# Back Translation Survey for Improving Text Augmentation

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Abstract—Natural Language Processing (NLP) relies heavily on training data. Transformers, as they have gotten bigger, have required massive amounts of training data. To satisfy this requirement, text augmentation should be looked at as a way to expand your current dataset and to generalize your models. One text augmentation we will look at is translation augmentation. We take an English sentence and translate it to another language before translating it back to English. In this paper, we look at the effect of 108 different language back translations on various metrics and text embeddings.

Index Terms-Embeddings, Translations

#### I. Introduction

Training machine learning models have always required an increasing amount of data for the increasing size of the architecture. This phenomenon has been exemplified in the NLP community with the recent explosion in use of the transformer [1]. Public datasets reflect this need for larger and larger data requirements in the recently released the 800GB Pile dataset [2]. In the absence of readily available data, an unsupervised way of text augmentation is needed.

Back translation is the unsupervised process of translating text from English to another language and then back to English. This text augmentation technique allows a variety of outputs for any input. A strategy might be to translate from English to many other languages and then back to English to create the most broad understanding of the input text. In this scenario, we envision that a system of back translations can provide transformers with the generalized data that they need to train larger and larger models.

To employ a complete text augmentation training strategy we need to understand the full effect of back translation. In this paper, we will investigate how each language's back translation effects various NLP metrics. We hope to decipher how and why some languages might be a better candidate for back translating to over any other language. We employ Google Translate's current Neural Machine Translator (NMT) [3] to receive over 108 languages translations.

# A. Background

Using text augmentation is a unsupervised way to expand your text training data. There are various text augmentations [4], for example the nlpaug package [5] summarizes them in 5 categories: insert, substitute, swap, delete or crop. Some examples from the nlpaug pacakge include: RandomWordAug

(Apply augmentation randomly), AntonymAug (Substitute opposite meaning word according to WordNet antonym), SplitAug (Split one word to two words randomly), WordEmbsAug (Leverage word2vec, GloVe or fasttext embeddings to apply augmentation).

Back translation is a version of the substitute augmentation. We take the imperfect system of translation in an attempt to increases generalizability of text models. This text augmentation has shown great performance for various tasks including text classification [6], machine translation [7] [8], and even in low data environments [9]. While back translation has been show to improve various NLP tasks, in some situations is has been shown to provide marginal, if any, results in modern, large transformer [10].

In addition, to showing various NLP metrics for all 108 Google Translate supported languages, we also update the BLEU metrics for the Google's current NMT model. Previous scores generated by Aiken in 2019 can be found here [11]. Of note is that all languages besides Latin use Google's NMT while Latin uses Google's Phrase-Based Machine Translation (PBMT).

## B. Reproducible

To allow reproducible for the following experiment a Google Collaboratory [12]. You can replicate the experiment in the following notebook. This colab includes all training data and models used.

# Reproducible Google Colaboratory

https://colab.research.google.com/drive/1XpdkDrNruJ5TDZlwtdSRgZlkDRjcUM7d?usp=sharing

#### II. EXPERIMENT

To investigate the effect of different language translations on various text metrics we run a series of test as outlined in [Figure 1]. We took 1000 random English tweets from the Sentiment-140 [13] dataset, and run them through the Google Translate API [14]. We translate to all 108 languages supported by Google Translate and then translated them back to English. We then analysed the differences using various text metrics: Bilingual Evaluation Understudy Score (BLEU) [15], BERT embedding distance [16], BART embedding distance [17], GPT embedding distance [18], XLNet embedding distance [19], GloVe embedding distance [20], Doc2Vec embedding

distance [21], NLTK Vader [22], Textblob Polarity and Subjectivity [23], Flair [24], and common Text Statistics (Flesch-Kincaid Grade, Flesch-Reading Ease) [25]. The following sections go into detail about each of these NLP metrics.

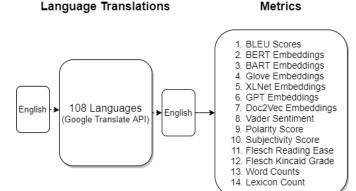


Fig. 1: Experimental flow diagram showing the languages used for translations followed by the metrics used to analysis the differences

### A. BLEU Scores

BLEU is a metric for evaluating a generated sentence to a reference sentence. Scores a translation on a scale of 0 to 1, in an attempt to measure the adequacy and fluency of the machine translation output. Scored by n-grams, BLEU-1 to BLEU-4. We use NLTK's BLEU [26] score method which can weight each of the n-grams scores independently.

## B. BERT Embeddings

Bidirectional Encoder Representations from Transformer (BERT) is an encoder encoder transformer architecture that trains by predicting masked words. By masking 15% of the words, BERT can also predict the position of words in a sentence. This allows BERT to be a general language model which can predict word embeddings alongside their positional embeddings. BERT was originally pre-trained on the English Wikipedia and Brown Corpus. Our implementation used bert-base-uncased [27], 12-layer, 768-hidden, 12-heads, 110M parameters.

# C. BART Embeddings

BART is a transformer that learns to train by generalizing the masking technique used by BERT to a random shuffle of the ordering of a sentence and a mask that spans many words. This unsupervised technique learns to map corrupted parts of a document and therefore performed SOTA on discriminative and text generation tasks in 2020. We use BART-Base [28], 12-layer, 768-hidden, 16-heads, 139M parameters, for our analysis.

## D. GPT Embeddings

GPT uses a decoder only transformer structure with masked self-attention to train the language mode. Originally published in 2018, GPT, once fine tuned for a task, was SOTA in many language tasks. This unsupervised pre-training transform architecture set the standard for the large transformer models to follow. We use open-gpt, GPT 1, [29], 12-layer, 768-hidden, 12-heads, 110M parameters.

## E. XLNet Embeddings

XLNet is a generalized autoregressive pretraining method that enables learning bidirectional contexts by maximizing the expected likelihood over all permutations of the factorization order. When released in 2020, XLNet outperformed BERT in many language tasks. We use xlnet-base-cased [30], 12-layer, 768-hidden, 12-heads, 110M parameters.

# F. GloVe Embeddings

Global Vectors for Word Representation, GloVe, is an unsupervised learning algorithm for obtaining vector representations for words. Training is performed on aggregated global word-word co-occurrence statistics from a corpus, and the resulting representations showcase interesting linear substructures of the word vector space [31]. GloVe was originally trained on 800 MB of text in Wikipedia 2014 and Gigaword 5. The model outputs a 100d vector.

## G. Doc2Vec Embeddings

Doc2Vec in an extension of the Word2Vec [32] architecture which uses either a skip-gram or continuous bag of words method. In addition to learning word vectors, Doc2Vec, also learns a paragraph vector which allows it to learn from documents of any length and format. We use the Associated Press News Skip-gram [33] [34] (0.6GB) which was trained on Wikipedia and AP News.

## H. Vader Compound Score

Vader is a simple ruled based sentiment analysis tool original made for real-time social media. Vader is constructed from a generalizable, valence-based, human-curated gold standard sentiment lexicon. They rule based approach was developed to be sensitive to both the polarity and the intensity of sentiments. To handle English idioms, a special rule set was constructed (the shit:+3, the bomb:+3, bad ass:+1.5, yeah right:-2, cut the mustard:+2, kiss of death:+1.5, hand to mouth:-2).

## I. Textblob Polarity/Subjectivity Score

Textblob employs a lexicon of words [35] (with cornettosynset-id and wordnet-id) and their part of speech, definition, polarity, subjectivity, and intensity. For example,

< word form="great", pos="JJ", sense="very good", polarity="1.0", subjectivity="1.0", intensity="1.0", confidence="0.9" >

Textblob uses the lexicon from the deprecated Pattern Library [36] (found via the WayBack Machine) which contains 2917 entries. We use both the Polarity score and the Subjectivity score in our analysis.

## J. Text Statistics

Text statistics include Flesch-Reading Ease, Flesch-Kincaid Grade, lexicon count (number of words) and sentence count (number of sentences). Flesch metrics. Both Flesch-Reading Ease (Range 0-100) and Flesch-Kincaid Grade (Range 0-18) [37] are metrics which uses total words, total sentences, and total syllables to calculate readability. The Flesch Reading Ease score is between 1 and 100, and the Flesch Kincaid Grade Level reflects the US education system.

# III. EVALUATION

We find the following 14 comparison metrics: BLEU, BERT Embeddings, BERT Embeddings, GPT Embeddings, XLNet Embeddings, Glove Embeddings, Doc2Vec Embeddings, Flair, Polarity, Subjectivity, Vader, Flesch-Kincaid Grade, Flesch Reading Ease, lexicon counts, and word counts for 108 languages. A summarization of all charts is located in the appendix alongside example back translations [Table I, Table II, Table III].

