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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`.

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

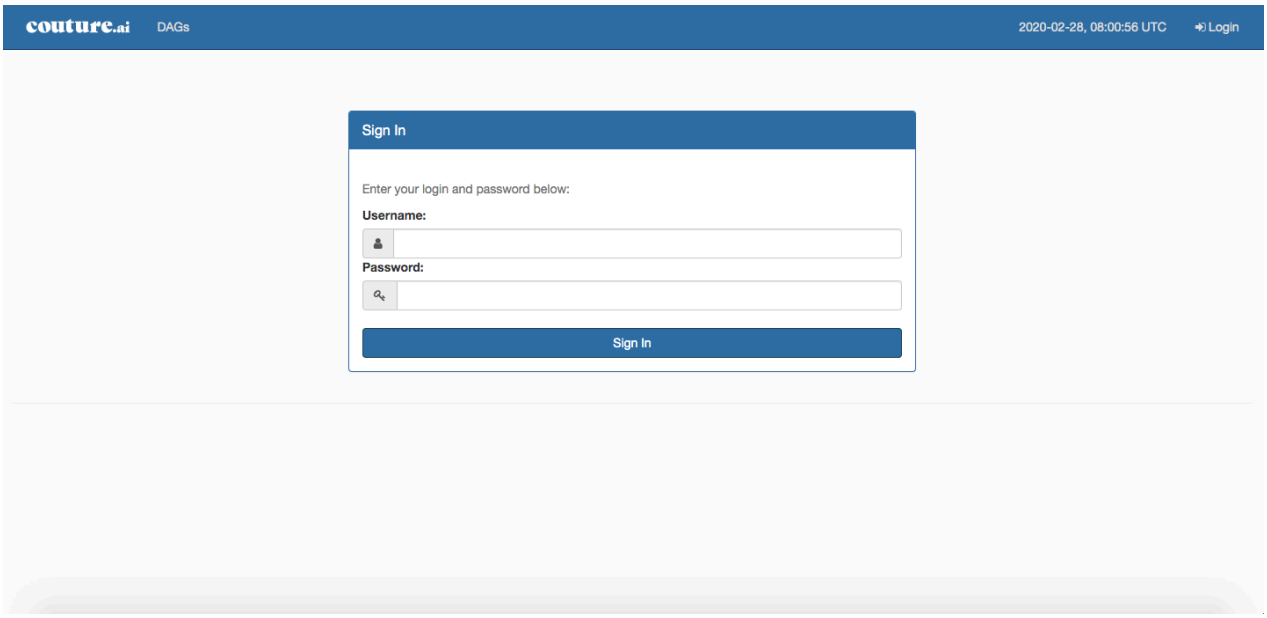
  ```
  docker tag CR1:5005/rabbitmq:3.7-management rabbitmq:3.7-management
  ```

  ```
  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

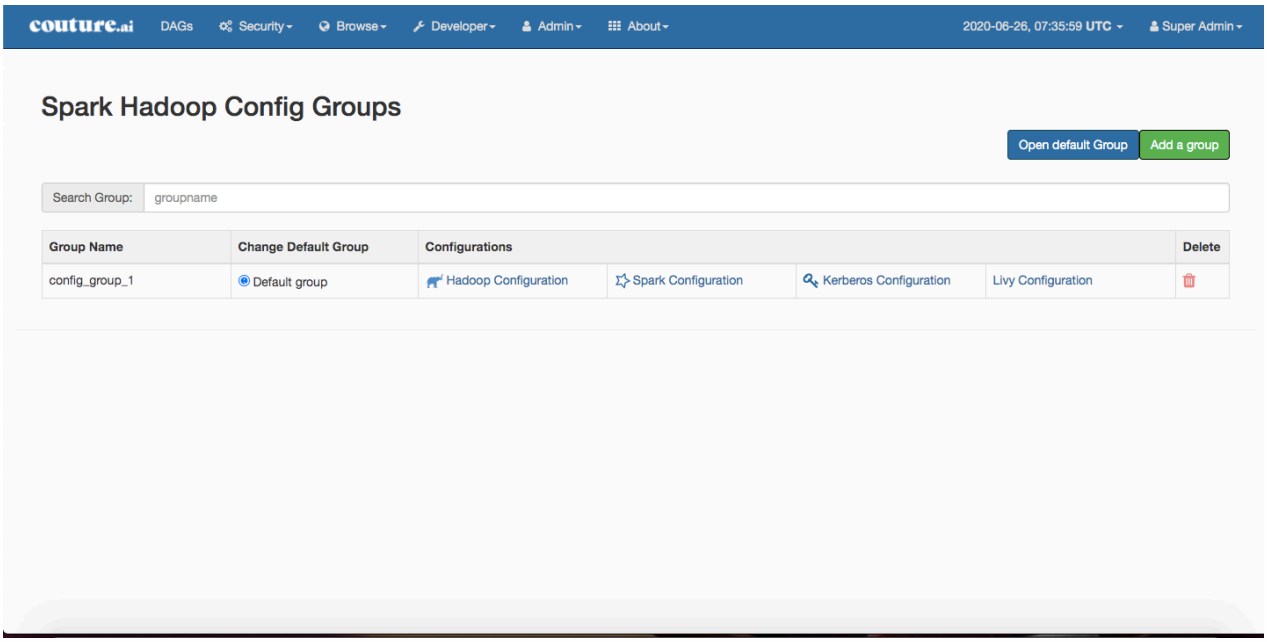
Login as an admin user and configure spark, hadoop, livy and kerberos configurations as followed.

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`

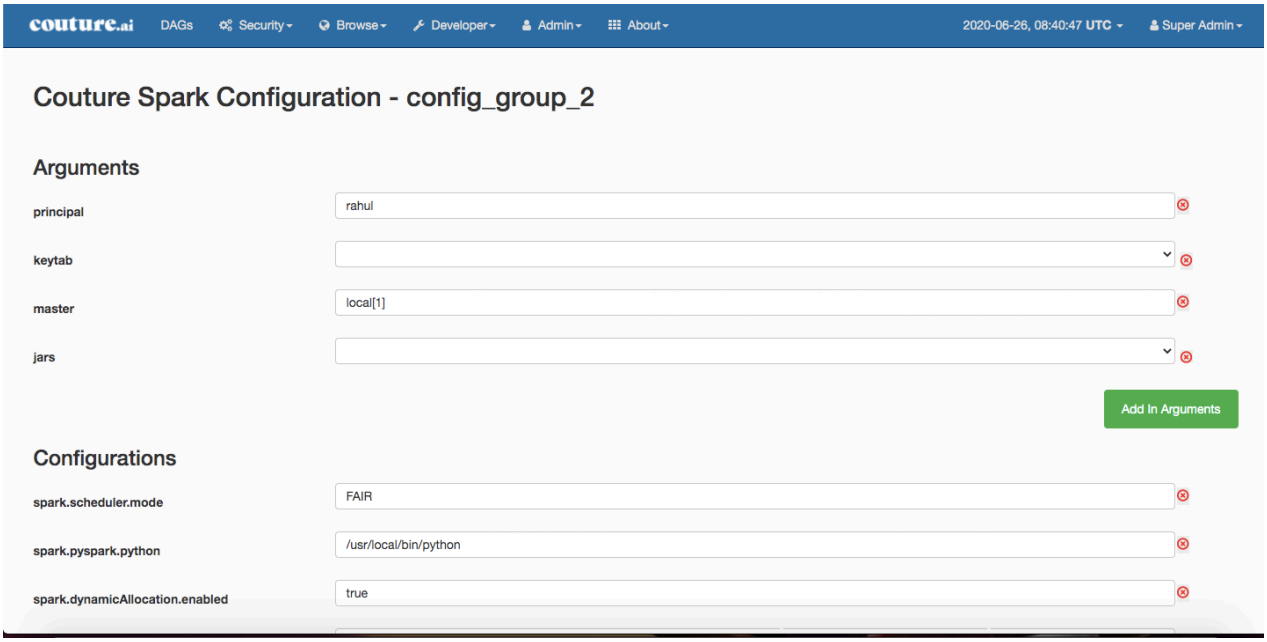
When you are running `Workflow` for the first time, there will not be any `config groups`. However, you can create a config group by clicking on `Add a group` button.



Spark Configuration

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

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



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.

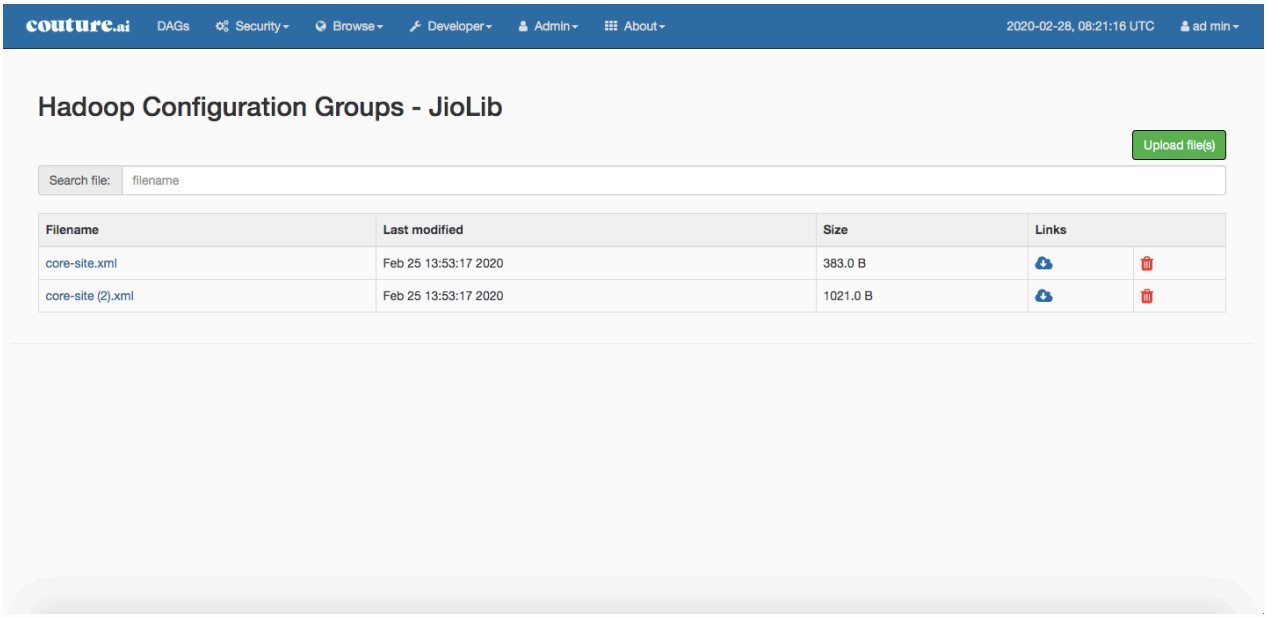
Note: New changes gets automatically picked up for all the *NEWLY* triggered spark jobs.

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.

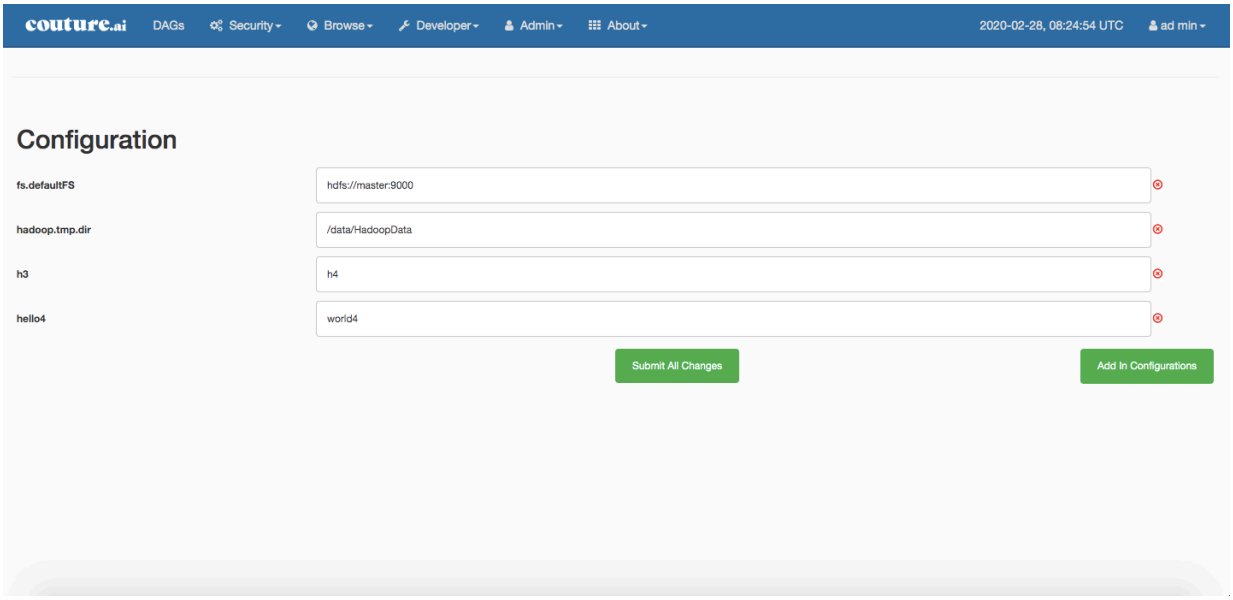
