Essay Writing Feedback

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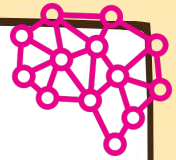
May 2023

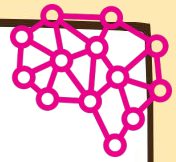
(From Kaggle Competition - Predicting Effective Arguments)

Agenda



- Problem Statement
- Current challenges & its impact
- Solution & Assumptions
- Success Metrics
- ML Model Pipeline
- Demo
- Application Architecture
- Responsible AI
- Achievements & Future Work

Motivation



Effective writing is critical for success in college and future careers, but few students graduate high school as proficient writers. According to the National Assessment of Educational Progress (NAEP), less than a third of high school seniors are proficient writers. That is especially true within marginalized communities of low-income, Black, and Hispanic students – less than 15% score proficient (NAEP).

Challenges & Impact

Challenge

Time consuming for teachers to provide necessary feedback for a student growth.

Impact

Students does not receive effective feedback to become a confident writer

Challenge

Present solutions are expensive and proprietary.

Impact

Less accessible for educators and students who needs it mostly

Challenge

Existing solutions are immature with limited accuracy. Helps to resolve only grammatical errors.

Impact

Students ability to improve writing skills and potentially hinders technology's adoption

Proposed Solution

Develop an Assisted Writing Feedback Tool (AWFT) for educators to give effective, personalized and timely feedback on student writing.

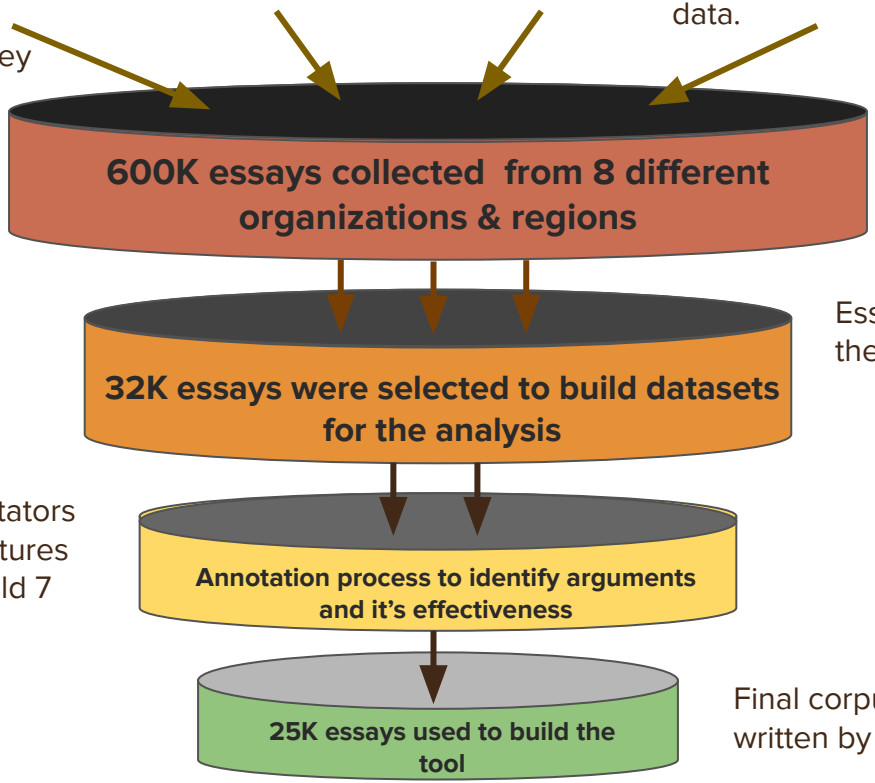
Applications:

- Streamlining the Grading Process
- Empowering Teachers
- Maximizing Student Potential

Assumptions based on Surveys

Various educators and academic organizations took part in the survey and provided feedback.

Suggestions and thorough discussions helped identify the right group and collect data.



Essays were selected based on the teacher advisory boards

Educators along with annotators build an argumentative features to annotate essays and build 7 unique elements to data.

Final corpus represents the essay written by students in 6-12 grades.

Expectations

Many people believe that the Electoral College should be abolished, while others believe that the Electoral College should stay as it is. However, what most people who want to keep the electoral college, do not know is that when you vote for a presidential candidate you are actually voting for a slate of electors, who in turn elect the president. Which means that the people do not get a direct vote towards the president. Therefore, it can cause disinterest in people who are eligible to vote. That is why I argue in favor of changing to election by popular vote for the president of the United States.

