Assignment: Building an ETL Pipeline with Apache Airflow

Documentation ETL Pipeline

Functions

We first made a sketch on the structure of what our pipeline could look like, based on what was requested for this assignment: download the Online Retail dataset from UCI, preprocess (clean and transform) our data, and finally load it up into MongoDB. For that matter, we started defining regular Python functions for each potential step:

* download dataset():

```
def download_dataset():
    url =
'https://archive.ics.uci.edu/ml/machine-learning-databases/00352/Online%20Ret
ail.xlsx'
    output_path = os.path.join(data_dir, 'online_retail.xlsx')

# Ensure the directory exists, if the directory does not exist, it will
be created
    os.makedirs(data_dir, exist_ok=True)

# Download the dataset
    response = requests.get(url)

# Check if download was successful
    if response.status_code == 200:
        with open(output_path, 'wb') as f:
            f.write(response.content)
            print(f"Dataset downloaded and saved to {output_path}")
    else:
            print(f"Failed to download dataset. Status code:
{response.status_code}")
```

Figure 1. Download Dataset Function

This first function downloads our desired dataset through a GET request, and saves it as an .xlsx file into the data_dir directory, which we defined to be created on the following path: data_dir = '/opt/airflow/dags/data'.

* clean dataset():

Figure 2. Clean dataset function

This second function reads our downloaded dataset from the previous task, groups the data by 'StockCode', which identifies each unique product inside the dataset, and we compute which 'Description' (Product Name) is the most concurrent one for each 'StockCode'. The reasoning behind this calculation relies on filling empty records of 'Description' based on what seems to be the correct Description for each 'StockCode'. Note that there are inconsistencies on the data, and not every 'StockCode' has a unique product name in the 'Description' column (some StockCodes have additional notes on the product in 'Description' instead of the actual product name).

Afterwards we convert the 'InvoiceDate' to a datetime variable, and the 'CustomerID' column to a string variable, as we will not be performing numerical calculations with these IDs.

Finally, we drop duplicate records within our dataset and save this "cleansed" dataframe as a .csv file into our defined output path.

* data transformation():

```
def data_transformation():
    input_path = os.path.join(data_dir, 'cleaned_online_retail.csv')
    output_path = os.path.join(data_dir, 'transformed_online_retail.csv')

# Read cleaned csv

df = pd.read_csv(input_path)

# Calculate Total Price

df['TotalPrice'] = df['Quantity'] * df['UnitPrice']

# Save transformed csv

df.to_csv(output_path, index = False)

print("Total Price column added successfully.")
```

Figure 3. Data transformation function

In this third function, we firstly read our cleansed dataset, and compute a new column, 'TotalPrice', which is quantified as the multiplication of the 'Quantity' of products in that order times the 'UnitPrice' of that specific product. Then we just saved this transformed dataframe into a .csv file.

* load to mongodb():

```
def load to mongodb():
   client = hook.get conn()
   print(f"Connected to MongoDB - {client.server info()}")
   path = os.path.join(data dir, 'transformed online retail.csv')
   df = pd.read csv(path)
   collection.create index([
    ('StockCode'),
    ('UnitPrice'),
    ('CustomerID'),
   total documents inserted = 0
           result = collection.insert many(chunk.to dict(orient='records'),
ordered=False)
           print(f"New documents inserted from chunk starting at row
            duplicates in chunk = len(e.details['writeErrors'])
            total duplicates += duplicates in chunk
            print(f"Duplicated documents in chunk starting at row {start}:
duplicates in chunk}")
```

```
print(f"Data insertion completed, new documents inserted
{total_documents_inserted}, duplicated documents {total_duplicates}")
    return total_documents_inserted
```

Figure 4. Load to MongoDB function

In this last function, we are ready to load our cleaned and transformed dataset into MongoDB, in this case using MongoHook, which wraps the PyMongo Python Driver. In order for this to work, we first needed to create a Connection inside Airflow's UI (Admin -> Connections). Following the tutorial <u>Using MongoDB with Apache Airflow</u>, we first installed the MongoDB Airflow provider: apache-airflow-providers-mongo. Then, we created the following connection (Password is censored for safety measures):

	Airflow DAGs Datasets	Security Browse Admin Docs
	Edit Connection	
	Connection Id *	mongo_default
	Connection Type *	MongoDB
		Connection Type missing? Make sure you've installed the corresponding Airflow Provider Package.
	Description	
	Host	cluster0.ij1pxim.mongodb.net
	Schema	
	Login	brandonalfaro00
	Password	
	Port	
		<pre>{ "srv": true }</pre>
	Extra	

Figure 5. MongoDB Connection

In this connection, Host refers to our MongoDB Atlas hostname; Login and Password refers to our database username and password, respectively; and Extra {"srv": true}, which eliminates the requirement

for every client to pass in a complete set of state information for the cluster.

