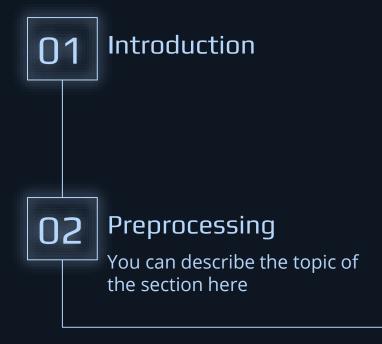


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Introduction

Apply clustering and association rule mining techniques on a dataset related to bullying statement detection.

Data set:

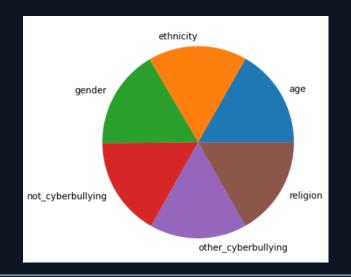
Having only 2 columns:

- tweet_text
- cyberbullying_type

Cyberbulling_types:

cyberbullying_type	
religion	7998
age	7992
gender	7973
ethnicity	7961
not_cyberbullying	7945
other_cyberbullying	7823

	tweet_text	cyberbullying_type
0	In other words #katandandre, your food was cra	not_cyberbullying
1	Why is #aussietv so white? #MKR #theblock #ImA	not_cyberbullying
2	$@ {\sf XochitlSuckkks} \ a \ {\sf classy} \ {\sf whore?} \ {\sf Or} \ {\sf more} \ {\sf red} \ {\sf ve}$	not_cyberbullying
3	@Jason_Gio meh. :P thanks for the heads up, b	not_cyberbullying
4	@RudhoeEnglish This is an ISIS account pretend	not_cyberbullying

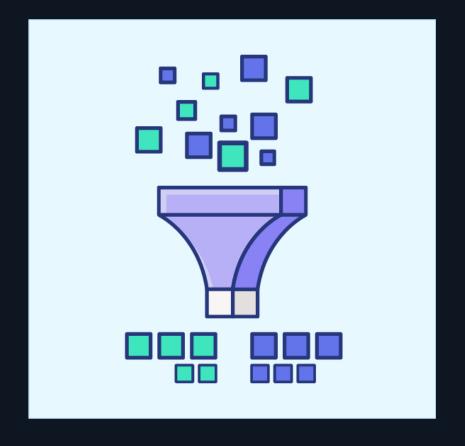


Data Cleaning:

```
def remove_punct(text):
  def decontract(text):
  def lower(text):
  def remove_stopwords(text):
  def smile_handle(word_list):
  def lemmatize(words):
```

Converting the text data into numerical features

TF-IDF:



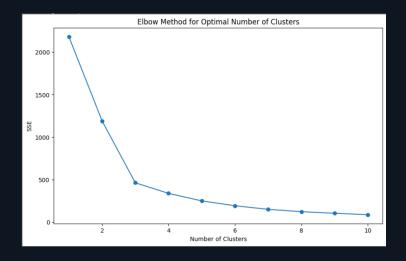
Cluster K-mean

K-Means

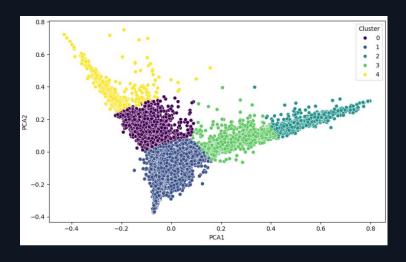
- Used for large data sets
- Efficient when we have to make equal no of clusters

Elbow method

- To find the optimal number of clusters, you look for the "elbow" point in the plot, where the SSE starts to decrease more slowly.
- Elbow appears is 3.
- After 3 clusters, the decrease in SSE becomes more gradual



K-Mean for k=5



- Cluster Separation: Cluster
 Characteristics: clusters 0 and 3
 appear more densely packed,
 whereas clusters 1 and 4 are more
 widely distributed.
- **Influence of PCA Components:**

