DeepFake Tweet Detection

Team 15: TextTechTitans

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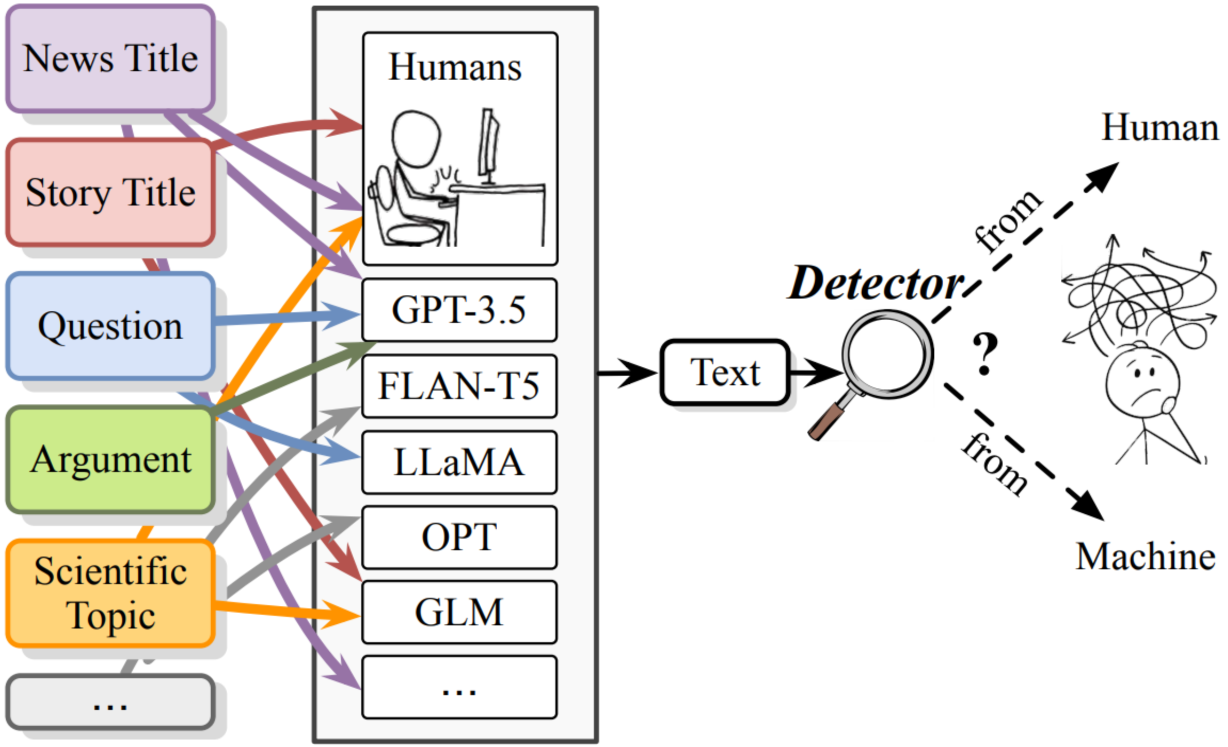
Plan of presentation

1. Introduction
2. Datasets description
3. Results
4. Concept and work plan

Deepfake

- ➢Deep learning + fakes.
- ➢Tweets – short texts without context used in social media interactions.
- ➢Humans' performance on this task.
- ➢Why is it a problem? Why do we need detection tools?



Source: Deepfake Text Detection in the Wild, Yafu Li and Qintong Li and Leyang Cui and Wei Bi and Longyue Wang and Linyi Yang

Our research questions

- Can we build a reliable deepfake detection algorithm? By reliable algorithm, meaning detecting generated tweets while avoiding assigning false positives.
- What are the most effective features for deep-fake detection in tweets?
- Are there any patterns that indicate the model-generated tweet content?

Hypothesis

- The use of emoticons may be higher in human generated content. [H0]
- The use of mentions of other users may be higher in human-generated content. [H1]
- There will be more misspelled words in content generated by bots. [H2]
- The impact of different URL encoding, e.g., encoding all URLs to a single token vs extracting the basepath of the URLs. [H3]

TweepFake - main dataset

- Contains 25,572 tweets.
- Equal split between human-generated and bot-generated tweets.
- 17 human accounts as the basis for imitation.
- 23 bot accounts that mimic the behavior of these human accounts.

dril	this is every thing and its only 11:am, https://t.co/XOioXnwFQh	human	human
nsp_gpt2	guy, you have a pretty amazing dick, you're awesome, I appreciate that	bot	gpt2

GPT-2 output dataset - secondary dataset

- Contains 500,000 text from web.
- Equal split between human-generated and bot-generated text.
- Those text are longer than tweets.

