LIKE A BILINGUAL BABY: 
THE ADVANTAGE OF VISUALLY GROUNDING A BILINGUAL LANGUAGE MODEL

Khai-Nguyen Nguyen
Bucknell University
Lewisburg, PA
nkn002@bucknell.edu

Zixin Tang
The Pennsylvania State University
State College, PA
zqt5035@psu.edu

Ankur Mali
University of South Florida
Tampa, FL
ankurarjunmali@usf.edu

M. Alex Kelly
Carleton University
Ottawa, Canada
alex.kelly@carleton.ca

ABSTRACT
Unlike most neural language models, humans learn languages in a rich, multi-sensory, and, often, multi-lingual environment. Conversely, language models are typically trained on only language data, and often on only one language. We hypothesize that perceptual grounding scaffolds language learning, including learning relationships between languages. To better understand multilingualism and the role of visual input in language understanding, we train a recurrent language model on images and corresponding text in English and Spanish from MS-COCO-ES. We find that visual grounding improves the model’s understanding of semantic similarity within and across languages and improves language generation. Our results provide evidence of the advantages of visually grounded language models. We posit that language learning is better understood as integral to the totality of a learner’s experiences, and thus there is a need for more naturalistic language data from multilingual speakers and multilingual datasets with perceptual grounding.

Keywords: natural language processing; multilingual models; grounded cognition; neural language models; recurrent neural network; natural language understanding

1 Introduction
With the effects of globalization on business, education, and culture, multilingualism—speaking two or more languages—is becoming more and more common. The prevalence of multilingualism and speech patterns peculiar to multilingualism creates a need for computational language models that can handle, process, and generate the language of multilingual communities.

It is well known that a person’s knowledge is inseparable from the physical or social context in which it is learned and used; as humans, we create a world model based on context [1]. Perceptual symbols theory states that language, reasoning, context, and cognition are grounded in perceptual features that provide visual clues to create world models [2]. Unlike state-of-the-art language models, humans learn languages in a rich perceptual environment. Perceptual data contributes to linguistic tasks and plays an important role in the acquisition of language in humans [3][4]. Perceptual grounding facilitates first language acquisition (e.g., the illustrations in children’s picture books) and second language acquisition (e.g., studying abroad). By using perceptual information, we can quickly understand the meaning of a new word when learning a language by mapping it to its real-world subject. Language models that incorporate visual data have a stronger correspondence to human judgments of word similarity and human reaction times on semantic priming tasks, especially for concrete nouns and visually descriptive words [5][6][7][8].

Recently it has been shown that recurrent neural network-based models are equivalent to universal computational models such as Turing Machines, even with finite precision [9][10][11] and even with bounded time [11]. As the brain
is widely understood to be a kind of Turing machine [12, 13], RNNs are an obvious choice to conduct this study. On the other hand, the self-attention layers of the popular transformer models [14] have restricted capability and fail to recognize context-free languages, even when allowed infinite precision in the weights [15], and have issues generalizing to unseen distributions. Hence to better study the role of visual grounding in multilingual language learning, we extend a Long Short Term Memory (LSTM) recurrent model with multimodal and multilingual inputs, trained on images and corresponding English and Spanish text. Our interest in images is largely due to the availability of visual datasets rather than a commitment to the vision to the exclusion of other senses being important for human-like language learning. Congenitally blind people’s language experience is perceptually grounded, just not visually grounded.

We aim to understand the process of using perceptual information in human language learning in language models, specifically facilitating multilingual learning using visual information, to examine if visual representation allows the model to understand better the relationship between words from different languages with the same semantic meaning. Perceptually grounded multilingual language models have the potential to be (1) more human-like in how they process multiple languages (i.e., better models of multilingual speakers) and (2) scaffold the acquisition of multiple languages given conditions of plentiful perceptual data and limited linguistic data (as is generally the case for human second language learners).

In what follows, we discuss related work on perceptually grounded and multilingual language modeling, describe our model, and present results (namely, overall perplexity in Spanish and English and both within and between language judgements of semantic similarity). We find that the use of visual information lowers perplexity and improves correlation to human judgements of semantic similarity both between and within languages. However, the performance improvement is least-significant for abstract words. Our results align with prior studies on images and monolingual data [16, 8]; visual grounding improves multilingual model performance on next-word prediction and semantic alignment across languages.

