

Table of Contents

[Table of Contents](#)

[Introduction](#)

[Release Notes](#)

[Installation](#)

[Installing workflow orchestrator \(with Internet\)](#)

[Installing workflow orchestrator \(without Internet\)](#)

[Getting Started](#)

[Spark Configurations and Dependencies](#)

[Hadoop Configurations](#)

[Kerberos Configurations](#)

[LDAP Configurations](#)

[Livy Configuration](#)

[Git Configuration](#)

[Code Artifacts](#)

[What is DAG?](#)

[Creating a DAG](#)

[Importing Modules](#)

[Default Arguments](#)

[Instantiate a DAG](#)

[Tasks](#)

[Setting up Dependencies](#)

[Adding a new DAG](#)

[Edit DAG code](#)

[Code Bricks](#)

[Run DAG](#)

[Master DAG](#)

[Importing Modules:](#)

[Linking DAGs](#)

[Conditionally trigger DAGs](#)

[Zoom into DAG](#)

[Import/Export Hadoop/Spark Configurations, Spark Dependencies, DAGS](#)

[Operators](#)

[BashOperator](#)

[PythonOperator](#)

[SparkOperator](#)

[CoutureSparkOperator](#)

[CoutureDaskYarnOperator](#)

[PySparkOperator](#)

[CouturePySparkOperator](#)

[TensorflowOperator](#)

[CoutureTensorflowOperator](#)

CoutureJupyterOperator

User Interface

- View DAGs
- Tree View
- Graph View
- Variable View
- Gantt Chart
- Task Duration
- Code View
- Task Instance Context Menu

Users

- Role Based Access Control
- User creation

Access Audit Logging

Jupyter Notebook

- Kernels supported by JupyterHub

DAG Runs

Trained Models

- Default Behavior of different Models

Exploratory Data Analysis

- Steps to perform EDA

Visualisations

Connections

Variables and XComs

- XComs
- Variables

SLAs

Introduction

Workflow Orchestrator is a platform to programmatically author, schedule, and monitor workflows.

When workflows are defined as code, they become more maintainable, versionable, testable, and collaborative.

Use this orchestrator to author workflows as directed acyclic graphs (DAGs) of tasks. The orchestrator scheduler executes your tasks on an array of workers while following the specified dependencies. Basically, it helps to automate scripts in order to perform tasks.

The rich user interface makes it easy to visualize pipelines running in production, monitor progress, and troubleshoot issues when needed.

Release Notes

- Base Airflow Version: 1.10.10.
- Support for LDAP Authentication and DB Authentication.
- Support for Configuration Groups .
- Support for Spark & Hadoop Clusters.
- Support for Jupyterhub & submitting Spark Jobs from Jupyterhub using Livy.
- Support for Tensorflow Serving.

Installation

Prerequisites : Docker and Docker-compose should be installed.

Installing workflow orchestrator (with Internet)

- **Fetching the dependencies:**
 - Get the docker-compose.yml file from shared artifacts.
- **Running orchestrator:**
 - Go to the directory where docker-compose.yml file is located.
 - Run the following command:
 - `sudo COUTURE_WORKFLOW_USER=<your name> docker-compose up -d worker`

Installing workflow orchestrator (without Internet)

- Configuring to access private docker registry:
- Add the following entry to /etc/hosts : 10.144.97.22 CR1
- Change /etc/docker/daemon.json file to add the following properties:

```
{  
  "insecure-registries" : ["CR1:5005"]  
}
```

If /etc/docker/daemon.json is not present, create and add the configuration assuming there are no other settings.

- Restart the docker daemon after updating the configurations:

```
sudo systemctl restart docker
```

- Fetching the dependencies:

Run the following commands to pull the images from private registry:

```
docker pull CR1:5005/rabbitmq:3.7-management
```

```
docker pull CR1:5005/mysql:5.7
```

```
docker pull CR1:5005/couture-workflow:1.0
```

- Tag the images

```
docker tag CR1:5005/rabbitmq:3.7-management rabbitmq:3.7-management
```

```
docker tag CR1:5005/mysql:5.7 mysql:5.7
```

```
docker tag CR1:5005/couture-workflow:1.0 couture-workflow
```

- Fetching the dependencies:

- Get the docker-compose.yml file from shared artifacts.

- Running orchestrator:

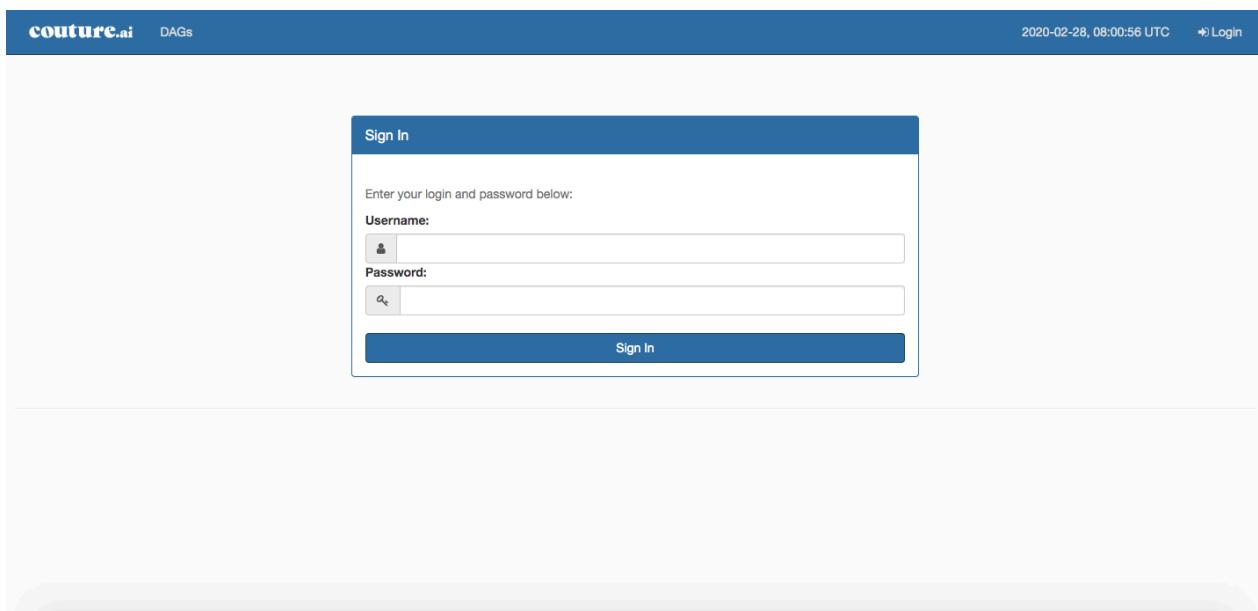
- Go to the directory where docker-compose.yml file is located.

- Run the following command:

- sudo COUTURE_WORKFLOW_USER=<your name> docker-compose up -d worker

- Note that COUTURE_WORKFLOW_USER is optional and can be used to have personalized dags view.

Go to <http://<HOST>:8080> to start the orchestrator, where <HOST> refers to the hostname of the server. For example, <http://localhost:8080>.



NOTE: RBAC (Role based access control) is used to provide security. Workflow is shipped with a user `superadmin` whose password is `couture@123`.

One can change the password by going to top right corner of Navigation bar, then clicking on :

Super Admin -> Reset my password -> Save.

Getting Started

Login as an admin user and configure spark and hadoop configurations as follows.

Spark Configurations and Dependencies

Easily configure spark jobs by providing options through orchestrator using below steps:

1. In the top navigation bar, go to Admin -> Spark Configuration.

The screenshot shows the 'couture.ai' web interface with the 'Admin' tab selected. The main content area is titled 'Configurations'. On the left, there's a section for 'Arguments' with fields for 'master' (set to 'local[1]'), 'jars' (with a placeholder 'Click to select jar files'), and 'py-files' (with a placeholder 'Click to select python files'). A dropdown menu is open over the 'py-files' field, listing options such as 'Spark Configuration', 'Hadoop Configuration', 'Spark Dependencies', etc. At the bottom right of the configuration section is a green button labeled 'Add In Arguments'. Below the configuration section, there's another section titled 'Configurations' with fields for 'spark.scheduler.mode' (set to 'FAIR'), 'spark.pyspark.python' (set to '/usr/local/bin/python'), 'spark.dynamicAllocation.enabled' (set to 'true'), and 'spark.shuffle.service.enabled' (set to 'true'). A URL 'localhost:8080/couture_config/executors' is visible at the bottom left.

2. Update existing arguments/configurations or add new ones by clicking on Add in buttons. Existing options can be deleted by clicking on delete option, next to the option.
3. Available jars to include on the driver and executor classpaths are listed under jars option. Similarly, available list of .zip, .egg, or .py files to place on the PYTHONPATH for Python apps are listed under py-files. To upload/delete these jars or python files, visit, Admin -> Spark Dependencies. Upon uploading new jars/python files under Spark Dependencies, the same will be added to respective dropdown here.

Note: New changes gets automatically picked up for all the NEWLY triggered spark jobs.

4. For pyspark jobs, to set python for the cluster (executors), in case python environment is required, configuration `spark.yarn.appMasterEnv.PYSPARK_PYTHON` can be added under Spark Configuration tab and same can be referred in individual workflow task by using `python_conf` attribute.

Hadoop Configurations

Configurations files required for runtime environment settings of a hadoop cluster can be easily configured with the help of Hadoop Configuration Groups through orchestrator using below steps:

In the top navigation bar, go to Admin -> Hadoop Configuration.

The screenshot shows the 'Hadoop Configuration Groups' page. A context menu is open over the row for 'JioLib'. The menu items are: Configurations, Spark Configuration, Hadoop Configuration, Spark Dependencies, LDAP Configuration, Kerberos Configuration, Connections, Pools, Variables, and XComs. At the bottom right of the menu is a 'Delete' button with the message 'Can't delete default group.' To the right of the menu, there are 'Open default Group' and 'Add a group' buttons.

1. When you are running Workflow for the first time, there will not be any config groups. However, you can create a config group by clicking on Add a group button.

The screenshot shows the 'Add a group' dialog box. It has a 'Group name' input field with the placeholder 'Group name' and a note below it: 'A group name can only contain A-Z, a-z, _, -, 0-9'. Below the input field are 'Close' and 'Add' buttons. In the background, the main 'Hadoop Configuration Groups' page is visible, showing the 'JioLib' group with its status as 'Default group'.

2. Once, you have successfully added the first group, it will be made as the default group. In the groups list, you can click on a group to see its configuration files.

Hadoop Configuration Groups - JioLib

[Upload file\(s\)](#)

Search file: filename

Filename	Last modified	Size	Links
core-site.xml	Feb 25 13:53:17 2020	383.0 B	
core-site (2).xml	Feb 25 13:53:17 2020	1021.0 B	

3. New hadoop conf files can be added to that group using **Upload file(s)** option. Please note that only XML files are allowed.
4. The configurations within a file can be updated by clicking on the respective file name.