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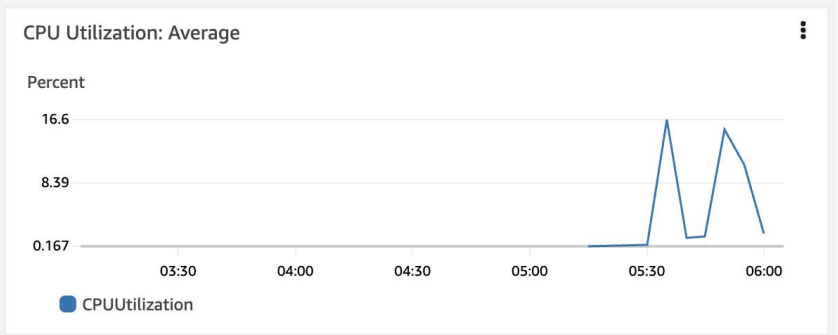
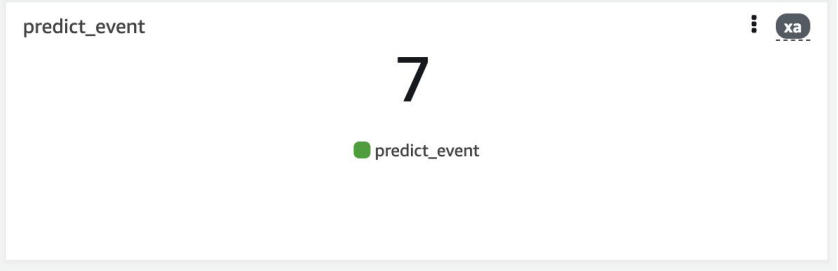
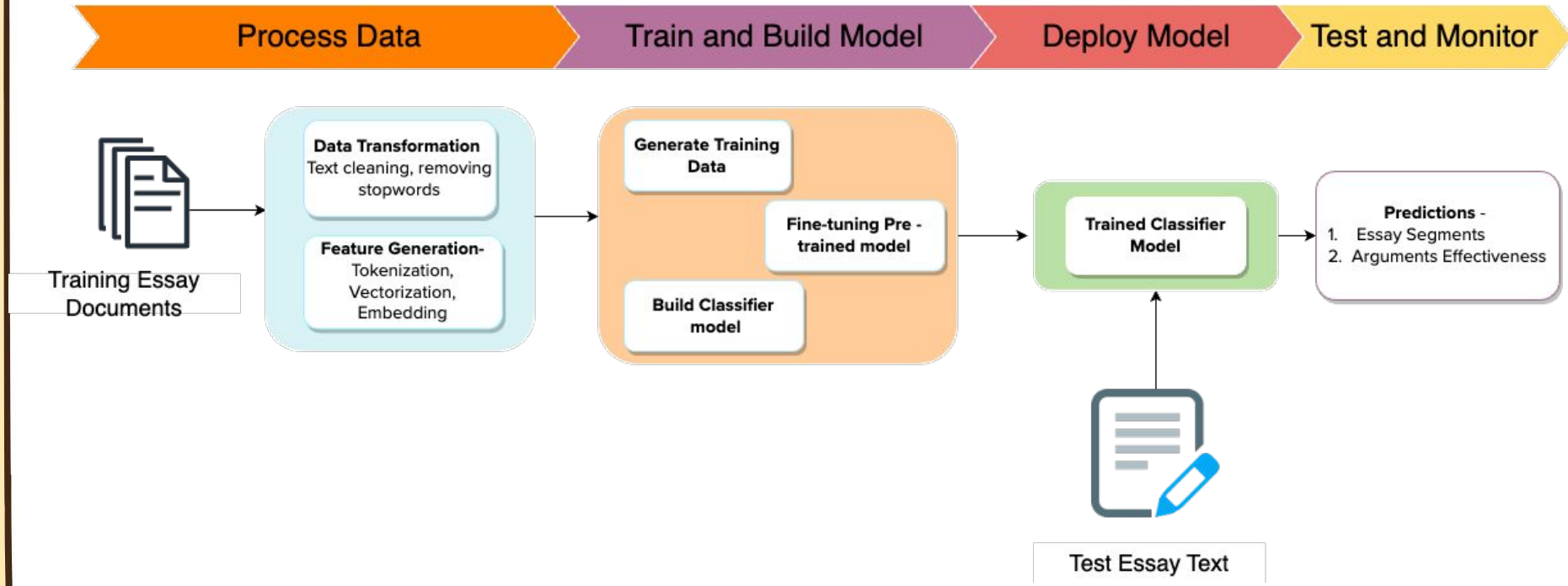
Success Metrics + Monitoring