Hadoop Configurations

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 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.



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.

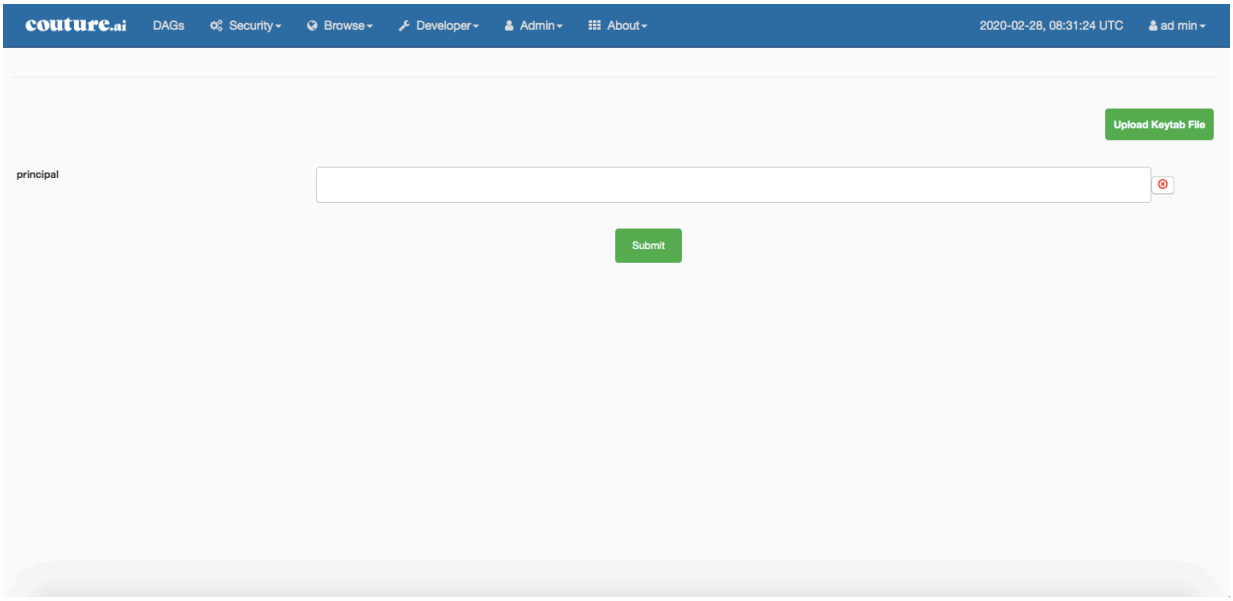


Kerberos Configurations

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.

2. Upload the `keytab` file from `Upload Keytab File` option. These configurations, if added, are automatically applied to the spark jobs which use that configuration group.

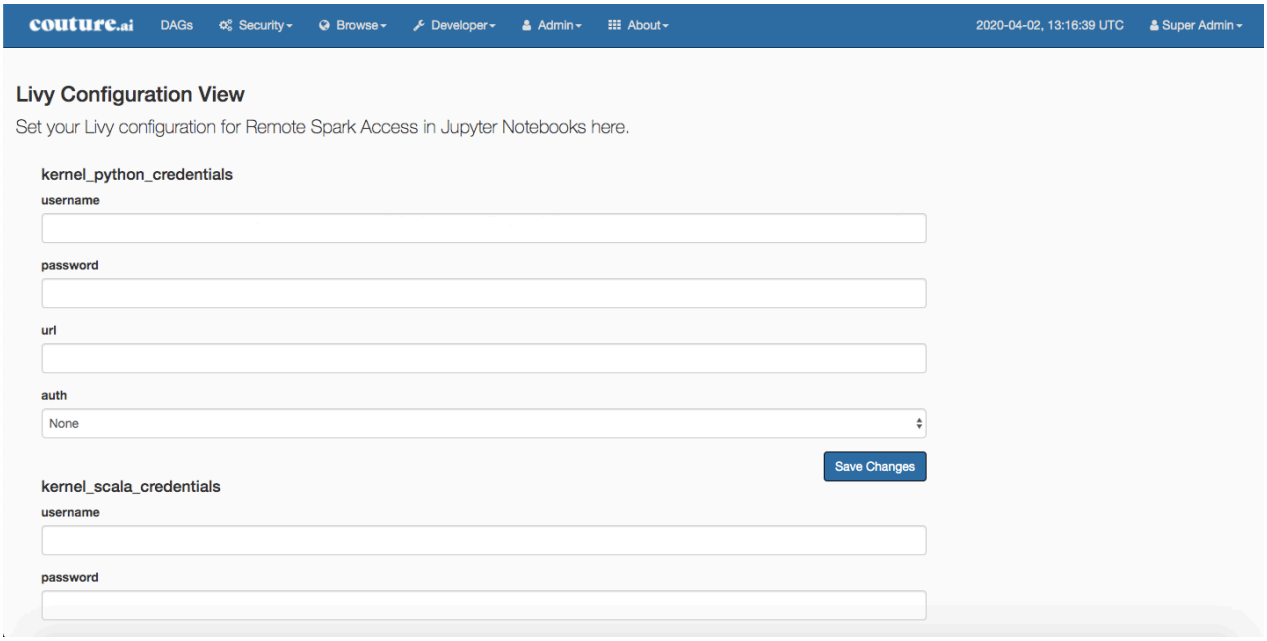


Livy Configuration

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.

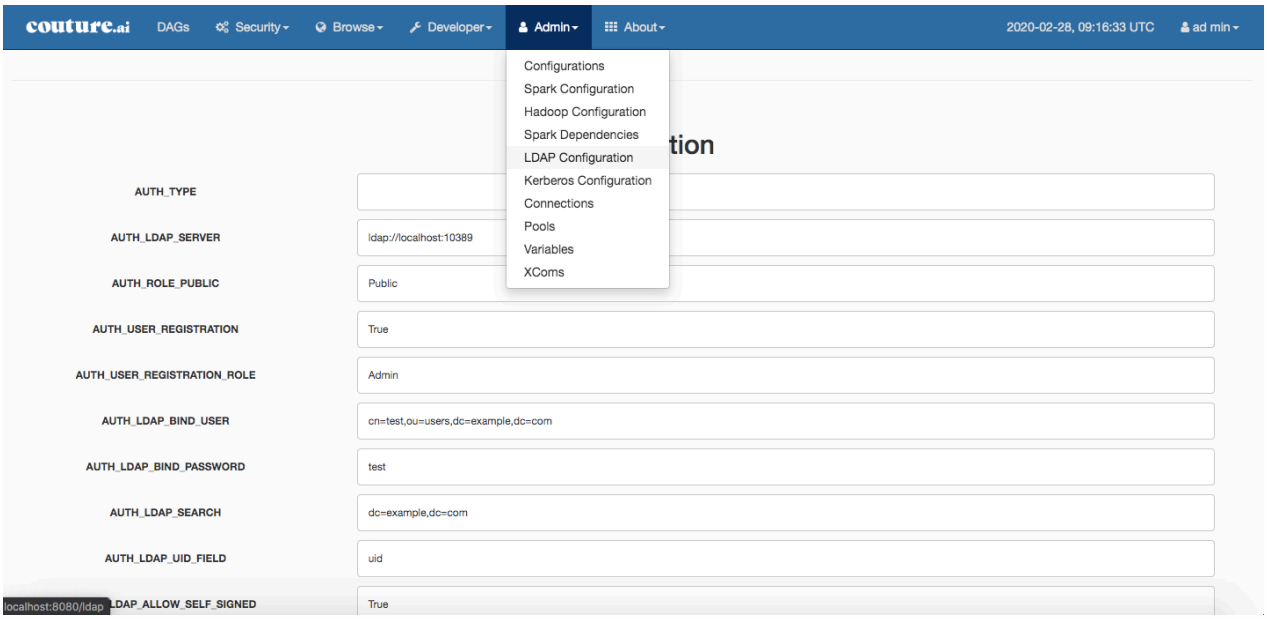
NOTE: The livy configuration of the default spark hadoop config group will be used with sparkmagic kernels in jupyterhub



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`.



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

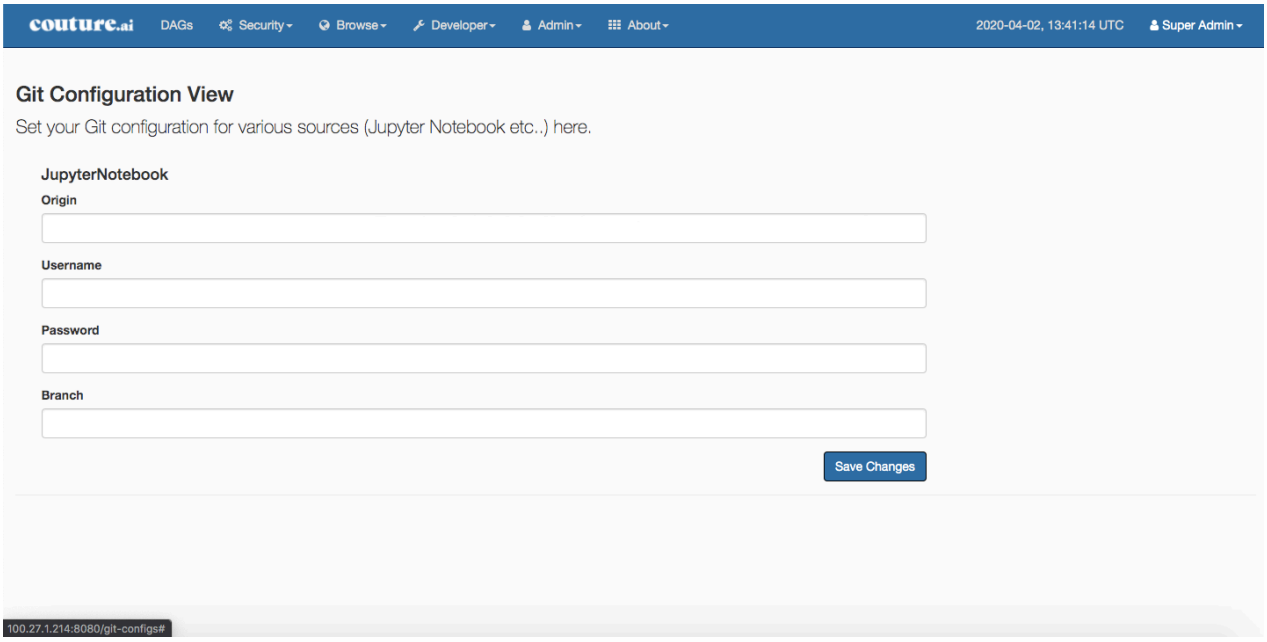
Config	Description
`AUTH_TYPE`	Set to `AUTH_LDAP`. This overrides the default setting, which is to use the MySQL database for authentication. Henceforth, only LDAP users will be able to login to workflow.
