

The Comparison of Local and Global Early Fake News Detection Methods

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01

Project goals

Main goals

1. Comparison of different **topic detection** models.
2. Comparison of **fake news detection** methods.
3. Introduction of **local** fake news detection methods.
4. Evaluation of the **local** approach, and comparison to corresponding **global** solutions.
5. Exploration of models **differences** between the two strategies with the usage of **XAI**.



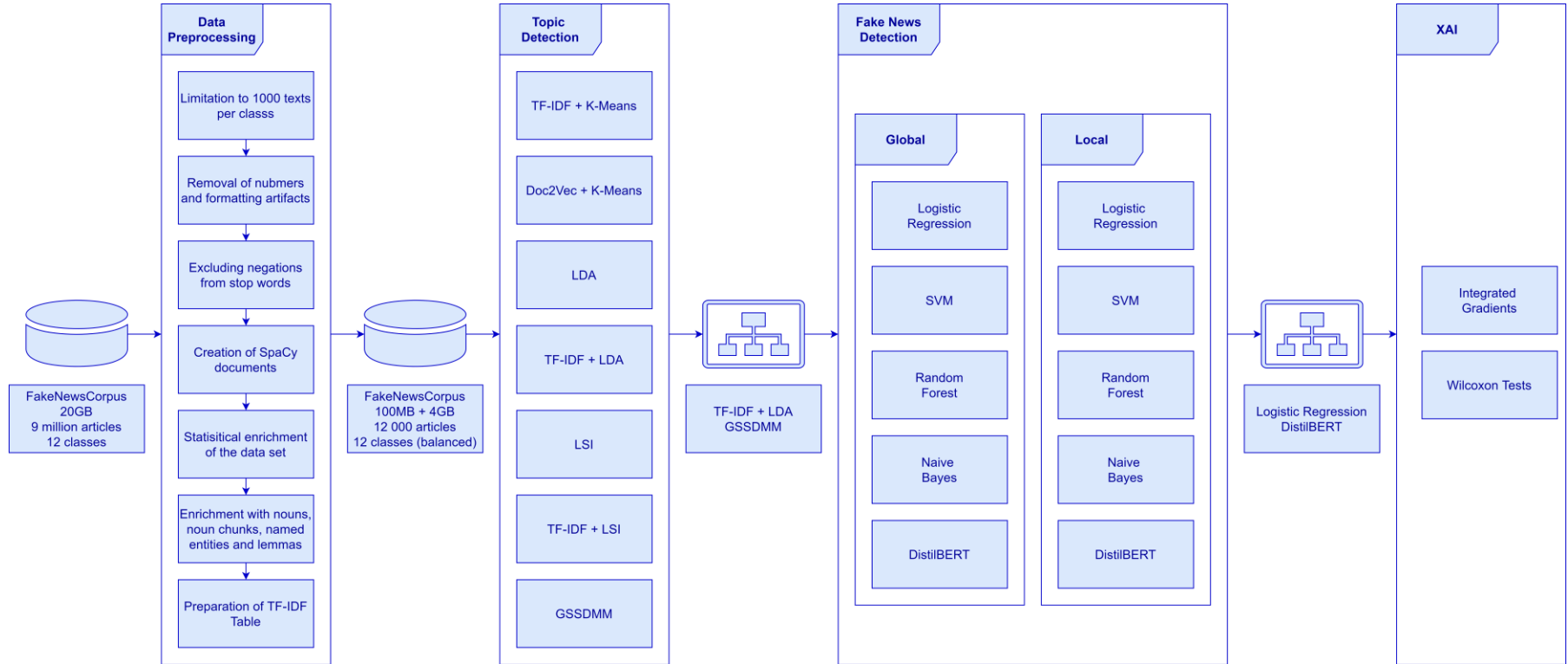
02

Proposed solution

Proposed solution

1. We used SOTA topic detection tools, namely: **K-Means**, **LDA**, **LSI**, and **GSSDMM**, based on **lemmas** and **noun chunks**.
2. We evaluated the clustering quality with SOTA approaches mentioned in the Literature Review, namely: **Coherence Score**, **Silhouette Score**, and **Calinski-Harabsz Index**.
3. We prepared a **train-test split** with regard to particular clusters (ex. 70% - 30%: training – testing).
4. We prepared a few (5) SOTA solutions for fake news detection methods, namely: **Logistic Regression**, **SVM**, **Random Forest**, **Naive Bayes**, and **DistilBERT**.
5. We trained and evaluated them on a **global** split.
6. We trained and evaluated them on **local** clusters.
7. We compared the results of global and local models in terms of **performance**.
8. We used **eXplainable AI (XAI)** methods to discover the most important indicators for global and local methods.

