Multilingual Multimodality: A Taxonomical Survey of Datasets, Techniques, Challenges and Opportunities

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Abstract
Contextualizing language technologies beyond a single language kindled embracing multiple modalities and languages. Individually, each of these directions undoubtedly proliferated into several NLP tasks. Despite this momentum, most of the multimodal research is primarily centered around English and multilingual research is primarily centered around contexts from text modality. Challenging this conventional setup, researchers studied the unification of multilingual and multimodal (MultiX) streams. The main goal of this work is to catalogue and characterize these works by charting out the categories of tasks, datasets and methods to address MultiX scenarios. To this end, we review the languages studied, gold or silver data with parallel annotations, and understand how these modalities and languages interact in modeling. We present an account of the modeling approaches along with their strengths and weaknesses to better understand what scenarios they can be used reliably. Following this, we present the high-level trends in the overall paradigm of the field. Finally, we conclude by presenting a road map of challenges and promising research directions.

Keywords: Multilingual, Cross-lingual, Multimodal

1. Introduction

Democratic reach of ubiquitous contexts from vision and language(s) mitigates digital divide and alleviates cultural inclusion.

Our world contextualizes information in various modalities, the expression of which varies based on the medium i.e., languages. The recent revolutions of (i) aggrandizing NLP technologies to multiple languages Dabre et al. (2020) to broaden the stakeholders to speakers of over 7000 living languages, and (ii) deriving context from multiple modalities Baltrusaitis et al. (2019) have mostly been independent of each other. However, to curtail the inequality of information access and cultural biases in building resources, discern multilingual and multimodal (MultiX) technologies is crucial. The status quo is still that English is the most prevalent language in grounded language agents. This creates a bottleneck for sharing information across models from other languages.

Despite the conventional trend of independent approaches to multilinguality and multimodality, researchers have sporadically yet consistently studied a confluence of these. This paper presents a comprehensive survey of tasks, datasets and methods tackling MultiX sce-
narios. We aggregated papers from the last 60 years based on keyword search for variants of each of multiple modalities and languages in the titles and abstracts. Upon this, we filtered the papers manually that conduct research on both multilinguality and multimodality, and annotated them for MultiX specifics. Distilling these learnings, we characterize an ontology of tasks and methods as depicted in Figure 1. The confluence of both ‘X’s brings about distinct challenges in dataset collection and methodologies which inspires this setup. Note that the names indicate how the modalities interact with several languages (as opposed to a inter-modal interactions with a single language). The rest of the survey is organized and presented according to the categories in Figure 1.

The main goal of this paper is to present insights into what distinguishes MultiX in terms of resources and modeling. Section 2 discusses the various tasks and datasets currently available. First, most MultiX datasets are built on top of existing visual or multimodal source datasets. To review this, we audit the source of the visuals used and the languages the corresponding tasks are explored in. Second, with the unique aspect of textual data present in multiple languages, we survey whether this data is parallel (each instance is present across languages), and third, if they are gold (human annotated), silver (weakly annotated with off-the-shelf tools and models), or direct (scraped as is from sources). §3 categorizes the modeling approaches for MultiX into 9 classes based on interactions between languages and modalities. A distinctive feature of MultiX in modeling is leveraging annotations from one language while predicting in another language, which is referred to as cross-lingual. In contrast, some methods are developed and scaled to several languages independent of one another. Finally §4 presents existing challenges in the bleeding edge of research along with guided promising directions to improve MultiX.
2. Tasks and Datasets

This section presents various tasks and the corresponding datasets as shown in Table 1.

