UNvotes

Hanh Nguyen

```r
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(unvotes)
```

```
## If you use data from the unvotes package, please cite the following:
##
## Erik Voeten "Data and Analyses of Voting in the UN General Assembly" Routledge Handbook of Internati
```

```r
library(ggplot2)
library(tidyr)
library(purrr)
```

```
##
## Attaching package: 'purrr'

## The following objects are masked from 'package:dplyr':
##
##     contains, order_by
```

```r
library(broom)
```

Erik Voeten "Data and Analyses of Voting in the UN General Assembly" Routledge Handbook of International Organization, edited by Bob Reinalda (published May 27, 2013).
Below is three datasets in the package and their following columns:
1. un_votes provides information on the voting history of the United Nations General Assembly. Contains one row for each country-vote pair.
- rcid: The roll call id; it is the primary key used to join with tables un_roll_calls and un_roll_call_issues
- vote: Vote result as a factor of yes/abstain/no (The original data included cases where a country was absent or was not yet a member. In this dataset these were filtered out to include only votes of Yes, Abstain, and No)
- country: Country name, by official English short name (ISO)

```r
head(un_votes)
```

```
## # A tibble: 6 × 3
##    rcid     country    vote
##   <dbl>       <chr>  <fctr>
## 1     3       Egypt abstain
## 2     3    Honduras     yes
## 3     3  Costa Rica     yes
## 4     3 El Salvador     yes
## 5     3      France      no
## 6     3     Uruguay     yes
```

```
unique(un_votes$vote)
```

```
## [1] abstain yes     no
## Levels: abstain no yes
```

2. un_roll_calls provies information on each roll call vote of the United Nations General Assembly.
• rcid: The roll call id
• session: Session number. The United Nations holds one session per year; these started in 1946
• importantvote: Whether the vote was classified as important by the U.S. State Department report "Voting Practices in the United Nations". These classifications began with session 39
• date: Date of the vote, as a Date vector
• unres: Resolution code
• amend: Whether the vote was on an amendment; coded only until 1985
• para: Whether the vote was only on a paragraph and not a resolution; coded only until 1985
• short: Short description
• descr: Longer description

```
head(un_roll_calls)
```

```
## # A tibble: 6 × 9
##    rcid session importantvote       date   unres amend  para
##   <dbl>   <dbl>         <dbl>     <date>   <chr> <dbl> <dbl>
## 1     3       1             0 1946-01-01  R/1/66     1     0
## 2     4       1             0 1946-01-02  R/1/79     0     0
## 3     5       1             0 1946-01-04  R/1/98     0     0
## 4     6       1             0 1946-01-04 R/1/107     0     0
## 5     7       1             0 1946-01-02 R/1/295     1     0
## 6     8       1             0 1946-01-05 R/1/297     1     0
## # ... with 2 more variables: short <chr>, descr <chr>
```

3. un_roll_call_issues provides issue (topic) classifications of roll call votes of the United Nations General Assembly, with one row for each pair of a roll call vote and an issue describing that vote. Many votes had no topic, and some have more than one.
• rcid: The roll call id; used to join with un_votes and un_roll_calls
• short_name: Two-letter issue codes
• issue: Descriptive issue name

```
head(un_roll_call_issues)
```

```
## # A tibble: 6 × 3
##    rcid short_name                issue
##   <dbl>      <chr>                <chr>
## 1    30         me Palestinian conflict
## 2    34         me Palestinian conflict
## 3    77         me Palestinian conflict
## 4  9002         me Palestinian conflict
## 5  9003         me Palestinian conflict
## 6  9004         me Palestinian conflict
```

Further details about the package and datasets can be found here https://github.com/dgrtwo/unvotes or by ??unvotes

We want to know the voting pattern by each year and each country. Therefore, we will merge **un_votes** and **un_roll_calls** by *rcid*. Furthermore, we will create another field named *year* derived from the column *date*

```
df = merge(x=un_votes, y=un_roll_calls, by="rcid", all.x=TRUE)
df$year <- as.numeric(format(df$date,"%Y"))
```

```r
head(df)
```

```
##   rcid     country    vote session importantvote       date  unres amend
## 1    3       Egypt abstain       1             0 1946-01-01 R/1/66     1
## 2    3    Honduras     yes       1             0 1946-01-01 R/1/66     1
## 3    3  Costa Rica     yes       1             0 1946-01-01 R/1/66     1
## 4    3 El Salvador     yes       1             0 1946-01-01 R/1/66     1
## 5    3      France      no       1             0 1946-01-01 R/1/66     1
## 6    3     Uruguay     yes       1             0 1946-01-01 R/1/66     1
##   para                          short
## 1    0 AMENDMENTS, RULES OF PROCEDURE
## 2    0 AMENDMENTS, RULES OF PROCEDURE
## 3    0 AMENDMENTS, RULES OF PROCEDURE
## 4    0 AMENDMENTS, RULES OF PROCEDURE
## 5    0 AMENDMENTS, RULES OF PROCEDURE
## 6    0 AMENDMENTS, RULES OF PROCEDURE
##
## 1 TO ADOPT A CUBAN AMENDMENT TO THE UK PROPOSAL REFERRING THE PROVISIONAL RULES OF PROCEDURE AND ANY
## 2 TO ADOPT A CUBAN AMENDMENT TO THE UK PROPOSAL REFERRING THE PROVISIONAL RULES OF PROCEDURE AND ANY
## 3 TO ADOPT A CUBAN AMENDMENT TO THE UK PROPOSAL REFERRING THE PROVISIONAL RULES OF PROCEDURE AND ANY
## 4 TO ADOPT A CUBAN AMENDMENT TO THE UK PROPOSAL REFERRING THE PROVISIONAL RULES OF PROCEDURE AND ANY
## 5 TO ADOPT A CUBAN AMENDMENT TO THE UK PROPOSAL REFERRING THE PROVISIONAL RULES OF PROCEDURE AND ANY
## 6 TO ADOPT A CUBAN AMENDMENT TO THE UK PROPOSAL REFERRING THE PROVISIONAL RULES OF PROCEDURE AND ANY
##   year
## 1 1946
## 2 1946
## 3 1946
## 4 1946
## 5 1946
## 6 1946
```