Proposed solution

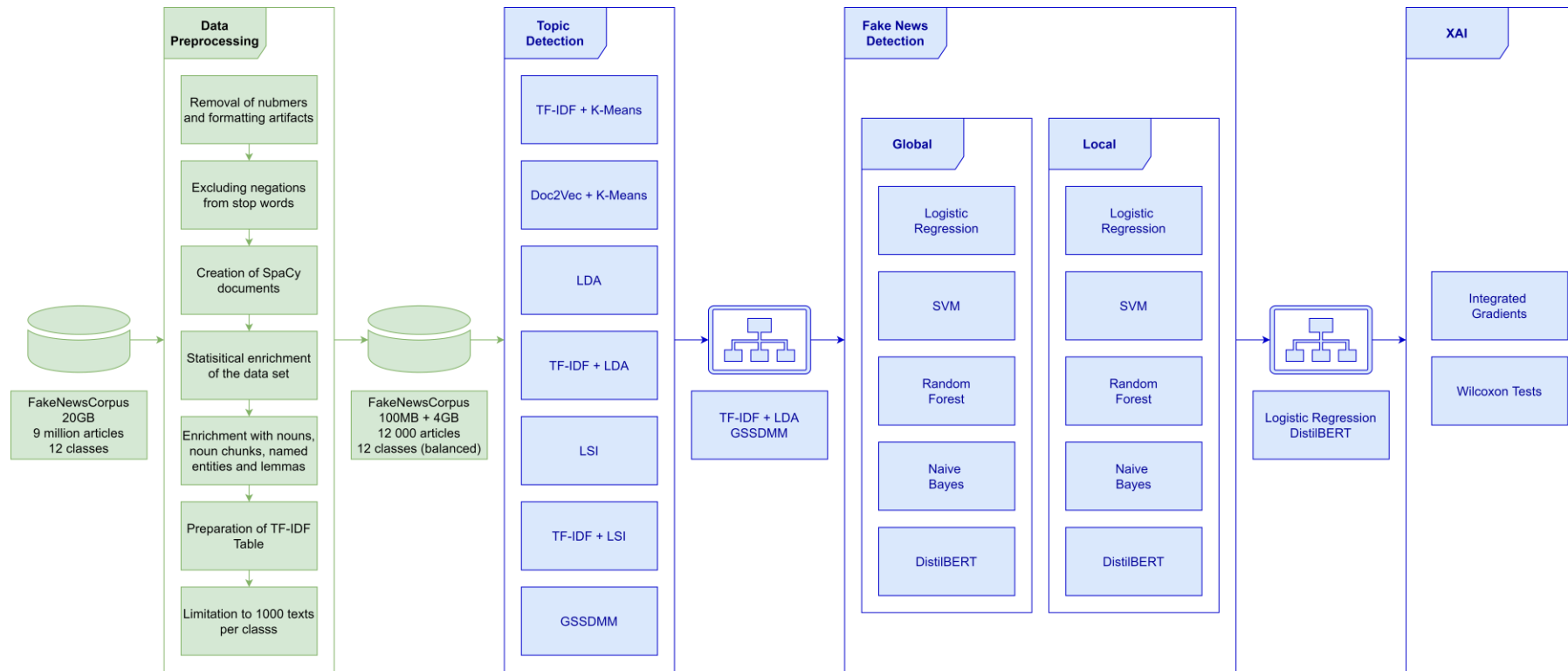




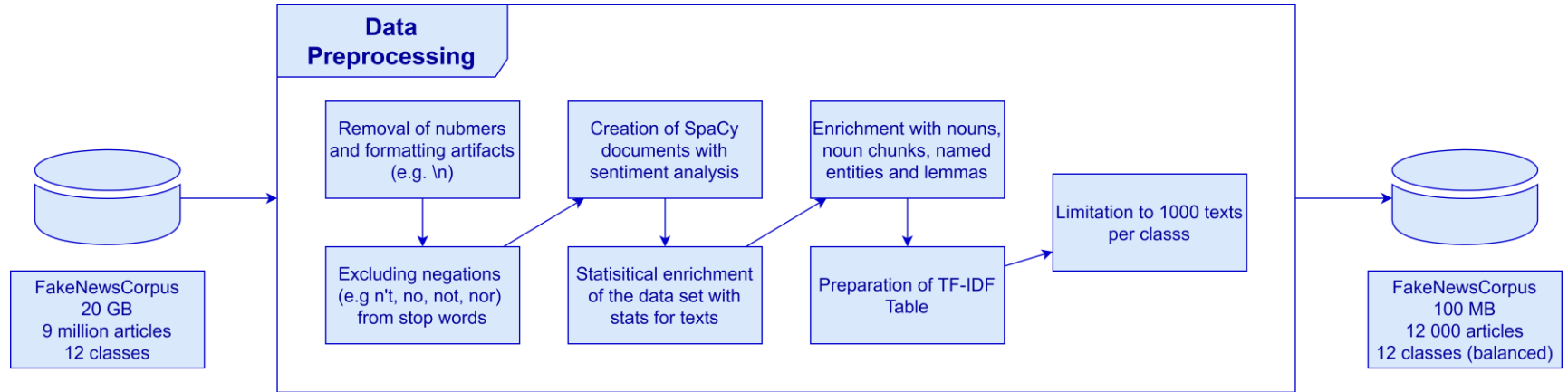
03

Data preprocessing + EDA

Proposed solution

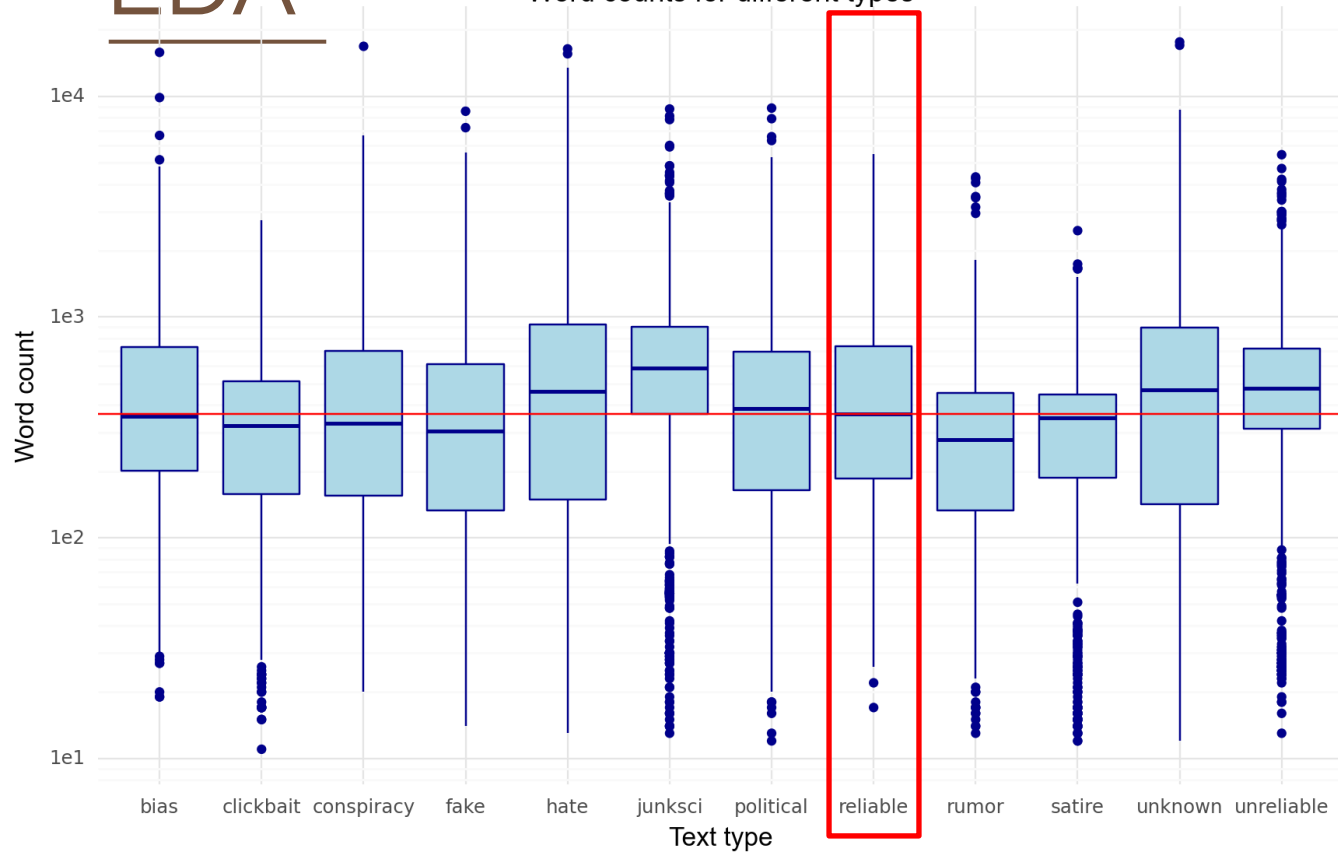


Preprocessing design

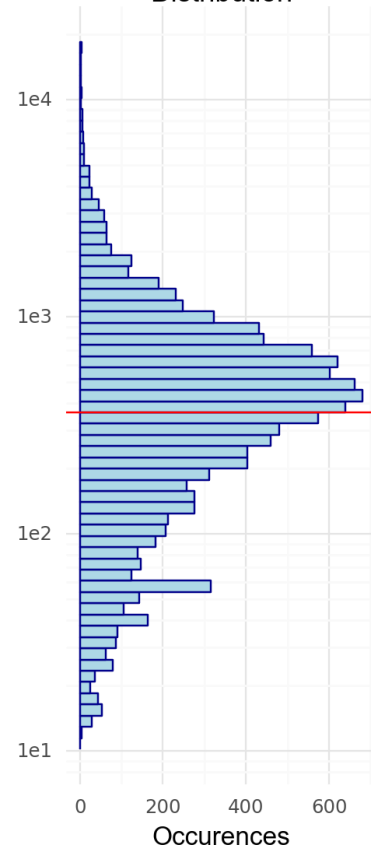


EDA

Word counts for different types

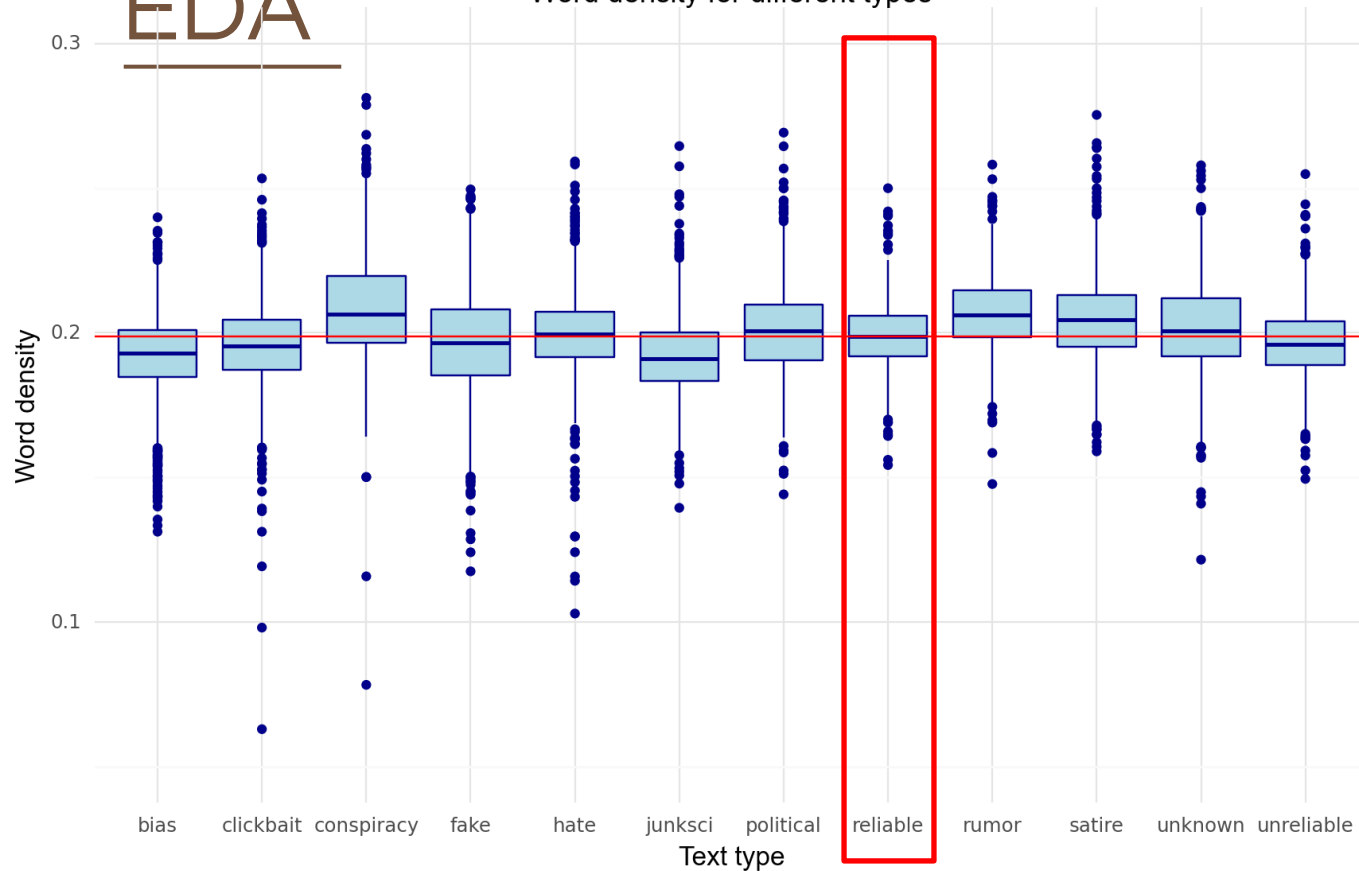


Distribution

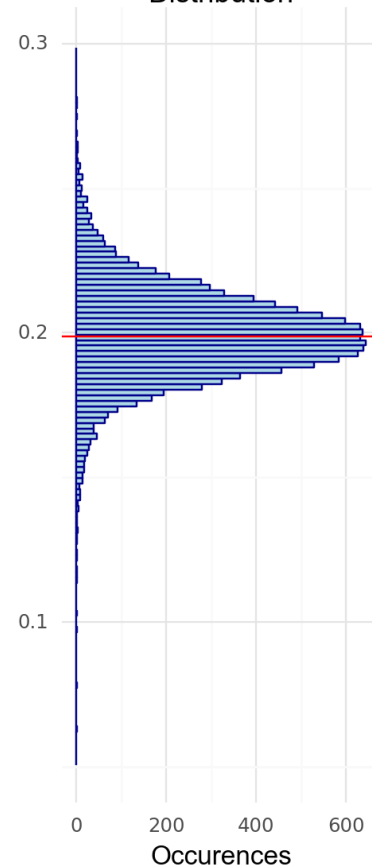


