The Dapper Squirrels

Using Spark GraphX

Spark and GraphFrames Set Up

```
# install java
!apt-get install openjdk-8-jdk-headless -qq > /dev/null

# install spark (change the version number if needed)
!wget -q https://archive.apache.org/dist/spark/spark-3.2.0/spark-3.2.0-bin-hadoop3.2.

# unzip the spark file to the current folder
!tar xf spark-3.2.0-bin-hadoop3.2.tgz

# set your spark folder to your system path environment.
import os
os.environ["JAVA_HOME"] = "/usr/lib/jvm/java-8-openjdk-amd64"
os.environ["SPARK_HOME"] = "/content/spark-3.2.0-bin-hadoop3.2"

# install findspark using pip
!pip install -q findspark

# install pyspark
!pip3 install pyspark==3.2.0

# install graphframes
!pip3 install graphframes
```

```
Requirement already satisfied: pyspark==3.2.0 in /usr/local/lib/python3.7/dist-p
Requirement already satisfied: py4j==0.10.9.2 in /usr/local/lib/python3.7/dist-p
Requirement already satisfied: graphframes in /usr/local/lib/python3.7/dist-pack
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: nose in /usr/local/lib/python3.7/dist-packages (f
```

Download the graphframes jar file from: [Graphframe jar file:]

Upload it in the Google Colab Files folder. Can be found in the left pane of this window.

```
!cp -v /content/graphframes-0.8.2-spark3.2-s_2.12.jar $SPARK_HOME/jars/
```

```
'/content/graphframes-0.8.2-spark3.2-s_2.12.jar' -> '/content/spark-3.2.0-bin-ha
```

```
#import the packages
from pyspark import *
from pyspark.sql import *
from graphframes import *
import findspark
import pandas as pd
import psycopg2
import networkx as nx
import matplotlib.pyplot as plt

findspark.init()

# Start a Spark session
spark = SparkSession.builder.master("local[*]").getOrCreate()
```

```
# access the postgresql server
conn = psycopg2.connect(
    host="codd04.research.northwestern.edu",
    port = "5433",
    database="postgres",
    user="cpdbstudent",
    password="DataSci4AI")
```

```
cursor = conn.cursor()
```

Question 1

Making nodes of officers and victims by their income, race, locations, and even unsupervised machine learning models to learn the cluster and see if there is a potential connection between officers and victims.

1.1 Learn the Connection from Race

Following query creates nodes and edges to answer the questions.

- **nodes**: race
- **edges**: src(officer id), dist(race) and relationship(complainat)

1.1.1 Graph Visualization Sample

In this section, we plot the visualized graph of the connection of the officer and the victim by race with part of the data.

Build GraphFrame

```
edges_query = "SELECT officer_id src, race dst,  count(data_complainant.allegation_id
```

```
nodes_query = "SELECT DISTINCT race id from data_complainant where not race ='';"
```

```
# query edges
cursor.execute(edges_query)
edges = cursor.fetchall()
df_edges = pd.DataFrame(edges)
colnames = [desc[0] for desc in cursor.description]
df_edges.columns = colnames
```

```
# quert nodes
cursor.execute(nodes_query)
nodes = cursor.fetchall()
print("shape is: " + str(len(nodes))) # 17465
df_nodes = pd.DataFrame(nodes)
colnames = [desc[0] for desc in cursor.description]
df_nodes.columns = colnames
```

```
shape is: 5
```

