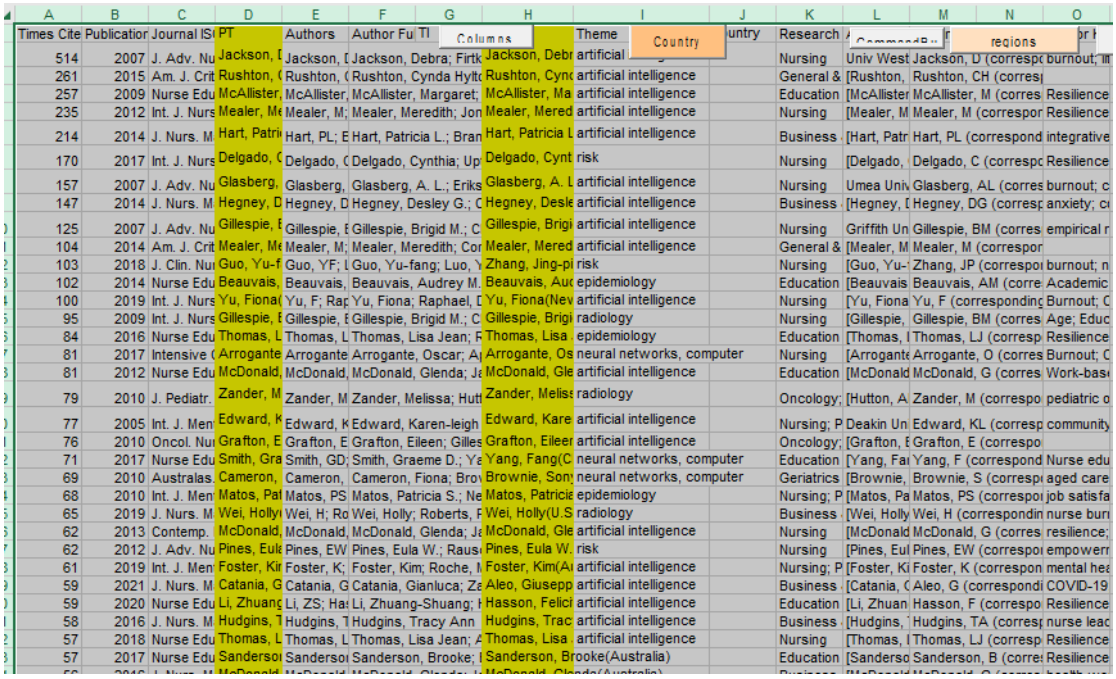
How to conduct this study



Times Cite	Publication	Journal IS	PT	Authors	Author Fu	TI	Columns	Theme	Country	untry	Research	L	M	regions	O
514	2007	J. Adv. Nu	Jackson, [	Jackson, [	Jackson, Debra; Firtk		Jackson, Debr	artificial			Nursing	Univ West	Jackson, D (corresp		burnout; In
261	2015	Am. J. Crit	Rushton, (	Rushton, (	Rushton, Cynda Hyltc		Rushton, Cync	artificial intelligence			General &	[Rushton,	Rushton, CH (corres		
257	2009	Nurse Edu	McAllister,	McAllister,	McAllister, Margaret;		McAllister, Ma	artificial intelligence			Education	[McAllister	McAllister, M (corres		Resilience
235	2012	Int. J. Nurs	Mealer, Mi	Mealer, M;	Mealer, Meredith; Jon		Mealer, Mered	artificial intelligence			Nursing	[Mealer, M	Mealer, M (corresp		Resilience
214	2014	J. Nurs. M	Hart, Patri	Hart, PL; E	Hart, Patricia L.; Bran		Hart, Patricia L	artificial intelligence			Business	[Hart, Patr	Hart, PL (correspond		integrative
170	2017	Int. J. Nurs	Delgado, (	Delgado, (	Delgado, Cynthia; Up		Delgado, Cynt	risk			Nursing	[Delgado,	Delgado, C (corresp		Resilience
157	2007	J. Adv. Nu	Glasberg,	Glasberg,	Glasberg, A. L.; Eriks		Glasberg, A. L	artificial intelligence			Nursing	Umea Univ	Glasberg, AL (corres		burnout; c
147	2014	J. Nurs. M	Hegney, D	Hegney, D	Hegney, Desley G.; C		Hegney, Desle	artificial intelligence			Business	[Hegney, D	Hegney, DG (corresp		anxiety; c
125	2007	J. Adv. Nu	Gillespie, E	Gillespie, E	Gillespie, Brigid M.; C		Gillespie, Brigi	artificial intelligence			Nursing	Griffith Un	Gillespie, BM (corres		empirical r
104	2014	Am. J. Crit	Mealer, Mi	Mealer, M;	Mealer, Meredith; Cor		Mealer, Mered	artificial intelligence			General &	[Mealer, M	Mealer, M (correspor		
103	2018	J. Clin. Nu	Guo, Yu-f	Guo, YF; L	Guo, Yu-fang; Luo, Y		Zhang, Jing-pi	risk			Nursing	[Guo, Yu-f	Zhang, JP (correspor		burnout; n
102	2014	Nurse Edu	Beauvais,	Beauvais,	Beauvais, Audrey M.		Beauvais, Auc	epidemiology			Education	[Beauvais	Beauvais, AM (corre		Academic
100	2019	Int. J. Nurs	Yu, Fiona(	Yu, F; Rap	Yu, Fiona; Raphael, D		Yu, Fiona(Nev	artificial intelligence			Nursing	[Yu, Fiona	Yu, F (corresponding		Burnout; C
95	2009	Int. J. Nurs	Gillespie, E	Gillespie, E	Gillespie, Brigid M.; C		Gillespie, Brigi	radiology			Nursing	[Gillespie,	Gillespie, BM (corres		Age; Educ
84	2016	Nurse Edu	Thomas, L	Thomas, L	Thomas, Lisa Jean; F		Thomas, Lisa	epidemiology			Education	[Thomas, L	Thomas, LJ (corresp		Resilience
81	2017	Intensive (	Arrogante	Arrogante	Arrogante, Oscar; Al		Arrogante, Os	neural networks, computer			Nursing	[Arrogante	Arrogante, O (corres		Burnout; C
81	2012	Nurse Edu	McDonald,	McDonald,	McDonald, Glenda; Ja		McDonald, Gle	artificial intelligence			Education	[McDonald	McDonald, G (corres		Work-bas
79	2010	J. Pediatr.	Zander, M	Zander, M	Zander, Melissa; Hut		Zander, Meliss	radiology			Oncology;	[Hutton, A	Zander, M (correspo		pediatric o
77	2005	Int. J. Men	Edward, K	Edward, K	Edward, Karen-leigh		Edward, Kare	artificial intelligence			Nursing; P	Deakin Un	Edward, KL (corresp		community
76	2010	Oncol. Nur	Grafton, E	Grafton, E	Grafton, Eileen; Gilles		Grafton, Eileer	artificial intelligence			Oncology;	[Grafton, E	Grafton, E (correspo		
71	2017	Nurse Edu	Smith, Gra	Smith, GD;	Smith, Graeme D.; Ya		Yang, Fang(C	neural networks, computer			Education	[Yang, Fai	Yang, F (correspond		Nurse edu
69	2010	Australas.	Cameron,	Cameron,	Cameron, Fiona; Bro		Brownie, Sony	neural networks, computer			Geriatrics	[Brownie,	Brownie, S (corresp		aged care
68	2010	Int. J. Men	Matos, Pat	Matos, PS	Matos, Patricia S.; Ne		Matos, Patricia	epidemiology			Nursing; P	[Matos, Pa	Matos, PS (correspo		job satisfa
65	2019	J. Nurs. M	Wei, Holly	Wei, H; Ro	Wei, Holly; Roberts, F		Wei, Holly(U.S	radiology			Business	[Wei, Holly	Wei, H (correspondin		nurse burı
62	2013	Contemp.	McDonald,	McDonald,	McDonald, Glenda; Ja		McDonald, Gle	artificial intelligence			Nursing	[McDonald	McDonald, G (corres		resilience;
62	2012	J. Adv. Nu	Pines, Eula	Pines, EW	Pines, Eula W.; Raus		Pines, Eula W.	risk			Nursing	[Pines, Eul	Pines, EW (correspo		empowerr
61	2019	Int. J. Men	Foster, Kir	Foster, K;	Foster, Kim; Roche, M		Foster, Kim(Au	artificial intelligence			Nursing; P	[Foster, Ki	Foster, K (correspon		mental hea
59	2021	J. Nurs. M	Catania, G	Catania, G	Catania, Gianluca; Za		Aleo, Giusepp	artificial intelligence			Business	[Catania, G	Aleo, G (correspondi		COVID-19
59	2020	Nurse Edu	Li, Zhuang	Li, ZS; Ha	Li, Zhuang-Shuang; H		Hasson, Felici	artificial intelligence			Education	[Li, Zhuan	Hasson, F (correspo		Resilience
58	2016	J. Nurs. M	Hudgins, T	Hudgins, T	Hudgins, Tracy Ann		Hudgins, Trac	artificial intelligence			Business	[Hudgins, T	Hudgins, TA (corresp		nurse lead
57	2018	Nurse Edu	Thomas, L	Thomas, L	Thomas, Lisa Jean; A		Thomas, Lisa	artificial intelligence			Nursing	[Thomas, L	Thomas, LJ (corresp		Resilience
57	2017	Nurse Edu	Sanderso	Sanderso	Sanderson, Brooke; I		Sanderson, Brooke(Australia)				Education	[Sanderso	Sanderson, B (corre		Resilience

Download data from WoS

To extract keywords plus in wos and keywords as well as MeSH in Pubmed

B	C	D	E	F
standards	epidemiology			
hip fracture	osteoporos	osteoporotic fractures		
osteoporos	osteoporos	tooth loss		
diagnostic :	value-based purchasing			
methods	diagnostic imaging			
absorptiom	bone densi	deep learni	diagnostic :	tomogra
diagnostic :	machine le	methods	workflow	
artificial int	bone densi	methods		
physiology	deep learni	metabolism		
bone densi	machine le	diagnostic :	methods	
diagnosis	methods	trends	machine learning	
methods	diagnostic :	diagnosis		
electronic h	unsupervised machine learning			
deep learni	diagnostic imaging			
artificial int	neural networks, computer			
artificial intelligence				
artificial int	radiograph	radiology		