EDA

Word density for different types

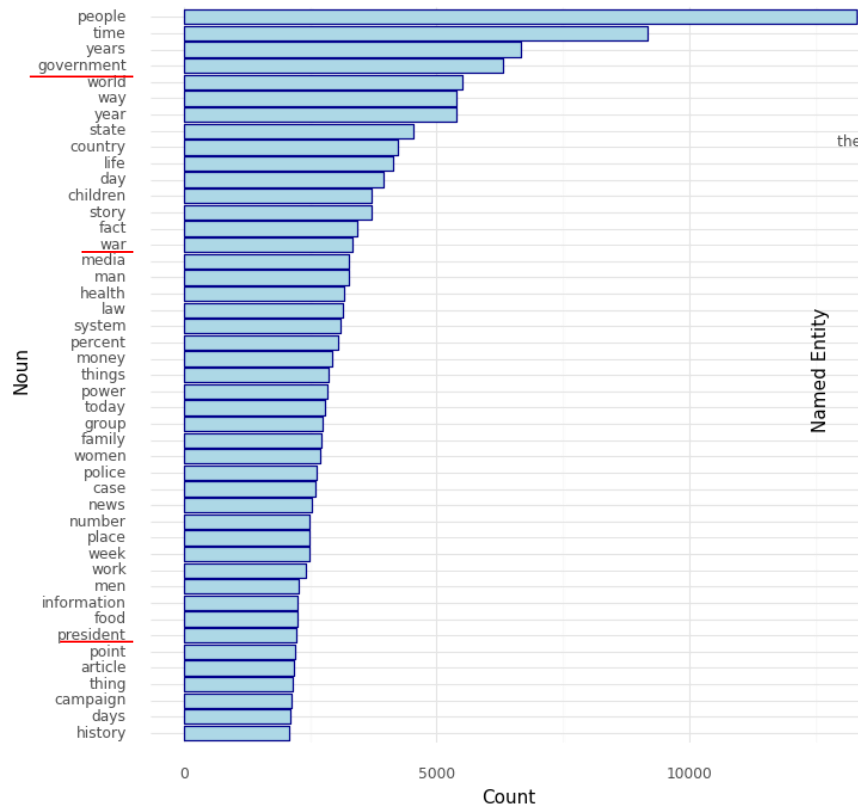


Distribution

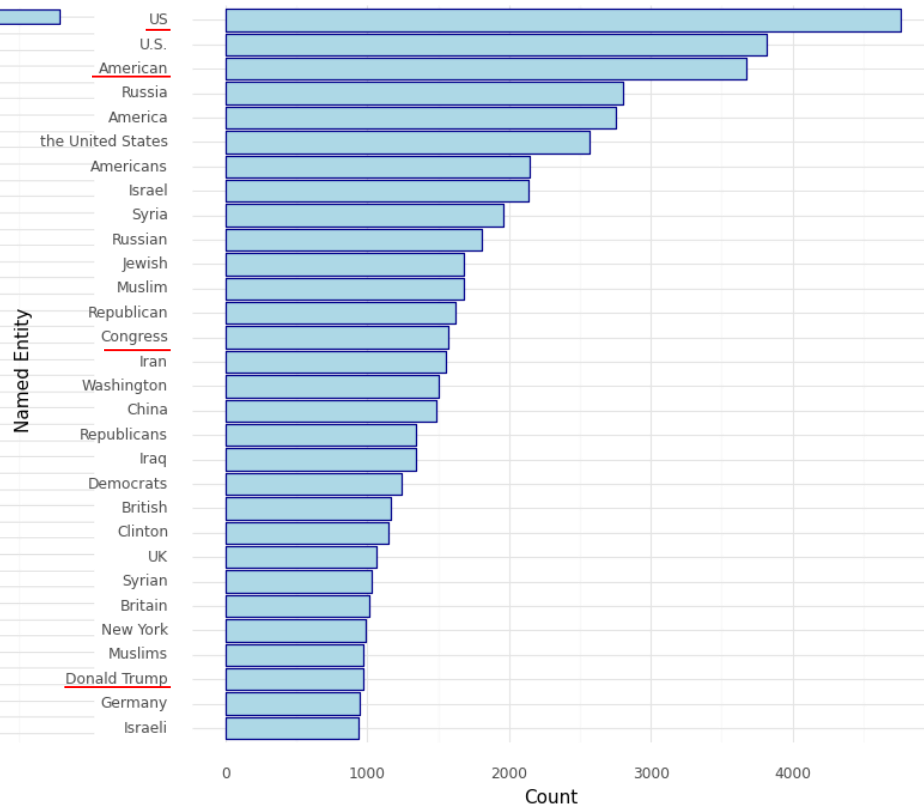


EDA

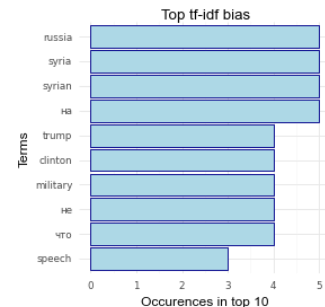
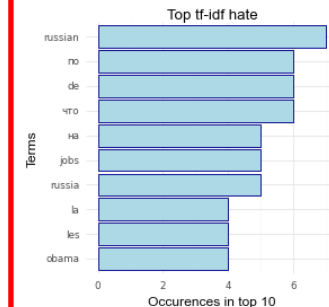
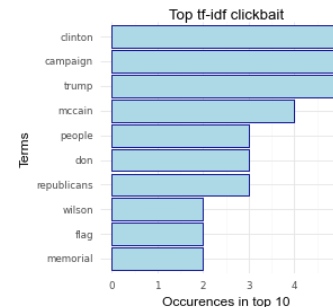
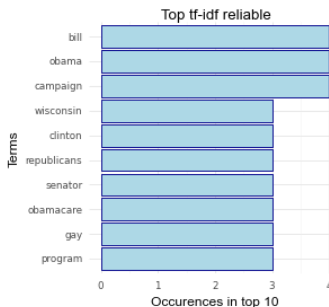
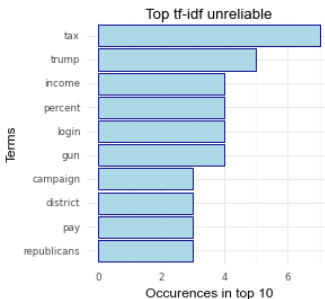
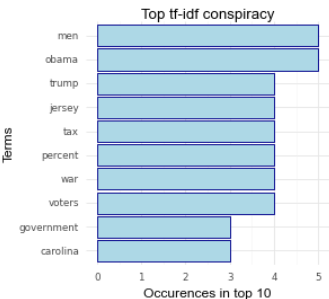
