

```
> inspect(SortedRules_lift[1:20])
```

	lhs	rhs	support	confidence	coverage	lift	count
[1]	{mainland}	=> {fresh}	0.1764706	1	0.1764706	4.25	3
[2]	{mainland}	=> {roast}	0.1764706	1	0.1764706	4.25	3
[3]	{fresh}	=> {roast}	0.2352941	1	0.2352941	4.25	4
[4]	{roast}	=> {fresh}	0.2352941	1	0.2352941	4.25	4
[5]	{fresh,mainland}	=> {roast}	0.1764706	1	0.1764706	4.25	3
[6]	{mainland,roast}	=> {fresh}	0.1764706	1	0.1764706	4.25	3
[7]	{dear,mainland}	=> {fresh}	0.1764706	1	0.1764706	4.25	3
[8]	{lover,mainland}	=> {fresh}	0.1764706	1	0.1764706	4.25	3
[9]	{coffee,mainland}	=> {fresh}	0.1764706	1	0.1764706	4.25	3
[10]	{dear,mainland}	=> {roast}	0.1764706	1	0.1764706	4.25	3

Introduction to Association Rule Mining (ARM)

-and -

Thinking Outside the Basket with Twitter

Dr. Ami Gates



Where does ARM fit in?

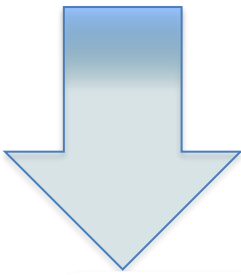
Idea or Goal

Decision-Making

Association Rule Mining

Data Gathering

- APIs, Sampling, experimentation, observation, etc.



Data Preparation

- Cleaning
- Formatting per model/method/goal
- EDA and Vis
- Normalization/Transformation
- Sampling

Conclusions/
Communication/ Vis

Analytics and Vis

- ML: Unsupervised/discovery
- ML: Supervised/classification/modeling

Evaluation/Results/ Vis

Data Science Lifecycle

Dr. Gates Talks on ARM

Talk 1: Association Rule Mining on Tweets in R

<https://www.youtube.com/watch?v=eOOhn9CX2qU>

Talk 2: Association Rule Mining on Twitter and Building Network Visualizations in R

https://www.youtube.com/watch?v=AIK_FRzyUEE

What is Association Rule Mining (ARM)

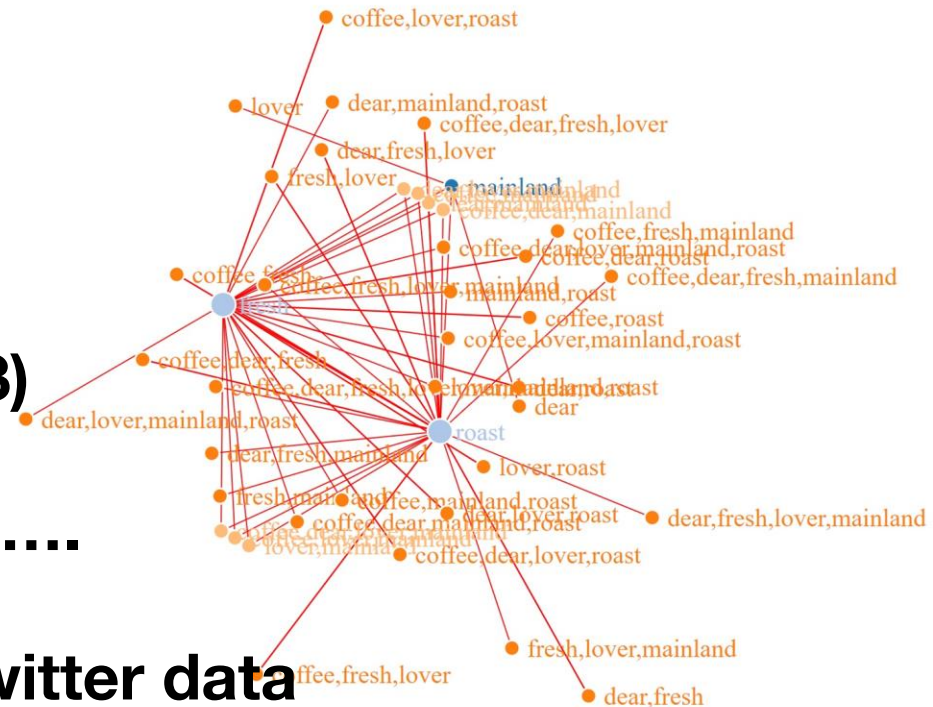
Unsupervised Learning – no labels –
discovery

Evaluates “**transactions**” for
correlations/associations.

