

Improve Your English Essay with Al



W266 NLP with DL

University of California, Berkeley April 18, 2023

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Agenda



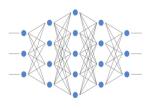




Dataset



Approaches



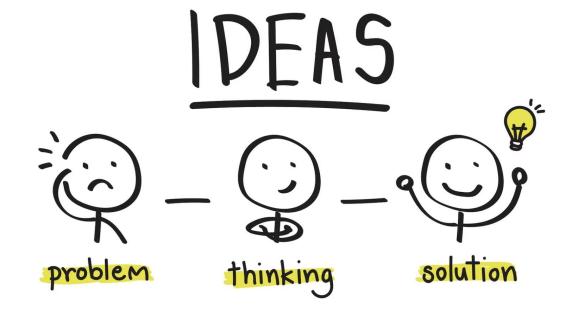
Results



Conclusion & Future Work



Motivation





Dataset

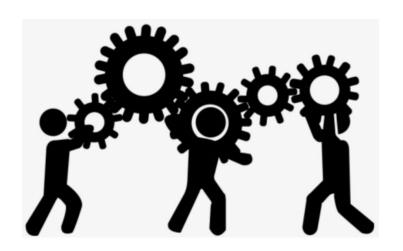


The dataset presented here (the **ELLIPSE corpus**) comprises argumentative **essays written by 8th-12th grade English Language Learners (ELLs)**. We have 3911 essays which have been scored according to six analytic measures: **cohesion**, **syntax**, **vocabulary**, **phraseology**, **grammar**, **and conventions**.

Each measure represents a component of proficiency in essay writing, with greater scores corresponding to greater proficiency in that measure. The scores **range from 1.0 to 5.0 in increments of 0.5**.



Approaches



- Transformer based language models (BERT base-cased and BERTweet base)
- Number of frozen and unfrozen layers
- Clustering
- Stratified Sampling

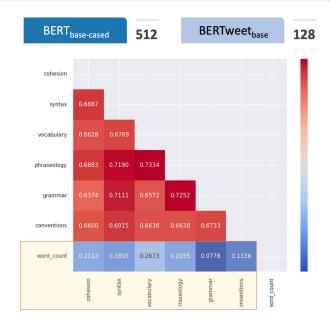


Model - Architecture & Token Length

Model Architecture

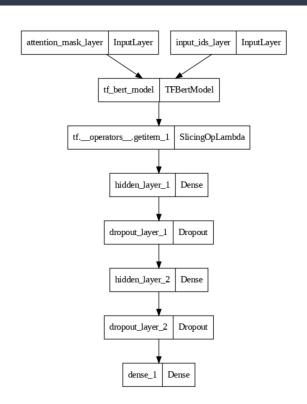
Predict Six Separate Scores for Each Essay MCRMSE Regression Layer Final T_N **Hidden State** Transformer BERT_{base-cased} OR **Encoder BERTweet**_{base} **Embedding** Layer **Tokenizer** Sentence 1

Input Token Length at Max





Model - Best Model



Best Set of Parameters from Training BERT_{base-cased}

Test MCRMSE Trainable Layers Learning Rate Hidden Layers Hidden Units Batch Size Dropout Epochs 0.4590 12 0.00001 2 64 8 0.1 10

Hyper Parameter Tuning





Results - BERTbase-cased VS. BERTweetbase



Adjusted MCRMSE Scores

	BERT _{base-cased}	BERTweet _{base}	
0 trainable layers	0.6350 Baseline	0.6549	
6 trainable layers	0.6271	0.6224	
12 trainable layers	0.5254	0.5536	

BERT_{base-cased}

% of Test Dataset Records that were *Correctly* Predicted Per Analytic Measure (Score within 0.5)

BERTweet_{base}

% of Test Dataset Records that were *Correctly* Predicted Per Analytic Measure (Score within 0.5)

