Aalto University
School of Science

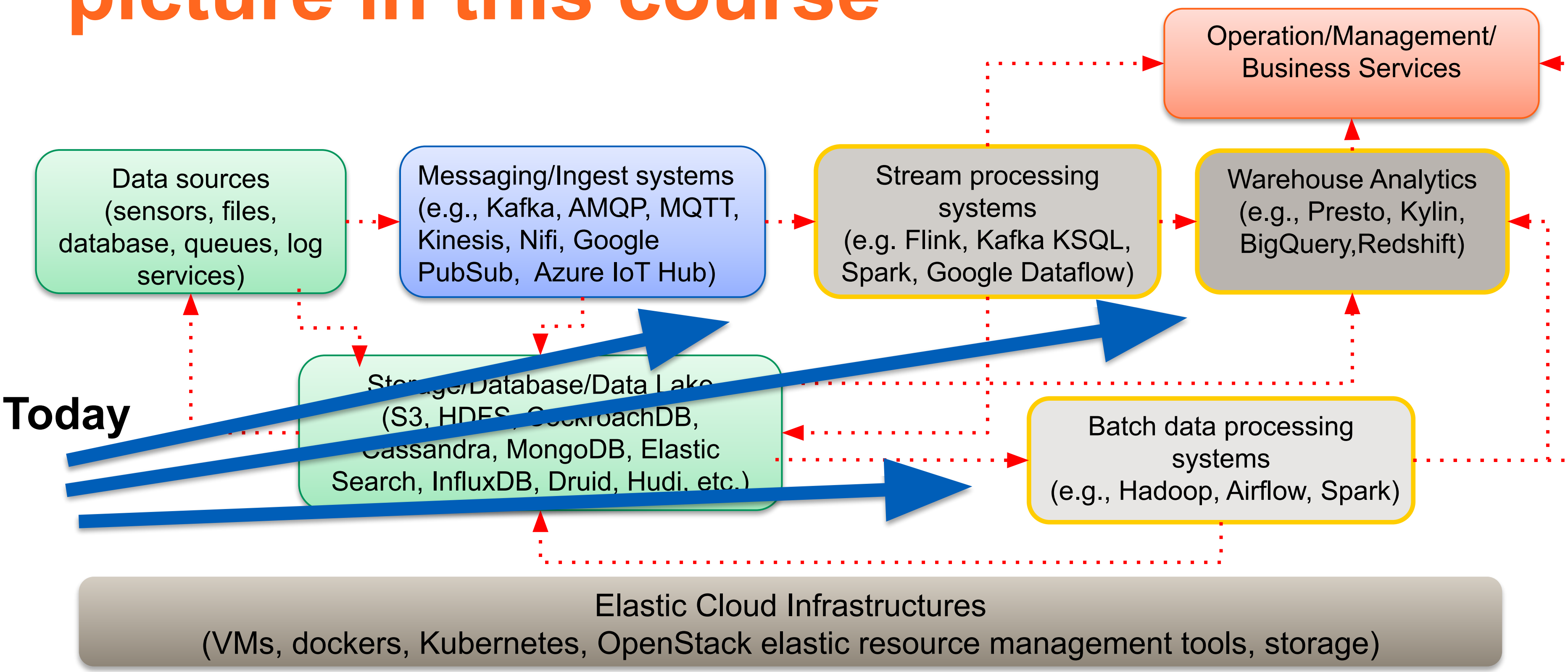
Workflows for Big Data Platforms

Hong-Linh Truong
Department of Computer Science
linh.truong@aalto.fi, *https://rdsea.github.io*