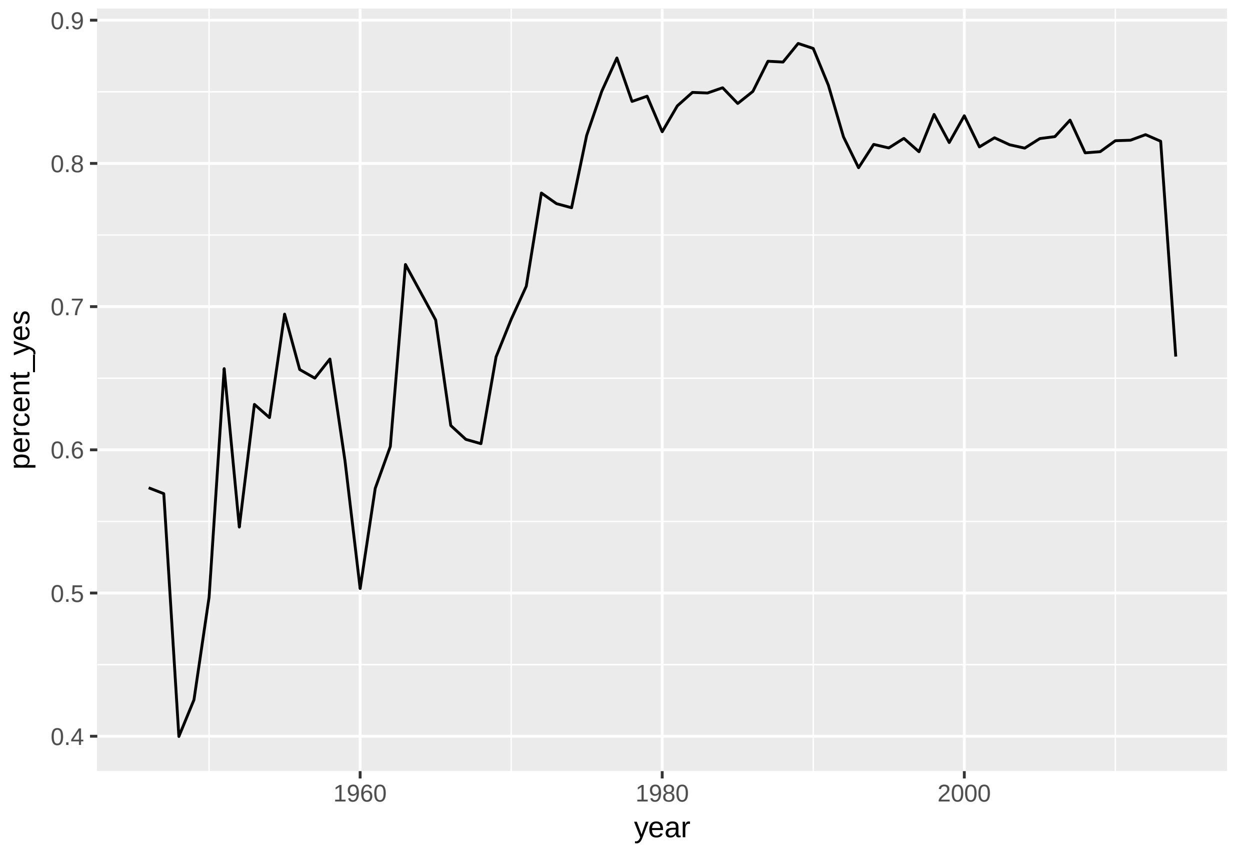
To see the voting pattern by year, we group the df by year using group_by() function

```r
by_year = df %>%
  group_by(year) %>%
  summarize(total=n(), percent_yes = mean(vote=="yes"))
head(by_year)
```

```
## # A tibble: 6 × 3
##    year total percent_yes
##   <dbl> <int>       <dbl>
## 1  1946  2143   0.5734951
## 2  1947  2039   0.5693968
## 3  1948  3454   0.3998263
## 4  1949  5700   0.4254386
## 5  1950  2911   0.4970800
## 6  1951   402   0.6567164
```

The data frame **by__year** is actually a time series and by looking at the visualization, we can see a trend over time

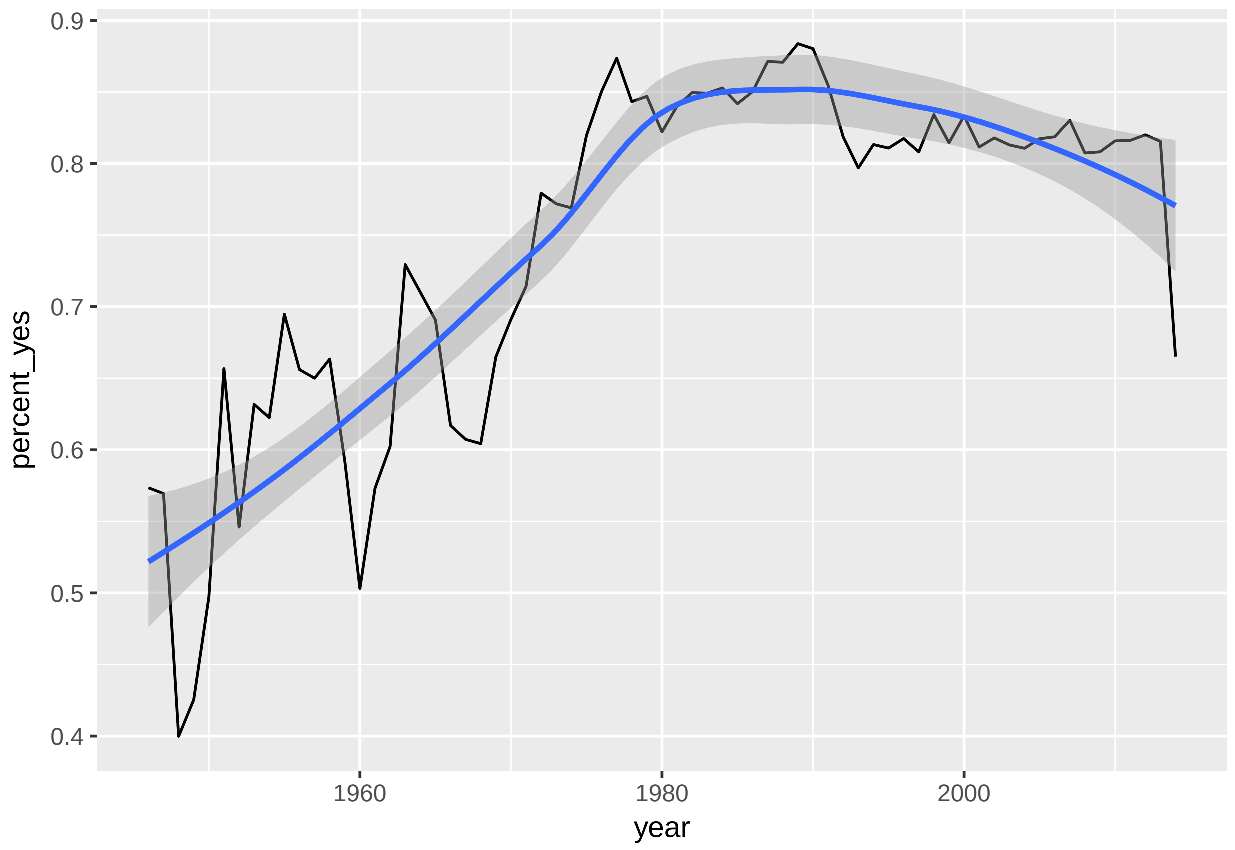
```r
ggplot(by_year, aes(year, percent_yes)) +
  geom_line()
```



Adding the geom_smooth() function

```
ggplot(by_year, aes(year, percent_yes)) +
  geom_line() +
  geom_smooth()
```

```
## `geom_smooth()` using method = 'loess'
```