Language	BLEU-1	BLEU-2	BLEU-3	BLEU-4	Language	BLEU-1	BLEU-2	BLEU-3	BLEU-4
Afrikaans	0.6619	0.4684	0.2483	0.2483	Lithuanian	0.5966	0.3759	0.1793	0.1793
Albanian	0.6637	0.4643	0.2565	0.2565	Luxembourgish	0.6229	0.4044	0.1845	0.1845
Amharic	0.4862	0.2171	0.0631	0.0631	Macedonian	0.6411	0.4356	0.2239	0.2239
Arabic	0.5174	0.3013	0.1215	0.1215	Malagasy	0.5058	0.2799	0.1051	0.1051
Armenian	0.6042	0.3794	0.1635	0.1635	Malay	0.6413	0.4255	0.2115	0.2115
Azerbaijani	0.5265	0.2764	0.0918	0.0918	Malayalam	0.3872	0.1668	0.0446	0.0446
Basque	0.6104	0.3465	0.1415	0.1415	Maltese	0.7265	0.5309	0.3185	0.3185
Belarusian	0.5683	0.3440	0.1443	0.1443	Maori	0.5603	0.3192	0.1295	0.1295
Bengali	0.5269	0.2744	0.0980	0.0980	Marathi	0.4848	0.2289	0.0704	0.0704
Bosnian	0.6025	0.3910	0.1842	0.1842	Mongolian	0.4601	0.2050	0.0502	0.0502
Bulgarian	0.5981	0.3862	0.1775	0.1775	Myanmar (Burmese)	0.4885	0.2321	0.0661	0.0661
Catalan	0.5504	0.3129	0.1292	0.1292	Nepali	0.4926	0.2297	0.0716	0.0716
Cebuano	0.6335	0.4292	0.2137	0.2137	Norwegian	0.7083	0.5470	0.3193	0.3193
Chinese (Simplified)	0.4817	0.2509	0.0853	0.0853	Nyanja (Chichewa)	0.5212	0.2871	0.1064	0.1064
Chinese (Traditional)	0.4830	0.2525	0.0860	0.0860	Odia (Oriya)	0.5146	0.2322	0.0625	0.0625
Corsican	0.6271	0.4044	0.1961	0.1961	Pashto	0.4685	0.2354	0.0659	0.0659
Croatian	0.6042	0.3959	0.1882	0.1882	Persian	0.4977	0.2967	0.1238	0.1238
Czech	0.6071	0.3877	0.1819	0.1819	Polish	0.5980	0.3653	0.1555	0.1555
Danish	0.7205	0.5678	0.3566	0.3566	Portuguese	0.6570	0.4500	0.2345	0.2345
Dutch	0.6674	0.4725	0.2516	0.2516	Punjabi	0.5354	0.2910	0.1042	0.1042
English	1.0000	0.9920	0.9500	0.9500	Romanian	0.6199	0.3973	0.1877	0.1877
Esperanto	0.6968	0.5320	0.3157	0.3157	Russian	0.5828	0.3611	0.1551	0.1551
Estonian	0.6044	0.3811	0.1696	0.1696	Samoan	0.5400	0.3133	0.1248	0.1248
Finnish	0.6156	0.4041	0.1882	0.1882	Scots Gaelic	0.6349	0.4170	0.1965	0.1965
French	0.6346	0.4226	0.2005	0.2005	Serbian	0.4944	0.2988	0.1206	0.1206
Frisian	0.7255	0.5640	0.3481	0.3481	Sesotho	0.5414	0.2961	0.1114	0.1114
Galician	0.5937	0.3644	0.1627	0.1627	Shona	0.5270	0.3064	0.1154	0.1154
Georgian	0.6055	0.3761	0.1570	0.1570	Sindhi	0.4755	0.2260	0.0597	0.0597
German	0.6345	0.4075	0.1875	0.1875	Sinhala (Sinhalese)	0.4646	0.1980	0.0506	0.0506
Greek	0.6374	0.4255	0.2104	0.2104	Slovak	0.5910	0.3779	0.1707	0.1707
Gujarati	0.5472	0.3017	0.1144	0.1144	Slovenian	0.5979	0.3754	0.1636	0.1636
Haitian Creole	0.6886	0.4966	0.2814	0.2814	Somali	0.5905	0.3468	0.1525	0.1525
Hausa	0.6460	0.4540	0.2395	0.2395	Spanish	0.6001	0.3697	0.1671	0.1671
Hawaiian	0.4993	0.2785	0.0978	0.0978	Sundanese	0.6523	0.4382	0.2261	0.2261
Hebrew	0.5618	0.3377	0.1446	0.1446	Swahili	0.6642	0.4616	0.2466	0.2466
Hindi	0.5345	0.2919	0.1050	0.1050	Swedish	0.6728	0.4985	0.2816	0.2816
Hmong	0.6311	0.4414	0.2253	0.2253	Tagalog (Filipino)	0.7298	0.5561	0.3349	0.3349
Hungarian	0.5593	0.3183	0.1202	0.1202	Tajik	0.5657	0.3265	0.1360	0.1360
Icelandic	0.6535	0.4635	0.2459	0.2459	Tamil	0.5012	0.2494	0.0792	0.0792
Igbo	0.5998	0.4059	0.1913	0.1913	Tatar	0.4109	0.1146	0.0122	0.0122
Indonesian	0.6353	0.4193	0.2092	0.2092	Telugu	0.5430	0.2867	0.1006	0.1006
Irish	0.6893	0.4715	0.2560	0.2560	Thai	0.4908	0.2598	0.0955	0.0955
Italian	0.6464	0.4451	0.2332	0.2332	Turkish	0.5029	0.2519	0.0786	0.0786
Japanese	0.4453	0.1957	0.0541	0.0541	Turkmen	0.3523	0.1843	0.0441	0.0441
Javanese	0.6430	0.1937	0.2033	0.2033	Ukrainian	0.4344	0.1843	0.1297	0.1297
Kannada	0.5162	0.4247	0.2033	0.2033	Urdu	0.3030	0.3300	0.1297	0.1297
Kazakh	0.3102	0.2031	0.0572	0.0572	Uyghur	0.4734	0.2433	0.0730	0.0730
Khmer	0.5303	0.2144	0.0372	0.0372	Uzbek	0.4734	0.2012	0.0551	0.0551
Kinyarwanda	0.5368	0.2983	0.1142	0.1142	Vietnamese	0.6403	0.4205	0.0000	0.00098
Kinyai wanda	0.3308	0.1980	0.1142	0.1142	Welsh	0.6812	0.4203	0.2434	0.2434
Kurdish	0.5965	0.1980	0.0578	0.0578	Xhosa	0.5184	0.4031	0.1002	0.1002
Kuruisii	0.3903	0.3630	0.1003	0.1003	Yiddish	0.6307	0.2804	0.1002	0.1002
Lao	0.4033	0.1617	0.0371	0.0371	Yoruba	0.6918	0.5009	0.3151	0.3151
Latin	0.3933	0.3390	0.1626	0.1626	Zulu	0.6375	0.3222	0.2238	0.2238
Latvian	0.4373	0.1882	0.0328	0.0328	Zulu	0.0373	0.4318	0.2238	0.2238
Latviali	0.0309	0.4310	0.2270	0.2270					

# A. BLEU Scores

These scores remearably will follow the trend for Google's Reported BLEU score with some variance for the lack of "high quality" reference sentence that BLEU usaslly requires. Instead, we have publicly scraped Tweets which sometimes only include a pronoun (i.e. @user1234) which Google Translate would just return as is.

The top BLEU-1 scores are for Tagalog (BLEU-1=0.7298), Maltese (BLEU-1=0.7265), Frisian (BLEU-1=0.7255) while the top average BLEU scores across all n-grams (25% weighted for each) are Danish (Weighted BLEU=0.4776), Frisian (Weighted BLEU=0.4719), Tagalog

(Weighted BLEU=0.4619).

On the other side the bottom BLEU-1 Scores are Malayalam (BLEU-1=0.3872), Kyrgyz (BLEU-1=0.4033), Tatar (BLEU-1=0.4109) while the bottom weighted BLEU score are Tatar (Weighted BLEU=0.0515), Kyrgyz (Weighted BLEU=0.0973), Malayalam (Weighted BLEU=0.1065).

The lower the BLEU score the less likely the reference sentence matches the back translation.

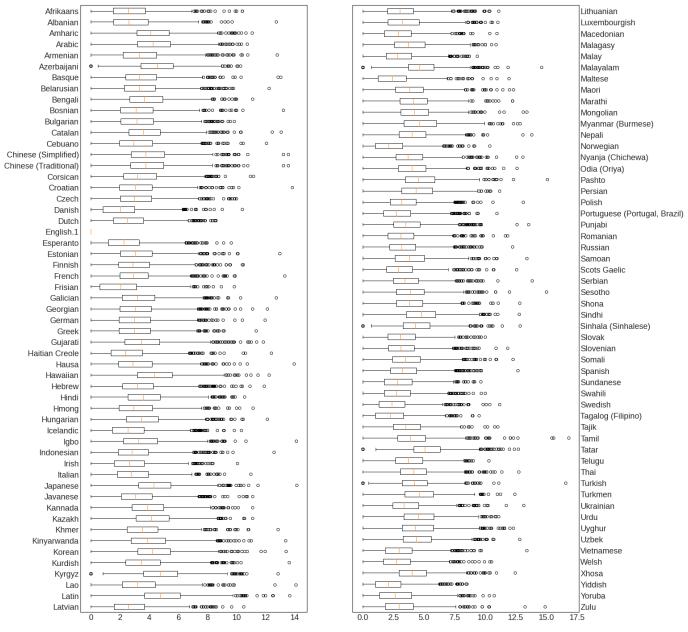


Fig. 2: BERT Euclidean Differences

# B. BERT Embeddings

Boxplot of absolute distance between BART embeddings. The closer the language is to English the closer the embeddings are to zero. BERT embeddings are of 768 dimensions and the distance is euclidean.

We find closest embeddings are Danish (2.0758  $\pm$  1.6713), Frisian (2.1105  $\pm$  1.7137), Yiddish (2.1669  $\pm$  1.6737). The furthest embeddings from the English reference are Tatar (5.2999  $\pm$  1.8633), Latin (4.9107  $\pm$  2.0689), Sindhi (4.8234  $\pm$  1.9959)

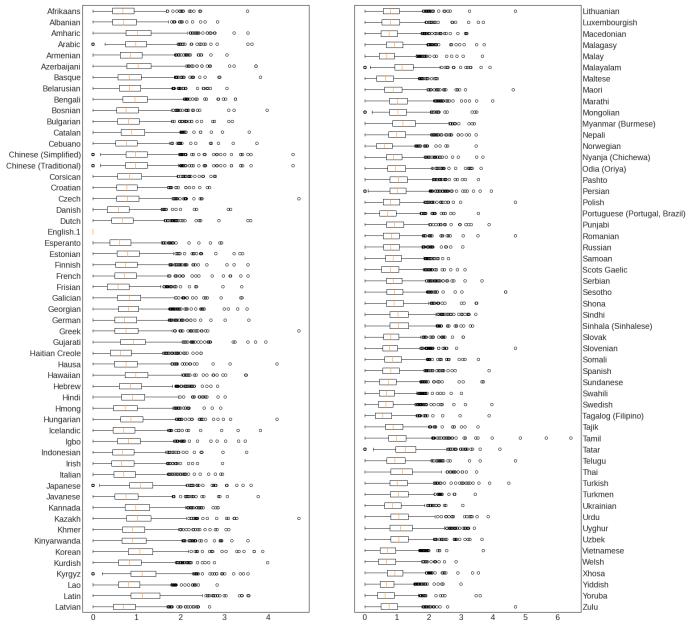


Fig. 3: BART Euclidean Differences

## C. BART Embeddings

Boxplot of absolute distance between BART embeddings. The closer the language is to English the closer the embeddings are to zero. BART embeddings are of 768 dimensions and the distance is euclidean.

We find closest embeddings are Danish (0.5903  $\pm$  0.4142), Frisian (0.5954  $\pm$  0.423), Tagalog (0.5976  $\pm$  0.4236). The furthest embeddings from the English reference are Tatar (1.309  $\pm$  0.5083), Myanmar (1.2359  $\pm$  0.554), Malayalam (1.2327  $\pm$  0.4586).

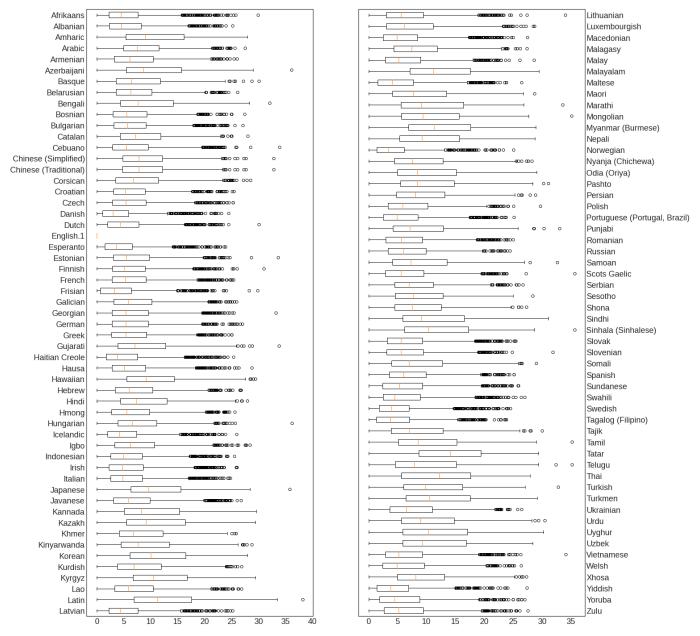


Fig. 4: GPT Euclidean Differences

## D. GPT Embeddings

Boxplot of absolute distance between GPT embeddings. The closer the language is to English the closer the embeddings are to zero. GPT embeddings are of 768 dimensions and the distance is euclidean.

We find closest embeddings are Danish (4.2798  $\pm$  4.5897), Norwegian (4.5235  $\pm$  4.5455), Frisian (4.5661  $\pm$  5.0261). The furthest embeddings from the English reference are Tatar (13.9721  $\pm$  6.4386), Malayalam (12.2058  $\pm$  6.3209), Latin (12.0613  $\pm$  6.6757).

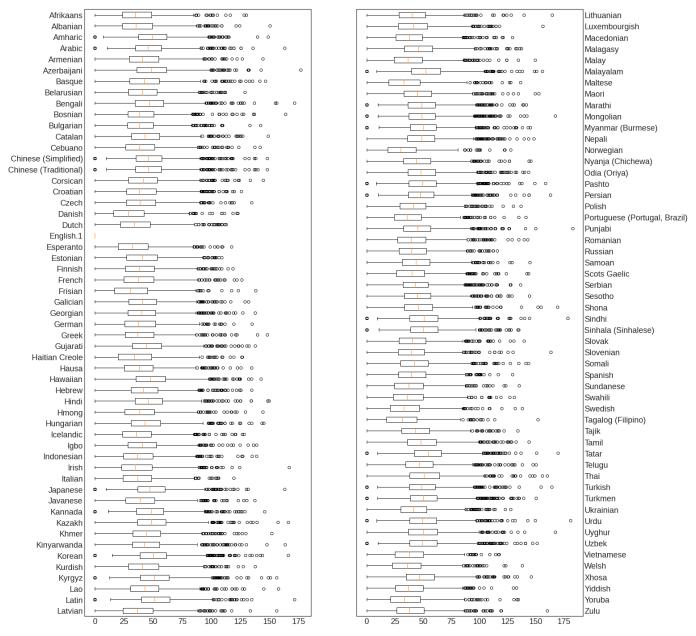


Fig. 5: XLnet Euclidean Differences

## E. XLnet Embeddings

Boxplot of absolute distance between XLnet embeddings. The closer the language is to English the closer the embeddings are to zero. XLnet embeddings are of 768 dimensions and the distance is euclidean.

