In [0]:

```
display(dbutils.fs.ls("/databricks-datasets"))
```

path	name	size	modificationTim
dbfs:/databricks-datasets/	databricks-datasets/	0	
dbfs:/databricks-datasets/COVID/	COVID/	0	
dbfs:/databricks-datasets/README.md	README.md	976	153246825300
dbfs:/databricks-datasets/Rdatasets/	Rdatasets/	0	
dbfs:/databricks-datasets/SPARK_README.md	SPARK_README.md	3359	145504349000
dbfs:/databricks-datasets/adult/	adult/	0	
dbfs:/databricks-datasets/airlines/	airlines/	0	
dbfs:/databricks-datasets/amazon/	amazon/	0	
dbfs:/databricks-datasets/asa/	asa/	0	
dbfs:/databricks-datasets/atlas_higgs/	atlas_higgs/	0	
dbfs:/databricks-datasets/bikeSharing/	bikeSharing/	0	
dbfs:/databricks-datasets/cctvVideos/	cctvVideos/	0	
dbfs:/databricks-datasets/credit-card-fraud/	credit-card-fraud/	0	
dbfs:/databricks-datasets/cs100/	cs100/	0	
dbfs:/databricks-datasets/cs110x/	cs110x/	0	
dbfs:/databricks-datasets/cs190/	cs190/	0	
dbfs:/databricks-datasets/data.gov/	data.gov/	0	
dbfs:/databricks-datasets/definitive-guide/	definitive-guide/	0	
dbfs:/databricks-datasets/delta-sharing/	delta-sharing/	0	
dbfs:/databricks-datasets/flights/	flights/	0	
dbfs:/databricks-datasets/flower_photos/	flower_photos/	0	
dbfs:/databricks-datasets/flowers/	flowers/	0	
dbfs:/databricks-datasets/genomics/	genomics/	0	
dbfs:/databricks-datasets/hail/	hail/	0	
dbfs:/databricks-datasets/identifying-campaign-effectiveness/	identifying-campaign-effectiveness/	0	
dbfs:/databricks-datasets/iot/	iot/	0	
dbfs:/databricks-datasets/iot-stream/	iot-stream/	0	
dbfs:/databricks-datasets/learning-spark/	learning-spark/	0	
dbfs:/databricks-datasets/learning-spark-v2/	learning-spark-v2/	0	
dbfs:/databricks-datasets/lending-club-loan-stats/	lending-club-loan-stats/	0	
dbfs:/databricks-datasets/med-images/	med-images/	0	
dbfs:/databricks-datasets/media/	media/	0	
dbfs:/databricks-datasets/mnist-digits/	mnist-digits/	0	
dbfs:/databricks-datasets/news20.binary/	news20.binary/	0	

path	name	size	modificationTim
dbfs:/databricks-datasets/nyctaxi/	nyctaxi/	0	
dbfs:/databricks-datasets/nyctaxi-with-zipcodes/	nyctaxi-with-zipcodes/	0	
dbfs:/databricks-datasets/online_retail/	online_retail/	0	
dbfs:/databricks-datasets/overlap-join/	overlap-join/	0	
dbfs:/databricks-datasets/power-plant/	power-plant/	0	
dbfs:/databricks-datasets/retail-org/	retail-org/	0	
dbfs:/databricks-datasets/rwe/	rwe/	0	
dbfs:/databricks-datasets/sai-summit-2019-sf/	sai-summit-2019-sf/	0	
dbfs:/databricks-datasets/sample_logs/	sample_logs/	0	
dbfs:/databricks-datasets/samples/	samples/	0	
dbfs:/databricks-datasets/sfo_customer_survey/	sfo_customer_survey/	0	
dbfs:/databricks-datasets/sms_spam_collection/	sms_spam_collection/	0	
dbfs:/databricks-datasets/songs/	songs/	0	
dbfs:/databricks-datasets/structured-streaming/	structured-streaming/	0	
dbfs:/databricks-datasets/timeseries/	timeseries/	0	
dbfs:/databricks-datasets/tpch/	tpch/	0	
dbfs:/databricks-datasets/travel_recommendations_realtime/	travel_recommendations_realtime/	0	
dbfs:/databricks-datasets/warmup/	warmup/	0	
dbfs:/databricks-datasets/weather/	weather/	0	
dbfs:/databricks-datasets/wiki/	wiki/	0	
dbfs:/databricks-datasets/wikipedia-datasets/	wikipedia-datasets/	0	
dbfs:/databricks-datasets/wine-quality/	wine-quality/	0	