	0 trainable layers	6 trainable layers	12 trainable layers		0 trainable layers	6 trainable layers	12 trainable layers
Cohesion	29.8% (75.9%) Baseline	30.0% (75.7%)	33.8% (83.7%)	Cohesion	27.3% (72.7%)	29.4% (75.6%)	35.6% (83.1%)
Syntax	34.1% (76.8%) Baseline	33.2% (77.4%)	37.8% (84.7%)	Syntax	33.5% (73.4%)	33.1% (75.1%)	35.6% (84.0%)
Vocabulary	37.5% (82.1%) Baseline	39.0% (83.3%)	44.2% (89.8%)	Vocabulary	33.8% (80.2%)	36.5% (85.4%)	39.2% (86.7%)
Phraseology	31.3% (78.2%) Baseline	32.7% (79.6%)	44.1%(88.8%)	Phraseology	29.8% (76.5%)	30.4% (79.2%)	35.4% (83.8%)
Grammar	27.7% (74.2%) Baseline	27.8% (72.0%)	33.5% (81.2%)	Grammar	25.0% (70.5%)	27.5% (74.3%)	36.5% (80.3%)
Conventions	31.7% (72.8%) Baseline	29.9% (74.5%)	38.1% (87.5%)	Conventions	30.9% (74.6%)	29.4% (75.0%)	35.6% (87.0%)

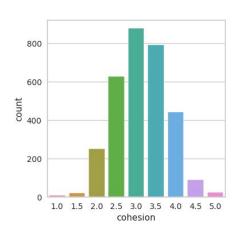


Results - BERTbase-cased VS. BERTweetbase

Clustering & Stratified Two-Fold Cross Validation

Adjusted MCRMSE Scores

	BERT _{base-cased}	BERTweet _{base}
0 trainable layers	0.6763	0.6907
6 trainable layers	0.6681	0.6688
12 trainable layers	0.6798	0.6652



(6.0-17.0)

(17.5-21.5)

(21.5-30.0)

BERT_{base-cased}

% of Test Dataset Records that were *Correctly* Predicted Per Analytic Measure (Score within 0.5)

BERTweet_{base}

% of Test Dataset Records that were *Correctly* Predicted Per Analytic Measure (Score within 0.5)

	0 trainable	6 trainable	12 trainable	0 trainable	6 trainable	12 trainable
	layers	layers	layers	layers	layers	layers
Cohesion	28.6%	28.2%	28.4%	28.0%	26.8%	25.4%
	(71.9%)	(73.9%)	(73.8%)	(70.0%)	(72.7%)	(72.0%)
Syntax	32.7%	30.0%	30.5%	30.7%	33.1%	32.2%
	(73.9%)	(73.4%)	(72.7%)	(72.4%)	(72.9%)	(73.9%)
Vocabulary	36.9%	37.2%	28.4%	31.2%	29.6%	29.6%
	(78.5%)	(79.2%)	(80.3%)	(77.7%)	(79.6%)	(81.2%)
Phraseology	30.5%	30.5%	29.0%	27.2%	30.5%	29.6%
	(73.4%)	(73.2%)	(73.1%)	(71.1%)	(73.3%)	(73.2%)
Grammar	27.8%	27.3%	24.5%	24.4%	25.8%	24.8%
	(70.0%)	(71.3%)	(70.2%)	(70.8%)	(70.5%)	(71.1%)
Conventions	30.8%	30.7%	28.6%	29.1%	30.9%	30.7%
	(71.8%)	(76.2%)	(70.4%)	(71.6%)	(73.9%)	(72.4%)



Conclusion

- With more unfrozen layers, the models were able to learn the training data
- Models struggled to predict extreme scores.
- Clustering through K-Means and K-fold cross validation to account for the lower and higher ends of the scores did not improve model performance



Future Work



- O2 Introduce larger versions of BERT and BERT-derived models
- O3 Evaluate essays together with key topical information
- Explore pre-transformer-based state-of-the-art models as well as models with BERT-based combinations



References

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- 2. https://www.freepik.com/free-vector/illustration-light-bulb-ideas_3139696.htm#query=motivation-li
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6.

