Quality-aware data analytics

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What this lecture is about

- Data analytics – general view
- Data analytics workflow structures and systems
- Enable quality of analytics (QoA) for data analytics
- Quality of data in data analytics workflows
- Data elasticity management

What this lecture is about

- After this lecture
  - Apply and revise the analytics part in your project
  - Deal with quality of analytics and see how you could offer quality-aware analytics in your project

Big Data

Data: facts, responses, events, measurement, etc.

{"station_id":"1160629000","datapoint_id":122,"alarm_id":310,"event_time":"2016-09-17T02:05:54.000Z","isActive":false,"value":6,"valueThreshold":10}

What does it mean "Big data"?

NYC Taxi Data

The official TLC trip record dataset contains data for over 1.1 billion taxi trips from January 2009 through June 2015, covering both yellow and green taxis. Each individual trip record contains precise location coordinates for where the trip started and ended, timestamps for when the trip started and ended, plus a few other variables including fare amount, payment method, and distance traveled.

Open Big Data / Telecommunications - SMS, Call, Internet - MI

Description Tabular Preview API Resources

Schema

1. **Square id**: the id of the square that is part of the Milano GRID; TYPE: numeric
2. **Time interval**: the beginning of the time interval expressed as the number of millisecond elapsed from the Unix Epoch on January 1st, 1970 at UTC. The end of the time interval can be obtained by adding 600000 milliseconds (10 minutes) to this value. TYPE: numeric
3. **Country code**: the phone country code of a nation. Depending on the measured activity this value assumes different meanings that are explained later. TYPE: numeric
4. **SMS-in activity**: the activity in terms of received SMS inside the Square id, during the Time interval and sent from the nation identified by the Country code. TYPE: numeric
5. **SMS-out activity**: the activity in terms of sent SMS inside the Square id, during the Time interval and received by the nation identified by the Country code. TYPE: numeric
6. **Call-in activity**: the activity in terms of received calls inside the Square id, during the Time interval and issued from the nation identified by the Country code. TYPE: numeric
7. **Call-out activity**: the activity in terms of issued calls inside the Square id, during the Time interval and received by the nation identified by the Country code. TYPE: numeric
8. **Internet traffic activity**: the activity in terms of performed internet traffic inside the Square id, during the Time interval and by the nation of the users performing the connection identified by the Country code . TYPE: numeric

Big Data

- Sources
  - Internet of Things, human participation, social networks, software services, environment monitoring, advanced science instruments, science discovery, etc.
- Several challenges in terms of data gathering, integration, and analytics

H. V. Jagadish, Johannes Gehrke, Alexandros Labrinidis, Yannis Papakonstantinou, Jignesh M. Patel, Raghu Ramakrishnan, and Cyrus Shahabi. 2014. Big data and its technical challenges. Commun. ACM 57, 7 (July 2014), 86-94. DOI=10.1145/2611567 http://doi.acm.org/10.1145/2611567

Characterize big data

- Big data is often characterized by the concepts of V*: Volume, Variety, Velocity, Veracity and Valence
  - Volume: size (big size, large-data set, massive of small data)
  - Variety: complexity (formats, types of data)
  - Velocity: speed (generating speed, data movement speed)
  - Veracity: quality is very different (bias, accuracy, etc.)
  - Valence: “chemical” relationships among different type of data w.r.t data combination

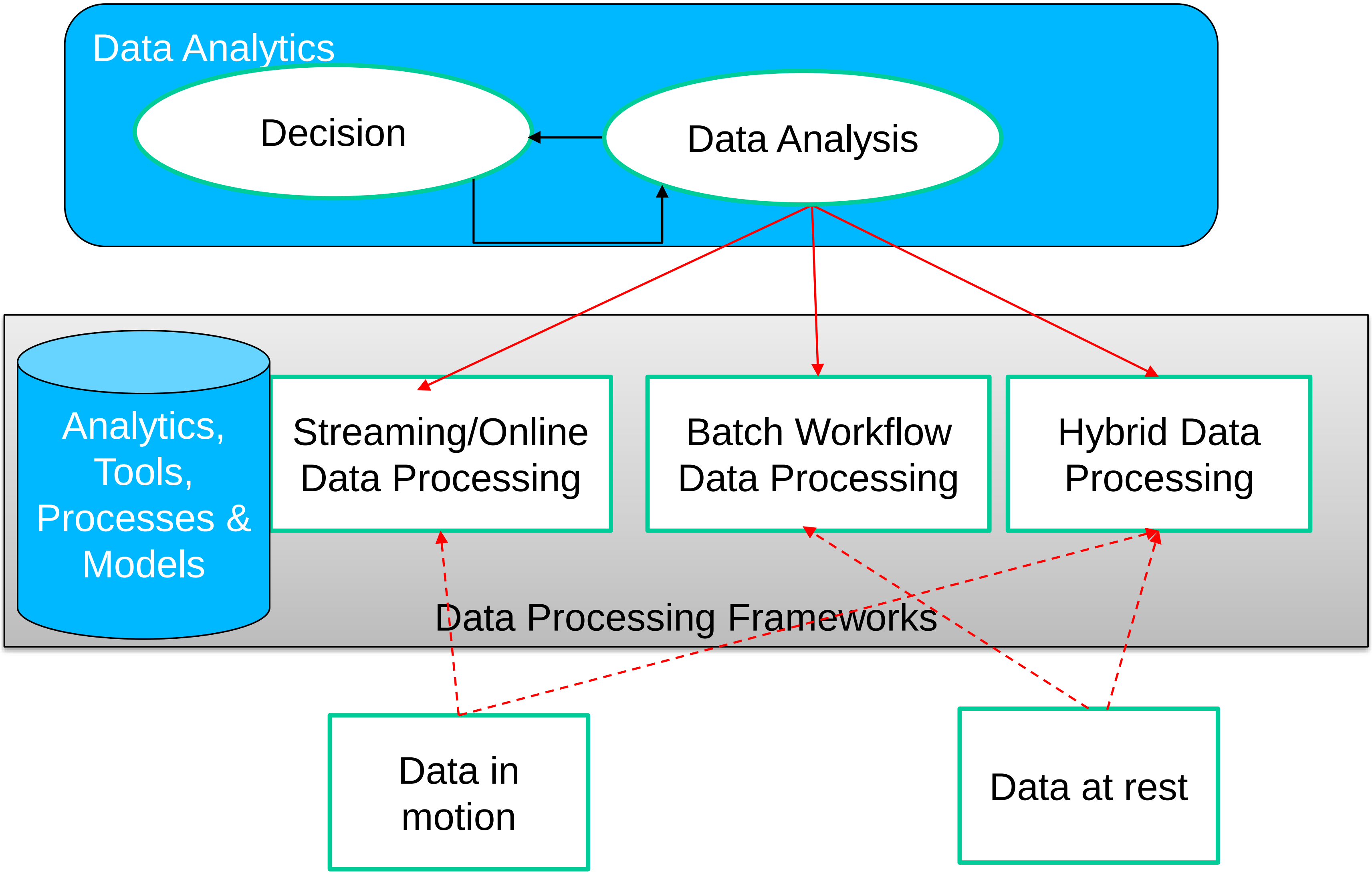
Data Management/Delivery Systems

- Static data – data at rest
  - Hadoop file systems
  - Large scale storage data systems
    - iRODS, BigQuery, and other NoSQL
  - Web services for Data-as-a-Service (e.g., GIS)
- Real time data – data in motion
  - Cloud data platforms
  - Several MOM (Message-oriented Middleware)
    - E.g., Apache Kafka
  - Domain-specific streamming systems (e.g., images)

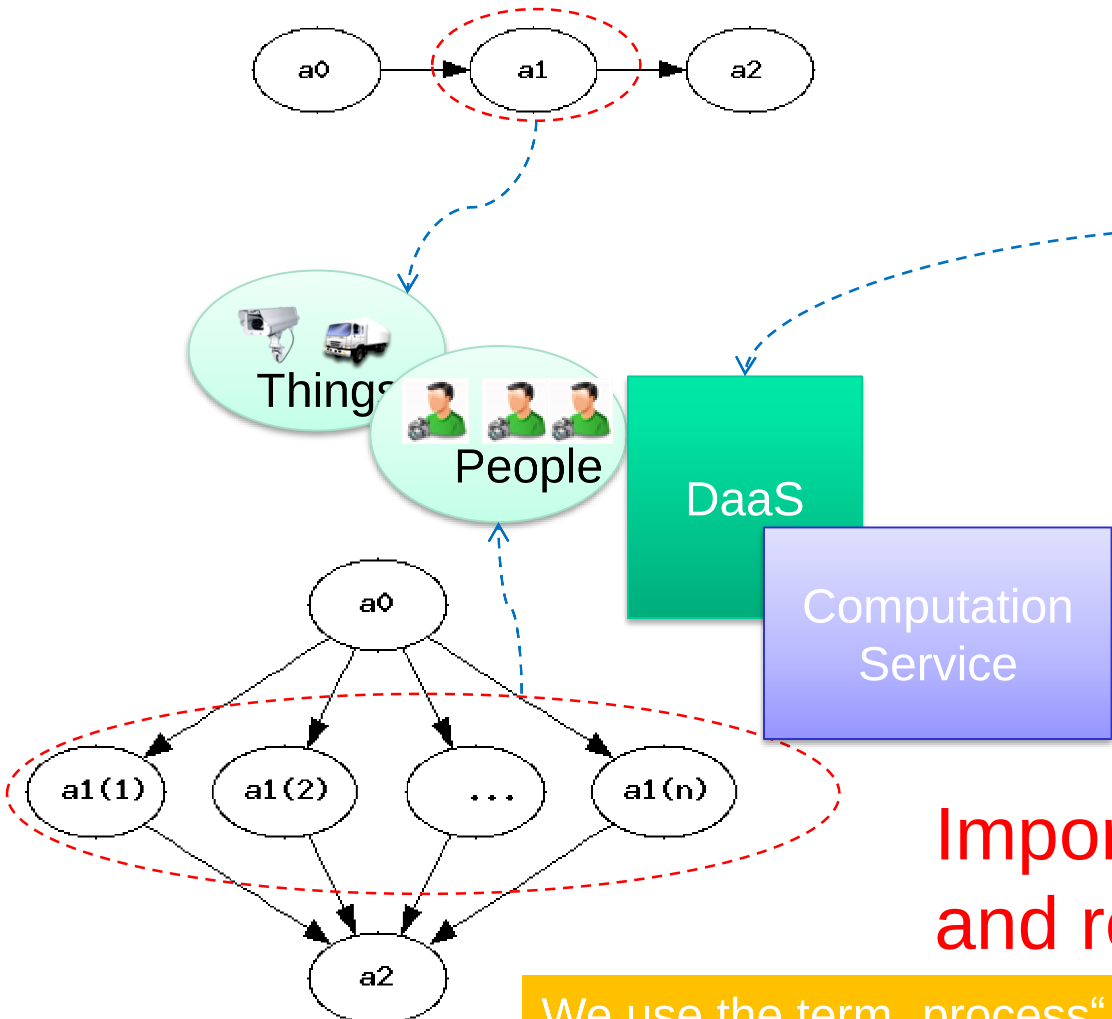
Data Processing Framework

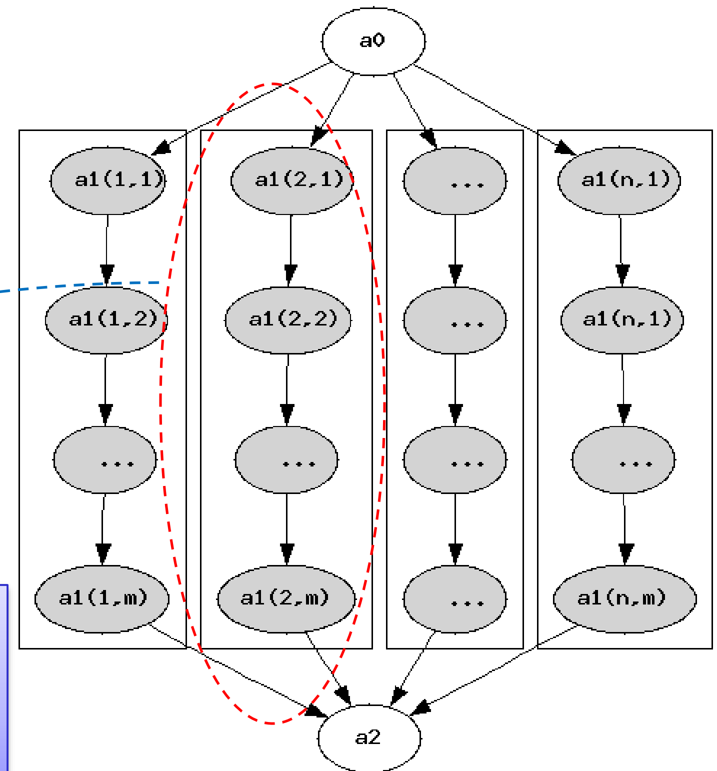
- Batch processing
  - Mapreduce/Hadoop
  - Scientific workflows
- (Near) realtime streaming processing
  - S4 & Storm, Apache Apex
- Hybrid data processing
  - Summingbird, Apache Kylin
  - Impala, Storm-YARN
  - Apache Spark