MeSH in Pubed

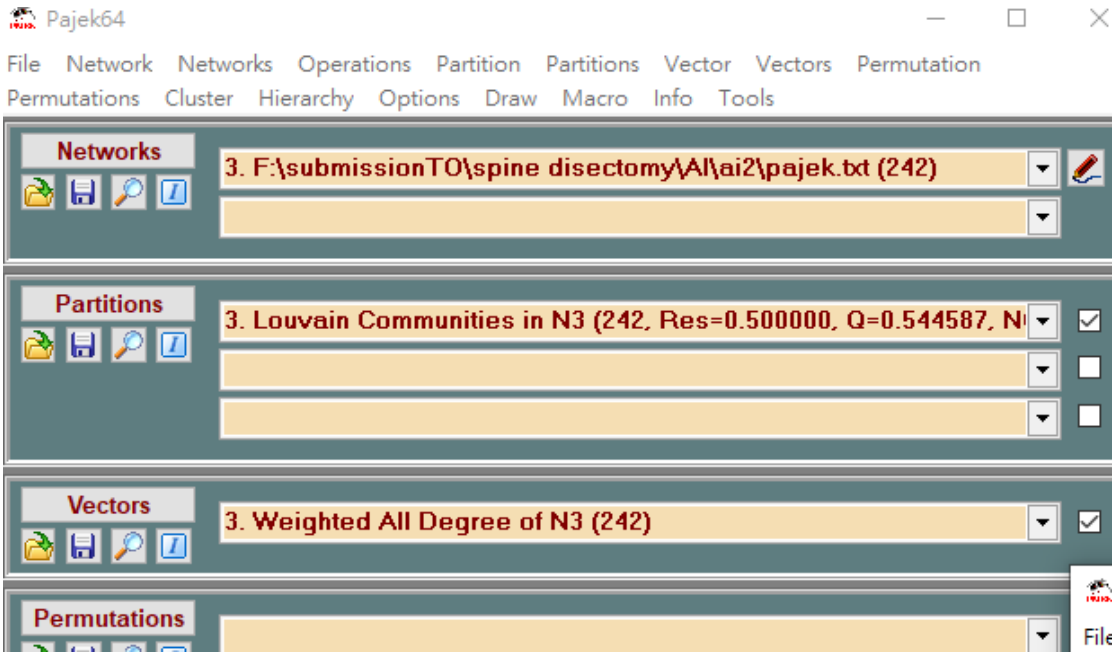
	A	B	C	D	E	F	G	H	I
	Pubmed Id							70	
	31290297	artificial intellige	radiography, der	radiology				35751803	osteoporo
	29698784							36140424	
	31760458	artificial intellige	diagnosis					35931902	
	33751686							36010220	
	32584712	diagnosis	epidemiology	machine learnin	adverse effects			36103890	osteoporo
	32749735	electronic health	unsupervised machine learning					35919046	
	31398274	artificial intellige	frailty	methods	diagnosis			35435584	osteoporo
	30852715	absorptiometry,	bone density	deep learning	diagnostic imagi	tomography, x-ray compute		35347425	artificial i
0	32207266	bone density	machine learnin	diagnostic imagi	methods			35928480	deep lear
1	33722728	fractures, bone	osteoporosis					35673469	
2	30928154	deep learning	diagnostic imaging					34989149	artificial i
3	33403479	standards	epidemiology					35646527	
4	32989561	artificial intellige	osteoporosis					35626185	
5	35347425	artificial intelligence						35364575	pedicle s
6	34761151	methods	lumbar vertebrae	diagnosis	support vector machine			35432776	
7	34020078	fractures, compr	osteoporotic frac	spinal fractures				35368375	

To match the two databases with keywords and MeSH terms

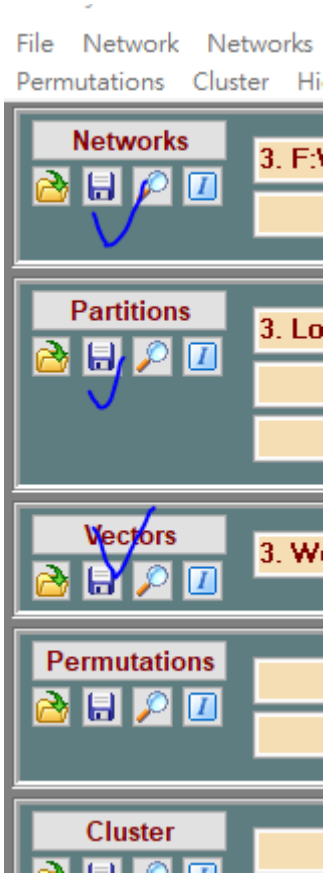
	C	D	E	F	G	H
1				Have one	Duplicate	Space
2	BONE-M	X-RAY AE	FIXATION	STRENGT	MEN	CT
3	MEDICA	SURGEON	TOOTH E	AMERICA	OSTEOPO	RISKS
4	NATION	FRACTUR	OSTEOPO	DIAGNOS	BURDEN	WOMEN
5	BONE-MI	ARTIFICIA	TEXTURE	NEURAL-I	HIP FRAC	COMPRES
6	ARTIFIC	HIP FRAC	OSTEOPO	RADIOGR	TRAUMA	CT
7	BODY C	ARTIFICIA	RISK	OSTEOPO	PREVALE	FRACTUR
8	COMPU	BODY CO	BONE-MI	AUTOMA	THORACC	CT
9	BONE-D	ARTIFICIA	OSTEOPO	DIAGNOS	FRACTUR	WOMEN
10	PRIMAR	RISK	Machine le	Artificial in	Deep learn	Endocrinol
11	Artificial	Convolutio	Deep learn	Ensemble r	Fresh fract	Magnetic r
12	RADIAT	CLASSIFI	CANCER	TRAUMA	RADIOGR	SEDATIO
13	Artificial	Fracture lia	Automated	Osteoporos	Health info	standards
14	TRABEC	FRACTUR	HIP FRAC	RISK-ASS	OSTEOPO	IDENTIFY
15	CONVOI	LUMBAR	VERTEBR	TEXTURE	LOW-BAC	PREDICTI

To generate code for pajek software

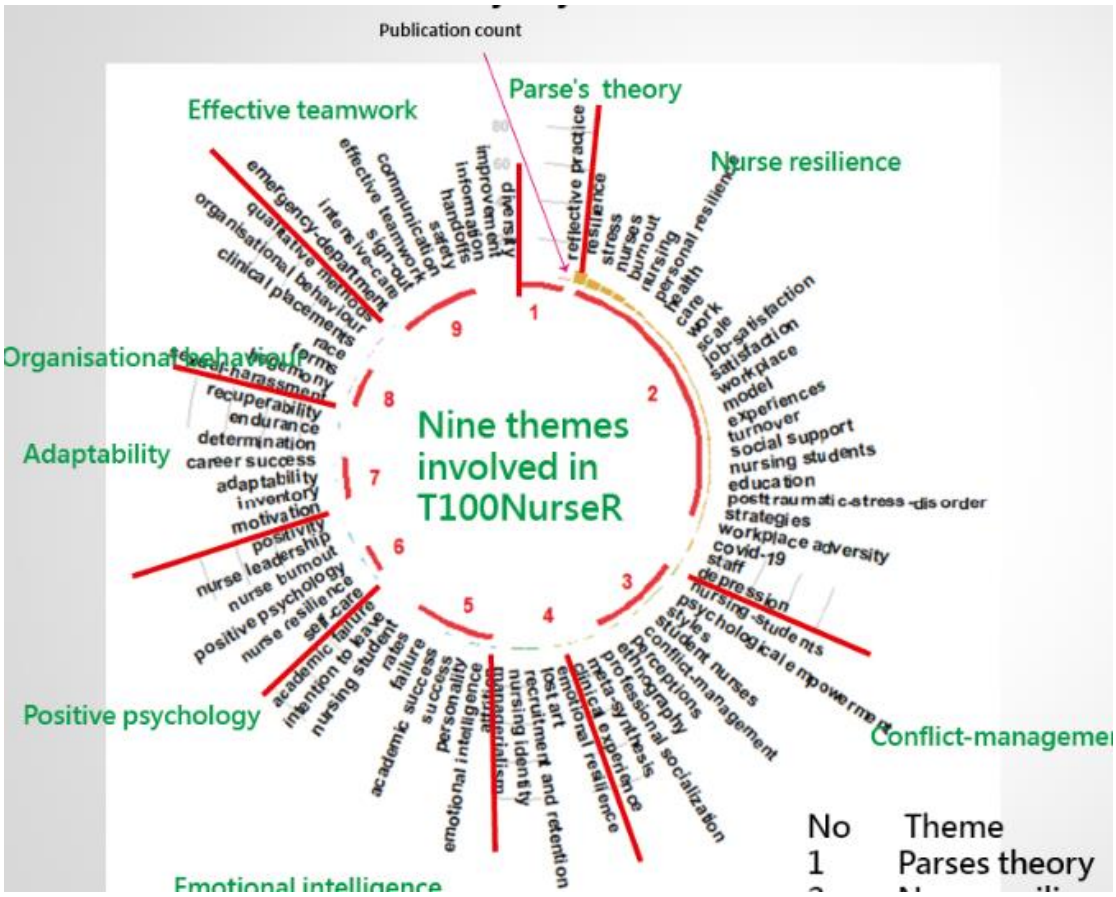
	A	B	C
1	*Vertices 242		
2	1 "artificial intelligence"		
3	2 "osteoporosis"		
4	3 "machine learning"		
5	4 "diagnosis"		
6	5 "artificial-intelligence"		
7	6 "deep"		
8	7 "classification"		
9	8 "dental caries"		
10	9 "osteoporotic fractures"		
11	10 "meta-analysis"		
12	11 "hip fractures"		
13	12 "bone-mineral density"		
14	13 "risk"		
15	14 "fracture liaison service"		
16	15 "automated fracture identification"		
17	16 "health informatics"		
18	17 "standards"		



To use Pajek to classify clusters and themes



Download data from Pajek to MS Excel


Publication count
Nine themes involved in T100NurseR
Parse's theory
Nurse resilience
Conflict-managemer
Emotional intelligence
Positive psychology
Adaptability
Organisational behaviour
Effective teamwork
No Theme
1 Parses theory