`AUTH_LDAP_SERVER`	The address of the `LDAP` server, for example `ldap://<ip_address>`, or `ldaps://<ip_address>` to connect to a secure `LDAP` server. If a secure `LDAP`` server is used, the AUTH_LDAP_USE_TLS` 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 `LDAP`server 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 ,cn=com)
AUTH_LDAP_APPEND_DOMAIN	Append a domain to all logins. No need to usejohn@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.

Git Configuration

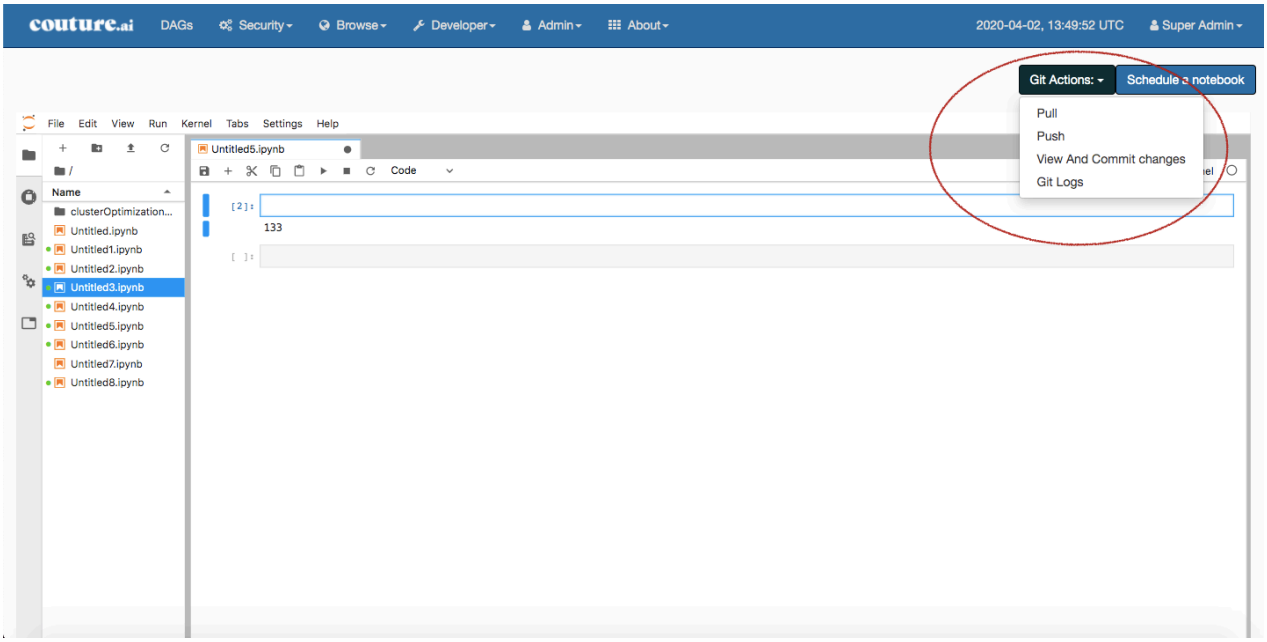
Developers can configure Workflow Orchestrator to connect their JupyterHub files to a remote repository and perform common git operators such as commiting files, pushing to remote repository, viewing logs etc.

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



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

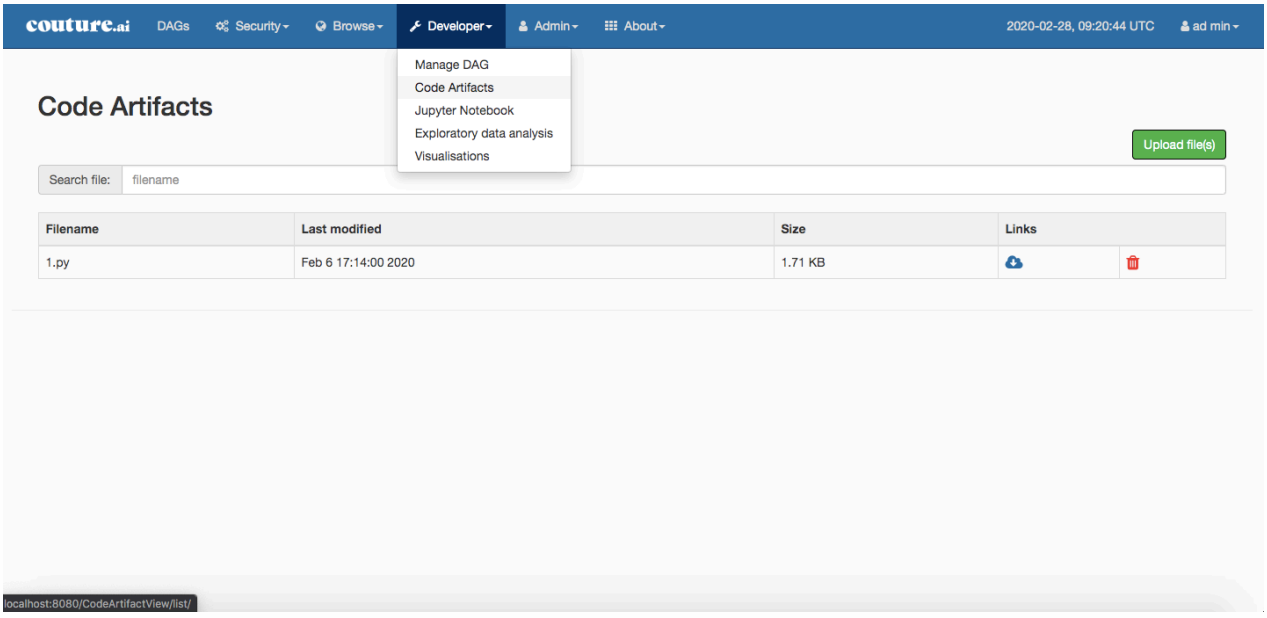
- You can only execute these commands after you have authenticated to jupyterhub server and your Jupyter server has started.



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 `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

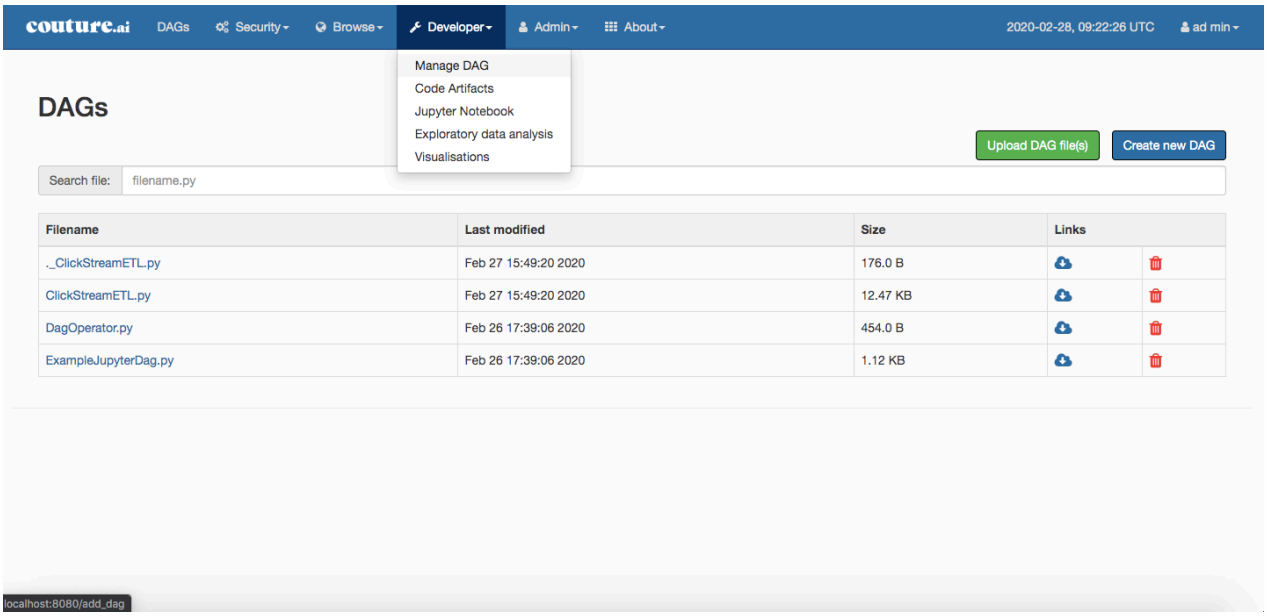
After creating a `<dag>.py` file on your local machine, add the new `dag` to server using below steps:

