Aalto University
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Workflows for Big Data Platforms

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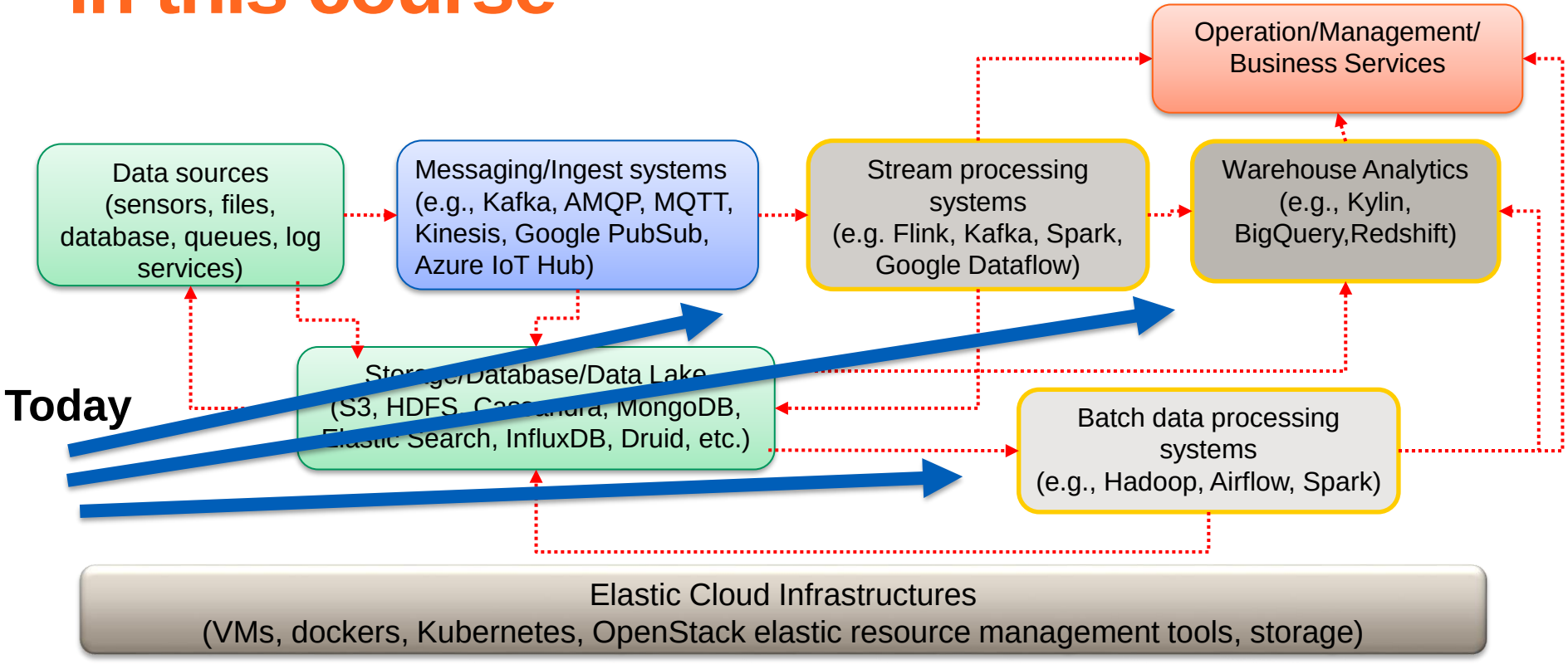
Learning objectives

- **Understand the role and use cases of workflows in big data platforms**
- **Understand key concepts and techniques in workflows and able to design workflows**
- **Able to apply common workflow technologies for practical work**

Big data at large-scale: the big picture in this course



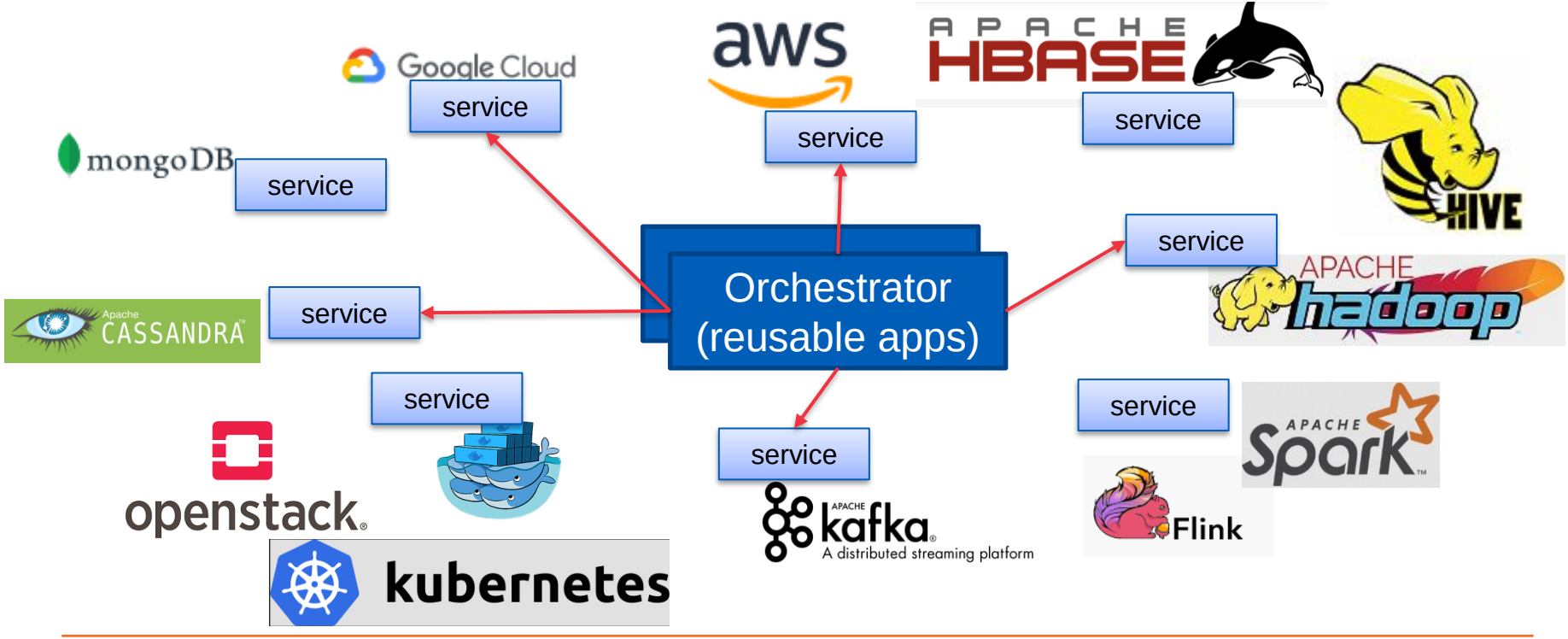
Tasks in big data platforms

- **Data collection and transformation**
  - data transfers, extraction, transformation,
- **Data processing, including machine learning**
  - data analytics, training, serving machine learning algorithms
- **Automation in big platform infrastructures**
  - service deployment, resource elasticity, backup/recovery
- **Business service integration with big data platforms**
  - integration with customer services, bringing insights from data analytics to business decision making

Many complex use cases

- **ETL, data cleansing and backup**
  - access and coordinate many different compute services, data sources, ingestion and extraction applications
- **Complex predictive maintenance**
  - coordination of machine learning pipelines and communication with humans/optimization services
- **Analytics-as a service**
  - metrics understanding, user activities analytics, customer understanding

Service Orchestration



Example of security data analytics

Security-related information and metrics from distributed customers

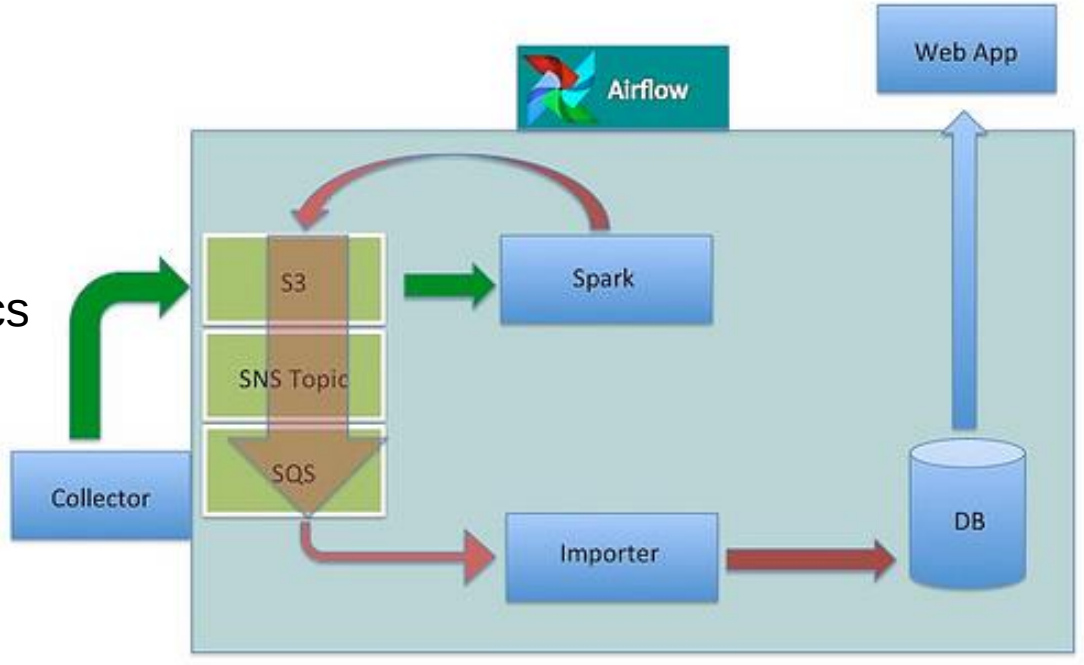


Figure Source: http://highscalability.com/blog/2015/9/3/how-agari-uses-airbnbs-airflow-as-a-smarter-cron.html

