Hadoop, Hive and Spark based distributed data processing and ML System building

1. Install and configure Hadoop
2. Install Hive on Hadoop
3. Run distributed query using Hive and do data query
4. Install Spark and load bank.csv and do data anyalse
5. Create RandomForestClassifier using Spark ML

Problem Statement - Implement data processing tasks using Spark DataFrame API

github link : https://github.com/bairagis/hadoop-spark-hive

```
import pandas as pd
import matplotlib.pyplot as plt
```

1. Utilize PySpark DataFrame API for tasks like filtering, grouping, and aggregation.

1. **Installing PySpark **:

```
!pip install pyspark
```

```
Requirement already satisfied: pyspark in /usr/local/lib/python3.11/dist-packages (3.5.1)
Requirement already satisfied: py4j==0.10.9.7 in /usr/local/lib/python3.11/dist-packages (from pyspark) (0.10.9.7)
```

2. **Creating a Spark Session**:

```
from pyspark.sql import SparkSession

# Create a SparkSession
spark = SparkSession.builder.appName("SparkSession").getOrCreate()
```

3. **Loading Dataset**:

```
# Import necessary libraries
from pyspark.sql.functions import col

# Load the dataset into a DataFrame
file_path = "bank.csv"
df = spark.read.csv(file_path, header=True, inferSchema=True)
```

```
# Show the schema of the DataFrame
df.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- marital: string (nullable = true)
 |-- education: string (nullable = true)
 |-- default: string (nullable = true)
 |-- balance: integer (nullable = true)
 |-- housing: string (nullable = true)
 |-- loan: string (nullable = true)
 |-- contact: string (nullable = true)
 |-- day: integer (nullable = true)
 |-- month: string (nullable = true)
 |-- duration: integer (nullable = true)
 |-- campaign: integer (nullable = true)
 |-- pdays: integer (nullable = true)
 |-- previous: integer (nullable = true)
 |-- poutcome: string (nullable = true)
 |-- y: string (nullable = true)
```

```
# Display the first few rows of the DataFrame
df.show()
```

```
+---+-------------+-------+---------+-------+-------+-------+----+--------+---+-----+--------+--------+-----+--------+--
|age|          job|marital|education|default|balance|housing|loan| contact|day|month|duration|campaign|pdays|previous|po
+---+-------------+-------+---------+-------+-------+-------+----+--------+---+-----+--------+--------+-----+--------+--
| 30|   unemployed|married|  primary|     no|   1787|     no|  no|cellular| 19|  oct|      79|       1|   -1|       0| u
| 33|     services|married|secondary|     no|   4789|    yes| yes|cellular| 11|  may|     220|       1|  339|       4| f
| 35|   management| single| tertiary|     no|   1350|    yes|  no|cellular| 16|  apr|     185|       1|  330|       1| f
| 30|   management|married| tertiary|     no|   1476|    yes| yes| unknown|  3|  jun|     199|       4|   -1|       0| u
| 59|  blue-collar|married|secondary|     no|      0|    yes|  no| unknown|  5|  may|     226|       1|   -1|       0| u
| 35|   management| single| tertiary|     no|    747|     no|  no|cellular| 23|  feb|     141|       2|  176|       3| f
| 36|self-employed|married| tertiary|     no|    307|    yes|  no|cellular| 14|  may|     341|       1|  330|       2|
| 39|   technician|married|secondary|     no|    147|    yes|  no|cellular|  6|  may|     151|       2|   -1|       0| u
| 41| entrepreneur|married| tertiary|     no|    221|    yes|  no| unknown| 14|  may|      57|       2|   -1|       0| u
| 43|     services|married|  primary|     no|    -88|    yes| yes|cellular| 17|  apr|     313|       1|  147|       2| f
| 39|     services|married|secondary|     no|   9374|    yes|  no| unknown| 20|  may|     273|       1|   -1|       0| u
| 43|       admin.|married|secondary|     no|    264|    yes|  no|cellular| 17|  apr|     113|       2|   -1|       0| u
| 36|   technician|married| tertiary|     no|   1109|     no|  no|cellular| 13|  aug|     328|       2|   -1|       0| u
| 20|      student| single|secondary|     no|    502|     no|  no|cellular| 30|  apr|     261|       1|   -1|       0| u
| 31|  blue-collar|married|secondary|     no|    360|    yes| yes|cellular| 29|  jan|      89|       1|  241|       1| f
| 40|   management|married| tertiary|     no|    194|     no| yes|cellular| 29|  aug|     189|       2|   -1|       0| u
| 56|   technician|married|secondary|     no|   4073|     no|  no|cellular| 27|  aug|     239|       5|   -1|       0| u
| 37|       admin.| single| tertiary|     no|   2317|    yes|  no|cellular| 20|  apr|     114|       1|  152|       2| f
| 25|  blue-collar| single|  primary|     no|   -221|    yes|  no| unknown| 23|  may|     250|       1|   -1|       0| u
| 31|     services|married|secondary|     no|    132|     no|  no|cellular|  7|  jul|     148|       1|  152|       1|
+---+-------------+-------+---------+-------+-------+-------+----+--------+---+-----+--------+--------+-----+--------+--
only showing top 20 rows
```

