Question 1: Chapter 6. Exercise 2

Recap

$$support = \frac{(X \cup Y).count}{n}$$

$$confidence = \frac{(X \cup Y).count}{X.count}$$

CustomerID	TransactionID	Items Bought
1	0001	$\{a, d, e\}$
1	0024	$\{a, b, c, e\}$
2	0012	$\{a, b, d, e\}$
2	0031	$\{a, c, d, e\}$
3	0015	$\{b, c, e\}$
3	0022	$\{b, d, e\}$
4	0029	$\{c, d\}$
4	0040	$\{a, b, c\}$
5	0033	$\{a, d, e\}$
5	0038	$\{a, b, e\}$

a. Compute the support for itemsets {e}, {b, d}, and {b, d, e} by treating each transaction ID as a market basket

Itemsets	Transaction	Support
$\{e\}$	0001, 0024, 0012, 0031, 0015, 0022, 0033, 0038	8/10 = 0.8 = 80%
$\{b,d\}$	0012, 0022	2/10 = 0.2 = 20%
$\{b, d, e\}$	0012, 0022	2/10 = 0.2 = 20%

b. Use the results in part(a) to compute the confidence for the association rules {b,d} -> {e} and {e} -> {b, d}. Is confidence a symmetric measure?

Recap

Confidence {b, d} -> {e} = $\frac{\{b,d,e\}.count}{\{b,d\}.count} = \frac{2}{2} = 100\%$

Confidence {e} -> {b, d} = $\frac{\{e,b,d\}.count}{\{e\}.count} = \frac{2}{8} = 25\ \%$

Based on the result above, confidence is NOT a symmetric measure.

c. Repeat part (a) by treating each customer ID as a market basket. Each item should be treated as a binary variable (1 if an item appears in at least one transaction bought by the customer, and 0 otherwise).

Reconstruct the table we have:

CustomerID	a	b	c	d	e
1	1	1	1	1	1
2	1	1	1	1	1
3	0	1	1	1	1
4	1	1	1	1	0
5	1	1	0	1	1

Itemsets	CustomerID	Support
{e}	1,2,3,5	4/5 = 0.8 = 80%
{b,d}	1,2,3,4,5	5/5 = 1 = 100%
{b, d, e}	1,2,3,5	4/5 = 0.8 = 80%

d. Use the results in part (c) to compute the confidence for the association rules {b, d} -> {e} and
{e} -> {b, d}

Confidence {b, d} -> {e} = $\frac{\{b,d,e\}.count}{\{b,d\}.count} = \frac{4}{5} = 80\%$

Confidence {e} -> {b, d} = $\frac{\{e,b,d\}.count}{\{e\}.count} = \frac{4}{4} = 100\ \%$

e. Suppose s_1 and c_1 are the support and confidence values of an association rule *r* when treating each transaction ID as a market basket. Also, let s_2 and c_2 be the support and confidence values of *r* when treating each customer ID as a market basket. Discuss whether there are any relationships between s_1 and s_2 or c_1 and c_2
It seems that s_2 is the generalized version of s_1 when we group transaction by customerID. Because there is no clear relationship between CustomerID and TransactionID in terms of items. So there is no clear relationship between s_1, c_1 and s_2, c_2

Question 3:

Our original dataset contains **5,312 records**

Homework Team 1: HW3_VinhNguyen_GhazanfarAli_Raihan

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
	text	favorited	favoriteC	replyToSN	created	truncated	replyToSI	id	replyToUI	statusSou	screenNa	retweetC	isRetweet	retweete	longitude	latitude
1	@russotalks Did you know a small hurricane is c	FALSE	0	russotalks	#########	TRUE	9.06E+17	9.06E+17	8.64E+08	<a href="h	cole_swee	0	FALSE	FALSE	NA	NA
2	@Mikel_Jollett Also, which "same week" are yc	FALSE	0	Mikel_Joll	#########	TRUE	9.05E+17	9.06E+17	5.94E+08	<a href="h	UnderDur	0	FALSE	FALSE	NA	NA
3	RT @BostonJerry: Harvey went from tropical de	FALSE	0	NA	#########	FALSE	NA	9.06E+17	NA	<a href="h	Keyshasay	72	TRUE	FALSE	NA	NA
4	@CNN My experience going through 2 hurricane	FALSE	1	CNN	#########	TRUE	9.06E+17	9.06E+17	759251	<a href="h	MsPamela	0	FALSE	FALSE	NA	NA
5	RT @DeeJones_: 1st Harvey formed and did dan	FALSE	0	NA	#########	FALSE	NA	9.06E+17	NA	<a href="h	DaT_Gator	2	TRUE	FALSE	NA	NA
6	RT @DeeJones_: 1st Harvey formed and did dan	FALSE	0	NA	#########	FALSE	NA	9.06E+17	NA	<a href="h	DeeJones	2	TRUE	FALSE	NA	NA
7	1st Harvey formed and did damage then Irma st	FALSE	0	DeeJones	#########	FALSE	9.06E+17	9.06E+17	2.34E+08	<a href="h	DeeJones	2	FALSE	FALSE	NA	NA
8	Harvey Soaks Southern Crops: Louisiana farmers	FALSE	0	NA	#########	FALSE	NA	9.06E+17	NA	<a href="h	VoiceofLa	0	FALSE	FALSE	NA	NA
9	@KadaburaDraws Good luck! I've got Harvey ov	FALSE	1	Kadabural	#########	FALSE	9.06E+17	9.06E+17	2.89E+09	<a href="h	Just_D3sp	0	FALSE	FALSE	NA	NA
10	Nashville, TN Tropical Depression Harvey Flood	FALSE	0	NA	#########	FALSE	NA	9.06E+17	NA	<a href="h	OnWeath	0	FALSE	FALSE	NA	NA
11	NEWS UPDATE	FALSE	0	NA	#########	TRUE	NA	9.06E+17	NA	<a href="h	VWNCont	0	FALSE	FALSE	NA	NA
12	RT @JointOceanCI: Tropical depression to Categ	FALSE	0	NA	#########	FALSE	NA	9.06E+17	NA	<a href="h	JaneLubch	1	TRUE	FALSE	NA	NA
13	Tropical depression to Category 4 in 48 hours: th	FALSE	0	NA	#########	FALSE	NA	9.06E+17	NA	<a href="h	JointOcea	1	FALSE	FALSE	NA	NA
14	Hurricane Harvey	FALSE	1	NA	#########	FALSE	NA	9.06E+17	NA	<a href="h	MissTexas	1	FALSE	FALSE	NA	NA
15	House approves first installment of Hurricane H	FALSE	0	NA	#########	FALSE	NA	9.06E+17	NA	<a href="h	ILoveourT	0	FALSE	FALSE	NA	NA
16	@LeoHirsbrunner @Hesiod2k11 So the Tropical	FALSE	1	LeoHirsbr	#########	FALSE	9.05E+17	9.05E+17	18541450	<a href="h	darthstar9	0	FALSE	FALSE	NA	NA
17	Harvey is gone. Irma is coming. Jose is close	FALSE	0	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	jsexton9	0	FALSE	FALSE	NA	NA
18	@realDonaldTrump Harvey last week. Irma this	FALSE	2	realDonal	#########	TRUE	9.05E+17	9.05E+17	25073877	<a href="h	KellyJGuic	0	FALSE	FALSE	NA	NA
19	@DaltonGarafolo it stronger. Harvey was a tropi	FALSE	7	newlonha	#########	FALSE	9.05E+17	9.05E+17	2.47E+09	<a href="h	newlonha	0	FALSE	FALSE	NA	NA
