# Towards Multi-Modal Text-Image Retrieval to improve Human Reading

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## Abstract

In primary school, children's books, as well as in modern language learning apps, multi-modal learning strategies like illustrations of terms and phrases are used to support reading comprehension. Also, several studies in educational psychology suggest that integrating cross-modal information will improve reading comprehension. We claim that state-of-the-art multi-modal transformers, which could be used in a language learner context to improve human reading, will perform poorly because of the short and relatively simple textual data those models are trained with. To prove our hypotheses, we collected a new multi-modal image-retrieval dataset based on data from Wikipedia. In an in-depth data analysis, we highlight the differences between our dataset and other popular datasets. Additionally, we evaluate several state-of-the-art multi-modal transformers on text-image retrieval on our dataset and analyze their meager results, which verify our claims.

## 1 Introduction

When we were babies, we learned our native language by combining our parents' words and visual hints. In primary school, children's books, as well as in modern language learning apps, like Babble[1] or Duolingo[2], this multi-modal learning strategy continues as illustrations of terms and phrases are used to support reading comprehension Also, multiple studies in educational psychology suggest that integrating cross-modal information will improve learning to read (Ecalle et al., 2009; Dalton and Grisham, 2011; Hahn et al., 2014; Gerbier et al., 2018; Kabooha and Elyas, 2018; Xie et al., 2019; Albahiri and Alhaj, 2020).

This paper presents initial research towards leveraging machine learning technology within a language learner context to improve human reading. In this scenario, the aim is to support a user's reading comprehension of arbitrary text by enhancing it with context-specific visual clues discovered by state-of-the-art multi-modal Transformers used within text-image retrieval.

The most popular training datasets for current models applied on text-image retrieval are MS COCO (Lin et al., 2014) and Flickr30k (Young et al., 2014; Plummer et al., 2015). Both datasets were created by crowdsourcing workers with the task to find short, simple and descriptive captions for images taken from Flickr[3]. We argue that sentences slightly advanced language learners might not comprehend are presumably more complex than the captions from COCO or Flickr30k. Hence we further claim that current models will perform poorly on more complex data.

The contributions of this work to verify these hypotheses are: *a*) the collection of a multi-modal dataset based on WikiCaps (Schamoni et al., 2018), which we call WISMIR (**WI**kiCaps **S**ubset for **M**ulti-Modal **I**mage-**R**etrieval); *b*) an in-depth analysis and comparison of WISMIR to other multi-modal datasets used for image-retrieval; *c*) a text-image retrieval evaluation of state-of-the-art image-retrieval models on WISMIR.

## 2 Related Work

During the last few years, there were significant breakthroughs in various computer vision tasks and models (Kirillov et al., 2020; Güler et al., 2018) as well as in the field of natural language processing. Especially with the recent dawn of transformers, models are increasingly capable of understanding text's semantics (Brown et al., 2020; Devlin et al., 2019; Yang et al., 2019). This progress of uni-modal models also led to a great leap forward in multi-modal visio-linguistic models, which are starting to leverage the power of transformers to

[1] https://babbel.com/

[2] https://duolingo.com/

[3] https://flickr.com/

work with text and images simultaneously. One of the several multi-modal tasks where these models pushed the boundaries is text-image retrieval, which we want to make use of in our language learner scenario. For this task, the model learns a metric function $\Phi_{k,l} : \mathbb{R}^{|S_k| \times |I_l|} \rightarrow [0,1]$ that measures the similarity of sentence $S_k$ and image $I_l$. The goal is to find the best matching image $I_k = \underset{l \in P}{\operatorname{argmax}} \Phi_{q,l}$ for a query sentence $q$ from a pool of images $P$, the similarity scores $\{\Phi_{q,l} \mid l \in P\}$ have to be computed. The input to multi-modal transformers applied on text-image retrieval are textual tokens of a sentence $S_k$ together with region features of an image $I_l$. Usually, textual tokens are generated by pre-trained BERT tokenizers (Wu et al., 2016). The visual region features are typically computed by pre-trained region and object detection and classification networks such as Faster-R-CNN with ResNet-101 (Ren et al., 2016; He et al., 2016; Anderson et al., 2018).