We find closest embeddings are Danish (30.1903  $\pm$  21.0538), Frisian (31.6068  $\pm$  21.6522), Norwegian (31.6301  $\pm$  20.7609). The furthest embeddings from the English reference are Tatar (55.9961  $\pm$  21.5646), Malayalam (54.7046  $\pm$  21.2162), Kyrgyz (52.7561  $\pm$  21.0698).

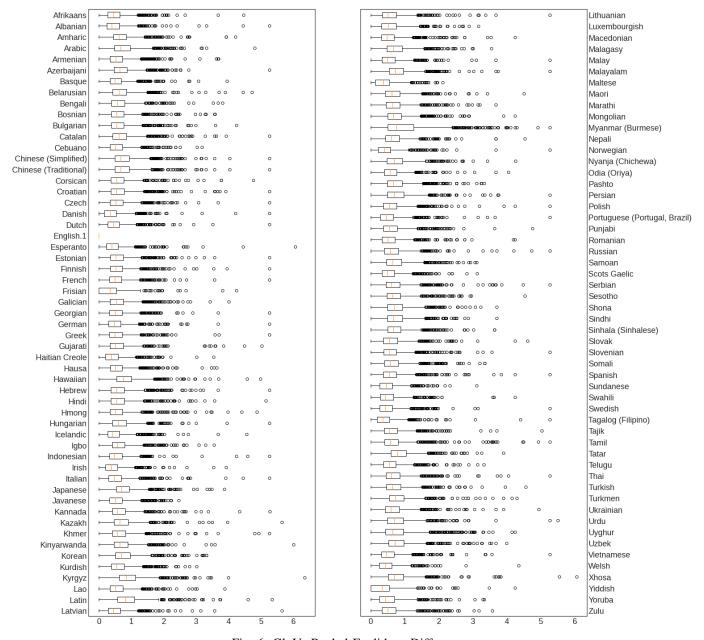


Fig. 6: GloVe Pooled Euclidean Differences

## F. Glove Embeddings

Boxplot of absolute distance between pooled Glove embeddings. The closer the language is to English the closer the embeddings are to zero. Glove embeddings are of 100 dimensions and the distance is euclidean.

We find closest embeddings are Frisian (0.3772  $\pm$  0.38), Maltese (0.3895  $\pm$  0.3353), Yiddish (0.3952  $\pm$  0.4116). The furthest embeddings from the English reference are Myanmar (0.9865  $\pm$  0.7875), Kyrgyz (0.9349  $\pm$  0.5172), Latin (0.8898  $\pm$  0.5298).

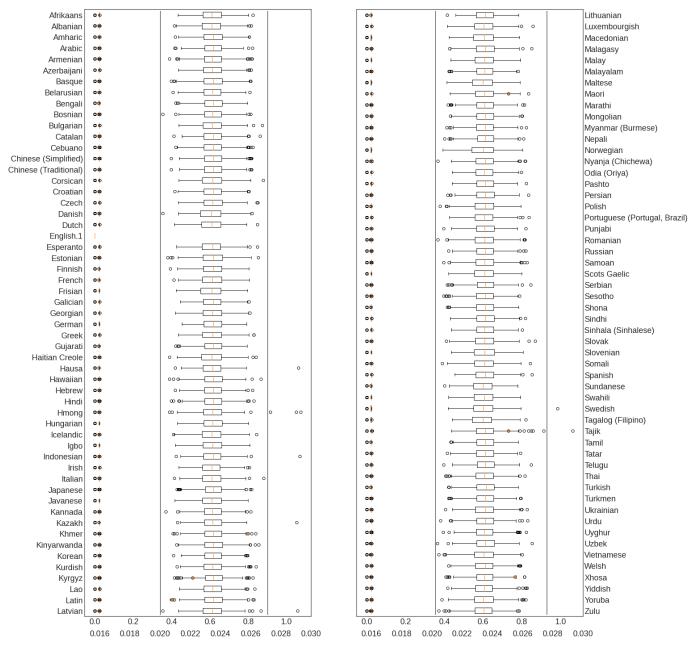


Fig. 7: Doc2Vec Euclidean Differences, Full size boxplot with zoomed in plot of the 25-75 percentile on the second x-axis

## G. Doc2Vec Embeddings

Boxplot of absolute distance between Doc2Vec embeddings and the English embedding. The closer the language is to English the closer the embeddings are to zero. Doc2Vec embeddings are of 300 dimension and the distance is euclidean. We show the overall graph in addition to the zoomed in portion on the 2nd x-axis.

The closest embeddings to English are much closer than the transformers embeddings regardless of the 300 dimension output. We find closest embeddings are Danish (0.0205  $\pm$  0.0079), Frisian (0.0206  $\pm$  0.0078), Tagalog (0.0207  $\pm$  0.0077). The furthest embeddings from the English reference are Hmong (0.025  $\pm$  0.0547), Tajik (0.0244  $\pm$  0.04), Kazakh (0.024  $\pm$  0.0328).

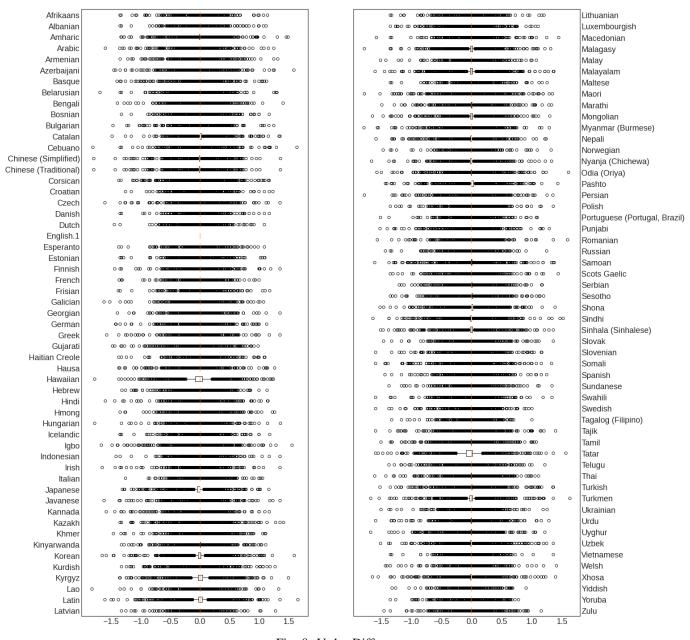


Fig. 8: Vader Differences

## H. Vader Compound Score

Boxplot of 1D distance between Vader sentiment compound score Compound score is a 'normalized, weighted composite score' is accurate by summing the valence scores of each word in the lexicon.

The Vader scores with means closest to English are Sesotho (0  $\pm$  0.2624), Vietnamese (-0.0001  $\pm$  0.196), Frisian (0.0002  $\pm$  0.1850) while the scores further from the reference are Tatar (-0.0388  $\pm$  0.3227), Japanese (-0.0326  $\pm$  0.2575), Uyghur (-0.0251  $\pm$  0.2666).

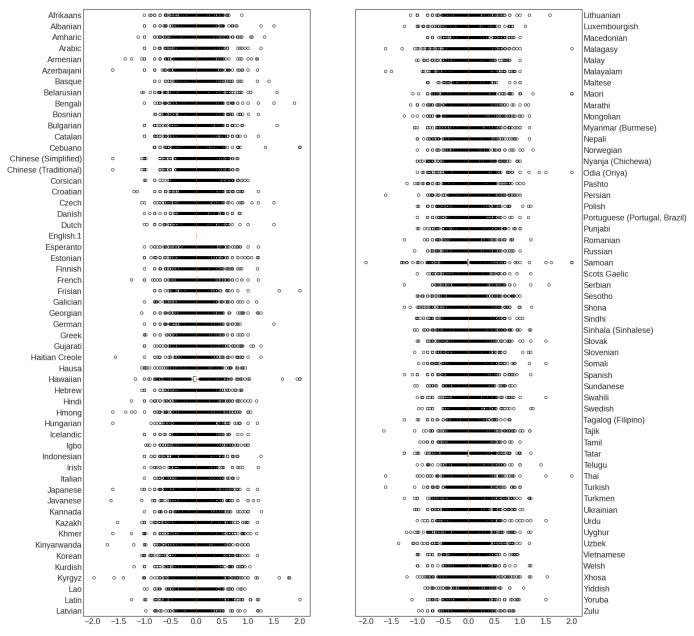


Fig. 9: Polarity Differences

## I. Textblob Polairty Score

Boxplot of 1D distance between textblob polarity scores The polarity score is a float within the range [-1.0, 1.0]. The subjectivity is a float within the range [0.0, 1.0] where 0.0 is very objective and 1.0 is very subjective.

The languages with the closest polarity scores are Icelandic (-0.0001  $\pm$  0.1387), Galician (0.0001  $\pm$  .1738), Odia (Oriya) (0.0001  $\pm$  0.2172) while the languages furthest from reference polarity are Samoan (-0.0256  $\pm$  0.2834), Serbian (0.023  $\pm$  0.1883), Latin (0.0191  $\pm$  0.2477).

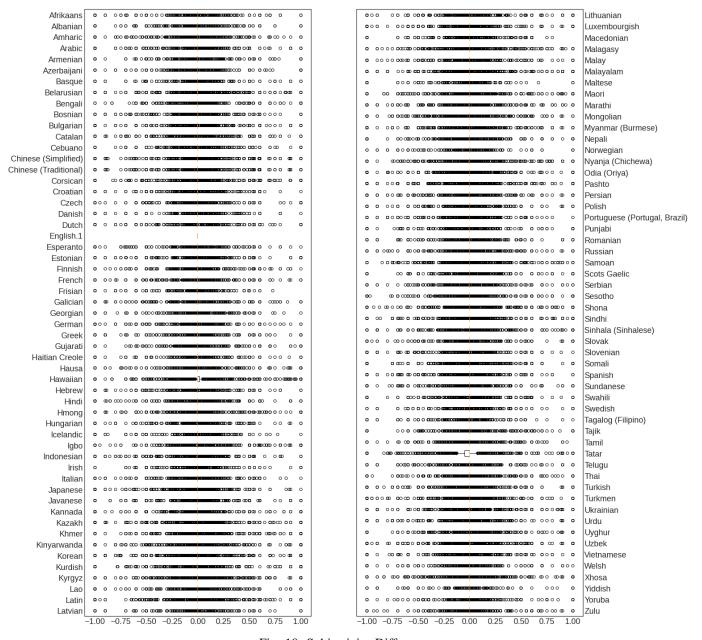


Fig. 10: Subjectivity Differences

## J. Textblob Subjectivity Score

Boxplot of 1D distance between textblob subjectivity scores. The polarity score is a float within the range [-1.0, 1.0]. The subjectivity is a float within the range [0.0, 1.0] where 0.0 is very objective and 1.0 is very subjective.

The closest embeddings to English are much closer than the BERT embeddings. We find the closest languages are Swahili (0.0000  $\pm$  0.1767), Swedish (-0.0001  $\pm$  0.1455), Xhosa (-0.0001  $\pm$  0.2472) while the languages furthest from the English reference are Tatar (-0.027  $\pm$  0.2726), Hawaiian (0.0261  $\pm$  0.2902), Odia (Oriya) (-0.0246  $\pm$  0.2345).

