Hate Speech Detection Using Machine Learning

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Task

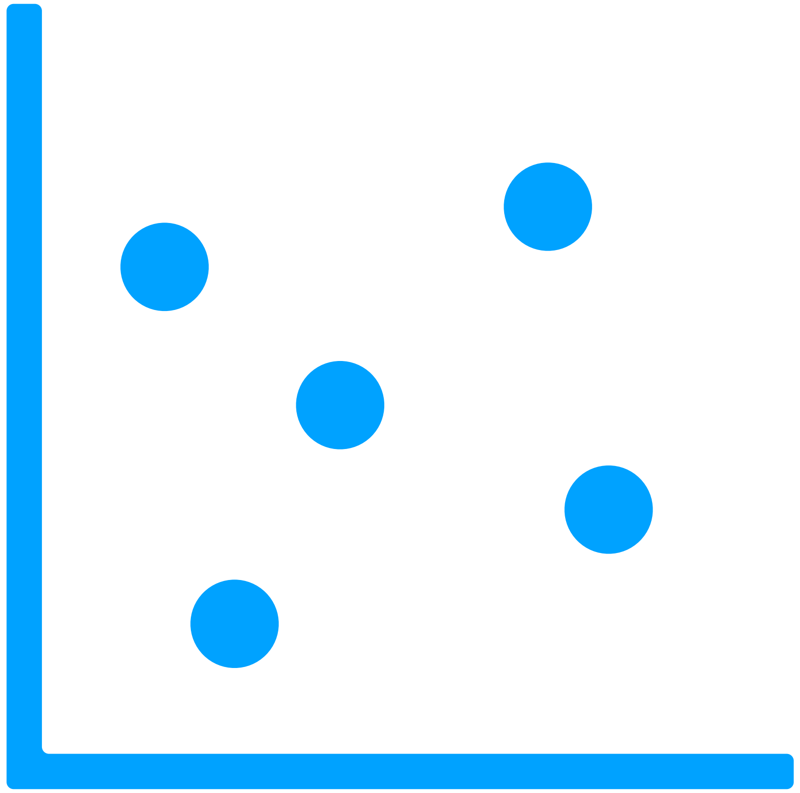
Train machine learning model to classify tweets from Twitter to following 3 classes

hate speech

offensive language

neither

Data Overview

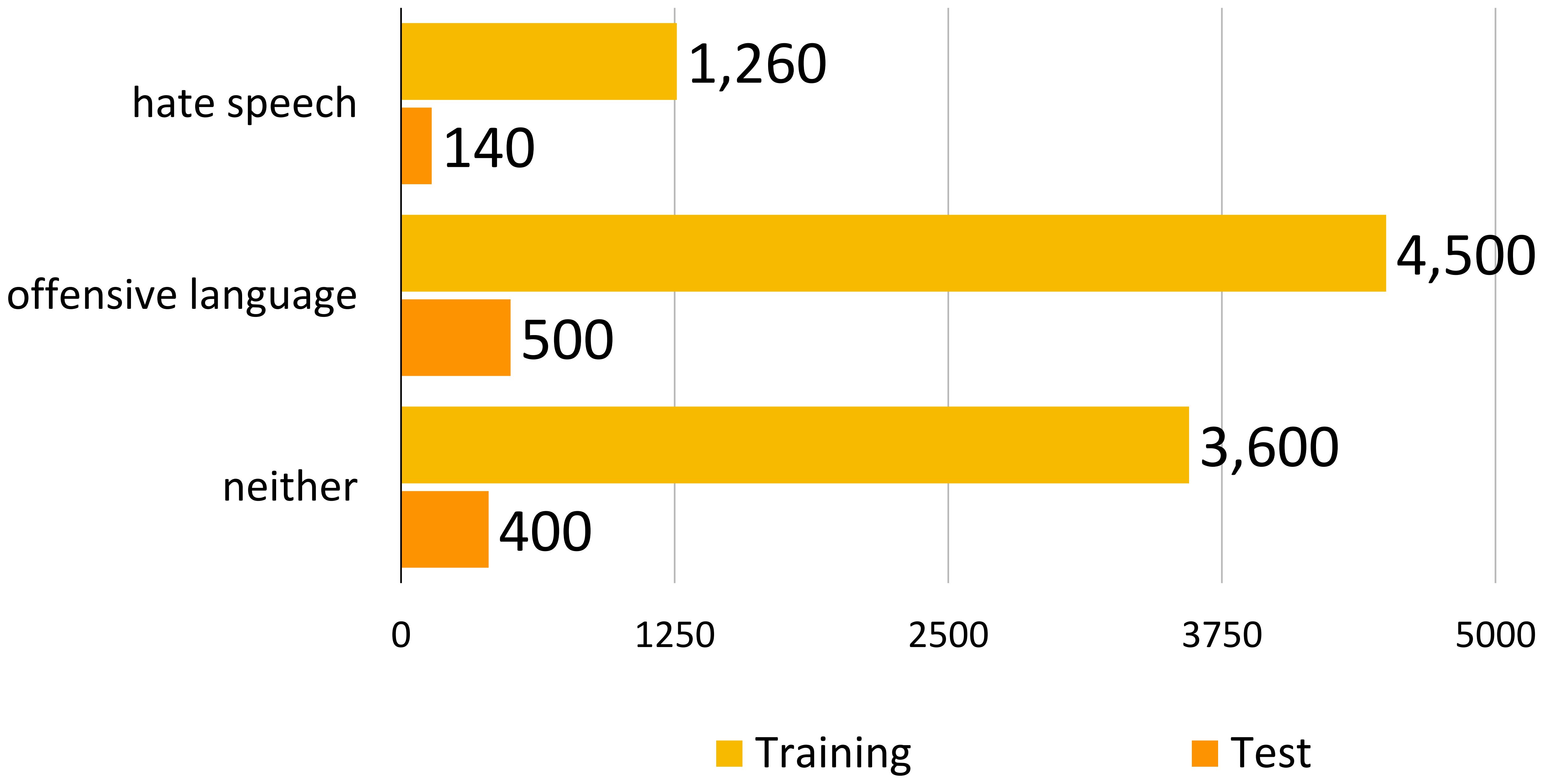


Data Overview

↓

cookies and crackers aren't even on the same level!

Data size by class



Data Augmentation with Google Translate

Original:

Fuck you pussy ass hater go suck a dick and die fast

Translate to French, German, Dutch

Translated to French:

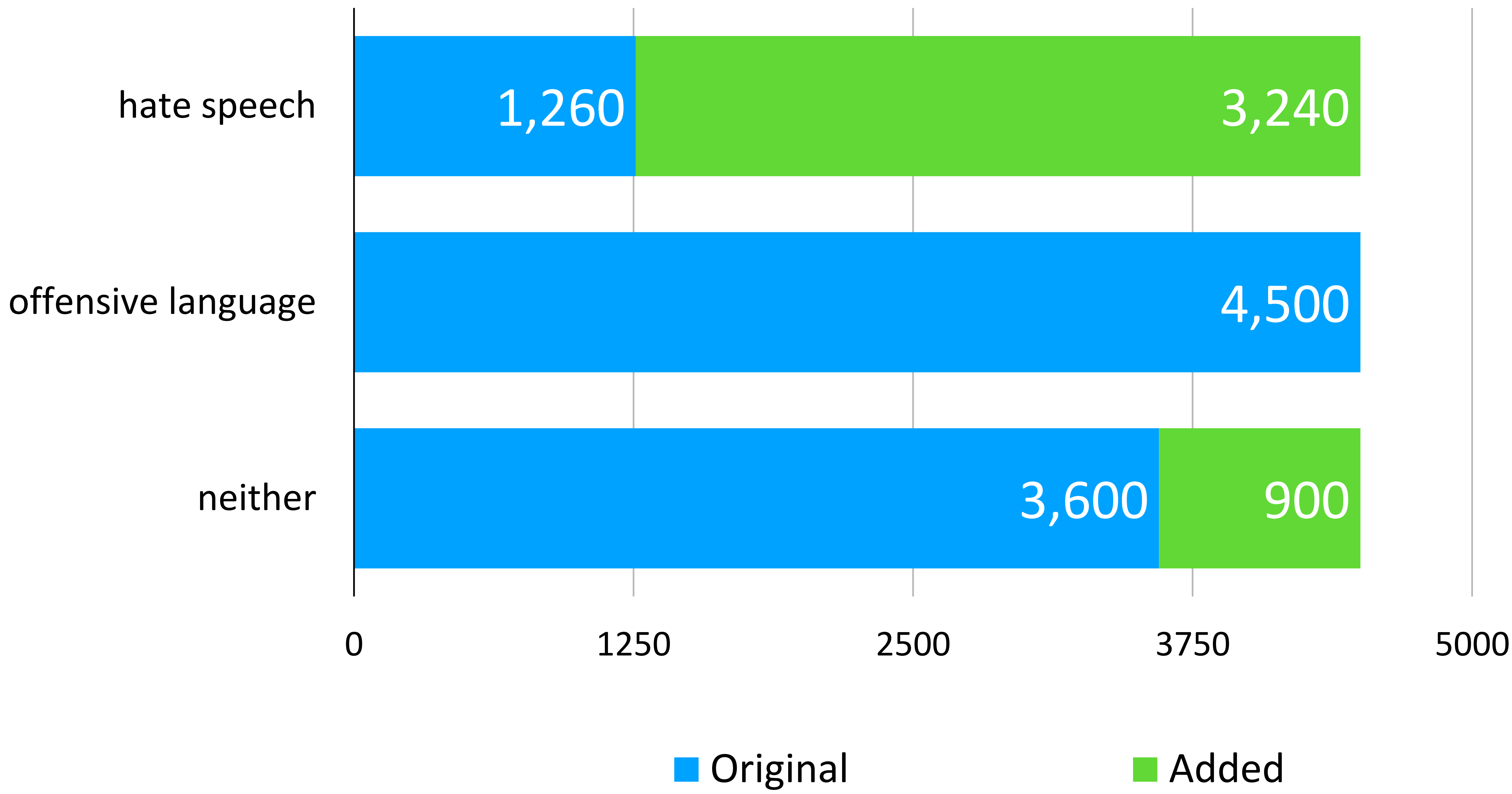
Va te faire foutre le cul chatte aller sucer une bite et mourir vite

