

CSE3021 : SOCIAL AND INFORMATION NETWORKS

ANALYSIS OF SINGAPORE

METRO STATIONS

NETWORK

Team Members:

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1. Introduction:

With increasing population, traffic demand is coupled with increasing number of vehicles on the road. As a result, we are facing many problems like traffic congestion, road accidents and environmental pollution. This can be reduced only when the number of vehicles on the roads is decreased. We can achieve this by increasing public transportation. One of the most accepted methods to improve public transportation is „**Mass Rapid Transit** „system. This has already been used in many of the developed countries and in developing countries including India. setting up metro stations involves the study of geographic and community factors in that particular surroundings. We have to understand the population around that particular metro rail station and then we have to construct the station. This will help the people to identify the station easily and use the station easily and hence they can effectively make use of the metro system.

If a particular station is located in populated community that station will be more important and if a station is more important that it may considered as located in populated community vice versa. Applications of social network analysis include identifying the most influential person(s) in social network, key infrastructure nodes in the internet or urban networks, rumour spreaders and disease spreaders. In the same way we could identify the important stations in MRT network using centrality

measures. In this paper we used network analysis to find the most important stations in Singapore metro networks. Here stations are considered as nodes. We used different centrality measures like degree centrality, betweenness centrality, Eigen vector centrality to achieve this. In graph theory and network analysis indicators of centrality identify the most important vertices in graph. We generated the different graph attributes like degree centrality, Betweenness centrality, closeness centrality to identify the tightly interlinked groups with in a network.

2.Literature Review Summary Table:

<i>Authors and Year (Reference)</i>	<i>Title (Study)</i>	<i>Concept / Theoretical model/ Framework</i>	<i>Methodology used/ Implementation</i>	<i>Dataset details/ Analysis</i>	<i>Relevant Finding</i>	<i>Limitations / Future Research/ Gaps identified</i>
1.Niraj sharma 2.rajni dhyani 2013	Critical issues related to metro rail projects India	Issues while constructing metro projects in India	Identifying different problems while constructing metro networks and proposing a solution to them	Daily passengers who uses metro	What are the environmental issues related To the metro construction	Theoretical analysis .Experimental results are required
c.prem Shankar R.vidya raj V.midhun raj K.sateesh kumar.	analysis of road network of buffer area of kochi metro rail using tools of social network analysis.	how road networks influence metro systems	used the tools of social network analysis to study the road network of kochi.	Kochi road networks	how road networks influence metro systems	Some other parts in kochi should be included.
Yew-Yih Cheng, Roy Ka-Wei Lee, Ee-Peng Lim and Feida Zhu	Measuring Centralities for Transportation Networks Beyond Structures	How people are effected by the network disturbances in their lives	Network centrality Visual analytics Transportation network	Singapore subway networks .	Use of centrality measures to find the critical nodes	can be used for other most used subways.

3. Objective of the project:

The main objective of this project is to analyse the Singapore metro networks and to find the most important station. This can be applied to any metro networks to find the important station during construction itself.

4. Innovation component in the project:

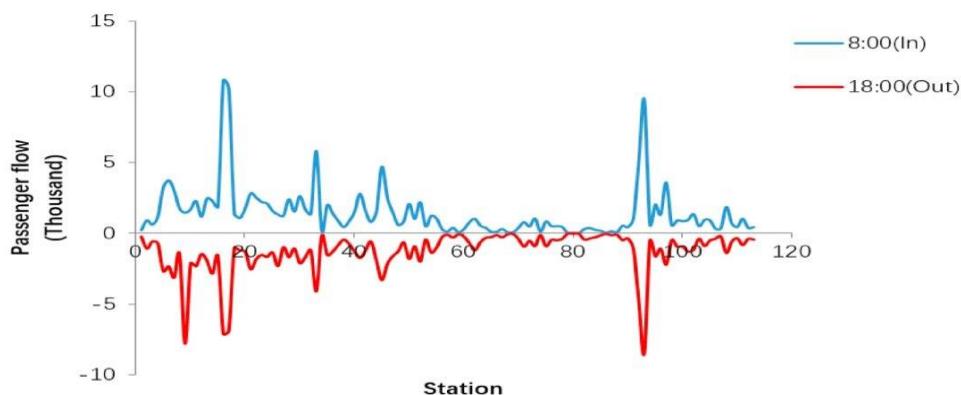
In this project we used the stations which are to be announced also. So, we can know the important stations even before announcing any trains to that particular station.

5.Data Collected:

We are working on the Singapore metro stations. We tried to apply the concept of network analysis on a network of connected railway stations, attempting to identify the important stations (nodes) in this network. The first step we implement is to collect the data from the Wikipedia page on “List of Singapore metro stations”. We take the data from the table “MRT Stations” mentioned in this Wikipedia page, which has all the details of stations involved in the mass rapid transit across Singapore. We used data scraping techniques and later we applied the data cleaning techniques to sort the required data in a proper way.

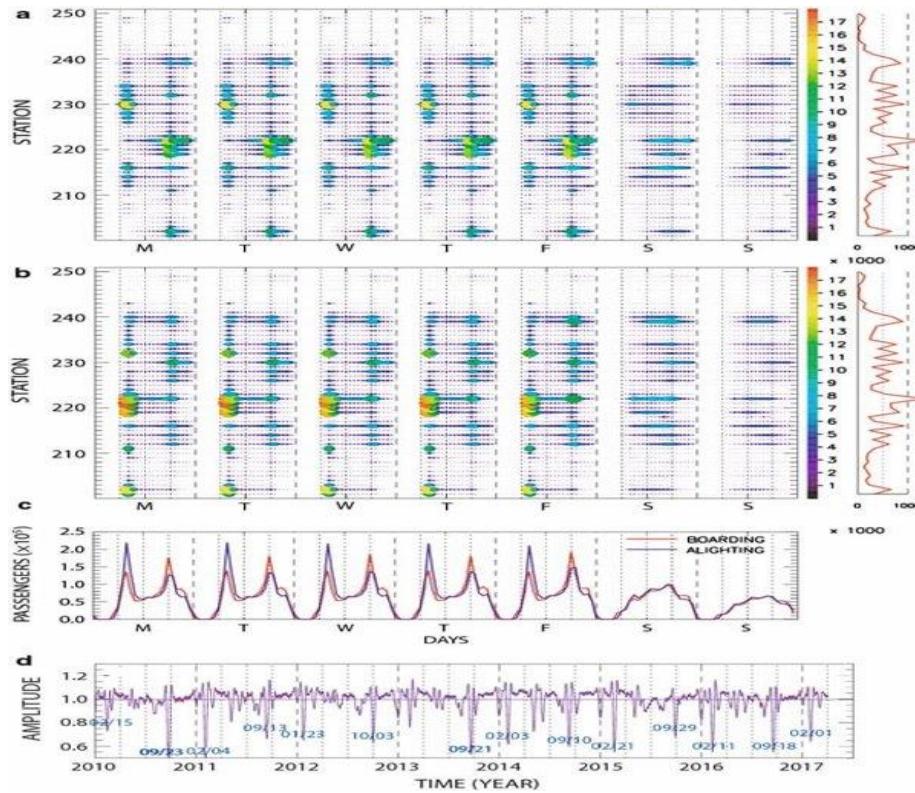
Passenger Flow Vs Station

— shows the statistics of daily passenger flow of metro in five working days. As can be seen from the figure, the passenger flow from Monday to Friday ranges from 1.20 million to 1.32 million. Passenger flow from Monday to Friday is increasing gradually, but the increase is not large, about 0.12 million. At the end of 2020, the permanent population of station was 8.27 million, which can be used to calculate the proportion of pedestrians to the permanent population in about one seventh.

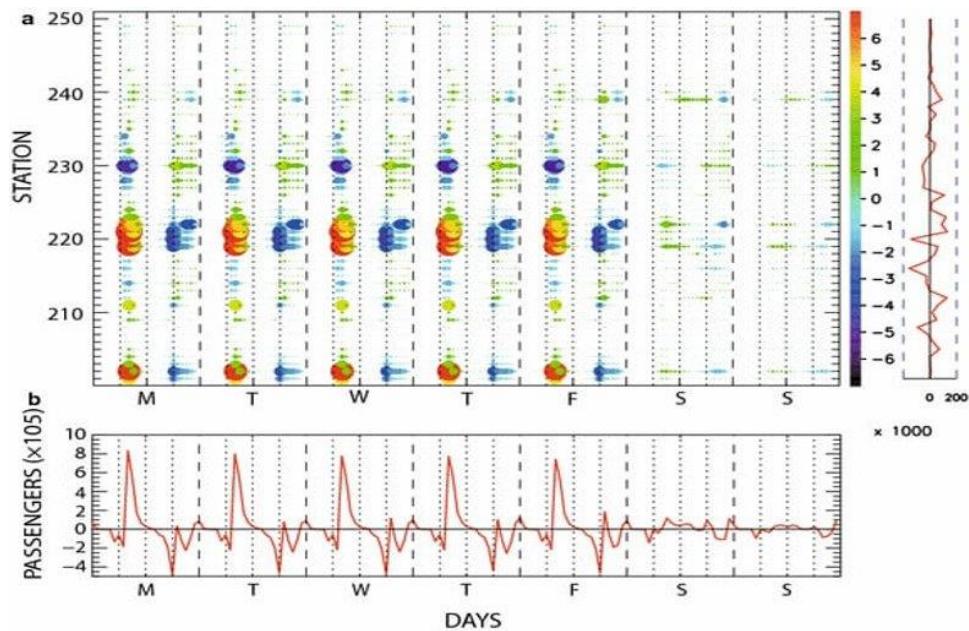


The below graphs show you the relations of different stations in week days...