2 Related Work

The importance of visual or perceptual features to language comprehension is widely studied in neuro-imaging, and behavioral studies [2, 3]. These studies provide substantial evidence that language and perception can benefit each other. This can also be seen in large vision-language models, where pre-training on language benefits visual processing [17, 18]. It is also evident from studies showing an infant’s world model is efficiently created by jointly learning different modalities [19]. Children or infants rapidly learn new words by inferring and analyzing information from their physical world [20]. Bayesian cognitive models have captured the rapid dynamics of children’s language acquisition by pairing syntactic information from language experience with semantic knowledge from world experience, such the learning in the two modalities bootstrap off of each other [21]. Thus, integrating vision and language can help us better understand language acquisition in human brains and can benefit artificial intelligence systems through efficient learning and reasoning.

Multilingual language models succeed in many tasks, including language comprehension, generation, cross-lingual translations, and information retrieval. Studies have found that after fine-tuning on target language pairs, pre-trained models can successfully handle multiple multilingual tasks, including but not limited to next-word prediction, translation, language generation for code-switching sentences, and speech recognition [22, 23, 24]. However, achieving human-like performance on tasks involving integration and interactions among multiple languages is still challenging. [25] found that even though pre-trained models succeed in multiple multilingual tasks, they may not perform well in forming representations of code-switching patterns in language production, indicating a lack of sufficiently deep integration and interactions between models’ representations across languages.

Furthermore, questions of how multilingual models integrate knowledge across languages and if that integration is human-like remain a matter of study [26]. Studies have found that even when multilingual models form language-integrated representations [27] and align similar knowledge among languages under similar representations [28], the models still may not achieve satisfying results on higher-level multilingual tasks such as translation alignment and language generation. In short, more studies are needed to understand better the mechanisms of language representations of multilingualism and how representations of different languages are involved in the language generation process.

3 Model Design

Using multilingual data, we will evaluate gated recurrent models such as long-short-term memory (LSTM). In this study, we show that having vision context or semantic input helps the model better understand the syntactic structure across languages. We first define the vanilla LSTM architecture, which is defined as follows:

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\[ i_t = \sigma(W^i x_t + V^i z_{t-1}) \]  
\[ f_t = \sigma(W^f x_t + V^f z_{t-1}) \]  
\[ g_t = \phi(W^g x_t + V^g h_{t-1}) \]  
\[ o_t = \sigma(W^o x_t + V^o z_{t-1}) \]  
\[ c_t = f_t \odot c_{t-1} + i_t \odot g_t \]  
\[ z_t = o_t \odot \phi(c_t) \]

where \( W \in \mathbb{R}^{m \times n} \) are input to hidden synaptic weights with \( m \) rows and \( n \) columns, \( \odot \) represents the Hadamard product, \( V \in \mathbb{R}^{n \times m} \) are hidden to hidden synaptic weights, \( \sigma(x) \) is the sigmoid \( (e^x/(1+e^x)) \) activation function, \( \phi(x) \) is the hyperbolic tangent \( (2\sigma(2x) - 1) \). \( z_t \) represents the hidden layer at time \( t \), \( i_t \) represents the input gate at time \( t \), \( f_t \) represents the forget gate at time \( t \), \( o_t \) represents the output gate at time \( t \) and \( c_t \) represents the cell state of the network. To integrate visual context information into the LSTM, we fuse or augment the network with a computer vision system, motivated by the prior work focused on image captioning [29]. We fine-tune one of the state-of-the-art vision model (Resnet-50) [30] on our benchmarks. The vision model was originally designed to perform classification, but by training it on a large corpus, it develops semantic representations. We extract semantic-level features by extracting synaptic weights, the visual context \( c_t \), from the final pooling layer, which we use to provide the language model with visually grounded information. This visual information is then incorporated into the LSTM by multiplying it with a learnable synaptic connection matrix \( M \) and altering the model’s hidden state \( z_t \) at time \( t \) as follows:

\[ z_t = [o_t \odot \phi(c_t)] \odot (Mc). \]

where \( c_t \) is the cell state at time \( t \), \( o_t \) is the output gate, and \( \odot \) is the Hadamard product.

