ABSTRACT
There has been a recent spike in interest in multi-modal Language and Vision problems. On the language side, most of these models primarily focus on English since most multi-modal datasets are monolingual. We try to bridge this gap with a zero-shot approach for learning multi-modal representations using cross-lingual pre-training on the text side. We present a simple yet practical approach for building a cross-lingual image retrieval model which trains on a monolingual training dataset but can be used in a zero-shot cross-lingual fashion during inference. We also introduce a new objective function which tightens the text embedding clusters by pushing dissimilar texts away from each other. For evaluation, we introduce a new 1K multi-lingual MSCOCO2014 caption test dataset (XTD10) in 7 languages that we collected using a crowdsourcing platform. We use this as the test set for zero-shot model performance across languages. We also demonstrate how a cross-lingual model can be used for downstream tasks like multi-lingual image tagging in a zero-shot manner. XTD10 dataset is made publicly available here: https://github.com/adobe-research/Cross-lingual-Test-Dataset-XTD10

CCS CONCEPTS
• Computing methodologies → Neural networks.

KEYWORDS
multi-modal, zero-shot, cross-lingual, image retrieval, image tagging, metric learning, e-commerce, machine translation, query understanding, dataset, multi-lingual

1 INTRODUCTION
Image retrieval is a well studied problem in both academia and industry [8, 21, 32, 37, 40]. Most research looks at image retrieval in a monolingual setup for a couple of reasons:
• Lack of multi-lingual Vision-Language datasets supporting a wide range of languages
• Extensibility towards new and low-resource language support

Multi-lingual dataset collection has always been a major hurdle when it comes to building models in a one-model-fits-all style that can provide good results for image retrieval across multiple languages. Most methods [22, 28, 31] rely on direct translations of English captions while others [12, 20] have used independent image and language text pairs. Based on previous research learning we try to explore following ideas in this paper:
• One-model-fits-all: Can we use pre-trained cross-lingual embeddings with monolingual image-text training data to learn representations in a common embedding space for image retrieval and tagging?

• Multi-lingual Eval Dataset: Build an evaluation set for multi-lingual image retrieval to test in a zero-shot retrieval setup.

In our approach we try to take advantage of the recent developments in cross-lingual sentence embeddings [3, 38] which are effective in aligning multiple languages in a common embedding space. Due to scarcity of multi-lingual sentence test datasets, for evaluation we combine 10 non-English language annotations to create a Cross-lingual Test Dataset called XTD10.

As an extension of [1], in this paper we also try to take advantage of the One-model-fits-all approach on multi-lingual image tagging and tackle it as a zero-shot problem. Monolingual image tagging models, in languages other than English face extensibility issues and training data constraints similar to the image retrieval problem. Using an English image tagger and direct translation at tag level is a straightforward solution but its error prone because of word ambiguity which word-level translation systems lack the context to capture. Spring in French has two translations: Printemps (Season...
Spring) and ReSSort (Bouncy Spring). Translation models will predominantly return Printemps even for an image of a Bouncy Spring due to its wider presence in translation training data. Our contextual approach tackles these issues by capturing both the image context and text semantics irrespective of the language.

## 2 RELATED WORK

In an image retrieval system, image metadata (like tags) is often noisy and incomplete. As a result, matching low-level visual information with the user’s text query intent have become popular over time for large scale image retrieval tasks [19]. Metric learning is one way to achieve this, by projecting samples from different modalities in a common semantic representation space. [15] is an early mono-lingual method that does this.

One of the primary goals of our exploration is multi-lingual retrieval support and hence multi-lingual multi-modal common representations become a key aspect of our solution. Recent multi-lingual metric learning methods [5, 41] have tried to minimize distance between image and caption pairs as well as multi-lingual pairs of text. These approaches are limited based on availability of large parallel language corpora. [12] uses images as pivots to perform metric learning which allows text in one language to be independent of the other languages. [20] uses a similar approach but adds visual object detection and multi-head attention [34] to selectively align salient visual objects with textual phrases to get better performance. Similarly, [4, 23, 27] use language-independent text encoders to align different languages to a common sentence embedding space using shared weights along with simultaneously creating a multi-modal embedding space. This approach allows better generalization. While the above approaches provide value and insights to building a cross-lingual multi-modal space, we choose to use [29] as our baseline to measure our model’s performance as this was the only method we found which followed a zero shot approach, but on word level.

