

CS 772: Regional Multi-lingual Negative Sentiment Detection in Online Media

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Team 10

Problem Statement

Demo - Sentiment value for different sentences

- Input: text in the form of a sentence or whole passage
- Output: Two subtasks
 - Classified into: Overtly, Covertly or Not Aggressive (OAG/CAG/NAG)
 - Also, gendered classification (GEN/NGEN) has been explored

Motivation

We have observed media and all forms of communication move to a digital format, over the internet. While this has had a positive impact by bringing the world together, it has several negative implications in the form of hate speech, aggression and misogyny spread. We hope to be able to identify the following in an automated manner.

Basic Paper(s)

Papers which form basis of our work

[1] Towards Sub-Word Level Compositions for Sentiment Analysis of Hindi-English Code Mixed Text

Aditya Joshi, Ameya Prabhu, Manish Shrivastava, Vasudeva Varma

<https://www.aclweb.org/anthology/C16-1234/>

[2] Aggression Identification in English, Hindi and Bangla Text using BERT, RoBERTa and SVM

Arup Baruah, Kaushik Das, Ferdous Barbhuiya, Kuntal Dey

<https://www.aclweb.org/anthology/2020.trac-1.12/>

Data

- **Description** - Developing a Multilingual Annotated Corpus of Misogyny and Aggression
 - From the book Proceedings of the Second Workshop on Trolling, Aggression and Cyberbullying (May 2020), European Language Resources Association (ELRA)
- **URL** – https://github.com/cozek/trac2020_submission/tree/master/data/hin

Data

Citation details:

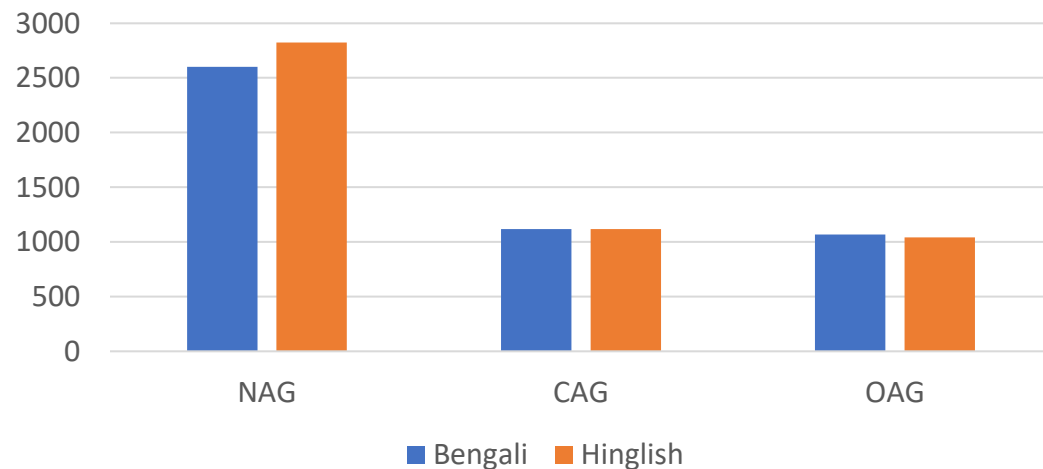
```
@InProceedings{trac2-dataset,  
  author = {Bhattacharya, Shiladitya and Singh, Siddharth and Kumar, Ritesh and Bansal, Akanksha  
and Bhagat, Akash and Dower, Yogesh and Lahiri, Bornini and Ojha, Atul Kr.},  
  title = {Developing a Multilingual Annotated Corpus of Misogyny and Aggression},  
  booktitle = {Proceedings of the Second Workshop on Trolling, Aggression and Cyberbullying},  
  month = {May},  
  year = {2020},  
  address = {Marseille, France},  
  publisher = {European Language Resources Association (ELRA)},  
  pages = {158--168},  
  url = {https://www.aclweb.org/anthology/2020.trac2-1.25}  
}
```

Data Statistics

Bengali Dataset

```
Total dev + train size = 4783  
  
NAG      2600  
CAG      1116  
OAG      1067  
Name: Sub-task A, dtype: int64  
  
NGEN     3880  
GEN       903  
Name: Sub-task B, dtype: int64
```

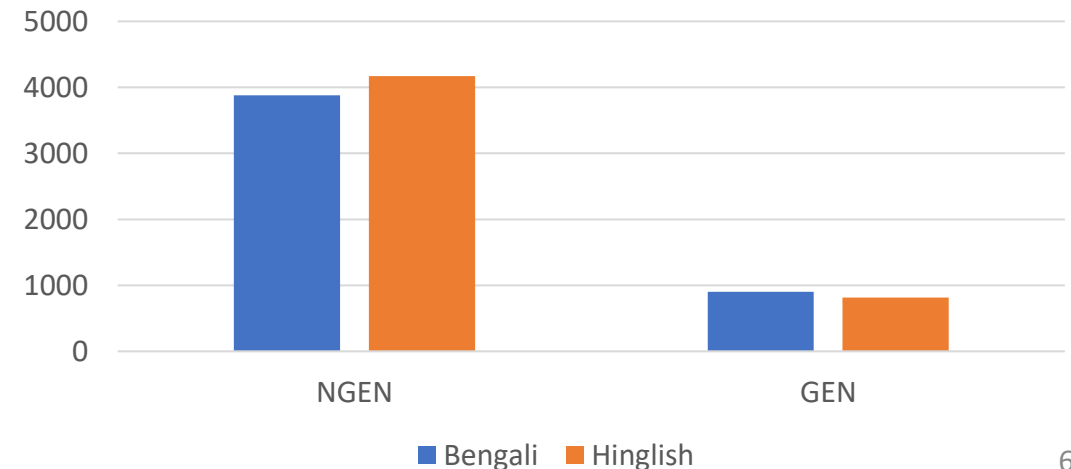
Aggression Level Chart



Hinglish Dataset

```
Total dev + train size = 4981  
  
NAG      2823  
OAG      1118  
CAG      1040  
Name: Sub-task A, dtype: int64  
  
NGEN     4168  
GEN       813  
Name: Sub-task B, dtype: int64
```