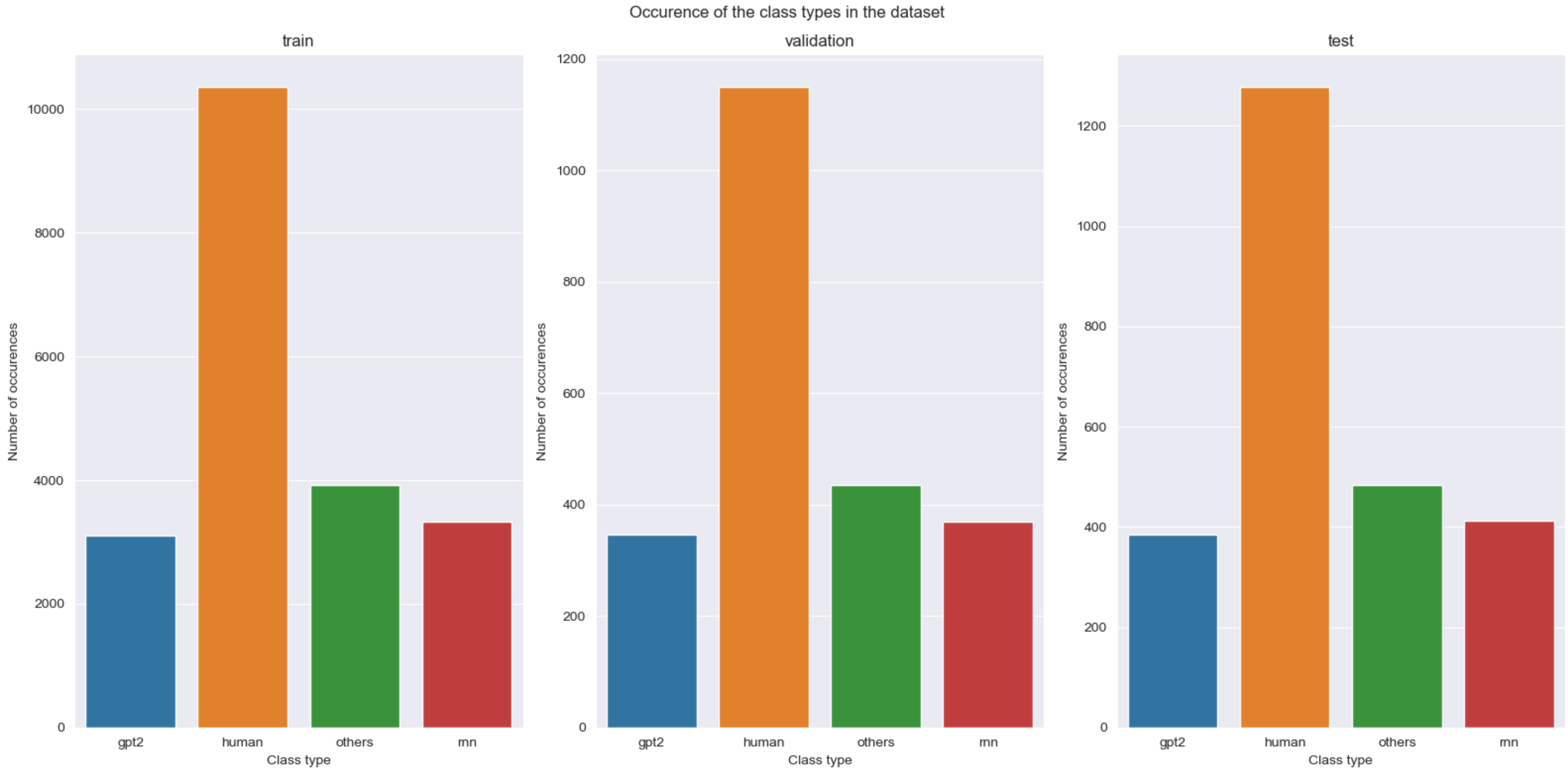
```
Real :: These girlfriends deserves a special mention for going that extra mile,
        hopefully doesn't set too many guys off on the path towards outrageous
        demands.\n\n1. She knows the severity of man-flu. ...

Fake :: As the final day of the presidential campaign approached Wednesday morning,
        polls suggested the race was closer than many had expected.
        Polls have shown Hillary Clinton leading Donald Trump by 9 percentage points
        since late September, with the Republican leading by 7 percent. ...
```