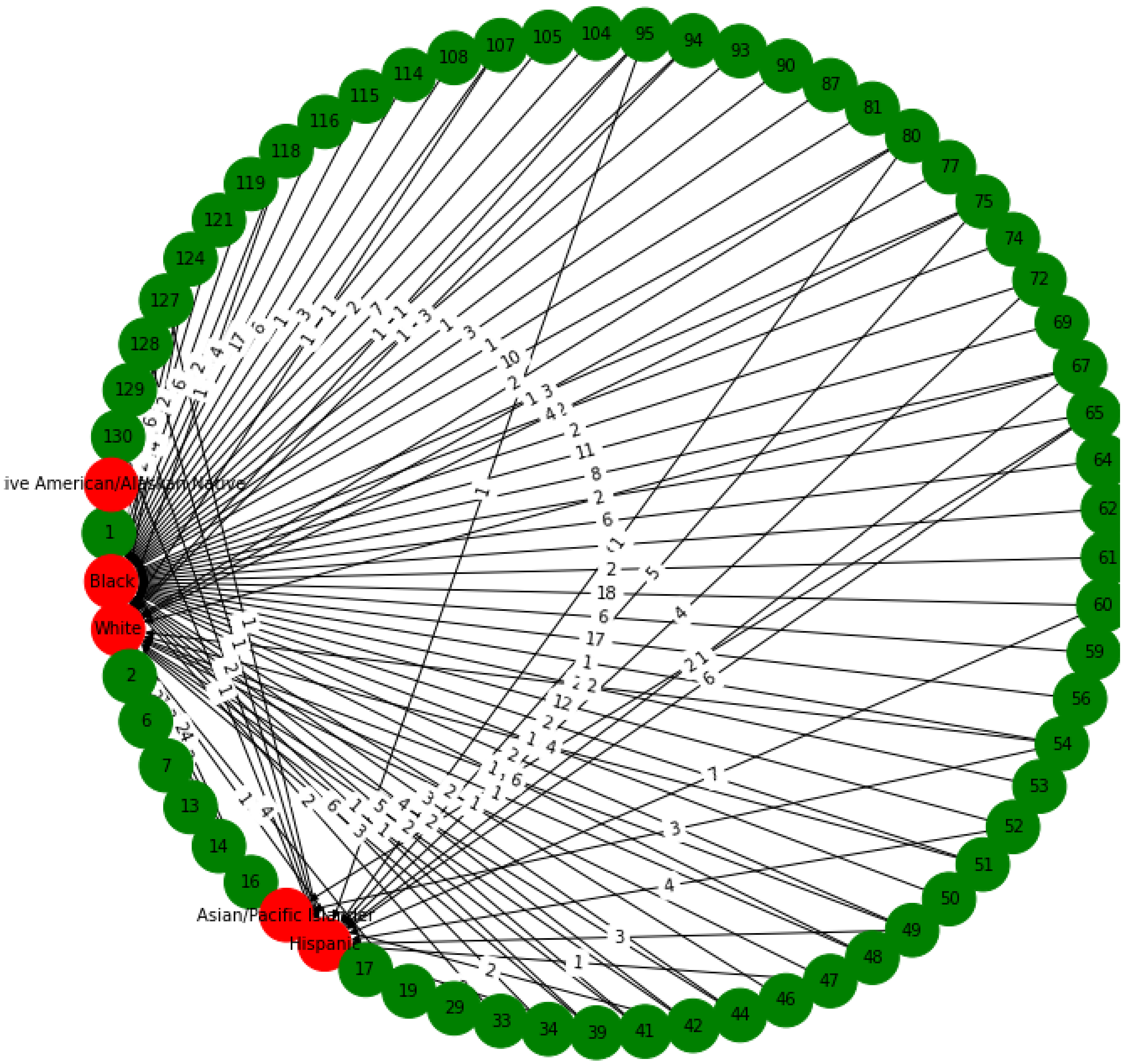
```
edges_ = spark.createDataFrame(df_edges)
nodes = spark.createDataFrame(df_nodes)
cpdb = GraphFrame(nodes, edges_)
```

```
edge_labels = []
edge_labels=dict([((row[0],row[1]),row[2])for i,row in df_edges.iterrows()])
gx = cpdb
g = nx.from_pandas_edgelist(df_edges, source='src', target='dst',edge_attr='relations
g.add_nodes_from(gx.vertices.toPandas()['id'])
color_map = ['red' if node in gx.vertices.toPandas()['id'].values else 'green' for no
pos = nx.shell_layout(g)
```

Plot

```
plt.figure(figsize=(10,10))
nx.draw(g, pos,with_labels=True, arrows = True,node_color = color_map,node_size=1000,
```

```
nx.draw_networkx_edge_labels(g, pos, edge_labels=edge_labels, label_pos=0.5, font_siz
plt.show()
```



Conclusion from graph

Since the graph is real huge, it is not possible to plot the whole graph here. However, we still can see there is tend that officers are more likely to offense black people in the sample graph. Therefore, we may find the potential connection between the victiom and the officer by the race with the whole data.

1.1.2 Graph Analysis on Race

Similarly, like the graph visualization, but we use all data now.

Build GraphFrame

```
edges_query = "SELECT officer_id src, race dst, data_complainant.allegation_id relati
nodes_query = "SELECT DISTINCT race id from data_complainant where not race ='';"
```

```
cursor.execute(edges_query)
edges = cursor.fetchall()
df_edges = pd.DataFrame(edges)
colnames = [desc[0] for desc in cursor.description]
df_edges.columns = colnames
```

```
cursor.execute(nodes_query)
nodes = cursor.fetchall()
df_nodes = pd.DataFrame(nodes)
colnames = [desc[0] for desc in cursor.description]
df_nodes.columns = colnames
```

```
edges_ = spark.createDataFrame(df_edges)
nodes = spark.createDataFrame(df_nodes)
cpdb = GraphFrame(nodes, edges_)
```

```
gx = cpdb
g = nx.from_pandas_edgelist(df_edges, source='src', target='dst',edge_attr='relations
g.add_nodes_from(gx.vertices.toPandas()['id'])
```

