

Workflows for Big Data Platforms

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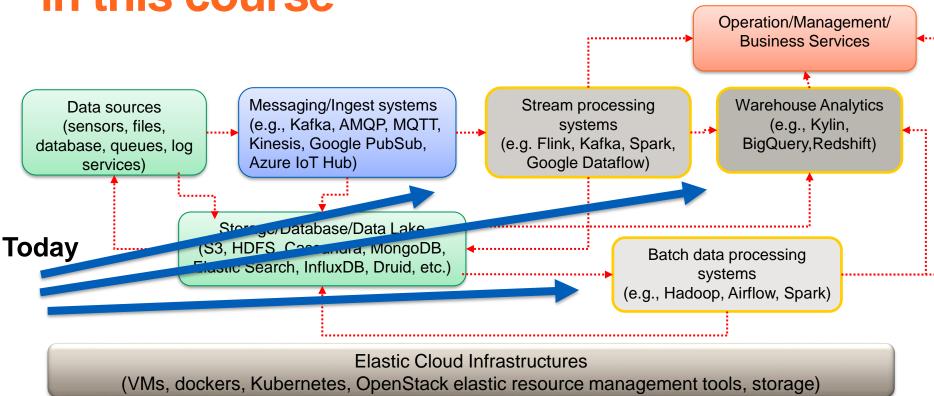
Learning objectives

 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

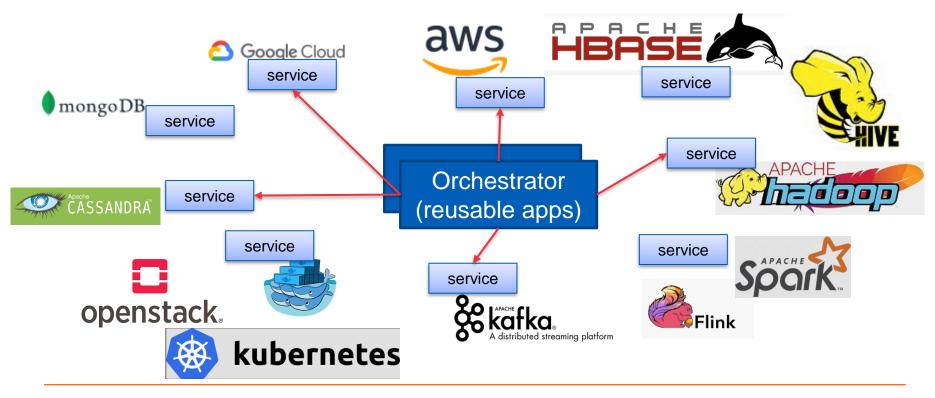
 coordination of machine learning pipelines and communication with humans/optimization services

Analytics-as a service

metrics understanding, user activities analytics, customer understanding



Service Orchestration





Example of security data analytics

Web App Airflow Security-related Spark 53 information and metrics from distributed **SNS Topic** customers SQS Collector DB Importer

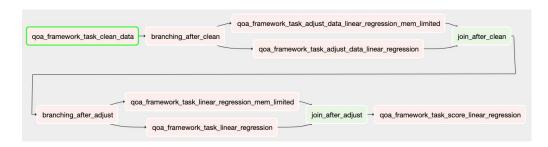
Figure Source: http://highscalability.com/blog/2015/9/3/how-agari-uses-airbnbs-airflow-as-a-smarter-cron.html

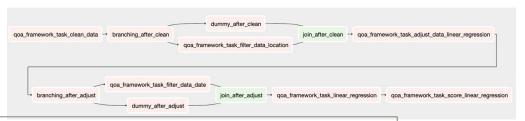


Example of industrial retail forecast

date	id	name	volume	price	cost	promo	category_net	margin	category 1	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



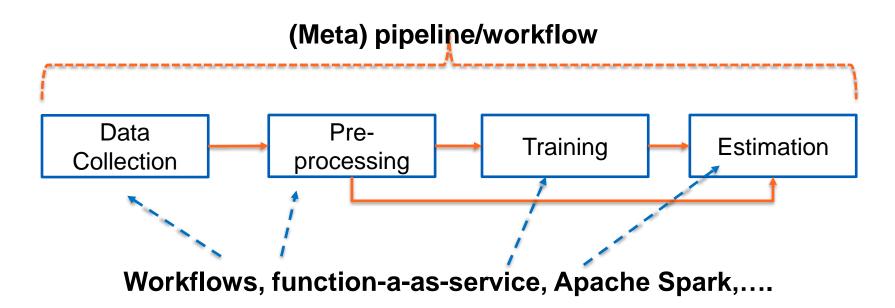


Source: Kreics Krists, "Quality of analytics management of data pipelines for retail forecasting,", Aalto CS Master thesis, 2019