Configuration

fs.defaultFS	hdfs://master:9000	
hadoop.tmp.dir	/data/HadoopData	
h3	h4	
hello4	world4	

[Submit All Changes](#)

[Add In Configurations](#)

Kerberos Configurations

Configurations for kerberos enabled hadoop clusters can be done by following the below steps:

1. In the top navigation bar, go to Admin -> Kerberos Configuration.
2. Upload the keytab file from Upload Keytab File option. These configurations, if added, are automatically applied to the spark jobs.

couture.ai DAGs Security Browse Developer Admin About 2020-02-28, 08:31:24 UTC ad min

principal Delete

Submit

LDAP Configurations

Configurations required for ldap can be done by following the below steps:

1. In the top navigation bar, go to Admin ->Ldap Configuration.

couture.ai DAGs Security Browse Developer Admin About 2020-02-28, 09:16:33 UTC ad min

AUTH_TYPE	<input type="text"/>	Configurations Spark Configuration Hadoop Configuration Spark Dependencies LDAP Configuration Kerberos Configuration Connections Pools Variables XComs
AUTH_LDAP_SERVER	<input type="text" value="ldap://localhost:10389"/>	
AUTH_ROLE_PUBLIC	<input type="text" value="Public"/>	
AUTH_USER_REGISTRATION	<input type="text" value="True"/>	
AUTH_USER_REGISTRATION_ROLE	<input type="text" value="Admin"/>	
AUTH_LDAP_BIND_USER	<input type="text" value="cn=test,ou=users,dc=example,dc=com"/>	
AUTH_LDAP_BIND_PASSWORD	<input type="text" value="test"/>	
AUTH_LDAP_SEARCH	<input type="text" value="dc=example,dc=com"/>	
AUTH_LDAP_UID_FIELD	<input type="text" value="uid"/>	
localhost:8080/ldap LDAP_ALLOW_SELF_SIGNED	<input type="text" value="True"/>	

Note: For configuration changes to reflect, run "docker-compose down" and restart the containers again.

Config	Description
AUTH_TYPE	Set to AUTH_LDAP. This overrides the default setting, which is to use the MySQL database for authentication. Henceforth, only LDAP users will be able to login to workflow.
AUTH_LDAP_SERVER	The address of the LDAP server, for example <code>ldap://<ip_address></code> , or <code>ldaps://<ip_address></code> to connect to a secure LDAP server. If a secure LDAP server is used, the <code>AUTH_LDAP_USE_TLS</code> property must be set to false.

AUTH_LDAP_SEARCH	The base dn that will be used when searching for a user, for example: ou=Users,dc=local,dc=company,dc=com
AUTH_LDAP_UID_FIELD	The name of the field that contains the username value. The domain name is not included in this field. For example, sAMAccountName.
AUTH_LDAP_BIND_USER	A generic search account to be used when searching for a user in a bind request, For example: cn=Search User,ou=Users,dc=local,dc=company,dc=com
AUTH_LDAP_BIND_PASSWORD	A generic password to supply in a bind request, For example: SearchPassword1
AUTH_LDAP_ALLOW_SELF_SIGNED	Set this to True to allow self-signed signatures to be used with TLS.
AUTH_LDAP_GROUP_SEARCH	The base dn that will be used when searching for a group, For example, ou=Groups,dc=local,dc=company,dc=com
AUTH_LDAP_USE_TLS	Set this to True to use Transport Layer Security. If this is set to True then the AUTH_LDAP_SERVER address must be of a standard LDAPserver rather than a secure LDAP server.
AUTH_LDAP_FIRSTNAME_FIELD	Default to givenName will use MSFT AD attribute to register first_name on the db.
AUTH_LDAP_EMAIL_FIELD	Default to mail will use MSFT AD attribute to register email on the db. If this attribute is null
AUTH_LDAP_LASTTNAME_FIELD	Default to sn will use MSFT AD attribute to register last_name on the db.
AUTH_USER_REGISTRATION	Set to True to enable user self registration.
AUTH_USER_REGISTRATION_ROLE	Set role name, to be assign when a user registers himself. This role must already exist. Mandatory when using user registration.
AUTH_LDAP_TLS_DEMAND	Demands TLS peer certificate checking (Bool)
AUTH_LDAP_SEARCH_FILTER	Filter or limit allowable users from the LDAP server, e.g., only the people on your team. AUTH_LDAP_SEARCH_FILTER = (memberOf=cn=group_name,OU=type,dc=ex,dc=com)
AUTH_LDAP_APPEND_DOMAIN	Append a domain to all logins. No need to use john@domain.local. Set it like: AUTH_LDAP_APPEND_DOMAIN = domain.local And the user can login using just john.
AUTH_LDAP_USERNAME_FORMAT	It converts username to specific format for LDAP authentications. For example, when username = userexample & AUTH_LDAP_USERNAME_FORMAT=format-%s, It authenticates with format-userexample.
AUTH_LDAP_TLS_CACERTDIR	CA Certificate directory to check peer certificate.
AUTH_LDAP_TLS_CACERTFILE	CA Certificate file to check peer certificate.
AUTH_LDAP_TLS_CERTFILE	Certificate file for client auth use with AUTH_LDAP_TLS_KEYFILE
AUTH_LDAP_TLS_KEYFILE	Certificate key file for client auth.

Livy Configuration

Livy enables programmatic, fault-tolerant, multi-tenant submission of Spark jobs from web/mobile apps. To configure default endpoints of sparkmagic kernels present in Jupyterhub, Admin will have to configure Livy Endpoints. To configure Livy from the UI, go to (Admin->Livy Configuration).

Livy Configuration View

Set your Livy configuration for Remote Spark Access in Jupyter Notebooks here.

kernel_python_credentials

username

password

url

auth
None

kernel_scala_credentials

username

password

Save Changes

Git Configuration

Developers can configure Workflow Orchestrator to connect their JupyterHub files to a remote repository and perform common git operators such as committing files, pushing to remote repository, viewing logs etc.

To connect the remote repository, from the UI, go to (Developer -> Git Configuration) and enter the details.

Git Configuration View

Set your Git configuration for various sources (Jupyter Notebook etc..) here.

JupyterNotebook

Origin

Username

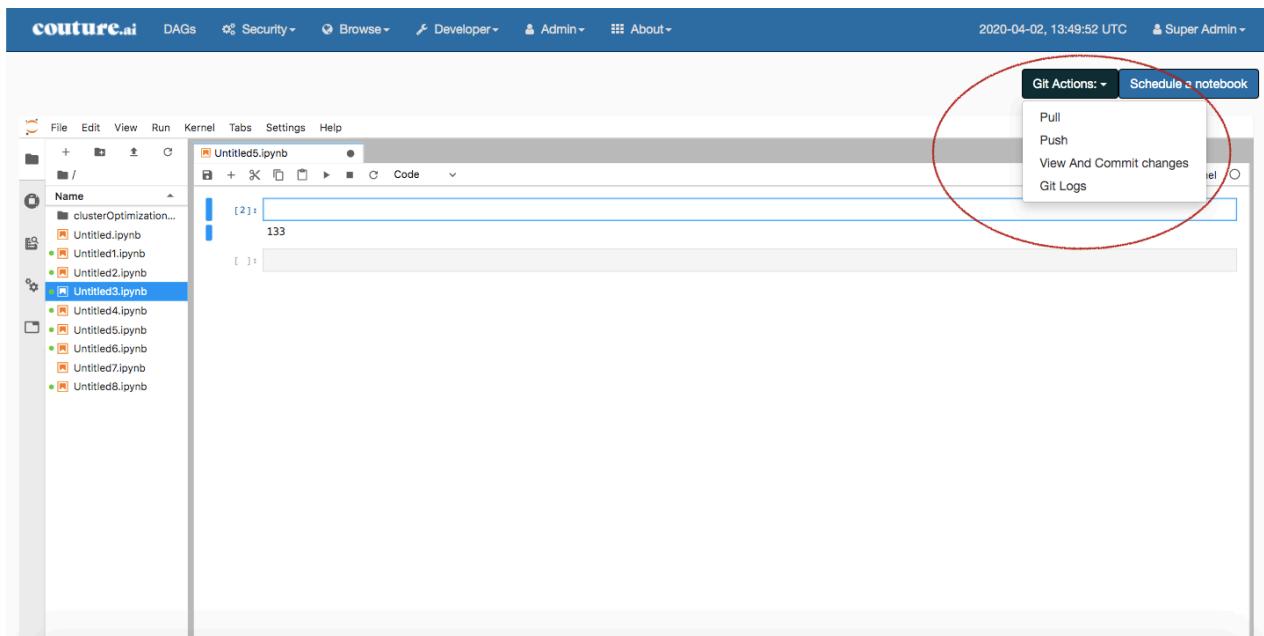
Password

Branch

Save Changes

100.27.1.214:8080/git-configs#

After saving the files, they can execute common git actions via the Git Actions button in (Developer->Jupyter Notebook) View.



Code Artifacts

To upload artifacts i.e. either your jar code for spark jobs or python files for py-spark jobs.

1. In the top navigation bar, go to Developer ->Code Artifacts.

The screenshot shows the 'Code Artifacts' page under the 'Developer' tab. The top navigation bar includes links for DAGs, Security, Browse, Developer (selected), Admin, and About. The date '2020-02-28, 09:20:44 UTC' and user 'ad min' are also present. The main content area has a title 'Code Artifacts' and a search bar labeled 'Search file: filename'. A dropdown menu is open over the search bar, listing 'Manage DAG', 'Code Artifacts' (which is highlighted in blue), 'Jupyter Notebook', 'Exploratory data analysis', and 'Visualisations'. To the right of the search bar is a green 'Upload file(s)' button. Below the search bar is a table with one row, showing a file named '1.py' with a last modified date of 'Feb 6 17:14:00 2020', a size of '1.71 KB', and two icons in the 'Links' column (a cloud icon and a trash bin icon). The URL 'localhost:8080/CodeArtifactView/list/' is visible at the bottom of the page.

The artifacts can be referred in your dag while creating tasks under `code_artifact` attribute as shown below:

```

Get_Ratings_History = CouturePySparkOperator(
    task_id='Get_Ratings_History',
    app_name=appName,
    code_artifact='PySpark.py',
    application_arguments=[],
    dag=dag,
    description='Get ratings history'
)

```

What is DAG?

In mathematics and computer science, a directed acyclic graph, is a finite directed graph with no directed cycles. That is, it consists of finitely many vertices and edges, with each edge directed from one vertex to another, such that there is no way to start at any vertex v and follow a consistently-directed sequence of edges that eventually loops back to v again. Equivalently, a DAG is a directed graph that has a topological ordering, a sequence of the vertices such that every edge is directed from earlier to later in the sequence.

DAG's are composed of tasks which are created by instantiating an **operator** class.

There are different types of operators available.

Example:

```

from datetime import datetime, timedelta

from airflow import DAG
from airflow.operators import CouturePySparkOperator

appName = 'FunWithPySpark'

default_args = {
    'owner': 'couture',
    'depends_on_past': False,
    'start_date': datetime(2018, 10, 8),
    'retries': 1,
    'retry_delay': timedelta(minutes=5),
}

schedule = None
dag = DAG('PySpark', default_args=default_args, catchup=False,
          schedule_interval=schedule)

Get_Ratings_Data = CouturePySparkOperator(
    task_id='Get_Ratings_Data',
    app_name=appName,
    code_artifact='Ratings.py',
    application_arguments=[],
    dag=dag,
)

```

```

        description='Dump ratings data in hdfs'
    )

Get_Ratings_History = CouturePySparkOperator(
    task_id='Get_Ratings_History',
    app_name=appName,
    code_artifact='History.py',
    application_arguments=[],
    dag=dag,
    description='Get ratings history'
)

Get_Ratings_Data >> Get_Ratings_History

```

Creating a DAG

Importing Modules

An orchestrator pipeline is just a Python script that happens to define a DAG object. Let's start by importing the libraries we will need.

```

# The DAG object; we'll need this to instantiate a DAG
from airflow import DAG
# Operators; we need this to operate!
from airflow.operators.bash_operator import BashOperator

```

To create spark and pyspark jobs, import operators CoutureSparkOperator and CouturePySparkOperator respectively.

```
from airflow.operators import CoutureSparkOperator
```

Default Arguments

We're about to create a DAG and some tasks, and we have the choice to explicitly pass a set of arguments to each task's constructor (which would become redundant), or (better!) we can define a dictionary of default parameters that we can use when creating tasks.

```

from datetime import datetime, timedelta
default_args = {
    'owner': 'couture',
    'depends_on_past': False,
    'start_date': datetime(2015, 6, 1),
    'email': ['couture@example.com'],
    'email_on_failure': False,
    'email_on_retry': False,
    'retries': 1
}

```

- `start_date` tells since when this DAG should start executing the workflow. This `start_date` could be a day which has already passed.
- The `retries` parameter retries to run the DAG X number of times in case of not executing successfully.

