

SemEval-2022

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IISERB Brains at SemEval 2022 Task 6: A Deep-learning Framework to Identify Intended Sarcasm in English

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Sarcasm in spoken or written form is a **type of verbal** irony that indicates the **difference between the literal and intended meanings** of an utterance.

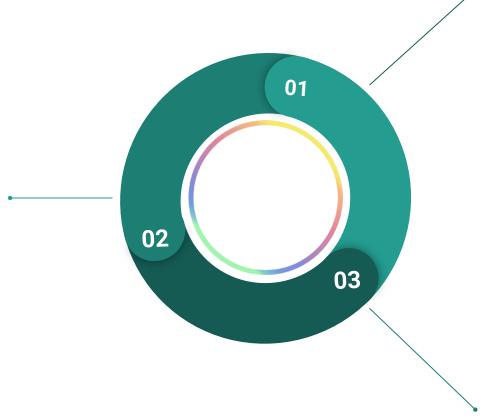
A large portion of the web and social media text is sarcastic, which creates a challenge for traditional natural language processing (NLP) tasks like sentiment classification, opinion mining, harassment detection, author profiling.

The **SemEval-2022 Task 6** identifies some of the challenges persisting till now, particularly in English and Arabic texts.

Task Details

Sub-task B:

This sub-task is designed for particularly English dataset. It is a binary multilabel classification task. Here, given a text, we have to determine which ironic speech category it belongs to, if any.



Sub-task A:

Given a text, determine whether it is sarcastic or non-sarcastic

Sub-task C:

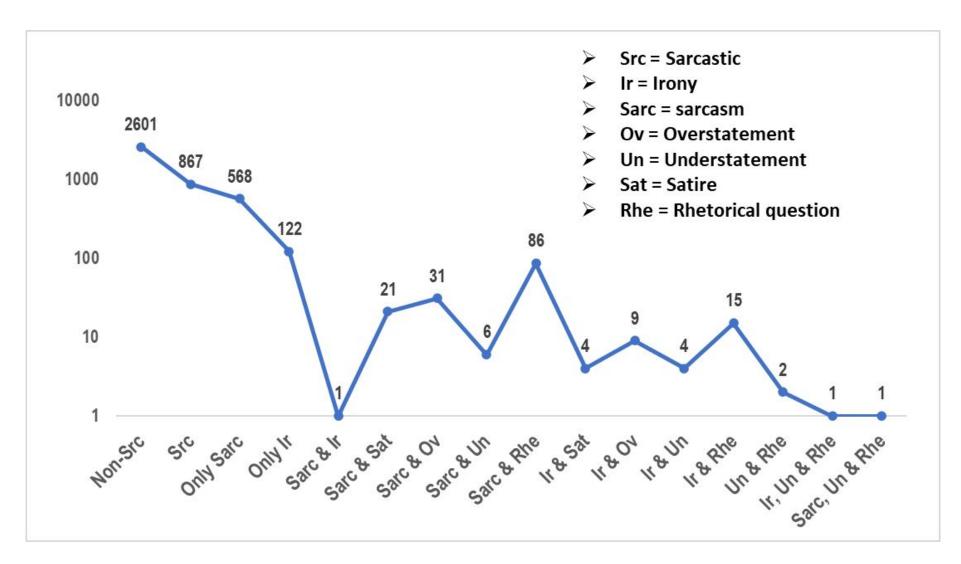
Given a sarcastic text and its non- sarcastic rephrase, i.e. two texts that convey the same meaning, determine which of the two is the sarcastic.