Example of industrial retail forecast

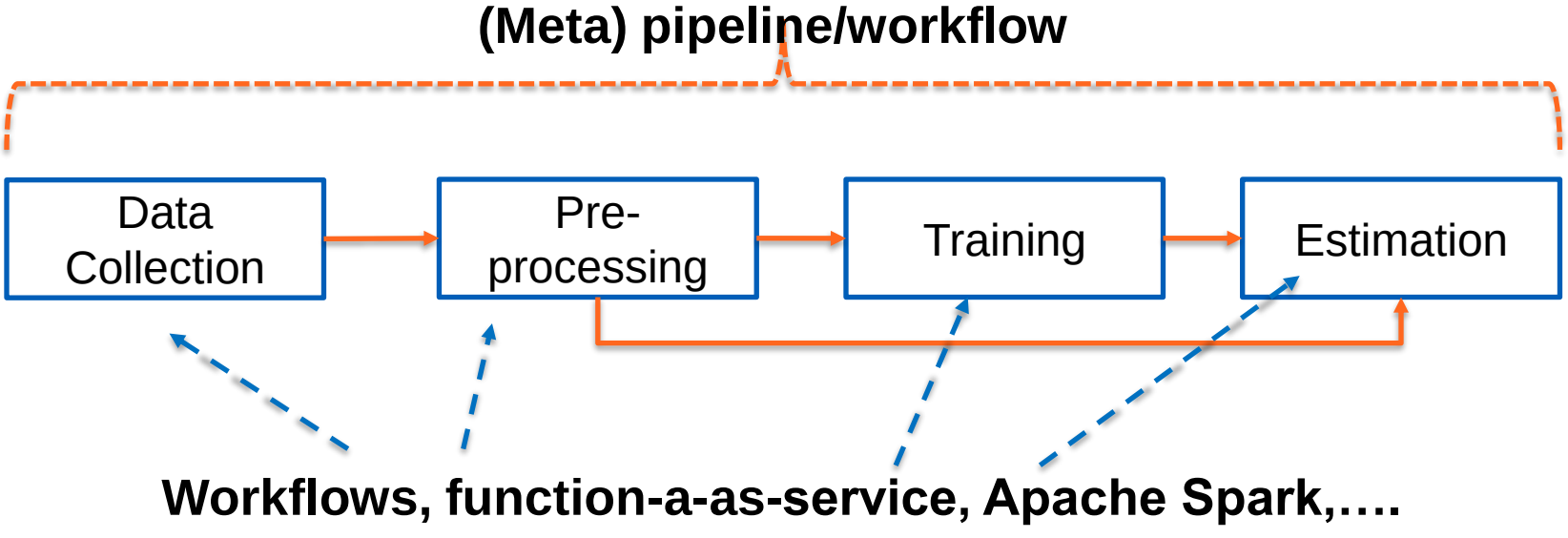
date	id	name	volume	price	cost	promo	category_net	margin	category1	category2	location	sales
07/01/2018	100	Chicken	38144.0	3.79	2.7	0	451692.0	0.25	Meat	Food	Helsinki	144565.76
14/01/2018	100	Chicken	36420.0	3.79	2.66	0	414342.0	0.25	Meat	Food	Helsinki	138031.8
21/01/2018	100	Chicken	35322.0	3.79	2.66	0	381854.0	0.25	Meat	Food	Helsinki	133870.38

Sellforte: forecast where to put marketing information

Source: Kreics Krists, „Quality of analytics management of data pipelines for retail forecasting,“, Aalto CS Master thesis, 2019

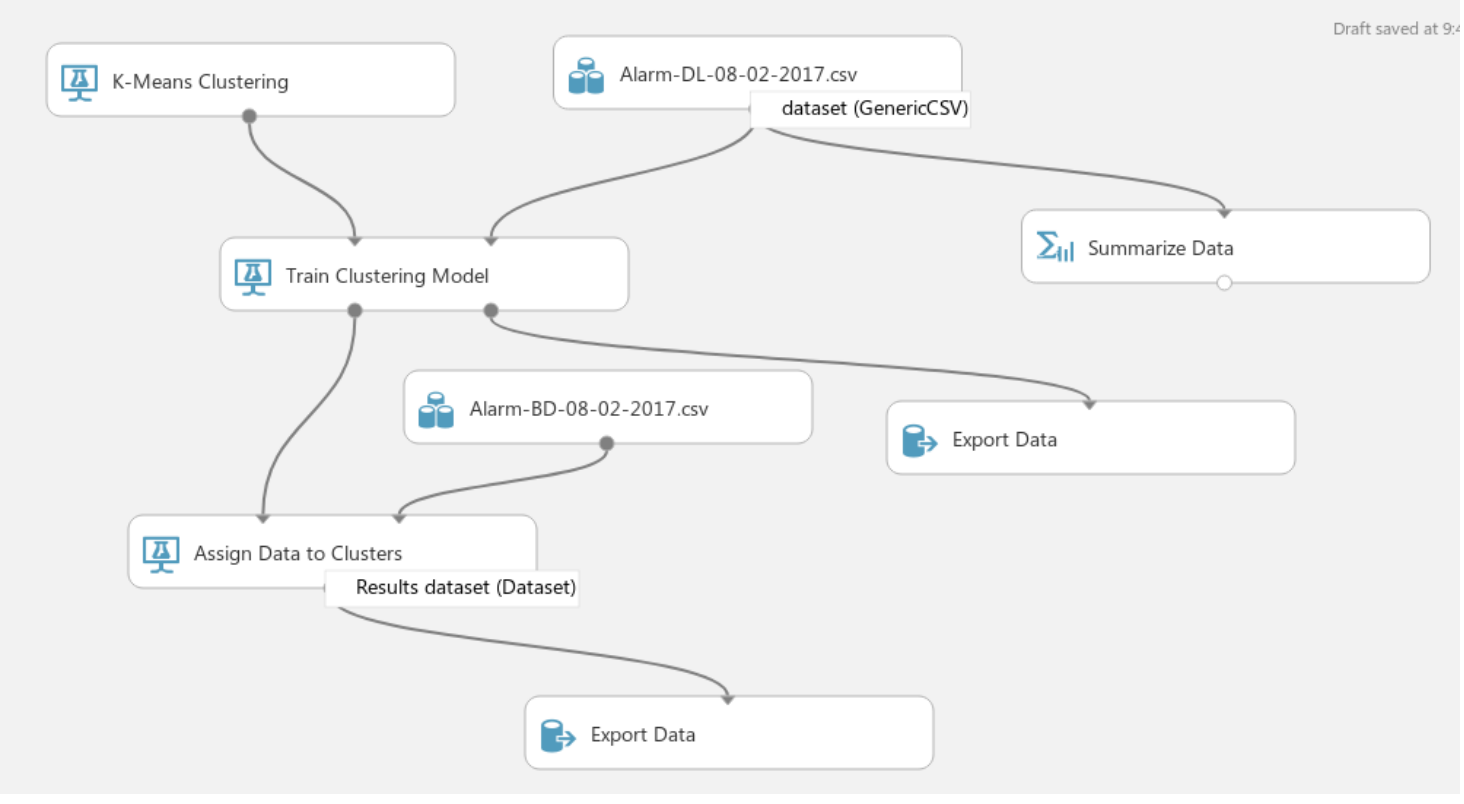
Example of ML workflows

- **meta-workflow vs inside each phase: pipeline/workflow or other types of programs**



Example of ML workflows

Azure ML



Workflows

A workflow specifies a process

- consists of a set of connected steps/tasks
- has steps/tasks carried out by diverse types of software services or humans, each performs a function
- can be automated with/without human intervention
- have data/control task dependencies
- can be reusable

Workflow technologies

- **Given many services offering different capabilities, we can combine them for different cases**
  - orchestration of capabilities from different services as the key!
  - reuse/customization of capabilities with a given set of services

- **Workflows are flexibly defined and changed**
  - services cannot be changed easily
  - but there are many ways to combine such services!
  - the integration is loosely coupled.

We have many workflows that are built in a flexible way for different goals

How to build the workflows and orchestrate tasks in these workflows?

