Microsoft

Three practical use cases with Azure Databricks

Solve your big data and AI challenges

Azure Databricks

What this e-book covers and why

Azure Databricks is a fast, easy, and collaborative Apache® Spark™ based analytics platform with one-click setup, streamlined workflows, and the scalability and security of Microsoft Azure.

Rather than describe what Azure Databricks does, we're going to actually show you: in this e-book, you'll find three scenarios where Azure Databricks helps data scientists take on specific challenges and what the outcomes look like. We will cover:

- A churn analysis model
- A movie recommender engine
- An intrusion detection demonstration

Notebooks explained

Notebooks on Azure Databricks are interactive workspaces for exploration and visualization and can be used cooperatively by users across multiple disciplines. With notebooks, you can examine data at scale, build and train models, and share your findings, iterating and collaborating quickly and effectively from experimentation to production. In this e-book, we'll show how notebooks come to life with example code and results, giving you a clear picture of what it's like to work in Azure Databricks.

Who should read this

This e-book was written primarily for data scientists, but will be useful for data engineers and business users interested in building, deploying, and visualizing data models.

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Getting started

The demos in this e-book show how Azure Databricks notebooks help teams analyze and solve problems. You can read through the demos here, or you can try using Azure Databricks yourself by **signing up for a free account**.

If you do want to try out the notebooks, once you've set up your free account, use the following initial setup instructions for any notebook.

Once you have selected Azure Databricks in the Azure Portal, you can start running it by creating a cluster. To run these notebooks, you can accept all the default settings in Azure Databricks for creating your cluster. The steps are:

1. Click on the clusters icon in the left bar.
2. Select "Create Cluster."
3. Input a cluster name.
4. Click the "Create Cluster" button.

You are all set to import the Azure Databricks notebooks.
To import the notebooks:

1. Click on the Workspace icon.
2. Select your directory in the user column.
3. Click on the dropdown for Import. Drop your notebooks files into this dialog.
4. In the notebook, click on the dropdown that says "Detached."
5. Select the cluster you created in the previous step.

Notebook 1

Churn analysis demo

Churn analysis demo

Customer Churn also known as customer attrition, customer turnover, or customer defection, is the loss of clients or customers. Predicting and preventing customer churn is vital to a range of businesses.

In this notebook we will use a pre-built model on Azure Databricks to analyze customer churn. With this model, we can predict when a customer is going to churn with 90% accuracy, so we can setup a report to show customers that are about to churn, and then provide a remediation strategy such as a special offer to try and prevent them from churning. In this example we are looking at cellular carriers, and the goal is to keep them from jumping to another carrier. This notebook:

- Contains functionality that is relevant to Data Scientists, Data Engineers and Business users.
- Lends itself to a data driven storytelling approach, that demonstrates how notebooks can be used within Azure Databricks.
- Uses a machine learning Gradient boosting algorithm implementation to analyze a Customer Churn dataset.
- Illustrates a simple churn analysis workflow. We use Customer Churn dataset from the UCI Machine Learning Repository.

Step 1: Ingest Churn Data to Notebook

We download the UCI dataset hosted at UCI site.

From the churn.names metadata file, we can see the meaning of the data columns:

- state: discrete.
- account length: continuous.
- area code: continuous.
- phone number: discrete.
- international plan: discrete.
- voice mail plan: discrete.
- number vmail messages: continuous.
- total day minutes: continuous.
- total day calls: continuous.
- total day charge: continuous.
- total eve minutes: continuous.
- total eve calls: continuous.
- total eve charge: continuous.
- total night minutes: continuous.
- total night calls: continuous.
- total night charge: continuous.
- total intl minutes: continuous.
- total intl calls: continuous.
- total intl charge: continuous.
- number customer service calls: continuous.
- churned: discrete <- This is the label we wish to predict, indicating whether or not the customer churned.

```
%sh
mkdir /tmp/churn
wget http://www.sgi.com/tech/mlc/db/churn.data -O /tmp/churn/churn.data
wget http://www.sgi.com/tech/mlc/db/churn.test -O /tmp/churn/churn.test
--2017-08-25 19:52:36--  http://www.sgi.com/tech/mlc/db/churn.data
Resolving www.sgi.com (www.sgi.com)... 192.48.178.134
Connecting to www.sgi.com (www.sgi.com)|192.48.178.134|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 376493 (368K) [text/plain]
Saving to: '/tmp/churn/churn.data'

     0K ......... ......... ......... ......... ......... 13%  131K 2s
    50K ......... ......... ......... ......... ......... 27%  650K 1s
   100K ......... ......... ......... ......... ......... 40%  336K 1s
   150K ......... ......... ......... ......... ......... 54%  672K 1s
   200K ......... ......... ......... ......... ......... 67% 57.9M 0s
   250K ......... ......... ......... ......... ......... 81%  667K 0s
   300K ......... ......... ......... ......... ......... 95% 69.0M 0s
   350K ......... .......                                  100%  166M=0.8s

2017-08-25 19:52:37 (485 KB/s) - '/tmp/churn/churn.data' saved
[376493/376493]

--2017-08-25 19:52:37--  http://www.sgi.com/tech/mlc/db/churn.test
Resolving www.sgi.com (www.sgi.com)... 192.48.178.134
Connecting to www.sgi.com (www.sgi.com)|192.48.178.134|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 188074 (184K) [text/plain]
Saving to: '/tmp/churn/churn.test'

     0K ......... ......... ......... ......... ......... 27%  160K 1s
    50K ......... ......... ......... ......... ......... 54%  329K 0s
   100K ......... ......... ......... ......... ......... 81%  665K 0s
   150K ......... ......... ......... ...                 100% 23.2M=0.5s

2017-08-25 19:52:37 (340 KB/s) - '/tmp/churn/churn.test' saved
[188074/188074]
```

