Analyzing Hotel Booking Cancellations with HDFS, Hive, and Spark

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In this comprehensive report, we journeyed through the realms of Hadoop Distributed File System (HDFS), Apache Hive, and Apache Spark to dissect, analyze, and predict hotel booking cancellations using the Hotel Bookings dataset. Each component is pivotal in handling big data, enabling efficient querying, and empowering machine learning capabilities.

1. Data Loading:

Our journey commences with acquiring the Hotel Bookings dataset from GitHub, a task accomplished by utilizing wget to fetch the data and hdfs dfs -put to transfer it to HDFS. The orchestration of our Hadoop ecosystem is simplified with Docker, facilitated by docker-compose up -d and accessing the master node using docker-compose exec master bash.

2. Hive – A Data Warehousing Solution:

As we navigate through vast datasets, Hive emerges as our first ally. With its SQL-like interface, Hive facilitates the creation of structured data tables. We initiate our journey by crafting a table through the CREATE TABLE statement, dictating the schema of our dataset.

The decision to CLUSTER BY and BUCKET the table by country is strategic. Clustering boosts data locality, optimizing query performance. Binning data into eight buckets enhances parallelism and further accelerates query processing. Our choice of ROW FORMAT DELIMITED and FIELDS TERMINATED BY ',' ensures seamless parsing of the CSV data, with STORED AS TEXTFILE aligning it conveniently for Hadoop's file handling. To ensure data quality, tblproperties ("skip.header.line.count"="1") skips the header line during ingestion.

Subsequently, we import our data into the Hive table, employing LOAD DATA INPATH to seamlessly transfer the contents of 'hotel bookings.csv' into our structured Hive table.

3. In-Depth Analysis with Hive:

Harnessing Hive's analytical capabilities, we delve into the intricacies of room allocation dynamics. By investigating the correlation between reserved and assigned room types, we unearth patterns that go beyond mere booking statistics. Filtering the results to consider only room types below the average reservation frequency provides a nuanced understanding of room allocation trends.

Taking a step further, we construct a view to calculate the average duration of stay based on matching reserved and assigned room types. This materialized view optimizes performance and provides a persistent snapshot, which is crucial for time-sensitive analyses.

4. Spark – Unleashing the Power of Distributed Computing:

The second leg of our journey introduces Spark, a robust distributed computing engine.

As our dataset grows, Spark accelerates data processing, fosters iterative algorithms, and facilitates machine learning operations.

Creating a Spark session bridges the gap between Spark and Hive, enabling seamless integration. Our choice to enable Hive support ensures fluid data interchange between the two components.

5. Machine Learning with Spark:

Our analytical journey takes a machine learning detour as we harness the predictive capabilities of Spark. Transferring data from Hive to Spark for model training, we prepare the dataset using the Vector Assembler. This transformation aggregates features into a single vector, readying the data for machine learning algorithms.

A pivotal point is partitioning our data into training and testing sets. With an 80/20 split, we ensure adequate training while preserving a substantial dataset for robust model evaluation.

6. Logistic Regression and Decision Trees:

The logistic regression model steps onto the stage first. Trained on our prepared dataset, the Binary Classification Evaluator evaluates the model. Calculating the area under the ROC curve provides insights into the model's predictive accuracy. With a resulting score of 0.538, we understand the model's discrimination capabilities.

Next in line is the Decision Tree model, following a similar evaluation metric. The resultant area under the ROC curve, pegged at 0.486, paints a distinct picture. A comparative analysis between logistic regression and decision trees unfolds, shedding light on their relative strengths and weaknesses.

7. Conclusion:

Our journey through HDFS, Hive, and Spark encapsulates the entire data lifecycle, from acquisition and storage to analysis and prediction. The strategic use of each component highlights its unique capabilities, catering to specific needs within the data analytics spectrum.

In conclusion, the harmonious collaboration of HDFS, Hive, and Spark provides a robust infrastructure for handling big data analytics and machine learning. The intricate dance between structured storage, SQL-like querying, and distributed computing has unveiled patterns, trends, and predictive insights in the realm of hotel booking cancellations, empowering decision-makers with actionable intelligence.

Hotel Booking Dataset Explanation:

Summary: This data set contains booking information for a city hotel and a resort hotel, and includes information such as when the booking was made, length of stay, the number of adults, children, and/or babies, and the number of available parking spaces, among other things.

