Very Large Data Bases 2011

An Algebraic Approach for Data-Centric Scientific Workflows

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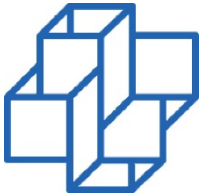
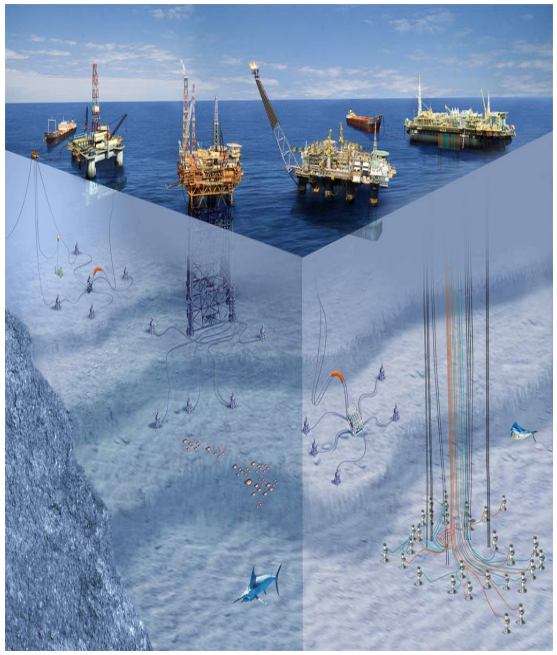


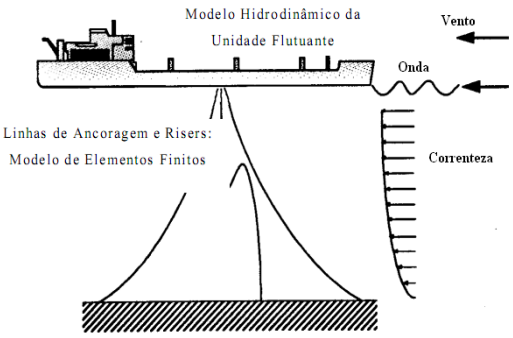
National Laboratory Scientific Computing

Risers' Fatigue Analysis in Ultra-Deep Waters

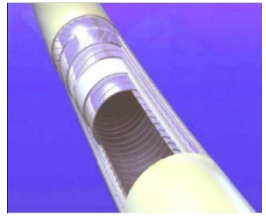


Input Data to simulate Environment conditions: Waves, wind, currents, bathymetry, etc.

1. Coupled movement Analysis (TPN or Prosim)

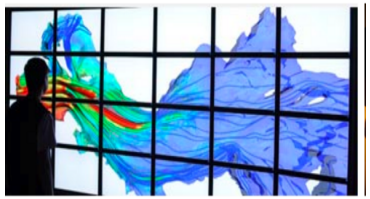


Generates large amount of data … (finite element meshes)



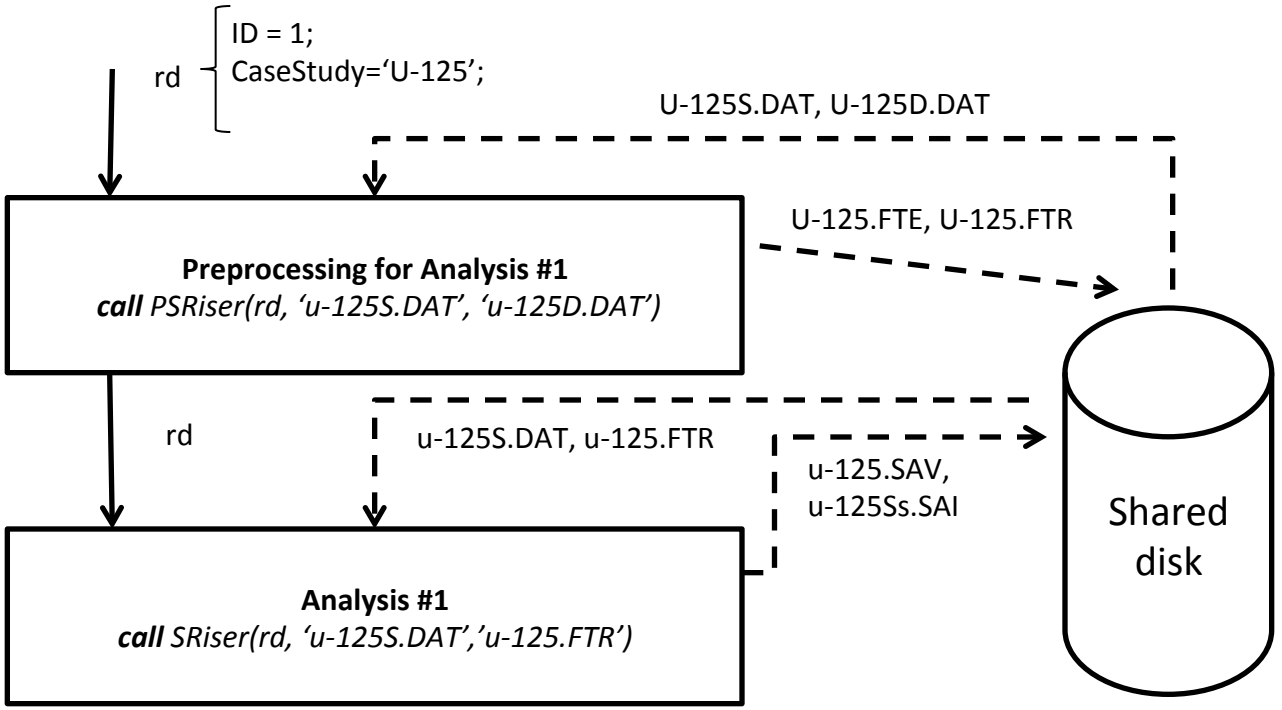
2. … to do Structural Analysis of Risers (ANFLEX)

