EMERGENT TRANSLATION IN MULTI-AGENT COMMUNICATION

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ABSTRACT

While most machine translation systems to date are trained on large parallel corpora, humans learn language in a different way: by being grounded in an environment and interacting with other humans. In this work, we propose a communication game where two agents, native speakers of their own respective languages, jointly learn to solve a visual referential task. We find that the ability to understand and translate a foreign language emerges as a means to achieve shared goals. The emergent translation is interactive and multimodal, and crucially does not require parallel corpora, but only monolingual, independent text and corresponding images. Our proposed translation model achieves this by grounding the source and target languages into a shared visual modality, and outperforms several baselines on both word-level and sentence-level translation tasks. Furthermore, we show that agents in a multilingual community learn to translate better and faster than in a bilingual communication setting.

1 INTRODUCTION

Building intelligent machines that can converse with humans is a longstanding challenge in artificial intelligence. Remarkable successes have been achieved in natural language processing (NLP) via the use of supervised learning approaches on large-scale datasets [Bahdanau et al., 2015; Wu et al., 2016; Gehring et al., 2017; Sennrich et al., 2017]. Machine translation is no exception: most translation systems are trained to derive statistical patterns from huge parallel corpora. Parallel corpora, however, are expensive and difficult to obtain for many languages. This is especially the case for low resource languages, where parallel texts are often small or nonexistent. We address these issues by designing a multi-agent communication task, where agents interact with each other in their own native languages and try to work out what the other agent meant to communicate. We find that the ability to translate foreign languages emerges as a means to achieve a common goal.

Aside from the benefit of not requiring parallel data, we argue that our approach to learning to translate is also more natural than learning from large corpora. Humans learn languages by interacting with other humans and referring to their shared environment, i.e., by being grounded in physical reality. More abstract knowledge is built on top of this concrete foundation. It is natural to use vision as an intermediary: when communicating with someone who does not speak our language, we often directly refer to our surroundings. Even linguistically distant languages will, by physical and cognitive necessity, still refer to scenes and objects in the same visual space.

We compare our model against a number of baselines, including a nearest neighbor method and a recently proposed model [Nakayama & Nishida, 2017] that maps languages and images to a shared space, but lacks communication. We evaluate performance on both word- and sentence-level translation, and show that our model outperforms the baselines in both settings. Additionally, we show

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that multilingual communities of agents, comprised of native speakers of different languages, learn faster and ultimately become better translators.

2 PRIOR WORK

Recent work has used neural networks and reinforcement learning in multi-agent settings to solve a variety of tasks with communication, including simple coordination (Sukhbaatar et al., 2016), logic riddles (Foerster et al., 2016), complex coordination with verbal and physical interaction (Lowe et al., 2017), cooperative dialogue (Das et al., 2017) and negotiation (Lewis et al., 2017).

At the same time, there has been a surge of interest in communication protocols or languages that emerge from multi-agent communication in solving these various tasks. Lazaridou et al. (2017) first showed that simple neural network agents can learn to coordinate in an image referential game with single-symbol bandwidth. This work has been extended to induce communication protocols that are more similar to human language, allowing multi-turn communication (Jorge et al., 2016), adaptive communication bandwidth (Havrylov & Titov, 2017) and multi-turn communication with a variable-length conversation (Evtimova et al., 2017), and simple compositionality (Kottur et al., 2017; Mordatch & Abbeel, 2017).

In machine translation, our work is related to image-guided approaches (Calixto et al., 2017; Elliott & Kádár, 2017; Caglayan et al., 2016). It is also related to previous work on multiagent translation for low-resource language pairs (without grounding) (He et al., 2016a) and learning multimodal multilingual representations (Gella et al., 2017). It was recently shown that zero-resource translation is possible by separately learning an image encoder and a language decoder (Nakayama & Nishida, 2017). The main difference to our work is that their models do not perform communication.

3 TASK AND MODELS

3.1 COMMUNICATION TASK

We let two agents communicate with each other in their own respective languages to solve a visual referential task. One agent sees an image and describes it in its native language to the other agent. The other agent is given several images, one of which is the same image shown to the first agent, and has to choose the correct image using the description. The game is played in both directions simultaneously, and the agents are jointly trained to solve this task. We only allow agents to send a sequence of discrete symbols to each other, and never a continuous vector.