Language	flesch reading ease	flesch kincaid grade	lexicon count	sentence count	Language	flesch reading ease	flesch kincaid grade	lexicon count	sentence count
Afrikaans	61.5	11.3	12786	482	Lithuanian	63.63	10.4	12958	530
Albanian	62.21	11	13109	508	Luxembourgish	62.92	10.7	12969	516
Amharic	65.56	9.7	13264	590	Macedonian	62.92	10.7	12668	504
Arabic	67.08	9.1	13584	646	Malagasy	65.35	9.8	12309	542
Armenian	61.8	11.1	12822	489	Malay	67.01	11.2	12940	440
Azerbaijani	62.61	10.8	12796	503	Malayalam	65.66	9.7	13631	609
Basque	62.31	11	12844	500	Maltese	59.57	12	12710	448
Belarusian	62.11	11	13229	511	Maori	69.75	10.2	12512	469
Bengali	67.59	8.9	13118	641	Marathi	66.07	9.5	12899	587
Bosnian	62.31	11	12819	498	Mongolian	65.25	9.8	12648	554
Bulgarian	63.32	10.6	12717	514	Myanmar (Burmese)	66.37	9.4	12283	565
Catalan	63.12	10.6	12563	504	Nepali	75.54	7.9	13068	622
Cebuano	61.8	11.1	12332	470	Norwegian	69.96	10.1	13120	496
Chinese (Simplified)	66.78	9.2	12923	607	Nyanja (Chichewa)	62.72	10.8	12528	495
Chinese (Traditional)	66.67	9.3	12863	602	Odia (Oriya)	65.46	9.7	13572	601
Corsican	63.22	10.6	12457	503	Pashto	67.18	9.1	12529	600
Croatian	62.31	11	12891	502	Persian	68.1	8.7	12810	642
Czech	64.54	10.1	12745	543	Polish	63.12	10.6	12944	520
Danish	69.45	10.3	13103	486	Portuguese (Portugal, Brazil)	62.01	11.1	13050	502
Dutch	62.51	10.9	12721	498	Punjabi	66.67	9.3	12442	582
English.1	65.29	11.9	12895	414	Romanian	64.14	10.3	12391	519
Esperanto	60.18	11.8	13204	475	Russian	70.57	9.9	13226	511
Estonian	63.63	10.4	12856	526	Samoan	60.69	11.6	12092	443
Finnish	61.6	11.2	13031	493	Scots Gaelic	63.63	10.4	12486	511
French	62.21	11	12708	493	Serbian	64.14	10.3	12851	537
Frisian	70.06	10	13097	496	Sesotho	62.51	10.9	12218	479
Galician	63.22	10.6	12610	509	Shona	64.34	10.2	12518	528
Georgian	62.92	10.7	12676	505	Sindhi	67.28	9	12956	622
German	69.96	10.1	12949	488	Sinhala (Sinhalese)	67.08	9.1	12689	603
Greek	63.83	10.4	12789	528	Slovak	63.93	10.3	12766	530
Gujarati	67.59	8.9	12871	629	Slovenian	63.43	10.5	12917	525
Haitian Creole	60.89	11.5	12913	477	Somali	61.9	11.1	12569	482
Hausa	61.4	11.3	12256	461	Spanish	62.92	10.7	12906	514
Hawaiian	64.95	9.9	12462	539	Sundanese	60.48	11.7	13048	475
Hebrew	67.38	9	12842	621	Swahili	59.47	12	12730	447
Hindi	66.78	9.2	12894	604	Swedish	70.67	9.8	12992	504
Hmong	70.87	9.7	12438	485	Tagalog (Filipino)	60.79	11.5	12915	475
Hungarian	64.54	10.1	12546	534	Tajik	64.04	10.3	12447	519
Icelandic	62.51	10.1	12935	507	Tamil	67.28	9	12941	621
Igbo	61.6	11.2	12267	465	Tatar	60.48	11.7	14279	520
Indonesian	60.38	11.7	12953	469	Telugu	74.42	8.4	13345	603
Irish	61.4	11.7	12933	483	Thai	68.13	10.8	12755	450
Italian	62.82	10.8	13129	521	Turkish	63.32	10.6	12733	524
Japanese	73.41	8.8	14919	645	Turkmen	68.13	10.8	13517	478
Javanese	59.37	12.1	12739	445	Ukrainian	63.43	10.8	12664	515
	66.67	9.3	13519	633	Urdu	76.76	7.5	12697	642
Kannada Kazakh	63.22	10.6	13077	527	Uyghur	65.76	9.6	13024	585
Kazakn	66.27	9.4	12714	584	Uzbek	73.21	8.8	13024	537
Kinyarwanda	67.32	9.4	13929	478	Vietnamese	61.19		12328	482
Kinyarwanda	67.32	9					11.4		
			13229	641	Welsh	59.67		12847	454
Kurdish	68.94	10.5	12892	469	Xhosa	60.99	11.5	12532	465
Kyrgyz	66.17	9.5	12232	559	Yiddish	66.67	9.3	13333	622
Lao	66.78	9.2	12315	577	Yoruba	60.79	11.5	12766	470
Latin	68.94	10.5	13874	504	Zulu	60.38	11.7	12550	454
Latvian	61.9	11.1	13000	498					

## K. Text Statistics

Here we analysis Flesh-reading ease, Flesh-kincaid grade, lexicon count, and sentence count.

The English Flesch Reading Ease for reference is 65.29. On the top of the list is Urdu (76.76), Nepali (75.54), Telugu (74.42) while on the bottom of the list is Javanese (59.37), Swahili (59.47), Maltese (59.57).

The English Flesch Kincaid Grade for reference is 11.9. On the top of the list is Javanese (12.1), Swahili (12), Maltese (12) while on the bottom fo the list is Urdu (7.5), Nepali (7.9),

Telugu (8.4).

The English Lexicon count for reference is 12895. On the top of the list is Japanese (14919), Tatar (14279), Kinyarwanda (13929) while on the bottom of the list is Samoan (12092), Sesotho (12218), Kyrgyz (12232).

The English Sentence count for reference is 414. On the top of the list is Arabic (646), Japanese (645), Urdu (642), while at the bottom of the list is Malay (440), Samoan (443), Javanese (445).

## IV. DISCUSSION

As shown the embedding space is quite consistently varied across all 108 languages. Languages with the furthest embeddings (and therefore the best for the most generalized models) are among the languages with the worst translations in the BLEU scores from the Google API. Embedding spaces for large scale transformers have more consistent movement in their feature space while most single metrics (unified sentiment scores) are mostly the same with only outliers not having the same sentiment score. The lexicon nature of those methods do not end up capturing the meaning of context of the sentence and therefore do not end up having their embedding space moved.

### V. CONCLUSION

Back translation show a significant ability to move the various NLP metrics in many transformer architectures. In this experiment, this text augmentation technique empirically shows back translation acts as a generalizable strategy. Specifically, the lack of good translation allows this technique to move the embedding space in various statistical ways. We show back translation to Tatar moves the embeddings the furthest while translating to Danish would not generalize as well.

# A. Next Steps

Showing the embedding space is only the first step in deciding which languages are the best for back translation during training. Training transformer architectures on these embeddings is the next step to guarantee a more generalizable model.

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### REFERENCES

- A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention is all you need," arXiv preprint arXiv:1706.03762, 2017.
- [2] L. Gao, S. Biderman, S. Black, L. Golding, T. Hoppe, C. Foster, J. Phang, H. He, A. Thite, N. Nabeshima *et al.*, "The pile: An 800gb dataset of diverse text for language modeling," *arXiv preprint* arXiv:2101.00027, 2020.
- [3] Y. Wu, M. Schuster, Z. Chen, Q. V. Le, M. Norouzi, W. Macherey, M. Krikun, Y. Cao, Q. Gao, K. Macherey *et al.*, "Google's neural machine translation system: Bridging the gap between human and machine translation," *arXiv preprint arXiv:1609.08144*, 2016.
- [4] A. Chaudhary, "A visual survey of data augmentation in nlp," 2020.[Online]. Available: https://amitness.com/2020/05/data-augmentation-for-nlp
- [5] E. Ma, "Nlp augmentation," 2019. [Online]. Available: https://github.com/makcedward/nlpaug
- [6] J. Wei and K. Zou, "Eda: Easy data augmentation techniques for boosting performance on text classification tasks," arXiv preprint arXiv:1901.11196, 2019.
- [7] R. Sennrich, B. Haddow, and A. Birch, "Improving neural machine translation models with monolingual data," arXiv preprint arXiv:1511.06709, 2015

[8] S. Edunov, M. Ott, M. Auli, and D. Grangier, "Understanding back-translation at scale," arXiv preprint arXiv:1808.09381, 2018.

- [9] M. Fadaee, A. Bisazza, and C. Monz, "Data augmentation for low-resource neural machine translation," arXiv preprint arXiv:1705.00440, 2017.
- [10] S. Longpre, Y. Wang, and C. DuBois, "How effective is task-agnostic data augmentation for pretrained transformers?" arXiv preprint arXiv:2010.01764, 2020.
- [11] M. Aiken and Z. Wong, "An updated evaluation of google translate accuracy," *Studies in linguistics and literature*, vol. 3, no. 3, pp. 253– 260, 2019.
- [12] https://colab.research.google.com/.
- [13] A. Go, R. Bhayani, and L. Huang, "Twitter sentiment classification using distant supervision," CS224N project report, Stanford, vol. 1, no. 12, p. 2009, 2009.
- [14] Google, "Google translate," 2020.
- [15] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, "Bleu: a method for automatic evaluation of machine translation," in *Proceedings of the 40th* annual meeting of the Association for Computational Linguistics, 2002, pp. 311–318.
- [16] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," arXiv preprint arXiv:1810.04805, 2018.
- [17] M. Lewis, Y. Liu, N. Goyal, M. Ghazvininejad, A. Mohamed, O. Levy, V. Stoyanov, and L. Zettlemoyer, "Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension," arXiv preprint arXiv:1910.13461, 2019.
- [18] A. Radford, K. Narasimhan, T. Salimans, and I. Sutskever, "Improving language understanding by generative pre-training," 2018.
- [19] Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. Salakhutdinov, and Q. V. Le, "Xlnet: Generalized autoregressive pretraining for language understanding," arXiv preprint arXiv:1906.08237, 2019.
- [20] J. Pennington, R. Socher, and C. D. Manning, "Glove: Global vectors for word representation," in *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, 2014, pp. 1532–1543.
- [21] Q. Le and T. Mikolov, "Distributed representations of sentences and documents," in *International conference on machine learning*, 2014, pp. 1188–1196.
- [22] C. Hutto and E. Gilbert, "Vader: A parsimonious rule-based model for sentiment analysis of social media text," in *Proceedings of the International AAAI Conference on Web and Social Media*, vol. 8, no. 1, 2014
- [23] S. Loria, "textblob documentation," Release 0.15, vol. 2, 2018.
- [24] A. Akbik, D. Blythe, and R. Vollgraf, "Contextual string embeddings for sequence labeling," in COLING 2018, 27th International Conference on Computational Linguistics, 2018, pp. 1638–1649.
- [25] R. Flesch, "Marks of readable style; a study in adult education." *Teachers College Contributions to Education*, 1943.
- [26] E. L. Bird, Steven and E. Klein, "Source code nltk bleu score," https://www.nltk.org/\_modules/nltk/translate/bleu\_score, 2019.
- [27] "bert-base-uncased · hugging face." [Online]. Available: https://huggingface.co/bert-base-uncased
- $[28] \enskip {\tt [Online]}. Available: https://huggingface.co/facebook/bart-base$
- [29] "openai-gpt · hugging face." [Online]. Available: https://huggingface.co/openai-gpt
- [30] "xlnet-base-cased · hugging face." [Online]. Available: https://huggingface.co/xlnet-base-cased
- [31] J. Pennington. [Online]. Available: https://nlp.stanford.edu/projects/glov
- [32] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," arXiv preprint arXiv:1301.3781, 2013.
- [33] jhlau, "doc2vec," https://github.com/jhlau/doc2vec, 2016.
- [34] J. H. Lau and T. Baldwin, "An empirical evaluation of doc2vec with practical insights into document embedding generation," arXiv preprint arXiv:1607.05368, 2016.
- [35] jhlau, "Sloria/textblob," https://github.com/sloria/TextBlob/blob/eb08c1 20d364e908646731d60b4e4c6c1712ff63/textblob/en/en-sentiment.xml, 2014.
- [36] CLiPS, "Pattern.web," web.archive.org/web/20191220013838/www.cli ps.uantwerpen.be/pages/pattern-web, 2010.
- [37] "The flesch reading ease and flesch-kincaid grade level," Nov 2020. [Online]. Available: https://readable.com/blog/the-flesch-reading-ease-and-flesch-kincaid-grade-level/