- 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.

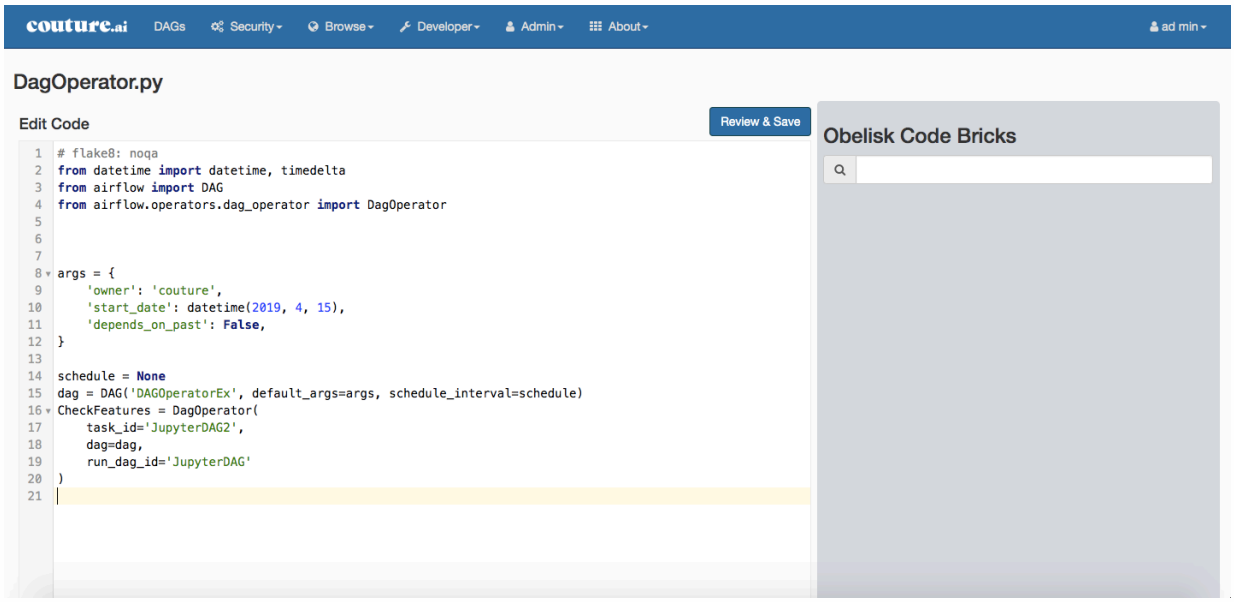


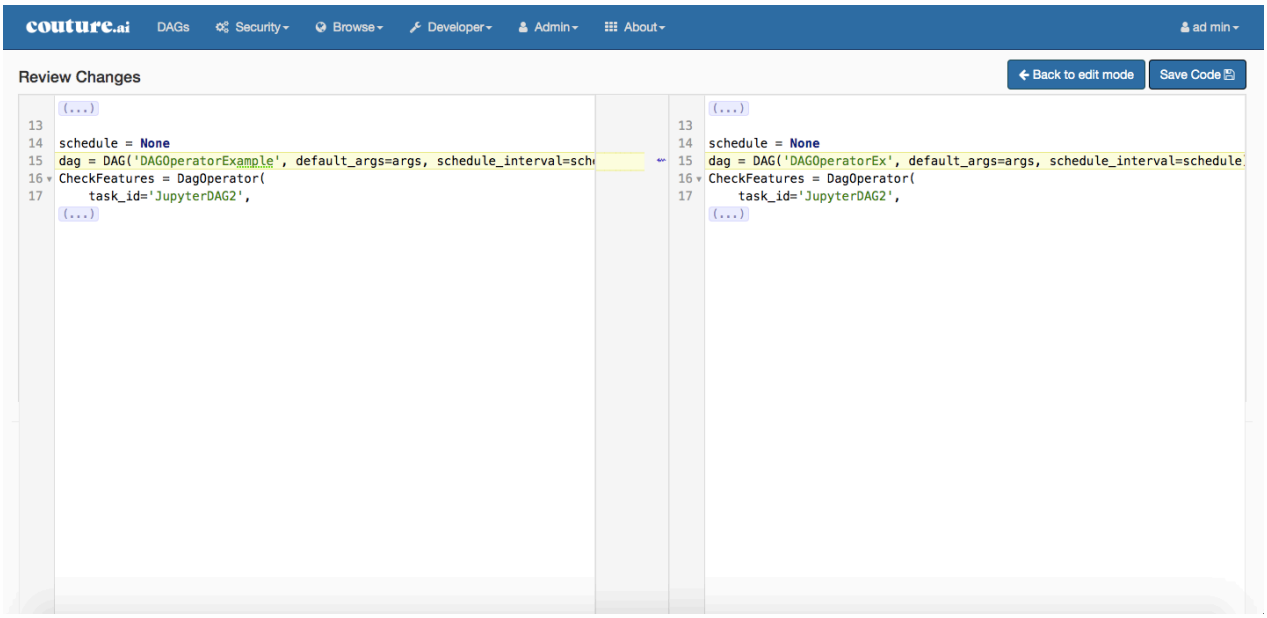
Edit DAG code

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.

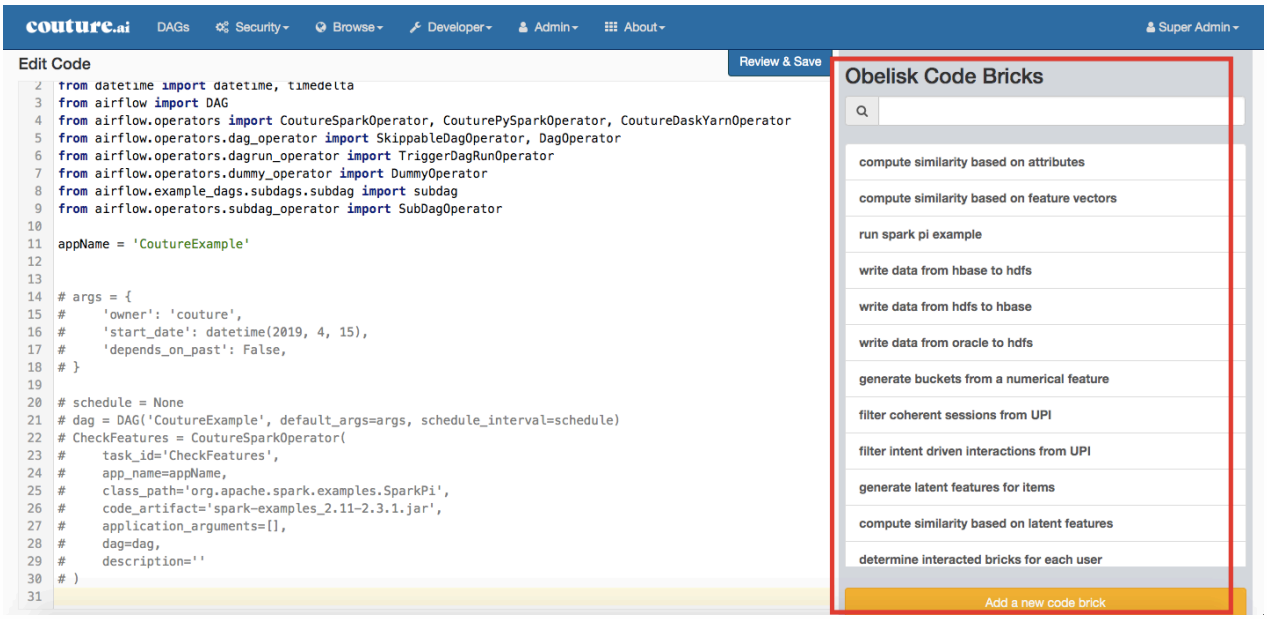




Code Bricks

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

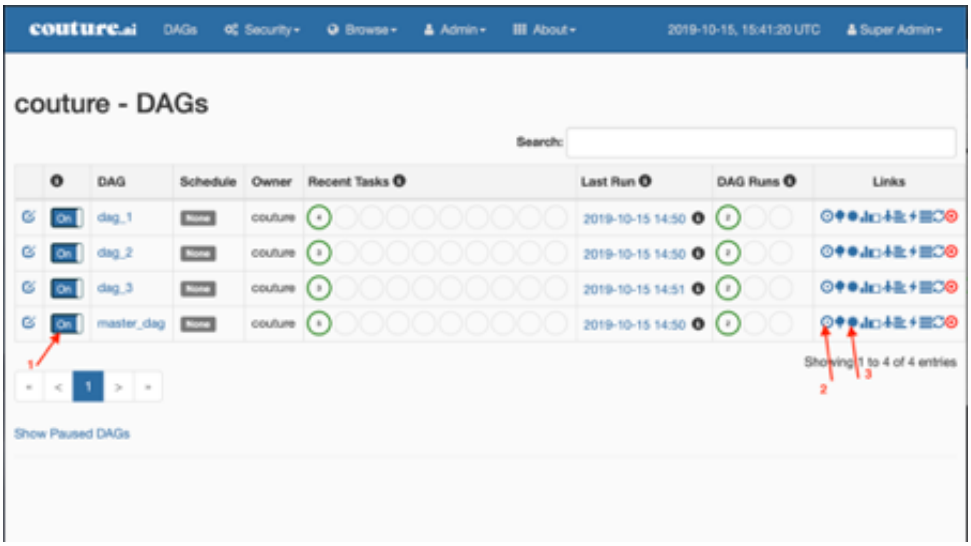
- Existing `code bricks` (code snippets) can be added to the `dags`, by visiting the `Code Bricks` repository and inserting the required code.
- New snippets can also be added by `Add a new code brick` option. Please note the `title` entered here, appears in the list.



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.

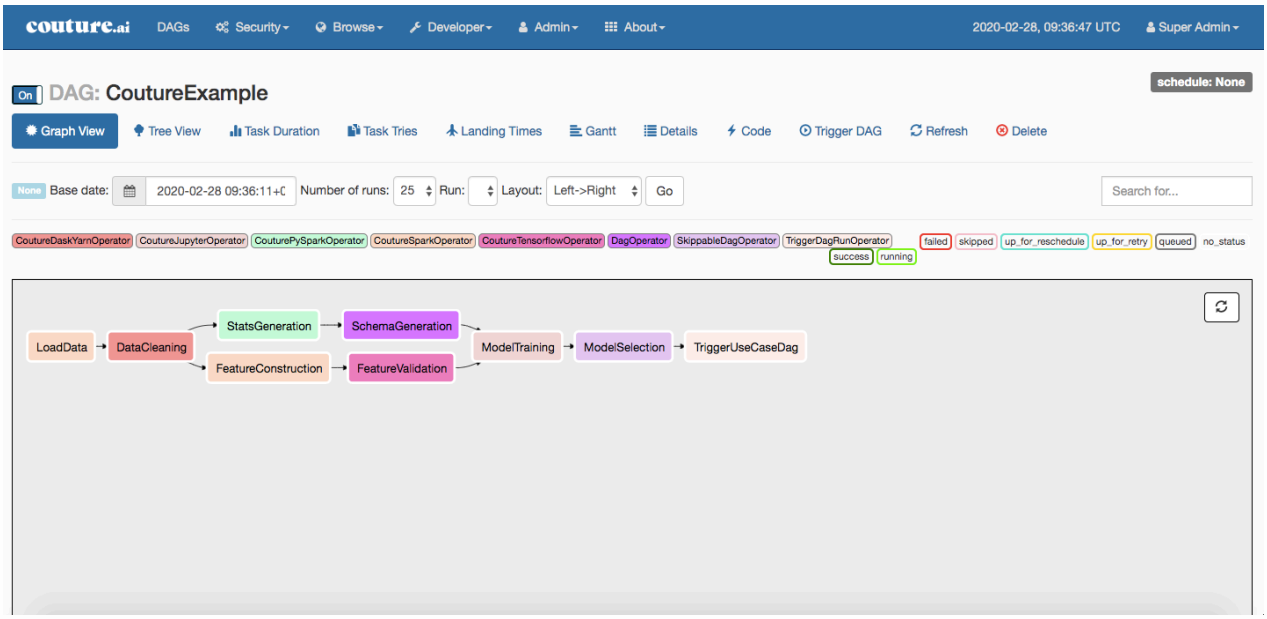


In order to start a `DAG` Run, first turn the `dag` `ON` (arrow **1**), then click the **Trigger Dag** button (arrow **2**) and finally, click on the **Graph View** (arrow **3**) to see the progress of the run.

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

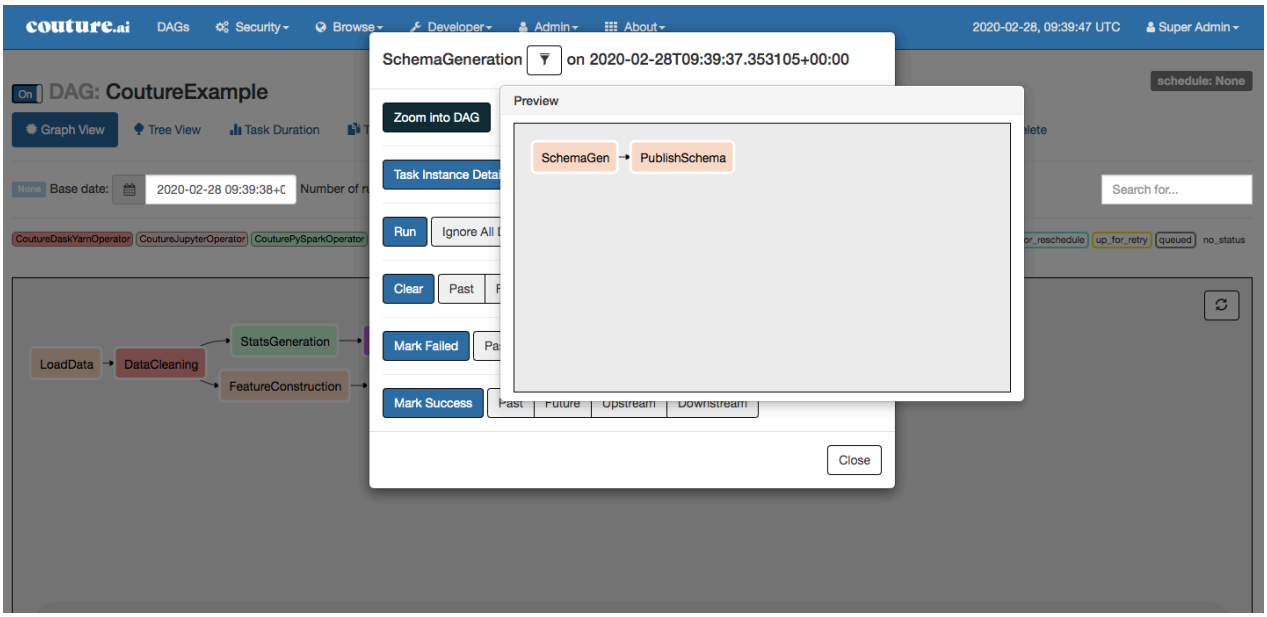
A condition can be set as to whether or not to trigger the remote `DAG`, by defining a `python function` as below.

