# TASK 2 TRUMP TWEETS TEXT ANALYSIS 

GROUP \#4

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## PROJECT GOAL

The objective of the project is to analyze Trump tweets in order to define the most used words and to classify them in categories thanks to SVD diagrams and
clustering methods

## DATASET USED

The dataset is composed by 4212 tweets, with only one column for each one, containing the text of the tweets.

## DATA CLEANING

$>$ Remove punctuation, numbers and isolate words;
$>$ Remove all the words without an utility for the project;
$>$ Cutoff all the words below an arbitrary thresholds, in this case study the threshold is 30;
$>$ Combine and insert some words particurarly relevant for the topic (e.g. "make America great again");

| Numero <br> di termini | Numero <br> di casi | Token per <br> Token totali | Numero di <br> maiuscola/minuscola | Suddividi non |
| ---: | ---: | ---: | ---: | ---: | ---: |
| casi non vuoti |  |  |  |  |
| vuoti per caso |  |  |  |  |

[^0]
## MOST COMMON WORDS

In Figure 2 and Figure 3 there is a representation of the most used words in the tweets such as «great», «people» and «president».


Figure 2- Word Cloud

## $\triangle$ Elenchi di termini e frasi

| Termine | Conteggio |  |
| :---: | :---: | :---: |
| great | 894 | $\wedge$ |
| people | 454 |  |
| president | 435 |  |
| democrats | 420 |  |
| country | 379 |  |
| china | 266 |  |
| border | 255 |  |
| good | 248 |  |
| fake news | 245 |  |
| media | 241 |  |
| time | 230 |  |
| trump | 213 |  |
| united states | 197 |  |
| job | 175 |  |
| deal | 166 |  |
| dems | 161 |  |
| wall | 160 |  |
| america | 155 |  |
| history | 154 |  |
| hunt | 148 |  |
| state | 143 |  |
| win | 141 |  |
| collusion | 137 |  |
| crime | 135 |  |
| work | 135 |  |
| economy | 134 | $\checkmark$ |

## SVD PLOTS

> The words appearing close to each other appear together frequently in documents in the corpus;
$>$ In the Figure 4 the two plots have a similar shape, even if there is a difference
in the concentration deriving from the number of points in each plot;
$>$ In the first plot there are some outliers, the clearest is reported beside.


[^1]
## TOP LOADINGS BY TOPIC

This fuction matches the words, according to the different topics. In particular they are divided in 10 groups:

1. Election campaign;
2. Immigration and Mexico;
3. Trump's opponents;
4. Import-export;
5. North Korea troubles;
6. Mass media;
7. Impeachment case;
8. Economy;
9. Domestic economy;
10. Middle east conlicts:

| Pesi principali per argomento |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Argomento 1 |  | Argomento 2 |  | Argomento 3 |  | Argomento 4 |  | Argomento 5 |  |
| Termine | Caricamento in corso | Termine Car | Caricamento in corso T | Termine | Caricamento in corso | Termine Car | Caricamento in corso | Termine | Caricamento in corso |
| amendment | 0,60192 | border | 0,65366 co | collusion | 0,57636 | dollars | 0,63248 no | north korea | 0,74222 |
| governor | 0,53740 | southern | 0,61894 cr | crooked | 0,48231 | china | 0,62040 ki | kim | 0,72570 |
| vote | 0,52517 | immigration | 0,48710 hil | hillary | 0,42930 | tariffs | 0,60712 ch | chairman | 0,57238 |
| vets | 0,49576 | laws | 0,46176 ob | obstruction | 0,39702 | billion | 0,53970 ko | korea | 0,53670 |
| republican | 0,47895 | mexico | 0,41224 re | report | 0,36354 | billions | 0,46402 so | south | 0,49246 |
| louisiana | 0,46703 | drugs | 0,40894 ca | campaign | 0,29530 | deal | 0,34515 m | meeting | 0,37920 |
| taxes | 0,35827 | wall | 0,40089 d | democrats | 0,28750 | trade | 0,31270 ec | economic | 0,29958 |
| military | 0,35721 | fix | 0,31663 hi | hillary clinton | 0,28144 | farmers | 0,29195 po | potential | 0,29531 |
| protect | 0,34195 | illegal | 0,30007 rus | russian | 0,27721 | usa | 0,28774 ja | japan | 0,22036 |
| north | 0,33836 | crisis | 0,29303 tr | trump | 0,26168 | paid | 0,26484 |  |  |
| carolina | 0,33579 | democrats | 0,28214 ru | russia | 0,25702 | companies | 0,26457 |  |  |
| crime | 0,31811 | stop | 0,27975 an | angry | 0,25188 |  |  |  |  |
| rally | 0,29108 | built | 0,27909 fb | fbi | 0,24775 |  |  |  |  |
|  |  | change | 0,27908 in | intelligence | 0,24682 |  |  |  |  |
|  |  |  |  | hunt | 0,24670 |  |  |  |  |
| Argomento 6 |  | Argomento 7 |  | Argomento 8 |  | Argomento 9 |  | Argomento 10 |  |
| Termine | Caricamento in corso | Termine | Caricamento in corso | Termine | Caricamento in corso | Termine | Caricamento in corso | to Termine | Caricamento in corso |
| fake news | 0,52877 | ukrainian | 0,5154 | 154 interest | 0,70297 | market | 0,6117 | 17 kurds | 0,76609 |
| media | 0,48130 | conversation | n 0,4542 | 42 rates | 0,65723 | stock | 0,6012 | 12 turkey | 0,71581 |
| post | 0,45755 | ukraine | 0,4431 | inflation | 0,56335 | unemployment | nt 0,4078 | 78 syria | 0,61736 |
| washington | 0,41521 | phone | 0,4296 | federal | 0,54365 | history | 0,3965 | 65 isis | 0,49777 |
| new york times | es 0,37590 | whistleblower | er 0,4202 | fed | 0,49691 | economy | 0,3507 | 07 fight | 0,37003 |
| story | 0,37563 | transcript | 0,4017 | 17 dollar | 0,42718 | lowest | 0,2805 | 05 fighting | 0,27629 |
| fake | 0,36678 | president | 0,3997 | rate | 0,34122 | impeach | 0,2727 | 727 protect | 0,19499 |
| corrupt | 0,35700 | scam | 0,3334 | 34 countries | 0,31436 | country | 0,2124 |  |  |
| failing | 0,33712 | democrat | 0,2553 |  |  | record | 0,2117 |  |  |
| stories | 0,29421 | impeachment | nt 0,2443 |  |  | enforcement | -0,2047 |  |  |
| cnn | 0,29065 | great | -0,2253 |  |  | law | -0,2045 |  |  |
| reporting | 0,29049 |  |  |  |  | biggest | 0,2025 |  |  |
| Figure 6-Top Loading Topic |  |  |  |  |  |  |  |  |  |

## CLUSTERING

The dataset is divided in 4 cluster, in this way is possible to delete non significant groups. It's evident that the biggest group is the red one, since the most common terms belong to this group.



[^0]:    Figure 1- Number of terms after data cleaning

[^1]:    Figure 4 - SVD plots

