

# HATE SPEECH DETECTION



A case of generated data

# THE DATA

## ENGLISH

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- Dynamically generated Hate Speech dataset
- Permutation of words in order for labels to be switched from Not Hateful to Hateful (Perturbation)
- Aim: robust algorithms for hate speech detection
- Binary Hate (53.8%) vs NotHate annotation
- “Target” annotation: 42 categories of hate

## FRENCH

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- French portion of a dataset for Multilingual and Multi-Aspect Hate Speech Analysis
- 4.014 entries



# DYNAMICALLY GENERATE HATE SPEECH DATASET



Binary classification:  
complete dataset  
(41.144 entries)

Multiclass classification: six most  
common hate categories  
(7.610 entries)

# BINARY CLASSIFICATION

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Hate (0) vs NotHate (1)



# MULTICLASS CLASSIFICATION

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Women (5)  
Black People (0)  
Jewish People (2)  
Muslim People (3)  
Trans People (4)  
Gay People (1)

# THE METHODS

## CLASSIFICATION PART 1

- Logistic Regression, XGBoost and SGD Classifier with Tf-Idf
- XGBoost and SGD Classifier with Word2Vec word embeddings trained on the training set
- XGBoost with W2V and FastText pretrained word embeddings
- All methods applied to both binary and multiclass classification

## CLASSIFICATION PART 2

- Convolutional Neural Network with W2V and FastText pretrained word embeddings (9 Conv1D layers)
- Bidirectional Long Short Term Memory Neural Network with W2V and FastText pretrained word embeddings (6 Bi-LSTM layers)
- All methods applied to both binary and multiclass classification

# THE METHODS

## WORD2VEC TRAINING

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- Context Window of 2 words
- Only using words that appear at least 10 times
- Vector size per word: 300, as for W2V and FastText provided by Gensim



# THE METHODS

## KEYWORDS AND KEYPHRASES

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WordClouds, 50 words  
KeyBert with one word, two words, and key phrases  
BerTopic

# BEFORE CLASSIFICATION

FOR ALL EXPERIMENTS



Stopwords removal

Exceptions: “they”,  
“them”, “no”, “not,  
“don’t”

Tokenization and  
Stemming  
(SnowballStemmer)

# CLASSIFICATION PART 1: RESULTS

## BINARY CLASSIFICATION

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<b>Algorithm - TF-IDF</b>	<b>Accuracy</b>
Logistic Regression	0.67
XGBoost	0.69
SGD Classifier	0.68

## MULTICLASS CLASSIFICATION

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<b>Algorithm- TF-IDF</b>	<b>Accuracy</b>
Logistic Regression	0.87
XGBoost	0.87
SGD Classifier	0.90

# CLASSIFICATION PART 1: RESULTS

## BINARY CLASSIFICATION

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Algorithm - Word Embeddings	Accuracy
XGBoost Trained W2V	0.59
SGD Trained W2V	0.59
XGBoost Pretrained W2V	0.61
XGBoost Pretrained FastText	0.61

## MULTICLASS CLASSIFICATION

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Algorithm - Word Embeddings	Accuracy
XGBoost Trained W2V	0.64
SGD Trained W2V	0.31
XGBoost Pretrained W2V	0.78
XGBoost Pretrained FastText	0.80

# CLASSIFICATION PART 1: RESULTS

## BINARY CLASSIFICATION

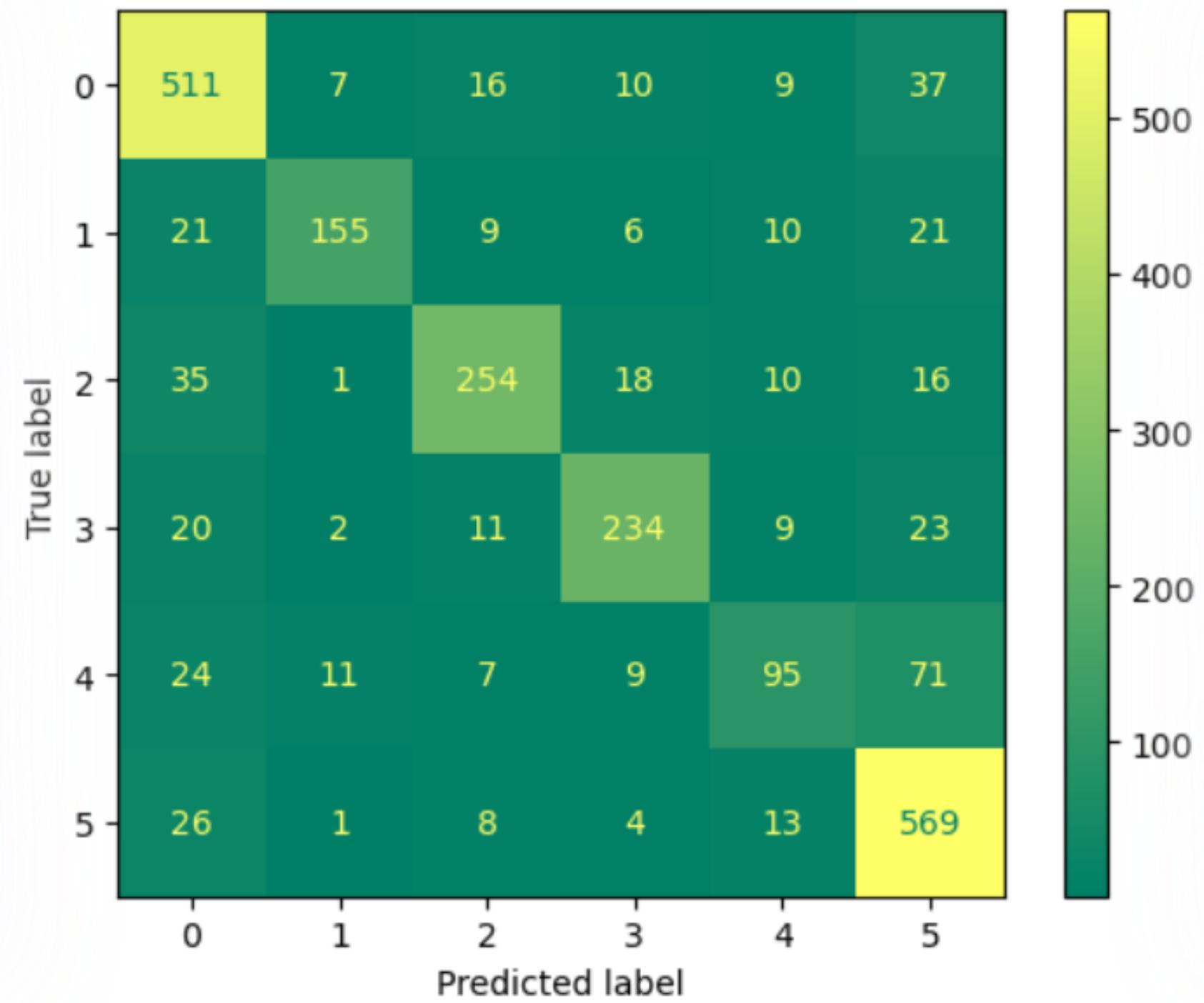
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- For Tf-Idf, all values of precision and recall are between 64% and 72%
- When training the embeddings SGD obtains a 92% recall on the Hate category, but 57% precision and a 19% recall for the NotHate category: the algorithm tends to classify most text as hateful
- Not enough data and too short a window to train embeddings, similar words for both categories
- Pretrained word embeddings do not significantly improve results
- Need for methods which better encapsulate context