Tasks and workflows

- **Diverse types of tasks**
  - task can be simple or complex (e.g., a task running an AI algorithm)
  - tasks are performed by software and humans
- **Workflow**
  - coordinate/orchestrate many tasks, *the function of tasks is not really "carried out" by workflows* → *orchestration/coordination*
  - workflow can be simple, like a pipeline of a sequence of tasks or complex with many forks/loops

Workflow and pipeline/data workflow

- **Data workflow → data pipeline**

  ” a pipeline is a set of data processing elements connected in series, where the output of one element is the input of the next one”

  Source: https://en.wikipedia.org/wiki/Pipeline_%28computing%29

- **Two interpretations:**
  - a pipeline is a simple workflow
  - a pipeline coordinates different (sub)workflows

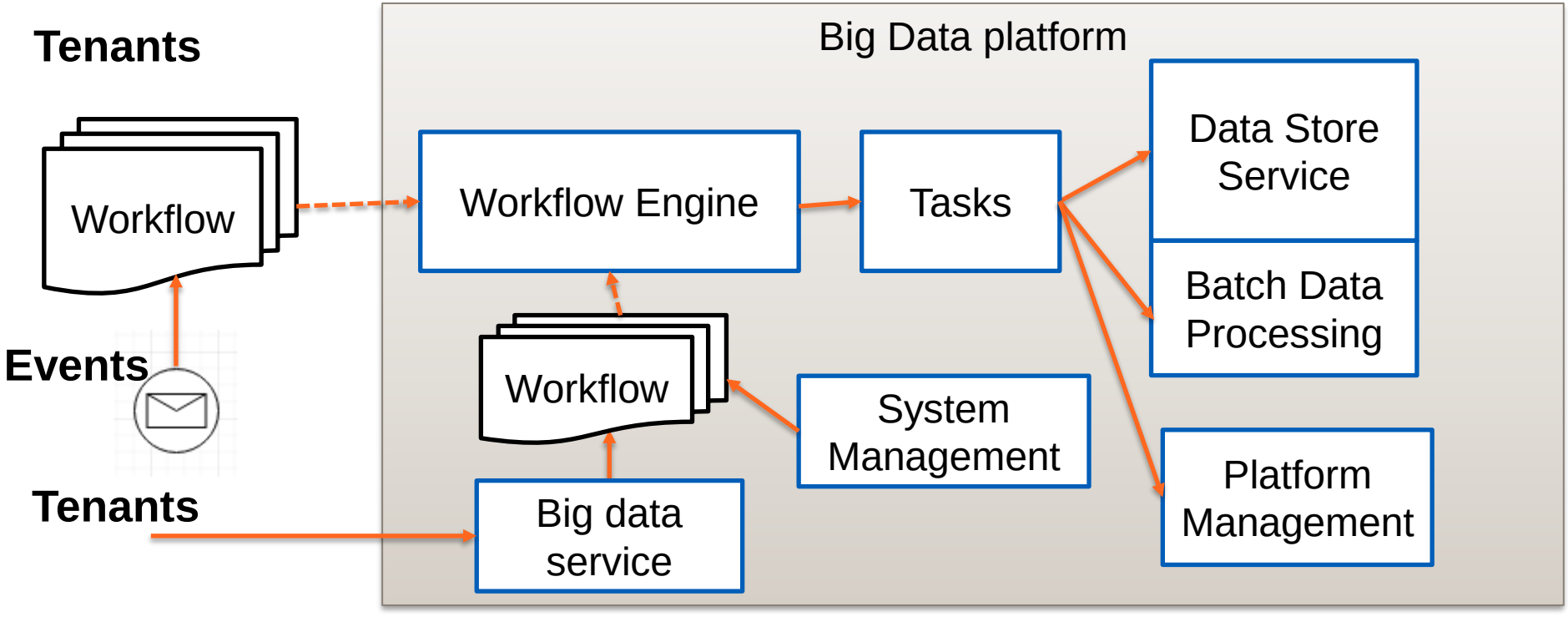
A long history – workflows are well-known!

- **Business workflows/processes**
  - business processes in enterprise computing (e.g., BI, ERP, and e-commerce)
- **Scientific workflows**
  - in scientific computing and high performance computing (e.g., bioinformatics, astrophysics, material science simulations)
- **Automation in system management**
  - at system level for automating infrastructure provisioning, system recovery, etc.

Key components

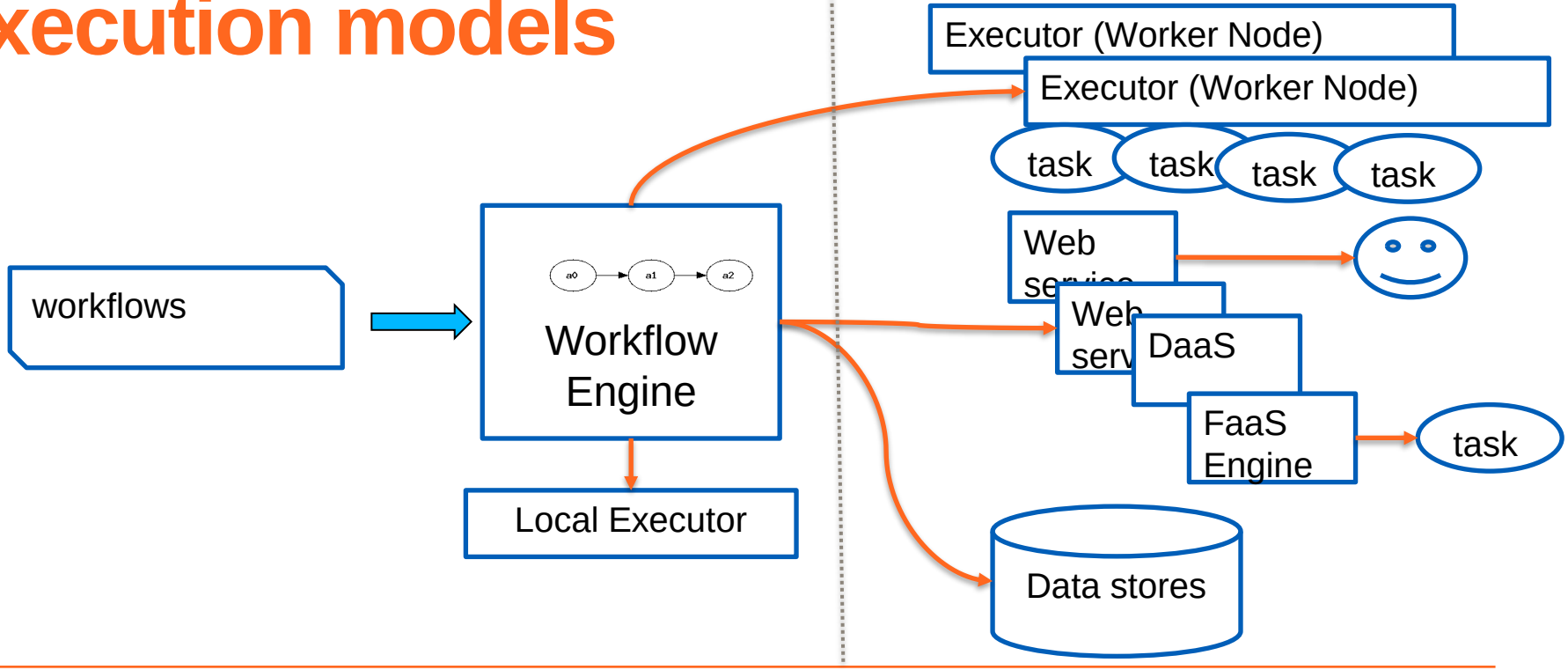
- **Tasks/activities/steps**
  - describe a single work (it does not mean small)
  - tasks can be carried out by humans, executables, scripts, batch applications, stream applications and other types of services.
- **Workflow languages**
  - structure/describe tasks, dataflows, and control flows
- **Workflow engines**
  - execute the workflow by orchestrating tasks
  - usually *call remote services* to run tasks

Workflows in big data platforms: more than analytics

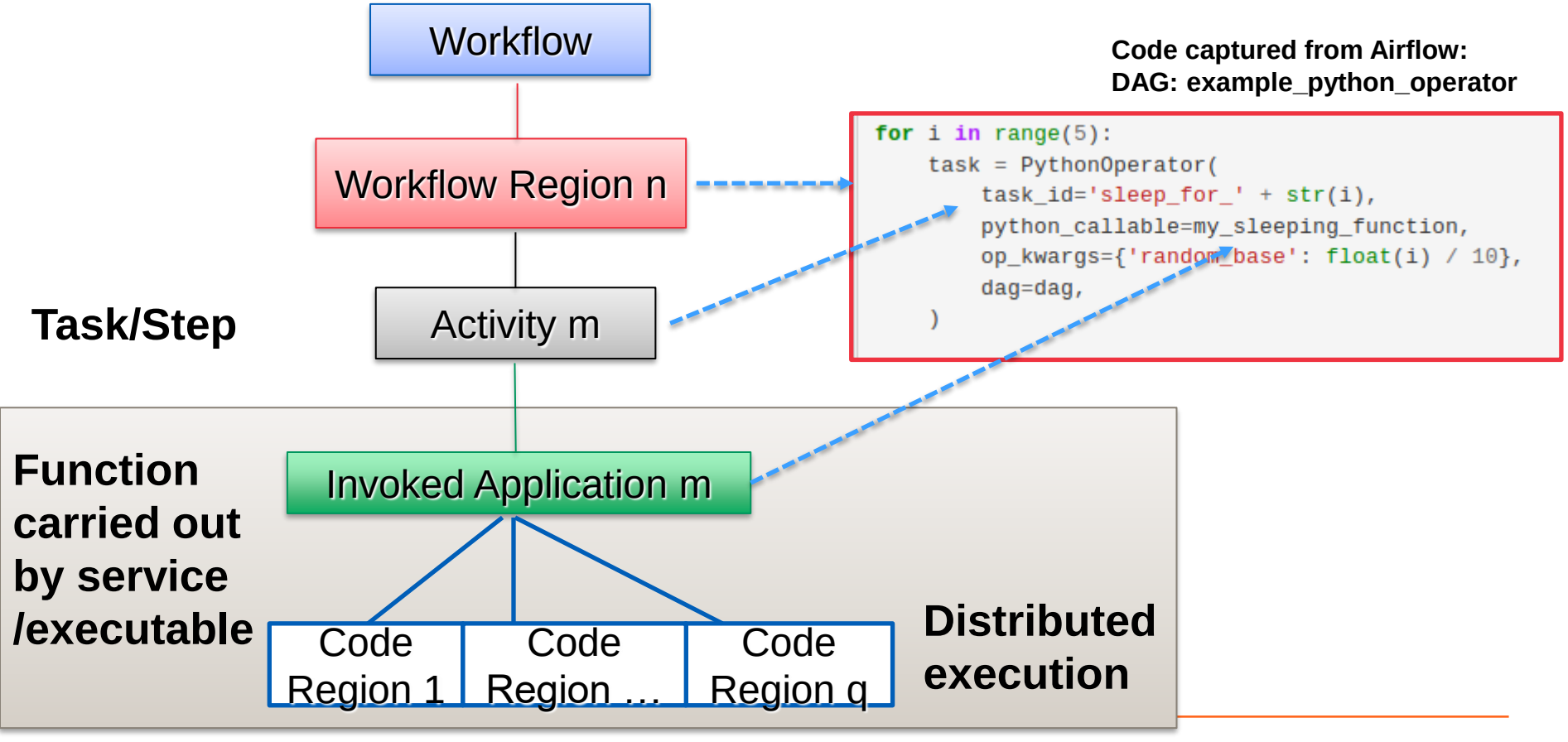


Common workflow execution models

Major works are carried out in distributed nodes (Kubernetes, Celery, Dask,…)