Conceptual View



Data analytics processes – a bird view





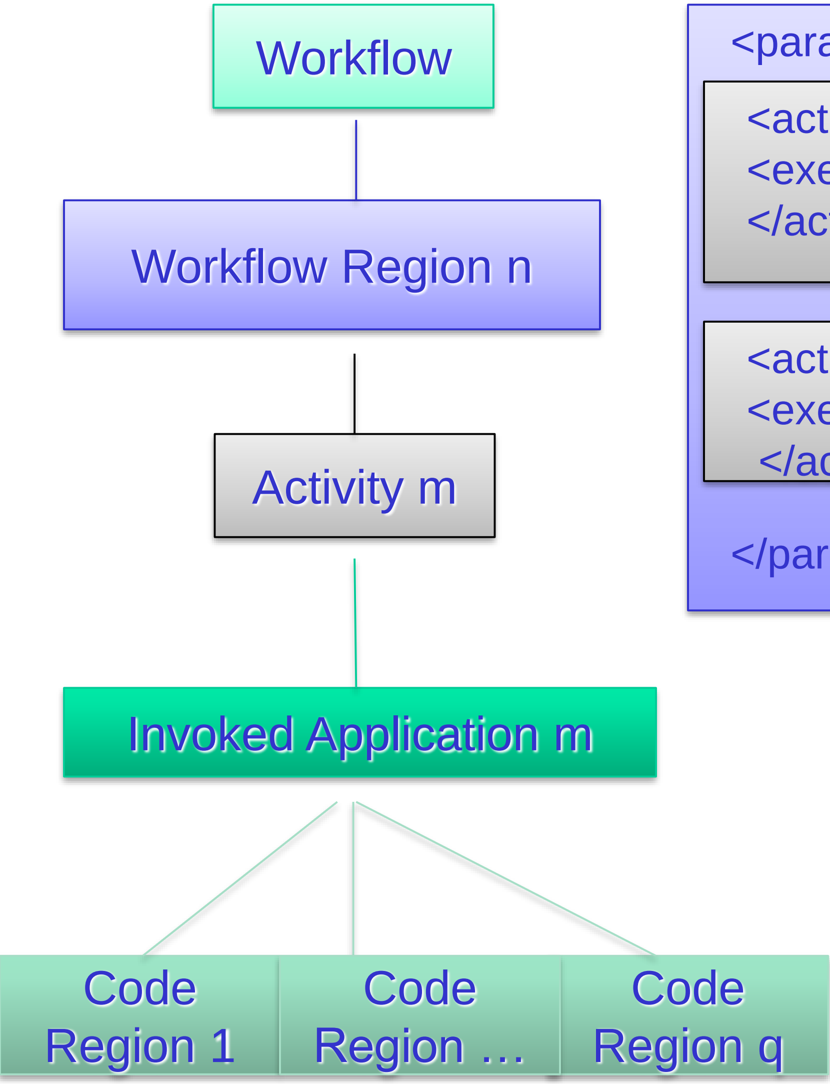
Important notes: Structures and resources

We use the term „process“ in a generic meaning!!!

Data analytics processes

- Main categories
  - (Batch) workflow-based processing
  - Stream data processing
  - Hybrid data processing

Workflow-based processing

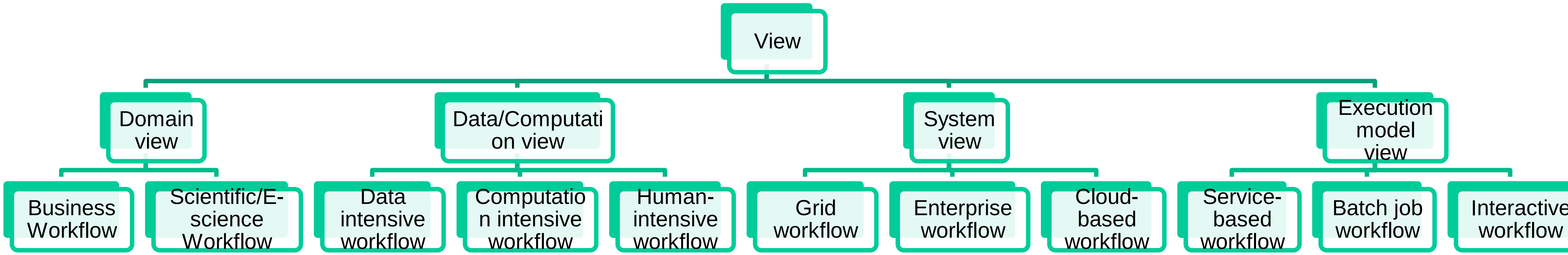



```
<parallel>
  <activity name="mProject1">
  <executable name="mProject1"/>
  </activity>

  <activity name="mProject2">
  <executable name="mProject2"/>
   </activity>

</parallel>
```

```
mProject1Service.java
        public void mProject1() {
                A();
                while () {
                ...
                }
}
```

Hong Linh Truong, Schahram Dustdar, Thomas Fahringer: Performance metrics and ontologies for Grid workflows. Future Generation Comp. Syst. 23(6): 760-772 (2007)

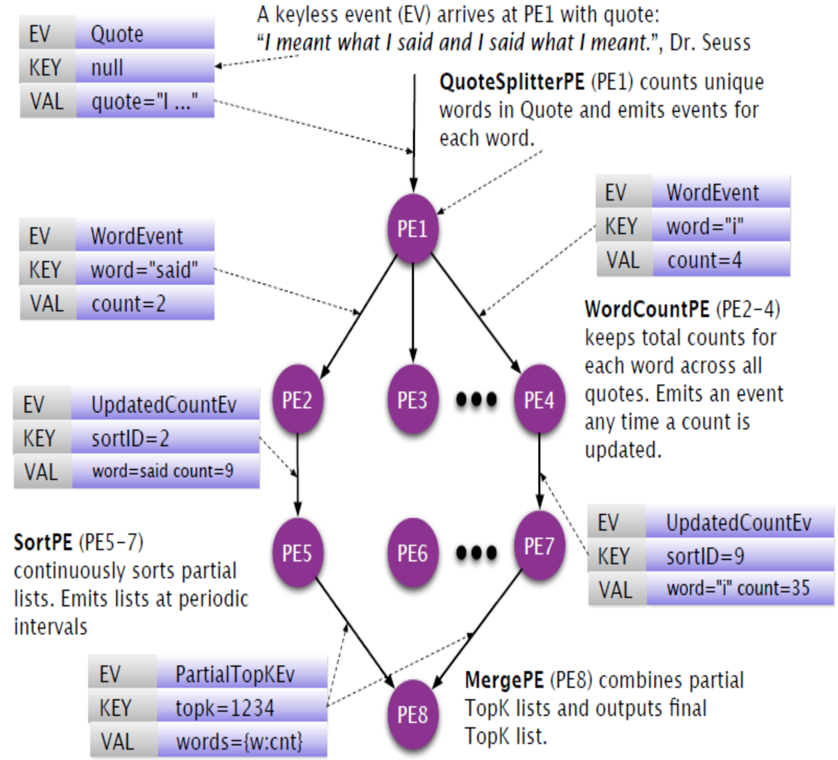
Different views of (data analytics) workflow systems



Stream data processing

- Processing elements/operators are arranged in graphs
- Streaming data comes to processing elements
- Results from an element are passed to another

Source: Neumeyer, L.; Robbins, B.; Nair, A.; Kesari, A., "S4: Distributed Stream Computing Platform," Data Mining Workshops (ICDMW), 2010 IEEE International Conference on , vol., no., pp.170,177, 13-13 Dec. 2010



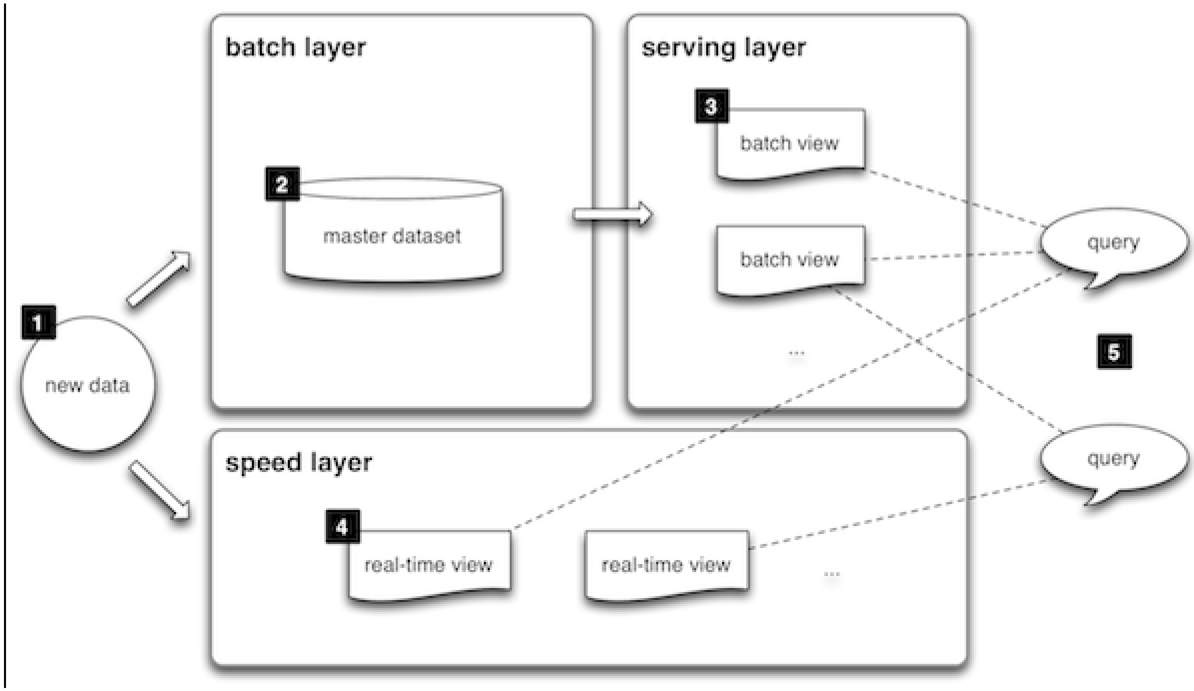
PE ID	PE Name	Key Tuple
PE1	QuoteSplitterPE	null
PE2	WordCountPE	word="said"
PE4	WordCountPE	word="i"
PE5	SortPE	sortID=2
PE7	SortPE	sortID=9
PE8	MergePE	topK=1234

