THE GEOMETRY OF MULTILINGUAL LANGUAGE MODELS: A FAIRNESS LENS

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ABSTRACT

Understanding the representations of different languages in multilingual language models is essential for comprehending their cross-lingual properties, predicting their performance on downstream tasks, and identifying any biases across languages. In our study, we analyze the geometry of three multilingual language models in Euclidean space and find that all languages are represented by unique geometries. Although languages tend to be closer according to their linguistic family, they are almost separable with languages from other families. We also introduce a Cross-Lingual Similarity Index to study the semantic similarity across languages. Our findings indicate that the representation of low-resource languages is significantly low compared to high-resource languages.

1 METHODOLOGY

We use the XNLI-15way dataset Conneau et al. (2018) and sample 300 parallel sentences from the 15 languages for our analysis. We use common multilingual transformers, mBERT Devlin et al. (2019), MiniLM Wang et al. (2020), and XLM-R Conneau et al. (2020). More details about the model and dataset are available in Appendix A. We study the geometric properties of multilingual models using three methods:

1) We visualise the embedding space of a group of languages by taking the 3 top PCA components.

2) **Cross-lingual Similarity Index Γ:** There have been many approaches to compute cross-lingual similarity such as Liu et al. (2020), however due to the extremely high anisotropy(average cosine similarity of any two randomly sampled words in the dataset) Ethayarajh (2019) of models like XLMR, it is difficult to make conclusions using cosine similarity. Thus we introduce a metric to quantify cross-lingual similarity. For a pair of languages, $l1, l2$, we take embeddings $s_{l1,i}, s_{l2,i \forall i \in [0,300]}$ using model $\mathcal{M}_l$ and calculate the Cross-lingual Similarity Index as follows:

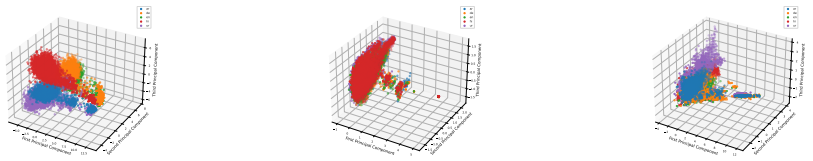
$$\Gamma_{l1,l2} = \frac{\frac{1}{n}\sum_{i=1}^{n} cosine(s_{l1,i}, s_{l2,i})}{Anisotropy(\mathcal{M}_l)} \tag{1}$$

For a model $\mathcal{M}_l$, Γ ranges from $-1/Anisotropy(M_l)$ to $1/Anisotropy(M_l)$. Low model anisotropy and high average cosine similarity is ideal, therefore higher Γ is ideal. Positive and negative values of Γ correspond to average directional orientation between embeddings. $|\Gamma| \leq 1/Anisotropy(M_l)$ would mean that the average similarity is less than the similarity for random words.

3) **Language Separability Φ:** We study the separation of different languages in embedding space by treating all the points belonging to a language as a single cluster and calculating the pairwise Geometric Separability Index Thornton (2008) between two languages.

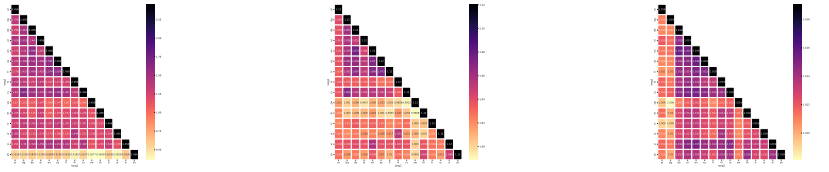
2 RESULTS

PCA Analysis: Figure 1 depicts the plots of one group (Hindi, Urdu, German, English, Arabic) for each model, while the remaining plots are available in the AppendixA.4. mBERT's word vectors demonstrate significant isolation, with the languages occupying different orientations in space. Conversely, MiniLM and XLMR's word embeddings appear less spread out, owing to their high