Graph Analysis

For this graph, inDegress is the number of CRs a complained by a race , and outDegrees is the number of Crs a officer recieved.

```
cpdb.inDegrees.sort(['inDegree'],ascending=[0]).show()
```

```
+--------------------+--------+
|                  id|inDegree|
+--------------------+--------+
|               Black|   67923|
|               White|   20519|
|            Hispanic|   12128|
|Asian/Pacific Isl...|     768|
|Native American/A...|     108|
+--------------------+--------+
```

```
cpdb.outDegrees.sort(['outDegree'],ascending=[0]).show()
```

```
+-----+---------+
|   id|outDegree|
+-----+---------+
|13937|       89|
|14442|       88|
|32159|       87|
| 3764|       86|
| 3605|       86|
|17613|       85|
|21098|       81|
|25898|       81|
|32164|       79|
|17647|       76|
| 8138|       76|
|27415|       75|
|16385|       75|
|10152|       75|
|32213|       75|
|31631|       74|
|32016|       74|
|31872|       74|
|31119|       73|
| 3897|       72|
+-----+---------+
only showing top 20 rows
```

1.1.3 Conclusion

We can find that the black community has a high volume of complaints. However, since the black people population is not extremely high in Chicago, we can assume there is a bias that may lead to over-policing.

We are not interested in the bias, this section is only used for proving our main theme, " Is there over-policing in low socio-eco status neighborhoods? " from a different aspect. There is more discussion in the following sections.

1.2 Learn the Connection from Location

Following query creates nodes and edges to answer the questions.

- **nodes**: community
- **edges**: src(officer name), dist(community name) and relationship(CRd/TRRd)

1.2.1 Graph Visualization Sample

In this section, we plot the visualized graph of the connection of the officer and the victim by the location with part of the data.

Build GraphFrame

```
edges_query = "SELECT d.name src, first_name || ' ' || last_name dst, count(*) relati
edges_query_1 = "SELECT  first_name || ' ' || last_name src,name dst, count(*) relati
nodes_query = "SELECT name id From data_area Where area_type = 'community';"
```

```
# query edge
cursor.execute(edges_query)
edges = cursor.fetchall()
cursor.execute(edges_query_1)
edges_1 = cursor.fetchall()
df_edges = pd.DataFrame(edges)
df_edges_1 = pd.DataFrame(edges_1)
df_edges = df_edges.append(df_edges_1)
colnames = [desc[0] for desc in cursor.description]
df_edges.columns = colnames
```

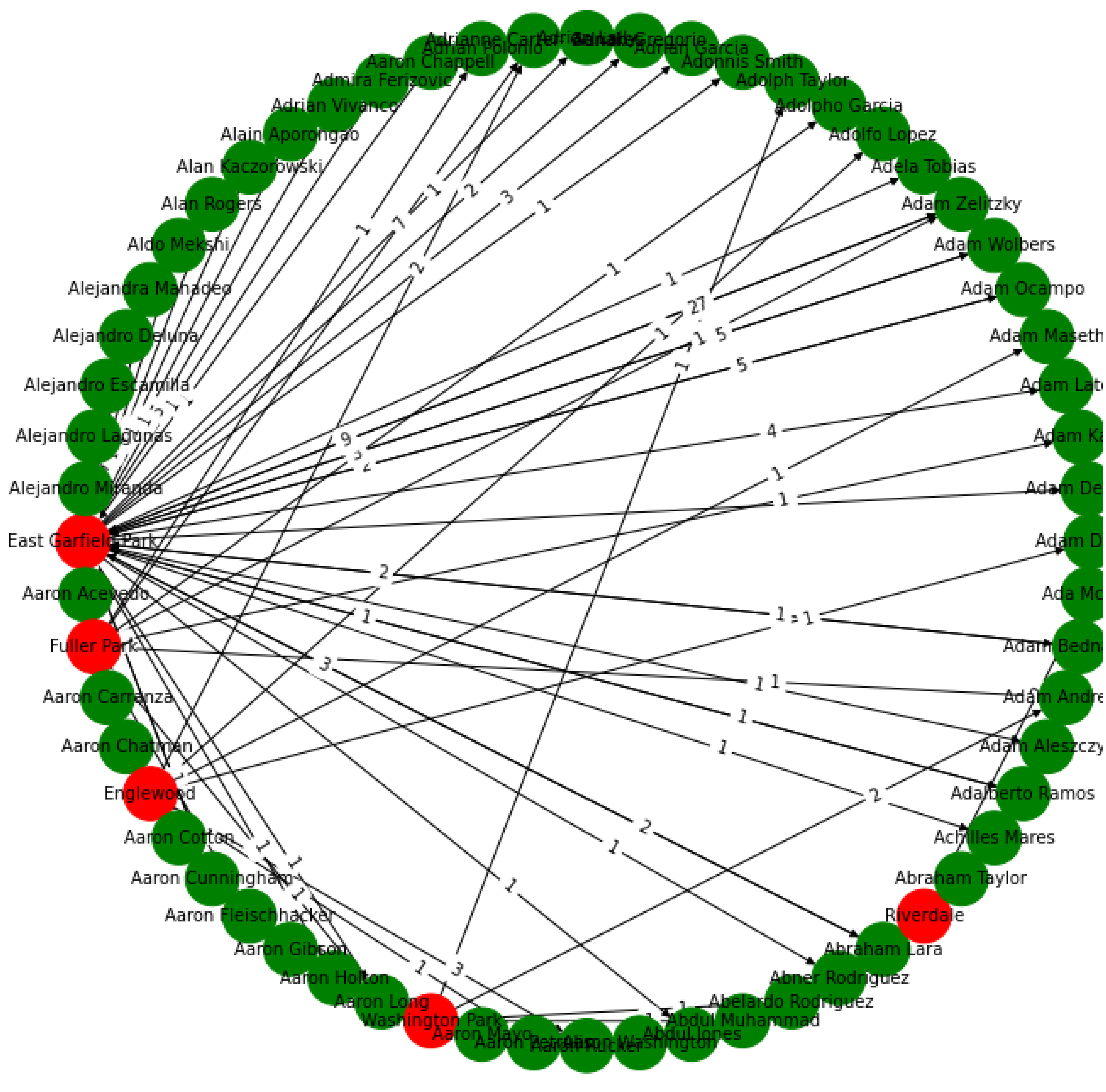
```
# query node
cursor.execute(nodes_query)
nodes = cursor.fetchall()
df_nodes = pd.DataFrame(nodes)
colnames = [desc[0] for desc in cursor.description]
df_nodes.columns = colnames
```

```
# creat GraphFram
edges_ = spark.createDataFrame(df_edges)
nodes = spark.createDataFrame(df_nodes)
cpdb = GraphFrame(nodes, edges_)
```

```
# edit edge label, color map...
edge_labels = []
edge_labels=dict([((row[0],row[1]),row[2])for i,row in df_edges.iterrows()])
gx = cpdb
g = nx.from_pandas_edgelist(df_edges, source='src', target='dst',edge_attr='relations
color_map = ['red' if node in gx.vertices.toPandas()['id'].values else 'green' for no
```