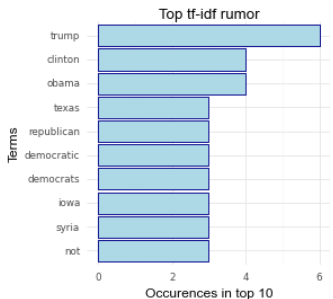
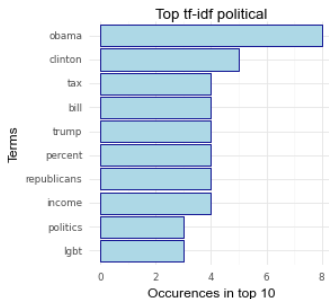
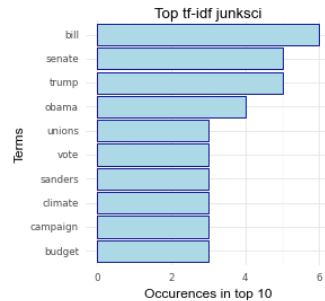
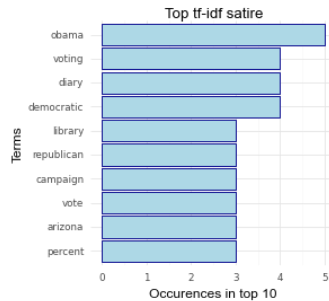
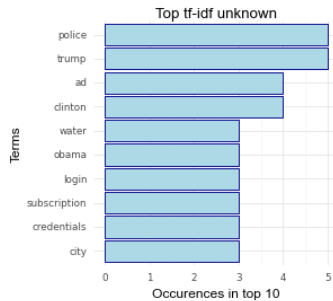
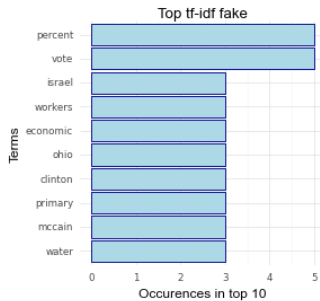
The most popular nouns



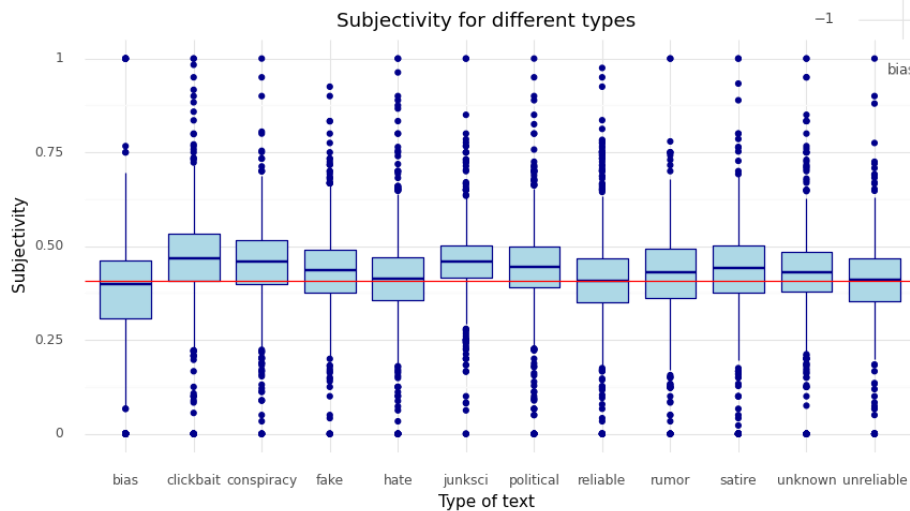
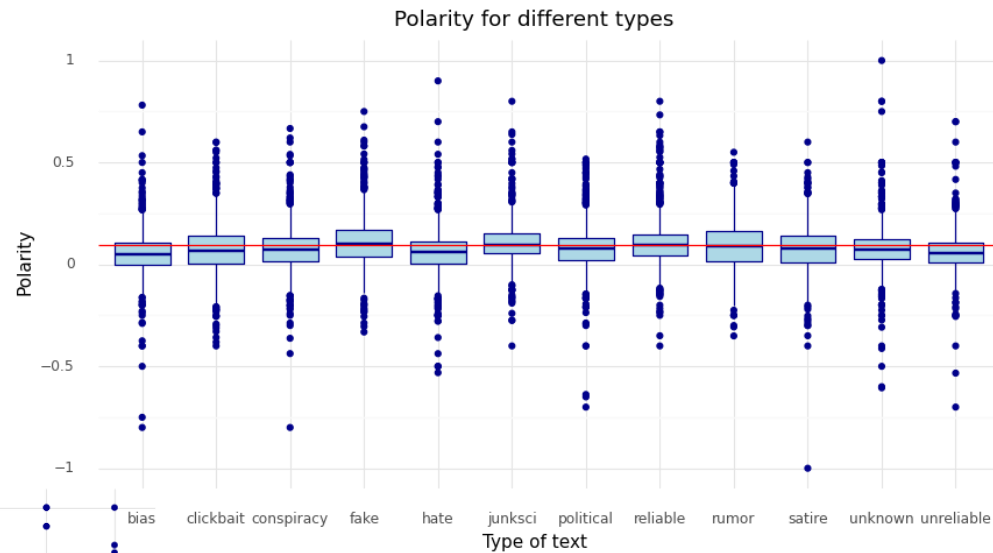
Most common named entities