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



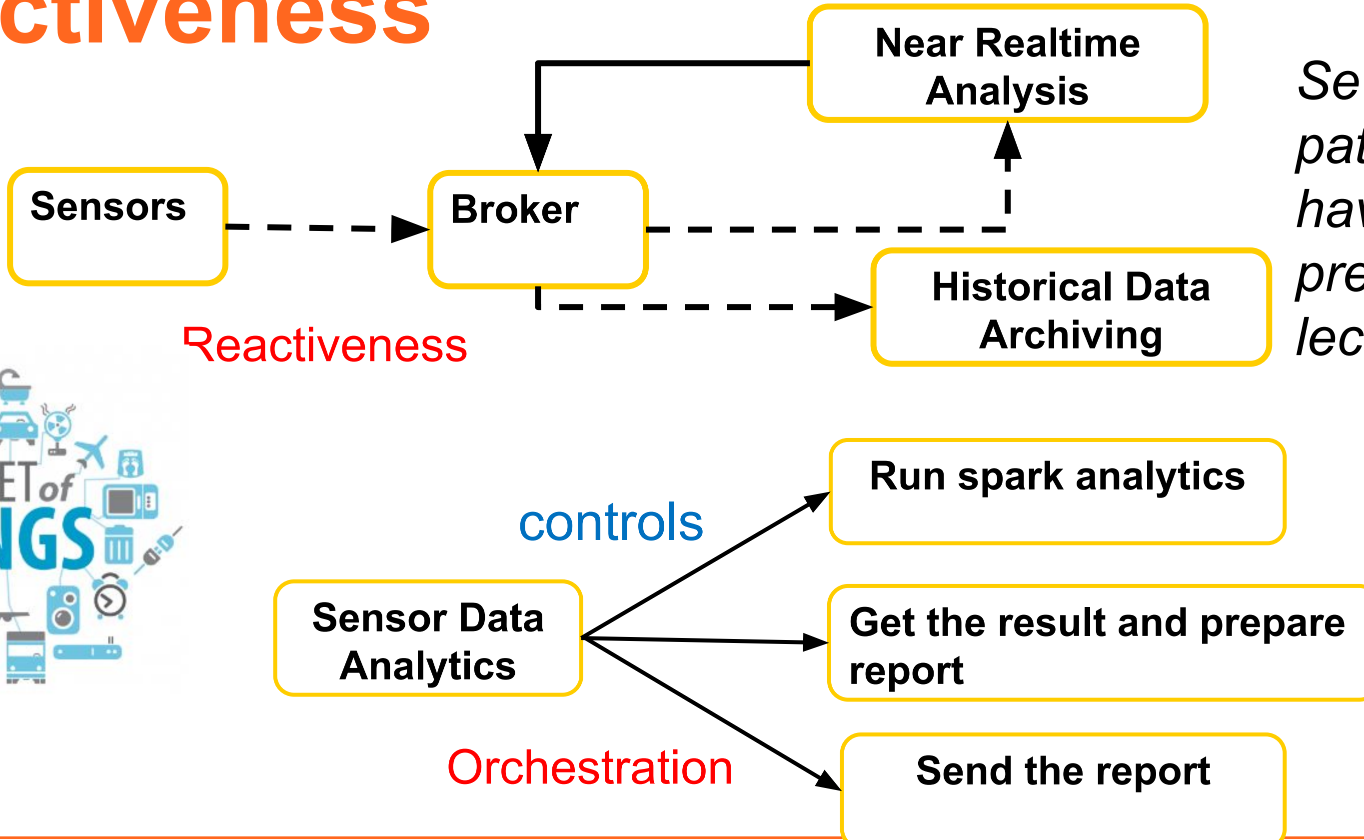
Tasks in big data platforms

- **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

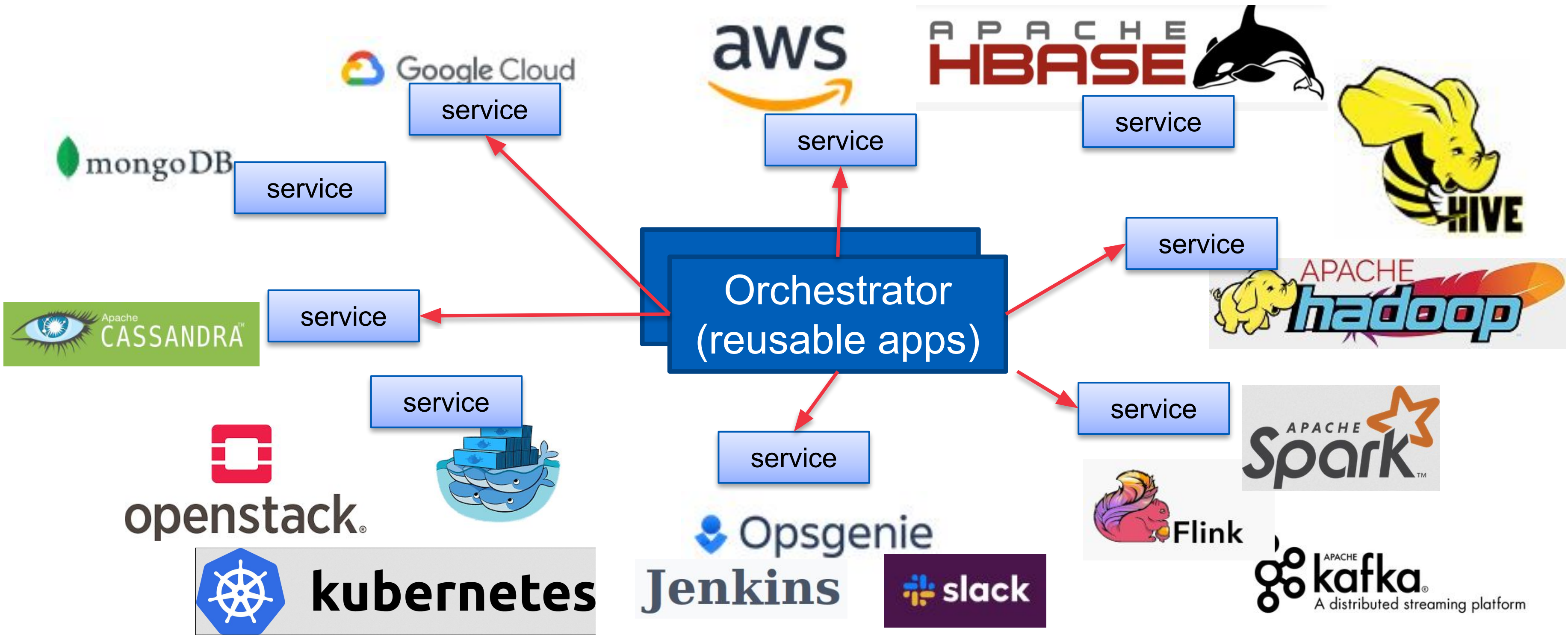
- **Deployment and configuration**
  - for big data components
- **ETL, data cleansing and backup**
  - access and coordinate many different compute services, data sources, ingestion and extraction applications
- **Complex predictive maintenance**
  - coordination of machine learning pipelines and communication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

Recall: Orchestration and Reactiveness



Several design patterns you have done in previous lectures

Service orchestration in big data platforms: more than just with “big data”



Example of security data analytics

Security-related information and metrics from distributed customers

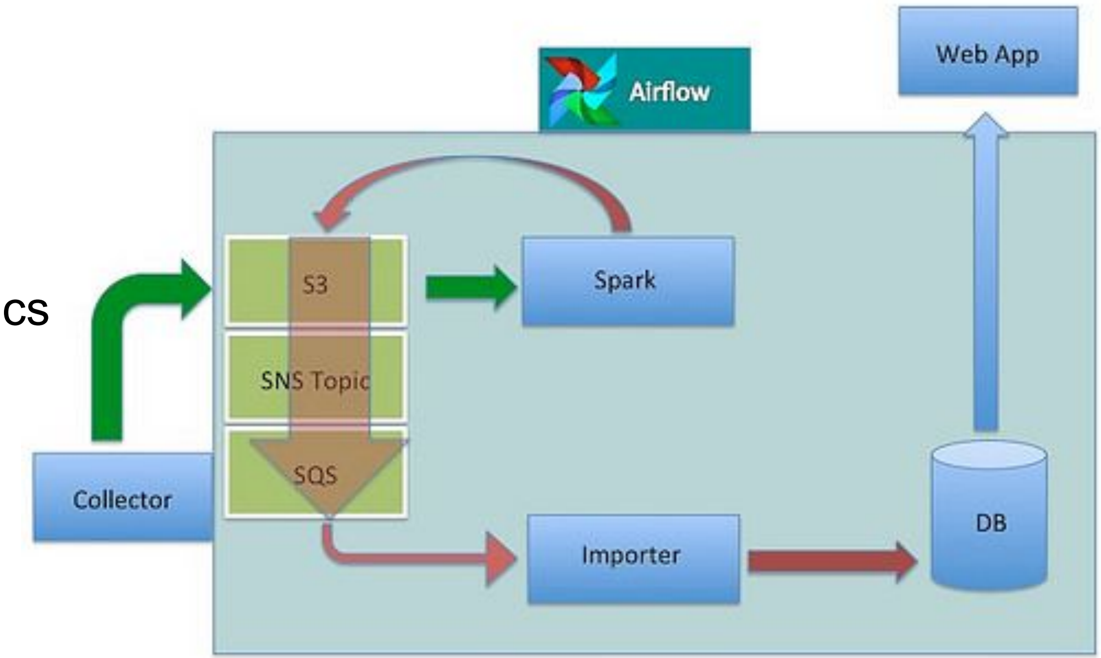
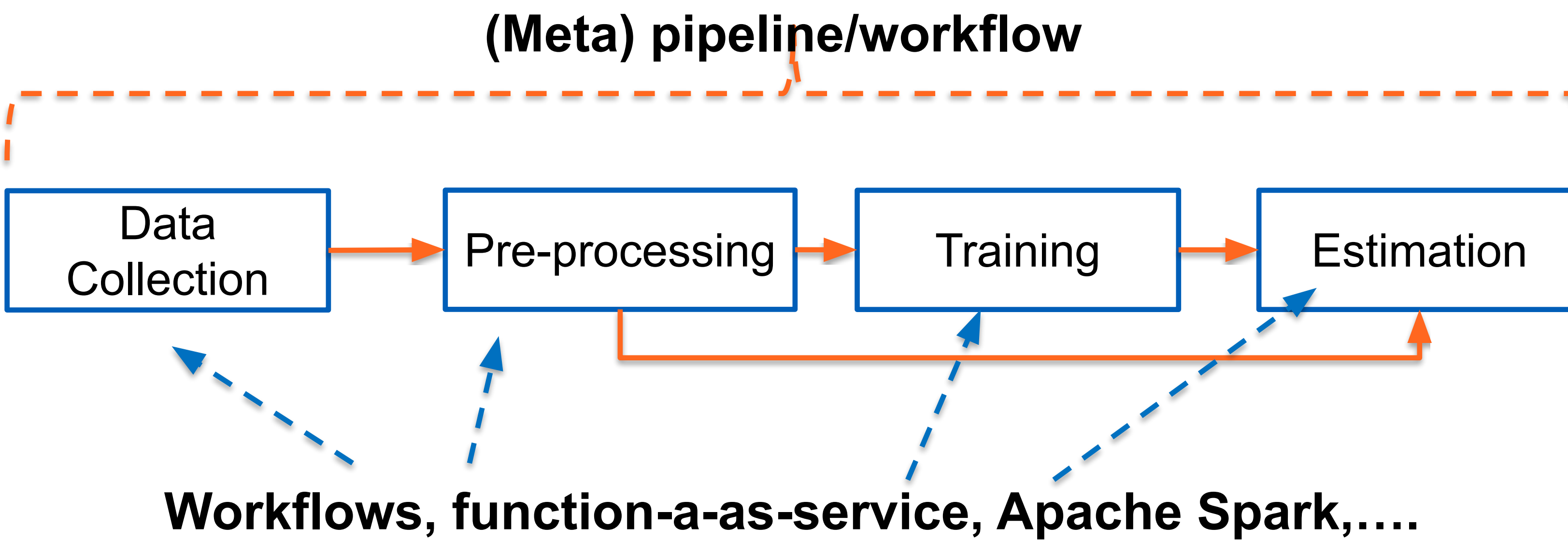


Figure Source:
http://highscalability.com/blog/2015/9/3/how-agari-uses-airbnbs-airflow-as-a-smarter-cron.html

Example of ML workflows

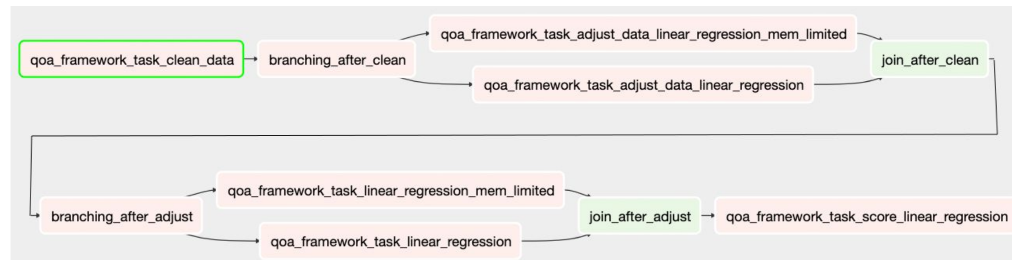
- **meta-workflow vs inside each phase: pipeline/workflow or other types of programs**