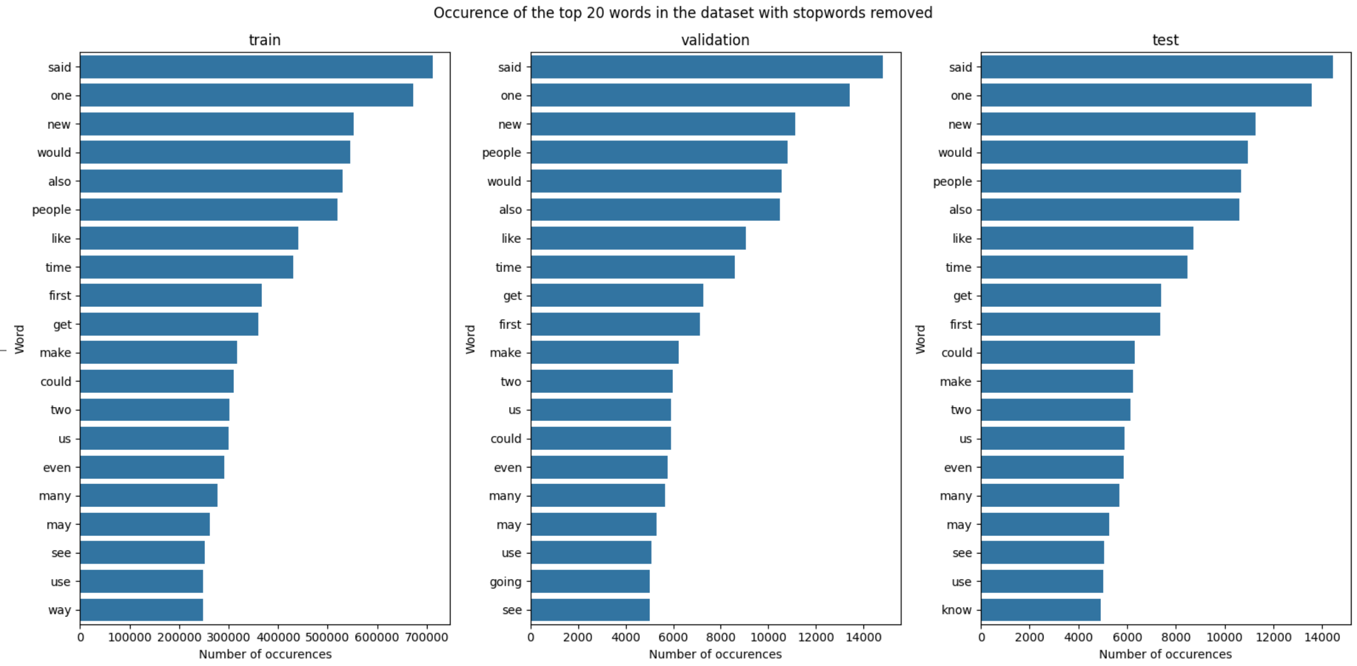
Methods outline

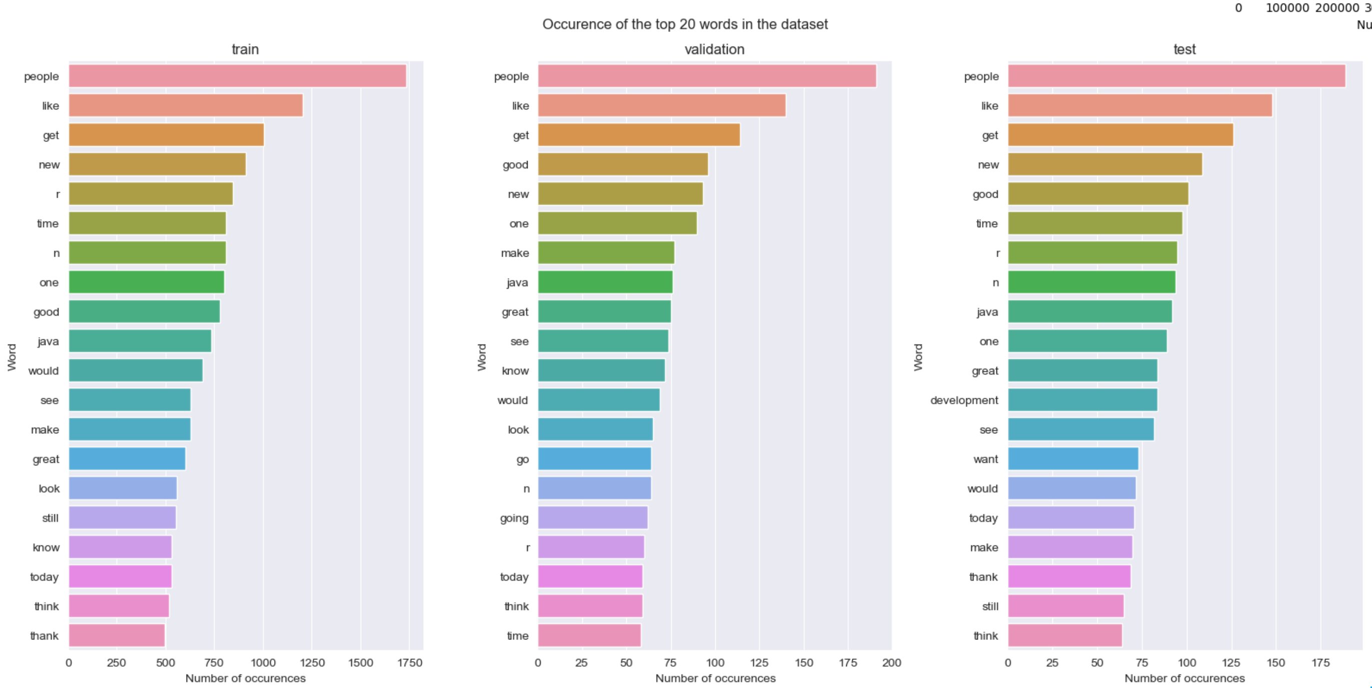
- General EDA
- Preprocessing: tagging hyperlinks, mentions, retweets, stemming, lemmatization
- Embedding:
  - TF-IDF
  - Bert
- Modeling:
  - ML methods: SVC, LGBM, RF, LR, XGB
  - DL methods: CNN, GRU, CNN + GRU
- Optuna optimizer for ML
- Char or word tokenizing for DL

