BDA Mini Project

1. Introduction:

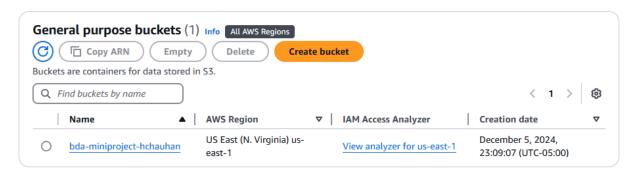
This comprehensive data analytics project focuses on processing Amazon's Digital Music review dataset(Amazon Reviews'23), which contains 130.4K reviews from 101K users across 70.5K items, totaling 11.4M review tokens. The pipeline implements a sophisticated architecture that combines AWS services with distributed computing frameworks: AWS S3 handles scalable storage, PySpark manages distributed data processing, AWS SageMaker powers machine learning capabilities, and QuickSight delivers data visualization. The dataset captures detailed customer interactions through a rich set of features including numerical ratings (1.0-5.0), timestamped reviews, purchase verification status, helpfulness votes, and review text. This structured approach enables efficient large-scale data processing while providing valuable insights into customer behavior and preferences in the digital music marketplace.

Example entry of Dataset: Digital_Music.jsonl

```
{"rating": 5.0, "title": "Nice", "text": "If i had a dollar for how many times I have played this cd and how many times I have asked Alexa to play it, I would be rich. Love this singer along with the Black Pumas. Finding a lot of new music that I like a lot on amazon. Try new things.", "images": [], "asin": "B004RQ2IRG", "parent_asin": "B004RQ2IRG", "user_id": "AFUOYIZBU3MTBOLYKOJE5Z35MBDA", "timestamp": 1618972613292, "helpful_vote": 0, "verified_purchase": true}
```

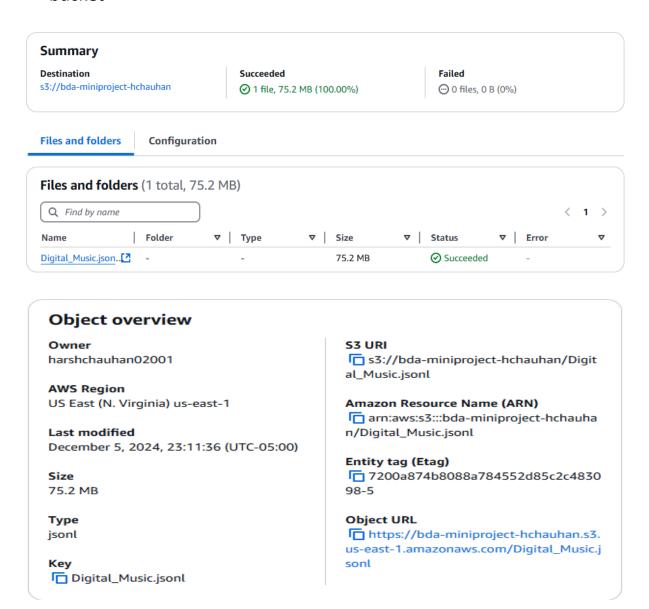
2. Environment Setup

- 1. AWS S3 for Data Storage:
 - a. Step 1 : Create an S3 bucket to store data.



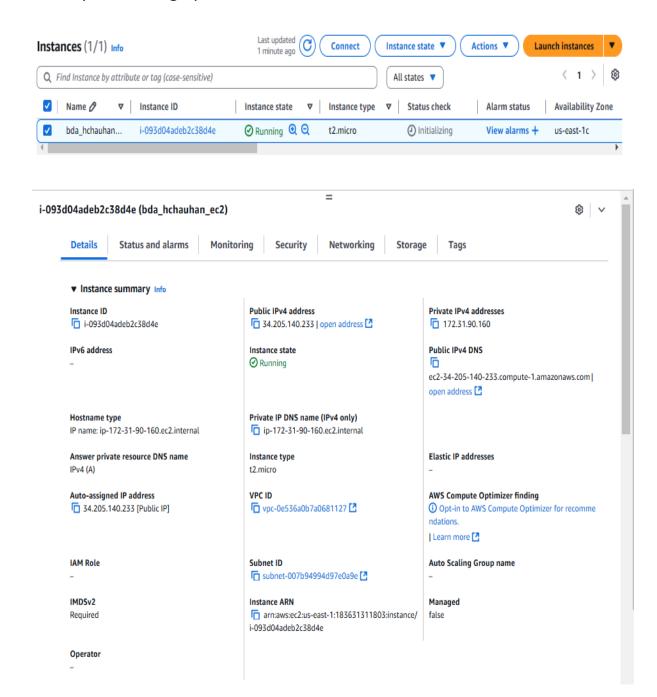
b. Step 2: Upload the raw dataset to the S3 bucket.

Uploaded Digital_music.jsonl to bda-miniproject-hchauhan S3 bucket



2. Linux Environment with PySpark

a. Step 1: Setting up Ubuntu EC2 Instance.



Established SSH connection:

```
П
                                                                                                                                               X
ubuntu@ip-172-31-90-160: ~
PS D:\Fall 2024\BDA\mini project> icacls
processed file: .\bda_hchauhan_key.pem
Successfully processed 1 files; Failed processing 0 files
                                                                     _key.pem" /inheritance:r /grant:r "$($env:USERNAME):(R)"
PS D:\Fall 2024\BDA\mini project> icacls
processed file: .\bda_hchauhan_key.pem
Successfully processed 1 files; Failed processing 0 files
PS D:\Fall 2024\BDA\mini project> <mark>ssh -i ".\bda_hchauhan_key.pem" ubuntu@ec2-34-205-140-233.compute-1.amazon.</mark>
The authenticity of host 'ec2-34-205-140-233.compute-1.amazonaws.com (34.205.140.233)' can't be established.
                                                                         .pem" ubuntu@ec2-34-205-140-233.compute-1.amazonaws.com
ED25519 key fingerprint is SHA256:rE9IZoQSWleY2W/n+77VNnJbC8nhoK3zCDwsTiswJtI.
This key is not known by any other names.
Are you sure you want to continue connecting (yes/no/[fingerprint])? Yes
Warning: Permanently added 'ec2-34-205-140-233.compute-1.amazonaws.com' (ED25519) to the list of known hosts.
Welcome to Ubuntu 24.04.1 LTS (GNU/Linux 6.8.0-1018-aws x86_64)
* Documentation: https://help.ubuntu.com
* Management: https://landscape.canonical.com
* Support: https://ubuntu.com/pro
System information as of Fri Dec 6 04:50:15 UTC 2024
 System load: 0.0
                                                                    106
                                        Processes:
 Usage of /: 24.9% of 6.71GB Users logged in:
                                        IPv4 address for enX0: 172.31.90.160
 Memory usage: 21%
  Swap usage:
                 9%
Expanded Security Maintenance for Applications is not enabled.
 updates can be applied immediately.
nable ESM Apps to receive additional future security updates.
See https://ubuntu.com/esm or run: sudo pro status
The list of available updates is more than a week old.
To check for new updates run: sudo apt update
Last login: Fri Dec 6 04:39:31 2024 from 18.206.107.28
To run a command as administrator (user "root"), use "sudo <command>".
See "man sudo_root" for details.
 buntu@ip-172-31-90-160:~$
```

b. Step 2: Install PySpark for distributed data processing.

