## Read Tweets

```
twitter = Import["/Users/dalila/data/twitter_text_0622_1931pm.xls", "XLS"];
```

```
twitter = twitter[[1]];
```

Dataset dimension

```
Dimensions[twitter]
```

```
{12 276, 4}
```

```
twitter[[1 ;; 3]]
```

We decided some of these words either represent places in UK or are the long version of the word UK

```
countryToChoose =
 {"kingdom", "england", "coventry", "poole", "leicestershire", "london", "uk"}
```

```
{kingdom, england, coventry, poole, leicestershire, london, uk}
```

Make twitter lower case, seperate the headings from the data

```
twitter = Map[Map[ToLowerCase[#] &, #] &, twitter];
```

```
twitterHeading = First[twitter];
```

```
twitterData = Rest[twitter];
```

## Get only UK tweets, and remove handels and URL links

```
onlyUK =
  Select[twitterData, StringContainsQ[#[[2]], {"kingdom", "england", "coventry",
      "poole", "leicestershire", "london", "uk"}] &];
```

```
twitterHand = Map[TextCases[#[[1]], "TwitterHandle"] &, onlyUK]
```

```
twitt = MapThread[StringDelete, {onlyUK[[All, 1]], twitterHand} ];
```

```
twitt = Map[StringDelete[#, TextCases[#, "URL"]] &, twitt]
```

Save tweets after removing the twitter handle and the urls'

```
Save["brexitTweets", twitt]
```

```
In[112]:= << brexitTweets
```

```
Export["/Users/dalila/data/clean.xls", twitt]
```

```
/Users/dalila/data/clean.xls
```

## Tokenize tweets, remove stop words, and stem words

```
cleanData = Map[WordStem[DeleteStopwords[TextWords[#]]] &, twitt];
```

```
(*Remove Duplicates*)
cleanData = Tally[cleanData][[All, 1]]
```

## Remove non words from the corrupt tweets.  Remove underscores, the words rt, amp, and exit

```
cleanData = Map[StringReplace[#, "_" → ""] &, cleanData];
cleanData = Map[StringReplace[#, "-" → ""] &, cleanData];
```

```
cleanData =
  Map[Select[#, ! StringContainsQ[#, RegularExpression["[^a-z0-9\#\'\-]+"]] &] &,
   cleanData];
```

```
f[l_] := Select[l, # ≠ "rt" &];
```

```
cleanData = Map[f[#] &, cleanData]
```

```
f[l_] := Select[l, # ≠ "amp" &];
cleanData = Map[f[#] &, cleanData]
```

```
Select[cleanData, MemberQ[#, "exit"] &]
```

```
Length[cleanData]
```

```
1668
```

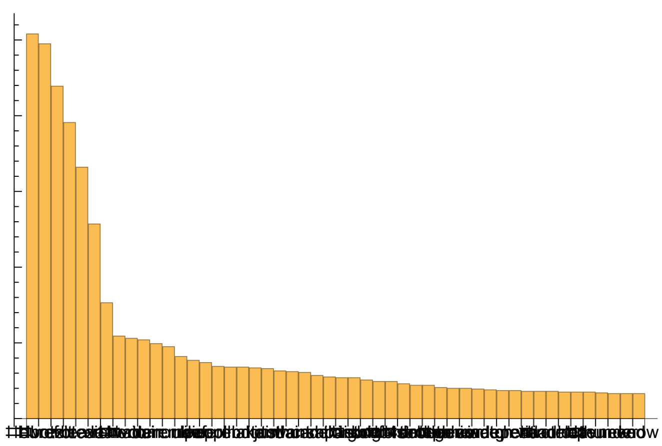
## Get words in all the tweets, and create a frequency bar chart

One notices that 7 words dominate the tweets chatter

```
tp = Flatten[cleanData]
```

```
tallyTweet = Reverse[SortBy[Tally[tp], Last]];
```

```
BarChart[Apply[Labeled, Reverse[%414[[1 ;; 50]], 2], {1}]]
```



```
Length[tallyTweet]
```