In [0]:

```
%fs ls databricks-datasets/adult/adult.data
```

path	name	size	modificationTime
dbfs:/databricks-datasets/adult/adult.data	adult.data	3974305	1444260537000

In [0]:

```
%sql
-- drop the table if it already exists
DROP TABLE IF EXISTS adult
```

In [0]:

```
%sql
-- create a new table in Spark SQL from the datasets already loaded in the underlying files
CREATE TABLE adult (
  age DOUBLE,
  workclass STRING,
  fnlwgt DOUBLE,
  education STRING,
  education_num DOUBLE,
  marital_status STRING,
  occupation STRING,
  relationship STRING,
  race STRING,
  sex STRING,
  capital_gain DOUBLE,
  capital_loss DOUBLE,
  hours_per_week DOUBLE,
  native_country STRING,
  income STRING)
USING com.databricks.spark.csv
OPTIONS (path "/databricks-datasets/adult/adult.data", header "true")
```

In [0]:

```
display(spark.sql("SELECT * FROM adult LIMIT 5"))
```

age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship
50.0	Self-emp-not-inc	83311.0	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband
38.0	Private	215646.0	HS-grad	9.0	Divorced	Handlers-cleaners	Not-in-family
53.0	Private	234721.0	11th	7.0	Married-civ-spouse	Handlers-cleaners	Husband
28.0	Private	338409.0	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Wife
37.0	Private	284582.0	Masters	14.0	Married-civ-spouse	Exec-managerial	Wife

In [0]:

```
# summary marital status rates by occupation
result = spark.sql(
  """
  SELECT
    occupation,
    SUM(1) as n,
    ROUND(AVG(if(LTRIM(marital_status) LIKE 'Married-%',1,0)),2) as married_rate,
    ROUND(AVG(if(lower(marital_status) LIKE '%widow%',1,0)),2) as widow_rate,
    ROUND(AVG(if(LTRIM(marital_status) = 'Divorced',1,0)),2) as divorce_rate,
    ROUND(AVG(if(LTRIM(marital_status) = 'Separated',1,0)),2) as separated_rate,
    ROUND(AVG(if(LTRIM(marital_status) = 'Never-married',1,0)),2) as bachelor_rate
  FROM
    adult
  GROUP BY 1
  ORDER BY n DESC
  """)
display(result)
```

occupation	n	married_rate	widow_rate	divorce_rate	separated_rate	bachelor_rate
Prof-specialty	4140	0.53	0.02	0.13	0.02	0.3
Craft-repair	4099	0.64	0.01	0.11	0.03	0.21
Exec-managerial	4066	0.61	0.02	0.15	0.02	0.2
Adm-clerical	3769	0.28	0.04	0.22	0.04	0.42
Sales	3650	0.47	0.03	0.12	0.03	0.36
Other-service	3295	0.24	0.05	0.15	0.06	0.5
Machine-op-inspct	2002	0.51	0.03	0.14	0.04	0.29
?	1843	0.36	0.08	0.1	0.04	0.42
Transport-moving	1597	0.63	0.02	0.11	0.02	0.21
Handlers-cleaners	1370	0.36	0.01	0.09	0.03	0.51
Farming-fishing	994	0.6	0.02	0.06	0.02	0.29
Tech-support	928	0.44	0.02	0.15	0.03	0.36
Protective-serv	649	0.6	0.01	0.12	0.02	0.24
Priv-house-serv	149	0.13	0.15	0.19	0.08	0.45
Armed-Forces	9	0.33	0.0	0.0	0.0	0.67