Plot

```
#plot
plt.figure(figsize=(10,10))
pos = nx.shell_layout(g)
nx.draw(g, pos,with_labels=True, arrows = True,node_color = color_map,node_size=1000,
nx.draw_networkx_edge_labels(g, pos, edge_labels=edge_labels, label_pos=0.3, font_siz
plt.show()
```



Conclusion from graph

Since the graph is really huge, it is not possible to plot the whole graph here. However, we still can see there is tend for officers to have more TRRs and CRs from some communities (East Garfield Park on this graph). Therefore, we may find the potential connection between the victims and the officer by the location.

1.2.2 Graph Analysis on Location

Similarly, like the graph visualization, but we use all data now.

Build GraphFrame

```
edges_query = "SELECT  d.name src, first_name || ' ' || last_name dst, d.id relations
nodes_query = "SELECT name id From data_area Where area_type = 'community';"
edges_query_1 = "SELECT  first_name || ' ' || last_name src,community_id dst,a.beat_i
```

```
cursor.execute(edges_query)
edges = cursor.fetchall()
print("shape is: " + str(len(edges))) # 17465


cursor.execute(edges_query_1)
edges_1 = cursor.fetchall()
print("shape is: " + str(len(edges_1))) # 17465

df_edges = pd.DataFrame(edges)
df_edges.loc[:,2] = 'CR'
df_edges_1 = pd.DataFrame(edges_1)
df_edges_1.loc[:,2] = 'TRR'
df_edges = df_edges.append(df_edges_1)
colnames = [desc[0] for desc in cursor.description]
df_edges.columns = colnames

df_edges.head(5)
```

```
shape is: 204806
shape is: 35648
```

	src	dst	relationship
0	West Pullman	Daniel Houlihan	CR

```
df_edges.tail(5)
```

	src	dst	relationship
35643	John Jankowski	West Garfield Park	TRR
35644	Anthony Brown	Austin	TRR
35645	Timothy Kinsella	East Garfield Park	TRR
35646	Pablo Guereca	Edgewater	TRR
35647	Allen Finley	Humboldt Park	TRR

```
edges_ = spark.createDataFrame(df_edges)
nodes = spark.createDataFrame(df_nodes)
cpdb = GraphFrame(nodes, edges_)
```

Graph Analysis

CRs:

> We can split the graph by its relationship between src and dst. For CRs, inDegress is the number of CRs an officer recieved, and outDegrees is the number of Crs a community complains.

```
cr = cpdb.filterEdges("relationship = 'CR'")
```

```
cr.inDegrees.sort(['inDegree'],ascending=[0]).show()
```

```
+----------------+--------+
|              id|inDegree|
+----------------+--------+
|      Joe Parker|     129|
|  Jerome Finnigan|     124|
|      Edward May|     114|
|  Charles Toussas|     114|
|     David Brown|     109|
|    Kevin Osborn|     108|
|  Maurice Clayton|     107|
|     Glenn Evans|     106|
|    Adam Zelitzky|     105|
```

```
|Jerome Turbyville|      99|
|     Robert Smith|      98|
|   Robert Johnson|      93|
|     James Grubbs|      93|
|      John Carney|      88|
|   Tyrone Jenkins|      87|
|  Gregory Jackson|      87|
|  Broderick Jones|      87|
|       Kevin Ryan|      85|
| Eugene Bikulcius|      85|
|    Edward Howard|      83|
+-----------------+--------+
only showing top 20 rows
```

```
cr.outDegrees.sort(['outDegree'],ascending=[0]).show()
```

```
+--------------------+---------+
|                  id|outDegree|
+--------------------+---------+
|              Austin|    10470|
|      West Englewood|     7979|
|                Loop|     7927|
|      Near West Side|     7411|
|     Near North Side|     7327|
|      Auburn Gresham|     6009|
|       Humboldt Park|     5760|
|      North Lawndale|     5503|
|           Englewood|     5360|
|           West Town|     5267|
|         South Shore|     4932|
|  East Garfield Park|     4900|
|            New City|     4891|
|            Roseland|     4763|
|        Chicago Lawn|     4741|
|        Logan Square|     4368|
|           Lake View|     4114|
|Greater Grand Cro...|     4088|
|              Uptown|     3833|
|            Woodlawn|     3752|
+--------------------+---------+
only showing top 20 rows
```