The overall amplitude which means the no of trains arriving per weak to the total time (year)



Overall Stations Vs Days in a Week:

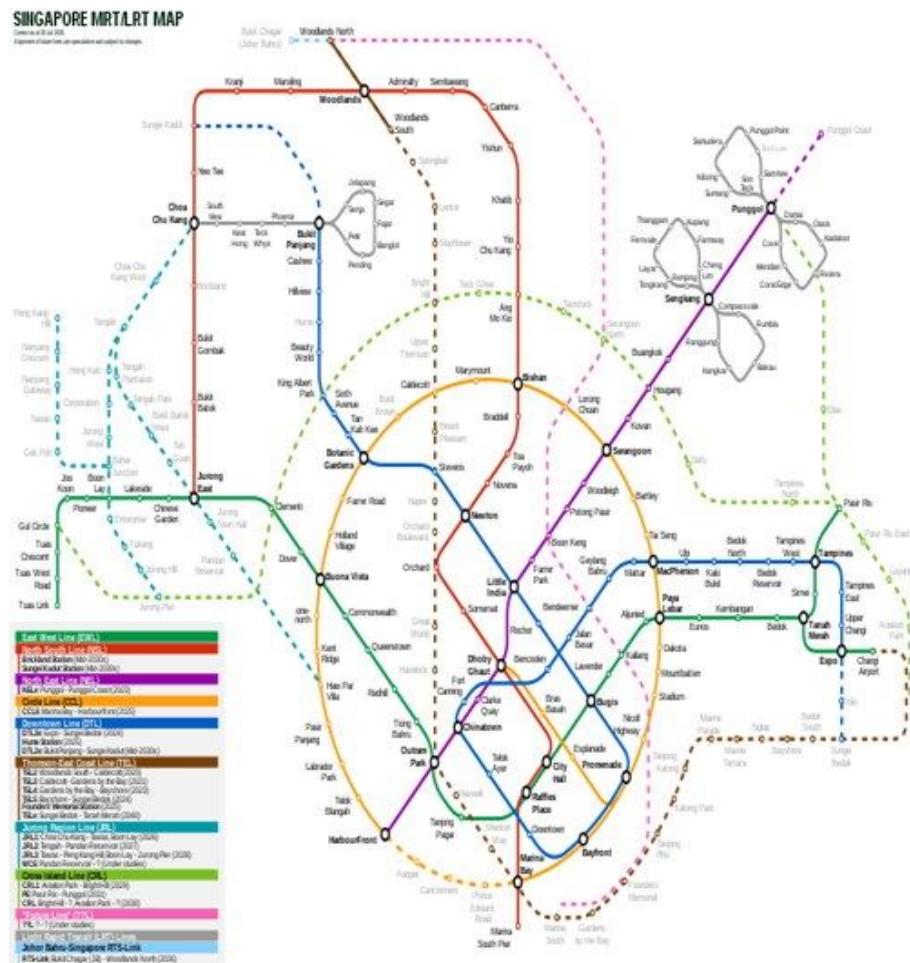


The Number of Stations and all their Networks:

This is a list of all mass rapid transit (mrt) stations in Singapore by their locations. for urban planning purpose, Singapore is officially divided into 55 planning areas by the urban redevelopment authority. this list includes operational, non-operational and confirmed future stations on the mrt network.

Some stations, such as bukit panjang and tai seng, are located on the boundaries of two or more planning areas, hence these stations will appear more than once in the list below. this takes into account the entire area of the station, both underground and above-ground sections, and not simply its above-ground features like exits (e.g., the underground segment of mountbatten station stretches across geylang and kallang planning areas, hence it will be stated as such in the list below, even when both its above-ground exits are located wholly within geylang planning area).

Downtown core has a total number of 14 stations located within and along its boundaries, making it the planning area with the greatest number of mrt stations. bedok and kallang rank second with 11 total stations.Clementi, marina east, and newton each have one station.Currently, 10 planning areas have no operational or planned mrt station - central water catchment, Changi bay, lim chu kang, mandai, north-eastern islands, paya lebar, seletar, simpang, southern islands, and western islands. however, this could change when the route of the future cross island line is fully confirmed. there will be additional mrt lines that will be announced for completion after 2031 but they are under planning.[1] the exact location of the new brickland mrt station is not yet known.If a station is partially completed, i.e. an existing station is slated to become an interchange with a future line, such a station will be listed under "operational stations". "future stations" strictly refer to those that are under construction, in various stages of planning, or completed stations that are not in service.



6. Work done and implementation

Methodology adapted:

We are working on the Singapore metro stations. We tried to apply the concept of network analysis on a network of connected railway stations, attempting to identify the important stations (nodes) in this network.

The first step we implement is to collect the data from the Wikipedia page on "List of Singapore metro stations". We take the data from the table "MRT Stations" mentioned in this Wikipedia page, which has all the details of stations involved in the mass rapid transit across Singapore. We used data scraping techniques and later we applied the data cleaning techniques to sort the required data in a proper way.

Codes Walkthrough

Installing the rvest package to scrape the list of MRT stations from wikipedia

```
1 install.packages("rvest")
2 library(rvest)
3
```

```
> library(rvest)
Loading required package: xml2
```

Before we can scrape the MRT stations data, we would need to ascertain the correct [XPath](#) to use.

1. navigate to the [wikipedia page](#) and fire up the developer tool
2. copy the table XPath

Now we are ready to do some real and dirty work, scraping and cleaning the data!

Data Scraping

```
> url <- "https://en.wikipedia.org/wiki/List_of_Singapore_MRT_stations"
> mrt_stn <- url %>%
+   read_html() %>%
+   #paste the copied xpath: html_nodes(xpath here)
+   html_nodes(xpath='//*[@id="mw-content-text"]/div[1]/table[2]') %>%
+   html_table(fill = TRUE)
>
> mrt <- mrt_stn[[1]]
```

Data Cleaning

```
> mrt <- mrt[,c(1:3,6,8:9)]
> names(mrt) <- c("Code","Name","Opening","Status","Location")
>
> mrt <- subset(mrt,Code != Name)
>
> mrt <- mrt[2:nrow(mrt),]
>
> mrt$Code <- substr(mrt$Code, 1, 4)
> mrt$Code <- iconv(mrt$Code, "ASCII", "UTF-8", sub="")
> mrt>Name <- gsub('\\\\[.\\\\]', "", mrt>Name)
> mrt <- mrt[mrt>Name != 'Reserved Station',]
> mrt <- mrt[mrt>Name != 'Punggol Coast',]
> mrt <- mrt[mrt>Status != 'TBA',]
```

Generating the MRT network's edge list

After, these data cleaning techniques are applied, we get the readable data. Now, we exclude the data that is not required for our study and collect the data that is required for our analysis.

There are different lines in the Singapore metro station network:

- North-south line (NSL line)
- East-West line (ESL line)

- Changi-Airport Branch line (CAL line)
- North-east line (NAL line) □ Circle line (CCL line)
- Downtown line (DTL line)

We collect only the required data i.e., the source, target and network line name from the cleaned data that we generated. So, the mrt edge list is ready. Similarly, we create another node list, which has details regarding each node. This node list has the following details regarding each node:

- Code – This indicates which line it belongs to.
- Id – This column has the names of the stations(nodes).
- It has other values like opening, status, location and label.

i. preparing the North-South Line (NSL) edge list

```
> ns_df <- mrt[substr(mrt$Code,1,2) == 'NS',]
>
> sourceList <- ""
> targetList <- ""
> for (i in 1:nrow(ns_df)-1) {
+   sourceList[i] <- ns_df>Name[i]
+   targetList[i] <- ns_df>Name[i+1]
+ }
>
> ns_edgelist <- data.frame(sourceList, targetList, "NSL")
> names(ns_edgelist) <- c("source", "target", "network")
```

ii. preparing the East-West Line (EWL) edge list

```
> ew_df <- mrt[substr(mrt$Code,1,2) == 'EW',]
>
> sourceList <- ""
> targetList <- ""
> for (i in 1:nrow(ew_df)-1) {
+   sourceList[i] <- ew_df>Name[i]
+   targetList[i] <- ew_df>Name[i+1]
+ }
>
> ew_edgelist <- data.frame(sourceList, targetList, "EWL")
> names(ew_edgelist) <- c("source", "target", "network")
```

iii. preparing the Changi Airport Branch Line (CAL) edge list

```

> cg_df <- mrt[substr(mrt$Code,1,2) == 'CG',]
>
> sourceList <- ""
> targetList <- ""
> for (i in 1:nrow(cg_df)-1) {
+   sourceList[i] <- cg_df>Name[i]
+   targetList[i] <- cg_df>Name[i+1]
+ }
>
> cg_edgelist <- data.frame(sourceList, targetList, "CAL")
> names(cg_edgelist) <- c("source", "target", "network")
>