Example of ML workflows

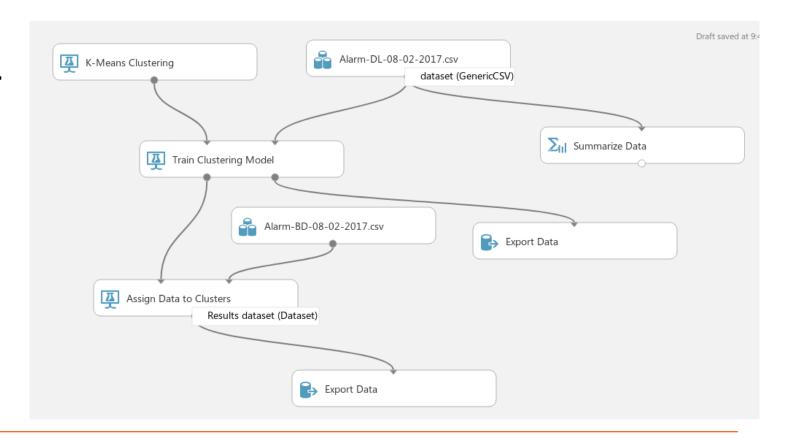
meta-workflow vs inside each phase: pipeline/workflow or other types of programs





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 workflows → 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

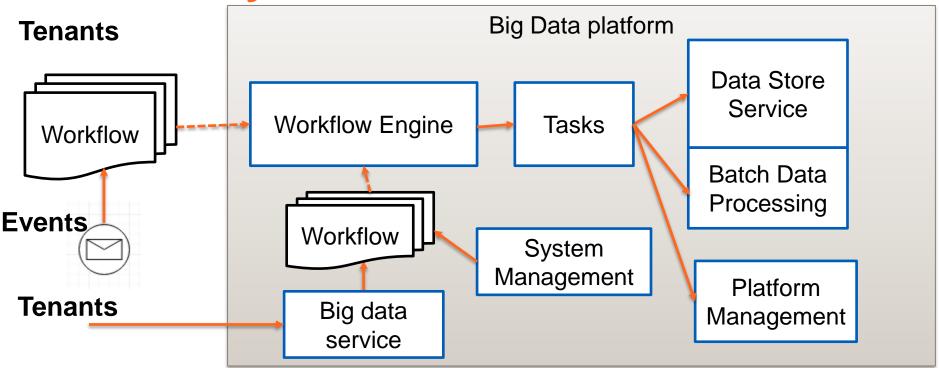
• in scientific computing and high performance computing (e.g., bioinformatics, astrophysics, material science simulations)

Automation in system management

 at system level for automating infrastructure provisioning, system recovery, etc.



Workflows in big data platforms: more than analytics

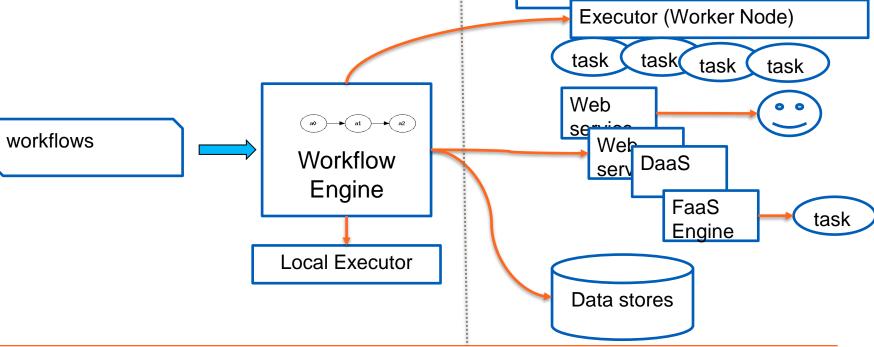




Common workflow execution models

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

Executor (Worker Node)





