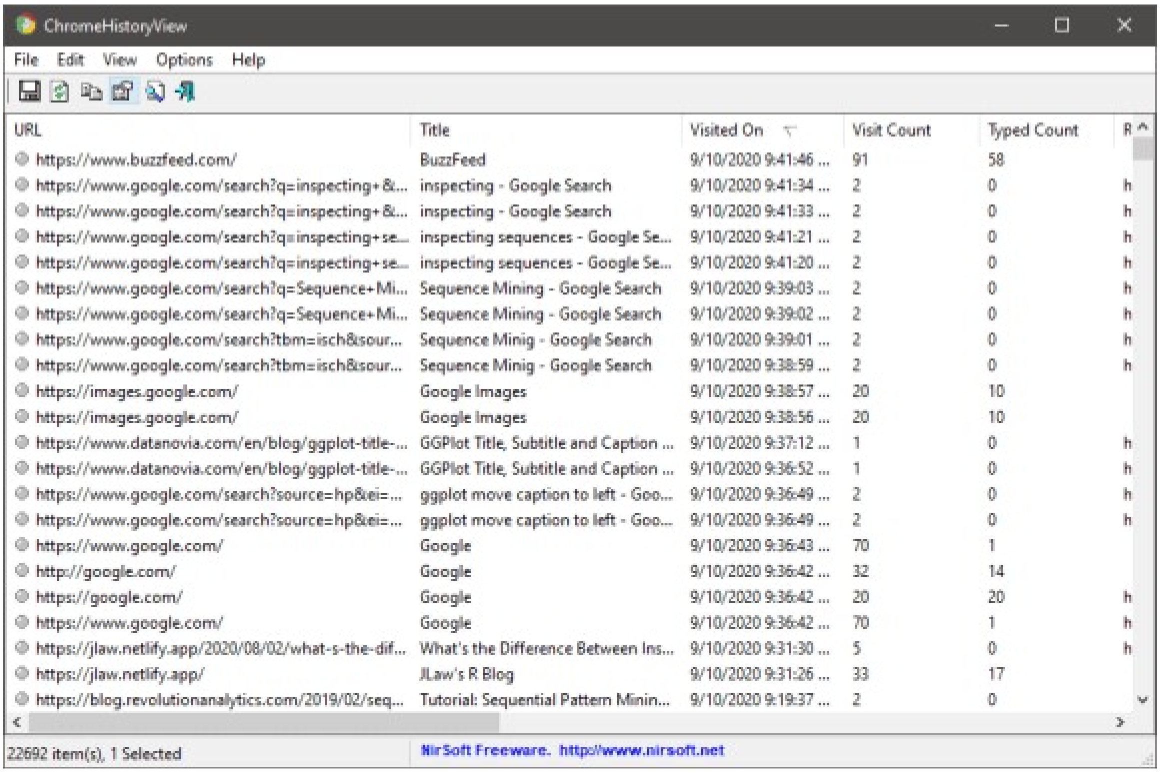
Typically when thinking of pattern mining people tend to think of Market Basket Analysis with the convent showing people typically buy both Beer and Diapers in the same trip. When order doesn't matter this is ca Association Rules Mining and is implemented by the `arules` package in R. In this example, the person is diapers and beer. It doesn't really matter if diapers led to the beer purchase or beer lead to the diaper pur However, there are instances where the order of events are important to what we'd consider a pattern. Fo "cause and effect" relationships imply order. Putting your hand on a hot stove leads to burning your hand. direction of burning your hand leading you to put your hand on a hot stove makes less sense. When the r is applied to association rules mining it becomes "Sequence Mining". And to do this, we'll use the `arule` package to run the [cSPADE](https://en.wikipedia.org/wiki/Sequential_pattern_mining) algorithm.

Unfortunately, I don't have access to grocery store data or much other data that would be an interesting u sequence mining. But what I do have is access to my own browsing history. So for this post, I'll be lookin sequential patterns in my web own browsing habits.

Getting the Data

I wasn't able to figure out how to extract my browsing history directly from Chrome in a way that would ea into R. However, there are 3rd party programs that can extract browsing histories. In this case, I used a p BrowsingHistoryView by Nir Sofer. The interface is very straight forward and allowed for extracting my bro to a CSV file.