```

iv. preparing the North-East Line (NEL) edge list

```

> ne_df <- mrt[substr(mrt$Code,1,2) == 'NE',]
>
> sourceList <- ""
> targetList <- ""
> for (i in 1:nrow(ne_df)-1) {
+   sourceList[i] <- ne_df>Name[i]
+   targetList[i] <- ne_df>Name[i+1]
+ }
>
> ne_edgelist <- data.frame(sourceList, targetList, "NEL")
> names(ne_edgelist) <- c("source", "target", "network")
>

```

v. preparing the Circle Line (CCL) edge list

```

> cc_df <- mrt[substr(mrt$Code,1,2) == 'CC',]
>
> sourceList <- ""
> targetList <- ""
> for (i in 1:nrow(cc_df)-1) {
+   sourceList[i] <- cc_df>Name[i]
+   targetList[i] <- cc_df>Name[i+1]
+ }
>
> cc_edgelist <- data.frame(sourceList, targetList, "CCL")
> names(cc_edgelist) <- c("source", "target", "network")
> dt_df <- mrt[substr(mrt$Code,1,2) == 'DT',]

```

vi. preparing the Downtown Line (DTL) edge list

```

> dt_df <- mrt[substr(mrt$Code,1,2) == 'DT',]
>
> sourceList <- ""
> targetList <- ""
> for (i in 1:nrow(dt_df)-1) {
+   sourceList[i] <- dt_df>Name[i]
+   targetList[i] <- dt_df>Name[i+1]
+ }
>
> dt_edgelist <- data.frame(sourceList, targetList, "DTL")
> names(dt_edgelist) <- c("source", "target", "network")
> mrt_edgelist <- rbind(ns_edgelist,ew_edgelist,cg_edgelist,ne_edgelist,cc_edgelist,dt
 _edgelist)
> mrt_edgelist

```

Console Terminal × Jobs ×

~/

	source	target	network
1	Jurong East	Bukit Batok	NSL
2	Bukit Batok	Bukit Gombak	NSL
3	Bukit Gombak	Choa Chu Kang	NSL
4	Choa Chu Kang	Yew Tee	NSL
5	Yew Tee	Kranji	NSL
6	Kranji	Marsiling	NSL
7	Marsiling	Woodlands	NSL
8	Woodlands	Admiralty	NSL
9	Admiralty	Sembawang	NSL
10	Sembawang	Canberra	NSL
11	Canberra	Yishun	NSL
12	Yishun	Khatib	NSL
13	Khatib	Yio Chu Kang	NSL
14	Yio Chu Kang	Ang Mo Kio	NSL
15	Ang Mo Kio	Bishan	NSL
16	Bishan	Braddell	NSL
17	Braddell	Toa Payoh	NSL
18	Toa Payoh	Novena	NSL
19	Novena	Newton	NSL
20	Newton	Orchard	NSL

21	Orchard	Somerset	NSL
22	Somerset	Dhoby Ghaut	NSL
23	Dhoby Ghaut	City Hall	NSL
24	City Hall	Raffles Place	NSL
25	Raffles Place	Marina Bay	NSL
26	Marina Bay	Marina South Pier	NSL
27	Marina South Pier	Orchard	NSL
28	Orchard	Marina Bay	NSL
29	Marina Bay	Choa Chu Kang	NSL
30	Choa Chu Kang	Jurong East	NSL
31	Jurong East	Ang Mo Kio	NSL
32	Pasir Ris	Tampines	EWL
33	Tampines	Simei	EWL
34	Simei	Tanah Merah	EWL
35	Tanah Merah	Bedok	EWL
36	Bedok	Kembangan	EWL
37	Kembangan	Eunos	EWL
38	Eunos	Paya Lebar	EWL
39	Paya Lebar	Aljunied	EWL
40	Aljunied	Kallang	EWL
41	Kallang	Lavender	EWL
42	Lavender	Bugis	EWL
43	Bugis	City Hall	EWL
44	City Hall	Raffles Place	EWL
45	Raffles Place	Tanjong Pagar	EWL
46	Tanjong Pagar	Outram Park	EWL
47	Outram Park	Tiong Bahru	EWL
48	Tiong Bahru	Redhill	EWL
49	Redhill	Queenstown	EWL
50	Queenstown	Commonwealth	EWL
51	Commonwealth	Buona Vista	EWL
52	Buona Vista	Dover	EWL
53	Dover	Clementi	EWL
54	Clementi	Jurong East	EWL
55	Jurong East	Chinese Garden	EWL
56	Chinese Garden	Lakeside	EWL
57	Lakeside	Boon Lay	EWL
58	Boon Lay	Pioneer	EWL
59	Pioneer	Joo Koon	EWL
60	Joo Koon	Gul Circle	EWL
61	Gul Circle	Tuas Crescent	EWL
62	Tuas Crescent	Tuas West Road	EWL
63	Tuas West Road	Tuas Link	EWL
64	Tuas Link	Outram Park	EWL
65	Outram Park	Tanah Merah	EWL
66	Tanah Merah	Boon Lay	EWL
67	Boon Lay	Pasir Ris	EWL
68	Expo	Changi Airport	CAL
69	Changi Airport	Changi Airport	CAL
70	Changi Airport	Expo	CAL
71	HarbourFront	Outram Park	NEL
72	Outram Park	Chinatown	NEL
73	Chinatown	Clarke Quay	NEL
74	Clarke Quay	Dhoby Ghaut	NEL
75	Dhoby Ghaut	Little India	NEL
76	Little India	Farrer Park	NEL
77	Farrer Park	Boon Keng	NEL
78	Boon Keng	Potong Pasir	NEL
79	Potong Pasir	Woodleigh	NEL
80	Woodleigh	Serangoon	NEL

81	Serangoon	Kovan	NEL
82	Kovan	Hougang	NEL
83	Hougang	Buangkok	NEL
84	Buangkok	Sengkang	NEL
85	Sengkang	Punggol	NEL
86	Punggol	Hougang	NEL
87	Hougang	Punggol	NEL
88	Dhoby Ghaut	Bras Basah	CCL
89	Bras Basah	Esplanade	CCL
90	Esplanade	Promenade	CCL
91	Promenade	Nicoll Highway	CCL
92	Nicoll Highway	Stadium	CCL
93	Stadium	Mountbatten	CCL
94	Mountbatten	Dakota	CCL
95	Dakota	Paya Lebar	CCL
96	Paya Lebar	MacPherson	CCL
97	MacPherson	Tai Seng	CCL
98	Tai Seng	Bartley	CCL
99	Bartley	Serangoon	CCL
100	Serangoon	Lorong Chuan	CCL
101	Lorong Chuan	Bishan	CCL
102	Bishan	Marymount	CCL
103	Marymount	Caldecott	CCL
104	Caldecott	Botanic Gardens • Kebun Bunga	CCL
105	Botanic Gardens • Kebun Bunga	Farrer Road	CCL
106	Farrer Road	Holland Village	CCL
107	Holland Village	Buona Vista	CCL
108	Buona Vista	one-north	CCL
109	one-north	Kent Ridge	CCL
110	Kent Ridge	Haw Par Villa	CCL
111	Haw Par Villa	Pasir Panjang	CCL
112	Pasir Panjang	Labrador Park	CCL
113	Labrador Park	Telok Blangah	CCL
114	Telok Blangah	HarbourFront	CCL
115	HarbourFront	Caldecott	CCL
116	Bukit Panjang	Cashew	DTL
117	Cashew	Hillview	DTL
118	Hillview	Beauty World	DTL
119	Beauty World	King Albert Park	DTL
120	King Albert Park	Sixth Avenue	DTL
121	Sixth Avenue	Tan Kah Kee	DTL
122	Tan Kah Kee	Botanic Gardens • Kebun Bunga	DTL
123	Botanic Gardens • Kebun Bunga	Stevens	DTL
124	Stevens	Newton	DTL
125	Newton	Little India	DTL
126	Little India	Rochor	DTL
127	Rochor	Bugis	DTL
128	Bugis	Promenade	DTL
129	Promenade	Bayfront	DTL
130	Bayfront	Downtown	DTL
131	Downtown	Telok Ayer	DTL
132	Telok Ayer	Chinatown	DTL
133	Chinatown	Fort Canning	DTL
134	Fort Canning	Bencoolen	DTL
135	Bencoolen	Jalan Besar	DTL
136	Jalan Besar	Bendemeer	DTL
137	Bendemeer	Geylang Bahru	DTL
138	Geylang Bahru	Mattar	DTL
139	Mattar	MacPherson	DTL
140	MacPherson	Ubi	DTL

```

141           Ubi          Kaki Bukit      Kaki Bukit      DTL
142           Kaki Bukit   Bedok North     Bedok North     DTL
143           Bedok North   Bedok Reservoir Bedok Reservoir DTL
144           Bedok Reservoir Tampines West Tampines West    DTL
145           Tampines West  Tampines        Tampines       DTL
146           Tampines      Tampines East   Tampines East   DTL
147           Tampines East Upper Changi  Upper Changi  DTL
148           Upper Changi Expo          Expo          DTL
149           Expo          Stevens        Stevens        DTL
> |

