BDI

Name: Kartik Jolapara **Branch:** Computer Engineering

SAP ID: 60004200107 **Batch:** B1

EXPERIMENT NO. 7
Execution of ML algorithms using Apache Spark MLlib

AIM: Implement and execute ML algorithms using Apche Spark MLlib.

THEORY:

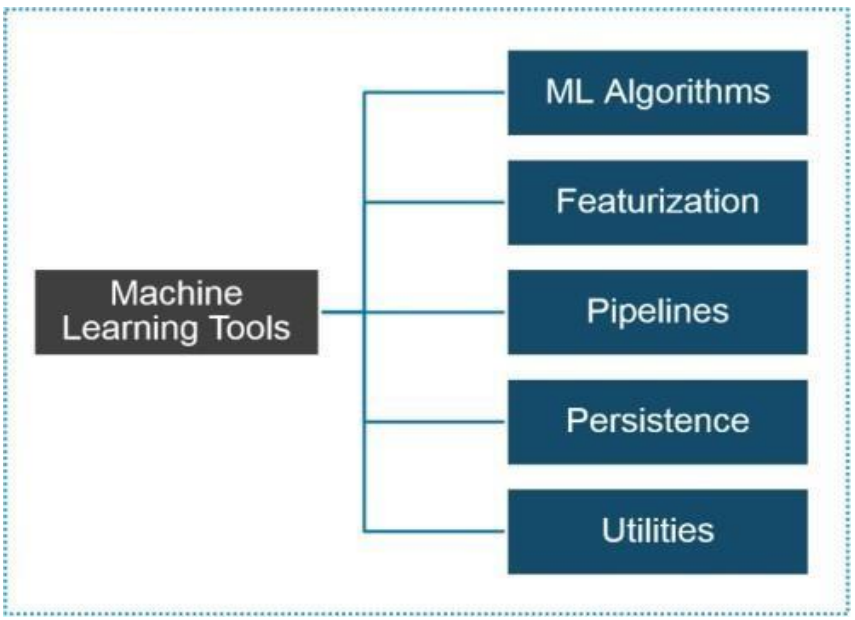
Spark MLlib is Apache Spark's Machine Learning component. MLlib consists of popular algorithms and utilities. MLlib in Spark is a scalable Machine learning library that discusses both high-quality algorithm and high speed. The machine learning algorithms like regression, classification, clustering, pattern mining, and collaborative filtering. Lower-level machine learning primitives like generic gradient descent optimization algorithm are also present in MLlib.

spark.mllib contains the original API built on top of RDDs. It is currently in maintenance mode.

spark.ml provides higher level API built on top of DataFrames for constructing ML pipelines. spark.ml is the primary Machine Learning API for Spark at the moment.

Spark MLlib Tools:

- **ML Algorithms:** ML Algorithms form the core of MLlib. These include common learning algorithms such as classification, regression, clustering and collaborative filtering.
- **Featurization:** Featurization includes feature extraction, transformation, dimensionality reduction and selection.
- **Pipelines:** Pipelines provide tools for constructing, evaluating and tuning ML Pipelines.
- **Persistence:** Persistence helps in saving and loading algorithms, models and Pipelines.
- **Utilities:** Utilities for linear algebra, statistics and data handling.



MLlib Algorithms:

The popular algorithms and utilities in Spark MLlib are:

- Basic Statistics
- Regression
- Classification
- Recommendation System
- Clustering
- Dimensionality Reduction
- Feature Extraction
- Optimization

Code:

```
# install pyspark
!pip install pyspark # initialise session
from pyspark.context import SparkContext
from pyspark.sql.session import SparkSession
from pyspark.sql import SQLContext sc =
SparkContext('local') spark =
SparkSession(sc) sqlContext = SQLContext(sc)
```