Following up with our function, we firstly establish the connection to MongoDB using MongoHook and the ConnectionID, and create our database and collection, where we'll store our dataset. After that, we defined an unique index for each combination of values, considering all of our columns. This would prevent adding duplicate documents into our database.

Now, since our dataset is too large, we would need to insert documents by chunks instead of the whole set of documents at once, since the maximum BSON document size is 16 mb (we tried using collection.insert many for all of the documents and got this error).

By chunks of 10,000 documents, all documents were finally added into the database. Note that we included a try/except block so all new documents could be added into db, but duplicated documents. Within each chunk, the number of new documents added to the database will be printed (len(result.inserted_ids), as well as the number of documents that were already loaded into it (duplicates in chunk):

```
# Split the DataFrame into chunks and insert each chunk separately (only non-duplicate data)
chunk_size = 10000
total_documents_inserted = 0
total_duplicates = 0
for start in range(0, len(df), chunk_size):
    chunk = df.iloc[start : (start + chunk_size)]
    try:
        #ordered=False ensures that the insertion continues even if some documents cause errors
        result = collection.insert_many(chunk.to_dict(orient='records'), ordered=False)
        total_documents_inserted += len(result.inserted_ids)
        print(f"New documents inserted from chunk starting at row {start}: {len(result.inserted_ids)}")
except pymongo.errors.BulkWriteError as e:
    # Count duplicate documents in chunk
    duplicates_in_chunk = len(e.details['writeErrors'])
    total_duplicates += duplicates_in_chunk
    print(f"Duplicated documents in chunk starting at row {start}: {duplicates_in_chunk}")

print(f"Data insertion completed, new documents inserted {total_documents_inserted}, duplicated documents {total_duplicates}")
return total_documents_inserted
```

Figure 7. Load to MongoDB function - dealing with duplicate docs

Skipping documents that are already loaded in the database, instead of adding duplicate documents is very helpful in day-to-day real world scenarios.

This would happen if, say, the Online Retail dataset was continuously updated with new transactions, obviously we would not like past transactions to be recorded into the db since we already have them loaded.

After uploading all 536,641 documents, this is how our NoSQL database looks like:

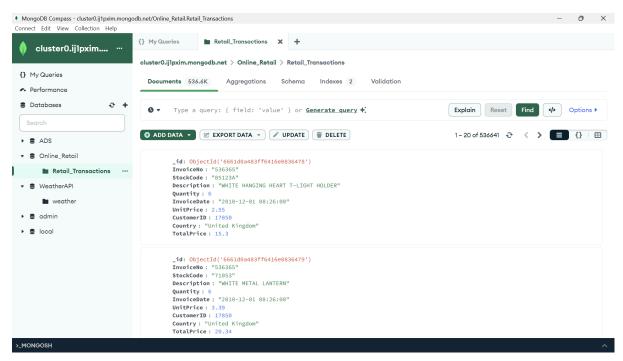


Figure 8. NoSQL database with loaded documents - MongoDB Compass View

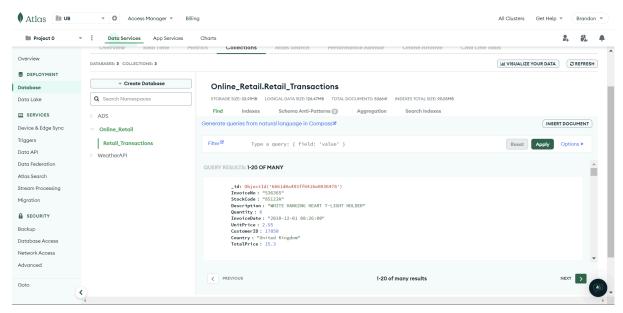


Figure 9. NoSQL database with loaded documents - MongoDB Atlas View

Inside the RetailTransactions.py file you can also find a version of load_to_mongodb() using only pymongo, with the traditional way of connecting from a Python script to MongoDB.