3. Results are analyzed POSFAL



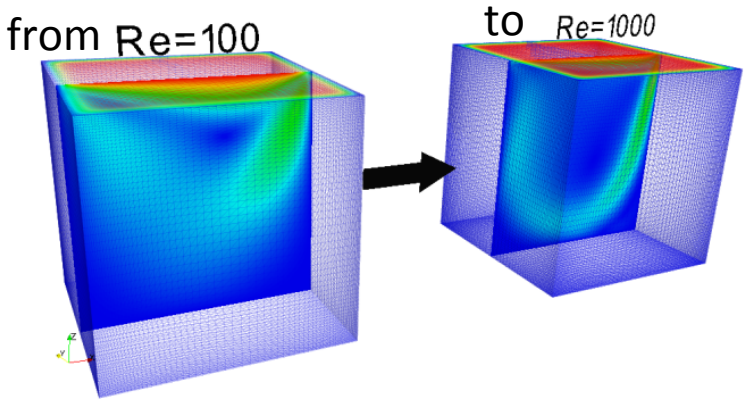
Estimate risers lifetime

Example of Small Scientific Workflow



Parameter Sweep

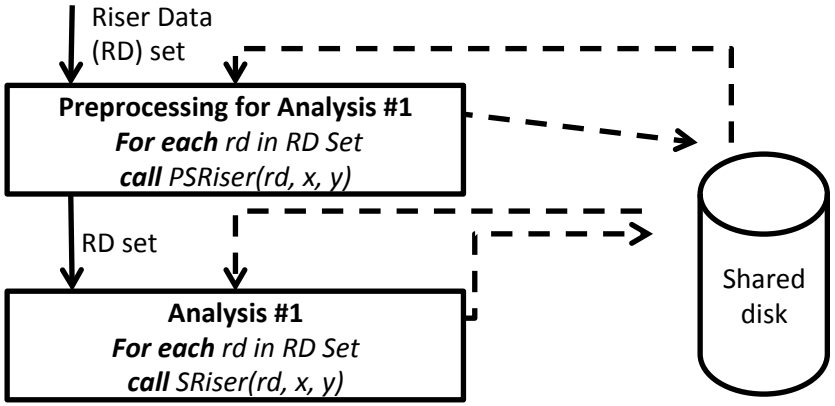
- Scientists have to explore the behavior of their model under different inputs.
  - This occurs in many areas such as computational fluid dynamics, bioinformatics, uncertainty quantification, dark energy analysis
- In parameter sweep we have multiple inputs for the workflow.



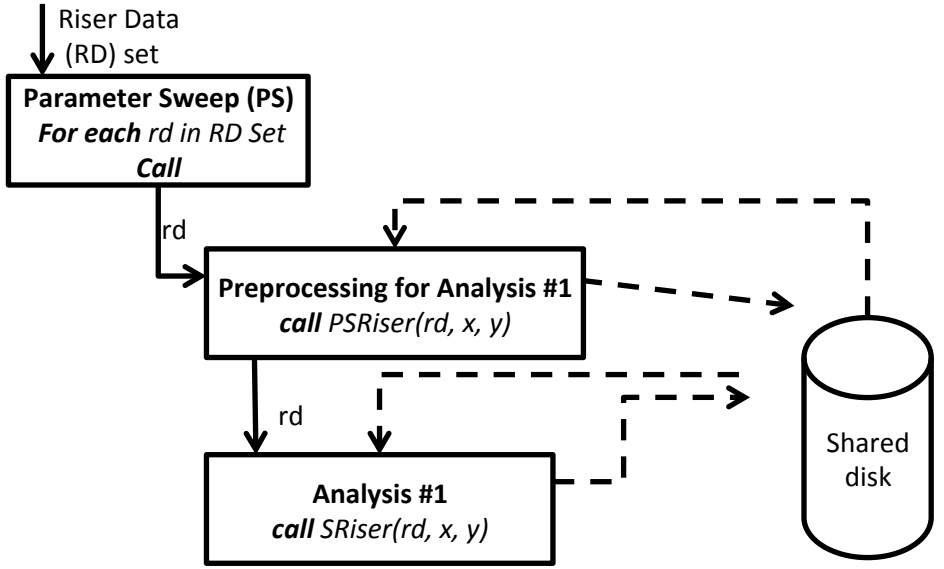
- These data-centric workflows becomes also computationally intensive and they may run for hours/days

Supporting Parameter Sweep

for each in all activities



for each invoking a group of activities



Parameter sweep are natural candidate for parallel processing

Current Approaches

- Parallel SWfMS
  - Swift: allows scientists to specify parallel workflows using a scripting language
- SWfMS Integration with Hadoop
  - Kepler+Hadoop: allows activities of a particular type to be parallelized
- SWfMS Integration with specialized middleware
  - VisTrails+Hydra: allows activities of a particular type to be parallelized

Fixed (rigid) execution plan

Problems

- Scientists must code low-level parallelization, thus limiting opportunities for automatic optimization
  - Huge amount of data consumed/produced
  - Ad-hoc and labor-intensive
- Engines are focused on scheduling activities of a fixed execution plan

Objectives

- Evaluate opportunities for optimization considering the entire workflow specification
- Transparent parallelization through strategies using automatic optimization
- View the workflow execution plan as a query optimization problem

Solution: An Algebraic Approach

- Data-Centric algebra for scientific workflows
  - Relations as data model for consumption and production
  - Operators that provide semantics to activities
  - Workflow execution model for this algebra based on activity activation

Relations as Data Model for Consumption and Production

- Relations are defined as sets of tuples of primitive types (integer, float, string, date etc) or complex data types (e.g. references to files)
- *Example: R($\mathcal{R}$)*

RID	CaseStudy	sdat	ddat
1	U-125	U-125S.DAT	U-125D.DAT
1	U-127	U-127S.DAT	U-127D.DAT
2	U-129	U-129S.DAT	U-129D.DAT

- $\mathcal{R}$ = *(RID: Integer, CaseStudy: String; SDat: FileRef, DDat: FileRef)*

Algebraic Operators for Data-Centric Activities

- Program invocation
  - Map (1:1)
  - SplitMap (1:n)
  - Reduce (n:1)
  - Filter (1:0-1)
- Relational Algebra Expressions
  - SRQuery
  - MRQuery

Split Map Activity (SplitMap)
T ← SplitMap(Y, a, R)

R

RID	RdZip
1	Project1.zip
2	Project2.zip

T ← SlipMap(extractRD, 'RdZip', R)

T

RID	Study	sdat	ddat
1	U-125	U-125S.DAT	U-125D.DAT
1	U-127	U-127S.DAT	U-127D.DAT
2	U-129	U-129S.DAT	U-129D.DAT

Reduce Activity (Reduce)

$T \leftarrow Reduce(Y, g_A, R)$

R

RID	Study	SsSai	DdSai	MEnv
1	U-125	U-125Ss.SAI	U-125Dd.SAI	U-125.ENV
1	U-127	U-127Ss.SAI	U-127Dd.SAI	U-127.ENV
2	U-129	U-129Ss.SAI	U-129Dd.SAI	U-129.ENV