Task 1: Filtering

```
import matplotlib.pyplot as plt

# Task 1: Filtering
# Filter the DataFrame to select rows where the 'Education' column is 'primary'
primary_df = df.filter(col("education") == "primary")
primary_df.show()

# Convert the filtered DataFrame to Pandas
primary_pandas_df = primary_df.toPandas()
```

```
+---+------------+--------+---------+-------+-------+-------+----+---------+---+-----+--------+--------+-----+--------+-
|age|         job| marital|education|default|balance|housing|loan|  contact|day|month|duration|campaign|pdays|previous|p
+---+------------+--------+---------+-------+-------+-------+----+---------+---+-----+--------+--------+-----+--------+-
| 30|  unemployed| married|  primary|     no|   1787|     no|  no| cellular| 19|  oct|      79|       1|   -1|       0|
| 43|    services| married|  primary|     no|    -88|    yes| yes| cellular| 17|  apr|     313|       1|  147|       2|
| 25| blue-collar|  single|  primary|     no|   -221|    yes|  no|  unknown| 23|  may|     250|       1|   -1|       0|
| 55| blue-collar| married|  primary|     no|    627|    yes|  no|  unknown|  5|  may|     247|       1|   -1|       0|
| 78|     retired|divorced|  primary|     no|    229|     no|  no|telephone| 22|  oct|      97|       1|   -1|       0|
| 55| blue-collar| married|  primary|     no|    145|     no|  no|telephone|  2|  feb|      59|       3|    5|       2|
| 26| blue-collar| married|  primary|     no|      0|    yes|  no|  unknown| 21|  may|     425|       1|   -1|       0|
| 32|entrepreneur|  single|  primary|    yes|   -849|    yes| yes| cellular|  4|  feb|     204|       1|   -1|       0|
| 45| blue-collar|divorced|  primary|     no|    844|     no|  no|  unknown|  5|  jun|    1018|       3|   -1|       0|
| 41| blue-collar| married|  primary|     no|   -516|     no| yes|telephone|  8|  jul|     554|       3|   -1|       0|
| 50| blue-collar|divorced|  primary|     no|    388|     no|  no| cellular|  5|  feb|     701|       1|   -1|       0|
| 60|     retired| married|  primary|     no|      5|     no|  no| cellular| 26|  aug|      63|       2|   -1|       0|
| 51| blue-collar| married|  primary|     no|   1466|    yes|  no|  unknown|  7|  may|     406|       2|   -1|       0|
| 35| blue-collar|  single|  primary|     no|    293|    yes|  no|  unknown| 30|  may|     521|       2|   -1|       0|
| 39| blue-collar| married|  primary|     no|    111|     no|  no| cellular| 18|  nov|     201|       2|   -1|       0|
| 34| blue-collar| married|  primary|     no|    455|    yes|  no|  unknown| 20|  jun|     372|       3|   -1|       0|
| 31|  unemployed|  single|  primary|     no|    406|     no|  no| cellular|  4|  feb|     736|       1|   -1|       0|
| 57|    services|  single|  primary|     no|   3777|    yes|  no|telephone| 13|  may|      65|       2|   -1|       0|
| 56|  unemployed| married|  primary|     no|   3391|     no|  no| cellular| 21|  apr|     243|       1|   -1|       0|
| 27|   housemaid| married|  primary|     no|      0|    yes|  no| cellular| 23|  jul|     435|       3|   -1|       0|
+---+------------+--------+---------+-------+-------+-------+----+---------+---+-----+--------+--------+-----+--------+-
only showing top 20 rows
```

