

Report on NFT Graph Data Analytics
CS 5413 Assignment 2

Project by Program 1 1(Group 1)

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Query 4:

The directed acyclic graph of buyer IDs will provide a visualization of the NFT transaction history. The directed edges between buyers will show the changes of ownership of the NFT, and the weights assigned to these edges will correspond to the prices paid for the NFT. The time tags associated with each buyer vertex will provide information on when the NFT transaction occurred, allowing for an analysis of the NFT market over time. This graph can also be used to draw conclusions about the behavior of individual buyers, such as which buyers are consistently paying higher prices or buying more NFTs. The resulting graph would represent the history of ownership of the NFT and the prices it has been sold for over time. Each vertex would represent the buyer ID of the current owner, and the edges would represent the transfer of ownership from one buyer to another. The weight associated with each edge would represent the price of the NFT at the time of the transfer. The time tag associated with each vertex would represent the time of the transfer. This graph could be used to analyze the history and trends in the price of the NFT over time as well as the buyers that have held the NFT.

Language Used: Python

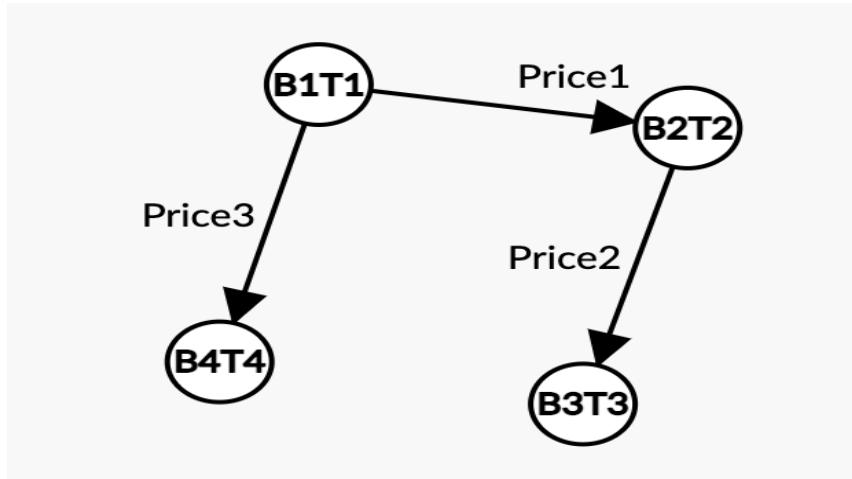
Input:

Give the input file as CSV which contains 92000 records.

Output:

Graph is generated as output which contains vertices as buyerID+UnixTimestamp and edges are built based on weights of transaction price for the buyers that are connected with token ID and NFT.

Expected output Graph:



Above is the sample graph for four buyers B1,B2,B3 and B4 with timestamps T1,T2,T3 and T4 respectively. Edge is constructed with transactions for NFT and token ID between two buyers.

Let's take B1=0x4549134864309380066061298379900077840065 (T1 = 1656633600, Price1=\$153.41)

B2 = 0x4750005827061159635699214683919627949761 (T2 = 1656633603, Price2=\$150.25)

B3 = 0x4090364571928113795646788656182272897496, (T3 = 1656633619, Price3=\$26.45)

B4 = 0x9923603659285563429655320278029540680998 (T4 = 1656633639, Price4 = \$6.77)

For all the edges above, price1, price2, Price3 and price4 are the weights of edges. NFT and Token ID for above edges are WizNFT and 648 respectively. NFT and token ID will be the same for all the edges since they are connected with each other.