- Number of unique essays.
- Increase in tool adoption i.e. number of predictions over time.
- Number of teachers on the platform
- Low processing time ~ 10ms

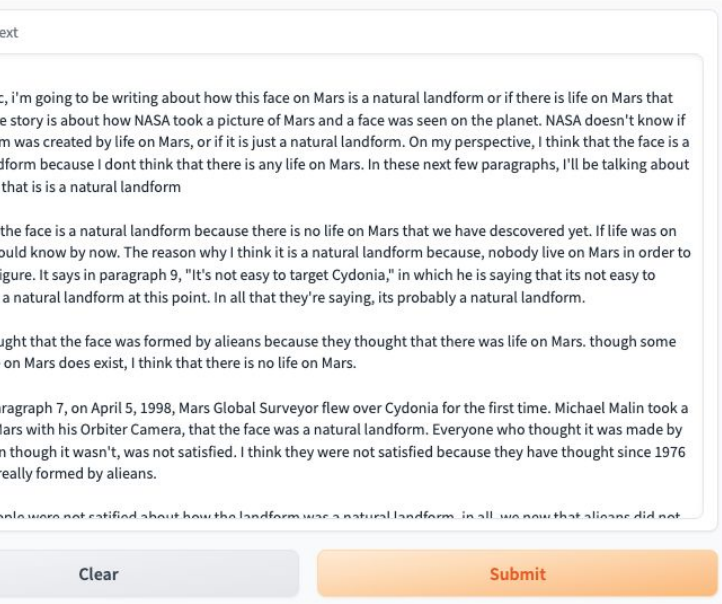


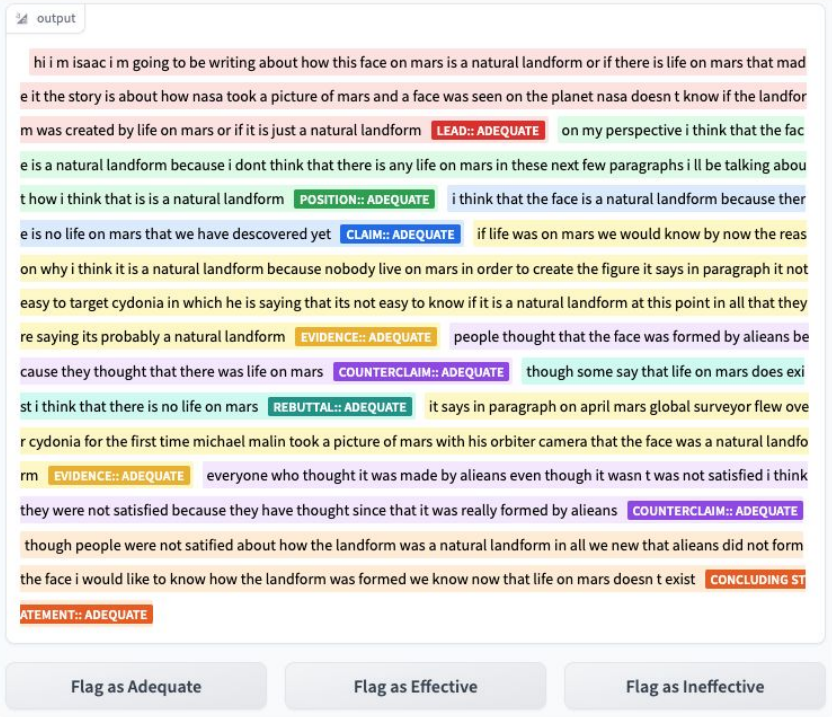


ML Model Pipeline

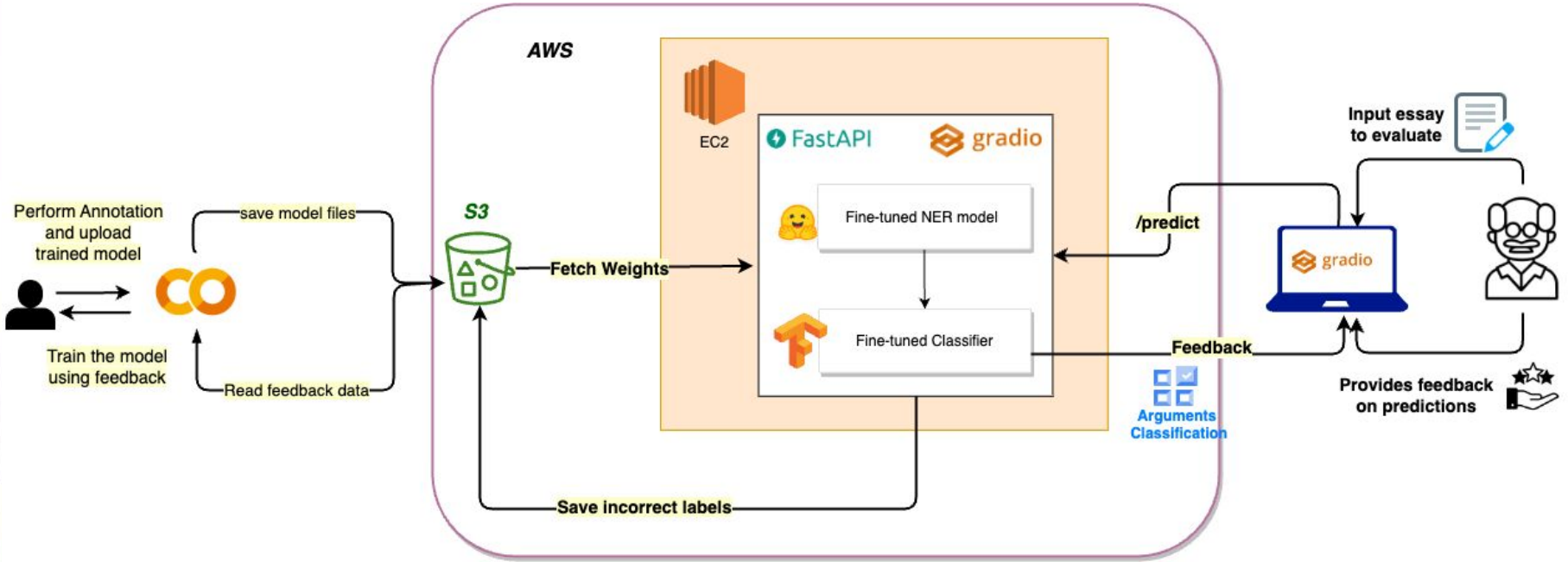


Demo





Application Architecture



Achievements

- Real-time end-to-end essay feedback ML solution.
- Quantitative/Qualitative methods to classify essay arguments.
- Most language models suffer with large texts, average size of essay is >1K words, I used longformer architecture models to overcome this problem.
- Trained and Optimized embedding models for improved classification accuracy.
- Successfully deployed ML app on EC2 instance with an intuitive UI.
- Prediction results are self explainable and easy to understand.

Responsible AI

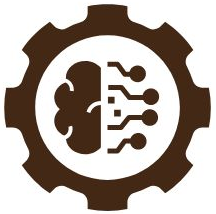
Privacy and Data Protection - Ensure handling of each student data privacy by handling data secure.

Collaborative and Diverse Development - Be more inclusive of diverse cultural, linguistic, or socioeconomic backgrounds.

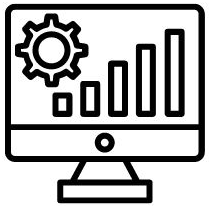
