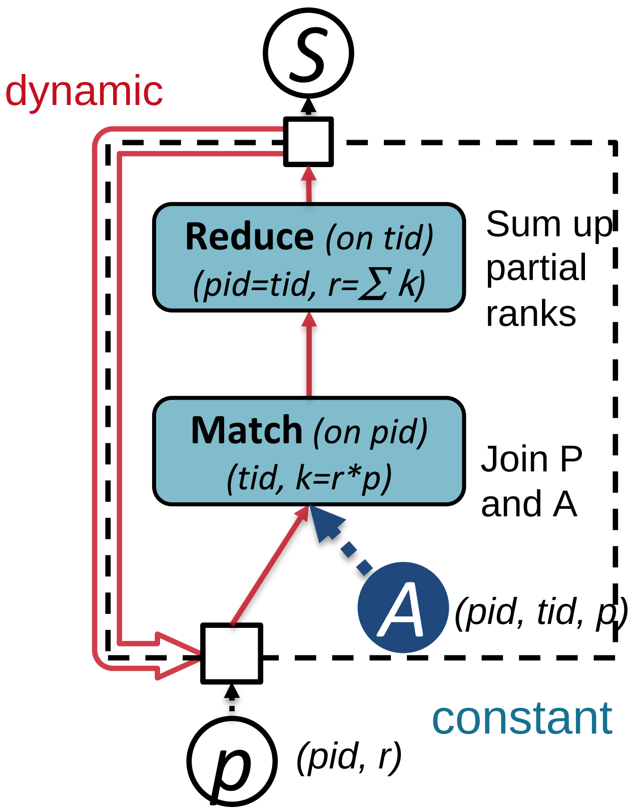
In VLDB'12 paper: Formal proofs and conditions for safe reorderings for all possible PACT pairs based on R_f, W_f, E_f



Support for Iterative queries

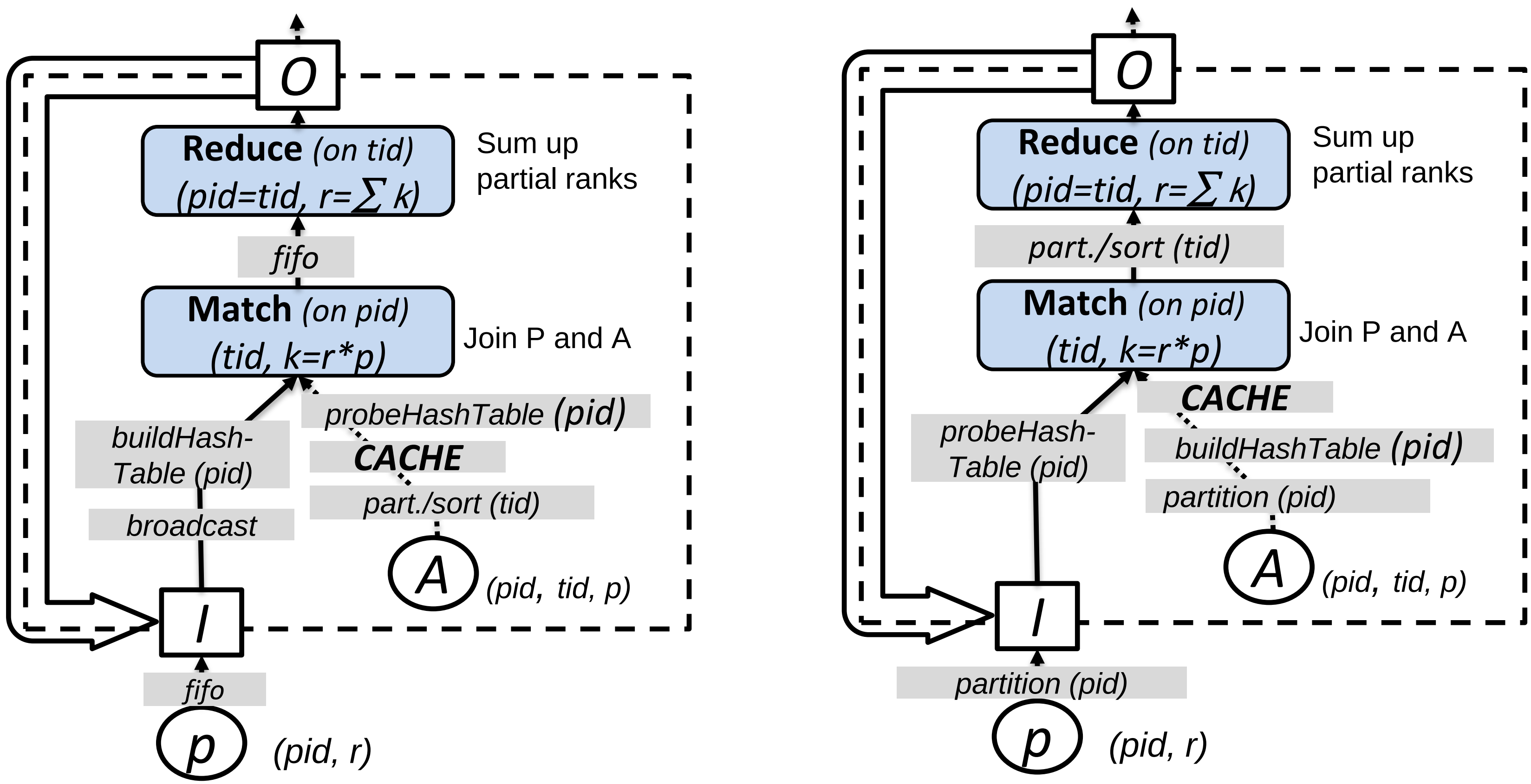
Spinning Fast Iterative Dataflows (VLDB 2012)