Gendered Count Chart



Techniques used

Deep Learning & Transformers are the primary techniques

- XLM-RoBERTa transformer
 - Implementation using XLM-RoBERTa - outperforms M-BERT in multiple cross-lingual benchmarks
 - Batch size is set to 32
 - 270M parameters with 12-layers, 768-hidden-state, 3072 feed-forward hidden-state, 8-heads,
 - Trained on 2.5 TB of newly created clean CommonCrawl data in 100 languages

Advantages of RoBERTa over BERT

Few modifications to the original model such as (BERT)

- Training on a larger dataset
- Dynamically masking out tokens compared to the original static masking
- Used pre-trained base versions made available by the HuggingFace Transformers library

Description of XLM-RoBERTa

- XLM-RoBERTa (Conneau et al., 2019) is a cross-lingual model that aims to tackle 'the curse of multilinguality problem' of cross-lingual models
- trained on up-to 100 languages and out-performs M-BERT in multiple cross-lingual benchmarks
- Base version coupled with an attention head classifier
- This model is used in the sub-tasks of the Hindi and Bangla language

Transformer: XLM-RoBERTa



```
graph TD; A[Transformer: XLM-RoBERTa] --> B[Bi-LSTM layer – 50 units – 0.1 dropout rate]; B --> C[GlobalMaxPool – 1D layer]; C --> D[Dense Layer – ReLU – 50 units]; D --> E[Dropout layer – Rate = 0.2]; E --> F[Dense layer – SoftMax – 2 or 3 units depending on subtask A or B];
```

Bi-LSTM layer – 50 units – 0.1 dropout rate

GlobalMaxPool – 1D layer

Dense Layer – ReLU – 50 units

Dropout layer – Rate = 0.2

Dense layer – SoftMax – 2 or 3 units
depending on subtask A or B

Results

| Sub-task | Train accuracy | Validation accuracy | F-score | Precision | Recall |
|----------|----------------|---------------------|---------|-----------|--------|
| A | 0.7358 | 0.6991 | 0.7305 | 0.6410 | 0.6234 |
| B | 0.8398 | 0.8475 | 0.8983 | 0.9142 | 0.8823 |

Confusion matrix for
sub-task A

```
[[479  23  76]
 [ 40 120  48]
 [ 80  33  98]]
```

Confusion matrix for
sub-task B

```
[[773  72]
 [103  49]]
```

Demo and Case Study

Qualitative / case studies - Hindi

1. Gendered sentences:

| Example sentence | GEN probability | NGEN probability |
|-----------------------------------|-----------------|------------------|
| Ladki pagal ho gayi hai | 0.7785 | 0.2215 |
| superb hai bhai. bohot accha kiya | 0.1871 | 0.8129 |

2. Aggression-level analysis:

| Example sentence | Not aggressive probability | Covertly aggressive probability | Overtly aggressive probability |
|--|----------------------------|---------------------------------|--------------------------------|
| Wo bohot hi sweet hai | 0.8188 | 0.1230 | 0.0582 |
| Do Chaar Murder hone k baad Hi Patta chalta hi ki Kaun Sachcha aur Jhootha | 0.2389 | 0.4716 | 0.2895 |
| Tere mar ja nay pai kisi ko fark nahi padta | 0.1710 | 0.3980 | 0.4309 |

Demo and Case Study

Qualitative / case studies - Bengali

1. Aggression-level analysis:

| Example sentence | Not aggressive probability | Covertly aggressive probability | Overtly aggressive probability |
|---|----------------------------|---------------------------------|--------------------------------|
| Tumi thik bolcho | 0.4515 | 0.2323 | 0.3160 |
| Tar jonno payer juto mathay uthano jay na | 0.2824 | 0.3704 | 0.3471 |
| Aaami tomaake ekdum jore maarbo | 0.2947 | 0.3465 | 0.3587 |

2. Gendered sentences:

| Example sentence | GEN probability | NGEN probability |
|--|-----------------|------------------|
| Jar jeta paowa uchit noy, seta take dite nei | 0.3813 | 0.6187 |
| Tumi paagol mohila | 0.6485 | 0.3514 |

Conclusion and Future Work

In our work we have observed that XLM-RoBERTa performs well under Hinglish and Bengali texts. We identify two extensions for this model and training:

1. Speech-to-text for hate speech in videos on social media platforms
2. Extension through more multilingual transformers like

Results (Bengali)

| Sub-task | Train accuracy | Validation accuracy | F-score | Precision | Recall |
|----------|----------------|---------------------|---------|-----------|--------|
| A | 0.5572 | 0.5549 | 0.2709 | 0.3251 | 0.3497 |
| B | 0.8259 | 0.8004 | 0.8679 | 0.9217 | 0.8223 |

Confusion matrix for
sub-task A

```
[[519    0    3]
 [208    0    9]
 [206    0   12]]
```

Confusion matrix for
sub-task B

```
[[706  60]
 [155  36]]
```