Copy into

To R

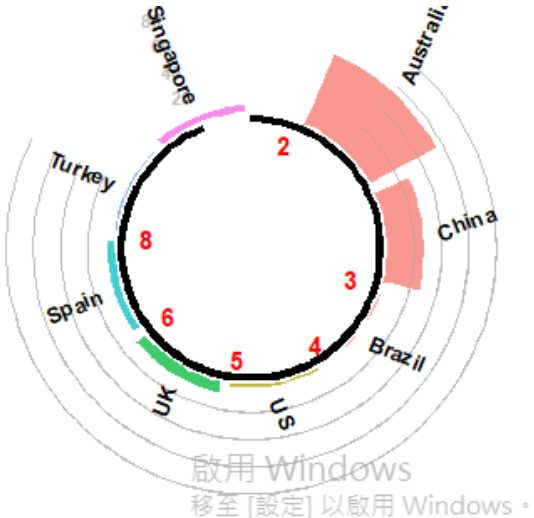
https://r-graph-gallery.com/297-circular-barplot-

```
library(tidyverse)

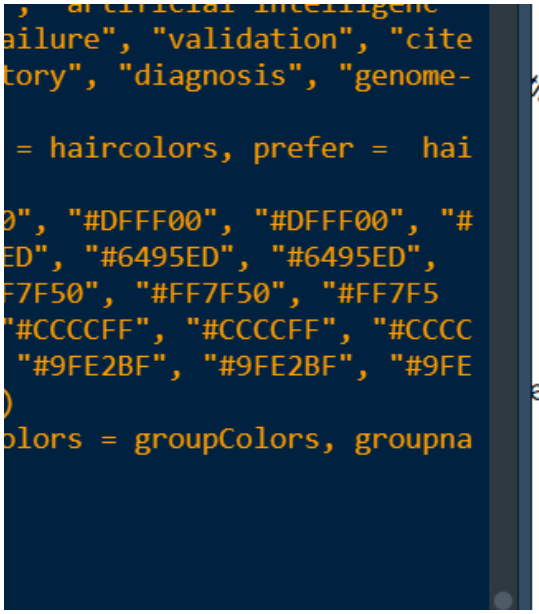
# Create dataset
data <- data.frame(individual=c("Australia","Chi
# Set a number of 'empty bar' to add
empty_bar <- 3
to_add <- data.frame( matrix(NA, e
colnames(to_add) <- colnames(data
```

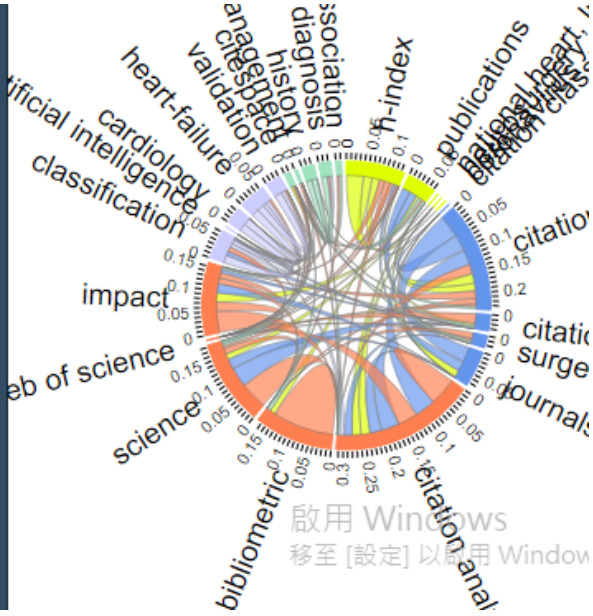
```
), color="black", fontfa
, angle= label_data$angl


ion
ata, aes(x = start, y =
olour = "black", alpha=
= FALSE )  +
, aes(x = title, y = -1
,0,0,0), colour = "red",
"bold", inherit.aes = FA
```



啟用 Windows
移至 [設定] 以啟用 Windows。



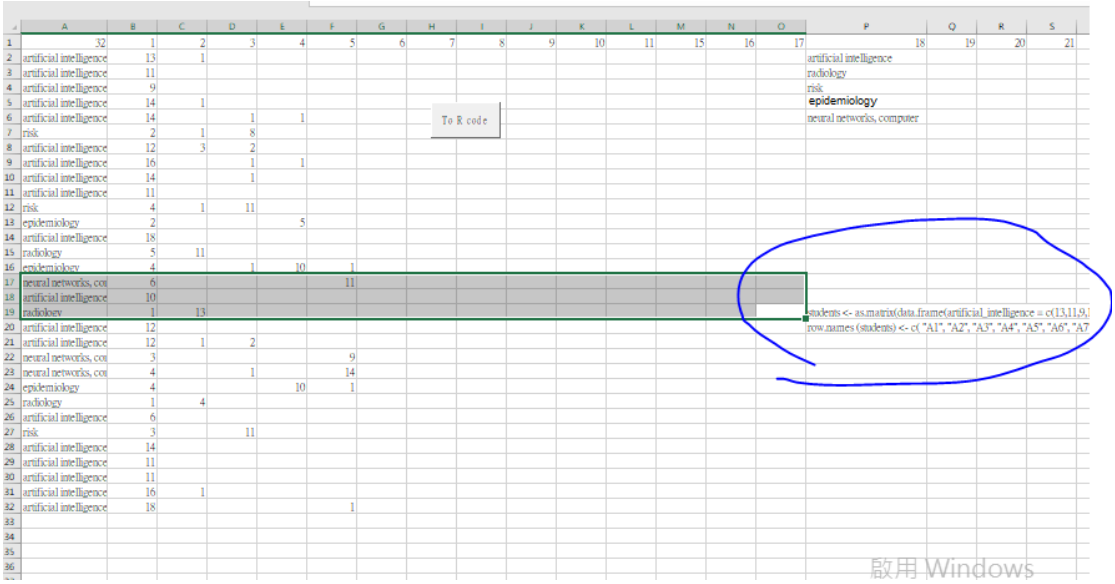


library(chorddiag)

Create dummy data

m <-matrix(c(2.09494324045408E-02, 0, 0, 0.041, 0.018, 0, 0, 0, 0, 0.008, 0.013, 0, 0.006, 0.008, 0.013, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0.007, 0, 0, 0, 0.018, 0, 0, 0.019, 0, 0, 0, 0.006, 0, 0, 0, 0, 0, 0, 0, 0, 0.006, 0.007, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0

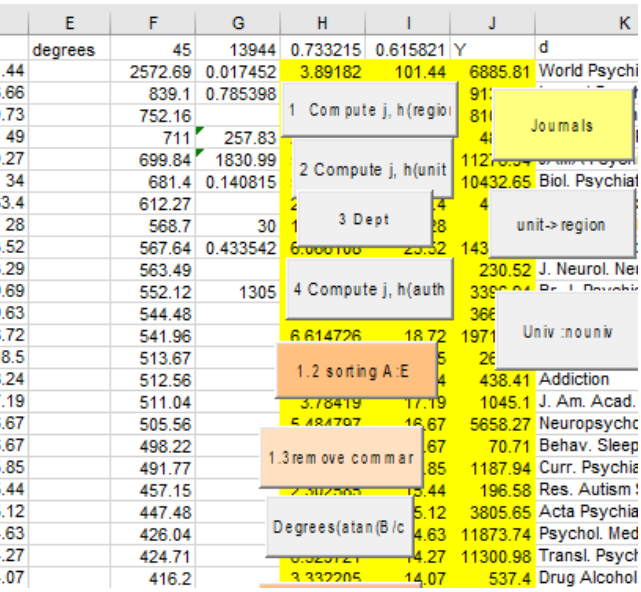
```
haircolors <- c("h-index", "publications", "national heart, lung, and blood institute (us)",
"neurosurgery", "coronavirus", "citation classics", "citation-classics", "citations", "surgery",
"journals", "citation analysis", "bibliometric", "science", "web of science", "impact",
"classification", "artificial intelligence", "cardiology", "heart-failure", "validation",
"citespace", "management", "history", "diagnosis", "genome-wide association")
dimnames(m) <- list(have = haircolors, prefer =    haircolors)
groupColors <- c("#DFFF00", "#DFFF00", "#DFFF00", "#DFFF00", "#DFFF00",
"#6495ED", "#6495ED", "#6495ED", "#6495ED", "#6495ED", "#FF7F50", "#FF7F50",
"#FF7F50", "#FF7F50", "#FF7F50", "#CCCCFF", "#CCCCFF", "#CCCCFF", "#CCCCFF",
"#CCCCFF", "#9FE2BF", "#9FE2BF", "#9FE2BF", "#9FE2BF", "#9FE2BF")
p <- chorddiag(m, groupColors = groupColors, groupnamePadding = 20)
p
```



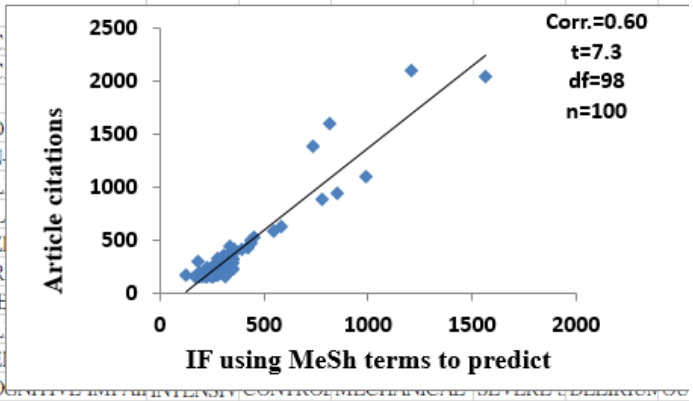
Data were organized in MS Excel for use in R language

Downloaded to MS Excel with 20606 records

	A	B	C	D	E	F	G	H	I	J	K
1	d	:dddd	FP	:dddd	degrees	45	13944	0.733215	0.615821	Y	d
2	World Psychiatry	4869	48	101.44		2572.69	0.017452	3.89182	101.44	6885.81	World Psychi
3	Lancet Psychiatry	6459	114	56.66		839.1	0.785398				
4	Am. J. Psychiat.	5732	113	50.73		752.16					
5	Psychother. Psychosor	343	7	49		711	257.83				
6	JAMA Psychiatry	7974	198	40.27		699.84	1830.99				
7	Biol. Psychiatry	7377	217	34		681.4	0.140815				
8	Depress. Anxiety	334	10	33.4		612.27					
9	Prog. Molec. Biol. Trans	56	2	28		568.7	30				
10	Mol. Psychiatr.	10112	430	23.52		567.64	0.433542				
11	J. Neurol. Neurosurg. P	163	7	23.29		563.49					
12	Br. J. Psychiatry	2402	122	19.69		552.12	1305				
13	Brain Behav. Immun.	2591	132	19.63		544.48					
14	Schizophr. Bull.	13944	745	18.72		541.96					
15	Psychosom. Med.	185	10	18.5		513.67					
16	Addiction	310	17	18.24		512.56					
17	J. Am. Acad. Child Ado	739	43	17.19		511.04					
18	Neuropsychopharmacc	4001	240	16.67		505.56					
19	Behav. Sleep Med.	50	3	16.67		498.22					
20	Curr. Psychiatry Rep.	840	53	15.85		491.77					
21	Res. Autism Spectr. Dis	139	9	15.44		457.15					
22	Acta Psychiatr. Scand.	2691	178	15.12		447.48					
23	Psychol. Med.	8396	574	14.63		426.04					
24	Transl. Psychiatr.	7991	560	14.27		424.71					
25	Drug Alcohol Depend.	380	27	14.07		416.2					