ChromeHistoryView

File Edit View Options Help

URL	Title	Visited On	Visit Count	Typed Count	R
https://www.buzzfeed.com/	BuzzFeed	9/10/2020 9:41:46 ...	91	58	
https://www.google.com/search?q=inspecting+&...	inspecting - Google Search	9/10/2020 9:41:34 ...	2	0	h
https://www.google.com/search?q=inspecting+&...	inspecting - Google Search	9/10/2020 9:41:33 ...	2	0	h
https://www.google.com/search?q=inspecting+se...	inspecting sequences - Google Se...	9/10/2020 9:41:21 ...	2	0	h
https://www.google.com/search?q=inspecting+se...	inspecting sequences - Google Se...	9/10/2020 9:41:20 ...	2	0	h
https://www.google.com/search?q=Sequence+Mi...	Sequence Mining - Google Search	9/10/2020 9:39:03 ...	2	0	h
https://www.google.com/search?q=Sequence+Mi...	Sequence Mining - Google Search	9/10/2020 9:39:02 ...	2	0	h
https://www.google.com/search?tbm=isch&sour...	Sequence Minig - Google Search	9/10/2020 9:39:01 ...	2	0	h
https://www.google.com/search?tbm=isch&sour...	Sequence Minig - Google Search	9/10/2020 9:38:59 ...	2	0	h
https://images.google.com/	Google Images	9/10/2020 9:38:57 ...	20	10	
https://images.google.com/	Google Images	9/10/2020 9:38:56 ...	20	10	
https://www.datanovia.com/en/blog/ggplot-title-...	GGPlot Title, Subtitle and Caption ...	9/10/2020 9:37:12 ...	1	0	h
https://www.datanovia.com/en/blog/ggplot-title-...	GGPlot Title, Subtitle and Caption ...	9/10/2020 9:36:52 ...	1	0	h
https://www.google.com/search?source=hp&ei=...	ggplot move caption to left - Goo...	9/10/2020 9:36:49 ...	2	0	h
https://www.google.com/search?source=hp&ei=...	ggplot move caption to left - Goo...	9/10/2020 9:36:49 ...	2	0	h
https://www.google.com/	Google	9/10/2020 9:36:43 ...	70	1	
http://google.com/	Google	9/10/2020 9:36:42 ...	32	14	
https://google.com/	Google	9/10/2020 9:36:42 ...	20	20	h
https://www.google.com/	Google	9/10/2020 9:36:42 ...	70	1	h
https://jlaw.netlify.app/2020/08/02/what-s-the-dif...	What's the Difference Between Ins...	9/10/2020 9:31:30 ...	5	0	h
https://jlaw.netlify.app/	JLaw's R Blog	9/10/2020 9:31:26 ...	33	17	
https://blog.revolutionanalytics.com/2019/02/seq...	Tutorial: Sequential Pattern Minin...	9/10/2020 9:19:37 ...	2	0	

22692 item(s), 1 Selected

NirSoft Freeware. http://www.nirsoft.net

From this program I was able to extract 85 days worth of browsing history from 2020-06-13 through 2020

Loading Libraries and Reading in Data

The libraries used in this analysis are the usual gang of `tidyverse`, `lubridate`, `ggtext` which are oft blog. Some new ones specific for this analysis are:

- `arulesSequences` – Which will run the sequence mining algorithm
- `tidygraph` and `ggraph` – Which will allow for plotting my browsing history as a directed graph

```
library(tidyverse) #Data Manipulation and Plotting
library(lubridate) #Date Manipulation
library(arulesSequences) #Running the Sequence mining algorithm
library(ggtext) #Making adding some flair to plots
library(tidygraph)  ## Creating a Graph Structure
library(ggraph) ## Plotting the Network Graph Structure
```

A .csv file was created from the Browsing History View software and read into R through `readr`.

```
browsing_history <- read_csv('browsing_history_v2.csv')
```

The read-in data looks as follows:

URL	Title	Visited On	Visit Count	Typed Count	Referrer	Visit ID	Profile	URL Length	Transiti Type
https://watch.wwe.com/original/undertaker-the-last-ride-134576	wwe network - undertaker: the last ride	6/13/2020 2:59:23 PM	2	1	NA	331141	Default	62	Typed
https://watch.wwe.com/original/undertaker-the-last-ride-134576	wwe network - undertaker: the last ride	6/13/2020 2:59:28 PM	2	1	NA	331142	Default	62	Link
https://www.google.com/search?q=vtt+to+srt&oq=vtt+to+srt&aqs=chrome.0.69i59j0l7.1395j0j4&sourceid=chrome&ie=utf-8	vtt to srt - google search	6/13/2020 4:33:34 PM	2	0	NA	331157	Default	113	Generate
https://www.google.com/search?q=vtt+to+srt&oq=vtt+to+srt&aqs=chrome.0.69i59j0l7.1395j0j4&sourceid=chrome&ie=utf-8	vtt to srt - google search	6/13/2020 4:33:37 PM	2	0	NA	331158	Default	113	Link
https://twitter.com/	home / twitter	6/13/2020 5:19:55 PM	98	90	NA	331167	Default	20	Typed
https://twitter.com/home	home / twitter	6/13/2020 5:20:03 PM	414	0	NA	331168	Default	24	Link

Looking at the data there are a number of cleaning steps that will need to be done to make the sequence useful.

1. The variable names are not machine friendly and contain spaces,
2. Some of the URLs are redirects or generated and therefore not URLs I specifically went to. I'll wan those.
3. *Visited On* is a character rather than a date
4. If we're looking for common patterns, I should probably limit the URLs to just the domains as its ve

I would read the same news articles multiple times.
  - Therefore I'll shorten "https://twitter.com/home" to just "twitter.com/"

The following code block carries out the cleaning steps outlined above:

```
browsing_history_cleaned <- browsing_history %>%
  #Make the names more R friendly
  janitor::clean_names() %>%
  #Subset to URLs I either typed or
  #Linked to (excluding redirects/form submissions)
  filter(transition_type %in% c('Link', 'Typed'),
         str_detect(transition_qualifiers, 'Chain Start')
         )%>%
  #Keep Only the Base URL and remove the prefix
  mutate(base_url = str_remove(url, '^https?:\\/\\/') %>%
           str_remove('^www\\.') %>%
           str_extract(., '^.+?\\/'),
         #Parse the Date Format
         dttm = mdy_hms(visited_on),
         ds = as.Date(dttm)
  ) %>%
  select(base_url, dttm, title, ds)
```

The above block:

1. Uses `janitor::clean_names()` to convert the column names into an R-friendly format (Visited
   visited_on)
2. Keeps only the 'Typed' and 'Link' transition types to keep only URLs I either typed to or clicked to
3. Keep only 'Chain Start' qualifiers to remove URLs that came from redirects
4. Create a `base_url` field by removing the "http[s]://" and "www." strings if they exist.
5. Converts `visited_on` into both a timestamp and a datestamp
6. Only keeps the four columns we're interested in.

After these changes, the data looks like:

base_url	dttm	title	ds
watch.wwe.com/	2020-06-13 14:59:23	wwe network - undertaker: the last ride	2020-06-13
watch.wwe.com/	2020-06-13 14:59:28	wwe network - undertaker: the last ride	2020-06-13
google.com/	2020-06-13 16:33:37	vtt to srt - google search	2020-06-13
twitter.com/	2020-06-13 17:19:55	home / twitter	2020-06-13
twitter.com/	2020-06-13 17:20:03	home / twitter	2020-06-13

Sessionizing the Data

Even though I have a date field for my browsing history, the cSPADE algorithm is going to want to be able differentiate between when one session begins and another session ends. While a reasonable choice mi break things apart by day, it's likely that on weekends I have multiple browsing sessions which can somet past midnight. So a more reasonable choice might be to say a new session begins if there is a gap of at l since the last page I browsed to.

Another aspect of the data that I'd like to deal with is to eliminate when I go to multiple pages within the s Having an eventual rule that "twitter.com/ -> twitter.com" isn't that interesting. So I will also remove any cc rows that have the same domain.

```
collapsed_history <- browsing_history_cleaned %>%
  #Order by Time
  arrange(dttm) %>%
  # Create a new marker every time a Page Browsing is more than 1 hour since
  # the last one
  # Also, create a segment_id to identify each session
  mutate(time_diff = dttm-lag(dttm),
         #Count Segments as more than an hour btw events
         new_segment = if_else(is.na(time_diff) | time_diff >= 60*60, 1, 0),
         segment_id = cumsum(new_segment)
  ) %>%
  group_by(segment_id) %>%
  arrange(dttm) %>%
  #Remove Instances where the same baseurl appears consecutively
  filter(base_url != lag(base_url) | is.na(lag(base_url))) %>%
  #Create Within Segment ID
  mutate(item_id = row_number()) %>%
  select(segment_id, ds, dttm, item_id, base_url) %>%
  ungroup() %>%
  #Convert Everything to Factor
  mutate(across(.cols = c("segment_id", "base_url"), .f = as.factor))
```

In order to create `segment_id`s to represent each session, I use `dplyr::lag()` to calculate the differe
seconds between each event. Then when the event occurs more than 1 hour after the prior event I mark
the `new_segment` column. Then using the `cumsum` option, I can fill down the segment_ids to all the othe
that session.

