ARGUMENT GATE

ECE1786 - CREATIVE APPLICATIONS OF NATURAL LANGUAGE PROCESSING - FINAL REPORT.

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WORD COUNT (Without References, Figures, etc.) - 1985
WORD COUNT (With References, Figures, etc.) - 2559
Penalty - 0%

Permissions:

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Permission to Post Video: Yes
Permission to Post Final Report: Yes
Permission to Post Source Code: Yes

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Permission to Post Video: Yes
Permission to Post Final Report: Yes
Permission to Post Source Code: Yes

Introduction:

If natural language processing (NLP) is meant to utilize computational techniques to emulate natural human dialogue, then it stands to reason that there should be paradigms for extracting and constructing a method for validating an assessment for perhaps what humans do most with their language - argue [1]. This field is referred to as computational argumentation which focuses on the analysis and synthesis of arguments that can be used in many applications such as virtual assistants [2], search engines [3], and writing.

The goal of the project is to classify an argument with respect to a given statement, judging the argument on multiple factors into four classes (changed view, excellent argument, adequate argument, inadequate argument). This would indeed help writers, debaters, journalists, and bloggers to assess their written work with feedback that target individual aspects of writing an argument. We assume an argument to be excellent since it has influenced a lot of people positively.

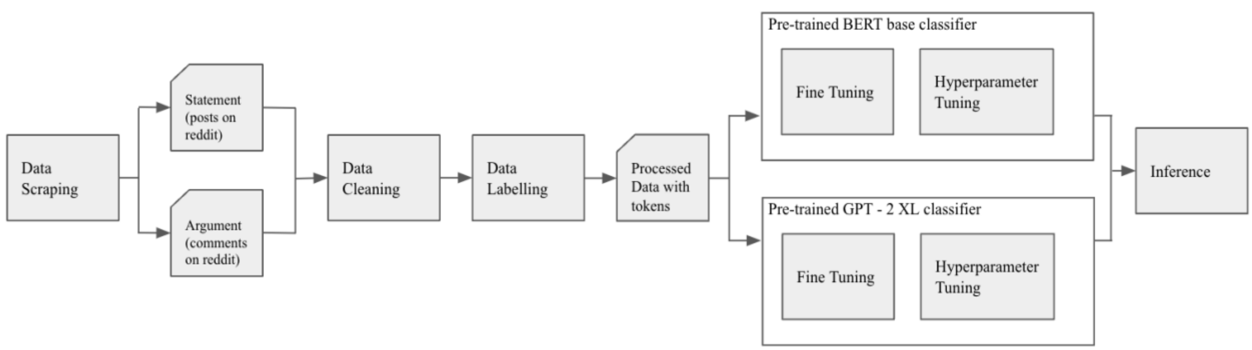


Figure 1: Working of Argument Gate.

Background & Related Work:

Researchers have been developing approaches to extract arguments from natural language text. These approaches belong to the task of Argument Mining, which not only aims to extract argumentative discourse units [4] but also tries to find different sub-structures within arguments [5].

Wachsmuth et al., 2017 [6] present a completely novel work on computational argumentation quality in natural language. It takes into consideration the diverse existing theories and approaches to assess logical, rhetorical, and dialectical quality dimensions and derives a systematic taxonomy from these. This paper defines a platform for the automatic assessment of argumentation quality in natural language.

Lauscher et al., 2020 [7] advance theory-based argument quality research by performing a thorough analysis covering three various domains of online argumentative writing: Q&A forums, debate forums, and review forums. They demonstrated that the relations between theory-based argument quality dimensions can be manipulated to yield performance improvements and demonstrates the utility of theory-based argument quality predictions with respect to the practical Argument Quality (AQ) assessment view. The paper suggests a novel approach of computational theory-based Argument Quality models and establishes that mutually predicting Argument Quality scores can improve the performance of the models (RQ3) and that generally, models benefit from involving out-of-domain training data (RQ4).

Swanson et al., [8] raised a litany of hand-curated features that they claim as indicators of argument presence and quality: Sentence Length (SLEN), Word Length (WLEN), Speciteller (SPTL), Kullback-Leibler Divergence (KLDiv), Discourse (DIS), Part-Of-Speech N-Grams (PNG), Syntactic and (SYN).

Data and Data Processing:

Data Source:

The data is scraped from the **ChangeMyView** subreddit. People post their views or opinions about different topics on this subreddit to have a healthy and open-minded argument. Users who have opposite views, comment on a logical and explained argument in response to the original statement.