Datasets/EDA

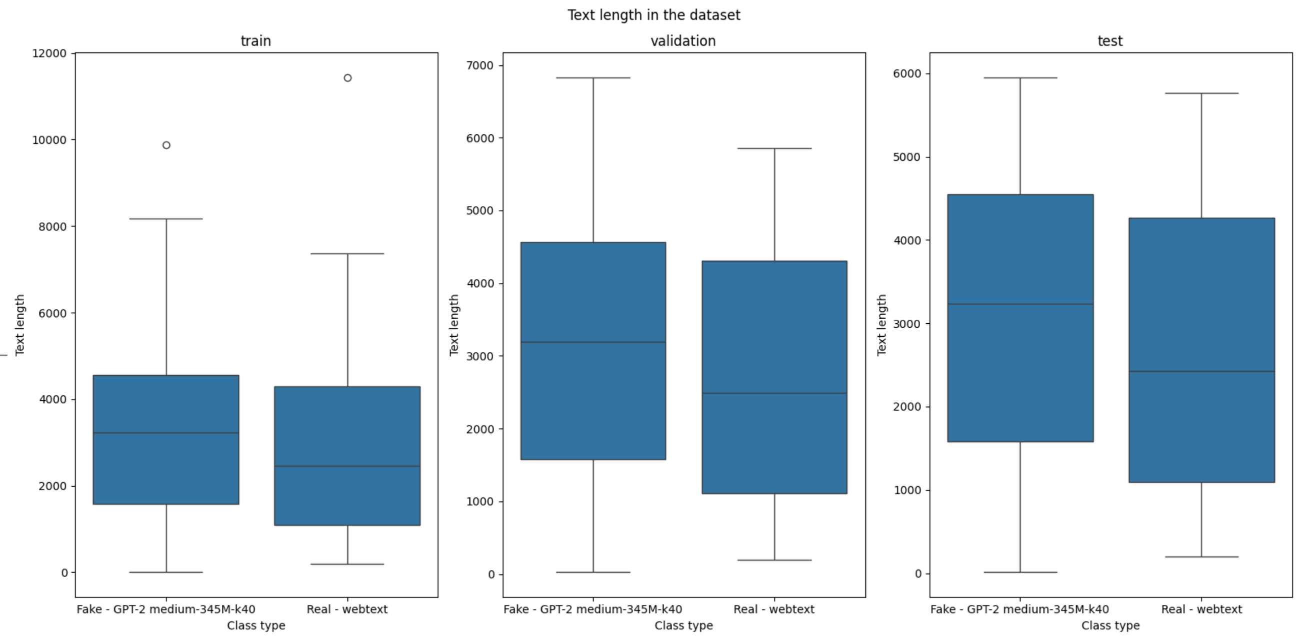


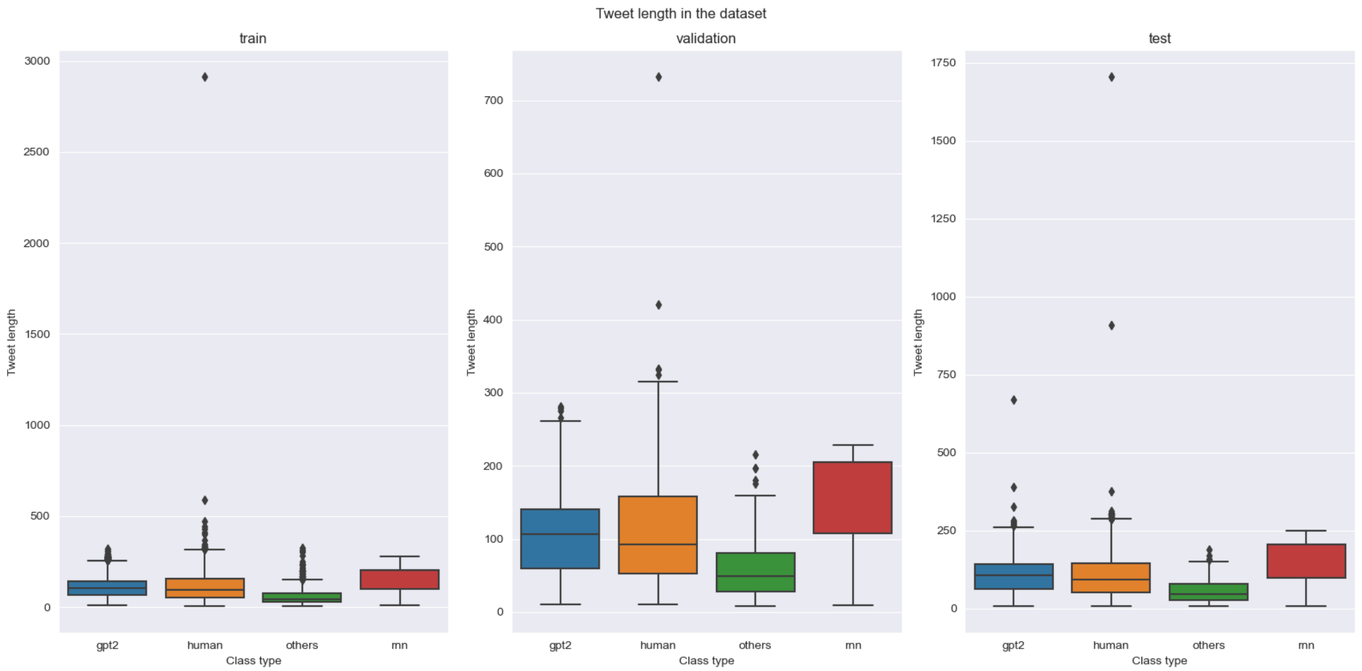
Datasets/EDA



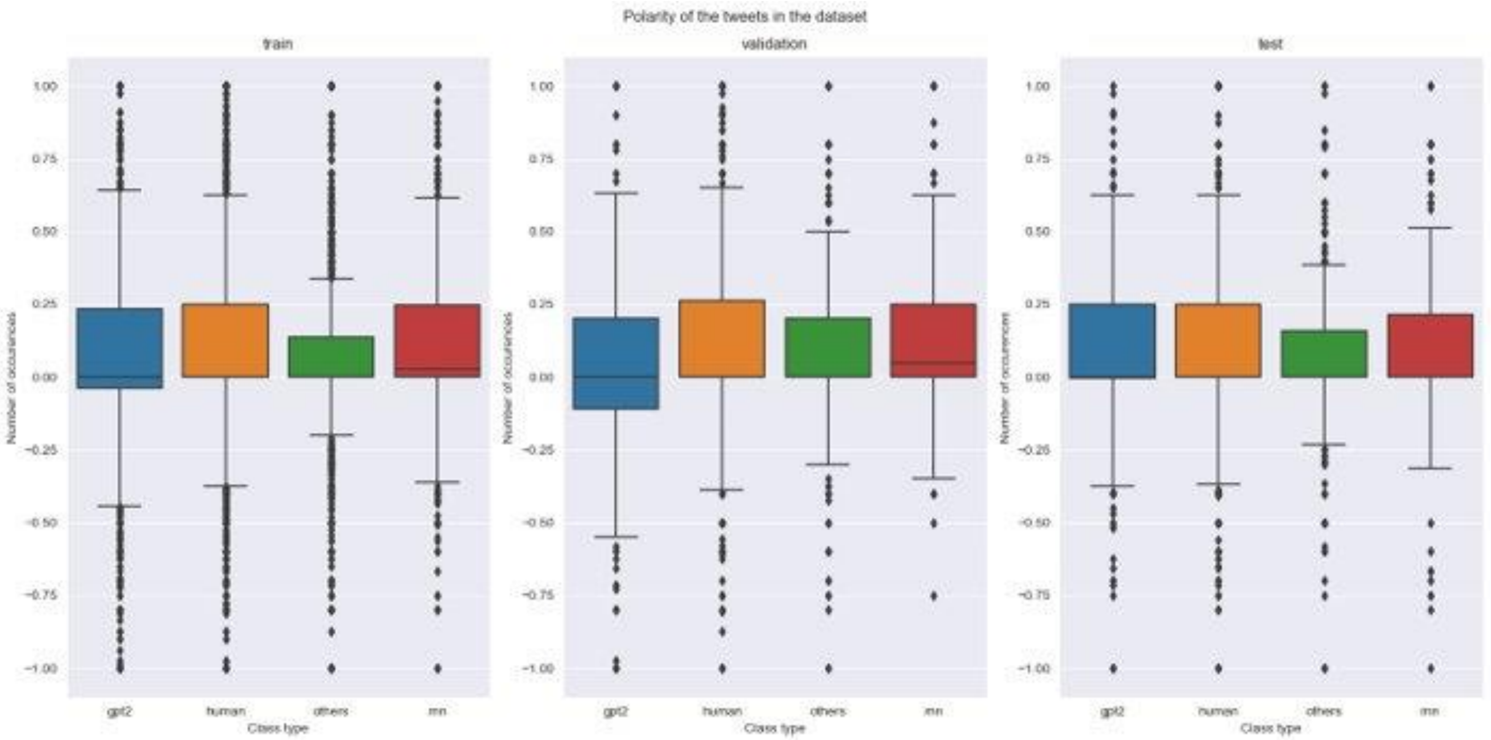