TRRs:

> We can split the graph by its relationship between src and dst. For TRRs, inDgress is the number of TTRs happen in the community, and outDegrees is the number of TRRs an officer has.

```
trr = cpdb.filterEdges("relationship = 'TRR'")
```

```
trr.edges.show()
```

```
+------------------+----------------+------------+
|               src|             dst|relationship|
+------------------+----------------+------------+
|     Michael Jacob|     Rogers Park|         TRR|
| Agustin Cervantes|        Avondale|         TRR|
|       Walter Ware|  North Lawndale|         TRR|
|        John Flisk|  North Lawndale|         TRR|
|     David Morales|  North Lawndale|         TRR|
|Demosthen Balodimas|  Belmont Cragin|         TRR|
|   Timothy Gilbert|East Garfield Park|         TRR|
|      Thomas Davey|  Near West Side|         TRR|
|    Brian Ferguson|   Humboldt Park|         TRR|
|      Paul Meagher|          Austin|         TRR|
|     Kent Erickson|          Uptown|         TRR|
|     Martin Teresi|         Beverly|         TRR|
|     Raymond Wilke|         Beverly|         TRR|
|  Nicolas Chapello|     Irving Park|         TRR|
|    Kerry Mc Guire|     Irving Park|         TRR|
|  Michael Leverett|East Garfield Park|         TRR|
|      Jeffrey Zwit|East Garfield Park|         TRR|
|   Timothy Gilbert|East Garfield Park|         TRR|
|      Joseph Simon|   Humboldt Park|         TRR|
|    Slawomir Plewa|   Humboldt Park|         TRR|
+------------------+----------------+------------+
only showing top 20 rows
```

```
trr.inDegrees.sort(['inDegree'],ascending=[0]).show()
```

```
+-----------------+--------+
|               id|inDegree|
+-----------------+--------+
|           Austin|    5721|
|    Humboldt Park|    2848|
|West Garfield Park|    2622|
|   South Lawndale|    2230|
|   North Lawndale|    2092|
|  Near North Side|    1721|
|   Near West Side|    1648|
|        West Town|    1607|
|East Garfield Park|    1502|
|   Belmont Cragin|    1064|
|        Lake View|    1033|
|      Rogers Park|     928|
|       North Park|     771|
|     Lincoln Park|     765|
|     Logan Square|     760|
|       West Ridge|     757|
|     Norwood Park|     747|
|           Uptown|     703|
|        Edgewater|     576|
```

```
|       Albany Park|     520|
+------------------+--------+
only showing top 20 rows
```

1.2.3 Conclusion

We can conclude that communities like Austin, West Englewood, and Loop have a high volume of complaint report to officers, and Austin, Humboldt Park, and West Garfield Park have a large amount of TRRs. From this result we can find in the high-income community, people are more likely to complain about the behavior of the police. People from low-income communities receive more "threats" of tactical response. One possible explanation is that people who live in high-income communities have time to report the misbehavior of over-policing officers. But in the low-income community, people have no power to against the over-policing. Anyway, a high amount of reports of tactical response shows that there is potential over-policing behavior in those areas. Combining with the result we find in Checkpoint 1, a community like West Garfield Park is a low-income area. Therefore, we can assume that there is over-policing in the socio-economy status community.

Question 2

Network dynamics of co-accused in each cohort can be interesting. The analytics can be done with the following:

1. Make use of Triangle Count Algorithms for each cohort.
2. Make use of the Page Rank Algorithm to find the most connected officer in all cohorts.
3. How many CRs that officers have and how many co-accused for each cohort.
4. Compare the top k largest cohort of police officers in high and low socio-economy status.

Following query creates nodes and edges to answer the questions for co-accused allegations.

1. Who among the officers have the most triangle counts?
2. Who have the most page rank score?
3. Are there any communities in the officers?
4. What are the allegation reports number for those officers inside a cluster?
5. What are the top large cohort of police officers in high and low socio-economy status?

This is how we define the nodes and edges for the graph.

- **nodes**: id, officer name and allegation count
- **edges**: src(officer1 id), dist(officer2 id) and relationship(allegation count)

These queries are to draw co-accussed officers from allegation database. Basic logic is to join the allegation table with itself on the condition of the same allegation id and unequal officerid.