| Task                  | Src               | Citation                                      | Languages | Gold/Silver | Parallel? |
|-----------------------|-------------------|-----------------------------------------------|-----------|-------------|-----------|
| Image Captioning      | IAPR              | Grubinger et al. (2006)                        | de, es    | Gold        | Yes       |
| Retrieval             | Pascal Sentences  | Funaki and Nakayama (2015)                    | ja        | Gold        | Yes       |
|                       | Flickr8k          | Li et al. (2010)                              | zh        | Gold Test   | Yes       |
|                       | Flickr30k         | Lan et al. (2017)                             | zh        | Gold Test   | Yes       |
|                       | Nakayama et al.   | zh                                              | ja        | Gold        | Yes       |
|                       | Ellinett et al.   | zh                                              | de, fr, cs| Gold        | Yes       |
|                       | Multi30k          | Lala and Specia (2018)                        | de, fr    | Silver + Gold| No        |
|                       | MSCOCO            | Li et al. (2019b)                             | zh        | Gold Test   | Yes       |
|                       | Retrieval         | Yoshikawa et al. (2017)                       | ja        | Silver      | Yes       |
|                       | Rajendran et al.  | de, fr                                          | Silver    | Yes         |
|                       | Hitschier et al.  | de                                              | Gold      | Yes         |
|                       | Elliott et al.    | de                                              | Gold      | Yes         |
|                       | Visual Genome     | Parida et al. (2021)                          | hi        | Gold        | Yes       |
|                       | CC                | Caglayan et al. (2021)                        | de        | Silver      | Yes       |
|                       | Flickr30k, MSCOCO | Suris et al. (2022)                           | 52 langs  | Silver      | Yes       |
| Transcription         | Video Interviews  | Jones and Muftic (2020)                        | kqz, maq  | Direct      | No        |
|                       | TED Talks         | Karakanta et al. (2020)                       | de, es, fr, it, nl, pt, ro | Direct | No |
|                       | Wilderness        | Black (2019)                                  | 700 languages | Direct | Yes (Silver) |
|                       | Twitch.tv         | Fu et al. (2017)                              | zh-tw, en | Direct      | No        |
|                       | YouTube           | Sanattra et al. (2018)                        | pt, en    | Direct      | No        |
|                       | Kinetics-600      | Wang et al. (2019b)                           | zh, en    | Gold        | Yes (Subset) |
| Description           | IKEA website      | Zhou et al. (2018)                            | en, de    | Direct      | Close     |
|                       | Euronews          | Att et al. (2017)                             | en, fr, ar, de, es, it, pt, tr, ua | Direct | Yes (Silver) |
| VQA                   | ImageNet+MSCOCO   | Ramnath et al. (2021)                         | hi, te    | Silver      | Yes       |
|                       |                    | Gao et al. (2015)                             | zh        | Gold        | No        |
|                       |                    | Koeva (2021)                                  | bg, hr, da, nl, en, fi, fr, el, it, lt, pl, pt, ro, sk, sl, es, sq, is, he, sr | Gold | No |
|                       | VQA 2.0           | Raj Khan et al. (2021)                        | hi, bn, es, de, fr, en-hi, en-bn, en-es, en-de, en-fr | Silver | Yes |
|                       |                    | Gupta et al. (2020)                           | hi, en-hi | Silver      | Yes       |
|                       | Visual Genome     | Shumma et al. (2018)                          | ja        | Gold        | Yes (Subset) |
|                       |                    | Pfeiffer et al. (2022)                        | en, de, bn, pt | Gold | Yes |
| Dialog                | Matterport3D      | Ku et al. (2020)                              | hi, te    | Gold        | No        |
|                       | Pentomino puzzle  | Zarrweti et al. (2016)                        | en, de    | Gold        | Yes       |
| Comparison            | Liu et al. (2021) | id, zh, sw, ta, tr                           |           | Gold        | No        |
| Misc                  | Alberts et al.    | alberts et al. (2021)                         | ar, zh, nl, en, fa, fr, de, it, ko, pl pt, ru, es, sv | Silver | Yes |
|                       |                    | Moneglia et al. (2014)                       | it, zh, es | Silver + Gold| No|
|                       | Sentiment Recogn. | Gella et al. (2019)                           | de, es    | Silver + Gold| Yes      |
|                       |                    | Bagher Zadeh et al. (2020)                    | es, pt, de, fr | Gold | No |

Table 1: Datasets along with languages (ISO codes) spanned, gold/silver nature of annotations and parallelism across languages.
2.1 Image Captions:

**IPAR-based:** Grubinger et al. (2006) collect a dataset of images of various locations and actions accompanied with captions in three languages including English, German, and Spanish.

**Flickr-based:** Instead of semi-synthetic captions, Flickr30k Entities Plummer et al. (2015) is extended to Japanese (F30kEnt-JP) Nakayama et al. (2020b) with phrase-to-region linking so the cross-lingual phrase-to-phrase relations can be exploited meaningfully. They are also extended to Chinese (Flickr8k-CN Li et al. (2016), Flickr30k-CN Burger et al. (2003)) with a semi-automatic and human post-editing step, and into Multi30k in German, French, Czech Elliott et al. (2016) with human translations. A similar adaptation from images and English captions of Flickr8k dataset is extended to automatically create Chinese captions Li et al. (2016) and a semi-human created test set.

**MS-COCO-based:** The MS-COCO captions Lin et al. (2014) are extended to Chinese Li et al. (2019b), Japanese Yoshikawa et al. (2017), German Rajendran et al. (2016); Hitschler et al. (2016) and French Rajendran et al. (2016). Excepting Hitschler et al. (2016), the rest are silver datasets, i.e., translated automatically from English captions.

**Visual Genome-based:** The annotations for Visual Genome Krishna et al. (2017) are partly reused by automatically translating them to Hindi using segment NMT model Parida and Bojar (2018). They are automatically translated to Hindi using segment NMT model Parida and Bojar (2018) and then humans edit the translation in based on the image. The challenge test set includes ambiguous English words (ambiguity determined by embedding similarity), which can be resolved by visual context alone. The same is replicated for Malayalam Visual Genome.

**Retrieval:** The OpenCLIR Challenge 2 is aimed to locate snippets of text and speech in documents of low-resourced languages such as Swahili. Several of the aforementioned captioning datasets are also studied for caption-retrieval in tandem to generation.