Tasks

After defining these functions, we now can delve into the creation of tasks and their dependencies inside the DAG.

```
# Task 1: Download data
download_task = PythonOperator(
    task_id='download_dataset',
    python_callable=download_dataset,
    dag=dag
)

# Task 2: Clean data
clean_task = PythonOperator(
    task_id='clean_dataset',
    python_callable=clean_dataset,
    dag=dag
)

# Task 3: Transform data
transformation_task = PythonOperator(
    task_id='data_transformation',
    python_callable=data_transformation,
    dag=dag
)

# Task 4: Load data into MongoDB
load_to_mongodb_task = PythonOperator(
    task_id='load_to_mongodb',
    python_callable=load_to_mongodb,
    dag=dag
)
```

Figure 10. DAG Tasks

As you can see, this links each one of our functions to a task. Then, dependencies or the order on how tasks will be run can be seen here:

```
download_task >> clean_task >> transformation_task >> load_to_mongodb_task
```

Figure 11. DAG Tasks Dependencies

Finally, we would just need to explain what the creation of the DAG looks like. We named it as online_retail_etl, specifying that this DAG should be run @daily, which makes sure the DAG runs once a day at midnight:

Figure 12. DAG

With all these, we successfully completed the required ETL process. Nonetheless, we decided to add an extra bonus to this process: send an email notification on success:

```
# Task 5: Email notification on success
success_email_task = EmailOperator(
   task_id='send_email_on_success',
   to='bralfarc7@alumnes.ub.edu',
   subject='ETL Pipeline Success',
   html_content=
   '''The ETL pipeline for the Online Retail dataset has completed
successfully.
   {{ task_instance.xcom_pull(task_ids="load_to_mongodb") }} new documents
were added to the database.''',
   dag=dag
)
```

Figure 13. Task: Email notification on success

If all of the previous tasks were successful, an email will be sent to bralfacr7@alumnes.ub.edu with the subject "ETL Pipeline Success" and the message "The ETL pipeline for the Online Retail dataset has completed successfully", also adding the total number of new documents that were loaded into our database (this was possible due to Xcom, a mechanism that lets tasks communicate with each other, this let us pass info from 'load_to_mongodb' task to 'success_email_task):

ETL Pipeline Success		
Traducir mensaje a: Español Nunca traduzcas de: Inglés		
В	brandonalfarocheca@gmail.com Para: BRANDON JERSAI ALFARO CHECA The ETL pipeline for the Online Retail dataset has complete	⊕ Responder ≪ Responder a todos → Reenviar │
	← Responder	

Figure 14. Email notification on success

ETL Pipeline Success		
Traducir mensaje a: Español Nunca traduzcas de: Inglés		
brandonalfarocheca@gmail.com Para: BRANDON JERSAI ALFARO CHECA The ETL pipeline for the Online Retail dataset has comp	⊕ Responder ≪ Responder a todos → Reenviar	
← Responder		

Figure 15. Email notification on success (no new docs added)

Finally let us take a look into the default_args that were passed on into the creation of our DAG. We set up just one retry per failed task, with a minute between retries.

Also note that email notifications will be also sent to that same email address if any of the tasks fail (email on failure = True).

```
default_args = {
    'owner': 'Brandon and Eddie',
    'depends_on_past': False, # Tasks will run regardless of the status of
the same task in the previous DAG run
    'start_date': datetime(2024, 6, 1),
    'email': 'bralfarc7@alumnes.ub.edu',
    'email_on_failure': True, # Send email on failure
    'email_on_retry': False, # Do not send email on retry
    'retries': 1, # Number of retries
    'retry_delay': timedelta(minutes=1) # Time between retries
}
```

