mOSCAR: A Large-scale Multilingual and Multimodal Document-level Corpus

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Abstract

Multimodal Large Language Models (mLLMs) are trained on a large amount of text-image data. While most mLLMs are trained on caption-like data only, Alayrac et al. [2022] showed that additionally training them on interleaved sequences of text and images can lead to the emergence of in-context learning capabilities. However, the dataset they used, M3W, is not public and is only in English. There have been attempts to reproduce their results but the released datasets are English-only. In contrast, current multilingual and multimodal datasets are either composed of caption-like only or medium-scale or fully private data. This limits mLLM research for the 7,000 other languages spoken in the world. We therefore introduce mOSCAR, to the best of our knowledge the first large-scale multilingual and multimodal document corpus crawled from the web. It covers 163 languages, 315M documents, 214B tokens and 1.2B images. We carefully conduct a set of filtering and evaluation steps to make sure mOSCAR is sufficiently safe, diverse and of good quality. We additionally train two types of multilingual model to prove the benefits of mOSCAR: (1) a model trained on a subset of mOSCAR and captioning data and (2) a model train on captioning data only. The model additionally trained on mOSCAR shows a strong boost in few-shot learning performance across various multilingual image-text tasks and benchmarks, confirming previous findings for English-only mLLMs. The dataset can be accessed here.²

1 Introduction

Multimodal large language models (mLLMs) are trained on large amounts of text-image data [Radford et al., 2021, Yu et al., 2022, Li et al., 2023, Wang et al., 2023, OpenAI, 2023, Gemini Team et al., 2023, Chameleon Team, 2024]. The main paradigm until recently was to train a model from a large collection of web-crawled images and their captions [Li et al., 2021, Wang et al., 2022, Chen et al., 2023b]. Models such as Flamingo [Alayrac et al., 2022] challenged this paradigm by being additionally trained on interleaved sequences of text and images from web documents, showing state-of-the-art results on various tasks and in-context learning capabilities that are not present in models trained on caption-like data only. Additionally, McKinzie et al. [2024] recently proved that including interleaved text-image data during training was necessary to get good few-shot learning performance. However, the datasets used to train mLLMs are either private [Alayrac et al., 2022],

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²https://oscar-project.github.io/documentation/versions/mOSCAR/

Le square René Viviani a été ouvert au public en 1928. Il occupait l'emplacement de l'annexe de l'Hôtel-Dieu (il est situé en face de Notre Dame) et d'une rangée de maisons longeant la rue de la Bücherie. Le conseiller municipal Léon Riotor et la Commission du Vieux Paris ont particulièrement oeuvré à sa création dans le but de préserver à la fois le dégagement de l'église Saint-Julien-le-Pauvre et la perspective de Notre-Dame. Quelques éléments architecturaux parsèment le parc, et contribuent à son charme : pinacles, chapiteaux, balustrades, provenant sans doute de la cathédrale Notre-Dame. [...]

Pinacles et chapiteaux ornent le parc : probablement des vestiges de Notre-Dame. La fine poussière derrière la balustrade de pierre provient du fort vent qui faisait s'envoler le sable et la terre. [...]

Figure 1: Example of a French document from mOSCAR.

monolingual or multilingual but only medium-scale [Srinivasan et al., 2021]. Some attempts have been made to reproduce these datasets [Zhu et al., 2023, Laurençon et al., 2023] but the resulting datasets are only available in English.

Few image-text datasets are multilingual and most of them are obtained by translating English caption-like datasets, such as multilingual Conceptual Captions [Sharma et al., 2018], into multiple languages using neural machine translation (NMT) systems [Surís et al., 2022, Maaz et al., 2024]. This presents some drawbacks such as some languages still being poorly translated by current state-of-the-art NMT models [Liu et al., 2020, Costa-jussà et al., 2022] and some cultural subtleties inherent in each language not being fully conveyed. Some efforts have been conducted to collect large-scale multilingual image captioning datasets, such as LAION-5B [Schuhmann et al., 2022], but they are limited to caption data too, are relatively noisy and more importantly contain a non-negligible share of "not safe for work" (NSFW) content such as pædopornographic images [Schuhmann et al., 2022].

This motivated us to collect and release the first large-scale multilingual and multimodal document dataset derived from Common Crawl.³ Our dataset, multimodal OSCAR (mOSCAR), follows the OSCAR initiative [Ortiz Suárez et al., 2019, Abadji et al., 2021, 2022] and covers 315M documents in 163 languages, 214B tokens and 1.2B images. Figure 1 shows an example of a document, more can be found in Appendix A.3. We carry out extensive filtering to increase its safety and quality. To prove mOSCAR's utility, we train a multilingual OpenFlamingo [Awadalla et al., 2023] from a Gemma-2B language model [Gemma Team et al., 2024] on a subset of mOSCAR and captioning data from LAION-400M [Schuhmann et al., 2021], recaptioned with BLIP [Li et al., 2022], filtered with CLIP [Radford et al., 2021] and translated with NLLB [Costa-jussà et al., 2022]. We compare against a similar model trained on captioning data only and show we obtain a strong boost in few-shot learning, confirming previous findings for English [Alayrac et al., 2022, McKinzie et al., 2024, Laurençon et al., 2024]. The dataset and models will be made publicly available.

2 Related Work

Large-scale web-based datasets Numerous datasets have been created by filtering web-crawled data. These include large-scale text-only datasets [Ortiz Suárez et al., 2019, Raffel et al., 2020, Wenzek et al., 2020, Gao et al., 2020, Abadji et al., 2021, Xue et al., 2021, Laurençon et al., 2022, Abadji et al., 2022, Penedo et al., 2023] and multimodal ones [Sharma et al., 2018, Changpinyo et al., 2021, Jia et al., 2021, Schuhmann et al., 2021, 2022, Byeon et al., 2022, Laurençon et al., 2023, Zhu et al., 2023, Gadre et al., 2024]. Even if these datasets are not as high quality as smaller and/or hand-crafted ones, they are now the standard to pretrain foundation models, as it has been shown that training bigger models on more data leads to better downstream performances [Brown et al., 2020, Hoffmann et al., 2022, Touvron et al., 2023a,b].

English image-text datasets The first open-source image-text datasets were manually created, small-scale and English-only [Ordonez et al., 2011, Lin et al., 2014, Plummer et al., 2015, Krishna

³https://commoncrawl.org/. The Common Crawl Foundation is a non-profit organization that crawls the web on a monthly basis.

et al., 2017]. Scaling up these datasets was an appealing solution to overcome limitations of previous image-text models; a few works [Sharma et al., 2018, Changpinyo et al., 2021] proposed to collect millions of image-text pairs from the web before filtering them with well-designed steps. Relaxing the filtering steps enabled the collection of more data and led to large-scale datasets to train image-text foundation models [Radford et al., 2021, Li et al., 2021, Schuhmann et al., 2021, 2022, Byeon et al., 2022]. However, these datasets generally contain caption-like image-text pairs only, and it is therefore difficult to observe in-context learning abilities similarly to text-only language models trained on raw documents [Raffel et al., 2020]. Alayrac et al. [2022] overcome this issue by training their model directly on documents with interleaved image-text data. While their results are promising, their M3W dataset is English-only and private. Recently, open-source efforts [Zhu et al., 2023, Laurençon et al., 2023] have been made to release a similar dataset but they are still monolingual.

Multilingual image-text datasets Only a few image-text datasets are available in multiple languages. One of the first focused on collecting Google images from short queries based on word frequencies from Wikipedia pages in 98 languages [Hewitt et al., 2018]. Later, Srinivasan et al. [2021] proposed the WIT dataset, an image-text dataset composed of Wikipedia pages. Although of high quality, it is only medium-scale even for high-resource languages and there are fewer than 50k unique images for most languages. Another approach lies in bootstrapping multilingual and multimodal data from a model trained with English-only data [Mohammed et al., 2023]. While effective for captioning, it is computationally expensive to implement in practice. Other multilingual image-text datasets exist but focus on captions only and are highly domain-specific [Kosar et al., 2022, Leong et al., 2022].

3 Dataset Creation Pipeline

3.1 Data collection

We collect mOSCAR from the Web ARchive Content (WARC) files of three 2023 Common Crawl dumps, processing them using the FastWARC library [Bevendorff et al., 2021]. We remove documents smaller than 500 bytes (50% of the documents), as we find they are usually too small to be considered documents and tend to contain noisy text. We then navigate through the entire Document Object Model (DOM) tree with a depth first search algorithm and ChatNoir library [Bevendorff et al., 2018] to extract nodes of interests corresponding to specific HTML tags.

Following previous work, we extract text from the tags that usually contain the main content of web pages (we refer to them as DOM text nodes), i.e. , <h*>, <title>, <description>, , , <aside>, <dl>, <dd>>, <dt>>. Similarly to [Laurençon et al., 2023], we choose to remove content as most often it is irrelevant and difficult to render. We extract all tags (we refer to them as DOM image nodes). We then remove documents with fewer than 3 text nodes (as they do not contain enough text) and more than 30 image nodes (as we found them to be too noisy).