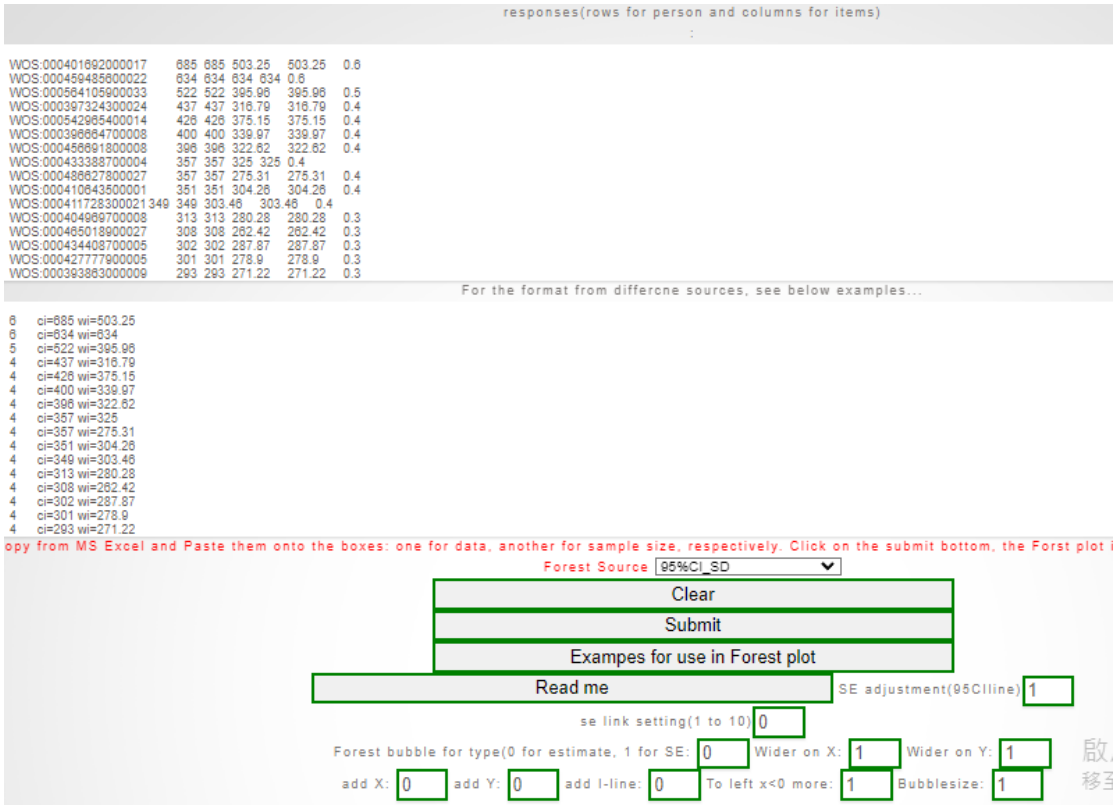
	A	B	C	D	E	F	G	H	I
1	0.951943	Times Cited, WoS Core		3 77	100				
2	1208.06	2093	CRITICALLY-ILL PAT	MECHANICALLY			POSTTRAUMAT		
3	1561.99	2047	EXPLICIT CRITERIA	DRUG-DRUG			DELIRIUM		
4	819.21	1603	CONFUSION ASSE	CRITICALLY-ILL			LIFE-PROGRAM		
5	735.46	1381	INTENSIVE-CARE-	MECHANICALLY	FUNCTION	REPEATA	DELIRIUM DUR		
6	992.1	1092	CENTRAL MEMOR	CANCER	TRANSPL	THERAPY	LYMPHOCYTES	ANTIBOD	CD19
7	851.33	941	ACUTE-RESPIRATC	QUALITY-OF-LIFE	SYNDROM	HEALTH-C	POSTTRAUMAT	PULMON	CRITICAL
8	778.42	879	CAR-T-CELLS						
9	583.45	629	INTENSIVE-CARE-U	IC					
10	544.97	578	INTENSIVE-CARE-U	IC					
11	448.59	527	PRESENTATIONS						
12	440.27	506	MURINE PRION DIS	ID					
13	435.54	473	TUMOR-NECROSIS-	IN					
14	335.87	436	INTENSIVE-CARE-U	AL					
15	423.92	429	CELL-WALL COMP	RL					
16	355.07	418	BYPASS GRAFT-SU	IIZ					
17	396.38	409	INTENSIVE-CARE-U	FR					
18	342.33	388	RANDOMIZED CONV	E					
19	361.03	387	ELDER-LIFE-PROG	AL					
20	332.4	353	CRITICALLY-ILL PA	TE					
21	305.89	353	RESPIRATORY-DIS	CO					
22	312.34	346	CONFUSION ASSES	ALLY VENTILATE	POSTOPE	ELDERLY	HIP FRACTURE	REDUCIN	PREDICTI

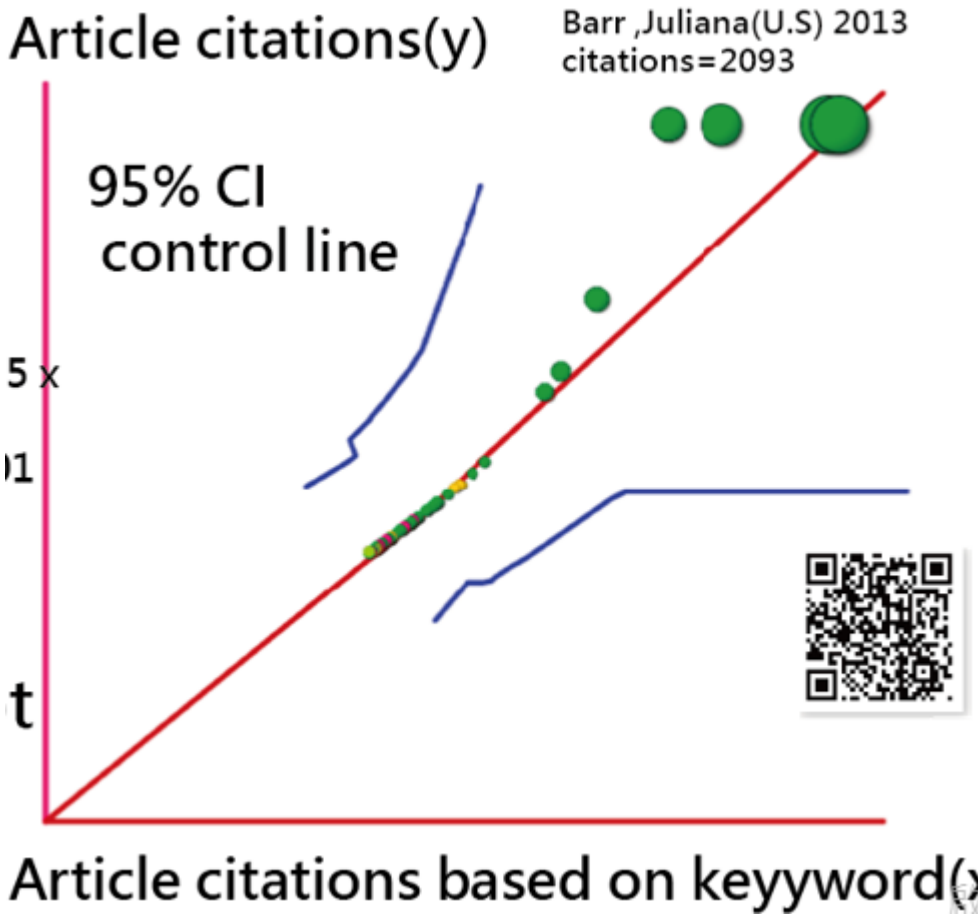


Predict article citations using the keyword IF

F	G	H	I	J	K	L	M	N
BarrJuliana	1208.06	2093	1208.06	2093	DELIRIUM	1	1	
RadcliffSue	1561.99	2047	1561.99	2047	DELIRIUM	1	1	
InouyeShar	819.21	1603	819.21	1603	DELIRIUM	1	1	
Pandharipa	735.46	1381	735.46	1381	DELIRIUM	1	1	
Kochender	992.1	1092	992.1	1092	DELIRIUM	1	1	
RogersJona	851.33	941	851.33	941	DELIRIUM	1	1	
LeeDaniel	778.42	879	778.42	879	DELIRIUM	1	1	
DevlinJohn	583.45	629	583.45	629	DELIRIUM	1	1	
DevlinJohn	544.97	578	544.97	578	DELIRIUM	1	1	
PatersonRo	448.59	527	448.59	527	BRAIN	2	2	
Cunningha	440.27	506	440.27	506	BRAIN	2	2	
Varatharaj	435.54	473	435.54	473	DELIRIUM	1	1	
SalluhJorge	335.87	436	335.87	436	DELIRIUM	1	1	
HooglandIr	423.92	429	423.92	429	DELIRIUM	1	1	
MeybohmF	355.07	418	355.07	418	DELIRIUM	1	1	
AldecoaCe	396.38	409	396.38	409	DELIRIUM	1	1	