Installing Python on EC2 instance:

```
П
                                                                                                                                          ×
ubuntu@ip-172-31-90-160: ~
                            $ sudo apt install python3-venv python3-full
Reading package lists... Done
Building dependency tree... Done
Reading state information... Done
The following additional packages will be installed:
 2to3 blt fontconfig-config fonts-dejavu-core fonts-dejavu-mono fonts-mathjax idle idle-python3.12 javascript-common
 libfontconfig1 libjs-jquery libjs-mathjax libjs-underscore libpython3.12-minimal libpython3.12-stdlib
 libpython3.12-testsuite libpython3.12t64 libtk8.6 libxft2 libxrender1 libxss1 net-tools python3-doc python3-examples python3-lib2to3 python3-pip-whl python3-setuptools-whl python3-tk python3.12 python3.12-doc python3.12-examples
 python3.12-full python3.12-minimal python3.12-venv tk8.6-blt2.5 x11-common
 uggested packages:
 blt-demo apache2 | lighttpd | httpd fonts-mathjax-extras fonts-stix libjs-mathjax-doc tk8.6 python3-dev tix
 python3-tk-dbg binutils python3.12-dev binfmt-support
The following NEW packages will be installed:
 2to3 blt fontconfig-config fonts-dejavu-core fonts-dejavu-mono fonts-mathjax idle idle-python3.12 javascript-common
 libfontconfig1 libjs-jquery libjs-mathjax libjs-underscore libpython3.12-testsuite libtk8.6 libxft2 libxrender1 libxss1 net-tools python3-doc python3-examples python3-full python3-lib2to3 python3-pip-whl python3-setuptools-whl
 python3-tk python3-venv python3.12-doc python3.12-examples python3.12-full python3.12-venv tk8.6-blt2.5 x11-common
The following packages will be upgraded:
 libpython3.12-minimal libpython3.12-stdlib libpython3.12t64 python3.12 python3.12-minimal
5 upgraded, 33 newly installed, 0 to remove and 35 not upgraded.
leed to get 40.3 MB of archives.
After this operation, 163 MB of additional disk space will be used.
Do you want to continue? [Y/n] Y
et:1 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble-updates/main amd64 libpython3.12t64 amd64 3.12.3-1ubuntu0.3
2333 kB1
Get:2 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble-updates/main amd64 python3.12 amd64 3.12.3-1ubuntu0.3 [651 kB
et:3 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble-updates/main amd64 libpython3.12-stdlib amd64 3.12.3-1ubuntu0
.3 [2068 kB]
Get:4 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble-updates/main amd64 python3.12-minimal amd64 3.12.3-1ubuntu0.3
[2333 kB]
Get:5 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble-updates/main amd64 libpython3.12-minimal amd64 3.12.3-1ubuntu
0.3 [834 kB]
Get:6 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble/universe amd64 python3-lib2to3 all 3.12.3-0ubuntu1 [78.0 kB]
Get:7 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble-updates/universe amd64 2to3 all 3.12.3-0ubuntu2 [11.0 kB]
et:8 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble/main amd64 fonts-dejavu-mono all 2.37-8 [502 kB]
Get:9 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble/main amd64 fonts-dejavu-core all 2.37-8 [835 kB]
et:10 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble/main amd64 fontconfig-config amd64 2.15.0-1.1ubuntu2 [37.3 k
et:11 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble/main amd64 libfontconfig1 amd64 2.15.0-1.1ubuntu2 [139 kB]
et:12 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble/main amd64 libxrender1 amd64 1:0.9.10-1.1build1 [19.0 kB]
et:13 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble/main amd64 libxft2 amd64 2.3.6-1build1 [45.3 kB]
Get:14 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble/main amd64 x11-common all 1:7.7+23ubuntu3 [21.7 kB]
Get:15 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble/main amd64 libxss1 amd64 1:1.2.3-1build3 [7204 B]
Get:16 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble/main amd64 libtk8.6 amd64 8.6.14-1build1 [779 kB]
Get:17 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble/main amd64 tk8.6-blt2.5 amd64 2.5.3+dfsg-7build1 [630 kB]
Get:18 http://us-east-1.ec2.archive.ubuntu.com/ubuntu noble/main amd64 blt amd64 2.5.3+dfsg-7build1 [4840 B]
```

Installing PySpark on EC2 instance:

```
puntu@ip-172-31-90-160:~$ python3 -m venv ~/pyspark_env
 ountu@ip-172-31-90-160:~$ source ~/pyspark_env/bin/activate
(pyspark_env) ubuntu@ip-172-31-90-160:~$ pip3 install pyspark
Collecting pyspark
 Downloading pyspark-3.5.3.tar.gz (317.3 MB)
                                               17.3/317.3 MB 2.0 MB/s eta 0:00:00
 Installing build dependencies \dots done
 Getting requirements to build wheel ... done
 Preparing metadata (pyproject.toml) ... done
Collecting py4j==0.10.9.7 (from pyspark)
 Downloading py4j-0.10.9.7-py2.py3-none-any.whl.metadata (1.5 kB)
Downloading py4j-0.10.9.7-py2.py3-none-any.whl (200 kB)
Building wheels for collected packages: pyspark
 Building wheel for pyspark (pyproject.toml) ... done
 Created wheel for pyspark: filename=pyspark-3.5.3-py2.py3-none-any.whl size=317840629 sha256=545a7981a8c9ae25c9a952879
385edb9dde5ed36d38c880017cb8d63f822e6e8
Stored in directory: /home/ubuntu/.cache/pip/wheels/07/a0/a3/d24c94bf043ab5c7e38c30491199a2a11fef8d2584e6df7fb7
Successfully built pyspark
Installing collected packages: py4j, pyspark
Successfully installed py4j-0.10.9.7 pyspark-3.5.3
(pyspark_env) ubuntu@ip-172-31-90-160:~$ _
```

c. Step 3: Configure AWS CLI to interact with S3 buckets.

Installation of AWS CLI:

```
Windows PowerShell
Copyright (C) Microsoft Corporation. All rights reserved.

Try the new cross-platform PowerShell https://aka.ms/pscore6

PS C:\Users\USER> aws --version
aws-cli/2.22.12 Python/3.12.6 Windows/10 exe/AMD64
PS C:\Users\USER> ___
```

3. Data Pipeline Implementation:

Task 1: Data Ingestion From S3: data-ingestion.py

Code:

```
ubuntu@ip-172-31-90-160: ~
  GNU nano 7.2
                                                                                                                                              data-ingestion.py
   om pyspark.sql import SparkSession
spark = SparkSession.builder
    .appName("BDA_MiniProject") \
    .config("spark.jars.packages", "org.apache.hadoop:hadoop-aws:3.3.4") \
.config("spark.hadoop.fs.s3a.access.key", "AKIASVQKHOO5U2ILKIAE") \
.config("spark.hadoop.fs.s3a.secret.key", "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") \
.config("spark.hadoop.fs.s3a.impl", "org.apache.hadoop.fs.s3a.S3AFileSystem") \
    .getOrCreate()
# Read data from S3
s3_path = "s3a://bda-miniproject-hchauhan/Digital_Music.jsonl"
df = spark.read.json(s3_path)
# Basic Dataset Information
print("Dataset Overview:")
 orint(f"Number of rows: {df.count()}")
print(f"Number of columns: {len(df.columns)}")
print("\nDataset Schema:")
df.printSchema()
# Show Sample data:")
print("\nSample Data:")
df.show(5)
```

Output:

```
| dubuntu@ip-172-31-90-160: \(^{\text{pyrank.em}}\) ubuntu@ip-172-31-90-160: \(^{\text{pyrank.em}}\) purbon3 data-ingestion.py
:: loading settings :: unl = jan-file:/home/ubuntu/.lvy2/cache
The jars for the packages stored in: /home/ubuntu/.lvy2/jars
org.apache.hadoopHadoop-ass added as a dependency
:: resolving dependencies :: org.apache.spark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espark.espar
```

```
24/12/86 23:04:08 WARN MetricsConfig: Cannot locate configuration: tried hadoop-metrics2-s3a-file-system.properties,hadoop-metrics2.properties
Dataset Overview:
Number of ross: 130434
```

Task 2: Data Processing With PySpark.