## MULTICLASS CLASSIFICATION

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- For Tf-Idf, more specific categories - with a more specific vocabularies lead to improved results; with SGD values for precisions or recall are over 80% for all categories
- Trained W2V doesn't improve results, with SGD completely misclassifying 3 of the 6 categories
- Pretrained word embeddings do not significantly improve results
- In all models but one the lower values for recall are detected for category 4



XGBoost Confusion Matrix for Multiclassification with FastText. For all models but one, recall for category 4 is the lowest; entries are mostly misclassified as category 5. As category 4 is the “Trans” category and 5 is “Women”, this could be because of the similarity in the vocabulary for the two; hate speech against trans people often refers to terms relating to gender, such as “Woman”, “Men” or “Girl”.

# CLASSIFICATION PART 2: RESULTS

## BINARY CLASSIFICATION

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Algorithm	Accuracy
CNN W2V	0.6775
CNN FastText	0.6812
Bi-LSTM W2V	0.6952
Bi-LSTM FastText	0.6923

## MULTICLASS CLASSIFICATION

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Algorithm	Accuracy
CNN W2V	0.7587
CNN FastText	0.7652
Bi-LSTM W2V	0.8178
Bi-LSTM FastText	0.8296

# CLASSIFICATION PART 2: RESULTS

## BINARY CLASSIFICATION

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- Results for accuracy on pair with the best performance obtained by XGBoost with TF-IDF
- Overfitting: training stops as early as after 12 epochs
- Values of binary cross-entropy all higher than 0.56
- Improvement of recall values for Hate category
- Need for more complex (deeper) network structure to avoid overfitting

## MULTICLASS CLASSIFICATION

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- Results for accuracy lower than those obtained with TF-IDF
- Overfitting: training stops as early as after 16 epochs
- Values of categorical cross-entropy all higher than 0.54 and as high as 0.89
- Values of accuracy and recall lower or comparable than those of Part 1
- Need for more complex (deeper) network structure to avoid overfitting

# KEYWORDS AND KEYPHRASES: RESULTS

## ENGLISH

vs

## FRENCH

- WordClouds for Hate, NotHate and Specific Categories
- KeyBert for Hate, NotHate and the six hate categories
- BerTopic with documentation suggested pipeline



- KeyBert for “individual”, “other”, “arabs” and “african descent” categories
- BerTopic with documentation suggested pipeline

For both languages, KeyBert for key phrases and BerTopic use Keyphrase TfIdf Vectorizer.



# DATA PREPARATION

## ENGLISH

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- WordClouds: stopwords removal
- BerTopic: automatically removes stopwords

