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Introduction

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

When workflows are defined as code, they become more maintainable, version-able, 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

- Support for Exploratory Data Analysis.
- Support for LDAP Authentication and DB Authentication.
- Support for Configuration Groups .
- Support for multiple Spark & Hadoop Clusters.
- Support for Jupyterhub & submitting Spark Jobs from Jupyterhub using Livy.
- Support for Tensorflow Serving and Pytorch Serving.
- Support for Openscoring – Spark Model 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 all the set of docker-compose.yml file are located.
 1. Open .env file and change ACCESS_HOST to the public ip of your server.
 2. Change WORKFLOW_IMAGE in your .env to refer to the image:tag of workflow you want to use.
 3. If tf-serving is needed to run on:
 1. CPU, then run docker-compose -f docker-compose.yml -f docker-compose.override.cpu.yml up -d
 2. GPU then run:
 1. python3 gpu-custom.py
 2. docker-compose -f docker-compose.yml -f docker-compose.override.gpu.yml up -d
- Note that COUTURE_WORKFLOW_USER is optional and can be used to have personalized dags view.

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/redis:3.2  
docker pull CR1:5005/couture/visualization-dashboard:latest  
docker pull CR1:5005/nginx:latest  
docker pull CR1:5005/couture/jupyterhub:latest  
docker pull CR1:5005/pytorch/torchserve  
docker pull CR1:5005/couture/tfserving:latest  
docker pull CR1:5005/couture/tfserving:latest-gpu  
docker pull CR1:5005/rabbitmq:3.7-management  
docker pull CR1:5005/couture/mysql:5.7
```

docker pull CR1:5005/couture/couture-workflow-orchestrator:latest. Instead of latest, use the image tag which is compatible with your hadoop cluster version.

- Tag all the images with CR1:5005 removed. Ex:

```
docker tag CR1:5005/rabbitmq:3.7-management rabbitmq:3.7-management  
docker tag CR1:5005/couture/mysql:5.7 couture/mysql:5.7
```

- **Fetching the dependencies:**

- Get the set of docker-compose files required for running WFO from shared artifacts.

- **Running orchestrator:**

- Go to the directory where all the set of docker-compose.yml file are located.
 1. Open .env file and change ACCESS_HOST to the public ip of your server.
 2. Change WORKFLOW_IMAGE in your .env to refer to the image:tag of workflow you want to use.
 3. If tfserving is needed to run on:
 1. CPU, then run docker-compose -f docker-compose.yml -f docker-compose.override.cpu.yml up -d

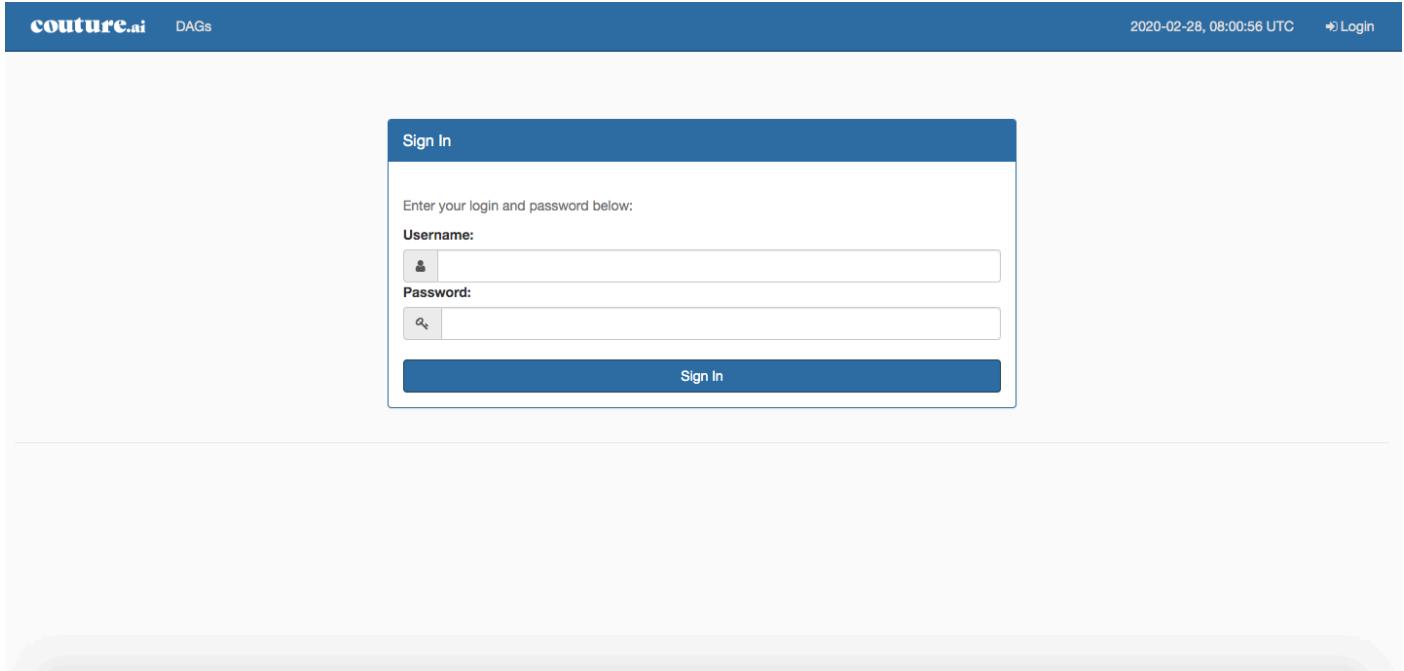
2. GPU then run:

1. `python3 gpu-custom.py`

2. `docker-compose -f docker-compose.yml -f docker-compose.override.gpu.yml up -d`

- 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.

Server Configuration QuickStart

For using your already configured hadoop and spark cluster with workflow, follow these steps.

- Create a new [spark hadoop config group](#). Set it as the default config group.
- Click on [hadoop configuration](#) for your group. You will be redirected to a page where you can upload your hadoop configuration files. Atleast 3 of them are required for your spark jobs to run be yarn: `hdfs-site.xml`, `core-site.xml`, `yarn-site.xml`
- NOTE: Incase you want to use other Hadoop services such as HBase, Hive, Impala, you need to add their respective configs such as [HBase Config](#), [Hive Config](#) etc. here as well.

- Come back and click on **spark configuration** of your group. This is the place where you the arguments and the configurations you would pass with your **spark-submit** command. Update it accordingly. At the very least, make sure **master** in Arguments is set to **yarn**.
 - You can set any argument or configuration meant to be passed with **spark-submit** command here. Arguments to be passed with **--conf** flag will go in **Configurations**. Others will go in **Arguments**.
 - A non exhaustive list of spark configurations: <https://spark.apache.org/docs/2.2.2/configuration.html>
- Go back and click on **kerberos configuration**. Upload your kerberos's **krb5.conf** and **keytab** files here. Select your keytab files in the list of **keytabs** and update your principal.
- Run one of our sample DAGs. For example, run **ExampleSchemaGeneration**. If everything runs successfully, then congrats  , you have successfully configured our workflow to run with your Spark Hadoop Cluster.

Getting Started

Login as an admin user and configure spark, hadoop, livy and kerberos configurations as followed.

Spark Hadoop Config Groups

Spark Hadoop Config Groups is used to configure multiple Hadoop / Ambari Clusters with the same workflow. After configuring them properly, you can easily switch b/w which one to use while running your CoutureSparkOperator and other Spark Hadoop cluster related operator tasks.

1. In the top navigation bar, go to Admin -> Spark Hadoop Config Groups

When you are running **Workflow** for the first time, there will be a single default **config** group. However, you can create a config group by clicking on **Add a group** button.

Spark Hadoop Config Groups

[Open default Group](#) [Add a group](#)

Search Group:

Group Name	Change Default Group	Configurations				Delete
config_group_1	Default group	 Hadoop Configuration	 Spark Configuration	 Kerberos Configuration	 Livy Configuration	

Spark Configuration

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

- In the Spark Hadoop Config Group page, select the Spark Configuration link of the respective group.

Couture Spark Configuration - config_group_2

Arguments

principal	<input type="text" value="rahul"/>
keytab	<input type="text"/>
master	<input type="text" value="local[1]"/>
jars	<input type="text"/>

[Add In Arguments](#)

Configurations

spark.scheduler.mode	<input type="text" value="FAIR"/>
spark.pyspark.python	<input type="text" value="/usr/local/bin/python"/>
spark.dynamicAllocation.enabled	<input type="text" value="true"/>

- 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.
- 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.

- 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 Spark Hadoop Config Group page, select the Hadoop Configuration link of the respective group. You will be redirected to a page containing configuration files for that group.

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	

- New hadoop conf files can be added to that group using Upload file(s) option. Please note that only XML files are allowed.
- 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:

In the Spark Hadoop Config Group page, select the Kerberos Configuration link of the respective group.

1. For configuring kerberos, you will have to specify the kerberos principal, and upload the `krb5.conf` and the keytab files.
2. After uploading the keytab file, you have to select the keytab file. These configurations, if added, are automatically applied to the spark and HDFS jobs which use that configuration group.

couture.ai
DAGs
Security
Browse
Developer
Admin
About
2020-10-12, 04:48:55 UTC
Super Admin

config_group_1 / Kerberos Configuration

Upload .keytab & krb5.conf Files

x.keytab	Oct 12 04:48:41 2020	12.0 B	
principal	<input type="text"/>		
keytab	<input type="button" value="Click to select keytab files"/>		

Submit

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.

In the Spark Hadoop Config Group page, select the Livy Configuration link of the respective group.

NOTE: The livy configuration of the default spark hadoop config group will be used with sparkmagic kernels in jupyterhub

- The username/password only needs to be filled when auth is Basic_Access.
- Kerberos Authentication is also supported, you just basically have to set auth to Kerberos, and the kerberos configuration (keytab and krb5.conf) of your default config group will automatically be picked up.

The screenshot shows the Livy Configuration View page on the couture.ai platform. The top navigation bar includes links for DAGs, Security, Browse, Developer, Admin, and About. The date and time (2020-04-02, 13:16:39 UTC) and user (Super Admin) are also displayed. The main content area is titled "Livy Configuration View" and contains instructions: "Set your Livy configuration for Remote Spark Access in Jupyter Notebooks here." It features two sections: "kernel_python_credentials" and "kernel_scala_credentials". Each section has fields for "username" and "password", and a "url" field. The "auth" dropdown is set to "None" for both sections. A "Save Changes" button is located at the bottom right of the form.

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		Configurations Spark Configuration Hadoop Configuration Spark Dependencies LDAP Configuration Kerberos Configuration Connections Pools Variables XComs
AUTH_LDAP_SERVER	ldap://localhost:10389	
AUTH_ROLE_PUBLIC	Public	
AUTH_USER_REGISTRATION	True	
AUTH_USER_REGISTRATION_ROLE	Admin	
AUTH_LDAP_BIND_USER	cn=test,ou=users,dc=example,dc=com	
AUTH_LDAP_BIND_PASSWORD	test	
AUTH_LDAP_SEARCH	dc=example,dc=com	
AUTH_LDAP_UID_FIELD	uid	
localhost:8080/ldap_LDAP_ALLOW_SELF_SIGNED	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: <code>ou=Users,dc=local,dc=company,dc=com</code>
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, <code>sAMAccountName</code> .
AUTH_LDAP_BIND_USER	A generic search account to be used when searching for a user in a bind request, For example: <code>cn=SearchUser,ou=Users,dc=local,dc=company,dc=com</code>
AUTH_LDAP_BIND_PASSWORD	A generic password to supply in a bind request, For example: <code>SearchPassword1</code>
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, <code>ou=Groups,dc=local,dc=company,dc=com</code>
AUTH_LDAP_USE_TLS	Set this to True to use Transport Layer Security. If this is set to True then the <code>AUTH_LDAP_SERVER</code> address must be of a standard LDAPserver rather than a secure LDAP server.
AUTH_LDAP_FIRSTNAME_FIELD	Default to <code>givenName</code> will use MSFT AD attribute to register <code>first_name</code> on the db.
AUTH_LDAP_EMAIL_FIELD	Default to <code>mail</code> will use MSFT AD attribute to register <code>email</code> on the db. If this attribute is null
AUTH_LDAP_LASTTNAME_FIELD	Default to <code>sn</code> will use MSFT AD attribute to register <code>last_name</code> 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. <code>AUTH_LDAP_SEARCH_FILTER = (memberOf=cn=group name,OU=type,dc=ex ,cn=com)</code>
AUTH_LDAP_APPEND_DOMAIN	Append a domain to all logins. No need to use <code>john@domain.local</code> . Set it like: <code>AUTH_LDAP_APPEND_DOMAIN = domain.local</code> And the user can login using just <code>john</code> .
AUTH_LDAP_USERNAME_FORMAT	It converts <code>username</code> to specific format for LDAP authentications. For example, when <code>username = userexample & AUTH_LDAP_USERNAME_FORMAT=format-%s</code> , It authenticates with <code>format-userexample</code> .
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 <code>AUTH_LDAP_TLS_KEYFILE</code>
AUTH_LDAP_TLS_KEYFILE	Certificate key file for client auth.

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.

couture.ai DAGs Security Browse Developer Admin About 2020-04-02, 13:41:14 UTC Super Admin

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.

- You can only execute these commands after you have authenticated to jupyterhub server and your Jupyter server has started.

couture.ai DAGs Security Browse Developer Admin About 2020-04-02, 13:49:52 UTC Super Admin

File Edit View Run Kernel Tabs Settings Help

Untitled5.ipynb

Name

- clusterOptimization...
- Untitled.ipynb
- Untitled1.ipynb
- Untitled2.ipynb
- Untitled3.ipynb
- Untitled4.ipynb
- Untitled5.ipynb
- Untitled6.ipynb
- Untitled7.ipynb
- Untitled8.ipynb

Git Actions: Schedule a notebook

- Pull
- Push
- View And Commit changes
- Git Logs

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' section of the couture.ai web application. At the top, there's a navigation bar with links for 'DAGs', 'Security', 'Browse', 'Developer' (which is currently selected), 'Admin', and 'About'. The date '2020-02-28, 09:20:44 UTC' and user 'ad min' are also at the top. Below the navigation, a search bar contains 'filename'. A table lists a single file: '1.py' (Last modified: Feb 6 17:14:00 2020, Size: 1.71 KB). To the right of the table are 'Links' icons for cloud storage and deletion. A context menu is open over the '1.py' row, with options: 'Manage DAG', 'Code Artifacts' (which is highlighted in grey), 'Jupyter Notebook', 'Exploratory data analysis', and 'Visualisations'. A green 'Upload file(s)' button is located on the right side of the page. The URL 'localhost:8080/CodeArtifactView/list/' is visible in the browser address bar.

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',  
    method_id='Get_Ratings_History',  
    app_name=appName,  
    code_artifact='PySpark.py',  
    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',
    method_id='Get_Ratings_Data',
    app_name=appName,
    code_artifact='Ratings.py',
    dag=dag,
    description='Dump ratings data in hdfs'
)

Get_Ratings_History = CouturePySparkOperator(
    task_id='Get_Ratings_History',
    method_id='Get_Ratings_History',
    app_name=appName,
    code_artifact='History.py',
    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',
    method_id = 'run_task',
    dag = dag,
    app_name = 'Couture',
    class_path = 'ai.couture.MainClass',
    code_artifact = 'couture.jar',
    description = ''
)
```

