

# Big 5 personality traits

Alexia

# Data Exploration

```
> summary(data)
```

```
 X.AUTHID      STATUS      X.1      X.2      X.3
Length:9916    Length:9916    Mode:logical    Mode:logical    Mode:logical
Class :character    Class :character    NA's:9916      NA's:9916      NA's:9916
Mode :character    Mode :character
```

```
 X.4      DATE      NETWORKSIZE      BETWEENNESS      NBETWEENNESS      DENSITY
Mode:logical    Length:9916    Min. : 24.0    Min. : 185.7    Min. :31.21    Min. :0.00000
NA's:9916      Class :character    1st Qu.: 196.0    1st Qu.: 16902.2    1st Qu.:93.77    1st Qu.:0.01000
Mode :character    Mode :character    Median : 317.0    Median : 47166.9    Median :96.44    Median :0.02000
Mean : 426.4    Mean : 135439.0    Mean :94.67    Mean :0.03029
3rd Qu.: 633.0    3rd Qu.: 196606.0    3rd Qu.:97.88    3rd Qu.:0.03000
Max. :1596.0    Max. :1251780.0    Max. :99.82    Max. :0.40000
```

```
 BROKERAGE      NBROKERAGE      TRANSITIVITY      cEXT      cNEU
Min. : 241    Min. :0.32    Min. :0.0000    Length:9916    Length:9916
1st Qu.: 17982    1st Qu.:0.49    1st Qu.:0.0600    Class :character    Class :character
Median : 48683    Median :0.49    Median :0.0900    Mode :character    Mode :character
Mean : 137656    Mean :0.49    Mean :0.1288
3rd Qu.: 198186    3rd Qu.:0.50    3rd Qu.:0.1700
Max. :1263790    Max. :0.50    Max. :0.6300

 cAGR      cCON      cOPN
Length:9916    Length:9916    Length:9916
Class :character    Class :character    Class :character
Mode :character    Mode :character    Mode :character
```

## STATUS

likes the sound of thunder.

is so sleepy it's not even funny that's she can't get to ...

is sore and wants the knot of muscles at the base of ...

likes how the day sounds in this new song.

is home. <3

[www.thejokerblogs.com](http://www.thejokerblogs.com)

**Task: to cluster the 250 users and explore the relationship between Big 5 personality and each cluster**

# Data Wrangling

STATUS
likes the sound of thunder.
is so sleepy it's not even funny that's she can't get to ...
is sore and wants the knot of muscles at the base of ...
likes how the day sounds in this new song.
is home. <3
<a href="http://www.thejokerblogs.com">www.thejokerblogs.com</a>

- `num_characters`: The number of characters in each post.
- `num_punc`: The number of punctuation marks used in each post (including `!`, `~`, and `#`).