Structured view of workflows

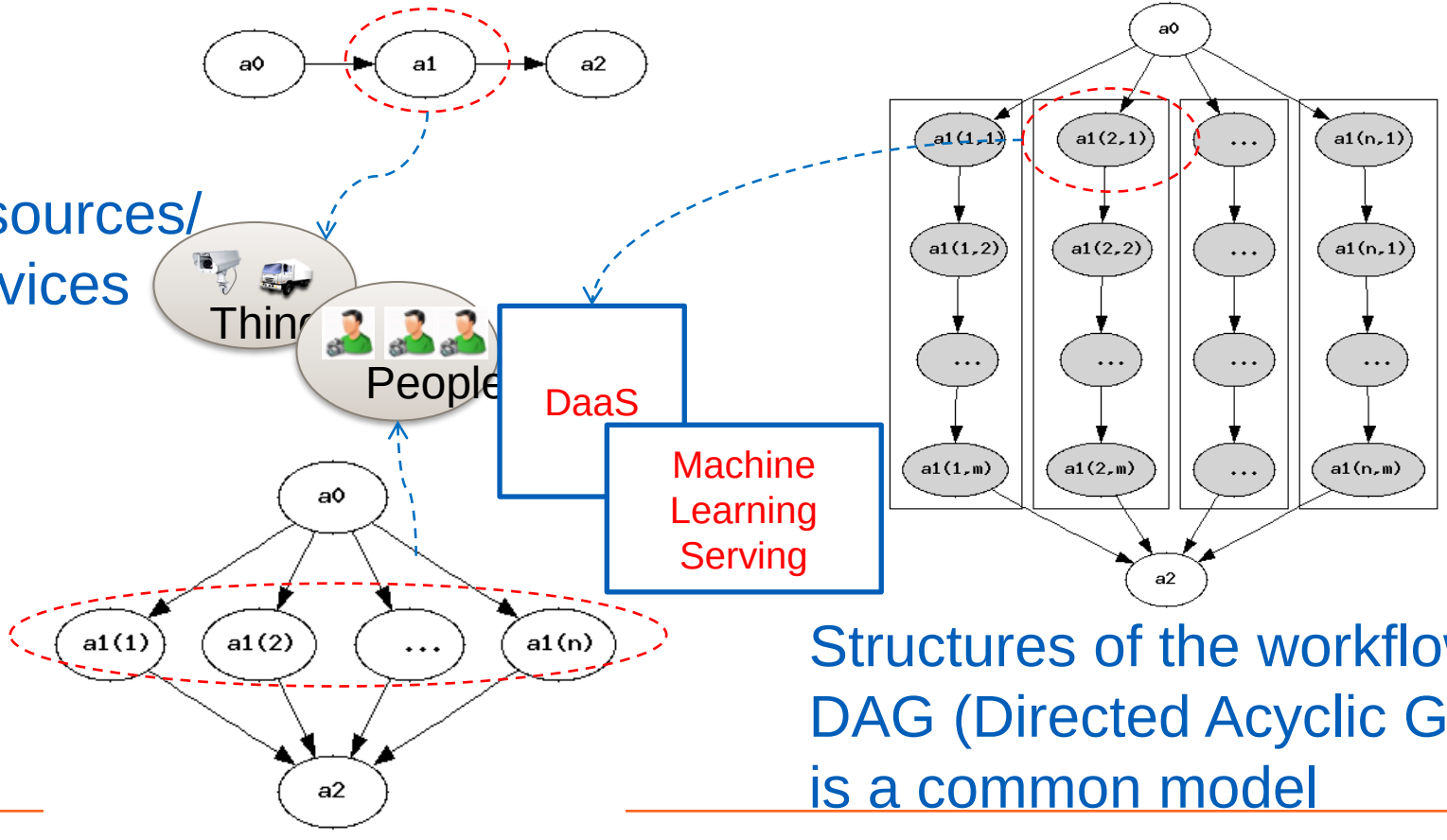


Describing workflows

- **Programming languages with procedural code**
  - general- and specific-purpose programming languages, such as Java, Python, Swift
  - common ways in big data platforms for data analytics and system automation

- **Descriptive languages with declarative schemas**
  - BPEL, YAML, JSON and several languages designed for specific workflow engines
  - common in business and scientific workflows

Tasks orchestration



Structures of the workflow: DAG (Directed Acyclic Graph) is a common model

Runtime aspects

- **Parallel and distributed execution**
  - tasks are executed in different machines (by external invoked applications/services), multiple running workflows
- **Long and/or periodic running**
  - can be hours or weeks! → pausing and resuming workflows are normal
- **Checkpoint and recovery**
  - dealing with failures at different levels: workflows and tasks retry/recovery
- **Monitoring and tracking**
  - States and performance metrics: queuing, running, idle, suspended, failed
- **Stateful management**
  - dependencies among tasks w.r.t control and data, stateful tasks → global services for managing states and data among tasks

Select/build workflows in your platforms

- **Rich data services**
  - for data storing/retrieving tasks
- **Big data computation engines**
  - for data processing tasks with different workload: ML and (batch/stream) big data processing
- **Different underlying cloud/distributed computing infrastructures**
  - for resource management tasks and workflow infrastructures
- **REST APIs and message systems integration**
  - for widely integration with other services (e.g., business services)

Select/build workflows in your platforms

- **Scheduling**
  - Scheduling in a large resource pool (e.g., using clusters)
- **Elasticity**
  - Elasticity controls of virtualized resources (VMs/containers/Kubernetes) for executing tasks
- **Multiple levels of parallelism**
  - Cluster level vs node level

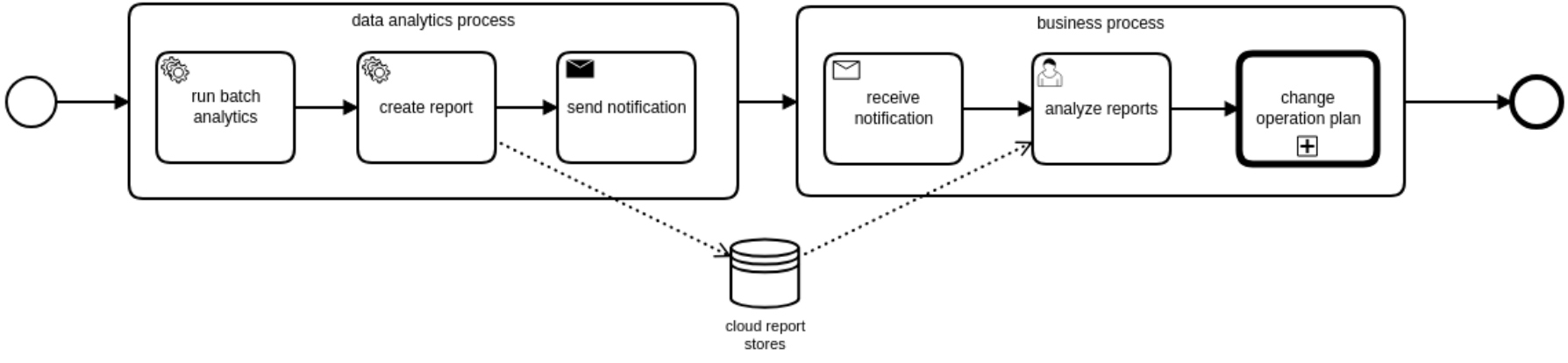
- **Examples**
  - Periodic cron schedules, backfill, opportunistic schedules
  - Increase number of distributed workers/cluster sizes
  - Heterogenous resources for tasks: lightweight compute nodes & high-end nodes

Wu, F., Wu, Q. & Tan, Y. Workflow scheduling in cloud: a survey. J Supercomput 71, 3373–3418 (2015). https://doi.org/10.1007/s11227-015-1438-4

Mainak Adhikari, Tarachand Amgoth, and Satish Narayana Srirama. 2019. A Survey on Scheduling Strategies for Workflows in Cloud Environment and Emerging Trends. ACM Comput. Surv. 52, 4, Article 68 (August 2019), 36 pages. https://doi.org/10.1145/3325097