Expected output Adjacency List:

```

["0x4549134864309380066061298379900077840065", "0x4750005827061159635699214683919627949761", "0x4090364571928113795646788656182272897496", "0x9923603659285563429655320278029540680998"], [{"source": "0x4549134864309380066061298379900077840065", "target": "0x4750005827061159635699214683919627949761", "weight": 153.41}, {"source": "0x4549134864309380066061298379900077840065", "target": "0x4090364571928113795646788656182272897496", "weight": 26.45}, {"source": "0x4549134864309380066061298379900077840065", "target": "0x9923603659285563429655320278029540680998", "weight": 6.77}, {"source": "0x4750005827061159635699214683919627949761", "target": "0x4090364571928113795646788656182272897496", "weight": 150.25}, {"source": "0x4750005827061159635699214683919627949761", "target": "0x9923603659285563429655320278029540680998", "weight": 150.25}, {"source": "0x4090364571928113795646788656182272897496", "target": "0x9923603659285563429655320278029540680998", "weight": 150.25}], [{"source": "0x4549134864309380066061298379900077840065", "target": "0x4750005827061159635699214683919627949761", "weight": 153.41, "nft": "WizNFT", "token_id": 648}, {"source": "0x4549134864309380066061298379900077840065", "target": "0x4090364571928113795646788656182272897496", "weight": 26.45, "nft": "WizNFT", "token_id": 648}, {"source": "0x4549134864309380066061298379900077840065", "target": "0x9923603659285563429655320278029540680998", "weight": 6.77, "nft": "WizNFT", "token_id": 648}, {"source": "0x4750005827061159635699214683919627949761", "target": "0x4090364571928113795646788656182272897496", "weight": 150.25, "nft": "WizNFT", "token_id": 648}, {"source": "0x4750005827061159635699214683919627949761", "target": "0x9923603659285563429655320278029540680998", "weight": 150.25, "nft": "WizNFT", "token_id": 648}, {"source": "0x4090364571928113795646788656182272897496", "target": "0x9923603659285563429655320278029540680998", "weight": 150.25, "nft": "WizNFT", "token_id": 648}], [{"id": "0x4549134864309380066061298379900077840065", "label": "B1T1", "x": 300, "y": 100}, {"id": "0x4750005827061159635699214683919627949761", "label": "B2T2", "x": 500, "y": 150}, {"id": "0x4090364571928113795646788656182272897496", "label": "B3T3", "x": 500, "y": 250}, {"id": "0x9923603659285563429655320278029540680998", "label": "B4T4", "x": 300, "y": 200}], [{"source": "0x4549134864309380066061298379900077840065", "target": "0x4750005827061159635699214683919627949761", "label": "Price1"}, {"source": "0x4549134864309380066061298379900077840065", "target": "0x4090364571928113795646788656182272897496", "label": "Price3"}, {"source": "0x4750005827061159635699214683919627949761", "target": "0x4090364571928113795646788656182272897496", "label": "Price2"}, {"source": "0x4549134864309380066061298379900077840065", "target": "0x9923603659285563429655320278029540680998", "label": "Price4"}]

```

From the above adjacency list, we can see that two vertices (buyer ID's) are connected with an edge of weight as transaction price with respective token ID, timestamp and price.

Adjacency matrix for the graph:

1	0x4549134864309380066061298379900077840065	0x4750005827061159635699214683919627949761	0xe3502772cd69f996a82429b5a86c2f397c450f47	0x7733912017670140619997752984250877318849
2	0.0	0.14201	0.0	0.0
3	0.0	0.0	0.205	0.0
4	0.0	0.0	0.0	0.28
5	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	0.0
10	0.0	0.0	0.0	0.0
11	0.0	0.0	0.0	0.0
12	0.0	0.0	0.0	0.0
13	0.0	0.0	0.0	0.0
14	0.0	0.0	0.0	0.0
15	0.0	0.0	0.0	0.0
16	0.0	0.0	0.0	0.0
17	0.0	0.0	0.0	0.0
18	0.0	0.0	0.0	0.0
19	0.0	0.0	0.0	0.0

Above image represents the adjacency matrix with rows and columns as buyers ID's and the corresponding values as the price of the transactions. '0' represents that there is no edge between two corresponding buyers.

Time taken to run the code:

```
mukarram@Mohammeds-Air-3 DS-2-assignment2 % python3 query_4.py
Enter the File path for the CSV input file. Ex: /home/Bob/Desktop/example.txt. The current directory is /Users/mukarram/DS-2-Final/DS-2-assignment2
nft_dataset.csv
Entered File path is nft_dataset.csv
The file exists

Starting the code

Creating the graph
The time of execution for generating the graph is: 115518133000 nano seconds
```

Time taken for generating the graph is 115518133000 nanoseconds.

Approach:

- We considered each vertex to be Buyer ID and respective timestamp to make the vertices unique.
- Edges are formed from buyer B1 to buyer B2 if only if there was a transaction taking place and change in ownership of NFT and token ID from B1 to B2. The weight of the edge will be the price of the transaction paid by the current buyer at that timestamp.
- We considered NFT and token ID should be present in common for an edge to be formed where ownership of NFT and token ID would be transferable at their respective timestamp.
- By considering token ID along with NFT, we should be able to track the buyers who are responsible for doing the price manipulation for a specific NFT.

- The buyers which do not have change of ownership of NFT will not form an edge and hence we give the value as ‘0’ to them.

Algorithm for Graph:

- Read the input csv file with 92000 records.
 - Take NFT, Token ID and Buyer ID in a list.
 - Convert the prices of NFT into dollars
- ```
do get_final_price(price) //conversion of currency
```
- While (buyer ID+Timestamp)
- Price = TransactionPrice(Buyer1\_Timestamp1)

```
#storing the data based on timestamp
while i<len(input) - 1:
 temp = []
 tempnft = []
 j = i+1

 #converting the NFT price to dollars
 price = get_final_price(input[i][9])
 temp.append([str(input[i][4])+str(input[i][1]), input[i][6], price, input[i][2]])
 while(input[i][1] == input[j][1] and j < len(input)-1):
 price = get_final_price(input[j][9])
 temp.append([str(input[j][4])+str(input[i][1]), input[j][6], price, input[j][2]])
 j += 1
 data[input[i][1]] = temp
 i = j
m = 0

#checking for similar token IDs:
while m < len(tokenID):
 nft = tokenID[m]
 buyerlist = []
 for key, value in data.items():
 for i in range(0, len(value)):
 if nft == value[i][1] and any(value[i][0] in sublist for sublist in buyerlist) == False:
 buyerlist.append([value[i][0], value[i][2], value[i][1], value[i][3]])
 k = 0
 l = 1
 while k < len(buyerlist) and l < len(buyerlist):
 graph.add_edge(buyerlist[k][0], buyerlist[l][0], weight = buyerlist[l][1])
 outputdict.append([buyerlist[k][0], buyerlist[l][0], buyerlist[l][1], buyerlist[l][3], buyerlist[l][2]])
 k = l
 l += 1
 m += 1
```