# Data Wrangling

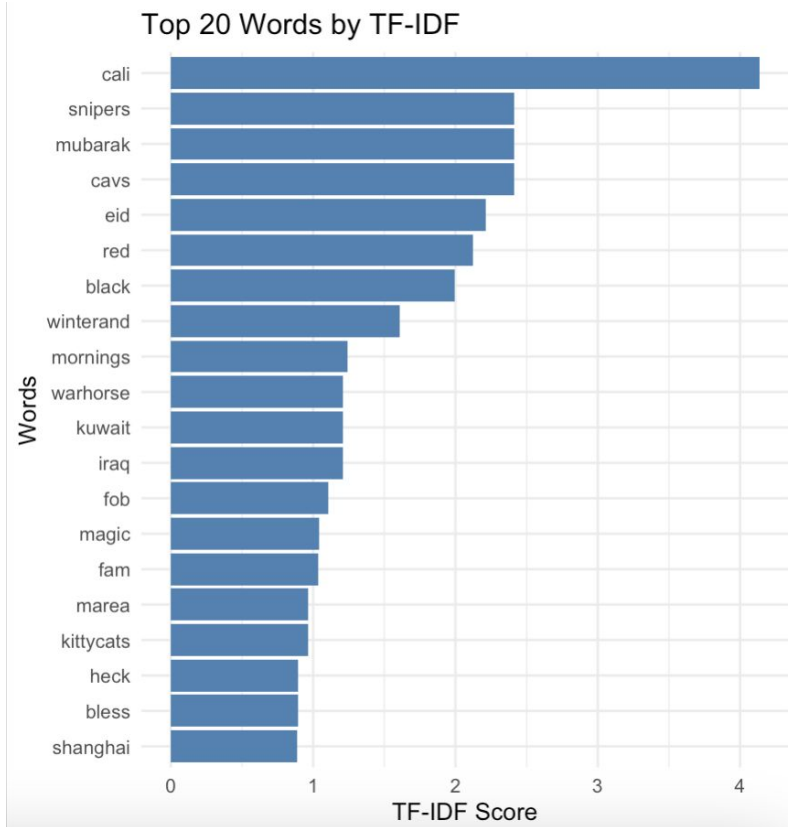
STATUS
likes the sound of thunder.
is so sleepy it's not even funny that's she can't get to ...
is sore and wants the knot of muscles at the base of ...
likes how the day sounds in this new song.
is home. <3
www.thejokerblogs.com



lowercase,  
remove punc,  
remove stop words,  
tokenise

word
likes
sound
thunder
sleepy
funny
sleep
sore

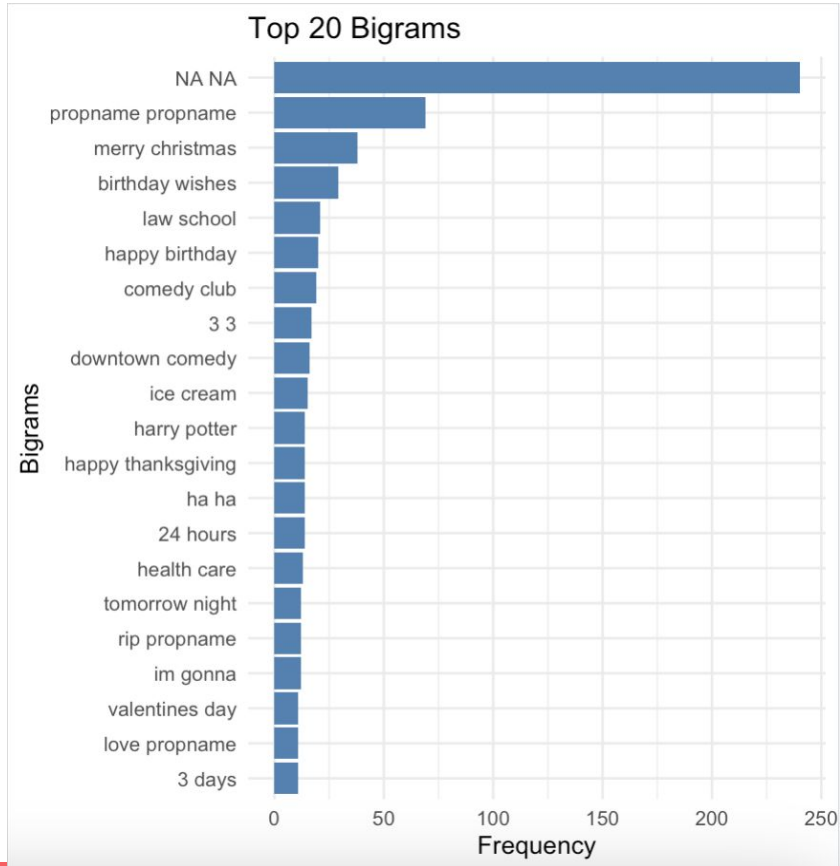
# Data Wrangling– TF-IDF



Term Frequency Inverse Document Frequency:

How important a word is to a document in a collection (or corpus) of documents

# Data Wrangling – N-grams



# Data Wrangling – Sentiment Analysis

TheMysMan\_bh@d4jk:



“My friend Kanye **punched** me because I cheated on him with his girlfriend Kim, but I still feel **happy** today for Kim’s **kiss**! **xoxo!!!**”



Positive ratio:  $3/(1+3)$

# Data Wrangling



```
$ cOPN          : chr  "y" "y" "y"  
$ num_punc      : int   0 0 1 0 0 0  
$ num_characters: int   26 59 116 4  
$ mean_tf_idf   : num   0.00634 0.0  
$ top_word      : chr   "3" "3" "3"  
$ positive_ratio: num   0.637 0.637
```



# Data Wrangling

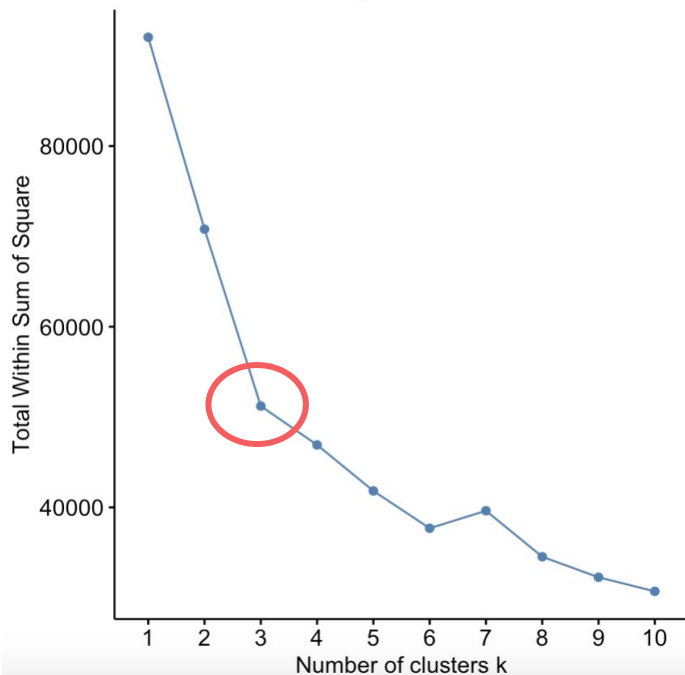


RF for feature importance (eg. **cEXT**)

	n	y	MeanDecreaseAccuracy	MeanDecreaseGini
NETWORKSIZE	11.023787	10.437391	12.831892	185.0561380
<del>BETWEENNESS</del>	<del>11.447184</del>	<del>11.205105</del>	<del>13.358052</del>	<del>185.7450730</del>
NBETWEENNESS	12.154502	10.844694	13.555254	171.8532026
NBROKERAGE	6.382967	7.028083	8.207925	70.0791159
DENSITY	8.588331	5.830041	9.444128	45.7282323
TRANSITIVITY	12.670610	11.238558	13.815618	249.3083881
num_punc	2.837492	1.181884	2.923152	0.4568379
num_characters	2.248371	1.396597	2.541610	0.6145732
mean_tf_idf	14.767135	10.831288	14.233036	159.0392216
positive_ratio	11.631051	11.407710	12.691495	88.4420601