Mount the data locally.

```
%py
dbutils.fs.mkdirs("/mnt/churn")
dbutils.fs.mv("file:///tmp/churn/churn.data", "/mnt/churn/churn.data")
dbutils.fs.mv("file:///tmp/churn/churn.test", "/mnt/churn/churn.test")

Out[2]: True
```

```
%fs ls /mnt/churn
```

path	name	size
dbfs:/mnt/churn/churn.data	churn.data	376493
dbfs:/mnt/churn/churn.test	churn.test	188074

The second step is to create the schema in the Data Frame.

```
from pyspark.sql.types import *

# The second step is to create the schema
schema =StructType([
    StructField("state",StringType(), False),
    StructField("account_length",DoubleType(), False),
    StructField("area_code",DoubleType(), False),
    StructField("phone_number",StringType(), False),
    StructField("international_plan",StringType(), False),
    StructField("voice_mail_plan",StringType(), False),
    StructField("number_vmail_messages",DoubleType(), False),
    StructField("total_day_minutes",DoubleType(), False),
    StructField("total_day_calls",DoubleType(), False),
    StructField("total_day_charge",DoubleType(), False),
    StructField("total_eve_minutes",DoubleType(), False),
    StructField("total_eve_calls",DoubleType(), False),
    StructField("total_eve_charge",DoubleType(), False),
    StructField("total_night_minutes",DoubleType(), False),
    StructField("total_night_calls",DoubleType(), False),
    StructField("total_night_charge",DoubleType(), False),
    StructField("total_intl_minutes",DoubleType(), False),
    StructField("total_intl_calls",DoubleType(), False),
    StructField("total_intl_charge",DoubleType(), False),
    StructField("number_customer_service_calls",DoubleType(), False),
    StructField("churned",StringType(), False)
])

df = (spark.read.option("delimiter", ",")
  .option("inferSchema", "true")
  .schema(schema)
  .csv("dbfs:/mnt/churn/churn.data"))
```

```
display(df)
```

state	account_length	area_code	phone_number	international_plan	voice_mail_plan	number_vmail_messages	total_day_minutes	total_day_calls	total_day_charge	tot
KS	128	415	382-4657	no	yes	25	265.1	110	45.07	197
OH	107	415	371-7191	no	yes	26	161.6	123	27.47	195
NJ	137	415	358-1921	no	no	0	243.4	114	41.38	121
OH	84	408	375-999	yes	no	0	299.4	71	50.9	61.9
OK	75	415	330-6626	yes	no	0	166.7	113	28.34	148
AL	118	510	391-8027	yes	no	0	223.4	98	37.98	220
MA	121	510	355-9993	no	yes	24	218.2	88	37.09	348
MO	147	415	329-9001	yes	no	0	157	79	26.69	103
LA	117	408	335-4719	no	no	0	184.5	97	31.37	351
WV	141	415	330-8173	yes	yes	37	258.6	84	43.96	222
IN	65	415	329-6603	no	no	0	129.1	137	21.95	228
RI	74	415	344-9403	no	no	0	187.7	127	31.91	16

Step 2: Enrich the Data to Get Additional Insights to Churn Dataset

We count the number of data points and separate the churned from the unchurned.

```
# Because we will need it later...
from pyspark.sql.functions import *
from pyspark.sql.types import *
```

We do a filter and count operation to find the number of customers who churned.

```
numCases = df.count()
numChurned = df.filter(col("churned") == ' True.').count()
```

```
numCases = numCases
numChurned = numChurned
numUnchurned = numCases - numChurned
print("Total Number of cases: {0:,}".format( numCases ))
print("Total Number of cases churned: {0:,}".format( numChurned ))
print("Total Number of cases unchurned: {0:,}".format( numUnchurned ))
Total Number of cases: 3,333
Total Number of cases churned: 483
Total Number of cases unchurned: 2,850
```

The data is converted to a parquet file, which is a data format that is well suited to analytics on large data sets.

```
df.repartition(1).write.parquet('/mnt/databricks-wesley/demo-data/
insurance/churndata')
```

Step 3: Explore Churn Data

We create a table on the parquet data to so we can analyze it at scale with Spark SQL.