- **Hotel:** Hotel (H1 = Resort Hotel or H2 = City Hotel)
- **Is canceled:** Value indicating if the booking was canceled (1) or not (0)
- Lead_time: Number of days that elapsed between the entering date of the booking into the PMS and the arrival date
- Arrival_date_year: Year of arrival date
- Arrival date month: Month of arrival date
- arrival date_week_number: Week number of year for arrival date
- arrival_date_day_of_month: Day of arrival date
- stays_in_weekend_nights: Number of weekend nights (Saturday or Sunday) the guest stayed or booked to stay at the hotel

• stays_in_week_nights: Number of week nights (Monday to Friday) the guest stayed or booked to stay at the hotel

• adults: Number of adults

• **children:** Number of children

• **babies:** Number of babies

- **meal:** Type of meal booked. Categories are presented in standard hospitality meal packages: Undefined/SC no meal package; BB Bed & Breakfast; HB Half board (breakfast and one other meal usually dinner); FB Full board (breakfast, lunch and dinner)
- **country:** Country of origin. Categories are represented in the ISO 3155–3:2013 format
- market_segment: Market segment designation. In categories, the term "TA" means "Travel Agents" and "TO" means "Tour Operators"
- **distribution_channel:** Booking distribution channel. The term "TA" means "Travel Agents" and "TO" means "Tour Operators"
- **is_repeated_guest:** Value indicating if the booking name was from a repeated guest (1) or not (0)
- **previous_cancellations:** Number of previous bookings that were cancelled by the customer prior to the current booking
- **previous_bookings_not_canceled:** Number of previous bookings not cancelled by the customer prior to the current booking

- **reserved_room_type:** Code of room type reserved. Code is presented instead of designation for anonymity reasons.
- assigned_room_type: Code for the type of room assigned to the booking. Sometimes the assigned room type differs from the reserved room type due to hotel operation reasons (e.g. overbooking) or by customer request. Code is presented instead of designation for anonymity reasons.
- **booking_changes:** Number of changes/amendments made to the booking from the moment the booking was entered on the PMS until the moment of check-in or cancellation
- **deposit_type:** Indication on if the customer made a deposit to guarantee the booking.

 This variable can assume three categories: No Deposit no deposit was made; Non Refund a deposit was made in the value of the total stay cost; Refundable a deposit was made with a value under the total cost of stay.
- **Agent:** ID of the travel agency that made the booking
- **Company:** ID of the company/entity that made the booking or responsible for paying the booking. ID is presented instead of designation for anonymity reasons
- days_in_waiting_list: Number of days the booking was in the waiting list before it was confirmed to the customer
- **customer_type:** Type of booking, assuming one of four categories: Contract when the booking has an allotment or other type of contract associated to it; Group when the booking is associated to a group; Transient when the booking is not part of a group or contract, and is not

associated to other transient booking; Transient-party – when the booking is transient, but is associated to at least other transient booking

- adr: Average Daily Rate as defined by dividing the sum of all lodging transactions by the total number of staying nights
- required_car_parking_spaces: Number of car parking spaces required by the customer
- total_of_special_requests: Number of special requests made by the customer (e.g. twin bed or high floor)
- reservation_status: Reservation last status, assuming one of three categories: Canceled booking was canceled by the customer; Check-Out customer has checked in but already departed; No-Show customer did not check-in and did inform the hotel of the reason why
- reservation_status_date: Date at which the last status was set. This variable can be used in conjunction with the ReservationStatus to understand when was the booking canceled or when did the customer checked-out of the hotel

Walkthrough With Screenshots:

- 1. Load Data
 - a. cd/home/siuweaver/dsc650-infra/bellevue-bigdata/hadoop-hive-spark-hbase/data
 - b. sudo wget https://raw.githubusercontent.com/siuweaver/weaver_portfolio/main/Big%20Data /hotel_bookings.csv

d. sudo head /home/siuweaver/dsc650-infra/bellevue-bigdata/hadoop-hive-spark-hbase/data/hotel bookings.csv

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processors | Intitudents | Description | Des
```

- 2. Environment Initialization
 - a. cd ..
 - i. Return to hadoop-hive-spark-hbase
 - b. sudo docker-compose up -d
 - c. sudo docker-compose exec master bash
- 3. Load
 - a. hdfs dfs -put /data/hotel bookings.csv /
- 4. Confirm data is loaded
 - a. hdfs dfs -ls /

c. hdfs dfs -cat /hotel bookings.csv | head

```
Note, is conscied, lead, time, arrival, date, year, setival, date, year, pusher, arrival, date, day, of month, stays, in, week, dights, stay, in, week, nights, shallen, behives, aead, country, market, segment, distribution, of received guest, personal cannot provide become great personal provided by the provided provided by the provided provid
```

5. Start Hive

b.

- a. hive
- 6. Create a Hive Table