```
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 worflow 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'
    )
```

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

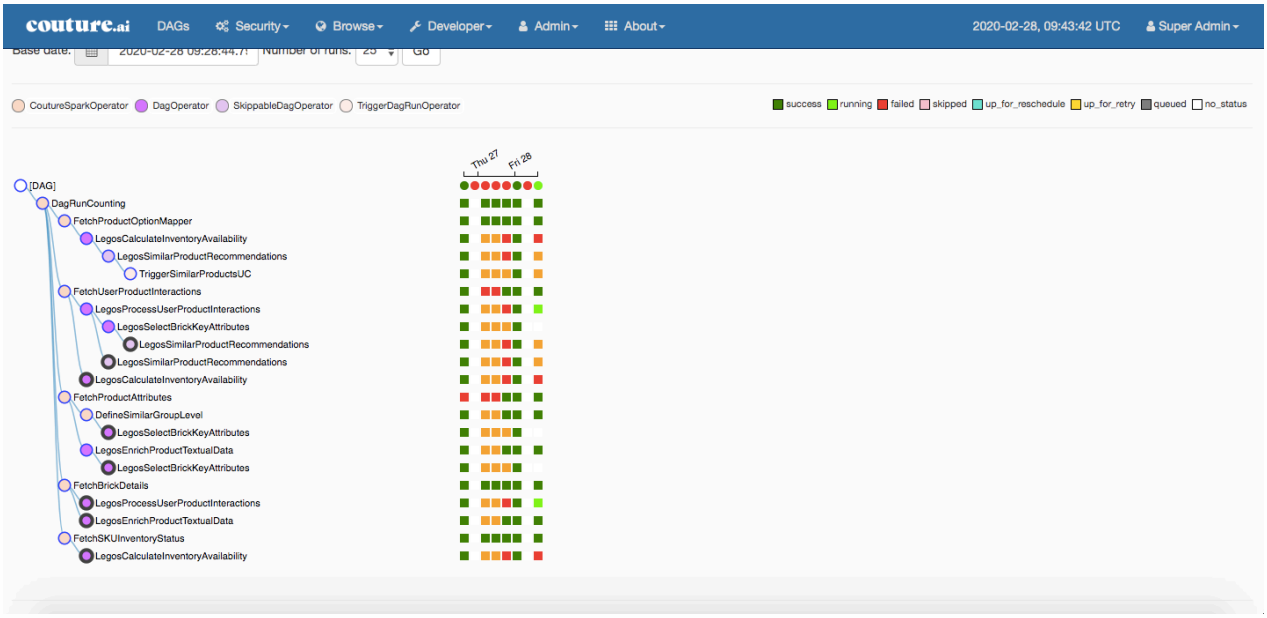
The Workflow UI makes it easy to monitor and troubleshoot your data pipelines. Here's a quick overview of some of the features and visualizations you can find in the Workflow UI.

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.

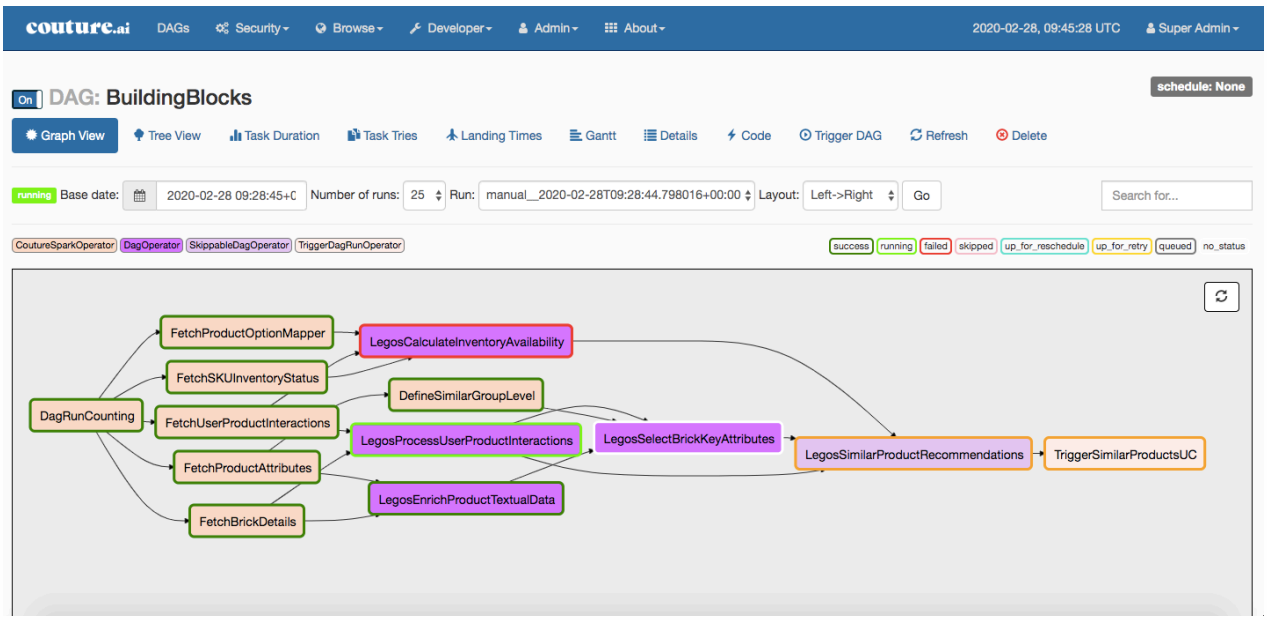
Tree View

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.



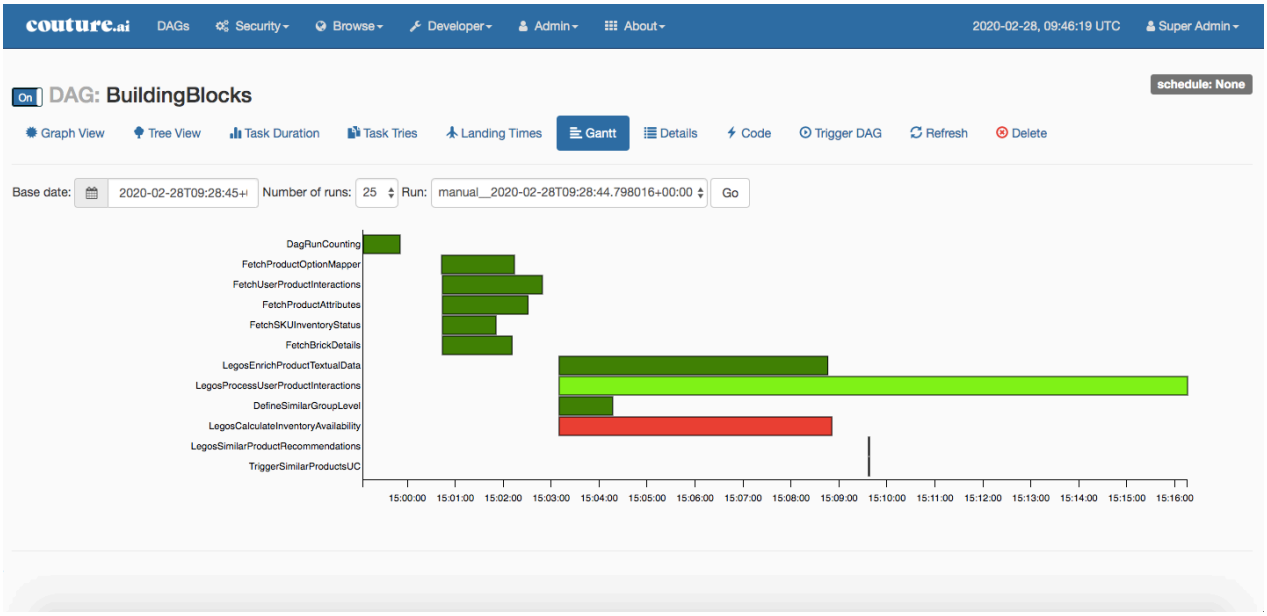
Here is the screenshot of the `DAG` executed. You can see rectangular boxes representing a `task`. You can also see different