Note: You could easily define different sets of arguments that would serve different purposes. An example of that would be to have different settings for production and development environment.

Instantiate a DAG

We'll need a DAG object to nest our tasks into. Here we pass a string that defines the `dag_id`, which serves as a unique identifier for your DAG. We also pass the default argument dictionary that we just defined and define a `schedule_interval` of 1 day for the DAG.

```

dag = DAG('dag',
          default_args=default_args,
          schedule_interval=timedelta(days=1))

```

Workflow consists of a `scheduler` which is monitoring process that runs all the time and triggers task execution based on `schedule_interval` and `execution_date`.

Tasks

Tasks are generated when instantiating operator objects. An object instantiated from an operator is called a constructor. The first argument `task_id` acts as a unique identifier for the task.

Task description describing its functionality can be added using `description` attribute.

```
t1 = BashOperator(  
    task_id = 'print_date',  
    bash_command = 'date',  
    dag = dag,  
    description = 'Print Date')
```

```
operator_task = CoutureSparkOperator(  
    task_id = 'operator_task',  
    dag = dag,  
    app_name = 'Couture',  
    class_path = 'ai.couture.MainClass',  
    code_artifact = 'couture.jar',  
    application_arguments = ['inputData', '/outputData'],  
    description = ''  
)
```

Setting up Dependencies

We have tasks t_1 , t_2 and t_3 that do not depend on each other. Here's a few ways you can define dependencies between them:

```
t1.set_downstream(t2)  
# This means that t2 will depend on t1  
# running successfully to run.  
  
# It is equivalent to:  
t2.set_upstream(t1)  
  
# The bit shift operator can also be  
# used to chain operations:  
t1 >> t2  
  
# And the upstream dependency with the  
# bit shift operator:  
t2 << t1  
  
# Chaining multiple dependencies becomes  
# concise with the bit shift operator:  
t1 >> t2 >> t3  
  
# A list of tasks can also be set as  
# dependencies. These operations  
# all have the same effect:  
t1.set_downstream([t2, t3])
```

```
t1 >> [t2, t3]
[t2, t3] << t1
```

Note: that when executing your *script*, orchestrator will raise exceptions when it finds cycles in your DAG or when a dependency is referenced more than once.

Adding a new DAG

After creating a `<dag>.py` file on your local machine, add the new dag to server using below steps:

- In the top navigation bar, go to Developer -> Manage DAGs.
- Click on Upload DAG file(s) and select `<dag>.py` file.

For creating a new `<dag>.py` file directly on the server, follow the below steps:

- In the top navigation bar, go to Developer -> Manage DAGs.
 - Click on Create New Dag and fill in the Name of the dag. Then click Add. You will be redirected to Edit DAG page. Note that DAG will only be created once you save the DAG content in Edit DAG Code page.

Note: Only `*.py` format is supported.

Filename	Last modified	Size	Links
_ClickStreamETL.py	Feb 27 15:49:20 2020	176.0 B	
ClickStreamETL.py	Feb 27 15:49:20 2020	12.47 KB	
DagOperator.py	Feb 26 17:39:06 2020	454.0 B	
ExampleJupyterDag.py	Feb 26 17:39:06 2020	1.12 KB	

Edit DAG code

If you have an existing dag added to the orchestrator, you can edit the same using below steps:

- In the top navigation bar, go to Developer -> Manage DAGs
- Search your dag from the search bar and click on it.

- Make the necessary changes, Click on Review & Save button. You will be shown you changes, which you can revert if you are unhappy with them. Click on Save Code to finally save the dag.
- One can review the new changes before saving.

```

couture.ai DAGs Security Browse Developer Admin About ad min

DagOperator.py

Edit Code Review & Save

1 # flake8: noqa
2 from datetime import datetime, timedelta
3 from airflow import DAG
4 from airflow.operators.dag_operator import DagOperator
5
6
7
8 args = {
9     'owner': 'couture',
10    'start_date': datetime(2019, 4, 15),
11    'depends_on_past': False,
12 }
13
14 schedule = None
15 dag = DAG('DAGOperatorEx', default_args=args, schedule_interval=schedule)
16 CheckFeatures = DagOperator(
17     task_id='JupyterDAG2',
18     dag=dag,
19     run_dag_id='JupyterDAG'
20 )
21

```

```

couture.ai DAGs Security Browse Developer Admin About ad min

Review Changes Back to edit mode Save Code

13 (...)
14 schedule = None
15 dag = DAG('DAGOperatorExample', default_args=args, schedule_interval=schedule)
16 CheckFeatures = DagOperator(
17     task_id='JupyterDAG2',
18     (...)

13 (...)
14 schedule = None
15 dag = DAG('DAGOperatorEx', default_args=args, schedule_interval=schedule)
16 CheckFeatures = DagOperator(
17     task_id='JupyterDAG2',
18     (...)


```

Code Bricks

Dags can be added/edited by visiting, Developer -> Manage DAGs.

- Existing code bricks (code snippets) can be added to the dags, by visiting the Code Bricks repository and inserting the required code.
- New snippets can also be added by Add a new code brick option. Please note the title entered here, appears in the list.

The screenshot shows the couture.ai web application. On the left, there is a code editor titled "Edit Code" containing Python code for defining a DAG. On the right, there is a panel titled "Obelisk Code Bricks" which lists various pre-built components or bricks. A red box highlights this panel.

```

from datetime import datetime, timedelta
from airflow import DAG
from airflow.operators import CoutureSparkOperator, CouturePySparkOperator, CoutureDaskYarnOperator
from airflow.operators.dag_operator import SkippableDagOperator, DagOperator
from airflow.operators.dagrun_operator import TriggerDagRunOperator
from airflow.operators.dummy_operator import DummyOperator
from airflow.example_dags.subdags.subdag import subdag
from airflow.operators.subdag_operator import SubDagOperator
app_name = 'CoutureExample'
# args = {
#     'owner': 'couture',
#     'start_date': datetime(2019, 4, 15),
#     'depends_on_past': False,
# }
# schedule = None
# dag = DAG('CoutureExample', default_args=args, schedule_interval=schedule)
# CheckFeatures = CoutureSparkOperator(
#     task_id='CheckFeatures',
#     app_name=app_name,
#     class_path='org.apache.spark.examples.SparkPi',
#     code_artifacts='spark-examples_2.11-2.3.1.jar',
#     application_arguments=[],
#     dag=dag,
#     description=''
# )
# 
```

Obelisk Code Bricks

- compute similarity based on attributes
- compute similarity based on feature vectors
- run spark pi example
- write data from hbase to hdfs
- write data from hdfs to hbase
- write data from oracle to hdfs
- generate buckets from a numerical feature
- filter coherent sessions from UPI
- filter intent driven interactions from UPI
- generate latent features for items
- compute similarity based on latent features
- determine interacted bricks for each user

Add a new code brick

Run DAG

The **Scheduler** is responsible at what time DAG should be triggered. By default all the dags are paused to be scheduled.

Also, please note that all the paused dags are hidden by default. To un-pause the dag, click on the Show Paused DAGs and switch ON the required dag.

The screenshot shows the "couture - DAGs" page. It displays a table of DAGs with columns for DAG name, Schedule, Owner, Recent Tasks, Last Run, DAG Runs, and Links. Four DAGs are listed: dag_1, dag_2, dag_3, and master_dag. Each row has a "Paused" button (indicated by a red arrow 1) and a "Trigger Dag" button (indicated by a red arrow 2). Red arrow 3 points to the "Graph View" link in the "Links" column for the master_dag row. A message at the bottom says "Showing 1 to 4 of 4 entries".

DAG	Schedule	Owner	Recent Tasks	Last Run	DAG Runs	Links
dag_1	None	couture	1	2019-10-15 14:50	1	Graph View
dag_2	None	couture	1	2019-10-15 14:50	1	Graph View
dag_3	None	couture	1	2019-10-15 14:51	1	Graph View
master_dag	None	couture	1	2019-10-15 14:50	1	Graph View

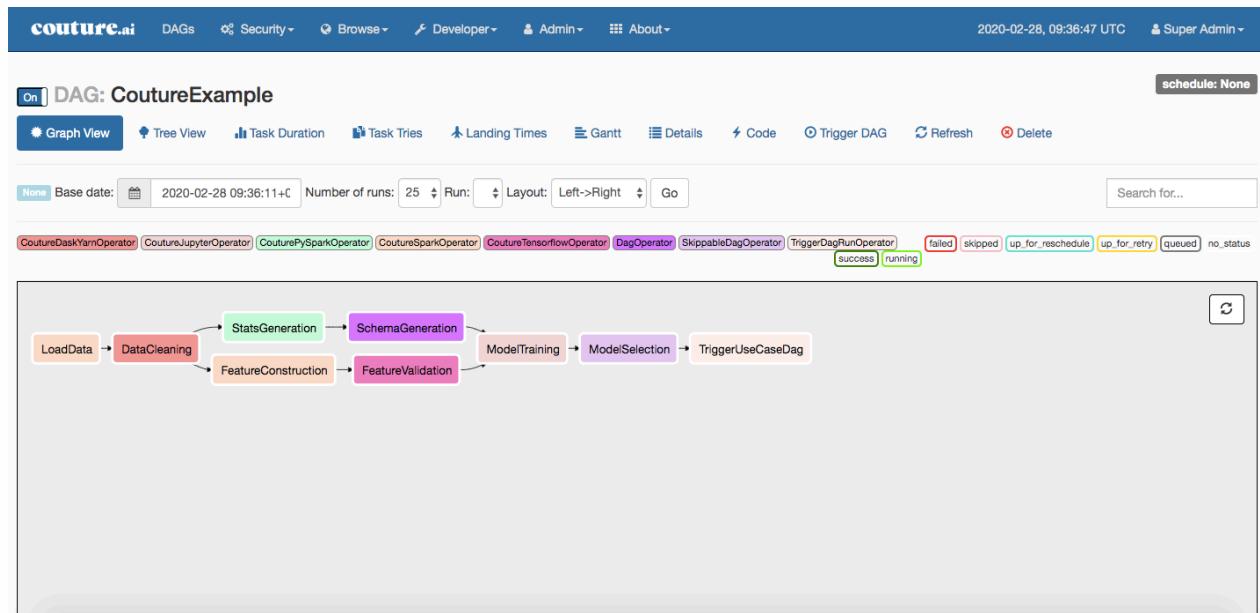
Show Paused DAGs

In order to start a DAG Run, first turn the dag **ON** (arrow 1), then click the **Trigger Dag** button (arrow 2) and finally, click on the **Graph View** (arrow 3) to see the progress of the run.

The graph view can be reloaded until all the tasks reach the status **Success**. You can also click on a task and then click **View Log** to see the log of task instance run.

Master DAG

An *end-to-end* pipeline can be designed by creating **master dag**, i.e. DAG of dags.