```
CREATE TABLE hotel_bookings (
hotel STRING,
is_canceled INT,
lead_time INT,
arrival_date_year INT,
arrival_date_month STRING,
arrival_date_week_number INT,
arrival_date_day_of_month INT,
stays_in_weekend_nights INT,
```

```
stays in week nights INT,
adults INT,
children INT,
babies INT,
meal STRING,
country STRING,
market segment STRING,
distribution_channel STRING,
is_repeated_guest INT,
previous cancellations INT,
previous bookings not canceled INT,
reserved room type STRING,
assigned_room_type STRING,
booking_changes INT,
deposit_type STRING,
agent INT,
company INT,
days in waiting list INT,
customer_type STRING,
adr DOUBLE,
required_car_parking_spaces INT,
total of special requests INT,
reservation status STRING,
reservation status date STRING
CLUSTERED BY (country) INTO 8 BUCKETS
ROW FORMAT DELIMITED
FIELDS TERMINATED BY ','
```

STORED AS TEXTFILE tblproperties("skip.header.line.count"="1");

- 7. Confirm table
 - a. show tables;

```
hive> show tables;
OK
grades
hotel_bookings
```

- 8. Load Data into table
 - a. LOAD DATA INPATH '/hotel_bookings.csv' INTO TABLE hotel_bookings;
- 9. Confirm Loading
 - a. select * from hotel bookings limit 5;

- 10. Create View for Average Room Type Match
 - a. View stores the percent of the time the reserved room type matches the assigned room type for all reservations that weren't cancelled. This will allow us to compare the overall average to the value for each individual room type

```
CREATE VIEW IF NOT EXISTS avg_reserve_room_type_match AS

SELECT sum(case when reserved_room_type = assigned_room_type then 1 else 0 end) / count(
AS perc

FROM hotel_bookings

WHERE is canceled = 0;
```

- b. Validate view
 - i. select * from avg_reserve_room_type_match;

```
hive> select * from avg_reserve_toom_type_match
> ;
2024-02-02 18:46:19,709 INFO [4e2fd4ec-3c9d-41c7-a578-534f60317acc main] reducesink.VectorReduceSinkEmptyKeyOperator: VectorReduceSinkEmptyKeyOperator: Vector ReduceSinkEmptyKeyOperator: Vector ReduceSinkEmptyKeyOperator: Vector ReduceSinkEmptyKeyOperator: Vector ReduceSinkEmptyKeyOperator: Vector ReduceSinkEmptyKeyOperator: Vector ReduceSinkEmptyKeyOperator: Vector ReduceSinkEmptyKeyOperator:
```

c. Return reserved room types below average

select reserved_room_type, count(*) reserve_count, sum(case when reserved_room_type = assigned_room_type then 1 else 0 end) / count(*) AS room_type_perc, arm.perc

from hotel_bookings hb

join avg_reserve_room_type_match arm

where is_canceled = 0

group by reserved_room_type, arm.perc

having sum(case when reserved_room_type = assigned_room_type then 1 else 0 end) / count(*) < arm.perc;

d. Create Materialized View

```
CREATE MATERIALIZED VIEW avg_stay_duration

AS

SELECT hotel, AVG(stays_in_weekend_nights + stays_in_week_nights) AS avg_duration

FROM hotel_bookings

GROUP BY hotel;
```

- 1. Validate results
 - a. Select * from avg stay duration;

```
hive> select * from avg_stay_duration

> ;