Getting dataset manually annotated in multiple languages can be a huge overhead, especially when dealing with large corpora. There have been initiatives to tackle this by web scraping, but many times the dataset ends up being very noisy. Datasets like [11, 14, 25, 36, 39] provide data with images for only 2-3 languages which do not help the dataset ends up being very noisy. Datasets like [11, 14, 25, 36, 39] have been initiatives to tackle this by web scraping, but many times a huge overhead, especially when dealing with large corpora. There have been initiatives to tackle this by web scraping, but many times the dataset ends up being very noisy. Datasets like [11, 14, 25, 36, 39] provide data with images for only 2-3 languages which do not help in scaling models to a large number of languages. Due to this, most of the models discussed above work with limited language support. Work that comes closest to ours is the Massively Multilingual Image Dataset [17] initiative. A big difference being they focus on parallel data for 100 languages, but the dataset is word-level concepts losing out on inter-concept and inter-object context within complex real world scenes that captions provide.

Image tagging has been typically addressed in a monolingual setting due to image tag data unavailability in multiple languages apart from English. Similar to the image retrieval problem, some efforts such as [25] assume the availability of labelled annotated images in multiple target languages and thereby are limited by their language inventory. Our solution in the cross-lingual space assumes or requires no labelled training corpus. Surprisingly, there are very few zero-shot cross lingual approaches, one of them being [35]. Wei et al proposes label-enhanced zero shot learning where they utilize a bi-skip model trained on English and Chinese corpus along with label scores from an English image tagger to create tag and image embeddings in a multi-modal bi-lingual space. Target tags are then generated using similarity based ranking. However, this method of creating multi-modal embeddings is dominant on the textual semantics and doesn’t accurately capture the image context which our approach tries to tackle.

## 3 PROPOSED METHOD

Towards solving the issues discussed above for multi-lingual image retrieval, we take a simple yet practical and effective zero-shot approach by training the model with only English language text-image pairs using metric learning to map the text and images in the same embedding space. We convert the English text training data into its cross-lingual embedding space for initialization which helps support multiple languages during inference. Figure 1 gives an overview of our approach.

### 3.1 Model Architecture

Most industry use cases involving images will have a pre-trained image embeddings model. It is expensive to build and index new embeddings per use case. Towards this optimization and without loss of generality, we assume there exists a pre-trained image embedding model like ResNet [16] trained on ImageNet [9]. We keep the image embedding extraction model frozen and do not add any trainable layers on the visual side. From pre-trained ResNet152 architecture, we use the last average pooled layer as the image embedding of size 2048.

On the text encoder end, we first extract the sentence level embeddings for the text data. We experiment with two state-of-the-art cross-lingual models - LASER [3] and Multi-lingual USE (or mUSE) [6, 38]. LASER uses a language agnostic BiLSTM [18] encoder to create the sentence embeddings and supports sentence-level embeddings for 93 languages. mUSE is a Transformer [34] based encoder which supports sentence-level embeddings for 16 languages. It uses a shared multi-task dual-encoder training framework for several downstream tasks.

After the sentence-level embedding extraction, we attach blocks of fully connected layer with dropout [33], rectified linear units (ReLU) activation layer [13] and l2-norm layer, in that order. The l2-norm layer helps to keep the intermediate feature values small. For the last block, we do not add l2-norm layer to be consistent with ResNet output features. From our experiments, 3 stacked blocks gave us the best results.

### 3.2 Training Strategy

For each text caption (anchor text) and (positive) image pair, we mine a hard negative sample within a training mini-batch using the online negative sampling strategy from [2]. We treat the caption corresponding to the negative image as the hard negative text.