Figure 1. Word Count Example

Check also: http://dsg.tuwien.ac.at/staff/truong/dst/pdfs/lecture5.pdf

Hybrid data processing

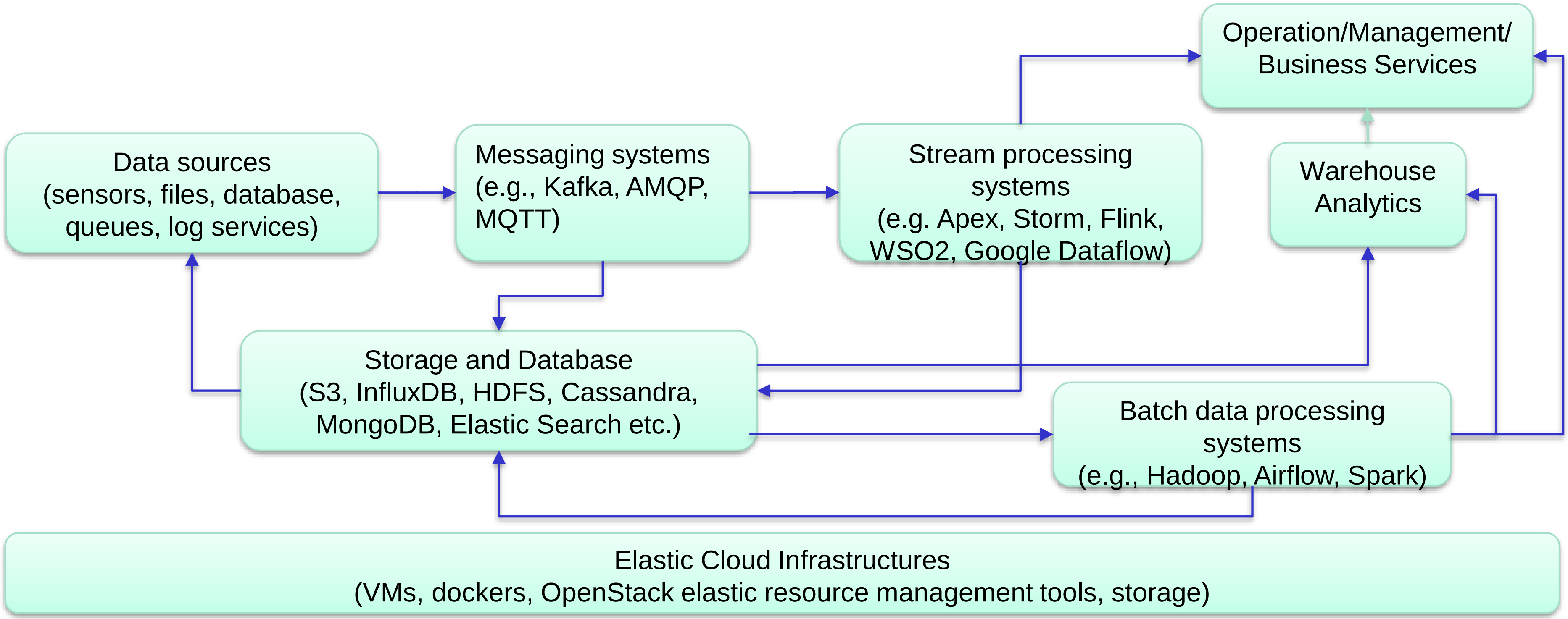
Combine batch processing and streaming processing
e.g., https://spark.apache.org/



Source:http://lambda-architecture.net/

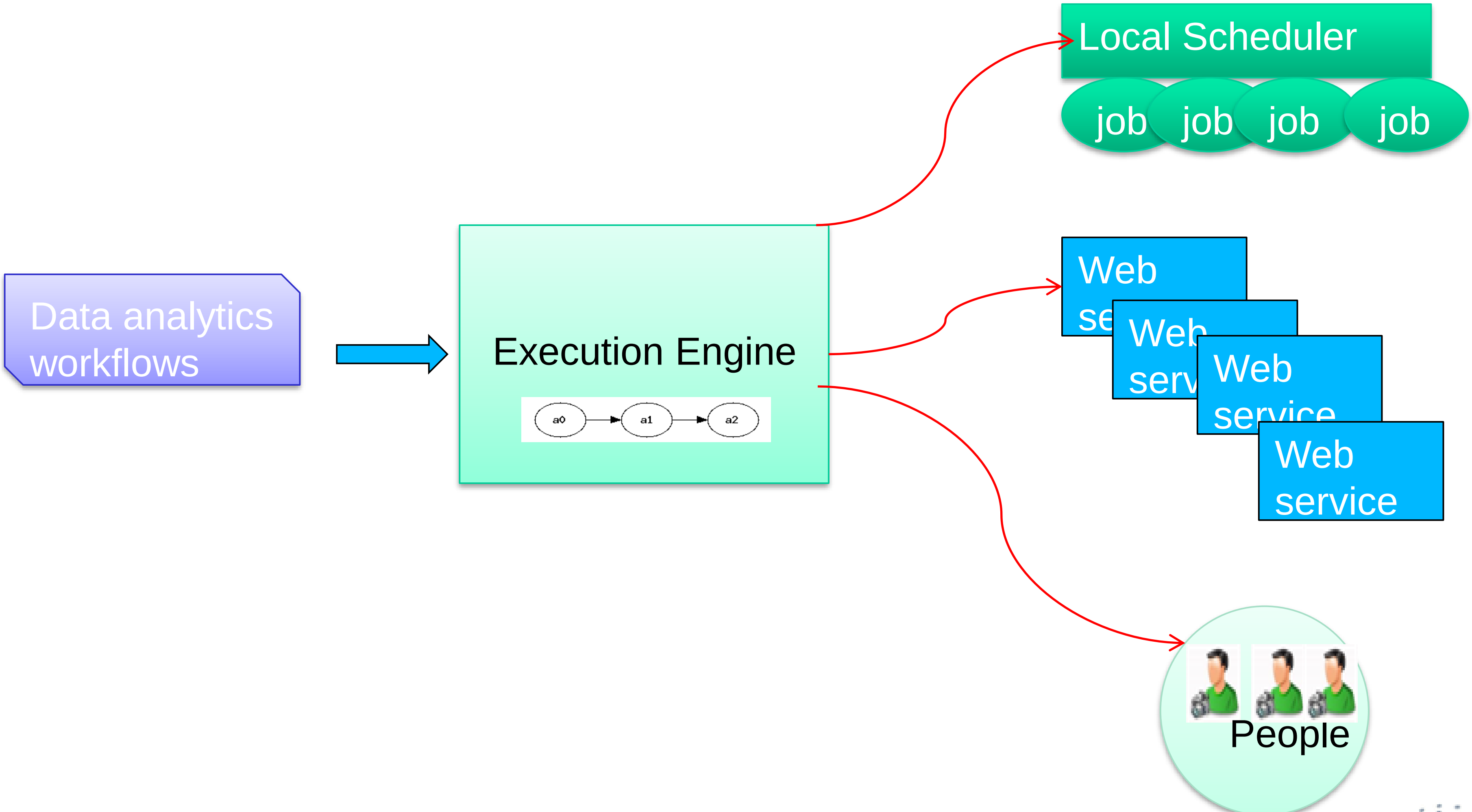
Which scenarios should we use a combination?

Cloud services and big data analytics

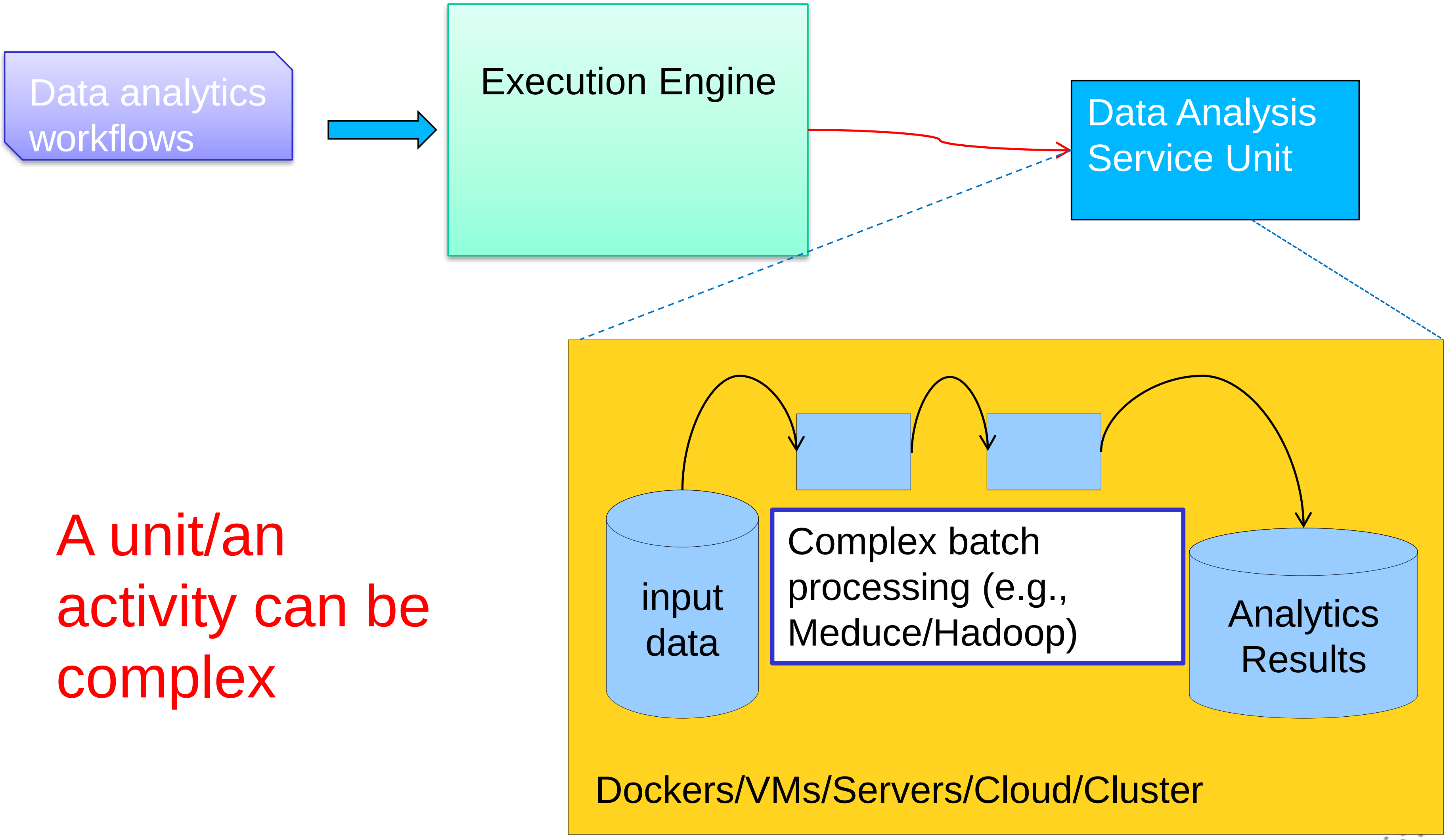


DATA ANALYSIS PROCESS (WORKFLOWS AND DATA PIPELINES)