2.2 Transcriptions:

Inspired from speech translation dataset MuST-C Gangi et al. (2019) with sentence-level transcriptions, Karakanta et al. (2020) released MuST-Cinema for subtitle generation of audio-visual content. It includes audio, transcription, translation triplets of TED talks in 7 languages including German, Spanish, French, Italian, Dutch, Portuguese, Romanian. Scaling this up with videos from the wild from YouTube, Sanabria et al. (2018) presented a large-scale dataset of How2 with of instructional videos on topics with ~ 8k clips and ~ 2k hours. In addition to being multimodal, translations into Portuguese are also collected making the dataset multilingual. These audio-visual recordings are valuable for (a) scaling multimodal multilingual resources and (b) maximizing the utility of available data in low resourced languages. (a) For scaling, Jones and Muftic (2020) collected interview recordings from audio visual legacy media in N—uu, Kora and Khoekhoe languages, emphasizing on the ethical steps to gather and publish such a dataset. (b) For utilizing available data,  

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1. [https://ufal.mff.cuni.cz/malayalam-visual-genome/wat2021-english-malayalam-multi](https://ufal.mff.cuni.cz/malayalam-visual-genome/wat2021-english-malayalam-multi)
2. [https://www.nist.gov/itl/iad/mig/openclir-challenge](https://www.nist.gov/itl/iad/mig/openclir-challenge)
Black (2019) massively scales to 700 languages with around 20 hours of speech for each language based on religious recordings from YouTube annotated with a multi-pass alignment technique. In addition to the video transcriptions, the chats based on videos signal important events or highlights. Fu et al. (2017) present a dataset with 300 videos of 30-50 minute games from Twitch.tv channels based on League of Legends championships and their corresponding ∼7k chats to study video highlight prediction. Wang et al. (2019b) present VATEX based on the Kinetics-600 actions dataset Kay et al. (2017) to perform the tasks of video captioning and video-guided machine translation.

**Online descriptions:** Internationally available online shopping platforms are a rich source of product descriptions in multiple languages ranging beyond simple image captions describing product semantics and their usage. Zhou et al. (2018) present a parallel dataset of product descriptions from IKEA’s and UNIQLO’s websites in 3 languages including English, French, and German. In contrast to image captioning, the descriptions are not exactly parallel and are longer than captions. Similarly, news outlets provide internationally viable descriptions across multiple languages. Afli et al. (2017) introduced MultiNews dataset comprising of images and their descriptions spanning 9 European languages sourced from Euronews website. The articles are not automatic translations but are aligned finely over sentences from human written texts in different languages.

### 2.3 Visual Interaction:

**Visual Question Answering:** Raj Khan et al. (2021) extended VQA 2.0 Goyal et al. (2017) to a silver dataset with 6 languages using Google translation and 5 pairs of code-switched languages using matrix language frame theory Myers-Scotton (1997). Prior to this, Gupta et al. (2020) translated these questions to Hinglish using question generation method by Gupta et al. (2018). In addition to text, Rammath et al. (2021) created a synthetic dataset for spoken-VQA in 3 languages including English, Hindi, and Turkish. To increase question diversity, Gao et al. (2015) crowdsourced FM-IQA dataset based on COCO images with unconstrained human annotations for questions and answers. Later, Shimizu et al. (2018) crowdsourced a Japanese visual question answering dataset with ∼700k QA pairs based on Visual Genome and Japanese question types, which are matched to the English versions to model cross-lingual transfer.

**Vision-Language Navigation:** Extending Room2Room Anderson et al. (2018), inspired from localized narratives. Ku et al. (2020) introduce a new dataset RoomXRoom in Hindi and Telugu. Zarrieß et al. (2016) also propose PentoRef with around 20k utterances in English and German transcribed and annotated with referring expressions for reference resolution and generation.

### 2.4 Sentiment/Emotion Recognition:

Bagher Zadeh et al. (2020) introduced CMU-MOSEAS based on Youtube monologues with ∼40k sentences in 4 languages including annotations for around 20 labels for sentiment, emotion, attributes etc.,
2.5 Comparison:

There is a stream of research on pivoting over the visual representations to map multiple languages (discussed in §3). While this hypothesis is justifiable for a majority of concepts, it does not cover culturally relevant and distinguishable concepts. Comparing similar yet distinct words based on cultural relevance and ambiguity is a unique challenge to MultiX. To address this, Liu et al. (2021) introduce MARVL, focusing on culturally relevant concepts in the corresponding nativities for 6 languages of Indonesian, Mandarin Chinese, Swahili, Tamil, and Turkish. Elliott et al. (2017) introduce Ambiguous COCO with a test set of ambiguous words in German, French and English. and Gella et al. (2019) present the MultiSense dataset for disambiguating verbs in different languages in German and Spanish.

Videos: So far we have seen several datasets for static visuals, which can be extended to videos Huang et al. (2021). This Multi-HowTo100M videos dataset includes 1.2 M videos, their corresponding speech and transcriptions from 9 languages which can be used for massive pretraining.

2.6 Miscellaneous Datasets

This section covers more of the datasets in MultiX that are not covered categorically in §2. IMAGACT Moneglia et al. (2014b) is based on an ontology of actions from spontaneous speech over visuals. It is also intended to be used as a multilingual dictionary of images. Gupta et al. (2021) worked towards building a language-ontology based sets of images for object detection and segmentation. Dominant classes and thematic domains are extracted from the ontology and they are used to retrieve similar images from the web. The effort targeted 20 European languages. Alberts et al. (2021) created a knowledge graph over 900k unique images with 1.3M multilingual gloss for 14 languages.

3. Techniques

This section presents a hierarchical categorization of modeling approaches as depicted in Table 2.

3.1 Modular:

Translation-first:

A broad idea of the modular approach to the translation-first approaches is presented in Figure 2. As we can see the first step here is to translate the source language input.
Table 2: Categories of modeling approaches serving cross-lingually with feature representations for modalities and languages.