20	Hurricane Harvey, Hurricane Irma, Tropical Storr	FALSE	1	NA	#########	TRUE	NA	9.05E+17	NA	<a href="h	zawmintu	0	FALSE	FALSE	NA	NA
21	Ok so.... Hurricane Harvey, Irma, tropical storm .	FALSE	1	NA	#########	TRUE	NA	9.05E+17	NA	<a href="h	Facey___	0	FALSE	FALSE	NA	NA
22	What if hurricane harvey was a precursor/warni	FALSE	0	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	xDEADMA	0	FALSE	FALSE	NA	NA
23	Hurricane Harvey, Hurricane Irma, Hurricane Jos	FALSE	2	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	Exercisms	0	FALSE	FALSE	NA	NA
24	Harvey jumped from tropical depression to a	FALSE	1	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	SoFLGroup	0	FALSE	FALSE	NA	NA
25	Harvey, Irma, Jose, tropical depression #13; may	FALSE	0	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	Scubagirl7	0	FALSE	FALSE	NA	NA
26	@YPSportsChat A1b: Never try playing a footbal	FALSE	1	YPSportsC	#########	FALSE	9.05E+17	9.05E+17	4.74E+09	<a href="h	BrianJLent	0	FALSE	FALSE	NA	NA
27	RT @writermelle: Tropical Depression 13 has de	FALSE	0	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	TuxiTalk1	1	TRUE	FALSE	NA	NA
28	Tropical Depression 13 has developed in the Gu	FALSE	1	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	writermel	1	FALSE	FALSE	NA	NA
29	@SherriWilkie We had a tropical depression off	FALSE	0	SherriWill	#########	FALSE	9.05E+17	9.05E+17	5.53E+08	<a href="h	KSinCFL	0	FALSE	FALSE	NA	NA
30	RT @KcharlesNewsNow: @EricaANjax Harvey, Ir	FALSE	0	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	Bearishell	1	TRUE	FALSE	NA	NA
31	Which is what they say HAARP is doin, While hu	FALSE	1	blumooor	#########	TRUE	9.05E+17	9.05E+17	2.19E+08	<a href="h	blumooor	0	FALSE	FALSE	NA	NA
32	@EricaANjax Harvey, Irma... now there's Jose Al	FALSE	0	EricaANja:	#########	FALSE	9.05E+17	9.05E+17	2.44E+09	<a href="h	KcharlesN	1	FALSE	FALSE	NA	NA
33	Hurricane Harvey, Hurricane Irma, Tropical storr	FALSE	0	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	R3start3d	0	FALSE	FALSE	NA	NA
34	Hurricane Harvey, Hurricane Irma, TS Jose and T	FALSE	0	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	christine_	0	FALSE	FALSE	NA	NA
35	Tropical Depression Harvey continues to cause r	FALSE	0	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	Railway_N	0	FALSE	FALSE	NA	NA
36	@CAM3R0NPH1L1P And the remnants of harvey	FALSE	1	CAM3R0N	#########	FALSE	9.05E+17	9.05E+17	8.54E+08	<a href="h	lauren062	0	FALSE	FALSE	NA	NA
37	It took approximately 56 hours for Harvey to evo	FALSE	0	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	OurWorld	0	FALSE	FALSE	NA	NA
38	The Tropical Depression tour: Hurricane Harvey	FALSE	0	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	TeazherM	0	FALSE	FALSE	NA	NA
39	RT @Yawdinn: Please donate to a student drive	FALSE	0	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	NISHITATA	2	TRUE	FALSE	NA	NA
40	RT @Yawdinn: Please donate to a student drive	FALSE	0	NA	#########	FALSE	NA	9.05E+17	NA	<a href="h	KaksKun	2	TRUE	FALSE	NA	NA