3.2 Language identification

We identify the language of each document using the state-of-the-art open-LID language detector [Burchell et al., 2023], covering 201 languages. We apply open-LID to each DOM text node and keep the three most probable languages with their respective probabilities. The language of the document is then determined by summing over the probabilities of each language detected for each text segment, weighted by the number of characters in the segment⁴ and taking the language with the highest score.

3.3 Text-only filtering

We apply a series of filtering steps to the text content of each document independently of the images, with the aim of discarding poor quality documents and cleaning text as best as possible. We first filter at the text-node level and then at the whole document level, before running near-deduplication to keep unique text nodes within a document and unique documents in the dataset.

⁴This is to avoid mis-assigning the language due to the presence of many short, non-informative DOM text nodes in the same language (e.g. "Cookies", "Subscribe", "Newsletter" etc.) and because language identification is generally less reliable for short segments.

Text node filtering We use a set of heuristics (see Appendix A.2) to extract as much humangenerated content as possible while discarding noisy text related to ads and website functions (e.g. "Instagram", "Facebook"). We then keep DOM text nodes with content over 10 bytes. This step, designed to improve the quality of extracted text, removes on average 55% of text nodes.

Document filtering We mostly filter "not safe for work" (NSFW) content at the document level. We use an English regular expression to detect adult content, similar to the one used by the Université Toulouse 1 Capitole⁵ and remove the entire document if there is a match with any of the DOM text nodes' contents, removing on average 0.5% of documents (mostly English ones). We acknowledge that there is a high probability that this also discards safe content, e.g. we could remove content from certain communities who use some explicit words in a non-sexual way [Sap et al., 2019]. However, we explicitly favour recall over precision to minimise the risk of unsafe content. We additionally remove documents containing fewer than five DOM text nodes and fewer than 300 characters after the previous filtering steps, removing 70.6% of documents.

Deduplication We conduct several types of per-language deduplication at different levels, as this has been shown to improve training efficiency [Abbas et al., 2023]. First, we keep unique documents only by removing exact duplicates at the document level. We also remove exact duplicates of text nodes within the same document (4% of text nodes) and near-duplicate text nodes (1% of text nodes) by computing the Levenshtein ratio [Levenshtein, 1966] between all text nodes within the same document and applying a threshold of 0.95. If near-duplicates are found, we keep the first one in the document. Finally, we conduct per language near-deduplication at the document level with MinHashLSH [Broder, 1997, Gionis et al., 1999] following Smith et al. [2022], removing on average 19% of documents: we turn documents into hashing vectors, compute min hashes from these vectors and perform Locality Sensitive Hashing to remove duplicates? (see Appendix A.5 for more details).

3.4 Image-only filtering

We downloaded images from the URLs in DOM image nodes using a modified version of the img2dataset toolkit [Beaumont, 2021] that includes an antivirus scan and follows robots.txt instructions to respect the Robots Exclusion Protocol. We then apply a series of filtering steps, first removing images based on heuristics, and then applying multiple NSFW detection models to remove undesirable content. Finally, we conduct a set of deduplication steps.

Rule-based filters Similarly to previous works [Schuhmann et al., 2021] and to avoid extracting low-resolution images and favicons, we keep images with a minimum height and width of 150 pixels. We restrict the aspect ratio to be between 3 and 1/3 (to remove banners), we remove images if their URLs contain the words "logo", "banner", "button", "widget", "icon" or "plugin" or if the image name from the URL matches "twitter", "facebook" or "rss" (to remove logos). This step removes 13.6% of the URLs. At this stage, we downloaded 2.5B images with an average success rate of 55%.

NSFW detection We use multiple NSFW automatic models to remove as much unsafe content as possible. We first combine two NSFW detectors: nsfw-detector [Laborde], a 5-class classifier with a MobileNet [Howard et al., 2017] backbone fine-tuned on 60GB of annotated data and NudeNet, ⁸ an object detector trained to detect different types of nudity in images. We combined the two models as we found the first to be gender-biased while the second gives a large number of false positives for non-human images. Concretely, we consider an image an NSFW candidate if the sum of the probabilities for the classes 'porn' and 'hentai' is superior to 0.8 using nsfw-detector. We then tag the image as NSFW if one of the sensitive 'exposed' classes of NudeNet gets a probability superior to 0.5. We additionally use Safer by Thorn⁹, a private pornography detector, and tag the image as NSFW if the probability of the class 'pornography' is superior to 0.8. If a document contains an image with an NSFW tag, we remove the entire document from the dataset, which removes 0.5% of

⁵https://dsi.ut-capitole.fr/blacklists/index_en.php

⁶With some disparity among languages as we found more duplicates for low- than high-resource languages.

⁷We performed this using the datasketch python library.

 $^{^8 {\}tt https://github.com/vladmandic/nudenet}$

⁹https://safer.io/

images. We manually inspecting 1,000 images of the remaining data and found no NSFW content. We manually inspected 1,000 images of the removed content and found 63.4% of NSFW images.

CSAM content Child Sexual Abuse Material (CSAM) is widespread on the internet and is therefore likely to be found in such a large-scale dataset crawled from the web. Removing CSAM is challenging as there is no training data nor open-source detection models available as these could be used in a harmful way. We again rely on Safer, a proprietary 3-class classifier trained to detect CSAM and pornography content from images. We tag the image as CSAM if the probability of the class CSAM is superior to 0.4 to favour recall over precision. As mentioned above, if a document contains an image with a CSAM tag, we remove it from the dataset. This step removes 0.07% of the images.

Deduplication To avoid memorisation issues often seen in models trained on datasets with many duplicated images [Somepalli et al., 2023, Carlini et al., 2023, Webster et al., 2023, Somepalli et al., 2024], we perform deduplication at the image level. We first remove duplicate images within the same document by URL matching (removing 8.7% of URLs). We then compute a perceptual hash (pHash) for each image using the imagehash library ¹⁰ and remove images with the same pHash within the same document, keeping only the first occurrence. We also limit the number of times an image can appear in the dataset per-language to 10 using both URL matching and perceptual hashing (this removes 2.5% of images). We do this per-language and not across languages as having the same images in documents from different languages could encourage cross-lingual transfer.

3.5 Data decontamination

LLMs and mLLMs are trained on web-crawled data that can contain the benchmarks they are tested on [Dodge et al., 2021]. As they are good at memorizing training data [Carlini et al., 2023], this data contamination is problematic. We therefore discard all images with the same perceptual hash as any of the images from the evaluation benchmarks (and their training sets) we use (see Section 5.1). This step removes on average 126,016 images for high-resource languages (up to 300K images for English), 6,862 images for mid-resource languages and 45 images for low-resource languages.

3.6 Text-image joint filtering

Our aim is to obtain truly multimodal documents where all images are related to at least one of the text nodes in some way¹¹ and vice versa. We choose to apply joint text-image filtering to discard images and/or text nodes that are irrelevant to the rest of the document (e.g. the case of ads and website functionalities). To do this, we use NLLB-SIGLIP¹² [Visheratin, 2023], a multilingual version of SIGLIP [Zhai et al., 2023] trained with the encoder of NLLB [Costa-jussà et al., 2022], which covers all mOSCAR languages. 13 We compute cosine similarity scores between all images and all paragraphs¹⁴ within a same document. To remove irrelevant text nodes or images in a document, we mimic a text-image retrieval task, which means we avoid using arbitrary cosine similarity thresholds for each language and can reduce length biases and those in favour of caption-like paragraphs. For each candidate pair we randomly sample 63 negative images and 63 negative similar-length paragraphs from the same language but other documents. We tag the text node (resp. image) as valid if the cosine similarity of the pair is among the top 8 of the text-to-image (resp. image-to-text) similarity scores computed with the candidate text node (resp. image) and all the negative images (resp. text nodes). This means that we tag the text node (resp. image) as valid if it has a significantly higher score than a score computed with a random image (resp. text) for at least one of the images (resp. text node) in the document. We then discard text nodes and images not tagged as valid (on average 35% of the DOM text nodes and 10% of the images within a document). After this filtering step, we apply additional text-only filters to keep documents superior to 100 bytes.

 $^{^{10} \}verb|https://github.com/JohannesBuchner/imagehash|$

¹¹We do not limit ourselves to caption-like relation and instead allow all types of text-image relation.

¹²siglip-base-patch16-224 as vision encoder and nllb-distilled-600M as text encoder.

¹³We use the open-clip [Ilharco et al., 2021] model version and the transformers [Wolf et al., 2020] library.

¹⁴We refer to paragraph as the text content in a DOM text node.