In [0]:

```
# register the df we just made as a table for spark sql
sqlContext.registerDataFrameAsTable(result, "result")
spark.sql("SELECT * FROM result").show(5)
```

```
+----------------+----+------------+----------+------------+--------------+-
------------+
|      occupation|   n|married_rate|widow_rate|divorce_rate|separated_rate|b
achelor_rate|
+----------------+----+------------+----------+------------+--------------+-
------------+
|  Prof-specialty|4140|        0.53|      0.02|        0.13|          0.02|
0.3|
|    Craft-repair|4099|        0.64|      0.01|        0.11|          0.03|
0.21|
| Exec-managerial|4066|        0.61|      0.02|        0.15|          0.02|
0.2|
|    Adm-clerical|3769|        0.28|      0.04|        0.22|          0.04|
0.42|
|           Sales|3650|        0.47|      0.03|        0.12|          0.03|
0.36|
+----------------+----+------------+----------+------------+--------------+-
------------+
only showing top 5 rows
```

In [0]:

```
# summary marital status rates by occupation
result = spark.sql(
  """
  SELECT
    education,
    ROUND(AVG(if(LTRIM(marital_status) = 'Never-married',1,0)),2) as bachelor_rate
  FROM
    adult
  GROUP BY 1
  ORDER BY bachelor_rate DESC
  LIMIT 1
  """)
display(result)
result.show()
```

education	bachelor_rate
12th	0.54

```
+---------+-------------+
|education|bachelor_rate|
+---------+-------------+
|     12th|         0.54|
+---------+-------------+
```

In [0]:

```
#  df from the sql df
df_adult = spark.table("adult")
cols = df_adult.columns # this will be used much later in the notebook, ignore for now
```

In [0]:

```
df_adult.printSchema()
```

```
root
 |-- age: double (nullable = true)
 |-- workclass: string (nullable = true)
 |-- fnlwgt: double (nullable = true)
 |-- education: string (nullable = true)
 |-- education_num: double (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: double (nullable = true)
 |-- capital_loss: double (nullable = true)
 |-- hours_per_week: double (nullable = true)
 |-- native_country: string (nullable = true)
 |-- income: string (nullable = true)
```

In [0]:

```
# import what we will need
from pyspark.sql.functions import when, col, mean, desc, round

# wrangle the data a bit
df_result = df_adult.select(
  df_adult['occupation'],
  # create a 1/0 type col on the fly
  when( col('marital_status') == ' Divorced' , 1 ).otherwise(0).alias('is_divorced')
)
# do grouping (and a round)
df_result = df_result.groupBy('occupation').agg(round(mean('is_divorced'),2).alias('divorce
# do ordering
df_result = df_result.orderBy(desc('divorced_rate'))
# show results
df_result.show(5)
```

```
+----------------+-------------+
|      occupation|divorced_rate|
+----------------+-------------+
|    Adm-clerical|         0.22|
| Priv-house-serv|         0.19|
| Exec-managerial|         0.15|
|    Tech-support|         0.15|
|   Other-service|         0.15|
+----------------+-------------+
only showing top 5 rows
```

In [0]:

```
# top 'bachelor_rate' by 'education' group using DataFrame
from pyspark.sql.functions import when, col, mean, desc, round

# wrangle the data a bit
df_result = df_adult.select(
  df_adult['education'],
  # create a 1/0 type col on the fly
  when( col('marital_status') == ' Never-married' , 1 ).otherwise(0).alias('bachelor_rate')
)
# do grouping (and a round)
df_result = df_result.groupBy('education').agg(round(mean('bachelor_rate'),2).alias('bachel
# do ordering
df_result = df_result.orderBy(desc('bachelor_rate'))
# show results
```