## FRENCH

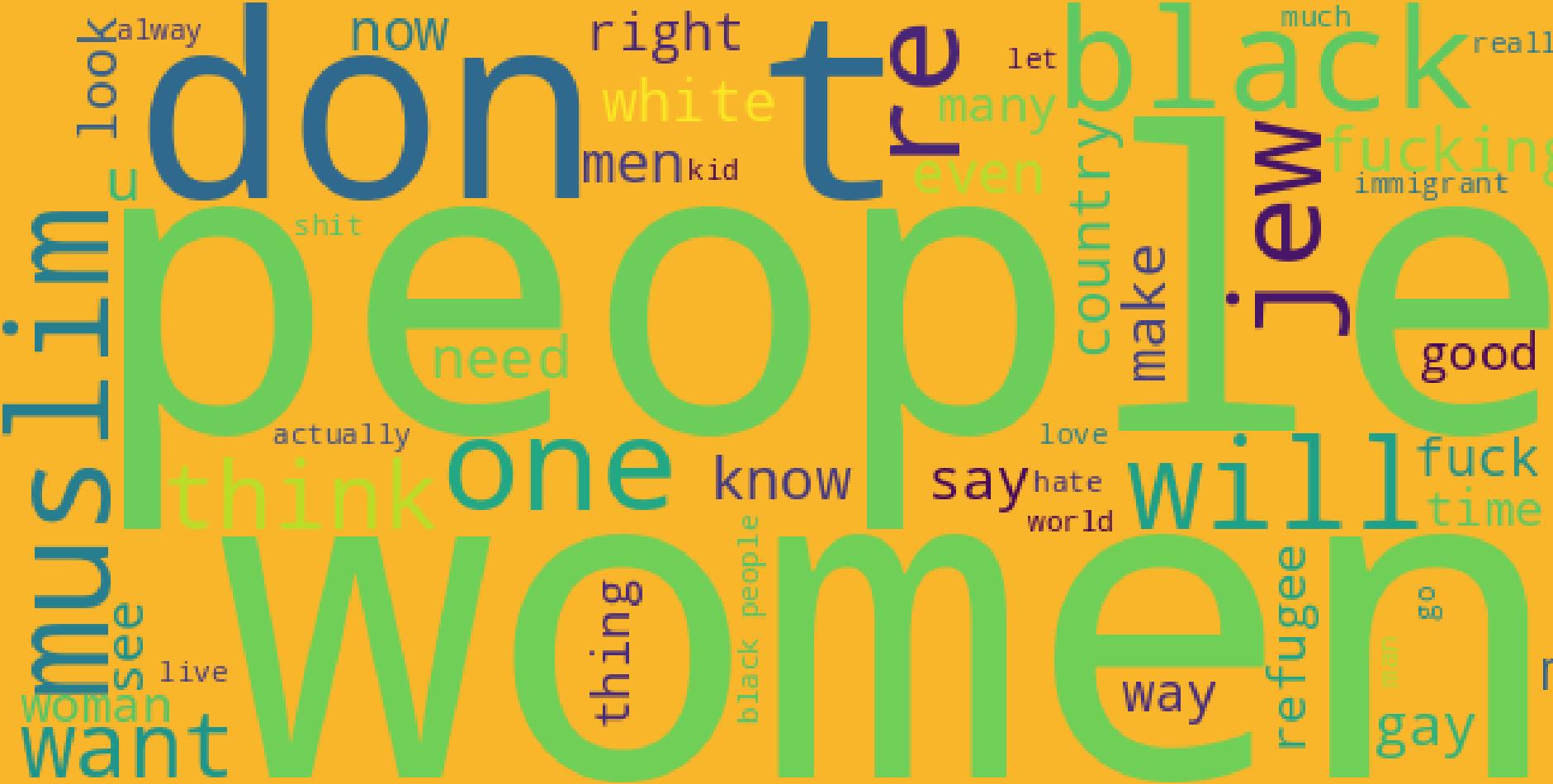
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- Text Cleaning
- BerTopic: automatically removes stopwords

DISCLAIMER: THE FOLLOWING SLIDES CONTAIN UNCENSORED DEROGATORY SPEECH AND SLURS, OFTEN VIOLENT IN NATURE.

# HATE CATEGORY CLOUD

WordClouds showed that both the Hate and NotHate category contain generic and neutral terms, category names, other than several overlapping terms.



# NO HATE CATEGORY CLOUD

**“People”, “women”, and “don’t” are three of the most common terms for both clouds; ulteriorly, the stopwords could have been expanded with terms such as “re”.**