Setting up Dependencies

We have tasks *t1*, *t2* and *t3* 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.

The screenshot shows the 'DAGs' section of the couture.ai web application. 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 '2020-02-28, 09:22:26 UTC' and a user 'ad min'. Below the navigation, there's a search bar with 'filename.py' typed in. A dropdown menu from the 'Developer' button includes options like 'Manage DAG', 'Code Artifacts', 'Jupyter Notebook', 'Exploratory data analysis', and 'Visualisations'. To the right are buttons for 'Upload DAG file(s)' and 'Create new DAG'. The main area displays a table of DAG files:

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 your 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.

The screenshot shows the 'Edit Code' page for 'DagOperator.py'. 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 '2020-02-28, 09:22:26 UTC' and a user 'ad min'. Below the navigation, there's a search bar with 'DagOperator.py' typed in. A button 'Review & Save' is visible. The main area contains the Python code for 'DagOperator.py':

```
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 v 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 v CheckFeatures = DagOperator(
17     task_id='JupyterDAG2',
18     dag=dag,
19     run_dag_id='JupyterDAG'
20 )
21
```

To the right, there's a sidebar titled 'Obelisk Code Bricks' with a search bar.

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 'Edit Code' section on the left and the 'Obelisk Code Bricks' sidebar on the right.

Edit Code:

```

2 from datetime import datetime, timedelta
3 from airflow import DAG
4 from airflow.operators import CoutureSparkOperator, CouturePySparkOperator, CoutureDaskYarnOperator
5 from airflow.operators.dag_operator import SkippableDagOperator, DagOperator
6 from airflow.operators.dagrun_operator import TriggerDagRunOperator
7 from airflow.operators.dummy_operator import DummyOperator
8 from airflow.example_dags.subdags.subdag import subdag
9 from airflow.operators.subdag_operator import SubDagOperator
10
11 appName = 'CoutureExample'
12
13
14 # args = {
15 #     'owner': 'couture',
16 #     'start_date': datetime(2019, 4, 15),
17 #     'depends_on_past': False,
18 # }
19
20 # schedule = None
21 # dag = DAG('CoutureExample', default_args=args, schedule_interval=schedule)
22 # CheckFeatures = CoutureSparkOperator(
23 #     task_id='CheckFeatures',
24 #     app_name=appName,
25 #     class_path='org.apache.spark.examples.SparkPi',
26 #     code_artifact='spark-examples_2.11-2.3.1.jar',
27 #     application_arguments=[],
28 #     dag=dag,
29 #     description=''
30 # )
```

Obelisk Code Bricks:

- compute similarity based on attributes
- compute similarity based on feature vectors
- run spark pi example
- write data from hbase to hdf5
- write data from hdf5 to hbase
- write data from oracle to hdf5
- 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.

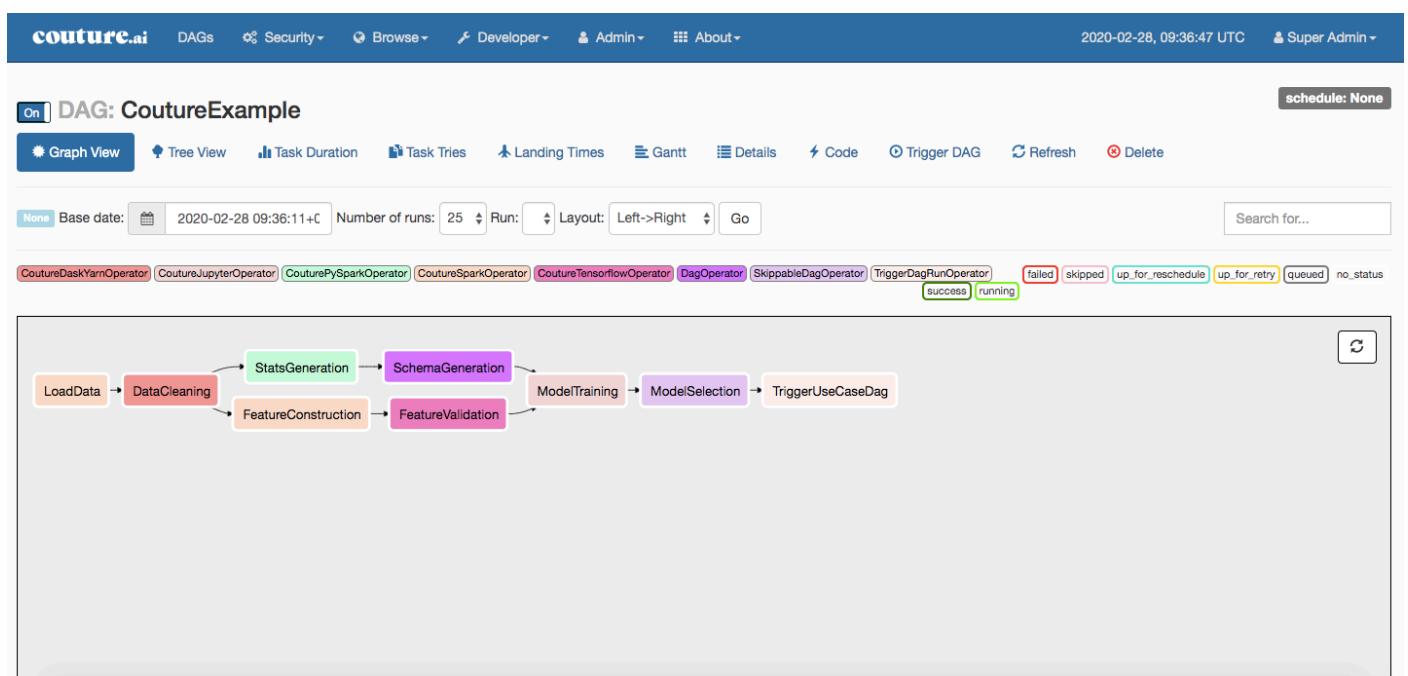
Also, please note that all the paused dags are hidden by default. To un-pause the dag, click on the Show Paused DAGs and switch ON the required dag.