Regulatory Compliance - Stay up-to-date with relevant laws and regulations regarding the used model and data linked with it.

Future Work

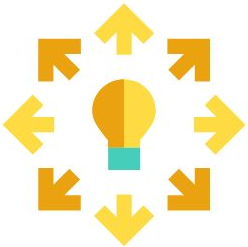
Collect more data to reduce imbalance data effect



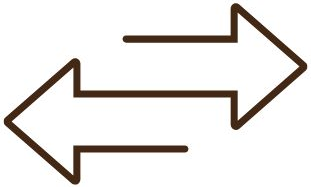
Continuous improvement on the model predictions



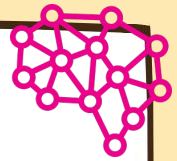
Monitoring system to track individual progress



Scalable solution to handle multiple users



Two-way interface for both students and teachers



A Big Thank you to

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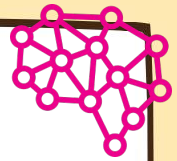
Questions??



Appendix

Data Stats

There are two different datasets for 2 different tasks:

1) **NER model - ** To identify arguments in the data. The dataset contains 144K rows of labeled discourse data with required feature of discourse text length and its type.

    a) Implemented baseline Longformer model through hugging face to create NER tokens and eventually train the model. It's an

2) **Classifier model -** To classify discourse arguments into 3 labels 'Adequate', 'Effective' , and 'Ineffective'. The dataset contains 36K rows of labeled argumentative discourse data with required feature of discourse type.