A different perspective is to see voting patterns among countries.

```r
by_country = df %>%
  group_by(country) %>%
  summarize(total=n(), percent_yes = mean(vote=="yes"))
head(by_country)
```

```
## # A tibble: 6 × 3
##                country total percent_yes
##                  <chr> <int>       <dbl>
## 1          Afghanistan  4824   0.8381012
## 2              Albania  3363   0.7204877
## 3              Algeria  4374   0.8978052
## 4              Andorra  1410   0.6510638
## 5               Angola  2950   0.9223729
## 6 Antigua and Barbuda  2521   0.9170964
```

We sort the data frame by the number of votes and the % of “yes” votes in the ascending order

```r
arrange(by_country, total)
```

```
## # A tibble: 200 × 3
##        country total percent_yes
##          <chr> <int>       <dbl>
## 1     Zanzibar     2   0.0000000
## 2     Kiribati    93   0.8172043
## 3  South Sudan    96   0.6979167
## 4   Montenegro   558   0.6433692
## 5       Tuvalu   576   0.8246528
## 6        Nauru   606   0.6089109
## 7  Timor-Leste   697   0.9670014
## 8        Tonga   775   0.7303226
## 9        Palau   777   0.3063063
## 10 Switzerland   857   0.6569428
## # ... with 190 more rows
```

```
arrange(by_country, percent_yes)
```

```
## # A tibble: 200 × 3
##                            country total percent_yes
##                              <chr> <int>       <dbl>
## 1                         Zanzibar     2   0.0000000
## 2                    United States  5237   0.2850869
## 3                            Palau   777   0.3063063
## 4                           Israel  4790   0.3503132
## 5      Federal Republic of Germany  2151   0.3984193
## 6  Micronesia, Federated States of  1341   0.4131245
## 7                   United Kingdom  5218   0.4269835
## 8                           France  5171   0.4320248
## 9                 Marshall Islands  1468   0.4788828
## 10                         Belgium  5238   0.4925544
## # ... with 190 more rows
```

We can recognize that the country that voted least frequently, Zanzibar, had only 2 votes in the entire dataset, thus its percent_yes is not meaningful. For this reason, we will exclude countries with fewer than 100 votes in total.

```
by_country %>%
  arrange(percent_yes) %>%
  filter(total >= 100)
```

```
## # A tibble: 197 × 3
##                            country total percent_yes
##                              <chr> <int>       <dbl>
## 1                    United States  5237   0.2850869
## 2                            Palau   777   0.3063063
## 3                           Israel  4790   0.3503132
## 4      Federal Republic of Germany  2151   0.3984193
## 5  Micronesia, Federated States of  1341   0.4131245
## 6                   United Kingdom  5218   0.4269835
## 7                           France  5171   0.4320248
## 8                 Marshall Islands  1468   0.4788828
## 9                          Belgium  5238   0.4925544
## 10                      Luxembourg  5169   0.5105436
## # ... with 187 more rows
```

Lastly, we want to summarize by both year and country, constructing a dataset that shows what fraction of the time each country votes “yes” in each year.

```
by_year_country = df %>%
  group_by(year, country) %>%
  summarize(total = n(),
            percent_yes = mean(vote == "yes"))
head(by_year_country)
```

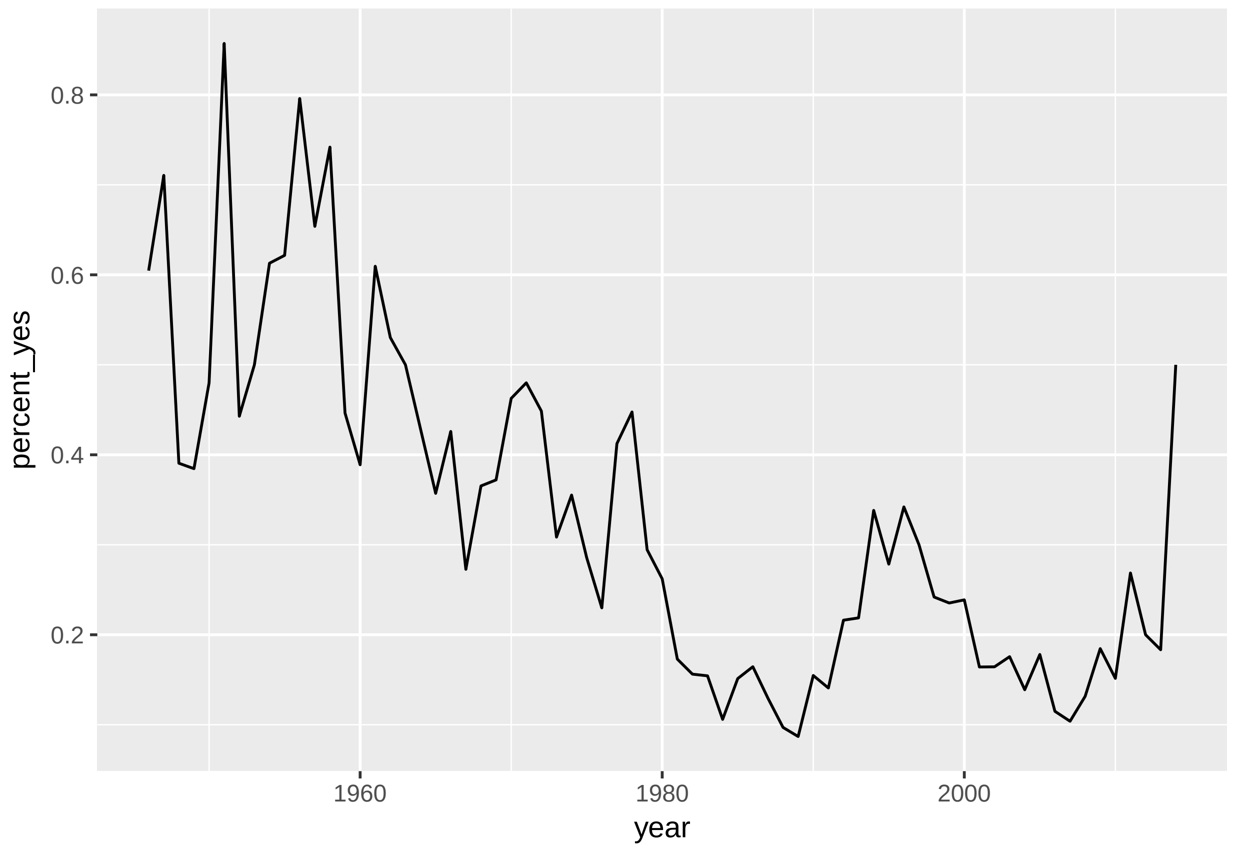
```
## Source: local data frame [6 x 4]
## Groups: year [1]
##
##    year                          country total percent_yes
##   <dbl>                            <chr> <int>       <dbl>
## 1  1946                      Afghanistan    17   0.4117647
## 2  1946                        Argentina    43   0.6976744
## 3  1946                        Australia    43   0.5581395
## 4  1946                          Belarus    43   0.4418605
## 5  1946                          Belgium    43   0.6046512
## 6  1946 Bolivia, Plurinational State of    43   0.6976744
```

Looking at the US data

```
US_by_year = by_year_country %>%
  filter(country=="United States")
head(US_by_year)
```

```
## Source: local data frame [6 x 4]
## Groups: year [6]
##
##    year       country total percent_yes
##   <dbl>         <chr> <int>       <dbl>
## 1  1946 United States    43   0.6046512
## 2  1947 United States    38   0.7105263
## 3  1948 United States    64   0.3906250
## 4  1949 United States   104   0.3846154
## 5  1950 United States    50   0.4800000
## 6  1951 United States     7   0.8571429
```