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

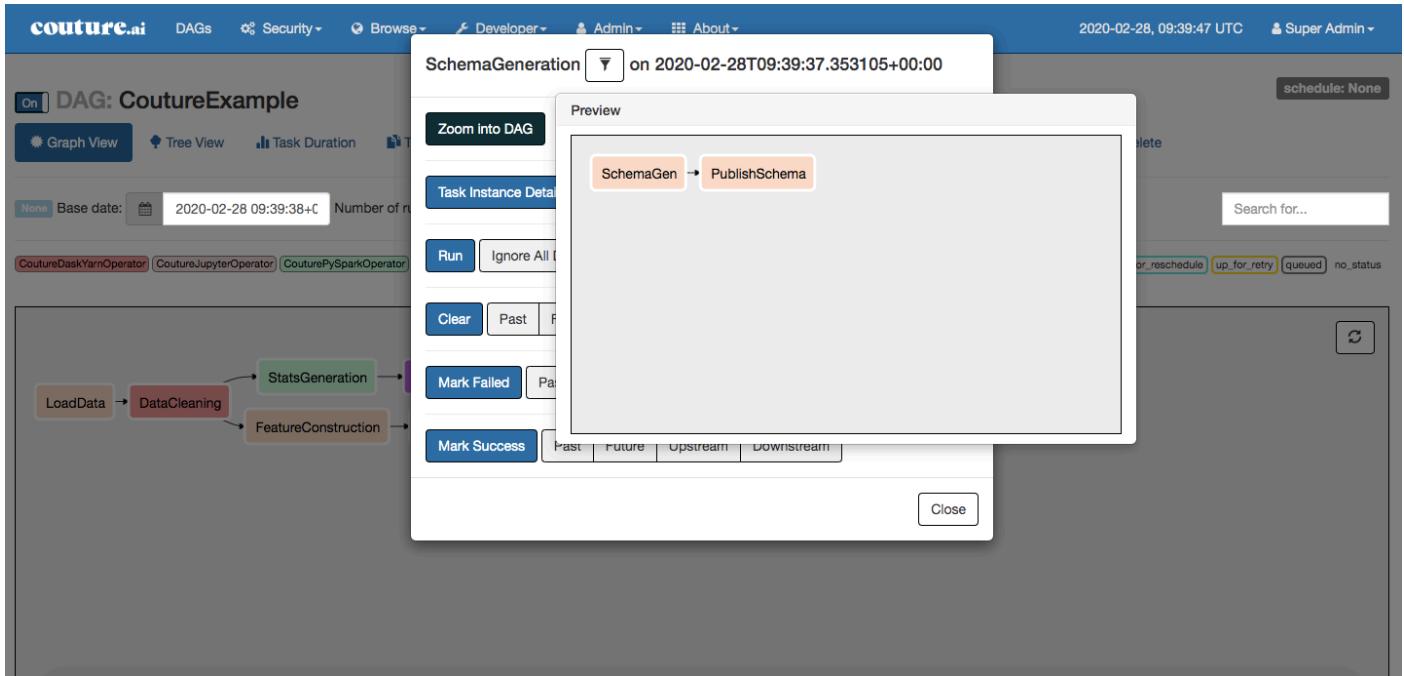
A condition can be set as to whether or not to trigger the remote DAG, by defining a `python` function as below.

```
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',
    method_id = 'run_task',
    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:

- **method_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. Method id and DAG id are also present in this json as **method_id** and **dag_id** respectively.

Example of final output:

```
'{"method_id": "LoadData", "dag_id": "video_embedding_dag", "method_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',
    method_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"},
    method_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:

- **method_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. Method id and DAG id are also present in this json as `method_id` and `dag_id` respectively.

Example of final output:

```
'{"method_id": "fetch_videos", "dag_id": "video_embedding_dag", "method_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',
    method_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',
    method_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:

- **method_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. Method id and DAG id are also present in this json as `method_id` and `dag_id` respectively.

Example of final output:

```
'{"method_id": "fetch_videos", "dag_id": "video_embedding_dag", "method_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',
    method_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"},
    method_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:

- **method_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. Method id and DAG id are also present in this json as `method_id` and `dag_id` respectively.

Example of final output:

```
'{"method_id": "fetch_videos", "dag_id": "video_embedding_dag", "method_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',
    method_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'},
    method_args_dict={'task_strategy': 'parallel'},
    description='A TF task'
)
```

CoutureLoopableBatchOperator

`CoutureLoopableBatchOperator` allows you to run a target dag in a loop by passing input from a csv file in batches. You can also provide an `offset`, `filter_by` a column to send rows which match a specific value.

Parameters:

- **batch_offset**: Default 0
- **batch_size**: Size of the batch. Defaults to 10.
- **filter_by**: Column name to filter_by. Defaults to `None`, which means all rows will be passed.
- **filter_values**: Values in a list with which the `filter_by` column must match against for a row to be passed to target dag.
- **run_dag_id**: Dag id of the target dag.
- **metadata_file**: File which contains the csv rows which should be passed. Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is

expected. A local file could be: <file:///localhost/path/to/table.csv>.

Ex:

```
import os
from datetime import datetime

from airflow.operators.dag_operator import DagOperator
from airflow.operators.dagrun_operator import TriggerDagRunOperator

from airflow import DAG
from airflow.operators import CoutureTensorflowOperator,
    CoutureLoopableBatchOperator

default_args = {
    'owner': 'couture',
    'depends_on_past': False,
    'start_date': datetime(2019, 4, 15),
    'retries': 0,
}

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

metadata_file = 'https://link/to/file/link.csv'

video_embedding_batch_task = CoutureLoopableBatchOperator(
    dag=dag,
    run_dag_id='operator_audio',
    task_id='audio_batch_processing',
    batch_size=2,
    batch_offset=0,
    metadata_file=metadata_file
)
```

The dag with dag_id operator_audio can have tasks like:

```
# Task : Video Scene Detection
convert_video_to_audio = CoutureTensorflowOperator(
    dag=dag,
    task_id='convert_video_to_audio',
    method_id='convert_video_to_audio_brick',
    code_artifact=code_artifact,
    input_base_dir_path=processed_dir,
    output_base_dir_path=processed_dir,
    input_filenames_dict={
        'input_file_pattern': 'video_id/video/video_name'
    },
```

```

output_filenames_dict={
    'output_file_pattern': 'video_id/audio/basename.wav'
},

method_args_dict={
    'processing_method': 'parallel',
    'num_cpu_cores': 6,
    'argument_filter': {
        'metadata_df': '{{dag_run.conf["metadata_df"]}}'
    },
    'input_file_extensions': ['.mp4'],
    'audio_sample_rate': 16000
},
description = "Sample"
)

```

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.