1. Regeression

```
df=sqlContext.read.format('com.databricks.spark.csv').options(
header = 'true', inferschema= 'true').load('healthcaredataset-
stroke-data.csv') df.take(1) pd_df = df.toPandas()
print(pd_df) pd_df.dtypes df.cache() df.printSchema()
df.cache() df.printSchema() df.head() from pyspark.ml.feature
import VectorAssembler vectorAssembler =
VectorAssembler(inputCols = ['age', 'avg_glucose_level',
'hypertension', 'heart_disease',
'stroke'], outputCol = 'features') tdf =
vectorAssembler.transform(df) print(tdf)
tdf = tdf.select(['features', 'stroke'])
tdf.show(3) splits =
tdf.randomSplit([0.7, 0.3]) train_df =
splits[0] test_df = splits[1]
from pyspark.ml.regression import LinearRegression
lr = LinearRegression(featuresCol = 'features',
labelCol='stroke', maxIter=10, regParam=0.3,
elasticNetParam=0.8) lr_model = lr.fit(train_df)
print("Coefficients: " + str(lr_model.coefficients))
print("Intercept: " + str(lr_model.intercept))
trainingSummary = lr_model.summary print("RMSE: %f" %
trainingSummary.rootMeanSquaredError) print("r2: %f" %
trainingSummary.r2)
```

2. Classification

```
df=sqlContext.read.format('com.databricks.spark.csv').options
( header = 'true', inferschema = 'true' ).load( 'salary.csv'
) df.take(1) df.cache() df.printSchema() df.dtypes from
pyspark.ml.feature import StringIndexer indexer0 =
```

```
StringIndexer(inputCol="workclass",
outputCol="workclassEncoded") indexed0 =
indexer0.fit(df).transform(df) indexer1 =
StringIndexer(inputCol="education",
outputCol="educationEncoded") indexed1 =
indexer1.fit(indexed0).transform(indexed0) indexer2 =
StringIndexer(inputCol="occupation",
outputCol="occupationEncoded") indexed2 =
indexer2.fit(indexed1).transform(indexed1) indexer3 =
StringIndexer(inputCol="sex", outputCol="sexEncoded")
indexed3 = indexer3.fit(indexed2).transform(indexed2)
indexer4 = StringIndexer(inputCol="native-country",
outputCol="countryEncoded") indexed4 =
indexer4.fit(indexed3).transform(indexed3) indexer5 =
StringIndexer(inputCol="salary", outputCol="salaryEncoded")
indexed5 = indexer5.fit(indexed4).transform(indexed4)
indexed5.show() from pyspark.ml.feature import
VectorAssembler vectorAssembler = VectorAssembler(inputCols =
['age', 'workclassEncoded', 'educationEncoded',
'occupationEncoded',
'sexEncoded', 'countryEncoded', 'education-num', 'capitalgain',
'hours-per-week', 'capital-loss'], outputCol =
'features') tdf = vectorAssembler.transform(indexed5)
print(tdf) tdf = tdf.select(['features',
'salaryEncoded']) tdf.show(3) train, test =
tdf.randomSplit([0.7, 0.3], seed = 2018)
print("Training Dataset Count: " + str(train.count()))
print("Test Dataset Count: " + str(test.count()))
from pyspark.ml.classification import LogisticRegression
from pyspark.ml.classification import LinearSVC lsvc =
LinearSVC(featuresCol = 'features', labelCol =
'salaryEncoded', maxIter=10, regParam=0.1) lr =
LogisticRegression(featuresCol = 'features', labelCol =
'salaryEncoded', maxIter=10) lsvcModel =
lsvc.fit(train) lrModel = lr.fit(train)
print("Coefficients: " + str(lsvcModel.coefficients))
print("Intercept: " + str(lsvcModel.intercept))
import matplotlib.pyplot as plt trainingSummary =
lrModel.summary roc = trainingSummary.roc.toPandas()
plt.plot(roc['FPR'],roc['TPR']) plt.ylabel('False
Positive Rate') plt.xlabel('True Positive Rate')
plt.title('ROC Curve') plt.show() print('Training set
areaUnderROC: ' + str(trainingSummary.areaUnderROC))
```

OUTPUT:

1. **Regression**

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	N/A	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24	never smoked	1
...	...	...	...	...	...	...	...	...	...	...	...	...
5105	18234	Female	80.0	1	0	Yes	Private	Urban	83.75	N/A	never smoked	0
5106	44873	Female	81.0	0	0	Yes	Self-employed	Urban	125.20	40	never smoked	0
5107	19723	Female	35.0	0	0	Yes	Self-employed	Rural	82.99	30.6	never smoked	0
5108	37544	Male	51.0	0	0	Yes	Private	Rural	166.29	25.6	formerly smoked	0
5109	44679	Female	44.0	0	0	Yes	Govt_job	Urban	85.28	26.2	Unknown	0

```
id                   int32
gender              object
age                float64
hypertension         int32
heart_disease        int32
ever_married        object
work_type           object
Residence_type      object
avg_glucose_level  float64
bmi                 object
smoking_status      object
stroke               int32
dtype: object
```

```
root
 |-- id: integer (nullable = true)
 |-- gender: string (nullable = true)
 |-- age: double (nullable = true)
 |-- hypertension: integer (nullable = true)
 |-- heart_disease: integer (nullable = true)
 |-- ever_married: string (nullable = true)
 |-- work_type: string (nullable = true)
 |-- Residence_type: string (nullable = true)
 |-- avg_glucose_level: double (nullable = true)
 |-- bmi: string (nullable = true)
 |-- smoking_status: string (nullable = true)
 |-- stroke: integer (nullable = true)
```