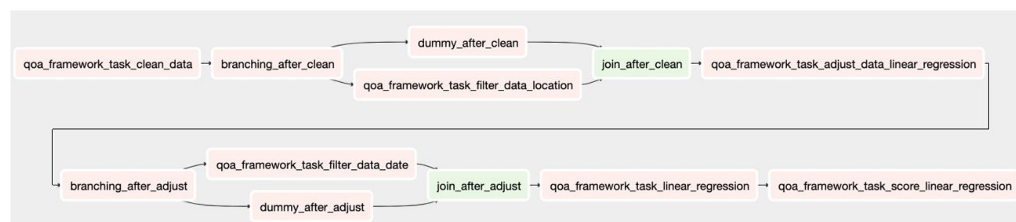


Example of industrial retail forecast

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

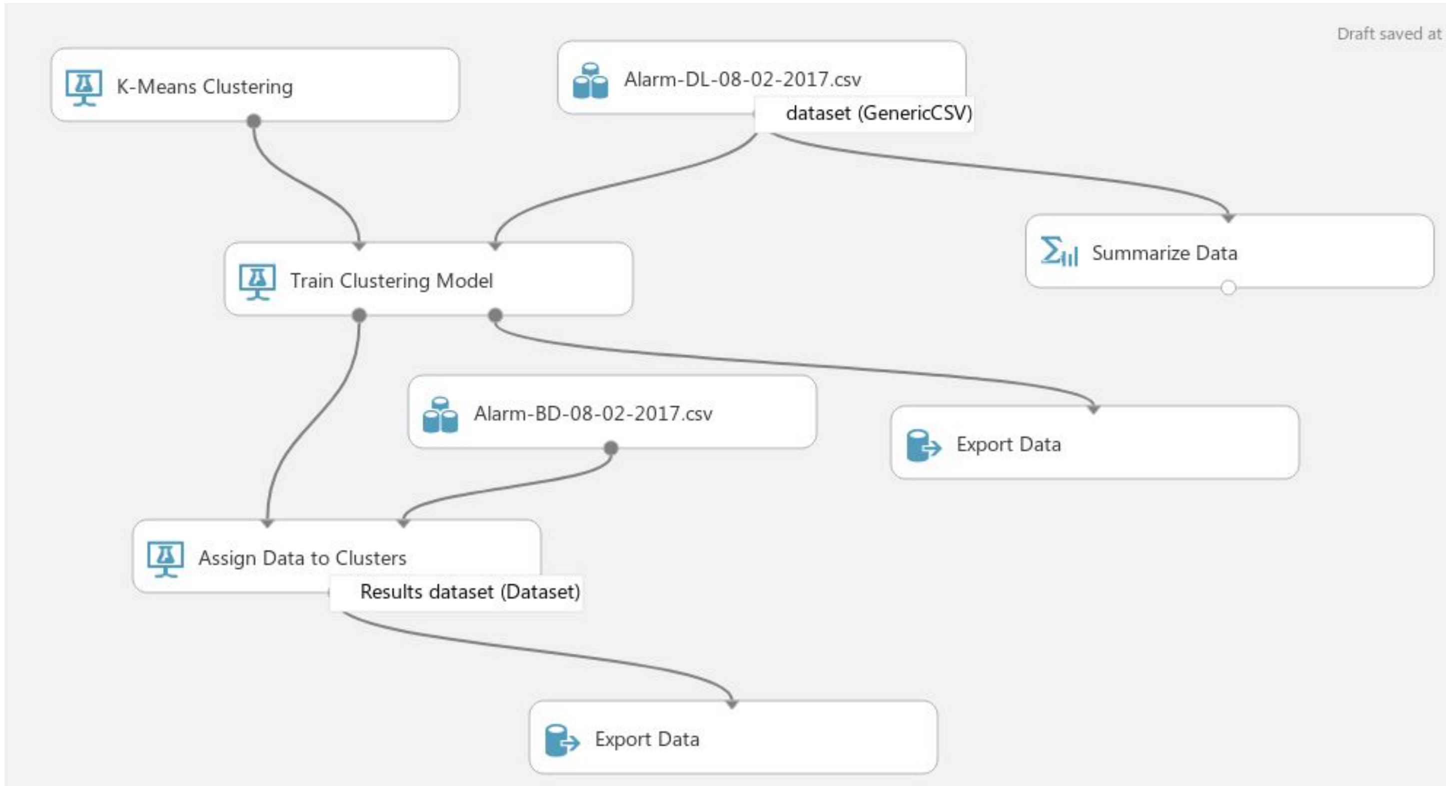




Source: Kreics Krists, „Quality of analytics management of data pipelines for retail forecasting,“, Aalto CS Master thesis, 2019

Example of ML workflows

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
- has data/control task dependencies
- can be reusable (tasks, part of the workflow and the whole workflow)

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
    - including IoT devices are robots
- **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 in practice:**
  - a pipeline is a workflow with a simple structure
  - a pipeline coordinates different (sub)workflows
- **Note: sometimes the “data pipeline” here is just an abstract design**

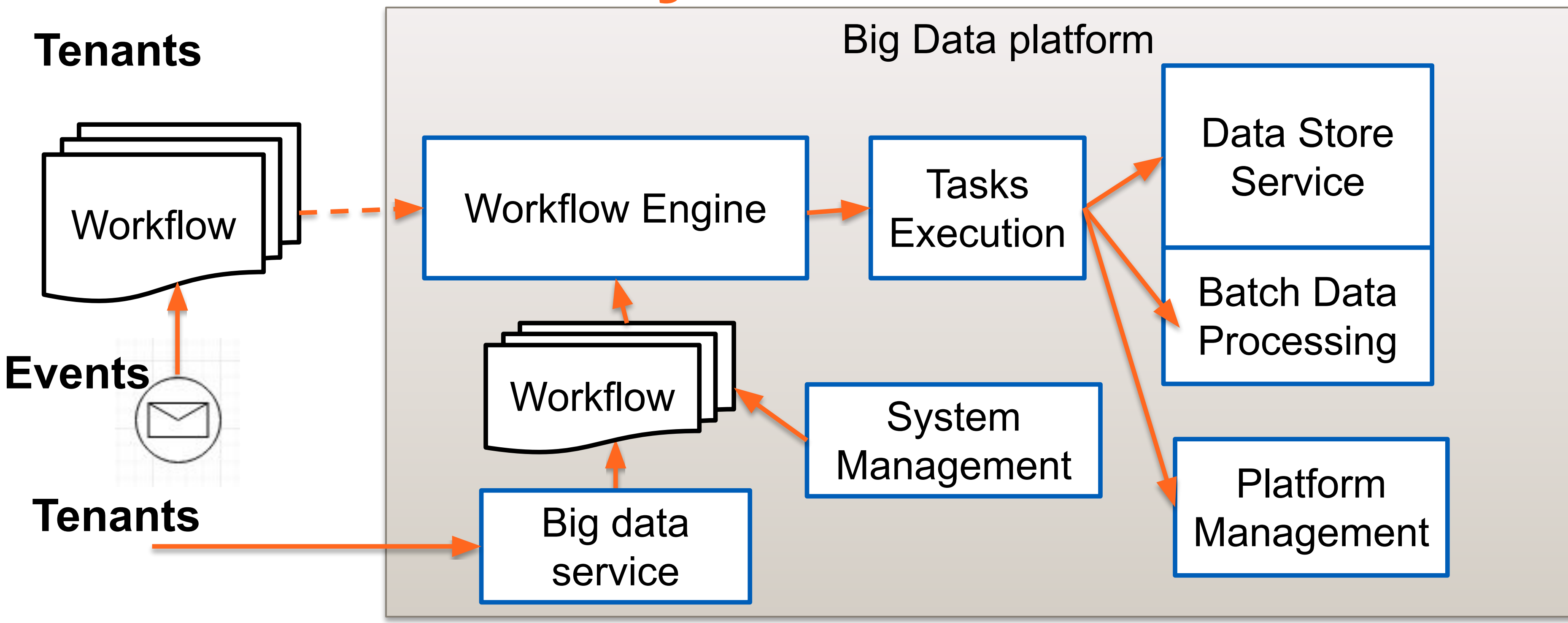
A long history – workflows are well-known!