Most common example:
Market Basket (Kumar, 2008)

Many applications, including....

- Image identification
- Text Analytics: like **Twitter data**
- Click streams
- Bio data – binding sites, AA's in
proteins





Thinking About ARM (with Tweets and Coffee)



#coffe

Tweet 1:

The **coffee festival** was **delicious**. **Loved** it.
Coffee good.

Tweet 2:

Coffee is **good** with **soymilk**. **Go** to the **Festival**.

Tweet 3:

The **coffee festival** had **soymilk**, **almond**, and
coconut creamers. **Delicious! Go!**

Convert to *Transaction Data*

Each Tweet is now a “transaction” made up of words

coffee	festival	delicious	love	good			
coffee	good	soymilk	go	festival			
coffee	festival	soymilk	almond	coconut	creamer	delicious	go

Where else can we find associations?

- 1) Reviews – patient, purchase, people, movie, book, etc.
- 2) Documents – speeches, novels
- 3) Articles – journal papers, news
- 4) Social Posts – Twitter, FB, etc.
- 5) Click Streams

Applications and Visual Options

- 1) Networks – how are things related?
- 2) Sentiment
- 3) Topic Modeling
- 4) Purchase preferences
- 5) Product placement/suggestion

Example 1

The Rules

<i>TID</i>	<i>Items</i>
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

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{Diapers} \Rightarrow {Beer}
{Milk, Bread} \Rightarrow {Coke}
{Milk, Bread} \Rightarrow {Coke, Diaper}
{Diapers} \Rightarrow {Beer, Bread}

**** Association (like correlation) is a measure of co-occurrence NOT causality.**

The Market Basket Example

The following few slides will cover the most classic example of ARM.

You can find this is Kumar's Data Mining book.

The Measures:

Support, Confidence, Lift

Let A and B be sets and assume rule $A \Rightarrow B$
(Remember, A and B are sets of zero or more items/words)

1) Support:

$$\text{Sup}(A, B) = P(A, B)$$

[How often items in A and items in B occur together relative to all transactions.]

$$(\text{Count of A and B together}) / (\text{Total \# Trans})$$

2) Confidence:

$$\text{Conf}(A, B) = P(B|A) = P(A,B) / P(A)$$

[How often items in A and items in B occur together – relative to transactions that contain A]

$$(\text{Count of A and B together}) / (\text{Count of A})$$

Lift

For Rules $A \rightarrow B$

$$\text{Lift}(A, B) = \frac{P(A, B)}{P(A)P(B)} = \frac{P(A | B)}{P(A)}$$

- 1) What is true if $\text{Lift}(A, B) = 1$?
- 2) What is true if $\text{Lift}(A, B) < 1$?
- 3) What is true if $\text{Lift}(A, B) > 1$?

Lift

For Rules $A \rightarrow B$

$$\text{Lift}(A, B) = P(A, B) / P(A)P(B)$$

- 1) What is true if $\text{Lift}(A, B) = 1$? **A and B are independent!**
- 2) What is true if $\text{Lift}(A, B) < 1$?
- 3) What is true if $\text{Lift}(A, B) > 1$?

Lift

For Rules $A \Rightarrow B$

$$\begin{aligned}\text{Lift}(A, B) &= P(A, B) / P(A)P(B) \\ &= P(A | B) P(B) / P(A) P(B) \\ &= P(A | B) / P(A)\end{aligned}$$

- 1) What is true if $\text{Lift}(A,B) = 1$? **A and B are independent**
- 2) What is true if $\text{Lift}(A,B) < 1$? **A and B are negatively correlated**
- 3) What is true if $\text{Lift}(A,B) > 1$?

Lift

For Rules $A \Rightarrow B$

$$\begin{aligned}\text{Lift}(A, B) &= P(A, B) / P(A)P(B) \\ &= P(A | B) P(B) / P(A) P(B) \\ &= P(A | B) / P(A)\end{aligned}$$

- 1) What is true if $\text{Lift}(A, B) = 1$? **A and B are independent**
- 2) What is true if $\text{Lift}(A, B) < 1$? **A and B are negatively correlated**
- 3) What is true if $\text{Lift}(A, B) > 1$? **A and B are positively correlated**

We will consider only the rules with **Lift > 1** because we are looking for associations.