	0	1	2	3	4
summary	count	mean	stddev	min	max
id	5110	36517.82935420744	21161.72162482715	67	72940
gender	5110	None	None	Female	Other
age	5110	43.226614481409015	22.61264672311348	0.08	82.0
hypertension	5110	0.0974559686888454	0.296606674233791	0	1
heart_disease	5110	0.05401174168297456	0.22606298750336554	0	1
ever_married	5110	None	None	No	Yes
work_type	5110	None	None	Govt_job	children
Residence_type	5110	None	None	Rural	Urban
avg_glucose_level	5110	106.14767710371804	45.28356015058193	55.12	271.74
bmi	5110	28.893236911794673	7.85406672968016	10.3	N/A
smoking_status	5110	None	None	Unknown	smokes
stroke	5110	0.0487279843444227	0.21531985698023753	0	1

```
Row(id=9046, gender='Male', age=67.0, hypertension=0, heart_disease=1, ever_married='Yes',
work_type='Private', Residence_type='Urban', avg_glucose_level=228.69, bmi='36.6',
smoking_status='formerly smoked', stroke=1)
```

```
[('id', 'int'),
 ('gender', 'string'),
 ('age', 'double'),
 ('hypertension', 'int'),
 ('heart_disease', 'int'),
 ('ever_married', 'string'),
 ('work_type', 'string'),
 ('Residence_type', 'string'),
 ('avg_glucose_level', 'double'),
 ('bmi', 'string'),
 ('smoking_status', 'string'),
 ('stroke', 'int')]
```



```
DataFrame[id: int, gender: string, age: double, hypertension: int, heart_disease: int,
ever_married: string, work_type: string, Residence_type: string, avg_glucose_level: double,
bmi: string, smoking_status: string, stroke: int, features: vector]
+--------------------+------+
|            features|stroke|
+--------------------+------+
|[67.0,228.69,0.0,...|     1|
|[61.0,202.21,0.0,...|     1|
|[80.0,105.92,0.0,...|     1|
+--------------------+------+
only showing top 3 rows
```

Final Predictions

```
Coefficients: [0.0,0.0,0.0,0.0,0.0]
Intercept: 0.048020219039595 62
```

```
RMSE: 0.213809
r2: -0.000000
```

2. Classification

```
[Row(age=39, workclass=' State-gov', fnlwgt=77516, education=' Bachelors',
education-num=13, marital-status=' Never-married', occupation=' Adm-clerical',
relationship=' Not-in-family', race=' White', sex=' Male', capital-gain=2174,
capital-loss=0, hours-per-week=40, native-country=' United-States', salary='
<=50K')]
```

```
root
 |-- age: integer (nullable = true)
 |-- workclass: string (nullable = true)
 |-- fnlwgt: integer (nullable = true)
 |-- education: string (nullable = true)
 |-- education-num: integer (nullable = true)
 |-- marital-status: string (nullable = true)
 |-- occupation: string (nullable = true)
 |-- relationship: string (nullable = true)
 |-- race: string (nullable = true)
 |-- sex: string (nullable = true)
 |-- capital-gain: integer (nullable = true)
 |-- capital-loss: integer (nullable = true)
 |-- hours-per-week: integer (nullable = true)
 |-- native-country: string (nullable = true)
 |-- salary: string (nullable = true)
```