Similarly I use the lag function to remove consecutively occurring identical `base_url`.

Finally, a quirk of the `arulesSequences` package is that the "items" or the URLs in this case must be fa

The data for the 154 browsing sessions now looks like:

```
collapsed_history %>% head(5) %>% knitr::kable()
```

segment_id	ds	dttm	item_id	base_url
1	2020-06-13	2020-06-13 14:59:23	1	watch.wwe.com/
2	2020-06-13	2020-06-13 16:33:37	1	google.com/
2	2020-06-13	2020-06-13 17:19:55	2	twitter.com/
2	2020-06-13	2020-06-13 17:20:09	3	gmail.com/
2	2020-06-13	2020-06-13 17:24:14	4	twitter.com/

Constructing the Transactions Data Set for arulesSequences

I haven't found a ton of resources online about using the `arulesSequences` package. This blog post frc
Analytics has been one of the best that I've found. However, their process involves exporting to .csv and
back in to create the transactions data set. Personally, I'd like to avoid doing as much outside of R as pos

However, the blog post does provide a good amount of detail about how to properly get the data in the pr
Using the `as` function, I can convert the previous data frame into a "transactions" format and set the follo

use in cSPADE:

- **items**: The elements that make up a sequence
- **sequenceID**: The identifier for each sequence
- **eventID**: The identifier for an item within a sequence

```
sessions <-  as(collapsed_history %>% transmute(items = base_url), "transacti
transactionInfo(sessions)$sequenceID <- collapsed_history$segment_id
transactionInfo(sessions)$eventID = collapsed_history$item_id
```

If I wanted to use better controls around time gaps, I would need to provide better information about time. is pretty basic, I don't use that field as the differentiation between sessions is enough.

The Transaction data class can be viewed with the `inspect()` function:

```
inspect(head(sessions))
##      items                   transactionID sequenceID eventID
## [1] {items=watch.wwe.com/} 1              1          1
## [2] {items=google.com/}     2              2          1
## [3] {items=twitter.com/}    3              2          2
## [4] {items=gmail.com/}      4              2          3
## [5] {items=twitter.com/}    5              2          4
## [6] {items=gothamist.com/} 6              2          5
```

Having the "items=" for every items is a little annoying so let's remove that by altering the `itemLabels` fo transactions set:

```
itemLabels(sessions) <- str_replace_all(itemLabels(sessions), "items=", "")
inspect(head(sessions))
##      items             transactionID sequenceID eventID
## [1] {watch.wwe.com/} 1              1          1
## [2] {google.com/}     2              2          1
## [3] {twitter.com/}    3              2          2
## [4] {gmail.com/}      4              2          3
## [5] {twitter.com/}    5              2          4
## [6] {gothamist.com/} 6              2          5
```

Much better.

Running the cSPADE algorithm

The sequence mining algorithm can be run by using the `cspade()` function in the `arulesSequences` p Before running the algorithm, I'll need to explain the concept of *support*. *Support* can be best thought of a proportion of sessions that contain a certain URL. Why that's important is that the cSPADE algorithm wor to find the frequent patterns starting with 1-item sets, then moving to 2-items, etc. In order to limit how mu algorithm will run for, you can set a minimum support threshold. Why this helps is that by definition the su 2-item set will be less than or equal to the support of either 1-item set. For example, if A occurs 40% of th B cannot occur more frequently.

So if A alone does not meet the support threshold, then we don't need to care about any 2 or more item s contain A.