Multi-modal transformer networks can be grouped into so-called "early-fusion" models and "late-fusion" models. In early-fusion models such as UNITER (Chen et al., 2020), OSCAR (Li et al., 2020), ImageBERT (Qi et al., 2020), VisualBert (Li et al., 2019), or VL-BERT (Su et al., 2019), tokens of both modalities form the input to the network. Self-attention heads in the transformer-encoder layers (Vaswani et al., 2017) then compute joint-representations of both modalities, i.e., fine-grained word-region-alignments of the words $w \in S_k$ and the visual tokens $v \in I_l$. The similarity function $\Phi_{k,l}$ is an arbitrary combination of those joint-representations that depends on the respective model. Despite their remarkable performance of tasks on typical datasets like COCO or Flickr30k, early-fusion models are not applicable in real-world information retrieval systems with large pool of images because it would require tremendous computational power and is therefore infeasible in time-critical applications.

As opposed to early-fusion models, in late-fusion models, the textual and visual modalities get forwarded through separate transformers for each modality. Later, the output of the textual transformer and the output of the visual transformer get fused depending on the model's specific implementation. For example, LXMERT (Tan and Bansal, 2019) and VilBERT (Lu et al., 2019) compute the fused cross-modality output with a third cross-modal transformer that takes the separate and uni-modal transformers' outputs as inputs. Other late-fusion models specially designed to solve multi-modal retrieval tasks like TERN (Messina et al., 2020) and TERAN (Nicola et al., 2020) use a more computationally efficient way. A significant advantage of late-fusion models over early-fusion models is that the output embeddings of the uni-modal transformers can be pre-computed and indexed. In real-world applications, with a large pool of images, this can save enormous amounts of time. By pre-computing the image embeddings, only the query embedding $q$ has to be computed to measure the similarities $\Phi_{q,l}$ between the query $q$ and all images $I_l \in P$ in the pool. Especially in TERN and TERAN, where the multi-modal fusion is not a complex neural network, this leads to short latency and enables real-world multi-modal information retrieval systems.

## 3 Dataset Collection

The most popular datasets for pre-training and fine-tuning multi-modal transformers applied on retrieval tasks are MS COCO and Flickr30k. Both are hand-crafted datasets, with short, descriptive and conceptual captions created by crowdsourcing workers describing mostly non-iconic images from Flickr. Within a language learner scenario, we argue that the sentences a user does not understand while reading are presumably more complex than the short and relatively simple caption sentences from COCO or Flickr30k. Consequently, we claim that models trained with this data will perform much worse on more complex textual data.

An example of a multi-modal dataset containing non-constrained and heterogeneous text-image pairs is WikiCaps (Schamoni et al., 2018), which contains about 3.8 million images and their respective English captions from Wikipedia articles. They are non-constrained, because the captions and the images of WikiCaps are not the outcomes of a particular (crowdsourcing) task, i.e., there are no constraints besides the terms of use of Wikipedia. They are heterogeneous, since the data of WikiCaps was randomly crawled from Wikipedia and does not follow any pattern, as opposed to COCO or Flickr30k images and captions, which got carefully collected according to several sophisticated rules.

The authors of WikiCaps only provide a tab-separated file containing the Wikimedia file IDs of the image and the respective caption together with a perl script to download the images serially.

To make the data more accessible, we developed an efficient python application, which we released on GitHub[4]. This tool is capable of collecting corpus statistics based on the captions using different models and frameworks, flexibly filtering the data with user-defined filters, downloading the images in parallel, applying customizable transformations to the images, and finally, persisting the data in an easy to use and efficient format. Using the tool, we collected and released two proof-of-concept versions of the dataset, which we refer to as (**Wi**kiCaps **S**ubset for **M**ulti-Modal **I**nformation **R**etrieval) version 1 and 2. After inspecting the meager results of several models trained and evaluated on the first version of WISMIR, we decided to collect the second version containing about twice as many text-image pairs in the training set to check if more data improves model performances. Information about the size of the dataset is listed in Table 1. The test set of WISMIR v1 is exactly equal to the test set of the second version. More details about these evaluations are described in Section 4.

| Version | Size | Train Split | Test Split |
|---|---|---|---|
| v1 | 187598 | 178218 | 9380 (5%) |
| v2 | 395874 | 386494 | 9380 (2.4 %) |

Table 1: Number of text-image pairs in WISMIR v1 and WISMIR v2 datasets and train-test splits.