Importing Modules:

Let's start by importing the libraries we will need.

```
from airflow.operators.dag_operator import DagOperator
```

Linking DAGs

An object should be instantiated from `DagOperator`. The first argument `task_id` acts as a unique identifier for the task.

```
schema_generation = DagOperator(  
    task_id='SchemaGeneration',  
    run_dag_id="ExampleSchemaGeneration",  
    python_callable=conditionally_trigger,  
    params={'condition_param': True, 'message': 'Hii there!!'},  
    dag=dag,  
)
```

Conditionally trigger DAGs

A condition can be set as to whether or not to trigger the remote DAG, by defining a `python` function as below.

```

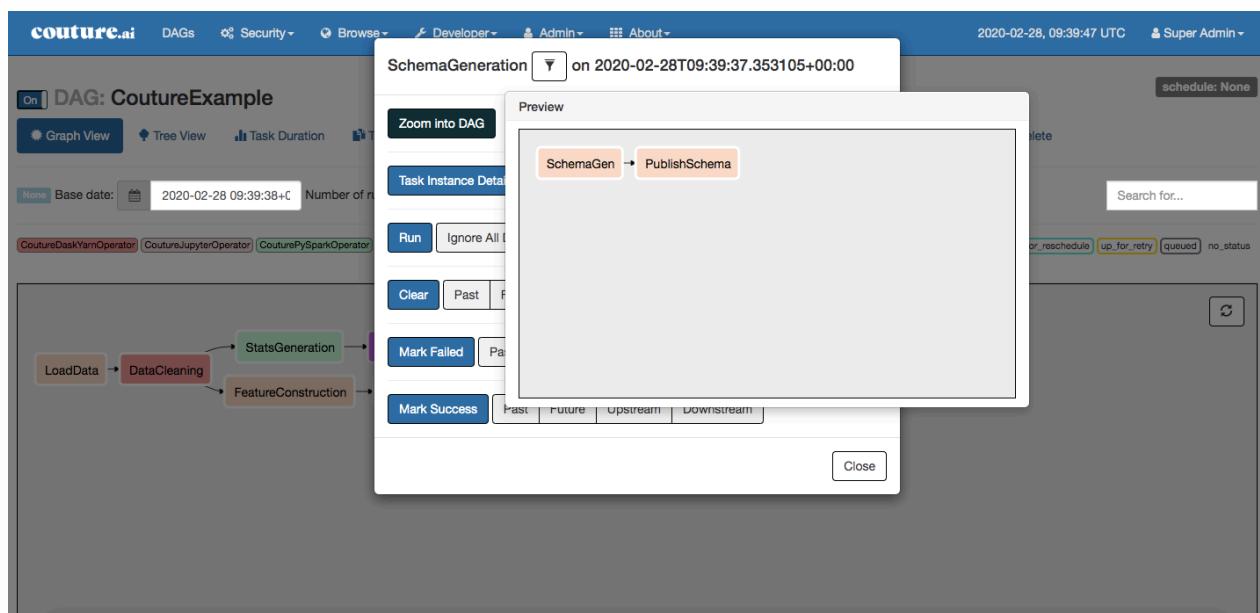
def conditionally_trigger(context, dag_run_obj):
    """This function decides whether or not to Trigger the remote DAG"""
    if context['params']['condition_param']:
        dag_run_obj.payload = {'message': context['params']['message']}
        return dag_run_obj

```

Note: All the dags which are part of master dag, should be ON.

Zoom into DAG

The dags which are part of master dag, can be visited by clicking on them and then clicking on Zoom into DAG. Their preview can be seen by hovering on the button Zoom into DAG .



Import/Export Hadoop/Spark Configurations, Spark Dependencies, DAGS

Workflow provides API to directly import/export various configurations, DAGS etc. How to use such APIs is listed below.

- Import/Export Hadoop/Spark Configurations

We can import and export our hadoop configuration groups, and our spark configurations using curl commands via an API:

- To export configs:

```
curl --location --request POST 'http://<server-ip>:8080/api/configs/' \
--header 'Content-Type: multipart/form-data' \
--form 'sources=@/path/to/configs.tar.gz'
```

- To import configs to server:

```
curl --location --request POST 'http://<server-ip>:8080/api/configs/' \
--header 'Content-Type: multipart/form-data' \
--form 'sources=@/path/to/configs.tar.gz'
```

- Import/Export Spark Dependencies

- To export dependencies:

```
curl --location --request GET 'http://<server-ip>:8080/api/dependencies/' > dependencies.tar.gz
```

- To import dependencies to server:

```
curl --location --request POST 'http://<server-ip>:8080/api/dependencies/' \
--header 'Content-Type: multipart/form-data' \
--form 'sources=@/path/to/dependencies.tar.gz'
```

- Import/Export DAGS

- To export DAGS:

```
curl --location --request GET 'http://<server-ip>:8080/api/dags/' > dags.tar.gz
```

- To import DAGS:

```
curl --location --request POST 'http://<server-ip>:8080/api/dags/' \
--header 'Content-Type: multipart/form-data' \
--form 'sources=@/path/to/dags.tar.gz'
```

Operators

While DAGs describe how to run a workflow, Operators determine what actually gets done by a task.

An operator describes a single task in a workflow. Operators are usually (but not always) atomic, meaning they can stand on their own and don't need to share resources with any other operators. The DAG will make sure that operators run in the correct order; other than those dependencies, operators generally run independently. In fact, they may run on two completely different machines.

Workflow provides operators for many common tasks, including:

BashOperator

Use the BashOperator to execute commands in a Bash shell.

```
from airflow.operators.bash_operator import BashOperator

run_this = BashOperator(
    task_id='run_after_loop',
    bash_command='echo 1',
    dag=dag,
)
```

PythonOperator

Use the PythonOperator to execute Python callables.

```
def print_context(ds, **kwargs):
    pprint(kwargs)
    print(ds)
    return 'Whatever you return gets printed in the logs'
```

```
run_this = PythonOperator(
    task_id='print_the_context',
    provide_context=True,
    python_callable=print_context,
    dag=dag,
)
```

SparkOperator

Use SparkOperator to create and submit a spark job on spark master. Task ID and DAG ID are passed as spark configuration `spark.workflow.taskId` and `spark.workflow.dagId` respectively. Application arguments can be defined here in a list format, which are passed to the main method of the main class, if any.

Name of the application should be passed through 'app_name' . It will be overridden if also defined within the Main class of the application.

For Java and Scala applications, the fully qualified classname of the class containing the main method of the application should be provided through 'class_path'. For example, org.apache.spark.examples.SparkPi

All the configurations defined under Admin -> Spark Configuration are considered while running the application. The developer code should be uploaded through Developer -> Code Artifacts and one can refer the same under 'code_artifact'.

```
from airflow.operators import SparkOperator

LoadData = SparkOperator(
    task_id='LoadData',
    app_name=appName,
    class_path='org.apache.spark.examples.SparkPi',
    code_artifact='spark-examples_2.11-2.3.1.jar',
    application_arguments=[],
    dag=dag,
    description='This task was inserted from the code bricks available on
from         Developer -> Manage Dags. The task name have been updated
according to the         scenario'
)
```

CoutureSparkOperator

Use CoutureSparkOperator to create and submit a spark job on spark master. This operator differs from SparkOperator in terms of optional parameters.

Optional Parameters:

- **task_args_dict** : Arguments required for main method of the main class. To be passed in dictionary format.
- **input_base_dir_path** : Base directory path for input files. This has to be a string
- **output_base_dir_path** : Base directory path for output files. This has to be a string
- **input_filenames_dict** : Relative file paths for input files w.r.t input base directory. To be passed in dictionary format.
- **output_filenames_dict** : Relative file paths for output files w.r.t output base directory. To be passed in dictionary format.

All the optional parameters, if present, are dumped as json which is passed on as string in the main method of main class. Task id and DAG id are also present in this json as **task_id** and **dag_id** respectively.

Example of final output:

```
'{"task_id": "fetch_videos", "dag_id": "video_embedding_dag",
"task_args_dict": {"task_strategy": "parallel"}, "input_base_dir_path":
"/usr/local/couture/input/", "output_base_dir_path":
"/usr/local/couture/processed/", "input_filenames_dict": {"tags_file":
"video_tags.csv"}, "output_filenames_dict": {"tags_file": "video_tags.csv"}}'
```

Name of the application should be passed through 'app_name' . It will be overridden if also defined within the Main class of the application.

For Java and Scala applications, the fully qualified classname of the class containing the main method of the application should be provided through 'class_path'. For example, org.apache.spark.examples.SparkPi

All the configurations defined under Admin -> Spark Configuration are considered while running the application. The developer code should be uploaded through Developer -> Code Artifacts and one can refer the same under 'code_artifact'.

```
from airflow.operators import CoutureSparkOperator

LoadData = CoutureSparkOperator(
    task_id='LoadData',
    app_name=appName,
    class_path='org.apache.spark.examples.SparkPi',
    code_artifact='spark-examples_2.11-2.3.1.jar',
    input_base_dir_path="/usr/local/couture/input/",
    output_base_dir_path="/usr/local/couture/processed/",
    output_filenames_dict={'tags_file': "video_tags.csv"},
    input_filenames_dict={'tags_file': "video_tags.csv"},
    task_args_dict={'task_strategy': "parallel"},
    dag=dag,
    description='This task was inserted from the code bricks available on
from           Developer -> Manage Dags. The task name have been updated
according to the           scenario'
)
```

CoutureDaskYarnOperator

Dask-Yarn deploys Dask on **YARN** clusters and mark the workflow task pass/fail according to the run status of the job.

Optional Parameters:

- **task_args_dict** : Arguments required for main method of the main class. To be passed in dictionary format.
- **input_base_dir_path** : Base directory path for input files. This has to be a string
- **output_base_dir_path** : Base directory path for output files. This has to be a string

- `input_filenames_dict` : Relative file paths for input files w.r.t input base directory. To be passed in dictionary format.
- `output_filenames_dict` : Relative file paths for output files w.r.t output base directory. To be passed in dictionary format.

All the optional parameters, if present, are dumped as json which is passed on as string in the main method of main class. Task id and DAG id are also present in this json as `task_id` and `dag_id` respectively.

Example of final output:

```
'{"task_id": "fetch_videos", "dag_id": "video_embedding_dag",
"task_args_dict": {"task_strategy": "parallel"}, "input_base_dir_path":
"/usr/local/couture/input/", "output_base_dir_path":
"/usr/local/couture/processed/", "input_filenames_dict": {"tags_file":
"video_tags.csv"}, "output_filenames_dict": {"tags_file":
"video_tags.csv"}}'
```

Name of the application should be passed through '`app_name`' . It will be overridden if also defined within the Main class of the application.

The developer code should be uploaded through Developer -> Code Artifacts and one can refer the same under '`code_artifact`'.

```
from airflow.operators import CoutureDaskYarnOperator

DataCleaning = CoutureDaskYarnOperator(
    task_id='DataCleaning',
    app_name=appName,
    code_artifact='spark-examples_2.11-2.3.1.jar',
    dag=dag,
    description='This task was inserted from the code bricks available on
from      Developer -> Manage Dags. The task name have been updated
according to the      scenario'
)
```

PySparkOperator

Use PySparkOperator to create and submit a pyspark job on spark master. Task ID and DAG ID are passed as spark configuration '`spark.workflow.taskId`' and '`spark.workflow.dagId`' respectively. Application arguments can be defined here in a list format, which are passed to the main method of the main class, if any.

Name of the application should be passed through '`app_name`' . It will be overridden if also defined within the Main class of the application.

All the 'Arguments' defined under Admin -> Spark Configuration are considered while running the application. The developer code should be uploaded through Developer -> Code Artifacts and one can refer the same under '`code_artifact`'.

```

from airflow.operators import PySparkOperator

StatsGeneration = PySparkOperator(
    task_id='StatsGeneration',
    app_name=appName,
    code_artifact='pi.py',
    application_arguments=[],
    dag=dag,
    description='Stats Generation'
)

```

CouturePySparkOperator

Use CouturePySparkOperator to create and submit a pyspark job on spark master. This operator differs from PySparkOperator in terms of optional parameters.

Optional Parameters:

- **task_args_dict** : Arguments required for main method of the main class. To be passed in dictionary format.
- **input_base_dir_path** : Base directory path for input files. This has to be a string
- **output_base_dir_path** : Base directory path for output files. This has to be a string
- **input_filenames_dict** : Relative file paths for input files w.r.t input base directory. To be passed in dictionary format.
- **output_filenames_dict** : Relative file paths for output files w.r.t output base directory. To be passed in dictionary format.