For this purpose I'll set a minimum support of 25%. The `cspade` function will return all of the frequent iter occur in my browsing data.

```
itemsets <- cspade(sessions,
                   parameter = list(support = 0.25),
                   control = list(verbose = FALSE))
```

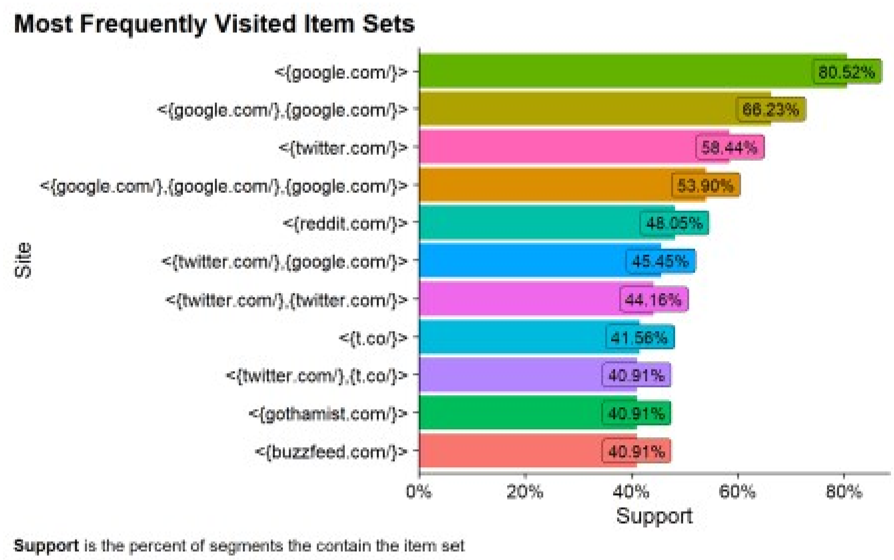
The `summary()` function will provide a lot of useful information, but we'll just look at the first few rows wit `inspect()`:

```
inspect(head(itemsets))
##    items                  support
##  1 <{buzzfeed.com/}>      0.4090909
##  2 <{en.wikipedia.org/}> 0.3311688
##  3 <{facebook.com/}>      0.3311688
##  4 <{github.com/}>        0.3051948
##  5 <{google.com/}>        0.8051948
##  6 <{gothamist.com/}>     0.4090909
##
```

Here we see the results of a series of 1-item sets where the support is the number of sessions containing visit to that URL. **Apparently I use google A LOT as it appears in 80% of my sessions**.

We can also convert the itemsets data back to a data frame using the `as()` function and go back to using `dplyr` or `ggplot` functions. For example, I can visualize the 10 Most Frequent Sequences I visit based metric:

```
#Convert Back to DS
itemsets_df <- as(itemsets, "data.frame") %>% as_tibble()

#Top 10 Frequent Item Sets
itemsets_df %>%
  slice_max(support, n = 10) %>%
  ggplot(aes(x = fct_reorder(sequence, support),
                    y = support,
                    fill = sequence)) +
    geom_col() +
    geom_label(aes(label = support %>% scales::percent()), hjust = 0.5) +
    labs(x = "Site", y = "Support", title = "Most Frequently Visited Item Set
         caption = "**Support** is the percent of segments the contain the it
    scale_fill_discrete(guide = F) +
    scale_y_continuous(labels = scales::percent,
                       expand = expansion(mult = c(0, .1))) +
    coord_flip() +
    cowplot::theme_cowplot() +
    theme(
      plot.caption = element_markdown(hjust = 0),
      plot.caption.position = 'plot',
      plot.title.position = 'plot'
    )
```



Now we see some of the 2-item sets. Not only do I use Google in 80% of sessions. In 66% of sessions I v
twice!

Turning Frequent Sequences into Rules

While knowing what URLs occur frequently is interesting, it would be more interesting if I could generate r
what websites lead to visits to other websites.

The `ruleInduction()` function will turn the item sets into "if A then B" style rules. To control the size of
will introduce the concept of *confidence*. The *Confidence* of an "If A then B" rule is the % of the times the
when A occurs. So if "if A then B" has a 50% confidence then when A occurs we have a 50% chance of s
vs. seeing anything other than B.

For this post, I'll use a minimum confidence of 60%.

```
rules <- ruleInduction(itemsets,
                       confidence = 0.6,
                       control = list(verbose = FALSE))

inspect(head(rules, 3))
##     lhs                         rhs                        support confidence     l
##   1 <{gothamist.com/}>     => <{westsiderag.com/}> 0.2727273  0.6666667 1.901235
##   2 <{gothamist.com/}>     => <{twitter.com/}>     0.2662338  0.6507937 1.113580
##   3 <{t.co/}>               => <{twitter.com/}>     0.3246753  0.7812500 1.336806
##
```

The returned data structure has 5 fields:

- **lhs**: Left-hand side - The "A" in our "if A then B" rule
- **rhs**: Right-hand side - The "B" in our "if A then B" rule
- **support**: The % of sessions where "A then B" occurs
- **confidence**: How often the rule is true (If A occurs the % of Time that B occurs)
- **lift**: The strength of the association. Defined as the ratio of support "A then B" divided by the Suppo
  the Support of B. In other words, how much more likely are we to see "A and B together" vs. what w
  expect if A and B were completely independent of each other.