Dataset



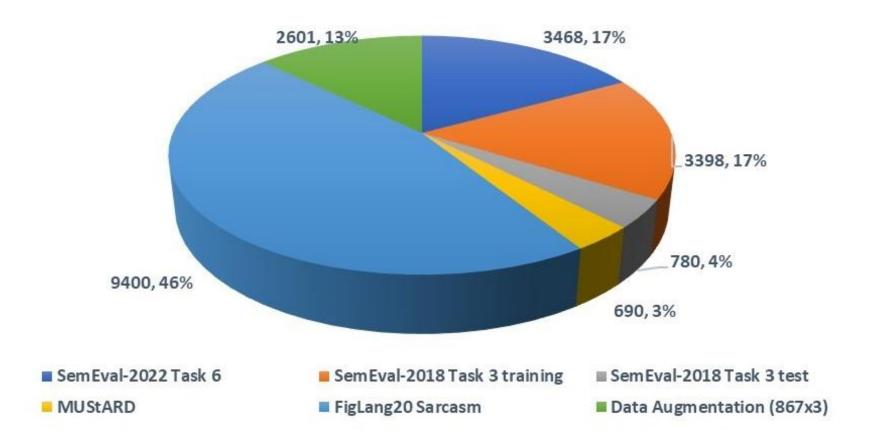
 For the subtasks, we used the English dataset provided by the task organizers. It has 3468 English tweets which included 867 sarcastic and 2601 nonsarcastic tweets.

 For each sarcastic tweet, the organizers have also provided the ironic sub-classes to which the tweet belongs. The sub-classes are sarcasm, irony, satire, understatement, overstatement, and rhetorical question.

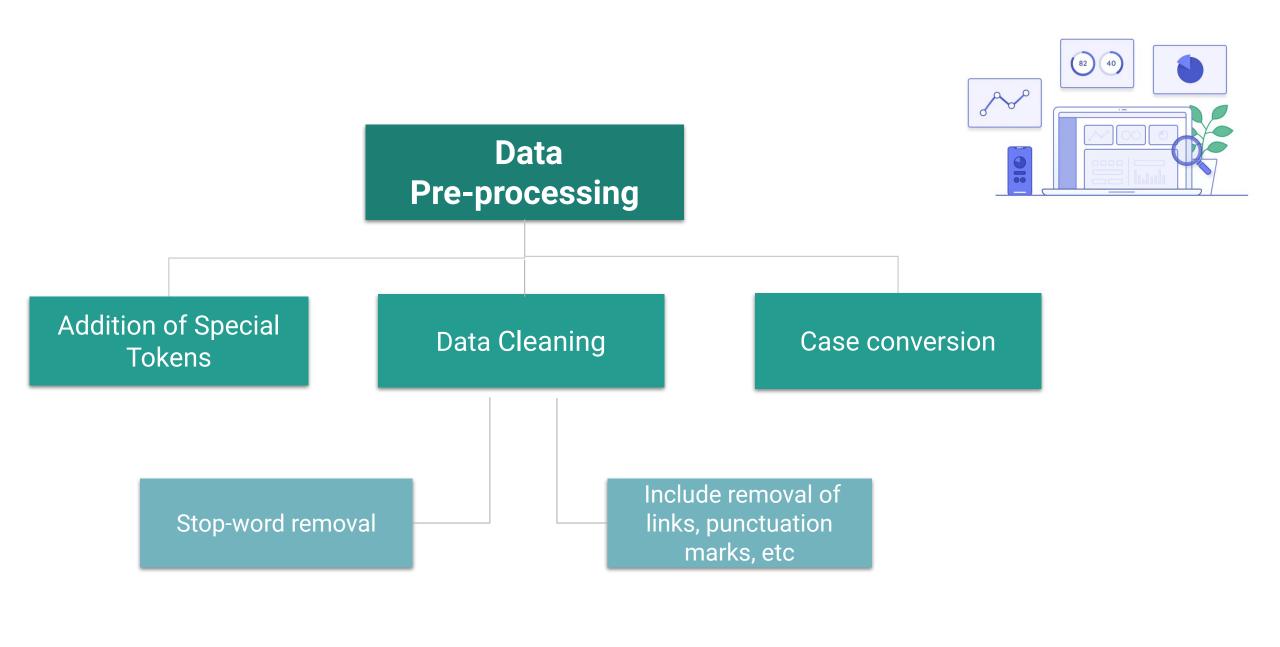








For the sub-task A and C, we considered additional publicly available dataset as shown above. We have used data augmentation for Sarcastic Class of SemEval-2022 Task 6 English Dataset.