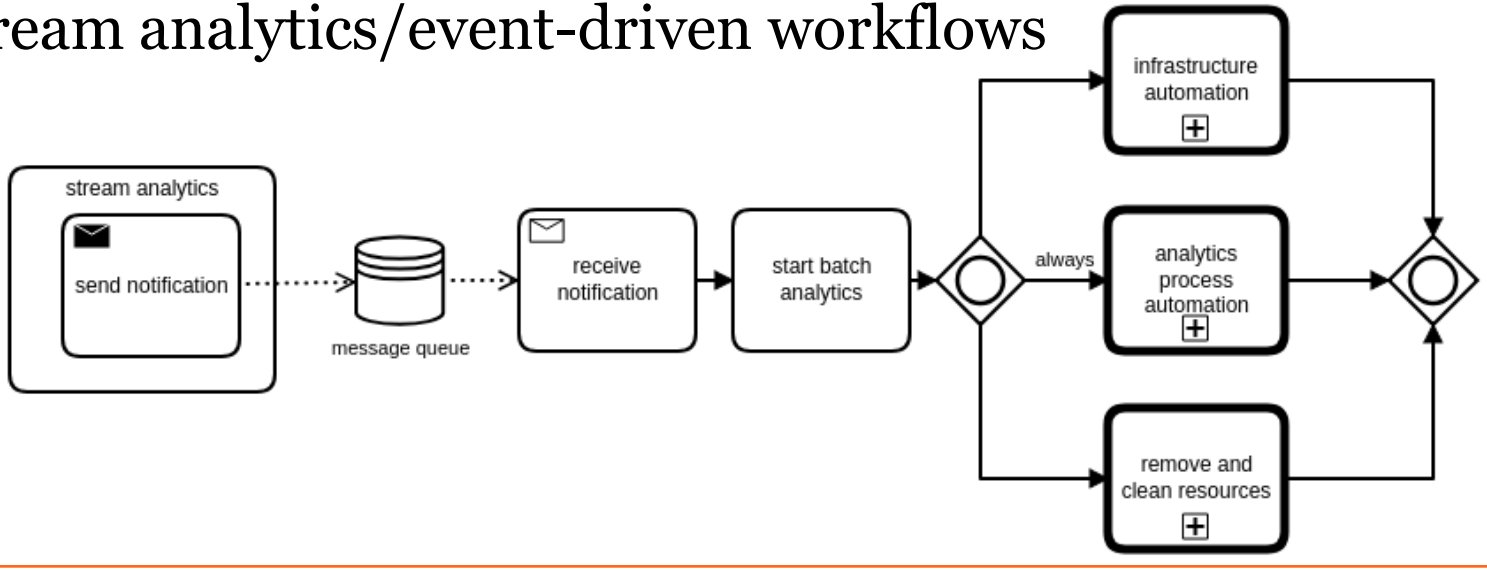
Select/build workflows in your platforms

- **Integration**
  - Data analytics processes and business processes
  - Include human-in-the-loop



Select/build workflows in your platforms

- **Integration**
  - Multiple types of workflows for services/infrastructure provisioning and analytics
  - Stream analytics/event-driven workflows



Existing frameworks for your study

- **Apache Oozie**
  - designed to work with Hadoop: orchestrating Hadoop jobs
- **Serverless-based: Function-as-a-Service**
  - e.g., Microsoft, Google, AWS serverless/function-as-a-service
- **Apache Airflow**
  - a generic workflow framework
- **Argo Workflows**
  - Container-native workflow engine
- **Uber Cadence (https://cadenceworkflow.io)/Camunda (https://camunda.com/)**
  - Connecting to business activities+ human in the loop

Example with Apache Airflow

https://airflow.apache.org

Airflow overview

- **Originally from Airbnb**
- **Features**
  - Dynamic, extensible, scalable workflows
  - Programmable language-based workflows
    - *Write workflows as procedural code*
- **Good and easy to study to understand concepts of workflows/data pipeline**
- **Google Cloud Composer is a cloud-provided version of Airflow**
  - https://cloud.google.com/composer/

Many connectors

async	`pip install 'apache-airflow[async]'`	Async worker classes
celery	`pip install 'apache-airflow[celery]'`	CeleryExecutor
cloudant	`pip install 'apache-airflow[cloudant]'`	Cloudant hook
crypto	`pip install 'apache-airflow[crypto]'`	Encrypt connection p
devel	`pip install 'apache-airflow[devel]'`	Minimum dev tools re
devel_hadoop	`pip install 'apache-airflow[devel_hadoop]'`	Airflow + dependenci
druid	`pip install 'apache-airflow[druid]'`	Druid related operatc
gcp	`pip install 'apache-airflow[gcp]'`	Google Cloud Platfor
github_enterprise	`pip install 'apache-airflow[github_enterprise]'`	GitHub Enterprise au
google_auth	`pip install 'apache-airflow[google_auth]'`	Google auth backend
hdfs	`pip install 'apache-airflow[hdfs]'`	HDFS hooks and ope
hive	`pip install 'apache-airflow[hive]'`	All Hive related opera
jdbc	`pip install 'apache-airflow[jdbc]'`	JDBC hooks and oper
kerberos	`pip install 'apache-airflow[kerberos]'`	Kerberos integration
kubernetes	`pip install 'apache-airflow[kubernetes]'`	Kubernetes Executor
ldap	`pip install 'apache-airflow[ldap]'`	LDAP authentication
mssql	`pip install 'apache-airflow[mssql]'`	Microsoft SQL Server
mysql	`pip install 'apache-airflow[mysql]'`	MySQL operators and
oracle	`pip install 'apache-airflow[oracle]'`	Oracle hooks and ope
password	`pip install 'apache-airflow[password]'`	Password authentica
postgres	`pip install 'apache-airflow[postgres]'`	PostgreSQL operator
qds	`pip install 'apache-airflow[qds]'`	Enable QDS (Qubole
rabbitmq	`pip install 'apache-airflow[rabbitmq]'`	RabbitMQ support as
redis	`pip install 'apache-airflow[redis]'`	Redis hooks and sens
s3	`pip install 'apache-airflow[s3]'`	`S3KeySensor`, `S3Prefi`
samba	`pip install apache-airflow[samba]'`	`airflow.operators.hiv`
slack	`pip install 'apache-airflow[slack']`	`airflow.operators.sla`
ssh	`pip install 'apache-airflow[ssh]'`	SSH hooks and Opera
vertica	`pip install 'apache-airflow[vertica]'`	Vertica hook support

From https://airflow.apache.org/installation.html#extra-packages

Cloud integration and big data support

- **Several supports with known cloud providers**
  - Microsoft Azure
  - Amazon Web Services
  - Databricks
  - Google Cloud Platform
- **Big data supports**
  - Hadoop, Hive, Druid, Presto
- **Distributed execution**

Airflow workflow structure

- **Workflow is a DAG (Direct Acyclic Graph)**
  - a workflow consists of a set of activities represented in a DAG
  - workflow and activities are programed using Python – structures described in code
- **Workflow activities are described by Airflow operator objects**
  - tasks are created when instantiating operator objects

Airflow operators/tasks

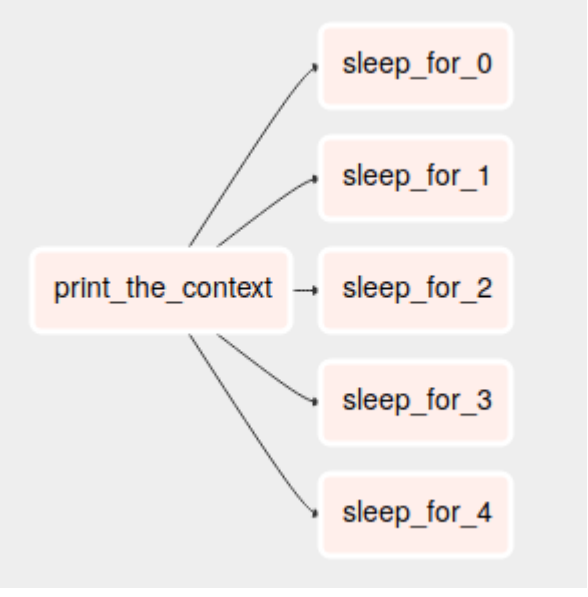
- **Tasks are implemented using operators**
- **Rich set of operators**
  - we can program different kinds of tasks and integrate with different systems

- **Different types of operators for workflow activities**
  - BashOperator, PythonOperator, EmailOperator, HTTPOperator, SqlOperator, Sensor, DockerOperator, HiveOperator, S3FileTransferOperator, PrestoToMysqlOperator, SlackOperator
- **Remember:**
  - such operators will be executed by corresponding services

Example of operators

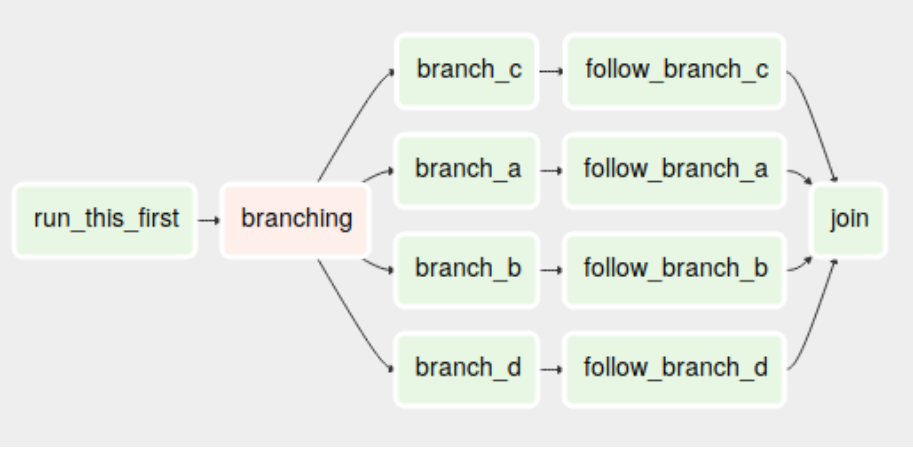
- **High-level structure is mapped to python and suitable operators**

```
for i in range(5):
    task = PythonOperator(
        task_id='sleep_for_' + str(i),
        python_callable=my_sleeping_function,
        op_kwargs={'random_base': float(i) / 10},
        dag=dag,
    )
```