T ← Reduce(CompressRD, {'RID'}, R)

T

RID	RdResultZip
1	ProjectResult1.zip
2	ProjectResult2.zip

Single Relation Query Activity (SRQuery)

T ← SRQuery(qry, R)

R

RID	Study	SsSai	Curvature
1	U-125	U-125Ss.SAI	1.5
1	U-126	U-126Ss.SAI	0.9
1	U-127	U-127Ss.SAI	1.2

$$T \leftarrow SRQuery(\pi_{RID,\ Study,\ SsSai,\ Curvature}(\sigma_{Curvature>1}(R)),\ R)$$

T

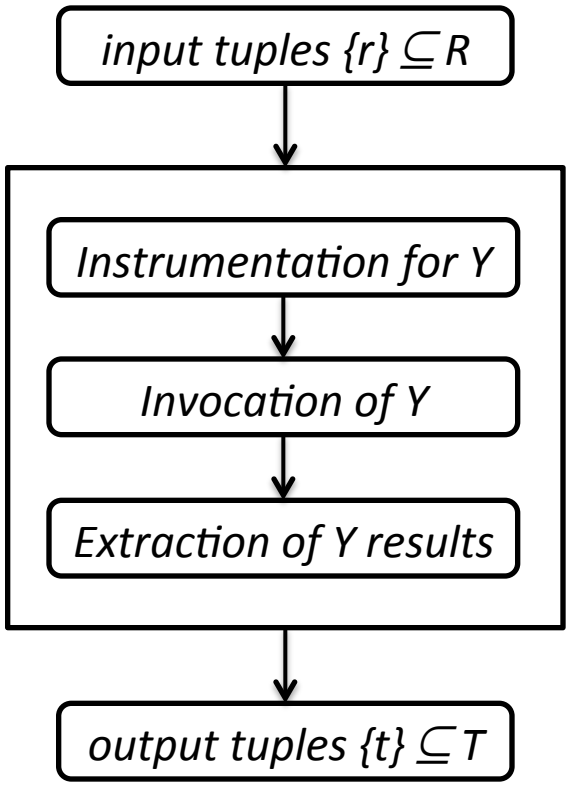
RID	Study	SsSai	Curvature
1	U-125	U-125Ss.SAI	1.5
1	U-127	U-127Ss.SAI	1.2

Workflow Execution Model

- Activity Activation
- Workflow Fragments
- Dataflow and Dispatching Strategies

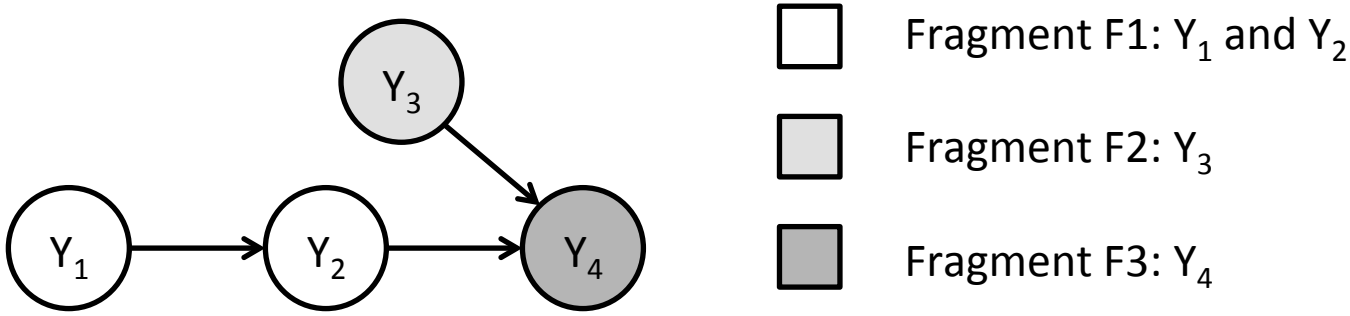
Activity Activation

- Activity activation is a self-contained object that holds all information needed (*i.e.* which program to invoke and which data to access) to execute an activity at any core
- Activations contain the finest unit of data needed by an activity to execute



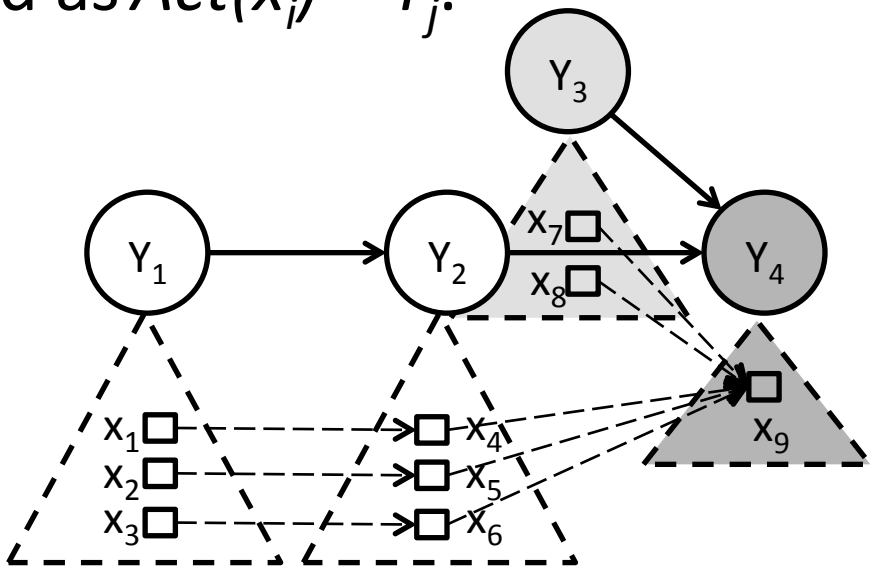
Workflow Fragments

- A fragment *F* of a workflow is a subset *F* of the activities of a workflow *W*:
  - either *F* is an unitary set
  - or $\forall Y_j \in F,\ \exists Y_i \in F \mid (Dep(Y_i, Y_j))\ v\ (Dep(Y_j, Y_i))$.