**Incorporating multilingualism** We utilize the multilingual pre-trained BPEmb subword embedding [31] containing 320,000 words and sub-words from 275 languages creating an embedding of size \( N \times 320000 \). This allows the model to be trained and tested in a multilingual setting. This corresponds to initializing \( W_i \) in the LSTM.

**Unimodal Multilingual LSTM** The unimodal multilingual LSTM (UM-LSTM) is an LSTM language model that utilizes the multilingual BPEmb embedding for multilingual learning. The unimodal multilingual LSTM architecture serves as the baseline model in our experiments.

**Multimodal Multilingual LSTM** The multimodal multilingual LSTM (MM-LSTM), based on the multimodal LSTM [15], but without peephole connection and utilizes the multilingual BPEmb embedding for multilingual learning. The MM-LSTM model takes two streams of input: the language input stream and the visual input stream. In the language input stream, the input text is tokenized and processed by the multilingual embedding layer and becomes the input to the LSTM. The input images are processed in the visual input stream by a frozen pre-trained ResNet50 [30]. We extract the vector produced from ResNet50’s final pooling layer to obtain a distributed representational vector of the image based on equation [7].

### 4 Experiments

**MS-COCO-ES** The MS-COCO-ES dataset [1] contains 100,000 human-annotated English captions from the MS-COCO dataset with around 19K unique tokens and 100,000 Spanish captions machine-translated from the English captions with around 21K unique tokens. Each image has five English captions and five Spanish captions. We split this data into training/validation/test sets with a ratio of 80/10/10.

#### 4.1 Training

We train both models, UM-LSTM and MM-LSTM, on the MS-COCO-ES training set with a batch size of 32 and a sequence length of 32 tokens for 15 epochs. Unlike the next-step prediction model proposed in prior work [16], all our models utilize the sequence-to-sequence training setup: Given an input sequence from 0 to \( t - 1 \), we predict its output from 1 to \( t \). We use the cross-entropy or negative log-likelihood loss function. As noted earlier, this work is focused on understanding how visual features contribute to multi-lingual language understanding. To do so, all our models are optimized to minimize negative-log likelihood. Our models focus on language understanding instead of specific tasks undertaken by image captioning or machine translation models. In other words, these models rank the output distribution.

[https://github.com/carlosGarciaHe/MS-COCO-ES](https://github.com/carlosGarciaHe/MS-COCO-ES)
based on the plausibility of the candidate output. We also clip the gradients to 2 to avoid vanishing/exploding gradient issues. We use stochastic gradient descent with an initial learning rate $\lambda = 1.0$ that is halved based on validation performance using patience scheduling = 3. Both models have one LSTM layer followed by a dropout layer with a dropout rate of 0.2. We train the models on an NVIDIA GeForce RTX 2080 Ti with 12 GB of RAM. We evaluate the models’ ability to understand the relationship between pairs of words in monolingual and cross-lingual contexts using semantic similarity judgment. All experiments are conducted for 3 trials with different random seeds. We report mean performance and standard error for all models; this also helps evaluate the uncertainty in our model’s prediction.

4.2 Semantic Similarity Judgement

The similarity of a pair of words can be calculated as the cosine similarity of the corresponding embedding vectors of the pair. We can evaluate the correctness of a model by comparing to human judgements of word similarity, using data gathered by explicitly asking participants to evaluate the synonymy or category of words $^{[32,5,33,6,34,12]}$ or tacitly inferred from semantic priming response times $^{[35,8]}$.

4.2.1 Data

The linguistic definition of word relatedness (e.g., *coffee* and *cup*) and word similarity (e.g., *coffee* and *tea*) may differ from the understanding that experiment participants have when asked to explicitly rate the similarity or relatedness of pairs of words $^{[36]}$. If the difference between relatedness and similarity is not specified to participants, the nature of the ratings is ambiguous. In our experiment, both relatedness and similarity are used as a metric to evaluate the models’ semantic understanding $^{[8]}$. We consider four relatedness and/or similarity datasets and their derivatives in Table 2.