In [0]:

```


import pandas as pd

# do some analysis
result = spark.sql(
  """
  SELECT
    occupation,
    AVG(IF(income = ' >50K',1,0)) as plus_50k
  FROM
    adult
  GROUP BY 1
  ORDER BY 2 DESC
  """)


df_pandas = pd.DataFrame(
  result.collect(),
  columns=result.schema.names
)

# look at df
print(df_pandas.head())
```

```
         occupation  plus_50k
0   Exec-managerial  0.484014
1    Prof-specialty  0.449034
2   Protective-serv  0.325116
3      Tech-support  0.304957
4             Sales  0.269315
```

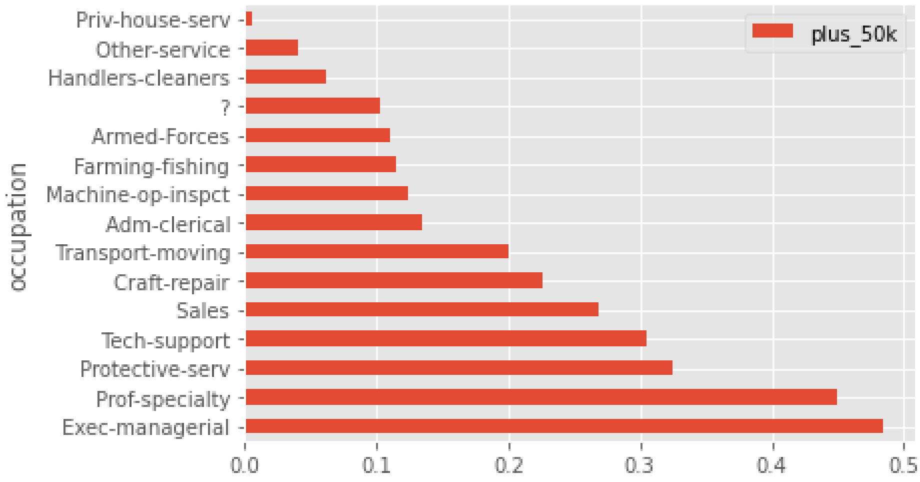
In [0]:

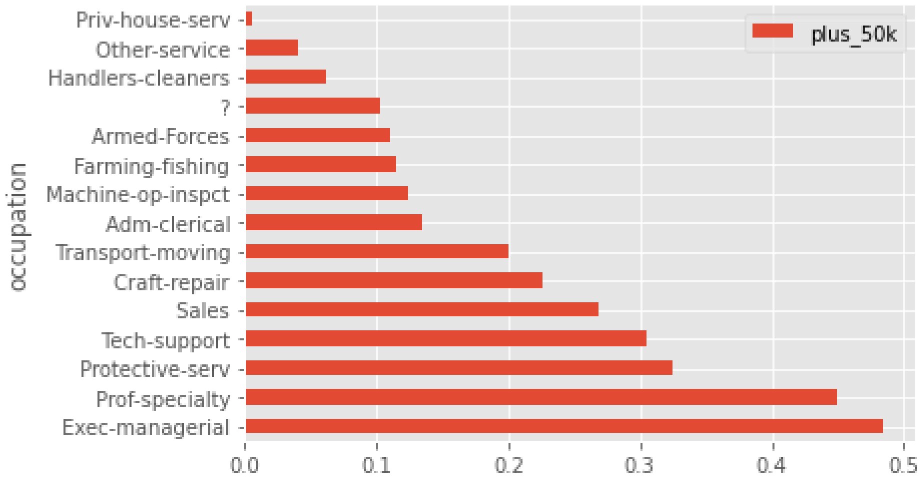
```
print(df_pandas.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15 entries, 0 to 14
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   occupation  15 non-null     object 
 1   plus_50k    15 non-null     float64
dtypes: float64(1), object(1)
memory usage: 368.0+ bytes
None
```