### 3.1 Data Analysis

In the following, typical captions of COCO, Flickr30k, and WISMIR are shown to give an impression of their textual differences.

***COCO**: ”people sit on benches near a street and shops.”*

***Flickr30k**: ”Two men with heads down signing a paper”*

***WISMIR**: ”View of the Kornmarkt in Trier, Rhineland-Palatinate, Germany. In the middle of the image is Stadtlesen, a mobile open air library; at left is the open air portion of the Bitburger Wirtshaus; the glass fronted building in the background at left is a bookshop.”*

To examine these differences for the complete datasets systematically, we used our tool to generate the corpus statistics discussed in the following. The differences between the first and second versions of WISMIR are neglectable and that the data visualized in the following figures is based on WISMIR v2. Since the models used to generate this data are not flawless, we utilized three different NLP frameworks, namely spaCy[5], NLTK[6], and Polyglot[7], to get a more reliable impression on the distribution of the data. Please note that we only show the three most notable distinctions of WISMIR, COCO, and Flickr30k in the following due to this paper’s brevity.

In the succeeding figures, multiple boxplots summarize statistics about various characteristics of the three datasets’ captions. In all three figures, we can observe the resemblance of COCO and Flickr30k and the disparity of the two compared to WISMIR. Figure 1 shows that the average number of tokens per caption is between 3.6 − 4.6 times higher in WISMIR than in COCO or Flickr30k. This is an essential property because language learners will most probably have more difficulties comprehending long paragraphs than short paragraphs. Also, training models on longer sentences might lead to problems (see Section 4.2). In Figure 2, we can see that there are at average up to 15 % more noun tokens per caption in WISMIR than in COCO or Flickr30k. Since all depictable entities are nouns, more nouns in the text might benefit a tighter alignment of the visual and textual embeddings. However, it also might result in the opposite, i.e., it could lead to a much looser word-region-alignment if most of the nouns are abstract concepts or part of named entities, as described below. The most sig-

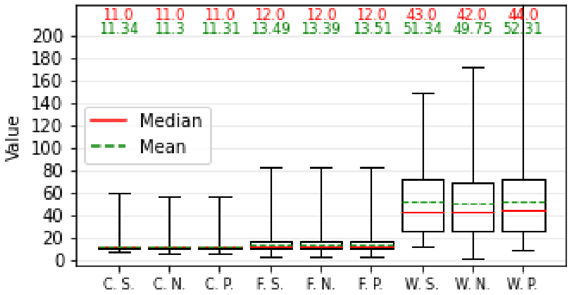

Figure 1: Boxplot diagrams for the **number of tokens per caption** in COCO, Flickr30k, and WISMIR, generated by different tokenization models. The median and mean are depicted in red and green font, while their whiskers indicate the minima and maxima. On the x-axis, C stands for COCO, F for Flickr30k, W for WISMIR, S for spaCy, N for NLTK, and P for polyglot.

[4] https://git.io/Jtw2P

[5] https://spacy.io/

[6] https://www.nltk.org/

[7] http://polyglot-nlp.com/

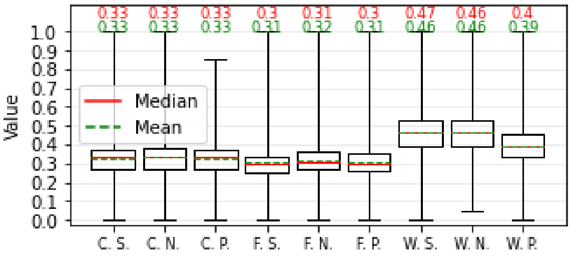

Figure 2: Boxplot diagrams for the **ratio of tokens tagged with NOUN and PROPN POS tags and all tokens of a caption** in COCO, Flickr30k, and WISMIR, generated by different POS tagger models. The median and mean are depicted in red and green font, while their whiskers indicate the minima and maxima. On the x-axis, C stands for COCO, F for Flickr30k, W for WISMIR, S for spaCy, N for NLTK, and P for polyglot.