Datasets/EDA

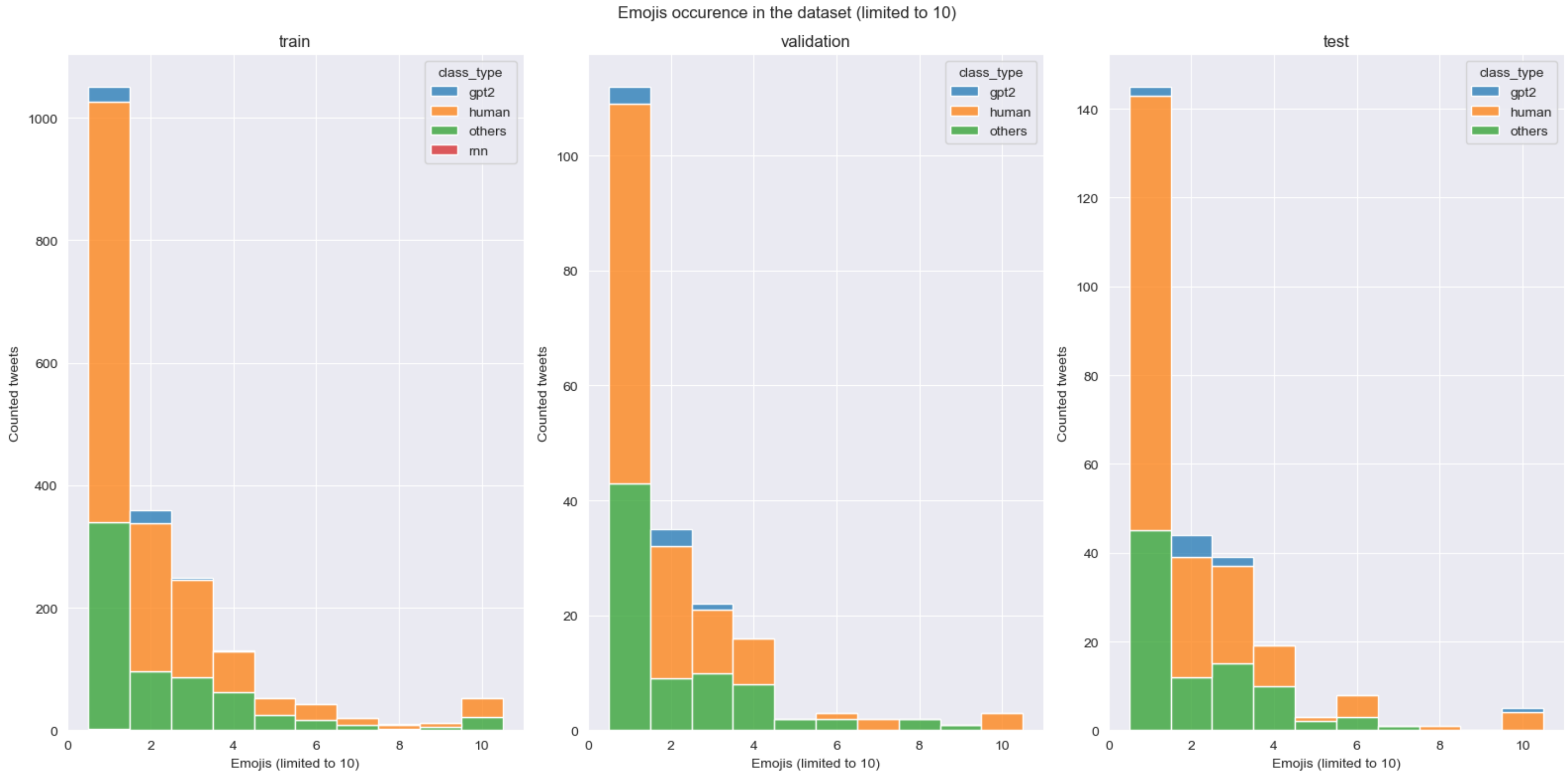




Datasets/EDA

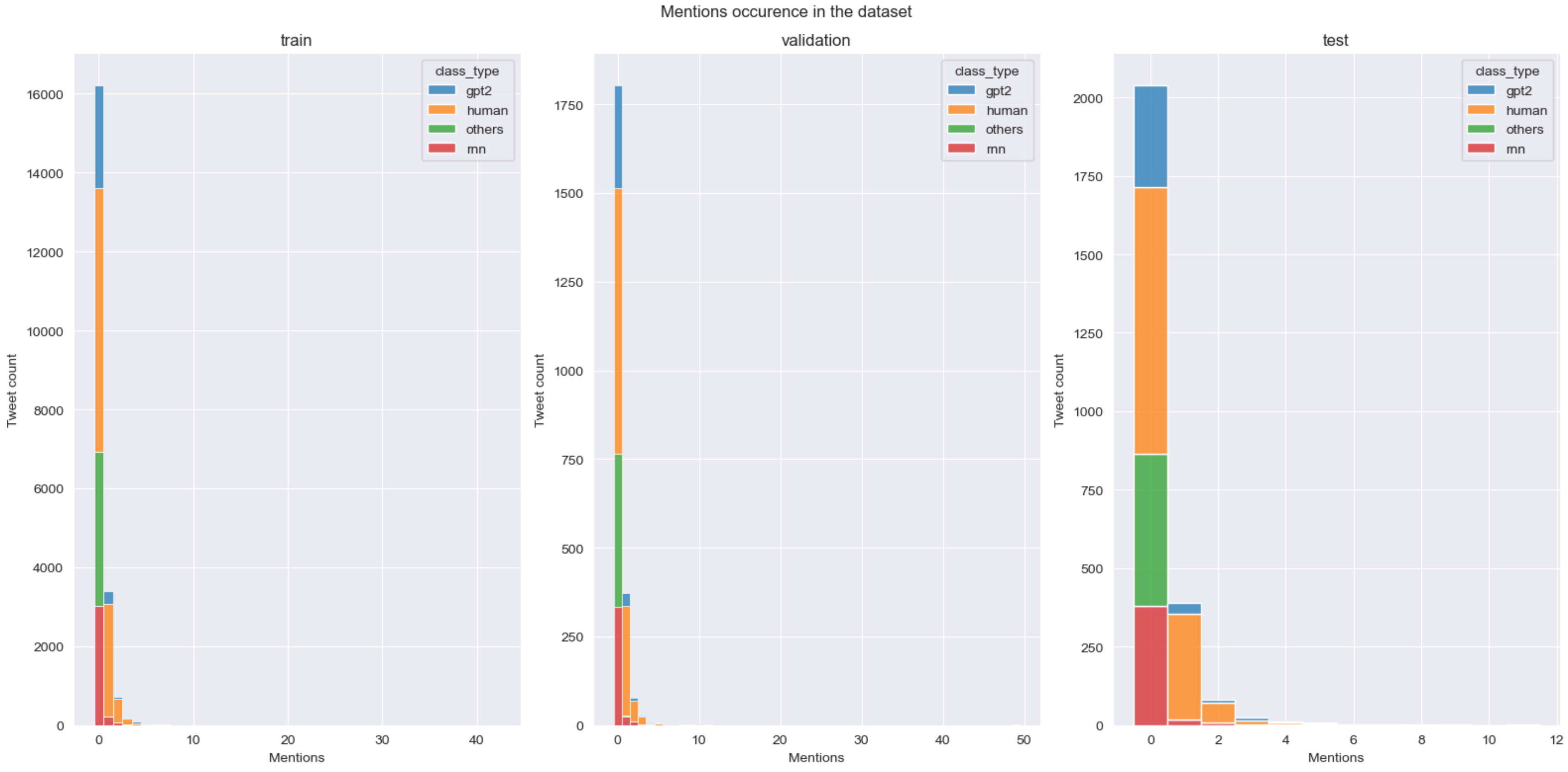