Task 2: Grouping and Aggregation

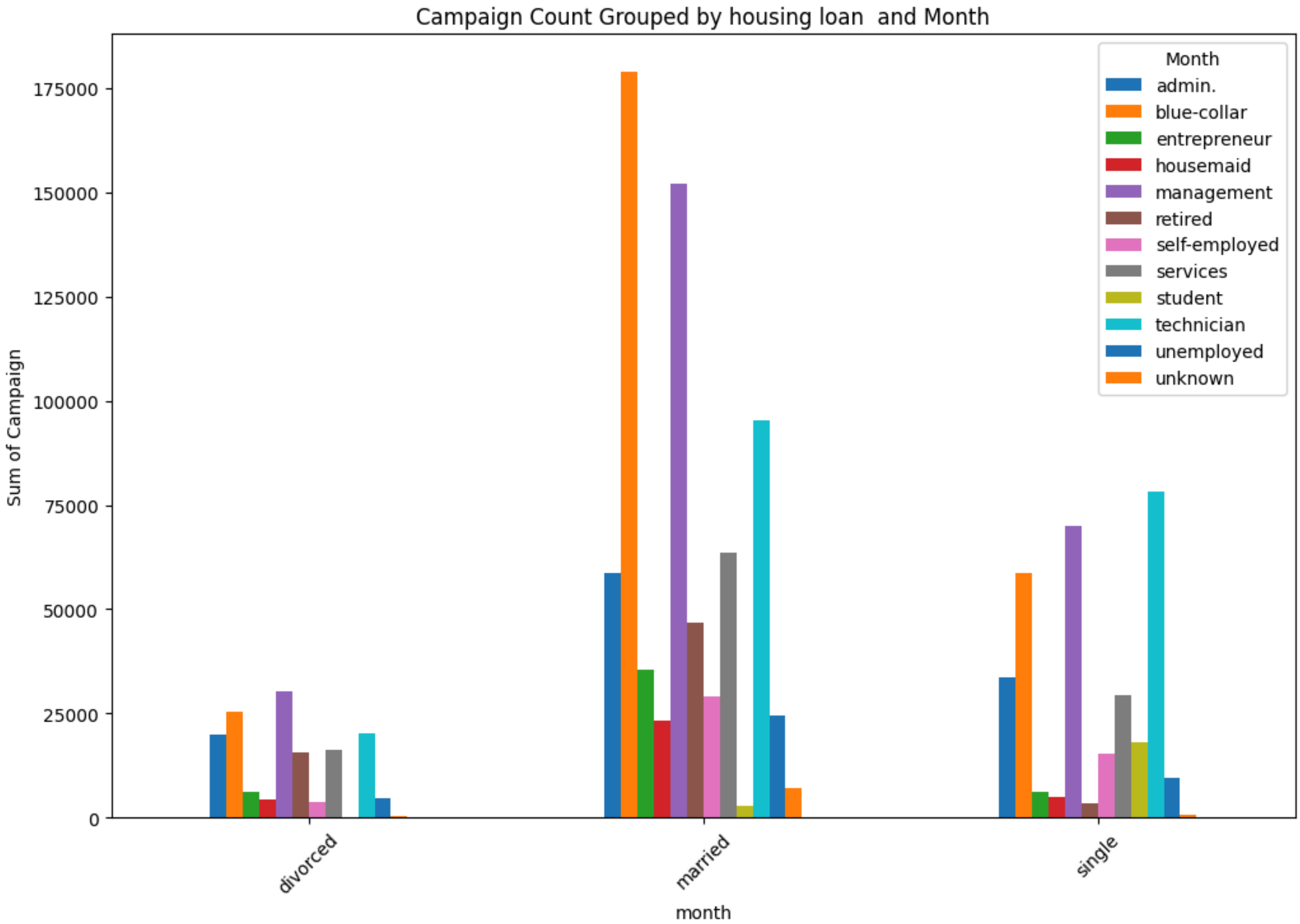
```
# Task 2: Grouping and Aggregation
# Group the DataFrame by 'marital' and 'job', then calculate the average the 'duration' for each group
grouped_df = df.groupBy("marital", "job").agg({"duration": "sum"})
grouped_df.show()

# Convert the grouped DataFrame to Pandas
grouped_pandas_df = grouped_df.toPandas()

# Pivot the DataFrame for easy plotting
pivot_df = grouped_pandas_df.pivot(index='marital', columns='job', values='sum(duration)')
```

```
# Plot a grouped bar chart
ax = pivot_df.plot(kind='bar', figsize=(12, 8), rot=45)
ax.set_xlabel('month')
ax.set_ylabel('Sum of Campaign')
ax.set_title('Campaign Count Grouped by housing loan  and Month')
plt.legend(title='Month')
plt.show()
```

```
+--------+-------------+-------------+
| marital|          job|sum(duration)|
+--------+-------------+-------------+
| married|self-employed|        29055|
|divorced|   management|        30232|
|divorced|self-employed|         3880|
|  single|self-employed|        15400|
| married| entrepreneur|        35516|
|divorced|      unknown|          385|
| married|       admin.|        58628|
|divorced|       admin.|        19885|
| married|   unemployed|        24440|
|  single|   management|        70045|
| married|     services|        63662|
|  single|     services|        29541|
| married|  blue-collar|       178968|
|divorced|     services|        16254|
| married|   technician|        95281|
|divorced| entrepreneur|         6306|
|  single|    housemaid|         5081|
|  single|      retired|         3328|
|  single|       admin.|        33659|
|divorced|   technician|        20328|
+--------+-------------+-------------+
only showing top 20 rows
```