First: We want to remove all retweets because they contribute no additional information. As shown in the shaded region above. This step can be done by filtering and get all isRetweet = FALSE.

Our dataset in this step shrinks down to 1,718 records. We name this dataset is TwitterData

text
@russotalks Did you know a small hurricane is coming here too? Or some tropical depression or something I don't knoâ€¦ https://t.co/GdfyDz5luK
@Mikel_Jollett Also, which "same week" are you referring too? Because Irma formed 9 DAYS after Harvey was in the Guâ€¦ https://t.co/UVoBwI3NB1
@CNN My experience going through 2 hurricanes and a stagnant tropical depression in Houston (NOT inc Harvey): FIVEâ€¦ https://t.co/k2nYWvl8Qm
1st Harvey formed and did damage then Irma started to form and Jose is right behind Irma as a tropical depression
Harvey Soaks Southern Crops: Louisiana farmers took the brunt of the rain and crop damage. https://t.co/Pixe07Ro42
@KadaburaDraws Good luck! I've got Harvey overhead here as a tropical depression, and it's still a pain
Nashville, TN Tropical Depression Harvey Flooding Closes I40 - 8/31/2017 https://t.co/LCH7OGXF2L https://t.co/fFTC1MRfeO
NEWS UPDATE
Tropical depression to Category 4 in 48 hours: the science behind #HurricaneHarveyâ€™s rapid intensification https://t.co/wsMlokR8Bn
Hurricane Harvey
House approves first installment of Hurricane Harvey disaster aid https://t.co/cVFUWc6JVC via @usatoday
@LeoHirsbrunner @Hesiod2k11 So the Tropical Depression in the Gulf got upgraded and got a name...that's where Harvey was born too.
Harvey is gone. Irma is coming. Jose is close behind. And now there's another one!
@realDonaldTrump Harvey last week. Irma this week. Jose in the Atlantic right behind Irma. New tropical depressionâ€¦ https://t.co/wcbLMDG2qB
@DaltonGarafolo it stronger. Harvey was a tropical depression and turned into a category 5 within under 48 hours
Hurricane Harvey, Hurricane Irma, Tropical Storm Jose, Tropical Depression THIRTEEN. Mother nature is angry!â€¦ https://t.co/4eIuhpIfSN
Ok so.... Hurricane Harvey, Irma, tropical storm JosÃ©, & NOW tropical depression 13 has formed in the gulf, like riâ€¦ https://t.co/CBfWMxiOON
What if hurricane harvey was a precursor/warning of the storms to come(irma,jose and a tropical depression forming in the gulf)

Data is good now we need to clean them. First, we must remove non-ansi characters as highlighted above. This step can be done in R with the following command

data <- iconv(TwitterData$text, "latin1", "ASCII", sub="") *//we remove non-ansi characters and copy to data*

New data below

```
 [2] "@Mikel_Jollett Also, which \"same week\" are you referring too? Because Irma formed 9 DAYS after Harvey was in the Gu https://t.co/UVoBwI3NB1"
 [3] "@CNN My experience going through 2 hurricanes and a stagnant tropical depression in Houston (NOT inc Harvey): FIVE https://t.co/k2nYWvl8Qm"
 [4] "1st Harvey formed and did damage then Irma started to form and Jose is right behind Irma as a tropical depression"
 [5] "Harvey Soaks Southern Crops: Louisiana farmers took the brunt of the rain and crop damage. https://t.co/Pixe07Ro42"
 [6] "@KadaburaDraws Good luck! I've got Harvey overhead here as a tropical depression, and it's still a pain"
 [7] "Nashville, TN Tropical Depression Harvey Flooding Closes I40 - 8/31/2017 https://t.co/LCH7OGXF2L https://t.co/fFTC1MRfeO"
 [8] "NEWS UPDATE\nTropical Depression Harvey\n\nThe death toll across the affected areas has risen to at least 70 - it coul https://t.co/x8STRyjvaD"
 [9] "Tropical depression to Category 4 in 48 hours: the science behind #HurricaneHarveys rapid intensification https://t.co/wsMlokR8Bn"
[10] "Hurricane Harvey\n\nTexas under water\n\nHurricane Irma\n\nTropical storm Jose\n\nTropical depression katia \n\nDACA\n\nCalifornia on fire \n\nTBC..."
[11] "House approves first installment of Hurricane Harvey disaster aid https://t.co/cVFUWc6JVC via @usatoday"
[12] "@LeoHirsbrunner @Hesiod2k11 So the Tropical Depression in the Gulf got upgraded and got a name...that's where Harvey was born too."
[13] "Harvey is gone. Irma is coming. Jose is close behind. And now there's another one!\n\nhttps://t.co/UH8LG7wxCZ"
[14] "@realDonaldTrump Harvey last week. Irma this week. Jose in the Atlantic right behind Irma. New tropical depression https://t.co/wcbLMDG2qB"
[15] "@DaltonGarafolo it stronger. Harvey was a tropical depression and turned into a category 5 within under 48 hours"
[16] "Hurricane Harvey, Hurricane Irma, Tropical Storm Jose, Tropical Depression THIRTEEN. Mother nature is angry! https://t.co/4eIuhpIfSN"
[17] "Ok so.... Hurricane Harvey, Irma, tropical storm Jos, &amp; NOW tropical depression 13 has formed in the gulf, like ri https://t.co/CBfWMxiOON"
[18] "What if hurricane harvey was a precursor/warning of the storms to come(irma,jose and a tropical depression forming in the gulf)"
[19] "Hurricane Harvey, Hurricane Irma, Hurricane Jose is forming in 24-36 hours &amp; a tropical depression is supposed to hit mexico. Were all dead."
[20] "Harvey jumped from tropical depression to a cat 4 hurricane in 60 hours, 2.5 days. Floridans have 4 day warning on a category 5.  \n#gtfo #fl"
```