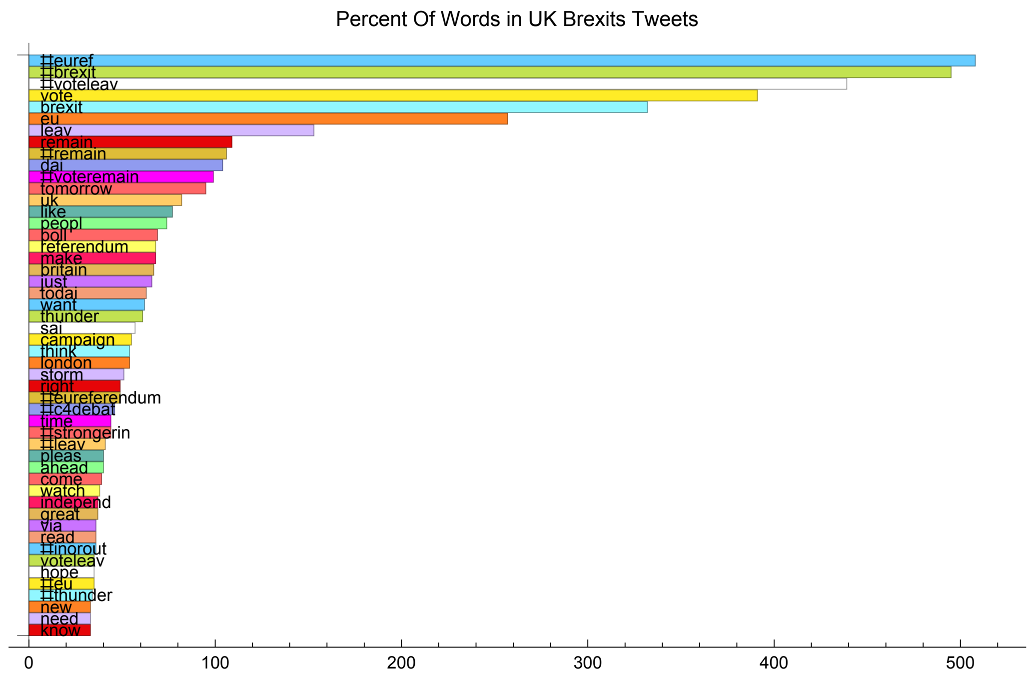
```
3466
```

## The 50 most common words in the tweet
## One notices that leave and its derivatives are in higher frequency than remain

## derivatives

```
tallyTop50 = Reverse[SortBy[tallyTweet, Last]][[1 ;; 50]]
tallyTop50 = SortBy[tallyTop50, Last]
tallyName = tallyTop50[[1 ;; 50, 1]];
tallyFreq = tallyTop50[[1 ;; 50, 2]];
```

```
BarChart[tallyFreq, BarOrigin → Left, ChartLabels → {Placed[tallyName, Left]},
 LabelingFunction → None, PlotLabel → "Percent Of Words in UK Brexits Tweets" ,
 ChartStyle → 60, BarSpacing → Automatic]
```




## Initial WordCloud, before combining synonyms

You will notice that Voteleave dominate voteremaine, or remain.  You also notice that many words represent the same thing (remain, voteremain, #remain, etc.)

```
WordCloud[tallyTop50]
```


```
Grid[%521]
```

| | |
|---|---|
| #euref | 508 |
| #brexit | 495 |
| #voteleav | 439 |
| vote | 391 |
| brexit | 332 |
| eu | 257 |
| leav | 153 |
| remain | 109 |
| #remain | 106 |
| dai | 104 |
| #voteremain | 99 |
| tomorrow | 95 |
| uk | 82 |
| like | 77 |
| peopl | 74 |
| poll | 69 |
| referendum | 68 |
| make | 68 |
| britain | 67 |
| just | 66 |
| todai | 63 |
| want | 62 |
| thunder | 61 |
| sai | 57 |
| campaign | 55 |

## Same words for leave. All these words are related to leave. Removed one word dontleav, which should be with remain

```
leaveWords = Tally[Select[tp, StringContainsQ[#, ___ ~~ "leav" ~~ ___] &]][[All, 1]]
```

```
{#voteleav, voteleav, leav, leavetheeu, leaveeuoffici, #beleav, beleav,
 #leav, #labourleav, #leaveeu, #voteleavetakebackcontrol, italeav,
 #loveeuropeleaveeu, #voteleavetakecontrol, leave-eu, #liberalleav, #leaveemtoit,
 #fishingforleav, #shakeitandleav, #dontleav, leavemedia, ukleaveeu,
 #votetoleav, #voteleave4uma, #ukleaveeucampaign, labourleav, #leavelillyleav}
```

```
leaveWords = {"#voteleav", "voteleav", "leav", "leavetheeu",
   "leaveeuoffici", "#beleav", "beleav", "#leav", "#labourleav", "#leaveeu",
   "#voteleavetakebackcontrol", "italeav", "#loveeuropeleaveeu",
   "#voteleavetakecontrol", "leave-eu", "#liberalleav", "#leaveemtoit",
   "#fishingforleav", "#shakeitandleav", "leavemedia", "ukleaveeu",
   "#votetoleav", "#voteleave4uma", "#ukleaveeucampaign", "labourleav",
   "#leavelillyleav", "pro-brexit", "leaveeu", "leavetheu", "leaveofficial"};
```

```
Save["cleanDataBrexit", cleanData]
```