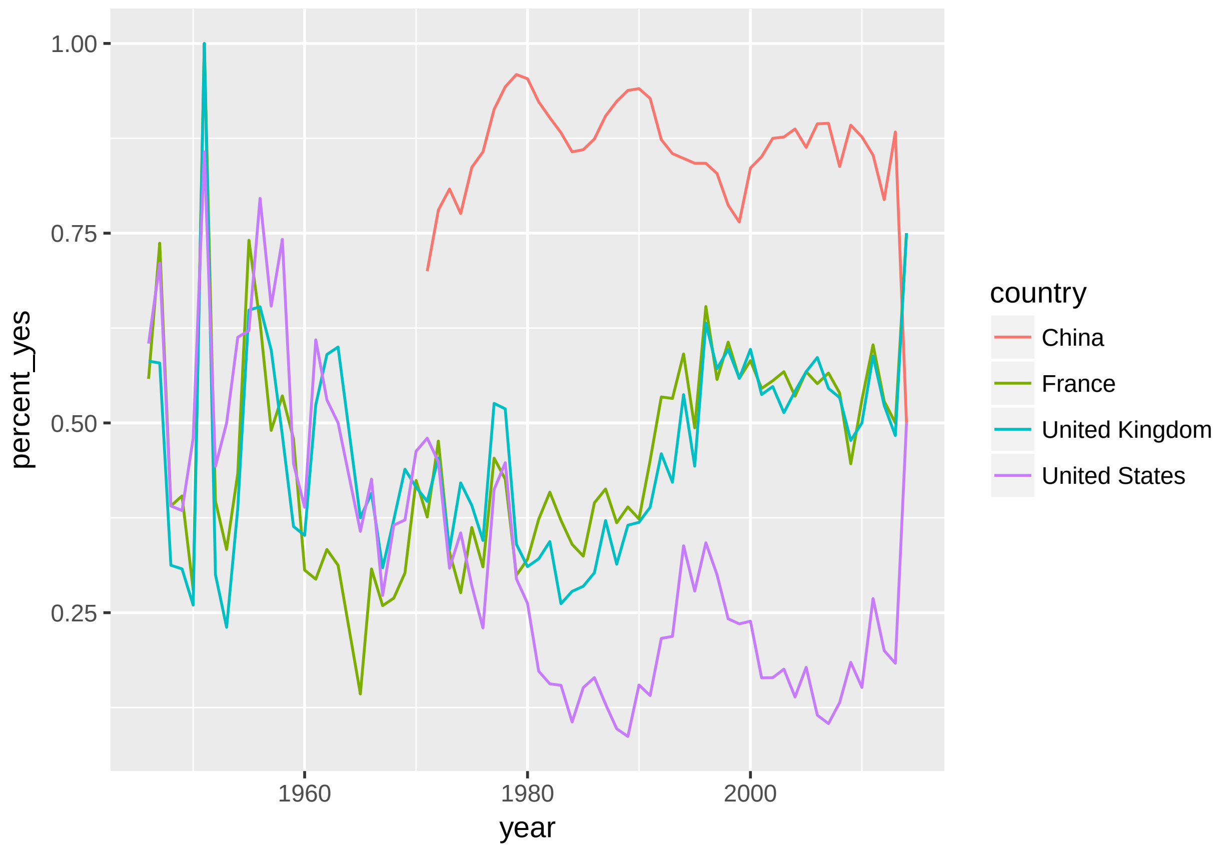
```
ggplot(US_by_year, aes(x=year,y=percent_yes)) +
  geom_line()
```



Plotting just one country at a time is interesting, but it'd be more insightful to compare trends between countries. For example, suppose we want to compare voting trends for the United States, the UK, France, and China.

```
countries_4 <- c("United States", "United Kingdom",
                "France", "China")
countries_4_by_year = by_year_country %>%
  filter(country %in% countries_4)
```

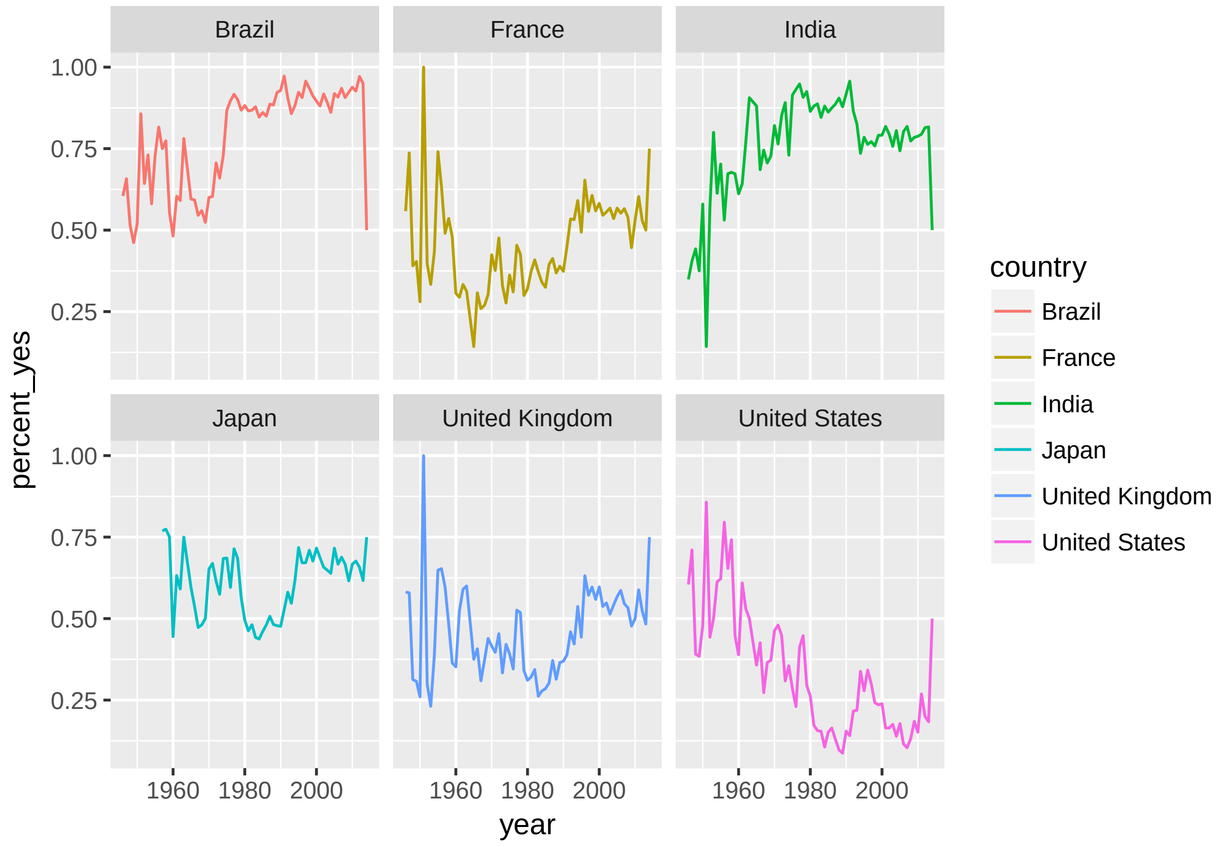
```
ggplot(countries_4_by_year, aes(x=year,y=percent_yes,color=country)) +geom_line()
```



However, if we want to include more countries, this type of graph could be tough to read. The alternative way is faceting.