color boxes on the top right of the greyed box, named: `success, running, failed` etc, representing `status` of the `task`.

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.

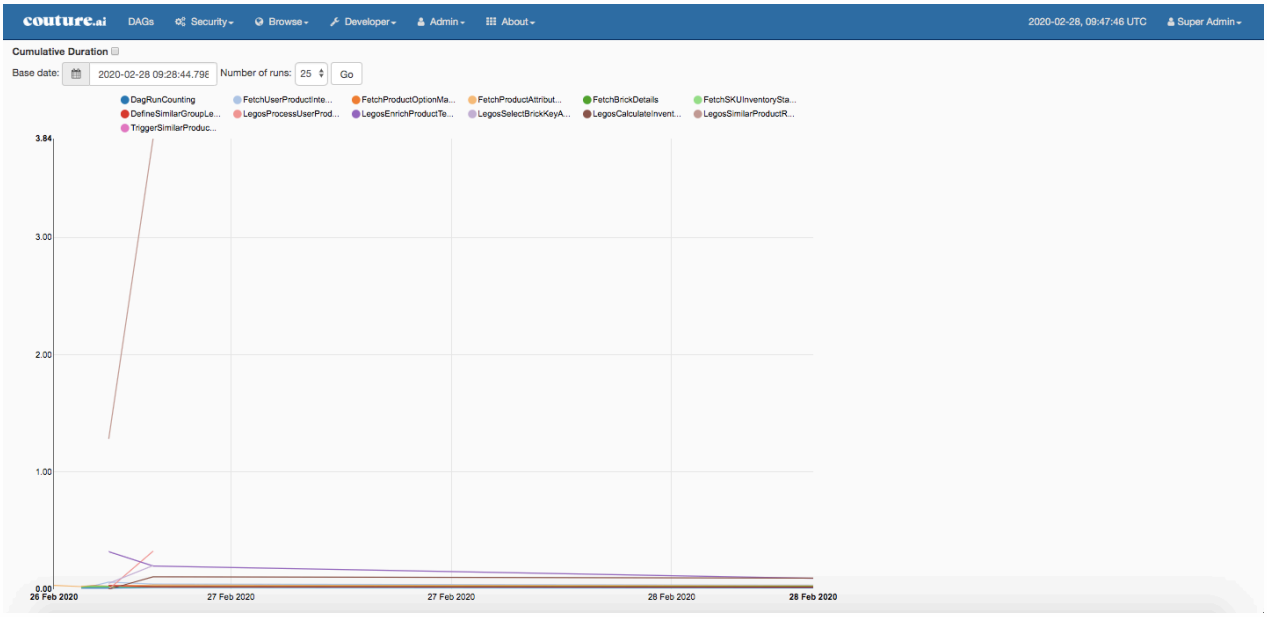
Gantt Chart

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.



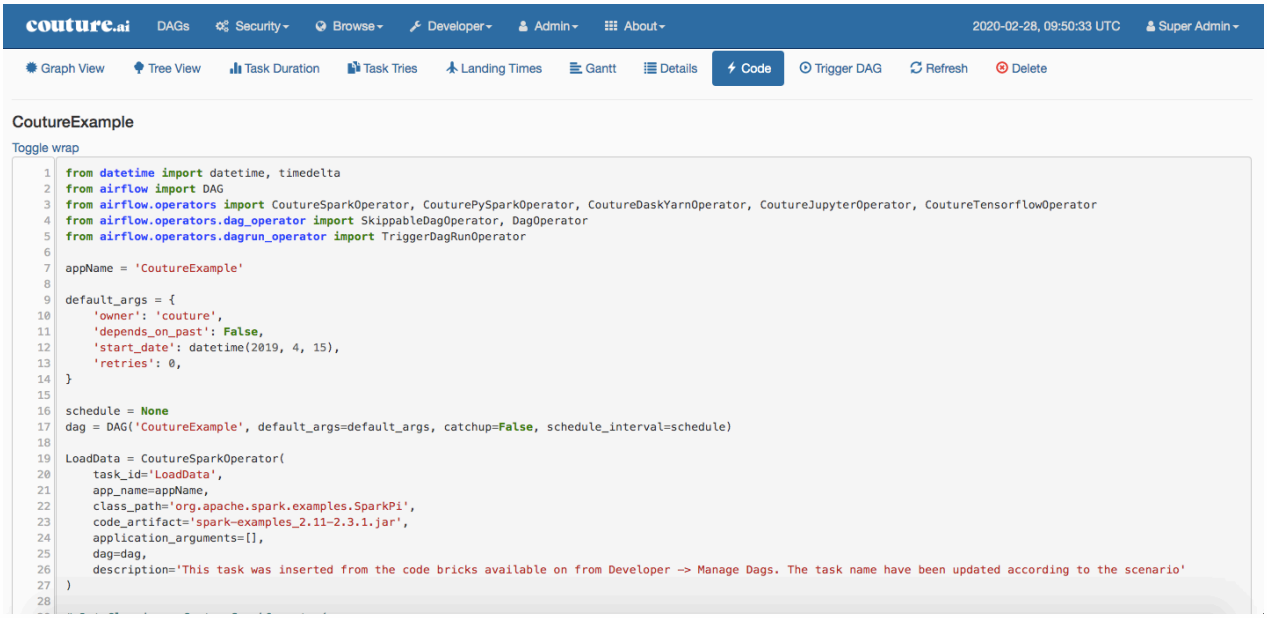
Task Duration

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.



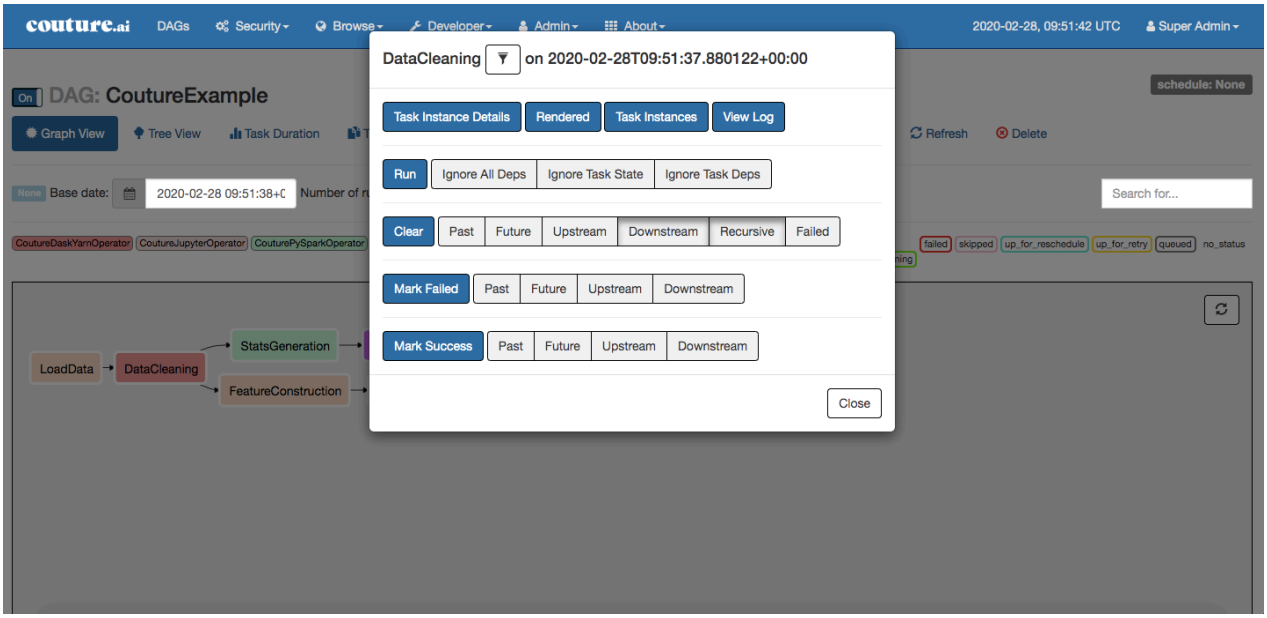
Code View

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.



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 aritfacts option`, `editing dags privileges`.

- **Op**

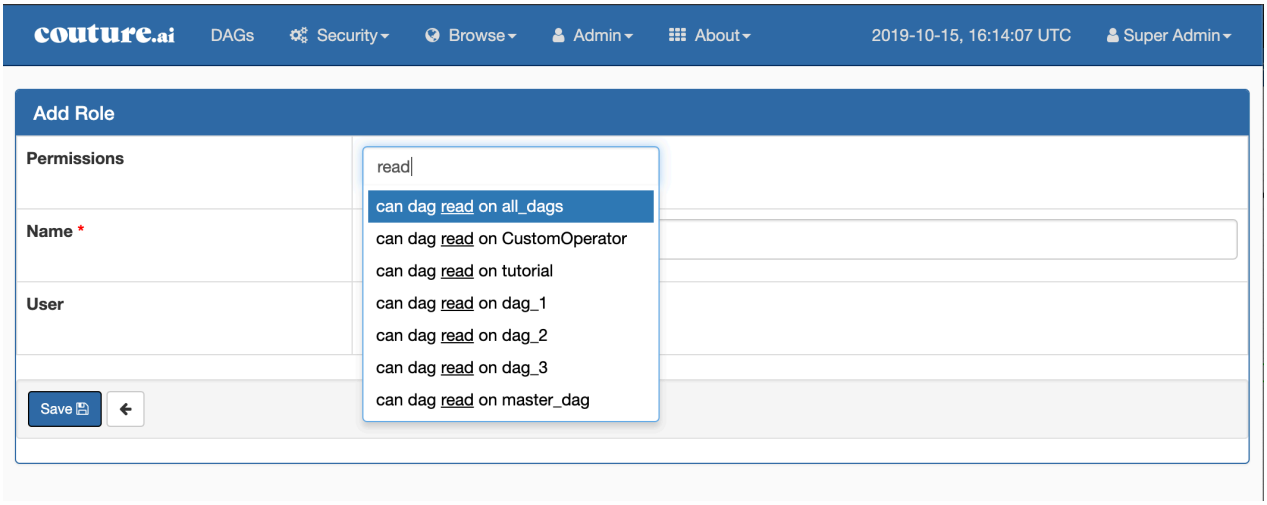
`Op` users have`User` permissions plus additional op permissions.