Code and figures captured from Airflow UI:
DAG: example_python_operator
schedule: None

Example of branching




```
run_this_first = DummyOperator(
    task_id='run_this_first',
    dag=dag,
)

options = ['branch_a', 'branch_b', 'branch_c', 'branch_d']

branching = BranchPythonOperator(
    task_id='branching',
    python_callable=lambda: random.choice(options),
    dag=dag,
)
run_this_first >> branching

join = DummyOperator(
    task_id='join',
    trigger_rule='one_success',
    dag=dag,
)
```

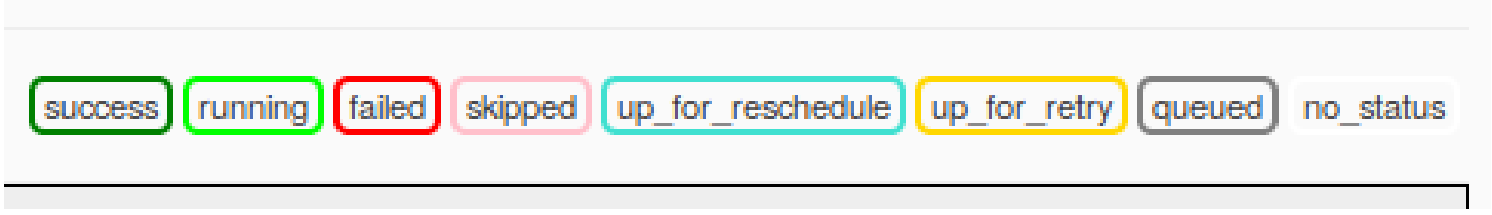
Code and figures captured from Airflow UI
DAG: example_branch_operator
schedule: @daily

Scheduling and execution

- **You can schedule the workflow like a cron job**
  - execute once, every minutes, hours, ...
- **Trigger from external**
  - tasks can be triggered as normal (upstream tasks finishes, dependencies)
  - or specific triggers
- **Very suitable ingestion and batch analytics job managements**
  - the ingestion and analytics are done within tasks

Task lifecycle

Different states

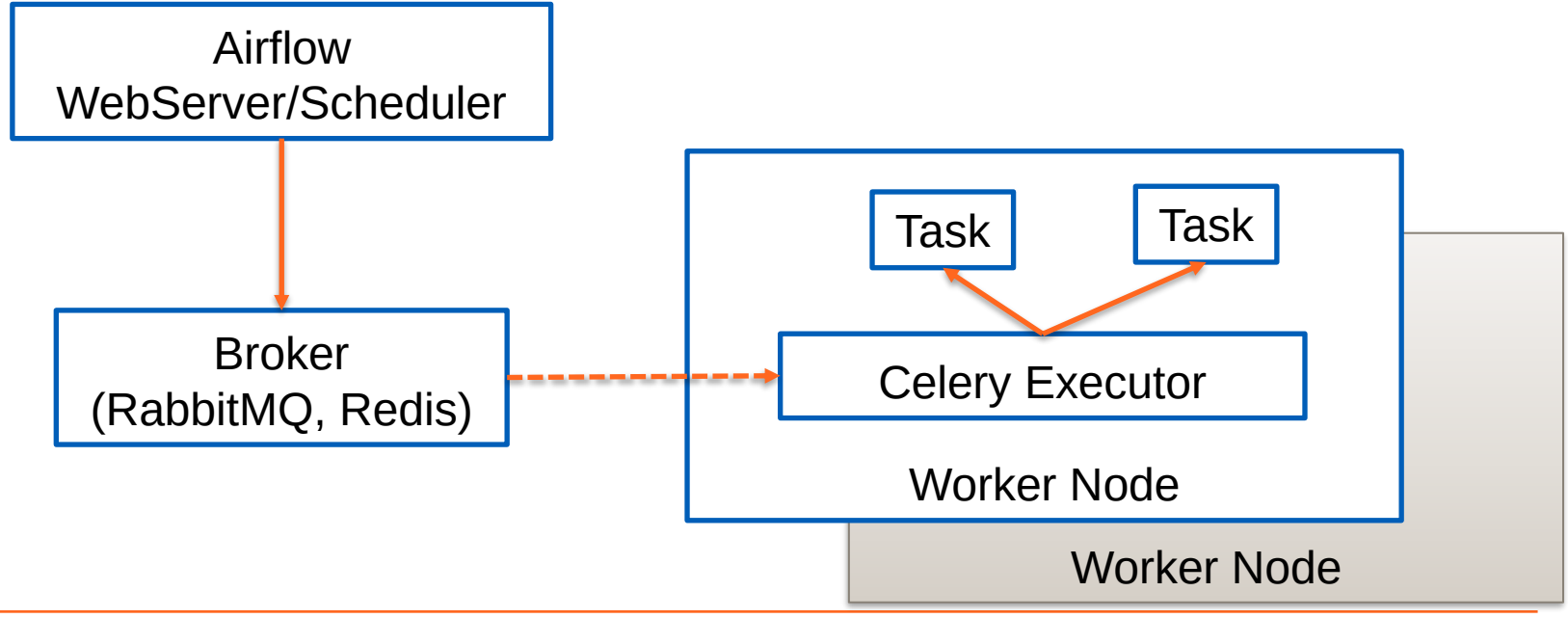


- **Performance metrics can be determined based on states and structures**

- **Interesting in performance analytics?**
  - **Check https://doi.org/10.1016/j.future.2007.01.003**

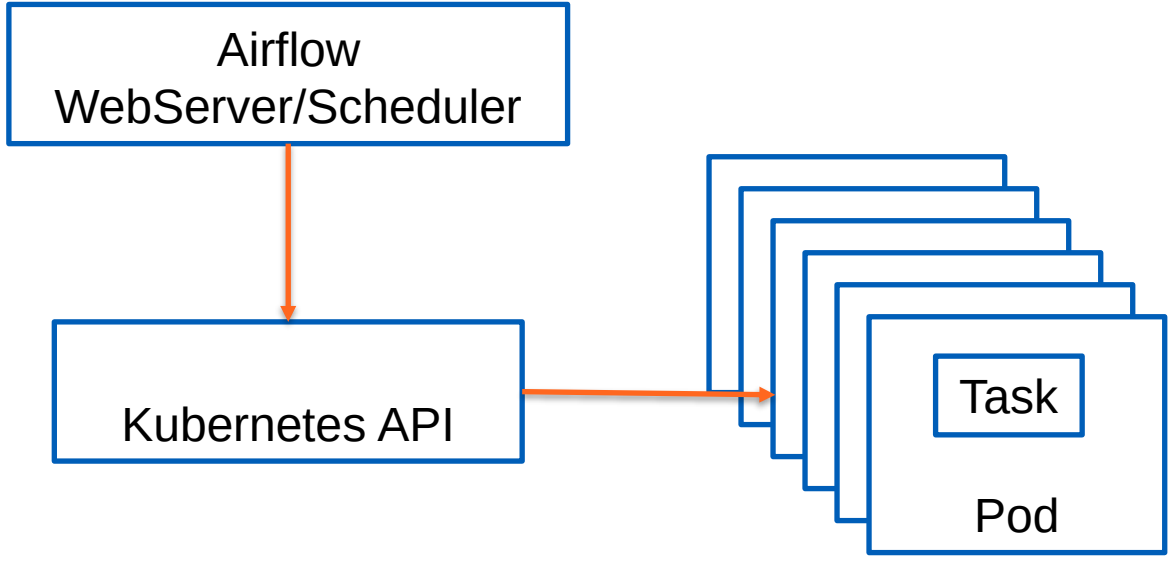
Distributed tasks

You can scale Airflow using workers deployed in different nodes managed by Celery (http://www.celeryproject.org)