Next we have to:

- remove all URLs (ie https://t.co/k2nYWvl8Qm)
  - gsub("http[^[:space:]]*", "", x)
- remove all people (ie @Mike)
  - gsub("@[^[:space:]]*", "", x)
- remove all punctuation
  - gsub("[^[:alpha:][:space:]]*", "", x)
- remove all stopwords
  - removeWords(x, c(stopwords("english"),"at","via","amp"))
- remove all whitespace
  - stripWhitespace(x)
- remove all new lines
  - gsub("\n", "", x)
- stemming the document
  - stemDocument(x)

The result of this step is shown as below

```
Console ~/
[272] "hurricaneharvey weaken tropic depress death toll rise"
[273] "latest offici rais harveyrel death toll houston ap latest tropic depress"
[274] "latest atlant tropic outlook nhc tropic depress harvey public advisori number"
[275] "hour am pm multipl radarmultipl sensor mrms rainfal estim tropic depress harvey"
[276] "tropic storm harvey photo mustse pictur storm"
[277] "tropic depress harvey public advisori number"
[278] "tropic depress harvey public advisori number"
[279] "tropic depress harvey advisori kt mph wind mb n w move ne kt mph tropic"
[280] "noaa tropic depress harvey public advisori number"
[281] "nhcatlant tropic depress harvey advisori now avail nhc websit"
[282] "noaa tropic depress harvey public advisori number"
[283] "harvey slog inland dump heavi rain amid flood threat memphi tenn ap tropic depress harvey s"
[284] "tropic depress harvey public advisori number"
[285] "tropic depress harvey public advisori number"
[286] "tropic depress harvey public advisori number"
[287] "tropic depress harvey public advisori number the nhc issu final advisori system public ad"
[288] "nhcatlant tropic depress harvey advisori now avail nhc websit"
[289] "tropic depress harvey public advisori number"
[290] "unfortun will stare tropic depress harvey pass direct bowl green"
[291] "tropic depress harvey public advisori number"
```

After cleaning the data, there are a lot of duplications, we need to remove them all and keep unique tweets. This can be done by the following command

cleaneddata <-unique(data)

Now, our final cleaned data has 1.025 tweets

Next step, we save the results as a csv file for association rules mining. We name the data as "basket"

write(cleaneddata,"basket")

Now we read the data as a transaction

trans = read.transactions("basket", format = "basket", sep=" ", rm.duplicates = TRUE);

inspect(trans)

The output of the transaction is:

```
[2]    {also,day,form,gu,harvey,irma,refer,week}
[3]    {depress,experi,five,go,harvey,houston,hurrican,inc,stagnant,tropic}
[4]    {behind,damag,depress,form,harvey,irma,jose,right,st,start,tropic}
[5]    {brunt,crop,damag,farmer,harvey,louisiana,rain,soak,southern,took}
[6]    {depress,good,got,harvey,ive,luck,overhead,pain,still,tropic}
[7]    {close,depress,flood,harvey,nashvill,tn,tropic}
[8]    {across,affect,area,coul,death,depress,harveyth,least,news,risen,toll,updatetrop}
[9]    {behind,categori,depress,hour,hurricaneharvey,intensif,rapid,scienc,tropic}
[10]   {dacacalifornia,depress,fire,harveytexa,hurrican,irmatrop,josetrop,katia,storm,tbc,waterhurrican}
[11]   {aid,approv,disast,first,harvey,hous,hurrican,instal}
[12]   {born,depress,got,gulf,harvey,namethat,tropic,upgrad}
[13]   {anoth,behind,close,come,gone,harvey,irma,jose,now,one,there}
[14]   {atlant,behind,depress,harvey,irma,jose,last,new,right,tropic,week}
[15]   {categori,depress,harvey,hour,stronger,tropic,turn,within}
[16]   {angri,depress,harvey,hurrican,irma,jose,mother,natur,storm,thirteen,tropic}
[17]   {depress,form,gulf,harvey,hurrican,irma,jos,like,now,ok,ri,storm,tropic}
[18]   {comeirmajos,depress,form,gulf,harvey,hurrican,precursorwarn,storm,tropic}
[19]   {dead,depress,form,harvey,hit,hour,hurrican,irma,jose,mexico,suppos,tropic}
[20]   {cat,categori,day,depress,fl,floridan,gtfo,harvey,hour,hurrican,jump,tropic,warn}
```