Our task is similar to Lazaridou et al. (2017), but with the following differences: communication (1) is bidirectional and (2) of variable length; (3) the speaker is trained on both the listener’s feedback and ground-truth annotations; and (4) the speaker only observes the target image and no distractors.

Let $P_A$ and $P_B$ be our agents, who speak the languages $L_A$ and $L_B$ respectively. We have two disjoint sets of image-annotation pairs: $(I_A, M_A)$ in language $L_A$ and $(I_B, M_B)$ in language $L_B$.

**Task in language $L_A$** : $P_A$ is the speaker and $P_B$ is the listener.

1. A target image and annotation $(i, m) \in \{I_A, M_A\}$ are drawn from the training set in $L_A$.
2. Given $i$, the speaker ($P_A$) produces a sequence of symbols $\hat{m}$ in language $L_A$ to describe the image and sends it to the listener. The speaker’s goal is to produce a message that is both an accurate prediction of the ground-truth annotation $m$, and helps the listener ($P_B$) identify the target image.
3. $K - 1$ distracting images are drawn from $I_A$ at random. The target image $i$ is added to this set and all $K$ images are shuffled.
4. Given the message $\hat{m}$ and the $K$ images, the listener’s goal is to identify the target image.

**Task with language $L_B$** : The agents exchange the roles and play similarly.
We explore two different settings: (1) a word-level task where the agents communicate with a single word, and (2) a sentence-level task where agents can transmit a sequence of symbols.

3.2 Model Architecture and Training

Each agent has an image encoder, a native speaker module and a foreign language encoder. In English-Japanese communication, for instance, the English-speaking agent $P_A$ consists of an image encoder $E_{IMG}^A$, a native English speaker module $S_{EN}^A$, and a Japanese encoder $E_{JA}^A$. Similarly, the Japanese-speaking agent $P_B = (E_{IMG}^B, S_{JA}^B, E_{EN}^B)$.

![Diagram](image)

(a) Communication task.

(b) Translation.

Figure 1: Sentence-level communication task and translation between English and Japanese. (a) The red dotted line delimits the agents and the gray dotted line delimits the communication tasks for different languages. Representations residing in the multimodal space of Agent A and B are shown in green and yellow, respectively. (b) An illustration of how the Japanese agent might translate an unseen English sentence to Japanese.

We now illustrate the architecture of our model using the English part of the communication task as an example (upper half of Figure 1a). We first describe the sentence-level model.

**Speaker ($P_A$)** Given an image-annotation pair $(i, m) \in \{I_{EN}, M_{EN}\}$ sampled from the English training set, let $i$ be represented as a $D_{img}$-dimensional vector. $P_A$’s speaker encodes $i$ into a $D_{hid}$-dimensional vector with a feedforward image encoder: $h_0 = E_{IMG}^A(i)$.

Our speaker module $S_{EN}^A$ is a recurrent neural network (RNN) with gated recurrent units (GRU, [Cho et al., 2014]). Our RNN takes the image representation $h_0$ as initial hidden state and updates its state as $h_{t+1} = \text{GRU}(h_t, m_t)$ where $m_t$ is the $t$-th token in $m$. The output layer projects each hidden state $h_t$ over the English vocabulary $V_{EN}$, followed by a softmax to predict the next token: $p_t = \text{softmax}(W_o h_t + b_o)$. The speaker’s predictions are trained on the ground truth English annotation $m$ using the cross entropy loss:

$$J_{EN}^{spk} = -\frac{1}{N_{EN}} \sum_{(i, m)} \sum_{t=1}^{T_m} \log p(m_t|m_{(t-1)}, i),$$

where $N_{EN}$ is the size of the English training set, and $T_m$ is the length of $m$.

To generate a sequence of tokens, we sample from the categorical distribution $\text{Cat}(p_t)$. However, sampling is a non-differentiable computation. To allow our model to be end-to-end differentiable, we use the straight-through Gumbel-softmax estimator ([Jang et al., 2017] [Maddison et al., 2017]) to sample from $\text{Cat}(p_t)$ and let the gradient flow, while the speaker sends a sequence of discrete symbols. The message $\hat{m}$ is a sequence of one-hot vectors: $\hat{m} = \{y_t\}_{t=1}^{T_m}$, where $y_t = \text{Gumbel}\_\text{ST}(p_t)$ is discretized in the forward pass.
**Listener** \((P_B)\) The Japanese-speaking agent \(P_B\) encodes the \(K\) images into \(D_{hid}\)-dimensional multimodal space with its own feedforward image encoder: \(\{E^{B}_{IMG}(i_k)\}_{k=1}^{K}\). It also feeds each token from \(\hat{m}\) into its English encoder RNN with \(D_{hid}\)-dimensional hidden states: \(s_{t+1} = \text{GRU}(s_t, \hat{m})\). Taking the last hidden state, the representation of \(\hat{m}\) is a \(D_{hid}\)-dimensional vector: \(E^{B}_{EN}(\hat{m}) = s_{T_m}\). Note, that encodings of the images and the message have the same dimensionality.