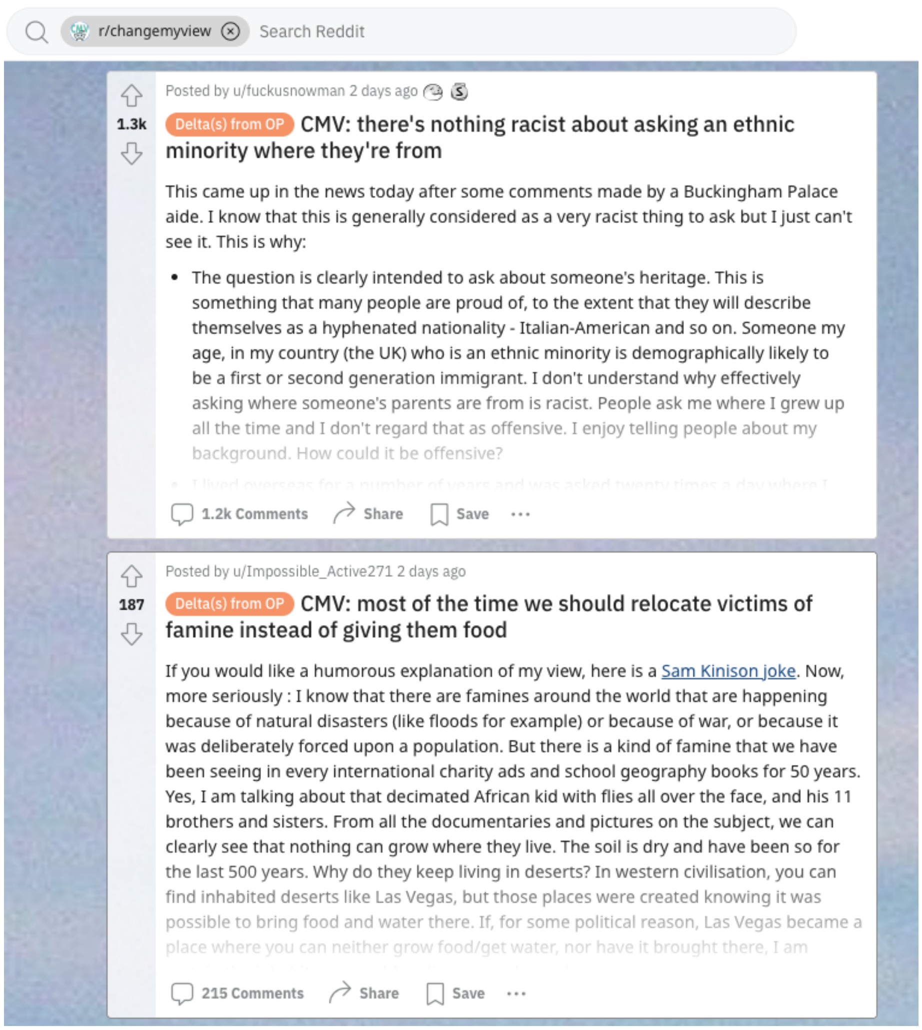
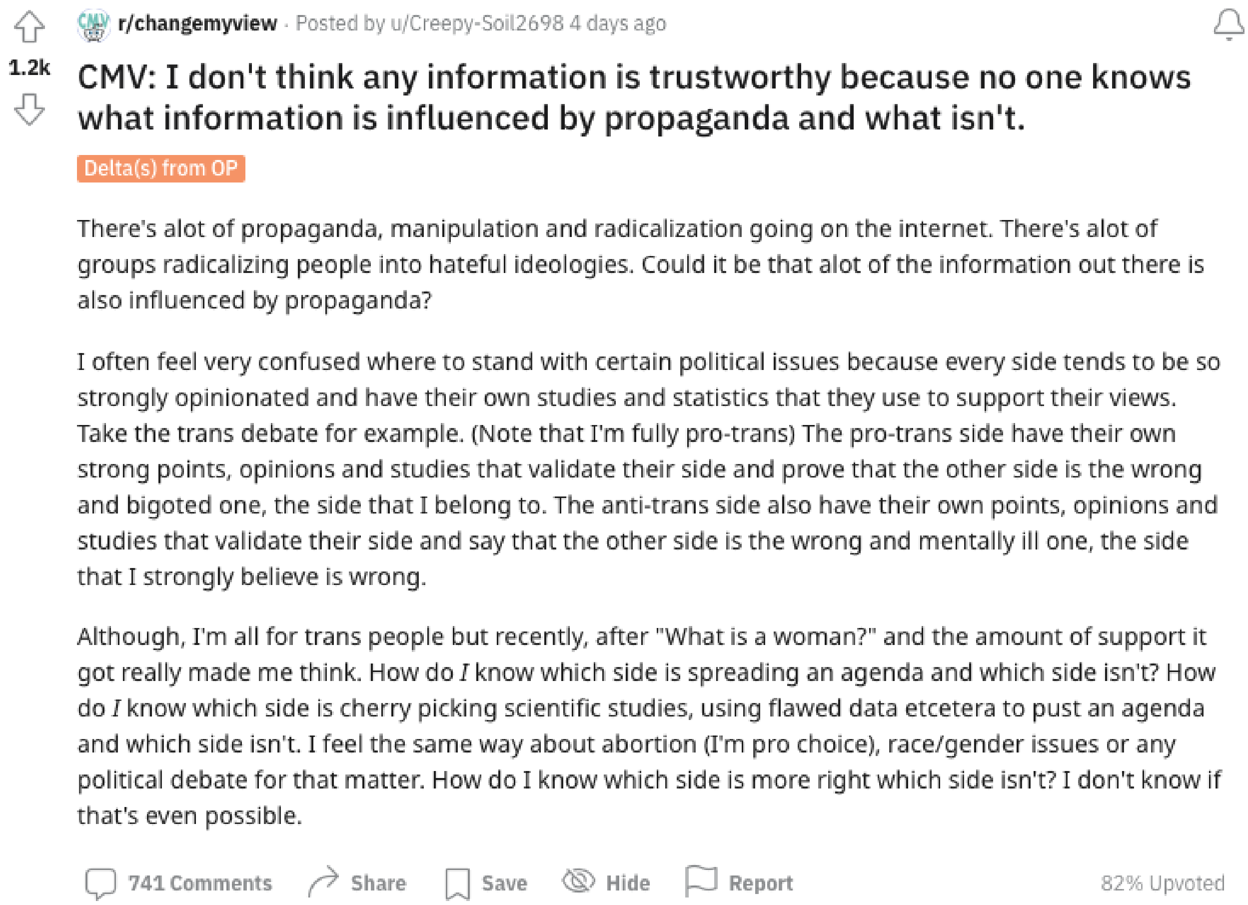


Figure 2: ChangeMyView SubReddit.

The main motivation to use this subreddit is due to the rich nature of the subreddit with respect to users, posts, comments, and methodologies to appreciate good content and not suffer from mass spam.