- **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

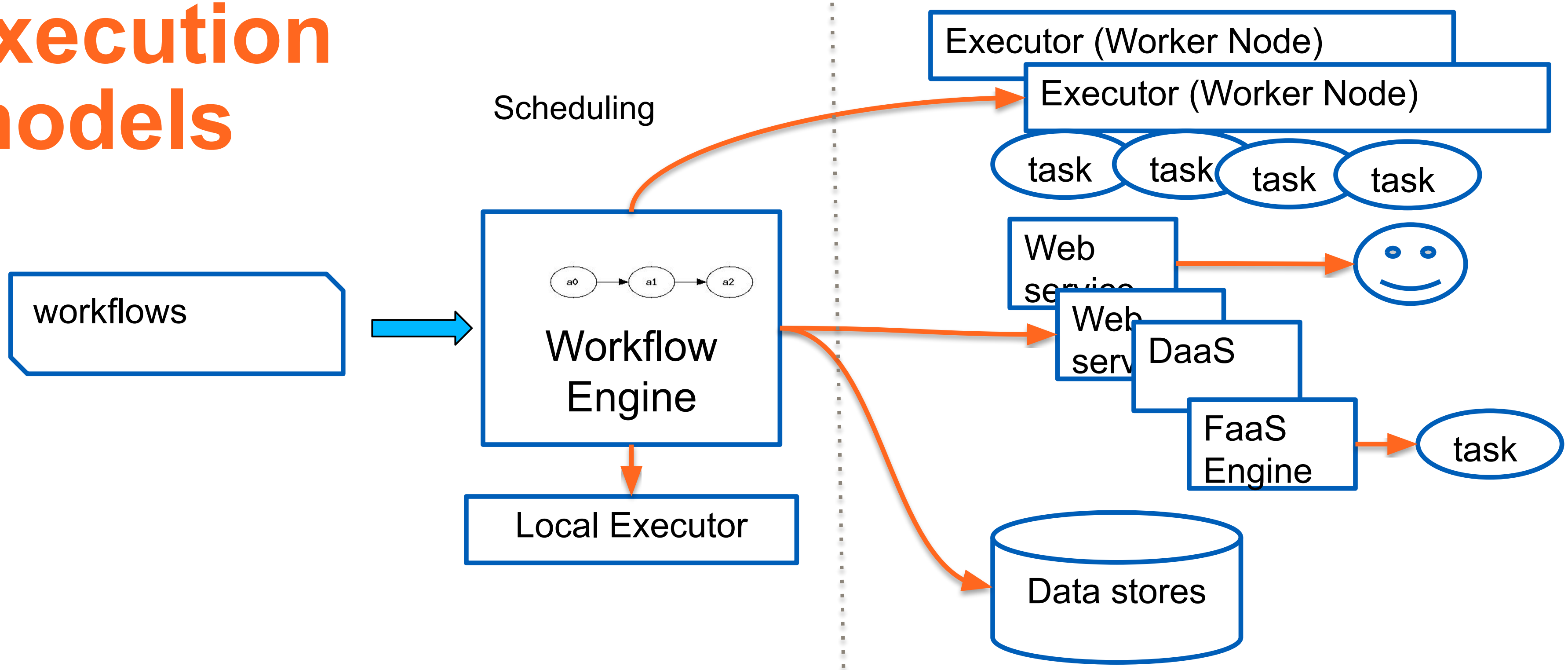
- **Tasks/activities/steps**
  - describe a single work (it does not mean small)
  - tasks can be carried out by humans, executables, scripts, batch applications, stream applications and other types of services.
- **Workflow languages**
  - structure/describe tasks, dataflows, and control flows
- **Workflow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