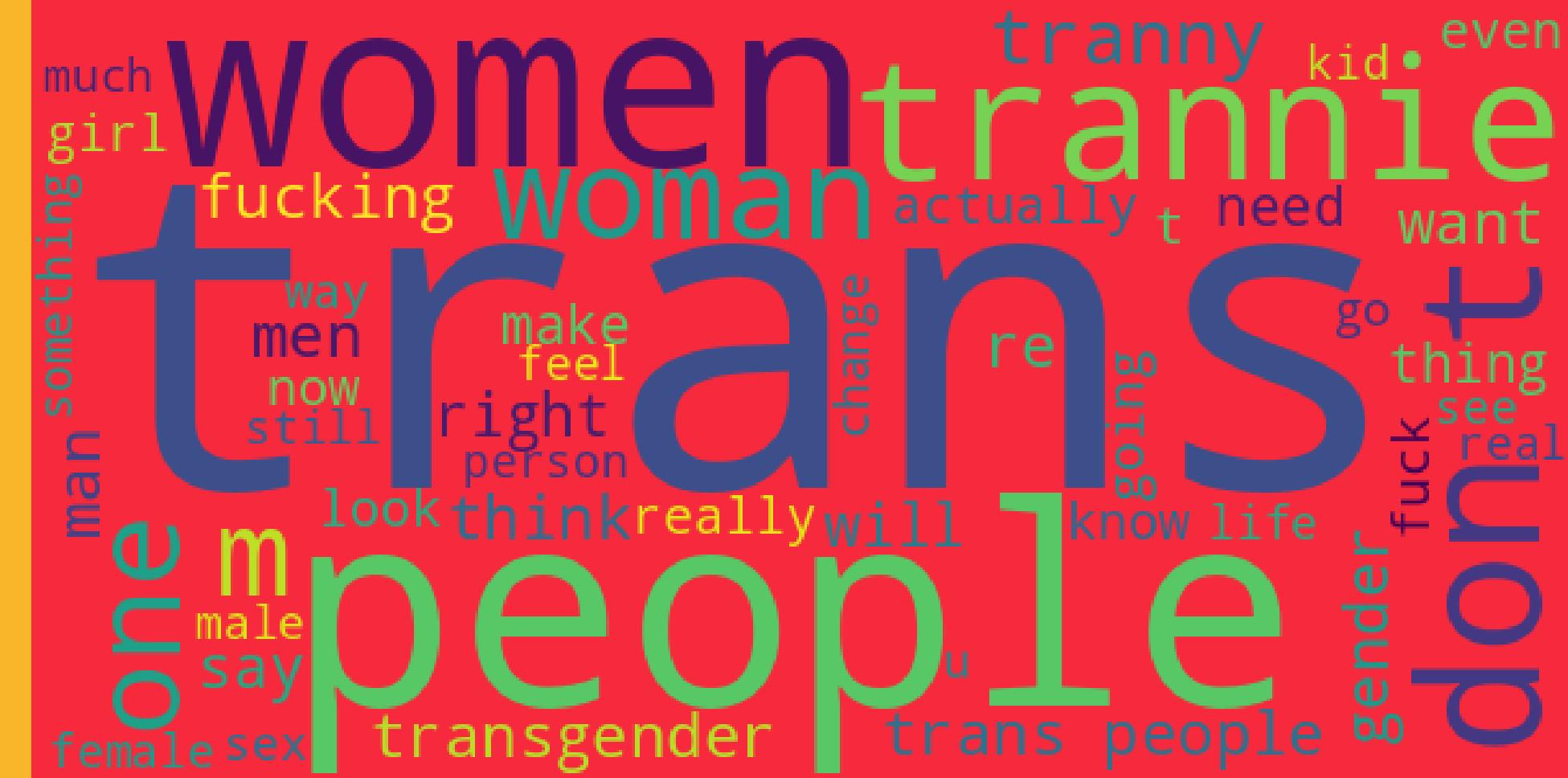
# JEWISH CATEGORY CLOUD

Slurs and insults are common, but also neutral terms such as “control” or “media”: sentiment polarity is not easy to integrate in hate speech detection



# TRANS CATEGORY CLOUD

Even specific categories can have overlapping vocabularies: hate speech for trans people is strongly related to the “women” category



# KEYBERT: ENGLISH

*"Immigrants dalits"*

*"Racists"*

*"Refugees"*

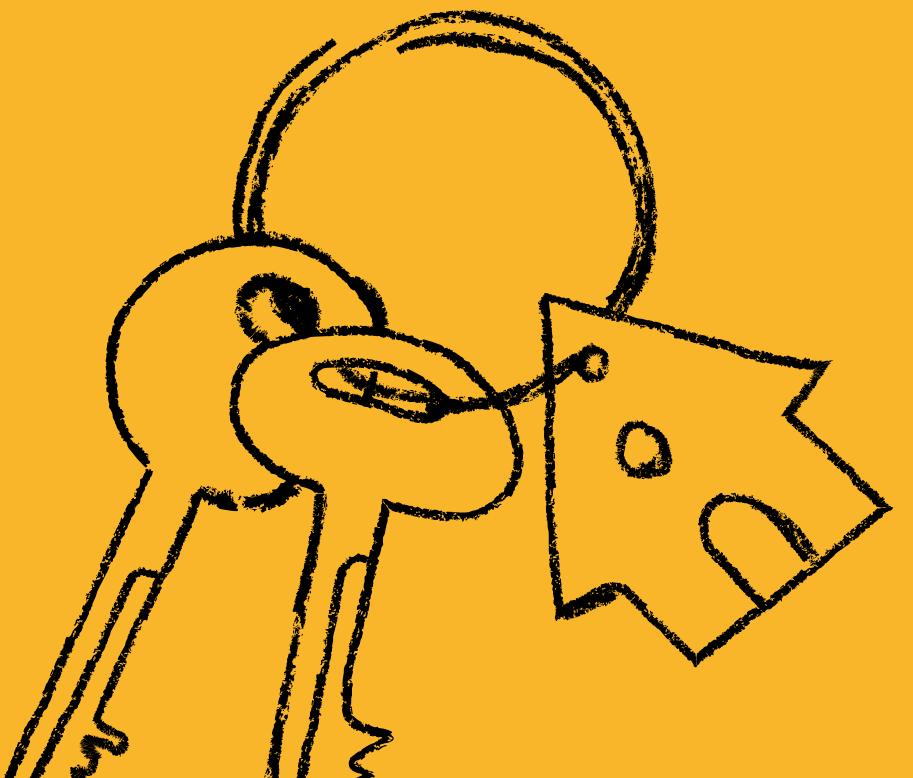
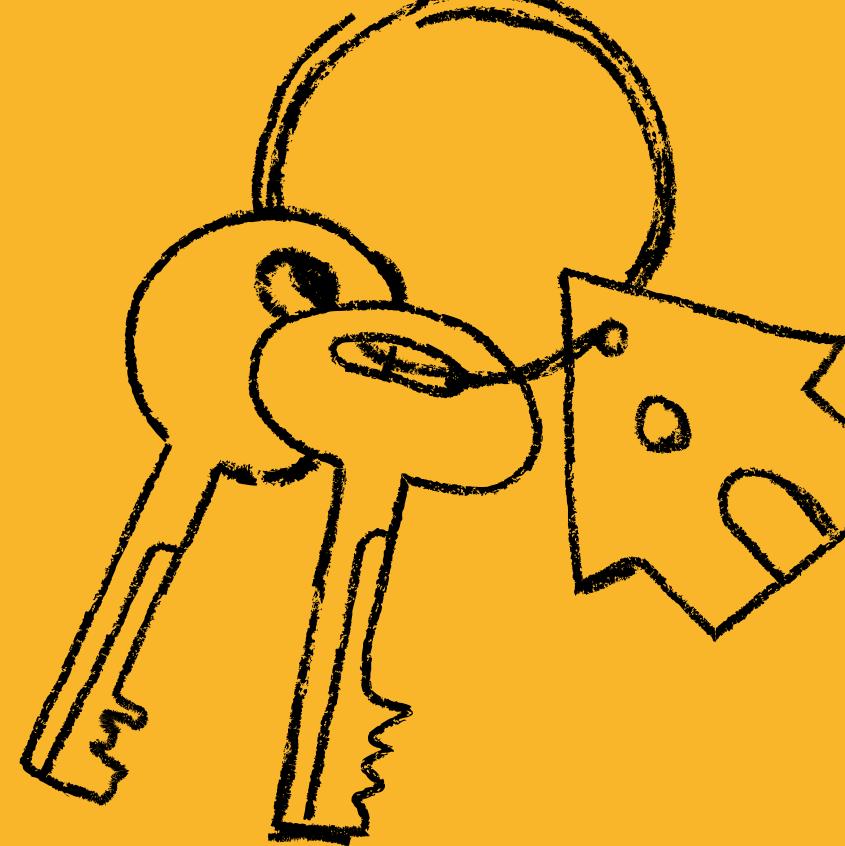
**HATE**