Activations in Workflow Fragments

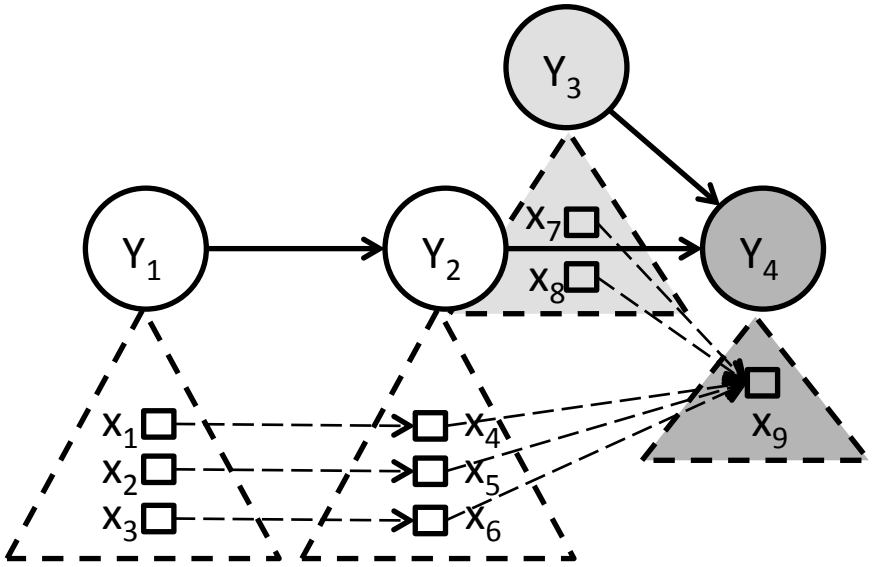
- Given a workflow W, a set $X=\{x_1, \ldots, x_k\}$ of activations is created for its execution.
- Each activation x_i belongs to a particular activity Y_j, which is represented as $Act(x_i) = Y_j$.



The execution model obeys the Dataflow and Dispatching Strategies assigned to each fragment

Dataflow Strategies

- *First Tuple First (FTF)* partitions a set of activations in a fragment into a complete list of dependent activations;
- *First Activity First (FAF)* partitions a set of activations in a fragment into a complete list of independent activations ordered by activity dependence.

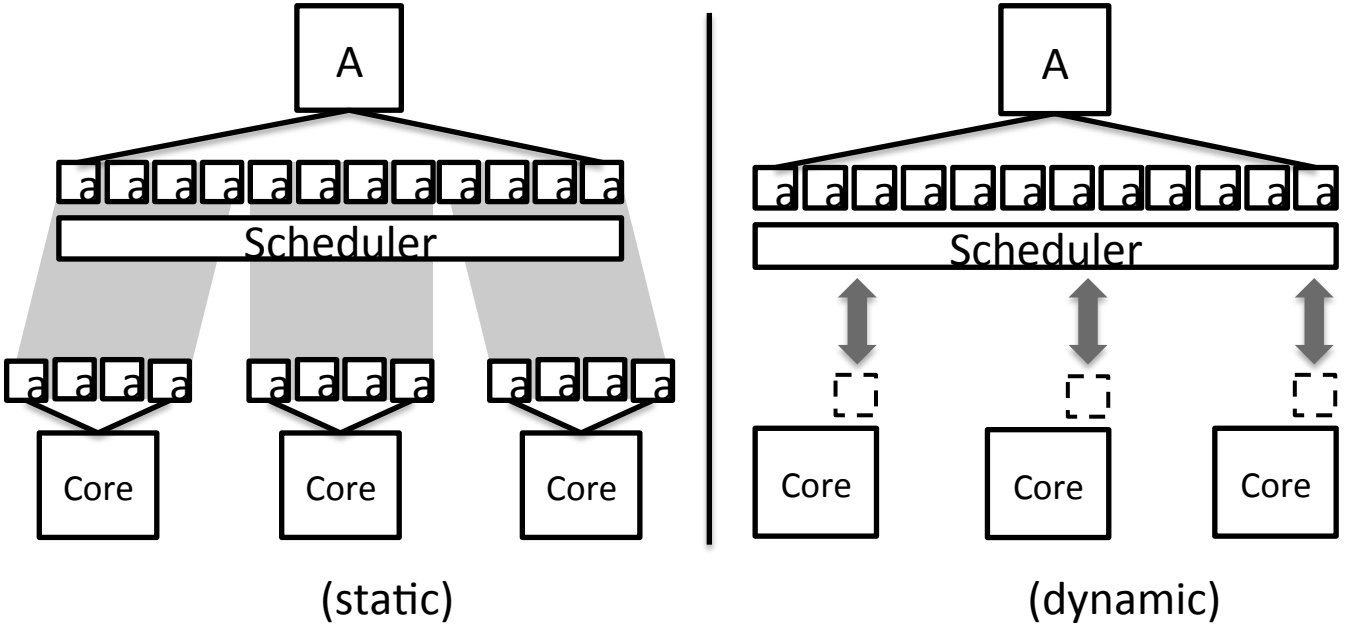


FTF:
{<x_1, x_4>, <x_2, x_5>, <x_3, x_6>}

FAF:
{<x_1>,<x_2>,<x_3>,
<x_4>,<x_5>,<x_6>}

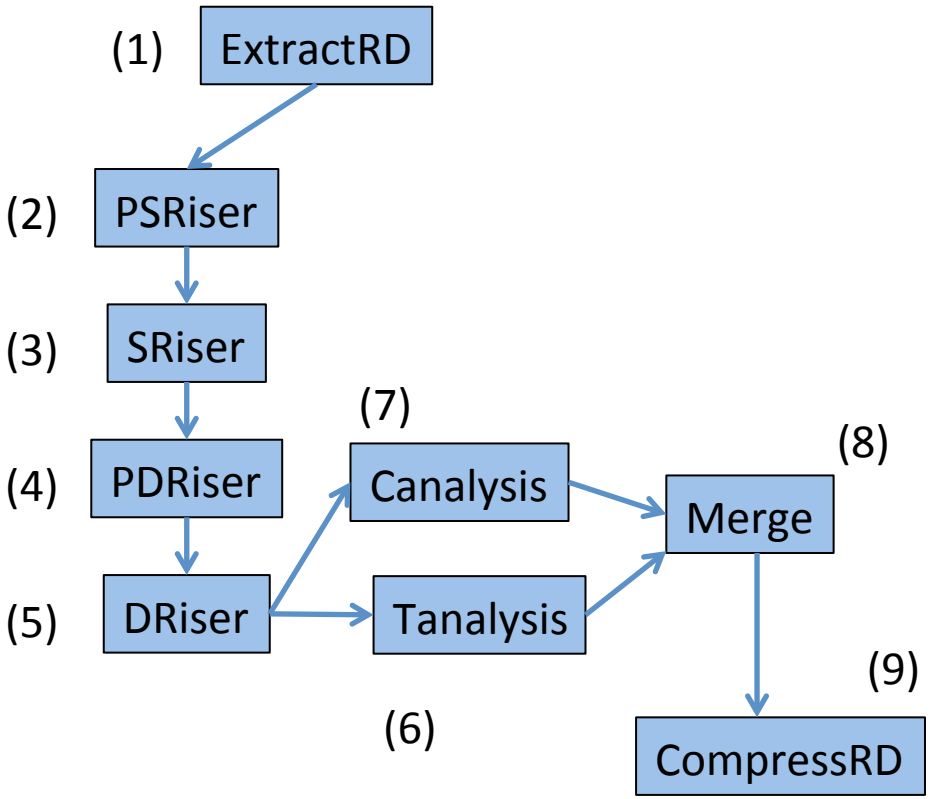
Dispatching Strategy

- In *static* dispatching strategy, activations are pre-allocated to each core before execution.
- In *dynamic* dispatching strategy activations are allocated to cores as a response to a request for activations.