We propose a new objective loss function called “Multi-modal Metric Loss (M3L)” which helps to reduce the distance between anchor text and its positive image, while pushing away both negative image and negative text from the anchor text.

$$L_{M3} = \frac{a_1 \cdot d(t_{an}, i_{mp})^\rho}{d(t_{an}, i_{an})^\rho} + \frac{a_2 \cdot d(t_{an}, i_{mp})^\rho}{d(t_{an}, t_{an})^\rho}$$  

(1)
Here \( tean \) is the text anchor, \( t_an \) is the negative text, while \( imp, im_n \) are the positive and negative images, respectively. \( d(x,y) \) is the square distance between \( x \) and \( y \). \( \rho \) controls the sensitivity of the change of distances. \( \alpha_1 \) and \( \alpha_2 \) are the scaling factors for each negative distance modality. For our experiments we see that when \( \rho = 4, \alpha_1 = 0.5 \) and \( \alpha_2 = 1 \), we get the best results. To confirm its efficiency, we compare our results with another metric learning loss called “Positive Aware Triplet Ranking Loss (PATR)” [2] which performs a similar task without negative text.

\[
L_{PATR} = d(tean, imp) + \max(0, \eta - d(tean, im_n)) \tag{2}
\]

here \( \eta \) penalizes the distance between anchor and negative image, therefore controlling the tightness of the clusters. In our experiments \( \eta = 1100 \) gave the best performance.

We use a learning rate of 0.001 along with Adam Optimizer [24] (beta1=0.99). We add a dropout of [0.2, 0.1, 0.0] for each of the fully connected layers of dimension [1024, 2048, 2048], respectively. As we want hard negatives from our mini-batch, we take a large batch size of 128 and train our model for 50 epochs.

3.3 Multi-lingual Downstream Tasks

Here we discuss how we utilize our model for downstream tasks like image retrieval and image tagging during inference in a multi-lingual fashion. Both tasks comprise of two phases: extraction and ranker.

3.3.1 Image Retrieval. We first extract and index the image embeddings for all the images in our retrieval corpus using the last average pooled layers of the ResNet152 architecture. Given a user text query in any language supported by the model, we extract its embedding using the last FC layer output of the trained cross-lingual multi-modal text encoder. We then find the similarity scores between the text embedding and the indexed image embeddings using a distance metric, for example cosine similarity or square distance. Finally, images are ranked based on their similarity scores. A threshold can be set on the similarity score below which the images will be filtered out.

3.3.2 Image Tagging. Figure 2 gives an overview of our approach on zero-shot multi-lingual image tagging as a downstream task. As aforementioned, cross-lingual image tagging utilizes an image tagging model trained to generate tags in the source language. We also assume source and target tags vocabulary availability in our solution.

The first step under extraction phase is to extract and index the text embeddings for the entire target language tag vocabulary using the last FC layer output of the trained cross-lingual multi-modal text encoder. Given a query image, we obtain source tags using an image tagger and extract the text embeddings for each of the tags again by using the trained text encoder. Similar to image retrieval task, the image embedding is extracted from the ResNet152 model using the last averaged pool layer.

For ranking, we compute two sets of cosine similarities using these embeddings: between image-target language tags (eq. 3) and source tags-target language tags (eq. 4). These two similarity values are then used to assign a score to each tag from target vocabulary per source tag (eq. 5).

4 EVALUATION

4.1 Dataset

We have used MSCOCO 2014 [26] along with our human annotated dataset XTD10 (Table 1) for testing and Multi30K dataset [10] for our experiments on image retrieval.