All the optional parameters, if present, are dumped as json which is passed on as string in the main method of main class. Task id and DAG id are also present in this json as **task_id** and **dag_id** respectively.

Example of final output:

```

'{"task_id": "fetch_videos", "dag_id": "video_embedding_dag",
"task_args_dict": {"task_strategy": "parallel"}, "input_base_dir_path": "/usr/local/couture/input/",
"output_base_dir_path": "/usr/local/couture/processed/", "input_filenames_dict": {"tags_file": "video_tags.csv"}, "output_filenames_dict": {"tags_file": "video_tags.csv"}}'

```

Name of the application should be passed through 'app_name' . It will be overridden if also defined within the Main class of the application.

All the 'Arguments' defined under Admin -> Spark Configuration are considered while running the application. The developer code should be uploaded through Developer -> Code Artifacts and one can refer the same under 'code_artifact'.

```

from airflow.operators import CouturePySparkOperator

```

```

StatsGeneration = CouturePySparkOperator(
    task_id='StatsGeneration',
    app_name=appName,
    code_artifact='pi.py',
    input_base_dir_path="/usr/local/couture/input/",
    output_base_dir_path="/usr/local/couture/processed/",
    output_filenames_dict={'tags_file': "video_tags.csv"},
    input_filenames_dict={'tags_file': "video_tags.csv"},
    task_args_dict={'task_strategy': "parallel"},
    dag=dag,
    description='Stats Generation'
)

```

TensorflowOperator

Use TensorflowOperator to run a tensorflow task.

The developer code should be uploaded through Developer -> Code Artifacts and one can refer the same under 'code_artifact'. Application arguments can be defined here in a string format, which are passed to the main method of the main class, if any.

```

from airflow.operators import TensorflowOperator

FeatureValidation = TensorflowOperator(
    task_id='FeatureValidation',
    code_artifact='pi.py',
    application_arguments="",
    dag=dag,
    description='Feature Validation'
)

```

CoutureTensorflowOperator

Use CoutureTensorflowOperator to run a tensorflow task. This operator differs from TensorflowOperator in terms of optional parameters.

Optional Parameters:

- **task_args_dict** : Arguments required for main method of the main class. To be passed in dictionary format.
- **input_base_dir_path** : Base directory path for input files. This has to be a string
- **output_base_dir_path** : Base directory path for output files. This has to be a string
- **input_filenames_dict** : Relative file paths for input files w.r.t input base directory. To be passed in dictionary format.

- `output_filenames_dict` : Relative file paths for output files w.r.t output base directory. To be passed in dictionary format.

All the optional parameters, if present, are dumped as json which is passed on as string in the main method of main class. Task id and DAG id are also present in this json as `task_id` and `dag_id` respectively.

Example of final output:

```
'{"task_id": "fetch_videos", "dag_id": "video_embedding_dag",
"task_args_dict": {"task_strategy": "parallel"}, "input_base_dir_path": "/usr/local/couture/input/",
"output_base_dir_path": "/usr/local/couture/processed/", "input_filenames_dict": {"tags_file": "video_tags.csv"}, "output_filenames_dict": {"tags_file": "video_tags.csv"}}'
```

The developer code should be uploaded through Developer -> Code Artifacts and one can refer the same under 'code_artifact'.

```
from airflow.operators import CoutureTensorflowOperator

fetch_videos = CoutureTensorflowOperator(
    dag=dag,
    task_id='fetch_videos',
    code_artifact=code_artifact,
    input_base_dir_path=input_dir,
    output_base_dir_path=processed_dir,
    output_filenames_dict={'tags_file': "video_tags.csv"},
    input_filenames_dict={'tags_file': "video_tags.csv"},
    task_args_dict={'task_strategy': "parallel"},
    description='A TF task'
)
```

CoutureJupyterOperator

You can schedule .ipynb notebooks to run in workflow by using the `CoutureJupyterNotebook` operator. You can also parameterize the notebook. To do this, tag notebook cells with parameters. These parameters are later used when the notebook is executed or run.

- Adding tags to a notebook:

1. Open the notebook on which you want to add tags.
2. Activate the tagging toolbar by navigating to **View**, **Cell Toolbar**, and then **Tags**.
3. Enter parameters into a textbox at the top right of a cell
4. Click Add Tag.



- How parameters work:

1. The `parameters` cell is assumed to specify default values which may be overridden by values specified at execution time.
2. We insert a new cell tagged `injected-parameters` immediately after the `parameters` cell which contains only the overridden parameters.
3. Subsequent cells are treated as normal cells, even if also tagged `parameters` if no cell is tagged `parameters`, the `injected-parameters` cell is inserted at the top of the notebook.
4. One caveat is that a `parameters` cell may not behave intuitively with inter-dependent parameters. Consider a notebook note.ipynb with two cells:

```
# parameters
a = 1
twice = a * 2
print("a =", a, "and twice =", twice)
```

when executed with parameters `{"a": 9}`, the output will be `a = 9` and `twice = 2`. (not `twice=18`).

Example code

```
from airflow import DAG
from airflow.operators.jupyter_operator import CoutureJupyterOperator
from datetime import datetime, timedelta

default_args = {
    'owner': 'Airflow',
    'depends_on_past': False,
    'start_date': datetime(2019, 1, 1),
    'email': ['airflow@example.com'],
    'email_on_failure': False,
    'email_on_retry': False,
    'retries': 1,
    'retry_delay': timedelta(minutes=5),
}

dag = DAG('JupyterDAG', default_args=default_args,
          schedule_interval=timedelta(days=10))

# t1 is an example of task created by instantiating CoutureJupyterOperator.
# input_nb and output_nb are notebook paths.
t1 = CoutureJupyterOperator(task_id='jupyter_task',
                            input_nb='testFile2.ipynb',
                            output_nb='plotTestFile2.ipynb',
                            parameters={"a": 10},
                            export_html=False,
                            dag=dag)
```

User Interface

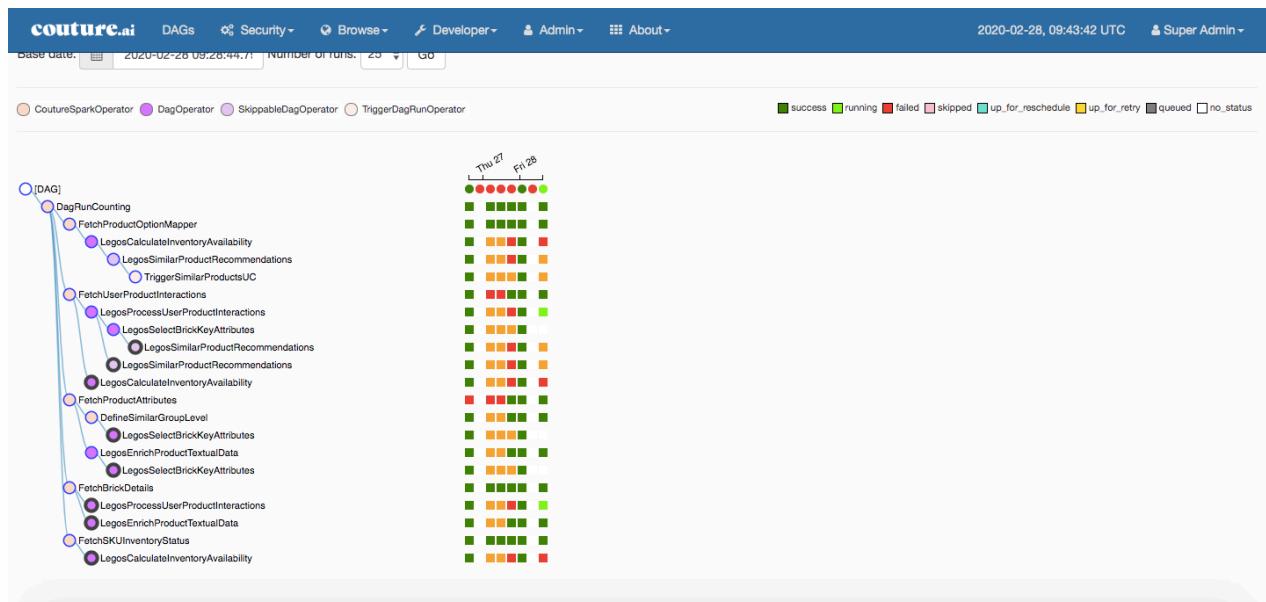
The Workflow UI makes it easy to monitor and troubleshoot your data pipelines. Here's a quick overview of some of the features and visualizations you can find in the Workflow UI.

View DAGs

List of the DAGs in your environment, and a set of shortcuts to useful pages. You can see exactly how many tasks succeeded, failed, or are currently running at a glance. In the top navigation bar, click on DAGs, situated near the COUTURE.AI logo on the top left side.

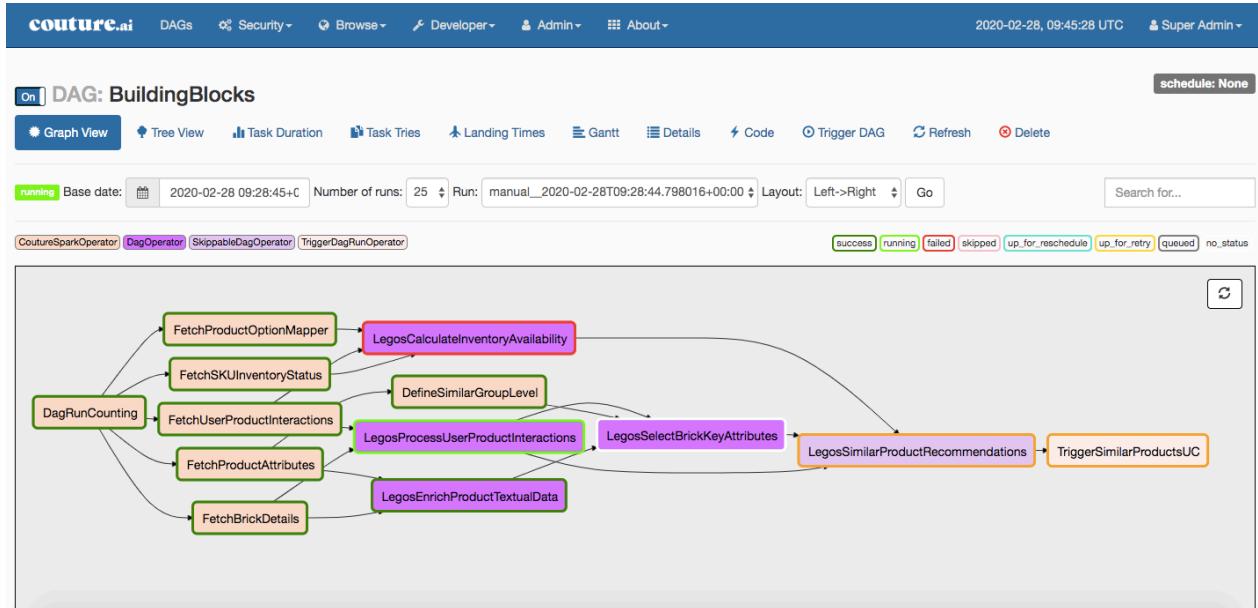
Tree View

A tree representation of the DAG that spans across time. If a pipeline is late, you can quickly see where the different steps are and identify the blocking ones.



Graph View

The graph view is perhaps the most comprehensive. Visualize your DAG's dependencies and their current status for a specific run.