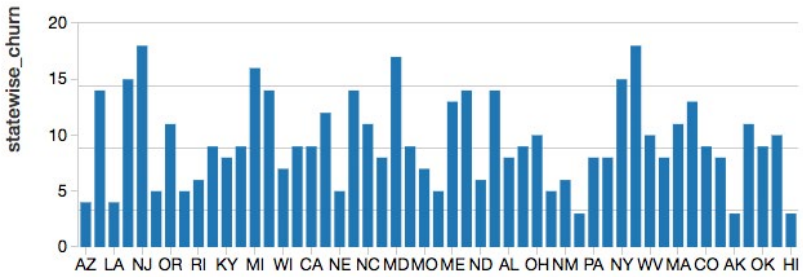
```
%sql

    Drop table temp_idsdata;

    CREATE TEMPORARY TABLE temp_idsdata
    USING parquet
    OPTIONS (
      path "/mnt/databricks-wesley/demo-data/insurance/churndata"
    )
OK
```

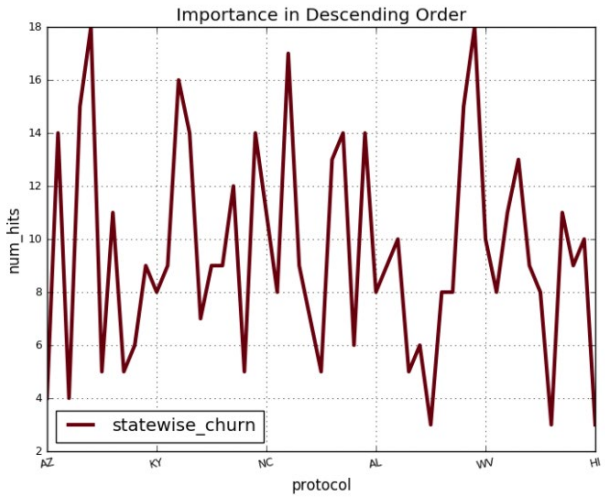
Churn by statewide breakup using databricks graph

```
%sql
SELECT state, count(*) as statewise_churn FROM temp_idsdata where
churned= " True." group by state
```



Churn by statewide breakup using python matplotlib

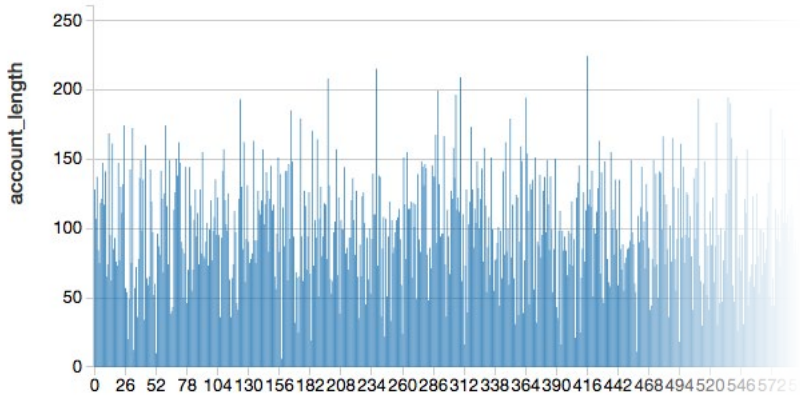
```
import matplotlib.pyplot as plt
importance = sqlContext.sql("SELECT state, count(*) as statewise_churn
FROM temp_idsdata where churned= ' True.' group by state")
importanceDF = importance.toPandas()
ax = importanceDF.plot(x="state", y="statewise_
churn",lw=3,colormap='Reds_r',title='Importance in Descending Order',
fontsize=9)
ax.set_xlabel("protocol")
ax.set_ylabel("num_hits")
plt.xticks(rotation=12)
plt.grid(True)
plt.show()
display()
```



Step 4: Visualization

Show the distribution of the account length.

```
display(df.select("account_length").orderBy(id))
```




```
df.printSchema()

root
 |-- state: string (nullable = true)
 |-- account_length: double (nullable = true)
 |-- area_code: double (nullable = true)
 |-- phone_number: string (nullable = true)
 |-- international_plan: string (nullable = true)
 |-- voice_mail_plan: string (nullable = true)
 |-- number_vmail_messages: double (nullable = true)
 |-- total_day_minutes: double (nullable = true)
 |-- total_day_calls: double (nullable = true)
 |-- total_day_charge: double (nullable = true)
 |-- total_eve_minutes: double (nullable = true)
 |-- total_eve_calls: double (nullable = true)
 |-- total_eve_charge: double (nullable = true)
 |-- total_night_minutes: double (nullable = true)
 |-- total_night_calls: double (nullable = true)
 |-- total_night_charge: double (nullable = true)
 |-- total_intl_minutes: double (nullable = true)
 |-- total_intl_calls: double (nullable = true)
 |-- total_intl_charge: double (nullable = true)
 |-- number_customer_service_calls: double (nullable = true)
 |-- churned: string (nullable = true)
```

Step 5: Model Creation

Create a table.