Data analytics workflow execution models



Data analytics workflow execution models



A unit/an activity can be complex

Representing and programming data analytics workflows/processes

- Programming languages
  - General- and specific-purpose programming languages, such as Java, Python, Swift
- Programming models
  - such as MapReduce, Hadoop, Complex event processing, Spark
- Descriptive languages
  - BPEL and several languages designed for specific workflow engines
- They can also be combined

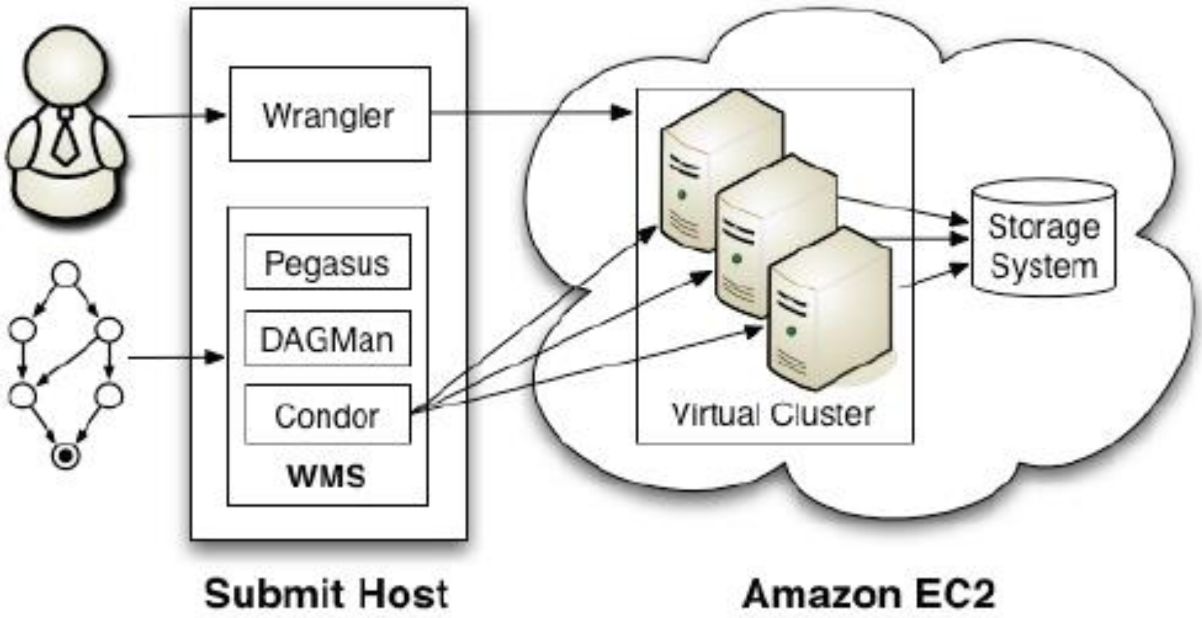
Examples of systems and frameworks for data analytics

- ASKALON
- KEPLER
- TAVERNA
- ADEPT
- MapReduce/Hadoop
- Google dataflow
- TRIDENT
- Apache ODE + WS-BPEL
- JOpera
- Pegasus
- Swift
- Airflow

Pros and cons of (data analytics) workflow systems

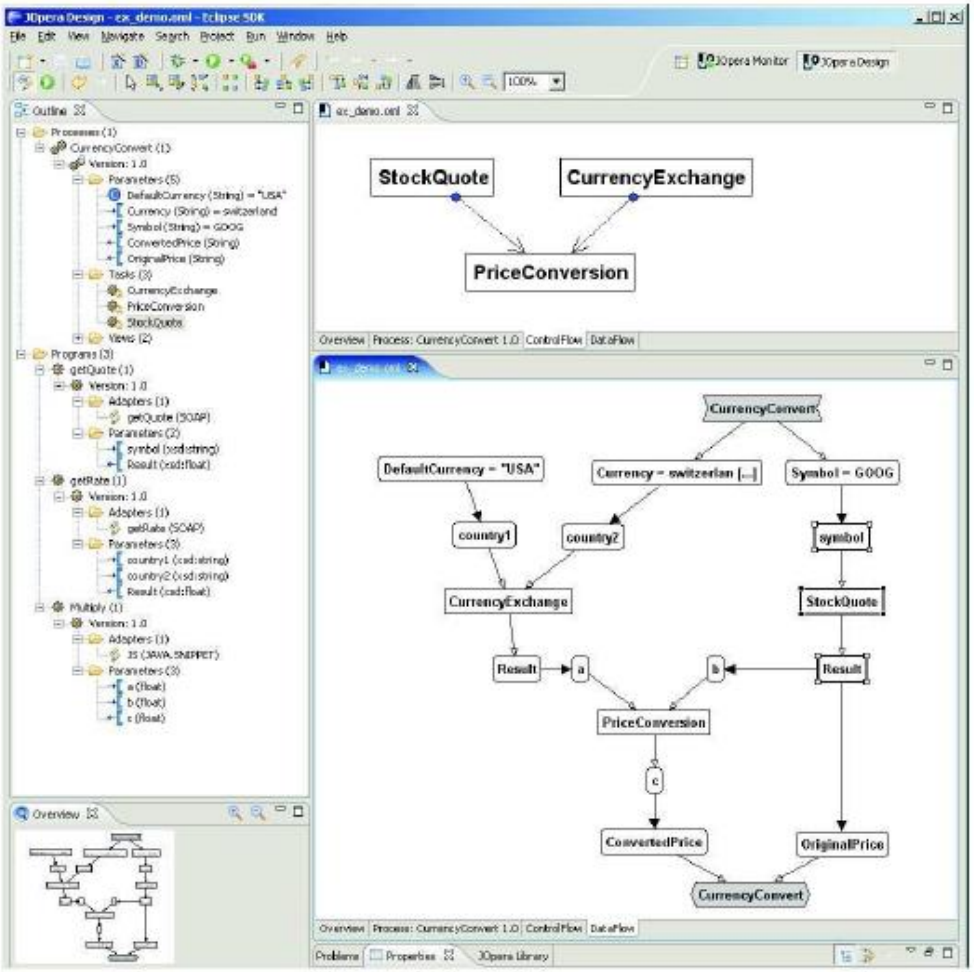
- Ian J. Taylor, Ewa Deelman, Dennis B. Gannon, and Matthew Shields. 2006. Workflows for E-Science: Scientific Workflows for Grids. Springer-Verlag New York, Inc., Secaucus, NJ, USA.
- Bertram Ludäscher, Mathias Weske, Timothy M. McPhillips, Shawn Bowers: Scientific Workflows: Business as Usual? BPM 2009: 31-47
- Mirko Sonntag, Dimka Karastoyanova, Frank Leymann: The Missing Features of Workflow Systems for Scientific Computations. Software Engineering (Workshops) 2010: 209-216
- Lavanya Ramakrishnan and Beth Plale. 2010. A multi-dimensional classification model for scientific workflow characteristics. In Proceedings of the 1st International Workshop on Workflow Approaches to New Data-centric Science (Wands '10). ACM, New York, NY, USA, , Article 4 , 12 pages. DOI=10.1145/1833398.1833402 http://doi.acm.org/10.1145/1833398.1833402
- Jia Yu and Rajkumar Buyya. 2005. A taxonomy of scientific workflow systems for grid computing. SIGMOD Rec. 34, 3 (September 2005), 44-49. DOI=10.1145/1084805.1084814 http://doi.acm.org/10.1145/1084805.1084814

Some examples (1)



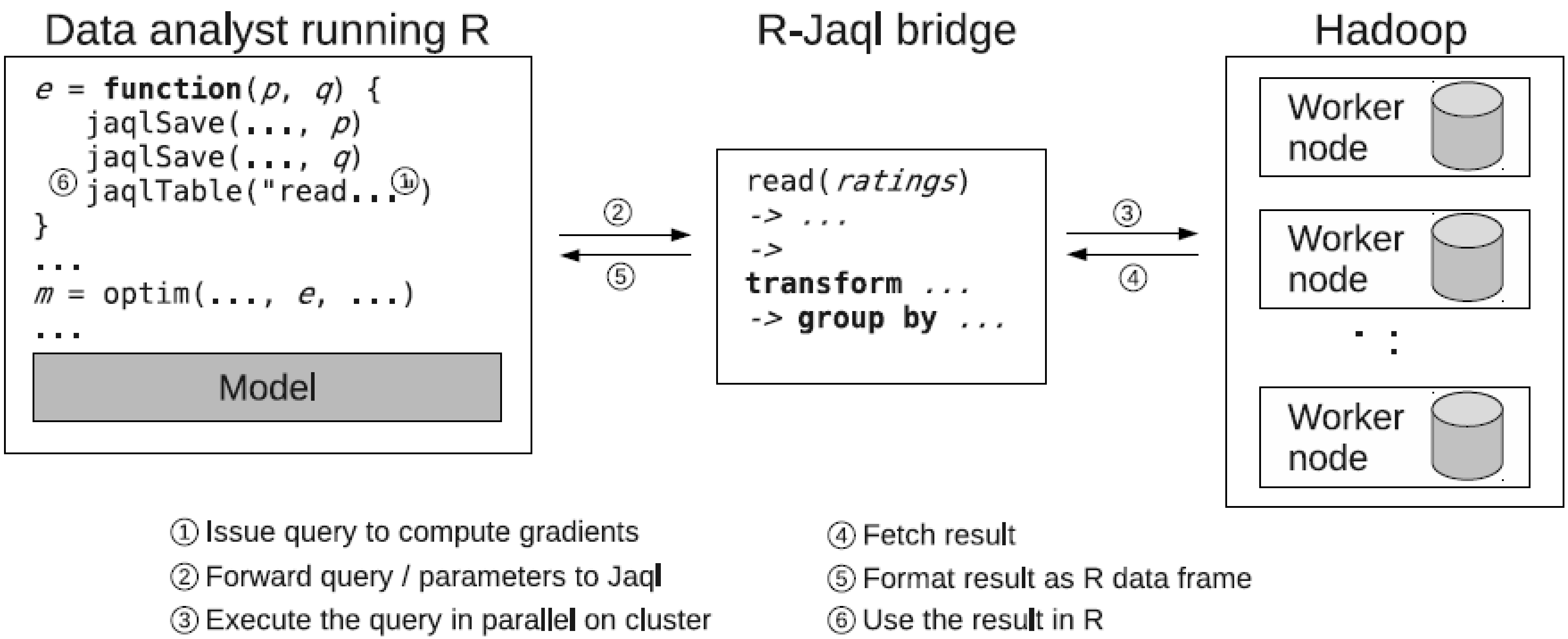
Source: Gideon Juve, Ewa Deelman, G. Bruce Berriman, Benjamin P. Berman, Philip Maechling: An Evaluation of the Cost and Performance of Scientific Workflows on Amazon EC2. J. Grid Comput. 10(1): 5-21 (2012)

Some examples (2)



Source: Cesare Pautasso, Thomas Heinis, Gustavo Alonso: JOpera: Autonomic Service Orchestration. IEEE Data Eng. Bull. 29(3): 32-39 (2006)

Some examples (3)



Source: Sudipto Das, Yannis Sismanis, Kevin S. Beyer, Rainer Gemulla, Peter J. Haas, and John McPherson. 2010. Ricardo: integrating R and Hadoop. In Proceedings of the 2010 ACM SIGMOD International Conference on Management of data (SIGMOD '10). ACM, New York, NY, USA, 987-998. DOI=10.1145/1807167.1807275 http://doi.acm.org/10.1145/1807167.1807275

Some examples (4): Airflow from Airbnb

- Workflow is a DAG (Direct Acyclic Graph)
  - http://airbnb.io/projects/airflow/

- Task/Operator:
  - BashOperator, PythonOperator, EmailOperator, HTTPOperator, SqlOperator, Sensor,
  - DockerOperator, HiveOperator, S3FileTransferOperator, PrestoToMysqlOperator, SlackOperator