### **Images for Input and Output:**

#### **Input Format:**

```
mmukarr@csx1:~/DS2/Assignment2$ python3 query_4.py
Enter the File path for the CSV input file. Ex: /home/Bob/Desktop/example.txt. The current directory is /home/mmukarr/DS2/Assignment2
nft_dataset.csv
Entered File path is nft_dataset.csv
The file exists
```

## Output Format:

```
('0x45913486438938006661298379900077840651656633680', '0x9637034171505332254973493305663776810661657844314', '->', ['price': 161.12631, 'Date Time': '7/15/2022 0:18', 'Token ID': '648.0']),
('0x9637034171505332254973493305663776810661657844314', '0x332084239499128657223646787457982221657929867', '->', ['price': 584.33845, 'Date Time': '7/16/2022 0:04', 'Token ID': '648.0']),
('0x3208423934974128657223646787457982221657929867', '0x249487819724863817982134553494974834165834968', '->', ['price': 6.54985, 'Date Time': '7/23/2022 0:09', 'Token ID': '648.0']),
('0x249487819724863817982134553494974834165834968', '0x24158624593208011345984887189472870888781659853894', '->', ['price': 3.92991, 'Date Time': '7/29/2022 0:18', 'Token ID': '648.0']),
('0x24158624593208011345984887189472870888781659853894', '0x71855769349268668135215362846598588621659572259', '->', ['price': 7.294835, 'Date Time': '8/4/2022 0:17', 'Token ID': '648.0']),
('0x71855769349268668135215362846598588621659572259', '0x187278148919371778746583783767877821659572451', '->', ['price': 1152.7756, 'Date Time': '8/10/2022 0:14', 'Token ID': '648.0']),
('0x187278148919371778746583783767877821659572451', '0x85927493311774681925973181569792434687816409895893', '->', ['price': 34.05221999999999, 'Date Time': '8/12/2022 0:07', 'Token ID': '648.0']),
('0x85927493311774681925973181569792434687816409895893', '0x8502781303848125911834976659846158121657166262867', '->', ['price': 7.85982, 'Date Time': '8/17/2022 0:18', 'Token ID': '648.0']),
('0x8502781303848125911834976659846158121657166262867', '0x4628386110284643537174648868269440954851669655805', '->', ['price': 1.792961, 'Date Time': '8/23/2022 0:05', 'Token ID': '648.0']),
('0x4628386110284643537174648868269440954851669655805', '0x286976465489937853718493122659652765166121317', '->', ['price': 18.33958, 'Date Time': '8/27/2022 0:25', 'Token ID': '648.0']),
('0x286976465489937853718493122659652765166121317', '0x726973997385371593933836797217656891661559988', '->', ['price': 25.61665, 'Date Time': '8/30/2022 0:17', 'Token ID': '648.0']),
('0x726973997385371593933836797217656891661559988', '0x8511935130389778185158864423427579898164326511', '->', ['price': 1.35758, 'Date Time': '9/1/2022 0:05', 'Token ID': '648.0']),
('0x8511935130389778185158864423427579898164326511', '0xc9ff14ad577077554c5b27fffa3348a47b0b8163632587', '->', ['price': 36.238193, 'Date Time': '9/20/2022 0:09', 'Token ID': '648.0']),
('0xc9ff14ad577077554c5b27fffa3348a47b0b8163632587', '0x88686294197744648981034880983788689276165669521692', '->', ['price': 1519.5652, 'Date Time': '9/15/2022 0:01', 'Token ID': '6853.0']),
('0x88686294197744648981034880983788689276165669521692', '0x356617944516923511278978321812313583361661361514', '->', ['price': 26.1994, 'Date Time': '8/25/2022 0:09', 'Token ID': '6853.0']),
('0x356617944516923511278978321812313583361661361514', '0x8337826823911229362286784451319958424831663719131', '->', ['price': 91.6979, 'Date Time': '9/21/2022 0:12', 'Token ID': '6853.0']),
('0x8337826823911229362286784451319958424831663719131', '0x845224045768569217924653179187141605421565226357', '->', ['price': 36.6646603880880005, 'Date Time': '8/28/2022 0:08', 'Token ID': '3012.0']),
('0x845224045768569217924653179187141605421565226357', '0x2142810665924420439494417568337584653161659312876', '->', ['price': 20.43515800000001, 'Date Time': '8/31/2022 0:07', 'Token ID': '3012.0']),
('0x2142810665924420439494417568337584653161659312876', '0x44144.0435158000000001, 'Date Time': '8/1/2022 0:01', 'Token ID': '3012.0']),
('0x44144.0435158000000001, '0x497674282892924675929946595282451314311669954688', '->', ['price': 5.23988, 'Date Time': '8/28/2022 0:18', 'Token ID': '3012.0']),
('0x497674282892924675929946595282451314311669954688', '0x88921375818825809941865236428197545956716622336892', '->', ['price': 12.3137188000000001, 'Date Time': '9/5/2022 0:14', 'Token ID': '3012.0']),
('0x88921375818825809941865236428197545956716622336892', '0x70565280262726727511662595308', '->', ['price': 12.477475, 'Date Time': '9/8/2022 0:01', 'Token ID': '3012.0']),
('0x70565280262726727511662595308', '0x32948396385237180778921714465365783916627768973', '->', ['price': 30.12931, 'Date Time': '9/10/2022 0:16', 'Token ID': '3012.0']),
('0x32948396385237180778921714465365783916627768973', '0x0441798771611499743341594643578880311663978487', '->', ['price': 1.30997e-88, 'Date Time': '9/24/2022 0:14', 'Token ID': '3012.0']),
('0x0441798771611499743341594643578880311663978487', '0x71443547887742379536888977267817603165786296', '->', ['price': 100.86749, 'Date Time': '7/6/2022 0:11', 'Token ID': '2194.0']),
('0x71443547887742379536888977267817603165786296', '0x4462622222277', '->', ['price': 154.764222222277, 'Date Time': '7/10/2022 0:03', 'Token ID': '2194.0']),
('0x4462622222277', '0x3986913387535804823235720866345814083731657938048', '->', ['price': 273.78373, 'Date Time': '7/16/2022 0:13', 'Token ID': '2194.0']),
('0x3986913387535804823235720866345814083731657938048', '0x151201435772817968733799567288689996083166694840', '->', ['price': 2881.934, 'Date Time': '8/17/2022 0:07', 'Token ID': '2194.0'])
```