Model Fitting and Summarization

```
from  pyspark.ml.feature import StringIndexer

indexer1 = (StringIndexer()
                    .setInputCol("churned")
                    .setOutputCol("churnedIndex")
                    .fit(df))
```

Create an array of the data.

```
indexed1 = indexer1.transform(df)
finaldf = indexed1.withColumn("censor", lit(1))

from pyspark.ml.feature import VectorAssembler
vecAssembler = VectorAssembler()
vecAssembler.setInputCols(["account_length", "total_day_calls",  "total_eve_calls", "total_night_calls", "total_intl_calls",  "number_customer_service_calls"])
vecAssembler.setOutputCol("features")
print vecAssembler.explainParams()

from pyspark.ml.classification import GBTClassifier

aft = GBTClassifier()
aft.setLabelCol("churnedIndex")

print aft.explainParams()
inputCols: input column names. (current: ['account_length', 'total_day_calls', 'total_eve_calls', 'total_night_calls', 'total_intl_calls', 'number_customer_service_calls'])
outputCol: output column name. (default: VectorAssembler_402dae9a2a13c5e1ea7f__output, current: features)
cacheNodeIds: If false, the algorithm will pass trees to executors to match instances with nodes. If true, the algorithm will cache node IDs for each instance.
Caching can speed up training of deeper trees. Users can set how often should the cache be checkpointed or disable it by setting checkpointInterval. (default: False)
checkpointInterval: set checkpoint interval (>= 1) or disable checkpoint (-1). E.g. 10 means that the cache will get checkpointed every 10 iterations. (default: 10)
```

```
featuresCol: features column name. (default: features)
labelCol: label column name. (default: label, current: churnedIndex)
lossType: Loss function which GBT tries to minimize (case-insensitive). Supported options: logistic (default: logistic)
maxBins: Max number of bins for discretizing continuous features.  Must be >=2 and >= number of categories for any categorical feature. (default: 32)
maxDepth: Maximum depth of the tree. (>= 0) E.g., depth 0 means 1 leaf node; depth 1 means 1 internal node + 2 leaf nodes. (default: 5)
maxIter: max number of iterations (>= 0). (default: 20)
maxMemoryInMB: Maximum memory in MB allocated to histogram aggregation. If too small, then 1 node will be split per iteration, and its aggregates may
exceed this size. (default: 256)
minInfoGain: Minimum information gain for a split to be considered at a tree node. (default: 0.0)
minInstancesPerNode: Minimum number of instances each child must have after split. If a split causes the left or right child to have fewer than
minInstancesPerNode, the split will be discarded as invalid. Should be >= 1. (default: 1)
predictionCol: prediction column name. (default: prediction)
seed: random seed. (default: 2857134701650851239)
stepSize: Step size to be used for each iteration of optimization (>= 0). (default: 0.1)
subsamplingRate: Fraction of the training data used for learning each decision tree, in range (0, 1]. (default: 1.0)
```

Building model on train data

```
from pyspark.ml import Pipeline

# We will use the new spark.ml pipeline API. If you have worked with scikit-learn this will be very familiar.
lrPipeline = Pipeline()

# Now we'll tell the pipeline to first create the feature vector, and then do the linear regression
lrPipeline.setStages([vecAssembler, aft])

# Pipelines are themselves Estimators -- so to use them we call fit:
lrPipelineModel = lrPipeline.fit(finaldf)
```

Using model for data predicition

```
predictionsAndLabelsDF = lrPipelineModel.transform(finaldf)
confusionMatrix = predictionsAndLabelsDF.select('churnedIndex', 'prediction')
```

Confusion Matrix for the churn model

```
from pyspark.mllib.evaluation import MulticlassMetrics
metrics = MulticlassMetrics(confusionMatrix.rdd)
cm = metrics.confusionMatrix().toArray()
```

Performance Metrics of the model

```
print metrics.falsePositiveRate(0.0)
print metrics.accuracy
```

```
0.0514705882353
0.891689168917
```

Results Interpretation

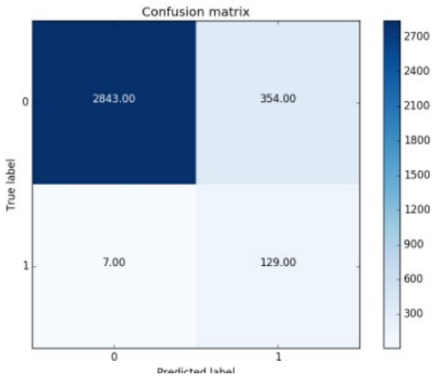
The plot to the right shows Index used to measure each of the churn type.

The customer churn index using gradient boosting algorithm gives an accuracy of close to 89%.

Confusion Matrix in matplotlib

```
%python
import matplotlib.pyplot as plt
import numpy as np
import itertools
plt.figure()
classes=list([0,1])
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion matrix')
plt.colorbar()
tick_marks = np.arange(len(classes))
plt.xticks(tick_marks, classes, rotation=0)
plt.yticks(tick_marks, classes)

fmt =  '.2f'
thresh = cm.max() / 2.
for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
    plt.text(j, i, format(cm[i, j], fmt),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")
plt.tight_layout()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()
display()
```



Notebook 2

Movie recommendation engine

Movie recommendation engine

Recommendation engines are used across many industries, from external use on retail sites, to internal use on employee sites. A recommendation engine delivers plans to end users based on points that matter to them.

This demonstration is a simple example of a consumer using a movie website to select a movie to watch. Recommendation engines look at historical data on what people have selected, and then predict the selection the user would make. This movie recommendation engine notebook:

- Is built on the Azure Databricks platform and uses a **machine learning ALS recommendation algorithm** to generate recommendations on movie choices.
- Demonstrates a movie recommendation analysis workflow, using movie data from the Kaggle Dataset.
- Provides one place to create the entire analytical application, allowing users to collaborate with other participants.
- Allows users to see ongoing accuracy that might drive improvements.