- You can only schedule notebooks present inside common_workspace and output notebooks inside common_workspace. If you output notebooks outside common_workspace then the notebook will be run successfully but the output notebook will be discarded.
- 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 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_notebook='testFile2.ipynb',
                            output_notebook='plotTestFile2.ipynb',
                            parameters={"a": 10},
                            dag=dag)
```

User Interface

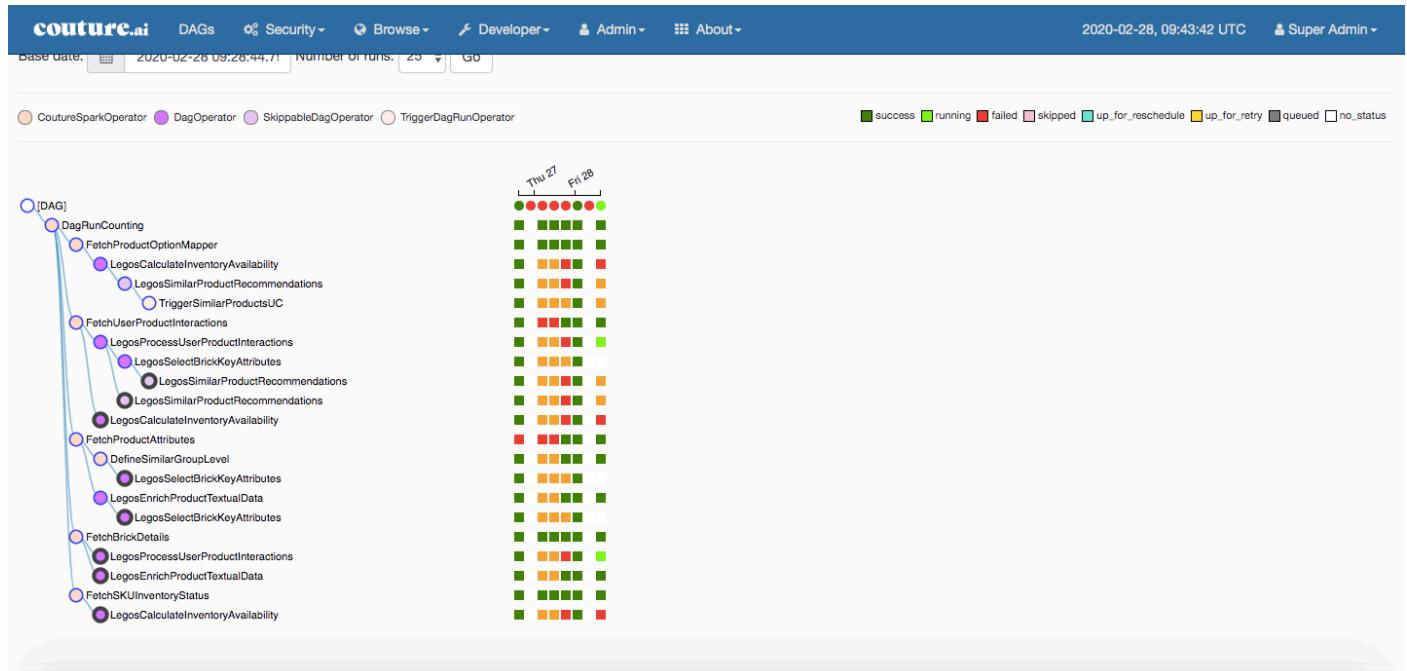
The Workflow UI makes it easy to monitor and troubleshoot your data pipelines. Here's a quick overview of some of the features and visualizations you can find in the Workflow UI.