Workflows in big data platforms: more than analytics

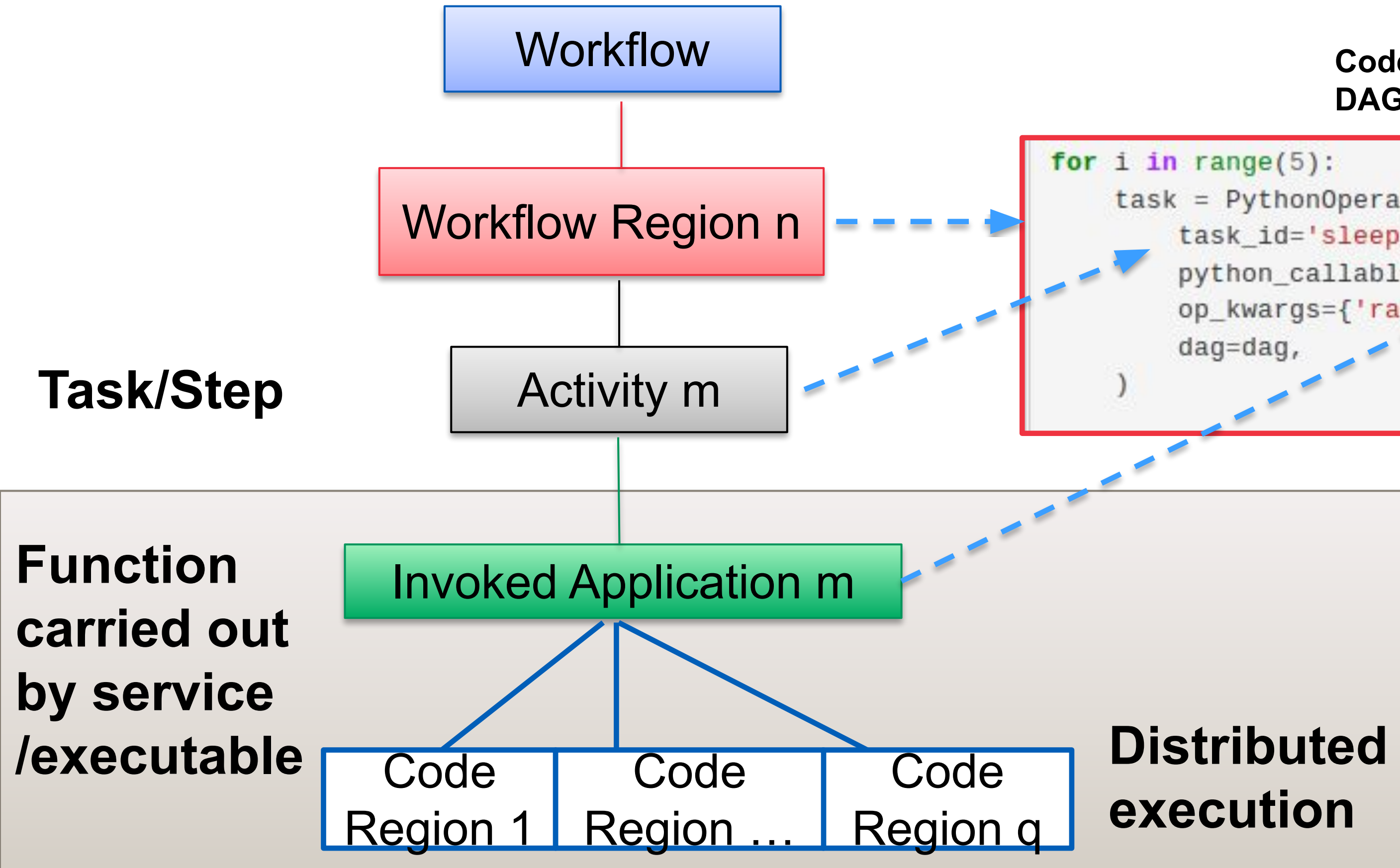


Common workflow execution models

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



Structured view of workflows



Code captured from Airflow:
DAG: example_python_operator

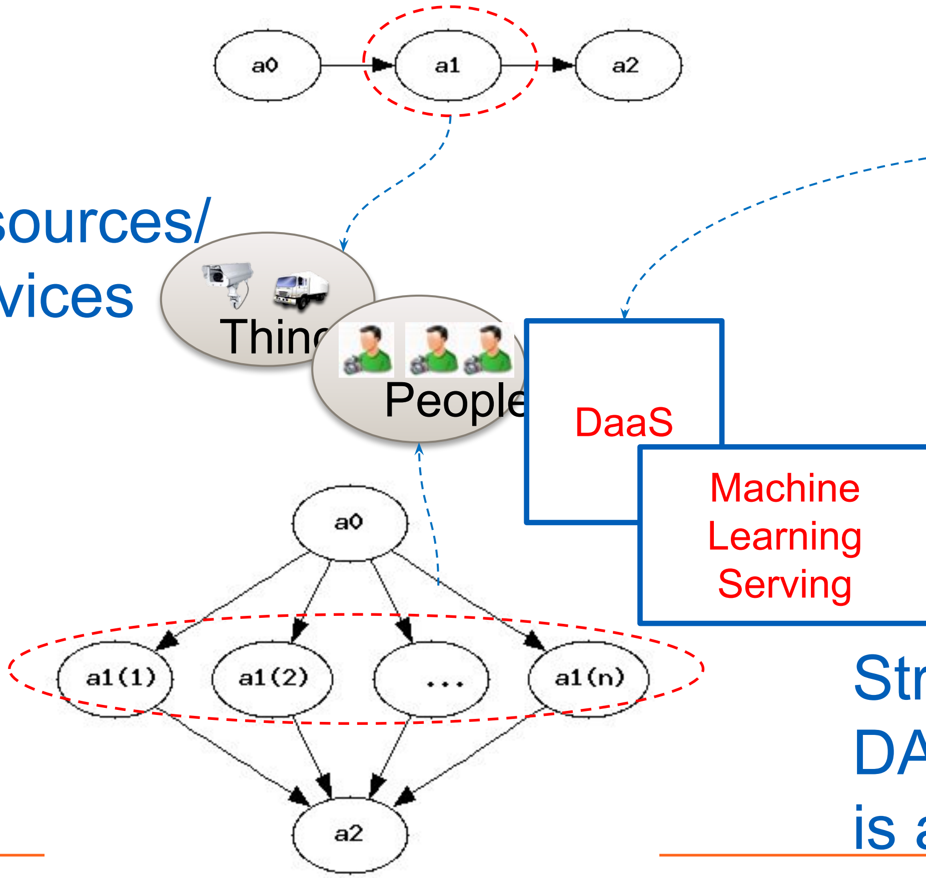
```
for i in range(5):
    task = PythonOperator(
        task_id='sleep_for_' + str(i),
        python_callable=my_sleeping_function,
        op_kwargs={'random_base': float(i) / 10},
        dag=dag,
    )
```

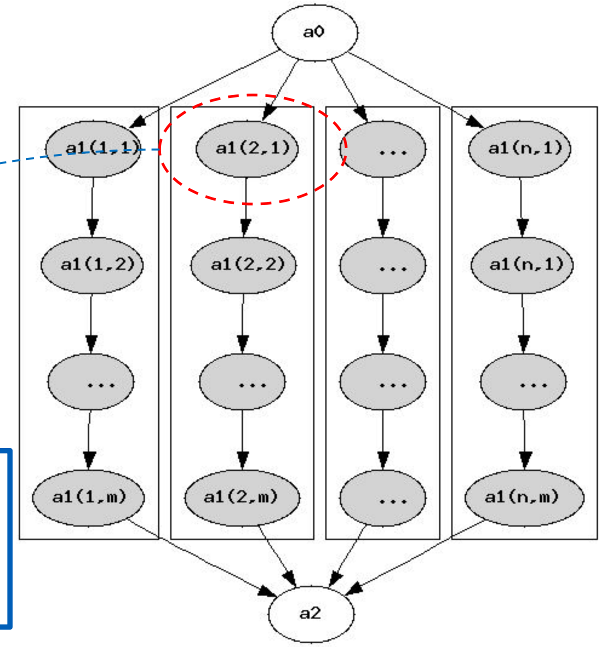
Describing workflows

- **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

Resources/
Services





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

Modern data workflows in clouds

- **Invoked applications**
  - Cloud services: diverse types of APIs and protocols
  - Serverless functions
- **Workers**
  - Distributed workers in data centers
    - *interfaces via APIs and messaging systems*
  - Containers and distributed task executors
  - Cloud orchestration
- **Python-based for data analytics and ML workflows**

Complex excution management

Example in data-intensive workflows in distributed centers

Scheduler in data centers

worker nodes

Figure source:

H.-L. Truong et al. / Future Generation Computer Systems 23 (2007) 760–772

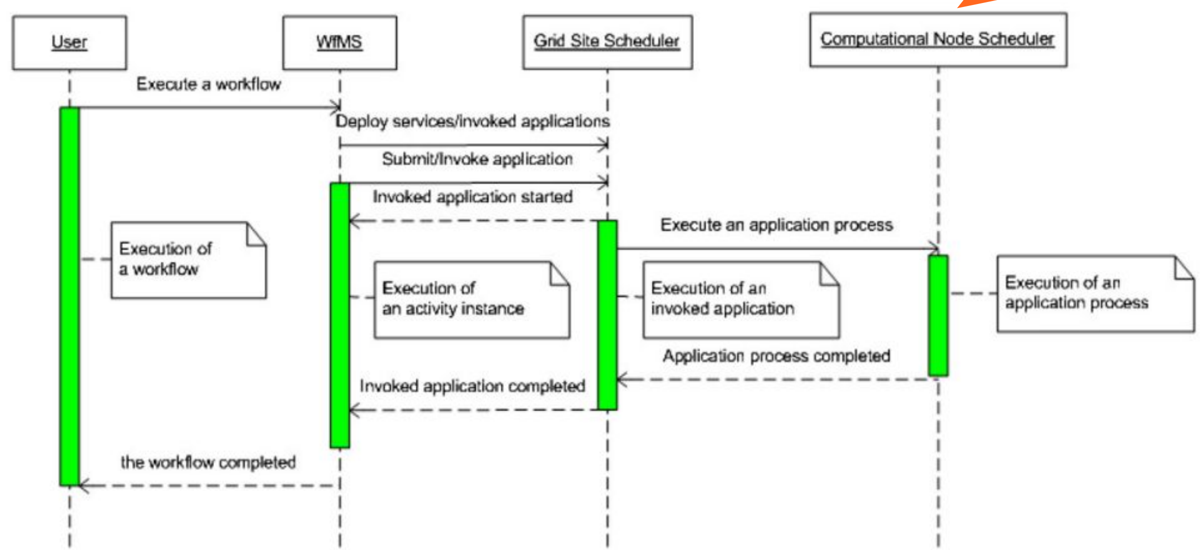


Fig. 2. Simplified execution model of a Grid workflow.

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

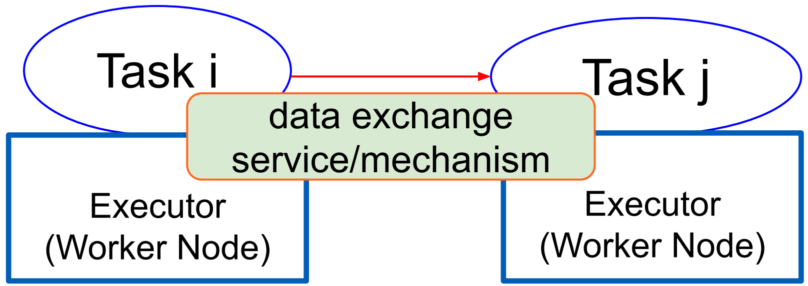
Select/build workflows in your platforms

- **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)

State and exchange data

- **How do tasks exchange data?**

By value or by reference exchange?



Possibilities:

- shared file systems
- global/common storage systems
- key/value database
- external processes for pulling data

Some important aspects:

- Asynchronous task execution in which the task results must be retrieved with a different method
- Idempotency (retries, fault-tolerance) and caching
- SerDe (serialization and deserialization)
- Performance of shared systems/services for data exchange
- Deployment consideration

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
  - Heterogeneous 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

Monitoring

- **Understand the states**
  - Workflow level vs task/activity level vs functions/invoked applications
- **Multiple level of instrumentation and monitoring**
  - Workflow Engine
  - Scheduler
  - External services/applications