## Query 5:

Perform DFS, topological sort and then strongly connected components. Then, output the acyclic component graph of the strongly connected components in a form of adjacency matrix.

Give your interpretation of the results in the context of buyers/NFT's/prices/time.

## Input:

Merged CSV files with 92000 records will be taken as input.

## Output:

The output prints the list of strongly connected components of the buyer node along with a timestamp.

## Language Used: Python

## Approach:

- The first step would be to derive a graph which has been implemented on query 4 and for that some portion of the 4th query has been included in query 5. Next implement the Depth First Search (DFS) algorithm to traverse the graph. This would involve starting with a given node and ‘visiting’ each of its adjacent nodes while keeping track of the order in which they are visited. The algorithm would continue until all nodes have been visited. Below is the code snippet for performing the Depth First Search.
- In our code we considered an empty directed graph and appended edges by performing DFS edge by edge and returning the final output graph. Below is the pseudo code for implementing DFS.

```

def dfs_get_tree(G, source=None, depth_limit=None):
 T = nx.DiGraph()
 if source is None:
 T.add_nodes_from(G)
 else:
 T.add_node(source)
 T.add_edges_from(dfs_get_edges(G, source, depth_limit))
 return T

def dfs_get_edges(G, source=None, depth_limit=None):
 if source is None:
 # edges for all components
 nodes = G
 else:
 # edges for components with source
 nodes = [source]
 visited = set()
 if depth_limit is None:
 depth_limit = len(G)
 for start in nodes:
 if start in visited:
 continue
 visited.add(start)
 stack = [(start, depth_limit, iter(G[start]))]
 while stack:
 parent, depth_now, children = stack[-1]
 try:
 child = next(children)
 if child not in visited:
 yield parent, child
 visited.add(child)
 if depth_now > 1:
 stack.append((child, depth_now - 1, iter(G[child])))
 except StopIteration:
 stack.pop()

```

### Pseudo Code for DFS:

#### **DFS(V ,E)**

For each  $u \in V$

Do  $\text{color}[u] \leftarrow \text{WHITE}$

$\text{Time} \leftarrow 0$

For each  $u \in V$

Do if  $\text{color}[u] = \text{WHITE}$

Then DFS-VISIT( $u$ )

#### **DFS-VISIT( $u$ )**

$\text{color}[u] \leftarrow \text{Gray}$

$\text{Time} \leftarrow \text{Time} + 1$

$D[u] \leftarrow \text{Time}$

For each  $v \in \text{Adj}[u]$

Do if  $\text{color}[v] = \text{WHITE}$

Then DFS-VISIT(v)