Translate back to English

After re-translation:

Fuck you pussy hater will suck a dick and die quick

Data After Augmentation



Preprocessing: Replacement

"@John: How was Japan?" Awesome ! 😀
RT@Hana miss Japan : ((😀)

@ mention to <user>

Indicate Reply

"<user>: How was Japan?" <reply> Awesome! : grinning_face:
<rt_from> miss Japan : sad_face:

Indicate Retweet

Replace emoji with corresponding meaning

Preprocessing: lemmatization

- Used Stanford CoreNLP Package[1] → Pipeline for doing various preprocessing

- POS tagging using GATE Twitter POStagger[2]

→ POS tagger trained with twitter tweet

- Lemmatize based on resulting POS tags

He ate cakes

↓ ↓ ↓

PRP VBD NNS

↓

He eat cake

1. https: //stanfordnlp.github.io/CoreNLP/extensions.html
2. https: //gate.ac.uk/wiki/twitter-postagger.html

Preprocessing: Others

- **Spell correct**

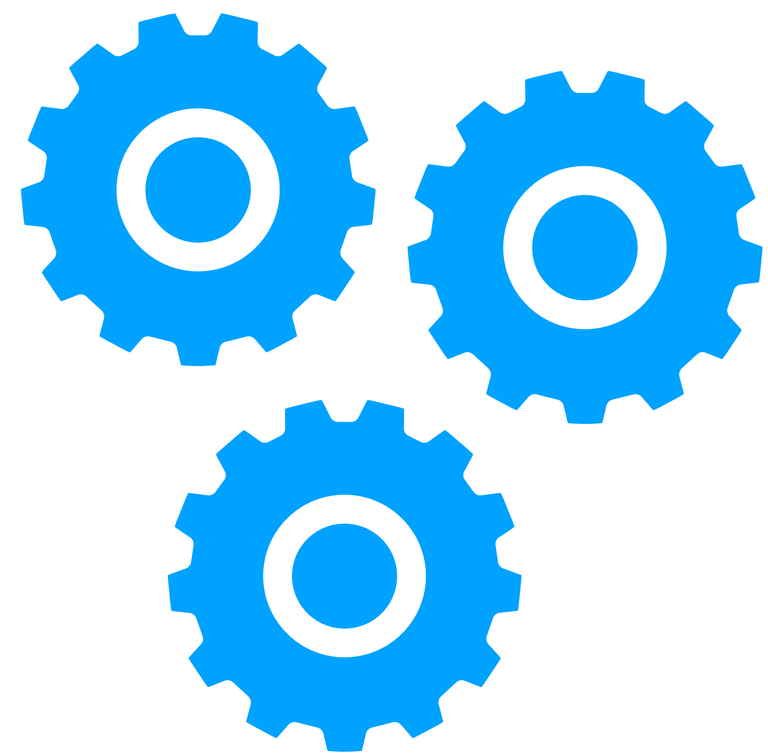
→ Used module autocorrect[1]

- **Fix abbreviation**

→ Used module contractions[2]

- **Remove punctuations other than ?!**
- **Make Everything into lower case**
- **Remove stopwords**

→ Used built in list from nltk[3]



1. https: //pypi.org/project/autocorrect/
2. https: //pypi.org/project/contractions/
3. https: //www.nltk.org/

Chosen Models

- Decision Tree
- LSTM

Decision Tree Parameter

	Only Original Data	Augmented Data
Max Depth	20	30
Minimum sample to create new branch	17.5%	15.5%
Featured considered at each branch	84%	82%

LSTM
Parameters · Model Structure

	Only Original Data	Augmented Data
embedding	20	20
LSTM Blocks	91	171
dropout	47%	63%
Softmax	3	3
Learning Rate	0.001	0.001

Model Structure

1. embedding layer

2. LSTM layer
Optimizer: Adam
Activation Func: layer → tanh
gates → hard sigmoid

3. Dropout

4. Output layer: softmax

Feature Extraction

- Decision Tree: TF-IDF

A. Give bigger weight to word occurring less frequent across all data.

B. Words, which occurrences are in top 30%, and bottom 0.4% are ignored

C. Combination of unigram and bigram

Feature Extraction

- LSTM : let model learn embedding

→allows to create embedding best fitted to the task

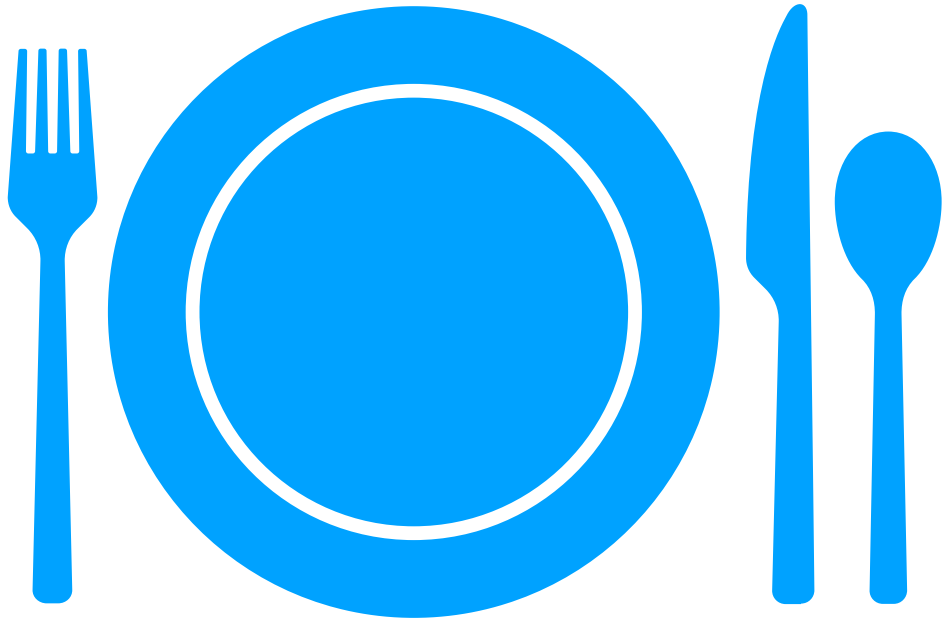
ex. words with closest cosine distance to 'white'

GloVe[1] (Twitter base）: black, blue, green, yellow, red, purple, tank

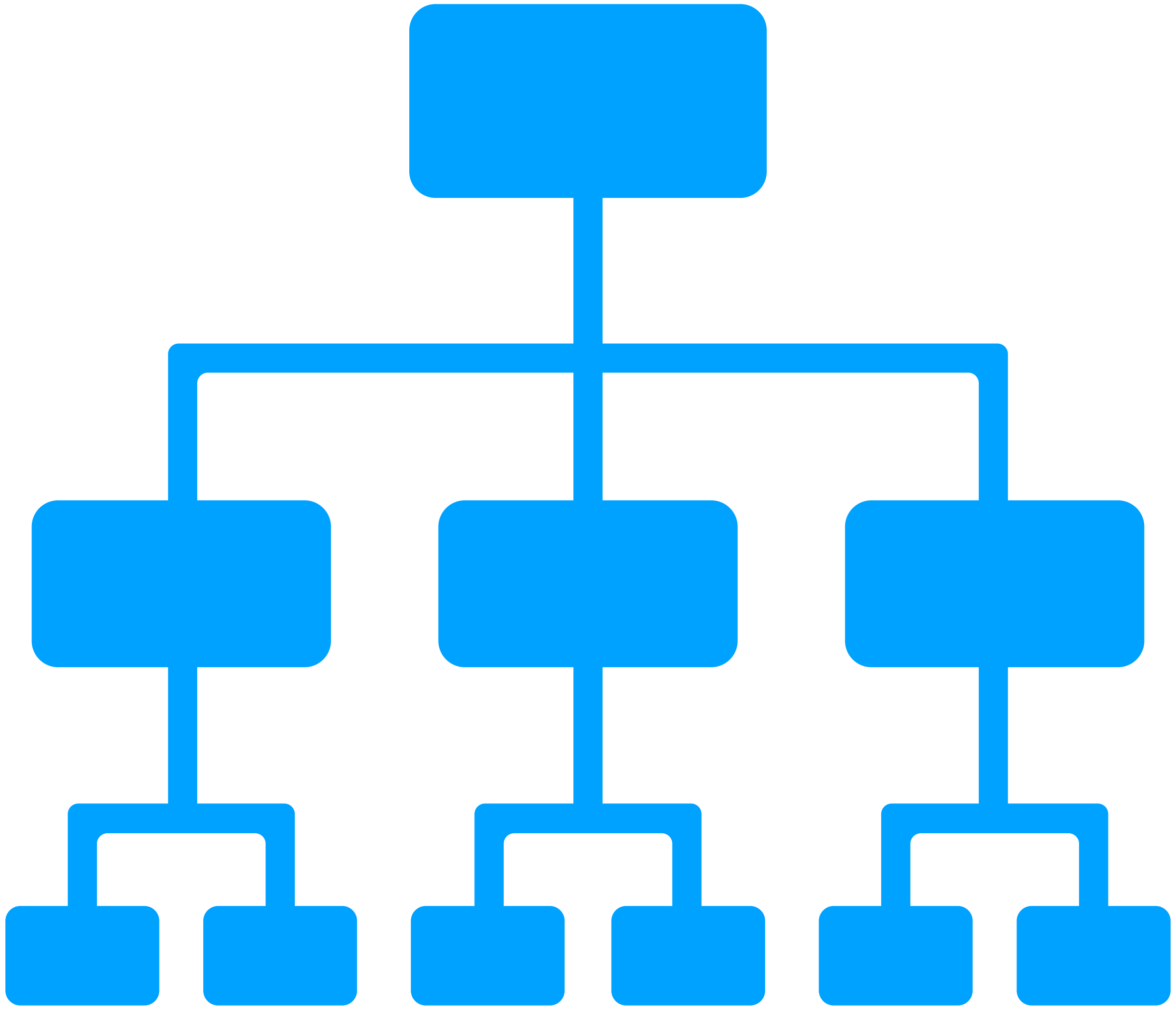
Embedding created by model : nigga, fuck, faggot, nigger, fag, ass, racist