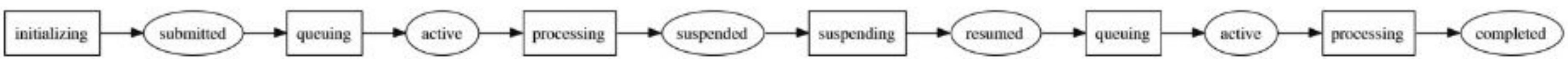
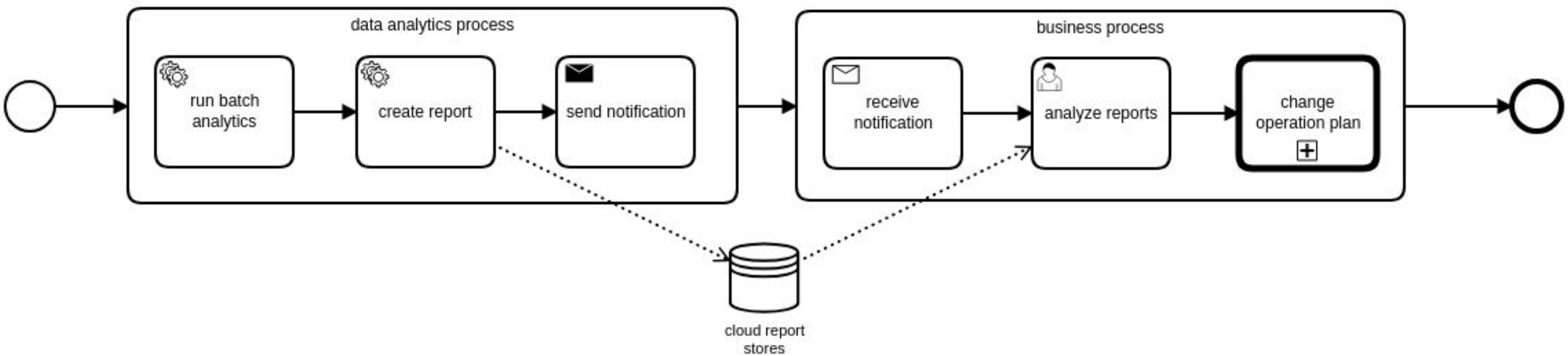


Fig. 3. Discrete process model of the tracing execution of an activity. ☐ represents an execution phase, ◯ represents an event.

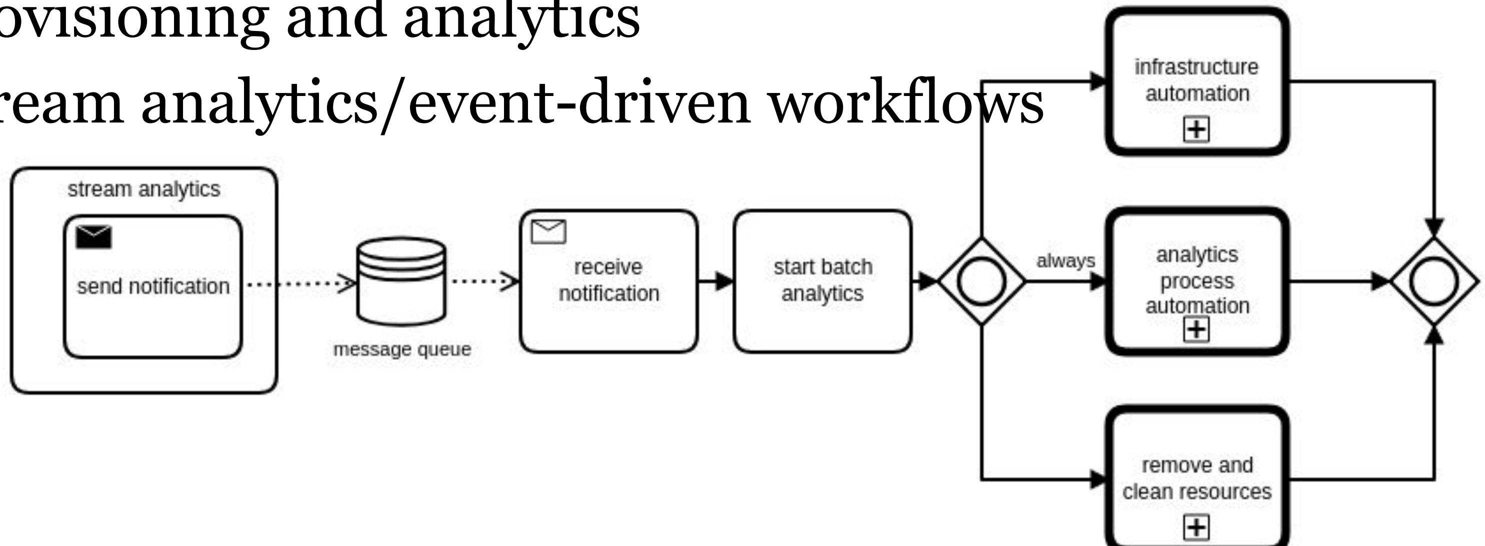
Select/build workflows in your platforms

- **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

- Airbyte
- Alibaba
- Amazon
- Apache Beam
- Apache Cassandra
- Apache Drill
- Apache Druid
- Apache HDFS
- Apache Hive
- Apache Kylin
- Apache Livy
- Apache Pig
- Apache Pinot
- Apache Spark
- Apache Sqoop
- Asana
- Celery
- IBM Cloudant
- Kubernetes
- Databricks
- Datadog
- DBT cloud
- Dingding
- Discord
- Docker
- Elasticsearch
- Exasol
- Facebook
- File Transfer Protocol (FTP)
- Github
- Google
- gRPC
- Hashicorp
- Hypertext Transfer Protocol (HTTP)
- Influx DB
- Internet Message Access Protocol (IMAP)
- Java Database Connectivity (JDBC)
- Jenkins
- Jira
- Microsoft Azure
- Microsoft PowerShell Remoting Protocol (PSRP)
- Microsoft SQL Server (MSSQL)
- Windows Remote Management (WinRM)
- MongoDB
- MySQL
- Neo4J
- ODBC
- OpenFaaS
- Opsgenie
- Oracle
- Pagerduty
- Papermill
- Plexus
- PostgreSQL
- Presto
- Qubole
- Redis
- Salesforce
- Samba
- Segment
- Sendgrid
- SFTP
- Singularity
- Slack
- Snowflake
- SQLite
- SSH
- Tableau
- Telegram
- Trino
- Vertica
- Yandex
- Zendesk

From https://airflow.apache.org/docs/

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**
  - Celery, Dask, Kubernetes

Airflow workflow structure

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

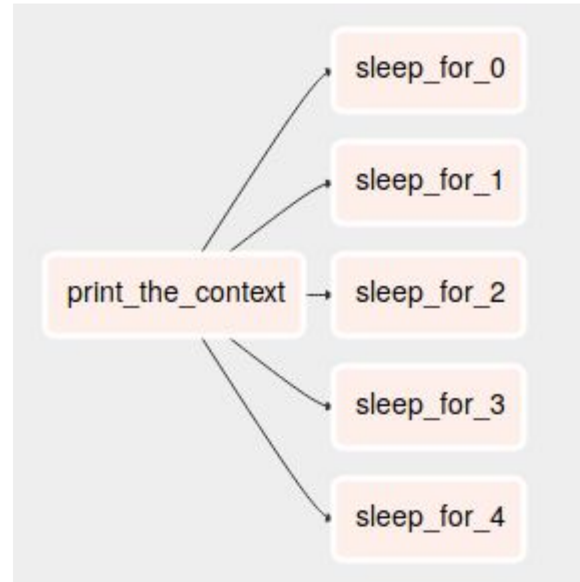
Airflow operators/tasks

- **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, SimpleHttpOperator, BaseSQLOperator, BaseSensorOperator, DockerOperator, HiveOperator, SparkSubmitOperator,SageMakerTrainingOperator, PrestoToMysqlOperator, SlackAPIPostOperator
- **Remember:**
  - such operators will be executed by corresponding services

Example of operators

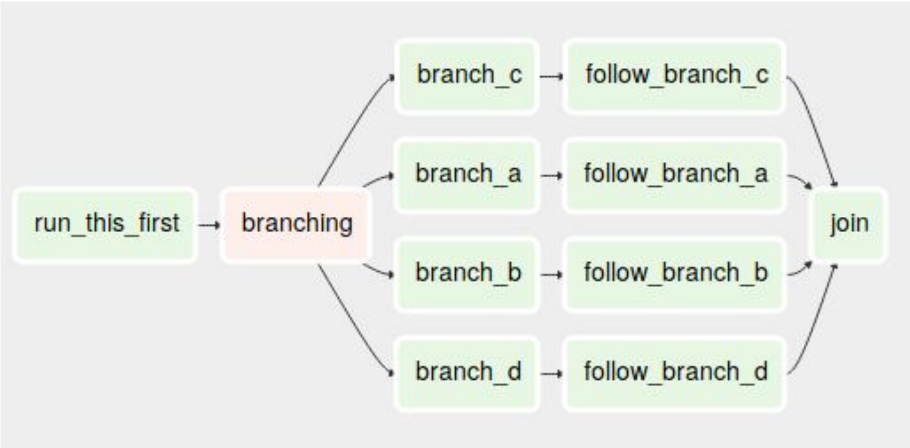
- **High-level structure is mapped to python and suitable operators**

```
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,
)
```