Experimental Evaluation with RFA

Workflow



Workflow expressed as algebraic expressions

$T_1 \leftarrow SplitMap(ExtractRD, R_1)$

$T_2 \leftarrow Map(PSRiser, T_1)$

$T_3 \leftarrow Map(SRiser, T_2)$

$T_4 \leftarrow Map(PDRiser, T_3)$

$T_5 \leftarrow Map(DRiser, T_4)$

$T_6 \leftarrow Filter(Tanalysis, T_5)$

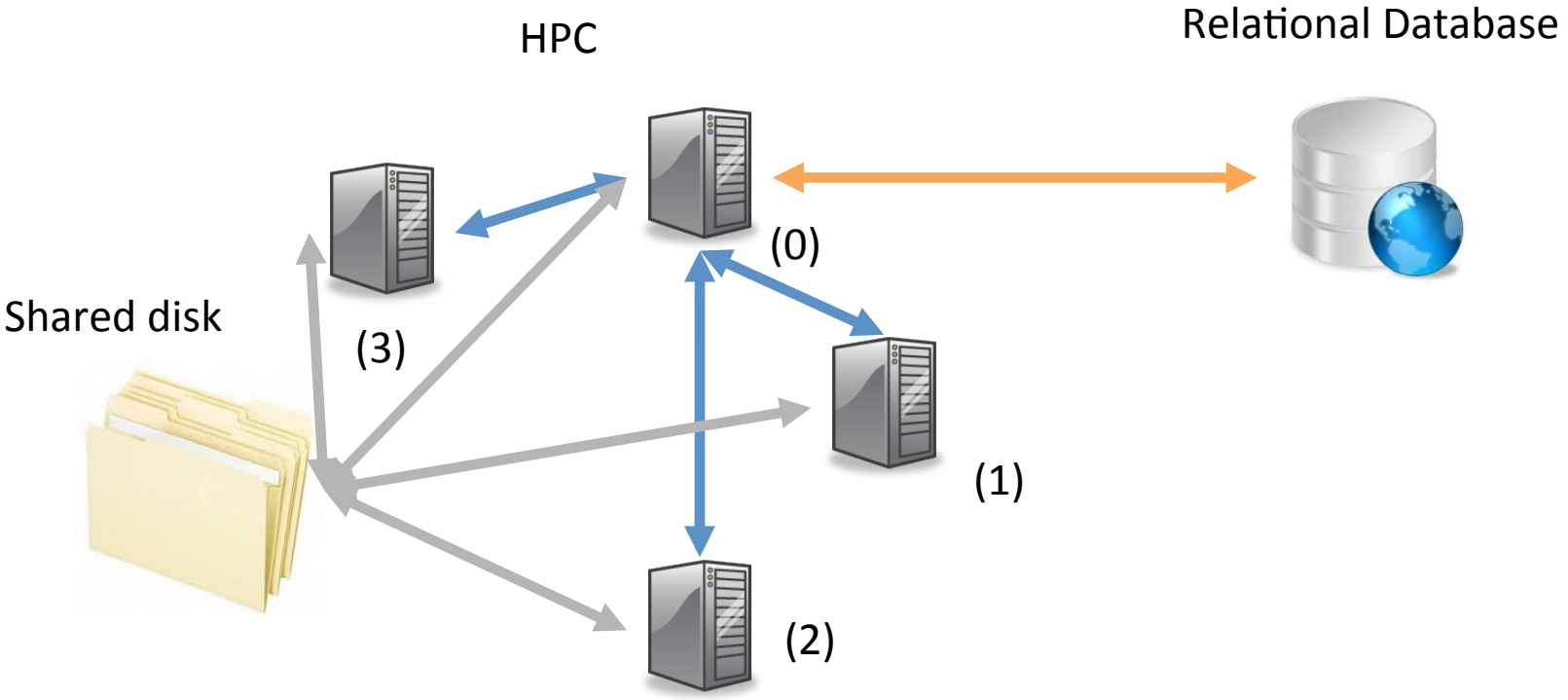
$T_7 \leftarrow Filter(Canalysis, T_5)$

$T_8 \leftarrow MRQuery(T_6 \bowtie T_7, \{T_6, T_7\})$