1. https: //nlp.stanford.edu/projects/glove/

Result

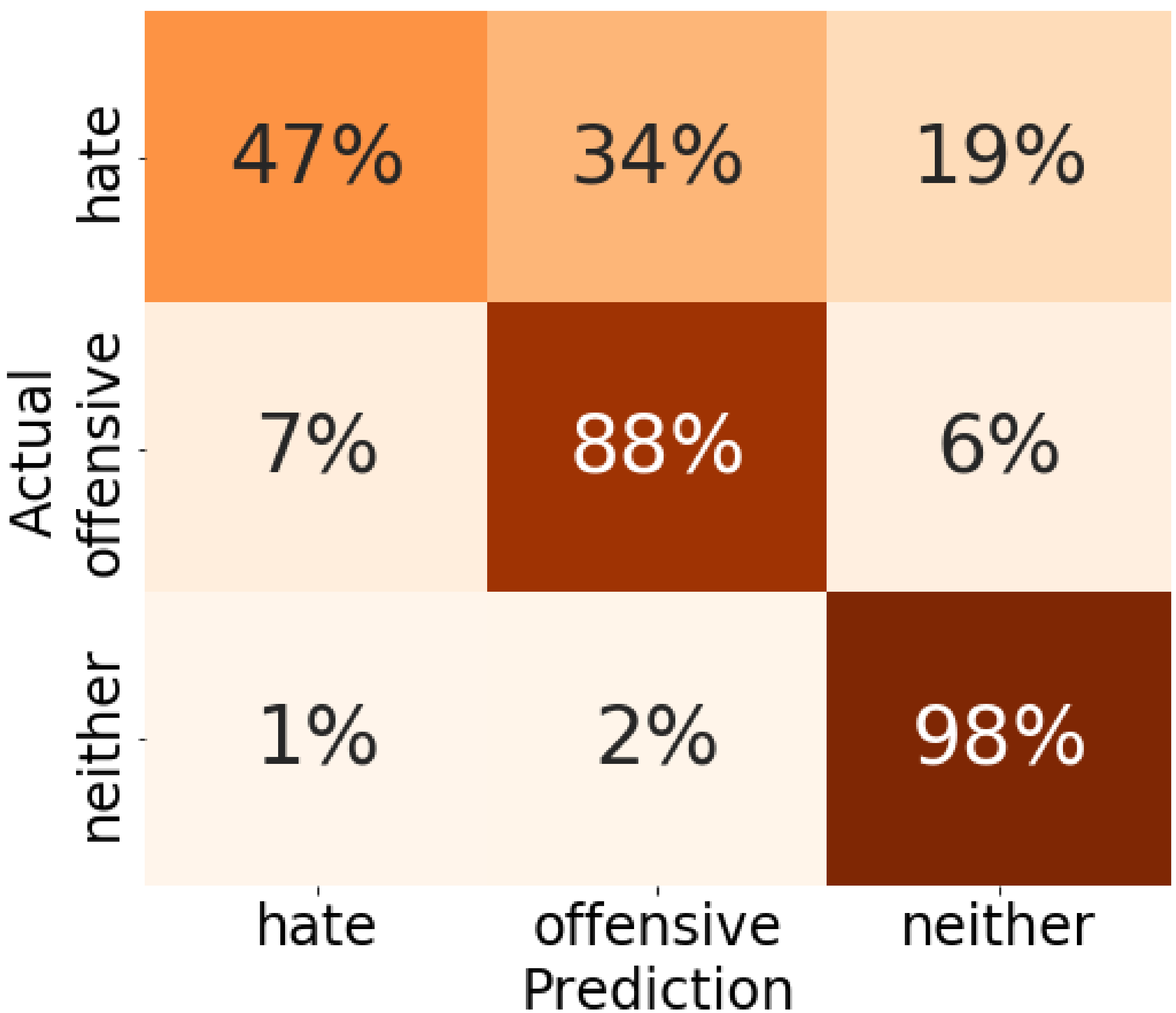


Decision Tree
CART



Result: Original Data Only

Classification Result（%）



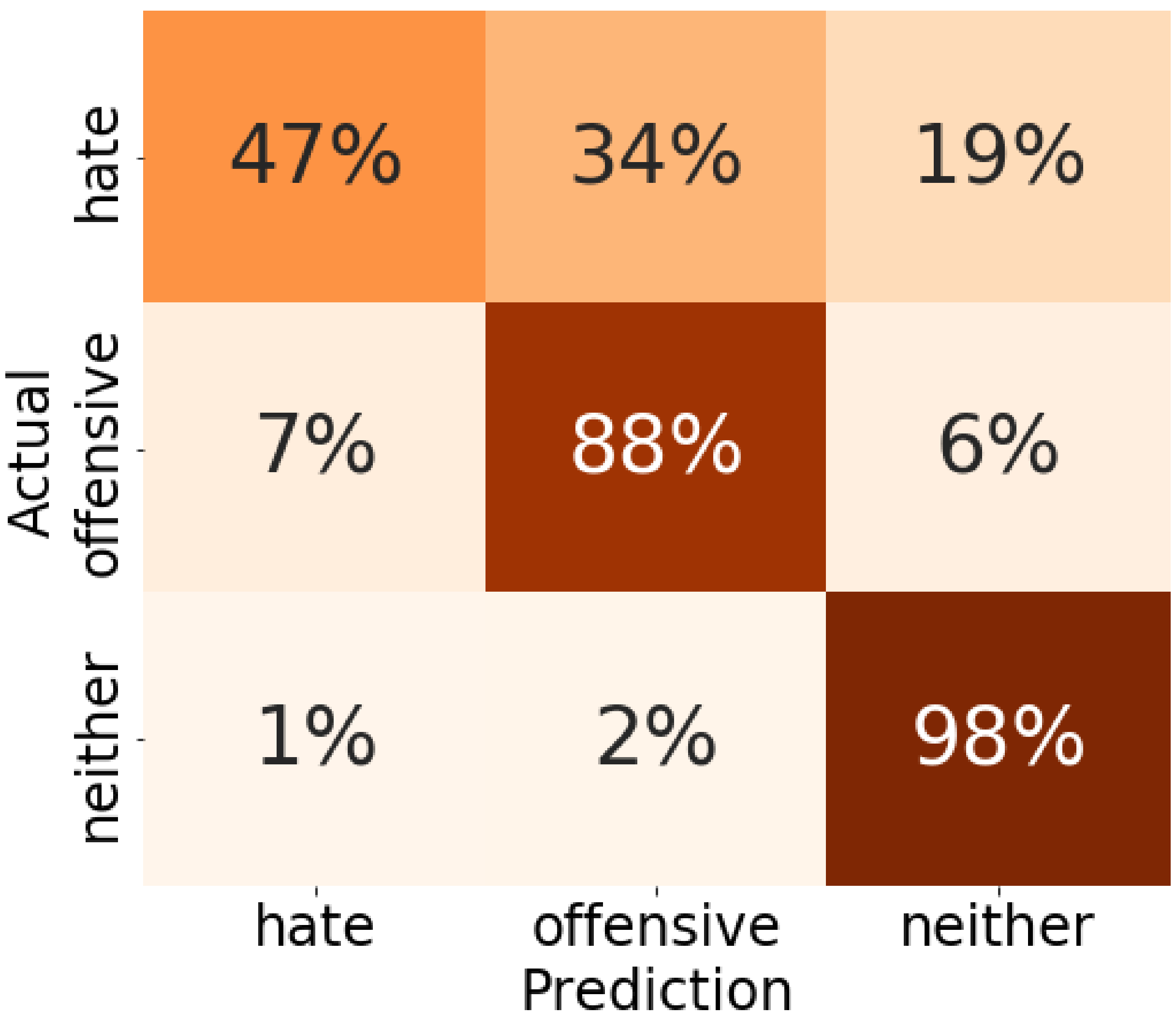
- Model can detect offensive language, neither well

