A General-Purpose Multilingual Document Encoder

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Problem Statement

1) Massively multilingual Transformers(MMTs) have drastically pushed the state-of-the-art in multilingual NLP...
2) …but standard transformer-based models process text **linearly**, which leads to suboptimal performance on document-level multilingual tasks.
   a) They do not correspond to the **hierarchical nature** of document organization, i.e. sequences of paragraphs and of sequences of sentences.
   b) Representing documents longer than the MMTs **maximal input length** requires either document trimming or segmentation.

Hierarchical Multilingual Document Encoder (HDME)

d_4: Random Wikipedia Article

Rand

Text: [BOS] w1,1 w1,2 … [EOS]
[BOS] w2,1 w2,2 … [EOS]
[BOS] w3,1 w3,2 … [EOS]
…

Category: Wikipedia category

d_1: en.wikipedia.org/wiki/Car

EN

Text: A car, or an automobile, is a motor vehicle with wheels. Most definitions of cars state that they run primarily roads, [...]

Category: Private Transport

d_2: de.wikipedia.org/wiki/Automobil

DE

Text: Ein Automobil, kurz Auto (in Deutschland amtlich Kraftfahrzeug, in der Schweiz amtlich Motorwagen), ist ein mehrspuriges [...]

Category: Automobile

d_3: en.wikipedia.org/wiki/Bicycle

EN

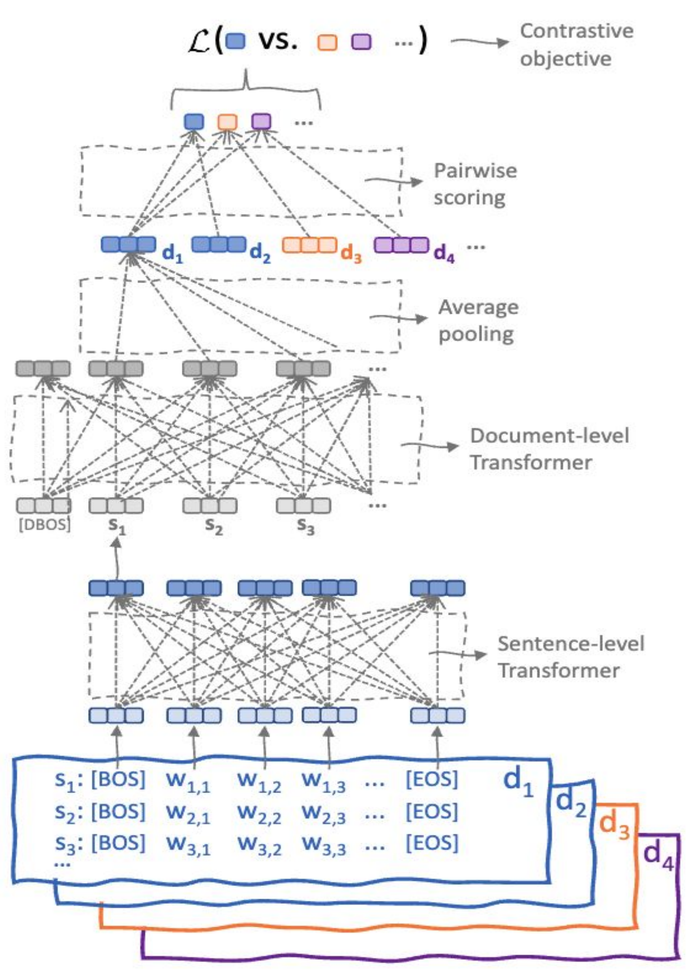
Text: A bicycle, also called a pedal cycle, bike, push-bike or cycle, is a human-powered or motor-powered assisted, pedal-driven [...]

