

END2END ETL PIPELINE

ABSTRACT

Use case study For The Credit Book

Muhammad Affan

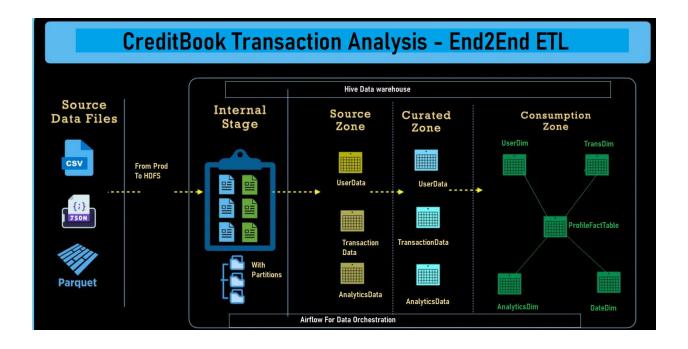
1. Introduction

This document outlines the design and implementation of an end-to-end ETL pipeline enriched with Apache Airflow integration. The pipeline is architected using Python, SQL, and various Apache tools, catering to the data processing needs of our client the CreditBook, with a focus on scalability, efficiency, and maintainability.

2. Infrastructure Setup

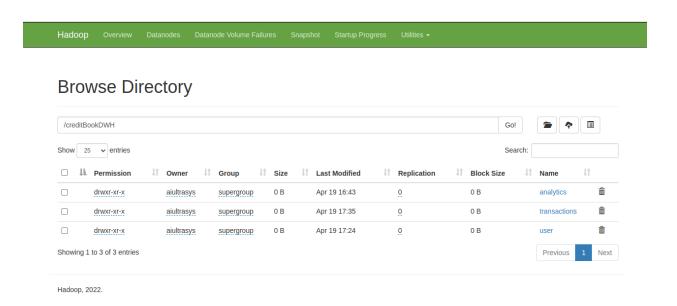
The infrastructure comprises several key components:

- **Storage Layer**: Hadoop Distributed File System (HDFS) is utilized for efficient storage and retrieval of large volumes of data.
- Data Warehousing: Apache Hive is employed as the data warehousing solution, providing structured querying capabilities.
- **ETL Engine**: Apache Spark serves as the ETL engine, enabling high-speed processing of data transformations.
- **Data Orchestration**: Apache Airflow is utilized for orchestrating the data pipeline, ensuring seamless execution of tasks.
- **Full Load & Incremental Load**: Using apache spark, I created a separate mechanism for full load and incremental load.
- **Query Monitoring**: Presto is integrated for monitoring query complexity and optimizing performance.

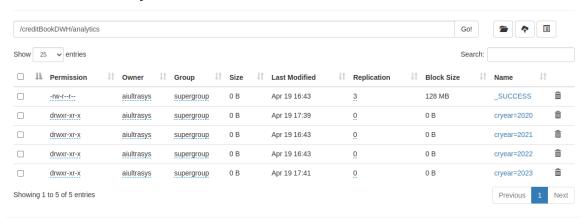


3. Data Ingestion

Data is ingested from the client's provided URLs and stored in HDFS in Parquet format with Snappy compression. This approach ensures efficient storage and retrieval of data, with partitions created based on date and time for enhanced query performance. Apache Spark is leveraged for data ingestion, facilitating parallel processing and scalability.