EDA



EDA

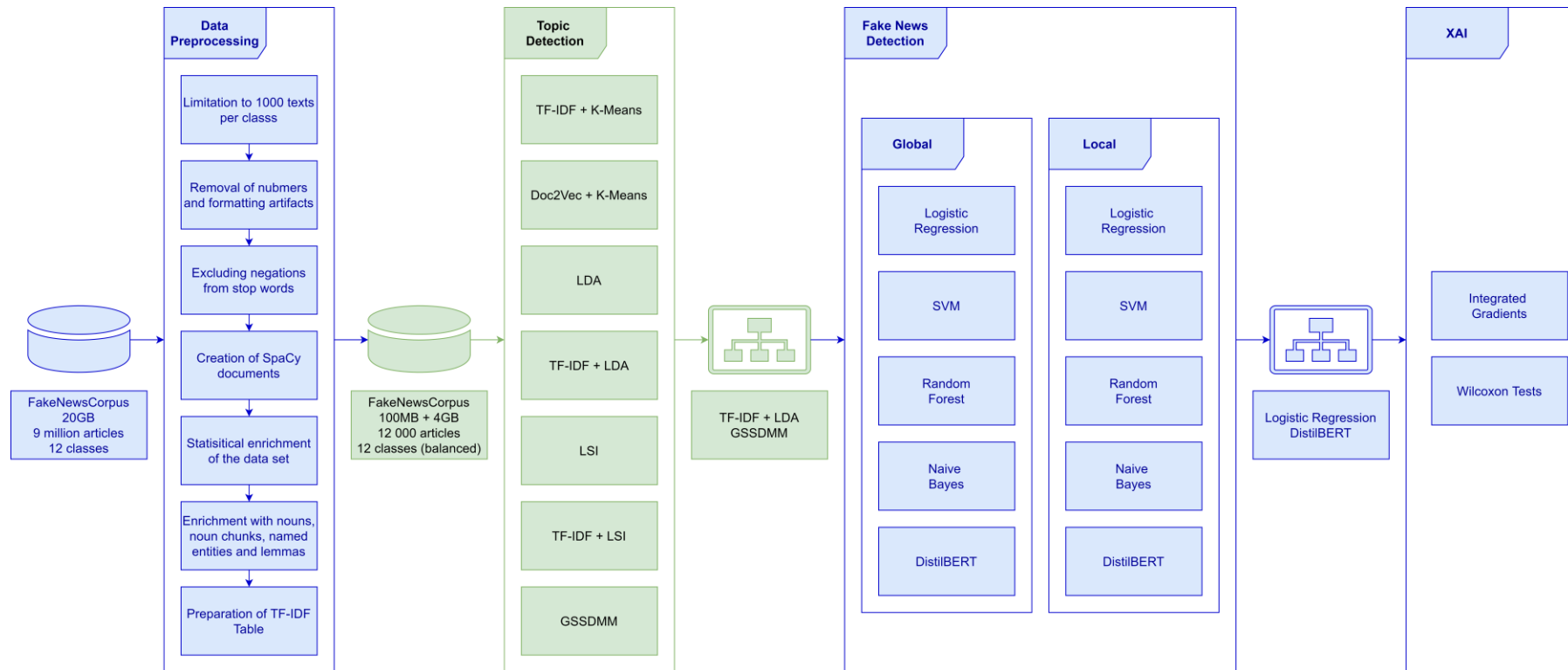




04

Topic Detection / Clustering

Experimental design

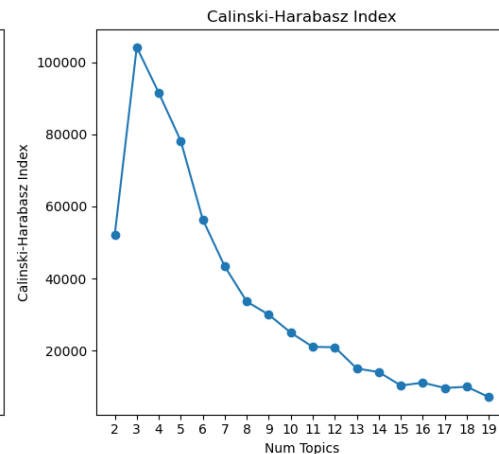
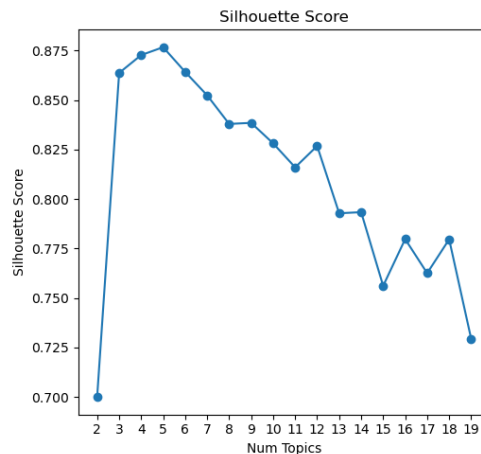
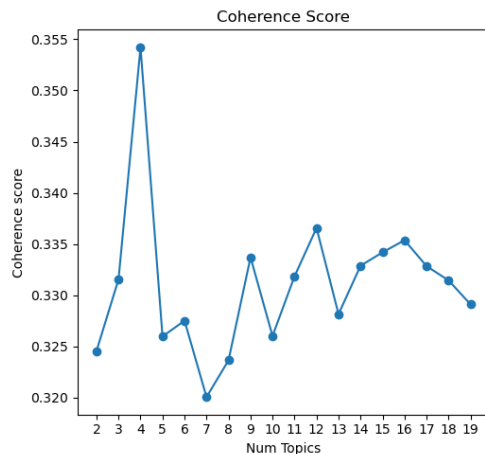


Used Methods

1. Classical clustering method with two document representations:
 - a. Doc2Vec + k-means
 - b. TF-IDF + k-means
2. Topic modeling method:
 - c. Latent Dirichlet Allocation (LDA)
 - d. Latent Semantic Indexing (LSI)
 - e. Gibbs Sampling Dirichlet Multinomial Mixture (GSSDMM)
3. Clustering performed on extracted noun chunks and lemmas.

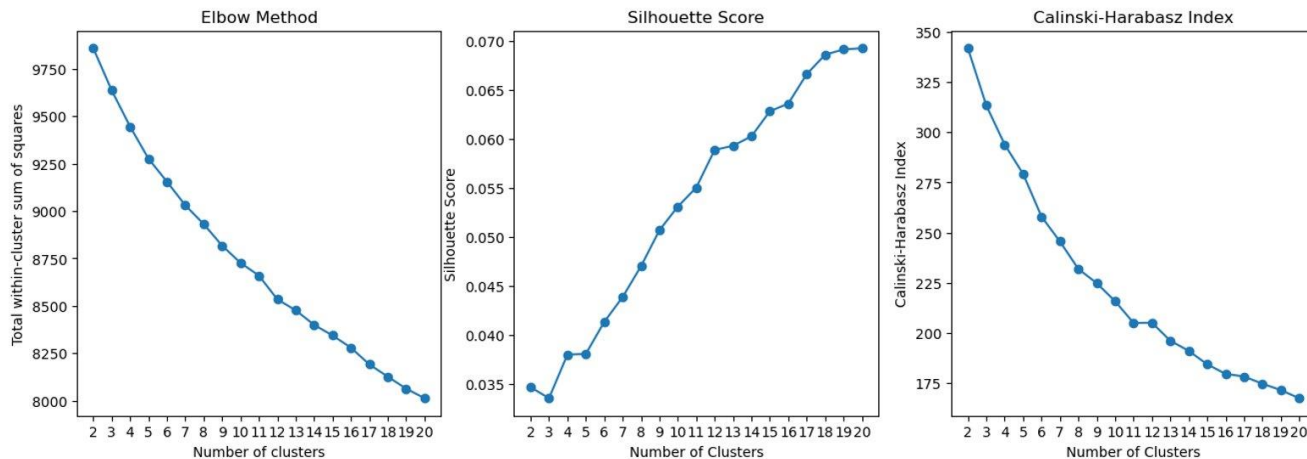
Choosing number of clusters

Metrics for TF-IDF + LDA clustering



Choosing number of clusters

Metrics for TF-IDF + k-means clustering



Results - lemmas

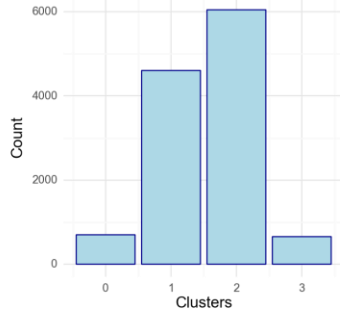
Clustering Algorithm	Silhouette Score	Calinski-Harabasz Score
TF-IDF + K-Means	0.038	293.9
Doc2Vec + K-Means	0.134	449.6
LDA	0.607	18668.8
TF-IDF + LDA	0.873	91490.7
LSI	-0.320	49.5
TF-IDF + LSI	0.469	1655.9
GSSDMM	0.714	529.4

Results – noun chunks

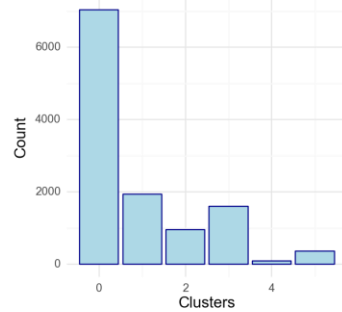
Clustering Algorithm	Silhouette Score	Calinski-Harabasz Score
TF-IDF + K-Means	0.067	314.1
Doc2Vec + K-Means	0.386	3473.24
LDA	0.883	110432.1
TF-IDF + LDA	0.929	323993.32
LSI	-0.512	132.0
TF-IDF + LSI	-0.290	393.5
GSSDMM	0.867	15681.4

Results

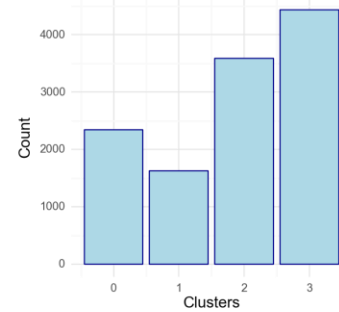
Cluster Distribution for TF-IDF + K-Means



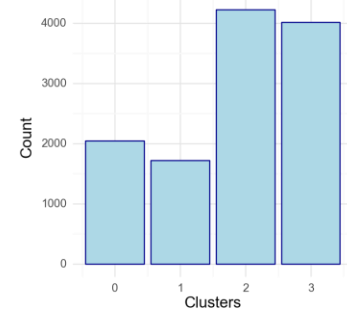
Cluster Distribution for Doc2Vec + K-Means



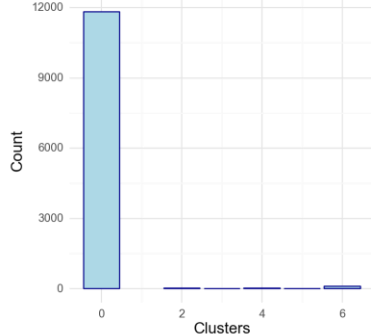
Cluster Distribution for LDA



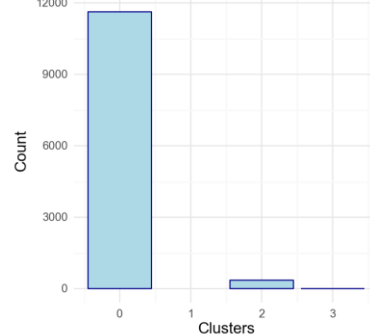
Cluster Distribution for TF-IDF + LDA



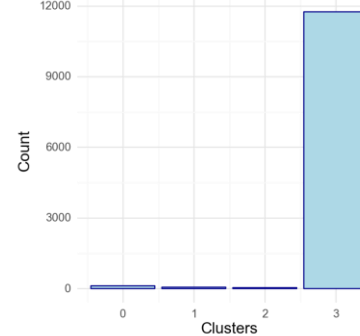
Cluster Distribution for LSI



Cluster Distribution for TF-IDF + LSI



Cluster Distribution for GSSDMM



Results

Diving into GSDMM clusters.