[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.

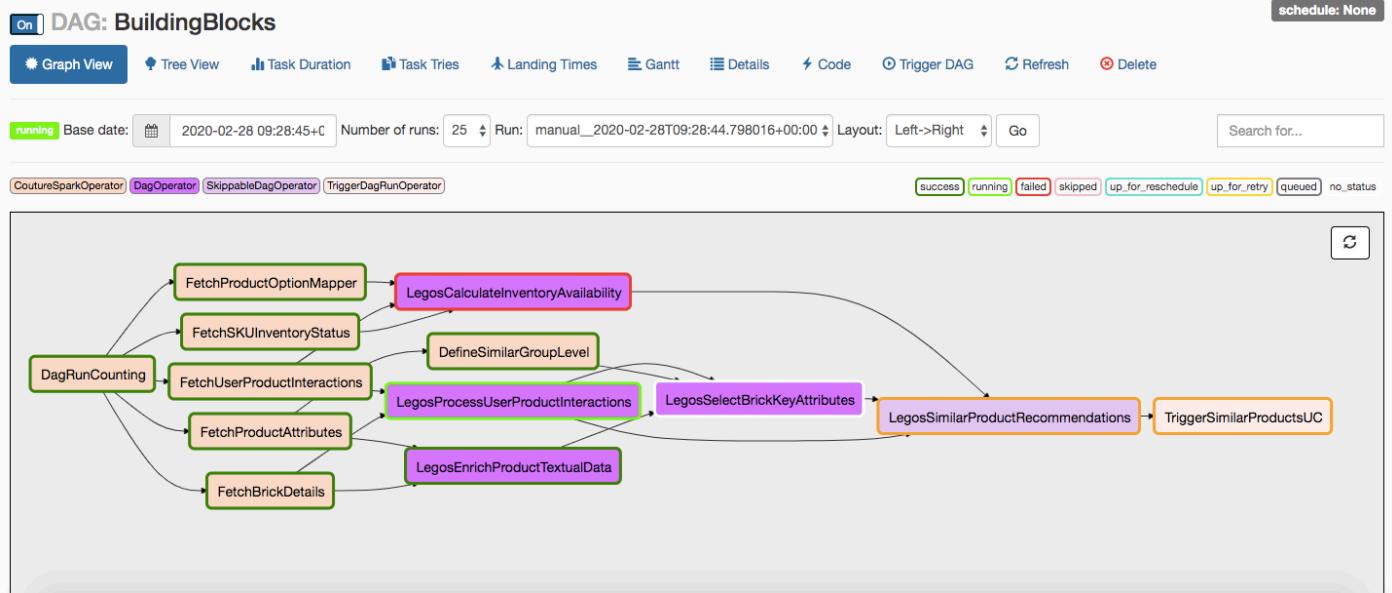
Tree View

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.

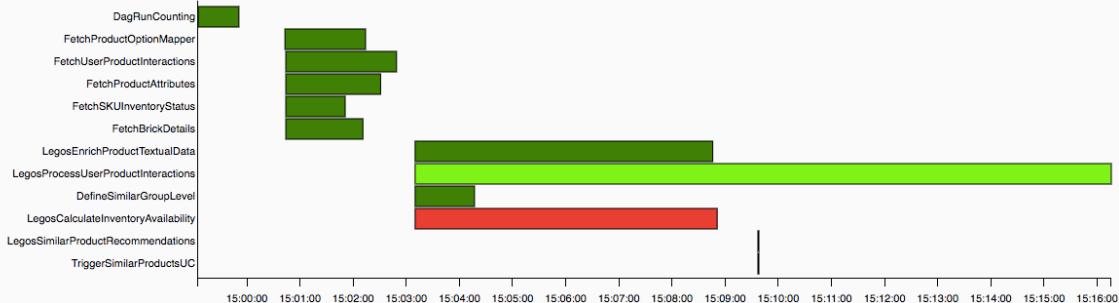
Gantt Chart

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.

On| DAG: BuildingBlocks

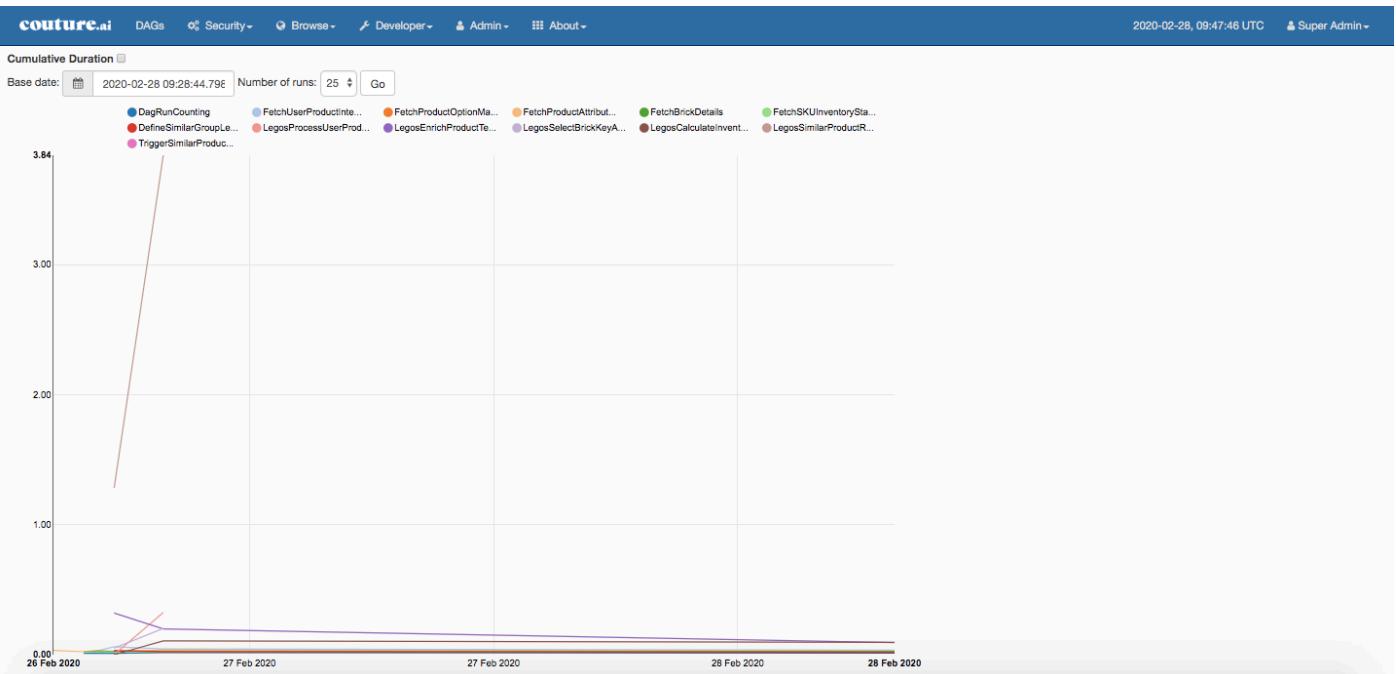
Graph View Tree View Task Duration Task Tries Landing Times Gantt Details Code Trigger DAG Refresh Delete

Base date: 2020-02-28T09:28:45+00:00 Number of runs: 25 Run: manual_2020-02-28T09:28:44.798016+00:00 Go



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

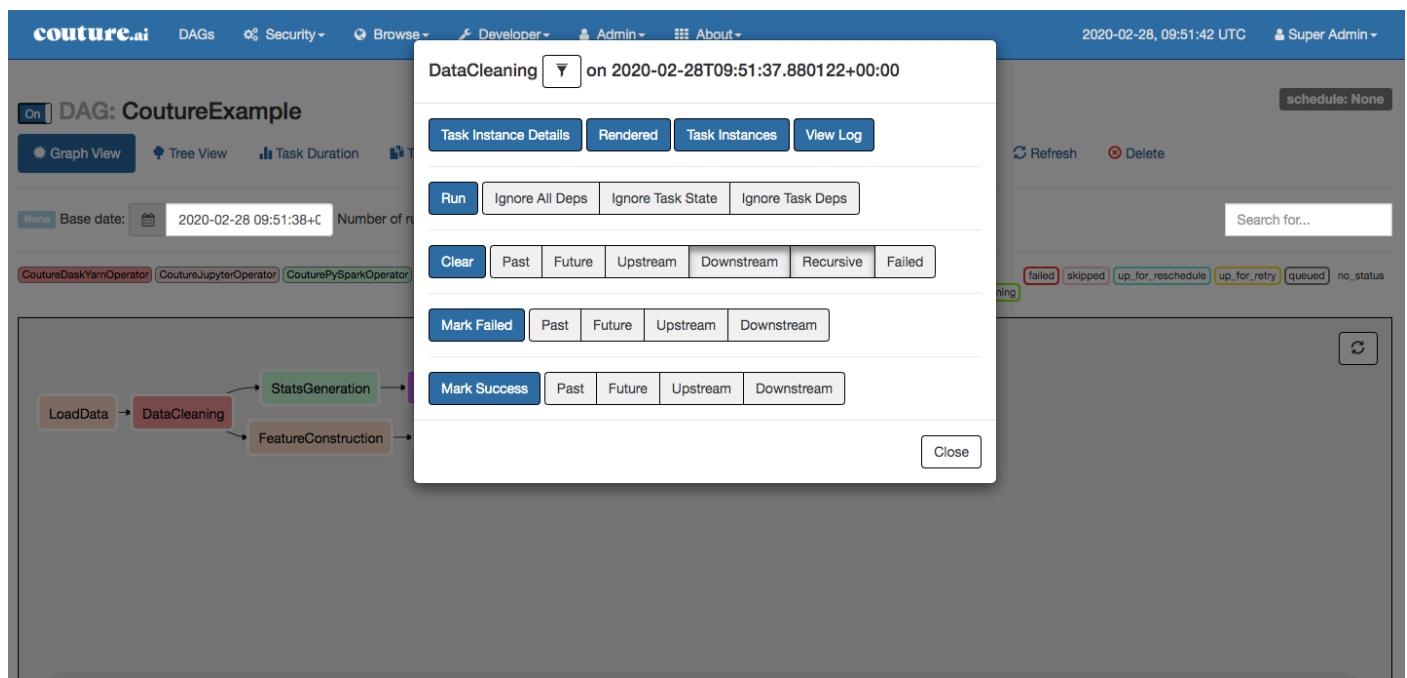
```