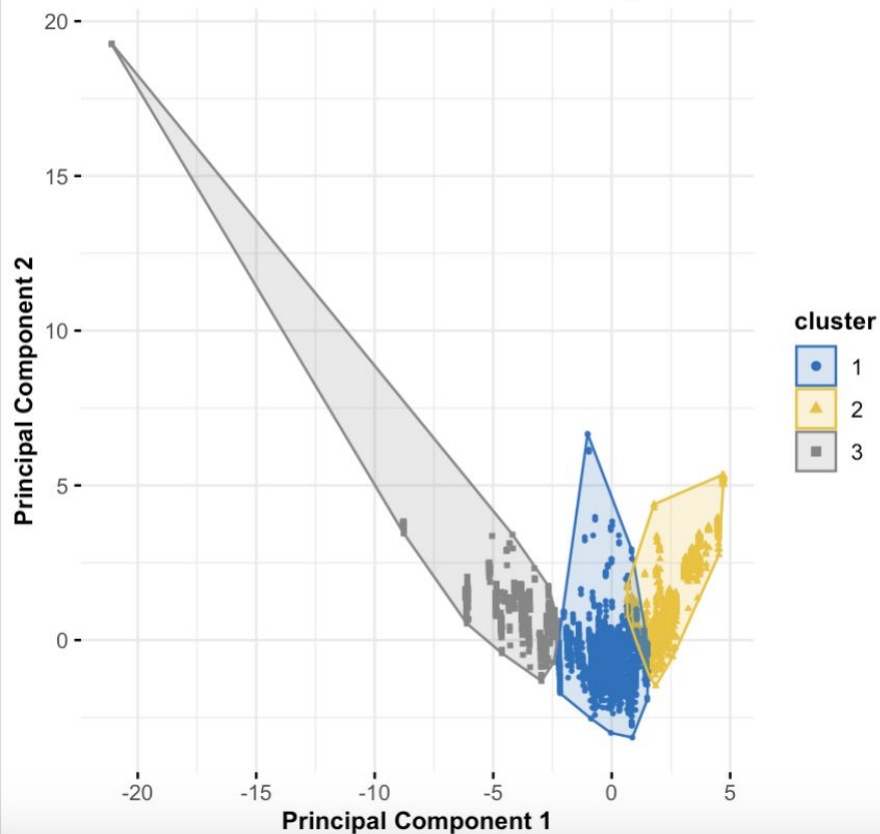
# K-Means

Elbow Method for Optimal Clusters



## K-Means Clustering Visualization

Clusters visualized after PCA dimensionality reduction



# K-means — evaluation

## Silhouette Plot for K-Means Clustering

n = 9886

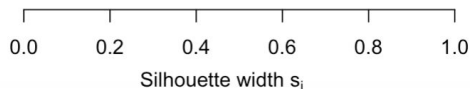
3 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$

1 : 6128 | 0.32

2 : 2577 | 0.28

3 : 1181 | 0.29

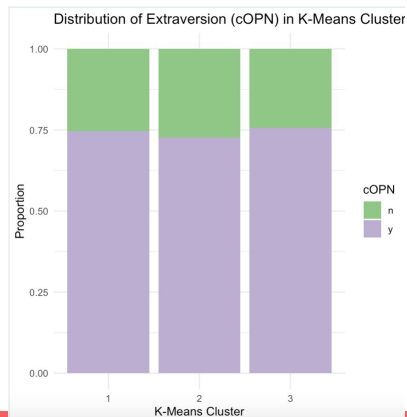
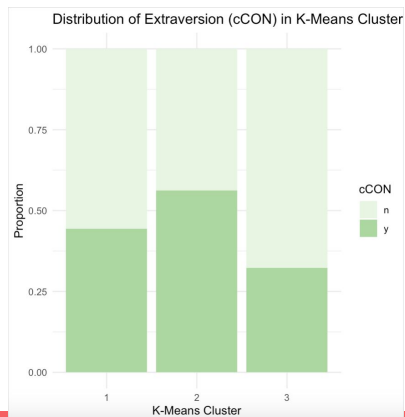
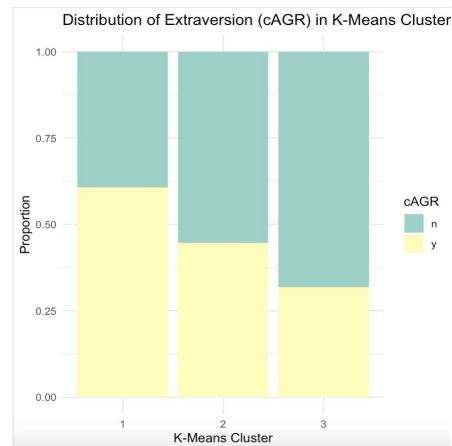
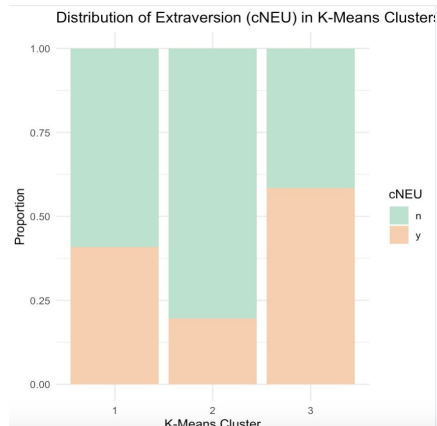
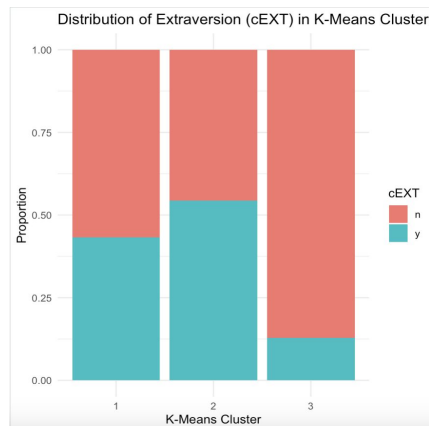