3. Handle missing data and outliers using Spark's data preprocessing capabilities.

1. **Fill Missing Values:**

For numeric columns, you can fill missing values with mean, median, or any other statistical measure.

```
df.show()
```

```
+---+-------------+-------+---------+-------+-------+-------+----+--------+---+-----+--------+--------+-----+--------+--
|age|          job|marital|education|default|balance|housing|loan| contact|day|month|duration|campaign|pdays|previous|po
+---+-------------+-------+---------+-------+-------+-------+----+--------+---+-----+--------+--------+-----+--------+--
| 30|   unemployed|married|  primary|     no|   1787|     no|  no|cellular| 19|  oct|      79|       1|   -1|       0| u
| 33|     services|married|secondary|     no|   4789|    yes| yes|cellular| 11|  may|     220|       1|  339|       4| f
| 35|   management| single| tertiary|     no|   1350|    yes|  no|cellular| 16|  apr|     185|       1|  330|       1| f
| 30|   management|married| tertiary|     no|   1476|    yes| yes| unknown|  3|  jun|     199|       4|   -1|       0| u
| 59|  blue-collar|married|secondary|     no|      0|    yes|  no| unknown|  5|  may|     226|       1|   -1|       0| u
| 35|   management| single| tertiary|     no|    747|     no|  no|cellular| 23|  feb|     141|       2|  176|       3| f
| 36|self-employed|married| tertiary|     no|    307|    yes|  no|cellular| 14|  may|     341|       1|  330|       2|
| 39|   technician|married|secondary|     no|    147|    yes|  no|cellular|  6|  may|     151|       2|   -1|       0| u
| 41| entrepreneur|married| tertiary|     no|    221|    yes|  no| unknown| 14|  may|      57|       2|   -1|       0| u
| 43|     services|married|  primary|     no|    -88|    yes| yes|cellular| 17|  apr|     313|       1|  147|       2| f
| 39|     services|married|secondary|     no|   9374|    yes|  no| unknown| 20|  may|     273|       1|   -1|       0| u
| 43|       admin.|married|secondary|     no|    264|    yes|  no|cellular| 17|  apr|     113|       2|   -1|       0| u
| 36|   technician|married| tertiary|     no|   1109|     no|  no|cellular| 13|  aug|     328|       2|   -1|       0| u
| 20|      student| single|secondary|     no|    502|     no|  no|cellular| 30|  apr|     261|       1|   -1|       0| u
| 31|  blue-collar|married|secondary|     no|    360|    yes| yes|cellular| 29|  jan|      89|       1|  241|       1| f
| 40|   management|married| tertiary|     no|    194|     no| yes|cellular| 29|  aug|     189|       2|   -1|       0| u
| 56|   technician|married|secondary|     no|   4073|     no|  no|cellular| 27|  aug|     239|       5|   -1|       0| u
| 37|       admin.| single| tertiary|     no|   2317|    yes|  no|cellular| 20|  apr|     114|       1|  152|       2| f
| 25|  blue-collar| single|  primary|     no|   -221|    yes|  no| unknown| 23|  may|     250|       1|   -1|       0| u
| 31|     services|married|secondary|     no|    132|     no|  no|cellular|  7|  jul|     148|       1|  152|       1|
+---+-------------+-------+---------+-------+-------+-------+----+--------+---+-----+--------+--------+-----+--------+--
only showing top 20 rows
```

```
# find missing values using pyspark
from pyspark.sql.functions import col,isnan, when, count

df.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in df.columns]
   ).show()
```

```