Distributed tasks

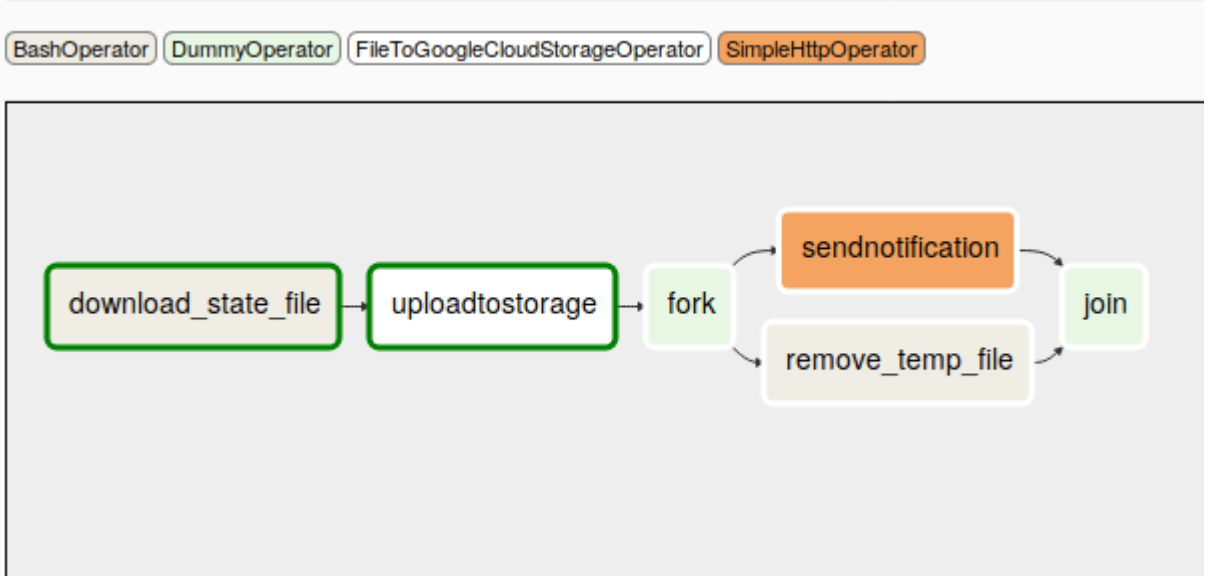
You can scale Airflow to run tasks in Kubernetes



Google Cloud Composer: use Kubernetes

Example

Scenarios: scan various local servers, obtain log files, store log files into Google, and send notifications



Example for uploading state logs

```
fork = DummyOperator(
    task_id='fork',
    trigger_rule='one_success',
    dag=dag
    )
join = DummyOperator(
    task_id='join',
    trigger_rule='one_success',
    dag=dag
    )

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

t_removefile =  BashOperator(
    task_id='remove_temp_file',
    bash_command=removetempfile,
    dag=dag,
    )
```

```
## change it suitable to your setting
t_analytics=  FileToGoogleCloudStorageOperator(
    task_id="uploadtostorage",
    src=destination_file,
    dst=gcsdir,
    bucket='mybdpairflow',
    google_cloud_storage_conn_id='gcsmybdp',
    dag = dag
    )
## change it suitable for your setting
t_sendresult =SimpleHttpOperator(
    task_id='sendnotification',
    method='POST',
    http_conn_id='notificationserver',
    endpoint='api/logUpdate',
    data=json.dumps({"source_file": source_file}),
    headers={"Content-Type": "application/json"},
    dag = dag
    )
```

In our GIT course (tutorials)

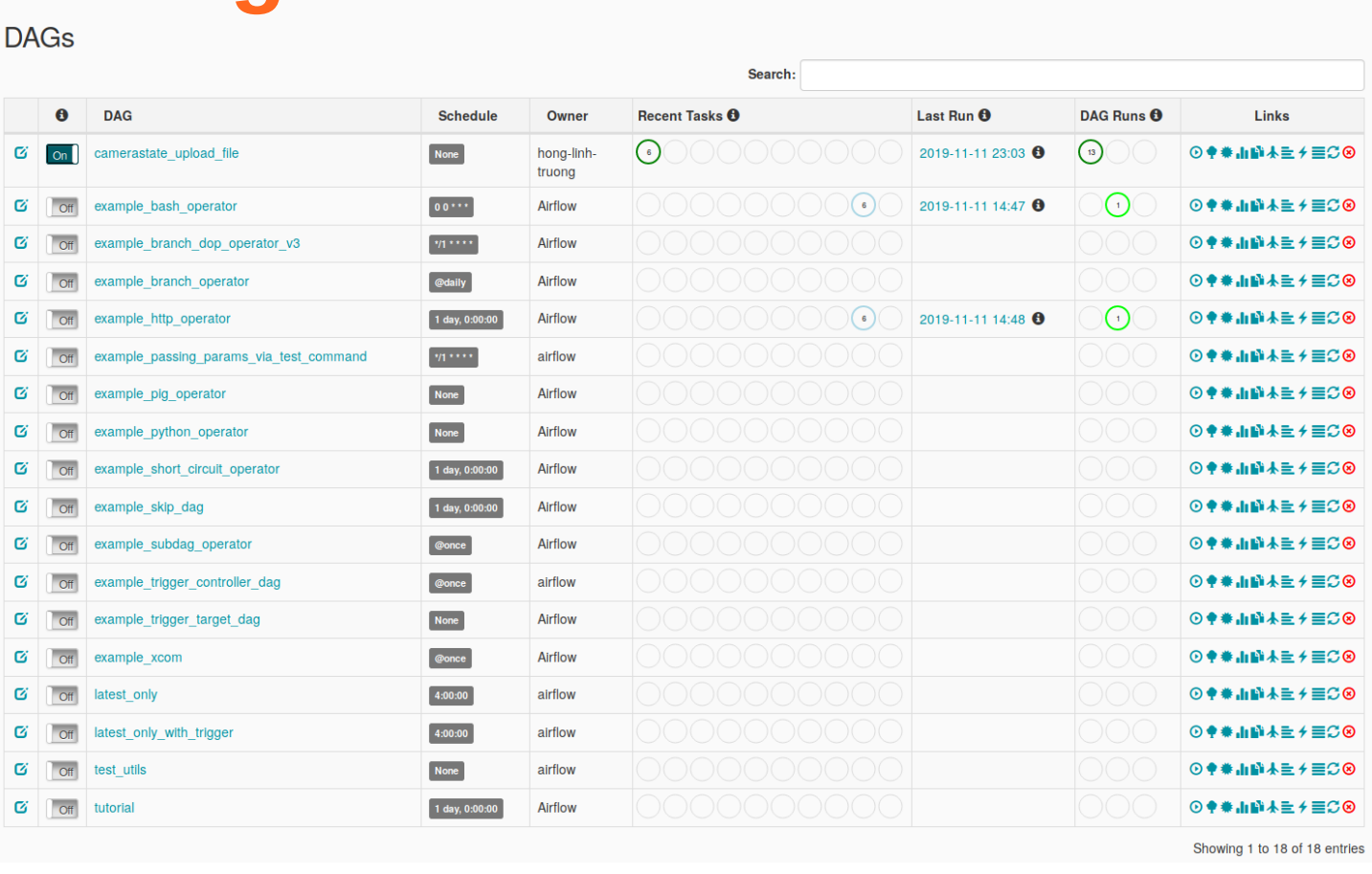
Example for uploading state logs

upstream task

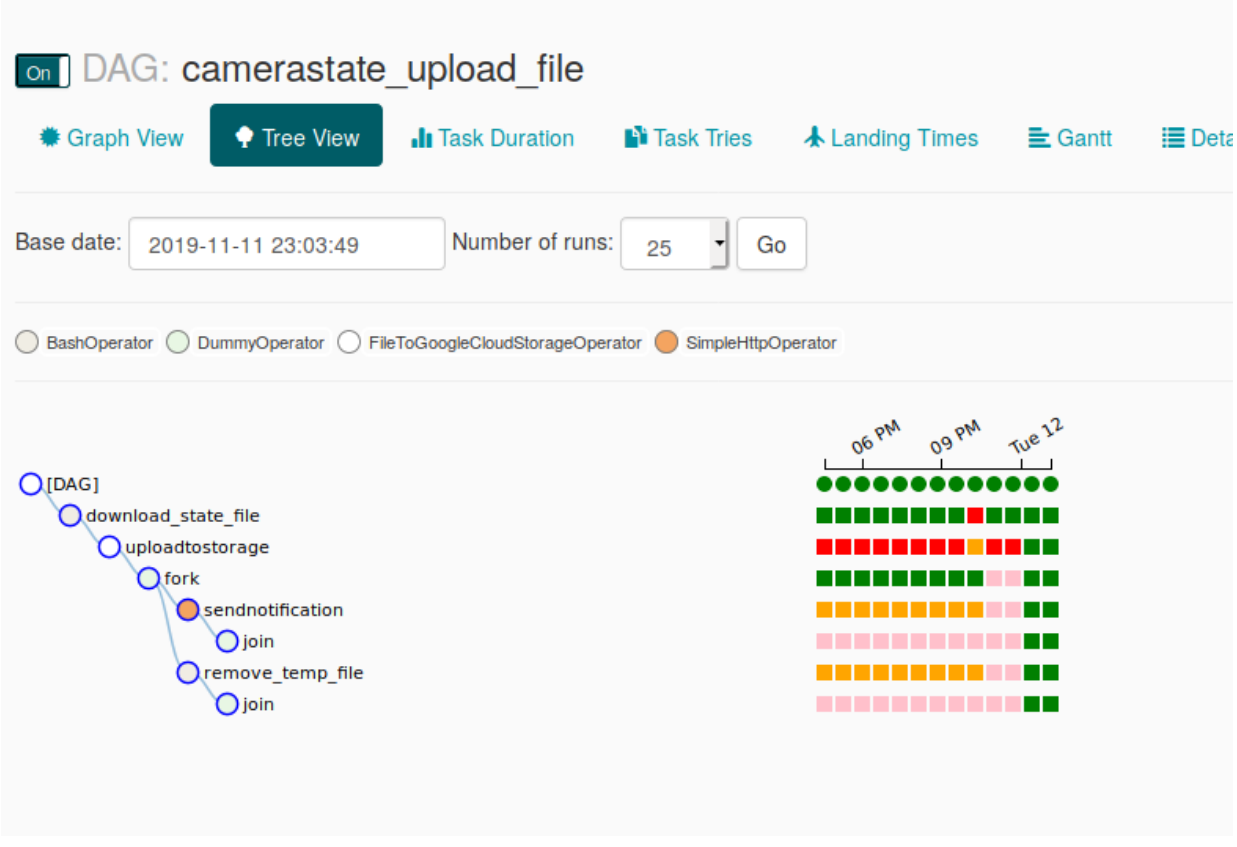
```
'''
the dependencies among tasks
'''
t_downloadlogtocloud >> t_analytics
t_analytics >> fork
fork >> t_sendresult
t_analytics >> fork
fork >> t_removefile
t_removefile >> join
t_sendresult >> join
```

downstream task

Monitoring UI



Monitoring UI



Example with serverless computing/function-as-a-service

Serverless/Function-as-a-service

- **Key principles**
  - running code without managing complex back-end server/application server infrastructures
  - tasks in your application: described as functions
    - *As you typically see in your Java/Python/JavaScript code*
  - functions are uploaded to FaaS engines and will be executed based on different triggers (e.g., direct call or events)
- **Event-driven triggers!**
  - triggered from HTTP calls, messages (brokers), storage events (e.g. new files are stored)