Average silhouette width : 0.31

```
> purity_cEXT .  
> print(purity.  
[1] 0.6613892  
> purity_cNEU .  
> print(purity.  
[1] 0.6598889  
> purity_cAGR .  
> print(purity.  
[1] 0.6143171  
> purity_cCON .  
> print(purity.  
[1] 0.59881  
> purity_cOPN .  
> print(purity.  
[1] 0.74366
```

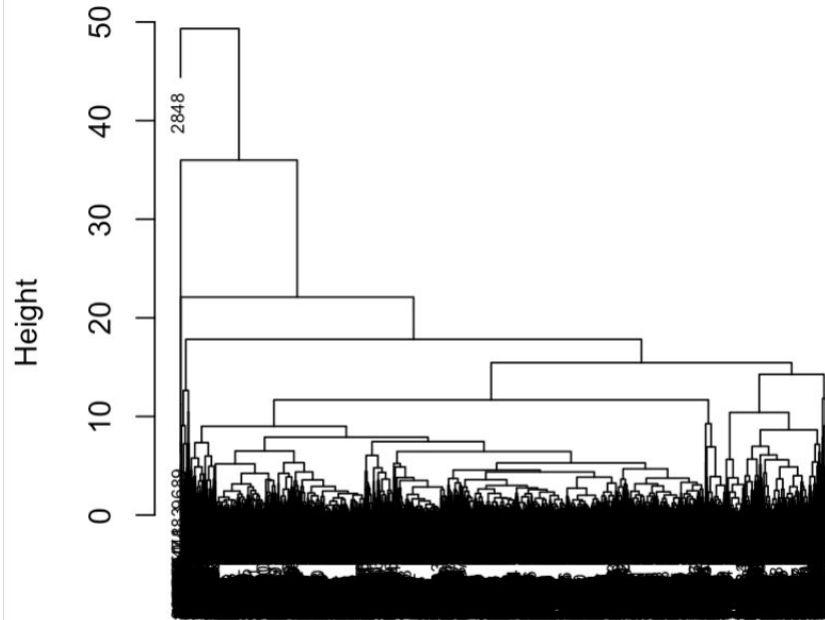
a measure of cluster quality in relation to each personality