Example for processing signal file

```
DAG_NAME = 'signal_upload_file'

default_args = {
    'owner': 'hong-linh-truong',
    'depends_on_past': False,
    'start_date': datetime.now(),
}

dag = DAG(DAG_NAME, schedule_interval=None, default_args=default_args)


stations=["station1", "station2"]

def checkSituation(**kwargs):
    f = 'f'
    t = 't'
    return t

downloadlogscript="curl  file:///home/truong/myprojects/mygit/rdsea-mobifone-training/data/opensignal/sample-Oct182016.csv -o /opt/data/air

t_downloadlogtocloud=  BashOperator(
    task_id="download_signal_file",
    bash_command=downloadlogscript,
    dag = dag
    )


t_analytics=  BashOperator(
    task_id="analyticsinternetusage",
    bash_command="/usr/bin/python /home/truong/myprojects/mygit/rdsea-mobifone-training/examples/databases/elasticsearch/uploader/src/uploa
    dag = dag
    )
t_sendresult =SimpleHttpOperator(
    task_id='sendresults',
    method='POST',
    http_conn_id='station1',
    endpoint='api/update/credit',
    data=json.dumps({"userphone": "066412345","credit":10}),
    headers={"Content-Type": "application/json"},
    dag = dag
    )

t_analytics.set_upstream(t_downloadlogtocloud)
t_sendresult.set_upstream(t_analytics)
```

Some examples (5): Mapreduce

```
map(String key, String value):
  // key: document name
  // value: document contents
  for each word w in value:
    EmitIntermediate(w, "1");

reduce(String key, Iterator values):
  // key: a word
  // values: a list of counts
  int result = 0;
  for each v in values:
    result += ParseInt(v);
  Emit(AsString(result));
```

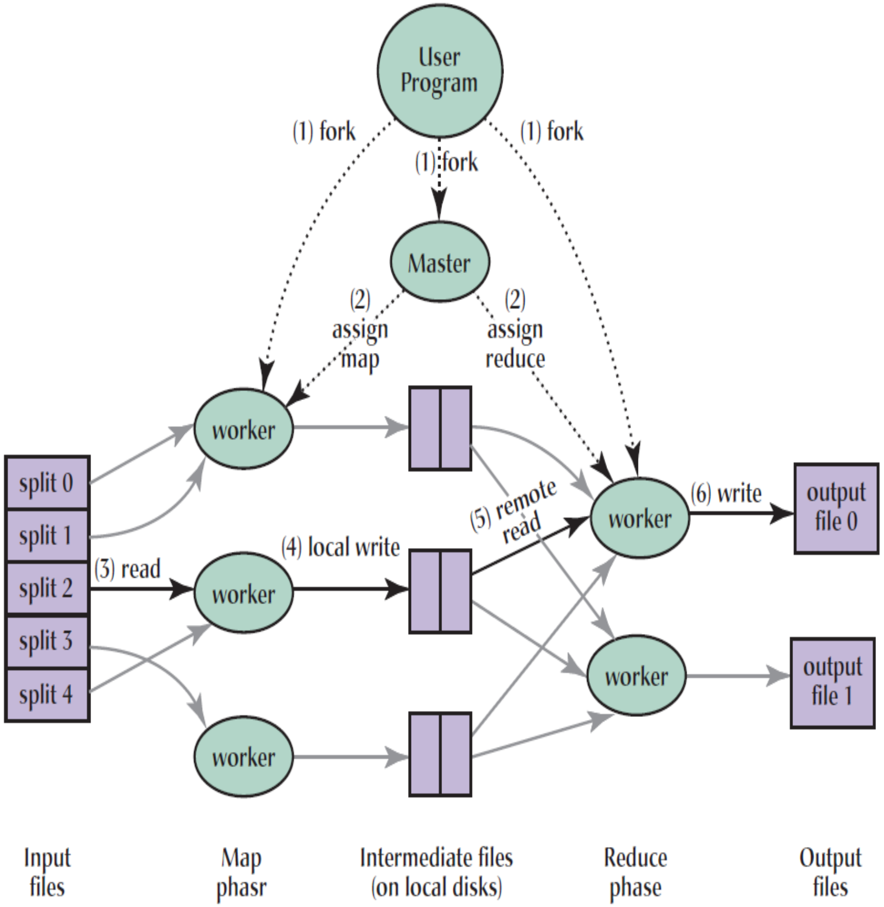


Fig. 1. Execution overview.

Source: Jeffrey Dean and Sanjay Ghemawat. 2008. MapReduce: simplified data processing on large clusters. Commun. ACM 51, 1 (January 2008), 107-113. DOI=10.1145/1327452.1327492 http://doi.acm.org/10.1145/1327452.1327492

Some examples (6): Apache Beam

- Goal: separate from pipelines from backend engines

Read data analytics → Post-processing result → Store analysis result

Apache Apex™ Flink APACHE Spark™ Dataflow

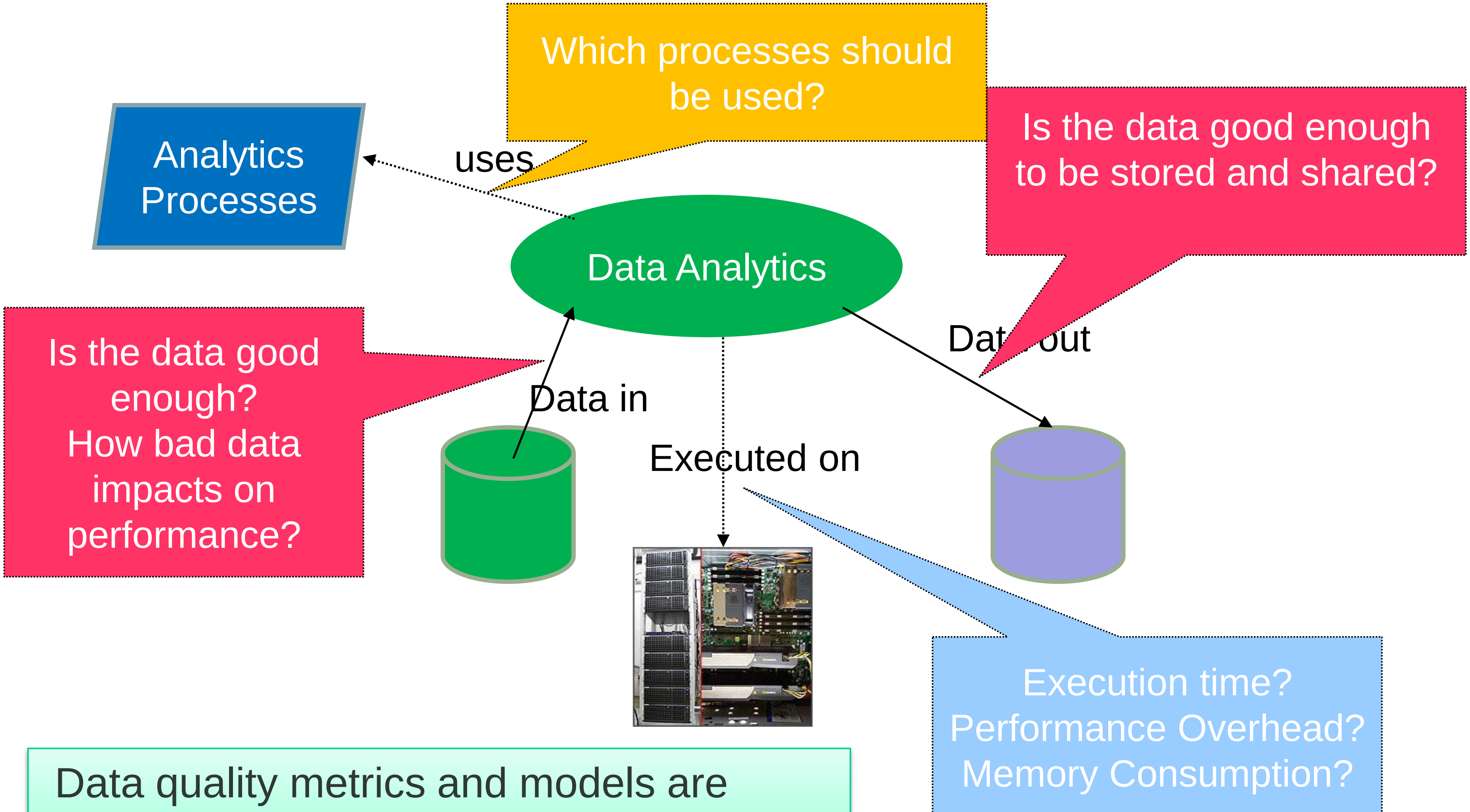
https://beam.apache.org/

QUALITY OF ANALYTICS

Quality of Analytics (QoA)

- Characterize the results of analytics processes
- Different elements of QoA
  - Performance (e.g. Execution time)
  - Data quality
  - Cost
  - Data format of output results
  - Etc.
- Customer: expects QoA
- Provider: offers QoA and enforces QoA

Performance and Data Quality Aspects



Data quality metrics and models are strongly domain-specific

So how do we enable QoA-aware analytics?

Solutions

- Computational resources provisioning?
- Replication of data analysis tasks ?
- Performance and cost measurement and optimization?
- Improve quality of input data ?
- Improve the quality of output data?

Which tools do you need for such solutions?

Mostly performance but not data quality

Logged in as: dr.who

All Applications

- Cluster
  - About
  - Nodes
  - Node Labels
  - Applications
    - NEW
    - NEW_SAVING
    - SUBMITTED
    - ACCEPTED
    - RUNNING
    - FINISHED
    - FAILED
    - KILLED
  - Scheduler
- Tools

Cluster Metrics

Apps Submitted	Apps Pending	Apps Running	Apps Completed	Containers Running	Memory Used	Memory Total	Memory Reserved	VCores Used	VCores Total	VCores Reserved	Active Nodes	Decommissioned Nodes	Lost Nodes	Unhealthy Nodes	Rebooted Nodes
299	0	0	299	0	0 B	12 GB	0 B	0	4	0	4	0	0	0	0

Scheduler Metrics

Scheduler Type	Scheduling Resource Type	Minimum Allocation	Maximum Allocation
Capacity Scheduler	[MEMORY]	<memory:256, vCores:1>	<memory:3072, vCores:1>

Show 20 entries Search:

ID	User	Name	Application Type	Queue	StartTime	FinishTime	State	FinalStatus	Progress	Tracking UI	Blacklisted Nodes
application_1494674366445_0299	liep	InA-BachPhu-BTS-Data-Analytics	SPARK	default	Fri Jun 2 04:31:00 +0200 2017	Fri Jun 2 04:32:35 +0200 2017	FINISHED	SUCCEEDED		History	N/A
application_1494674366445_0298	liep	InA-BachPhu-BTS-Data-Analytics	SPARK	default	Fri Jun 2 03:54:18 +0200 2017	Fri Jun 2 03:55:39 +0200 2017	FINISHED	SUCCEEDED		History	N/A
application_1494674366445_0297	liep	InA-BachPhu-BTS-Data-Analytics	SPARK	default	Fri Jun 2 03:43:46 +0200 2017	Fri Jun 2 03:44:32 +0200 2017	FINISHED	SUCCEEDED		History	N/A
application_1494674366445_0296	liep	InA-BachPhu-BTS-Data-Analytics	SPARK	default	Thu Jun 1 18:42:49 +0200 2017	Thu Jun 1 18:44:13 +0200 2017	FINISHED	SUCCEEDED		History	N/A
application_1494674366445_0295	liep	InA-BachPhu-BTS-Data-Analytics	SPARK	default	Thu Jun 1 18:39:11 +0200 2017	Thu Jun 1 18:40:03 +0200 2017	FINISHED	SUCCEEDED		History	N/A
application_1494674366445_0294	liep	InA-BachPhu-	SPARK	default	Thu Jun 1 18:28:15 +0200	Thu Jun 1 18:29:00 +0200 2017	FINISHED	SUCCEEDED		History	N/A