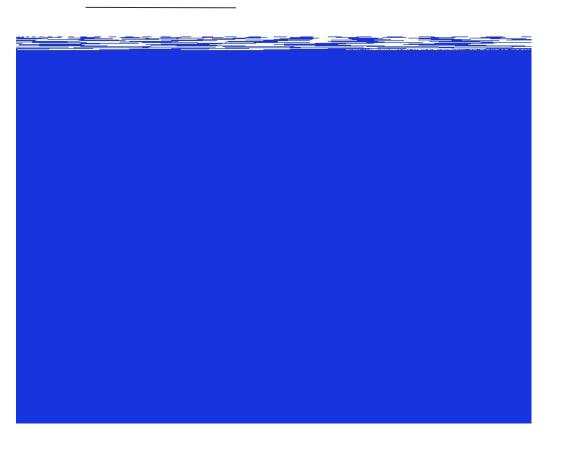


Methodology



- We relied on transformer based architectures to design our models for all sub-tasks.
- We built our models using the hugging face transformer library. They support generic transformer based architectures with the ability to seamlessly initialize the tokens with different pre-trained embeddings.
- In addition we use Data Augmentation using the python **nlpaug library**. For increasing the instances labeled with subcategories in the train data library.

Models



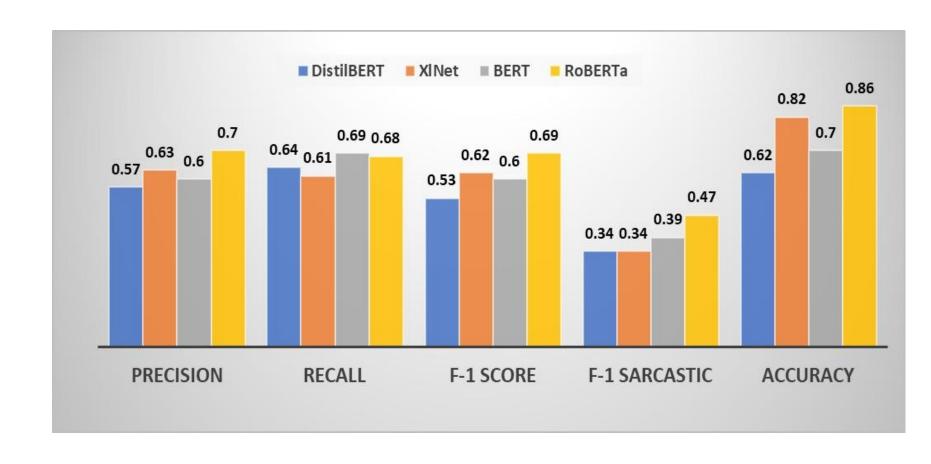
- Sub-task A: For this sub-task, we deployed the binary classifier versions of different transformer based architectures.
- Sub-task B: Here, instead of using a multilabel classifier, we used six binary classifier versions of the transformer based architectures.
- **Sub-task C:** We formulated this sub-task as a **parallel combination** of two sub-task A models

Results



To evaluate our systems we compare our results with the results provided by organizer and calculate F1 score.

Results of each Sub-task are shown alongside.



Results



SubTask A	
Model: BERT	F1=0.34
SubTask B	
Model: BERT	Macro-F1=0.0751
SubTask C	
Model: BERT	Accuracy=0.62

Conclusion



- We applied different transformer-based models to tackle the subtasks..
- **RoBERTa** performs relatively well in our overall experiments.
- Our model achieved the 19th rank out of 43 teams on sub-task A, 8th rank out of 22 teams on subtask B and 13th rank out of 16 teams in sub-task C.

Thank