TABLE I: 108 Back Translations of a Tweet from the Sentiment 140 Dataset

Language	Translated Sentence	Language	Translated Sentence
Afrikaans	I love Fridays! Held by the pool	Lithuanian	I love Fridays! Laying by the pool
Albanian	I love Fridays! Laying by the pool	Luxembourgish	I love Fridays! Laying of pool
Amharic	I love Friday! Parking at the ready:	Macedonian	Love Friday! Set by the pool
Arabic	I love Fridays! Put on a swimming pool	Malagasy	I love Fridays! Laying by the pool
Armenian	I love Fridays! Laying by the pool	Malay	I love Fridays! Laying by the pool
Azerbaijani	I love Fridays! shoot pool	Malayalam	I love Fridays! laying pool
Basque	I love Fridays! Laying the pool	Maltese	I love Fridays! Placing the pool
Belarusian	I love Fridays! Moore poolside	Maori	I love Friday! Laying in the pit
Bengali	I love Friday! Laying by the pool	Marathi	I love Friday! Laying by the pool
Bosnian	I love Fridays! Laying by the pool	Mongolian	I love Fridays! Laying by the pool
Bulgarian	I love Friday! Laying the pool	Myanmar (Burmese)	I love Friday! Laying by the poor
Catalan	I love Friday! Lie by the pool	Nepali	I love Friday! Laying by the pool
Catalan		i i	I love Fridays! Laying by the pool
	I love Fridays! Laying the lake	Norwegian	
Chinese (Simplified)	I love Fridays! Laying by the pool	Nyanja (Chichewa)	I love the snow! putting pool
Chinese (Traditional)	I love Fridays! Laying by the pool	Odia (Oriya)	I love Fridays! Laying by the pool
Corsican	I love Fridays! Set from pool	Pashto	I love Fridays! Placed by the pool
Croatian	I love Fridays! Laying by the pool	Persian	I'm in love Fridays! Laying by the pool
Czech	I love Fridays! Laying by the pool	Polish	I love Fridays! Lying by the pool
Danish	I love Fridays! Laying by the pool	Portuguese	I love Fridays! Laying by the pool
Dutch	I love Fridays! Laying by the pool	Punjabi	I love Friday! Pool
English	I love Fridays! Laying by the pool	Romanian	I love Fridays! Laying pool
Esperanto	I love Friday! Putting the pool	Russian	I love Fridays! Laying by the pool
Estonian	I love Fridays! laying the pool	Samoan	I love Friday! Laying by the pool
Finnish	I love Fridays! Lay in a pond	Scots Gaelic	I love Friday! Laying with that the swimming
French	I love Fridays! Laying the pool	Serbian	I love Fridays! Laying by the pool
Frisian	I love Fridays! Laying by the pool	Sesotho	I like Friday! Laying by the pool
Galician	I love Friday! Lying in pool	Shona	I love Fridays! putting pool
Georgian	I love Fridays! Laying pool	Sindhi	I love Fridays! Laying Pool
German	I love Fridays! Laying by the pool	Sinhala (Sinhalese)	I love Fridays! Shooting pool
Greek	I love Fridays! Mounting poolside	Slovak	I love Fridays! Laying by the pool
Gujarati	I love Fridays! Laying by the pool	Slovenian	I love heels! Laying by the pool
Haitian Creole	I love Fridays! Laying the pool	Somali	I love Fridays! Laying pool
Hausa	I love Fridays! Laying the pool	Spanish	I love fridays! Lie by the pool
Hawaiian	I love Fridays! Lying by the pool	Sundanese	I love Fridays! Laying by the pool
Hebrew	I love Fridays! And lie by the pool	Swahili	Let me Friday! Keep the pool
Hindi	Mujee like Friday! Laying by the pool	Swedish	I love Fridays! Laying by the pool
Hmong	I love Fridays! Laid by the pool	Tagalog (Filipino)	I love every Friday! Laying by the pool
Hungarian	I love Fridays! Laying the pool	Tajik	I love Fridays! Laying out by the pool
Icelandic	I love Fridays! Laying by the pool	Tamil	I love Fridays! Laying by the pool
	I love Fridays! To set the pool		I am in love on Friday! Laying pool
Igbo		Tatar	, , , ,
Indonesian	I love Fridays! Laying by the pool	Telugu	I love Fridays! Laying by the pool
Irish	I love Fridays! To lay by the pool	Thai	I love Fridays! Place the pool
Italian	I love Fridays! Laying in the pool	Turkish	I love Fridays! The pool floor
Japanese	I love Friday! Laying by the pool	Turkmen	I love anna! the foundation stone of the pool
Javanese	I Friday! Laying by the pool	Ukrainian	I love Fridays! Laying pool
Kannada	I love Fridays! Laying by the pool	Urdu	I love Fridays! Laying by the pool
Kazakh	I love Fridays! the construction of a swimming pool	Uyghur	I love Fridays! Pavement with pool
Khmer	I love Fridays! basin	Uzbek	On Friday, I love you! swimming board
Kinyarwanda	I love the fifth! Laying the pool	Vietnamese	I love Friday! Put the pool
Korean	I love Fridays! Lying by the pool	Welsh	I love Fridays! Laying by the pool
Kurdish	I love Fridays! Lying by the pool	Xhosa	I love Fridays! To put it in the pool
Kyrgyz	I love Fridays! by the pool	Yiddish	I love Fridays! Installation by the pool
Lao	I love Friday! By the pool	Yoruba	I love Fridays! Laying by the pool
Latin	I love Fridays? Laying in the pool	Zulu	I love Fridays! Setting up the pool
d.	I love Fridays! Putting the pool	-	