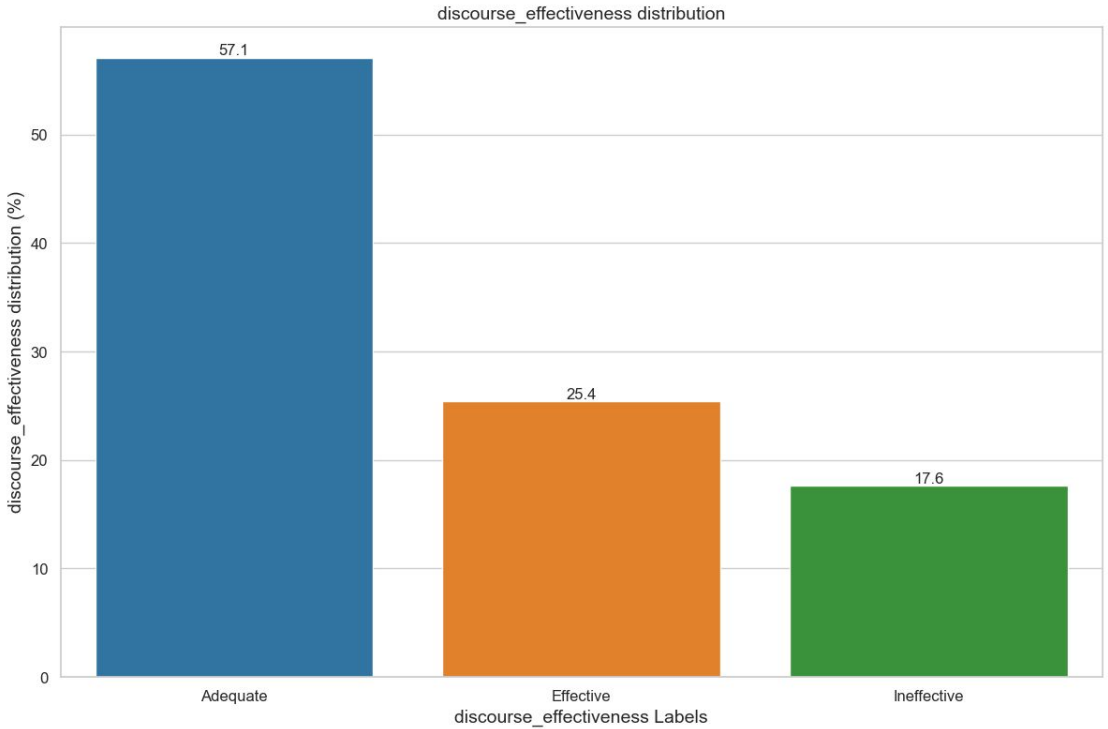
    a) Started of with vectorizer approach to understand the baseline accuracy achievement and data learning.
    b) Fine-tuned multiple pretrained transformer models such as BERT and DistilBERT.
    c) Fine-tuned tensorflow hub model universal sentence encoder
    d) Fine-tuned state-of-the-art python framework text embeddings model.

Discourse Types

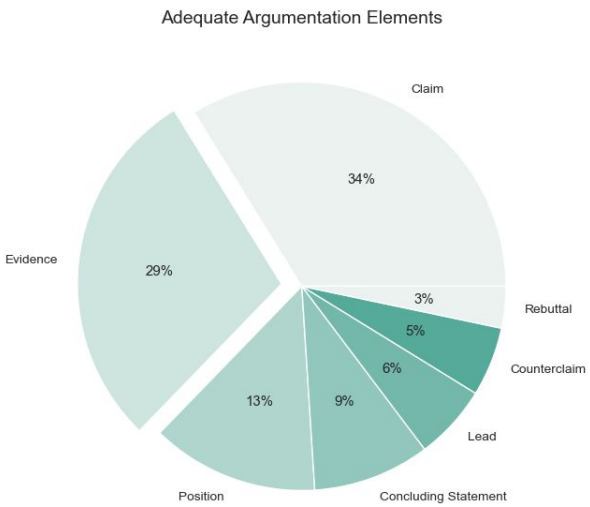
The dataset presented here contains argumentative essays written by U.S students in grades 6-12. These essays were annotated by expert raters for discourse elements commonly found in argumentative writing:

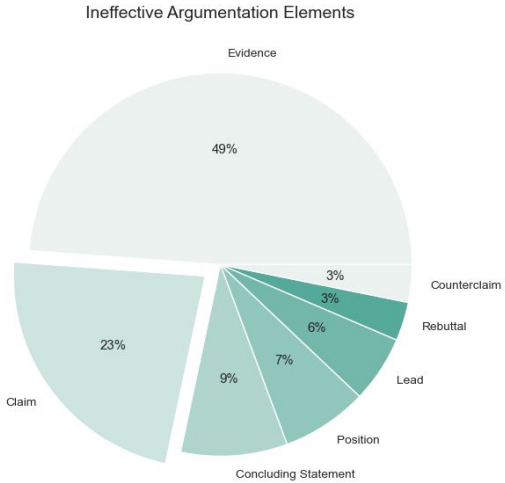
- **Lead -** an introduction that begins with a statistic, a quotation, a description, or some other device to grab the reader's attention and point toward the thesis
- **Position -** an opinion or conclusion on the main question
- **Claim -** a claim that supports the position
- **Counterclaim -** a claim that refutes another claim or gives an opposing reason to the position
- **Rebuttal -** a claim that refutes a counterclaim
- **Evidence -** ideas or examples that support claims, counterclaims, or rebuttals.
- **Concluding Statement -** a concluding statement that restates the claims