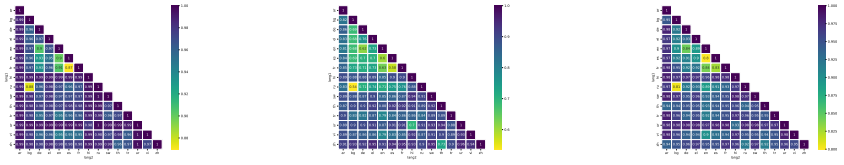
(a) mBert (b) MiniLM (c) XLMR

Figure 1: Visualisation of PCA plots



(a) mBert (b) MiniLM (c) XLMR

Figure 2: Cross-lingual Similariy Γ



(a) mBert (b) MiniLM (c) XLMR

Figure 3: Language Separability Φ

anisotropy, but the languages still occupy different affines relative to one another. It is interesting to note that in XLMR, low-resource languages such as Urdu and Swahili are significantly more dispersed than high-resource languages.

Cross-lingual Similarity: Since the sentences are perfect translations of each other and the model embeds different languages in a shared region of the embedding space, the Γ for all the language pairs should be close to $1/Anisotropy$, however, this is not the case. We observe that the Language Model starts by representing a language in relative isolation, and the more text it sees, the more it contextualizes that language in terms of the other languages, leading to better Γ for high-resource languages and languages from same families. The pre-training procedure of models also makes a difference in the language representations, for example, Γ for Chinese is significantly low for mBERT which might be because Chinese is a purely ideographic language. In contrast, English has high Γ on XLMR, possibly because of the cross-lingual pretraining procedure.

Geometric Separability A good multilingual model should avoid clustering embeddings of specific languages and ensure equal assimilation of different language embeddings in the vector space, however this is not observed. The intra-family Φ is relatively low for all linguistic families. In the case of mBERT and XLMR, Φ of language clusters is extremely high, indicating that the languages form near-isolated vector spaces. In the case of MiniLM, the Φ for Germanic, Romantic, Slavic and Hellenic families is low, indicating that the word vectors of these languages are assimilated, however, this trend is not observed in the case of other families.

3 Conclusion and Future Work

We believe that our findings are crucial for developing more inclusive and accurate multilingual language models. The contextuality, topology and hyperbolic geometry of multilingual embeddings can be explored in the future. Analysing the changes in geometry when a model is finetuned on a certain task is also an interesting avenue for research.

URM STATEMENT

"The authors acknowledge that at least one key author of this work meets the URM criteria of ICLR 2023 Tiny Papers Track."

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A APPENDIX

A.1 DATASET DETAILS

The XNLI-15 dataset has 112,500 parallel sentences in 15 languages: English (en), French (fr), Spanish (es), German (de), Greek (el), Bulgarian (bg), Russian (ru), Turkish (tr), Arabic (ar), Vietnamese (vi), Thai (th), Chinese (zh), Hindi (hi), Swahili (sw) and Urdu (ur). We sample the first 300 sentences from each dataset and perform our analysis on a vocabulary of 45889 words.

A.2 MODEL DETAILS

The various transformer based pre-trained models used in our system are as follows:

- **mBERT:** mBERT refers to multilingual BERT trained on 104 languages on the Wikipedia corpus. It is pretrained in a self-supervised fashion, with two pre-training objectives: 1)

Masked Language Modelling (MLM) where 15% of the words of a sentence are randomly masked, and the model predicts the masked words. 2) Next Sentence Prediction (NSP): Given a pair of sentences, the model has to predict whether one sentence succeeds the other. We use the 'bert-base-multilingual-cased' implementation of mBERT [1].