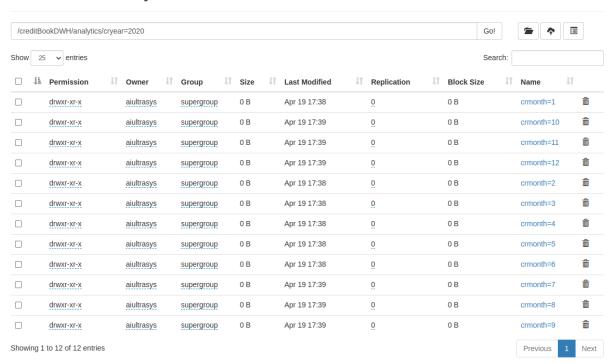


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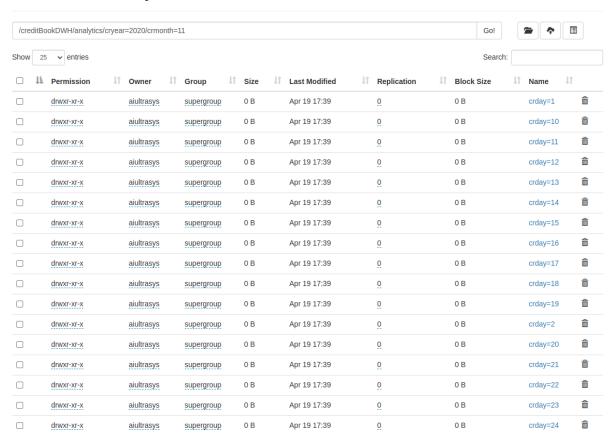


Hadoop, 2022.

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4. Layered Approach

The ETL pipeline is structured into three layers:

Source Layer

In the Source Layer, data is loaded into an external Hive table from HDFS. This enables seamless querying of raw data using Hive or Presto CLI, providing flexibility in data exploration.

Curated Layer

The Curated Layer focuses on data transformation and preparation. Various transformations such as cleaning, datatype correction, formatting, column creation, aggregation, and joins are performed to prepare the data for analysis. The transformed data is stored in an internal Hive table, ensuring curated data is readily accessible for downstream processing.