Nodes can be generated with data_officer table or allegation id by counting the number of allegation id. Here we chose data_officer table by removing Nan or 0s on allegation_count.

Note: These queries are copied and modified from the GraphX demo class, which shares similar analysis goal as us.

2.1 Community finding by Label propagation

Build GraphFrame

```
edges_query = "SELECT da1.officer_id src, da2.officer_id dst, COUNT(DISTINCT da1.alle
```

```
nodes_query = "SELECT  id, first_name || ' ' || last_name officer_name, allegation_co
```

```
cursor.execute(edges_query)
edges = cursor.fetchall()
df_edges = pd.DataFrame(edges)
colnames = [desc[0] for desc in cursor.description]
df_edges.columns = colnames
```

```
cursor.execute(nodes_query)
nodes = cursor.fetchall()
df_nodes = pd.DataFrame(nodes)
colnames = [desc[0] for desc in cursor.description]
df_nodes.columns = colnames
```

```
edges_ = spark.createDataFrame(df_edges)
nodes = spark.createDataFrame(df_nodes)
cpdb = GraphFrame(nodes, edges_)
```

Label propagation algorithm is helpful to us for finding communities in officers. It is a semi-supervised algorithm which starts with a subset of labeled nodes and propagate the labels to unlabled data. After several iterations, all data are labeled and form a group of communities.

The first step here is to run the algorithm by calling the API. We have also presented the output here with a new column called label here to indicate the comminity id for all the nodes. Also, we

found over 2,800 different comminities, which indicates the frequently-seen co-accused sceneario.

Note: These code are copied and modified from the GraphX demo class, which shares similar

```
communities = cpdb.labelPropagation(maxIter=20)
communities.persist().show(20)
print (f"There are {communities.select('label').distinct().count()} communities in th
```

```
+----+----------------+----------------+-----+
|  id|    officer_name|allegation_count|label|
+----+----------------+----------------+-----+
|  29|    Henry Abrams|               6| 6534|
| 474|Ignacio Alvarado|               7|28838|
| 964|  Colleen Austin|               6| 3744|
|1677|    Chad Behrend|              25|17372|
|1950|    Thomas Beyna|              22|  442|
|2214|    Calvin Blunt|              21|28273|
|2250|Kathleen Boehmer|               2|17372|
|2453|   Joseph Boston|              59|28838|
|2509|  Rosalind Bowie|              14|32382|
|2529|     Emmett Boyd|              11|12644|
|3091|  Michael Browne|               9|32041|
|3506|John Butterfield|               1| 3506|
|3764|   Sean Campbell|              90|28838|
|4894|Danyelle Cochran|               1| 4894|
|5385|  Gerald Corless|               2|27851|
|5409|  Rodolfo Corona|               4|17372|
|5556| Ramon Covington|               6|11980|
|7225|     Judy Dotson|               2| 7225|
|7279| Terrence Downes|               6|17372|
|7747|     Donald Eddy|               4| 7747|
+----+----------------+----------------+-----+
only showing top 20 rows

There are 2809 communities in this sample graph.
```

Recognising the largest comminites are important. So we ranked the label propagtion algorithm result by sorting descendingly the number of members in the commnity.

```
communities.select('label').groupby('label').count().sort(['count'],ascending=False).
```

```
+-----+-----+
|label|count|
+-----+-----+
|17372| 8316|
| 3744| 1636|
|29511| 1224|
|11980|  652|
|28273|  596|
|28838|  450|
|32014|  364|
```

```
|32068|  323|
|32382|  257|
|26622|  257|
|13631|  256|
|14106|  243|
|32274|  211|
|32041|  207|
| 6534|  187|
|18915|  186|
|23787|  173|
| 2981|  162|
|21912|  155|
|23033|  115|
+-----+-----+
only showing top 20 rows
```

```
cpdb_com = GraphFrame(communities, edges_)
```

After identifying those top big communities, we are also interested in how the community are contructed and their internal architecture.

We plotted the 22809 community which is consisted of over 50 nodes. It is clear to us that officer 2612, 30237, and 21028 are among those "leading" nodes with multiple indegree and outdegrees inside the clique.