Figure 16. Default Arguments for DAG initialization

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Airflow alert: <TaskInstance: online_retail_etl.download_dataset manual_2024-06-06T16:44:31.017128+00:00 [failed]>

| Traducir mensaje a: Español | Nunca traduzcas de: Inglés

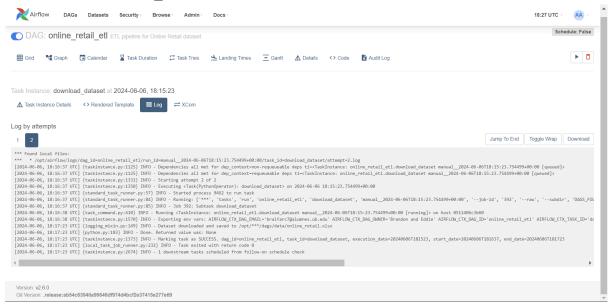
| B | brandonalfarocheca@gmail.com | Compared to the para: BRANDON JERSAI ALFARO CHECA | Jue 2024-06-06 18:46 |
| Try 2 out of 2 | Exception: | [Errno 13] Permission denied: '/opt/airflow/dags/data/online_retail.xlsx' | Log: Link | Host: 0511406c3b60 | Mark success: Link | Link |

Figure 17. Task failure alert via email notification

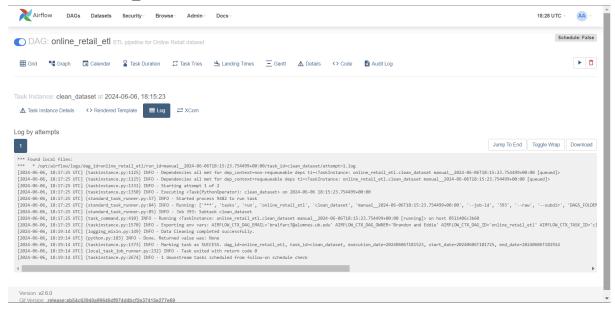
(In this case I had the .xlsx opened on Excel, which prevented any modifications and hence the task download dataset failed.)

Logs Execution

* Task 1: download dataset

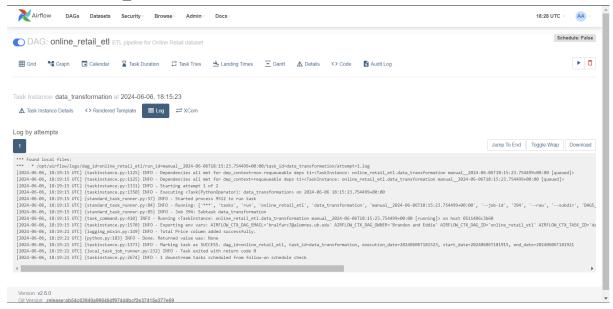


* Task 2: clean_dataset

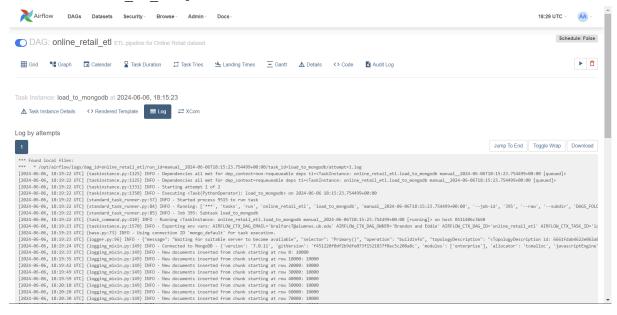


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* Task 3: data transformation