Datasets/EDA - verification of hypothesis



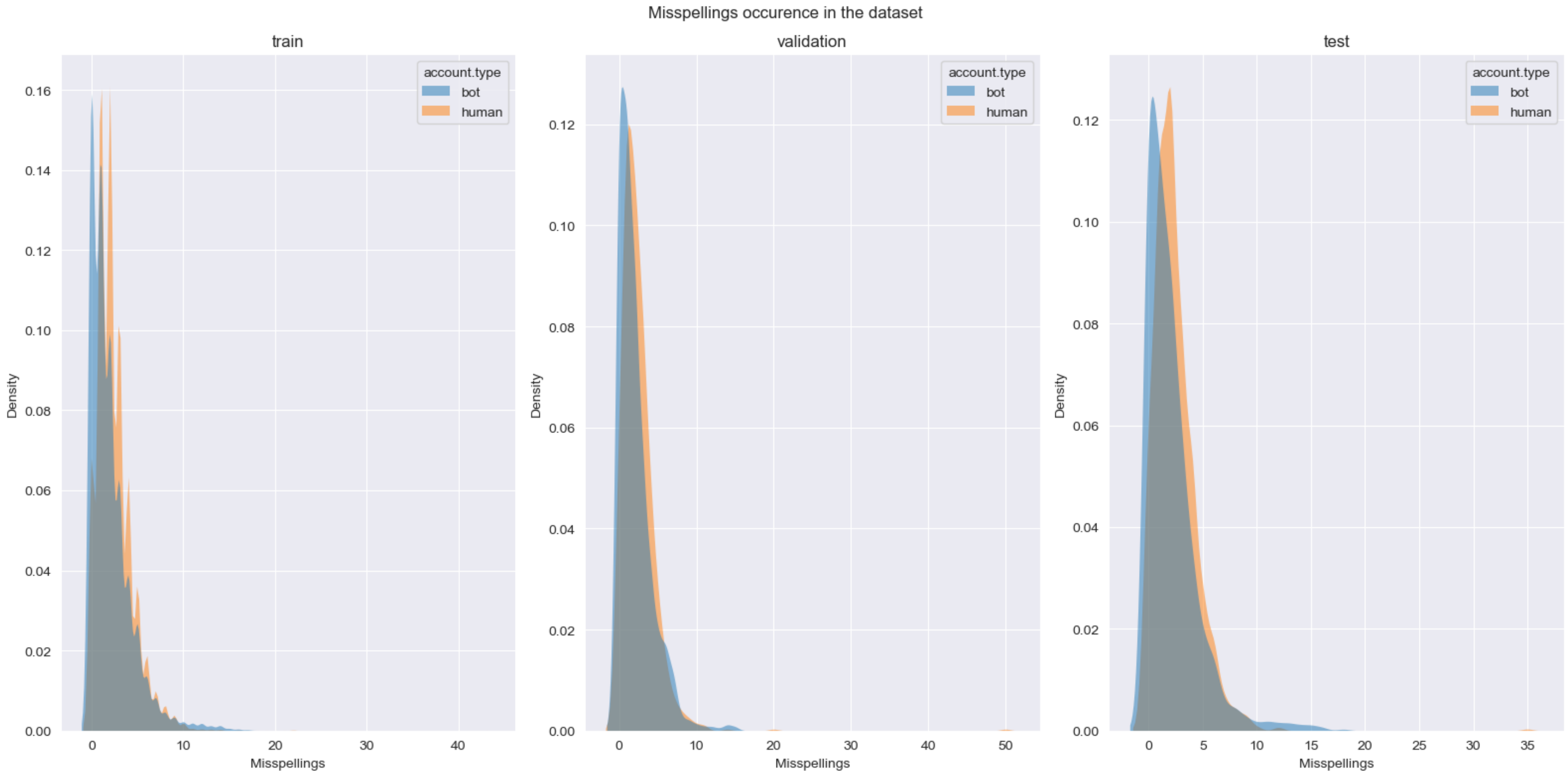
H0: The use of emoticons may be higher in human generated content.