Color[u]  $\leftarrow$  Black

Time  $\leftarrow$  time + 1

F[u]  $\leftarrow$  time

- The next step would be to perform a topological sort. This would involve arranging the nodes of the graph in a linear order such that if there is a path from node A to node B, node A appears before node B in the order. This would provide a logical order for the nodes that can be used to determine the relationships between them. Below is the snippet of the code which implements topological sort on The DFS performed graph.

```
def topological_sort(G):
 for generation in topological_generations(G):
 yield from generation

def topological_generations(G):
 multigraph = G.is_multigraph()
 indegree_map = {v: d for v, d in G.in_degree() if d > 0}
 zero_indegree = [v for v, d in G.in_degree() if d == 0]

 while zero_indegree:
 this_generation = zero_indegree
 zero_indegree = []
 for node in this_generation:
 if node not in G:
 raise RuntimeError("Graph changed during iteration")
 for child in G.neighbors(node):
 try:
 indegree_map[child] -= len(G[node][child]) if multigraph else 1
 except KeyError as err:
 raise RuntimeError("Graph changed during iteration") from err
 if indegree_map[child] == 0:
 zero_indegree.append(child)
 del indegree_map[child]
 yield this_generation

 if indegree_map:
 raise nx.NetworkXUnfeasible(
 "Graph contains a cycle or graph changed during iteration"
)
```

### Pseudo code for Topological Sort:

**Topological\_sort(G)** //G is the graph obtained after calling DFS(G)

Return the vertices of decreasing order to the list

- The last step would be to find the strongly connected components of the graph. This would involve grouping nodes together that are connected to each other. The result would be a set of components, each of which would have nodes that are connected to each other but not to nodes in other components. Below is the code snippet to generate the strongly connected components.

```
def strongly_connected_components(G):
 preorder = {}
 lowlink = {}
 scc_found = set()
 scc_queue = []
 i = 0 # Preorder counter
 neighbors = {v: iter(G[v]) for v in G}
 for source in G:
 if source not in scc_found:
 queue = [source]
 while queue:
 v = queue[-1]
 if v not in preorder:
 i = i + 1
 preorder[v] = i
 done = True
 for w in neighbors[v]:
 if w not in preorder:
 queue.append(w)
 done = False
 break
 if done:
 lowlink[v] = preorder[v]
 for w in G[v]:
 if w not in scc_found:
 if preorder[w] > preorder[v]:
 lowlink[v] = min([lowlink[v], lowlink[w]])
 else:
 lowlink[v] = min([lowlink[v], preorder[w]])
 queue.pop()
 if lowlink[v] == preorder[v]:
 scc = {v}
 while scc_queue and preorder[scc_queue[-1]] > preorder[v]:
 k = scc_queue.pop()
 scc.add(k)
 scc_found.update(scc)
 yield scc
 else:
 scc_queue.append(v)
```

- The output of this process would be an adjacency List that represents the acyclic component graph. This matrix would show the relationships between the nodes in a visual form. The rows of the matrix would represent the nodes, while the columns would represent the edges connecting them. Each cell in the matrix would contain a value indicating whether or not an edge exists between two nodes.

## Images of Input and Output:

### Input Format:

```
mmukarr@csx1:~/DS2/Assignment2$ python3 query_5.py
Enter the File path for the CSV input file. Ex: /home/Bob/Desktop/example.txt. The current directory is /home/mmukarr/DS2/Assignment2
nft_dataset.csv
Entered File path is nft_dataset.csv
The file exists
```

### Output Format:

#### Output on Console:

Just saves the output in a file called “query5\_output.txt” as shown below

```
mmukarr@csx1:~/DS2/Assignment2$ python3 query_4.py
Enter the File path for the CSV input file. Ex: /home/Bob/Desktop/example.txt. The current directory is /home/mmukarr/DS2/Assignment2
nft_dataset.csv
Entered File path is nft_dataset.csv
The file exists

Starting the code

Creating the graph
Exporting the output

The output file query4_output.txt has been generated at /home/mmukarr/DS2/Assignment2

mmukarr@csx1:~/DS2/Assignment2$ ls
nft_dataset.csv query4_output.txt query_4.py query_5.py query_7.py
```

Below is the Output screenshot saved to the file “query5\_output.txt”. The output prints the list of strongly connected components of the buyer node along with a timestamp. After performing the DFS and topological sort to perform SCC we get individual nodes as strongly connected components.

```
Scc 0
(*'0xc0ff4140d577e77554c5b2ffffa334896a47bd0b8*', 'Unix timestamp:', "1663632587')*)
Scc 1
(*'0x8519635133589701859158366422462767898398*', 'Unix timestamp:', "1663286711")*
Scc 2
(*'0x8886388656724266379777798284517351710188*', 'Unix timestamp:', "1661817798")*
Scc 3
(*'0x726093909378537150739033836979217656896*', 'Unix timestamp:', "1661559908")*
Scc 4
(*'0x2860964654809383876371849312265596527655*', 'Unix timestamp:', "1661213117")*
Scc 5
(*'0x46283881182845435371764886826944955485*', 'Unix timestamp:', "1660695585")*
Scc 6
(*'0x0562781383848125911834976669846158121657*', 'Unix timestamp:', "1660262867")*
Scc 7
(*'0x85927493317744819259731815697924346578*', 'Unix timestamp:', "1660090593")*
Scc 8
(*'0x918727034891387317897685378374707076782*', 'Unix timestamp:', "1659572618")*
Scc 9
(*'0x7105575934926668135215352046958958568862*', 'Unix timestamp:', "1659572259")*
Scc 10
(*'0x2415862459320811345964880718947287098878*', 'Unix timestamp:', "1659853894")*
Scc 11
(*'0x5087798656574176254248182768938698507136*', 'Unix timestamp:', "1664497867")*
Scc 12
(*'0x798233648189564281584628712569216315432*', 'Unix timestamp:', "1664864683")*
Scc 13
(*'0x6798233648189564281584628712569216315432*', 'Unix timestamp:', "1663546631")*
Scc 14
(*'0x565884f8c21bfff391bf38f298ad912b643ee6cd5*', 'Unix timestamp:', "1662589465")*
Scc 15
(*'0x9773711181739653448106635685223173639158*', 'Unix timestamp:', "1661126593")*
```