- **XLM-RoBERTa:** XLM-RoBERTa is a multilingual version of RoBERTa, pre-trained on 2.5TB of filtered CommonCrawl data in 100 languages. RoBERTa builds on BERT's architecture but uses more data and modifies key hyperparameters such as larger mini-batches and learning rates. It doesn't pretrain on the NSP task. We use the 'xlm-roberta-base' implementation of the XLMR model from HuggingFace. [2].
- **MiniLM:** MiniLM generalises distillation of deep self-attention by using by using self-attention relation distillation for task-agnostic compression of pre-trained Transformers. This eliminates the restriction on the number of attention heads in the student model. The model we use is distilled from XLM RoBERTa base. MiniLM has a significant speed-up compared to it's teacher models and gives a competitive performance. We use the 'Multilingual-MiniLM-L12-H384' implementation of the MiniLM model as found on HuggingFace [3]

A.3 Linguistic Families

Table 1: Languages and their Linguistic Families

Language	Family	Code
English	Germanic	en
German	Germanic	de
Hindi	Hindustani	hi
Urdu	Hindustani	ur
Arabic	Arabic	ar
Spanish	Romance	es
French	Romance	fr
Russian	Slavic	ru
Bulgarian	Slavic	bg
Swahili	Niger-Congo	sw
Thai	Tai	th
Vietnamese	Vietic	vi
Chinese	Chinese	zh
Greek	Hellenic	el
Turkic	Turkic	tr

A.4 Metrics

Anisotropy: Anisotropy of a model is defined as the cosine similarity of any two word embeddings selected on random. For a set of languages $\mathcal{L}$, with n sentences in each language and a model $\mathcal{M}_l$, the anisotropy can be found by taking the average of the cosine similarity of all possible sentence pairs from $|\mathcal{L}| * n$ sentences. The absolute value is taken.

$$Anisotropy(\mathcal{M}_l) = \mod \frac{\sum_{l_u,l_v \in \mathcal{L}} \sum_{i=1}^{n} \sum_{j=i+1}^{n} cosine(s_{l_u,i}, s_{l_v,j})}{\binom{|\mathcal{L}|*n}{2}} \tag{2}$$

Geometric Separability Index Φ: calculates the average number of instances that share the same class label as their nearest neighbours.

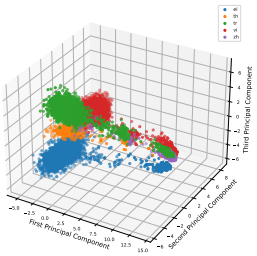
$$GSI(f) = \frac{\sum_{i=1}^{n} \left(f\left(x_i\right) + f\left(x_i'\right) + 1\right) \bmod 2}{n} \tag{3}$$

Here, f is a target function that maps instances to their cluster label, x_i' is the nearest neighbour of x_i and n is the total number of data points.

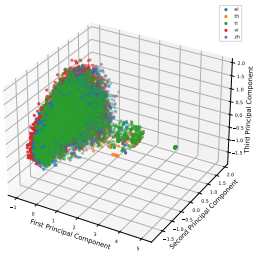
[1] https://huggingface.co/bert-base-multilingual-cased
[2] https://huggingface.co/xlm-roberta-base
[3] https://huggingface.co/microsoft/Multilingual-MiniLM-L12-H384

A.5 ADDITIONAL INFORMATION

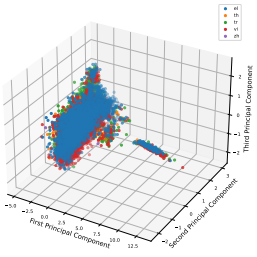
Other PCA plots



(a) mBert

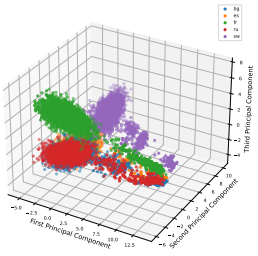


(b) MiniLM

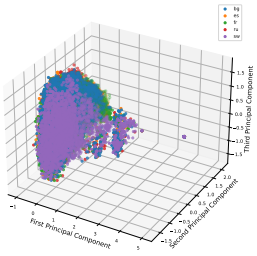


(c) XLMR

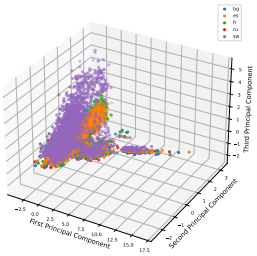
Figure 4: PCA Plots of group (Greek,Turkic,Thai,Vietnamese,Chinese)