Step 1: Ingest Movie Data to Notebook

We will extract the movie dataset hosted at Kaggle.

Select 10 random movies from the most rated, as those as likely to be commonly recognized movies. Create Azure Databricks Widgets to allow a user to enter in ratings for those movies.

```
sqlContext.sql("""
    select
      movie_id, movies.name, count(*) as times_rated
    from
      ratings
    join
      movies on ratings.movie_id = movies.id
    group by
      movie_id, movies.name, movies.year
    order by
      times_rated desc
    limit
      200
    """
).registerTempTable("most_rated_movies")
```

```
if not "most_rated_movies" in vars():
  most_rated_movies = sqlContext.table("most_rated_movies").rdd.
takeSample(True, 10)
  for i in range(0, len(most_rated_movies)):
    dbutils.widgets.dropdown("movie_%i" % i, "5", ["1", "2", "3", "4", "5"],
most_rated_movies[i].name)
```

Change the values on top to be your own personal ratings before proceeding.

```
from datetime import datetime
from pyspark.sql import Row
ratings = []
for i in range(0, len(most_rated_movies)):
  ratings.append(
    Row(user_id = 0,
        movie_id = most_rated_movies[i].movie_id,
        rating = float(dbutils.widgets.get("movie_%i" %i))))
myRatingsDF = sqlContext.createDataFrame(ratings)
```

Step 2: Enrich the Data and Prep for Modeling

```
%sql select min(user_id) from ratings
```

min(user_id)
1

```
from pyspark.sql import functions

ratings = sqlContext.table("ratings")
ratings = ratings.withColumn("rating", ratings.rating.cast("float"))
```

```
(training, test) = ratings.randomSplit([0.8, 0.2])
```

Step 3: Model Creation

Fit an ALS model on the ratings table.

```
from pyspark.ml.recommendation import ALS

als = ALS(maxIter=5, regParam=0.01, userCol="user_id", itemCol="movie_id",
ratingCol="rating")
model = als.fit(training.unionAll(myRatingsDF))
```

Step 4: Model Evaluation

Evaluate the model by computing Root Mean Square error on the test set.

```
predictions = model.transform(test).dropna()
predictions.registerTempTable("predictions")
```

```
%sql select user_id, movie_id, rating, prediction from predictions
```

user_id	movie_id	rating	prediction
4227	148	2	2.6070688
1242	148	3	2.5327067
1069	148	2	3.8583977
2507	148	4	3.8449543
53	148	5	3.940087
216	148	2	2.2447278
2456	148	2	3.5586698
4169	463	2	2.7173512
4040	463	1	2.1891994

```
from pyspark.ml.evaluation import RegressionEvaluator

evaluator = RegressionEvaluator(metricName="rmse", labelCol="rating",
predictionCol="prediction")
```

```
rmse = evaluator.evaluate(predictions)
```

```
displayHTML("<h4>The Root-mean-square error is %s</h4>" % str(rmse))
```

The Root-mean-square error is 0.897631907219

Step 5: Model Testing

Let's see how the model predicts for you.

```
mySampledMovies = model.transform(myRatingsDF)
mySampledMovies.registerTempTable("mySampledMovies")
```

```
display(sqlContext.sql("select user_id, movie_id, rating, prediction
from mySampledMovies"))
```

user_id	movie_id	rating	prediction
0		5	NaN
0		5	NaN
0		4	NaN
0		5	NaN
0		4	NaN
0		5	NaN
0		3	NaN

```
my_rmse = evaluator.evaluate(mySampledMovies)
```

```
displayHTML("<h4>My Root-mean-square error is %s</h4>" % str(my_rmse))
```

My Root-mean-square error is 0.418569215012

```
from pyspark.sql import functions
df = sqlContext.table("movies")
myGeneratedPredictions = model.transform(df.select(df.id.alias(
"movie_id")).withColumn("user_id", functions.expr("int('0')")))
myGeneratedPredictions.dropna().registerTempTable("myPredictions")
```

```
%sql
SELECT
  name, prediction
from
  myPredictions
join
  most_rated_movies on myPredictions.movie_id = most_rated_movies.movie_id
order by
  prediction desc
LIMIT
  10
```

name	prediction
Star Trek: The Wrath of Khan	6.1421475
Star Wars: Episode IV - A New Hope	5.3213224
Raiders of the Lost Ark	5.295201
Casablanca	5.278496
Star Trek IV: The Voyage Home	5.251287

Results Interpretation

The table shown above gives the top ten recommended movie choices for the user based on the predicted outcomes using the movie demographics and the ratings provided by the user.

Notebook 3

Intrusion detection system demo

Intrusion detection system demo

Intrusion Detection System (IDS) is a device or software application that monitors a network or systems for malicious activity or policy violations.