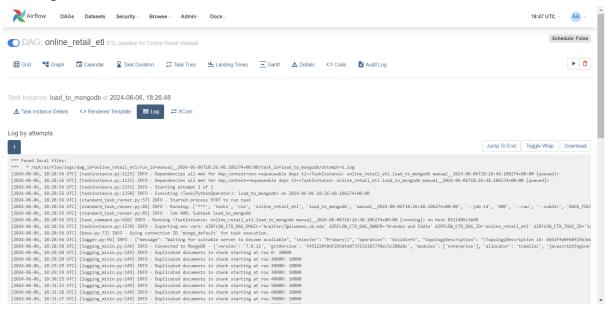


* Task 4: load to mongodb

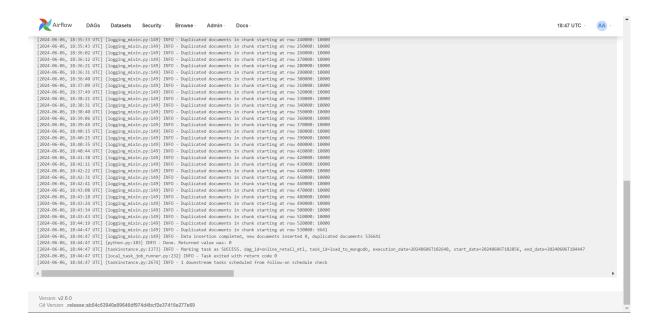




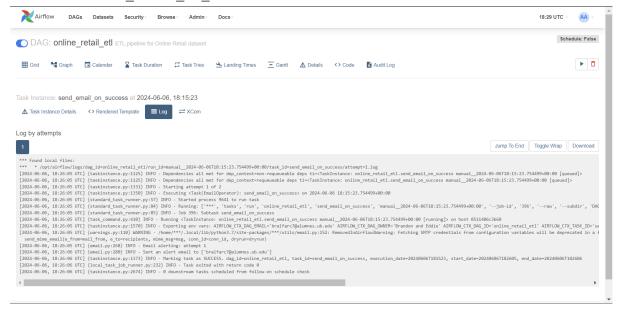
* Task 4B: load_to_mongodb (case when we have past documents loaded already into database)



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* Task 5: send email on success



Docker extras

In order to work with packages that are not included within the original <u>Basic Airflow cluster configuration for CeleryExecutor with Redis and PostgreSOL</u>, we need to use a custom image containing the necessary dependencies we use in our DAG tasks: 'pandas', 'pymongo', 'openpyxl' and MongoDB's Airflow provider: 'apache-airflow-providers-mongo'.

For this matter, we created a DockerFile adding the necessary packages on top of the base Apache Airflow 'apache/airflow:2.6.0':

```
FROM apache/airflow:2.6.0

RUN pip install pymongo apache-airflow-providers-mongo pandas requests openpyxl
```

Then we can just add the extended image into our docker-compose.yml file to build and run the extended Airflow image with CeleryExecutor, Redis, and PostgreSQL.

```
x-airflow-common:
placed the docker-compose.yaml
build the images.
postgresql+psycopg2://airflow:airflow@postgres/airflow
postgresql+psycopg2://airflow:airflow@postgres/airflow
```

```
AIRFLOW_SMTP_SMTP_SSL: 'false'

AIRFLOW_SMTP_SMTP_USER: ${SMTP_USER}

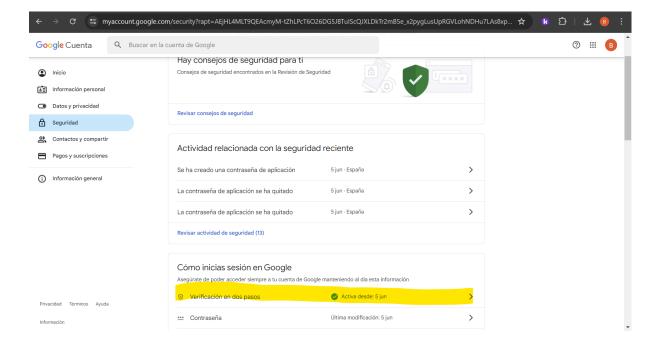
AIRFLOW_SMTP_SMTP_PASSWORD: ${SMTP_PASSWORD}

AIRFLOW_SMTP_SMTP_PORT: '587'

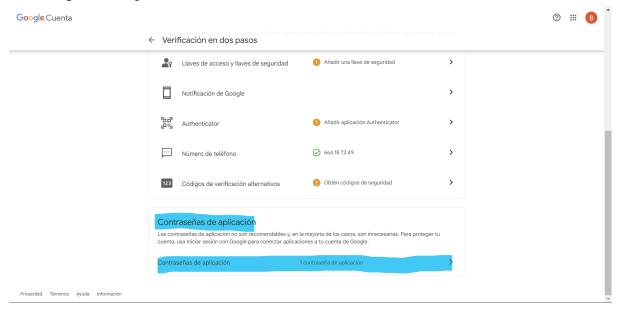
AIRFLOW_SMTP_SMTP_MAIL_FROM: ${SMTP_USER}
```

Note that we also added several environment variables, which refer to the Simple Mail Transfer Protocol (SMTP) configuration needed to send email notifications. For this DAG, we used a gmail.com email account to send the emails.

One important aspect to note here is that Gmail will not allow Airflow to connect into the email account, because of security reasons. For that matter, we first need to turn-on the two-step verification with your Gmail account:



Then, we would be able to generate an app password, which is a a 16-digit passcode that gives a less secure app or device permission to access your Google Account.



After generating this password, we can just copy it into our AIRFLOW__SMTP_SMTP_PASSWORD environment variable, and email notifications will be set successfully.