Key components

Tasks/Activities

- 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

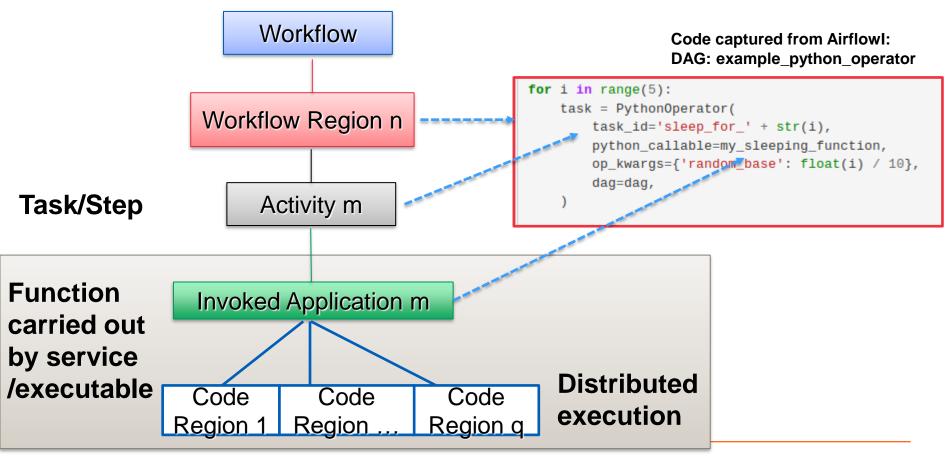
structure/describe tasks, dataflows, and control flows

Workflow Engines

- execute the workflow by orchestrating tasks
- usually call remote services to run tasks



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

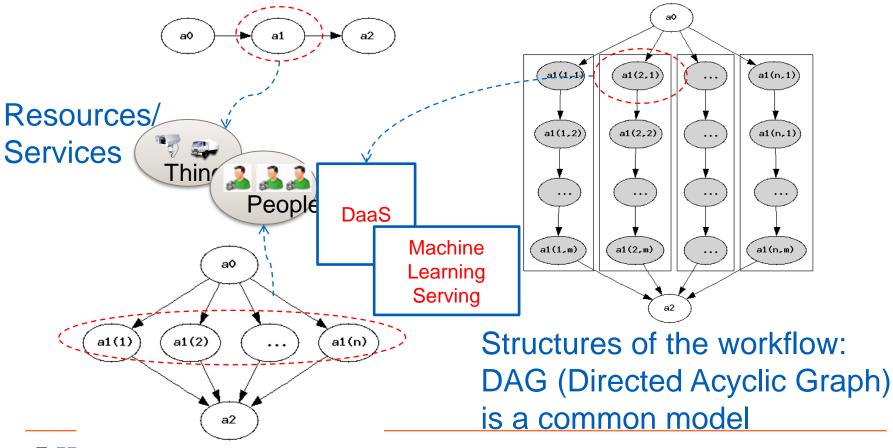
Descriptive languages with declarative schemas

- BPEL and several languages designed for specific workflow engines
- common in business and scientific workflows



Tasks orchestration

Auto University
School of Science



Runtime aspects

Parallel and distributed execution

 tasks are executed in different machines (by external invoked applications/services), multiple running workflows

Long 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



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)



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

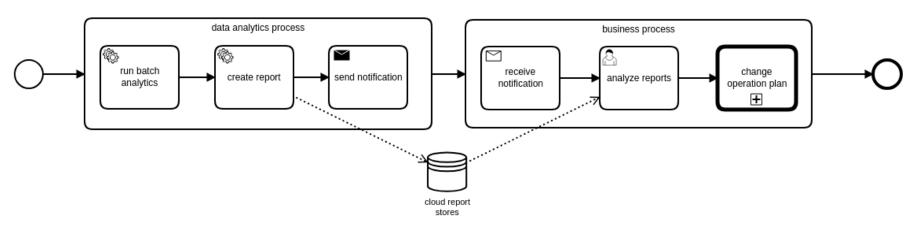
Wu, F., Wu, Q. & Tan, Y. Workflow scheduling in cloud: a survey. J Supercomput 71, 3373–3418 (2015). https://doi.org/10.1007/s11227-015-1438-4

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



Integration

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





Integration

Multiple types of workflows for services/infrastructure provisioning and analytics

Stream analytics/event-driven workflows infrastructure automation \blacksquare stream analytics analytics always receive start batch process send notification analytics notification automation message gueue remove and clean resources +