(often times unimodally in textual modality) into the processing language which is equipped with the multimodal model to predict the output. This chain of models can either be independently trained or jointly trained end to end. Often times, the strategy is to translate into the language that has a stronger performing multimodal model in a high-resource language, which resolves to be English most of the times.

Most methods for spoken-VQA Zhang et al. (2017) includes a two-step process of performing ASR and then answer prediction. In contrast, Ramnath et al. (2021) proposes to use speech embeddings directly to predict the answer. This is particularly useful when there are limited resources to perform ASR and translation from low-resourced languages. Similarly, Huang et al. (2020) use Google translate to translate the COCO captions to French and German for pretraining followed by visual pivoting for training. In the same spirit of modularity, Arora et al. (2020) approach this with individual components for speech processing,
translating the query and then performing retrieval in the target language. Dictionaries (from the Kamusi project https://kamusi.org/) and phrase based SMT Koehn et al. (2003) models with the MOSES toolkit Koehn et al. (2007) is used for query translation followed by keyword search Trmal et al. (2017) for retrieval. de Melo and Weikum (2010) also translate Wikipedia pages first using Google Translate to respond to a user’s lexical queries by responding with multilingual and multimodal information using token similarity (for the first sense) and etymological approximation. Route et al. (2019) use OpenNMT seq2seq framework to multitask decoder with input as text and MFCC features for the task of TTS and use the hidden state of the first output to predict IPA. Bugliarello et al. (2022) introduce the IGLUE benchmark by aggregating pre-existing datasets and also collecting new ones across several tasks such as —visual question answering, cross-modal retrieval, grounded reasoning, multimodal entailment etc.,. They observe that “translate-test transfer is superior to zero-shot transfer and that few-shot learning is hard to harness for many tasks” making this approach both a very strong baseline and state of the art.

**Additional data (weak labels):**

Annotating the data with additional labels that can assist in modeling is another way to approach multiple modalities and languages. This approach on a broad level is presented in Figure 3. In the case of vision and language tasks, either the images are annotated with labels in a processing language or the source language input is annotated with additional labels in a processing language. These annotations are often obtained using off-the-shelf tools as weakly supervised labels. Upon the completion of this module, these additional annotations obtained are used along with the initial inputs are given to a multimodal model for the final predictions.

Gupta et al. (2021) use image recognition models to extract object tags in English in the first stage to subsequently use them as weak labels in the encoder to decode in a different language. This cross-lingual learning from English tags helps map textual co-occurrences for different images in text modality in addition to the image information. Calixto and Liu (2017a) use global image features extracted from VGG19 as additional data to initialize the encoder and the decoder hidden states in the RNNs. Barrault et al. (2018) assimilate findings from various systems for multimodal machine translation and observe that data augmentation significantly improves the task performance. Along the same lines, Lala et al. (2018) augment n-best lists of translated data from French, German and Czech to English to train an NMT model. Despite being noisy, this augmentation of silver data performs better than the corresponding baseline.
3.2 Embedding Projections:

Fusion and Gating:

![Figure 4: Fusion based approaches](image)

Fusion based approaches combine the information from different modalities, and the text from different languages in a defined design. They can be categorized into early fusion in which the inputs are combined at the feature embedding level or late fusion where the projections are learnt by a deep task dependent network, which are combined in at a later position. While early fusion is considered an integration at the feature level, the late fusion is considered an integration at the semantic level. An example of the approaches based on fusion is presented in Figure 4 in the recent era of pretraining. The signals from both the languages are integrated using a translation based objective described in detail in the following paragraph. The objective across modalities is optimized with image region based objectives.

Zhang et al. (2020) introduce universal visual representations (UVR) to perform multimodal machine translation by leveraging a group of images that have similar topics contained in the source sentence. This similarity is determined by tf-idf scores followed by the fusion of the visual information with gating to predict the target translations. Similarly, Parida et al. (2021) performs region specific captioning by fusing image features with region coordinates features. Caglayan et al. (2021) extend the TLM (translation language model) objective Conneau and Lample (2019) to include regional image features via VTLM model that concatenates the translations of both languages as input to the same encoder optimized for masked textual and visual tokens. The model is optimized for TLM and MRC (masked region classification) where the visual and textual tokens in the input are masked. In addition, a simple concatenation of image features and source language features also demonstrate decent performance and are also used as baselines for several tasks. For instance, Parida et al. (2020) represent images using InceptionResNetv2 and text using transformers and combine their representations to perform multimodal machine translation. Similarly, Gella et al. (2019) concatenate the visual and textual features for predicting the word sense in another language. Instead of direct concatenation, Fu et al. (2017) add an MLP layer on the modality representations to predict highlights in a video. The recent era of pretraining also relies on these heavily silver standard data by using automatic translation tools to first translate the data Zhou et al. (2021) and use them for MultiX modeling.
Matching:

![Diagram of matching based approaches]

Figure 5: Matching based approaches

The matching based techniques are also specific to the task at hand. The embedding projections for both the languages are first combined. This combine multilingual embedding is matched with the visual input to predict the output. An overview of these approaches is presented in Figure 5.