To encourage the listener to align the message representation closest to the target image, it is trained using a cross entropy loss where the logits are given by the reciprocal of the mean squared error (MSE) between the target image and the message representation: \(\{1/(E^{B}_{EN}(\hat{m}) - E^{B}_{IMG}(i_k))^2\}_{k=1}^{K}\).

\[
  J_{\text{lsn}}^{EN} = -\frac{1}{N_{\text{EN}}} \sum_{i \in I_{\text{EN}}} \sum_{\hat{m}} \log \left(1/(E^{B}_{EN}(\hat{m}) - E^{B}_{IMG}(i))^2\right)
\]

We found this formulation to give better validation performance than directly minimizing the MSE, and leave the more thorough comparison and analysis between this loss and the other alternatives, such as ranking loss, as future work.

**Training** These two agents are jointly trained by minimizing the sum of speaker and listener loss:

\[
  J = \sum_{x \in \{\text{EN,JA}\}} (J^x_{\text{spk}} + J^x_{\text{lsn}}).
\]

Note that the listener is only trained on \(J_{\text{lsn}}\), while the speaker is trained on both \(J_{\text{lsn}}\) and \(J_{\text{spk}}\).

**Word-level model** The word-level model has a similar architecture to the sentence-level one: instead of an RNN, the speaker module \(S^A_{EN}\) is a feedforward layer that projects \(h_0\) over the native vocabulary. We again use a straight-through Gumbel-softmax to sample a one-hot vector. Similarly, the foreign language encoder consists simply of the \(D_{hid}\)-dimensional foreign word embeddings.

**General training details** In both word- and sentence-level experiments, we use 2048-dimensional pre-softmax features from a pre-trained ResNet with 50 layers \(\text{He et al.} [2016b]\), instead of raw images. Our models are trained using stochastic gradient descent with the Adam optimizer \(\text{Kingma \\ & Ba} [2014]\). The norm of the gradient is clipped with a threshold of 1 \(\text{Pascanu et al.} [2013]\).

### 3.3 How Translation Arises

To translate an English sentence \(m_{\text{src}}\) to Japanese, we let the Japanese-speaking agent \(P_B\) encode \(m_{\text{src}}\) with its English encoder, and decode this representation using its Japanese speaker module: \(m_{\text{hyp}} = S^B_{EN}(E^B_{EN}(m_{\text{src}}))\) (see Figure 1b). Solving the image referential task requires aligning the foreign (source) sentence representation with the representation of the correct image, which will allow the speaker module to describe the source sentence in its native (target) language, as though it were an image.

### 4 Word-level Experiments

**Task and dataset** We train our model on a word-level communication task, where the agent \(P_A\) is given an image and needs to find the right word to communicate it so that the agent \(P_B\) can pick the right image from a set of distractors. We use the Bergsma500 dataset \(\text{Bergsma \\ & Van Durme} [2011]\), a collection of up to 20 image search results per concept and language, for 500 common concepts across 6 languages: English, Spanish, German, French, Italian and Dutch. We train on 80% of the images, and choose the model with the best communication accuracy on the 20% validation set when reporting translation performance.

**Baselines** For our baselines, we use a variety of nearest neighbor methods based on similarity metrics in the ConvNet feature space \(\text{Kiela et al.} [2015]\). Given a set of 20 ResNet image vectors per concept and language, we can either average them (CNN-Mean) or take the dimension-wise maximum (CNN-Max) to derive a single aggregated image vector. To find the German word for dog,
for instance, we rank all German words based on cosine similarity between the image vector of dog and their image vectors. We then examine precision in retrieving the correct German word, Hund. Alternatively, we also consider the similarities between individual image vectors instead of their aggregation: Bergsma & Van Durme (2011) propose taking the average of the maximum similarity scores (CNN-AvgMax) and the maximum of the maximum similarity scores (CNN-MaxMax).