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://camunda.com/)
 (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	<pre>pip install 'apache-airflow[async]'</pre>	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	<pre>pip install 'apache-airflow[devel_hadoop]'</pre>	Airflow + dependenci
druid	pip install 'apache-airflow[druid]'	Druid related operato
gcp	<pre>pip install 'apache-airflow[gcp]'</pre>	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

pip install 'apache-airflow[kubernetes]'	Kubernetes Executor
<pre>pip install 'apache-airflow[ldap]'</pre>	LDAP authentication
pip install 'apache-airflow[mssql]'	Microsoft SQL Server
<pre>pip install 'apache-airflow[mysql]'</pre>	MySQL operators and
pip install 'apache-airflow[oracle]'	Oracle hooks and ope
<pre>pip install 'apache-airflow[password]'</pre>	Password authentica
pip install 'apache-airflow[postgres]'	PostgreSQL operator
<pre>pip install 'apache-airflow[qds]'</pre>	Enable QDS (Qubole
<pre>pip install 'apache-airflow[rabbitmq]'</pre>	RabbitMQ support as
<pre>pip install 'apache-airflow[redis]'</pre>	Redis hooks and sens
pip install 'apache-airflow[s3]'	S3KeySensor , S3Prefi
<pre>pip install apache-airflow[samba]'</pre>	airflow.operators.hiv
pip install 'apache-airflow[slack']	airflow.operators.sla
<pre>pip install 'apache-airflow[ssh]'</pre>	SSH hooks and Opera
pip install 'apache-airflow[vertica]'	Vertica hook support
	pip install 'apache-airflow[ldap]' pip install 'apache-airflow[mssql]' pip install 'apache-airflow[mysql]' pip install 'apache-airflow[oracle]' pip install 'apache-airflow[password]' pip install 'apache-airflow[postgres]' pip install 'apache-airflow[rabbitmq]' pip install 'apache-airflow[redis]' pip install 'apache-airflow[s3]' pip install apache-airflow[samba]' pip install 'apache-airflow[slack'] pip install 'apache-airflow[slack']

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

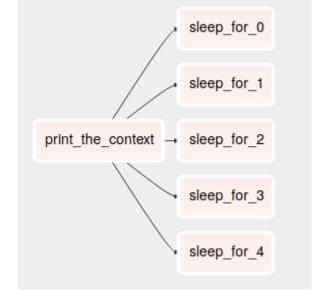
operators

```
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:

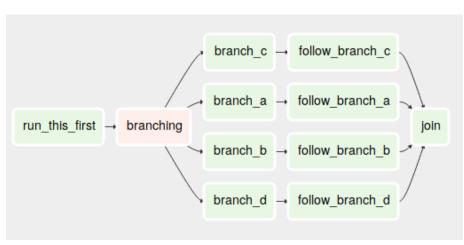
DAG: example_python_operator

schedule: None





Example of branching



Code and figures captured from Airflow UI DAG: example_branch_operator

schedule: @daily

```
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,
```



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

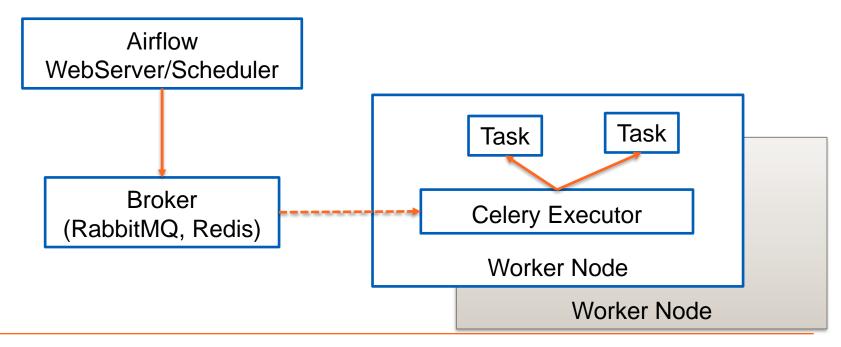
Different states