+---+---+-------+---------+-------+-------+-------+----+-------+---+-----+--------+--------+-----+--------+--------+---+
|age|job|marital|education|default|balance|housing|loan|contact|day|month|duration|campaign|pdays|previous|poutcome|  y|
+---+---+-------+---------+-------+-------+-------+----+-------+---+-----+--------+--------+-----+--------+--------+---+
|  0|  0|      0|        0|      0|      0|      0|   0|      0|  0|    0|       0|       0|    0|       0|       0|  0|
+---+---+-------+---------+-------+-------+-------+----+-------+---+-----+--------+--------+-----+--------+--------+---+
```

Implement a Classification AI Model using Spark

```
# import pyspark ml
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.classification import RandomForestClassifier
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
```

```
# train test split
train_df, test_df = df.randomSplit([0.7, 0.3], seed=42)
# train the random forest classifier
```

Task

Use spark ml randomforestclassifier to train the model with train_df and test_df. Explain the selected code. Explain the error in the selected code. If possible, fix the error and incorporate the changes into the existing code. Otherwise, try to diagnose the error.

Identify categorical columns

Subtask:

Determine which columns in the DataFrame are of string type and need to be converted.

Reasoning: Iterate through the columns and check their data types to identify string columns.

```
string_cols = [col_name for col_name, col_type in df.dtypes if col_type == 'string']
print("String columns:", string_cols)
```

```
String columns: ['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact', 'month', 'poutcome', 'y']
```

Apply string indexing

Subtask:

Use `StringIndexer` to convert each categorical string column into a numerical index column.

Reasoning: Convert the categorical string columns to numerical indices using StringIndexer as identified in the previous step.

```
from pyspark.ml.feature import StringIndexer

string_cols = [col_name for col_name, col_type in df.dtypes if col_type == 'string']
indexed_cols = [col_name + "_indexed" for col_name in string_cols]

indexer = StringIndexer(inputCols=string_cols, outputCols=indexed_cols)
indexed_df = indexer.fit(df).transform(df)

indexed_df.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- marital: string (nullable = true)
 |-- education: string (nullable = true)
 |-- default: string (nullable = true)
 |-- balance: integer (nullable = true)
 |-- housing: string (nullable = true)
 |-- loan: string (nullable = true)
 |-- contact: string (nullable = true)
 |-- day: integer (nullable = true)
 |-- month: string (nullable = true)
 |-- duration: integer (nullable = true)
 |-- campaign: integer (nullable = true)
 |-- pdays: integer (nullable = true)
 |-- previous: integer (nullable = true)
 |-- poutcome: string (nullable = true)
 |-- y: string (nullable = true)
 |-- job_indexed: double (nullable = false)
 |-- marital_indexed: double (nullable = false)
 |-- education_indexed: double (nullable = false)
 |-- default_indexed: double (nullable = false)
 |-- housing_indexed: double (nullable = false)
 |-- loan_indexed: double (nullable = false)
 |-- contact_indexed: double (nullable = false)
 |-- month_indexed: double (nullable = false)
 |-- poutcome_indexed: double (nullable = false)
 |-- y_indexed: double (nullable = false)
```