**Experimental settings** We train with 1 distractor \((K = 2)\), learning rate \(3e^{-4}\), and minibatch size 128. The embedding and hidden state dimensionalities are set to 400. We use the Gumbel-softmax with temperature \(\tau = 1.0\). When the validation accuracies of both the speaker and the listener stop improving, training terminates and we evaluate the performance on the word-level translation task, as described in §3.3. We consider all 15 language pairs in both directions, reporting results averaged across 30 translation scenarios.

**Results** In all 15 language pairs, we observe that translation performance improves with communication performance (Figure 3). In translation, our model outperforms all the other nearest neighbor baselines (Table 2). This shows that our agents can learn foreign word representations that are not only effective in solving referential tasks, but also more meaningful than raw image features in translation. It also demonstrates that communication helps to identify and learn correspondences between concepts in different languages.

| Model          | P@1 | P@5 | P@20 |
|----------------|-----|-----|------|
| CNN-AvgMax     | 33.00 | 68.30 | 78.36 |
| CNN-MaxMax     | 49.85 | 65.91 | 77.17 |
| CNN-Mean       | 51.89 | 66.47 | 77.14 |
| CNN-Max        | 33.81 | 50.62 | 65.81 |
| Our model      | 56.39 | 70.43 | 79.19 |

Figure 2: Word-level translation results, in precision at \(k\). Results are averaged over 30 translation scenarios.

Figure 3: Learning curve for the EN-DE word-level model.

**Qualitative analysis** As our agents learn foreign words by grounding them in visual space, we expect the learned foreign word embeddings to be semantically similar to corresponding images. We inspect the nearest neighbors of foreign word embeddings in each language, and find that concepts with similar images indeed have close word embeddings. See Appendix A for a discussion and relevant examples.

5 **Sentence-level Experiments**

**Task** We next train our models on a sentence-level communication task where agent \(P_A\) is given an image, and needs to communicate its content in a sentence in its language \(L_A\) to allow agent \(P_B\) to identify the right image from a set of distractors (see §3.1).

**Datasets and preprocessing** We use three datasets of images with annotations in multiple languages. The Multi30k (Elliott et al., 2016) dataset contains 30k images and two types of bilingual annotations for two different tasks:

- (Task 1) Translation task from English to German, where this can be aided by images; and
- (Task 2) German image captioning task, where this can be helped with English captions.

Training data for Task 1 consists of 1 English caption for each image and its German translation, translated by a professional translator. For Task 2, five English and five German captions are collected independently for every image. We use the original data split: 29k training, 1k validation and 1k test images.

Additionally, we train on English-Japanese. We use MS COCO (Lin et al., 2014; Chen et al., 2015), which contains 120k images and 5 captions per image, and STAIR (Yoshikawa et al., 2017), a collection of Japanese annotations of the same dataset (also 5 per image). Following Karpathy & Li (2015), we use 110k training, 5k validation and 5k test images.
To ensure no parallel corpus is used to train our models, we partition the images in the training set into two parts (one for each language) and only use captions in one language for each half and not the other. With Multi30k, for instance, we have 14.5k English training images (whose German captions we discard) and 14.5k German training images.

We use tokenized Japanese captions in STAIR.\footnote{https://github.com/STAIR-Lab-CIT/STAIR-captions} We lowercase, normalize and tokenize English and German captions using preprocessing scripts from Moses.\footnote{https://github.com/moses-smt/mosesdecoder} In addition, we tokenize German captions into subword symbols using the byte pair encoding (BPE) algorithm with 10k merge operations (Sennrich et al., 2015).

**Baselines** We compare against several baselines that similarly only make use of paired image-language data. In increasing order of sophistication:

**Nearest neighbor** To translate an English sentence into German, we use its corresponding image to find the closest image in our German training set. We then retrieve all corresponding German captions and compute BLEU score against the ground truth German test captions. This model is similar to our word-level nearest neighbor baselines.

**NMT with neighboring pairs** Given our non-aligned training set of English and German image captions, without any overlapping images, we can form new EN-DE sentence pairs by finding the closest German training image for every English training image. We then pair every corresponding German caption with every corresponding English caption, and train a standard NMT model without attention (Cho et al., 2014; Sutskever et al., 2015) on these pairs.

