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| **SemEval-2023 Task 4: Identification of Human Values behind Arguments** |
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Abstract

This paper is for shared task 4: Identification of Human Values behind Arguments. Given a textual argument and a human value category, classify whether the argument draws on that category. This task mainly focuses on a set of 20 value categories compiled from the social science literature. Arguments are given as premise text, conclusion text, and binary stance of the premise to the conclusion.

Introduction

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Data

We have introduced four different datasets in our research: WhitePaper, EarlyBird, Training, Full. Each dataset gathered from different resources. The dataset split into two parts: labels and argument. Each argument consists of one premise, one conclusion, and a stance attribute indicating whether the premise is in favor or against the conclusion.

**WhitePaper** This dataset is being used in the white paper “Identifying the Human Values behind Arguments”. It has 5270 samples with additional column for resource like country resource. We drop that column for this task.

**EarlyBird** This dataset is being released since the organizer of SemEval-2023 Task 4 has been announced. It has 5220 samples.

**Training** This dataset is being released on Dec 5. The completed dataset has been released along with validation dataset and testing dataset. The testing dataset is not labeled so we going to use model to output prediction and submit for evaluation for the task. The training set has 5393 sample

**Full** This dataset is generated from combine two validation dataset and training dataset into one large dataset for training. The full set has 7389 sample.

Data Model

The original F1 scores from the paper’s level 2 model were 0.34 for BERT, 0.30 fro SVM, and 0.28 for the baseline. The model we built using BERT achieved a 0.41 F1 score, which was slightly better than the paper. The model was built from pulling in the small uncased BERT model and adding layers on top of it for fine tuning. Those layers were two cycles of a linear layer followed by dropout of 0.2 followed by ReLU. The first cycle’s node numbers went from the hidden size of the BERT model to 256 and the second went from 256 to 128. The idea behind this was to give the model space to recognize more specific features before collapsing the layer to the 20 mode output. Dropout and ReLU were used because they had had previous beneficial properties from previous models I had built. The learning rate was 0.001 and the epoch number was 4. I found adding more epochs didn’t improve the outcome and took a really long time to run. For the best model I let BERT train along with my added layers, when I froze BERT the F1 score was 0.38. It ended up not being a huge difference.

We use the original data model for evaluate the four dataset we introduced above. Due to retraining limitation. When we retrain the BERT model, it took 58 hours to finish the training on Full dataset. Thus, we decide to predict all four dataset and testing dataset with previous model.

We modify the parameter and configuration for the data model so the data model can accept new dataset as input and perform prediction. We also modify the evaluation file to clean the output without level and country because they introduce the level and country features in the white paper

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|  | Precision | Recall | F1 | Accuracy |
| 1-Baseline | 0.16 | 1 | 0.27 | 0.16 |
| Bert | 0.46 | 0.28 | 0.35 | 0.86 |
| SVM | 0.33 | 0.2 | 0.25 | 0.82 |

Table 1: Result for WhitePaper

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| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1 | Accuracy |
| 1-Baseline | 0.17 | 1 | 0.27 | 0.17 |
| Bert | 0.94 | 0.79 | 0.86 | 0.97 |
| SVM | 0.93 | 0.86 | 0.89 | 0.97 |

Table 2: Result for EarlyBird

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| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1 | Accuracy |
| 1-Baseline | 0.17 | 1 | 0.29 | 0.17 |
| Bert | 0.86 | 0.64 | 0.74 | 0.93 |
| SVM | 0.8 | 0.66 | 0.72 | 0.91 |

Table 3: Result for Training

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| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1 | Accuracy |
| 1-Baseline | 0.17 | 1 | 0.29 | 0.17 |
| Bert | 0.85 | 0.62 | 0.71 | 0.92 |
| SVM | 0.78 | 0.62 | 0.69 | 0.91 |

Table 4: Result for Full

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| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1 | Accuracy |
| 1-Baseline | 0.17 | 1 | 0.29 | 0.17 |
| Bert | 0.23 | 0.04 | 0.07 | 0.84 |
| SVM | 0.98 | 0.98 | 0.98 | 0.99 |

Table 5: Bad Result for Full of partial retrain

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| Figure 1: A figure with a caption that runs for more than one line**.** |

References

Rie Kubota Ando and Tong Zhang. 2005. A frameworkfor learning predictive structures from multiple tasksand unlabeled data. *Journal of Machine Learning Research*, 6:1817–1853.