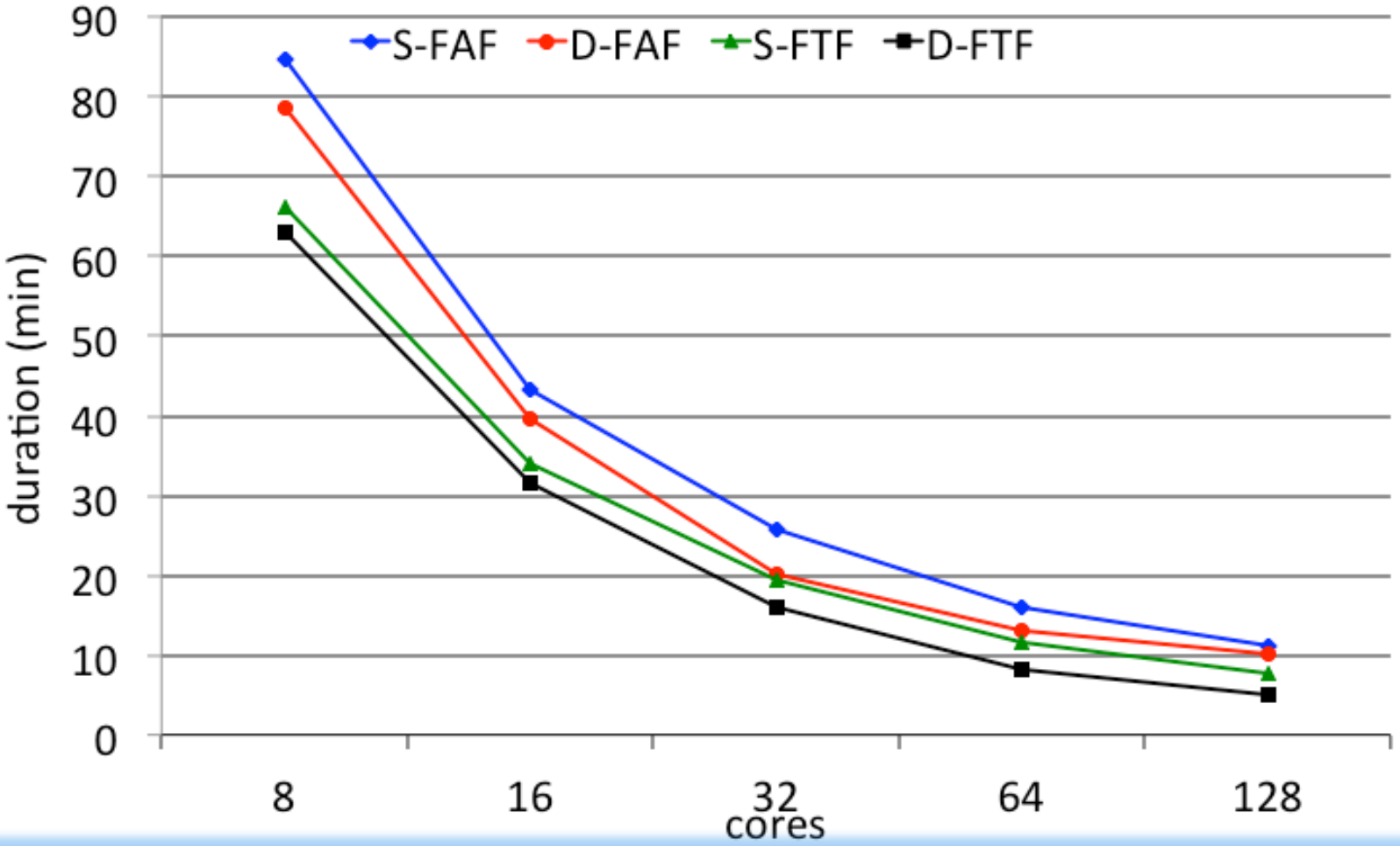
$T_9 \leftarrow Reduce(CompressRD, T_8)$

Chiron

- Chiron is a data-centric scientific workflow engine
- Implemented in Java using MPJ
- Provenance Stored in Relation Database



Evaluation of RFA Workflow with 358 Case Studies

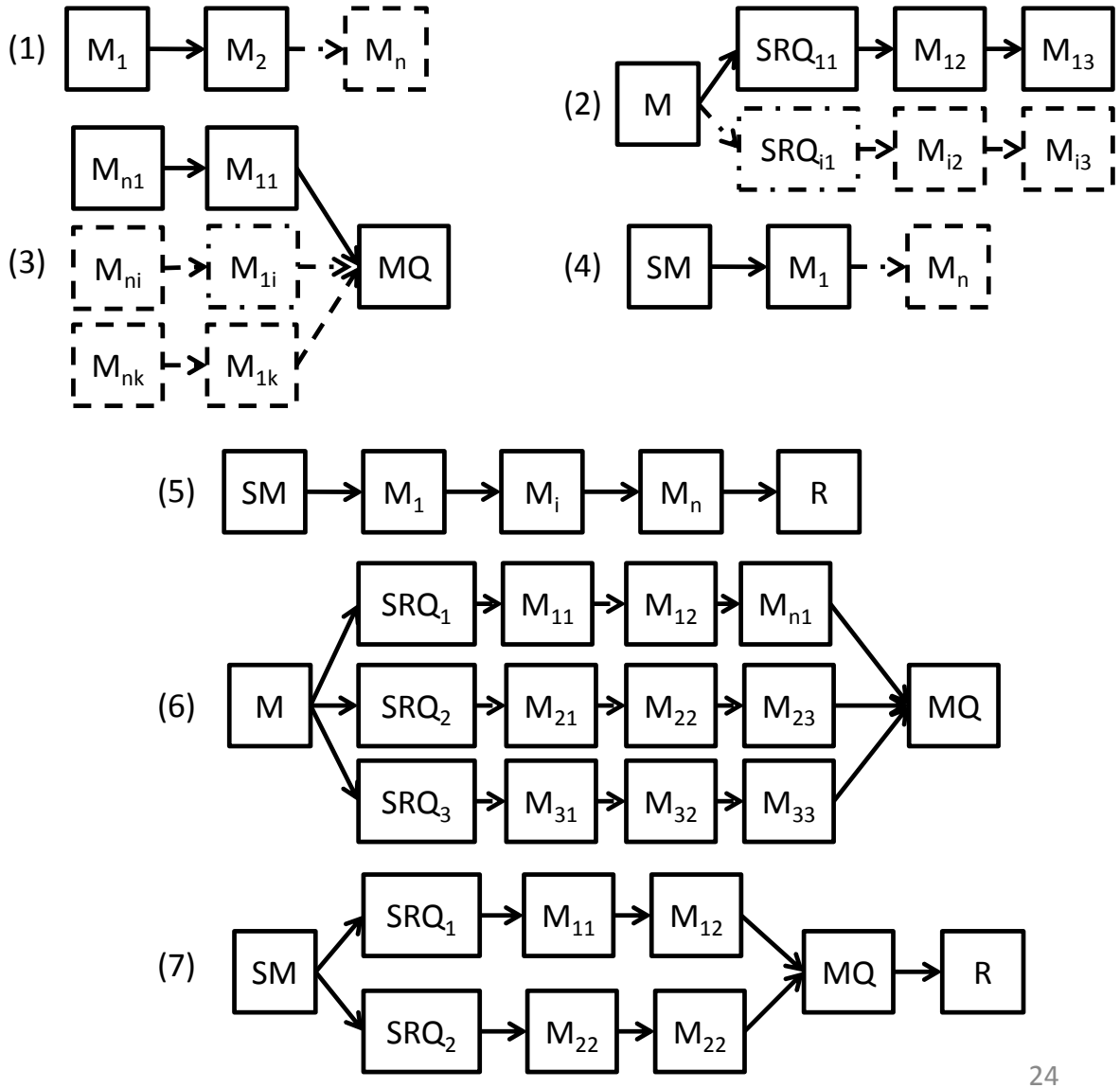


1438 activations, 16765 files
Performance difference of 226% between D-FTF versus S-FAF for 128 cores