```

Closing the loop for the graph network

```

> mrt_edgelist$target <- as.character(mrt_edgelist$target)
> mrt_edgelist$source <- as.character(mrt_edgelist$source)
> mrt_edgelist$network <- as.character(mrt_edgelist$network)
> mrt_edgelist[nrow(mrt_edgelist)+1,] <- c("Bayfront", "Marina Bay", "CEL")
> mrt_edgelist[nrow(mrt_edgelist)+1,] <- c("Bayfront", "Promenade", "CCL")
> mrt_edgelist[nrow(mrt_edgelist)+1,] <- c("Tanah Merah", "Expo", "CAL")

```

Specifying this network to be an undirected graph network

```
> mrt_edgelist$type <- "undirected"
```

Exporting the mrt edge list to csv

```
> write.csv(mrt_edgelist, file="mrt_edgelist1.csv", row.names=F)
```

Generating the MRT network's node list

```

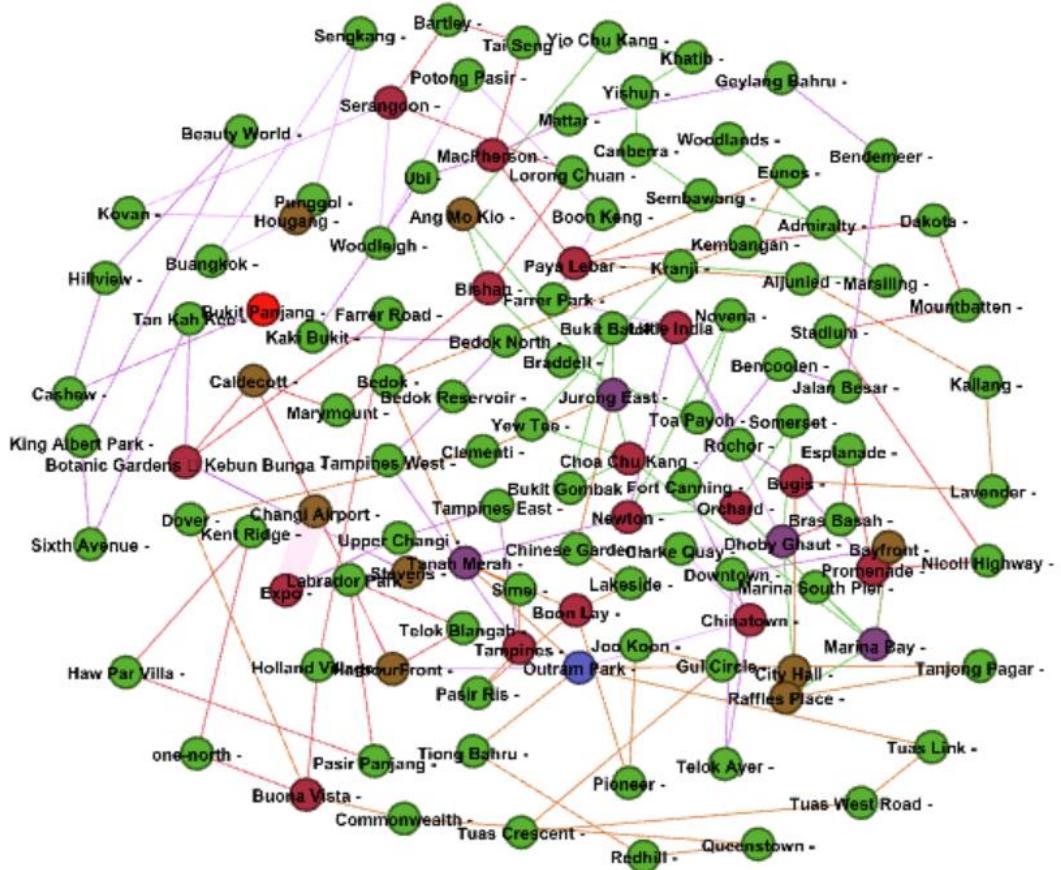
> mrt_node <- mrt[substr(mrt$Code,1,2) != 'TE',]
> names(mrt_node)[2] <- "id"
> mrt_node$label <- mrt_node$id
> # removing duplicated mrt names/nodes (nodes in a network should be unique)
> mrt_nodes <- unique(mrt_node)
> mrt_nodes <- mrt_nodes[!duplicated(mrt_nodes$id),]
> mrt_nodes$Code <- substr(mrt_nodes$Code, 1, 2)

```

Exporting the mrt nodes to csv

```
> write.csv(mrt_nodes, file="mrt_nodes1.csv", row.names=F)
```

Visualisation of the MRT network using Gephi



Visualisation of the MRT network using R igraph package

```
> install.packages("igraph")
WARNING: Rtools is required to build R packages but is not currently installed. Please
download and install the appropriate version of Rtools before proceeding:
```

<https://cran.rstudio.com/bin/windows/Rtools/>
Installing package into 'C:/Users/Vyshnavi/Documents/R/win-library/4.0'
(as 'lib' is unspecified)
trying URL 'https://cran.rstudio.com/bin/windows/contrib/4.0/igraph_1.2.6.zip'
Content type 'application/zip' length 9345285 bytes (8.9 MB)
downloaded 8.9 MB

```
package 'igraph' successfully unpacked and MD5 sums checked
```

```
The downloaded binary packages are in  
  C:\Users\Vyshnavi\AppData\Local\Temp\Rtmp44oev8\downloaded_packages  
> library(igraph)
```

```
Attaching package: 'igraph'
```

```
The following objects are masked from 'package:stats':
```

```
  decompose, spectrum
```

```
The following object is masked from 'package:base':
```

```
  union
```

```

> # renaming for igraph edgelist format
> names(mrt_edgelist) <- c("from","to","network","type")
> # rearranging for igraph nodelist format
> mrt_nodes <- mrt_nodes[c(2,6,1,3,4,5)]

```

Setting up the graph network

```

> g = graph.data.frame(mrt_edgelist, mrt_nodes, directed=F)
> # Removing self loops
> g = simplify(g, remove.loops = T)

```

Checking if multiple edges exists in the graph network

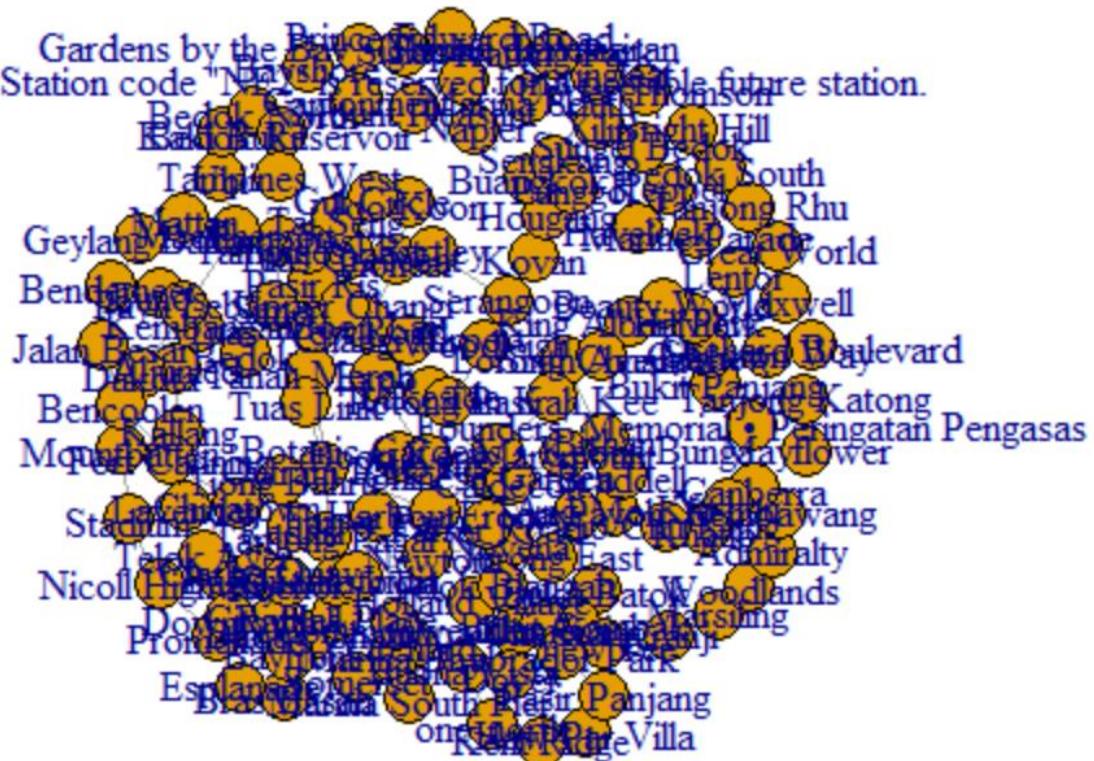
```

> any_multiple(g)
[1] FALSE
> which_multiple(g)
[1] FALSE FALSE
[14] FALSE FALSE
[27] FALSE FALSE
[40] FALSE FALSE
[53] FALSE FALSE
[66] FALSE FALSE
[79] FALSE FALSE
[92] FALSE FALSE
[105] FALSE FALSE
[118] FALSE FALSE
[131] FALSE FALSE
[144] FALSE FALSE FALSE FALSE
> count_multiple(g)
[1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[41] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[81] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[121] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
> which_multiple(simplify(g))
[1] FALSE FALSE
[14] FALSE FALSE
[27] FALSE FALSE
[40] FALSE FALSE
[53] FALSE FALSE
[66] FALSE FALSE
[79] FALSE FALSE
[92] FALSE FALSE
[105] FALSE FALSE
[118] FALSE FALSE
[131] FALSE FALSE
[144] FALSE FALSE FALSE FALSE
> all(count_multiple(simplify(g)) == 1)
[1] TRUE
> simple_g <- g
> any_multiple(simple_g)
[1] FALSE