In [0]:

```
import matplotlib.pyplot as plt

# i like ggplot style
plt.style.use('ggplot')

myplot = df_pandas.plot(kind='barh', x='occupation', y='plus_50k')

display(myplot.figure)
```





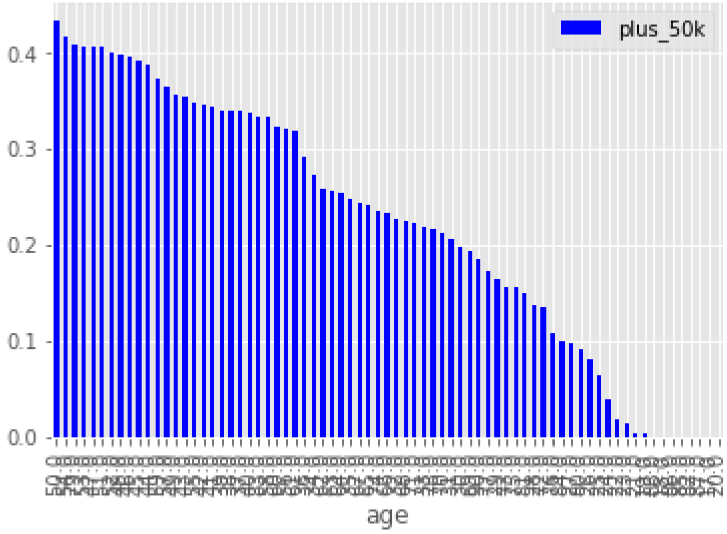
In [0]:

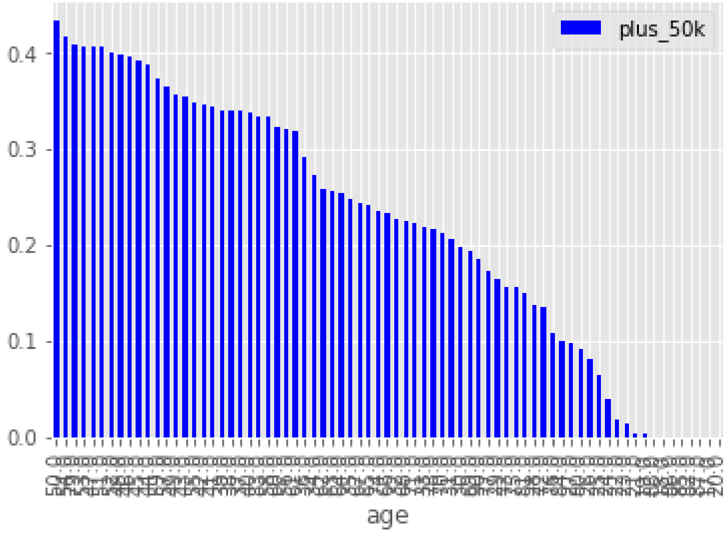
```

import pandas as pd

# do some analysis
result = spark.sql(
  """
  SELECT
    age,
    AVG(IF(income = ' >50K',1,0)) as plus_50k
  FROM
    adult
  GROUP BY 1
  ORDER BY 2 DESC
  """)

# collect results into a pandas df
df_pandas = pd.DataFrame(
  result.collect(),
  columns=result.schema.names
)

# look at df
print(df_pandas.head())
```

```
    age  plus_50k
0  50.0  0.433555
1  54.0  0.416867
2  79.0  0.409091
3  53.0  0.407328
4  47.0  0.406780
```

In [0]:

```
import matplotlib.pyplot as plt
plt.style.use('ggplot')

myplot = df_pandas.plot(kind='bar', x='age', y='plus_50k',color='blue')
display(myplot.figure)
```





In [0]:

```
# describe df
df_adult.select(df_adult['age'],df_adult['education_num']).describe().show()
```

```
+-------+------------------+------------------+
|summary|               age|     education_num|
+-------+------------------+------------------+
|  count|             32560|             32560|
|   mean|38.581633906633904| 10.08058968058968|
| stddev|13.640641827464002|2.5727089681052058|
|    min|              17.0|               1.0|
|    max|              90.0|              16.0|
+-------+------------------+------------------+
```