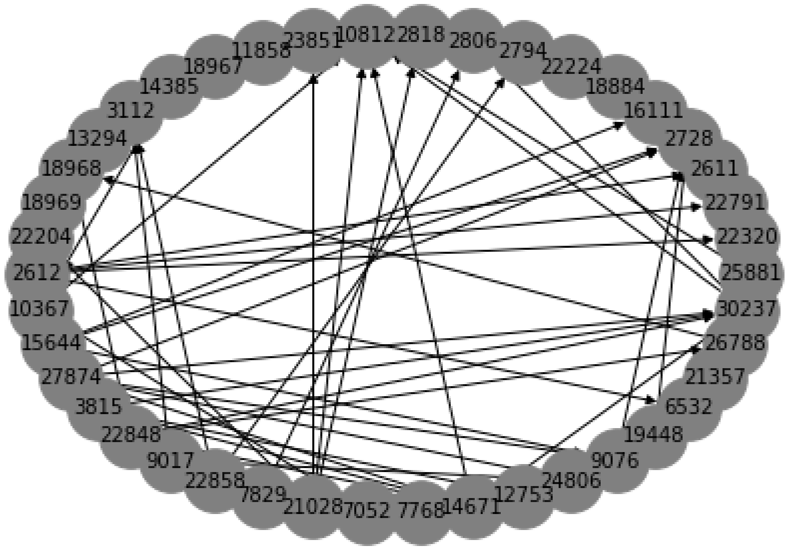
```
cpdb_com1 = cpdb_com.filterVertices("label = 22809").dropIsolatedVertices()
```

```
def plot_graph(gx):
    g = nx.DiGraph(directed = True)

    g = nx.from_pandas_edgelist(gx.edges.toPandas(),'src','dst')
    g.add_nodes_from(gx.vertices.toPandas()['id'])

    nx.draw_shell(g, with_labels=True, arrows = True, node_color='grey', node_size=10
```

```
plot_graph(cpdb_com1)
```



2.2 Triangle Count analysis

Triangle counting algorithm is to count the triangle like relationship among 3 nodes which have connected in pairs. We want to find out those outstanding nodes in the graph which have a lot more triangle counts.

```
tc_cpdb = cpdb.triangleCount()
tc_cpdb.select("id", "count").show()
```

```
+-----+-----+
|   id|count|
+-----+-----+
|33748|    0|
|33751|    0|
|33724|    0|
|33798|    0|
|33755|    0|
|33746|    0|
|33749|    0|
|33737|    0|
|33725|    0|
|33738|    0|
|33728|    0|
|33752|    0|
|33711|    0|
|33723|    0|
|33750|    0|
|32312|   37|
|32358|  109|
```

```
|33753|    0|
|33758|    0|
|33709|    0|
+-----+-----+
only showing top 20 rows
```

In this part, we sorted all the nodes according to their triangle counts. We can see over 20 nodes appearing in over 18,000 triangle relationships, which indicates strong community leader potential like officer 6315 and 3033.

```
tc_cpdb.sort(['count'],ascending=False).show()
```

```
+-----+-----+-----------------+---------------+
|count|   id|     officer_name|allegation_count|
+-----+-----+-----------------+---------------+
|32118| 6315|    Terence Davis|             38|
|32117| 3033|   Raimondo Brown|             17|
|32073| 3744|   Derek Campbell|              8|
|27855|18042|    Donald Mc Coy|             22|
|27823|  441|  Fernando Alonzo|             16|
|23900|21530|Michael Overstreet|             56|
|23518|27349|  Charles Stanton|             11|
|23499| 5180|   Stephen Conner|              9|
|23487| 5667|    Jerry Crawley|             30|
|23477|16747|    Evetta Lundin|              7|
|23475| 8844|     Thomas Flynn|             19|
|23472|23654|       Lloyd Reid|              4|
|23472|14750|  William Kissane|             23|
|20185|19856|  Ronald Muhammad|             11|
|19322| 8138|      Glenn Evans|            132|
|18773|29882|      Fred Waller|             49|
|18648|28273|     James Taylor|             36|
|18602|28459|    Curtis Thomas|             36|
|18539| 5577|      Michael Cox|             20|
|18502|30841|  Teresa Williams|             37|
+-----+-----+-----------------+---------------+
only showing top 20 rows
```

2.3 Page Rank analysis to find key nodes

Page rank algorithm is developed to find out important nodes inside a graph by iterations of calculations of the possiblities to get to the node by starting randomly.

```
pr_cpdb = cpdb.pageRank(resetProbability=0.15, tol=0.01)
#look at the pagerank score for every vertex
pr_cpdb.vertices.orderBy('pagerank', ascending=False).show()
```

```
+-----+-----------------+---------------+------------------+
|   id|     officer_name|allegation_count|          pagerank|
+-----+-----------------+---------------+------------------+
|32442|      John Zinchuk|             23|127.52903862900281|
|32440|       Mark Zawila|             34| 90.32581504596747|
|32425|    Perry Williams|             27| 75.93393690155354|
|32350|    Robert Spiegel|             20| 72.52408784740014|
|32410|     Joseph Watson|             29|  71.8959609008098|
|32430|    Michael Wrobel|             22|  70.6024730642657|
|32074|    Ronald Jenkins|             46| 70.26504490198167|
|32284|         Mark Reno|             76| 68.44254003101547|
|32351|  Boonserm Srisuth|             25| 66.23218732944623|
|32433|     Kenneth Yakes|             29| 63.74966193544296|
|32419|         Eric Wier|             18| 60.25243358901534|
|32384|     Edwin Utreras|             47| 59.71305480353141|
|32435|    Mohammad Yusuf|             22| 59.31175673367685|
|32413| Carl Weatherspoon|             69|58.047513284732524|
|32337|       Louis Silva|             21| 57.93147265165182|
|32431|     Albert Wyroba|             15|57.773544505418506|
|32289|       John Rivera|             44|56.566183401162725|
|32401|    Joshua Wallace|             45| 55.97258828063104|
|32375|James Triantafillo|             31| 50.60713162542214|
|32436|   Edmund Zablocki|             28| 48.62194138740303|
+-----+-----------------+---------------+------------------+
only showing top 20 rows
```

From the above calculations, we can identify officers with sigificant impact in the graph. For example, officer 32442 and 32440 are major part in the clique and may be the "bad apple" in the organization.