- **SimLex-999** $^{[36]}$ consists of 999 pairs of words in English scored on a scale of 0 to 10 specifically by semantic similarity rather than relatedness.
- **MEN** $^{[5]}$ consists of 3000 pairs of words in English scored by semantic relatedness on a scale of 0 to 50. Data was collected by showing two word pairs at a time to subjects and asking them to choose the more related pair. Words in MEN have strong visual references due to the use of visual words.
- **WordSim353** $^{[37]}$ consists of 353 pairs of words in English scored by semantic similarity on a scale of 0 to 10. Since the participants are not instructed to judge for relatedness or similarity, the score is considered hybrid by recent studies. $^{[38]}$ split the dataset into two subsets, one for evaluating similarity (WordSim353-S) and one for evaluating relatedness (WordSim353-R). We abbreviate the WordSim datasets as WS.
- **RG-65** $^{[39]}$ consists of 65 pairs of words in English scored by semantic similarity on a scale of 0 to 4. Pairs are scored by examining the proportion of words common to the contexts of words A and B. $^{[40]}$ presents a Spanish version of the dataset (RG-65$_{ES}$) with the same number of word pairs as the original and a cross-lingual version in English and Spanish of the dataset (RG-65$_{EN-ES}$) with 126 word pairs.

Table 1: Number of word pairs originally in each dataset and number of word pairs used for evaluation. Pairs are dropped if they have at least one word not in the embedding matrix

| Dataset          | Original | Used |
|------------------|----------|------|
| SimLex-999       | 999      | 731  |
| MEN              | 3000     | 2037 |
| WordSim-S        | 203      | 160  |
| WordSim-R        | 252      | 195  |
| WordSim353       | 353      | 274  |
| RG-65$_{EN-ES}$  | 126      | 53   |
| RG-65$_{ES}$     | 65       | 18   |
| RG-65            | 65       | 41   |

Following the procedures in $^{[8]}$, for each model, we calculate the cosine similarity of the output embedding vectors of each word pair. We then compute the $r$ correlation coefficient between the cosine and the human annotations for each model. Pairs with at least one word not in the output embedding matrix are dropped from the calculation. The number of used pairs can be found at Table 1. We also calculate the partial correlation of the MM-LSTM model with the UM-LSTM model as the control variable.

$^{2}$The hyperparameters are chosen based on prior work $^{[16]}$. 

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Table 2: The Pearson correlation between the two models and human annotations, the partial-$r$ of the MM-LSTM with the UM-LSTM as the control variable, and the adjusted $p$-value using the procedure in [41] ($*: p < .05$, $**: p < .01$) for each LSTM hidden unit. A greater partial-$r$ means a greater portion of correlation in the human annotations is explained by the MM-LSTM than the baseline UM-LSTM model. Note: UM is Unimodal Multilingual model and MM stands for Multimodal Multilingual model.

| #Hidden units | SimLex-999 | MEN | WS-S | WS-R | WS353 | RG-65<sub>EN</sub>−<sub>ES</sub> | RG-65<sub>ES</sub> | RG-65 |
|---------------|------------|-----|------|------|------|-----------------|-----------------|------|
| #Hidden units=128 |            |     |      |      |      |                 |                 |      |
| $r_{UM-LSTM}$ | -0.055     | 0.327 | 0.293 | 0.024 | 0.154 | 0.372           | 0.317           | 0.352 |
| $r_{MM-LSTM}$ | **0.018**  | **0.425** | **0.326** | **0.03** | **0.176** | **0.486**       | **0.426**       | **0.457** |
| partial-$r$   | 0.096      | 0.314 | 0.156 | 0.09  | 0.068 | 0.336           | 0.547           | 0.333 |
| $p$-value     | *          | **   |       |       |       |                 |                 |      |
| #Hidden units=256 |            |     |      |      |      |                 |                 |      |
| $r_{UM-LSTM}$ | -0.046     | 0.364 | 0.337 | 0.043 | 0.183 | 0.421           | 0.392           | 0.373 |
| $r_{MM-LSTM}$ | **0.013**  | **0.477** | **0.358** | **0.030** | **0.190** | **0.523**       | **0.493**       | **0.472** |
| partial-$r$   | 0.094      | 0.369 | 0.127 | -0.028 | 0.052 | 0.343           | 0.435           | 0.35  |
| $p$-value     | *          | **   |       |       |       |                 |                 |      |
| #Hidden units=512 |            |     |      |      |      |                 |                 |      |
| $r_{UM-LSTM}$ | -0.052     | 0.386 | 0.342 | 0.046 | 0.188 | 0.533           | 0.436           | 0.472 |
| $r_{MM-LSTM}$ | **0.01**   | **0.493** | **0.356** | **0.058** | **0.199** | **0.571**       | **0.531**       | **0.536** |
| partial-$r$   | 0.132      | 0.365 | 0.105 | 0.042 | 0.068 | 0.284           | 0.431           | 0.290 |
| $p$-value     | **   *     | **   |       |       |       |                 |                 |      |