Table 1: Test Dataset languages and families

| Language        | Family           |
|-----------------|------------------|
| English(en)     | Germanic         |
| German(de)      |                  |
| French(fr)      | Slavic           |
| Italian (it)    |                  |
| Spanish (es)    |                  |
| Russian(ru)     | Japonic          |
| Polish(pl)      | Sino-Tibetan     |
| Korean(ko)      |                  |
| Turkish(tr)     |                  |
| Chinese Simplified(zh) |                |
| Japanese(ja)    |                  |

Figure 2: Overview of Multi-lingual Tagger during inference

\[
T_i \in \text{TargetVocab} \\
S_j \in \text{SourceTags} \\
Sim_{Img,T_i} = \cosim(\text{embedding}_{img}, \text{embedding}_{T_i}) \tag{3} \\
Sim_{S_j,T_i} = \cosim(\text{embedding}_{S_j}, \text{embedding}_{T_i}) \tag{4} \\
\text{for each } S_j \in \text{SourceTags} : \\
\text{for each } T_i \in \text{TargetVocab} : \\
\text{Score}_{T_i} = W_1 \ast Sim_{Img,T_i} + W_2 \ast Sim_{S_j,T_i} \tag{5} \\
\text{Rank TargetVocab tags}
\]

Upon ranking on the basis of these scores per source tag, the top tag is taken as the target language annotation for that source tag. If top tag has already been taken as annotation for one of the previous source tags, the next highest ranked tag is used. We rank per source tag to maintain the equality in source and target language annotations.

The equation variables are corpus dependent. In our experiments we observed best results on 0.65 and 0.35 for \( W_1, W_2 \) respectively.
Table 2: Image Retrieval Recall @10 on the XTD10 dataset for 11 different languages including English

| Model       | en  | de  | fr  | it  | es  | ru  | ja  | zh  | pl  | tr  | ko  |
|-------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| LASERPATR   | 0.803 | 0.702 | 0.686 | 0.673 | 0.682 | 0.677 | 0.572 | 0.672 | 0.666 | 0.597 | 0.518 |
| mUSEPATR    | 0.836 | 0.712 | 0.756 | 0.769 | 0.761 | 0.734 | 0.643 | 0.736 | 0.718 | 0.669 | 0.694 |
| LASERM3L    | 0.815 | 0.706 | 0.712 | 0.701 | 0.714 | 0.686 | 0.583 | 0.717 | 0.689 | 0.652 | 0.533 |
| mUSEM3L     | 0.853 | 0.733 | 0.789 | 0.789 | 0.767 | 0.736 | 0.678 | 0.761 | 0.717 | 0.709 | 0.707 |

Table 3: Image Retrieval Recall @10 Multi30K dataset

| Text (en)                                                                 | en  | de  | fr  | it  | es  | ru  | ja  | zh  | pl  | tr  | ko  |
|---------------------------------------------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| two computer screens and keyboards side by side on a desktop              |     |     |     |     |     |     |     |     |     |     |     |
| a person in ski attire posing under a sign giving directions               |     |     |     |     |     |     |     |     |     |     |     |
| a group of pedestrians walking past a subway train at a subway station     |     |     |     |     |     |     |     |     |     |     |     |
| a large pizza with pepperoni and a beer are seen here                      |     |     |     |     |     |     |     |     |     |     |     |
| a cute little brown teddy bear sits on a rock by a bush                    |     |     |     |     |     |     |     |     |     |     |     |
| a close up of a traffic light with a building in the background           |     |     |     |     |     |     |     |     |     |     |     |

Figure 3: Recall@1 qualitative results. We have mentioned only English language captions in this figure. The results which are correctly ranked as 1 for their corresponding language's caption are bordered green.

Table 3: Image Retrieval Recall @10 Multi30K dataset

| Model     | train langs | en  | de  | fr  |
|-----------|--------------|-----|-----|-----|
| Baseline  | en,fr,de     | 0.546 | 0.450 | 0.469 |
| Ours      | en,fr,de     | 0.581 | 0.522 | 0.572 |
| Baseline  | en           | 0.566 | 0.442 | 0.460 |
| Ours      | en           | 0.591 | 0.488 | 0.548 |

4.1.1 MSCOCO 2014 and XTD10. For MSCOCO2014 dataset, we use the train-val-test split provided in [30]. To convert the test set into 1K image-text pairs, for each image we sample the longest caption. As MSCOCO2014 dataset is only in English, to evaluate our model we use the French and German translations provided by [30]. Japanese annotations for the 1K images provided by [39] and for the remaining 7 languages, we got 1K test human translated captions. Except for Japanese, all other languages are direct translations of the English test set. Together, we call this test set the Cross-lingual Test Dataset 10 (XTD10).