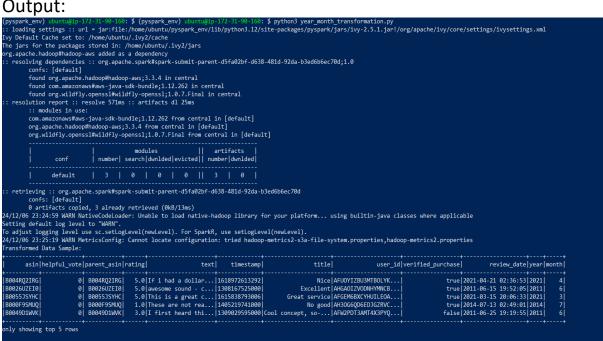
1) Data Transformation: Year , Month Transformation year_month_transformation.py

Code:

```
    ubuntu@ip-172-31-90-160: ~

  GNU nano 7.2
                                                                                                                                                                                                  vear month transformation.pv
    om pyspark.sql import SparkSession
    om pyspark.sql.functions import from_unixtime, year, month
    ark = SparkSession.builder \
     rk = sparksession.dulider \
.appName("BDA_MiniProject") \
.config("spark.jars.packages", "org.apache.hadoop:hadoop-aws:3.3.4") \
.config("spark.hadoop.fs.s3a.access.key", "AKIASVQKH005UZILKIAE") \
.config("spark.hadoop.fs.s3a.secret.key", "wNS6JjPH6y8Y49hXNVYJhkH1d8g8tRgYQ1T1UapO") \
.config("spark.hadoop.fs.s3a.impl", "org.apache.hadoop.fs.s3a.S3AFileSystem") \
.config("spark.hadoop.fs.s3a.aws.credentials.provider", "org.apache.hadoop.fs.s3a.SimpleAWSCredentialsProvider") \
getOrCreate()
      .getOrCreate()
 f <mark>Read data from 53</mark>
33 path = "s3a://bda-miniproject-hchauhan/Digital Music.jsonl"
        spark.read.json(s3_path)
 df_transformed = df \
      .withColumn("review_date", from_unixtime(df.timestamp/1000)) \
.withColumn("year", year("review_date")) \
.withColumn("month", month("review_date"))
 df_transformed_simple = df_transformed.select(
       'asin', 'helpful_vote', 'parent_asin', 'rating', 'text',
'timestamp', 'title', 'user_id', 'verified_purchase',
'review_date', 'year', 'month'
 # Show transformed data
print("Transformed Data Sample:")
 f_transformed_simple.show(5)
 #f_transformed_simple.write.option("header", "true").csv("transformed_data", mode="overwrite")
```

Output:



2) Data Aggregration:

The 5 key Metric performed are as follows:

- Rating Distribution by Year Shows the average ratings and total review count for each year, helping track how product satisfaction has evolved over time. This metric reveals long-term trends in customer satisfaction.
- Helpful Vote Analysis by Rating Analyzes the relationship between rating scores (1-5) and helpful votes, showing which ratings tend to be considered most helpful by other users. This helps understand community engagement with different types of reviews.
- Verified Purchase Impact Compares ratings between verified and non-verified purchases across years, helping assess the credibility and potential bias in reviews. The sample shows both true/false verification status.
- Monthly Review Volume

Tracks the number of reviews submitted each month across different years, revealing seasonal patterns and overall review activity trends.

Top Reviewers Analysis
 Identifies the most active reviewers based on review count, average rating, and helpful votes, helping understand user engagement patterns.

Code:

```
ubuntu@ip-172-31-90-160: ~
                                                                                                                                                                                                                                                                                        data_aggregration.py
    om pyspark.sql.functions import from_unixtime, year, month, avg, count, desc
spark = SparkSession.builder
    ark = SparkSession.bullder \
.appName("BDA_MiniProject") \
.config("spark.jars.packages", "org.apache.hadoop:hadoop-aws:3.3.4") \
.config("spark.hadoop.fs.s3a.access.key", "AKIASVQKHOO5U2ILKIAE") \
.config("spark.hadoop.fs.s3a.secret.key", "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") \
.config("spark.hadoop.fs.s3a.impl", "org.apache.hadoop.fs.s3a.S3AFileSystem") \
.config("spark.hadoop.fs.s3a.aws.credentials.provider", "org.apache.hadoop.fs.s3a.SimpleAWSCredentialsProvider") \
.config("spark.hadoop.fs.s3a.aws.credentials.provider") \
.config("spa
/early_ratings.show()
nelpful_votes_analysis.show()
/erified_impact.show()
onthly_volume.show()
 top_reviewers = df_transformed_simple.groupBy("user_id") \
       .limit(10)
 top_reviewers = df_transformed_simple.groupBy("user_id") \
     .agg(count("*").alias("review_count"),
avg("rating").alias("avg_rating"),
avg("helpful_vote").alias("avg_helpful_votes")) \
.orderBy(desc("review_count")) \
  op_reviewers.show()
```

Output:

1) Rating Distribution By Year:

```
1. Rating Distribution by Year:
|year| avg_rating|review_count|
1997 5.0 2
2006 4.477292965271594
                          1123
2007 4.454377311960543
                          1622
2008 4.434092112228693
                          1889
|2009|4.4973776223776225|
                          2288
                          2624
3347
|2010| 4.508384146341464|
|2011| 4.412309530923215|
                          4380
8521
|2012| 4.518949771689497|
2013 4.526229315808004
                      11796|
14340|
13183|
|2014| 4.526788741946422|
2015 4.614016736401673
|2016| 4.578699840703937|
                          13183
only showing top 20 rows
```

2) Helpful Vote Analysis by Rating:

3) Verified Purchase Impact by Year:

ified_purchase	year	avg_rating	review_count
false	1997	5.0	2
false	1998	4.65	20
true	1998	5.0	1
false	1999	4.51948051948052	77
true	1999	5.0	1
false	2000	4.338383838383838	396
true	2000	4.5	20
false	2001	4.254794520547946	365
true	2001	4.608695652173913	23
false	2002	3.949675324675325	616
true	2002	4.068181818181818	44
false	2003	4.358078602620087	229
true	2003	4.5333333333333333	15
false	2004	4.510695187165775	374
true	2004	3.5217391304347827	23
false	2005	4.41044776119403	938
true	2005	4.324324324324325	74
false	2006	4.503913894324853	1022
true	2006	4.207920792079208	101
false	2007	4.495633187772926	1374

4) Monthly Review Volume:

ear m	onth	review_count	
+-		· -	
	12	1	
997	9	1	
	10	2	
	11	2	
	12	5	
	4	1	
	6	2	
998	7	2	
998	8	3	
998	9	4	
999	1	1	
999	10	11	
999	11	13	
999	12	14	
	2	3	
999	3	4	
999	4	4	
999	5	6	
999	6	4	
999	7	3	

5) Top Review Analysis:

Task 3: Store Processed Data back to S3:

Step 1: Saving metrics to csv file_to_csv.py

Code:

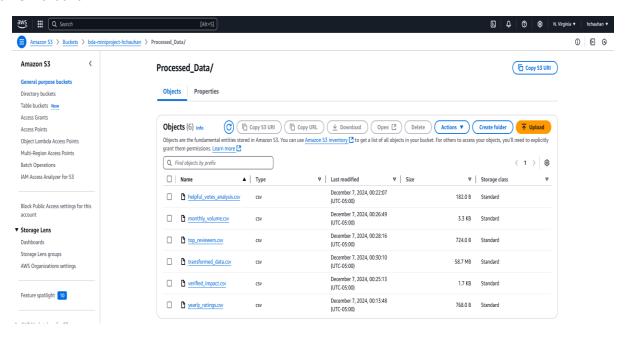
```
ubuntu@ip-172-31-90-160: ~
                                                                                                                                          \times
GNU nano 7.2
                                                                    file to csv.py
  rom pyspark.sql import SparkSession
  rom pyspark.sql.functions import avg, count, desc
spark = SparkSession.builder \
   .appName("BDA_MiniProject") \
.appName("BDA_MiniProject") \
.config("spark.jars.packages", "org.apache.hadoop:hadoop-aws:3.3.4") \
.config("spark.hadoop.fs.s3a.access.key", "AKIASVQKH005U2ILKIAE") \
.config("spark.hadoop.fs.s3a.secret.key", "vNS6JjPH6y8Y49hXNVYJhkH1d8g8tRgYQ1T1UapO") \
.config("spark.hadoop.fs.s3a.impl", "org.apache.hadoop.fs.s3a.S3AFileSystem") \
.config("spark.hadoop.fs.s3a.aws.credentials.provider", "org.apache.hadoop.fs.s3a.SimpleAWSCredentialsProvider")>
    .getOrCreate()
df = spark.read.json("s3a://bda-miniproject-hchauhan/Digital_Music.jsonl")
df_transformed_simple = spark.read.csv("transformed_data", header=<mark>True</mark>)
yearly_ratings.write.csv('yearly_ratings', header=True, mode='overwrite')
print("Successfully saved yearly_ratings.csv")
helpful_votes_analysis.write.csv('helpful_votes_analysis', header=<mark>True, mode=</mark>'overwrite')
print("Successfully saved helpful_votes_analysis.csv")
print("Successfully saved verified_impact.csv")
 monthly_volume.write.csv('monthly_volume', header=True, mode='overwrite')
print("Successfully saved monthly_volume.csv")
 f 5. Top Reviewers Analysis
cop_reviewers = df_transformed_simple.groupBy("user_id") \
    agg(count("*").alias("review_count"),
   avg("rating").alias("avg_rating"),
   avg("helpful_vote").alias("avg_helpful_votes")) \
.orderBy(desc("review_count")) \
top_reviewers = df_transformed_simple.groupBy("user_id") \
     .agg(count("*").alias("review_count"),
    avg("rating").alias("avg_rating"),
    avg("helpful_vote").alias("avg_helpful_votes")) \
.orderBy(desc("review_count")) \
     .limit(10)
top_reviewers.write.csv('top_reviewers', header=True, mode='overwrite')
print("Successfully saved top_reviewers.csv")
```

Output:

```
l60:~$ (pyspark_env) ubuntu@ip-172-31-90-
                                                                                   160:~$ python3 file_to_csv.py
 : loading settings :: url = jar:file:/home/ubuntu/pyspark_env/lib/python3.12/site-packages/pyspark/jars/ivy-2.5.1.ja
r!/org/apache/ivy/core/settings/ivysettings.xml
Ivy Default Cache set to: /home/ubuntu/.ivy2/cache
The jars for the packages stored in: /home/ubuntu/.ivy2/jars
org.apache.hadoop#hadoop-aws added as a dependency
:: resolving dependencies :: org.apache.spark#spark-submit-parent-90048e76-6770-4403-9270-187<u>b9b6f65f9;1.0</u>
        confs: [default]
         found org.apache.hadoop#hadoop-aws;3.3.4 in central
        found com.amazonaws#aws-java-sdk-bundle;1.12.262 in central
         found org.wildfly.openssl#wildfly-openssl;1.0.7.Final in central
:: resolution report :: resolve 609ms :: artifacts dl 23ms
        :: modules in use:
        com.amazonaws#aws-java-sdk-bundle;1.12.262 from central in [default]
        org.apache.hadoop#hadoop-aws;3.3.4 from central in [default]
        org.wildfly.openssl#wildfly-openssl;1.0.7.Final from central in [default]
                                           modules
                                                                      artifacts
                 conf
                              | number | search | dwnlded | evicted | | number | dwnlded |
                default
:: retrieving :: org.apache.spark#spark-submit-parent-90048e76-6770-4403-9270-187b9<u>b6f65f9</u>
        confs: [default]
        0 artifacts copied, 3 already retrieved (0kB/12ms)
24/12/07 05:10:35 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java
classes where applicable
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
24/12/07 05:10:57 WARN MetricsConfig: Cannot locate configuration: tried hadoop-metrics2-s3a-file-system.properties,h
adoop-metrics2.properties
Successfully saved yearly_ratings.csv
Successfully saved helpful_votes_analysis.csv
Successfully saved verified_impact.csv
Successfully saved monthly\_volume.csv
Successfully saved top_reviewers.csv
```

Moving these csv files to new S3 folder along with transformed data:

```
(pyspark_env) ubuntu@ip-172-31-90-160:-$ ls yearly_ratings
_SUCCESS part-00000-dd51cbe0-dc1e-4016-a29d-15d202c350e5-c000.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ mv yearly_ratings/part-00000-*.csv yearly_ratings.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ aws s3 cp yearly_ratings.csv s3://bda-miniproject-hchauhan/Processed_Data/
upload: ./yearly_ratings.csv to s3://bda-miniproject-hchauhan/Processed_Data/yearly_ratings.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ mv helpful_votes_analysis/part-00000-*.csv helpful_votes_analysis.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ aws s3 cp helpful_votes_analysis.csv s3://bda-miniproject-hchauhan/Processed_Data/helpful_votes_analysis.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ mv verified_impact/part-00000-*.csv verified_impact.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ mv verified_impact.csv s3://bda-miniproject-hchauhan/Processed_Data/upload: ./verified_impact.csv to s3://bda-miniproject-hchauhan/Processed_Data/verified_impact.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ mv wonthly_volume/part-00000-*.csv wonthly_volume.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ mv monthly_volume/part-00000-*.csv monthly_volume.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ mv monthly_volume/part-00000-*.csv monthly_volume.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ mv monthly_volume/part-00000-*.csv monthly_volume.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ mv top_reviewers.csv top_reviewers.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ mv top_reviewers.csv s3://bda-miniproject-hchauhan/Processed_Data/
upload: ./top_reviewers.csv to s3://bda-miniproject-hchauhan/Processed_Data/miniproject-hchauhan/Processed_Data/
upload: ./top_reviewers.csv to s3://bda-miniproject-hchauhan/Processed_Data/transformed_data.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ aws s3 cp transformed_data.csv s3://bda-miniproject-hchauhan/Processed_Data/
upload: ./transformed_data.csv to s3://bda-miniproject-hchauhan/Processed_Data/transformed_data.csv
(pyspark_env) ubuntu@ip-172-31-90-160:-$ aws s3 cp tr
```



Task 4: Data Analysis With Spark SQL:

Code:

```
ubuntu@ip-172-31-90-160: ~
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          ×
      GNU nano 7.2
                                                                                                                                                                                                                                         sql analysis.py
       om pyspark.sql import SparkSession
     rom pyspark.sql.functions import from_unixtime, year, month
 spark = SparkSession.builder \
              rk = SparkSession.Oullder \
appName("BDA_MiniProject") \
.config("spark.jars.packages", "org.apache.hadoop:hadoop-aws:3.3.4") \
.config("spark.hadoop.fs.s3a.access.key", "AKIASVQKHOO5U2ILKIAE") \
.config("spark.hadoop.fs.s3a.secret.key", "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") \
.config("spark.hadoop.fs.s3a.impl", "org.apache.hadoop.fs.s3a.S3AFileSystem") \
.config("spark.hadoop.fs.s3a.aws.credentials.provider", "org.apache.hadoop.fs.s3a.SimpleAWSCredentialsProvider") \
.config("spark.hadoop.fs.s3a.aws.credentials.provider") \
.config("
                 .getOrCreate()
df = spark.read.csv("s3a://bda-miniproject-hchauhan/Processed_Data/transformed_data.csv", header=True)
# Create temporary view for SQL queries
df.createOrReplaceTempView("digital_music")
 query1 = ""'
     ELECT asin, title,
    ROUP BY asin, title
AVING COUNT(*) > 10
    RDER BY avg_rating DESC
IMIT 5
 # 2. Monthly Review Growth Analysis
query2 = """
    ELECT year, month,
COUNT(*) as review_count,
    ROUP BY year, month
RDER BY year, month
```

```
ubuntu@ip-172-31-90-160: ~
                                                                                                                           Χ
GNU nano 7.2
                                                         sql_analysis.py
₩ 3. Verified vs Non-Verified Purchase Impact
query3 = """
 ELECT verified_purchase,
       AVG(CAST(rating AS DOUBLE)) as avg_rating,
       AVG(CAST(helpful_vote AS DOUBLE)) as avg_helpful_votes
 ROM digital_music
 ROUP BY verified_purchase
# 4. Most Helpful Reviews Analysis
query4 = """
SELECT user_id, rating, title, helpful_vote
 ROM digital_music
 IMIT 10
# 5. Yearly Rating Distribution
query5 = """
       AVG(CAST(rating AS DOUBLE)) as avg_rating,
       COUNT(CASE WHEN CAST(rating AS DOUBLE) >= 4 THEN 1 END) as positive_reviews
 ROM digital_music
 ROUP BY year
 RDER BY year
print("\nExecuting SQL Queries for Digital Music Analysis:")
queries = [query1, query2, query3, query4, query5]
titles = [
    "Verified vs Non-Verified Purchase Impact",
    "Yearly Rating Distribution"
for i, (query, title) in enumerate(zip(queries, titles), 1):
   print(f"\n{i}. {title}:")
    spark.sql(query).show(truncate=False)
```