This notebook demonstrates how a user can get a better detection of web threats. We show how to monitor network activity logs in real-time to generate suspicious activity alerts, support a security operations center investigation into suspicious activity and develop network propagation models to map network surface and entity movement to identify penetration points. This notebook:

- Is a pre-built solution on top of Apache® Spark™, written in Scala inside the Azure Databricks platform.
- Uses a **logistic regression** to identify intrusions by looking for deviations in behavior to identify new attacks.
- Includes a dataset with a subset of simulated network traffic samples.
- Demonstrates how the first three insights are gained through the visualization.
- Allows data scientists and data engineers to improve the accuracy by getting more data or improving the model.

Step 1: Ingest IDS Data to Notebook

The CIDDS-001 data set.zip can be downloaded from CIDDS site.

Unzip the data and upload the CIDDS-001>traffic>ExternalServer>*.csv
from unziped folder to Databricks notebooks.

```
val idsdata = sqlContext.read.format("csv")
  .option("header", "true")
  .option("inferSchema", "true")
  .load("/FileStore/tables/ctrdsk051502399641231/")

display(idsdata)
```

Date first seen	Duration	Proto	Src IP Addr	Src Pt	Dst IP Addr	Dst Pt	Packets	Bytes	Flows	Flags	Tos	class	attackType	attackID	attackDescription
2017-03-15T00:01:16.632+0000	0	TCP	192.168.100.5	445	192.168.220.16	58844	1	108	1	.AP...	0	normal	---	---	---
2017-03-15T00:01:16.552+0000	0	TCP	192.168.100.5	445	192.168.220.15	48888	1	108	1	.AP...	0	normal	---	---	---
2017-03-15T00:01:16.551+0000	0.004	TCP	192.168.220.15	48888	192.168.100.5	445	2	174	1	.AP...	0	normal	---	---	---
2017-03-15T00:01:16.631+0000	0.004	TCP	192.168.220.16	58844	192.168.100.5	445	2	174	1	.AP...	0	normal	---	---	---
2017-03-15T00:01:16.552+0000	0	TCP	192.168.100.5	445	192.168.220.15	48888	1	108	1	.AP...	0	normal	---	---	---
2017-03-15T00:01:16.631+0000	0.004	TCP	192.168.220.16	58844	192.168.100.5	445	2	174	1	.AP...	0	normal	---	---	---

```
val newNames = Seq("datefirstseen", "duration", "proto", "srcip","srcpt","dstip","dstpt","packets","bytes","flows","flags","tos","transtype","label","attackid","attackdescription")
val dfRenamed = idsdata.toDF(newNames: _*)
val dfReformat = dfRenamed.select("label","datefirstseen", "duration", "proto",
"srcip","srcpt","dstip","dstpt","packets","bytes","flows","flags","tos","transtype","attackid","attackdescription")
newNames: Seq[String] = List(datefirstseen, duration, proto, srcip, srcpt, dstip, dstpt, packets, bytes, flows, flags, tos, transtype, label, attackid, attackdescription)
dfRenamed: org.apache.spark.sql.DataFrame = [datefirstseen: timestamp, duration: double ... 14 more fields]
dfReformat: org.apache.spark.sql.DataFrame = [label: string, datefirstseen: timestamp ... 14 more fields]
```

Step 2: Enrich the Data to Get Additional Insights to IDS Dataset

We create a temporay table from the file location "/tmp/wesParquet" in paraquet file format.

Parquet file format is the prefered file format since it's optimized for the notebooks in the Azure Databricks platform.

```
%sql

    CREATE TEMPORARY TABLE temp_idsdata
    USING parquet
    OPTIONS (
      path "/tmp/wesParquet"
    )
Error in SQL statement: TempTableAlreadyExistsException:
Temporary table 'temp_idsdata' already exists;
```

Calculate statistics on the Content Sizes returned.

```
%sql
select min(trim(bytes)) as min_bytes,max(trim(bytes)) as max_
bytes,avg(trim(bytes)) as avg_bytes from temp_idsdata
```

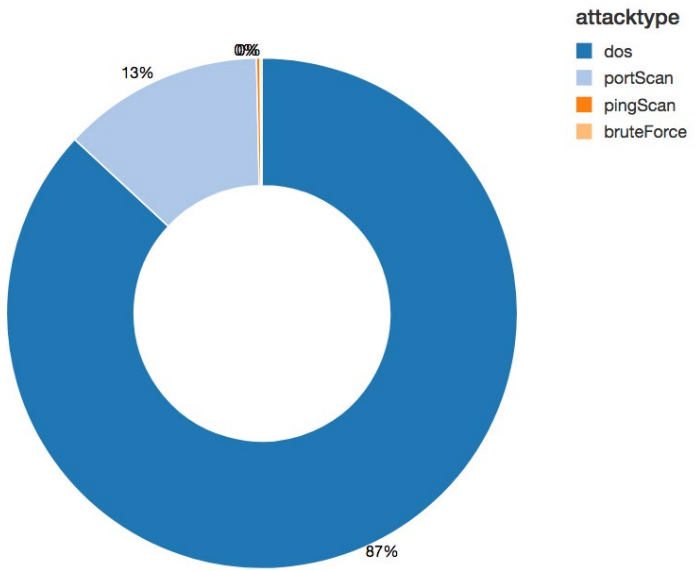
min_bytes	max_bytes	avg_bytes
1.0 M	99995	1980.1018585682032

Step 3: Explore IDS Data by Capturing the Type of Attacks on the Network

Analysis of Attack type caught

```
%sql

select attacktype, count(*) as the_count from temp_idsdata where
attacktype <> '---' group by attacktype order by the_count desc
```



Step 4: Visualization

Visualizing and find outliers.