Quick Measure Examples

<i>TID</i>	<i>Items</i>
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

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Given: **{Diaper}**? **{Beer}**

$$\text{Sup}(\{\text{Diaper}\}, \{\text{Beer}\}) = 2/5 = .40 = 40\%$$

$$\text{Conf}(\{\text{Diaper}\}, \{\text{Beer}\})$$

$$= P(\{\text{Diaper}\}, \{\text{Beer}\}) / P(\{\text{Diaper}\})$$

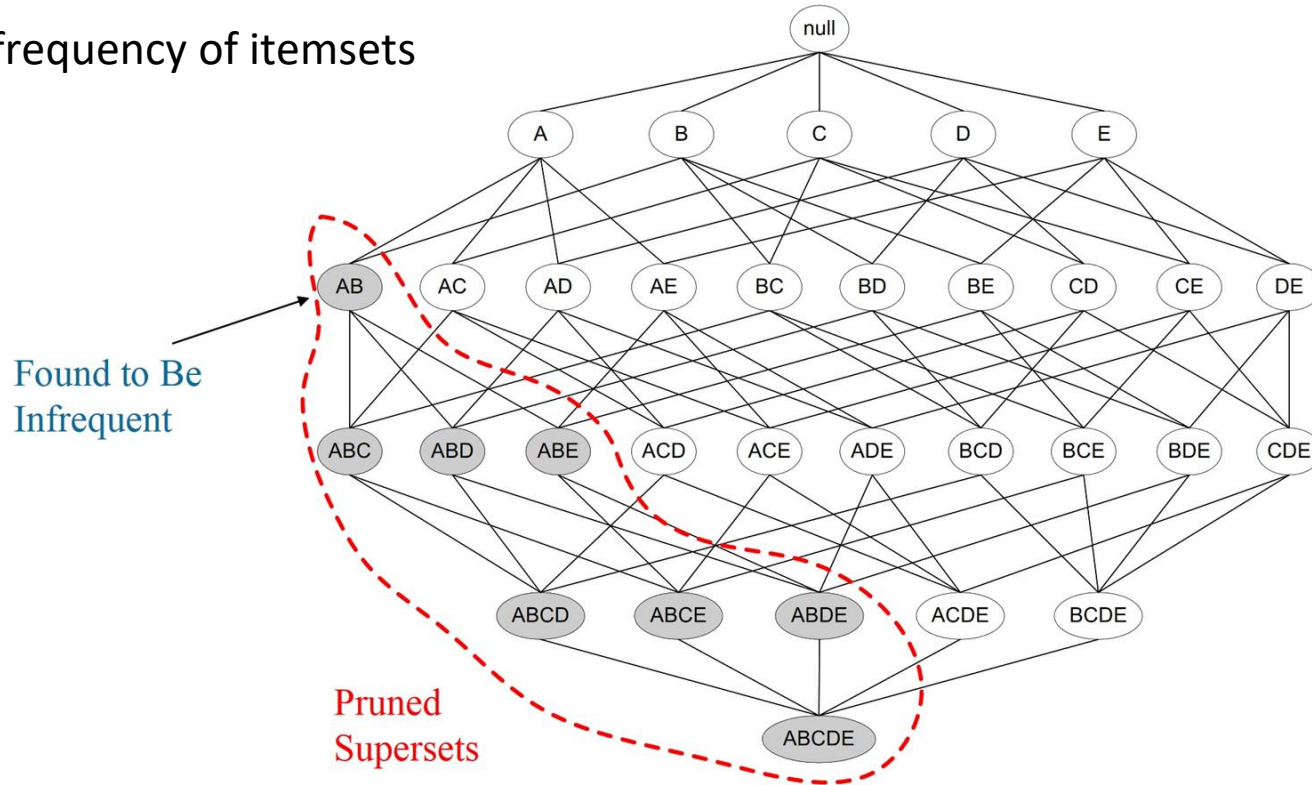
$$= (2/5) / (3/5) = 66.7\%$$

$$\text{Lift}(\{\text{Diaper}\}, \{\text{Beer}\}) = \text{Sup}(\{\text{Diaper}\}, \{\text{Beer}\}) / P(\{\text{Diaper}\}) * P(\{\text{Beer}\})$$

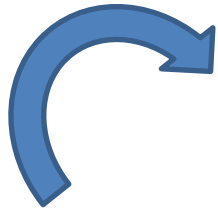
$$= (2/5) / (3/5) * (3/5) = 1.11$$

Quick Reminder: The apriori algorithm

Based on frequency of itemsets



Other Ways to Represent Transaction Data



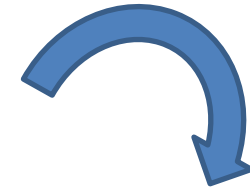
TID	Items
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