Table 3: The test perplexity (Lower is better ↓) of the UM-LSTM (baseline) and MM-LSTM averaged over 3 trials for each LSTM’s hidden unit size. VL+VL represents the model trained and tested with visual information, whereas VL+L indicates the model trained using visual features but tested without a visual cue. Note: CotM represents the model with fixed or non-trainable memory matrix M.

| Model          | n=128 | n=256 | n=512  |
|----------------|-------|-------|--------|
| UM-LSTM        | 18.20 | 15.29 | 14.30  |
| MM-LSTM (ours) |       |       |        |
| VL+VL (ours)   | 15.0  | 13.28 | 13.18  |
| VL+L (ours)    | 41.5  | 42.04 | 46.4   |
| CotM           |       |       |        |
| VL+VL          | 20.55 | 17.26 | 16.26  |
| VL+L           | 20.63 | 17.35 | 16.14  |

5 Results

As hypothesized, visually grounded information better assists the MM-LSTM model in learning English and Spanish. Table 3 illustrates how the MM-LSTM consistently outperforms the baseline UM-LSTM model and shows better generalization on the MS-COCO-ES dataset. In particular, to show the consistency of our results across various settings, we conduct experiments with varied hidden layer sizes ($n = 128$, 256 or 512). It can be seen throughout all hidden layer sizes that models augmented with visual clues during testing and training consistently outperform language-only models by a wide margin. Whereas it is interesting to see when we remove visual clues while testing (VL+L), the model has difficulty understanding the language. This correlates with psychological studies where authors have shown that the absence of partial vision hampers language understanding [42, 43]. Hence our “blinded” model (VL+L) shows losing visual capability hampers the overall performance. It is interesting to note that the vision+language model learns different vector space embedding representations compared to the language-only model. This is evident from the VL+L model performance, where removing visual or semantic cues leads to poor performance. To further validate our hypothesis, we fixed the learnable memory synaptic matrices $M$. In other words, the memory matrix is randomly initialized and never learned during training, and thus the model does not learn to depend on it to represent linguistic information. As evident from our result in Table 3, a model with non-learnable memory matrices (M), referred to as CotM in our table, behaves nearly identically in the presence or absence of visual cues at test, whereas the model that jointly learns our memory matrix achieves enhanced language understanding as long as it still has access to visual information when tested. This result supports the importance of jointly learning vision and language.

**Similarity-based Evaluation** We next focus on a more complex scenario concerning similarity-based evaluation. As hypothesized in this work, visual features are more human-like and can better facilitate human language learning and
Table 4: Generated captions by MM-LSTM on images randomly sampled from the MS-COCO-ES test set. For the prompt, we feed the first word of the true caption as the prompt for text generation in one language. To force the model to generate caption in the other language, we use the prompt "a" for English and "un" for Spanish.