View a list of IPAddresses that has accessed the server more than N times.

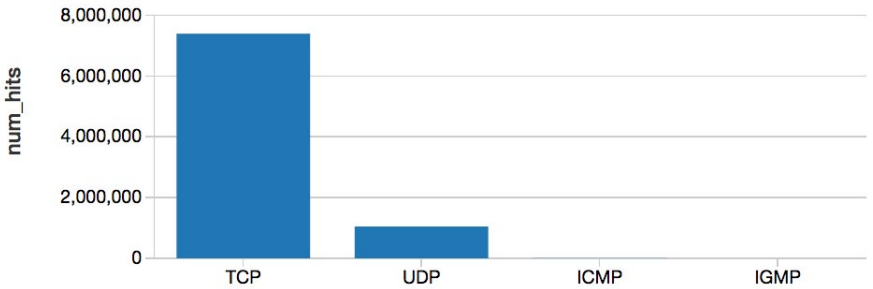
Explore the Source IP used for attacks

```
%sql
-- Use the parameterized query option to allow a viewer to dynamically specify a value for N.
-- Note how it's not necessary to worry about limiting the number of results.
-- The number of values returned are automatically limited to 1000.
-- But there are options to view a plot that would contain all the data to view the trends.
SELECT srcip, COUNT(*) AS total FROM temp_idsdata GROUP BY srcip HAVING total > $N order by total desc
```

```
Command skipped
```

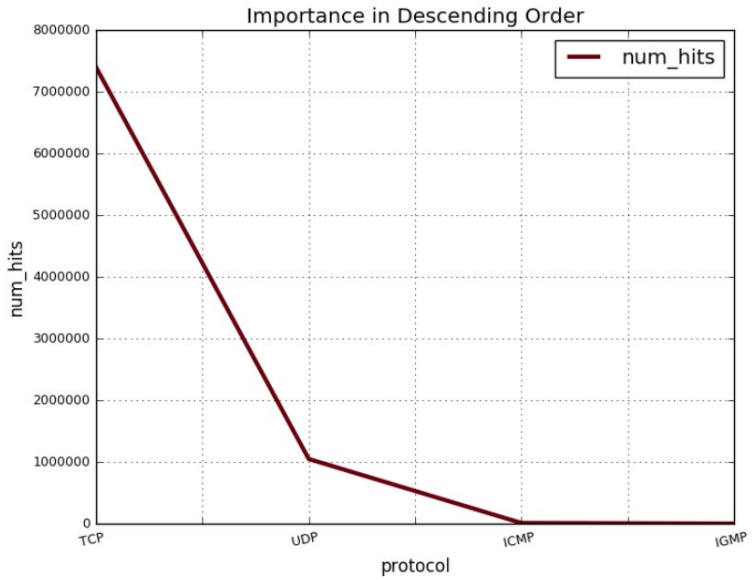
Explore Statistics about the protocol used for attack using Spark SQL

```
%sql
-- Display a plot of the distribution of the number of hits across the endpoints.
SELECT Proto, count(*) as num_hits FROM temp_idsdata GROUP BY Proto ORDER BY num_hits DESC
```



Explore Statistics about the protocol used for attack using Matplotlib

```
%python
import matplotlib.pyplot as plt
importance = sqlContext.sql("SELECT Proto as protocol, count(*) as
num_hits FROM temp_idsdata GROUP BY Proto ORDER BY num_hits DESC")
importanceDF = importance.toPandas()
ax = importanceDF.plot(x="protocol", y="num_hits",
lw=3,colormap='Reds_r',title='Importance in Descending Order',
fontsize=9)
ax.set_xlabel("protocol")
ax.set_ylabel("num_hits")
plt.xticks(rotation=12)
plt.grid(True)
plt.show()
display()
```




```
%r
library(SparkR)
library(ggplot2)
importance_df  = collect(sql(sqlContext,'SELECT Proto as protocol,
count(*) as num_hits FROM temp_idsdata GROUP BY Proto ORDER BY num_hits
DESC'))
ggplot(importance_df, aes(x=protocol, y=num_hits)) + geom_
bar(stat='identity') + scale_x_discrete(limits=importance_
df[order(importance_df$num_hits), "protocol"]) + coord_flip()
```