Susanto et al. (2021) use the universal visual representations described earlier and compute similarities with the language encodings obtained from mBART. Similarly, Fei et al. (2021) perform entity, sentence and image retrieval on VisualSem knowledge graph by computing the similarity between image embeddings and text embeddings in multiple languages. The visual representation is derived using the CLIP image encoder Radford et al. (2021) and the textual representation is derived using the CLIP text encoder for English and SBERT model paraphrase-multilingualmpnet-base-v2 Reimers and Gurevych (2019) for other languages. An agent similar to Reinforced Cross-Modal Matching Wang et al. (2019a) is adapted by replacing LSTMs with successive 1D convolutions to encode longer utterances for multilingual navigation in RXR Ku et al. (2020). They note that despite 3 times the data, training a single multilingual agent on several languages performs worse compared to their monolingual counterparts, while the multilingual agent outperforms with a multitask setting combining annotations from Room2Room. For matching textual representations to visual inputs and combining constituents, Shi et al. (2019) optimize for the hinge triplet loss jointly by building constituency structures recursively Kitaev and Klein (2018) with a bottom-up score-sample-combine approach. The visual semantic embedding space Kiros et al. (2014) is created with cosine similarity based matching score in the joint space. Likewise, Mohammadshahi et al. (2019) computes this similarity where the text representation is a combination of multiple languages with internal alignment using kNN based algorithm. Afli et al. (2017) use word based and named entity based scoring strategies to align news corpora from Euronews spread across 9 languages.

Canonical Correlations:

Canonical Correlation Analysis (CCA) is a method to infer information from cross-covariance matrices. With multiple vectors of random variables along with correlations among these variables, then this method is used to find a linear combination of these variables with maximum correlation among themselves. This is depicted in Figure 6.
Nakayama et al. (2020a) use a generalized CCA (GCCA) Gong et al. (2014) to include English translation as an additional modality to perform phrase localization in images using Japanese text. This technique is earlier developed to use higher level semantics as the third modality to perform text-to-image alignment. Similarly, Japanese, English and images are the three modalities where the nearest embedding in the canonical subspace is retrieved. GCCA can thus perform cross-lingual retrieval. Instead of including an additional modality, Rotman et al. (2018) present partial CCA (PCCA) to maximize the canonical correlation of the multilingual descriptions in two languages conditioned on the shared variable of the image representation. The difference between PCCA and GCCA is that the former attempts to maximize the canonical correlations of all pairs of views whereas the latter condition two variables on the third shared one. Leviant and Reichart (2015) extended SimLex-999 and wordsim353 annotations to Italian, German, and Russian, which are later experimented for CCA performance by Rotman et al. (2018).

**Distillation:**

Under the continued presupposition that the performance of the multimodal models is better in a high resource language. As a teacher model is learnt in this high resource language (usually English), the student model imitates this teacher model to learn task specific parameters to achieve a generalized performance. This is presented in Figure 7.

Building on top of the monolingual multimodal models, Raj Khan et al. (2021) use distillation methods to transfer the learning to multilingual and code-mixed scenarios for VQA. The teacher network is trained based on English LXMERT model, the parameters
of which are used to train the student network to optimize for 2 mean squared errors and 2 binary cross entropy losses. The MSE are computed for the CLS token, object attention loss and the BCE losses are computed between the answer probability scores of teacher and student networks, and between the gold and the predicted answer from the student network.

3.3 Pivoting

Pivoting on the image:
Multilingual multimodal datasets are often translated to different languages for the same visual context. Huang et al. (2021) use a noise contrastive objective to the visually pivoted translation pairs between languages in inter-modal (i.e one language and visual), and intra-modal (i.e 2 languages and visual) ways. The goal of optimizing these objectives is to align the visual to the transcriptions in different languages. Prior to this, they perform pseudo visual pivoting Huang et al. (2020) motivated by back translation to align multilingual spaces for the same image. Synthetic multilingual captions from the source image are used to reconstruct the synthetic captions from their corresponding translations and for translation of the paired captions. Kádár et al. (2018) train a multilingual model to minimize the ranking loss updated for the prediction of image and caption of one language from caption in another language. A very similar approach with two pairwise ranking objectives scoring sentences and images and another scoring sentences in two different languages is also used by Calixto and Liu (2017b). Gella et al. (2017) optimize for a pivoted loss function on the image to bring gold description and image closer compared to other irrelevant captions using monolingual corpora from multiple languages.

Alignment:

![Figure 8: Alignment based approaches](image)

Alignment is the method of forming a grouped plan to relate the languages and the modalities. Typically, this is achieved using an attention matrix. The attention based methods are described in detailed after this method. Specifically, in Figure 8 the positioning
matrix between the image (on the y-axis) and one of the languages (on the x-axis) to make predictions in the second language.