## Find synonyms to referendum, remain, and brexit

```
Tally[Select[tp, StringContainsQ[#, ___ ~~ "ref" ~~ ___] &]][[All, 1]]
```

```
referendumWord =
 {"#euref", "referendum", "referend---world", "#eureferendum", "#referendum",
  "indyref", "ref", "euref", "#ukreferendum", "eureferendum", "referundum"}
```

```
{#euref, referendum, referend---world, #eureferendum, #referendum,
 indyref, ref, euref, #ukreferendum, eureferendum, referundum}
```

```
remainWords =
 Tally[Select[tp, StringContainsQ[#, ___ ~~ "remain" ~~ ___] &]][[All, 1]]
```

```
{"#voteremain", "remain", "#remain", "#bremain", "#remainineu",
 "bremain", "#remainathom", "#iminsanevoteremain", "#remainin", "dontleav"}
```

```
remainWords = Join[remainWords, {"#dontleav"}]
```

```
Select[twitterData[[All, 1]], StringContainsQ[#, __ ~~ "#brexitdeb" ~~ __] &]
```

```
Tally[Select[tp, StringContainsQ[#, ___ ~~ "brexit" ~~ ___] &]]
```

```
brexitWords = {{"#brexit", 495}, {"brexit", 332}, {"brexit-", 2}, {"#brexitornot", 6},
  {"brexit'", 3}, {"#brexitdeb", 4}, {"#brexitfact", 1}, {"#brexitclub", 2}}
```

```
brexitWords = brexitWords[[All, 1]]
```

## Now, we can draw a WordCloud, but first we need to combine all the words that are the same

```
tp = StringReplace[tp,
  {leaveWords → "leav", remainWords → "remain", referendumWord → "referendum",
   brexitWords → "#brexit", ukWord → "uk", euWord → "eu"}]
```

```
ukWord = {"uk", "britain", "#uk", "british"};
```

```
euWord = {"#eu", "europe", "europ"}
```

```
{#eu, europe, europ}
```

```
Tally[Select[tp, StringContainsQ[#, ___ ~~ "referend" ~~ ___] &]][[All, 1]]
```

Some other words we found that are related to referendum

```
referWord =
 {"referendumorm", "referendumerendum", "referendumus", "referendumerundum"}
```

```
{referendumorm, referendumerendum, referendumus, referendumerundum}
```

```
tp = StringReplace[tp, {leaveWords  → "leav", remainWords → "remain",
    referendumWord → "referendum", brexitWords → "#brexit",
    ukWord → "uk", euWord → "eu", referWord → "referendum"}];
```

```
tp = StringReplace[tp, "leaveeu" → "leav"]
```

```
tp = StringReplace[tp, "#london" → "london"]
```

```
tp = StringReplace[tp, "#" → ""]
```

## Tally the words in all cleaned tweets

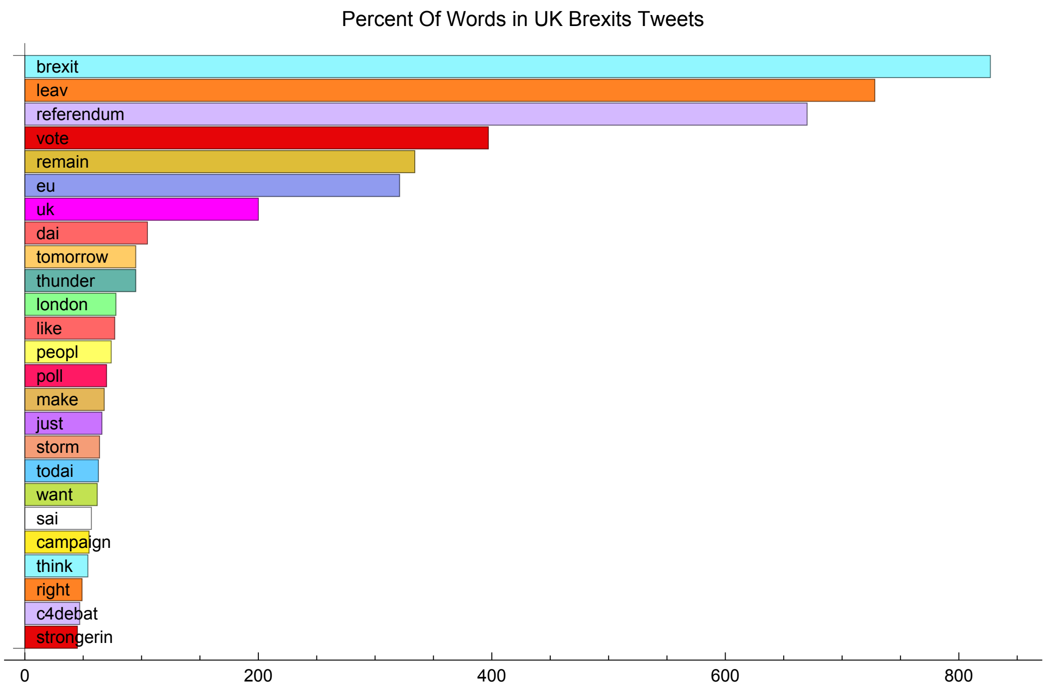
```
tallyTweet = Reverse[SortBy[Tally[tp], Last]]
```