Most frequent nouns in cluster 4:

1. Trump
2. Obama
3. people
4. Congress
5. Republicans
6. America
7. Donald Trump
8. Democrats
9. Clinton
10. Hillary Clinton

Most frequent nouns in cluster 0:

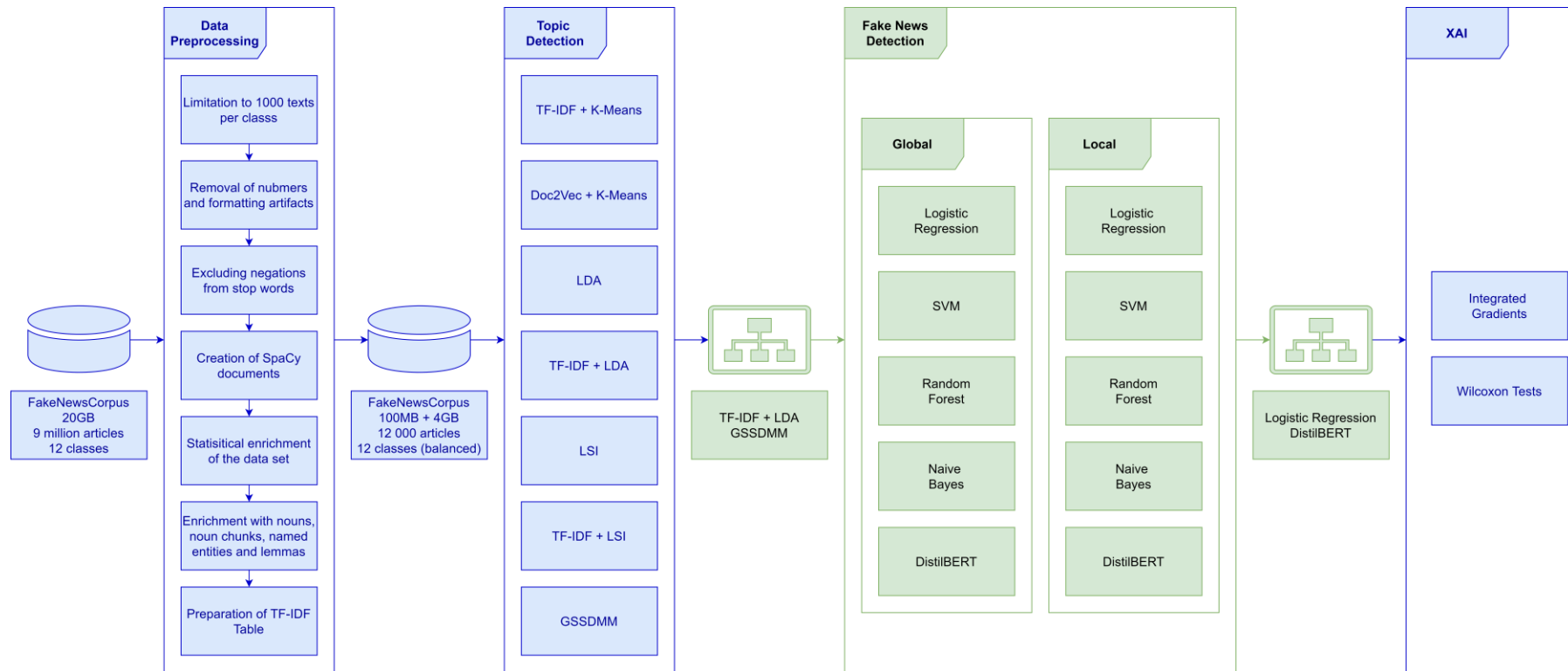
1. Russia
2. Syria
3. Israel
4. people
5. Iran
6. Iraq
7. Europe
8. China
9. Britain
10. ISIS



05

Fake News Detection

Experimental design



Tokenization

- Lowering the case of the entire string
- Adding special tokens to mark the start and end of the string
- Splits uncommon words into several tokens

"tokenizer" -> "token" + "##izer"

- Punctuation removal
- Separating input text into individual sentences
- Removal of unnecessary whitespaces
- Padding and truncating