4.1.2 Multi30K. In Multi30K dataset, every image has a caption in English, French and German. We split the data 29000/1014/1000 as train/dev/test sets.

4.2 Quantitative Results

4.2.1 Image Retrieval. We report the Recall@10 using XTD10 dataset for each of the models trained only on English language in Table 2. We show the comparison between LASER and mUSE sentence-embeddings using PATR and M3L metric learning losses. Because the train data is only in English, we see stronger performance with English which acts as our upper bound. With zero-shot learning, we obtain comparable performance for all the other 10 non-English languages that we test on. We observe best results when applying M3L + mUSE as the addition of negative text in the loss function creates tighter text clusters in the metric space. However, for Slavic
Towards Zero-shot Cross-lingual Image Retrieval and Tagging

Figure 4: Visualization of the Multi-modal Cross-lingual space: t-SNE Scatter Plot for Italian text embeddings ("o") overlayed on ResNet152 Image embeddings ("x"). Subcategories are plotted based on ResNet152 clustering (best seen in color).

Figure 5: Visualization of the Cross-lingual space: Multi-lingual USE vs LASER: t-SNE Scatter Plots represent non-English cross-lingual embeddings ("x") overlayed on their respective English cross-lingual embeddings ("o").

languages like Russian and Polish, we don’t see much difference in performance when using mUSE with negative text in English. On clustering the cross-lingual non-English embeddings with respective English embeddings for both mUSE and LASER, we saw very clear overlapping for mUSE compared to LASER across all languages. Therefore, we see consistency in the performance across all languages for models trained with mUSE. We also see a similar trend in performances reported in Table 2 between mUSE and LASER in Table 7 in [38]. We also suspect that because LASER is trained with more languages and is a less complex model, it generalizes more than mUSE.

We also report the Recall@10 using Multi30K dataset with our model trained on M3L + mUSE and [29] as our baseline in Table 3. The Baseline uses MUSE [7] cross-lingual word embeddings for training. Our method outperforms Baseline in both multi-lingual and zero-shot training. Comparing multi-lingual vs zero-shot training, we see that training with all languages decreases performance for English due to model generalization. In zero-shot setup, the recall accuracies for German and French dip slightly yet are comparable with the multi-lingual training result.

4.3 Qualitative Results

4.3.1 Image Retrieval. In Figure 5 we see that the English and non-English mUSE cross-lingual embeddings are more tightly clustered with each other as compared to LASER embeddings. This explains why we get retrieval results for non-English languages closer to its English counterpart for mUSE as compared to LASER. We use USEM3L model results trained on MSCOCO2014 dataset for next two observations. Figure 4 demonstrates the visual embeddings alignment with Italian multi-modal cross-lingual clustering. In Figure 3 we have visualized the images retrieved at Rank 1 for 11 languages. Our model is able to capture all the objects in most results across all languages. The R@1 for 3rd and 6th example for languages which do not give the desired image as Rank 1, still cover all the object concepts in their corresponding text captions. For the 5th example, we see that for French, the image at R@1, the 2 objects rock and bush are covered in the image, but not teddy bear. This is because its French caption “un petit ourson brun mignon assis sur un rocher par un buisson” doesn’t cover teddy concept as when translated to English it says ‘a cute little brown bear sitting on a rock by a bush’. But we do get the desired result when we use the Google translated English to French caption instead.

4.3.2 Image Tagger. For our experiments we use an image tagger created using 6M Adobe Stock images to generate only English tags, while the source and target language tags vocabulary is created using Adobe Stock unique image tags. The cross-lingual multi-modal text encoder is trained on 20M Adobe Stock image-caption pairs and 6M Adobe Stock clickthrough dataset with the same architecture and parameter specifications mentioned in this paper. We want to emphasize that the solution is independent of the source image tagger, text encoder and tag vocabularies which can be easily replaced.