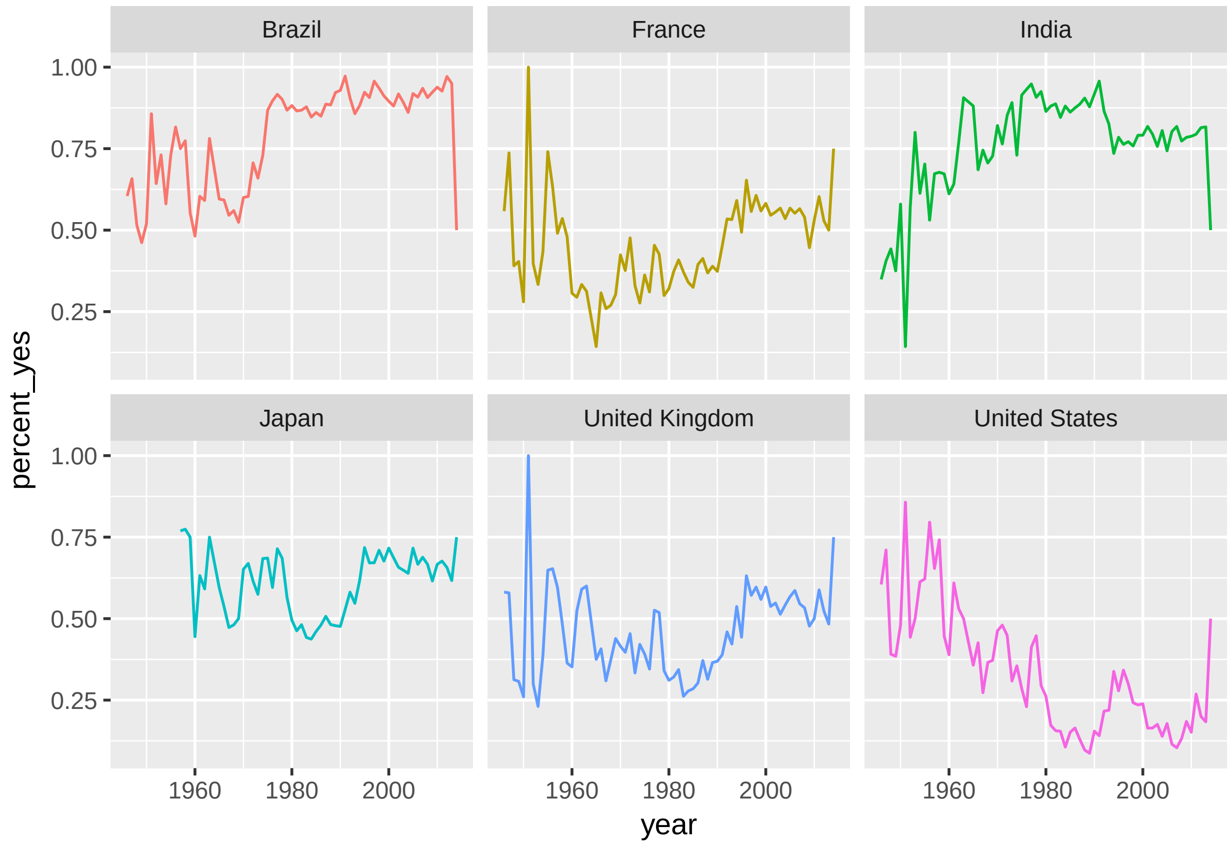
```
countries_6 <- c("United States", "United Kingdom",
                "France", "Japan", "Brazil", "India")
countries_6_by_year = by_year_country %>%
  filter(country %in% countries_6)

ggplot(countries_6_by_year, aes(x=year,y=percent_yes,color=country)) + geom_line() + facet_wrap(~ count
```



The legend seems redundant so we remove it

```
ggplot(countries_6_by_year, aes(x=year,y=percent_yes,color=country)) + geom_line() + facet_wrap(~ count
```



Optional: Feel free to add countries that you're interested in!

MODELING

Linear regression on the United States

```
US_fit = lm(percent_yes ~ year, data= US_by_year)
summary(US_fit)
```

```
##
## Call:
## lm(formula = percent_yes ~ year, data = US_by_year)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.20064 -0.08413 -0.01884  0.07237  0.40291
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 14.1619466  1.5138661   9.355 1.02e-13 ***
## year        -0.0069835  0.0007644  -9.135 2.50e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1259 on 66 degrees of freedom
## Multiple R-squared:  0.5584, Adjusted R-squared:  0.5517
## F-statistic: 83.46 on 1 and 66 DF,  p-value: 2.502e-13
```

Fit models for 4 countries

```
UK_by_year = by_year_country %>%
  filter(country=="United Kingdom")
UK_fit = lm(percent_yes ~ year, data= UK_by_year)

France_by_year = by_year_country %>%
  filter(country=="France")
France_fit = lm(percent_yes ~ year, data= France_by_year)

China_by_year = by_year_country %>%
  filter(country=="China")
China_fit = lm(percent_yes ~ year, data= China_by_year)
```

Tidy models and combine them together

```
US_tidied = tidy(US_fit)
UK_tidied = tidy(UK_fit)
France_tidied = tidy(France_fit)
China_tidied = tidy(China_fit)
```

Analysis of Resolution Type

A different angle is to look at the types of resolutions. There are 6 issue types as below

```
unique(un_roll_call_issues$issue)
```

```
## [1] "Palestinian conflict"
## [2] "Nuclear weapons and nuclear material"
## [3] "Arms control and disarmament"
## [4] "Human rights"
## [5] "Colonialism"
## [6] "Economic development"
```

We want to know if countries have any preference or particular voting patern for any issue. First, we join two datasets un_votes and un_roll_call_issues using rcid

```
head(un_votes)
```

```
## # A tibble: 6 × 3
##    rcid     country    vote
##   <dbl>       <chr>  <fctr>
## 1     3       Egypt abstain
## 2     3    Honduras     yes
## 3     3  Costa Rica     yes
## 4     3 El Salvador     yes
## 5     3      France      no
## 6     3     Uruguay     yes
```

```
head(un_roll_call_issues)
```