Consumption Layer

The Consumption Layer is where the transformed data is modeled for analytics purposes. A star schema is implemented, comprising fact and dimensional tables. Surrogate keys and foreign keys are established to maintain relationships between dimension and fact tables. Aggregate data is incorporated into the fact table to facilitate efficient analytics. Separate internal Hive tables are created for each dimension and fact table, organized based on primary keys, surrogate keys, and foreign keys.

```
CREATE EXTERNAL TABLE IF NOT EXISTS creditbook_sourcelayer.user_details (
    user_id STRING,
    business id STRING,
    rating STRING,
    created_at STRING,
    processed_at timestamp
partitioned by (cryear INT,crmonth INT,crday INT)
ROW FORMAT DELIMITED FIELDS TERMINATED BY ','
STORED AS PARQUET
LOCATION '/creditBookDWH/user'
;
create table IF NOT EXISTS creditbook_curatedlayer.user_details (
    user_id STRING,
    business id STRING,
    rating STRING,
    created at STRING,
    processed_at timestamp,
    signup_since_days INT,
    cryear INT,
    crmonth INT,
    crday INT);
```

```
create table IF NOT EXISTS creditbook_consumplayer.user_dim(
    user_id_pk INT PRIMARY KEY DISABLE NOVALIDATE,
    user_id STRING,
    business_id STRING,
    rating STRING,
    created_at STRING,
    processed_at STRING,
    signup_since_days STRING,
    cryear INT,
    crmonth INT,
    crday INT,
    isActive CHAR(1)
);
```

```
Query 20240422_144046_00149_w3iyx, RUNNING, 1 node

Splits: 18 total, 0 done (0.00%)

[Latency: client-side: 0:06, server-side: 63ms] [0 rows, 0B] [0 rows/s, 0B/s]

Query aborted by user

presto:creditbook_consumplayer> show schemas;

Schema

...

creditbook_consumplayer

creditbook_curatedlayer

creditbook_public

creditbook_sourcelayer
```

```
presto:creditbook_sourcelayer> select count(*) from analytics_details;
_col0
92869
(1 row)
Query 20240422_144637_00157_w3iyx, FINISHED, 1 node
Splits: 819 total, 819 done (100.00%)
[Latency: client-side: 0:01, server-side: 0:01] [92.9K rows, 4.36MB] [152K rows/s, 7.15MB/s]
presto:creditbook_sourcelayer> select count(*) from trans_details;
_col0
696618
(1 row)
Query 20240422_144646_00158_w3iyx, FINISHED, 1 node
Splits: 950 total, 950 done (100.00%)
[Latency: client-side: 0:01, server-side: 0:01] [697K rows, 12.2MB] [837K rows/s, 14.7MB/s]
presto:creditbook_sourcelayer> select count(*) from user_details;
_col0
   64
(1 row)
Query 20240422_144657_00159_w3iyx, FINISHED, 1 node
Splits: 42 total, 42 done (100.00%)
[Latency: client-side: 373ms, server-side: 369ms] [64 rows, 52KB] [173 rows/s, 141KB/s]
```

```
presto:creditbook curatedlayer> show tables;
       Table
analytics_details
trans_details
user_details
(3 rows)
Query 20240422_144748_00164_w3iyx, FINISHED, 1 node
Splits: 19 total, 19 done (100.00%)
[Latency: client-side: 137ms, server-side: 133ms] [3 rows, 141B] [22 rows/s, 1.04KB/s]
presto:creditbook_curatedlayer> select count(*) from analytics_details;
_col0
92869
(1 row)
Query 20240422 144759 00165 w3iyx, FINISHED, 1 node
Splits: 43 total, 43 done (100.00%)
[Latency: client-side: 103ms, server-side: 97ms] [92.9K rows, 13.8MB] [957K rows/s, 142MB/s]
presto:creditbook_curatedlayer> select count(*) from trans_details;
_col0
696618
(1 row)
Query 20240422_144806_00166_w3iyx, FINISHED, 1 node
Splits: 28 total, 28 done (100.00%)
[Latency: client-side: 91ms, server-side: 87ms] [697K rows, 147MB] [8.01M rows/s, 1.65GB/s]
presto:creditbook_curatedlayer> select count(*) from user_details;
 _col0
    25
(1 row)
```

```
presto:creditbook_consumplayer> show tables;
       Table
 analytics_dim
date_dim
 profile_fact
trans_dim
user_dim
(5 rows)
Query 20240422_144943_00180_w3iyx, FINISHED, 1 node
Splits: 19 total, 19 done (100.00%)
[Latency: client-side: 142ms, server-side: 136ms] [5 rows, 215B] [36 rows/s, 1.54KB/s]
presto:creditbook_consumplayer> select * from trans_dim limit 2;
                                    transaction id
                                                                                                                                                      business id
 trans id pk |
                                                                                                 user id
        145549 | a22655b0-b571-4323-a172-be03a7f4894a | 49a9d296-e5a6-4c23-bf5e-9897dee07917 | 6fa4ccfc-2a88-4dc2-9692-400ef50623f
145550 | 89ba45fe-c42b-49bd-abb5-2840e2af3cfc | 49a9d296-e5a6-4c23-bf5e-9897dee07917 | 6fa4ccfc-2a88-4dc2-9692-400ef50623f
(2 rows)
Query 20240422_145001_00181_w3iyx, FINISHED, 1 node
Splits: 22 total, 21 done (95.45%)
[Latency: client-side: 107ms, server-side: 103ms] [15.1K rows, 3.34MB] [147K rows/s, 32.4MB/s]
```

5. Data Modeling

The data modeling approach revolves around a star schema, which provides a structured and optimized data model for analytics. This schema consists of:

- **Fact Table**: Represents the core metrics of interest (e.g., transactions), containing surrogate keys and foreign keys to related dimension tables.
- **Dimension Tables**: Represent descriptive attributes (e.g., user details, date information), providing context to the facts. Each dimension table contains surrogate keys for efficient querying and joins.