  f1-score 約90%

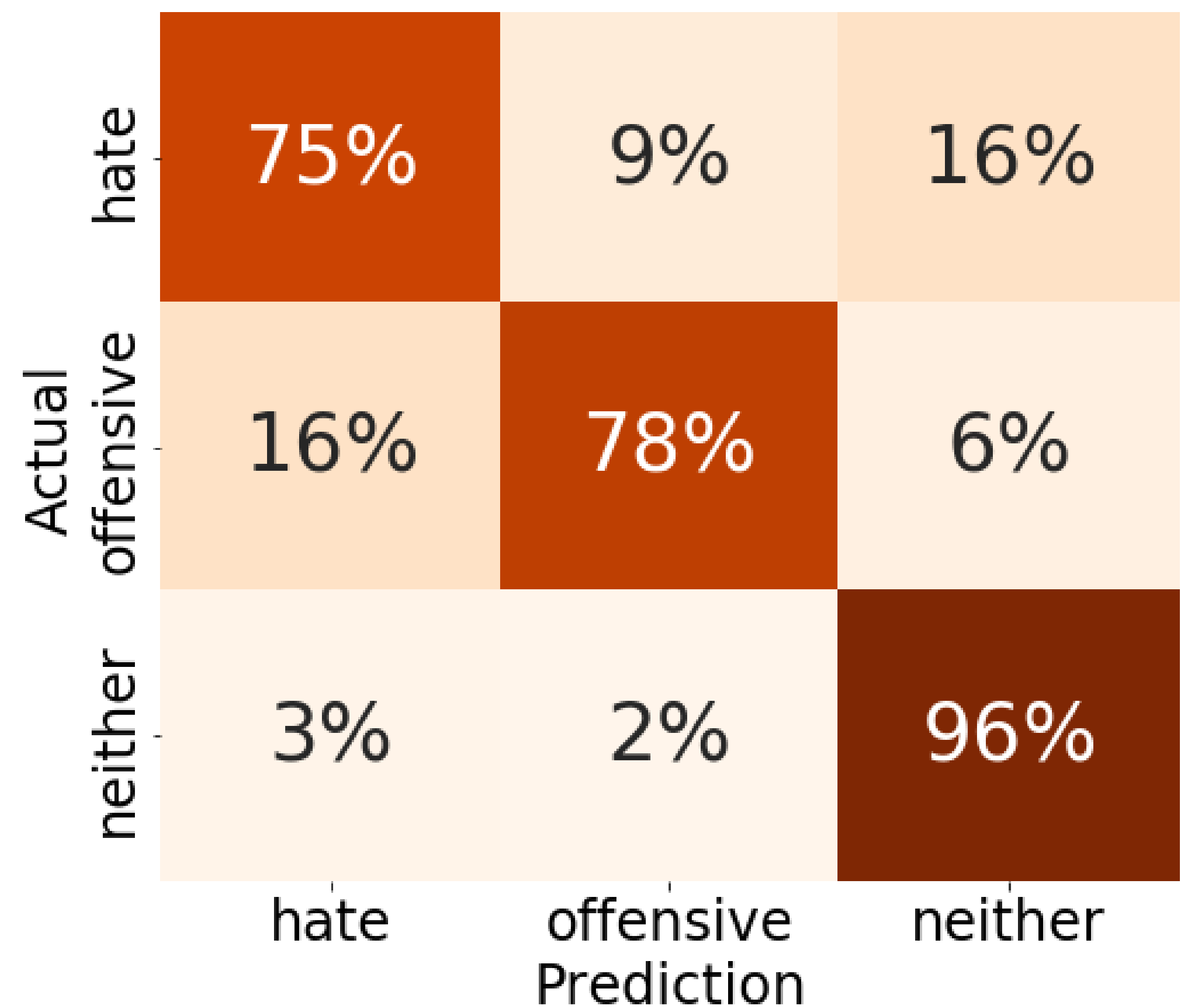
- Not successful at detecting hate speech
- Especially, there is problem distinguishing hate speech and offensive language
- f1-macro: 78%
- f1-weighted: 85%