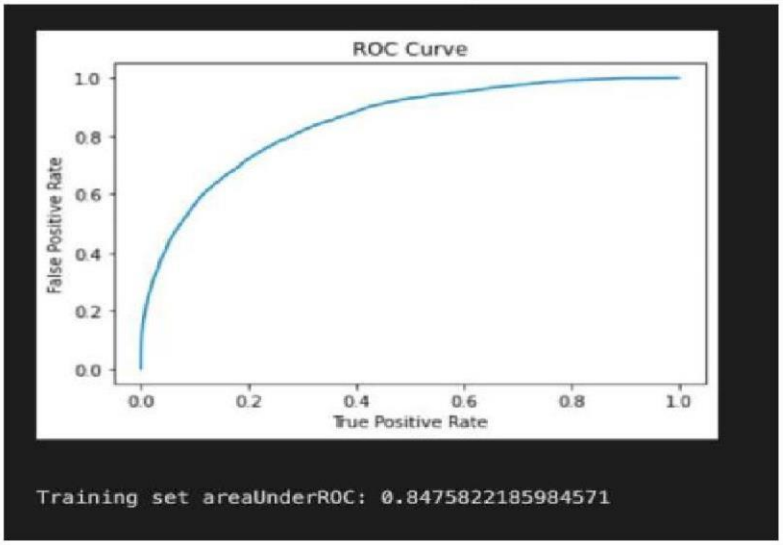
```
|age|       workclass|fnlwgt|   education|education-num|      marital-status|        occupation|  relationship|      race|   sex|capital-gain|capital-loss|hours-per-
week|native-country|salary|workclassEncoded|educationEncoded|occupationEncoded|sexEncoded|countryEncoded|salaryEncoded|

| 39|       State-gov| 77516|   Bachelors|           13|       Never-married|      Adm-clerical| Not-in-family|     White|  Male|        2174|           0|        40|
United-States| <=50K|     4.0|      2.0|      3.0|   0.0|      0.0|      0.0|
| 50|Self-emp-not-inc| 83311|   Bachelors|           13|  Married-civ-spouse|   Exec-managerial|       Husband|     White|  Male|           0|           0|        13|
United-States| <=50K|     1.0|      2.0|      2.0|   0.0|      0.0|      0.0|
| 38|         Private|215646|     HS-grad|            9|            Divorced| Handlers-cleaners| Not-in-family|     White|  Male|           0|           0|        40|
United-States| <=50K|     0.0|      0.0|      9.0|   0.0|      0.0|      0.0|
| 53|         Private|234721|        11th|            7|  Married-civ-spouse| Handlers-cleaners|       Husband|     Black|  Male|           0|           0|        40|
United-States| <=50K|     0.0|      5.0|      9.0|   0.0|      0.0|      0.0|
| 28|         Private|338409|   Bachelors|           13|  Married-civ-spouse|    Prof-specialty|          Wife|     Black|Female|           0|           0|        40|
Cuba| <=50K|     0.0|      2.0|      0.0|   1.0|      9.0|      0.0|
| 37|         Private|284582|     Masters|           14|  Married-civ-spouse|   Exec-managerial|          Wife|     White|Female|           0|           0|        40|
United-States| <=50K|     0.0|      3.0|      2.0|   1.0|      0.0|      0.0|
| 49|         Private|160187|         9th|            5|Married-spouse-a...|     Other-service| Not-in-family|     Black|Female|           0|           0|        16|
Jamaica| <=50K|     0.0|     10.0|      5.0|   1.0|     11.0|      0.0|
```

```
DataFrame[age: int, workclass: string, fnlwgt: int, education: string, education-num: int,
marital-status: string, occupation: string, relationship: string, race: string, sex: string,
capital-gain: int, capital-loss: int, hours-per-week: int, native-country: string, salary:
string, workclassEncoded: double, educationEncoded: double, occupationEncoded: double,
sexEncoded: double, countryEncoded: double, salaryEncoded: double, features: vector]
+--------------------+-------------+
|            features|salaryEncoded|
+--------------------+-------------+
|[39.0,4.0,2.0,3.0...|          0.0|
|[50.0,1.0,2.0,2.0...|          0.0|
|(10,[0,3,6,8],[38...|          0.0|
+--------------------+-------------+
only showing top 3 rows
```

Final Predictions

```
Coefficients:
[0.009679140612290072,0.01342892012614891,0.02288921743340083,-0.02078106627747353,-0.2950315
05,0.008667393334614108,0.0003678549301454241]
Intercept: -2.5735276509983613
```




```
Training set areaUnderROC: 0.8475822185984571
```

CONCLUSION: Hence, with the help of the above experiment, we have successfully executed two ML algorithms using Apache Spark MLlib and compared its accuracy.