Apply one-hot encoding

Subtask:

Use `OneHotEncoder` to convert the indexed columns into one-hot encoded vector columns.

Reasoning: Import OneHotEncoder and apply it to the indexed columns to create one-hot encoded vector columns as per the instructions.

```
from pyspark.ml.feature import OneHotEncoder

indexed_cols = [col_name + "_indexed" for col_name, col_type in df.dtypes if col_type == 'string']
encoded_cols = [col_name + "_vec" for col_name in indexed_cols]

encoder = OneHotEncoder(inputCols=indexed_cols, outputCols=encoded_cols)
encoded_df = encoder.fit(indexed_df).transform(indexed_df)

encoded_df.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- marital: string (nullable = true)
 |-- education: string (nullable = true)
 |-- default: string (nullable = true)
 |-- balance: integer (nullable = true)
 |-- housing: string (nullable = true)
 |-- loan: string (nullable = true)
 |-- contact: string (nullable = true)
 |-- day: integer (nullable = true)
 |-- month: string (nullable = true)
 |-- duration: integer (nullable = true)
```

```
 |-- campaign: integer (nullable = true)
 |-- pdays: integer (nullable = true)
 |-- previous: integer (nullable = true)
 |-- poutcome: string (nullable = true)
 |-- y: string (nullable = true)
 |-- job_indexed: double (nullable = false)
 |-- marital_indexed: double (nullable = false)
 |-- education_indexed: double (nullable = false)
 |-- default_indexed: double (nullable = false)
 |-- housing_indexed: double (nullable = false)
 |-- loan_indexed: double (nullable = false)
 |-- contact_indexed: double (nullable = false)
 |-- month_indexed: double (nullable = false)
 |-- poutcome_indexed: double (nullable = false)
 |-- y_indexed: double (nullable = false)
 |-- job_indexed_vec: vector (nullable = true)
 |-- marital_indexed_vec: vector (nullable = true)
 |-- education_indexed_vec: vector (nullable = true)
 |-- default_indexed_vec: vector (nullable = true)
 |-- housing_indexed_vec: vector (nullable = true)
 |-- loan_indexed_vec: vector (nullable = true)
 |-- contact_indexed_vec: vector (nullable = true)
 |-- month_indexed_vec: vector (nullable = true)
 |-- poutcome_indexed_vec: vector (nullable = true)
 |-- y_indexed_vec: vector (nullable = true)
```

Update vectorassembler

Subtask:

Include the newly created one-hot encoded columns in the `VectorAssembler` input columns.