Output:

```
(pyspark_env) ubuntu@ip-172-31-90-160: $ (pyspark_env) ubuntu@ip-172-31-90-160: $ python3 sql_analysis.py
:: loading settings :: url = jar:file:/home/ubuntu/pyspark_env/lib/python3.12/site-packages/pyspark/jars/ivy-2.5.1.jar!,
org/apache/ivy/core/settings/ivysettings.xml
Ivy Default Cache set to: /home/ubuntu/.ivy2/cache
The jars for the packages stored in: /home/ubuntu/.ivy2/jars
org.apache.hadoop#hadoop-aws added as a dependency
:: resolving dependencies :: org.apache.spark#spark-submit-parent-ac91b3e4-309f-4293-b835-0ff69073592f;1.0
       confs: [default]
       found org.apache.hadoop#hadoop-aws;3.3.4 in central
       found com.amazonaws#aws-java-sdk-bundle;1.12.262 in central
       found org.wildfly.openssl#wildfly-openssl;1.0.7.Final in central
:: resolution report :: resolve 550ms :: artifacts dl 14ms
       :: modules in use:
       com.amazonaws#aws-java-sdk-bundle;1.12.262 from central in [default]
       org.apache.hadoop#hadoop-aws;3.3.4 from central in [default]
       org.wildfly.openssl#wildfly-openssl;1.0.7.Final from central in [default]
               | modules || artifacts
              conf | number | search | dwnlded | evicted | | number | dwnlded |
            default | 3 | 0 | 0 | 0 || 3 | 0 |
:: retrieving :: org.apache.spark#spark-submit-parent-ac91b3e4-309f-4293-b835-0ff69073592f
       confs: [default]
       0 artifacts copied, 3 already retrieved (0kB/14ms)
24/12/07 06:54:04 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java cl
asses where applicable
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
24/12/07 06:54:26 WARN MetricsConfig: Cannot locate configuration: tried hadoop-metrics2-s3a-file-system.properties,hado
op-metrics2.properties
Executing SQL Queries for Digital Music Analysis:

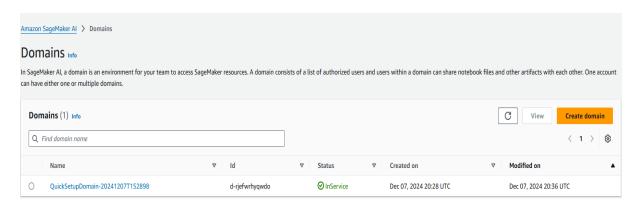
    Top-Rated Products Analysis:

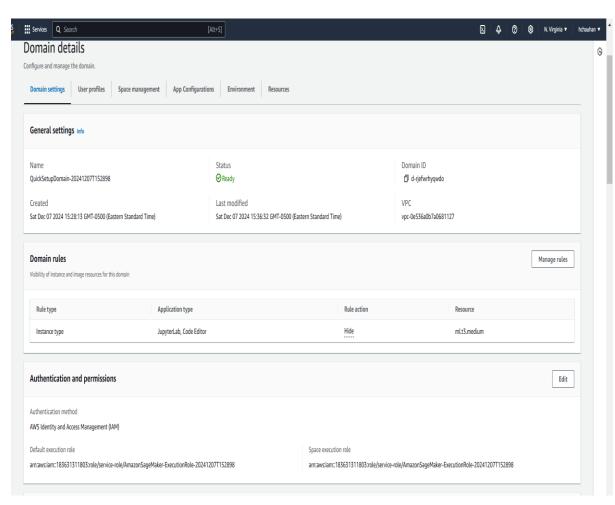
        title |avg_rating|review_count|
asin
|B001EJH4SW|Five Stars|5.0
                               130
|B0009PUCUE|Five Stars|5.0
                                34
                               117
|B00ZUPPH5S|Five Stars|5.0
|B00PG5G5QC|Five Stars|5.0
                               15
|B00IKM5NZC|Five Stars|5.0
                               15
```

```
2. Monthly Review Growth Analysis:
|year|month|review_count|prev_month_count|
|1997|12
                         NULL
1997 9
           2
1998 10
                         .
|NULL
1998 11
1998 12
1998 4
1998 6
1998 7
                         į2
           |3
|4
1998 | 8
                         2
1998 9
           |1
|11
1999 1
                         NULL
1999 10
                         |1
|11
           |13
|14
1999|11
1999 12
                         |13
|14
           |3
|4
|4
1999 2
                         |3
|4
1999 3
1999 4
1199915
           16
                         14
                         ĺ6
1999 6
1999 7
                         14
only showing top 20 rows
Verified vs Non-Verified Purchase Impact:
verified_purchase|avg_rating
                                     |total_reviews|avg_helpful_votes |
false
                  4.411412458940147|34401
                                                    |1.904072556030348
                  4.576333135484677|96033
                                                    |0.7373298761883935|
true
4. Most Helpful Reviews Analysis:
                              |rating|title
                                                                                                   |helpful_vote|
luser id
AFCRT2KE2N5P4VSA7MY74SGRV6AA|2.0
                                     Overpriced for what you get.
                                                                                                   259
AGAWJK3Z57FRGCVR5TNWIQIDQ2SA 5.0
                                      Let's set the record straight...
                                                                                                   213
AHVIMKECEZDXXK5QIGX7KWJPN6DQ|4.0
                                                                                                   191
                                      A Grimm, Grimm tale
AGK5K3EAMWHSIPWG2VXJP7W32M7Q|4.0
                                      1991 Gramophone Award Winner
                                                                                                    162
AGY3BQJXYGHK7OVCFHCEXBCIWPNA 5.0
                                      ANTHOLOGY 1 - MAINLY FOR BEATLES FANS AND COLLECTORS ONLY 160
AFPRDHJPDFDTVOSZKAE5F2U56LBQ|5.0
                                      The Clash of Titans
                                                                                                   157
AH64C6DXEZN3IMX4W2SDHXKJP5GA 1.0
                                      Where are the "Unleashing" techniques?
                                                                                                    148
AH2NK6SZGQXS6NSD4VVP20U4HTWA 5.0
                                      Beyond Awesome!
                                                                                                   |141
AHSF3JIVAMNDRI7PLZ7373VXISHA|5.0
                                      |The Two Origins
                                                                                                   140
AFIV4IC7VU6FRI364KGJKBPXXJFA|4.0
                                      |Bodes well for Clooney's future behind the camera!
                                                                                                   1130
Yearly Rating Distribution:
|year|total_reviews|avg_rating
                                      |positive_reviews|
1997|2
                    15.0
                    1998 21
                    4.5256410256410255 70
1999 78
2000 416
                    4.346153846153846 349
2001 388
                    4.275773195876289 317
2002 660
                    3.9575757575757575 473
 2003 244
                    4.368852459016393 206
2004 | 397
                    4.4534005037783375 345
 2005 | 1012
                    4.404150197628459 | 861
                    |4.477292965271594 |979
|4.454377311960543 |1422
|4.434092112228693 |1641
2006 1123
2007 1622
2008 | 1889
2009 | 2288
                    |4.4973776223776225|2013
                    4.508384146341464 | 2331
2010 2624
                    4.412309530923215 |2867
2011|3347
                    4.518949771689497
2012 4380
                                       13868
2013 | 8521
                    14.526229315808004
                                       17483
                   |4.526788741946422 |10369
|4.614016736401673 |12915
2014 | 11796
2015 14340
                    4.578699840703937 | 11781
2016 | 13183
only showing top 20 rows
(pyspark_env) ubuntu@ip-172-31-90-160:~$
```