Now we are good to run the algorithm

First, we want to find all rules with default values: *minsupport = 0.1, minconfidence =0.8*

rules <-apriori(trans)

We got totally 85 rules

```
Console ~/

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen maxlen target   ext
        0.8    0.1    1 none FALSE            TRUE       5     0.1      1     10  rules FALSE

Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 101

set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[1597 item(s), 1018 transaction(s)] done [0.00s].
sorting and recoding items ... [11 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 3 4 done [0.00s].
writing ... [85 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].
```

Inspect the rules : *inspect(rules)* we got

```
> inspect(rules)
     lhs                        rhs       support   confidence lift     count
[1]  {}                      => {depress} 0.8870334 0.8870334  1.000000 903
[2]  {}                      => {tropic}  0.9037328 0.9037328  1.000000 920
[3]  {}                      => {harvey}  0.9341847 0.9341847  1.000000 951
[4]  {move}                  => {harvey}  0.1041257 0.9814815  1.050629 106
[5]  {weaken}                => {depress} 0.1218075 0.9185185  1.035495 124
[6]  {weaken}                => {tropic}  0.1257367 0.9481481  1.049147 128
[7]  {weaken}                => {harvey}  0.1247544 0.9407407  1.007018 127
[8]  {rain}                  => {depress} 0.1031434 0.9545455  1.076110 105
[9]  {rain}                  => {tropic}  0.1041257 0.9636364  1.066285 106
[10] {rain}                  => {harvey}  0.1070727 0.9909091  1.060721 109
[11] {hurrican}              => {depress} 0.1257367 0.8951049  1.009099 128
[12] {hurrican}              => {tropic}  0.1326130 0.9440559  1.044618 135
[13] {hurrican}              => {harvey}  0.1345776 0.9580420  1.025538 137
[14] {flood}                 => {depress} 0.1296660 0.9295775  1.047962 132
[15] {flood}                 => {tropic}  0.1355599 0.9718310  1.075352 138
[16] {flood}                 => {harvey}  0.1365422 0.9788732  1.047837 139
[17] {now}                   => {depress} 0.1611002 0.9479769  1.068705 164
```

Given a minsupport =0.2 and minconf = 0.2 we run the algorithm

rules2 <-apriori(trans,parameter = list(supp = 0.2, conf = 0.2))

we got total 13 rules that satisfy the conditions.

```
> inspect(rules2)
     lhs                 rhs        support   confidence lift     count
[1]  {}               => {downgrad} 0.2023576 0.2023576  1.000000 206
[2]  {}               => {depress}  0.8870334 0.8870334  1.000000 903
[3]  {}               => {tropic}   0.9037328 0.9037328  1.000000 920
[4]  {}               => {harvey}   0.9341847 0.9341847  1.000000 951
[5]  {depress}        => {tropic}   0.8703340 0.9811739  1.085690 886
[6]  {tropic}         => {depress}  0.8703340 0.9630435  1.085690 886
[7]  {depress}        => {harvey}   0.8467583 0.9545958  1.021849 862
[8]  {harvey}         => {depress}  0.8467583 0.9064143  1.021849 862
[9]  {tropic}         => {harvey}   0.8693517 0.9619565  1.029728 885
[10] {harvey}         => {tropic}   0.8693517 0.9305994  1.029728 885
[11] {depress,tropic} => {harvey}   0.8408644 0.9661400  1.034207 856
[12] {depress,harvey} => {tropic}   0.8408644 0.9930394  1.098820 856
[13] {harvey,tropic}  => {depress}  0.8408644 0.9672316  1.090412 856
```