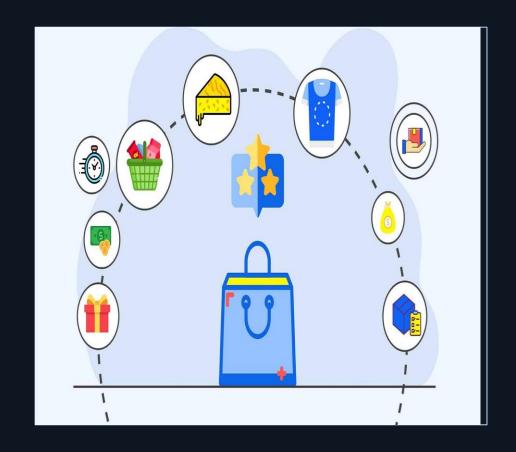
Association:

Apriori algorithm

Apriori algorithm

It operates by:

- identifying the frequent itemset in a dataset
- extending them to larger itemset if they meet a specified minimum support threshold.



Implementation:

```
frequent_itemsets_fp = fpgrowth(oht_df_bool, min_support=0.01, use_colnames=True)
[24] # Step 3: Generate Association Rules
     rules = association_rules(frequent_itemsets_fp, metric='confidence', min_threshold=0.5)
[25]
     # Step 4: Set thresholds and filter meaningful rules
     filtered_rules = rules[(rules['lift'] > 1) & (rules['confidence'] > 0.5)]
```

Implementation:

```
[26] # Interpret the results
     print(filtered rules[['antecedents', 'consequents', 'support', 'confidence', 'lift']])
₹
                                                                    support confidence
                                                                                               lift
              antecedents
                                                      consequents
            (school, not)
                                                          (bulli)
                                                                   0.017487
                                                                                0.923588
                                                                                           4.478219
                                                                                0.818449
             (not, bulli)
                                                         (school)
                                                                   0.017487
                                                                                           4.819545
            (school, but)
                                                          (bulli)
                                                                   0.025036
                                                                               0.950637
                                                                                           4.609371
             (bulli, but)
                                                          (school)
                                                                   0.025036
                                                                               0.863965
                                                                                           5.087570
           (school, like)
                                                          (bulli)
                                                                   0.034870
                                                                                0.962384
                                                                                           4.666331
                              (tayyoung, nigger, fuck, dumb, as)
                                                                   0.010211
                                                                                0.868093
                                                                                          46.258186
     1740
              (rt, obama)
     1741
               (dumb, rt)
                              (tayyoung, nigger, fuck, obama, as)
                                                                   0.010211
                                                                                0.563006
                                                                                          30.000974
                            (tayyoung, nigger, fuck, obama, dumb)
                                                                   0.010211
     1742
                 (rt, as)
                                                                                0.762128
                                                                                          40.611647
     1743
              (obama, as)
                              (tayyoung, nigger, rt, fuck, dumb)
                                                                   0.010211
                                                                                0.503099
                                                                                          49.268595
     1744
               (tayyoung)
                             (nigger, rt, fuck, obama, dumb, as)
                                                                   0.010211
                                                                                0.523656 50.452925
     [1745 rows x 5 columns]
```

Implementation:

High confidence and lift values indicate strong association. For example, (school, not) => (bulli) with a confidence of 0.923588 and a lift of 4.478219 shows a strong association between these terms.

The rules with antecedents containing terms like (rt, obama), (dumb, rt), and (tayyoung) have very high lift values (ranging from 30 to 50), indicating exceptionally strong associations in those contexts.

Prototype system:

Real-Time Bullying Statement Detection Enter a statement: Analyze

Recommendation:

- Cluster-Based Association Rule Mining: First, use clustering
 - (e.g., K-Means or DBSCAN) to group similar instances.
 - Then, apply association mining techniques (e.g., Apriori or FP-Growth) Utilize **multimodal data**, including images and videos, to capture a broader spectrum of bullying behaviors.
- Advanced Text Analysis Techniques: (NLP) techniques, such as transformer-based models like BERT and GPT.
- Contextual and Behavioral Analysis: having more contextual information, such as users' past behaviors and engagement patterns,

Thanks!

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