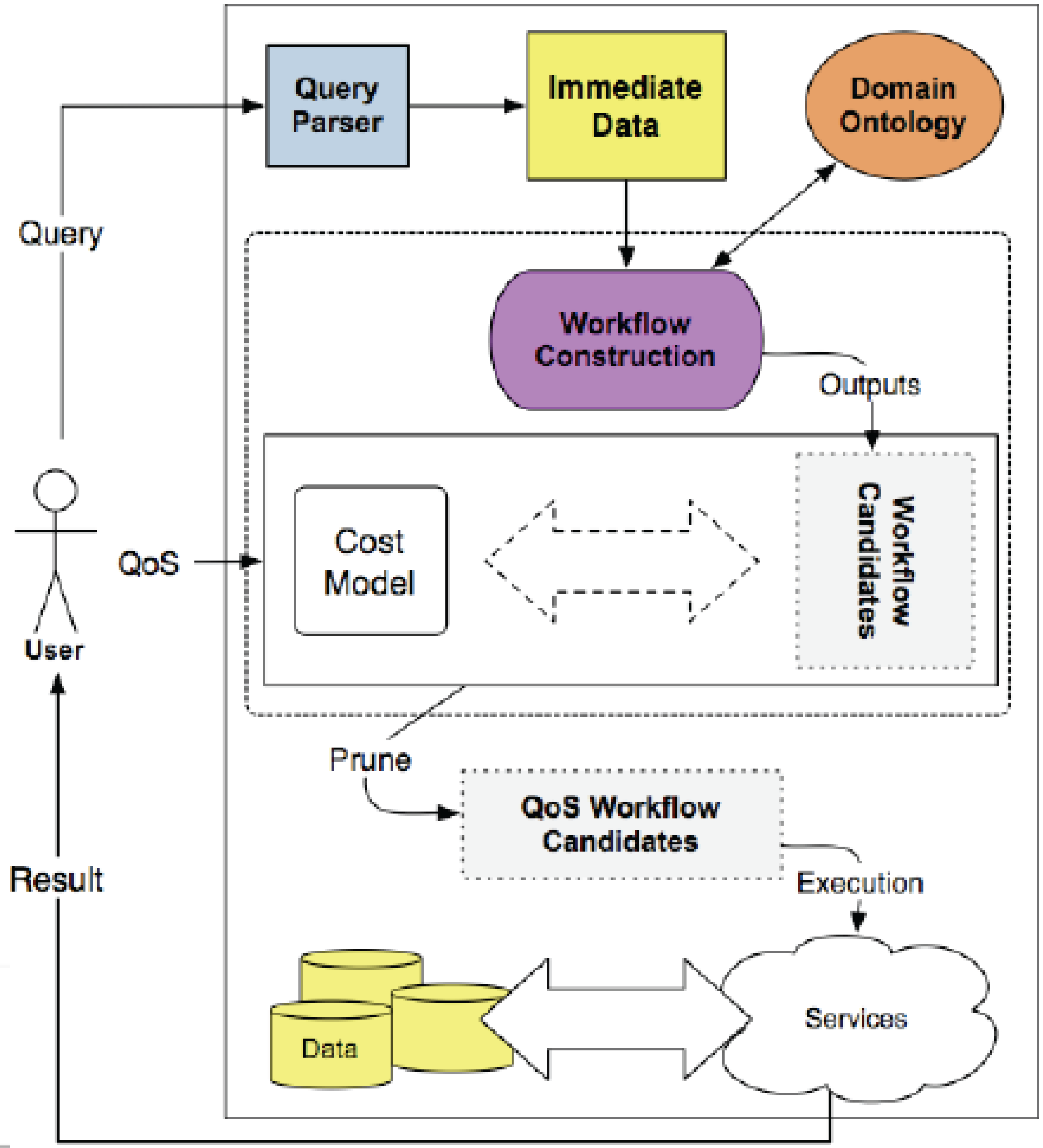
Executors

Summary

	RDD Blocks	Storage Memory	Disk Used	Cores	Active Tasks	Failed Tasks	Complete Tasks	Total Tasks	Task Time (GC Time)	Input	Shuffle Read	Shuffle Write
Active(8)	0	0.0 B / 3.7 GB	0.0 B	7	0	0	550	550	2.8 m (5.6 s)	29.0 MB	270.3 KB	690.4 KB
Dead(0)	0	0.0 B / 0.0 B	0.0 B	0	0	0	0	0	0 ms (0 ms)	0.0 B	0.0 B	0.0 B
Total(8)	0	0.0 B / 3.7 GB	0.0 B	7	0	0	550	550	2.8 m (5.6 s)	29.0 MB	270.3 KB	690.4 KB

If a job is failed due to the quality of data, how do you know?

Well-addressed concerns – performance/cost



Source: David Chiu, Sagar Deshpande, Gagan Agrawal, Rongxing Li: Cost and accuracy sensitive dynamic workflow composition over grid environments. GRID 2008: 9-16

Data Operations and cost with BigQuery

Action	Cost	Notes
Storage	$0.02 per GB, per month	First 10 GB is free each month, see Storage pricing for details.
Long Term Storage	$0.01 per GB, per month	See Long term storage pricing.
Streaming Inserts	$0.05 per GB	See Storage pricing.
Queries	$5 per TB	First 1 TB per month is free, see On-demand pricing for details. Flat-rate pricing is also available for high-volume customers.
Loading data	Free	See Loading data into BigQuery.
Copying data	Free	See Copying an existing table.
Exporting data	Free	See Exporting data from BigQuery.
Metadata operations	Free	List, get, patch, update and delete calls.

If you want to implement cost together data size and performance, what would be your way?

Provenance info

NiFi Data Provenance

Displaying 1,000 of 1,000
Oldest event available: 06/08/2017 04:27:03 UTC

Showing the most recent 1,000 of 1,000+ events, please refine the search.

Filter | by component name

	Date/Time	Type	FlowFile Uuid	Size	Component Name	Component Type
	06/09/2017 04:26:33.202 UTC	DROP	5f5e74f6-f28e-4cb8-b70e-07c5f8407bc4	8.33 MB	PutBachPhuHDFS-DYNAMIC-DATA	PutHDFS
	06/09/2017 04:26:33.202 UTC	ATTRIBUTES_MODIFIED	5f5e74f6-f28e-4cb8-b70e-07c5f8407bc4	8.33 MB	PutBachPhuHDFS-DYNAMIC-DATA	PutHDFS
	06/09/2017 04:26:33.202 UTC	SEND	5f5e74f6-f28e-4cb8-b70e-07c5f8407bc4	8.33 MB	PutBachPhuHDFS-DYNAMIC-DATA	PutHDFS
	06/09/2017 04:26:32.703 UTC	RECEIVE	5f5e74f6-f28e-4cb8-b70e-07c5f8407bc4	8.33 MB	GetBachPhuSFTP-DYNAMIC-DATA	GetSFTP
	06/09/2017 04:26:32.200 UTC	RECEIVE	348c8722-7d2b-44d6-9103-d7e699ee19f0	1.79 KB	Get-INA-OPYSPARK-HDFS	GetHDFS
	06/09/2017 04:26:32.195 UTC	DROP	64457e3f-0699-4404-a80f-5740674eab82	1.79 KB	Put-INA-BP-SFTP	PutSFTP
	06/09/2017 04:26:30.513 UTC	RECEIVE	31eb9ddc-ebb2-47cb-b09c-0ba1f7598f7a	1.79 KB	Get-INA-OPYSPARK-HDFS	GetHDFS
	06/09/2017 04:26:30.505 UTC	DROP	14571cd6-e4fa-4cda-8038-7906d9263d4e	1.79 KB	Put-INA-BP-SFTP	PutSFTP
	06/09/2017 04:26:28.765 UTC	RECEIVE	9030a70d-7b2f-4657-88d7-553021b072e2	1.79 KB	Get-INA-OPYSPARK-HDFS	GetHDFS
	06/09/2017 04:26:28.761 UTC	DROP	eb142c05-b27e-4a43-bd7c-bc4ed83c8c46	1.79 KB	Put-INA-BP-SFTP	PutSFTP
	06/09/2017 04:26:27.037 UTC	RECEIVE	f512b40e-9ba7-4f4f-aea5-171abc8cb26c	1.79 KB	Get-INA-OPYSPARK-HDFS	GetHDFS
	06/09/2017 04:26:27.027 UTC	DROP	b7ac1627-7c74-48a8-98da-6ff22ec099f9	1.79 KB	Put-INA-BP-SFTP	PutSFTP
	06/09/2017 04:26:25.259 UTC	RECEIVE	d1eb4033-5cc7-42ec-8268-ffaa6a70b2ce	1.79 KB	Get-INA-OPYSPARK-HDFS	GetHDFS
	06/09/2017 04:26:25.253 UTC	DROP	9be59f31-03f7-4cae-8288-6487a3f40bb2	1.79 KB	Put-INA-BP-SFTP	PutSFTP
	06/09/2017 04:26:23.551 UTC	RECEIVE	86ca4fa5-3b93-4546-842c-be0fc9747a3d	1.79 KB	Get-INA-OPYSPARK-HDFS	GetHDFS
	06/09/2017 04:26:23.542 UTC	DROP	9fd8ee9f-1522-408c-96fb-8788021d060f	1.79 KB	Put-INA-BP-SFTP	PutSFTP
	06/09/2017 04:26:21.813 UTC	RECEIVE	1cd88fd8-eb8d-4ec0-aa37-7430d5584cd9	1.79 KB	Get-INA-OPYSPARK-HDFS	GetHDFS
	06/09/2017 04:26:21.802 UTC	DROP	bdc4f5e6-2bac-41d6-a6db-fc50ecd19946	1.79 KB	Put-INA-BP-SFTP	PutSFTP
	06/09/2017 04:26:20.094 UTC	RECEIVE	5b8d9cee-6309-4e24-be75-6ed6e3ec1447	1.79 KB	Get-INA-OPYSPARK-HDFS	GetHDFS
	06/09/2017 04:26:20.081 UTC	DROP	59b60a7f-11b5-4dc6-bfde-ea220002e536	1.79 KB	Put-INA-BP-SFTP	PutSFTP
	06/09/2017 04:26:18.366 UTC	RECEIVE	ad652e87-3e34-4072-bc7a-51c5a067e39e	1.79 KB	Get-INA-OPYSPARK-HDFS	GetHDFS
	06/09/2017 04:26:18.363 UTC	DROP	a08b2524-49c4-40ac-b2cd-c33499e6cb4f	1.79 KB	Put-INA-BP-SFTP	PutSFTP
	06/09/2017 04:26:16.494 UTC	RECEIVE	7e108a1a-e66e-485e-9b5f-486d0cac7a55	1.79 KB	Get-INA-OPYSPARK-HDFS	GetHDFS
	06/09/2017 04:26:16.490 UTC	DROP	d98e6150-3144-4039-bbd8-f3517b70be87	1.79 KB	Put-INA-BP-SFTP	PutSFTP
	06/09/2017 04:26:15.351 UTC	DROP	7c172491-855f-450e-a052-d5cf49757626	301 bytes	PutBachPhuStaticData-HDFS	PutHDFS
	06/09/2017 04:26:15.351 UTC	ATTRIBUTES_MODIFIED	7c172491-855f-450e-a052-d5cf49757626	301 bytes	PutBachPhuStaticData-HDFS	PutHDFS

Last updated: 04:27:10 UTC

If you are able to detect a quality problem in the analysis phase, can you trace back to the data sources? what would be your way?