Currently cross-lingual multi-modal domain doesn’t offer evaluation datasets for image tagging, therefore for multi-lingual image tagging we compare our results with direct word translation using Google Translate. We are working on creating a dataset like the proposed XTD10 for image tags which we will release in our future work. We demonstrate our results on French and German as target

2https://translate.google.com/
3https://stock.adobe.com/
| Image | Source Tags | French | German |
|-------|-------------|--------|--------|
| river, water, landscape, forest, park, reflection, trees, grass, pond, scene, clouds, bank | rivière, eau, paysage, forêt, parc, réflexion, arbres, héte, étang, scène, nuages, banque | fluss, wasser, landschaft, wald, park, reflexion, bäume, teich, see, wohnen, bank | architektur, gebäude, bank, weiß, wind, front, struktur, fasade, für, wohnung, eigentum, isoliert |
| architecture, building, bank, white, wall, front, structure, facade, door, apartment, property, isolated | architecture, bâtiment, banque, blanc, mur, avant, structure, façade, porte, appartement, propriété, isolé | architektur, gebäude, bank, weiß, wind, front, struktur, fasade, für, wohnung, eigentum, isoliert | architektur, gebäude, bank, weiß, wind, front, struktur, fasade, für, wohnung, immobilien, isoliert |
| turkey, bird, poultry, farm, red, grass, hen, food, feathers, black, tail, meat | dinde, oiseau, volaille, ferme, rouge, herbe, poule, nourriture, plumes, noir, queue, viande | truthahn, vogel, geschlüpft, baumhoch, rot, gras, hennen, rühren, federn, schwarz, schwanz, fleisch | truthahn, vogel, geschlüpft, baumhoch, rot, gras, hennen, rühren, federn, schwarz, schwanz, fleisch |
| instantbush, monkey, turkey, architecture, minaret, religion, dome, turkish, hagia sofi, ottoman, old, monument | instantbush, mosquée, dinde, architecture, minaret, religion, dôme, turc, hagia sofia, ottoman, vieux, monument | instantbush, mosquée, truthahn, architectur, minaret, religion, kupel, türkisch, hagia sofia, ottomane, alte, denkmal | instantbush, mosquée, turke, architectur, minaret, religion, kupel, türkisch, hagia sofia, ottomane, alt, denkmal |
| spring, metal, spiral, object, wire, steel, silver, abstract, equipment, metallic, curve, shiny | printemps, métal, spirale, objet, fil, acier, argent, résumé, équipement, métallique, courbe, brillant | frühlings, metall, spirale, objet, drah, stahl, silber, abstrakt, australian, metallisk, kurve, glänzend | feder, metall, spirale, objet, drah, stahl, silber, abstrakt, australian, metallisk, kurve, glänzend |
| trees, spring, blossom, nature, landscape, grass, pink, green, flowers, park, blooming, meadow | arbres, printemps, fleurir, nature, paysage, herbe, rose, vert, fleurs, parc, floraison, pré | bümle, frühlings, blüte, natur, landschaft, gras, rosa, grün, blumen, park, blüte, wiese | bümle, frühlings, blüte, natur, landschaft, rosa, rosa, grün, blumen, park, blüte, wiese |
| building, architecture, flat, sky, urban, city, exterior, residential, balcony, house, window, glass | bâtiment, architecture, plat, ciel, urbain, ville, extérieur, résidentiel, balcon, maison, fenêtre, verre | gebäude, architektur, eben, himmel, stad, stad, außen, wohnen, balkon, haus, fenster, glas | gebäude, architektur, wohnung, himmel, stad, stad, außen, wohnen, balkon, haus, fenster, glas |