**N&N** We implement and train end-to-end models from (Nakayama & Nishida, 2017). Their two-way model learns separate encoders to align the source language and images in a multimodal space. Then, a captioning model in the target language is trained on image representations, and is used to decode source representations to translate them. While their model unit-normalizes the output of every encoder, we found this to consistently hurt performance, so do not use normalization for fair comparison with our models. Their three-way models align both source and target languages with images using a target language encoder. They propose three different decoders, all of which we implement and evaluate. These approaches are most similar to our model, but are trained on a fixed corpus, without interaction between agents or learned communication.

**Models** In our base model, the agents learn to speak their native languages simultaneously as they learn to communicate with each other (not pretrained). In a sense, this can be seen as a tabula rasa situation where both agents start from a blank slate. However, we also experiment with agents who already speak their languages, by using the weights from pretrained image captioning models in both languages to initialize our speaker modules and image encoders. Furthermore, we can freeze the parameters of image encoders or speaker modules to investigate their impact on communication and translation performance. In the most extreme case, where we pretrain and fix the speaker modules and image encoders (pretrained, spk & enc fixed), we only train the foreign language encoder, using only the listener loss. All other models are trained on both the speaker and listener loss.

**Experimental settings** We train with 1 distractor ($K = 2$) and minibatch size 64. The hidden state size and embedding dimensionalities are 1024 and 512, respectively. Learning rate, dropout rate, Gumbel-softmax temperature are tuned on the validation set for each task.

We train the model on the communication task, and early stop when the validation translation BLEU score stops improving. We do not use beam search on any of the models, and instead only use greedy decoding.

**Results** We find that naively looking up the nearest training image and retrieving its captions gives relatively poor BLEU scores (Table 1, Nearest neighbor). On the other hand, training an NMT model on these visually closest neighbor pairs gives much better translation performance.

We observe that the approaches from (Nakayama & Nishida, 2017) perform worse than our models. We conjecture that our listeners become better at aligning multimodal representations compared to
Table 1: Test BLEU scores for each model and dataset. The best performer for each dataset is shown in bold. *Pretrained* denotes initializing the speaker modules and image encoders with pretrained image captioning models. *Fixed* denotes fixing the parameters of either the speaker module or the image encoder.

| Baselines                                      | Multi30k Task 1 | Multi30k Task 2 | COCO & STAIR |
|-----------------------------------------------|-----------------|-----------------|--------------|
|                                               | EN-DE DE-EN     | EN-DE DE-EN     | EN-JA JA-EN  |
| Nearest neighbor                              | 1.41 1.77       | 3.75 5.87       | 15.88 10.94  |
| NMT with neighboring pairs                    | 3.54 5.84       | 8.97 15.96      | 27.33 23.14  |
| N&N, 2-way, img decoder                       | 3.27 5.3        | 8.95 17.15      | 27.67 22.58  |
| N&N, 3-way, desc decoder                      | 4.46 5.21       | 10.32 15.68     | 23.27 15.34  |
| N&N, 3-way, both decoder                      | 4.17 6.4        | 10.37 17.03     | 27.94 22.23  |
| not pretrained                                 | 5.13 6.51       | 11.23 16.64     | 27.98 22.36  |
| pretrained, spk & enc fixed                   | 5.23 6.7        | 10.93 16.97     | 29.57 23.45  |
| pretrained, spk fixed                          | 5.51 6.76       | 11.4 17.6       | 27.07 22.12  |
| pretrained, not fixed                          | 4.08 5.83       | 11.05 17.06     | 27.93 22.39  |

In contrast to (Nakayama & Nishida, 2017), where the best performance was obtained with end-to-end trained models, we find that our models benefit from initializing weights with pretrained captioning models. The model with fixed speaker modules and non-fixed image encoders gave best results in two out of three datasets, even outperforming the (spk & enc fixed) model, which only produces messages that are trained to predict ground truth captions. This shows that learning to send messages differently from the pretrained image captioning models achieves better translation performance than learning to send ground truth captions. We provide sample translations for our baselines and models in Appendix B. We also qualitatively examine completely zero-resource German-Japanese translation in Appendix E.