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```
> inspect(Foods)
  items                transactionID
[1] {Bread,Coke,Milk}      1
[2] {Beer,Bread}          2
[3] {Beer,Coke,Diaper,Milk} 3
[4] {Beer,Bread,Diaper,Milk} 4
[5] {Coke,Diaper,Milk}    5
>
```

1 Bread
 1 Coke
 1 Milk
 2 Beer
 2 Bread
 3 Beer
 3 Coke
 3 Diaper
 3 Milk
 4 Beer
 4 Bread
 4 Diaper
 4 Milk
 5 Coke
 5 Diaper
 5 Milk



TID	Bread	Coke	Beer	Diaper
1	1	0	1	1
2	1	0	1	0
3	0	1	1	1
4	1	1	1	0
5	0	0	1	1

quinoa	soymilk	coffee	chocloate	
quinoa	soymilk	kale	tea	
quinoa	kale			
quinoa	soymilk	coffee	chocloate	
quinoa	soymilk	carrot	tea	
quinoa	kale			
quinoa	soymilk	coffee	chocloate	carrot
quinoa	soymilk	kale	tea	
quinoa	carrot			
quinoa	soymilk	coffee	chocloate	
quinoa	soymilk	kale	tea	
quinoa	carrot			
quinoa	soymilk	coffee	chocloate	carrot
quinoa	soymilk		tea	
quinoa	kale			
quinoa	soymilk	coffee	chocloate	
quinoa	soymilk	carrot		
quinoa	carrot			
quinoa	soymilk	coffee	chocloate	
quinoa	soymilk			

Transaction Data

Notice: It is not necessary to have a numbered transaction ID

Basic ARM R Code

```
library(arules)
```

```
Foods <- read.transactions("HealthyBasketData.csv",  
                           rm.duplicates = FALSE,  
                           format = "basket",  
                           sep="," ,  
                           cols=NULL)
```

```
inspect(Foods)
```

```
rules <- arules::apriori(Foods, parameter = list(support=.2,  
                                                confidence=.2, minlen=2))
```

```
inspect(rules)
```

```
SortedRules <- sort(rules, by="confidence", decreasing=TRUE)  
inspect(SortedRules[1:10])
```

```
SortedRulesL <- sort(rules, by="lift", decreasing=TRUE)  
inspect(SortedRulesL[1:10])
```

```
> SortedRules <- sort(rules, by="confidence", decreasing=TRUE)
```

```
> inspect(SortedRules[1:10])
```

	lhs	rhs	support	confidence	lift	count
[1]	{kale}	=> {quinoa}	0.30	1	1.000000	6
[2]	{tea}	=> {soymilk}	0.25	1	1.428571	5
[3]	{tea}	=> {quinoa}	0.25	1	1.000000	5
[4]	{carrot}	=> {quinoa}	0.35	1	1.000000	7
[5]	{coffee}	=> {chocolate}	0.35	1	2.857143	7
[6]	{chocolate}	=> {coffee}	0.35	1	2.857143	7
[7]	{coffee}	=> {soymilk}	0.35	1	1.428571	7
[8]	{coffee}	=> {quinoa}	0.35	1	1.000000	7
[9]	{chocolate}	=> {soymilk}	0.35	1	1.428571	7
[10]	{chocolate}	=> {quinoa}	0.35	1	1.000000	7

```
>
```

```
> SortedRulesL <- sort(rules, by="lift", decreasing=TRUE)
```

```
> inspect(SortedRulesL[1:10])
```

	lhs	rhs	support	confidence	lift	count
[1]	{coffee}	=> {chocolate}	0.35	1.000000	2.857143	7
[2]	{chocolate}	=> {coffee}	0.35	1.000000	2.857143	7
[3]	{coffee,soymilk}	=> {chocolate}	0.35	1.000000	2.857143	7
[4]	{chocolate,soymilk}	=> {coffee}	0.35	1.000000	2.857143	7
[5]	{coffee,quinoa}	=> {chocolate}	0.35	1.000000	2.857143	7
[6]	{chocolate,quinoa}	=> {coffee}	0.35	1.000000	2.857143	7
[7]	{coffee,quinoa,soymilk}	=> {chocolate}	0.35	1.000000	2.857143	7
[8]	{chocolate,quinoa,soymilk}	=> {coffee}	0.35	1.000000	2.857143	7
[9]	{tea}	=> {soymilk}	0.25	1.000000	1.428571	5
[10]	{soymilk}	=> {tea}	0.25	0.3571429	1.428571	5

Read Two Common Formats