```

Displaying descriptive statistics of the graph network

```
> v(simple_g)
+ 149/149 vertices, named, from 42d64e0:
[1] Jurong East
[2] Bukit Batok
[3] Bukit Gombak
[4] Choa Chu Kang
[5] Yew Tee
[6] Kranji
[7] Marsiling
[8] Woodlands
[9] Admiralty
[10] Sembawang
+ ... omitted several vertices
> E(simple_g)
+ 147/147 edges from 42d64e0 (vertex names):
[1] Jurong East --Bukit Batok    Jurong East --Choa Chu Kang
[3] Jurong East --Ang Mo Kio     Jurong East --Clementi
[5] Jurong East --Chinese Garden  Bukit Batok --Bukit Gombak
[7] Bukit Gombak --Choa Chu Kang  Choa Chu Kang--Yew Tee
[9] Choa Chu Kang--Marina Bay     Yew Tee      --Kranji
[11] Kranji          --Marsiling       Marsiling   --Woodlands
[13] Woodlands        --Admiralty       Admiralty    --Sembawang
[15] Sembawang        --Canberra        Canberra    --Yishun
[17] Yishun          --Khatib         Khatib      --Yio Chu Kang
[19] Yio Chu Kang --Ang Mo Kio     Ang Mo Kio   --Bishan
+ ... omitted several edges
> plot(simple_g)
```



```
> # Network Density  
> graph.density(simple_g,loop=FALSE)  
[1] 0.01333212  
> # greatest distance between any pair of vertices  
> diameter(simple_g)  
[1] 17  
> # Average Path Length  
> mean_distance(simple_g, directed=F)  
[1] 6.776751
```

 HTML Report

Graph Distance Report

Parameters:

Network Interpretation: undirected

Results:

Diameter: 17
Radius: 9
Average Path length: 6.776750700280112

Degree centrality

```
> #Degree Centrality  
> V(simple_g)$degree=degree(simple_g, mode="all")
```

Betweenness centrality

```
> #Betweenness Centrality  
> V(simple_g)$betweenness=betweenness(simple_g, normalized=T)
```

Closeness centrality

```
> #Closeness Centrality  
> V(simple_g)$closeness=closeness(simple_g, normalized=T)
```

Eigen vector centrality

```
> #Eigenvector Centrality  
> V(simple_g)$eigen=evcent(simple_g)$vector
```

Maximum Degree Centrality

Degree centrality measures how connected an entity is by counting the number of direct links each entity has to others in the network.

```
> #Degree  
> V(simple_g)$name[degree(simple_g)==max(degree(simple_g))]  
[1] "Outram Park"
```

Maximum Closeness Centrality

Closeness centrality measures the proximity of an entity to the other entities in the social network.

```
> #Closeness  
> V(simple_g)$name[closeness(simple_g)==max(closeness(simple_g))]  
[1] "Outram Park"
```

Maximum Eigenvector centrality

Eigenvector measures how connected an entity is and how much direct influence it might have over other connected entities in the network.

```
> #EigenVector  
> V(simple_g)$name[which.max(V(simple_g)$eigen)]  
[1] "Marina Bay"
```

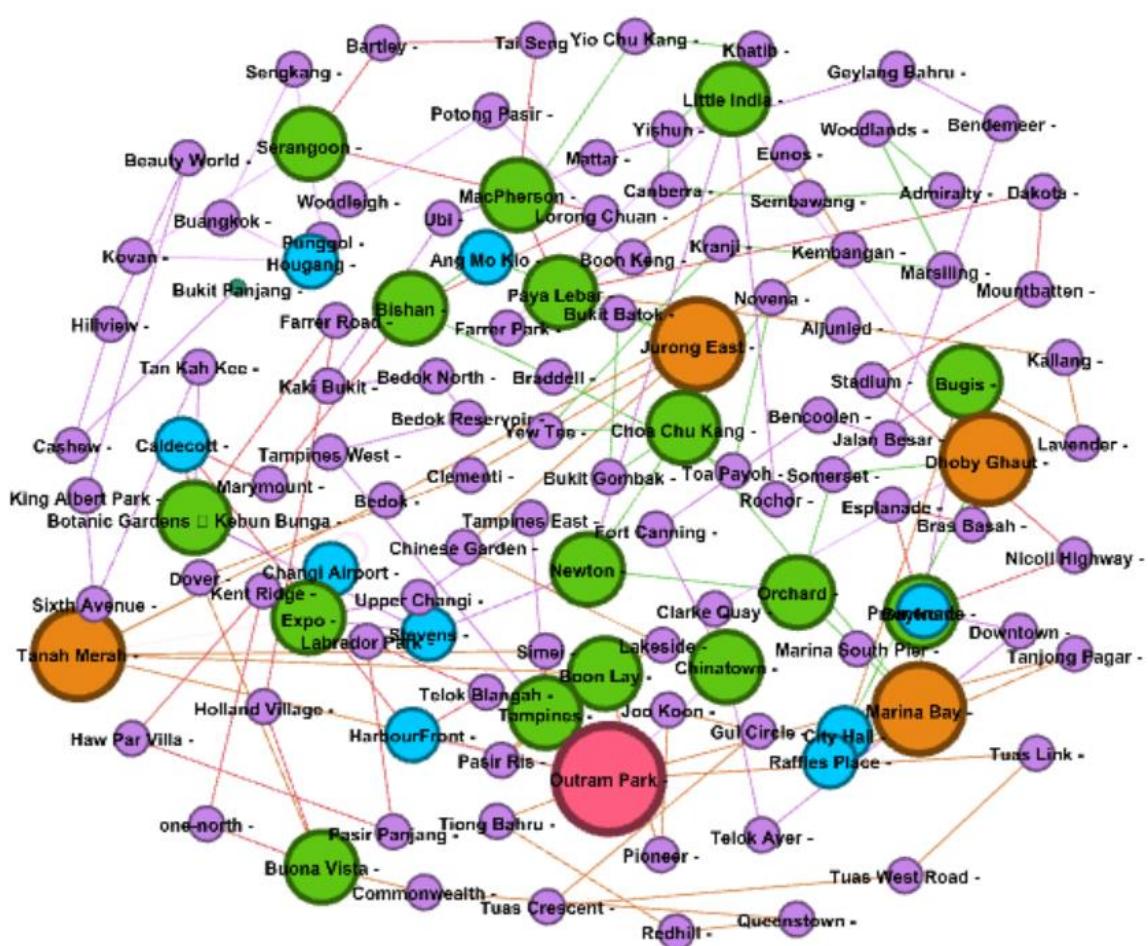
Maximum Betweenness Centrality

Betweenness centrality measures the number of paths that pass through each entity.

```
> #Betweenness  
> V(simple_g)$name[betweenness(simple_g)==max(betweenness(simple_g))]  
[1] "Outram Park"
```