Organizing data in MS Excel

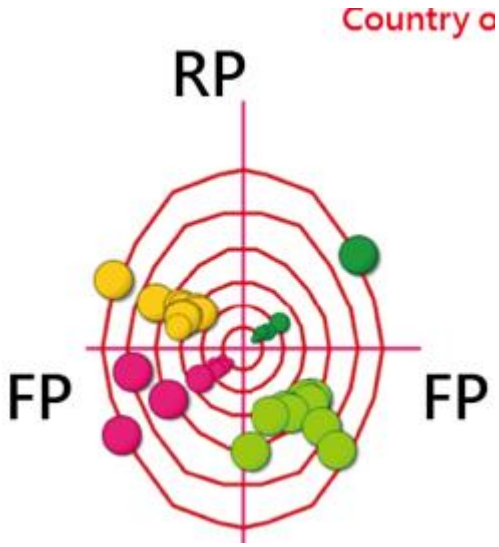




U	V	W	X	Y	Z	AA	AB	AC	AD	AE
1										
U.S	0.712145	0.712145	0.692064	0.692064	18861.23	1	RP=4155 FP=4096 k=0.99 theta=45.41 CJA=1886			
China	0.285334	0.285334	0.299968	0.299968	9248.93	1	RP=1698 FP=1741 k=0.41 theta=44.28 CJA=9248			
	266356	0.266356	0.314985	0.314985	8037.53	1	RP=1635 FP=1778 k=0.41 theta=42.6 CJA=8037.5			
	207913	0.207913	0.163744	0.163744	5096.68	1	RP=1155 FP=1025 k=0.26 theta=48.41 CJA=5096			
	171802	0.171802	0.167378	0.167378	4781.06	1	RP=1003 FP=990 k=0.24 theta=45.37 CJA=4781.(			
	174281	0.174281	0.165432	0.165432	4609.78	1	RP=1011 FP=985 k=0.24 theta=45.75 CJA=4609.7			
	130445	0.130445	0.132147	0.132147	3890.98	1	RP=769 FP=774 k=0.19 theta=44.81 CJA=3890.9(			
	122786	0.122786	0.123127	0.131812	3660.96	1	RP=722 FP=723 k=0.18 theta=44.96 CJA=3660.9(			
	126707	0.126707	0.131812	0.100493	3179.7	1	RP=752 FP=767 k=0.14 theta=44.43 CJA=3179.7			
	101514	0.101514	0.100493	0.107897	3061.52	1	RP=595 FP=592 k=0.15 theta=45.14 CJA=3061.5			
Kings Coll Lond	0.620289	0.620289	-0.73685	0.172427	2572.69	2	RP=456 FP=497 k=0.96 theta=42.54 CJA=2572.6(			
Shanghai Jiao T	0.245475	0.245475	-0.26539	0.120812	839.1	2	RP=176 FP=183 k=0.36 theta=43.88 CJA=839.1			
Univ Pittsburgh(	0.161511	0.161511	-0.22391	0.113013	752.16	2	RP=124 FP=146 k=0.28 theta=40.34 CJA=752.16			
Ctr Addict & Me	0.212759	0.212759	-0.19285	0.142172	711	2	RP=146 FP=139 k=0.29 theta=46.41 CJA=711			
Peking Univ(Chi	0.184248	0.184248	-0.18709	0.132384	699.84	2	RP=130 FP=131 k=0.26 theta=44.78 CJA=699.84			
Karolinska Inst(	0.149396	0.149396	-0.15509	0.16957	681.4	2	RP=106 FP=108 k=0.22 theta=44.46 CJA=681.4			
UCL(U.K)	0.156062	0.156062	-0.193	0.164518	612.27	2	RP=116 FP=129 k=0.25 theta=41.96 CJA=612.27			
Columbia Univ(U	0.136847	0.136847	-0.17094	0.165385	568.7	2	RP=102 FP=114 k=0.22 theta=41.82 CJA=568.7			
Sichuan Univ(C	0.12954	0.12954	-0.14661	0.145044	567.64	2	RP=94 FP=100 k=0.2 theta=43.23 CJA=567.64			
Cent South Univ	0.14158	0.14158	-0.13304	0.143309	563.49	2	RP=98 FP=95 k=0.19 theta=45.89 CJA=563.49			
Psychiat	-0.63358	0.633578	-0.73219	0.140753	14603.71	3	RP=3253 FP=3497 k=0.97 theta=42.93 CJA=1460			
Psychol	-0.16245	0.162454	-0.18347	0.15615	3555.26	3	RP=829 FP=881 k=0.25 theta=43.26 CJA=3555.2(			
Psychiat & Psyc	0.07128	0.071279	0.0733	0.151003	1894.34	3	RP=355 FP=360 k=0.1 theta=44.6 CJA=1894.34			

Copy 1

Copy 2



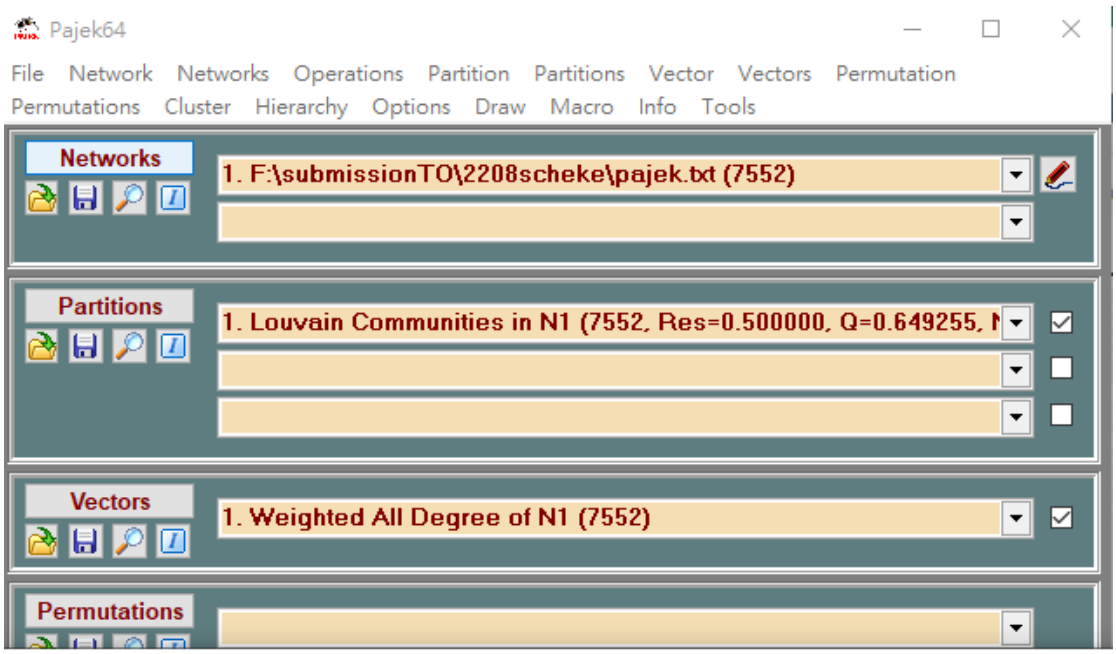
	C	D	E	F	G	H
					Space no use	
	CRITICALLY-ILL PATIEI	MECHANICALLY	CONFUSIC	TORSADES	POSTTRAUMAT	LONG-TE
	EXPLICIT CRITERIA	DRUG-DRUG	DEMENTIA	RISK	DELIRIUM	SLEEP
	CONFUSION ASSE	CRITICALLY-ILL I	POSTOPE	HIP-FRACT	LIFE-PROGRAM	FUNCTIC
	INTENSIVE-CARE-I	MECHANICALLY	FUNCTION	REPEATA	DELIRIUM DUR	SURVIVC
	CENTRAL MEMORY	CANCER	TRANSPL	THERAPY	LYMPHOCYTES	ANTIBOD
	ACUTE-RESPIRATO	QUALITY-OF-LIFE	SYNDRO	HEALTH-I	POSTTRAUMAT	PULMON
	CAR-T-CELLS	B-CELL	CORNELL	THERAPY	BLINATUMOMA	NEUROT
	INTENSIVE-CARE-U	ICALLY-ILL PATIE	MECHAN	CONFUSI	QUALITY-OF-L	POSTTRA
	INTENSIVE-CARE-U	ICALLY-ILL PATIE	MECHAN	ANALGES	LONG-TERM SE	RESPIRA
	PRESENTATIONS	BRAIN	COVID-19	SARS-Co	Vencephalitis	ADEM
	MURINE PRION DIS	OID PRECURSOR PI	TRANSGE	LONG-TE	CENTRAL-NER	NF-KAPP
	TUMOR-NECROSIS-	IN-VITRO MODEL	CENTRAL	EXPERIM	LIPOPOLYSACC	EXPERIM
	INTENSIVE-CARE-U	ALLY VENTILATEI	CONFUSI	RANDOM	TERM COGNITI	IN-HOSPI
	CELL-WALL COMP	RLY-LIFE INFECTI	MEMORY	GLIAL AC	FREUNDS-ADJU	MOUSE M
	BYPASS GRAFT-SU	MIZED CONTROLLE	ACUTE K	CARDIAC	MYOCARDIAL-	DOUBLE-