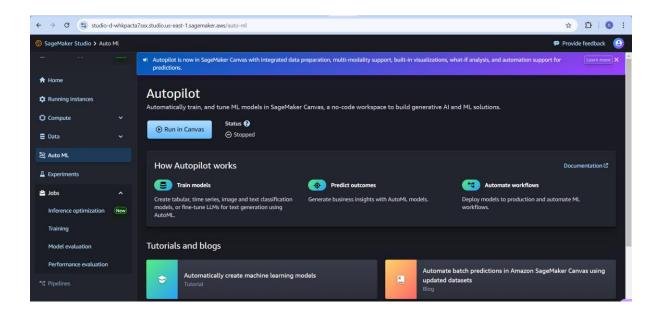
Task 5: Machine Learning with AWS Sagemaker Autopilot

Created Domain on SageMaker



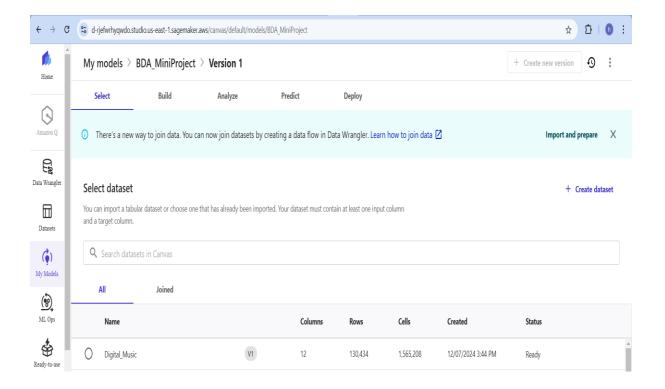


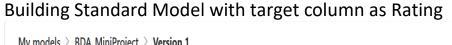
Connected to AWS Studio:

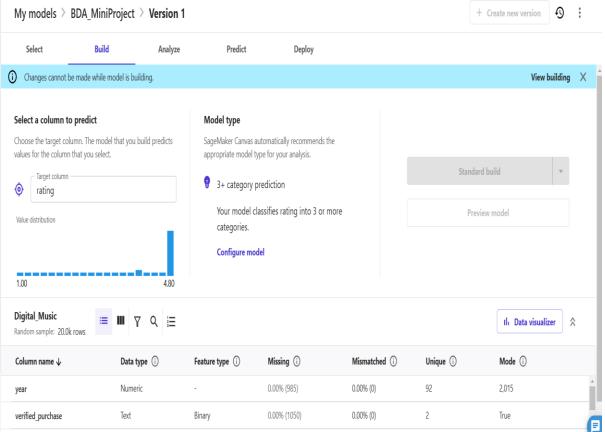


Connected to Canvas for AutoML:

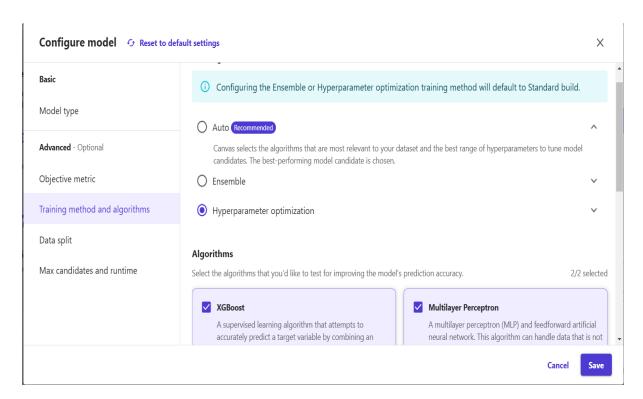
Imported Dataset to Canvas

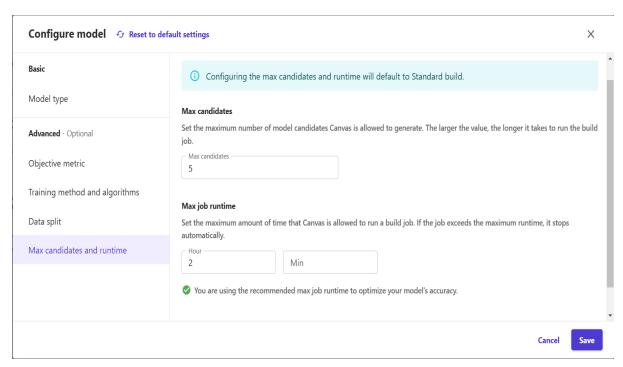




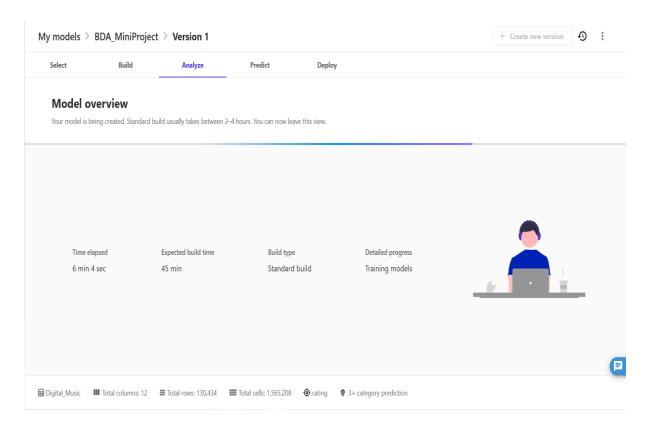


Configuring Model Setting:



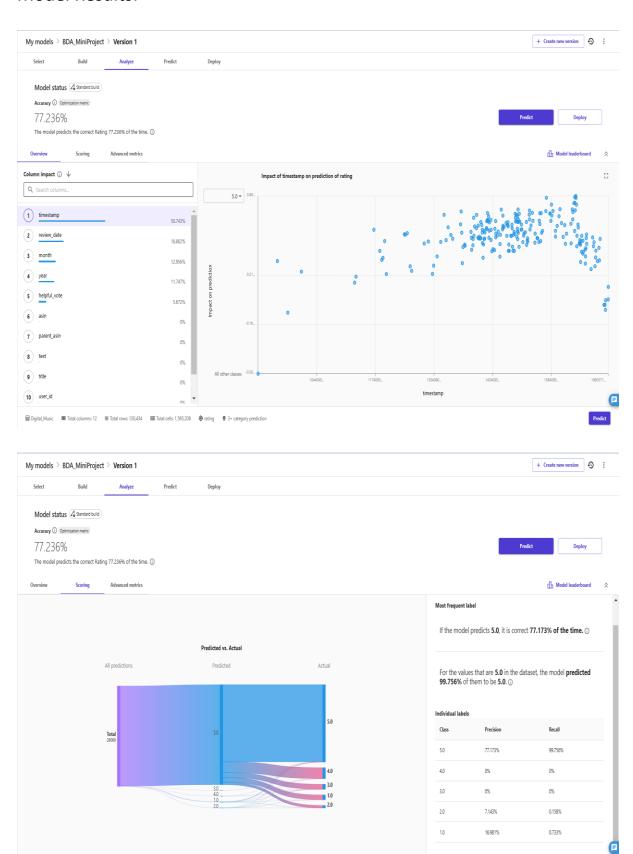


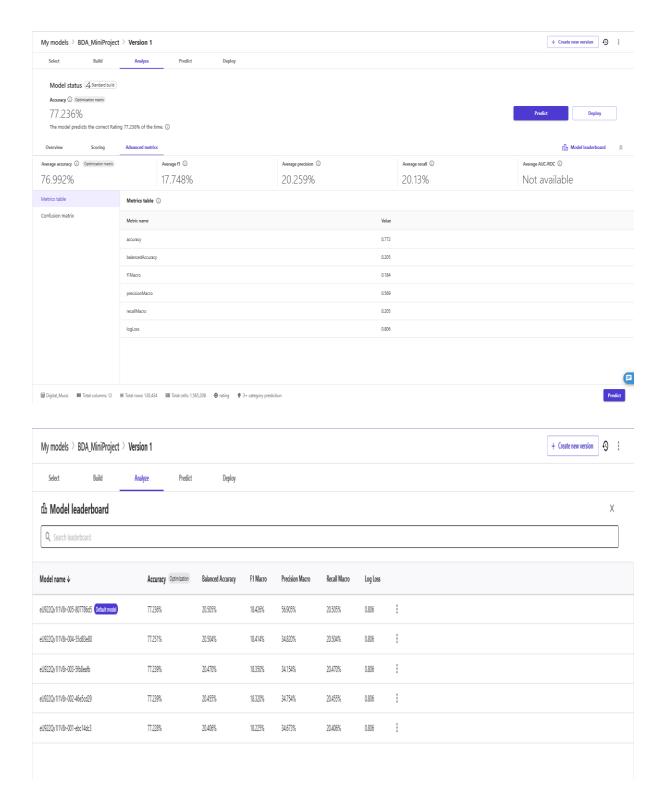
Model Training:



Model Results:

☐ Digital_Music
IIII Total columns: 12
☐ Total rows: 130,434
☐ Total cells: 1,565,208
⑥ rating
⑦ 3+ category prediction

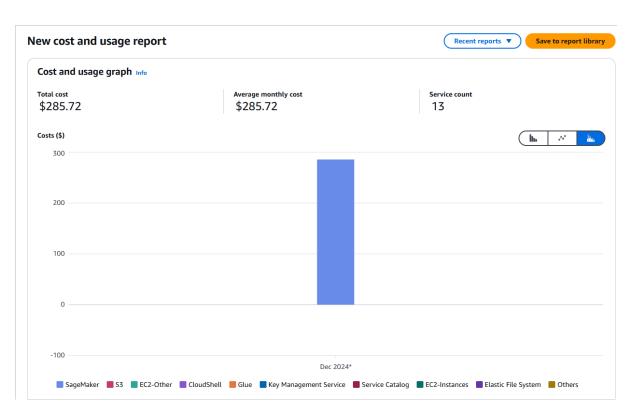


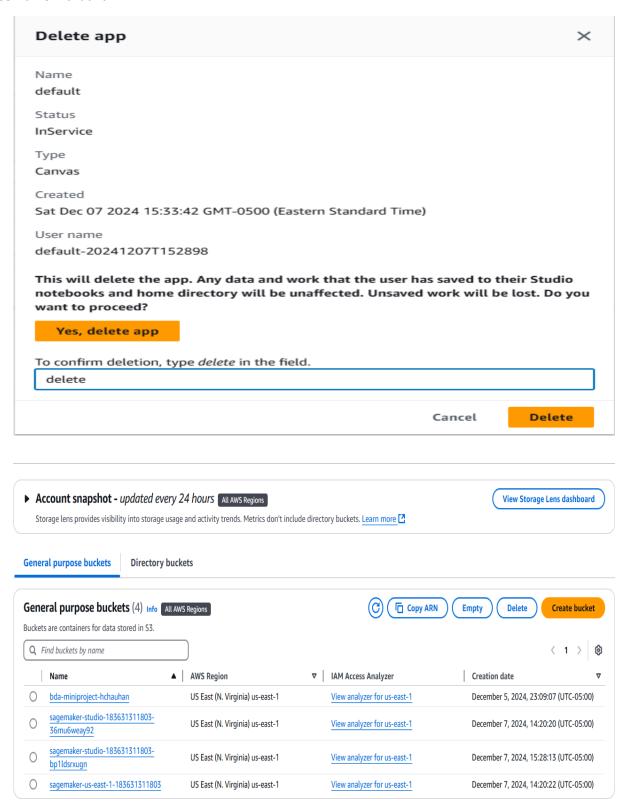


The results show a strong bias towards predicting class 5.0, with 77.173% precision and 99.756% recall for this class. This indicates that the dataset likely has a significant imbalance, with class 5.0 being the dominant category. The model shows very poor performance on other classes (4.0, 3.0, 2.0, 1.0), with 0% precision and recall for most of

them. This further confirms the class imbalance issue and suggests the model struggles to identify less common categories. The advanced metrics show average accuracy (76.992%), F1 score (17.748%), precision (20.259%), and recall (20.13%), which are relatively low, indicating that while the model performs well on the dominant class, it struggles with overall balanced performance across all classes. These results suggest that the dataset has a significant class imbalance issue, and the model has overfit to the majority class (5.0). To improve results, we may need to address the class imbalance, possibly through resampling techniques, class weighting, or collecting more data for underrepresented classes.

Incurred charges for AWS Sagemaker:



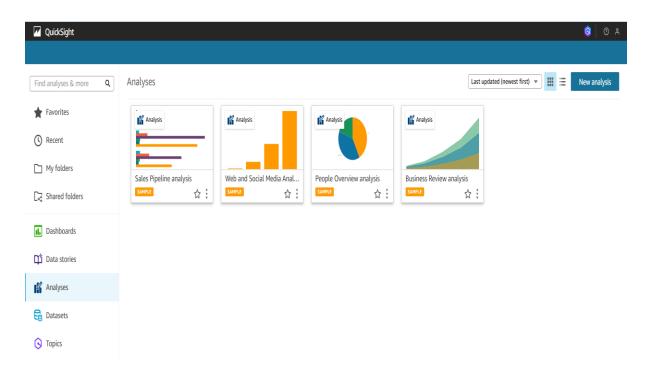


Even though I have set domain rule to ml.t3.medium and modified the model to only use hyperparameter optimization algorithm, setting the number of candidates to 5 and maximum run job time to 2 hours, using memory only till 5gb from 100 gb and still I incurred charges from AWS Sagemaker so I have deleted the Model, Domain, all the S3

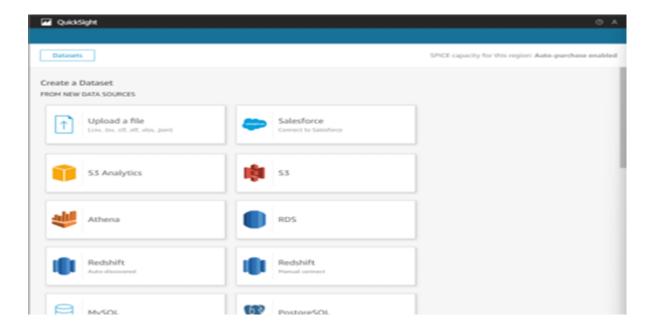
buckets along with EC2 instances.