Data Explanation - Posts:

Users create posts with a statement and an explanation of a topic and their opinions. These posts are created with the intention for vivid users to comment and discuss different opinions and in the process, maybe, change the view of a user.



r/changemyview · Posted by u/Creepy-Soil2698 4 days ago

1.2k

CMV: I don't think any information is trustworthy because no one knows what information is influenced by propaganda and what isn't.

Delta(s) from OP

There's alot of propaganda, manipulation and radicalization going on the internet. There's alot of groups radicalizing people into hateful ideologies. Could it be that alot of the information out there is also influenced by propaganda?

I often feel very confused where to stand with certain political issues because every side tends to be so strongly opinionated and have their own studies and statistics that they use to support their views. Take the trans debate for example. (Note that I'm fully pro-trans) The pro-trans side have their own strong points, opinions and studies that validate their side and prove that the other side is the wrong and bigoted one, the side that I belong to. The anti-trans side also have their own points, opinions and studies that validate their side and say that the other side is the wrong and mentally ill one, the side that I strongly believe is wrong.

Although, I'm all for trans people but recently, after "What is a woman?" and the amount of support it got really made me think. How do *I* know which side is spreading an agenda and which side isn't? How do *I* know which side is cherry picking scientific studies, using flawed data etcetera to pust an agenda and which side isn't. I feel the same way about abortion (I'm pro choice), race/gender issues or any political debate for that matter. How do I know which side is more right which side isn't? I don't know if that's even possible.

741 Comments · Share · Save · Hide · Report · 82% Upvoted

Figure 3: Example of a post in ChangeMyView Subreddit.

Data Explanation - Comments:

Individuals who wish to provide their opinion or argument on a topic can provide so with the mechanism of a comment. Comments serve as the argument to the problem statement i.e., the post to our model. If an argument changed someone's perspective, they comment a delta (represent change) on that to show appreciation. Moreover, they upvote an excellent argument and downvote an inadequate argument. We scrape these metrics (delta and votes) provide us with information on whether arguments are best or worst for a given statement.

Delta
UpVote
DownVote

Figure 4: Example of a comment in ChangeMyView Subreddit.

Data Scrapping:

Data is scrapped using the PRAW library. We scrapped all the posts from November 2013 till November 2022. Then all the corresponding comments along with metadata are fetched such as the number of upvotes, and depth in the comment tree. We have scrapped 107717 posts and 1425075 comments in total.

The logs of delta reward given to a comment are present on Delta Log Reddit. In total, we scrapped 56121 delta comments. This metadata is then merged with the main scrapped dataset to build a combined dataset. We also added a data_id column through which can uniquely identify our data point.

	data_id	delta	statement_id	statement	statement_author	arguement_id	argument	argument_author	upvotes	depth
0	1088814	4.0	orxd63	CMV: Covid Vaccination is NOT going to end covid	TruerInfo	h6kuc06	>Malta has vaccinated the entire eligible popu...	Runiat	13.0	0.0
1	1088815	4.0	orxd63	CMV: Covid Vaccination is NOT going to end covid	TruerInfo	h6kvaje	>Isn't it better to not have ANY covid in your...	edwardlleandre	9.0	0.0
2	1088819	4.0	orxd63	CMV: Covid Vaccination is NOT going to end covid	TruerInfo	h6ku8gs	>Malta has vaccinated the entire eligible popu...	barbodelli	5.0	0.0
3	762913	3.0	gattcf	cmv: The concept of cultural appropriation is ...	Jamo-duroo	fp2ndod	I think there needs to be a distinction betwee...	moon_truthr	41.0	0.0
4	1085413	3.0	ou1oho	[deleted by user]	0	h6z8r01	>Our government however is much more likely to...	dublea	10.0	0.0
...	...	...	...	...	...	...	...	...	...	...
1425070	1240015	0.0	7hqddz	CMV: 'The Future is Female' movement should r ...	FluffyRadcliffe	dqtav9s	Their goal is not "equality" though. Their goa...	cdb03b	-170.0	0.0
1425071	115349	0.0	b0iwy1	CMV: Transgender athletes shouldn't compete in...	Hey-I-Read-It	eif15m4	Your post is extremely insensitive and I advis...	Misspelt	-186.0	0.0
1425072	919286	0.0	anivfz	CMV: The controversy surrounding Liam Neeson's...	OddlySpecificReferen	eftvkhm	[deleted]	0	-206.0	0.0
1425073	919285	0.0	anivfz	CMV: The controversy surrounding Liam Neeson's...	OddlySpecificReferen	eftod8v	Reasons why people may be mad: \n\n1. He is tr...	Helpfulcloning	-246.0	0.0
1425074	1088751	0.0	orzj99	CMV: The US should not re-impose lockdowns/res...	0	h6lcgs2	>the vaccines have been proven effective with ...	roofied_elephant	-267.0	0.0

Figure 5: A screenshot of scrapped data along with meta data

Data Cleaning:

After scrapping, the first cleaning step was to remove all the rows which have upvotes less than 1. These comments with negative upvotes were mostly derogatory or misinformed and does not contribute to productive arguments. As a result, we end up with 1313022 data points after this step.

Next, there were comments and posts that had multiple keywords such as [deleted], "your submission has been deleted" and [removed]. So, we removed all the data points which had any of these keywords in the text and very short comments.