```
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.

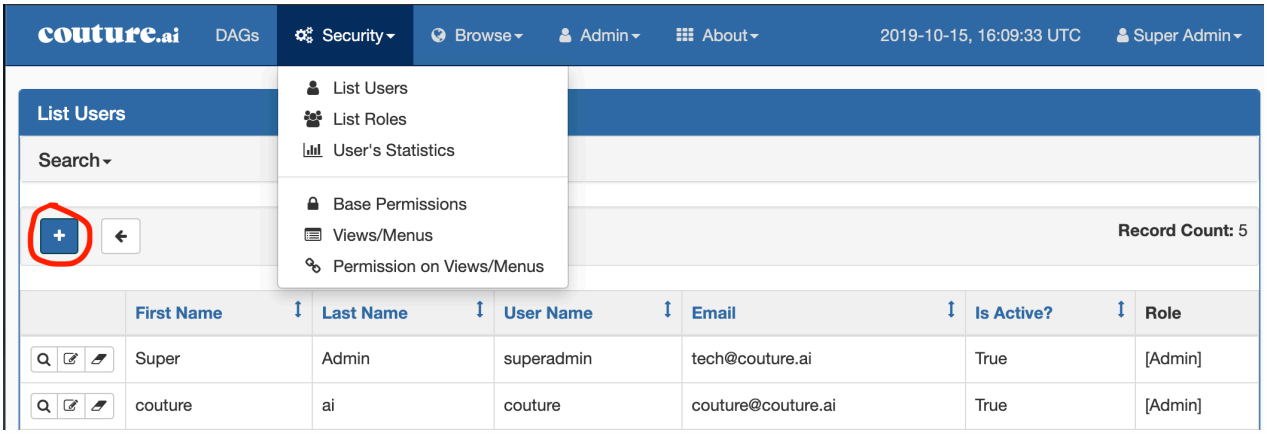


The image shows the creation of a role which can only read all dags.

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`.

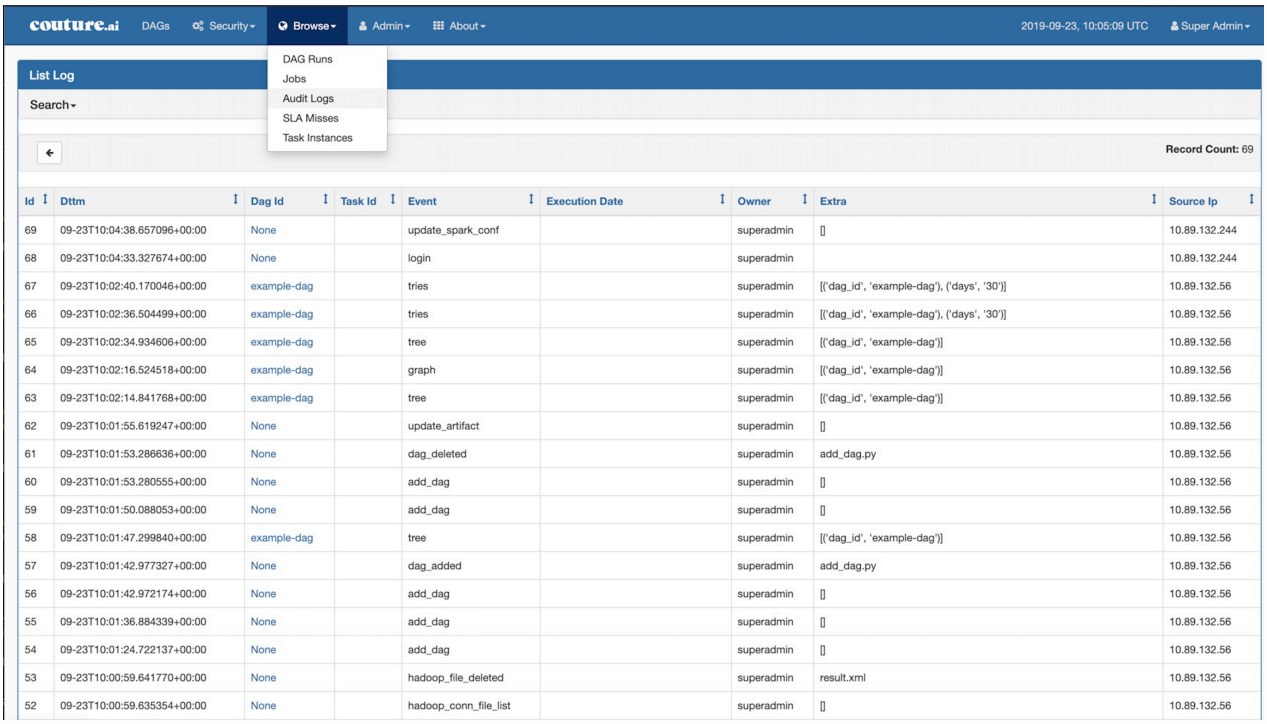
To add new user, click the '+' as shown below.



Note: Only admin can create new users.

Access Audit Logging

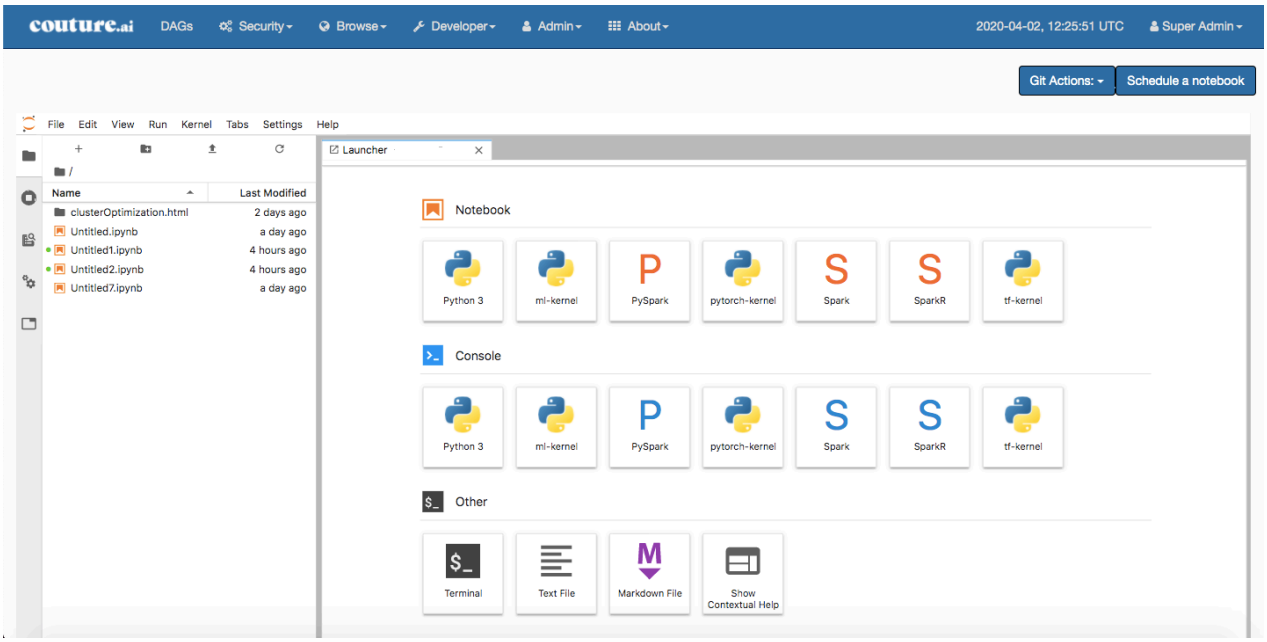
`User` journey can be easily tracked by audit logs. Audit logs can be viewed by going to `Browse` and clicking on Audit Logs. All the activities/events are captured. Also, the source `IP address` from where the event occurred is captured as shown below.



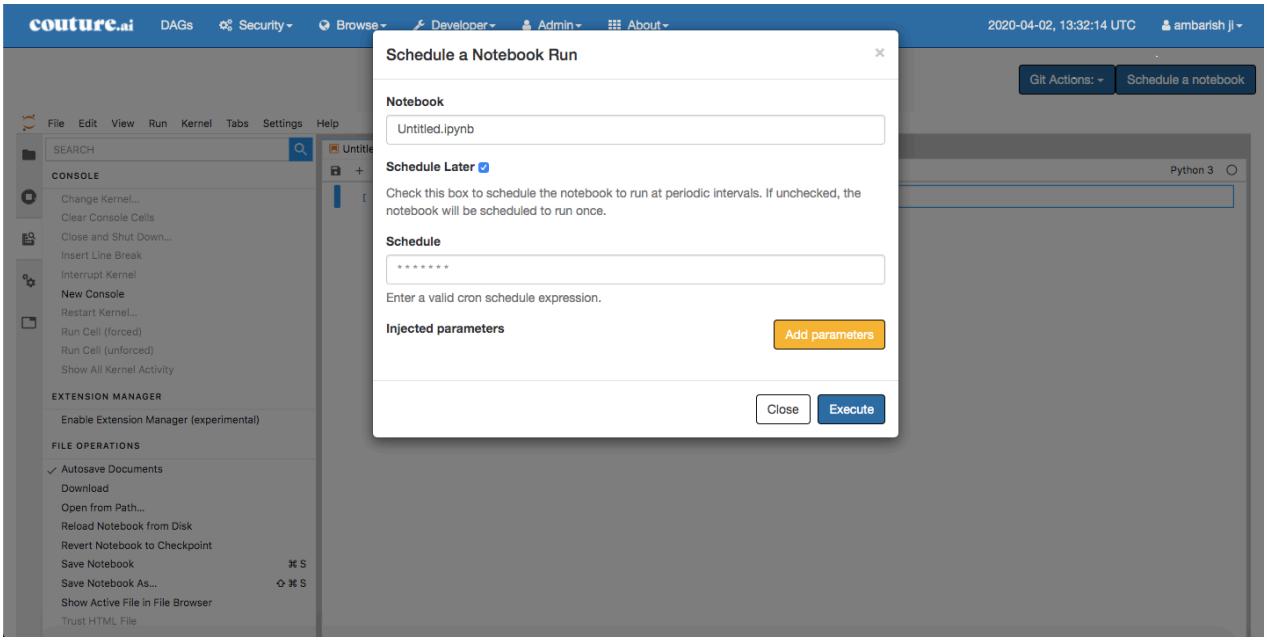
Jupyter Notebook

`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.