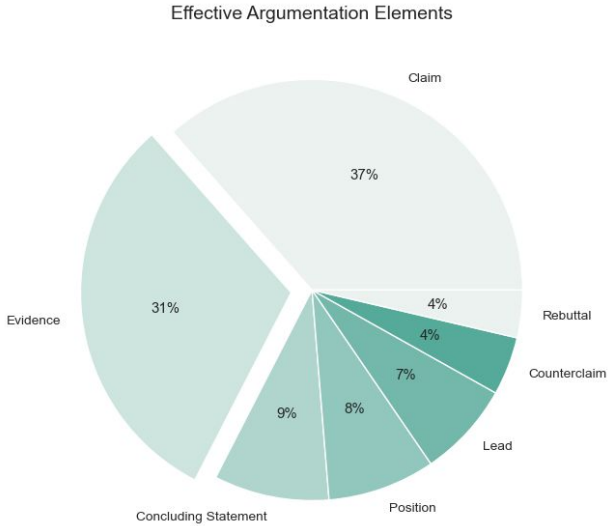
EDA - Target class overall distribution



EDA - Target class by discourse type



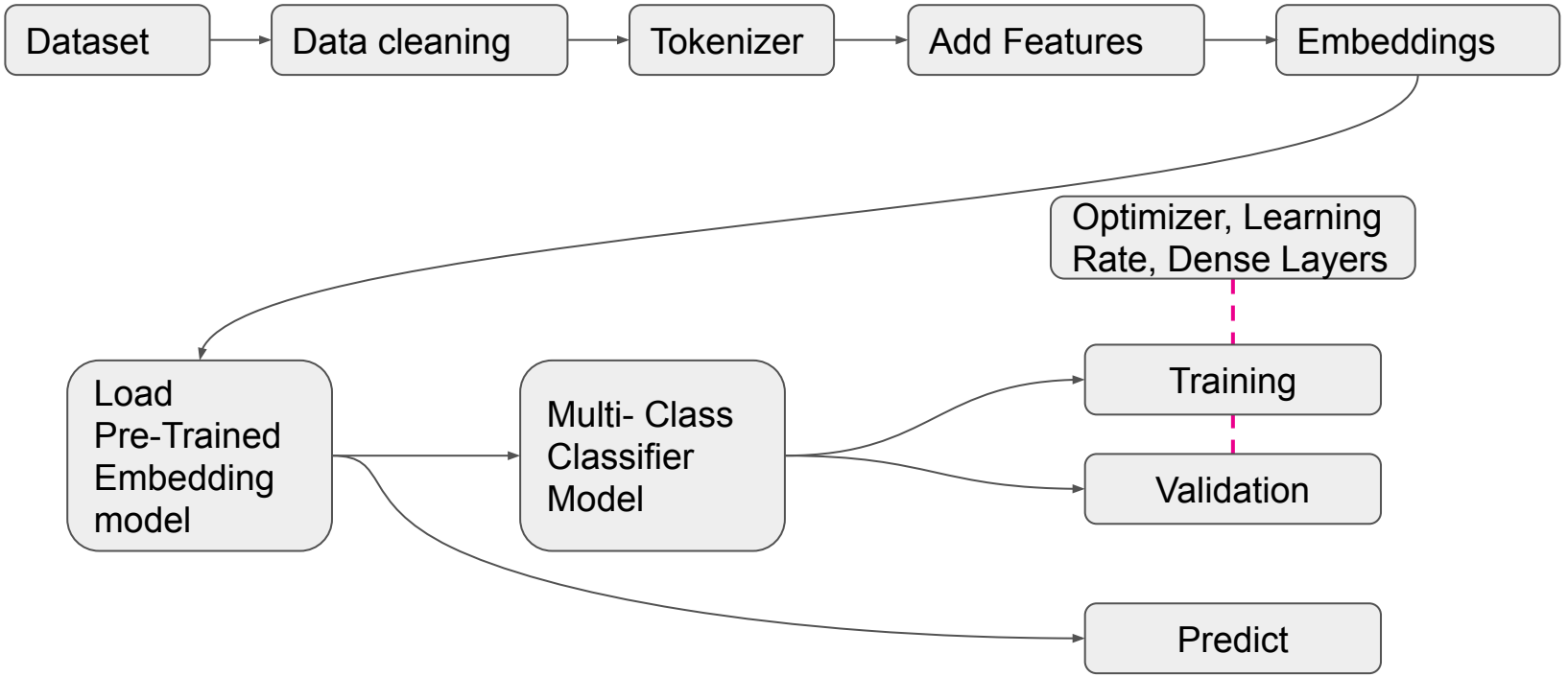




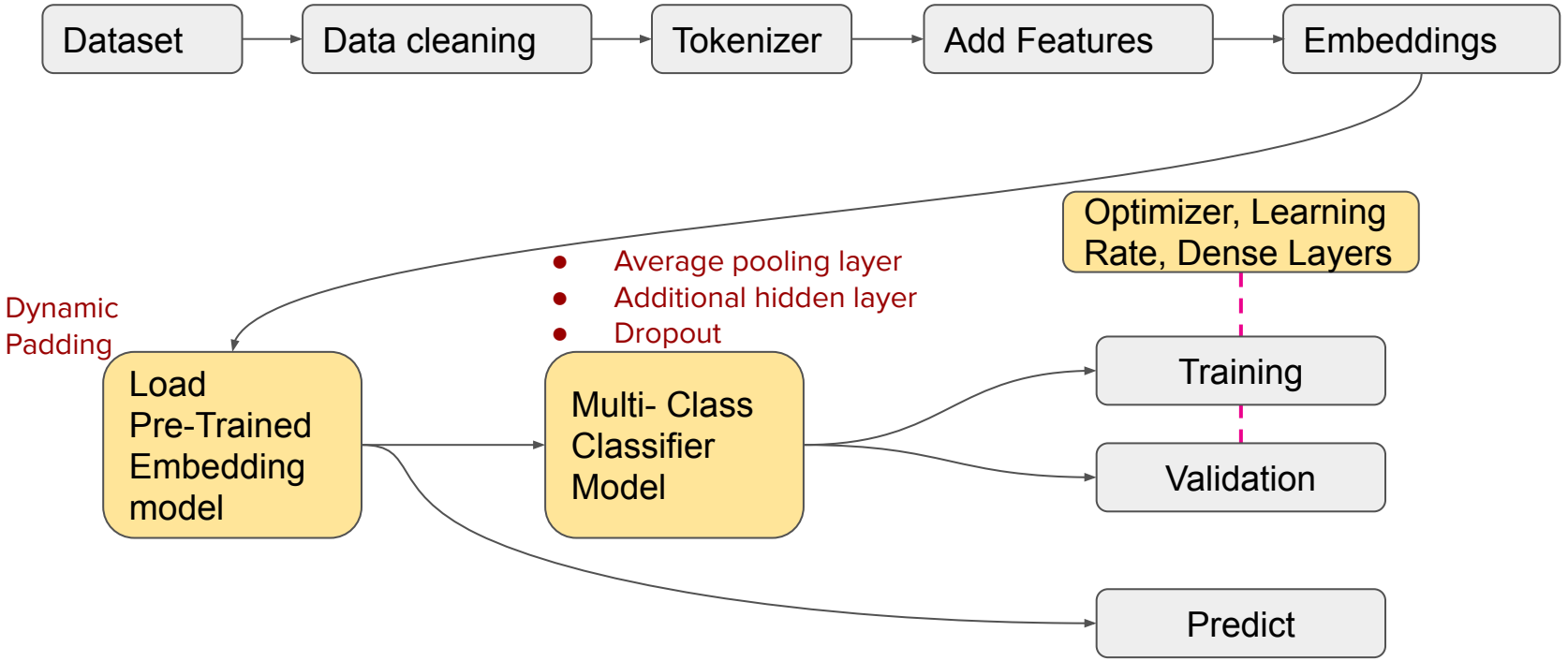
Feature Engineering

- Discourse Text
- Discourse Type + Tokenizer Separator + Discourse Text
- Discourse Type + Spacing + Discourse Text + Tokenizer Separator