The first row shows two NYC specific blogs, one of NYC overall and one for the Upper West Side. The su
that 27% of my sessions include these two blogs. The confidence shows that if I visit Gothamist there's 6

visit WestSideRag after. Finally, the lift shows that the likelihood of this rule is 90% higher than you'd expe
was no relation between my visiting these sites.

Redundant Rules

In order to create the most effective and simplest rules we'll want to remove redundant rules. In this conte *redundant* when a subset of the left-hand side has a higher confidence than the rule with more items on t side. In simpler terms, we want to simplest rule that doesn't sacrifice information. For example, {A, B, C} - redundant of {A, B} -> {D} if the confidence of the 2nd rule is greater than or equal to the 1st

A real example from this data is:

lhs	rhs	support	confidence	lift
<{t.co/}>	=> <{twitter.com/}>	0.3246753	0.7812500	1.336806
<{twitter.com/}, {t.co/}>	=> <{twitter.com/}>	0.3181818	0.7777778	1.330864

The addition of "twitter.com" to the left-hand side does not make for a more confident rule so therefore it i

Removing redundant rules can be done easily with the `is.redundant()` function:

```
rules_cleaned <- rules[!is.redundant(rules)]
```

The rules class can also be converted back to a data.frame with the `as()` function. Then we can use `tidyr::separate()` to break apart the `rule` column into the `lhs` and `rhs` columns.

```
rules_df <- as(rules_cleaned, "data.frame") %>%
  as_tibble() %>%
  separate(col = rule, into = c('lhs', 'rhs'), sep = " => ", remove = F)
```

Now we can look at the highest confidence rules:

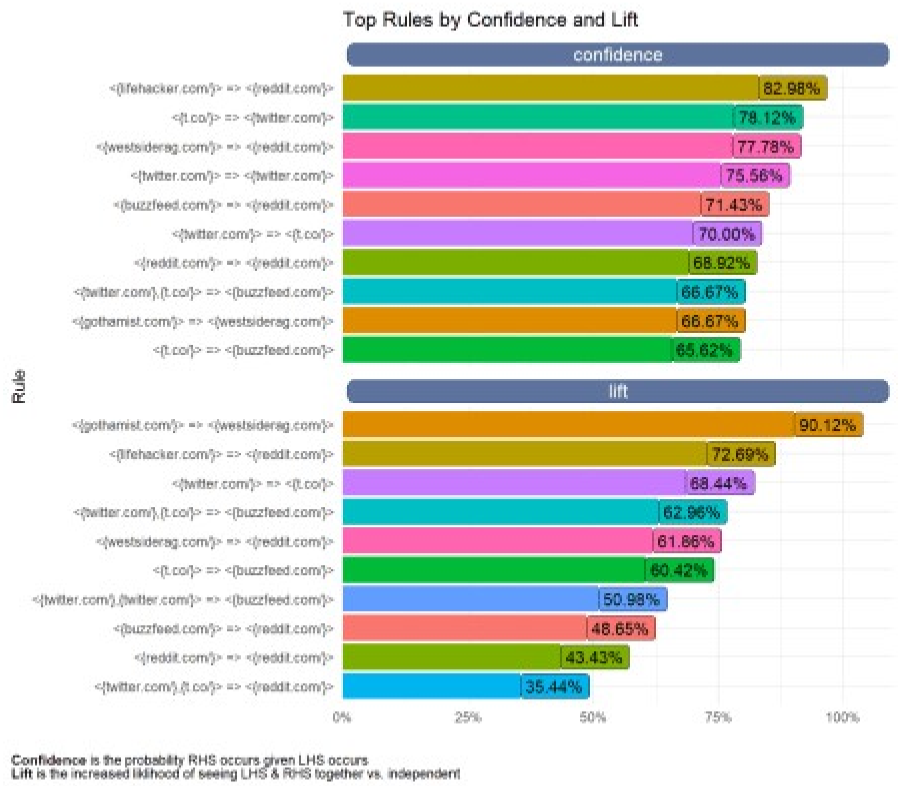
```
rules_df %>%
  arrange(-confidence) %>%
  select(lhs, rhs, support, confidence, lift) %>%
  head() %>%
  knitr::kable()
```