Next, we used the NLTK library along with regular expressions to clean the text. Some comments had external links, references, and pictures. We removed all this non-textual information from both statements and comments. After all the cleaning, we had 1208959 data points.

```
Statement :  CMV: Covid Vaccination is NOT going to end covid
Argument :  >Malta has vaccinated the entire eligible population at 73.5%. However they had a recent rise. If cova
x was so effective, this should not have happened.

So there is a R naught which states how many people a typical infected person will infect. The higher the R naught
the more people need to be vaccinated in order to achieve herd immunity. The fact that places with high vaccine ra
tes still experience spikes only tells us that they have not achieved herd immunity. Nothing more nothing less. Th
e fact that Coronavirus has an unusually high R naught is hardly new information.

>Covid is highly mutating. Vaccines against highly mutating viruses does not work. 2019 Flu vaccine was only 39% e
ffective for example.

So far the vaccines are holding firm against variants.

>The ONLY solution is to drive covid to ZERO like New Zealand has. These are seen as draconian measures that most
countries such as USA would not adopt. Greenzone strategy proposed by [https://zerocovid.us/](https://zerocovid.u
s/) is probably the only real way to eliminate covid.
>
>Isn't it better to not have ANY covid in your system, neither from the virus nor the covax?

One important aspect of the Covid vaccine is that IT DOES NOT PREVENT INFECTIONS. You can still get sick and test
positive for coronavirus even if you are completely vaccinated. What it does do is make the likely hood of you hav
ing complications due to Coronavirus significantly less likely. This is a big problem with the common understandin
g of what vaccines actually do. They prepare your system to fight the virus. They don't necessarily make it imposs
ible for the virus to infect you.
```

Figure 6: Example of Unprocessed Statement and Argument

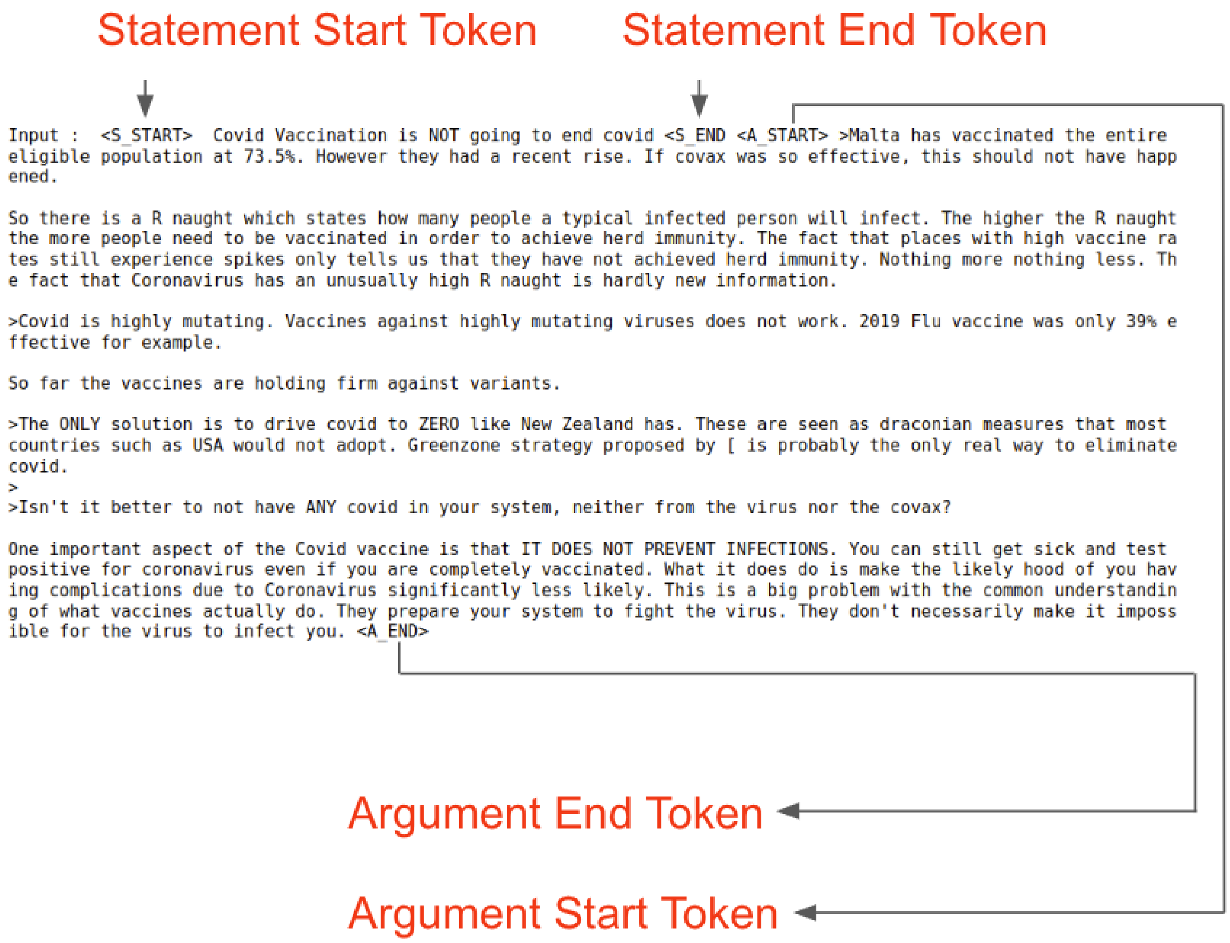


Figure 7: A cleaned and processed Input and Label for the above example.

Lastly, the argument and statement are combined using start and end tokens which will be our final input to the model.

Data Labelling:

We gave deltas more importance because they drive the change. We sorted all the data points based on the number of deltas they received. Then the result was again sorted on the number of upvotes. This ordered data is divided equally into 4 quality groups and each group is labeled from 3 - 0, (3 to the best).