**NOT HATE**

*"Pakistanis"*

*"Cunts"*

*"Foreigners Disgusting"*



# KEYBERT: ENGLISH

## HATE SUBCATEGORIES

*“Feminist”*

*“Patriarchy”*

*“Islamophobia”*

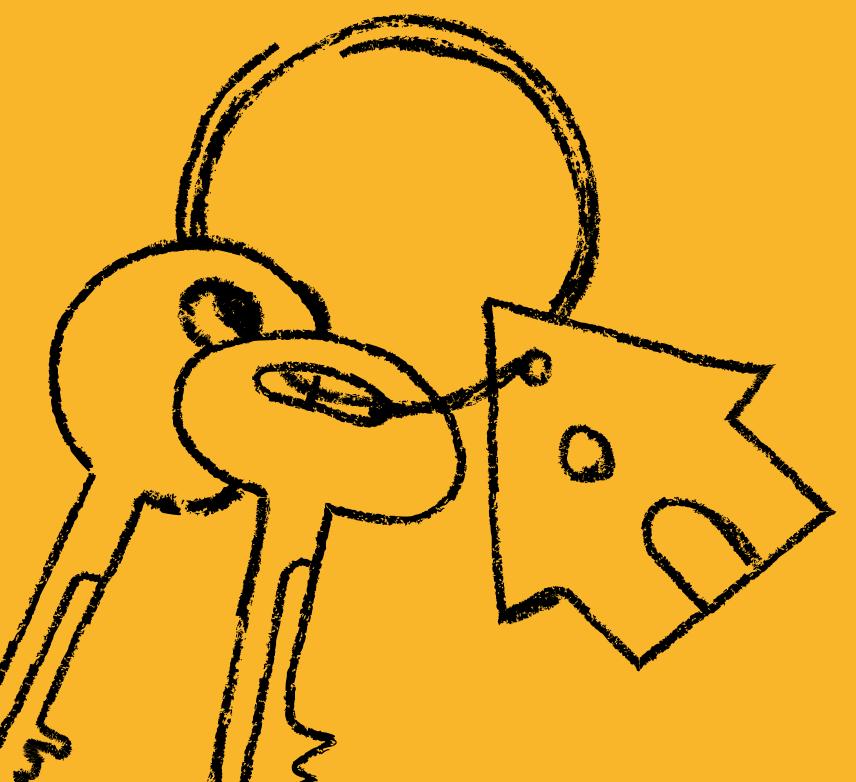
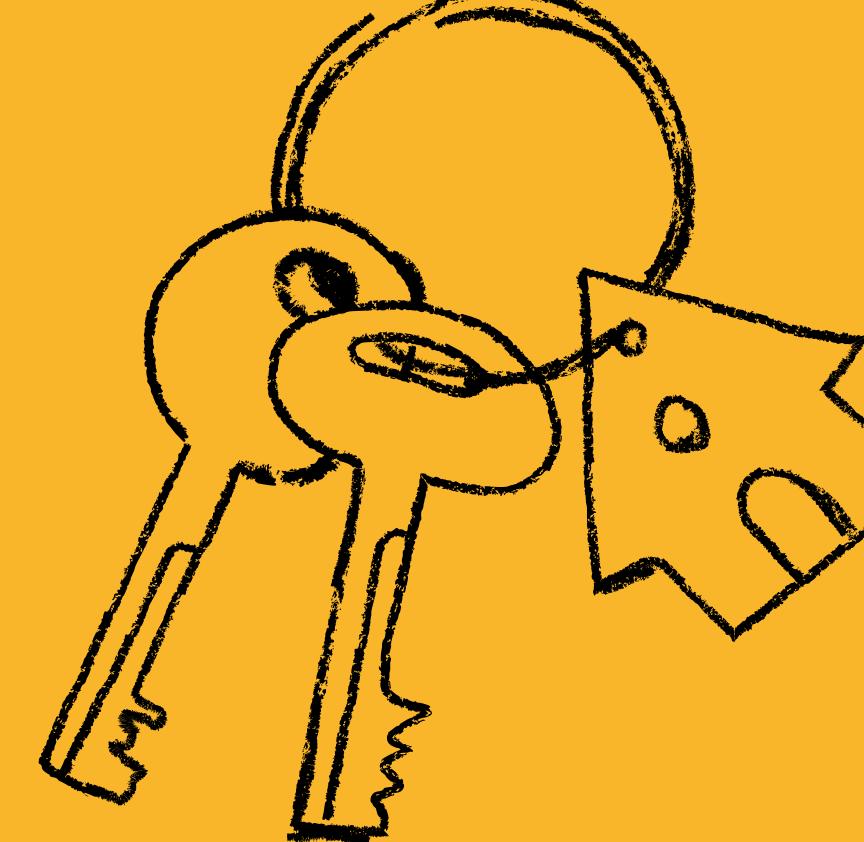
Words with clear and strict relationship with the topic