Result: With Data Augmentation

Without Data Augmentation



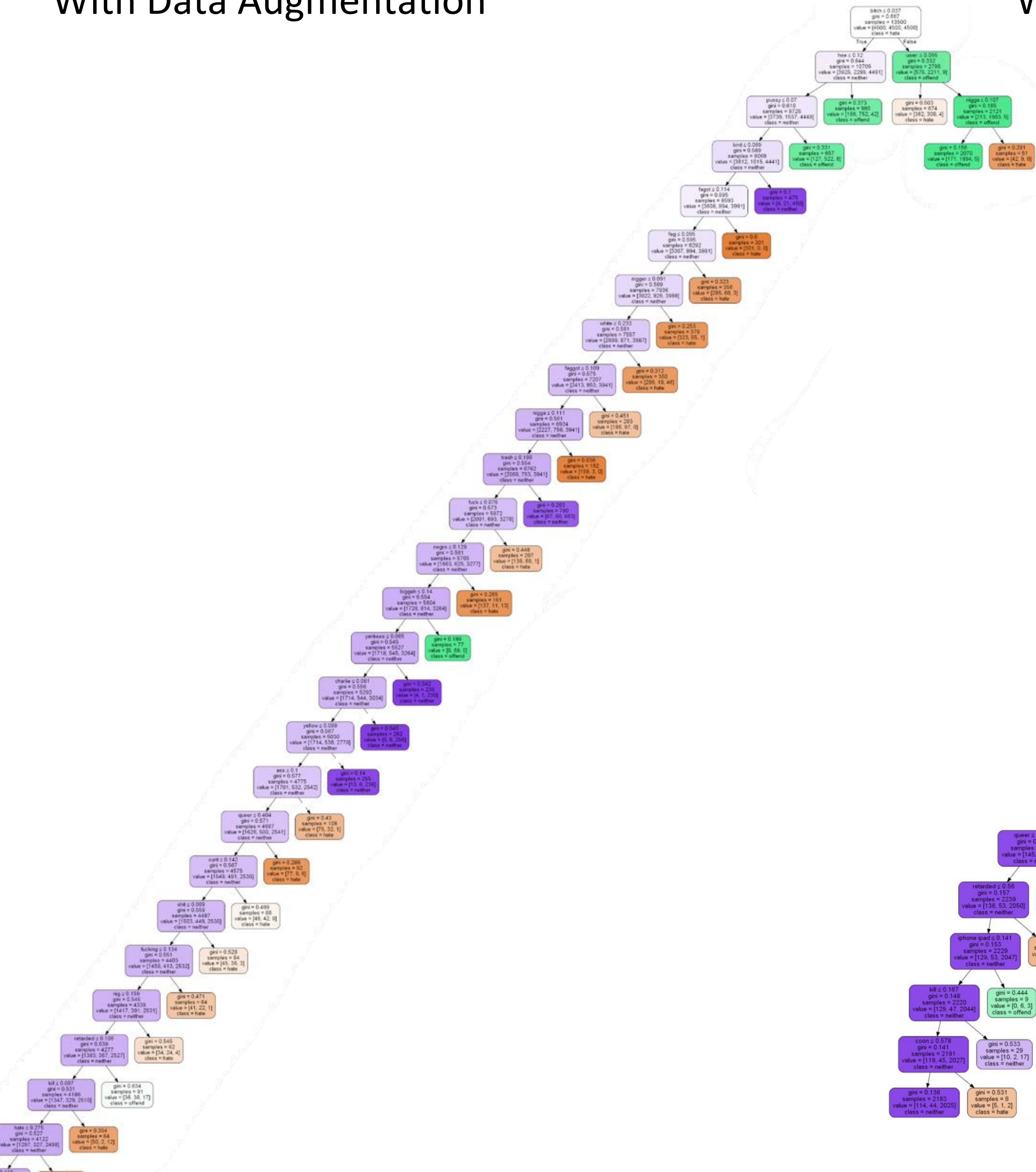
With Data Augmentation



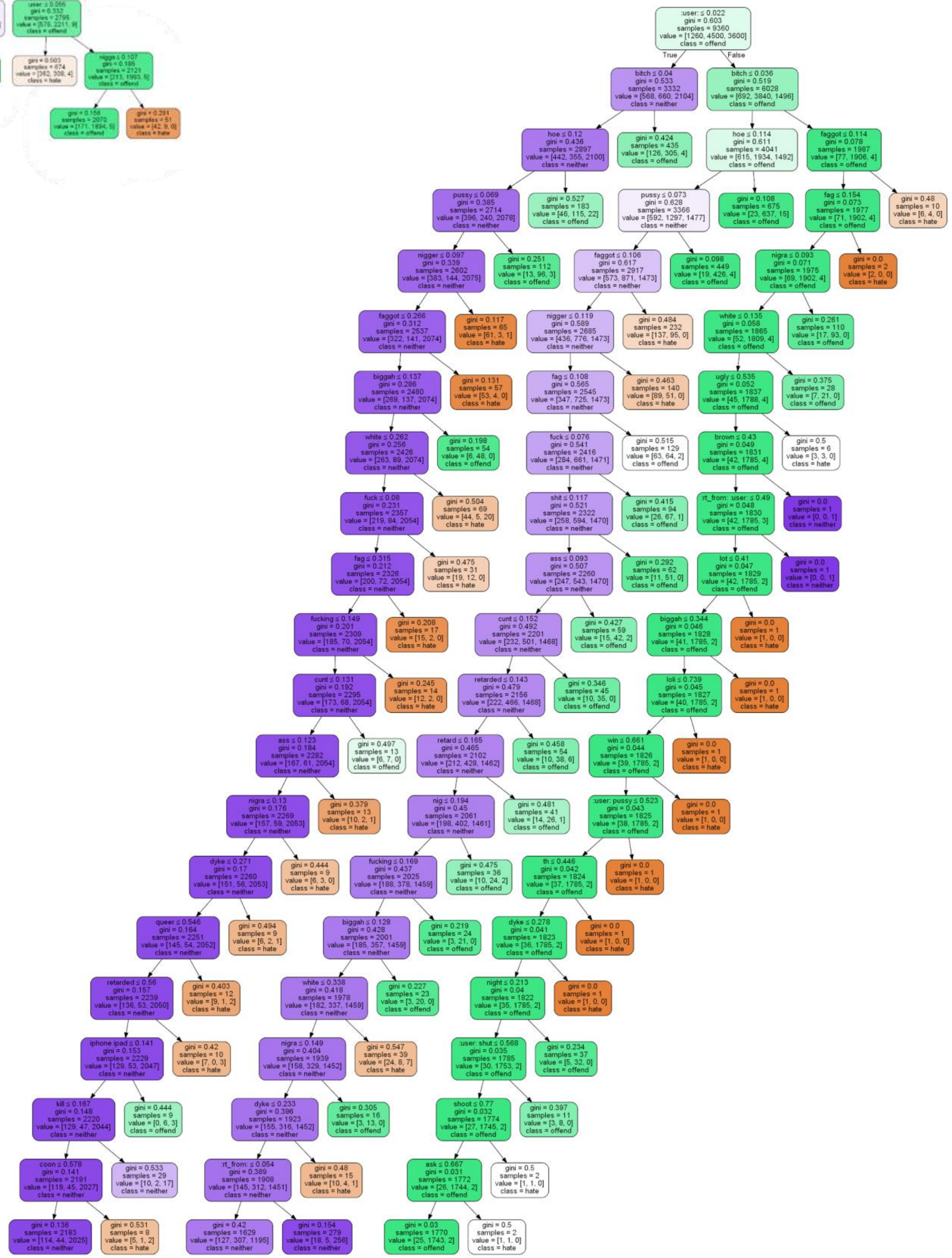
- hate speech's true positive improved greatly
- More data was mistakenly classified as hate speech

- f1-macro: 78% → 80%
- f1-weighted: 85% → 85%

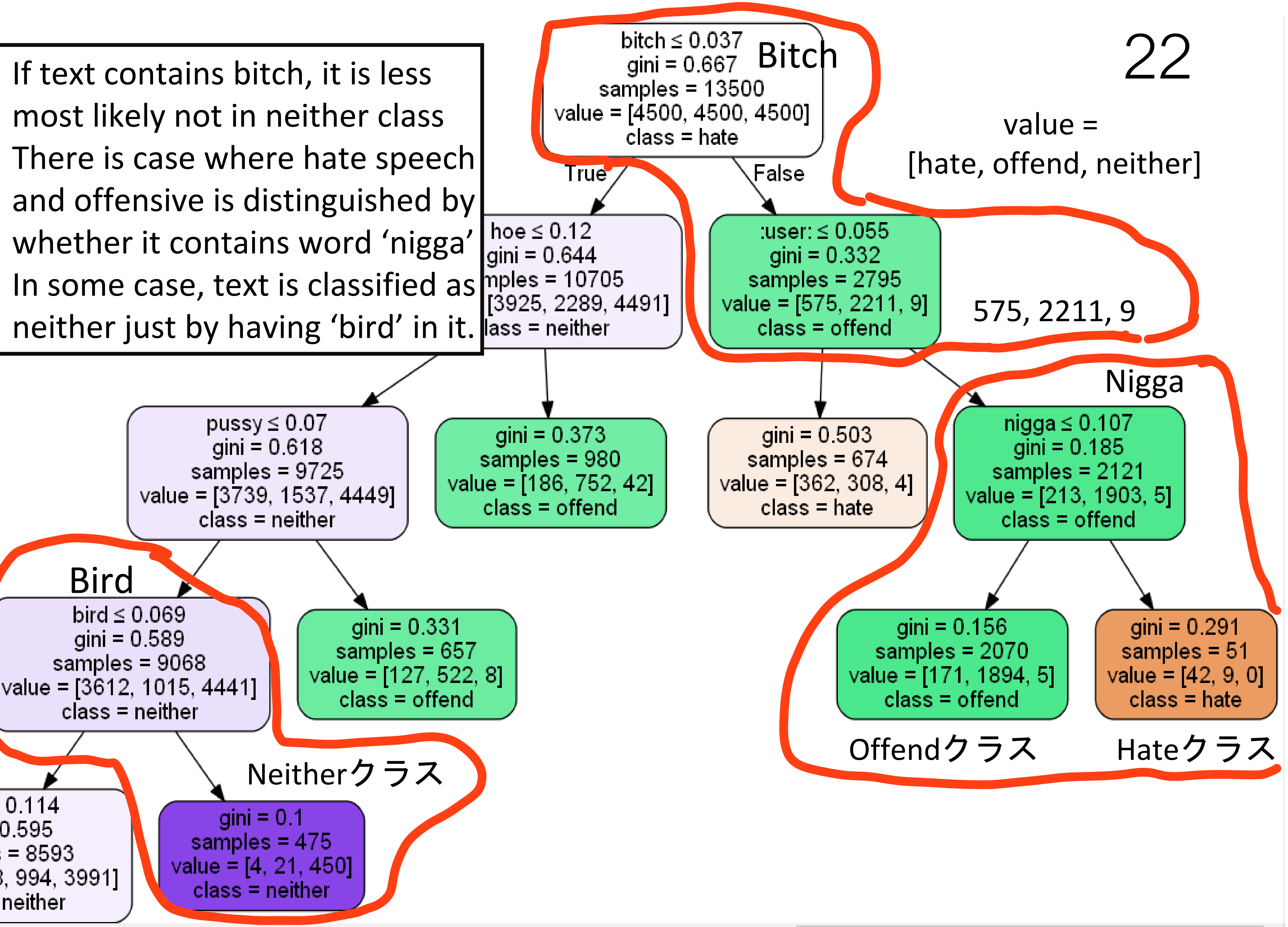
With Data Augmentation



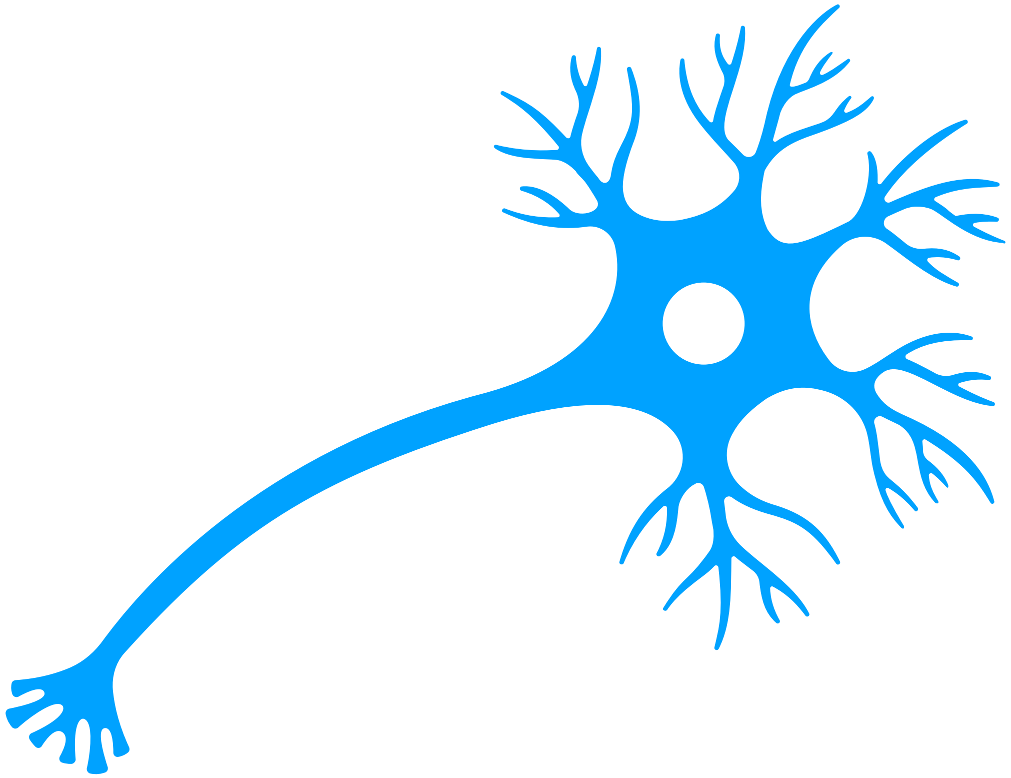
Without Data Augmentation



If text contains bitch, it is less most likely not in neither class
There is case where hate speech and offensive is distinguished by whether it contains word ‘nigga’
In some case, text is classified as neither just by having ‘bird’ in it.