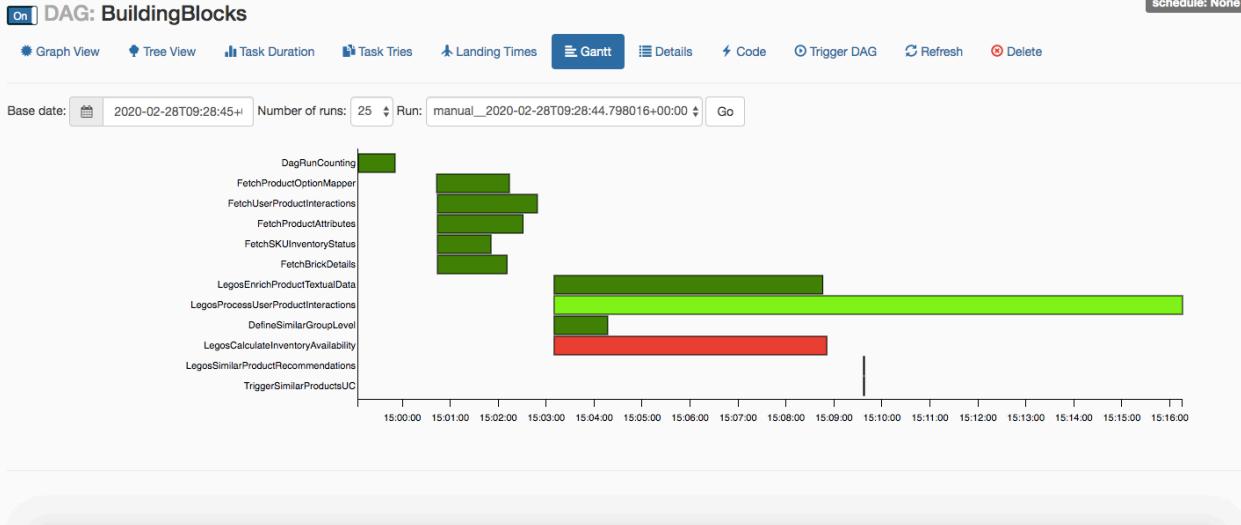
Here is the screenshot of the DAG executed. You can see rectangular boxes representing a task. You can also see different color boxes on the top right of the greyed box, named: success, running, failed etc, representing status of the task.

Variable View

The variable view allows you to list, create, edit or delete the key-value pair of a variable used during jobs. Value of a variable will be hidden if the key contains any words in ('password', 'secret', 'passwd', 'authorization', 'api_key', 'apikey', 'access_token') by default, but can be configured to show in clear-text.

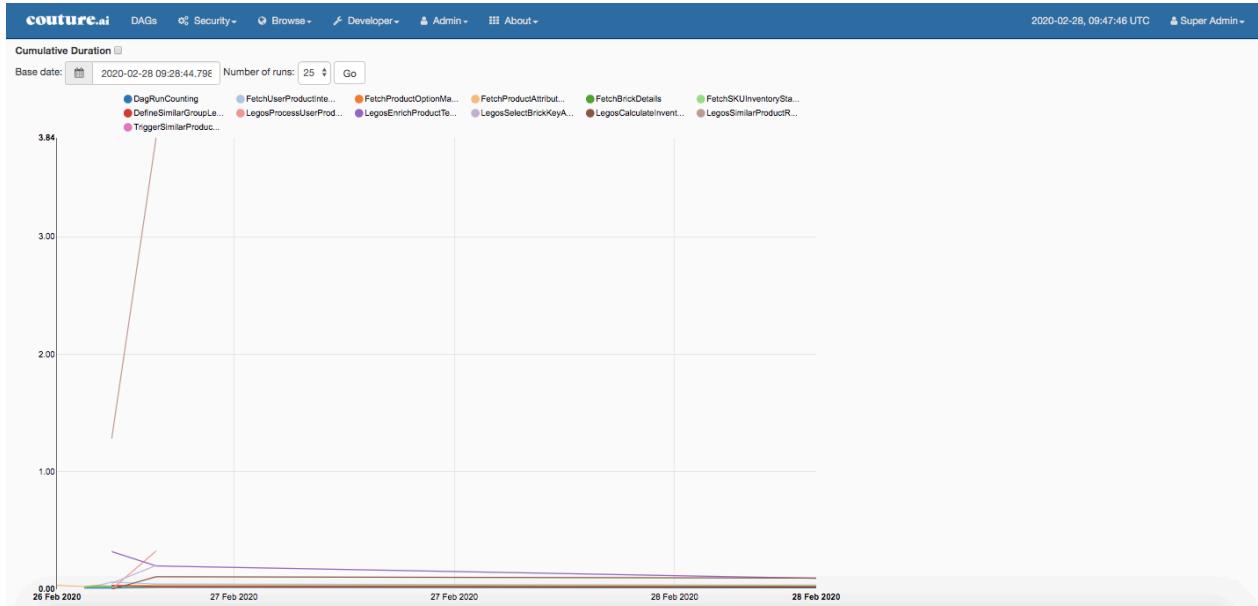
Gantt Chart

The Gantt chart lets you analyse task duration and overlap. You can quickly identify bottlenecks and where the bulk of the time is spent for specific DAG runs.



Task Duration

The duration of your different tasks over the past N runs. This view lets you find outliers and quickly understand where the time is spent in your DAG over many runs.



Code View

Transparency is everything. While the code for your pipeline is in source control, this is a quick way to get to the code that generates the DAG and provide yet more context.

CoutureExample

Toggle wrap

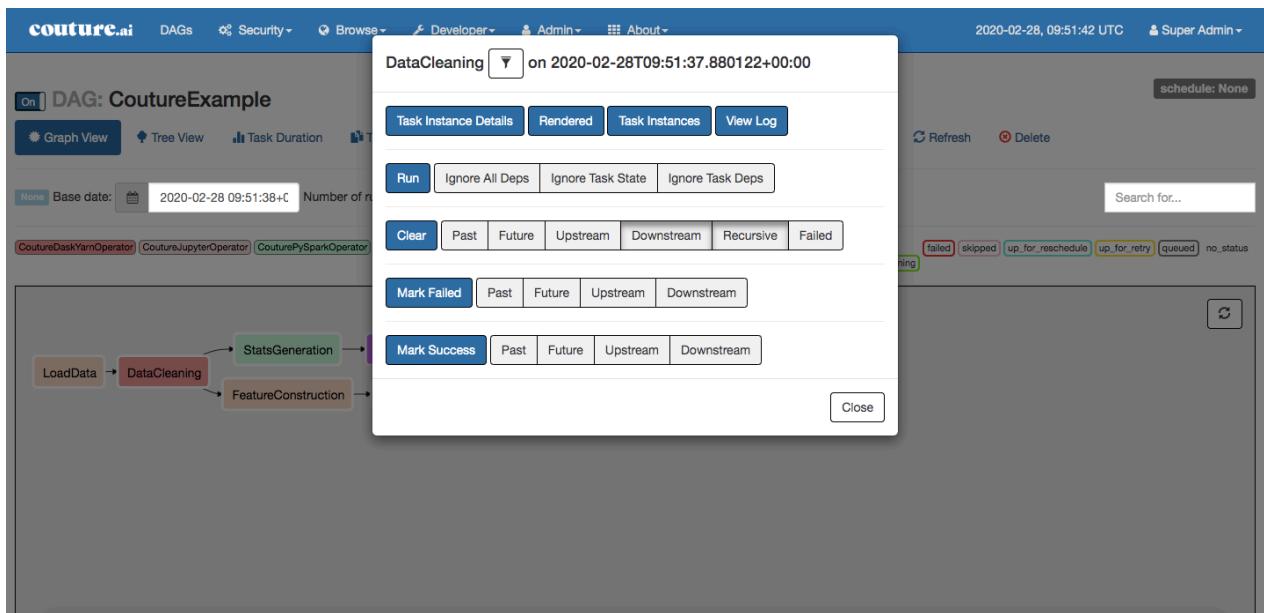
```

1 from datetime import datetime, timedelta
2 from airflow import DAG
3 from airflow.operators import CoutureSparkOperator, CouturePySparkOperator, CoutureDaskYarnOperator, CoutureJupyterOperator, CoutureTensorflowOperator
4 from airflow.operators.dag_operator import SkippableDagOperator, DagOperator
5 from airflow.operators.dagrun_operator import TriggerDagRunOperator
6
7 appName = 'CoutureExample'
8
9 default_args = {
10     'owner': 'couture',
11     'depends_on_past': False,
12     'start_date': datetime(2019, 4, 15),
13     'retries': 0,
14 }
15
16 schedule = None
17 dag = DAG('CoutureExample', default_args=default_args, catchup=False, schedule_interval=schedule)
18
19 LoadData = CoutureSparkOperator(
20     task_id='LoadData',
21     app_name=appName,
22     class_path='org.apache.spark.examples.SparkPi',
23     code_artifact='spark-examples_2.11-2.3.1.jar',
24     application_arguments=[],
25     dag=dag,
26     description='This task was inserted from the code bricks available on from Developer -> Manage Dags. The task name have been updated according to the scenario'
27 )
28

```

Task Instance Context Menu

From the pages seen above (tree view, graph view, gantt, ...), it is always possible to click on a task instance, and get to this rich context menu that can take you to more detailed metadata, and perform some actions.



Users

Role Based Access Control

Workflow provides **role-based access control** (RBAC), allowing you to configure varying levels of access across all Users within your Workspace.

There are six roles created for Workflow by default: Admin, Developer, User, Op, Viewer, and Public.

- **Admin**

Admin users have all possible permissions, including granting or revoking permissions from other users.

- **Public**

Public users (anonymous) don't have any permissions.

- **Viewer**

Viewer users have limited viewer permissions

```
VIEWER_PERMS = {
    'menu_access',
    'can_index',
    'can_list',
    'can_show',
    'can_chart',
    'can_dag_stats',
    'can_dag_details',
    'can_task_stats',
    'can_code',
    'can_log',
    'can_get_logs_with_metadata',
    'can_tries',
    'can_graph',
    'can_tree',
    'can_task',
    'can_task_instances',
    'can_xcom',
    'can_gantt',
    'can_landing_times',
    'can_duration',
    'can_blocked',
    'can_rendered',
    'can_pickle_info',
    'can_version',
}
```

on limited web views.

```
VIEWER_VMS = {
    'Airflow',
    'DagModelView',
```

```
'Browse',
'DAG Runs',
'DagRunModelView',
'Task Instances',
'TaskInstanceModelView',
'SLA Misses',
'SlaMissModelView',
'Jobs',
'JobModelView',
'Logs',
'LogModelView',
'Docs',
'Documentation',
'GitHub',
'About',
'Version',
'VersionView',
}
```

▪ User

User users have Viewer permissions plus additional user permissions.

```
USER_PERMS = {
    'can_dagrun_clear',
    'can_run',
    'can_trigger',
    'can_add',
    'can_edit',
    'can_delete',
    'can_paused',
    'can_refresh',
    'can_success',
    'muldelete',
    'set_failed',
    'set_running',
    'set_success',
    'clear',
    'can_clear',
}
```

on User web views which is the same as Viewer web views.

▪ Developer

Developer users have User permissions plus additional developer permissions like access to jupyter notebook, uploading code artifacts option, editing dags privileges.

▪ Op

Op users haveUser permissions plus additional op permissions.

```
OP_PERMS = {
    'can_conf',
    'can_varimport',
}
```

on User web views plus these additional op web views.

```
OP_VMS = {
    'Admin',
    'Configurations',
    'ConfigurationView',
    'Connections',
    'ConnectionModelView',
    'Pools',
    'PoolModelView',
    'Variables',
    'VariableModelView',
    'XComs',
    'XComModelView',
}
```

The Admin could create a specific role which is only allowed to read/write certain DAGs. To configure a new role, go to Security tab and click List Roles in the new UI.

The image shows the creation of a role which can only read all dags.