OK

City Hotel 2.9777867426439073

Resort Hotel 4.318547179231153

hotel NULL

Time taken: 0.169 seconds, Fetched: 3 row(s)
```

ii. View Trending over Time

```
SELECT

arrival_date_year,

arrival_date_month,

COUNT(*) AS bookings_count

FROM hotel_bookings

GROUP BY arrival_date_year, arrival_date_month

ORDER BY arrival_date_year, arrival_date_month;
```

```
arrival_date_year,
arrival_date_month,
COUNT(*) AS bookings_count
FAILED: SemanticException [Error 10025]: Line 2:2 Expression not in GROUP BY key 'arrival_date_year'
       >> SELECT
> arrival_date_year,
> arrival_date_month,
> COUNT(*) AS bookings_count
> FROM hotel_bookings
> GROUP BY arrival_date_year, arrival_date_month
> ORDER BY arrival_date_year, arrival_date_month;
2024-02-04 02:05:04,218 INFO [bab15aae-2661-42a9-94a2-79fa2e544c11 main] reducesink.VectorReduceSinkOb
Info@23389e2b
Ouery ID = root_20240204020504_e486c2be-cbfc-4134-8f04-d3a39aa2b965
Total jobs = 1
Launching Job 1 out of 1
Status: Running (Executing on YARN cluster with App id application_1707009169585_0006)
                                                      STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
             VERTICES
Map 1 ..... container
                                                     SUCCEEDED
Reducer 2 ..... container Reducer 3 ..... container
                                                      SUCCEEDED
             arrival_date_month
August 3889
December 292
July 2776
November 234
2015
2015
                                         2340
             October 4957
2015
2015
             September
April 5428
August 5063
December
                                         5114
                                         3860
3891
2016
             February
January 2248
                           4572
5292
2016
              June
                          4824
5478
              March
             May 5478
May 5478
November
October 6203
September
April 5661
August 4917
2016
2016
                                          5394
             February
January 3681
             June
March
                           5647
4970
2017 May 6313
Time taken: 7.821 seconds, Fetched: 27 row(s)
```

Spark-Shell

1. spark_shell

- bash-5.0# spark-shell
- 2. import org.apache.spark.sql.SparkSession
 - a. This line of code imports the SparkSession class from the Apache Spark SQL library, allowing the creation of a unified entry point to access data and execute Spark functionalities in a Spark application.
- 3. val spark =

SparkSession.builder.appName("HotelBookingsSpark").enableHiveSupport().getOrCreat e()

a. This code initializes a SparkSession named "HotelBookingsSpark" with Hive support enabled, allowing seamless integration with Hive and creating a unified environment for executing Spark operations.

```
scals> import org.apache.spark.sql.SparkSession
import org.apache.spark.sql.SparkSession
scals> val spark = SparkSession.builder.appName("HotelBookingsSpark").enableHiveSupport().getOrCreate()
188015 [main] WARN org.apache.spark.sql.SparkSessionSBuilder - Using an existing SparkSession; the static sql configurations will not take effec
138016 [main] WARN org.apache.spark.sql.SparkSessionSBuilder - Using an existing SparkSession; some spark core configurations may not take effec
spark: org.apache.spark.sql.SparkSession = org.apache.spark.sql.SparkSession@9baZS170
```

- 4. Read Hive Table into Spark DataFrame:
 - a. val hiveTableDF = spark.sql("SELECT * FROM hotel_bookings")