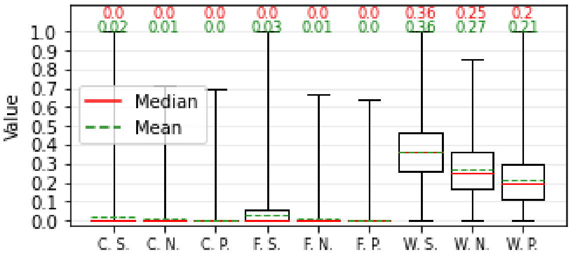

Figure 3: Boxplot diagrams for the **ratio of tokens contained in named entities and all tokens of a caption** in COCO, Flickr30k, and WISMIR, generated by different tokenizers and named entity recognition models. The median and mean are depicted in red and green font, while their whiskers indicate the minima and maxima. On the x-axis, C stands for COCO, F for Flickr30k, W for WISMIR, S for spaCy, N for NLTK, and P for polyglot.

nificant difference between the datasets is shown in Figure 3: In COCO and Flickr30k, there are almost no named entities, while in WISMIR, between $21 - 36$ % of a captions' tokens are part of named entities on average. This might be problematic during the model's training, as described in Section 4.2.

#### 3.1.1 Readability Comparison

To further underline the differences between COCO, Flickr30k, and WISMIR and to show the suitability of WISMIR in our language learner scenario, we computed the Flesch-Kincaid (Farr et al., 1951) (FK) and Dale-Chall (Chall and Dale, 1995) (DC) readability scores for random samples of the datasets containing $10^6 \pm 0.1\%$ characters. Because these readability scores depend on the number of sentences, words, and syllables in the text, counted by imperfect models, we use two different implementations[8, 9] to obtain more reliable results. In Figure 4, we can observe that the captions of COCO and Flickr30k should be easily understood by an average 4th to 6th-grade US student. In contrast, WISMIR captions are recommended for college students or higher, according to the FK and DC scores.

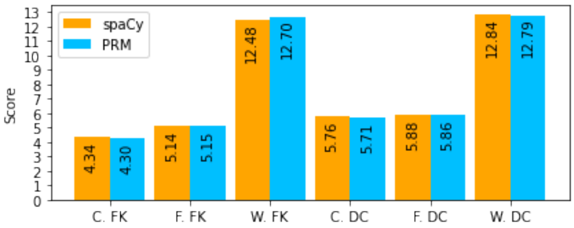

Figure 4: Comparison of Flesch-Kincaid (FK) and Dale-Chall (DC) readability scores of randomly sampled subsets of COCO (C), Flickr30k (F), and WISMIR (W) captions containing $10^6 \pm 0.1\%$ characters computed by two different frameworks (spaCy and PRM).

## 4 Model Evaluations

In order to verify our claim that models pre-trained solely on COCO and Flickr30k perform poorly on text-image retrieval with more complex and heterogeneous data like WISMIR, we trained and evaluated several models on our datasets.

### 4.1 Image-Retrieval Evaluations

As listed in Table 2, evaluation scores on both versions of WISMIR, especially for COCO and Flickr30k pre-trained TERAN models, are meager and fall way below the baseline of state-of-the-art models on text-image retrieval as reported by Chen et al. (2020). It seems to be the case that COCO and Flickr30k did not contribute anything meaningful in the models' training process at all when evaluating them for text-image retrieval on WISMIR. The same appears to be true for the other way around, i.e., TERAN models trained on WISMIR perform very badly on COCO and Flickr30k. Even $\text{UNITER}_{\text{base}}$ pre-trained with much more data (5.6M samples) from COCO, Visual Genome (Krishna et al., 2017), Conceptual Captions (Sharma et al., 2018), and SBU Captions (Ordonez et al., 2011) performed poorly, albeit outperforming $\text{TERAN}_{\text{C}}$ and $\text{TERAN}_{\text{F}}$ by

[8] spaCy-readability (https://git.io/JtgjK)