(a) mBert



(b) MiniLM



(c) XLMR

Figure 5: PCA Plots of group (Bulgarian,Russian,Spanish,French,Swahili)

Cross-lingual Similarity Index (Γ) values: These are the exact Γ values

Table 2: Γ values of mBert

lang	ar	bg	de	el	en	es	fr	hi	ru	sw	th	tr	ur	vi	zh
ar	2.455	1.377	1.295	1.427	1.272	1.375	1.278	1.374	1.389	1.119	1.325	1.277	1.384	1.251	0.552
bg	1.377	2.455	1.483	1.519	1.409	1.485	1.43	1.361	1.652	1.121	1.262	1.358	1.232	1.389	0.523
de	1.295	1.483	2.455	1.439	1.595	1.541	1.498	1.297	1.527	1.106	1.144	1.345	1.211	1.398	0.584
el	1.427	1.519	1.439	2.455	1.351	1.498	1.425	1.379	1.475	1.196	1.323	1.364	1.273	1.456	0.539
en	1.272	1.409	1.595	1.351	2.455	1.59	1.574	1.236	1.495	1.048	1.096	1.283	1.173	1.473	0.606
es	1.375	1.485	1.541	1.498	1.59	2.455	1.592	1.272	1.564	1.147	1.197	1.376	1.188	1.451	0.612
fr	1.278	1.43	1.498	1.425	1.574	1.592	2.455	1.266	1.487	1.019	1.197	1.301	1.154	1.423	0.563
hi	1.374	1.361	1.297	1.379	1.236	1.272	1.266	2.455	1.354	1.122	1.263	1.311	1.448	1.302	0.418
ru	1.389	1.652	1.527	1.475	1.495	1.564	1.487	1.354	2.455	1.045	1.226	1.3	1.212	1.447	0.552
sw	1.119	1.121	1.106	1.196	1.048	1.147	1.019	1.122	1.045	2.455	1.167	1.206	1.235	1.143	0.367
th	1.325	1.262	1.144	1.323	1.096	1.197	1.197	1.263	1.226	1.167	2.455	1.214	1.214	1.219	0.364
tr	1.277	1.358	1.345	1.364	1.283	1.376	1.301	1.311	1.3	1.206	1.214	2.455	1.254	1.343	0.563
ur	1.384	1.232	1.211	1.273	1.173	1.188	1.154	1.448	1.212	1.235	1.214	1.254	2.455	1.159	0.392
vi	1.251	1.389	1.398	1.456	1.473	1.451	1.423	1.302	1.447	1.143	1.219	1.343	1.159	2.455	0.593
zh	0.552	0.523	0.584	0.539	0.606	0.612	0.563	0.418	0.552	0.367	0.364	0.563	0.392	0.593	2.455