4 Multimodal Open Super-large Crawled Aggregated coRpus (mOSCAR)

mOSCAR is extracted from three Common Crawl dumps from 2023. Due to computational constraints and in order to extract a maximum number of documents for low-resource languages, we extracted all languages from the first dump only. We removed the 6 most high-resource languages from the second dump and only extracted the languages with fewer than 1M documents for the last dump. Table 1 shows a distribution of the total number of languages and their number of documents.

To avoid data poisoning [Carlini et al., 2024], we release a hash (sha512) with each mOSCAR image.

#documents	10M	5M	1M	500K	200K	50K	10K	5K	1K
#languages	10	15	38	49	58	82	129	142	163

Table 1: Number of languages with at least N documents

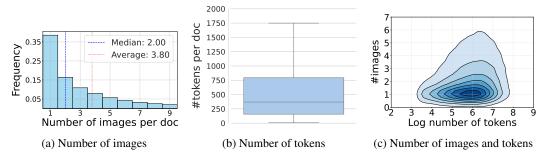


Figure 2: Distributions of numbers of tokens and images per document

mOSCAR is composed of 315M documents (214B tokens, 1.2B images) from 163 languages. Figure 2 shows the distribution of images and tokens per document and their joint distribution. As shown in Figure 2a, the mean and median number of images per document is 2 and 3.80.

4.1 Quality vs Diversity

While improving overall data quality, the filtering steps we applied (see Section 3) necessarily have a negative impact on diversity. We therefore study the trade-off between quality and diversity and compare against previously published, well-used datasets.

4.1.1 Text content

Diversity By contruction, mOSCAR is diverse in terms of number of languages, so we focus on the diversity of mOSCAR's English documents and compare against mmc4 [Zhu et al., 2023], OBELICS [Laurençon et al., 2023] and the English subset of WIT [Srinivasan et al., 2021]. We compute the Vendi score [Friedman and Dieng, 2023] on a set of SimCSE embeddings [Gao et al., 2021] with a RoBERTa encoder [Liu et al., 2019] to evaluate the content diversity. Since embedding-based diversity metrics target content diversity well but are less relevant for lexical diversity [Tevet and Berant, 2021], we measure lexical diversity via the distinct n-gram ratio [Li et al., 2016].

Comparison with other datasets For content diversity, we randomly sample 30M documents for mOSCAR, mmc4 and OBELICS and 3M documents for WIT and represent the documents by their SimCSE embedding. We compute the Vendi Score with cosine similarity on a randomly sampled subset of 65,536 documents. Table 2 shows that mOSCAR English content is more diverse than mmc4 and OBELICS but less diverse than WIT. For lexical diversity, we randomly sample 3M documents for mOSCAR, mmc4, OBELICS and WIT and compute the distinct *n*-gram ratio on a subset of 8,192 documents for *n* from 1 to 4. Table 2 shows that mOSCAR is slightly less lexically diverse than OBELICS and mmc4, while WIT is by far the most diverse.

Quality To evaluate document quality, we focus on English documents and compute their perplexity using Gemma-2B [Gemma Team et al., 2024]. Figure 3 shows the kernel density estimation of

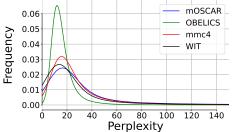


Figure 3: Perplexity of 100K random documents from different datasets.

	Vendi score	Dist. n -gram ratio
mOSCAR mmc4 OBELICS WIT	$69.05 (\pm 0.14)$ $67.93 (\pm 0.12)$ $58.49 (\pm 0.09)$ $73.30 (\pm 0.09)$	$\begin{array}{c} 0.472 \ (\pm \ 0.002) \\ \underline{0.494} \ (\pm \ 0.002) \\ \overline{0.488} \ (\pm \ 0.001) \\ \textbf{0.530} \ (\pm \ 0.001) \end{array}$

Table 2: Average text diversity scores (\pm standard error) of text documents.

the distribution of the perplexity of 100K randomly sampled documents from different datasets: mOSCAR is comparable to mmc4 and WIT, while OBELICS appears to be the of the highest quality. mOSCAR is therefore comparable to other interleaved image-text dataset in terms of quality and diversity of its English subset. It is however more diverse than English-only datasets by its multilingual construction and more than 10 times larger than existing multilingual interleaved image-text datasets such as WIT.

4.1.2 Image diversity

mOSCAR	LAION-400M	WIT	English	All
$55.74 (\pm 0.16)$	67.59 (± 0.16)	$36.14 (\pm 0.08)$	$52.36 (\pm 0.18)$	54.78 (± 2.29)

(a) Comparison of different datasets.

(b) mOSCAR (English vs. any language).

Table 3: Average Vendi score (\pm standard error) of images.

Comparison with other datasets We compute the Vendi Score on random samples of images for different datasets, comparing the images from English mOSCAR documents with those from Conceptual Captions [Changpinyo et al., 2021], LAION-400M [Schuhmann et al., 2021] and WIT [Srinivasan et al., 2021]. We represent each image by its SigLIP¹⁵ [Zhai et al., 2023] embedding and compute the Vendi score on batches of size 65,536 and a total of 1M images for each dataset. In Table 3a, we notice that the set of images in mOSCAR documents are more diverse than images from WIT documents but less diverse than LAION-400M.

Multilingual diversity We also compare the diversity of images from English documents and of images sampled from documents of any language (English included). We use multilingual SigLIP [Chen et al., 2023a] trained on WebLI [Chen et al., 2023b] to compute image embeddings used to get the Vendi score. We again use a batch of size 65,536 and a total of 3M images, and we do not sample multiple images from a same document. For the multilingual setting, we randomly sample 50 languages and an equal number of images for each language to build the batch. As we did not do any image deduplication across languages, we could expect to have less diversity in the multilingual setting. However, Table 3b shows that the set of images is on average more diverse when sampled from all documents than from English-only documents. This means that the distribution of images is not exactly the same across languages, potentially due to cultural differences.

5 Training a multilingual multimodal language model

We train a multilingual Flamingo-like model on mOSCAR. As adding captioning data to training data has been shown to improve zero-shot performance [McKinzie et al., 2024], we additionally train on LAION-400M, which we re-captioned using BLIP [Li et al., 2022], filtered with CLIP score [Radford et al., 2021] and translated using distilled NLLB-600M [Visheratin, 2023] following the proportion of languages found in mOSCAR. We use Gemma-2B [Gemma Team et al., 2024] as the

¹⁵We use siglip-base-patch16-224.

underlying language model and we train the model on 35M mOSCAR documents and 70M randomly sampled image-text pairs. We also train a model on 300M image-text pairs as a comparison baseline. We additionally compare with OpenFlamingo-3B-MPT [Awadalla et al., 2023] as the *translate-test* baseline. The full list of languages for training and the implementation details can be found in Appendix A.5.

5.1 Evaluation setup

We evaluate the models using a broad set of image-text multilingual tasks and benchmarks. We use the IGLUE benchmark [Bugliarello et al., 2022] composed of XVNLI, MaRVL [Liu et al., 2021] to test reasoning, xGQA [Pfeiffer et al., 2022] to test visual question answering capabilities and xFlickr&CO [Young et al., 2014, Karpathy and Fei-Fei, 2015, Yoshikawa et al., 2017] for captioning. We also include Crossmodal-3600 (XM3600) [Thapliyal et al., 2022] and MaXM [Changpinyo et al., 2022] as they cover a broader range of languages. To test to what extent models trained on mOSCAR can perform zero-shot multimodal machine translation (MMT), we also test on Multi30K [Elliott et al., 2016, 2017, Barrault et al., 2018] and CoMMuTE [Futeral et al., 2023]. For captioning we compute the CideR [Vedantam et al., 2015] score and we tokenize references and model outputs with the Stanford Core NLP tokenizer for English and Stanza [Qi et al., 2020] tokenizers for other languages. To evaluate Multi30k, we compute BLEU [Papineni et al., 2002] score from Sacrebleu [Post, 2018] with *13a* tokenization and default parameters. We use accuracy for CoMMuTE. More details can be found in Appendix A.5.3.

5.2 Results

Tables 4 and 5 show the average results across all languages. Full results are available in Appendix A.6. We notice that the multilingual OpenFlamingo trained additionally on mOSCAR gets better results than the model trained on captioning data only while having seen fewer image-text pairs during training. More importantly, when increasing the number of few-shot examples from 0 to 16, it sees gains of on average +8.19 points on VQA benchmarks and +16.07 CideR points on captioning benchmarks. In contrast, the model trained on text-image pairs only sees gains of +2.82 and +9.08 points respectively. In cross-modal machine translation, the model additionally trained on interleaved data is again far better than the one trained on just captioning data, which is not able to translate the Multi30k benchmark at all. Moreover, mOSCAR helps the model to learn to zero-shot disambiguate translations as shown by the improved average score on CoMMuTE (63.75) compared to the model trained on captions only (61.36).