Fact and Dimension Table:

- 1. Datedim
- UserDim
- 3. TransDim
- 4. AnalyticsDim
- ProfileFact

1. Datedim:

```
create table IF NOT EXISTS creditbook_consumplayer.date_dim(
date_id_pk INT PRIMARY KEY DISABLE NOVALIDATE,
trans_date
                           date,
trans year
                         INT,
                         INT,
trans month
trans_quarter
                         INT,
trans_day
                         INT.
trans_dayofweek
                         INT,
trans_dayname
                         STRING,
trans dayofmonth
                         INT,
                         STRING);
trans weekday
```

UserDim

```
create table IF NOT EXISTS creditbook_consumplayer.user_dim(
    user_id_pk INT PRIMARY KEY DISABLE NOVALIDATE,
    user_id STRING,
    business_id STRING,
    rating STRING,
    created_at STRING,
    processed_at STRING,
    signup_since_days STRING,
    cryear INT,
    crmonth INT,
    crday INT,
    isActive CHAR(1)
);
```

3. TransDim

);

```
create table IF NOT EXISTS creditbook_consumplayer.trans_dim(
    trans_id_pk INT PRIMARY KEY DISABLE NOVALIDATE,
   transaction_id STRING,
   user_id STRING,
    business id STRING,
    amount STRING,
   transaction_type STRING,
    type STRING,
    created_at STRING,
   processed_at timestamp,
   cryear INT,
    crmonth INT,
    crday INT,
   trans_date string,
    debit_count BIGINT,
    credit_count BIGINT,
    total_trans_count BIGINT,
   debitamount_inmillion DOUBLE,
    creditamount inmillion DOUBLE,
   totaltransamount_inmillion DOUBLE,
    isActive CHAR(1)
```

```
create table IF NOT EXISTS creditbook_consumplayer.analytics_dim(
      analytics_id_pk INT PRIMARY KEY DISABLE NOVALIDATE,
      user_id STRING,
      event_date STRING,
      category STRING,
      mobile_brand_name STRING,
      mobile_model_name STRING,
      mobile_os_hardware_model STRING,
      operating_system STRING,
      operating system version STRING,
     city STRING,
      country STRING,
      appversion STRING,
      processed at timestamp,
      cryear INT,
      crmonth INT,
      crday INT,
      isActive CHAR(1)
 );
create table IF NOT EXISTS creditbook_consumplayer.profile_fact(
   profile_id_pk INT PRIMARY KEY DISABLE NOVALIDATE,
   user_id_fk INT,
   trans_id_fk INT,
   analytics_id_fk INT,
   date_id_fk INT,
    gmv_per_month DOUBLE,
    avgtranspermonth DOUBLE
 );
 alter table creditbook_consumplayer.profile_fact add constraint fk_user_id FOREIGN KEY (user_id_fk) REFERENCI
 alter table creditbook_consumplayer.profile_fact add constraint fk_trans_id FOREIGN KEY (trans_id_fk) REFEREN
 alter table creditbook_consumplayer.profile_fact add constraint fk_analytics_id FOREIGN KEY (analytics_id_fk'
```

alter table creditbook_consumplayer.profile_fact add constraint fk_date_id FOREIGN KEY (date_id_fk) REFERENCI

6. Apache Airflow Integration

Apache Airflow is seamlessly integrated into the pipeline to orchestrate tasks and automate workflow execution. Directed Acyclic Graphs (DAGs) are created to define the workflow, ensuring tasks are executed sequentially or in parallel based on dependencies and schedules. This integration enhances pipeline reliability, scalability, and monitoring capabilities.



7. Full Load and Incremental Load Mechanisms

Within the Spark code, a separate mechanism is implemented to handle both full load and incremental load scenarios. This mechanism allows for flexibility in data loading strategies based on the requirements:

- **Full Load**: When the ETL code is executed with the "FullLoad" parameter, the entire dataset is processed and loaded from one layer to another. This ensures that all data is transferred and refreshed, useful for periodic updates or initial data setup.
- **Incremental Load**: In contrast, when the ETL code is executed with the "IncrementalLoad" parameter, only new or updated data is processed and loaded. This mechanism identifies changes since the last load and selectively transfers the relevant data, reducing processing time and resource utilization.

By implementing both full load and incremental load mechanisms, the ETL pipeline optimizes data processing efficiency and ensures that the most up-to-date information is available for analysis without unnecessary reprocessing of unchanged data.