lhs	rhs	support	confide
<{google.com/},{google.com/},{google.com/},{google.com/}>	<{google.com/}>	0.3701299	0.919
<{github.com/}>	<{google.com/}>	0.2792208	0.914
<{buzzfeed.com/},{google.com/}>	<{google.com/}>	0.2597403	0.851
<{t.co/},{google.com/}>	<{google.com/}>	0.2727273	0.840
<{lifehacker.com/}>	<{reddit.com/}>	0.2532468	0.829
<{google.com/}>	<{google.com/}>	0.6623377	0.822

And this is pretty boring. I wind up on Google a lot, so it appears in a lot of the rules. So let's make this m by removing Google from the results and by also looking at both confidence and lift.

```
rules_df %>%
  #Remove All Rules that Involve Google
  filter(!str_detect(rule, '\\{google.com\\/\\}')) %>%
  #Keep only Rule, Confidence, and Lift - 1
  transmute(rule, confidence, lift = lift - 1) %>%
```

```
  #Pivot Lift and confidence into a single column
  pivot_longer(cols = c('confidence','lift'),
               names_to = "metric",
               values_to = "value") %>%
  group_by(metric) %>%
  #Keep only the Top 10 Rules for Each Metric
  top_n(10, value) %>%
  ungroup() %>%
  # Reorder so that order is independent for each metrics
  ggplot(aes(x = tidytext::reorder_within(rule, value, metric),
             y = value,
             fill = rule)) +
    geom_col() +
    geom_label(aes(label = value %>% scales::percent()),
               hjust = 0) +
    scale_fill_discrete(guide = F) +
    tidytext::scale_x_reordered() +
    scale_y_continuous(label = scales::percent,
                       limits = c(0, 1),
                       expand = expansion(mult = c(0, .1))) +
    labs(x = "Rule",
         y = "",
         title = "Top Rules by Confidence and Lift",
         caption = "**Confidence** is the probability RHS occurs
         given LHS occurs

         **Lift** is the increased liklihood of seeing LHS & RHS together vs.
independent") +
    facet_wrap(~metric, ncol = 1, scales = "free_y") +
    coord_flip() +
    theme_minimal() +
    theme(
      plot.caption = element_markdown(hjust = 0),
      plot.caption.position = 'plot',
      strip.text = element_textbox(
        size = 12,
        color = "white", fill = "#5D729D", box.color = "#4A618C",
        halign = 0.5, linetype = 1, r = unit(5, "pt"), width = unit(1, "npc")
        padding = margin(2, 0, 1, 0), margin = margin(3, 3, 3, 3)
      )
    )
```



Some of the high lift rules that occur are:

- I visit WestSideRag after Gothamist
- I visit Reddit after LifeHacker
- I visit Buzzfeed after Twitter.

By the way, all this is true. My usually weekday pattern tends to be Twitter -> Gothamist -> WestSideRag ILoveTheUpperWest -> Buzzfeed -> LifeHacker -> Reddit.

So it does appear that the Sequence Mining rules do in fact represent my browsing habits! But certain sit Upper West Side blog did not make the top rules.

Visualizing these relationships as a graph

Ultimately, my browsing habits can be restructured as a directed graph where each URL leads to another rather than relying on statistical measures like Support, Confidence, and Lift, I can visualize my browsing However, to turn my data into an edge list I need to re-structure the URLs from a sequential list into a ser "Source/Destination" edges.

To do this, I'll group by each browsing session, setting the URL to the "source' and using `dplyr::lead(` URL from the next row to form the destination. Then since for the last URL, the destination will be null, I'll endpoints from the data. Finally, to create edge weightings I'll count the number of instances for each source/destination pair.

```
collapsed_history_graph_dt <- collapsed_history %>%
  group_by(segment_id) %>%
  transmute(item_id, source = base_url) %>%
  mutate(destination = lead(source)) %>%
  ungroup() %>%
  filter(!is.na(destination)) %>%
  select(source, destination, segment_id) %>%
  count(source, destination, name = 'instances')
```

In order to create the graph, I'll be using the `tidygraph` and `ggraph` packages to convert the data fram appropriate format and visualize the network in a ggplot style.