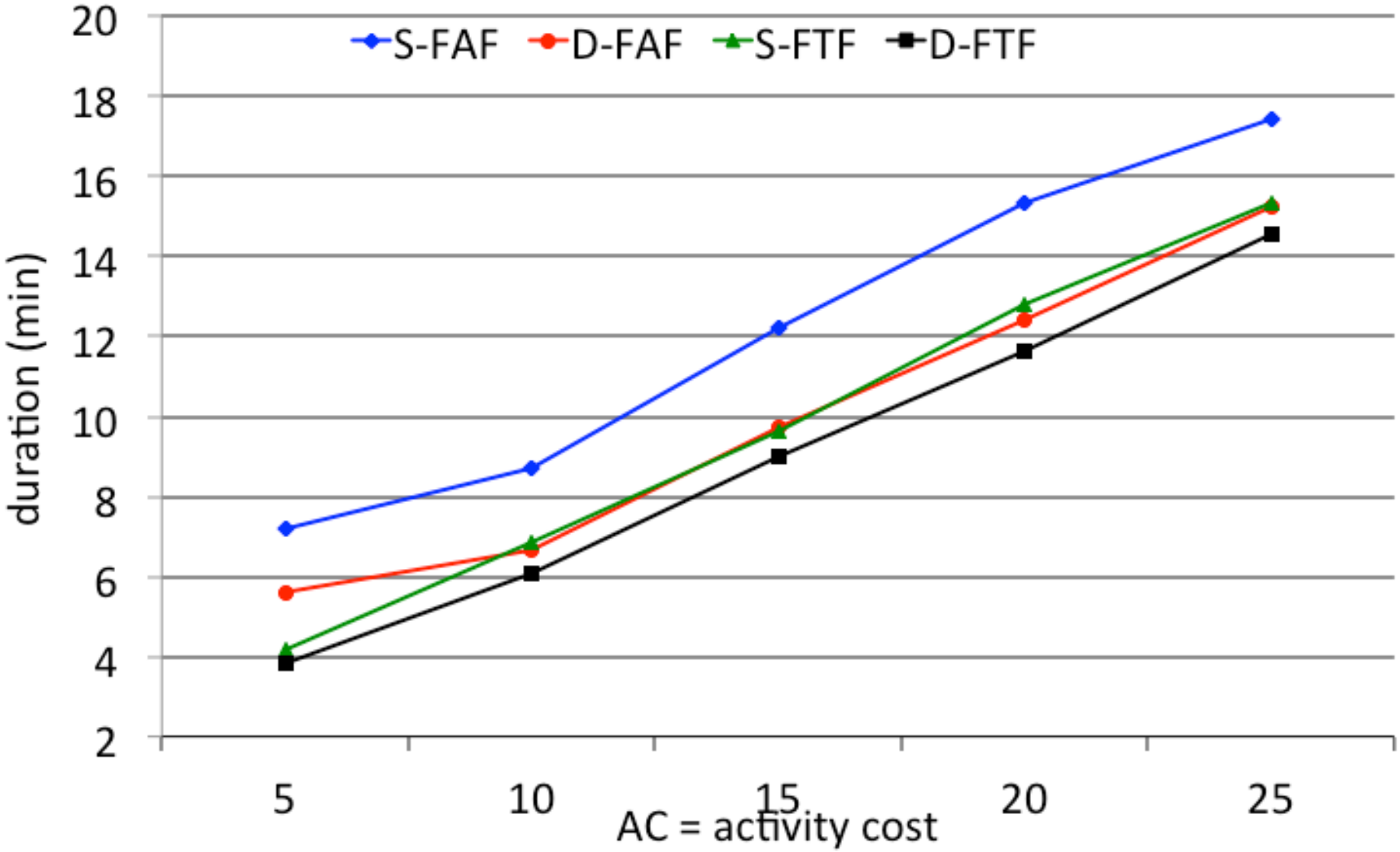
Experiments Using Synthetic Data

Studied variables:

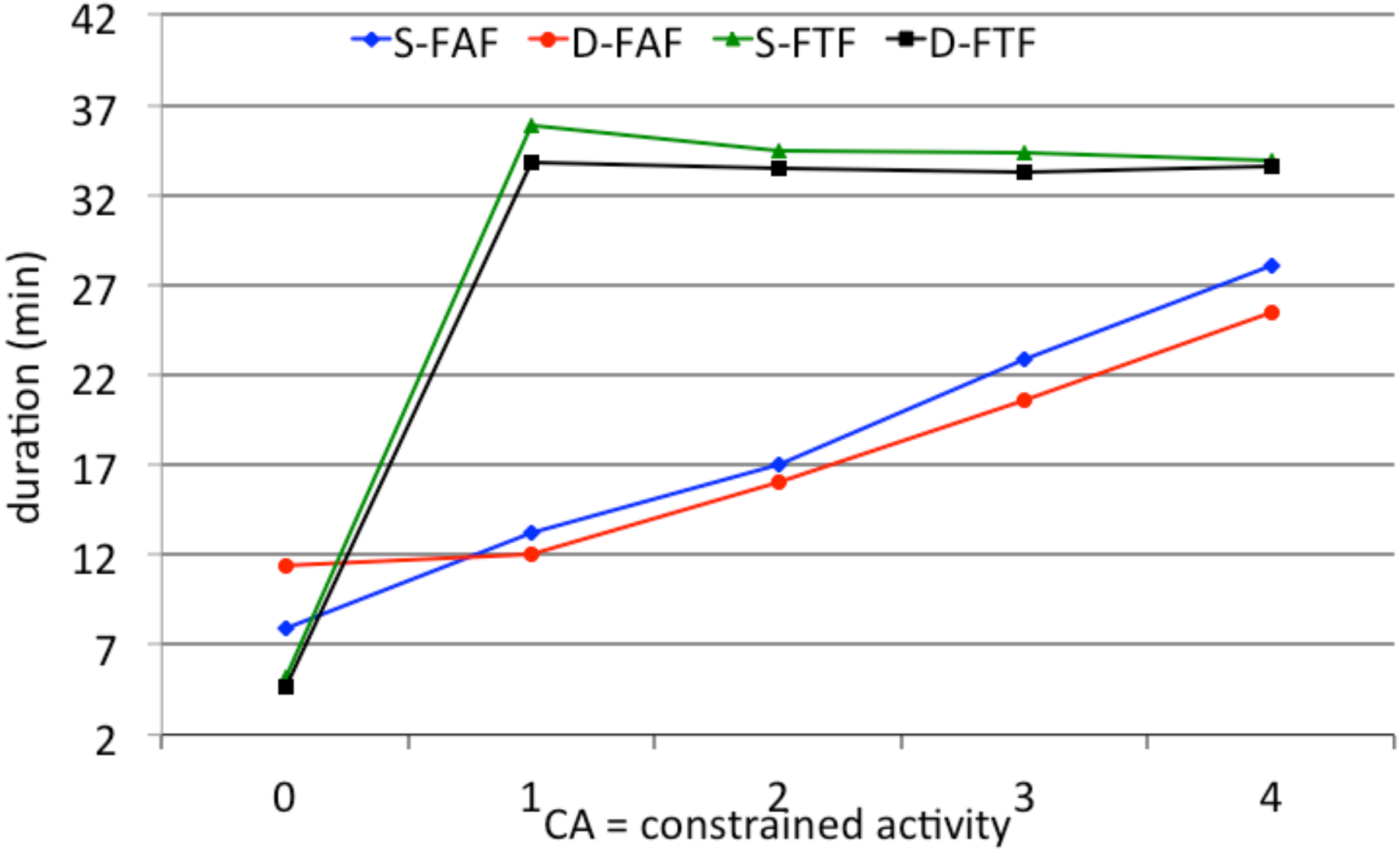
Activity Cost
Constrained Activity
Input Tuples
Sequence Length
Fan-In/Fan-Out
Split Factor/Reduce Factor