Multilingual Open Flamingo trained on mOSCAR & text-image pairs is also better than Open-Flamingo 3B MPT evaluated on translate test benchmarks. However, we obtain the best results (except for MaXM) by evaluating our multilingual Open Flamingo on the translate-test benchmarks since the underlying language model (Gemma-2B) is far better in English than other languages. We also notice that all models struggle with reasoning classification tasks (MaRVL, XVNLI) where they obtain scores close to random guessing.

	#shots	xFlickR&CO	XM3600	xGQA	MaXM	MaRVL	XVNLI	Multi30K	CoMMuTE
	0	19.07	8.73	25.08	19.64	49.77	33.01	22.70	63.75
Multi. OF	4	34.32	20.59	31.90	23.90	49.67	36.07	22.79	63.65
full	8	36.77	22.15	33.9	24.41	49.72	37.16	23.21	63.00
	16	37.63	22.24	35.71	25.38	49.73	35.36	23.48	62.77
	0	9.57	4.21	8.62	4.01	49.88	33.76	0.00	61.36
Multi. OF	4	13.20	9.26	13.45	4.15	49.54	32.04	0.00	61.13
cap. only	8	18.00	10.35	12.82	4.88	49.65	33.71	0.01	60.90
- •	16	19.87	12.07	13.37	4.89	49.79	32.70	0.74	60.25

Table 4: Results averaged over all languages.

We additionally compare results at different training steps, defined by the number of images seen during training. Figure 4 shows the difference of averaged scores between the model trained on all

¹⁶Most of the time, the model is not able to follow the prompt and only outputs the end of sequence token.

	#shots	xGQA	MaXM	MaRVL	XVNLI
	0	18.34	7.68	49.75	32.73
OF 2D MDT	4	22.97	7.82	49.70	35.82
OF-3B MPT	8	28.57	8.32	49.71	31.29
	16	31.82	9.04	49.72	33.29
	0	30.16	10.06	49.93	34.66
Multi. OF	4	35.55	9.89	48.99	36.10
full	8	36.78	10.12	50.54	39.69
	16	37.75	11.49	49.57	37.97

Table 5: Translate-test results averaged over languages.



Figure 4: Score differences averaged over benchmarks and languages between the model trained on mOSCAR + text-image pairs and the model trained only on text-image pairs.

data and the model trained only on text-images pairs. We notice that the gap first decreases until 20M images seen and keep increasing over training at all training steps after that. Particularly, the gap is wider for few-shot learning.

6 Conclusion, Limitations and Societal Impacts

We introduce mOSCAR, a large-scale multilingual and multimodal dataset covering 163 languages and composed of 315M documents, 214B tokens and 1.2B images. We show that mOSCAR is of good quality, diverse and can be used to train a multilingual and multimodal LLM. We ensure that mOSCAR is as safe as possible by applying a series of filtering steps to remove NSFW content. We however did not conduct any toxicity analysis or evaluate its biases as this is challenging in a multilingual setting. As it is crawled from the internet, it is possible that mOSCAR reflects biases widespread on it. Nevertheless, by its multilingual nature, mOSCAR is a step towards the inclusion of more languages, cultures and people in accessing mLLMs.

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A Appendix

A.1 mOSCAR languages & statistics

	Language	es			Statistics	
Lang. name	Code	Family	Script	#documents	#images	#tokens
Acehnese	ace_Latn	Austronesian	Latin	7,803	32,461	2,889,134
Mesopotamian Arabic	acm_Arab	Afro-Asiatic	Arabic	2,274	10,620	1,047,748
Tunisian Arabic	aeb_Arab	Afro-Asiatic	Arabic	7,640	41,570	2,715,187
Afrikaans		Indo-European	Latin	54,895	247,774	39,956,585
South Levantine Arabic	ajp_Arab	Afro-Asiatic	Arabic	12,098	87,837	5,167,813
Tosk Albanian	als_Latn	Indo-European	Latin	861,678	2,569,164	452,737,251
Amharic	amh_Ethi	Afro-Asiatic	Ge'ez	39,588	152,646	35,089,019
North Levantine Arabic	apc_Arab	Afro-Asiatic	Arabic	19,904	128,966	9,560,701
Modern Standard Arabic	arb_Arab	Afro-Asiatic	Arabic	3,936,851	15,126,931	3,401,919,964
Najdi Arabic	ars_Arab	Afro-Asiatic	Arabic	60,229	296,741	43,610,873
Moroccan Arabic		Afro-Asiatic	Arabic	142,386	698,051	204,723,454
Egyptian Arabic	arz_Arab	Afro-Asiatic	Arabic	835,529	4,054,632	653,626,387
Assamese	asm_Beng	Indo-European	Bengali	3,948	9,210	640,390
Asturian	ast_Latn	Indo-European	Latin	165,745	962,723	37,547,944
Awadhi	awa_Deva	Indo-European	Devanagari	29,324	107,483	4,961,635
Central Aymara	ayr_Latn	Aymaran	Latin	27,384	151,889	5,148,970
South Azerbaijani	azb_Arab		Arabic	8,274	38,233	5,256,693
North Azerbaijani	azj_Latn	Turkic	Latin	516,021	1,808,060	257,825,849
Bashkir	bak_Cyrl	Turkic	Cyrillic	4,532	17,174	3,038,766
Bambara	bam_Latn	Manding	Latin	7,674	39,190	1,243,332
Balinese	ban_Latn	Austronesian	Latin	1,886	11,266	542,015
Belarusian	bel_Cyrl	Indo-European	Cyrillic	63,309	287,539	72,976,520
Bemba	bem_Latn	Atlantic-Congo	Latin	1,096	7,479	1,340,471
Bengali	ben_Beng	Indo-European	Bengali	270,406	947,035	35,858,814
Bhojpuri	bho_Deva	Indo-European	Devanagari	6,366	28,131	875,463
Banjar	bjn_Latn	Austronesian	Latin	5,427	27,803	1,898,526
Bosnian	bos_Latn	Indo-European	Latin	1,960,599	7,633,049	1,255,000,505
Buginese	bug_Latn	Austronesian	Latin	3,312	18,648	588,678
Bulgarian	_ ,	Indo-European	Cyrillic	2,591,998	11,670,028	1,760,971,620
Catalan		Indo-European	Latin	1,153,864	4,736,634	606,447,390
Cebuano		Austronesian	Latin	16,990	91,234	10,748,818
Czech		Indo-European	Latin	3,918,837	13,291,309	2,823,172,996
Central Kurdish		Indo-European	Arabic	36,725	136,566	22,322,689
Crimean Tatar	crh_Latn		Latin	6,376	24,124	1,742,727
Welsh		Indo-European	Latin	40,408	165,897	27,748,345
Danish		Indo-European	Latin	2,076,298	9,559,600	1,238,277,499
German		Indo-European	Latin	20,662,696	87,976,200	8,544,986,218
Southwestern Dinka		Nilo-Saharan	Latin	1,712	6,635	1,319,943
Greek		Indo-European	Greek	4,916,081	15,209,058	2,923,201,041
English	•	Indo-European	Latin	52,215,013	207,904,315	33,570,108,782
Esperanto	epo_Latn		Latin	25,157	124,996	28,586,195
Estonian	est_Latn		Latin	1,040,368	5,217,366	619,215,048
Basque	eus_Latn		Latin	849,043	3,445,539	277,145,498
Faroese		Indo-European	Latin	15,411	60,340	6,691,327
Fijian	5 –	Austronesian	Latin	1,528	8,776	487,388
Finnish	fin_Latn		Latin	2,396,033	10,365,333	1,781,044,864
French		Indo-European	Latin	20,305,739	78,179,601	14,362,579,829
Friulian	_	Indo-European	Latin	37,290	256,456	5,949,600
Nigerian Fulfulde		Atlantic-Congo	Latin	1,568	7,124	401,852
West Central Oromo	0 -	Afro-Asiatic	Latin	4,058	11,763	1,786,093
Scottish Gaelic		Indo-European	Latin	29,710	153,249	14,605,090
Irish		Indo-European	Latin	68,858	315,132	47,438,400
Galician		Indo-European	Latin	518,973	2,381,475	217,063,180
Guarani	${\tt grn_Latn}$	•	Latin	490,945	2,416,633	89,921,114
Gujarati	guj_Gujr	Indo-European	Gujarati	23,062	91,320	3,324,866
Haitian Creole	hat_Latn	Indo-European	Latin	257,745	1,570,699	62,847,106