```
Foods <- read.transactions("KumarGroceriesTransData.csv",
  rm.duplicates = FALSE,
  format = "single", ##or basket
  sep="," ,
  skip=0,
  cols=c(1,2) ## for single, 1 ID col , 2 is item
  ## default is NULL for basket. Null means no IDs
)
arules::inspect(Foods)
```

```
Foods2 <- read.transactions("KumarGroceriesTransData_ASTRANS.csv",
  rm.duplicates = FALSE,
  format = "basket",
  sep="," ,
  cols=1 ##ID in col 1 if no ID then cols=NULL
)
arules::inspect(Foods2)
```

Thinking Outside the Basket

Twitter Data

- 1) Will need to create a “**document of transactions**” – one for each Tweet.
- 2) ** **Each row is a Tweet.**
- 3) Each column is a word (token) in that Tweet.
- 4) Order does not matter.
- 5) No duplicates

R Association Rules and Twitter: libraries

library(arules)

library(rtweet)

library(twitteR)

library(ROAuth)

library(jsonlite)

#library(streamR)

library(rjson)

library(tokenizers)

library(tidyverse)

library(plyr)

library(dplyr)

library(ggplot2)

#install.packages("syuzhet")

sentiment analysis

library(syuzhet)

library(stringr)

library(arulesViz) ## load last

Trouble with arulesViz?

FIRST - you MUST register and log into github

install_github("mhahsler/arulesViz")

RE: <https://github.com/mhahsler/arulesViz>

Trouble with arules not working suddenly

detach("package:arules", unload=TRUE)

library("arules")

Set Up Twitter Dev Account First

<https://developer.twitter.com/en/portal/apps>

The screenshot shows the Twitter Developer Portal interface. The browser address bar displays the URL `https://developer.twitter.com/en/portal/apps/13500791/settings`. The left sidebar contains navigation options: Developer Portal, Dashboard, Projects & Apps, Overview, STANDALONE APPS, GatesTwitterMining, and Products (NEW). The main content area shows the app name **GatesTwitterMining** and the **Settings** tab selected. The **Keys and tokens** sub-tab is highlighted with a red box. A red arrow points from the text "Get all 4 passcodes...." to this tab. Another red arrow points from the text "You will need to Create a new App. Mine is called GatesTwitterMining" to the app name. A third red arrow points from the text "URL and you will need to get a Twitter Developer Account and read and follow instructions in the Portal, etc." to the browser address bar. The "App Details" section is partially visible, showing the app name "GatesTwitterMining" and an app icon of a blue Twitter bird with a gear.

R Twitter Options

```
##### Using twittR #####  
setup_twitter_oauth(consumerKey,consumerSecret,access_Token,access_Secret)  
  
Search<-twitter::searchTwitter("#ILoveChocolate",n=100,since="2018-09-09")  
(Search_DF <- twListToDF(Search))  
TransactionTweetsFile = "Choc.csv"
```


(Search_DF <- twListToDF(Search))

```

1 The other day I woke up craving chocolate cupcakes. Today I'm craving @HersheyCompany chocolate bars.
  think the u... https://t.co/NtGH4eaSRc
2 WHO SAID "CHOCOLATE"? \n_____ \n#feed #feedsmartfood #honey #we
ovechocolate... https://t.co/DzzmvJlKEH
3 @ClaireValy @LowngSnake @firebox #ILOVECHOCO
ATE\nI love chocolate very very much.
4 #HealthTips #momlife #sahmlife #toddlers #ilovechocolate #homeschoolmom #bethechange #
oingitformygirls #fitmom #feeltheburn
5 RT @Kelly_Hawrylysh: #Fairtrade sourcing needed more than ever to avoid chocapocalypse!!! https://t.
o/dbxw3eQfTc #SDG12 @FairtradeAfrica...
6 RT @Kelly_Hawrylysh: #Fairtrade sourcing needed more than ever to avoid chocapocalypse!!! https://t.
o/dbxw3eQfTc #SDG12 @FairtradeAfrica

```

	favorited	favoriteCount	replyToSN	created	truncated	replyToSID
1	FALSE	0	<NA>	2018-09-27 12:12:52	TRUE	<NA>
2	FALSE	0	<NA>	2018-09-27 10:51:42	TRUE	<NA>
3	FALSE	0	ClaireValy	2018-09-27 00:45:43	FALSE	1044897146326208513
4	FALSE	0	templin_katie	2018-09-26 19:49:55	FALSE	1045037612388536321
5	FALSE	0	<NA>	2018-09-26 16:24:22	FALSE	<NA>
6	FALSE	0	<NA>	2018-09-26 16:23:42	FALSE	<NA>

	id	replyToUID
1	1045285140505735169	<NA>
2	1045264712118734848	<NA>
3	1045112213915226113	2878148959
4	1045037771050618881	1035584652722036736
5	1044986045975220224	<NA>
6	1044985877456392194	<NA>