Statement	**Argument**	**Delta**	**UpVote**	**Label**	**Meaning**
XYZ	ABC	>=1	-	3	Changed an opinion
XYZ	DEF	0	>=30	2	Excellent argument
XYZ	GHI	0	>15 & <=10	1	Adequate
XYZ	JKL	0	==1	0	Inadequate

Table 1: Data Labeling Examples.

Architecture:

The Language model that we are going for this to use is GPT-2. The main reason for our choice is their remarkable success in complex language tasks. A pre-trained GPT-2 Large model will be used which consists of 48 layers and 25 heads. This version of GPT-2 has more than 1.5 billion parameters which are 5-10 times more as compared to our baseline BERT models.

A classification head will be used for output and will be mapped into 4 different classes. A SoftMax will be applied to these classes to get probabilities and the highest probability class will be our final prediction. A Cross Entropy loss will be used on these probabilities during training which will be minimized by Adam Optimizer.

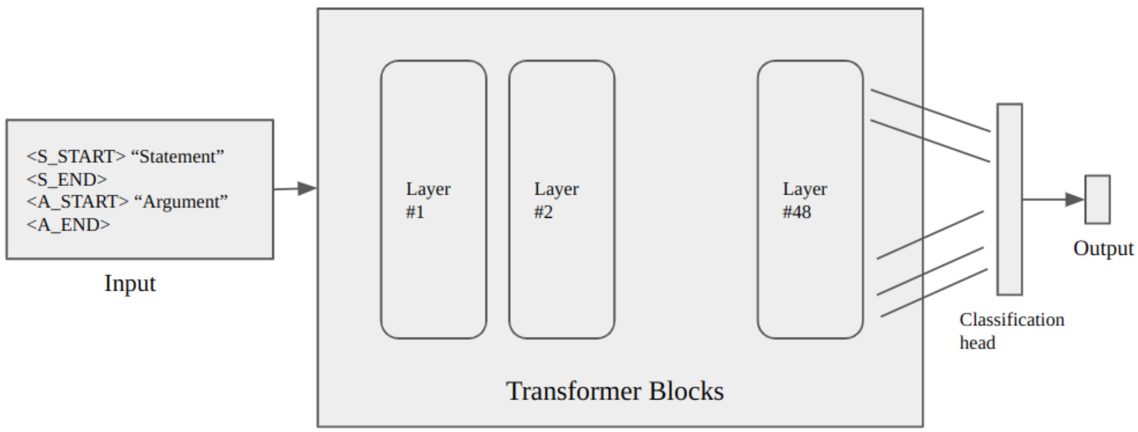


Figure 8: End-to-End Architecture Diagram

Hyperparameters

- Learning Rate - 1e-6 with linear decay
- Weight Decay - 0.1
- Dropout - 0.5
- Batch Size - 256
- Training Size - 113363
- Number of Epochs - 10 (Early stopping at 9 to prevent overfitting)
- Optimizer – AdamW

Baseline Model:

We employ a BERT-based [9] model as our baseline model. BERT's model architecture is a multi-layer bidirectional Transformer encoder based on the original implementation described in [10] and released in the tensor2tensor library. We report results on one model size: BERTBASE (L=12, H=768, A=12, Total Parameters=110M). We intend to use pre-trained BERT and make use of the classification head to fine-tune it.

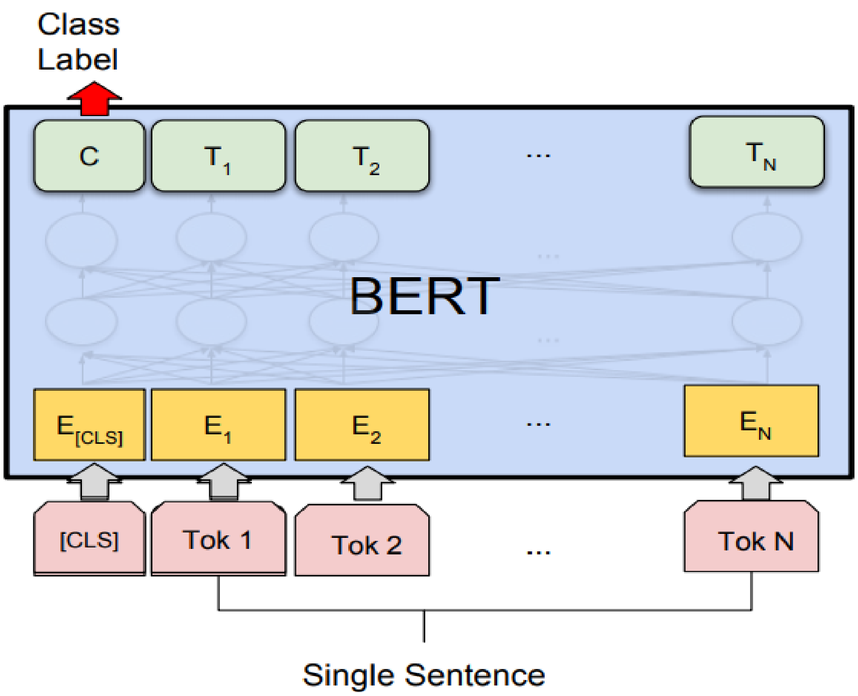


Figure 9: Bert Architecture Diagram

Hyperparameters:

- Learning Rate - 1e-6
- Weight Decay - 0.05
- Dropout - 0.5
- Batch Size - 512
- Training size - 113363
- Number of Epochs - 30
- Optimizer – AdamW

Quantitative Results:

The metrics that we use to measure results are as follows:

- **Accuracy** - The fraction of predictions a model got right.
- **Precision** - Quantifies the number of positive class predictions that belong to the positive class.
- **Recall** - Quantifies the number of positive class predictions made of all positive examples in the dataset.
- **F1** - Harmonic mean of precision and recall.
- **Training Loss** - Metric used to assess how a model fits the training data.
- **Test Loss** - Metric used to assess the performance of a model on the Test set.