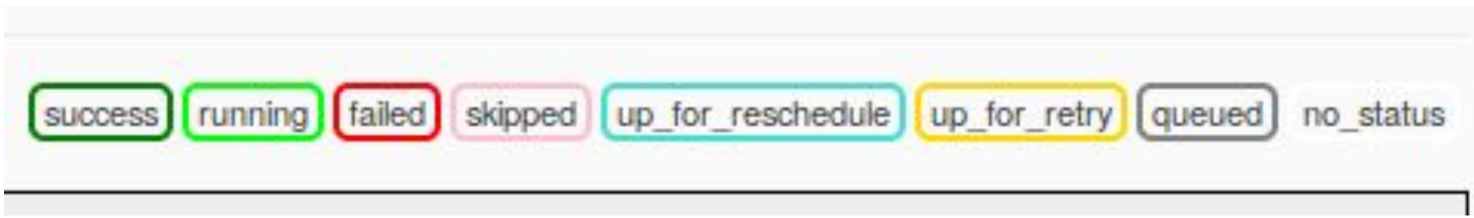
Source: code and figures captured from Airflow UI
DAG: example_branch_operator
schedule: @daily

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
  - schedule based on analytics needs

Task lifecycle

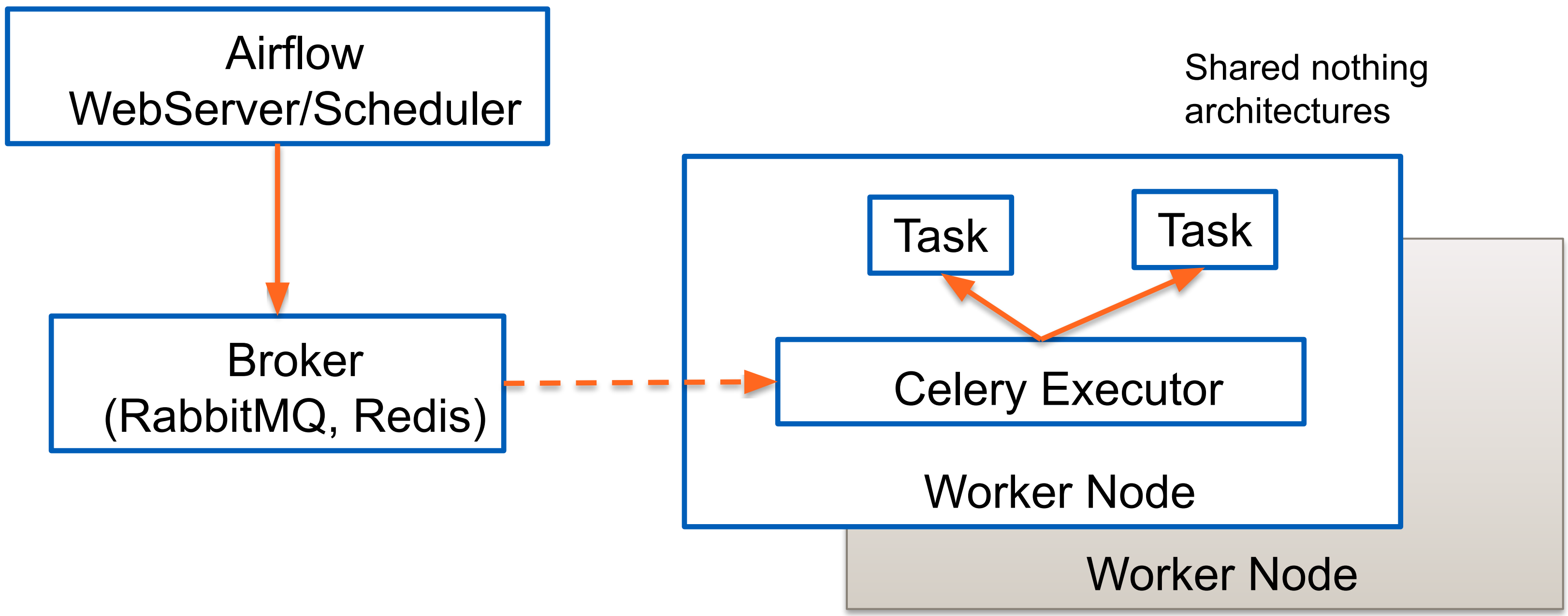
Different states



- **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**

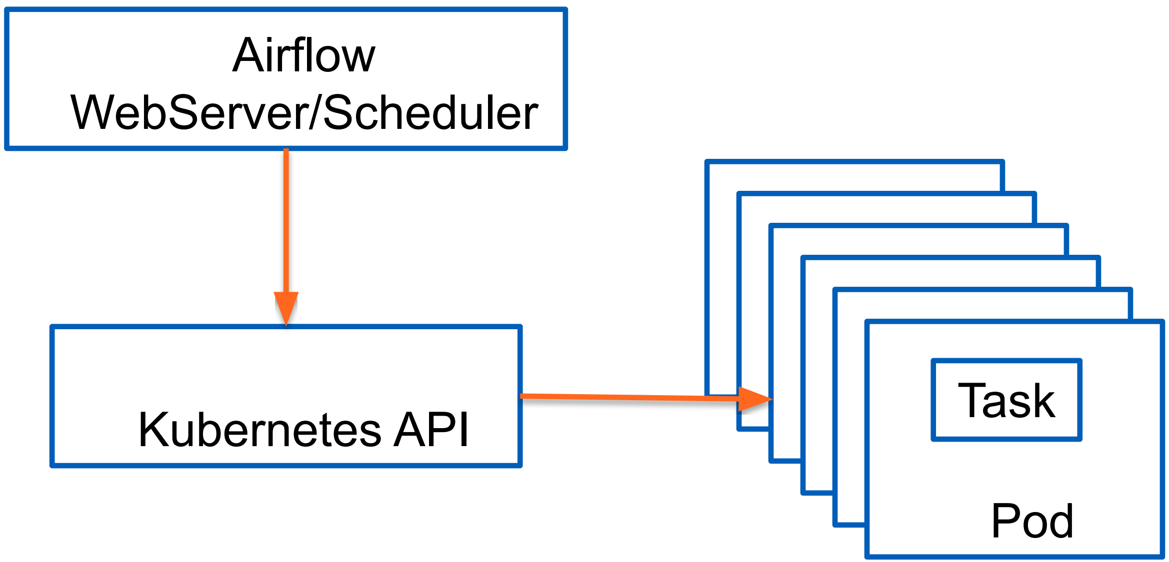
Distributed tasks

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



Distributed tasks

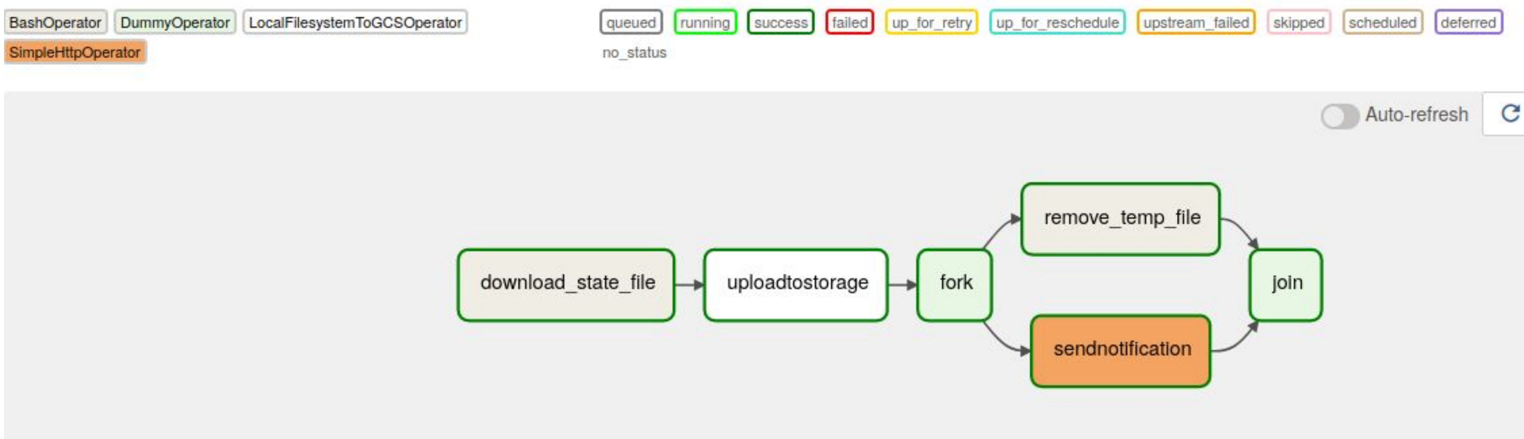
You can scale Airflow to run tasks in Kubernetes