```

1 <a href="http://twitter.com/download/android" rel="nofollow">Twitter for Android</a>
2 <a href="http://instagram.com" rel="nofollow">Instagram</a>
3 <a href="http://twitter.com" rel="nofollow">Twitter Web Client</a>
4 <a href="http://twitter.com/download/iphone" rel="nofollow">Twitter for iPhone</a>
5 <a href="http://twitter.com/download/android" rel="nofollow">Twitter for Android</a>
6 <a href="http://twitter.com/download/android" rel="nofollow">Twitter for Android</a>

```

	screenName	retweetCount	isRetweet	retweeted	longitude	latitude
1	RachelTBue	0	FALSE	FALSE	<NA>	<NA>
2	Niklaus_R	0	FALSE	FALSE	4.35008	50.845
3	saminaseem16	0	FALSE	FALSE	<NA>	<NA>

Build the Transaction File: Step 1

- 1) Each tweet should be one transaction.
- 2) Each word (token) in the tweet should be in its own column.

```
> (Search_DF$text[1])
```

```
[1] "The other day I woke up craving chocolate cupcakes. Today I'm craving @HersheyCompany chocolate bars. I think the u... https://t.co/NtGH4eaSRc"
```

Build The Transaction File: Step 2

```
## Start the file
Trans <- file(TransactionTweetsFile)
## Tokenize to words
Tokens<-tokenizers::tokenize_words(Search_DF$text[1],stopwords = stopwords::stopwords("en"),
    lowercase = TRUE, strip_punct = TRUE, strip_numeric = TRUE,simplify = TRUE)
## Write squished tokens
cat(unlist(str_squish(Tokens)), "\n", file=Trans, sep=",")
close(Trans)

## Append remaining lists of tokens into file
## Recall - a list of tokens is the set of words from a Tweet
Trans <- file(TransactionTweetsFile, open = "a")
for(i in 2:nrow(Search_DF)){
  Tokens<-tokenize_words(Search_DF$text[i],stopwords = stopwords::stopwords("en"),
    lowercase = TRUE, strip_punct = TRUE, simplify = TRUE)
  cat(unlist(str_squish(Tokens)), "\n", file=Trans, sep=",")
}
close(Trans)
```


Read and Inspect the Transactions

```
##### Read in the tweet transactions
TweetTrans <- read.transactions(TransactionTweetsFile,
                                rm.duplicates = FALSE,
                                format = "basket",
                                sep=","
                                ## cols =
                                )

inspect(TweetTrans)
## See the words that occur the most
Sample_Trans <- sample(TweetTrans, 50)
summary(Sample_Trans)
```

most frequent items:

https
35

t.co
35

chocolate ilovechocolate
25 23

rt
9

```
[59] {1,  
    along,  
    box,  
    chocolates,  
    days,  
    domme,  
    findom,  
    finsub,  
    godiva,  
    ilovechocolate,  
    pay,  
    send}  
[60] {chocolate,  
    delicious,  
    food,  
    foodporn,  
    https,  
    instafood,  
    introducing,  
    love,  
    mango,  
    marzipan,  
    sweets,  
    t.co,  
    truffles,  
    u17wpqhxxh,  
    yummy}
```

Transaction Sets and Summary

Clean Up

```
## Read the transactions data into a dataframe
```

```
TweetDF <- read.csv(TransactionTweetsFile, header = FALSE, sep = ",")  
head(TweetDF)
```

```
> TweetDF <- read.csv(TransactionTweetsFile, header = FALSE, sep = ",")
```

```
> head(TweetDF)
```

	v1	v2		v3	v4	v5							
1	day	woke		craving	chocolate	cupcakes							
2	said	chocolate			feed	feedsmartfood							
3	clairevaly	lowngsnake		firebox	ilovechocolate	love							
4	healthtips	momlife		sahmlife	toddlers	ilovechocolate							
5	rt kelly_hawrylysh			fairtrade	sourcing	needed							
6	rt kelly_hawrylysh			fairtrade	sourcing	needed							
	v6	v7	v8	v9	v10	v11	v12					v13	
1	today	craving	hersheycompany	chocolate	bars	think	u					https	
2	honey	welovechocolate	https	t.co	dzzmvjlkeh								
3	chocolate	much											
4	homeschoolmom	bethechange	doingitformygirls	fitmom	feeltheburn								
5	ever	avoid	chocapocalypse	https	t.co	dbxw3eqftc	sdg12	fairtradeafrica					
6	ever	avoid	chocapocalypse	https	t.co	dbxw3eqftc	sdg12	fairtradeafrica					

most frequent items:

https
35

t.co
35

chocolate
25

ilovechocolate
23

rt
9

Specifically Remove Words