One can see that word leave comes second only brexit and its frequency is more than twice that of remain

```
tmp = SortBy[tallyTweet[[1 ;; 25]], Last]
```

```
{{strongerin, 45}, {c4debat, 47}, {right, 49}, {think, 54}, {campaign, 55}, {sai, 57},
 {want, 62}, {todai, 63}, {storm, 64}, {just, 66}, {make, 68}, {poll, 70}, {peopl, 74},
 {like, 77}, {london, 78}, {thunder, 95}, {tomorrow, 95}, {dai, 105}, {uk, 200},
 {eu, 321}, {remain, 334}, {vote, 397}, {referendum, 670}, {leav, 728}, {brexit, 827}}
```

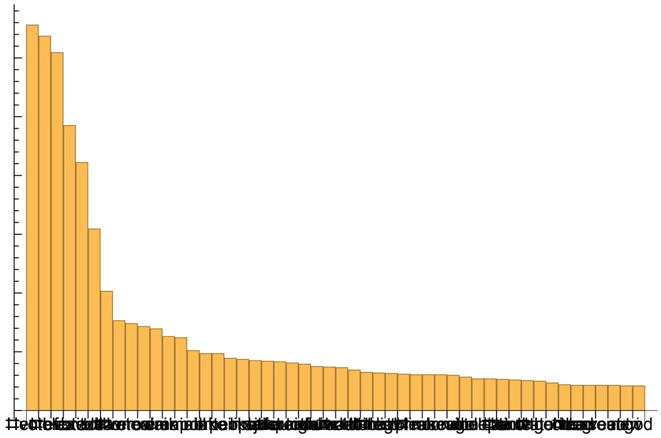
```
BarChart[tmp[[All, 2]], BarOrigin → Left, ChartLabels → {Placed[tmp[[All, 1]], Left]},
 LabelingFunction → (Placed[Panel[tmp[[All, 1]], FrameMargins → 0], Above]),
 PlotLabel → "Percent Of Words in UK Brexits Tweets" ,
 ChartStyle → 60, BarSpacing → Automatic]
```




The WordCloud reinforce the predominence of Leave.  One can also notice

```
WordCloud[tp]
```

```
BarChart[Apply[Labeled, Reverse[%376, 2], {1}]]
```



```
uniqueLocations = Select[uniqueLocations, ! MemberQ[
     StringMatchQ[#, WordBoundary ~~ DigitCharacter .. ~~ WordBoundary], True] &]
```

```
uniqueLocations = DeleteCases[uniqueLocations, {}]
```

```
countryRule = {"kingdom" → "uk", "england" → "uk", "coventry" → "uk",
   "poole" → "uk", "leicestershire" → "uk", "london" → "uk",
   "leeds" → "uk", "glasgow" → "uk", "sheffield" → "uk", "bradford" → "uk",
   "manchester" → "uk", "liverpool" → "uk", "edinburgh" → "uk",
   "bristol" → "uk", "scotland" → "uk", "wales" → "uk", "northern ireland"}
{"19600858", "99047821"}
```

```
{kingdom → uk, england → uk, coventry → uk, poole → uk, leicestershire → uk, london → uk}
```

```
{19600858, 99047821}
```

## Now we Go back to Clean Data and remove unecessary words, and get ready for graph network

```
word2Remove = {{"87rt", 1}, {"847", 1}, {"75", 1}, {"6k", 1}, {"60bn", 1}, {"60", 1},
   {"5h", 1}, {"5am-7am", 1}, {"58-42", 1}, {"5000", 1}, {"50", 1}, {"49", 1},
   {"46", 1}, {"43", 1}, {"41", 1}, {"3rd", 1}, {"3k", 1}, {"38", 1}, {"33", 1},
   {"322278", 1}, {"32", 1}, {"2mrw", 1}, {"2moro", 1}, {"28th", 1}, {"28", 1},
   {"256", 1}, {"25", 1}, {"20yr", 1}, {"2040", 1}, {"2020", 1}, {"2015", 1},
   {"2010-2016", 1}, {"2008", 1}, {"1987", 1}, {"1982", 1}, {"1951", 1},
   {"17th-22nd", 1}, {"17", 1}, {"16", 1}, {"11pm", 1}, {"10p", 1}, {"10a", 1},
   {"1066", 1}, {"103", 1}, {"10", 1}, {"01223", 1}, {"007", 1}, {"''", 1},
   {"'", 1}, {"-", 1}}
```

```
{{87rt, 1}, {847, 1}, {75, 1}, {6k, 1}, {60bn, 1}, {60, 1}, {5h, 1},
 {5am-7am, 1}, {58-42, 1}, {5000, 1}, {50, 1}, {49, 1}, {46, 1}, {43, 1},
 {41, 1}, {3rd, 1}, {3k, 1}, {38, 1}, {33, 1}, {322278, 1}, {32, 1}, {2mrw, 1},
 {2moro, 1}, {28th, 1}, {28, 1}, {256, 1}, {25, 1}, {20yr, 1}, {2040, 1},
 {2020, 1}, {2015, 1}, {2010-2016, 1}, {2008, 1}, {1987, 1}, {1982, 1},
 {1951, 1}, {17th-22nd, 1}, {17, 1}, {16, 1}, {11pm, 1}, {10p, 1}, {10a, 1},
 {1066, 1}, {103, 1}, {10, 1}, {01223, 1}, {007, 1}, {'', 1}, {', 1}, {-, 1}}
```

```
word2Remove = word2Remove[[All, 1]]
```

```
{87rt, 847, 75, 6k, 60bn, 60, 5h, 5am-7am, 58-42, 5000, 50,
 49, 46, 43, 41, 3rd, 3k, 38, 33, 322278, 32, 2mrw, 2moro, 28th, 28,
 256, 25, 20yr, 2040, 2020, 2015, 2010-2016, 2008, 1987, 1982, 1951,
 17th-22nd, 17, 16, 11pm, 10p, 10a, 1066, 103, 10, 01223, 007, '', ', -}
```