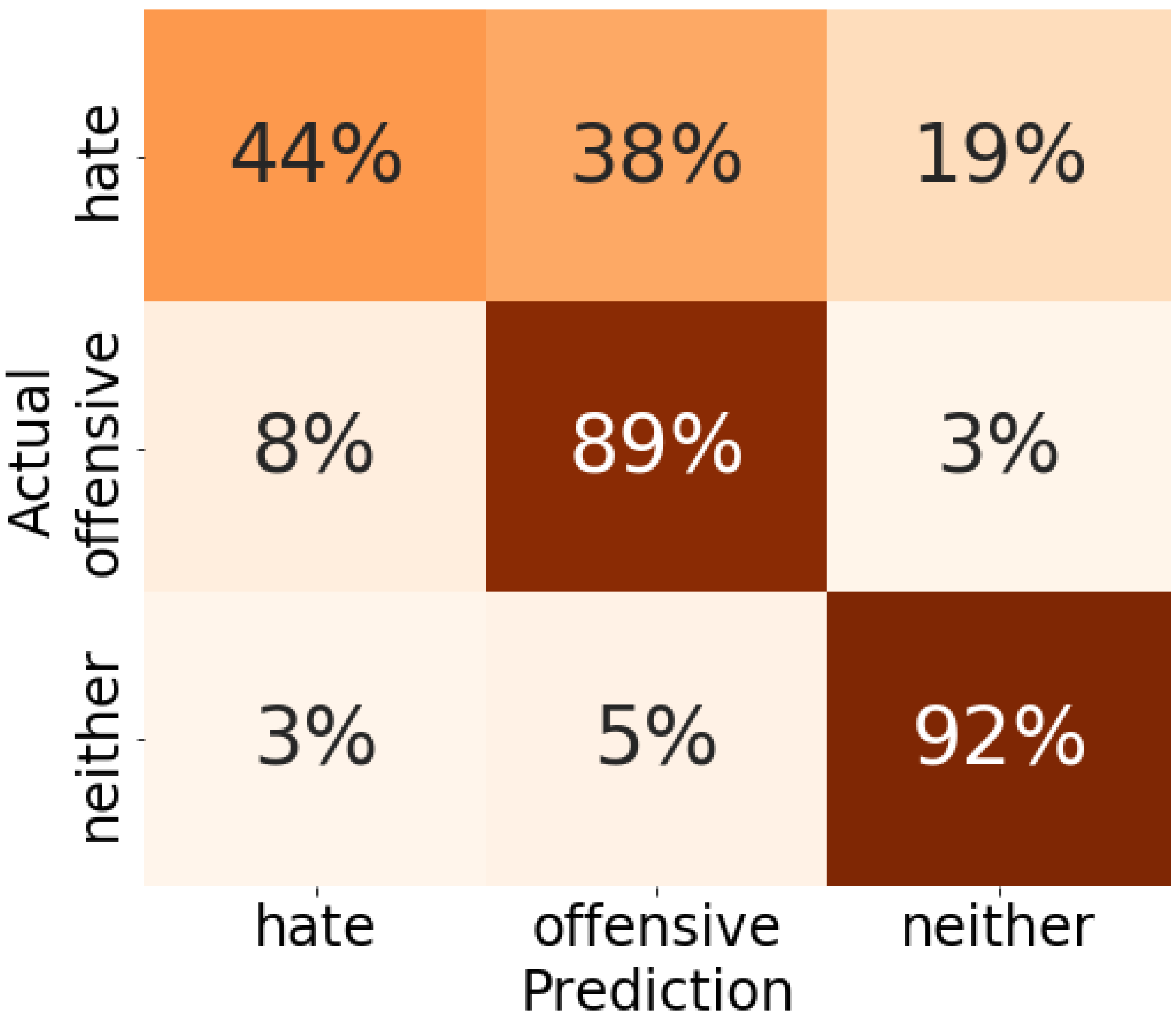


LSTM



Result: Original Data Only

Classification Result（%）



- Similar to decision tree, offensive, and neither are classified well

  f1-score 90%

- Accuracy for hate speech is bad

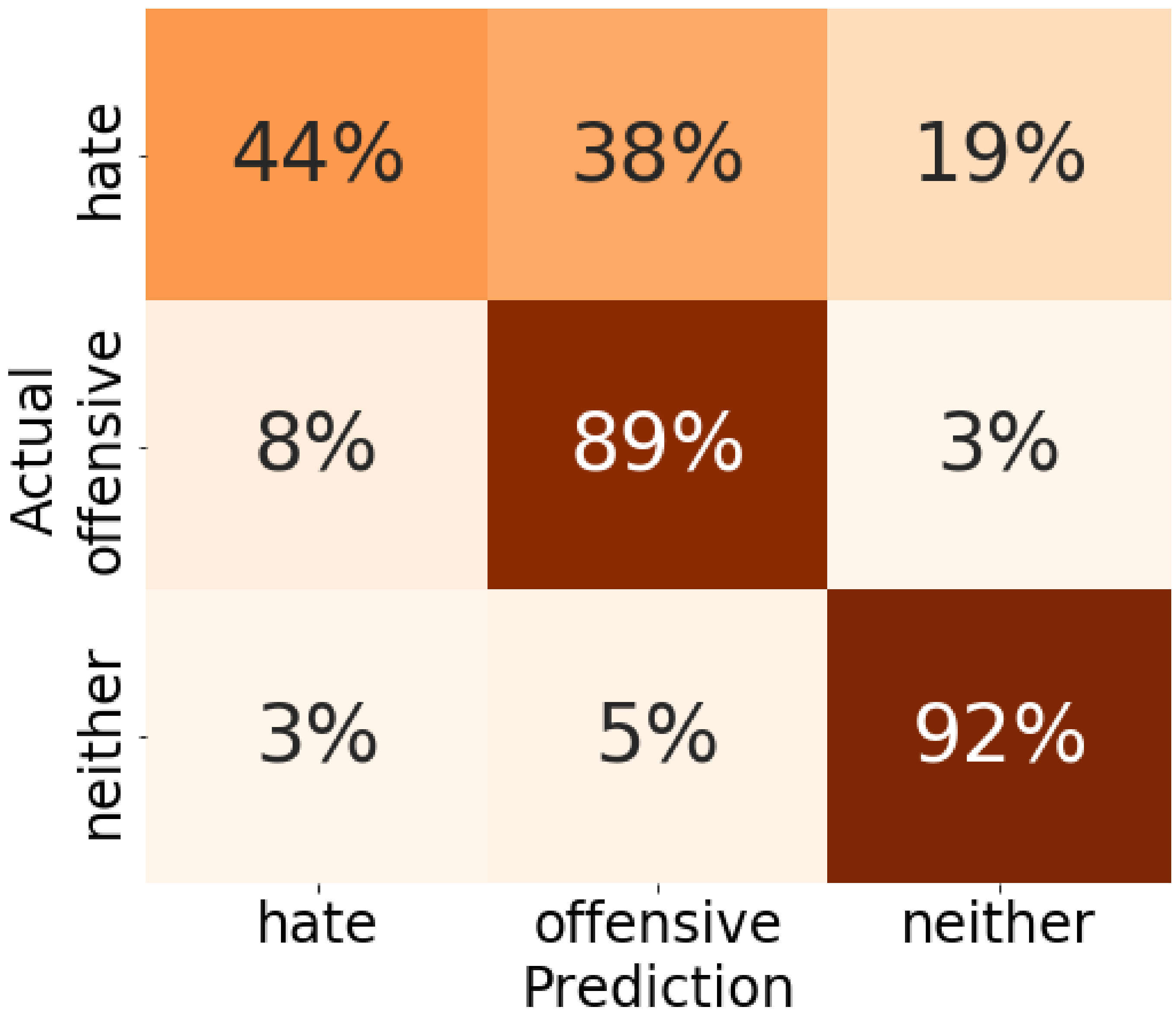
  → 38% is classified as offensive

- f1-macro: 76%

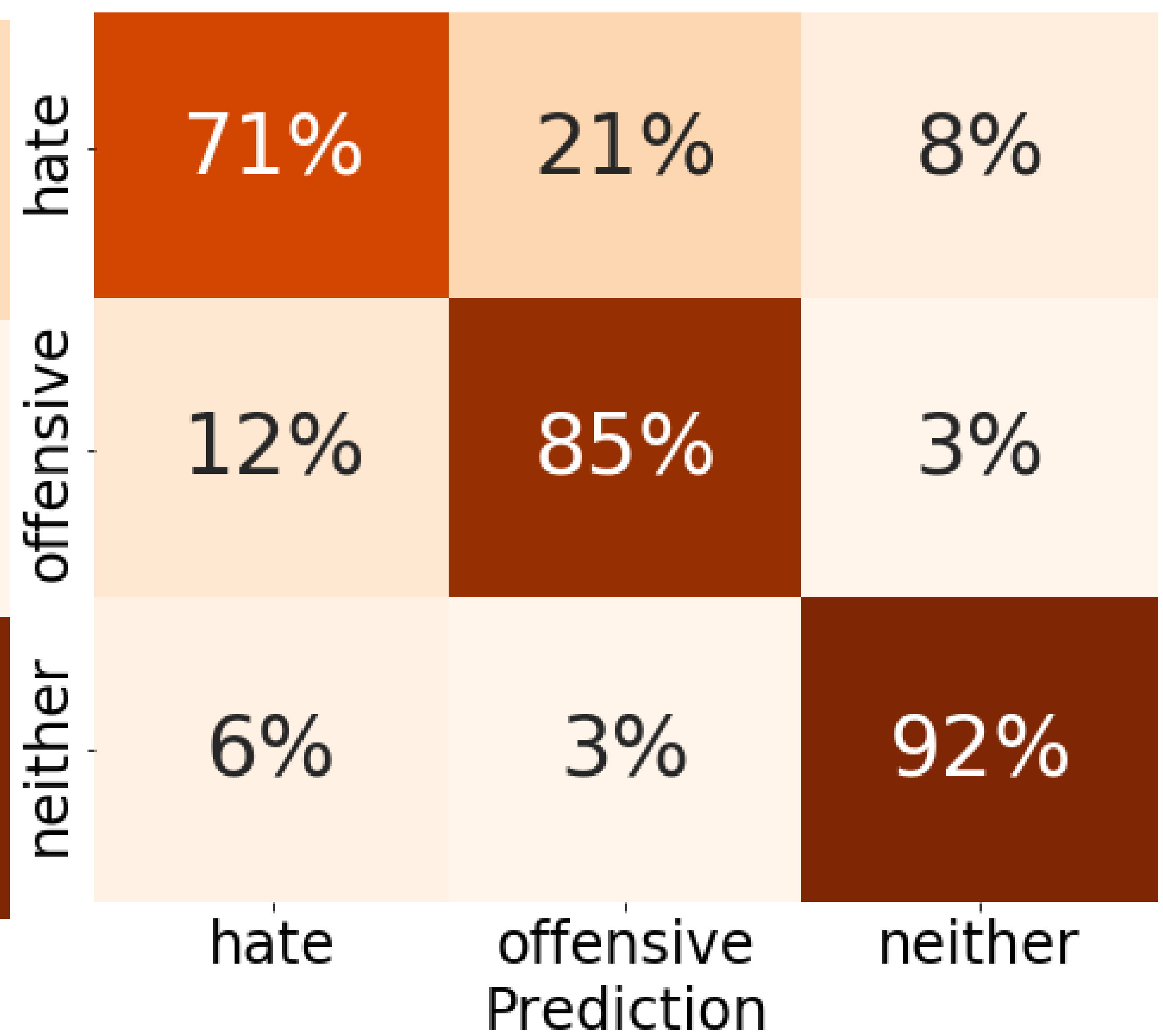
- f1-weighted: 83%

Result: With Data Augmentation

Without Data Augmentation

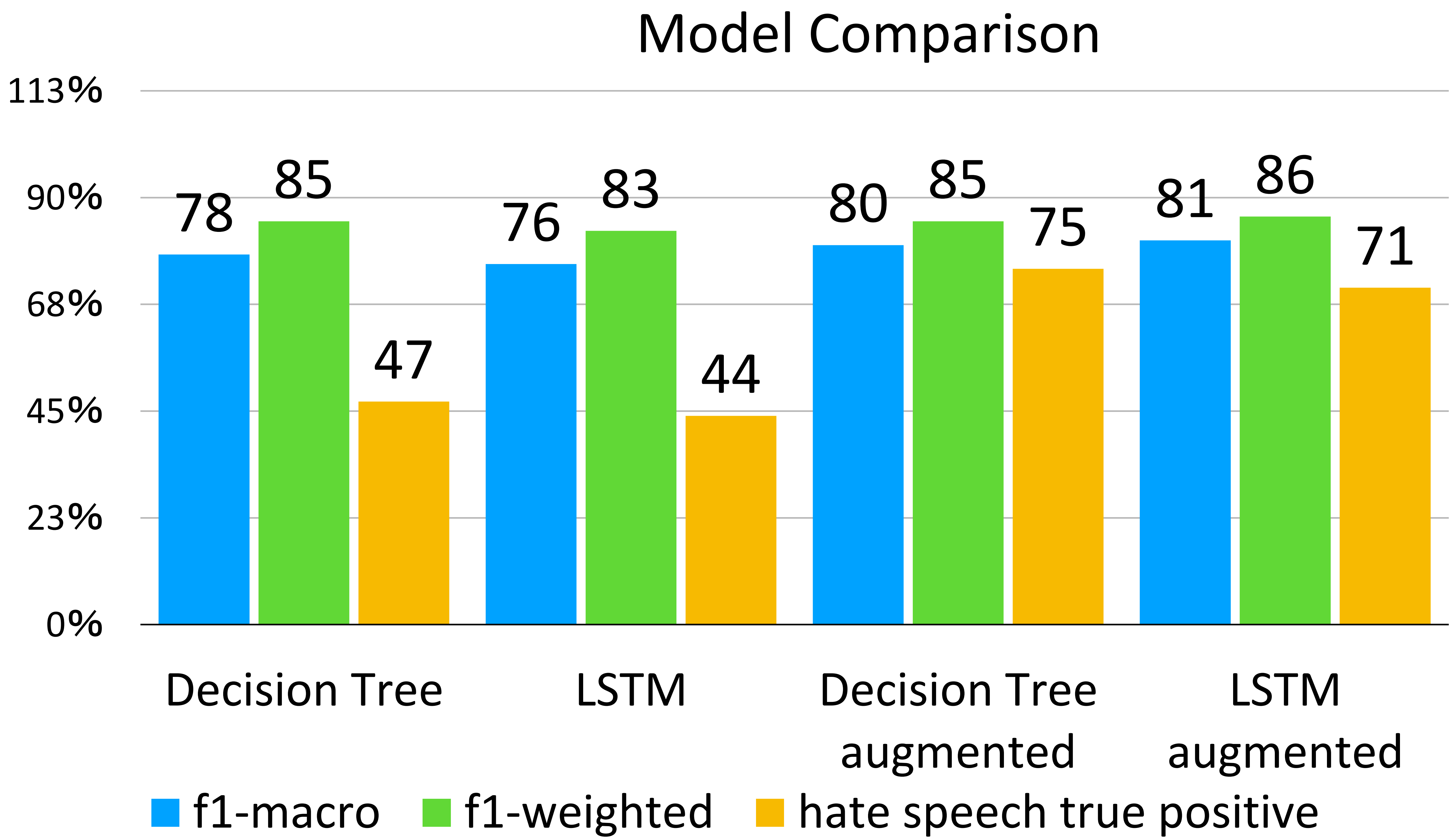


With Data Augmentation