#### Time taken for the execution of query 5:

Below image shows the execution time for query5.

Time taken for the execution time for query5 is 49915100 nanoseconds.

```

○ mukarram@Mohammeds-Air-3 DS-2-assignment2 %
● mukarram@Mohammeds-Air-3 DS-2-assignment2 % python3 query_5.py
Enter the File path for the CSV input file. Ex: /home/Bob/Desktop/example.txt. The current directory is /Users/mukarram/DS-2-Final/DS-2-assignment2
nft_dataset.csv
Entered File path is nft_dataset.csv
The file exists
Starting the code
Creating the graph
Performing DFS on the graph
Performing Topological Sort on the graph
Getting the Strongly Connected Components
Exporting the output

The output file query5_output.txt has been generated at /Users/mukarram/DS-2-Final/DS-2-assignment2
The time of execution for generating the graph is: 499151000 nano seconds
○ mukarram@Mohammeds-Air-3 DS-2-assignment2 %

```

## Query 6:

Ignore the directions on the edges, and then identify a minimum spanning tree and a maximum spanning tree. Then, output each tree in a form of adjacency matrix along with min or max total and the NFTs involved.

Give your interpretation of the results in the context of buyers/NFT's/prices/time.

### Input:

The input is the single merged csv file of 92000 records.

### Output:

The Minimum Spanning Tree and a Maximum Spanning Tree costs are shown in the output. Here, the buyers serve as nodes/vertices, and the transaction prices between the two buyers which are termed as vertices serve as edges by connecting the two vertices.

### Language Used: JAVA

### Approach:

- At first, we have given a merged csv file of 92000 records as input and then generated the directed acyclic graph and adjacency list based on the query4 criteria (which is basically the output of query4).
- From the adjacency list, we have constructed an undirected graph and then found out the connected components based on Token ID as the obtained undirected graph has many disconnected subgraphs.
- The algorithm we have used to find out the Minimum and Maximum Spanning Tree for each connected component is Kruskal's. We have chosen this algorithm instead of Prims because Prims

doesn't work if the input graph is a disconnected graph and doesn't give the minimum/maximum spanning tree.

- In order to find the edges with the least weight for the lowest spanning tree and the edges with the most weight for the maximum spanning tree in each connected component, we implemented Kruskal's. For each connected component, there will be one Minimum Spanning Tree and one Maximum Spanning Tree.
- Inside the Kruskal's algorithm, Quick Sort is used to get the least weight edge in order to find the Minimum Spanning Tree and the total cost of it.
- We have used the reverse sorted edge on the above result to get the maximum weight edge in order to find the Maximum Spanning Tree and the total cost of it.
- At last, we will get the Minimum and Maximum Spanning Trees costs for each connected component in the undirected graph.

### **Pseudo Code to find Minimum and Maximum Spanning tree:**

#### **Kruskal(V,E,w)**

A <-  $\emptyset$

For each vertex  $v \in V$

do MAKE-SET( $v$ )

Sort E into nondecreasing order by weight w

for each  $(u,v)$  taken from the sorted list

do if FIND-SET( $u$ )  $\neq$  FIND-SET( $v$ )

then A <- A  $\cup \{(u,v)\}$

UNION( $u,v$ )

return A

### **Images of Input and Output:**

#### **Input Format:**

```
mmukarr@csx1:~/DS2/Assignment2$ javac query_6.java
mmukarr@csx1:~/DS2/Assignment2$ java query_6
Enter the csv file name
nft_dataset.csv
Initializations Done.. !
```

## Output Format:

### Output on Console:

Displaying the minimum and maximum spanning tree with their respective costs as shown below on the console.

```
[mmukarr@csx1:~/DS2/Assignment2$ javac query_6.java
[mmukarr@csx1:~/DS2/Assignment2$ java query_6
Enter the csv file name
nft_dataset.csv
Initialization Done.. !
0x3038102398553060089714521220293469622474 0.0
0x6850352171343995355781384643036830667295 528864.0
Output has been exported to the file query6_output.txt and saved in the current directory]
```

The above highlighted output screenshot indicates that the two vertices represent the root nodes of the minimum and maximum spanning trees respectively along with their costs.