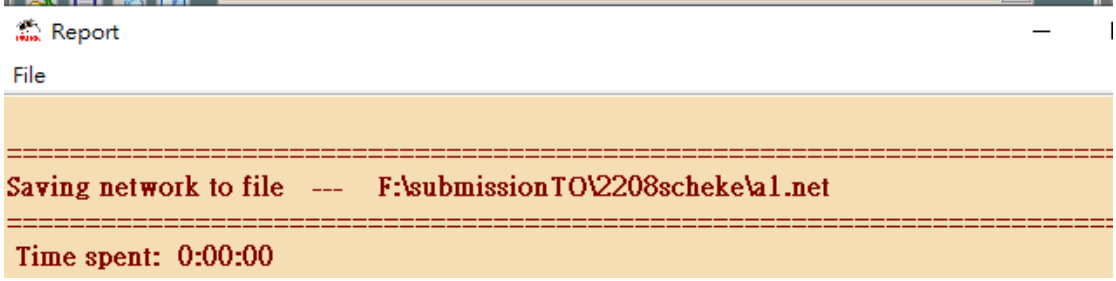
SNA

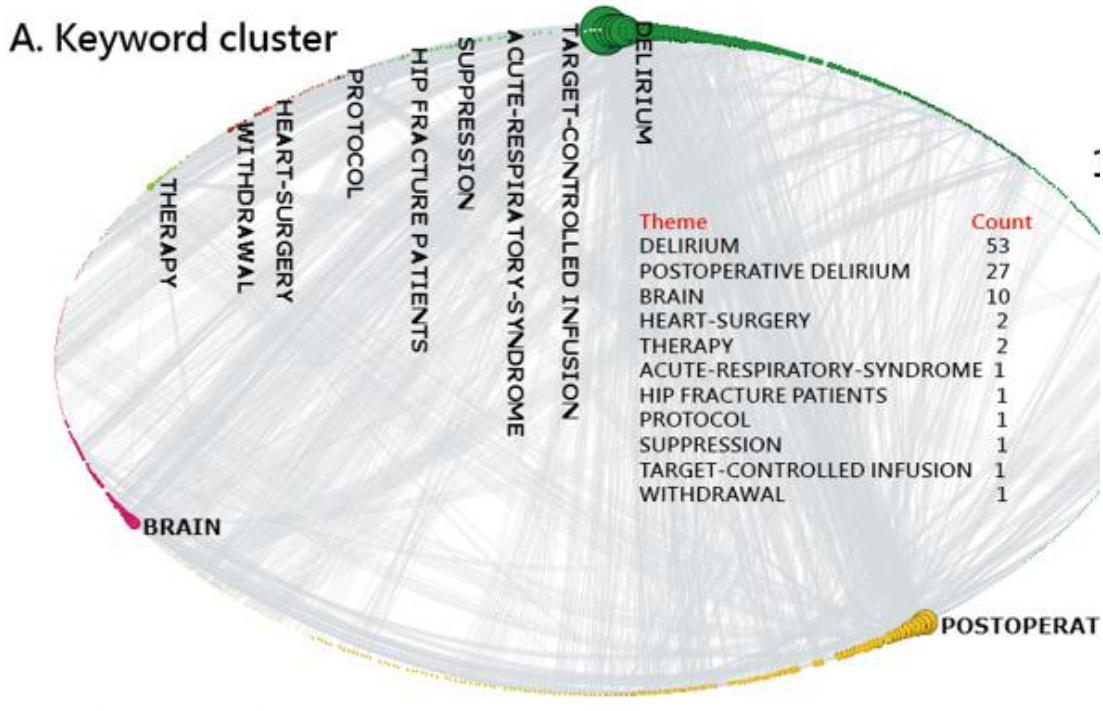
	A	B	C
1			
2	CRITICALLY-ILL PA	MECHANICALLY V	1.29525
3	OXIMETRY	deliberate hypotensic	1448.90245
4	CRITICALLY-ILL PA	TORSADES-DE-POI	0.00956
5	CRITICALLY-ILL PA	POSTTRAUMATIC-	0.18029
6	CRITICALLY-ILL PA	LONG-TERM SEDA	0.07279
7	CRITICALLY-ILL PA	QUALITY-OF-LIFE	0.16103
8	CRITICALLY-ILL PA	ANALGESIA-BASE	0.03340
9	CRITICALLY-ILL PA	CHEST TUBE REMO	0.00216
10	CRITICALLY-ILL PA	NONSTEROIDAL A	0.00480
11	CRITICALLY-ILL PA	agitation	0.04172
12	CRITICALLY-ILL PA	analgesia	0.06074
13	CRITICALLY-ILL PA	critical care medicine	0.00543
14	CRITICALLY-ILL PA	delirium	0.82640
15	CRITICALLY-ILL PA	evidence-based medi	0.00960
16	CRITICALLY-ILL PA	GRADE	0.01605
17	CRITICALLY-ILL PA	guidelines	0.00911
18	CRITICALLY-ILL PA	intensive care	0.12588
19	CRITICALLY-ILL PA	outcomes	0.03153

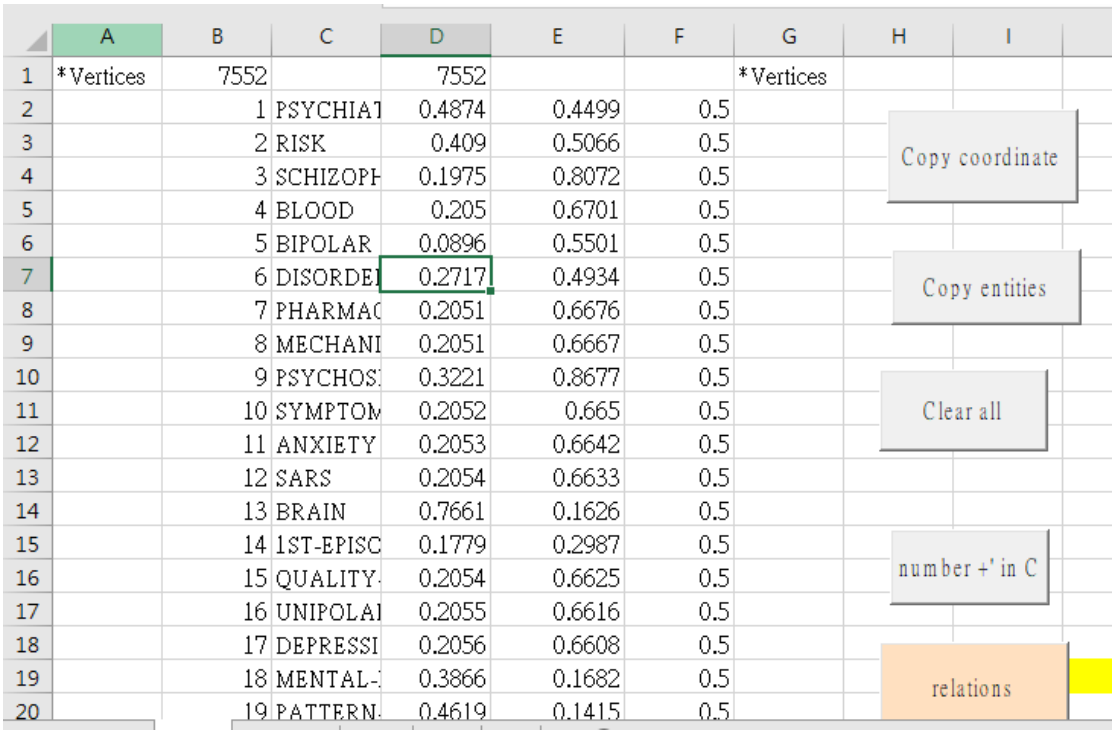
	A	B	C	D
1	*Vertices 7552			
2	1 "PSYCHIATRIC-DISORDERS"			
3	2 "RISK"			
4	3 "SCHIZOPHRENIA"			
5	4 "BLOOD"			
6	5 "BIPOLAR DISORDER"			
7	6 "DISORDERS"			
8	7 "PHARMACOLOGY"			
9	8 "MECHANISMS"			
10	9 "PSYCHOSIS"			
11	10 "SYMPTOMS"			
12	11 "ANXIETY"			
13	12 "SARS"			
14	13 "BRAIN"			
15	14 "1ST-EPISODE PSYCHOSIS"			
16	15 "QUALITY-OF-LIFE"			
17	16 "UNIPOLAR DEPRESSION"			
18	17 "DEPRESSIVE SYMPTOMS"			
19	18 "MENTAL-DISORDERS"			

Codes for Pajek


Pajek64
File Network Networks Operations Partition Partitions Vector Vectors Permutation
Permutations Cluster Hierarchy Options Draw Macro Info Tools
Networks
1. F:\submissionTO\2208scheke\pajek.txt (7552)
Partitions
1. Louvain Communities in N1 (7552, Res=0.500000, Q=0.649255, N
Vectors
1. Weighted All Degree of N1 (7552)
Permutations


Report
File
Saving network to file --- F:\submissionTO\2208scheke\a1.net
Time spent: 0:00:00


A. Keyword cluster
DELIRIUM
TARGET-CONTROLLED INFUSION
ACUTE-RESPIRATORY-SYNDROME
SUPPRESSION
HIP FRACTURE PATIENTS
PROTOCOL
HEART-SURGERY
WITHDRAWAL
THERAPY
BRAIN
POSTOPERAT
Theme Count
DELIRIUM 53
POSTOPERATIVE DELIRIUM 27
BRAIN 10
HEART-SURGERY 2
THERAPY 2
ACUTE-RESPIRATORY-SYNDROME 1
HIP FRACTURE PATIENTS 1
PROTOCOL 1
SUPPRESSION 1
TARGET-CONTROLLED INFUSION 1
WITHDRAWAL 1

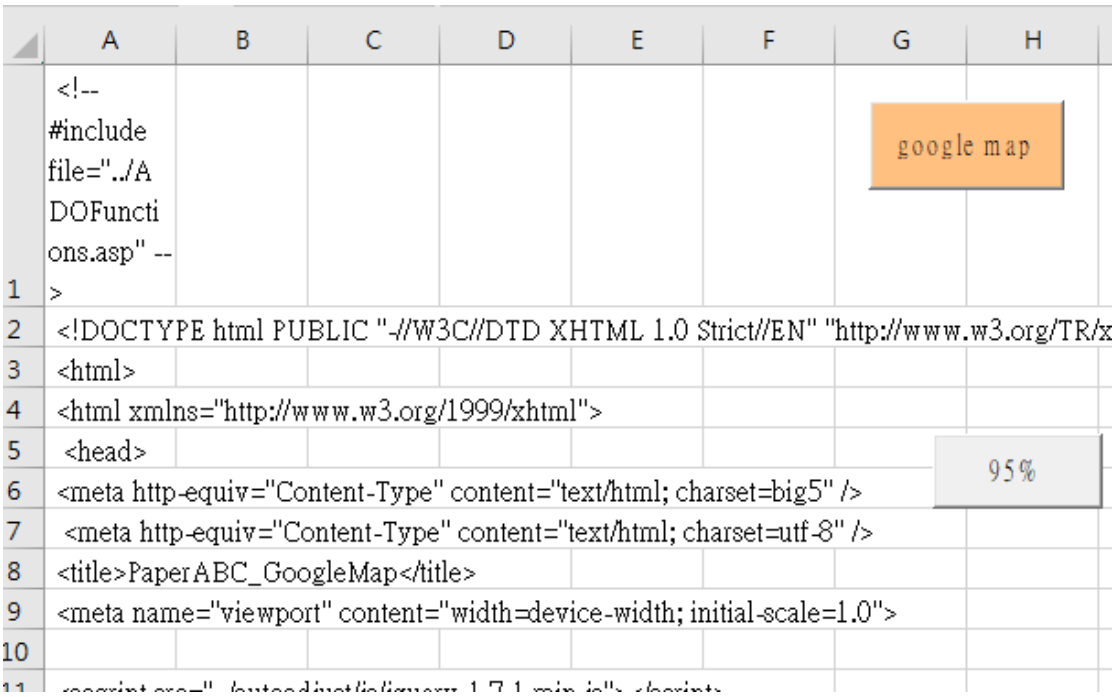


	A	B	C	D	E	F	G	H	I
1	*Vertices	7552		7552			*Vertices		
2		1	PSYCHIAT	0.4874	0.4499	0.5			
3		2	RISK	0.409	0.5066	0.5			
4		3	SCHIZOPH	0.1975	0.8072	0.5			
5		4	BLOOD	0.205	0.6701	0.5			
6		5	BIPOLAR	0.0896	0.5501	0.5			
7		6	DISORDEI	0.2717	0.4934	0.5			
8		7	PHARMAC	0.2051	0.6676	0.5			
9		8	MECHANI	0.2051	0.6667	0.5			
10		9	PSYCHOSI	0.3221	0.8677	0.5			
11		10	SYMPTOM	0.2052	0.665	0.5			
12		11	ANXIETY	0.2053	0.6642	0.5			
13		12	SARS	0.2054	0.6633	0.5			
14		13	BRAIN	0.7661	0.1626	0.5			
15		14	1ST-EPISC	0.1779	0.2987	0.5			
16		15	QUALITY-	0.2054	0.6625	0.5			
17		16	UNIPOLAI	0.2055	0.6616	0.5			
18		17	DEPRESSI	0.2056	0.6608	0.5			
19		18	MENTAL-	0.3866	0.1682	0.5			
20		19	PATTERN-	0.4619	0.1415	0.5			