“Bulk” Iterations



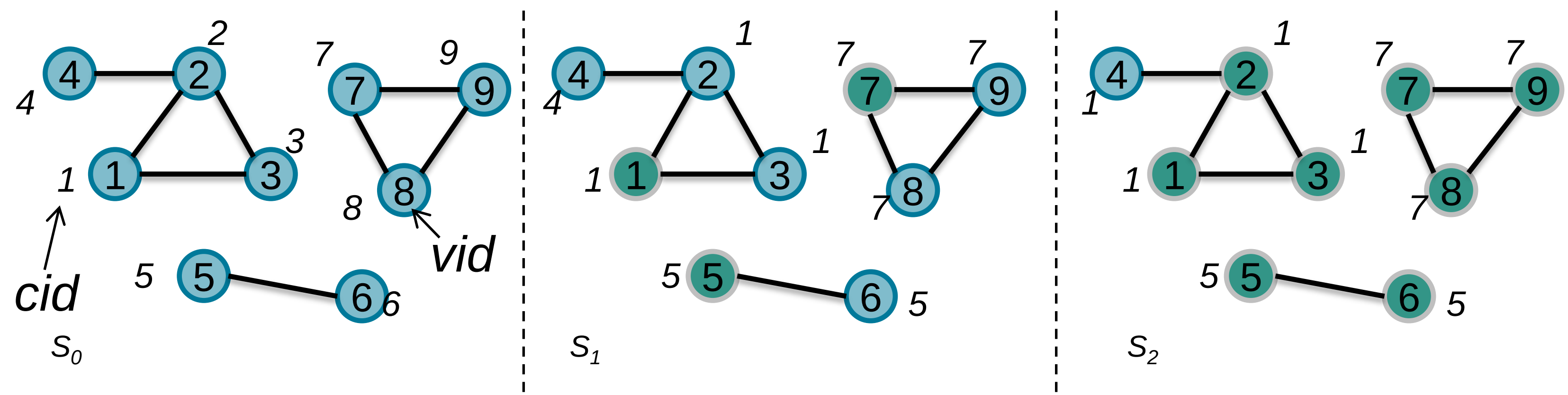
- Recompute state at each iteration
- Conceptual feedback edge in the dataflow – lazy unrolling possible
- Distinguish **dynamic data path** (*different data each iteration*) and **constant data path** *(same)*
  - Caching heuristics were constant and dynamic paths meet
  - Cached data may be indexed
- Optimizer weighs costs for constant and dynamic data path differently
  - Automatically favors plans that push work to the constant path

PageRank: Two Optimizer Plans



Sparse Computational Dependencies

- Parts of the state change at each iteration, based on the parts that changed at the previous iteration
  - Most graph algorithms and beyond
  - Huge savings if we do not recompute the whole state
- Need in-place updates in persistent state while surfacing a pure functional model