Also, output for query 6 has been saved in a text file(query6\_output.txt). Below screenshot represents the minimum and spanning tree costs for the respective buyers and it is saved to the file “query6\_output.txt”.

| vertex                                      | min span tree cost | max span tree cost |
|---------------------------------------------|--------------------|--------------------|
| 0x8e11d80e78980e2da7dc06sda2a3da2009446c0c  | 102.17766          | 102.17766          |
| 0x7645903915338211838286928981845278994698  | 51.08883           | 51.08883           |
| 0x3aa2481845fcd12157a26532e3205a6c4ceeb8be  | 5.763868           | 5.763868           |
| 0x3ad353e2845b96fb1b58c1aca0cdca46b87de8d6f | 13.2216            | 13.2216            |
| 0xa03bc3a6812d3ba3e549dcc14697a19320fc45    | 5.23988            | 5.23988            |
| 0x3d5cc43debe487d29dd368f4853385135f97e9d   | 286.88343000000003 | 286.88343000000003 |
| 0x32d22632e344058773778c2ed9ba9287d2c819d2  | 392.991            | 392.991            |
| 0x2fd813ea3e4a9efed854a77a01fc7743959728b1  | 301.29310000000004 | 301.29310000000004 |
| 0xb8a3d632ca3a1f5568bbcbb9c47d6e8df5778     | 10.47976           | 10.47976           |
| 0x4560bb2b9080751286bf9adff9d9c33be08a654d5 | 108.4171200000001  | 108.4171200000001  |
| 0x784677643951913596962797958298238522278   | 320.94265          | 320.94265          |
| 0xd0dbb4a01e582d5c1f9566bad37155bd42ec72    | 610.924            | 610.924            |
| 0x928e7aea4af2883b342962b317a1b98cd401fcc6  | 708.3880762533835  | 708.3880762533835  |
| 0xf19e64088f224bc453e61d1c8d814a7c2c91e1a5  | 1.30997            | 1.30997            |
| 0x1634859129095561911671792238772135884648  | 98.11675299999999  | 98.11675299999999  |
| 0x39c0b6d087bcd54814af58ef138c0a141ab38918  | 157.1964           | 157.1964           |
| 0x581342da6b9b44ead49b9b5d3601d8543361b71   | 13.0997            | 13.0997            |
| 0x73d604e093a09dca4b705f6285f4a7bc64f813e   | 716.6265625338351  | 716.6265625338351  |

The above output screenshot indicates the minimum and maximum spanning tree cost for each source vertex( which are connected components).

### Query 7:

Identify a shortest path tree from an arbitrary buyer. Then, output the shortest path tree in the form of an adjacency matrix filled with the shortest weight sum and the NFT's on the path. Give your interpretation of the results in the context of buyers/NFT's/prices/time.

### Input:

Previously generated graphs with nodes as Buyer IDs connected with edges and the weight of edges as transaction price is taken as input to generate the shortest path tree.

### **Output:**

The shortest path tree for an arbitrary(random) buyer with the lowest edge weight of transaction price and the NFTs is derived.

### **Language Used:** Python

### **Approach:**

The algorithm used to find the shortest path tree is Dijkstra's. The above-generated graph is provided as an input which has the vertex as Buyer ID and the weight of the edge as the price of the transaction paid by the buyer. Initially, we chose a source to traverse through the graph to find the shortest path. The edge with the lowest edge weight is tracked and updated every time the graph is traversed. Once finding the lowest edge weight between the Buyer IDs, the path is stored. The process continues until we visit all the buyer IDs and keep track. Thus, we derive the final path that connects the source node and the destination node, possibly the shortest way to reach each buyer. Please find the below code snippet.

```
def single_source_dijkstra(G, source, target=None, cutoff=None, weight="weight"):
 return multi_source_dijkstra(
 G, {source}, cutoff=cutoff, target=target, weight=weight
)

def multi_source_dijkstra(G, sources, target=None, cutoff=None, weight="weight"):
 if not sources:
 raise ValueError("sources must not be empty")
 for s in sources:
 if s not in G:
 raise nx.NodeNotFound(f"Node {s} not found in graph")
 if target in sources:
 return (0, [target])
 weight = weightFunction(G, weight)
 paths = {source: [source] for source in sources} # dictionary of paths
 dist = _dijkstra_multisource(
 G, sources, weight, paths=paths, cutoff=cutoff, target=target
)
 if target is None:
 return (dist, paths)
 try:
 return (dist[target], paths[target])
 except KeyError as err:
 raise nx.NetworkXNoPath(f"No path to {target}.") from err
```

```

def _dijkstra_multisource(G, sources, weight, pred=None, paths=None, cutoff=None, target=None):
 G_succ = G._adj # For speed-up (and works for both directed and undirected graphs)
 push = heappush
 pop = heappop
 dist = {} # dictionary of final distances
 seen = {}
 # fringe is heapq with 3-tuples (distance,c,node)
 # use the count c to avoid comparing nodes (may not be able to)
 c = count()
 fringe = []
 for source in sources:
 seen[source] = 0
 push(fringe, (0, next(c), source))
 while fringe:
 (d, _, v) = pop(fringe)
 if v in dist:
 continue # already searched this node.
 dist[v] = d
 if v == target:
 break
 for u, e in G_succ[v].items():
 cost = weight(v, u, e)
 if cost is None:
 continue
 vu_dist = dist[v] + cost
 if cutoff is not None:
 if vu_dist > cutoff:
 continue
 if u in dist:
 u_dist = dist[u]
 if vu_dist < u_dist:
 raise ValueError("Contradictory paths found: ", "negative weights?")
 elif pred is not None and vu_dist == u_dist:
 pred[u].append(v)
 elif u not in seen or vu_dist < seen[u]:
 seen[u] = vu_dist
 push(fringe, (vu_dist, next(c), u))
 if paths is not None:
 paths[u] = paths[v] + [u]
 if pred is not None:
 pred[u] = [v]
 elif vu_dist == seen[u]:
 if pred is not None:
 pred[u].append(v)
 return dist