Model	Train Size	Test Size	Accuracy	Precision	Recall	F1	Training Loss	Test Loss
Baseline (BERT)	113363	28341	0.44	0.44	0.43	0.44	1.19	1.19
Main (GPT-2)	113363	28341	0.63	0.63	0.66	0.65	0.86	0.86

Table 2: Quantitative Results for both the models.

The results rightly indicate that the GPT-2 model outperforms the BERT language model with fewer epochs on the same training data and validation data.

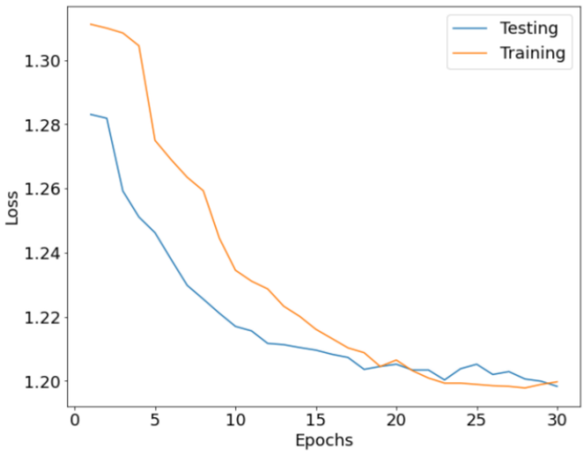


Figure 10: Baseline (BERT) model training & test loss.

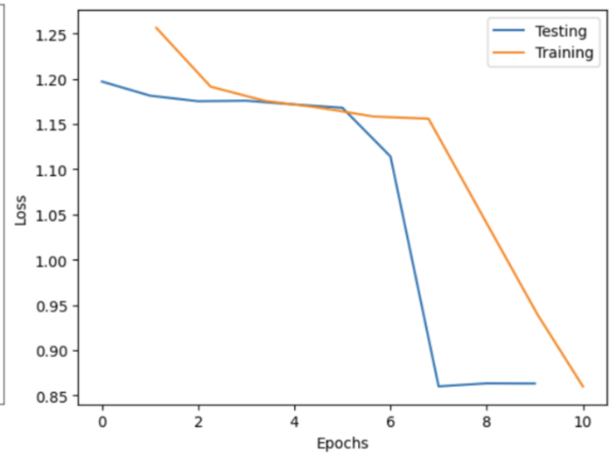


Figure 11: Main (GPT-2) model training & test loss.

The loss curves do also represent the same phenomena uncovered with the various classification metrics that the GPT-2 model performs much better than the BERT base language model. The GPT-2 model shows convergence right after some epochs which is not the case with BERT where the learning slows down after a certain number of epochs.

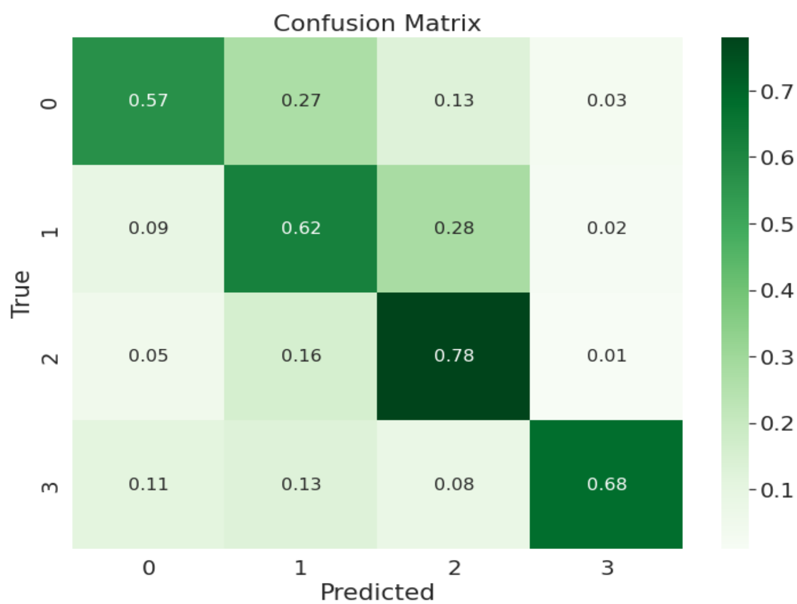


Figure 12: Confusion Matrix for main model (GPT - 2).

The confusion matrix confirms that the model is classifying well on the different balances of the dataset and not on any one class. There are a few instances where the model is predicting a label into the neighboring class. For example, the model is predicting label 0 to be in label 1, 27% of the time, and label 1 to be in label 2, 28% of the time. This is quite acceptable due to the nature of our problem and does not possess an immediate concern to be reconsidered.

Qualitative Results:

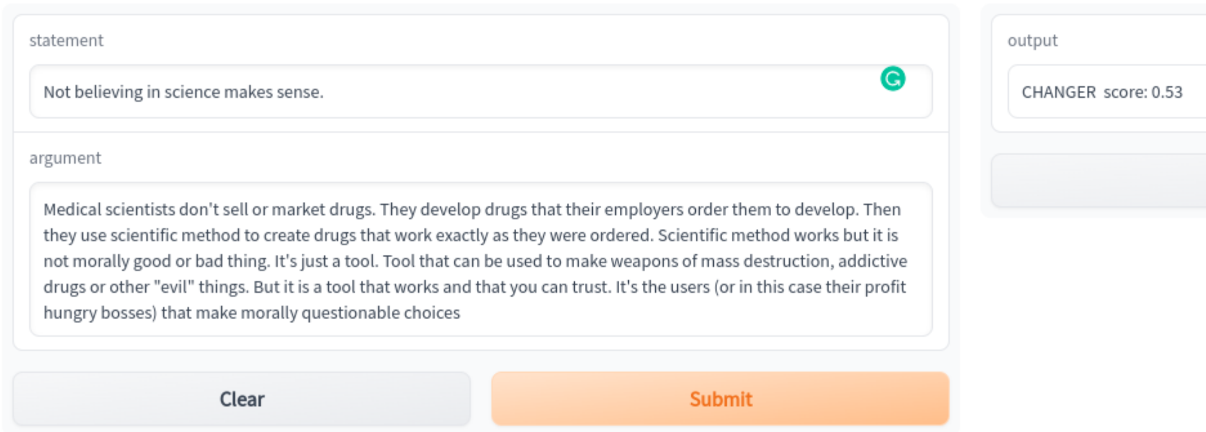


Figure 13: Example of a statement that is classified as “CHANGER”.

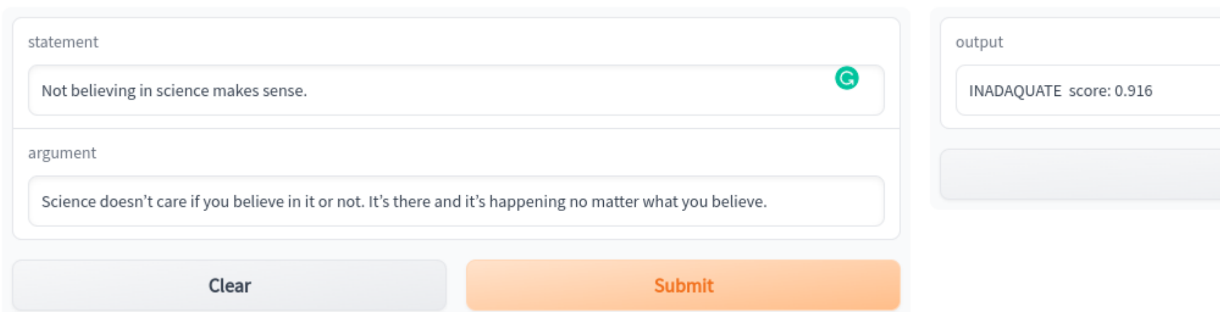


Figure 14: Example of a statement that is classified as “INADAQUATE”.

In Figure 13, the argument is very well explained with proper example from the medical science. The model has good confidence in predicting it as **“changed a view”** argument. On the other hand, the second example (Figure 14) is bad. The model predicts it is as **“Inadequate”** with very high confidence.

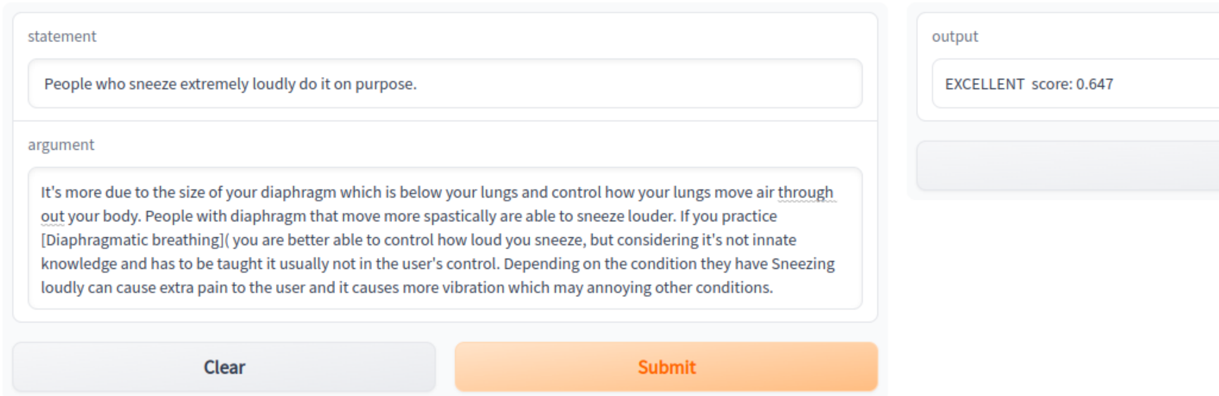


Figure 15: Example of a statement that is classified as "EXCELLENT".

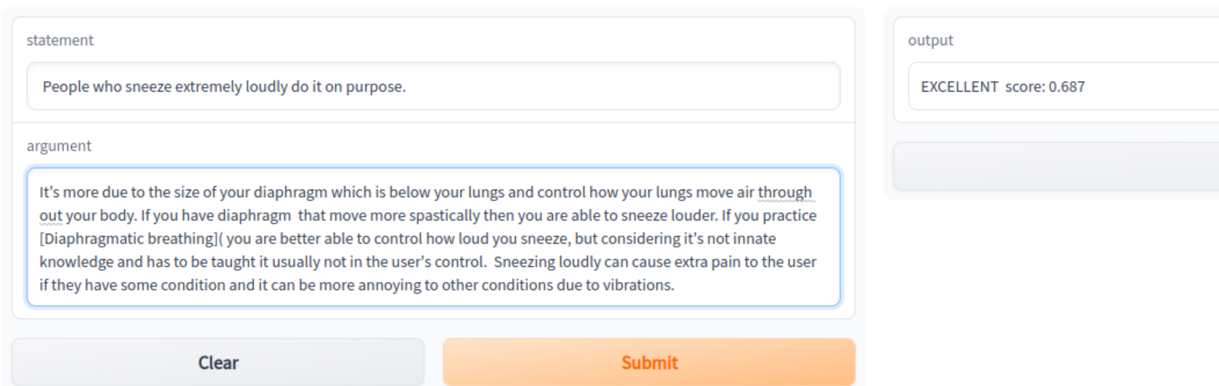


Figure 16: Rephrased example of the statement in Figure 15 that is classified as "EXCELLENT".