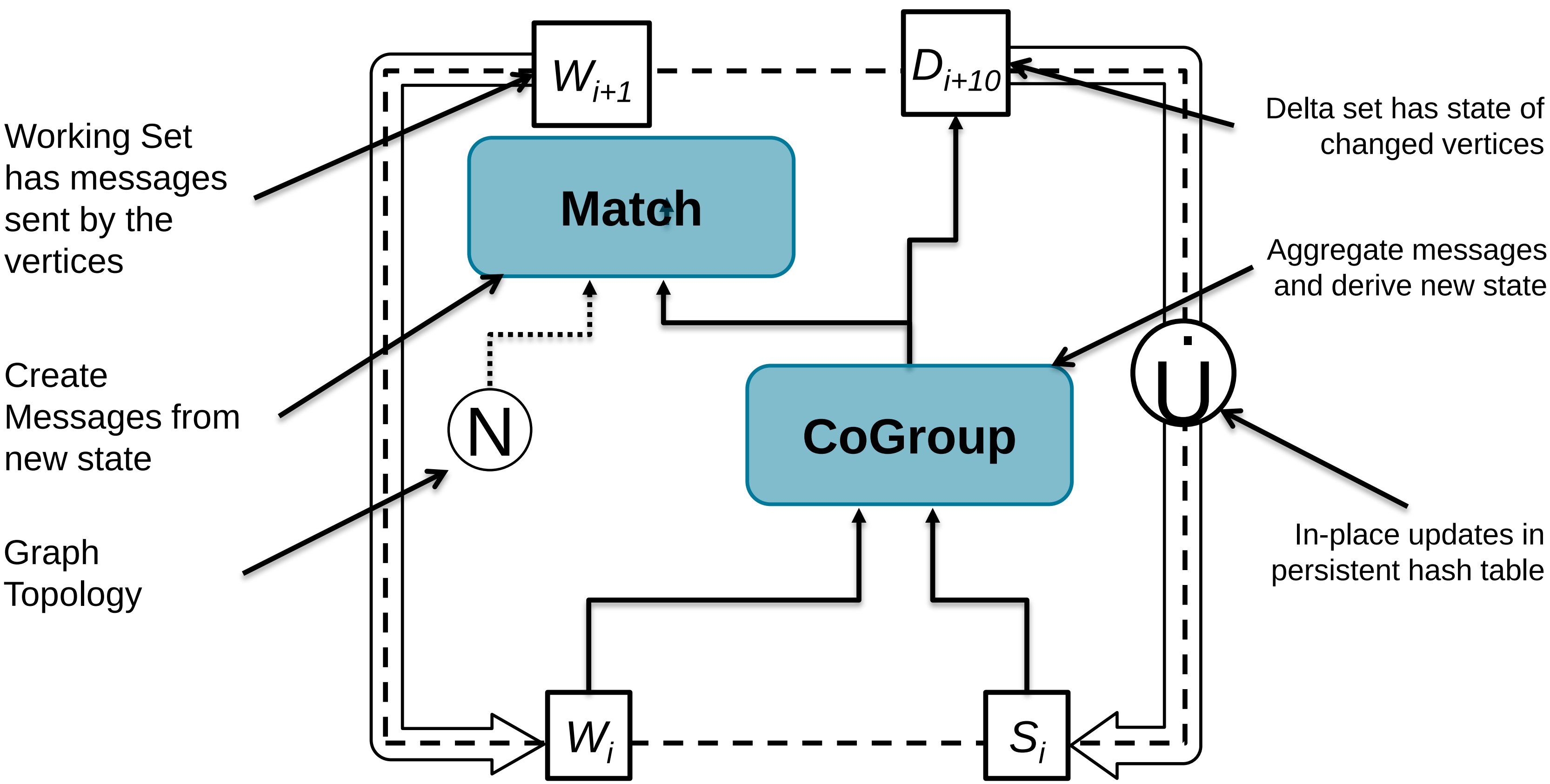
“Incremental” Iterations

- Different programming abstraction based on *workset algorithms*
- Algorithm works on two sets: *Solution Set* and *Workset*
- A *delta* to the solution set is computed from the workset
- A new workset is recomputed at each iteration
- Solution set is efficiently merged with delta set

function FIXPOINT(f, s)
  while $s \prec f(s)$ **do**
    $s = f(s)$

function INCR(δ,u,S,W)
  while $W \neq \emptyset$ **do**
    $D \leftarrow u(S, W)$
    $W \leftarrow \delta(D, S, W)$
    $S = S \dot{\cup} D$

Pregel as an Extended PACT Plan



Big Data looks Tiny from the Stratosphere

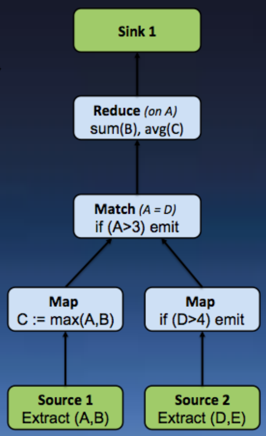
Stratosphere is a declarative, massively-parallel Big Data Analytics System,
funded by DFG and EIT, available open-source under the Apache license

Data analysis program

```
$employees = read 'employees.json';
$result = transform $emp in $employees
    into {
        taxes: $emp.brutto - $emp.netto
        address: {
            $emp.address.*,
            country: 'Germany'
        }
    };
write $result to 'output.json';
```

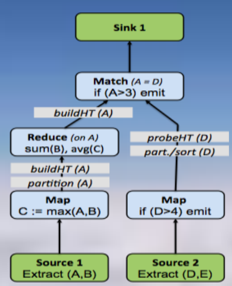
Program compiler

PACT Dataflow

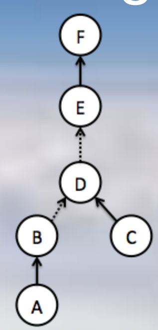


Stratosphere optimizer
Automatic selection of parallelization, shipping and local strategies, operator order and placement

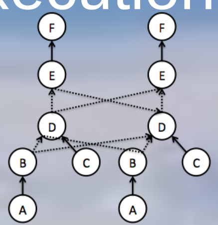
Execution plan



Job graph



Execution graph



Runtime operators
Hash- and sort-based out-of-core operator implementations, memory management

Parallel execution engine
Task scheduling, network data transfers, resource allocation, checkpointing

http://www. stratosphere.eu