In [0]:

```
from pyspark.ml import Pipeline
from pyspark.ml.feature import OneHotEncoder , StringIndexer, VectorAssembler

categoricalColumns = ["workclass", "education", "marital_status", "occupation", "relationsh
stages = [] # stages in our Pipeline

for categoricalCol in categoricalColumns:
    # Category Indexing with StringIndexer
    stringIndexer = StringIndexer(inputCol=categoricalCol, outputCol=categoricalCol + "Inde
    # Use OneHotEncoder to convert categorical variables into binary SparseVectors
    encoder = OneHotEncoder(inputCols=[stringIndexer.getOutputCol()], outputCols=[categoric
    # Add stages.  These are not run here, but will run all at once later on.
    stages += [stringIndexer, encoder]
```

In [0]:

```
# Convert label into label indices using the StringIndexer
label_stringIdx = StringIndexer(inputCol="income", outputCol="label")
stages += [label_stringIdx]
```

In [0]:

```
# Transform all features into a vector using VectorAssembler
numericCols = ["age", "fnlwgt", "education_num", "capital_gain", "capital_loss", "hours_per
assemblerInputs = [c + "classVec" for c in categoricalColumns] + numericCols
assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="features")
stages += [assembler]
```

In [0]:

```
# Create a Pipeline.
pipeline = Pipeline(stages=stages)
# Run the feature transformations.
#  - fit() computes feature statistics as needed.
#  - transform() actually transforms the features.
pipelineModel = pipeline.fit(df_adult)
dataset = pipelineModel.transform(df_adult)
# Keep relevant columns
selectedcols = ["label", "features"] + cols
dataset = dataset.select(selectedcols)
display(dataset)
```

label	features	age	workclass	fnlwgt	education	education_num	marital_status	occupation	rel
0.0	Map(vectorType -> sparse, length -> 100, indices -> List(1, 10, 23, 31, 43, 48, 52, 53, 94, 95, 96, 99), values -> List(1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 50.0, 83311.0, 13.0, 13.0))	50.0	Self-emp-not-inc	83311.0	Bachelors	13.0	Married-civ-spouse	Exec-managerial	
	Map(vectorType -> sparse, length -> 100, indices -> List(0, 8, 25, 38, 44, 48, 52, 53,							Handlers	

In [0]:

```
### Randomly split data into training and test sets. set seed for reproducibility
(trainingData, testData) = dataset.randomSplit([0.7, 0.3], seed=100)
print(trainingData.count())
print(testData.count())
```

```
22831
9729
```

In [0]:

```
from pyspark.sql.functions import avg

# get the rate of the positive outcome from the training data to use as a threshold in the
training_data_positive_rate = trainingData.select(avg(trainingData['label'])).collect()[0][

print("Positive rate in the training data is {}".format(training_data_positive_rate))
```

```
Positive rate in the training data is 0.2398931277648811
```

In [0]:

```
from pyspark.ml.classification import LogisticRegression

# Create initial LogisticRegression model
lr = LogisticRegression(labelCol="label", featuresCol="features", maxIter=10)

# set threshold for the probability above which to predict a 1
lr.setThreshold(training_data_positive_rate)
# lr.setThreshold(0.5) # could use this if knew you had balanced data

# Train model with Training Data
lrModel = lr.fit(trainingData)

# get training summary used for eval metrics and other params
lrTrainingSummary = lrModel.summary
print(lrTrainingSummary)
```

```
<pyspark.ml.classification.BinaryLogisticRegressionTrainingSummary object at
0x7f4df6773f70>
```