User creation

To add new user, go to Security tab and click List Users in the UI. This can also be integrated with Kerberos or LDAP.

To add new user, click the '+' as shown below.

couture.ai	DAGs	Security	Browse	Admin	About	2019-10-15, 16:09:33 UTC	Super Admin
List Users		List Users List Roles User's Statistics					
Search▼		Base Permissions Views/Menus Permission on Views/Menus		Record Count: 5			
		First Name	Last Name	User Name	Email	Is Active?	Role
	Super		Admin	superadmin	tech@couture.ai	True	[Admin]
	couture		ai	couture	couture@couture.ai	True	[Admin]

Note: Only admin can create new users.

Access Audit Logging

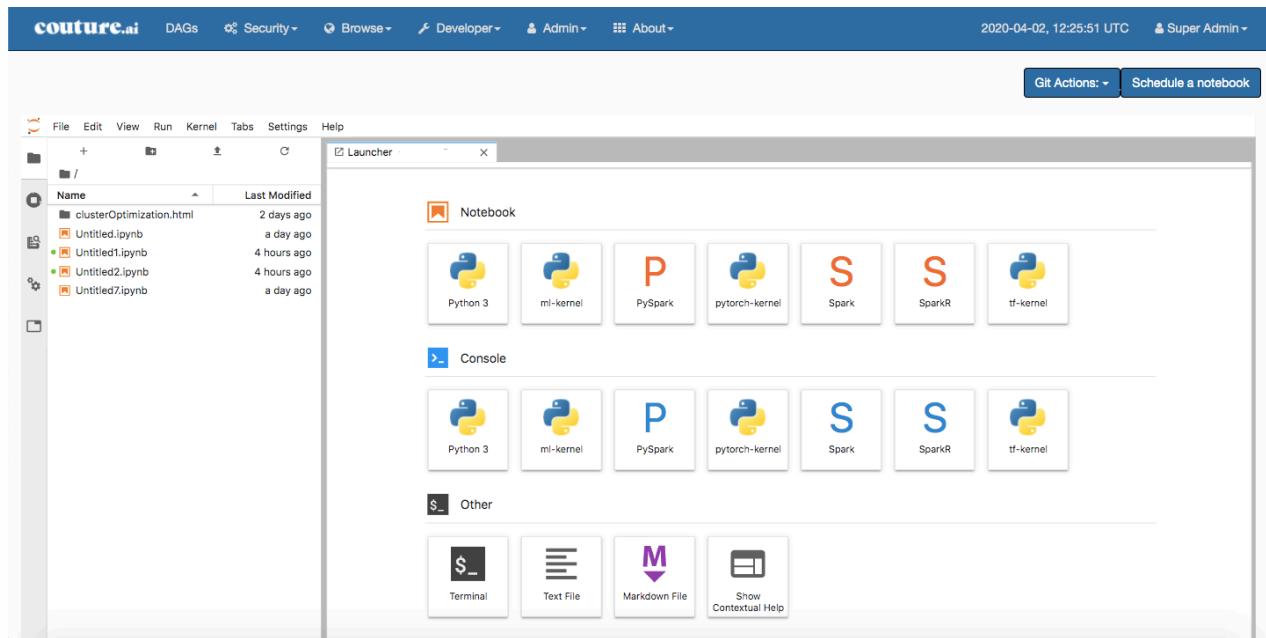
User journey can be easily tracked by audit logs. Audit logs can be viewed by going to Browse and clicking on Audit Logs. All the activities/events are captured. Also, the source IP address from where the event occurred is captured as shown below.

couture.ai	DAGs	Security	Browse	Admin	About	2019-09-23, 10:05:09 UTC	Super Admin			
List Log		DAG Runs Jobs Audit Logs SLA Misses Task Instances		Record Count: 69						
		Id	Dttm	Dag Id	Task Id	Event	Execution Date	Owner	Extra	source_ip
69	09-23T10:04:38.657096+00:00	None			update_spark_conf			superadmin	[]	10.89.132.244
68	09-23T10:04:33.327674+00:00	None			login			superadmin	[]	10.89.132.244
67	09-23T10:02:40.170046+00:00	example-dag			tries			superadmin	[{"dag_id": "example-dag"}, {"days": "30"}]	10.89.132.56
66	09-23T10:02:36.504499+00:00	example-dag			tries			superadmin	[{"dag_id": "example-dag"}, {"days": "30"}]	10.89.132.56
65	09-23T10:02:34.934806+00:00	example-dag			tree			superadmin	[{"dag_id": "example-dag"}]	10.89.132.56
64	09-23T10:02:16.524518+00:00	example-dag			graph			superadmin	[{"dag_id": "example-dag"}]	10.89.132.56
63	09-23T10:02:14.841768+00:00	example-dag			tree			superadmin	[{"dag_id": "example-dag"}]	10.89.132.56
62	09-23T10:01:55.619247+00:00	None			update_artifact			superadmin	[]	10.89.132.56
61	09-23T10:01:53.286636+00:00	None			dag_deleted			superadmin	add_dag.py	10.89.132.56
60	09-23T10:01:53.280555+00:00	None			add_dag			superadmin	[]	10.89.132.56
59	09-23T10:01:50.088053+00:00	None			add_dag			superadmin	[]	10.89.132.56
58	09-23T10:01:47.299840+00:00	example-dag			tree			superadmin	[{"dag_id": "example-dag"}]	10.89.132.56
57	09-23T10:01:42.977327+00:00	None			dag_added			superadmin	add_dag.py	10.89.132.56
56	09-23T10:01:42.972174+00:00	None			add_dag			superadmin	[]	10.89.132.56
55	09-23T10:01:36.884339+00:00	None			add_dag			superadmin	[]	10.89.132.56
54	09-23T10:01:24.722137+00:00	None			add_dag			superadmin	[]	10.89.132.56
53	09-23T10:00:59.641770+00:00	None			hadoop_file_deleted			superadmin	result.xml	10.89.132.56
52	09-23T10:00:59.635354+00:00	None			hadoop_conn_file_list			superadmin	[]	10.89.132.56

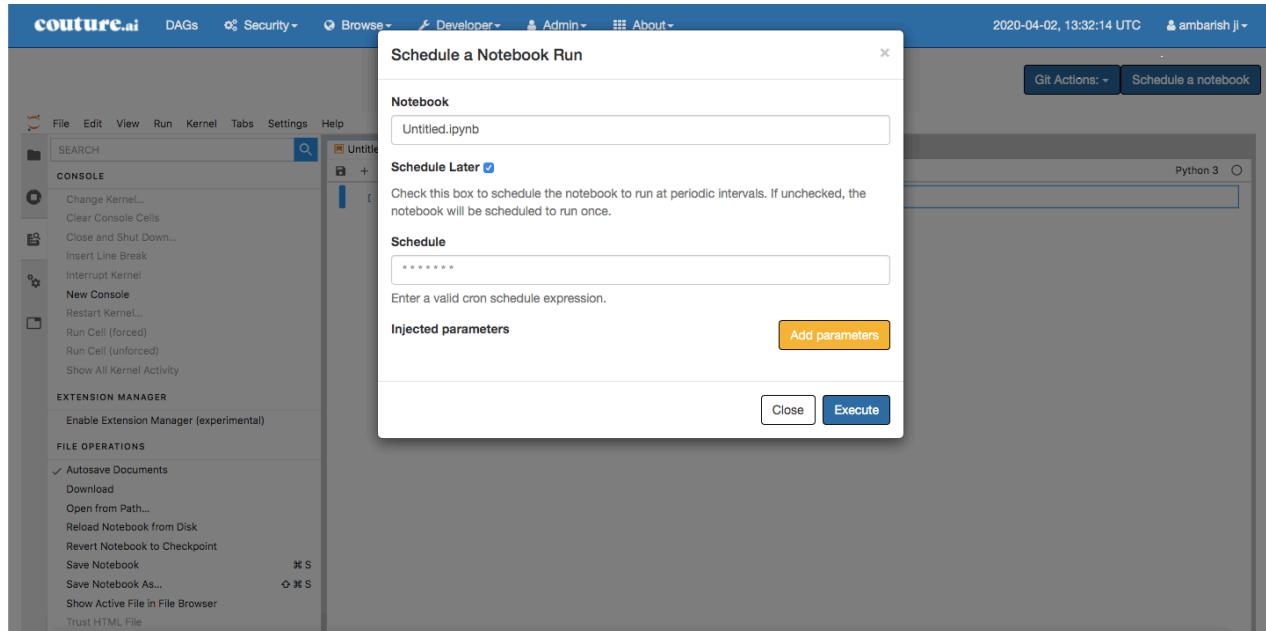
Jupyter Notebook

Jupyter notebook can be accessed under Developer menu and clicking on 'Jupyter Notebook' option. These feature is available for both Developer or Admin users.

NOTE: Jupyter Notebook View might prompt you for authentication. Use the same credentials which was used while logging in to Workflow Orchestrator



Workflow also has an option to schedule jupyter notebooks to run as DAGs. Click on the button **Schedule a notebook**. You can schedule to run it once or provide a cron expression (For example, a cron schedule for running the notebook every 5 minutes is `*/5 * * * *`) to running it periodically. Also, you can add parameters to the notebook by clicking on **Add parameters** which will be injected when the notebook is run. For more info on **parameters**, see [CoutureJupyterOperator](#)



Upon scheduling a notebook, a Dag will be dynamically created and you will be redirected to the DAG page where you can check the status of your Notebook run. This can be used to schedule run notebooks periodically to generate reports etc.

You can also **parameterize** the notebook. To do this, tag notebook cells with **parameters**. These **parameters** are later used when the notebook is executed or run.

Kernels supported by JupyterHub

Out of the box, Workflow Orchestrator offers support for 7 kernels, including [sparkmagic](#) kernels. Sparkmagic is a set of tools for interactively working with remote Spark clusters through [Livy](#), a Spark REST server, in [Jupyter](#) notebooks.

- **Python3:** A simple python3 kernel, provided by default by jupyterlab.
- **ml-kernel:** A kernel with the most commonly used Machine Learning python packages preinstalled.
- **tf-kernel:** A kernel with TensorFlow and commonly used packages preinstalled.
- **pytorch-kernel:** A kernel with Pytorch and commonly used packages preinstalled.
- **pySpark:** Sparkmagic's pyspark kernel.
- **Spark:** Sparkmagic's spark kernel.
- **SparkR:** Sparkmagic's R kernel.

To configure default Livy Endpoints, visit [Livy Configuration](#).

DAG Runs

A DagRun is the instance of a DAG that will run at a time. When it runs, all task inside it will be executed.

DAG Runs tell how many times a certain DAG has been executed. **Recent Tasks** tells which task out of many tasks within a DAG currently running and what's the status of it.