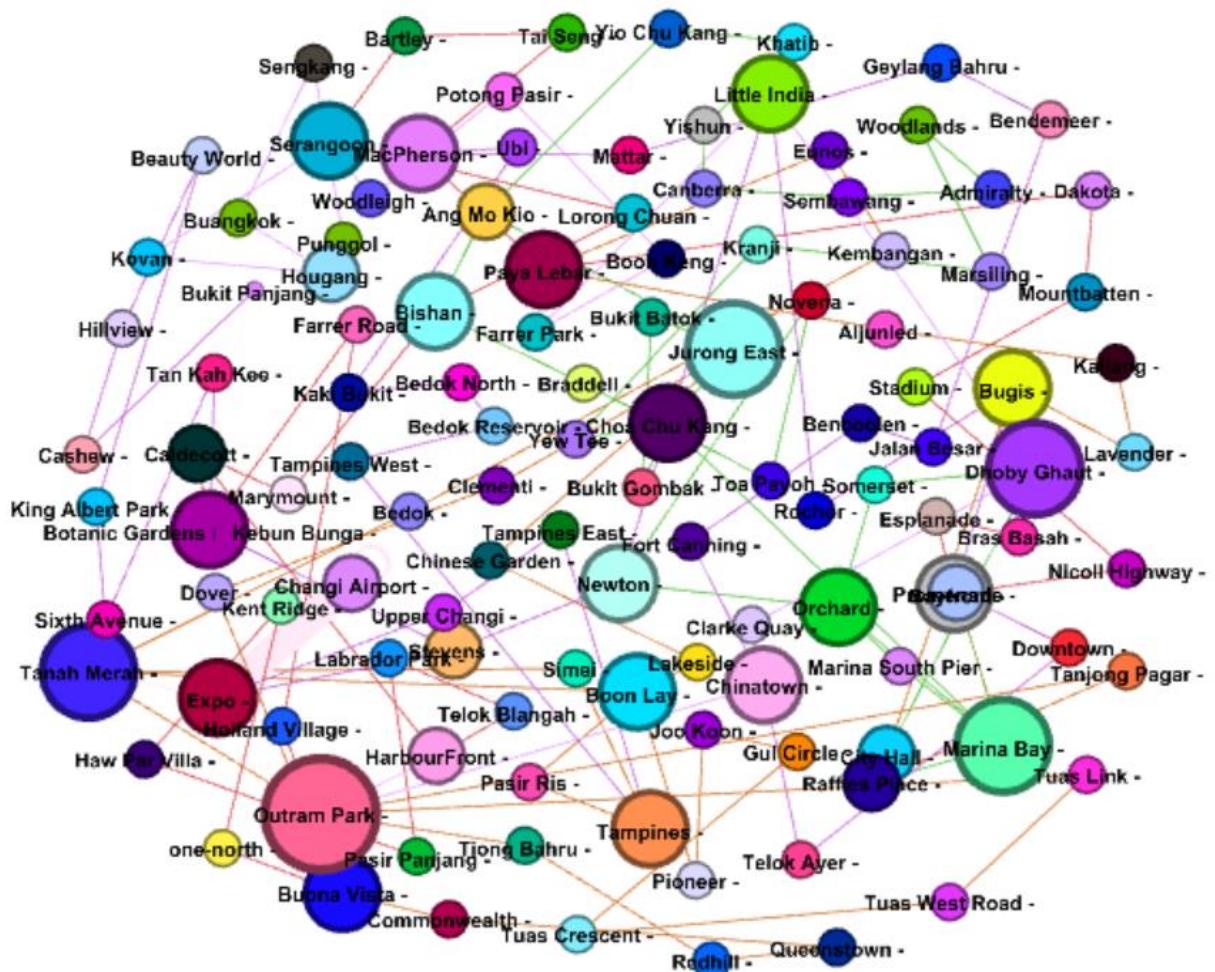
Attributes Dataframes

```
> attr = data.frame(row.names=V(simple_g)$name,degree=V(simple_g)$degree,  
+                    betweenness=V(simple_g)$betweenness,  
+                    closeness=V(simple_g)$closeness,eigen=V(simple_g)$eigen)  
  
> table(attr$degree)  
  
0  1  2  3  4  5  6  
29  2 89  8 16  4  1
```



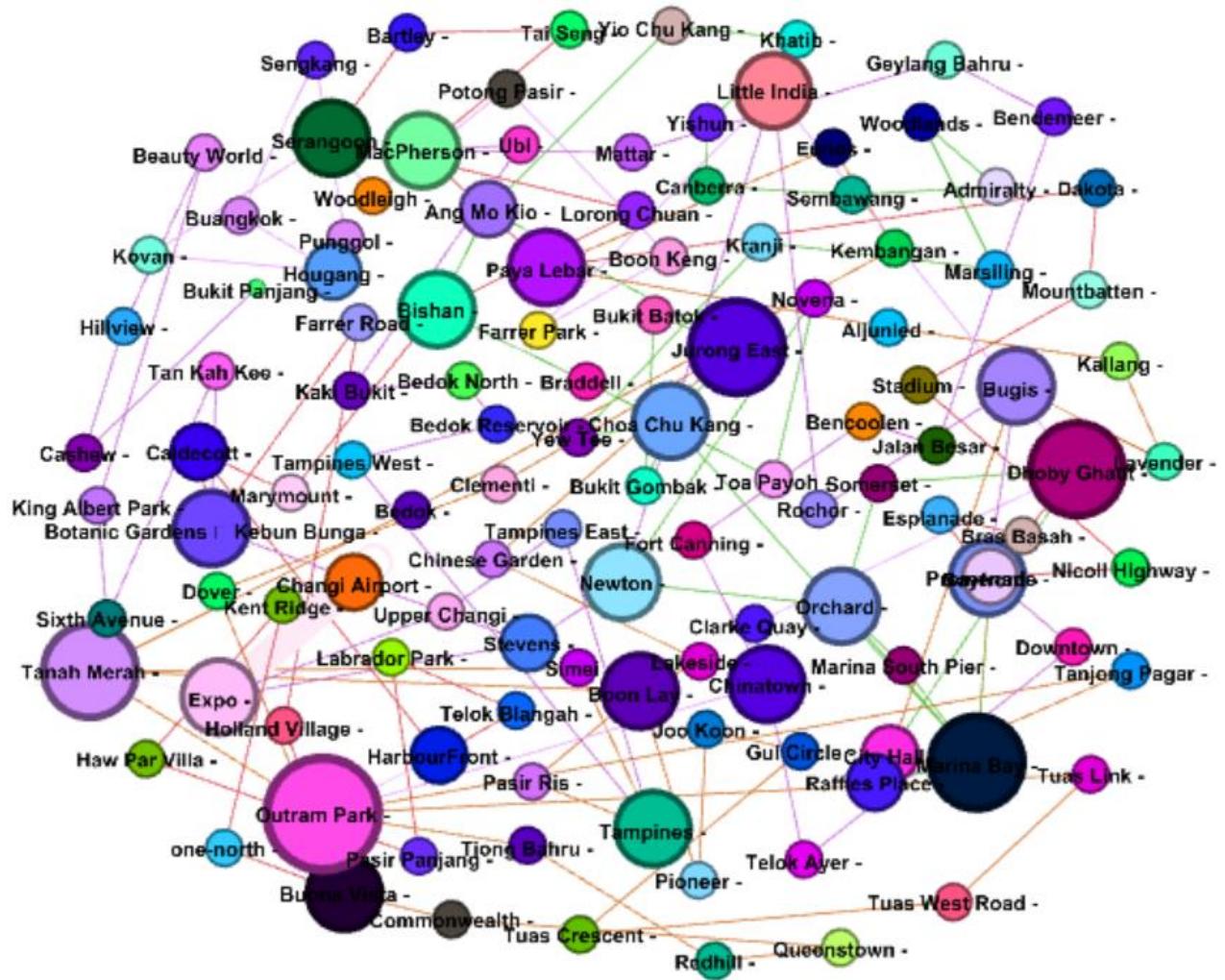
```
> table(attr$betweenness)
```

0	4.59643316786174e-05	0.0016700373843231	0.00192437335294478
32	1	1	1
0.00235184163755592	0.00238248452534167	0.00375703692030223	0.00389930747073604
1	1	1	1
0.0045045045045045	0.00517864803579089	0.00521695164552307	0.00537782680639824
1	1	1	2
0.00555402341116627	0.00577312005883435	0.00664184592756021	0.00720720720720721
1	1	1	1
0.00720873935159649	0.00896304467733039	0.00961880247594533	0.00971160665038216
1	1	1	1
0.0100287605389646	0.0102546423974995	0.0104461604461604	0.0106100998958142
1	1	1	1
0.0106621928050499	0.0108475822761537	0.0112980327266042	0.0114276083663839
1	1	1	1
0.0114650364650365	0.0117423545994975	0.0117745296316725	0.0118204939633511
1	1	1	1
0.0118826552500022	0.0119430655144941	0.012156033584605	0.0121621621621622
1	1	1	1
0.0130011206541819	0.0136590672304958	0.0139333210761782	0.0143025678739964
1	1	1	1
0.0145343594323186	0.0148342219770791	0.0149664241500976	0.0150741120128875
1	1	1	1
0.0155681191395477	0.0158347122632837	0.0161610590182019	0.0162070233498805
1	1	1	1
0.0162845060804244	0.0171508242936814	0.017306446388079	0.0174128209842496
1	1	1	1
0.0198846076397097	0.0204464668750383	0.0205077526506098	0.0215113072255929
1	1	1	1
0.0216568609425752	0.0220567506281792	0.02211956854814	0.0226711405282834
1	1	1	1
0.0228114411787881	0.0229799770616097	0.0230344776263144	0.023447937733652
1	1	1	1
0.0245066495066495	0.0249555678127107	0.0265459336887908	0.0301142979714408
1	1	1	1
0.0302828338542624	0.0307326276714032	0.0314932279217993	0.0319467426610284
1	1	1	1
0.0319911748483177	0.0320371391799963	0.032123814776876	0.0333777655206227
1	1	1	1
0.0336489550775265	0.0355242998100141	0.0356851749708893	0.0358000858000858
1	1	1	1
0.0362835867937909	0.0375775921694289	0.0379588772445915	0.0382458260009281
1	1	1	1
0.0384767420481706	0.0396628406832489	0.0401192008334866	0.0409894588466017
1	1	1	1
0.0412363529710469	0.0413295949010235	0.0421516998047611	0.042287185144328
1	1	1	2
0.0430832435934477	0.0523993381136238	0.0549019865346396	0.0563507384935956
1	1	1	1
0.057635551002898	0.0612603857501817	0.0623276337562052	0.0634935956364527
1	1	1	1
0.0647232509477407	0.0715995149668619	0.0772353986639701	0.0781640970416481
1	1	1	1
0.0801909051909052	0.0804100018385733	0.0917135065094249	0.091764723907581
1	1	1	1
0.0940119419711256	0.0971685971685972	0.0973478580621437	0.107047864190721
1	1	1	1
0.108566219280505	0.113032420175277	0.120084224165857	0.155558619844334
1	1	1	1