Datasets/EDA - verification of hypothesis



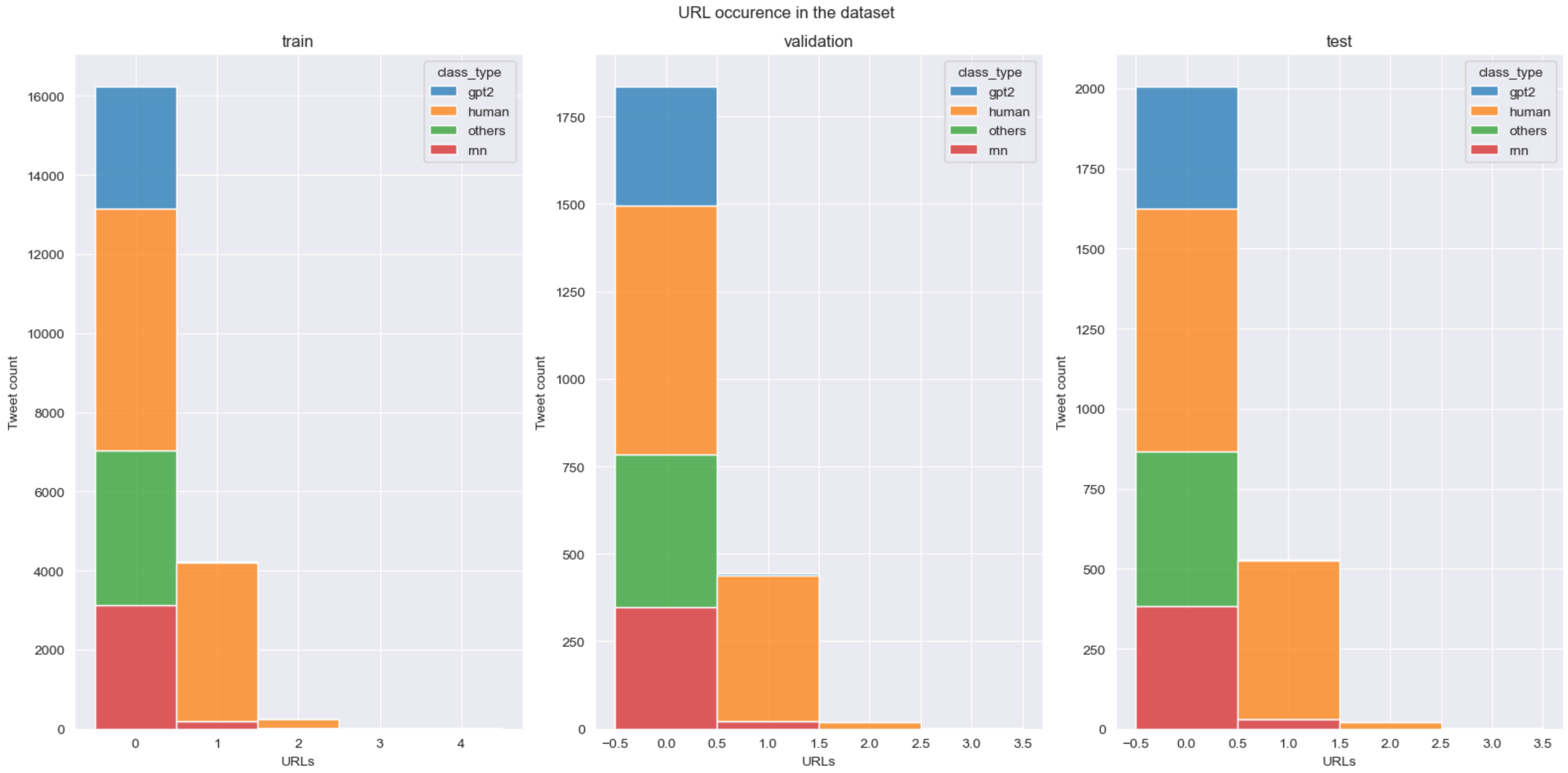
H1: The use of mentions of other users may be higher in human-generated content.