State	Dag Id	Execution Date	Run Id	External Trigger
failed	PySpark	10-16T06:36:53.387072+00:00	manual__2019-10-16T06:36:53.387072+00:00	True
success	PySpark	10-16T06:32:14.503166+00:00	manual__2019-10-16T06:32:14.503166+00:00	True
success	PySpark	10-16T06:31:39.604312+00:00	manual__2019-10-16T06:31:39.604312+00:00	True
success	PySpark	10-15T13:41:22.037615+00:00	manual__2019-10-15T13:41:22.037615+00:00	True
failed	PySpark	10-15T13:09:15.581768+00:00	manual__2019-10-15T13:09:15.581768+00:00	True
failed	PySpark	10-15T12:49:54.767437+00:00	manual__2019-10-15T12:49:54.767437+00:00	True
running	tutorial	2017-07-09T00:00:00+00:00	scheduled__2017-07-09T00:00:00+00:00	False
running	tutorial	2017-07-08T00:00:00+00:00	scheduled__2017-07-08T00:00:00+00:00	False
running	tutorial	2017-07-07T00:00:00+00:00	scheduled__2017-07-07T00:00:00+00:00	False
running	tutorial	2017-07-06T00:00:00+00:00	scheduled__2017-07-06T00:00:00+00:00	False
running	tutorial	2017-07-05T00:00:00+00:00	scheduled__2017-07-05T00:00:00+00:00	False

Trained Models

Workflow Orchestrator allows us to upload Machine Learning models and expose them via an API so that they can be used by clients. Currently, we support 3 different types of models, i.e Tensorflow Models, Spark Models and Other Models. To upload a trained model, visit **Developer->Trained Models**. You will see an UI as attached below:

The screenshot shows the 'Trained Models' section of the Workflow Orchestrator interface. At the top, there's a navigation bar with links for DAGs, Security, Browse, Developer, Admin, and About. On the right, it shows the date '2020-04-01, 09:11:45 UTC' and a user 'Super Admin'. The main area has a sidebar on the left with categories: Trained Models, TF_MODELS, SPARK_MODELS, and OTHER_MODELS. The 'TF_MODELS' section is currently active, showing a large box for file upload with the placeholder 'Drop files here to upload'. Below this is a search bar labeled 'Search file: filename'. A table lists two entries: 'action_recognition' (Last modified Mar 31 10:39:48 2020, Size 4.0 KB) and 'audio_classification' (Last modified Mar 31 10:35:23 2020, Size 4.0 KB). The 'SPARK_MODELS' section is also shown with its own upload box and a table for uploaded files.

Default Behavior of different Models

- **Tensorflow Models:** Upload a **.tar** or **.tar.gz** archive of your model. The archive will be extracted in the background, and in < 10 minutes, the model will be exposed via the serving APIs on ports 8500 for gRPC, 8501 for REST. For details on how to access serving APIs, visit [TFX serving guide](#).
- **Spark Models:** Any file can be uploaded in this section. Models added in this section are currently not exposed by an API.
- **Other Models:** There might be some models which you don't want to serve, but might still need. You can upload a **.tar** or **.tar.gz** of your model and the archive will be extracted in the background. However, Models added in this section are not exposed by an API.

Exploratory Data Analysis

Workflow Orchestrator allows us to add and perform Exploratory Data Analysis (EDA) on a SQL database, TSV or CSV file and HDFS data sources. To perform EDA on a data source, go to **Developer->Exploratory Data Analysis**.

Steps to perform EDA

1. Navigate to Developer->Exploratory Data Analysis Page.
2. Add a new Data Source. The data source can be any one of SQL Database, CSV/ TSV, or HDFS Source (optional).
 1. If you select to use SQL Database, you will be redirected to Couture Dashboard, where you will have to select a table from one of the existing databases from SQL Lab view.
3. Once you have your required Data source added, you need to click on the play button to start EDA.

The screenshot shows the 'Exploratory Data Analysis' section of the Couture.ai web interface. At the top, there is a message 'Source Added.' with a close button. Below it, the title 'Exploratory Data Analysis' is displayed. Under 'Raw Inputs', there is a search bar labeled 'Search source:' and a dropdown menu titled 'Define the source of your data:' with options 'SQL Database' (selected), 'Excel/CSV/TSV', and 'HDFS'. A source entry 'hdfs://path/to/EDA/source' is listed with a 'Run EDA on this data source.' button next to it. In the 'Processed Outputs' section, there is a link 'outputs'. The URL in the browser's address bar is '100.27.1.214:8080/eda/sources/#'.

4. Once an output of EDA is generated, it will be in the Processed Outputs Section of the same page. Click on the output and you will be redirected to a new tab showing the EDA Results.

Visualisations

You can directly access Couture Dashboard from Couture Workflow Orchestrator. To go to Couture Dashboard, from the UI, go to (Developer->Visualisations). Couture Dashboard is a modern, enterprise-ready business intelligence web application.

Couture Dashboard provides:

- An intuitive interface to explore and visualize datasets, and create interactive dashboards.
- A wide array of beautiful visualizations to showcase your data.
- Easy, code-free, user flows to drill down and slice and dice the data underlying exposed dashboards. The dashboards and charts act as a starting point for deeper analysis.
- A state of the art SQL editor/IDE exposing a rich metadata browser, and an easy workflow to create visualizations out of any result set.
- An extensible, high granularity security model allowing intricate rules on who can access which product features and datasets. Integration with major authentication backends (database, OpenID, LDAP, OAuth, REMOTE_USER, ...)
- A lightweight semantic layer, allowing to control how data sources are exposed to the user by

- defining dimensions and metrics
- Out of the box support for most SQL-speaking databases
- Deep integration with Druid allows for Superset to stay blazing fast while slicing and dicing large, realtime datasets
- Fast loading dashboards with configurable caching.

Connections

The connection information to external systems is stored in the workflow metadata database and managed in the UI (Menu -> Admin -> Connections). A `conn_id` is defined there and `hostname` / `login` / `password` / `schema` information attached to it. Pipelines can simply refer to the centrally managed `conn_id` without having to hard code any of this information anywhere.

Many connections with the same `conn_id` can be defined, workflow will choose one connection randomly, allowing for some basic load balancing and fault tolerance when used in conjunction with `retries`.

Variables and XComs

XComs

XComs let tasks exchange messages, allowing more nuanced forms of control and shared state. The name is an abbreviation of "cross-communication". Any object that can be pickled can be used as an XCom value, so users should make sure to use objects of appropriate size.

XComs can be pushed (sent) or pulled (received). When a task pushes an XCom, it makes it generally available to other tasks. Tasks can push XComs at any time by calling the `xcom_push()` method. In addition, if a task returns a value (either from its Operator's `execute()` method, or from a PythonOperator's `python_callable` function), then an XCom containing that value is automatically pushed.

Tasks call `xcom_pull()` to retrieve XComs, optionally applying filters based on criteria like `key`, `source_task_ids`, and `source_dag_id`. By default, `xcom_pull()` filters for the keys that are automatically given to XComs when they are pushed by being returned from execute functions (as opposed to XComs that are pushed manually).

If `xcom_pull` is passed a single string for `task_ids`, then the most recent XCom value from that task is returned; if a list of `task_ids` is passed, then a corresponding list of XCom values is returned. If you set `provide_context=True`, the returned value of the function is pushed itself into XCOM which on itself is nothing but a DB table.

```

# inside a PythonOperator called 'pushing_task'
def push_function():
    return value

# inside another PythonOperator
def pull_function(task_instance):
    value = task_instance.xcom_pull(task_ids='pushing_task')

```

Note that XComs are similar to Variables, but are specifically designed for inter-task communication rather than global settings.

Example:

```

def parse_recipes(**kwargs):
    return 'RETURNS parse_recipes'
def download_image(**kwargs):
    ti = kwargs['ti']
    v1 = ti.xcom_pull(key=None, task_ids='parse_recipes')
    print('Printing Task 1 values in Download_image')
    print(v1)
    return 'download_image'

```

The first task has no such changes other than providing `**kwargs` which let share key/value pairs. The other is setting `provide_context=True` in each operator to make it *XCom compatible*. For instance:

```

opr_parse_recipes = PythonOperator(task_id='parse_recipes',
                                   python_callable=parse_recipes,
                                   provide_context=True)

```

The `download_image` will have the following changes:

```

def download_image(**kwargs):
    ti = kwargs['ti']
    v1 = ti.xcom_pull(key=None, task_ids='parse_recipes')
    print('Printing Task 1 values in Download_image')
    print(v1)
    return 'download_image'

```

The first line is `ti=kwargs['t1']` get the instances details by access `ti` key. In case you wonder why this has been done, if you print `kwargs` it prints something like below in which you can find keys like `t1`, `task_instance` etc to get a task's pushed value.

```

{'dag': <DAG: parsing_recipes>,
 'ds': '2018-10-02',

```

```

'next_ds': '2018-10-02',
'prev_ds': '2018-10-02',
'ds_nodash': '20181002',
'ts': '2018-10-02T09:56:05.289457+00:00',
'ts_nodash': '20181002T095605.289457+0000',
'yesterday_ds': '2018-10-01',
'yesterday_ds_nodash': '20181001',
'tomorrow_ds': '2018-10-03',
'tomorrow_ds_nodash': '20181003',
'END_DATE': '2018-10-02',
'end_date': '2018-10-02',
'dag_run': <DagRunParsing_recipes@2018-10-02T09: 56: 05.289457+00: 00:
manual__2018-10-02T09: 56: 05.289457+00: 00, externallytriggered: True>,
'run_id': 'manual__2018-10-02T09:56:05.289457+00:00',
'execution_date': <Pendulum[2018-10-02T09: 56: 05.289457+00: 00]>,
'prev_execution_date': datetime.datetime(2018, 10, 2, 9, 56, tzinfo=
<TimezoneInfo[UTC, GMT, +00: 00: 00, STD]>),
'next_execution_date': datetime.datetime(2018, 10, 2, 9, 58, tzinfo=
<TimezoneInfo[UTC, GMT, +00: 00: 00, STD]>),
'latest_date': '2018-10-02',
'params': {},
'tables': None,
'task': <Task(PythonOperator): download_image>,
'task_instance': <TaskInstance: parsing_recipes.download_image2018-10-02T09:
56: 05.289457+00: 00[running]>,
'ti': <TaskInstance: parsing_recipes.download_image2018-10-02T09: 56:
05.289457+00: 00[running]>,
'task_instance_key_str': 'parsing_recipes__download_image__20181002',
'test_mode': False,
'var': {'value': None, 'json': None},
'inlets': [],
'outlets': [],
'templates_dict': None}

```

Next, `xcom_pull` can be called to put the certain task's returned value. In my the task id is `parse_recipes`:

```
v1 = ti.xcom_pull(key=None, task_ids='parse_recipes')
```

For each task, xcoms can be viewed under View logs -> XCom.

Key	Value

Variables

Variables are a generic way to store and retrieve arbitrary content or settings as a simple key-value store within workflow. Variables can be listed, created, updated and deleted from the UI. (Admin -> Variables). In addition, json settings files can be bulk uploaded through the UI. While your pipeline code definition and most of your constants and variables should be defined in code and stored in source control, it can be useful to have some variables or configuration items accessible and modifiable through the UI.

```
from airflow.models import Variable
foo = Variable.get("foo")
bar = Variable.get("bar", deserialize_json=True)
baz = Variable.get("baz", default_var=None)
```

The second call assumes json content and will be deserialized into bar. Note that Variable is a sqlalchemy model and can be used as such. The third call uses the default_var parameter with the valueNone, which either returns an existing value or None if the variable isn't defined. The get function will throw a KeyError if the variable doesn't exist and no default is provided.

Variables can be pushed and pulled in a similar fashion to XComs:

```
config = Variable.get("db_config")
set_config = Variable.set(db_config)
```

Note: Although variables are Fernet key encrypted in the database, they are accessible in the UI and therefore should **not** be used to store **passwords** or **other sensitive data**.

When to use each?

In general , since XComs are meant to be used to communicate between tasks and store the "conditions" that led to that value being created, they should be used for values that are going to be changing each time a workflow runs.

Variables on the other hand are much more natural places for constants like a list of tables that need to be synced, a configuration file that needs to be pulled from, or a list of IDs to dynamically generate tasks from.

Both can be very powerful where appropriate, but can also be dangerous if misused.

SLAs

Service Level Agreements, or time by which a task or DAG should have succeeded, can be set at a task level as a `timedelta`. If one or many instances have not succeeded by that time, an alert email is sent detailing the list of tasks that missed their SLA. The event is recorded in the database and made available in the web UI under **Browse->SLA Misses** where events can be analyzed and documented.

SLAs can be configured for scheduled tasks by using the `sla` parameter. In addition to sending alerts to the addresses specified in a task's `email` parameter, the `sla_miss_callback` specifies an additional Callable object to be invoked when the SLA is not met.