TABLE II: Language Metrics Mean and Standard Deviation

Language	BERT	xlnet	bart	ant	alovo	Doc2Vec	VADER	Polarity	Cubicotivity
Language			0.7063 ± 0.4114	gpt	glove	0.0219 ± 0.0060	-0.0074 ± 0.2076		Subjectivity
Afrikaans	$2.6753 \pm 1.7894$	$36.5315 \pm 20.8224$		5.7252 ± 5.2914	$0.5019 \pm 0.4145$			-0.0008 ± 0.1559	$-0.0087 \pm 0.1757$
Albanian	$2.7292 \pm 1.8679$	$37.2732 \pm 21.9942$	$0.7189 \pm 0.4193$	5.9409 ± 5.3134	$0.4683 \pm 0.4172$	$0.0216 \pm 0.0064$	$-0.0056 \pm 0.2004$	$0.0041 \pm 0.1674$	$-0.0163 \pm 0.1759$
Amharic	$4.2694 \pm 1.8715$	50.2214 ± 20.3938	$1.0572 \pm 0.4652$	$10.6803 \pm 6.6559$	$0.6867 \pm 0.4313$	$0.0229 \pm 0.0038$	$-0.0137 \pm 0.2816$	$0.0002 \pm 0.2007$	$-0.0145 \pm 0.2155$
Arabic	$4.3220 \pm 1.8829$	47.2316 ± 19.7599	$1.0103 \pm 0.4135$	8.6844 ± 5.4613	$0.7693 \pm 0.4834$	$0.0232 \pm 0.0030$	$-0.0242 \pm 0.2374$	$0.0035 \pm 0.1754$	$-0.0145 \pm 0.1993$
Armenian	$3.3922 \pm 2.0027$	$42.5497 \pm 21.0910$	$0.8890 \pm 0.4417$	$7.5857 \pm 5.9067$	$0.5808 \pm 0.4238$	$0.0224 \pm 0.0051$	$-0.0078 \pm 0.2294$	$-0.006 \pm 0.1841$	$-0.0072 \pm 0.177$
Azerbaijani	$4.5472 \pm 1.8635$	$50.2426 \pm 22.0118$	$1.0690 \pm 0.4685$	$10.3279 \pm 6.4566$	$0.7133 \pm 0.4366$	$0.0229 \pm 0.0039$	$-0.0066 \pm 0.2559$	$-0.0018 \pm 0.1743$	$-0.0081 \pm 0.1693$
Basque	$3.4175 \pm 1.8110$	$43.3499 \pm 22.1301$	$0.8516 \pm 0.4420$	$8.1463 \pm 6.1391$	$0.5432 \pm 0.3888$	$0.0225 \pm 0.0050$	$-0.005 \pm 0.2389$	$0.0081 \pm 0.1489$	$0.0008 \pm 0.1524$
Belarusian	$3.4442 \pm 1.8929$	$42.1689 \pm 20.3298$	$0.8668 \pm 0.4231$	$7.4848 \pm 5.4101$	$0.6803 \pm 0.4671$	$0.0225 \pm 0.0049$	$-0.005 \pm 0.2368$	$0.0077 \pm 0.2081$	$0.0026 \pm 0.2123$
Bengali	$3.7937 \pm 1.8846$	$48.1835 \pm 21.9692$	$0.9935 \pm 0.4678$	$9.3810 \pm 6.5568$	$0.6196 \pm 0.4292$	$0.0229 \pm 0.0041$	$-0.0022 \pm 0.2327$	$0.0116 \pm 0.1953$	$0.0011 \pm 0.1850$
Bosnian	$3.2100 \pm 1.9337$	$40.2262 \pm 21.0845$	$0.8063 \pm 0.4368$	$6.6938 \pm 5.2725$	$0.6114 \pm 0.4419$	$0.0223 \pm 0.0054$	$0.0006 \pm 0.2131$	$0.0112 \pm 0.1806$	$-0.0149 \pm 0.1885$
Bulgarian	$3.2032 \pm 1.8526$	39.5151 ± 19.3191	$0.8310 \pm 0.4307$	$6.9228 \pm 5.4705$	$0.6180 \pm 0.4370$	$0.0224 \pm 0.0050$	$0.0031 \pm 0.2178$	$0.0036 \pm 0.1820$	$-0.0079 \pm 0.1963$
Catalan	$3.7035 \pm 1.8844$	44.4201 ± 21.2358	$0.9172 \pm 0.4408$	$8.4720 \pm 5.7828$	$0.6943 \pm 0.4918$	$0.0226 \pm 0.0047$	$0.0164 \pm 0.2448$	$-0.006 \pm 0.2019$	$-0.0137 \pm 0.2155$
Cebuano	$3.1232 \pm 1.9017$	39.5497 ± 21.7279	$0.7828 \pm 0.4377$	$6.9678 \pm 5.8215$	$0.5668 \pm 0.3904$	$0.0221 \pm 0.0057$	$0.0042 \pm 0.2449$	$0.0047 \pm 0.2130$	$-0.0005 \pm 0.1686$
Chinese (Simp.)	$3.9368 \pm 1.9524$	$47.6320 \pm 20.6808$	$1.0247 \pm 0.4771$	$8.9017 \pm 5.7305$	$0.7676 \pm 0.4848$	$0.0229 \pm 0.0039$	$-0.0166 \pm 0.2556$	$0.0032 \pm 0.1982$	$-0.0014 \pm 0.2275$
Chinese (Trad.)	$3.9115 \pm 1.9621$	47.5426 ± 20.8729	$1.0218 \pm 0.4800$	$8.9060 \pm 5.7579$	$0.7681 \pm 0.4932$	$0.0229 \pm 0.0040$	$-0.0167 \pm 0.2553$	$0.0031 \pm 0.1986$	$-0.0013 \pm 0.2281$
Corsican	3.3429 ± 1.9639	41.7332 ± 22.3249	$0.8559 \pm 0.4762$	8.1193 ± 6.3887	$0.5986 \pm 0.4575$	$0.0219 \pm 0.0060$	$-0.002 \pm 0.2604$	$0.0086 \pm 0.1926$	$0.0088 \pm 0.2209$
Croatian	3.1456 ± 1.9034	40.8590 ± 21.5791	$0.7901 \pm 0.4028$	$6.5720 \pm 5.2830$	$0.6174 \pm 0.4898$	$0.0223 \pm 0.0053$	$0.0054 \pm 0.2067$	$0.0105 \pm 0.1721$	-0.0098 ± 0.1646
Czech	$3.1310 \pm 1.8350$	$40.1054 \pm 20.7646$	$0.8152 \pm 0.4348$	6.7120 ± 5.3675	$0.5822 \pm 0.4293$	$0.0224 \pm 0.0052$	-0.0055 ± 0.2321	$-0.0013 \pm 0.1812$	-0.009 ± 0.1804
Danish	2.0758 ± 1.6713	$30.1903 \pm 21.0538$	$0.5903 \pm 0.4142$	$4.2798 \pm 4.5897$	$0.4041 \pm 0.4014$	$0.0205 \pm 0.0079$	-0.0011 ± 0.1806	$0.0013 \pm 0.1331$	-0.0023 ± 0.1469
Dutch	2.6448 ± 1.7705	$35.1354 \pm 21.1426$	$0.6975 \pm 0.4358$	5.6755 ± 5.2079	$0.4924 \pm 0.4191$	$0.0215 \pm 0.0066$	-0.0063 ± 0.1935	$0.0009 \pm 0.1618$	-0.0026 ± 0.1776
English.1	$0.0000 \pm 0.0000$	$0.0000 \pm 0.0000$	$0.0000 \pm 0.0000$	$0.0000 \pm 0.0000$	$0.0000 \pm 0.0000$	$0.0000 \pm 0.0000$	$0.0000 \pm 0.0000$	$0.0000 \pm 0.0000$	$0.0000 \pm 0.0000$
Esperanto	$2.3467 \pm 1.7330$	$33.1779 \pm 21.0201$	$0.6306 \pm 0.4066$	$4.8847 \pm 4.8762$	$0.4573 \pm 0.4409$	$0.0212 \pm 0.0071$	$-0.0137 \pm 0.2001$	$0.0000 \pm 0.0000$ $0.0044 \pm 0.1696$	-0.0198 ± 0.188
Estonian	$3.1483 \pm 1.8573$	$41.0236 \pm 21.0431$	$0.8218 \pm 0.4516$	$7.0421 \pm 5.6867$	$0.5903 \pm 0.4497$	$0.0212 \pm 0.0071$ $0.0222 \pm 0.0055$	$-0.0137 \pm 0.2001$ $-0.002 \pm 0.208$	$0.0019 \pm 0.1815$	-0.0047 ± 0.183
Finnish	$3.0003 \pm 1.8270$	39.4413 ± 20.4864	$0.7904 \pm 0.4394$	$6.4888 \pm 5.2860$	$0.5781 \pm 0.4414$	$0.0222 \pm 0.0055$ $0.0222 \pm 0.0055$	$0.0032 \pm 0.208$ $0.0032 \pm 0.2167$	$0.0019 \pm 0.1613$ $0.0020 \pm 0.1663$	$-0.0027 \pm 0.1833$
French	$3.0003 \pm 1.8270$ $3.0026 \pm 1.8019$	$38.7591 \pm 21.2701$	$0.7695 \pm 0.4505$	$6.8370 \pm 5.7311$	$0.5781 \pm 0.4414$ $0.5468 \pm 0.4153$	$0.0222 \pm 0.0053$ $0.0220 \pm 0.0059$	$0.0032 \pm 0.2107$ $0.0023 \pm 0.1985$	$-0.0020 \pm 0.1003$ $-0.0048 \pm 0.1815$	$-0.0027 \pm 0.1833$ $-0.0086 \pm 0.1887$
Frisian	$2.1105 \pm 1.7137$	$31.6068 \pm 21.6522$	$0.7693 \pm 0.4303$ $0.5954 \pm 0.4230$	$4.5661 \pm 5.0261$	$0.3468 \pm 0.4133$ $0.3772 \pm 0.3800$	$0.0220 \pm 0.0039$ $0.0206 \pm 0.0078$	$0.0023 \pm 0.1983$ $0.0002 \pm 0.1850$	$0.0048 \pm 0.1813$ $0.0003 \pm 0.1522$	-0.0086 ± 0.1887
Galician	$3.3084 \pm 1.8283$	41.5002 ± 20.6445	$0.8464 \pm 0.4474$	$7.3423 \pm 5.6460$	$0.6065 \pm 0.4407$	$0.0224 \pm 0.0050$	$-0.0054 \pm 0.2207$	$0.0001 \pm 0.1738$	$-0.0119 \pm 0.1991$