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 certainDAGs. To configure a new role, go to Security tab and click List Roles in the new UI.

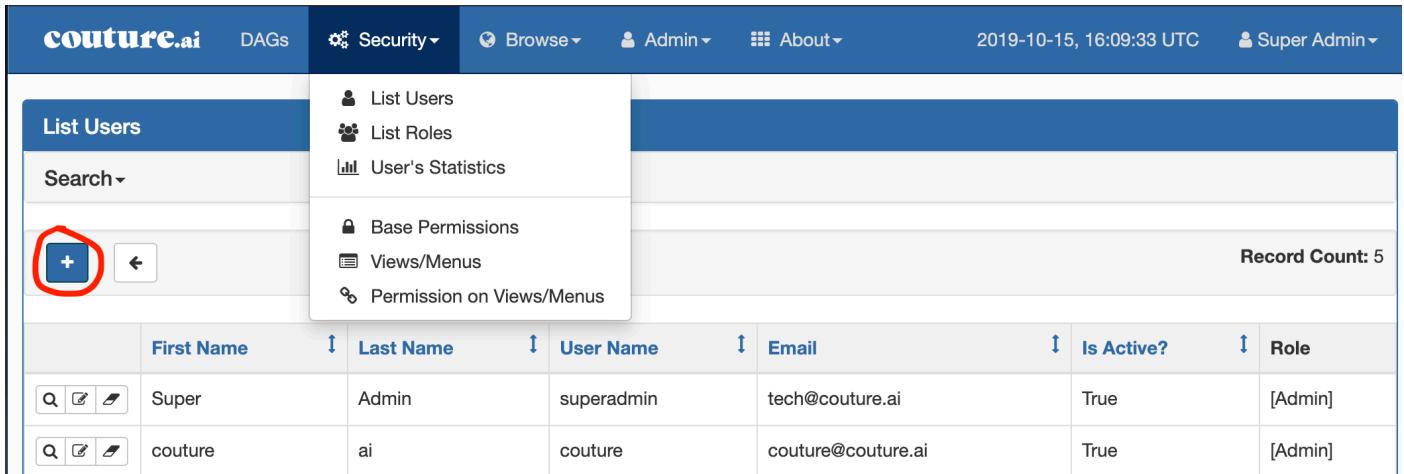
The screenshot shows the 'Add Role' page of the couture.ai web application. At the top, there is a navigation bar with links for DAGs, Security, Browse, Admin, About, and a timestamp of 2019-10-15, 16:14:07 UTC. On the right, it shows the user is a Super Admin. The main form has fields for 'Name *' (with a red asterisk), 'User', and 'Permissions'. A modal window is open over the 'Permissions' field, listing several options, with 'can dag read on all_dags' highlighted in blue. At the bottom left of the form are 'Save' and 'Cancel' buttons.

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.



The screenshot shows the 'List Users' page of the couture.ai application. At the top, there are navigation links: DAGs, Security (selected), Browse, Admin, About, and a timestamp (2019-10-15, 16:09:33 UTC). On the right, there's a Super Admin dropdown. Below the header, there are sections for 'List Users', 'Search', and 'Record Count: 5'. The 'List Users' section includes links for 'List Users', 'List Roles', and 'User's Statistics'. The 'Search' section has a search bar and a '+' button, which is circled in red. The main table lists users with columns: First Name, Last Name, User Name, Email, Is Active?, and Role. Two users are listed: 'Super' and 'couture'.

	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 Search 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	09-23T10:02:34.934606+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.

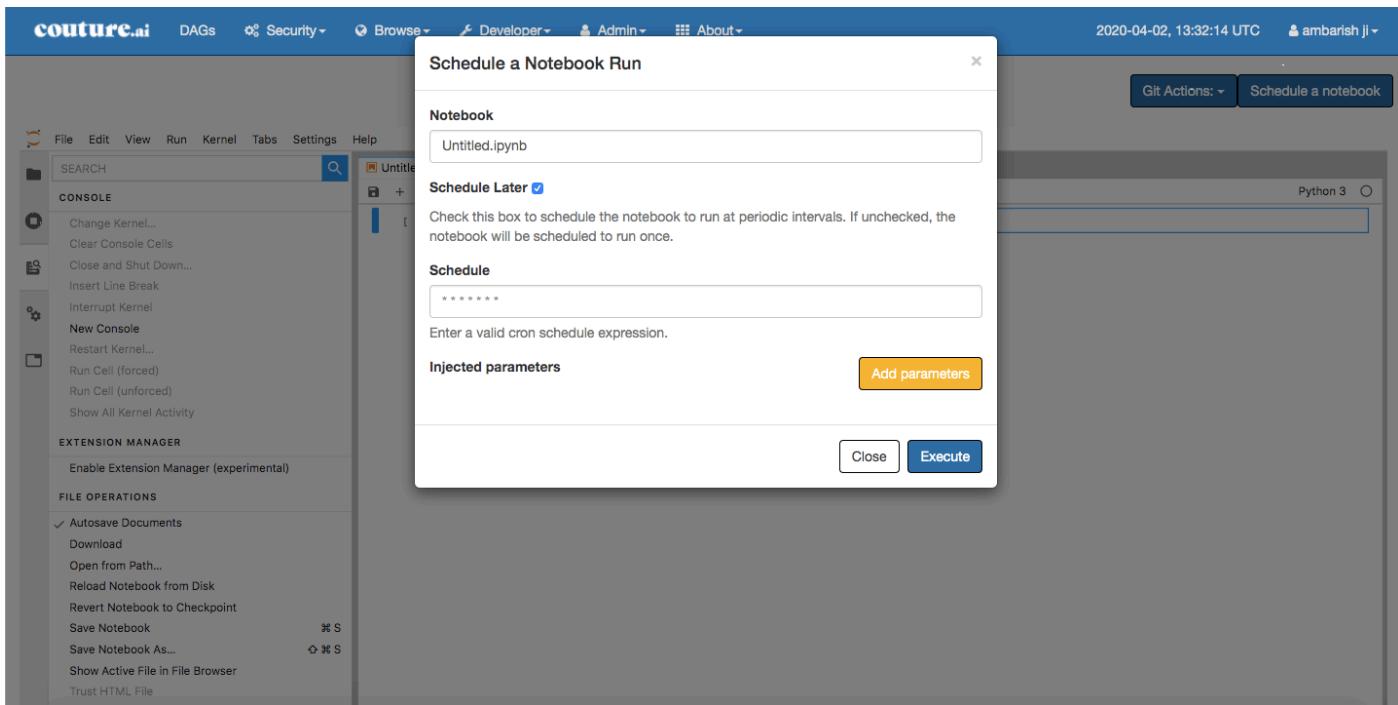
NOTE: Jupyter Notebook View might prompt you for authentication. Use the same credentials which was used while logging in to Workflow Orchestrator

couture.ai DAGs Security Browse Developer Admin About 2020-04-02, 12:25:51 UTC Super Admin

Git Actions: Schedule a notebook

The screenshot shows the Jupyter Notebook interface within a web-based developer environment. On the left, there is a file browser window showing several Jupyter notebook files (Untitled.ipynb, Untitled2.ipynb, etc.) and a terminal window. On the right, there is a 'Launcher' window containing sections for 'Notebook' (Python 3, ml-kernel, PySpark, pytorch-kernel, S, SparkR, tf-kernel), 'Console' (Python 3, ml-kernel, PySpark, pytorch-kernel, S, Spark, S, tf-kernel), and 'Other' (Terminal, Text File, Markdown File, Show Contextual Help).

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.