Step 5: Model Creation

```
import org.apache.spark.ml.linalg.Vector;
import org.apache.spark.ml.feature._;
import org.apache.spark.ml.classification.LogisticRegression
import org.apache.spark.ml.feature.StringIndexer

case class Data(label: Double, feature: Seq[Double])

val indexer1 = new StringIndexer()
                    .setInputCol("proto")
                    .setOutputCol("protoIndex")
                    .fit(dfReformat)

val indexed1 = indexer1.transform(dfReformat)

val indexer2 = new StringIndexer()
                    .setInputCol("label")
                    .setOutputCol("labelIndex")
                    .fit(indexed1)

val indexed2 = indexer2.transform(indexed1)

val features = indexed2.rdd.map(row =>
Data(
   row.getAs[Double]("labelIndex"),
   Seq(row.getAs[Double]("duration"),row.getAs[Double]("protoIndex"))
)).toDF


val assembler = new VectorAssembler()
  .setInputCols(Array("duration", "protoIndex"))
  .setOutputCol("feature")

val output = assembler.transform(indexed2)
println("Assembled columns 'hour', 'mobile', 'userFeatures' to vector
column 'features'")
```

```
output.select("feature", "labelIndex").show(false)

val labeled = output.rdd.map(row =>
LabeledPoint(
   row.getAs[Double]("labelIndex"),
   row.getAs[org.apache.spark.ml.linalg.Vector]("feature")
)).toDF


val splits = labeled randomSplit Array(0.8, 0.2)

val training = splits(0) cache
val test = splits(1) cache

val algorithm = new LogisticRegression()
val model = algorithm fit training

val prediction = model.transform(test)

val predictionAndLabel = prediction.rdd.zip(test.rdd.map(x =>
x.getAs[Double]("label")))

predictionAndLabel.foreach((result) => println(s"predicted label:
${result._1}, actual label: ${result._2}"))
Assembled columns 'hour', 'mobile', 'userFeatures' to vector column 'features'
+-----------+----------+
|feature    |labelIndex|
+-----------+----------+
|(2,[],[])  |0.0       |
|(2,[],[])  |0.0       |
|[0.004,0.0]|0.0       |
|[0.004,0.0]|0.0       |
|(2,[],[])  |0.0       |
|[0.004,0.0]|0.0       |
|(2,[],[])  |0.0       |
|(2,[],[])  |0.0       |
|(2,[],[])  |0.0       |
|(2,[],[])  |0.0       |
```

```
|(2,[],[])    |0.0        |
|(2,[],[])    |0.0        |
|[0.082,0.0]  |0.0        |
|[0.083,0.0]  |0.0        |
|[0.089,0.0]  |0.0        |
|[0.083,0.0]  |0.0        |
|[0.089,0.0]  |0.0        |
|[0.086,0.0]  |0.0        |
|[0.0,1.0]    |0.0        |
|[0.0,1.0]    |0.0        |
+-------------+-----------+
only showing top 20 rows

warning: there were two feature warnings; re-run with -feature for
details
import org.apache.spark.ml.linalg.Vector
import org.apache.spark.ml.feature._
import org.apache.spark.ml.classification.LogisticRegression
import org.apache.spark.ml.feature.StringIndexer
defined class Data
indexer1: org.apache.spark.ml.feature.StringIndexerModel = strIdx_8d1e73586ec7
indexed1: org.apache.spark.sql.DataFrame = [label: string,
datefirstseen: timestamp ... 15 more fields]
indexer2: org.apache.spark.ml.feature.StringIndexerModel = strIdx_
cf17935c04d4
indexed2: org.apache.spark.sql.DataFrame = [label: string,
datefirstseen: timestamp ... 16 more fields]
features: org.apache.spark.sql.DataFrame = [label: double, feature:
array<double>]
assembler: org.apache.spark.ml.feature.VectorAssembler = vecAssembler_
c4fe808dd912
output: org.apache.spark.sql.DataFrame = [label: string, datefirstseen:
timestamp ... 17 more fields]
labeled: org.apache.spark.sql.DataFrame = [label: double, features: vector]
splits: Array[org.apache.spark.sql.Dataset[org.apache.spark.sql.Row]]
= Array([label: double, features: vector], [label: double, features:
vector])
training: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] =
[label: double, features: vector]
test: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [label:
double, features: vector]
algorithm: org.apache.spark.ml.classification.LogisticRegression =
logreg_96ba18adfd6f
model: org.apache.spark.ml.classification.LogisticRegressionModel =
logreg_96ba18adfd6f
prediction: org.apache.spark.sql.DataFrame = [label: double, features:
vector ... 3 more fields]
predictionAndLabel: org.apache.spark.rdd.RDD[(org.apache.spark.sql.Row,
Double)] = ZippedPartitionsRDD2[610] at zip at command-622314:55
```

```
val loss = predictionAndLabel.map { case (p, l) =>
  val err = p.getAs[Double]("prediction") - l
  err * err
}.reduce(_ + _)

val numTest = test.count()
val rmse = math.sqrt(loss / numTest)
loss: Double = 407383.0
numTest: Long = 1687519
rmse: Double = 0.491334336329945
```

Results Interpretation

The plot above shows Index used to measure each of the attack type.

1. The most common type of attack were Denial of Service (DoS), followed by port scan.
2. IP 192.168.220.16 was the origin for most of the attacks, amounting to at least 14% of all attacks.
3. Most of the Atacks used TCP protocol.
4. As you can infer from the RMSE on running the model on the test data to predict the type of network attack we got a good accuracy of 0.4919.

Conclusion

Microsoft

Find relevant insights in all your data

As you can see from the preceding scenarios, Azure Databricks was designed to give you more ways to enhance your insights and solve problems. It was built to work for you and your team, giving you more avenues for collaboration, more analytics power, and a faster way to solve the problems unique to your business. We hope you found it helpful and will try using Azure Databricks yourself.

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