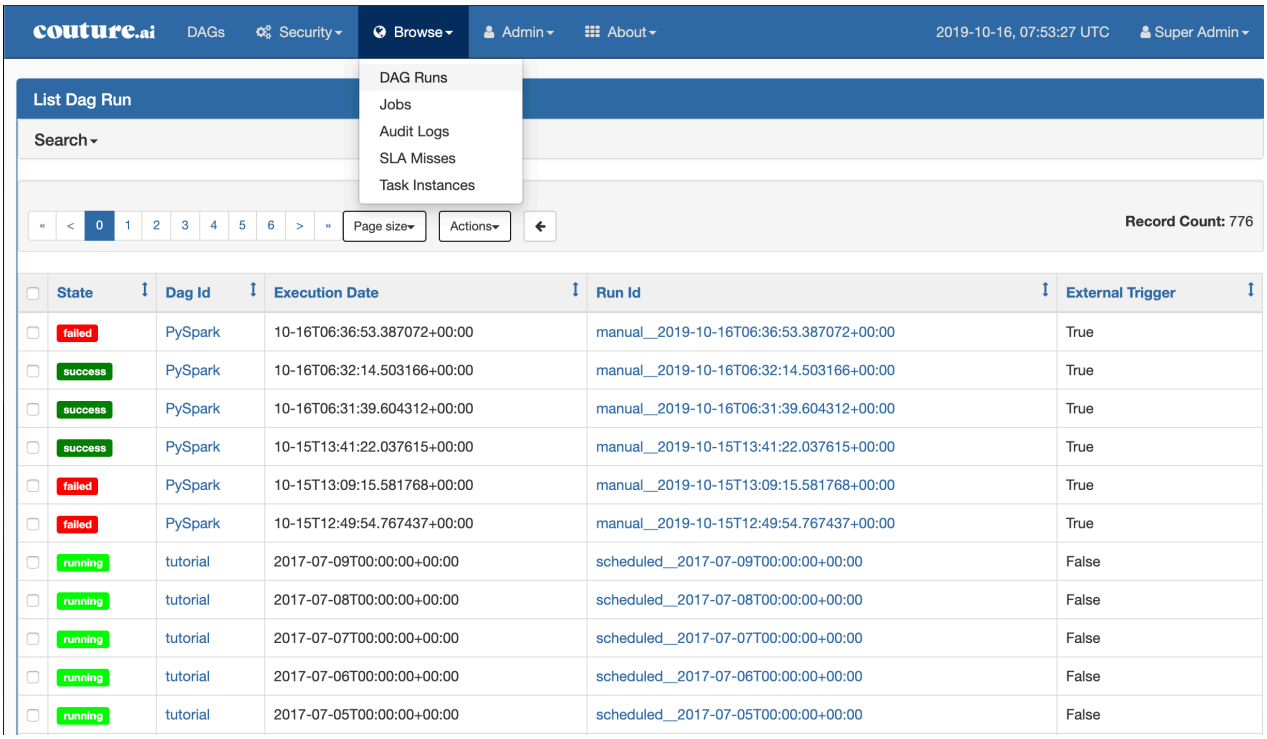
- `Python3`: A simple python3 kernel, provided by default by jupyterlab.
- `ml-kernel`: A kernel with the most commonly used Machine Learning python packages preinstalled.
- `tf-kernel`: A kernel with `TensorFlow` and commonly used packages preinstalled.
- `pytorch-kernel`: A kernel with `Pytorch` and 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

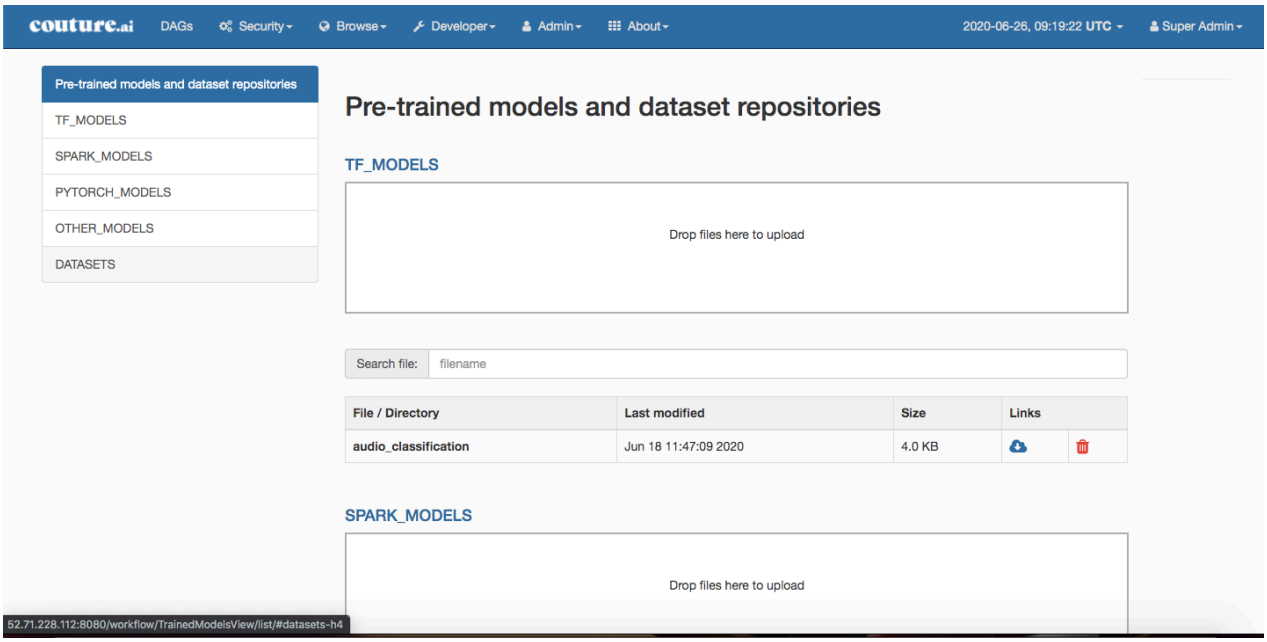
A `DagRun` is the instance of a `DAG` that will run at a time. When it runs, all task inside it will be executed.

`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.



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:



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.
- Pytorch 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.
- `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

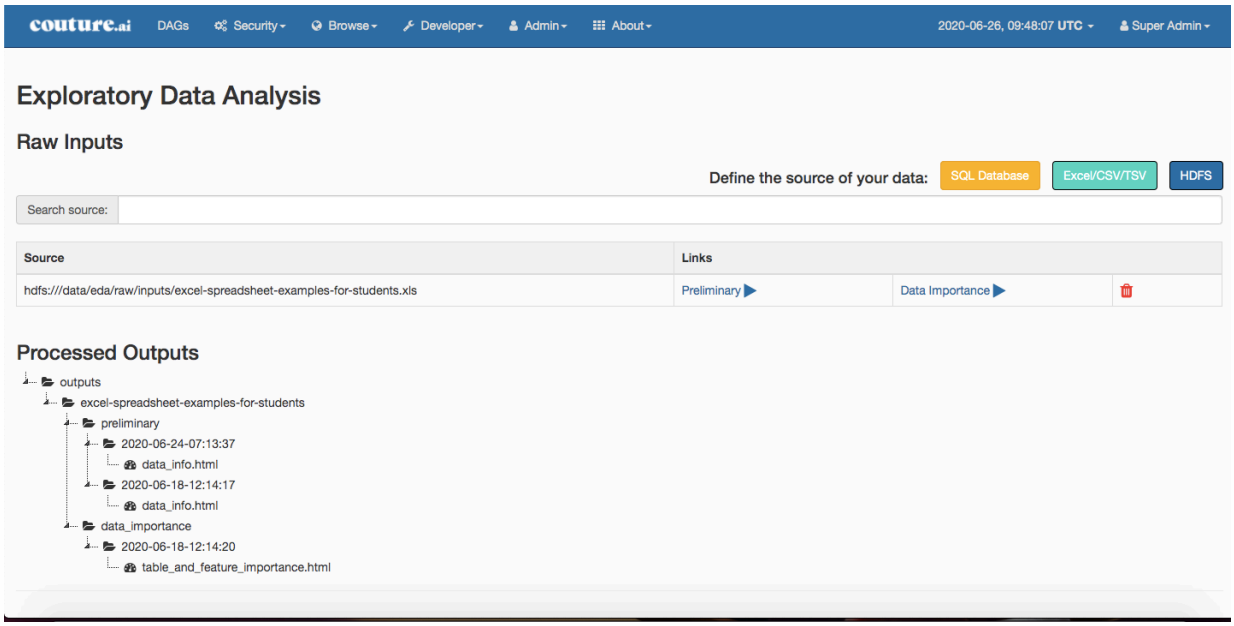
Workflow Orchestrator allows us to add and perform Exploratory Data Analysis (EDA) on a SQL database, TSV or CSV file and HDFS data sources. To perform `EDA` on a data source, go to `Developer->Exploratory Data Analysis`.

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.



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.

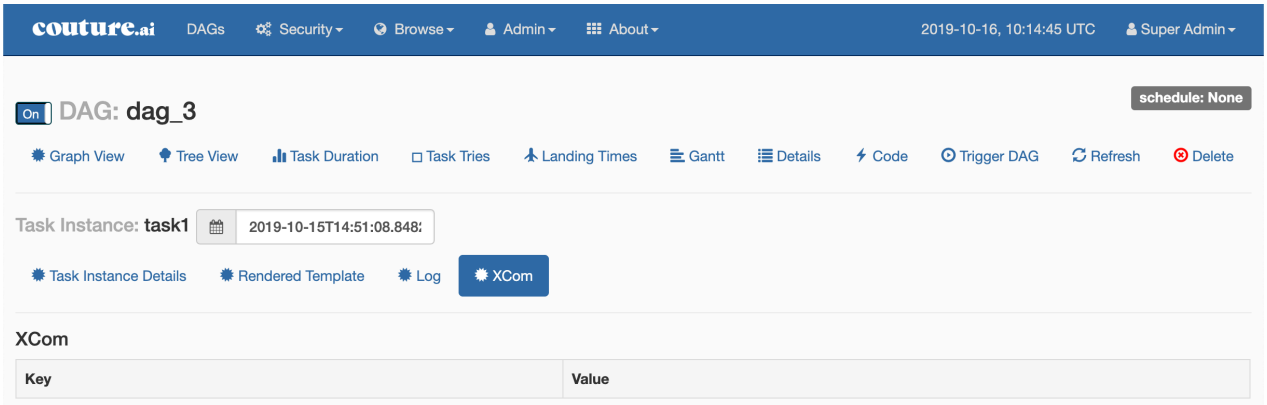
```
{'dag': <DAG: parsing_recipes>,
 'ds': '2018-10-02',
 'next_ds': '2018-10-02',
 'prev_ds': '2018-10-02',
 'ds_nodash': '20181002',
 'ts': '2018-10-02T09:56:05.289457+00:00',
 'ts_nodash': '20181002T095605.289457+0000',
 'yesterday_ds': '2018-10-01',
 'yesterday_ds_nodash': '20181001',
 'tomorrow_ds': '2018-10-03',
 'tomorrow_ds_nodash': '20181003',
```

```
 'END_DATE': '2018-10-02',
 'end_date': '2018-10-02',
 'dag_run': <DagRunparsing_recipes@2018-10-0209: 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`.



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 value`None`, 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.