# K-means evaluation



# Hierarchical Clustering

Dendrogram for Hierarchical Clustering



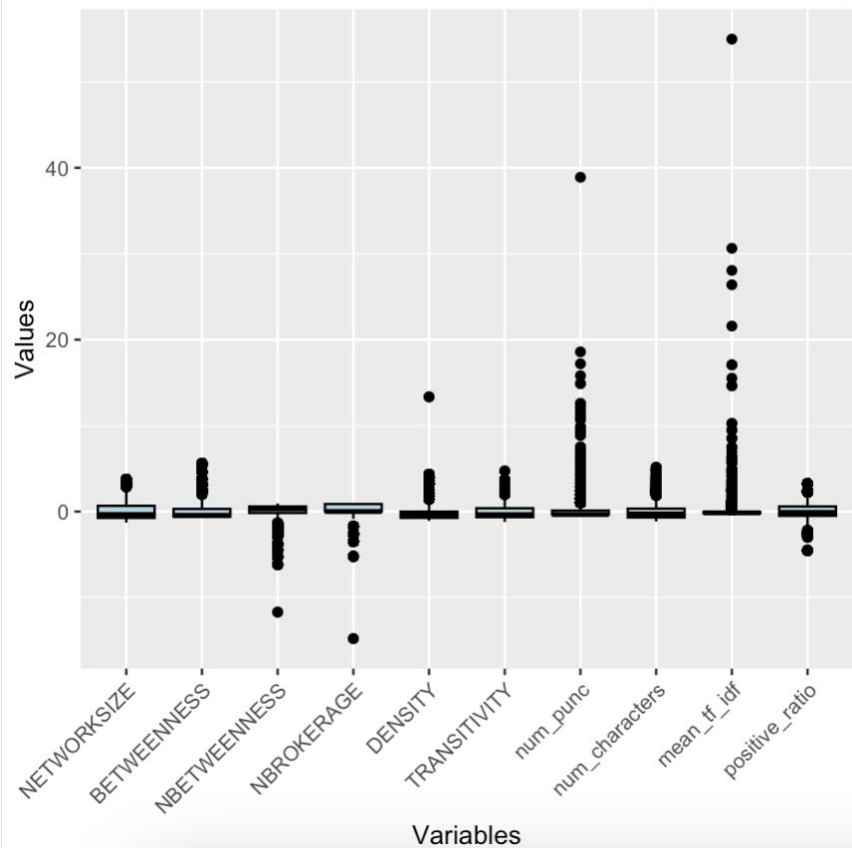
# Hierarchical Clustering — evaluation

```
> print(Hmean_silhouette)
[1] 0.8726472
```

Well-separated pt;  
Compact clusters -- minimal  
overlap between

```
> print(paste("Purity for cEXT:", purity.
[1] "Purity for cEXT: 0.858140240817566"
> purity_cNEU <- purity_score(dw_clean$h
> print(paste("Purity for cEXT:", purity.
[1] "Purity for cEXT: 0.875341495497319"
> purity_cAGR <- purity_score(dw_clean$h
> print(paste("Purity for cAGR:", purity.
[1] "Purity for cAGR: 0.843940773719181"
> purity_cCON <- purity_score(dw_clean$h
> print(paste("Purity for cCON:", purity.
[1] "Purity for cCON: 0.846639009747378"
> purity_cOPN <- purity_score(dw_clean$h
> print(paste("Purity for cOPN:", purity.
[1] "Purity for cOPN: 0.914938109211103"
```

Boxplots for Selected Variables







# Advantages & disadvantages

## – Advantages

1. Integration of Structured and Unstructured Data
2. Model Evaluation
3. Real-World Application

## – Disadvantages

1. Text Complexity
2. Moderate K-Means Performance
3. Feature Selection Limitations

# Potential Challenges and Considerations

## 1. Data Overlap

overlapping nature of personality traits  
(e.g., Agreeableness and Conscientiousness)

## 2. Scalability

## 3. Text Data Variability

Variations in language usage, slang, and punctuation

# Ethical considerations

## 1. User Privacy

Maintaining anonymity and protecting users from re-identification is crucial

## 2. Data Sensitivity

Social media data can be misused in harmful ways

## 3. Algorithmic Fairness

Ensure that clustering methods do not reinforce biases or stereotypes



**THANK**

**YOU !**