Figure 6: Comparison of our contextual multi-lingual image tagging with word level tag translation

language. In Figure 6 we demonstrate the difference between word-level translation and our image context based tagger. We can see that for ambiguous words like spring, turkey, bank, etc. google translation results are same even if the image context is different. Our tagger accurately captures the context. It can distinguish between spring as a season or as an object; turkey as a bird or as a country; Bank as a monetary bank or as a river bank. For the image of an apartment building, we manually replaced the source tag apartment with flat. Our multi-lingual tagger is able to capture the context of the image and provide the correct translation appartements instead of Plat for French and wohnung instead of eben for German. We can also observe that for river bank and spring season images, our multi-lingual tagger results differ from google translation for the tag grass. The English translations for the tags gazon, rasen for French, German respectively is closer to a lawn than grass as a plant. Our tagger is able to extract that context from these images which is missing in google translation.

5 CONCLUSION

We propose a zero-shot setup for cross-lingual image retrieval and evaluated our models with 10 non-English languages. This practical approach can help scale to languages in scenarios where multi-lingual training data is scarce. We also demonstrate how this model can be applied in a zero-shot manner to a downstream task like multi-lingual image tagging. In future we plan to investigate few-shot setup where some training data is available per language and fine-tuning the image side along with the text side in an end-to-end fashion further improves the retrieval accuracy. We also plan on creating a new evaluation dataset for multi-lingual image tagging to help standardize efforts in this domain.

6 ACKNOWLEDGMENT

We thank Tracy King for guiding us through this project and Mayank Dutt for assisting in the dataset annotation process.

REFERENCES

[1] Pranav Aggarwal and Ajinkya Kale. 2020. Towards Zero-shot Cross-lingual Image Retrieval. arXiv:2012.05107 [cs.CL]
[2] Pranav Aggarwal, Zhe Lin, Baldo Faieta, and Saeid Motiian. 2019. Multitask Text-to-Visual Embedding with Titles and Clickthrough Data. CoRR abs/1905.13339 (2019). arXiv:1905.13339 http://arxiv.org/abs/1905.13339
[3] Mikel Artetxe and Holger Schwenk. 2018. Massively Multilingual Sentence Embeddings for Zero-Shot Cross-Lingual Transfer and Beyond. CoRR abs/1812.10464 (2018). arXiv:1812.10464 http://arxiv.org/abs/1812.10464
[4] Andrea Burus, Donghyun Kim, Derry Wijaya, Kate Saenko, and Bryan A. Plummer. 2020. Learning to Scale Multilingual Representations for Vision-Language Tasks. arXiv:2004.04312 [cs.CV]
[5] Jacer Calixto, Qun Liu, and Nick Campbell. 2017. Multilingual Multi-modal Embeddings for Natural Language Processing. arXiv:1702.01101 [cs.CL]
[6] Muthuraman Chidambaram, Yinfei Yang, Daniel Cer, Steve Yuan, Yuan-Hsuan Sung, Brian Strope, and Ray Kurzweil. 2018. Learning Cross-Lingual Sentence Representations via a Multi-task Dual-Encoder Model. CoRR abs/1810.12836 (2018). arXiv:1810.12836 http://arxiv.org/abs/1810.12836
[7] Alexis Conneau, Guillaume Lample, Marc'Aurelio Ranzato, Ludovic Denoyer, and Hervé Jégou. 2018. Word Translation Without Parallel Data. arXiv:1710.04087 [cs.CL]
[8] Ritendra Datta, Dhiraj Joshi, Jia Li, and James Z Wang. 2008. Image retrieval: Ideas, influences, and trends of the new age. ACM Computing Surveys (Csur) 40, 2 (2008), 1–60.
[9] J. Deng, W. Dong, R. Socher, L. Li, Kai Li, and Li Fei-Fei. 2009. ImageNet: A large-scale hierarchical image database. In 2009 IEEE Conference on Computer Vision and Pattern Recognition. 248–255.
[10] Desmond Elliott, Stella Frank, Loïc Barrault, Fethi Bougares, and Lucia Specia. 2017. Findings of the Second Shared Task on Multimodal Machine Translation and Multilingual Image Description. In Proceedings of the Second Conference on