comprehension. Thus we evaluate our model performance with human-annotated word similarity scores. In particular, we report the Pearson correlation between human similarity scores and the models’ similarity scores in Table 2. As evident from our experiments, both models positively correlate with a human-annotated score, thus showing both approaches learn useful information. However, the model coupled with visual clues consistently outperforms the language-only model and thus is much closer to human evaluation. This indicates that the MM-LSTM is more human-like than the UM-LSTM. Looking at the partial-R values in all but the WordSim-R, WordSim-S, and WordSim353 datasets, we see that the MM-LSTM’s similarity scores explain a significant correlation to the human-annotated scores with the baseline model as the control variable. While both models get negative correlation scores in the SimLex-999 dataset, partial-R values still hold for the SimLex-999 dataset, despite having negatively correlated human-annotated scores. One reason for having a negative correlation but positive R-values can be attributed to credit assignment issues which plague the generalization capability of LSTM-based models [44,45], resulting in sub-optimal performance on a few scenarios. Future work on designing forward propagation and local learning approaches might provide evidence of the importance of visual features in more difficult datasets like WordSim.
5.1 Sampling

As a “sanity check” that the MM-LSTM is working correctly and can generate text in both languages, in Table 4 we include sample text generated by the MM-LSTM using image prompts. The text was generated using beam search with top-k \(k = 10\), and top-p \(p = 0.3\) sampling. We restrict the sampling procedure to be equal to ground-truth caption length. Finally, words are ranked based on model probabilities to generate the text. As evident in Table 4, the proposed model can generate text in English and Spanish, thus demonstrating both language competencies.

6 Discussion

To test the hypothesis that visual grounding yields better language generation and more human-like semantic similarity judgments in the context of multilingual language models, we train a multimodal multilingual Long Short-Term Memory (LSTM) neural network on images and texts in English and Spanish. We compare our proposed model performance to a unimodal multilingual LSTM trained only on texts. When evaluated on semantic similarity and relatedness, the multi-modal model (MM-LSTM) outperforms the baseline unimodal model (UM-LSTM) on multiple datasets in both English and Spanish. As expected, the embeddings of the MM-LSTM model are significantly more correlated than the UM-LSTM to human judgments in the MEN dataset (English words scored on relatedness) since textual information in the data shares strong visual references. Notably, MM-LSTM is significantly more correlated to human judgments of cross-lingual word similarity than the UM-LSTM on the RG-65 \(EN-ES\) dataset, which suggests that perceptual grounding may indeed help integrate language knowledge across different languages, as we hypothesized. However, where the correlation between visual and textual information is minimal, the advantage of the visually-grounded model over the language model is unreliable and non-significant, as in the WordSim datasets.

Our experiments on semantic similarities align with our hypothesis and show that our model acquires a better representation to facilitate improved bilingual and cross-lingual language modeling whenever the corpus supports a correlation between visual and textual context. Thus visual information is useful for improving the performance of language models in terms of both language generation and correlation to human judgments of semantic similarity.

The study conducted in this work offers a promising research direction and is not confined to a single domain, such as machine learning. By providing further evidence for the importance of perceptual grounding, this study informs the study of language in psychology and cognitive science, and can aid in designing computational models to study language acquisition in the visually impaired or help us better understand how language acquisition is facilitated by knowledge from the physical world.

7 Conclusion

We explore the effect of visual grounding on a multilingual language model. We hypothesize that, like in humans, visual information can play a crucial role in the process of language learning, representation, and generation in neural language models. We propose the MM-LSTM multimodal multilingual LSTM model to study visually-aided language generation. We train the model on MS-COCO-ES, an English and Spanish image captioning dataset. In Table 3, we observe that adding visual information during training improves language generation. In Table 2, we observe that the visually grounded model better understands the relationship between words (especially nouns) within and between languages than the baseline model. It should be noted that the role of the visual context is crucial as without it, the model performed notably worse than the baseline across our experiments. In future work, we intend to design a pre-training strategy \([46]\) that jointly learns vision-language space and allows the model to extrapolate to language generation in the absence of a visual signal.

Our results provide preliminary evidence of the advantages of visually grounded language models. Future work in this area demands better datasets. The fact that the MS-COCO-ES dataset is small and machine-translated limits our ability to make strong claims. Currently, most image captioning datasets are unilingual, most multilingual datasets lack perceptual grounding of any kind, and most multilingual datasets are parallel corpora where languages are never mixed organically, lacking features characteristic of communication between multi-lingual speakers, such as code-switching. We posit that language learning is better understood as integral to the totality of a learner’s experiences across sensory modalities, and the languages are known to the learner. Thus there is a need for more naturalistic language data from multilingual speakers and multilingual datasets with perceptual grounding.
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