Model Card - Multimodal Clustering Model

Model Details

- Developed by Uri Berger[a b], Gabriel Stanovsky[a], Omri Abend[a] and Lea Frermann[b]
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- A visual ResNet50 encoder and a simple probabilistic text encoder mutually trained to predict matching clusters for $(image, caption)$ pairs
- For more details, we refer to our paper [Berger et al., 2022]
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Intended Use

- This model can be utilized in one of several use cases: Word categorization, Word concreteness estimation, and Image zero-shot classification and segmentation

Factors

- While the model is not human-centric, it is sensitive to biases embedded in the caption annotators and therefore factors highly depend on the training data. For example, in MSCOCO [Lin et al., 2014], gender is a relevant factor [see Zhao et al., 2017]

Metrics

- The model can be measured for taxonomic or syntagmatic word categorization. Words with taxonomic relations are words that can occur in similar contexts (e.g., *dog*, *giraffe*, *elephant*). Words with syntagmatic relations are words that are likely to occur together in the same sentence (e.g., *dog*, *bark*, *collar*)
- For taxonomic categorization, we use F-Score, which is the harmonic mean of precision and recall of the model's produced clusters when compared to ground-truth categories
- For syntagmatic categorization we use mean association strength computed across all word pairs in which both words were assigned the same cluster by this clustering solution. The association strength of a pair of words is extracted from the Small World of Words (SWOW) dataset [De Deyne et al., 2019]
- For concreteness estimation we compute the pearson correlation coefficient of the estimation of all words with ground-truth concreteness values
- For image classification and segmentation we use F-Score (the harmonic mean of precision and recall)

Evaluation Data

- Taxonomic categorization is evaluated against the categorization dataset by Fountain and Lapata [2010], transformed into hard categories by assigning each noun to its most typical category as extrapolated from human typicality ratings
- Concreteness estimation is evaluated against a concreteness dataset by Brysbaert et al. [2013]
- Image classification and segmentation is evaluated on the MSCOCO test split [Lin et al., 2014]

Training Data

- Model is trained on $(image, caption)$ pairs taken from the MSCOCO train split [Lin et al., 2014]
- Preprocessing includes tokenization of captions

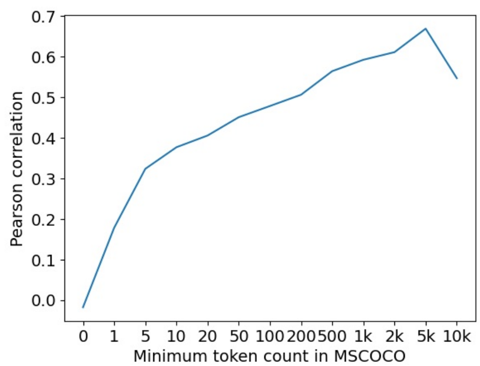
Ethical Considerations

- The model was trained on the publicly available MSCOCO [Lin et al., 2014] and may capture social biases which manifest in its training data

Quantitative Analyses

Taxonomic categorization F-Score	0.33 ± 0.0109
Syntagmatic categorization MAS	7.45 ± 0.33
Image classification F-Score	0.28 ± 0.01
Image segmentation F-Score	0.178 ± 0.01

Table 1: Model results on Taxonomic/Syntagmatic categorization, and Image classification/Segmentation.



Pearson correlation with ground-truth concreteness values, as a function of the word frequency in the training set.

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References

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