```

### Pseudo Code to find the shortest path tree:

#### **DIJKSTRA(V, E, w, s)**

Init-Single-Source(V, s)

$S \leftarrow \emptyset$

$Q \leftarrow V$

while  $Q \neq \emptyset$

    Do  $u \leftarrow \text{Extract-Min}(Q)$

$S \leftarrow S \cup \{u\}$

    For each vertex  $v \in \text{Adj}[u]$

        Do Relax ( $u, v, w$ )

### Images of Input and Output:

#### Input Format:

```

mmukarr@csx1:~/DS2/Assignment2$ python3 query_7.py
Enter the File path for the CSV input file. Ex: /home/Bob/Desktop/example.txt. The current directory is/home/mmukarr/DS2/Assignment2
nft_dataset.csv
Entered File path is nft_dataset.csv
The file exists

Starting the code

Creating the graph

```

## Output on console:

```
mmukarr@csx1:~/DS2/Assignment2$ python3 query_7.py
Enter the File path for the CSV input file. Ex: /home/Bob/Desktop/example.txt. The current directory is /home/mmukarr/DS2/Assignment2
nft_dataset.csv
Entered File path is nft_dataset.csv
The file exists

Starting the code

Creating the graph
Finding the shortest path by using a arbitrary Node 0x07766170478378811105417596142586897730391656634094
Exporting the output

The output file query7_output.txt has been generated at /home/mmukarr/DS2/Assignment2
```

Also, output for query 7 has been saved in a text file(query7\_output.txt). Below is the output screenshot saved to the file “query7\_output.txt”.

```
["path=", ["'0x07766170478378811105417596142586897730391656634094'", 'weight=0']]
('path', ['0xb87652cd5e7af8495271c9aca229d7eb682bc416566345861', 'weight=298.8752'])
('path', ['0xb87652cd5e7af8495271c9aca229d7eb682bc416566345861', '0x8518677358562112880918667268972461333231656634850'], 'weight=402.2226500000000')
('path', ['0xb87652cd5e7af8495271c9aca229d7eb682bc416566345861', '0x8518677358562112880918667268972461333231656634850', '0x458844ab3c3c9ae7af4e81aa
f639dccc2fa641656634850'], 'weight=693.0778500000001')
('path', ['0xb87652cd5e7af8495271c9aca229d7eb682bc416566345861', '0x8518677358562112880915067268972461333231656634850', '0x458844ab3c3c9ae7af4e81aa
f639dccc2fa641656634850'], 'weight=983.9738500000001')
('path', ['0xb87652cd5e7af8495271c9aca229d7eb682bc416566345861', '0x7f7650fbfd3e373ecaf6588254af0fb43787fb2f216566349905'], 'weight=983.9738500000001')
('path', ['0xb87652cd5e7af8495271c9aca229d7eb682bc416566345861', '0x27397986616198962613843182949267597105811656633827'], 'weight=0')
('path', ['0xb87652cd5e7af8495271c9aca229d7eb682bc416566345861', '0x27397986616198962613843182949267597105811656633827'], 'weight=1021.7766")
```

## Time taken to run the code:

```
mukarram@mohammeds-air-3 DS-2-assignment2 % python3 query_7.py
Enter the File path for the CSV input file. Ex: /home/Bob/Desktop/example.txt. The current directory is /Users/mukarram/DS-2-Final/DS-2-assignment2
nft_dataset.csv
Entered File path is nft_dataset.csv
The file exists

Starting the code

Creating the graph
Finding the shortest path by using a arbitrary Node 0x8415767583900247711785183009464972390821657238828
Exporting the output

The output file query7_output.txt has been generated at /Users/mukarram/DS-2-Final/DS-2-assignment2

The time of execution for generating the graph is: 223000 nano seconds

mukarram@mohammeds-air-3 DS-2-assignment2 %
```

Time taken for execution of query 7 is 223000 nanoseconds.