[9] py-readability-metrics (https://git.io/JtgPG)

| Text-image retrieval | | | | |
|---|---|---|---|---|
| Model | Data | R@1 | R@5 | R@10 |
| TERAN$_{\mathrm{W1}}$ | W1 | 8.9 | 26.9 | 38.2 |
| TERAN$_{\mathrm{W2}}$ | W1 | **17.8** | **45.7** | **59.4** |
| TERAN$_{\mathrm{C}}$ | W1 | 1.1 | 3.7 | 5.6 |
| TERAN$_{\mathrm{F}}$ | W1 | 0.9 | 2.7 | 4.4 |
| UNITER$_{\mathrm{base}}$ | W1 | 5.31 | 13.28 | 18.75 |
| TERAN$_{\mathrm{W1}}$ | C | 2.0 | 6.9 | 11.5 |
| TERAN$_{\mathrm{W2}}$ | C | 3.1 | 10.9 | 17.6 |
| TERAN$_{\mathrm{C}}$ | C | 42.6 | 72.5 | 82.9 |
| UNITER$_{\mathrm{base}}$ | C | **50.33** | **78.52** | **87.16** |
| TERAN$_{\mathrm{W1}}$ | F | 4.6 | 14.5 | 22.6 |
| TERAN$_{\mathrm{W2}}$ | F | 8.1 | 22.9 | 33.1 |
| TERAN$_{\mathrm{F}}$ | F | 59.4 | 84.8 | 90.5 |
| UNITER$_{\mathrm{base}}$ | F | **72.52** | **92.36** | **96.08** |

Table 2: Recall@K evaluation results of different models on text-image retrieval on multiple test sets. The letters C for COCO, F for Flickr30k, or W1 and W2 for WISMIR version 1 and 2 respectively are the datasets' abbreviations. In the subscripts, it indicates the training data of the TERAN model.

| Samples | A | B | C |
|---|---|---|---|
| test set | 51.00 | 0.4618 | 0.3542 |
| train set | 51.35 | 0.4637 | 0.3598 |
| R@1 | 51.05 | 0.4617 | 0.3559 |
| not R@1 | 50.99 | 0.4618 | 0.3538 |
| R@5 | 50.85 | 0.4600 | 0.3533 |
| not R@5 | 51.13 | 0.4632 | 0.3549 |
| R@10 | 50.76 | 0.4607 | 0.3536 |
| not R@10 | 51.35 | 0.4633 | 0.3549 |

Table 3: A comparison of average properties of captions from different subsets of WISMIR samples. **A:** the average number of tokens; **B:** the ratio of tokens tagged with NOUN or PROPN POS tags and all other tokens; **C:** the ratio of tokens related to named entities and all other tokens. In the samples column, ”R@k” refers to the set of samples where the $TERAN_{W2}$ model correctly ranked the respective image in the first $k$ positions. Samples referred to as ”not R@k”, are samples, where the model did not retrieve the correct image in the first $k$ ranks.

a large margin. While things look much better for TERAN$_{\mathrm{W1}}$ and TERAN$_{\mathrm{W2}}$, it is still unsatisfactory and far behind the results of TERAN$_{\mathrm{C}}$ or TERAN$_{\mathrm{F}}$ and UNITER achieved on COCO or Flickr30k.

A noticeable outcome is that the TERAN model trained on WISMIR v2 performs way better than the TERAN model trained on the first version of WISMIR. Since WISMIR v2 has about twice as many training samples, this result underlines our dataset's (textual) complexity. That is, it indicates how hard it is for state-of-the-art transformers to learn tight word-region-alignments and global text-image similarities from complex multi-modal datasets like WISMIR.

### 4.2 Error Analysis

To ensure that the poor performance of the models listed in Table 2 does not originate from an eventual imbalance between the train and test set, we compared the data distribution between different subsets of WISMIR. As shown in Table 3, the differences in the principal characteristics of WISMIR between the training and the test split are neglectable. The same is true for the differences between samples correctly ranked and incorrectly ranked by the $TERAN_{W2}$ according to Recall at 1, 5, and 10 metrics. Further, we found that the model has seen that 84% of the token types, 72% of the noun token types, and 80% of the named entity types of the test set during training. From these findings, we can conclude that the model's difficulties with WISMIR do not originate from surface forms of the dataset's captions but from a deeper semantic or discourse level.