We compare our results with a standard non-attentional NMT model trained with parallel data. On COCO & STAIR, we observe a gap of approximately 5 BLEU compared to our best models (34.61 for EN-DE, 28.84 for JA-EN). On Multi30k Task 2, which is slightly smaller, the gap grows to 7-8 BLEU scores (19.22 for EN-DE, 24.11 for DE-EN). On Multi30k Task 1, which is the smallest, we observe nearly 20 BLEU score difference (23.95 for EN-DE, 25.14 for DE-EN). Note, however, that our speaker modules and foreign language encoders are trained on half the dataset, whereas the NMT model is trained on the entire dataset. In other words, we find that our approach performs closer to supervised NMT as more training data is available, but that there still is a gap, which is unsurprising given the lack of parallel data.

**Qualitative analysis** We conjecture that our models learn to translate by having a shared visual space to ground source and target languages onto. Indeed, we show that our translation system fails without a common visual modality (see Appendix C). We note that using a larger number of distractors helps the model learn faster initially, but does not affect translation performance (see also Appendix C).

As expected, our models struggle with translating abstract sentences, although we observe that they can capture some visual elements in the source sentence (see Appendix D). This observation applies to most current grounded NMT systems, and it is an avenue worth exploring in future work but beyond the scope of the current work.

Inspired by the movie *Arrival* (2016), we show that our agents can learn to play the referential game, and learn to translate, using an alien language (Klingon) with only a small number of captions (see Appendix F). This example is meant to illustrate the point that our models can learn to translate even in situations where there is no knowledge whatsoever of the other language, and where educating a professional translator would potentially take a long time.
6 Multilingual Community of Agents

Task and dataset Humans learn to speak languages within communities. We next investigate whether we can learn to translate better in a community of different language speakers, where every agent interacts with every other agent. We use the recently released multilingual Multi30k Task 1, which contains annotations in English, German and French for 30k images. We train a community of three agents (each speaking one language) and let each agent learn the other two languages simultaneously.

We again partition the set of images into two halves (M1 and M2 in Figure 4), and ensure that the speaker and the listener do not see the same set of images (see Figure 4a for example). We experiment with two different settings: 1) a full community model, where having a multilingual community allows us to expose agents to more data than in the single-pair model while maintaining disjoint sets of images between agents (Figure 4c); and 2) a fair community model where the agents are trained on exactly the same number of training examples (Figure 4b). We point out that the difference in training data should mainly affect the speaker module; the image encoder and foreign language encoder are trained on the same number of examples in all the models.

![Figure 4: Training data in single-pair and community models. M1_EN denotes the English annotations for the first half images in Multi30k. Red and blue indicate training data for the English and the German agents’ speaker modules, respectively. Note that compared to the single pair model, English and German speakers see twice the amount of training data in the full model, but see the same number of examples in the fair model.](image)

Experimental settings We train our base model (not pretrained) on a three-way sentence-level communication task. We sample a language pair with an equal probability every minibatch and let the two agents communicate. Every agent has one image encoder, one native speaker module and two foreign language encoders. We tokenize every corpus using BPE with 10k merge operations. We use the same architecture for the three models: $D_{emb} = 128, D_{hid} = 256$ and we use a learning rate of $3e-4$ and batch size of 128. We tune the dropout rate on the validation set.

| Model | EN-DE | DE-EN | EN-FR | FR-EN | DE-FR | FR-DE |
|-------|-------|-------|-------|-------|-------|-------|
| Single | 3.26  | 5.29  | 4.56  | 5.32  | 3.99  | 3.67  |
| Fair  | 2.79  | 5.63  | 4.24  | 6.03  | 4.48  | 3.56  |
| Full  | 4.42  | 7.13  | 6.72  | 7.98  | 5.94  | 4.94  |

![Figure 5: DE-EN learning curve for different models.](image)

Table 2: Multi30k Task 1 Test BLEU scores. Results should be compared with the first two columns in Table 1.

Results We observe that multilingual communities learn better translations. By having access to more target-side data, the full community model achieves the best translation performance in every language pair (Table 2). The fair community model achieves comparable performance to the single pair model.

We show the learning curves of different models in Figure 5. The full community model clearly learns much faster than the other two. The fair community also learns faster than the single-pair model, as it learns with equivalent speed but with less exposure to individual language pairs, since we sample a language pair for each batch, rather than always having the same one.
7 Conclusions and Future Work

In this paper, we have shown that the ability to understand a foreign language, and to translate it in the agent’s native language, can emerge from a communication task. We argue that this setting is natural, since humans learn language in a similar way: by trying to understand other humans while being grounded in a shared environment.