Results from SNA and transform data into data below

	A	B	C	D	E
1		#REF!	#REF!	21881.85	0.68
2	SCHIZOPHRENIA	-30.72	-54.45	956.1718	0.62
3	BIPOLAR DISORDER	-5.01	-73.872	392.4725	0.54
4	RISK	-0.66	-16.38	339.9538	0.53
5	METAANALYSIS	14.84	-21.42	306.055	0.52
6	PSYCHOSIS	-36.77	-32.022	236.1895	0.50
7	RISK-FACTORS	-15.91	-52.938	226.7092	0.49
8	ASSOCIATION	-15.32	-52.758	208.2116	0.49
9	SYMPTOMS	-16.5	-53.064	206.1575	0.48
10	1ST-EPISODE PSYCHOSIS	20.13	-57.978	180.7478	0.47
11	MAJOR DEPRESSIVE DISORDI	-13.32	-51.444	144.7719	0.45
12	FOLLOW-UP	-13.17	-51.3	143.2608	0.45
13	MORTALITY	-14.18	-52.128	141.502	0.45

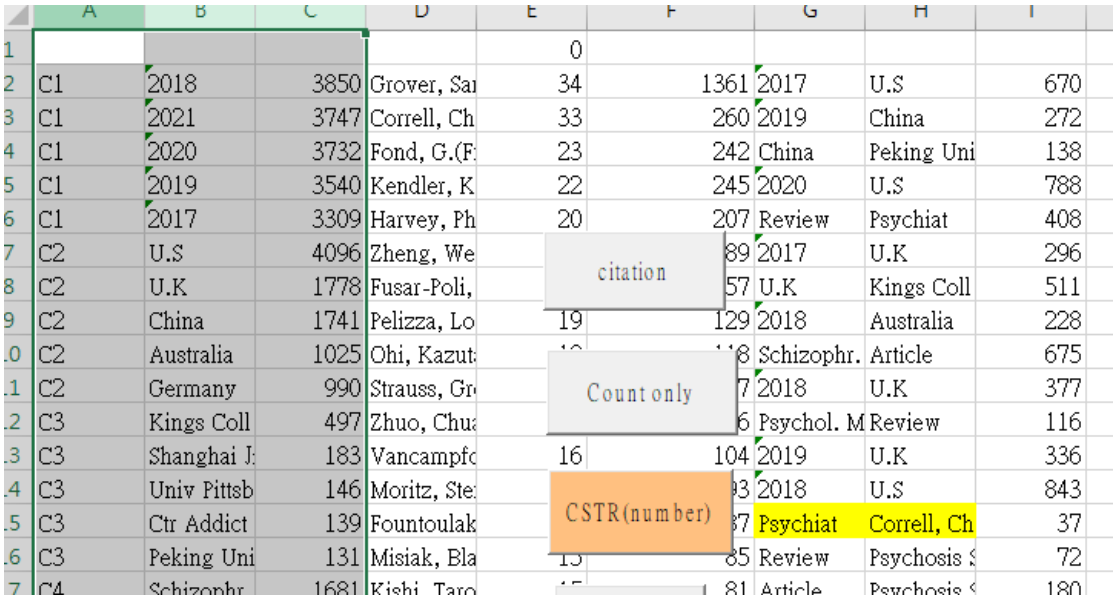
In excel



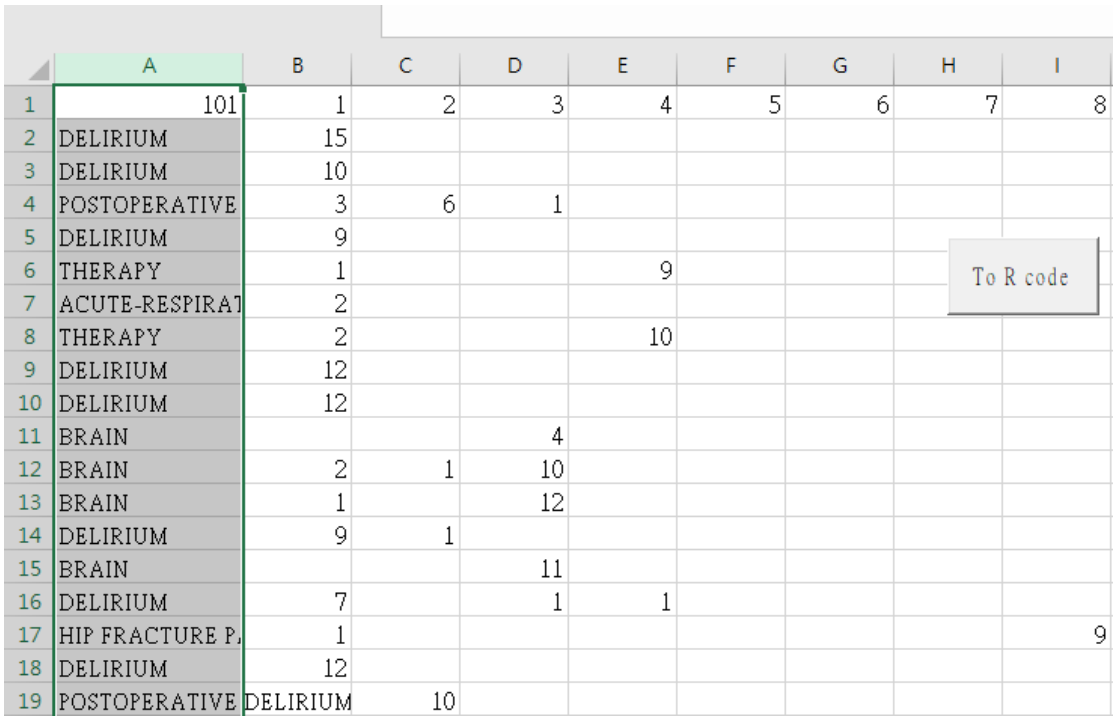
Got the HTML

	Times Cited, WoS C	Volume	country	institute	Publicatio	Documer	dept	PT
2	685	2017	U.S	Northwell Hlth(U.S)	World Psy	Article		Correll, Chris
3	634	2019	China	Peking Univ(China)	Lancet Ps	Article	Natl Clin	Huang, Yueq
4	522	2020	Spain	Univ Complutense(Spa	Lancet Ps	Article	Child &	Moreno, Car
5	437	2017	Denmark	Copenhagen Univ Hosp	Lancet Ps	Article	Mental H	Hjorthoj, Car
6	426	2020	U.S	Univ Calif San Diego(U	Brain Beh	Review	Psychiat	Troyer, Emily
7	400	2017	U.K	Kings Coll London(U.K	Am. J. Ps	Review	Clin Sci	Howes, Olive
8	396	2018	Australia	Univ Queensland(Austr	Schizophr	Article		Charlson, Fic
9	357	2018	U.K	UCL(U.K)	BMC Psy	Review	Psychiat	Wang, Jingyi
10	357	2019	Canada	Margaret & Wallace M	Lancet Ps	Review	Margaret	Lai, Meng-Cl
11	351	2017	U.K	Univ Oxford(U.K)	Psychol. I	Review	Psychiat	Freeman, D.(
12	349	2017	Belgium	Univ Leuven(Belgium)	World Psy	Review	Rehabil S	Vancampfort
13	313	2017	Sweden	Karolinska Inst(Sweden	JAMA Ps	Article	Clin Neu	Tiihonen, Jar
14	308	2019	U.K	Kings Coll London(U.K	Lancet Ps	Article	Social Ge	Di Forti, Mar
15	302	2018	U.S	Northwell Hlth(U.S)	JAMA Ps	Review	Psychiat	Correll, Chris
16	301	2018	U.S	Univ Wisconsin(U.S)	Biol. Psyc	Review	Psychiat	Hiser, Jaryd(
17	293	2017	Switzerla	World Hlth Org(Switze	World Psy	Article		Liu, Nancy H