Note: Serverless technologies are lectured *in CS-E4190 - Cloud Software and Systems*

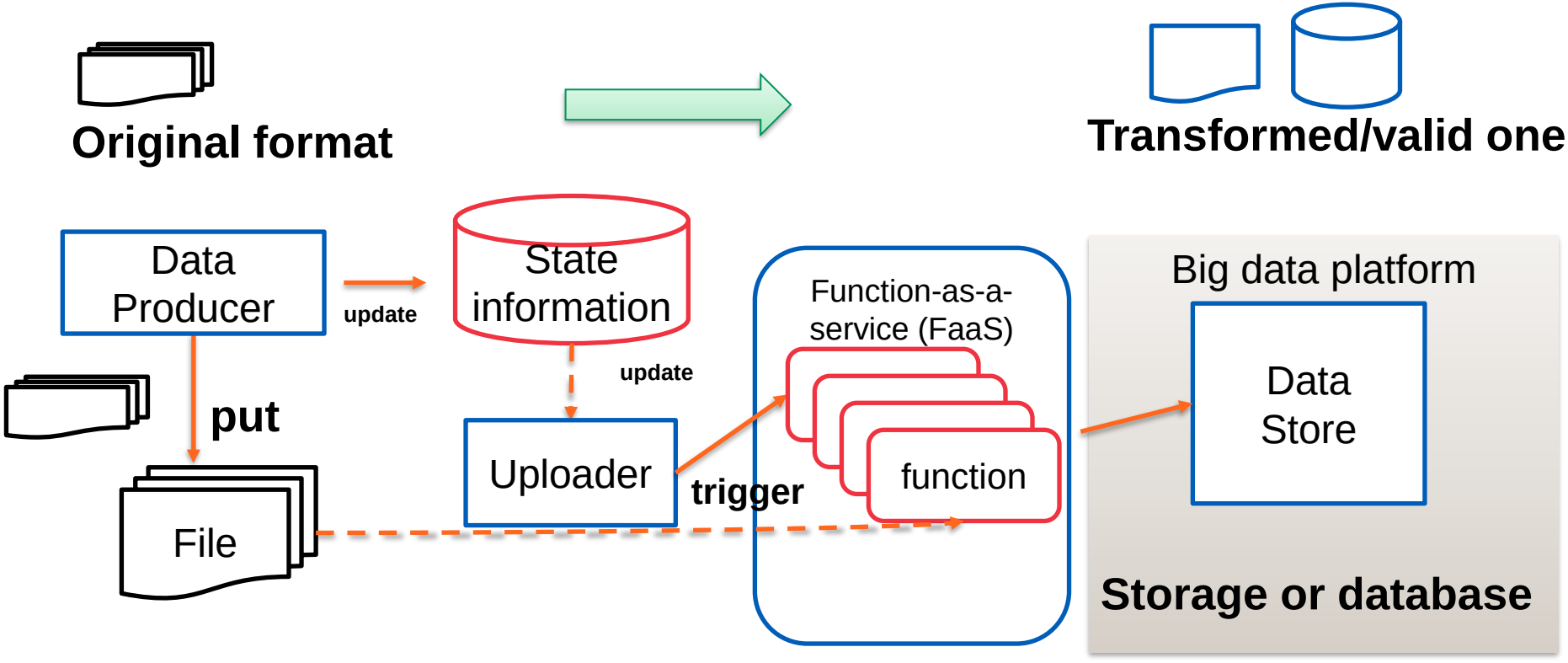
Function-as-a-service and workflows

- **Basic tasks can be implemented as a function**
  - follow the function-as-a-service model (serverless)
  - FaaS engine is a service for executing tasks
- **Workflow coordination with additional features**
  - using coordination engines: explicitly coordinate functions by calling functions executed by FaaS engines
  - implicitly coordinate functions –as a workflows - using connectors and triggers

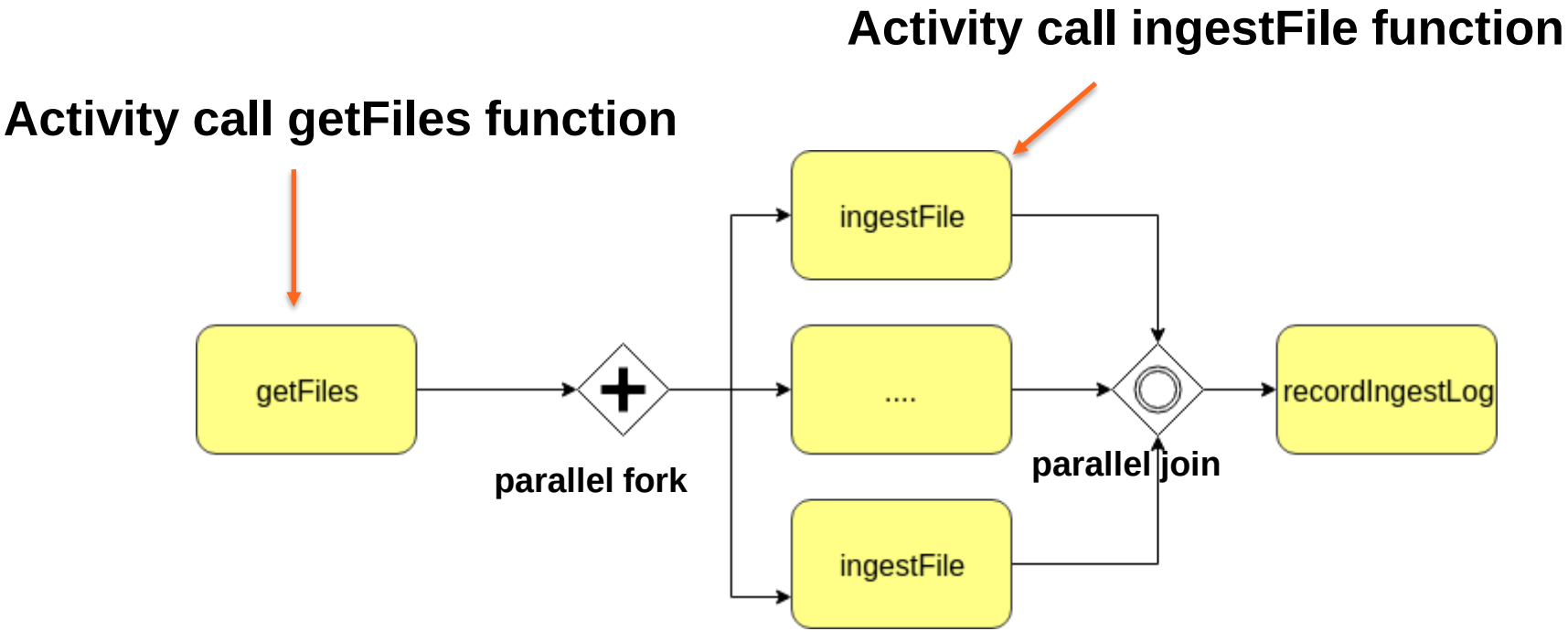
Using function-as-a-service in clouds

- **Azure**
  - Azure Function for tasks
  - Azure durable functions (https://docs.microsoft.com/en-us/azure/azure-functions/durable/durable-functions-orchestrations)
- **Amazon Web services**
  - AWS Lambda for tasks/functions
  - AWS Step Functions (https://aws.amazon.com/step-functions/)

Recall: data ingestion



Example of Azure durable functions



Code

```
module.exports = df.orchestrator(function* (context,req) {
    const tasks = [];

    //....
    //....

    const files = yield context.df.callActivity("getFiles", username);
    for (const file in files) {
        console.log("Deal with file "+file);
        tasks.push(yield context.df.callActivity("ingestFile", file));
    }
    return tasks;

});
```

Pros and cons

- **Pros:**
  - work well in big data ecosystems offered with cloud providers
  - easy to integrate with other cloud services
- **Cons**
  - lock-in with big cloud providers
    - *Difficult if you must change services in your ecosystem*
  - limited coordination/workflow engines compared with well-known scientific/data-intensive analytics workflows

Summary

- **Focus:**
  - practical programming with:
    - *Apache Airflow: for data analytics and platform management*
    - *Workflows using function-as-a-service: for service integration in clouds*
    - *Kubeflow: for machine learning with big data platforms (if you like ML)*
- **Action:**
  - hands-on and work on concrete examples
    - *Try to see if you can implement previous use cases/scenarios in your work with workflows*
  - offering workflows as a service in your platform!

Thanks!

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