Table 3: Γ values of MiniLM

lang	ar	bg	de	el	en	es	fr	hi	ru	sw	th	tr	ur	vi	zh
ar	1.12	1.041	1.038	1.042	1.04	1.037	1.033	1.036	1.036	1.014	1.023	1.022	1.027	1.036	1.028
bg	1.041	1.12	1.061	1.057	1.058	1.061	1.055	1.035	1.068	1.0	1.002	1.03	1.021	1.037	1.016
de	1.038	1.061	1.12	1.05	1.075	1.064	1.067	1.033	1.055	1.009	1.008	1.035	1.025	1.04	1.025
el	1.042	1.057	1.05	1.12	1.045	1.052	1.052	1.034	1.051	0.995	1.008	1.027	1.018	1.037	1.015
en	1.04	1.058	1.075	1.045	1.12	1.07	1.069	1.038	1.054	1.009	1.016	1.033	1.023	1.057	1.036
es	1.037	1.061	1.064	1.052	1.07	1.12	1.072	1.028	1.051	1.012	1.0	1.03	1.018	1.04	1.019
fr	1.033	1.055	1.067	1.052	1.069	1.072	1.12	1.028	1.048	1.002	0.995	1.022	1.016	1.038	1.009
hi	1.036	1.035	1.033	1.034	1.038	1.028	1.028	1.12	1.035	0.998	1.017	1.026	1.053	1.041	1.029
ru	1.036	1.068	1.055	1.051	1.054	1.051	1.048	1.035	1.12	0.991	1.004	1.029	1.014	1.037	1.023
sw	1.014	1.0	1.009	0.995	1.009	1.012	1.002	0.998	0.991	1.12	0.988	1.004	1.009	1.002	0.999
th	1.023	1.002	1.008	1.008	1.016	1.0	0.995	1.017	1.004	0.988	1.12	1.006	1.001	1.035	1.045
tr	1.022	1.03	1.035	1.027	1.033	1.03	1.022	1.026	1.029	1.004	1.006	1.12	1.02	1.028	1.024
ur	1.027	1.021	1.025	1.018	1.023	1.018	1.016	1.053	1.014	1.009	1.001	1.02	1.12	1.026	1.015
vi	1.036	1.037	1.04	1.037	1.057	1.04	1.038	1.041	1.037	1.002	1.035	1.028	1.026	1.12	1.047
zh	1.028	1.016	1.025	1.015	1.036	1.019	1.009	1.029	1.023	0.999	1.045	1.024	1.015	1.047	1.12

Table 4: Γ values of XLMR

lang	ar	bg	de	el	en	es	fr	hi	ru	sw	th	tr	ur	vi	zh
ar	1.019	1.011	1.01	1.012	1.011	1.01	1.01	1.011	1.011	1.009	1.011	1.009	1.01	1.011	1.011
bg	1.011	1.019	1.01	1.011	1.011	1.01	1.01	1.011	1.011	1.008	1.009	1.009	1.01	1.011	1.01
de	1.01	1.01	1.019	1.014	1.015	1.014	1.014	1.013	1.014	1.011	1.012	1.012	1.012	1.013	1.013
el	1.012	1.011	1.014	1.019	1.015	1.014	1.014	1.014	1.015	1.011	1.013	1.013	1.012	1.014	1.013
en	1.011	1.011	1.015	1.015	1.019	1.015	1.015	1.014	1.015	1.012	1.013	1.013	1.012	1.015	1.013
es	1.01	1.01	1.014	1.014	1.015	1.019	1.014	1.013	1.014	1.011	1.012	1.012	1.012	1.014	1.013
fr	1.01	1.01	1.014	1.014	1.015	1.014	1.019	1.013	1.014	1.01	1.012	1.012	1.011	1.014	1.012
hi	1.011	1.011	1.013	1.014	1.014	1.013	1.013	1.019	1.014	1.011	1.013	1.012	1.014	1.014	1.014
ru	1.011	1.011	1.014	1.015	1.015	1.014	1.014	1.014	1.019	1.011	1.013	1.012	1.012	1.014	1.013
sw	1.009	1.008	1.011	1.011	1.012	1.011	1.01	1.011	1.011	1.019	1.011	1.01	1.01	1.011	1.011
th	1.011	1.009	1.012	1.013	1.013	1.012	1.012	1.013	1.013	1.011	1.019	1.012	1.012	1.013	1.014
tr	1.009	1.009	1.012	1.013	1.013	1.012	1.012	1.012	1.012	1.01	1.012	1.019	1.012	1.013	1.012
ur	1.01	1.01	1.012	1.012	1.012	1.012	1.011	1.014	1.012	1.01	1.012	1.012	1.019	1.013	1.012
vi	1.011	1.011	1.013	1.014	1.015	1.014	1.014	1.014	1.014	1.011	1.013	1.013	1.013	1.019	1.014
zh	1.011	1.01	1.013	1.013	1.013	1.013	1.012	1.014	1.013	1.011	1.014	1.012	1.012	1.014	1.019