QUALITY OF DATA IN DATA ANALYTICS WORKFLOWS

Research questions

- What are main QoD metrics, what are the relationship between QoD metrics and other service level objectives, and what are their roles and possible trade-offs?
- How to support different domain-specific QoD models and link them to workflow structures?
- How to model, evaluate and estimate QoD associated with data movement into, within, and out to workflows? When and where software or scientists can perform automatic or manual QoD measurement and analysis
- How to optimize the workflow composition and execution based on QoD specification?
- How does QoD impact on the provisioning of data services, computational services and supporting services?

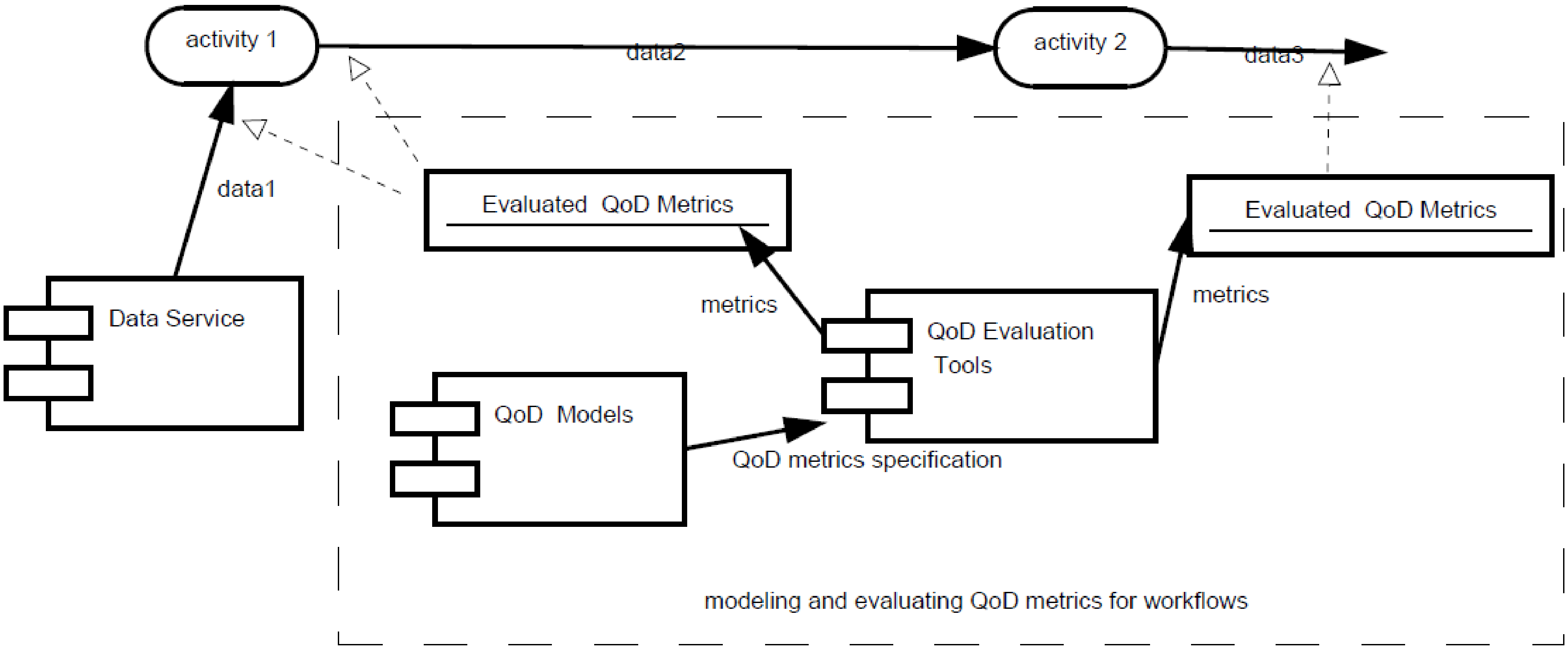
Approach

Core models, techniques and algorithms to allow the modeling and evaluating QoD metrics

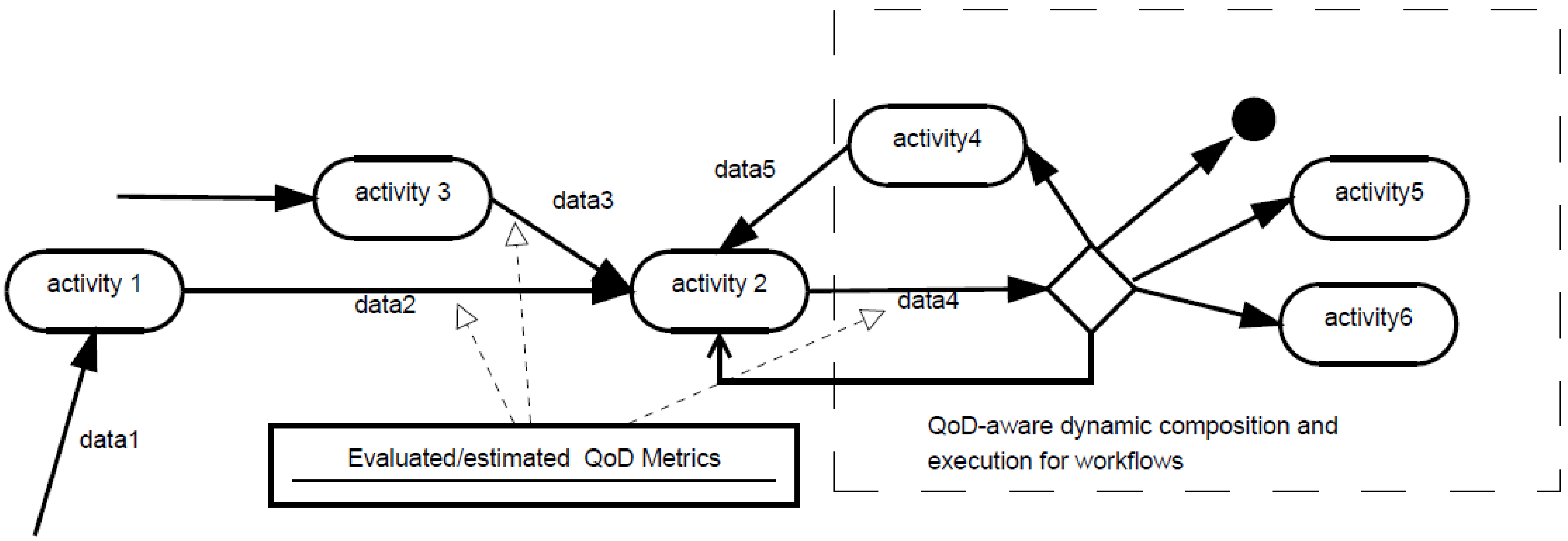
QoD-aware composition and execution

QoD-aware service provisioning and infrastructure optimization

Modeling and evaluating QoD metrics for data analytics workflows



QoD-aware optimization for data analytics workflow composition and execution



How to integrate QoD evaluators? And which concerns need to be considered?

QoD metrics evaluation

- Domain-specific metrics
  - Need specific tools and expertise for determining metrics
- Evaluation
  - Cannot done by software only: humans are required
- Complex integration model
  - Where to put QoD evaluators and why?
  - How evaluators obtain the data to be evaluated?
- Impact of QoD evaluation on performance of data analytics workflows

what kind of optimization can be done?

QoD-aware optimization for data analytics workflows

- Improving quality of analytics
- Reducing analytics costs and time
- Enabling early failure detection
- Enabling elasticitiy of services provisioning
- Enabling elastic data analytics support
- Etc.

EXAMPLE: QOD-AWARE SIMULATION WORKFLOWS

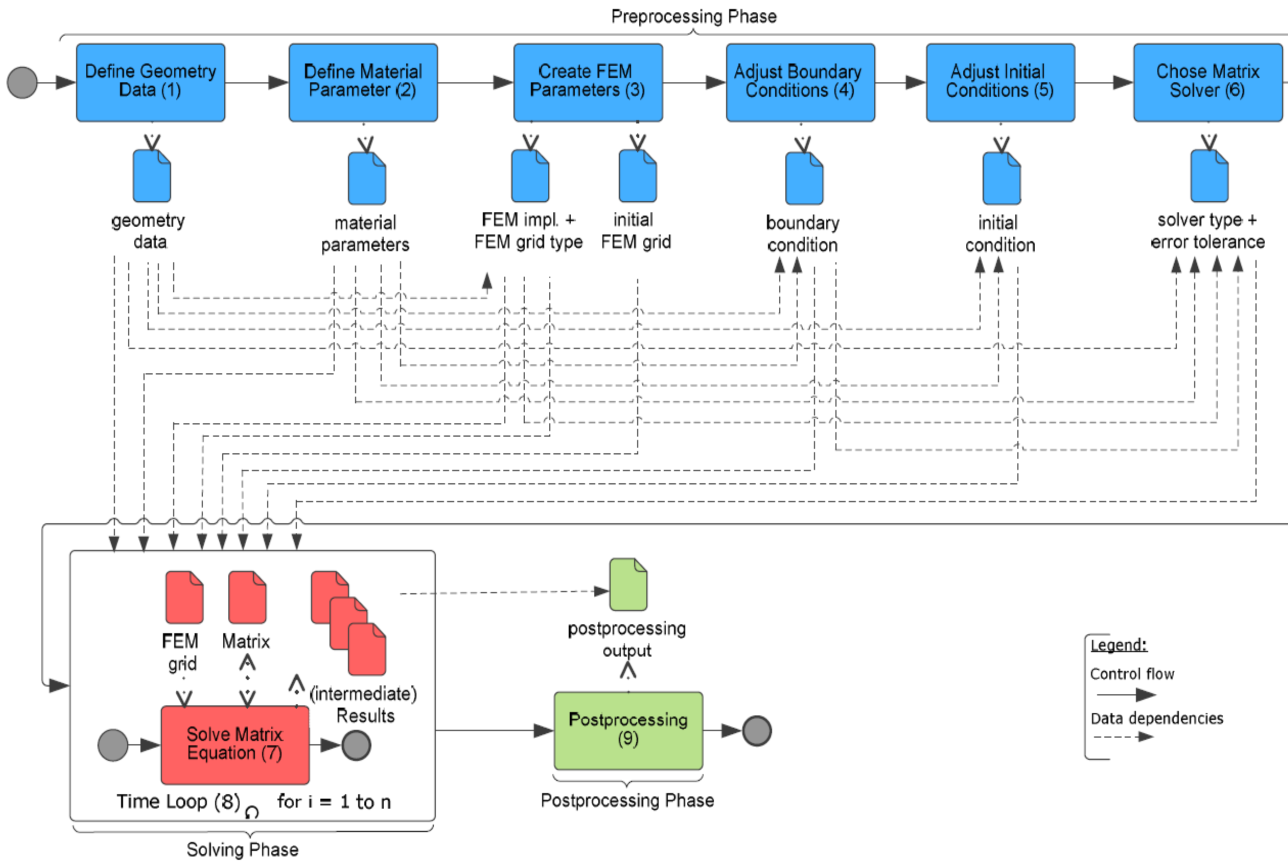
Scientific workflows

- Qurator workbench
  - “Personal quality models” can be expressed and embedded into query processors or workflows.
  - Assume that quality evidence is presented
- Kepler
  - A data quality monitor allows user to specify quality thresholds.
  - Expect that rules can be used to control the execution based on quality.