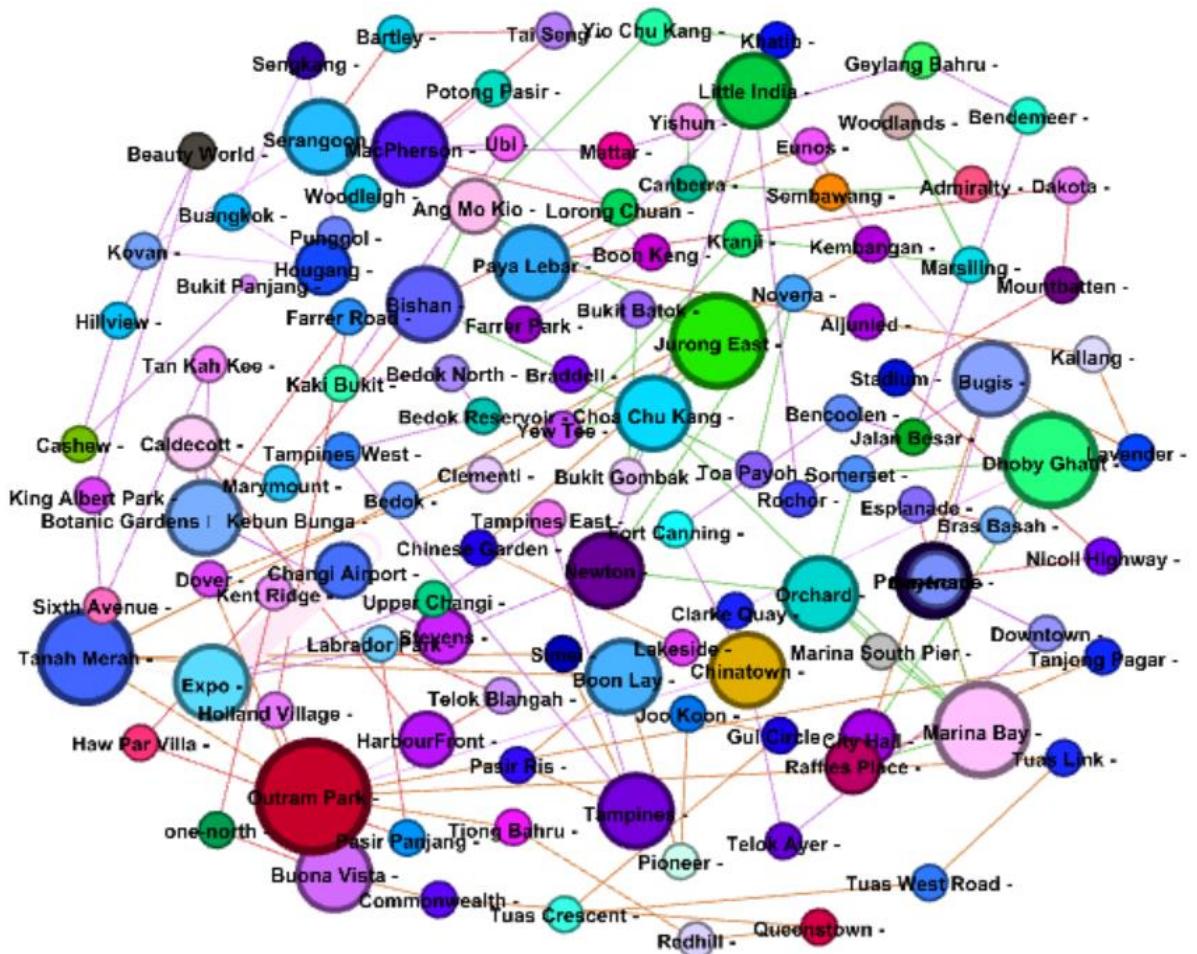
```
> table(attr$closeness)
```

4.53473607836024e-05	0.000174520069808028	0.000178189593727726	0.000181225081551287		
29	1	1	1	1	1
0.000181950509461427	0.000182315405651778	0.00018254837531946	0.000185048112509252		
1	1	1	1	1	1
0.000185116623472788	0.000185459940652819	0.000185804533630621	0.00018828845791753		
2	1	1	1	2	
0.000188572506128606	0.000188786105342647	0.000189035916824197	0.000189178963299281		
1	1	1	1	1	1
0.000189214758751183	0.000189250567751703	0.000189753320683112	0.000189933523266857		
1	1	1	1	1	1
0.000189969604863222	0.000190585096245474	0.000190621425848265	0.000190912562046583		
1	1	1	1	1	1
0.00019105846388995	0.000191204588910134	0.000191314329443275	0.000191681042744873		
1	1	1	1	1	1
0.000191901746305891	0.00019208605455244	0.000192566917003659	0.000192678227360308		
1	1	1	1	1	1
0.000192752505782575	0.000193124758594052	0.000193274062620796	0.000193423597678917		
1	1	1	1	2	
0.000193685841564982	0.000193760899050572	0.000193798449612403	0.00019387359441644		
2	1	1	1	1	1
0.000194024058983314	0.000194325689856199	0.000194363459669582	0.000194552529182879		
1	1	1	1	1	1
0.000195236235845373	0.000195427008012507	0.00019546520719312	0.000195618153364632		
1	1	1	1	2	
0.000195771339075959	0.00019588638589618	0.000196001568012544	0.000196425063838146		
1	1	1	1	2	
0.000196734212079481	0.000196850393700787	0.000196966712625566	0.000197199763360284		
2	1	1	1	1	1
0.00019723865877712	0.000197316495659037	0.000197355437142293	0.00019739439399921		
1	1	1	1	1	1
0.000197472353870458	0.000197511356903022	0.000197667523225934	0.000197706603400554		
1	1	1	1	1	1
0.000197863078749505	0.000197941409342835	0.000198059021588433	0.000198176773682124		
1	1	1	1	1	1
0.000198216055500496	0.000198333994446648	0.000198412698412698	0.000198609731876862		
2	1	1	1	1	1
0.000198925800676348	0.000198965380023876	0.000199084212621939	0.000199163513244374		
1	2	1	1	1	1
0.000199322304165836	0.000199760287654814	0.000199840127897682	0.000199920031987205		
2	1	1	1	1	1
0.0001999600079984	0.000200280392549569	0.000200601805416249	0.000200803212851406		
2	2	1	1	1	1
0.00020096463022508	0.000201005025125628	0.000201207243460765	0.00020124773596297		
1	1	1	1	1	1
0.00020096463022508	0.000201005025125628	0.000201207243460765	0.00020124773596297		
1	1	1	1	1	1
0.000201369311316955	0.000201450443190975	0.000201572263656521	0.00020185708518369		
1	1	1	1	2	
0.000202061022428773	0.000202183582693085	0.000202224469160768	0.000202388180530257		
1	1	1	1	1	1
0.000202470135654991	0.000202511138112596	0.00020259319286872	0.000202963263649279		
1	1	1	1	1	1
0.000203086921202275	0.000203541624262162	0.000204498977505112			
1	1	1			



```
> table(attr$eigen)
```