## Make sure to have a new version with synonyms taken into account

```
cleanData = Map[StringReplace[#, word2Remove → ""] &, cleanData]
```

```
clean2Data = Map[StringReplace[#, {leaveWords  → "leav", remainWords → "remain",
      referendumWord → "referendum", brexitWords → "#brexit",
      ukWord → "uk", euWord → "eu", referWord → "referendum"}] &, cleanData];
clean2Data = Map[StringReplace[#, "leaveeu" → "leav"] &, clean2Data]
clean2Data = Map[StringReplace[#, "#london" → "london"] &, clean2Data]
clean2Data = Map[StringReplace[#, "#" → ""] &, clean2Data]
```

## Make sure to remove duplicates.  Now we are ready for the next analysis

```
clean2Data = Map[DeleteDuplicates[#] &, clean2Data]
```

```
Save["FinalCleanBrexit", clean2Data]
```

## Now, we can start the interesting part:  Graph the tweets, and cluster the graph

### This code is to create undirected graphs from lists

```
f[re_List] := Module[{flatTread, i, j}, Flatten[Map[(Thread[# → #, #]) &, re ]];
  flatTread =
   Table[Thread[re[[i]] →  re[[j]]], {i, Length[re - 1]}, {j, i + 1, Length[re]}];
  flatTread = Flatten[flatTread];
  UndirectedEdge @@@ flatTread]
```

Sample example

```
 e1 = f[clean2Data[[1]]];
e2 = f[clean2Data[[2]]];
Dimensions[e1];
t = {e1, e2};
r = Flatten[t];
r = DeleteDuplicates[r]
```

```
{brexit ⟷ episod, brexit ⟷ delai, brexit ⟷ thur, brexit ⟷ share, brexit ⟷ like,
 brexit ⟷ hell, episod ⟷ delai, episod ⟷ thur, episod ⟷ share, episod ⟷ like,
 episod ⟷ hell, delai ⟷ thur, delai ⟷ share, delai ⟷ like, delai ⟷ hell,
 thur ⟷ share, thur ⟷ like, thur ⟷ hell, share ⟷ like, share ⟷ hell, like ⟷ hell}
```