8. Conclusion

In conclusion, the implemented ETL pipeline fulfills the client's requirements for transforming and aggregating their production database into a usable format for the data team. The modular design, coupled with the use of scalable technologies, ensures the pipeline's efficiency, flexibility, and maintainability.

presto:creditbook_consumplayer> select ccud.user_id, ccud.rating, ccud.signup_since_days,ccpf.gmv_per_month , ccpf.avgtranspermonth,										
user_id		signup_since_days	gmv_per_month	avgtranspermonth	trans_date	trans_year	trans_month	trans_quarter	trans_weekday	trans_dayname
	+ 4	+ 928	+ 6.57996998E7	2154.188895072843					+ Weekend	+
	4	1333	1.059017875E8	3965.4679660001498		2021	11	4		Tuesday
031e8f64-0e97-4f42-ab91-45569d114f0d	5	1030	1.7495383505E8	5849.342529254431	2022-07-26	2022			Weekday	Tuesday
cc0e78f9-305e-48e0-a4cf-72a79fb8a7d0	4		8.777229381E7	2599.5822121194174	2022-03-31	2022			Weekday	Thursday
3febcb3d-3acc-4b14-95ef-caba16777a9e	5	1101	8.904266475999999E7	2458.7233124395966	2022-04-28	2022			Weekday	Thursday
4ddd310d-ccfa-4126-9c2a-1d37b07a36ed	4	1216	9.391771534E7	2724.22669586657	2022-12-31	2022	12		Weekend	Saturday
671d933f-f411-49f5-9a90-7875db66e984	5	1084	6.57996998E7	2154.188895072843	2022-08-18	2022			Weekday	Thursday
65feb711-a05b-4eca-bfb5-ed7af23a2309	4	1333	1.4809863511E8	4154.355945748829	2022-05-14	2022			Weekend	Saturday
45afcadc-3da4-44b6-96f0-b9a864d3b8f6	4	791	1.136326355E8	3241.8302949903	2022-09-16	2022	9	3	Weekday	Friday
60b0bca5-aba2-4170-beb0-554b9e0b2a4e	1 4	928	7.839444281E7	2085.3468148325487	2022-06-20	2022	6	2	Weekday	Monday
3febcb3d-3acc-4b14-95ef-caba16777a9e	j 5	1101	7.839444281E7	2085.3468148325487	2022-06-24	2022	6		Weekday	Friday
dee57139-26ca-4dde-b9b1-ec42014cd394	4	1183	8.777229381E7	2599.5822121194174	2022-03-14	2022	3	1	Weekday	Monday
b2ea88b8-a17b-4d89-913d-5a2fe9b4a277	4	1176	1.4809863511E8	4154.355945748829	2022-05-01	2022	5	2	Weekend	Sunday
a50fc2e9-1454-4754-96d9-86a0e0fdc36c	4	1155	6.6117154E7	2216.9853468799247	2022-02-03	2022	2	1	Weekday	Thursday
a8a45c83-ae63-40ef-8fc0-4b958fdc90bc	i 4	1148	9.391771534E7	2724.22669586657	2022-12-01	I 2022	12		Weekday	Thursday
hrV880mZteSZwb7ZH1pOo2lJT8i2	i 4	537	1.1045658175E8	2060.834018993246	2022-11-02	I 2022	11		Weekdav	. Wednesday
6ab12451-393e-401a-a111-e7f2a47178f8	i 4	1231	8.904266475999999E7	2458.7233124395966	2022-04-22	2022	4	2	Weekday	Friday
671d933f-f411-49f5-9a90-7875db66e984	5	1084	8.904266475999999E7	2458.7233124395966		2022		2		Friday
7e848c3c-0f00-4c6a-98e7-65734cadf6c4	i 5	914	5.9137735913E8			2022	1		Weekend	Sunday
49a9d296-e5a6-4c23-bf5e-9897dee07917 (20 rows)	5	925	9.191531319E7		2023-01-13	2023			Weekday	Friday
(END)										