Further problems could be introduced by the large number of tokens per caption on average. Most of the words in a lengthy caption are probably not grounded in an image region and can therefore be regarded as noise for word-region-alignments. When too many words are not depictable or are not grounded in ROIs, it leads to loose coupling between the caption and the image, which is clearly not beneficial for the models' training.

Other sources of issues might lie in the architecture or the training process of the models. TERAN is composed of two separate transformer modules - one for textual and one for visual data. Those transformer modules are responsible for high-level reasoning "about the spatial and abstract relationships between elements in the image and in the text separately" (Nicola et al., 2020) and output a contextual embedding per visual and textual input token. All weights of the model are trained via hinge-based triplet-loss leveraging global image-caption similarity scores computed by pooling matrices that contain the cosine-similarities between the visual and textual contextual embeddings. For long sentences with many words and a limited number of

36 visual tokens per image, it could be challenging to sample good (anchor, positive, negative) triplets required by the loss function and finally cause problems while training the model.

On the other hand, UNITER consists of a singular transformer component for both modalities. The model is pre-trained by a combination of several sophisticated self-supervised training tasks specially designed to tighten the alignment between words and image regions. This model architecture and the training process are more robust against long inputs because the self-attention heads can work on an arbitrary number of input tokens and the models' weights are directly updated by backpropagation. These advantages of UNITER compared to TERAN presumably result in much tighter word-region-alignments. Together with the considerably larger pre-training dataset, it would further explain why UNITER's results are much better than those of $\text{TERAN}_{\text{COCO}}$ and $\text{TERAN}_{\text{Flickr30k}}$.

By looking at the results in Table 2 and comparing them with the evaluation scores of the models trained and evaluated on COCO and Flickr30k, we can follow that the main reason all of the models perform poorly are the characteristics and distribution of WISMIR. TERAN models trained on COCO or Flickr30k perform much worse than the UNITER model, presumably because of the disadvantages in their architecture and training process. The TERAN model's evaluation scores trained on WISMIR clearly show the impact of the differences of the dataset compared to COCO, Flicker30k, and most probably also the other pre-training datasets of UNITER.

### 4.3 Future Experiments

As described in the previous sections, we identified multiple obstacles that need to be overcome to leverage multi-model transformers like TERAN for real-world information retrieval systems within a language learner context. Several experiments are planned for future work to tackle the issues: We will collect a new version of WISMIR where we augment the NEs in the data with their corresponding labels (”PER”, ”ORG”, etc.), and further increase the size of the dataset to examine the number of samples at which the performance does no longer improve. We will train and evaluate a new TERAN model on the improved WISMIR version to verify that the performance improves.

Text-image retrieval is hard to evaluate because the quality of the models' outcomes is subjective, and there are multiple relevant and ”correct” images for a given query. To overcome this issue, non-exact metrics like DCG or NDCG, which rely on relevance scores between the model results, are often used to evaluate information retrieval systems. The problem we are faced with is that there is no straightforward solution to compute these relevance scores for WISMIR. Therefore a small-scale user study planned to be conducted on Amazons' crowdsourcing platform, MTurk[10], to let humans assess the models' performance.

Additionally, we will collect a text-only L2 language learner dataset and let TERAN models trained on COCO, F30k, and WISMIR perform text-image retrieval with the sentences in the collected dataset. Afterward, we will conduct another crowdsourcing user study to assess the retrieved images' relevance according to the respective sentence. This study is an essential milestone on our roadmap to leverage state-of-the-art multi-modal transformer models since it will provide valuable hints towards our primary research goal.

## 5 Conclusion

In this paper, we verify our claim that state-of-the-art multi-modal Transformers for image-retrieval, which are pre-trained on common datasets like COCO and Flickr30k, cannot generalize well on more complex textual data. Therefore, we collected a multi-modal image-retrieval dataset based on data from Wikipedia, WISMIR, and conducted several data analysis experiments that underline its differences to COCO and Flickr30k. Additionally, we evaluated two state-of-the-art multi-modal transformers on text-image retrieval on this novel dataset to verify our claim. We discovered significant problems the evaluated models have with our dataset and in the dataset itself, which we will address in future work.

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[10] https://www.mturk.com/

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