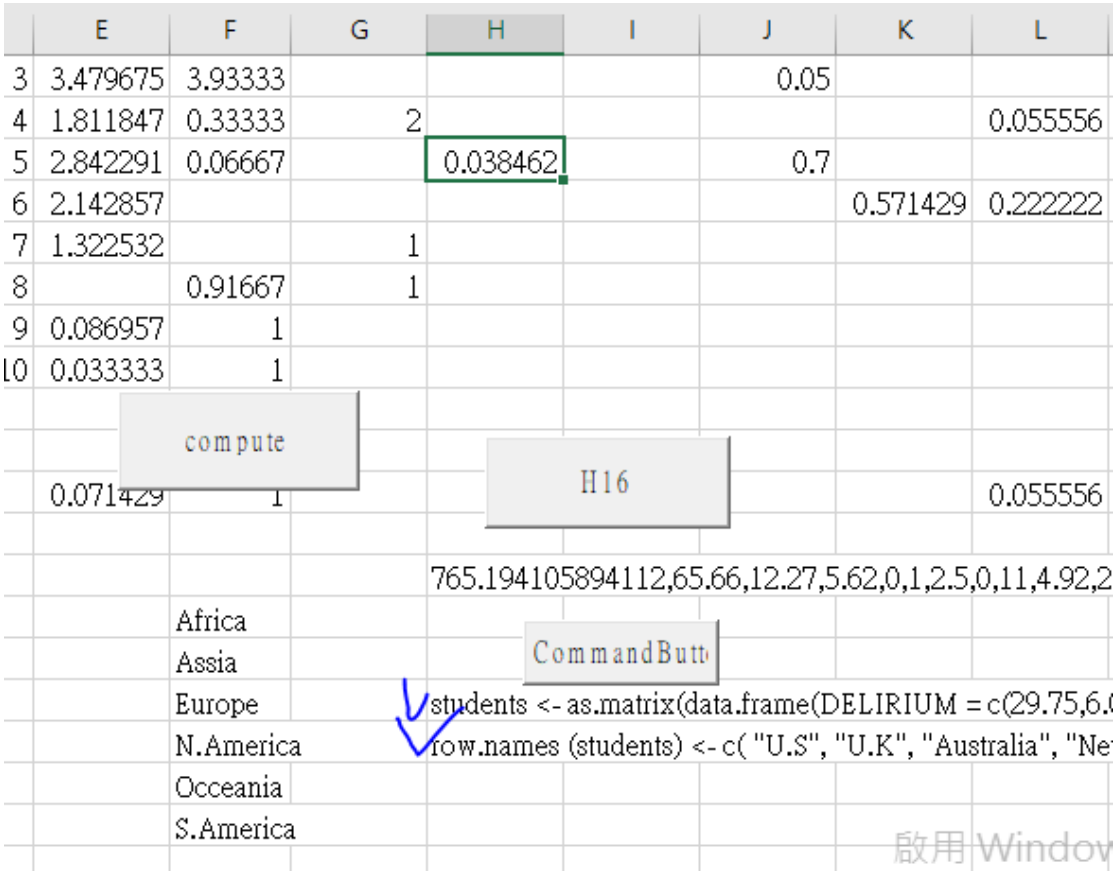
To draw the Alluvial plot



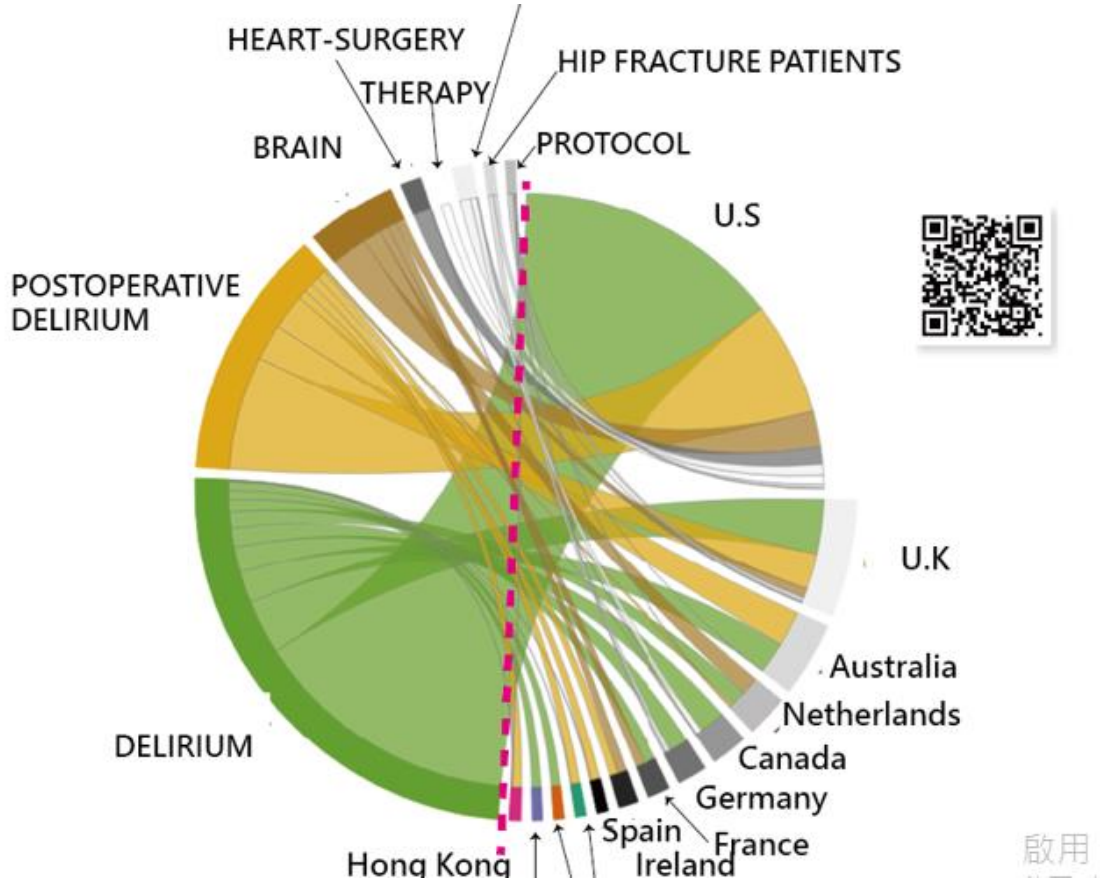
Nodes and edges contructed



Using the module to classify the category for each article



To get the R code for drawing the chord diagram




```
library(chorddiag)
students <- as.matrix(data.frame(DELIRIUM =
c(29.75,6.08,3.48,1.81,2.84,2.14,1.32,0,0.09,0.03,1,1,0.07),POSTOPERATIVE_DELIRIUM
= c(12.73,4.02,3.93,0.33,0.07,0,0,0.92,1,1,0,0,1),BRAIN =
c(4,1,0,2,0,0,1,1,0,0,0,0,0),HEART_SURGERY =
c(1.92,0.05,0,0,0.04,0,0,0,0,0,0,0,0),THERAPY =
c(1,0,0,0,0,0,0,0,0,0,0,0,0),ACUTE_RESPIRATORY_SYNDROME =
c(1.2,0.05,0.05,0,0.7,0,0,0,0,0,0,0,0),HIP_FRACTURE_PATIENTS =
c(0.43,0,0,0,0,0.57,0,0,0,0,0,0,0),PROTOCOL =
c(0.06,0.56,0,0.06,0,0.22,0,0,0,0,0,0,0.06)))
row.names (students) <- c( "U.S", "U.K", "Australia", "Netherlands", "Canada",
"Germany", "France", "Ireland", "Spain", "South Korea", "Japan", "Pakistan", "Hong
Kong")
chorddiag(students, type = "bipartite", showTicks = FALSE, groupnameFontsize = 14,
groupnamePadding = 10, margin = 90)
ents, type = "bipartite", showTicks = FALSE, groupnameFontsize = 14,
groupnamePadding = 10, margin = 90)
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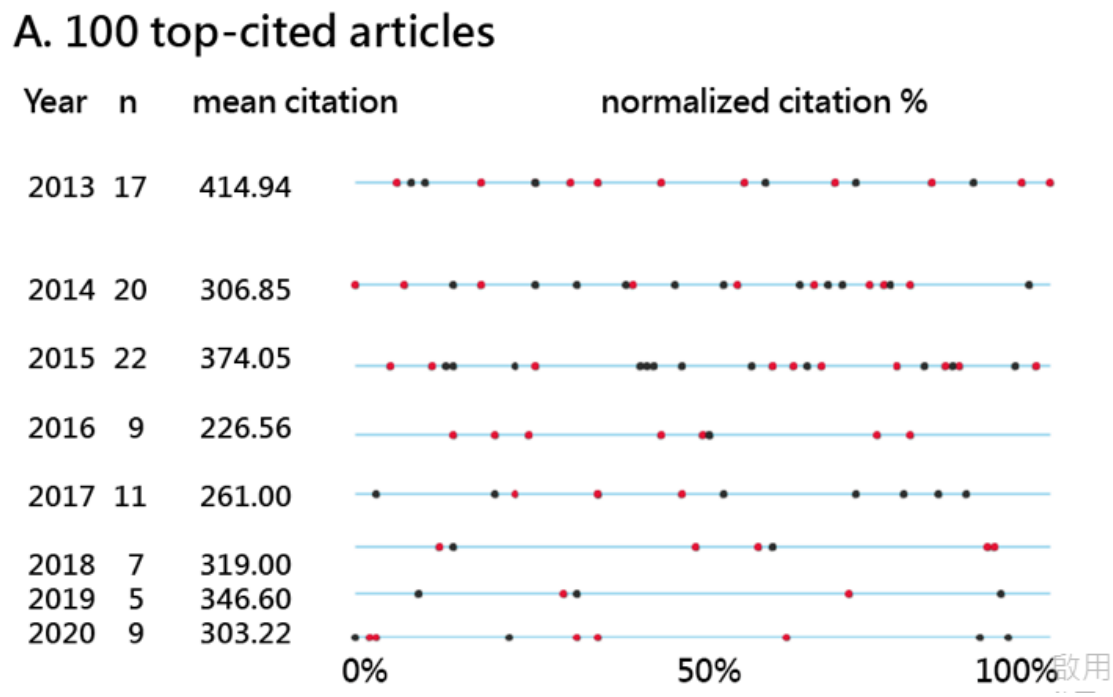
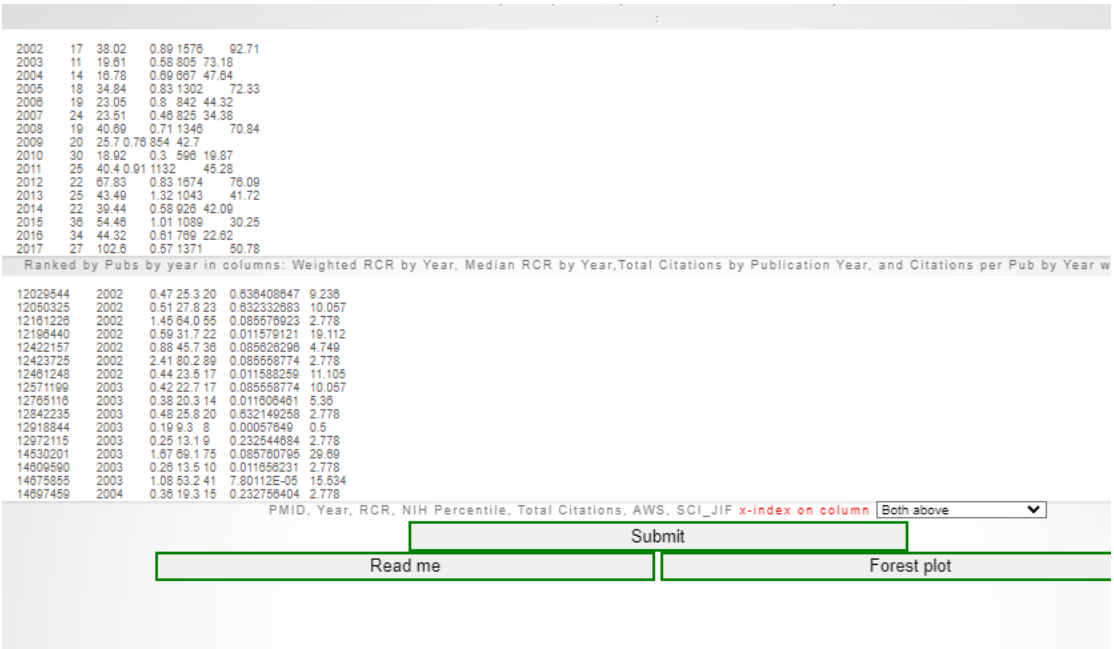
Chien TW. 100 top-cited articles in this study. Online at

http://www.healthup.org.tw/html100/delirium100.htm (accessed Oct.4, 2022)