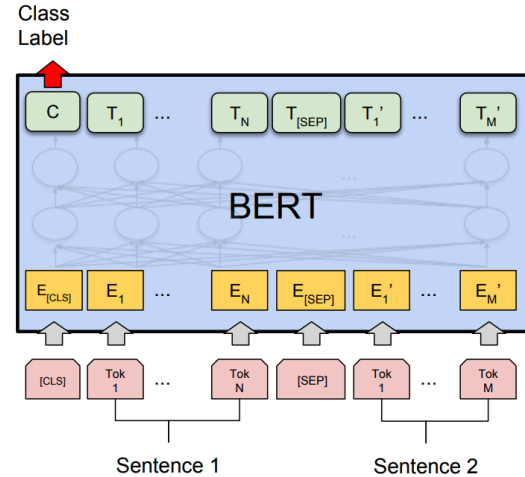
Model choice

1. Statistical models

- Logistic regression
- Support Vector Machines
- Random Forest
- Naive Bayess

2. Transformers

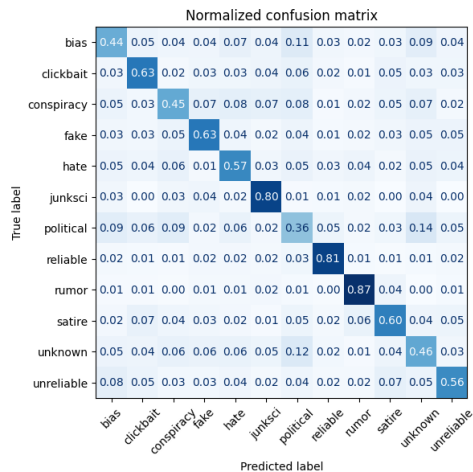
- DistilBERT



Results

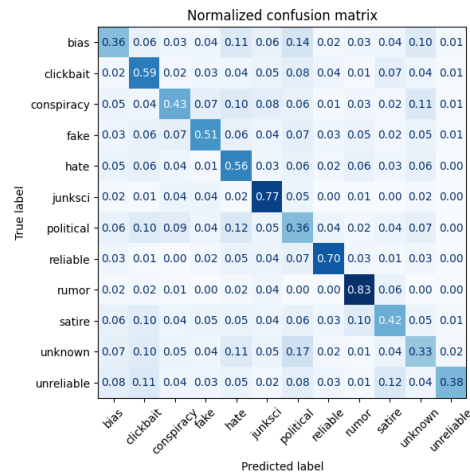
Before topic detection

Logistic regression



Accuracy = 0.598

SVM

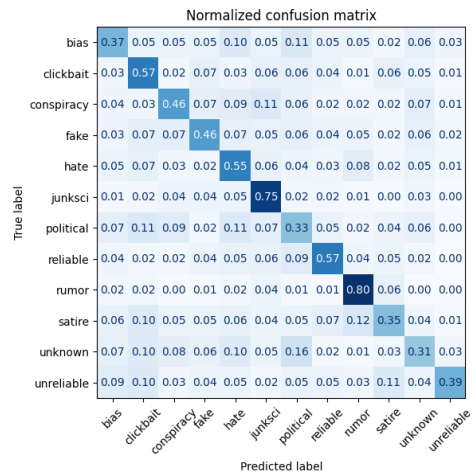


Accuracy = 0.518

Results

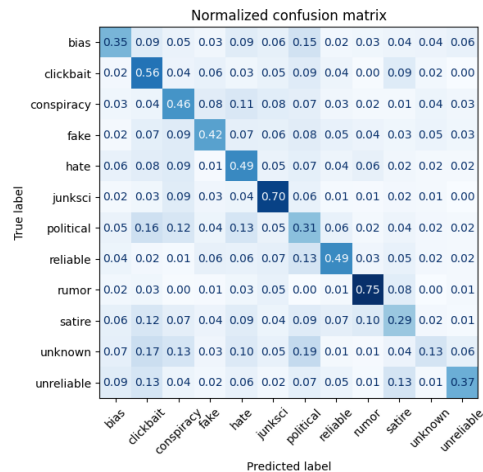
Before topic detection

Random forest



Accuracy = 0.491

Naive Bayes

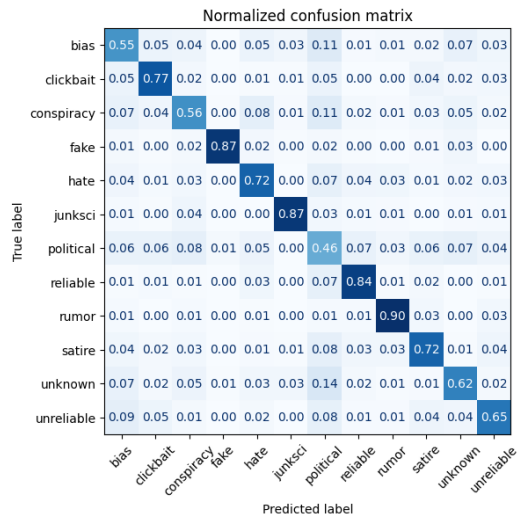


Accuracy = 0.444

Results

Before topic detection

DistilBert

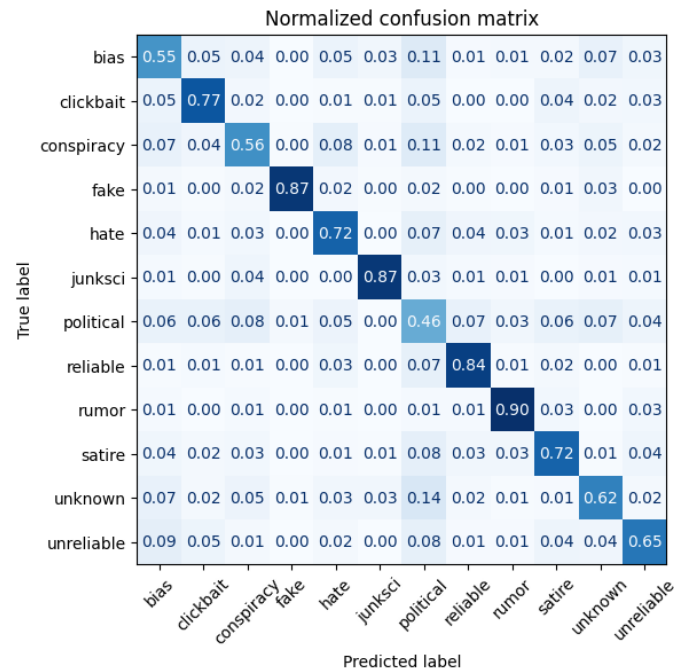


Accuracy = 0.710

Results

Clustering results

Weighted accuracy = accuracy * size / sum(size)



	bias	clickbait	conspiracy	fake	hate	junksci	political	reliable	rumor	satire	unknown	unreliable	accuracy	accuracy w/o political	size
0	0.44	0.61	0.41	0.49	0.61	0.61	0.38	0.74	0.77	0.51	0.41	0.50	0.54	0.58	2995
1	0.29	0.60	0.46	0.42	0.36	0.74	0.28	0.68	0.78	0.49	0.40	0.46	0.50	0.55	2862
2	0.47	0.58	0.45	0.53	0.52	0.63	0.33	0.68	0.79	0.56	0.42	0.51	0.53	0.59	2981
3	0.29	0.62	0.38	0.57	0.68	0.75	0.28	0.76	0.81	0.38	0.27	0.46	0.52	0.59	3162

Results

LDA clustering

Logistic regression

Weighted accuracy = 0.523

	bias	clickbait	conspiracy	fake	hate	junksci	political	reliable	rumor	satire	unknown	unreliable	accuracy	accuracy without political	size
0	0.44	0.61	0.41	0.49	0.61	0.61	0.38	0.74	0.77	0.51	0.41	0.50	0.54	0.58	2995
1	0.29	0.60	0.46	0.42	0.36	0.74	0.28	0.68	0.78	0.49	0.40	0.46	0.50	0.55	2862
2	0.47	0.58	0.45	0.53	0.52	0.63	0.33	0.68	0.79	0.56	0.42	0.51	0.53	0.59	2981
3	0.29	0.62	0.38	0.57	0.68	0.75	0.28	0.76	0.81	0.38	0.27	0.46	0.52	0.59	3162

DistilBERT

Weighted accuracy = 0.619

	bias	clickbait	conspiracy	fake	hate	junksci	political	reliable	rumor	satire	unknown	unreliable	accuracy	accuracy without political	size
0	0.53	0.70	0.53	0.92	0.71	0.78	0.52	0.60	0.87	0.54	0.49	0.63	0.65	0.70	2995
1	0.37	0.74	0.61	0.89	0.55	0.80	0.17	0.72	0.82	0.71	0.57	0.47	0.63	0.69	2862
2	0.49	0.64	0.56	0.82	0.57	0.80	0.34	0.65	0.76	0.70	0.43	0.46	0.59	0.67	2981
3	0.30	0.79	0.33	0.88	0.74	0.91	0.54	0.78	0.78	0.37	0.48	0.43	0.61	0.71	3162

Results

GSDMM clustering

Logistic regression

	bias	clickbait	conspiracy	fake	hate	junksci	political	reliable	rumor	satire	unknown	unreliable	accuracy	accuracy without political	size
0	0.69	0.33	0.36	0.50	0.60	0.00	0.32	0.45	0.73	0.45	0.32	0.41	0.52	0.54	1393
1	0.21	0.25	0.69	0.56	0.52	0.55	0.33	0.61	0.58	0.41	0.25	0.25	0.49	0.54	1296
2	0.80	0.41	0.56	0.88	0.25	0.33	0.10	0.79	0.96	0.57	0.00	0.63	0.70	0.75	951
3	0.10	0.53	0.32	0.63	0.30	0.73	0.28	0.72	0.83	0.49	0.14	0.15	0.54	0.58	1028
4	0.14	0.74	0.26	0.28	0.43	0.20	0.61	0.42	0.00	0.57	0.44	0.10	0.46	0.52	1766
5	0.15	0.70	0.68	0.40	0.50	0.45	0.05	0.80	0.84	0.61	0.23	0.41	0.58	0.63	1057
6	0.40	0.53	0.24	0.35	0.72	0.86	0.27	0.72	0.74	0.30	0.38	0.76	0.55	0.61	4509

Weighted accuracy = 0.540

Results

GSDMM clustering

DistilBERT

	bias	clickbait	conspiracy	fake	hate	junksci	political	reliable	rumor	satire	unknown	unreliable	accuracy	accuracy without political	size
0	0.71	0.00	0.47	0.81	0.29	0.00	0.00	0.05	0.92	0.83	0.46	0.21	0.50	0.54	1393
1	0.00	0.42	0.55	0.97	0.67	0.97	0.60	0.63	0.75	0.27	0.11	0.00	0.57	0.64	1296
2	0.76	0.14	0.00	0.89	0.00	0.00	0.00	0.78	0.95	0.69	0.00	0.00	0.58	0.59	951
3	0.00	0.86	0.27	0.76	0.17	0.89	0.06	0.61	0.70	0.73	0.00	0.00	0.55	0.60	1028
4	0.22	0.76	0.10	0.81	0.50	1.00	0.81	0.05	0.00	0.52	0.55	0.17	0.53	0.67	1766
5	0.15	0.77	0.65	0.67	0.50	0.20	0.00	0.90	0.77	0.69	0.00	0.00	0.57	0.61	1057
6	0.45	0.68	0.47	0.94	0.76	0.85	0.38	0.73	0.64	0.58	0.60	0.79	0.67	0.75	4509