Fei et al. (2021) perform cross-lingual cross-modal pretraining with a unified framework using pretrained objectives adopted from prior studies including MLM (Masked Language Modeling) Devlin et al. (2019), MRC (Masked region classification) Li et al. (2020); Su et al. (2020), TLM, CLTR (Cross-lingual text recovery), and CMTR (Cross-modal text recovery) Huang et al. (2019a). Specifically, CLTR handles alignment of the parallel sentences in different languages by using bi-linear attention mechanism to compute an attended representation of the input sentence in the source language and its parallel sentence in a different language. Similarly, CMTR computes the alignment between word features and bounding box features by computing their bi-linear attention. Similar alignment techniques are also used to compute cross-lingual attention Garg et al. (2019). Nishihara et al. (2020) use a transformer based multimodal neural machine translation model with an image and source language sentence encoder and a target language decoder. The main addition to leverage cross-lingual information is derived by minimizing the cross entropy between one attention head of the multi-head cross-lingual attention and the word alignments obtained using MGIZA Garg et al. (2019). This cross-lingual alignment techniques such as XeroAlign Gritta and Iacobacci (2021) and CrossAligner Gritta et al. (2022) is very prevalent in unimodal multilingual scenarios. Introducing a diversity objective to explicitly capture different forms in the joint embedding space is an effective way to align terms in multiple languages pivoted on an image Huang et al. (2019b). They perform multi-head attention to attend to different visual objects and the textual semantics in the caption with a margin-based diversity loss. Recently, Suris et al. (2022) present a modeling technique to learn aligned embedding space through a vision-based transitive relation across languages that learns an alignment model across languages if and only if the visuals associated with them are similar.

Attention:

Bagher Zadeh et al. (2020) use multimodal transformer Tsai et al. (2019) composed of Conv1D and transformer to encode each modality to benchmark CMU-MOSEAS. Each language is independently modeled with the visual attributes without relying on cross-lingual information. Rammath et al. (2021) use a co-attention mechanism to fuse selective information from the image and question for spoken visual question answering. Self-attention is performed on the speech signal and the question embeddings are used to query the attention on the image to answer a question from knowledge graphs represented by IaK Rammath and Hasegawa-Johnson (2020). Instead of fusing the attended representation, Shimizu et al. (2018) replace the visual attention maps learnt from English to perform VQA in Japanese. The motivation for this idea is despite varying attention maps, their foci corresponding to the answer or the subject of the question have reasonable overlap across languages. This is followed by parallel coattention between visual and textual features. Similar cross attention on a single input language also shows improvements in multimodal machine translation in addition to multitasking with the auxiliary objective to construct a vision and language joint semantic embedding Zhou et al. (2018). Attention-based NMT frameworks with attention on spatial features in the images are also used by combining multiple languages.
Singh et al. (2021). They define three types of mapping based on the source and target languages - many to one, one to many and many to many (where first and second indicate the number of source and target languages respectively). The many to one and many to many paradigms are cross-lingual where text from other languages is used during training. A similar approach of attending to the source sentence and the image is performed by Imankulova et al. (2020) for the task of simultaneous multimodal machine translation using wait-k approach. Instead of attention across languages, batching the data from different languages during training enables learning a multilingual representation Gupta et al. (2020). Sharing this representation is also extended to attention based soft layer-sharing by attending over the encoder for each language and each layer fusing the modalities with bilinear attention.

Other:
Karakanta et al. (2021) use speech translation based on an audio encoder and a text decoder using listen-and-translate Berard et al. (2016) and direct foreign speech translation Weiss et al. (2017). These techniques are combined with the efficiency of the wait-k strategy Ma et al. (2019). Karakanta et al. (2020) present an NMT based model for subtitle generation of audio visual content using a transformer based seq2seq architecture for text only (visual features are not used in the model). Liu et al. (2021) set up baselines for MARVL on monolingual multimodal models including VL-BERT Su et al. (2020), VisualBERT Li et al. (2019a), ViLBERT Lu et al. (2019), LXMERT, and by extending English based multimodal models to multilingual scenarios. UNITER Chen et al. (2020) is extended by initializing the text encoder with mBERT and XLM-R as mUNITER and xUNITER respectively. A similar approach is adopted by Mitzalis et al. (2021) to propose BERTGEN by fusing VL-BERT with M-BERT initialization. Specifically, it is demonstrated successfully for the task of MMT where unrolling is used as masking to create the next example and self attention is performed at every time step.

Systems and Analysis
Akhlaghi et al. (2020) built LARA (Learning and Reading Assistant) which is an open source platform that converts plain texts into multimodal online versions. It involves semiautomatically tagging text, adding annotations, recording audio to highlight relevant information for suitable for language learners. Along similar lines, Willemesen et al. (2018) also develop an L2 acquisition (L2TOR ITS) with a curriculum, state tracking and a template based NLG module for interaction. Vilares et al. (2020) developed a description generator module for visually-impaired users to play 3 rogue-like games (The Inner Eye, The Accessible Dungeon, Hamsun’s Amulet). They follow a modular approach to content planning, micro-planning and surface realization of the NLG system proposed by Reiter and Dale (1997) using textual features at lexical, syntactic (POS tags), semantic (Multilingual Central Repository Agirre et al. (2012)), discourse and pragmatic levels. Xu et al. (2020a) built Xiaomingbot which is a software news reading robot with the capabilities of news generation, news translation into other languages, news reading along with avatar animation. The text for summarization is represented using BERT and a neural network with sliding window is used to generate smooth animations for the reader. Poignant et al. (2016) built a framework CAMOMILE client-server platform which is a collaborative annotation framework for collecting multimodal, multimedia, multilingual (3M) data. It is used to collect data for for
MediaEval task with 20 annotators and up to 73k annotations. Rinsche (2005) presents LTC Communicator offering software web-based multilingual support for vendors of international markets to support customers across countries interacting in multiple languages, which can be extended to information exchange via visuals of the products.

**Analysis** Moneglia and Varvara (2020) perform analysis on IMAGACT Moneglia et al. (2014a) to understand the relation between thematic structure and semantic and lexical variation of action words.