Georgian	$3.1359 \pm 1.9296$	$41.5282 \pm 21.2911$	$0.8393 \pm 0.4507$	$6.9871 \pm 5.8524$	$0.5619 \pm 0.4255$	$0.0224 \pm 0.0052$	$-0.0041 \pm 0.2067$	$0.0068 \pm 0.1653$	$-0.0051 \pm 0.1654$
German	$3.0523 \pm 1.8728$	38.8812 ± 21.1129	$0.7681 \pm 0.4358$	$6.8274 \pm 5.7338$	$0.5270 \pm 0.4218$	$0.0222 \pm 0.0056$	$-0.0095 \pm 0.2294$	$0.0009 \pm 0.1652$	$-0.0149 \pm 0.1882$
Greek	$3.0388 \pm 1.8310$	$38.5410 \pm 21.5254$	$0.7858 \pm 0.4563$	$6.6580 \pm 5.5103$	$0.5591 \pm 0.4279$	$0.0220 \pm 0.0059$	$-0.0043 \pm 0.2288$	$0.0015 \pm 0.1600$	$-0.0057 \pm 0.1789$
Gujarati	$3.5816 \pm 2.0118$	$45.9618 \pm 21.6391$	$0.9498 \pm 0.4864$	$8.7021 \pm 6.3993$	$0.5882 \pm 0.4797$	$0.0228 \pm 0.0043$	$-0.0182 \pm 0.2498$	$0.0122 \pm 0.1941$	$0.0070 \pm 0.1845$
Haitian Creole	$2.4935 \pm 1.7943$	$35.1527 \pm 22.1554$	$0.6506 \pm 0.4146$	$5.4482 \pm 5.2776$	$0.4396 \pm 0.3751$	$0.0213 \pm 0.0070$	$-0.0002 \pm 0.2061$	$0.0054 \pm 0.1587$	$-0.0066 \pm 0.1645$
Hausa	$3.0370 \pm 1.9173$	$38.3269 \pm 21.4406$	$0.7694 \pm 0.4485$	$6.6423 \pm 5.5684$	$0.5737 \pm 0.4244$	$0.0230 \pm 0.0335$	$-0.0156 \pm 0.246$	$-0.0056 \pm 0.1898$	$0.0089 \pm 0.2029$
Hawaiian	$4.3917 \pm 2.0020$	$49.2824 \pm 21.7270$	$1.0079 \pm 0.4585$	$10.3520 \pm 6.5060$	$0.8243 \pm 0.4839$	$0.0228 \pm 0.0042$	$-0.0236 \pm 0.327$	$-0.0188 \pm 0.2746$	$0.0261 \pm 0.2902$
Hebrew	$3.3267 \pm 1.8875$	$43.2773 \pm 19.9098$	$0.8887 \pm 0.4219$	$7.5287 \pm 5.7295$	$0.6314 \pm 0.4726$	$0.0229 \pm 0.0038$	$-0.0112 \pm 0.2348$	$0.0037 \pm 0.1807$	$-0.0178 \pm 0.1888$
Hindi	$3.7218 \pm 1.8764$	47.2855 ± 20.9455	$0.9400 \pm 0.4265$	$8.8569 \pm 5.9814$	$0.6278 \pm 0.4590$	$0.0230 \pm 0.0038$	$-0.0065 \pm 0.2332$	$0.0050 \pm 0.1950$	$-0.0081 \pm 0.2007$
Hmong	$3.0967 \pm 1.8916$	39.2700 ± 21.5981	$0.7575 \pm 0.4370$	$6.9259 \pm 5.7573$	$0.5994 \pm 0.5008$	$0.0250 \pm 0.0547$	$0.0145 \pm 0.2360$	$0.0095 \pm 0.2231$	$0.0166 \pm 0.2259$
Hungarian	$3.5887 \pm 1.9075$	$44.1854 \pm 21.7258$	$0.9007 \pm 0.4560$	$8.0363 \pm 5.7908$	$0.6660 \pm 0.4395$	$0.0225 \pm 0.0048$	$-0.0005 \pm 0.2233$	$-0.0004 \pm 0.1775$	$-0.0155 \pm 0.1822$
Icelandic	$2.6405 \pm 1.8053$	36.4142 ± 20.9481	$0.7191 \pm 0.4278$	$5.5187 \pm 5.0761$	$0.4915 \pm 0.4133$	$0.0217 \pm 0.0064$	$-0.0015 \pm 0.2054$	$-0.0001 \pm 0.1387$	$-0.009 \pm 0.1561$
Igbo	$3.4281 \pm 1.9496$	$41.2788 \pm 21.5776$	$0.8291 \pm 0.4534$	$7.7875 \pm 6.0819$	$0.6407 \pm 0.4314$	$0.0221 \pm 0.0057$	$-0.0035 \pm 0.2895$	$0.0121 \pm 0.2010$	$0.0225 \pm 0.2272$
Indonesian	2.9717 ± 1.8386	$37.5045 \pm 21.2866$	$0.7086 \pm 0.4175$	$6.3412 \pm 5.3137$	$0.5467 \pm 0.4315$	$0.0230 \pm 0.0337$	$-0.0028 \pm 0.2055$	$-0.008 \pm 0.1777$	-0.016 ± 0.1931
Irish	2.6636 ± 1.7391	36.4281 ± 21.8509	$0.6890 \pm 0.4175$	$6.2791 \pm 5.7358$	$0.4246 \pm 0.3723$	$0.0216 \pm 0.0065$	$-0.0106 \pm 0.2102$	$-0.0032 \pm 0.1465$	$-0.0043 \pm 0.1464$
Italian	$2.8866 \pm 1.8009$	$36.8250 \pm 20.3264$	$0.7365 \pm 0.4360$	$6.3374 \pm 5.4678$	$0.5332 \pm 0.4516$	$0.0217 \pm 0.0063$	$0.0077 \pm 0.1950$	$-0.0042 \pm 0.1596$	-0.0183 ± 0.1867
Japanese	4.4044 ± 1.8878	49.7830 ± 20.5813	$1.1171 \pm 0.4531$	10.8755 ± 6.2951	$0.7712 \pm 0.4370$	$0.0231 \pm 0.0032$	$-0.0326 \pm 0.2575$	$-0.0104 \pm 0.2126$	$-0.0229 \pm 0.2095$
Javanese	3.1578 ± 1.9123	$39.1957 \pm 21.9393$	$0.7776 \pm 0.4673$	$7.2494 \pm 5.9900$	$0.5517 \pm 0.3895$	$0.0218 \pm 0.0062$	$-0.0103 \pm 0.2398$	$-0.0003 \pm 0.1801$	-0.0018 ± 0.1809
Kannada	3.9152 ± 1.8317	$48.7288 \pm 20.9314$	$1.0231 \pm 0.4551$	$9.9590 \pm 6.5459$	$0.6442 \pm 0.4502$	$0.0229 \pm 0.0038$	-0.0108 ± 0.2474	$0.0119 \pm 0.1797$	-0.0068 ± 0.2071
Kazakh	$4.1914 \pm 1.8486$	50.2691 ± 21.5751	$1.06251 \pm 0.4802$	$10.6689 \pm 6.6364$	$0.7273 \pm 0.4659$	$0.0240 \pm 0.0328$	$-0.0043 \pm 0.2616$	$-0.0049 \pm 0.225$	$-0.0009 \pm 0.2508$
Khmer	$3.6325 \pm 1.8034$	45.7669 ± 19.8676	$0.9482 \pm 0.4302$	8.4474 ± 5.9054	$0.6743 \pm 0.4798$	$0.0240 \pm 0.0328$ $0.0238 \pm 0.0246$	$0.0079 \pm 0.2355$	$0.0110 \pm 0.2183$	$0.0149 \pm 0.2218$
Kinyarwanda	$3.9645 \pm 2.0135$	45.1762 ± 21.7999	$0.9595 \pm 0.4812$	$9.2847 \pm 6.4706$	$0.7150 \pm 0.4545$	$0.0238 \pm 0.0240$ $0.0228 \pm 0.0044$	$0.0079 \pm 0.2558$ $0.0015 \pm 0.2558$	$-0.0035 \pm 0.2228$	$-0.0076 \pm 0.2604$
Kinyai wanda	$4.3485 \pm 1.8834$	$52.2174 \pm 21.6723$	$0.9393 \pm 0.4812$ $1.1133 \pm 0.4722$	$11.1366 \pm 6.4485$	$0.7793 \pm 0.4660$	$0.0228 \pm 0.0044$ $0.0231 \pm 0.0032$	$-0.0074 \pm 0.2906$	$0.0080 \pm 0.2228$	$0.0022 \pm 0.2383$
Kurdish	$3.5824 \pm 2.0262$	$42.2055 \pm 21.8016$	$0.8620 \pm 0.4643$	8.3174 ± 6.1876	$0.6097 \pm 0.4069$	$0.0231 \pm 0.0032$ $0.0222 \pm 0.0055$	$-0.0074 \pm 0.2565$	$-0.0080 \pm 0.2292$ $-0.0043 \pm 0.1914$	$-0.0022 \pm 0.2383$ $-0.002 \pm 0.2121$
Kyrgyz	4.7914 ± 1.9145	$52.7561 \pm 21.0698$	$1.1718 \pm 0.4801$	$11.6158 \pm 6.4069$	$0.9349 \pm 0.5172$	$0.0236 \pm 0.0158$	$-0.0031 \pm 0.3103$	$0.0116 \pm 0.2699$	$0.0123 \pm 0.2555$
Lao	$3.3175 \pm 1.9198$	$43.6135 \pm 21.6109$	$0.8391 \pm 0.4251$	$7.4923 \pm 5.9334$	$0.5750 \pm 0.4177$	$0.0225 \pm 0.0049$	$0.0022 \pm 0.2218$	$-0.003 \pm 0.1703$	$-0.0022 \pm 0.2022$
Latin	$4.9107 \pm 2.0689$	52.5410 ± 21.2892	$1.2010 \pm 0.5471$	$12.0613 \pm 6.6757$	$0.8898 \pm 0.5298$	$0.0233 \pm 0.0126$	-0.0033 ± 0.3289	$0.0191 \pm 0.2477$	-0.0006 ± 0.2383
Latvian	$2.6936 \pm 1.7852$	$37.3776 \pm 21.3996$	$0.7204 \pm 0.4138$	$5.6136 \pm 5.0254$	$0.5063 \pm 0.4181$	$0.0228 \pm 0.0334$	$-0.0049 \pm 0.1962$	$0.0063 \pm 0.1574$	$-0.0083 \pm 0.1664$