P Missier, S M Embury, M Greenwood, A D Preece, & B Jin, Managing Information Quality in e-Science: the Qurator Workbench, Proc ACM International Conference on Management of Data (SIGMOD 2007), ACM Press, pages 1150-1152, 2007.

Aisa Na’im, Daniel Crawl,Maria Indrawan, Ilkay Altintas, and Shulei Sun. Monitoring data quality in kepler. In Salim Hariri and Kate Keahey, editors, HPDC, pages 560–564. ACM, 2010.

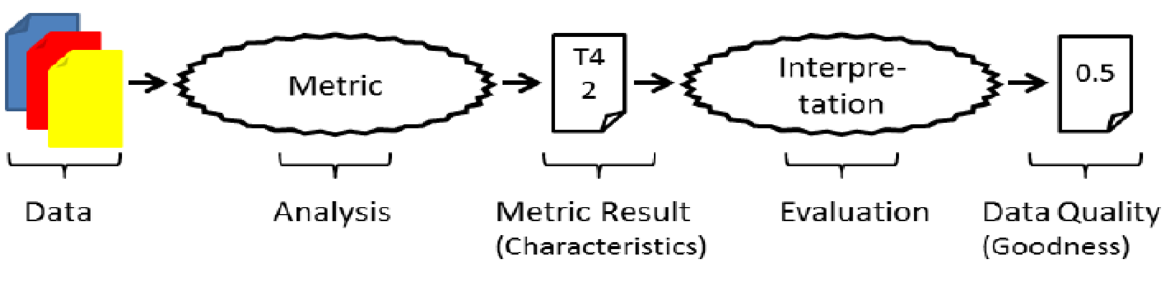
QoD-aware simulation workflows



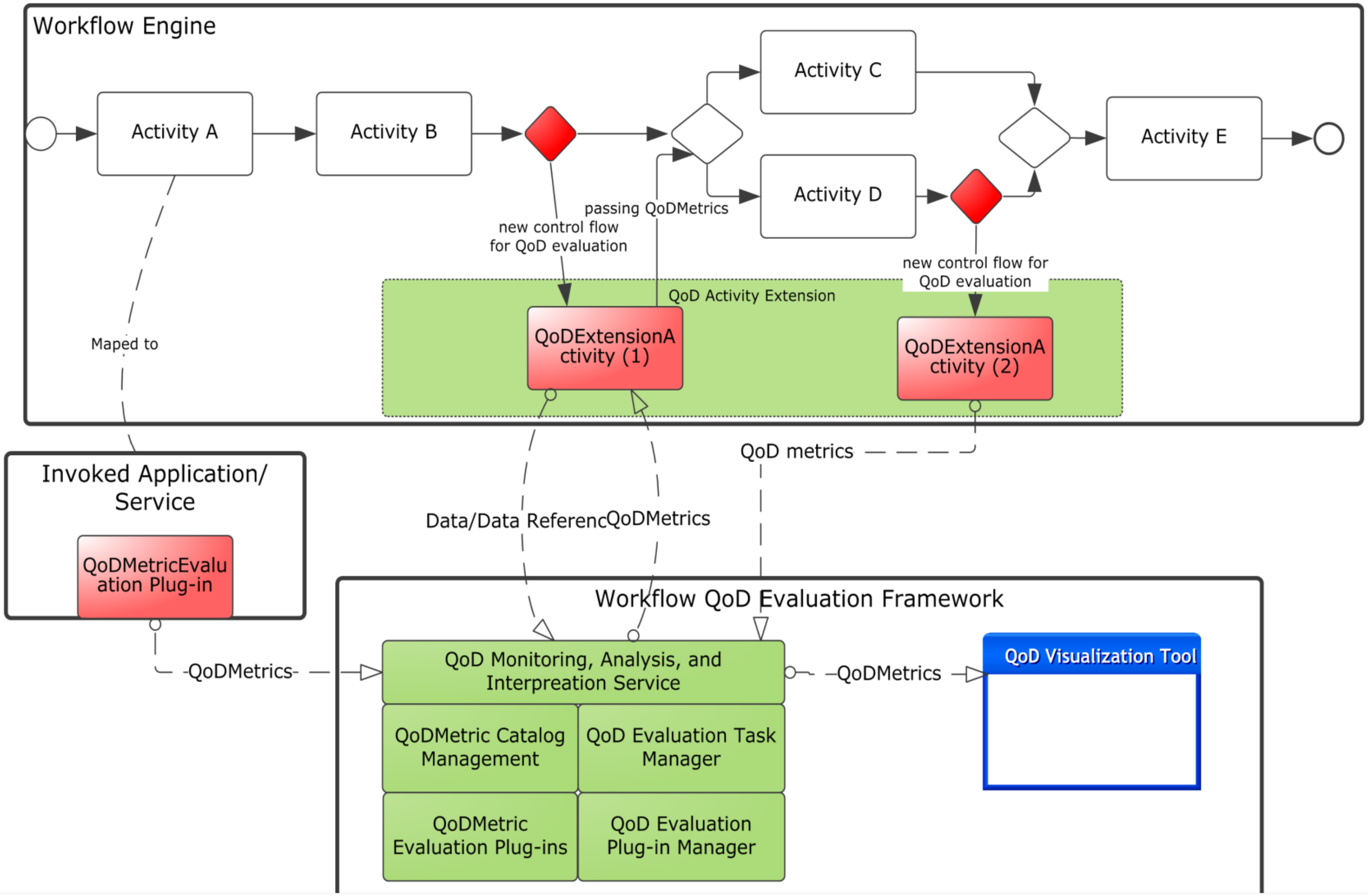
Michael Reiter, Hong Linh Truong, Schahram Dustdar, Dimka Karastoyanova, Robert Krause, Frank Leymann, Dieter Pahr: On Analyzing Quality of Data Influences on Performance of Finite Elements Driven Computational Simulations. Euro-Par 2012: 793-804
Michael Reiter, Uwe Breitenbücher, Schahram Dustdar, Dimka Karastoyanova, Frank Leymann, Hong Linh Truong: A Novel Framework for Monitoring and Analyzing Quality of Data in Simulation Workflows. eScience 2011: 105-112

Hybrid resources needed for quality evaluation

- Challenges:
  - Subjective and objective evaluation
  - Long running processes
- Our approach
  - Different QoD measurements
  - Human and software tasks



Evaluating quality of data in workflows



Michael Reiter, Uwe Breitenbücher, Schahram Dustdar, Dimka Karastoyanova, Frank Leymann, Hong Linh Truong: A Novel Framework for Monitoring and Analyzing Quality of Data in Simulation Workflows. eScience 2011: 105-112

QoD Evaluator

- Software-based QoD evaluators
  - Can be provided under libraries integrated into invoked applications
  - Web services-based evaluators
- Human-based QoD evaluators
  - Built based on the concept human-based services
  - Can be interfaces via Human-Task
  - Simple mapping at the moment
    - Human resources from clouds/crowds

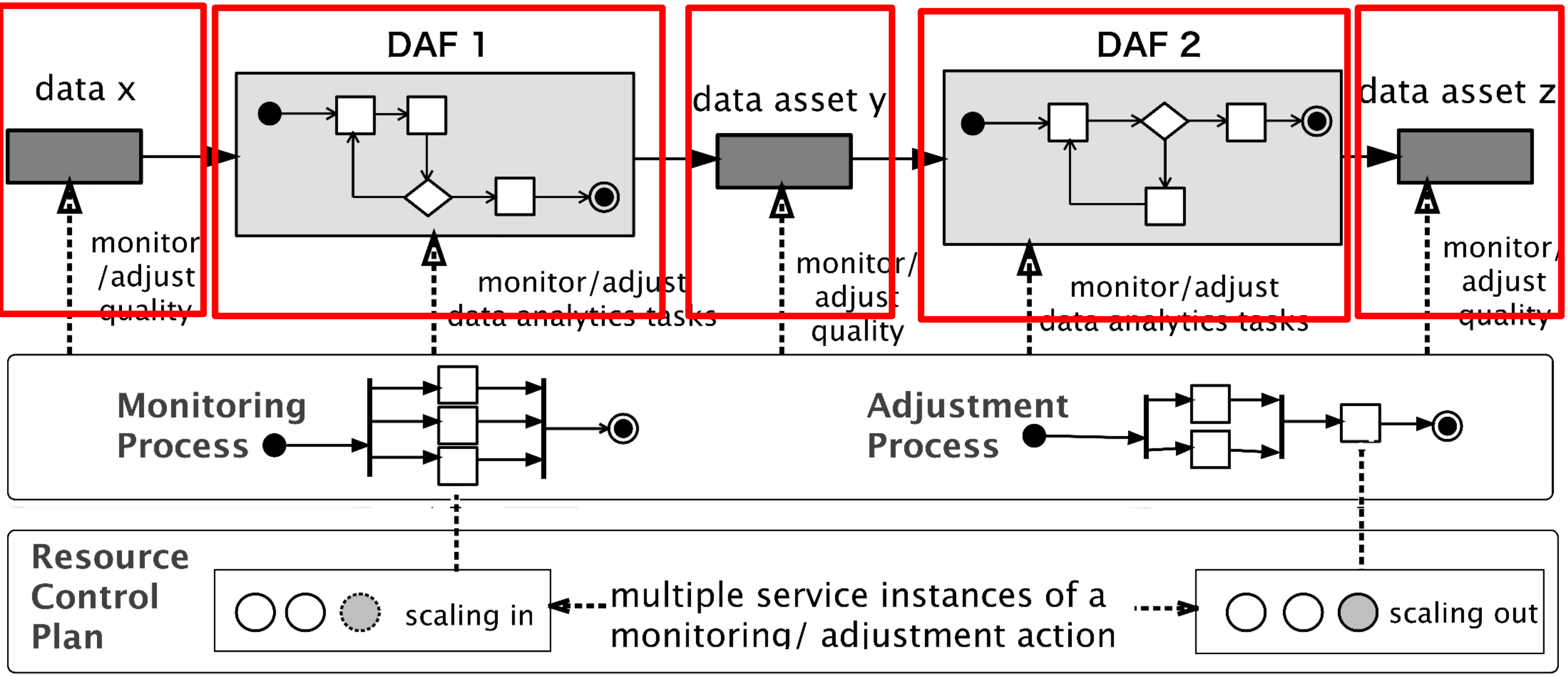
How to support QoA driven analytics with tradeoffs of multiple criteria?

QoA: QoD, performance, cost, etc.

Quality-of-analytics driven workflows

- How to support QoA driven analytics?
- Some basic steps
  - Conceptualize expected QoA
  - Associate the expected QoA with workflow activities
  - Use the expected QoA
    - to match/select underlying services (e.g., data sources, cloud IaaS, etc
  - Utilize the expected QoA and the measured QoA and apply elasticity principles for
    - Refine the workflow structure
    - Provision computation, network and data

Using Data Elasticity Management Process to ensure QoA



Tien-Dung Nguyen, Hong Linh Truong, Georgiana Copil, Duc-Hung Le, Daniel Moldovan, Schahram Dustdar: On Developing and Operating of Data Elasticity Management Process. ICSOC 2015: 105-119

Data elasticity

- Key techniques
  - Monitoring QoD for streaming and big data
    - Lecture 4
  - Monitoring cloud resources
    - Lecture 5
  - Having multiple data analysis algorithms
  - Using elasticity rules for cloud resources and analysis algorithms
    - Building your own elasticity rules/models

Exercises

- Read mentioned papers
- Discuss pros and cons of descriptive languages - and programming languages – based data analytics workflows
- Examine how QoD evaluators can be integrated into different programming models for QoA-aware data analytics workflows
- Implement some QoD evaluators
- Develop techniques for determining places where QoD evaluators can be performed in your mini projects
- Support data elasticity management in your mini project

Thanks for your attention

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