	Language	es			Statistics	
Lang. name	Code	Family	Script	#documents	#images	#tokens
Hausa		Afro-Asiatic	Latin	25,364	104,934	13,089,932
Hebrew		Afro-Asiatic	Hebrew	1,109,591	4,766,483	893,327,320
Hindi	_	Indo-European	Devanagari	579,430	1,830,667	122,558,353
Chhattisgarhi	_	Indo-European	Devanagari	1,581	7,263	273,174
Croatian		Indo-European	Latin	1,719,617	8,425,510	1,010,674,096
Hungarian	hun_Latn		Latin	3,534,506	15,390,083	2,831,715,050
Armenian		Indo-European	Armenian	339,962	1,141,885	205,635,952
Igbo	_	Atlantic-Congo	Latin	11,529	68,049	8,701,070
Ilocano	_	Austronesian	Latin	78,872	523,195	8,116,113
Indonesian Icelandic	- ·	Austronesian	Latin Latin	7,016,291	17,324,777	3,981,843,468
Italian		Indo-European	Latin	244,676 12,937,153	1,027,465 47,476,971	137,015,973
Javanese		Indo-European Austronesian	Latin	24,785	135,583	8,311,790,842 16,908,805
Japanese	jpn_Jpan		Kanji	14,415,292	23,893,768	8,923,348,944
Kabyle		Afro-Asiatic	Latin	18,508	106,730	4,079,553
Kannada	kan_Knda		Kannada	12,978	42,621	1,442,776
Kashmiri		Indo-European	Arabic	3,109	11,408	5,731,910
Georgian		Kartvelian	Georgian	354,436	1,304,281	275,223,026
Kazakh	kaz_Cyrl		Cyrillic	252,242	732,648	140,049,214
Halh Mongolian	khk_Cyrl		Cyrillic	124,412	508,217	84,535,241
Khmer		Austroasiatic	Kher	24,495	122,243	3,043,925
Kinyarwanda	_	Atlantic-Congo	Latin	30,401	172,201	12,049,616
Kyrgyz	kir_Cyrl		Cyrillic	53,010	199,713	34,404,281
Northern Kurdish		Indo-European	Latin	39,262	164,666	23,834,960
Korean	kor_Hang	Koreanic	Hanja	2,614,089	13,563,283	2,006,080,705
Lao	lao_Laoo		Lao	50,611	208,768	31,029,380
Ligurian	lij_Latn	Indo-European	Latin	8,751	56,266	2,958,179
Limburgish	lim_Latn	Indo-European	Latin	189,547	1,076,047	42,534,327
Lingala	lin_Latn	Atlantic-Congo	Latin	24,614	152,132	4,053,459
Lithuanian		Indo-European	Latin	1,688,811	8,869,443	1,161,476,040
Lombard		Indo-European	Latin	30,506	151,855	9,058,614
Latgalian		Indo-European	Latin	11,948	61,624	4,148,492
Luxembourgish		Indo-European	Latin	44,987	246,346	16,676,872
Ganda	O-	Afro-Asiatic	Latin	1,878	7,215	789,917
Mizo	_	Sino-Tibetan	Latin	7,880	26,817	4,978,472
Standard Latvian		Indo-European	Latin	896,243	4,141,648	587,653,855
Magahi		Indo-European	Devanagari	1,097	3,847	205,763
Malayalam Marathi	mal_Mlym		Malayalam Devanagari	14,140	52,679	1,689,010
Marathi Minangkahau	_	Indo-European Austronesian	Latin	50,391 9,341	163,868 35,309	6,689,250
Minangkabau Macedonian	_	Indo-European		542,250	1,853,070	1,256,931 307,232,151
Maltese		Afro-Asiatic	Cyrillic Latin	120,888	709,242	36,097,957
Maori		Austronesian	Latin	24,322	130,137	24,957,914
Burmese	_	Sino-Tibetan	Mon	8,144	44,188	539,527
Dutch		Indo-European	Latin	17,096,727	65,606,013	9,670,041,731
Norwegian Nynorsk		Indo-European	Latin	199,355	1,012,313	67,799,774
Norwegian Bokmål	_	Indo-European	Latin	2,229,702	9,698,128	1,294,178,095
Nepali		Indo-European	Devanagari	31,239	127,193	3,138,539
Nyanja		Atlantic-Congo	Latin	12,047	67,192	8,596,769
Occitan		Indo-European	Latin	164,852	671,881	59,309,549
Odia		Indo-European	Odia	4,319	15,574	378,635
Pangasinan		Austronesian	Latin	4,214	32,287	546,071
Eastern Panjabi		Indo-European	Gurmukhi	11,497	46,168	1,887,991
Papiamento	pap_Latn	Indo-European	Latin	55,224	363,015	10,002,655
Southern Pasto		Indo-European	Arabic	32,604	110,807	29,170,322
Western Persian		Indo-European	Arabic	7,048,946	25,200,571	6,210,479,015
Plateau Malgasy		Austronesian	Latin	32,521	120,673	29,263,848
Polish	pol_Latn	Indo-European	Latin	14,549,605	60,639,244	11,104,144,109
Portuguese		Indo-European	Latin	8,145,664	26,530,423	4,760,063,083
Dari		Indo-European	Arabic	515,041	2,589,859	517,053,967
Ayacucho Quechua	. .	Quechuan	Latin	1,578	11,817	362,690

	Language	es			Statistics	
Lang. name	Code	Family	Script	#documents	#images	#tokens
Romanian	ron_Latn	Indo-European	Latin	5,180,171	17,964,048	3,548,291,261
Rundi	run_Latn	Atlantic-Congo	Latin	20,001	67,096	8,686,054
Russian	rus_Cyrl	Indo-European	Cyrillic	15,913,845	69,542,828	18,909,213,208
Sango	sag_Latn	Atlantic-Congo	Latin	2,124	13,556	454,455
Sicilian	scn_Latn	Indo-European	Latin	73,199	424,362	27,110,743
Sinhala	sin_Sinh	Indo-European	Sinhalese	58,767	221,183	14,270,972
Slovak	slk_Latn	Indo-European	Latin	3,008,599	15,067,234	1,963,804,563
Slovenian	slv_Latn	Indo-European	Latin	1,472,025	7,210,285	935,834,754
Samoan	smo_Latn	Austronesian	Latin	12,346	71,359	14,954,824
Shona	sna_Latn	Atlantic-Congo	Latin	12,698	68,782	6,112,600
Sindhi	snd_Arab	Indo-European	Arabic	21,095	74,289	17,647,825
Somali	som_Latn	Afro-Asiatic	Latin	77,343	301,429	34,554,975
Southern Sotho	sot_Latn	Atlantic-Congo	Latin	7,718	43,146	6,156,450
Spanish	spa_Latn	Indo-European	Latin	22,713,366	78,361,087	14,616,773,475
Sardinian	srd_Latn	Indo-European	Latin	675,539	4,059,493	106,159,957
Serbian		Indo-European	Cyrillic	604,557	2,286,171	401,223,741
Sundanese	sun_Latn	Austronesian	Latin	44,310	236,025	13,627,832
Swedish	swe_Latn	Indo-European	Latin	3,302,730	10,860,518	1,779,284,152
Swahili	swh_Latn	Atlantic-Congo	Latin	137,134	593,418	59,454,896
Silesian	_	Indo-European	Latin	23,535	132,459	5,996,972
Tamil	tam_Taml	Dravidian	Tamil	36,196	167,669	4,834,946
Tatar	tat_Cyrl		Cyrillic	37,188	143,842	22,831,350
Telugu		Dravidian	Telugu	22,974	81,033	2,273,772
Tajik	tgk_Cyrl		Cyrillic	125,236	417,591	90,503,778
Tagalog		Austronesian	Latin	151,437	673,814	97,708,639
Thai	tha_Thai		Thai	2,983,837	11,621,786	2,839,211,104
Tigrinya	_	Afro-Asiatic	Ge'ez	2,657	8,707	1,725,422
Tok Pisin	_	Indo-European	Latin	5,063	35,169	460,853
Turkmen	tuk_Latn		Latin	13,024	57,354	9,766,999
Turkish	tur_Latn		Latin	4,478,700	12,401,091	2,394,669,068
Twi	_	Atlantic-Congo	Latin	3,305	13,634	495,220
Uyghur	uig_Arab		Arabic	10,713	41,709	6,785,318
Ukrainian	0-	Indo-European	Cyrillic	2,721,424	10,929,796	1,928,351,595
Urdu	- ,	Indo-European	Arabic	407,098	1,239,125	242,007,283
Northern Uzbek	uzn_Latn	1	Latin	156,632	798,155	89,022,562
Venetian	_	Indo-European	Latin	330,611	1,830,777	71,077,531
Vietnamese		Viet-Muong	Latin	12,621,521	47,411,488	11,616,191,199
Wolof	_	Atlantic-Congo	Latin	4,658	20,380	1,596,432
Xhosa		Atlantic-Congo	Latin	25,950	142,387	15,809,823
Eastern Yiddish		Indo-European	Hebrew	12,486	57,510	17,369,727
Yoruba		Atlantic-Congo	Latin	56,700	286,933	32,614,558
Yue Chinese		Sino-Tibetan	Hant	33,671	203,513	24,172,441
Chinese (Simplified)		Sino-Tibetan	Hanzi	9,861,262	36,152,754	8,078,842,701
Chinese (Traditional)		Sino-Tibetan	Hant	3,967,966	16,307,258	2,962,854,441
Standard Malay	_	Austronesian	Latin	1,179,744	5,488,632	432,667,199
Zulu	- ·	Atlantic-Congo	Latin	30,717	156,639	11,345,288
	Zui_Latii	7 Manue-Congo	Latin	50,717	150,059	11,575,200

Table 6: Languages & Statistics

A.2 Heuristics to increase the quality of documents

We use a set of heuristics to improve the quality of the documents by discarding some text nodes. We first consider text nodes to be written in Latin scripts if more than 50% of the characters are Latin. In detail, we discard the text node if:

- 1. It is empty.
- 2. It contains fewer than 5 bytes for Latin scripts and fewer than 15 bytes for non-Latin scripts.
- 3. More than 30% of the characters are digits.
- 4. It contains more than one date.