Reasoning: Identify the numerical and one-hot encoded columns and update the VectorAssembler.

```
# Apply the assembler transformation to the encoded_df
assembled_df = assembler.transform(encoded_df)

# Split the assembled_df into training and testing sets
train_data, test_data = assembled_df.randomSplit([0.7, 0.3], seed=42)

train_data.printSchema()
test_data.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- marital: string (nullable = true)
 |-- education: string (nullable = true)
 |-- default: string (nullable = true)
 |-- balance: integer (nullable = true)
 |-- housing: string (nullable = true)
 |-- loan: string (nullable = true)
 |-- contact: string (nullable = true)
 |-- day: integer (nullable = true)
 |-- month: string (nullable = true)
 |-- duration: integer (nullable = true)
 |-- campaign: integer (nullable = true)
 |-- pdays: integer (nullable = true)
 |-- previous: integer (nullable = true)
 |-- poutcome: string (nullable = true)
 |-- y: string (nullable = true)
 |-- job_indexed: double (nullable = false)
 |-- marital_indexed: double (nullable = false)
 |-- education_indexed: double (nullable = false)
 |-- default_indexed: double (nullable = false)
 |-- housing_indexed: double (nullable = false)
 |-- loan_indexed: double (nullable = false)
 |-- contact_indexed: double (nullable = false)
 |-- month_indexed: double (nullable = false)
 |-- poutcome_indexed: double (nullable = false)
 |-- y_indexed: double (nullable = false)
 |-- job_indexed_vec: vector (nullable = true)
 |-- marital_indexed_vec: vector (nullable = true)
 |-- education_indexed_vec: vector (nullable = true)
 |-- default_indexed_vec: vector (nullable = true)
 |-- housing_indexed_vec: vector (nullable = true)
 |-- loan_indexed_vec: vector (nullable = true)
 |-- contact_indexed_vec: vector (nullable = true)
 |-- month_indexed_vec: vector (nullable = true)
 |-- poutcome_indexed_vec: vector (nullable = true)
 |-- y_indexed_vec: vector (nullable = true)
 |-- features: vector (nullable = true)
```

```
root
 |-- age: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- marital: string (nullable = true)
 |-- education: string (nullable = true)
 |-- default: string (nullable = true)
 |-- balance: integer (nullable = true)
 |-- housing: string (nullable = true)
 |-- loan: string (nullable = true)
 |-- contact: string (nullable = true)
 |-- day: integer (nullable = true)
 |-- month: string (nullable = true)
 |-- duration: integer (nullable = true)
 |-- campaign: integer (nullable = true)
 |-- pdays: integer (nullable = true)
 |-- previous: integer (nullable = true)
 |-- poutcome: string (nullable = true)
 |-- y: string (nullable = true)
```

Train the model

Subtask:

Retrain the RandomForestClassifier with the transformed data.

Reasoning: Retrain the RandomForestClassifier model with the transformed data.

```
# Initialize and train the RandomForestClassifier model
# Use 'y_indexed' as the label column as it's the numerical representation of the target variable
rf_model = RandomForestClassifier(labelCol="y_indexed", featuresCol="features", numTrees=10)
rf_model = rf_model.fit(train_data)

# Make predictions on the test data
predictions = rf_model.transform(test_data)

# Evaluate the model
# Use 'y_indexed' as the label column for evaluation
evaluator = MulticlassClassificationEvaluator(labelCol="y_indexed", predictionCol="prediction", metricName="accuracy")
accuracy = evaluator.evaluate(predictions)

print(f"Test Accuracy = {accuracy}")
```

```
Test Accuracy = 0.9968944099378882
```

Summary:

Data Analysis Key Findings

- The categorical string columns in the dataset were identified as: `job`, `marital`, `education`, `default`, `housing`, `loan`, `contact`, `month`, `poutcome`, and `y`.
- These string columns were successfully converted into numerical indexed columns using `StringIndexer`, adding columns with a `_indexed` suffix (e.g., `job_indexed`).
- The indexed columns were further transformed into one-hot encoded vector columns using `OneHotEncoder`, resulting in columns with a `_vec` suffix (e.g., `job_indexed_vec`).
- The `VectorAssembler` was updated to include both the numerical columns and the newly created one-hot encoded vector columns as features.
- The data was successfully split into training and testing sets *after* applying the `VectorAssembler` transformation to the DataFrame containing the one-hot encoded features.
- A `RandomForestClassifier` model was initialized with `y_indexed` as the label column and `features` as the features column.
- The model was successfully trained on the `train_data` and used to make predictions on the `test_data`.
- The model's performance was evaluated using `MulticlassClassificationEvaluator`, yielding a test accuracy of approximately 0.997.

Insights or Next Steps

- The high accuracy suggests the model is performing very well on the test set; further investigation into potential overfitting or evaluation with different metrics (like precision, recall, F1-score) on a validation set would be beneficial.
- Consider exploring hyperparameter tuning for the `RandomForestClassifier` (e.g., `numTrees`, `maxDepth`, `maxBins`) to potentially improve performance further or address overfitting.