In [0]:

```
fMeasure = lrTrainingSummary.fMeasureByThreshold
maxFMeasure = fMeasure.groupBy().max('F-Measure').select('max(F-Measure)').head()
lrBestThreshold = fMeasure.where(fMeasure['F-Measure'] == maxFMeasure['max(F-Measure)']) \
    .select('threshold').head()['threshold']

print("Best threshold based on model performance on training data is {}".format(lrBestThres
```

```
Best threshold based on model performance on training data is 0.317813913075
4516
```

In [0]:

```
lrPredictions = lrModel.transform(testData)

# display predictions
display(lrPredictions.select("label", "prediction", "probability"))
```

label	prediction	probability
0.0	1.0	Map(vectorType -> dense, length -> 2, values -> List(0.1602132525712759, 0.8397867474287242))
0.0	1.0	Map(vectorType -> dense, length -> 2, values -> List(0.7013547171086596, 0.2986452828913404))
0.0	1.0	Map(vectorType -> dense, length -> 2, values -> List(0.5284674080969827, 0.47153259190301733))
0.0	1.0	Map(vectorType -> dense, length -> 2, values -> List(0.6757968481659136, 0.32420315183408643))
0.0	1.0	Map(vectorType -> dense, length -> 2, values -> List(0.620038493322546, 0.379961506677454))
0.0	1.0	Map(vectorType -> dense, length -> 2, values -> List(0.607404569017195, 0.392595430982805))
0.0	1.0	Map(vectorType -> dense, length -> 2, values -> List(0.5992215790962835, 0.4007784209037165))

In [0]:

```

from pyspark.ml.evaluation import BinaryClassificationEvaluator
from pyspark.mllib.evaluation import BinaryClassificationMetrics, MulticlassMetrics

def print_performance_metrics(predictions):
  # Evaluate model
  evaluator = BinaryClassificationEvaluator(rawPredictionCol="rawPrediction")
  auc = evaluator.evaluate(predictions, {evaluator.metricName: "areaUnderROC"})
  aupr = evaluator.evaluate(predictions, {evaluator.metricName: "areaUnderPR"})
  print("auc = {}".format(auc))
  print("aupr = {}".format(aupr))

  # get rdd of predictions and labels for mllib eval metrics
  predictionAndLabels = predictions.select("prediction","label").rdd

  # Instantiate metrics objects
  binary_metrics = BinaryClassificationMetrics(predictionAndLabels)
  multi_metrics = MulticlassMetrics(predictionAndLabels)

  # Area under precision-recall curve
  print("Area under PR = {}".format(binary_metrics.areaUnderPR))
  # Area under ROC curve
  print("Area under ROC = {}".format(binary_metrics.areaUnderROC))
  # Accuracy
  print("Accuracy = {}".format(multi_metrics.accuracy))
  # Confusion Matrix
  print(multi_metrics.confusionMatrix())


  # F1
  print("F1 = {}".format(multi_metrics.fMeasure(0.0)))
  # Precision
  print("Precision = {}".format(multi_metrics.precision(0.0)))
  # Recall
  print("Recall = {}".format(multi_metrics.recall(0.0)))
  # FPR
  print("FPR = {}".format(multi_metrics.falsePositiveRate(0.0)))
  # TPR
  print("TPR = {}".format(multi_metrics.truePositiveRate(0.0)))


print_performance_metrics(lrPredictions)
```

```
auc = 0.9022382581905842
aupr = 0.7639327846135503
/databricks/spark/python/pyspark/sql/context.py:165: FutureWarning: Deprecat
ed in 3.0.0. Use SparkSession.builder.getOrCreate() instead.
  warnings.warn(
Area under PR = 0.550904296478963
Area under ROC = 0.8214764233357801
Accuracy = 0.8119025593586185
DenseMatrix([[5913., 1452.],
             [ 378., 1986.]])
F1 = 0.8659929701230228
Precision = 0.9399141630901288
Recall = 0.8028513238289205
FPR = 0.1598984771573604
TPR = 0.8028513238289205
```

In [0]:

```
```