TABLE III: Language Metrics Mean and Standard Deviation

Language	BERT	xlnet	bart	gpt	glove	Doc2Vec	VADER	Polarity	Subjectivity
	3.1533 ± 1.8887	40.9943 ± 20.4055	$0.8371 \pm 0.4415$	6.9824 ± 5.6158	$0.5906 \pm 0.4520$	$0.0225 \pm 0.0050$	-0.0073 ± 0.2184	$0.0005 \pm 0.1962$	$0.0016 \pm 0.2072$
Lithuanian									
Luxembourgish	$3.3228 \pm 2.0873$	41.8774 ± 22.4604	$0.8264 \pm 0.4693$	$7.8428 \pm 6.5077$	$0.5650 \pm 0.4214$ $0.5389 \pm 0.4325$	$0.0220 \pm 0.0058$	$-0.0239 \pm 0.2423$	$-0.0054 \pm 0.1864$	-0.016 ± 0.203
Macedonian	$2.9089 \pm 1.8076$	$38.2254 \pm 20.8129$	$0.7846 \pm 0.4521$	6.2868 ± 5.4331		$0.0220 \pm 0.0058$	$0.0033 \pm 0.2172$	$0.0142 \pm 0.1611$	-0.0083 ± 0.1569
Malagasy	$3.8505 \pm 1.9621$	46.8842 ± 21.4363	$0.9550 \pm 0.4609$	$8.5786 \pm 5.8147$	$0.7328 \pm 0.4480$	$0.0227 \pm 0.0045$	$-0.0096 \pm 0.2748$	$-0.0048 \pm 0.2342$	$0.0020 \pm 0.2364$
Malay	$2.9645 \pm 1.7530$	$37.6486 \pm 21.2125$	$0.7135 \pm 0.4255$	$6.6351 \pm 5.4766$	$0.5458 \pm 0.4164$	$0.0221 \pm 0.0057$	$0.0003 \pm 0.2124$	$-0.0042 \pm 0.1736$	$-0.0039 \pm 0.1938$
Malayalam	$4.8056 \pm 1.7677$	$54.7046 \pm 21.2162$	$1.2327 \pm 0.4586$	$12.2058 \pm 6.3209$	$0.7960 \pm 0.4608$	$0.0233 \pm 0.0022$	$-0.0161 \pm 0.3098$	$-0.004 \pm 0.2204$	$0.0007 \pm 0.2301$
Maltese	$2.4760 \pm 1.8293$	$33.9896 \pm 22.4921$	$0.6439 \pm 0.4210$	$5.6176 \pm 5.4907$	$0.3895 \pm 0.3353$	$0.0210 \pm 0.0074$	$0.0067 \pm 0.1889$	$0.0027 \pm 0.1226$	$-0.0123 \pm 0.1361$
Maori	$3.8948 \pm 1.9485$	$45.9441 \pm 21.5976$	$0.9146 \pm 0.4648$	$9.1761 \pm 6.4592$	$0.6779 \pm 0.4333$	$0.0234 \pm 0.0228$	$-0.0074 \pm 0.2998$	$-0.0098 \pm 0.2442$	$0.0027 \pm 0.2453$
Marathi	$4.1627 \pm 1.8884$	$50.2687 \pm 21.2404$	$1.0691 \pm 0.4794$	$10.6952 \pm 6.7298$	$0.7018 \pm 0.4285$	$0.0230 \pm 0.0035$	$0.0032 \pm 0.2582$	$0.0026 \pm 0.2057$	$-0.0073 \pm 0.227$
Mongolian	$4.2479 \pm 1.9028$	$50.4806 \pm 21.6242$	$1.0513 \pm 0.4389$	$10.5640 \pm 6.3119$	$0.7400 \pm 0.4417$	$0.0229 \pm 0.0040$	$-0.0091 \pm 0.2827$	$-0.0008 \pm 0.2194$	$-0.0101 \pm 0.2155$
Myanmar	$4.7016 \pm 2.1506$	$51.2371 \pm 21.4917$	$1.2359 \pm 0.5540$	$11.9276 \pm 6.6944$	$0.9865 \pm 0.7875$	$0.0229 \pm 0.0040$	$-0.0165 \pm 0.2696$	$0.0067 \pm 0.2006$	$-0.0082 \pm 0.2115$
Nepali	$4.0612 \pm 1.8466$	49.6141 ± 21.5517	$1.0406 \pm 0.4593$	$10.4111 \pm 6.5645$	$0.6683 \pm 0.4215$	$0.0230 \pm 0.0036$	$-0.0231 \pm 0.2732$	$-0.0133 \pm 0.1988$	$-0.0076 \pm 0.206$
Norwegian	$2.2990 \pm 1.7932$	$31.6301 \pm 20.7609$	$0.6194 \pm 0.4124$	$4.5235 \pm 4.5455$	$0.4440 \pm 0.4034$	$0.0209 \pm 0.0074$	$-0.0033 \pm 0.1962$	$0.0058 \pm 0.1506$	$-0.0113 \pm 0.1498$
Nyanja	$3.8558 \pm 1.9052$	$45.4260 \pm 20.7191$	$0.9354 \pm 0.4475$	$9.0426 \pm 6.2212$	$0.7501 \pm 0.4549$	$0.0227 \pm 0.0044$	$-0.0119 \pm 0.2524$	$-0.0116 \pm 0.2206$	$0.0104 \pm 0.2311$
Odia	$4.0704 \pm 1.9244$	49.8328 ± 22.4855	$1.0118 \pm 0.4827$	$10.1309 \pm 6.6468$	$0.6151 \pm 0.3989$	$0.0229 \pm 0.0040$	$-0.0105 \pm 0.2847$	$0.0001 \pm 0.2172$	$-0.0246 \pm 0.2345$
Pashto	$4.6559 \pm 1.9994$	51.1143 ± 21.3486	$1.0847 \pm 0.4492$	$10.2268 \pm 6.4966$	$0.7500 \pm 0.4439$	$0.0231 \pm 0.0033$	$0.0089 \pm 0.2680$	$-0.0038 \pm 0.2037$	$-0.0081 \pm 0.2333$
Persian	$4.4312 \pm 1.9276$	$49.8650 \pm 20.9929$	$1.0657 \pm 0.4699$	$9.3400 \pm 5.9010$	$0.7933 \pm 0.5017$	$0.0232 \pm 0.0030$	$-0.0071 \pm 0.2667$	$0.0109 \pm 0.2062$	$-0.0065 \pm 0.2187$
Polish	$3.3162 \pm 1.8666$	42.0087 ± 20.5787	$0.8431 \pm 0.4436$	$7.3200 \pm 5.5842$	$0.6051 \pm 0.4539$	$0.0225 \pm 0.0049$	$0.0076 \pm 0.2281$	$0.0006 \pm 0.1747$	$-0.0077 \pm 0.1833$
Portuguese	$2.8800 \pm 1.8530$	37.1307 ± 20.6883	$0.7394 \pm 0.4346$	$6.2778 \pm 5.4059$	$0.5168 \pm 0.4336$	$0.0219 \pm 0.0060$	$-0.003 \pm 0.1948$	$0.0036 \pm 0.1565$	$-0.0101 \pm 0.1773$
Punjabi	$3.6739 \pm 1.9488$	46.4990 ± 21.4981	$0.9605 \pm 0.4559$	$8.9806 \pm 6.4451$	$0.6107 \pm 0.4314$	$0.0230 \pm 0.0038$	$-0.0054 \pm 0.2478$	$0.0076 \pm 0.1807$	$-0.0086 \pm 0.1828$
Romanian	3.1778 ± 1.8677	$40.9882 \pm 21.9662$	$0.8431 \pm 0.4585$	$6.9520 \pm 5.5552$	$0.5621 \pm 0.4292$	$0.0223 \pm 0.0054$	$-0.0044 \pm 0.2284$	$0.0015 \pm 0.1592$	-0.0068 ± 0.1805
Russian	$3.3236 \pm 1.8926$	41.1866 ± 19.9059	$0.8444 \pm 0.4155$	$7.1935 \pm 5.3579$	$0.6554 \pm 0.4803$	$0.0225 \pm 0.0051$	-0.0062 ± 0.214	$0.0073 \pm 0.1843$	-0.0057 ± 0.2009
Samoan	$3.8749 \pm 1.9240$	44.4024 ± 20.8871	$0.9006 \pm 0.4179$	$8.9794 \pm 6.2978$	$0.7198 \pm 0.4375$	$0.0225 \pm 0.0031$ $0.0225 \pm 0.0049$	$-0.0118 \pm 0.2908$	$-0.0256 \pm 0.2834$	$-0.002 \pm 0.2353$
Scots Gaelic	$3.0683 \pm 1.8886$	$40.3800 \pm 21.6171$	$0.8097 \pm 0.4434$	$6.9198 \pm 5.7215$	$0.5381 \pm 0.3810$	$0.0220 \pm 0.0059$	$-0.0002 \pm 0.229$	$-0.0067 \pm 0.1535$	-0.0015 ± 0.178
Serbian	3.6279 ± 1.7905	45.0025 ± 20.4254	$0.9349 \pm 0.4339$	8.3136 ± 5.4780	$0.7145 \pm 0.5159$	$0.0232 \pm 0.0031$	$0.0112 \pm 0.2407$	$0.0235 \pm 0.1883$	-0.0098 ± 0.1977
Sesotho	$3.9322 \pm 1.9724$	45.9501 ± 21.0958	$0.9544 \pm 0.4555$	8.9511 ± 5.9904	$0.7115 \pm 0.4515$	$0.0227 \pm 0.0045$	0 ± 0.2624	-0.0071 ± 0.2077	$-0.0055 \pm 0.2282$
Shona	$3.8570 \pm 1.8870$	$46.3480 \pm 21.6009$	$0.9344 \pm 0.4393$ $0.9486 \pm 0.4390$	8.8672 ± 5.9634	$0.7478 \pm 0.4487$	$0.0227 \pm 0.0045$ $0.0227 \pm 0.0045$	$-0.0012 \pm 0.2807$	$-0.0069 \pm 0.2265$	$0.0103 \pm 0.2232$ $0.0103 \pm 0.2553$
Sindhi	$4.8234 \pm 1.9959$	$51.6873 \pm 21.0672$	$1.1107 \pm 0.4948$	$10.9663 \pm 6.5925$	$0.7565 \pm 0.4359$	$0.0227 \pm 0.0043$ $0.0232 \pm 0.0029$	$-0.0012 \pm 0.2885$	$-0.0039 \pm 0.2203$ $-0.0034 \pm 0.1985$	$0.0103 \pm 0.2333$ $0.0059 \pm 0.2285$
Sinhala	$4.4288 \pm 1.8908$	$51.9869 \pm 21.3391$	$1.0986 \pm 0.4804$	$11.4927 \pm 6.7297$	$0.7300 \pm 0.4338$ $0.7300 \pm 0.4338$	$0.0232 \pm 0.0029$ $0.0230 \pm 0.0037$	$-0.0118 \pm 0.2883$ $-0.0128 \pm 0.2897$	$-0.0004 \pm 0.1239$	$0.0039 \pm 0.2283$ $0.0072 \pm 0.2366$
Slovak	3.2220 ± 1.8268	$41.3408 \pm 20.6178$	$0.8377 \pm 0.4268$	$7.0250 \pm 5.5250$	$0.6229 \pm 0.4468$	$0.0230 \pm 0.0037$ $0.0224 \pm 0.0051$	$0.0038 \pm 0.2269$	$-0.0004 \pm 0.2239$ $-0.0009 \pm 0.1864$	$-0.0072 \pm 0.2300$ $-0.0081 \pm 0.1917$
Slovenian	$3.2220 \pm 1.8208$ $3.2271 \pm 1.8310$	$40.4570 \pm 20.0673$	$0.8125 \pm 0.4246$	$6.8675 \pm 5.2968$	$0.6132 \pm 0.4481$	$0.0224 \pm 0.0031$ $0.0226 \pm 0.0046$	-0.0038 ± 0.2269	$-0.0009 \pm 0.1804$ $-0.0045 \pm 0.1705$	-0.0081 ± 0.1917 -0.0178 ± 0.1876
Somali	$3.6107 \pm 1.9481$	$42.9309 \pm 21.9753$	$0.8125 \pm 0.4240$ $0.8895 \pm 0.4700$	$8.5719 \pm 6.2760$	$0.6382 \pm 0.4526$	$0.0220 \pm 0.0040$ $0.0222 \pm 0.0056$	$-0.0205 \pm 0.2593$	-0.0043 ± 0.1703	-0.0178 ± 0.1876
Spanish	$3.3843 \pm 1.8808$	$42.9309 \pm 21.9733$ $40.6751 \pm 19.7936$	$0.8406 \pm 0.4395$	$7.4043 \pm 5.5196$	$0.6218 \pm 0.4724$	$0.0222 \pm 0.0030$ $0.0225 \pm 0.0050$	$0.0054 \pm 0.2251$	$-0.0014 \pm 0.1873$ $-0.0023 \pm 0.1972$	$-0.0087 \pm 0.1973$ $-0.0208 \pm 0.2025$
					$0.6218 \pm 0.4724$ $0.4759 \pm 0.3581$				
Sundanese	$2.9151 \pm 1.8701$	$38.0154 \pm 21.1152$	$0.7447 \pm 0.4526$	$6.7278 \pm 5.8818$		$0.0217 \pm 0.0063$	$0.0014 \pm 0.2095$	$0.0040 \pm 0.1690$	$-0.0127 \pm 0.199$
Swahili	$2.8426 \pm 1.8273$	36.7274 ± 21.6291	$0.6900 \pm 0.4117$	$6.2376 \pm 5.5779$	$0.5004 \pm 0.3981$	$0.0217 \pm 0.0064$	$0.0005 \pm 0.2129$	$0.0071 \pm 0.1719$	$0.0000 \pm 0.1767$
Swedish	$2.4565 \pm 1.7945$	34.4340 ± 21.1383	$0.6789 \pm 0.4336$	5.2523 ± 5.0355	$0.4806 \pm 0.4066$	$0.0225 \pm 0.0311$	$-0.0136 \pm 0.2135$	$0.0005 \pm 0.1513$	-0.0001 ± 0.1455
Tagalog	$2.3192 \pm 1.7408$	$31.9010 \pm 21.4409$	$0.5976 \pm 0.4236$	$5.0015 \pm 4.9439$	$0.4048 \pm 0.3955$	$0.0207 \pm 0.0077$	-0.0007 ± 0.172	$-0.0025 \pm 0.1454$	-0.0115 ± 0.1486
Tajik	$3.6327 \pm 1.8610$	$44.0494 \pm 20.7996$	$0.9278 \pm 0.4599$	$8.6401 \pm 6.3315$	$0.6218 \pm 0.4344$	$0.0244 \pm 0.0400$	$0.0136 \pm 0.2585$	$0.0178 \pm 0.2109$	$0.0062 \pm 0.2101$
Tamil	$4.0502 \pm 2.0863$	$49.8349 \pm 21.9587$	$1.0498 \pm 0.5492$	$10.1832 \pm 6.6707$	$0.6747 \pm 0.5646$	$0.0229 \pm 0.0040$	$-0.0168 \pm 0.2599$	$-0.0021 \pm 0.1816$	-0.0029 ± 0.1866
Tatar	$5.2999 \pm 1.8633$	$55.9961 \pm 21.5646$	$1.3090 \pm 0.5083$	$13.9721 \pm 6.4386$	$0.8622 \pm 0.4289$	$0.0232 \pm 0.0030$	$-0.0388 \pm 0.3227$	$-0.0181 \pm 0.2454$	$-0.027 \pm 0.2726$
Telugu	$3.7709 \pm 1.8097$	$47.7764 \pm 21.5175$	$0.9947 \pm 0.4750$	$9.6866 \pm 6.7028$	$0.5838 \pm 0.3905$	$0.0229 \pm 0.0040$	$-0.0151 \pm 0.2313$	$0.0024 \pm 0.1797$	$-0.0041 \pm 0.1871$
Thai	$4.2052 \pm 1.9011$	$52.3345 \pm 22.5921$	$1.1586 \pm 0.4787$	$11.6755 \pm 6.6255$	$0.7069 \pm 0.4669$	$0.0231 \pm 0.0032$	$-0.0014 \pm 0.2581$	$0.0023 \pm 0.2101$	$0.0036 \pm 0.2037$
Turkish	$4.2634 \pm 1.8235$	$50.1228 \pm 21.2174$	$1.0676 \pm 0.4914$	$10.8648 \pm 6.4401$	$0.7234 \pm 0.4525$	$0.0230 \pm 0.0038$	$-0.0038 \pm 0.2788$	$0.0021 \pm 0.2076$	$-0.0241 \pm 0.2286$
Turkmen	$4.6553 \pm 1.8657$	$52.6054 \pm 22.3110$	$1.0889 \pm 0.4439$	$11.8237 \pm 6.7022$	$0.8106 \pm 0.4712$	$0.0231 \pm 0.0034$	$-0.0115 \pm 0.2965$	$0.0030 \pm 0.2239$	$-0.0224 \pm 0.2394$
Ukrainian	$3.5216 \pm 1.9053$	$42.8676 \pm 20.1638$	$0.8892 \pm 0.4196$	$7.7542 \pm 5.6084$	$0.6736 \pm 0.4630$	$0.0226 \pm 0.0047$	$0.0040 \pm 0.2281$	$0.0050 \pm 0.1930$	$0.0020 \pm 0.2158$
Urdu	$4.6288 \pm 1.8598$	$51.8213 \pm 21.1784$	$1.1069 \pm 0.4547$	$10.3984 \pm 6.1689$	$0.7847 \pm 0.4910$	$0.0233 \pm 0.0027$	$-0.0079 \pm 0.2553$	$0.0049 \pm 0.2023$	$-0.0079 \pm 0.2119$
Uyghur	$4.4782 \pm 2.1602$	$50.8991 \pm 21.7484$	$1.1623 \pm 0.5640$	$11.4469 \pm 6.9056$	$0.7948 \pm 0.6075$	$0.0229 \pm 0.0039$	$-0.0251 \pm 0.2666$	$-0.0173 \pm 0.2182$	$0.0017 \pm 0.2251$
Uzbek	$4.4620 \pm 1.8179$	$51.5030 \pm 21.9078$	$1.1060 \pm 0.4634$	$11.0946 \pm 6.6179$	$0.8107 \pm 0.4898$	$0.0231 \pm 0.0034$	$-0.001 \pm 0.284$	$-0.0021 \pm 0.222$	$-0.0121 \pm 0.253$
Vietnamese	3.0241 ± 1.8411	$38.3290 \pm 20.3990$	$0.7485 \pm 0.4310$	$6.8053 \pm 5.7475$	$0.5340 \pm 0.4371$	$0.0221 \pm 0.0056$	$-0.0001 \pm 0.196$	$-0.0021 \pm 0.18$	-0.0063 ± 0.2022
Welsh	$2.8045 \pm 1.8026$	$36.3720 \pm 20.9603$	$0.7044 \pm 0.4320$	$6.6622 \pm 5.8721$	$0.4618 \pm 0.3712$	$0.0218 \pm 0.0063$	$0.0021 \pm 0.2133$	$0.0083 \pm 0.1573$	$-0.0056 \pm 0.171$
Xhosa	$4.1014 \pm 1.9087$	48.1886 ± 21.5661	$0.9588 \pm 0.4316$	$9.3353 \pm 5.9511$	$0.7828 \pm 0.5315$	$0.0235 \pm 0.0238$	$-0.0245 \pm 0.2816$	$-0.0022 \pm 0.2329$	$-0.0001 \pm 0.2472$
Yiddish	$2.1669 \pm 1.6737$	37.7814 ± 19.9013	$0.7111 \pm 0.3881$	$4.8267 \pm 4.6606$	$0.3952 \pm 0.4116$	$0.0222 \pm 0.0055$	-0.0121 ± 0.1721	$0.0025 \pm 0.1317$	-0.0069 ± 0.1388
Yoruba	2.7452 ± 1.9641	34.5736 ± 21.7557	$0.6621 \pm 0.4389$	$6.0572 \pm 5.6836$	$0.5101 \pm 0.4320$	$0.0211 \pm 0.0072$	$-0.0102 \pm 0.2006$	$0.0027 \pm 0.1647$	$0.0033 \pm 0.1639$
Zulu	3.0442 ± 1.9465	38.9466 ± 21.0533	$0.7747 \pm 0.4438$	$6.7784 \pm 5.7828$	$0.5749 \pm 0.4456$	$0.0220 \pm 0.0059$	-0.0023 ± 0.2255	$0.0024 \pm 0.1712$	$0.0030 \pm 0.1826$