Language Separability (Φ) Values: These are the exact Φ values

Table 5: Φ values of mBert

lang	ar	bg	de	el	en	es	fr	hi	ru	sw	th	tr	ur	vi	zh
ar	1.0	0.986	0.987	0.985	0.989	0.985	0.988	0.991	0.986	0.991	0.988	0.99	0.991	0.991	0.989
bg	0.986	1.0	0.96	0.963	0.967	0.963	0.966	0.989	0.876	0.983	0.983	0.975	0.994	0.977	0.983
de	0.987	0.96	1.0	0.965	0.904	0.929	0.934	0.989	0.963	0.967	0.975	0.954	0.992	0.957	0.976
el	0.985	0.963	0.965	1.0	0.967	0.952	0.962	0.991	0.979	0.98	0.978	0.969	0.994	0.963	0.984
en	0.989	0.967	0.904	0.967	1.0	0.9	0.905	0.989	0.969	0.968	0.974	0.949	0.992	0.945	0.978
es	0.985	0.963	0.929	0.952	0.9	1.0	0.869	0.99	0.958	0.969	0.978	0.958	0.993	0.952	0.975
fr	0.988	0.966	0.934	0.962	0.905	0.869	1.0	0.99	0.967	0.973	0.978	0.964	0.993	0.953	0.976
hi	0.991	0.989	0.989	0.991	0.989	0.99	0.99	1.0	0.993	0.99	0.991	0.986	0.979	0.989	0.99
ru	0.986	0.876	0.963	0.979	0.969	0.958	0.967	0.993	1.0	0.995	0.993	0.985	0.996	0.982	0.985
sw	0.991	0.983	0.967	0.98	0.968	0.969	0.973	0.99	0.995	1.0	0.974	0.964	0.992	0.971	0.985
th	0.988	0.983	0.975	0.978	0.974	0.978	0.978	0.991	0.993	0.974	1.0	0.971	0.994	0.981	0.96
tr	0.99	0.975	0.954	0.969	0.949	0.958	0.964	0.986	0.985	0.964	0.971	1.0	0.99	0.962	0.966
ur	0.991	0.994	0.992	0.994	0.992	0.993	0.993	0.979	0.996	0.992	0.994	0.99	1.0	0.995	0.995
vi	0.991	0.977	0.957	0.963	0.945	0.952	0.953	0.989	0.982	0.971	0.981	0.962	0.995	1.0	0.972
zh	0.989	0.983	0.976	0.984	0.978	0.975	0.976	0.99	0.985	0.985	0.96	0.966	0.995	0.972	1.0