Insults, slurs, words with modified spelling, noun +  
derogatory insult combinations

*“Feminist bitch”*

*“Jewsss”*

*“Trans freaks”*



# KEYBERT: FRENCH

*“Mongole”*

*“Communiste”*

*“Arabe”*



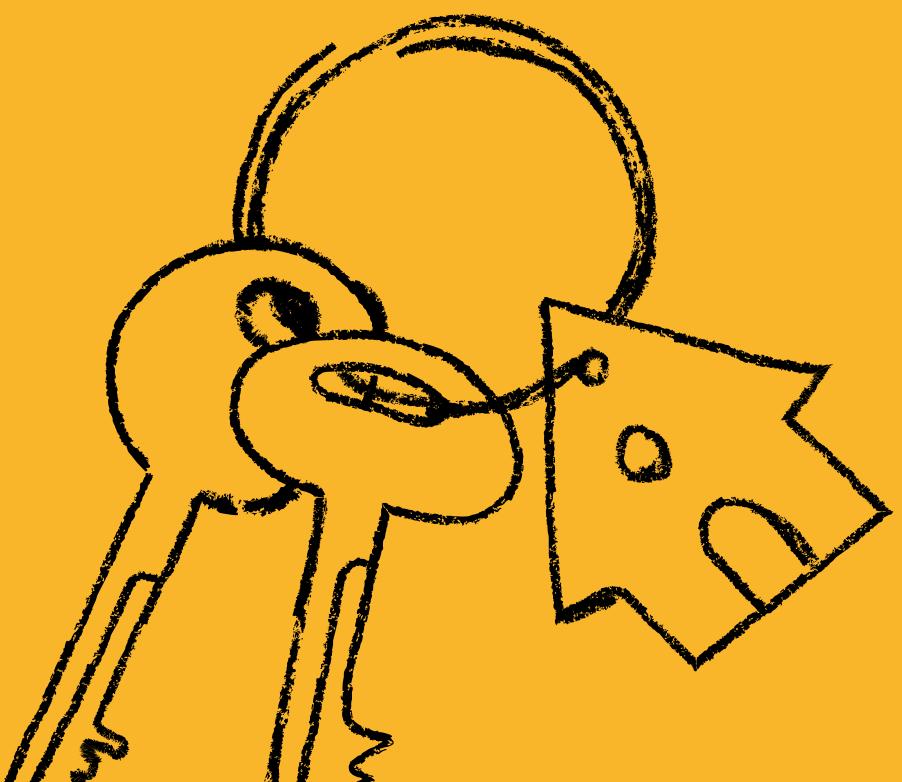
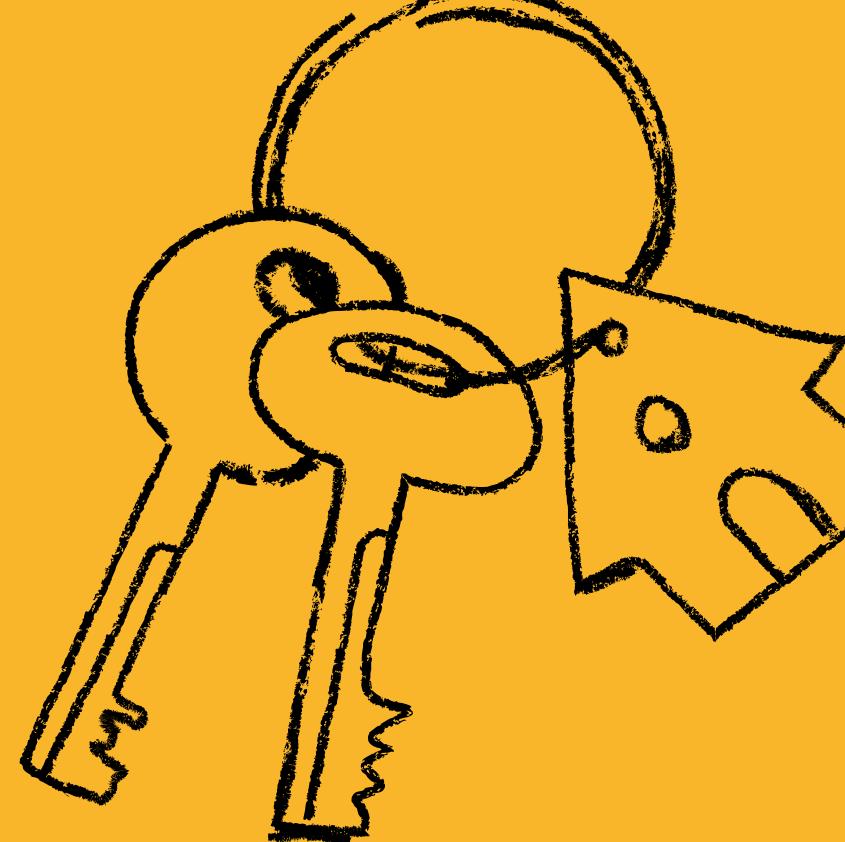
Insults and slurs are similarly detected; the dataset seem to contain more political references and ableist insults



*“Macron terrorisme”*

*“Vraiment mongol”*

*“Militantiste”*



# FRENCH VS ENGLISH

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Beside the presence of slurs and derogatory terms, we notice some detected key phrases have almost direct correspondence in the two languages.