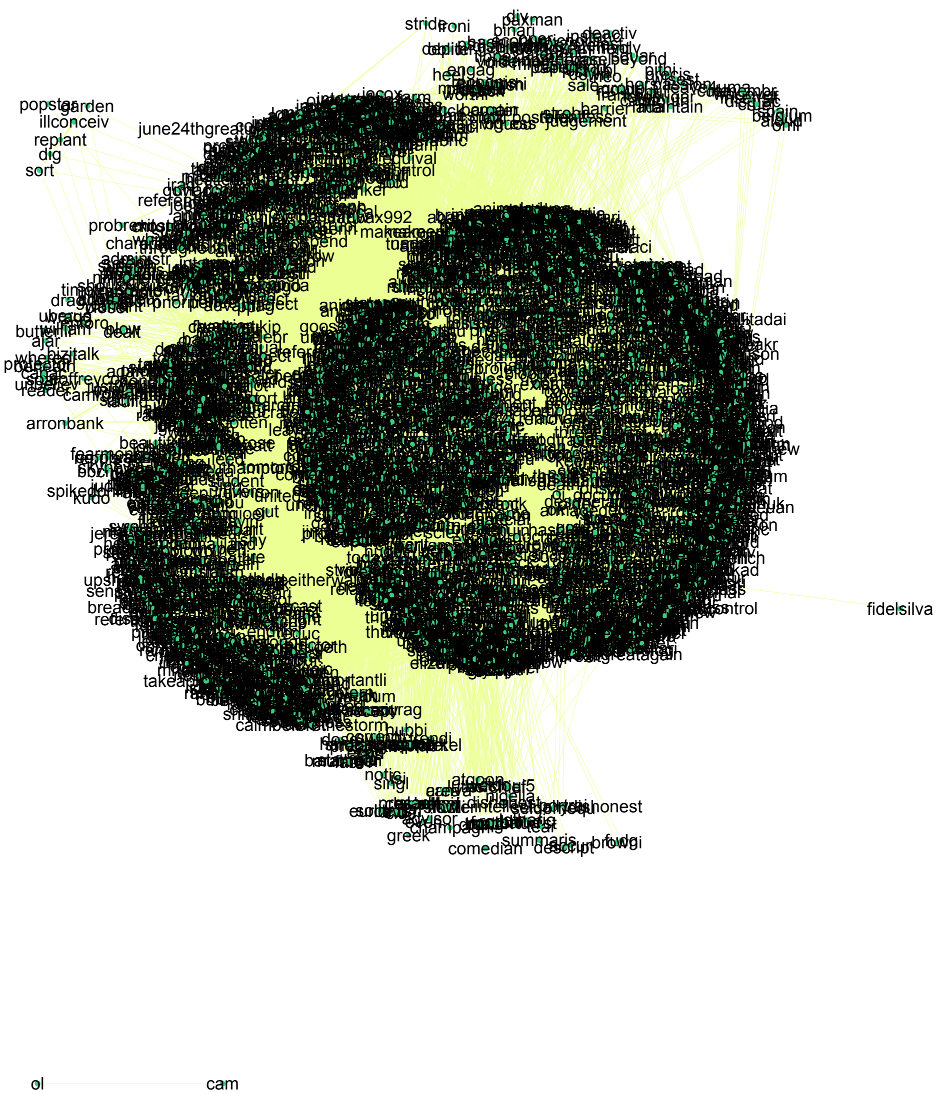
Create graphs for all tweets

```
result = Map[f, clean2Data];
result = Flatten[result];
result = DeleteDuplicates[result];
Dimensions[result]
```

```
{40 300}
```

Draw graph with Spring Embedding (this is similar to clustering in graph space. You notice the interesting shape of the graph. We have 7 regions with high density and few words outside the graph network. We can also see if we can find cliques, or how big is the largest clique

```
sg = Graph[result, {VertexLabels → Placed ["Name", Center],
   EdgeStyle → RGBColor[0.92, 1., 0.58], VertexStyle → RGBColor[0.23, 0.8, 0.5],
   VertexLabelStyle → Directive[FontFamily -> "Arial", 9, Black]},
  GraphLayout -> "SpringEmbedding"]
```




```
Thread
```

## Sentiment Analysis and Profanity

clean the tweets text

```
txtRm = Map[StringDelete[#, {"rt", ":", "amp"}] &, twitt]
```

### How many messages had sentiments (903), and how many had profanity(54). Show

### one remove profanities? Yes

We expected to find more tweets with sentiments, still this number represents more than 50% of all tweets

```
Length[DeleteCases[Map[TextCases[#, "PositiveSentiment"] &, txtRm], {}]]
```

```
903
```

```
Length[DeleteCases[Map[TextCases[#, "Profanity"] &, txtRm], {}]]
```

```
54
```

```
positiveBrexit = DeleteCases[Map[TextCases[#, "PositiveSentiment"] &, txtRm], {}];
```

```
txtRm = Map[StringReplace[#, RegularExpression["[e]{2,10}"] → "e"] &, txtRm];
```

```
txtRm = Map[StringReplace[#, leaveWords → "leav"] &, txtRm]
```

```
txtRm = Map[StringDelete[#, RegularExpression["[^a-z0-9\\s\#\'\-]+"]] &, txtRm]
```

```
txtRm = Map[StringReplace[#, word2Remove → ""] &, txtRm]
txtRm = Map[StringReplace[#, {leaveWords → "leav", remainWords → "remain",
      referendumWord → "referendum", brexitWords → "#brexit",
      ukWord → "uk", euWord → "eu", referWord → "referendum"}] &, txtRm];
txtRm = Map[StringReplace[#, "leaveeu" → "leav"] &, txtRm];
txtRm = Map[StringReplace[#, "#london" → "london"] &, txtRm];
txtRm = Map[StringReplace[#, "#" → ""] &, txtRm];
txtRm = Map[StringReplace[#, "byebyeuk" → "leav"] &, txtRm];
txtRm = Map[StringReplace[#, "leav" → "leave"] &, txtRm]
```

```
Select[txtRm, StringContainsQ[#, "remainathom"] &]
```

```
{in tomorrows referendum make sure you leavemtoit and remainathome}
```

```
Save["cleantxtBrexit", txtRm]
```

```
In[111]:= << cleantxtBrexit
```

```
Length[clean2Data]
```

```
1668
```

## Clustering

### We can either use the Jacquard or Cosine. Still we have to write our own code for both distance measure

Jacquard dissimilarity distance = n01+n10/(n11+n01+n10)

$\frac{\text{(Length[SetA}\subset\text{SubB]+Length[SetB}\subset\text{SubA])}}{\text{(Length[SetA}\subset\text{SetB]+Length[SetA}\subset\text{SetB]+Length[SetA}\cap\text{SetB])}}$. In here we modified it to take into consideration the length of the tweets. If a tweet is a subset to another tweet, than one should expect the distance between it and the longest tweet to be 0.