- Again, true positive of hate speech class improved
- False positive of hate speech worthened

- f1-macro: 76% → 81%
- f1-weighted: 83% → 86%



- Both models have similar result

Conclusion

Conclusion

- Trained decision tree and LSTM
- offensive language and neither classes can be detected well

  → both models are good if only trying to detect those two

- There is still problem in classifying hate speech

Conclusion: hate vs offensive

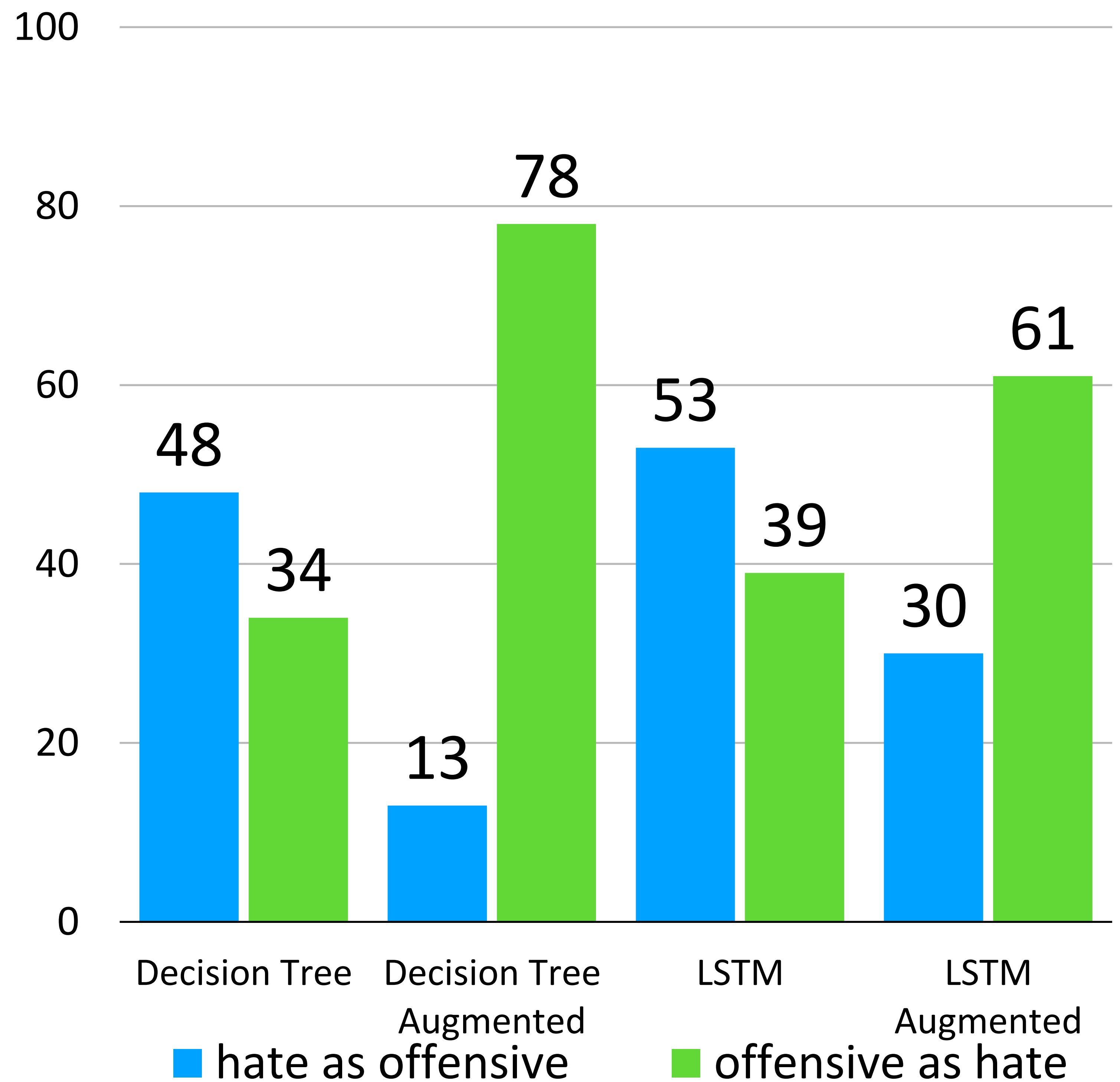
- Models had difficulty distinguishing these two classes