```
scales val hiveTableDF = spark.cgl ("SELECT * EROM horel_bookings")
330609 [main] WARN org.spache.hadoop.hive.conf. HiveConf of name hive.strict.managed.tables does not exist
330609 [main] WARN org.spache.hadoop.hive.conf. HiveConf of name hive.create.as.insert.only does not exist
330612 [main] WARN org.spache.spack.cgl.hive.colient.HiveConf thure.create.as.insert.only does not exist
330612 [main] WARN org.spache.spack.cgl.hive.colient.HiveConf.thure.create.dive.comf.hive.execution.engine is 'tez' and will be reset to 'mr' to disable useless hive logic
hiveTableDF: org.spache.spark.sql.DataFrame = [hotel: string, is_canceled: int ... 30 more fields]
```

- c. Confirm data loaded
 - i. hiveTableDF.show(10)

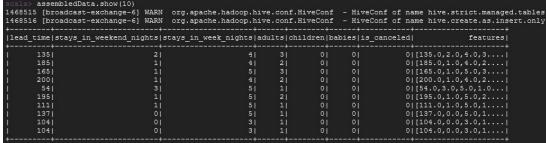
	bleDF.show(1													
						_week_number arrival_								
				not_cance:	led reserved	_room_type assigned_r	com_type boo	king_chanç	iea c	ieposit_type a	gent c	company days	_in_waiti	ng_lis
			ion_status_date											
City Hotel		212	2017	August		35		28						
101						A	Al			No Deposit		null		
104 m. Hanal I	01	Check-Out 210	2017-09-04	August		351		281						21
City Hotel TO			201/	August		A)	Al		01	No Deposit		nulli		
		Check-Out	2017-09-04							No Deposito				
City Hotel		47	2017	August										
TO										No Deposit				
		Check-Out	2017-09-04											
City Hotel				August										
101	21	Check-Out	2017-09-031				Al			No Deposit	91	null		
City Hotel		1491	2017-09-03	August				301						21
TO	01		20271	nagaso,		Al	Al			No Deposit!	281	null!		- '
		Check-Out	2017-09-03											
City Hotel			2017	August				291						21

5. Prepare data for model

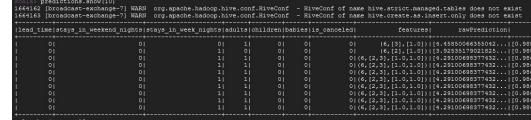
ii.

- a. Import Vector Assembler
 - i. import org.apache.spark.ml.feature.VectorAssembler
- b. Identify Feature Columns into an array
 - i. val featureCols = Array("lead_time", "stays_in_weekend_nights", "stays in week nights", "adults", "children", "babies")
- c. Vector Assembler
 - i. val assembler = new VectorAssembler().setInputCols(featureCols).setOutputCol("features").set HandleInvalid("keep")
 - 1. This code defines a VectorAssembler named "assembler" that combines specified input columns into a single feature column named "features," preserving invalid values during the assembly process.
 - ii. val assembledData = assembler.transform(data)

- 1. This code applies the previously defined VectorAssembler ("assembler") to transform the input DataFrame "data," creating a new DataFrame named "assembledData" with the assembled features.
- d. validate assembled data
 - i. assembledData.show(10)



- only showing top 10 rows
- e. Train/Test Split
 - i. val Array(trainData, testData) = assembledData.randomSplit(Array(0.8, 0.2), seed = 123)
- 6. Train Logistic Regression
 - a. Import and Train
 - i. import org.apache.spark.ml.classification.LogisticRegression
 - ii. val lr = new
 LogisticRegression().setLabelCol("is_canceled").setFeaturesCol("features
 ")
 - This code initializes a Logistic Regression model ("lr") and specifies the label and features columns for training, with the label column set to "is_canceled" and the features column set to "features."
 - iii. val model = lr.fit(trainData)
 - b. Predict on Test Data
 - i. val predictions = model.transform(testData)
 - ii. Validate Output
 - 1. Predictions.show(10)



- c. Evaluate Model
 - i. import org.apache.spark.ml.evaluation.BinaryClassificationEvaluator
 - ii. val evaluator = new
 BinaryClassificationEvaluator().setLabelCol("is_canceled").setRawPredic
 tionCol("rawPrediction").setMetricName("areaUnderROC")

- This code creates a Binary Classification Evaluator ("evaluator")
 for evaluating the Logistic Regression model, specifying the label
 column as "is_canceled," raw prediction column as
 "rawPrediction," and metric name as "areaUnderROC."
- iii. val auc = evaluator.evaluate(predictions)
- iv. show evaluation
 - 1. println(s"Area under ROC curve: \$auc")

```
import org.apache.spark.ml.evaluation.BinaryClassificationEvaluator
import org.apache.spark.ml.evaluation.BinaryClassificationEvaluator
import org.apache.spark.ml.evaluation.BinaryClassificationEvaluator

colls val evaluator = new BinaryClassificationEvaluator().setLabelCol("is_canceled").setRawPredictionCol("rawPrediction").setMetricName("area
evaluator: org.apache.spark.ml.evaluation.BinaryClassificationEvaluator = BinaryClassificationEvaluator: uid=binEval_D85cate36955, metricName=
colls val auc = evaluator.evaluate(predictions)
302435 [broadcast-exchange=5] MARN org.apache.hadoop.hive.conf.HiveConf = HiveConf of name hive.strict.managed.tables does not exist
302440 [broadcast-exchange=5] MARN org.apache.hadoop.hive.conf.HiveConf = HiveConf of name hive.create.as.insert.only does not exist
auc: bomble = 0.537556783026383

colls println(s"Area under ROC curve: Sauc")
Area under ROC curve: 0.5375567833026383
```

7. Train Decision Tree

- a. Import and Train
 - i. import org.apache.spark.ml.classification.DecisionTreeClassifier
 - ii. val dt = new
 DecisionTreeClassifier().setLabelCol("is_canceled").setFeaturesCol("feat
 ures")
 - iii. val dt model = dt.fit(trainData)
- b. Predict
 - i. val dt predictions = dt model.transform(testData)

```
| Case |
```

- ii. c. Evaluate
 - i. val dt_evaluator = new BinaryClassificationEvaluator().setLabelCol("is_canceled").setRawPredic tionCol("rawPrediction").setMetricName("areaUnderROC")
 - ii. val dt_auc = dt_evaluator.evaluate(dt_predictions)
 - iii. println(s"Area under ROC curve: \$dt auc")

References:

Antonio, N. (2019, February). Hotel Booking Demand, Version 1. Retrieved February 4, 2024 from https://www.kaggle.com/datasets/jessemostipak/hotel-booking-demand/data.