### 4. Roadmap

Assimilating the takeaways from tasks and modeling for MultiX, we investigate the forefront of current challenges and promising directions.

#### 4.1 General Trends

Generally speaking, the studies on MultiX has seen a paradigm shift with pretraining that demands a vast amount of data. Unlike monolingual processing that just needs raw data for self-supervised learning, the constraints of modalities and languages requires a degree of *parallelness* in the data. Catering to this need, the field also obliged to using silver standard translated data to perform large scale modeling of MultiX compared to prior approaches of annotating gold standard multilingual data.

The base architectures or backbone models catering to the language aspect are mostly multilingual models such as mBART Liu et al. (2020), etc., Prior to the advent of pretrained multilingual models, most of the backbone architectures are CNN and LSTM based for visual and textual information respectively. Similarly, MFCC features are extracted to represent the speech modality. Some multilingual models also train on multiple languages together with an identifier token to uniquely identify to predict for that specific language Mitzalis et al. (2021).

Overall, the field of multimodality seems to be extending a welcoming hand by monolingual unimodal processing towards MultiX. However, the gap still remains owing to the inter-disciplinary topics of translation and multimodality. This creates an opportunity to progress in the field to build equitable technologies for all languages.

#### 4.2 Challenges and Directions

**Comparison to Unimodal approaches:** From the findings of the shared task in Multimodal Machine Translation, Barrault et al. (2018) note that text only models are as competitive as multimodal models. While this is a common problem in monolingual multimodal cases, this observation is also an emerging trend in MultiX owing to the lack of strong underlying backbone architectures. We encourage the community to scrupulously sub-select instances in the dataset containing concepts/words with ambiguity that enforces understanding of both modalities to predict the correct output. Maintaining the training data distributions with a wide coverage of high quality instances with this unimodal or monolingual ambiguity is promising to better compare unimodal and multimodal models.

*Direction:* Designing tasks with ambiguous relations where a single modality curtails quality predictions are critical.
Figure 9: Distribution of MultiX datasets for languages with the number of speakers and Wikipedia articles

**Few shot Cross-lingual Transfer:** Blasi et al. (2022) presented disparities in NLP technologies due to the societal and academic factors. In a similar spirit, we present the demographic utility of MultiX datasets in Figure 9, which proliferate to modeling resources. We can observe that the digital presence in terms of the number of Wikipedia articles is correlated with datasets built in these languages irrespective of the number of speakers. In this sub-optimal reality, incentivizing research in underrepresented and endangered languages Bird (2020) is practical with zero or few-shot transfer. Lauscher et al. (2020) study the relationship between the success of transfer with varying levels of tasks, language proximity, amount of target language data. concluding that few shot finetuning has significant boost over zero-shot transfer. A common approach for a multilingual multimodal model, finetune the model for the task on a high-resourced language, perform 0-shot or few-shot finetuning on the low-resourced languages.

*Direction: Leveraging shared linguistic units grounded visually at syntactic & lexical levels to maximize supervision, assists transfer from high resourced languages.*

**Multi vs Bilingual:** Multilingually aware end-to-end systems are better for error propagation Zhu et al. (2019); Xu et al. (2020b) in unimodal scenarios. Various studies demonstrate that multilingual training improves performance over bilingual training, or by extrapolation, monolingual training Kádár et al. (2018). Similarly, the asymmetric loss Vendrov et al. (2016) in pivoted models by Gella et al. (2017) suggest that multilingual information sharing is useful. This observation motivates that when collecting multimodal data for a new language, it is beneficial to collect for the same images with existing data in another language Chandu et al. (2021) to exploit caption-to-caption prediction objectives along with image prediction objectives. However, we need to be cognizant of the aberrations where Ku et al. (2020) were not able to directly improve performance by multilingual models, so they take the task diversity as an additional dimension for multitasking to improve multilingual navigation.

*Direction: Multilingual learning has the potential to enhance MultiX, which benefits from parallel/pseudo-parallel data across multiple languages.*
**Curse of Multilinguality:** Monolingual performance with fixed model capacity trained on multiple languages starts weakening with the addition of new languages, known as the curse of multilinguality Conneau et al. (2020). This problem of locked capacity can be fixed with augmentation of model parameters and data. First, augmenting data can be noisy supervision with silver annotations or unsupervised data. Second, augmenting models involves adding language specific adapters Pfeiffer et al. (2020) or multilingual tokenizers Rust et al. (2021). The language and task specific adapters are tuned separately and the adapter of the source language is replaced with that of the target language in inference for the same multimodal model. However, a very recent work by Bapna et al. (2022) showed that the curse of multilinguality does not hold when there are several more languages of the order of thousands based on experiments conducted where the authors do not observe this interference effect on a single multilingual model.

*Direction:* Adapter based tuning is a parameter-efficient way to ensure continual cross-lingual transfer for pretrained multimodal models.