2.4 The Corelation Between Police Cohort and CRs/TRRs

In this section, each police are counted for the time they had the same allegation with other police officers. The counted number will then be compared with the CRs and TRRs they gave and received to find the correlation between them. The goal of the correlation is to find whether police officers are more likely to misconduct when working as a group.

Build GraphFrame

```
edges_query = "SELECT  d.name src, first_name || ' ' || last_name dst, d.id relations
nodes_query = "SELECT name id From data_area Where area_type = 'community';"
edges_query_1 = "SELECT  first_name || ' ' || last_name src,community_id dst,a.beat_i
```

```
cursor.execute(edges_query)
edges = cursor.fetchall()
```

```
cursor.execute(edges_query_1)
edges_1 = cursor.fetchall()
df_edges = pd.DataFrame(edges)
df_edges.loc[:,2] = 'CR'
df_edges_1 = pd.DataFrame(edges_1)
df_edges_1.loc[:,2] = 'TRR'
df_edges = df_edges.append(df_edges_1)
colnames = [desc[0] for desc in cursor.description]
df_edges.columns = colnames
```

```
edges_ = spark.createDataFrame(df_edges)
nodes = spark.createDataFrame(df_nodes)
cpdb = GraphFrame(nodes, edges_)
```

Graph Analysis

```
cr = cpdb.filterEdges("relationship = 'CR'")
```

```
trr = cpdb.filterEdges("relationship = 'TRR'")
```

```
trr_out=trr.outDegrees.sort(['outDegree'],ascending=[0]).toPandas()
cr_in = cr.inDegrees.sort(['inDegree'],ascending=[0]).toPandas()
```

```
officer_id = """SELECT DISTINCT first_name || ' ' || last_name id, officer_id officer
    WHERE trr_trr.officer_id = data_officer.id"""

cursor.execute(officer_id)
officer = cursor.fetchall()
df_officer = pd.DataFrame(officer)
df_officer.columns =['id', 'officer_id']
```

```
misconduct = pd.merge(cr_in, trr_out, how="left", on="id").fillna(0)
misconduct = pd.merge(misconduct, df_officer, how = "left", on = "id")
misconduct["cohart count"] = None
misconduct
```

	id	inDegree	outDegree	officer_id	cohart count
0	Joe Parker	129	0.0	21837.0	None
1	Jerome Finnigan	124	1.0	8562.0	None
2	Edward May	114	2.0	17816.0	None
3	Charles Toussas	114	0.0	NaN	None
4	David Brown	109	0.0	3005.0	None
...	...	...	...	...	...
21811	Ronald Trublar	1	0.0	NaN	None

```
same_case = "SELECT da1.officer_id src, da2.officer_id dst, COUNT(DISTINCT da1.allega

cursor.execute(same_case)
case = cursor.fetchall()
df_case = pd.DataFrame(case)
df_case.columns =['member1', 'member2', 'co-case count']
df_case.head(5)
```

	member1	member2	co-case count
0	12478	32166	53
1	8562	27778	47
2	1553	10724	43
3	2725	21703	41
4	3605	14442	41

```
cohart_count = []
for officer_id in misconduct["officer_id"]:
  if officer_id > 0:
    cohart_count.append(len(df_case["member1"][df_case["member1"] == int(officer_id)]
  else:
    cohart_count.append(0)
misconduct["cohart count"] = cohart_count
misconduct
```

	id	inDegree	outDegree	officer_id	cohart count
0	Joe Parker	129	0.0	21837.0	27
1	Jerome Finnigan	124	1.0	8562.0	119
2	Edward May	114	2.0	17816.0	86
3	Charles Toussas	114	0.0	NaN	0
4	David Brown	109	0.0	3005.0	9
...	...	...	...	...	...
21811	Ronald Trublar	1	0.0	NaN	0
21813	Anthony Alviani	1	0.0	NaN	0

21816 rows × 5 columns

```
correlation_cr = misconduct["cohart count"].corr(misconduct["inDegree"])
correlation_trr = misconduct["cohart count"].corr(misconduct["outDegree"])
```

```
correlation_cr
```

```
0.4151983851569962
```

```
correlation_trr
```

```
0.21054139647875614
```

Conclusion

The correlation between group allegation and complaint reports is positively correlated, and the group allegation is less correlated to tactical response reports. It is possible that when police officers are co-accused, they are more likely to have actual misconduct activity. It is because if they gave more tactical responses than receive complaints, or if they have a fairly equal amount of tactical responses and complaints, they would be less likely to have misconduct.