“Sale arabe”

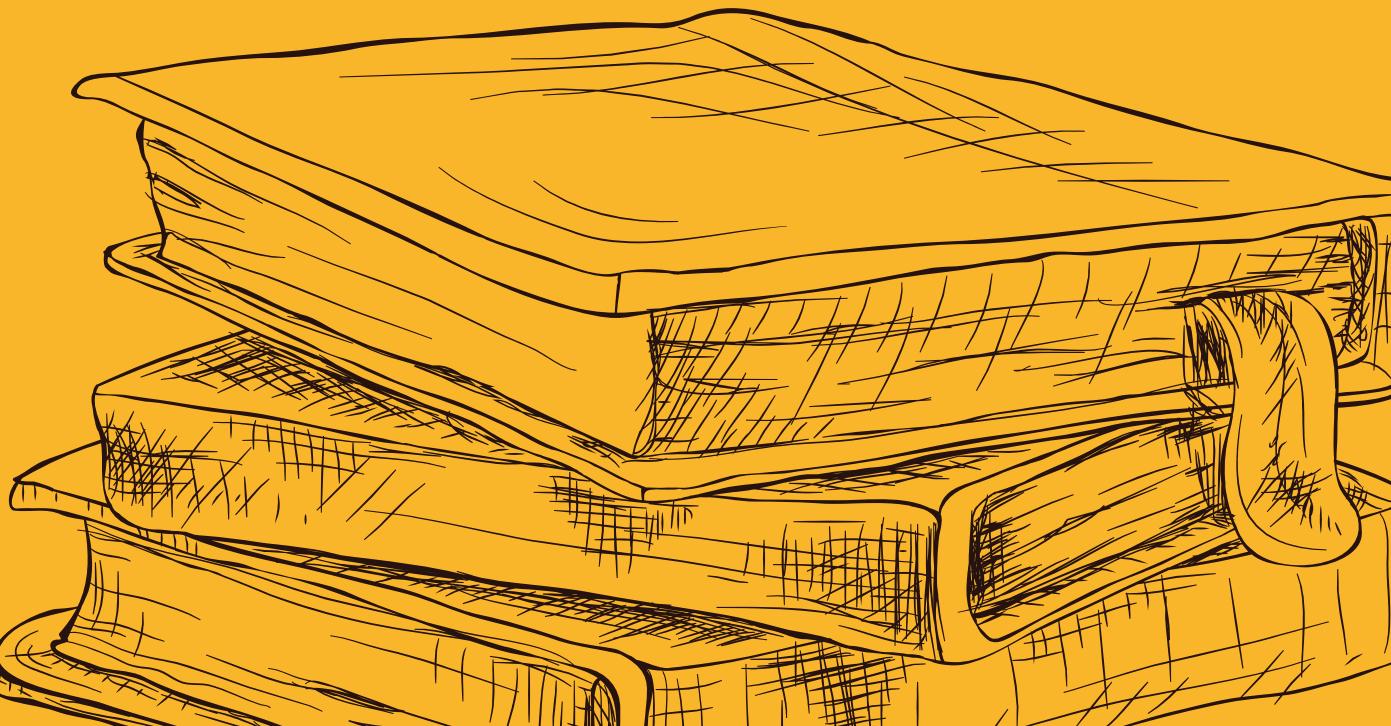
*Translates to*

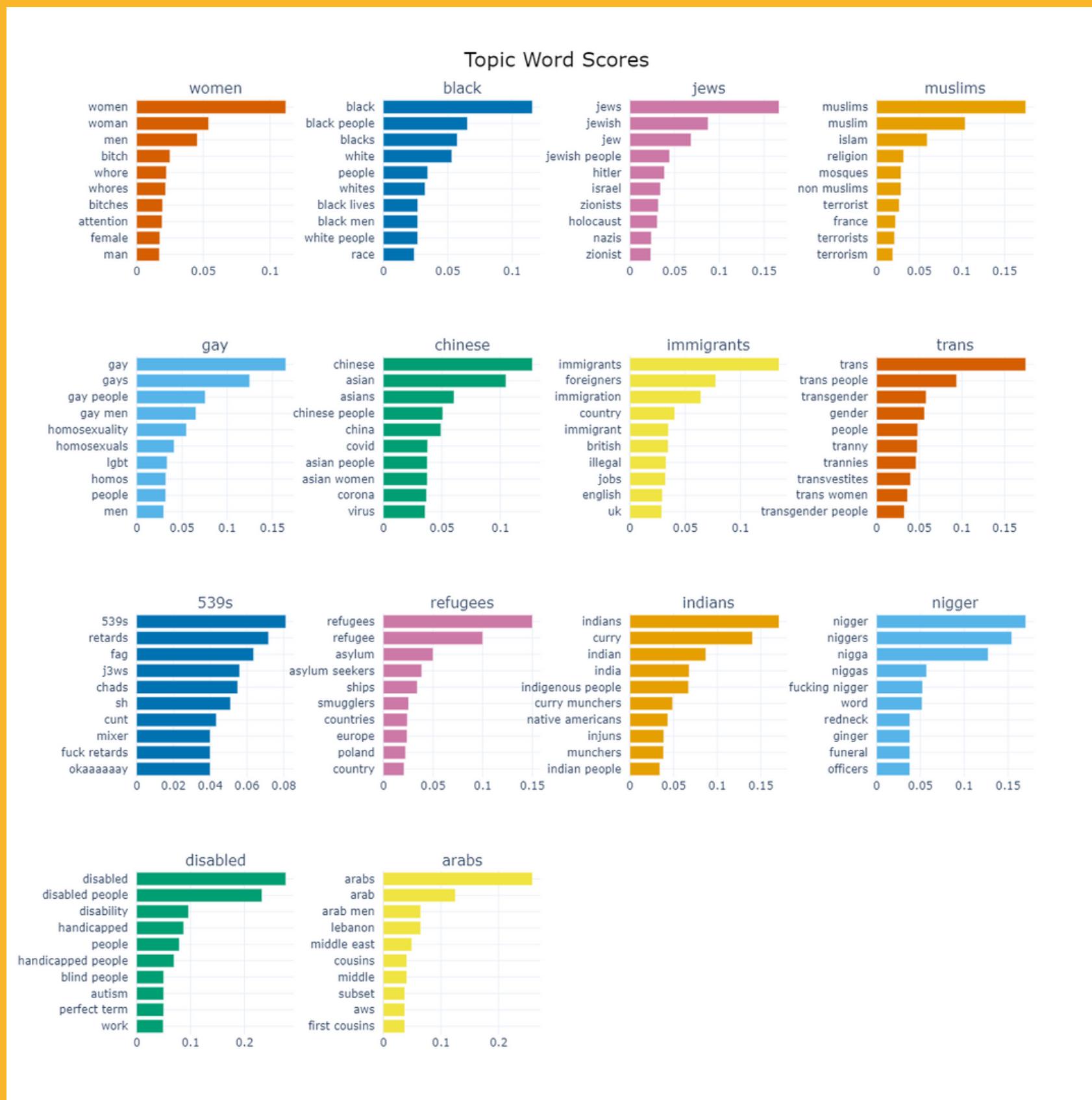
“Dirty arab”



*Similar in meaning to*

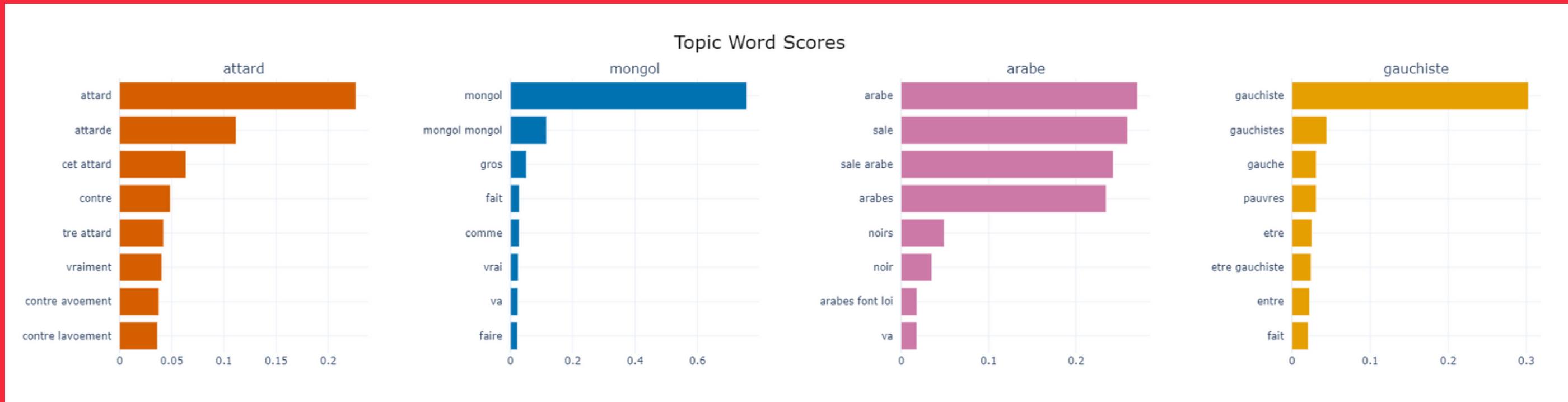
“Dirty Muslim”





## BERTOPIC: ENGLISH

- 14 Topics detected, with presence of similar ones that could be integrated
- One category of numbers, misspellings and social media terminology (“chad”)
- Coherence with previous findings and dataset category annotation
- Keywords connected to stereotypes: “Chinese” category contains “covid”, “Indians” contains “curry”
- Keywords connected to socio-political discussions: “officers” and “white” connected to Black people



## BERTOPIC:FRENCH

- 10 Topics are detected, but it shows the need for better text cleaning, specific to the French language: many of the detected words are generic, verbs or connectives
- As for English, some of the topics detected are duplicates, while the relevant keywords contain slurs and derogatory terms

# Conclusions

1

While Binary Classification can achieve 69% accuracy, Multiclass Classification reaches much better results (up to 90% accuracy)

2

This can be explained by the much more specific vocabulary of hate subcategories, while the Hate and NotHate category present many overlapping common terms

3

The presence of common terms with neutral meaning makes it difficult to integrate sentiment polarity in classification; more advanced techniques to leverage context and semantics should be implemented

4

A first step to improve this work could be taken by restricting the vocabulary for Binary Classification by removing common terms shared by the Hate and NotHate categories

**THANK YOU FOR YOUR  
ATTENTION!**

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# **TEXT MINING AND SENTIMENT ANALYSIS**

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