Deep Learning Model Flow



Hyperparameter Tuning

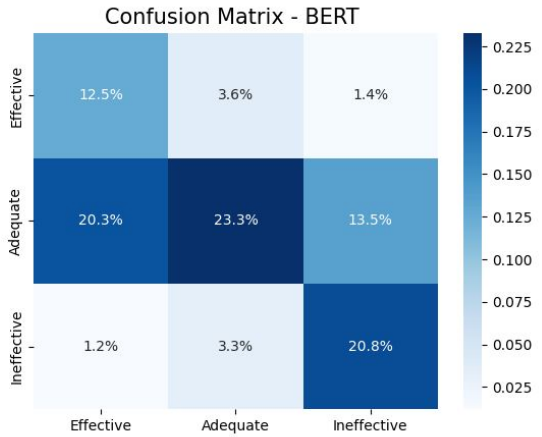


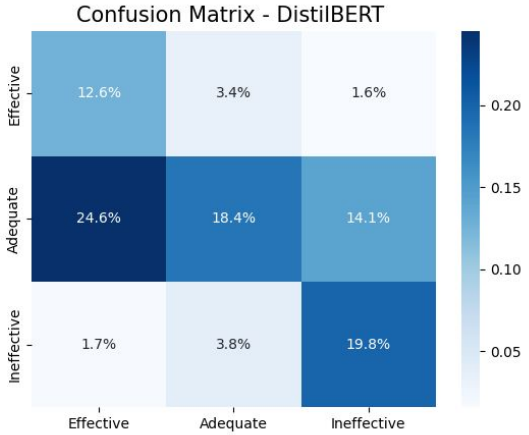
Evaluation Metric

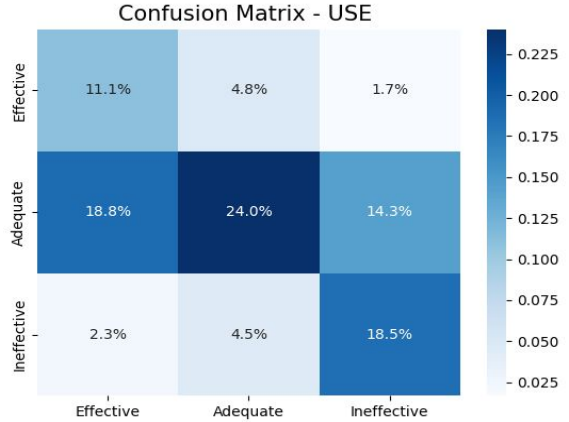
1) F1 score **(Imbalanced dataset)**

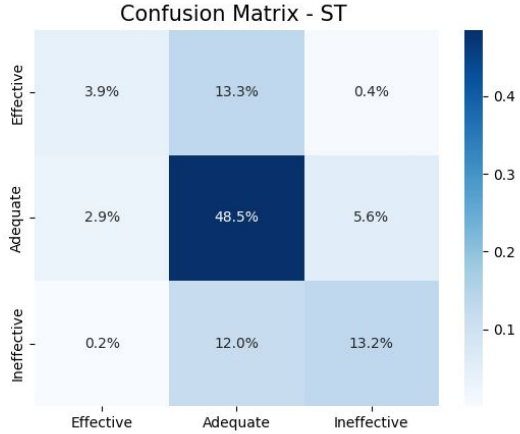
2) AUC-ROC Curve **(Multi Class Classifier)**

Results









Results

BERT performance is better than other models

F1 Score

Label	BERT	DistilBERT	Universal Sentence Encoder	Sentence Transformer
Effective	0.49	0.45	0.45	0.46
Adequate	0.53	0.44	0.53	0.69
Ineffective	0.68	0.65	0.62	0.63

AUC-ROC Curve

Label	BERT	DistilBERT	Universal Sentence Encoder	Sentence Transformer
AUC-ROC	0.82	0.78	0.76	0.78

Metrics → / Models ↓	Weighted F1 Score	AUC-ROC score
TFIDF + Naïve Bayes Clf	0.58	0.7
W2V + Multi Class Clf	0.58	0.6
BERT DNN Classifier	0.56	0.8
DistilBERT DNN Classifier	0.55	0.78
Universal Sentence Encoder DNN Classifier	0.54	0.76
Sentence Encoder DNN Classifier	0.63	0.78