Category: Private Transport

In-Batch Negative Example

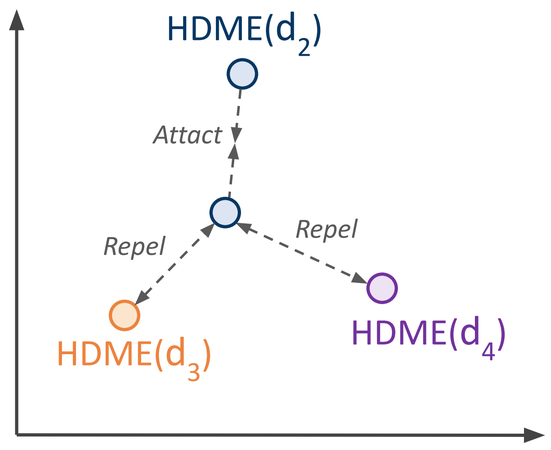
Positive Example

Hard Negative Example



Pre-training Objective

InfoNCE Loss (Oord et al. 2018)



$$\mathcal{L} = -\sum_{i=1}^{N}\left[\frac{1}{\tau}s(\mathbf{d}_1^{(i)},\mathbf{d}_2^{(i)}) - \log\left(e^{s(\mathbf{d}_1^{(i)},\mathbf{d}_{neg}^{(i)})/\tau} + \sum_{j=1}^{N} e^{s(\mathbf{d}_1^{(i)},\mathbf{d}_2^{(j)})/\tau}\right)\right]$$

s = cosine similarity

τ = temperature parameter

Main Results

Models and Baselines

Standard Multilingual Transformers

- Sentence Encoder: LaBSE (Feng et al. 2022)
- Vanilla mPLM: XLM-R (Conneau et al. 2019)
- Vanilla mPLM: mBERT (Devlin et al. 2018)

Multilingual Long Document Encoders

- Sliding Window: LaBSE-Seg (size=128, stride=42)
- Multilingual Longformer (Beltagy et al. 2020)
  - Parameters are initialized from LaBSE
  - MLM pretraining on the same corpus as HMDE

HDME (ours)

- Pre-trained on four languages (HDME, **XLW-4L**, shown in Tbl. 1 and 2): EN, DE, FR and IT.
- Pre-trained on twelve languages (HDME, **XLW-12L**): EN, FR, RU, JA, ZH, HU, FI, AR, FA, TR, GK and MS.

Model	En	Es	De	Fr	It	Ru	Ja	Zh	AVG
Standard Multilingual Transformers									
LaBSE	95.5	79.0	89.6	87.2	76.8	63.9	**80.8**	86.1	82.4
XLM-R	93.0	84.6	**92.5**	87.1	73.2	68.9	78.2	85.8	83.0
mBERT	**96.9**	81.9	88.3	83.1	74.1	72.3	74.6	84.4	82.0
Multilingual Long Document Encoders									
LaBSE-Seg	94.0	82.9	90.2	89.9	78.1	71.9	75.5	88.4	84.0
mLongformer	95.8	**87.0**	93.4	91.9	**80.6**	71.7	79.5	88.5	86.1
HMDE	95.4	85.6	91.2	**92.0**	78.5	**83.9**	76.3	**89.5**	**86.8**

Table 1: **Supervised document classification** results (MLDOC) in terms of Accuracy. Best result per language highlighted in **blue**.

Experimental Results

- Evaluate HDME as a document encoder on a **supervised classification task**, MLDoc (Schwenk and Li, 2018)
  - Apply classification (FFN) layer on top of encoder.
  - Our model and mLongformer trained on four languages (XLW-4) **outperform** all of the standard MMTs.
- We evaluate HDME representations on **unsupervised cross-lingual IR**, CLEF-2003 (Braschler et al. 2003)
  - Bi-Encoder Paradigm: Encode queries and documents independently, rank according to cosine sim.
  - Our model trained on four languages (XLW-4L) **outperforms baselines** by a large margin.
  - HDME sems to **generalize well to unseen languages**, i.e. languages that are not included in XLW-4/12L.

Model	En–Fi	En–It	En–Ru	En–De	De–Fi	De–It	De–Ru	Fi–It	Fi–Ru	AVG
Standard Multilingual Transformers										
LaBSE	.247	.224	.131	.138	.247	.214	.135	.211	.125	.186
mBERT	.145	.146	**.167**	.107	.151	.116	**.149**	.117	.128	.136
Multilingual Long Document Encoders										
LaBSE-Seg	.243	.169	.107	.194	.268	.178	.104	.153	.014	.159
mLongformer	.150	.088	.094	.082	.190	.072	.120	.097	.091	.109
HMDE	**.389**	**.282**	.141	**.326**	**.352**	**.259**	.130	**.238**	**.129**	**.249**

Table 2: **Unsupervised cross-lingual document retrieval** results (CLEF-2003) in terms of Mean Average Precision (MAP). Best results per language highlighted in **blue**.

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