**Translationese artifacts:** While translating existing monolingual multimodal resources offers developing parallel data effective for cross-lingual learning, they often fall prey to translationese without explicit caution. Translationese Koppel and Ordan (2011) is characterized as the language style resulting from a translator attempting to closely replicate the properties of source text thereby heavily biasing it. Translations are often error-proned with low-resourced languages and colloquial usage of terms adversely impacting evaluation Graham et al. (2020). Partial translations can help mitigate this. Studies show that this language style also adversely impacts the evaluation Graham et al. (2020). First, translating continuous monolingual chunks instead of full sentences inherently models cross-lingual contextual information. A multimodal code-switched stream is explored in pretraining M3P Ni et al. (2021) and in unimodal tasks Qin et al. (2020); Krishnan et al. (2021) with random replacements. Second, a hybrid approach is translating approximated or delexicalized templates and then filling in with regionally relevant tokens in the translated template Ding et al. (2022), which can also help reduce human effort and cost for annotations. Therefore, translating partial utterances grounded in entities, context, etc., mitigates translating entire source annotation, thereby reducing bias.

*Direction:* Minimizing source language artifacts to ground cross-lingual annotations curbs translationese.

**Language Pivoting:** As we studied in §3, pivoting is primarily done on the image. Realistically, availability of data for the axes, (i) paired images and text, compared to other languages, and (ii) paired translations for English is relatively more common. This imminently rises the opportunity to pivot on a resource rich languages common between both axes. Gu et al. (2018) studied this way of unpaired captioning with language pivoting performing machine translation and autoencoding with paired data to in turn perform captioning without paired data. However, selecting English as the pivot language is not the best choice Anastasopoulos and Neubig (2020) and this selection based on typological distance is still unsolved.
Direction: Pivoting on a resource rich common language is promising for unpaired learning with a preference of common language proximal to target language.

Expansive X: Societal grounding influences regional language usage, making the dialects, vernaculars, accents, idiolects and other colloquial variants different from the language itself. In addition, catering to domain shifts Ramponi and Plank (2020) in languages encourages out-of-distribution generalization. Expanding to these ever-evolving variants of Xs demands reliable evaluations in an ever-evolving area that we need to be cognizant of.

Direction: Sustainable research demands developing comparable evaluation framework leaning into the cultural differences and morphological richness.

With the rapid development of multimodal and multilingual axes independently, it is now more critical than ever to build multimodal models accommodative of several languages. With this broad goal, this paper presents categories of tasks, datasets, and methods along with sketching out existing challenges and a roadmap ahead.

Limitations
This paper studies unifying two of the important dimensions in contexts. However, the dimensions are not limited to the scope of multiple languages or modalities. First, on top of the variants discussed in §4 in “Expansive X”, domains are an important category of language usage that warrant specialized care to ensure competitive performance. This survey does not broadly include the domains within X, however, it is imperative to understand the effects of domains and distributional shifts as we progress on the dimensions of languages and modalities. Note that with the existing two dimensions, the distributional shift can occur within a language or the visual sources, thereby coupling the complexity of the space. Second, the majority of the work covered in this paper does not address underrepresented languages due to lack of existing literature. However, we need to take inspiration from the growing research on low resourced languages Hedderich et al. (2021) to ensure we learn from what works best in such unimodal cases to coalesce with the multimodal techniques. To deliver an equitable societal impact of language technologies, it is important to address this long-tail of low-resourced languages as well.

Broader Impact
The fields of multilingual NLP and multimodality are racing with the vibrant and fierce contributions from our community. However, these resources and methods are not directly trivially extensible to languages other than the one they are developed in, which is English in most cases. Hence, it is important essential to retrospect the resources and techniques that researchers proposed in MultiX to assimilate the takeaways to consequently build informed and equitable models. Extending existing vision-and-language resources to multiple languages ensures not only the re-usability of the work done so far but also builds an ecosystem to compare the scalability and robustness of the models for continued research. We hope this work can be used as an index into the wealth of scattered resources unifying
multimodality and multilinguality for researchers in both these fields to be cognizant of the challenges and promising directions to invest upon while making modeling choices.

Ethical Considerations

We do not presage any immediate ethical concerns arising directly from our work on surveying the landscape of MultiX. The taxonomy of datasets and techniques focuses on multilingual multimodality i.e., MultiX, which does not address undesired and harmful biases inherently present in the datasets. Moreover, the cultural norms dictate the linguistic acceptability of translated resources. Therefore the proposed translation based weak supervision methods need to carefully take into account cultural qualifications specific to each language and region.
Appendix A. Acronyms

Here are some of the acronyms discussed in the paper along with their expansions.

- ASR: Automatic Speech Recognition
- BCE: Binary Cross Entropy
- COCO: Common Objects in Context
- CCA: Canonical Correlation Analysis
- CLIP: Contrastive Language–Image Pre-training
- CMU-MOSEAS: CMU Multimodal Opinion Sentiment, Emotions and Attributes
- FM-IQA: Freestyle Multilingual Image Question Answering
- IaK: Image as Knowledge
- IPA: International Phonetic Alphabet
- MARVL: Multicultural Reasoning over Vision and Language
- MFCC: Mel Frequency Cepstral Coefficient
- MMT: Multimodal Machine Translation
- MSE: Mean squared error
- MuST-C: Multilingual Speech Translation Corpus
- MuST-Cinema: a Multilingual Speech Translation Cinema
- NMT: Neural Machine Translation
- OpenCLIR: Open Cross Language Information Retrieval
- OpenNMT: Open Neural Machine Translation
- QA: Question Answering
- RNN: Recurrent Neural Network
- seq2seq: sequence to sequence
- TED: Technology, Entertainment, and Design
- TTS: Text-to-Speech
- VQA: Visual Question Answering
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