7.30604920606494e-18	0.000154881507965341	0.000494614475258369	0.0010401857695776
29	1	1	1
0.0014246710309335	0.00166091790217456	0.00166091790217457	0.00213380462102125
1	1	1	1
0.00331085798972081	0.00350345229686652	0.00405507595349635	0.00426395962146019
1	1	1	1
0.00458357598805216	0.00480230027724479	0.00653352324436609	0.00660201365342882
1	1	1	1
0.00734282818803907	0.00762510297197871	0.00810413790653631	0.00843942848313553
1	1	1	1
0.00873414405104212	0.00876318223778098	0.00905447887499985	0.0102951296965518
1	1	1	1
0.0115252239644098	0.0117039974477907	0.0158242368417344	0.0162812465046619
1	1	1	1
0.0164623656360214	0.0170079568399616	0.0185297442436664	0.0212970082774384
1	1	1	1
0.0224771235254446	0.0230902101546933	0.0236404775538424	0.0254120481804312
1	1	1	1
0.0260928543668846	0.026621148930521	0.0286135622949502	0.0290523128656054
1	1	1	1
0.0300954814778261	0.0305612213583995	0.0327507550219344	0.0343140688487249
1	1	1	1
0.0381392495875336	0.0383248554724156	0.0431919109468019	0.0449591400608149
1	1	1	1
0.0451883447793734	0.0466898488781656	0.0508486099247228	0.0553183834276055
1	1	1	1
0.0599079102204517	0.0605159009848361	0.0626831508575472	0.0650044986655938
1	1	1	1
0.0670564945212339	0.0720989592670032	0.0729566210061339	0.0790675910613562
1	1	1	1
0.0794865814847264	0.093064392461044	0.0957049326594976	0.0957693709440998
1	1	1	1
0.096887275088277	0.0992155498639656	0.109951673656711	0.112890093450687
1	1	1	1
0.118216235429992	0.122109236618126	0.132199316446206	0.133771598115319
1	1	1	1
0.146567829224392	0.154182269520442	0.159685791577978	0.161840272991293
1	1	1	1
0.166629123641734	0.170019049829044	0.171126483016777	0.177621473968208
1	1	1	1
0.184501815641657	0.190504602036361	0.204768449403281	0.204836154933052
1	1	1	1
0.219526523922046	0.221941324468511	0.224597389937396	0.226743191981378
1	1	1	1
0.234203973112663	0.234436458282763	0.2438884806339	0.246379724159496
1	1	1	1
0.252410555100189	0.264450610377109	0.267494687406495	0.26751486534141
1	1	1	1
0.311610331920564	0.33233549278111	0.346764235448642	0.348680573059656
1	1	1	1
0.389459617346603	0.407548820839864	0.422178841054371	0.427828812802805
1	1	1	1
0.436005330798049	0.437063072143383	0.483048342077561	0.483809692039499
1	1	1	1
0.510321617287931	0.523333572166081	0.582045803507609	0.585257554653847
1	1	1	1
0.588177308990057	0.621571910658208	0.629702572544711	0.633844085302707
1	1	1	1
0.679642910742591	0.758540007127527	0.760691900375003	0.869021435089023
1	1	1	1



Gephi 0.9.2 - sinproject.gephi

File Workspace View Tools Window Help

Overview Data Laboratory Preview

Workspace 1

Data Table X

Nodes Edges Configuration Add node Add edge Search/Replace Import Spreadsheet Export table More actions Filter: Id

Jurong East
Bukit Batok
Bukit Gombak
Choa Chu Kang
Yew Tee
Kranji
Marsiling
Woodlands
Admiralty
Sembawang
Canberra
Yishun
Jiathib
Yio Chu Kang
Ang Mo Kio
Bishan
Braddell
Toa Payoh
Novena
Newton
Orchard

Somerset
Dhoby Ghaut
City Hall
Raffles Place
Marina Bay
Marina South Pier
Pasir Ris
Tampines
Simei
Tanjah Merah
Bedok
Kembangan
Eunos
Paya Lebar
Aljunied
Kallang
Lavender
Bugis
Tanjong Pagar
Outram Park

Tiong Bahru
Redhill
Queenstown
Commonwealth
Buona Vista
Dover
Clementi
Chinese Garden
Lakeside
Boon Lay
Pioneer
Joo Koon
Gul Circle
Tuas Crescent
Tuas West Road
Tuas Link
Expo
Changi Airport
HarbourFront
Chinatown
Clarke Quay

Little India
Farrer Park
Boon Keng
Potong Pasir
Woodleigh
Serangoon
Kovan
Hougang
Buangkok
Sengkang
Punggol
Bras Basah
Esplanade
Promenade
Nicoll Highway
Stadium
Mountbatten
Dakota
MacPherson
Tai Seng
Bartley

1180.983333
25.583333
20.933333
1057.0
449.583333
342.583333
235.583333
128.583333
49.0
42.416667
115.416667
222.416667
329.416667
436.416667
998.216667
1229.566667
97.5
78.4
122.9
850.269048
388.183333

40.869048
431.452381
250.569048
468.659524
1022.661905
0.0
132.3
363.083333
246.616667
1306.27619
458.52619
394.692857
349.442857
597.22381
158.104762
162.804762
216.304762
416.038095
366.033333
1692.166667

271.466667
176.3
113.633333
104.633333
412.916667
288.766667
347.516667
389.433333
386.433333
690.683333
189.416667
78.416667
18.166667
56.75
155.583333
266.583333
704.095924
0.0
874.7
778.859524
249.97619

626.959524
255.066667
186.566667
151.566667
172.25
1058.95
460.0
348.5
58.5
0.5
58.5
72.25
25.916667
408.769048
188.259524
129.259524
109.092857
141.42619
666.390476
418.55
445.883333

Id	Label	Interval	Degree	Eigenvector Centrality	Closeness Centrality	Betweenness Centrality
Lorong Chuan		2	0.24086	0.169516	840.166667	
Marymount		2	0.263402	0.183559	612.963333	
Caldecott		3	0.39918	0.193496	872.316667	
Botanic Gardens ↔ Kebun Bunga		4	0.451965	0.1904	1164.466667	
Farrer Road		2	0.217102	0.165049	239.933333	
Holland Village		2	0.176933	0.150442	169.35	
one-north		2	0.144665	0.130913	129.916667	
Kent Ridge		2	0.099222	0.120202	56.333333	
Haw Par Villa		2	0.084451	0.120202	60.416667	
Pasir Panjang		2	0.086112	0.129771	128.083333	
Labrador Park		2	0.111356	0.145477	223.083333	
Telok Blangah		2	0.20567	0.166667	327.583333	
Bukit Panjang		1	0.030407	0.084457	0.0	
Cashew		2	0.054312	0.092177	118.0	
Hillview		2	0.068492	0.101277	234.0	
Beauty World		2	0.075984	0.112158	348.0	
King Albert Park		2	0.084706	0.125395	460.0	
Sixth Avenue		2	0.111021	0.141836	570.0	
Tan Kah Kee		2	0.196602	0.162791	678.0	
Stevens		3	0.557899	0.197347	997.659524	
Rochor		2	0.369458	0.164138	163.97619	
Id	Label	Interval	Degree	Eigenvector Centrality	Closeness Centrality	Betweenness Centrality
King Albert Park		2	0.084706	0.125395	460.0	
Sixth Avenue		2	0.111021	0.141836	570.0	
Tan Kah Kee		2	0.196602	0.162791	678.0	
Stevens		3	0.557899	0.197347	997.659524	
Rochor		2	0.369458	0.164138	163.97619	
Bayfront		3	0.519046	0.174231	448.569048	
Downtown		2	0.249132	0.164365	115.983333	
Telok Ayer		2	0.269599	0.17	132.233333	
Fort Canning		2	0.237005	0.162347	334.309524	
Bencoolen		2	0.121079	0.145299	248.142857	
Jalan Besar		2	0.089019	0.133708	177.142857	
Bendemeer		2	0.086471	0.126059	124.309524	
Geylang Bahru		2	0.105427	0.122807	105.642857	
Mattar		2	0.166431	0.128649	140.583333	
Ubi		2	0.166657	0.12851	161.366667	
Kaki Bukit		2	0.106592	0.121181	111.55	
Bedok North		2	0.091353	0.123572	127.733333	
Bedok Reservoir		2	0.105998	0.13034	175.8	
Tampines West		2	0.170824	0.140165	240.616667	
Tampines East		2	0.213986	0.146914	62.8	
Upper Changi		2	0.271221	0.163462	124.716667	

7. Results and discussion:

From the results obtained from the different centrality measures applied to the MRT network, we could often see that the station '**Outram Park**' frequently appears as one of the significant nodes suggesting that it could likely be the most important node in the MRT network.

The consequences of removing such a node might *breaks the network into different smaller networks and reduce connectivity among the network*, seriously impairing the connectivity and coverage of the MRT services.

Id	Label	Interval	Degree	Eigenvector Centrality	Closeness Centrality	Betweenness Centrality
Somerset		2	0.459566	0.168794	40.869048	
Choby Ghaut		5	0.743997	0.180577	431.452381	
City Hall		3	0.578163	0.179217	250.569048	
Raffles Place		3	0.599121	0.18949	468.659524	
Marina Bay		5	0.927122	0.192557	1022.661905	
Marina South Pier		2	0.507736	0.168794	0.0	
Pasir Ris		2	0.298958	0.159304	132.3	
Tampines		4	0.365586	0.154545	363.083333	
Simei		2	0.404249	0.170977	246.616667	
Tanah Merah		5	0.910191	0.201014	1306.7619	
Bedok		2	0.34094	0.177083	458.526119	
Kembangan		2	0.175788	0.161465	394.692857	
Eunos		2	0.182506	0.151207	349.442857	
Paya Lebar		4	0.321219	0.149686	597.22381	
Allied		2	0.175348	0.140165	158.104762	
Kallang		2	0.144412	0.141667	162.804762	
Lavender		2	0.225401	0.151786	216.304762	
Bugis		4	0.532036	0.168555	416.038095	
Tanjong Pagar		5	0.484036	0.191935	366.033333	
Outram Park		6	1.0	0.209139	169.166667	

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