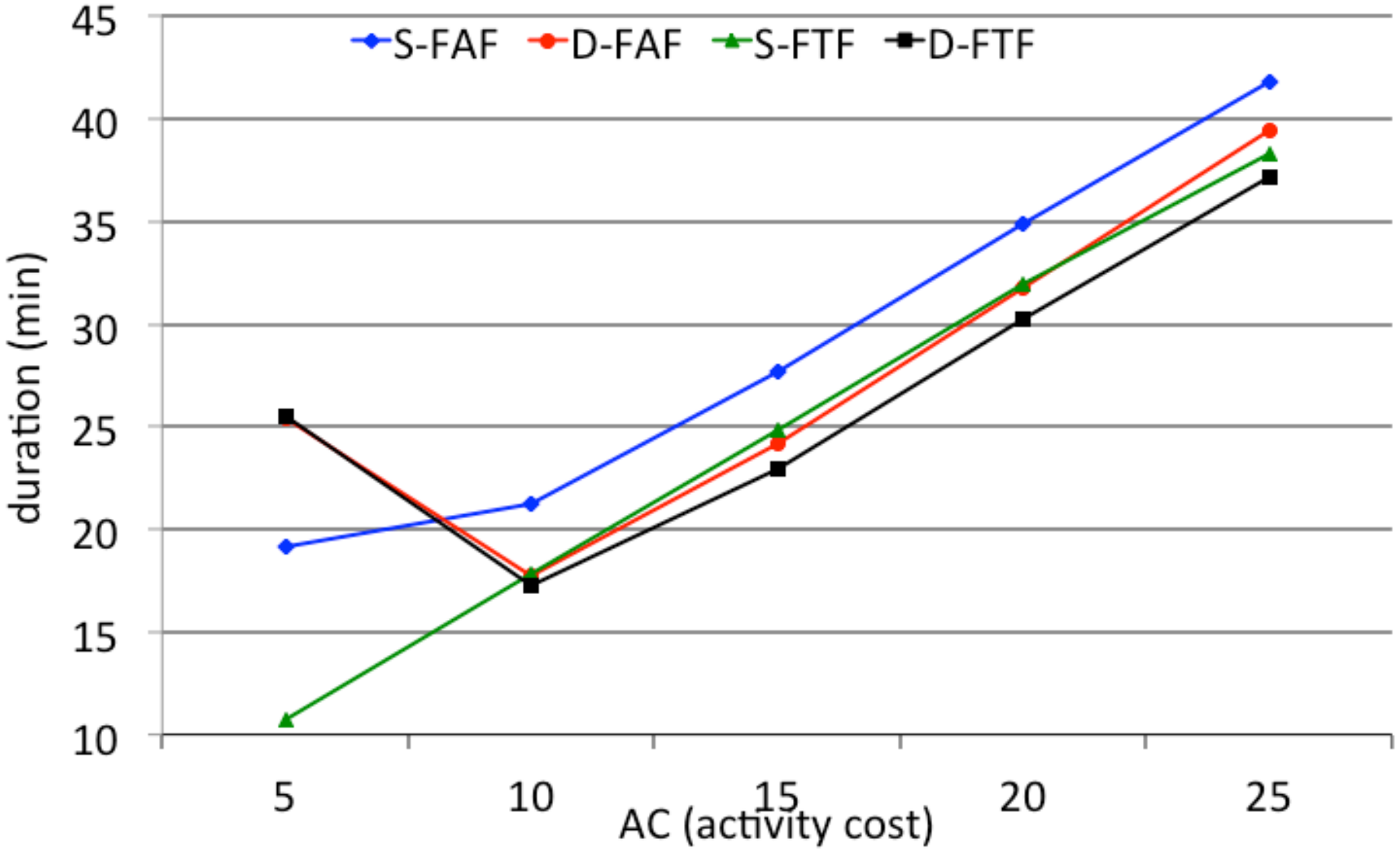
Scenario #1: Sequence of Activities



Scenario #1: Sequence with Constrained Activities



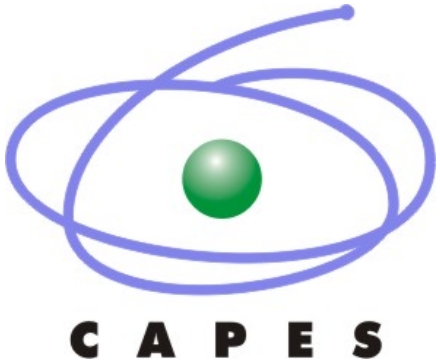
Scenario #6: Mixed Fan-Out/Fan-In



Conclusion

- We proposed a algebraic approach with an execution model for parallel processing
- We conducted a thorough experimental evaluation using Chiron, a data-centric scientific workflow engine.
- We evaluated our approach using Petrobras RFA application and synthetic data.
- The performance results show a variation of up to 226% when we compare the best with the worst performance results.
- As future work we intent to perform automatic optimization through algebraic transformations based on heuristics

Acknowledgements



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