- 5. It contains the sequence "lorem ipsum".
- 6. The ratio of non-alphabetic characters is superior to 0.33.
- 7. The symbols '{' or ''}' are in the text.
- 8. The symbols $'\geq'$, $'\leq'$, '>' or '<' are more than 2 times in the text.
- 9. "Follow us", "javascript", "copyright" or "©" are in the text.
- 10. The ratio of capitalized letters is superior to 0.2.
- 11. The text exactly matches with "comment", "facebook", "instagram", "twitter", "rss", "newsletter", "share" or "follow us".
- 12. A character is more than 33% of the total number of characters in the string.

We then also apply some filters to clean the text as much as possible:

- 1. Remove URLs from all documents.
- 2. Normalize consecutive special characters ('\t', '\n', '#', '/', '\$', ')', '(', '[', ']', '!', '?', '%', '<', '>') to keep only one.

Following previous steps, we keep the text node if it is superior to 5 bytes and we keep the final document if it is superior to 100 bytes.

A.3 Examples of documents



Autour des greens notre créativité est souvent mise à rude épreuve. En effet les bosses, la vitesse et la fermeté des greens, les obstacles à sauter, tous ces éléments nous poussent parfois à devoir modifier nos trajectoires de balles. Dans ces variations existe le lob shot! Cette balle haute qui a pour objectif de survoler un obstacle et s'arrêter rapidement est souvent perçue comme un calvaire par les joueurs amateurs. Mais est ce si difficile? Existe-t-il une manière de faire, « simple et répétitive », pour appréhender une première version de ce lob shot? Je vais m'appuyer sur Jon Rahm, 7 ème cette année au Scrambling du PGA Tour* en dessous de 30m, pour vous apporter quelques explications pour améliorer ce domaine dans votre chipping.

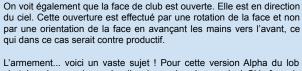
Les premiers éléments à maitriser dans tous coups de golf sont les éléments de la posture ! Un stance (position des pieds) assez étroit. L'extérieur des pieds étant à l'intérieur de la largeur des épaules. Identique à la position classique de chipping. Le poids sur le pied avant = le droit pour les gauchers, le gauche pour les droitiers. Le club dans l'axe de l'aine et de l'avant bras comme indiqué par le trait vert.















L'armement... voici un vaste sujet! Pour cette version Alpha du lob shot, je vais vous demander d'envisager les choses ainsi. Si la face de club à l'adresse est ouverte le club en devient moins puissant. Exemple un F9 est moins puissant qu'un F5 ceci étant du, entre autre à l'ouverture de la face. Si le club est moins puissant et donc ici peu puissant, c'est un sand-wedge dont J. Rahm a ouvert la face, il faut pas mal d'amplitude même pour faire peu de distance. Si il faut de l'amplitude il faut, comme dans tout swing, se mettre à armer le club. L'armement dans cette version Alpha du lob shot n'est donc pas volontaire! [...]

Figure 5: Example of a French document.



群馬県伊勢崎市でレジェンドたちと野球教室 ~! 本日、群馬県伊勢崎市にて野球教室でした~。プロ野球OBクラブ更に「大東建託」さん主催! 中学校の野球部の選手達へ熱血指導~。

Figure 6: Example of a Japanese document.



Собаки в еде! Необычный профиль в Instagram взорвал весь интернет. Данный аккаунт приглянется всем тем, кто не мыслит своей жизни без вкуснейшей еды и просто обожает братьев меньших, в особенности милых пёсиков. Только представьте себе, что у вас на тарелке лежит еда, но только в ней вы видите ещё и мордочку мопсика. Странно звучит, правда? Но вот комуто эта идея пришла в голову и этот «кто-то» даже решил реализовать её. В Instagram в январе 2018 года появился весьма необычный профиль — @dogs_infood. В нём публикуются очень оригинальные и забавные иллюстрации, где изображена еда в тандеме с фотографиями собак.

Так что же можно там увидеть? Например, печенье с мордочкой мопса, веточка винограда со смешным французским бульдожкой, кренделёк с доберманом или шпиц в форме тефтельки. Это не только звучит забавно, но ещё и выглядит очень смешно. Кстати, любой желающий может прислать фотографию своего любимца автору профиля, и кто знает, может, следующий пост будет посвящён именно ему. [...]



Figure 7: Example of a Russian document.

Nel mese di settembre c'è un altro evento sportivo che coinvolge soprattutto gli appassionati di corsa ed è il "Bibione is surprising run". É una gara internazionale di 10 miglia con percorsi che si intrecciano lungo il litorale toccando i punti più belli di Bibione. Anche per i meno allenati, è una buona occasione per far conciliare benessere fisico e salute. Ci sono tante proposte di strutture ricettive a Bibione che offrono pacchetti famiglia economici con la possibilità non solo di partecipare alla gara ma anche di fare un bel tuffo in mare. Il periodo di settembre è adatto per le famiglie con bambini: il mare è calmo e le giornate sono calde. Ritagliati un week-end last minute prima di tornare al lavoro e iniziare con la routine quotidiana. Di seguito sono elencati appartamenti confortevoli ed hotel economici che garantiscono risparmio e qualità al tuo soggiorno.



Rimani aggiornato sulle migliori offerte per Bibione. Residence con piscina - appartamento con barbecue e posto auto.



Figure 8: Example of an Italian document.

Nissan ចាប់ដៃគ្នាជាមូ New Balance បញ្ចេញគំរូរថយន្តដ៏ពិសេសដែលមិនធ្លាប់មានពីមុនមក បែកធ្លាយរូបរាងឡាន Tacoma ជំនាន់ថ្មី ចេញពីរូបប៉ាតង់ថ្មី មើលមកដូចកូន Tundra ៤ឆ្នាំទៀត Porsche និងឈប់ផលិត Macan ប្រើសាំង







សមាជិក Blackpink សហការជាមួយ Porsche ឌីស្សាញម៉ូឌែលរថយន្តដ៏ពិសេសសម្រាប់ខ្លួនឯង

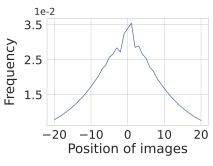
Figure 9: Example of a Khmer document.

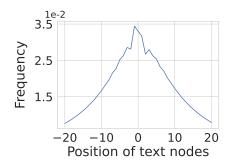
بوسٹن: ایپل کا سب سے پہلا مکمل طور پر فعال ایپل 1 کمپیوٹر نیلامی کے لیے پیش کر دیا گیا، میڈیا رپورٹ کے مطابق اس مشین، جس پر ایپل کے بانی اسٹیو جابز نے اپنے باتھوں سے نمبر ڈالے تھے، کے ساتھ وہ تمام چیزیں آئیں گی جو اس مشین کو چلانے کے لیے ضروری ہیں۔ فی الحال اس کمپیوٹر کی نیلامی کی بولی 2 لاکھ 41 ہزار 557 ڈالرز پر ہے جو 15 دسمبر کو ختم ہوجائے گی لیکن ایک الحال اس کمپیوٹر کی نیلامی کی حتمی بولی 3 لاکھ 75 ہزار ڈالرز تک جائے گی۔ 1976 میں متعارف کروایا جائے والا ایپل 1 اس ٹیک کمپنی کی سب سے پہلی شے تھی جو ایک اسمبلڈ سرکٹ بورڈ کے طور پر بیچی گئی تھی اس میں بنیادی چیزیں جیسے کہ کی بورڈ یا مانیٹر نہیں تھا۔ لیکن دیگر ایپل 1 کمپیوٹرز کے بر عکس اس یونٹ کے گئی تھی اس میں بنیادی چیزیں جیسے کہ کی بورڈ یا مانیٹر نہیں تھا۔ لیکن دیگر ایپل 1 کمپیوٹرز کے بر عکس اس یونٹ کے فزیکل بورڈ میں کسی قسم کی کوئی تبدیلی نہیں کی گئی ہے اور اس کا نمونہ صاف اور بغیر کسی استعمال شدہ ہے۔ بوسٹن کے آگشن ہاؤس کے مطابق ایک تفصیلی ٹیسٹ میں اس سسٹم کو تقریبا آٹھ گھنٹے تک چلایا گیا جس میں کوئی خرابی سامنے نہیں آگشن ہاؤس کے مطابق ایک تفصیلی ٹیسٹ میں اس سسٹم کو تقریبا آٹھ گھنٹے تک چلایا گیا جس میں کوئی خرابی سامنے نہیں آئیٹر نہوں کے مطابق ایک تقصیلی ٹیسٹ میں اس سلائیڈ شوز

Figure 10: Example of an Urdu document.