```
success running failed skipped up_for_reschedule up_for_retry queued no_status
```

- 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

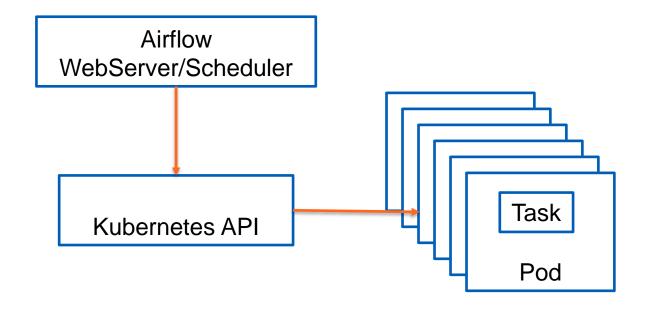
You can scale Airflow using workers deployed in different nodes managed by Celery (http://www.celeryproject.org)





Distributed tasks

You can scale Airflow to run tasks in Kubernetes

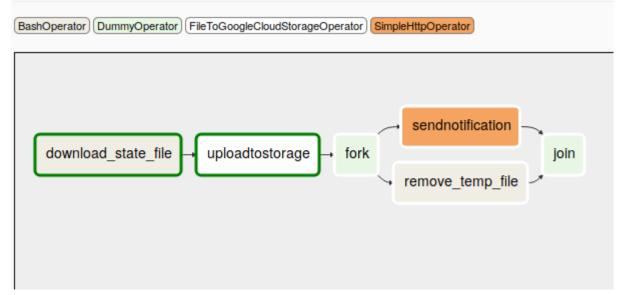


Google Cloud Composer: use Kubernetes



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

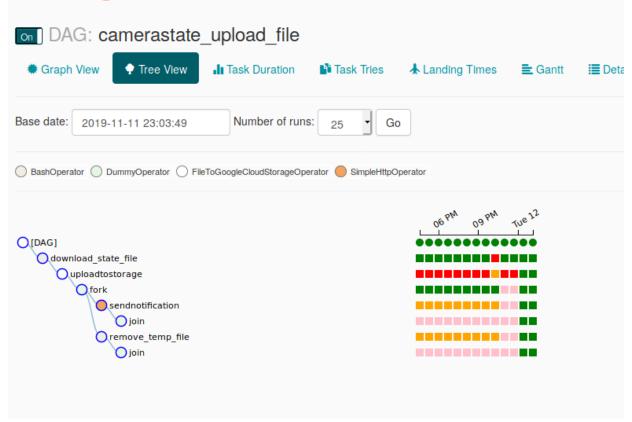
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Ø	Off	example_pig_operator	None	Airflow				⊙♥ ₩₼₽ ★≘∮≣♡⊗
Ø	Off	example_python_operator	None	Airflow				⊙♥ ₩₼₽ ★≘∮≣♡⊗
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Ø	Off	example_skip_dag	1 day, 0:00:00	Airflow				⊙♥ ₩₼₽ ★≘∮≣♡⊗
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Monitoring 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

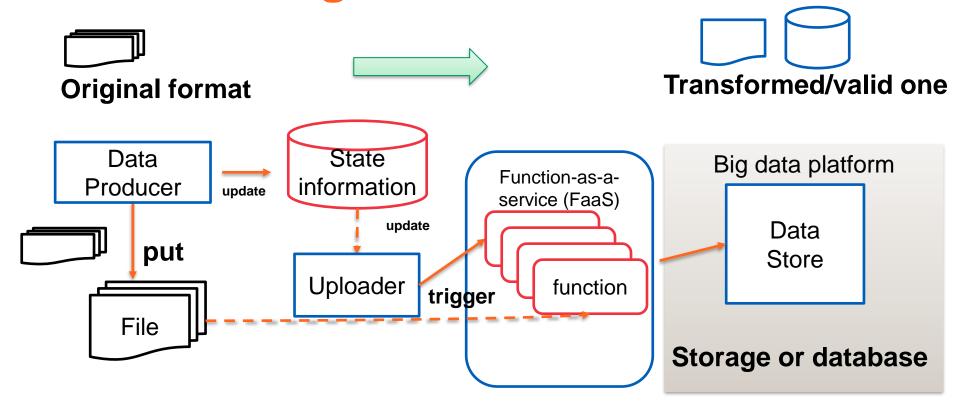
Azure

- Azure Function for tasks
- Azure durable functions (https://docs.microsoft.com/en-us/azure-functions/durable-functions-durable-functions-durable-functions
 orchestrations

Amazon Web services

- AWS Lambda for tasks/functions
- AWS Step Functions (https://aws.amazon.com/step-functions/)

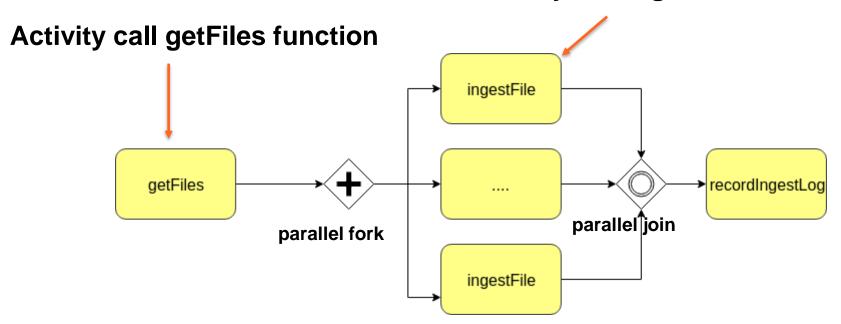
Recall: data ingestion





Example of Azure durable functions

Activity call ingestFile function





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
 - Function-as-a-service: for service integration
 - 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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