We empirically confirm that the capability to translate is facilitated by the fact that agents have a shared visual modality they can refer to in their respective languages. Our experiments show that our model outperforms recently proposed baselines where agents do not communicate, as well as several nearest neighbor based baselines, in both sentence- and word-level scenarios.

In future work, we plan to examine how we can enrich our agents with the ability to understand and translate abstract language, possibly through multi-task learning.

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A  Word-Level Nearest Neighbor Analysis

Table 3 showcases three concepts in English and German, where for each concept, the most representative image is shown, as well as the five nearest neighboring words (by cosine similarity).

| Word   | Neighbors                                      |
|--------|------------------------------------------------|
| (a) Galaxy | Universe, Comet, Meteor, Exoplanet, Planet   |
| (b) Galaxie | Universum, Exoplanet, Komet, Meteor, Planeten |
| (c) Plant   | Leaf, Flower, Sunflower, Tree, Cucumber       |
| (d) Pflanze | Blatt, Gurke, Blume, Baum, Garten            |
| (e) Fox     | Celebrity, Girl, Hair, Woman, Bell            |
| (f) Fuchs   | Känguru, Löwe, Hirsch, Esel, Wolf            |

Table 3: Nearest neighbors of foreign word embeddings learned from communication, along with a sample image for each concept in the dataset. The English word embeddings were learned by the German agent and vice versa.

We note that nearest neighbors for most words correspond to our semantic judgments: galaxy is closest to universe in English and Galaxie to Universum in German. Similarly, plant or Pflanze is closest to leaf or Blatt. For concepts that evoke different senses across languages, however, we observe different nearest neighbors. For example, most images for Fox in the dataset contain a person, whereas images for Fuchs contain an animal. This encourages the German agent to associate Fox closely with Celebrity and Girl, whereas the English agent learns that Fuchs is a furry animal, similar to Känguru or Löwe.

B  Sentence-Level Sample Translations

| Src | ein mann hängt an einem seil mit rollen das über ein wasser gespannt ist. ein skateboarder an einer böschung zu einem parkplatz. ein hund springt auf einer wiese vor einem weißen zaun in die luft. |
| Ref | a man wearing bathing trunks is parasailing in the water. a skateboard is grinding on a curb with his skateboard. a dog runs on the green grass near a wooden fence. |
| NN  | police watch some punk rock types at a protest. a man is standing on the streets taking photographs. a brunette photographer is kneeling down to take a photo. |
| NMT | a man in a blue shirt is riding a bike. a man in a blue shirt is riding a bike. a man in a blue shirt is walking down the sidewalk. |
| N&N | a man in a wetsuit is surfing a large wave. a man in a blue shirt and black pants is skateboarding. two dogs playing with a ball in the grass. |

Table 4: Sample DE-EN translations from Multi30k Task 2 test set. Images were not used to aid translation and are only shown for references. We show the source sentence as Src and one of the five target sentences as Trg. The outputs from the nearest neighbor baseline are shown as NN, NMT baseline with neighbor pairs as NMT, the 3-way, both decoder model from [Nakayama & Nishida, 2017] as N&N, and our (pretrained, spk fixed) model as Model.
In Table 4, we compare sample translations from our nearest neighbor and NMT baselines, as well as the best model from (Nakayama & Nishida, 2017) and our best model. We observe that the nearest neighbor baseline generates translations that are mostly unrelated to the reference sentence. The NMT baseline, on the other hand, often generates the correct subject of the sentence, and seems capable of capturing the main actor in the scene. The 3-way, both decoder model from (Nakayama & Nishida, 2017) captures the main actors and the environment in the scene. Our model appears to capture even the minor details, such as quantity (number of dogs) and specific activity (parasailing, skateboarding).

C **Sentence-level Qualitative Analysis**

![Figure 6: Sharing $E^f$](image)

![Figure 7: Number of distractors.](image)

We conjectured that grounding the native and foreign languages into a shared visual space allows agents to understand foreign languages. To verify this, we trained our base model (not pretrained) on COCO & STAIR, where agents have language-specific image encoders, e.g. the English agent has two separate image encoders: one for the English speaking module and another for the Japanese encoder. We compare this with our original model with the same architecture. We plot the communication accuracy and JA-EN validation BLEU scores in Figure 6. Red curves indicate validation communication accuracy (left axis), and green curves indicate BLEU score (right axis). Solid lines denote the standard model and dotted lines denote the model without sharing the image encoder.