A.4 Text-Image similarity and DOM Tree

As we rely on the DOM Tree to build the documents and the order of appearance of the nodes could differ from HTML rendering, we attempt to assess to what extent it is a relevant way of constructing a multimodal document. To do so, we rely on the results of the text-image joint filtering step where we compute the ranks of relevant text nodes (resp images) for each image. We plot the distribution of the closest most relevant node for each modality in Figures 11a and 11b. We notice that the most relevant node to either a text node or an image is their closest node in the DOM tree. The cumulative distribution of the distribution of the closest node reaches 25% for nodes positioned between -5 and 5, which confirms the relevance of using the DOM tree to represent a document.





- (a) Relative position in the document of relevant text nodes with respect to images.
- (b) Relative position in the document of relevant images with respect to text nodes.

Figure 11: Relative positions of most relevant images and text nodes with respect to the other modality.

A.5 Implementation details

A.5.1 Text deduplication parameters

Following previous work, we near-deduplicate documents using MinHashLSH. We first vectorize the documents using HashingVectorizer from scikit-learn with 2,097,152 features computed on 4-grams and 5-grams within word boundaries. We then compute MinHashes from those vectors with 256

permutations and we finally run Locality Sensitive Hashing with a threshold Jaccard Similarity of 0.8 for finding near-duplicates.

A.5.2 Training implementation details

We train multilingual OpenFlamingo on mOSCAR and multilingual text-image pairs. We use a batch of size 64 for mOSCAR and 128 for captioning data, limiting the number of tokens to 256 for mOSCAR and 32 for captioning data. Similarly to Flamingo and OpenFlamingo, text tokens can only attend to the previous image in the sequence. To increase diversity in the training batch, we randomly reject 2/3 of the documents if they contain only one image. We limit the maximum number of images in a sequence to 8. We randomly sample 8 languages per batch and upsample low-resource languages. We train multilingual OpenFlamingo on 43 languages covering all the languages of the benchmarks we evaluate the models on (see Section A.5.3).

We use Gemma-2B as the underlying language model behind multilingual OpenFlamingo and CLIP ViT-L-14 as the image encoder. We add a cross-attention layer after each decoder layer. Following OpenFlamingo, we add the two special tokens <image> and<|endofchunk|>, whose embeddings were trained. Only the Perceiver Resampler, cross-attention layers and these two embeddings were trained; everything else remained frozen. During training, we apply a factor of 0.2 for the captioning data loss function.

We train the model using the Adam optimizer and a maximum learning rate of 1e-4. We use a constant learning rate scheduler with 1875 warm-up steps. We use 4 accumulation gradient steps to have an effective batch of size 256 for mOSCAR and 512 for captioning data. We train the model on 35M documents and 70M image-text pairs on 8 Nvidia A100 for 120h.

A.5.3 Evaluation details

	Metric	#examples	Languages
xFlickr&CO	CideR	2,000	Chinese, English, German, Indonesian, Japanese, Russian, Spanish, Turkish
XM3600	CideR	3,600	Arabic, Czech, Danish, German, Greek, English, Spanish, Farsi, Finnish, French, Hebrew, Hindi, Croatian, Hungarian, Indonesian, Italian, Japanese, Korean, Dutch, Norwegian, Poland, Portuguese, Romanian, Russian, Swedish, Telugu, Thai, Turkish, Ukrainian, Vietnamese, Chinese
xGQA	Accuracy	9,666	Bengali, German, English, Indonesian, Korean, Portuguese, Russian, Chinese
MaXM	Accuracy	~ 170	English, French, Hindi, Hebrew, Romanian, Thai, Chinese
MaRVL	Accuracy	$\sim 1{,}150$	Indonesian, Swahili, Tamil, Turkish, Chinese
XVNLI	Accuracy	1,164	English, Arabic, Spanish, French, Russian
Multi30k	BLEU	1,000	French, German, Czech
CoMMuTE	Accuracy	310	Czech, French, German

Table 7: Overview of the benchmarks used to evaluate our multilingual OpenFlamingo.

We evaluate on a set of eight benchmarks: xFlickr&CO, XM3600, xGQA, MaXM, MaRVL, XVNLI, Multi30k (Test2016 subset) and CoMMuTE; covering 5 different tasks and 43 languages. Details about the languages, the number of examples and the metric used can be found in Table 7. We used the *translate-test*¹⁷ samples provided by the authors of the benchmarks if available. No translate test samples were provided for MaXM, so we translated the test set using the NLLB-600M distilled model. As no training set was available for MaXM, we use the few-shot examples from xGQA. Since we use Stanza tokenizers, we could not evaluate on all languages from XM3600 as 3 of them were not available. Filipino was also not into the list of mOSCAR languages, so we skip this language during evaluation. The CoMMuTE evaluation set involves choosing between two different translations of a same source text (one correct and one incorrect depending on an image provided to disambiguate the

¹⁷Benchmark automatically translated into English.

text). We use the lowest perplexity between the two translations as the model's prediction. We also use Multi30k training set as few-shot examples.

Prompting Following previous works, the zero-shot setting is composed of two few-shot examples without providing the images. The prompts we use for the different tasks are as follows:¹⁸

For captioning tasks, we use the prompt:

"<image>Output:[Caption]<|endofchunk|><image>Output:",

where [Caption] is replaced by the caption.

For visual question answering tasks, we use the prompt:

```
"<image>Question: [Question] Short Answer: [Answer] <|endofchunk|><image>Question: [Question] Short Answer:",
```

where [Question] and [Answer] are replaced by the question and the answer respectively.

For multimodal machine translation tasks, we use the prompt:

```
"<image>Sentence:'[Caption]'. Translation: [Translation] <|endofchunk|><image>Output:",
```

where [Caption] is replaced by the sentence to translate and [Translation] is replaced by its translation.

For MaRVL, we use the prompt:

```
"<image> '[Statement]'. True of False? [Answer]<|endofchunk|><image> '[Statement]'. True of False?",
```

where [Statement] is replaced by the statement and [Answer] by the answer. We also concatenate the left and right image into a single image.

For XVNLI, we use the prompt:

```
"<image> '[Statement1]' - '[Statement2]'. entailment, neutral or contradiction? Output: [Answer]<|endofchunk|><image> '[Statement1]' - '[Statement2]'. entailment, neutral or contradiction? Output:",
```

where [Statement1], [Statement2] and [Answer] are replaced by XVNLI test data.

A.6 Detailed results

	#shots	De	En	Es	Id	Ja	Ru	Tr	Zh
	0	28.87	33.42	16.35	33.26	4.33	13.99	3.68	18.65
Multilingual OF	4	53.99	46.53	35.87	48.85	12.44	31.88	11.35	33.64
mOSCAR + caps.	8	56.05	52.99	37.28	52.51	15.13	32.76	11.69	35.78
	16	55.44	56.78	37.72	49.06	17.10	35.43	12.72	36.82
	0	16.72	24.57	3.80	10.82	2.82	8.20	2.79	6.82
Multilingual OF	4	21.10	31.05	7.52	9.63	3.84	13.21	7.01	12.20
captions only	8	32.56	35.73	13.35	15.85	5.96	18.13	6.97	15.47
- •	16	29.86	40.57	13.75	23.83	6.92	20.40	7.90	15.73

Table 8: Captioning results (CideR scores) on xFlickr&CO. **Bold** is best result.

¹⁸We show the prompts we used with one context example.