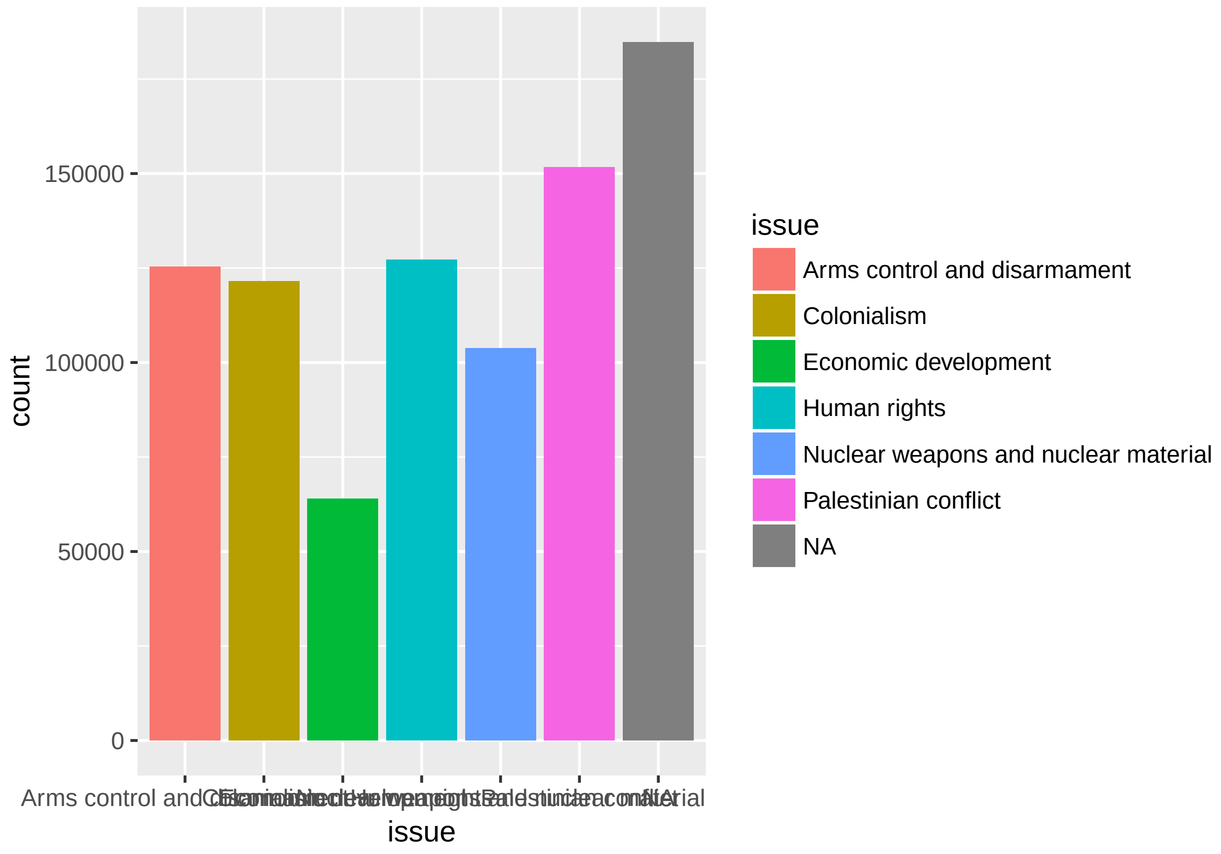
```
## # A tibble: 6 × 3
##    rcid short_name                issue
##   <dbl>      <chr>                <chr>
## 1    30         me Palestinian conflict
## 2    34         me Palestinian conflict
## 3    77         me Palestinian conflict
## 4  9002         me Palestinian conflict
## 5  9003         me Palestinian conflict
## 6  9004         me Palestinian conflict
```

```
df2 = merge(x=un_votes, y=un_roll_call_issues, by="rcid", all.x=TRUE)
head(df2)
```

```
##   rcid     country    vote short_name issue
## 1    3       Egypt abstain       <NA>  <NA>
## 2    3    Honduras     yes       <NA>  <NA>
## 3    3  Costa Rica     yes       <NA>  <NA>
## 4    3 El Salvador     yes       <NA>  <NA>
## 5    3      France      no       <NA>  <NA>
## 6    3     Uruguay     yes       <NA>  <NA>
```

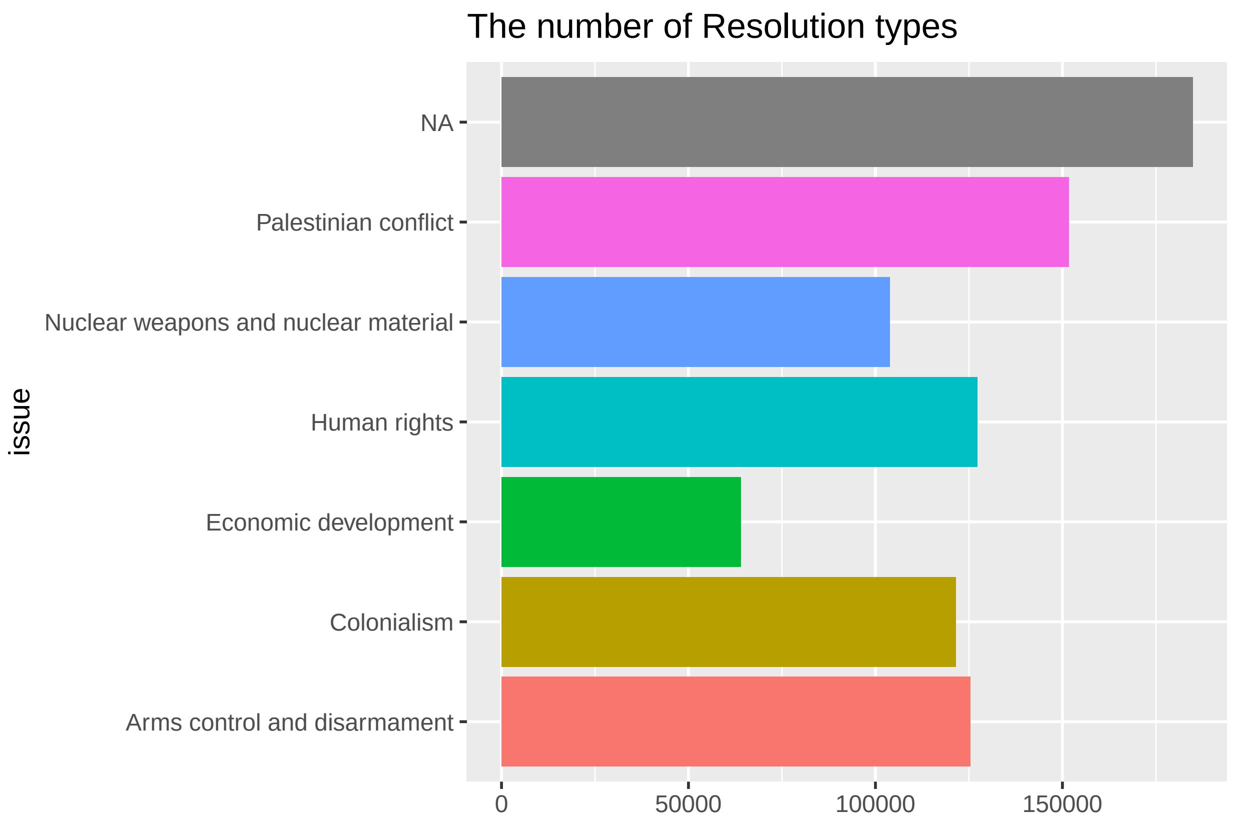
Plotting the data frame to see the number of resolutions by issue

```
df2 %>%
  ggplot(aes(x=issue)) +
  geom_bar(aes(fill=issue))
```



Adding features to enhance the look

```r
df2 %>%
  ggplot(aes(x=issue)) +
  geom_bar(aes(fill=issue)) +
  coord_flip() +
  theme(legend.position="none") +
  ggtitle("The number of Resolution types") +
  ylab("")
```



From the chart, Palestinian conflict is the major concern of United Nation during 1946-2014, following by Human rights, Arms control and disarmament and Colonialism. Interestingly, economic development gets the least attention.