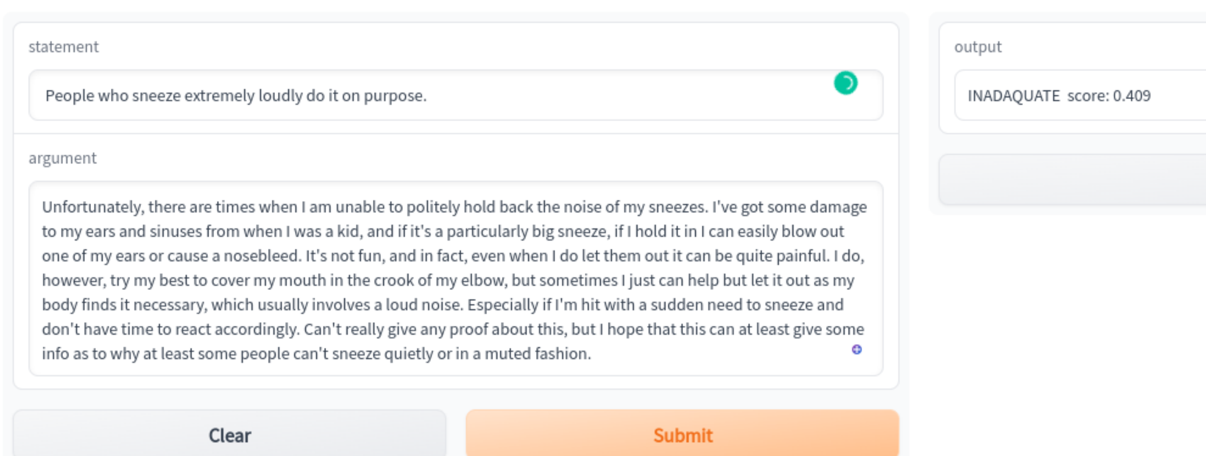


Figure 17: Example of a statement that is classified as "INADAQUATE".

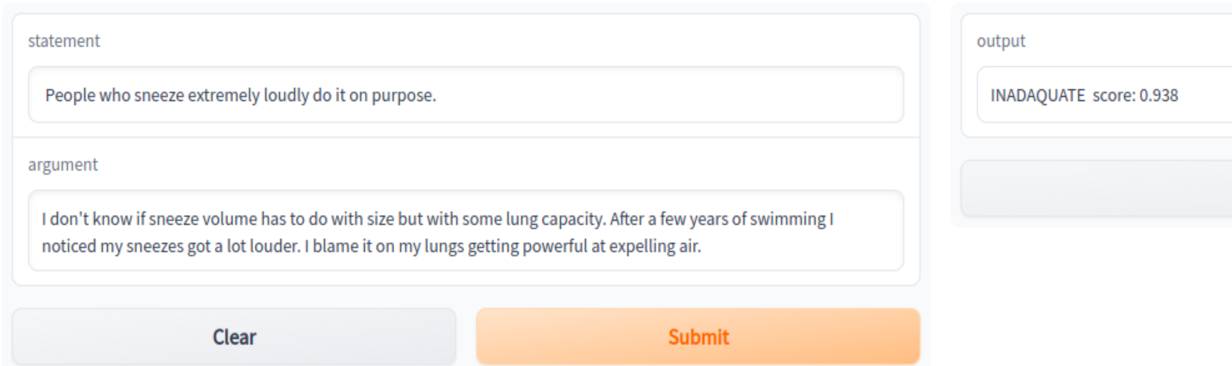


Figure 18: Example of a statement that is classified as "INADAQUATE".

In Figure 15, the example is well framed and gives proper explanation using science. The model is able to predict it properly with good confidence. In Figure 16, we did rephrasing of some sentences from the first example. But despite of that, model is very accurately able to identify it as an excellent argument.

Figure 17 is an example of a wrong prediction as its actual label is adequate and the model is predicting it as inadequate. This result is still not too bad because confidence score for this prediction is low.

In Figure 18, the argument is very vague and convincing. The model is able to predict it as inadequate with very high confidence.

Discussions and Learnings:

The baseline model as intended does not match the capabilities offered by the main model even though the main model ran for fewer epochs (~10) than the baseline model (~30). The results produced by the main model are remarkable in terms of the fewer number of epochs and small training size. Our prediction right now is that the model would not adapt to the entire dataset due to the biased way of the data labeling process. The results are similar with respect to the balance of the dataset where each class is well represented and well predicted by the main model.

The results are matching our expectations and did not hit us with any surprises. With enough computational power and time, we would very much like to run the models on more training data and epochs to maximize the accuracy as high as possible. Our learnings are very clear with the fact in mind that the data handling process is much more sensitive, and important than any other part of the project. With correct data, an individual can very easily tune any model to adapt to their dataset and with the wrong data, even the strongest model would fail to perform. Another important takeaway for us was to understand the importance of overfitting prevention techniques and their usage in huge language models.

Individual Contributions:

	Task	Contributions
1	More Thorough research of existing literature	Both
2	Data Scraping	Umarpreet
3	Data Cleaning & Preprocessing	Both
4	Baseline Model Implementation & Training	Dhiraj
5	Progress report	Both
6	GPT & Training Loop implementation	Both
7	Fine Tuning	Both
8	Testing on different examples	Umarpreet
9	UI Setup	Dhiraj
10	Deployment on Server	Umarpreet
11	User Testing	Dhiraj
12	Final Presentation	Both
13	Final Report	Both

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