Weighted accuracy = 0.593

Results

Comparison of DistilBERTs

Accuracy w/o clustering = 0.710

Weighted accuracy LDA = 0.619

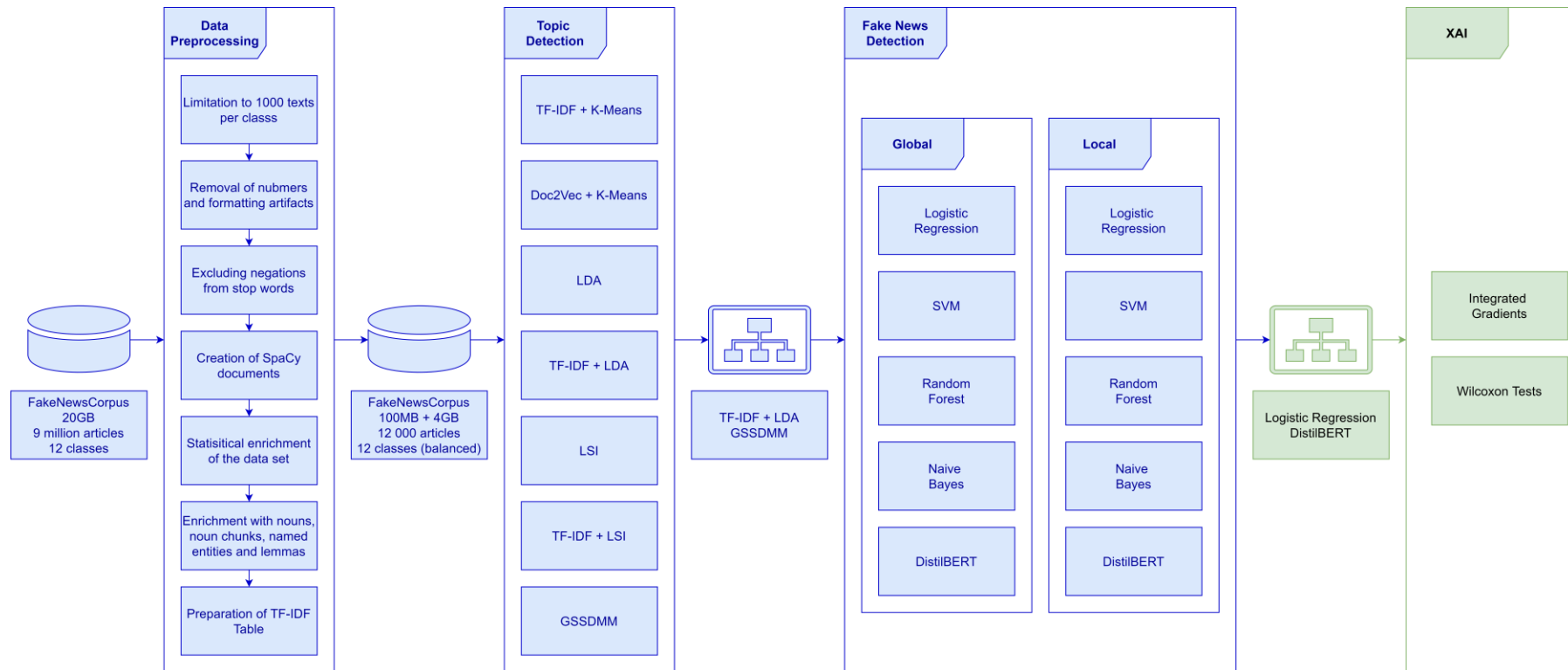
Weighted accuracy GSDMM = 0.593



06

Models explanations

Experimental design



Explanations

1. The best model turned out to be the fine-tuned DistilBERT.
2. Consequently, only these models will be used to create explanations.
3. The explanation method is based on Integrated Gradients (IG). It is given by the following formula,
where i – label, x – input, x' – baseline input.

$$\text{IntegratedGrads}_i(x) ::= (x_i - x'_i) \times \int_{\alpha=0}^1 \frac{\partial F(x' + \alpha \times (x - x'))}{\partial x_i} d\alpha$$

4. The equality of explanations will be determined by running the Wilcoxon statistical test with FDR correction.

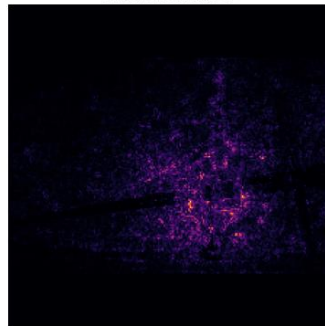
Baseline image



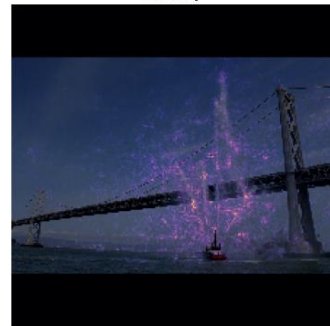
Original image



Attribution mask



Overlay



Explanations

[CLS] donald trump welcomed the new england patriots to the white house wednesday afternoon to cong ##rat ##ulate them for their historic comeback victory and fifth super bowl championship for the franchise . the president addressed the patriots players , coaches and owner robert kraft on the south lawn in recognition of their thrilling comeback win in which they overcame a - deficit to push the game into overtime and take home another lombard ##i trophy . (video : rob gr ##on ##kowski crashes white house press briefing) “ with your backs against the wall - and

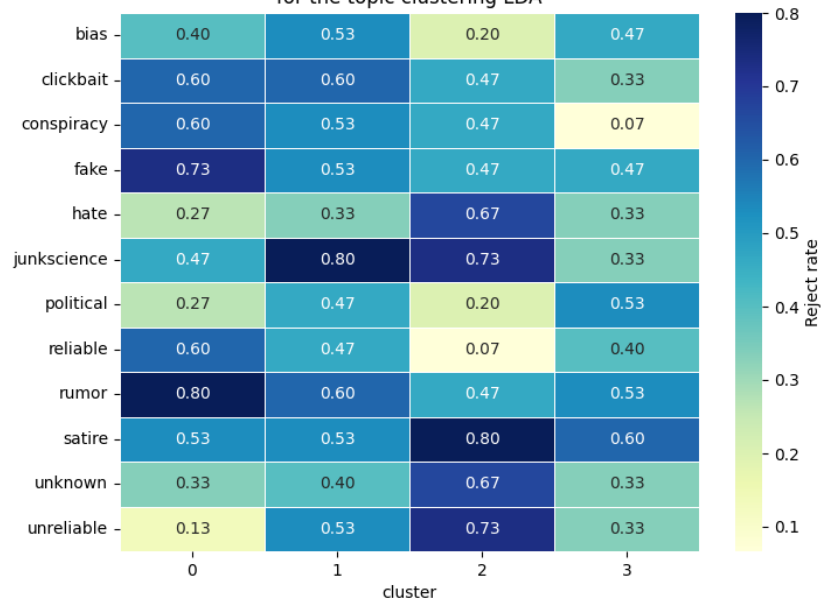
Global model

[CLS] donald trump welcomed the new england patriots to the white house wednesday afternoon to cong ##rat ##ulate them for their historic comeback victory and fifth super bowl championship for the franchise . the president addressed the patriots players , coaches and owner robert kraft on the south lawn in recognition of their thrilling comeback win in which they overcame a - deficit to push the game into overtime and take home another lombard ##i trophy . (video : rob gr ##on ##kowski crashes white house press briefing) “ with your backs against the wall - and

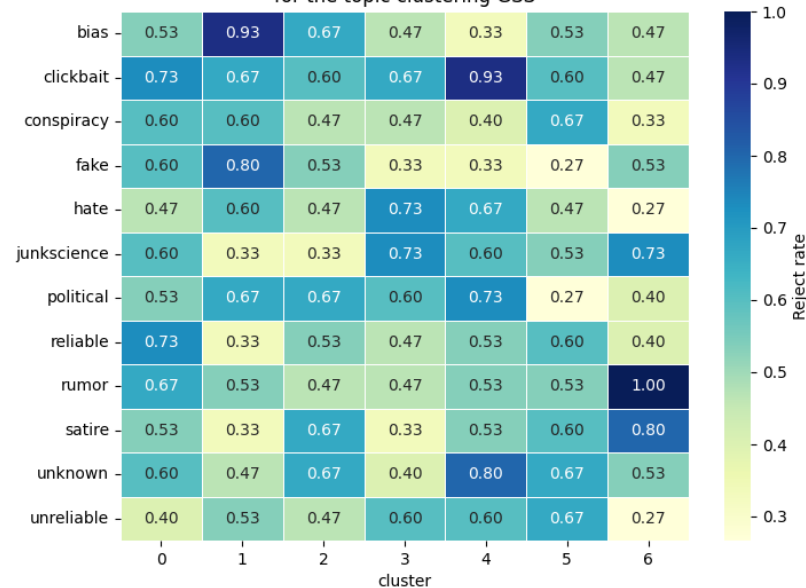
Local model

Explanations

Heatmap of reject rate ($\alpha = 0.05$) of the hypothesis of the equality of explanations for the topic clustering LDA



Heatmap of reject rate ($\alpha = 0.05$) of the hypothesis of the equality of explanations for the topic clustering GSS





07

Conclusions

Conclusions

1. We trained a variety of models. The best ones turned out to be DistilBert.
2. We split the input dataframe by using topic detection methods. Further, we trained models to detect classes in each of the clusters.
3. The performance of models trained on the specific clusters turned out to be, unfortunately, worse. This could be a result of similar concept (topics) inside clusters or smaller amount of data per model.
4. The models were compared also based on the explainability technique Integrated Gradients. This approach proved that topic-specific models put focus on different words than a global model. Moreover, the Wilcoxon test results showed that the differences are real.




08

Further Works

Further Works

1. The local approach proves to be ineffective for now. To fix this we plan to enhance the amount of data (5 times), and reduce number of fake news types (end up with 2 and 4 classes).
2. To gain more time for training we will limit ourselves to the DistilBERT at first.
3. If the approach works, we plan to try a new, bigger model (maybe some LLM).
4. We want to introduce a new clustering method of BERTopic, which may contribute positively to the final results, as BERTopic is easily interpretable.



Thank you for your attention!