Another way to get a similar result is to group by the dataset by issue as follows:

```r
by_issue = df2 %>%
  group_by(issue) %>%
  summarize(total = n(), percent_yes = mean(vote == "yes"))

head(by_issue)
```

```
## # A tibble: 6 × 3
##                                 issue  total percent_yes
##                                 <chr>  <int>       <dbl>
## 1         Arms control and disarmament 125332   0.8296046
## 2                         Colonialism 121523   0.7952486
## 3                 Economic development  63915   0.8253931
## 4                         Human rights 127195   0.7495814
## 5 Nuclear weapons and nuclear material 103804   0.8096123
## 6                 Palestinian conflict 151624   0.8379412
```

All resolutions but Human Rights has 80% and above concensus ("yes" votes). Human Rights Resolutions have 75% votes with "yes".

Now we want to look at the data not only by issue but also by country

```
by_issue_country = df2 %>%
  group_by(issue, country) %>%
  summarize(total = n(), percent_yes = mean(vote == "yes"))

head(by_issue_country)
```

```
## Source: local data frame [6 x 4]
## Groups: issue [1]
##
##                          issue             country total percent_yes
##                          <chr>               <chr> <int>       <dbl>
## 1 Arms control and disarmament         Afghanistan   787   0.8729352
## 2 Arms control and disarmament             Albania   505   0.6594059
## 3 Arms control and disarmament             Algeria   785   0.8522293
## 4 Arms control and disarmament             Andorra   325   0.6246154
## 5 Arms control and disarmament              Angola   591   0.9018613
## 6 Arms control and disarmament Antigua and Barbuda   562   0.9448399
```

Let's take US as an example to see the country's voting pattern on different issues

```
US_by_issue = by_issue_country %>%
  filter(country=="United States")

US_by_issue
```

```
## Source: local data frame [7 x 4]
## Groups: issue [7]
##
##                                  issue       country total percent_yes
##                                  <chr>         <chr> <int>       <dbl>
## 1         Arms control and disarmament United States   834   0.2961631
## 2                         Colonialism United States   955   0.1706806
## 3                 Economic development United States   448   0.1674107
## 4                        Human rights United States   871   0.2732491
## 5 Nuclear weapons and nuclear material United States   696   0.2298851
## 6                 Palestinian conflict United States  1026   0.1354776
## 7                                 <NA> United States  1516   0.4267810
```

The United States seems to disagree with most resolutions, lowest "yes" voting is to Palestinian conflict.

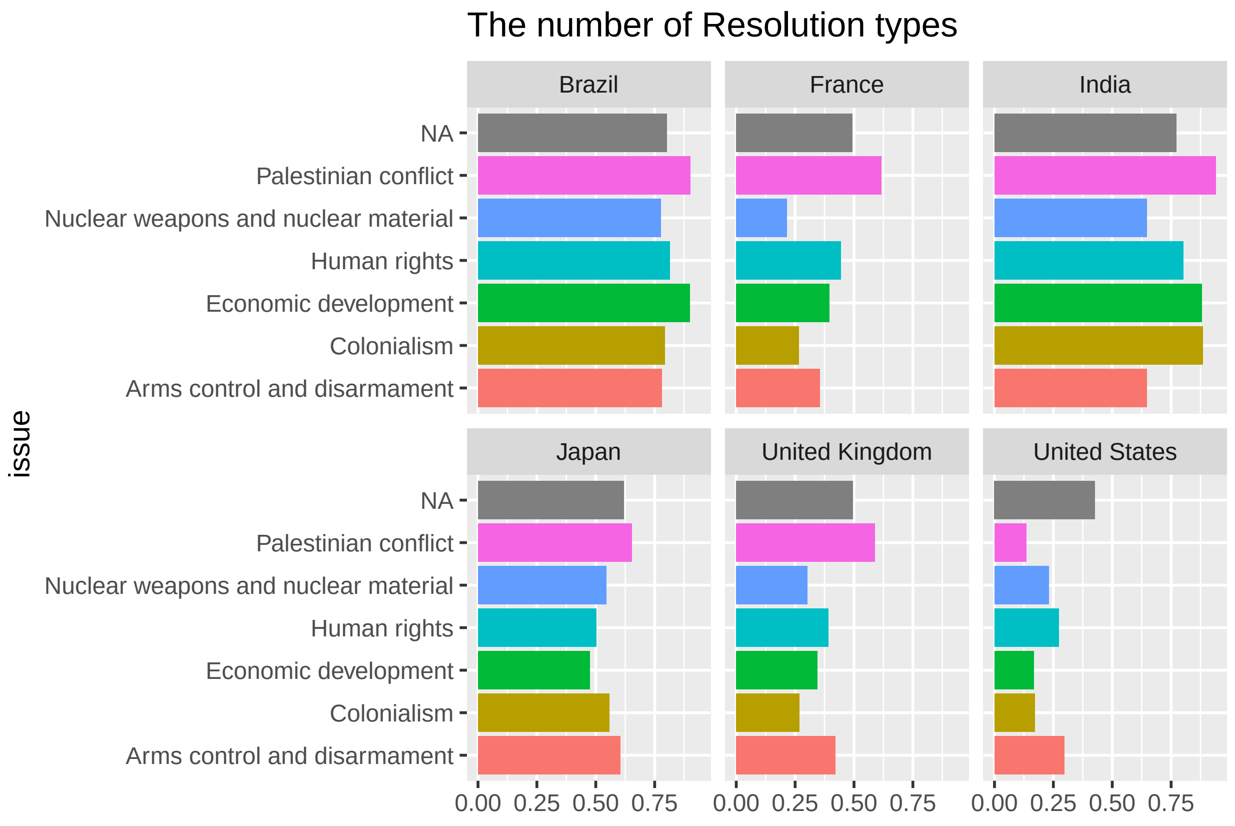
Again, we want to see 6 countries at one view for comparison.

```
countries_6 <- c("United States", "United Kingdom",
               "France", "Japan", "Brazil", "India")

countries_6_by_issue = by_issue_country %>%
  filter(country %in% countries_6)

countries_6_by_issue %>%
  ggplot(aes(x=issue,y=percent_yes)) +
  geom_bar(stat="identity",aes(fill=issue)) +
  coord_flip() +
  theme(legend.position="none") +
```

```r
  ggtitle("The number of Resolution types") +
  ylab("") +
  facet_wrap(~ country)
```