- Original data only

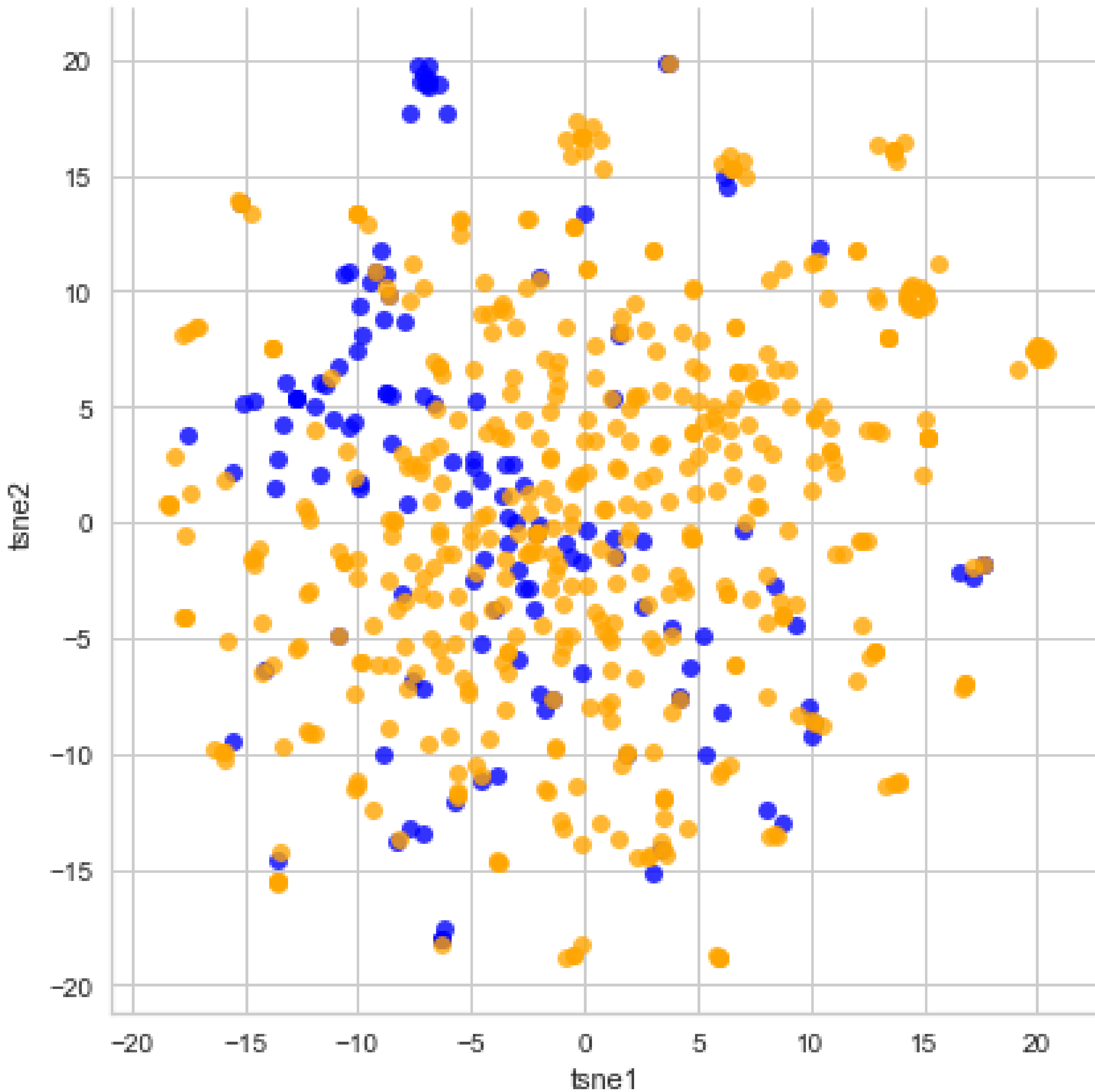
→hate speech likely to be classified as offensive language

- With data augmentation

→offensive language likely to be classified as hate speech



Visualization using TSNE



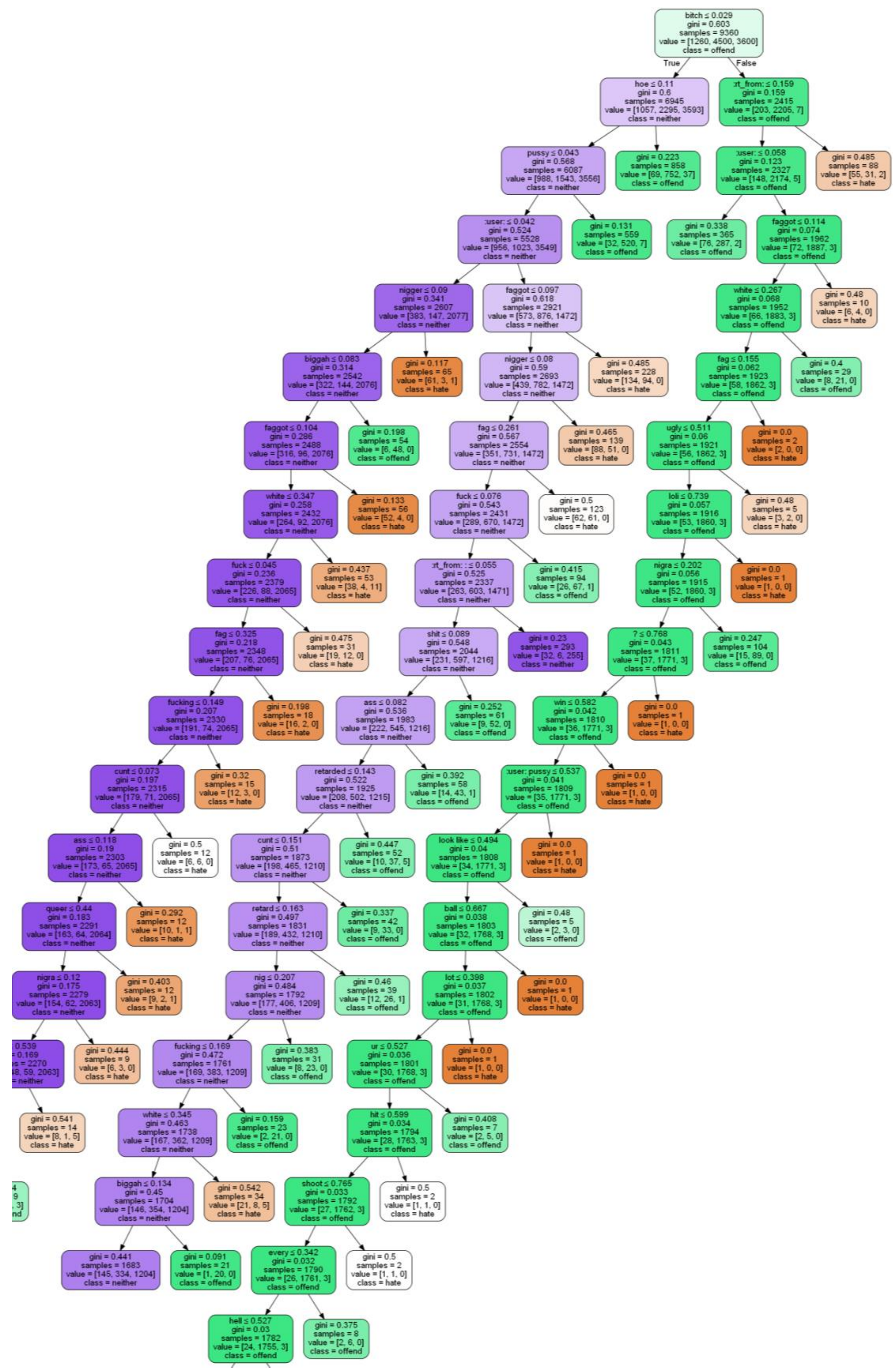
2 classes are overlapping, maybe this is why the classification did not go well

hate speech

offensive language

Decision Tree

Best Model



Conclusion: Best Model

- It is easier to explain why the model has made its decision

  →Can give explanation, when we delete posts from user

  →less likely to damage user experience

- Performance is satisfactory

  → f1-weighted 85%

Future Work

1. More data
2. Improv faults in decision tree
3. Try more advanced models