In[86]:=
```
myDistance [u_, v_] :=
 If[Length[u] == Length [v], (Length[Complement[u, v]] + Length[Complement[v, u]]) /
   (Length[Intersection[u, v]] + Length[Complement[u, v]] + Length[Complement[v, u]]),
  If[Length[u] < Length[v], Length[Complement[u, v]] /
    (Length[Complement[u, v]] + Length[Intersection[u, v]]), Length[
     Complement[v, u]] / (Length[Complement[v, u]] + Length[Intersection[u, v]])]]
```

example

In[90]:=
```
myDistance[{"apple", "box"}, {"apple", "paper", "tent"}]
```

Out[90]= $\frac{1}{2}$

In[7]:=
```
memberOf[c1_, l_] := If[MemberQ[c1, l], 1, 0]

cosineDist[c1_, c2_] :=
 Module[{univ = {}, x1 = {}, x2 = {}, cosD = 0}, univ = Union[c1, c2];
  x1 = Map[{#, memberOf[c1, #]} &, univ];
  x2 = Map[{#, memberOf[c2, #]} &, univ];
  cosD = 1 -
    (Total[x1[[All, 2]] * x2[[All, 2]]] / (Total[x1[[All, 2]]] * Total[x2[[All, 2]]]))
 ]
```

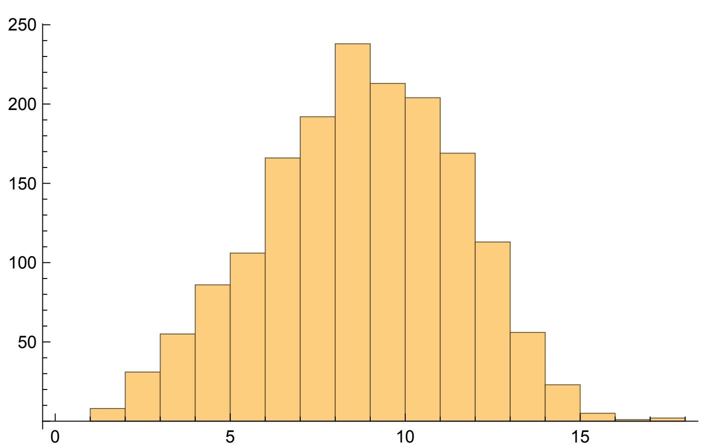
In[35]:=
```
cosineDist[{"baby", "boy", "boom", "tak"}, {"baby", "boom", "tak"}]
```

Out[35]= $\frac{3}{4}$

Histogram of tweets length. One can see that the length goes from 1 to 17. The wide length implies that Jacquard distance is not appropriate

```
lengthofTweet = Map[Length[#] &, clean2Data]

Histogram[lengthofTweet]
```




Let’s perform clustering with all the tweets using cosineDist. You will notice that we get 4 clusters.

```
c = FindClusters[clean2Data, DistanceFunction → cosineDist]
```

```
Length[c[[1]]]
```

```
985
```

```
Length[c[[2]]]
```

```
276
```

```
Length[c[[3]]]
```

```
407
```

We save our clusters as a mathematica variable but also in text documents

```
Save["BrexitClusters", c]
```

```
Export["brexitClustersC1.txt", c[[1]]]
```

```
brexitClustersC1.txt
```

```
Export["brexitClustersC2.txt", c[[2]]]
Export["brexitClustersC3.txt", c[[3]]]
```

```
CosineDistance
```

```
In[1]:= << BrexitClusters
```