To make the resulting network more readable, I'll filter my edge list to only those with at least 15 occurren use `tidygraph::as_tbl_graph` to convert to a graph-friendly data type.

```
g <- collapsed_history_graph_dt %>%
  filter(instances > 14) %>%
  as_tbl_graph()
```

Creating Graph Clusters

To make the visualization a little more interesting I thought it would be fun to cluster the network. The `igraph::cluster_optimal` function will calculate the optimal community structure of the graph. This label then gets applied as a node attribute to the graph object `g` created in the prior code block.

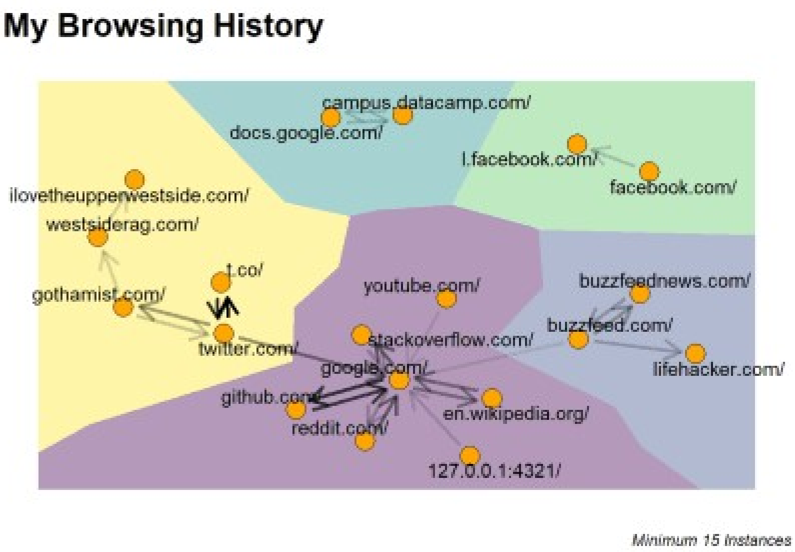
```
clp <- igraph::cluster_optimal(g)

g <- g %>%
  activate("nodes") %>%
  mutate(community = clp$membership)
```

Plotting the Network WIth ggraph

Ggraph follows a similar syntax to ggplot where the data object is based in and then there are geoms to r nodes/edges of the plot. The layout option specifies how the nodes and edges will be laid out. Here I'm u results of the Fruchterman-Reingold algorithm for a force-directed layout. As used in this code block the r geoms are:

- `geom_node_voronoi` - Used to plot the clustering as the background of the graph
- `geom_edge_parallel` - Since this is a directional graph, it will draw separate parallel arrows for direction. The shading will be based on the log number of instances.
- `geom_node_point` - Plots a circle for each node
- `geom_node_text` - Plots the names of the nodes and reduces overlap

```
set.seed(20201029)
ggraph(g, layout = 'fr') +
  geom_node_voronoi(aes(fill = as.factor(community)), alpha = .4) +
  geom_edge_parallel(aes(edge_alpha = log(instances)),
                 #color = "#5851DB",
                 edge_width = 1,
                 arrow = arrow(length = unit(4, 'mm')),
                 start_cap = circle(3, 'mm'),
                 end_cap = circle(3, 'mm')) +
  geom_node_point(fill = 'orange', size = 5, pch = 21) +
  geom_node_text(aes(label = name), repel = T) +
  labs(title = "My Browsing History",
       caption = "Minimum 15 Instances") +
  scale_fill_viridis_d(guide = F) +
  scale_edge_alpha_continuous(guide = F) +
  theme_graph()
```



This graph shows 5 clusters:

1. Twitter -> Gothamist -> WestSideRag -> ILoveTheUpperWestSide
    - The websites I typically visit after work on weekdays
2. Datacamp / Google Docs
    - When I did some Datacamp courses, I take notes in Google Docs so constantly switching ba makes sense.
3. Facebook.com / l.facebook.com
    - This is just using Facebook. But interesting that Facebook has no frequent connection outsi Facebook ecosystem.
4. BuzzFeed/LifeHacker
    - This a the last piece of my usual post-work routine. But perhaps it occurs later after the Twitt Cluster
5. The Google Centered Cluster
    - Google is the center of my browsing universe but some fun connections here are 127.0.0.1:4 the local instance when I'm developing this blog. This co-occurs with lots to trips to Google, Stack Overflow while I try to figure out / debug aspects of my blog development pipeline.