Google Cloud Composer: use Kubernetes

Example

Scenarios: scan various local servers (via pre-defined API/endpoints), 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=  LocalFilesystemToGCSOperator(
    task_id="uploadtostorage",
    src=destination_file,
    dst=gcsdir,
    bucket=GCS_BUCKET,
    gcp_conn_id=GCS_CONN_ID,
    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)

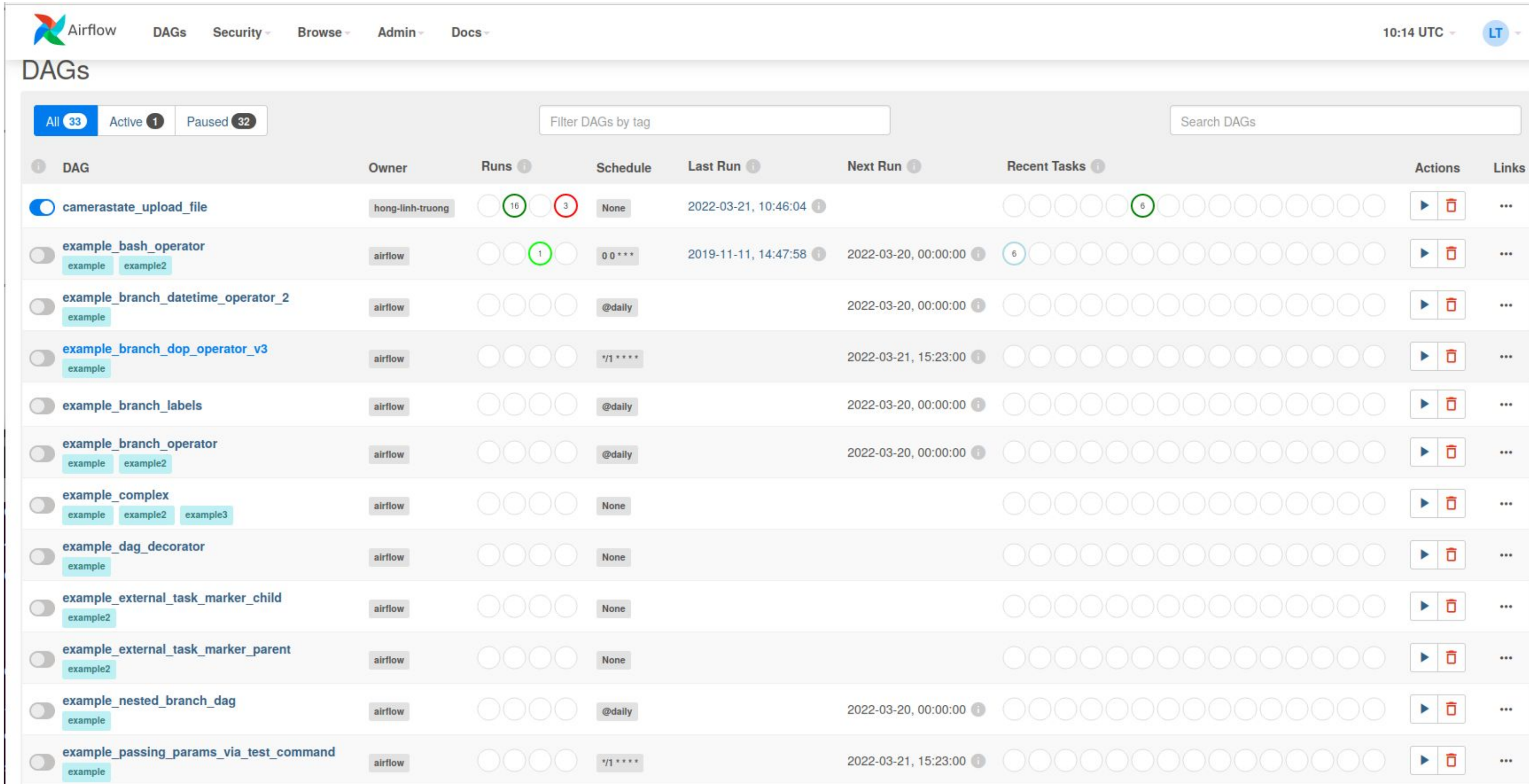
Example for uploading state logs

upstream task

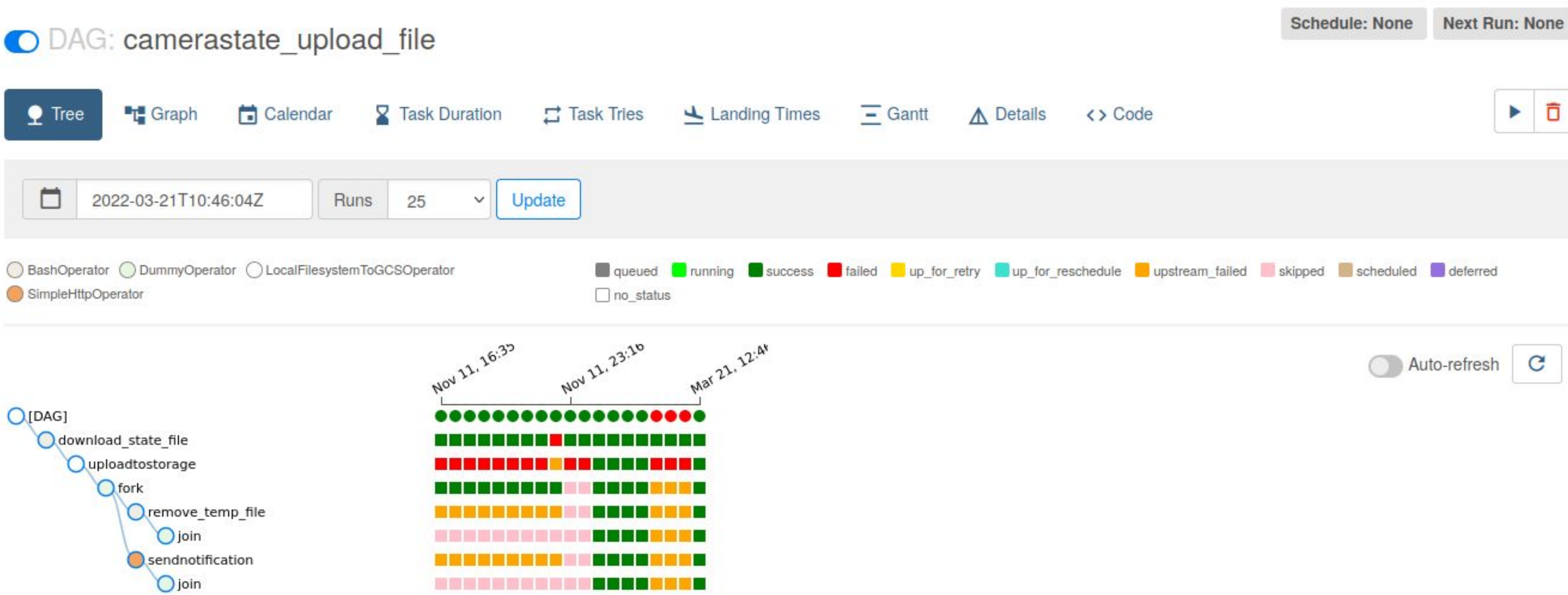
```
'''
the dependencies among tasks
'''
t_downloadlogtocloud >> t_analytics
t_analytics >> fork
fork >> t_sendresult
t_analytics >> fork
fork >> t_removefile
t_removefile >> join
t_sendresult >> join
```

downstream task

Monitoring UI



Monitoring UI



Summary

- **Focus:**
  - practical programming with:
    - *Apache Airflow: for data analytics and platform management*
    - *Serverless workflows using function-as-a-service: e.g., AWS Steps*
    - *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!
    - *suggest to do some hands-on by configuring and deploying Airflow*

Thanks!

Hong-Linh Truong
Department of Computer Science

rdsea.github.io