	#shots	Ar	Cs	Da	De	El	En	Es	Fa	Fi	Fr	Не
	0	6.18	2.02	11.06	9.12	0.90	43.49	18.01	10.41	1.30	20.61	3.21
Multi. OF	4	21.55	5.93	28.21	21.97	3.38	74.71	36.93	26.27	6.48	39.41	10.34
full	8	23.15	6.23	31.33	24.53	3.47	75.29	37.58	28.84	7.65	43.40	10.83
	16	23.80	6.86	31.92	24.92	3.59	76.24	38.39	26.78	7.61	43.26	11.78
	0	2.24	0.97	6.42	6.46	3.68	10.02	9.32	4.95	1.14	16.15	0.78
Multi. OF	4	5.36	1.36	13.11	11.82	7.78	35.52	19.96	9.62	1.86	22.48	2.29
Caps only	8	6.76	1.40	15.29	14.39	7.21	37.28	21.90	12.19	2.08	23.27	1.71
	16	6.25	2.29	17.96	15.11	7.64	48.03	25.39	9.21	2.10	30.16	2.72
	#shots	Hi	Hr	Hu	Id	It	Ja	Ko	NI	No	Pl	Pt
	0	2.80	1.47	1.85	9.98	11.15	2.07	1.67	18.97	9.63	4.32	15.49
Multi. OF	4	10.62	7.48	5.51	22.63	27.88	16.87	9.24	42.30	22.35	14.20	29.35
full	8	11.12	7.54	5.91	25.39	29.34	19.35	9.99	46.79	23.54	15.43	32.69
	16	12.18	7.71	6.03	23.89	29.17	18.84	9.75	46.95	23.79	15.93	31.98
	0	2.29	0.97	3.51	2.98	7.96	1.85	1.05	4.88	5.78	0.92	9.79
Multi. OF	4	4.57	1.72	7.57	6.39	16.23	3.47	4.33	11.26	11.99	1.16	15.93
Caps only	8	5.94	2.17	7.83	9.93	15.40	7.93	5.34	11.87	13.79	1.38	17.50
	16	6.36	2.42	9.55	11.77	17.43	10.44	6.03	12.98	14.65	1.28	20.32
	#shots	Ro	Ru	Sv	Te	Th	Tr	Uk	Vi	Zh		
	0	2.19	6.80	11.45	0.87	8.36	3.11	3.04	21.99	7.19		
Multi. OF	4	5.63	20.50	25.59	2.29	21.66	10.87	10.43	38.43	19.34		
full	8	6.04	23.11	26.44	3.06	25.19	12.95	10.56	39.75	20.18		
	16	6.43	21.15	26.51	3.42	25.31	13.57	10.45	40.85	20.46		
	0	2.24	1.93	4.55	0.67	2.34	2.68	0.80	8.55	2.70	·	·
Multi. OF	4	5.35	6.29	15.66	0.77	7.21	5.94	1.76	20.69	7.80		
Caps only	8	5.18	7.58	14.01	1.00	6.81	8.90	2.73	23.05	8.99		
	16	5.06	9.06	20.60	1.18	8.35	10.25	3.47	25.16	11.05		

Table 9: Captioning results (CideR scores) on XM3600. **Bold** is best result.

	#shots	Bn	De	En	Id	Ko	Pt	Ru	Zh
	0	20.99	22.57	32.60	22.45	26.44	23.54	25.31	26.77
Multilingual OF <i>mOSCAR</i> + <i>caps</i> .	4	25.72	32.71	38.02	30.74	31.49	31.53	31.75	33.26
	8	26.87	35.60	39.16	34.25	32.25	34.93	33.59	34.55
	16	29.11	37.01	40.64	36.37	34.20	37.15	34.87	36.29
	0	10.54	6.51	10.43	7.74	7.50	7.79	8.62	9.84
Multilingual OF	4	12.54	11.90	15.78	13.95	13.70	12.01	12.73	15.03
captions only	8	11.62	11.70	17.29	13.86	12.85	11.60	12.65	15.35
	16	9.77	11.86	18.37	13.24	12.48	11.25	11.24	14.33
			Tran	slate Tes	t				
	0	18.64	18.67	-	18.36	17.54	19.21	18.88	17.11
OF-3B MPT	4	23.23	23.40	-	22.95	22.46	23.52	22.41	22.85
OL-3P MILI	8	28.22	29.44	-	28.21	27.67	29.58	28.21	28.63
	16	31.31	32.58	-	31.82	31.42	32.74	31.62	31.22
	0	30.41	32.1	-	29.35	29.99	31.39	29.06	28.81
Multilingual OF $mOSCAR + caps$.	4	34.89	36.32	-	35.50	35.64	36.84	35.05	34.60
	8	35.95	37.65	-	36.78	37.14	37.81	36.17	35.98
	16	36.78	38.78	-	37.52	37.73	38.68	37.91	36.84

Table 10: VQA results on xGQA. **Bold** is best result.

	#shots	En	Fr	Hi	Не	Ro	Th	Zh
	0	34.24	15.91	18.08	16.43	13.73	25.75	13.36
Multi. OF	4	36.19	21.21	20.77	19.29	19.01	31.72	19.13
mOSCAR + caps	8	36.96	17.80	20.00	20.36	17.96	33.96	23.83
·	16	36.19	18.18	21.92	20.71	16.90	41.04	22.74
	0	9.73	0.38	7.69	1.43	0.00	5.22	3.61
Multi. OF	4	9.34	2.65	5.00	2.50	0.00	5.60	3.97
captions only	8	9.34	1.89	8.08	5.00	1.06	3.36	5.42
	16	8.56	1.14	5.00	8.21	0.35	3.36	7.58
Translate test								
OF-3B MPT	0	=	12.50	22.31	0.36	10.92	0.00	0.00
	4	-	10.98	25.38	0.36	10.21	0.00	0.00
	8	-	10.98	27.31	0.36	11.27	0.00	0.00
	16	-	13.26	26.54	1.07	13.38	0.00	0.00
	0	-	18.18	28.08	0.00	13.73	0.00	0.36
Multi. OF <i>mOSCAR</i> + <i>caps</i>	4	-	15.91	30.38	0.36	12.68	0.00	0.00
	8	-	15.15	30.77	0.00	14.79	0.00	0.00
_	16	-	15.91	35.77	0.36	16.90	0.00	0.00

Table 11: VQA results on MaXM. Bold is best result.

	#shots	Id	Sw	Ta	Tr	Zh	
Random chance		50.00	50.00	50.00	50.00	50.00	
	0	50.00	49.46	49.76	49.83	49.80	
Multilingual OF	4	49.91	49.55	49.28	49.83	49.80	
mOSCAR + caps	8	50.62	48.65	49.68	49.83	49.80	
	16	50.18	49.01	49.76	49.83	49.90	
	0	51.33	49.01	49.52	49.83	49.70	
Multilingual OF	4	49.73	49.64	49.19	49.41	49.70	
captions only	8	49.91	49.10	49.60	49.75	49.90	
	16	50.09	49.73	49.60	49.75	49.80	
Translate test							
	0	50.00	49.37	49.76	49.83	49.80	
OF-3B MPT	4	50.00	49.64	49.52	49.75	49.60	
OL-2D ML I	8	49.82	49.46	49.28	50.08	49.90	
	16	50.00	49.37	49.44	50.00	49.80	
	0	49.07	49.79	49.52	50.34	49.60	
Multilingual OF	4	49.99	49.79	48.23	49.75	49.76	
mOSCAR + caps	8	50.00	48.92	50.64	50.42	48.90	
	16	49.84	50.00	50.24	48.90	49.75	

Table 12: Classification results on MaRVL. **Bold** is best result.

	#shots	Ar	En	Es	Fr	Ru	
Random chance		33.33	33.33	33.33	33.33	33.33	
Multilingual OF. mOSCAR + caps.	0 4 8 16	32.90 36.94 37.80 34.97	34.02 36.17 39.86 38.92	31.44 34.19 34.97 32.30	33.85 34.54 35.74 34.97	32.82 38.49 37.46 35.65	
Multilingual OF. captions only	0 4 8 16	35.48 32.04 34.02 32.04	34.02 31.79 33.76 32.99	33.51 32.73 32.04 33.76	34.45 32.22 35.57 33.17	31.36 31.44 33.16 31.53	
Translate test							
OF-3B MPT	0 4 8 16	32.65 36.25 31.27 33.68	- - -	31.01 35.82 31.10 33.25	31.44 35.57 31.10 32.99	35.82 35.65 31.70 33.25	
Multilingual OF. <i>mOSCAR</i> + <i>caps</i> .	0 4 8 16	34.88 36.25 39.60 37.54	- - -	34.88 36.17 39.52 37.89	34.54 35.91 40.29 37.46	34.36 36.08 39.35 39.00	

Table 13: Classification results on XVNLI. **Bold** is best result.

	#shots	Cs	De	Fr
	0	3.22	28.86	36.01
Multi. OF	4	3.16	28.99	36.22
full	8	3.44	28.76	37.41
	16	3.73	29.19	37.53
	0	0.00	0.00	0.00
Multi. OF caps. only	4	0.00	0.00	0.00
	8	0.00	0.00	0.03
-	16	0.00	0.40	1.82

Table 14: En \rightarrow X translation results on Multi30k. **Bold** is best result.

	#shots	Cs	De	Fr
Multi. OF full	0 4 8 16	59.09 58.77 56.82 57.79	63.67 63.67 63.67 62.67	68.51 68.51 68.51 67.86
Multi. OF caps. only	0 4 8 16	58.12 59.09 59.09 58.12	61.67 61.00 59.34 58.67	64.29 63.31 64.29 63.96

Table 15: En \rightarrow X CoMMuTE results. **Bold** is best result.