Sample of what cluster 2 contains

```
In[99]:= c[[2]][[1 ;; 50]]

Out[99]= {{rich, come, remain, nh, school, etc, nt, affect, afford, privat, leav},
  {leav, retweet, go, tomorrow, takecontrol, projecthop},
  {agre, tomorrow, chanc, leav}, {leav, starter, pack},
  {eu, confirm, referendumorm, leav, control}, {leav, remain},
  {go, wors, leav}, {leav, said, pai, tomorrow, chanc, takebackcontrol},
  {leav, win, vote, rememb, acknowledg, god, merci, nation, guid, leader, choic},
  {wow, final, vote, freedom, democraci, independ, leav, uk},
  {juncker, uk, voter, know, kind, renegoti, fight, leav},
  {eu, referendumorm, uk, leav, unreferendumorm, lexit, snpout},
  {leav, pathet, think, go, rig, vote, clearli, confid, remain},
  {hope, leav, carri, like, eu, unmitig, disast},
  {want, leav, eu, sun, newspap, support, need, valid, reason, remain, just},
  {good, hear, bnp, mention, bbcdebat, issu, remain, tri, us, smear, leav},
  {plane, leav, banner, fli, directli, jo, cox, memori, trafalgar, sq,
   actual, troll, funer}, {promot, remain, time, tl, todai, leav, dodgi},
  {feel, incred, proud, leav, campaign, led, team, haringei, tomorrow},
  {leav, insist, eu, nation, uk, abl, stai, immigr, lawyer, sai, simpl},
  {care, nh, pleas, end, unfair, eu, chanc, leav, thank}, {like, muslim, leav},
  {c4debat, labour, voter, shock, secur, worker, right, eu, takebackcontrol, leav},
  {half, brain, vote, remain, leader, know, mind, offer, empti, promis, leav},
  {joepattinson, eu, loserdom, leav},
  {bold, brave, believ, leav, goodnight, , pleas, globe},
  {leav, break, eu, open, new, membership, talk, turkei, june, 30th},
  {follow, leav, remain, campaign, chose, month, research, want, uk, great},
  {shall, independencedai, leav}, {islington, elitist, take,
   moment, speak, littl, peopl, provinc, leav, takebackcontrol},
  {sum, debat, perfectli, imo, vote, leav, remain},
  {yeah, understand, set, leav, due, fact, dad, incom, affect, eu, regul, fish},
  {watch, cast, vote, god, sake, throw, awai, countri, leav},
  {sad, legitim, reason, peopl, vote, leav}, {uk, voter, pleas, vote, leav,
   tomorrow, million, fought, di, democraci, throw, awai}, {uk, stai, leav},
  {proeu, labour, campaign, sai, go, wooooh, attract, prospect, peopl, leav},
  {sjpowel, sky, new, just, poll, expert, sai, weight, leav},
  {leav, light, end, tunnel, tomorrow, brighter, futur, c4debat},
  {bruh, acc, scare, leav, win, pleas, uk, public, remain},
  {leav, implement, australian, style, pointsbas, immigr, system, takecontrol},
  {eu, leav}, {undecid, vote, leav, wai, ticket, remain, room, decid, futur},
  {leav, takebackcontrol}, {vote, leav, todai, remain, lock, car, driven,
   uncertain, direct}, {road, diverg, wood, took, travel, differ, leav},
  {leav, read, german, industri, call, free, trade, deal, tomorrow},
  {choos, hope, fear, democraci, bureaucraci, opportun, obfusc, leav},
  {read, peopl, referendumerendum, britexit, leav, ukindepend},
  {futur, gener, elect, meaningless, unless, takebackcontrol, leav, law}}

In[6]:= << cleanDataBrexit

In[9]:= << FinalCleanBrexit
```

What if we allow only tweets with at least 4 words? We get only 2 clusters, but cluster 2 has only one tweet.

In[83]:=
```
onlyTweet4orMore = Select[clean2Data, Length[#] ≥ 4 &]
```

Out[83]=
```
{{brexit, episod, delai, thur, share, like, hell},
 {rich, come, remain, nh, school, etc, nt, affect, afford, privat, leav},
 ··· 1570 ···, {million, tweet, leav, trend}, {immigg, knew, bear, referendum}}
```

large output | show less | show more | show all | set size limit...

In[28]:=
```
cOp = FindClusters[onlyTweet4orMore,
  DistanceFunction → cosineDist, Method -> "Agglomerate"]
```

In[100]:=
```
Length[cOp]
```

Out[100]= 2

In[102]:=
```
Length[cOp[[2]]]
```

Out[102]= 1

In[32]:=
```
cOp[[2]]
```

Out[32]=
```
{{steve, hilton, sai, saw, foot, high,
  pile, paperwork, week, down, st, half, came, brussel}}
```

In[24]:=
```
Length[cc4]
```

Out[24]= 0

We also decided to use our new Jacquard distance and see how many clusters we will get. In here, we get 2 clusters, but cluster 2 has 626 tweets. Of course, an analysis of the tweets in same clusters should be done. Still, it is nice to see that we didn't get almost empty clusters

In[91]:=
```
cJacquard = FindClusters[onlyTweet4orMore, DistanceFunction → myDistance]
```

Out[91]=
```
{{{brexit, episod, delai, thur, share, like, hell},
  {rich, come, remain, nh, school, etc, nt, affect, afford, privat, leav},
  ··· 944 ···, {half, brain, vote, remain, leader, know, mind, offer, empti},
  {brexit, leav, countri, need, vote, todai, make, uk, greater}}, {··· 1 ···}}
```

large output | show less | show more | show all | set size limit...

In[109]:=
```
{Length[cJacquard], Length[cJacquard[[1]]], Length[cJacquard[[2]]]}
```

Out[109]= {2, 948, 626}

In[113]:=
```
Save["SaveAllVariableBrexit", {twitt, cleanData, clean2Data, txtRm}]
```