We want to use k-means clustering to divide countries into 2 groups: “yes” group and “no” group. First, we remove countries that have small number of votes because the percentage might not be meaningful with small sample sizes.

```r
# remove countries with total votes less than 10 for each period each issue
by_issue_country = by_issue_country %>%
  filter(total >= 100)
dff1 = subset(by_issue_country,select=-total)
dff1$issue[dff1$issue=="Arms control and disarmament"] = "Arms"
dff1$issue[dff1$issue=="Human rights"] = "Human"
dff1$issue[dff1$issue=="Nuclear weapons and nuclear material"] = "Nuclear"
dff1$issue[dff1$issue=="Palestinian conflict"] = "Palestinian"
dff1$issue[dff1$issue=="Economic development"] = "Economic"
dff1$issue[is.na(dff1$issue)] = "Other"

dff2 = dff1 %>%
  spread(issue,percent_yes)
head(dff2)
```

```
## # A tibble: 6 × 8
##               country      Arms Colonialism  Economic     Human   Nuclear
##                 <chr>     <dbl>       <dbl>     <dbl>     <dbl>     <dbl>
## 1         Afghanistan 0.8729352   0.9055300 0.9158654 0.8583851 0.9044684
## 2             Albania 0.6594059   0.8357558 0.7949640 0.7031746 0.5951327
## 3             Algeria 0.8522293   0.9645293 0.9604938 0.8549811 0.8836141
## 4             Andorra 0.6246154   0.7727273 0.7086614 0.5267857 0.4880000
## 5              Angola 0.9018613   0.9775281 0.9867987 0.8319605 0.9196787
## 6 Antigua and Barbuda 0.9448399   0.9406780 0.9488189 0.8458498 0.9287305
## # ... with 2 more variables: Other <dbl>, Palestinian <dbl>
```

```
summary(dff2)
```

```
##    country                 Arms         Colonialism       Economic     
##  Length:197         Min.   :0.2962   Min.   :0.1707   Min.   :0.1674  
##  Class :character   1st Qu.:0.7025   1st Qu.:0.7316   1st Qu.:0.7390  
##  Mode  :character   Median :0.8998   Median :0.8711   Median :0.9023  
##                     Mean   :0.8230   Mean   :0.8053   Mean   :0.8276  
##                     3rd Qu.:0.9422   3rd Qu.:0.9355   3rd Qu.:0.9416  
##                     Max.   :0.9924   Max.   :1.0000   Max.   :1.0000  
##                     NA's   :2                         NA's   :11      
##      Human           Nuclear           Other         Palestinian     
##  Min.   :0.2732   Min.   :0.2016   Min.   :0.4268   Min.   :0.01762  
##  1st Qu.:0.6674   1st Qu.:0.6411   1st Qu.:0.7079   1st Qu.:0.75235  
##  Median :0.8071   Median :0.9048   Median :0.8159   Median :0.88741  
##  Mean   :0.7398   Mean   :0.7951   Mean   :0.7924   Mean   :0.82981  
##  3rd Qu.:0.8478   3rd Qu.:0.9463   3rd Qu.:0.8824   3rd Qu.:0.95610  
##  Max.   :0.9863   Max.   :0.9930   Max.   :0.9744   Max.   :1.00000  
##                   NA's   :3        NA's   :8        NA's   :1        
```

```
dff2 =na.omit(dff2)

set.seed(20)
kmc <- kmeans(dff2[,-1], centers=2, iter.max=1000)
kmc
```

```
## K-means clustering with 2 clusters of sizes 48, 138
## 
## Cluster means:
##        Arms Colonialism  Economic     Human   Nuclear     Other
## 1 0.6066172   0.5706019 0.5685406 0.5158260 0.5052855 0.6320169
## 2 0.9023907   0.8938900 0.9177192 0.8272374 0.9036598 0.8497849
##   Palestinian
## 1   0.6566774
## 2   0.9041908
## 
## Clustering vector:
##   [1] 2 1 2 1 2 2 2 2 1 1 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2
##  [36] 2 2 2 2 2 2 1 2 2 1 2 1 2 2 2 2 2 2 2 2 1 2 1 2 1 1 2 2 1 2 1 2 1 2 2
##  [71] 2 2 2 2 2 1 1 2 2 2 2 1 1 1 2 1 2 2 2 2 1 2 2 2 1 2 2 2 2 1 1 1 1 2 2
## [106] 2 2 2 2 1 2 2 2 1 1 1 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 2 1 1 2 2 1
## [141] 2 2 2 2 2 1 2 2 2 2 2 2 1 1 2 2 1 1 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2 1
## [176] 1 2 2 2 2 2 2 2 2 2 2
## 
## Within cluster sum of squares by cluster:
## [1] 5.952613 4.968272
##  (between_SS / total_SS =  68.9 %)
## 
## Available components:
## 
## [1] "cluster"      "centers"      "totss"        "withinss"    
## [5] "tot.withinss" "betweenss"    "size"         "iter"        
## [9] "ifault"
```

```
# append cluster assignment
dff2_cluster <- data.frame(dff2, kmc$cluster)
head(dff2_cluster)
```

```
##                 country      Arms Colonialism  Economic     Human   Nuclear
## 1           Afghanistan 0.8729352   0.9055300 0.9158654 0.8583851 0.9044684
## 2               Albania 0.6594059   0.8357558 0.7949640 0.7031746 0.5951327
## 3               Algeria 0.8522293   0.9645293 0.9604938 0.8549811 0.8836141
## 4               Andorra 0.6246154   0.7727273 0.7086614 0.5267857 0.4880000
## 5                Angola 0.9018613   0.9775281 0.9867987 0.8319605 0.9196787
## 6 Antigua and Barbuda 0.9448399   0.9406780 0.9488189 0.8458498 0.9287305
##       Other Palestinian kmc.cluster
## 1 0.7192362   0.9427027           2
## 2 0.6517533   0.8220859           1
## 3 0.8651786   0.9830688           2
## 4 0.7078652   0.7774936           1
## 5 0.9334443   0.9713877           2
## 6 0.9365427   0.8853503           2
```

```
dim(dff2_cluster)
```

```
## [1] 186   9
```

```
countries_6 <- c("United States", "United Kingdom",
                 "France", "Japan", "Brazil", "India")
countries_6_cluster = dff2_cluster %>%
  filter(country %in% countries_6)
countries_6_cluster
```

```
##           country      Arms Colonialism  Economic     Human   Nuclear
## 1          Brazil 0.7799274   0.7928496 0.9002268 0.8151550 0.7763348
## 2          France 0.3555018   0.2663755 0.3968610 0.4449541 0.2151163
## 3           India 0.6474128   0.8837696 0.8797327 0.8016055 0.6455331
## 4           Japan 0.6048780   0.5577157 0.4740566 0.5012255 0.5437318
## 5 United Kingdom 0.4216867   0.2675906 0.3458980 0.3926941 0.3015873
## 6  United States 0.2961631   0.1706806 0.1674107 0.2732491 0.2298851
##       Other Palestinian kmc.cluster
## 1 0.8017128   0.9020568           2
## 2 0.4936793   0.6163583           1
## 3 0.7721268   0.9404878           2
## 4 0.6181102   0.6531027           1
## 5 0.4947090   0.5890944           1
## 6 0.4267810   0.1354776           1
```

Sources:
https://github.com/dgrtwo/unvotes
https://www.kaggle.com/karimkardous/vote-dynamics/code