Table 6: Φ values of MiniLM

lang	ar	bg	de	el	en	es	fr	hi	ru	sw	th	tr	ur	vi	zh
ar	1.0	0.821	0.859	0.831	0.814	0.841	0.85	0.893	0.833	0.894	0.871	0.895	0.887	0.89	0.911
bg	0.821	1.0	0.685	0.684	0.681	0.687	0.726	0.876	0.536	0.883	0.898	0.833	0.895	0.868	0.927
de	0.859	0.685	1.0	0.764	0.615	0.703	0.712	0.884	0.707	0.874	0.896	0.817	0.899	0.863	0.919
el	0.831	0.684	0.764	1.0	0.726	0.704	0.726	0.892	0.742	0.895	0.916	0.867	0.912	0.859	0.95
en	0.814	0.681	0.615	0.726	1.0	0.602	0.634	0.847	0.71	0.847	0.882	0.787	0.872	0.787	0.912
es	0.841	0.687	0.703	0.704	0.602	1.0	0.576	0.895	0.746	0.855	0.918	0.84	0.908	0.833	0.943
fr	0.85	0.726	0.712	0.726	0.634	0.576	1.0	0.899	0.764	0.871	0.921	0.858	0.913	0.853	0.945
hi	0.893	0.876	0.884	0.892	0.847	0.895	0.899	1.0	0.875	0.937	0.911	0.859	0.696	0.922	0.931
ru	0.833	0.536	0.707	0.742	0.71	0.746	0.764	0.875	1.0	0.905	0.89	0.84	0.908	0.874	0.902
sw	0.894	0.883	0.874	0.895	0.847	0.855	0.871	0.937	0.905	1.0	0.922	0.894	0.932	0.905	0.946
th	0.871	0.898	0.896	0.916	0.882	0.918	0.921	0.911	0.89	0.922	1.0	0.887	0.939	0.901	0.732
tr	0.895	0.833	0.817	0.867	0.787	0.84	0.858	0.859	0.84	0.894	0.887	1.0	0.882	0.891	0.896
ur	0.887	0.895	0.899	0.912	0.872	0.908	0.913	0.696	0.908	0.932	0.939	0.882	1.0	0.933	0.955
vi	0.89	0.868	0.863	0.859	0.787	0.833	0.853	0.922	0.874	0.905	0.901	0.891	0.933	1.0	0.94
zh	0.911	0.927	0.919	0.95	0.912	0.943	0.945	0.931	0.902	0.946	0.732	0.896	0.955	0.94	1.0

Table 7: Φ values of XLMR

lang	ar	bg	de	el	en	es	fr	hi	ru	sw	th	tr	ur	vi	zh
ar	1.0	0.946	0.98	0.966	0.971	0.971	0.978	0.984	0.967	0.985	0.935	0.984	0.978	0.98	0.939
bg	0.946	1.0	0.92	0.916	0.9	0.916	0.95	0.971	0.805	0.971	0.943	0.961	0.978	0.958	0.948
de	0.98	0.92	1.0	0.932	0.845	0.911	0.916	0.973	0.919	0.948	0.949	0.936	0.981	0.939	0.958
el	0.966	0.916	0.932	1.0	0.892	0.897	0.922	0.971	0.925	0.965	0.95	0.954	0.981	0.939	0.967
en	0.971	0.9	0.845	0.892	1.0	0.8	0.841	0.96	0.89	0.931	0.927	0.916	0.972	0.899	0.952
es	0.971	0.916	0.911	0.897	0.8	1.0	0.828	0.976	0.914	0.94	0.944	0.935	0.981	0.926	0.952
fr	0.978	0.95	0.916	0.922	0.841	0.828	1.0	0.977	0.934	0.953	0.951	0.951	0.985	0.937	0.97
hi	0.984	0.971	0.973	0.971	0.96	0.976	0.977	1.0	0.966	0.983	0.957	0.972	0.931	0.975	0.965
ru	0.967	0.805	0.919	0.925	0.89	0.914	0.934	0.966	1.0	0.975	0.935	0.96	0.98	0.95	0.919
sw	0.985	0.971	0.948	0.965	0.931	0.94	0.953	0.983	0.975	1.0	0.955	0.953	0.983	0.951	0.97
th	0.935	0.943	0.949	0.95	0.927	0.944	0.951	0.957	0.935	0.955	1.0	0.946	0.969	0.939	0.916
tr	0.984	0.961	0.936	0.954	0.916	0.935	0.951	0.972	0.96	0.953	0.946	1.0	0.972	0.948	0.949
ur	0.978	0.978	0.981	0.981	0.972	0.981	0.985	0.931	0.98	0.983	0.969	0.972	1.0	0.983	0.965
vi	0.98	0.958	0.939	0.939	0.899	0.926	0.937	0.975	0.95	0.951	0.939	0.948	0.983	1.0	0.955
zh	0.939	0.948	0.958	0.967	0.952	0.952	0.97	0.965	0.919	0.97	0.916	0.949	0.965	0.955	1.0