We observe no significant difference in the communication performance: the model that does not share the image encoder performs just as well in the communication task. However, translation performance greatly suffers without access to the shared visual modality.

In Figure 7, we show the learning curve of four base models, with different number of distractors ($K$). We observe that a larger number of distractors helps the model learn faster initially, but otherwise gives no performance benefit.

D **Translation in Non-concrete Domains**

As our agents understand foreign languages through grounding in the visual modality, we investigate their ability to generalize to non-visual, abstract domains. We train our (pretrained, spk fixed) model on Multi30k Task 2, and let it translate German sentences from WMT’15 DE-EN validation and test set. See Table 5.

We note that our model is able to capture some visual elements in a sentence, such as snow or mountain, but generally produces poor quality translations. We observe that most words in the source sentence from WMT’15 do not occur in Multi30k’s training set, hence our model mostly receives <UNK> vectors.

E **Zero-resource Translation**

To showcase our models’ ability to learn to translate without parallel corpora, we train our base model on a communication task between a low-resource language pair: German and Japanese. We take the German corpus from Multi30k Task2, the Japanese corpus from STAIR, and train two
models on a sentence-level communication task between the two languages. In Tables 6 and 7 we show the Japanese source sentence (src), the model output in German (hyp), and their translation to English using Google Translate. We observe that our model mostly generates reasonable sentences, and captures properties such as color and action in the scene.

| Src | Schnee liegt insbesondere auf den Straßen im Riesengebirge und im Gebirge Orlické hory. |
|-----|------------------------------------------------------------------------------------------|
| Ref | Snow is particularly affecting the roads in the Krkonose and Orlicke mountains.          |
| Hyp | a man is standing on a snow covered mountain.                                              |

| Src | Das Tote Meer ist sogar noch wärmer und dort wird das ganze Jahr über gebadet. |
|-----|--------------------------------------------------------------------------------|
| Ref | The Dead Sea is even warmer, and people swim in it all year round.               |
| Hyp | a man is surfing in the ocean.                                                   |

| Src | Es folgten die ersten Radfahrer und Läufer um 10 Uhr. |
|-----|--------------------------------------------------------|
| Ref | Then it was the turn of the cyclists and runners, who began at 10 am.            |
| Hyp | a man in a red and white uniform is riding a dirt bike in front of a crowd.      |

| Src | Das Baby, das so ergreifend von einem Spezialeinsatzkommando in Sicherheit getragen wurde |
|-----|------------------------------------------------------------------------------------------|
| Ref | The baby who was carried poignantly to safety by a special forces commando             |
| Hyp | a baby in a yellow shirt is sleeping.                                                    |

Table 5: Sample translations from WMT’15 DE-EN validation and test set.

| Src | フリスビーをキャッチしようと構える犬 |
|-----|----------------------------------|
| Hyp | ein hund fängt einen frisbee.     |

| Src (en) | Dog keeps trying to catch Frisbee |
|---------|----------------------------------|
| Hyp (en) | a dog catches a frisbee.          |

Table 6: Sample JA-DE translations
To demonstrate our models’ ability to learn to translate only with monolingual captions, we experiment with a language for which no parallel corpus exists, nor the knowledge of the language itself: Klingon. As no image captions are available in Klingon, we translate 15k English captions in Multi30k Task 1 into Klingon pIqaD using Bing Translator. We tokenize the Klingon captions and discard words occurring less than 5 times in the training data. We then train our base model (no pre-training) on English and Klingon communication. In Tables 8 and 9, the source sentence in English is shown as src, the Klingon model output in hyp, and the English translation of the output in hyp (en) (using Bing Translator). Although the Klingon training data is noisy and imperfect, we observe that our model learns to translate only with 15k Klingon captions. This example illustrates how we can learn to translate even if there is no knowledge of the other language, and where a professional translator would take a long time to first acquire the other language.
a brown dog picks up a <UNK> g from a stone surface.
a woman in a mostly black outfit and white helmet riding a bike with blurred trees in the background.
a man sings and plays the guitar into a microphone.

Brown the meat in you must go through grass bicycle ride on him, saying, this man shirt Red and purple, and bald.
It was, he was a man and song microphone.

Figure 9: Sample English-Klingon translations