```
## Convert all columns to char
TweetDF<-TweetDF %>%
  mutate_all(as.character)
(str(TweetDF))
# We can now remove certain words
TweetDF[TweetDF == "t.co"] <- ""
TweetDF[TweetDF == "rt"] <- ""
TweetDF[TweetDF == "http"] <- ""
TweetDF[TweetDF == "https"] <- ""

## Clean with grepl - every row in each column
MyDF<-NULL
for (i in 1:ncol(TweetDF)){
  MyList=c() # each list is a column of logicals ...
  MyList=c(MyList,grepl("[[:digit:]]", TweetDF[[i]]))
  MyDF<-cbind(MyDF,MyList) ## create a logical DF
  ## TRUE is when a cell has a word that contains digits
}
## For all TRUE, replace with blank
TweetDF[MyDF] <- ""
(TweetDF)
```



```

## Clean with grep1 - every row in each column
MyDF<-NULL
MyDF2<-NULL
MyDF3<-NULL
for (i in 1:ncol(TweetDF)){
  MyList=c() # each list is a column of logicals ...
  MyList=c(MyList,grep1("[[:digit:]]", TweetDF[[i]]))

  MyList2=c()## for small words
  MyList2=c(MyList2,grep1("[A-z]{4,}", TweetDF[[i]]))

  MyList3=c()## for large words
  MyList3=c(MyList3,grep1("[A-z]{12,}", TweetDF[[i]]))

  MyDF<-cbind(MyDF,MyList) ## create a logical DF
  MyDF2<-cbind(MyDF2,MyList2)
  MyDF3<-cbind(MyDF3,MyList3)
}
## For all TRUE, replace with blank
TweetDF[MyDF] <- ""
TweetDF[!MyDF2] <- ""
TweetDF[MyDF3] <- ""
(head(TweetDF,10))

```


Association Rule Mining

```
[70] {chocolate,  
delicious,  
food,  
foodporn,  
instafood,  
introducing,  
love,  
mango,  
marzipan,  
sweets,  
truffles,  
yummy}
```

