# Recitation 4 Group 7 Report

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## Task 1

### What does the code in PageRank.scala do?

The code is used to rank the web page for the follower. The result of the code shows the relationship among the followers.

# What is the convergence criteria for PageRank in the example?

```
val ranks = graph.pageRank(0.0001).vertices
```

This line is the convergence criteria of the PageRank in this example. When the value is smaller than 0.0001. The algorithm converges and stop.

#### ScreenShot

# Task 2

#### Part 1

```
In [20]: sc.stop()
import pyspark
from pyspark.sql import SparkSession
sc = pyspark.SparkContext(appName="sparkSQL")
ss = SparkSession(sc)
In [21]: data = "file:///Users/weijiasun/CloudComputing18/CloudComputingRec4/Task2_problems/kddcup.data
raw = sc.textFile(data).cache()
```

#### DataFrame ¶

A DataFrame is a Dataset organized into named columns. It is conceptually equivalent to a table in a relational database or a data frame in R/Python, but with richer optimizations under the hood. DataFrames can be constructed from a wide array of sources such as: structured data files, tables in Hive, external databases, or existing RDDs

We want to convert our raw data into a table. But first we have to parse it and assign desired rows and headers, something like csy format

Once we have our RDD of Row we can infer and get a schema. We can operate on this schema with SQL queries.

```
In [24]: kdd_df = sqlContext.createDataFrame(row_data)
kdd_df.registerTempTable("KDDdata")
```

In [25]: # Select tcp network interactions with more than 2 second duration and no transfer from destina
tcp\_interactions = sqlContext.sql("SELECT duration, dst\_bytes FROM KDDdata WHERE protocol\_type
tcp\_interactions.show(10)

```
|duration|dst bytes
     5057
                   0
     5059
                   0
     5051
                   0
     5056
                   0
     5051
                   0
     5039
                   0
     5062
                   0
     5041
                   0
                   0
     5056
     5064
                   0
```

only showing top 10 rows

```
In [26]: # Complete the query to filter data with duration > 2000, dst_bytes = 0.
# Then group the filtered elements by protocol_type and show the total count in each group.
# Refer - https://spark.apache.org/docs/latest/sql-programming-guide.html#dataframegroupby-reta
kdd_df.select("protocol_type", "duration", "dst_bytes").filter(kdd_df.duration>2000)#.more quer
```

Out[26]: DataFrame[protocol\_type: string, duration: bigint, dst\_bytes: bigint]

 ${\tt Out[27]: '\nWrite \ a \ query \ to \ select \ label, \ngroup \ it \ and \ then \ count \ total \ elements \nin \ that \ group \n'}$ 

We can use other dataframes for filtering our data efficiently.

```
In [28]: kdd_labeled.select("label", "protocol_type", "dst_bytes").groupBy("label", "protocol_type", kdd
```

```
|label|protocol_type|(dst_bytes = 0)| count|
false| 70169|
null
           tcp
 null
                      false 15594
            udp
                      true 119896
 null
            tcp
                       true | 4760
 null
            udp
                       true 283602
           icmp
 null
```

It can be inferred that we have large number of tcp attacks with zero data transfer = 110583 as compared to normal tcp = 9313.

This type of analysis is known as exploratory data analysis

```
In [ ]:
```

#### Part 2

```
In [1]: import pyspark
            from pyspark.sql import SparkSession
            sc = pyspark.SparkContext(appName="sparkSQL")
            ss = SparkSession(sc)
 In [4]: lata = "file:///Users/weijiasun/Downloads/Rec4_Sol/Task2/recitation4/problems/kddcup.data_10_per
           aw = sc.textFile(data).cache()
             We will create a local dense vector for our KDD dataset.
M In [5]: raw.take(1)
 In [6]: import numpy as no
            def parse_kdd(line):
                 split = line.split(",")
                 # we will keep just numeric and logical values
# discard any string values
symbolic_indexes = [1,2,3,41]
                 clean_split = [item for i,item in enumerate(split) if i not in symbolic_indexes]
                 return np.array([float(x) for x in clean_split])
            vector data = raw.map(parse kdd)
 In [7]: from pyspark.mllib.stat import Statistics
            from math import sqrt
             # Compute column summary statistics.
            summary = Statistics.colStats(vector_data)
            print ("Duration Statistics:")
                      Mean: {}".format(round(summary.mean()[0],3)))
St. deviation: {}".format(round(sqrt(summary.variance()[0]),3)))
            print ("
print ("
            print (" St. devlation: {} .format(round(sqtr(summary.variance()[0]),3)))
print (" Max value: {}".format(round(summary.max()[0],3)))
print (" Min value: {}".format(round(summary.min()[0],3)))
print (" Total value count: {}".format(summary.count()))
print (" Number of non-zero values: {}".format(summary.numNonzeros()[0]))
               Duration Statistics:
                Mean: 47.979
                St. deviation: 707.746
                Max value: 58329.0
                Min value: 0.0
                Total value count: 494021
                Number of non-zero values: 12350.0
             We are interested in preparing a classification system for attack/no attack or different attack types. This requires us to use label
             along with summary statistics and analyse data properly.
 In [8]: # Create a function to return a tuple with label as its zeroth index
            # and corresponding summary statistic as its first index.
def parse_kdd_label(line):
                 split = line.split(",")

# we will keep just numeric and logical values

# discard any string values
                 label = split[41]
symbolic_indexes = [1,2,3,41]
                 clean split = [item for i,item in enumerate(split) if i not in symbolic_indexes]
return (label, np.array([float(x) for x in clean_split]))
  In [9]: def summary_by_label(raw_data, label):
                 label_vector_data = raw_data.map(parse_kdd_label).filter(lambda x: x[0]==label)
return Statistics.colStats(label_vector_data.values())
 "warezmaster."]
 In [11]: label_summary_dict = {label:summary_by_label(raw,label) for label in label_list}
# Create a dictionary of key = label_list elements, value = corresponding summary statistics
```

n our case, the interesting part of the summary statistics comes from being able to get them through cyber attacks or "tags" types in our dataset. By doing so, we will be able to better characterize our dataset dependent variables based on the range of independent values of the values.

If we want to do something like this, we can filter the RDD containing the label as a key and a vector as a value. To do this, we only need to adjust our parse\_interaction function to return a tuple containing two elements.

```
In [11]: label summary_dict = {label:summary_by_label(raw,label) for label in label_list}
# Create a dictionary of key = label_list elements, value = corresponding summary statistics

In [13]: label = 'buffer_overflow.'
    print ("Duration Statistics for label : '" + label + "'")
    print ("Mean: {}".format(round(label_summary_dict[label].mean()[0],3)))
    print ("Max value: {}".format(round(sqrt(label_summary_dict[label].max()[0],3)))
    print ("Min value: {}".format(round(label_summary_dict[label].max()[0],3)))
    print ("Total value count: {}".format(label_summary_dict[label].count()))
    print ("Number of non-zero values: {}".format(label_summary_dict[label].numNonzeros()[0]))
    print()

Duration Statistics for label : 'buffer_overflow.'
    Mean: 91.7
    St. deviation: 97.515
    Max value: 321.0
    Min value: 0.0
    Total value count: 30
    Number of non-zero values: 22.0

In []:
```