The screenshot shows the 'DAG Runs' section of the couture.ai web application. The top navigation bar includes links for 'DAGs', 'Security', 'Browse', 'Admin', 'About', and the current date and time '2019-10-16, 07:53:27 UTC'. A dropdown menu from the 'Browse' button lists 'DAG Runs', 'Jobs', 'Audit Logs', 'SLA Misses', and 'Task Instances'. Below this is a search bar and a table with the following data:

	State	Dag Id	Execution Date	Run Id	External Trigger
<input type="checkbox"/>	failed	PySpark	10-16T06:36:53.387072+00:00	manual_2019-10-16T06:36:53.387072+00:00	True
<input type="checkbox"/>	success	PySpark	10-16T06:32:14.503166+00:00	manual_2019-10-16T06:32:14.503166+00:00	True
<input type="checkbox"/>	success	PySpark	10-16T06:31:39.604312+00:00	manual_2019-10-16T06:31:39.604312+00:00	True
<input type="checkbox"/>	success	PySpark	10-15T13:41:22.037615+00:00	manual_2019-10-15T13:41:22.037615+00:00	True
<input type="checkbox"/>	failed	PySpark	10-15T13:09:15.581768+00:00	manual_2019-10-15T13:09:15.581768+00:00	True
<input type="checkbox"/>	failed	PySpark	10-15T12:49:54.767437+00:00	manual_2019-10-15T12:49:54.767437+00:00	True
<input type="checkbox"/>	running	tutorial	2017-07-09T00:00:00+00:00	scheduled_2017-07-09T00:00:00+00:00	False
<input type="checkbox"/>	running	tutorial	2017-07-08T00:00:00+00:00	scheduled_2017-07-08T00:00:00+00:00	False
<input type="checkbox"/>	running	tutorial	2017-07-07T00:00:00+00:00	scheduled_2017-07-07T00:00:00+00:00	False
<input type="checkbox"/>	running	tutorial	2017-07-06T00:00:00+00:00	scheduled_2017-07-06T00:00:00+00:00	False
<input type="checkbox"/>	running	tutorial	2017-07-05T00:00:00+00:00	scheduled_2017-07-05T00:00:00+00:00	False

Models and Datasets

Workflow Orchestrator allows us to upload Machine Learning models and datasets and expose them via an API so that they can be used by clients. Currently, we support 4 different types of models, i.e Tensorflow Models, Spark Models, Pytorch models and Other Models, and a Dataset Repository. To upload a trained model, visit [Developer->Models and Datasets](#). You will see an UI as attached below:

Pre-trained models and dataset repositories

TF_MODELS

Drop files here to upload

File / Directory	Last modified	Size	Links
audio_classification	Jun 18 11:47:09 2020	4.0 KB	

SPARK_MODELS

Drop files here to upload

52.71.228.112:8080/workflow/TrainedModelsView/list/#datasets-h4

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

`.pmmml` files can be uploaded in this section. Models added in this section are exposed by an inference API on port 8000 in < 10 minutes. For information on how to use the REST API for inference checkout the [Openscoring model inference guide](#).

You can export your Apache Spark models in the Predictive Model Markup Language(PMML) using the [Spark documentation on PMML export](#).

Pytorch Models

.mar files can be uploaded in this section. Models added in this section are currently exposed by an inference API on port 8600. For information on how to use this API, visit [pytorchserve-inference-api](#).

Before you upload your PyTorch model using the provided drag and drop utility, it needs to be processed by the [torch-model-archiver](#).

To do so, follow the steps below:

- **Install torch-model-archiver** : To install the torch-model-archiver, clone the pytorch/serve repository and install the model-archiver utility using pip, as follows:

```
git clone https://github.com/pytorch/serve.git
cd serve/model-archiver
pip install .
```

- To run the torch-model-archiver that you've installed you are required to provide the following information:

- A name for your model
 - Model's version
 - The model file
 - The serialized file
 - Index to name JSON file
 - Handler Type
- Run the following command:

```
torch-model-archiver
--model-name <model_name>
--version <model_version_number>
--model-file <path_to_model_architecture_file>
--serialized-file <path_to_serialized_file> --extra-files
<path_to_index_to_name_json_file>
--handler <handler_type>
```

- Model Name: You can choose any name for your model based on your discretion.
- Version Number: You can choose a version number for your model. The latest version is served in deployment.
- Model File: The path and name of your model architecture file needs to be provided here.
- Index to name JSON file: A JSON file containing the mapping of predicted index to class needs to be provided here.
- Handler: **torch-model-archiver** supports four handlers out of the box, these are:
 - image-classifier
 - object-detector
 - text-classifier
 - Image-segmenter

A default or custom handler needs to be provided here. For more information on supported handlers, check handler documentation.

- An example to explain the usage of torch-model-archiver as follows:

```
torch-model-archiver --model-name densenet161 --version 1.0 --model-file examples/image_classifier/densenet_161/model.py --serialized-file densenet161-8d451a50.pth --extra-files examples/image_classifier/index_to_name.json --handler image_classifier
```

For more information on using torch-model-archiver use the documentation available [here](#). Following this process would generate a .mar file, which is your required model archive file.

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.

Datasets

Any file can be uploaded in this section. Files added in this section are treated as datasets and can be used in DAGs.

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**.

There are two kinds of EDA:

- L0 EDA or Preliminary EDA
- L1 EDA or Feature Importance EDA

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.
 2. If you are using a Excel/CSV/TSV Datasource, only Preliminary EDA will be run on the file uploaded, and the file uploaded will not be added to sources list. If you are doing this, you can skip 3rd step.
3. Once you have your required Data source added, you need to click on the play button to start EDA. You will see a flash message with the output path of the EDA run where the output will be stored once run completes successfully.

The screenshot shows the Couture Dashboard 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 and time (2020-06-26, 09:48:07 UTC) and a user role (Super Admin). Below the header, the main title is "Exploratory Data Analysis". Under "Raw Inputs", there's a search bar and a table with columns for "Source" and "Links". A single row is shown: "hdfs://data/eda/raw/inputs/excel-spreadsheet-examples-for-students.xls" with a "Preliminary" link and a "Data Importance" link. A red trash icon is also present. In the "Processed Outputs" section, there's a hierarchical tree view under "outputs". It starts with "excel-spreadsheet-examples-for-students", which has "preliminary" and "data_importance" sub-folders. "preliminary" contains two timestamped folders: "2020-06-24-07:13:37" and "2020-06-18-12:14:17", each with a "data_info.html" file. "data_importance" contains a folder for "2020-06-18-12:14:20" with a "table_and_feature_importance.html" file.

4. Once an output of EDA is generated, it will be in the Processed Outputs Section of the same page. Use the output path described in the last step to find that output. 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',
 'owner': 'airflow'}

```

```

'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,
'ver': {'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.

The screenshot shows the couture.ai web interface with the following details:

- Header:** couture.ai, DAGs, Security, Browse, Admin, About, 2019-10-16, 10:14:45 UTC, Super Admin
- DAG Selection:** DAG: dag_3 (On)
- Task Instance:** task1 (Selected)
- Date Filter:** 2019-10-15T14:51:08.848Z
- Navigation:** Graph View, Tree View, Task Duration, Task Tries, Landing Times, Gantt, Details, Code, Trigger DAG, Refresh, Delete
- Buttons:** Task Instance Details, Rendered Template, Log, XCom (highlighted)
- XCom Table:**

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.