```
[71] {bali's,  
big,  
check,  
chocolatiers,  
ilovechocolate,  
six,  
theyakmag,  
theyakmagazine,  
yak}
```



Example cleaner tweets as individual transactions.

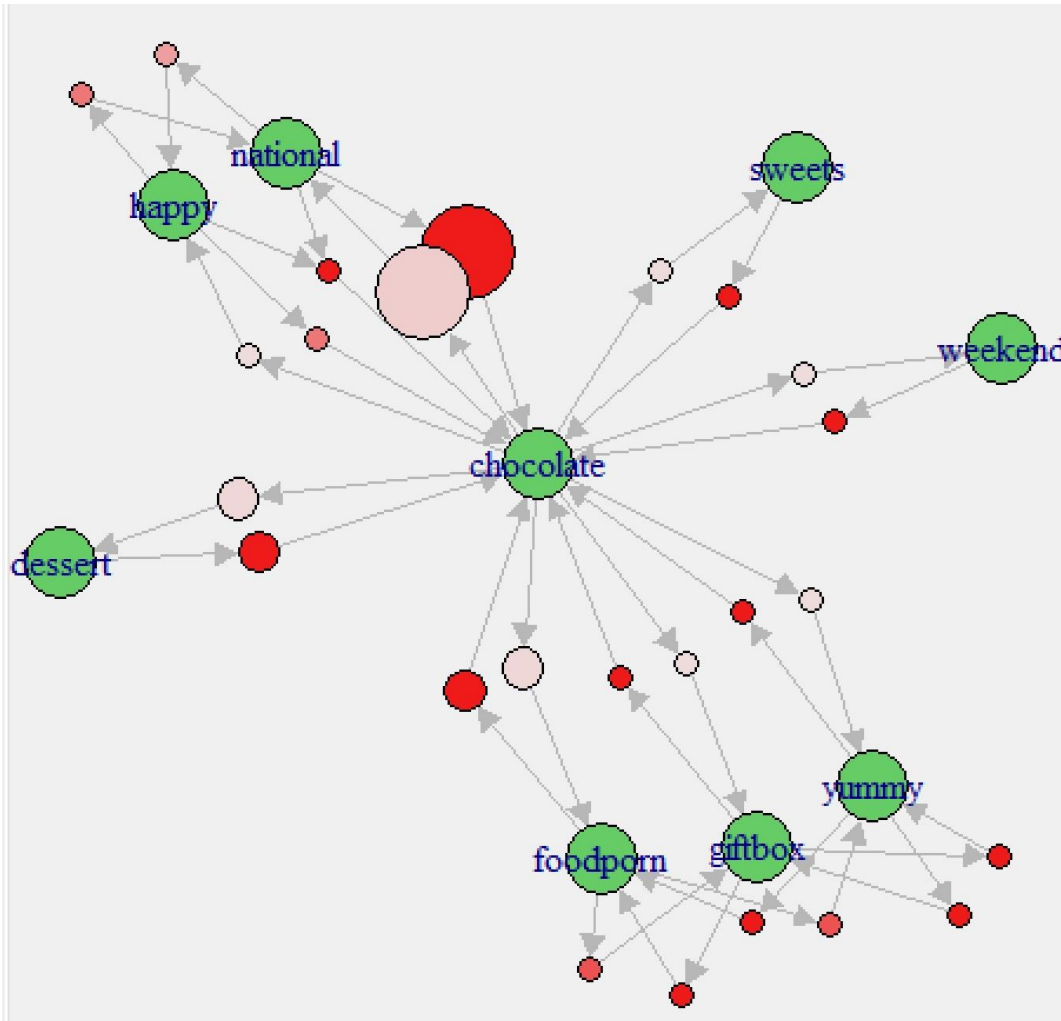
```
TweetTrans_rules = arules::apriori(TweetTrans,  
  parameter = list(support=.0001, confidence=.0001, minlen=2, maxlen=6))  
  #minlen=2, maxtime=10))  
inspect(TweetTrans_rules[1:30])  
## sorted  
SortedRules_sup <- sort(TweetTrans_rules, by="support", decreasing=TRUE)  
inspect(SortedRules_sup[1:20])
```

```
> inspect(SortedRules_sup[1:20])
```

	lhs	rhs	support	confidence	lift	count
[1]	{national}	=> {chocolate}	0.11267606	1.00000000	1.731707	8
[2]	{chocolate}	=> {national}	0.11267606	0.19512195	1.731707	8
[3]	{dessert}	=> {chocolate}	0.07042254	1.00000000	1.731707	5
[4]	{chocolate}	=> {dessert}	0.07042254	0.12195122	1.731707	5
[5]	{foodporn}	=> {chocolate}	0.07042254	1.00000000	1.731707	5
[6]	{chocolate}	=> {foodporn}	0.07042254	0.12195122	1.731707	5
[7]	{happy}	=> {national}	0.05633803	0.66666667	5.916667	4
[8]	{national}	=> {happy}	0.05633803	0.50000000	5.916667	4
[9]	{happy}	=> {chocolate}	0.05633803	0.66666667	1.154472	4
[10]	{chocolate}	=> {happy}	0.05633803	0.09756098	1.154472	4
[11]	{weekend}	=> {chocolate}	0.05633803	1.00000000	1.731707	4
[12]	{chocolate}	=> {weekend}	0.05633803	0.09756098	1.731707	4
[13]	{sweets}	=> {chocolate}	0.05633803	1.00000000	1.731707	4
[14]	{chocolate}	=> {sweets}	0.05633803	0.09756098	1.731707	4
[15]	{giftbox}	=> {yummy}	0.05633803	1.00000000	17.750000	4
[16]	{yummy}	=> {giftbox}	0.05633803	1.00000000	17.750000	4
[17]	{giftbox}	=> {foodporn}	0.05633803	1.00000000	14.200000	4
[18]	{foodporn}	=> {giftbox}	0.05633803	0.80000000	14.200000	4
[19]	{giftbox}	=> {chocolate}	0.05633803	1.00000000	1.731707	4
[20]	{chocolate}	=> {giftbox}	0.05633803	0.09756098	1.731707	4

A Quick Plot

```
library(arulesViz)
SortedRules_sup <- sort(TweetTrans_rules, by="support", decreasing=TRUE)
inspect(SortedRules_sup[1:20])
plot (SortedRules_sup[1:25],method="graph",engine='interactive',shading="confidence")
```



Size: support
Color (dark=higher): conf