4. Visualizations:

Created Quicksight Account:

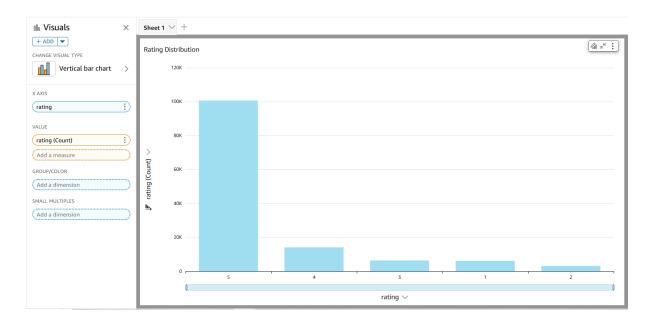


Importing Dataset From S3:

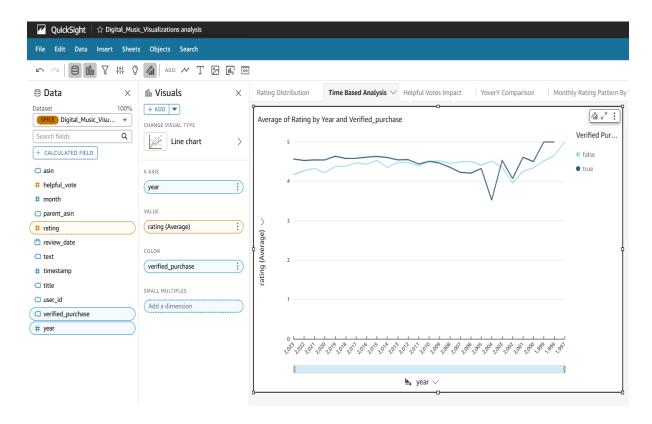


Visualizations:

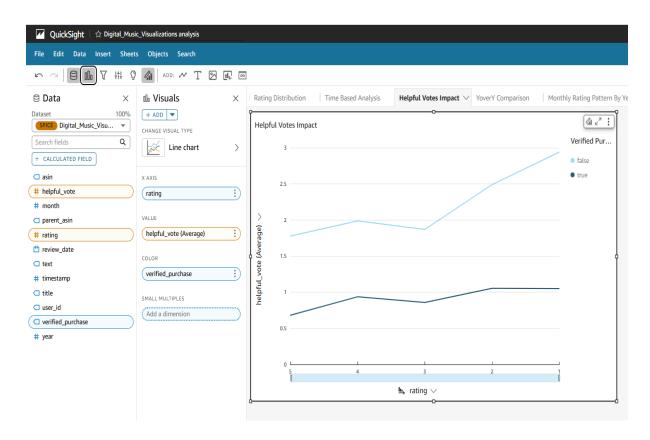
1)Rating Distribution:



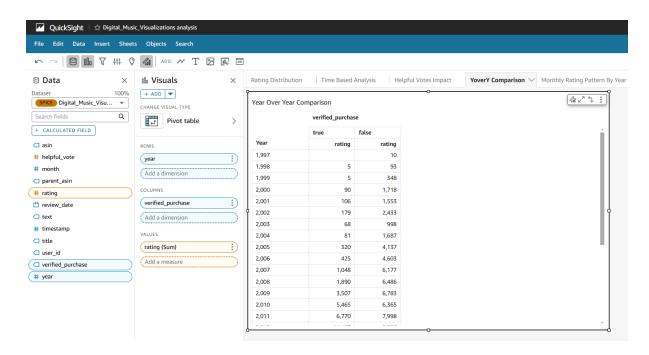
2) Time Based Analysis



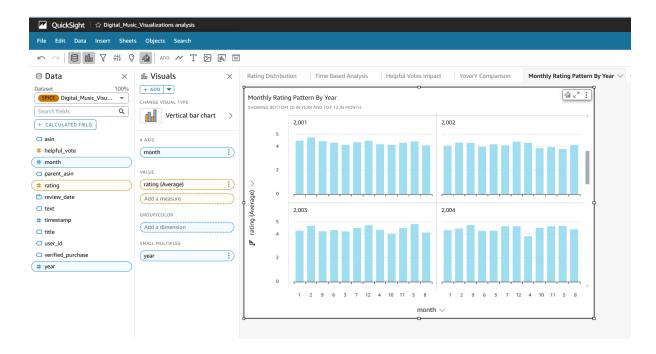
3) Helpful Votes Impact



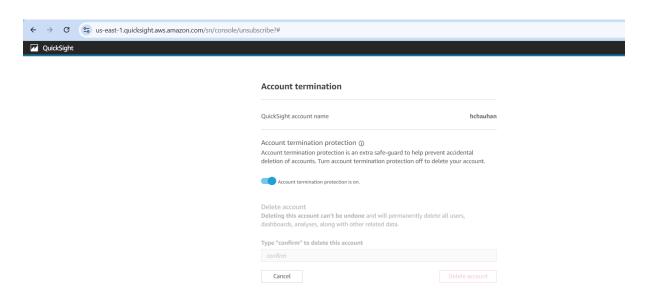
4) Year Over Year Comparison



5) Monthly Rating Pattern by Year



Deleting the Quicksight account: In order to not incur any further charges, I have deleted the account.



5. Results and Analysis:

1) Machine Learning Results: Sagemaker Model Analysis:

Model achieved 77.236% accuracy.

Performance metrics:

F1 Macro: 17.748%
 Precision: 20.259%

3) Recall: 20.13%

The results show a strong bias towards predicting class 5.0, with 77.173% precision and 99.756% recall for this class. This indicates that the dataset likely has a significant imbalance, with class 5.0 being the dominant category. The model shows very poor performance on other classes (4.0, 3.0, 2.0, 1.0), with 0% precision and recall for most of them. This further confirms the class imbalance issue and suggests the model struggles to identify less common categories. The advanced metrics show average accuracy (76.992%), F1 score (17.748%), precision (20.259%), and recall (20.13%), which are relatively low, indicating that while the model performs well on the dominant class, it struggles with overall balanced performance across all classes. These results suggest that the dataset has a significant class imbalance issue, and the model has overfit to the majority class (5.0). To improve results, we may need to address the class imbalance, possibly through resampling techniques, class weighting, or collecting more data for underrepresented classes.

2) Visualization Analysis:

1) Rating Distribution

The rating distribution shows a strong positive skew with 5-star ratings dominating at approximately 100,000 counts, while ratings 4 through 1 have significantly lower frequencies around 10,000-20,000 counts each.

2) Time Based Analysis:

The graph shows average ratings over time (1997-2023) with verified purchases consistently rating slightly higher than non-verified ones, both generally maintaining ratings between 4.0-4.5 stars.

3)Helpful Votes Impact

The graph shows that helpful votes increase as the rating increases, with verified purchases having a higher impact on helpfulness across all ratings.

4)Year over Year Comparison

The data shows a consistent year-over-year increase in both verified and non-verified purchase ratings from 1997 to 2011, with non-verified purchases maintaining higher volumes throughout the period.

5) Monthly rating pattern by Year

The monthly rating patterns across 1997-2023 show consistent average ratings between 4-5 stars with slight seasonal fluctuations but overall stable performance throughout each year.

6. Challenges:

- 1) Challenges faced with the AWS Sagemaker model configuration.
- 2) Incurred unexpected AWS charges (\$285.72) primarily from using Sagemaker.

7. Conclusion:

This project highlights the power of combining distributed computing frameworks and cloud-based tools to process and analyze large-scale datasets. By leveraging AWS S3, PySpark, AWS SageMaker, and QuickSight, the study successfully processed Amazon's Digital Music review dataset, providing valuable insights into customer behavior, preferences, and review patterns. Key findings include the dominance of 5-star ratings, seasonal trends in review activity, and the impact of verified purchases on helpfulness and satisfaction scores.

The machine learning model developed using SageMaker achieved a 77.236% accuracy but revealed significant challenges related to class imbalance, overfitting, and limited generalization across all rating categories. This underlines the need for future improvements, such as balancing datasets through resampling or class weighting, to enhance model performance.

While the project faced challenges, including unexpected AWS charges and configuration issues with SageMaker, these experiences offered practical insights into the complexities of cloud-based analytics workflows. The visualizations created through QuickSight provided intuitive representations of trends and patterns, aiding in comprehending the dataset's dynamics.

This project underscores the importance of careful resource management and configuration in cloud services and demonstrates the potential of data analytics to derive actionable insights in the digital music domain. Future efforts could expand on this foundation by addressing identified limitations and exploring other feature sets within the dataset.

8. References:

- a) AWS Documentation.
- b) Sagemaker Documention.
- c) PySpark Documentation.
- d) Amazon Review Dataset: Amazon Reviews'23
- e) Quicksight Documentation
- f) Reffered Perplexity.ai for setup error and configuration doubts.