Datasets/EDA - verification of hypothesis



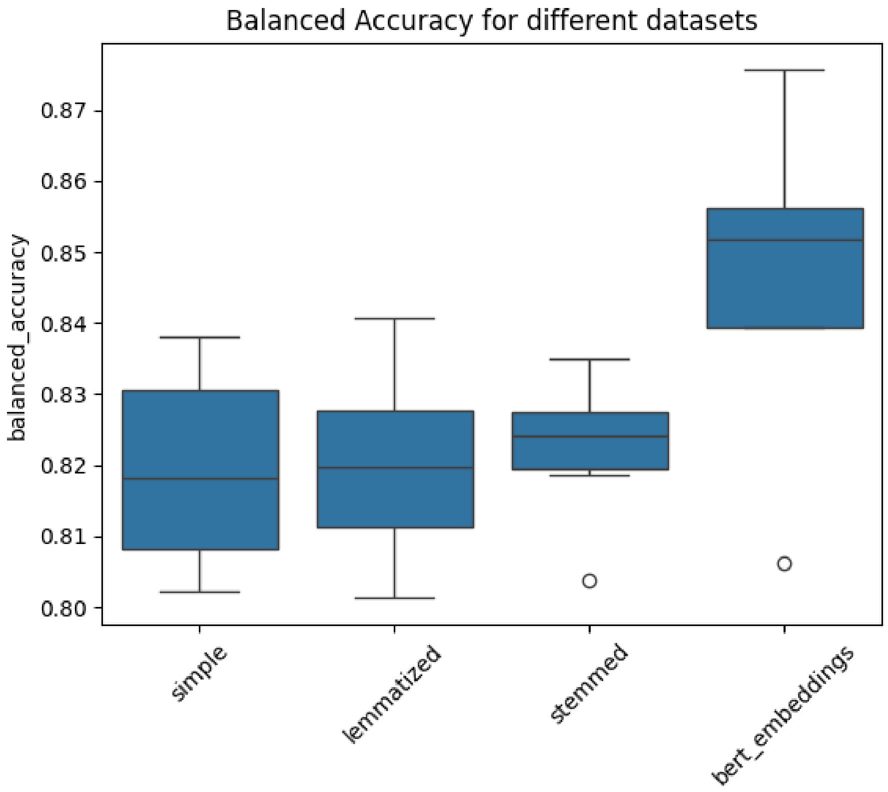
H2: There will be more misspelled words in content generated by bots.

Datasets/EDA - verification of hypothesis



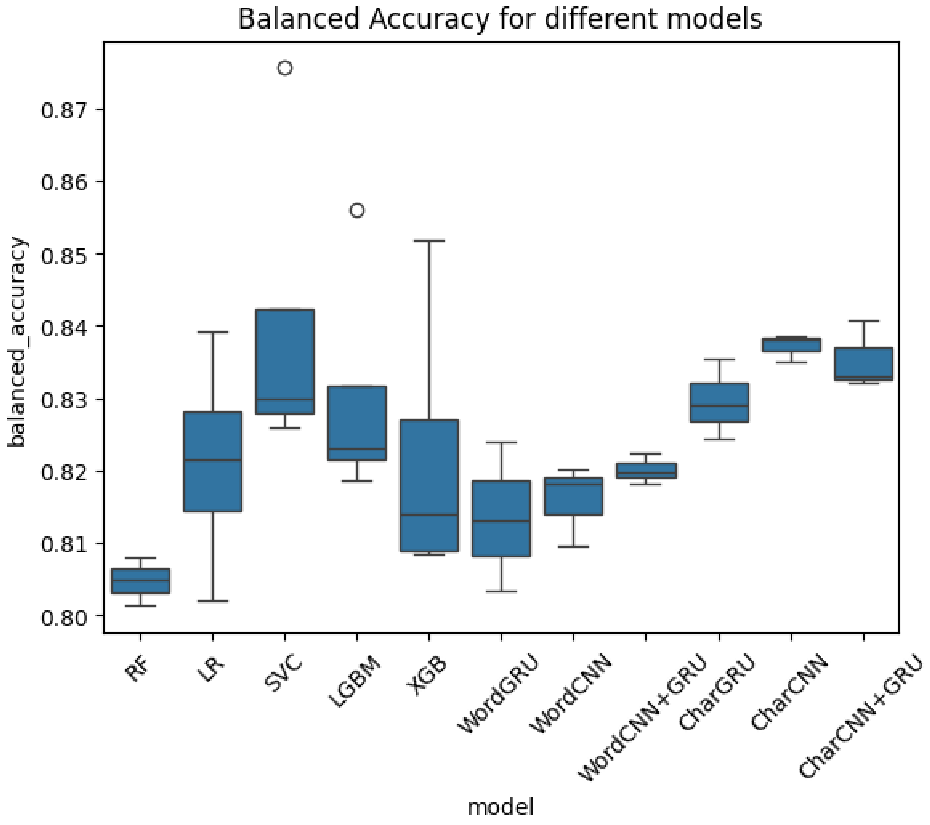
H3: The impact of different URL encoding, e.g., encoding all URLs to a single token vs extracting the basepath of the URLs.

Results



Balanced Accuracy for different datasets
balanced_accuracy
0.80
0.81
0.82
0.83
0.84
0.85
0.86
0.87
simple
lemmatized
stemmed
bert_embeddings
dataset

Results



Balanced Accuracy for different models
balanced_accuracy
0.87
0.86
0.85
0.84
0.83
0.82
0.81
0.80
RF
LR
SVC
LGBM
XGB
WordGRU
WordCNN
WordCNN+GRU
CharGRU
CharCNN
CharCNN+GRU
model

Results

model	dataset	balanced_accuracy	f1_score	precision	recall
SVC	bert_embeddings	**0.876**	**0.876**	**0.873**	0.880
LGBM	bert_embeddings	0.856	0.859	0.843	0.876
XGB	bert_embeddings	0.852	0.855	0.839	0.870
CharCNN+GRU	lemmatized	0.841	0.852	0.798	**0.914**
LR	bert_embeddings	0.839	0.842	0.830	0.853
CharCNN	lemmatized	0.839	0.845	0.813	0.880
CharCNN	simple	0.838	0.843	0.818	0.870
CharGRU	simple	0.835	0.842	0.810	0.877
CharCNN	stemmed	0.835	0.837	0.826	0.849
CharCNN+GRU	stemmed	0.833	0.844	0.792	0.904

Future works

- Fine-tuning transformers
  - With/without GPT-2 output dataset
- XAI

Thank you

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